

Controlling Smart Inverters using Proxies: A Chance-Constrained DNN-based Approach

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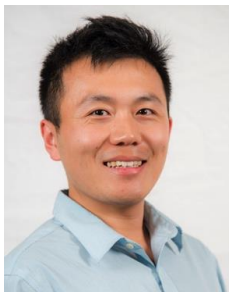
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*Panel on Machine Learning Applications in Power
Distribution System Operation*



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Acknowledgements

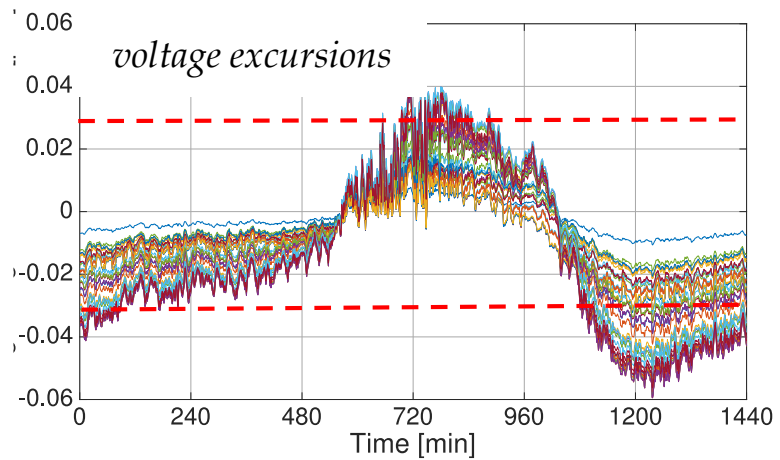
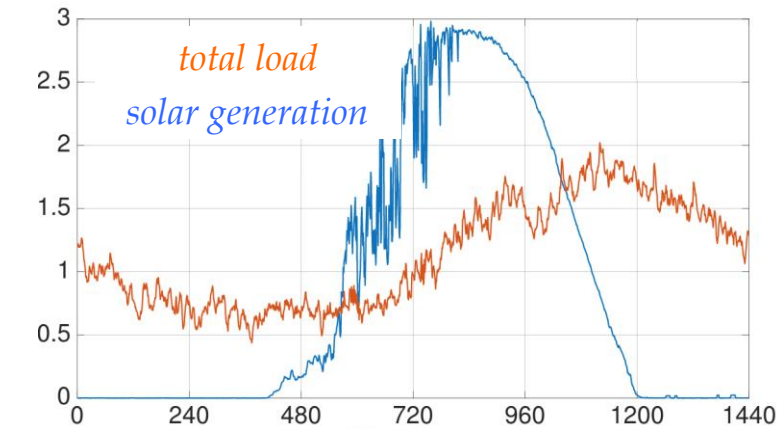
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Motivation

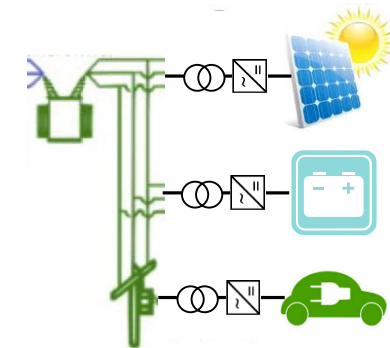
- Voltage fluctuations due to solar and other DERs



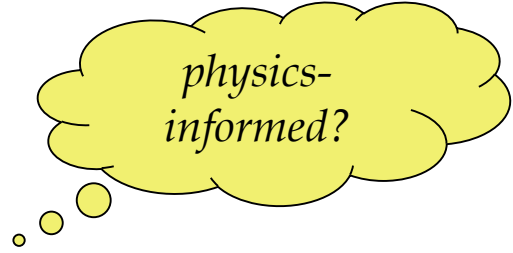
- Inefficiency of voltage control devices



- Reactive power control using smart inverters



- Deep learning to expedite optimal DER dispatch



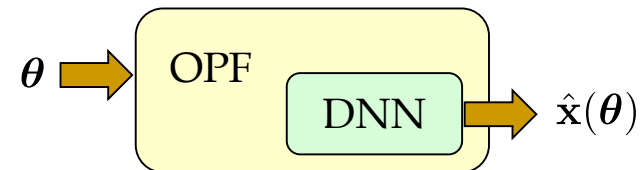
grid
conditions



- minimizers [Wang-Yu-Gao+'19], [Zhang-Deghanpour-Wang+'21]
- warm-starts and linearization [Zamzam-Baker'20]
- binding constraints [Guha'19], [Deka-Misra'19], [Chen-Zhang'20]

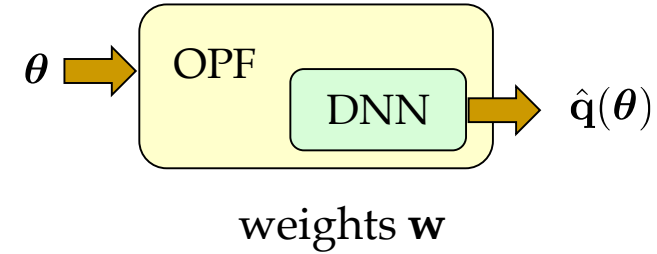


OPF-then-Learn

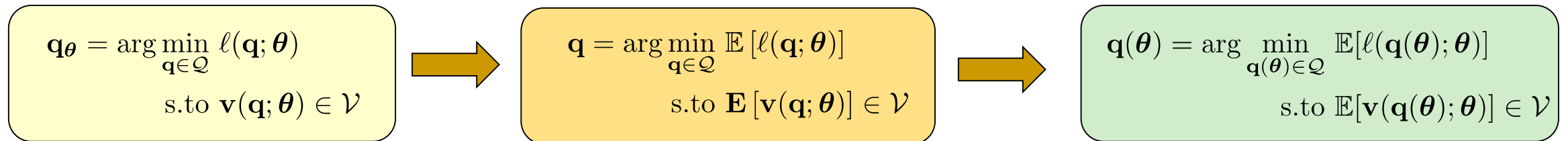


OPF-and-Learn

- Decide VAR inverter setpoints via *control rules or policies*



- Key idea:* incorporate DNN into OPF



- Benefits from *OPF-and-Learn* scheme
 - no need for OPF labels
 - uncertain grid conditions

- Solve with stochastic primal-dual updates [Eisen-Zhang-Chamon-Lee-Ribeiro'19]

$$\mathbf{w}_{t+1} := \left[\mathbf{w}_t - \mu (\nabla_{\mathbf{w}} \ell_t - \boldsymbol{\lambda}_t^\top \nabla_{\mathbf{w}} \mathbf{v}_t) \right]_{\mathcal{Q}} \quad \leftarrow \text{enforced with tanh}$$

$$\boldsymbol{\lambda}_{t+1} := [\boldsymbol{\lambda}_t + \mu \mathbf{v}_t]_+$$

- How to compute gradients?

$$\nabla_{\mathbf{w}} \mathbf{v} = \nabla_{\mathbf{u}} \mathbf{v} \cdot \nabla_{\mathbf{q}} \mathbf{u} \cdot \nabla_{\mathbf{w}} \mathbf{q}$$

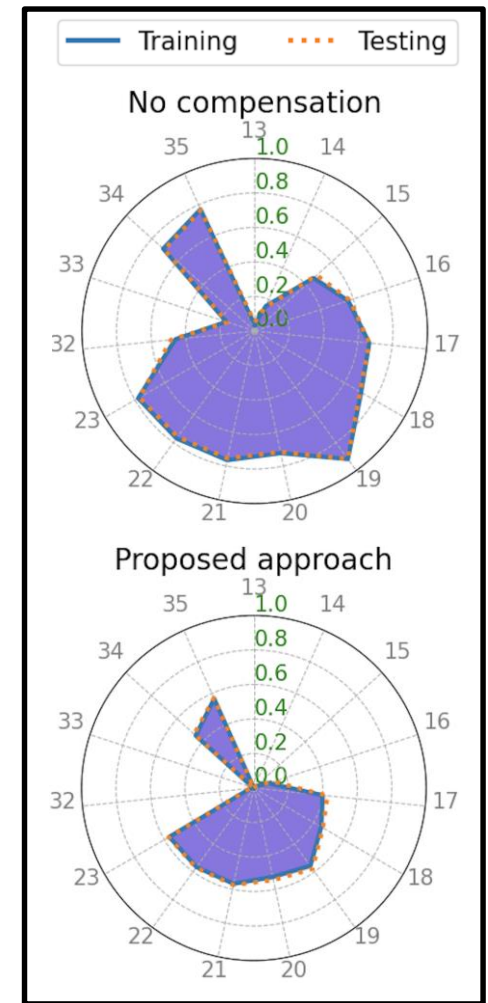
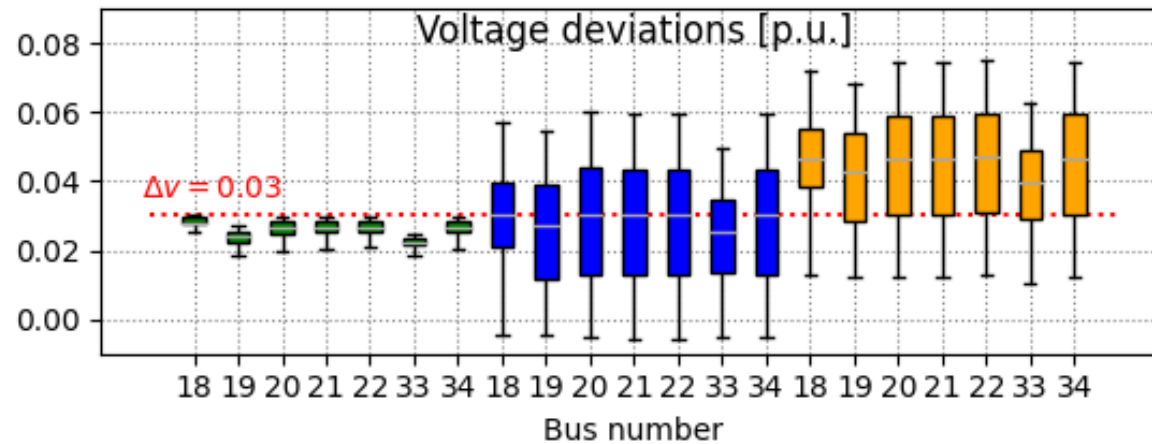
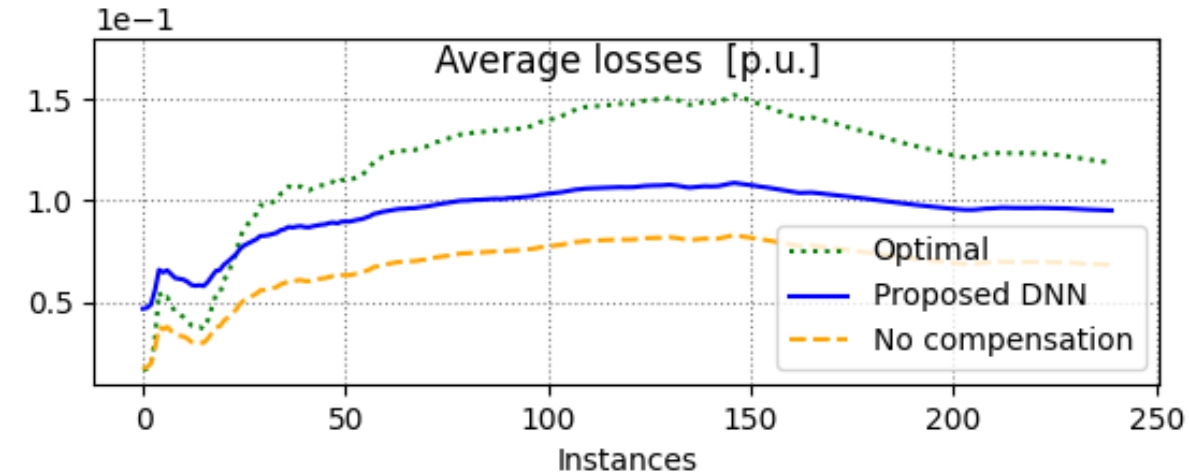
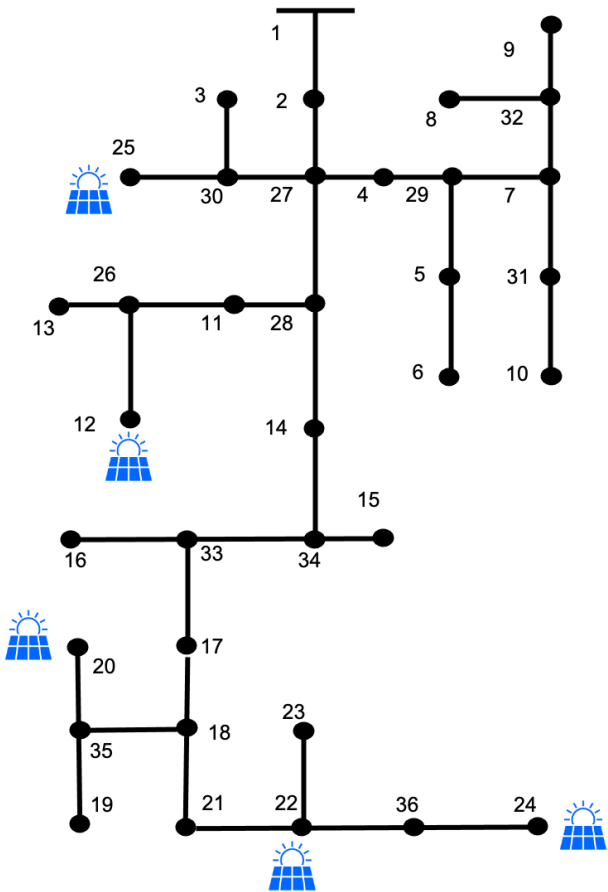
inverse function theorem
 $\nabla_{\mathbf{s}} \mathbf{u} = (\nabla_{\mathbf{u}} \mathbf{s})^{-1}$
DNN back-propagation

- What if you don't have the feeder model, but a *digital twin*?

$$\hat{\nabla}_{\mathbf{q}} \mathbf{v} = \frac{\mathbf{v}(\mathbf{q} + \epsilon \check{\mathbf{q}}; \boldsymbol{\theta}) - \mathbf{v}(\mathbf{q} - \epsilon \check{\mathbf{q}}; \boldsymbol{\theta})}{2\epsilon} \check{\mathbf{q}}^\top$$

lazy differentiation

Average formulation

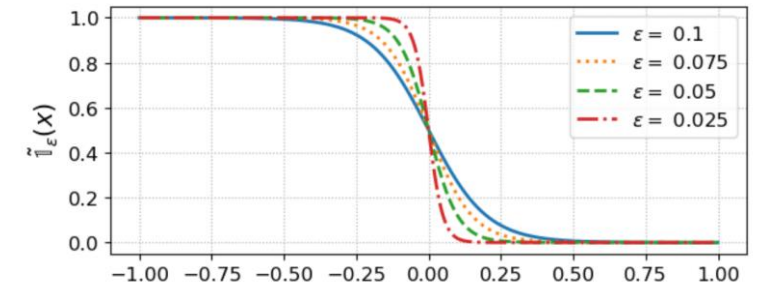


voltage violation probability per node

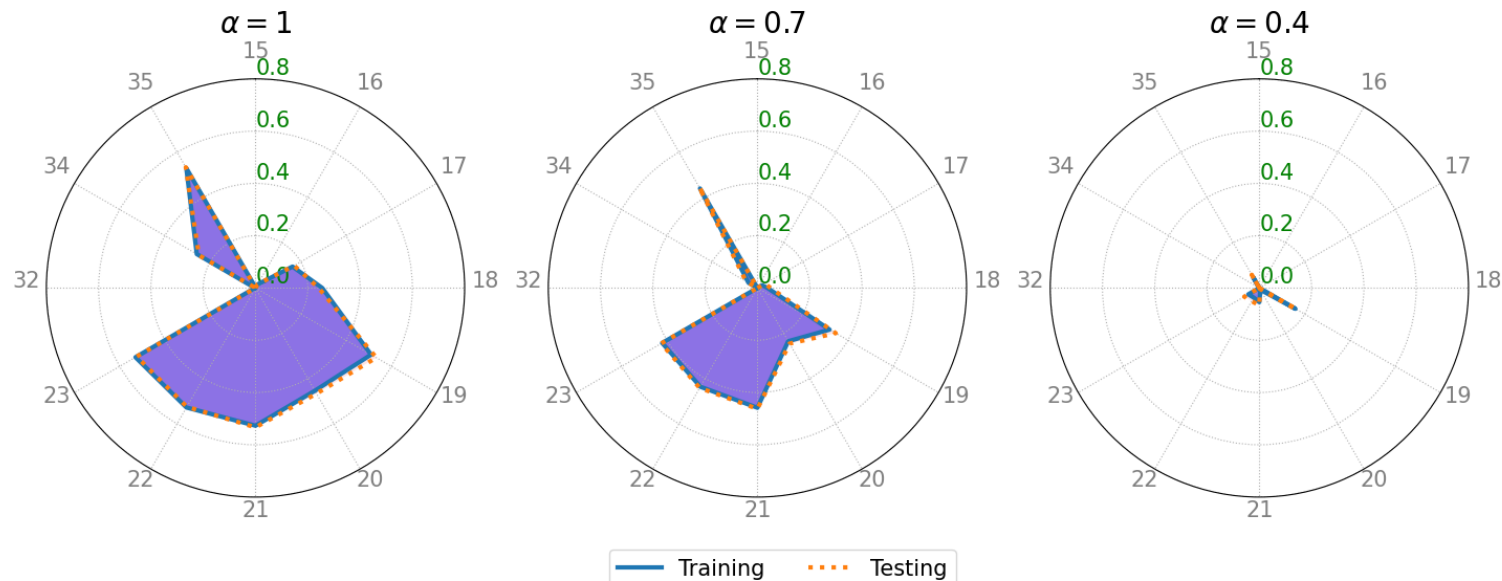
Probabilistic formulation

$$\mathbb{E}[v_n] \leq \bar{v}_n \longrightarrow \Pr(v_n \geq \bar{v}_n) \leq \alpha \longrightarrow \mathbb{E}[[z_n + \bar{v}_n - v_n]_+] \leq \alpha z_n \longrightarrow$$

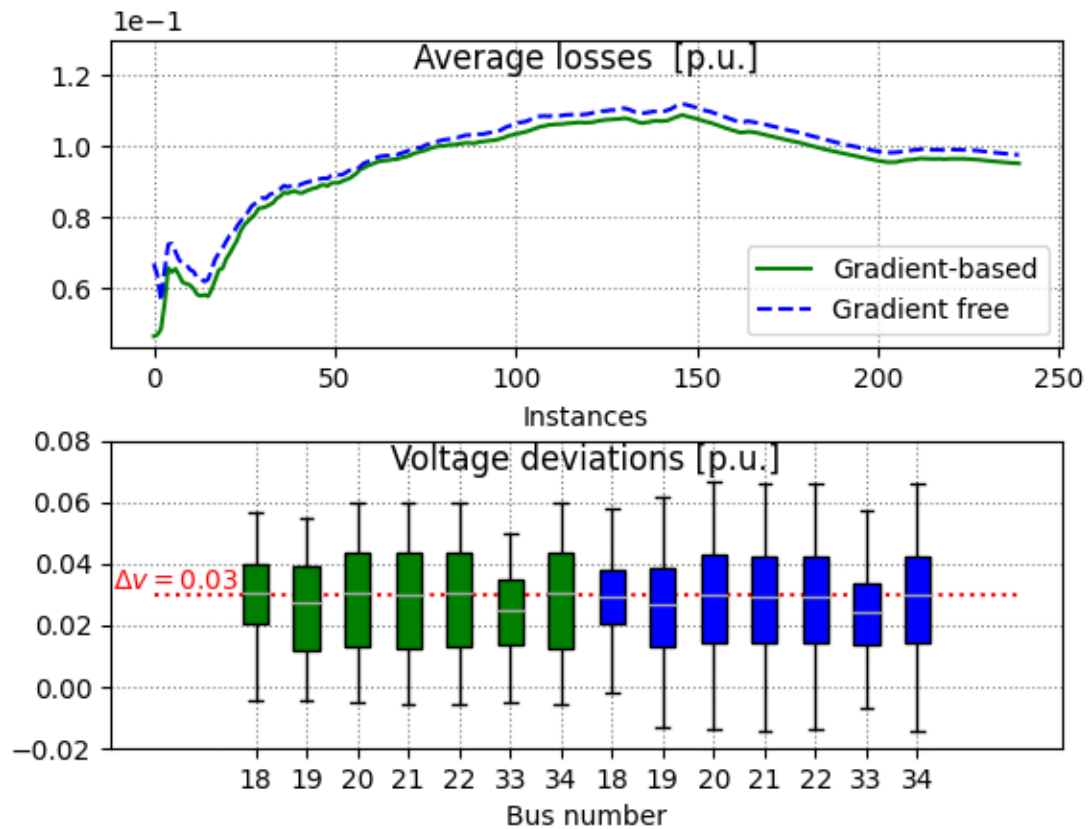
average constraint non-convex chance constraint convex restriction
 [Nemirovski-Shapiro'07]



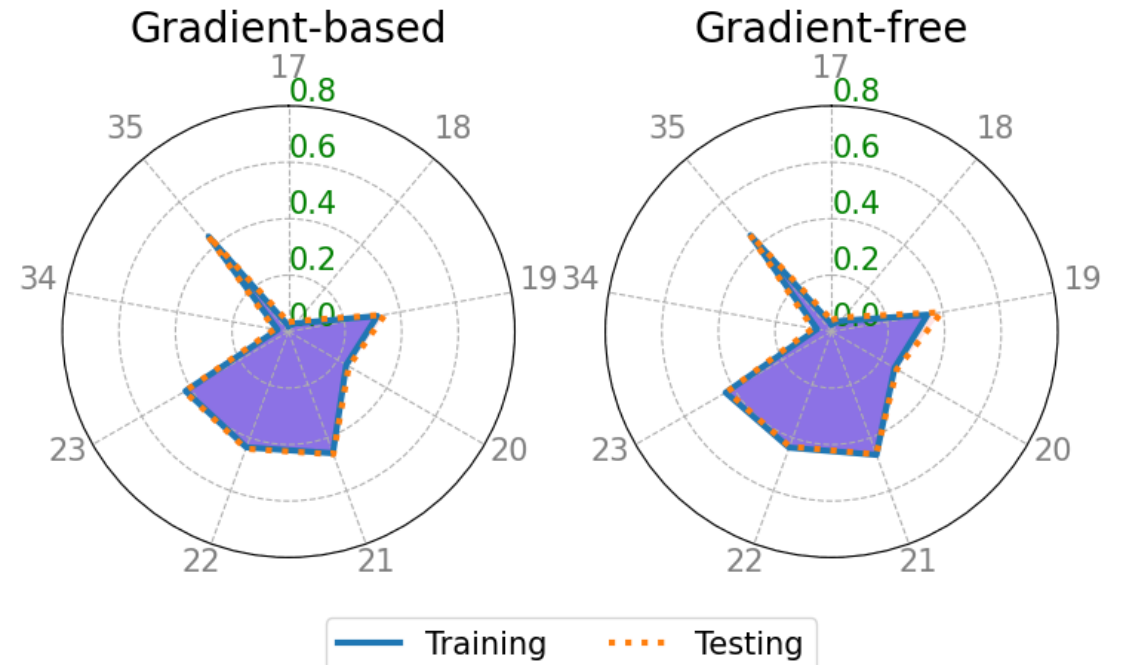
- Constraint can be handled by *OPF-and-Learn* framework with minimal increase in complexity



Gradient-free learning



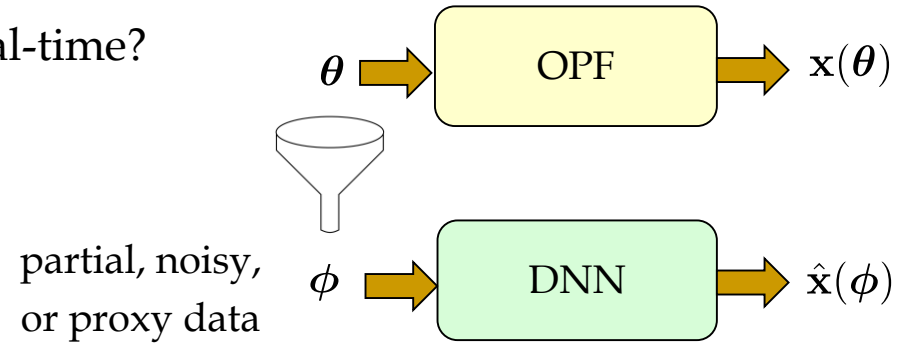
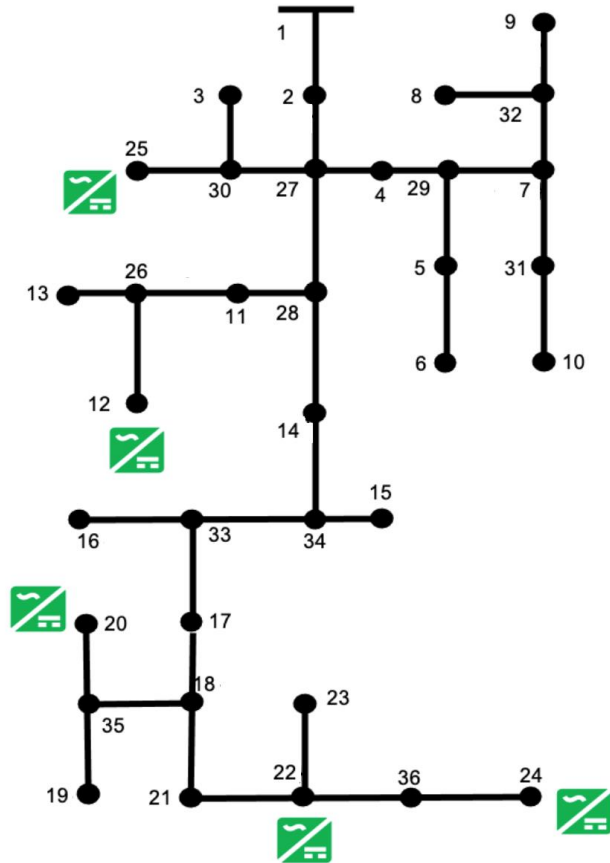
average formulation



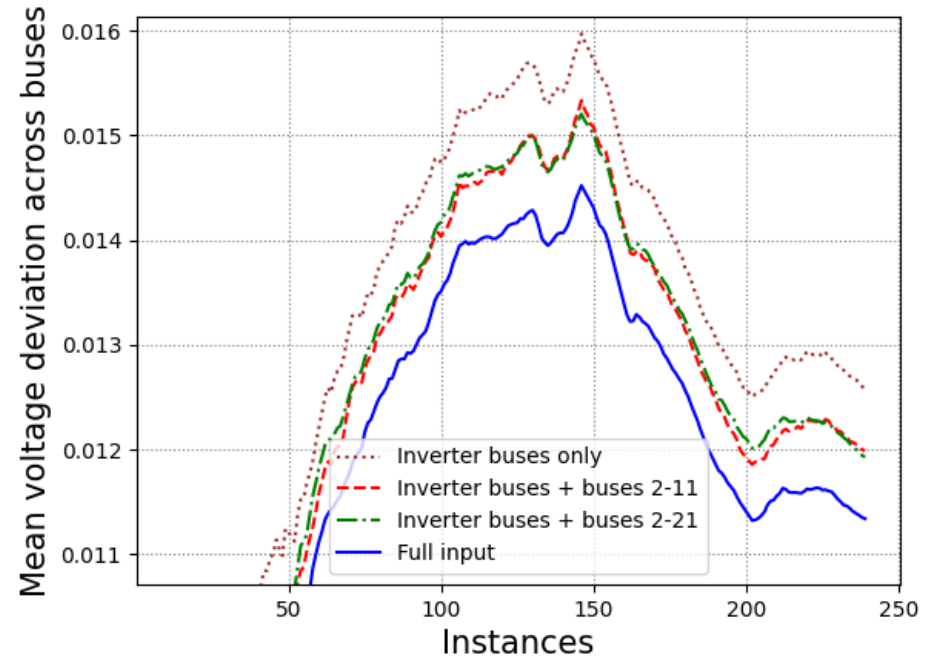
probabilistic formulation

OPF with proxies

- What if grid conditions are not fully known in real-time?

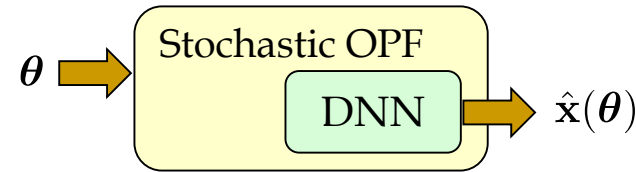


partial, noisy,
or proxy data

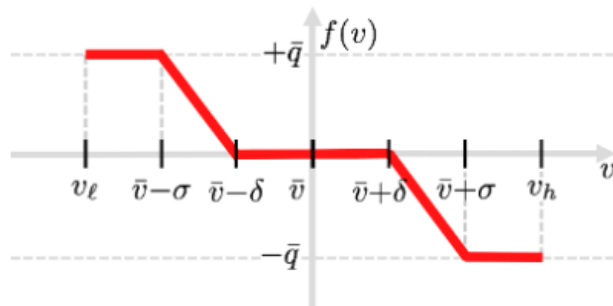


OPF-and-Learn

- ✓ train DNN through stochastic OPF
- ✓ OPF with proxy inputs
- ✓ digital twin for lazy differentiation



Thank You!



- VVR rules to reduce imbalance
- solve OPF on a data budget

S. Gupta, V. Kekatos, and M. Jin, "Controlling Smart Inverters using Proxies: A Chance-Constrained DNN-based Approach," *IEEE Trans. on Smart Grid*, March 2022.