Physics-aware and Risk-aware Machine Learning for Power System Operations

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Power of AI/ML

- Unprecedented opportunities offered by diverse sources of data
  - Synchrophasor and IED data
  - Smart meter data
  - Weather data
  - GIS data, ..... 

How to harness the power of ML to tackle problem-specific challenges in real-time power system decision making?
Overview

- We visit three problems that use domain knowledge to better design learning models that are physics-informed and risk-aware.

**Topology-aware learning in large-scale power systems:**
Simpler model structure

**Risk-aware learning for grid-edge coordination:**
Reduced risks of voltage violations

**Reinforcement learning for dynamical resources:**
More efficient representation
Part I: Topology-aware Learning in Large-scale Power Systems
ML for optimal power flow (OPF)

- Attain a pre-trained OPF input-output mapping from available samples
Existing work and our focus

- Integration of renewable, flexible resources increases the grid variability and motivates real-time, feasible OPF via training a neural network (NN)
  - Warm start the search for ac feasible solution [Baker ’19]
  - Feasible domain to reduce limit violation [Zamzam et al’20][Zhao et al’21]
  - KKT conditions based regularization [Zhang et al’22] [Nellikkath et al’22]
- Connection to the duality analysis of convex OPF [Chen et al’20] [Singh et al’20]
- Rely on FCNN architecture and cannot adapt to varying topology

Focus: graph learning approach for complexity reduction & topology adaptivity
Real-time OPF

- Power network modeled as a graph $G = (\mathcal{V}, \mathcal{E})$ with $N$ nodes
- ac-OPF for all nodal injections

\[
\begin{align*}
\min_{\mathbf{p}, \mathbf{q}, \mathbf{v}} & \quad \sum_{i=1}^{N} c_i(p_i) \\
\text{s.t.} & \quad \mathbf{p} + j\mathbf{q} = \text{diag} (\mathbf{v}) (\mathbf{Yv})^* \\
& \quad \mathbf{V} \leq |\mathbf{v}| \leq \bar{\mathbf{V}} \\
& \quad \underline{\mathbf{p}} \leq \mathbf{p} \leq \bar{\mathbf{p}} \\
& \quad \underline{\mathbf{q}} \leq \mathbf{q} \leq \bar{\mathbf{q}} \\
& \quad s_{ij}(\mathbf{v}) \leq \bar{s}_{ij}, \quad \forall (i, j) \in \mathcal{E}
\end{align*}
\]

- Nodal input:
  \[ x_i \triangleq [\bar{p}_i, p_i, \bar{q}_i, q_i, c_i] \in \mathbb{R}^d \]
  power limits + costs
- Nodal output: optimal p/q

Each FCNN layer has $O(N^2)$ parameters!
Topology dependence

- [Owerko et al’20] using graph learning to predict p/q
- But topology dependence (locality) of output label is crucial!
- Locational marginal price from (very few) crowded lines
- Voltage magnitude |v| approximated using q injection

\[
\begin{align*}
\min_p & \quad \sum_{i=1}^N c_i(p_i) \\
{\text{s.t.}} \quad & 1^T p = 0 : \lambda \\
& p \leq \bar{p} \\
& \bar{f} \leq Sp \leq \bar{f} : [\mu; \bar{\mu}] \\
p + jq &= \text{diag}(v)(Yv)^* \\
\pi^* &= \lambda^* \cdot 1 - S^T(\bar{\mu}^* - \mu^*) \\
S^T &= B^{-1}A^TX^{-1} \\
\Delta |v| &\approx -B^{-1}\Delta q
\end{align*}
\]

Spanned from the eigen-space of Bbus matrix B (graph Laplacian)
Locational marginal price (LMP) map
Graph NN (GNN)

- Input formed by nodal features as rows
  \( X^0 = \{ x_i \} \in \mathbb{R}^{N \times d} \)

- GNN layer \( l \) with learnable parameters
  \[
  X^{l+1} = \sigma (W^l X^l H^l + b^l)
  \]
  - Topology-based graph filter \( W^l \in \mathbb{R}^{N \times N} \)
    \[
    [W^l]_{ij} = 0 \text{ if } (i, j) \notin \mathcal{E}
    \]
  - Feature filters \( \{ H^l \} \) for higher-dim. nonlinearity

- GNN used for grid fault location [Li-Deka’21]


\[
W = \begin{bmatrix}
W_{11} & W_{12} & 0 & W_{14} & 0 & 0 \\
W_{21} & W_{22} & W_{23} & 0 & 0 & 0 \\
0 & W_{32} & W_{33} & W_{34} & 0 & W_{36} \\
W_{41} & 0 & W_{43} & W_{44} & W_{45} & 0 \\
0 & 0 & W_{54} & W_{55} & 0 & W_{56} \\
0 & 0 & W_{63} & W_{64} & 0 & W_{66}
\end{bmatrix}
\]

Input feature \( X^0 \) is a 6xd matrix

Prop. 1 (GNN complexity):
If lines are sparse \( |\mathcal{E}| \sim \mathcal{O}(|\mathcal{V}|) \)
and let \( D = \max_t \{ d_t \} \), then the number of parameters for each GNN layer is \( \mathcal{O}(N + D^2) \).

Compared to FCNN’s \( \mathcal{O}(N^2) \)
From GNN outputs to OPF variables

- LMP decides (feasible) $p$ from economics
  \[ \hat{p}_i = \arg\min_{p_i \leq p_i \leq \bar{p}_i} c_i(p_i) - \hat{\pi}_i p_i \]
- Decoupled (d-)PF approximates angle
  \[ \hat{\theta} \approx \theta_o + J_{p\theta}^{-1}(\hat{p} - p_o) \]
- GNN outputs of LMP and $|v|$ can fully determine the power flow

https://arxiv.org/pdf/2205.10129
Feasibility regularization (FR)

- Loss function for predicting LMP and $|v|$
  \[
  \mathcal{L}(\phi) := \|\pi^* - \hat{\pi}\|_2^2 + \|v^* - \hat{v}\|_2^2 + \lambda_\infty \|\pi^* - \hat{\pi}\|_\infty
  \]
  - Infinity-norm on LMP due to its larger variability than $|v|$

- Network-wide line limits are difficult to satisfy

- FR to reduce line flow violations: $\mathcal{L}'(\phi) := \mathcal{L}(\phi) + \lambda \|P_{[0,\infty]}[\hat{s} - \bar{s}]\|_1$

Prop. 2 (Feasibility): ac-FR based OPF learning is a fully feed-forward NN. The proposed FR term still allows for efficient using autograd and backpropagation. The feasibility of both predicted $|\hat{v}|$ and $\hat{P}$ can be strictly enforced via projections, as well.

Benchmark results

- 118-bus and 1354-bus for ac-opf
- **Metrics**: normalized MSE; line flow limit violation rate; model complexity
- GNN, FCNN, both + feasibility regularization (FR)
OPF learning under contingency

- Topology-agnostic NNs lack in transfer capability
  - Sample re-generation and re-training are time-consuming
- OPF outputs tend to be stable under line outages
  - Thanks to stability of the eigen-space
    \[ \text{span}\{U\} \quad \text{with} \quad B^{-1} = U\Lambda U^T \]
    - LMP outputs slightly vary with the outages of multiple lines (of high capacity)
- We have established analytical bounds for this perturbation on graph subspace
Stability analysis

- Under line $k$ outage, rank-one perturbations on $B' = B - \frac{1}{x_k} a_k a_k^\top$ and its inverse

  $$(B')^{-1} = B^{-1} + \Delta_k = B^{-1} + \frac{B^{-1} a_k a_k^\top B^{-1}}{x_k - a_k^\top B^{-1} a_k}$$

  [Matrix inversion lemma]

- Difference between the corresponding (sub)spaces

  $$d(\text{span}\{U\}, \text{span}\{U'\}) := \|\text{diag}(\sin \theta_1, \cdots, \sin \theta_{N-1})\|_F \text{ with } \theta_i := \theta(u_i, u'_i)$$

\text{Prop. 3 (Bounded subspace difference):} Let $\{\lambda_i\}_{i=1}^{N-1}$ and $\{\lambda'_i\}_{i=1}^{N-1}$ represent the respective positive eigenvalues of $B^{-1}$ and $(B')^{-1}$ in non-increasing order. Consider the first $s$ eigenvalues with the minimum separations $\delta \triangleq \min_{1 \leq i \leq s-1} (\lambda_i - \lambda_{i+1})$ and $\delta' \triangleq \min_{1 \leq i \leq s-1} (\frac{1}{\lambda_{i+1}} - \frac{1}{\lambda_i})$.

We can bound the difference between the leading sub-spaces $\text{span}(U_s) \triangleq \text{span}([u_1, \cdots, u_s])$

$$d(\text{span}\{U_s\}, \text{span}\{U'_s\}) \leq \min \left( \frac{\|\Delta_k\|_F}{\delta}, \frac{2}{x_k \cdot \delta'} \right).$$
GNN topology transfer learning

- Perturb the original system with the outages of 2-4 lines of high capacity
- Pre-trained GNN for the original system has reasonable error rates
  - warm-start the re-training using only half of samples
- GNN exhibits excellent adaptivity to the varying grid topology
  - Re-training takes only 3-5 epochs to converge to the original performance
Centralized load shedding

- Grid resilience challenged by resource variability and extreme weather
- Optimal load shedding (OLS) is a special case of ac-OPF

- Centralized optimization using system-wide information
- However, need very fast-speed communication links and computation capability
- Can we use ML to enable scalable OLS at each node using local information only?
ML for decentralized load shedding

- Each load center learns the decision rule from historical or synthetic scenarios

```
```

- Input feature:

```
x_i = [p_i^d, q_i^d, V_i', \{p_{ij}'\}, \{q_{ij}'\}, \omega_i']
```

- Local reduction solutions:

```
y_i = [p_i^s, q_i^s]
```
Prediction under single line outage

- IEEE 14-bus system; quadratic cost functions
- All \((N - 1)\) contingency scenarios, under different load conditions (1000 samples for each scenario)
Part II: Risk-aware Learning for Voltage Safety in Distribution Grids
ML for distributed energy resources (DERs)

- Rising DERs at grid edge motivate scalable and efficient coordination to support the operations of connected distribution grids
  - Lack of frequent, real-time communications
  - Distribution control center may broadcast messages to every DER

Distribution Substation


Prior work

- Scalable DER coordination as an instance of optimal power flow (OPF)
  - Kernel support vector machines [Karagiannopoulos et al’ 19] [Jalali et al’ 20]
  - Deep neural network for ac-OPF [Zamzam et al’ 20][Gupta et al’ 21] [Nellikkath et al’ 21]
  - Deal with worst-case dc-OPF guarantees by post-analysis [Venzke et al’ 20]
  - Reinforcement learning for dynamic coordination [Yang et al’ 20] [Cao et al’ 21]

- Enforcing network-wide constraints is challenging
  - Project OPF solutions for global learning [Zamzam et al’ 20] [Jalali et al’ 20]
  - Penalize the constraint violation via regularization [Karagiannopoulos et al’ 19] [Pan et al’ 19] [Yang et al’ 20]
  - Chance-constrained formulation for optimization-and-learn [Gupta et al’ 21]

- **Focus:** Use statistical risks to improve the safety of DER actions for (network-wide) limits
Centralized DER coordination

- Controllable DER reactive power for voltage optimization

\[ z = \min_{q \in Q} \text{loss}(q) \]

\[ \text{s. to } \begin{bmatrix} Xq + h(y) - \bar{v} \\ -Xq - h(y) + v \end{bmatrix} \leq 0 \]

- \( Q \): available reactive power
- \( X \): network matrix
- \( y \): operating condition
- \( v, \bar{v} \): voltage limits

- Linearized DistFlow (LDF) model, even for multiphase systems, leads to quadratic programs

- Centralized solutions require high communication rates and communication availability
Scalable design

- Aim to predict from data to the optimal $\Phi(y) \rightarrow z$

- Scalable neural network (NN) architecture to obtain the mapping for each individual node $n$
  $$y_{n}^{t+1} = \sigma(W_{n}^{t}y_{n}^{t} + b_{n}^{t})$$
  - $\varphi := \{W_{n}^{t}, b_{n}^{t}\}$ : NN parameters

- Convergence analysis in our recent work [Kwon et al’22]

- The average loss under mean squared error (MSE)
  $$\min_{\varphi} f(\varphi) := \frac{1}{K} \sum_{k=1}^{K} \ell(\Phi(y_{k}; \varphi), z_{k})$$
  with $\ell(\Phi(y_{k}; \varphi), z_{k}) = \|\Phi(y_{k}; \varphi) - z_{k}\|_{2}^{2}$ for each sample $k$
Risk-aware learning

- Conditional value-at-risk (CVaR) metric (empirical approx. of the worst-case mean)

\[ \gamma_\alpha(\varphi) := \frac{1}{\alpha K} \sum_{k=1}^{K} \ell(\Phi(y_k; \varphi), z_k) \times \mathbb{1}\{\ell(\Phi(y_k; \varphi), z_k) \geq v\} \]

- \( \alpha \in (0, 1) \) : significance level
- \( v \) : \( \alpha \)-VaR

- Risk-aware learning going beyond MSE

\[ \min_{\varphi} f(\varphi) + \lambda \gamma_\alpha(\varphi) \]

- \( \lambda > 0 \) : hyperparameter balances between average and worst-case performances

Features of CVaR metric

- In addition to $q$, consider voltage deviation risk (turns out numerically powerful)

$$\gamma^v_\alpha(\varphi) := \frac{1}{\alpha K} \sum_{k=1}^K |v_n(\Phi(y_k; \varphi))| \times \mathbb{1}\{|v_n(\Phi(y_k; \varphi))| \geq v\}$$

- CVaR can be recast as a convex problem, using the projection operator $[a]_+ \triangleq \max\{0, a\}$:

$$\gamma_\alpha(\varphi) := \min_{\beta \in \mathbb{R}} \left\{ \beta + \frac{1}{\alpha K} \sum_{k=1}^K [\ell(\Phi(y_k; \varphi), z_k) - \beta]_+ \right\}$$

  - The optimal $\beta$ turns out to be the $\alpha$-VaR value
  - But risk-aware learning is not convex due to nonlinear $\Phi(\cdot; \varphi)$

- CVaR gradient evaluation can be simplified by replacing $[a]_+$ with soft projection (softplus)
**Accelerated CVaR learning**

**Key challenge:** the training efficiency with CVaR is worse than that of average loss

- Reduced sample number affecting the statistical significance of sample-based gradient estimation
- Gradient computation cost increased, as well

- Typical NN training uses subset of samples per iteration like the mini-batch method

- Accelerating the CVaR training by *selecting mini-batches* with sufficient statistical significance

Predicting reactive power $q$

- IEEE 123-bus test case with 6 DERs, each with its own controllable $q$
  - Decision rules are learned using local nodal measurements and some feeder head broadcast

- Prediction error is very close among all three approaches due to high prediction accuracy

- Proposed mini-batch selection algorithm (Alg1) reduces training time for CVaR

<table>
<thead>
<tr>
<th>Loss obj.</th>
<th>Epoch [s]</th>
<th>Total [s]</th>
</tr>
</thead>
<tbody>
<tr>
<td>MSE</td>
<td>0.52</td>
<td>46.48</td>
</tr>
<tr>
<td>CVaR(qg)</td>
<td>1.07</td>
<td>38.70</td>
</tr>
<tr>
<td>CVaR(qg)+Alg1</td>
<td>0.61</td>
<td>35.63</td>
</tr>
</tbody>
</table>
Reducing voltage deviation risk

- Further incorporated CVaR regularization on voltage deviation error

- CVaR metric can reduces the worst-case voltage deviation and leads to improved system safety

- Training time is accelerated using the proposed mini-batch selection algorithm (Alg1)
  - Even faster than the $q$ prediction CVaR only case

### Computational Time

<table>
<thead>
<tr>
<th>Loss obj.</th>
<th>Epoch [s]</th>
<th>Total [s]</th>
</tr>
</thead>
<tbody>
<tr>
<td>MSE</td>
<td>0.54</td>
<td>44.89</td>
</tr>
<tr>
<td>CVaR(qg,dv)</td>
<td>0.77</td>
<td>31.73</td>
</tr>
<tr>
<td>CVaR(qg,dv)+Alg 1</td>
<td>0.51</td>
<td>25.93</td>
</tr>
</tbody>
</table>
Part III: RL for Dynamical Resources using Efficient Representation
RL for dynamical grid resources

- DERs (energy storage/loads) and external inputs (price/weather) are dynamical
- Motivate a RL approach to learn $a_t \leftarrow \pi(s_t)$
  - data-driven, not requiring the probability
  - adaptive to varying online conditions

**Key Challenge:** abundant, heterogenous resources at grid edge need powerful state/action representation

Electrical vehicle charging station (EVCS) problem

- Arriving EV $i$ with demand $d_{i,t}$ and parking time $p_{i,t}$
- EVCS decides which EVs to charge ($a_{i,t} = 1$) from electricity at price $\rho_t$
- Clearly, the state/action space incurs high complexity due to large, time-varying dimensionality
- How to represent state/action to allow for efficient RL training?
An aggregation scheme

\begin{tabular}{|c|c|c|c|c|}
\hline
\( p_{i,t} \) & 5 & 2 & 3 & 4 \\
\hline
\( d_{i,t} \) & 3 & 2 & 2 & 3 \\
\hline
\( \ell_{i,t} \) & 2 & 0 & 1 & 1 \\
\hline
\end{tabular}

\textbf{<Original State>}

EV \( i \) with \( d_{i,t}, p_{i,t} \)

Laxity (priority): \( \ell_{i,t} = p_{i,t} - d_{i,t} \)

\textbf{<Aggregated State>}

State representing the number of EVs with the same laxity (max \( L \))

\[
s'_t = [\rho_t, n^{(0)}_t, n^{(1)}_t, \ldots, n^{(L)}_t]
\]

Prop 1: If the EVCS total charging schedule \( \{a_t\}_{t \in T} \) is feasible (corresponds to some feasible schedule for individual EVs that ensure all fully charged before departure), then Algorithm 1 can produce such a feasible schedule for all EVs.

- Basically, LLF ensures the feasibility of the recovered actions

**Proof idea:** Any feasible schedule equivalent to one satisfying LLF [Wang et al’21]
Equivalence of state aggregation

- Ideally, we want the new state represents the same MDP
- This equivalence requires two conditions:
  1. **Reward homogeneity**: same reward for any states aggregated into the same new state
  2. **Dynamic Homogeneity**: same transition kernel for any aggregated states

**Prop 2:** The original MDP for \( s_t / a_t \) is equivalent to the new one for \( s'_t / a_t \) using the total charging action. Accordingly, the optimal policy (or action) obtained from the new MDP through aggregation are equivalent to that for the original one.

**Intuitions** for dyn. homogeneity:
Under the LLF rule, charge either one of 2 EVs at the same laxity leads to the same transition of new state or aggregated state.

Kyung-Bin Kwon and H. Zhu, “Efficient representation for electric vehicle charging station operations using reinforcement learning,” HICCS 2022
https://arxiv.org/abs/2108.02336
Numerical tests

- Daily charging at 15-min intervals ($T = 96$)
  - Realistic EV arrival model
  - ERCOT real-time price
- 20 daily scenarios for training; 5 for testing
- Comparing proposed Alg 2 with Alg. QE in [Wang et al’21] by approximating the Q-function
Convergence => further aggregation

- Parameter convergence
- Most weight parameters are very small; except for $\rho_t$ and $n_t^{(0)}$
- **Remark:** we can further reduce # of states by grouping higher-laxity EVs!
- Possible to consider nonlinear policies as well

<table>
<thead>
<tr>
<th>$\rho_t$</th>
<th>$n_t^{(0)}$</th>
<th>$n_t^{(1)}$</th>
<th>$n_t^{(2)}$</th>
<th>$n_t^{(3)}$</th>
<th>$n_t^{(4)}$</th>
<th>$n_t^{(5)}$</th>
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<tbody>
<tr>
<td>-1.9735</td>
<td>1.8628</td>
<td>0.5772</td>
<td>0.3674</td>
<td>0.2651</td>
<td>0.3485</td>
<td>0.1191</td>
</tr>
<tr>
<td>0.2021</td>
<td>0.1404</td>
<td>0.1386</td>
<td>0.1592</td>
<td>0.0975</td>
<td>0.0693</td>
<td>0.0797</td>
</tr>
</tbody>
</table>
Case study – testing result

- Alg. 2 improves the reward of Alg. QE [Wang et al’21] by ~4.2%
- Example charging profile indicates Alg. 2 very sensitive to price peaks and strategically reducing $a_t$, while Alg. QE fails to do so

### Table: Testing Results

<table>
<thead>
<tr>
<th></th>
<th>Test 1</th>
<th>Test 2</th>
<th>Test 3</th>
<th>Test 4</th>
<th>Test 5</th>
<th>Average</th>
</tr>
</thead>
<tbody>
<tr>
<td>Alg. 2</td>
<td>-5016.2</td>
<td>-5022.6</td>
<td>-5009.5</td>
<td>-5012.8</td>
<td>-5007.8</td>
<td>-5013.8</td>
</tr>
<tr>
<td>Alg. QE</td>
<td>-5240.1</td>
<td>-5240.3</td>
<td>-5234.2</td>
<td>-5239.3</td>
<td>-5230.6</td>
<td>-5236.9</td>
</tr>
<tr>
<td>Increase (%)</td>
<td>4.27</td>
<td>4.15</td>
<td>4.29</td>
<td>4.32</td>
<td>4.26</td>
<td>4.26</td>
</tr>
</tbody>
</table>

Algorithm QE: Estimating an approximate Q-function [Wang et al’21]
Summary

- I: Generalized transfer capability in graph-based learning
- II: Convergence analysis and strengthened safety guarantees
- III: Comprehensive grid-edge resource coordination

**Topography-aware learning in large-scale power systems:**
Simpler model structure

**Risk-aware learning for grid-edge coordination:**
Reduced risks of voltage violations

**Reinforcement learning for dynamical resources:**
More efficient representation
Related Work

Learning and Optimization for Smarter Electricity Infrastructure

Learning for grid resilience
Learning for dynamical resources
Learning for inverter-based resources
....

Thank you!