Deep learning architectures for inference of AC-OPF solutions

Tackling Climate Change with Machine Learning
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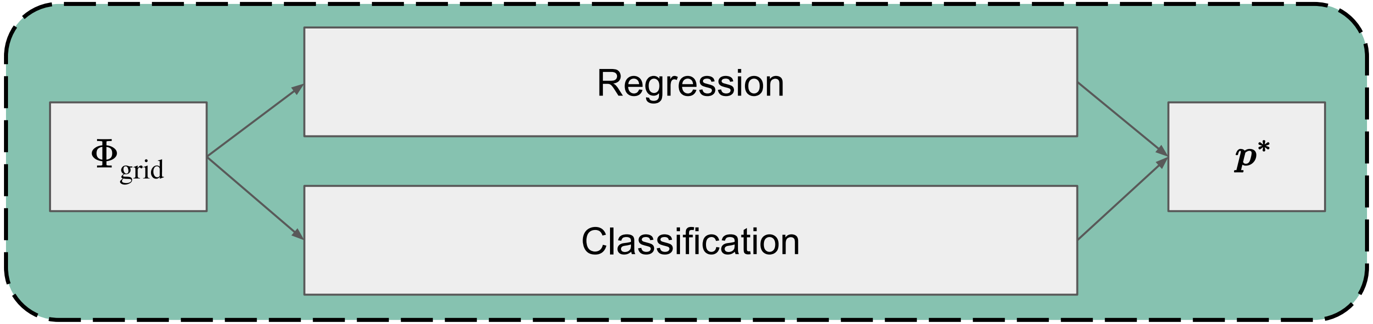
Thomas Falconer, UCL Energy Institute (Energy & AI Lab)
Letif Mones, Invenia Labs

Optimal Power Flow (OPF) Challenges

- Proliferation of intermittent renewable energy resources in power systems.
  - Difficult to sustain accurate representation of system state.
  - Requires OPF solutions in **near real-time.**
- Computational complexity.
  - Fundamental form (AC-OPF) is a **non-convex and non-linear** optimization problem.
  - Exacerbated with inclusion of:
    - Unit commitment.
    - Security constraints and post-contingency corrective actions.
    - Generator-wise emissions costing [1].
- Sub-optimality of cheap approximations.
  - e.g. DC-OPF.
  - Economic losses.
  - Wasted generation => unnecessary emissions.

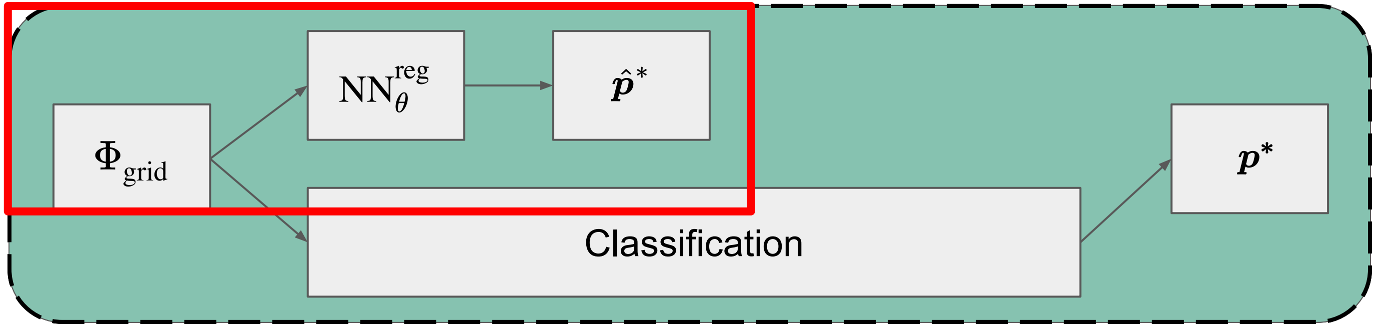
ML Aided OPF

- Use ML to assist solving OPF at scale.
  - Leverage underlying structure.
  - Train offline with real-time inference => **negligible online computation.**
- Main strategies:
  - Regression [2-5].
  - Classification [6-8].



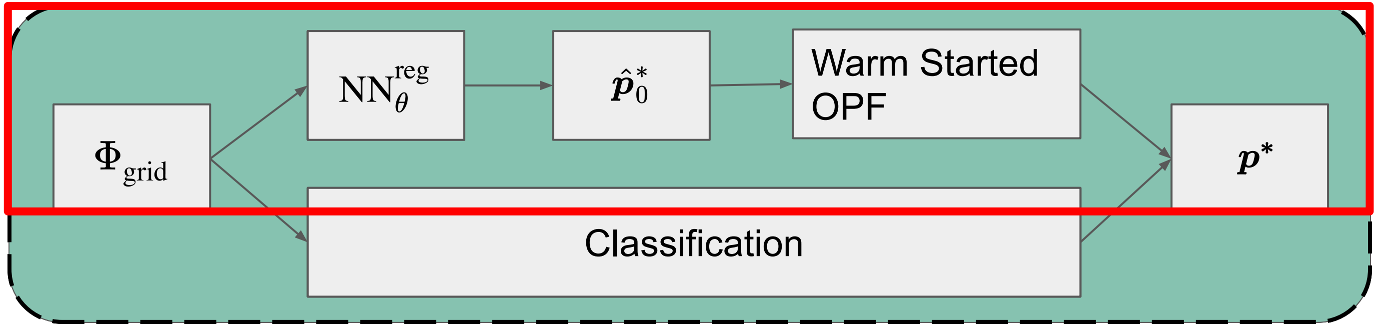
ML Aided OPF: Regression

- End-to-end [2]
  - Advantages:
    - Doesn’t require conventional (online) optimization.
  - Challenges:
    - Not a smooth function of the grid parameters => requires a lot of training data.
    - **No guarantee of feasibility** (or optimality) => poses security risks to the grid.



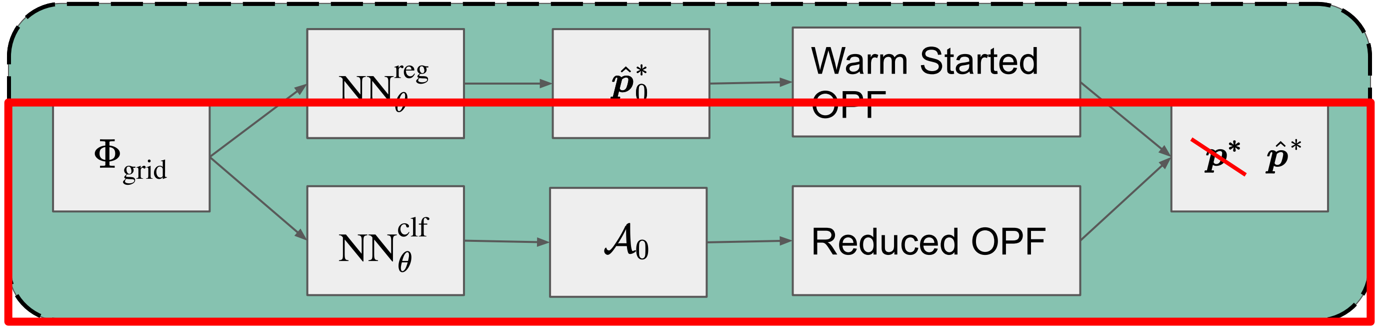
ML Aided OPF: Regression

- Warm start [2]
  - Advantages:
    - Can theoretically expedite convergence to the optimal solution.
    - Feasibility enforced by the iterative solver (optimality guaranteed).
  - Challenges:
    - Marginally sub-optimal initialization could increase computational burden.
    - Only primal variables are initialised => duals still need to converge.



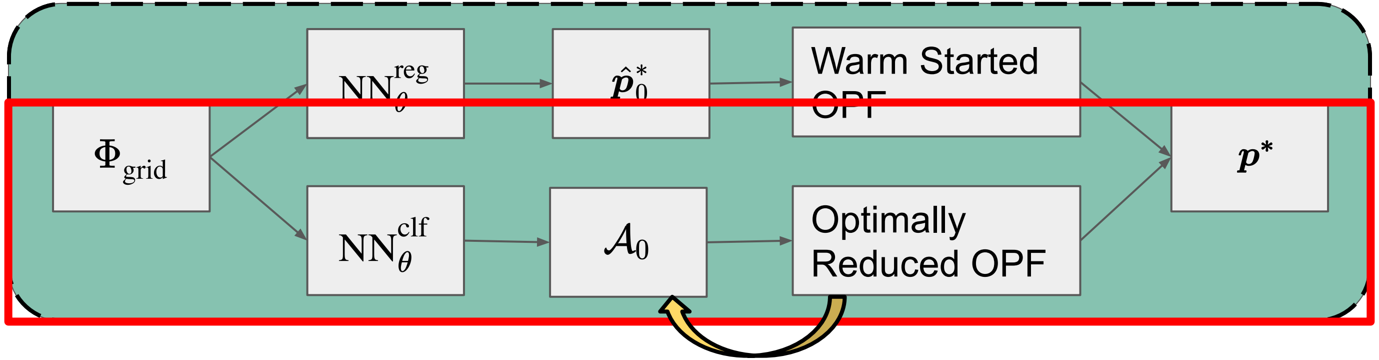
ML Aided OPF: Classification

- Reduced OPF [6]
  - Advantages:
    - Only a fraction of constraints are binding at the optimum.
      - Reduced optimization problem.
  - Challenges:
    - Potential omission of important constraints => **false negatives.**
    - Poses security risks to the grid.



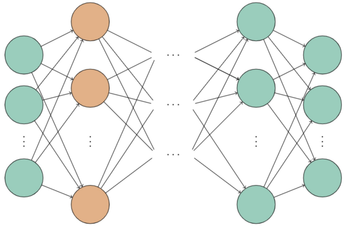
ML Aided OPF: Classification

- Optimally Reduced OPF [10]
  - Advantages:
    - **Feasibility and optimality guaranteed.**
      - Converges to objective akin to that of the full problem.
  - Challenges:
    - Requires iterative feasibility test.

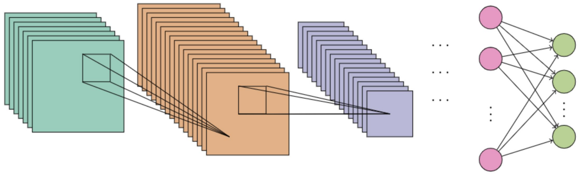


Examined NN Architectures

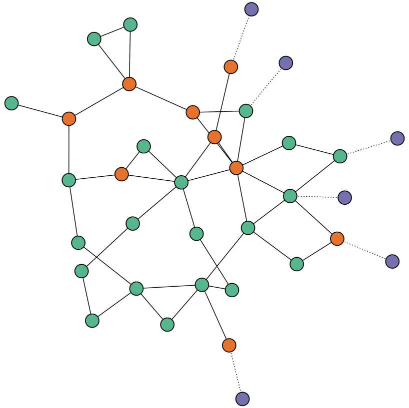
- Fully-connected NN (FCNN)
  - Vectorised input domain.
  - Lacks sufficient relational inductive bias to exploit underlying structure.



- Convolutional NN (CNN) [11]
  - Represent the electrical grid as a *pseudo*-image.
    - Exploit spatial correlations within the electrical grid.
  - Dependant upon geometric priors not observed in the graph domain.
    - e.g. shift invariance.



- Graph NN (GNN) [12]
  - Represent the electrical grid as a graph.
    - Assumption of shift invariance drops
      - Filters no longer node agnostic.
    - Lack of natural order.
      - Operations are permutation invariant.
  - Directly incorporate important topological information of power grids in the NN model.



Experimental Setup

- Grids
  - Synthetic grids from Power Grid Library (benchmarks).
- Sample Generation
  - 10k samples generated for two input domains.
    - Load active/reactive power.
    - Load active/reactive power, maximum active/reactive generator output, line resistance/reactance values and line thermal limits.
- Computational Tools
  - Data generated in Julia using PowerModels.jl to solve OPF (IPOPT solver).
  - Models constructed in Python (3.0) using PyTorch and PyTorch Geometric.
- Systematic Evaluation
  - Input domain
  - Model Architecture
    - FCNN, CNN and GNN (GCN, CHNN, SNN).
  - Learning Framework
    - Regression
    - Classification

Spectral Graph Convolution:

- GCNConv
- ChebConv

Spatial Graph Convolution:

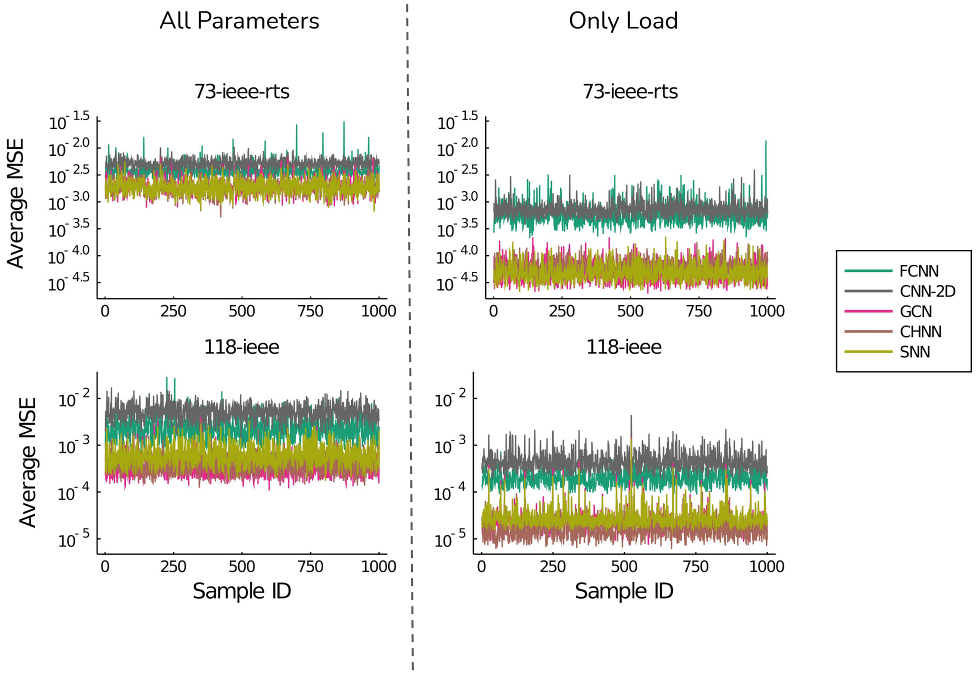
- SplineConv

Results: Regression

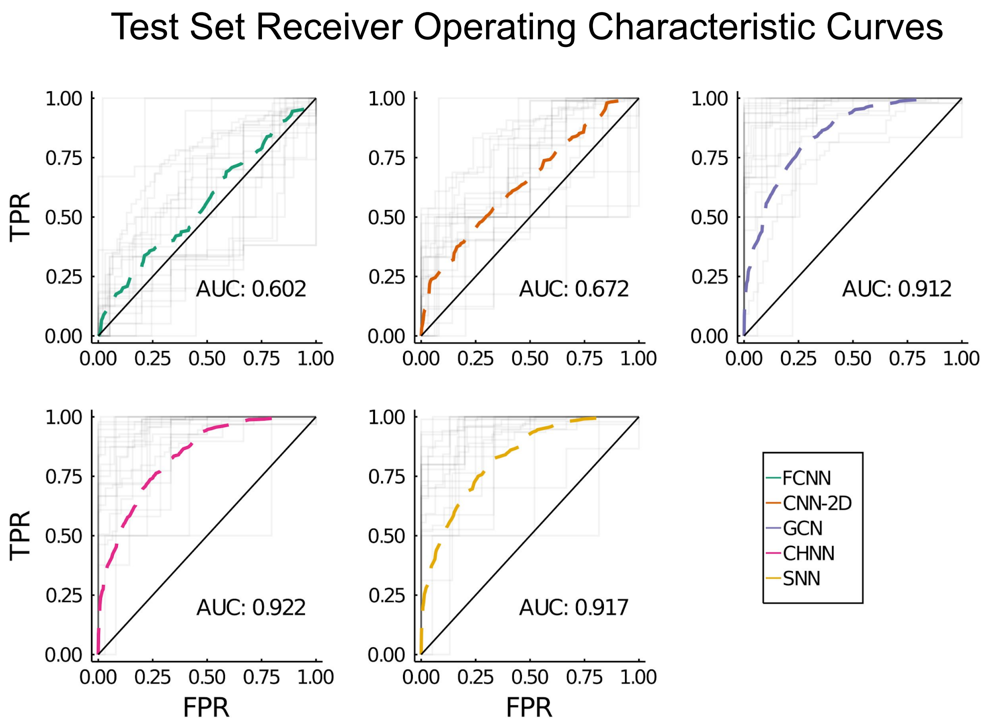
Average test set MSE values of regression models.

Case ($\Phi = \Phi_{\text{load}}$)		FCNN	CNN	GCN	CHNN	SNN
73-ieee-rts	10^{-4}	6.613	7.625	0.556	0.612	**0.527**
118-ieee	10^{-4}	2.171	3.042	**0.306**	0.334	0.329
162-ieeet-dtc	10^{-3}	9.492	6.026	3.341	3.039	**2.145**
300-ieee	10^{-2}	3.654	5.973	2.283	2.156	**1.948**
Case ($\Phi = \Phi_{\text{all}}$)		**FCNN**	**CNN**	**GCN**	**CHNN**	**SNN**
73-ieee-rts	10^{-3}	4.916	5.241	2.011	1.953	**1.247**
118-ieee	10^{-3}	2.621	3.487	0.396	0.450	**0.372**
162-ieeet-dtc	10^{-2}	2.783	4.585	1.411	1.682	**1.229**
300-ieee	10^{-1}	1.293	1.466	0.723	0.711	**0.574**

Average Test Set MSE



Results: Classification



Next Steps

- Regression
  - Incorporate methods to **maximise legality** of inferred optimal solution.
    - Parameter scaling.
    - Penalisation of constraint violation in objective.
- Classification
  - More sophisticated objective functions.
    - Explicit encoding of number of **false negatives.**
    - Weighted binary cross entropy.
    - Weighting individual constraints.
  - Applying predictive performance of GNNs to augment **meta-optimization** [10].

Thank You!

Thomas Falconer, UCL Energy Institute (Energy & AI Lab) thomas.falconer.19@ucl.ac.uk
Letif Mones, Invenia Labs

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