Reduction of the Optimal Power Flow Problem through Meta-Optimization

Alex Robson[1], Mahdi Jamei[1], Cozmin Ududec[1] and Letif Mones[1]
[1]Invenia Labs, Cambridge, UK {firstname.lastname}@invenialabs.co.uk

- Optimal Power Flow (OPF) has a central role in dispatching generation in order to meet demand at minimal cost
- Recently, two ML methods have been introduced to reduce the computational cost of OPF, but neither guarantees feasibility
- We introduce a *meta-optimization* technique, which guarantees optimal solution based on a series of reduced OPF problems

1) Introduction

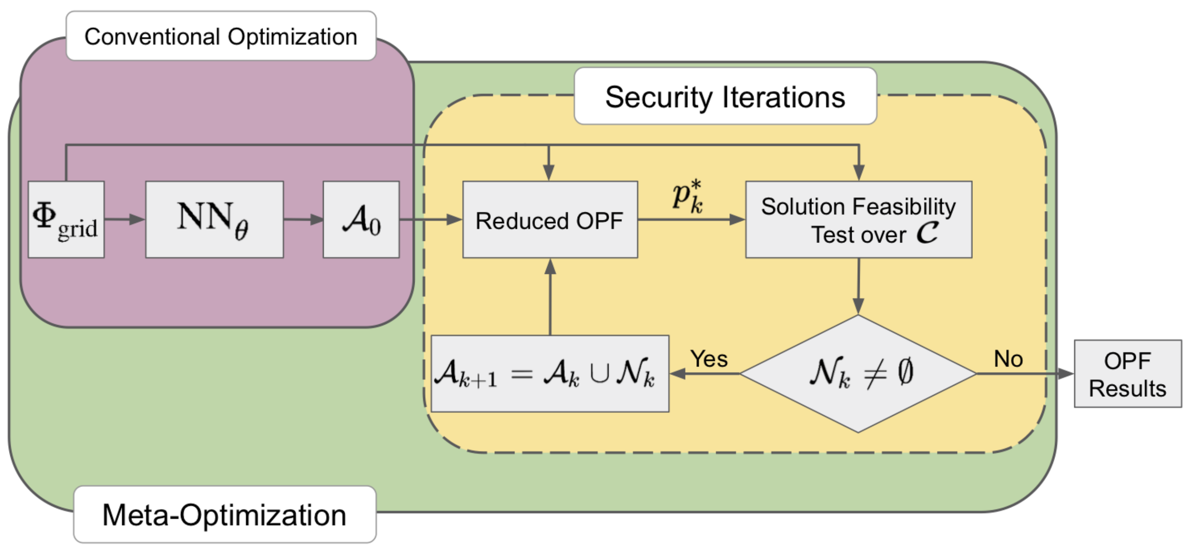
- OPF is a **non-convex** and **non-linear constrained optimization problem** that can be mixed integer in its full form.
- Increasing grid uncertainty due to renewable integration, and accounting for greenhouse gas emission reduction, lead to **increased complexity**[1] of the OPF problem, with limited solution-time.
- There are two potential OPF-agnostic ML methods to reduce the computational cost: 1) **regression** to predict the solution[2] and 2) **classification** to predict the binding constraints and solve a reduced OPF, with predicted non-binding constraints removed. However, neither provides a guaranteed optimal solution[3].
- We introduce an OPF problem reduction method incorporating a **security iteration procedure** that reduces the computational time and guarantees optimal (and so feasible) OPF solution.

2) Optimal Power Flow

- Given the input **grid parameter** vector Φ_{grid}, the typical objective of OPF is to minimize generation cost subject to constraint set $\mathcal{C}$ representing power balance, branch flow and generation capacities.
- The **solution** p^* of OPF includes the power generation of each generator and the voltage magnitude and angle at each bus.
- **Interior-point** solvers are widely used (e.g. Ipopt) to solve OPF.

3) Methodology

- The classifier predicts an initial set of active constraints, $\mathcal{A}_0 = \text{NN}_\theta(\Phi_{\text{grid}})$. A reduced OPF solution (p_0^*) is then obtained.
- At each **security iteration**, $k \in 0 \ldots K$, the solution of the corresponding reduced OPF problem (p_k^*) is validated against the full constraint list $\mathcal{C}$. Violated constraints at each step ($\mathcal{N}_k$) are added to the list of binding constraints to form $\mathcal{A}_{k+1}$ for the next step. The procedure continues until $\mathcal{N}_K = \emptyset$.
- A **meta-loss** is defined as the total computational cost of the series of reduced OPF calculations in the security iteration procedure.
- The meta-loss is optimized over the classifier weights (meta-optimization). Since the meta-loss is a non-differentiable function of θ, the gradient-free Particle Swarm Optimization (PSO) is used.



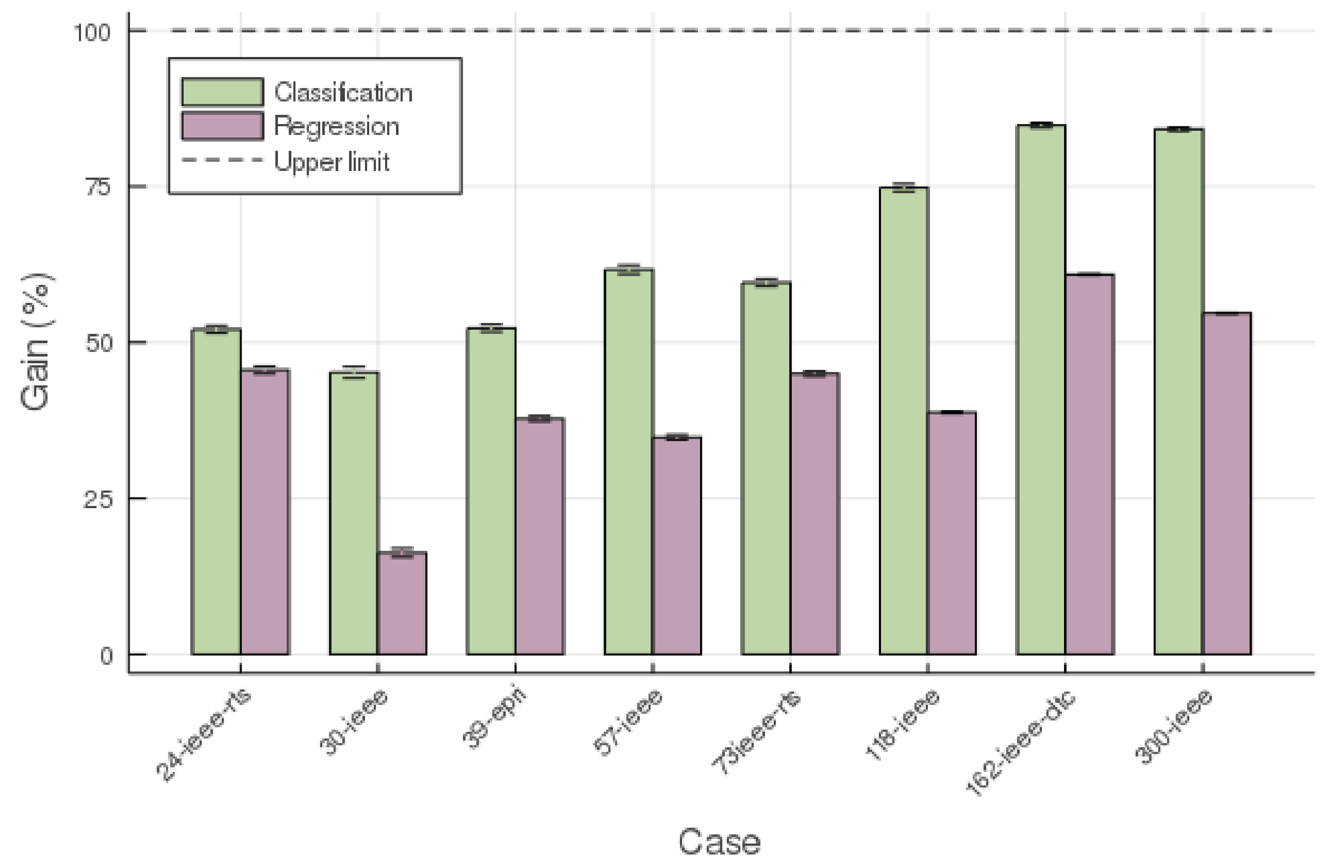
- Configuration: 3-layer NN with 50×50 middle size layer, 10 particles with 10 iterations for PSO, and 900, 100, and 100 samples for the conventional-, meta-training and test sets, respectively.
- Focusing on DC-OPF here, we ran OPF with `PowerModels.jl`[4].

3) Results

- Training/test data were generated by varying original grid parameters[5], which results in higher numbers of distinct sets of active constraints compared to standard approaches:

Case	# of grid params (neural net input)	# of constraints (neural net output)	# of active sets [3]	# of active sets This work
24-ieee-rts	125	140	5	15
30-ieee	105	86	1	1
39-epri	123	112	2	8
57-ieee	206	168	3	8
73-ieee-rts	387	432	21	8
118-ieee	490	410	2	66
162-ieee-dtc	693	592	9	188
300-ieee	1080	936	22	835

- We performed a comparison between the perfect regression and classification to find the maximum achievable computational gain.
- Observation: as the grid size increases, classification has a much higher achievable gain ($\frac{t_0 - t}{t_0} \times 100$):



- Main results: comparing the computational gain of the meta-optimized NN and the conventionally trained one.

Case	118-ieee	162-ieee-dtc	300-ieee
Gain (%)	14.4±3.1	46.2±3.1	49.2±5.2

- We observed no improvement for small grids but the gain increases significantly for larger grids. We also note that for all grids presented, post meta-optimization outperforms the full formulation.

4) Conclusion and Future Work

- We introduced a meta-loss that measures the computational cost of obtaining guaranteed optimal solution of an OPF problem.
- The pipeline starts by solving a reduced OPF problem using only binding constraints as predicted by a classifier, iteratively extending the binding constraints list and solving the extended OPF, and meta-optimizing the classifier to minimize the meta-loss.
- The conventional classifier loss function is suitable where the number of distinct active sets is low (small grids), while the meta-loss is the right metric for grids with a high number of active sets.
- We have begun preliminary investigations into AC-OPF and leave a full investigation to future work.

1. Gholami, A., Ansari, J., Jamei, M., and Kazemi, A. Environmental/economic dispatch incorporating renewable energy sources and plug-in vehicles. IET Generation, Transmission & Distribution, 8(12):21832198, 2014
2. Guha, N., Wang, Z., and Majumdar, A. Machine learningfor ac optimal power flow. ICML, Climate Change: HowCan AI Help? Workshop, 2019.
3. Ng, Y., Misra, S., Roald, L. A., and Backhaus, S. Statistical Learning For DC Optimal Power Flow.arXiv e-prints,art. arXiv:1801.07809, Jan 2018.
4. Carelton Coffrin, Russel Bent, Kaarthik Sundar, PowerModels.jl: An Open-Source Framework for Exploring Power Flow Formulations, URL arXiv:1711.01728v3
5. https://github.com/power-grid-lib/pglib-opf