Meta-Optimization of Optimal Power Flow

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Abstract

The planning and operation of electricity grids is carried out by solving various forms of constrained optimization problems. With the increasing variability of system conditions due to the integration of renewable and other distributed energy resources, such optimization problems are growing in complexity and need to be repeated daily, often limited to a 5 minute solve-time. To address this, we propose a *meta-optimizer* that is used to initialize interior-point solvers. This can significantly reduce the number of iterations to converge to optimality.

1. Introduction

Optimization methods are increasingly being used for planning and operations of complex systems such as electricity grids. A central part of daily planning and operations of electricity grid operators (Tong, 2004) is to dispatch generation in order to meet demand at minimum cost, while respecting reliability and security constraints. This is done by solving a constrained optimization problem, often referred to as Optimal Power Flow (OPF). The OPF problem is in general challenging because, 1) it is a non-convex and non-linear constrained optimization problem that can also be mixed integer in its full form, and 2) it is computationally expensive due to the large size of power grids and high number of constraints. In order to reduce the time complexity of the OPF problem the general practice is to use an approximate form that is convex and has a reduced number of variables and constraints. However, the solution to this simplified problem is known to be far from the optimal one and can lead to inefficiencies in grid operations (Ilic et al., 2006).

According to the United States Environmental Protection Agency (epa, 2019), electricity production contributed to 27.5% of the total U.S. greenhouse gas (GHG) emissions in 2017 placing this sector in the second place among GHG producers. With increasing concerns over climate change, multiple studies have suggested that reducing overall emissions from generation should be taken into account in OPF (Gholami et al., 2014), which makes the problem more complex. Further, the integration of renewable energy sources such as wind and solar add other complications to OPF due to the volatility of these resources. To deal with this volatility, OPF should be solved as near to real-time as possible, which would require improvements to OPF convergence times and robustness.

2. Proposed Methodology

Non-linear and non-convex constrained optimization problems can be solved by interior-point methods such as IPopt (Wächter & Biegler, 2006). They can take as input a given initialization (called warm-start). A good initialization is important for two reasons: 1) it can help avoid poor local minima and reach the global minimum, and 2) it can speed up convergence to this global minimum. We propose an algorithm that outputs the initialization for interior-point solvers, through *meta-optimization*. This algorithm can be trained by using a loss metric as the number of iterations needed to solve the problem. This approach is inspired by recent work in the meta-learning literature, including (Ravi & Larochelle, 2017) and (Finn, 2017).

Our model is trained not to optimize a single instance of an OPF problem, but a family of them. It takes as input a formulation of the problem, and outputs an initialization. Advantages of this method include: 1) leveraging already well-established constrained optimization solvers, and 2) getting guaranteed solutions to the true problem. However, a limitation of this approach is needing to train over all potential grid sizes. To resolve this, we consider grid compression techniques. Initialization is "decompressed" such that only the original OPF formulation is solved.

The following terminology is used in the rest of the paper:

- **Scenario generation**: Given a grid, it creates new cases for train / testing by mutating grid parameters.
- **Model:** Neural Network (NN) that is trained to output solution initialization for OPF given grid input data.
- **Conventional Loss:** Quality metric on initialization (e.g., MSE to final solution for a convex OPF).
- **Meta-Loss:** Sum over the number of interior-point

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steps to reach optimal solution for selected scenarios.

Fig. 1 shows the components of the proposed methodology:

- **Problem Features:** x contains all the input parameters (e.g., lines, generators...) that define the OPF problem.
- **Meta-Optimizer:** The meta-optimizer is trained over a class of OPF problems, with the objective of minimizing the meta-loss. At test-time, the initializations of OPF solvers result in faster convergence.
- **Reduced Features:** Not all the features that define an OPF problem are necessary to find a good initialization for an interior-point solver. Further, it would be cumbersome to retrain the meta-optimizer for every new grid or OPF problem. We propose a solution where separate meta-optimizers are trained for a set of pre-defined grids denoted by $\mathcal{G}$, and a grid compression (see e.g., (Wang et al., 2010)) is used to reduce a given grid down to the nearest available size in $\mathcal{G}$ and therefore to obtain the reduced features (x^{red}). The recommended initialization (y_0^{red}) is then decompressed (y_0) before IPopt solves the original OPF.
- **OPF Solver:** Solves the OPF model using the recommended initialization (Coffrin et al., 2018).

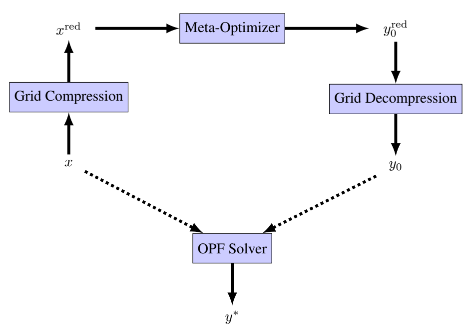

Figure 1. Proposed workflow of meta-optimized OPF.

3. Preliminary Results

To demonstrate the core concept, we pick different grids from the pglib-v19.05 (pgl) library treating them as members of the set $\mathcal{G}$, for which we want to train the meta-optimizer. For each case, we start with scenario generation. Grid compression / decompression has not been included in this experiment as we are only dealing with members of $\mathcal{G}$ for now. For this experiment we use DC-OPF as an approximation for simplicity and employ Ipopt solver to solve the optimization. Given the non-differentiable metaloss-function, we consider gradient-free optimization (GFO), such as Particle Swarm Optimization (PSO) to train the "meta-optimizer".

To motivate the importance of good initialization we refer to Fig. 2. Here, we use a metric of efficiency where 0% efficiency is the number of iterations that takes the solver to find the optimal point using a heuristic initialization, and 100% efficiency is for the case when both the primal and dual variables are initialized with the exact solution. In our experiments we focus on initializers for primals only and investigate how much we can approach the theoretical upper-bound of efficiency (i.e. using the exact primals as initializers). The importance of initialization will be a function of grid complexity, such as the size of the feasible region. What we present here are the statistics of primal initialization efficiency across a family of grid states.

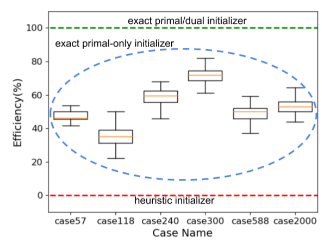

Figure 2. Efficiency of primal initialization

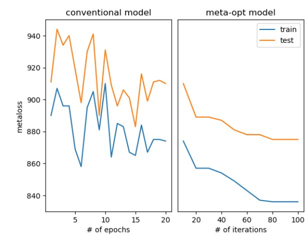

Figure 3. Meta-loss minimization using the proposed method

In order to highlight the advantages of meta-optimization, we compare a conventional NN supervised learning using a $MSE(y_0^{NN}, y^*)$ objective on the metaloss, followed by the meta-training in Fig. 3. As can be seen, the meta-training could further minimize the meta-loss and can therefore lead to better initializations.

4. Challenges and Future Direction

There are three challenging problems we face in this design:

- **Problem Representation:** A challenging part of the meta-optimization pipeline is to encode the OPF formulation into a family that has been meta-trained.
- **Meta-Optimizer Training:** The optimizers such as Ipopt are generally complex pieces of software so unlike (Finn, 2017) we are unable to backpropagate gradients through this part of the pipeline and that is why we used a GFO. We want to investigate the implementation of constrained optimization solvers in differentiable programming languages (Amos & Kolter, 2017).
- **Scalability:** Different electrical grids exist, and further, grids themselves change over time. We plan to train multiple meta-optimizers over a set of pre-defined grid sizes and compress any grid to its nearest grid size in that set.

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