Machine learning for Meta-Optimization of Optimal Power Flow Problem

Abstract

Scheduling electric generators to meet the demand at the minimum cost is currently carried out by solving a non-convex constrained optimization problem which is computationally highly demanding and is solved ahead of time. With the increasing penetration of renewable resources that are inherently volatile, scheduling the generators should be done as close as possible to real-time that requires the problem to be solved many times over the course of the day. Adding greenhouse gas emission reduction as a co-objective in the generator scheduling problem is vital but makes the problem even more complicated. To overcome this problem, we propose to use a machine learning based meta-optimizer to predict a good starting point for the optimization problem above that significantly facilitates the convergence (i.e., less number of iterations) to the global optimum.

1. Introduction

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 the main GHGs producers. Burning fossil fuels, mainly coal and natural gas, provides 62.9% of the US electricity (epa, 2019).

Planning and operation of the electricity generation in major part of the US are deregulated, in which market participants (generators, loads and virtual utilities) participate in a two-settlement market, namely day-ahead and real-time market, where the offers and bids are placed to generate and consume the electricity, respectively (Tong, 2004). The Independent System Operator (ISO), who is responsible to run the market, collects the offer/bid data along with the grid data to solve a constrained optimization problem, in which the goal is to dispatch generators to meet the demand at the minimum cost, while respecting reliability and security constraints. The core of this process is referred to as Optimal Power Flow (OPF), which can take different forms depending on the market time-line (day-ahead or real-time) or approximations. There are different aspects to the problem that makes it a challenging problem to solve:

- OPF in its original form is a non-convex and non-linear constrained optimization that can also be mixed integer problem, and thus finding the global optimum point is not guaranteed most of the times
- Solving OPF is a very computationally-heavy task due to the large size of power grid and high number of constraints

The general industry practice to reduce time complexity of the OPF problem is to use a convex surrogate model with a reduced number of variables. However, the solution of this simplified problem is known to be far from the optimal one and it leads to inefficiencies in operating the grid.

With increasing concerns over climate change due to GHGs, multiple studies have suggested that reducing the overall emission from the generators should be taken into account as an objective in the OPF optimization problem (see e.g. (Gholami et al., 2014)). This in turn increases the time and dimension complexity of the problem. To achieve the maximum possible emission reduction while having the minimum generation cost, the solution should be as close as possible to the global optimum point of the original problem (without approximations) to avoid high emission rates and cost of running power plants.

Using renewable energy sources such as wind and solar is another solution to alleviate the emission from the electricity sector. However, volatility of these resources usually makes the generation planning a hard task as predicting the renewable resources output long ahead of time is not easy. To deal with the volatility, it would be ideal to run OPF as close as possible to real-time which means that OPF needs to be solved in the shortest possible time.

One can note from the above that in order to have a generation planning that minimizes both GHG emission and production cost, and at the same time is able to incorporate high volumes of renewable resources in the generation portfolio, we need to find a solution for constrained optimizations problems (OPF in this case) that is very close (or accurate) to the global optimizer of the problem and can be found in a short amount of time.

2. Proposed Methodology

Solvers that are widely used to solve non-linear and non-convex constrained optimization problems such as IPopt can take as input a starting point to warm-start the solver. A descent starting point can be important from two aspects:

- it can help avoiding local minima and reach the global optimizer of the problem if it exists
- it can speed up the convergence to this global minimum

It is however very hard to come up with a starting point that satisfies the requirements above. Our idea is to use Machine Learning (ML) to optimize the optimization of these problems by suggesting a good starting point.

The ML system can be trained to optimize the optimization process, for example using a loss metric of the time taken to solve the problem, or the final solution quality. We refer to the ML component that suggests good starting points as the meta-optimizer. We call the a meta-optimizer in likeness to the meta-learner. It is trained not to optimize a single instance of a grid problem with a single set of constraints but to solve a family of them. It has as input a reduced representation of the problem, and outputs a suggested starting point. Advantages of this method over directly using machine learning to learn a solution to the optimization problems include:

- leveraging the already well-established constrained optimization methods.
- guaranteed solutions to the true problem, rather than to the representation that the ML system takes as inputs.

Fig. 1 presents blocks of the proposed methodology that are discussed in more details as follows:

- **Problem Features:** This block contains all the input parameters that define OPF problem. This includes the buses, lines, generators and loads data as well as offer and bid curves.
- **Reduced Features:** Not all the features that define an OPF problem are necessary to be passed to the ML model to find a good initial point. Also, different grids have different sizes and therefore the input data to the ML model has different dimensions too. It would be cumbersome to retrain the meta-optimizer for every grid size. We propose a solution where separate meta-optimizers are trained for a set of pre-defined grid sizes, and a ML-based grid compression is used to compress grids down to the nearest available size in this set that the meta-optimizer has been trained for. Then the predicted starting point needs to be expanded to distribute values associated with compressed nodes to all the original nodes; before the optimizer solves the complete optimization problem.
- **Meta-Optimizer:** We train the meta-optimizer over a class of OPF problems. The aim is to predict initial points that would result in quick convergence to the global optima once it is fed to the OPF solver.
- **OPF Solver:** The OPF solver takes the OPF model along with the initial point and runs the optimization.

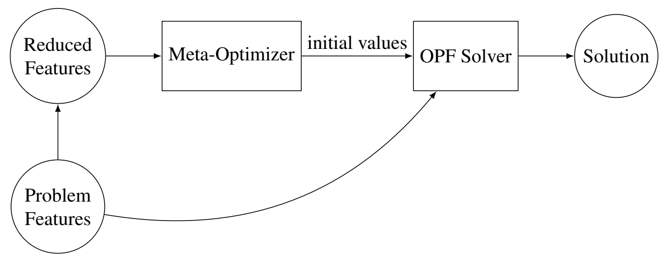

Figure 1. Proposed OPF Meta-optimizer

3. Challenges and Future Direction

There are 3 challenging problems we face in this design:

- **Problem Representation:** A challenging part of the model is to encode the OPF features into proper inputs that are amendable to the meta-optimizer.
- **Meta-Optimizer Training:** The loss function for the meta-optimizer comes from the performance of the optimizer over a set of problems in the training set. The optimizers themselves are generally complex pieces of software. One possible solution is to use gradient free optimization, but we also want to investigate the implementation of constrained optimization solvers in differentiable programming languages.
- **Scalability:** Different electrical grids exist, and further, grids themselves change over time. As it was discussed, 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. One possible solution is to use NN for this grid compression.

References

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