EE394V Power System Operations and Control Learning for DC-OPF: Classifying active sets using neural nets

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March 29, 2020

Abstract

Optimal power flow is used in power system operational planning to estimate the most economical efficiency solution while satisfying demand and safety margins. Due to increasing uncertainty and variability in energy sources and demand, the optimal solution needs to be updated near real-time to respond to observed uncertainty realizations. However, the existing method of solving the optimal problem could not cope with frequent updating due to the high computational complexity. To address this issue, a method was proposed to learn the mapping between the uncertainty realization and the active constraints set at optimality. In this paper, we propose the use of neural networks as a classifier learning the mapping between the uncertainty realization and the active constraints set at optimality, which has an extremely low computational complexity. Through numerical experiments, we demonstrate the remarkable performance of this approach on systems in the IEEE PES PGLib-OPF benchmark library.

1 Introduction

A more detailed and technical version of the abstract. Review of existing approaches could be also included here. Clearly identify one to three contributions that you are targeting.

2 Problem Formulation

Introduce the input data and parameters, problem variables (output), possible auxiliary variables. Introduce the problem statement with an objective. Comment on the availability of data (the data sources) or how you plan to generate synthetic data using simulation tools; review of existing approaches; or proposed work (machine learning/statistical estimation/performance analysis, etc).

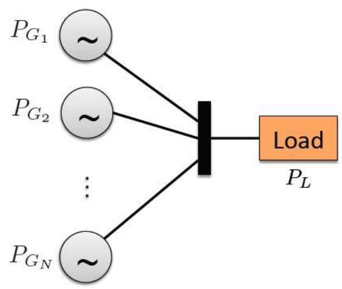

Figure 1: Sample figure.

Algorithm 1 Sample algorithm

Require: Input variables.

Step 1.
for $i = 1, 2, \ldots,$ **do**
  Step 2.a.
end for

$$
\begin{aligned}
\rho^{\star}(\omega) \in \underset{p}{\text{argmin}}\ & c^{\top} p && (2.1)\\
\text{s.to}\ \ & e^{\top} p = e^{\top}(d - \mu - \omega) && (2.2)\\
& p^{min} \le p \le p^{max} && (2.3)\\
& f^{min} \le M(Hp + \mu + \omega - d) \le f^{max} && (2.4)
\end{aligned}
$$

$$
\begin{aligned}
\mathcal{P}(\omega) = \{p \in \mathbb{R}^n : \quad & p^{min} \le p \le p^{max},\\
& f^{min} \le M(Hp + \mu + \omega - d) \le f^{max},\\
& e^{\top} p = e^{\top}(d - \mu - \omega)\} && (2.5)
\end{aligned}
$$

$$
\begin{aligned}
\mathcal{P}(\omega) = \{p : \quad & Ap \le b + C\omega,\\
& e^{\top} p = e^{\top}(d - \mu - \omega)\} && (2.6)
\end{aligned}
$$

3 Numerical Experiments

Describe your simulation set up. Put figures/tables here.

4 Concluding Remarks

References

[1] A. J. Wood, B. F. Wollenberg, and G. B. Sheble. Power Generation, Operation, and Control, Wiley, 2014.

[2] S. Boyd and L. Vandenberghe. Convex Optimization, Cambridge University Press, 2004.