Dynamic OPF-Net:
Real-Time Stability Constrained AC Optimal Power Flow

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Introduction

The Alternating Current Optimal Power Flow (AC-OPF) problem is a cornerstone of power systems operations, which consists of determining the most cost-effective generator dispatches that meet demand while adhering to physical and engineering constraints. Traditionally addressed as a *steady-state* snapshot, the AC-OPF must be solved frequently (e.g., every 10-15 minutes) due to fluctuating loads, making it crucial for operational continuity and system stability (Hatziargyriou et al. 2021).

The problem's inherent non-convexity, high dimensionality, and computational intensity have motivated the adoption of Learning to Optimize (LtO) methods (Kotary et al. 2021) as alternatives to traditional numerical solvers. However, as we show in (Vito et al. 2024), existing LtO approaches, such as those proposed by (Donti, Rolnick, and Kolter 2020) and (Fioretto, Mak, and Van Hentenryck 2020), focuses on steady-state formulations and may fail to address dynamic system requirements adequately.

The stochastic nature of renewable energy sources, along with the need for stable frequency maintenance and the system's dynamic nature, demand power flow models that incorporate these dynamic behaviors.

Problem setting

The integrating of generator dynamics and associated stability constraints into the AC-OPF formulation results in the *stability-constrained* AC-OPF problem, described in (Vito et al. 2024). In this problem, the decision variables include generator power outputs and bus voltages, while the state variables represent generator rotor angles and speeds. The objective is to minimize power dispatch costs while satisfying demand, network constraints, and ensuring system stability. Fully integrating these dynamics into the AC-OPF model, however, introduces complex interdependencies among the problem variables, significantly increasing the computational complexity.

Proposed Approach

To address these challenges, we propose Dynamic-OPF Net (Dyn-OPF Net), a dual network architecture consisting of a Learning to Optimize model to approximate the decision variables and neural-ODE models (Chen et al. 2018), to capture the dynamic behaviors of individual generators. The neural-ODE models are integrated within the Learning to Optimize pipeline by adopting a primal-dual method, which allows seamless integration of static and dynamic constraints within model training.

Experimental Results

Our approach is compared against state-of-the art LtO methods which tackle the steady-state AC-OPF, across a suite of benchmarks, including the WSCC-9 and IEEE-57 bus systems. The experimental results discussed in (Vito et al. 2024) show that the integration of the generator dynamics within model training allows to produce high-quality approximation of the decision variables in near real-time, while also adhering to the system dynamic requirements. In contrast, all the baseline methods generates solutions which often violate the stability constraints, which is unacceptable in practice. The results underscore the potential of DE-OP to handle complex power flow models, offering a robust alternative to traditional AC-OPF formulations. Furthermore, as the generator dynamics are independent and modeled using separate neural ODEs, their computations can be parallelized. This highlights the potential for DynOPF-Net to address large-scale power system optimization tasks.

Conclusion

Dynamic-OPF Net enables the integration of generator dynamics within model training, a critical step for ensuring system stability for power systems operations. By combining Learning to Optimize techniques with neural-ODEs, our approach offers a scalable and efficient solution for addressing AC-OPF problems with dynamic requirements.

References

Chen, R. T. Q.; Rubanova, Y.; Bettencourt, J.; and Duvenaud, D. 2018. Neural ordinary differential equations. In *Proceedings of the 32nd International Conference on Neural Information Processing Systems*, NIPS'18, 6572–6583. Curran Associates Inc.

Donti, P. L.; Rolnick, D.; and Kolter, J. Z. 2020. DC3: A learning method for optimization with hard constraints. In *ICLR*.

Fioretto, F.; Mak, T. W.; and Van Hentenryck, P. 2020. Predicting AC Optimal Power Flows: Combining Deep Learning and Lagrangian Dual Methods. *Proceedings of the AAAI Conference on Artificial Intelligence*, 34(01): 630–637.

Hatziargyriou, N.; et al. 2021. Definition and Classification of Power System Stability – Revisited & Extended. *IEEE Transactions on Power Systems*, 36(4): 3271–3281.

Kotary, J.; Fioretto, F.; Van Hentenryck, P.; and Wilder, B. 2021. End-to-End Constrained Optimization Learning: A Survey. In *Proceedings of the Thirtieth International Joint Conference on Artificial Intelligence, IJCAI-21*, 4475–4482.

Vito, V. D.; Mohammadian, M.; Baker, K.; and Fioretto, F. 2024. Learning to Optimize meets Neural-ODE: Real-Time, Stability-Constrained AC OPF. *CoRR*, abs/2410.19157.