

grid-feedback-optimizer: A Python package for feedback-based optimization of power grids

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Summary

The increasing integration of distributed energy resources (DERs)—such as photovoltaics, electric vehicles, and battery storage systems—into electrical distribution networks has led to more frequent voltage and congestion issues. Ensuring secure and efficient operation of modern distribution grids requires real-time control of fast-responding inverter-interfaced DERs, achieved through dynamic optimization of their active and reactive power setpoints.

Online feedback optimization has recently emerged as a promising framework for this purpose (Dall'Anese & Simonetto, 2018; Haberle et al., 2021). It iteratively drives the physical system toward an optimal operating point by embedding optimization algorithms directly within the feedback loop (Hauswirth et al., 2024). This approach performs reliably even under imprecise system models, measurement errors, outdated data, and disturbances (Zhan et al., 2025), as it relies on real-time measurements rather than perfect forecasts or full observability.

grid_feedback_optimizer is an open-source Python package implementing the principles of online feedback optimization for power distribution networks. It couples iterative optimization algorithms—such as projected gradient descent (Haberle et al., 2021) and primal-dual methods (Dall'Anese & Simonetto, 2018)—with a nonlinear power flow solver, enabling closed-loop optimal control of grid-connected DERs. The package supports network data in JSON or Excel formats and features a modular, extensible architecture suitable for both research and practical applications.

Statement of need

Several open-source packages are available for solving optimal power flow (OPF) problems. Pandapower (Thurner et al., 2018) employs PYPOWER (Zimmerman et al., 2011) as its optimization engine, supporting both linearized DC and full AC OPF problems through an interior-point solver. It also integrates PowerModels.jl, which mainly uses Ipopt [WachterBiegler2006] as the internal solver but can be extended to other solvers. PyPSA is another open-source OPF framework that allows multi-period formulations and uses HiGHS (Huangfu & Hall, 2018) as its default solver, with the option to interface with additional solvers.

In summary, all existing libraries require formulating a full AC OPF problem and depend on nonlinear programming solvers to compute optimal operating points. In contrast, grid_feedback_optimizer adopts a fundamentally different approach. It leverages power flow calculations as feedback and employs simple first-order algorithms—projected gradient descent or primal-dual method—to iteratively update DER setpoints. Notably, when using the primal-dual algorithm and when DERs are subject only to quadratic or box-type reactive power constraints, the projection steps can be easily solved analytically. As a result, the overall optimization process can operate efficiently entirely without external solvers. By integrating power flow calculations directly into the feedback loop, grid_feedback_optimizer inherently

compensates for modeling inaccuracies and ensures that grid operational constraints are satisfied. This feedback-based approach provides robustness not typically achievable with convex relaxation methods.

The package can be applied to a wide range of use cases, including solving static OPF problems, demonstrating and validating online feedback optimization algorithms, benchmarking real-time control strategies for distribution grids, supporting educational activities in power systems and optimization, managing microgrids and virtual power plants under distribution system operator (DSO) coordination, and prototyping or evaluating voltage and congestion management algorithms prior to deployment by DSOs.

Implementation

Figure 1 illustrates the feedback optimization calculation process. The optimization algorithm engine receives the network state computed by the power flow engine as feedback and uses it to generate updated setpoints for DERs. These new setpoints are then fed back into the power flow engine to compute the corresponding network state. This iterative process continues until convergence to a steady-state optimum, where all operational constraints of the distribution grid are satisfied.

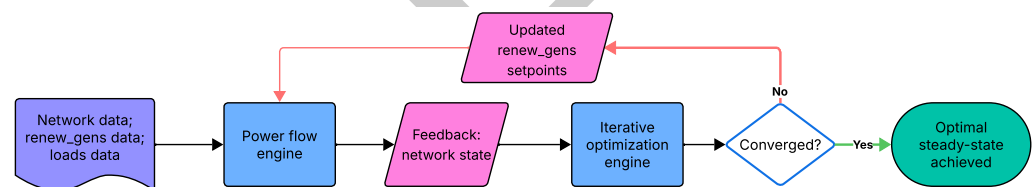


Figure 1: Flowchart of the feedback optimization calculation process.

The projected gradient descent algorithm is formulated as a convex conic program and is, by default, solved using the CLARABEL solver (Goulart & Chen, 2024). The primal-dual method dualizes network constraints and enforces individual DER constraints through projection, which is also solved, by default, by CLARABEL when analytical solutions are not available. Compared to projected gradient descent, the primal-dual algorithm typically requires more parameter tuning—particularly the selection of multiple step sizes—but offers a lower computational cost per iteration. Power flow programs are efficiently solved using power-grid-model (Xiang et al., n.d., 2023).

The library also includes several example notebooks demonstrating its capabilities, featuring both static results for a 97-bus low-voltage network and dynamic, time-varying simulations.

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Conflicts of interest

The author declares no conflicts of interest.

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