

# Diagnosing and Mitigating Infeasibilities in Power Grid Optimization Using Machine Learning and Counterfactual Explanations

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## Introduction

Electric power grids are essential components of modern life. To economically deliver reliable power, grid system operators repeatedly solve a complex optimization problem to balance supply and demand without violating the constraints of the physical system. When this problem becomes infeasible, system operators must quickly determine techniques to maintain grid stability such as shedding load or bringing additional generation online.

Fixing infeasibilities in optimal power flow (OPF) problems are often either done manually or via computationally burdensome approaches (Gunda, Harrison, and Djokic 2016). Although some work has been done to identify infeasibilities in both OPF (Jereminov et al. 2020) and power flow (Passos Filho, Martins, and Djalma 2009), end-to-end frameworks which both identify and mitigate infeasibilities on fast timescales appropriate for real system operation are limited (Foster, Pandey, and Pileggi 2022), and can be prohibitively time-consuming in practice.

In this abstract, we discuss an explainable learning framework to quickly diagnose infeasibilities in the OPF problem, and minimally relax appropriate constraints to return the problem to the feasible domain. This framework allows flexibility in which constraints are adjusted and provides multiple solutions for mitigating infeasibility. Preliminary framework results promise speedups for identifying and fixing these feasibility issues in power grid operation.

## Problem Setup

The test case employed in this study is the IEEE 30-bus system. The DC Optimal Power Flow (DCOPF) problem, outlined in (Mohammadian et al. 2022), aims to minimize the total generation cost while adhering to key operational constraints, including power balance, generation limits, and line flow limits. Infeasibilities in the DCOPF arise primarily from line flow constraint violations, as the scenarios ensure total generation exceeds total load. 10,000 samples were generated for training and testing purposes. The load values for each sample were randomly perturbed within a range of  $\pm 65\%$  of the base load. The DCOPF problem was solved for each scenario, yielding two balanced classes of 5,000

feasible and 5,000 infeasible solutions. The dataset was partitioned into 80% for training and 20% for testing, maintaining class balance within each subset.

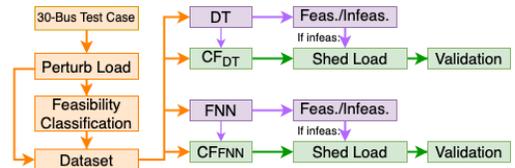


Figure 1: Infeasibility Mitigation Information Flow

## Preliminary Results

To classify the feasibility of DCOPF solutions, a Decision Tree (DT) and a Feedforward Neural Network (FNN) were used. Two separate counterfactual (CF) models were built on the DT and FNN. The classification models achieved high classification accuracy: 99% for the DT and 97.5% for the FNN. Following the classification, a subset of 100 infeasible load vectors from the test dataset were adjusted using the CF models. The CF models decreased the loads (e.g. performed load shedding) to resolve infeasibilities, minimizing deviations from the original loads. To validate the output of the CF models, the modified samples were re-evaluated using the DCOPF solver. The accuracy of these solutions in restoring feasibility over 10 trials is demonstrated in Table 1. Fig. 1 outlines the described information flow.

Method	Min Acc.	Average Acc.	Max Acc.	Std.
$CF_{DT}$	93	96	98	1.4
$CF_{FNN}$	100	100	100	0.0

Table 1: Percentage of valid counterfactuals.

## Conclusion and Future Outlook

The preliminary results indicate how explainable machine learning can be used to 1) rapidly detect if an optimization problem is infeasible and 2) rapidly find a suite of possible solutions to mitigate infeasibility. Future work will expand the framework to larger systems and more complex optimization formulations.

## References

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