OPF-Learn: A software package for efficiently creating AC optimal power flow machine learning datasets

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Introduction

A significant power systems research area is addressing challenges operators face when determining how to **fulfill electric power demand at the lowest cost**, referred to as **AC optimal power flow (AC-OPF)**

+ Renewable energy resources are a key factor in the transition to a more sustainable power grid.
− However, these resources make operating the grid economically more challenging, due to their variable and distributed nature.

AC-OPF is central in determining how to best operate the grid but increasing levels of **distributed renewable generation make this problem computationally challenging.**

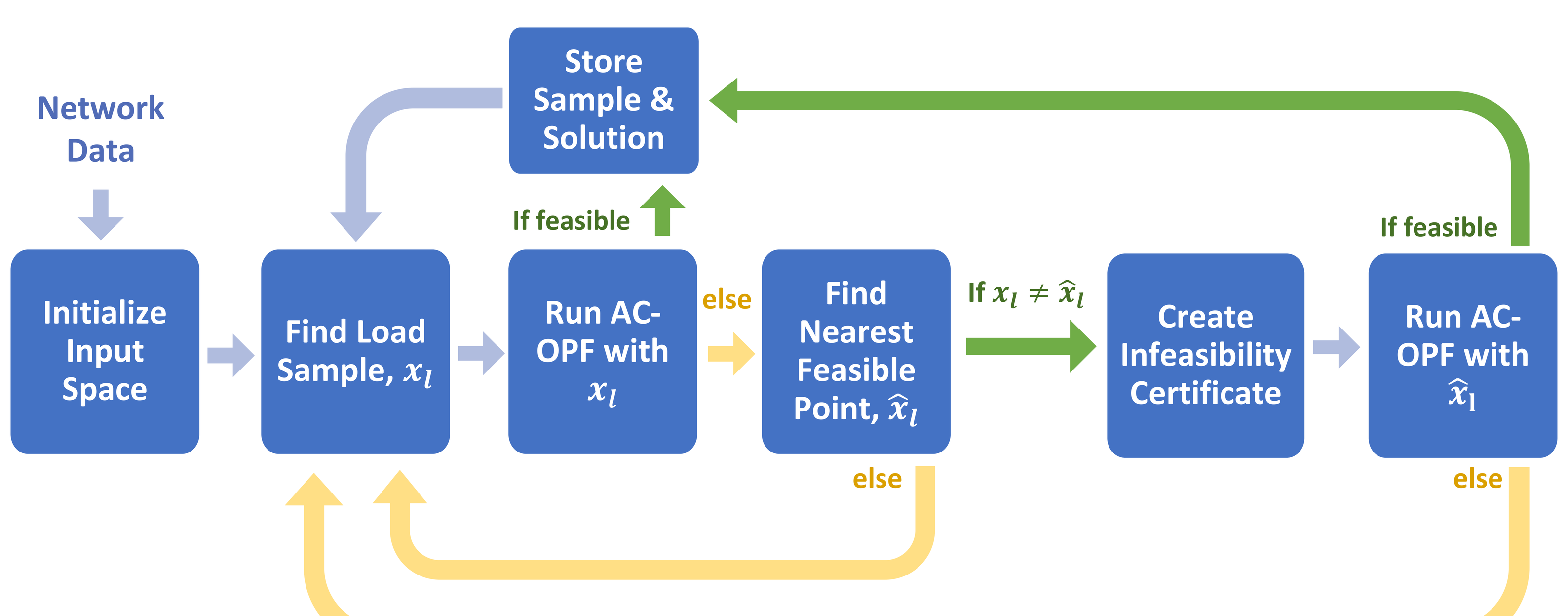
+ One possible solution is applying **machine learning (ML) methods** to solve AC-OPF problems more efficiently.
− A **lack of disciplined dataset creation** and benchmarking prohibiting useful comparisons between ML methods.

Research Question

How can datasets that are representative of the entire AC-OPF feasible input space be efficiently created for machine learning applications to solving AC-OPF?

OPF-Learn Software Package

OPF-Learn efficiently creates datasets mapping input load profiles to optimal generator setpoints for machine learning applications.



OPF-Learn software flow chart for creating AC-OPF samples.

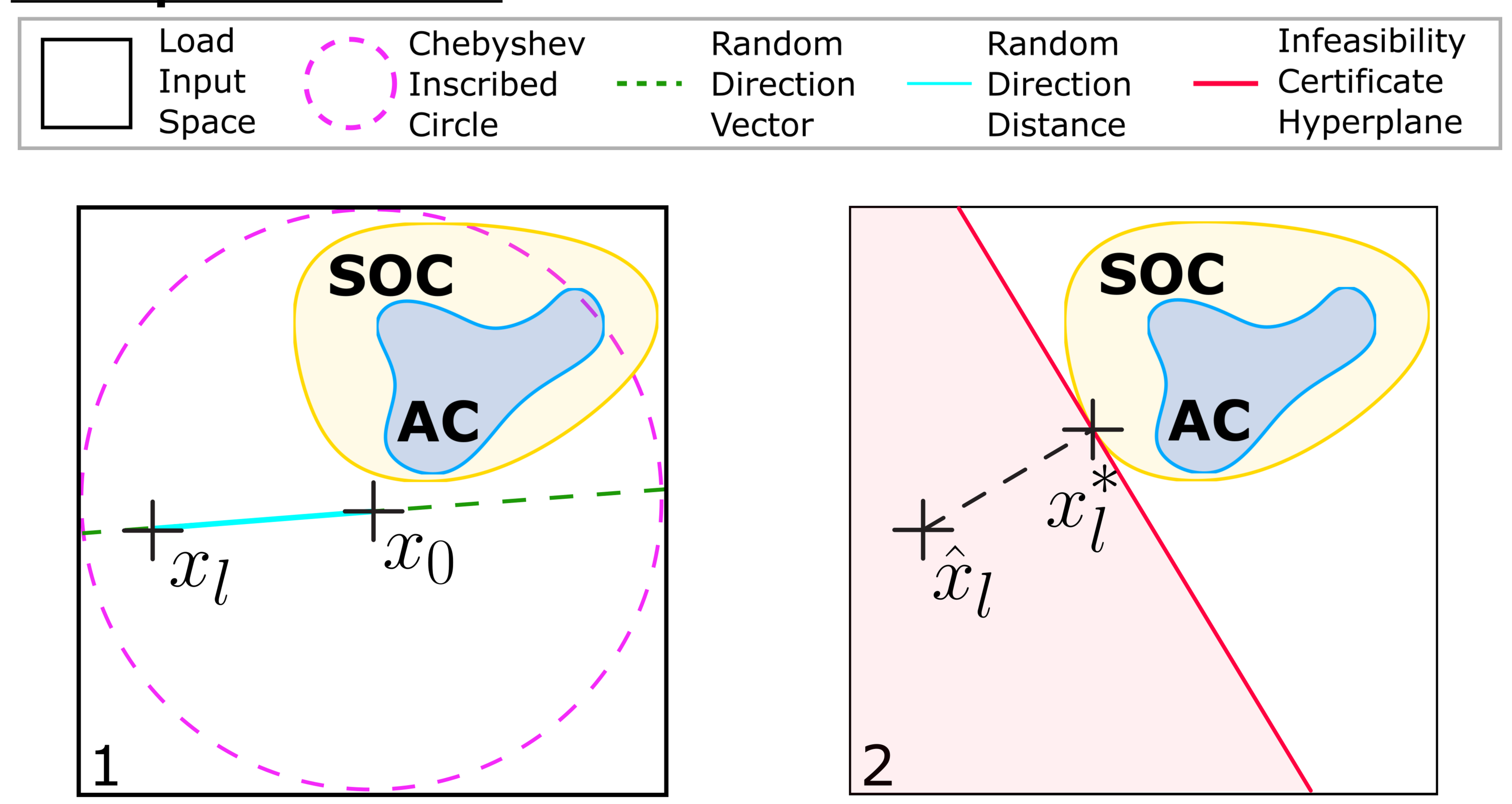
Typical AC-OPF datasets contain only a small subset of the AC-OPF feasible loads space. OPF-Learn improves upon this using the following features,

- **Uniformly Samples Input Space:** The input space, containing the entire AC-OPF feasible region, is uniformly sampled.
- **Reduces Input Space with Infeasibility Certificates:** Infeasibility certificates are created to reduce the input space as specified in. Hyperplanes are created using a convex AC-OPF formulation, the second-order cone (SOC) relaxation, to find the nearest feasible point.

AC-OPF Dataset Creation

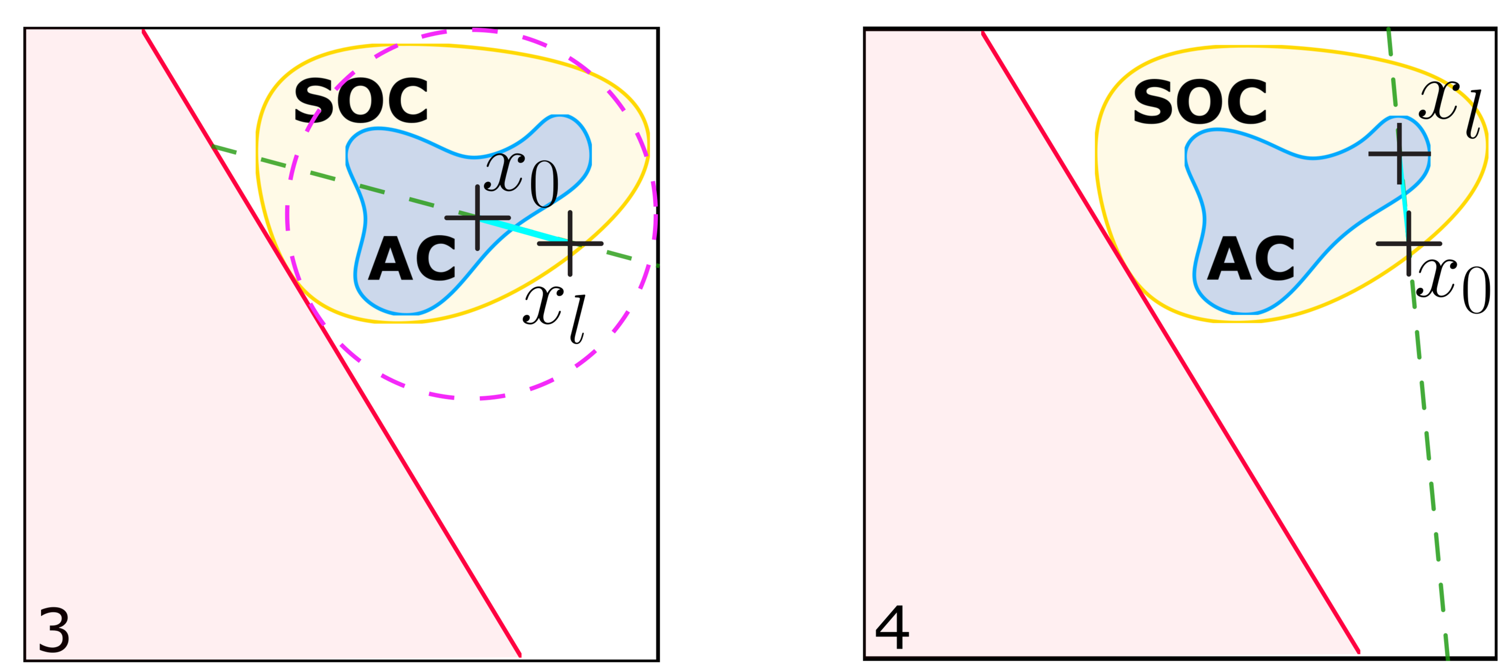
An example of the methodology used to find load samples can be seen below,

Example Iterations



1. Find the Chebyshev center, x_0. Generate a random direction vector and travel a random distance along this vector to find a new load sample, x_l.

2. Check if x_l is AC-OPF feasible. If not feasible, find the nearest SOC feasible point, x_l^*. Since $\hat{x}_l \neq x_l^*$, define a new infeasibility certificate at x_l^* with normal, $\vec{n} = \hat{x}_l - x_l^*$.

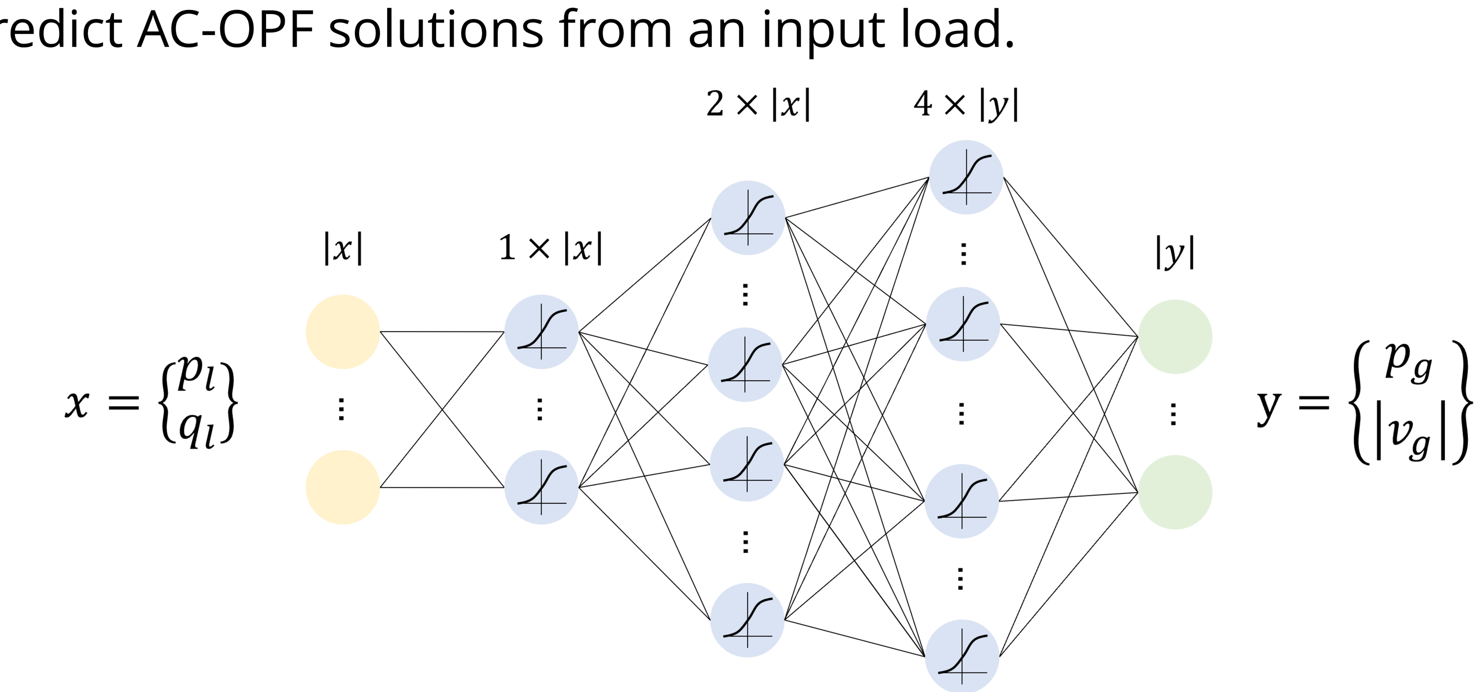


3. Gather a new sample, x_l, as in step 1. Check if the new x_l sample value is AC-OPF feasible. Here it is not, so the nearest SOC feasible point is found. $\hat{x}_l = x_l$, so discard this sample.

4. Sample a new load profile, x_l, as in step 1, but starting from the last point, now x_0. Check if x_l is AC-OPF feasible. x_l is AC-OPF feasible, so store x_l and its AC-OPF optimal solution.

Training Neural Networks

To test datasets generated using OPF-Learn, neural networks (NN) were trained on OPF-Learn datasets as well as "typical" datasets to predict AC-OPF solutions from an input load.



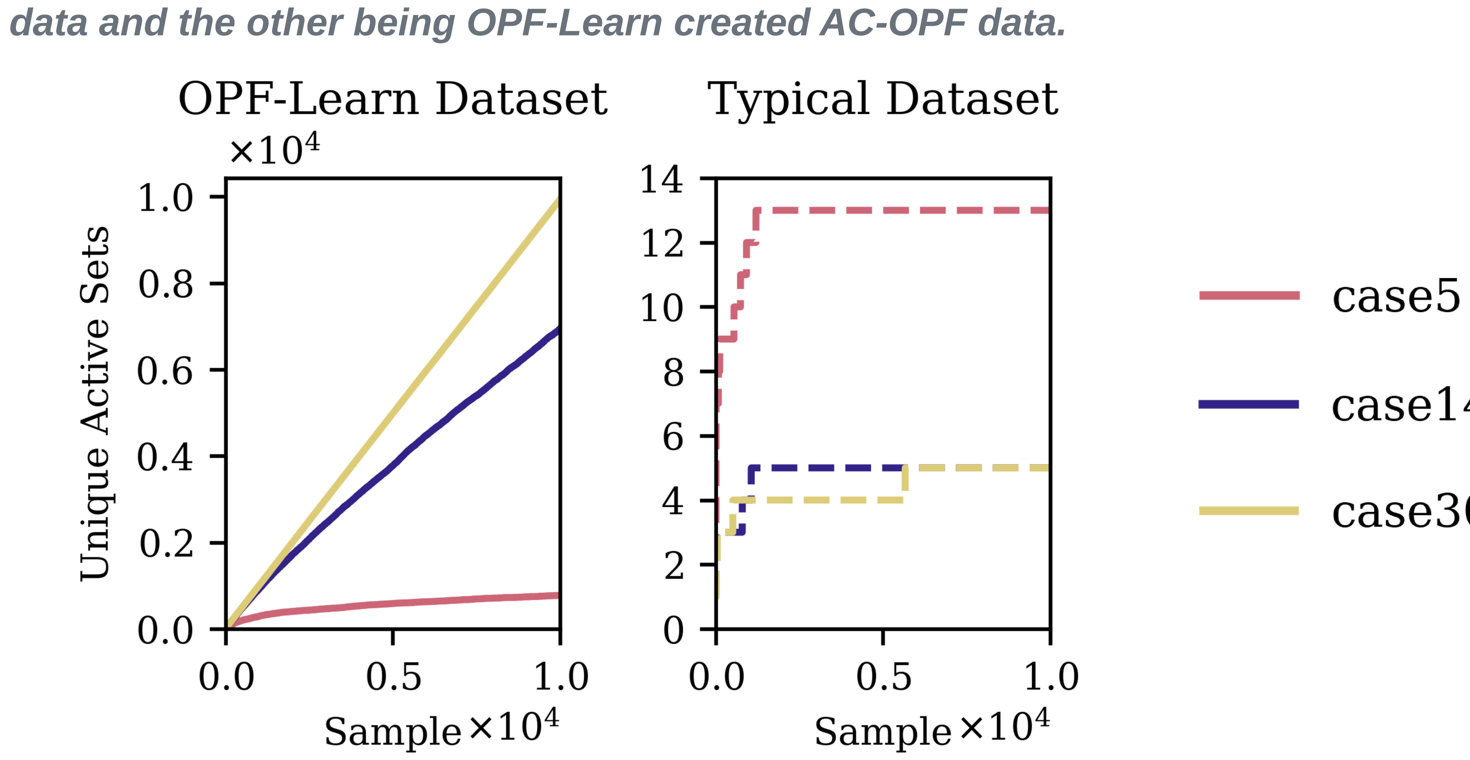
Neural network model with three hidden layers and sigmoid activation functions.

Results

- OPF-Learn is a publicly available Julia & Python package to create representative AC OPF datasets
  - Able to find more unique active sets of constraints in load samples than typical dataset creation methods.
  - NN models trained on OPF-Learn data have less mean squared error (MSE) when tested on representative test sets compared to the same model trained on a typical dataset.

	OPF-Learn Dataset Trained Model		Typical / OPF-Learn	Typical Dataset Trained Model		OPF-Learn / Typical
Test Dataset:	OPF-Learn	Typical		OPF-Learn	Typical	
case5	2.17E-2	1.86E-3	**8.57E-2**	1.33E+0	9.08E-6	**1.46E+5**
case14	2.75E-4	1.01E-4	**3.67E-1**	3.94E-2	9.41E-7	**4.19E+4**
case30	1.55E-4	5.46E-4	**3.52E+0**	8.17E-3	1.60E-8	**5.11E+5**
case118	6.97E-2	2.35E-1	**3.37E+0**	4.47E-1	4.47E-3	**1.00E+2**

NN mean squared errors for the OPF-Learn dataset trained and Typical dataset trained P_g NN models. Each NN was tested with two test datasets, that the models had not seen during training, with one dataset containing typically created AC-OPF data and the other being OPF-Learn created AC-OPF data.



Plot of unique active sets found over time with a typical dataset creation methods and the OPF-Learn dataset creation method. Note the difference in the y-axis scale

Conclusion & Future Work

Creating more representative AC-OPF datasets allows for the benchmarking and comparison of machine learning approaches over the entire AC-OPF feasible load space.

Future work:

- Understand the mapping of load profiles to optimal generator setpoints within unique active sets.
- Comparison of proposed machine learning approaches using OPF-Learn generated datasets

GitHub

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