Revisiting Deep AC-OPF

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Introduction

AC optimal power flow (AC-OPF) is a constrained optimization problem, fundamental to the operation of electrical power grids. The objective of AC-OPF is to minimise the cost of generating real electrical power while satisfying physical and operational constraints. Conventional solvers for this problem can be prohibitively slow especially given increased variability from renewable generation. This has motivated extensive research on machine learning (ML) approaches to solving or accelerating the solving of AC-OPF[1,2]. In this work we present the following:

- Implementation of a transformer-based model, OPFormer-V,
- Comparison of OPFormer-V against DeepOPF-V (FCNN)
- Comparison of both architectures against relatively simple models and an observation of the surprisingly high performance achieved by simple linear models

Model Architecture

OPFormer-V is a transformer-based model that treats an N-bus grid as a sequence of N tokens, each encoding node-level features. The tokens are passed through a transformer encoder. The encoder outputs are then concatenated and passed through a feedforward head to predict voltage magnitudes and angles at all buses.

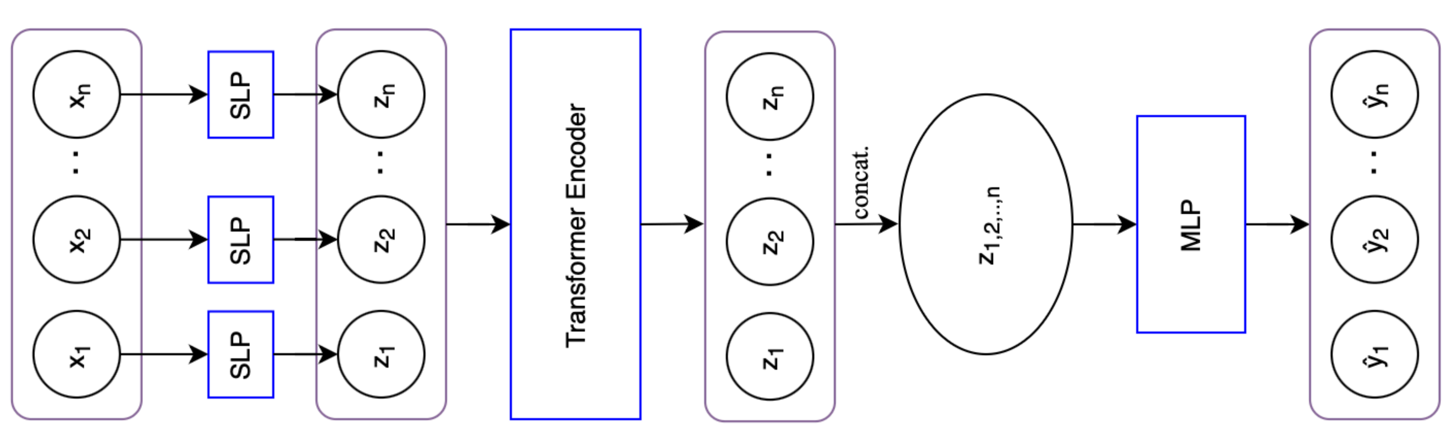
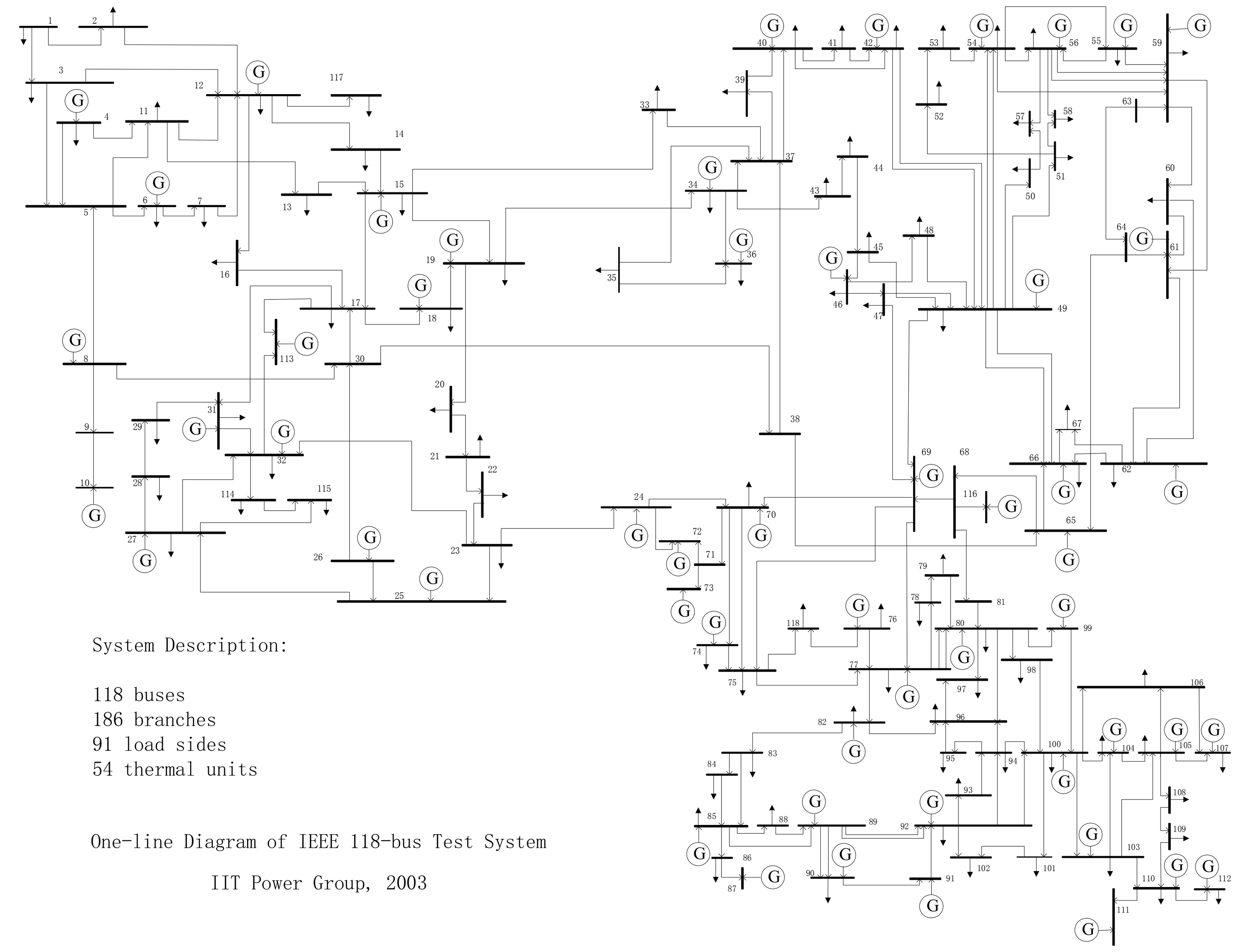


Illustration of OPFormer-V Model Architecture

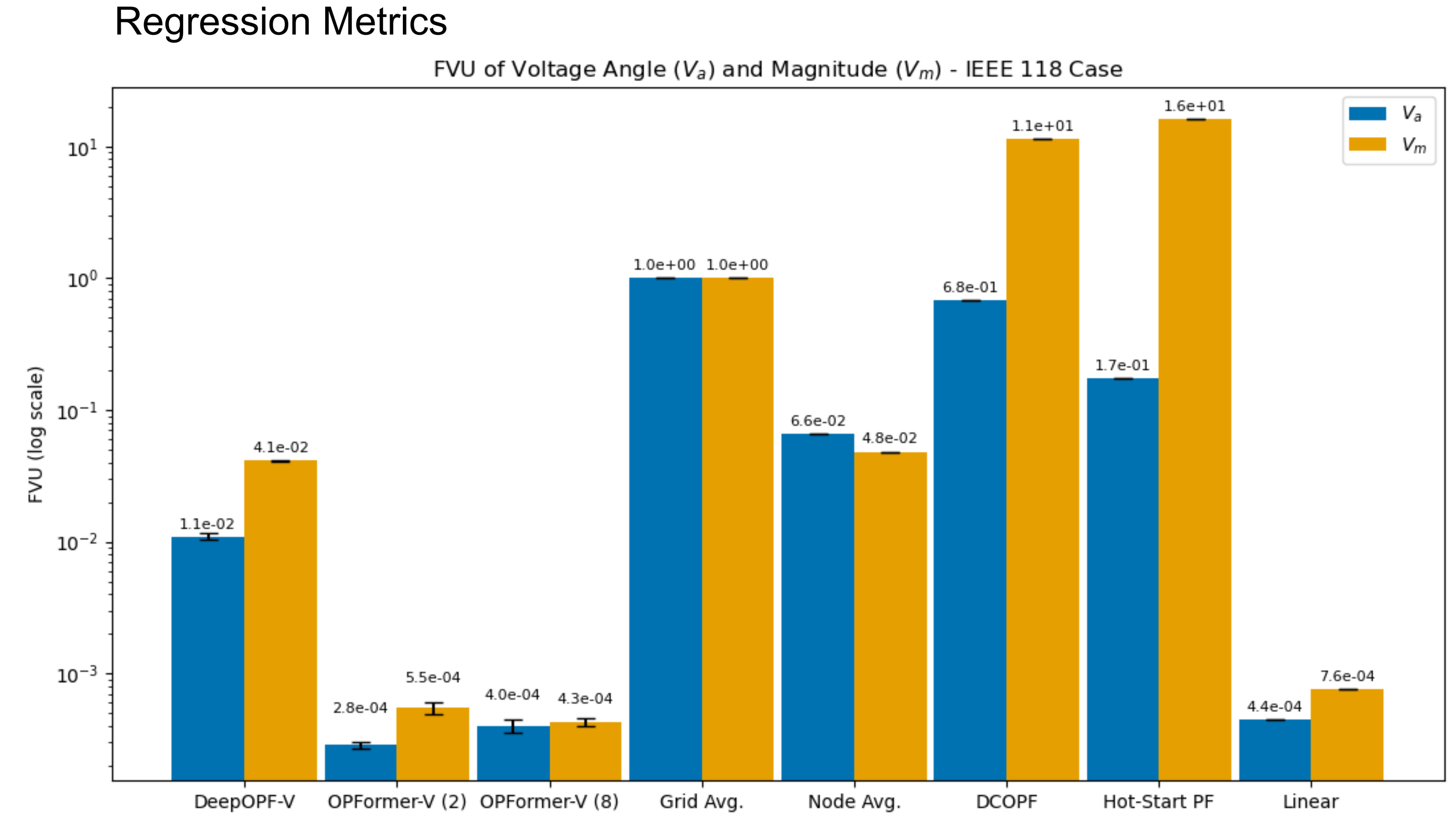
Experiments & Results



Illustrative One-Line Diagram of the IEEE-118 Node Test Case [3]

We evaluated on 2 synthetic datasets based on the **IEEE-30** and **IEEE-118** grids. Generated by taking the nominal loading scenario and sampling random variations around that nominal loading scenario. We consider a ±50% variation from the nominal load case at each node. In this poster we present results from the 118 node case.

Regression Metrics



Power Metrics

IEEE case 118	DeepOPF-V	OPFormer-V
Relative Opt. Diff. (%)	-0.618 ±0.012	**-0.153** ±0.053
Abs. Relative Opt. Diff. (%)	1.713 ±0.018	**0.323** ±0.045
Pg Violation Rate (%)	21.799 ±0.044	**16.468** ±0.306
Qg Violation Rate (%)	12.605 ±0.114	**11.771** ±0.742
Abs. Relative Tot. Pd err. (%)	1.242 ±0.012	**0.245** ±0.035
Abs. Relative Tot. Qd err. (%)	1.472 ±0.006	**0.241** ±0.011
Avg. Abs. Relative Nonzero Pd err. (%)	16.242 ±0.140	**4.053** ±0.182
Avg. Abs. Relative Nonzero Qd err. (%)	17.648 ±0.252	**4.934** ±0.112

A table comparing the OPF solutions from DeepOPF-V and OPFormer-V (feats-8) on the test split on the IEEE case118 datasets. Comparing the average relative gap from optimality, the rate of violation of generation limits, the average relative difference between ground truth load and the effective load derived using predicted voltage at both a grid level and at a nodal level for = 0 loads.

Conclusion and Future Works

We revisit machine learning approaches for solving AC optimal power flow (AC-OPF) and introduce **OPFormer-V**, a transformer-based model for predicting bus voltages. While OPFormer-V consistently outperforms the state-of-the-art DeepOPF-V in both regression and power metrics, our findings reveal that **simple linear baselines**—such as nodewise averaging and linear regression—can achieve **comparable performance**. This challenges the perceived superiority of complex ML models and underscores the importance of including strong linear baselines in future evaluations. Overall, attention-based models like OPFormer-V show promise, but the **incremental gains** over simpler methods suggest a need for **more rigorous benchmarking** in ML-based OPF research.

References

Priya L. Donti, David Rolnick, and J. Zico Kolter. Dc3: A learning method for optimization with hard constraints, 2021.

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