A Machine Learning Approach for Solving AC Optimal Power Flow

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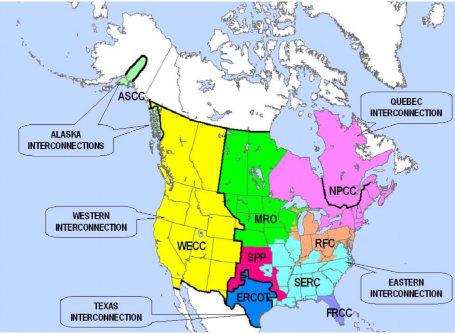
Electricity Generation and Distribution Requires Stability of Large, Interconnected Power Grids

Power Grid Structure

- Buses = power demand
- Generators = power production
- Branches = links between buses and generators

Grids can be modeled as networks where buses and generators are nodes and branches are edges



North American Power Grids

Solving this system for optimal generator settings forms the basis of the OPF (Optimal Power Flow) problem.

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The OPF Problem is Strictly Constrained by Physical Laws

- **N**: Set of Buses
- **G**: Set of Generators
- C_i: Cost Function for generator i
- P_i: Real power demand/ generation at bus/ generator i
- Q_i: Reactive power demand/ generation at bus/ generator i
- V_i: Voltage magnitude at bus/ generator i
- δ_i: Voltage angle at bus/ generator i

$$
\begin{aligned}
&\underset{P_i^G}{\text{minimize}} \quad \sum_{i \in G} C_i(P_i^G), \\
&\text{subject to} \\
&P_i(V, \delta) = P_i^G - P_i^L, && \forall i \in \mathbf{N} \\
&Q_i(V, \delta) = Q_i^G - Q_i^L, && \forall i \in \mathbf{N} \\
&P_i^{G,\min} \leq P_i^G \leq P_i^{G,\max}, && \forall i \in \mathbf{G} \\
&Q_i^{G,\min} \leq Q_i^G \leq Q_i^{G,\max}, && \forall i \in \mathbf{G} \\
&V_i^{\min} \leq V_i \leq V_i^{\max}, && \forall i \in \mathbf{N} \\
&\delta_i^{\min} \leq \delta_i \leq \delta_i^{\max}, && \forall i \in \mathbf{N}
\end{aligned}
$$

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Numerical Methods for Solving OPF are too Slow

- OPF is a high dimensional, non-convex problem
- This system relies on having an input close to the true solution
- Optimizers that find good solutions exists but can take up to 15 minutes to solve for a realistic power grid

$$
\begin{aligned}
&\underset{P_i^G}{\text{minimize}} \quad \sum_{i \in G} C_i(P_i^G), && \\
&\text{subject to} && \\
&P_i(V,\delta) = P_i^G - P_i^L, && \forall i \in \mathbf{N} \\
&Q_i(V,\delta) = Q_i^G - Q_i^L, && \forall i \in \mathbf{N} \\
&P_i^{G,\min} \le P_i^G \le P_i^{G,\max}, && \forall i \in \mathbf{G} \\
&Q_i^{G,\min} \le Q_i^G \le Q_i^{G,\max}, && \forall i \in \mathbf{G} \\
&V_i^{\min} \le V_i \le V_i^{\max}, && \forall i \in \mathbf{N} \\
&\delta_i^{\min} \le \delta_i \le \delta_i^{\max}, && \forall i \in \mathbf{N}
\end{aligned}
$$

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Faster Methods Save Money and Reduce Emissions

- Generators have to produce sufficient power for feasible demand changes within the time required to run the model
- Shorter model run times allow operators to keep generator output closer to anticipated demand
- Generator output closer to real demand allows lower energy production, saving money and reducing emissions.

California ISO Control Room

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Machine Learning Could Offer Multiple Benefits Over Numerical Methods with Some Costs

Solving OPF with a machine learning regression algorithm could,

- Decrease computation times
- Bypass non-convexity of the solution space
- Build a better estimation to enter into a higher fidelity model

However, machine learning also has downsides

- Can give physically impossible ('illegal') results
- Is limited to a specific network topology

MATPOWER is a Package of Numerical Algorithms for Solving OPF

MATPOWER: MATLAB program for OPF

- Hundreds of predefined systems
- Multiple numerical methods for solving the OPF problem
- Research standard
- Used to generate data for machine learning algorithm

Research Goals

- Identify optimal machine learning methods to analyze 30 and 300 bus systems according to
  - Computational cost
  - Model accuracy
  - Adherence to physical laws
- Assess viability of machine learning to model large scale power grids
- Investigate optimizing metrics
- Find a model that will allow analysis of extreme conditions or deviations from the norm

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We Generated Data Sets By Modifying Power Demand in MATPOWER Cases

Normally perturbed power demand around the base values for each bus with a standard deviation of 10% and solved in MATPOWER

1. 30 bus system
    - Training Data: 16,637
    - Testing Data: 4,160
    - Model of 1961 US power grid
2. 300 bus system
    - Training Data: 16,347
    - Testing Data: 4,087
    - Model of 1993 US power grid

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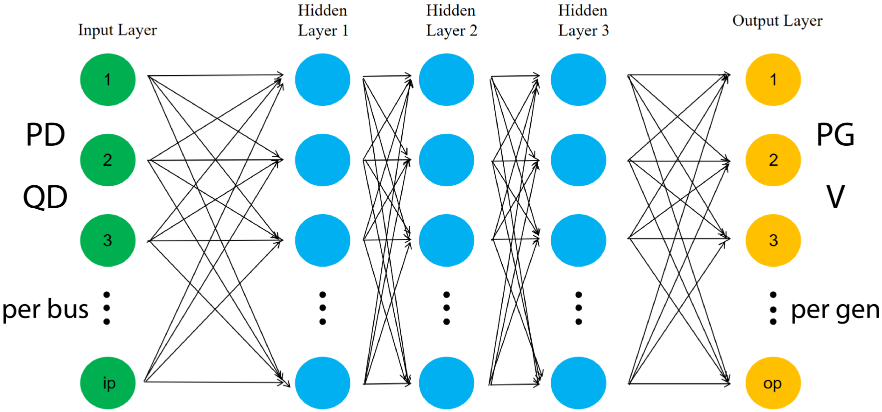
Neural network algorithms include an input, output, and hidden layers in between



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No Single Network is Optimal in all Machine Learning Metrics for 30 bus systems

Hidden Layers	Nodes	Activation Function	Validation Accuracy	Legality Rate	Cost Deviation
1	10	Relu	0.8769	86%	0.0063
2	100/100	Relu	0.9663	74%	0.0042
3	5/10/5	Relu	0.8724	98%	0.0071
3	50/50/50	Relu	0.9820	76%	0.0038
3	100/50/100	Relu/Tanh/ Relu	0.9880	75%	0.0030
3	100/100/100	Relu	0.9911	80%	0.0025
3	100/100/100	Tanh	0.9418	94%	0.0127
3	100/200/100	Relu	0.9863	72%	0.0046
5	100 - 100	Relu	0.9932	76%	0.0060

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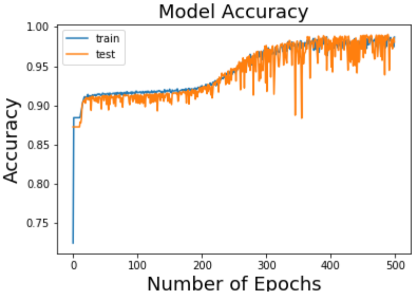
Accuracy around 99% with 80% legality for 30 bus neural network model



R^2 Values are Negatively Correlated with Legality Rates in XGBoost Models

Used XGBoost models to test OPF on a newer machine learning design

	Num of Trees	R^2 Score	Avg. Cost Dev.	Legality
1	100	0.7890	0.0141	86.13%
2	150	0.8044	0.0118	85.19%
3	200	0.8148	0.0104	84.76%
4	250	0.8226	0.0097	84.25%
5	300	0.8293	0.0093	84.18%
6	400	0.8411	0.0078	84.13%
7	600	0.8659	0.0074	83.82%
8	800	0.8738	0.0072	83.89%
9	1000	0.8809	0.0068	83.77%

Table: XGBoost configurations

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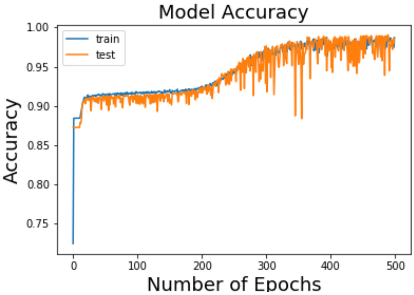
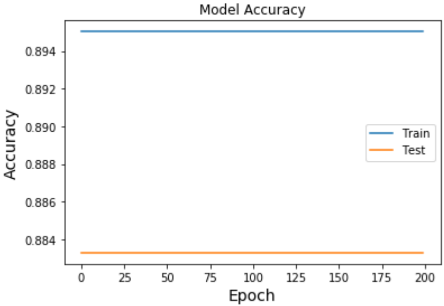
Our Machine Learning Algorithms were Insufficient to a 300 Bus System

Training Model



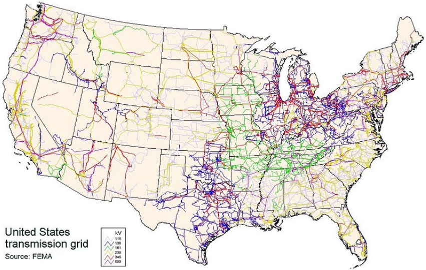
Non-Training Model



Conclusions

- Our machine learning algorithms were significantly faster than numerical methods: The neural network was orders of magnitude faster than MATPOWER.
- Neural networks were strong on all metrics but no single network was best on all metrics
- XGBoost was able to achieve high accuracy and legality. Even though they were negatively correlated, the legality decreased by a very small margin.
- We were unable to expand either of our machine learning algorithms to a higher node system

Future Work



Possibilities for future research on the OPF models:

1. Generalize the neural network model for higher nodal systems
2. Investigate higher estimators for the XGBoost model
3. Optimality classifications for both models
4. Analysis of extreme deviations from the norm

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QUESTIONS?