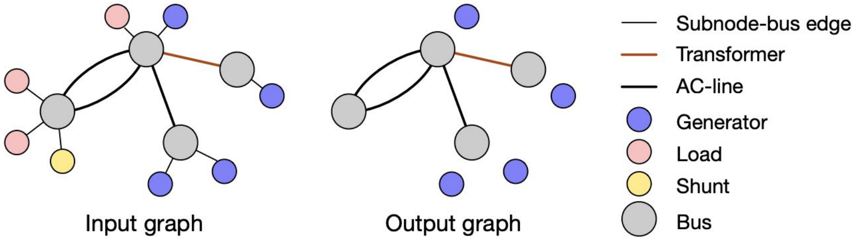
AI-driven Grid Optimization Can Reduce Emissions



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The optimization at the core of grid operations

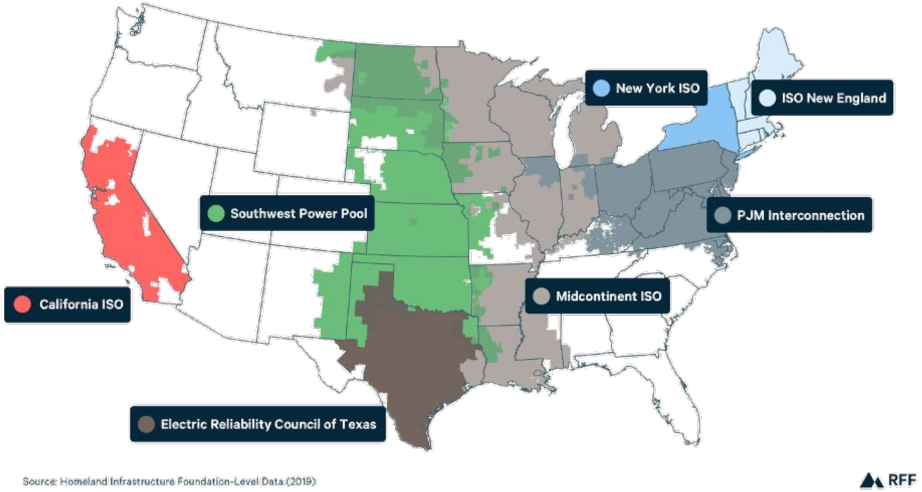
1960's: Carpentier formalized the idea of "optimal power flow (**OPF**)" in electricity grids[1].

1990's: Deregulation of power grid operations began in the United States.

Now:

Varying levels of deregulation and market participation exist throughout the country.

Seven main **independent system operators (ISOs)** run competitive wholesale power markets which **run an optimization problem** to match supply and demand economically and reliably



[1]*Carpentier, J. "Contribution a l'etude du dispatching economique." Bulletin de la Societe Francaise des Electriciens, 1962.*

Grid operators make simplifications ("DC OPF") to the true physics

Most US grids run based on a linear approximation (DC OPF) of the true problem (AC OPF).

Since DC OPF is not physically feasible, they perform post-processing where they adjust variables
- introducing inefficiencies!

AC OPF

Physically-representative models

Models voltage and reactive power

Very hard to solve

What we want

...what we got

DC OPF

Convex, easier to solve

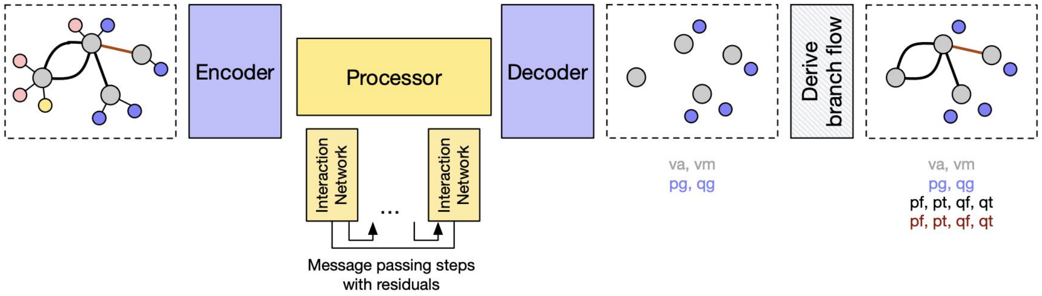
Ignores reactive power

Assumes all voltage magnitudes are equal

Ignores losses

We want AC OPF! For reliability, cost, and emissions

Idea: Bypass solving an optimization problem altogether



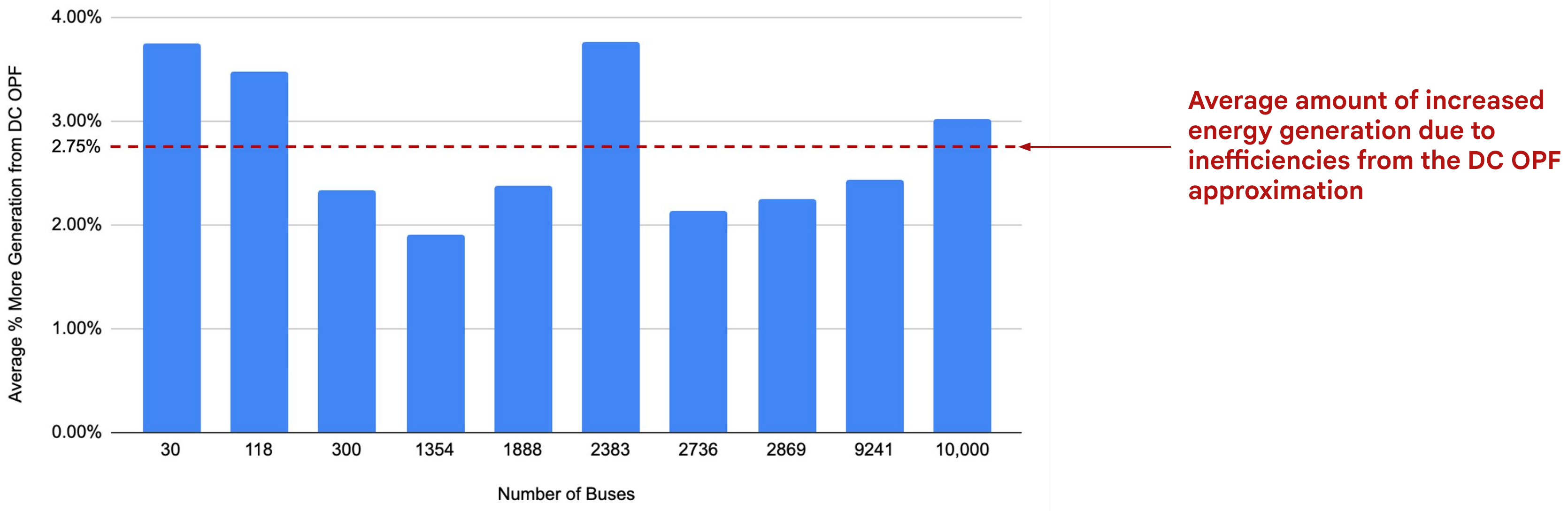
Let's consider the **10,000** bus Graph Neural Network (GNN) from DeepMind in the 2024 CANOS paper [Piloto et al., https://arxiv.org/abs/2403.17660].

This system size is bigger than ERCOT (Texas). If we want to train realistically sized grids, what's the carbon footprint from training now?

The benefit from AI-based grid optimization

AI can get us very close to true AC OPF solutions reliably, fast enough for real time system operation (5-minutes).

Using AC OPF instead of an approximation **lowers the amount of power generation** by 2.75% on average (in the considered systems)

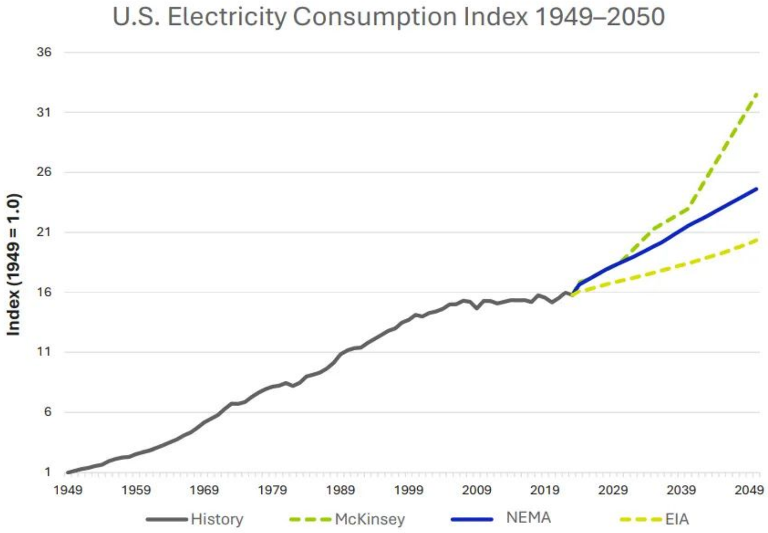


2% less power generation = significant

If our total generation in the U.S. in a year is 4300 TWh, 2% of this is 86 TWh.

That’s the annual electrical energy consumption of 12 million homes!

[https://www.epa.gov/energy/greenhouse-gas-equivalencies-calculator]

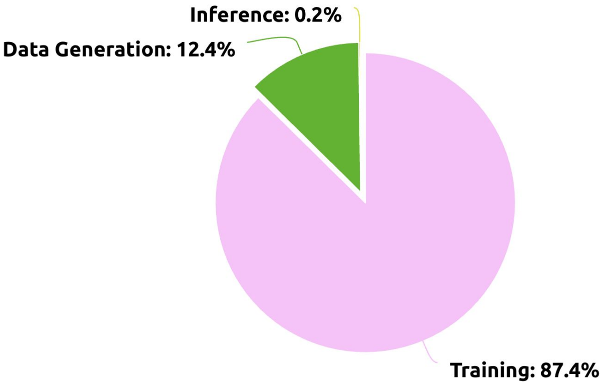


Source: Utility Dive

But how much energy does it take to train CANOS?

Across a year, we looked at:

- Energy from dataset generation.
- Energy from model training, evaluation, hyperparameter tuning
- Energy from performing inference (using CANOS)
  - Plus AC power flows for post-processing feasibility



- And finally, energy from the power plants themselves, given the decisions produced by CANOS

Status Quo optimization compared to AI-based optimizers

Table 1: Consumption breakdown excluding generation

Energy Use Type	Annual kWh
Data Generation (AC OPF)	20–780
Training (incl. tuning)	2,600–5,500
Inference	11–12
Assumed Total for Analysis	6,000
DC OPF + AC PF	36–652

Training / using CANOS

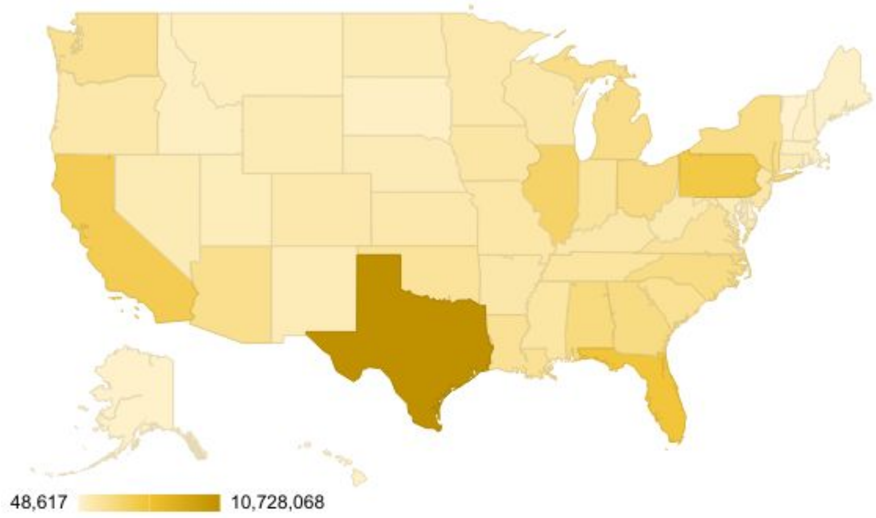
Running status-quo optimizers

Using the status-quo optimizer wins by far (600 kWh vs 6,000 kWh) because it takes more energy to train a graph neural network.

But what about the optimality of the power plant dispatch decisions?

Hypothetical energy savings across the U.S. with CANOS

Assuming a prediction error consistent with Piloto et. al of 1% for active power, and a 2% energy reduction from AC OPF vs. DC OPF, we see annual savings of up to **10 TWh** (Texas)



The energy to train CANOS is offset by its benefits within **minutes of operation**

What about carbon?

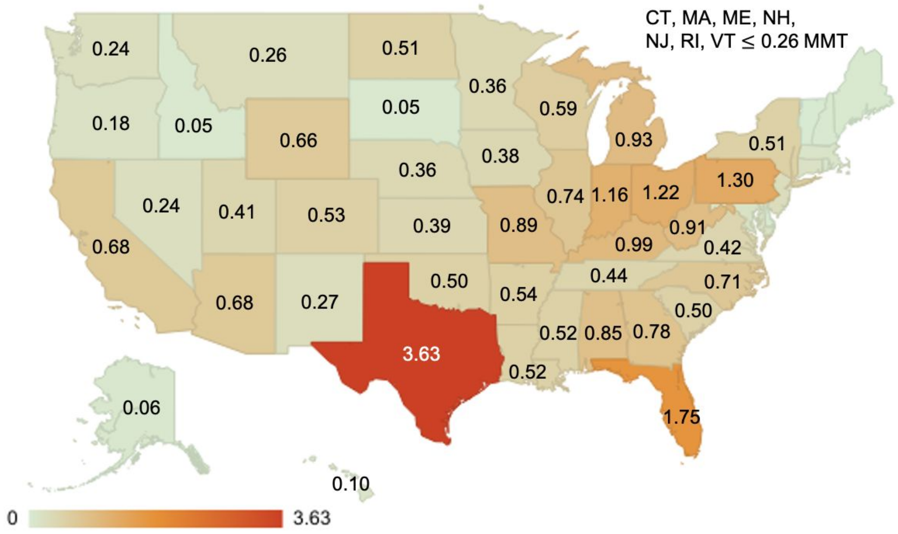
Each state's generation mix has varying levels of carbon intensity.

A purely renewable state would not have benefits!

But no state is purely renewable.

Here is the annual decrease in CO_2

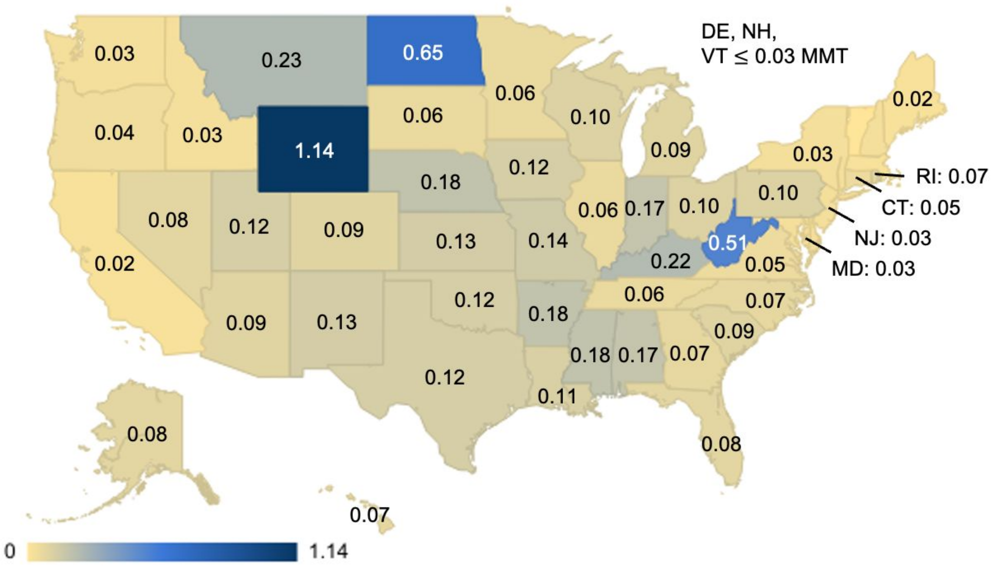
emissions from generation (MMT) if we use CANOS.



Carbon reduction per capita

States with high **carbon** intensity, high **electrification**, and **low population** benefit most

Alaska has high fossil fuel use, but low electrification (heating is often fossil-fuel based and not electric)



Conclusions

Moving to an AI-based optimizer can help us achieve more efficient grid operations, reducing energy consumption and consequently, emissions.

Under these assumptions, an AI-based grid optimizer can lower annual emissions equivalent to **~28 MMT of CO_2**, or:

- Removing 6.5 million gas-powered mid-size passenger vehicles from the road for a year.
- 95% of the annual CO_2 emissions of Denmark.
- 50,000 roundtrip flights from San Francisco to New York.
- The production of one hamburger for every person on the planet.
- The annual CO_2 emissions of 26 gas-fired power plants.