Google DeepMind

AI-driven Grid Optimization Can Reduce Emissions

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Current Grid Operations

Many countries use **linear models** (or no models at all) of the power grid in order to decide which generators to turn on, and how much they should produce.

This approximation in U.S. grid operators is called **"DC Optimal Power Flow (OPF)."**

The "true" problem with real grid physics is called **"AC Optimal Power Flow (OPF)."**

AC OPF is **NP-hard, nonconvex**, and hard to solve quickly and reliably for real-time grid operations.

However, AI can help us solve this hard problem.

AC OPF vs. DC OPF

AC OPF uses nonlinear equations for power flow and optimizes for the lowest cost to supply power to customers.

A (very simple) AC OPF problem looks something like this:

AC OPF

$$
\begin{aligned}
&\min_{\mathbf{v},\mathbf{p}_g} \sum_{j\in\mathcal{G}} a_j p_{g,j}^2 + b_j p_{g,j} + c_j \\
&\text{s.t}: \\
&\quad |v_i| \sum_{m\in\mathcal{N}} |v_m|(G_{im}\cos(\theta_{im}) + B_{im}\sin(\theta_{im})) = p_{l,i} - \sum_{k\in\mathcal{G}_i} p_{g,k}, \quad \forall i \in \mathcal{N} \\
&\quad |v_i| \sum_{m\in\mathcal{N}} |v_m|(G_{im}\sin(\theta_{im}) - B_{im}\cos(\theta_{im})) = q_{l,i} - \sum_{k\in\mathcal{G}_i} q_{g,k}, \quad \forall i \in \mathcal{N} \\
&\quad \underline{p}_{g,j} \le p_{g,j} \le \overline{p}_{g,j}, \quad \forall j \in \mathcal{G} \\
&\quad \underline{q}_{g,j} \le q_{g,j} \le \overline{q}_{g,j}, \quad \forall j \in \mathcal{G} \\
&\quad \underline{|v|} \le |v_i| \le \overline{|v|}, \quad \forall i \in \mathcal{N}.
\end{aligned}
$$

We make **many assumptions** to solve this in real grids:

- All voltage magnitudes are the same throughout the grid.
- There is no reactive power.
- There are no line losses.
- Voltage angles at neighboring buses are similar.

This results in a convex optimization problem (DC OPF).

This approximate problem is **not physically feasible** and results in inefficiencies [2], and requires post-processing

DC OPF

$$
\begin{aligned}
&\min_{\mathbf{p}_g} \sum_{j\in\mathcal{G}} a_j p_{g,j}^2 + b_j p_{g,j} + c_j \\
&\text{s.t}: p_{l,i} - \sum_{k\in\mathcal{G}_i} p_{g,k} = \sum_{m\in\mathcal{N}} B_{im}\theta_{im}, \; \forall i \in \mathcal{N} \\
&\qquad -F_{im} \le B_{im}\theta_{im} \le F_{im}, \; \forall im \in \mathcal{L}
\end{aligned}
$$

References

[1] Piloto et. al, "CANOS: A Fast and Scalable Neural AC-OPF Solver Robust To N-1 Perturbations," 2024

[2] Baker, "Solutions to DC OPF are Never AC Feasible," 2021.

[3] U.S. Energy Information Administration (EIA). Electric power annual 2023.

[4] U.S. Energy Information Administration (EIA). Table co2.6. electric power sector co2 emissions estimates from energy consumption, 2023,

How are Emissions Reduced?

By shifting the computational burden of solving AC OPF offline to training, we can use AI models during operation time and **solve AC OPF** instead of using linear approximations.

This results in:

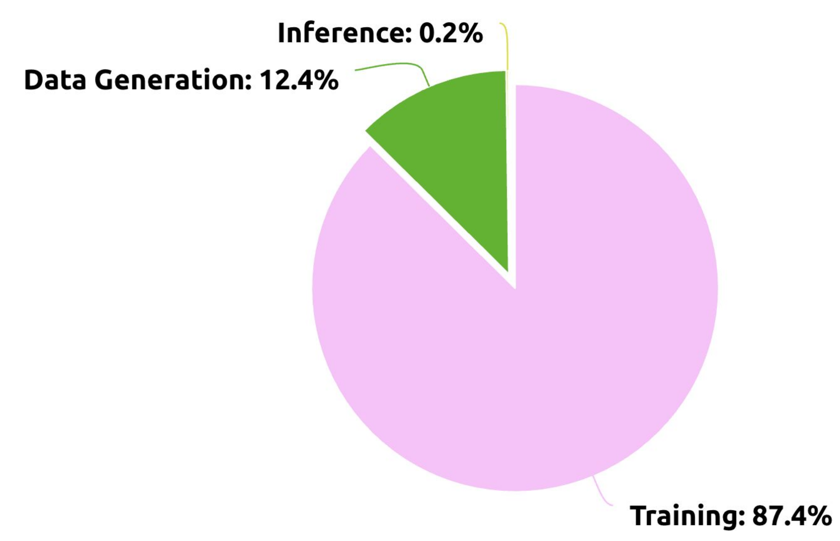
- More optimal decisions, resulting in more efficient grid operations
- Which reduces energy generation and losses
- **And reduces emissions from power generation.**

What About Emissions from Training These Models?

⟶ Measured **actual energy consumption** from training and inference for our largest model [1] (a 10,000 node grid, larger than any state)

⟶ This totaled **6 MWh,** less than the average U.S. home's annual energy consumption

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

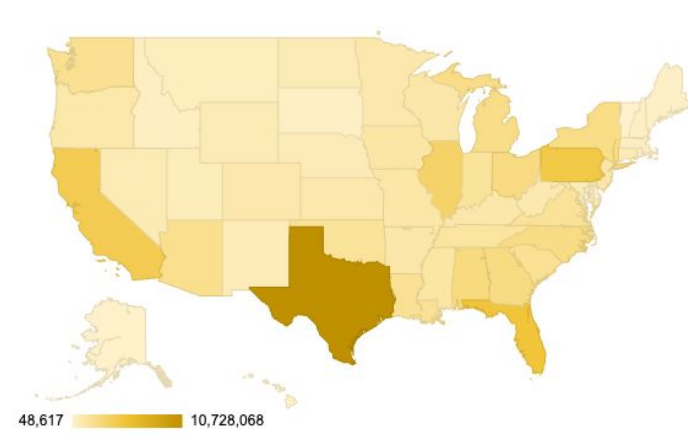


The training energy/carbon is offset ("paid back") within minutes for most states.

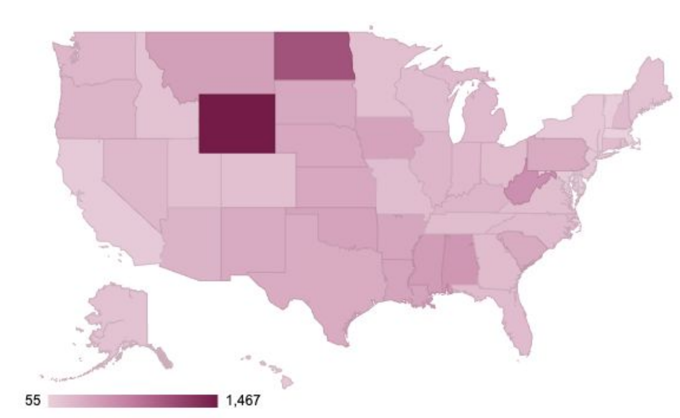
Energy Reductions from Better Grid Optimization

Using prediction errors from [1], we measured the difference in total generation using the status quo (DC OPF) and our AI optimizer. Both used the post-processing step that is used by current grid operators.

Then, we estimated per-state savings from actual electrical energy consumption in 2023 [3].



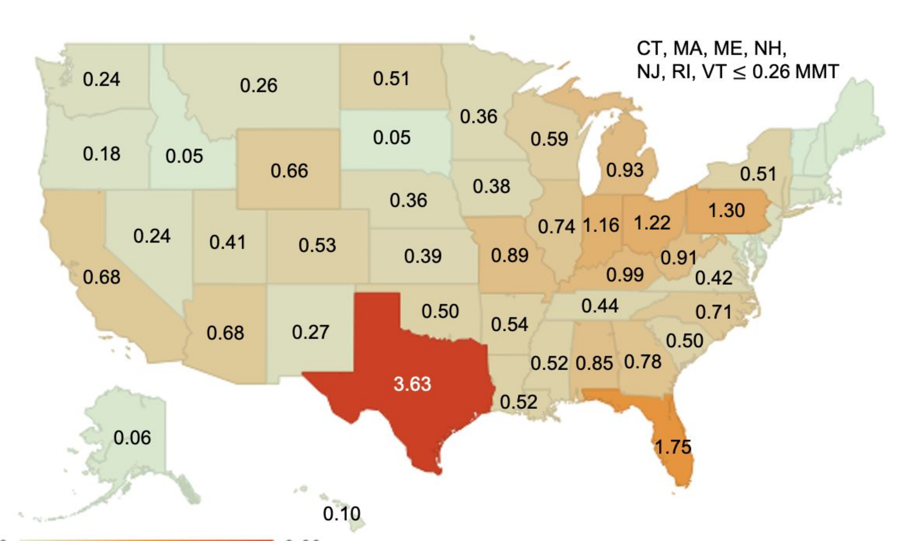
Hypothetical MWh savings per-state



Per-capita MWh savings per-state

Operational Carbon Emissions Reductions

Using each state's grid mixture carbon intensity [4], we determined what this level of energy reduction represents for operational carbon emissions from power plants.



Annual decrease in carbon emissions from generation (MMT) per state

Country-wide, this is equivalent to:

- Removing 6.5 million gas cars from the road for a year.
- 95% of the annual CO2 emissions from Denmark.
- 50,000 roundtrip flights from San Francisco to New York.
- The production of 1 hamburger for every person on the planet.
- The annual CO2 emissions of 26 gas-fired power plants.