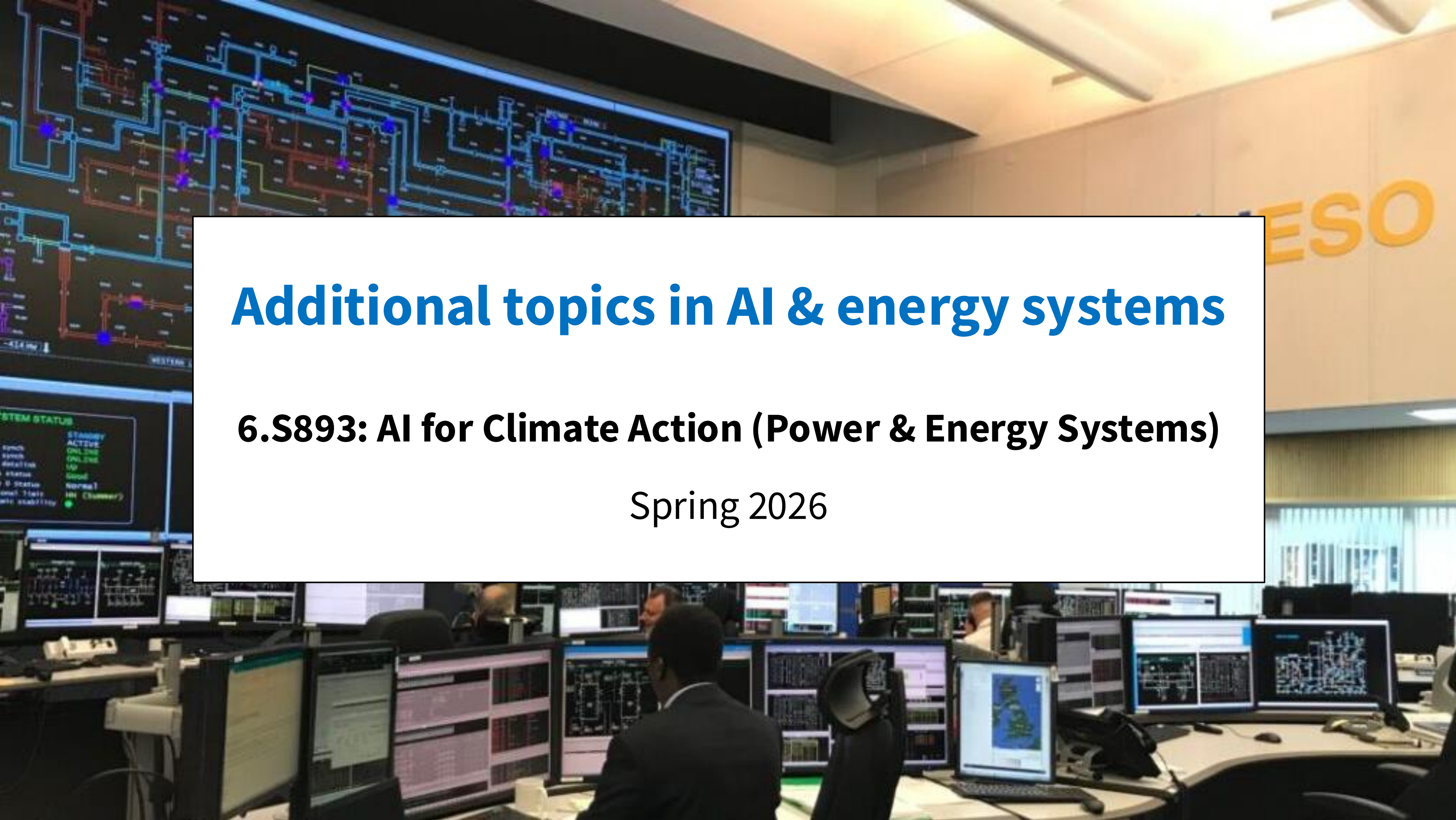


Additional topics in AI & energy systems

6.S893: AI for Climate Action (Power & Energy Systems)

Spring 2026

Outline

Additional topics in power & energy systems

AI for energy systems: Synthesis and recurring themes

Energy for AI

Outline

Additional topics in power & energy systems

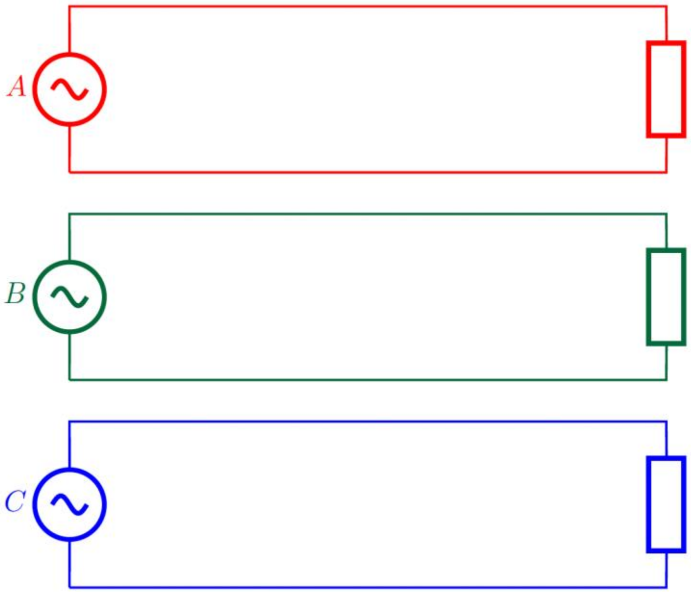
AI for energy systems: Synthesis and recurring themes

Energy for AI

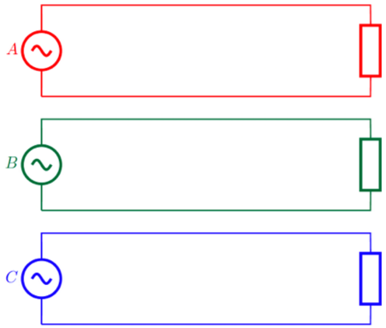
Three-phase systems

Image from: www.solarlandlease.com/how-to-identify-a-three-phase-power-line

Three-phase systems

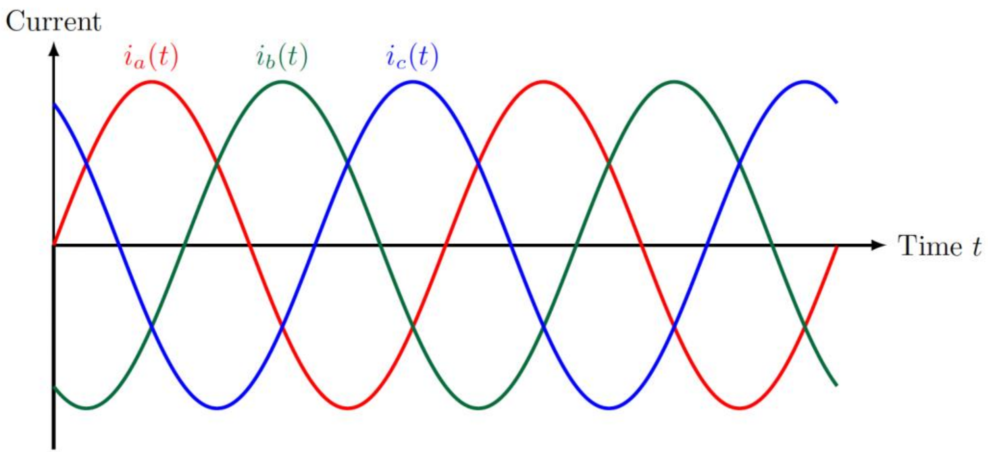


6 wires for three circuits

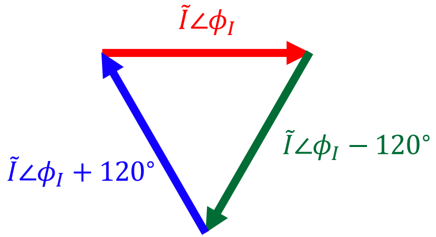


Three-phase systems

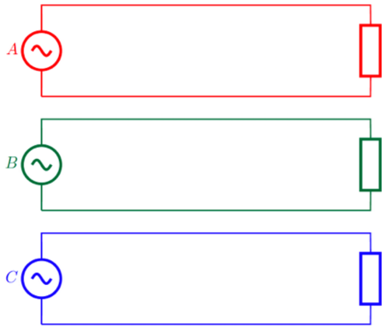
Suppose we stagger the AC currents in each circuit by 120°



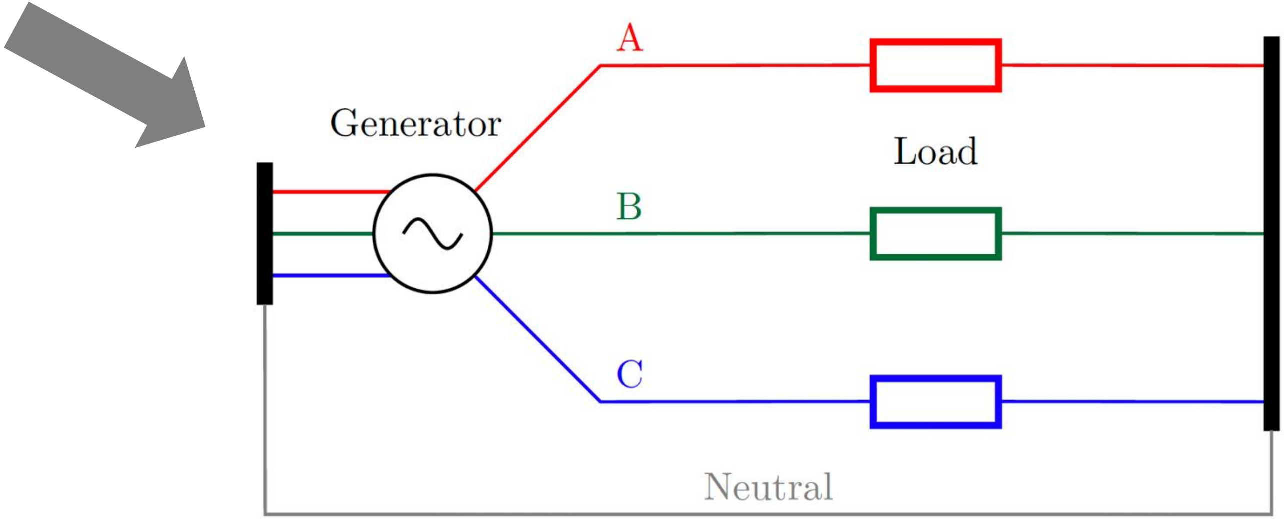
$$\cos(\omega t + \phi_I) + \cos(\omega t + \phi_I - 120°) + \cos(\omega t + \phi_I + 120°) = 0$$



Currents from three AC phases, if balanced (same magnitude) and if staggered by 1/3 cycle, always add to zero.



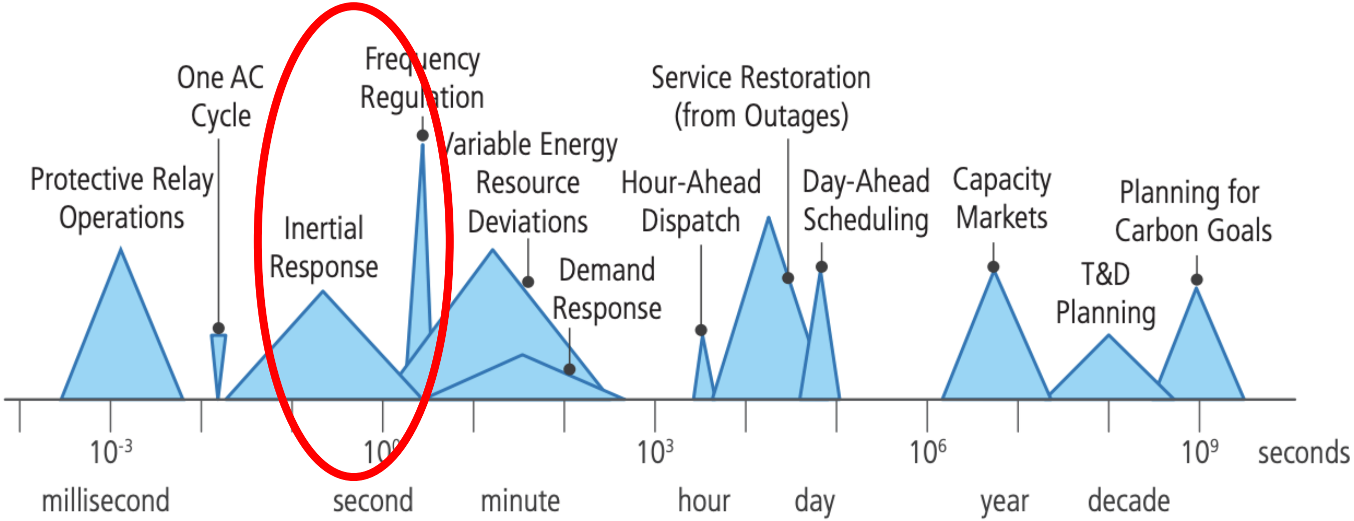
Three-phase systems



Can combine return conductors for the three circuits!
Ideally, current in “neutral” should be zero.

6 wires → 4 wires for three circuits

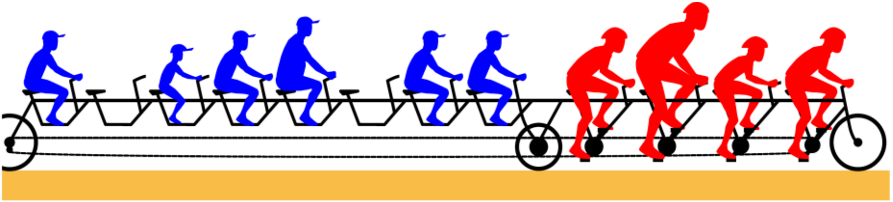
Figure S-5. System Reliability Depends on Managing Multiple Event Speeds

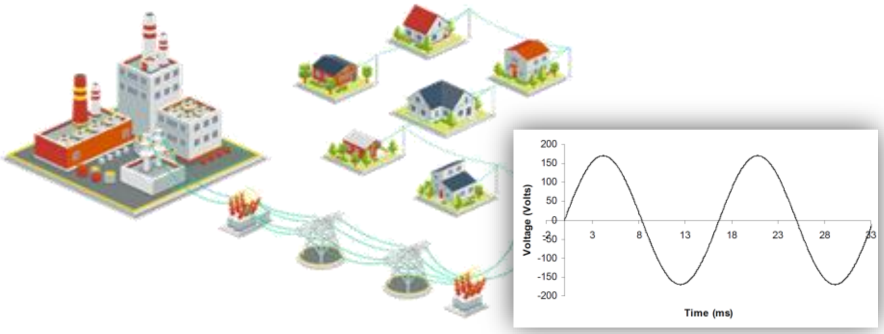


Capacity markets, day-ahead scheduling, and hour-ahead dispatch are well-understood tools for managing supply variability (mid-right axis). Beyond capacity contracts, traditional transmission and distribution (T&D) system long-term planning methods work to map and price investment requirements to ensure grid reliability (right end of axis). However, the widespread integration of variable energy resources significantly expands the time dimensions in which grid operators must function, ranging from hourly to minute to second intervals (mid-left axis). And, in a world of subsecond decision making (i.e., inertial response, one alternating current (AC) cycle, and protective relay operations), dispatch effectiveness will require the integration of automated grid management (left end of axis).

Figure source: US Department of Energy Quadrennial Energy Review (January 2017)

Power system frequency





Constant speed of bike (no acceleration)

$$\text{Force}_{\text{Pedalers}} = \text{Force}_{\text{Load}}$$

Inertia of the bike reduces acceleration if there is ever a mismatch between pedaling/braking

Constant system frequency

$$\text{Power}_{\text{GEN}} = \text{Power}_{\text{LOAD}}$$

Inertia of the rotating generators reduces dynamics of frequency deviation if there is a mismatch between generation/load

Analogy: Lennart Soeder, IEEE Power Engineering, April 2002
Graphics: Stefan Fassbinder, Bruno De Wachter (leonardo-energy.org)

Slide credit: Rajeev Ram

Frequency control

1. Primary frequency control: Arrest any change in frequency by restoring power balance as quickly as possible [within seconds]

- Implemented locally via governor response
- Also known as turbine-governor control

2. Secondary frequency control: Return the steady frequency to its nominal value [tens of seconds to minutes]

- Central control center sends signals to individual generators
- Also known as load-frequency control or automatic generation control (AGC)

3. Tertiary frequency control: Dispatch generators via centralized optimization taking cost into account [five minutes to a day]

- Economic dispatch, optimal power flow, etc.

Frequency control: Bathtub analogy

Goal: Keep water level (frequency) at a particular height (nominal frequency)

- Rate of inflow ≠ rate of outflow → water level rises or falls

Primary frequency control: Restore inflow = outflow to stop change in water level

Secondary frequency control: Get water level back to desired height

Tertiary frequency control: Dispatch water from faucets using centralized optimization accounting for cost?

Image source: DALL-E

Figure S-5. System Reliability Depends on Managing Multiple Event Speeds

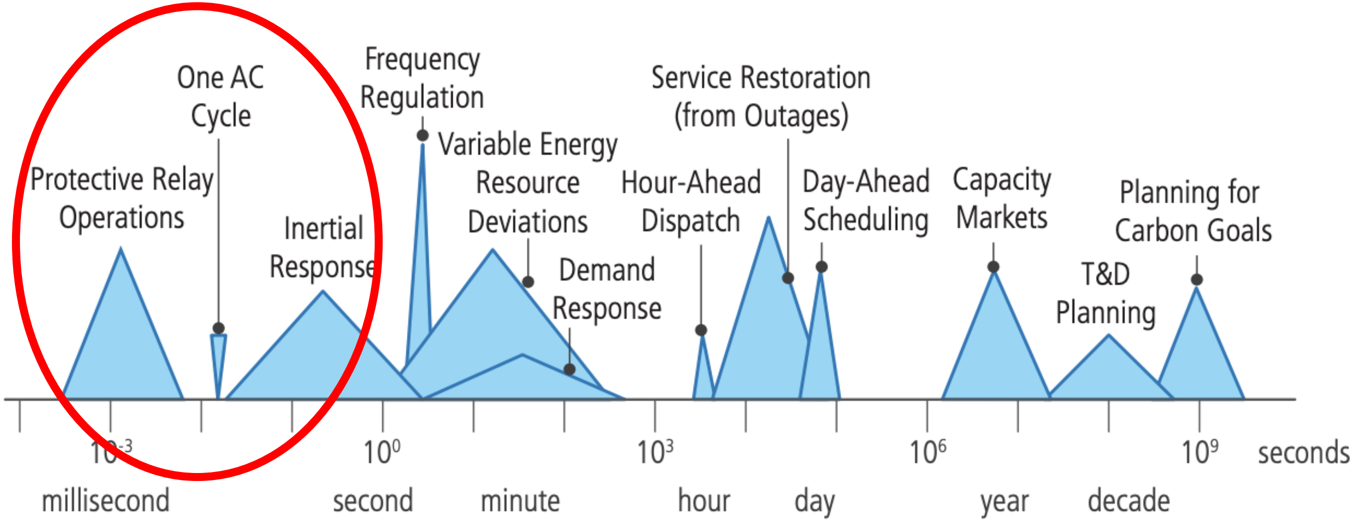


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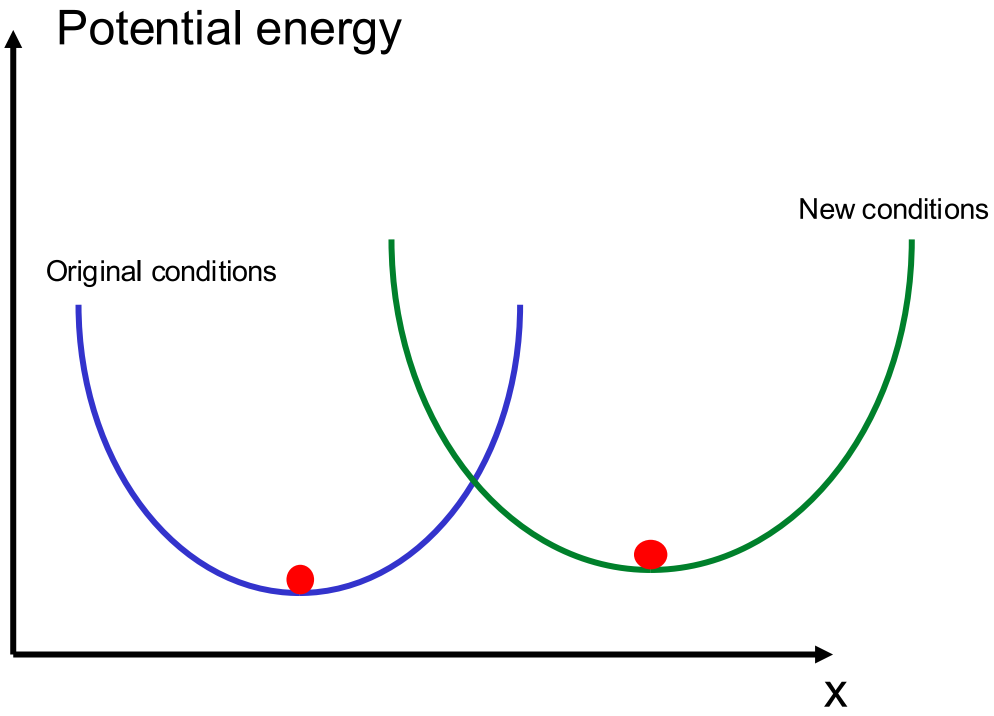
Figure source: US Department of Energy Quadrennial Energy Review (January 2017)

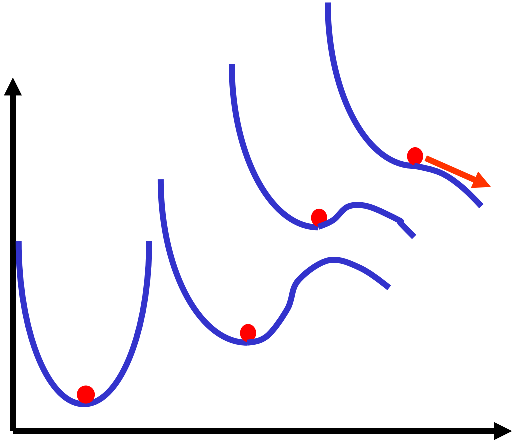
Quasi-steady state: Slow evolution of stable system



Stability limits

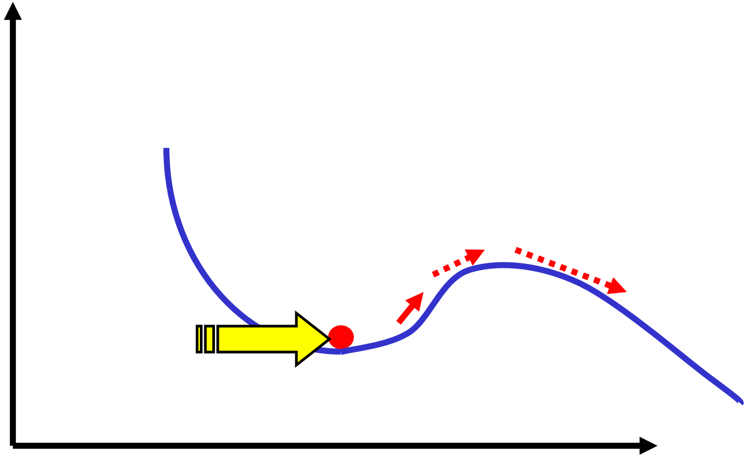
Steady state stability:

- Will the system collapse if a line or generator is disconnected?



Transient stability:

- Will a fault kick the system into instability?



Additional topics in power & energy systems

- Power generation, conversion, and storage
- Non-electric energy systems
  - Fuel supply systems (e.g., natural gas networks, provision of cooking fuels)
  - Heating and cooling networks
- Water-energy nexus
- …

Outline

Additional topics in power & energy systems

AI for energy systems: Synthesis and recurring themes

Energy for AI

AI for energy systems: Recurring themes

See also: Donti, P. L. & Kolter, J. Z. (2021). Machine learning for sustainable energy systems. *Annual Review of Environment and Resources*, *46*, 719-747.

AI for energy systems: Recurring themes

Distilling raw data into insights (solar panels, emissions, grid infrastructure, patents)

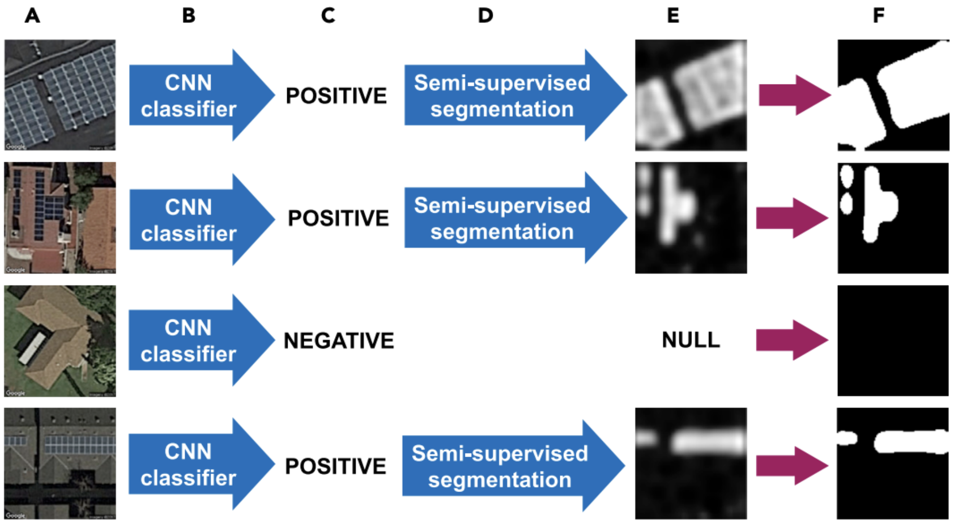


Figure source: Yu, Wang, Majumdar, Rajagopal (2018)

See also: Donti, P. L. & Kolter, J. Z. (2021). Machine learning for sustainable energy systems. *Annual Review of Environment and Resources*, *46*, 719-747.

AI for energy systems: Recurring themes

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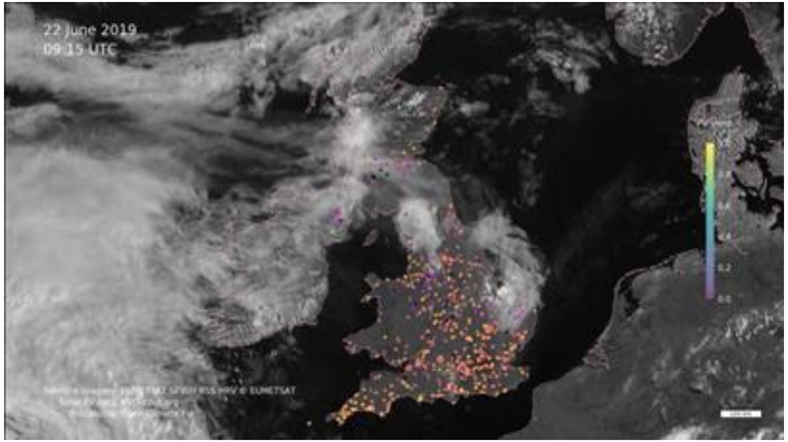

Image source: Open Climate Fix

See also: Donti, P. L. & Kolter, J. Z. (2021). Machine learning for sustainable energy systems. *Annual Review of Environment and Resources*, *46*, 719-747.

AI for energy systems: Recurring themes

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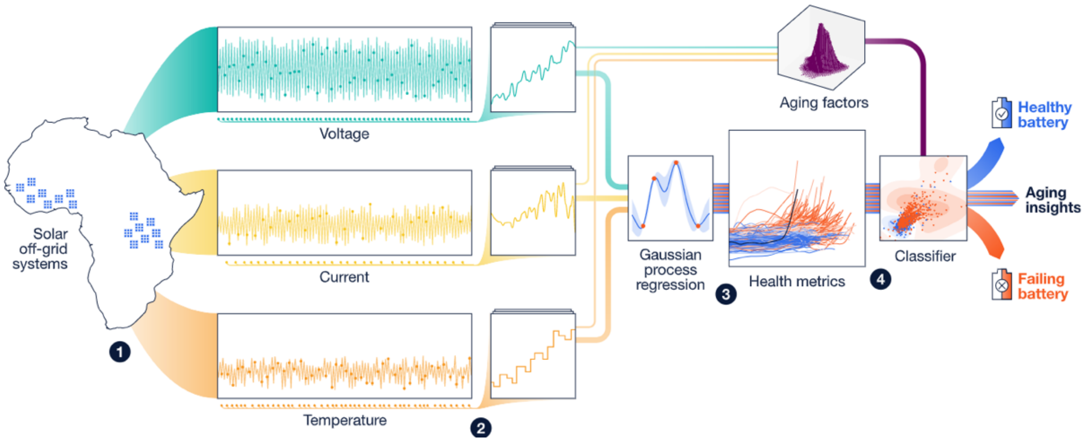

Figure source: Aitio & Howey (2021)

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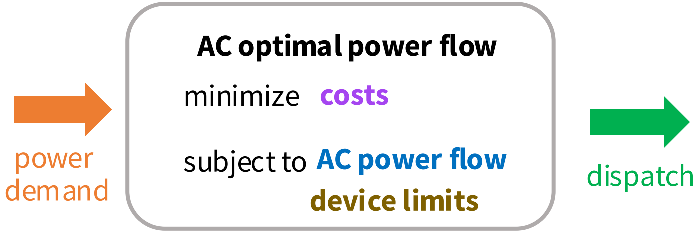

Figure source: Donti, Rolnick, Kolter (2021)

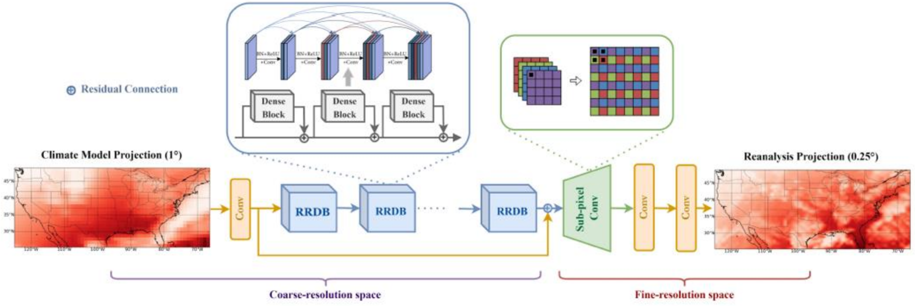

Figure source: Harilal, Hodge, Monteleoni, Subramanian (2022)

See also: Donti, P. L. & Kolter, J. Z. (2021). Machine learning for sustainable energy systems. *Annual Review of Environment and Resources*, *46*, 719-747.

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Fast and dynamic control
(topology opt., voltages, V2G, DR)

Image source: L2RPN Challenge

See also: Donti, P. L. & Kolter, J. Z. (2021). Machine learning for sustainable energy systems. *Annual Review of Environment and Resources*, *46*, 719-747.

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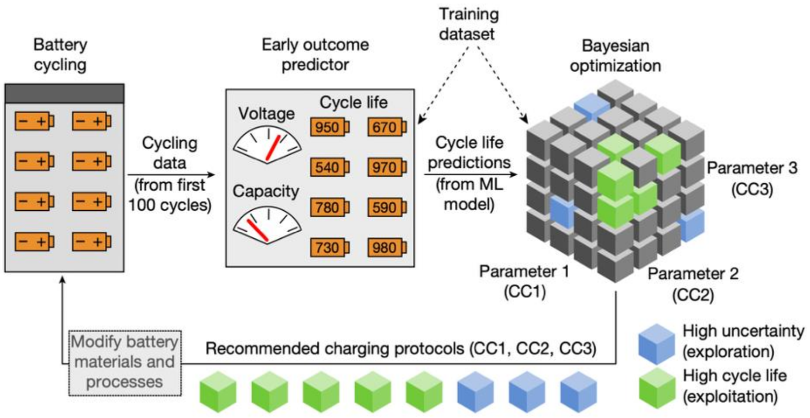

Figure source: Attia et al. (2020)

See also: Donti, P. L. & Kolter, J. Z. (2021). Machine learning for sustainable energy systems. *Annual Review of Environment and Resources*, *46*, 719-747.

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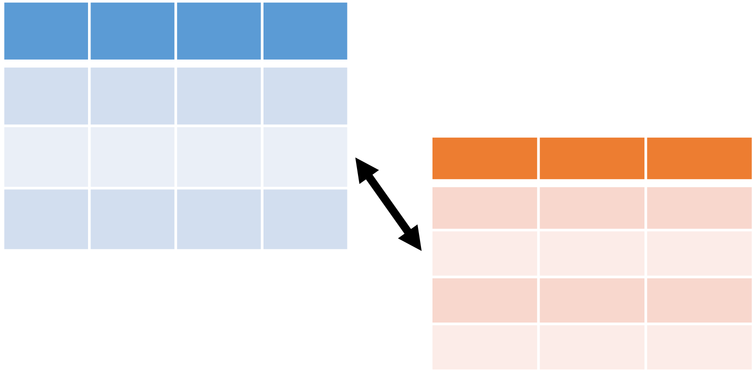

Figure based on work by: Catalyst Cooperative

See also: Donti, P. L. & Kolter, J. Z. (2021). Machine learning for sustainable energy systems. *Annual Review of Environment and Resources*, *46*, 719-747.

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Data mgmt. (entity matching, querying)

Synthetic data generation
(smart meter data, scenarios)

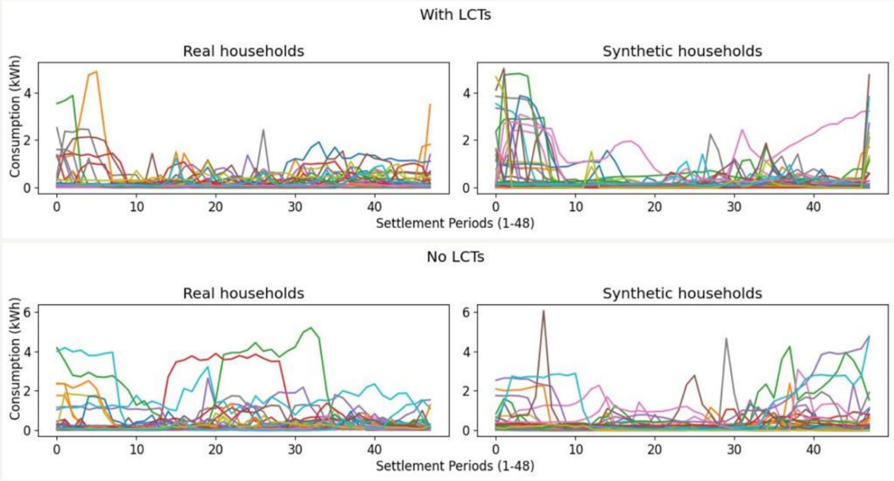


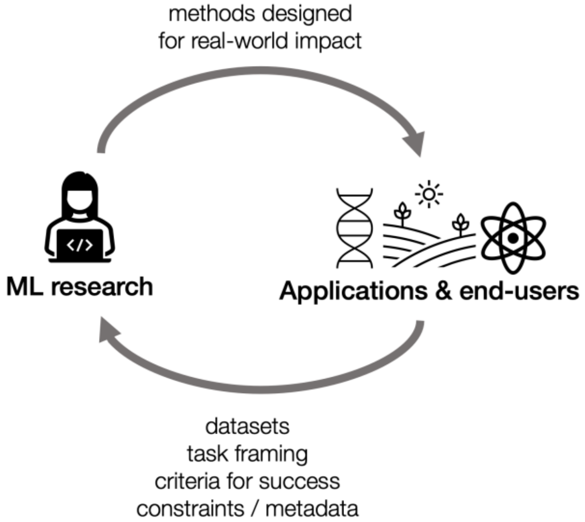
Figure source: Chai & Chadney (2024)

See also: Donti, P. L. & Kolter, J. Z. (2021). Machine learning for sustainable energy systems. *Annual Review of Environment and Resources*, *46*, 719-747.

Considerations for ML in power & energy systems

Different requirements for ML models and their outputs, depending on the context

- Accuracy/solution quality (better than SOTA)
- Safety & physical feasibility
- Robustness
- Interpretability, explainability, & auditability
- Uncertainty quantification
- Fast running time
- Hardware integration
- Data efficiency
- Generalizability
- Multi-agent and human-in-the-loop
- Privacy preservation
- Usability and accessibility
- Meeting regulatory standards



David Rolnick, Alan Aspuru-Guzik, Sara Beery, Bistra Dilkina, Priya L. Donti, Marzyeh Ghassemi, Hannah Kerner, Claire Monteleoni, Esther Rolf, Milind Tambe, Adam White. "Position: Application-driven innovation in machine learning." *ICML 2024.*

Enablers for advancing ML in energy systems

More openness in data (incl. synthetic data), beyond bilateral agreements and limited access

Simulators and test beds, with realistic/diverse scenarios and easy-to-use interfaces

- Incl. digital twins, but also simpler frameworks (e.g., Grid2Op)
- Need for *progression pathways* from basic to advanced simulators/test beds

Evaluation metrics / benchmarks: What does it mean for a method to succeed (or fail)?

Mathematical formulations and transparent writeups of important "challenge problems"

Modular, "open-source" software, enabling integration & evaluation of new methods

Translational research exchange: Enhanced collaboration between academia, national labs, solutions providers, and energy industry players (power system operators, utilities)

Note: None of these enablers are solely about ML!

Outline

Additional topics in power & energy systems

AI for energy systems: Synthesis and recurring themes

Energy for AI

AI and climate change

AI applications for climate action

Impacts from AI computation & hardware

AI's system-level impacts

AI applications that increase emissions

Kaack, L. H., Donti, P. L., Strubell, E., Kamiya, G., Creutzig, F., & Rolnick, D. (2022). Aligning artificial intelligence with climate change mitigation. *Nature Climate Change*, 1-10.

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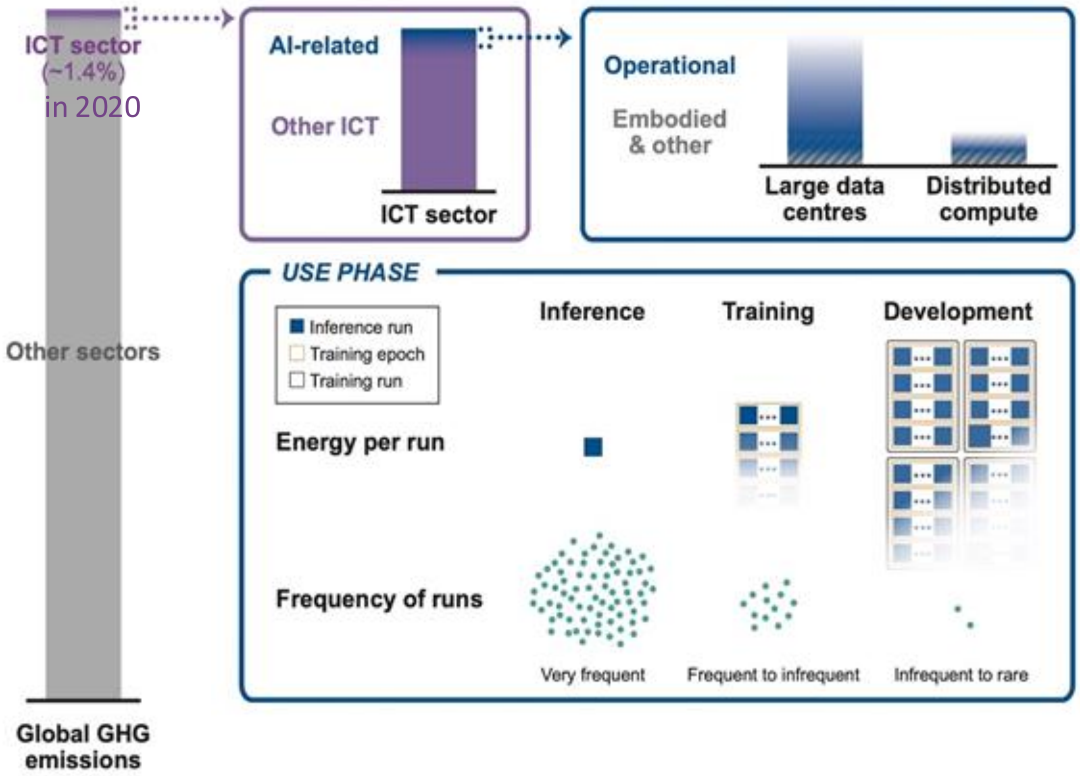
Direct impacts from AI computation & hardware

Operational impacts from energy & water consumed during computation

Embodied emissions & materials impacts from production, transport, and disposal of hardware



Kaack, L. H., Donti, P. L., Strubell, E., Kamiya, G., Creutzig, F., & Rolnick, D. (2022). Aligning artificial intelligence with climate change mitigation. *Nature Climate Change*, 1-10.

Different models have different direct impacts

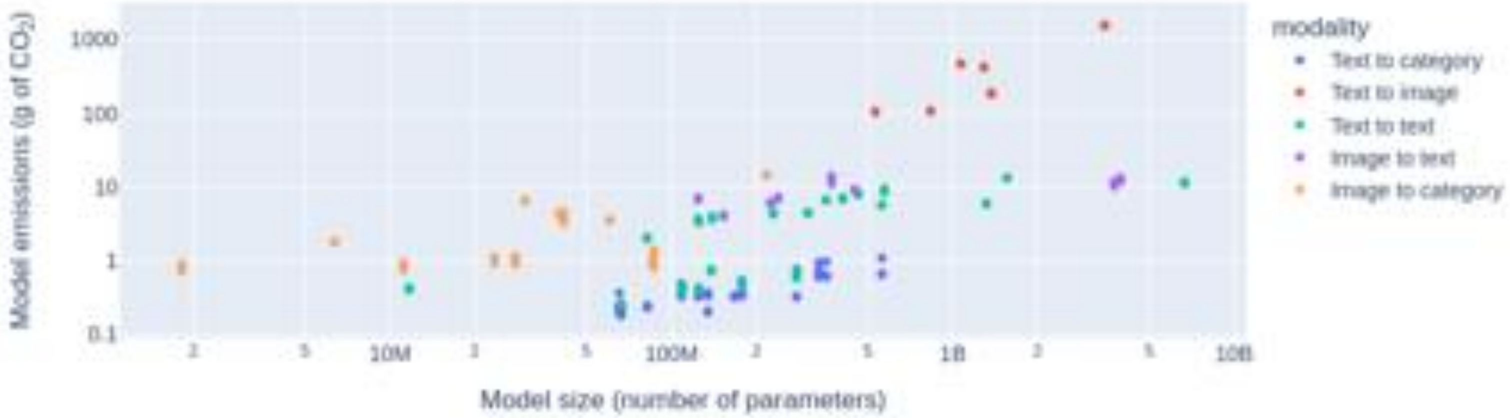
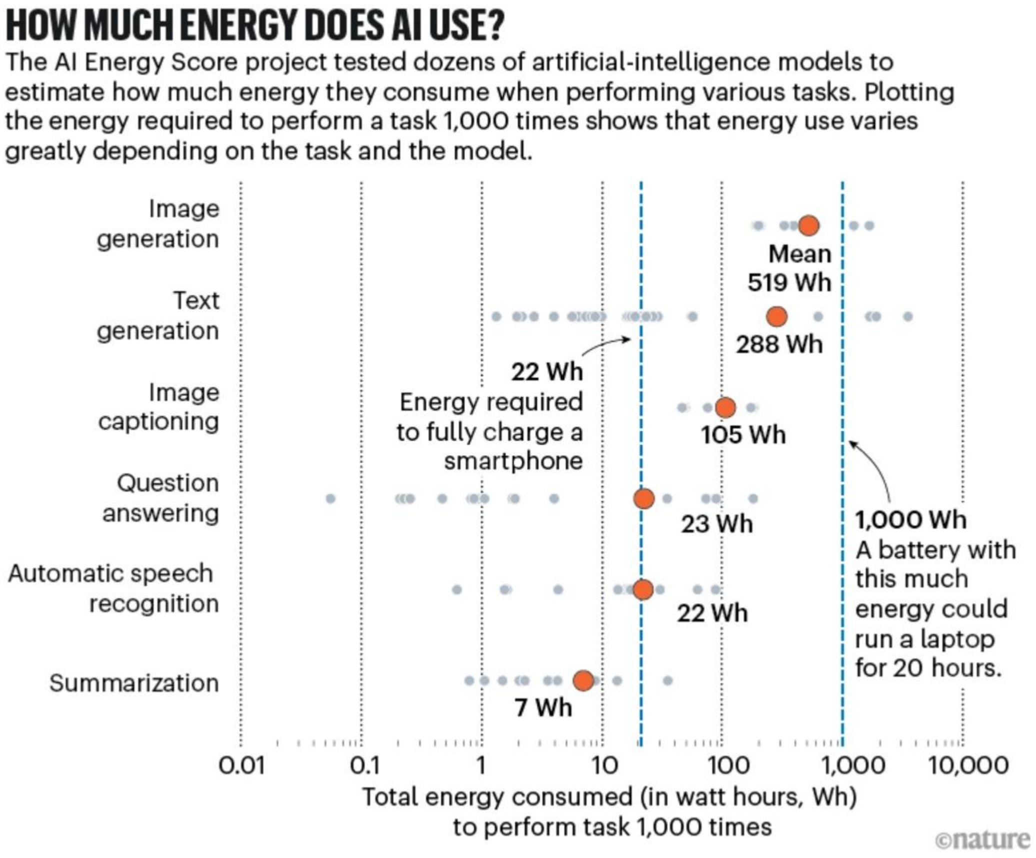


Fig. 2. The 5 modalities examined in our study, with the number of parameters of each model on the x axis and the average amount of carbon emitted for 1000 inferences on the y axis. NB: Both axes are in logarithmic scale.

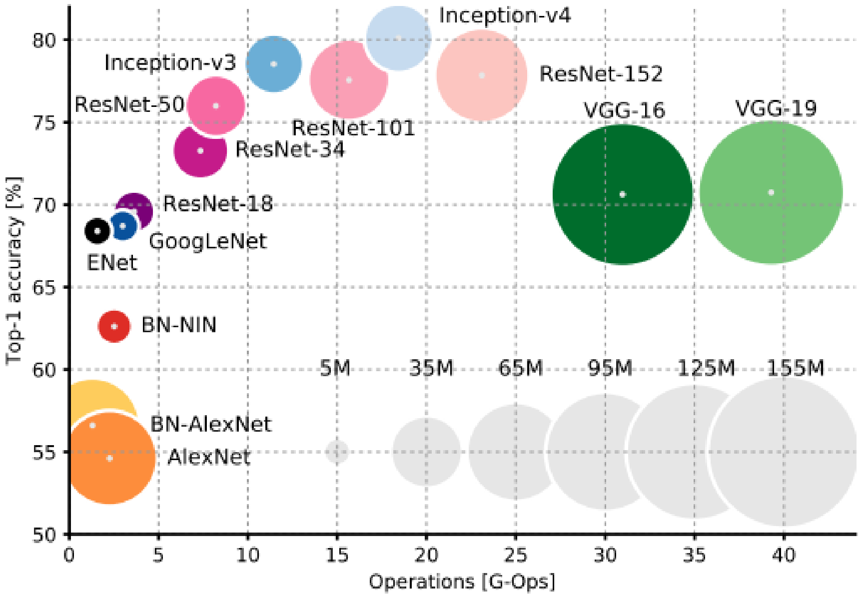
Luccioni, Alexandra Sasha, Jernite, Yacine, and Strubell, Emma. "Power Hungry Processing: ⚡Watts⚡ Driving the Cost of AI Deployment?" *ACM FAccT* (2024).

Different models have different direct impacts



https://www.nature.com/articles/d41586-025-00616-z (via Hugging Face AI Energy Score Leaderboard)

Effectiveness and model size may not be directly correlated



Canziani, Alfredo, Adam Paszke, and Eugenio Culurciello. "An analysis of deep neural network models for practical applications." *arXiv preprint arXiv:1605.07678* (2016).

Electricity demand is rapidly growing

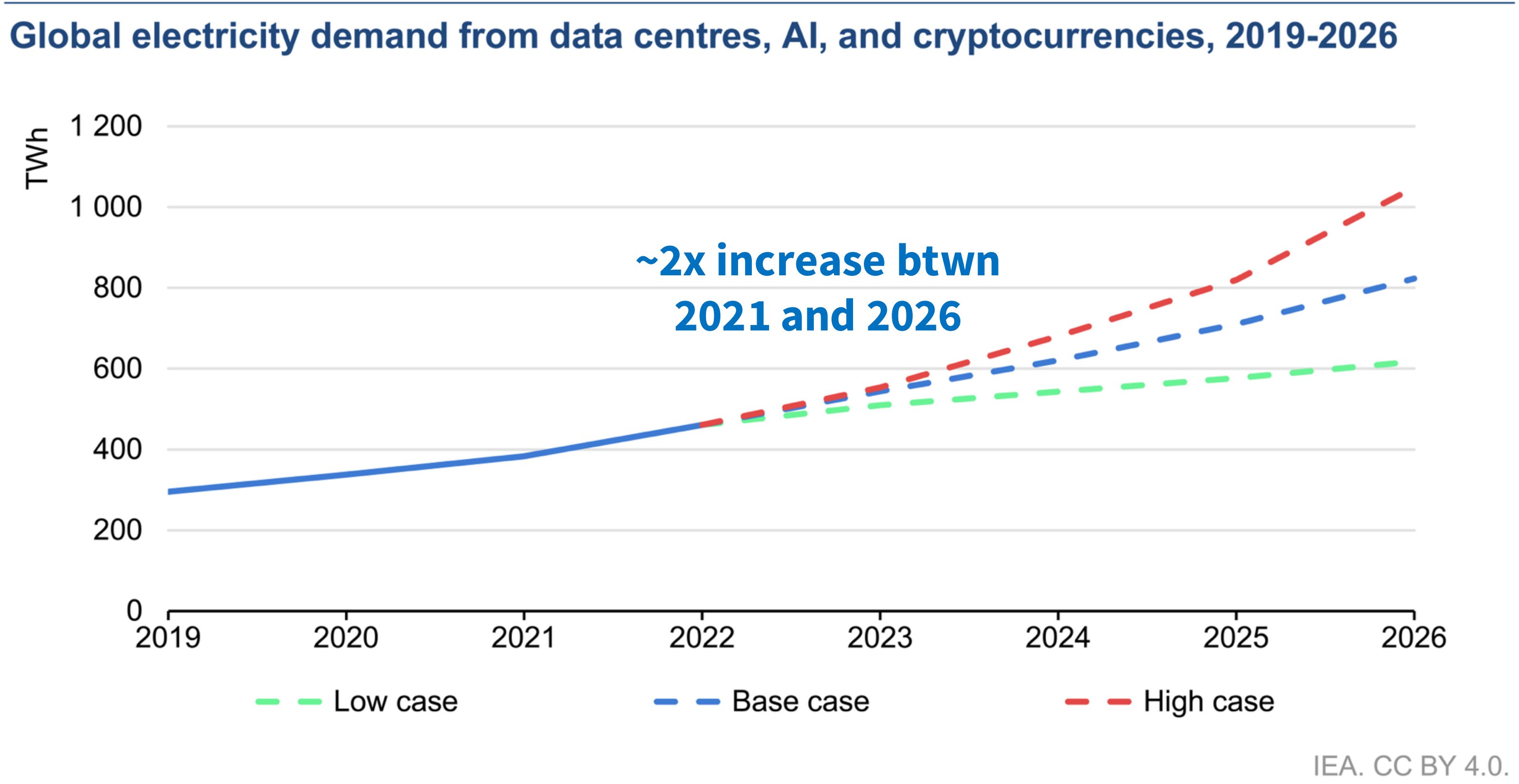


Figure source: IEA (International Energy Agency), “Electricity 2024: Analysis and forecast to 2026”

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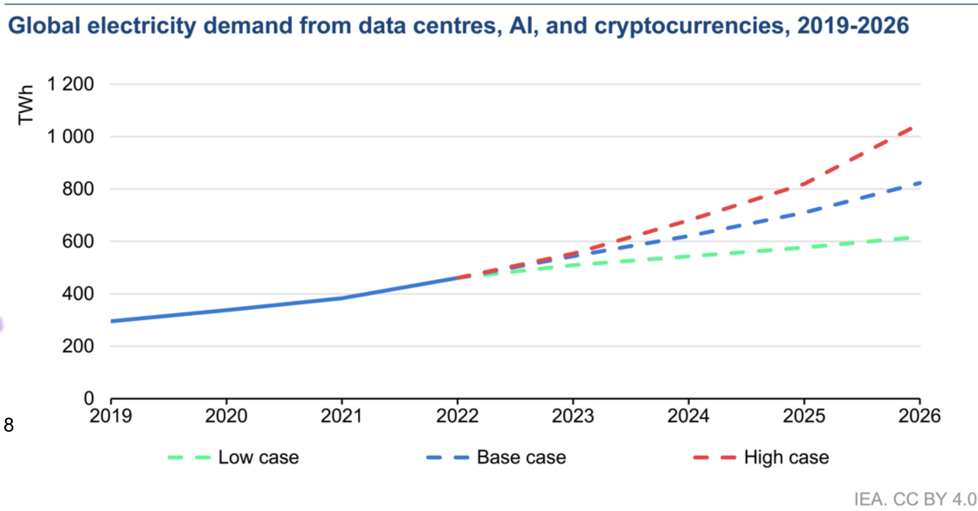


6% increase
btwn 2010 and 2018

(despite 5.5x increase in compute instances)

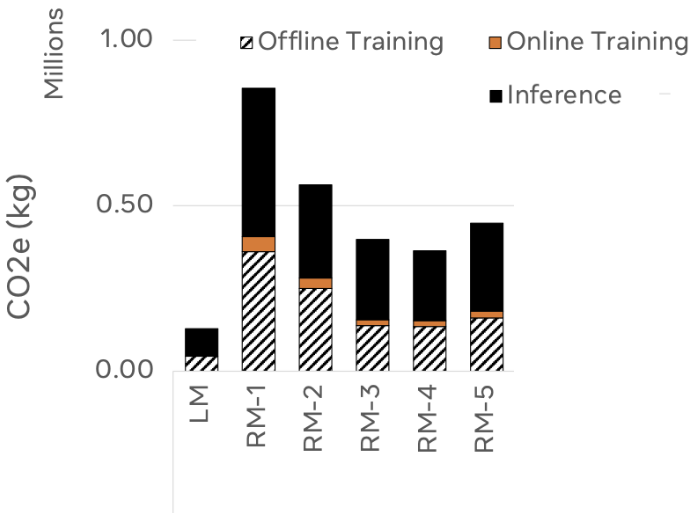
> 2x increase
btwn 2019 and 2026

Rough estimates, based on:
Masanet, Eric, et al. "Recalibrating global data center energy-use estimates." Science (2020)

Source: IEA, "Electricity 2024: Analysis and forecast to 2026"

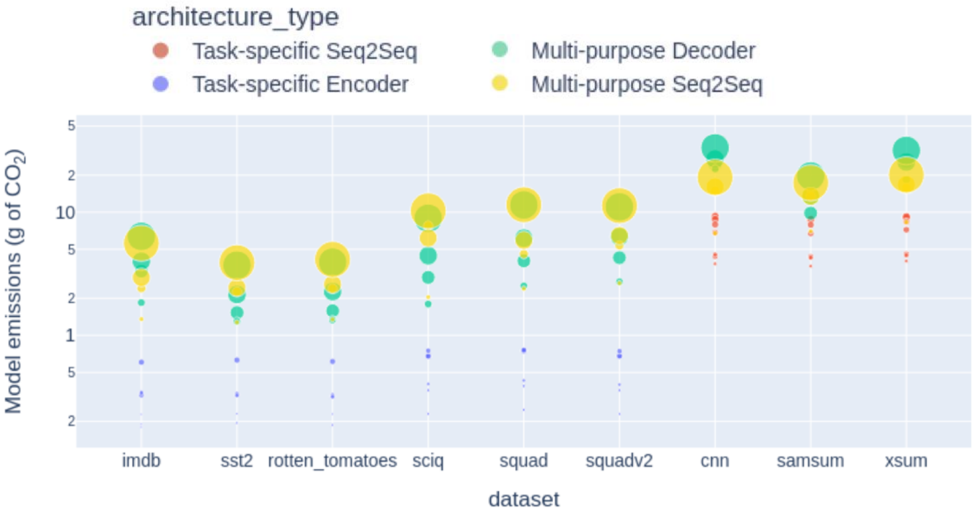
Changing emissions impacts of training vs. inference

Facebook: “The carbon footprint of the LM model is dominated by Inference whereas, for RM1 – RM5, the carbon footprint of Training versus Inference is roughly equal”



Wu, Carole-Jean, et al. "Sustainable AI: Environmental implications, challenges and opportunities." *Proceedings of Machine Learning and Systems* 4 (2022): 795-813.

Per inference, multi-purpose models can be orders of magnitude more expensive than task-specific models



Luccioni, Alexandra Sasha, Jernite, Yacine, and Strubell, Emma. "Power Hungry Processing: ⚡Watts ⚡ Driving the Cost of AI Deployment?" *ACM Conference on Fairness, Accountability, and Transparency* (2024).

Grid integration of data centers: Spiky power consumption

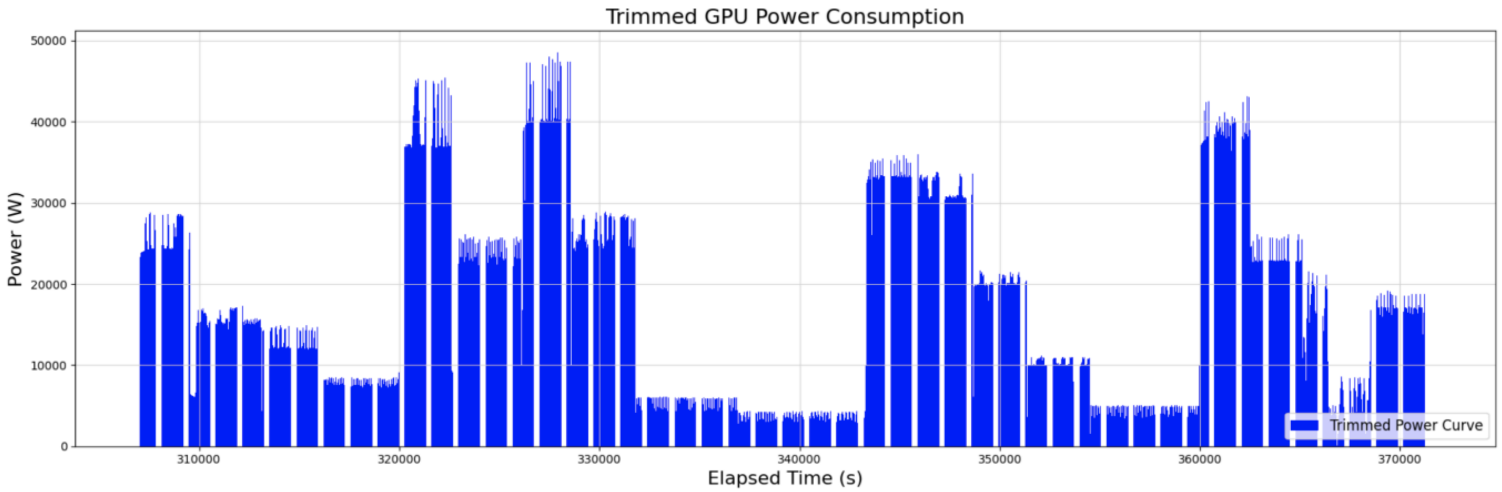


Fig. 6. Power Consumption of BERT in MIT Supercloud Dataset (Peak power consumption of approximately 48.70 kW, with an average consumption of 17.80 kW and a standard deviation of 12.39 kW. The job ran for an extended period of 4 days).

Li, Yuzhuo, et al. "The unseen AI disruptions for power grids: LLM-induced transients." *arXiv preprint arXiv:2409.11416* (2024).

“Greening the grid” is important but insufficient

The path to net zero emissions is narrow: staying on it requires immediate and massive deployment of all available clean and efficient energy technologies. In the net zero emissions pathway presented in this report, the world economy in 2030 is some 40% larger than today but uses 7% less energy. A major worldwide push to increase energy efficiency is an essential part of these efforts, resulting in the annual rate of energy intensity improvements averaging 4% to 2030 – about three-times the average rate achieved over the last two decades.

Source: IEA, “Net Zero by 2050: A Roadmap for the Global Energy Sector” (2021)

While the carbon costs of data centers have been the primary focus of attention in the news, data centers also rely on immense amounts of water for both electricity production and cooling. To supply their centers, many tech firms draw from public water supplies and aquifers, adding to regional water stress—while being built in some of the world’s most drought-prone areas.

Source: Amba Kak and Sarah Myers West, “AI Now 2023 Landscape: Confronting Tech Power,” AI Now Institute (2023).

The term “artificial intelligence” may invoke ideas of algorithms, data, and cloud architectures, but none of that can function without the minerals and resources that build computing’s core components.

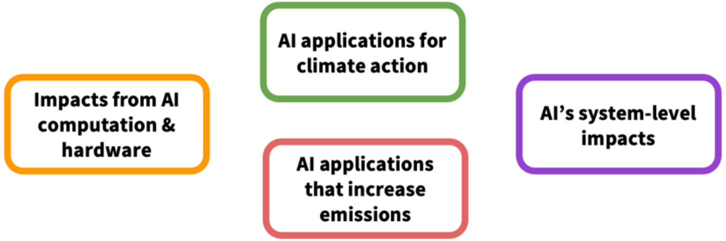
Source: Kate Crawford, “Atlas of AI” (2021)

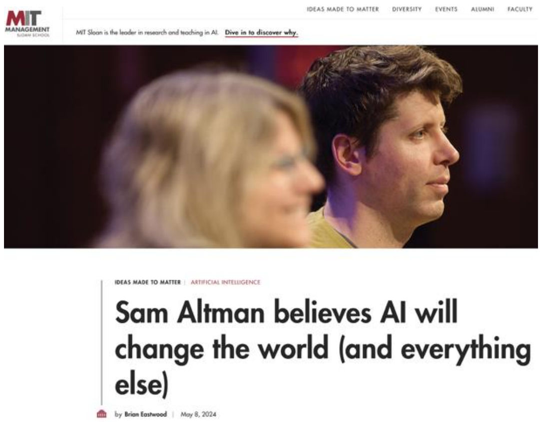
Common fallacies: Energy & emissions of AI

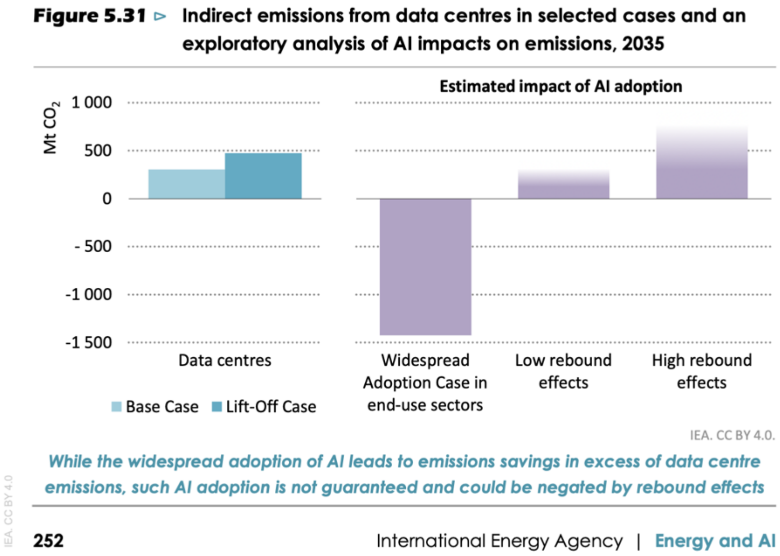
Narrowing discussion to a subset of impacts

Using AI-for-climate as justification for large models

“Chronic potential-itis”*: Assuming best-case adoption scenarios for AI-for-climate deployment







* Vlad Coroamă (https://www.linkedin.com/pulse/chronic-potentialitis-digital-enablement-vlad-constantin-coroam%C4%83-crtjc/)

Takeaways

⚡ **Additional power & energy systems topics**

- Three-phase systems
- Frequency control
- Power system stability

🔎 **AI for energy systems: Synthesis and recurring themes**

- Many different uses across different energy systems applications
- Enablers: Methodological & broader

💪 **Energy (and other) impacts of AI systems:**

- Direct impacts (operational & embodied), application-related impacts (good & bad), and systemic shifts
- Modeling choices, dynamics, and use of AI systems shape overall impacts