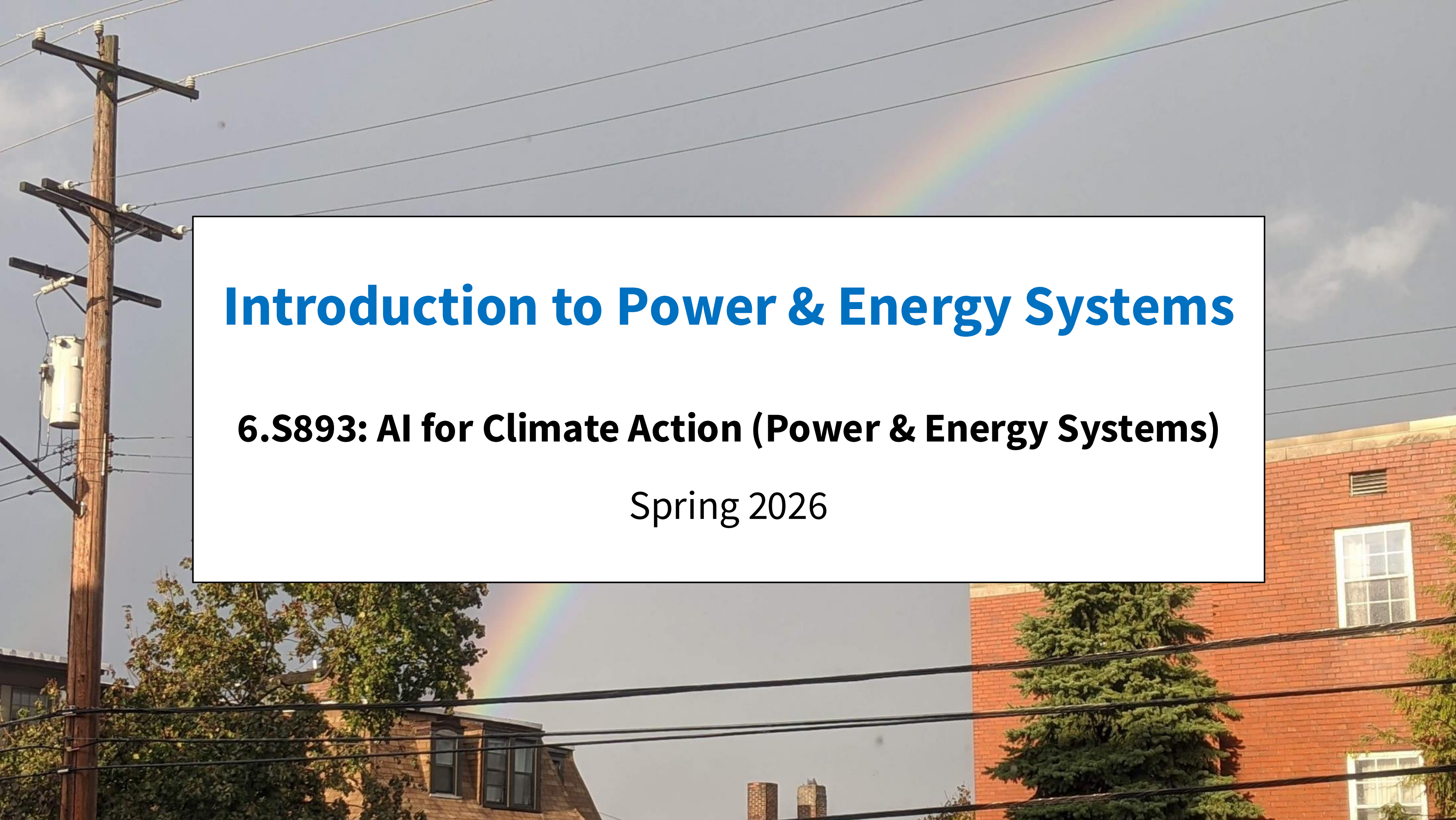

Introduction to Power & Energy Systems

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

Spring 2026

Outline

Context on transformation of power & energy systems

Electric power systems: What they are and how they work

Applications of ML for power & energy systems

Important considerations

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Energy supply sector

“[A]ll the infrastructure and equipment used to extract, transform, transport, transmit, and convert energy to provide energy services” [IPCC2022]

- Electric power systems
- Fuel supply systems (e.g., natural gas networks, provision of cooking fuels)
- Heating and cooling networks

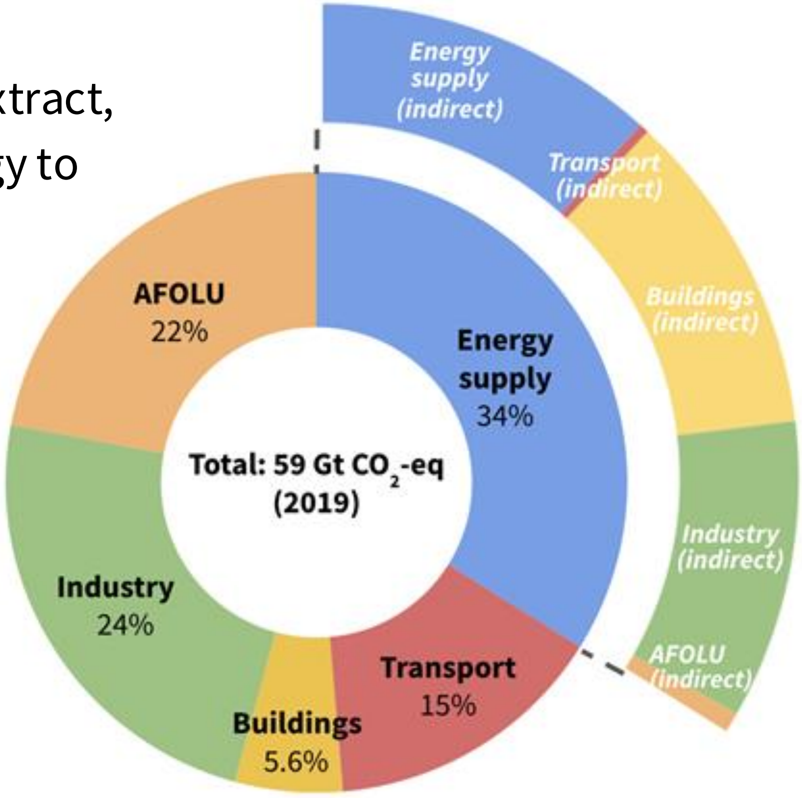
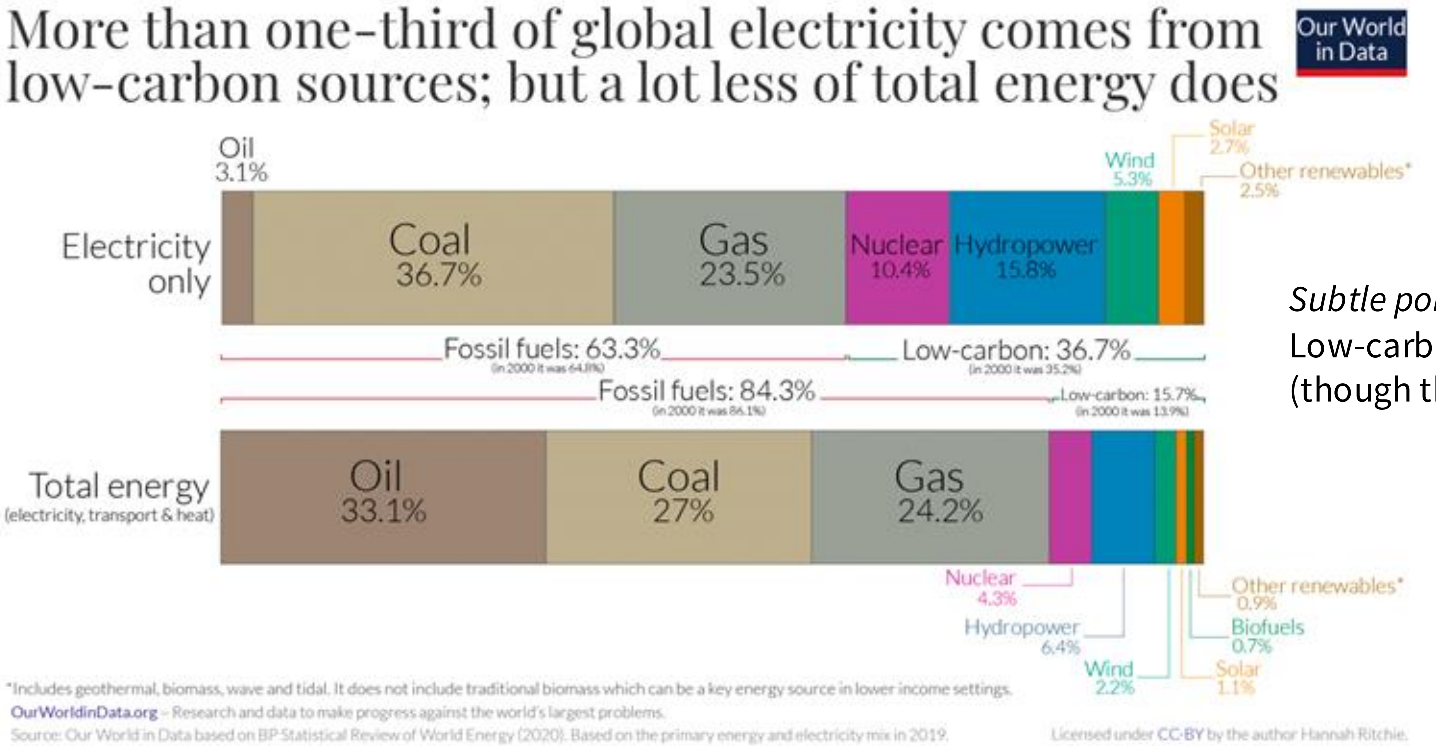


Figure data based on [IPCC2022]. Percentages shown do not add to exactly 100% due to rounding to two significant figures.

Low-carbon sources are still in the minority

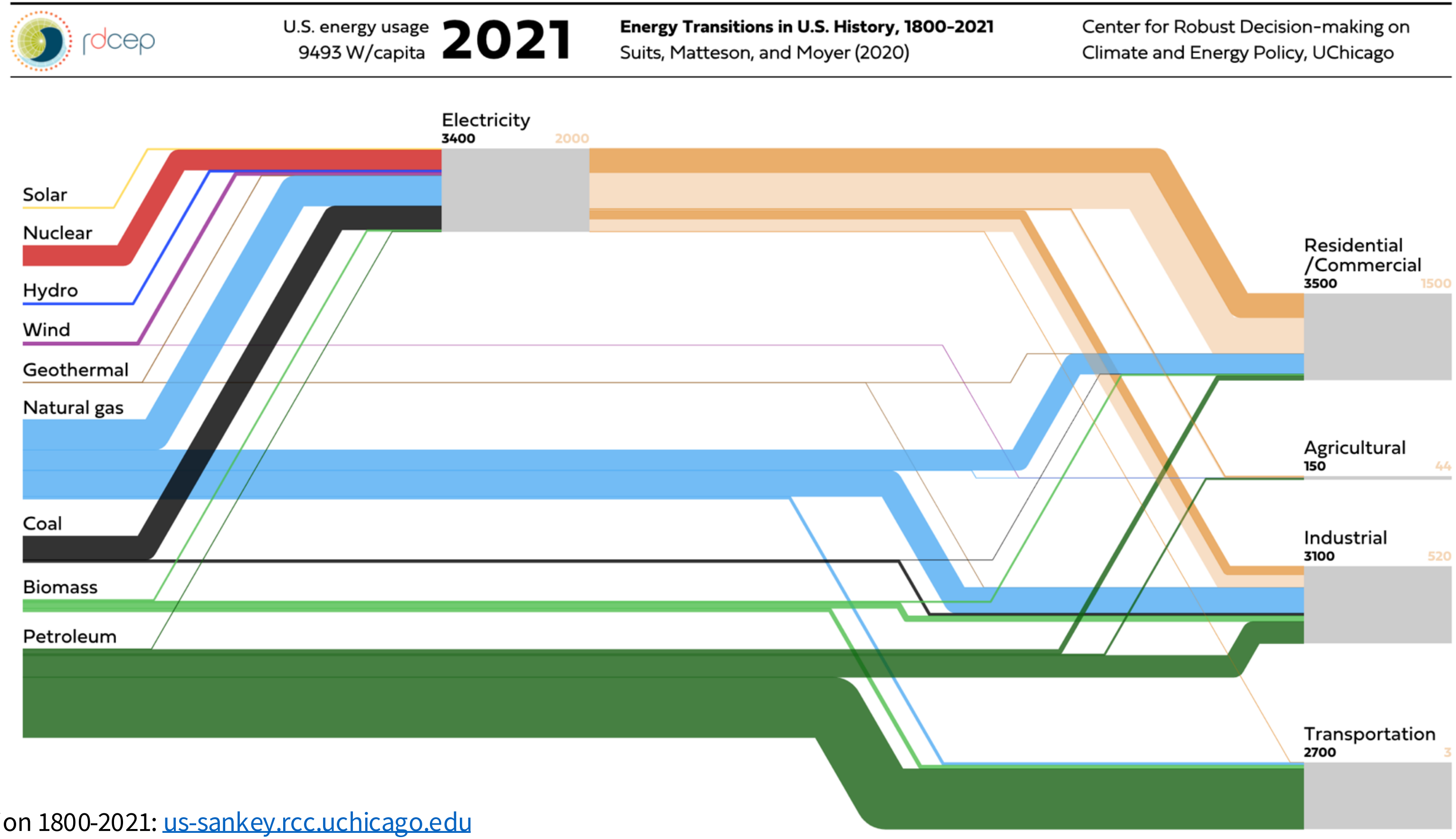


Subtle point:

Low-carbon ≠ renewable (though there is overlap)

Figure source: [RRR2022]

US energy production/consumption

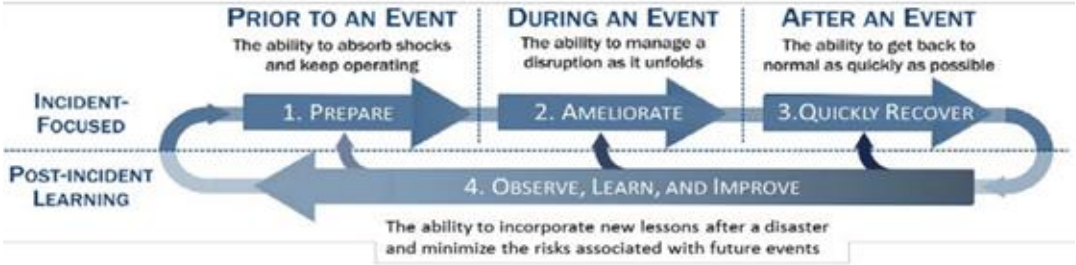


Visualization 1800-2021: us-sankey.rcc.uchicago.edu

Climate change adaptation & energy systems

Extreme events: Fostering robustness & resilience

- Accommodating correlated failures due to extreme heat/cold or drought
- Enabling quick repair after large storms & hurricanes



Accommodating changing energy supply/demand patterns: Changes in weather impact energy production (e.g. solar/wind) and consumption (e.g. heating/cooling)

Building adaptive capacity: Energy access and reliability are strong drivers of economic development, and thus of capacity to adapt to climate change

Figure source: [NAS2017]

Energy systems are necessary for development

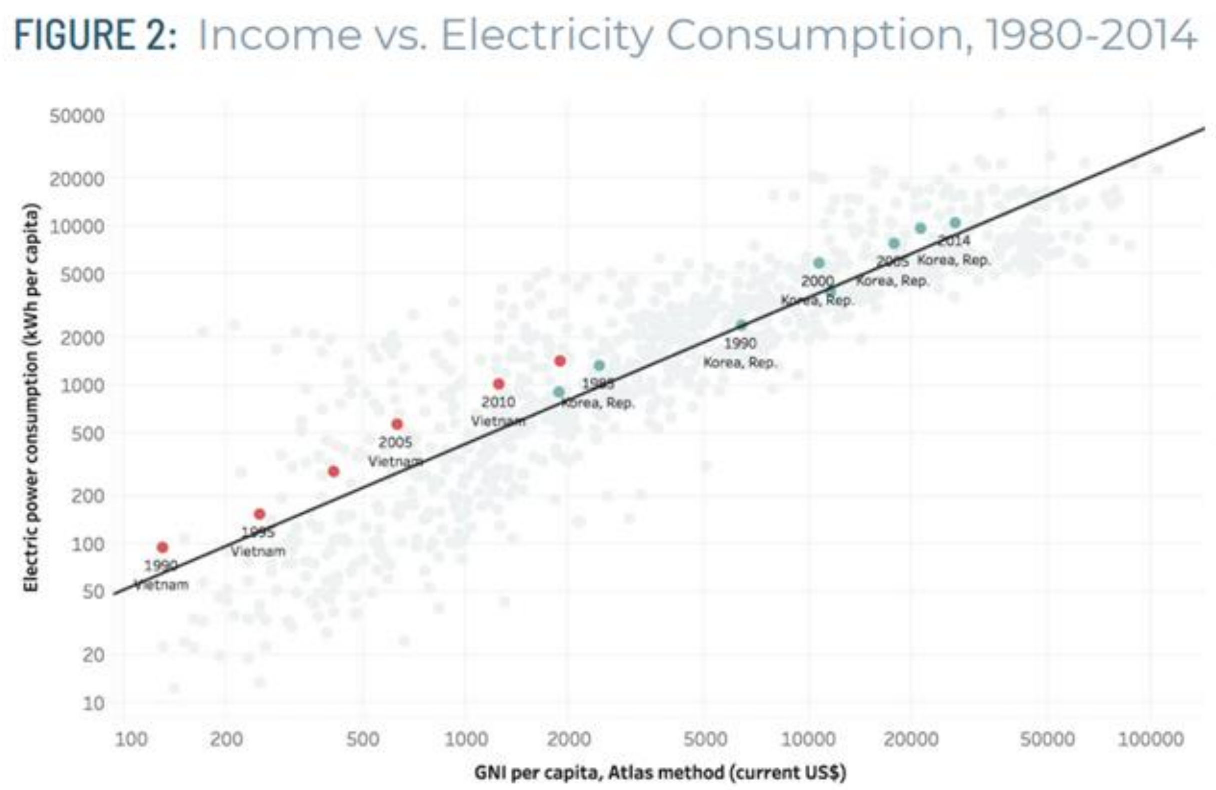


Figure source: [MBB+2020]

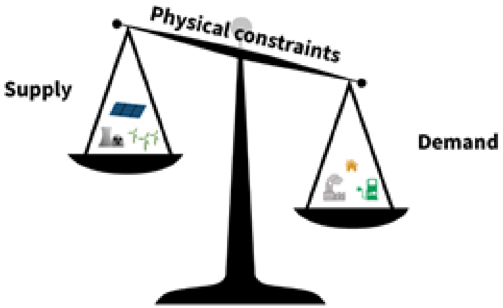
Transforming energy systems?

(Fun fact: This poster was originally designed for Westinghouse Electric)

Energy systems transformation: Key questions

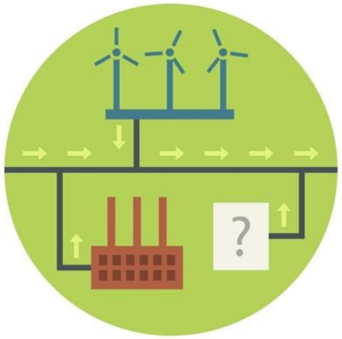
Operations: How can we operate energy systems to

- Integrate low-carbon energy (incl. time-varying renewables),
- Improve efficiency/reduce waste,
- Improve/maintain reliability, robustness, and resilience?



Planning: How can we reinforce existing systems and components and build new ones to:

- Enable mitigation and adaptation goals,
- Ensure high-quality energy access?



US electricity production 1800-2019

We’ve seen rapid changes in the electricity landscape before!

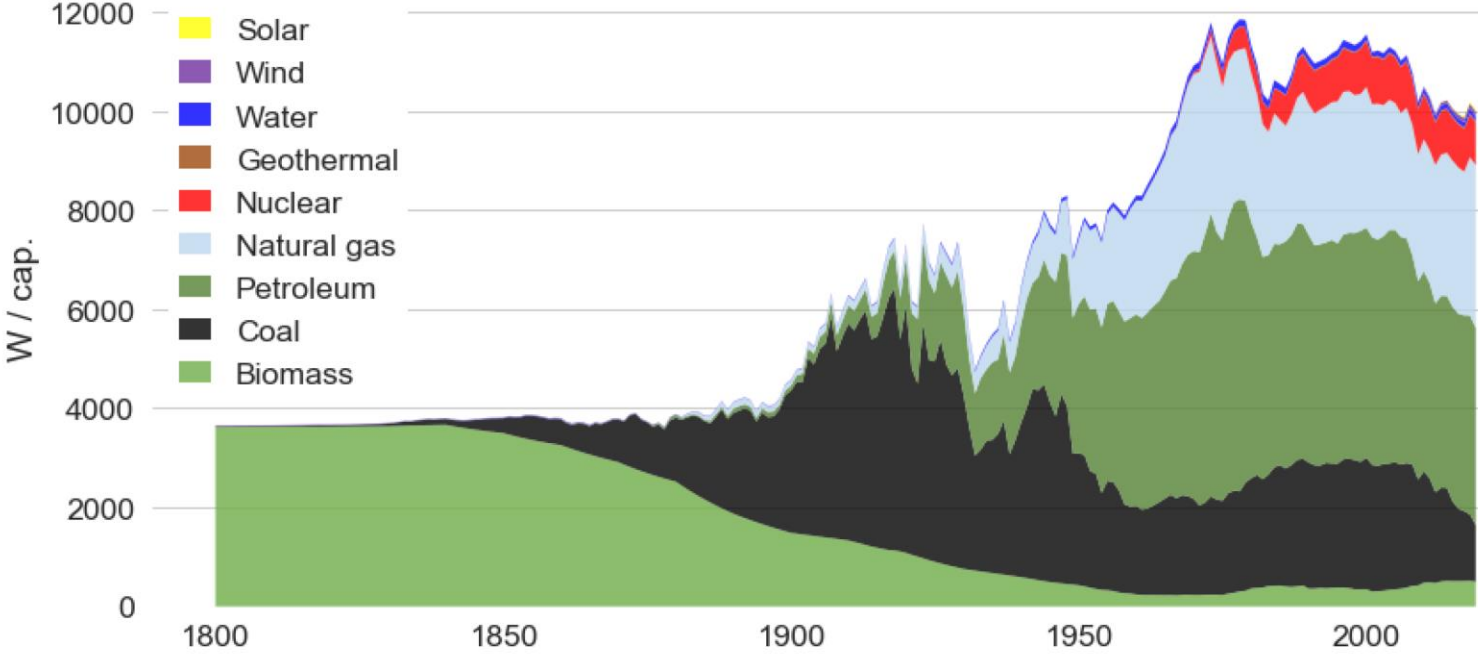
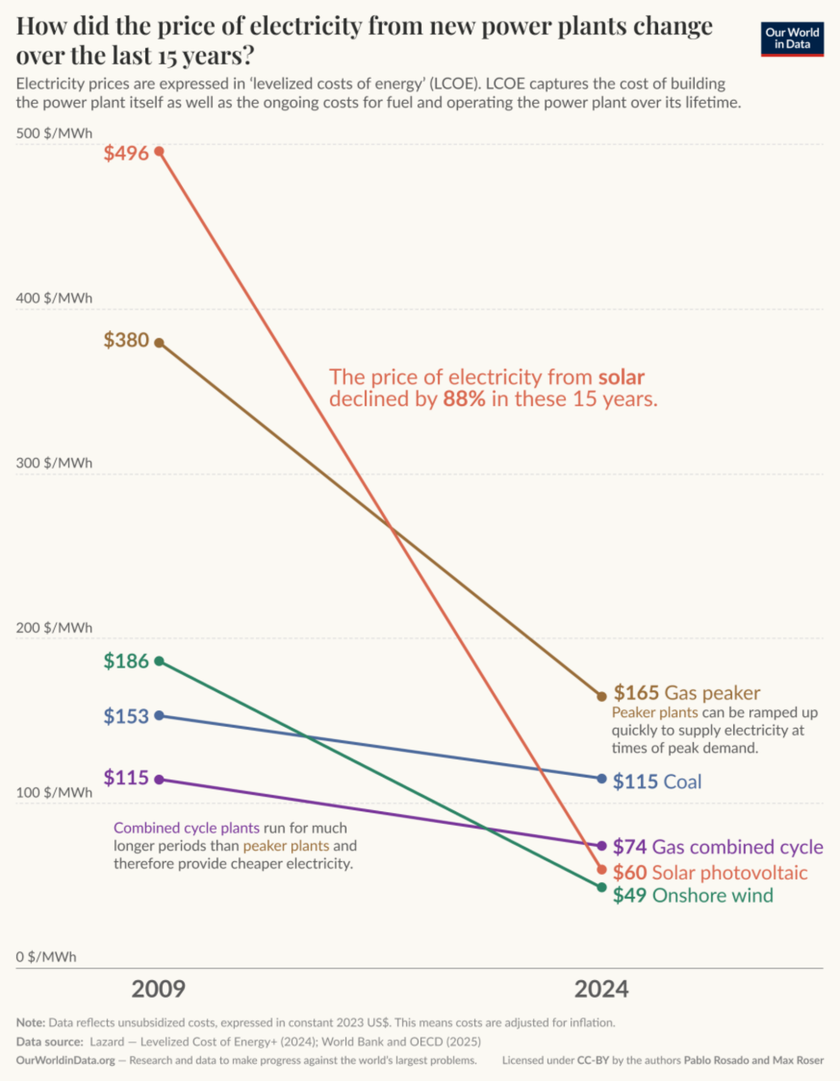
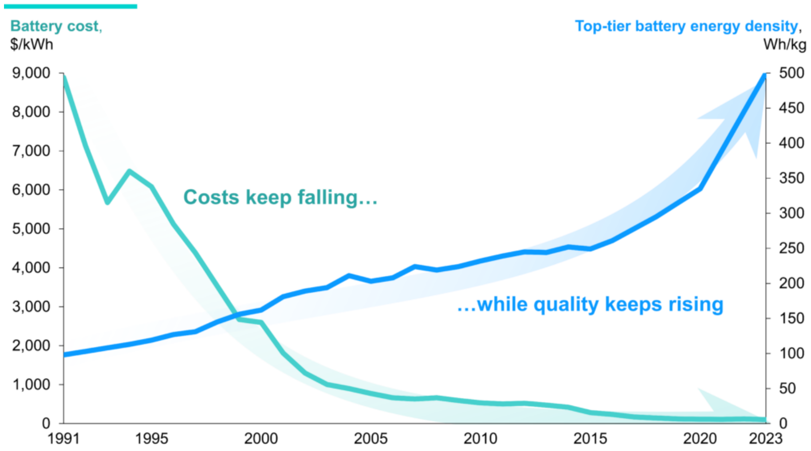


Figure source: Robert Suits, Nathan Matteson, and Elisabeth Moyer. *Energy Transitions in US History, 1800–2019*. Center for Robust Decisionmaking on Climate Energy and Policy, University of Chicago, 2020. http://www. rdcep. org/s/Suits_Matteson_Moyer_2020_Energy_Transitions. pdf, 2020.



Clean technologies are often less expensive



Ziegler and Trancik (2021) before 2018 (end of data), BNEF *Long-Term Electric Vehicle Outlook* (2023) since 2018, BNEF *Lithium-Ion Battery Price Survey* (2023) for 2015-2023, RMI analysis.

US energy transition: Need for transmission

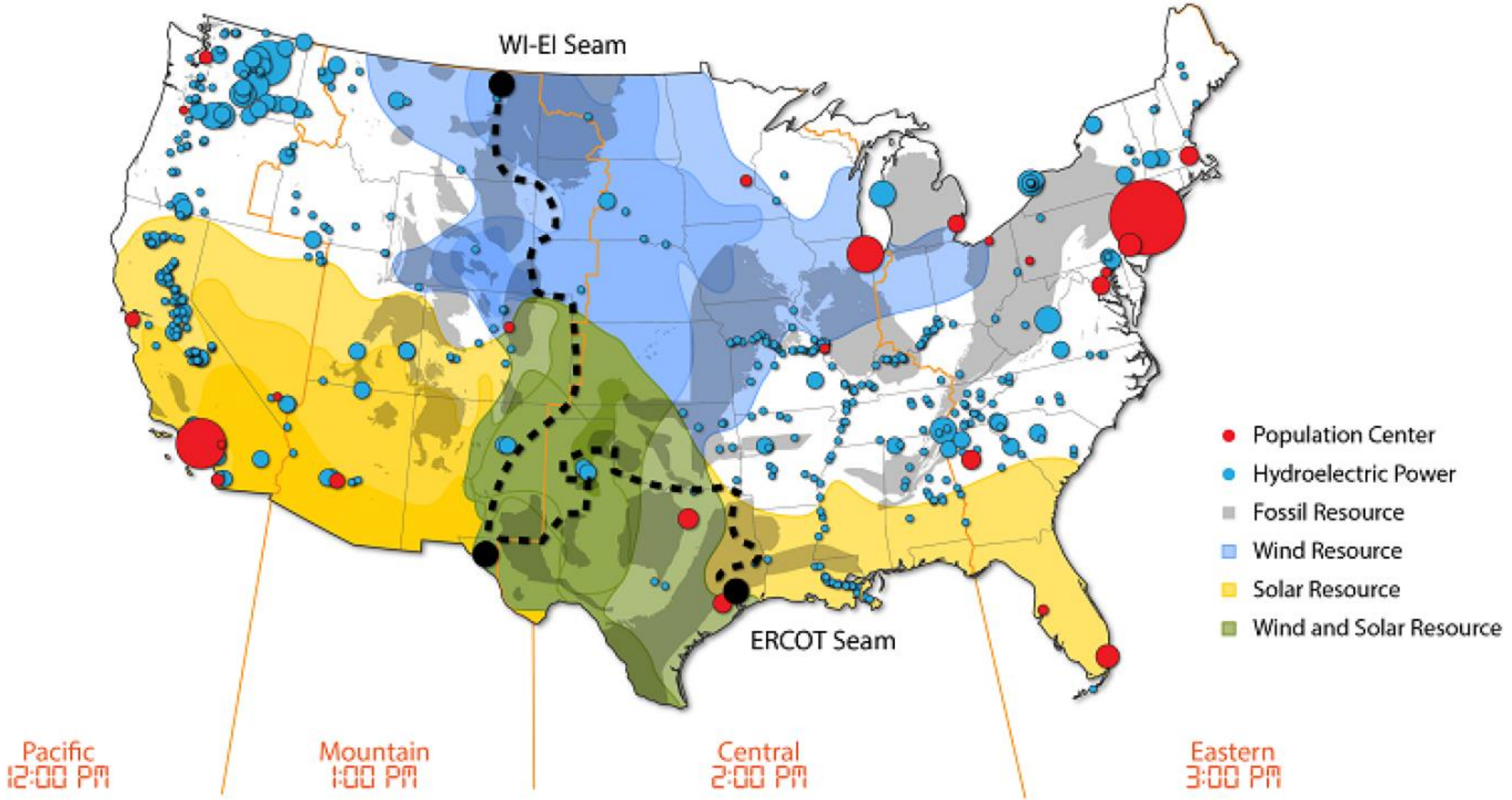


Image from: https://www.energy.gov/eere/articles/east-meets-west-lab-study-focuses-connecting-power-grid-coast-coast

Outline

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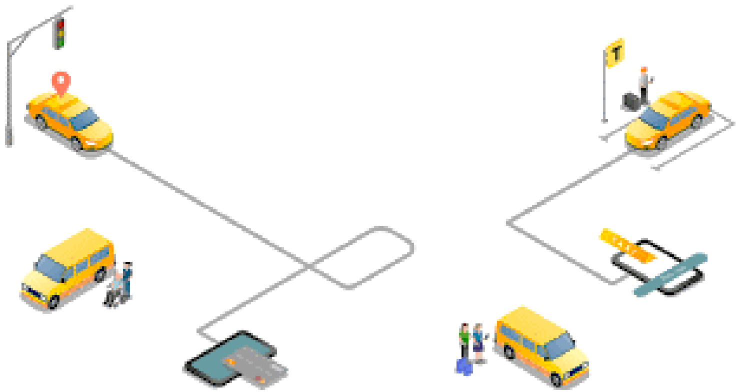
Electricity is NOT…

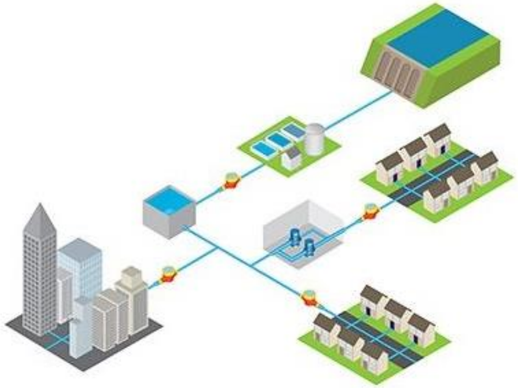
Rideshare



Customers don't schedule when they want to use electricity

Electrical power is (usually) available when needed

Water



The utility doesn't store electricity for on-demand use

Electrical power is delivered within seconds of generation

Slide credit: Rajeev Ram

Electricity today is NOT…

Isolated generators and load

Slide credit: Rajeev Ram

Conventional power system

Generation ➔ Transmission ➔ Distribution ➔ Consumption

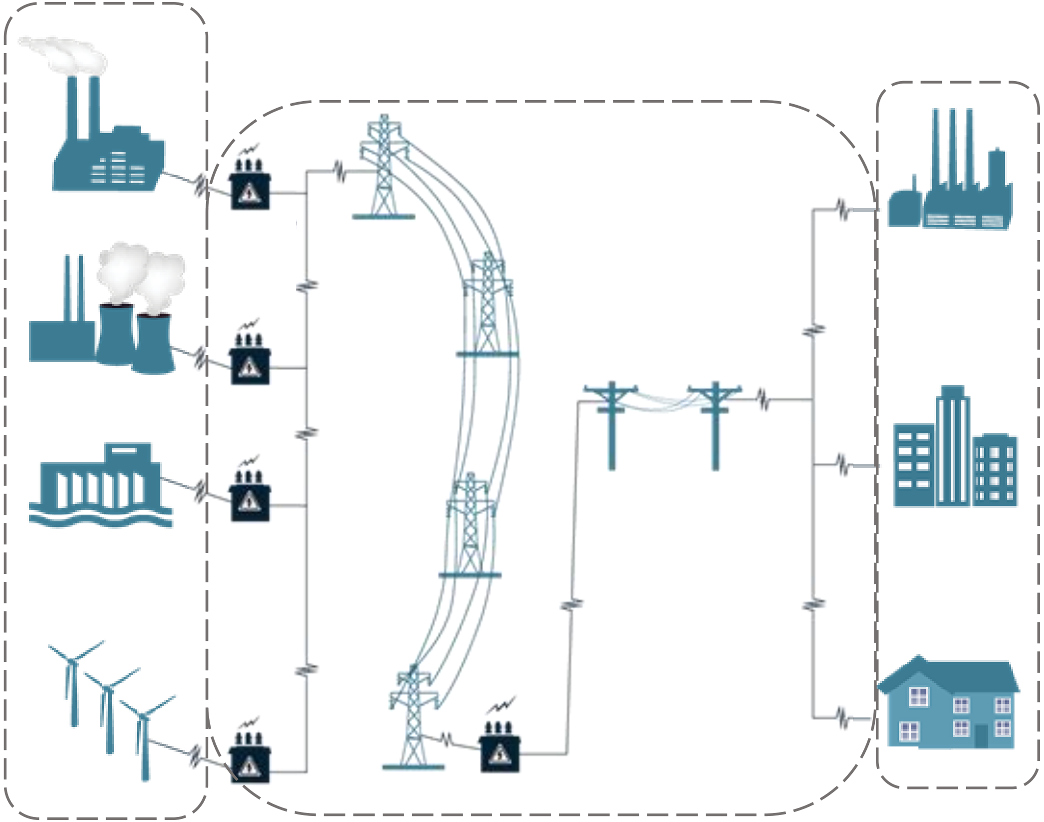


Figure adapted from [CBO2020]

“The world’s largest machine”

As of December 31, 2022, there were **25,378** electric generators at about 12,538 utility-scale electric power plants in the US.

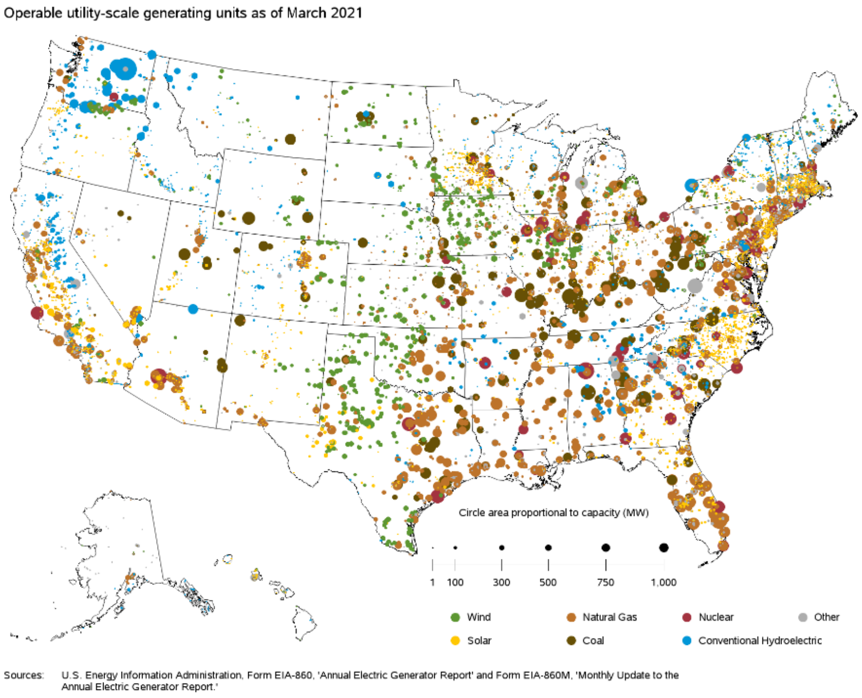


Figure source: www.eia.gov/electricity/data/eia860m/

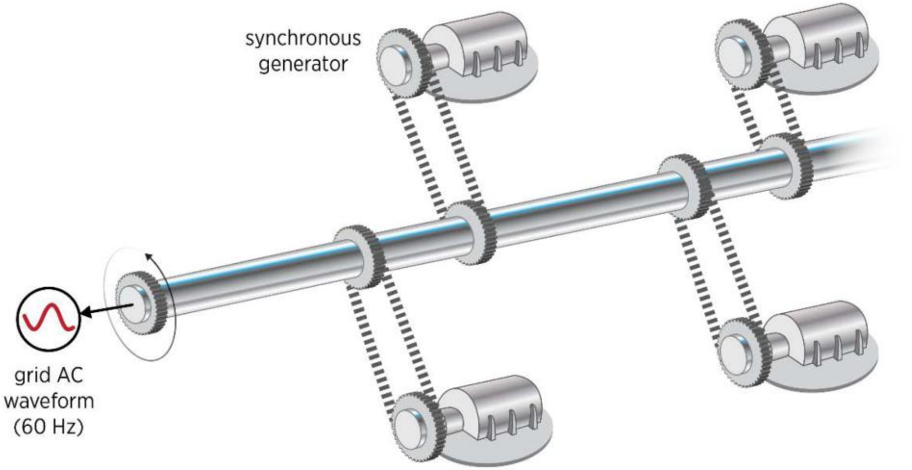
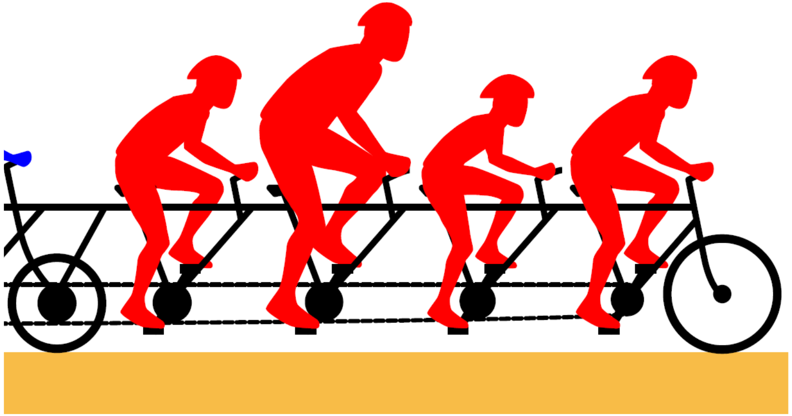


Figure source: Denholm, Paul, et al. *Inertia and the power grid: A guide without the spin*. National Renewable Energy Lab (2020).

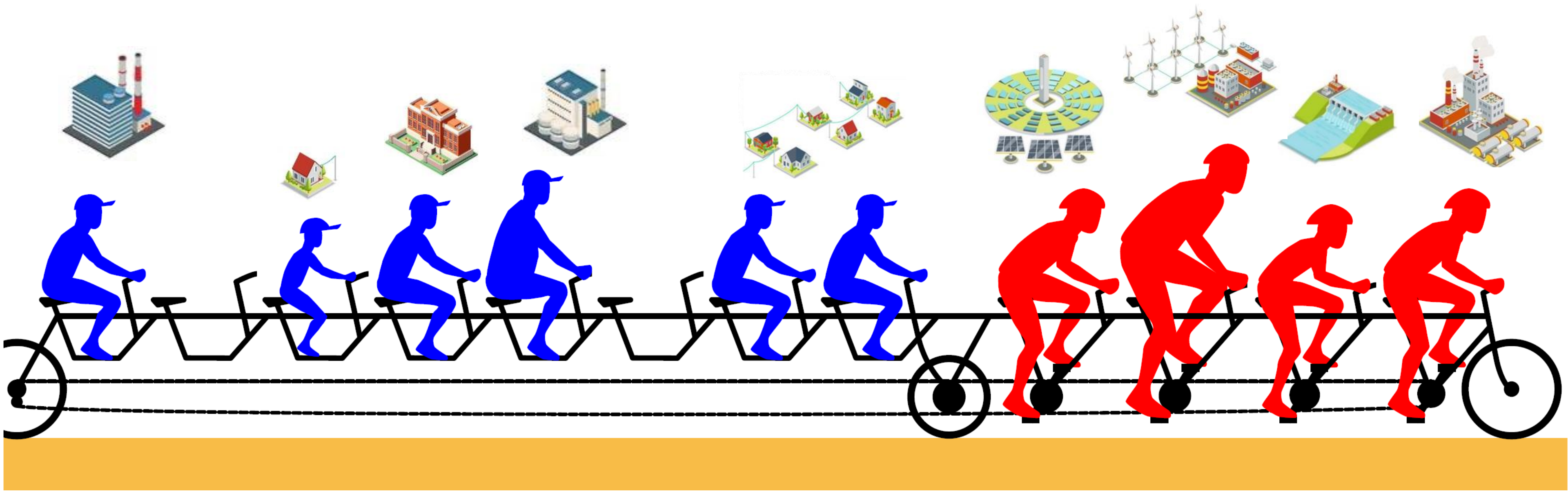
Slide credit: Rajeev Ram

Tandem bike: Synchronous interconnection analogy



Slide credit: Rajeev Ram

Tandem bike: Synchronous interconnection analogy

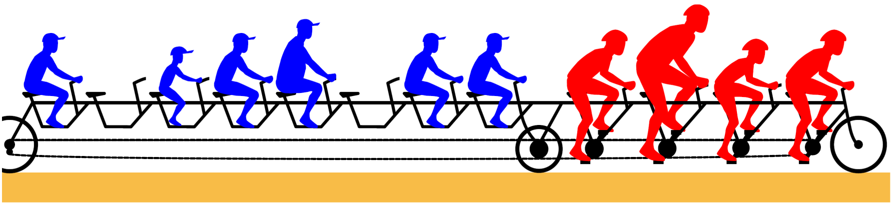


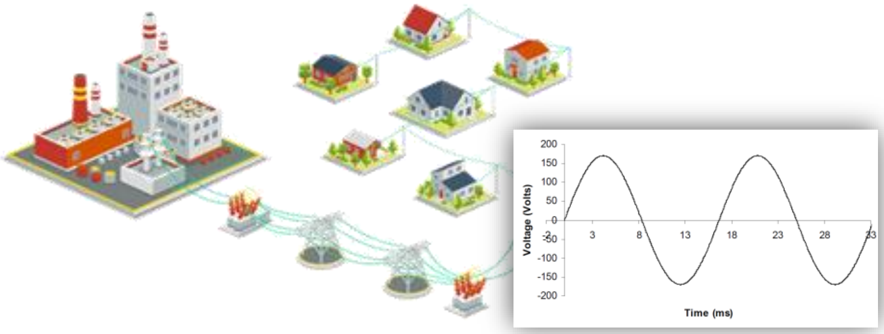
Constant speed of bike (no acceleration) $\text{Force}_{\text{Pedalers}} = \text{Force}_{\text{Load}}$

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

Slide credit: Rajeev Ram

Maintaining constant speed (system frequency)





Constant speed of bike (no acceleration)

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

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

Constant system frequency

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

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

Power systems are diverse & rapidly changing

Variable generation
- E.g., solar and wind

Bi-directional power flows
- Distributed energy resources (DERs) – rooftop solar, batteries

Non-centralized control
- Demand response
- Distributed vs. decentralized

Microgrids
- On-grid (e.g., MIT microgrid)
- Off-grid (e.g., islands, rural areas)

Impact of **AI & data infra. loads**

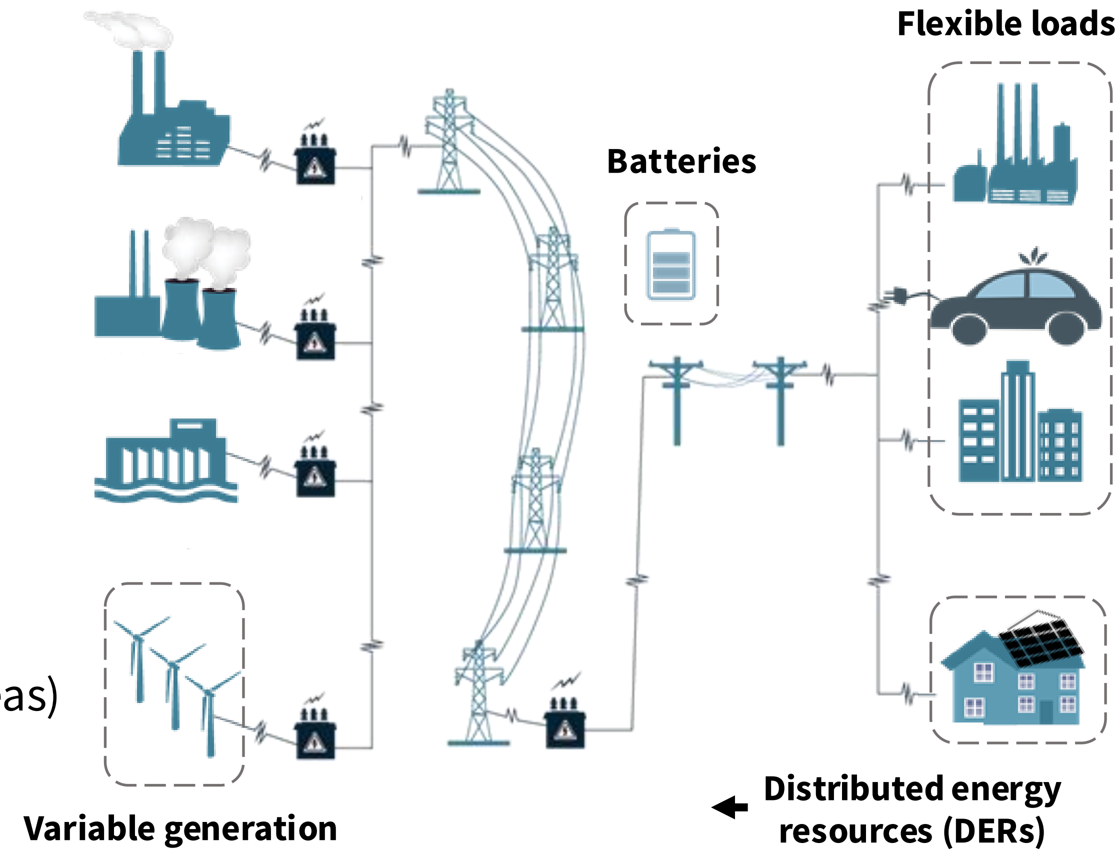
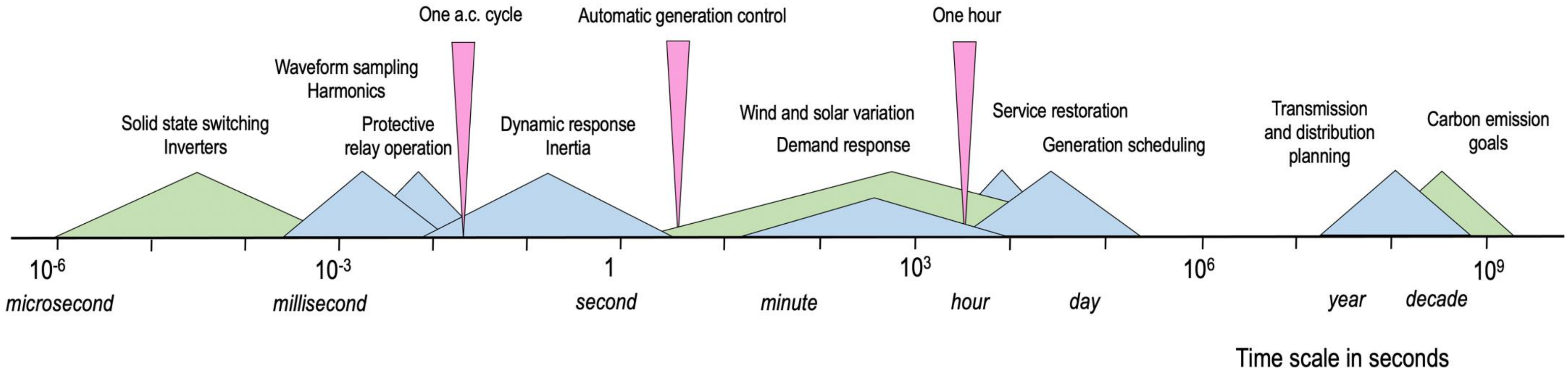


Figure adapted from [CBO2020]

Time scales in grid operations and planning



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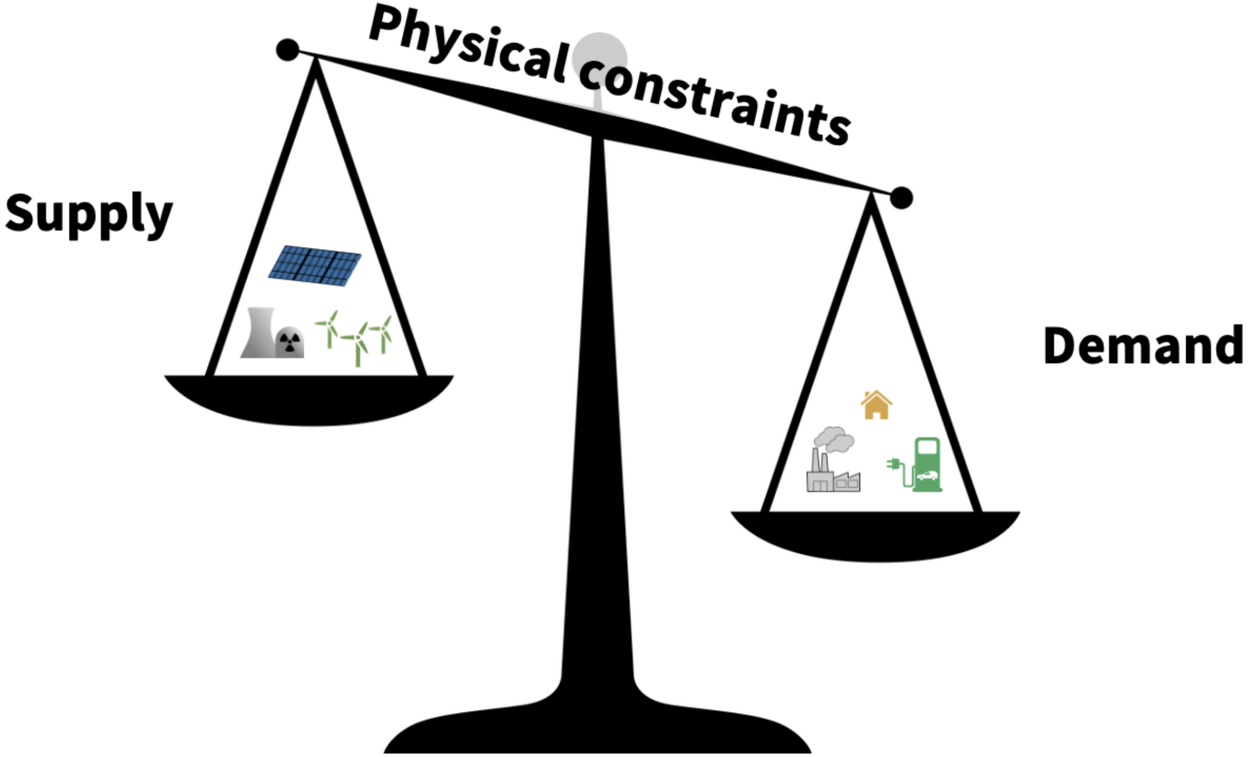
Operational constraints on electric power systems



Idealized grid operation: AC optimal power flow (ACOPF)

Goal: System operator "dispatches" power and voltages at controllable generators to

- Meet power consumption (true consumption minus losses & distributed generation)
- Minimize fuel costs (in normal conditions) or load loss (in extreme conditions)
- Satisfy grid and operational constraints

$$\underset{z := [p_g^T, q_g^T, |v|^T, \delta^T]^T}{\text{minimize}} \quad f_c(p_g)$$

(objective: min. fuel costs or load loss)

$$\text{subject to } Az = b$$

(linear equality constraints, e.g., quantity conversions, fixed values)

$$g(z) \leq h$$

(inequality constraints, e.g., device limits, thermal limits)

$$(p_g - p_d) + (q_g - q_d)j = \text{diag}(v)\bar{Y}\bar{v}$$

(power flow constraint over complex powers, voltages, and admittances)

λ (prices) are dual variables

Reality is more complicated

Proxy procedures: ACOPF is expensive → cheap approx. (DCOPF, economic dispatch)

Multiple time steps: Need to decide ahead of time which generators to turn on/off *and* how much power they should produce *(unit commitment* with *ramp rates*)

System uncertainties: Electricity demand and variable power generation are not perfectly predictable - requires (e.g.) *automatic generation control* in real time

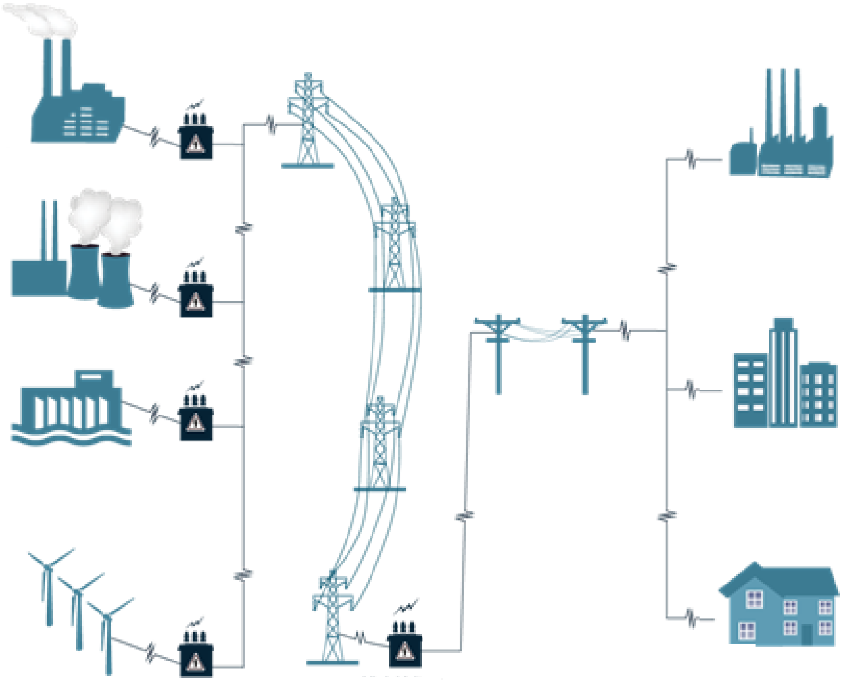
Accounting for outages & maintenance: *Security-constrained optimal power flow*

Accounting for dynamic stability, rather than only static/steady-state operation

Power pricing: Most consumers don't face real-time wholesale prices

- Lots of power procured through *power purchase agreements*
- Out-of-market payments, e.g., *uplift payments* and *capacity markets*
- Highly subsidized retail prices (less than wholesale) in some regions

Stakeholders and regulatory considerations



Grids are “natural monopolies”

- Management by public or tightly-regulated private entities

Stakeholders:

- Regulatory commissions
- System operators
- Utilities
- Suppliers, demand aggregators
- Consumers, prosumers

Considerations:

- Differing assumptions on 24/7 reliable power
- Regulated rate of return

Figure adapted from [CBO2020]

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Overview of ML applications in energy systems

Operations

- Situational awareness
- Prediction
- Optimization & control

Planning

- Infrastructure mapping
- Speeding up simulations
- Scenario generation

Enablers – facilitating innovation, policy & markets, and management of data

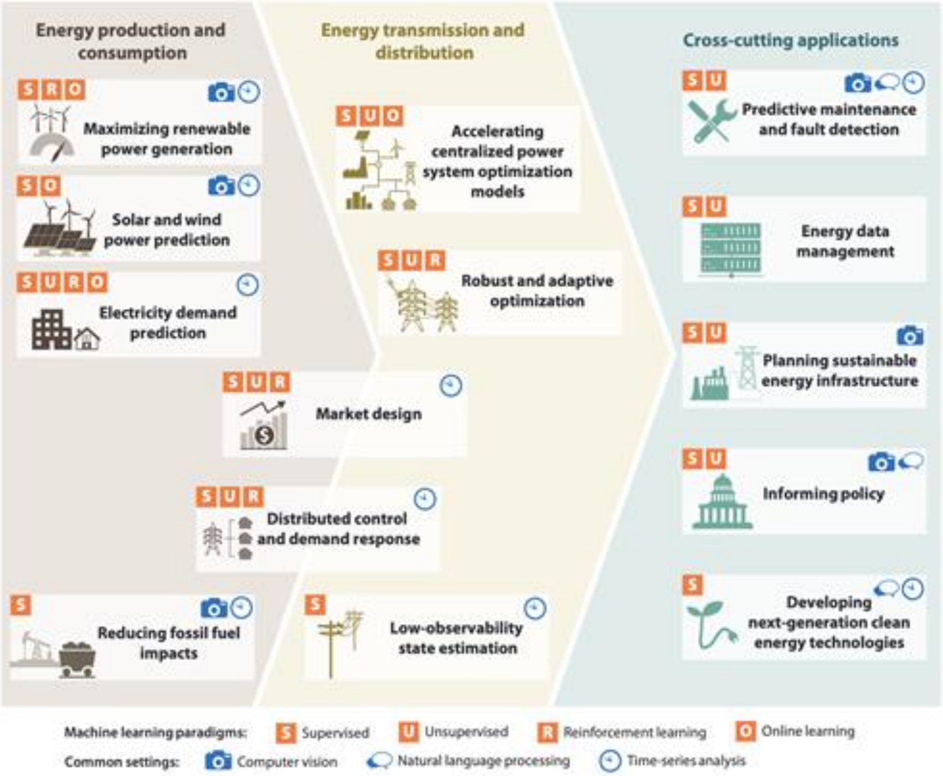


Figure source: Donti, P. L. & Kolter, J. Z. (2021). Machine learning for sustainable energy systems. *Annual Review of Environment and Resources*, 46, 719-747.

Operations >> Situational Awareness & Prediction

Assessing the state of the power system

- Current state: State estimation (voltages), topology estimation, outages
- Future state: Forecasting of supply, demand, emissions

Approaches: Rule-based, physics-based, optimization, statistics, ML

ML pros: Fast, can use multimodal data, powerful near-term predictions
ML cons: Need consistent data, struggles with long-term trends, interpretability(?)

ML example: Nowcasting (Open Climate Fix & National Grid ESO)

- **Demand:** Used Temporal Fusion Transformer to reduce error by 2-3x for 30-min- and 48-hr-ahead national demand forecasts [CRDK+2021]
- **Solar PV:** Used time series data, satellite data, and numerical weather predictions to reduce error by ~3x of 2-hr-ahead forecasts [K2022]

Image from [OCF2019]

Operations >> Predictive Maintenance & Efficiency Improvement

Detect inefficiencies or outages preemptively and/or in real time

Approaches: Manual inspection, signal processing, ML

ML pros/cons: [Similar to “situational awareness & prediction”]

Example ML applications:

- Detecting methane leaks in natural gas infrastructure [WJR+2022]
- Detecting anomalies in solar panels, wind turbines, batteries [AH2021]
- Detecting non-technical losses (e.g., theft, meter tampering)

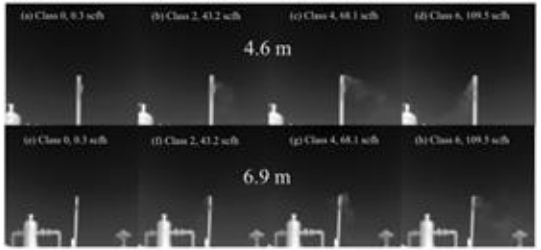


Image from: [WJR+2022]

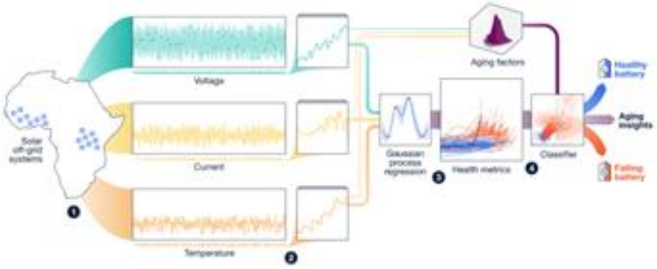
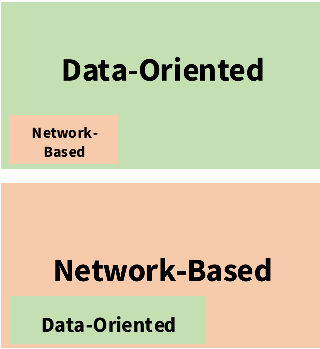


Figure from: [AH2021]



Operations >> Centralized Optimization

Dispatching controllable power generation (recall: ACOPF)

- Goal: Integrate time-varying renewables, improve robustness, reduce waste
- Challenge: Need to increase speed, scale, and fidelity of existing methods

Approaches: Optimization (incl. relaxation), ML

ML examples:

- Speeding up ACOPF (active constraint prediction, warm start points, full approx.)
- Reinforcement learning for topology switching and redispatch [L2RPN2022]

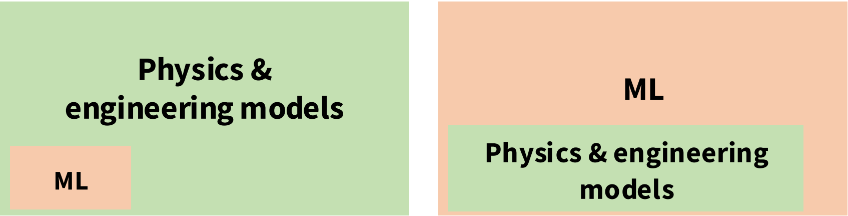


Image from: [L2RPN2022]

Operations >> Distributed Control & Demand Response

Control of distributed resources (e.g., solar inverters, batteries, flexible loads)

- Goal: Integrate renewables, improve robustness/resilience/reliability, reduce waste
- Need: Control strategies that are fast, flexible, scalable, robust, physically feasible

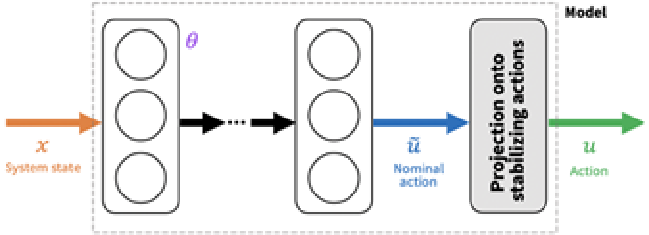
Approaches: Control theory, ML (reinforcement learning)

ML pros: Expressive and complex policies (well-performing)
ML cons: Generally don’t ensure robustness

Example: Merging reinforcement learning and robust control [CJZ2022, DRK2021, RCMW2022]

❓Untrusted (performant)

✔ Trusted (robust)



Planning >> Infrastructure Mapping

Understand where infrastructure currently is, to facilitate planning (and operations)

Approaches: Manual surveying (of sites and documents), ML

Examples: Mapping power lines, solar & wind infrastructure from satellite and aerial imagery [DS2018, GRL2019, ONM2022, TWMR2019, YWMR2018]

Figure from: [TWMR2019]

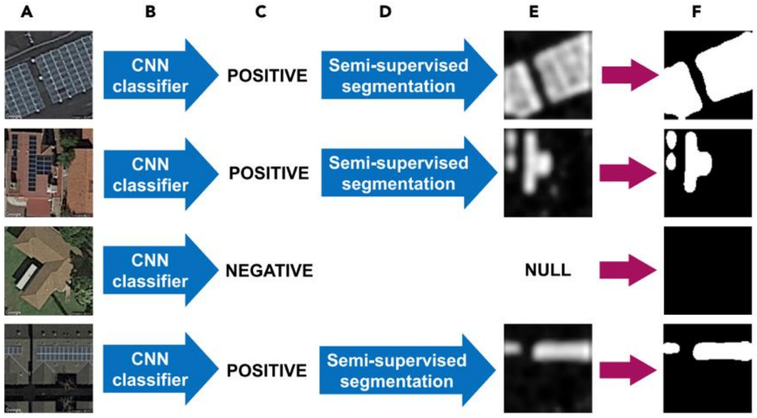


Figure from: [YWMR2018]

Planning >> Simulation & Scenario Generation

Model how future systems should be built out

Approaches: Physical simulation, multi-objective optimization, ML

Note: Planning models are simply an *input* to overall planning processes

AI/ML examples:

- Multi-objective optimization of hydropower dam placement [ASG+2019, WGS+2018]
- Aiding long-term demand estimation for new customers [AWDJ2021, FMWMT2022, L2023]
- Climate model downscaling [HHMS2022] and synthetic scenario generation [CWZ2018]

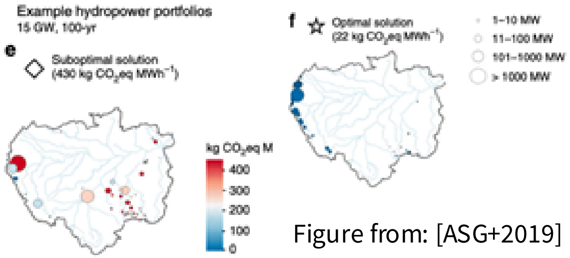


Figure from: [ASG+2019]

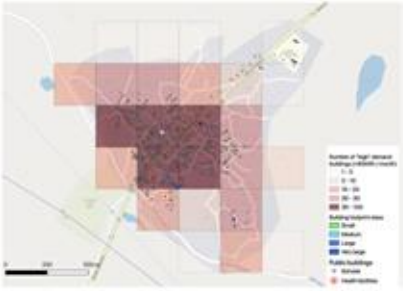


Figure from: [VDA2020]

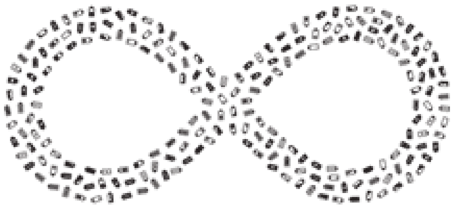
Innovation

Develop new technologies to more effectively produce low carbon energy, improve energy storage, or improve sequestration of emissions

Approaches: Human-guided experiments (potentially assisted by ML)

ML examples:

- Accelerated battery design: Physics-constrained ML to suggest promising experiments, leading to 10x reduction in # of experiments [CRDK+2021]
- Nuclear fusion: Spatio-temporal deep learning to predict disruptions [KST2019]



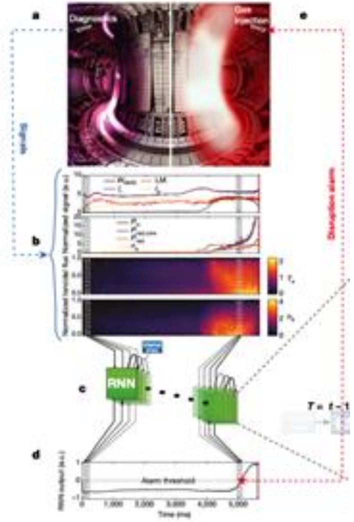


Figure from: [KST2019]

Policy & Markets

Provide input to the design and monitoring of policy, regulation, and markets

Approaches: Policy analysis, market & mechanism design (supplemented by ML)

ML examples:

- Reinforcement learning for setting energy market prices [DL2019]
- Analyzing trends in solar power patents [VR2015]

Figure from: [DL2019]

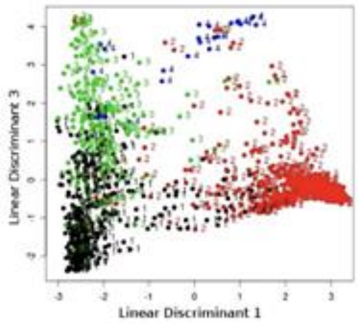


Figure from: [VR2015]

Data Management

Facilitate data cleaning, condense or compress data, create derived data

Approaches: Manual data cleaning, traditional compression, synthetic data generation (supplemented by ML)

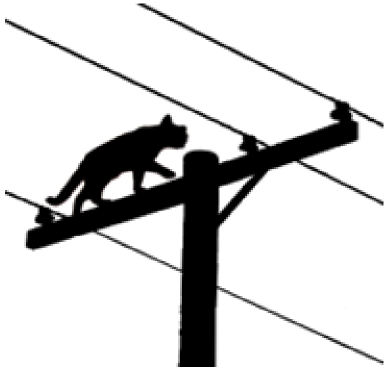


Image from: [C2022]

ML examples:

- “Record matching” between datasets [C2022]
- Synthetic smart meter data generation [CC2024]

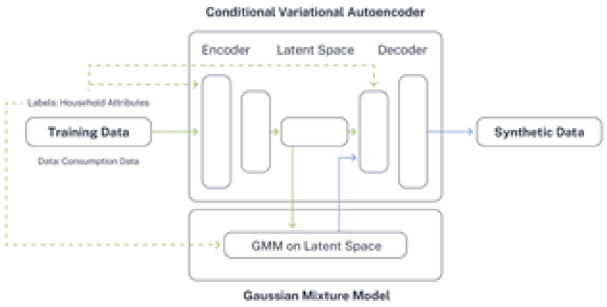


Image from: [CC2024]

Recap: Overview of ML applications in energy systems

Operations

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- Speeding up simulations

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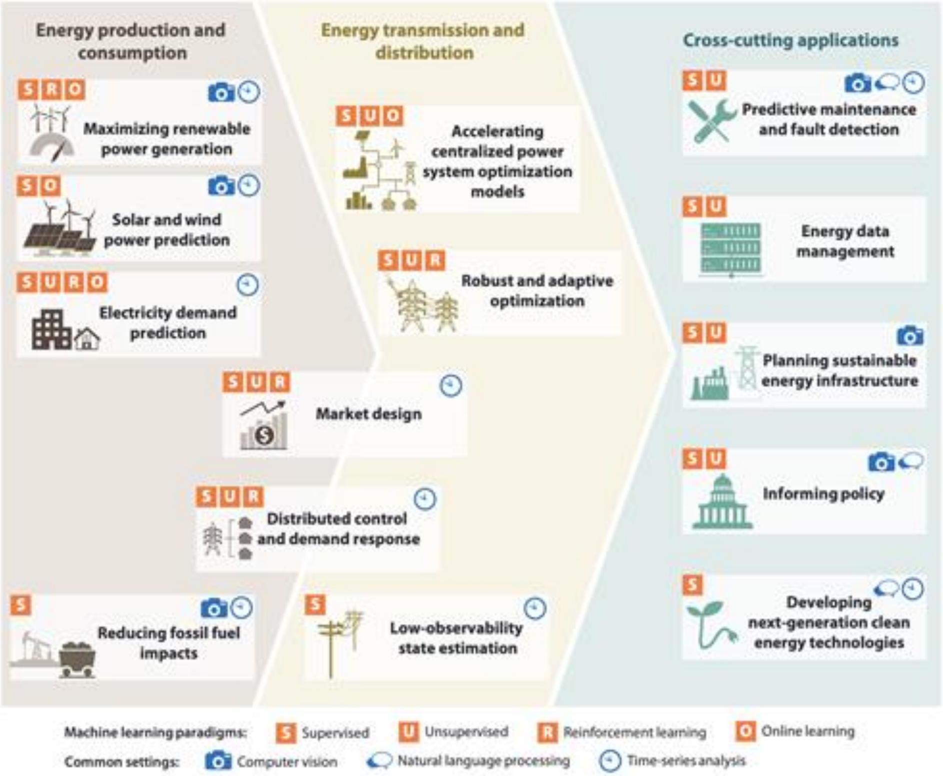

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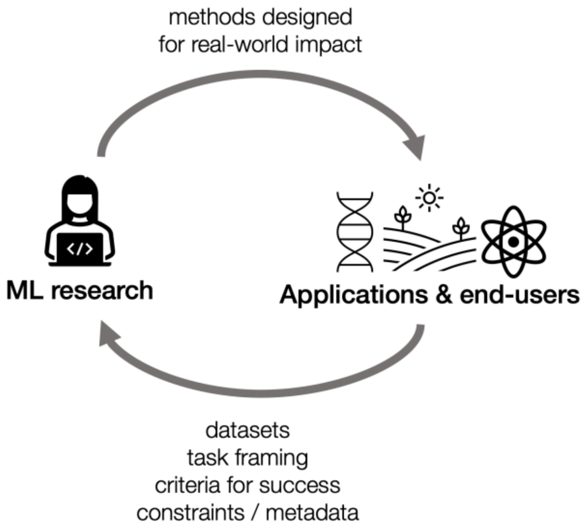
Considerations for ML in power & energy systems

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.*

Responsible AI in power & energy systems

Mitigating biases in data and models

- E.g., Power infrastructure data: Geographic disparities in availability
- E.g., Weather models: Calibration may be optimized for particular regions

Improving trustworthiness and accountability

- Safety and robustness: Critical in, e.g., power system operations
- Interpretability, auditability, and human-in-the-loop approaches: Critical in, e.g., policymaking contexts

Centering equity and climate justice

- Centering diverse stakeholders: E.g., in industrialized vs. emerging economies
- Avoiding centralization: Democratized capacity and compute, digital divide
- Avoiding digital colonialism: E.g., smart meters, analysis of remote sensing data

Accounting for potential "dual use"

Enablers for advancing AI 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 AI!

Takeaways

Energy systems transformation is needed due to climate change mitigation, adaptation, and sustainable development

- Key axes: Operations and planning

Power grids are "the world's largest machine"

- Requires *constantly* maintaining energy balance, including decision-making across many timescales (sub-seconds to decades)
- Many different stakeholders: Regulators, operators, suppliers, consumers, etc.

Many applications of AI in power & energy systems

- Important to understand application-driven requirements, responsible AI considerations, and enablers for deployment
- Lots of room for both existing methods and new innovations

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