ML for Power & Energy Systems

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Climate Change AI Summer School

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Session goals: ML for Power & Energy Systems

- Describe mitigation, adaptation, and sustainable development strategies
- Describe how electric power systems work
- Share opportunities and considerations for ML in power & energy systems
- Provide concrete examples of ML use cases
- Provide insight on responsibly framing & scoping projects
- Share potential entry points and next steps

Outline: ML for Power & Energy Systems

1. Importance of power and energy systems
2. Strategies for mitigation, adaptation, and sustainable development
3. How electric power systems work
4. Overview of ML applications
5. Selected case studies
6. Next steps and opportunities for involvement

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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" (IPCC AR6 WG3)

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

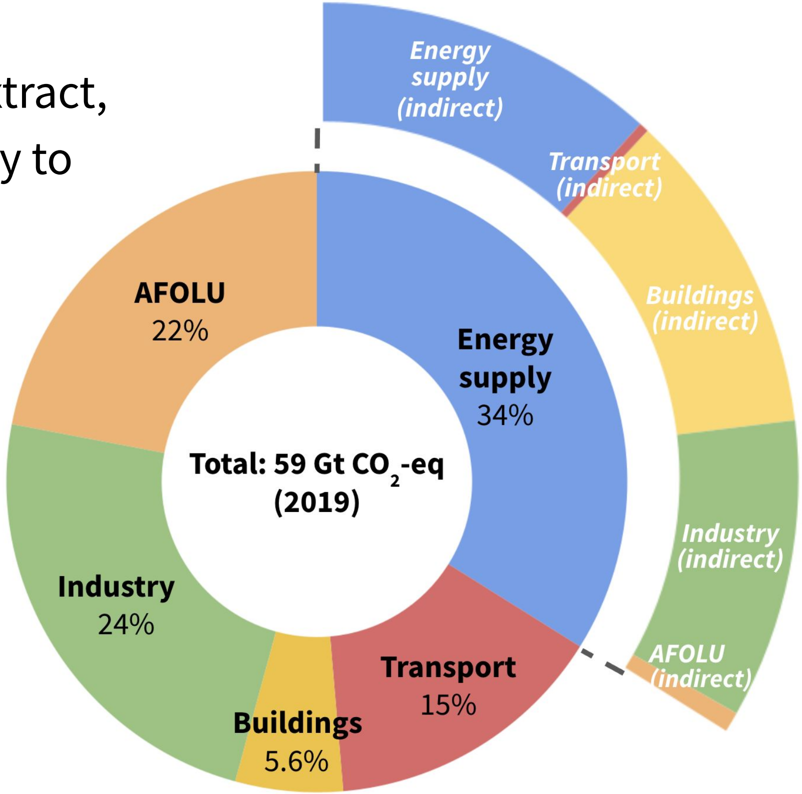
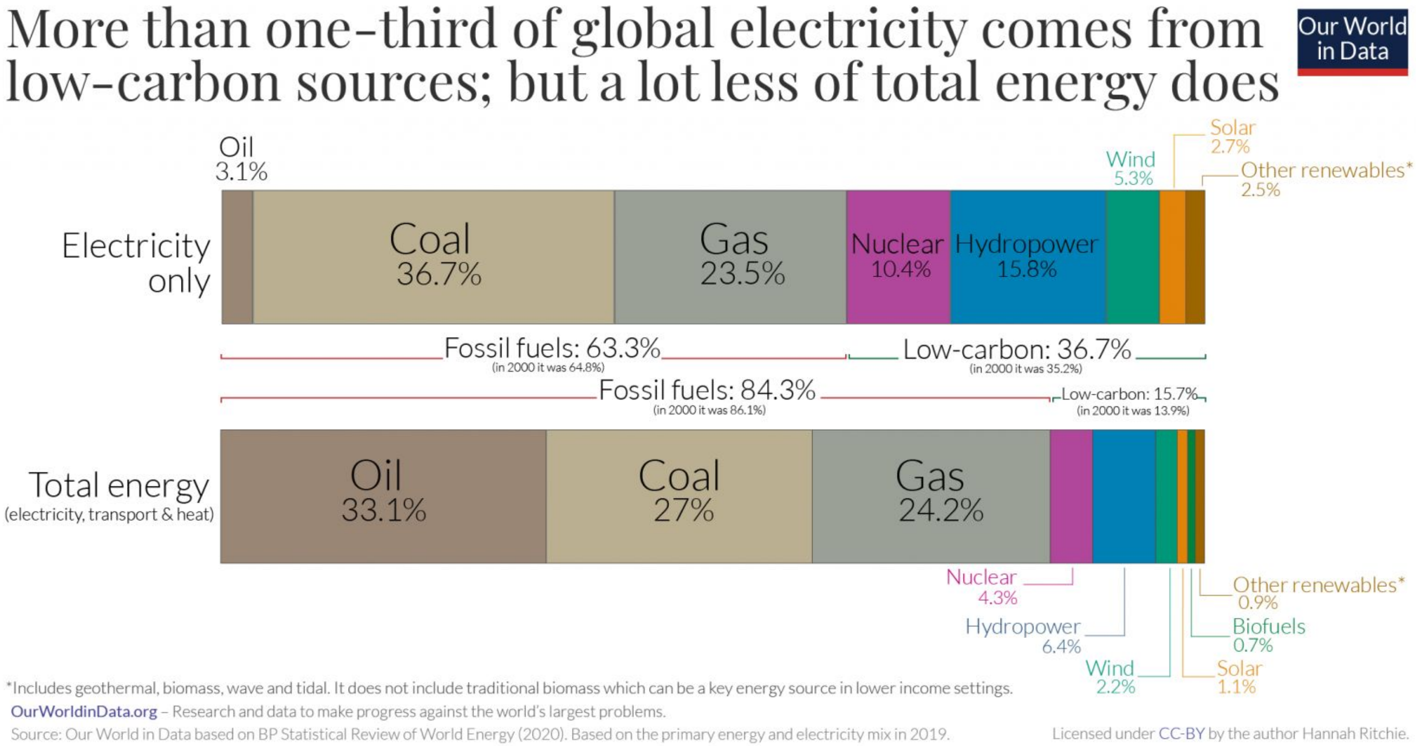


Figure data based on [IPCC2022]. Percentages shown do not add to exactly 100% due to rounding to two significant figures.

Low-carbon sources are still in the minority



Subtle point: Low-carbon ≠ renewable (though there is overlap)

Figure source: [RRR2022]

Importance of climate adaptation in energy systems

Increasing pressure from climate change

- Increasing number, intensity, and variability of climate-related events
- Shifting demand patterns (e.g., for HVAC) in response to climate changes

Transitioning energy system

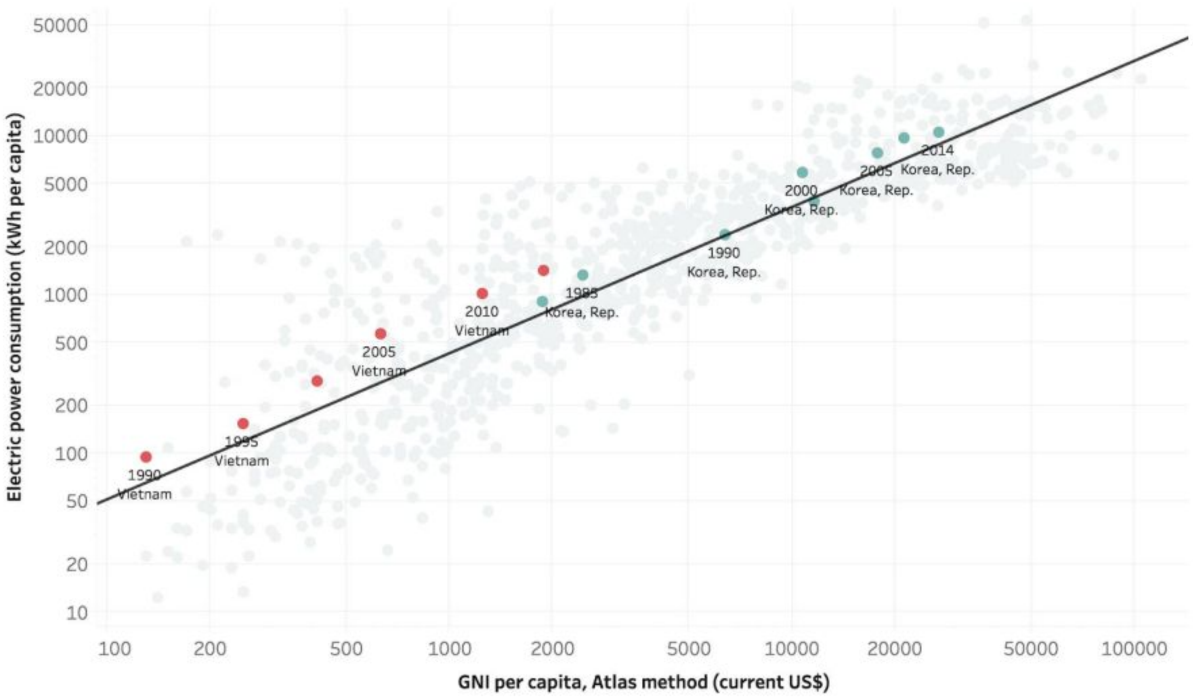
- Shift towards low-carbon sources with different climate-related vulnerabilities and weather-dependent production patterns

Expansion of energy infrastructure

- Growing global population
- Infrastructure expansion especially occurring in places with high climate risk

Energy systems are necessary for development

FIGURE 2: Income vs. Electricity Consumption, 1980-2014



Income growth is tied to growth in electricity usage

Figure source: [MBB+2020]

Sustainable development in light of climate change

Global responsibility towards sustainable development

Industrialized economies
Reduce GHG emissions while maintaining development levels

Emerging economies
Increase development levels while maintaining or reducing GHG emissions

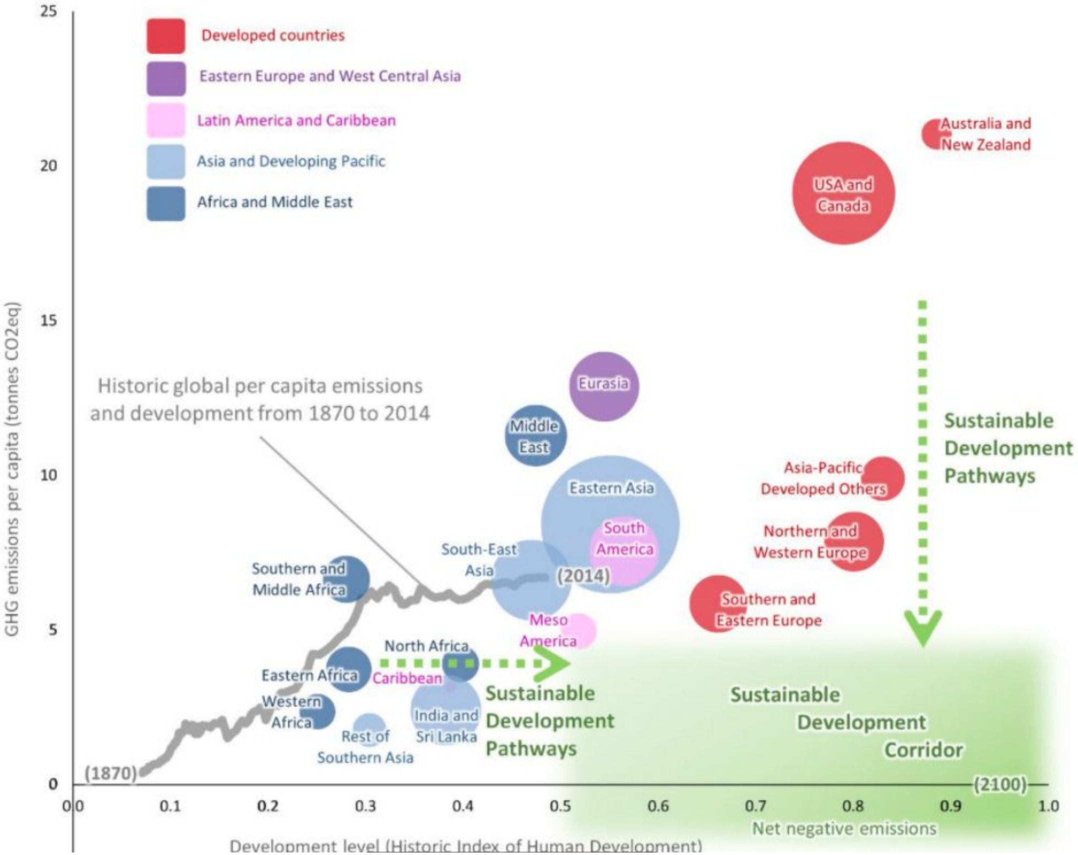


Figure source: [IPCC2022]

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What are some strategies to decarbonize energy systems?

Strategies to decarbonize energy systems

"Net Zero energy systems will share common characteristics, but the approach in every country will depend on national circumstances." [IPCC AR6 WG3, 2022]

Conceptual framework based on **Kaya identity**:

$$\left(\text{GHG emissions} = \text{population} \times \frac{\text{service}}{\text{population}} \times \frac{\text{energy}}{\text{service}} \times \frac{\text{GHG emissions}}{\text{energy}} \right)$$

Connects supply side & demand sides (e.g., transport, buildings, industry)

More details on the Kaya identity

$$\left(\text{GHG emissions} = \text{population} \times \frac{\text{service}}{\text{population}} \times \frac{\text{energy}}{\text{service}} \times \frac{\text{GHG emissions}}{\text{energy}} \right)$$

More details on the Kaya identity

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Reducing consumption

Example: Passenger cars *Service = vehicle-kilometers* 	Reduce number of kilometers driven ▸ Individual change: Move closer to work ▸ Systemic change: Dense urban areas Increase passengers per trip and vehicle
General energy-related sectors	Individual behavior changes Systemic changes & structural improvements

More details on the Kaya identity

$$\left(\text{GHG emissions} = \text{population} \times \frac{\text{service}}{\text{population}} \times \boxed{\frac{\text{energy}}{\text{service}}} \times \frac{\text{GHG emissions}}{\text{energy}} \right)$$

Improving efficiency

Example: Passenger cars *Service = vehicle-kilometers* 	Improve vehicle efficiency (e.g., fuel economy) Drive more efficiently Switch to other transport modes (e.g., bikes)
General energy-related sectors	Efficient end-use technologies Efficient generation technologies

More details on the Kaya identity

$$\text{GHG emissions} = \text{population} \times \frac{\text{service}}{\text{population}} \times \frac{\text{energy}}{\text{service}} \times \boxed{\frac{\text{GHG emissions}}{\text{energy}}}$$

Switching to clean energy

Example: Passenger cars *Service = vehicle-kilometers* 	Switch to battery electric vehicles Switch to alternative fuels (e.g., electrofuels, solar fuels, hydrogen)
General energy-related sectors	Electrify & switch to low-carbon power Replace fossil fuels with clean alternative fuels

More details on the Kaya identity

$$\left[\text{GHG emissions} = \text{population} \times \frac{\text{service}}{\text{population}} \times \frac{\text{energy}}{\text{service}} \times \frac{\text{GHG emissions}}{\text{energy}} \right]$$

Reducing consumption

Improving efficiency

Switching to clean energy

Economy-wide strategies to reduce total GHGs

- Targets
- Regulation, standards, investments
- Carbon pricing
- CO_2 removal

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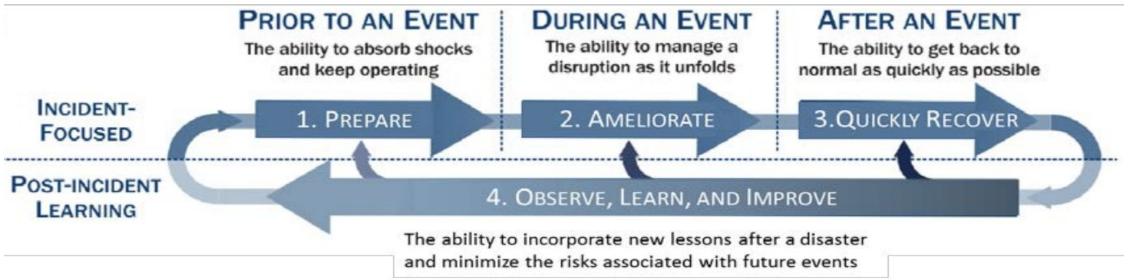
What are some strategies to adapt energy systems to climate change?

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]

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What is an electric power system?

Introduction to electric power systems

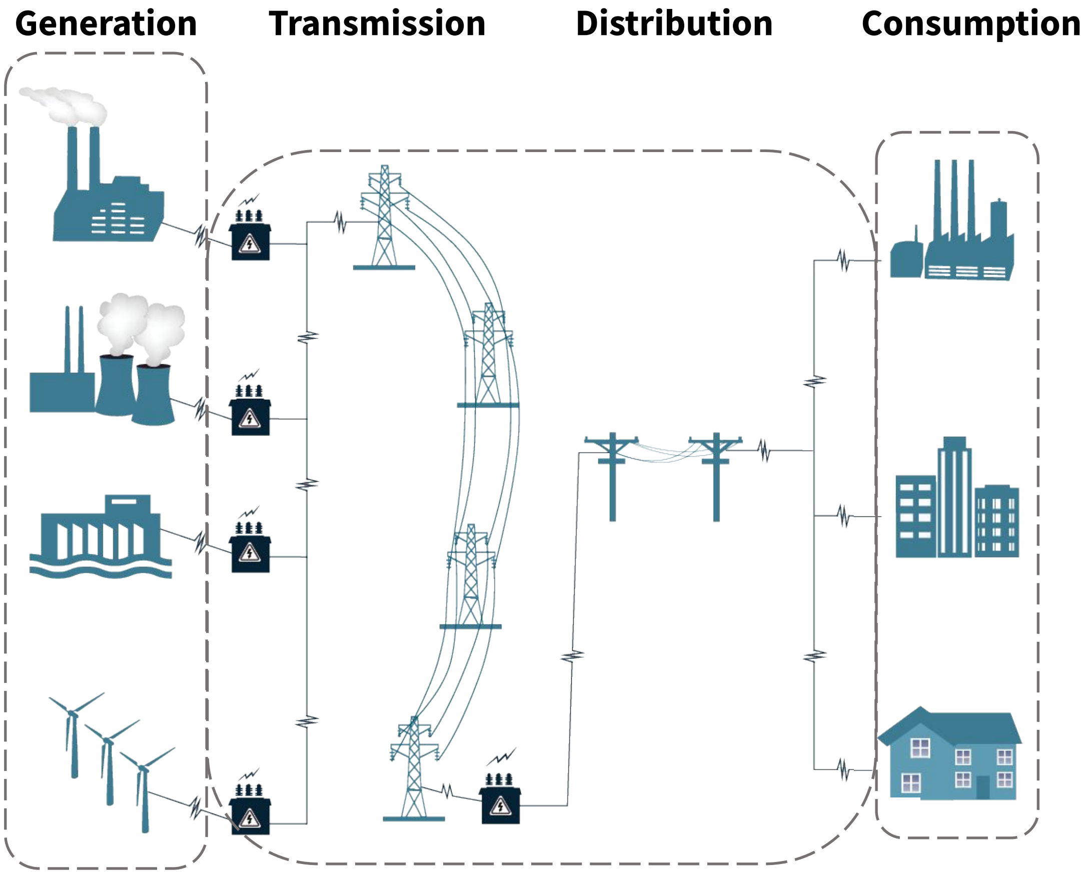


Figure adapted from [CBO2020]

Electric power systems are rapidly changing

Bi-directional power flows

- Distributed energy resources (DERs) - rooftop solar, batteries

Non-centralized control

- Demand response
- Distributed vs. decentralized

On- vs. off-grid setups

- Islands & rural areas
- Homes w/ personal power sources

Impact of **AI & data infrastructure loads**

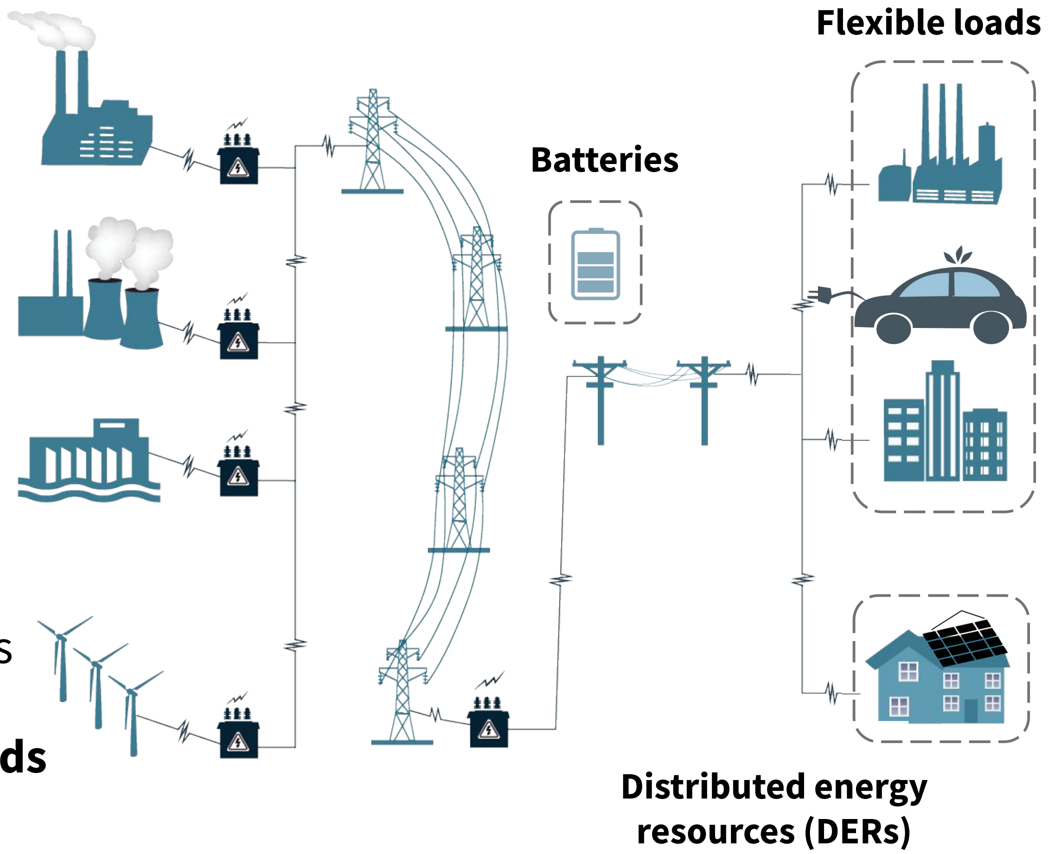
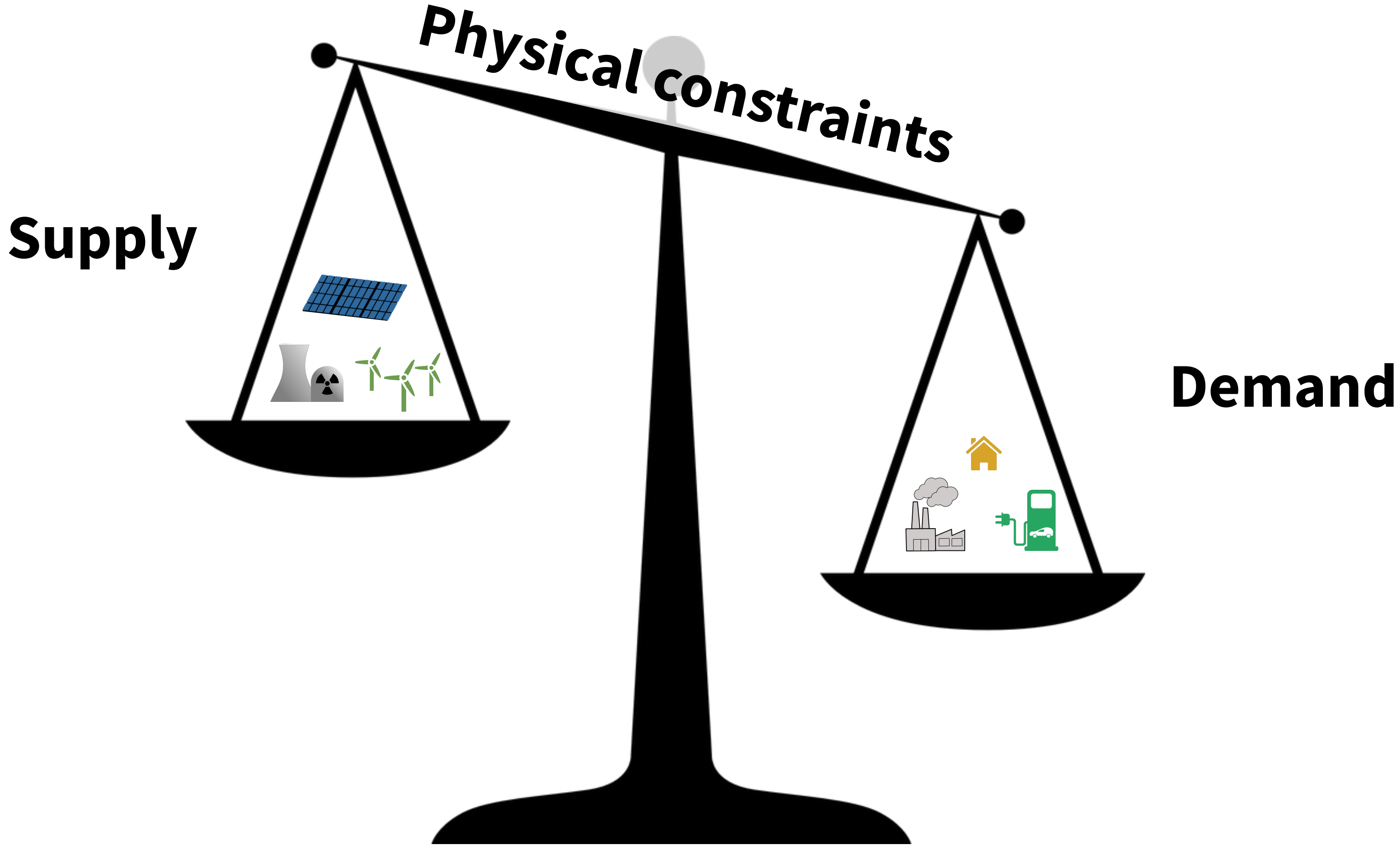


Figure adapted from [CBO2020]

Operational constraints on electric power systems



Idealized power system operation: AC optimal power flow (ACOPF)

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

- Meet power consumption (true consumption minus losses & distributed generation)
- Minimize fuel costs (based on generator bids)
- Satisfy grid & operational constraints

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

(objective: minimize cost of power gen)

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

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

$$g(z) \le h$$

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

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

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

λ (prices) are dual variables

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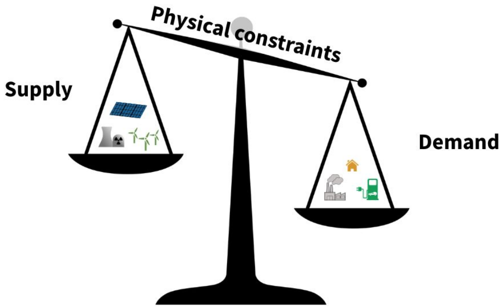
What are some ways in which operating a power system might be more complicated?



AC optimal power flow (ACOPF)

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

$$g(z) \leq h$$

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

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*

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

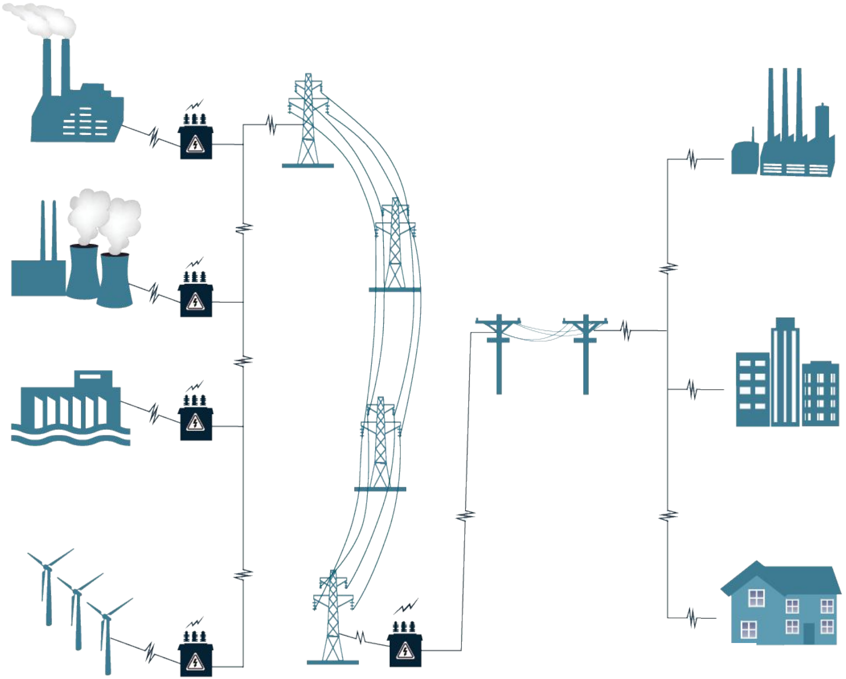

Figure adapted from [CBO2020]

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

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Overview of ML applications

Operations

- Situational awareness
- Centralized optimization
- Distributed control & demand response
- Predictive maintenance & efficiency improvement

Planning

Innovation

Policy & Markets

Data Management

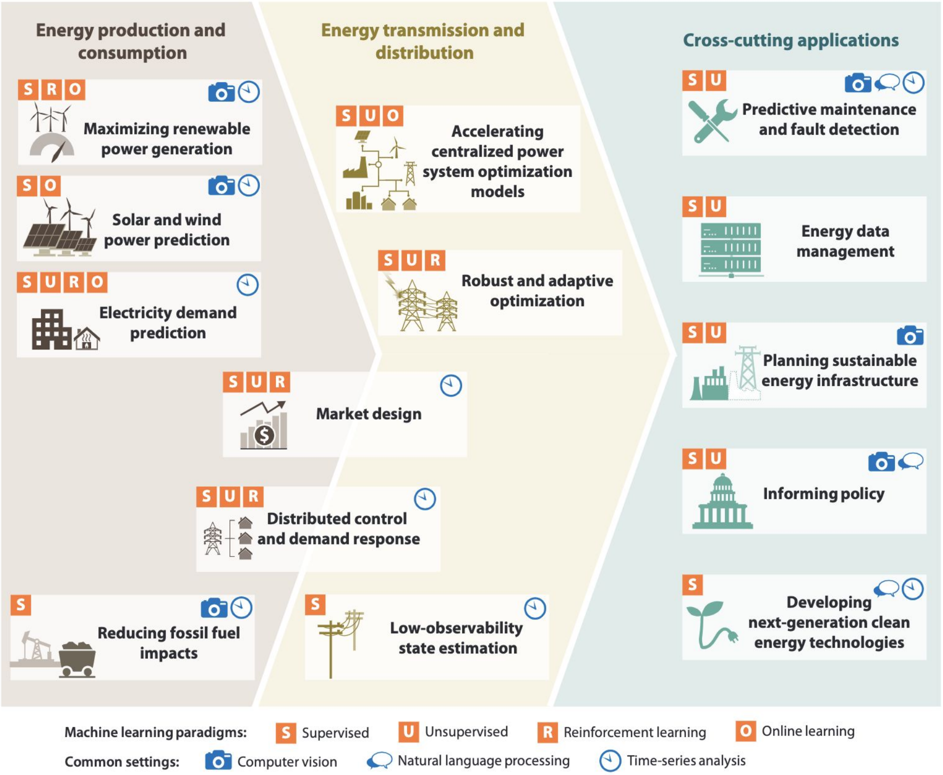

Figure source: [DK2021]

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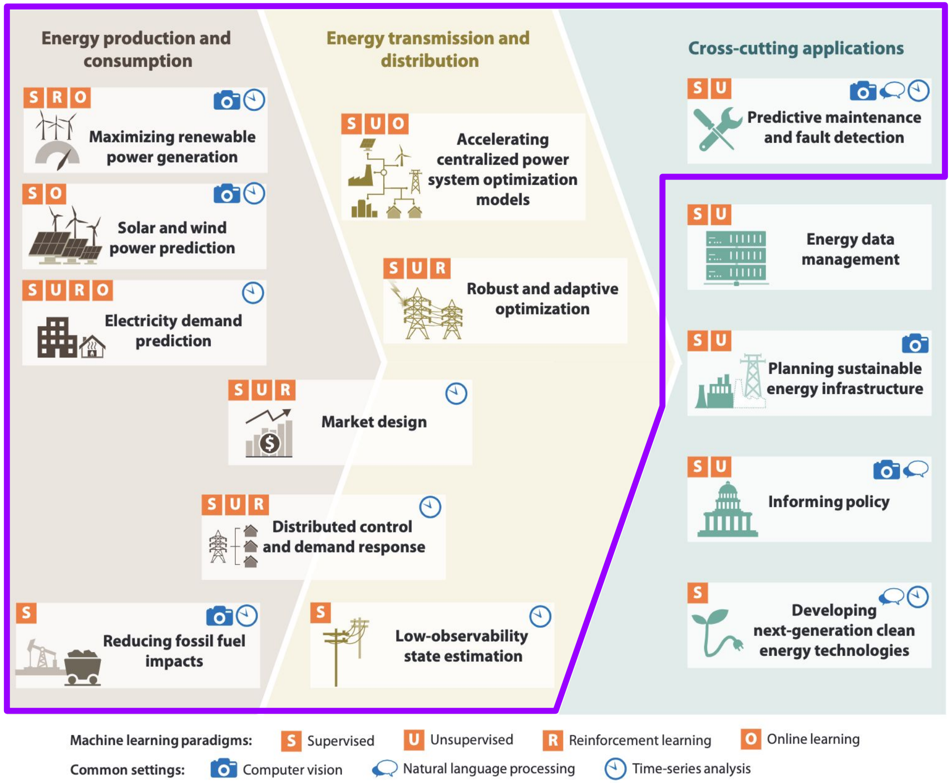


Figure source: [DK2021]

Operations >> Situational Awareness

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]

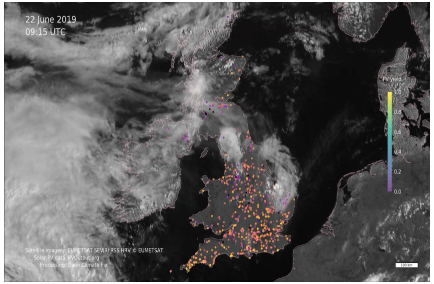


Image from [OCF2019]

Operations >> Centralized Optimization

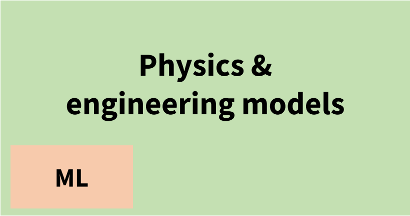
Dispatching controllable power generation (recall: ACOPF)

- 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]



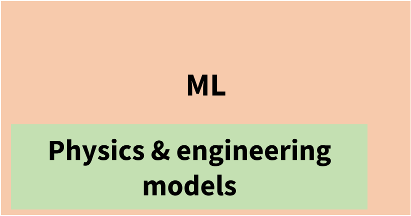


Image from: [L2RPN2022]

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

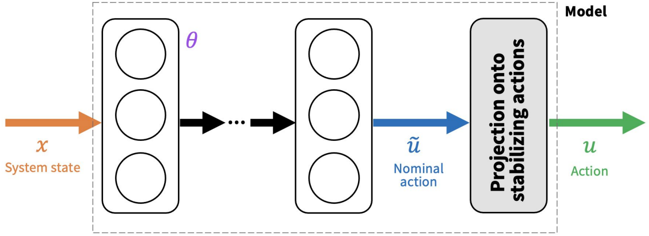
Approaches: Control theory, ML (reinforcement learning)

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)



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”]

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)

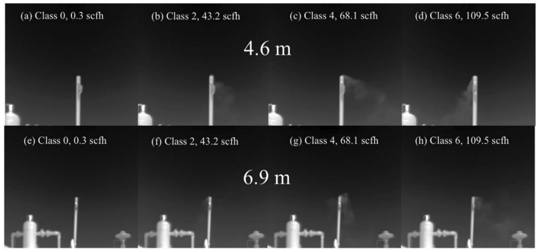


Image from: [WJR+2022]

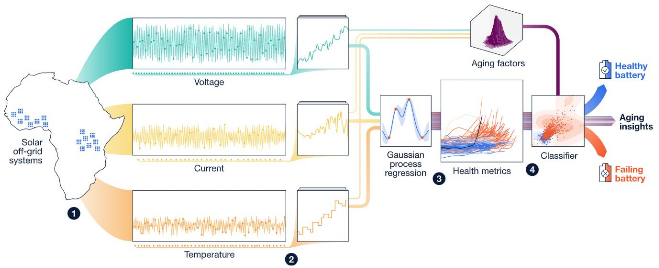
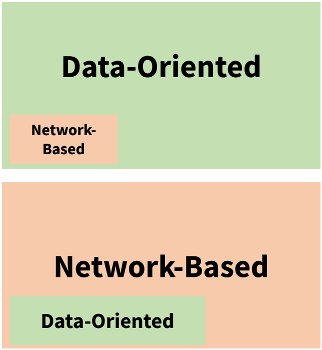


Figure from: [AH2021]



Preliminary Recap: Overview of ML applications

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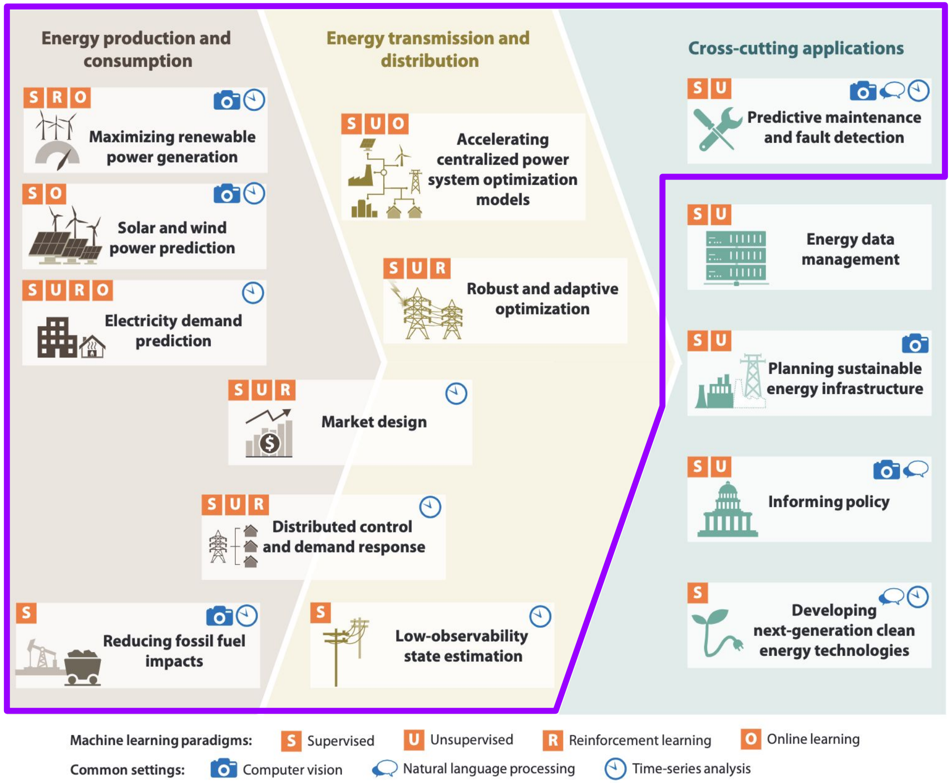

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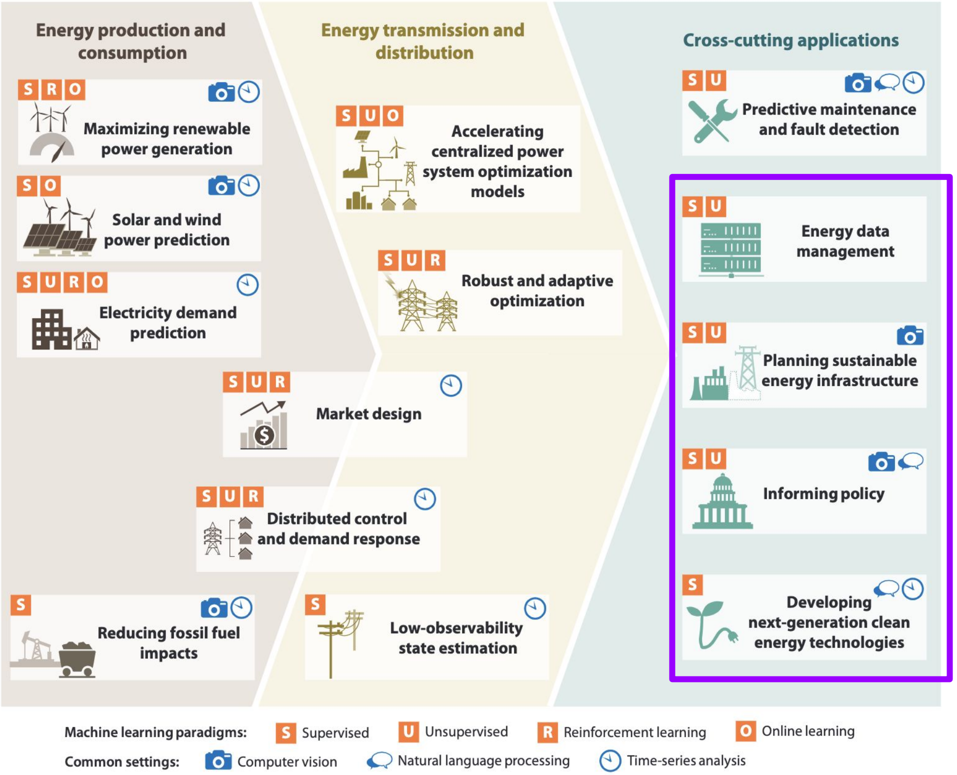


Figure source: [DK2021]

Planning

Design/construction of new components, reinforced infrastructure, and/or new systems

- Goal: Build low-carbon sources, strengthen connections, improve access/reliability

Approaches: Physical simulation, multi-objective optimization, manual surveying, stakeholder consensus building, ML

ML examples:

- Mapping power lines, solar & wind infrastructure [DS2018, GRL2019, ONM2022, TWMR2019]
- Multi-objective optimization of hydropower dam placement [ASG+2019, WGS+2018]
- Aiding long-term demand estimation for new customers [AWDJ2021, FMWMT2022, L2023]

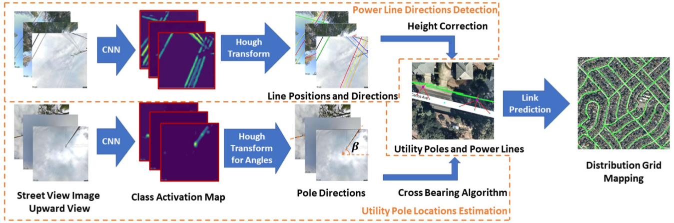


Image from: [TWMR2019]

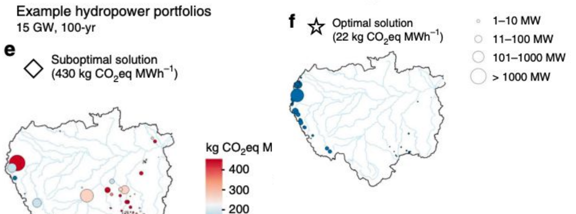


Figure from: [ASG+2019]

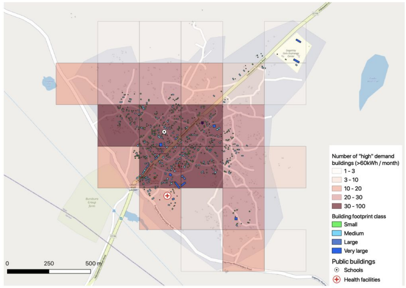


Figure from: [VDA2020]

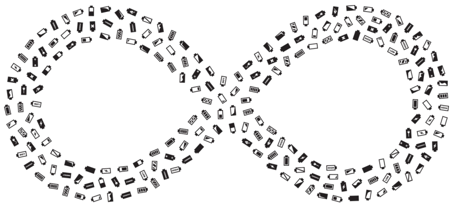
Innovation

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]



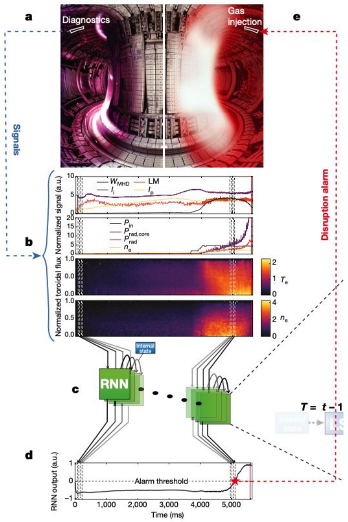


Figure from: [KST2019]

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]
- Generating power system scenario forecasts, based on historical data [CWZ2018]

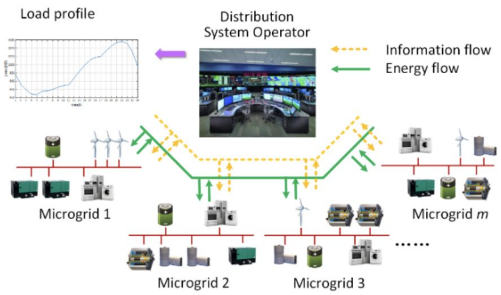


Figure from: [DL2019]

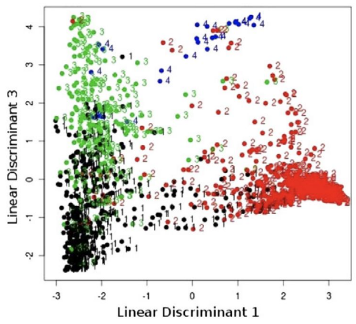


Figure from: [VR2015]

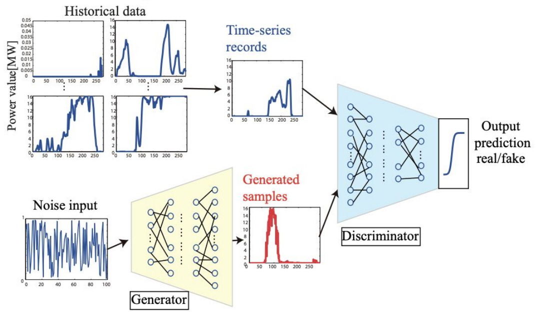


Figure from: [CWZ2018]

Data Management

Facilitate data cleaning, condense or compress data

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

ML example: “Record matching” (Catalyst Cooperative)

- Identify records in two different US electricity data sources (FERC 1 and EIA data) that refer to the same power plants, using logistic regression [C2022]

Image from: [C2022]

Recap: Overview of ML applications

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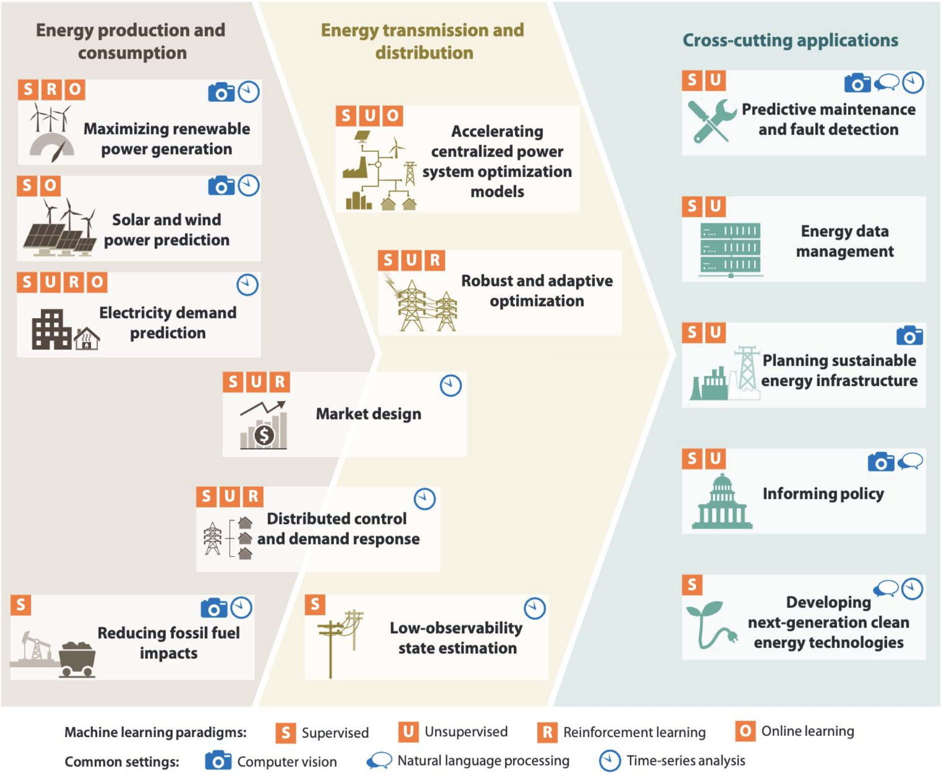

Figure source: [DK2021]

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What are important considerations to keep in mind when using ML for energy systems?

Considerations for ML in Power & Energy systems

Different requirements for ML model outputs, depending on the context

- Safety and robustness
- Physical feasibility
- Interpretability
- Meeting regulatory standards
- Performance (better than SOTA)
- Fast running time
- Integration with infrastructure/hardware
- Usability and accessibility
- Privacy preservation
- Data efficiency

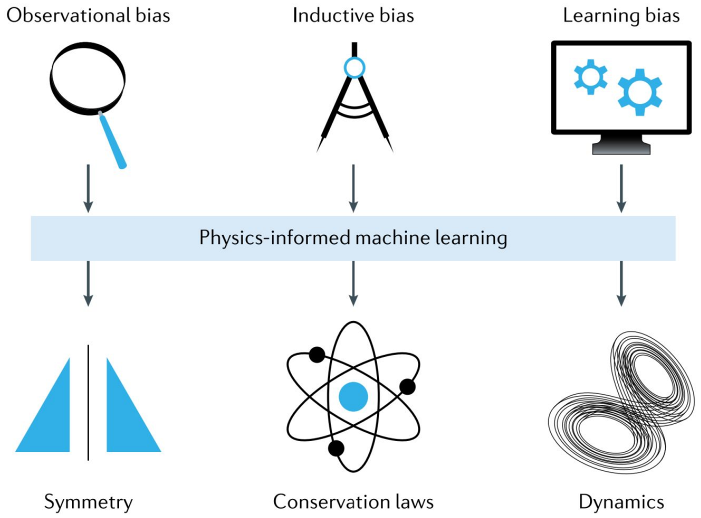

Figure source: [KKLPWY2021]

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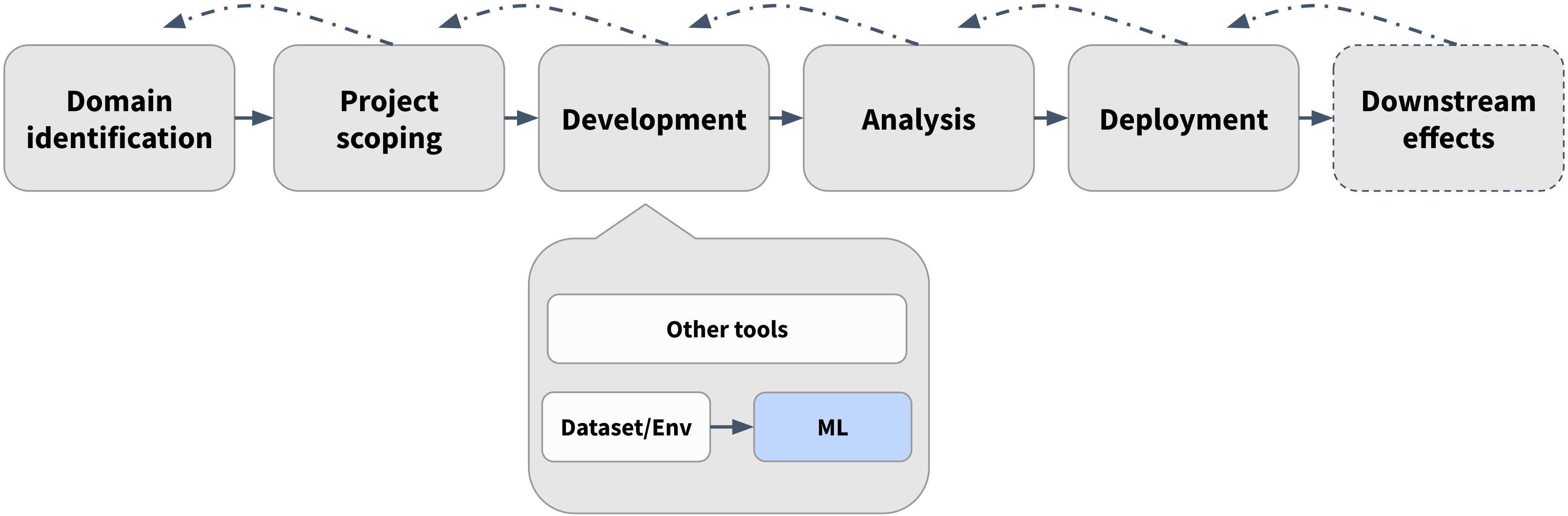
ML-for-climate: Pathway to impact



Case Study: Mapping utility scale solar in India [1/3]

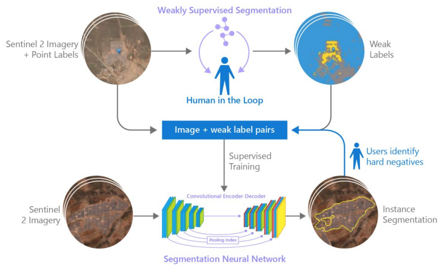


Figure source: [ONM+2022]

Background

- 500 GW renewable energy capacity by 2030
- Net zero emissions by 2070

Problem: Lack of updated & accurate geo-spatial information on utility scale solar projects

Possible approaches: Collating information from utilities, survey, OSM , detection using satellite imagery

Pathway to impact

- Support transmission infrastructure development & grid integration
- Monitoring progress towards targets
- Quantify the impact of RE on land-use & socioeconomic development

Stakeholders: Energy planners, policy makers, communities

Case Study: Mapping utility scale solar in India [2/3]

Datasets, Simulators, & Tools

- **Dataset:** Small set of solar PV farms point labels, 12 of out 13 Sentinel 2 spectral bands, land cover and land use datasets

ML approach

- **Human-Machine approach for semantic label generations:** Pixel clustering with human feedback for weak semantic label generation.
- **Supervised semantic segmentation:** Train model to segment solar PV farms using Hard Negative Mining for improved detection.

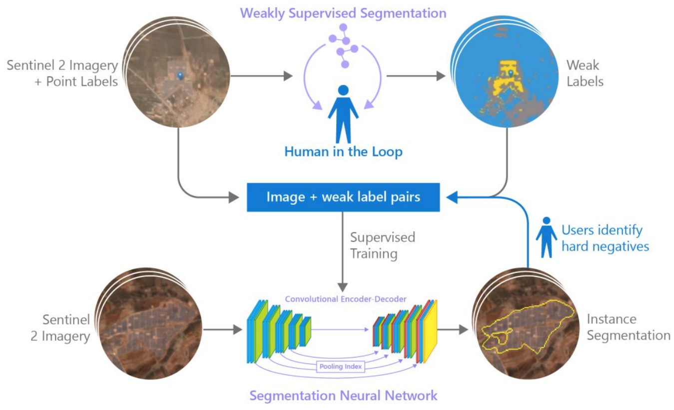


Figure source: [ONM+2022]

Case Study: Mapping utility scale solar in India [3/3]

Metrics

- **Model performance:** Mean Intersection over Union (mIOU), precision and recall
- **Decision making:** PV locations and size, timing of deployment, changes in land-use and land-cover

Boundaries of methodology:

- Focus on PV footprint over power related metrics

Deployment considerations:

- **Generalization:** Regional differences, panel sizes, validation
- **Extensions to wind**: Global Renewables Watch

Downstream effects: Privacy implications of sharing generation asset locations

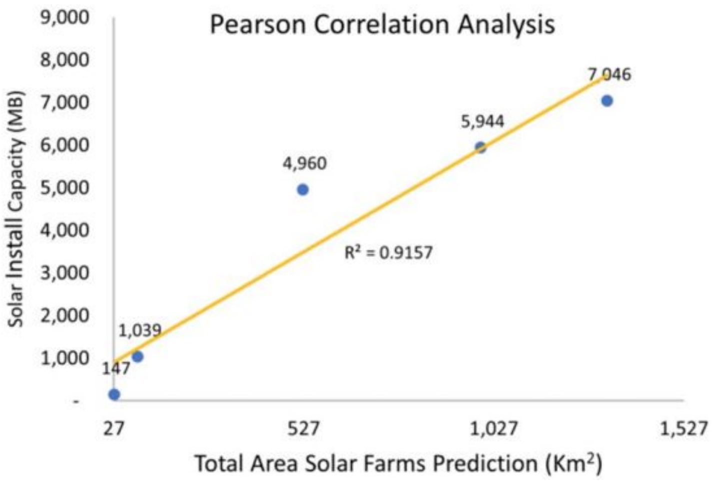


Figure source: [ONM+2022]

Case Study: Downscaling Solar Irradiance from Climate Model Projections [1/3]

Background: In system planning, need to account for how changing climate will affect renewable energy production

Problem: Lack of downscaled climate scenarios reflecting how exactly renewable energy production may change

Possible approaches: Use of historical data, generative approaches, finer-grained climate modeling, statistical downscaling

Pathway to impact: Use for power systems planning (e.g., siting new renewable energy sources)

Stakeholders: System planners, policy analysts, utilities

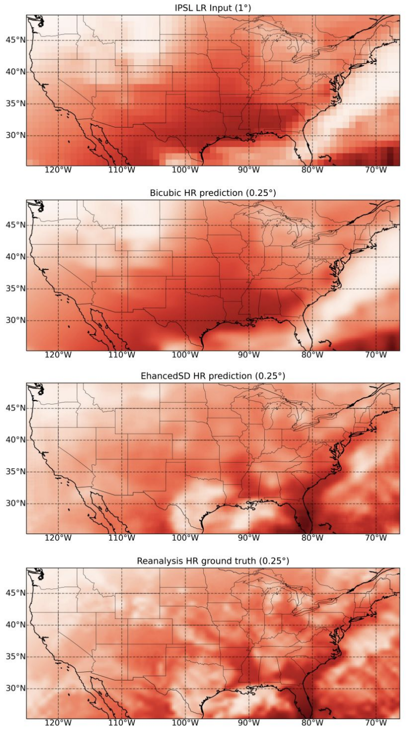


Figure from: [HHMS2022]

Case Study: Downscaling Solar Irradiance from Climate Model Projections [2/3]

Datasets, Simulators, & Tools

- **Dataset:** Coarse-scale climate model outputs of solar irradiance, from IPSL-CM6A
- **Dataset:** Fine-grained reanalysis for solar irradiance, from ERA5 (“ground truth”)

ML approach: End-to-end super-resolution deep learning model, using Residual-in-Residual Dense Blocks (RRDBs) and sub-pixel convolution

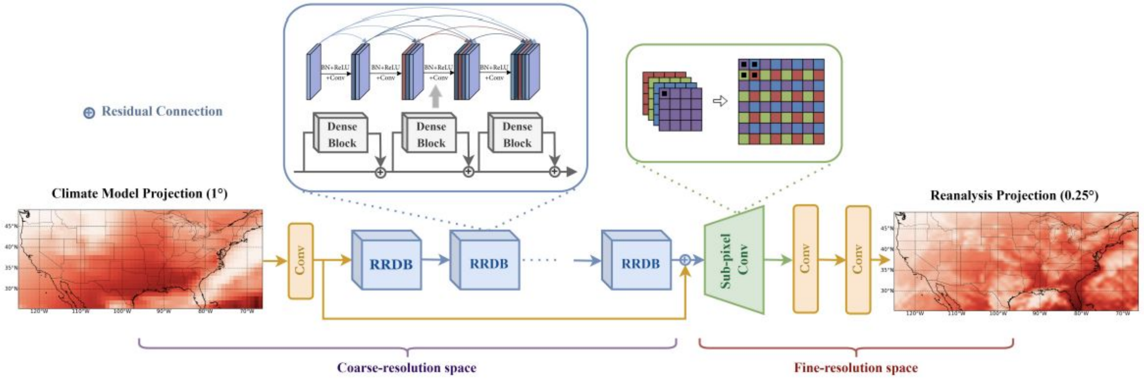


Figure from: [HHMS2022]

Case Study: Downscaling Solar Irradiance from Climate Model Projections [3/3]

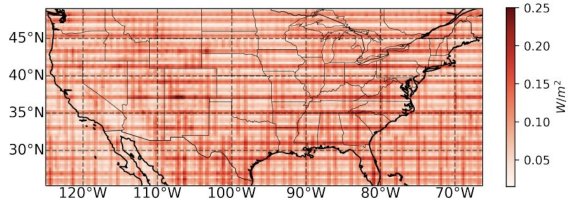


Figure 3: RMSE computed at each location using EnhancedSD with deconvolutions over test-period, showing the checkerboard error pattern [16].

Figure from: [HHMS2022]

Metrics:

- Relative error on ground truth [RMSE ÷ Capacity]
- Structural Similarity Index Measure (SSIM) between climate model projection and ground truth

Boundaries of methodology:

- Generalization (data-rich to data-poor, past to future)
- Planning must also consider grid constraints (e.g., congestion)

Deployment considerations: Will the desired end users be able to actually access, discover, and use the data/insights?

Downstream effects: Implications of insights' accessibility to different stakeholders

Case Study: RL for topology switching [1/3]

Background: Need to increase renewables and adapt to extremes

Problem:

- Existing power system optimization methods are not sufficiently dynamic, adaptive, robust, or fast
- Lack of infrastructure for validation and deployment

Possible approaches:

- Methods: Optimization, control theory, data-driven
- Enabling infrastructure: Simulators/testbeds, digital twins

Pathway to impact: Use by power system operator, either autonomously or human-in-the-loop

Stakeholders: System operators, software providers?

L2RPN
Learning to Run a Power Network
2022

Image from: [L2RPN2022]

Case Study: RL for topology switching [2/3]

Project: Learning to Run a Power Network Challenge (L2RPN), run by RTE France, Electric Power Research Institute, and additional (academic & non-academic) stakeholders

Datasets, Simulators, & Tools

- **Simulator:** Grid2Op platform (OpenAI Gym compatible)
- **Datasets:** Topology and demand datasets, both synthetic and reflecting RTE system

ML approach

- A variety of reinforcement learning (RL) methods combining data, heuristics, and physical knowledge

Image from: [L2RPN2022]

Case Study: RL for topology switching [3/3]

Metrics:

- **Dispatch costs:** Cost/price associated with solution
- **Physical robustness:** Does the grid stay up?
- **Speed:** Computation within operational time window

Boundaries of methodology: Still reflecting synthetic/small environment, not testing “human-in-the-loop” capability

Deployment considerations: How different system operators’ control rooms work, different centralized vs. decentralized modes of grid operation

Downstream effects: Implications for pricing, trust, jobs of system operators, switch to different market structures, making fossil generator use more efficient

Image from: [L2RPN2022]

Case Study: Synthetic smart meter data [1/3]

Background: Public energy systems data is crucial to enable research & modeling for operations & planning

Problem:

- Regulatory or cultural barriers to data sharing
- Privacy issues with sharing personal data

Possible approaches:

- Create synthetic data (manually or automatically)
- Facilitate sharing of real data - technical methods (e.g., add noise), policy/organizational change

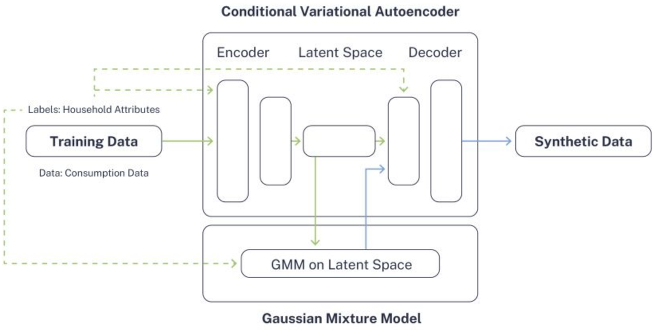


Image from: [CC2024]

Pathway to impact & stakeholders: Public or controlled data/model release for use by researchers, private sector, decision-makers, advocates, market participants, etc.

Case Study: Synthetic smart meter data [2/3]

Project: Faraday (by Centre for Net Zero), to generate synthetic smart meter readings (daily load profiles)

Datasets, Simulators, & Tools

- **Dataset:** Proprietary dataset of over 300M smart meter readings (Octopus Energy)

ML approach

- Conditional Variational Autoencoder (VAE) to map training data to a latent space
- Train Gaussian Mixture Model (GMM) to learn distribution of latent space
- Sample from GMM, and pass through trained decoder

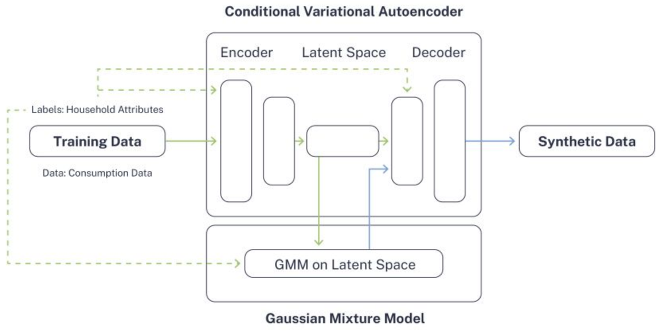


Image from: [CC2024]

Case Study: Synthetic smart meter data [3/3]

Metrics:

- **Fidelity:** Statistical & physical similarity between synthetic and real data
- **Utility:** Is the synthetic data useful in real-life applications? Does it provide reasonable insights?
- **Privacy:** Is original/private data exposed?

Boundaries of methodology: Still an open question how to verify and/or ensure the above metrics

Deployment considerations: Tradeoffs between the above metrics; regulatory requirements; trust; who can access and use the data in practice?

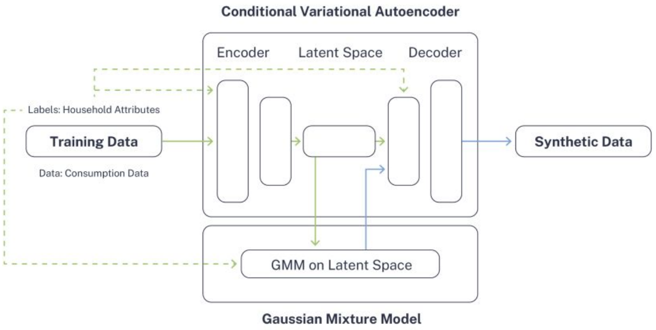


Image from: [CC2024]

Downstream effects: Improved access for everyone ("good actors" and "bad actors")

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

These are not exhaustive - **work with relevant stakeholders**!

Outline: ML for Power & Energy Systems

1. Importance of power and energy systems
2. Strategies for mitigation, adaptation, and sustainable development
3. How electric power systems work
4. Overview of ML applications
5. Selected case studies
6. **Next steps and opportunities for involvement**

Priya’s journey into ML & power systems

Formative experiences:


DOI:10.1145/2133806.2133825

A research agenda for making the smart grid a reality.

BY SARVAPALI D. RAMCHURN, PERUKRISHNEN VYTELINGUM, ALEX ROGERS, AND NICHOLAS R. JENNINGS

Putting the ‘Smarts’ into the Smart Grid: A Grand Challenge for Artificial Intelligence

Computational Sustainability Network

Positions & collaborations:

Watson Fellow

Carnegie Mellon University Computer Science Department

Carnegie Mellon University Engineering & Public Policy

PhD @ CMU

NREL NATIONAL RENEWABLE ENERGY LABORATORY

nationalgridESO

Internships: NREL, National Grid ESO

Climate Change AI

Co-founded CCAI

EPRI

GLOBAL PST CONSORTIUM

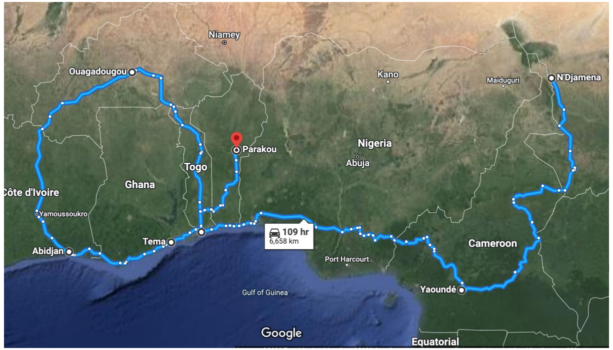
Collaborations: AI.EPRI, G-PST, Catalyst Cooperative

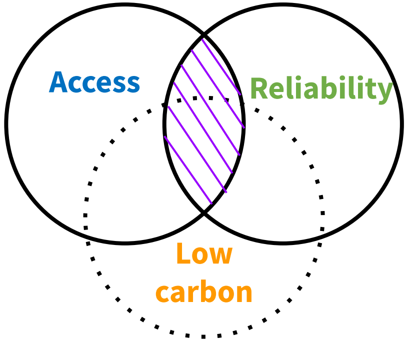
Top tips:

- Take classes in multiple disciplines
- Explore via internships/ secondments
- Attend conferences of multiple communities
- Engage with local organizations
- Reach out to people (& do your “homework”)

Nsutezo's journey into ML & power systems

Formative experiences





My journey

Quadracci SUSTAINABLE ENGINEERING LAB.

PhD @ Columbia University

IBM Research | Africa

AI For Good Research Lab

Industrial labs

2iE Institut International d'Ingénierie de l'Eau et de l'Environnement

International Institute for Applied Systems Analysis IIASA

Interdisciplinary & multi-university initiatives: eGUIDE, IIASA, 2iE

Kenya Power

VIDA Village Data Analytics

UMEME Powering Uganda

Rwanda Energy Group REG

Stakeholders

Tips:

- Find topics you care about
- Build knowledge & intuitions through internships
- Participate in competitions
- Engage stakeholders in the early stages of the project
- Enjoy the process!

Further resources

Datasets and simulators:

- See Electricity Systems page (and subpages) on CCAI Wiki
- Open Energy Data Initiative (OEDI)
- Sample IEEE datasets
- A need for development of additional datasets, simulators, toolkits, & libraries
  - See also: CCAI Dataset Wishlist

Collaborations, readings, & further discussion:

- See listing of communities on CCAI Wiki
- Power and Energy Systems space on CCAI Community Platform
- [Power & Energy] tag in CCAI Newsletter

⚡ Submit in Poll ⚡

What will be your next step in your ML + climate/energy journey?

Session recap: ML for Power & Energy Systems

- Framework for mitigation, adaptation, and sustainable development
- Overview of how electric power systems work
- Opportunities and considerations for ML in power systems
- Tips for responsibly framing & scoping projects
- Potential entry points and next steps

References

[AH2021] Aitio, Antti, and David A. Howey. "Predicting battery end of life from solar off-grid system field data using machine learning." *Joule* 5.12 (2021): 3204-3220.
[ASG+2019] Almeida, Rafael M., et al. "Reducing greenhouse gas emissions of Amazon hydropower with strategic dam planning." *Nature Communications* 10.1 (2019): 4281.
[AWDJ2021] Allee, Andrew, et al. "Predicting initial electricity demand in off-grid Tanzanian communities using customer survey data and machine learning models." *Energy for Sustainable Development* 62 (2021): 56-66.
[C2021] Kate Crawford, "Atlas of AI" (2021).
[C2022]. Catalyst Cooperative. "Public Utility Data Liberation Project: pudl.analysis.ferc1_eia" (2022). Link here.
[CBO2020] U.S. Congressional Budget Office. "Enhancing the Security of the North American Electric Grid" (2020). Link here.
[CC2024] Chai, Sheng, and Gus Chadney. "Faraday: Synthetic Smart Meter Generator for the smart grid." *arXiv preprint arXiv:2404.04314* (2024).
[CDG] Center for Global Development. "Electricity consumption and development indicators" (). Link here
[CJZ2022] Cui, Wenqi, Yan Jiang, and Baosen Zhang. "Reinforcement learning for optimal primary frequency control: A Lyapunov approach." *IEEE Transactions on Power Systems* 38.2 (2022): 1676-1688.
[CRDK+2021] Clutton-Brock, Peter, Rolnick, David, Donti, Priya L., Kaack, Lynn, et al. Climate Change and AI: Recommendations for Government Action. Online (2021). Link here.
[CWZ2018] Chen, Yize, Xiyu Wang, and Baosen Zhang. "An unsupervised deep learning approach for scenario forecasts." *Power Systems Computation Conference (PSCC)*. IEEE, 2018.
[DK2021] Donti, Priya L., and J. Zico Kolter. "Machine learning for sustainable energy systems." *Annual Review of Environment and Resources* 46 (2021): 719-747.
[DL2019] Du, Yan, and Fangxing Li. "Intelligent multi-microgrid energy management based on deep neural network and model-free reinforcement learning." *IEEE Transactions on Smart Grid* 11.2 (2019): 1066-1076.
[DRK2021] Donti, Priya L., et al. "Enforcing robust control guarantees within neural network policies." *International Conference on Learning Representations* (2021).
[DS2018]. Development Seed. "Optimization: Signal Detection Threshold" (2018). Link here.
[FMWMT2022] Fobi, Simone, et al. "Predicting Levels of Household Electricity Consumption in Low-Access Settings." *Proceedings of the IEEE/CVF Winter Conference on Applications of Computer Vision*. 2022.
[GRL2019] Gershenson Dimitry, Rohrer Brandon and Lerner Anna "A new predictive model for more accurate electrical grid mapping" (2019). Link here.
[HHMS2022] Harilal, Nidhin, et al. "EnhancedSD: Downscaling Solar Irradiance from Climate Model Projections." *Tackling Climate Change with Machine Learning: Workshop at NeuriPS 2022* (2022).
[IEA2021] International Energy Agency. "Global Energy Review 2021" (2021). Link here.
[IEA2021] IEA, "Net Zero by 2050: A Roadmap for the Global Energy Sector" (2021). Link here.
[IEA2024] IEA (International Energy Agency), "Electricity 2024: Analysis and forecast to 2026." Link here.
[IPCC2022] IPCC Working Group III "Climate change 2022: Mitigation of climate change."
[K2022] Krasuka, Kasia. "Six Months into the Nowcasting Project Our Results Are Highly Promising" (2022). Link here.
[KDSKCR2022] 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.
[KKLPWY2021] Karniadakis et al. "Physics-informed machine learning"(2021). Link here
[KST2019] Kates-Harbeck, J., Svyatkovskiy, A., & Tang, W. (2019). Predicting disruptive instabilities in controlled fusion plasmas through deep learning. Nature, 568(7753), 526-531.
[KW2023] Amba Kak and Sarah Myers West, "AI Now 2023 Landscape: Confronting Tech Power," AI Now Institute (2023). Link here.
[L2023] Multimodal Data Fusion for Estimating Electricity Access and Demand. Link here.
[LWPACOWMKHPFSSHSRKRCDBDDTGGM2021] Lamb, William F., et al. "A review of trends and drivers of greenhouse gas emissions by sector from 1990 to 2018." *Environmental research letters* 16.7 (2021): 073005.
[L2RPN2022] Learning to Run a Power Network Challenge (2022). Link here.
[MBB+2020] Moss, T., et al. "The Modern Energy Minimum: The case for a new global electricity consumption threshold." *Energy for Growth Hub* (2020).
[MSLSK2020] Masanet, Eric, et al. "Recalibrating global data center energy-use estimates." *Science* (2020)
[NAS2017] National Academies of Sciences, Engineering, and Medicine. *Enhancing the resilience of the nation's electricity system*. National Academies Press, 2017.
[OCF2019] Open Climate Fix. "Solar PV power and clouds over UK in January 2019." Youtube video (2019). Link here.
[ONM2022] Ortiz, Anthony, et al. "An Artificial Intelligence Dataset for Solar Energy Locations in India." *Scientific Data* 9.1 (2022): 497.
[RCMW2022] Rutten, Daan, Christianson, Nicolas, Mukherjee, Debankur, and Wierman, Adam "Online optimization with untrusted predictions." *arXiv preprint arXiv:2202.03519* (2022).
[RRR2022] Our World in Data. "Electricity Mix." Link here
[TWMR2019] Fine-Grained Distribution Grid Mapping Using Street View Imagery. Link here
[VDA2020] Village Data Analytics. "Electricity demand estimation and viability analysis for offgrid villages in Kenya." Link here.
[VR2015] Venugopalan, Subhashini, and Varun Rai. "Topic based classification and pattern identification in patents." *Technological Forecasting and Social Change* 94 (2015): 236-250.
[WGS+2018] Wu, Xiaojian, et al. "Efficiently approximating the pareto frontier: hydropower dam placement in the amazon basin." *Proceedings of the AAAI conference on artificial intelligence*. Vol. 32. No. 1. 2018.
[WJR+2022] Wang, Jingfan, et al. "VideoGasNet: Deep learning for natural gas methane leak classification using an infrared camera." *Energy* 238 (2022): 121516.