Climate Change AI

AI for Power and Energy Systems

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Pre-readings

Energy systems + AI overview

Donti & Kolter (2021), *Machine Learning for Sustainable Energy Systems*

https://doi.org/10.1146/annurev-environ-020220-061831

AI for climate action overview, section on energy and power systems

Rolnick et al. (2019), *Tackling Climate Change with Machine Learning*

https://arxiv.org/abs/1906.05433

Responsible AI / human oversight

NIST AI RMF 1.0, *Appendix C: AI Risk Management and Human-AI Interaction*

https://airc.nist.gov/airmf-resources/airmf/appendices/app-c-ai-risk-management-and-human-ai-interaction/

LLMs and deployment in the power sector

EPRI Journal (2026), *Benchmarking Large Language Models for the Electric Power Sector*

https://eprijournal.com/benchmarking-large-language-models-for-the-electric-power-sector/

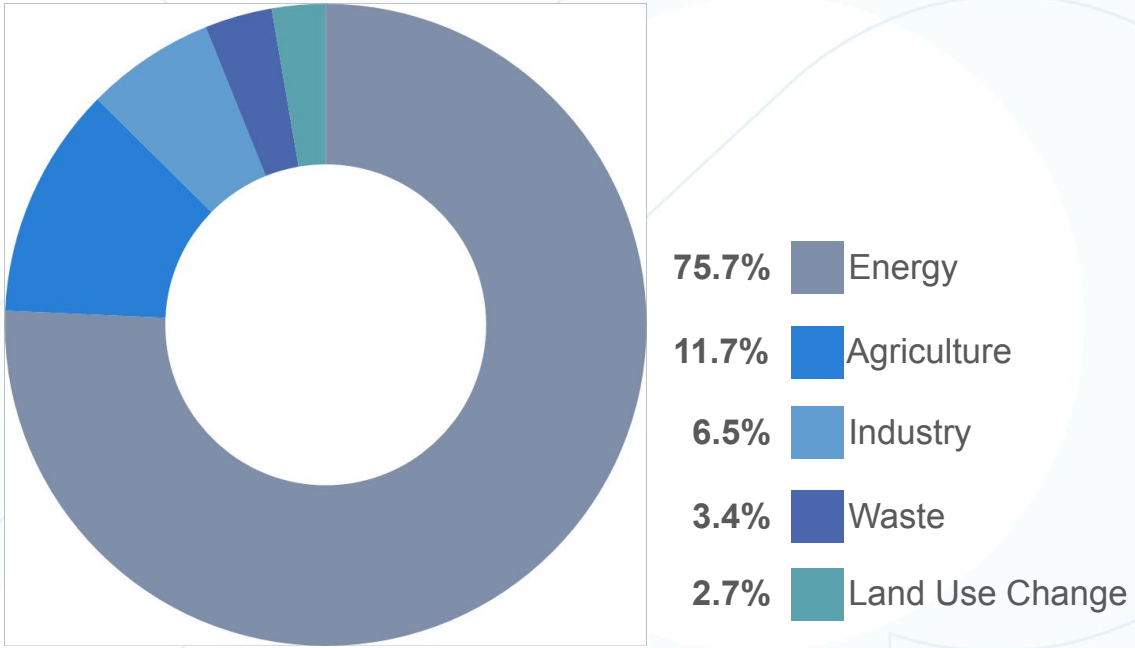
Agenda

1. Introduction to Power and Energy Systems
2. AI for Energy Systems
3. Renewable supply, and Demand Forecasting
4. Physics-Constrained AI and Optimization
5. Model Deployment Challenges and Data Scarcity
6. Concluding Remarks

Introduction to Power and Energy Systems

Energy and Climate: Gas Emissions

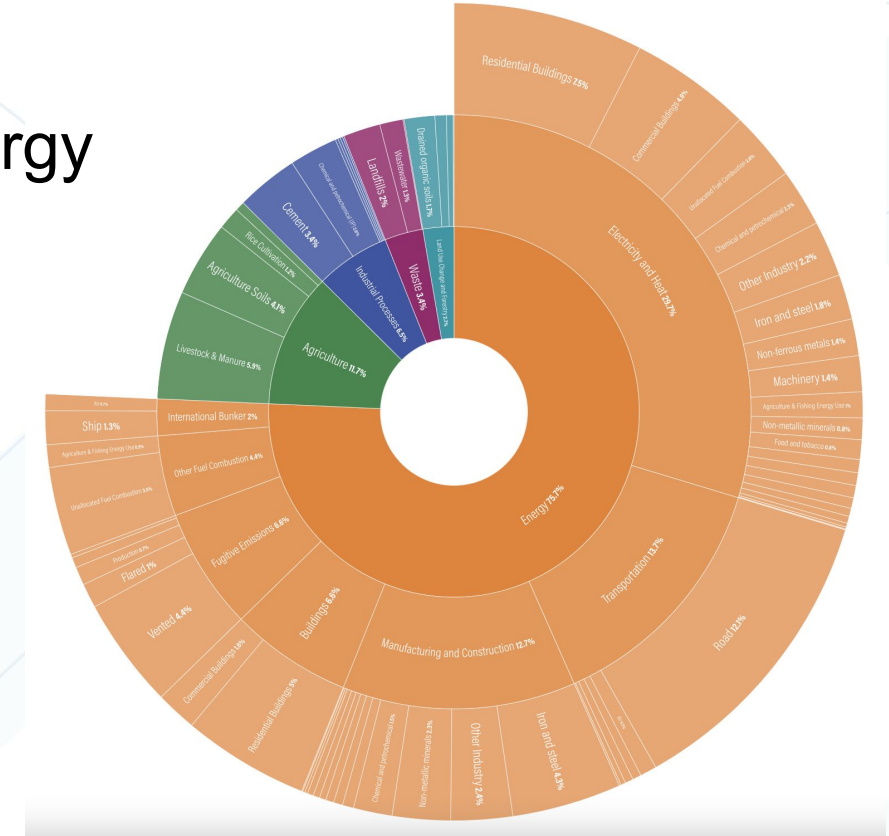
The **energy sector** produces the most greenhouse **gas emissions** by far, accounting for a whopping **75.7%** worldwide.



Global greenhouse gas emissions by sector and end use, 2021. Source: (World Resources Institute 2024)

Electricity share of Energy Demand

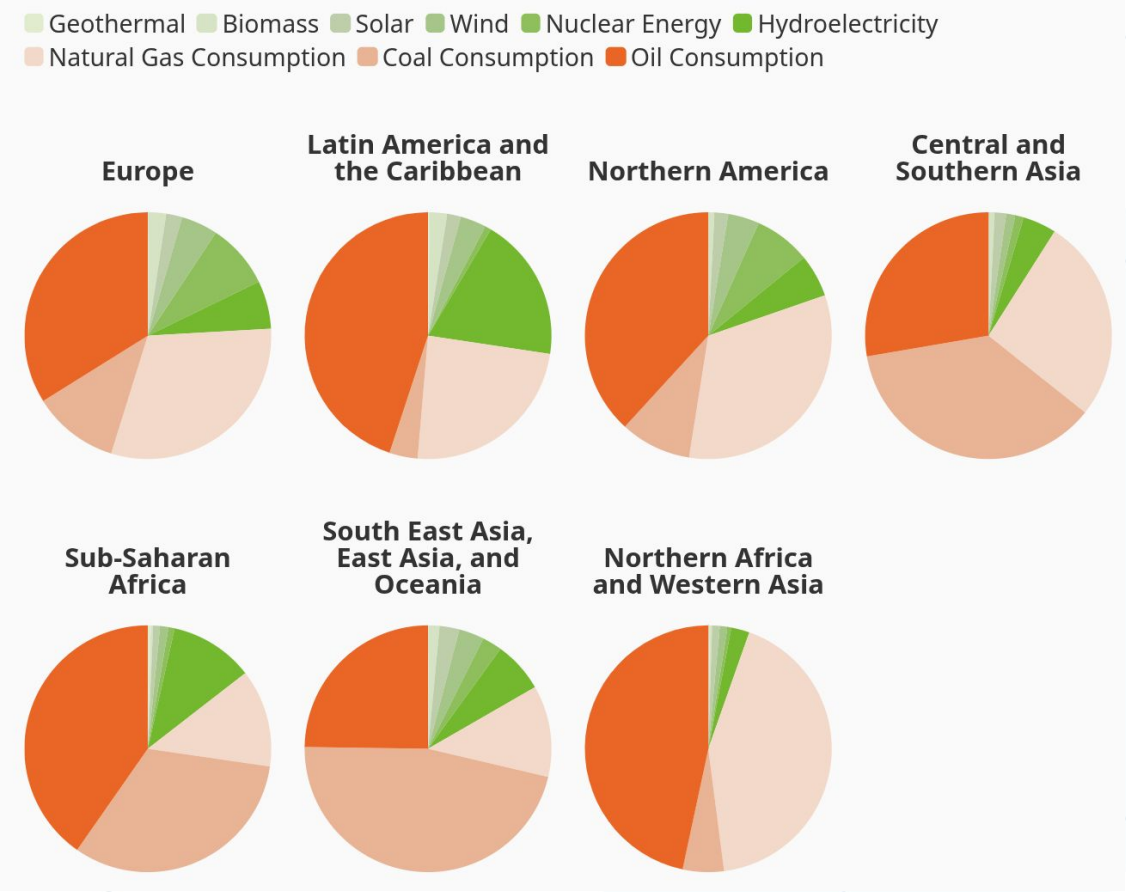
The **energy sector** produces the most greenhouse **gas emissions** by far, accounting for a whopping **75.7%** worldwide.



Global greenhouse gas emissions by sector and end use, 2021. Source: (World Resources Institute 2024)

Energy Consumption by Source

About two-thirds of global coal use is for power **generation** in **electricity** systems (IEA 2025), alongside hydro, nuclear, wind and solar as major sources

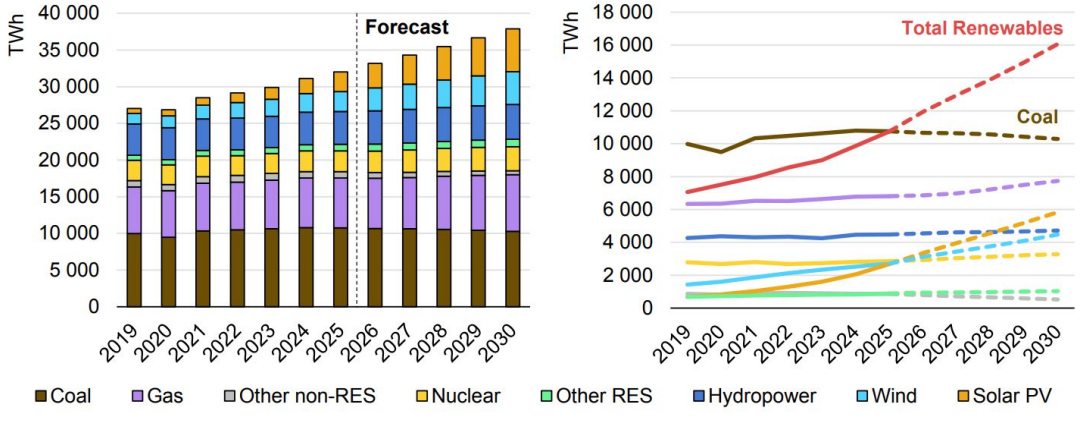


Source: WIPO estimates based on GII Database and the EI Statistical Review of World Energy.

Energy mix is becoming cleaner

In 2025, EU wind generation fell about 2.6% because of reduced wind speeds, while hydropower fell about 13% due to reduced rainfall increasing gas use by around 8% (IEA 2026).

Global electricity generation by source, 2019-2030



IEA. CC BY 4.0.

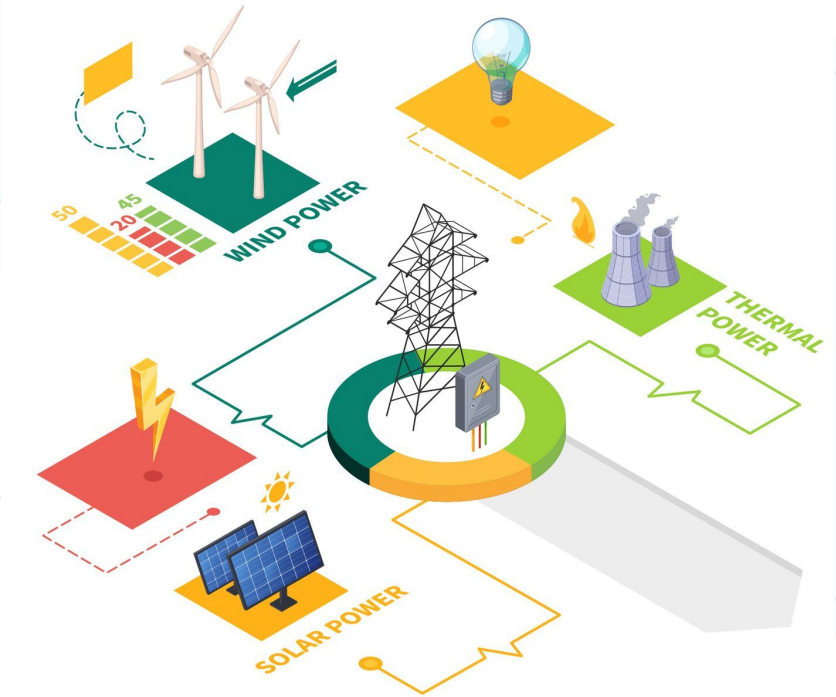
Notes: RES = renewable energy sources. 'Other non-RES' includes oil, waste and other non-renewable sources. 'Other RES' includes geothermal, bioenergy, concentrated solar power (CSP), and ocean energy. Data for 2026-2030 are forecast values.

Source: WIPO estimates based on GII Database and the EI Statistical Review of World Energy.

Grids make electrical energy available

Integrating different energy sources make managing energy a complex problem.

Tasks such as planning, operating, maintaining now depend on variable factors.

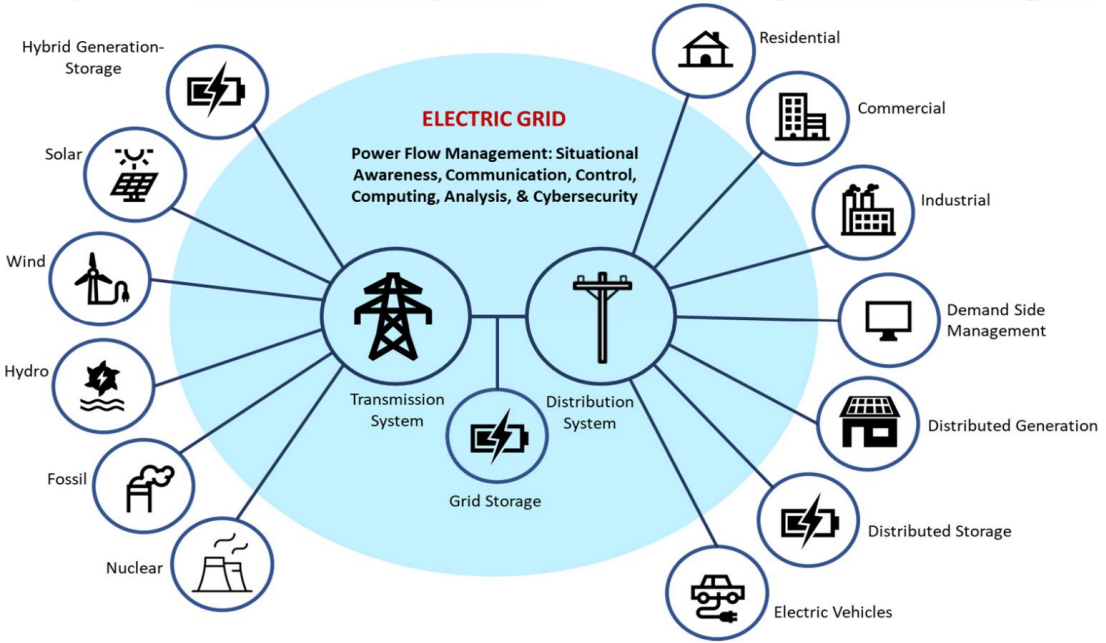


Grid Integration. Source: Nigeria Energy Transition Plan (ETP 2025)

Delivering electrical energy is a complex problem

From generation to consumption: arguably the most complex engineering system

Even more complexity: add demand pattern shifts

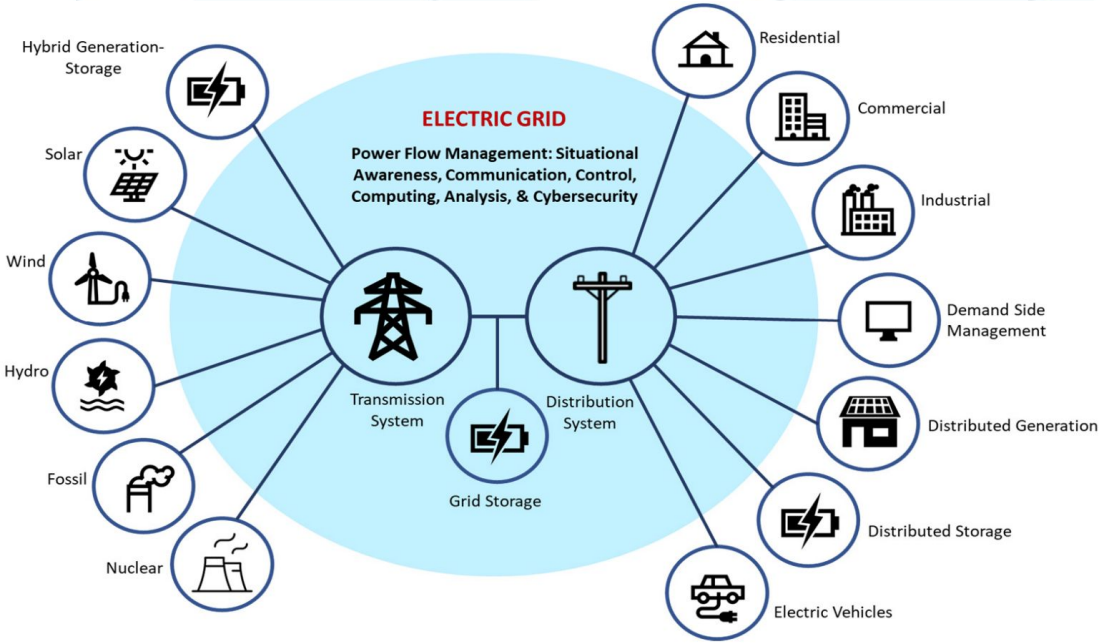


Source: U.S. Department of Energy, Office of Electricity, Next-Generation Grid Technologies, Figure 2, 2021

Delivering electrical energy is a complex problem

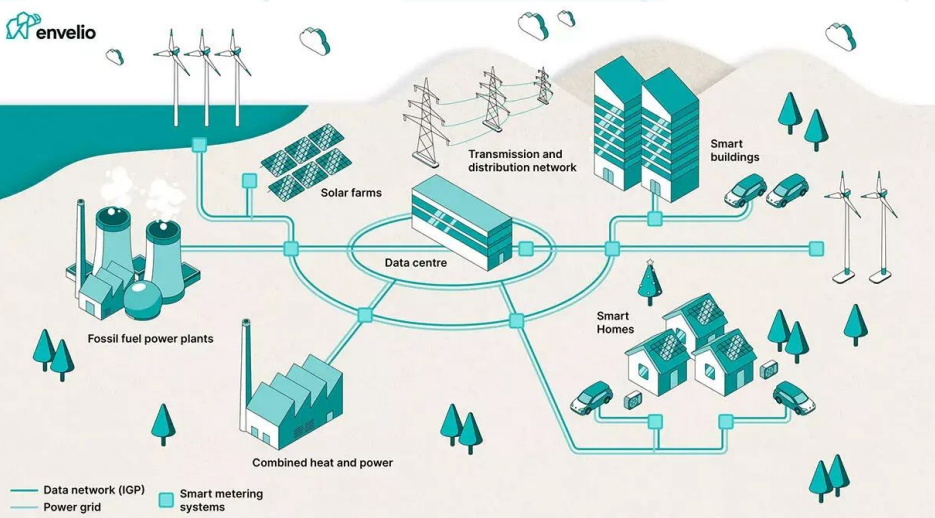
Many engineering tasks:

Unit commitment and economic dispatch, demand forecasting, generation and transmission expansion planning, state estimation, power flow analysis, market clearing, voltage and frequency control, protections, fault detection, maintenance, load balancing…



Source: U.S. Department of Energy, Office of Electricity, Next-Generation Grid Technologies, Figure 2, 2021

Why AI for Energy?



Smart Grid – How intelligent power grids enable the energy transition.(Envelio 2025)

- Modern grids face **growing complexity**: more renewables, real-time balancing, patchy data, shifting demand.
- **AI adds adaptive, data-driven intelligence**: better forecasts, risk-aware decisions, real-time responses.
- Challenge: time to revisit power systems operations

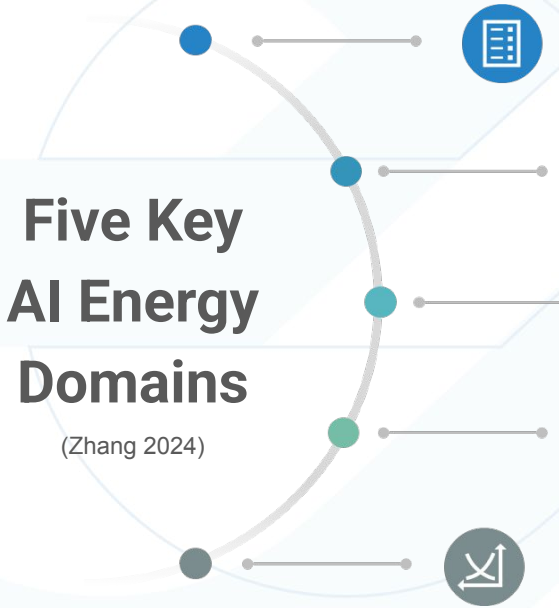


Poll

What makes operating a power grid hard?

AI for Energy Systems

AI emerges as critical enabler for updating energy applications



Planning
Long-term capacity optimization and infrastructure development

Operation
Real-time grid management, resource scheduling and monitoring

Maintenance
Predictive analytics for equipment reliability

Markets
Dynamic pricing and energy trading optimization

End Users
Demand response and consumption optimization

AI Methods and Energy Problems

AI/ML Methods Used

Time Series Analysis
Load, renewable, generation forecasting

Deep Learning and Neural Networks (NN)
Forecasting, anomaly detection, modeling.

Computer Vision
Asset mapping, monitoring, PV planning

Reinforcement Learning
Demand response, storage, grid control

Constraint aware/PINNs
Optimal decisions, dispatch, power flows

Key Energy Problems

Forecasting
From stable demand patterns to uncertain renewables

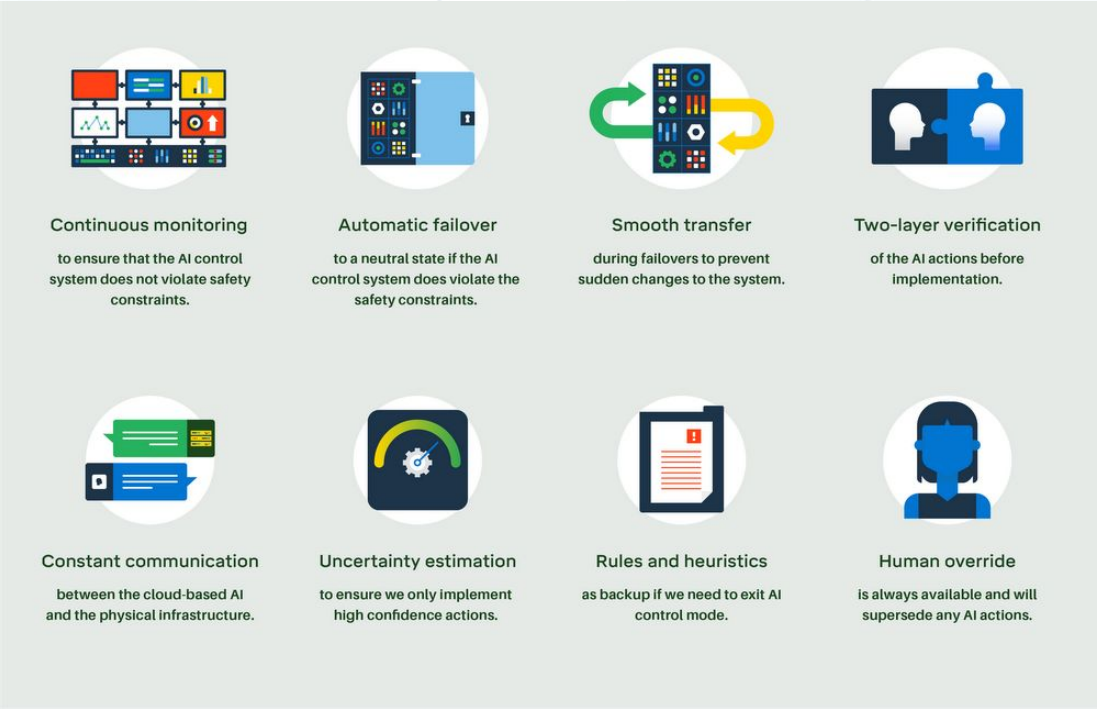
Optimal Dispatch
From static models to sensor-enhanced decisions

Asset Health
From reactive to predictive maintenance

Network Expansion
From slow planning to data-driven grid siting

Markets and flexibility
From fixed operation to dynamic responses

From grid data to safe AI-assisted decisions



"Safety-first AI for autonomous data center cooling and industrial control", (Google 2018)

From grid data to safe AI-assisted decisions

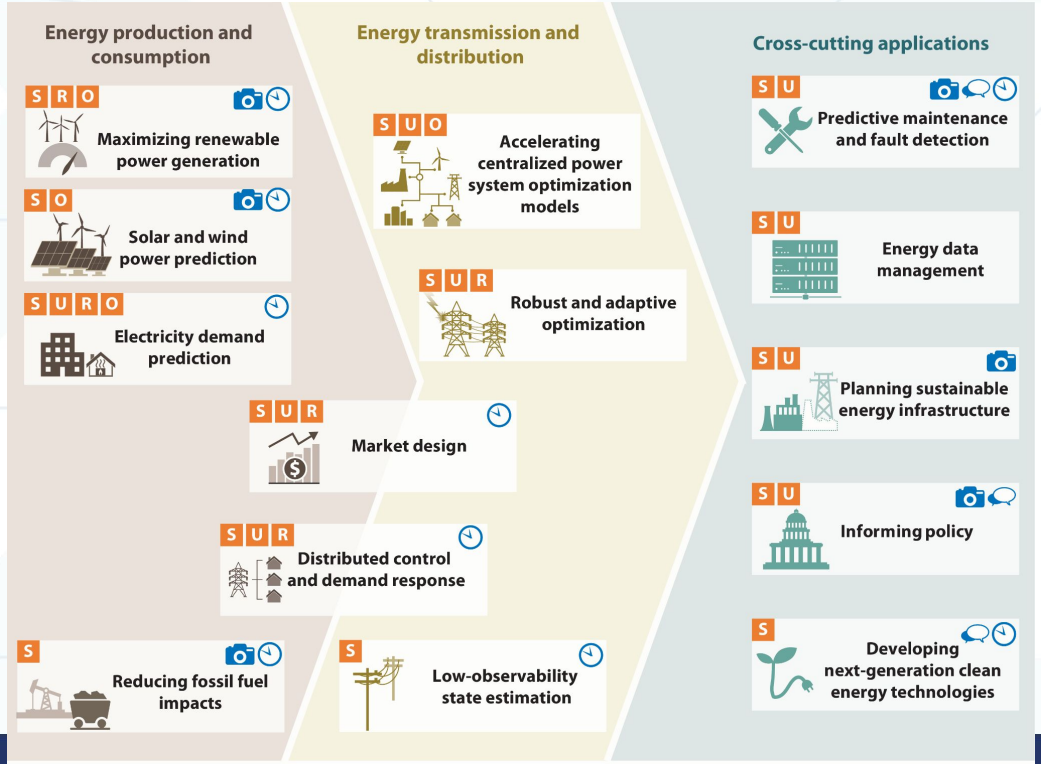
Data:

- **PMUs**: voltage, current, phase angle, frequency, ~ms
- **SCADA / EMS**: generator, substation, breaker, voltage, power-flow data, seconds-level monitoring
- **Smart meters / AMI**: demand, voltage, outages, often 5–60 min intervals
- **DERs & devices**: PV inverters, batteries, EV chargers, building sensors, weather/NWP data

Decisions:

- Forecast renewable generation and demand
- Detect faults, outages, anomalies, and sensor errors
- Estimate grid state and congestion risks
- Support dispatch, OPF, storage, EV charging, and demand response
- Send recommendations to operators, markets, or local controllers

Sustainable Energy Systems Applications

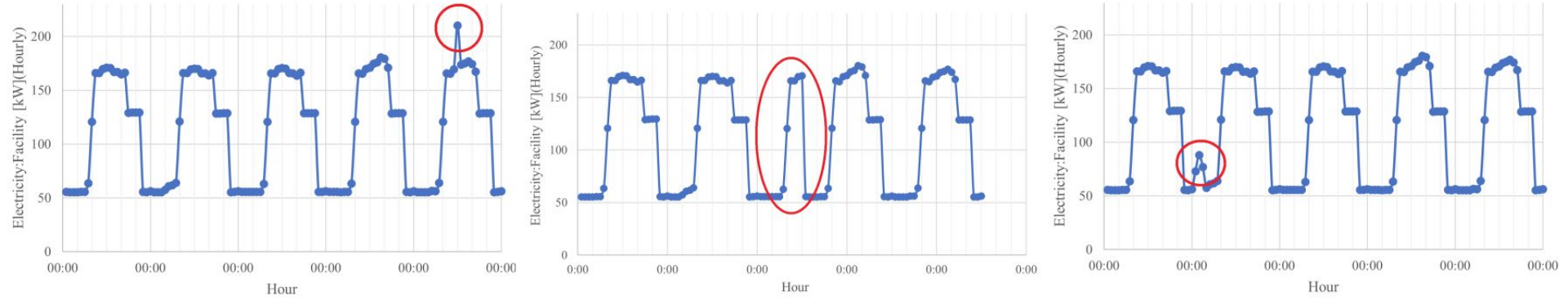


Fault detection, identification, localization

Normal operation patterns can be learned from SCADA, high resolution sensor data, inspections and logs to generate early warnings:

- Anomaly detection
- Autoencoders
- Fault classifiers

Illustration of three types of outlier in an hourly load dataset of a restaurant. Data acquired from Open EI (Zhang et al. 2021)

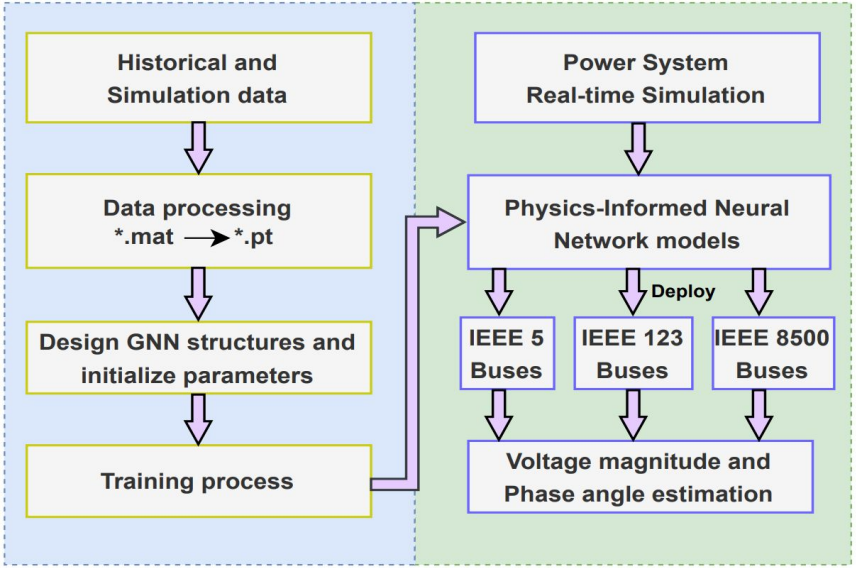


No full data? Low-observability State Estimation

Distribution grids lack updated topology data and sensors:

- Physics-informed **GNNs** combine grid topology, sparse sensor data, and power-system equations to estimate unmeasured voltages and states.

Results within **10e-6** for standard test systems (Ngo et al. 2023)



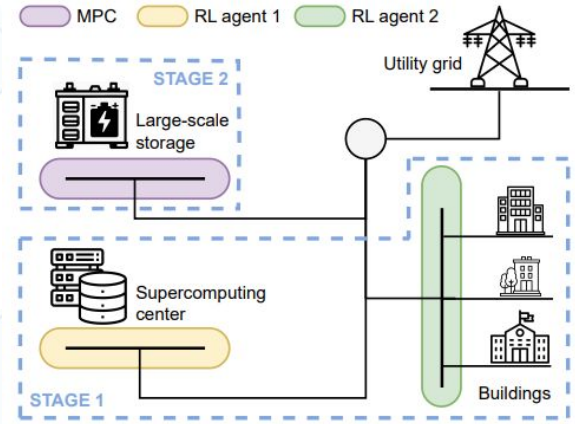
PINN framework (Ngo et al. 2023)

Demand response and distributed control

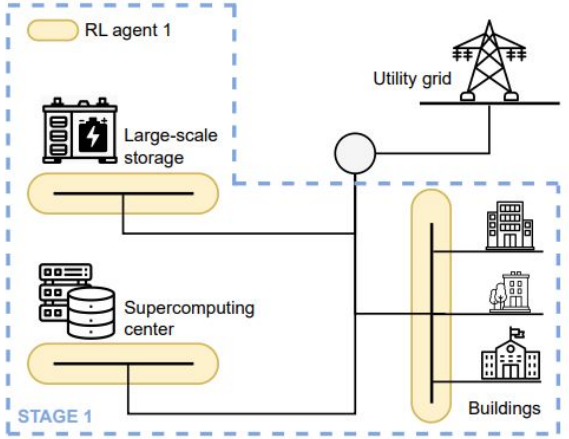
RL can **learn control** policies for:

- Flexible loads
- DERs
- Storage
- EV charging
- Demand response

Control flow during training and deployment in CommonPower. (Eichelbeck 2024)



(a) Two-stage control with balancing assets operated by an MPC and two different coalitions controlled by multi-agent RL.



(b) Centralized control using RL.

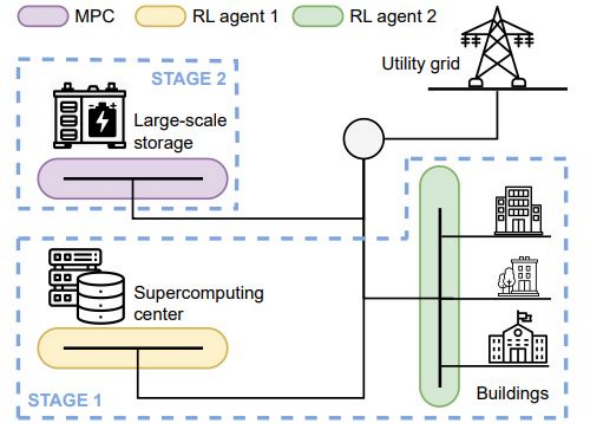
Challenge is multiobjective: peak reduction, cost savings, comfort, voltage stability, physical constraints, and **new for the sector**: sim-to-real transfer, operator explainability, and cybersecurity resilience.

Demand response and distributed control

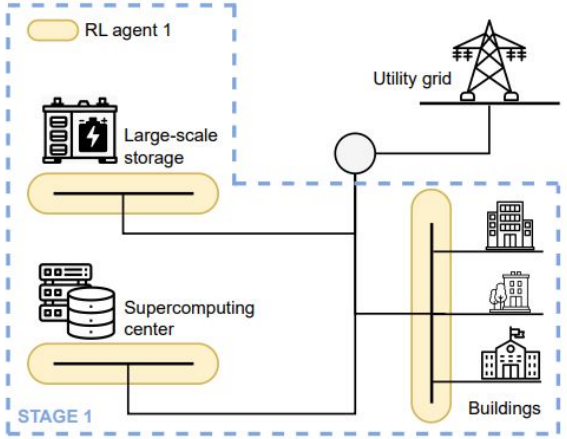
Control flow during training and deployment in CommonPower. (Eichelbeck 2024)

PPO/SAC (Eichelbeck 2024) with safety filters enforcing constraints per action.:

- >90% constraint sat.
- Safe testbeds for RL evaluation



(a) Two-stage control with balancing assets operated by an MPC and two different coalitions controlled by multi-agent RL.



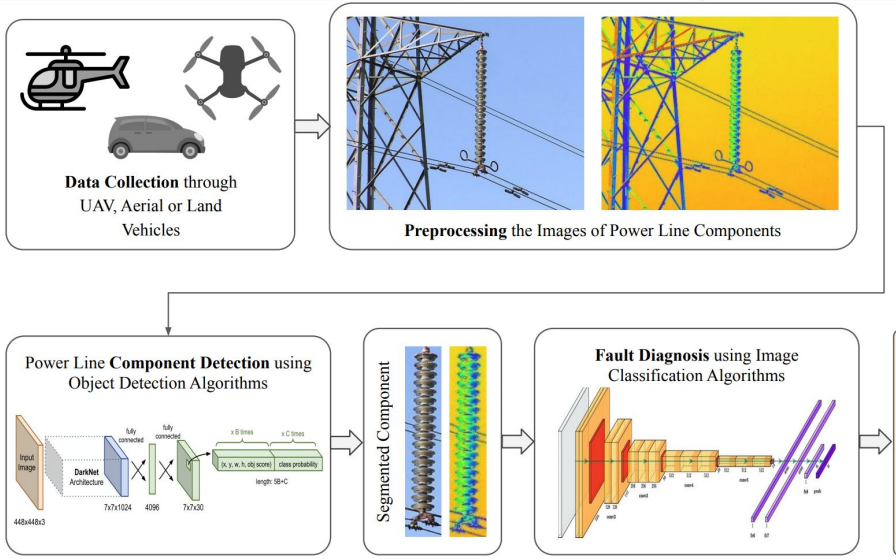
(b) Centralized control using RL.

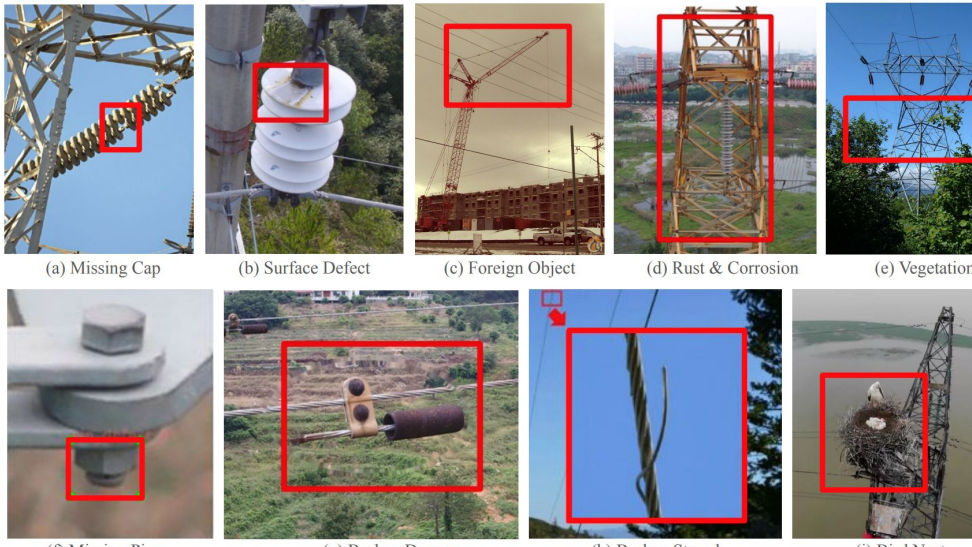
Challenge is multiobjective: peak reduction, cost savings, comfort, voltage stability, physical constraints, and **new for the sector**: sim-to-real transfer, operator explainability, and cybersecurity resilience.

Infrastructure detection and health monitoring

Bring **computer vision** into power systems planning for expansion of electricity access, heterogeneous data:

- Maps, buildings, open infrastructure data, usage, overhead imagery
- Automating power infrastructure inspection (Faisal et al. 2025)

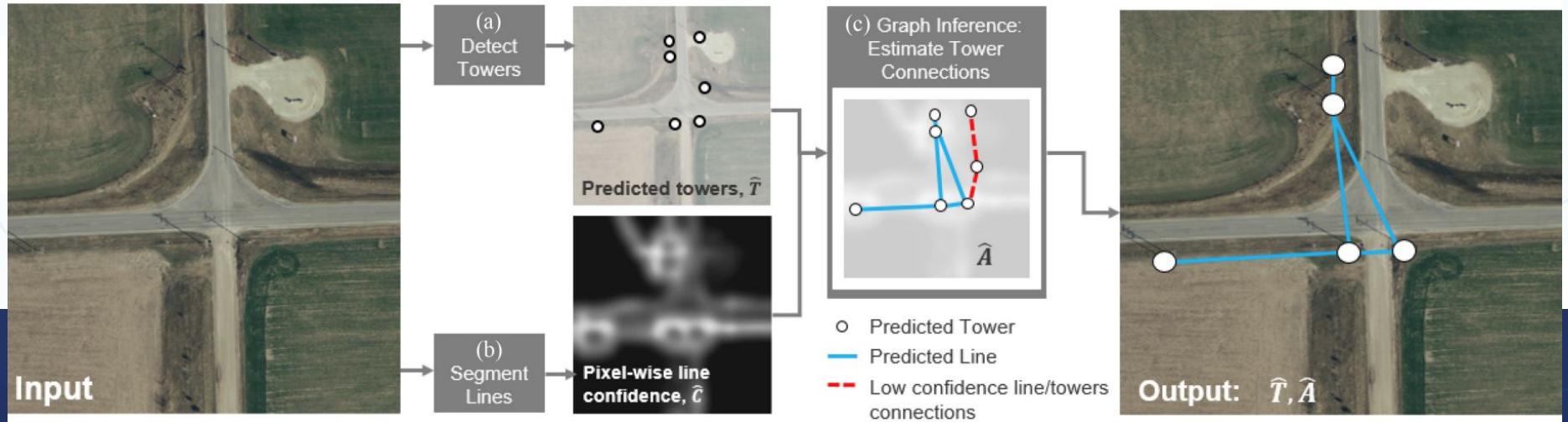




Infrastructure detection and health monitoring

Bring **computer vision** into power systems planning for expansion of electricity access, heterogeneous data:

- Maps, buildings, open infrastructure data, usage, overhead imagery
- Detecting topology and line interconnections is needed for capacity expansion (Huang et al. 2021)





Poll

Which power systems task is most deployment-ready today?

Forecasting for Energy Systems

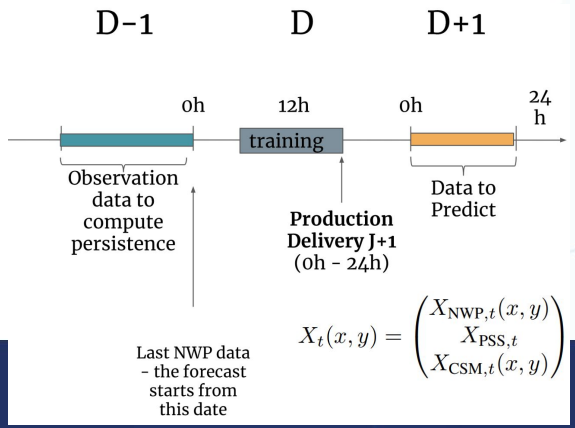
What are we forecasting?

Supports dispatch, storage, markets, demand response, renewable integration:

- Demand/load, solar, wind, hydro, prices, grid carbon intensity, flexibility.

From statistical forecasting to ML: main shift from stable to weather-driven supply

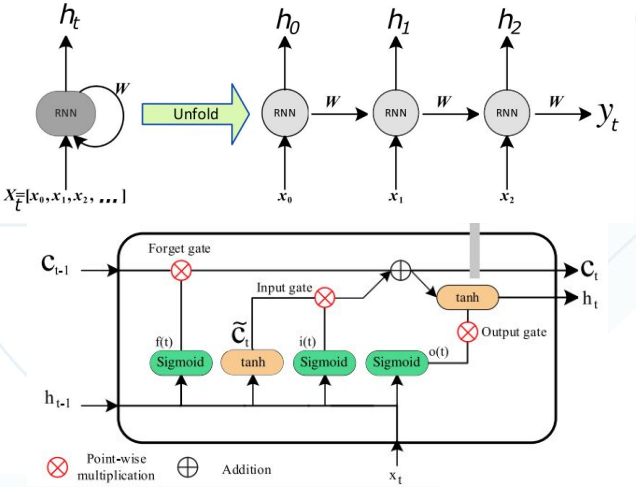
- **Inputs**: historical generation, SCADA, weather stations, satellite/cloud images, NWP, terrain/site metadata.
- **Outputs**: point + probabilistic forecasts.



Timeline of day ahead prediction with feature aggregation of standard models and weather (Mathe et al. 2019)

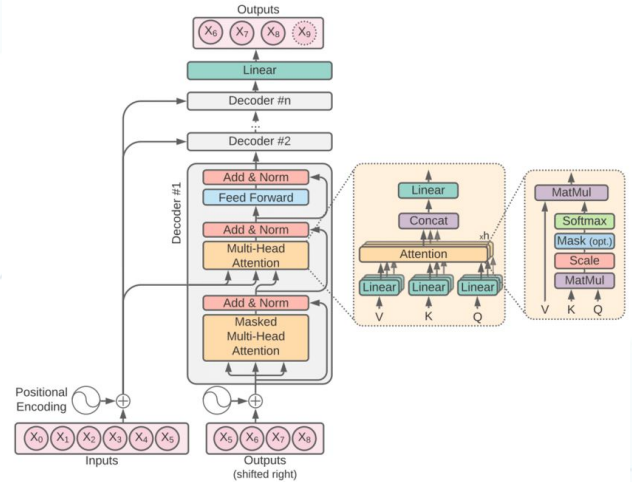
Deep learning for solar & wind forecasting

RNN / GRU / LSTM / Bi-LSTM: widely used for time-series (short-term forecasting) (Guanoluisa-Pineda 2022, Díaz-Bedoya 2023)



"Forecasting Univariate Solar Irradiance using Machine learning models: A case study of two Andean Cities" (Diaz-Bedoya 2023)

Transformers architectures: for multi-site horizon modeling. (Nascimento 2023)

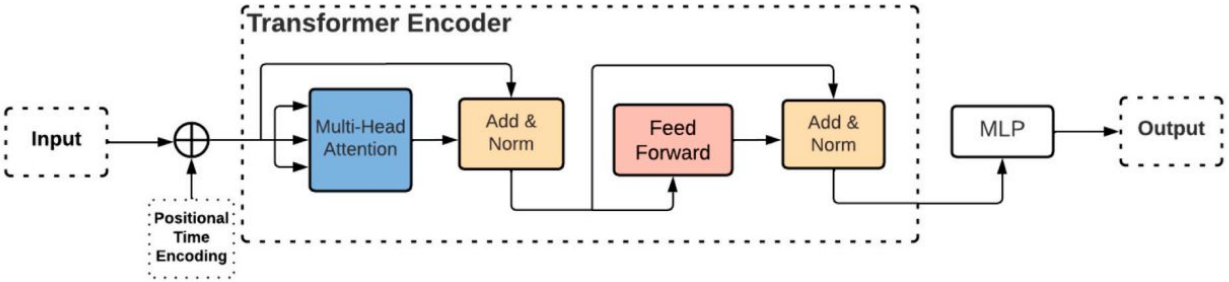


"Evaluation of the Transformer Architecture for Univariate Time Series Forecasting", (Lara-Benitez 2021)

What about small scale scenarios?

Small sites often lack big data from sensors, simple baselines can beat deep models when data are scarce.

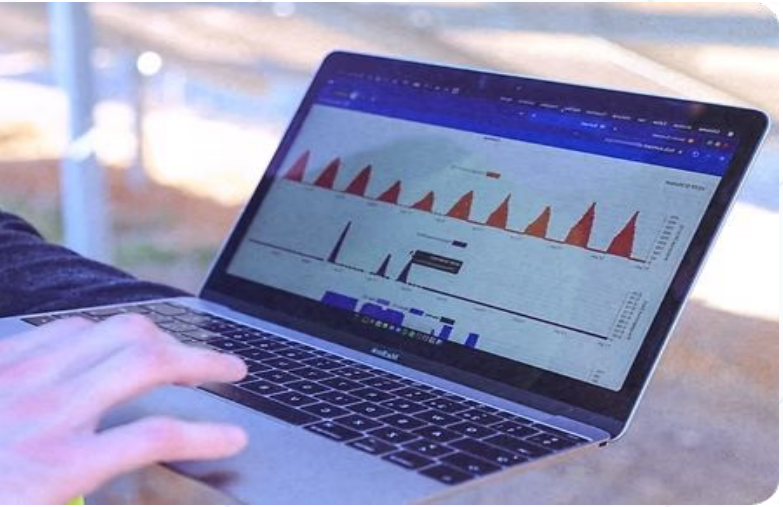
Leveraging inductive priors: (Nascimento et al 2023) Transformer integrated with wavelet transform for wind speed and power forecasting across multiple anemometric towers in brazilian cities and heights (100–150 m).



"A transformer-based deep neural network with wavelet transform for forecasting wind speed and wind energy", (Nascimento et al 2023)

Wavelet-Transformer achieved lower forecasting errors than LSTM at most sites and heights, showing better consistency in wind speed and derived power estimates.

Large-scale operational forecasting



Meteorological forecasting services by SunCast, Chile. Source: (SunCast 2025)

At country scale, ML usually improves or post-processes weather, demand, and operator data

CountryF	Methods	Main results
Chile: Wind speed for operation	Hybrid TiDE + GraphCast	Improvements by 4–21% short-term and 5–23% medium-term (Suri et al. 2024)
France: Country-scale solar and wind	ML with ERA5 weather	Neural networks reached 4–10% nRMSE (Lindas et al. 2025)
Greece: day-ahead load	RNN + active learning + digital-twin pipeline	Specific models still outperform generalist ones (Mylonas et al. 2024)
Europe weather variables	GNN + transformer weather model	Comparative performance as NWP and surface observations (Lang et al. 2024)

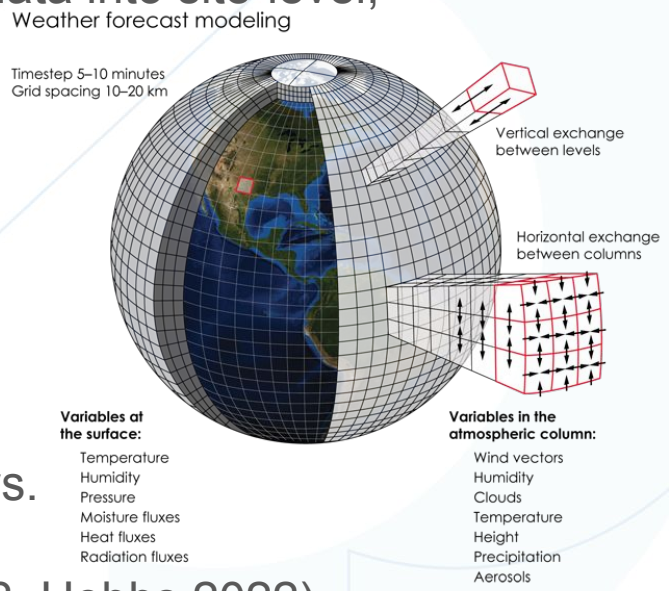
Downscaling and spatial forecasting

ML can translate coarse weather forecasts or satellite data into site-level, high-resolution renewable forecasts.

Wind: Temporal attention on NWP + turbine SCADA, spatial graph encoders for farm layout.

Hydro: Rainfall-runoff + ML residual correction for inflows and short-term turbine set-points.

Potential: Reviews report ~15–25% RMSE reduction vs. persistence and ~10–15% reserve savings when probabilistic forecasts are used in dispatch (Haupt 2018, Hobbs 2022).

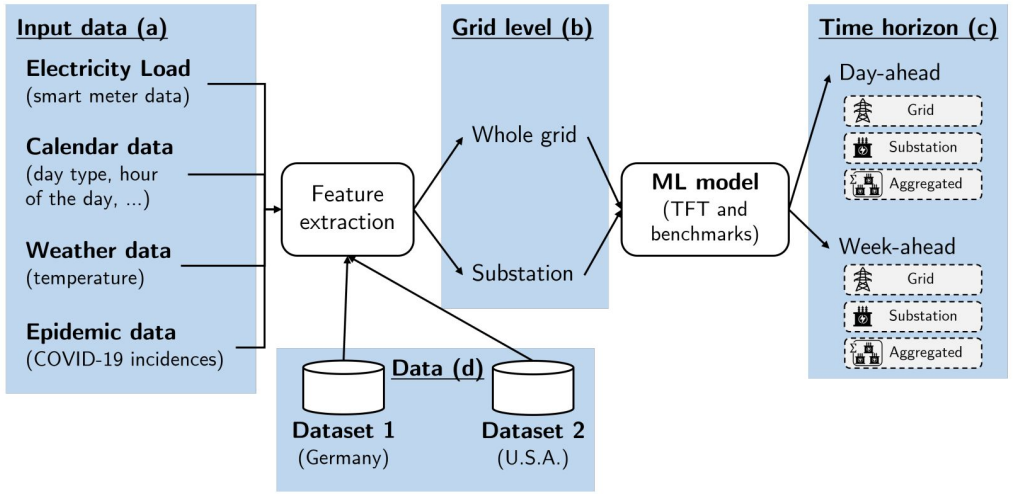


(K. Cantner AGI 2019)

Demand/load forecasting in the energy transition

Demand is less predictable with EVs, heat pumps, prosumers, behind-the-meter PV, and behavior changes.

ML helps at feeder/substation/community level (Giacomazzi et al 2023).

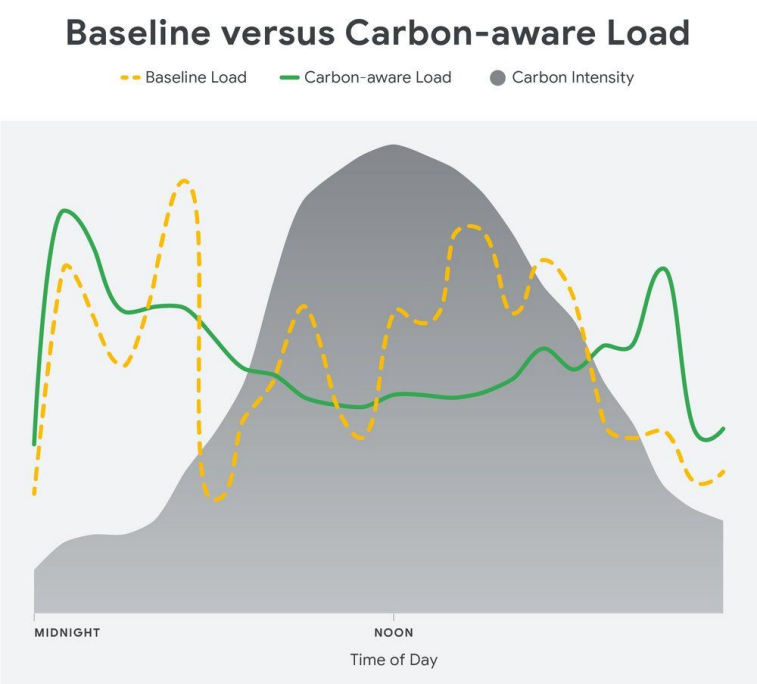


Forecasts become actions

Forecasts feed:

- Dispatch
- Reserves
- Market bids
- Storage schedule
- Carbon-aware load shifting
- Operator recommendations.

(Still) an open challenge:
Uncertainty-aware forecasts are more useful than single-point predictions.



"Our data centers now work harder when the sun shines and wind blows", (Radovanovic 2020)

Open question

What should a forecast optimize for?

Break

5 minutes



Poll

What is worse?

Physics-Constrained AI and Optimization

Why black-box neural networks are not enough

AI for grid operation is not only prediction:

- It must respect physics, safety, and operational constraints.

OPF: Optimal Power Flow is at the core of operating electricity systems

- Minimize the cost of operating the grid subject to power balance, voltage limits, thermal limits, generator limits

$$\min_{y} \quad f(y; x)$$

$$\text{s.t.} \quad g(y; x) \leq 0, \qquad h(y; x) = 0$$

Learning feasibility only from data is wasteful when we know some physics.

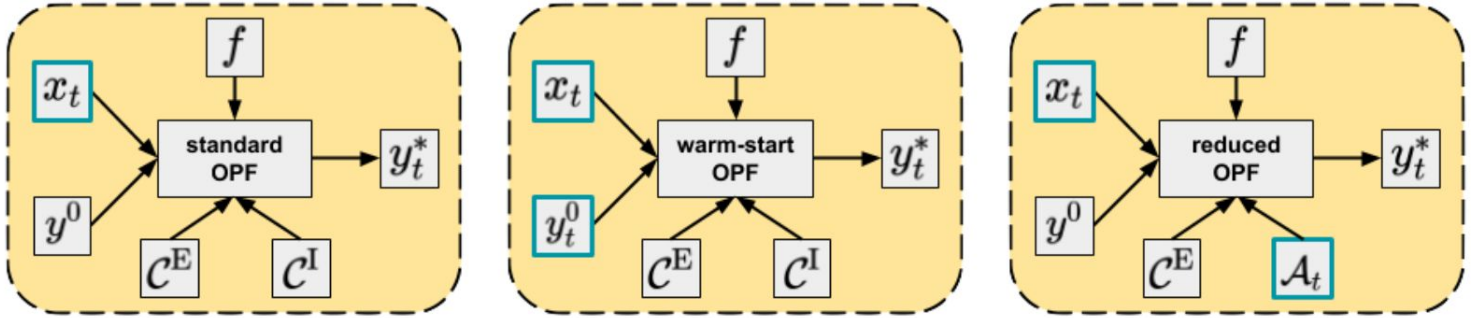
Learning Strategies

Learning solutions directly

- Use NNs as regressors. Maps parameters to OPFs.
- No immediate guarantee of feasibility.
- Another option: reduced-variable prediction

Learning indirect models

- Warm-start: use predicted output and run the optimization problem
- Use NNs as classification. Learn only the active set.

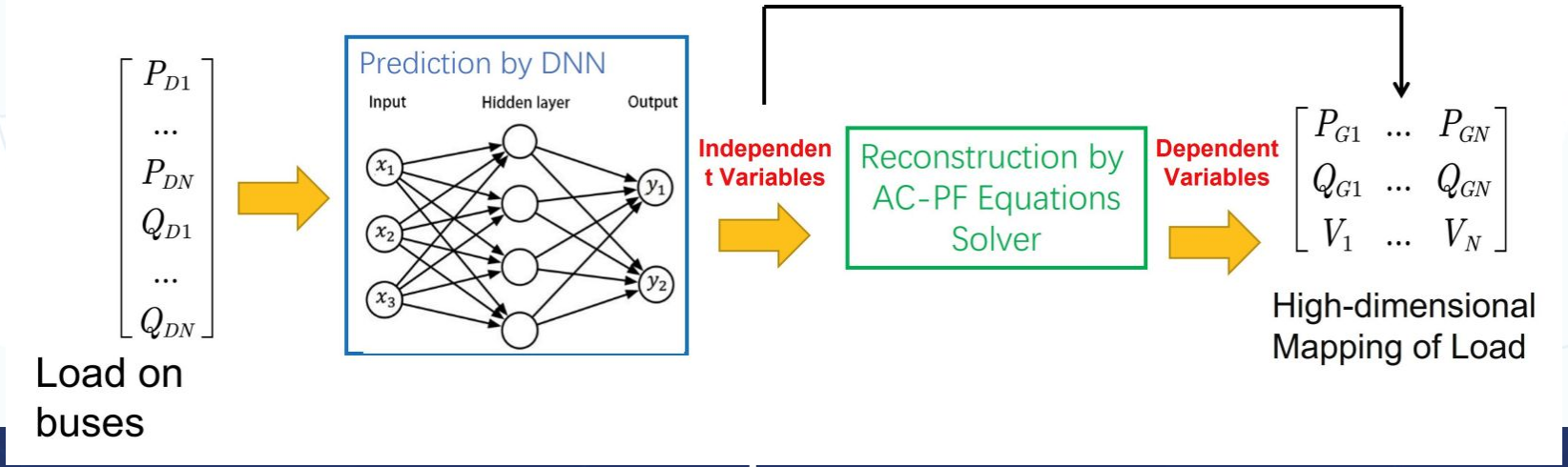


Main approaches to solving OPF. Varying arguments are highlighted, while other arguments are potentially fixed. (Mones 2021)

Why OPF must be solved more often now

Renewables, DERs, EVs, storage, uncertainty create many scenarios:

- An approach (Pan et al. 2020), **value**: solutions speed up, a new way to operate a grid



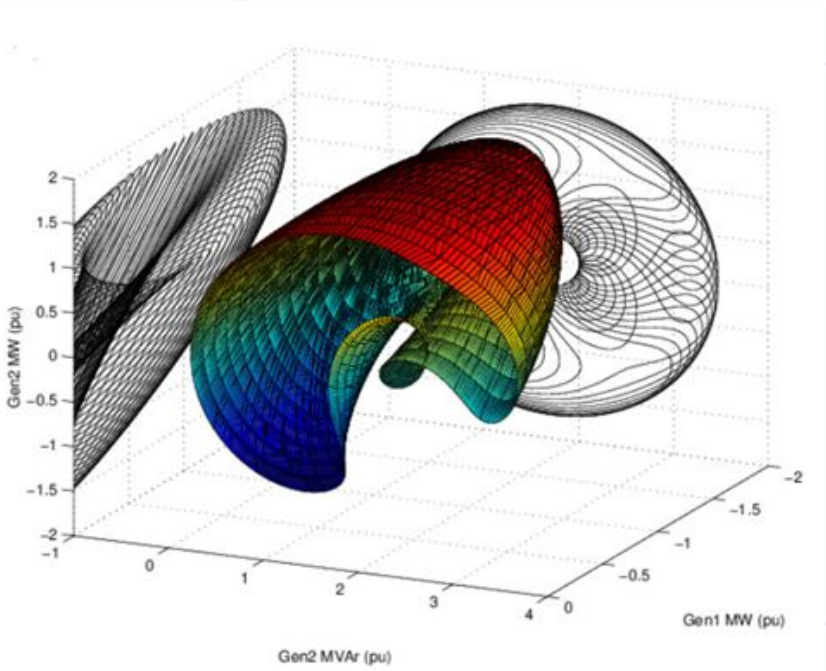
How do NNs integrate physical knowledge?

Challenges:

- Non-convex nature of power systems.
- Large-scale and complex networks.
- Ensuring secure and reliable operation.

Approaches:

- Penalty losses
- Constrained architectures
- Differentiable and implicit power flow layers.

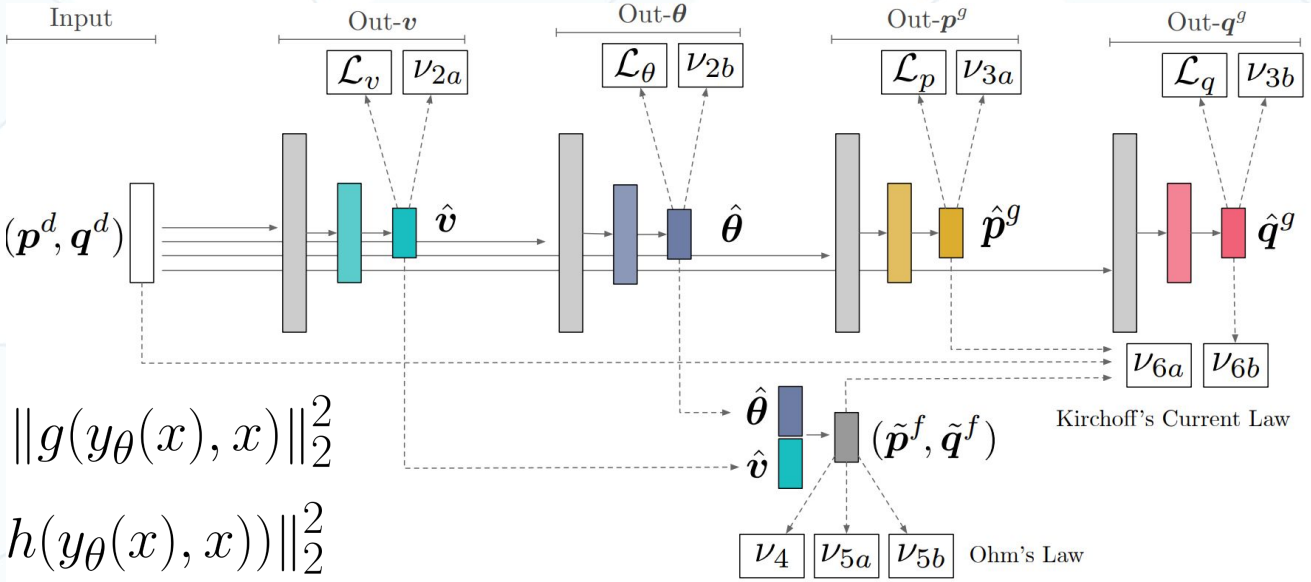


Feasible space of power flow. Source: (Babiker 2025)

PINNs and penalties

Use constraints when are known as Lagrangian penalties (Chatzos et al. 2020):

$$\mathcal{L}(\theta) = \mathcal{L}_{\text{data}}(\theta) + \lambda_g \left\| g(y_\theta(x), x) \right\|_2^2 + \lambda_h \left\| \max(0,\ h(y_\theta(x), x)) \right\|_2^2$$



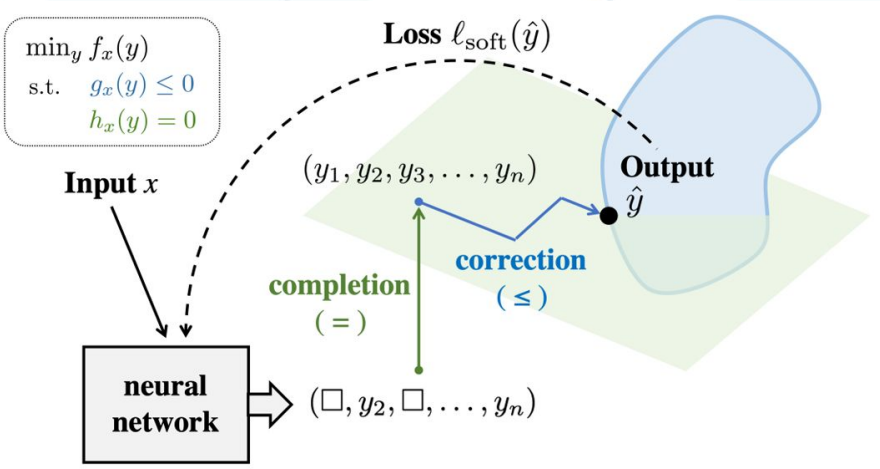
OPF-DNN model (Chatzos et al. 2020)

Integrating Systems Constraints into NNs

We could learn to predict a partial solution:

- Complete equalities
- Correct inequalities

Then, optimize objective (Donti et al. 2021)



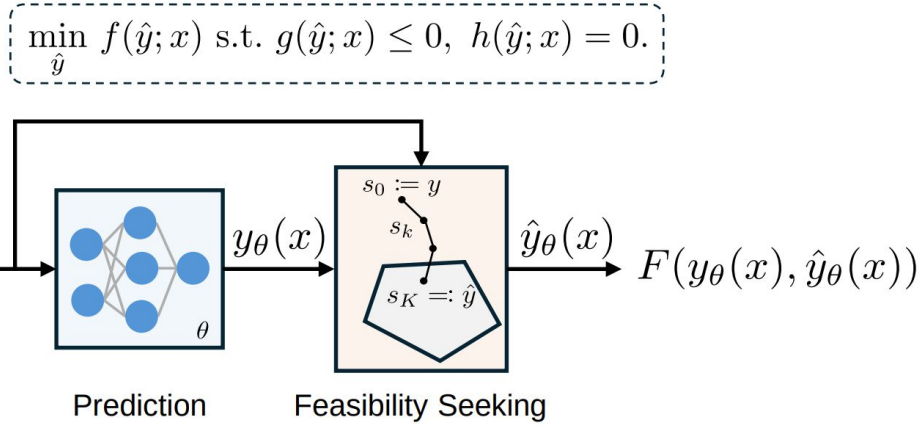
A schematic of the DC3 framework. Source: (Donti 2021)

Integrating Systems Constraints into NNs

A second optimization step can help us to seek feasibility before correction by optimizing (Nguyen and Donti 2025):

$$\phi(s;x) = \|h(s;x)\|_2^2 + \left\|g^+(s;x)\right|$$

$$s_{k+1} = s_k - \eta_\phi \nabla_s \phi(s_k;x)$$

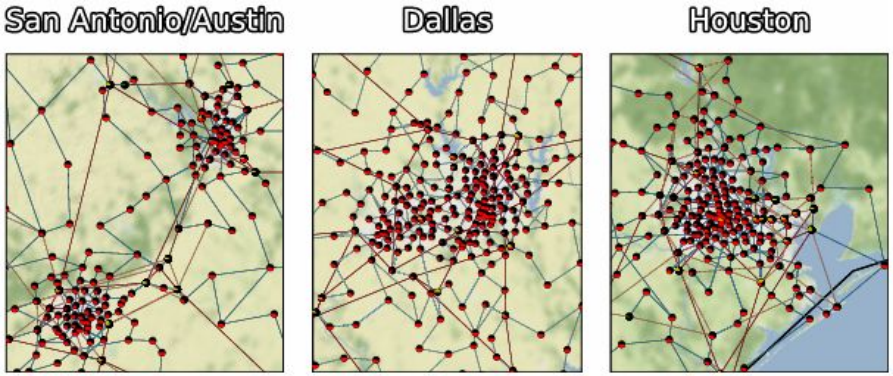


A schematic of the FSNet framework. Source: (Nguyen and Donti 2025)

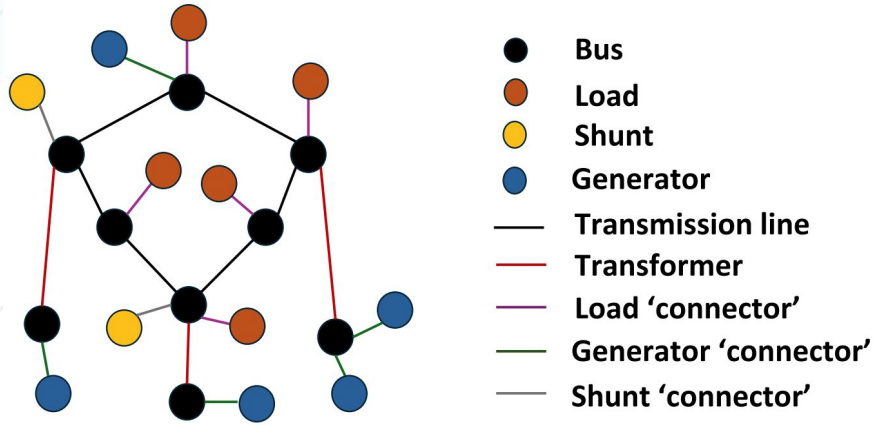
Then train with the loss: $\mathcal{L}(\theta) = f(\hat{y}_\theta(x);x) + \frac{\rho}{2}\|y_\theta(x) - \hat{y}_\theta(x)\|_2^2$

Representation learning of System Structure

Power grids are graphs, use grid as model structure: from initial solutions for OPF, enhancing optimization efficiency (Diehl 2019) to <1% optimality gap and <3% **zero-shot N-1 contingency gap** (Arowolo & Cremer 2025)



Map of the synthetic TEXAS dataset. Source: (Diehl 2019)



Heterogeneous graphs with different node and edge types (Arowolo & Cremer 2025)

Model Deployment Challenges and Data Scarcity

Responsible AI in power systems: what can go wrong?

In power systems, AI failure is not only a prediction error

- It can become a reliability, safety, equity, or cybersecurity problem.

Physical Safety
Infeasible or unsafe controls, increased delays

Equity
Models may underperform in data-scarce grids

Automation & Out-of-the-Loop
Operators may over-trust AI, specially under time pressure

Accountability
Robust logs, model cards, data sheets, and clear responsibility

Human override: from advisory AI to autonomy

Advisory	**AI:** Forecasts, detects anomalies, recommends. **Human:** Decides and executes action.	**Yes, common for grid**
Approve-to-act	**AI:** Suggests dispatch/control action. **Human:** Approves before execution.	**Possible for slower decisions**
Fully Autonomous	**AI:** Plans, calls tools, acts across systems. **Human:** Mostly absent.	**Not ready for grid operations**

NIST AI RMF, App. C (2023), EPRI Journal (2026)



Final Poll

Should an AI agent control the grid?

Why not agentic AI for mission-critical grid control yet?

Unpredictable Chains

Small errors can cascade through multiple tool calls dynamically.

Over-Privileged Access

Agents with broad permissions can act faster than humans can review.

Difficult Accountability

Unclear which prompt, tool, memory, or system state caused an action.

Security Risks

Connectors, tools, and context sharing expand the potential attack surface.

Challenges of dmodel deployment in the Global South



(Filho 2024)

3.5 Billion people affected by power quality/reliability in LMICs (Flashpohler et al. 2024)

Scarce grid data is a deployment bottleneck

Open data unlocks innovation but can amplify inequality:

- Broaden data representation considering anonymization, aggregation, or differential privacy.
- Co-design data initiatives with local institutions and affected communities.
- Pair open data with local training and governance frameworks (e.g., ISO 50001, UNESCO AI Ethics).



"The Difference Between Data Governance vs. Data Management", (Semer 2019)

From deployment constraints to reusable AI benchmarks

GridWatch: low-cost plug-in sensor with battery + cellular link.

- ~1,300 sensors in Accra deployed over 4 years, collecting voltage/frequency data every 2 minutes.

Accra Power: first long-term LMIC grid dataset (SAIDI, SAIFI, undervoltage) drives AI-for-energy research.



“Helping global grids work smarter, not harder”, (Flashpohler et al. 2024)

Concluding Remarks

Concluding remarks

AI as an accelerator: Integrate forecasting, control, and automation pilots that show measurable **reliability**.

Pilot design: From research to deployment with clear **KPIs** — accuracy, resilience (SAIDI/SAIFI), and tCO_2 avoided.

Safety: Establish basic data-sharing rules, and safety layers (**constraint-aware** learning, **human-in-the-loop**).

… and **open models and data**!



Thank you

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