IMPERIAL

Energy Forecasting for Power System Operations

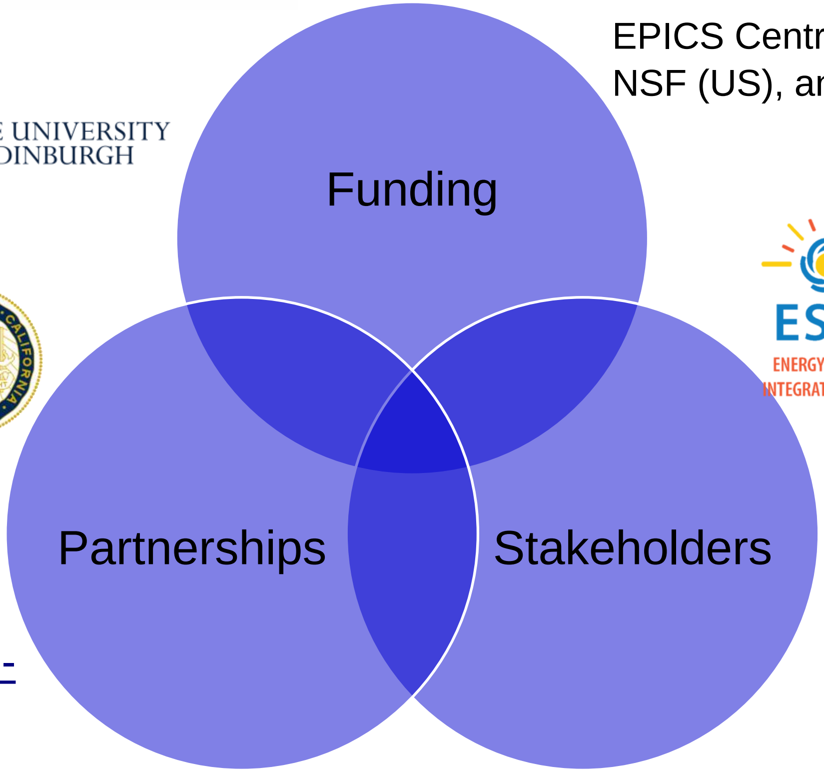
Resilient and Application-driven Forecasts

Dr Akylas Stratigakos, Research Associate (a.stratigakos@imperial.ac.uk)
Dr Wangkun Xu, Research Associate (wangkun.xu18@imperial.ac.uk)

G-PST/ ESIG webinar series – 26 February 2025

Acknowledgements

EPICS Centre funded by CSIRO (AU), NSF (US), and UKRI (UK)

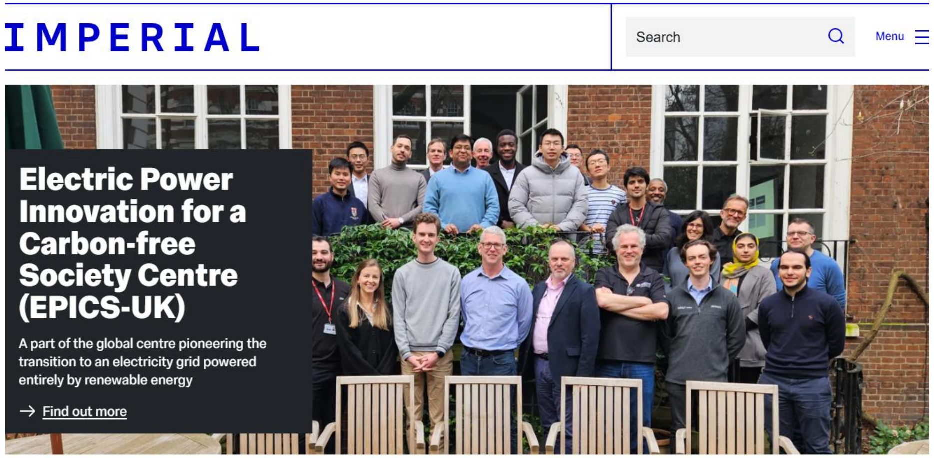


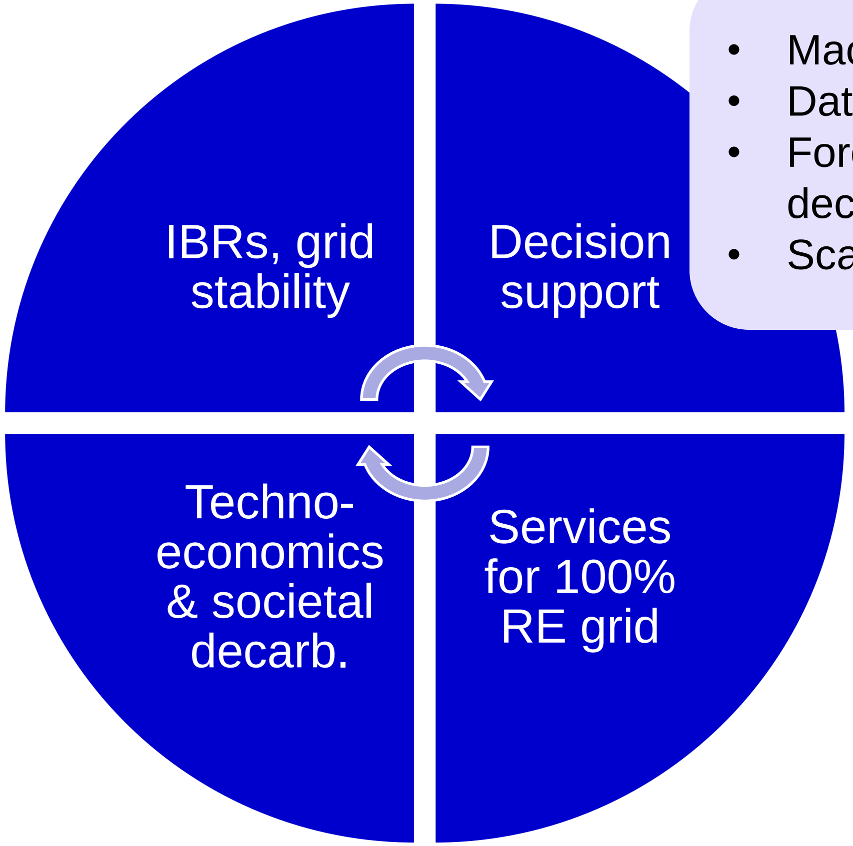
[Electric Power Innovation for a Carbon-free Society Centre (EPICS-UK)]

Catalyst/G-PST AI workshop, Feb. 2024

Research on Low-carbon Power and Energy Systems

EPICS-UK
- Imperial: >30 persons (15 PhD students, 7 postdocs)
- Holistic research to support the transition towards renewables-dominated power grid





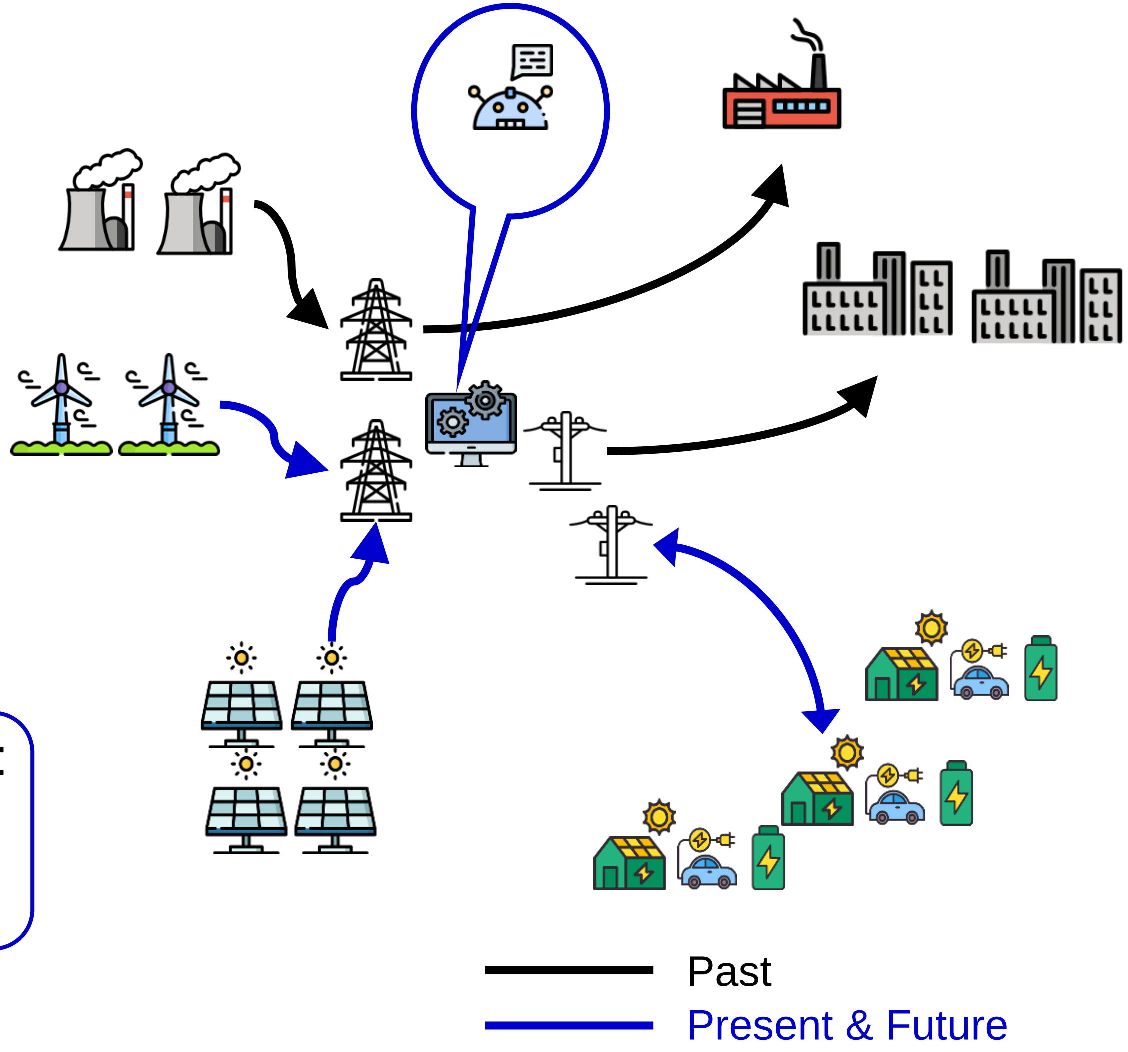
- Machine learning & optimization
- Data (weather, tabular, images)
- Forecasting & uncertainty-aware decisions
- Scalable decision-making

Energy Forecasting in Low-carbon Systems

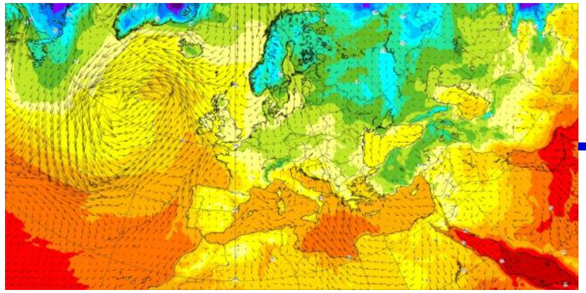
The importance of energy forecasting:
- Safe, reliable, and economic operations
- Awareness and risk-management
- Reserve and ramping requirements

Beyond accuracy:
- Do our forecasts lead to better (safer, economical) actions?
- Can we trust our models under adversity?

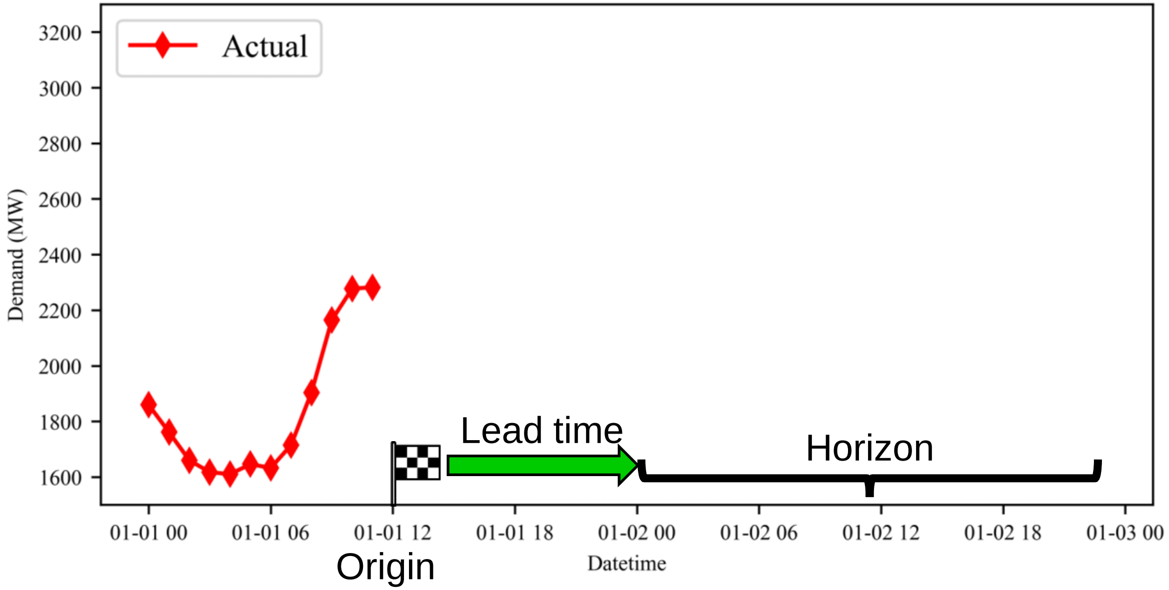
Machine learning & traditional optimization to improve:
- **Resilience** to adversarial inputs
- **Forecast value** for downstream applications



Energy Forecasting through the Years



Temperature and wind forecast
(source: ECWMF)



Point: Generation scheduling

PIs: Reserve requirements

Scen.: Contingency analysis

1970
- Demand
- Look-up tables
- Statistical methods

1980
- Wind power
- First machine learning applications
- Numerical Weather Predictions (NWP) as input

1990

2000
- Solar power
- Probabilistic forecasting
- Ensembles, combinations

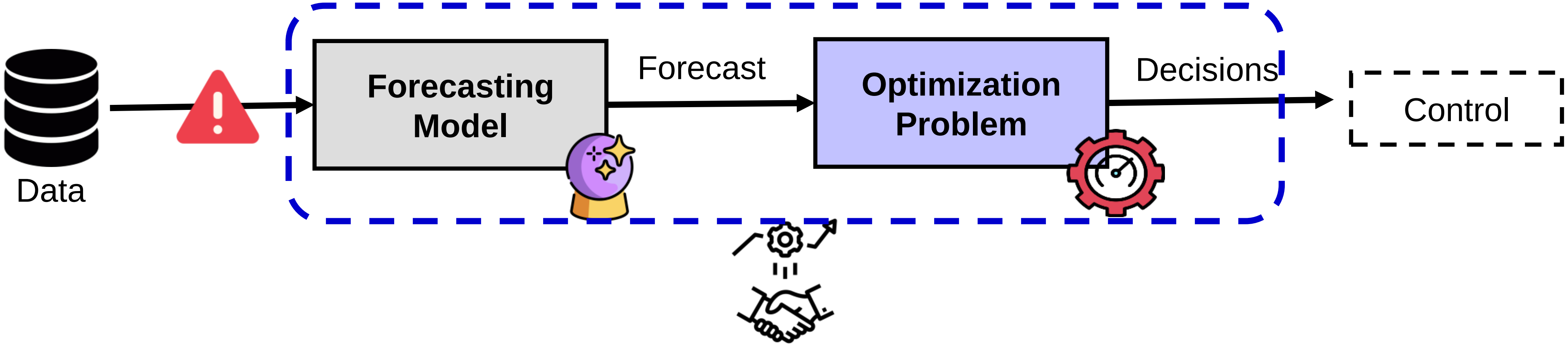
2010

2020-2025
- EVs, DERs, smart meters, etc.
- Privacy concerns, zero-shot forecasting

Application Methodology

Moving from Data to Decisions

The model chain that goes from data to decisions and actions:



Challenges and opportunities:

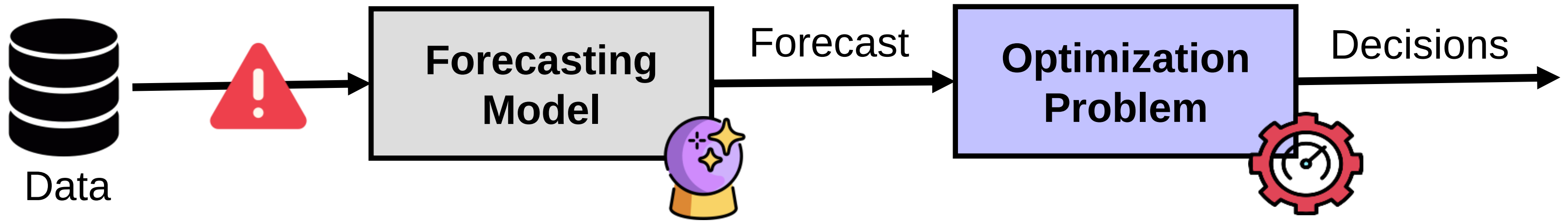
Seamlessly adapting to missing data during real-time operations

Application-driven forecasting for better decisions

IMPERIAL

Forecasting with Missing Data during Real-time Operations

Missing Input Data during Real-time Operations



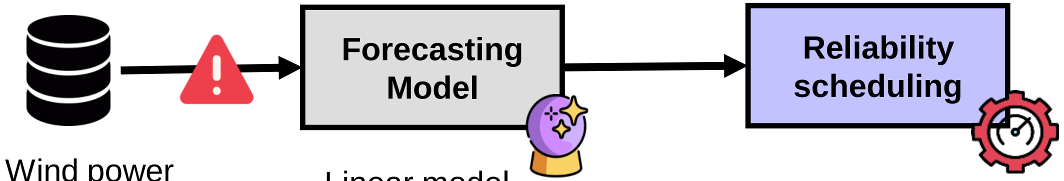
Forecasting models deployed and used operationally:

- Disruptions, equipment failures, cyberattacks leading to missing inputs
- EC survey: "… fewer than 40% of users reported that data were always there when needed."
- Forecast accuracy compromised → suboptimal downstream decisions

- Is this model chain **resilient** to missing inputs?
- Do we address missing data fast and within **strict time constraints**?

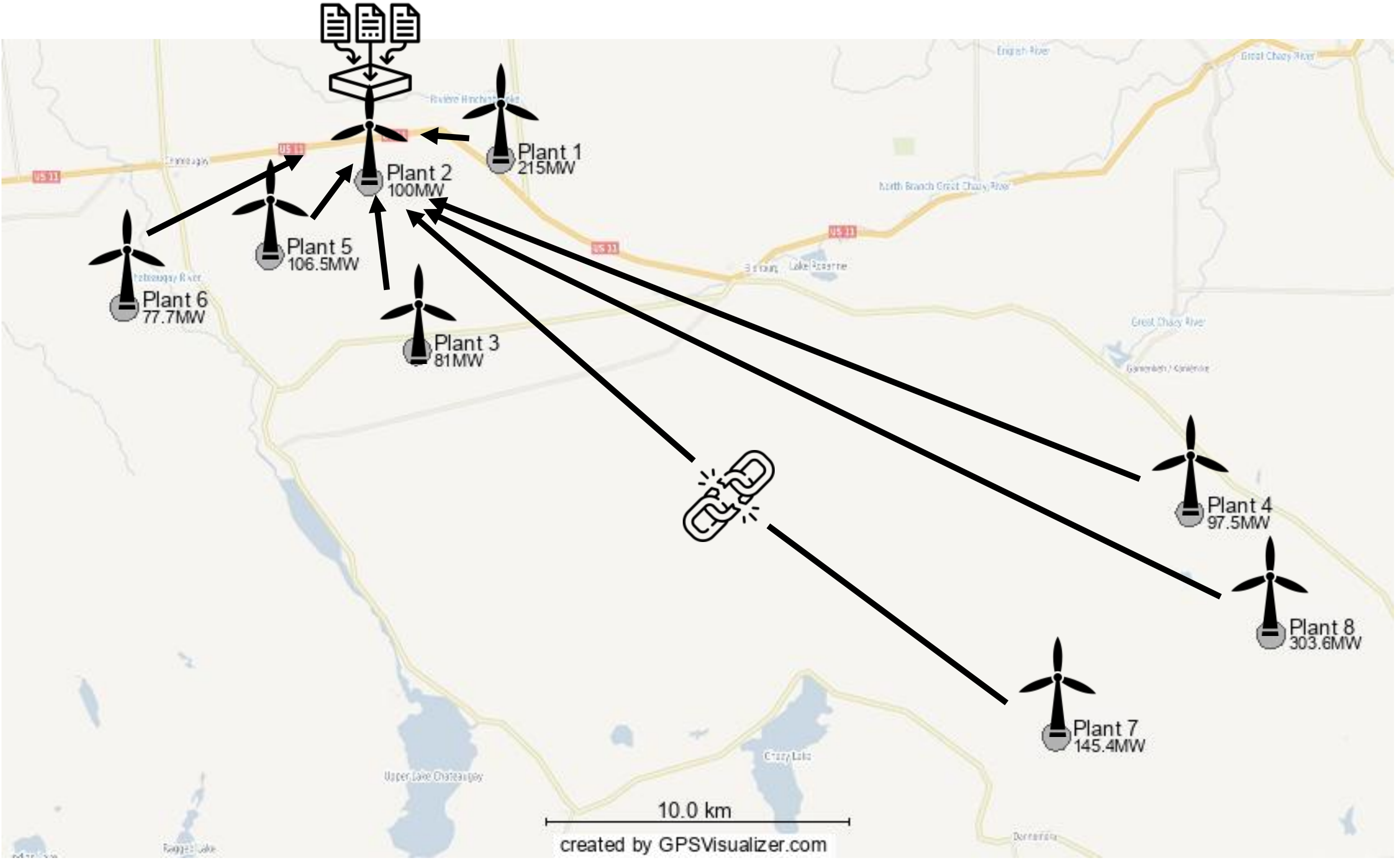
Short-term Wind Power Forecasting
Motivating Example

- **Inputs**: Current and past measurements of adjacent plants, weather [1]
- **Setting**: 15-min freq., 15 min-4 hours ahead horizon
- **Applications**: Reliability scheduling, …



- Wind power measurements
- Weather

- Linear model
- Neural networks



[1] R. Bryce, et al., "Solar, wind, and load forecasting dataset for MISO,NYISO, and SPP balancing areas," 2023. (https://www.nrel.gov/docs/fy24osti/83828.pdf)

Model Parameters Adapting to Available Information

Forward fill last measurement

- **(+)** Fast, **(-)** Performance gap

Retrain new model

- **(+)** Optimal, **(-)** Computational/ memory cost

Adaptive forecasting models

- Data-driven partitions of missing input combinations
- Linear adaptation to available inputs
- **(+)** No computational cost at inference, no dependence on historical missing data patterns

Example: A model with up to 3 missing inputs

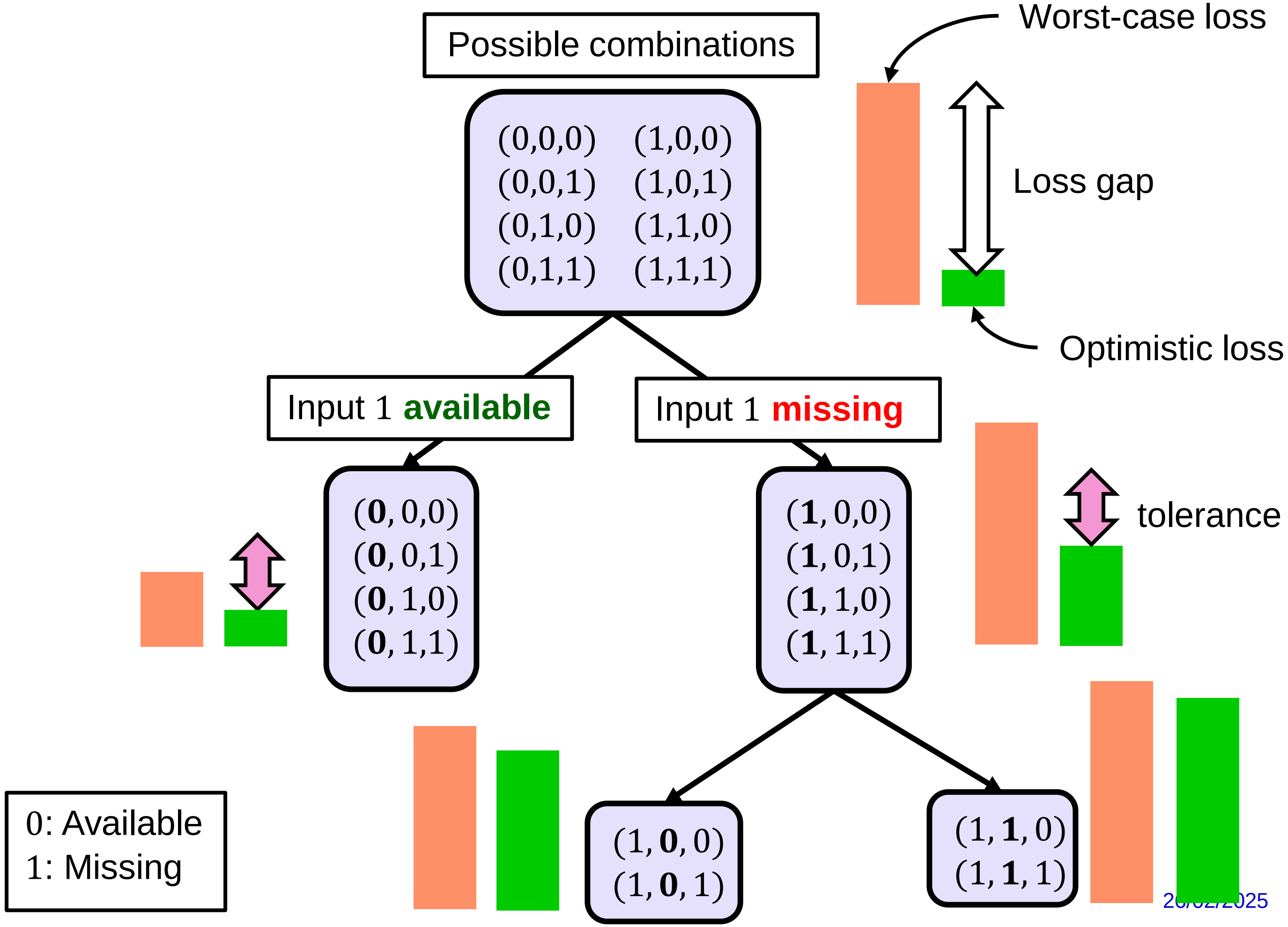
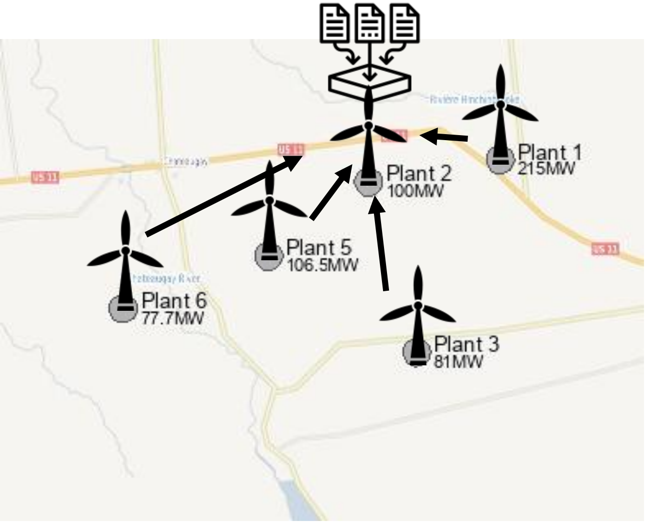
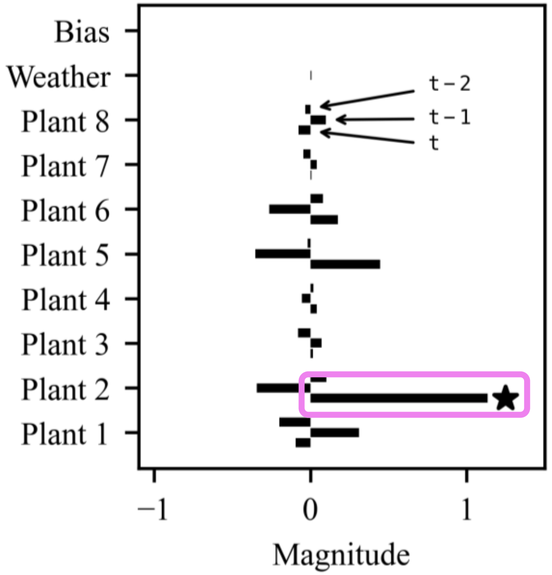


Illustration on Short-term Wind Power Forecasting



A closer look at the adjacent plants

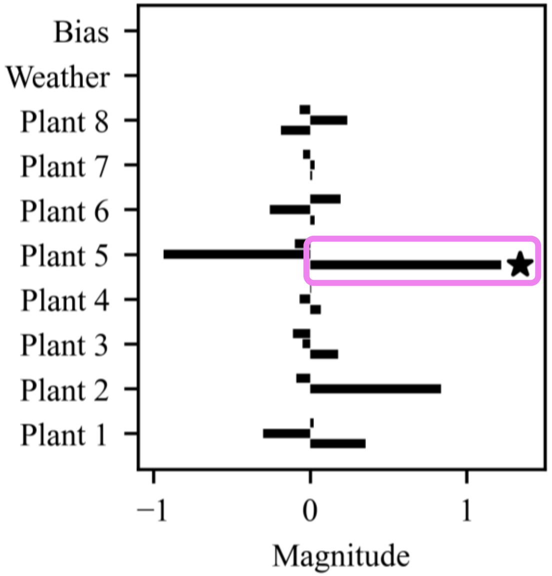
Linear model weights when all inputs are **available**



Plant 2, period t
available

⋮

Plant 2, period t
missing

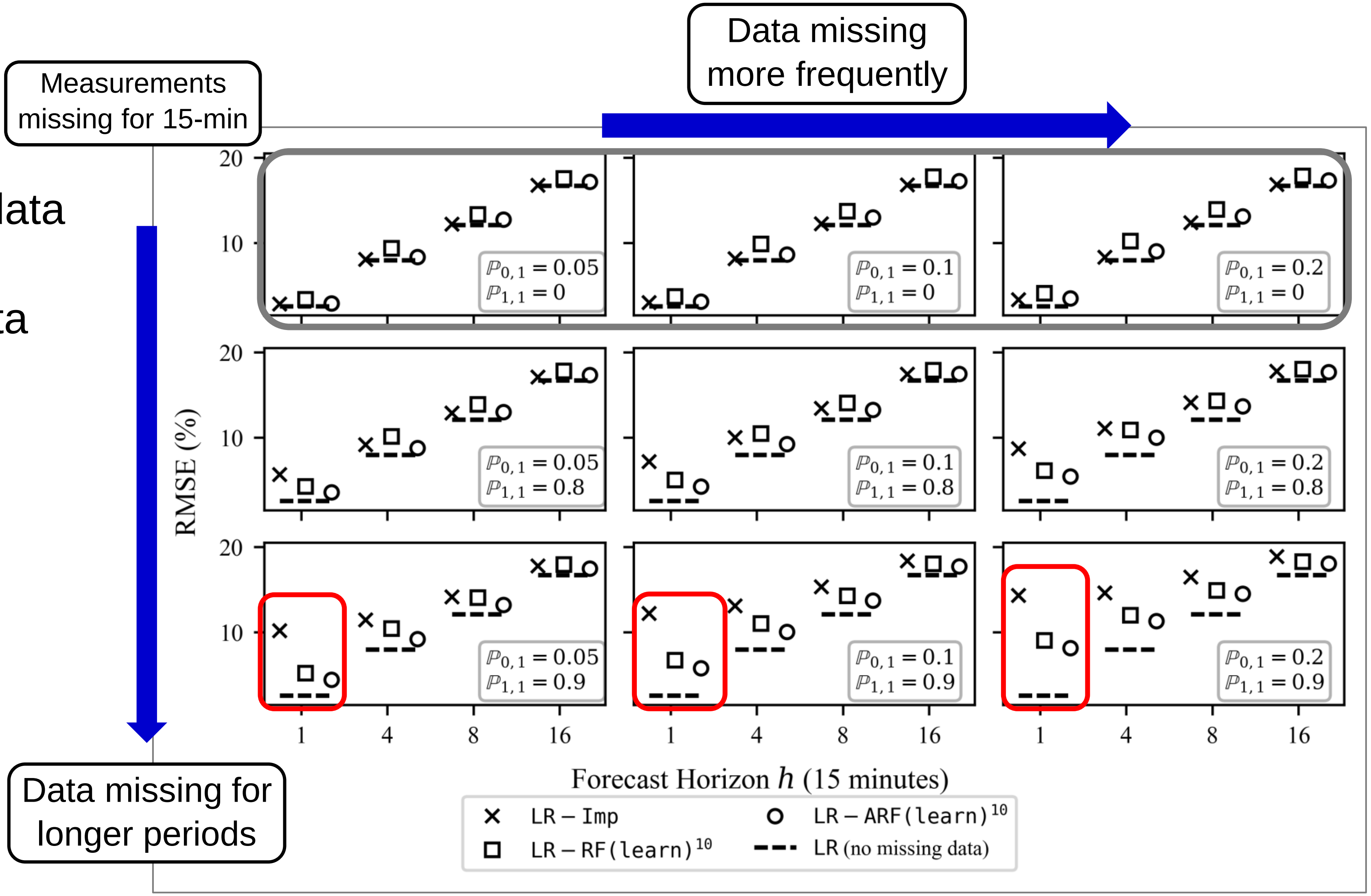


Forecasting with Missing Data

Numerical Experiments

Adaptive models are:

- On par with imputation when data are missing for short periods
- Around ~**20% better** when data are missing for longer periods
- Hedging against worst-case scenarios

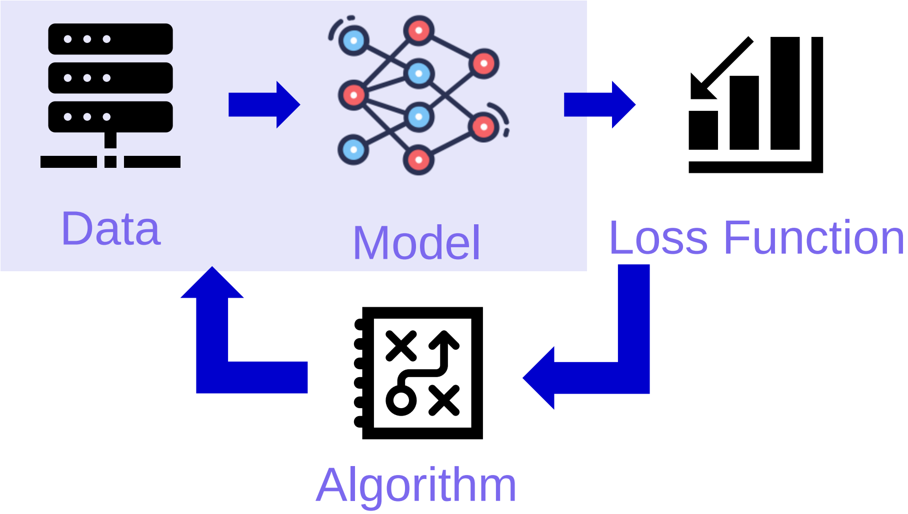


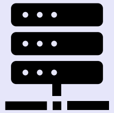
IMPERIAL

Application-driven Energy Forecasting

Accuracy-driven or Application-driven?

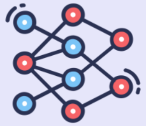
- The component of training an energy forecaster:





- Challenges: Uncertain renewable energy.
- New trend: Increased data size and heterogeneous source.

To boost the forecast accuracy

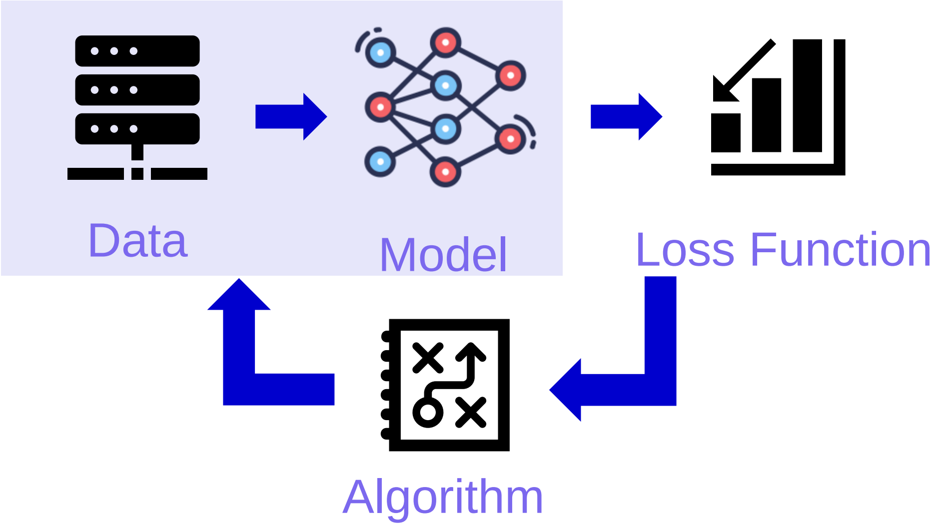


- Innovation on **model structure**: transformer, state-space model (MAMBA), etc.

Accuracy-driven

Accuracy-driven or Application-driven?

- The component of training an energy forecaster:

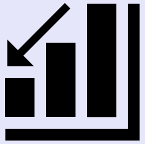


What else can we do?

As power system engineers, we know how the forecast will be used in the following activities, such as operation and control.

Accuracy of the forecaster → **Operation Cost of the Generator**

To boost the forecast value

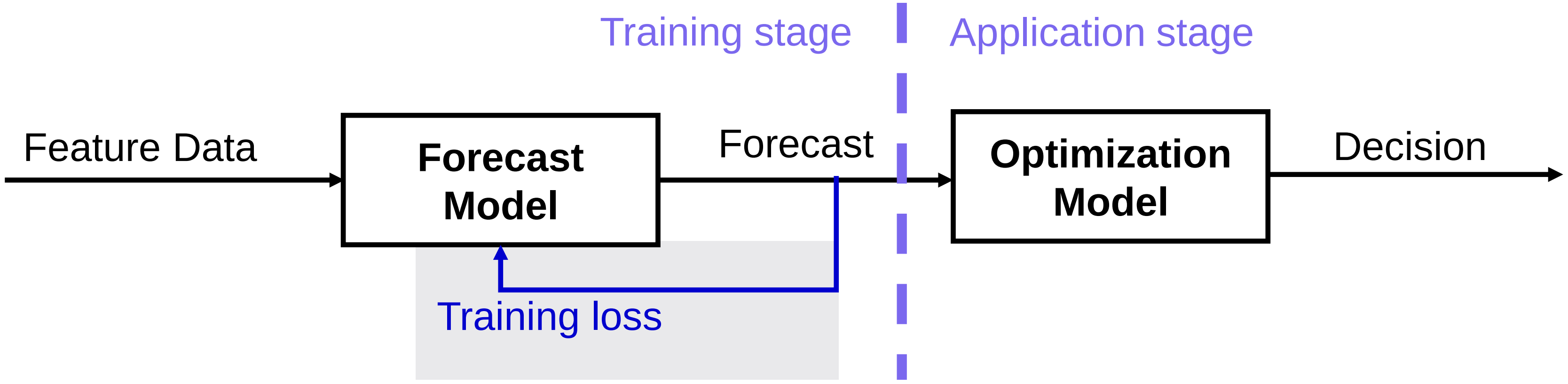


This allows us to design tailor-made "**loss function**" to better align with the power system decision making and operation cost.

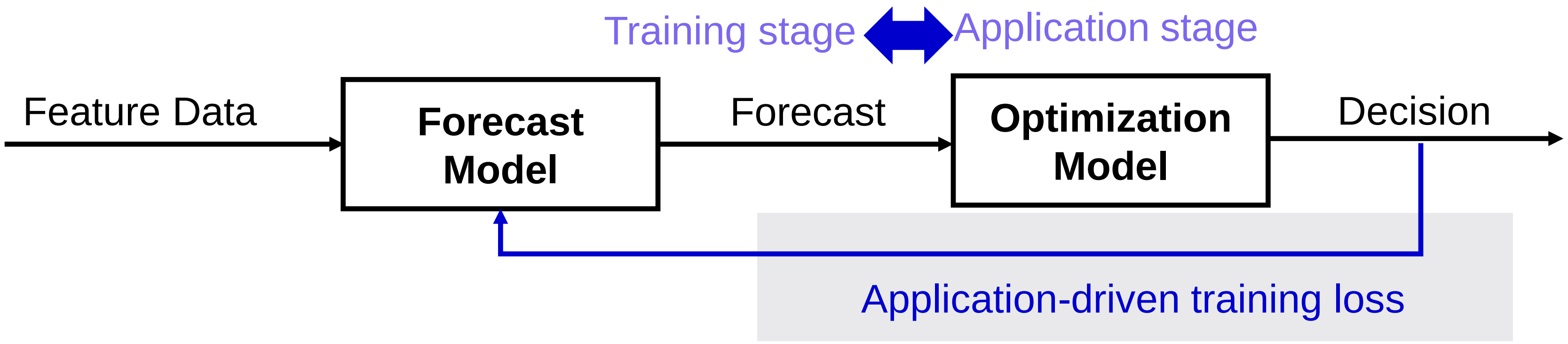
Application-driven Forecast

Accuracy-driven or Application-driven?

Accuracy-driven Forecast:



Application-driven Forecast:



“What You Train Is What You Get!”
For AI to make reliable decisions, the conditions it faces in reality must be faithfully reflected in its training.

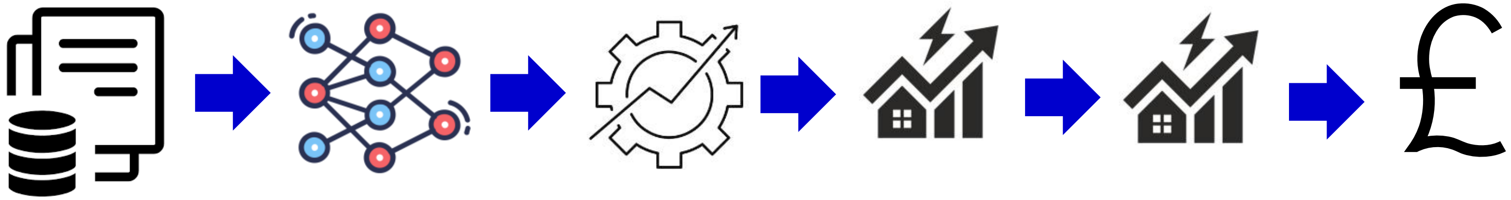
Related research:
[Technical Paper] **W. Xu and F. Teng** (2024). Task-aware machine unlearning and its application in load forecasting. *IEEE Transactions on Power Systems.*
[Technical Paper] **W. Xu**, J. Wang and **F. Teng** (2024). E2E-AT: A Unified Framework for Tackling Uncertainty in Task-Aware End-to-End Learning. *AAAI-24*.
[Review Paper] R. Li, H. Zhang, M. Sun, C. Wan, S. Pineda, G. Kariniotakis, **W. Xu, F. Teng** (2024). Decision-oriented learning for future power system decision-making under uncertainty. On Arxiv preprint.

Case Study

Centralized Power System Operations

- **System**: IEEE 5-generator 14-bus system with data in [1].
- **Forecast**: Integrated load and renewable at multiple locations.
- **Decision making**: Centralized power system operation including unit commitment (UC) and redispatch (RD).
- **Why this example?** It is a “Predict + Optimize” task.

[1] Lu, Jin, et al. "A Synthetic Texas Power System with Time-Series High-Resolution Weather-Dependent Spatio-Temporally Correlated Grid Profiles." *arXiv preprint arXiv:2302.13231* (2023). (https://rpglab.github.io/papers/JinLu-TX-123BT/)



Weather Forecast Data + Calendar → Energy Forecaster: NN → Forecast → UC → RD → Operation Cost

Performance

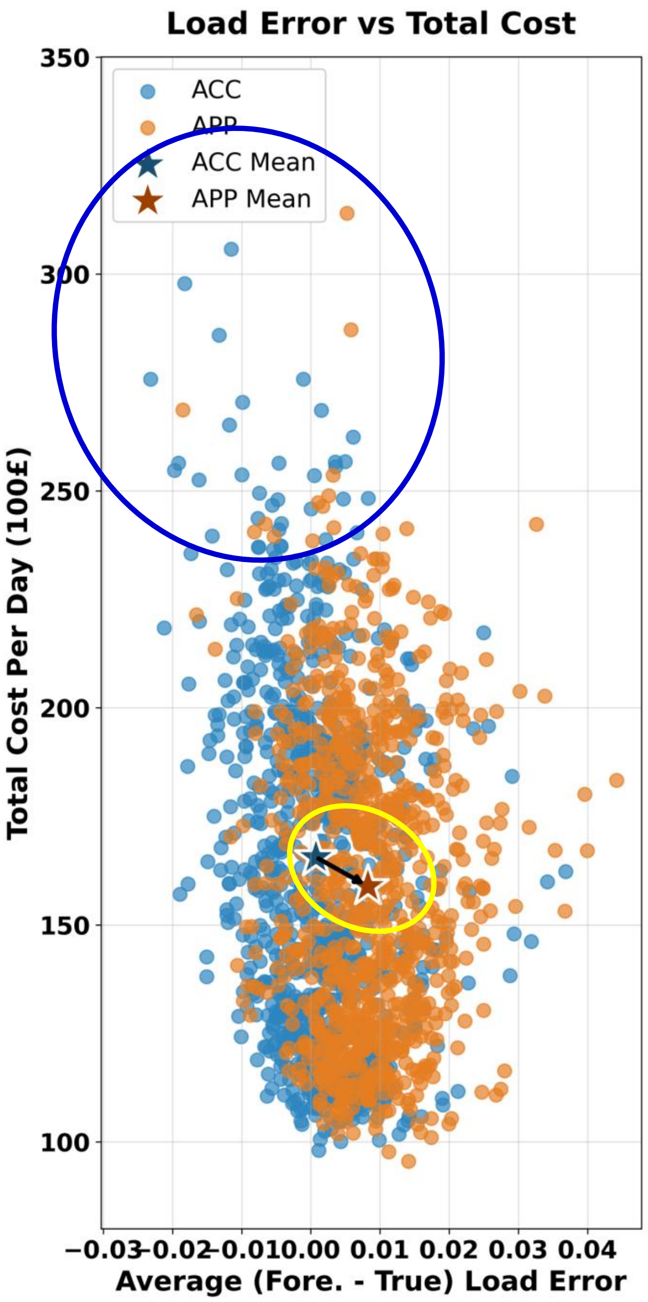
Neural Network-based Forecaster:

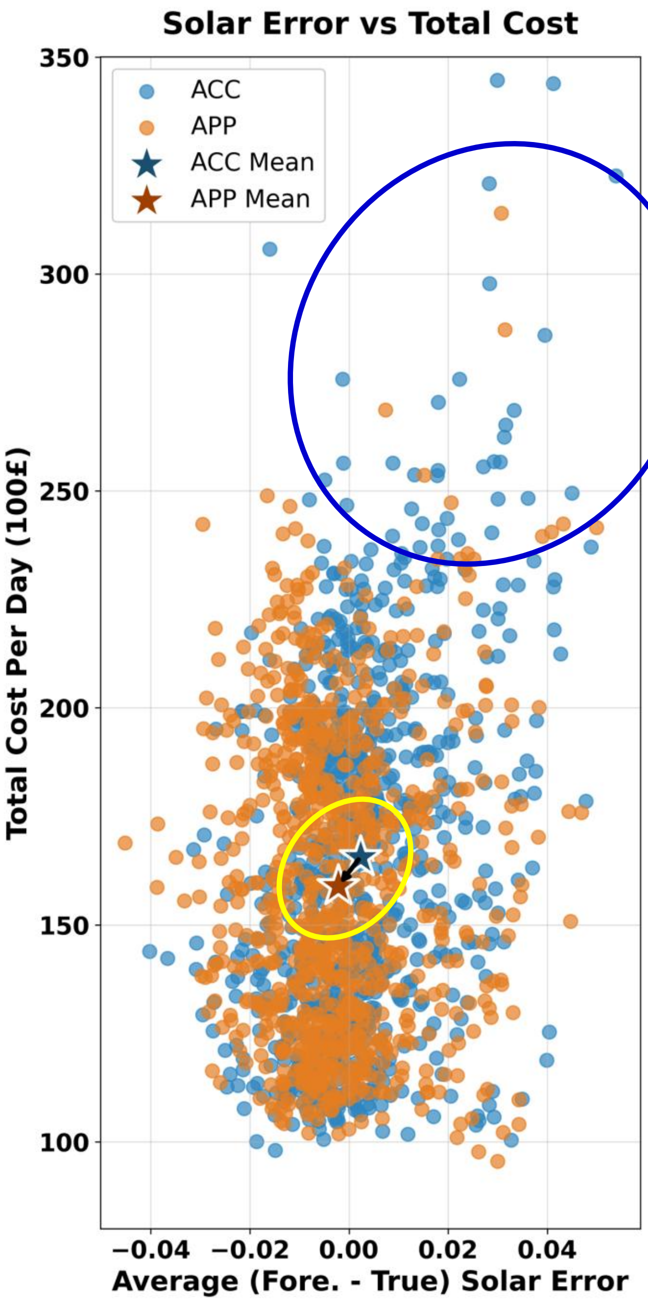
- Input size: [time steps(24), no_node(14), no_fearture(10)]
- Output size; [times steps(24), no_load(11)+no_renewable(4)]
- No of parameters: 16.7k
- Dataset of a year (8760 samples)
- Performance are averaged on test dataset
- [GitHub] https://github.com/xuwkk

	Load MAPE (%)	Renew. MAPE (%)	Cost (£/24h)
True Data	0	0	14052.17
ACC Forecast	4.33	15.80	16559.58
APP Forecast	5.50 (+1.17)	17.16 (+1.36)	**15892.45 (-4%)**

Observations:

- From **accuracy-driven forecast (blue)**, under/over forecast on load/renewable is more costly because the generator and reserve need to be rescheduled more frequently at real time.
- Therefore, **application-driven** forecast (orange) tends to over/under forecast load/renewable.
- There are more reasons to attain better operation cost, all governed by the optimization problems.





Conclusions and Ongoing Work

Seamlessly handling missing data:

- Model parameters adapt to available information
- No additional computations required operationally
- Hedging against worst-case scenarios

Thanks for listening!

Application-driven forecasting:

- Maximizing forecast value by integrating forecasting-optimization
- Does not change the downstream decision-making process, integrated within current pipelines

Ongoing work:

- Forecasting reliability constraints to improve market & operations (e.g., reserve deliverability)
- Extending the framework with control in the loop: Forecasting-Optimization-Control integration