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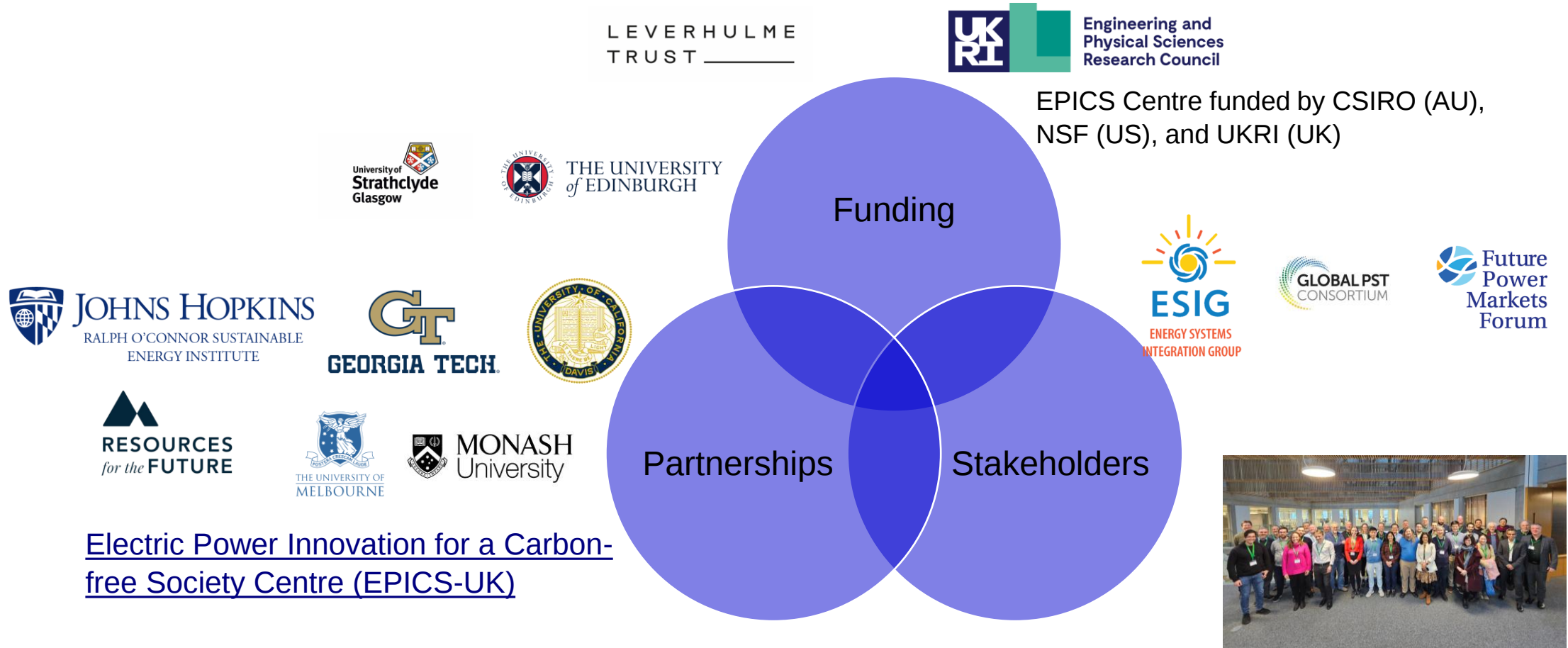
Energy Forecasting for Power System Operations

Resilient and Application-driven Forecasts

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Acknowledgements



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

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Search

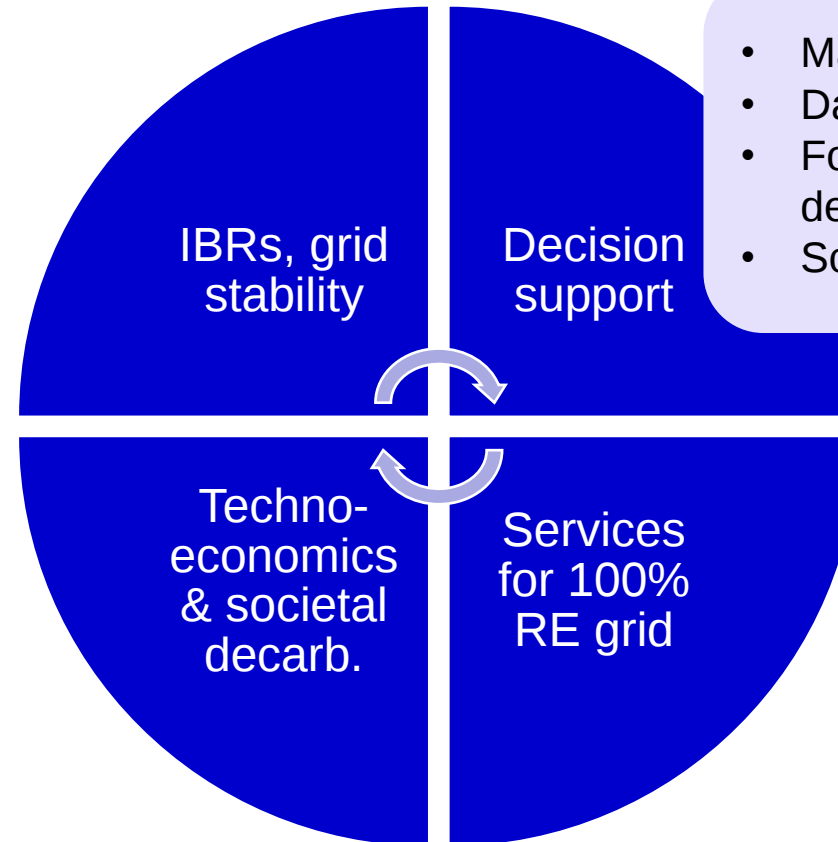


Menu

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

A part of the global centre pioneering the transition to an electricity grid powered entirely by renewable energy

→ [Find out more](#)



- 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:

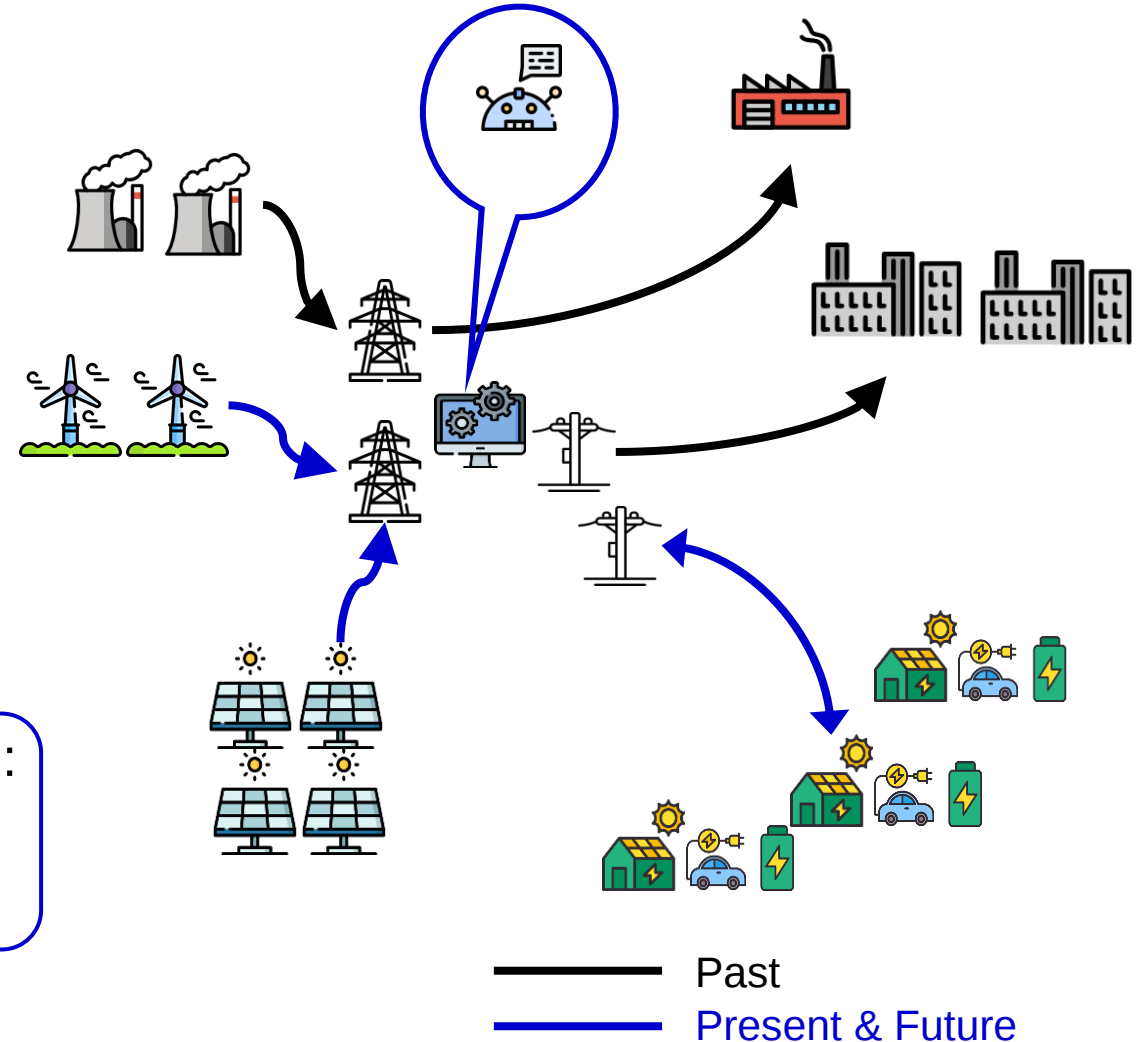
- Safe, reliable, and economic operations
- Awareness and risk-management
- Reserve and ramping requirements

Beyond accuracy:

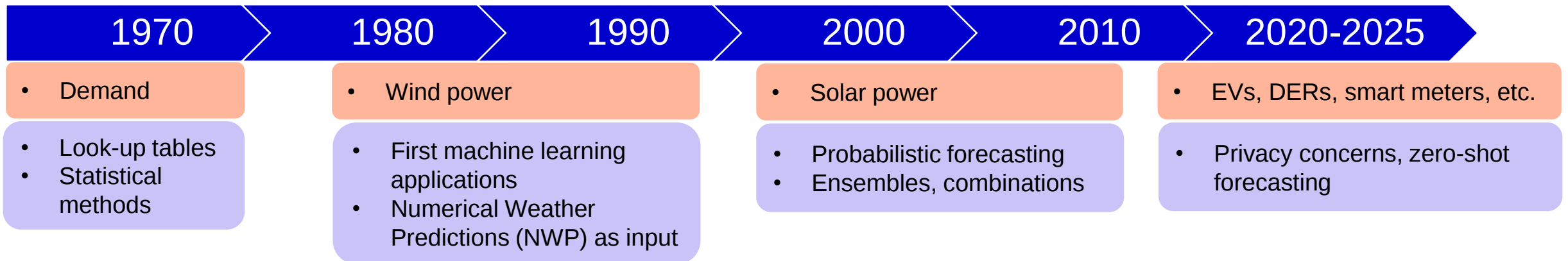
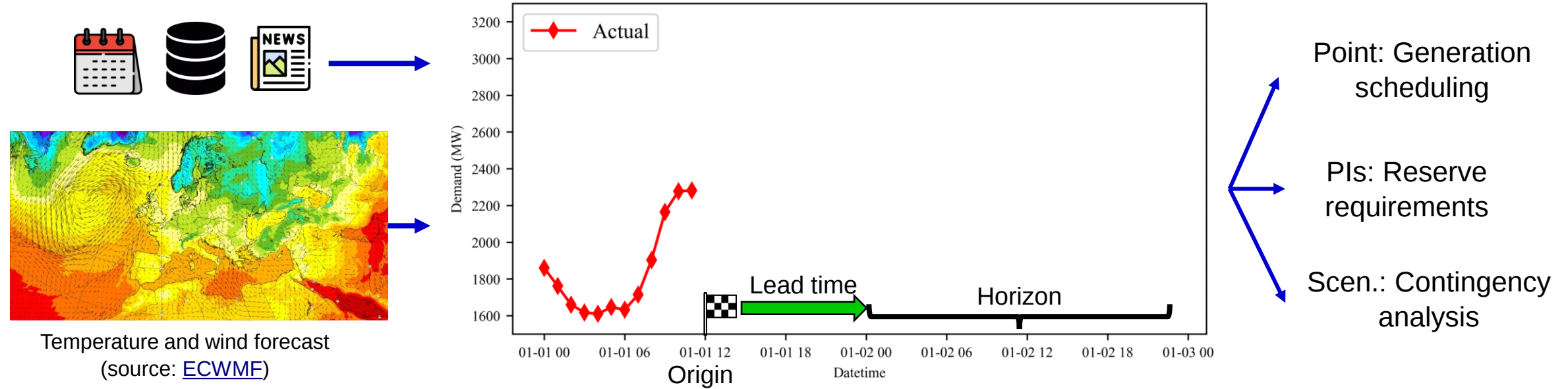
- Do our forecasts lead to better (safer, economical) actions?
- Can we trust our models under adversity?

Machine learning & traditional optimization to improve:

- **Resilience** to adversarial inputs
- **Forecast value** for downstream applications

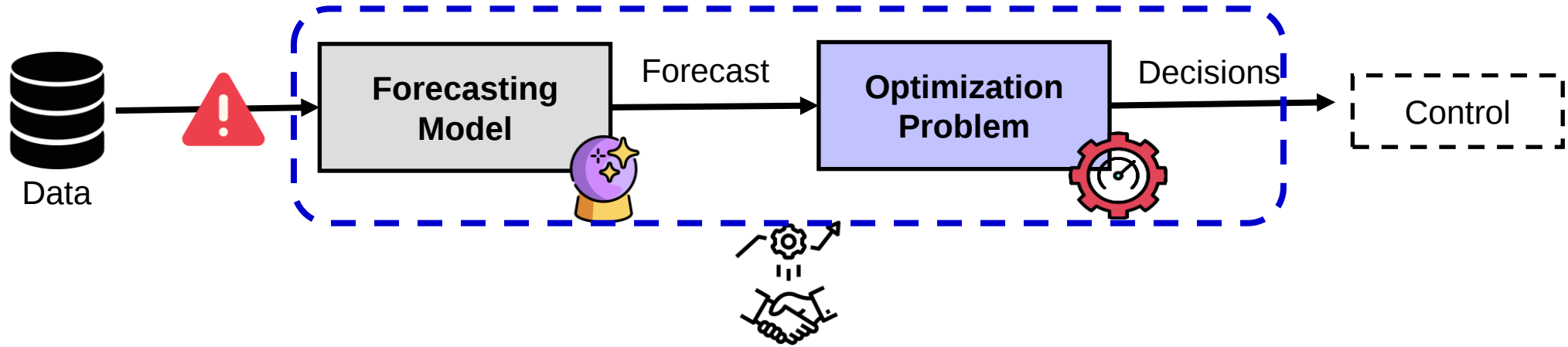


Energy Forecasting through the Years



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

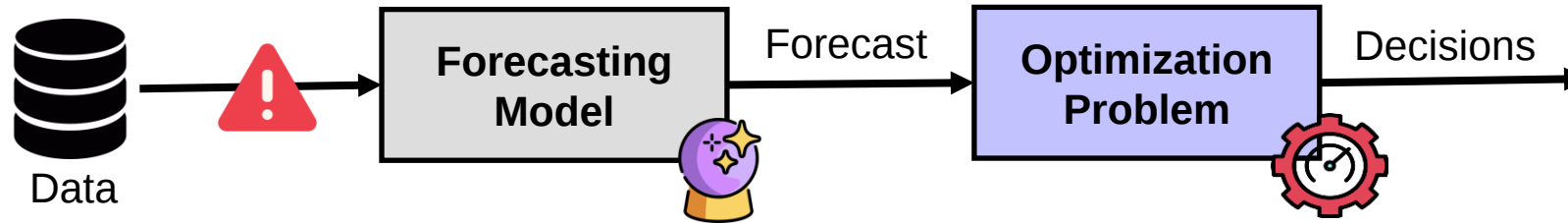


Application-driven forecasting for better decisions

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Forecasting with Missing Data during Real-time Operations

Missing Input Data during Real-time Operations



Forecasting models deployed and used operationally:

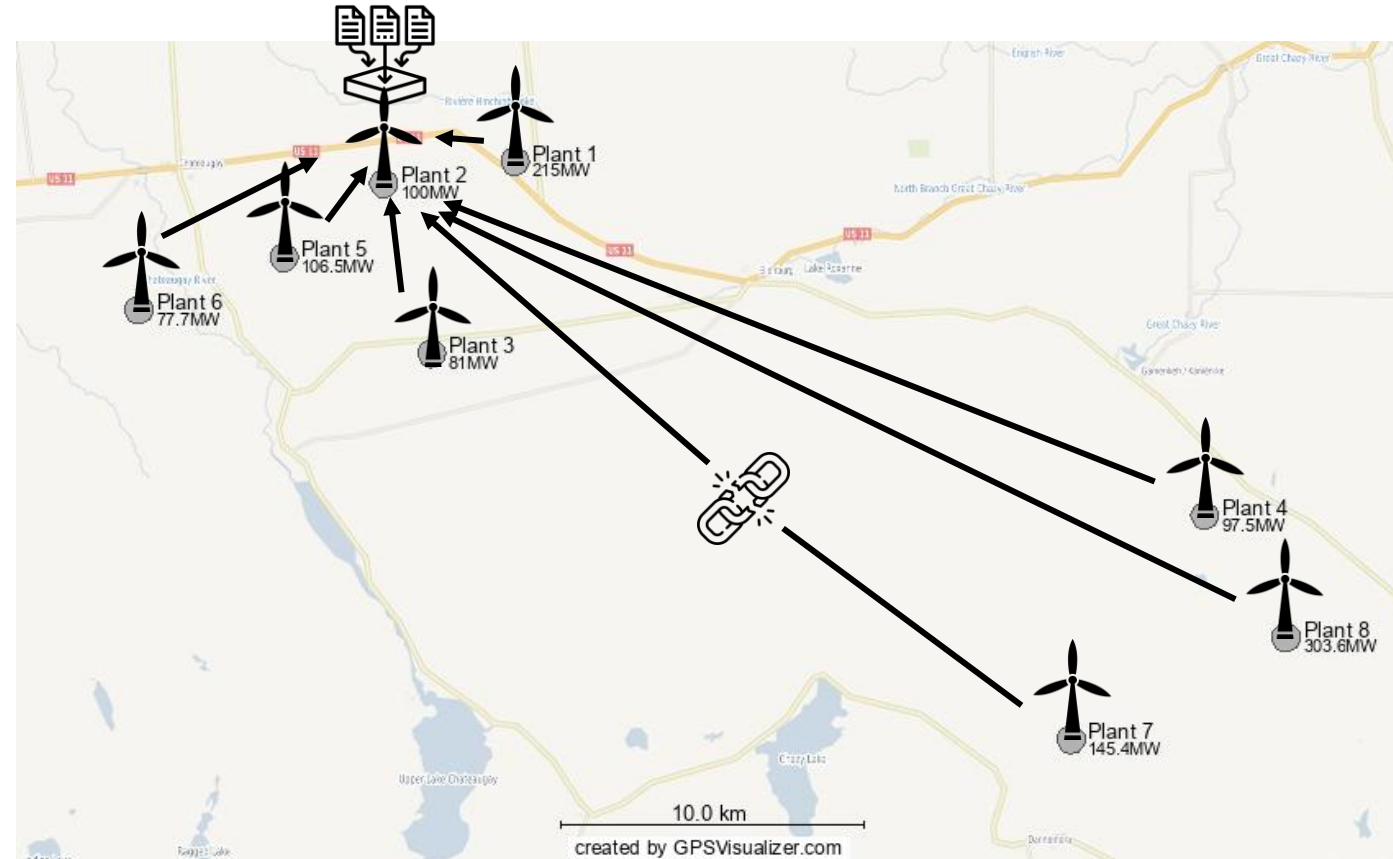
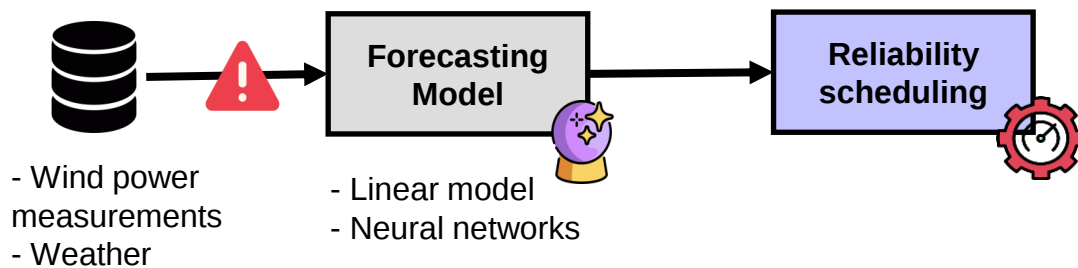
- Disruptions, equipment failures, cyberattacks leading to missing inputs
- EC survey: "... fewer than 40% of users reported that data were always there when needed."
- Forecast accuracy compromised → suboptimal downstream decisions

- 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, ...



[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

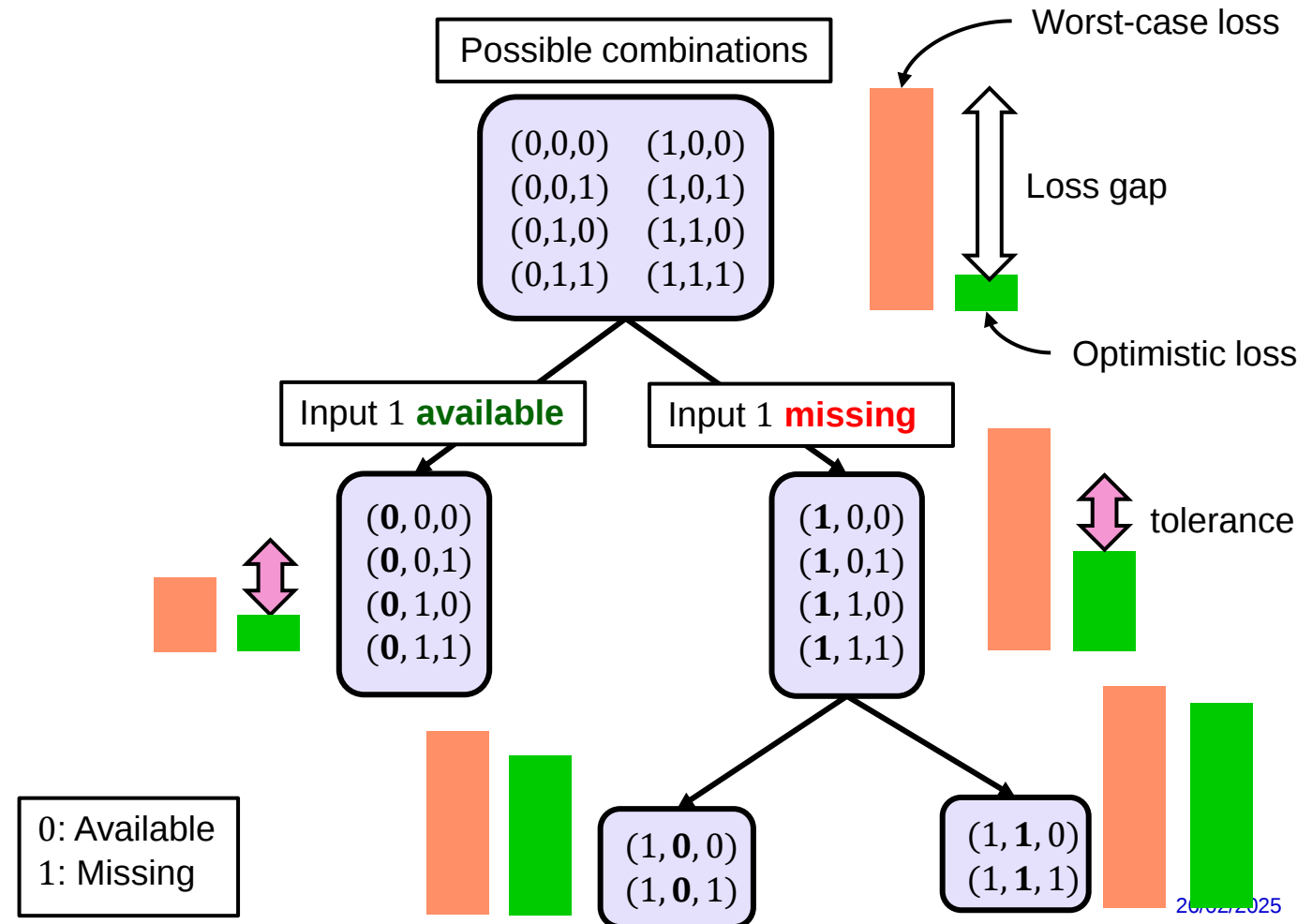
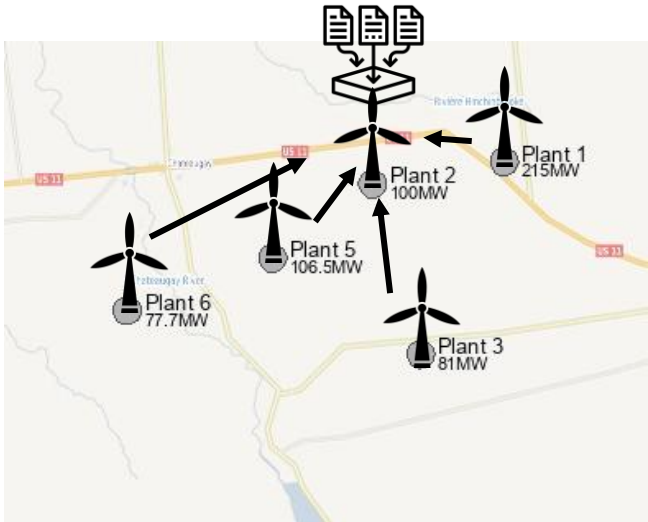


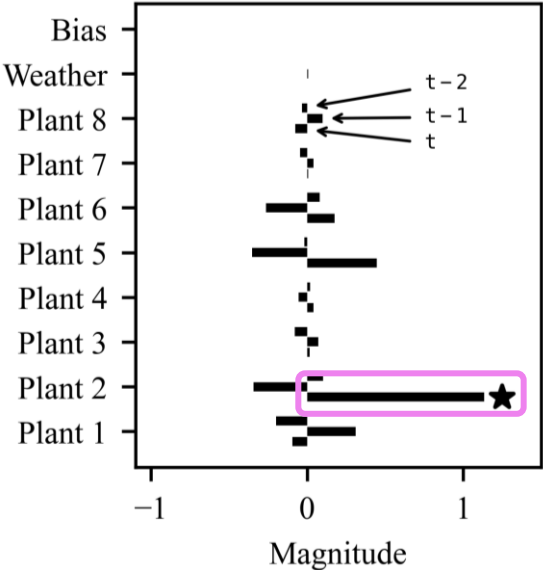
Illustration on Short-term Wind Power Forecasting

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

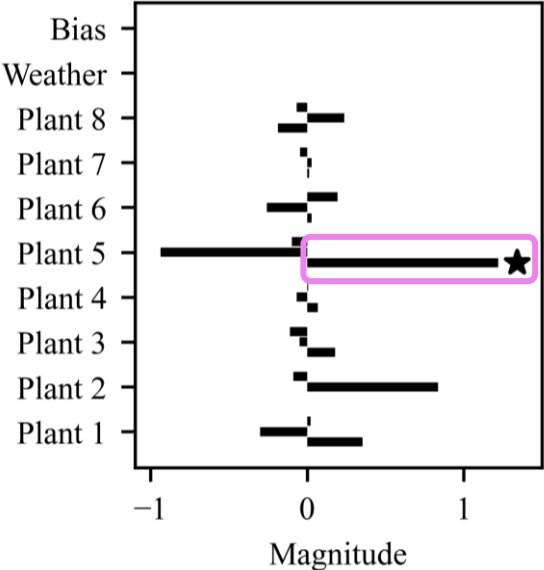


A closer look at the adjacent plants

Plant 2, period t
available



Plant 2, period t
missing

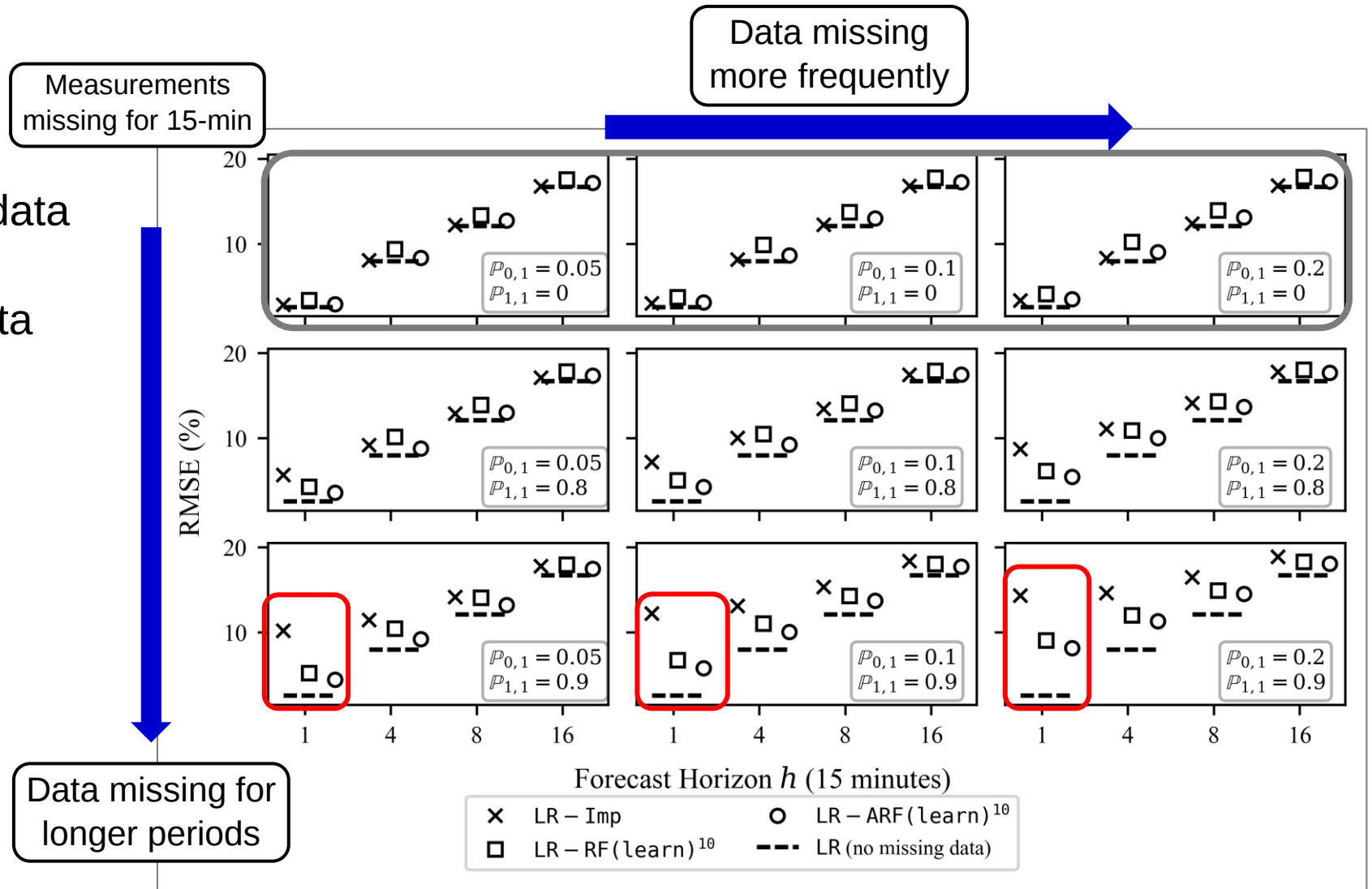


Forecasting with Missing Data

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

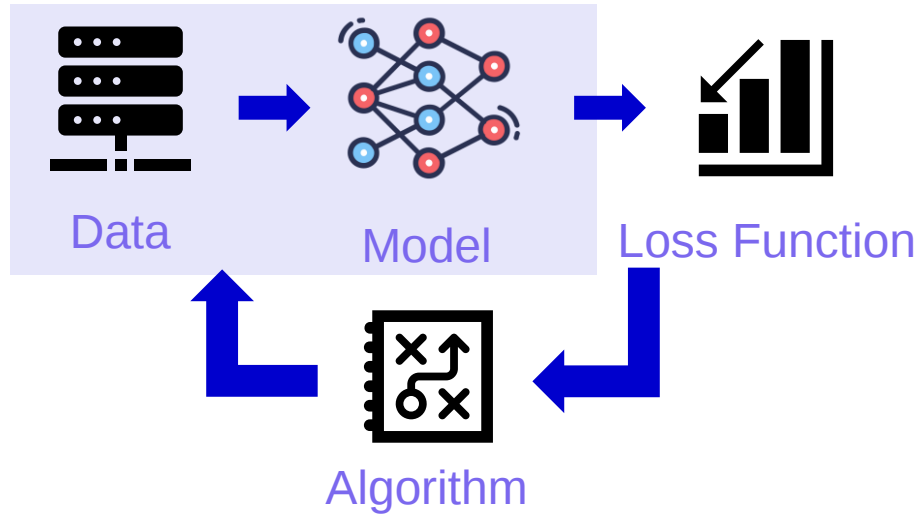


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Application-driven Energy Forecasting

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

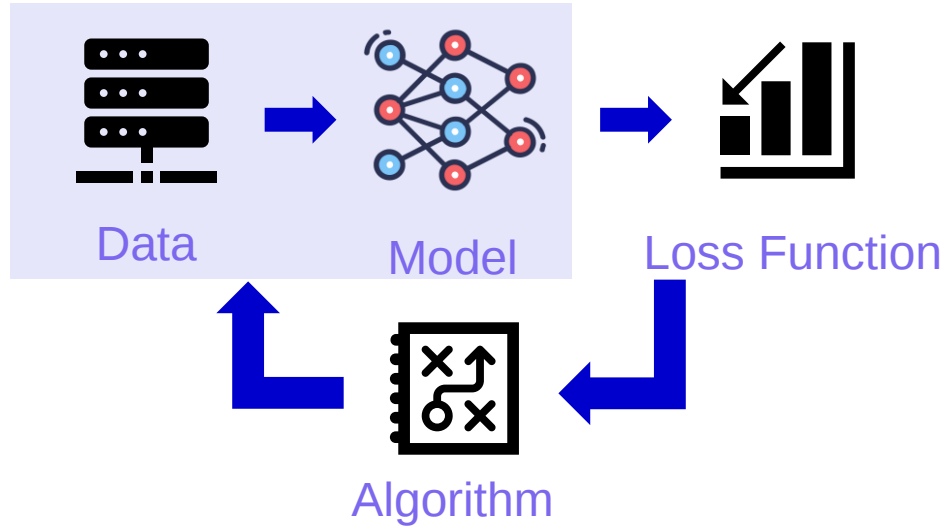


- Innovation on **model structure**: transformer, state-space model (MAMBA), etc.

Accuracy-driven

Accuracy-driven or Application-driven?

- The component of training an energy forecaster:



What else can we do?

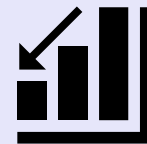


As power system engineers, we know how the forecast will be used in the following activities, such as **operation and control**.

Accuracy of the forecaster

Operation Cost of the Generator

To boost the forecast value

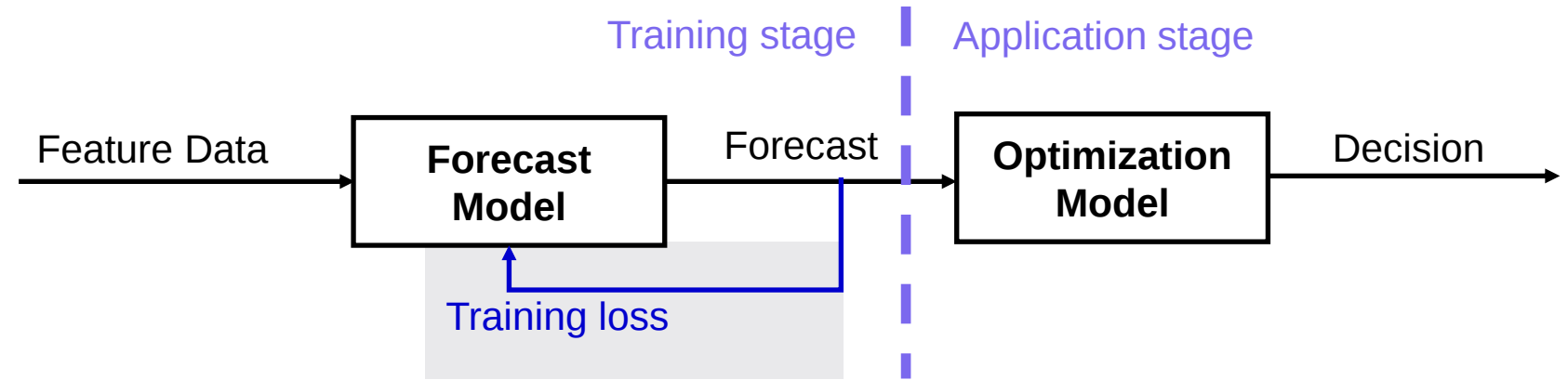


This allows us to design tailor-made “**loss function**” to better align with the power system decision making and operation cost.

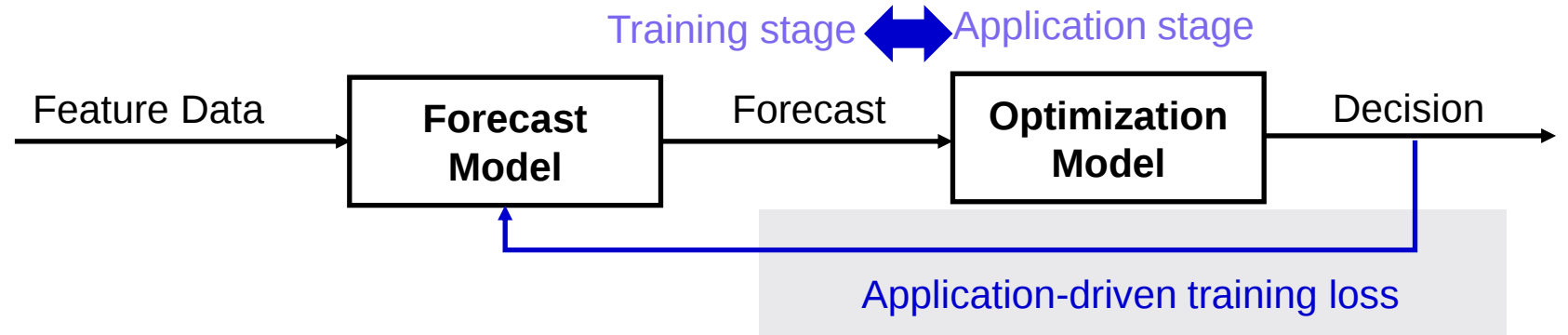
Application-driven Forecast

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.

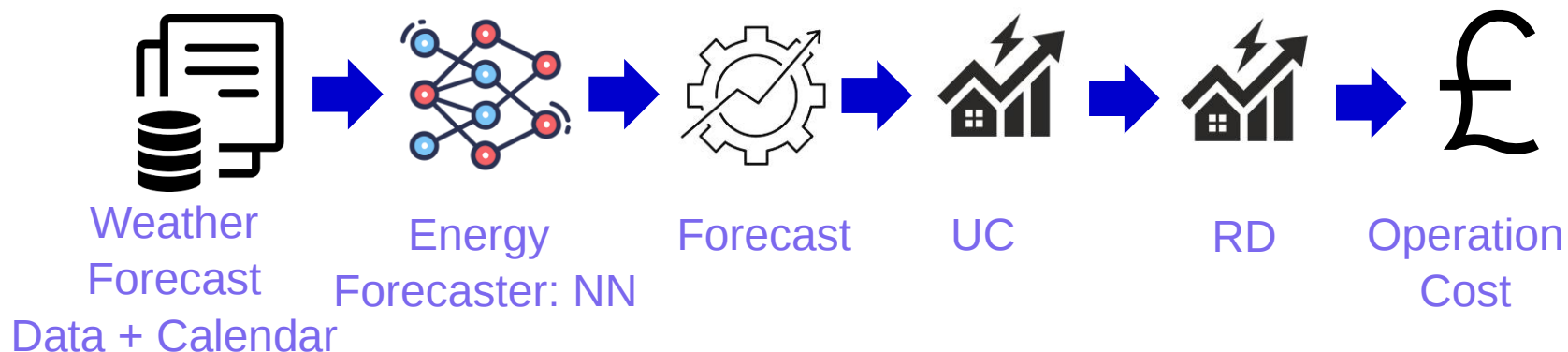
Case Study

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/>)



Performance

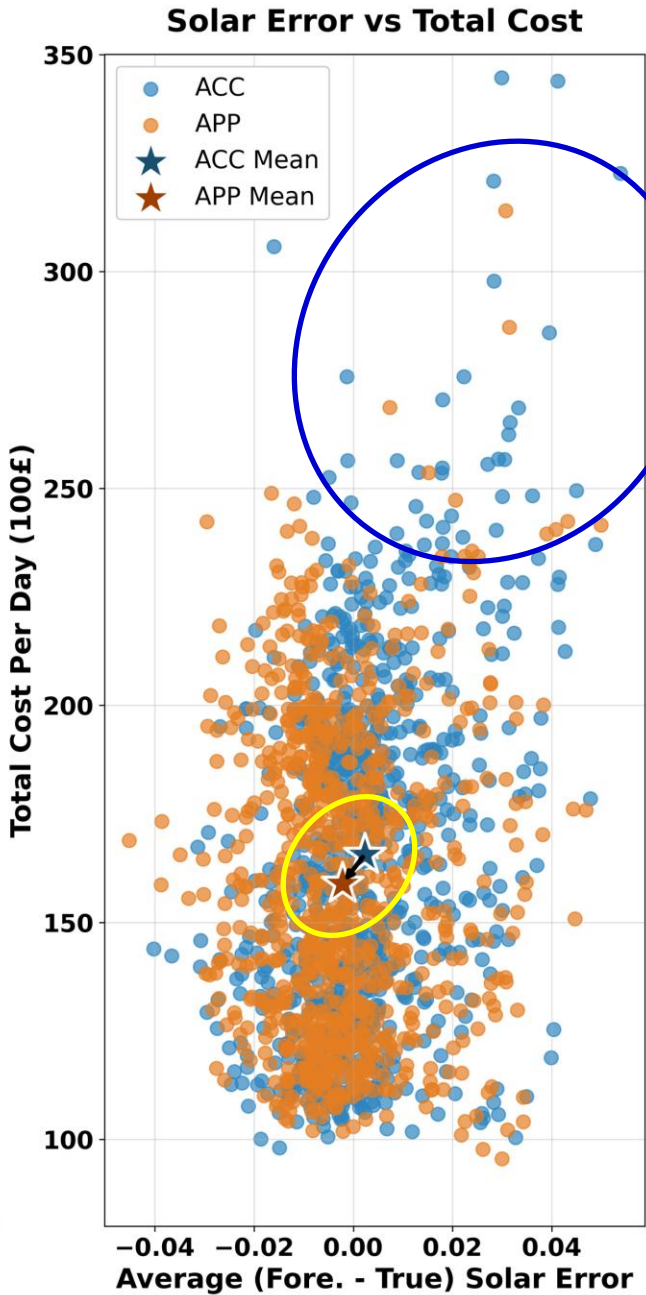
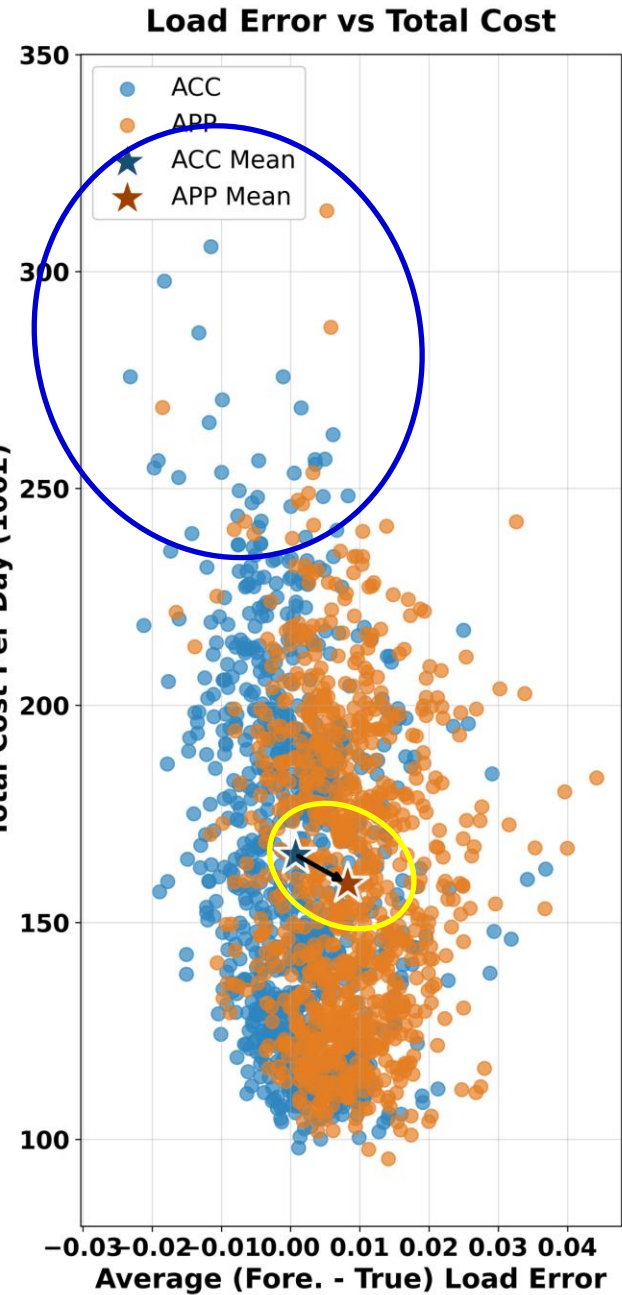
Neural Network-based Forecaster:

- 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

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

Thanks for
listening!