Probabilistic Energy Forecasting: Methodologies, Implementations, and Applications

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Probabilistic Energy Forecasting: Methodologies, Implementations, and Applications

Part 4: Using Probabilistic Forecasts: Tools and Industry Practice

Instructor: Dr Bri-Mathias Hodge

Learning objectives

By the end of this course, students should be able to:

Part 1

- Identify, list, and describe the different types of probabilistic forecast

Part 2

- Use a range of metrics and visualizations to evaluate probabilistic forecasts

Part 3

- Describe the processes and data required to produce probabilistic wind and solar power forecasts, electricity price forecasts, and electric load forecasts

Part 4

- List contemporary statistical and machine learning methods used in probabilistic forecasting, their characteristics and available software implementations
- Describe how probabilistic energy forecasting is used in power systems operation, control, and market participation

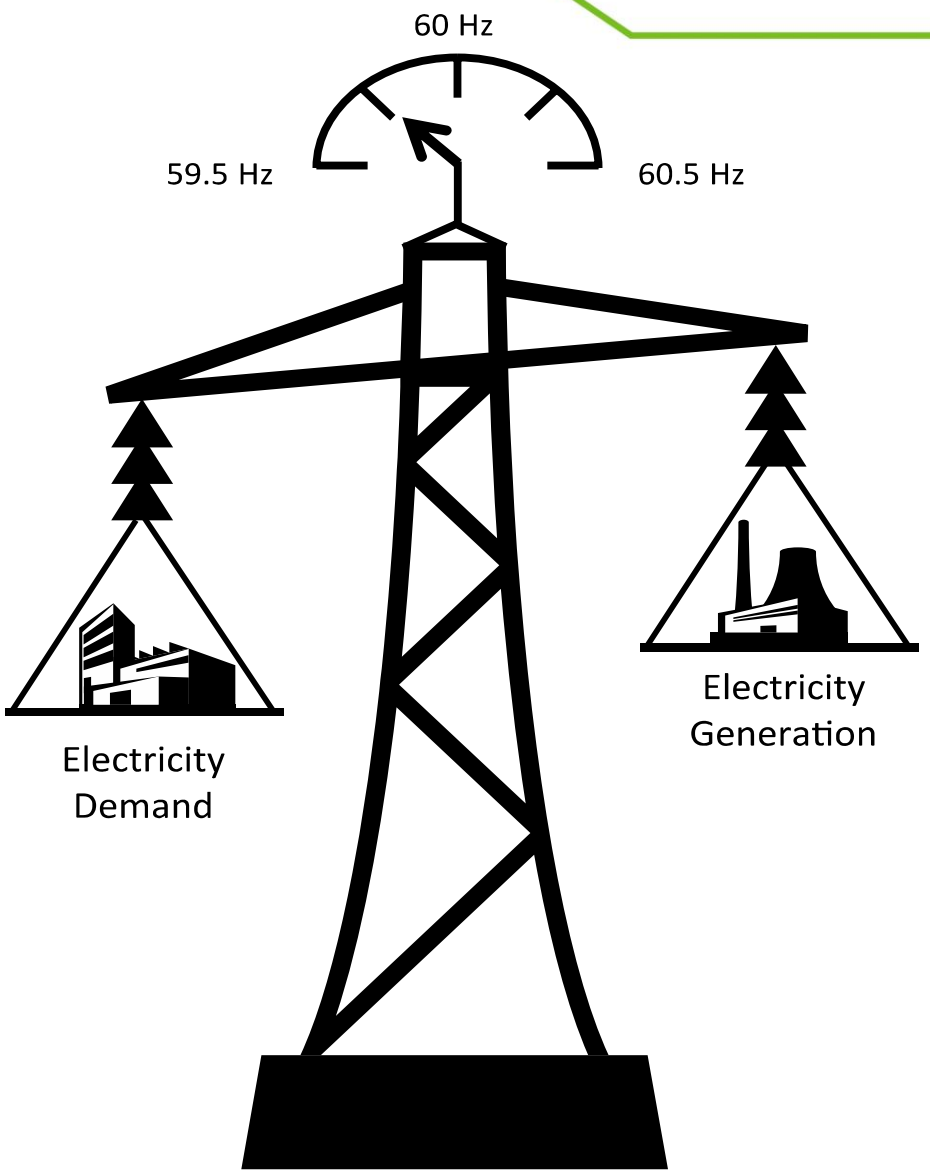
Motivation and principles

Power System Operations

Power System Objectives

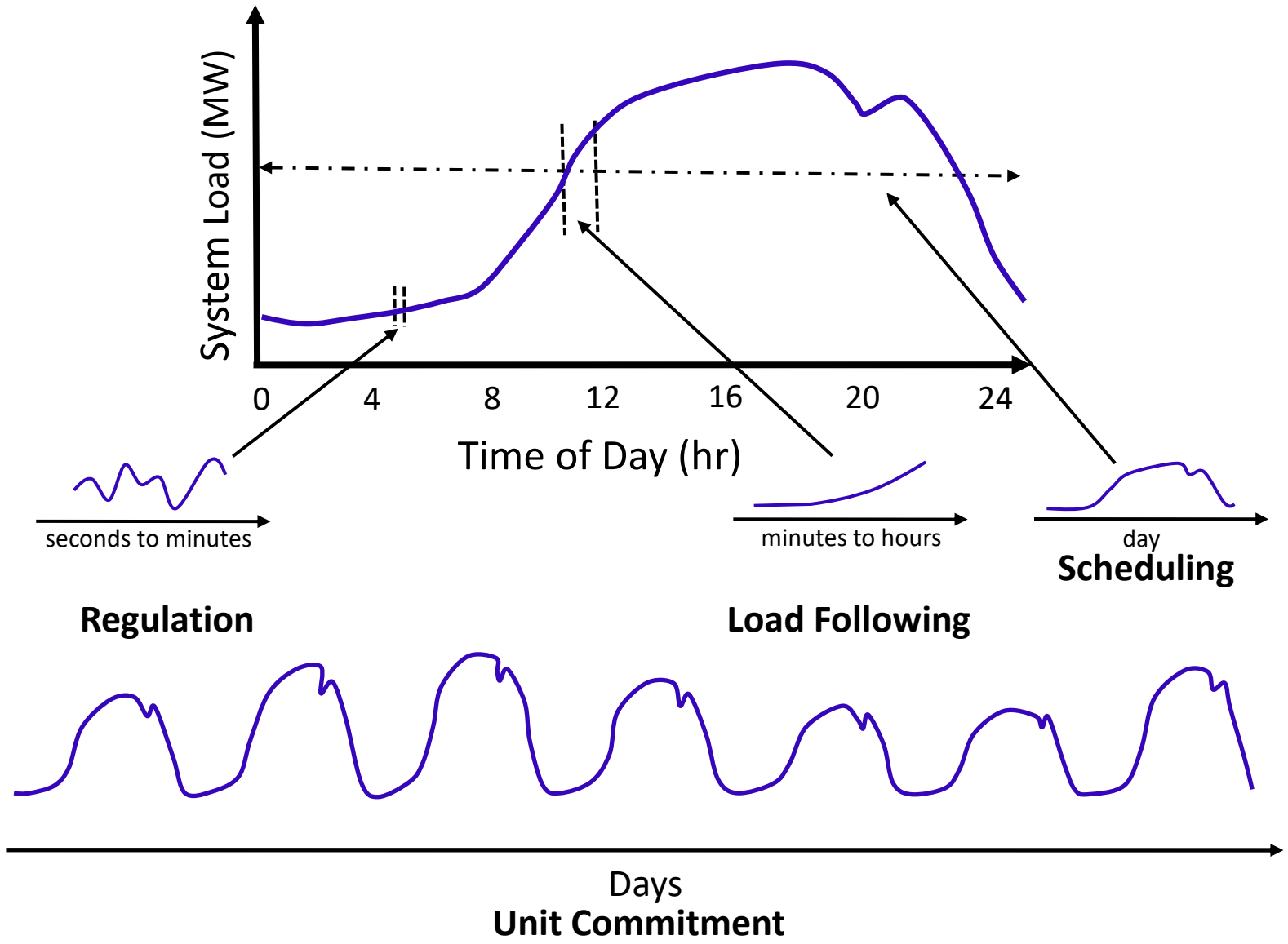
- ***Supply electric power to customers***
  - Reliably
  - Economically

- Consumption and production must be ***balanced <u>continuously</u> and <u>instantaneously</u>***



Adapted from: B. Kirby

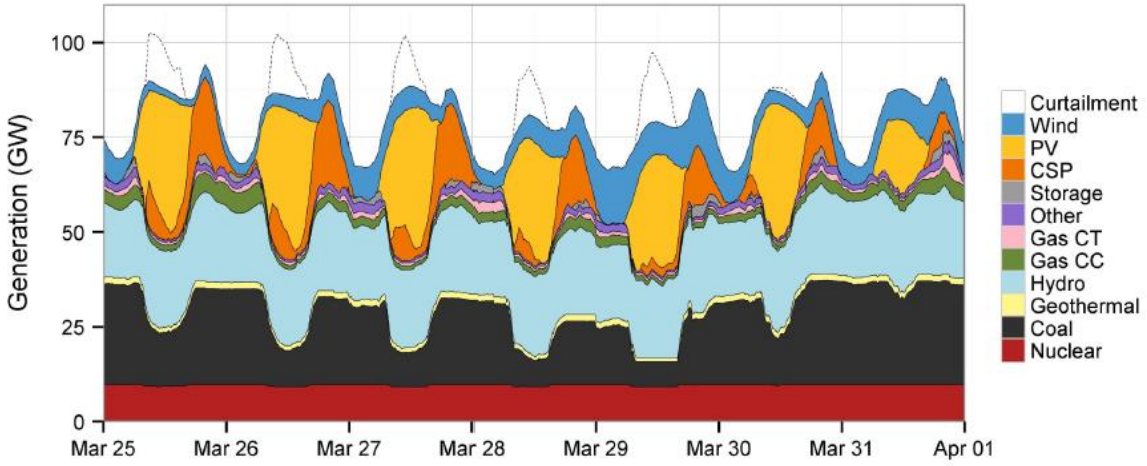
Power System Operations Timescales



Unit Commitment

Scheduling Large Power Plants – Part 1

- Some thermal units take a long time to start up, so need to tell them a day (or more) in advance if they will be on
- Use forecasted load to schedule the generation mix
- Optimization problem, minimize cost of serving expected load, usually MILP
- Results of the optimization are what units are on the next day, and at what levels they generate

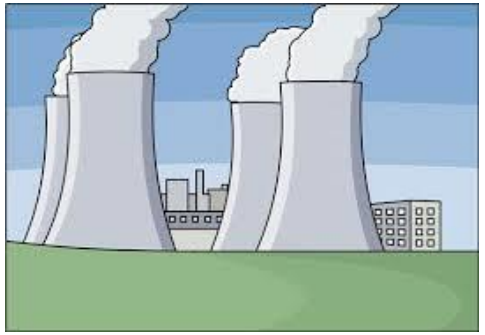


Solar is 60% PV and 40% Concentrating Solar Power with 6 hours thermal storage

Unit Commitment

Scheduling Large Power Plants – Part 2

- Constraints to ensure a feasible solution: generator minimum up/down times, ramping limits, minimum generation levels, transmission constraints, etc.



- Security constrained unit commitment ensures feasible power flows during (n-1) contingencies
- Usually co-optimize energy and ancillary services (reserves)

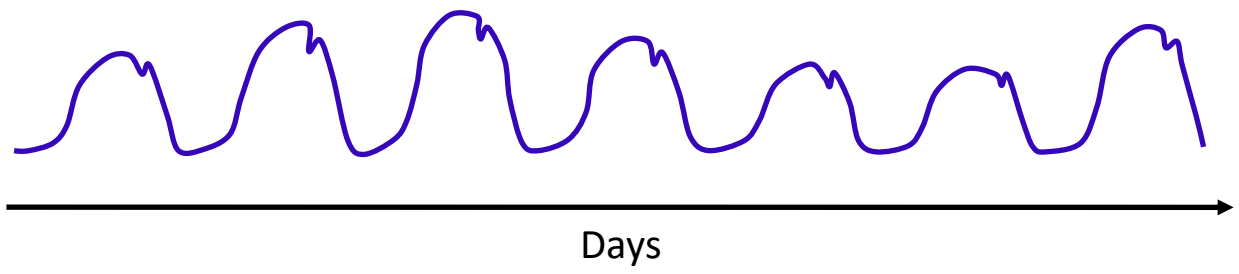
Economic Dispatch

Adjusting the Schedule with New Information

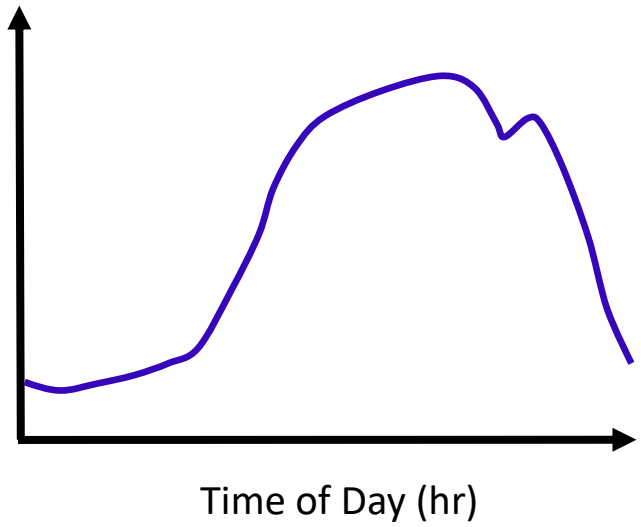
- Closer to the operating hour perform a “true-up” with better forecasts
- Can change output levels of units that are on (within ramping constraints) but only start up and shut down really fast units
- Also an optimization problem
  - LP if no start up shut down
  - MILP with fast start units

How do System Operators use Forecasts?

- **Long-term forecasts (1 week+)**
  - Estimates of “typical” generation used for resource and O&M planning



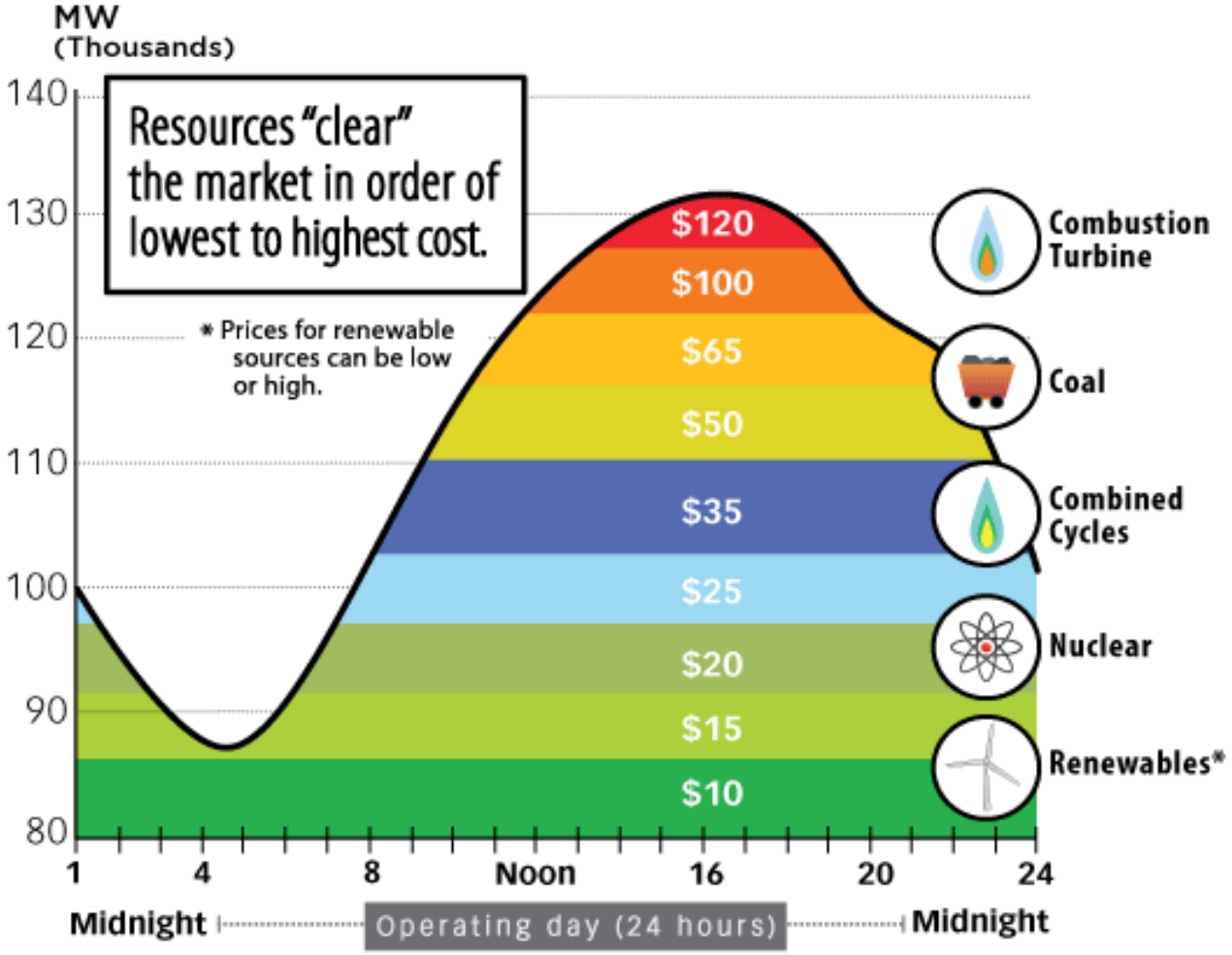
- **Day-ahead unit commitment**
  - Day-ahead forecast, along with uncertainty band, is fed into scheduling and market decisions



- **Intra-day adjustments**
  - Meteorologist flags changes to real-time traders
  - Reconfigure peaking plant schedules

Dispatch Stacks

Determining the Marginal Generator and Costs

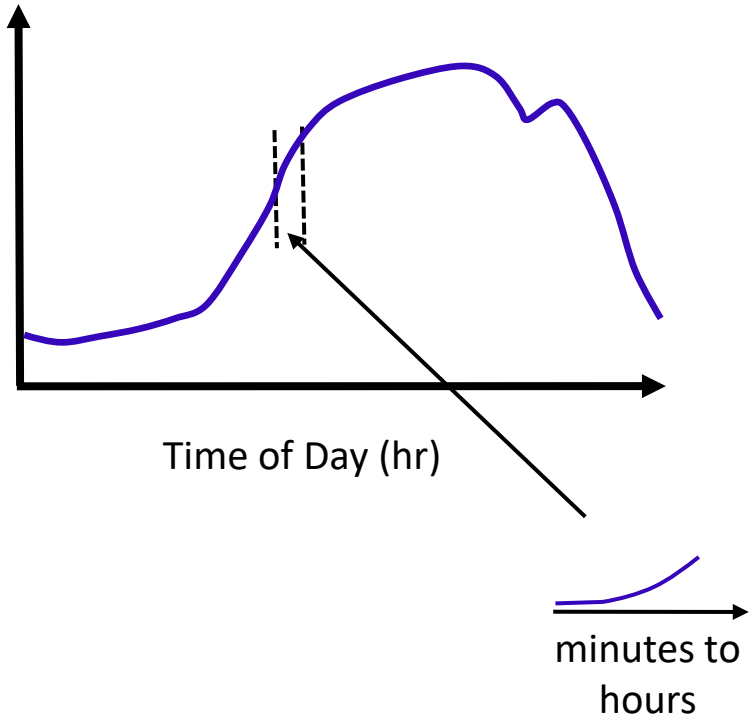


Source: PJM

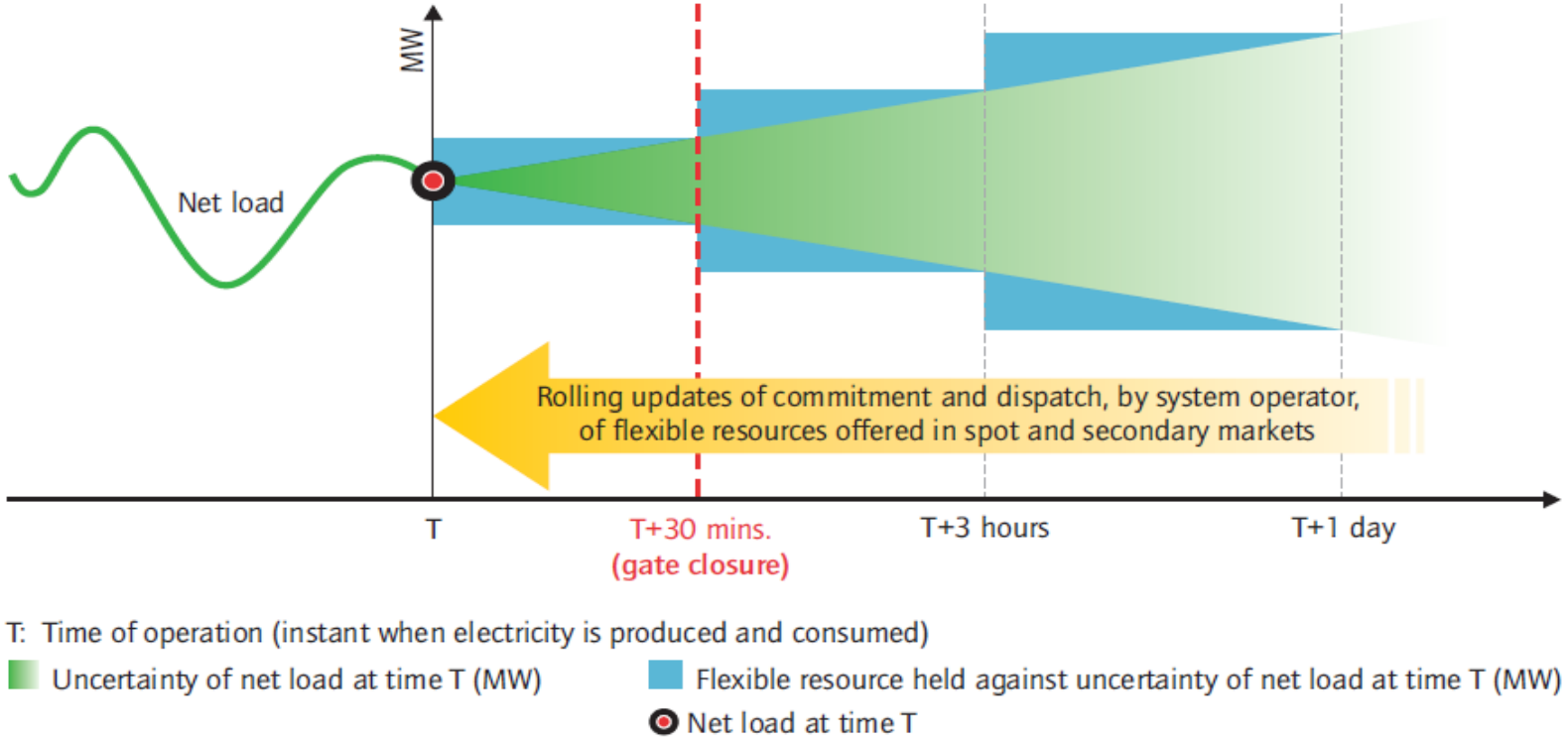
How do System Operators use Forecasts?

- **Hour-ahead scheduling and trading**
  - Meteorologist provides high/low uncertainty band
  - Use revised forecasts to optimize resources, markets, transmission; trading with neighbors

- **Intra-hour dispatch**
  - Value of forecast shifts to control room
  - Operators move other generators up/down in response to fluctuations
  - Assess reserves
    - Are reserves sufficient to last until next dispatch interval?
    - Can we handle ramps?
    - Are peaking resources needed?



More Frequent Decisions Reduce Uncertainty



While more frequent forecasts provide greater accuracy, they are only useful to the system operator up to the timeframe in which actions can be taken in response to the forecast.

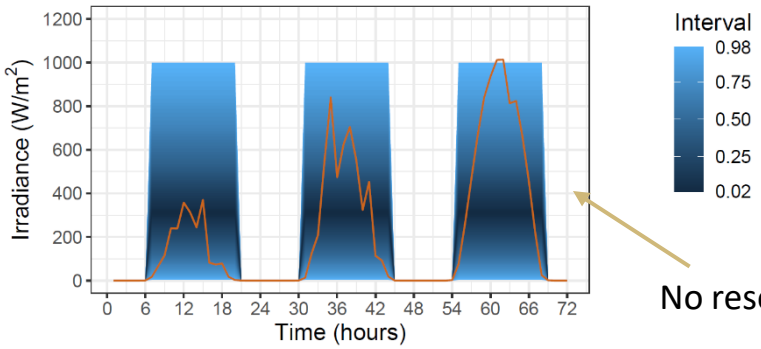
Source: Harnessing Variable Renewables – A Guide to the Balancing Challenge, International Energy Agency, 2011

Probabilistic Forecasting Use Cases

What does a user want out of forecasts?

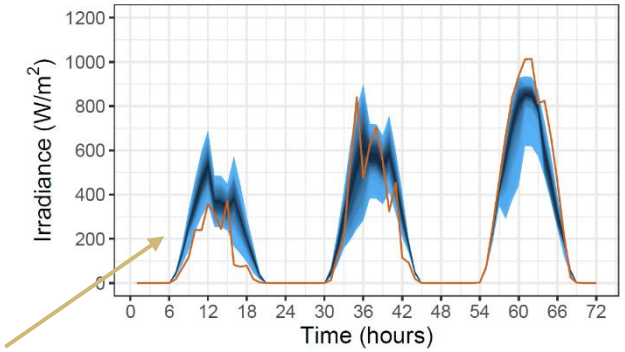
Baseline Forecasts

Climatology



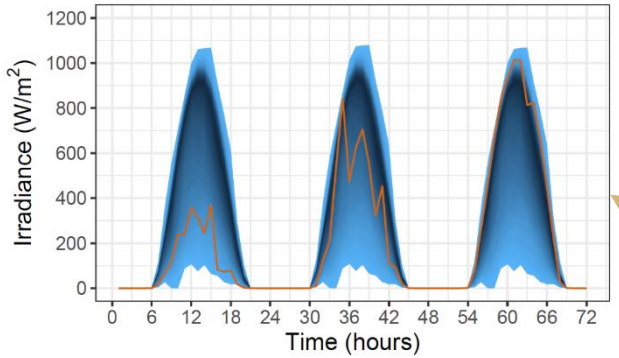
No resolution

Raw NWP Ensemble

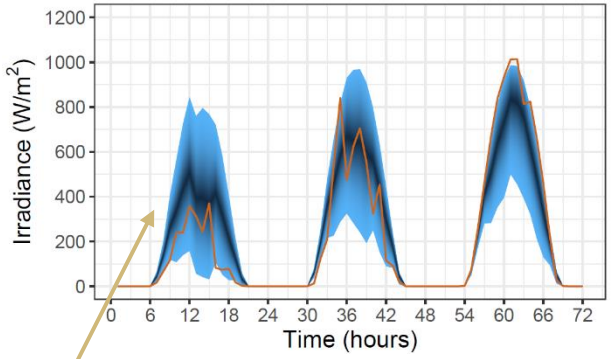


Very sharp, unreliable

Complete-History Persistence Ensemble



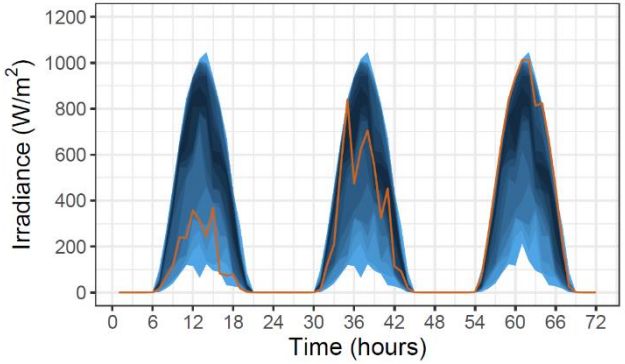
Gaussian Error Distribution



Basic diurnal resolution

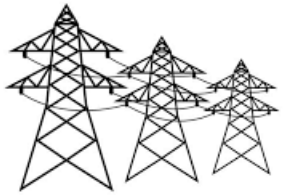
Intermediate sharpness

20-day Persistence Ensemble

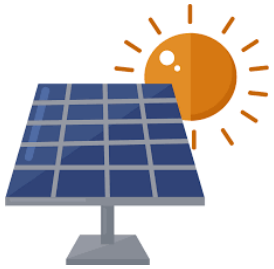


Different Users

Different Uses and Needs



- System Operators:
  - Aggregate Forecasts
  - Risk of needing additional generation or curtailment



- Plant Owner/Operator
  - Plant level forecast
  - Additional information with which to bid, or risk of non-compliance with bids

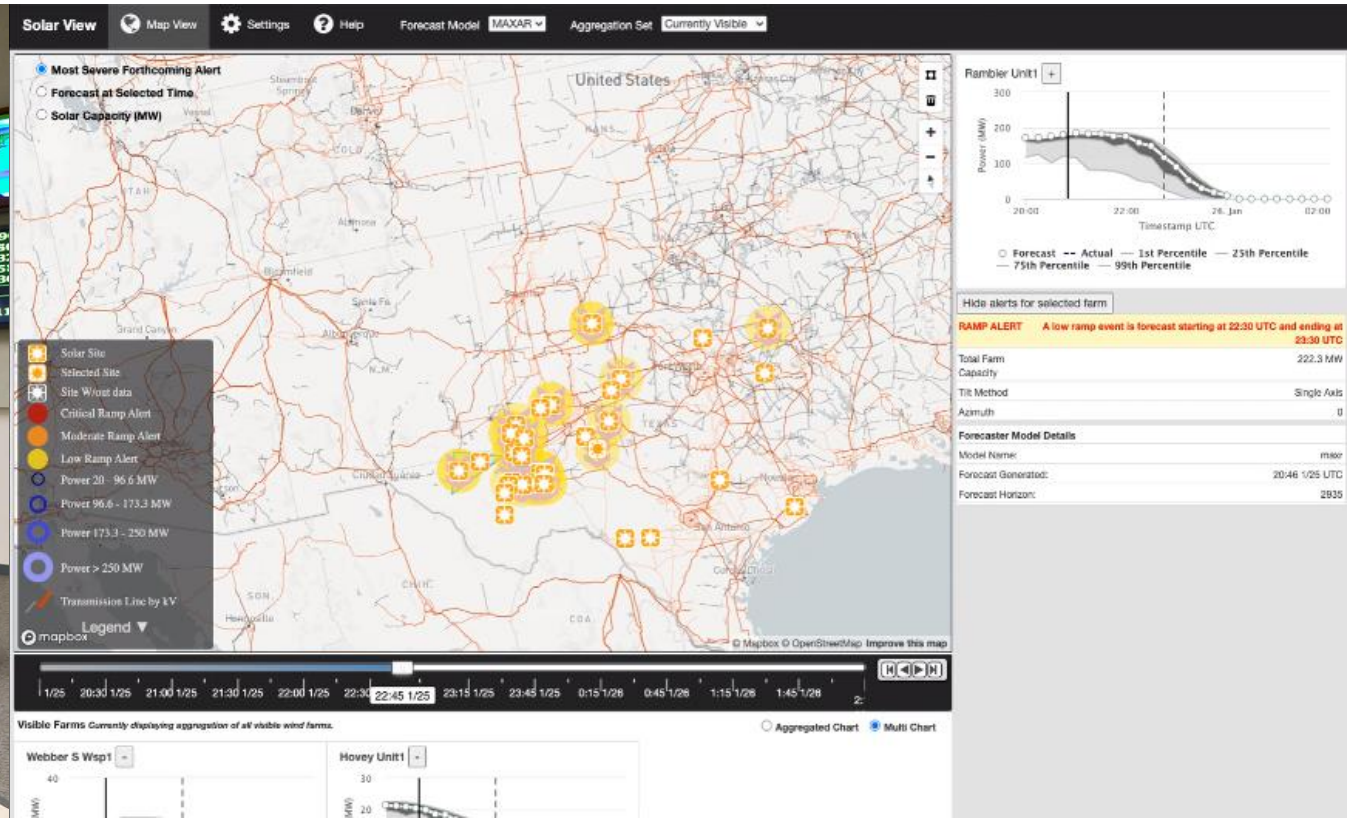
Traders
  - Generally aggregate forecasts, perhaps individual plant forecasts
  - More focus on rare events?

Situational Awareness

Understanding Uncertainty to Inform Actions

What is Situational Awareness?

Providing the Operator with Additional Information for Decision Support



Source: CNET, ISO-NE

Example System

Small Power System – 3 Generators – Point Forecast

- Load: 60 MW

Should I turn on Diesel 2?

- Wind: Point Forecast: 12 MW, Max Capacity: 120 MW

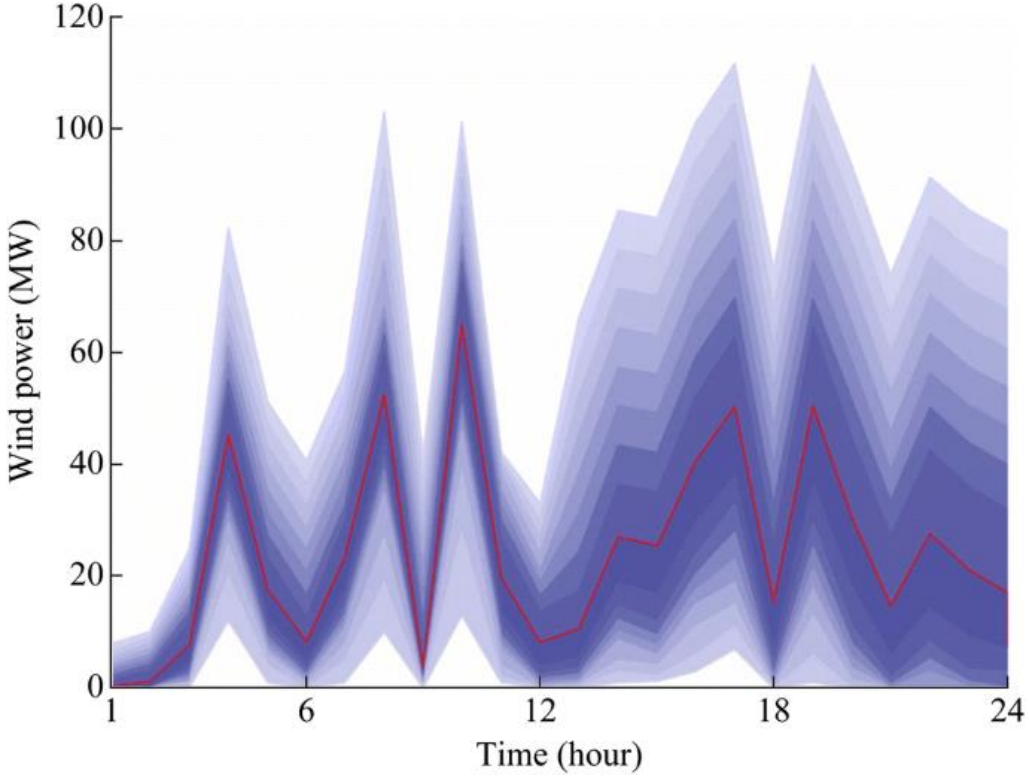
- Diesel 1: Max Capacity: 50 MW

- Diesel 2: Max Capacity: 10 MW

Wind Power Forecast Representation

Same System: Point Forecast at 12 PM = 12 MW

Given this information, should I turn on Diesel 2?



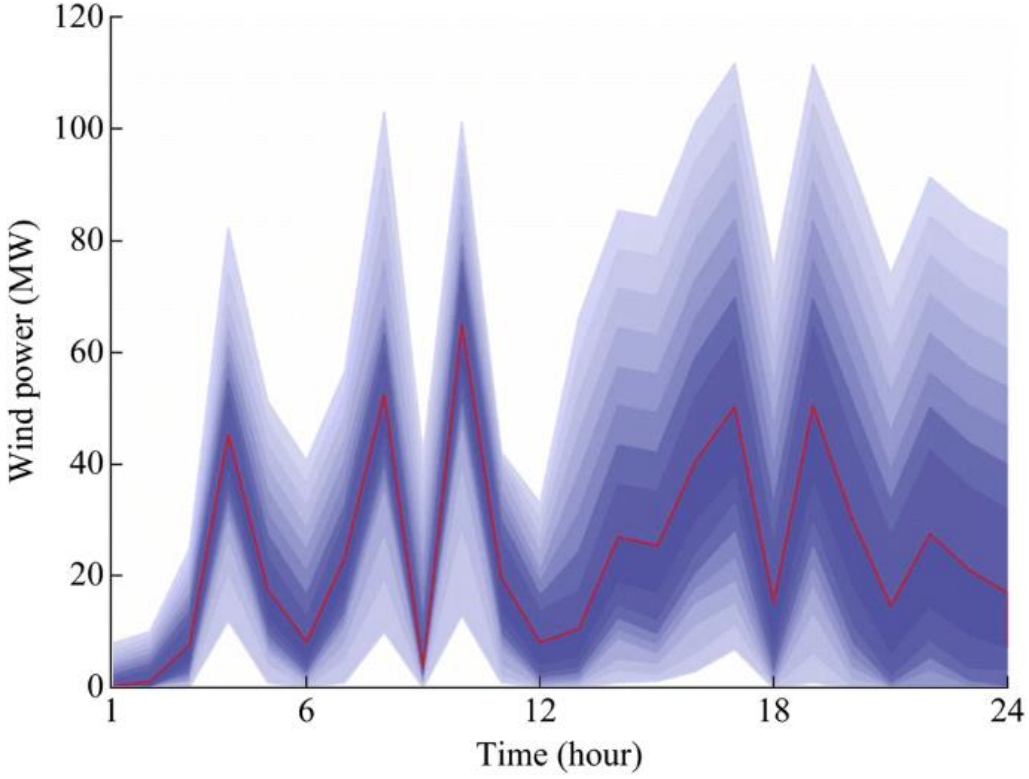
- Wind Probability of Exceedance at 12 PM:
  - 95%: 2 MW
  - 80%: 5 MW
  - 60%: 10 MW
  - 50%: 12 MW

Source: Yuan et al., Irregular Distribution of Wind Power Prediction, 2019

Wind Power Forecast Representation

Same System Conditions: Point Forecast at 17:00 = 45 MW

Given this information, should I turn on Diesel 2?



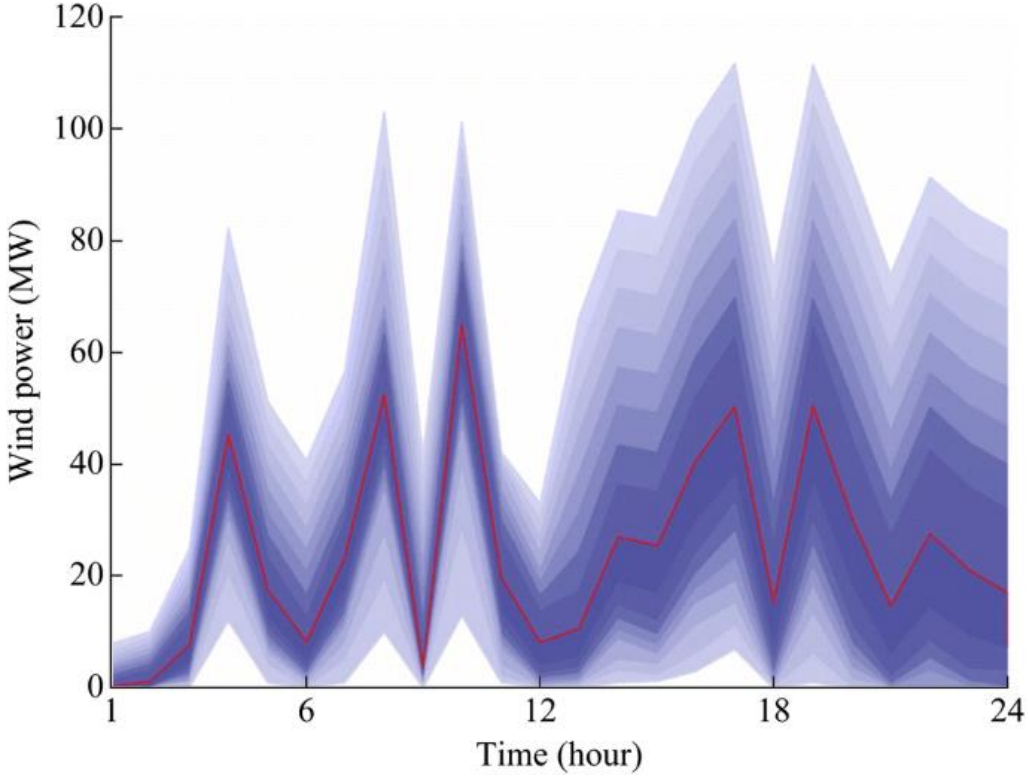
- Wind Probability of Exceedance at 17:00:
  - 99%: 8 MW
  - 95%: 18 MW
  - 90%: 25 MW
  - 80%: 30 MW
  - 50%: 45 MW

Source: Yuan et al., Irregular Distribution of Wind Power Prediction, 2019

Wind Power Forecast Representation

Same System Conditions: Point Forecast at 17:00 = 45 MW

Given this information, should I turn on Diesel 2?



- How would your answer change given the downramp predicted at 18:00?
  - Forecasting errors are not just in magnitude, but often also encounter phase errors

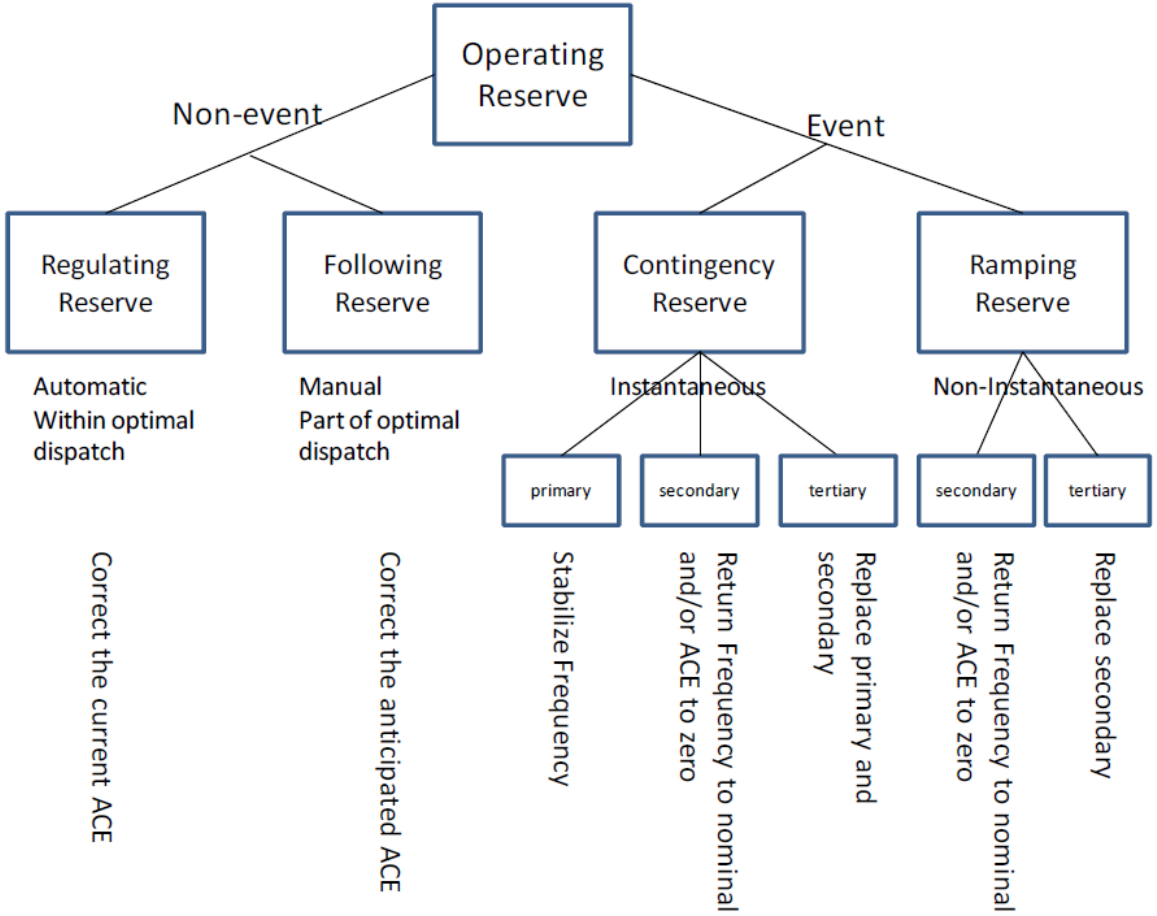
Source: Yuan et al., Irregular Distribution of Wind Power Prediction, 2019

Dynamic Reserves

Adjusting to reflect forecasting uncertainty

What are Reserves?

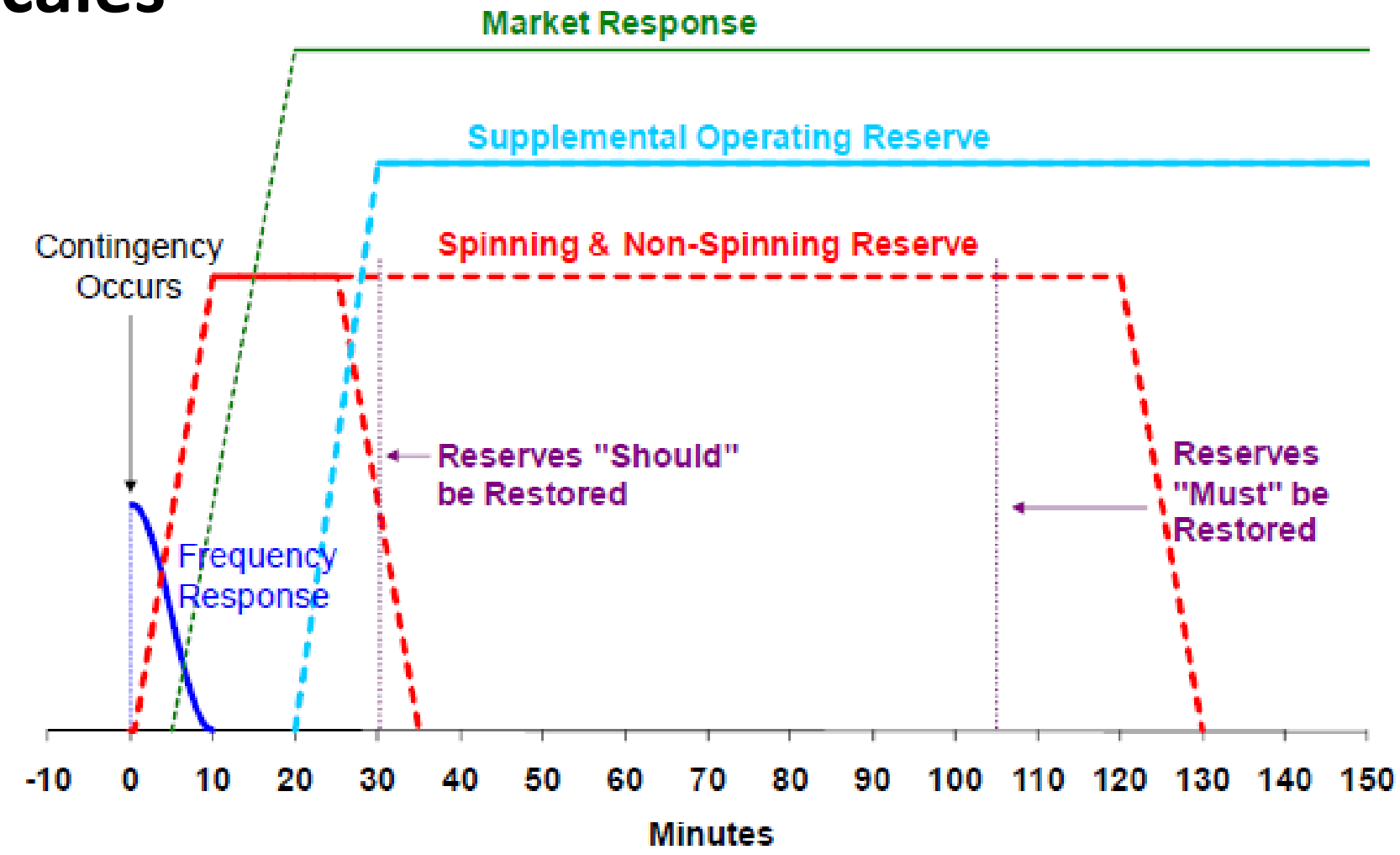
Helping the Power System Deal with Uncertainty



Source: NREL

Contingency Reserves

Timescales

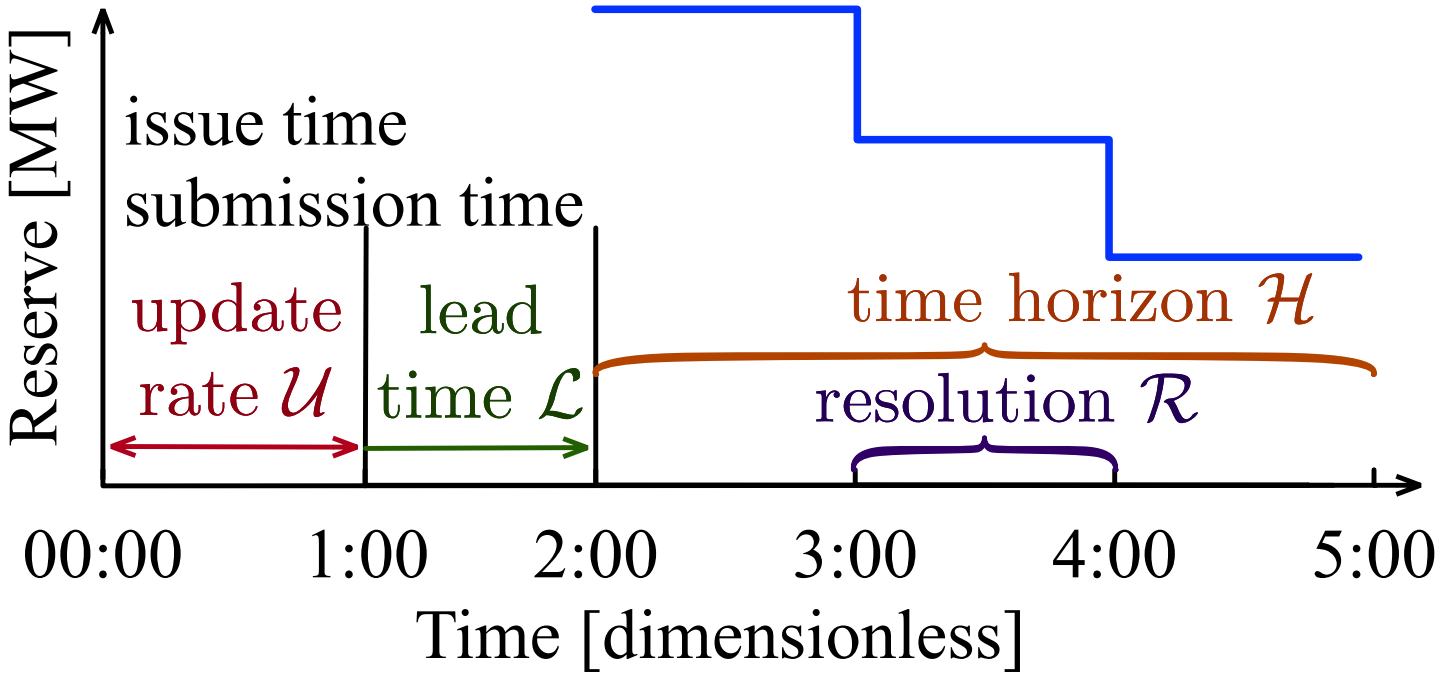


Source: NREL

Non-Spinning Reserve Determination

Electric Reliability Council of Texas (ERCOT) Solar Example

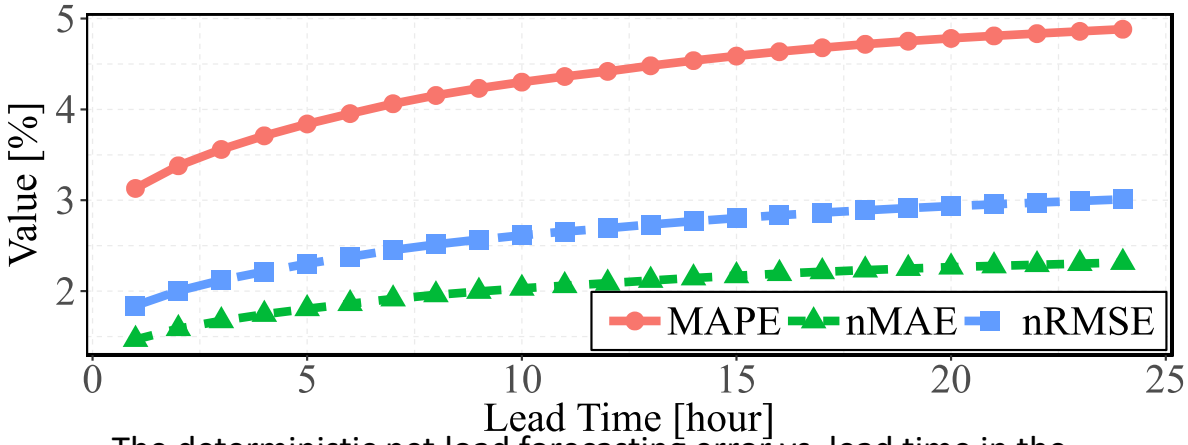
- Selected scenarios (multi-time scale)
  - ✓ ($L^{12\ days}$, $H^{1\ year}$, $R^{1\ hour}$, $U^{1\ year}$)
  - ✓ ($L^{1\ week}$, $H^{1\ week}$, $R^{1\ hour}$, $U^{1\ week}$)
  - ✓ ($L^{1\ day}$, $H^{1\ day}$, $R^{1\ hour}$, $U^{1\ day}$)
  - ✓ ($L^{1\ hour}$, $H^{1\ hour}$, $R^{1\ hour}$, $U^{1\ hour}$)



The NSRR determination timeline

Forecasting Errors over Time

Impacts on Reserves?



The deterministic net load forecasting error vs. lead time in the historical forecasts

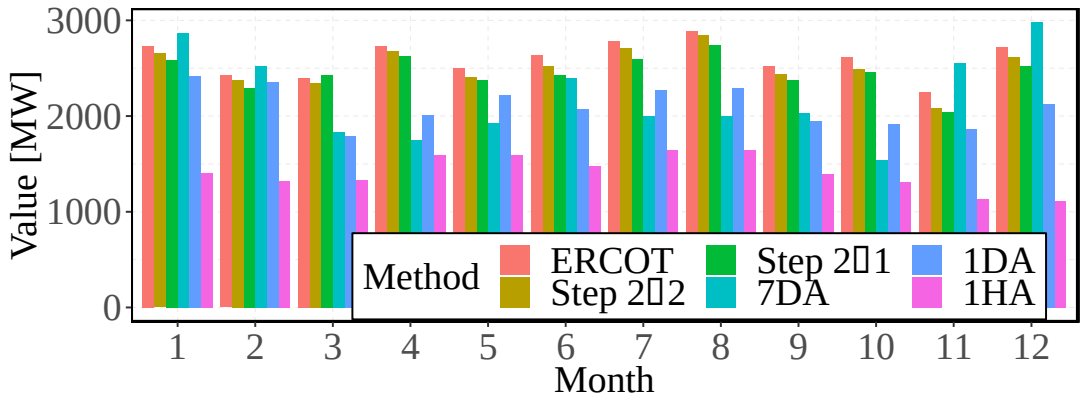
Forecasting result evaluation [%]

Step	Deterministic forecasting			Probabilistic forecasting
	nMAE	nRMSE	MAPE	nPL
2	4.05	5.42	8.69	1.52
3	2.37	3.04	5.04	0.94
4	1.55	1.98	3.37	0.67

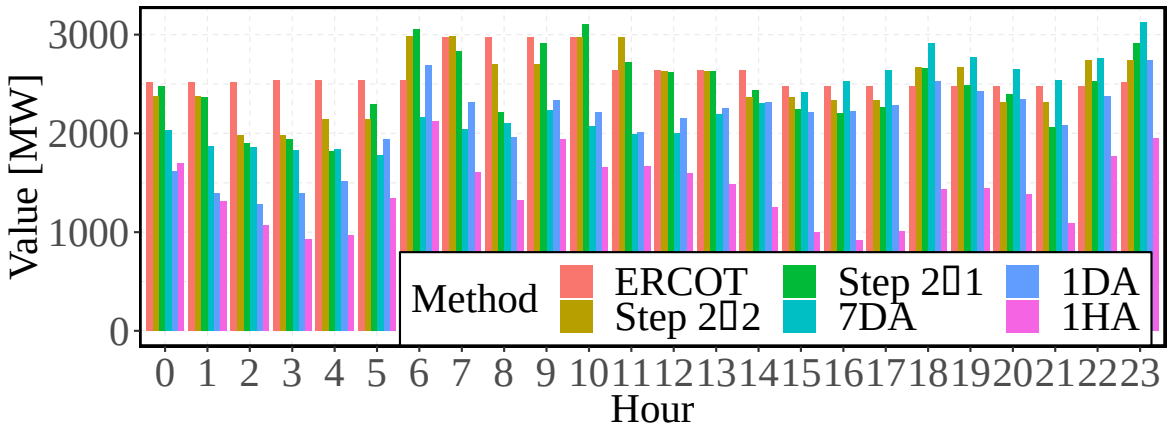
- Forecasting error increases with lead time in the historical data
- Forecasting error increases with the lead time in three steps of the developed method

Reserve Reductions

More Recent Information Leads to Savings



Hourly non-spinning reserve requirement in each month



Hourly non-spinning reserve requirement in each hour

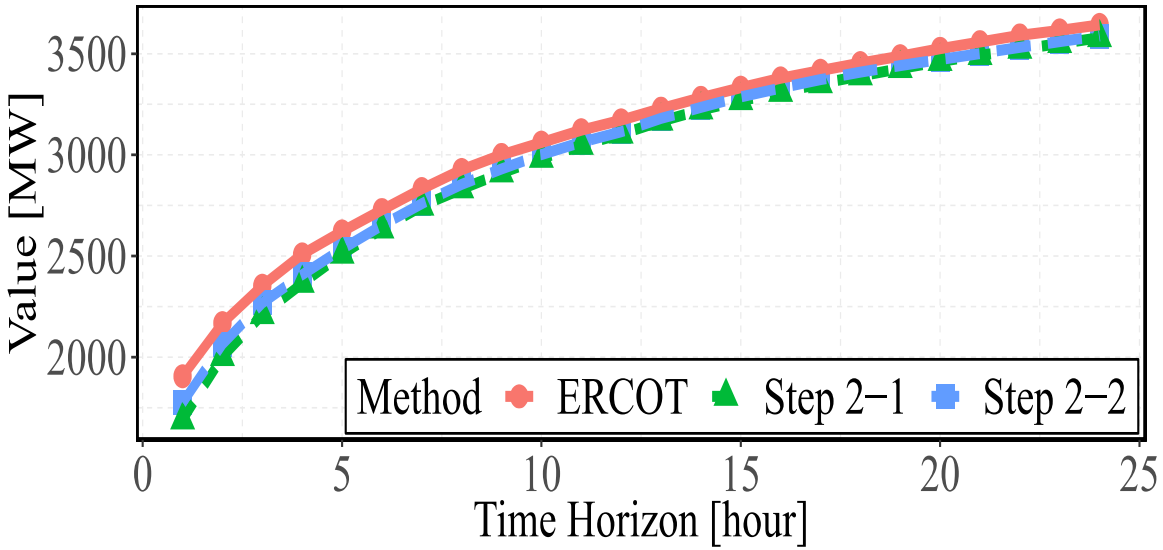
Hourly average NSRR [MW]

Method	Note	Hourly average
ERCOT	The current ERCOT method	2353.87
Step 1 (R^2_{hour})	Result from step 1 with a 2-hour resolution	2268.05
Step 1 (R^1_{hour})	Result from step 1 with a 1-hour resolution	2210.16
Step 2	Weekly updated reserve	2026.09
Step 3	Hourly updated reserve	1857.32
Step 4	Hourly updated reserve	1165.33

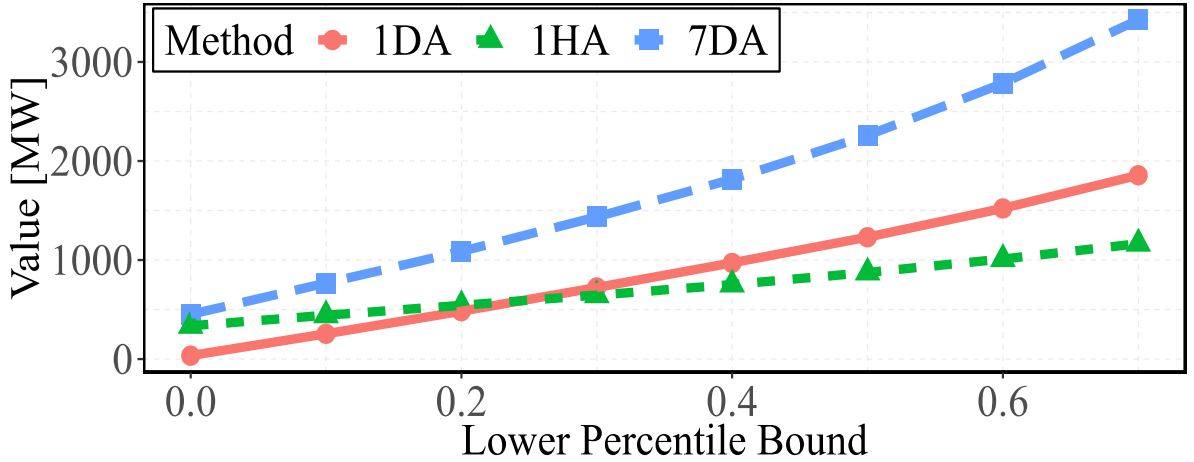
- NSRR reduction: 13.93%, 21.10%, 50.62% for three steps
- Consistent over different hours and months

Changes in Reserve Requirements

Changes over Time Horizon and Percentiles



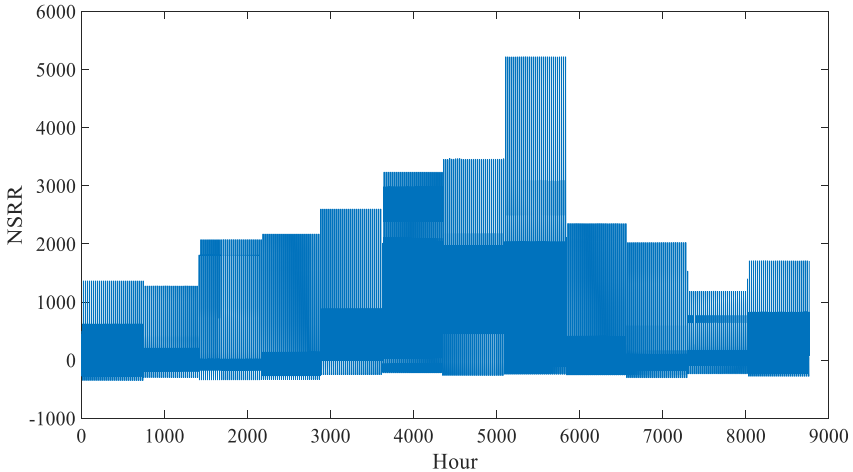
Hourly NSRR vs. time horizon of historical forecasts



Hourly NSRR vs. lower percentile bound

- NSSR increases with time horizon of historical forecasts and lower percentile bound
- NSSR is flexible by adjusting these two parameters

Changes with Increased Solar Shares



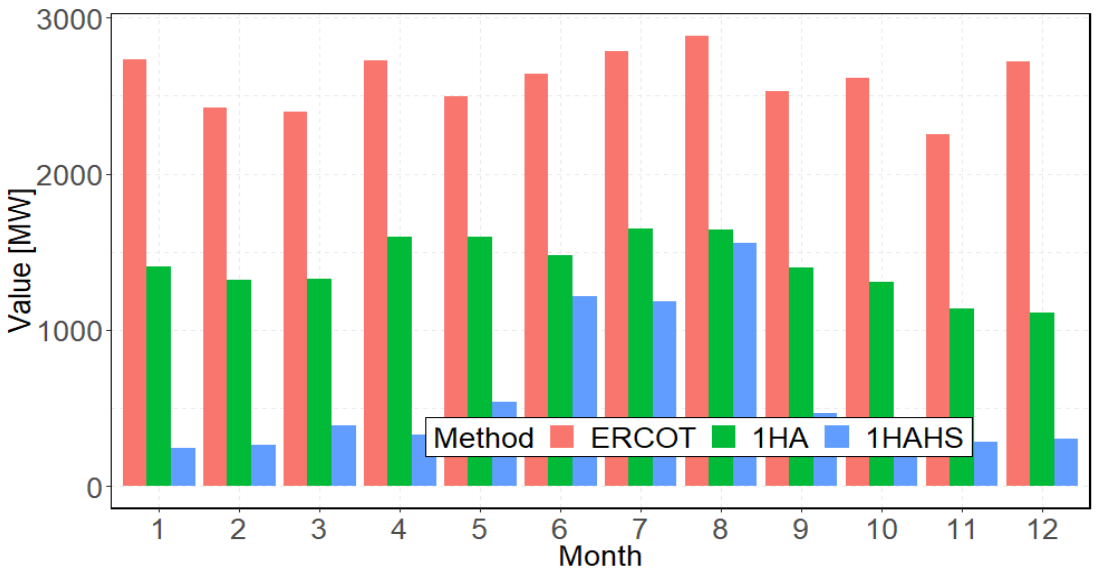
NSRR time series under a high solar penetration

Hourly average NSRR [MW]

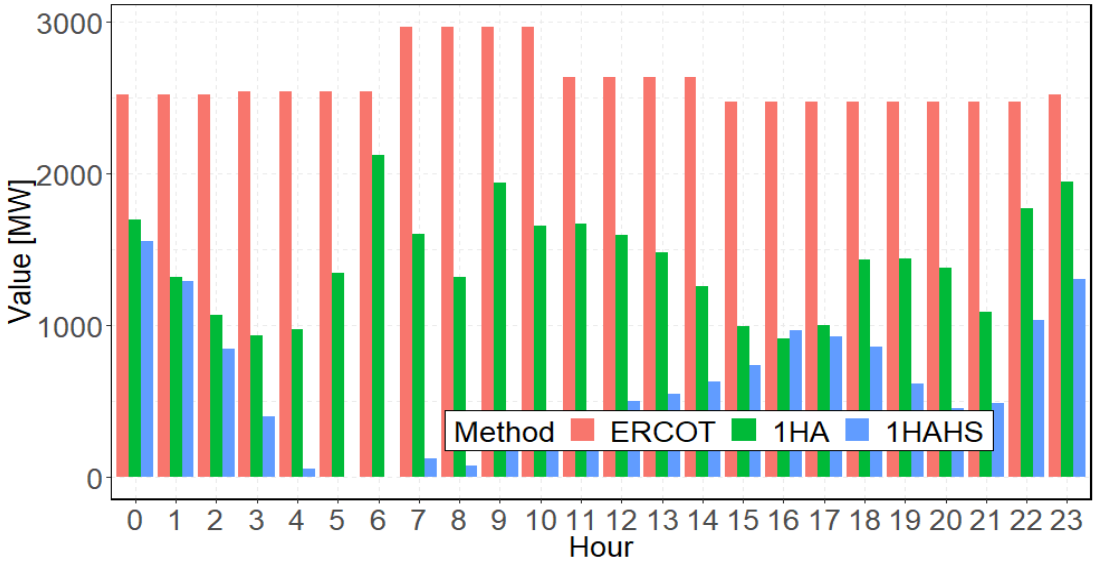
Method	Note	Hourly average
ERCOT	The current ERCOT method	2353.87
1HA	Hourly updated reserve under low solar	1414.75
1HAHS	Hourly updated reserve under high solar	539.82

- The hourly NSRR is reduced by 39.89%, 77.07% based on 1HA forecasts under low and high solar penetration
- Negative values mean no NSRR is required during these time periods
  - High penetration of solar power results in lower net load uncertainty
  - Replace negative values with 0 in the post-processing

Seasonal and Diurnal Patterns



Hourly non-spinning reserve requirement in each month



Hourly non-spinning reserve requirement in each hour

- NSRR with adaptive scheduling indicate seasonal and diurnal patterns
- NSSR decreases with high solar penetration
- Consistent in different hours and months

Hydro Forecasting

Extended Range Hydro Inflow Forecasting

Quality vs. Value

Extended Range Hydro Inflow Forecasting

Context:
Range of weather forecasts extending all of the time
Hydro plant incentivised to operate flexibly

Opportunity?
Can be forecast inflow beyond one week-ahead?
What is the value?

Image: https://www.sserenewables.com/hydro/great-glen/

R.M. Graham, J. Browell, D. Bertram and C.J. White, "The application of sub-seasonal to seasonal (S2S) predictions for hydropower forecasting", *Meteorological Applications*, 29(1), e2047, 2022, doi: 10.1002/MET.2047

Courtesy of Jethro Browell, Robert Graham & sse Renewables

Quality vs. Value

Extended Range Hydro Inflow Forecasting

Weather Forecast → Inflow & Water Level Forecast → Operational Decisions

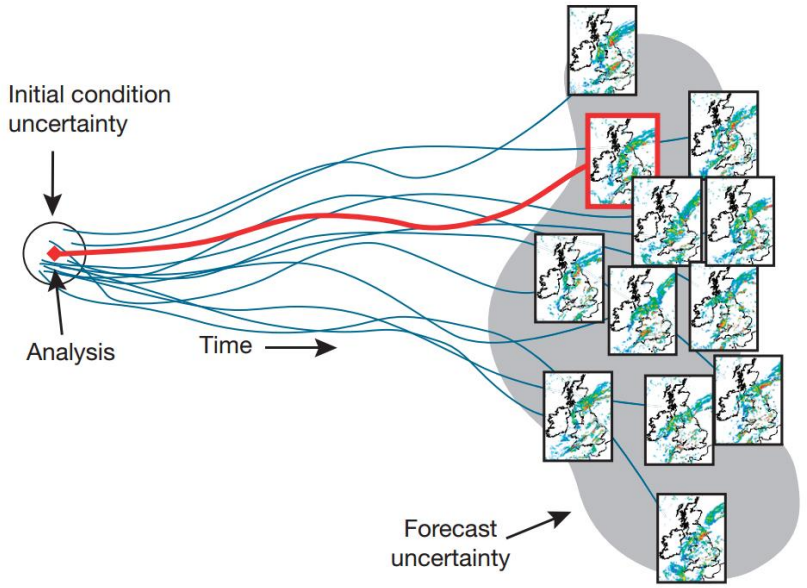
Quality vs. Value

Extended Range Hydro Inflow Forecasting

Weather Forecast → Inflow & Water Level Forecast → Operational Decisions

- Probabilistic forecasts of precipitation and temperature
- Produced by Ensemble Numerical Weather Prediction

- Evaluation: Skill score (**relative to model climatology**)
- Weekly totals 1 to 6 weeks ahead

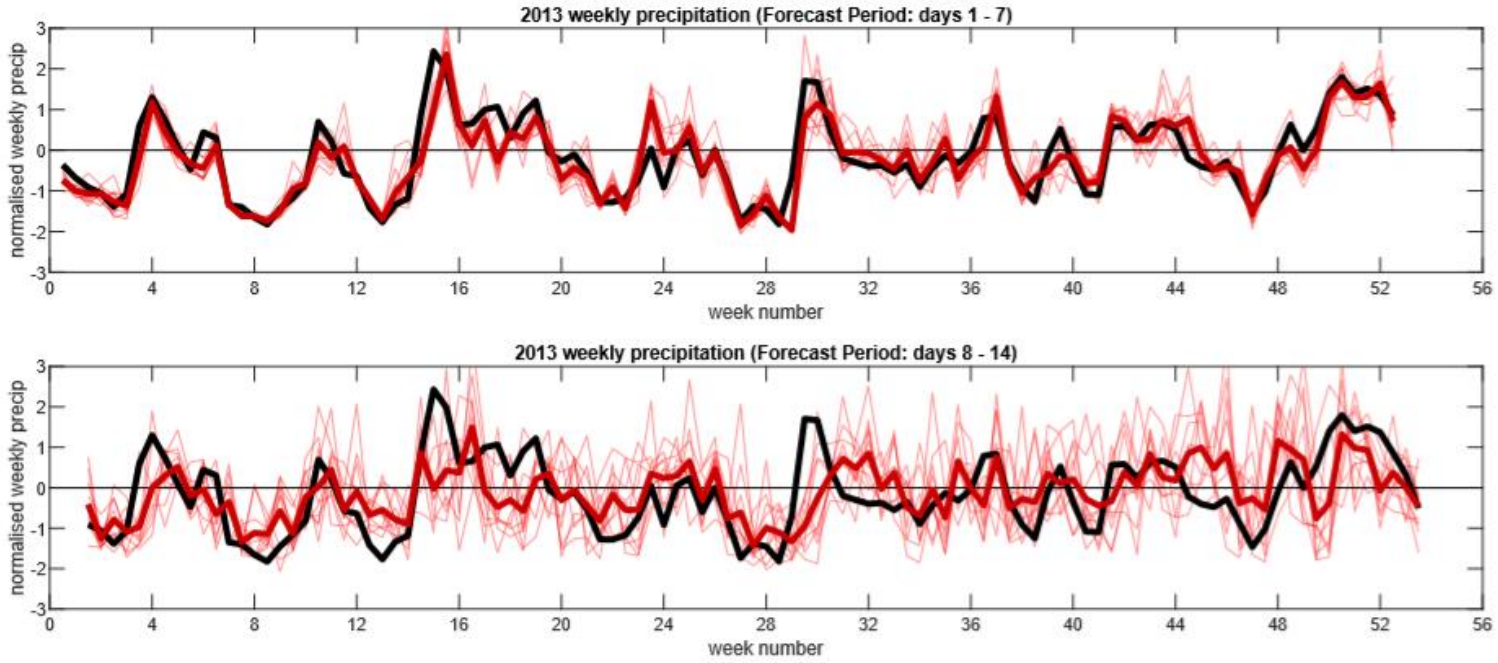


Source: Bauer, Thorpe and Brunet, *"The quiet revolution of numerical weather prediction,"* Nature, 2015

Quality vs. Value

Extended Range Hydro Inflow Forecasting

Weather Forecast → Inflow & Water Level Forecast → Operational Decisions



Forecast **Mean** and Ensemble Members

Actual Precipitation

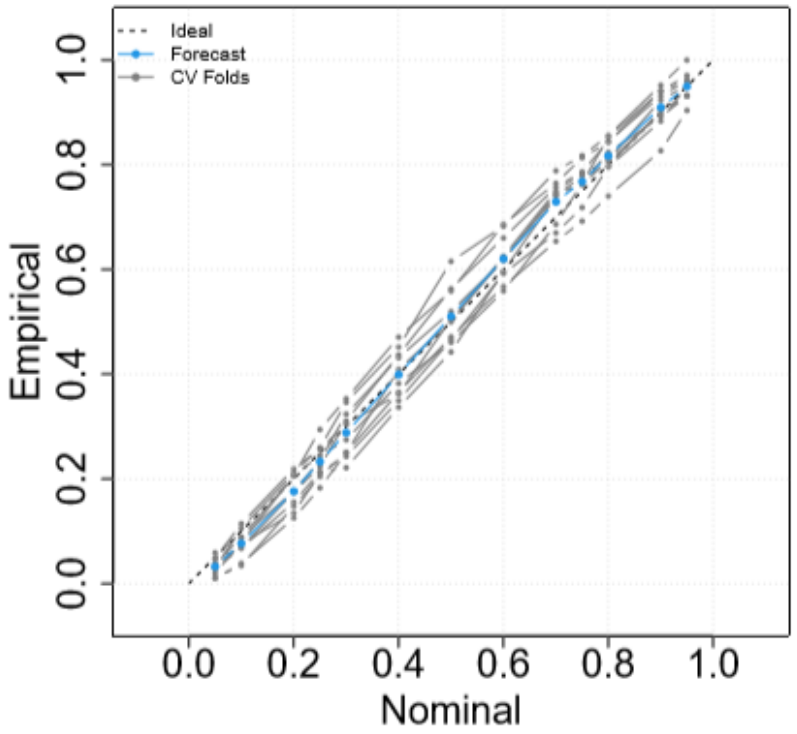
Quality vs. Value

Extended Range Hydro Inflow Forecasting

Weather Forecast → **Inflow & Water Level Forecast** → Operational Decisions

- Probabilistic forecast of inflow at specific location
- Post-processing required: *gamlss* model with Gamma distribution

Evaluation relative to observations: calibration and skill



Quality vs. Value

Extended Range Hydro Inflow Forecasting

Weather Forecast → **Inflow & Water Level Forecast** → Operational Decisions

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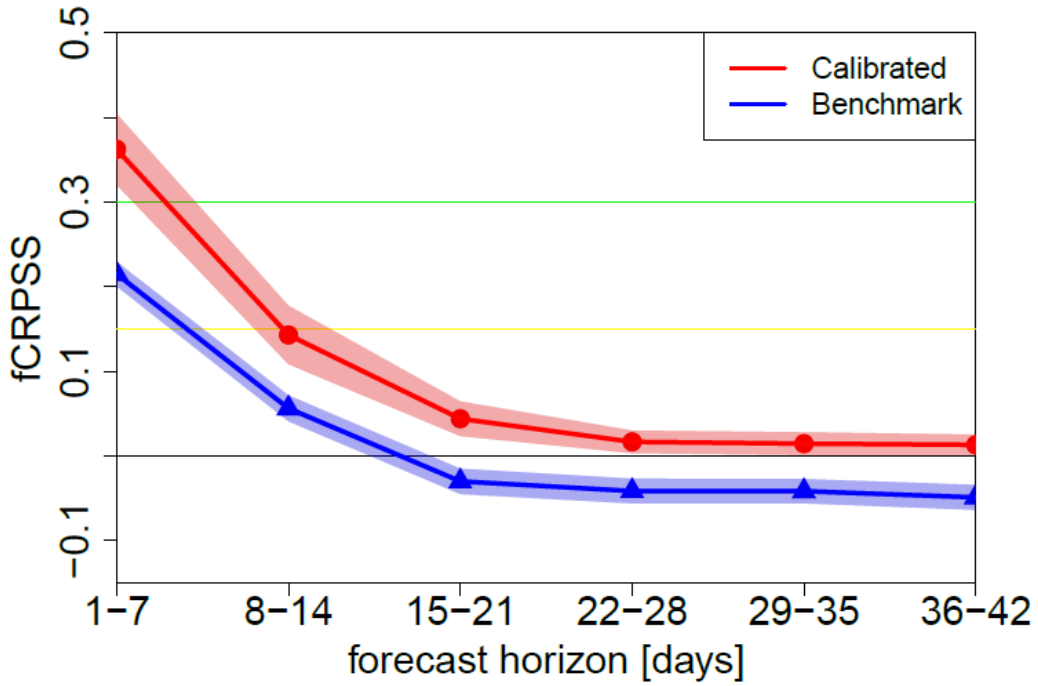


Quality vs. Value

Extended Range Hydro Inflow Forecasting

Need to capture how forecast inform decisions, working with end users:

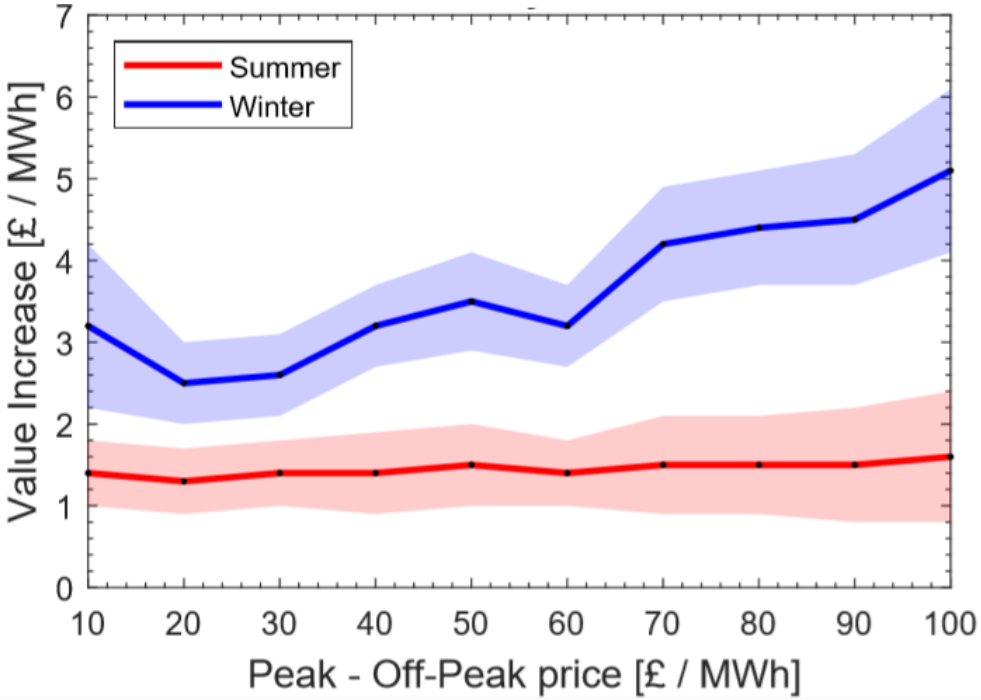
1. Day-to-day: Change generation schedule to manage water level – converting water to energy at peak or off-peak price
   - Costs associated with changed generation schedule (based on forecast)
   - Costs associated with resulting inflow and water level (based on actuals)
2. Large inflow events: Avoid bad situations – water spill, safe limits on water levels and down-stream flow

Quality vs. Value

Extended Range Hydro Inflow Forecasting

Weather Forecast → Inflow & Water Level Forecast → **Operational Decisions**

- Compare "value of water" based on using climatology vs forecast:
- Stylised model, but indicative numbers
- Significant value!
- Likely that some of this value already realised
- Is value sufficient to justify new product and change in practice?



Quality vs. Value

Extended Range Hydro Inflow Forecasting

Weather Forecast → Inflow & Water Level Forecast → Operational Decisions

Evaluation

Weather Model Skill → Site-specific Post-processing → Business Value

Good practice to make sensible modelling decisions and maximise **potential** value.

Engagement with users critical for meaningful and credible evaluation.

Probabilistic Forecasts and Unit Commitment

Incorporating Uncertainty Forecasts into Power System Operations

Main Methods and Forecasts Used

Deterministic Optimization

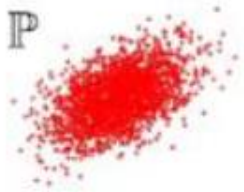
$$\inf_{\mathbf{x}} \; f(\mathbf{x}, \boldsymbol{\xi})$$
$$\text{s.t. } \mathbf{x} \in X$$

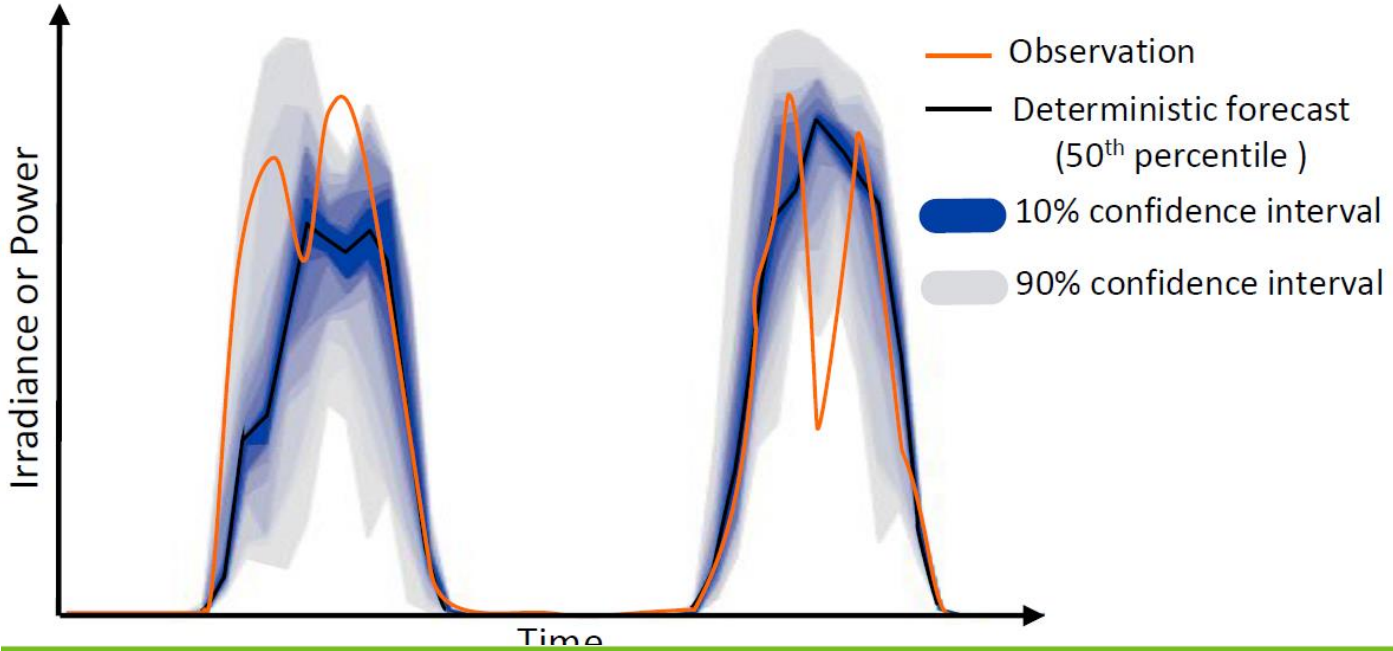
Robust Optimization

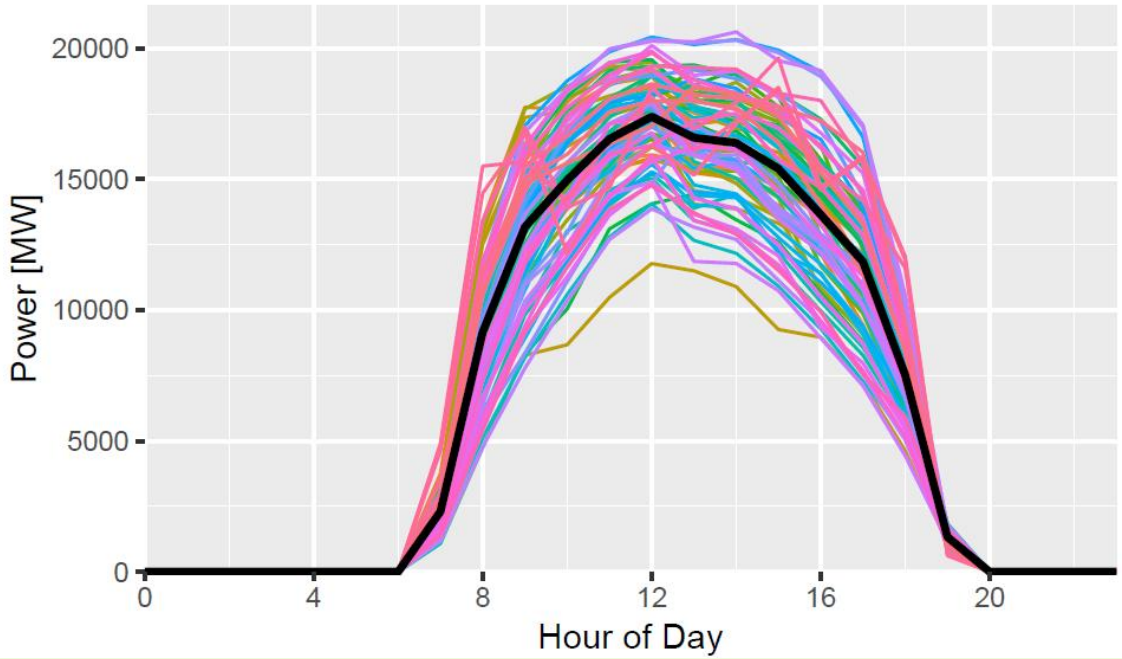
$$\inf_{\mathbf{x}} \; \sup_{\boldsymbol{\xi} \in U} \; f(\mathbf{x}, \boldsymbol{\xi})$$
$$\text{s.t. } \mathbf{x} \in X$$

Stochastic Programming

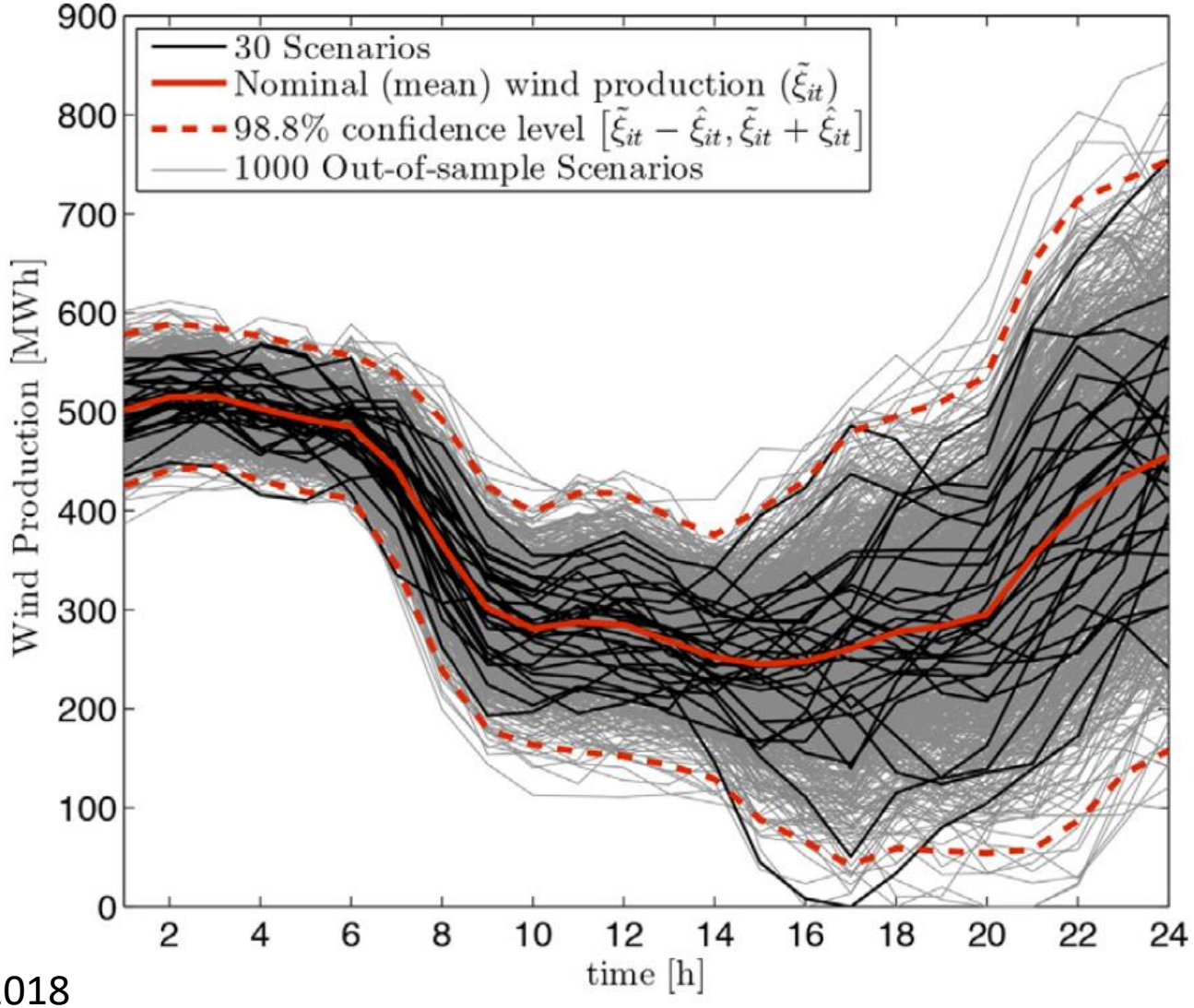
$$\inf_{\mathbf{x}} \; \mathbb{E}_{\mathbb{P}}\{f(\mathbf{x}, \boldsymbol{\xi})\}$$
$$\text{s.t. } \mathbf{x} \in X$$





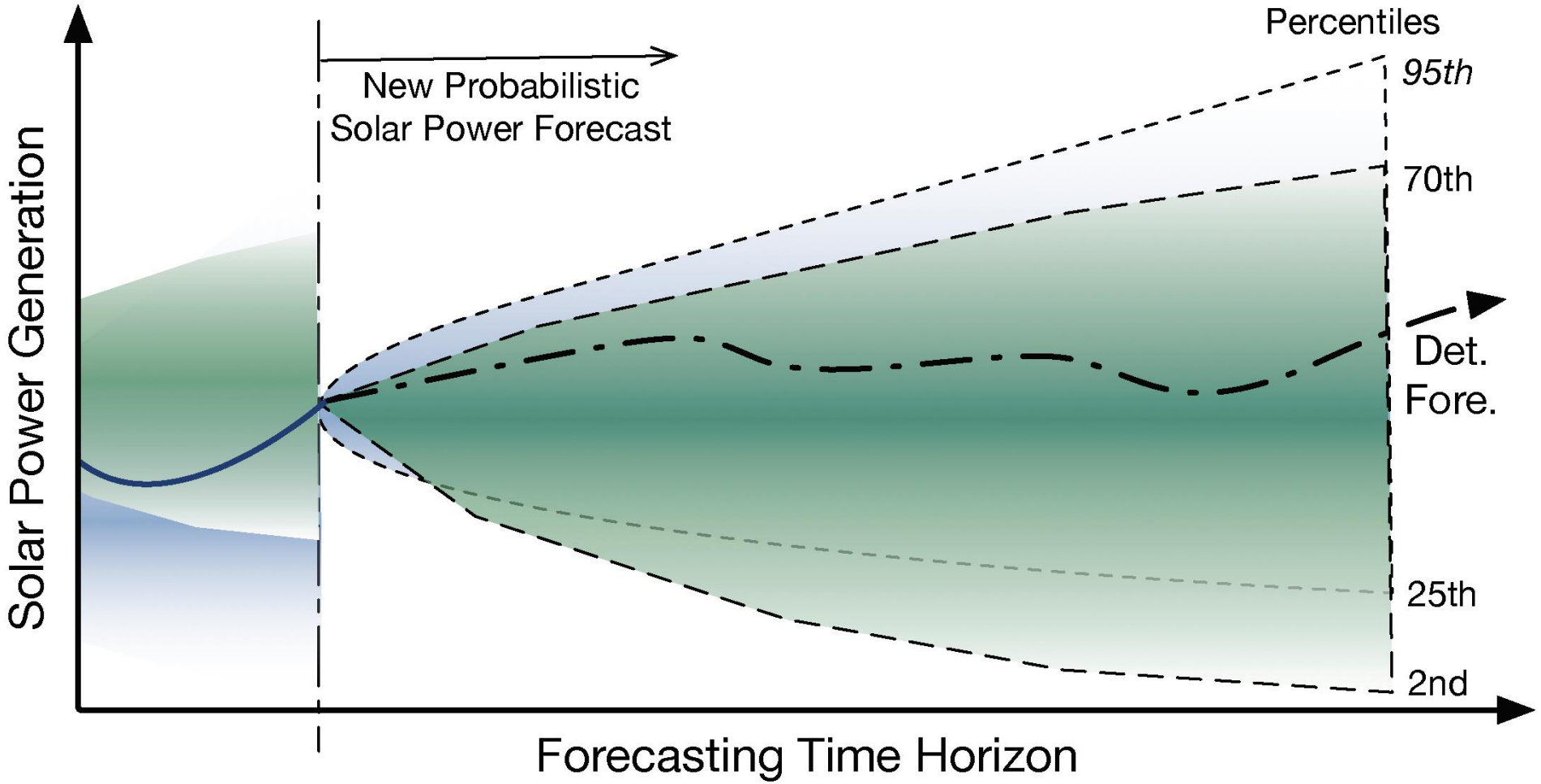


Robust Unit Commitment



Source: Morales-Espana et al. 2018

Adaptive Approaches



Challenges in Implementation

Why aren't we using these in power markets already?

- Computational Challenges
  - Input data requirements for Energy Management Systems
  - Solve times
- Number of Scenarios
  - Need ~1000 scenarios for decent representation of extremes
  - But then these are reduced for computational reasons, what information is lost?
- Market Issues
  - What does this do to LMPs?
  - How do you compensate for events that do not happen?
- Current underrepresentation of the cost of extreme events
  - Reliability vs. Economics

Conclusions

Tools and Industry Practice

- Probabilistic forecasts can provide additional information that can aid in integrating renewable energy sources into the power grid
- Probabilistic forecasting is more advanced than power system use cases
  - Research on how to automate the utilization of the additional information provided is needed
- The best forecast is worthless if its not integrated into a decision-making process

Thank you!