Operational Probabilistic Tools for Solar Uncertainty (OPTSUN)

Solar Forecasting 2
Annual Review and Workshop

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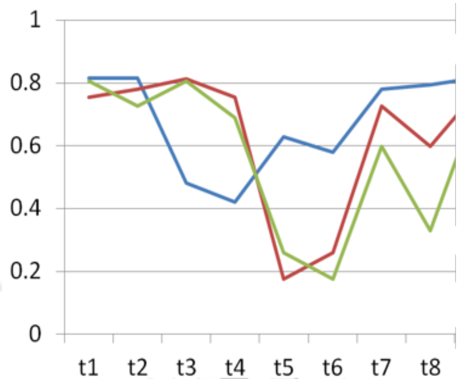
October 8th, 2019

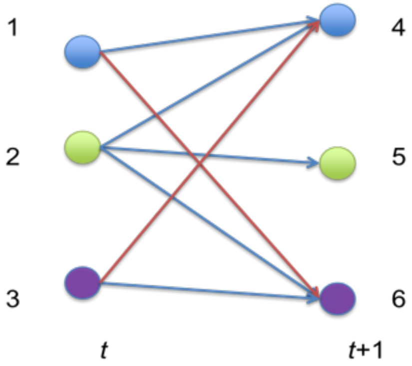
Overview

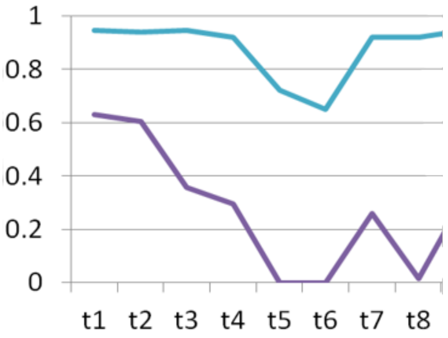
- Background/Current Status
- Probabilistic Forecasts (UL)
- Using Probabilistic Forecasts for Reserves
- Update on Case Studies
- Wrap Up

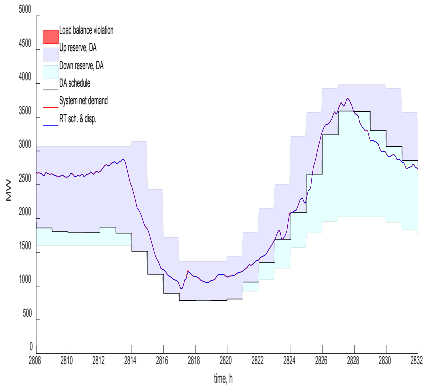
Background/Current Status

Project Motivation: Using Advanced Methods for Operating Systems With Uncertainty







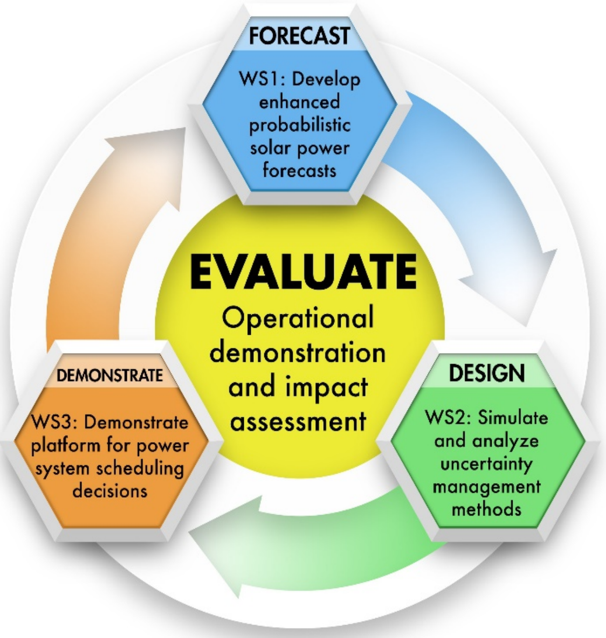


	Stochastic UC	Interval UC	Robust UC	Dynamic Reserves
Uncertainty Model	Scenarios	Inter-temporal rates	Uncertainty range	Requirements
Objective	$\min \mathrm{E}\{\mathrm{cost}\}$	Minimize cost to meet central forecast	$\min\{\max\{\min f\}\}$	Minimize operating cost to meet forecast
Security	Depends on the scenarios	Inter-temporal ranges	Uncertainty Budget	Confidence interval
Scalability	Low	High	Variable (high)	High

Can we use other methods to deal with uncertainty/variability?

Project Reminder– Three Workstreams

- A Forecasting Work Stream to develop and deliver probabilistic forecasts with targeted improvements for utility scale and behind-the-meter (BTM) solar
- A Design Work Stream to identify advanced methods for managing uncertainty based on results from advanced scheduling tools
- A Demonstration Work Stream to develop and demonstrate a scheduling management platform (SMP) to integrate probabilistic forecasts and scheduling decisions in a modular and customizable manner



AWS TRUEPOWER
DUKE ENERGY.
VT
SOUTHERN COMPANY
POLARIS SYSTEMS OPTIMIZATION
Hawaiian Electric

Current Status

- Generally on track, with some contracting/NDA delays
- WS1: Forecasts starting to be delivered and will be improved upon in BP2; scenario generation further than original planned
- WS2: Model improved up for Hawaii, close for southeast utilities (final tweaks and data); methods for reserves determined, stochastic UC to come
- WS3: Starting in BP2 will develop demonstration capabilities for side by side comparison and decision support/visualization tools

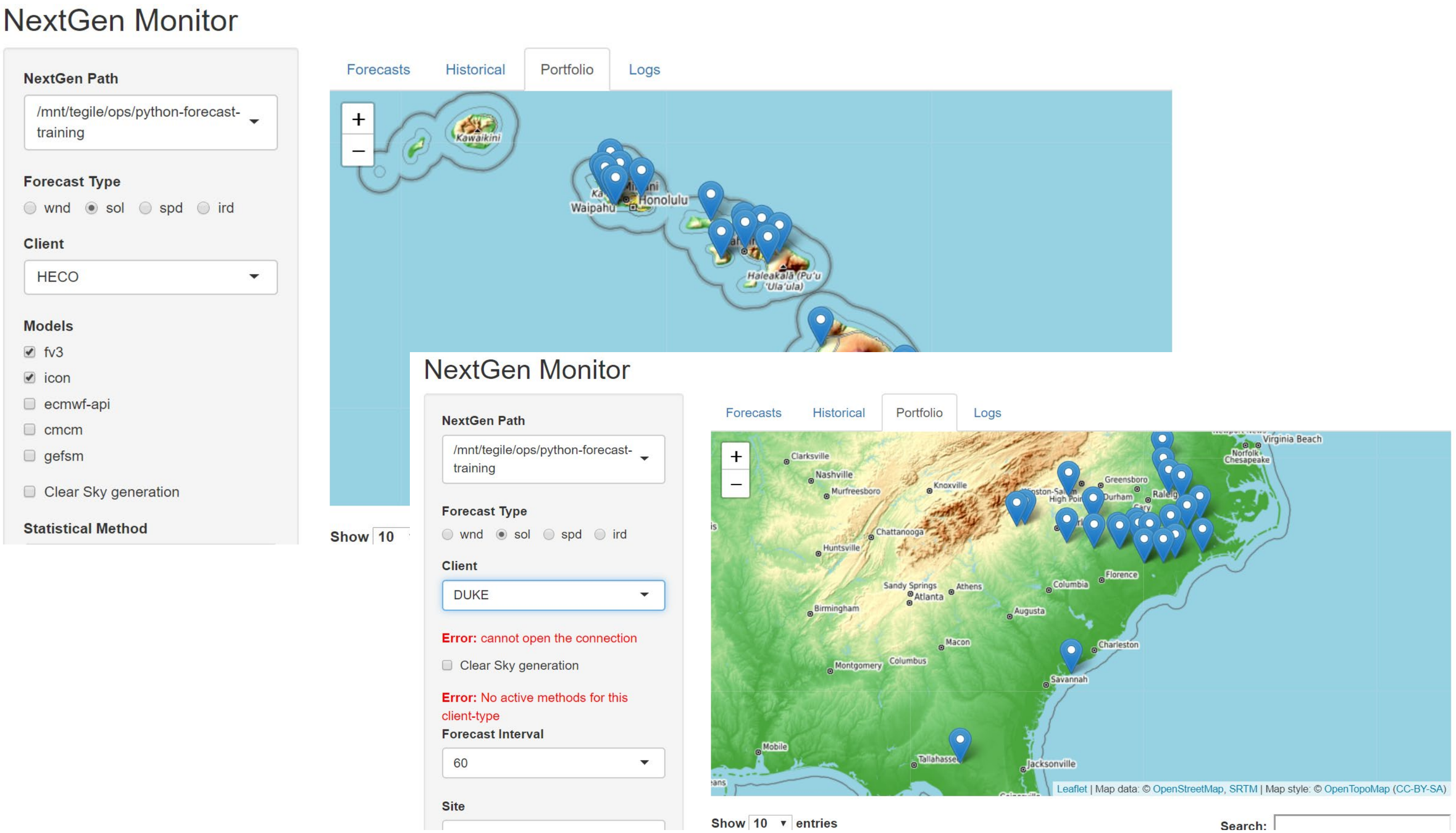
Initial Setup Nearly Complete – Expecting to See Results Soon!

Renewables

SETTING UP PROBABILISTIC FORECASTS FOR UTILITIES

Daniel Kirk-Davidoff, Jiaxin Black, Paulino Tardáguila, UL LLC

FORECAST SYSTEM SETUP



UL is setting up operational probabilistic forecast for Duke Energy, HECO and the Southern company. To date, our methodology for these forecast has been a simple application of quantile regression tuned from the historical timeseries of our final ensemble-derived single-valued forecasts.

WHERE DOES THE PROBABILISTIC INFORMATION COME FROM?

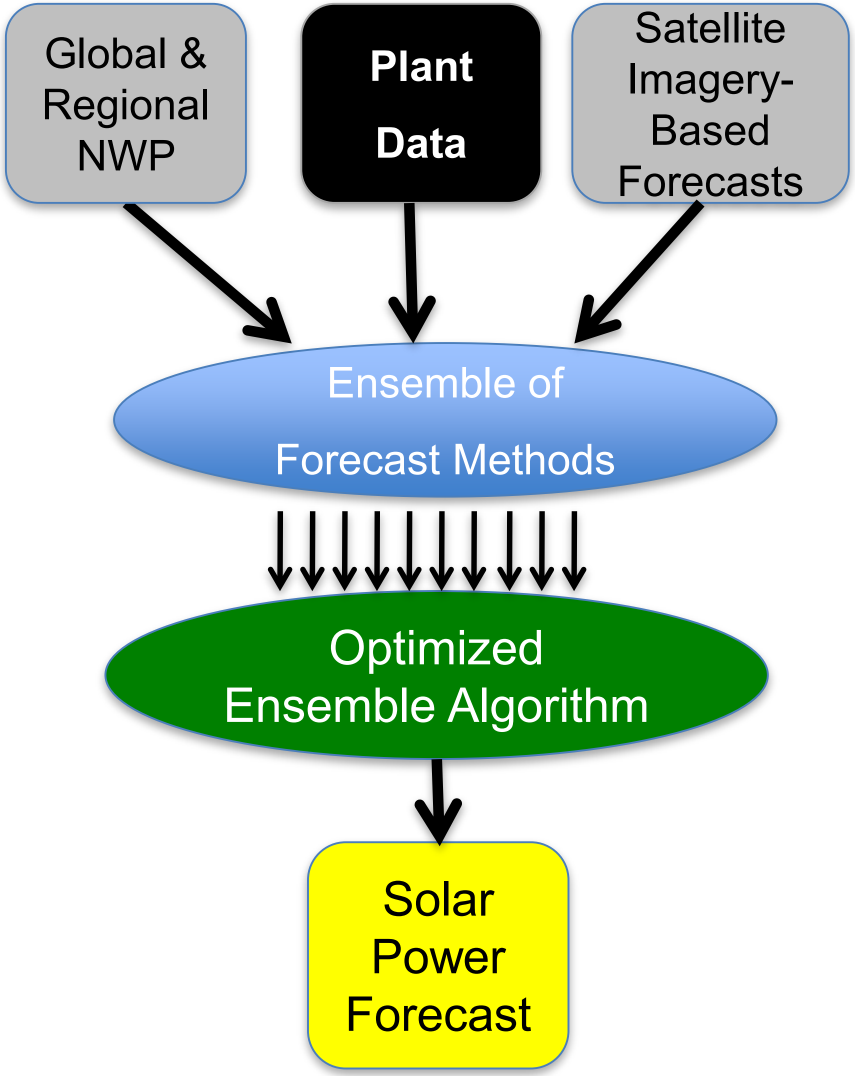
Probabilistic forecasting in essence is about reviewing a history of forecasts, and finding out how reality turned out for a set of partitions of the forecast value.

The interesting part is, how do you partition the past forecasts?

Quantile regression: forecast partitioned by their magnitude

Analog ensemble: forecast partitioned by their trajectory in time

Machine learning: forecast partitioned by a sort of cluster analysis

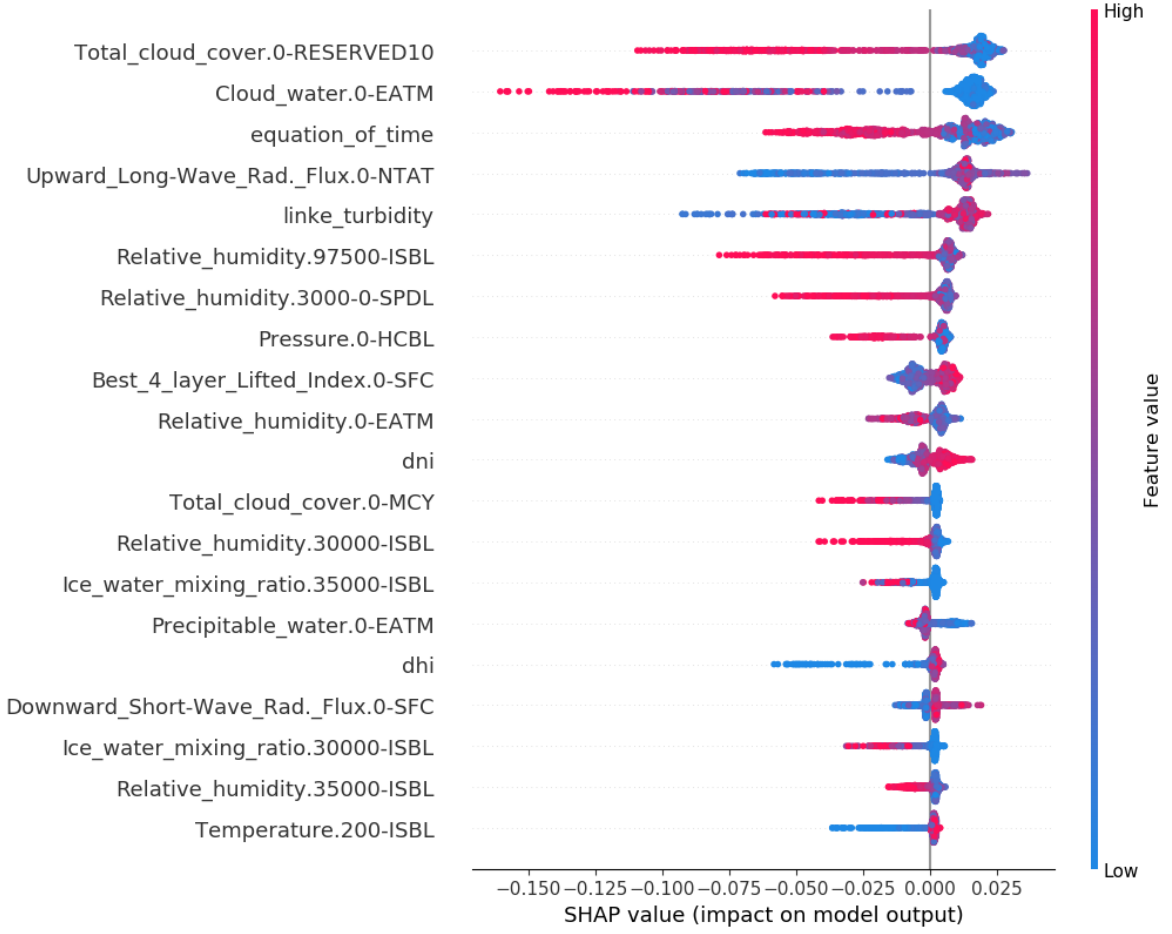


PROBABILISTIC FORECASTING USING MACHINE LEARNING

SHAP diagrams allows us to inspect the dependencies that Machine Learning algorithms derive from predictors to predictands.

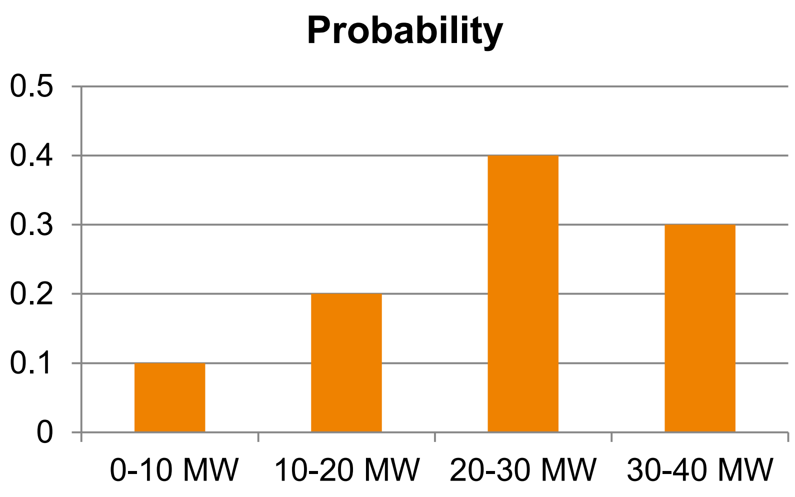
By contrast with wind generation forecasting, the list of NWP variables that have a big impact on a machine-learning post-processed forecast of solar generation is intuitively reasonable.

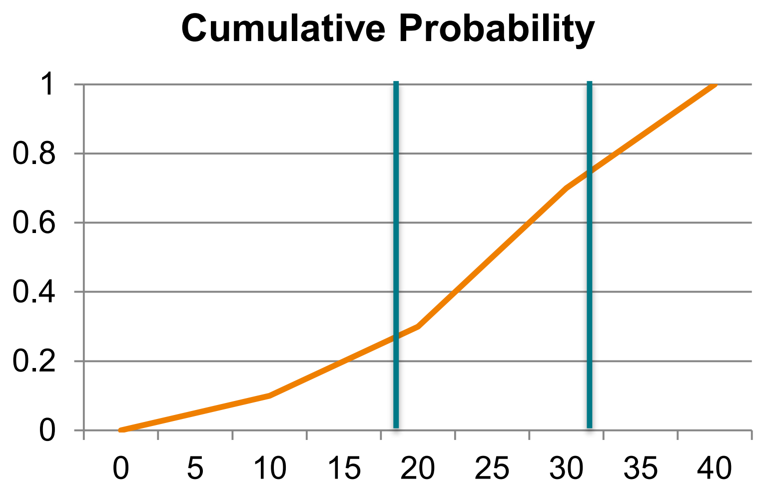
In our first round of forecasts we are combining multiple variables from several NWP models in a single Machine Learning process



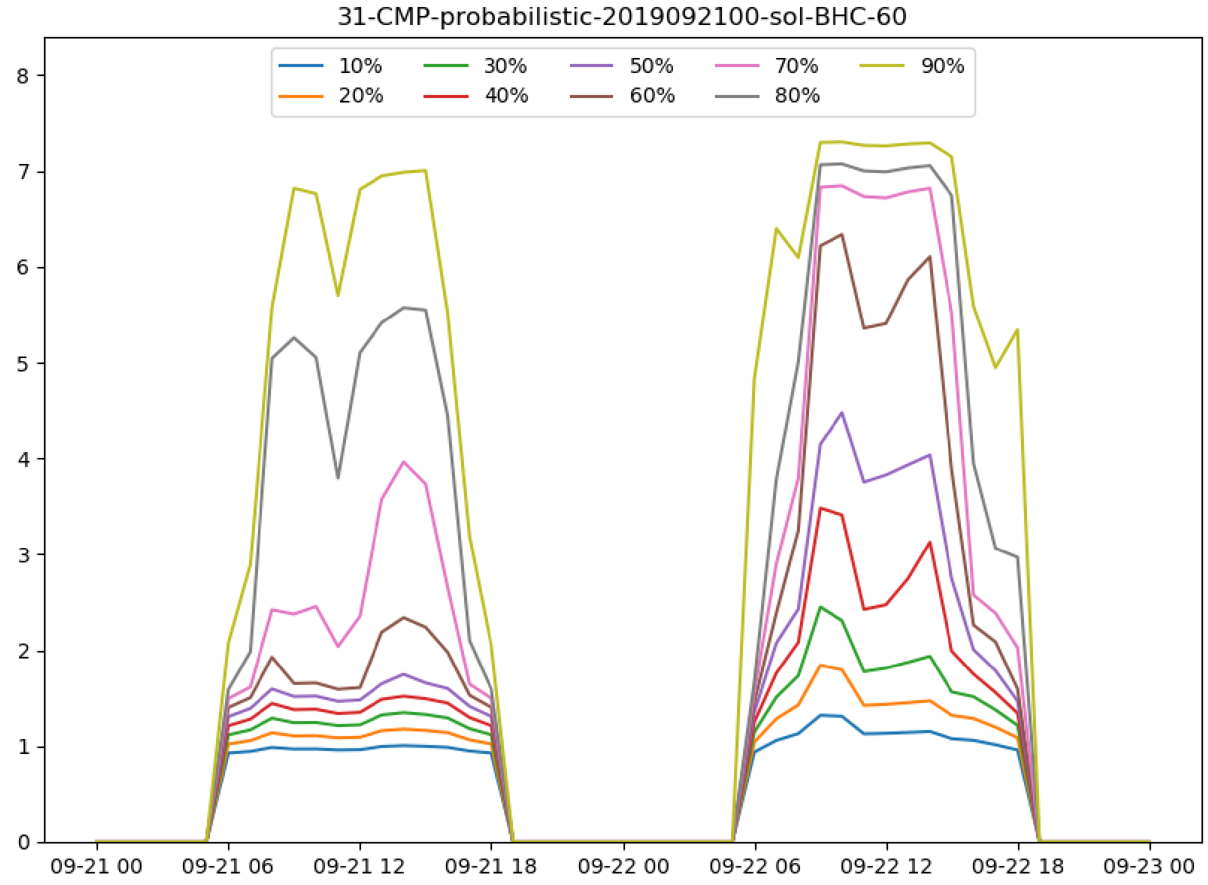
PROBABILISTIC FORECASTING USING MACHINE LEARNING

A lot of the heritage of machine learning techniques involves categorical prediction (is the image more likely of a cat or a dog)? This means that many of the popular techniques are well-suited to probabilistic forecasts.





SAMPLE SOLAR FORECASTS USING XGBOOST



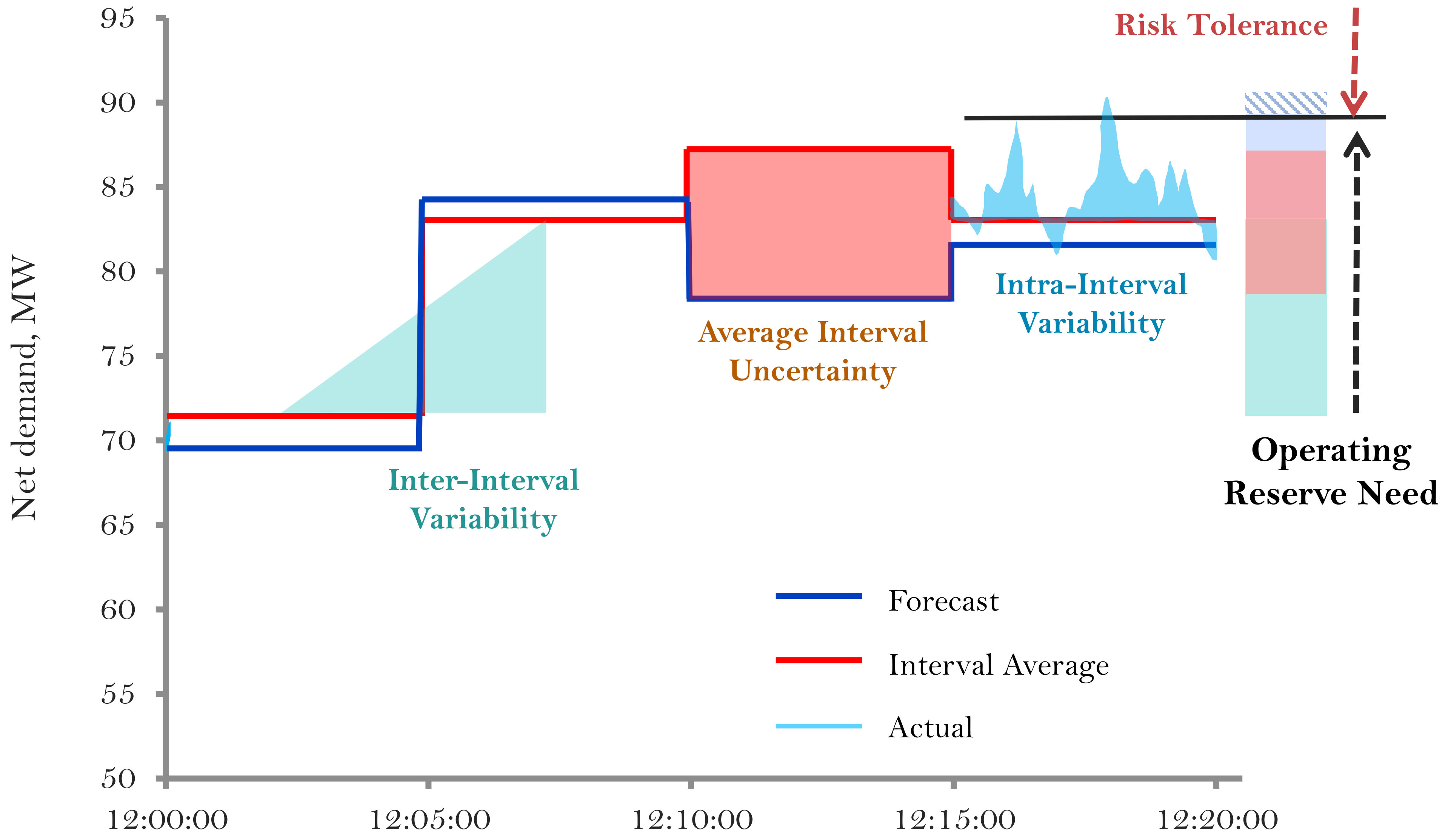
FORECAST IMPROVEMENT STRATEGY

- We plan a series of experiments with machine-learning based methods to determine:
  - Optimal number of NWP model variables to incorporate
  - Best use of post-processing to normalize probabilities against observed errors
  - Relative merit of
    - including inputs from multiple NWP models in a single machine-learning algorithm
    - generating multiple probabilistic forecasts from multiple models
    - generating probabilistic forecast from tuned individual NWP-based deterministic models
  - Best strategy to blend short-term (< 3 hours leadtime) data-based forecasts with longer term NWP-based forecasts

Using Probabilistic Forecasts for Operating Reserve Determination

Lead: Miguel Ortega-Vazquez

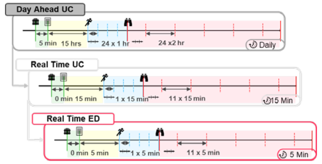
Central Reserve Needs



Dynamic Reserve Requirement Method

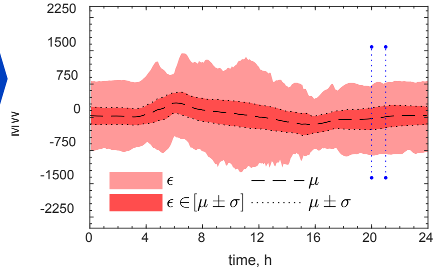
Reserve Characteristics

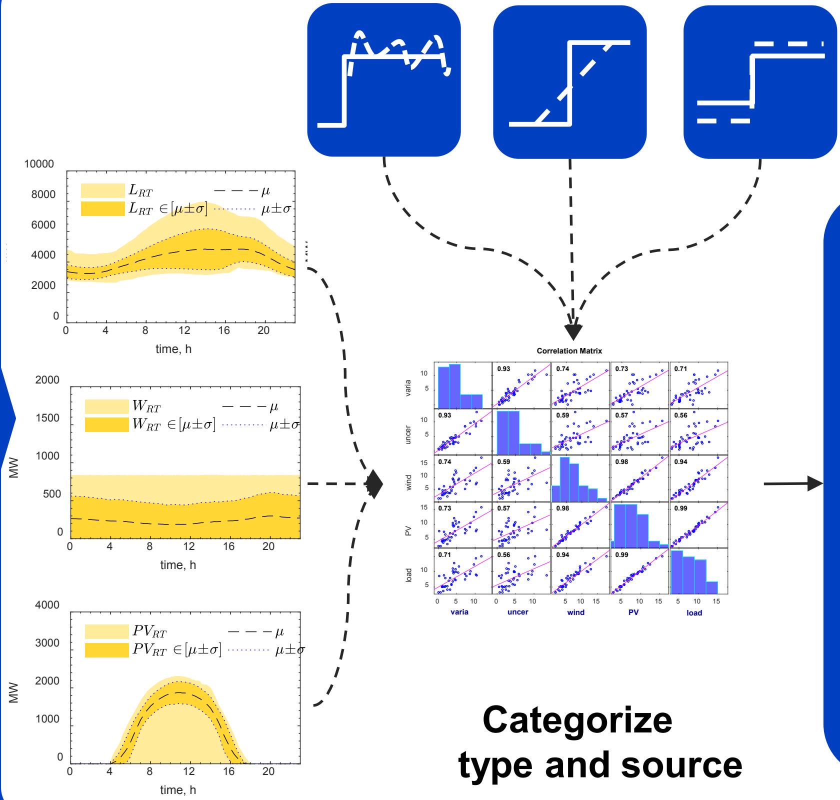
BA process:
- Held
- Released
- Direction



Historical Assessment

Historical assessment to determine the exact reserve requirements

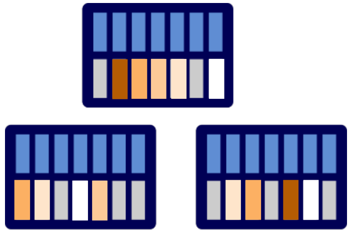




Categorize type and source

Explanatory variable (EV):
- Temporal:
  - Hour
  - Season
  - Week/wknd
- Production:
  - P-level
  - $\Delta\rightarrow$
  - $\Delta\leftarrow$
  - $|\Delta|$

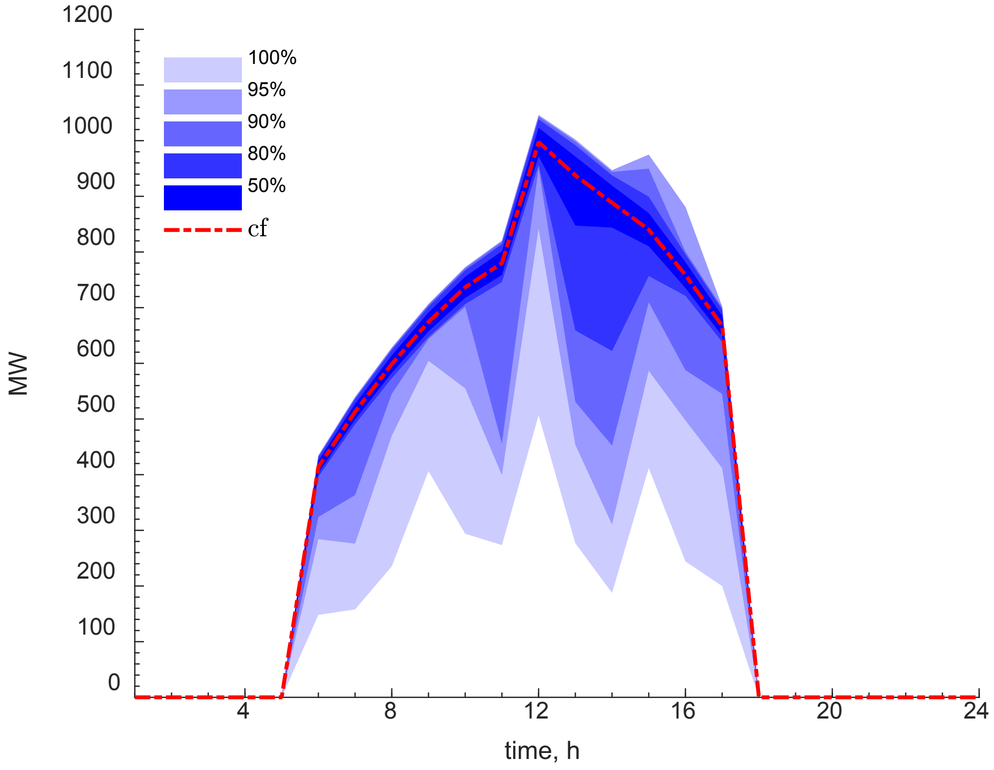
Assemble using best explanatory variables



$R_t = f(\cdot)$

"Forecasting" Reserve Requirements

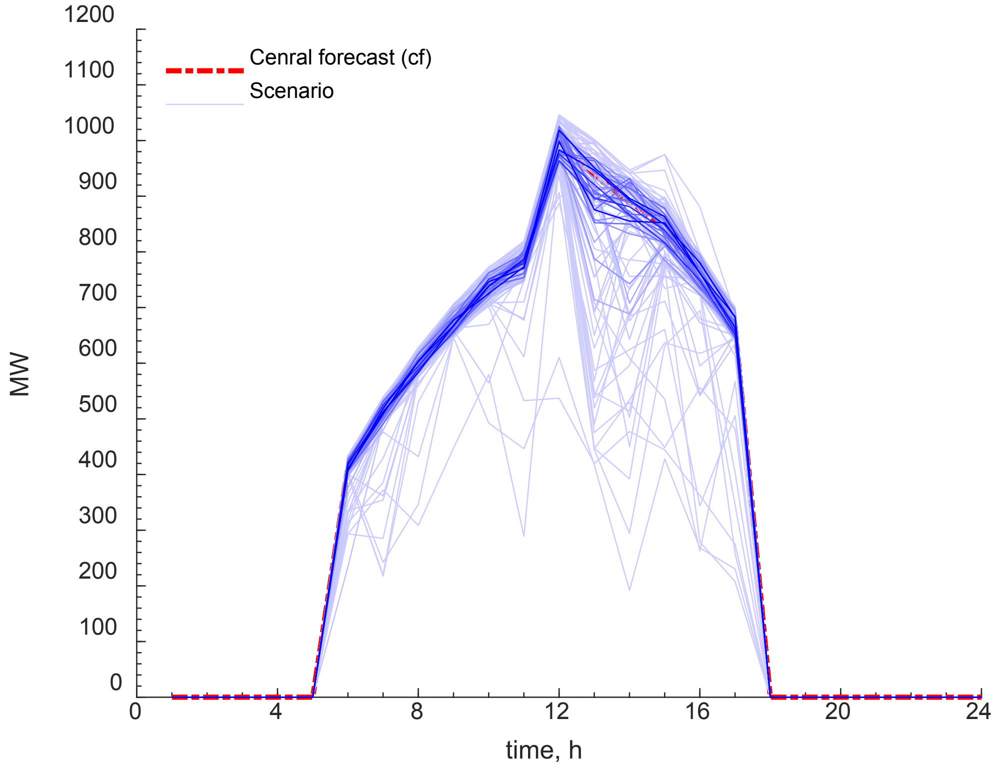
Incorporation of Probabilistic Forecasts



- System operators rely on **point forecasts** to draw the operating plans of their system
- Probabilistic forecasts provide **abundant information** on uncertainty
- Explore different **methods** to process the probabilistic information
- **Adapt** the reserve determination method to each of the proposed methods
- Two approaches are proposed for reserves:
  1. Incorporate probabilistic information via scenarios
  2. Incorporate probabilistic information via desired confidence interval of forecasted PDF

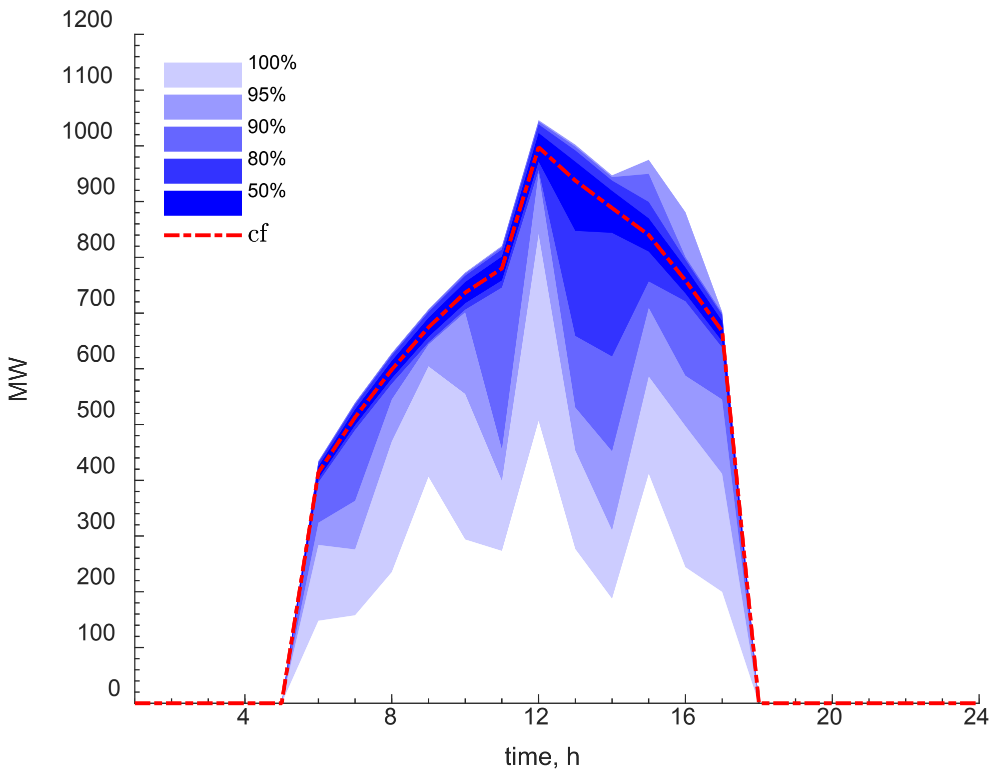
1) Scenario Creation

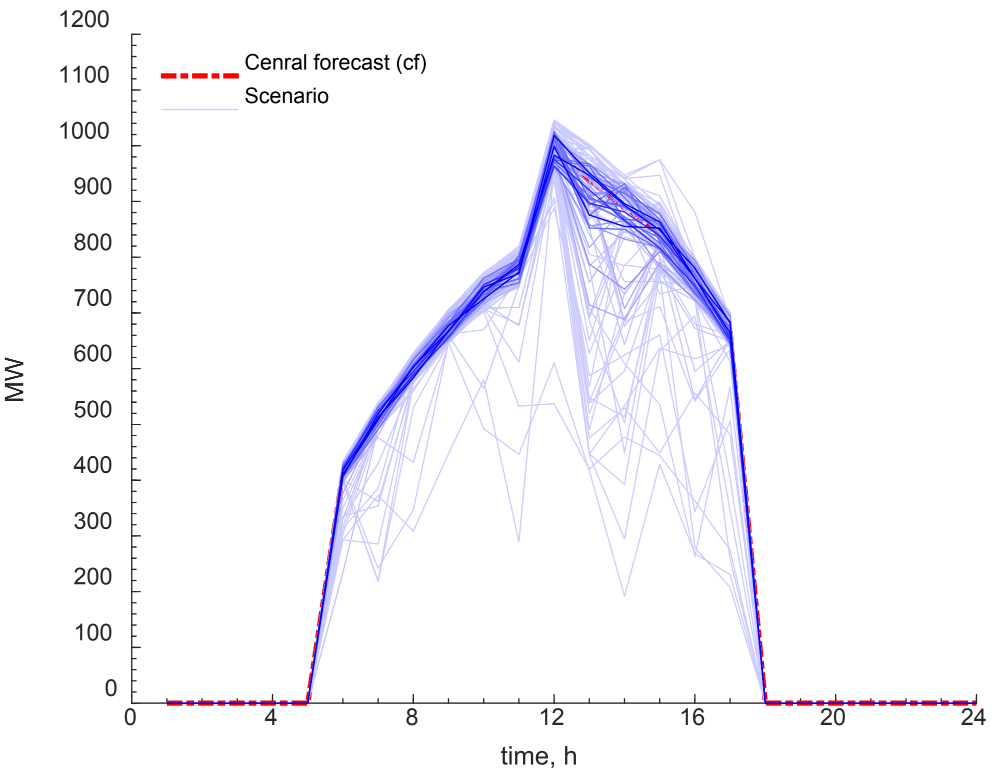
- Create Scenarios via random multivariate trials
- Trials' characteristics:
  - Follow the probability distributions of the forecasts at each period
  - Intertemporal correlation and correlation decay between samples
- Method:
  - Creation of standard normal multivariate trials
  - Induce temporal correlation and correlation decay
  - Convert to uniformly distributed trials
  - Map to forecast distributions



1) PF via Scenarios

- Sample data:





Probabilistic forecast from UL

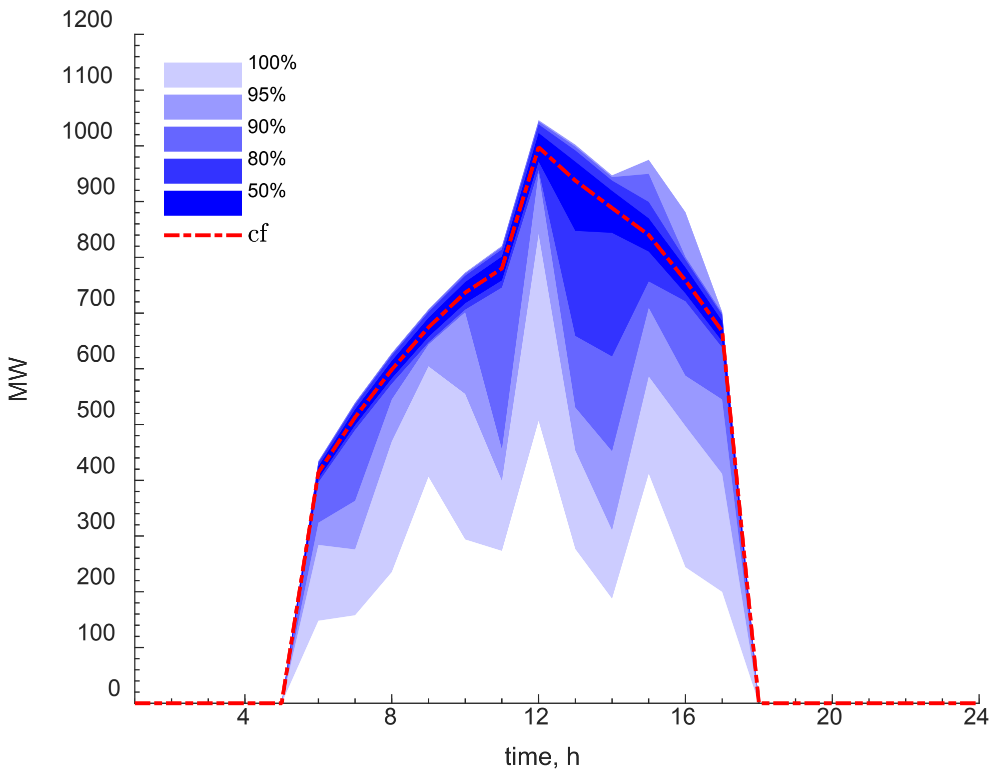
11 probability bins

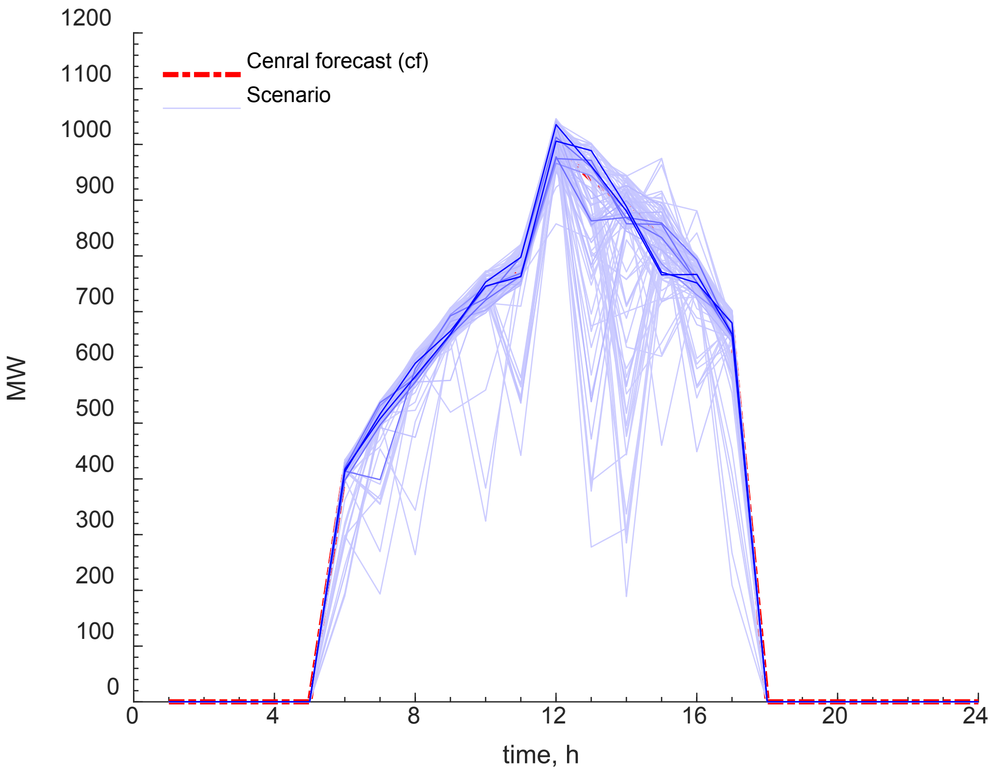
100 probabilistic scenarios: ρ = 0.80; ω = 0.08

The color intensity is proportional to the probability

1) PF via Scenarios (weak intertemporal correlation)

- Sample data:





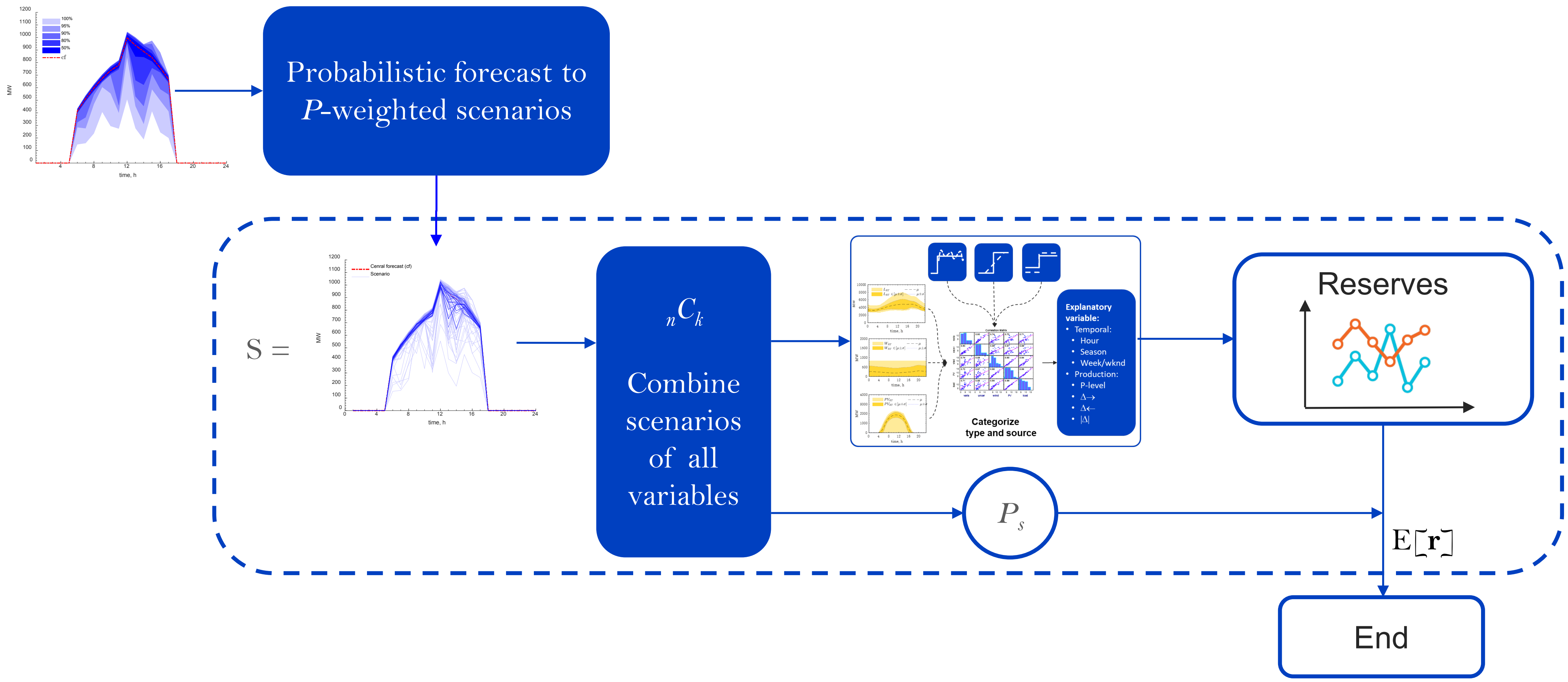
Probabilistic forecast from UL.

11 probability bins

100 probabilistic scenarios: ρ = 0.08; ω = 0.08

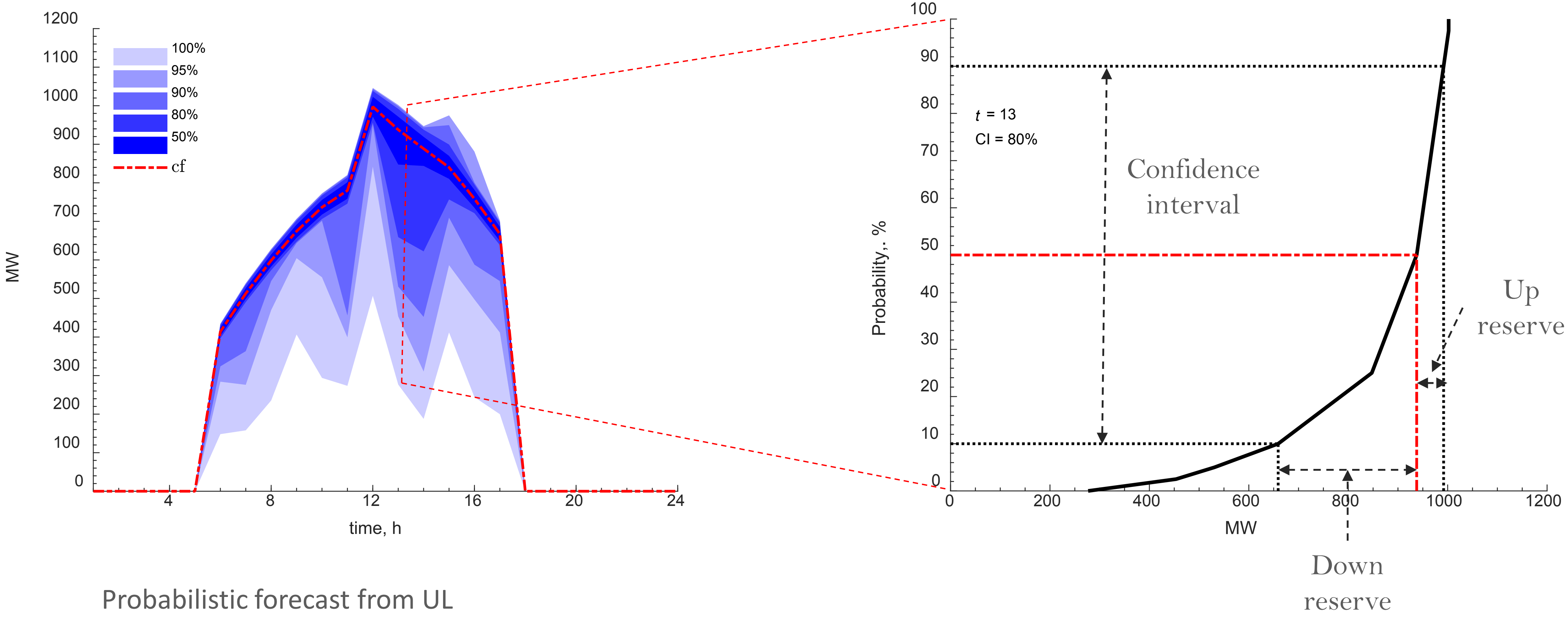
The color intensity is proportional to the probability

1) Integration into Operating Reserve Calculator



2) PF for a desired CI

- Reserve requirements for a given time period:

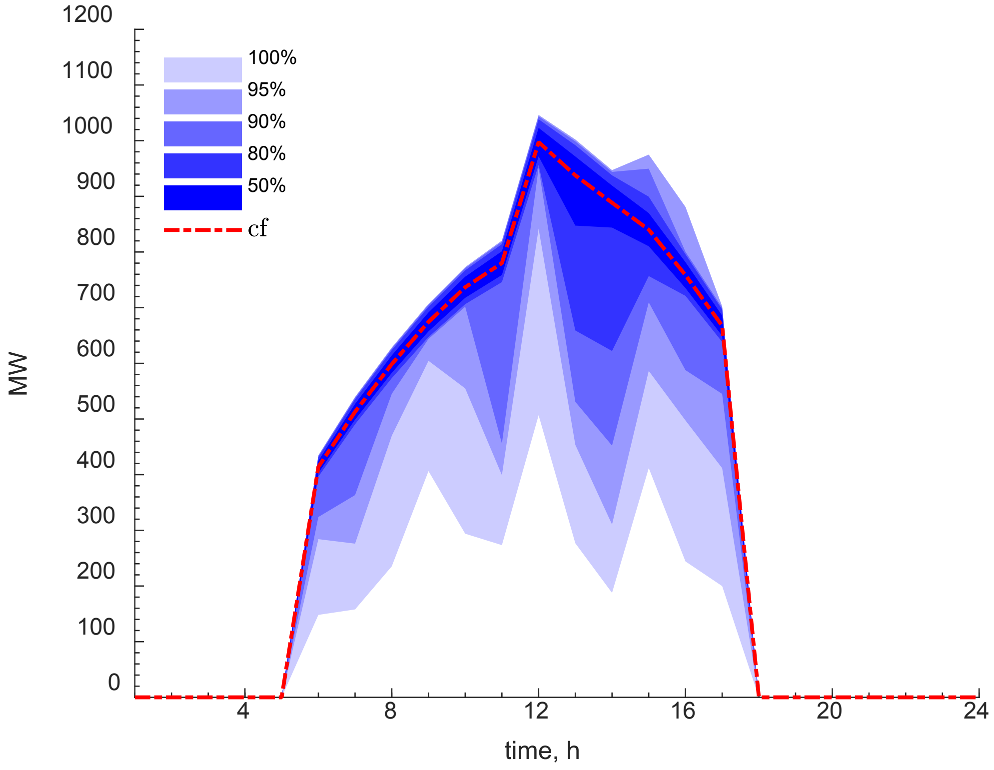


Probabilistic forecast from UL

11 probability bins

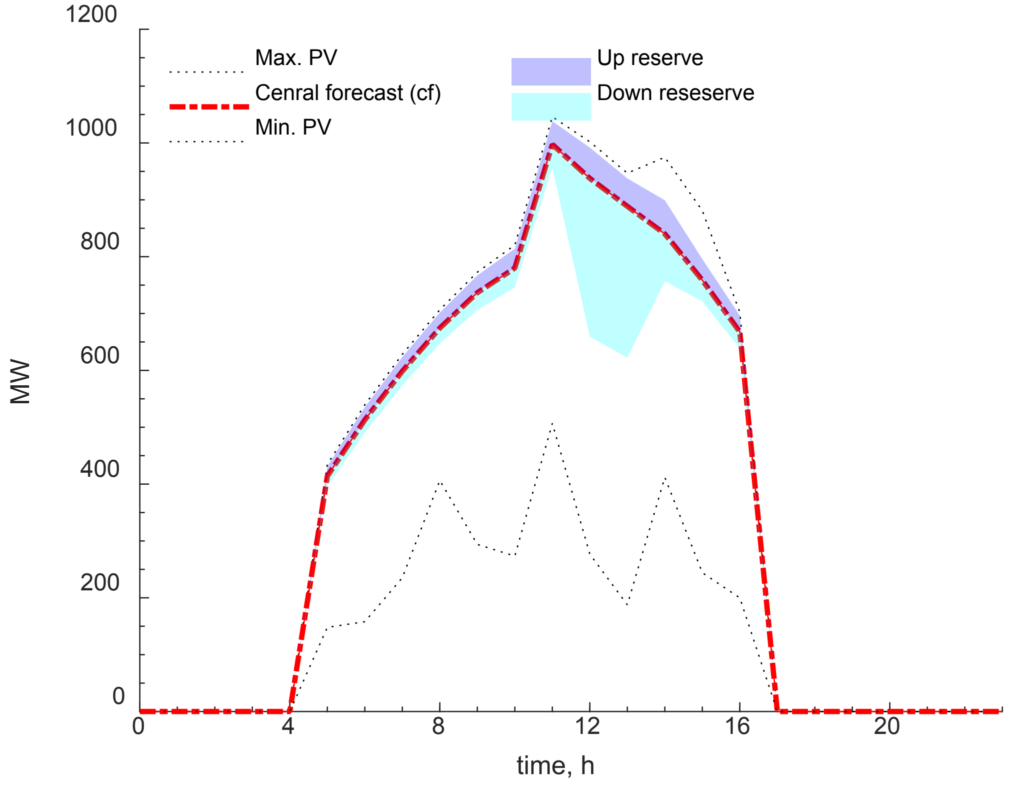
2) PF via CI of the PDF

- Sample data:



Probabilistic forecast from UL

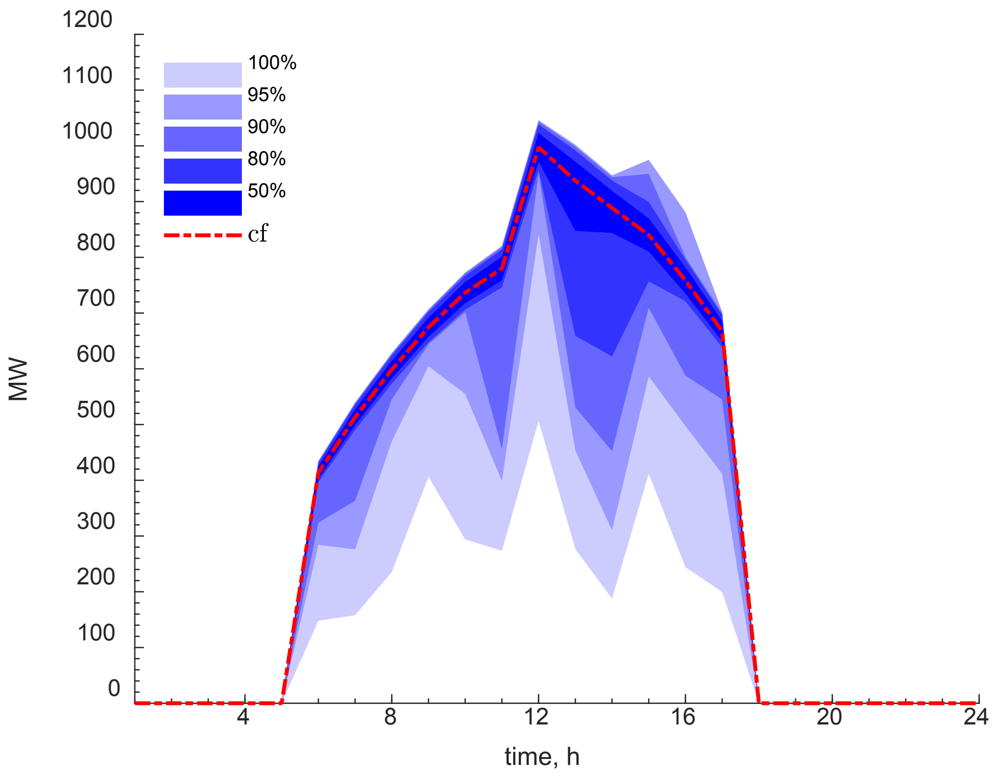
11 probability bins



Direct estimation of the up and down reserve requirements for a CI of 80%

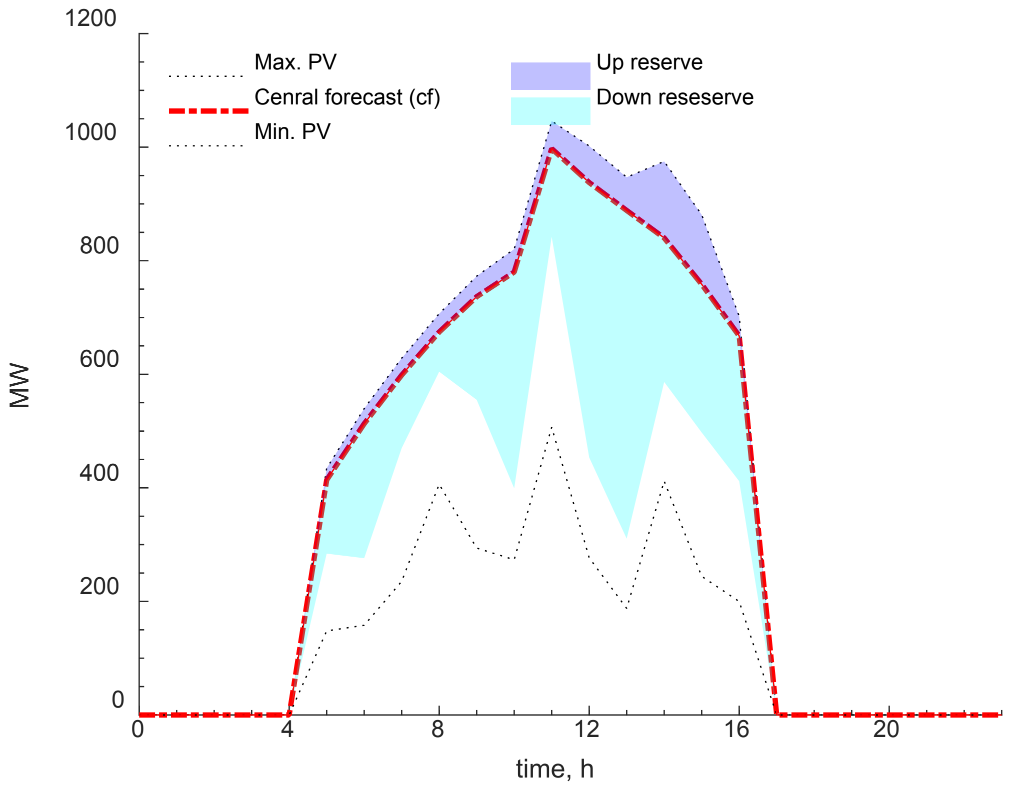
2) PF via CI of the PDF

- Sample data:



Probabilistic forecast from UL

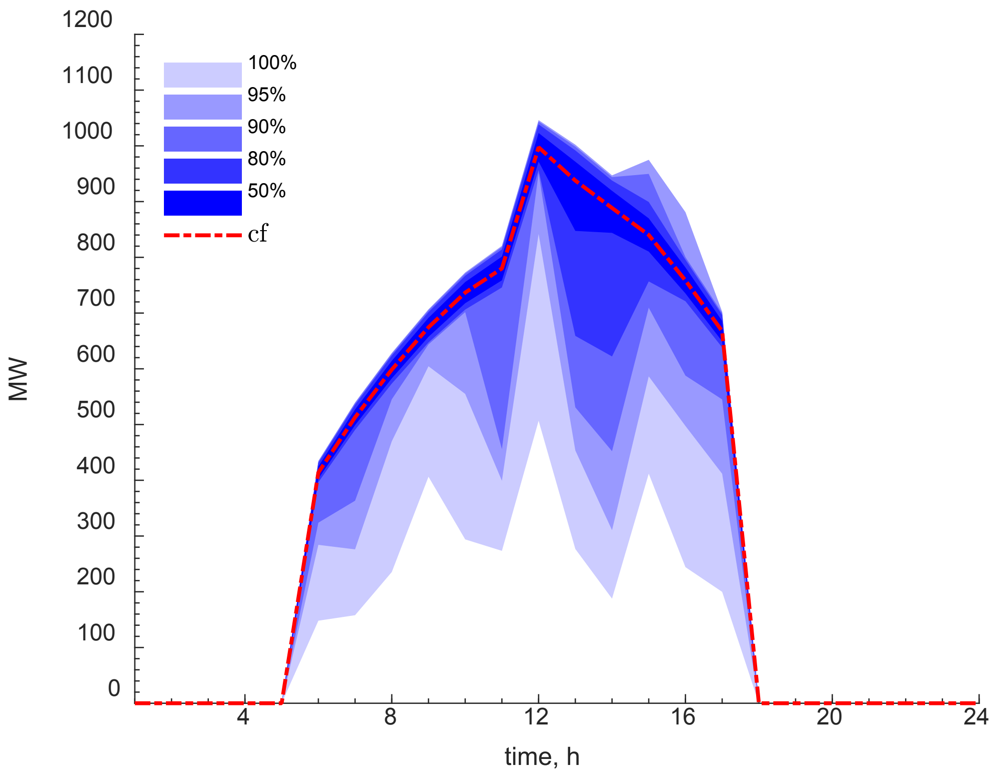
11 probability bins

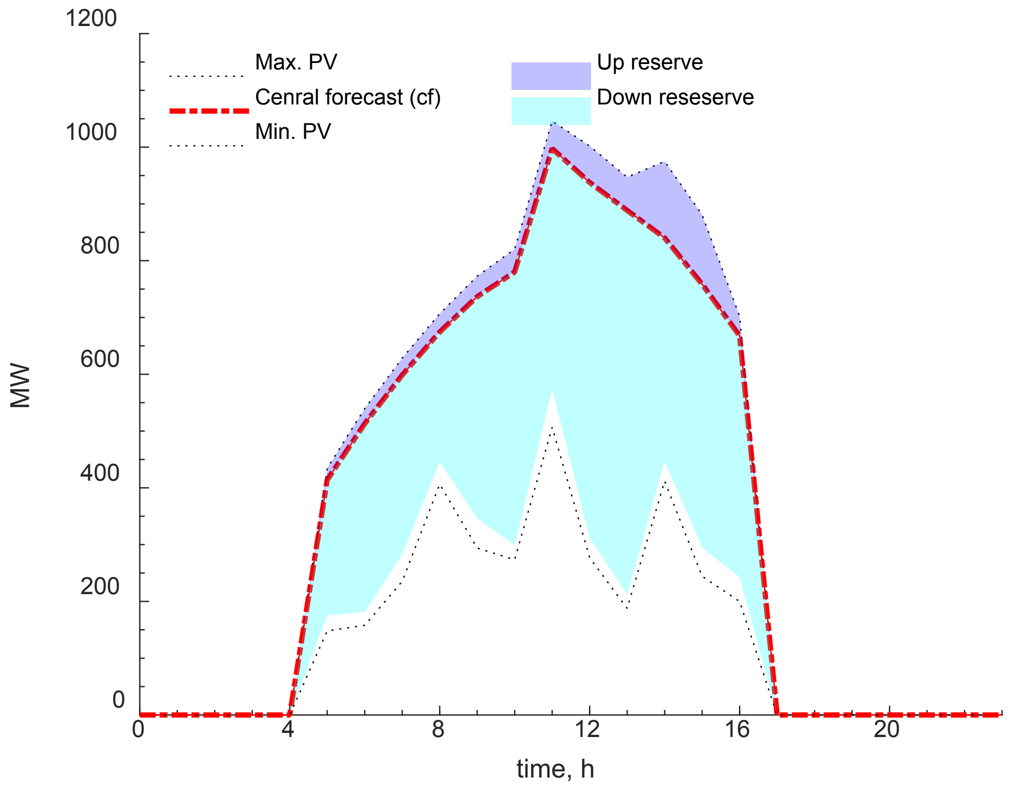


Direct estimation of the up and down reserve requirements for a CI of 95%

2) PF via CI of the PDF

- Sample data:



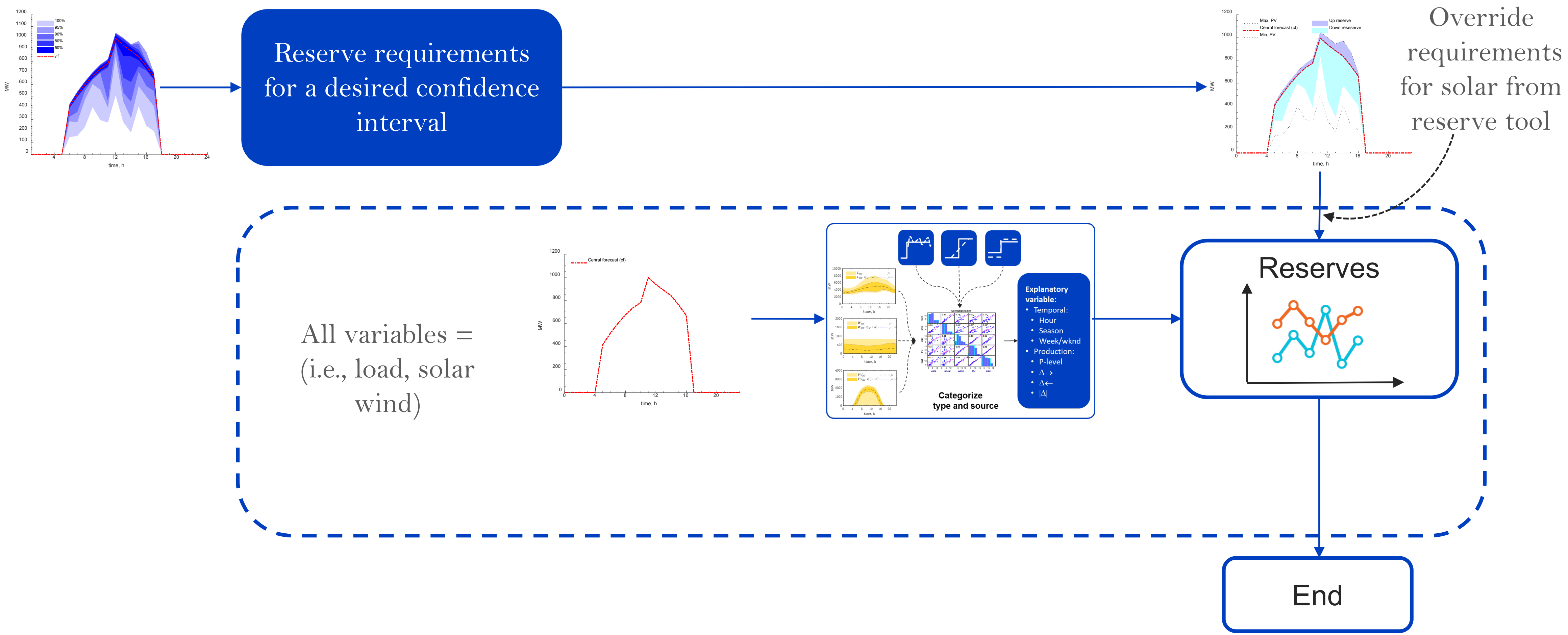


Probabilistic forecast from UL

11 probability bins

Direct estimation of the up and down reserve requirements for a CI of 99%

2) Integration into Operating Reserve Calculator



Next Steps for Reserve Requirements

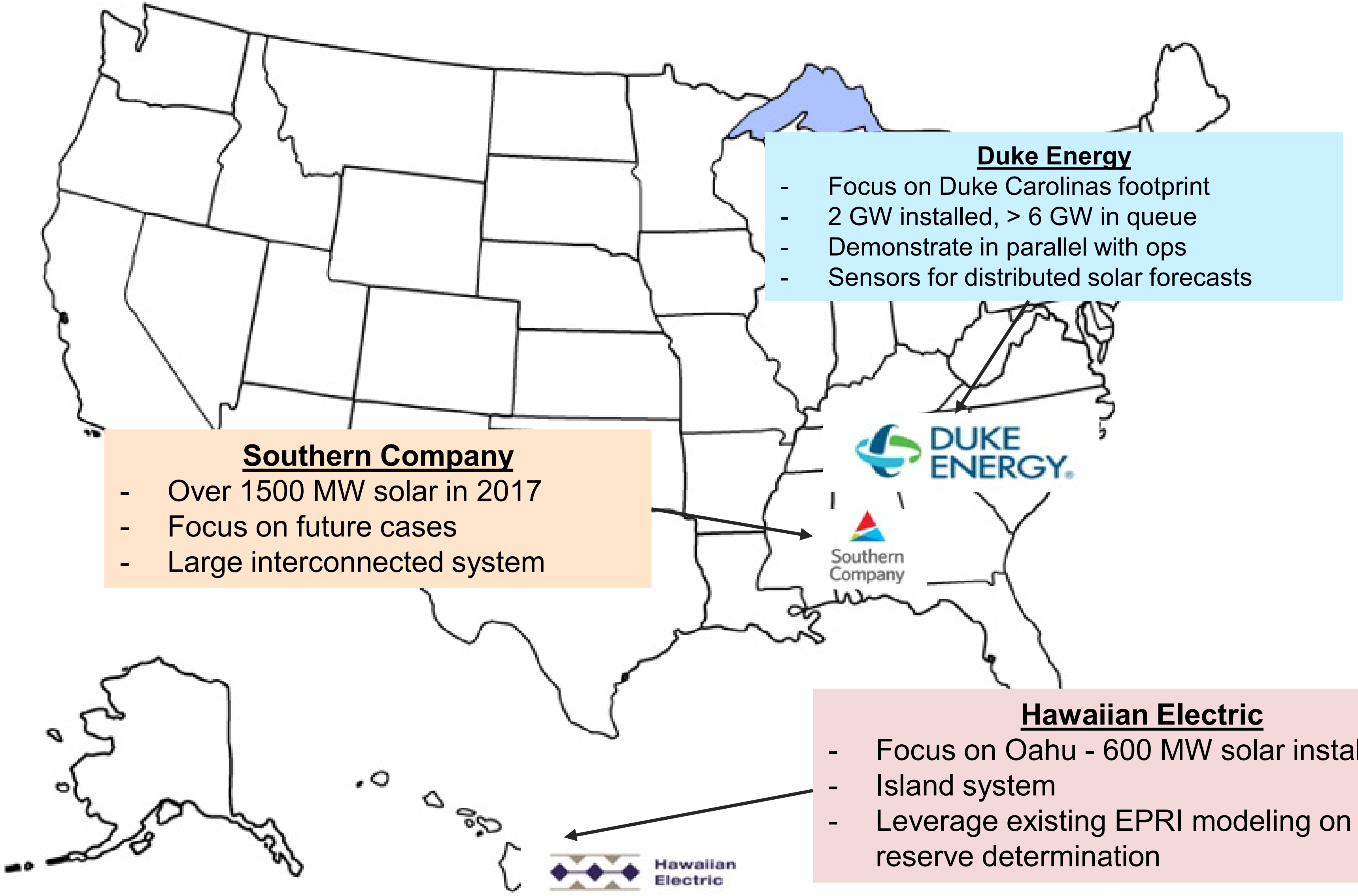
- Finalize integration of probabilistic forecast methods into the reserve determination tool
- Coordination with UL to generate larger sets of data for testing
  - System being explored: RTS-GMLC*
- Produce results on test system
- Qualitative analysis of the results
- Assessment using a production cost tool
- Move to larger case study systems (Hawaii first, then Southern and Duke)
- Compare to explicit representation of probability in UC/ED (BP3)

* https://github.com/GridMod/RTS-GMLC

Case Studies

Lead: Nikita Singhal, Robin Hytowitz, Qin Wang

Utility Demonstrations



Duke Energy

- Focus on Duke Carolinas footprint
- 2 GW installed, > 6 GW in queue
- Demonstrate in parallel with ops
- Sensors for distributed solar forecasts

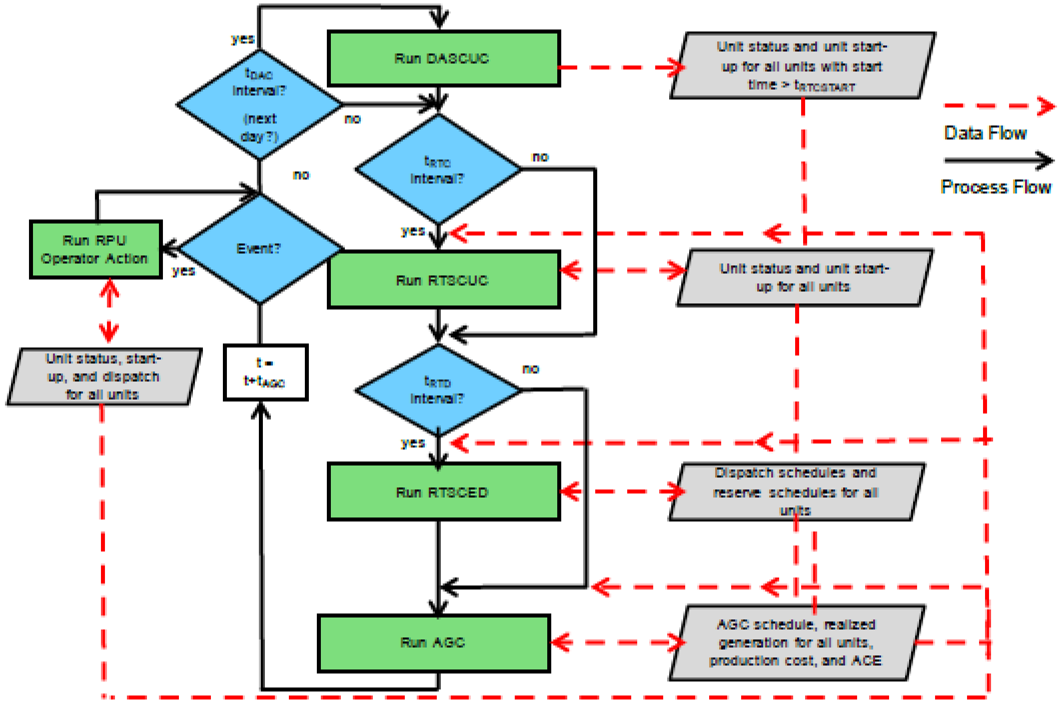
Southern Company

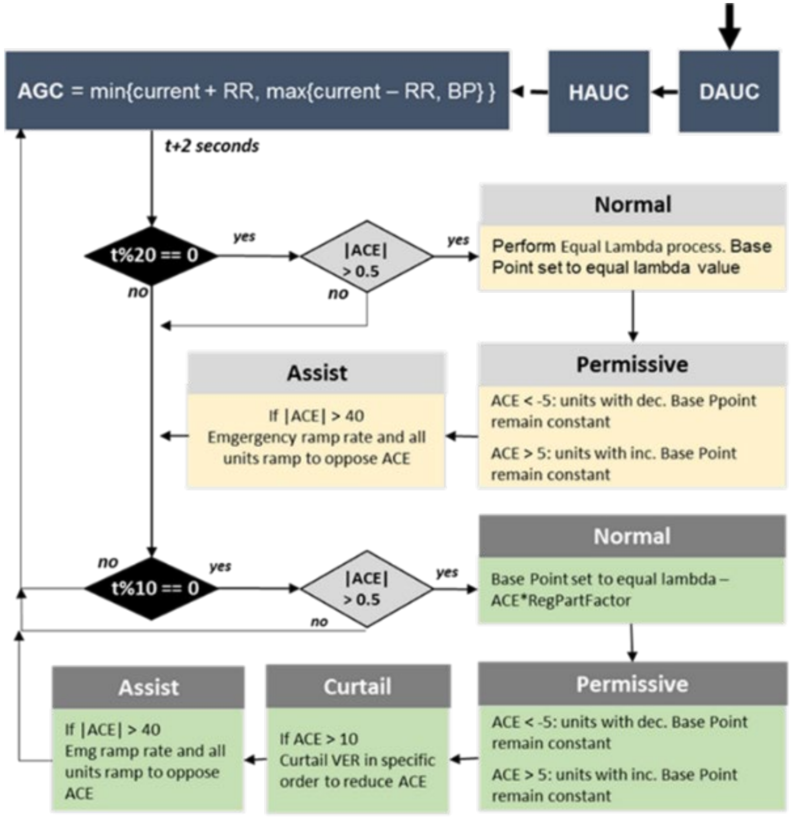
- Over 1500 MW solar in 2017
- Focus on future cases
- Large interconnected system

Hawaiian Electric

- Focus on Oahu - 600 MW solar installed
- Island system
- Leverage existing EPRI modeling on reserve determination

PCM Software Abilities: FESTIV





- Equal Lambda -
Simplified Description

Step 1: Choose starting lambda

Step 2: For all AGC units P=(lambda-b)/2a
Units below pmin or above pmax are fixed to those values

Step 3: Is Sum(P) minus current net load below stopping criterion (currently 1 MW), or is iteration count exceeded (currently 10)? If yes, go to Step 5. If no, go to Step 4.

Step 4: Set new lambda based on detailed algorithm. Go to Step 2 to repeat.

Step 5: If Max iteration hit and lambda is less than the minimum thermal unit inc. cost, begin to curtail VER in specific order

Step 6: Set BP equal to last determined schedules

HECO: Model Development

- **FESTIV** model enhancements (i.e., functional and formulation modifications) for HECO utilization in operations to enhance modeling accuracy (assists in obtaining realistic cost estimates)
  - Incorporation of logic around variable startup types (hot, warm, and cold)
  - Incorporation of staffing constraints and staff shift time constraints that impact resource schedules and operation
  - Incorporation of must-run requirements, daily minimum run time requirements, and planned resource outage schedules
- **Preliminary results** (1-week): Increase in system operating costs with added modifications/restrictions on resource operation and schedules (benchmark: 10%)
- **Current status**:
  - Validating the model and results on multiple weeks of data to ensure accuracy
  - Dynamic reserve requirement determination, using: 1) deterministic, and 2) probabilistic forecasts
  - Integration of dynamic reserve requirements within FESTIV

Duke Energy: System Data

- Duke system characteristics (DEC and DEP)
  - Conventional generation (steam, coal, CC, CTs): approx. 33 GW
  - Hydro: 1445 MW
  - Pumped Storage Hydro: 2140 MW
  - VER*: approx. 2 GW
- Data collected (new forecast and actual data)

	Load	Solar	Hydro**
Week-ahead (hourly)	√ (Jan17-May19)	pending	√ Fixed to actual
Day-ahead actual (hourly)	√ (Jan17-May19)	pending	√ (Jan17-May19)

* Dependent on the case study scenario – current system shown here

** Hydro schedule deemed as known for scheduling and dispatch purposes.

Southern Company: System Data

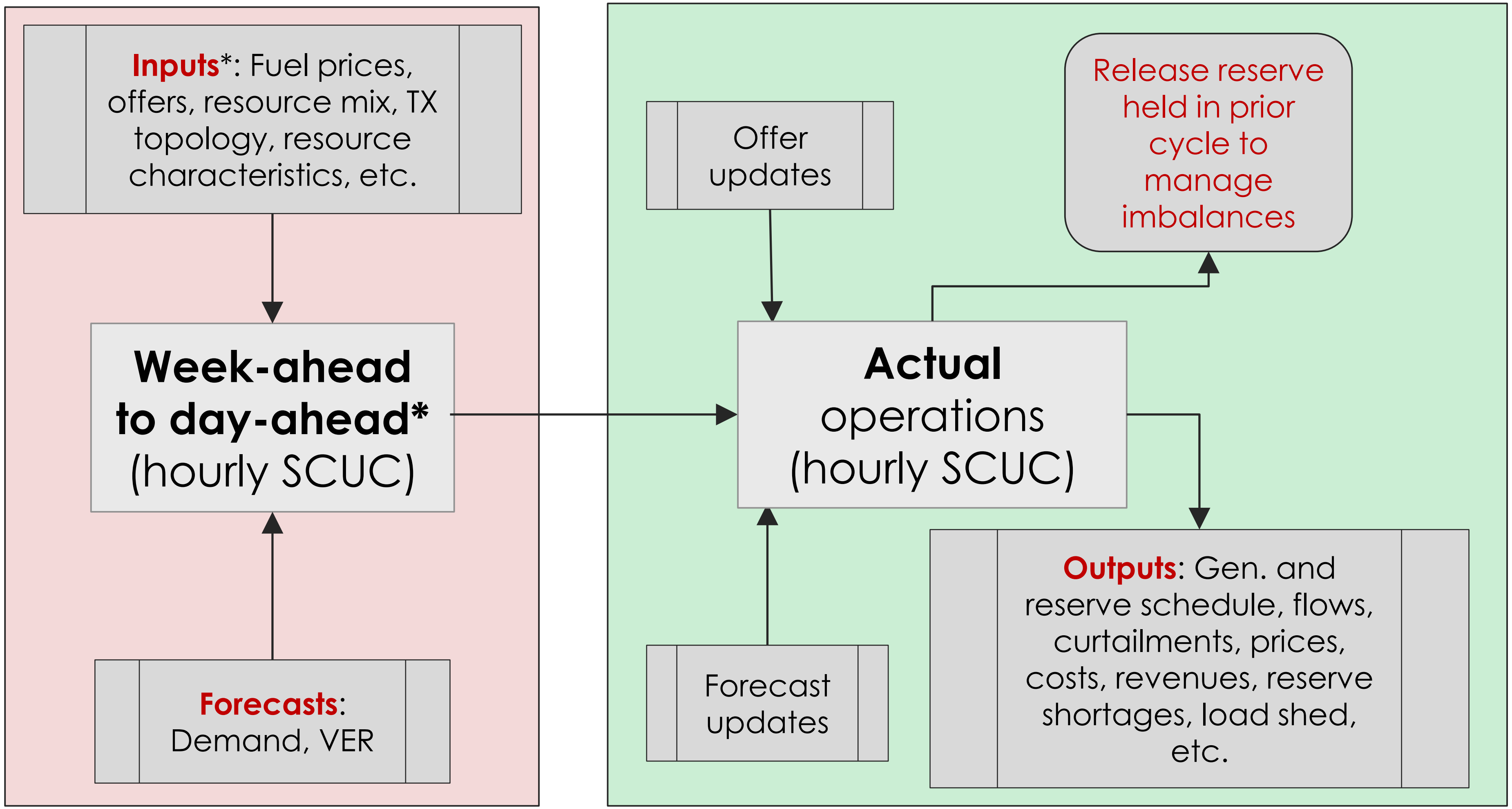
- Summary of Data
  - 287 generators (54 GW capacity)
  - 10-minute time-series data for Demand, Hydro (including pumped-storage) generation, solar and wind generation
  - Previously used for EPRI flexibility analysis work, extended here to do full simulation

- Test Scenarios
  - Low: ~1.5 GW PV capacity
  - Medium: ~ 6 GW PV capacity
  - High : ~10 GW PV capacity

Maximum 3hr Net Load Ramp at different solar levels

Solar Capacity	1.3GW	5GW	10GW	20GW
Max 3hr NL Ramp (MW)	6,515	8,122	11,278	18,131
Max 1hr NL Ramp (MW)	3,407	4,442	8,203	16,090

Utility Operations: PSO Software Abilities



*SCUC is run at 7AM on the current operating day due to less stressed conditions from midnight – 7am (ISOs/RTOs typically run their DAM at 11AM on the previous operating day or midnight), and run to end of 7 days out

Utility Operations: Scheduling Process

Cluster 1

Cycle 1 (Weekly)

All units can be committed

Run 7 days with forecast outlooks

Forecast CD	Forecast 1D	Forecast 2D	Forecast 3D	Forecast 4D	Forecast 5D	Forecast 6D
Jan. 4	Jan. 5	Jan. 6	Jan. 7	Jan. 8	Jan. 9	Jan. 10

Cycle 2 (24 hour)

All units can be committed

Actuals
Jan. 4

Cluster 2

Rolling Horizon

Cycle 1 (Weekly)

Forecast CD	Forecast 1D	Forecast 2D	Forecast 3D	Forecast 4D	Forecast 5D	Forecast 6D
Jan. 5	Jan. 6	Jan. 7	Jan. 8	Jan. 9	Jan. 10	Jan. 11

Cycle 2 (24 hour)

Actuals
Jan. 5

Next Steps: Case Studies

- Finalize data and models (BP1)

- Benchmark systems against utility studies/operations (BP1)
  - Production costs within agreeable level
  - Generation by type, reserve requirements, etc.
  - Cycles represent reality closely enough to be insightful

- Add probabilistic forecasts (BP2)
  - Dynamic reserves (deterministic and probabilistic)
  - Stochastic UC

- Visualization tools/scheduling management platform (BP2/3)

Together…Shaping the Future of Electricity

Methods to Respond to Variability and Uncertainty…

2014

•Use of **multi-cycle** production cost simulation

•Demonstration of use of these tools to show **benefits** of advanced reserve and scheduling

•Benefits of **dynamic vs. static reserve**

•**Stochastic UC** can be feasible on large-scale systems

2015

Introduction of **3 needs for reserve** and how these can be calculated

Reserve through **explicit reserve** requirements vs **implicit advanced scheduling**

Comparison of needs and **implicit vs explicit** reserve scheduling

Impact of scheduling formulation on reserve adequacy

2016

Scale comparison of advanced scheduling and dynamic reserve on large-scale practical system

Understanding of **additional practical challenges** of advanced scheduling and dynamic reserve

Understanding of advanced scheduling and dynamic reserve on **different scheduling processes**

2017

•Translate three reserve needs to **implementable reserve requirements**

•Start to finish dynamic reserve requirement **proposal for use in BAs**

•Study comparison of **benefits of dynamic reserve** and EPRI reserve proposal

• Additional studies complete on Hawaiian Electric Company

•**Software tool** that includes method for calculation

2018

Enhanced method to determine **dynamic reserve requirements using ANN**

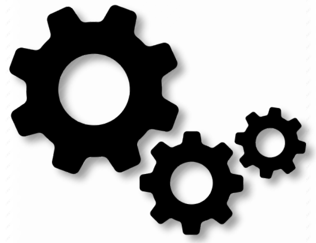
Comparison of the ANN method against original approach

•Additional studies complete on a utility member

Software tool that includes ANN method for calculation

2019

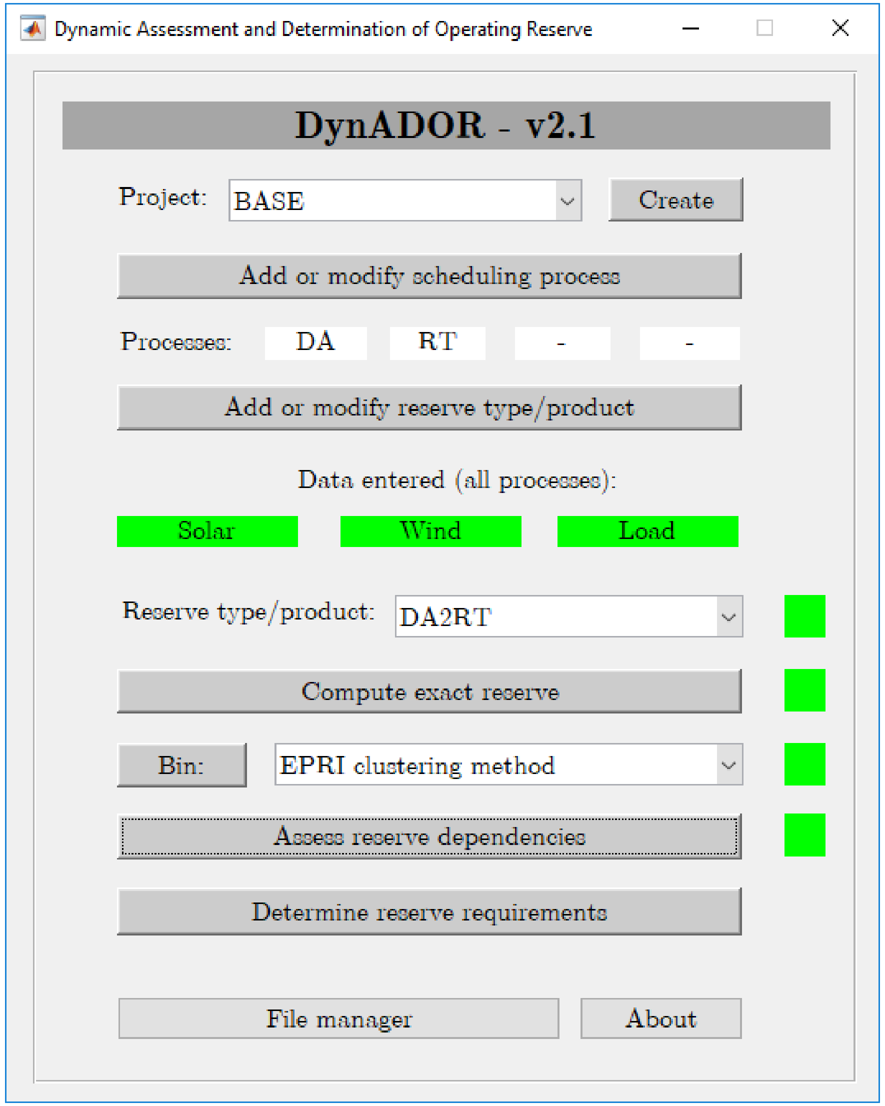
Work in progress …



Mitigation of potential imbalances due to variability and uncertainty, and enhance operating efficiency

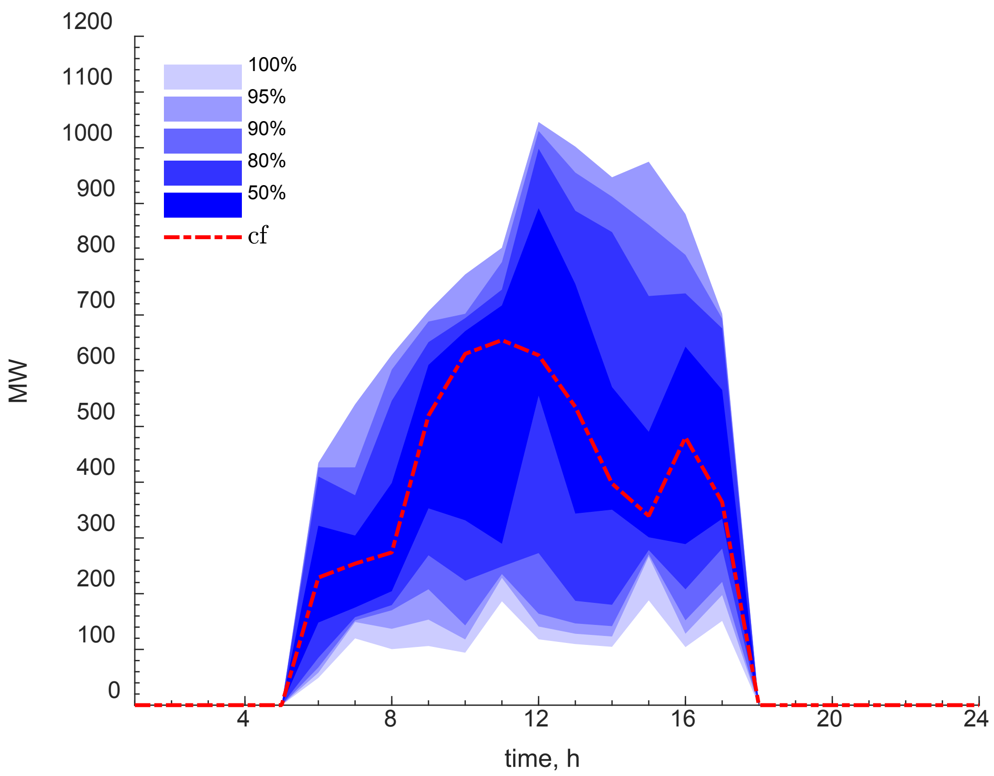
DynADOR Tool

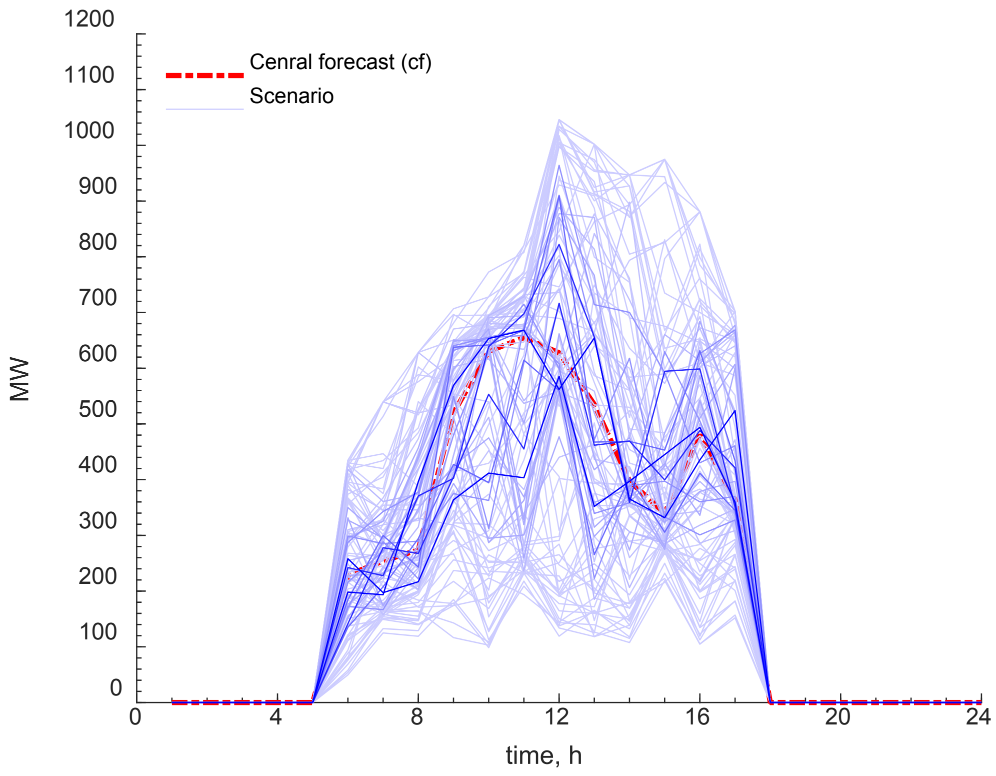
- Dynamic Assessment and Determination of Operating Reserve (DynADOR)
- Application of EPRI's **research methods** by development of software tool to determine "smart" reserve requirements
- Can be used in **operations or in studies**:
  - Day-ahead, month-ahead, real-time, input into long-term renewable integration study
- Applicable to different **balancing areas** types:
  - ISO/RTO, utility BA, International TSO, isolated system vs. large area
- Validation of results by means of detailed simulation studies



1) PF via Scenarios (different day)

- Different days:





Probabilistic forecast from UL.

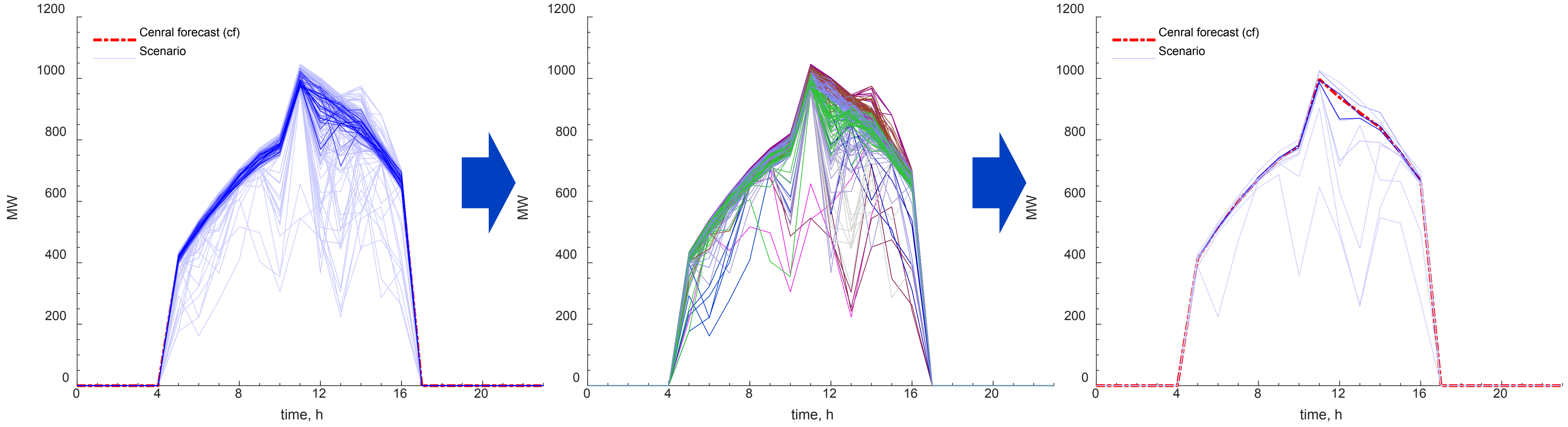
11 probability bins

100 probabilistic scenarios: ρ = 0.80; ω = 0.08

The color intensity is proportional to the probability

1) Scenario Reduction

- Populated sets of scenarios guarantees complying with desired statistical properties
- Computationally intensive for tools that optimize over the complete set
- Reduce to a set with a desired cardinality using k-means
- Grouping scenarios: 1) adding their probabilities, and 2) probability-weighed averages



Dynamic Reserve Requirement Methods

Reserve Characteristics

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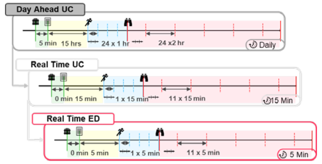
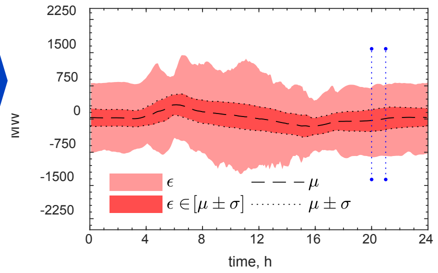
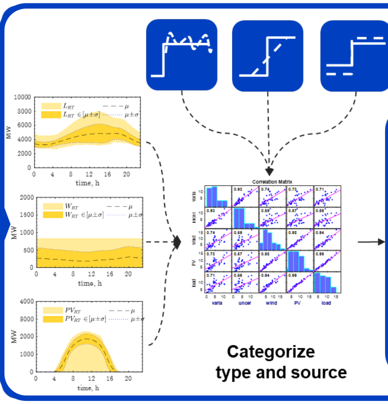
- Released
- Direction



Historical Assessment

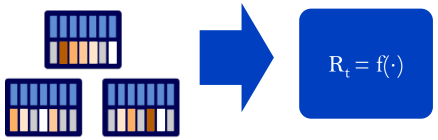
Historical assessment to determine the exact reserve requirements



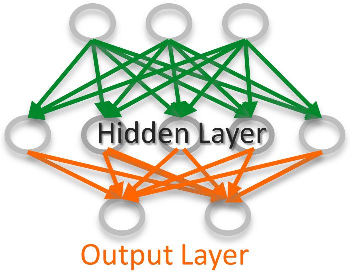


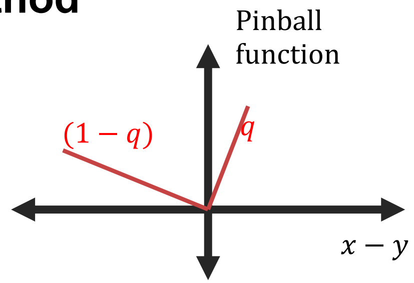
Explanatory variable:
- Temporal:
  - Hour
  - Season
  - Week/wknd
- Production:
  - P-level
  - $\Delta\rightarrow$
  - $\Delta\leftarrow$
  - $|\Delta|$

Assemble using best explanatory variables

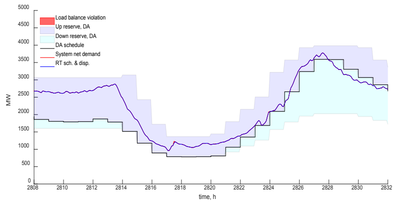


ANN Method





Determine Dynamic Reserve Requirements



Alternative Methods to Determine Reserve Requirements

1) Intertemporal Correlation