Cornell University

Development and Testing of New Tools

Tools for Multi-period Stochastic Optimization with Evolving Information

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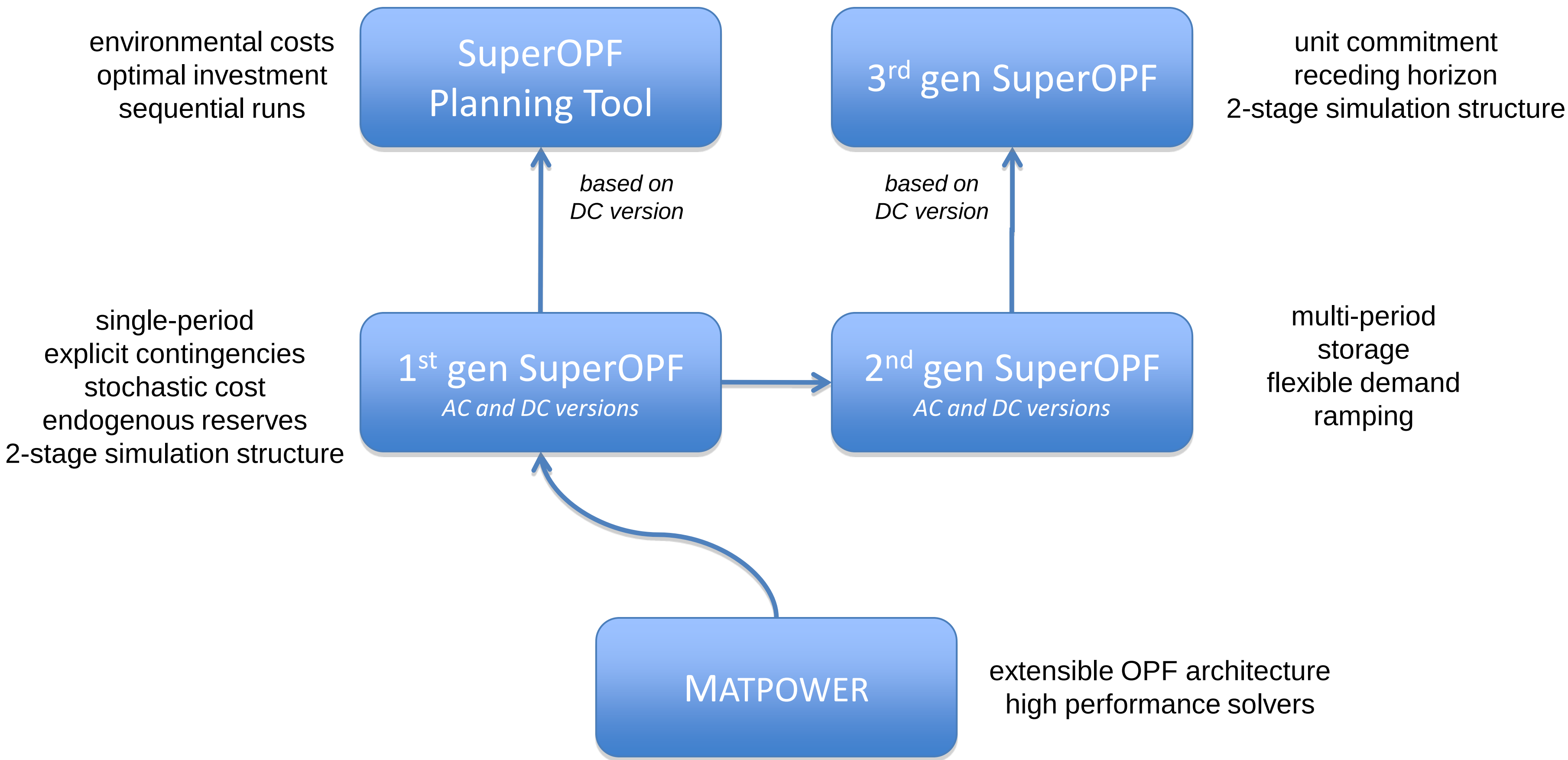
CERTS
CONSORTIUM FOR ELECTRIC RELIABILITY TECHNOLOGY SOLUTIONS

Outline

- Project Overview
  - progress on underlying tools
  - current focus
- Design of Receding Horizon Framework
- Uncertainty in Receding Horizon Input Data

  (i.e. “feeding the monster”)

SuperOPF Map



Need for New Tools

Driven by …

- variability
  – large changes from one period to the next means you need look-ahead planning (e.g. for ramping)
- uncertainty
  – must plan for range of realizations (e.g. wind)
- storage and flexible demand
- environmental policy

Unifying Themes

- simultaneous, explicit modeling of multiple states
  - each state has full set of OPF vars, constraints, costs
- stochastic or weighted cost
- additional variables, constraints and costs that tie these states together

Progress on Underlying Tools

- MATPOWER
  - used worldwide in teaching, research and more
  - v4.1 released in 2012, v4 over 25,000 downloads
- SuperOPF Planning Tool
  - used by Project 2E: Mapping Energy Futures: SuperOPF Planning Tool *(Bill Schulze)*
- 2nd gen (multiperiod) SuperOPF
  - used by Project 2A: Evaluating Effects of Managing Controllable Demand & DER *(Tim Mount)*

MATPOWER

v4.1 & recent dev versions, added support for:

- more high performance solvers
  - Knitro, Gurobi, CPLEX 12.4
- dispatchable DC lines
- systems with islands
  - new tools for detection and manipulation, running PFs
- generalized software object used to build and manage optimization models
- uniform interface for solving MILP/MIQP problems
  - foundation for UC in 3rd gen SuperOPF

SuperOPF Planning Tool

- 1st gen (single-period) SuperOPF
  - minor bug fixes
  - reduced number of constraints by reformulating some
- Planning Tool
  - added build limits by type/region
  - solving model of Eastern Interconnect
    - 5222 buses
    - 2882 gens
    - 14225 branches

Multiperiod SuperOPF

2nd gen SuperOPF

- bug fixes, code cleanup, performance tuning
- reduced number of constraints by reformulating some
- internal rewrite to use new optimization model object
- improvements to price coordination used in AC version
  - new adaptive strategies for some parameters
- improved modeling of the residual value of stored energy in terminal states
  - driven by results from Mount’s project
  - several iterations of design, latest needs more testing
  - turns out to have significant impact

Focus for 3rd gen SuperOPF

Choosing to focus on aspects of problem that can be explored with DC network model:

(AC problem is HARD, but not unimportant)

- benchmarking stochastic framework
- adding UC to solver
- getting the simulation environment right
  - with uncertainty, receding horizon is crucial

Benchmarking Stochastic Framework

Benchmarking SuperOPF tools requires creating "current practice" tools to compare against:

- any comparison involves some apples vs. oranges, outcomes sensitive to assumptions, no other choice

- Previous comparisons
  - single-period SuperOPF vs. OPF with fixed zonal reserve
    - uncertainty driven by low probability contingencies

Designing New Benchmark Tests

- New comparisons
  - multi-period SuperOPF vs. multi-period OPF wth fixed zonal reserve
    - uncertainty driven by wind
- Significant effort has gone into designing new testing scenarios:
  - 118-bus case
  - realistic wind inputs, load profiles
  - contingencies

Add Unit Commitment to Solver

- new MILP/MIQP interface code in MATPOWER lays foundation
- straightforward addition of commitment variables, min up/down-time constraints, startup/shutdown costs
- FERC has recently made available new UC test case

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Design of Receding Horizon Framework

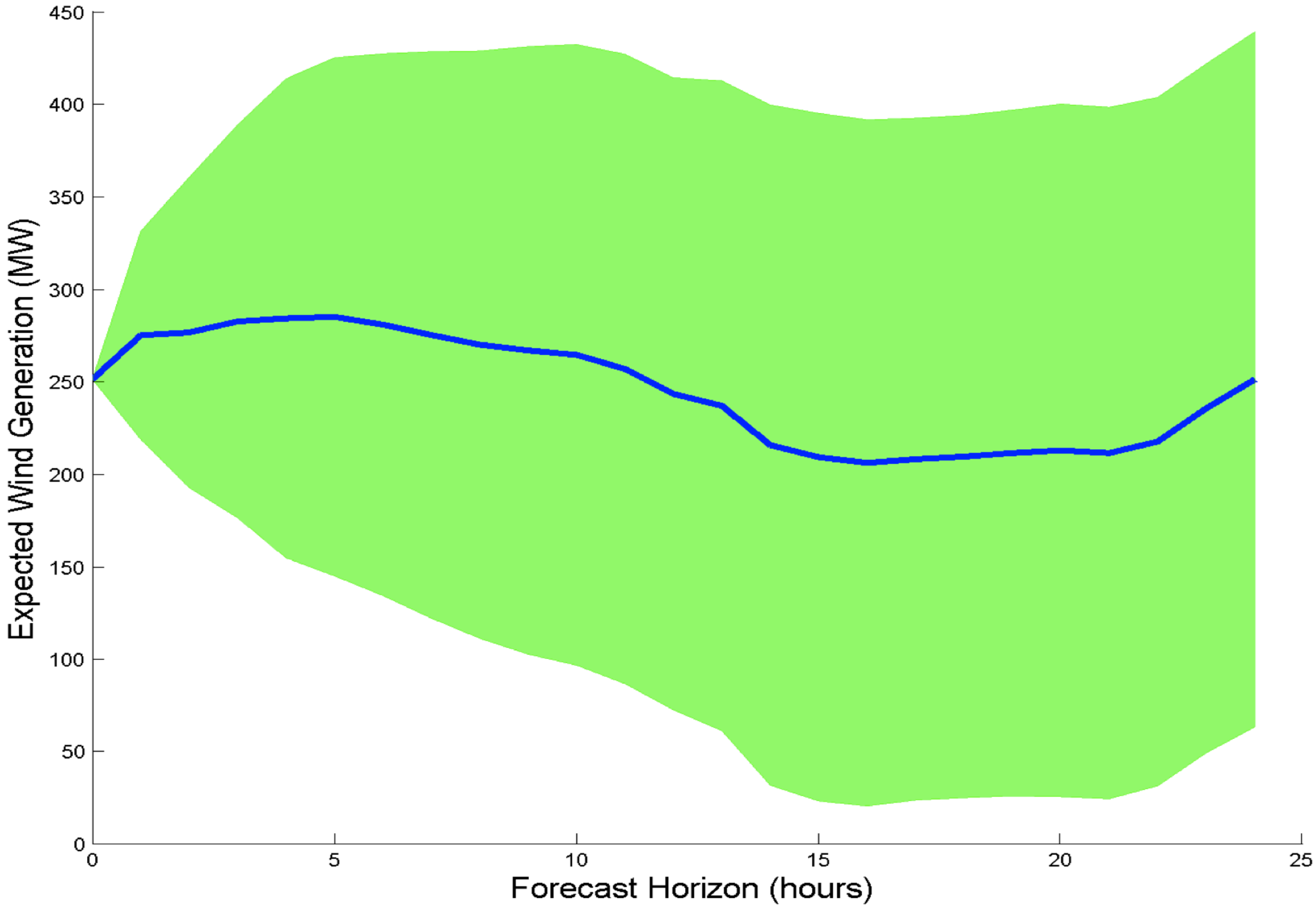
Carlos E. Murillo-Sánchez

- AC Multi-Period SuperOPF: improvements on speed, but still not usable for general users. Not a “shake and bake” tool; needs careful tuning. But 10x improvements have been obtained for systems such as the IEEE 118 bus.
- DC Multi-period SuperOPF: adding unit commitment (MIP) and general linear system dynamics driven by the injections. Motivation: to model time-dependent pollutant transport. Additionally, further refinements to the storage resource modeling have been added and are being tested.

Motivation

- The 2nd generation Multi-Period SuperOPF is based on the day-ahead paradigm, planning a stretch of 24 hours at a time. In actual operation, it is assumed that a second-stage solver redispatches close to real-time, adjusting the 24 hour plan.
- But that far into the future the error bounds for wind forecasts are very large, and the system state could be different in general

Expected Output with Error Bounds



Incorporating new information

- In real life, there is new information arriving every instant in the form of improved forecasts and actual measurements of the system's state
- Ideally, this new information should be incorporated as soon as it arrives. The current decisions must be made with the best information available.
- Similarly, some decisions should be made at a later time whenever possible, when there is more confidence in forecasts.

Receding horizon

- Keep most characteristics of the unique approach used at Cornell:
  - whole-day planning horizon,
  - stochastic cost,
  - cooptimization of energy and both ramping and contingency reserves
  - post-contingency security
  - operating envelope modeling rather than trajectory scenarios, for tracktability and ensured security
  - transition probabilities to gauge the ramping needs (security of operation is still key!)
  - freedom to use storage for either arbitraging, mitigating uncertainty and contingency recovery
- But now, re-solve every hour with new information

- Some quantities for next few hours could already be “firm”, fixed by decisions that were required to be made earlier, and their redispatch would be like an almost real-time adjustment
- Further ahead in the horizon, other quantities will still need to be determined (amount of contingency and ramp reserves, contracted energy quantities, commitment status)
- Offers need to be firm for the planning horizon (needed for co-optimization)
- Can have different lock-in lead times for each resource; if a decision can be deferred without consequences, it may be more advantageous to delay making it.
- Can publish non-binding quantities and prices even before lock-in (units with non-firm fuel contracts will appreciate this)

Related to: Model predictive control (MPC)

- Mature technique already used in industry
- Instead of a feedback law computed by a dynamic system, as in many traditional control schemes, the decisions in MPC are the result of an intertemporal optimization
- Made possible by advances in QP solving in the 80's and 90's

Principles:

- Re-computation of controls using new measurements and a receding horizon replaces classical feedback
- Always use the latest measurements, forecasts, or information

Structure of 3rd generation SuperOPF

- Keep two stage structure
- Ideally, look at horizons that are at least as long as the load variation cycle to properly handle storage
- The first stage does the look-ahead; the second dispatches securely within the limits imposed by stage 1, like the 1st and 2nd generation SuperOPFs.
- For simulation purposes, can stop at the level of detail provided by stage 2.
- In practice, a third pricing-only real-time OPF would be run.

Timeline for receding horizon

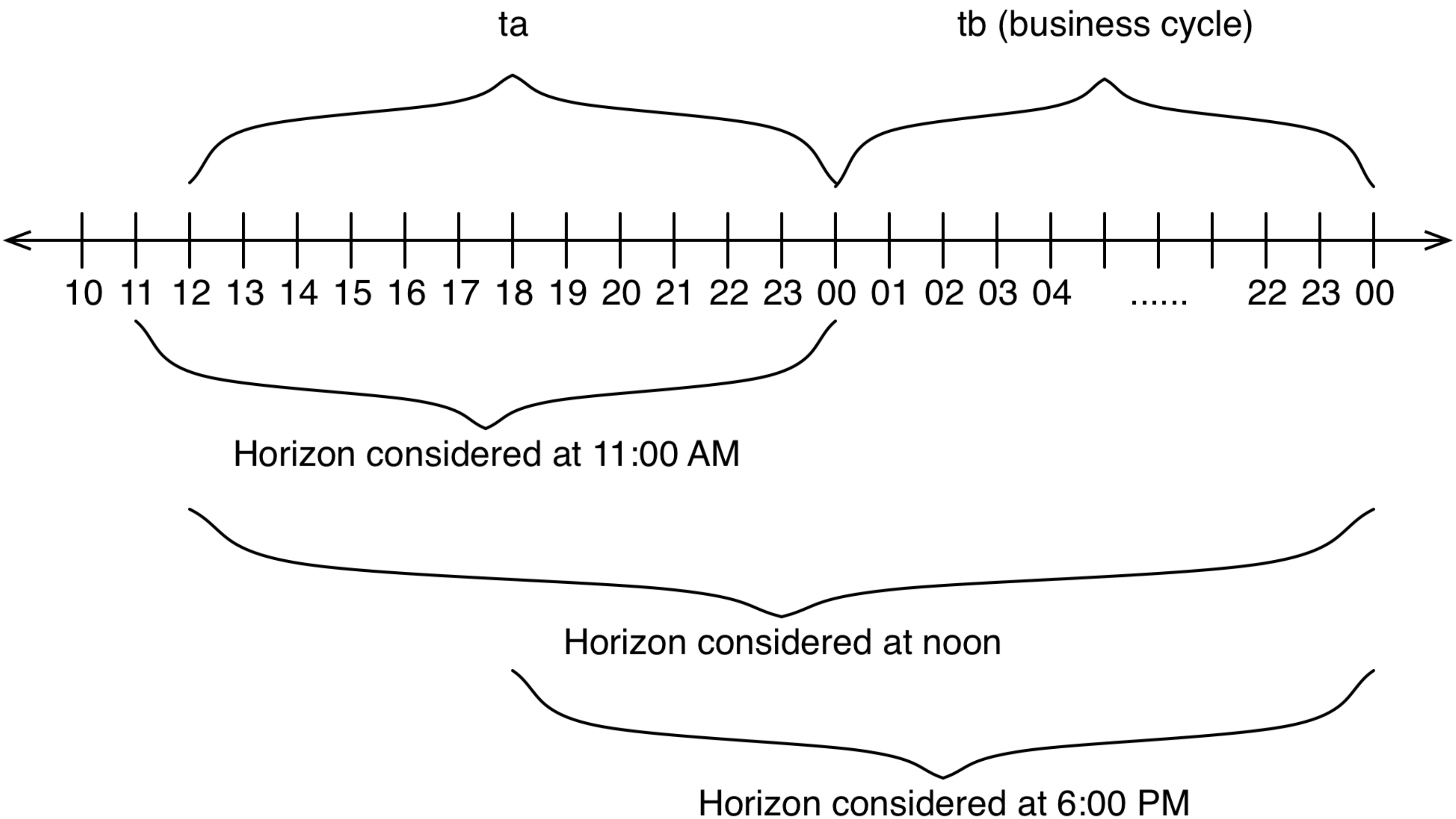
- At time t, the horizon {t+1, t+2 … t+N}, where t+N is the furthest point in time for which we have offer information, is considered as an optimization problem, and decisions {u(t+1), … u(t+N)} are computed.
- Only decision u(t+1) is actually implemented, meaning that starting now (t) the system will be driven so that it will be at the desired state in t+1.
- Decision u(t+2) will be recomputed, with new information (updated forecasts and current system state) at time t+1, using the new horizon {t+2, t+3, … t+N}.

- If in any given instant new offers become available, N is updated accordingly.
- There might be a need to consider an additional “computational delay” if the time required to solve the stage 1 problem is comparable to that represented in each period or “hour”.
- Within each “hour”, the second-stage solver is run several times, trying to steer the system in a trajectory interpolated from the current state to the state that we want to be right on the hour, as computed in the latest optimization. This solver enforces contracted limits.

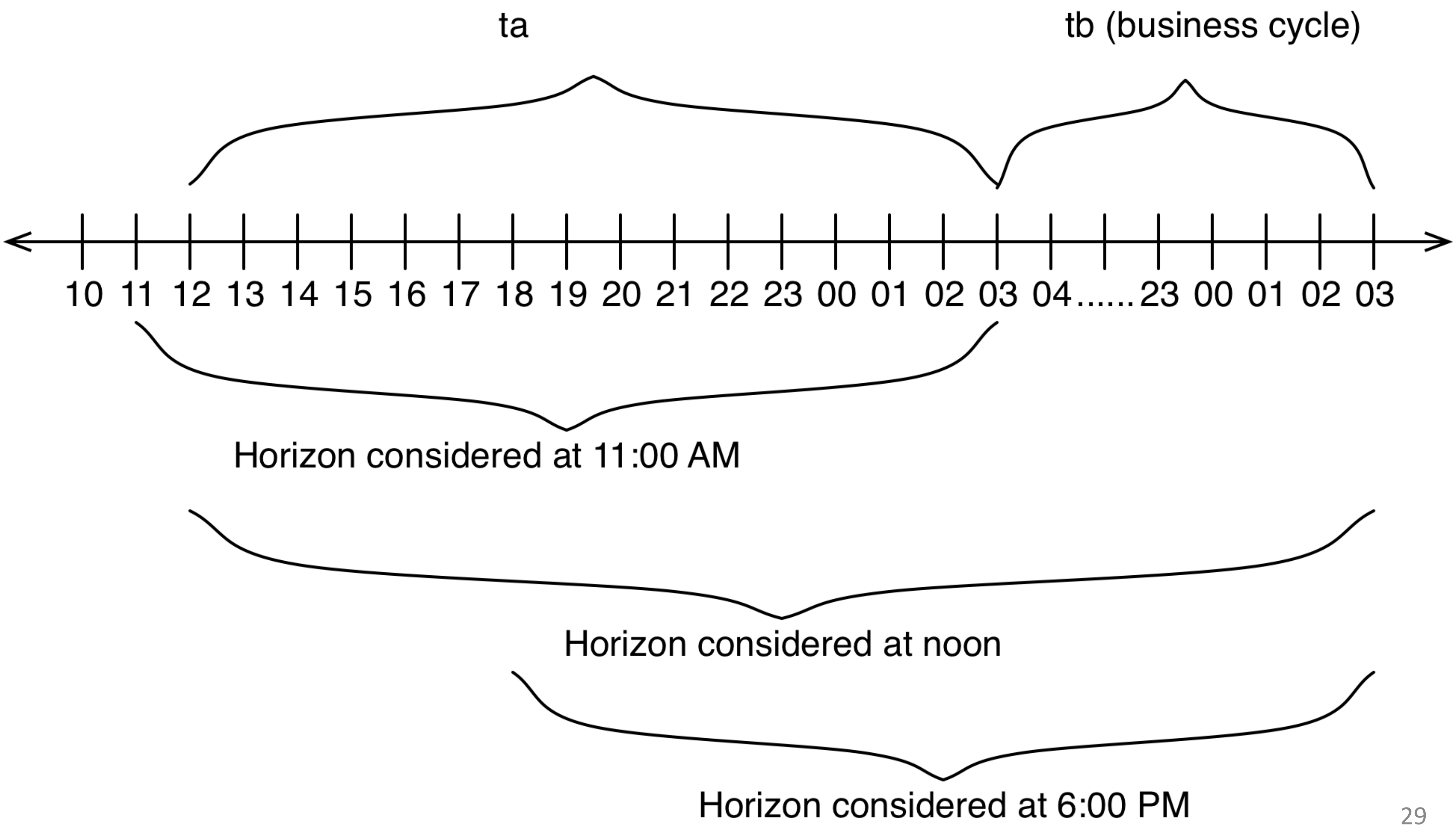
Temporal structure

- Three basic time parameters needed to define the temporal structure
- τb is the periodicity of offer reception (e.g., every 24 hours; the length of the "business" cycle)
- τs is the hour, within the "day", at which the business cycle begins
- τa is the lead time for offers (how many hours ahead of the start of the business cycle the offers become available)

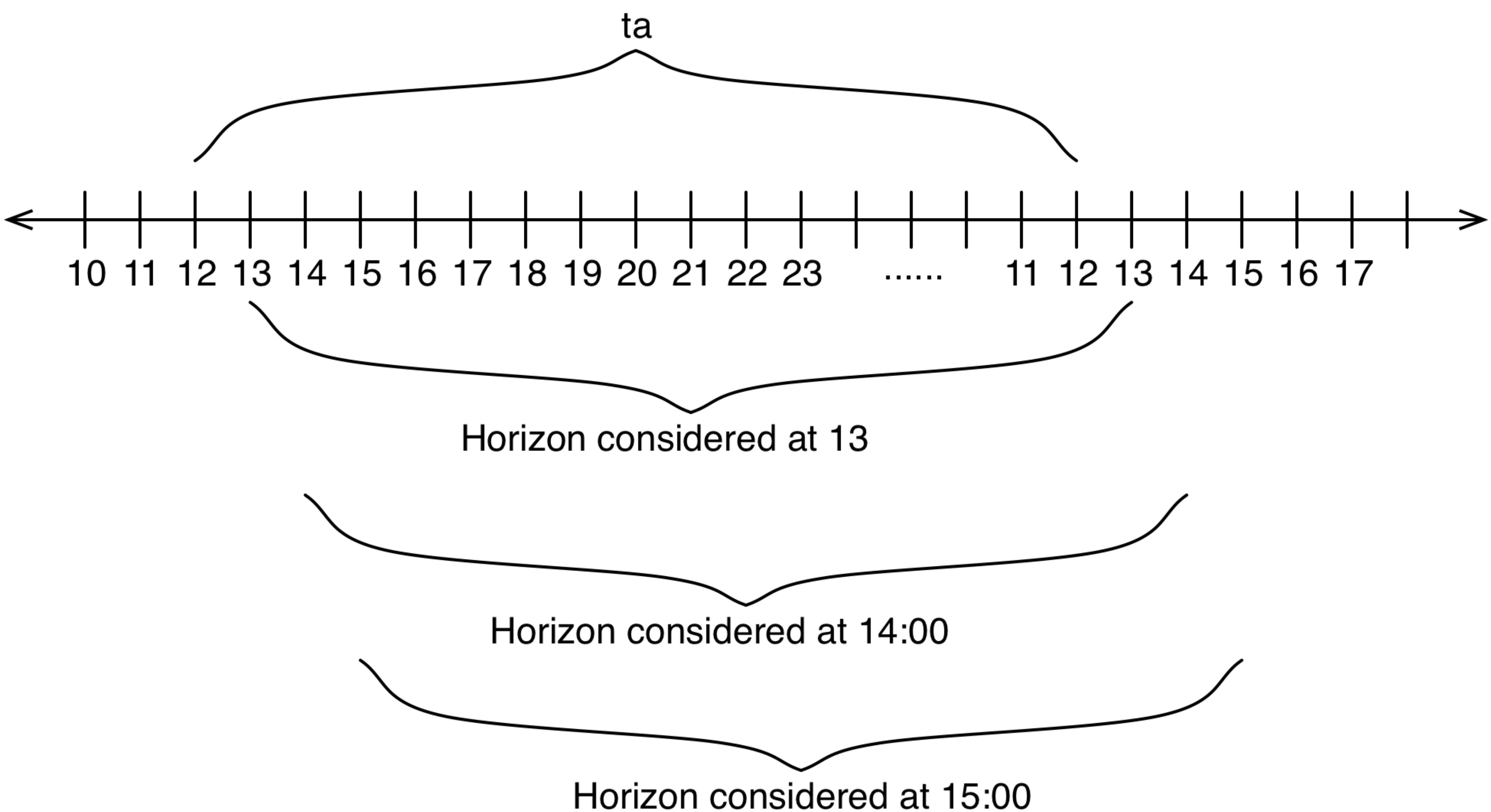
Offers for next day available at noon: τb = 24, τs = 0, τa = 12



Offers for day starting at 03:00 available at noon previous day: $\tau b = 24$, $\tau s = 3$, $\tau a = 15$.



Offers just for t+24 available hourly: τb = 1, τs=0, τa = 24



Using it / testing it

- Generating evolving forecasts becomes necessary! Huge effort to characterize wind realizations conditional on an evolving, dynamic forecast. But that is how it would be used in practice.
- The proposed approach needs a dynamic simulation in order to be tested appropriately.

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Representing Uncertainty in a Receding Horizon Formulation

C. Lindsay Anderson

Amandeep Gupta

Representing Wind Uncertainty

- Ability to forecast wind generation improves as the forecast horizon becomes shorter
- *evolving information* is fundamental advantage of receding horizon framework
- dynamic *evolution of uncertainty* must be properly represented in model inputs, to justify the approach

Characteristics of Wind Forecasts

Planning scenarios should conditioned on *a priori* day ahead forecast

These wind (and load) forecasts must:

•represent a time series of distributions

•exist throughout the entire horizon

•have accuracy inversely correlated with forecast horizon

•preserve serial correlation over the forecast horizon

SuperOPF Wind Inputs

1. Classification of “days” based on the current operating point and forecast type
2. Scenarios to represent possible evolutions resulting from similar forecasts
3. Analysis of SuperOPF performance through actual realizations in operational simulations

To meet these needs, we develop the SuperOPF inputs according to the following algorithm

Wind Input Development Map

Development of Forecasts

- Develop complete simulated forecasts,
- Interpolation of inter-window forecasts

Filtering Historical Data

- Classify realizations based on similar
  - Initial condition
  - Forecast over horizon

Scenarios resulting from common forecast

- Conditional on similar forecast
- Develop hourly output scenarios with empirical transitions

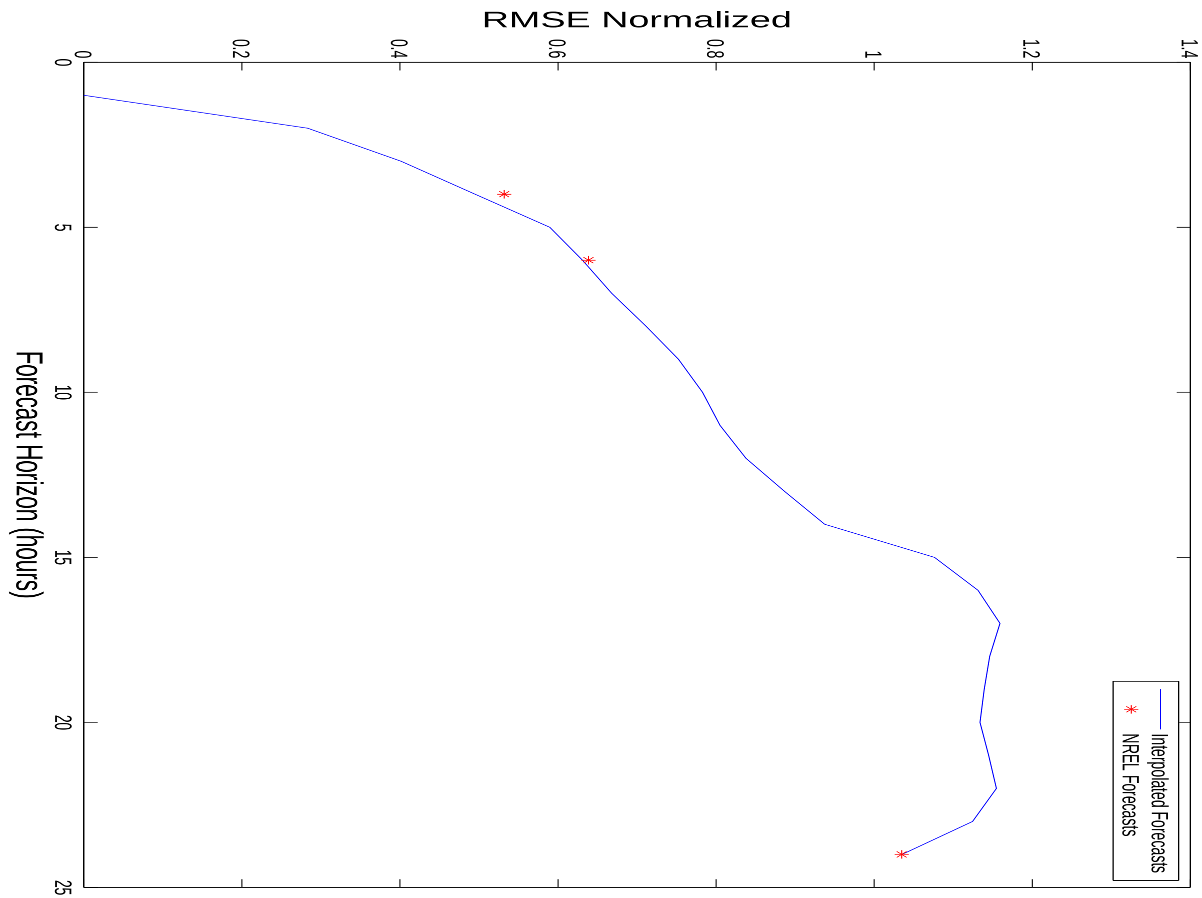
Assessment of operational plan

- SuperOPF performance:
  - Planned using conditional scenarios
  - Run on realized days

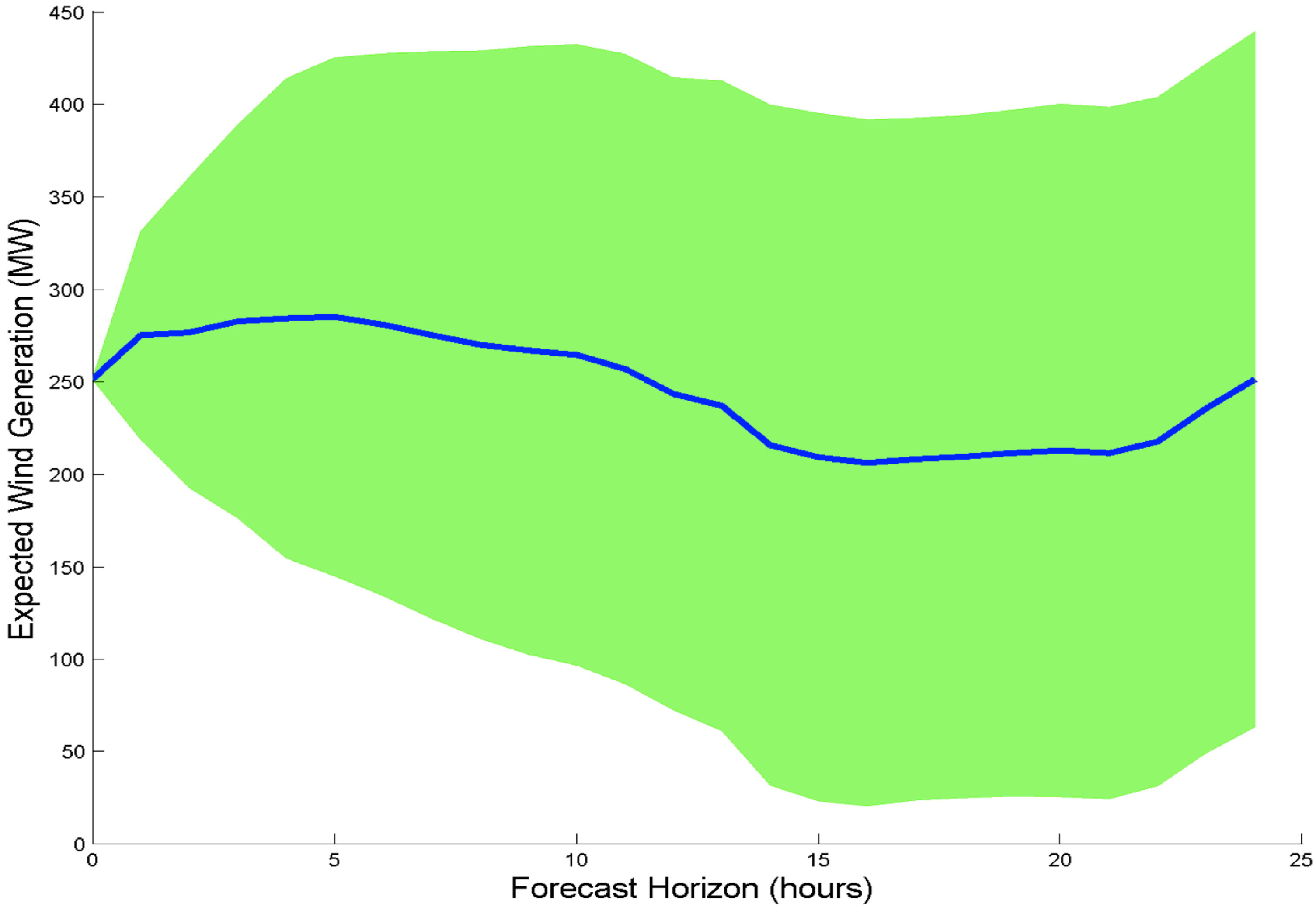
1. Development of Forecasts

- Important to take day-ahead forecasts into account when developing realistic scenarios
- Using NREL-EWITS data, we develop daily forecast trajectories from 1 to 24 hours ahead
  - Interpolation of simulated forecasts to complete horizon as first attempt
  - Assessment of error evolution to test the realism of resulting synthetic forecast data

Normalized RMSE Comparison



Expected Output with Error Bounds

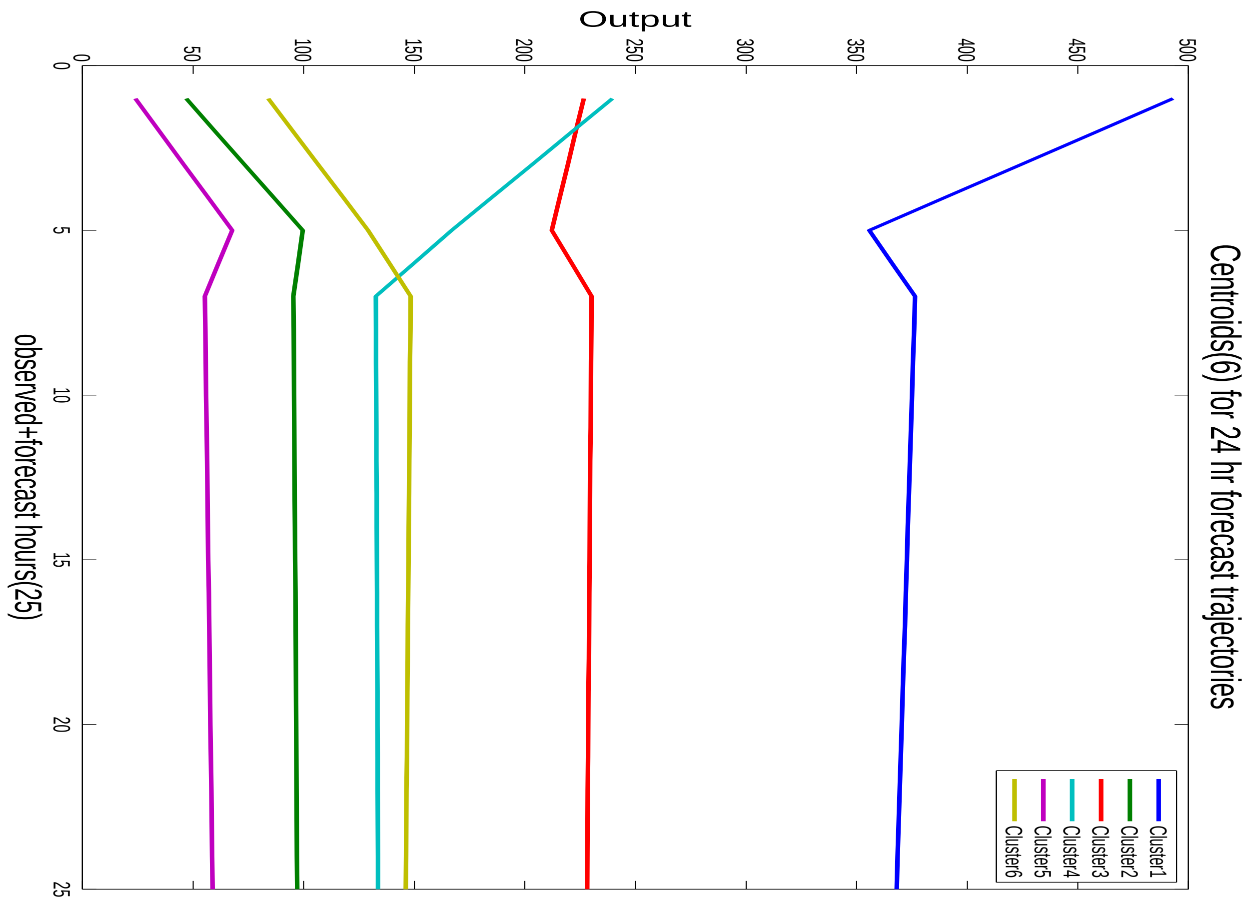


2. Filtering Historical Data

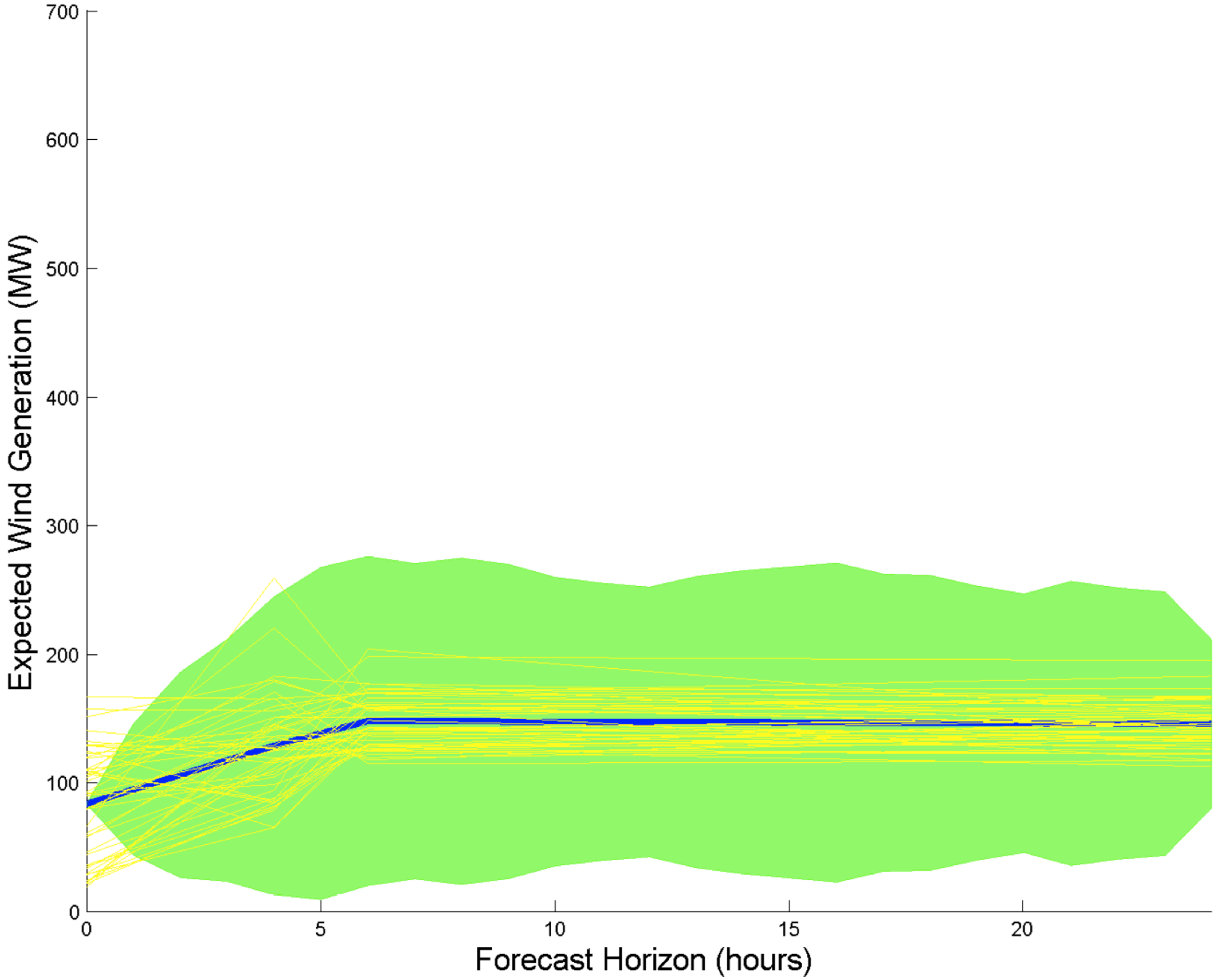
Purpose: To identify similar days in historical data

- Filtering data to identify similar
  - current state, and
  - forecast horizons
- Trajectories are clustered in 2 steps:
  1. On similar current state across all wind farms
  2. On forecasted wind output and load

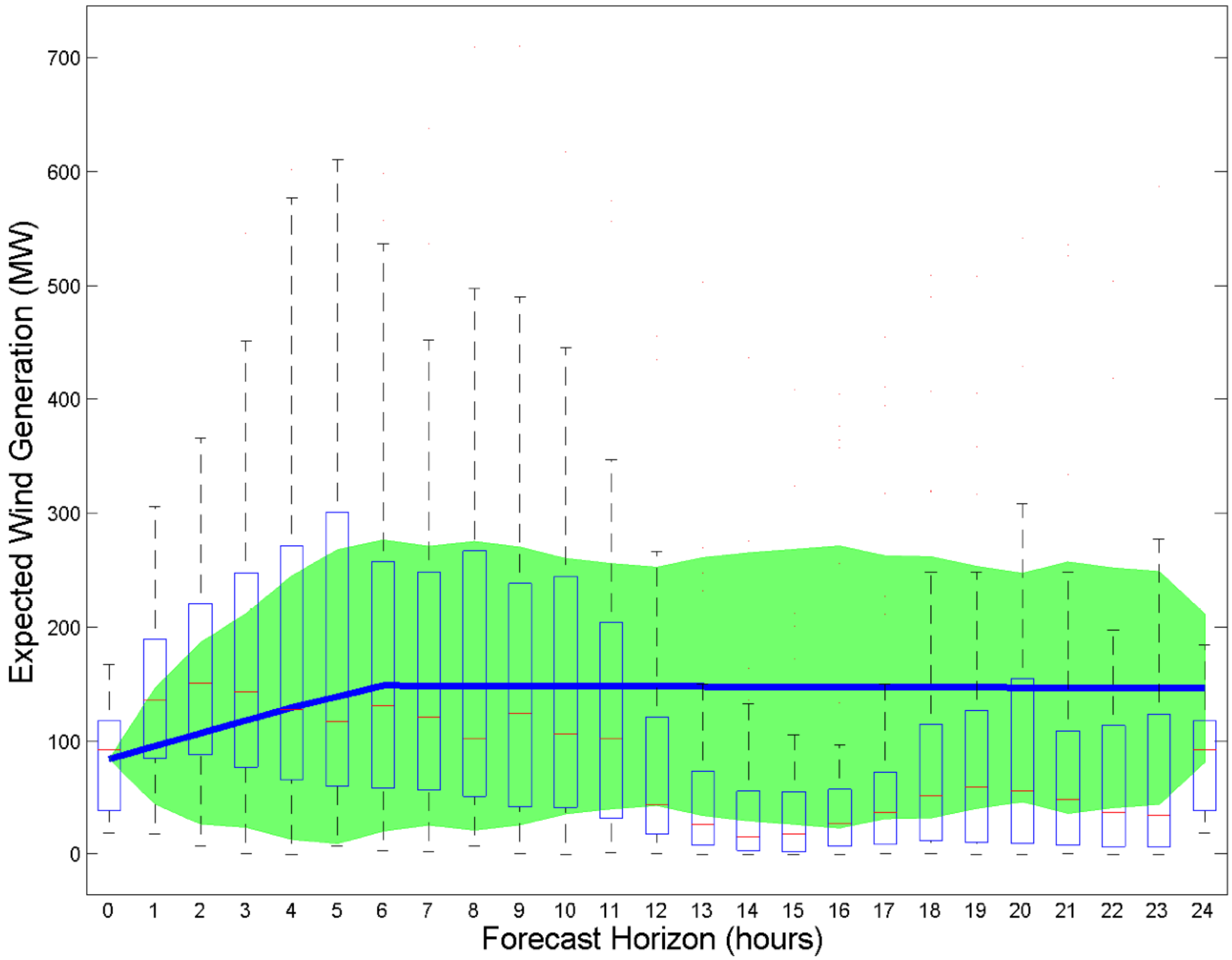
Classifications of Forecast Type



Forecasted Wind Output and Error Bounds



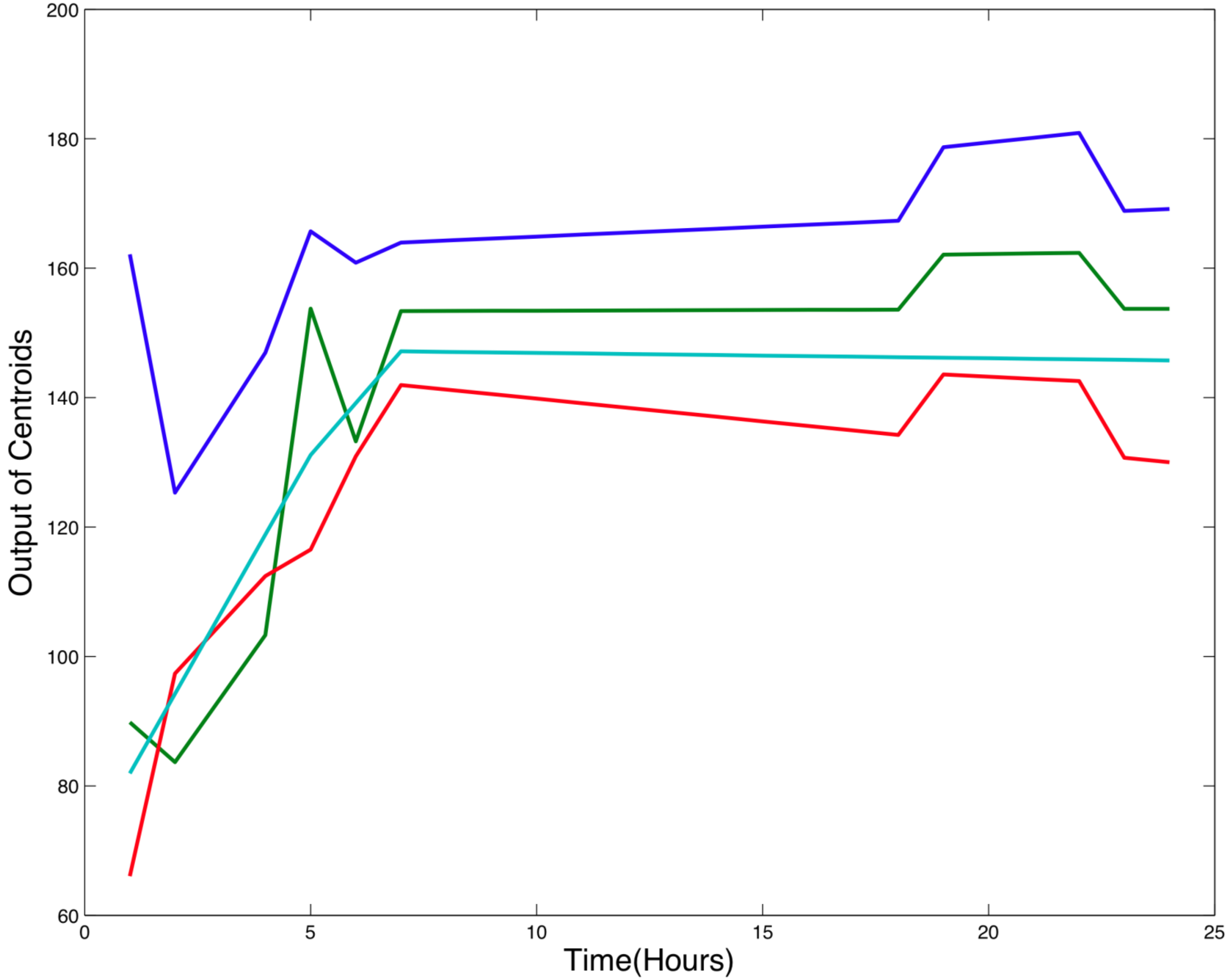
Expected Forecast and Observed Output



3. Identifying Scenarios from common forecast

- From set of similar forecasts
- Represent all possible outcomes with finite set of scenarios
- This was the basis of much of scenario work in 2011/12

High Probability Scenarios



Scenarios evolve through the horizon

- As the SuperOPF co-optimization is applied through the receding horizon, wind states must evolve to represent
  - possible states at each hour
  - reasonable transitions among states
- Represented by hourly states with markov transition probabilities forward through the horizon

Benchmarking with Realizations

- With the realistic SuperOPF inputs, can benchmark the performance of the optimal day-ahead plan
  - day-ahead plan determined with the scenarios conditioned on the forecast
  - re-run throughout a complete day with sampled <u>realizations</u> that are revealed hourly
  - ability of the planned dispatches to meet the needs of the realized days evaluated

Application to Receding Horizon

- The data analytics are even more important in the receding horizon formulation
- Methods developed here are applicable, but entire filtering approach applied hourly for the next 24 hours
- Very data intensive, but reproduce operational procedure for system operators

One More Thing

Daniel Muñoz-Álvarez exploring concept of flexibility rights, demand side of reserves.

- idea is to create a market where resources causing uncertainty are the ones who pay for it
- everyone contracts for certain quantity of power
- some resources deviate without notice (demand side, need to procure flexibility rights)
- some resources deviate on command (supply side, provide reserves)
- similar idea could be applied to variability

Thank You!