Estimating and Visualizing the Impact of Forecast Errors on System Operations

Los Alamos National Laboratory

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Zeb Tate

University of Toronto

Dept. of Electrical and Computer Engr.

Energy Systems Group

e-mail: zeb.tate@utoronto.ca

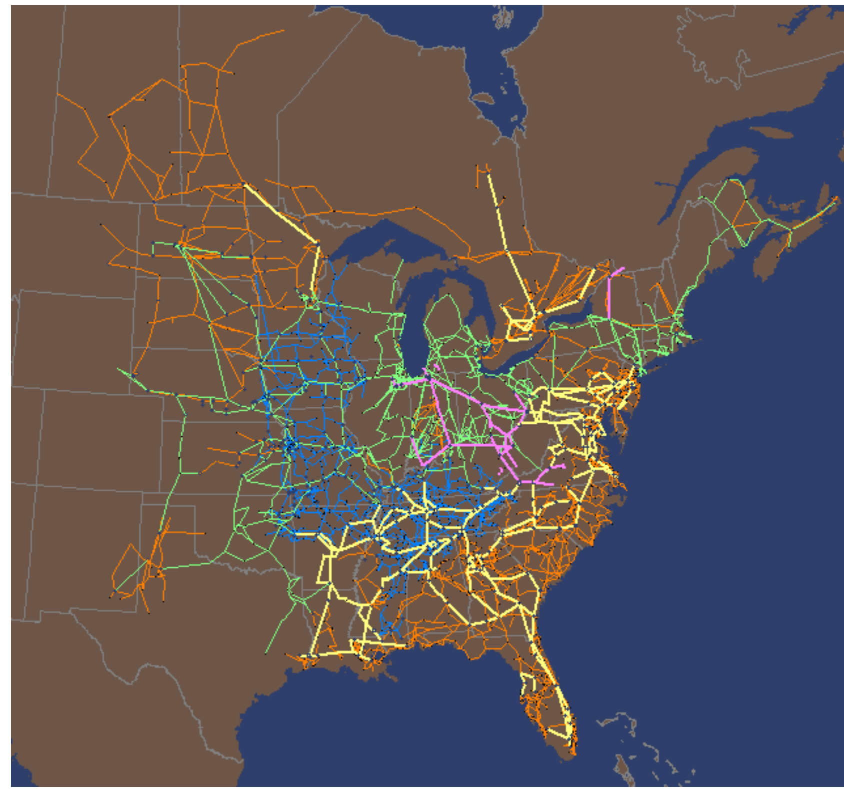
Overview

- Control center operations
- Modeling the impact of uncertainty
  - Modeling the uncertainty in variable generation forecasts
  - Modeling the reaction to forecast deviations
- Determining the impact of forecast deviations
- Extensions and future work

CONTROL CENTER OPERATIONS & SITUATIONAL AWARENESS

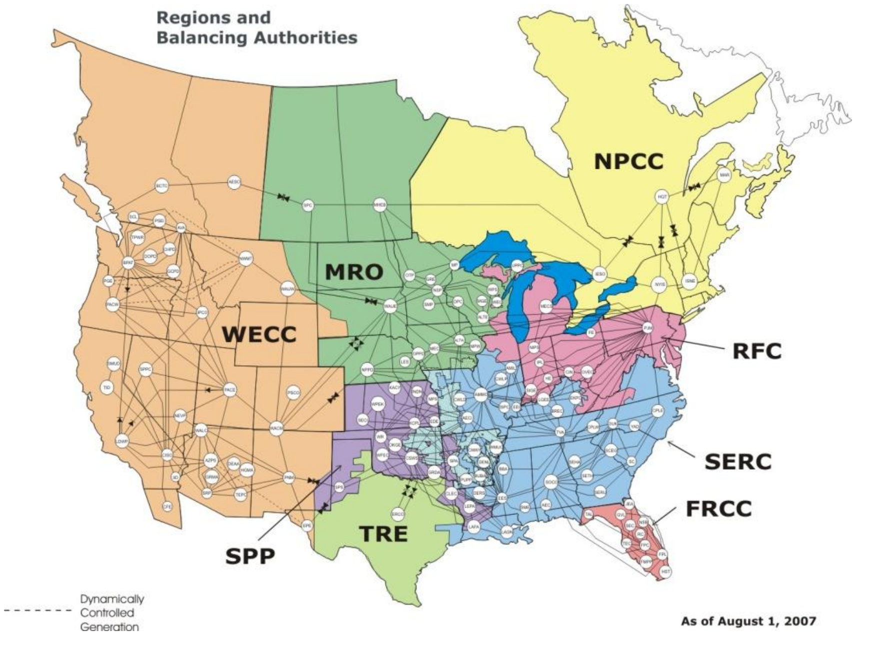
Background on Power System Operations

- Synchronized power grids are (arguably) the most complex systems ever constructed
  - Eastern Interconnection has over 100,000 miles of transmission, over 600 GW of installed capacity
- In the North American power grid, system control is split amongst over 100 "balancing authorities"



Control Center Operations

- Control centers operate their systems to meet performance standards set by:
  - International and national organizations (e.g., NERC)
  - Regional coordinating councils (e.g., NPCC, WECC)
  - Local rules (e.g., IESO and PJM Market Rules)



Responsibilities of Operators

- Maintaining sufficient primary frequency response resources
- Balancing power consumption and production
- Meeting voltage requirements
- Maintaining sufficient online and offline generation reserves
- Determining dispatch and commitment schedules

Situational Awareness (SA)

What do grid operators need in order to responsibly manage their network?

Situational awareness is “[u]nderstanding the current environment and being able to accurately anticipate future problems to enable effective actions.” [definition from PNNL]

SA in Power Systems: "Understanding the Current Environment"

- In power system operations, operators must have a sufficient grasp of current grid conditions so they can identify any existing problems and, when necessary, take immediate corrective actions
- Various data processing and visualization tools built into modern energy management systems (EMSs) for this purpose

Alarms	Contingency Analysis
State estimation	Dynamic security assessment
Topology processing	Voltage contours

Example of a Modern Control Room

Dynamic map board showing flows, voltages, and status information from the Independent Electricity System Operator (IESO)

SA in Power Systems: "Being Able to Accurately Anticipate Future Problems to Enable Effective Actions"

- Knowing there are no existing problems isn't sufficient—operators must also be able to foresee future problems so they have sufficient time to act
  - 4 to 6 hours for changes to generator commitment schedules
- In an ideal world, the fidelity of these predictions would be sufficient to take any actions needed to maintain grid reliability
  - In reality, computational demands & forecast errors make this difficult

Impact of Poor SA on Grid Reliability

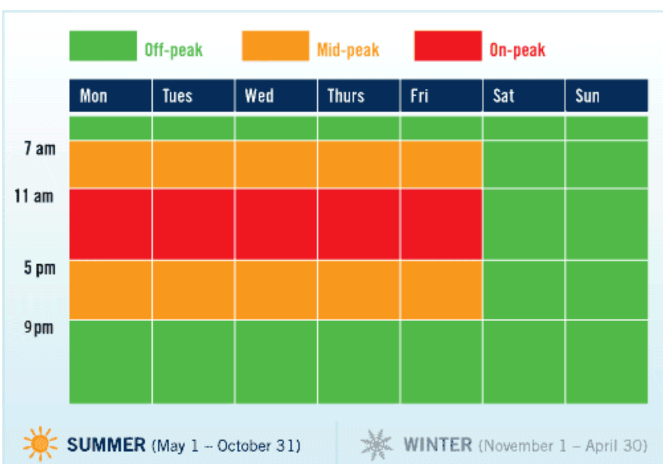
- Of the 6 major blackouts in North America within the past 50 years, 4 were due in part to a lack of SA
  - **November 9, 1965 Blackout**: Operators unaware of relay operations that eventually led to a cascading blackout (20,000 MW, 30 million people)
  - **December 22, 1982 Blackout**: Volume and format of raw data made it hard to gauge the extent of a disturbance and determine the corrective action to take (12,350 MW, 5 million people)
  - **August 10, 1996 Blackout**: Operators unaware of insecure system state after initial unscheduled line openings (28,000 MW, 7.5 million people)
  - **August 14, 2003 Blackout**: First Energy, MISO operators unaware of problems (61,800 MW, 50 million people)

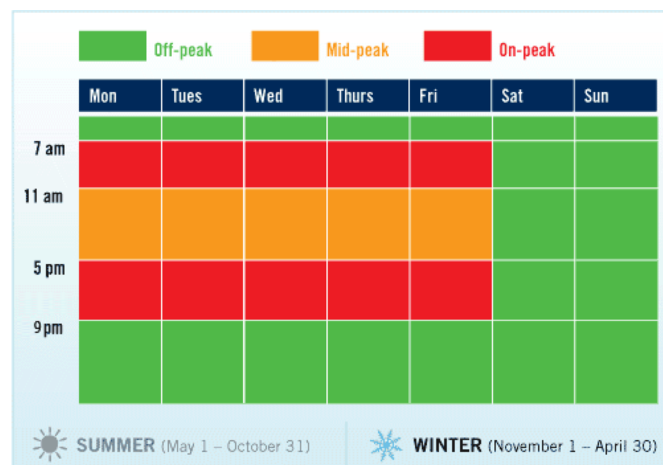
Impact of Variable Generation on SA

- There is a concerted effort by many federal and regional governments to promote generation technologies that are fundamentally stochastic, namely wind & solar generation
- A large build-up of variable generation will impact the ability of operators to:
  - Identify existing problems (lack of telemetry, particularly for VG connected to a distribution network)
  - Anticipate problems (forecast uncertainty)
  - Choose appropriate control actions (lack of actionable information to drive control decisions)

Daily Load Variation

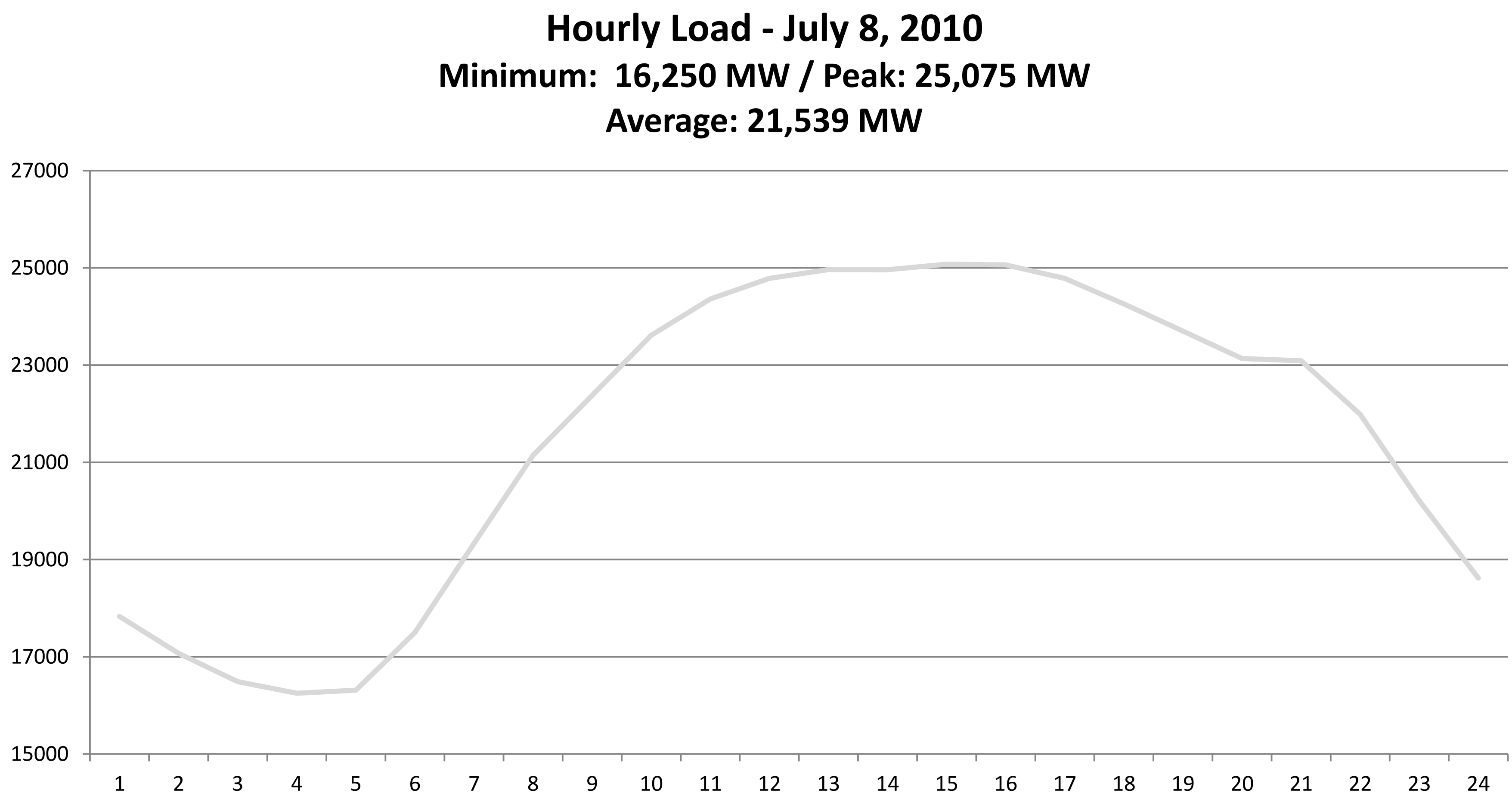
- The load variation throughout the day is highly predictable based on season, time of day, day of the week, and precipitation
  - Basis for time-of-use rates, which designate off-, mid-, and on-peak prices (and demand) for Ontario customers





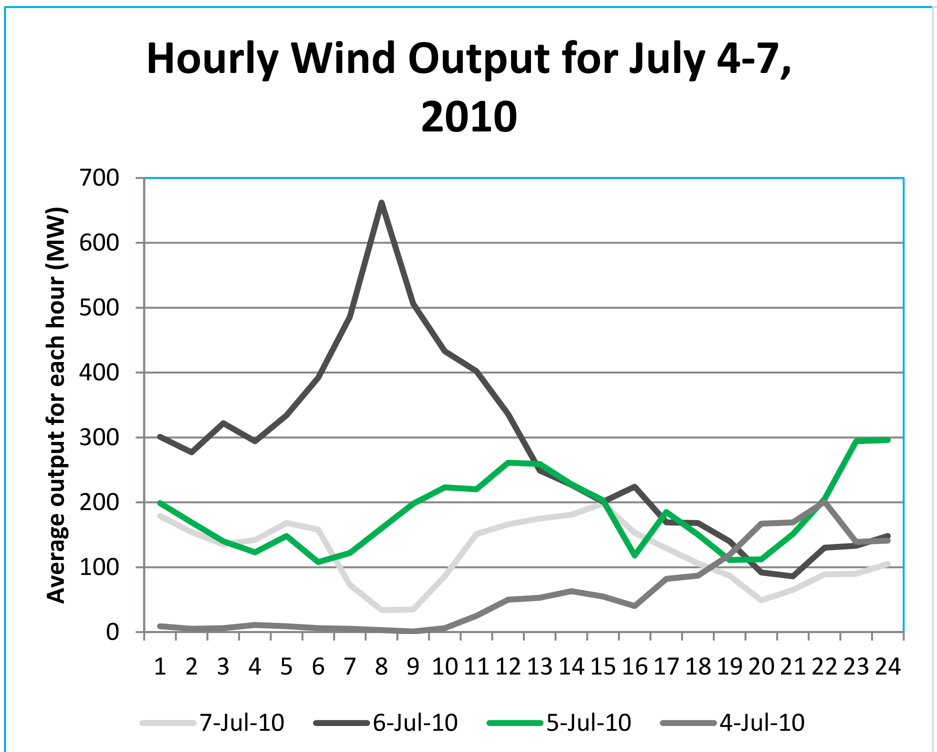
http://www.ieso.ca/imoweb/siteshared/tou_rates.asp

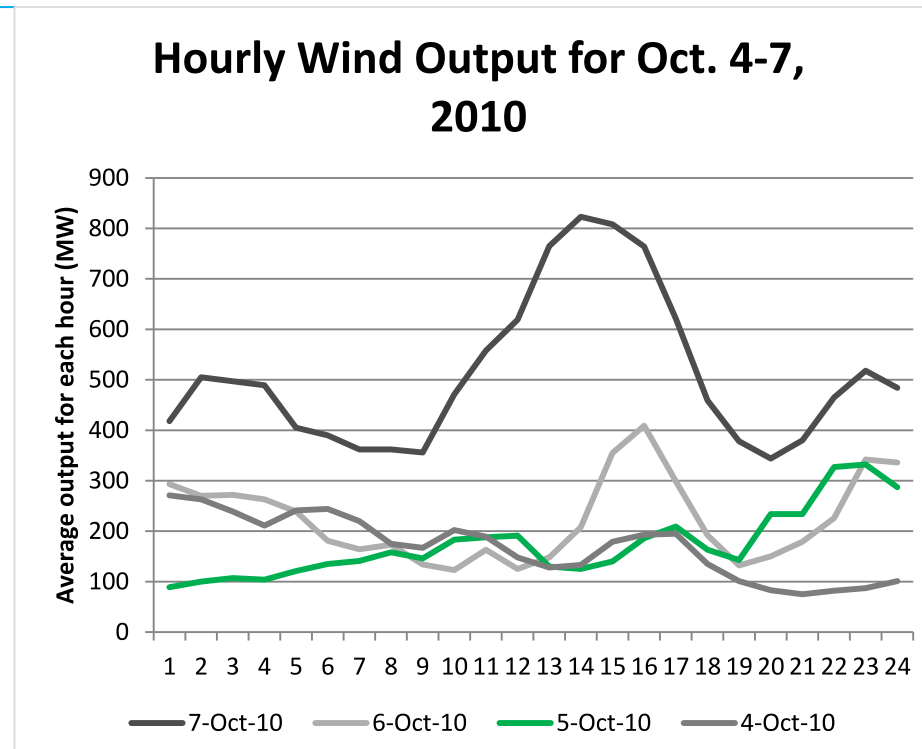
Sample Daily Load Curve



Wind Variation

- Wind power output is much less predictable than the load, so old thinking and old tools built around load forecasting are unlikely to translate over directly





MODELING THE UNCERTAINTY IN VARIABLE GENERATION FORECASTS

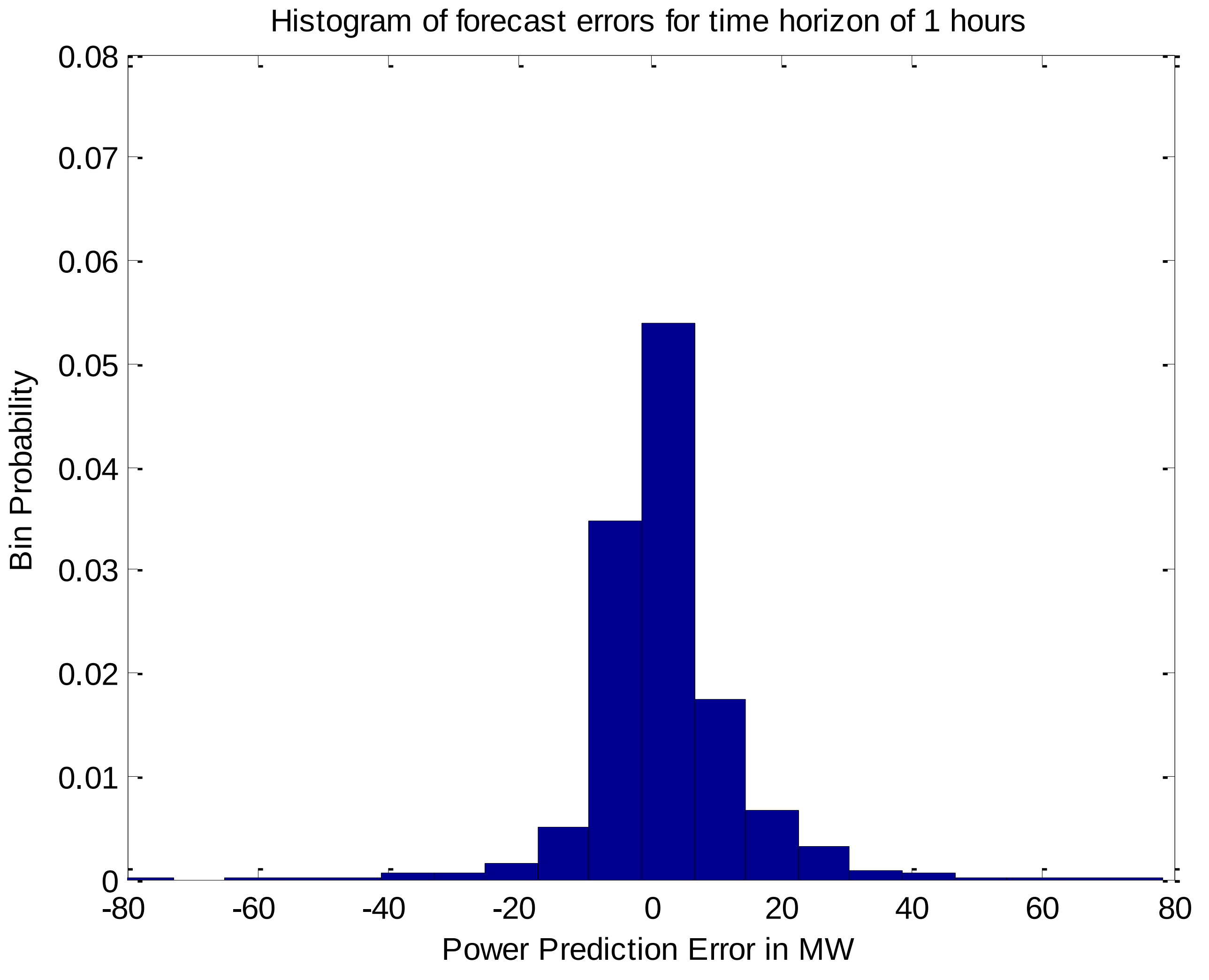
Mitigating Potential Degradation in Reliability

- The additional operational challenges associated with variable generation are due primarily to the uncertainty of output forecasts
- Reducing the uncertainty in renewable plant output can improve reliability and efficiency by:
  - Allowing operators to identify potential regulation shortfalls further in advance
  - Reducing the unnecessary commitment of additional generators or curtailment of variable generation due to overly conservative reserve estimates
- Complete elimination of uncertainty is not possible, but characterizing and improving forecast accuracy can and should be done insofar as it is possible

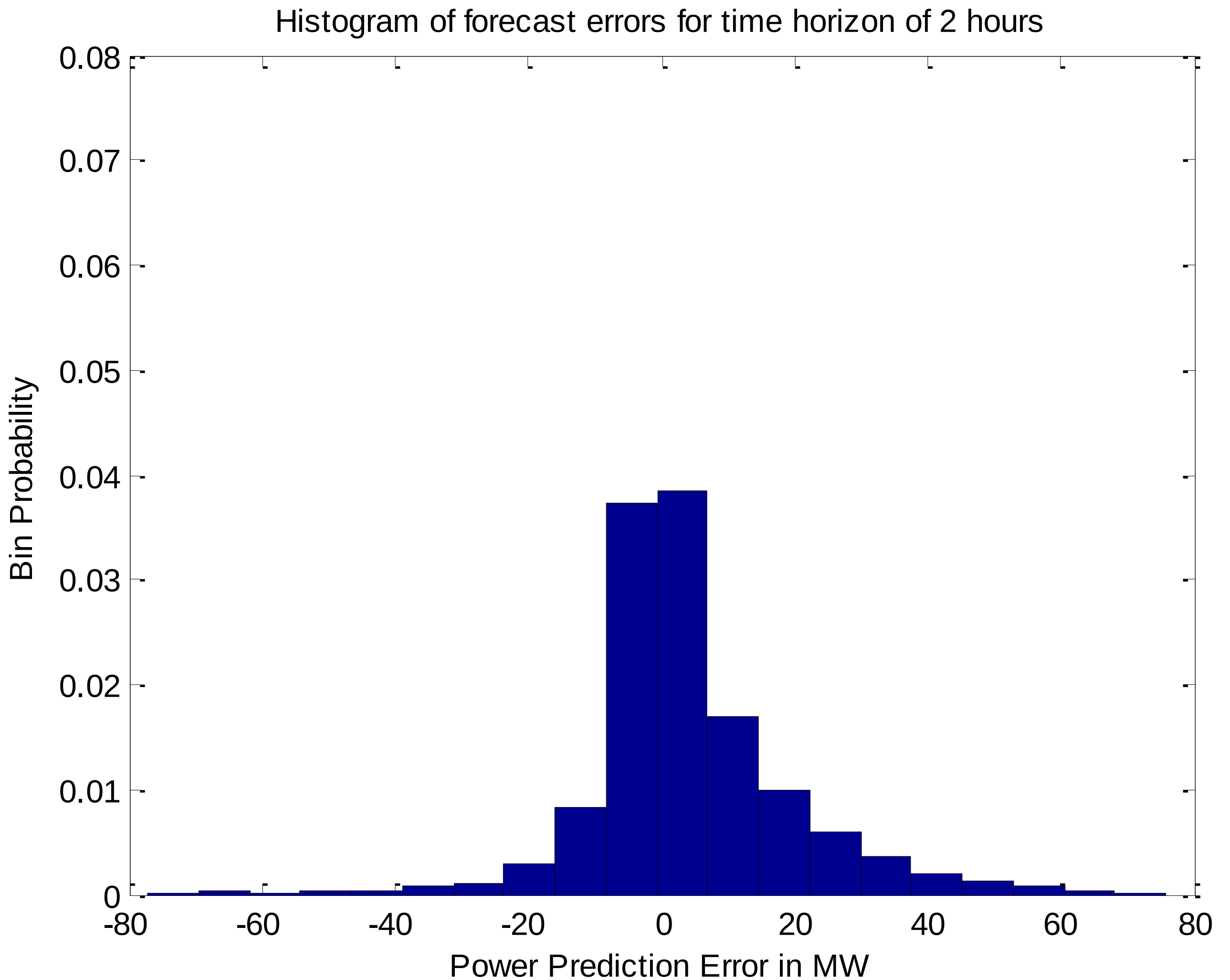
Data Driven Characterization of Forecast Uncertainty

- Development and population of renewable generation data archives is the first step towards improving the performance of renewable output forecasts and characterizing forecast errors
- Example: estimating the error distribution of a vendor's forecast product for a specific time horizon & output interval
  - Create a histogram of historical forecast error measurements and either use this directly for subsequent analyses or fit the histogram to a distribution via parameter estimation techniques
  - Empirical probability mass function will become a better approximation to the probability density function of the error as more samples are used, but this is limited by data availability
  - Can use results to conduct sensitivity analysis on interval length (e.g., evaluate the impact on NERC CPS2 performance by looking at 10-minute forecast errors) and forecast horizon (e.g., determine the minimum horizon that results in certain bounds on the forecast error)

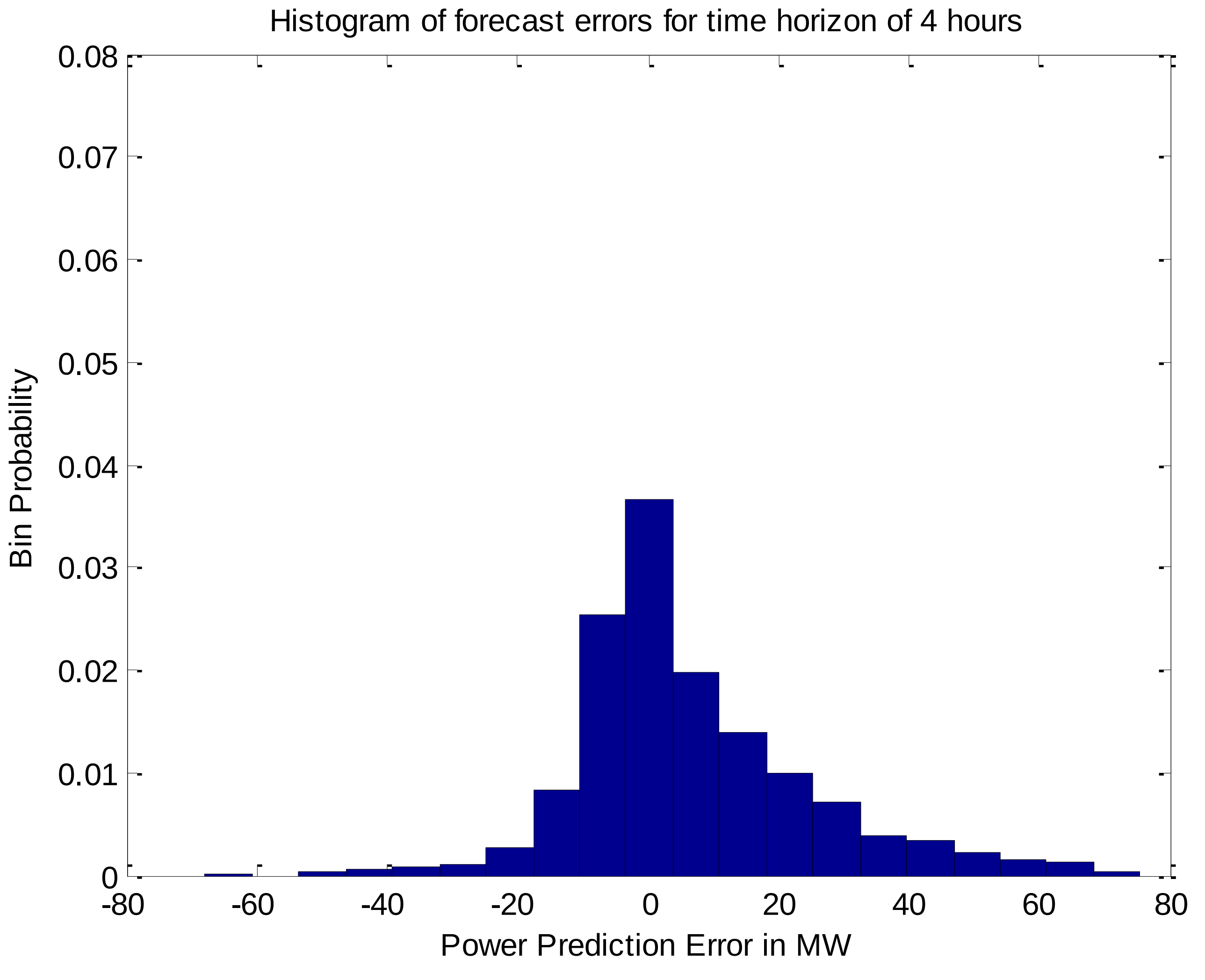
ARMA Forecast Error for 1-Hour Output Interval with Time Horizon of 1 Hour



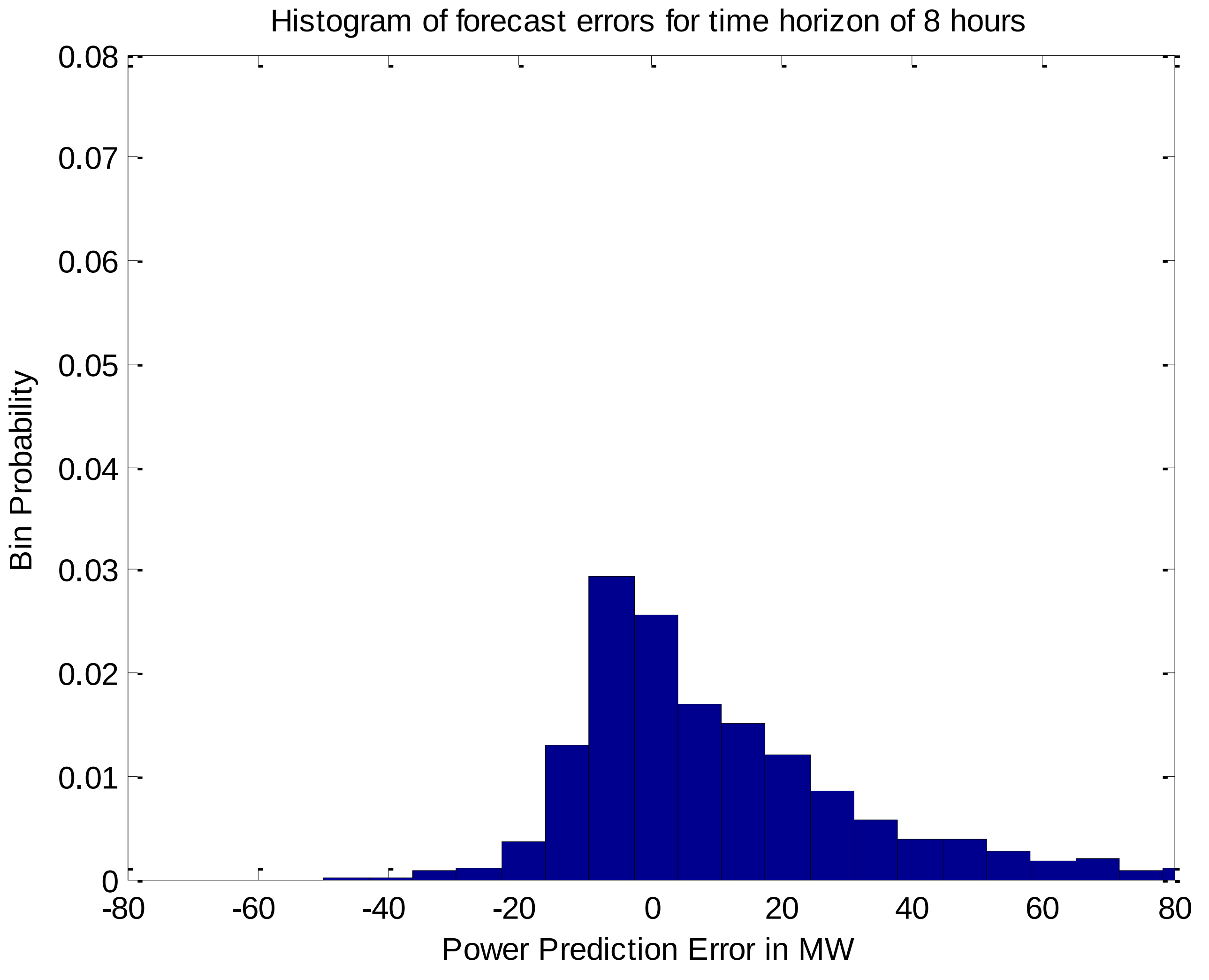
ARMA Forecast Error for 1-Hour Output Interval with Time Horizon of 2 Hours



ARMA Forecast Error for 1-Hour Output Interval with Time Horizon of 4 Hours



ARMA Forecast Error for 1-Hour Output Interval with Time Horizon of 8 Hours



Data Driven Characterization of Forecast Uncertainty

- By utilizing a sufficiently large data set, such histograms could be used to approximate the distribution of forecast errors or error correlations between sites
- Example of comprehensive wind farm data collection
  - On the HQ system, SNC-Lavalin has installed a data collection system (SAGIPE) that collects 45,000 telemetry points every 10 minutes from 8 wind farms (total installed capacity of 990 MW)
  - Results in storage requirements of (45,000 x 6 x 24 x 365) = 2.365 x 109 points per year = 8.81 GB per year (assuming single precision)
  - Extrapolating out to 4,000 MW = 35.6 GB per year
  - Manageable data requirements suggest that it should be possible to collect and archive the complete set of 10-minute data for every turbine

MODELING THE REACTION TO FORECAST DEVIATIONS

System Response to Forecast Error

- Substantial deviations from forecast could exhaust reserve margins
  - Operating reserve margins are based on the ability of the system to continue operating despite the occurrence of instantaneous, unscheduled events (e.g., trip of a nuclear plant or transmission line)
    - e.g., NPCC Operating Reserve Criteria require 10-minute reserves to be greater than or equal to the first contingency loss & 30-minute reserves to be greater than or equal to the second contingency loss
  - Managing uncontrolled, sustained ramps in generation could be more challenging than the loss of any single unit (e.g., 2000 MW / 1 hour vs. 1000 MW / instant)
- Method of modeling the redispatch due to forecast error is critical in evaluating reserve adequacy with variable generation

Statement of the Problem

- On the power grid, there must be a balance of produced and consumed power in the network
  - Otherwise, sustained frequency excursions will occur
- When there is a deviation from the scheduled output of a VG, the shortfall/surplus in generation must be compensated by other sources of generation
- Even if losses are neglected and a linearization of the power network equations is used, modeling the re-dispatch of the remaining system resources is nontrivial

$$\mathbf{1}_{1\times\mathcal{G}}\mathbf{\Delta P_G} + \mathbf{1}_{1\times\mathcal{V}}\mathbf{\Delta P_V} = \mathbf{0}$$

$\mathbf{\Delta P_G} \in \Re^{\mathcal{G}}$: vector of redispatch in controllable resources

$\mathbf{\Delta P_V} \in \Re^{\mathcal{V}}$: vector of forecast errors at each wind site

Approaches to Redispatch Modeling

- One common approach is to have a single generator (the "slack" generator) provide all necessary regulation

$$\boldsymbol{\Delta}\mathbf{P}_{\mathbf{G}}^{\text{slack}} = \begin{bmatrix} 0 & 0 & \cdots & 0 & -\mathbf{1}_{1\times\mathcal{V}}\boldsymbol{\Delta}\mathbf{P}_{\mathbf{V}} & 0 & \cdots & 0 \end{bmatrix}^T$$

- A generalization of the slack generator approach is to proportionally assign the forecast error to the controllable resources (a.k.a. re-dispatch using "participation factors")

$$\boldsymbol{\Delta}\mathbf{P}_{\mathbf{G}}^{\text{p.f.}} = \left(-\mathbf{1}_{1\times\mathcal{V}}\boldsymbol{\Delta}\mathbf{P}_{\mathbf{V}}\right)\begin{bmatrix} \alpha_1 & \alpha_2 & \cdots & \alpha_{\mathcal{G}} \end{bmatrix}^T$$
$$\sum_{i=1}^{\mathcal{G}} \alpha_i = 1$$

Comments on the Participation Factor Approach

- The participation factor approach is based on the assumption that the best way to allocate the forecast error to the remaining resources is known a priori
  - If this *is* known, then using the participation factor approach can be much faster than other methods of modeling forecast error reaction
  - However, participation factors have to be redistributed when an up/down re-dispatch limit is hit, and so are likely to only be valid for very small forecast errors

Optimal Reaction to Forecast Error

- An alternative method is to optimally re-dispatch the remaining generation (e.g., to minimize cost, control movement, or line violations) while enforcing generation limits and power balance

$$\begin{aligned} \mathbf{\Delta P_G^*} &= \arg\min_{\mathbf{\Delta P_G}} f\left(\mathbf{\Delta P_G}, \mathbf{\Delta P_V}\right) \\ \text{subject to} \quad & \mathbf{\Delta P_G^{\min}} \preceq \mathbf{\Delta P_G} \preceq \mathbf{\Delta P_G^{\max}} \\ & \mathbf{1}_{1\times\mathcal{G}} \mathbf{\Delta P_G} + \mathbf{1}_{1\times\mathcal{V}} \mathbf{\Delta P_V} = \mathbf{0} \end{aligned}$$

DETERMINING THE IMPACT OF FORECAST DEVIATIONS

Determining the Impacts of Forecast Deviations

- Assessing the impact of uncertainty is challenging, but it will be increasingly important as system operations becomes more reliant on probabilistic information
- We want to develop tools that quantify the impact of forecast errors based on three principles:
  1. **Forecast error distribution is important**: a forecast with an error bound of +/- 10% at a confidence level of 99% has the potential to cause more trouble than a forecast with an error bound of +/- 1% at the same confidence level
  2. **Location is important**: The transmission network may restrict which generators can compensate which VGs' forecast errors
  3. **Speed is important**: Any metrics and visualizations should be easy to explain, provide predictable output, and have computation times that make it usable in control centers

Modeling the Effects of VG & Non-VG Generator Output on Line Flows

- Model impacts on branch flows using dc (or linearized ac) power flow equations

$$\mathbf{\Delta f} = \mathbf{ISF_G}\mathbf{\Delta P_G} + \mathbf{ISF_V}\mathbf{\Delta P_V}$$

$$\mathbf{\Delta f} \in \Re^{L} : \text{change in flow on branches}$$

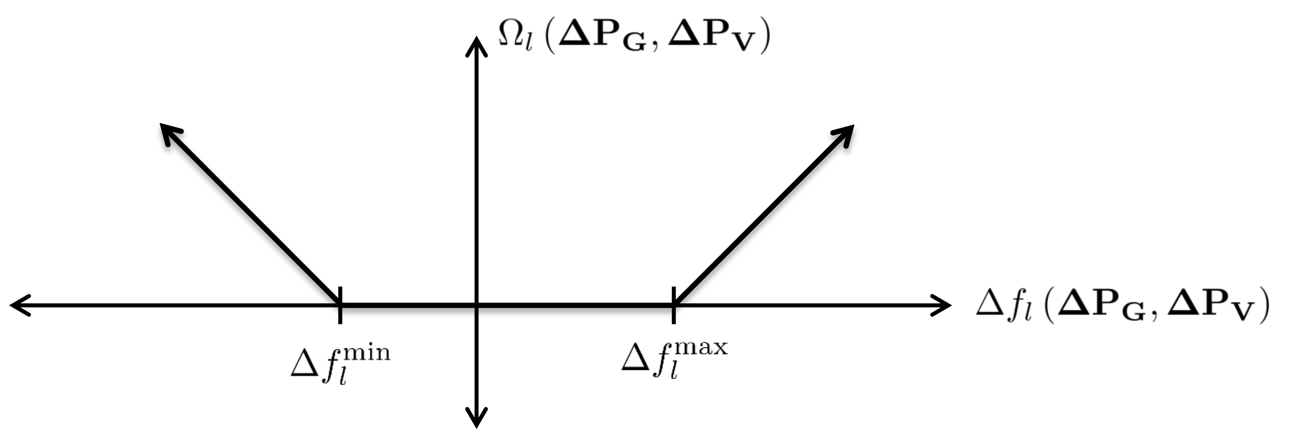
$$\mathbf{\Delta P_G}\ (\mathbf{\Delta P_V}) \in \Re^{\mathcal{G}}\ \left(\Re^{\mathcal{V}}\right) : \text{change in output of controllable (variable) generators}$$

$$\mathbf{ISF_G}\ (\mathbf{ISF_V}) \in \Re^{L\times\mathcal{G}}\ \left(\Re^{L\times\mathcal{V}}\right) : \text{injection shift factors for controllable (variable) generators}$$

- The elements within the $\mathbf{ISF}$ matrix are used for contingency analysis and transmission loading relief, so the need for this data is unlikely to be a stumbling block for implementation

Ranking System-Level Impacts

- In contingency ranking and other techniques where the system impact of different events are being considered, penalty functions are often used to indicate the importance of violations
- For example, to penalize branch overcurrent:



Determining the Worst Case Forecast Deviation

- Using the models described above, the "worst case forecast deviation", $\mathbf{\Delta P_V}^*$, is defined by:

$$\Delta\mathbf{P}^*_{\mathbf{V}} = \arg\max_{\Delta\mathbf{P_V}} \mathbf{1}_{1\times\mathcal{L}}\mathbf{\Omega}\left(\mathbf{\Delta f}\right)$$

$$\begin{aligned}
\text{subject to} \quad & \mathbf{\Delta f} = \mathbf{ISF_G}\mathbf{\Delta P_G} + \mathbf{ISF_V}\mathbf{\Delta P_V} \\
& \Delta\mathbf{P_V} \in \left\{\left[\Delta P_{V_1}^{\min}, \Delta P_{V_1}^{\max}\right] \times \cdots \times \left[\Delta P_{V_\mathcal{V}}^{\min}, \Delta P_{V_\mathcal{V}}^{\max}\right]\right\} \\
& \mathbf{\Delta P_G} \in \left\{ \begin{array}{ll} & \arg\min_{\mathbf{\Delta P'_G}} \mathbf{1}_{1\times\mathcal{L}}\mathbf{\Omega}'\left(\mathbf{\Delta f}'\right) \\ \text{subject to} & \mathbf{\Delta f}' = \mathbf{ISF_G}\mathbf{\Delta P'_G} + \mathbf{ISF_V}\mathbf{\Delta P_V} \\ & \mathbf{\Delta P_G^{\min}} \preceq \mathbf{\Delta P'_G} \preceq \mathbf{\Delta P_G^{\max}} \\ & \mathbf{1}_{1\times\mathcal{G}}\mathbf{\Delta P'_G} + \mathbf{1}_{1\times\mathcal{V}}\mathbf{\Delta P_V} = \mathbf{0} \end{array} \right\}
\end{aligned}$$

$$\mathbf{\Omega} = \begin{bmatrix} \Omega_1\left(\Delta f_1\right) \\ \vdots \\ \Omega_L\left(\Delta f_L\right) \end{bmatrix} \in \Re^{\mathcal{L}} : \text{vector of penalty function evaluations for each line}$$

$$\left[\Delta P_{V_i}^{\min}, \Delta P_{V_i}^{\max}\right] \in \Re : \text{confidence interval of variable generator } i$$

- "Maximin", infinite Stackelberg game

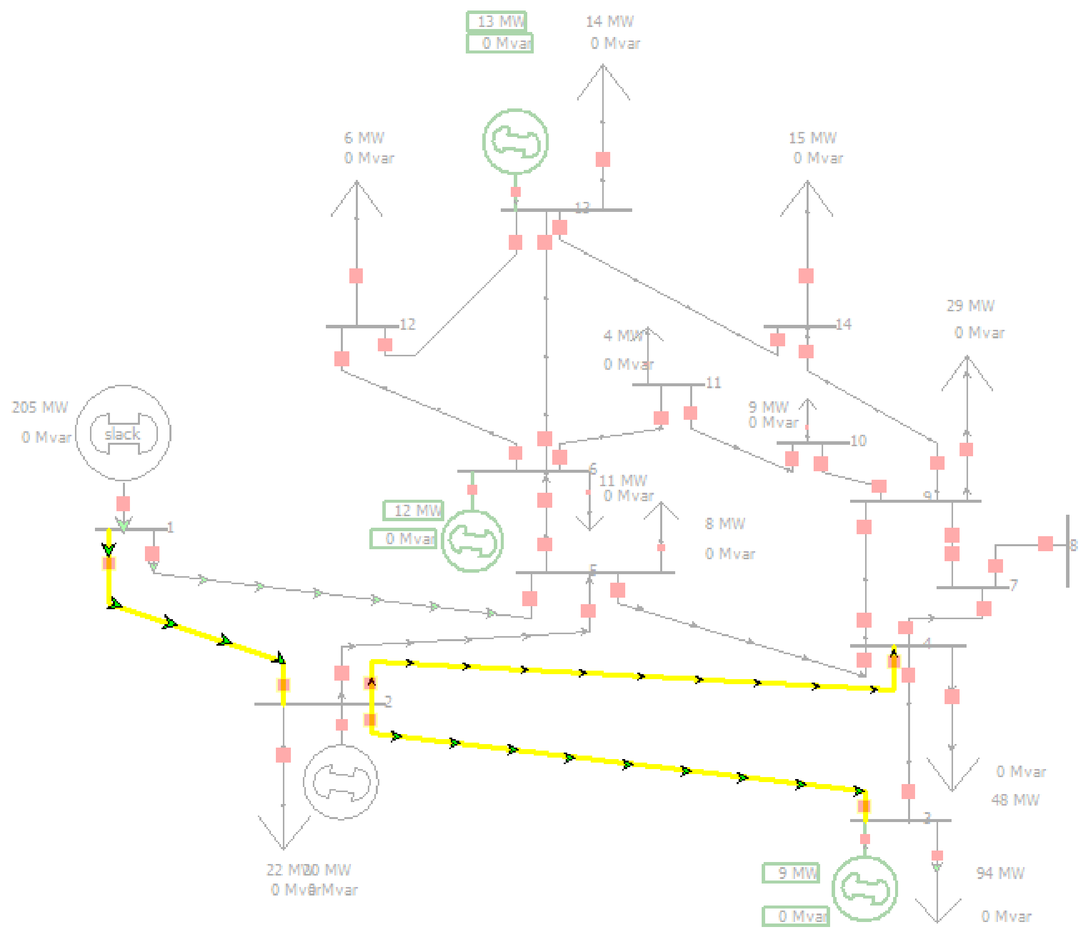
Challenges with the Original Formulation: Inner Equilibrium Constraint

- One problem with the above formulation is that the feasible space of solutions is defined by an objective function (referred to as a mathematical programs with equilibrium constraints, or MPEC, in the literature)
- Because the inner optimization is a linear program, the equilibrium constraint can be replaced by the stationarity and complementarity conditions which must be satisfied
- Becomes a linear program with SOS1 constraints

Challenges with the Original Formulation: Non-Convex Outer Objective

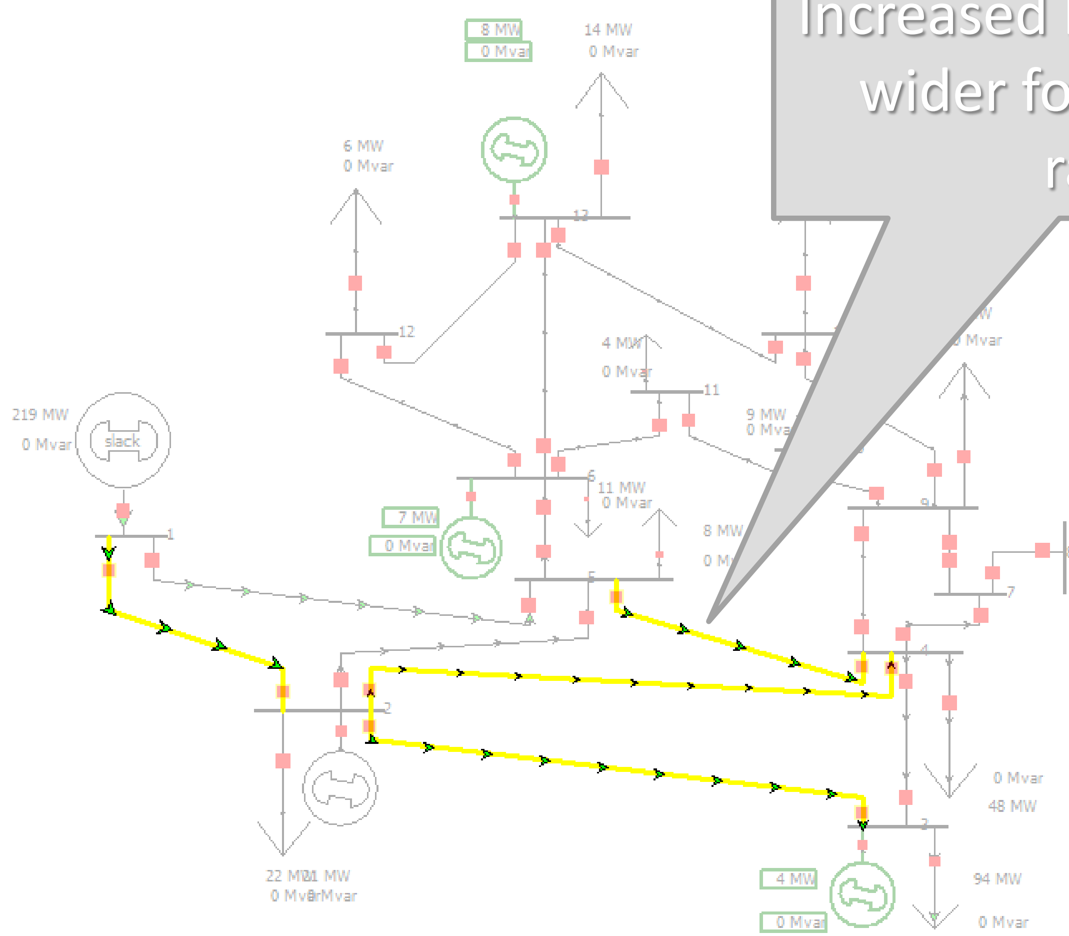
- The outer optimization is a maximization over a sum of piecewise convex functions
- Can be rewritten as a linear program with SOS2 constraints
- Using these transformations, the problem can be solved using a standard ILP solver (e.g., CPLEX, GUROBI)

Case Study:
14 Bus System (Confidence Level: 50%)

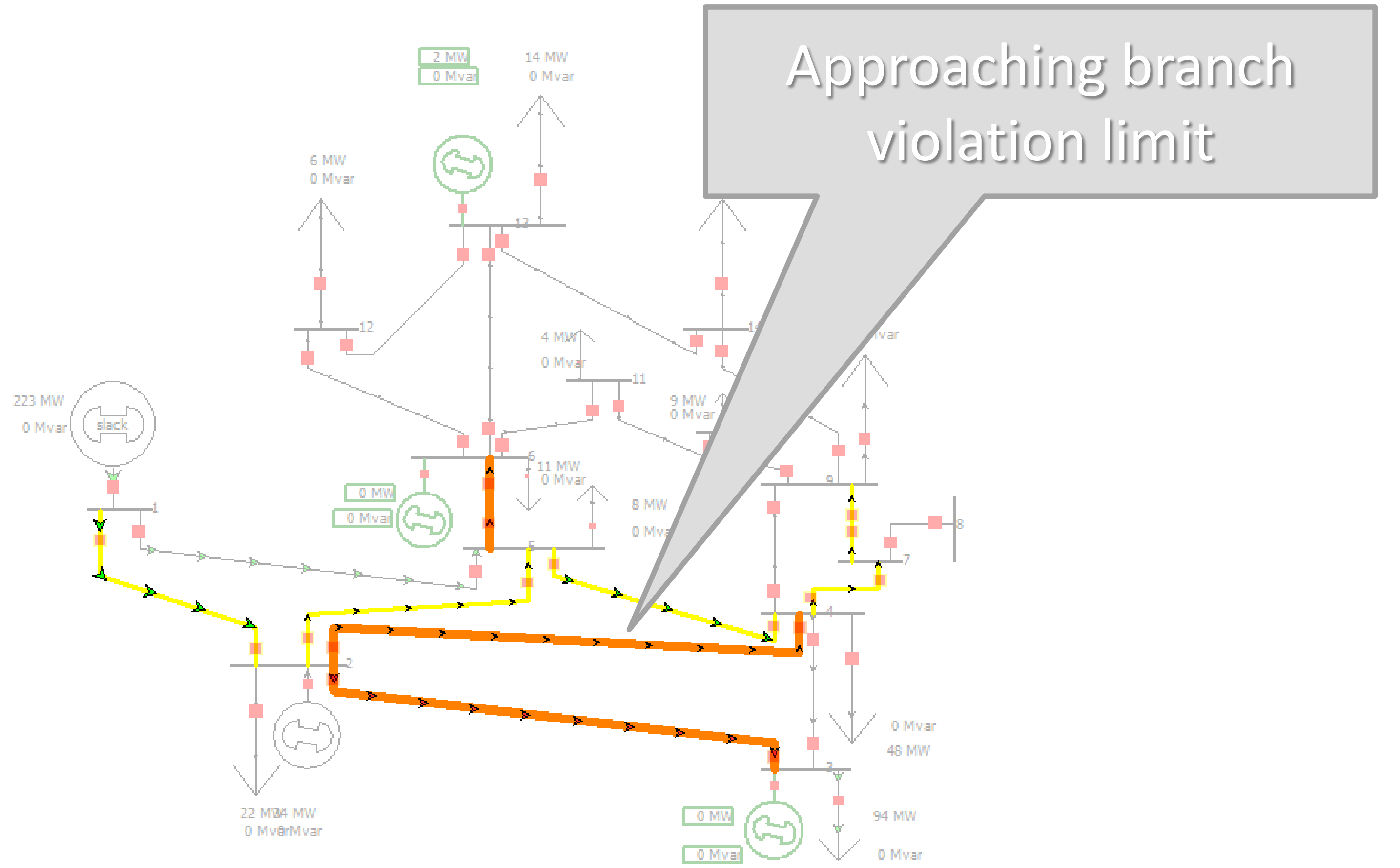


Case Study:
14 Bus System (Confidence Level: 75%)

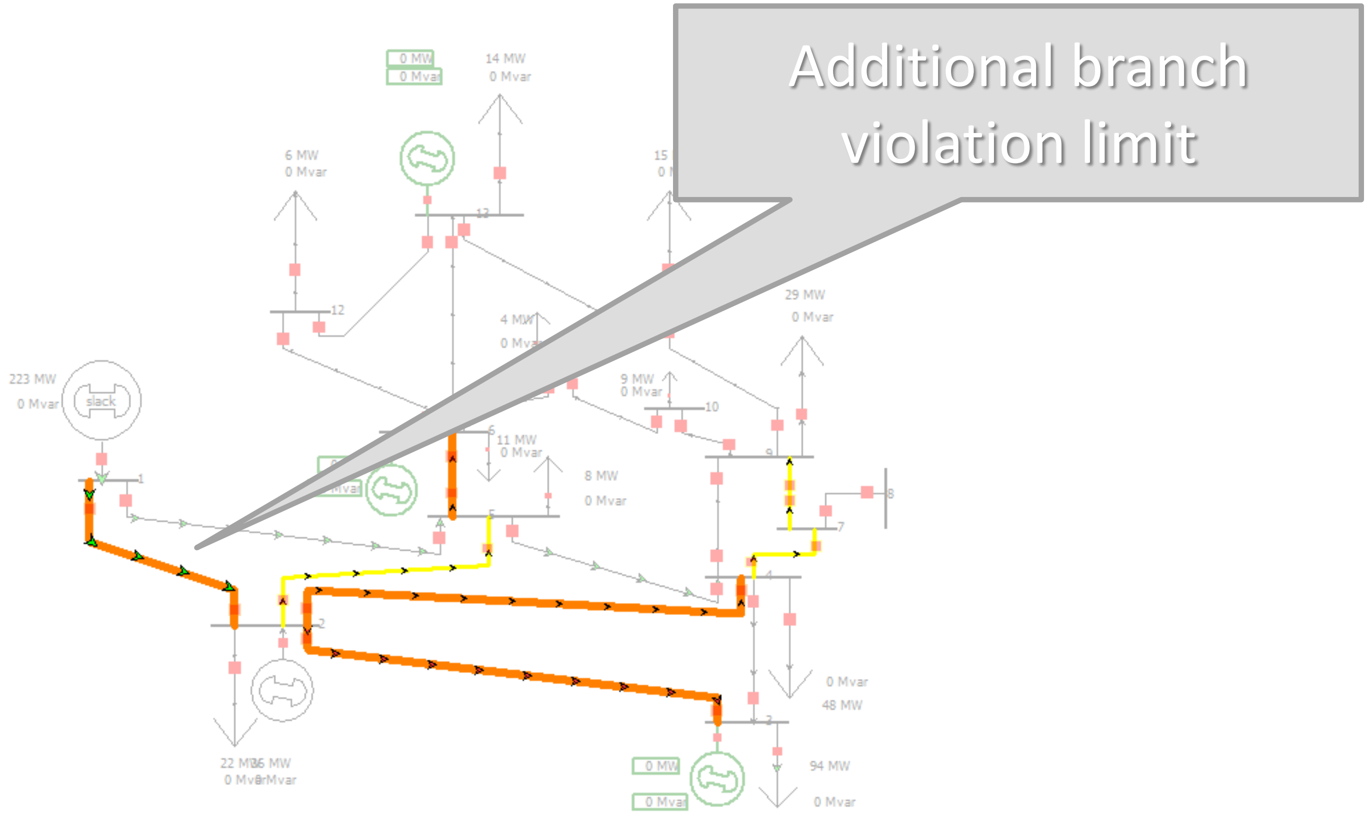
Increased loading due to wider forecast error range



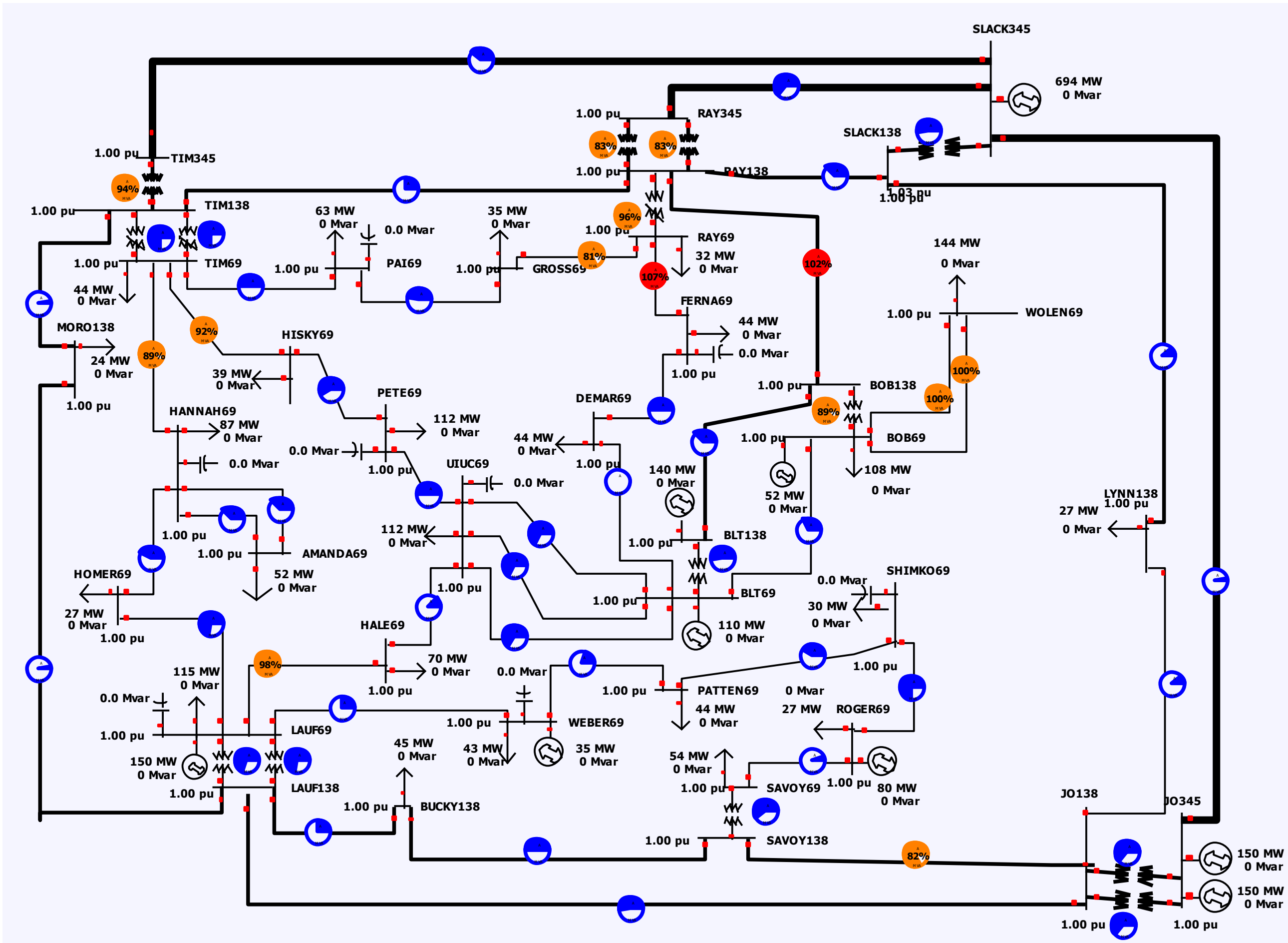
Case Study:
14 Bus System (Confidence Level: 95%)



Case Study:
14 Bus System (Confidence Level: 99%)

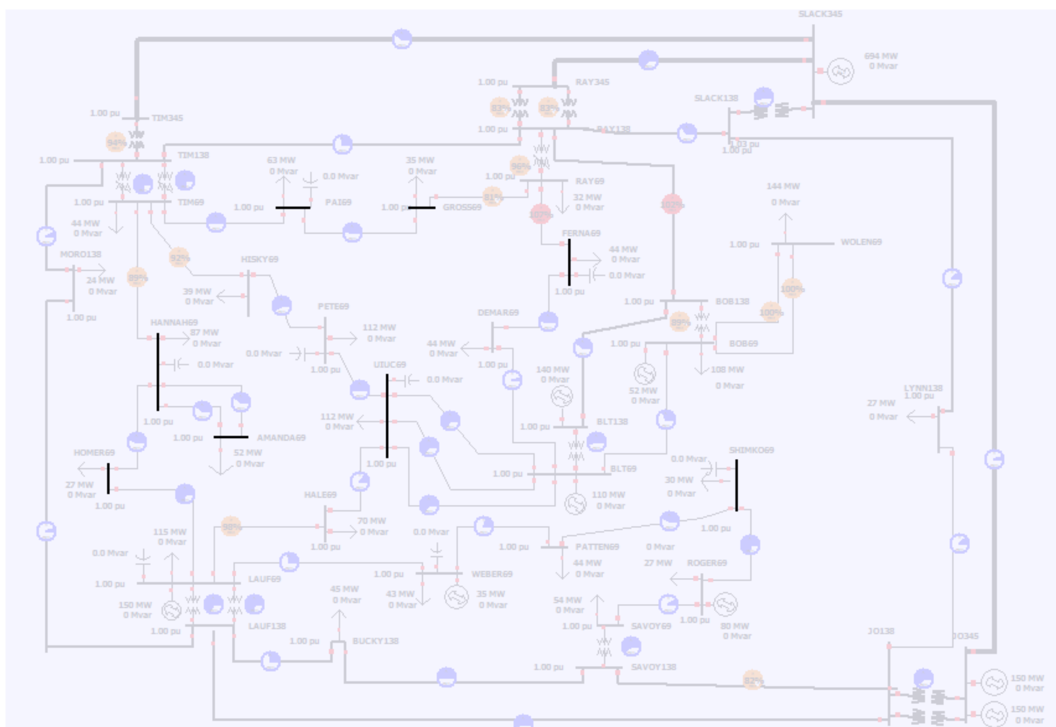


Case Study:
37 Bus System Oneline Diagram



Case Study:
37 Bus Study Parameters

- Controllable generation capacity: 1828 MW
- Load: 1544 MW

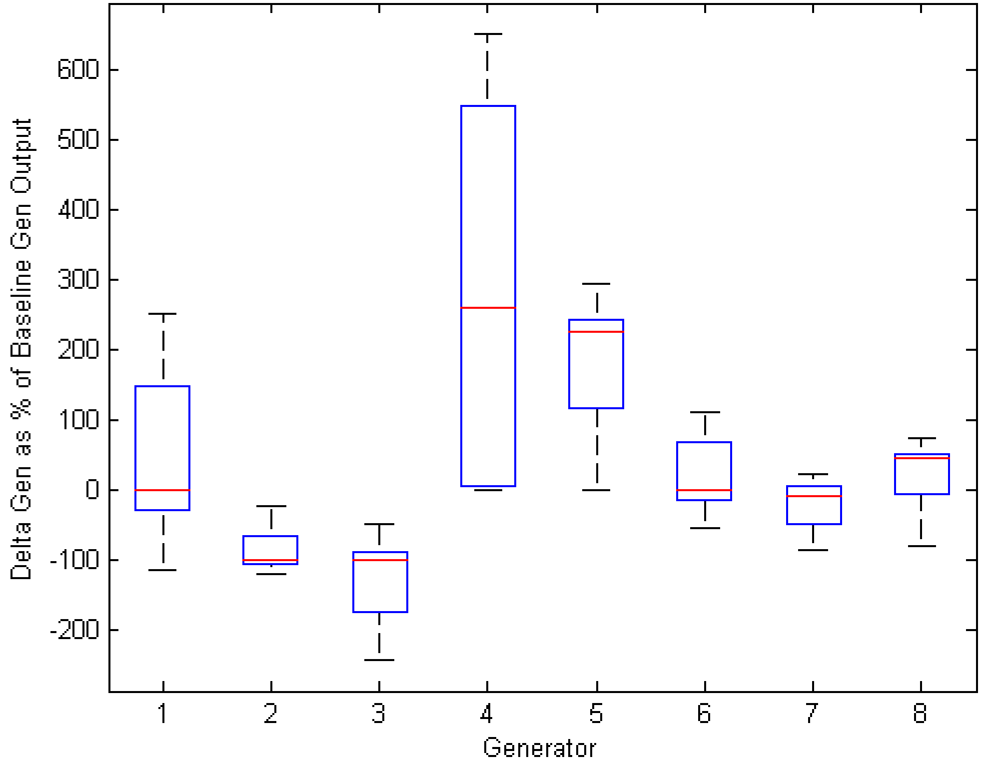


Case Study: 37 Bus - High Forecast Error

- Forecast: 55 MW
- Forecast error: +5/-50 MW
- Solution found with GUROBI in 10 seconds
- Maximum line overload is 6.65%
- Worst case wind error: [-50, +5, -50, -50, -50, +5, -50, -50]
  - Optimal re-dispatch: [+20, -166, +350, +87, -30, +46, -81, +63]

Case Study:
37 Bus – Variation in Participation Factors

- Tested boundary points from high forecast error (55 MW, +5 MW/-50 MW) set of data



Case Study:
37 Bus - Low Forecast Error

- Forecast: 15 MW
- Forecast Error: +10/-15 MW
- Solution found with GUROBI in 4 seconds
- Sum of overloads: 0%
- Maximum line overload: 0%
- Sample re-dispatch: [-19, -174, +59, +87, +30, +46, 0, +40]

Extensions

- Inclusion of commitment as decision variable
- Clearly show the tradeoff between the confidence level used to bound the forecast error & the maximal loading
- Use ramp up/down instead of line loading—should indicate where reserves are critical
- Extension to correlated forecast errors

Closing Remarks

- Developing new tools that help operators understand existing and potential system conditions should be a top priority, since they are ultimately responsible for maintaining a reliable electricity supply
- Thank you

…and special thanks to Xiaoguang Li, the M.A.Sc. student who's been working with me on this research.

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