

2011 DOE Applied Mathematics Program Meeting
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Fusing Models and Data for a Dynamic Paradigm of Power Grid Operations

ASCR Project: Advanced Kalman Filter for Real-Time Responsiveness in Complex Systems

Henry Huang*, Greg Welch**, Ning Zhou*, Yulan Li*, Patrick Nichols*, Daniel Chavarria*

*Pacific Northwest National Laboratory, Richland, WA

**University of North Carolina at Chapel Hill, Chapel Hill



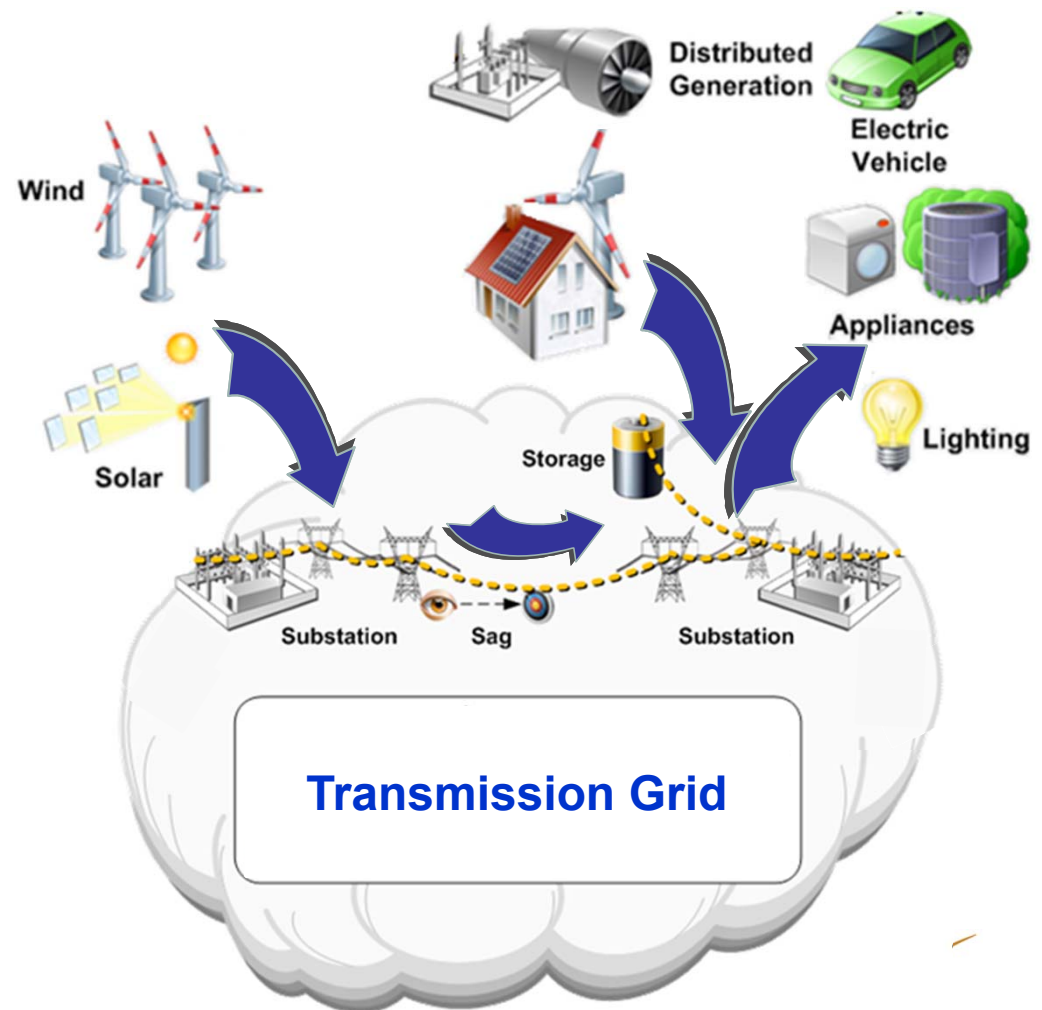
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Challenges in Future Power Grid Operations

“Grid evolution meets information revolution”

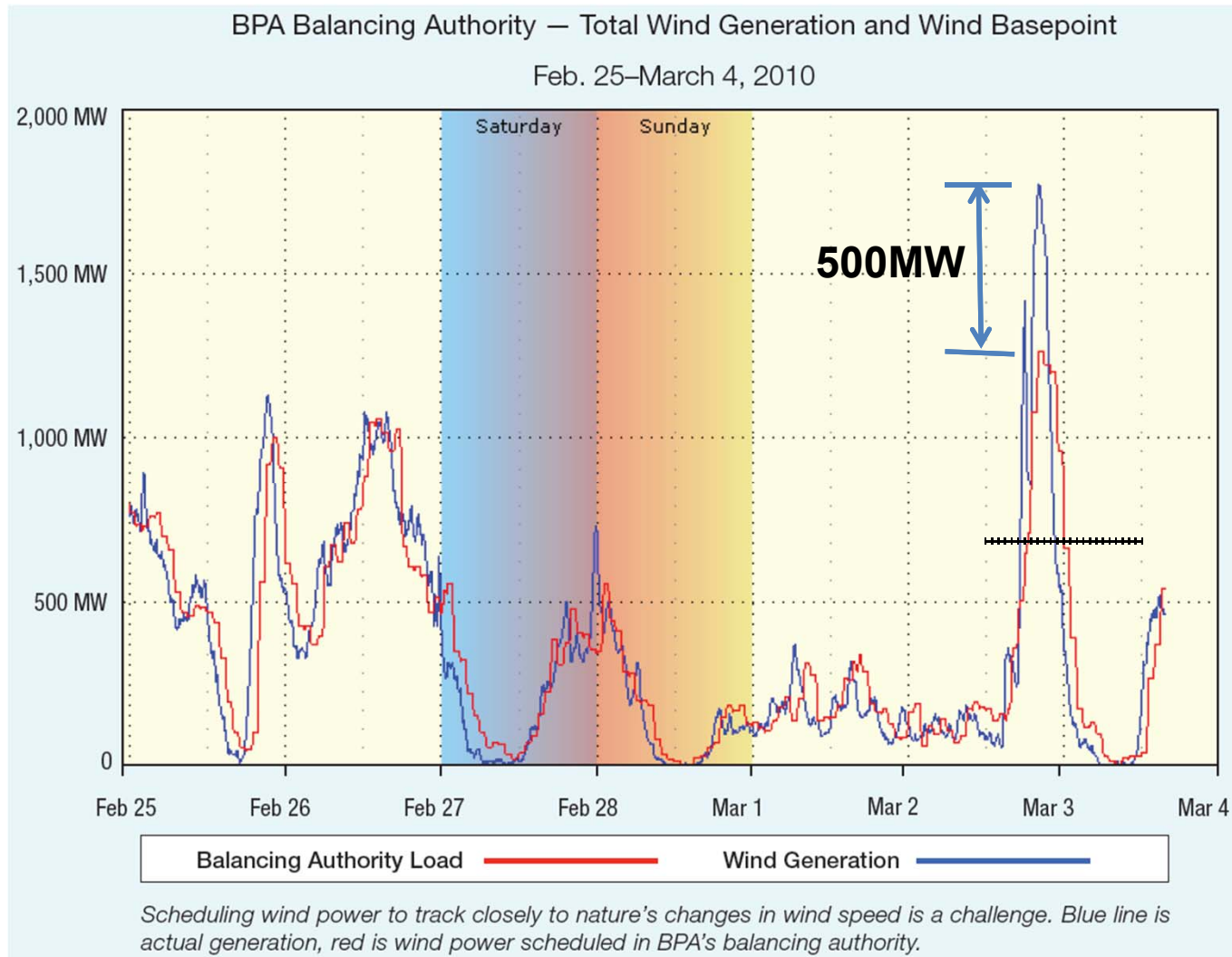
- ▶ **Grid Evolution –**
stochastic & dynamic
 - Generation: intermittent renewable energy, distributed generation,
 - Demand: smart loads, plug-in hybrids,
 - Other: storage, new market design/incentives
- ▶ **Information Revolution**
– data rich but information scarce
 - Large number of phasor measurement units and smart meters
 - Requirements of cyber security



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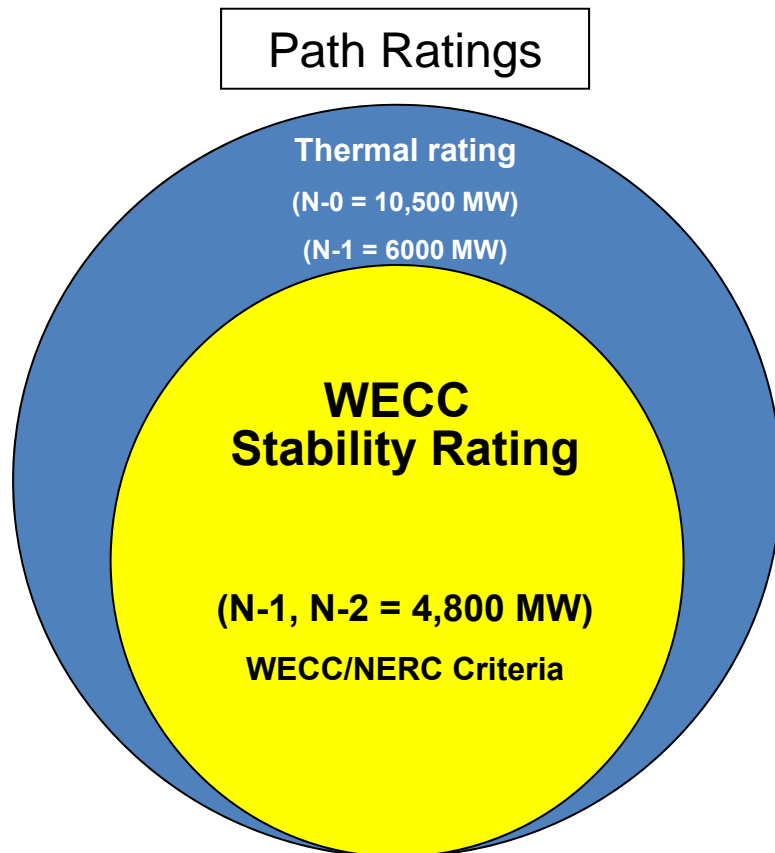
Mitigate Intermittency of Renewable Energy



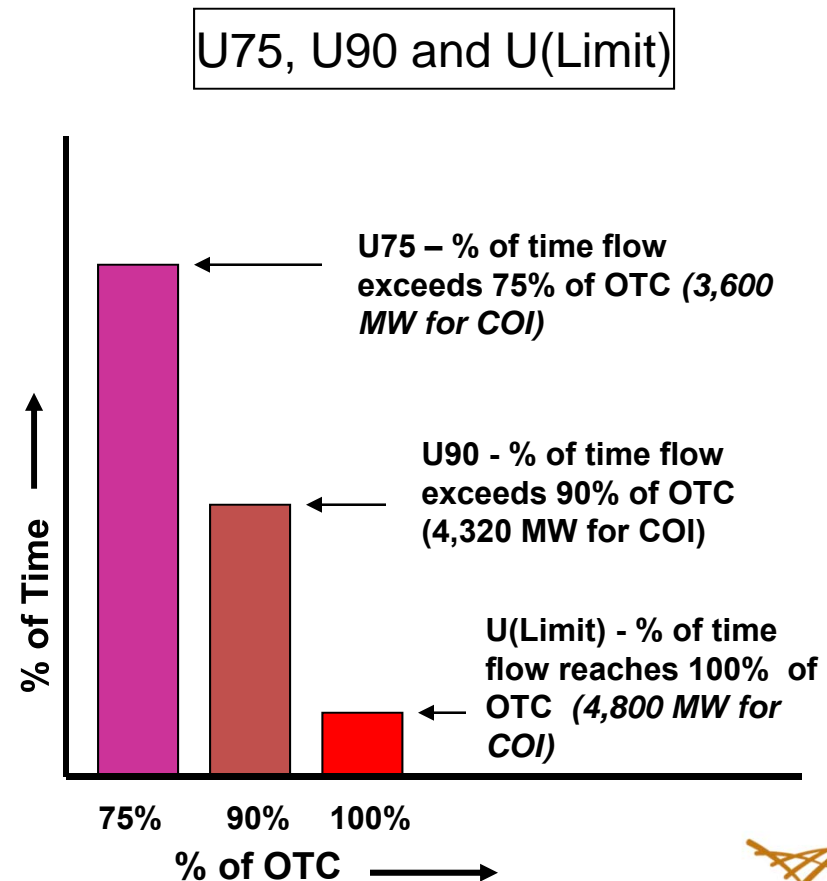
Source: BPA Fact Sheet, "BPA's wind power efforts surge forward", March 2010

Enable Real-time Rating for Better Asset Utilization

Transfer Capacity Example – California Oregon Intertie (COI)

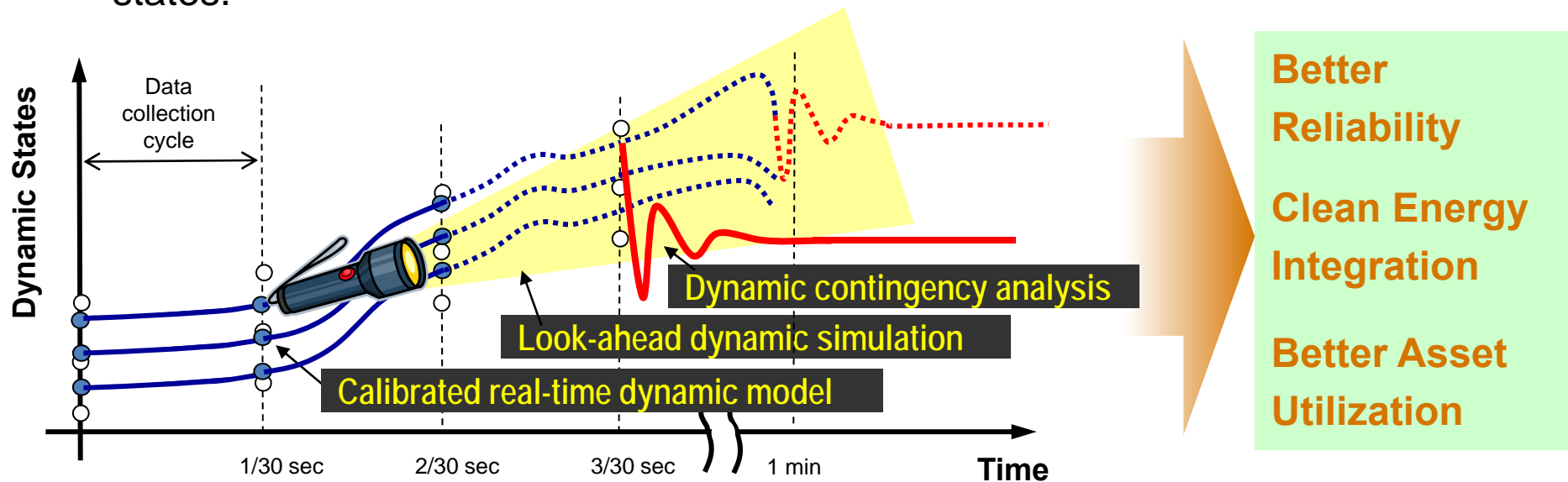


Source : Western interconnection 2006 congestion management study

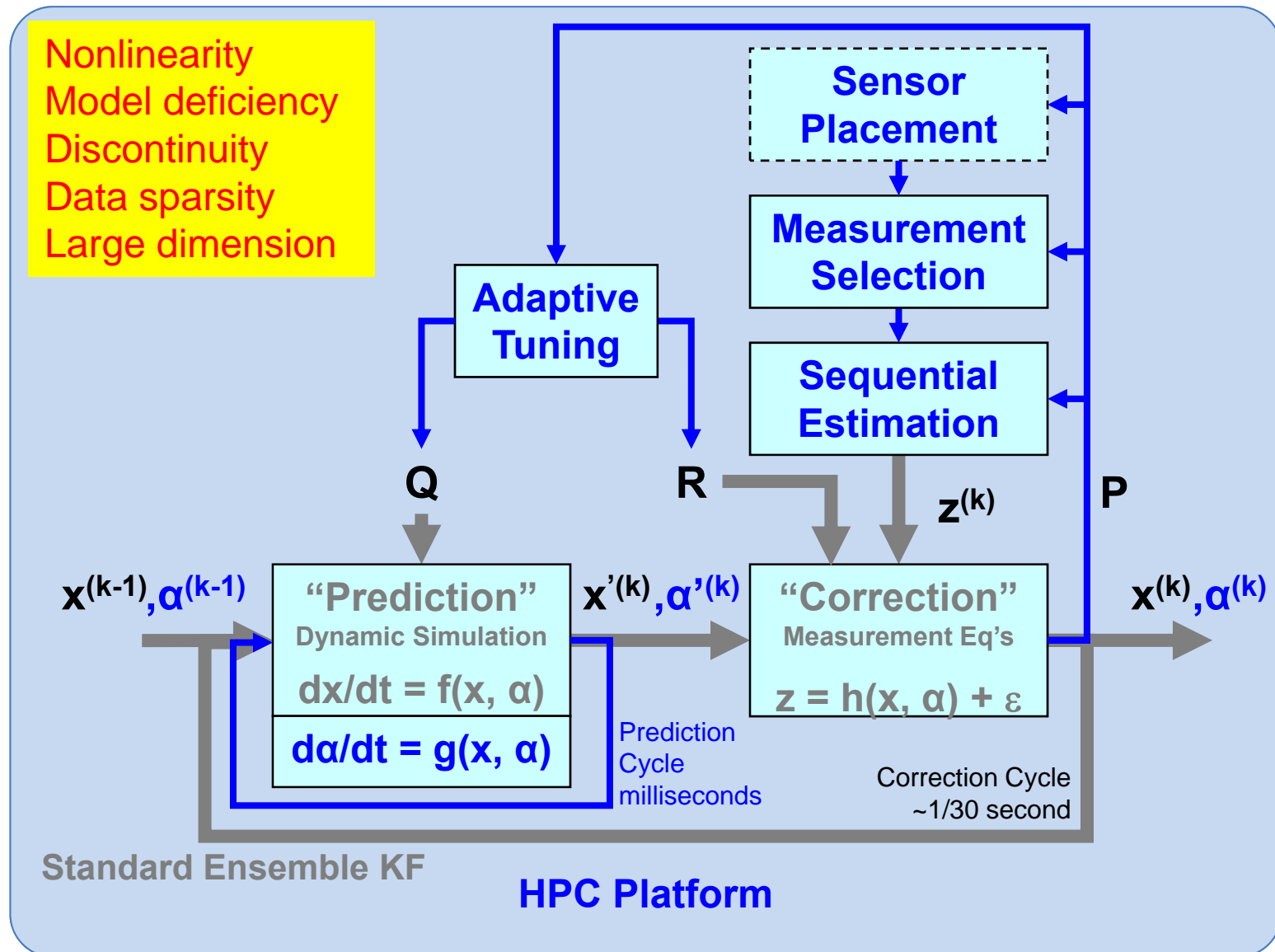


Dynamic Paradigm of Power Grid Operations

- ▶ **National Driver:** Clean and Efficient Power Grid as well as being affordable, reliable, and secure → **Operation: static & slow to dynamic & fast.**
- ▶ **Technical Approach:** combine model prediction and measurement observations to determine **where we are, where we are going, and what-ifs.**
 - Fuse models and data with nonlinearity, discontinuity, model deficiency, and data sparsity.
 - Develop Advanced Kalman Filter and HPC codes to estimate states and models
 - Solve a large number of ODE systems to predict future states and alternative states.



Advanced Kalman Filter for Complex Systems



Advances from Standard Ensemble Kalman Filter

Optimal sensor placement

$$P^\infty = \lim_{k \rightarrow \infty} E[(x_k - \hat{x}_k)(x_k - \hat{x}_k)^T]$$

$$\min_{loc(z)} (P^\infty)$$

Adaptive tuning

$$S_k = \tilde{H} P_k^- H^T + R$$

$$T_k = R S_k^{-1} R$$

$$Q_k = f(T_k)$$

$$R_k = f(T_k)$$

Prediction

Parameter calibration

$$x_k = [x_k \quad \alpha_k]$$

$$q_i \sim \text{normal}(0, Q_k)$$

$$\hat{X}_{k-1} = [\hat{x}_{k-1} + q_1 \quad \hat{x}_{k-1} + q_2 \quad \cdots \quad \hat{x}_{k-1} + q_N]$$

$$X_k^- = \hat{X}_{k-1} + f(\hat{X}_{k-1}, Y_{k-1}, 0) \Delta t$$

$$X_a^- = X_k^- - \text{mean}(X_k^-)$$

Multi-step prediction

$$\text{Repeat prediction steps}$$

Correction

$$Z_a^- = h(X_k^-, 0) - \text{mean}(h(X_k^-, 0))$$

$$r_i \sim \text{normal}(0, R_k)$$

$$Z_k = [z_k + r_1 \quad z_k + r_2 \quad \cdots \quad z_k + r_N]$$

$$P_k^- H_k^T = \frac{1}{N-1} Z_a^- (X_a^-)^T \quad H_k P_k^- H_k^T = \frac{1}{N-1} Z_a^- (Z_a^-)^T$$

Measurement selection

$$z_k \leftarrow C^T z_k, \quad \max_C \text{tr} \left\{ \frac{C^T H \hat{P}_k^- \hat{P}_k^- H^T C}{C^T (H \hat{P}_k^- H^T + \hat{R}) C} \right\}$$

Sequential estimation

$$P^- = U \cdot D \cdot U^T$$

$$H' = H U$$

$$r_1 = \left[\frac{H'_{11}{}^2}{R_{11}} \quad \frac{H'_{21}{}^2}{R_{22}} \quad \frac{H'_{31}{}^2}{R_{33}} \quad \cdots \quad \frac{H'_{m1}{}^2}{R_{mm}} \right]^T$$

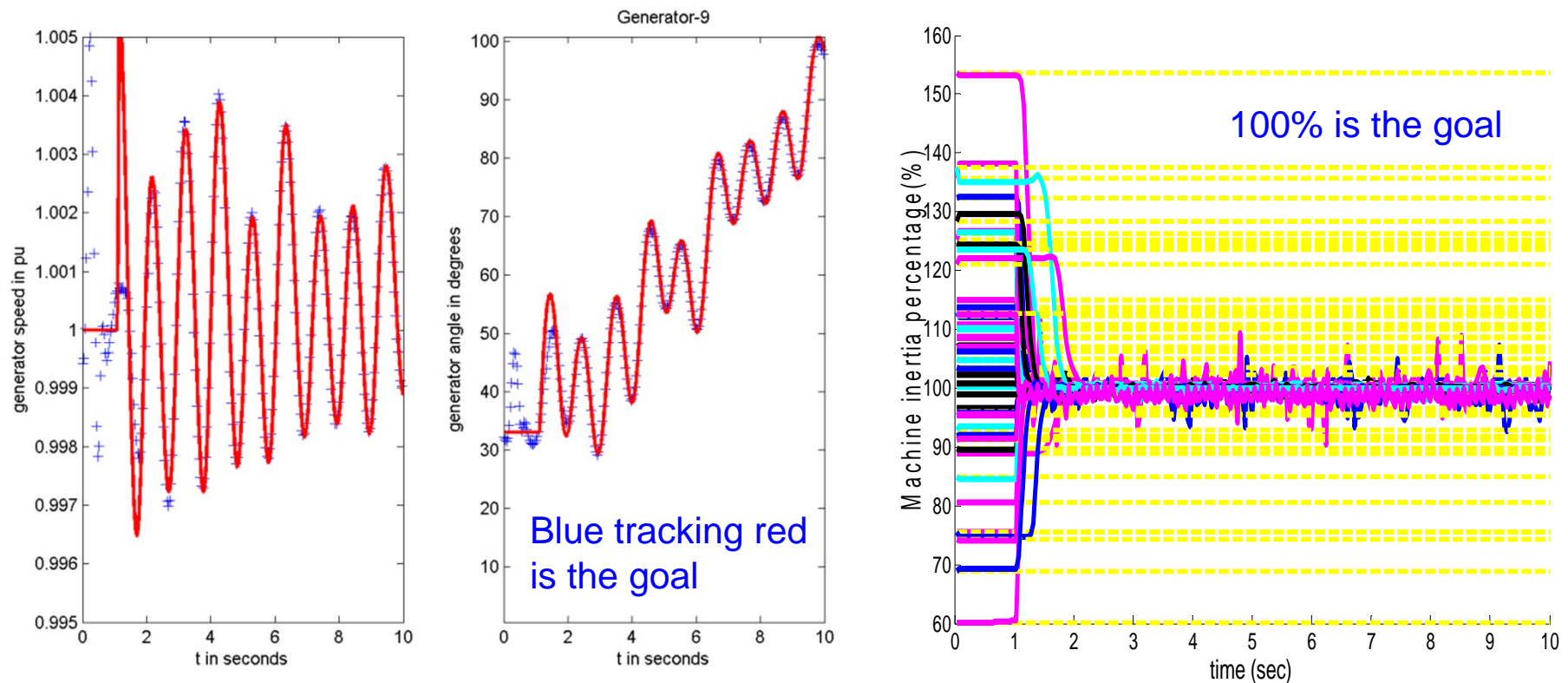
Select top z_k per r ranking

$$K_k = (P_k^- H_k^T) (H_k P_k^- H_k^T + R_k)^{-1}$$

$$\tilde{X}_k = X_k^- + K_k (Z_k - h(X_k^-, 0))$$

Estimation Performance – estimation accuracy

- ▶ Excellent tracking with realistic evaluation conditions
 - 3% measurement noise; 40 ms measurement cycle; 10 ms model prediction cycle; 20% parameter errors; unknown topology change; unknown initial states.



Estimation Performance – measurement handling

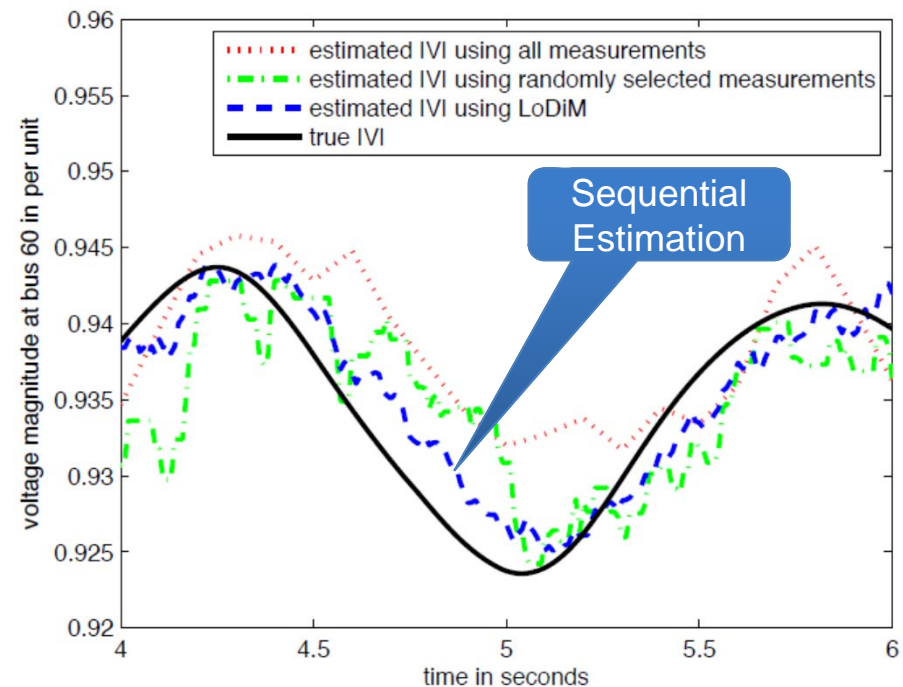
► Measurement selection

- Pseudo inverse test: 1000 measurements, 50 states

	No selection	With selection				
Measurements	1000	100	50	25	12	6
Time	7.82 sec	1.31 sec	0.60 sec	0.52 sec	0.53 sec	0.58 sec
Rel Accuracy	100%	100%	100%	59%	32%	17%

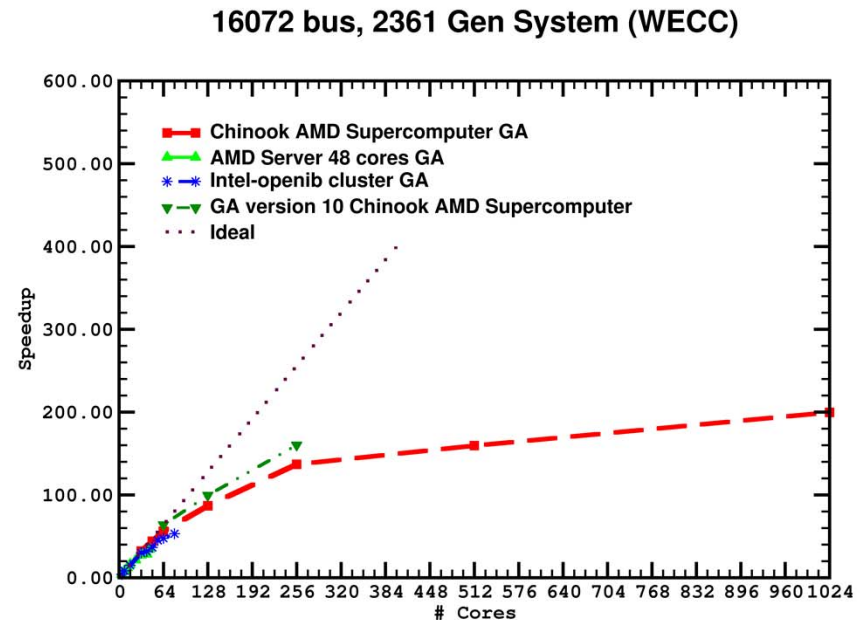
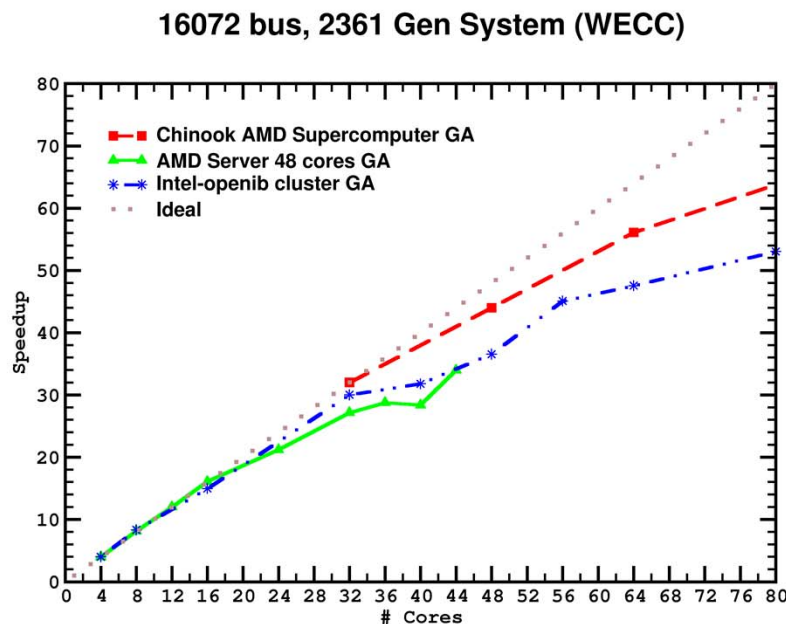
► Sequential estimation

- Trade-off between computation time and number of measurements
- Sequential estimation maximizes estimation quality with available computing resources
- Choose measurements with most “value” – largest *sensitivity-to-uncertainty* ratio



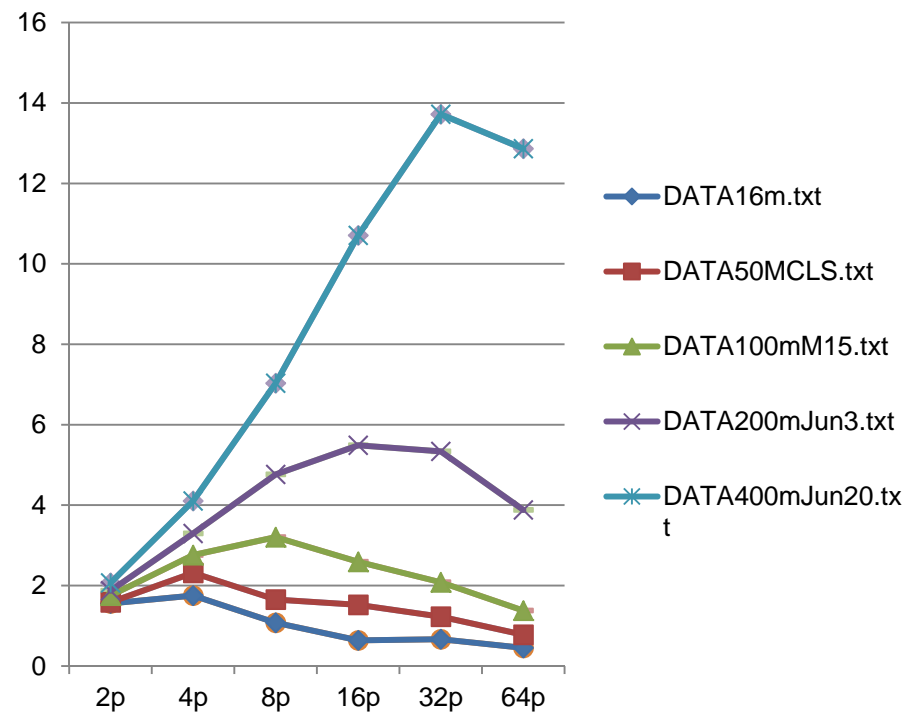
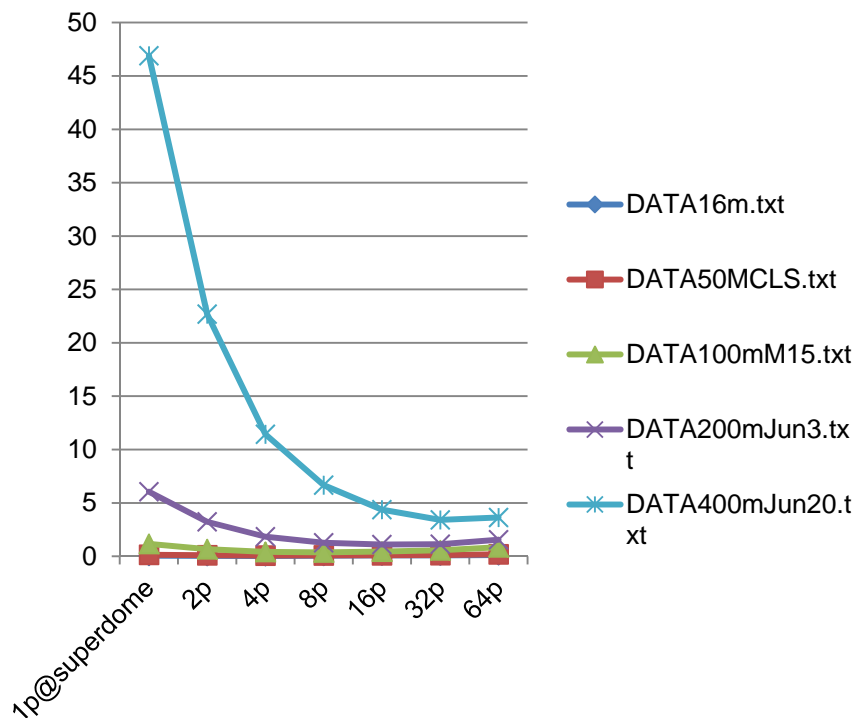
Computational Performance – scalability

- ▶ Current codes scale to ~1000 cores
- ▶ Rate-limiting step is some dense matrix multiplies and a Cholesky decomposition
- ▶ A peta-scale problem
 - Western US power grid: 16072 Buses, 2361 Generators $\rightarrow 1.7 \times 10^{13}$ flops
 - To complete each step in 0.03 sec $\rightarrow 0.6$ Petaflops/sec (ideal)
 - Data movement limits efficiency to <10% $\rightarrow >6$ PF



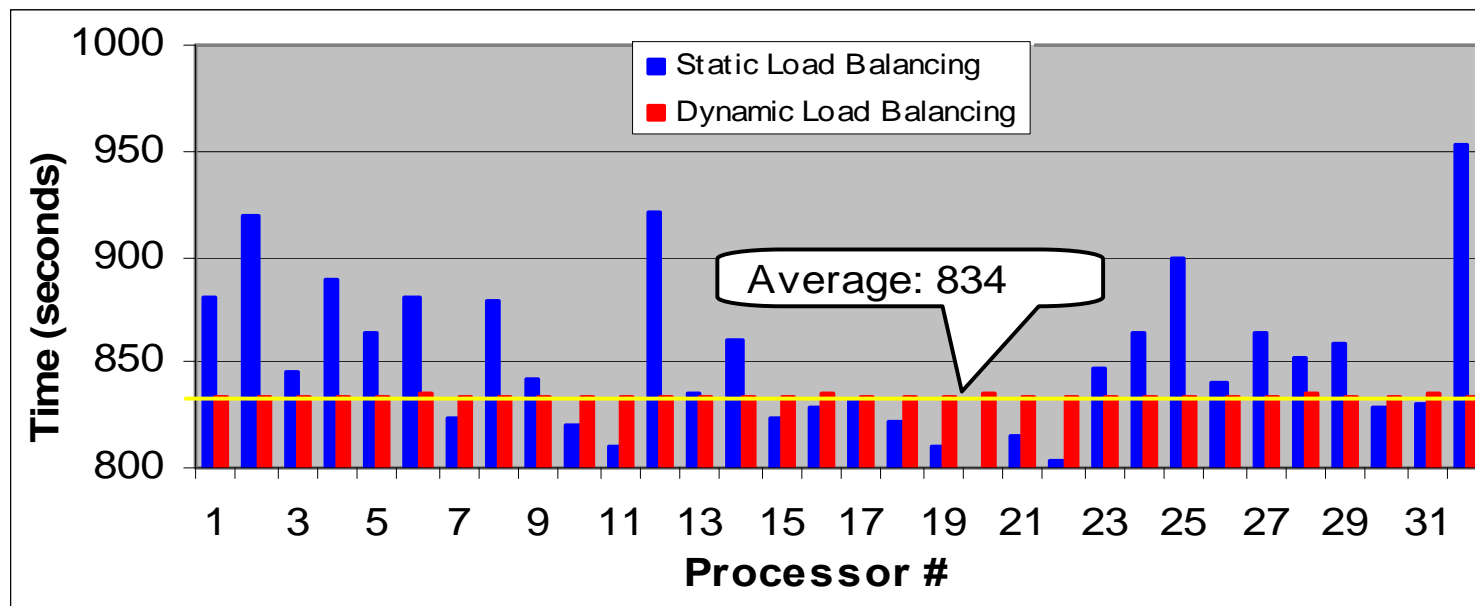
Synergetic Work – look-ahead dynamic simulation

- ▶ ODEs: achieved 14x speed-up for a 400 machine system.
- ▶ Speed-up performance is expected to be better with larger system sizes (e.g. WECC has 3000 generator).
- ▶ Promising for look-ahead capabilities.



Synergetic Work – dynamic contingency analysis

- ▶ A large set of ODEs
- ▶ Computational challenge is load balancing – dynamic load balancing vs. static load balancing
- ▶ Results on steady-state contingency analysis shows a promising path forward



Next Steps

- ▶ Within the current project:
 - Refine the Advanced Kalman Filter algorithm and mathematics
 - Scale to 10,000-100,000 cores
 - Demonstrate value with integrated testing of developed algorithms
- ▶ Remaining challenges – beyond the current project :
 - Develop real-time HPC platform: hardware and software stacks
 - Solve a large set of high-dimension ODEs in real time
 - Look-ahead dynamic simulation
 - Dynamic contingency analysis
 - Integrate technical elements for the dynamic grid operation paradigm

Summary

- ▶ Grid operations: from static & slow to dynamic & fast ← grid evolution meeting information revolution.
 - Enabling technologies are computation advancement and data development
- ▶ Advanced Kalman Filter has been developed to fuse models and data to determine **where we are** – foundation for a dynamic paradigm of grid operation
- ▶ Excellent estimation accuracy and computational performance have been demonstrated with tests using power grid models and data.
- ▶ An integrated platform and software package are being developed for the dynamic operation paradigm – **where we are, where we are going, and what-ifs.**



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Questions?

Please come visit our posters:

Monday 3:15PM

- Poster #18: Zhenyu Huang, “Fusing Models and Data for a Dynamic Paradigm of Power Grid Operations”
- Poster #08: Jinghe Zhang, “Adaptable Kalman Filtering for Robust Power System State Tracking”



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