



# Towards Continuous-time Optimization Models for Power Systems Operation

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FERC Technical Conference on Increasing Real-Time and Day-Ahead Market Efficiency  
through Improved Software, Washington, DC

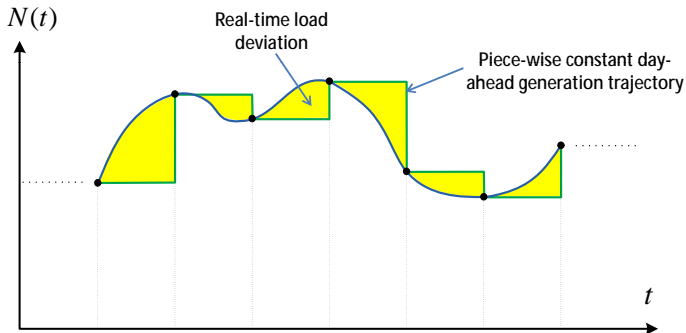
June 27-29, 2016

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- Current practice: break down the problem into different time scales, from several days ahead to real-time operation, solving discrete-time optimization problems for each time scale.



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- If the real-time ramping requirement is beyond the available ramping capacity → ramping scarcity event

# Continuous-time Generation and Ramping Trajectories

- Instead of discrete-time schedules, assume that a set of  $K$  generating units are modeled by:
  - Continuous-time generation trajectories:  $\mathbf{G}(t) = (G_1(t), \dots, G_K(t))^T$
  - Continuous-time commitment variables:  $\mathbf{I}(t) = (I_1(t), \dots, I_K(t))^T$

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- We define the **continuous-time ramping trajectory** of unit  $k$  as the time derivative of its continuous-time generation trajectory:

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- Explicit definition of ramping trajectories allows us to define cost functions that are also functions of ramping trajectories:

$$C_k(G_k(t), \dot{G}_k(t), I_k(t))$$

# Continuous-time Unit Commitment Model

- Continuous-time Unit Commitment:

$$\min \sum_{k=1}^K \int_{\mathcal{T}} C_k(G_k(t), \dot{G}_k(t), I_k(t)) dt$$

$$\text{s.t.} \quad \sum_{k=1}^K G_k(t) = N(t) \quad \forall t \in \mathcal{T}$$

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⇒ We need to *reduce dimensionality* of the problem. Idea:

① Subdivide  $\mathcal{T}$  into  $M$  intervals:  $\mathcal{T}_m = [t_m, t_{m+1})$ ,  $\mathcal{T} = \cup_{m=0}^{M-1} \mathcal{T}_m$ .

② Map the parameters and decision variables in each interval into a finite-dimensional function space.

# Continuous-time Trajectories in a Function Space

- Assume that in  $\mathcal{T}$ , except for a small residual error, the continuous-time load trajectory  $N(t)$  lies in a countable and finite function space of dimensionality  $P$ , spanned by a set of basis functions  $\mathbf{e}(t) = (e_1(t), \dots, e_P(t))^T$ , that is:

$$N(t) = \sum_{p=1}^P N_p e_p(t) + \epsilon_N(t) = \mathbf{N}^T \mathbf{e}(t) + \epsilon_N(t)$$

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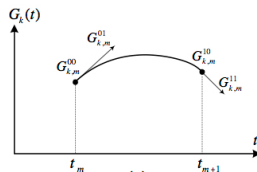
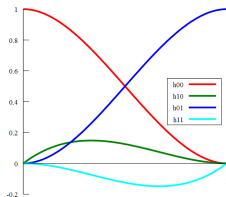
$\mathbf{N} = (N_1, \dots, N_P)^T$ : *coordinates* of the approximation onto the subspace spanned by  $\mathbf{e}(t)$ .

- To ensure the power balance in continuous-time, any generation trajectory should have a component that lies in the same subspace spanned by  $\mathbf{e}(t)$  and one that is orthogonal to it, i.e.,:

$$G_k(t) = \sum_{p=1}^P G_{k,p} e_p(t) + \epsilon_{G_k}(t) = \mathbf{G}_k^T \mathbf{e}(t) + \epsilon_{G_k}(t).$$

# Spline Representation using Cubic Hermite Polynomials

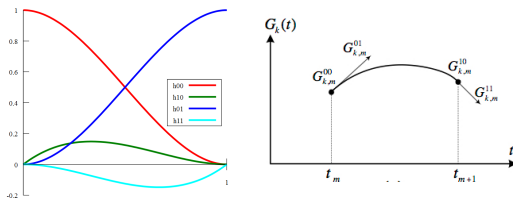
- **Cubic Hermite Polynomials:** four polynomials in  $t \in [0, 1]$ , forming the vector:  $\mathbf{H}(t) = (H_{00}(t), H_{01}(t), H_{10}(t), H_{11}(t))^T$





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- Modeling the continuous-time load and generation trajectories in spline function space of cubic Hermite:

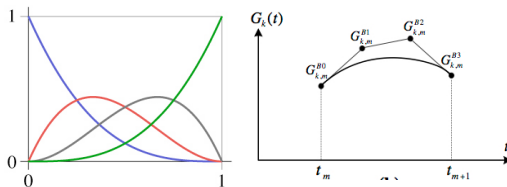
$$\hat{N}(t) = \sum_{m=0}^{M-1} \mathbf{H}^T(\tau_m) \mathbf{N}_m^H, \quad G_k(t) = \sum_{m=0}^{M-1} \mathbf{H}^T(\tau_m) \mathbf{G}_{k,m}^H$$

$\mathbf{N}_m^H$  and  $\mathbf{G}_{k,m}^H$  are the vectors of Hermite coefficients.

# Spline Representation using Bernstein Polynomials

- **Bernstein Polynomials of degree  $Q$** :  $Q + 1$  polynomials in  $t \in [0, 1)$ , forming the vector  $\mathbf{B}_Q(t) = (B_{0,Q}, \dots, B_{q,Q}, \dots, B_{Q,Q})^T$ , where  $B_{q,Q}(t) = \binom{Q}{q} t^q (1-t)^{Q-q}$
- Modeling the continuous-time load and generation trajectories in spline function space of Bernstein polynomials of degree 3:

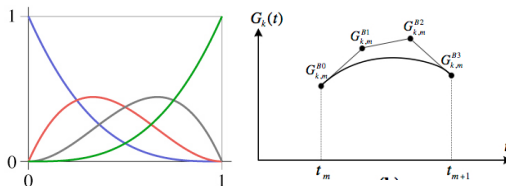
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- The Bernstein and Hermite coefficients are linearly related:

$$\mathbf{G}_{k,m}^B = \mathbf{W}^T \mathbf{G}_{k,m}^H, \quad \mathbf{N}_{k,m}^B = \mathbf{W}^T \mathbf{N}_{k,m}^H$$

# Why Bernstein Polynomials?

- Bernstein coefficients of the derivative of generation trajectory are linearly related with the coefficients of the generation trajectory:

$$\dot{G}_k(t) = \sum_{m=0}^{M-1} \mathbf{B}_2^T(\tau_m) \dot{\mathbf{G}}_{k,m}^B, \quad \dot{\mathbf{G}}_{k,m}^B = \mathbf{K}^T \mathbf{G}_{k,m}^B = \mathbf{K}^T \mathbf{W}^T \mathbf{G}_{k,m}^H$$

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- **Convex hull property** of the Bernstein polynomials: trajectories are bounded by the convex hull formed by the four Bernstein points:

$$\min_{t_m \leq t \leq t_{m+1}} \{ \mathbf{B}_3^T(\tau_m) \mathbf{G}_{k,m}^B \} \geq \min \{ \mathbf{G}_{k,m}^B \}$$

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# Representation of Cost Function and Balance Constraint

- Piecewise linear continuous-time cost function can be written in terms of the spline coefficients of generation and ramping trajectories:

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- Continuous-time power balance is ensured by balancing the four cubic Hermite coefficients of the continuous-time load and generation trajectory in each interval:

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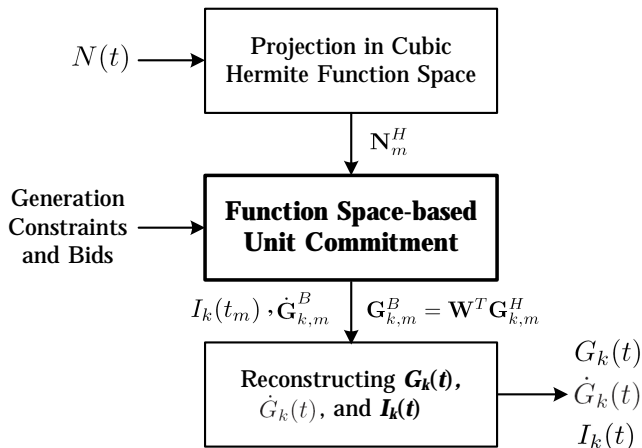
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- DC power flow constraints can be modeled similarly.

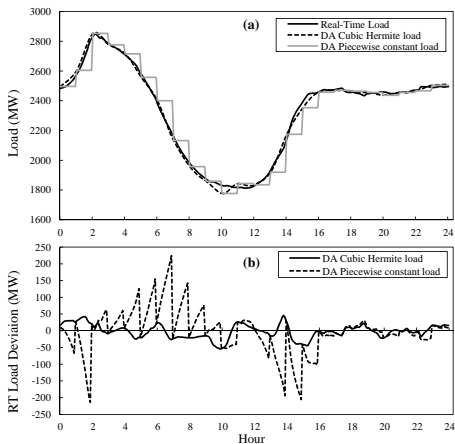


# Continuous-time UC Solution



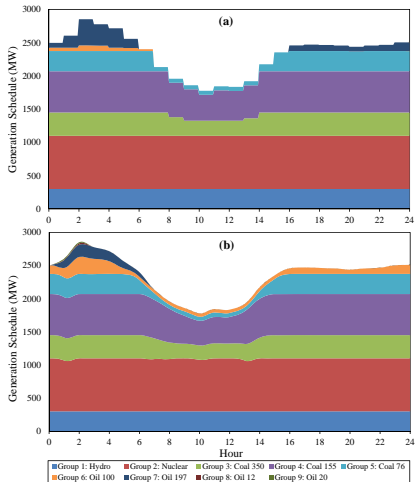
# Simulation Results: IEEE-RTS + CAISO Load

- The data regarding 32 units of the IEEE-RTS and load data from the CAISO are used here.
- Both the day-ahead (DA) and real-time (RT) operations are simulated.
- The five-minute net-load forecast data of CAISO for Feb. 2, 2015 is scaled down to the original IEEE-RTS peak load of 2850MW, and the hourly day-ahead load forecast is generated where the forecast standard deviation is considered to be %1 of the load at the time.



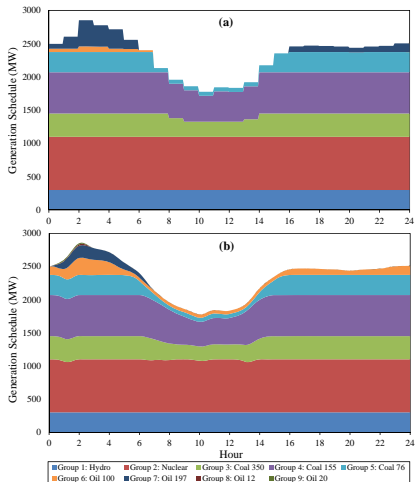
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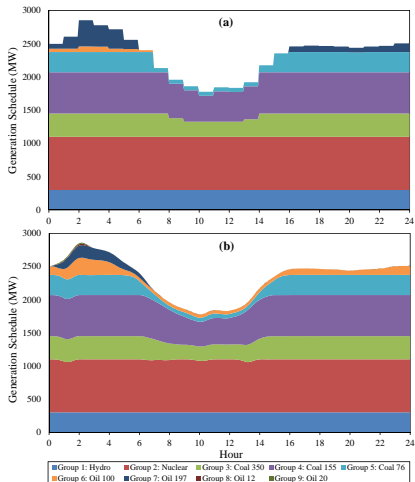


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Case	DA Operation Cost (\$)	RT Operation Cost (\$)	Total DA and RT Operation Cost (\$)	RT Ramping Scarcity Events
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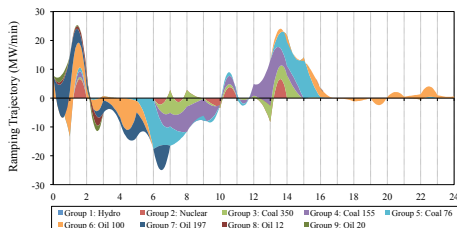
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Continuous-time ramping trajectories

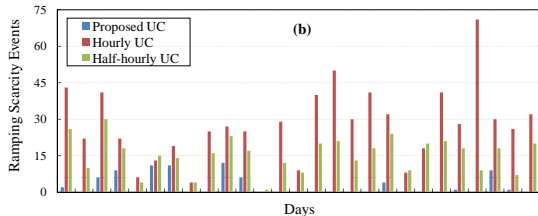
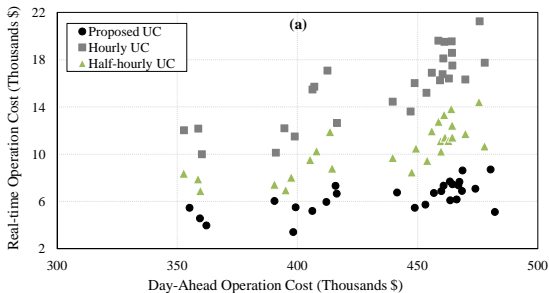


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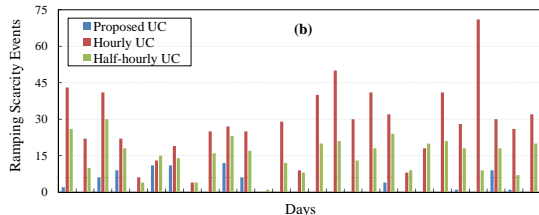
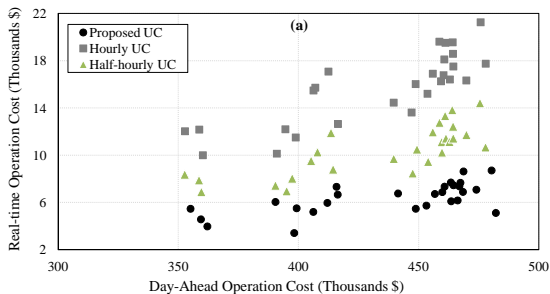
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- Computation time for Feb. 2, 2015 load data:
  - Hourly UC: 0.257s
  - Half-hourly UC: 0.572s
  - Proposed UC: 1.369s





# Conclusions

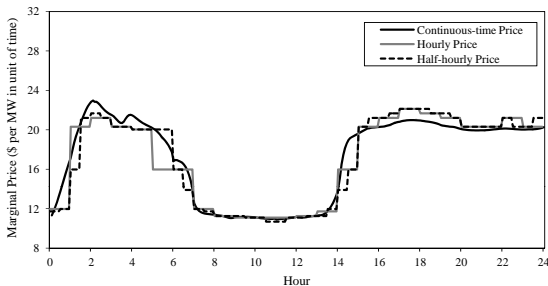
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- Continuous-time models define ramping trajectory as an explicit decision variable and enable accurate ramping valuation in markets
- Enabling the definition of *continuous-time marginal electricity price*:



## Further Reading

- M. Parvania, A. Scaglione, “Unit Commitment with Continuous-time Generation and Ramping Trajectory Models,” *IEEE Transactions on Power Systems*, vol. 31, no. 4, pp. 3169-3178, July 2016.
- M. Parvania, A. Scaglione, “Generation Ramping Valuation in Day-Ahead Electricity Markets,” in Proc. *49th Hawaii International Conference on System Sciences (HICSS)*, Kauai, HI, Jan. 5-8, 2016.

