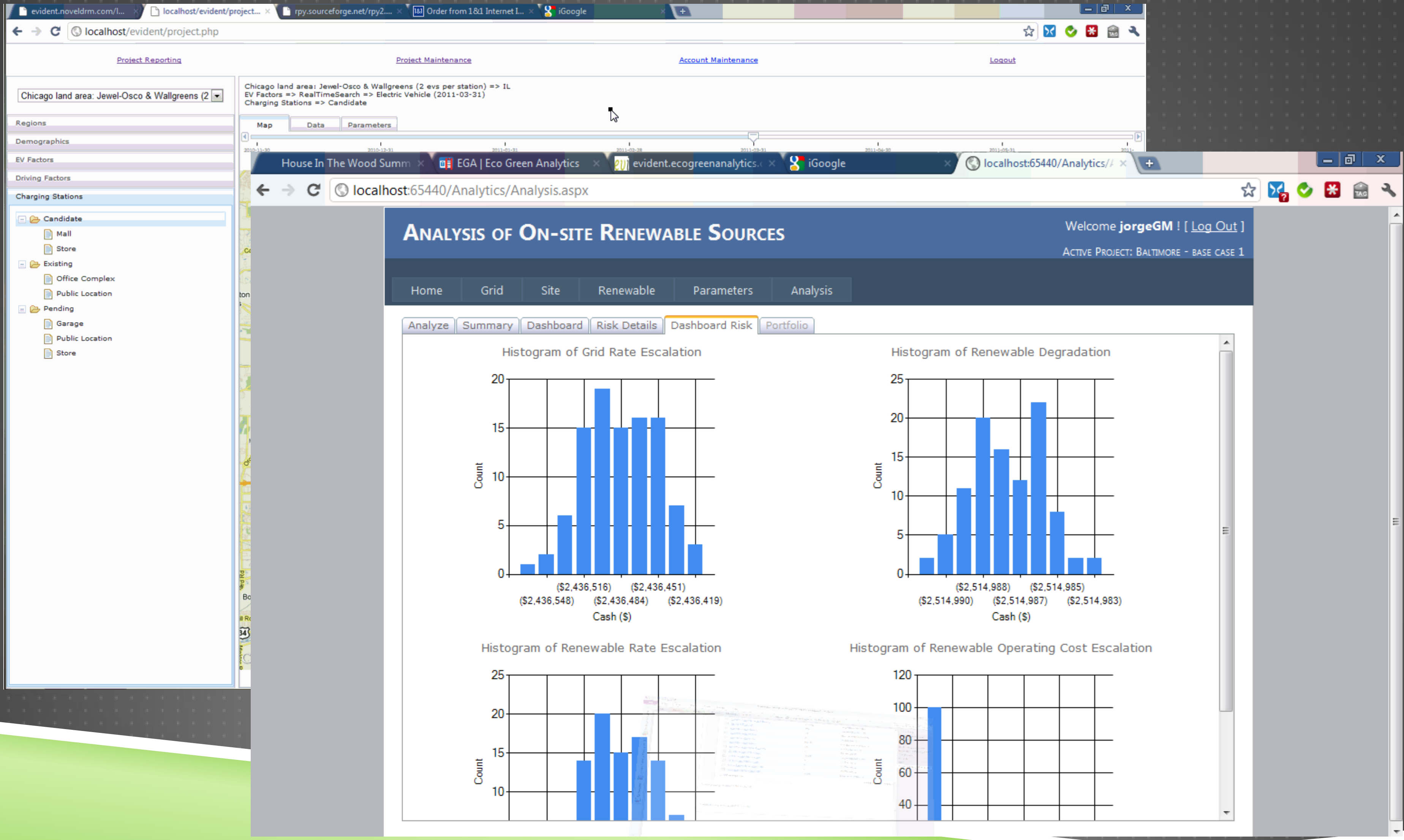
DAY AHEAD STOCHASTIC UNIT COMMITMENT WITH DEMAND RESPONSE AND LOAD SHIFTING

Diego Klabjan, Frank Schneider

Washington DC, 06/29/2011

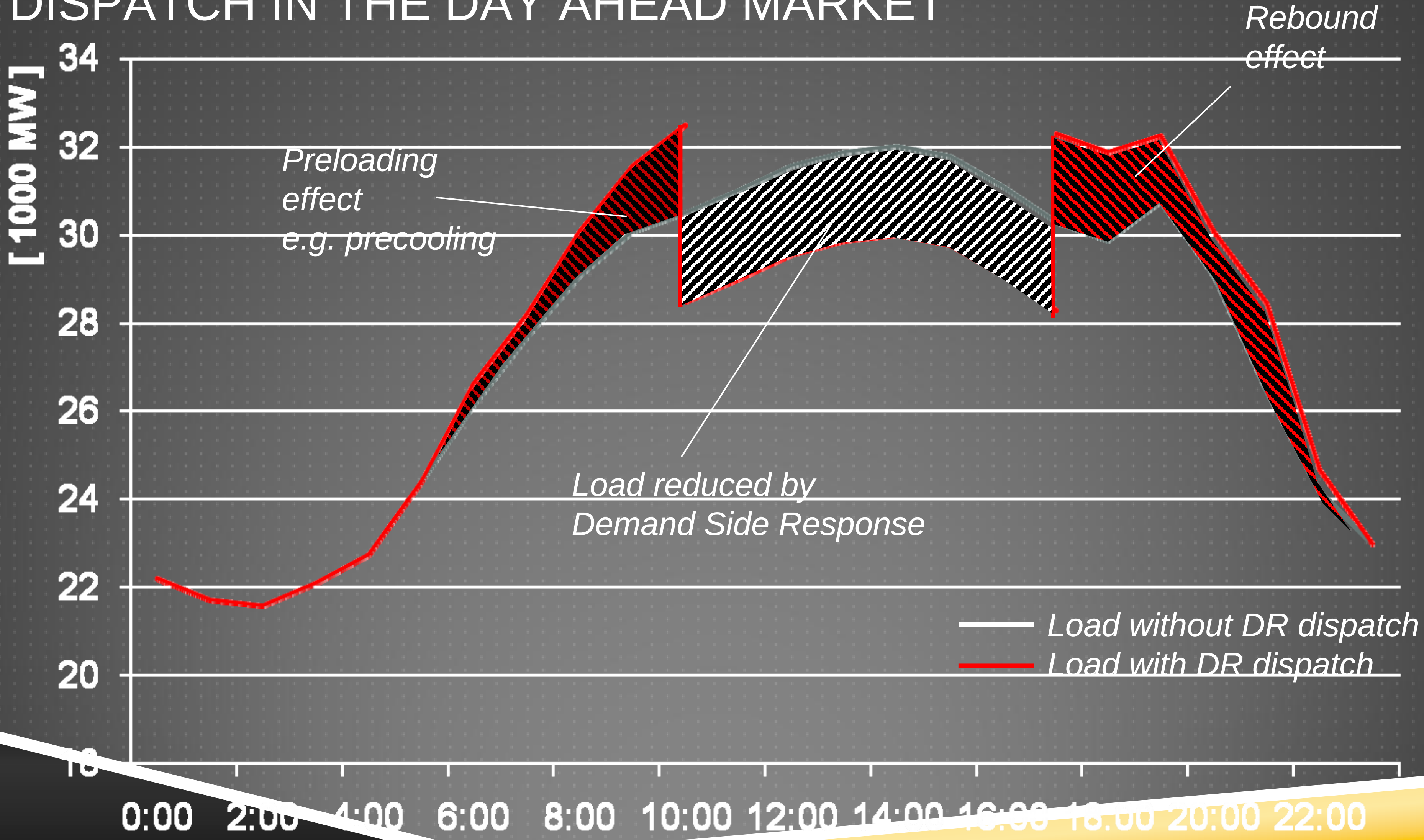
OTHER PET PROJECTS



OUTLINE

- Problem Statement
- Model
- Algorithmic Approach
- Data Sets
- Numerical Results
- Conclusions

LOAD SHIFTING EFFECTS INDUCED BY A DEMAND SIDE RESOURCE DISPATCH IN THE DAY AHEAD MARKET



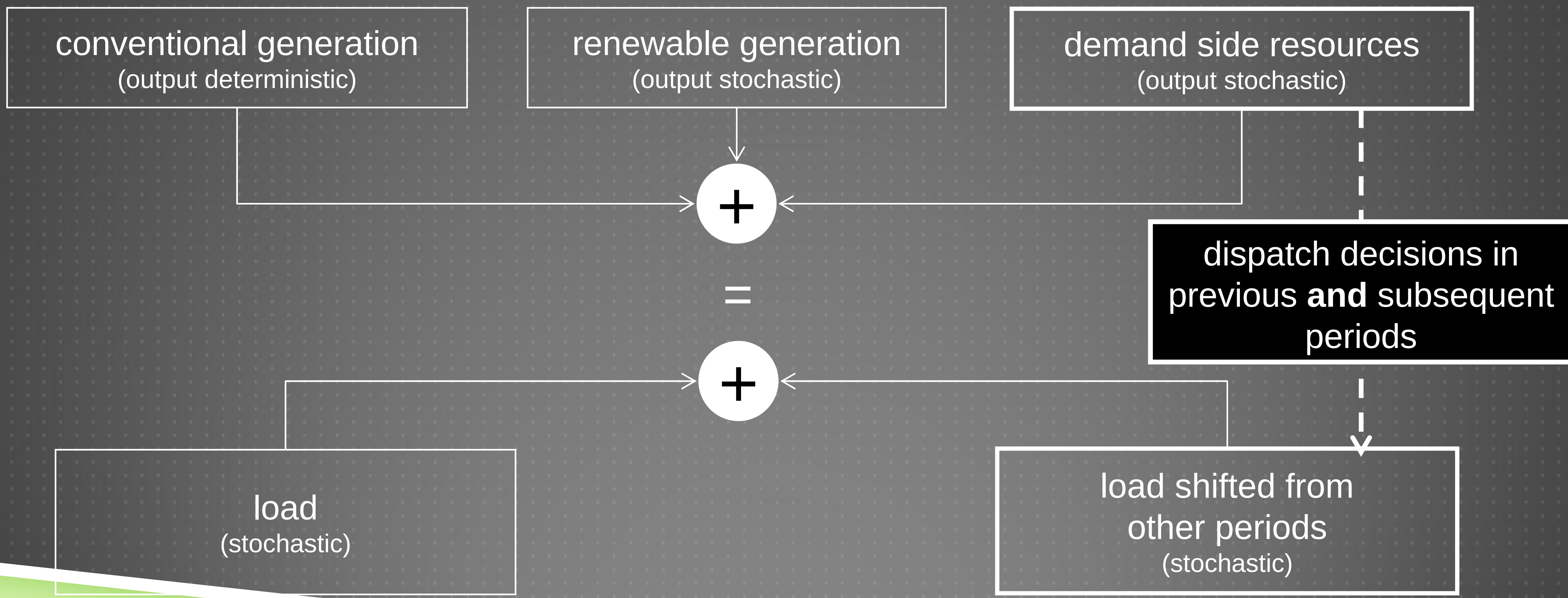
GOALS

- Model DR in a UC setting
- Study the impact of solar
- Study the potential of DR to mitigate intermittency of renewable sources
  - Solar, wind

PROBLEM FORMULATION

Minimize total generation cost (nonlinear)

Subject to:



- Minimum Uptime and Downtime Constraints
- Ramping Constraints
- Spinning Reserve Constraints

OUTLINE

- Problem Statement
- Model
- Algorithmic Approach
- Data Sets
- Numerical Results
- Conclusions

PROBLEM FORMULATION & SOLUTION APPROACH

- Formulation as a dynamic program
- Load shifting to period t may depend on dispatch decisions in periods t-1,t-2,… and on dispatch decisions in periods t+1, t+2, …

⬇

$$V_t(S_t) = \min_{x_t}\{E\{C_t(x_t, S_t, W_t) + V_{t+1}(S_{t+1}(x_t, S_t, W_t))\}\}$$

Classical DP formulations cannot handle this.

⬇

$$V_t{}^Z(S_t) = \min_{x_t}\left\{E\left\{C_t(z_t, x_t, S_t, W_t) + V_{t+1}{}^Z(S_{t+1}(z_t, x_t, S_t, W_t)\right\}\right\}$$

- We make the Value Function dependant on a vector of parameters Z.
- Vector Z in our case represents a complete schedule of DR dispatch decisions.

MODEL – MATHEMATICAL FORMULATION

- Attributes for each generator

$$\begin{bmatrix} a_1 \\ a_2 \\ a_3 \\ a_4 \\ a_5 \end{bmatrix} = \begin{bmatrix} \text{generator index} \\ \text{uptime [hrs]} \\ \text{downtime [hrs]} \\ \text{online [1/0]} \\ \text{operating level [\% of max]} \end{bmatrix}$$

→ In state space, a_5 is clustered into intervals of size $\left\lceil \frac{1}{ramp\ rate} \right\rceil$

- Possible actions for each generator (subject to constraints)

$$\begin{bmatrix} x_1 \\ x_2 \\ x_3 \\ x_4 \end{bmatrix} = \begin{bmatrix} \text{do nothing} \\ \text{commit generator} \\ \text{decommit generator} \\ \text{ramp to level} \end{bmatrix}$$

MODEL – MATHEMATICAL FORMULATION

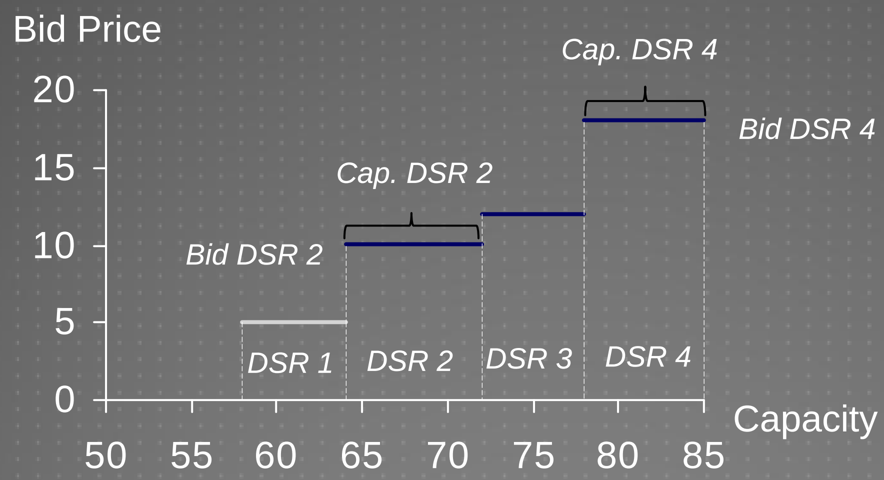
- Attribute transition function for each generator

$$a_{t+1} = \begin{bmatrix} a_{1,t} \\ a_{2,t}+1 \\ a_{3,t}+1 \\ a_{4,t} \\ 0 \end{bmatrix} + \begin{bmatrix} 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & -1-a_{t,2} & 0 & 0 \\ 0 & -1-a_{t,3} & 0 & 0 & 0 \\ 0 & 1 & -1 & 0 & 0 \\ 0 & 0 & 0 & 0 & 1 \end{bmatrix} x_t$$

- (Disaggregate) state space R is count of generators with a certain value of the attribute vector
  - Size: $|R| = \prod_{i=1}^{5} |a_i|$
  - State space is binary, since a_1 is generator index

UNIQUE MODEL FEATURES

- Segments DR bid curves are modeled as individual resources with corresponding bid price and capacity



- Model captures preload and rebound effect on load
  - In periods before and after dispatch of a Demand Side Resource (DSR)

- Continuous dispatch decisions (segments can be dispatched partially)

- Monotone bid curves

UNIQUE MODEL FEATURES

- Residual load:

Bid Capacity

$$L_{res}(t) = \underbrace{L(t) - S(t) - W(t)}_{\text{Load minus renewables}} + \sum_{i=0}^{i=DR} z_i C_i \beta_{i,t}$$ ← load shifted to period t

dispatch dec. $(0 \le z_i \le 1)$

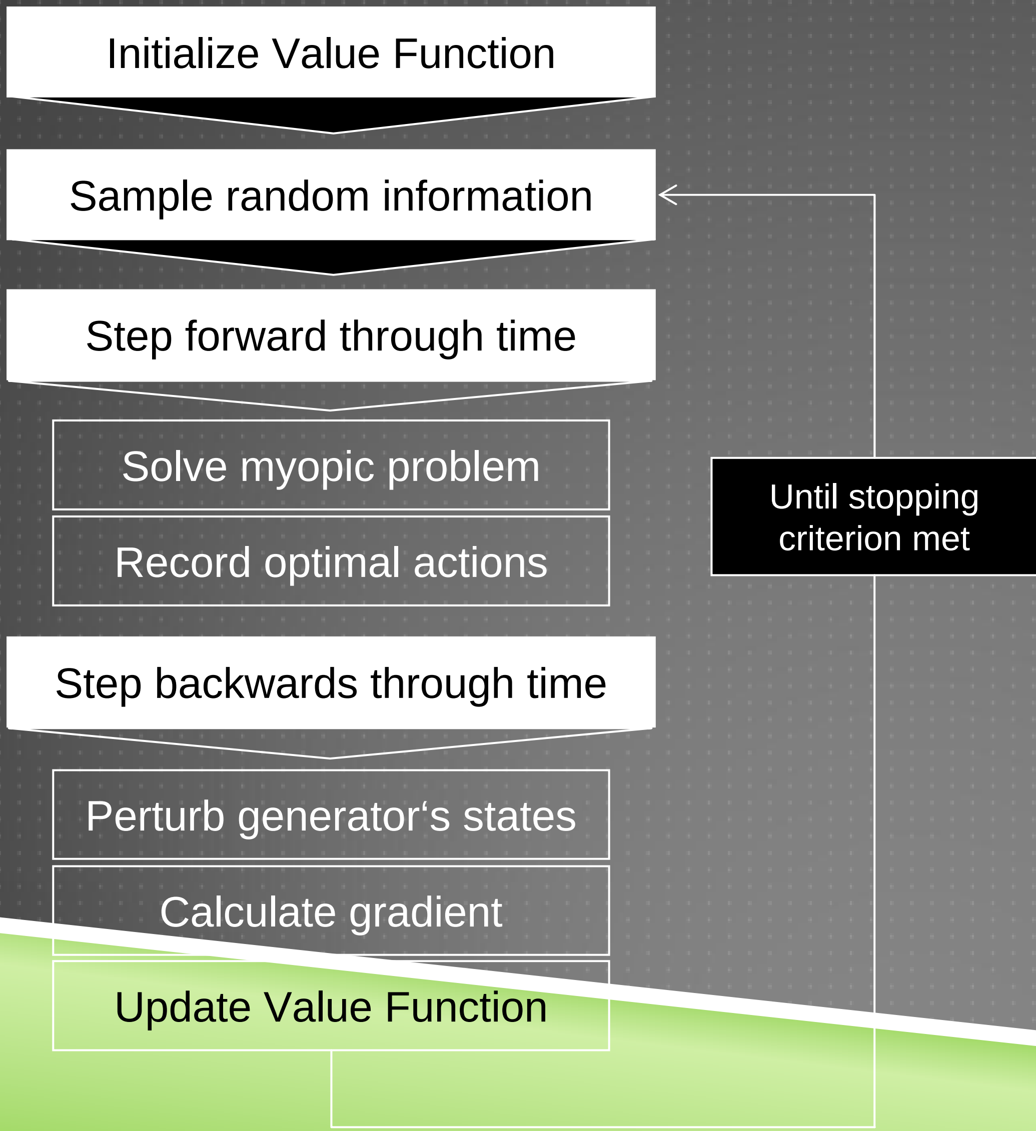
- Random variable $\beta_{i,t}$: portion of load shifted to period t by dispatching DSR i
  - $\sum_{\tau=0}^{T} \beta_{i,\tau}$ gives total percentage of load shifted (can be < 100% or > 100%).

- Spinning reserve requirements modeled as chance constraint
  - Dispatch of DSRs influences variance of $L_{res}(t)$

OUTLINE

- Problem Statement
- Model
- Algorithmic Approach
- Data Sets
- Numerical Results
- Conclusions

APPROXIMATE DYNAMIC PROGRAMMING



- No explicit calculation of expected value inside minimization
- Instead sampling of random variables
- Stepping forward through time with current value function approximation
- Choosing right structure of value function is crucial
- Aggregation of “similar states“
- Then use separable piecewise linear approximation for each aggregated state

INCLUDING DEMAND RESPONSE – SOLUTION APPROACH

- Progressive hedging based approach

$$\min_{Z} V_0{}^{Z}(S_0) = \min_{Z,x_0} \left\{ E\{C_0(Z, x_0, S_0, W_0) + V_1{}^{Z}(S_1(Z, x_0, S_0, W_0)\} \right\}$$

- Allow vector to take different values in different periods $t, \hat{t}$

- Solve $\min_{Z^0} \tilde{V}_0{}^{Z^0}(S_0)$ with

$$\tilde{V}_t{}^{Z^t}(S_t) = \min_{Z_t, x_t} \left\{ E\left\{ C_t(Z^t, x_t, S_t, W_t) + V_{t+1}{}^{Z^{t+1}}(S_{t+1}(Z^t, x_t, S_t, W_t) \right\} + \langle Z^t, W^t \rangle + \frac{r}{2} \|Z^t - \bar{Z}\|^2 \right\}$$

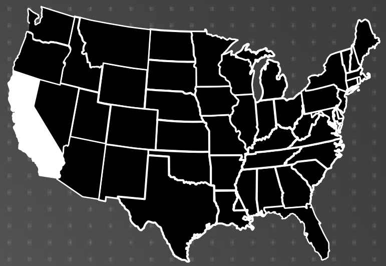
  - In each iteration update $W^{n+1}{}_t = W^n{}_t + r(Z^t - \bar{Z})$ and $\bar{Z}^{n+1} = \frac{1}{T}\sum_{i=0}^{T} Z^t$
  - After each update $\bar{Z}$ represents an implementable schedule of DR dispatch decisions.

- It can be shown that the proposed algorithm converges, if the inner DP is solved optimally and the resulting problem $\min_{Z} V_t{}^{Z}(S_t)$ are convex in Z.

OUTLINE

- Problem Statement
- Model
- Algorithmic Approach
- Data Sets
- Numerical Results
- Conclusions

DATA SETS



Load, Solar and Wind

- Historic hourly load data from CAISO region over 10 years

- Simulated hourly output of 47,151 photovoltaic installations in California using radiation data from NREL over 8 years

- Simulated hourly output of 122 windfarms in California using meterological data from NREL over 3 years

➔ Estimated parameters for normal distribution from observations

Generators

- Different number of generators 10 – 250
  - Parameters have been chosen according to industry standards

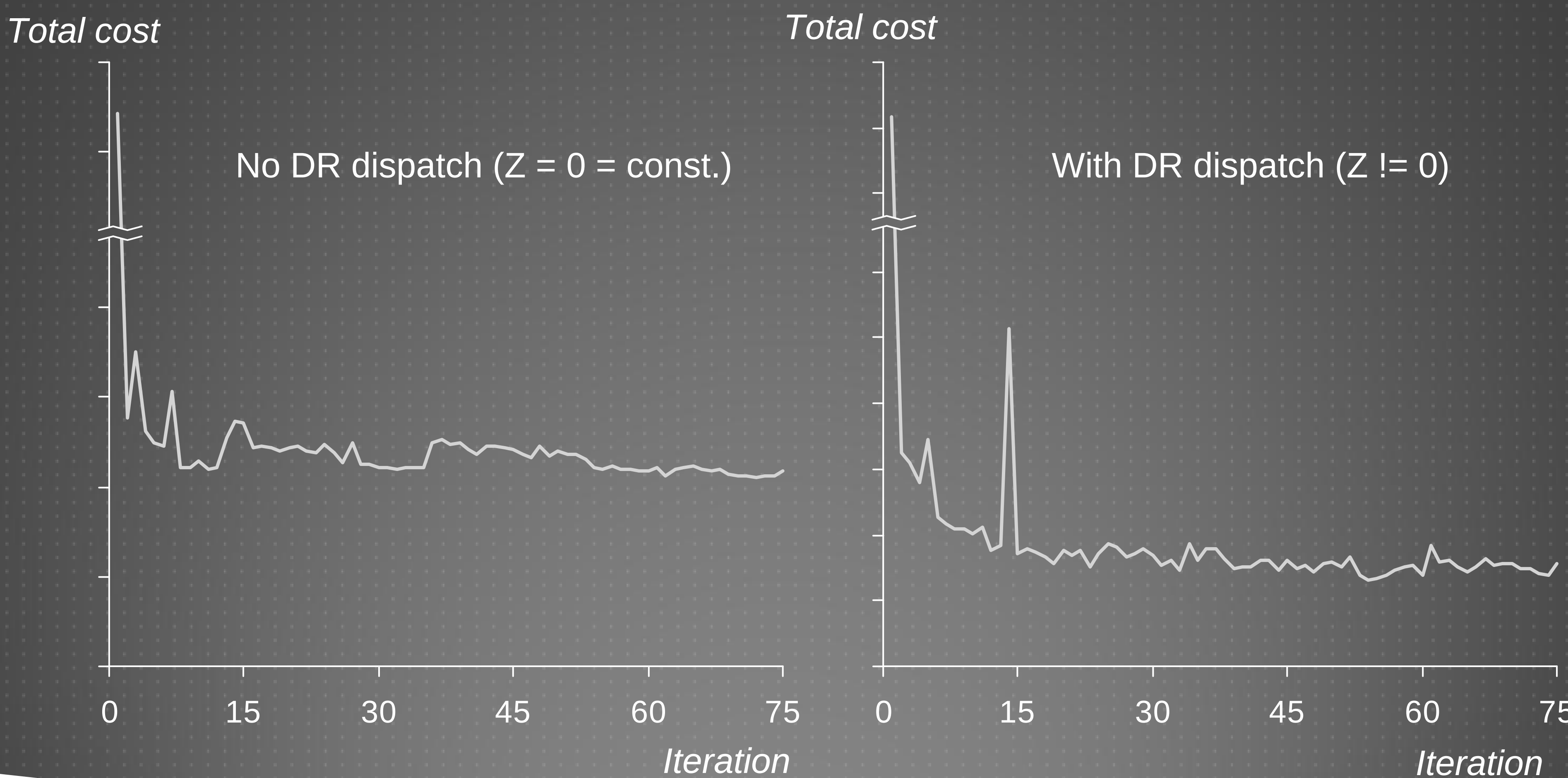
Demand Side Resources

- No real world DR data is available
  - Different scenarios were created (differing in DR capacity, load shifting distributions and DR bid prices)

OUTLINE

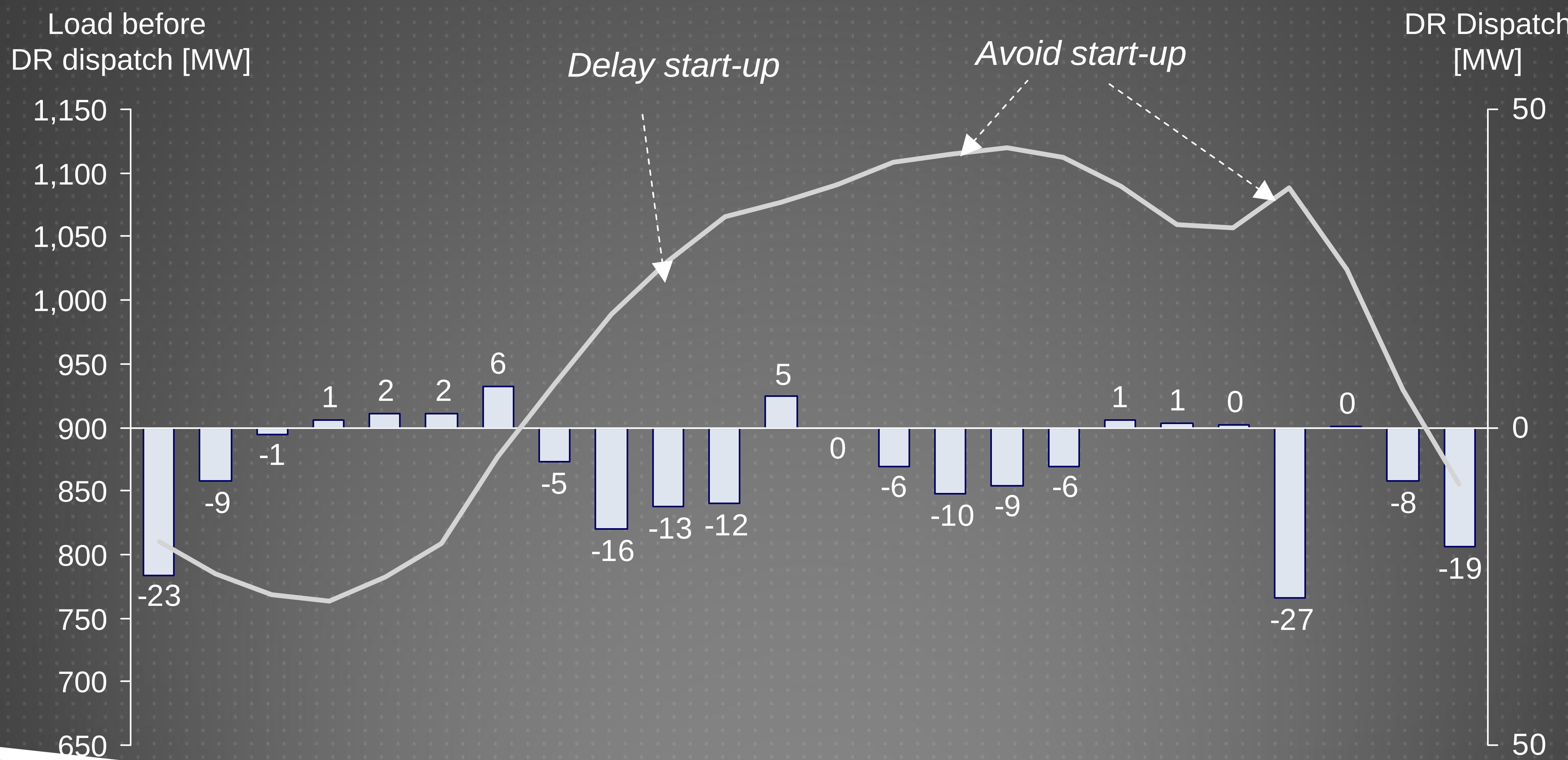
- Problem Statement
- Model
- Algorithmic Approach
- Data Sets
- Numerical Results
- Conclusions

ALGORITHMIC BEHAVIOR



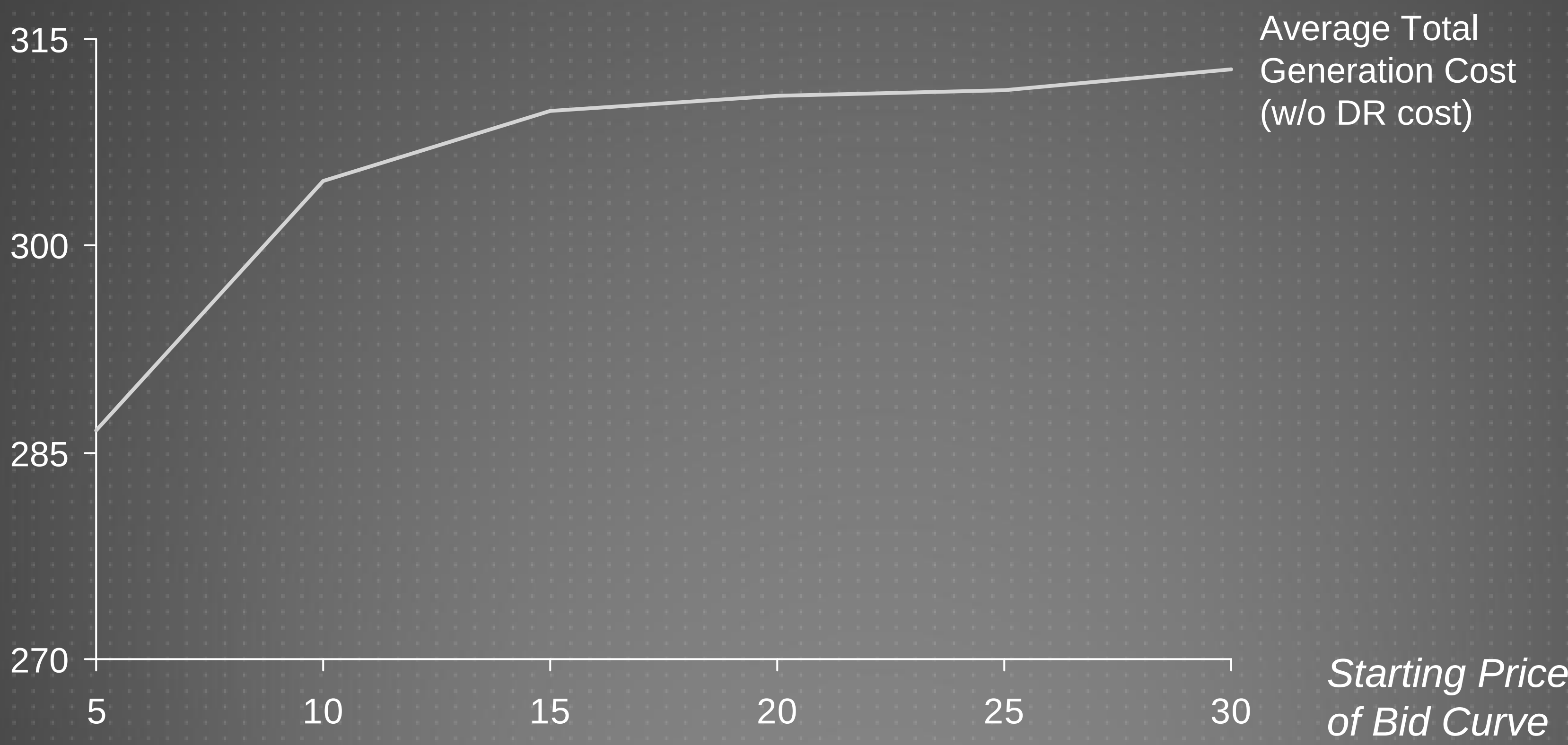
- DR dispatch leads to slightly higher fluctuations
- Tailing off is achieved later

RESULTING LOAD AFTER SHIFTING BY DR DISPATCH



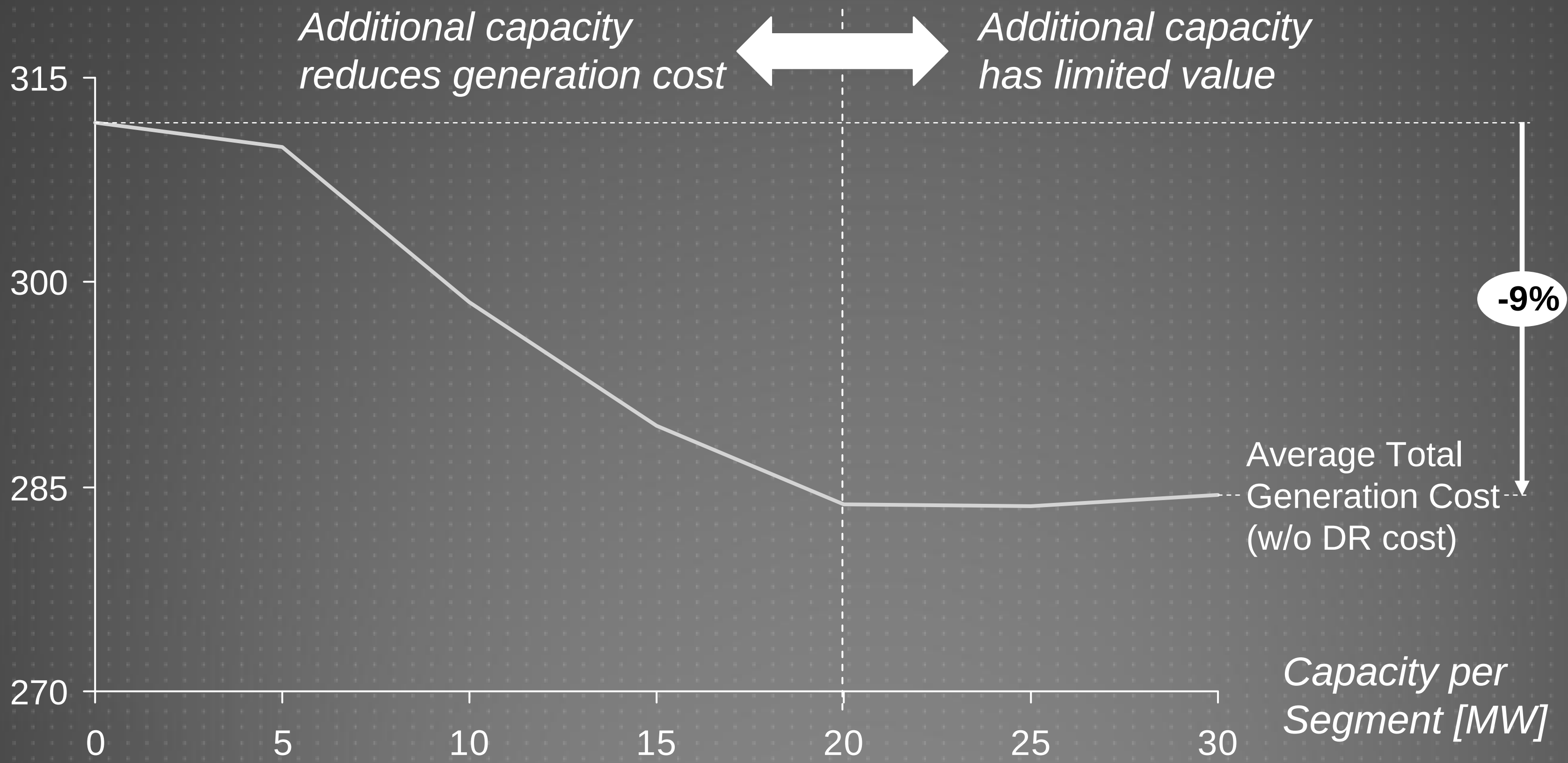
- DR helps to prevent start up of peakers in high load periods
- In this scenario a 50 % of load was assumed to be lost

COST IMPACT OF VARYING DR BID PRICES



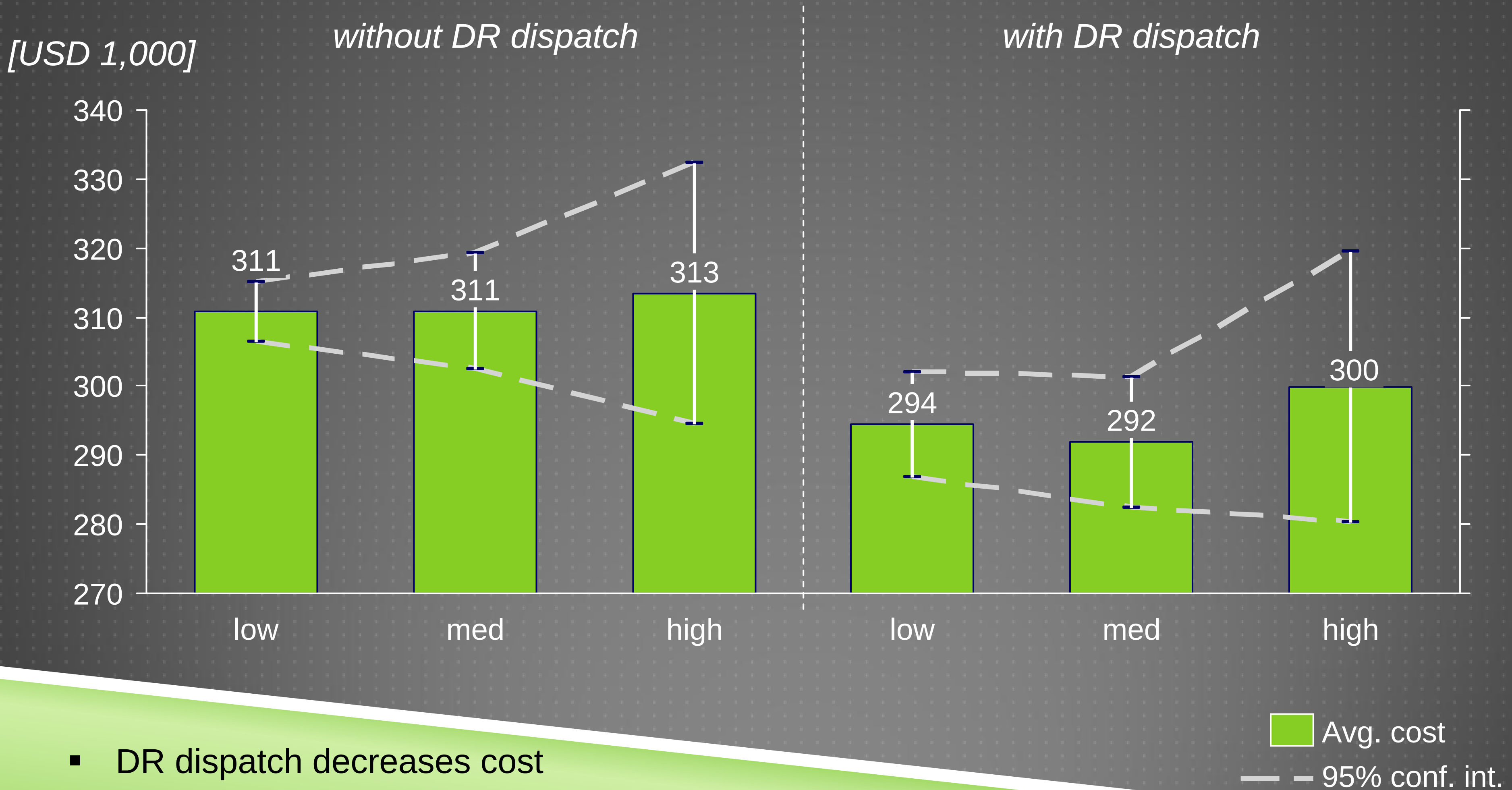
- Bid curves with 5 segments, 15MW each, USD 3 increment

COST IMPACT OF INCREASING DR CAPACITY



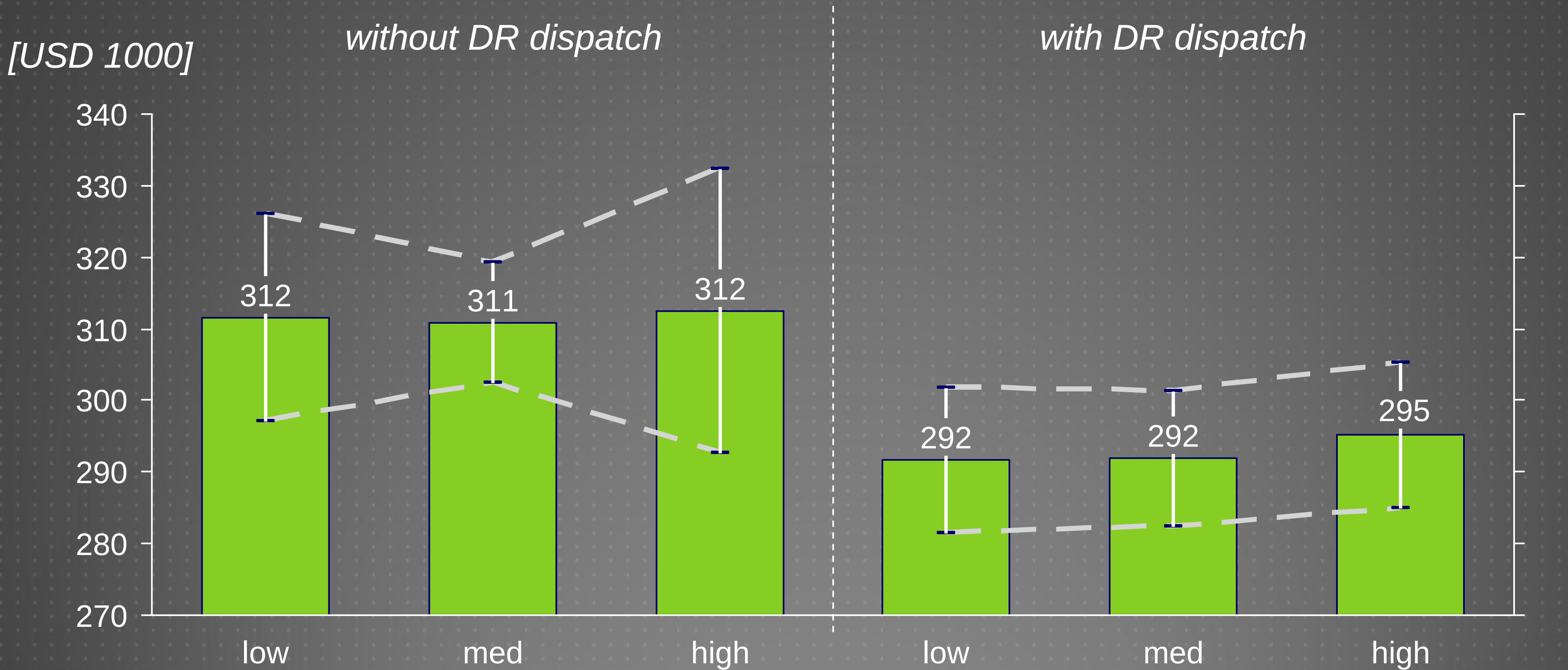
- Bid curves with 5 segments, starting at USD 8, USD 3 increment

IMPACT OF LOAD VARIANCE ON COST AND SAVINGS THROUGH DR



- DR dispatch decreases cost
- Variance is not considerably higher

IMPACT OF RENEWABLE VARIANCE ON COST AND SAVINGS THROUGH DR



- Renewable output and load correlate negatively
- DR reduces variance introduced by renewables

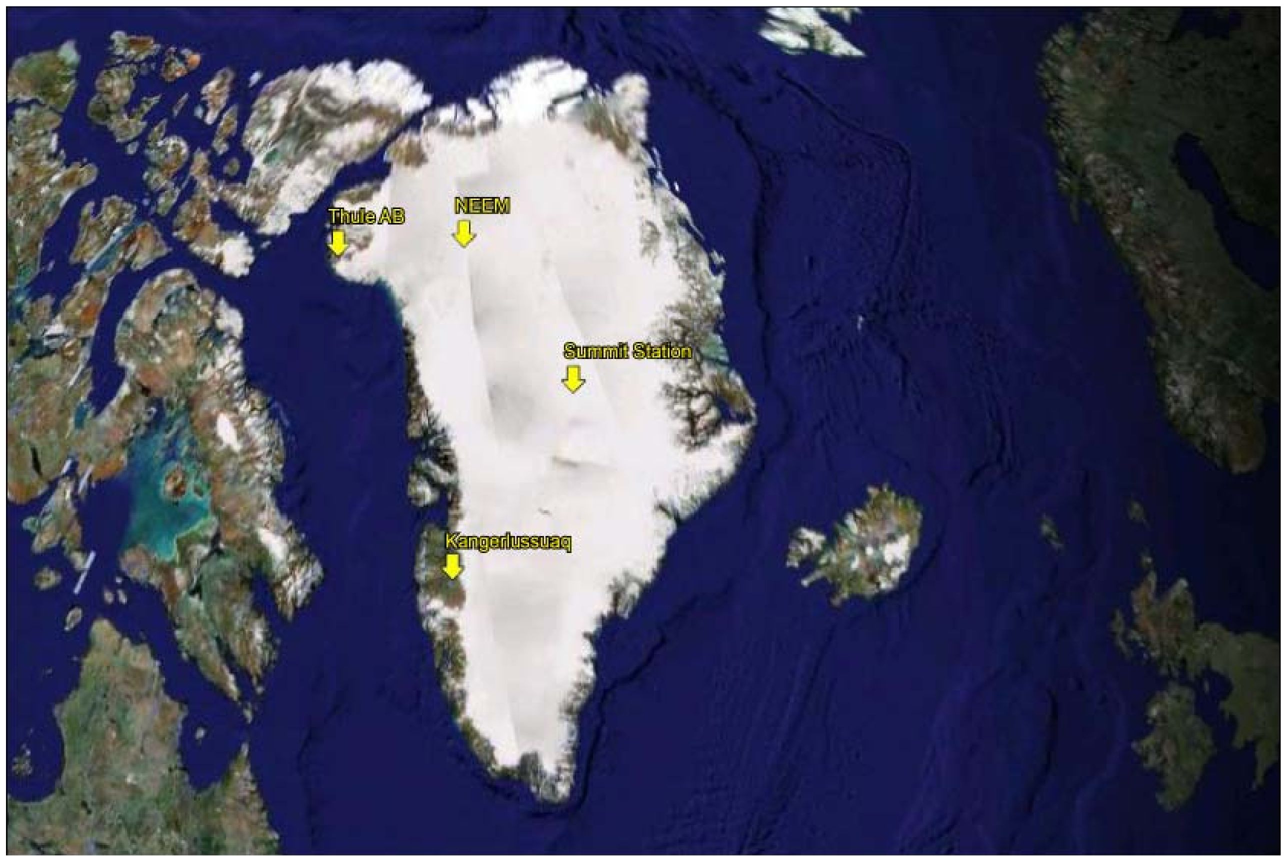
CONCLUSIONS

- Load shifting should not be neglected
- DSRs can serve to reduce variability in load and generation introduced by stochasticity
- Usefulness of DR capacity decreases from certain point on

WHAT'S AHEAD

- Improve scalability
  - More efficient ways to calculate gradients
  - Distributed computing
- Use Lagrangian combined with Benders to obtain optimality gaps
  - Provides a bound only over sampled scenarios
  - Debugging
- Energy storage
  - No major changes to the model and algorithms
- Incorporation of transmission constraints

CHICAGO, COLD?



ACKNOWLEDGEMENT

- Victor Zavala from Argonne National Lab
  - Providing data