Environmental Energy Technologies Division Lawrence Berkeley National Laboratory

Endogenous Assessment of the Capacity Value of Solar PV in Generation Investment Planning Studies

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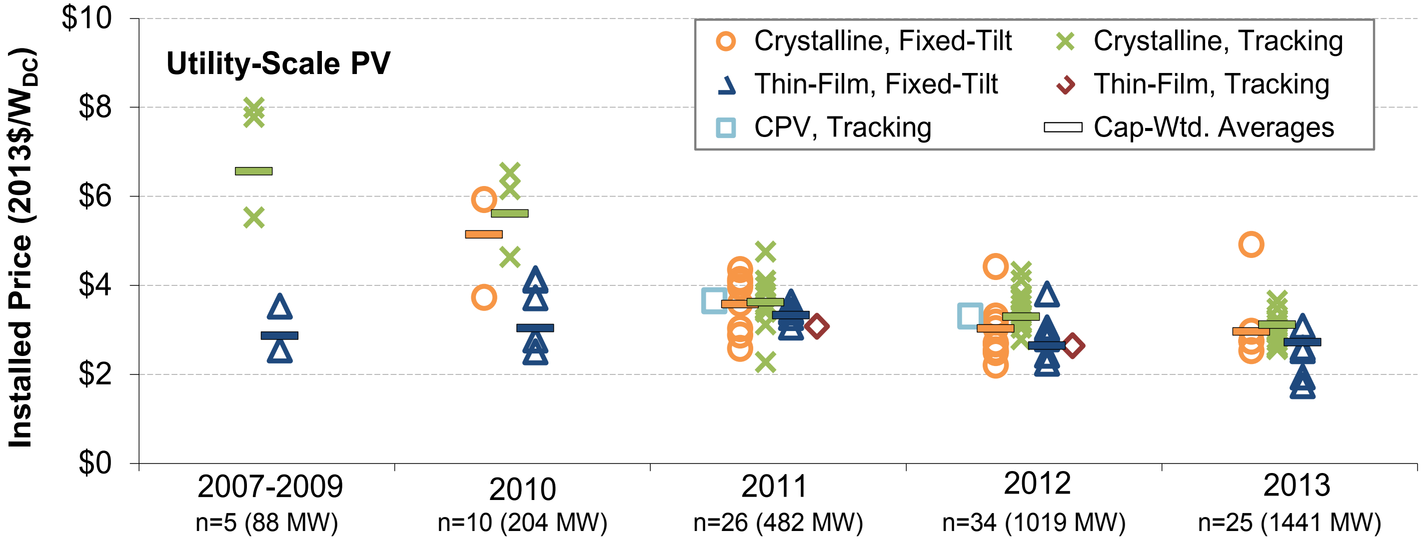
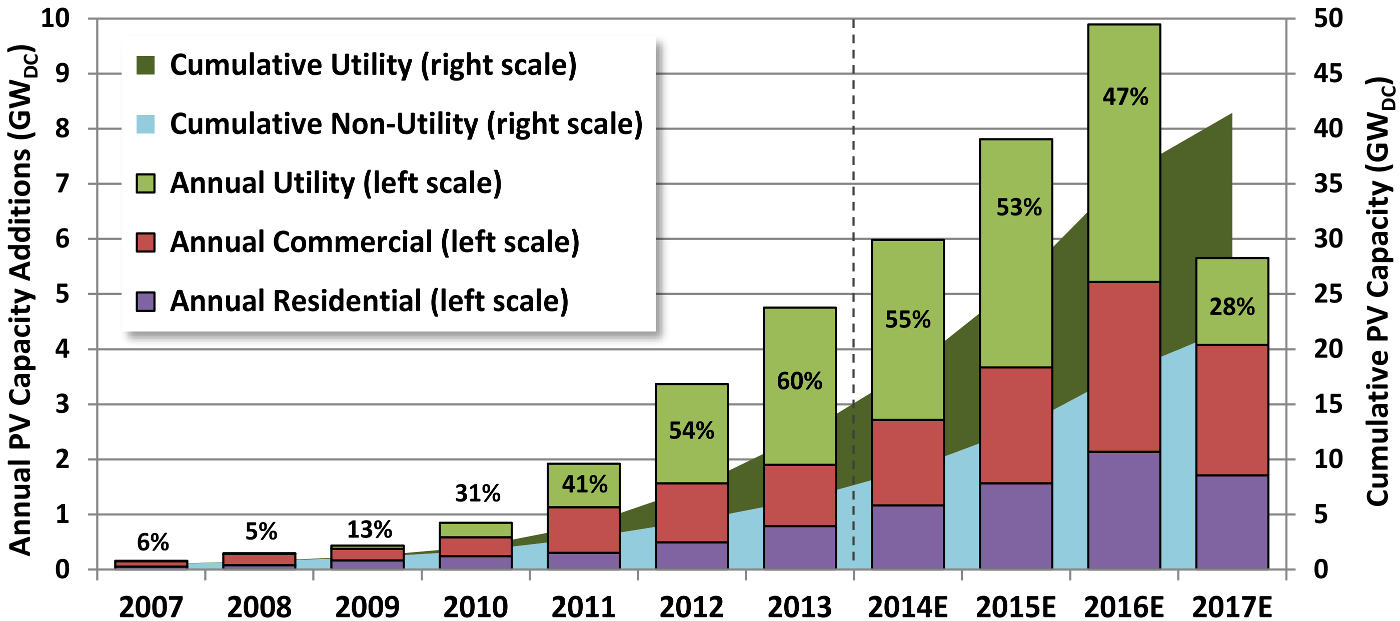
Overview

- Reductions in solar costs makes accurate representation of solar in capacity expansion models more important
- Capacity value of solar is one key driver of economic value in models
- Capacity value of solar depends on capacity expansion decisions, including solar penetration
- Comparison of capacity expansion decisions based on endogenous vs. exogenous capacity value of solar PV shows importance of endogenous approach with high solar PV penetration

Reductions in PV cost and increased deployment

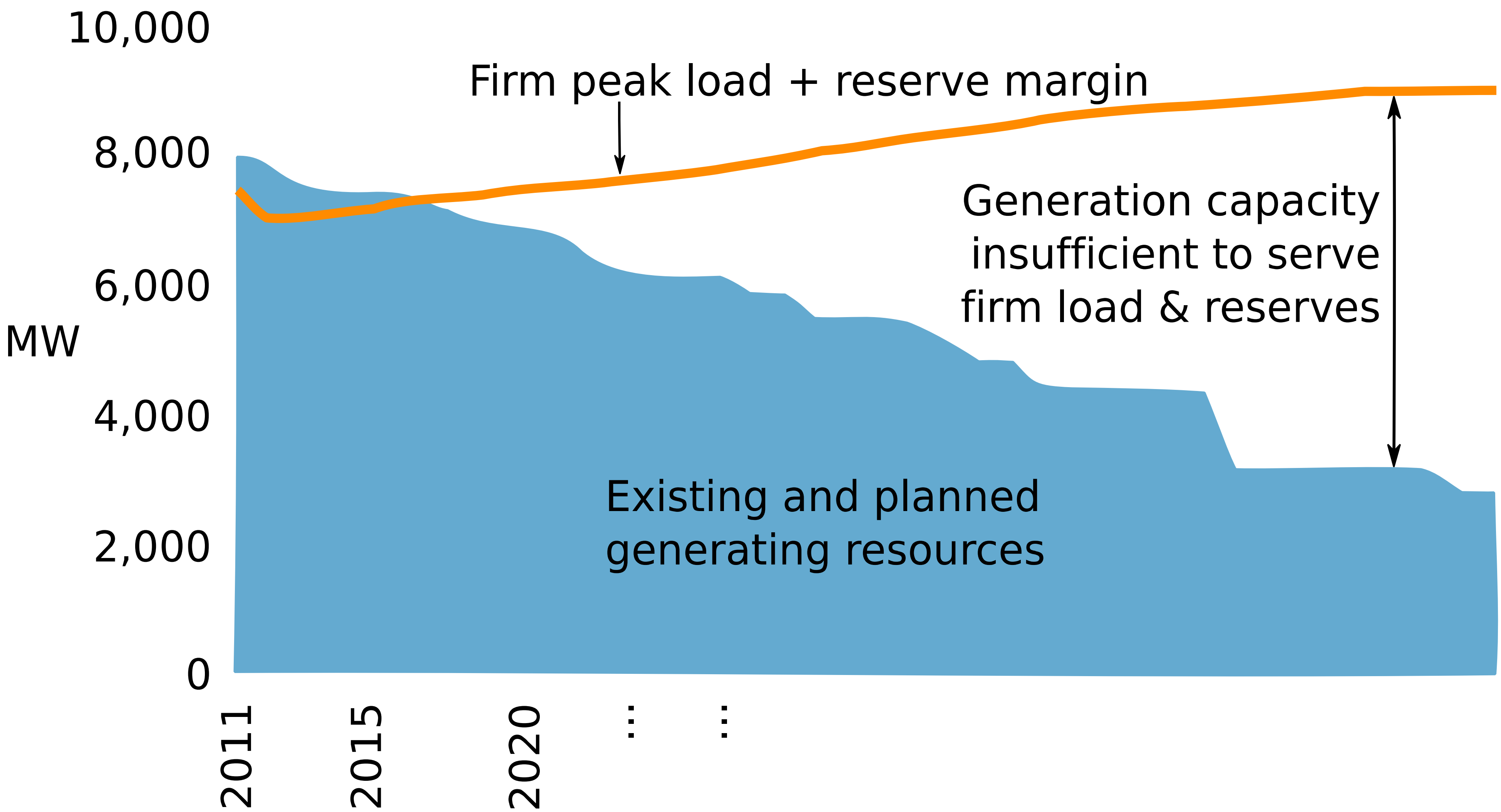


Source: Feldman et al 2014



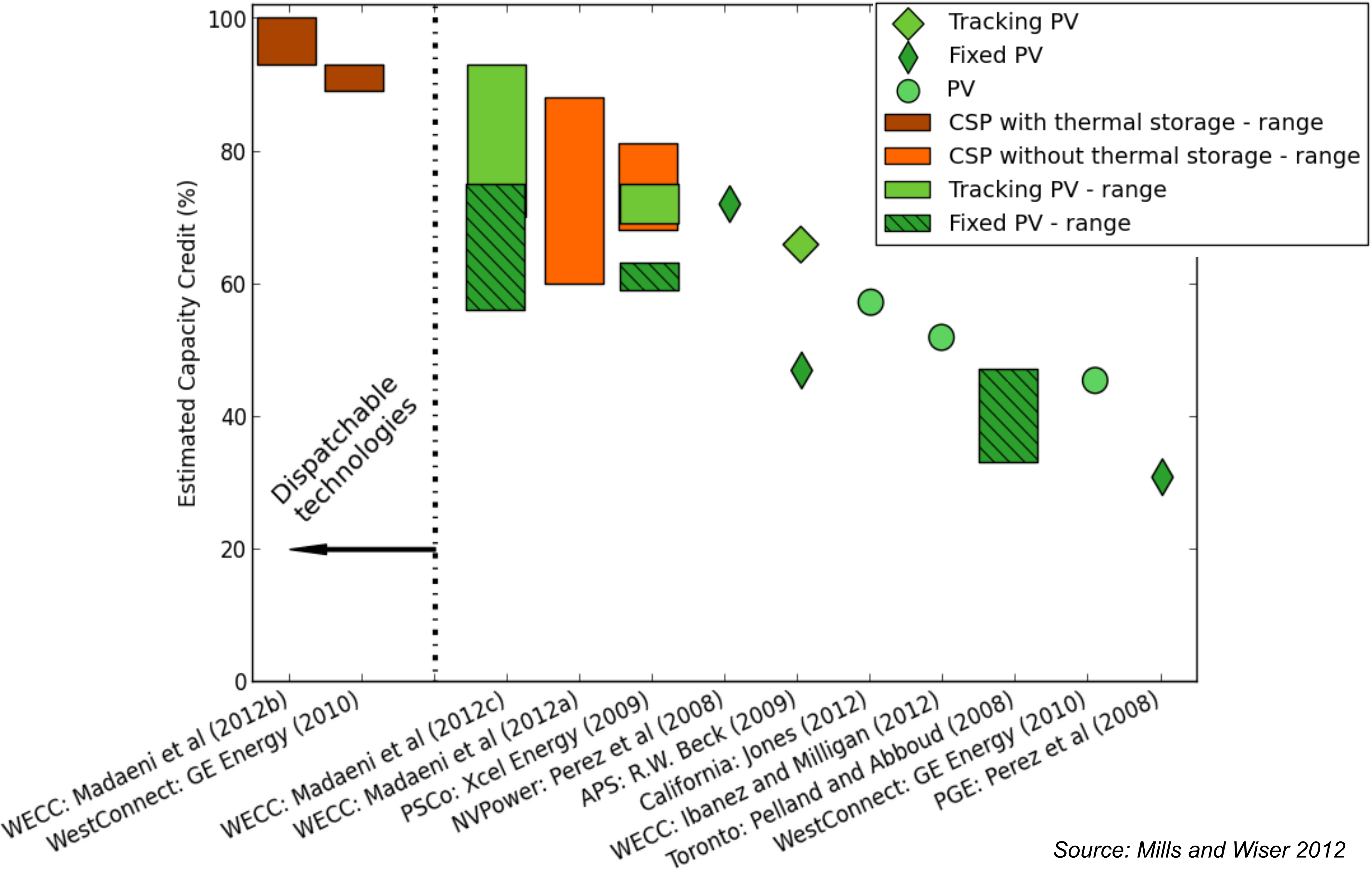
Source: GTM/SEIA 2014

Capacity value is one of key drivers of economic value of solar in capacity expansion models



Example from Public Service of Colorado Electric Resource Plan

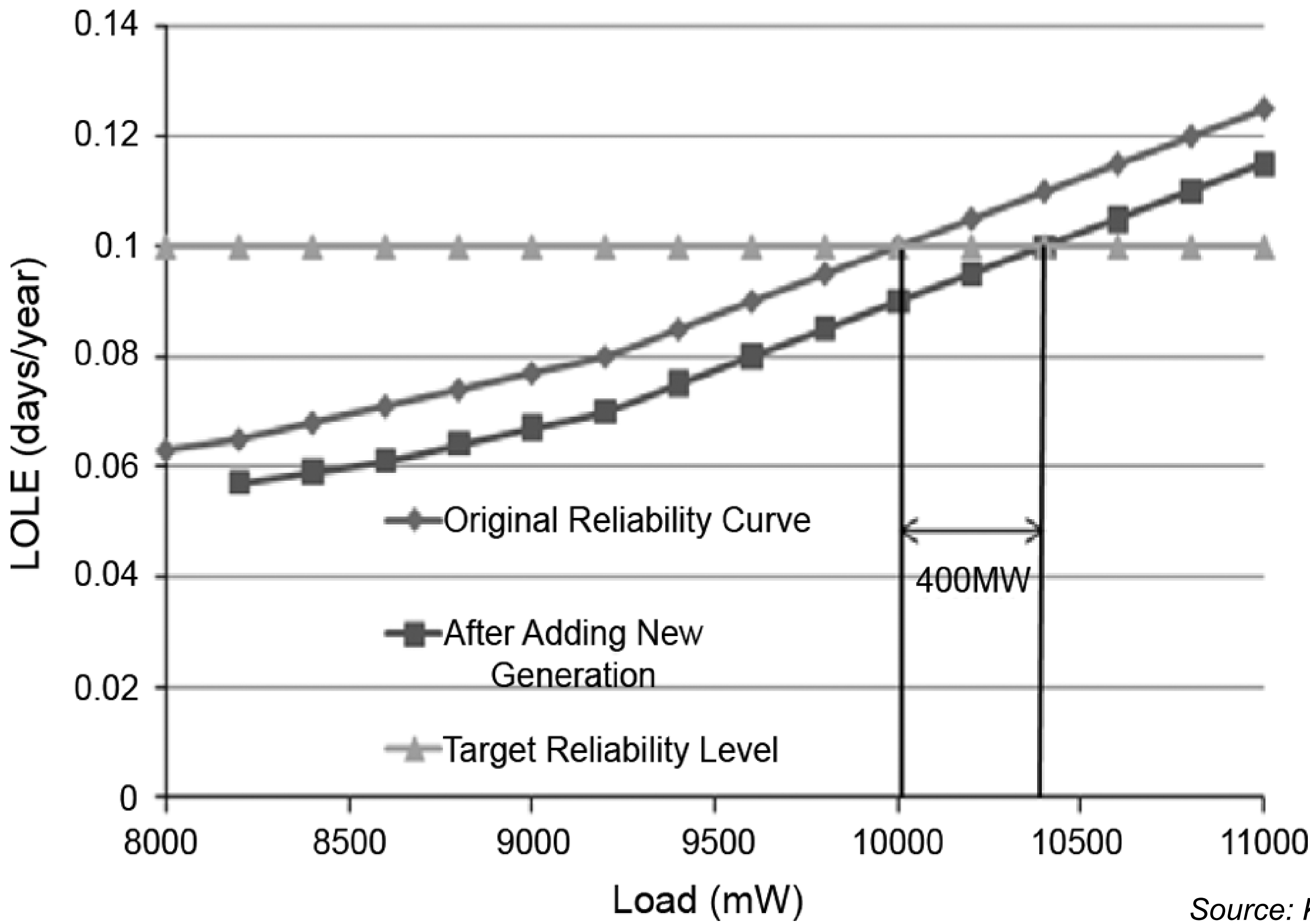
Estimates of capacity value of PV



Source: Mills and Wiser 2012

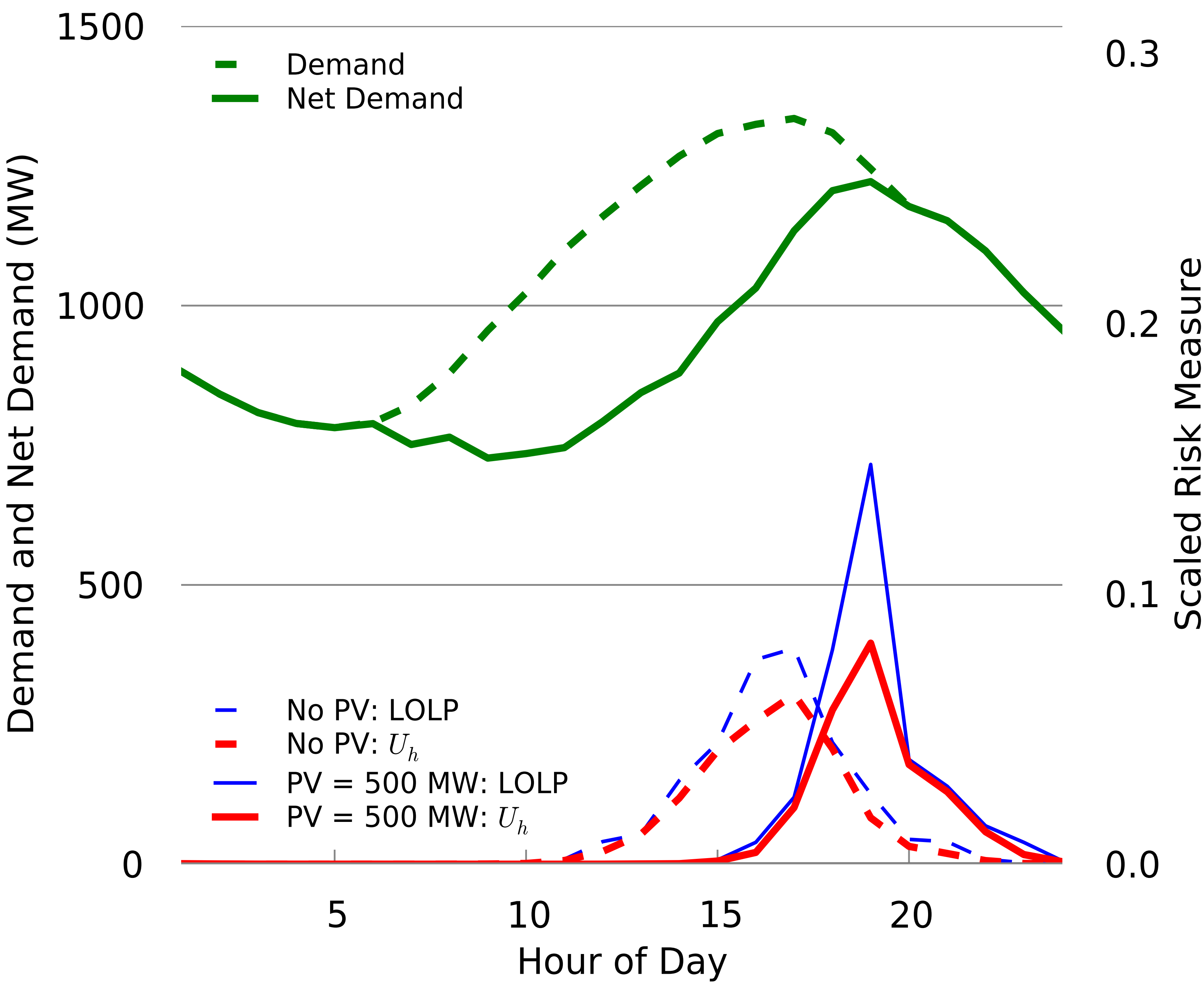
Effective load carrying capability

$$LOLE = \sum_{h \in H} P(D_h > G_h)$$



Source: Keane et al 2011

Capacity value depends on penetration level



Three capacity expansion models

Probabilistic

- Fully account for generator outages
- Risk-based generation capacity constraint
- Endogenous evaluation of PV capacity value

Deterministic

- No simulation of generator outages
- Planning reserve margin constraint
- Exogenous, constant PV capacity value

Virtual Demand Curtailment (VDC)

- No simulation of generator outages
- Allow virtual demand curtailment when net demand is high
- Constrain total amount of VDC
- Endogenous approximation of PV capacity value

Probabilistic model

Objective:
Minimize capital cost and fuel cost across all possible outage scenarios

$$min \sum_{g \in G} CC_g x_g + \sum_{s \in S(x)} P_s(X) \sum_{g \in G} MC_g y_{ghs}$$

Subject to:

Load balance:

$$\sum_{g \in G} y_{ghs} + u_{hs} = ND_h \quad \forall h \in H, s \in S(x)$$

Generation limits:

$$y_{ghs} \leq AV_{ghs}(X) CAP_g x_g \quad \forall g \in G, h \in H, s \in S(x)$$

Limit unserved energy:

$$\sum_{s \in S} P_s \sum_{h \in H} u_{hs} \leq EUE \sum_{h \in H} D_h$$

Binary investments:

$$x_g \in \{0, 1\} \quad \forall g \in G$$

Non-negativity:

$$y_{ghs}, u_{hs} \geq 0 \quad \forall g \in G, h \in H, s \in S(x)$$

Outage probabilities:

$$P(X)_s = \prod_{g \in G} (1 - AV_{gs}(X)) FOR_g + AV_{gs}(X)(1 - FOR_g)$$

Deterministic model

Objective:
Minimize capital cost and fuel cost

$$min \sum_{g \in G} CC_g x_g + \sum_{g \in G} MC_g y_{gh}$$

Subject to:

Load balance:

$$\sum_{g \in G} y_{gh} = ND_h \quad \forall h \in H$$

Generation limits:

$$y_{gh} \leq (1 - FOR_g) CAP_g x_g \quad \forall g \in G, h \in H$$

Reserve margin:

$$\sum_{g \in G} CAP_g x_g + CPV \geq (1 + RM) D_{h^*}$$

Binary investments:

$$x_g \in \{0, 1\} \quad \forall g \in G$$

Non-negativity:

$$y_{gh} \geq 0$$

Virtual demand curtailment (VDC) model

Objective:
Minimize capital cost and fuel cost

$$min \sum_{g\in G} CC_g x_g + \sum_{g\in G} MC_g y_{gh}$$

Subject to:

Load balance:

$$\sum_{g\in G} y_{gh} = ND_h \quad \forall h \in H$$

Generation limits:

$$y_{gh} \leq (1 - FOR_g)CAP_g x_g \quad \forall g \in G, h \in H$$

Modified reserves:

$$\sum_{g\in G} CAP_g x_g \geq (1 + RM)(ND_h - v_h) \quad \forall h \in H$$

VDC limit:

$$\sum_{h\in H} v_h \leq \delta \sum_{h\in H} D_h$$

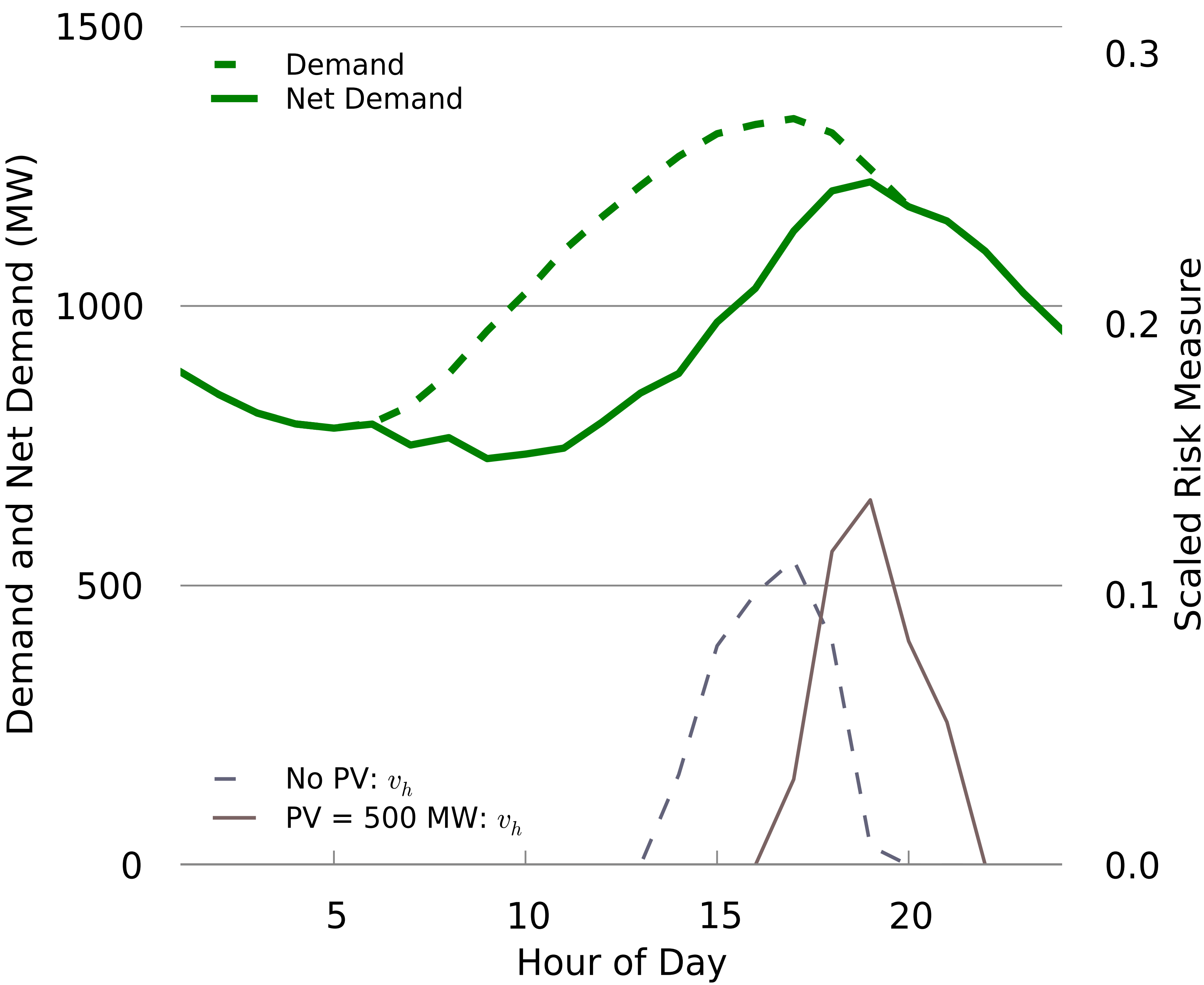
Binary investments:

$$x_g \in \{0, 1\} \quad \forall g \in G$$

Non-negativity:

$$y_{gh} \geq 0$$

Virtual demand curtailment constraint behaves similar to probabilistic risk-based measures



Test case

Analytical approach

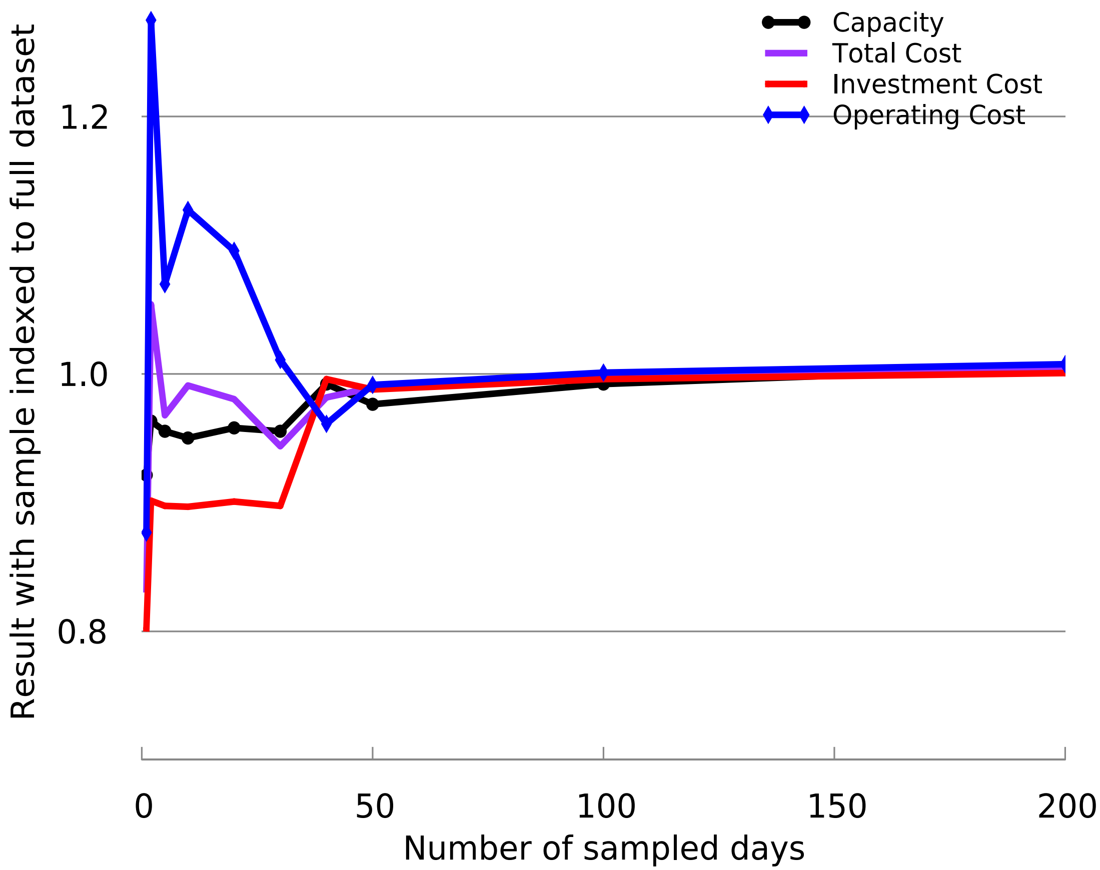
- Find optimal generation investments and dispatch given assumed PV (or wind) penetration
- Compare decisions across models with same assumptions

Data sources

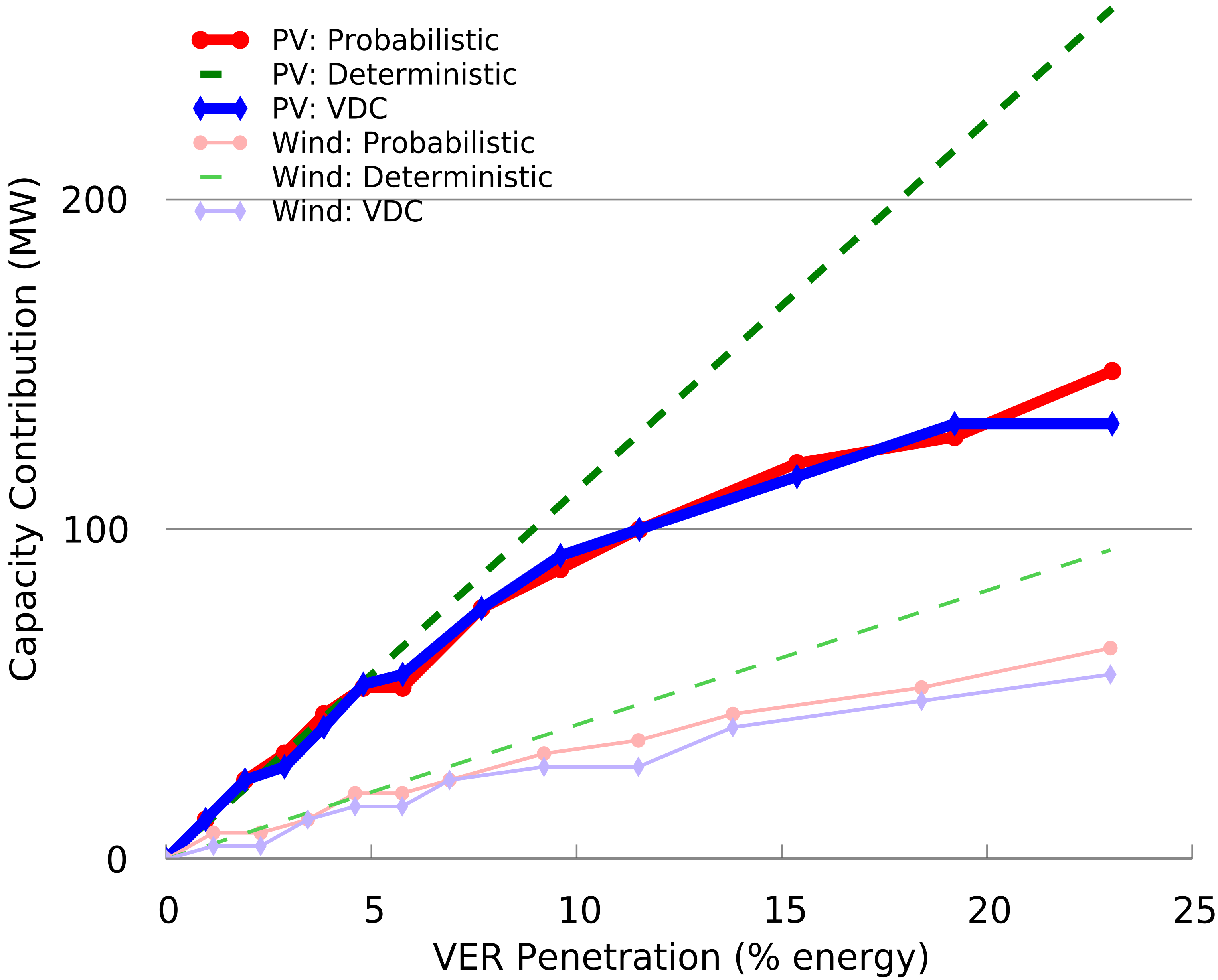
- Generators:
  - 32 generators from IEEE Reliability Test System
  - Updated costs from EIA
- Load:
  - Hourly load between 2003-2009 for utility in SW US
- Solar PV:
  - Hourly satellite derived insolation (NSRDB) between 2003-2009 converted to mix of fixed and tracking PV with PVWatts
- Wind:
  - Hourly wind between 2004-2006 from sites in NREL's Western Wind dataset

Sampling can reduce computational burden

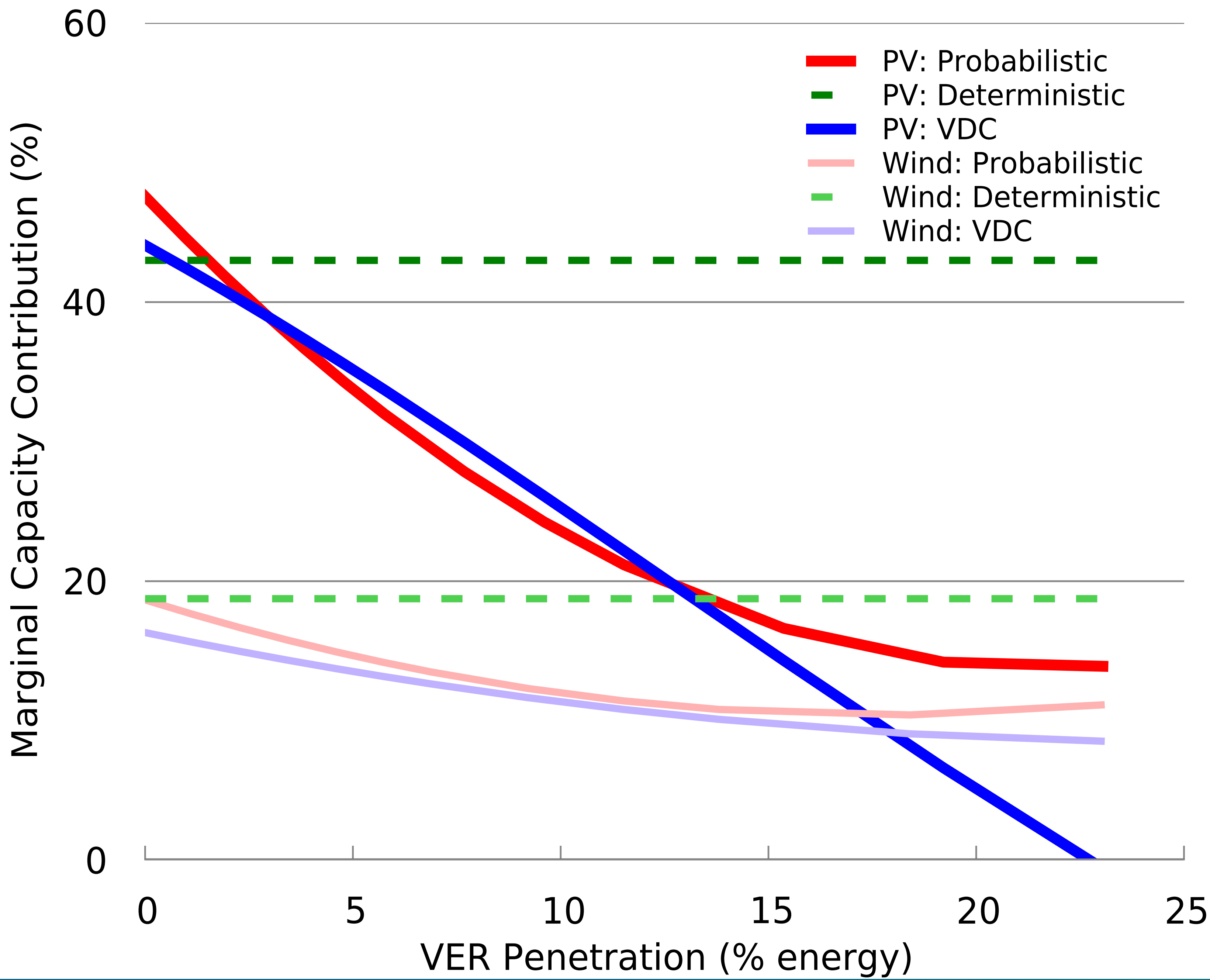
- Computational burden depends on length of time series
- We use a moment-matching technique to find subsets of days that are similar to full seven years of data
- We use the probabilistic model to compare the optimal investments from the subset of days to the investments from the full seven years
- Investment decisions and costs are within +/- 2.5% after 50 sampled days



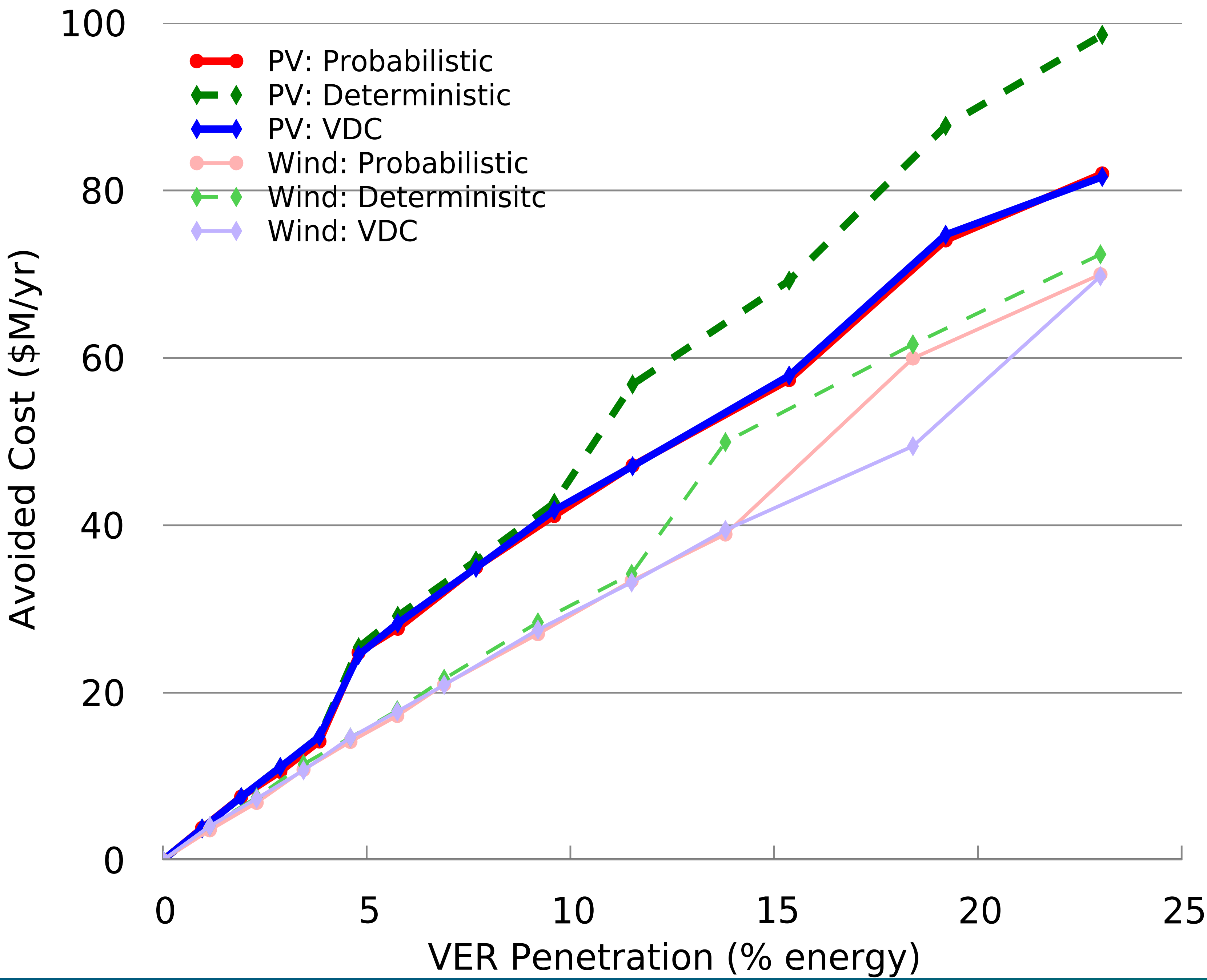
Capacity contribution of solar is non-linear with increasing penetration



Marginal capacity contribution declines with increasing penetration



Deterministic model overstates avoided cost for higher penetration levels



Conclusions

- Capacity contribution of solar (and wind) can be represented endogenously in capacity expansion models
- Deterministic models with constant capacity value of solar are accurate for low (<5%) penetration levels
- At high penetration, deterministic model does not reflect change in capacity contribution observed in probabilistic model, thereby becoming less accurate with higher penetration
- The proposed modification to the deterministic model (the VDC model) maintains accuracy without significantly increasing the computational burden
- Sampling can also reduce computation needs: 50 days were required to maintain accuracy to within +/-2.5%

For additional information…

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