



House of
Energy Markets
& Finance



Integrated day-ahead and intraday self-schedule bidding for energy storages using approximate dynamic programming

Benedikt Finnah, Jochen Gönsch, Florian Ziel*
University of Duisburg-Essen (UDE)

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Open-Minded



Agenda

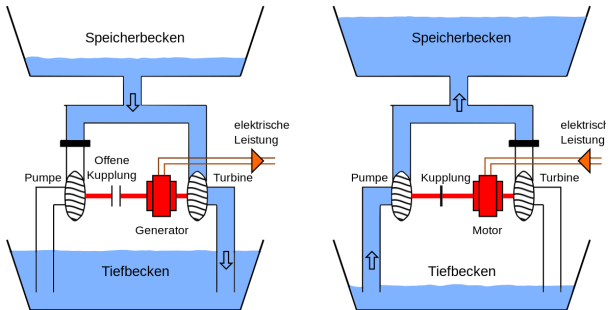
- i) Storage and market setting
- ii) Dynamic program
- iii) Numerical study
- iv) Summary

Energy storage

Consider storage with following properties:

- ▶ Capacity R_{\max}
- ▶ Minimum and maximum power x_{\min}^{pump} , x_{\max}^{pump} , $x_{\min}^{\text{turbine}}$, $x_{\max}^{\text{turbine}}$
- ▶ Efficiencies η^{pump} , η^{turbine}
- ▶ Start-up cost c_{su}^{pump} , c_{su}^{turbine}
- ▶ Ramping time Δt^{ramp}

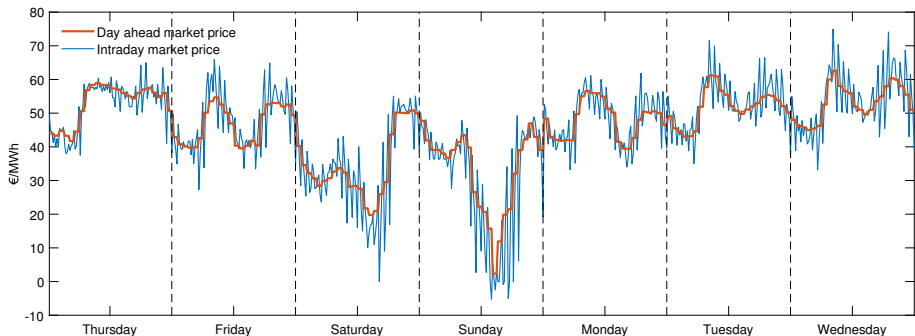
e.g. hydro pump storage:



Considered German electricity markets

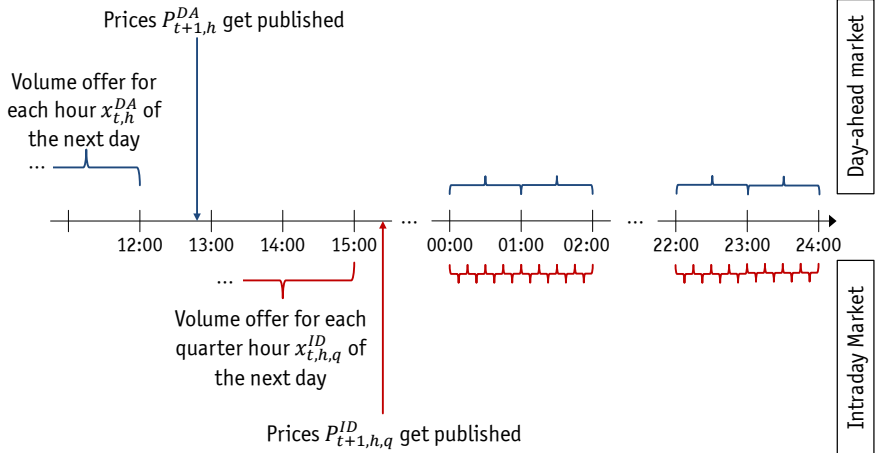
DA: PCR Day-Ahead Auction (daily at 12:00, hourly products)

ID: EPEX Intraday Auction (daily at 15:00, quarterhourly products)



- ▶ Ignore all other markets (OTC, Intraday continuous, EXAA, derivative markets, etc.), and complex/smart/block bids

Information Flow



- ▶ time index (day, hour, quarterhourly) $\equiv (t, h, q)$

Dynamic Programming

Ingridients

- ▶ Exogenous information (price processes)
- ▶ State Variable
- ▶ Action Variable
- ▶ Contribution Function
- ▶ Transition function
- ⇒ Policy

Exogenous Information: Price Processes

DA day-ahead auction price process:

$$P_{t+1,h}^{DA} = \beta_{0,h}^{DA} + \sum_{j=1}^7 \beta_{j,h}^{DA} DoW_{t+1}^j + \sum_{j=1}^7 \sum_{k=0}^{23} \beta_{j,k,h}^{DA} P_{t+1-j,k}^{DA} + \epsilon_{t+1,h}^{DA} \forall h \in \{0, \dots, 23\}$$

$$\epsilon_{t+1}^{DA} = \left(\epsilon_{t+1,0}^{DA}, \dots, \epsilon_{t+1,23}^{DA} \right) \sim N \left(0, \Sigma^{DA} \right),$$

ID intraday opening auction price process:

$$P_{t+1,h,q}^{ID} = \beta_{0,h,q}^{ID} + \sum_{j=1}^7 \beta_{j,h,q}^{ID} DoW_{t+1}^j + \sum_{j=0}^7 \sum_{k=0}^{23} \beta_{j,k,h,q}^{ID} P_{t+1-j,k}^{DA}$$

$$+ \sum_{j=1}^7 \sum_{k=0}^{23} \sum_{m=0}^3 \beta_{j,k,m,h,q}^{ID} P_{t-j,k,m}^{ID} + \epsilon_{t+1,h,q}^{ID} \forall h \in \{0, \dots, 23\}, q \in \{0, \dots, 3\}$$

$$\epsilon_t^{ID} = \left(\epsilon_{t,0,0}^{ID}, \dots, \epsilon_{t,23,3}^{ID} \right) \sim N \left(0, \Sigma^{ID} \right)$$

- ▶ High-dimensional regression model, trained by CV-lasso
- ▶ Depends on past prices (also cross-products) and weekday

State Variable

- ▶ State S_t^{DA} just before day-ahead market decision x_t^{DA} :

$$\begin{aligned} S_t^{DA} &= (R_t^{start}, x_t^{start}, P_{t-6}^{DA}, \dots, P_t^{DA}, P_{t-6}^{ID}, \dots, P_t^{ID}) \\ &= (R_t^{start}, x_t^{start}, P_t^{history}) \end{aligned} \quad (1)$$

- ▶ State S_t^{ID} just before intraday market decision x_t^{ID} and day-ahead market prices P_{t+1}^{DA} :

$$S_t^{ID} = (S_t^{DA}, x_t^{DA}, P_{t+1}^{DA}) \quad (2)$$

Action variable for DA and ID

► DA action:

$x_t^{DA} = (x_{t,0}^{DA}, \dots, x_{t,23}^{DA})$ s.t. for all $h \in \{0, 1, \dots, 23\}$:

i) (no physical short-selling / speculation) $x_{t,h}^{DA} \in [-x_{max}^{turbine}, x_{max}^{pump}]$

Action variable for DA and ID

► DA action:

$x_t^{DA} = (x_{t,0}^{DA}, \dots, x_{t,23}^{DA})$ s.t. for all $h \in \{0, 1, \dots, 23\}$:

i) (no physical short-selling / speculation) $x_{t,h}^{DA} \in [-x_{max}^{turbine}, x_{max}^{pump}]$

► ID action:

$x_t^{ID} = (x_{t,0,0}^{ID}, \dots, x_{t,23,3}^{ID})$ s.t. for all $q \in \{0, 1, 2, 3\}$ and $h \in \{0, \dots, 23\}$:

ii) (traded vol. = stored - generated energy) $x_{t,h}^{DA} + x_{t,h,q}^{ID} = x_{t,h,q}^{pump} - x_{t,h,q}^{turbine}$

iii) (binary decisions) $y_{t,h,q}^{pump} = 1\{x_{t,h,q} > 0\}$, $y_{t,h,q}^{turbine} = 1\{x_{t,h,q} < 0\} \in \{0, 1\}$

iv) (feasible region for pumping power) $x_{min}^{pump} y_{t,h,q}^{pump} \leq x_{t,h,q}^{pump} \leq x_{max}^{pump} y_{t,h,q}^{pump}$

v) (feasible region for power generation)

$x_{min}^{turbine} y_{t,h,q}^{turbine} \leq x_{t,h,q}^{turbine} \leq x_{max}^{turbine} y_{t,h,q}^{turbine}$

vi) (either pump or generate) $y_{t,h,q}^{pump} + y_{t,h,q}^{turbine} \leq 1$

vii) (storage level constraint) $R_{t,h,q} \in [0, R_{max}]$

viii) (new storage level) $R_{t,h,q} =$

$R_{t,h,q-1} + \eta^{pump} \left(\Delta t^{ID} x_{t,h,q}^{pump} - \frac{\Delta t^{ramp}}{2} \Delta x_{t,h,q}^{pump,up} + \frac{\Delta t^{ramp}}{2} \Delta x_{t,h,q}^{pump,down} \right) -$

$\frac{1}{\eta^{turbine}} \left(\Delta t^{ID} x_{t,h,q}^{turbine} - \frac{\Delta t^{ramp}}{2} \Delta x_{t,h,q}^{turbine,up} + \frac{\Delta t^{ramp}}{2} \Delta x_{t,h,q}^{turbine,down} \right)$

Action variable for DA and ID (continued)

ix) (ramping pump to get $x_{t,h,q}^{pump}$)

$$\Delta x_{t,h,q}^{pump,up} - \Delta x_{t,h,q}^{pump,down} = x_{t,h,q}^{pump} - x_{t,h,q-1}^{pump}$$

x) (ramping turb. to get $x_{t,h,q}^{turbine}$)

$$\Delta x_{t,h,q}^{turbine,up} - \Delta x_{t,h,q}^{turbine,down} = x_{t,h,q}^{turbine} - x_{t,h,q-1}^{turbine}$$

xi) (binary start-up decisions)

$$z_{t,h,q}^{pump} = 1\{y_{t,h,q}^{pump} - y_{t,h,q-1}^{pump} > 0\}, z_{t,h,q}^{turbine} = 1\{y_{t,h,q}^{turbine} - y_{t,h,q-1}^{turbine} > 0\} \in \{0, 1\}$$

xii) (pump start-up constraint) $y_{t,h,q}^{pump} - y_{t,h,q-1}^{pump} \leq z_{t,h,q}^{pump}$

xiii) (generation start-up constraint) $y_{t,h,q}^{turbine} - y_{t,h,q-1}^{turbine} \leq z_{t,h,q}^{turbine}$

xiv) (positivity I) $x_{t,h,q}^{pump}, x_{t,h,q}^{turbine}, z_{t,h,q}^{pump}, z_{t,h,q}^{turbine} \geq 0$

xv) (positivity II) $\Delta x_{t,h,q}^{pump,up}, \Delta x_{t,h,q}^{pump,down}, \Delta x_{t,h,q}^{turbine,up}, \Delta x_{t,h,q}^{turbine,down} \geq 0$

with $(\cdot)_{t,h,4} = (\cdot)_{t,h+1,0}$, $R_{t,0,-1} = R_t^{start}$, $x_{t,0,-1}^{pump} = (x_t^{start})^+$ and

$x_{t,0,-1}^{turbine} = (x_t^{start})^-$, $y_{t,0,-1}^{pump} = 1\{x_t^{start} > 0\}$ and $y_{t,0,-1}^{turbine} = 1\{x_t^{start} < 0\}$.

Contribution function

Day-ahead market revenue

$$\blacktriangleright C_t^{DA} (S_t^{DA}, x_t^{DA}, W_{t+1}^{DA}) = - \sum_{h=0}^{23} \underbrace{\Delta t^{DA} P_{t+1,h} x_{t,h}^{DA}}_{\text{DA buy/sell}}$$

Intraday market revenue

$$\begin{aligned} \blacktriangleright C_t^{ID} (S_t^{ID}, x_t^{ID}, W_{t+1}^{ID}) &= \sum_{h=0}^{23} \sum_{q=0}^3 - \underbrace{\Delta t^{ID} P_{t+1,h,q}^{ID} x_{t,h,q}^{ID}}_{\text{ID buy/sell}} - \underbrace{\Delta t^{ID} c^{gf} x_{t,h,q}^{pump}}_{\text{grid fees}} \\ &+ \underbrace{Q_{t+1,h,q}^{over} (\Delta x_{t,h,q}^{pump,up} + \Delta x_{t,h,q}^{turbine,up}) - Q_{t+1,h,q}^{under} (\Delta x_{t,h,q}^{pump,down} + \Delta x_{t,h,q}^{turbine,down})}_{\text{balancing costs due to over/under-supply during ramping}} \\ &- \underbrace{c^{pump} z_{t,h,q}^{pump} - c^{turbine} z_{t,h,q}^{turbine}}_{\text{start-up costs}} \end{aligned}$$

► Assumption balancing penalty linear in $P_{t+1,h,q}^{ID}$:

$$Q_{t+1,h,q}^{over} = \frac{\Delta t^{ramp}}{2} \left(Q_{intercept}^{over} + Q_{slope}^{over} P_{t+1,h,q}^{ID} \right)$$

$$Q_{t+1,h,q}^{under} = \frac{\Delta t^{ramp}}{2} \left(Q_{intercept}^{under} + Q_{slope}^{under} P_{t+1,h,q}^{ID} \right)$$

Transition function

- From Day-ahead auction to Intraday auction ($DA_t \rightarrow ID_t$):

$$S_t^{ID} = S^{M,DA} (S_t^{DA}, x_t^{DA}, W_{t+1}^{DA}) = (S_t^{DA}, x_t^{DA}, P_{t+1}^{DA}) \quad (3)$$

- From Intraday auction to Day-ahead auction ($ID_t \rightarrow DA_{t+1}$):

$$\begin{aligned} S_{t+1}^{DA} &= S^{M,ID} (S_t^{ID}, x_t^{ID}, W_{t+1}^{ID}) = (R_{t+1}^{start}, x_{t+1}^{start}, P_{t+1}^{history}) \\ &= (R_{t,23,3}, x_{t,23}^{DA} + x_{t,23,3}^{ID}, P_{t-5}^{DA}, \dots, P_{t+1}^{DA}, P_{t-5}^{ID}, \dots, P_{t+1}^{ID}) \end{aligned} \quad (4)$$

where $R_{t,23,3}$ follows the storage level equation [viii](#)).

Problem statement and value function

- Policy π maps states S_t^{DA} and S_t^{ID} to decision $X_t^{DA,\pi}(S_t^{DA})$ and $X_t^{ID,\pi}(S_t^{ID})$

$$\max_{\pi} \mathbb{E} \left[\underbrace{\sum_{t=0}^{T-1} C_t^{DA} \left(S_t^{DA}, X_t^{DA,\pi}(S_t^{DA}), W_{t+1}^{DA} \right)}_{\text{DA contribution}} + \underbrace{C_t^{ID} \left(S_t^{ID}, X_t^{ID,\pi}(S_t^{ID}), W_{t+1}^{ID} \right)}_{\text{ID contribution}} \middle| S_0^{DA} \right]$$

- Alternative formulation using the recursive Bellman equations:

$$V_t^{DA} (S_t^{DA}) = \max_{x_t^{DA}} \mathbb{E} [C_t^{DA} (S_t^{DA}, x_t^{DA}, W_{t+1}^{DA}) + V_t^{ID} (S_t^{ID}) | S_t^{DA}] \quad (5)$$

$$V_t^{ID} (S_t^{ID}) = \max_{x_t^{ID}} \mathbb{E} [C_t^{ID} (S_t^{ID}, x_t^{ID}, W_{t+1}^{ID}) + V_{t+1}^{DA} (S_t^{DA}) | S_t^{ID}] \quad (6)$$

with the boundary condition $V_T^{DA} (S_T^{DA}) = 0$

Policy model

- ▶ Replace alternating decision stages by expectation model.
- ▶ Policy model:

$$S_t^{policy} = S_t^{DA} = \left(R_t^{start}, x_t^{start}, P_t^{history} \right) \quad (\text{state variable})$$

$$x_t^{policy} = \left(x_t^{DA}, x_t^{ID} \right) \quad (\text{action variable})$$

$$W_{t+1}^{policy} = \left(W_{t+1}^{DA}, W_{t+1}^{ID} | W_{t+1}^{DA} \right) \quad (\text{exogenous information})$$

$$\begin{aligned} S_{t+1}^{policy} &= S^{M,policy} \left(S_t^{policy}, x_t^{policy}, W_{t+1}^{policy} \right) \\ &= S^{M,ID} \left(S^{M,DA} \left(S_t^{DA}, x_t^{DA}, W_{t+1}^{DA} \right), x_t^{ID}, W_{t+1}^{ID} \right) \end{aligned} \quad (\text{new state variable})$$

- ▶ The value function is:

$$V_t^{policy} \left(S_t^{policy} \right) = \max_{x_t^{policy}} \left\{ C_t^{policy} \left(S_t^{policy}, x_t^{policy} \right) + \mathbb{E} \left[V_{t+1}^{policy} \left(S_{t+1}^{policy} \right) | S_t^{policy} \right] \right\}$$

$$\text{s.t. } V_T^{policy} \left(S_T^{policy} \right) = 0 \text{ and } i) - xv),$$

Approximation of value function

- ▶ The value function V_t^{policy} is approximated by \bar{V}_t^{policy} :

Considered different techniques for approximating \bar{V}_t^{policy} :

- Backwards approximate dynamic programming (BADP)
- Weighted backwards approximate dynamic programming (w-BADP)
- Lasso based Least Squares Monte Carlo (LSMC-lasso)
- Approximate dual dynamic programming algorithm (ADDP)

And other benchmarks:

- ◆ 7 days-horizon expectation model (EM-7)
- ◆ Perfect foresight

Backwards approximate dynamic programming (BADP)

Algorithm 1 BADP

- 1: sample scenario lattice $P_{t,n}^{history}, t \in \{1, \dots, T\}, n \in \{1, \dots, N\}$
- 2: initialize lookup table $\bar{V}_T^{pol} = 0$
- 3: **for** $t = T - 1$ to 0 **do**
- 4: **for** $n = 1$ to N **do**
- 5: compute expected price history $\bar{P}_{t,t+1,n}^{history} := \mathbb{E} \left[P_{t+1}^{history} | P_{t,n}^{history} \right]$
- 6: $(\bar{\rho}_1, \dots, \bar{\rho}_N) := \arg \min_{\rho_1, \dots, \rho_N} \left\| \bar{P}_{t,t+1,n}^{history} - \sum_{k=1}^N \rho_k P_{t+1,k}^{history} \right\|_2$
- 7: **for** $R_t^{start} = 0$ to R_{max} **do**
- 8: **for** $x_t^{start} = -x_{max}^{turbine}$ to x_{max}^{pump} **do**
- 9: $\bar{V}_t^{pol} \left(S_{t,n}^{pol} \right) := \max_{x_t^{pol}} \left\{ C_t^{pol} \left(S_t^{pol}, x_t^{pol} \right) + \sum_{k=1}^N \bar{\rho}_k \bar{V}_{t+1}^{pol} \left(S_{t+1}^{pol} | P_{t+1,k}^{hist} \right) \right\}$
- 10: **end for**
- 11: **end for**
- 12: **end for**
- 13: **end for**

Numerical study

► Parameter setting (realistic pumped hydro storage):

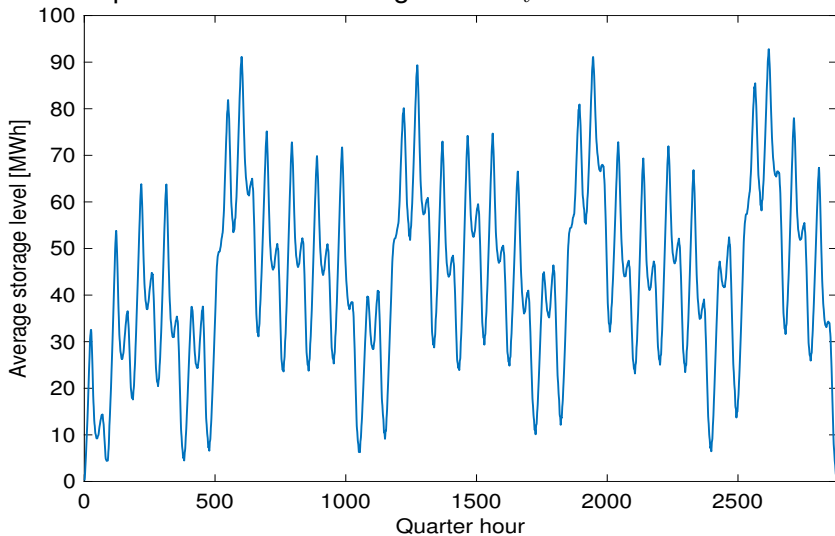
- Capacity: $R_{max} = 100$ MWh
- pump and turbine power range:
 $[x_{min}^{pump}, x_{max}^{pump}] = [x_{min}^{turbine}, x_{max}^{turbine}] = [5, 10]$ MW
- efficiencies: $\eta^{pump} = \eta^{turbine} = 0.9$
- start-up costs: $c^{pump} = c^{turbine} = 15$ EUR
- ramping times: $\Delta t^{ramp} = 2$ min
- balancing cost parameters:
 $Q_{intercept}^{over} = -3$ EUR/MWh, $Q_{slope}^{over} = 1/1.2$,
 $Q_{intercept}^{under} = 3$ EUR/MWh, $Q_{slope}^{under} = 1.2$
 (deviation from commitments is financially unattractive)
- optimization horizon: $T = 30$

► Backtesting setting (validate on 4×30 days):

Season	Training data	Test data
Winter	16.01.2019 to 15.01.2020	16.01.2020 to 14.02.2020
Spring	02.05.2019 to 30.04.2020	01.05.2020 to 30.05.2020
Summer	01.08.2018 to 31.07.2019	01.08.2019 to 30.08.2019
Autumn	17.10.2019 to 15.10.2020	16.10.2020 to 14.11.2020

Numerical study - Results

- ▶ Example: Evolution of storage level R_t over time

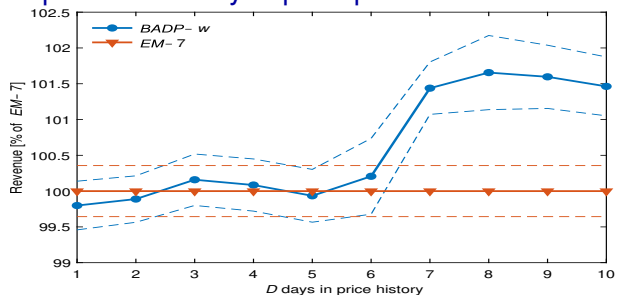


Numerical study - Results

Algorithm	Rel. revenue	95% confidence	Machine time [s]
<i>EM-7</i>	100.00 %	[99.64, 100.36]	0
<i>BADP</i>	99.70 %	[99.09, 100.30]	1, 401
<i>BADP-w</i>	101.44 %	[101.04, 101.84]	1, 412
<i>BADP-w</i> (re-opt.)	101.47 %	[101.00, 101.93]	2, 139
<i>LSMC-lasso</i>	94.31 %	[93.62, 95.00]	4, 316
<i>ADDP</i>	82.80 %	[82.17, 83.44]	5, 172
<i>Perfect foresight</i>	185.70 %	—	0

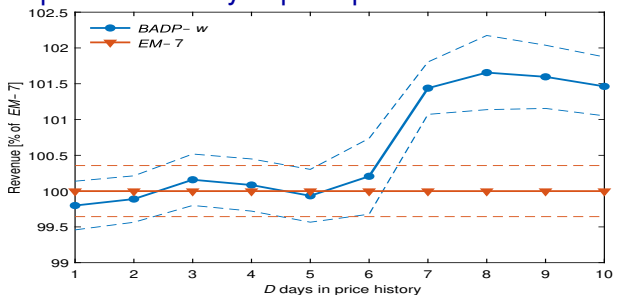
- ▶ *BADP-w* about 1.5% revenue increase compared to *EM-7*
profit increase in practice usually substantially larger
- ▶ *EM-7* is quite competitive

Impact of memory in price process:



- ▶ History in price process matters

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Impact of integrated bidding:

Trading and optimization	Relative revenue	95% confidence band
Only day-ahead (DA)	39.75%	[39.03, 40.47]
Only intraday (ID)	97.51%	[97.20, 97.83]
DA+ID, sequential	91.98%	[91.74, 92.22]
DA+ID, integrated	100.00%	[99.61, 100.39]

- ▶ Integrated bidding yields +9% revenue

Summary results

- ▶ Integrated bidding for storages on day-ahead and intraday auction feasible
- ▶ Weighted backwards approximate dynamic programming (BADP) gives 1.5% improvement over expectation model
- ▶ Memory in price process important
- ▶ Integrated bidding substantially better than sequential bidding (+9% revenue!)

Summary results

- ▶ Integrated bidding for storages on day-ahead and intraday auction feasible
- ▶ Weighted backwards approximate dynamic programming (BADP) gives 1.5% improvement over expectation model
- ▶ Memory in price process important
- ▶ Integrated bidding substantially better than sequential bidding (+9% revenue!)

Thank you for your attention!