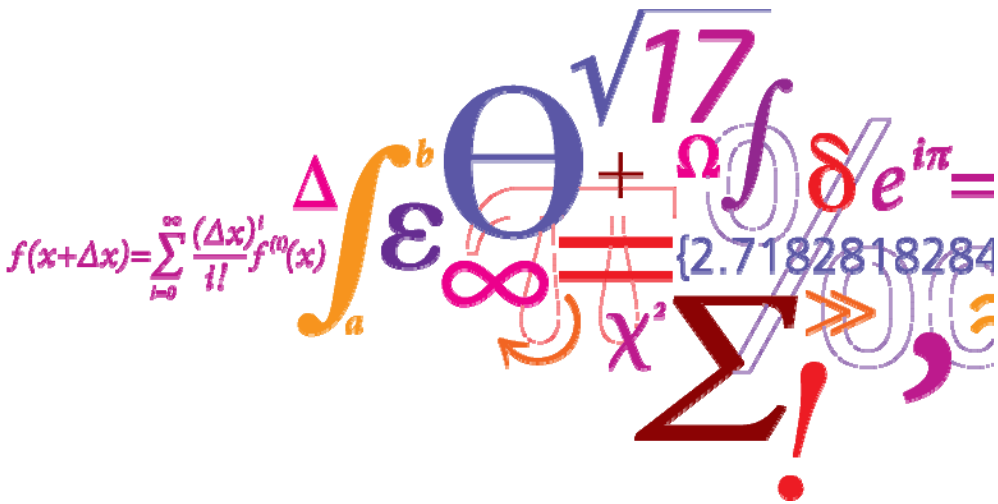
EES-UETP

DTU

Electricity Markets With Renewables

Jalal Kazempour

(Technical University of Denmark)



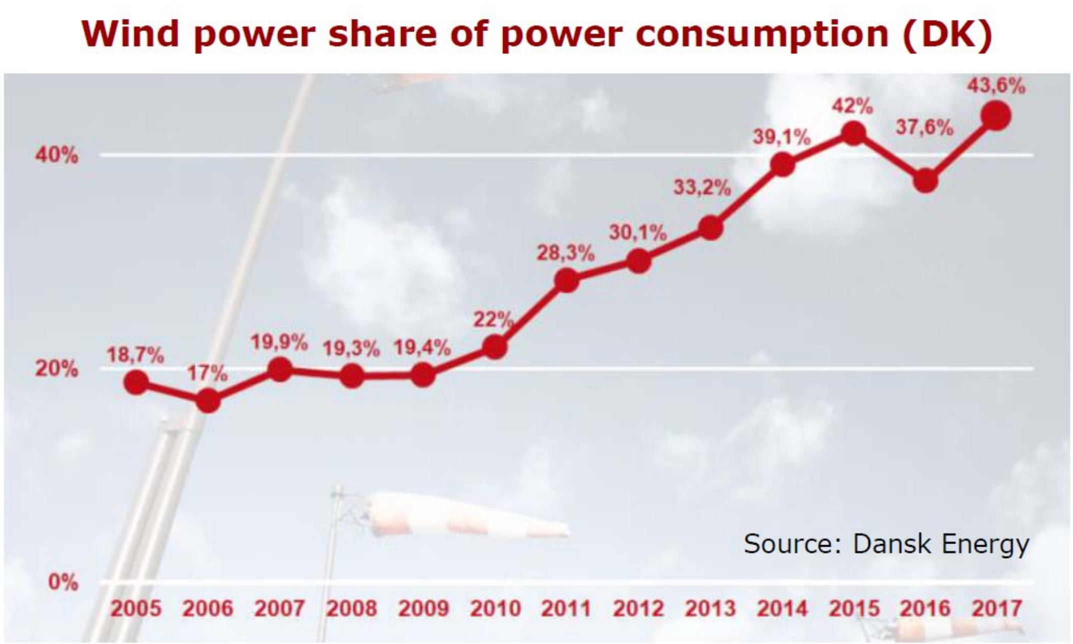
DTU CEE Summer School 2018,

28 June 2018

DTU Electrical Engineering
Department of Electrical Engineering

This is happening in Denmark!

Large-scale penetration of renewable energy sources in power system



In 2017:

- **43.6%** of electricity consumption covered by wind (target: 100% in 2050)
- **1,460 hours** of excess wind

- Manage high uncertainty in demand and supply
- Increased need for flexibility in the power systems

Why Flexibility?

Electricity Market

Goal: meeting demand at the minimum system cost
(or the maximum social welfare)

- **Renewables** (with stochastic generation) bring uncertainty – inaccurate forecast may result in wrong commitment and dispatch decisions, with **increased** system cost

Why Flexibility?

Electricity Market

Goal: meeting demand at the minimum system cost
(or the maximum social welfare)

- **Renewables** (with stochastic generation) bring uncertainty – inaccurate forecast may result in wrong commitment and dispatch decisions, with **increased** system cost

- **How to manage renewable power uncertainty:**
  - ✓ Flexibility integration (fast generators, demand response, etc)
  - ✓ Proper market design

Questions

What is the cost of wind uncertainty and value of flexibility?

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Do we need the system operator to do stochastic unit commitment--or can some market players attain the least-cost solution on their own?

Two-Stage Settlement, 1 Day Horizon

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Day-ahead Market

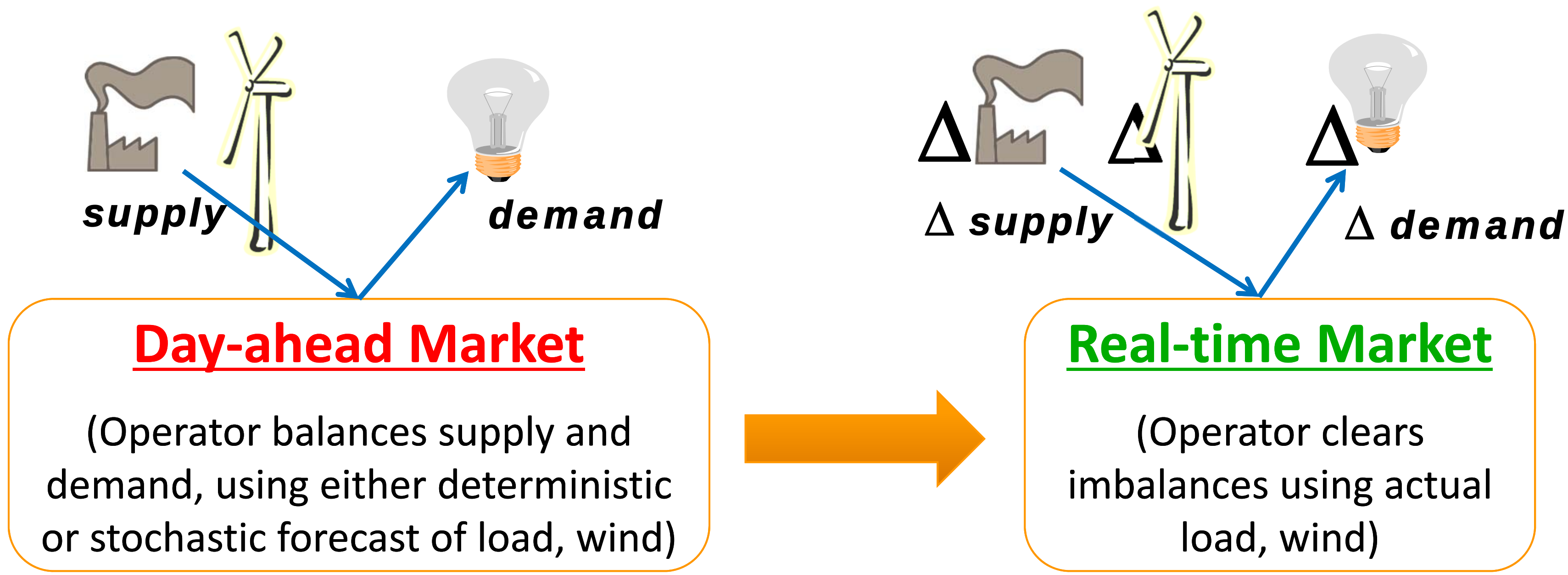
(Operator balances supply and demand, using either deterministic or stochastic forecast of load, wind)

→

Real-time Market

(Operator clears imbalances using actual load, wind)

Two-Stage Settlement, 1 Day Horizon

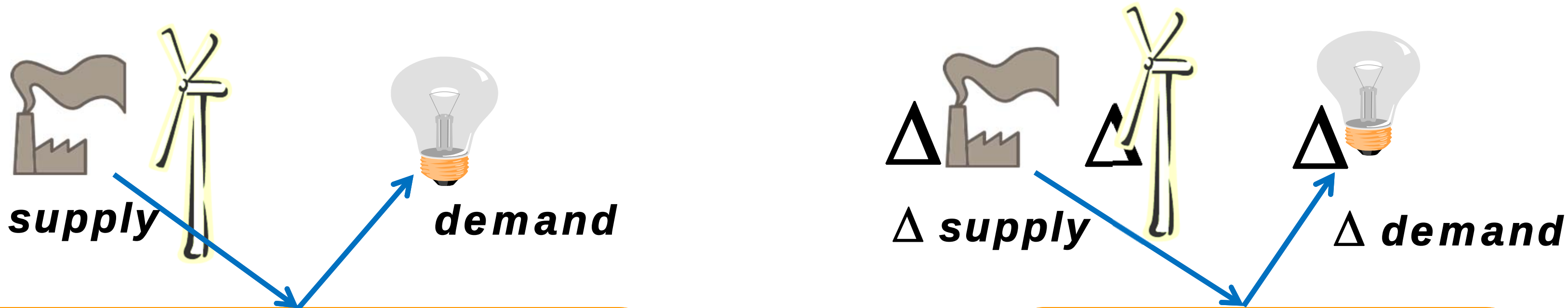


Generators:

Demand Response (DR) Resources:

Virtual Bidders (Financial Arbitragers):

Two-Stage Settlement, 1 Day Horizon



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Generators:

- Slow generators commitment (*u*)
- Fast generators *tentative* commitment (*u*) → Fast generator *revised* commitment: (Δu)
- Generator energy *tentative* (*p*) → Generator energy *revised* (Δp)

Demand Response (DR) Resources:

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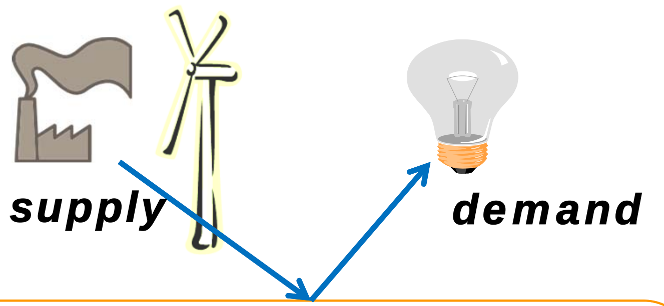

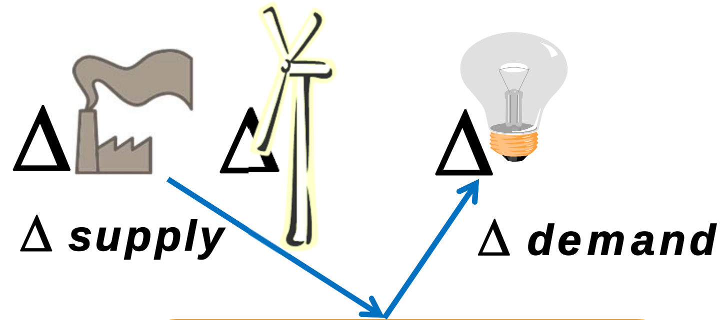

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Demand Response (DR) Resources:

- Slow DR (*d*)
- Fast DR *tentative* (*d*) → Fast DR *revised* (Δ*d*)

Virtual Bidders (Financial Arbitragers):

Two-Stage Settlement, 1 Day Horizon

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Demand Response (DR) Resources:

- Slow DR (d)
- Fast DR *tentative* (d) → Fast DR *revised* (Δd)

Virtual Bidders (Financial Arbitragers):

- Virtual bidder buys/sells ($+v$) → Bidder sells/buys ($-v$)

Virtual Bidding

- It exists in current US electricity markets, e.g., CAISO, PJM and MISO
- The virtual bidder has no physical asset!
- The virtual bidder buys (sells) in the day-ahead market and then sells (buys) the same amount back in the real-time market.

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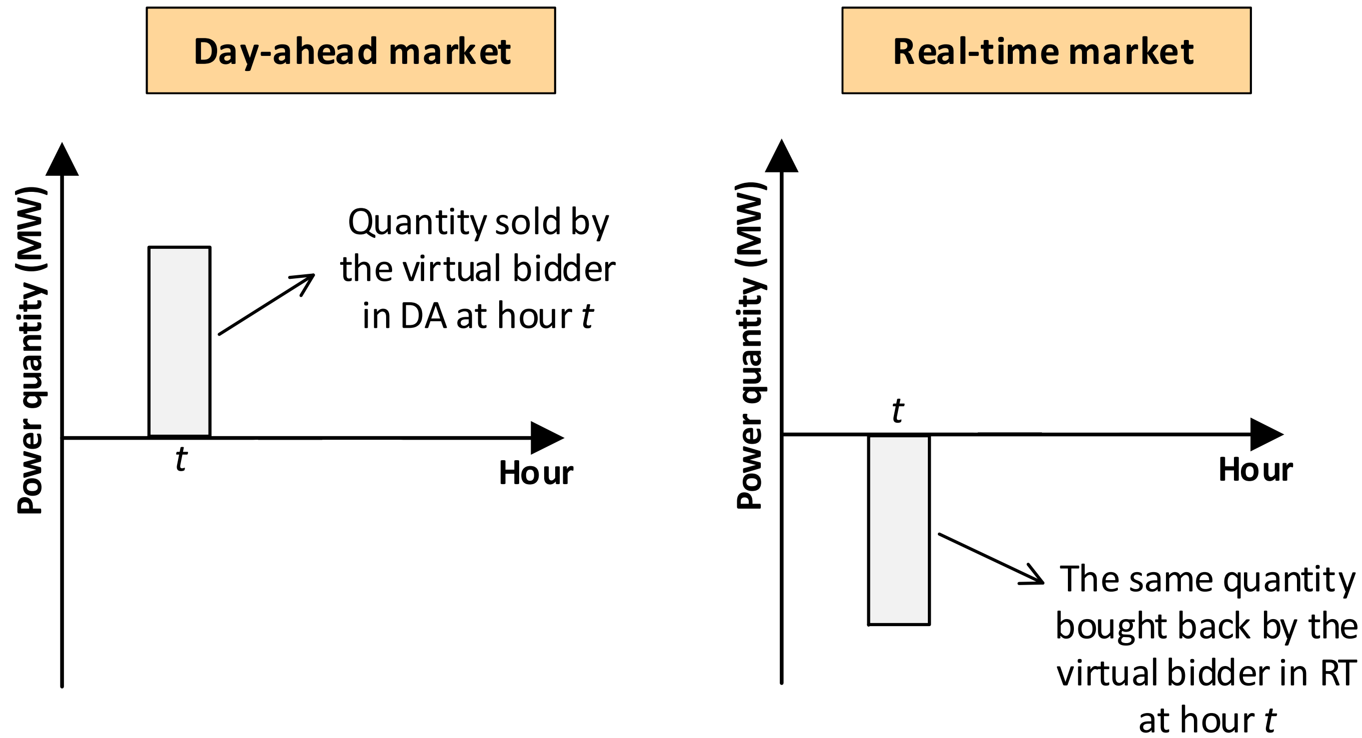

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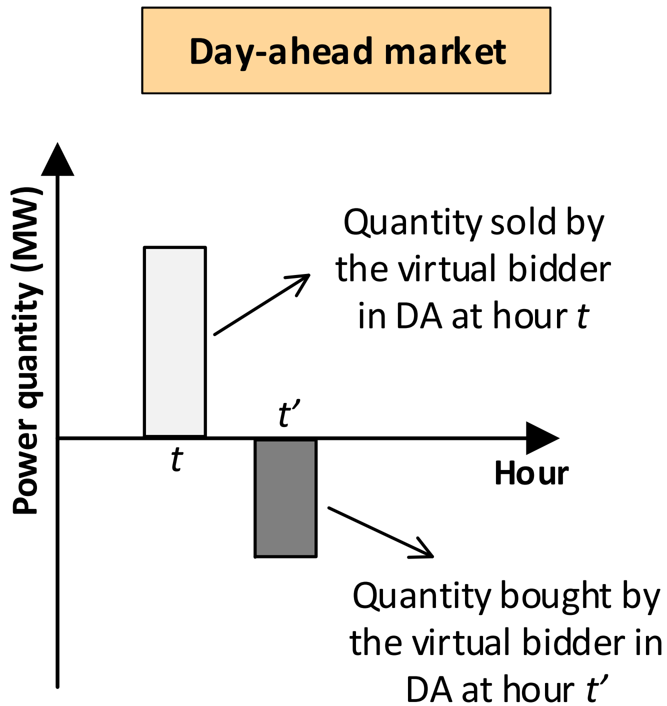

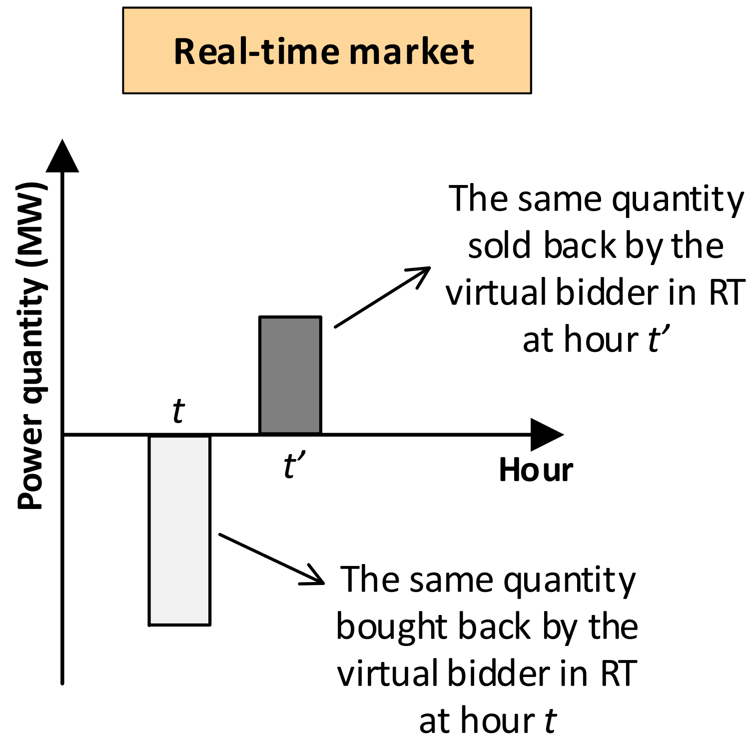

Alternative Market Clearing Models

Model 1: Stochastic Market Clearing (ideal solution)

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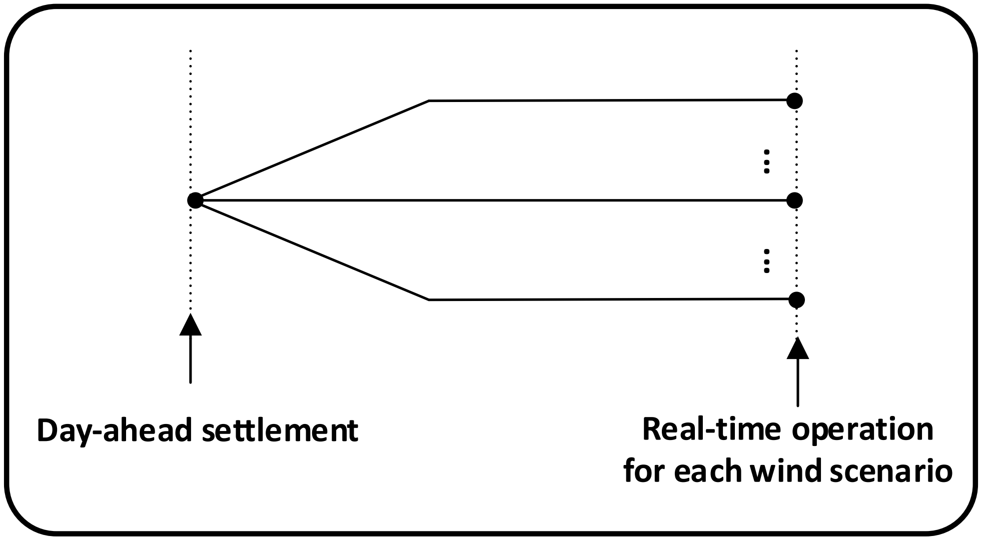
- The set of wind scenarios and their probabilities are known in day-ahead stage, but which one actually occurs in real-time stage is unknown.



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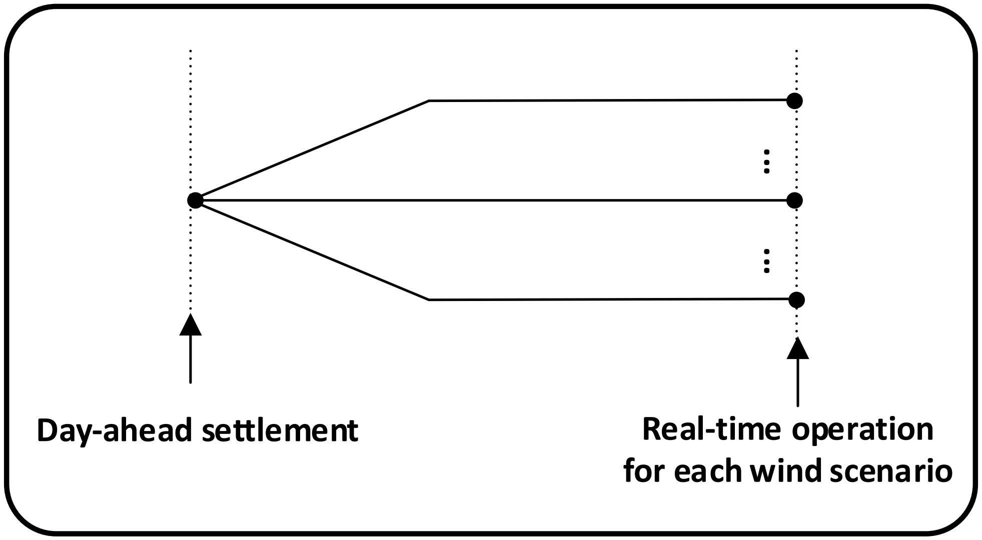


- ❑ The system operator solves a single *stochastic optimization* problem, considering day-ahead and real-time markets *simultaneously*.

Total expected cost minimization:

Minimize [cost in day ahead] + [expected cost in real time]

Alternative Market Clearing Models

Model 1: Stochastic Market Clearing (ideal solution) as an *Optimization* Form

DA: day-ahead stage RT: real-time stage

Minimize (cost in DA) + (expected cost in RT)

subject to:

- Production limits (in DA and RT)
- Transmission network limits (in DA and RT)
- Load shedding limits (in RT)
- Energy balances (in DA and RT)

- G. Pritchard, G. Zakeri, and A. Philpott, "A single-settlement, energy-only electric power market or unpredictable and intermittent participants," *Oper. Res.,* vol. 58, no. 4, pp. 1210-1219, Jul. -Aug. 2010.
- J. M. Morales, A. J. Conejo, K. Liu, and J. Zhong, "Pricing electricity in pools with wind producers," *IEEE Trans. Power Syst*., vol. 27, no.3, pp. 1366-1376, Aug. 2012.

Alternative Market Clearing Models

Model 1: Stochastic Market Clearing (ideal solution) as an *Equilibrium* Form

Each conventional generator:

Maximize expected profit
subject to:
Production limits (in DA and RT)

Each stochastic generator:

Maximize expected profit
subject to:
Production limits (in DA and RT)

Grid operator:

Maximize expected profit
subject to:
Network limits (in DA and RT)

Each load (inelastic):

Minimize expected cost
subject to:
Load shedding limits (in RT)

Market clearing:

Energy balances (in DA and RT)

- B. F. Hobbs, "Linear complementarity models of Nash-Cournot competition in bilateral and POOLCO power markets," *IEEE Trans. Power Syst.*, vol. 16, no. 2, pp. 194-202, May 2001.

Model 1: Stochastic Market Clearing (ideal solution)

- Equivalent optimization and equilibrium models: identical set of KKT conditions

- Each player maximizes/minimizes its expected objective: Symmetric equilibrium problem

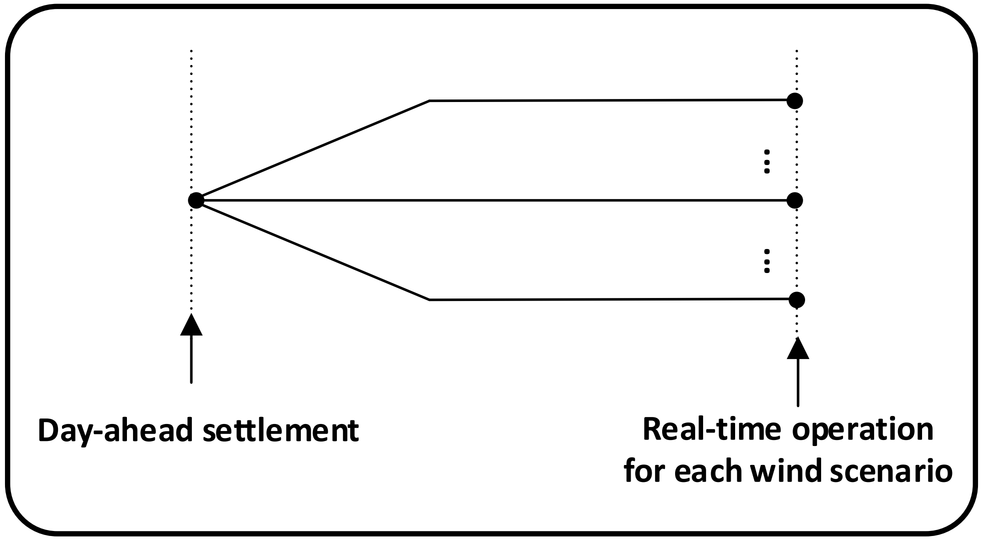
- Square system → single solution

- DA price = expected RT price

Alternative Market Clearing Models

Model 1: Stochastic Market Clearing (ideal solution)

Challenges:



Total expected cost minimization:

Minimize [cost in day ahead] +
[expected cost in real time]

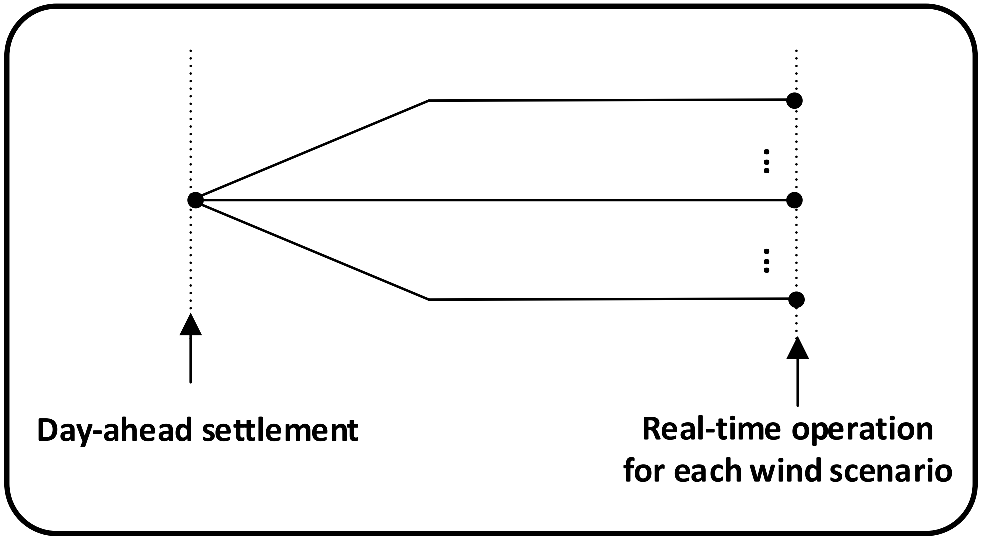
Alternative Market Clearing Models

Model 1: Stochastic Market Clearing (ideal solution)

Challenges:

- Stochastic market clearing is *incompatible* with the current practice of real-world electricity markets!

- Its implementation would place a *large burden* on the system operator to develop this information and to obtain stakeholder consent for the procedures involved!



Total expected cost minimization:

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Alternative Market Clearing Models

Model 2: Sequential Deterministic Market Clearing

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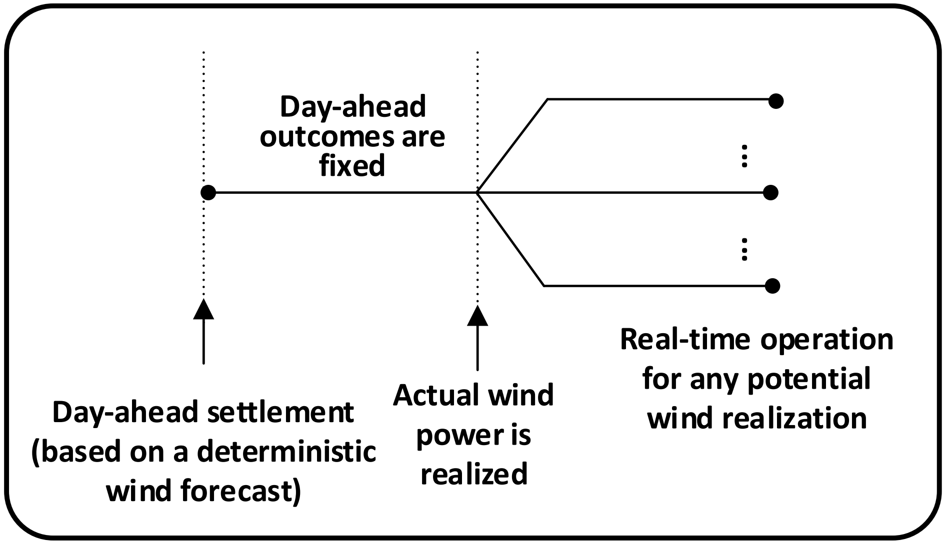
- ***First,*** the system operator clears the day-ahead market using a deterministic forecast, ***then*** clears the real-time market.



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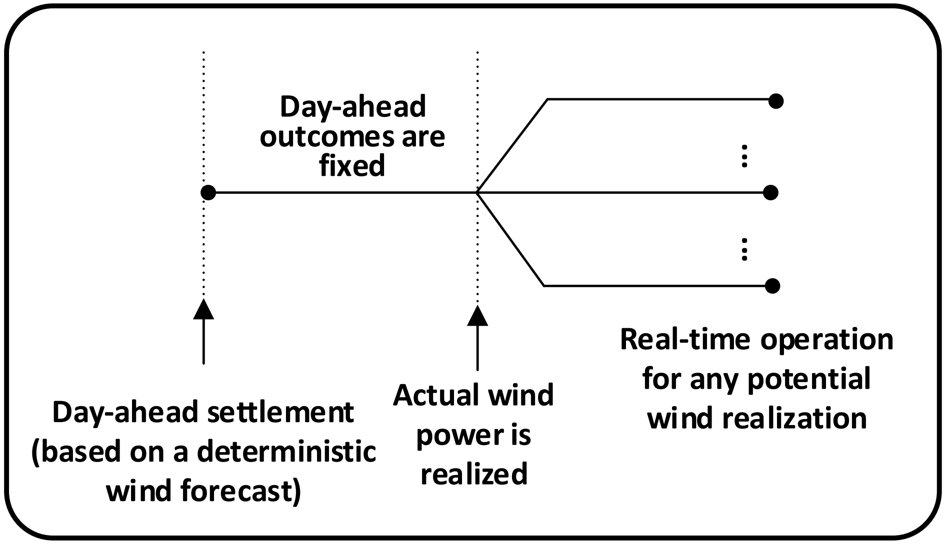

- Each stage's optimization is a ***deterministic*** problem

Day-ahead market:

Minimize [cost in day ahead]

Real-time market for each scenario:

Minimize [cost in real time]

Model 3: Sequential Deterministic Market Clearing with Virtual Bidders as Stochastic Decision-Makers

Alternative Market Clearing Models

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Day-ahead market:

Minimize [cost in day ahead]

Real-time market for each scenario:

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Alternative Market Clearing Models

Model 3: Sequential Deterministic Market Clearing with Virtual Bidders as Stochastic Decision-Makers

Day-ahead market:

Minimize [cost in day ahead]

Real-time market for each scenario:

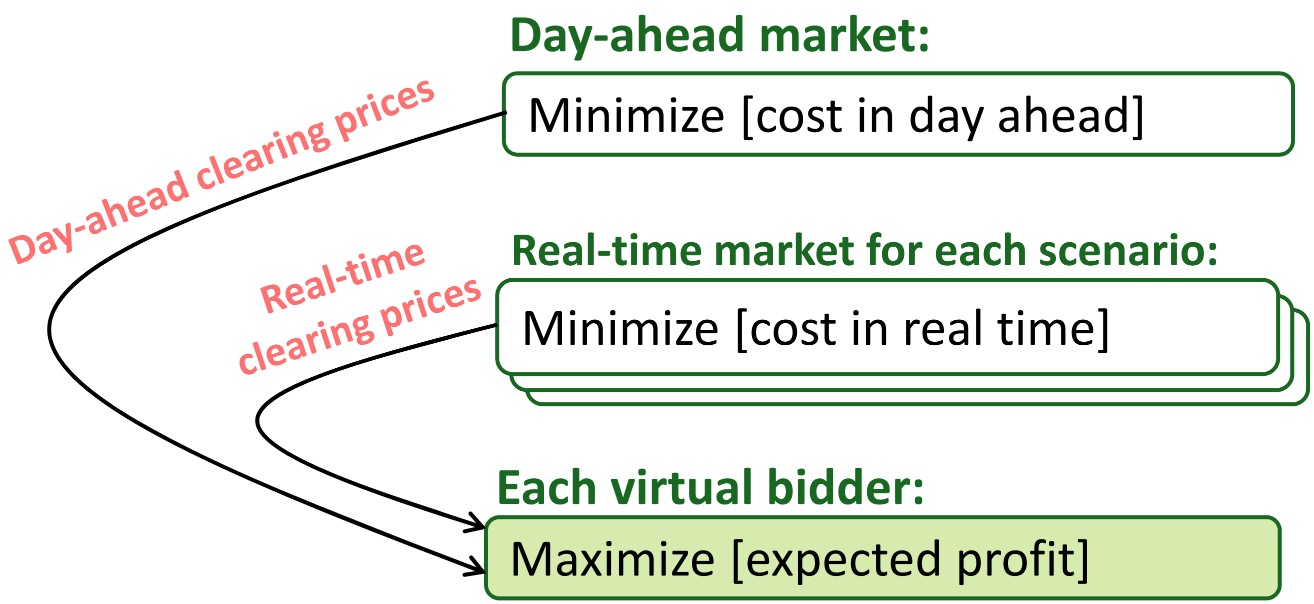
Minimize [cost in real time]

Each virtual bidder:

Maximize [expected profit]

Alternative Market Clearing Models

Model 3: Sequential Deterministic Market Clearing with Virtual Bidders as Stochastic Decision-Makers

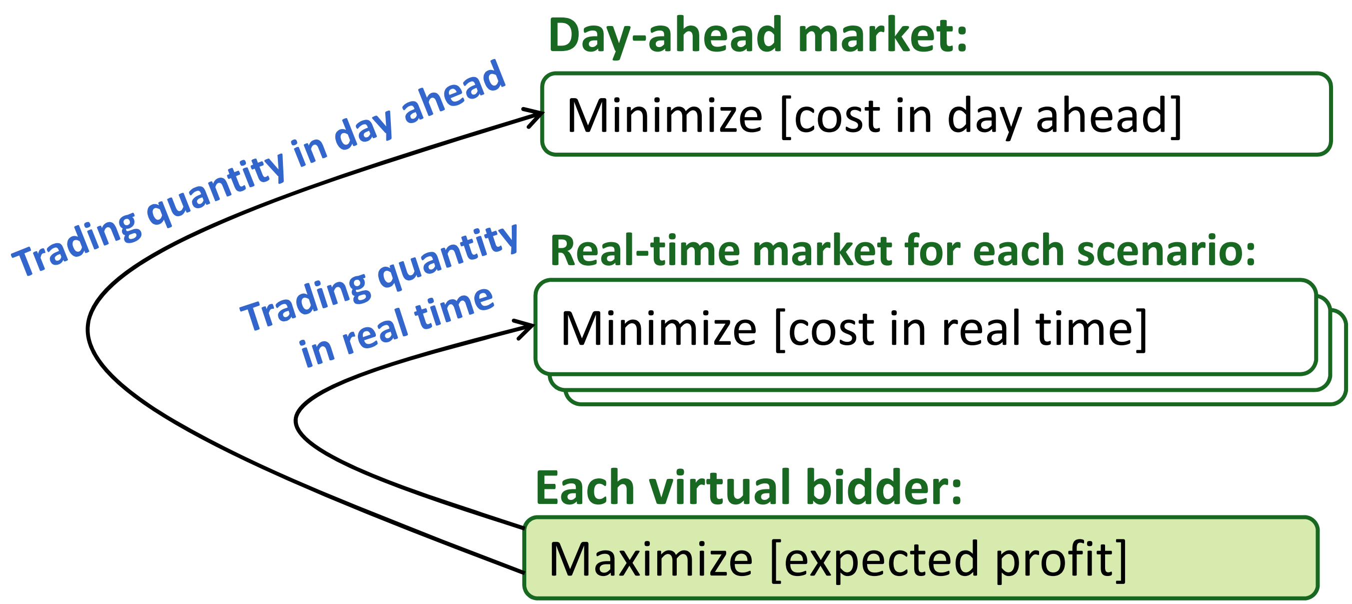


Assumption: Virtual bidders are perfect, in the sense that they have "perfect" information about day-ahead and distribution of real-time prices!

- These prices are dual variables of clearing problems, while parameters in virtual bidders' problems!

Alternative Market Clearing Models

Model 3: Sequential Deterministic Market Clearing with Virtual Bidders as Stochastic Decision-Makers



These trading quantities [MW] are primal variables in virtual bidders' optimization problems, while parameters in market-clearing problems!

Alternative Market Clearing Models

Model 3: Sequential Deterministic Market Clearing with Virtual Bidders as Stochastic Decision-Makers

Deterministic optimization problems →

Day-ahead market:

Minimize [cost in day ahead]

Real-time market for each scenario:

Minimize [cost in real time]

Stochastic optimization problem →

Each virtual bidder:

Maximize [expected profit]

Remark: Market-clearing problems are **deterministic**, while markets allow the participation of **stochastic decision-makers** who make their own dispatch decisions outside the market!

Alternative Market Clearing Models

Model 3: Sequential Deterministic Market Clearing with Virtual Bidders as Stochastic Decision-Makers

Day-ahead market:

Minimize [cost in day ahead]

Real-time market for each scenario:

Minimize [cost in real time]

Each virtual bidder:

Maximize [expected profit]

This is an equilibrium problem (not optimization!)

Alternative Market Clearing Models

Model 3: Sequential Deterministic Market Clearing with Virtual Bidders as Stochastic Decision-Makers

- Extended version of Model 2 (sequential market clearing)
- Virtual bidders are the only market players who "perfectly" know the distribution of real-time prices across scenarios!
- Unlike the system operator who sequentially solves deterministic problems, each virtual bidder solves a two-stage stochastic problem.

Day-ahead market:

Minimize [cost in day ahead]

Real-time market for each scenario:

Minimize [cost in real time]

Each virtual bidder:

Maximize [expected profit]

This is an equilibrium problem (not optimization!)

Model 4: Sequential Deterministic Market Clearing with Virtual Bidders and Self-Scheduling Slow Generators

Alternative Market Clearing Models

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Real-time market for each scenario:

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Alternative Market Clearing Models

Model 4: Sequential Deterministic Market Clearing with Virtual Bidders and Self-Scheduling Slow Generators

Day-ahead market:

Minimize [cost in day ahead]

Real-time market for each scenario:

Minimize [cost in real time]

Each virtual bidder:

Maximize [expected profit]

Each self-scheduling slow generator:

Maximize [expected profit]

Alternative Market Clearing Models

Model 4: Sequential Deterministic Market Clearing with Virtual Bidders and Self-Scheduling Slow Generators

- ✓ Similar to virtual bidders (arbitragers without asset), generators (usually slow-start ones) can also behave as "stochastic decision-makers" (arbitragers with asset), as long as their total production (P^{DA}+P^{RT}) lies between their P^{min} and P^{max}.
- ✓ Self-scheduling generators exist in some US markets, e.g., CAISO.

Day-ahead market:

Minimize [cost in day ahead]

Real-time market for each scenario:

Minimize [cost in real time]

Each virtual bidder:

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Each self-scheduling slow generator:

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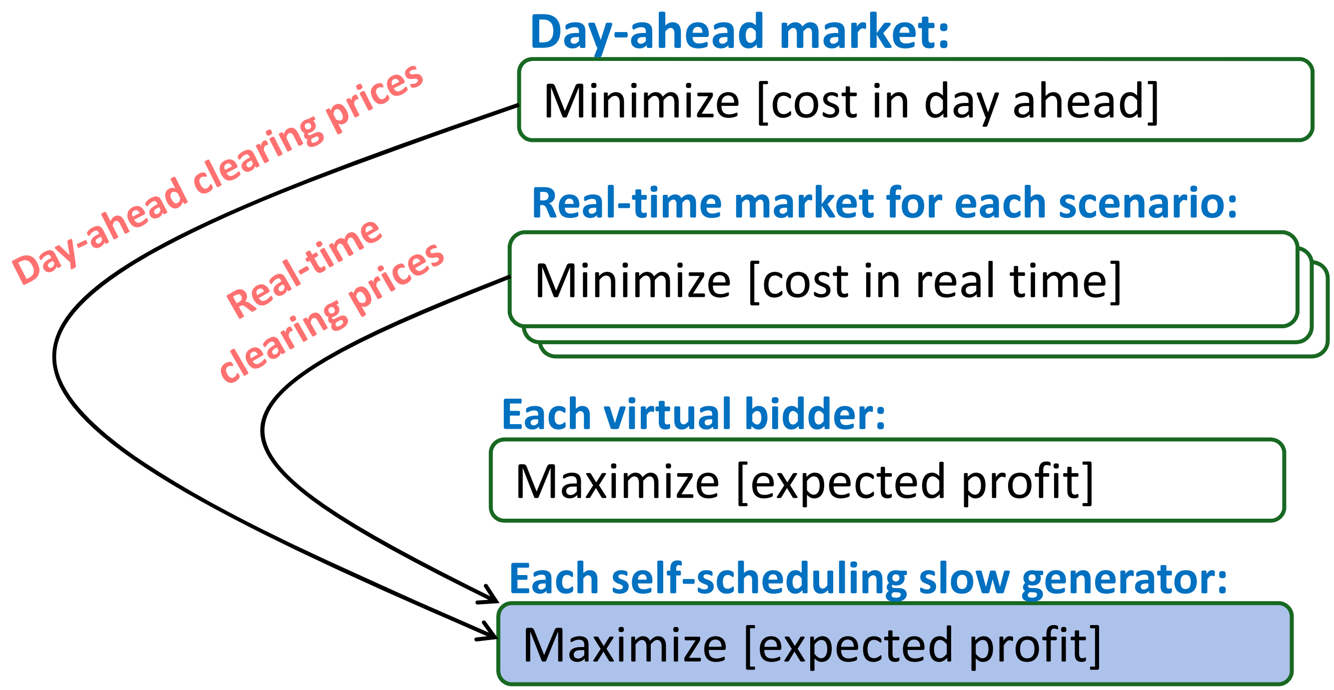

Assumption: Self-scheduling generators are perfect, in the sense that they have "perfect" information about day-ahead and distribution of real-time prices!

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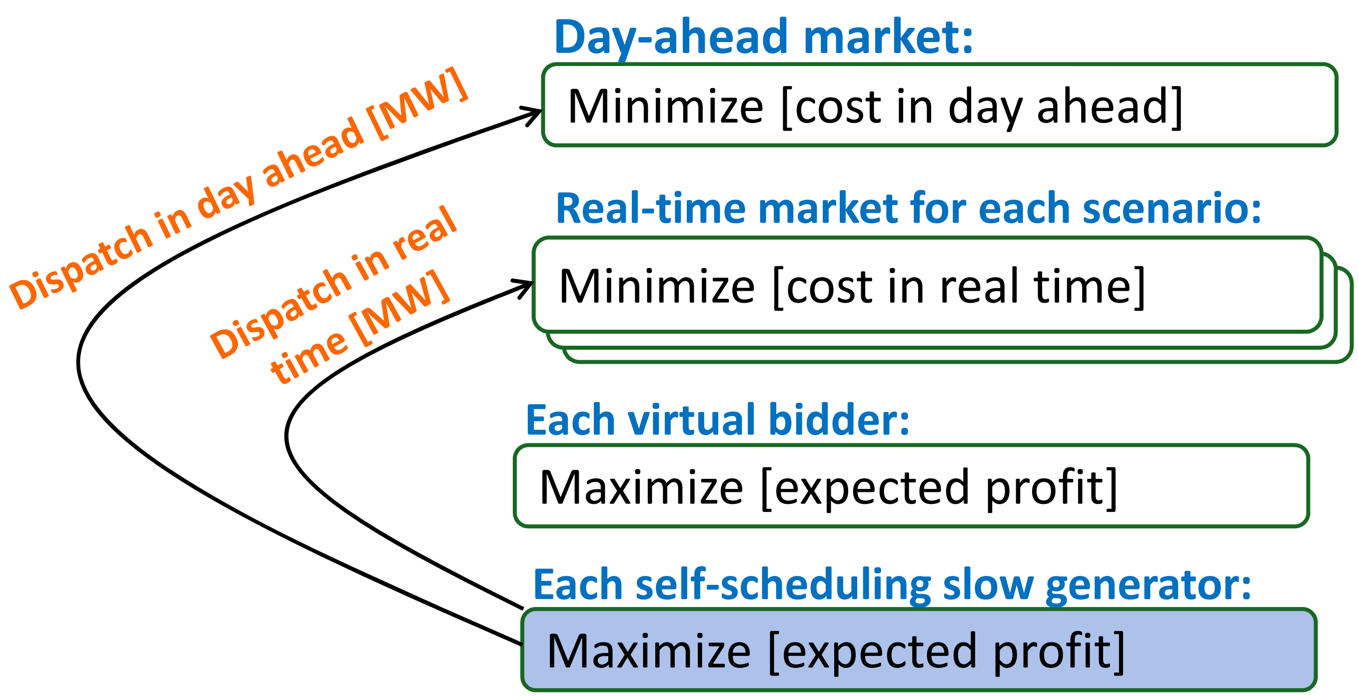
Alternative Market Clearing Models

Model 4: Sequential Deterministic Market Clearing with Virtual Bidders and Self-Scheduling Slow Generators



These dispatch quantities [MW] are primal variables in self-schedulers' optimization problems, while parameters in market-clearing problems!

Alternative Market Clearing Models

Model 4: Sequential Deterministic Market Clearing with Virtual Bidders and Self-Scheduling Slow Generators

Deterministic optimization problems

Day-ahead market:

Minimize [cost in day ahead]

Real-time market for each scenario:

Minimize [cost in real time]

Stochastic optimization problems

Each virtual bidder:

Maximize [expected profit]

Each self-scheduling slow generator:

Maximize [expected profit]

Remark: Market-clearing problems are **deterministic**, while markets allow the participation of **stochastic decision-makers** who make their own dispatch decisions outside the market!

Alternative Market Clearing Models

Model 4: Sequential Deterministic Market Clearing with Virtual Bidders and Self-Scheduling Slow Generators

- ✓ Stochastic decision-makers (virtual bidders and self-scheduling generators) are dispatched outside the market (based on their own decisions).
- ✓ **However, the self-scheduling generators are paid based on market-clearing prices!**

Day-ahead market:

Minimize [cost in day ahead]

Real-time market for each scenario:

Minimize [cost in real time]

Each virtual bidder:

Maximize [expected profit]

Each self-scheduling slow generator:

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Alternative Market Clearing Models

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Model 4: Sequential Deterministic Market Clearing with Virtual Bidders and Self-Scheduling Slow Generators

- Extended version of Model 3 (sequential market clearing with virtual bidders)

- Virtual bidders and self-scheduling slow generators are the only market players who "perfectly" know the distribution of real-time prices across scenarios!

Day-ahead market:

Minimize [cost in day ahead]

Real-time market for each scenario:

Minimize [cost in real time]

Each virtual bidder:

Maximize [expected profit]

Each self-scheduling slow generator:

Maximize [expected profit]

This is an equilibrium problem (not optimization!)

Solution Technique

- Unit commitment constraints are formulated as TRUC (Tight Relaxed Unit Commitment) problem (S. Kasina, S. Wogrin, B.F. Hobbs, *Johns Hopkins University Working Paper*, Nov. 2014.)

- Equilibrium models are solved by considering the Karush-Kuhn-Tucker (KKT) conditions of all optimization problems simultaneously.

Illustrative Example: Single-Node Case

- Two slow conventional generators: G1 and G2
- One fast conventional generators: G3
- A single wind power producer: WP
- A single inelastic load
- A virtual bidder: VB

Illustrative Example: Single-Node Case

- Technical characteristics of conventional generators:

Gen.	Type	Pmin [MW]	Pmax [MW]	Ramp [MW/h]	Marginal Cost [$/MWh]	Start-up cost [$]
G1	Slow	1000	1000	1000	50	15,000
G2	Slow	0	1000	1000	60	10,000
G3	Fast	0	500	500	120	1000

Illustrative Example: Single-Node Case

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G2	Slow	0	1000	1000	60	10,000
G3	Fast	0	500	500	120	1000

- Wind power forecast:
  - In day-ahead stage: 250 MW
  - In real-time stage, scenario 1: 0 MW (probability: 0.5)
  - In real-time stage, scenario 2: 500 MW (probability: 0.5)
- Load: 1000 MW

Illustrative Example: Results

Market equilibrium model	**Total expected system cost [$]**
Model 1 (stochastic market clearing)	47,500

Illustrative Example: Results

Market equilibrium model	Total expected system cost [$]
Model 1 (stochastic market clearing)	47,500

- Generator G3 (fast unit, but expensive) is not committed (always off).

- Generator G2 (slow unit) is committed appropriately in day-ahead market, and manages all power imbalances in real time.

Illustrative Example: Results

Market equilibrium model	Total expected system cost [$]
Model 1 (stochastic market clearing)	47,500
Model 2 (sequential market clearing)	56,500

Illustrative Example: Results

Market equilibrium model	Total expected system cost [$]
Model 1 (stochastic market clearing)	47,500
Model 2 (sequential market clearing)	56,500

- Cost of uncertainty: $9,000 [$56,500 – $47,500]
- Flexible resources can reduce the cost of uncertainty.
- In Model 2, fast generator G3 is committed in real time, because slow generator G2 is not committed in day ahead (wrong dispatch).

Illustrative Example: Results

Market equilibrium model	Total expected system cost [$]
Model 1 (stochastic market clearing)	47,500
Model 2 (sequential market clearing)	56,500
Model 3 (sequential market clearing) with virtual bidding	55,000

Illustrative Example: Results

Market equilibrium model	Total expected system cost [$]
Model 1 (stochastic market clearing)	47,500
Model 2 (sequential market clearing)	56,500
Model 3 (sequential market clearing) with virtual bidding	55,000

- Virtual bidding reduces the cost of uncertainty, but the system cost is still different than the ideal solution (Model 1).
- The virtual bidder buys 250 MW in day ahead, and sells it back in real time. The fast generator G3 is always off, but the day ahead dispatch of slow generator G2 is still wrong!

Illustrative Example: Results

Market equilibrium model	Total expected system cost [$]
Model 1 (stochastic market clearing)	47,500
Model 2 (sequential market clearing)	56,500
Model 3 (sequential market clearing) with virtual bidding	55,000
Model 4 (sequential market clearing) with virtual bidding, while slow generator G2 self-schedules	47,500

Illustrative Example: Results

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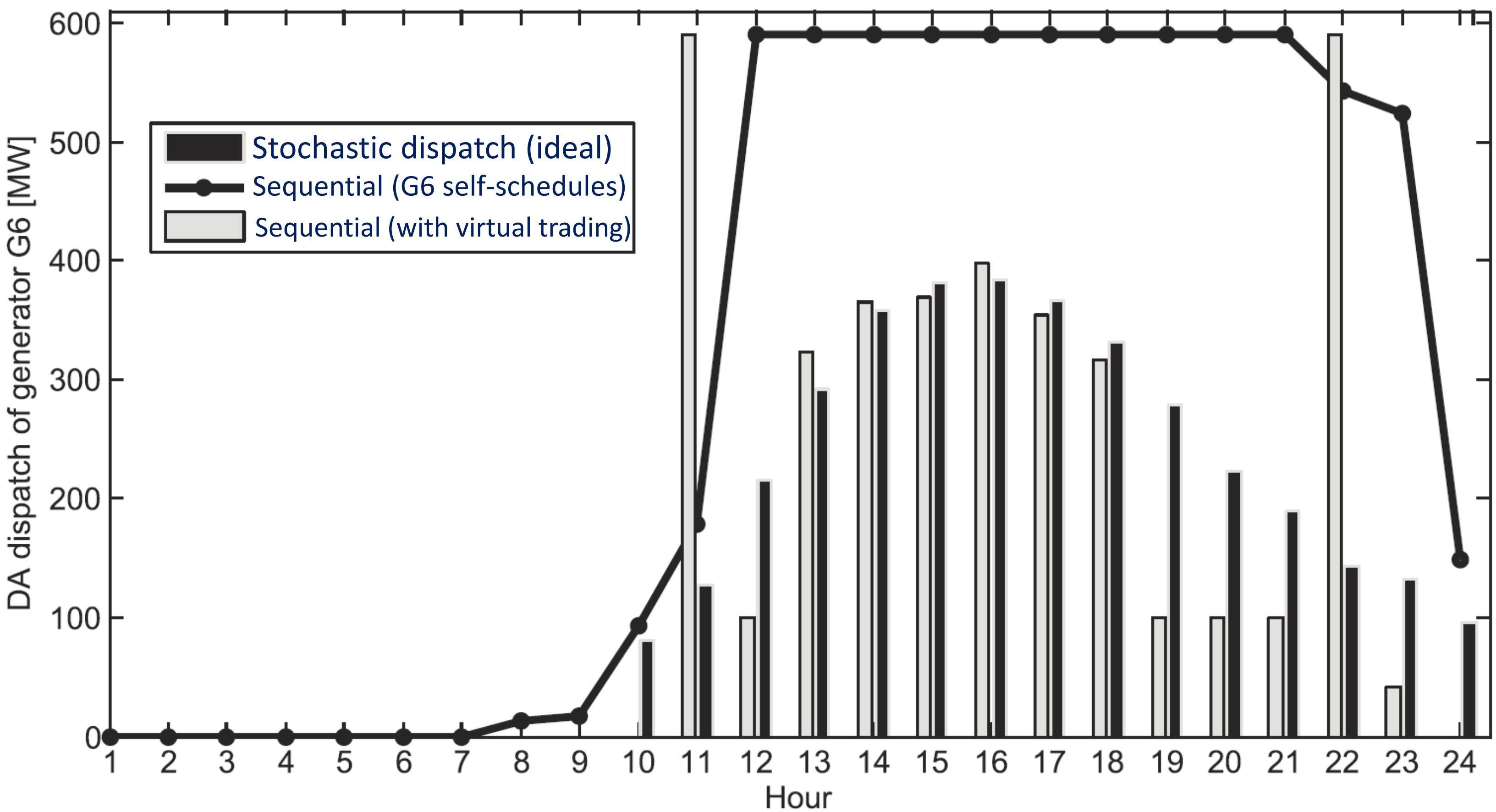
Model 2 (sequential market clearing)	56,500
Model 3 (sequential market clearing) with virtual bidding	55,000
Model 4 (sequential market clearing) with virtual bidding, while slow generator G2 self-schedules	47,500

- In this specific case, virtual bidding together with self-scheduling by a slow generator, can enable a deterministic day-ahead market to choose the most efficient unit commitment.

IEEE 24-Node Reliability Test System with 24 Hours

Day-ahead (DA) schedule of a sample slow-start generator (G6) in different models:



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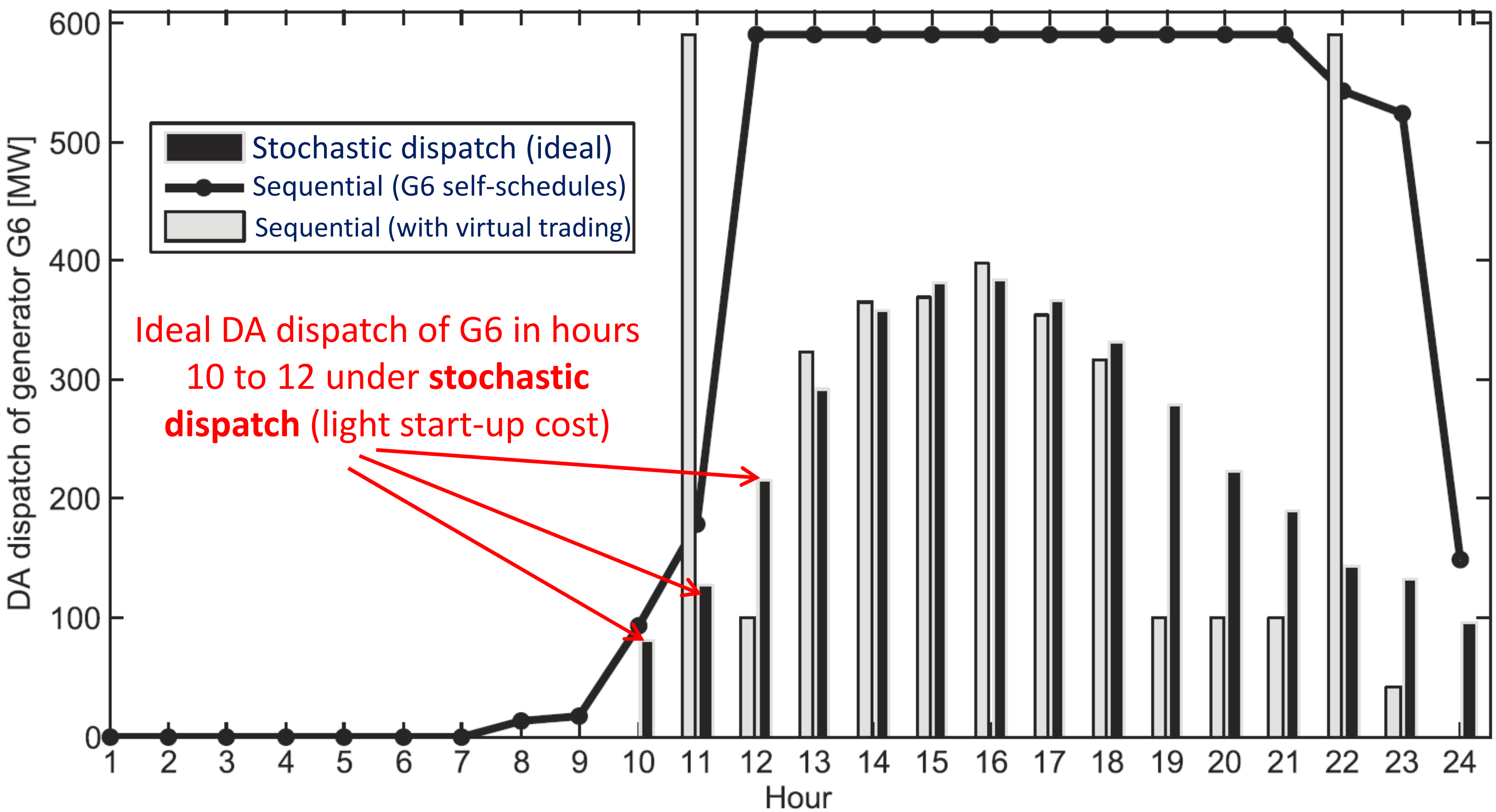

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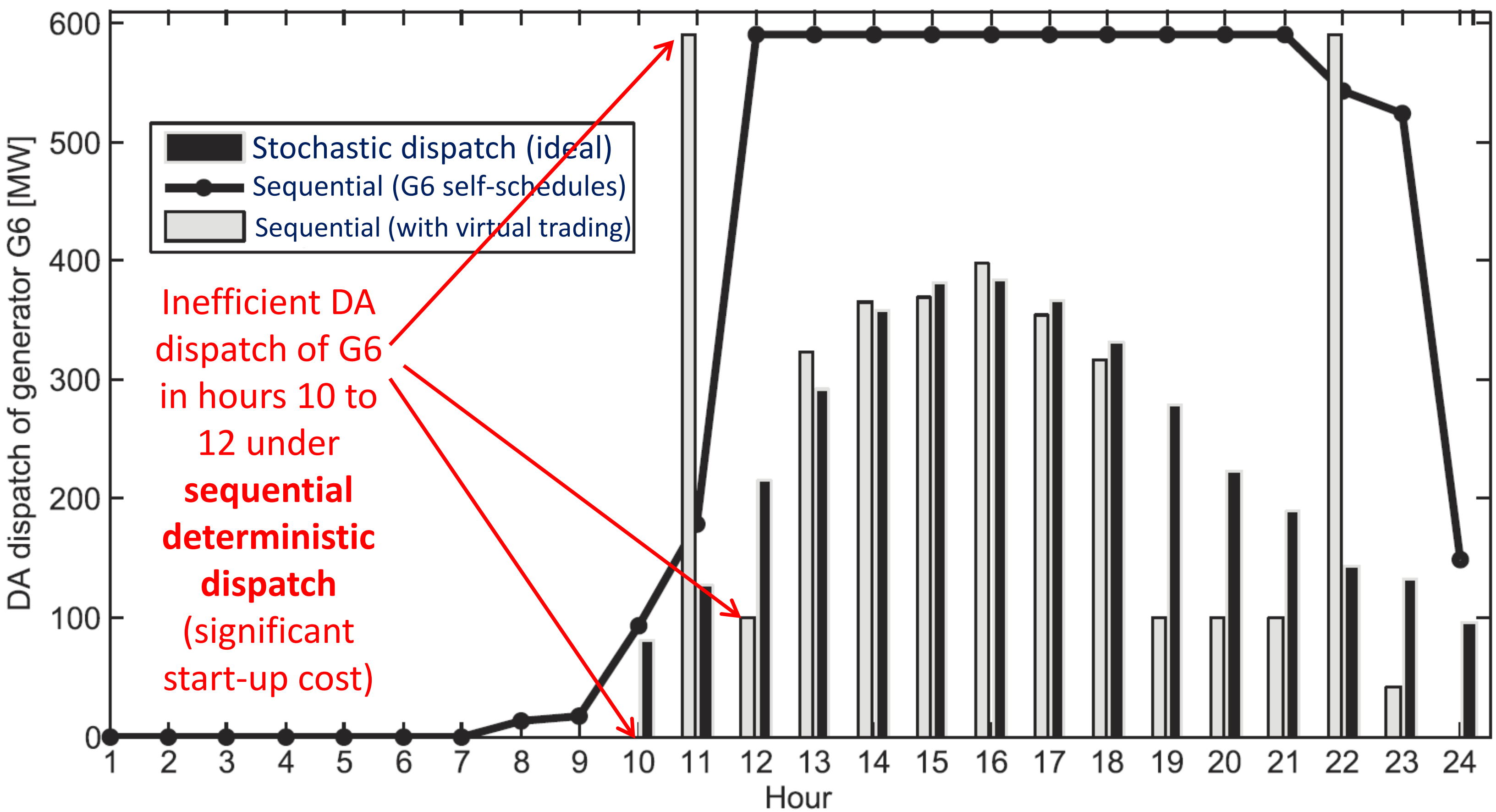

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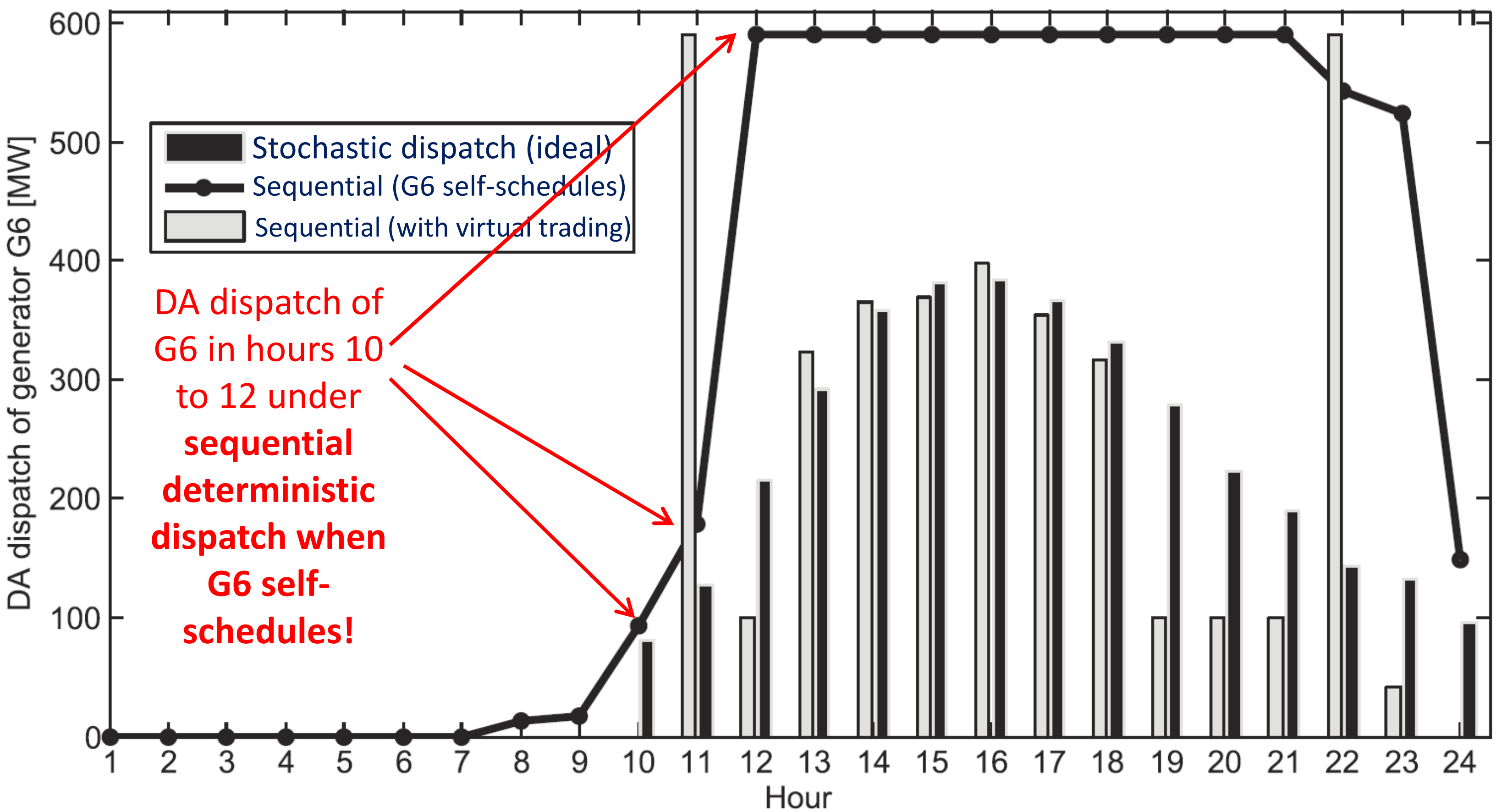

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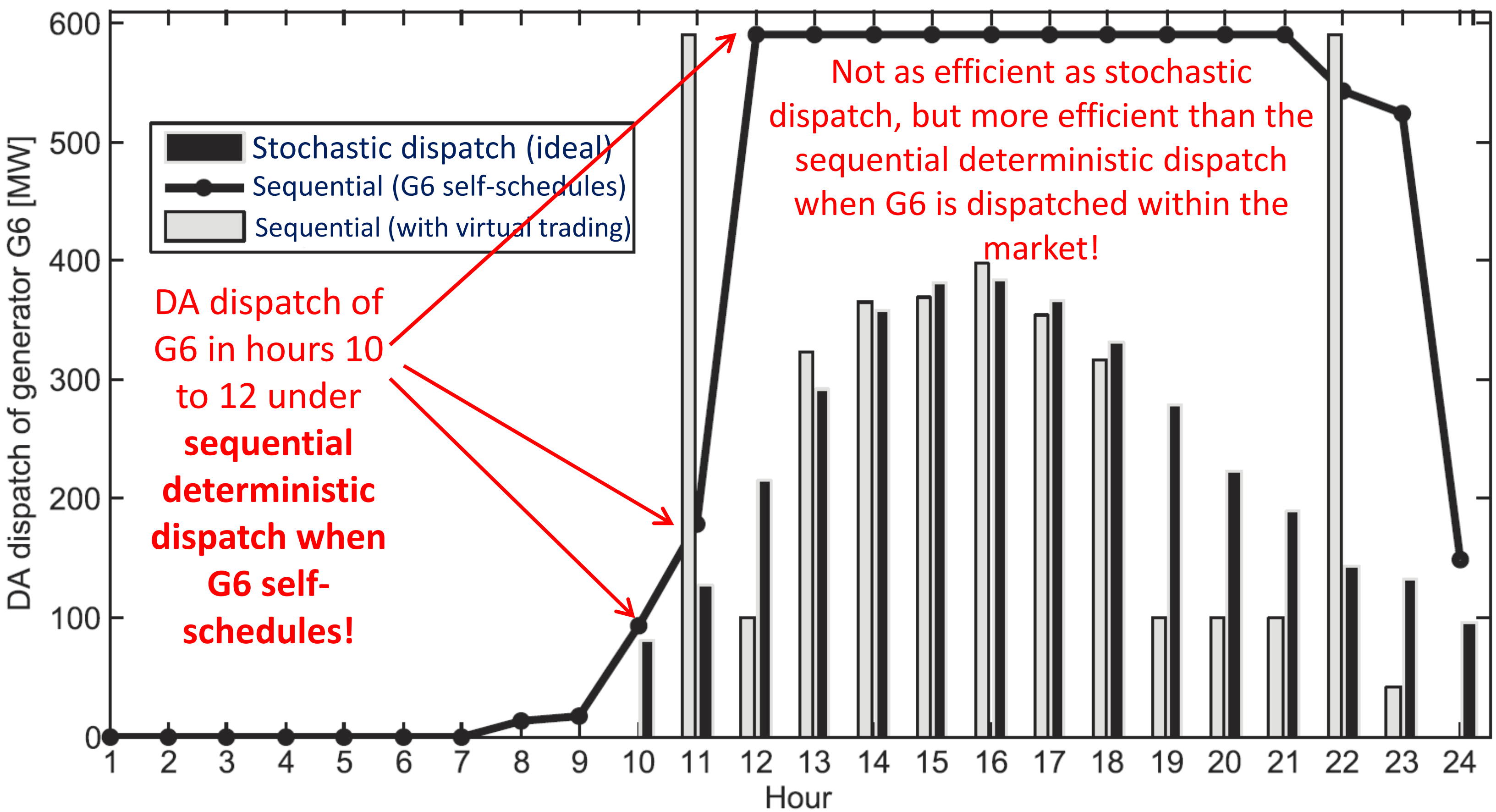


Conclusion

- We present different stochastic and deterministic two-stage (day-ahead and real-time) market designs, including virtual bidding and self-scheduling generators.

- A comparison of different market designs enables us to derive the cost of uncertainty and the value of flexible resources.

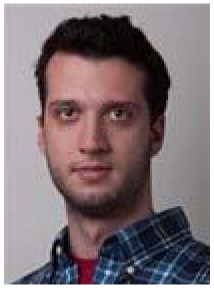
Main Message

- We suggest that the system operators should not rush to embrace the stochastic market clearing!

- It is possible that a subset of market parties acting on high quality stochastic information can help the market achieve the same efficiencies as stochastic clearing by the system operator!

Ongoing Work

Anna Schwele
(PhD student, DTU)



Christos Ordoudis
(PhD student, DTU)

- **Goal:** Increasing the coordination of electricity and natural gas markets in a two-settlement setup, yielding a reduced total system cost!
- **Tool:** Virtual bidders (in both electricity and gas sides) and self-schedulers (especially gas-fired electricity producers)

A Few Questions for Future Works

- How does "imperfect" knowledge of virtual bidders and self-schedulers about market prices change their decisions and thereby market outcomes?

- How do "strategic gaming" and/or "risk aversion" affect virtual bidders' and self-schedulers' decisions?

- Under which circumstances is it beneficial for a generator to do self-schedule (instead of bidding to the market)?

A two-series paper

- J. Kazempour and B. F. Hobbs, "Value of flexible resources, virtual bidding, and self-scheduling in two-settlement electricity markets with wind generation: Part I: principles and competitive model," *IEEE Transactions on Power Systems*, vol. 33, no. 1, pp. 749-759, Jan. 2018.

- J. Kazempour and B. F. Hobbs, "Value of flexible resources, virtual bidding, and self-scheduling in two-settlement electricity markets with wind generation: Part II: ISO models and application," *IEEE Transactions on Power Systems*, vol. 33, no. 1, pp. 760-770, Jan. 2018.

Thanks for your attention!

__Email__: seykaz@elektro.dtu.dk