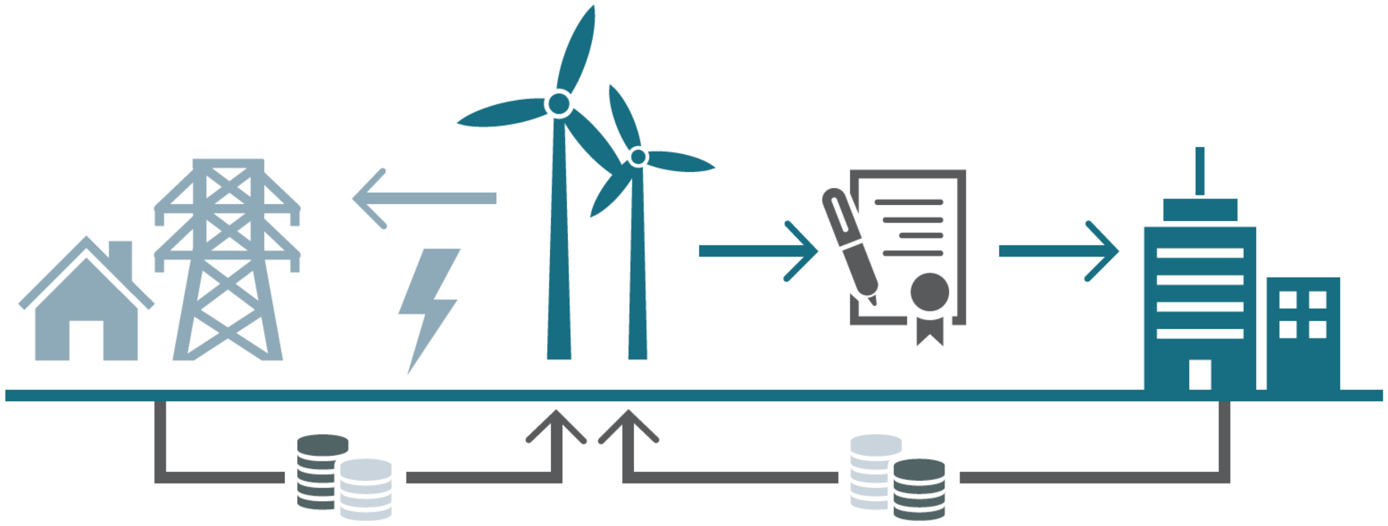


Meeting Corporate Renewable Power Targets

Alessio Trivella

University of Twente

Joint work with Danial Mohseni-Taheri (UIC) and Selva Nadarajah (UIC)

Enschede, 04.11.22

Background

University of Milan
BSc & MSc in Mathematics
(2007-2012)

Bip. Consulting
Management Consulting
(2012-2015)

Technical Univ. of Denmark
PhD in Operations Research
(2015-2018)

ETH Zurich (IVT)
Postdoc
(2019-2021)

UT (BMS, IEBIS)
Assistant Professor of Operations Research
(2022-)

My Research Interests

1. ENERGY OPERATIONS

- Renewable energy
- Energy systems and markets
- Real options

2. TRANSPORT and LOGISTICS

- Commodity network flows
- Packing and loading problems
- Railway scheduling

SUSTAINABILITY

- EE transport operations

3. APPROXIMATE DYNAMIC PROGRAMMING

- Solution of high-dimensional stochastic optimization problems

Teaching at the UT

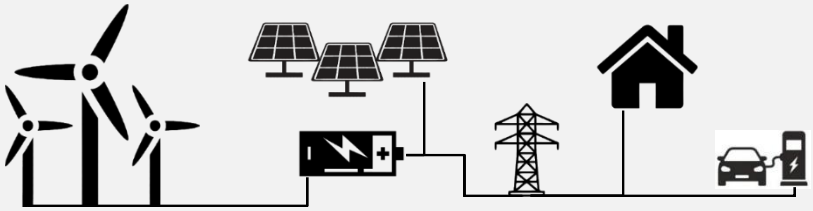
I teach in the Industrial Engineering and Management BSc and MSc programs

1. Operations Research Techniques 1 (MSc IEM)

2. Modeling and Analysis of Stochastic Processes (BSc IEM, M8)

3. Optimization of Sustainable Energy Systems

New MSc course offered in Q2, jointly with D.Guericke



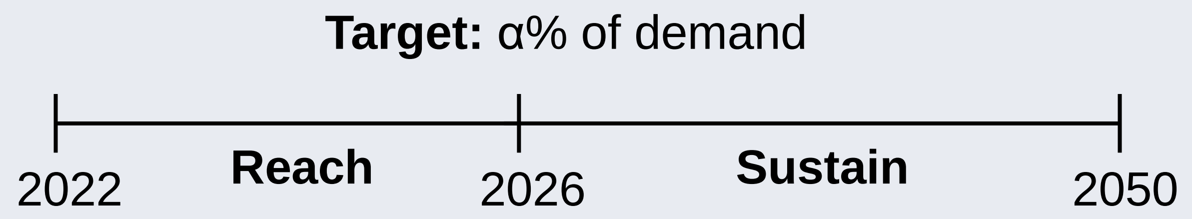
- Tackle optimization problems that arise in the energy sector, involving energy systems, electricity markets, real options, and modern challenges related to the energy transition
- Deterministic and stochastic optimization techniques (MILP, SP, MDP)

Corporate Sustainability Goals

Over 60% the Fortune 500 companies have committed to sustainability / climate targets (Cervantes et al. 2021)

- GHG emission reduction
- Energy efficiency
- **Renewable energy procurement**

Corporate commitments to satisfy a percentage of energy demand via renewable sources



2021: ~100 of Fortune 500, ~60 of which with a 100% target (Cervantes et al. 2021)

Meeting a Renewable Power Target

Two dominant approaches:

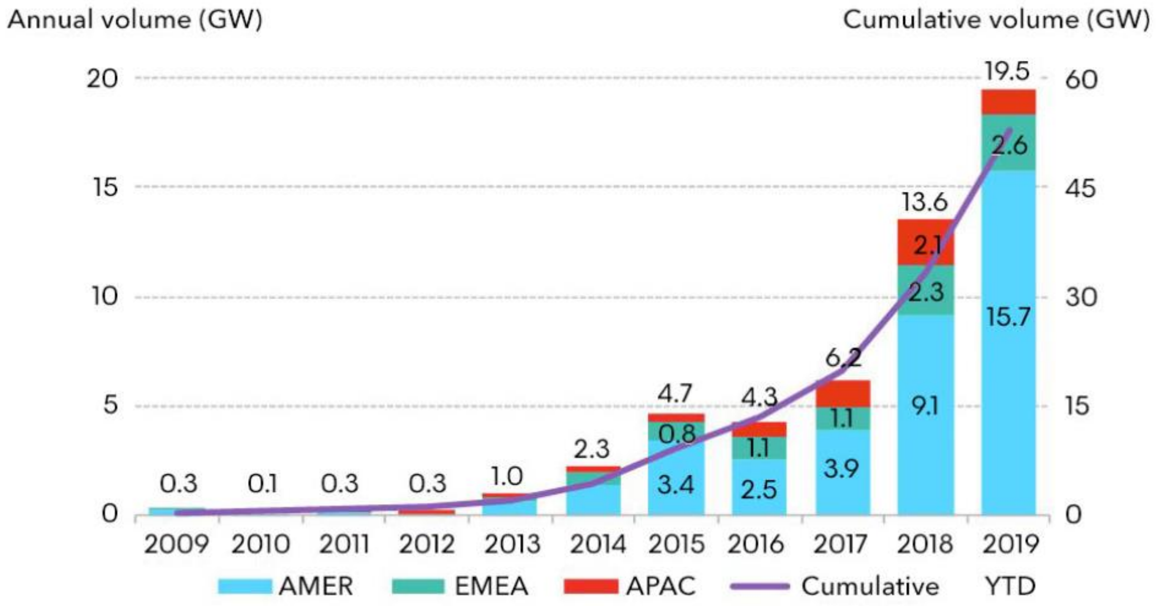
1. Short-term strategy
   - Purchase electricity from the utility
   - Purchase unbundled renewable energy certificates (**RECs**) when needed

2. Enter into **corporate power purchase agreements (PPAs)**
   - Long-term contracts between company and generator
   - Deliver both energy and RECs at fixed strike price

(from IRENA 2018)

We focus on the most-common virtual (or synthetic) PPAs

Corporate Power Purchase Agreements



- Global PPA volumes are rising sharply (BloombergNEF 2018, 2020)
- Despite encouraging trends, the majority of corporations have not signed PPAs yet

Goal of our work is understanding:

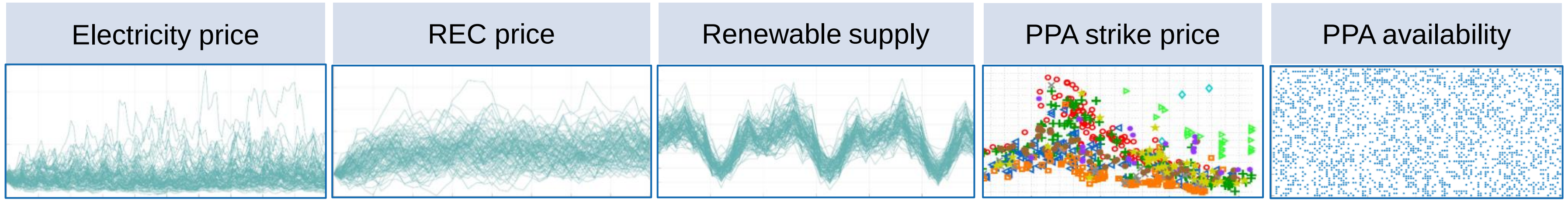
1. When a PPA is an effective procurement vehicle for renewable power
2. How a firm can reduce procurement costs while meeting a renewable energy target, potentially using a portfolio with multiple PPAs

Challenges for Decision Making

Ideally, a company wants to fulfill the target at minimum cost, but:

1. Long-term planning horizon (e.g., 40 years)
2. PPAs are fairly new and “non-traditional” procurement instruments
3. Different decisions to make:

4. Many uncertainties:



Overcoming these challenges entails solving a complex problem

Finite-horizon Markov decision process

$$\min_{\pi\in\Pi} \mathbb{E}\left[\sum_{i\in\mathcal{I}} \delta^i c_i(x_i^\pi, w_i, a_i^\pi(x_i^\pi, w_i)) \middle| (x_0, w_0)\right]$$

Stochastic dynamic programming formulation

$$V_I(x_I, w_I) = c_I(x_I, w_I),\ \forall (x_I, w_I) \in \mathcal{X}_I \times \mathcal{W}_I,$$

$$V_i(x_i, w_i) = \min_{a_i\in\mathcal{A}_i(x_i)} \left\{c_i(x_i, w_i, a_i) + \delta\mathbb{E}\left[V_{i+1}\left(f_i(x_i, a_i), w_{i+1}\right) \middle| w_i\right]\right\}$$
$$\forall (i, x_i, w_i) \in \mathcal{I} \times \mathcal{X}_i \times \mathcal{W}_i$$

Stages $i \in \mathcal{I} = \{0, 1, \ldots, I-1\}$

Endogenous state $x_i \in \mathcal{X}_i$

Exogenous state $w_i \in \mathcal{W}_i$

Action $a_i \in \mathcal{A}_i(x_i)$

Immediate cost $c_i(x_i, w_i, a_i)$

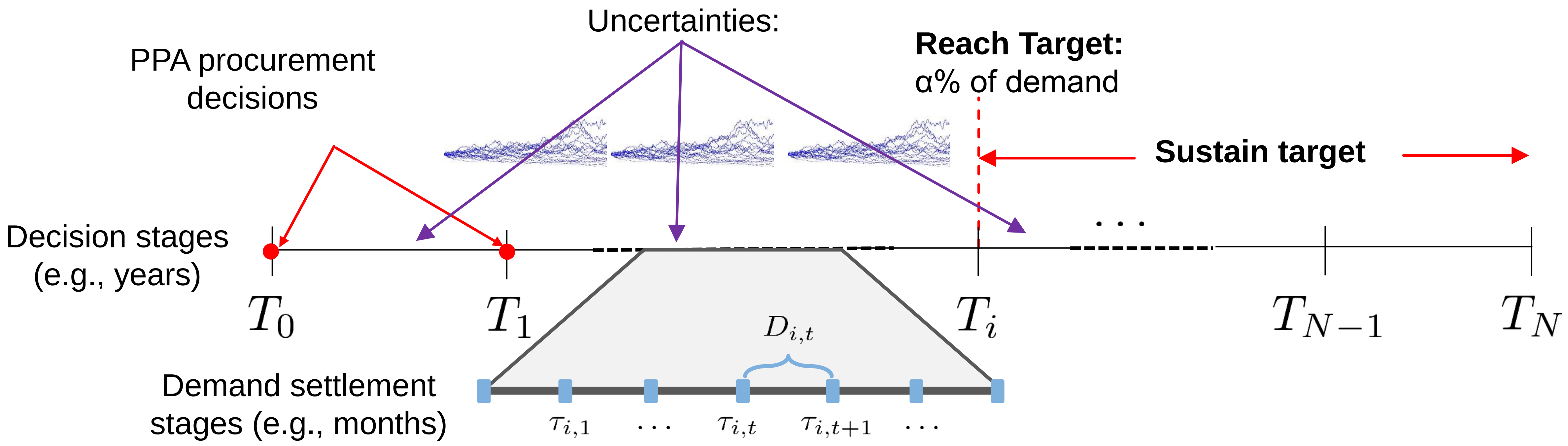
Transition $x_{i+1} = f_i(x_i, a_i) \in \mathcal{X}_{i+1}$

Policy $\pi = \{a_i(\cdot,\cdot) : \mathcal{X}_i \times \mathcal{W}_i \longrightarrow \mathcal{A}_i, i \in \mathcal{I}\} \in \Pi$

Usually intractable because of the “curses of dimensionality”

- High-dimensional state space
- High-dimensional action space / difficult optimization, e.g., non-convex
- High-dimensional outcome space / hard to compute expectations

Our MDP

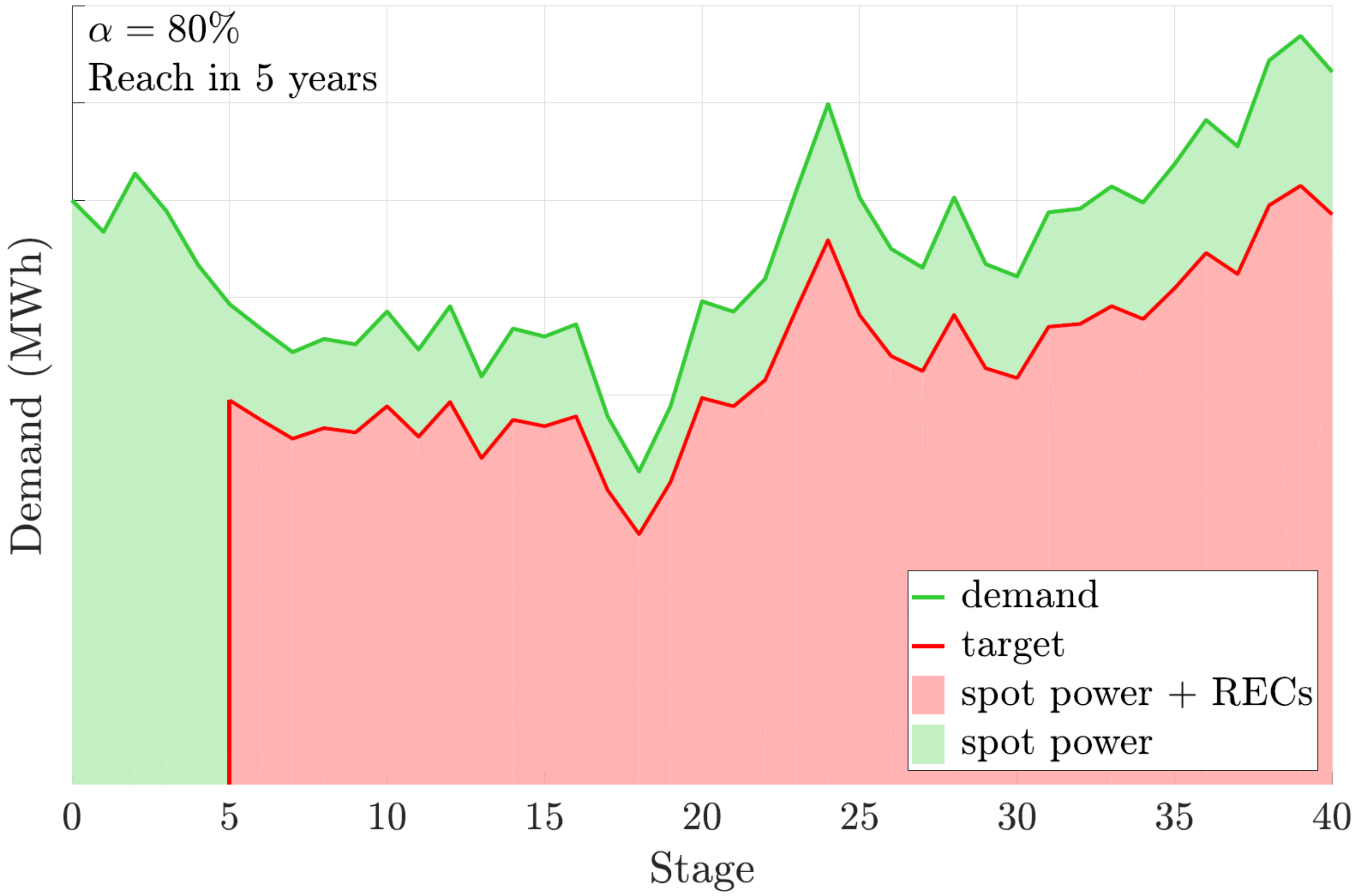


In our numerical study, this MDP has:

25-dim continuous endogenous state	5-dim continuous action space
26-dim continuous exogenous state	Non-convex action space and value function

Simplest Benchmark: short-term

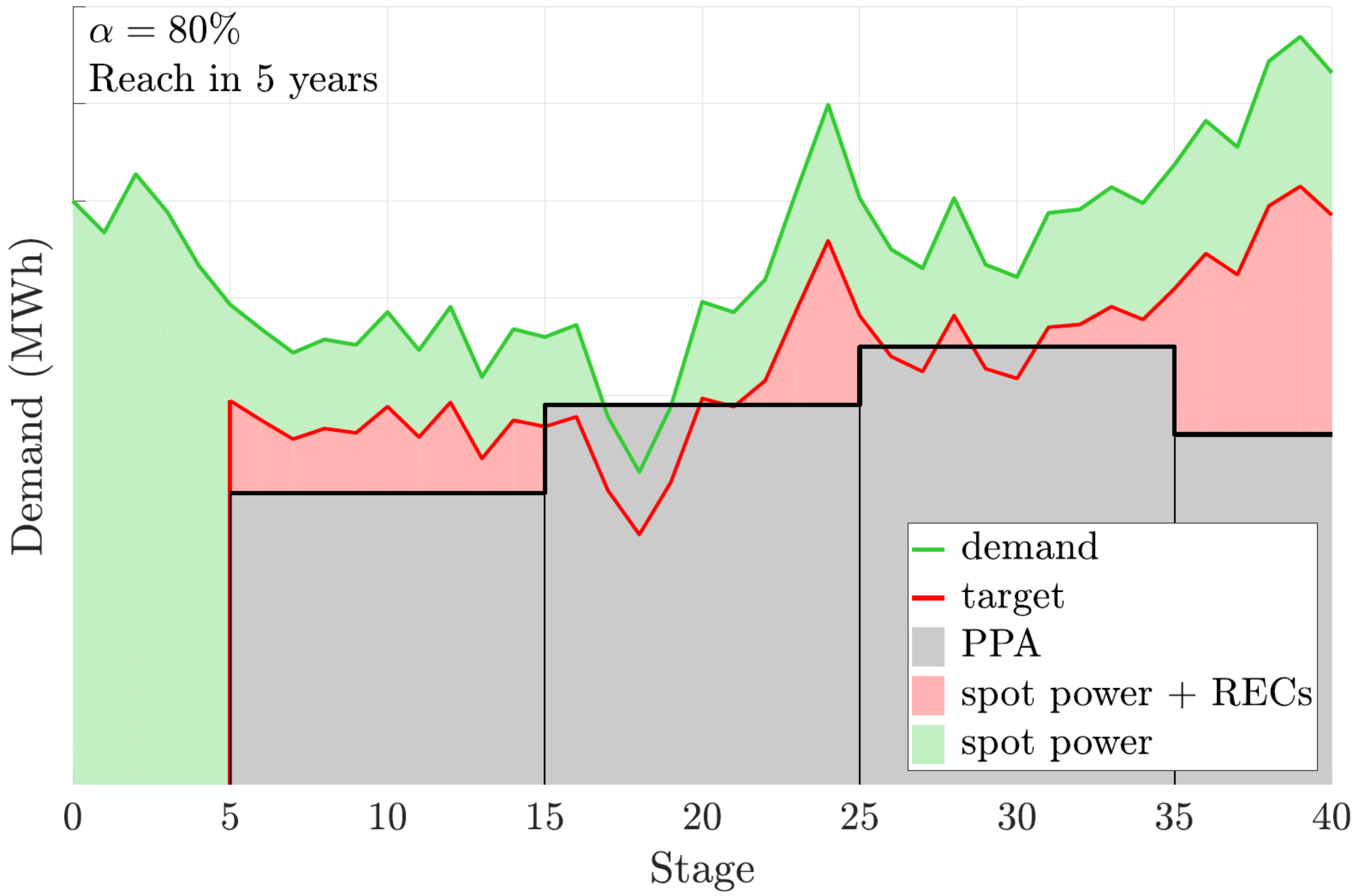
Electricity and unbundled RECs are purchased from the short-term market/utility



- No analytics needed
- Fully exposed to price risk

Forecast-based Block Heuristic (FBH)

Traditional use of PPAs renewed in a rolling fashion (WBCSD 2018)



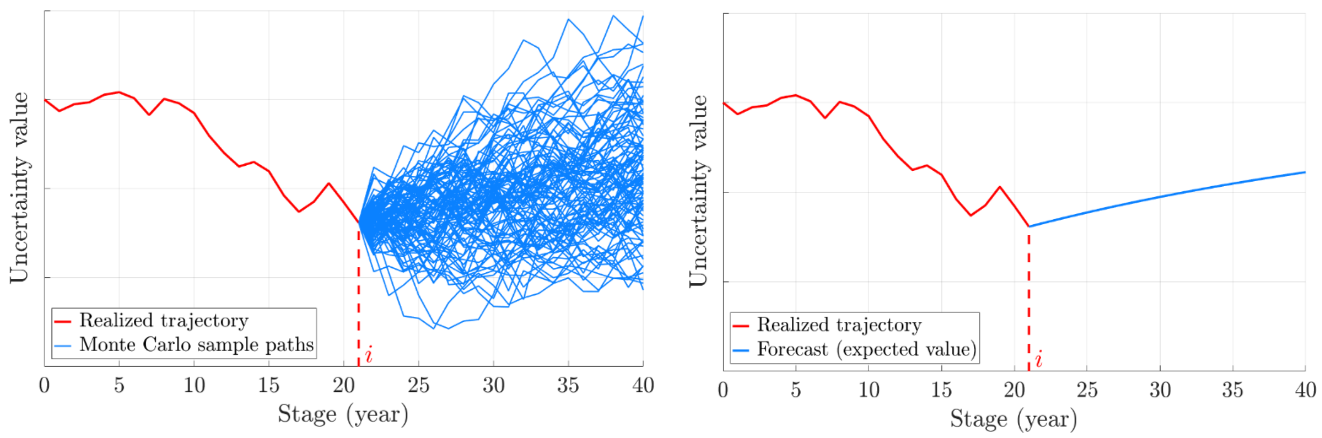
- Hold a single PPA at any time
- Renew it when needed

Forecast-based Reoptimization Heuristic (FRH)

Popular in operations management problems under uncertainty (Sethi and Sorger 1991, Chand et al. 2002, Sethi et al 2004, Bertsekas 2005, Balakrishnan and Cheng 2009, Lian et al. 2009)

At a stage i:

1. Replace future uncertainty by forecasts
2. Solve deterministic optimization model
3. Implement current decision only
4. Move to $i+1$ and repeat



- We can vary the **sourcing** and **timing flexibility**
- FRH does not **directly account** for the unfolding of uncertainty (based on a static model)
- FRH provides a policy but no **lower (dual) bound** to assess its quality

Information Relaxation and Duality

- Dual bounds based on perfect information are often loose

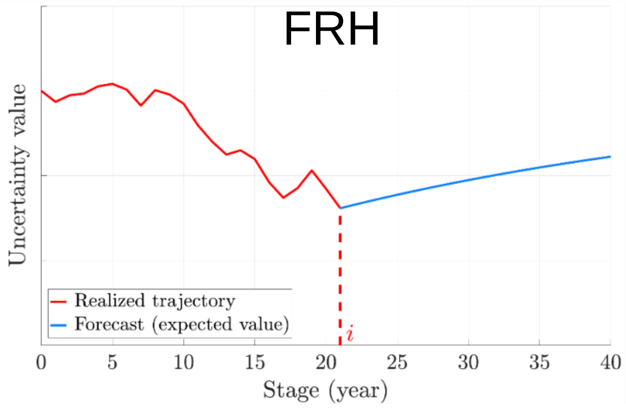
- Information relaxation and duality is a more general approach (Brown et al. 2010, 2014, Brown and Haugh 2017, Nadarajah and Secomandi 2018, Ye et al. 2018)
  1. Penalize knowledge of future information using a dual penalty function
  2. Solve a deterministic problem with costs corrected by the dual penalty

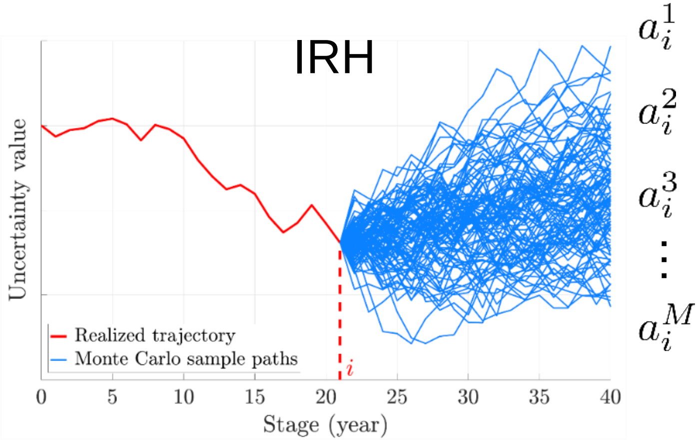
- There are different ways of defining dual penalties, e.g.:
  1. Standard procedure given an MDP value function approximation
  2. Linear penalties in the action or state

Information-relaxation based Reoptimization Heuristic (IRH)

Combine reoptimization with information relaxation and duality

1. Solve deterministic hindsight optimization on sample paths, with costs corrected by dual penalty

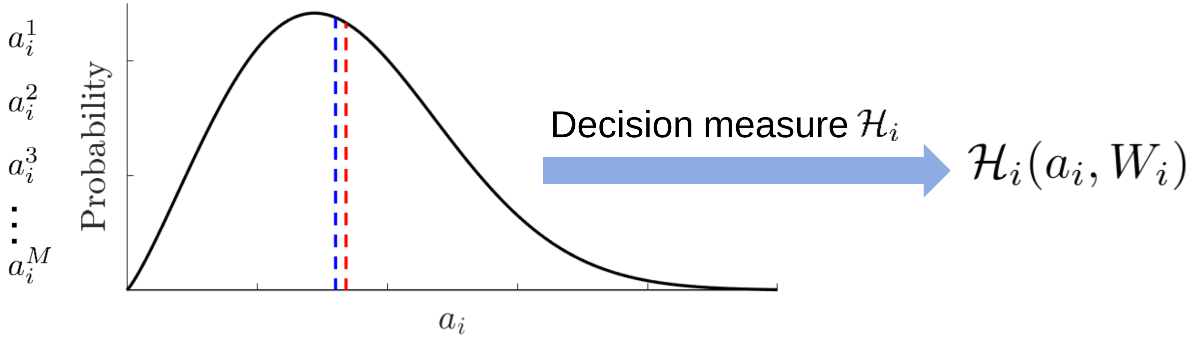




Distribution of optimal actions

2. Extract a non-anticipative decision from the action distribution (mean, median, …)

3. We obtain at the same time a dual bound



We have theoretical results on feasible decisions, optimality, convexity…

Numerical Study

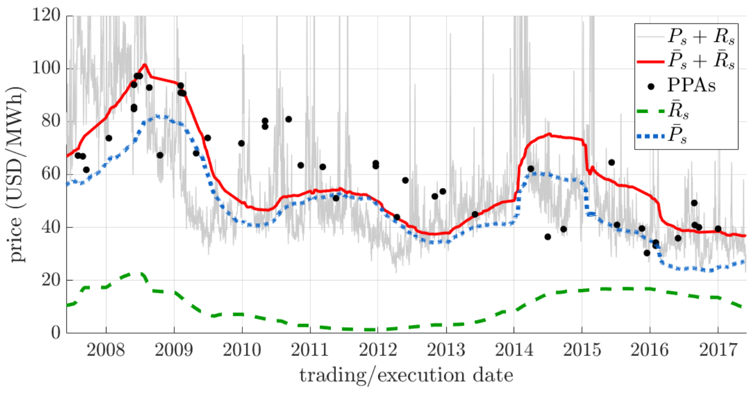
1 Procurement and operational parameters

- Instances based on two large data centres
- 40 years (stages) with a 90% target to reach in 5 years
- Contract lengths: 5, 10, 15, 20, 25 years based on Google's portfolio
- Discount factors, min/max PPA size, premia,etc.

2 Stochastic models of the uncertainty calibrated on market data

- Electricity prices: mean reverting process with jumps and seasonality (Lucia and Schwartz 2002, Cartea and Figueroa 2005, Weron 2014)
- Renewable energy supply: mean reverting process (Loukatou et al. 2018)
- RECs prices: Jacobi diffusion process (Zeng et al. 2015)
- Contract availability: Bernoulli random variables

3 Novel PPA strike price model calibrated on electricity price, REC price, and PPA prices (Berkeley Lab 2020)

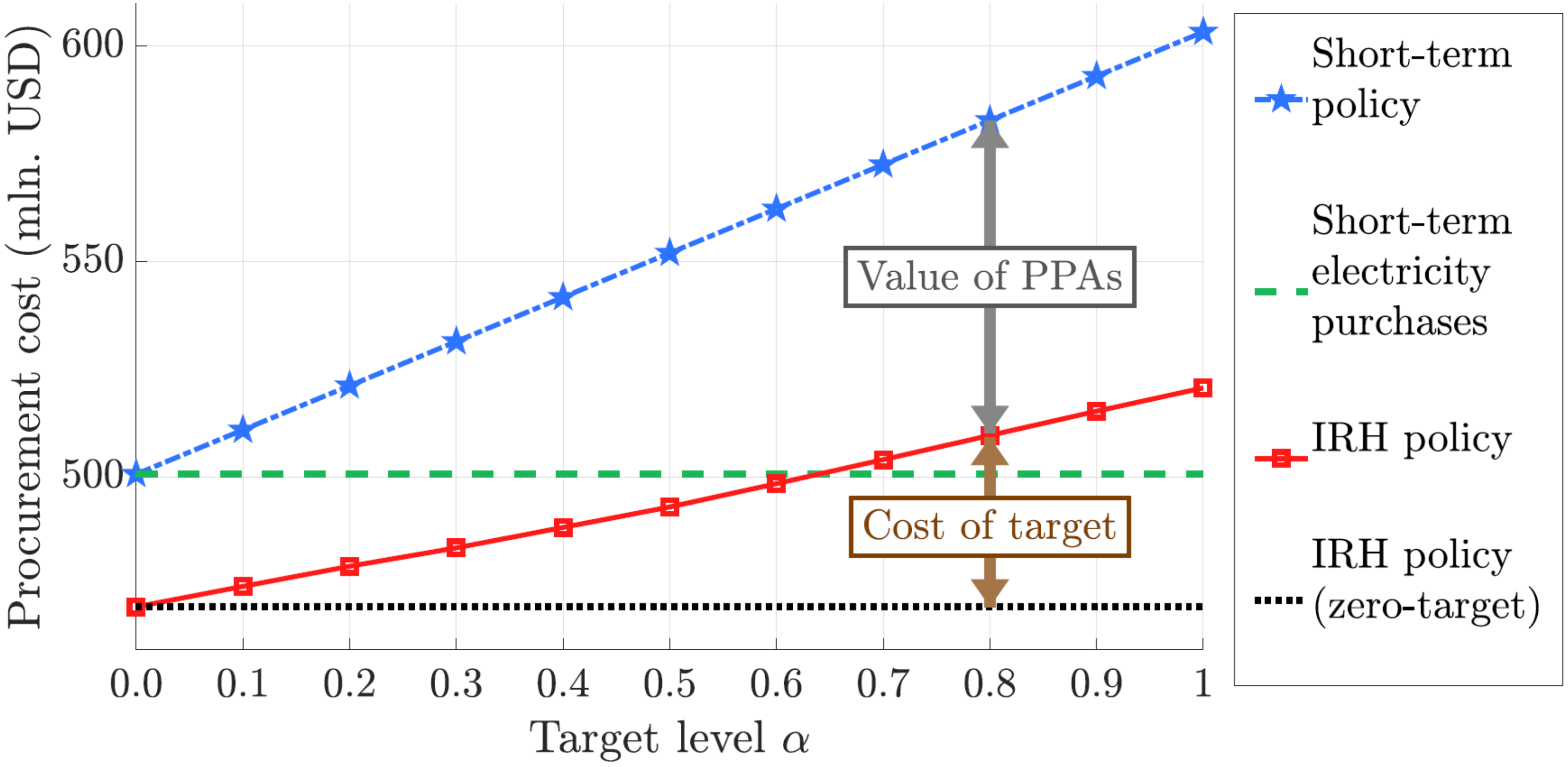


Value of Accounting for the Uncertainty

Policy/Bound	Procurement cost (mln.USD)	Optimality gap (%)
Short-term	593.1	23.0
FRH	537.8	11.6
IRH	515.3	6.9
Dual bound	482.1	-

- Short-term policy implies much larger costs and gaps
- IRH outperforms FRH

Cost of a Renewable Target and Relevance of PPAs



The “cost of the target”

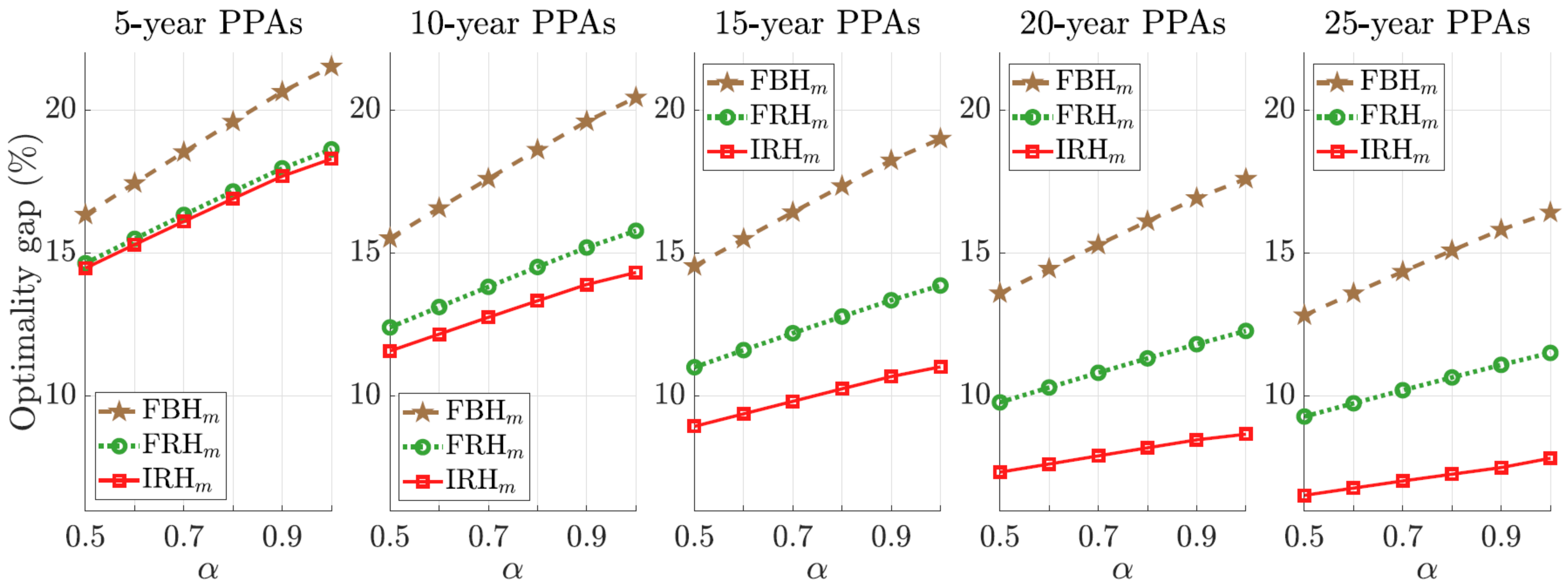
- depends the policy
- increases linearly
- is lower if PPAs are used

PPAs:

- Help decresing the cost of the target
- Are useful even with a zero target

Value of Timing Flexibility

We compare single-contract policies: timing flexibility reduces costs **by 3.5%** on average

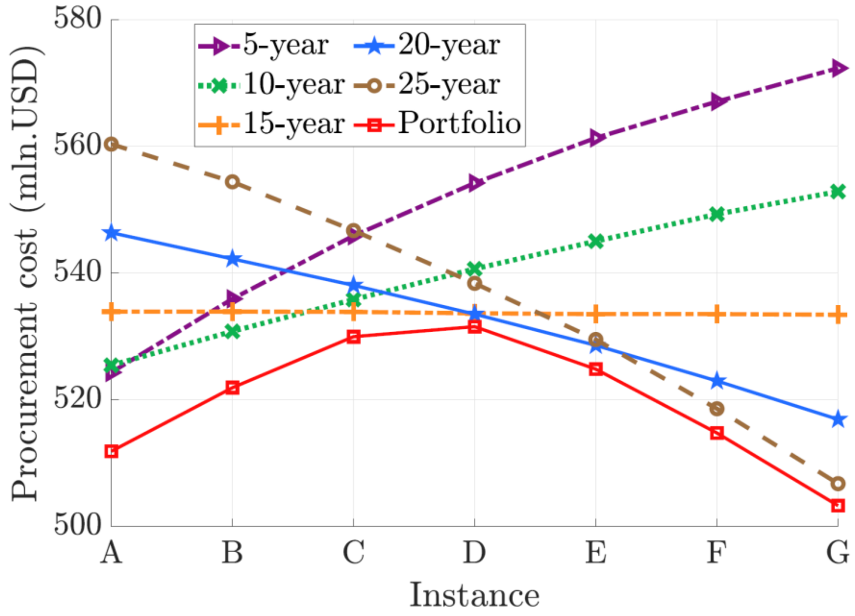


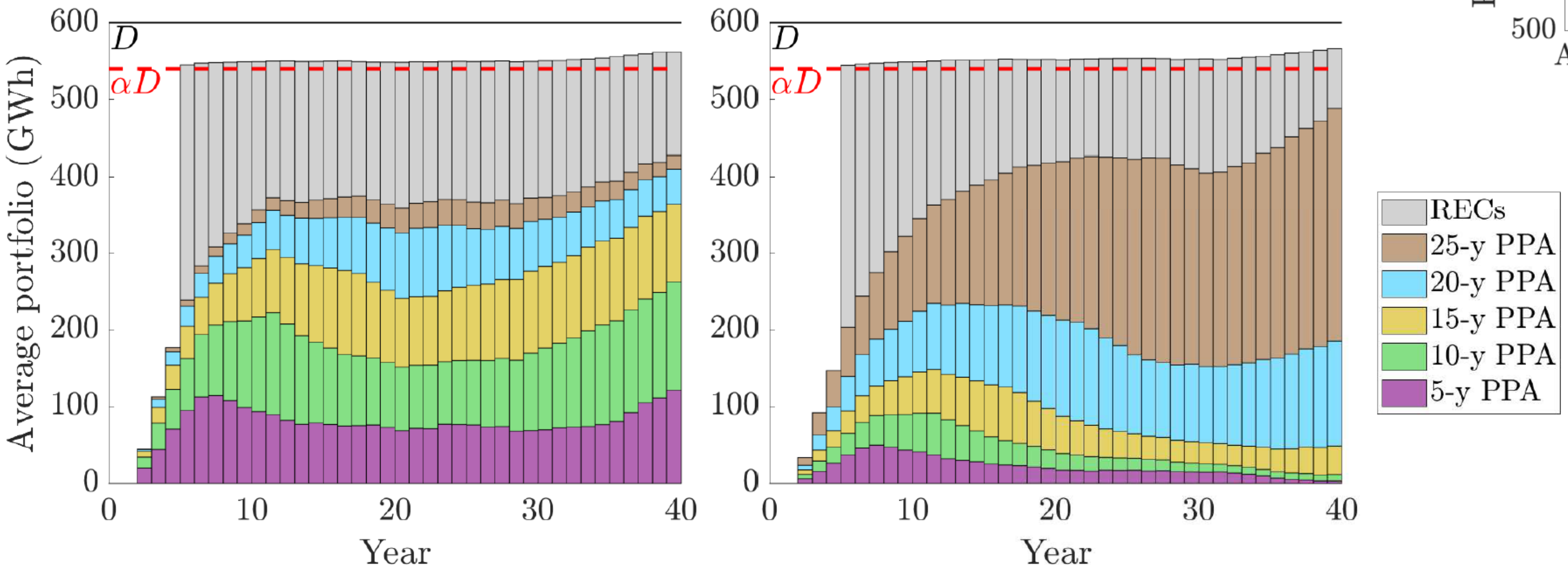
Timing flexibility translates to the optionality of reserving some renewable power capacity to future better deals, that occur in the future with a certain probability

Value of Sourcing Flexibility - PPA portfolios

- Portfolios including multiple contracts with different duration are more robust when market parameters vary, with average improvement of **4%**

- E.g., portfolios allows for better adapting to the relative attractiveness of different PPA types





Conclusion

- Corporate renewable power purchases can significantly help with the renewable energy transformation to meet global climate goals
- We study the use of **PPAs** to meet a renewable power purchase target while managing costs, which is a **contemporary** and **challenging** problem
- We consider simple benchmarks and forecast-based reoptimization heuristics consistent with practice, and develop a novel information relaxation-based reoptimization heuristic
- Sourcing and timing flexibilities significantly decrease procurement costs, and our information-relaxation policy outperforms other policies
- The managerial insights we uncovered can help companies balancing **climate goals** (i.e., meeting the renewable target) and **financial performance** (i.e., energy costs)

Future work on Targets (1/2)

- The work I presented deals with an “average” target on renewable energy in a year
- Leading companies in renewable energy procurement are thinking about the next level target

(100%) renewable energy targets → 24/7 matching

(Current paper)

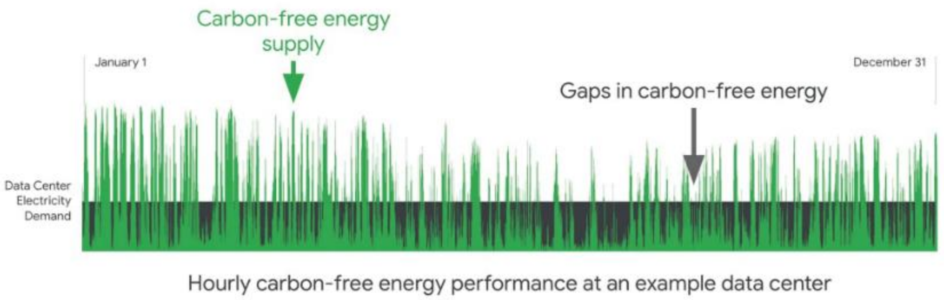
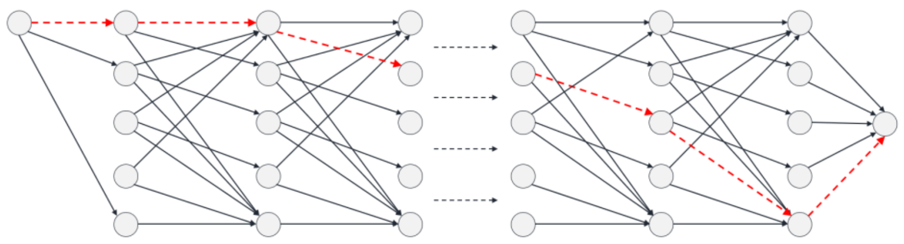


Image: https://www.weforum.org/agenda/2021/11/no-more-greenwashing-24-7-clean-energy/

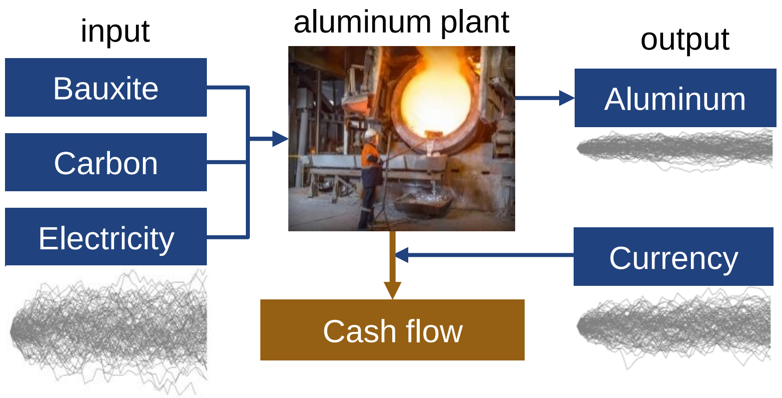
- How? PPAs + storage + demand response / Optimization and AI
- I started to write a proposal for an “NWO Open Competition Domain Science – M”

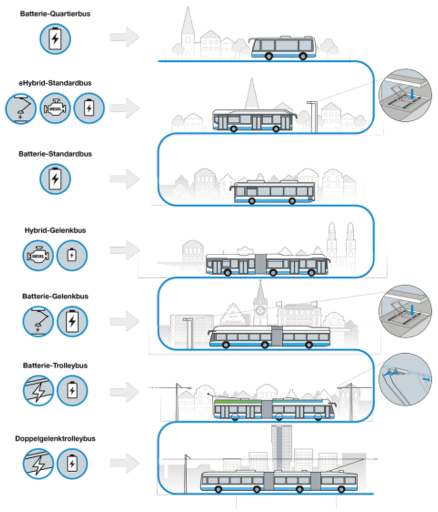
Future work on Reoptimization (2/2)

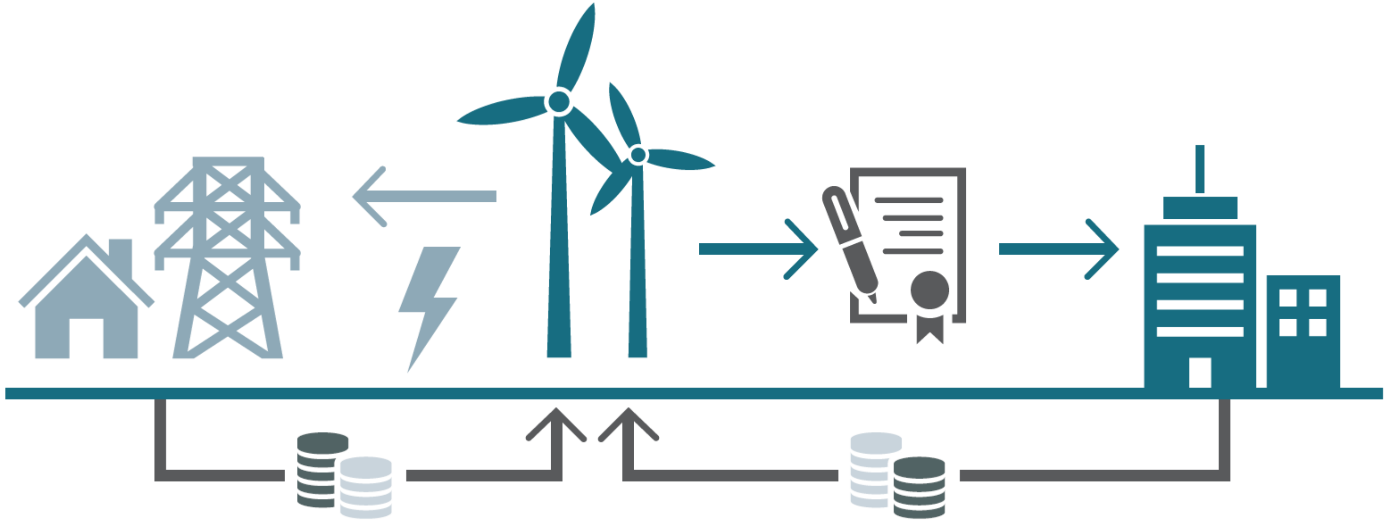
- I am working on a methodological extension of IRH to tackle a class of MDPs (energy real option problems)
- This method uses network algorithms and information relaxations to provide a policy and dual bound



- Promising preliminary experiments on energy production and fleet upgrade applications







Appendix

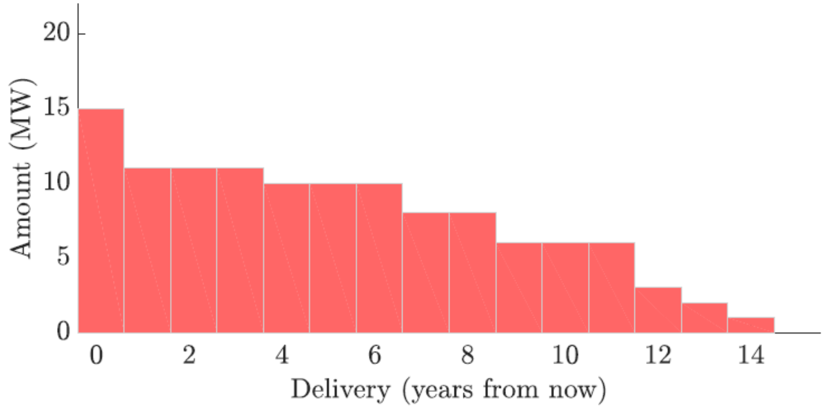
Summary of Contributions

1. **Framework**: Propose a Markov decision process (MDP) that accounts for **timing flexibility**, **sourcing flexibility**, and **uncertainty** when making procurement decisions

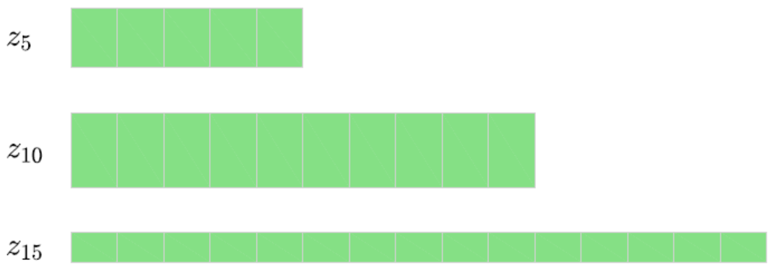
2. **Procurement tools:**
   - Consider forecast-based reoptimization heuristics and simple benchmarks (they sacrifice some MDP properties)
   - Develop a novel dual reoptimization heuristic that is consistent with the MDP policy properties, and has desirable theoretical support

3. **Computation and insights:** Define new PPA strike price model, calibrate stochastic models of uncertainty to real data, perform a comparison of procurement policies to meet a renewable target using PPAs, and understand what makes such policies effective

Endogenous States, Actions, Transitions

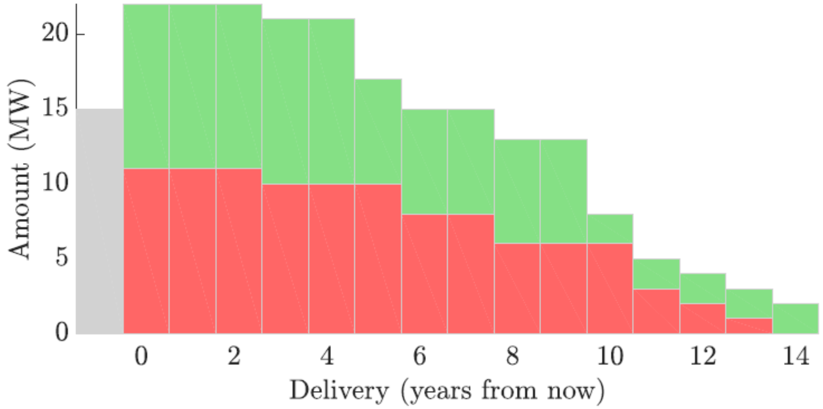


(a) Current stage i state x_i



(b) PPA investment decision at state i

(c) Power delivery profile from new PPAs



(d) New state x_{i+1}

Procurement Analytics

The optimal MDP policy is challenging to compute: MDP is intractable to solve when using realistic models of uncertainty and incorporating contract minima

Current practice

- Short-term procurement or simple algorithms
- Typically rolling horizon strategies based on forecasts
- Also known as model predictive control

Our approach

- New ADP method
- Based on the information relaxation and duality approach
- Decisions explicitly account for the unfolding of future uncertainty

Need for a new method?

EXOGENOUS state: LOW dim → HIGH dim

ENDOGENOUS state: LOW dim → HIGH dim

1

SDP

stochastic dynamic programming

(Puterman 2005)

2

LSM

least squares Monte Carlo

(Longstaff and Schwartz 2001, Tsitsiklis and Van Roy 2001)

3

ALP, SDDP

approximate linear programming, stochastic dual dynamic programming

(de Farias and Van Roy 2003, Pereira and Pinto 1991)

4

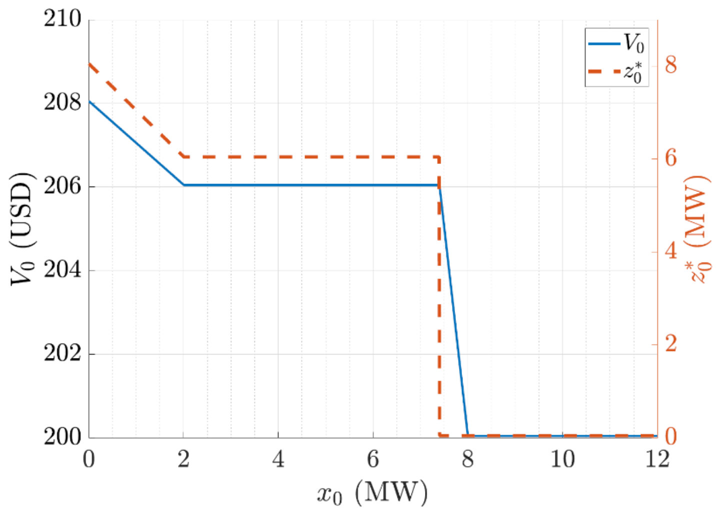
(FRH) Limited

sophisticated policy iteration methods, e.g., LSM extensions

→ rely on convexity

(Nadarajah and Secomandi 2017)

IRH Theory



- We show that our model (MDP value function) is
  - Non-convex, in general
  - Convex when we relax some assumptions

- We characterize when the IRH decision measure leads to a feasible action, e.g.
  - The mean is feasible under some assumptions
  - The component-wise median leads to a feasible action also in the presence of non-convexities

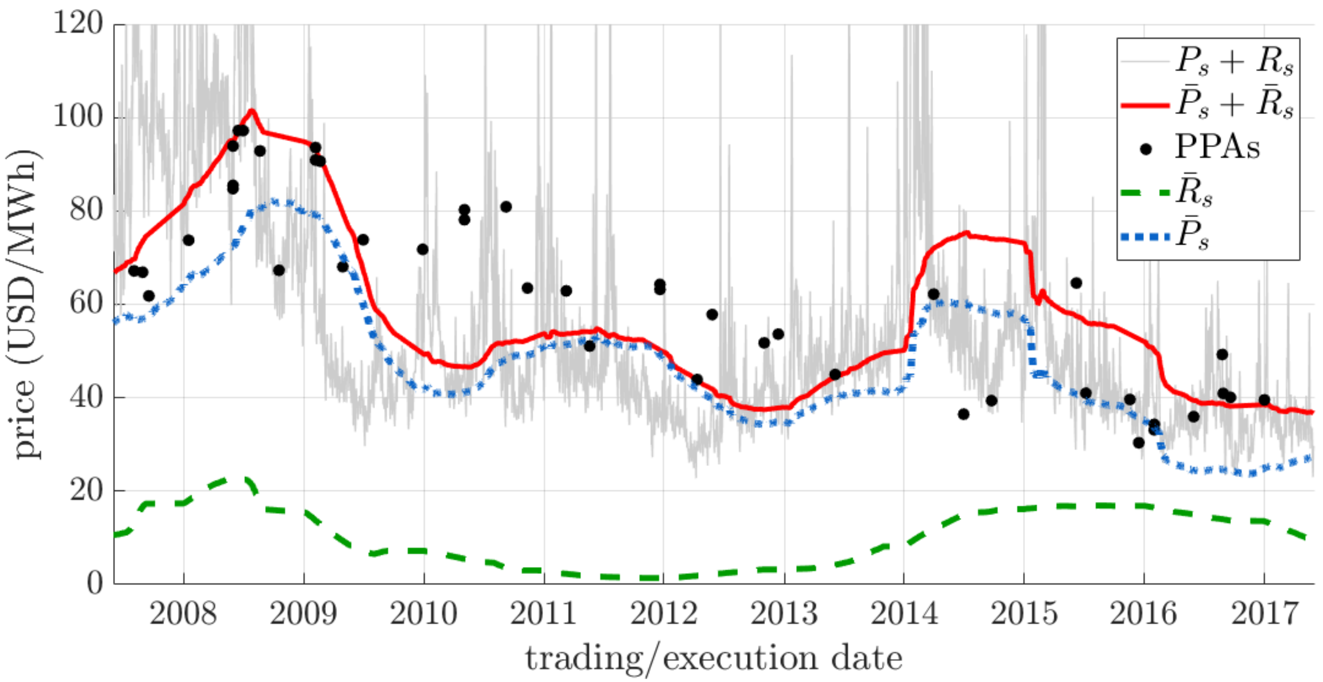
- We show that our IRH method is optimal (on every sample) when using an “ideal” penalty

More on Strike Price Model

PPA strike price

Generator model: calculate NPV and set strike price such that NPV is positive after return on investment (NREL 2017)

Market model: baseline value based on electricity and REC prices, plus a latent variable / stochastic variations



- Baseline: past-year averages
- Stochastic factor: mean-reverting and bounded process (Jacobi)
- Calibrated on electricity price, REC price, and PPA prices (Berkeley Lab 2020)

Summary of Methods

Policy	Accounts for the uncertainty	Includes PPAs	Has timing flexibility	Has sourcing flexibility
Short-term policy	NO	NO	NO	NO
FBH_m (single-contract)	NO	YES	NO	NO
FRH_m (single-contract)	NO	YES	YES	NO
FRH (portfolio)	NO	YES	YES	YES
IRH_m (single-contract)	YES	YES	YES	NO
IRH (portfolio)	YES	YES	YES	YES

IRH can be used with:

- Zero penalty vs optimized penalty (local search guided by dual bound estimate)
- Mean vs median decision measure

More on Policy Comparison

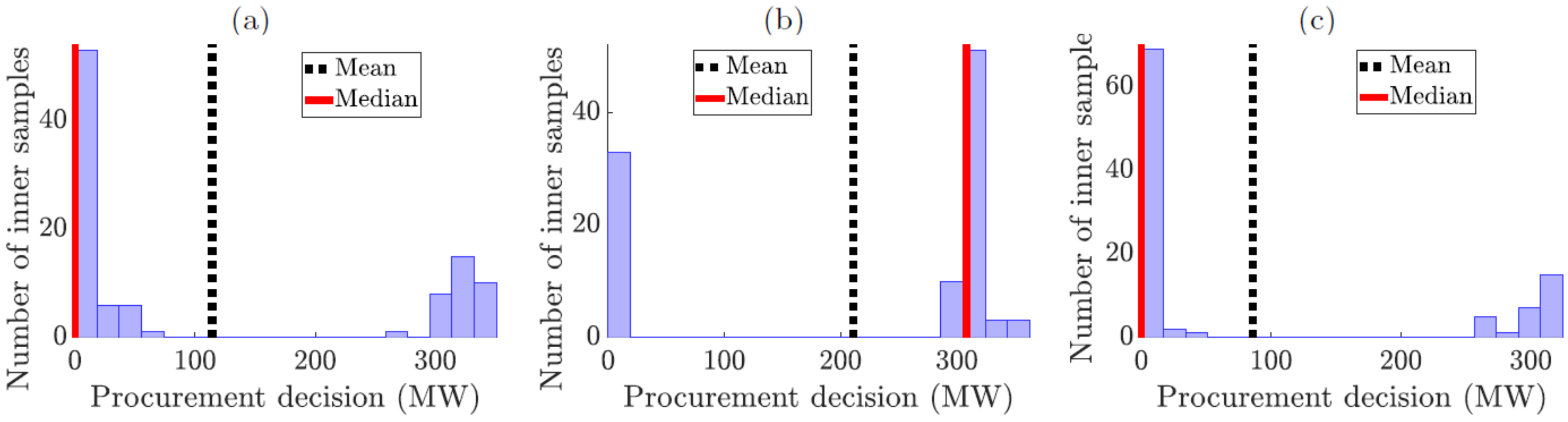
Procurement cost (mln.USD) and optimality gap (%) for reference instance using 90% target, and on average over 11 instances with target varying from 0% to 100%.

	Procurement cost		Optimality gap	
Policy/Bound	Reference	Average	Reference	Average
Short-term	593.1	552.0	23.0	18.0
FRH	537.8	512.8	11.6	9.6
IRH_0(avg)	526.3	502.4	9.2	7.4
IRH_0(med)	522.0	499.5	8.3	6.8
IRH_+(avg)	520.6	499.0	8.0	6.7
IRH_+(med)	515.3	494.2	6.9	5.6
Dual bound_0	468.5	457.2	−2.8	−2.2
Dual bound_+	482.1	467.5	-	-

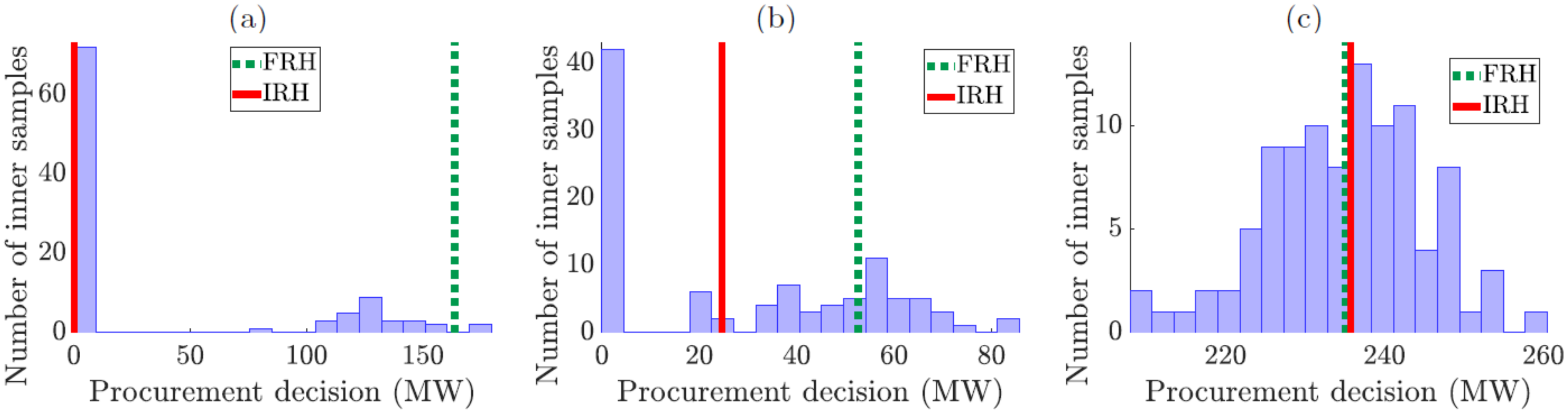
We focus on the best IRH variant

- Short-term policy implies very larger costs and gaps
- All IRH variants outperform FRH
- Optimizing the dual penalty is useful
- The median decision measure is slightly better than mean

Comparison of Procurement Decisions



IRH mean vs IRH medial



FRH vs IRH

More on the Value of Timing Flexibility

- Flexible policies FRH_m / IRH_m sign smaller contracts more frequently

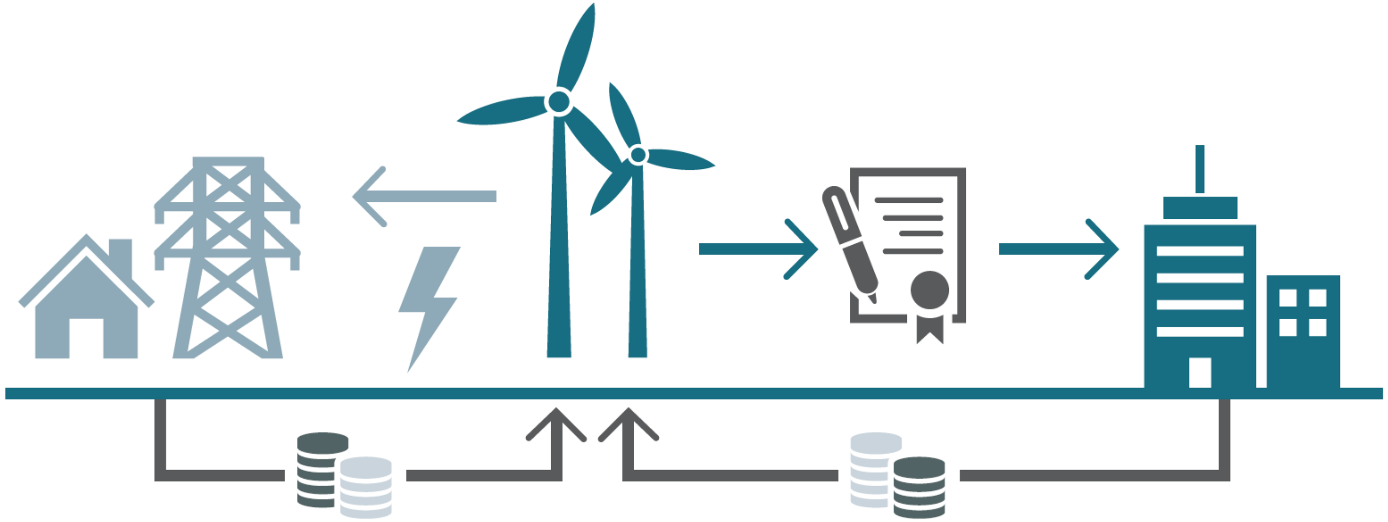
$m \in \mathcal{M}$	Average frequency (years)					Average contract size (MW)				
	5	10	15	20	25	5	10	15	20	25
FBH_m	8.6	13.0	17.1	20.7	25.9	186.3	186.5	186.8	187.3	187.5
FRH_m	8.4	11.1	11.9	14.0	15.7	167.5	151.9	139.4	138.4	141.8
IRH_m	8.6	11.2	12.3	13.3	14.5	159.4	146.9	142.2	141.3	148.7

- Timing flexibility translates to the optionality of reserving some renewable power capacity to future better deals, that occur in the future with a certain probability

- Thus, FRH_m / IRH_m sign cheaper deals on average

$m \in \mathcal{M}$	5	10	15	20	25
FBH_m	43.7	43.5	43.2	41.9	41.7
FRH_m	38.2	38.5	38.5	38.2	37.6
IRH_m	36.6	35.9	35.5	34.7	34.1

Average weighted strike price in USD/MWh of the contracts signed



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2021 Best Paper Award by CEMA (Commodity and Energy Markets Association)