Direct investments in renewable energy portfolios: Stochastic NPV-based capacity budgeting

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- Optimal renewable energy portfolio decision from an investor's point of view:
  - What is the optimal level of investment in renewables?
  - What is the optimal generation mix?
- Classical approach to capital budgeting problem: Markowitz (1952)
- We propose an alternative stochastic and data-driven modeling approach in the "minimum exceedance probability framework"
- Optimal renewable energy portfolio has the property:
  - 1. Minimizes capital expenditures
  - 2. Subject to probabilistic constraint on the profitability of the investment

#### Framework





#### Framework







- Optimal investment decision in the portfolio-theoretic context has been applied in the field of energy economics (Bar-Lev & Katz, 1976; Awerbuch & Berger 2003; Awerbuch & Young 2005)
- In direct investment domain size of investment is not fixed by investor's initial wealth but investment levels have to be determined explicitly
- Profitabiliy of investment by techno-economic assessment (Sommerfeldt & Madani, 2017) via NPV (Short et al., 1995)
- In our model we deal with two main sources of uncertainty:
  - Uncertain production volumes (wind and solar, e.g. Tietjen et al., 2016)
  - Profitability requirement via probabilistic constraint (Charnes & Cooper, 1959) on the NPV of the investment project

## The Model 1/2



- Models with probabilistic constraints gaining increasing attention (Geng & Xie, 2019)
- Ondra et al. (2021) discuss investment problem from prosumer's point of view (stochastic hourly supply-demand constraint)
- We abstract from variable costs

$$\min_{x_1,\dots,x_n} \sum_{i=1}^n c_i x_i$$

s.t. 
$$\Pr{\{\operatorname{NPV}(\mathbf{x}) \ge \theta\}} \ge \chi$$
.

- $x_i$  ... capacity of i-th technology
- $c_i \ \dots \ \text{price per unit of installed } x_i$
- $\theta$  ... threshold probability
- $\chi$  ... confidence parameter

# The Model 2/2



$$\Pi(\mathbf{x}) = \sum_{i=1}^{n} \sum_{t=1}^{y\Delta T} S_t p_{it} x_i \left(1 + \frac{r}{\Delta T}\right)^{-t} = \sum_{i=1}^{n} x_i \tilde{\pi}_i,$$

$$\operatorname{NPV}(\mathbf{x}) = \sum_{i=1}^{n} x_i \left(\tilde{\pi}_i - c_i\right) = \sum_{i=1}^{n} x_i \pi_i$$

$$x_i \dots \text{ capacity of i-th technology} \qquad \tilde{\pi}_i \dots \text{ revenue per unit of } x_i$$

$$\pi_i \dots \operatorname{NPV} \text{ per unit of } x_i \qquad \Delta T \dots \text{ hours in one year (8760)}$$

$$p_{it} \dots \text{ power output per unit of } x_i \qquad S_t \dots \text{ spot market price}$$



- ► CAPEX minimizing renewable energy portfolio (wind and solar) s.t probability to obtain NPV over the lifetime of the energy park y = 25ylarger than  $\theta = 1$   $Mio \in$  is at least  $\chi$
- Prices of investment in renewables (wind and solar):

$$c_1 = 2.000 \in /kW, \ c_2 = 800 \in /kW$$

Sample from real world data of solar irradiance and wind speed in Schwechat, Austria (ASOS and CAMS solar radiation, hourly data available from 2012-2018); hourly electricity spot market prices from EXAA



Wind speed and solar irradiance are translated into power output via the physical energy model



#### Model calibration





Hourly values for: (a) wind power output per installed MW (b) solar power output per installed MW and (c) energy price ( $\in$ /MWh)



- Create sample to simulate NPV over expected useful lifetime of the energy park via block-bootstrapping
- Block size of 3 days to incorporate short and long term weather trends

#### Model calibration





Aggregated data over lifetime of the energy park: (a) revenues ( $M \in /MW$ ) per MW installed capacity of wind technology (b) revenues ( $M \in /MW$ ) per MW installed capacity of wind technology



Replace probabilistic constraint by deterministic sample:

$$\Pr\{\operatorname{NPV}(\mathbf{x}, \boldsymbol{\xi}) \ge \theta\} \ge \chi \quad \longleftarrow \quad \operatorname{NPV}(\mathbf{x}, \boldsymbol{\xi}^{(i)}) \ge \theta, \qquad i = 1, \dots, N$$

$$\boldsymbol{\xi} = (\operatorname{spot price, production volume, \dots)}$$
set of all uncertain parameters

- Sample approximation introduced in Calafiore & Campi (2005)
- Sample & Discard algorithm (Campi & Garatti, 2011): Remove (reliability dependent) number of constraints according to any algorithm
- $\blacktriangleright$  Solution is robustly feasible with reliability level  $\chi$



$$\min_{x_1, x_2} c_1 x_1 + c_2 x_2 \quad s.t.$$

$$x_1(\tilde{\pi}_1^{(1)} - c_1) + x_2(\tilde{\pi}_2^{(1)} - c_2) \ge \theta$$

$$\vdots$$

$$x_1(\tilde{\pi}_1^{(N)} - c_1) + x_2(\tilde{\pi}_2^{(N)} - c_2) \ge \theta$$

$$x_1, x_2 \ge 0, N = 1000.$$





(a) Optimal level of investment in the energy park (b) validation to assess the quality of the solution based on resampled scenarios



Introducing a budget constraint I<sup>\*</sup> endogenizes maximum reliability χ<sup>\*</sup> (or equivalently minimum level of risk ε<sup>\*</sup> = 1 − χ<sup>\*</sup>)



### Minimum level of risk



- Optimization problem can be solved iteratively via a bi-sectioning approach
- Endogenized level of risk corresponds to minimum level of project failure (probabilistic constraint is not fulfilled) that the investor has to accept





- Probabilistic modelling approach to the MEP using empirical distributions
- Decision-support tool for investment decisions in the energy sector
- Determine optimal level of investment in RES subject to probabilistic constraint
- Quantify the minimum level of risk that investor has to accept in case of a budget constraint

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### Thank you for your attention!