Strategic risk management: A framework for renewable generation investment under uncertainty

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Joint work with S. Ahmed, A. Shapiro & A. Street

Contents

Renewable Energy

- Wind Power – depends on wind uncertainty
- Small Hydro – typically Run Of River with small or no Dam
  - Low environmental footprint (+)
  - No control over energy output (-)

Brazilian Market: 100% demand on contracts

Regulated Trading Environment (RTE)

- Least price Auctions
- Contracts for Distribution Companies
- 72% market
- Hydro and wind dominated (special auctions)

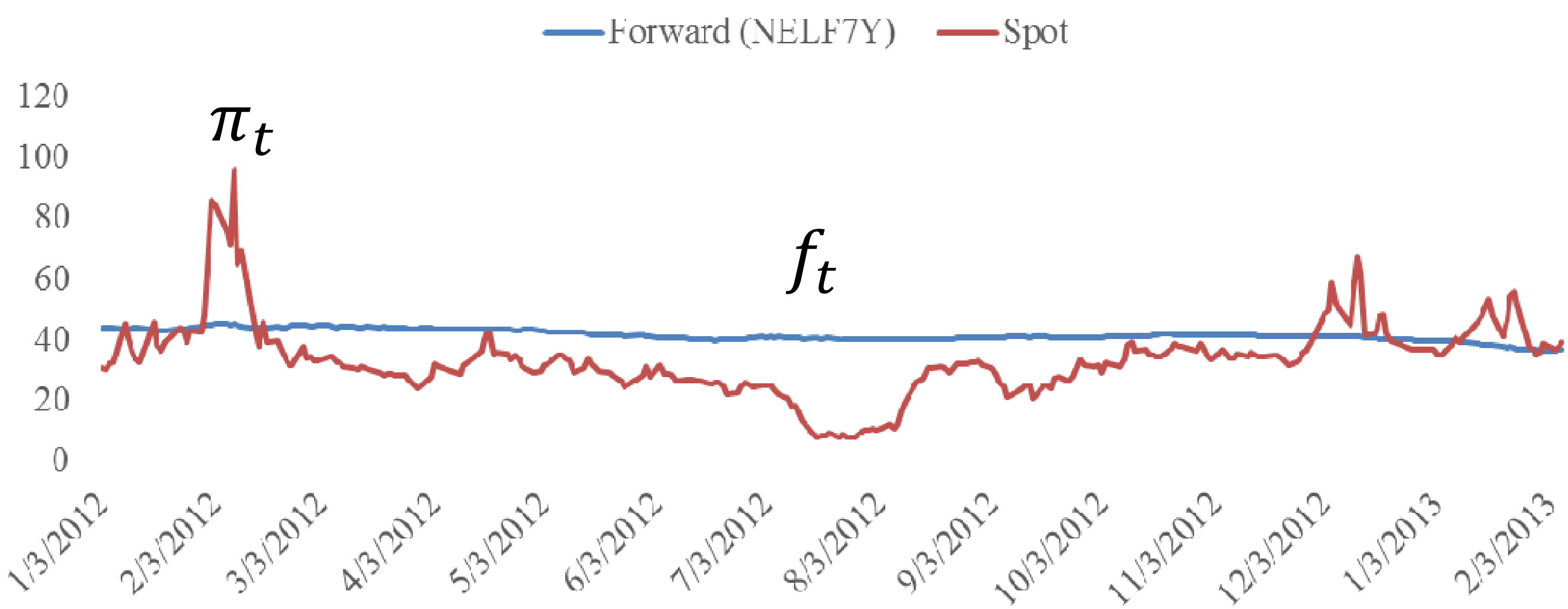
Free Trading Environment (FTE)

- Bilateral contracts
- Special consumers
- Tariff discounts
- 28% market (45%?)

Clearance with *spot price*

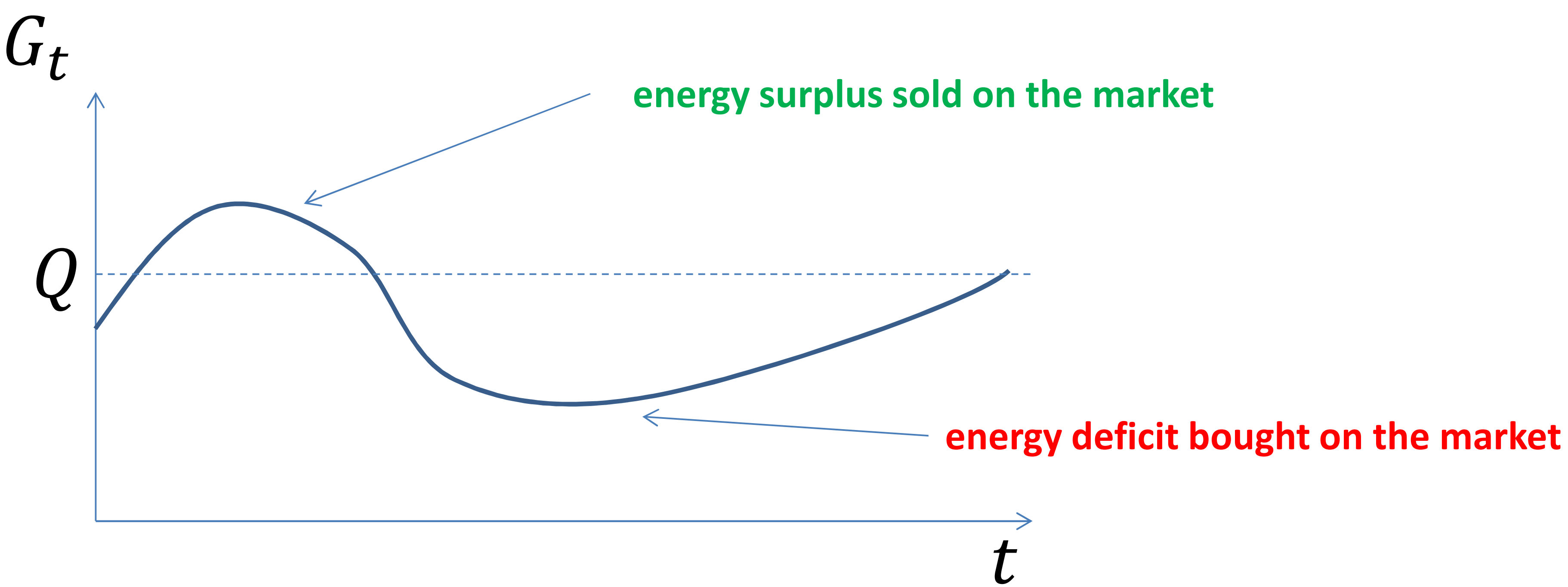
Uncertainty Sources

- Energy spot prices (π_t) are uncertain in Brazil, like most markets all over the world
- (Forward) Contracting (f_t) is usually necessary



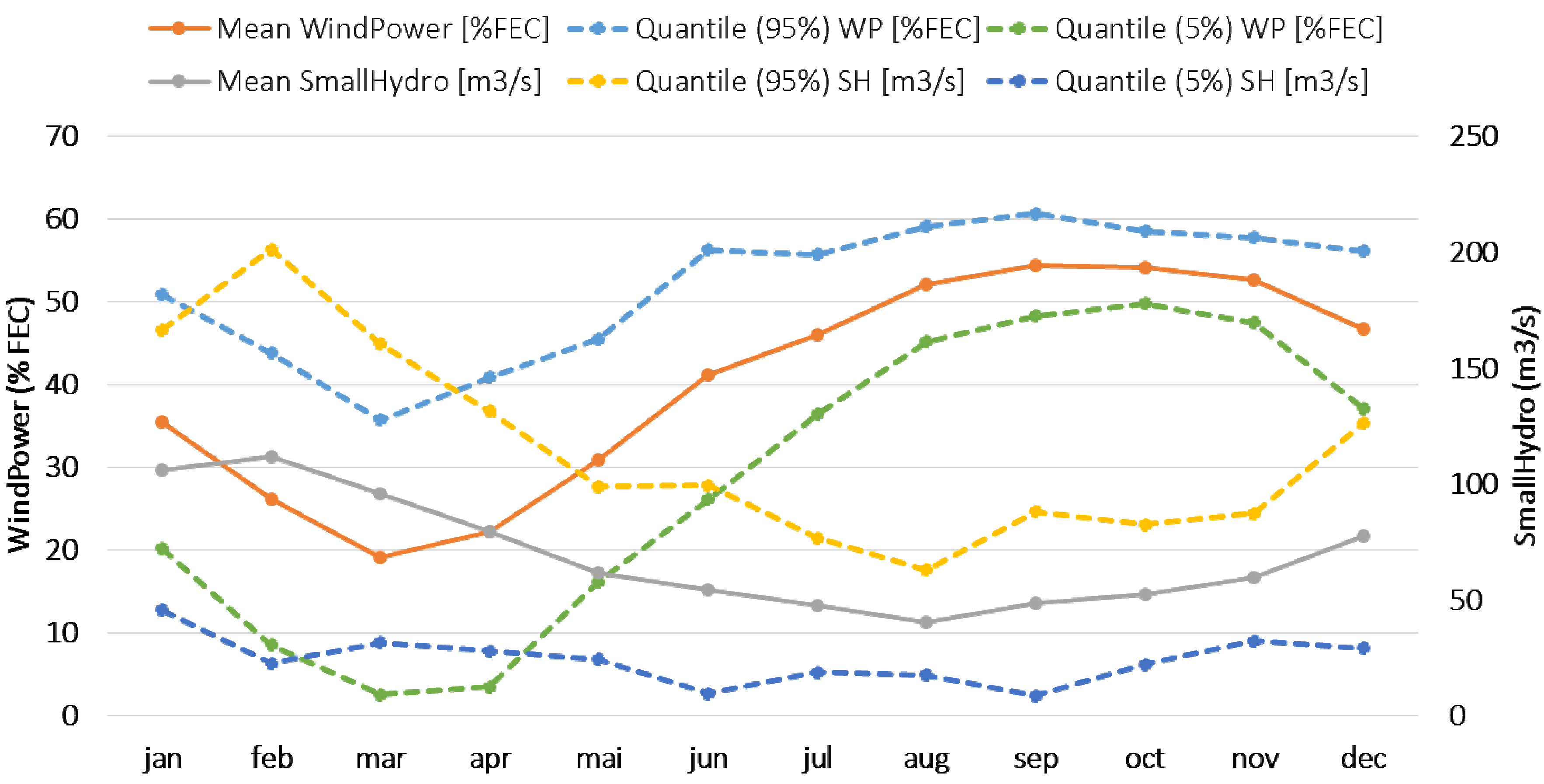
Uncertainty Sources

- Forward (Quantity) Contracts traded OTC on the FTE
  - Fixed revenue from Forward Contract, and
  - Stochastic revenue/loss: clearing difference at spot price between quantity Q and generation G_t on the market



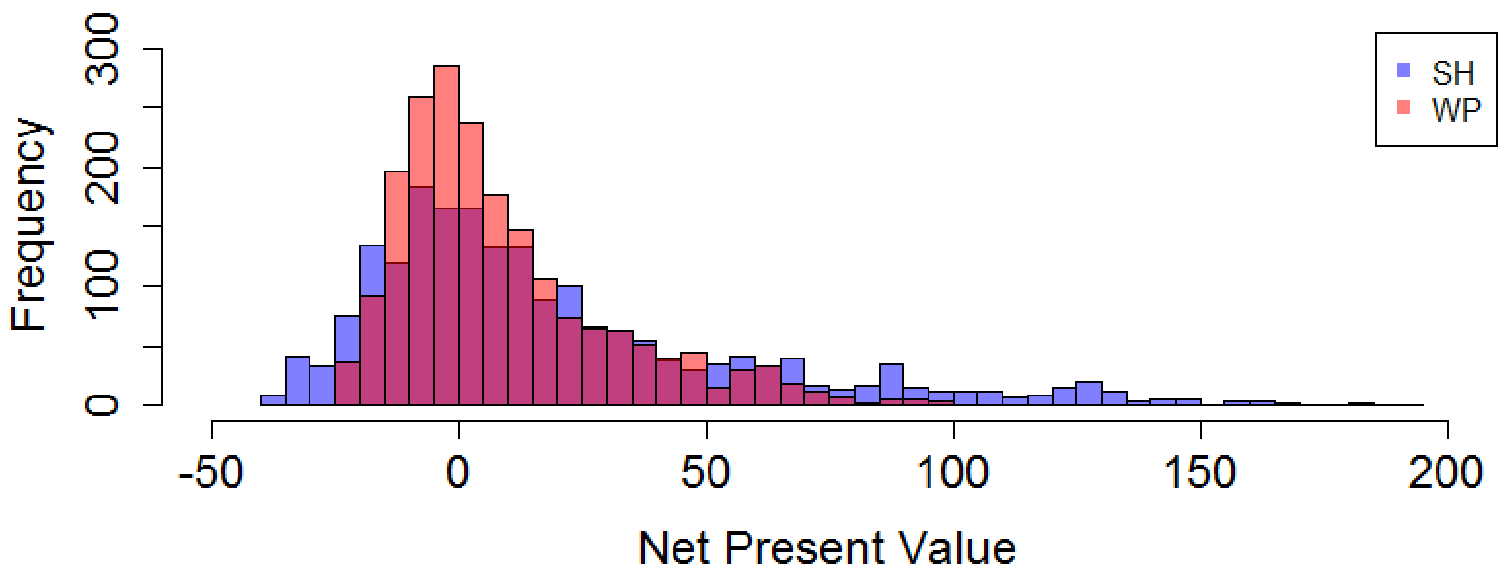
Renewable Energy

- Renewable generation is uncertain..
  - ..but there is complementary seasonality in Brazil



High exposure without risk management

- Uncertainty = high risk of losses
  - Projects hard to fund, despite positive E[NPV]
  - Can we create *attractive* portfolios?



Objective

- Present a *Strategic Risk Management framework* to foster investment in portfolio of complementary renewables in the FTE (or similar) market.
  - With forward contracting
  - generation and prices as stochastic processes
  - Using coherent risk measures to manage risk
- Allow option to postpone
  - Multistage stochastic programming problem not solvable by standard methods

Contributions

- A Framework for investment under uncertainty in renewable energy portfolio with risk management techniques
  - Representing uncertainty sources by stochastic processes
  - Multistage generalization of Street et al (2009)
- Approximate Dynamic Programming Solution algorithm based in Stochastic Dual Dynamic Programming (SDDP) method
    - Integrality is relaxed in the backward step
    - Circumvent stagewise independency hypothesis with Markov Chain
      - Price dynamics is approximated by regression
      - Transition probabilities are equiprobable – no need to estimate them

Data Model

Uncertain data (**monthly periods $\boldsymbol{\tau}$**):

$$\xi_\tau := \left(I_\tau^k, \pi_\tau^k, f_\tau^k, G_\tau\right)$$

I_τ^k: inflow of submarket k at time τ (in m3/s)

π_τ^k : spot price of submarket k at time τ (in \$/MW)

- Inflow and Spot price data from 2000 *simulated* series from **NEWAVE** model

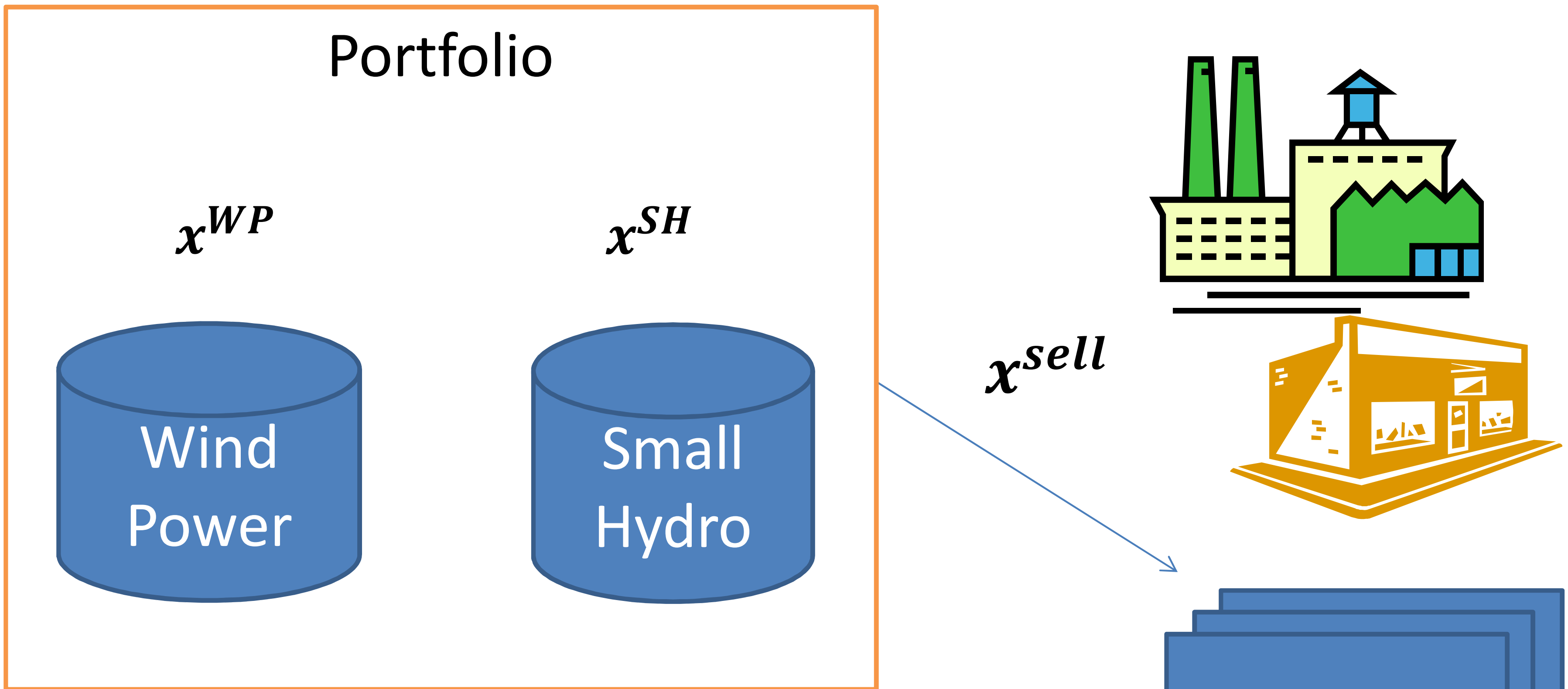
f_τ^k : forward price of submarket k at time τ (in \$/MW)

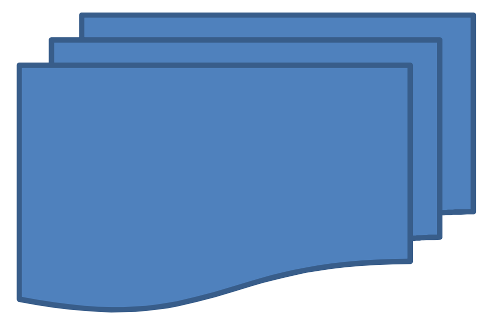
- Multiperiod forward (swap) over the project lifetime. Calibrated with OTC data using Schwartz-Smith (SS) model.

$G_\tau = (G_\tau^1, \dots, G_\tau^n)$: energy generated by renewable project j (in MW), $j = 1, \dots, n$.

- Energy as VAR model considering submarket inflows as explanatory variables.
    - Parameters estimated by historical data
    - 2000 sample series correlated with NEWAVE data

Example Strategy with two projects



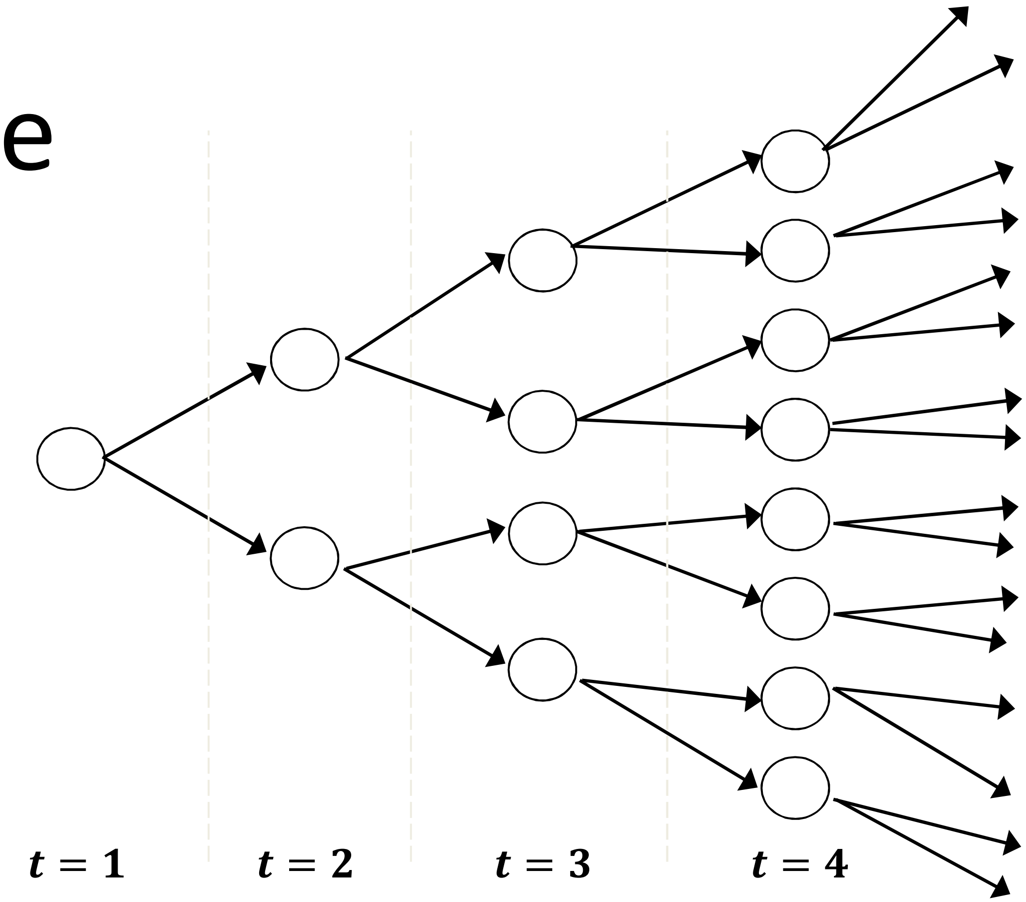


When should we invest?

How much should we invest? Contract amount?

Model Outline

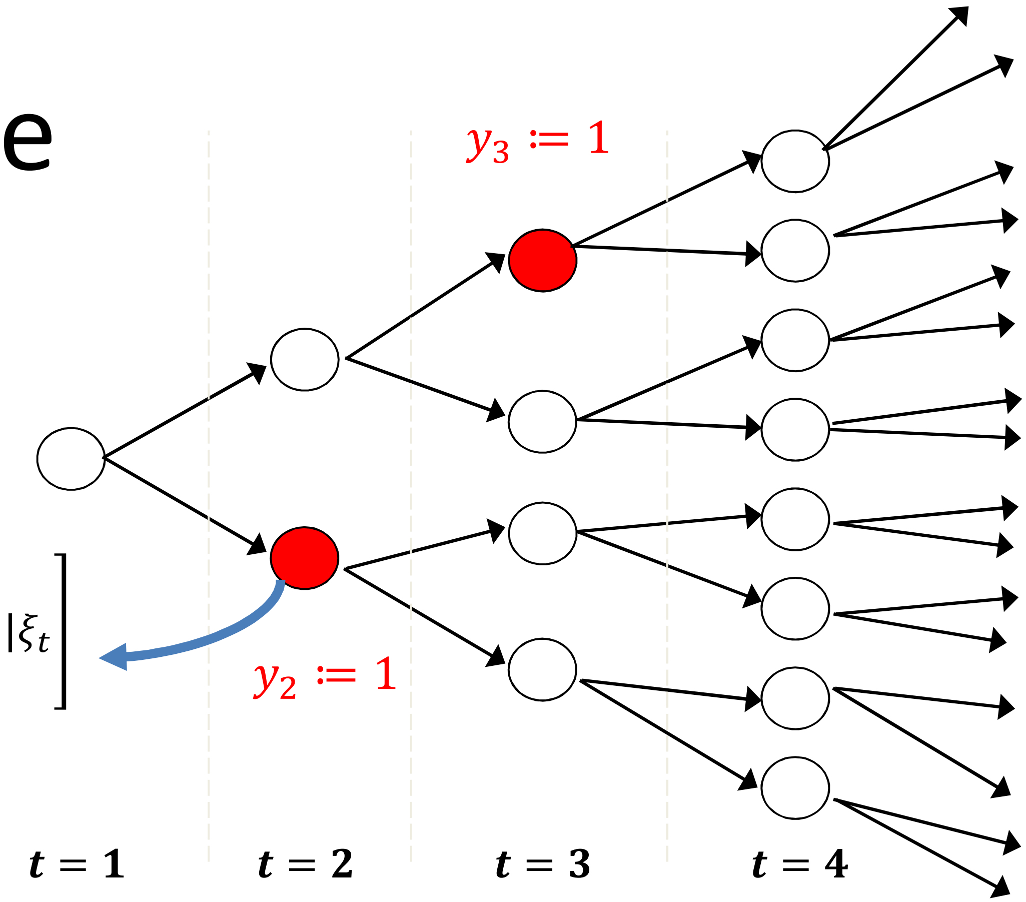
yearly periods $\boldsymbol{t}$



Binary variables:

- $y_t \coloneqq 1$: decision to invest in year t
  - Binary decision occurs in only one period
  - Must define portfolio at the same time

Model Outline



$$V_t = \max_{\substack{x_t \\ x_T \in X_T}} a_t x_t + \mathbb{E}\left[\sum_{\hat{t}=t+b}^{t+b+l-1} \frac{c_{\hat{t}} x_t}{(1+r)^{(\hat{t}-t)}} | \xi_t\right]$$

Continuous Variables $\quad x_t := \left(x_t^1, \dots, x_t^n, {x^1}_t^{sell}, \dots, {x^K}_t^{sell}\right)$

x_t^j := share (in %) on each renewable project $j = 1, \dots, n$.

${x^k}_t^{sell}$: forward contract (in % of FEC) sold at price f_t^k on market $k = 1, \dots, K$

Proposed Model

$$\max_{\mathrm{x_t,y_t}} \mathbb{E}\left[\sum_{t=1}^{T} g_t(x_t) y_t (1+\rho_c)^{-(\mathrm{t}-1)}\right]$$

$$g_t(x_t) = a_t x_t + \sum_{\hat{t}=t+b}^{t+b+l-1} c_{\hat{t}} x_t (1+\rho_c)^{(t-\hat{t})}, \forall t$$

$$x_t \in X_t, \forall t$$

$$\sum_{t=1}^{T} y_t \leq 1,$$

$$y_t \in \{0,1\}, \forall t$$

$$x_t, y_t \ \mathcal{F}_t - adapted, \forall t$$

We will replace the expectation with a coherent risk measure to manage risk

Solution Approach

- Assume lifetime up to end of horizon
- For simplicity, build time b=1, $\rho_c = 0$

$$Q_t(x_{t-1}, z_{t-1}, \xi_t) := \max_{x_t, z_t, y_t} a_t y_t x_t + c_t x_t z_{t-1} + E\left[Q_{t+1}(x_t, z_t, \tilde{\xi}_{t+1}) | \xi_1, \ldots, \xi_t\right]$$

$$z_t = y_t + z_{t-1}$$

$$x_t = x_{t-1}, if\, z_{t-1} = 1,$$

$$x_t = 0, if\, z_t = 0,$$

$$x_t \in X_t$$

$$y_t, z_t \in \{0,1\}$$

- Can be linearized

Solution Approach

- Linearizing model

$$Q_t(\, x_{t-1}, z_{t-1}, \xi_t):=$$
$$\max_{x_t, z_t, \alpha_t, y_t} a_t(x_t - x_{t-1}) + c_t x_{t-1} + E\left[Q_{t+1}\left(\, x_t, z_t, \tilde{\xi}_{t+1}\right) | \xi_1, \dots, \xi_t\right]$$
$$z_t = y_t + z_{t-1}$$
$$x_t \leq x_{t-1} + (1 - z_{t-1}),$$
$$x_t \geq x_{t-1},$$
$$x_t \leq z_t,$$
$$x_t \in X_t$$
$$\boxed{y_t, z_t \in \{0,1\}}$$

$$a_t y_t x_t \;\leftrightarrow a_t(x_t - x_{t-1}) \qquad c_t x_t z_{t-1} \leftrightarrow c_t x_{t-1}$$

Solution Approach

- T+1: last stage

$$Q_{T+1}(\, x_T, z_T, \xi_{T+1}) := \sum_{t=T+1}^{T+l} c_t x_{T-1}$$

SDDP: considering stagewise independence

$$Q_t(x_{t-1}, z_{t-1}, \xi_t) :=$$

$$\max_{x_t, z_t, y_t} a_t(x_t - x_{t-1}) + c_t x_{t-1} + E[Q_{t+1}(x_t, z_t, \xi_{t+1})]$$

$$z_t = y_t + z_{t-1}$$

$$x_t \leq x_{t-1} + (1 - z_{t-1}),$$

$$x_t \geq x_{t-1},$$

$$x_t \leq z_t,$$

$$x_t \in X_t$$

$$y_t, z_t \in \{0,1\}$$

SDDP: considering stagewise independence

$$Q_t(x_{t-1}, z_{t-1}, \xi_t) :=$$

$$\max_{\mathrm{x_t, z_t}, y_t} a_t(x_t - x_{t-1}) + c_t x_{t-1} + \underline{\Psi}_{t+1}(x_t, z_t)$$

$$z_t = y_t + z_{t-1}$$

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$$x_t \leq z_t,$$

$$x_t \in X_t$$

$$y_t, z_t \in \{0,1\}$$

$$\underline{\Psi}_{t+1}(x_t, z_t) \coloneqq \max\{\theta_t : \theta_t \leq \alpha_l x_t + \beta_l z_t + \gamma_l \forall l \in C_t\}$$

SDDP: Forward step

Sample M scenarios $\{\xi_t^m\}, t = 1..T + l, m = 1 \dots M$
For $t = 1, \dots, T+1$, solve the **MIP** subproblems

$$Q_t(x_{t-1}, z_{t-1}, \xi_t^m) :=$$
$$\max_{\mathrm{x_t, z_t}, y_t} a_t(x_t - x_{t-1}) + c_t x_{t-1} + \underline{\Psi}_{t+1}(x_t, z_t)$$
$$z_t = y_t + z_{t-1}$$
$$x_t \le x_{t-1} + (1 - z_{t-1}),$$
$$x_t \ge x_{t-1},$$
$$x_t \le z_t,$$
$$x_t \in X_t$$
$$y_t, z_t \in \{0,1\}$$

- Store each$(x_{t-1}, z_{t-1},)^m$, make $f_t^m = a_t(x_t - x_{t-1}) + c_t x_{t-1}$
- $LB := \frac{1}{M} \sum_{m \in \{1,\dots M\}, t \in \{1,..,T\}} f_t^m$ is a ***lower bound*** for the problem's optimal value

SDDP: Backward step

1. For $t = T + 1, \dots, 2$, for each$(x_{t-1}, z_{t-1},)^m, m = 1 \dots M$
   1. Sample N_t scenarios $\{\xi_t^{N_t}\}$,
   2. For j= $1..N_T,$ solve the **LINEAR** subproblems

$$Q_t\left(x_{t-1}, z_{t-1}, \xi_t^j \right)^j :=$$

$$\max_{x_t, z_t, y_t} a_t^j (x_t - x_{t-1}) + c_t^j x_{t-1} + \underline{\Psi}_{t+1}(x_t, z_t)$$

$$z_t = y_t + z_{t-1}$$

$$x_t \le x_{t-1} + (1 - z_{t-1}),$$

$$x_t \ge x_{t-1},$$

$$x_t \le z_t,$$

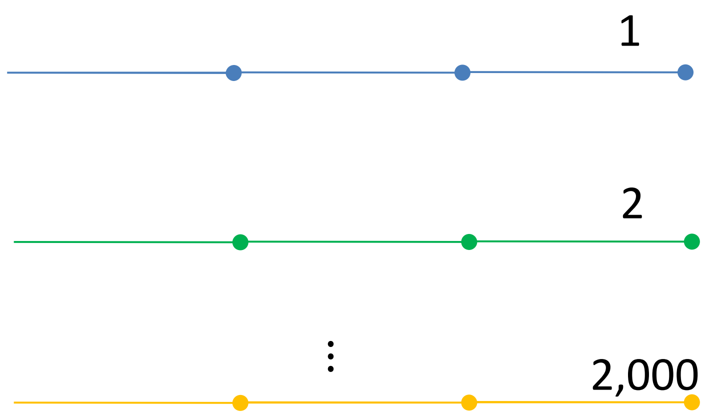
$$x_t \in X_t$$

$$y_t, z_t \in [0,1]$$

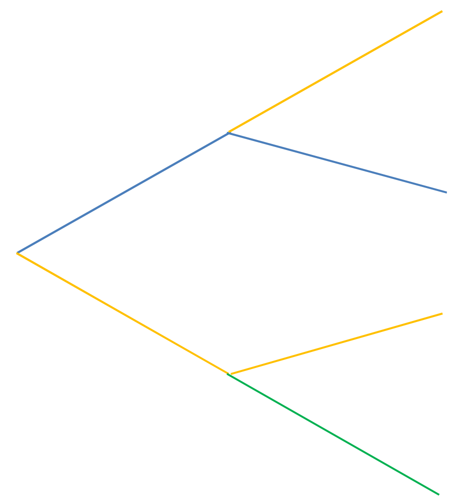
- Compute a new cut $\theta_t \le \alpha_m x_t + \beta_m z_t + \gamma_m$ as usual

Our data

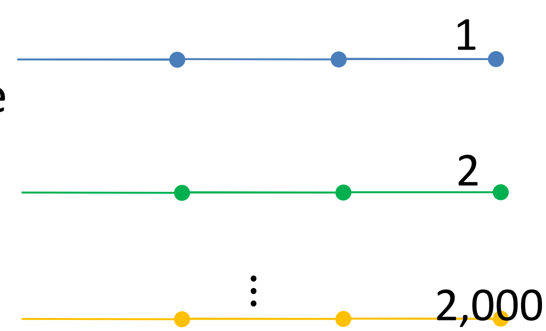
2,000 Monte Carlo simulations of data process ξ_t



- We sample independently from the Monte Carlo series
  - Stagewise assumption on *yearly* periods



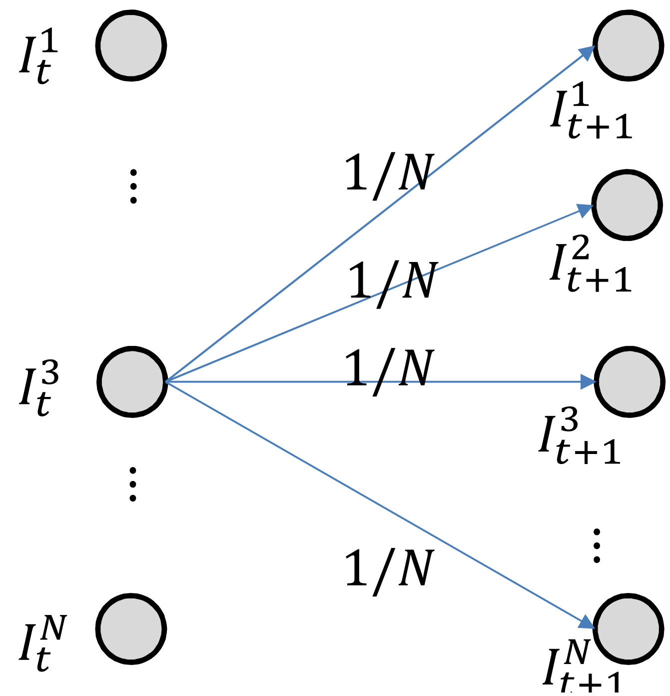
- Quality of solution is evaluated out of sample
  - Evaluate policy for the original 2,000 scenarios



SDDP: Dependency by Markov Chain

- Two assumptions used to model spot price dependency
  1. Independence hypothesis over I_t , G_t
  2. Approximate spot price by a function of inflows

States are represented by equiprobable Markov Chain (due to independency)



SDDP: Dependency by Markov Chain

Spot prices approximated by linear regression:

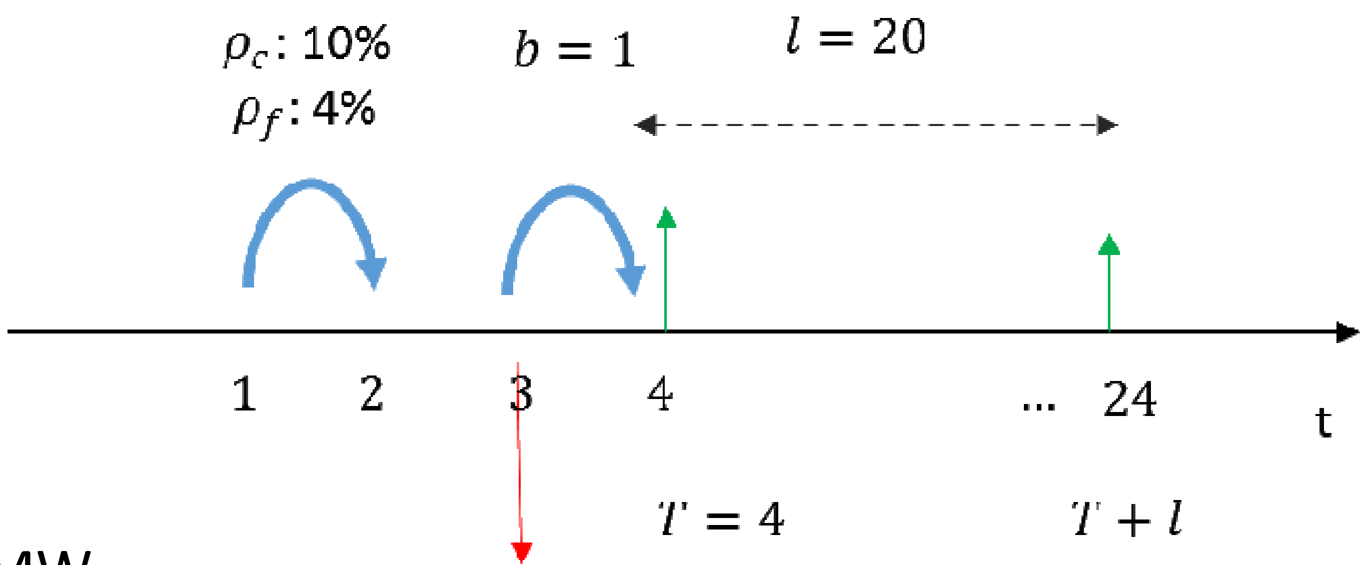
$$\log \pi_{\tau}^{s} = \sum_{m \leq \tau} \sum_{k=1}^{4} \gamma_{\tau m}^{k} I_{m}^{k} + \epsilon_{\tau}$$

- $\gamma_{\tau m}^{k}$: inflow regression coefficient of market k
- I_{m}^{k} : Inflow of market k of previous time $\mathrm{m} \leq \tau$ up to January of preceding year

- Forward prices as a function of spot price

Case Study

Portfolio: One windpower(WP) and one Small Hydro(SH)
Both in **SouthEast Market**



FEC^{SH}=17,6 MW
FEC^{WP}=12,0 MW
RP: zero risk premium

v^{SH}: R$ 134,9 million
v^{WP}: R$ 91,6 million

SDDP: SAA study

- #N’ = 10 independent evaluations of the problem
- *Single forward sample.* ***Stops when # iterations = 100***

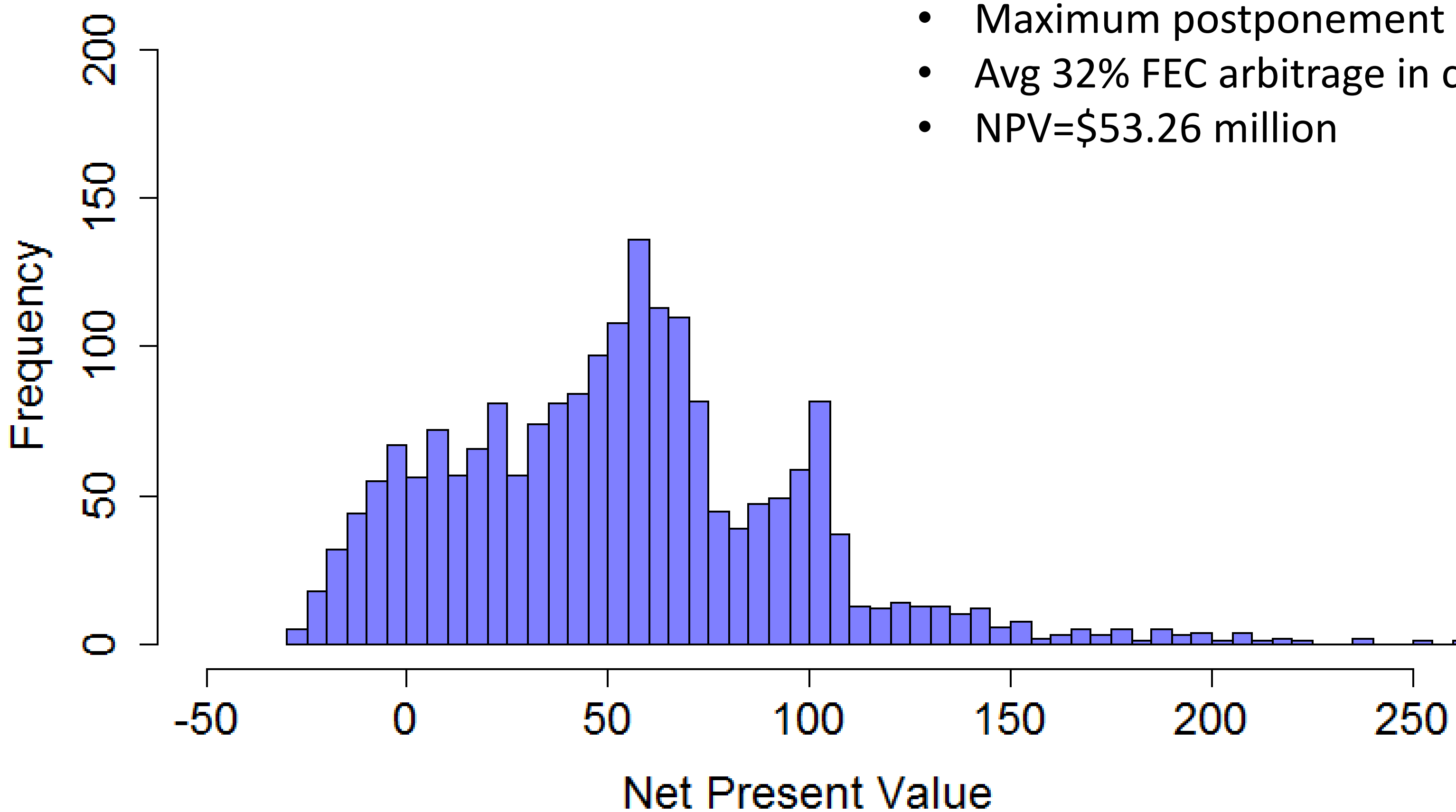
- $\#N_t = 30, \forall\ t$ (backward step samples)

- Also, evaluate performance of policy out of sample (original 2,000 scenarios)
- Series projected in each stage state using *Euclidian distance*

Histogram of best risk neutral policy

Policy facts:

- 100% both projects
- Maximum postponement
- Avg 32% FEC arbitrage in contracts
- NPV=$53.26 million



SDDP: risk averse results

- Risk aversion given by AV@R measure.

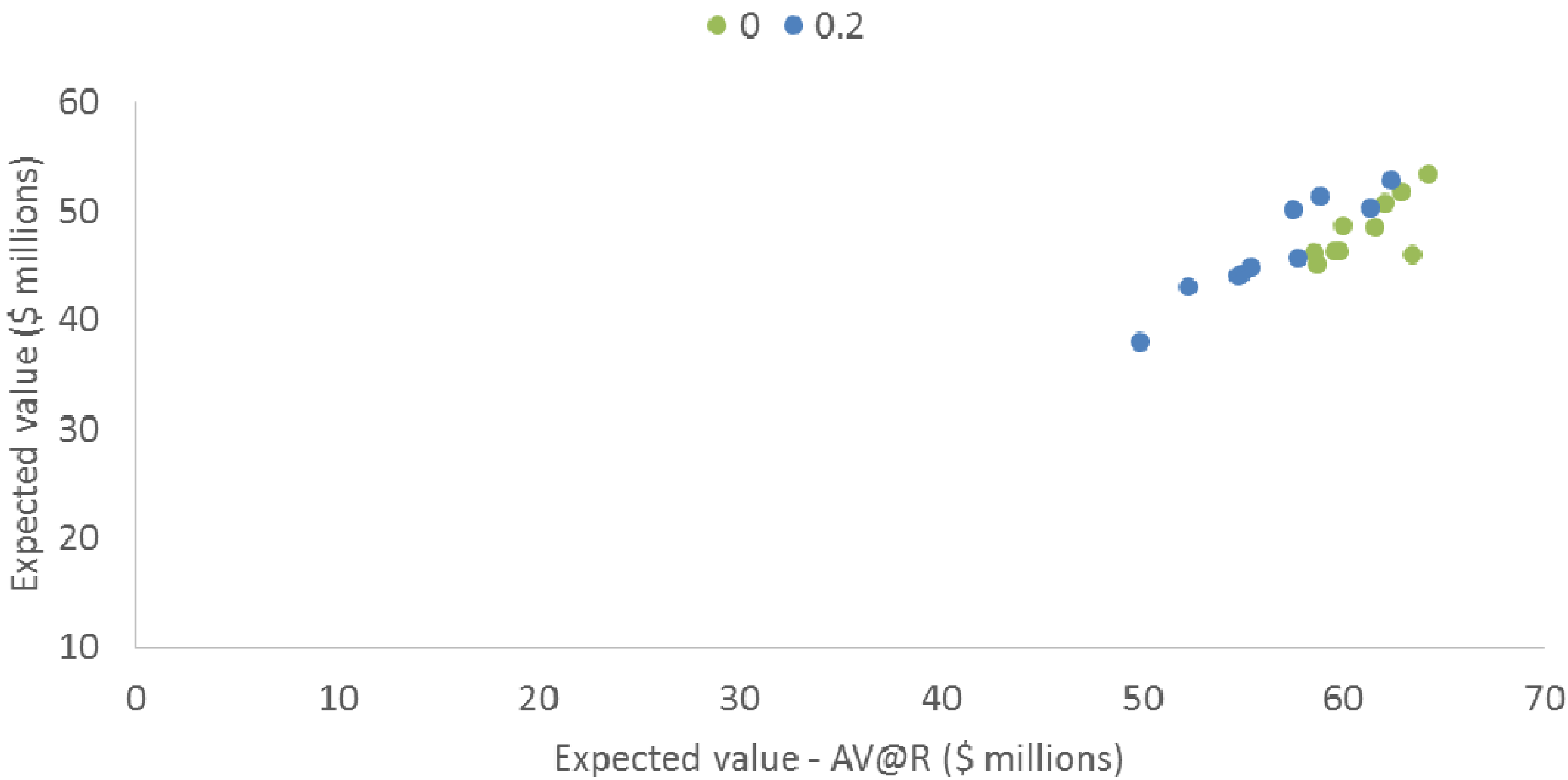
- Optimization of functional
$$(1-\lambda)\, E[Q(x)] + \lambda AV@R_{\alpha}\ [Q(x)]$$

- $\alpha \coloneqq 0.9$ (10%) worst scenarios
- $\lambda \in [0,1]$, according to degree of risk aversion
- $\#N_t = 50, \forall\ t$ (backward step samples)

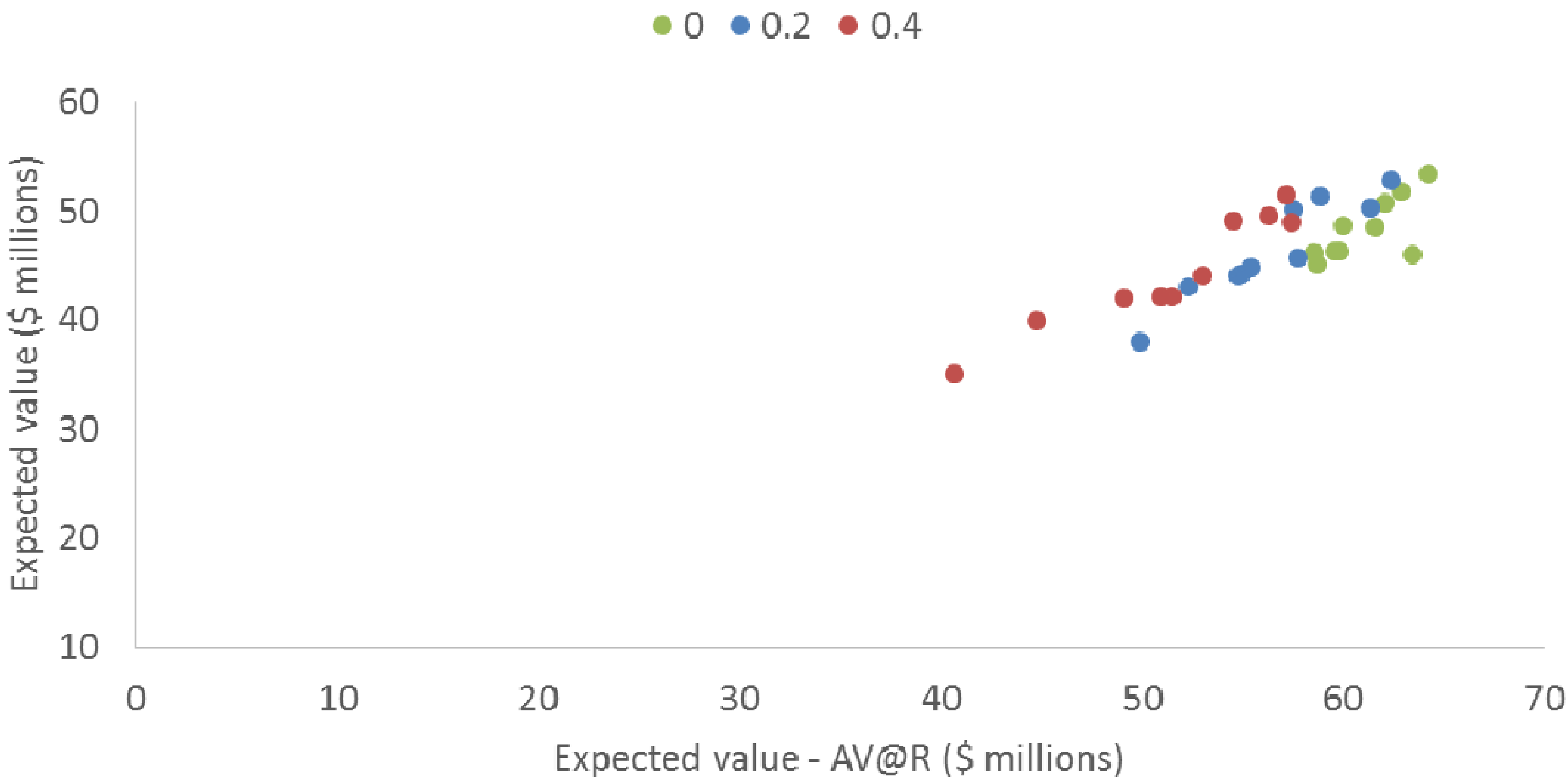
- *Single forward sample.* ***Stops when # iterations = 40***

Sensitivity to lambda

Sensitivity to lambda



Sensitivity to lambda



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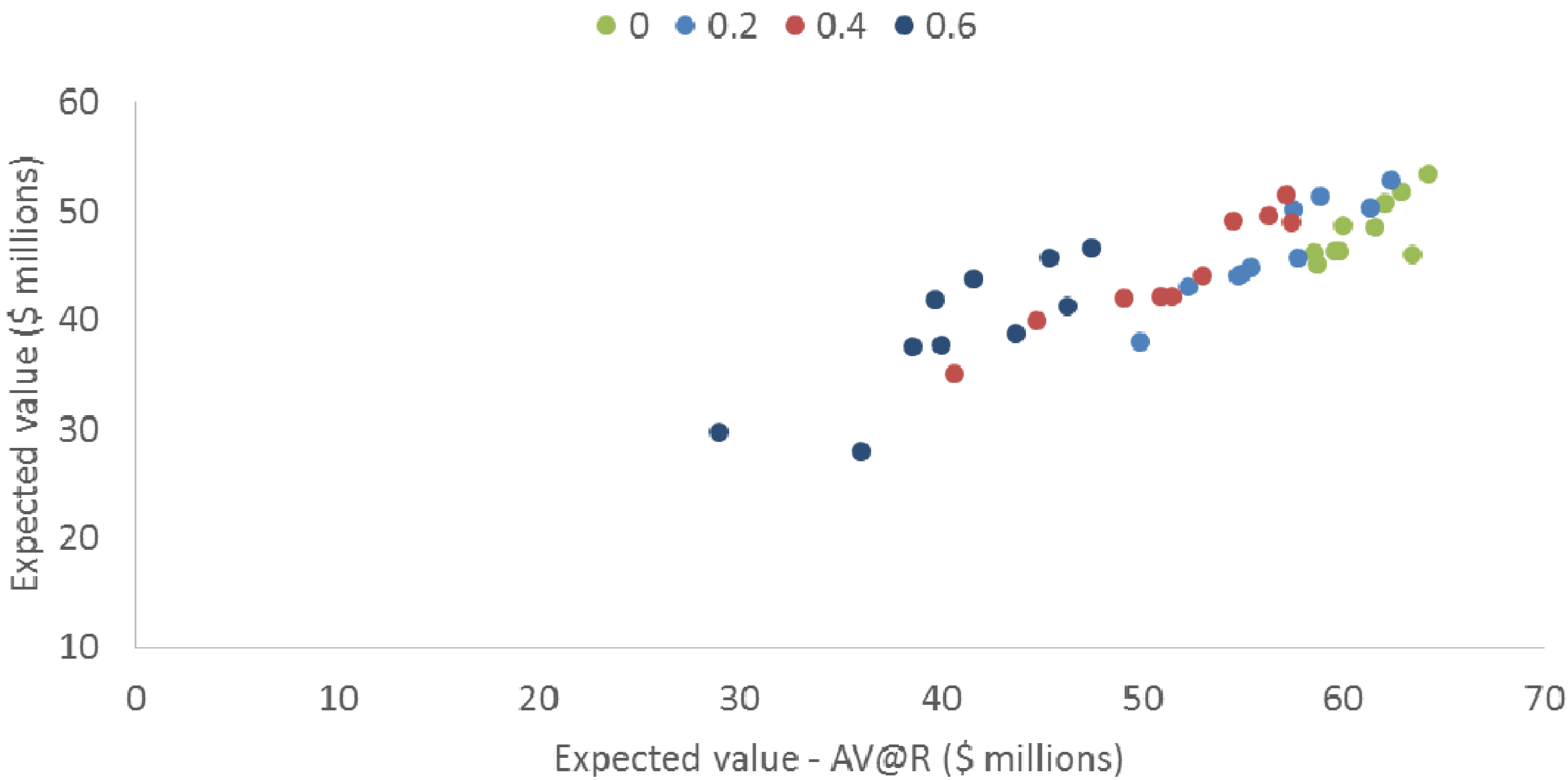

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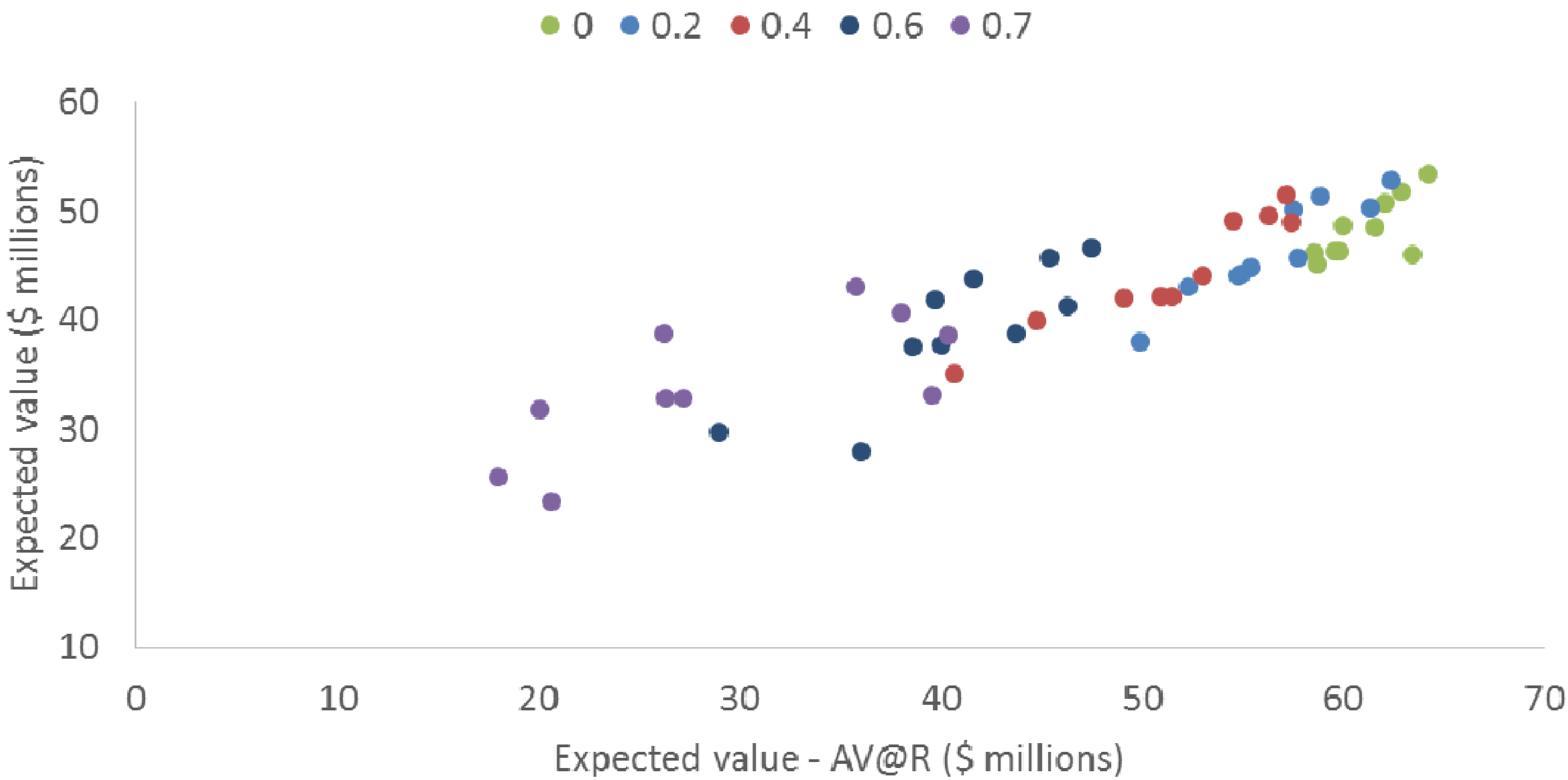
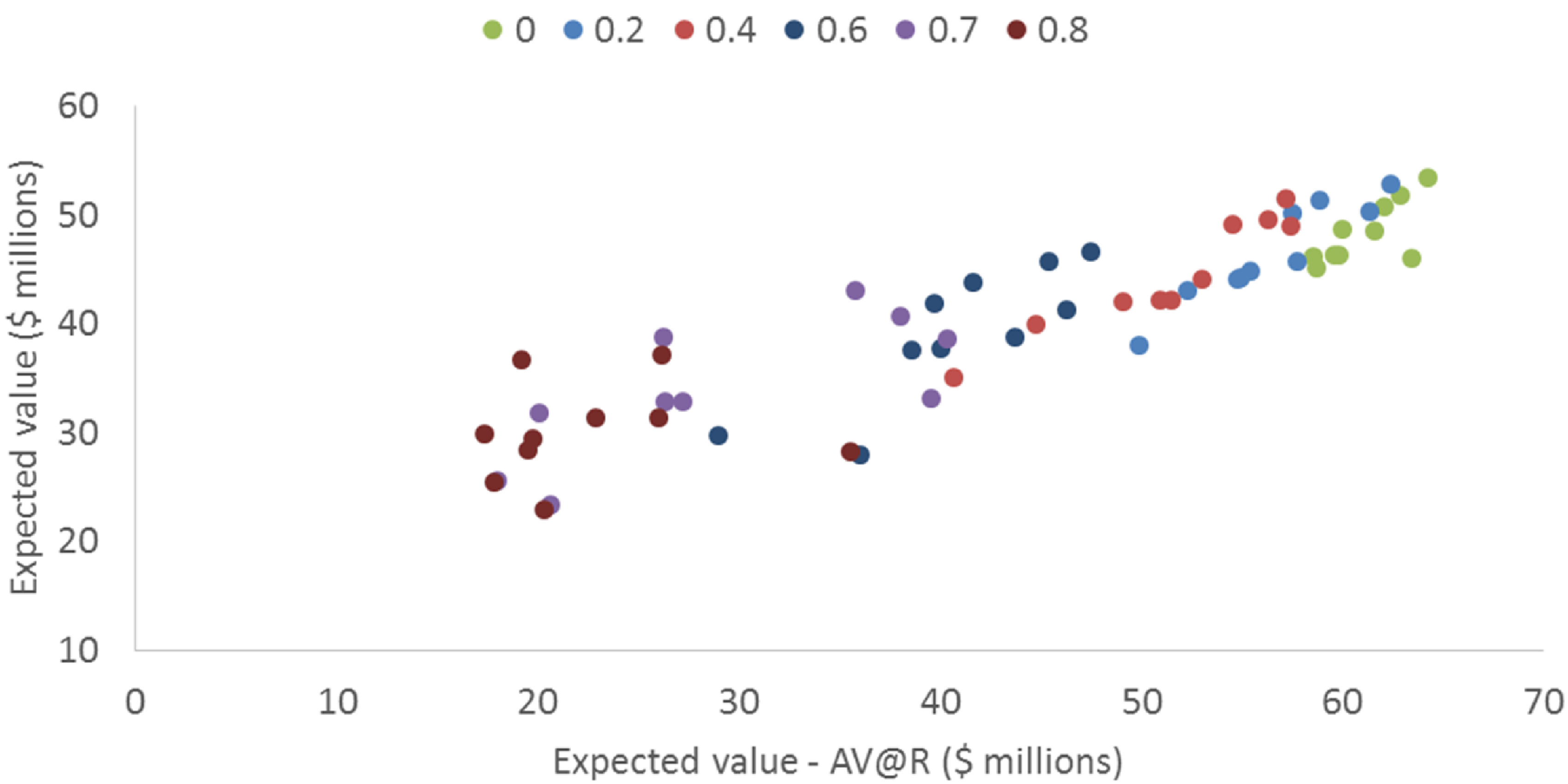
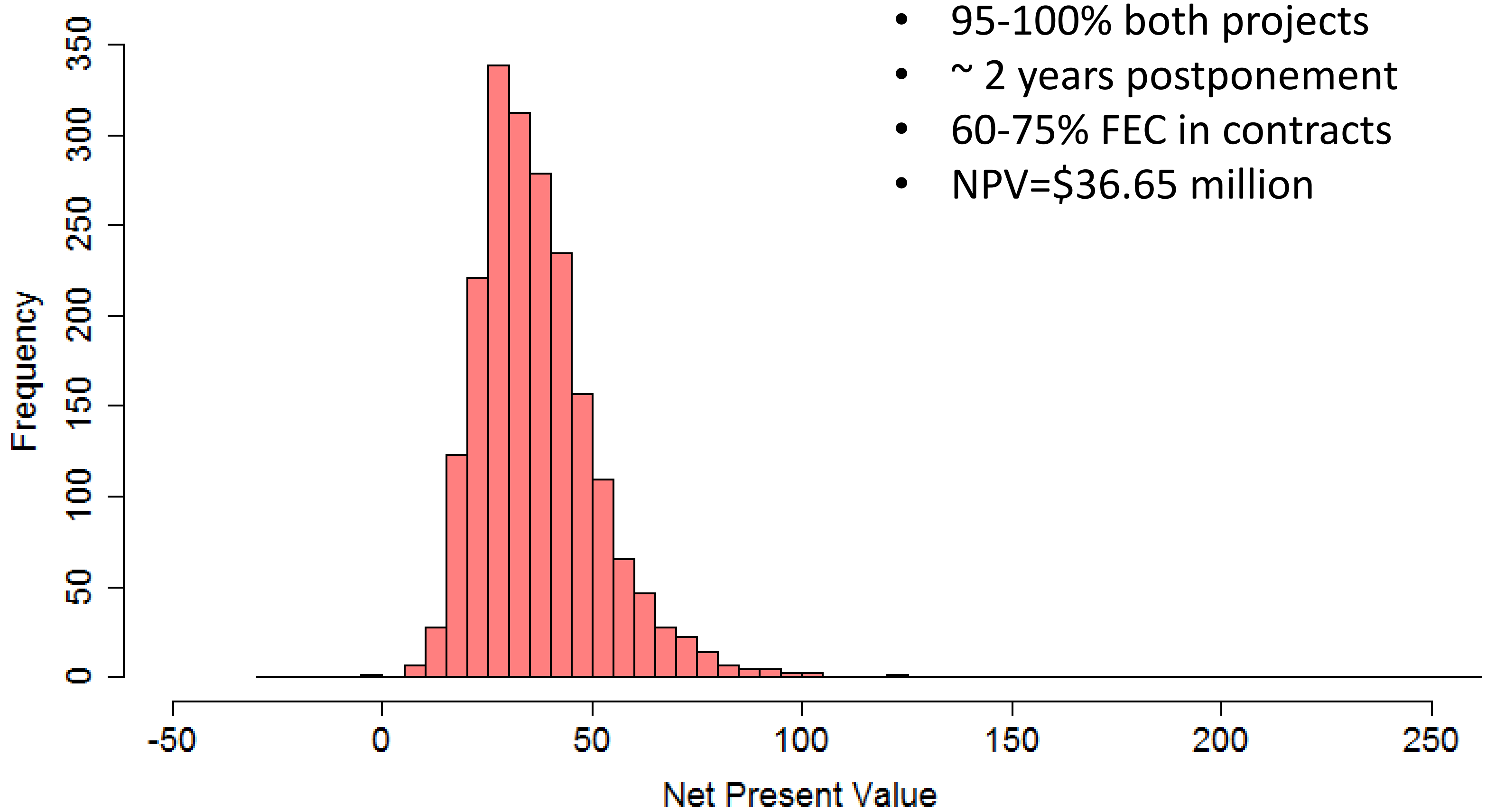


Sensitivity to lambda



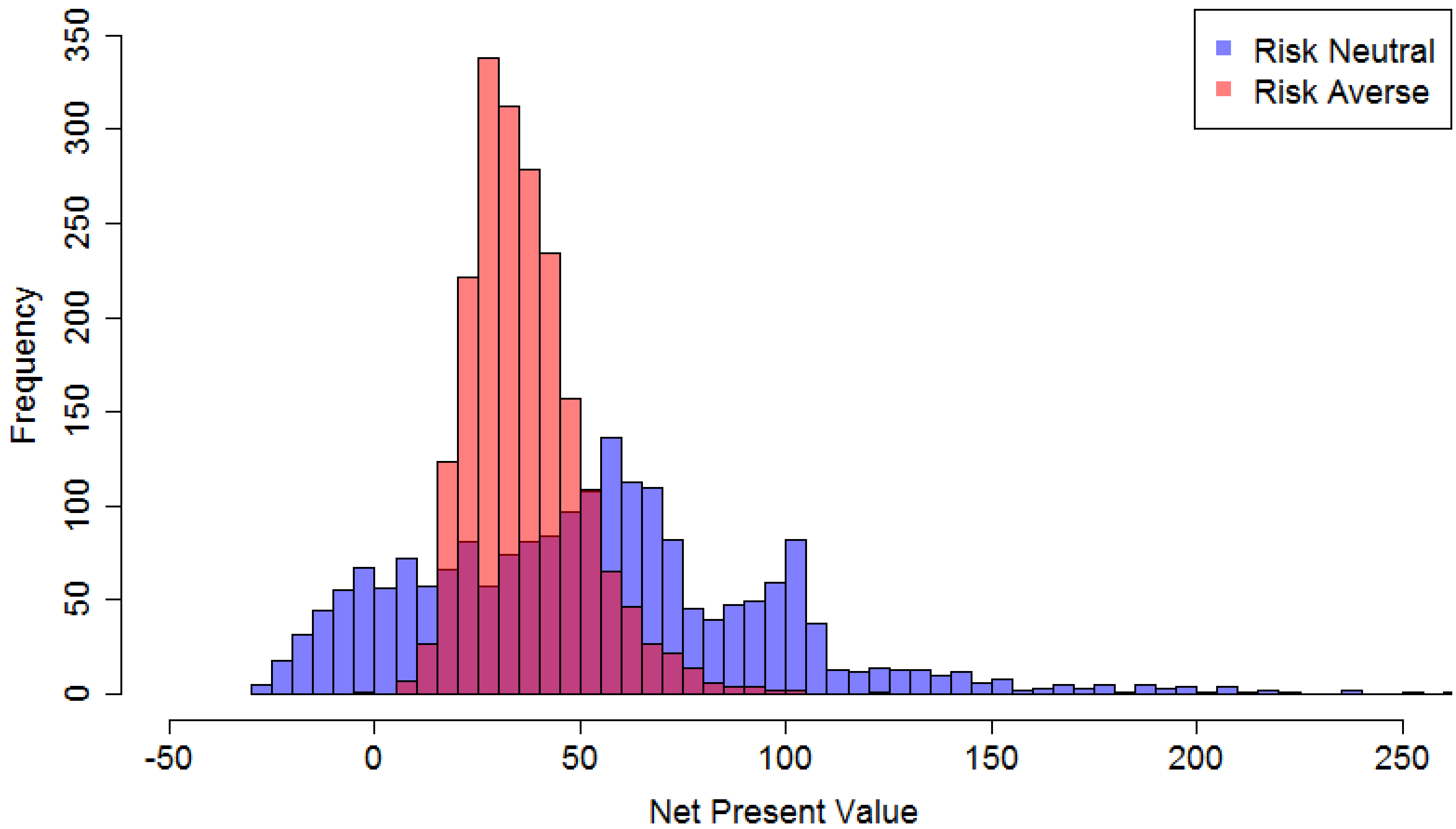
Histogram of risk averse solution (lambda=0.8)



Policy facts:

- 95-100% both projects
- ~ 2 years postponement
- 60-75% FEC in contracts
- NPV=$36.65 million

Histograms compared



Conclusions and Future Work

- We presented a framework to foster the development of renewables
  - May be applied to the FTE or similar market
  - Usage of Monte Carlo simulations of problem data
  - Incorporates the most used tools in risk management
- The SDDP heuristic provided good approximations
  - Managed to circumvent nonlinearities
  - Solutions close to their linear relaxation
  - Able to manage risk, generating different policies
  - Dependent on the function to approximate spot price
- Exploring different strategies to approximate prices may provide better policies
  - Use of NEWAVE data may help to evaluate transition probabilities in the Markov Chain

Thank you!

Questions?