A RELIABILITY BASED DESIGN APPROACH TO STOCHASTIC SUPPLY PLANNING

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OVERVIEW

- Introduction: Deterministic power procurement problem
- Model design: *Incorporate the risks associated with power supply*
- Application to use case: Generation expansion problem (GEP)

Construction
- Stochastic extension of deterministic model
- Application of RBDO

Calibration
- Parameters of probability densities
- Interpolated by Fourier Series

Validation
- Consider subproblem of maximum reliable supply
- Backtest different models

General Model Design

Application to a use case
- Solve the reliability-based extension of the GEP

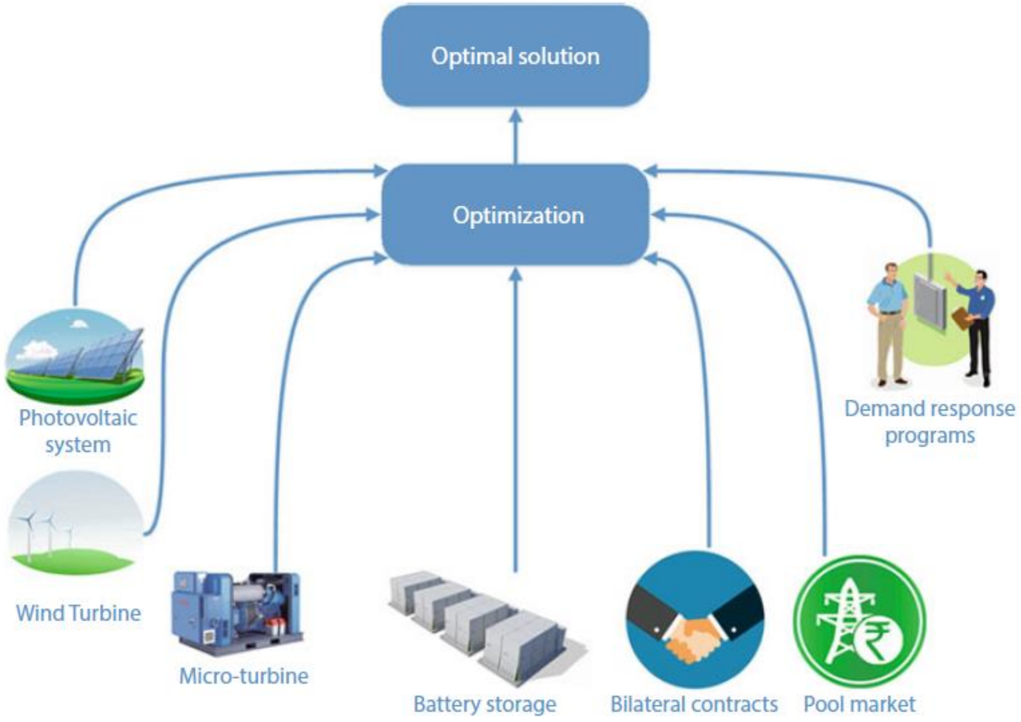
Model Application

INTRODUCTION 1

- Main objective: Procuring required power at minimum possible cost

$$\min_{x \in X} f(x) \quad \text{s.t.} \quad \sum_i P_{it}(x) \geq d_t, \quad \forall t \in T$$

Model Variables	
f	Objective: System costs
P_{it}	Power available from i-th energy asset at point of time $t \in T$
d_t	Demand at point of time $t \in T$
x	Endogenous variables (Installed capacity, shares used in the strategy, ...)



Source: Nojavan et al., (2019)

INTRODUCTION 2

- Deterministic approaches can lead to procurement plans which are infeasible or overly expensive (Beraldi et al., 2017)
- Uncertainty in power output is addressed to be a major problem (Hemmati et al., 2017)
- Task of supplying predefined load in economic matter is challenging but a key factor in energy planning problems (Monishaa et al., 2013)
- *"The best managers are the ones who cope best with their uncertainty" (H. Markowitz, Interview in: https://www.thiscomplexworld.com/nl/put-eggs-basket-interview-harry-markowitz/)*

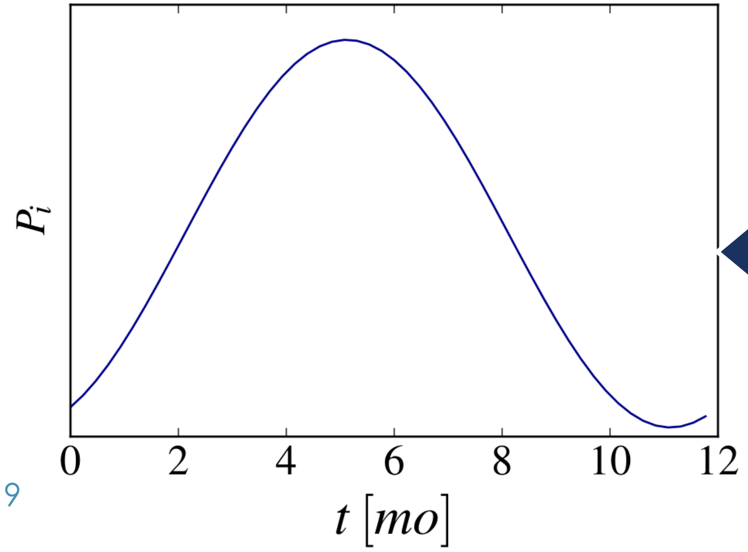
INCLUDING RISK OF SUPPLY SHORTAGES

FROM DETERMINISTIC TO STOCHASTIC

"[...] the unpredictability (…in the power output…) is not considered. "
(Delarue et. al., 2011)

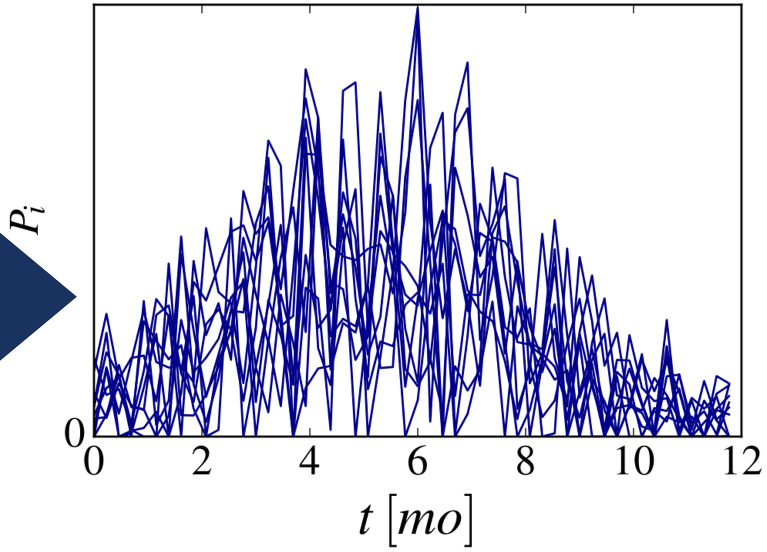
From deterministic to stochastic

Stochastic paradigm: Consider the aleatoric risk of the power supply



Deterministic

Stochastic



INCLUDING RISK OF SUPPLY SHORTAGES

METHODOLOGY: RELIABILITY BASED DESIGN OPTIMIZATION (RBDO)

- RBDO to model the „safety-under-uncertainty“ aspect (Lopez and Beck, 2012)
- RBDO has a twofold goal (Geletu et al., 2013): System performance and system reliability
- Elaborate a risk-based inspection of the objective

Deterministic Design

$$\min_{x \in X} f(x) \quad \text{s.t.} \quad \sum_i P_{it}(x) \geq d_t, \qquad \forall t \in T$$

Stochastic Design

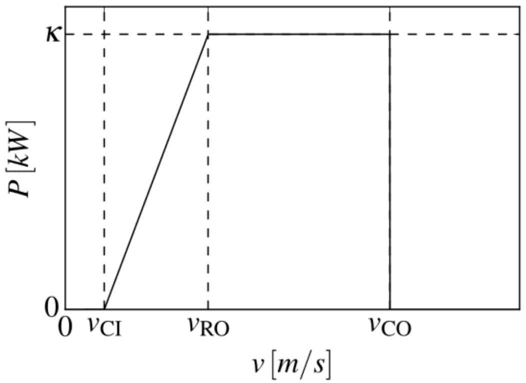
$$\min_{x \in X} E\left[\tilde{f}(x)\right] \quad \text{s.t.} \quad \Pr\left\{\sum_i \tilde{P}_{it}(x) \geq d_t\right\} \geq \chi, \qquad \forall t \in T$$

RBDO via probability chance constraints

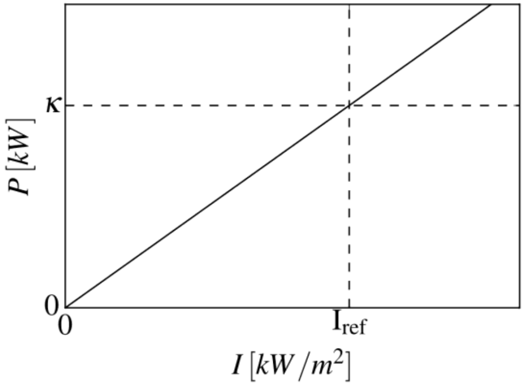
THE ENERGY MODEL: INCLUDING RES

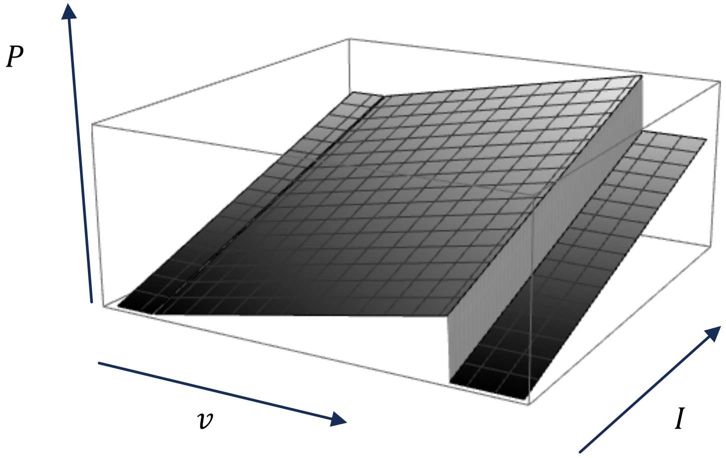
WIND & SOLAR POWER

v_t



I_t



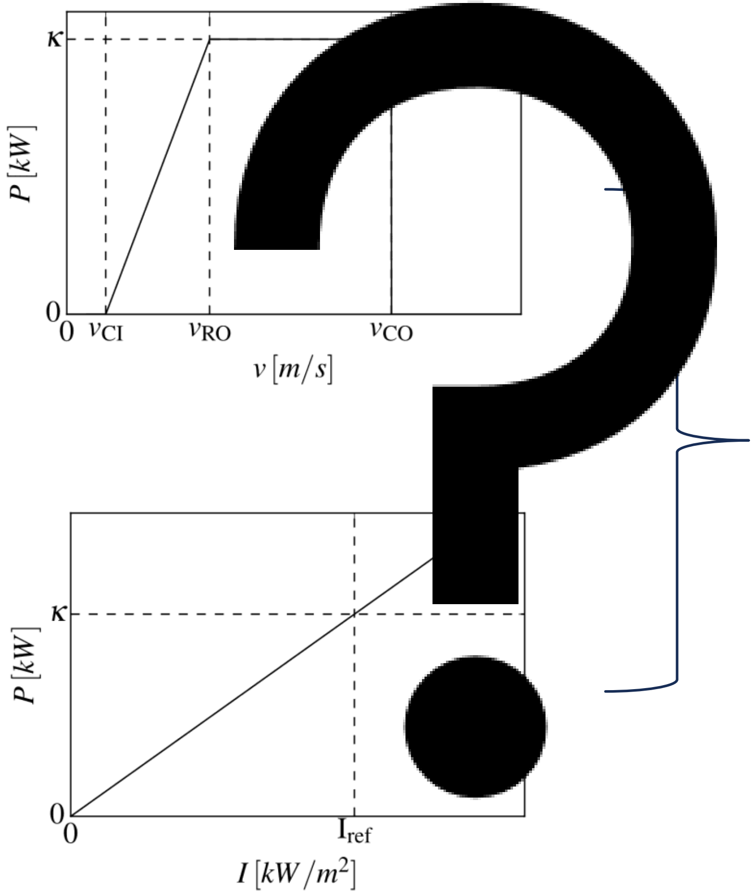


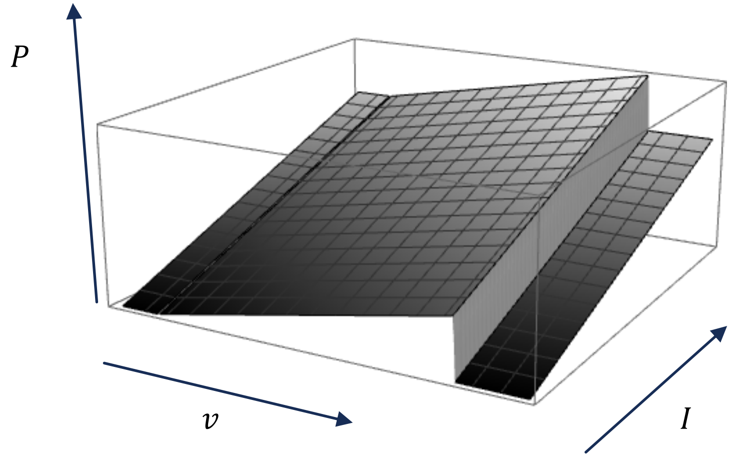
THE ENERGY MODEL: INCLUDING RES

WIND & SOLAR POWER

v_t

I_t





UNDERLYING PROBABILISTIC DISTRIBUTIONS

FROM GAUSSIAN TO ADAPTED PDF'S

Energy assets

Solar Irradiance I_t

Wind speed v_t

...

Gaussian (M0)

Weibull (M1)

Exponential (M2)

Beta (M3)

Log-Normal (M4)

Gaussian (M0)

Weibull (M1)-(M4)

...

In problems where reliability constraints are incorporated: Assumption of Gaussian distributions (Garifi et al. (2018), Hemmati et al. (2017), Huang et al. (2018),...)

Compare & validate different models

EVALUATION OF PREDICTIVE PROPERTIES 1

- Model properties depend on the estimated *reliable* power
- Consider the subproblem of the maximum supply s_t of an existing energy park in a use case
- "Fundamental building block" of the model
- Which model M1- M4 performs best in predicting the maximum reliable power supply from an energy park in comparison to the benchmark model M0 assuming Gaussian distributions?

$$\max_{s_t \geq 0} s_t \quad \text{s.t.} \quad \Pr\left\{\sum_i \tilde{P}_{it} \geq s_t\right\} \geq \chi$$

EVALUATION OF PREDICTIVE PROPERTIES 2

- Model accuracy in terms of the CV(RMSE) (Aman et al., 2014)

$$CV(RMSE) = \frac{1}{\bar{o}} \sqrt{\frac{\sum_{i=1}^{n}(p_i - o_i)^2}{n}}$$

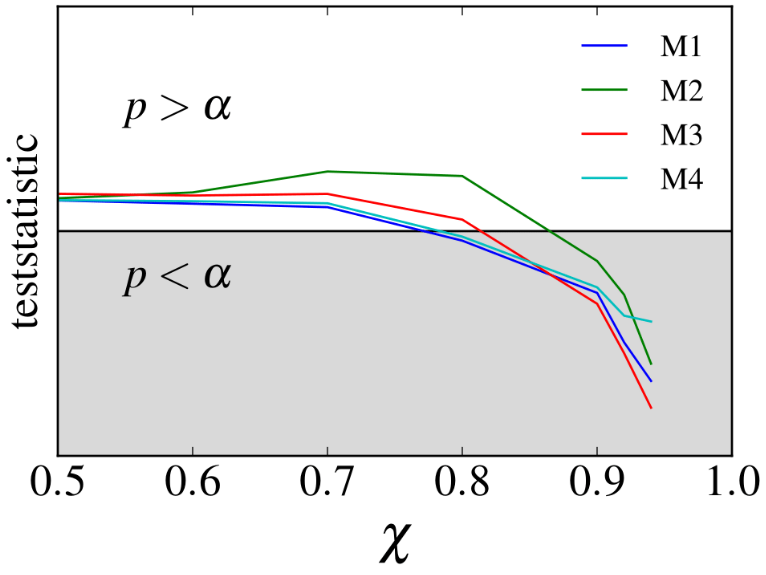
Variables	
p_i	Predicted value
o_i	Observed value
$\bar{o}$	Mean of observed values
n	Sample size

- Compare the sample means, bootstrapping of n=10000 simulations and comparing the distribution of the CV(RMSE)'s mean for the benchmark and the other models (α=5%)

$$H_0\!: \mu_{M_0} \geq \mu_{M_i}, \qquad H_1: \mu_{M_i} < \mu_{M_0}$$

EVALUATION OF PREDICTIVE PROPERTIES 3

- Observe different behaviour according to ex-ante specified level of reliability χ
- For lower levels of reliability, no difference compared to the benchmark model
- For higher values $\chi \gtrsim 0.8$ models (M1) - (M4) outperform benchmark model



significantly outperform benchmark model of Gaussian

INTERMEZZO: SOLVING THE STOCHASTIC OPTIMIZAZION PROBLEM
THE SAMPLE APPROACH

Solution for generic probabilistic distributions via

1. Sample approach (Calafiore and Campi 2005, 2006; Calafiore 2010)
2. Sample and discard algorithm (Campi and Garatti 2011)

PCC

- $\min\limits_{x \in X} E\left[\tilde{f}(x)\right]$ s.t. $\Pr\left(\sum_i \tilde{P}_{it}(x) \geq d_t\right) \geq \chi$

Sampled

- $\min\limits_{x \in X} E\left[\tilde{f}(x)\right]$ s.t. $\sum_i P_{it}^{(j)}(x) \geq d_t, \quad j = 1, \dots, N$

Solution

- Solve with standard methods

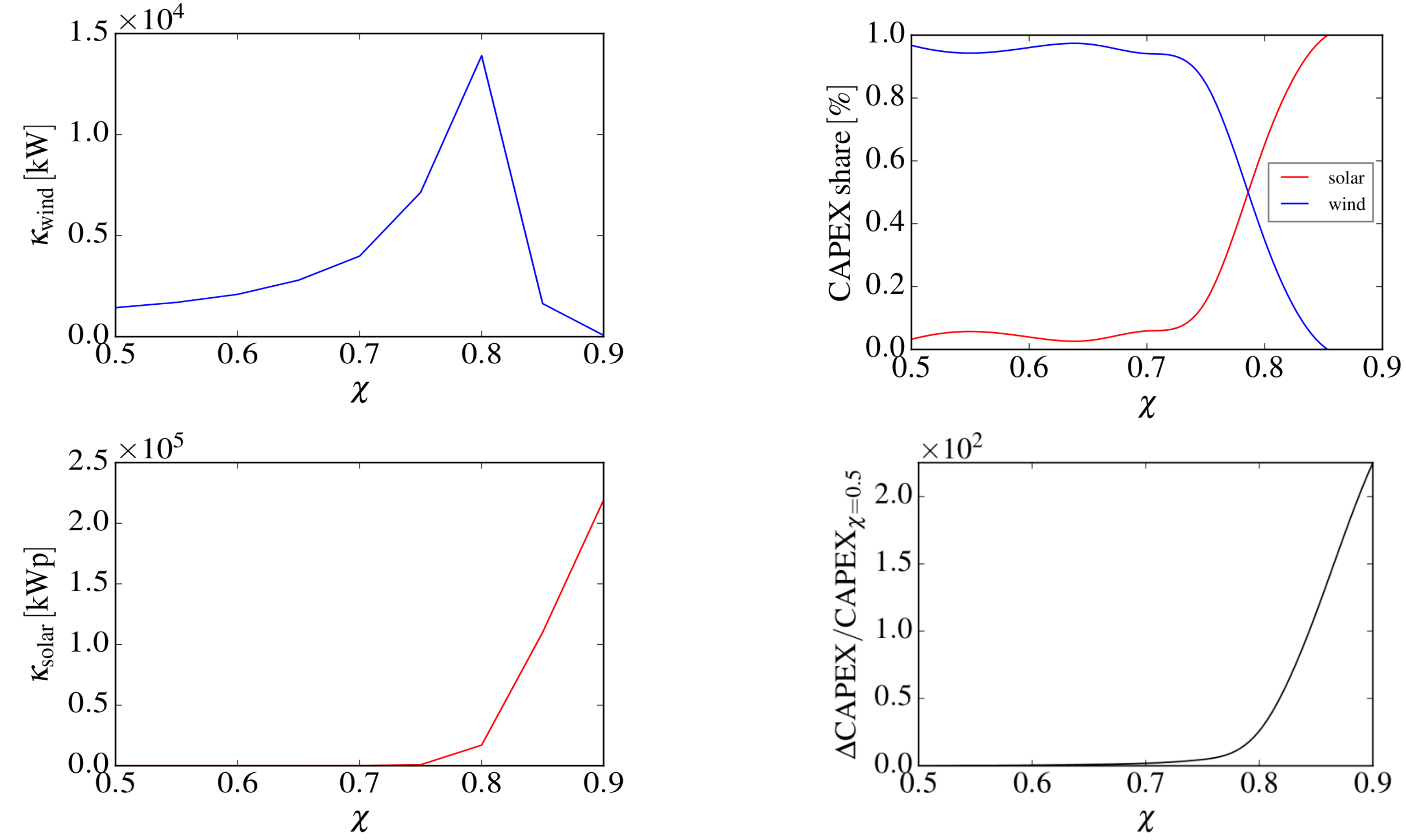
Solution is robust, whenever N is “adequately” large

USE CASE: GENERATION EXPANSION PROBLEM

- Find capacities κ_i to supply given demand d_t for every point in the planning horizon and a given level of reliability χ in an economic way (capacity budgeting problem)
- Costs are measured by CAPEX: the amount per installed capacity (wind: $\xi_1 \approx 1500\ {}^{€}/_{kW}$, solar: $\xi_2 \approx 2300\ {}^{€}/_{kW}$) (Cucchiella et al., 2015)
- What is the influence of the system reliability on the system costs?

$$\min_{\kappa_i \geq 0} \sum_i \kappa_i\, \xi_i \quad \text{s.t.} \quad \Pr\left\{\sum_i \tilde{P}_{it}(\kappa_i) \geq d_t\right\} \geq \chi, \qquad \forall t \in \mathrm{T}$$

RESULTS


$\times 10^4$
κ_{wind} [kW]
0.0
0.5
1.0
1.5
0.5
0.6
0.7
0.8
0.9
χ
CAPEX share [%]
0.0
0.2
0.4
0.6
0.8
1.0
solar
wind
$\times 10^5$
κ_{solar} [kWp]
0.0
0.5
1.0
1.5
2.0
2.5
$\times 10^2$
$\Delta\mathrm{CAPEX}/\mathrm{CAPEX}_{\chi=0.5}$

CONCLUSION

- Extension of deterministic procurement problem to consider risks associated with supply shortages
- Adapted pdf’s to estimate maximum reliable supply
- Flexible tool to support managerial decisions, applied in a use case

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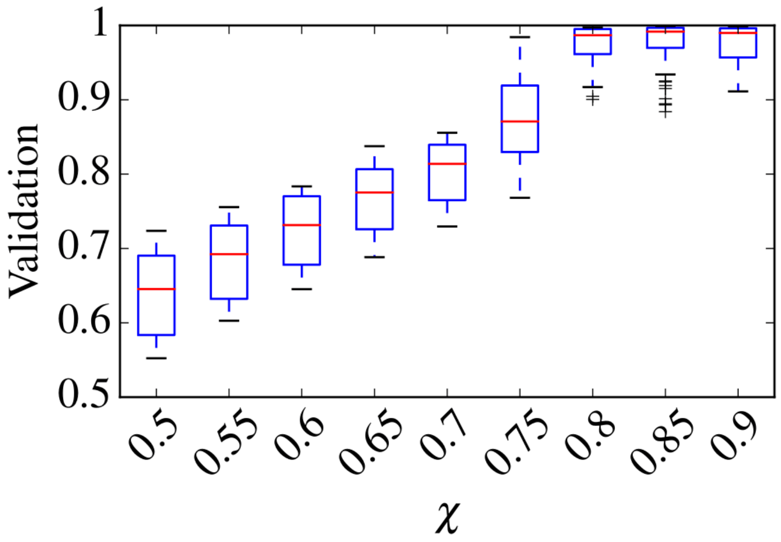
MODEL VALIDATION

- A posterioi assessment of the use case
- Sample N constraints and compute empirical probability of constraint validation (s.t. empirical probability is close ε=0.01 to true value with confidence greater than 95% (Calafiore and Campi, 2005))
- At low levels of reliability sample & discard algorithm introduces conservatism



THE SAMPLE APPROACH

- Fix 2 parameters: (1) reliability parameter $0<\chi<1$ and (2) confidence parameter $0<\beta<1$
- Then choose the sample size (Calafiore and Campi 2005), sample size refined in (Calafiore and Campi 2005)

$$N > \frac{n}{(1-\chi)\beta} - 1$$

- Then with probability not smaller than 1- β, the sampled program returns an optimal solution which is robustly feasible, i.e.

$$\Pr\left(\sum_i \tilde{P}_{it} \geq d_t \right) \geq \chi$$