

ECSP
2014



EURO MINI CONFERENCE
ON STOCHASTIC PROGRAMMING
AND ENERGY APPLICATIONS

24-26 SEPTEMBER, 2014 - PARIS

Robust optimization for strategic energy planning

September 24th 2014

Stefano Moret^{*a}, Michel Bierlaire^b, François Maréchal^a

stefano.moret@epfl.ch

^aIndustrial Process and Energy Systems Engineering Group (IPESE), EPFL

^bTransport and Mobility Laboratory (TRANSP-OR), EPFL

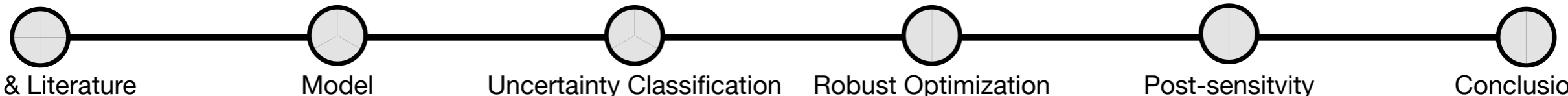


ÉCOLE POLYTECHNIQUE
FÉDÉRALE DE LAUSANNE

OUTLINE

Robust optimization for strategic energy planning

- Introduction & Literature Review
- The optimization model
- Uncertainty classification
- Robust optimization
- Post-sensitivity
- Conclusions & Next Steps



INTRODUCTION

Outline

The energy transition

Energy systems forecasting
and uncertainty

Literature review

Goals & Approach



Intro & Literature



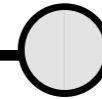
Model



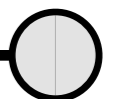
Uncertainty Classification



Robust Optimization



Post-sensitivity



Conclusions

INTRODUCTION

Outline

The energy transition

Energy systems forecasting
and uncertainty

Literature review

Goals & Approach



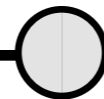
Intro & Literature



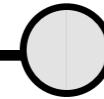
Model



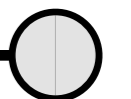
Uncertainty Classification



Robust Optimization



Post-sensitivity



Conclusions

INTRODUCTION

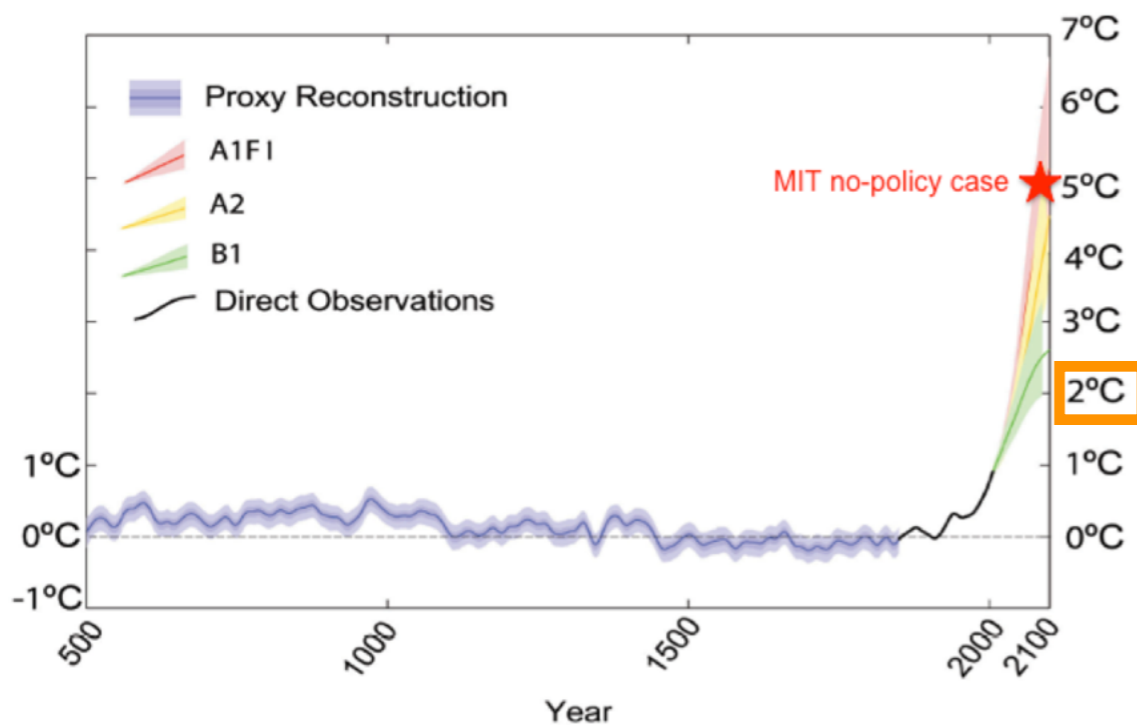
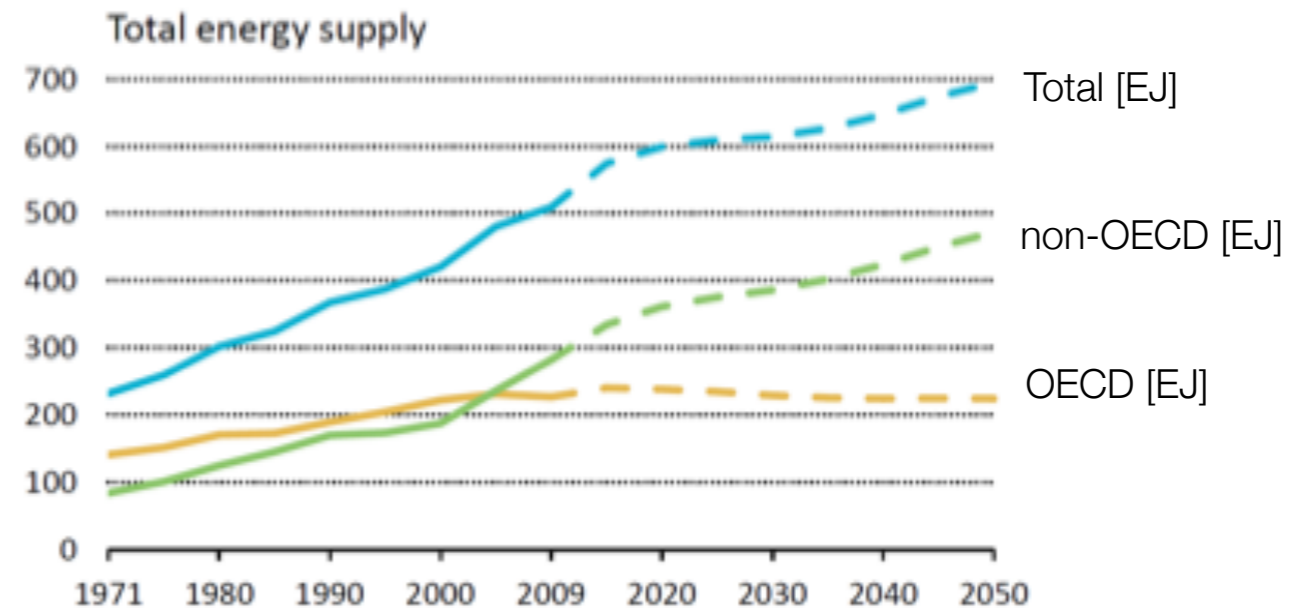
The energy transition

Sources:

- Copenhagen Diagnosis 2009, with MIT data taken from Sokolov et al. 2009.
- Jonathan Koomey, "Energy and society" lecture notes, UC Berkeley 2011
- IPCC 2013 report, Climate change 2013 - The physical science basis
- IEA, ETP 2012

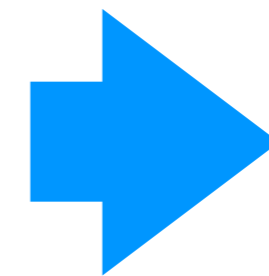
Growing trend in energy consumption, mainly from non-OECD countries

CO₂ Emissions 2050 = **2x** emissions today



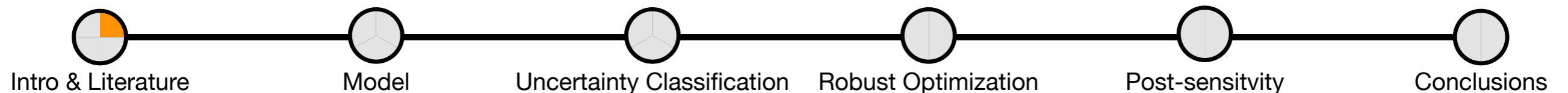
IPCC 2013: climate has changed due to human activities

To target the **2°C ΔT limit** CO₂ emissions need to be halved by 2050



Challenge: **4x** emissions reduction by:

- efficiency
- renewables
- technologies



INTRODUCTION

The energy transition

Sources:

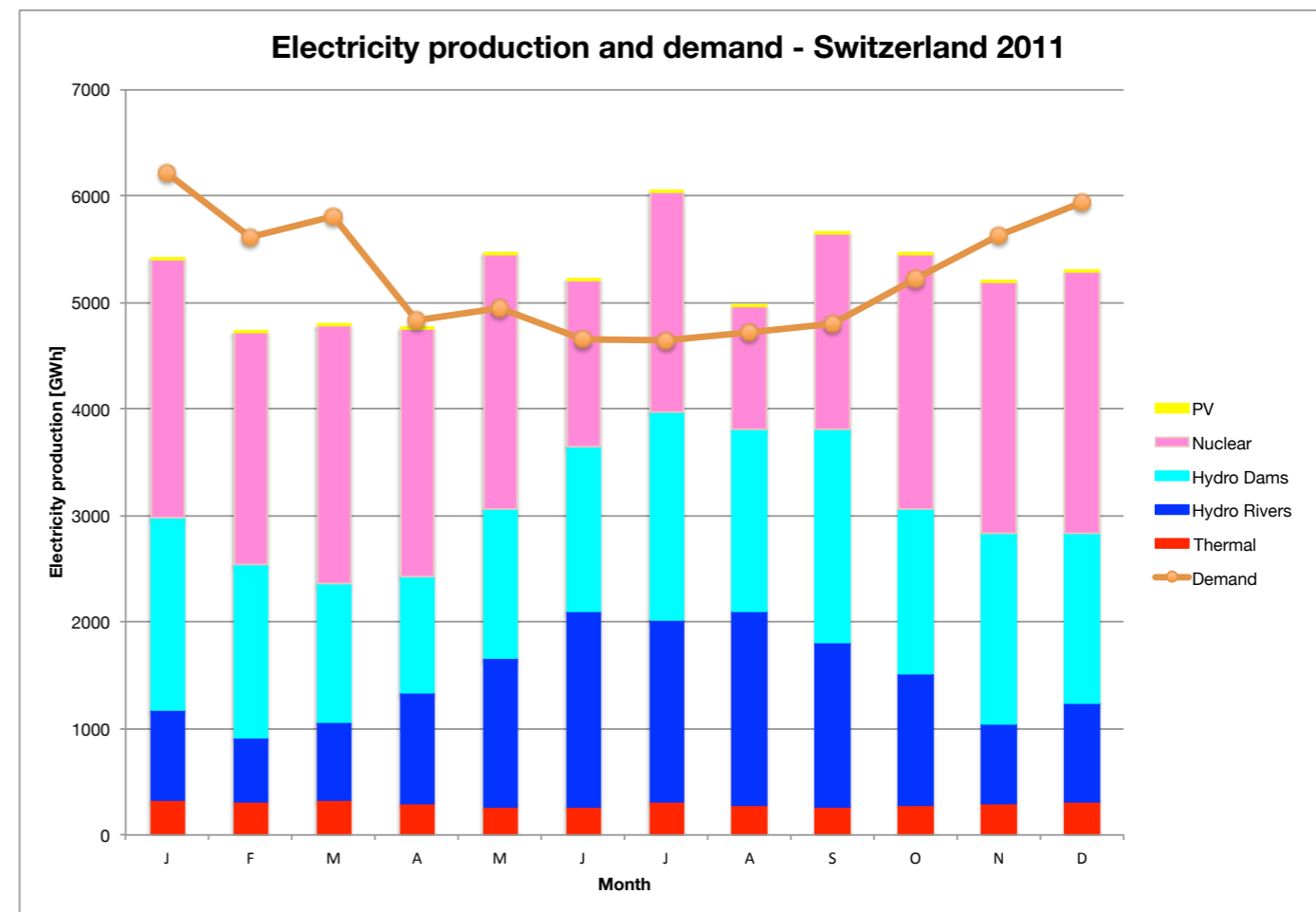
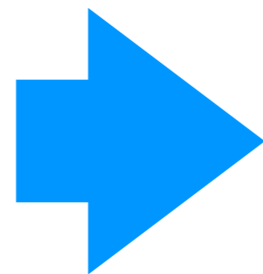
- SFOE, Swiss electricity statistics 2011
- SFOE, Energy strategy 2050 explanatory document

Various countries taking strategic decisions about their energy future



March 11th, 2011

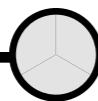
Fukushima nuclear disaster



2034: Phase-out of nuclear power plants
Strategic decisions for the energy future!



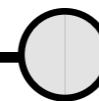
Intro & Literature



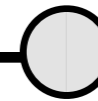
Model



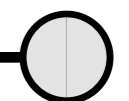
Uncertainty Classification



Robust Optimization



Post-sensitivity



Conclusions

INTRODUCTION

The energy transition

Sources:

- SFOE, Swiss electricity statistics 2011
- SFOE, Energy strategy 2050 explanatory document

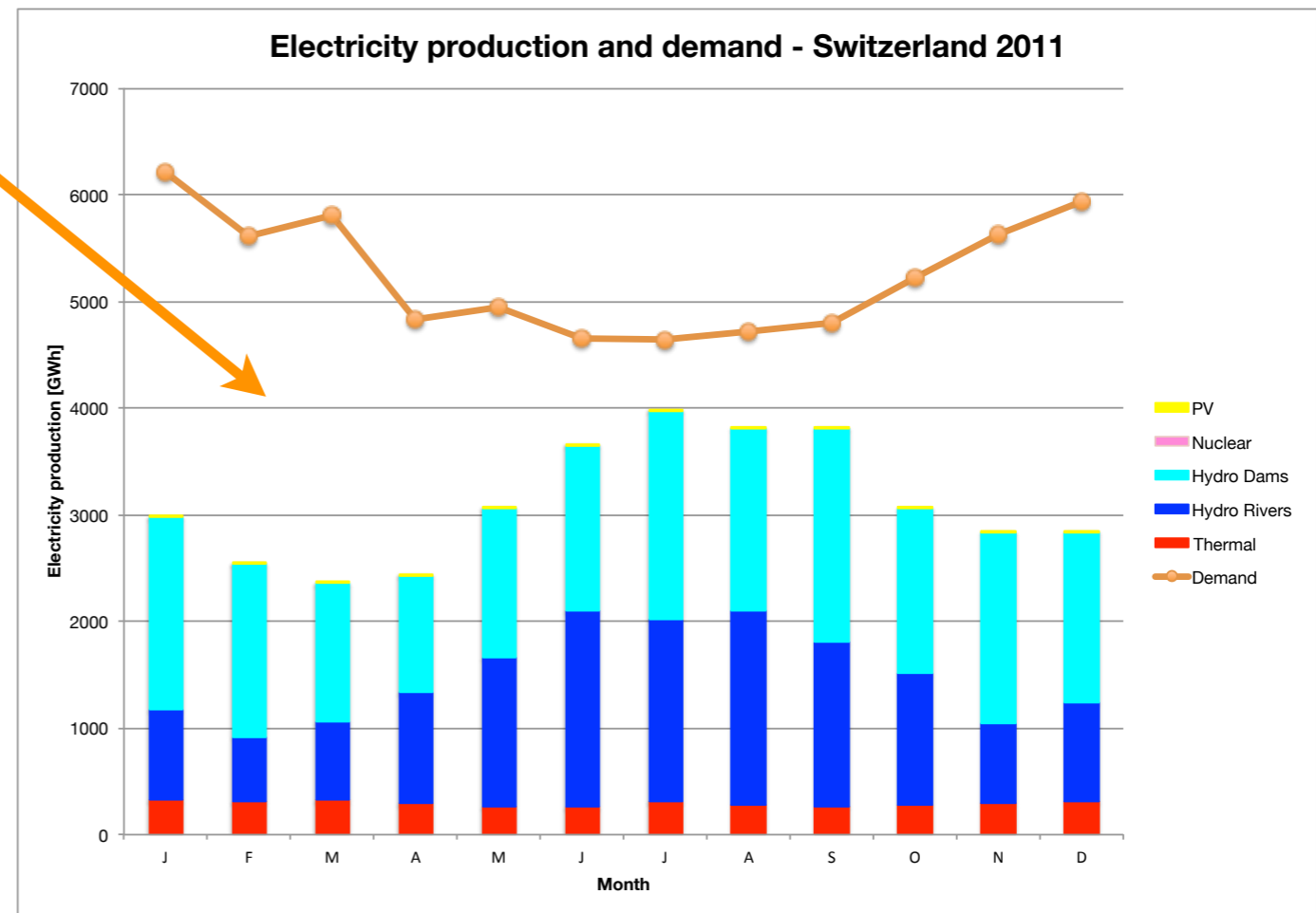
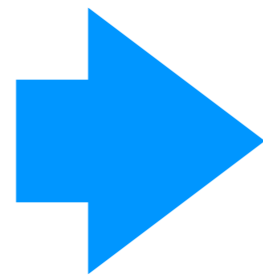
Various countries taking strategic decisions about their energy future

How to fill the gap?



March 11th, 2011

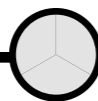
Fukushima nuclear disaster



2034: Phase-out of nuclear power plants
Strategic decisions for the energy future!



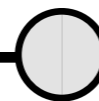
Intro & Literature



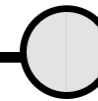
Model



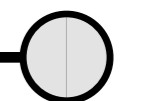
Uncertainty Classification



Robust Optimization



Post-sensitivity



Conclusions

INTRODUCTION

Outline

The energy transition

Energy systems forecasting
and uncertainty

Literature review

Goals & Approach



Intro & Literature



Model



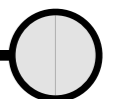
Uncertainty Classification



Robust Optimization



Post-sensitivity

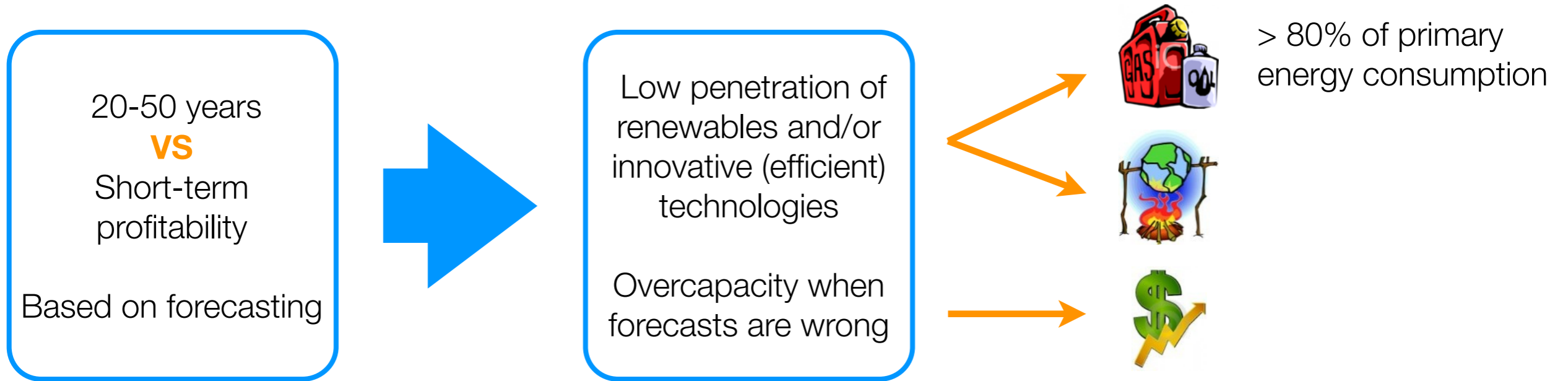


Conclusions

INTRODUCTION

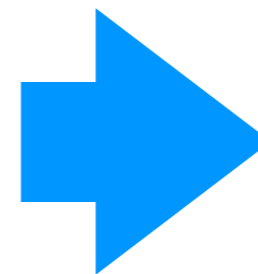
Energy forecasting: learning from the past

Long-term, strategic planning for urban and national energy systems

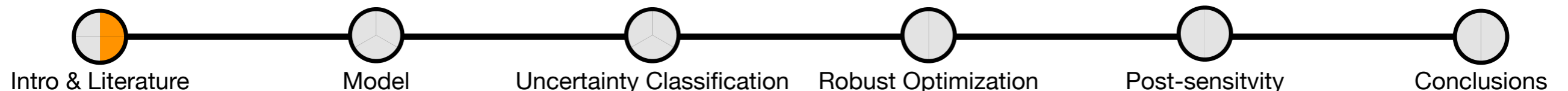


Standard approach: deterministic modelling of energy systems over time. But...

- energy models are “**non-validatable**”, i.e. doomed to inaccuracy
- backcasting: models have missed pivotal events



It's most likely vane to hope that a huge modelling effort will make us able to “know” the future!



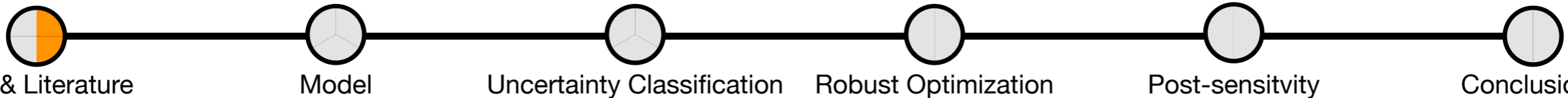
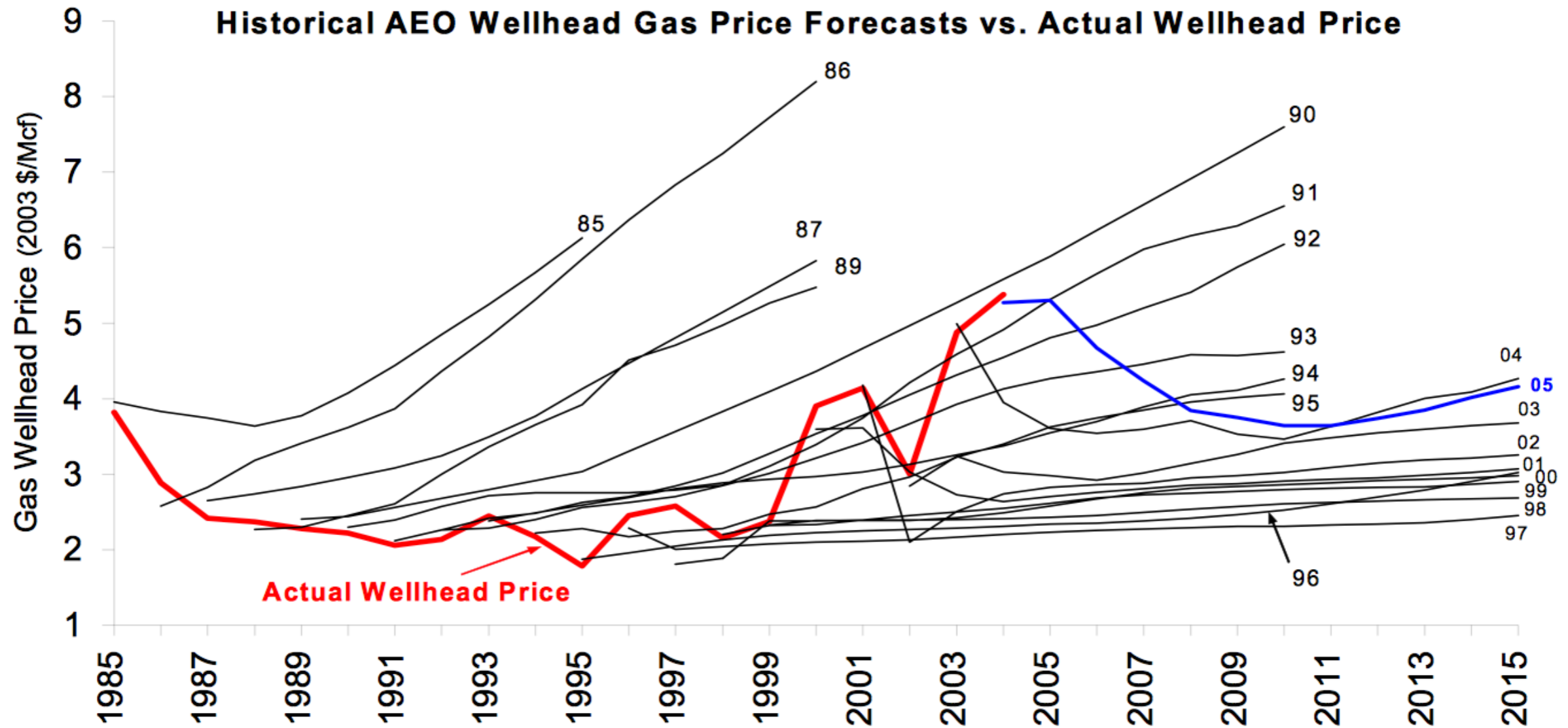
INTRODUCTION

Energy forecasting: learning from the past

Sources:

- Chris Marnay and Afzal S. Siddiqui. Addressing an uncertain future using scenario analysis. 2006
- U.S. EIA - Energy Information Administration. Natural gas data.

Fossil fuel prices forecasting models are subject to very relevant errors..



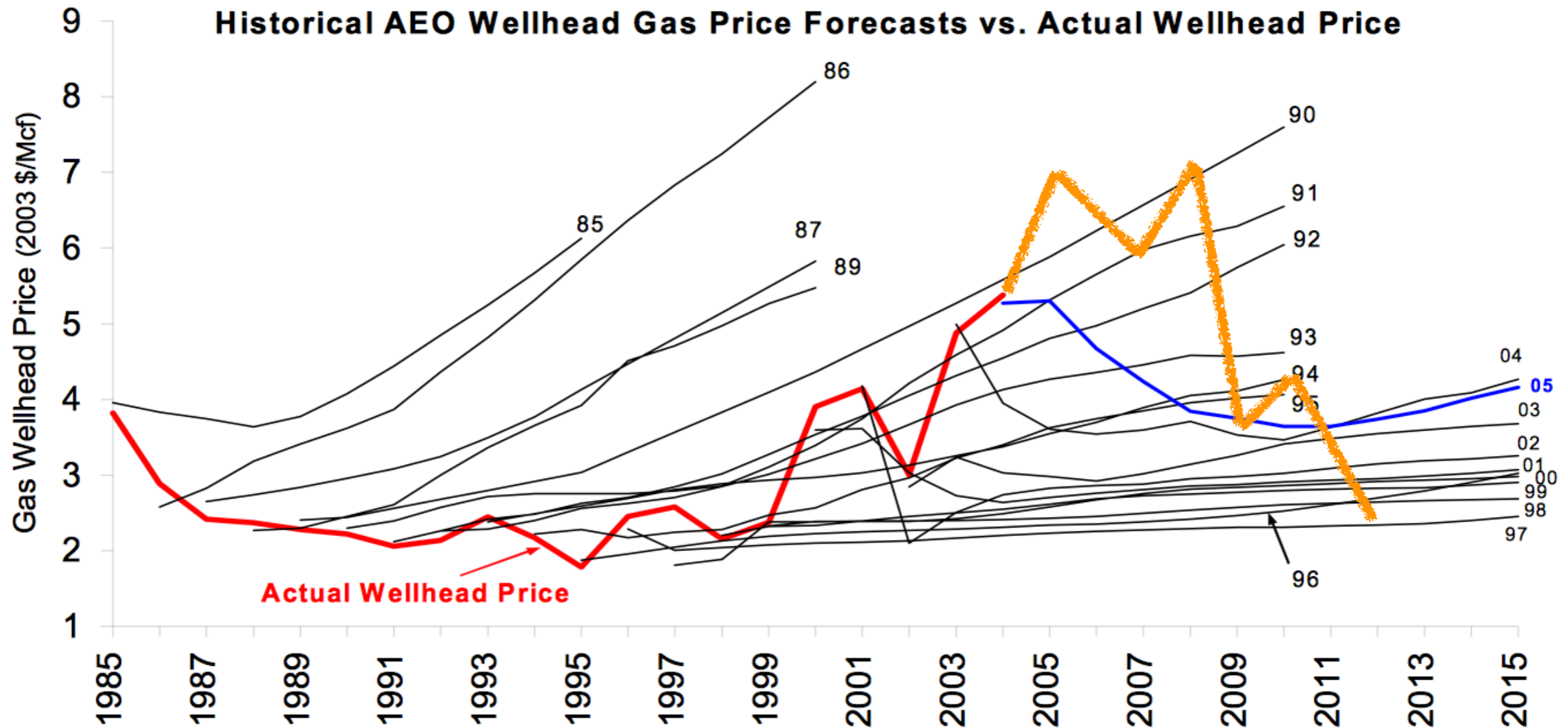
INTRODUCTION

Sources:

- Chris Marnay and Afzal S. Siddiqui. Addressing an uncertain future using scenario analysis. 2006
- U.S. EIA - Energy Information Administration. Natural gas data.
- oregonstate.edu: conversion factors for 2003 \$ table

Energy forecasting: learning from the past

Fossil fuel prices forecasting models are subject to very relevant errors..



Intro & Literature



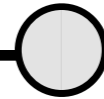
Model



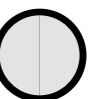
Uncertainty Classification



Robust Optimization



Post-sensitivity



Conclusions

Sources:

- Eurelectric report 2011
- TERNA - Dati statistici sull'energia elettrica in Italia - anno 2011
- Paul Krugman. Gambling with civilization. *The New York Review of Books*, November 2013.
- William D. Nordhaus. The allocation of energy resources. *Brookings Papers on Economic Activity*, 1973.
- De Volkskrant, 6.2.2014

INTRODUCTION

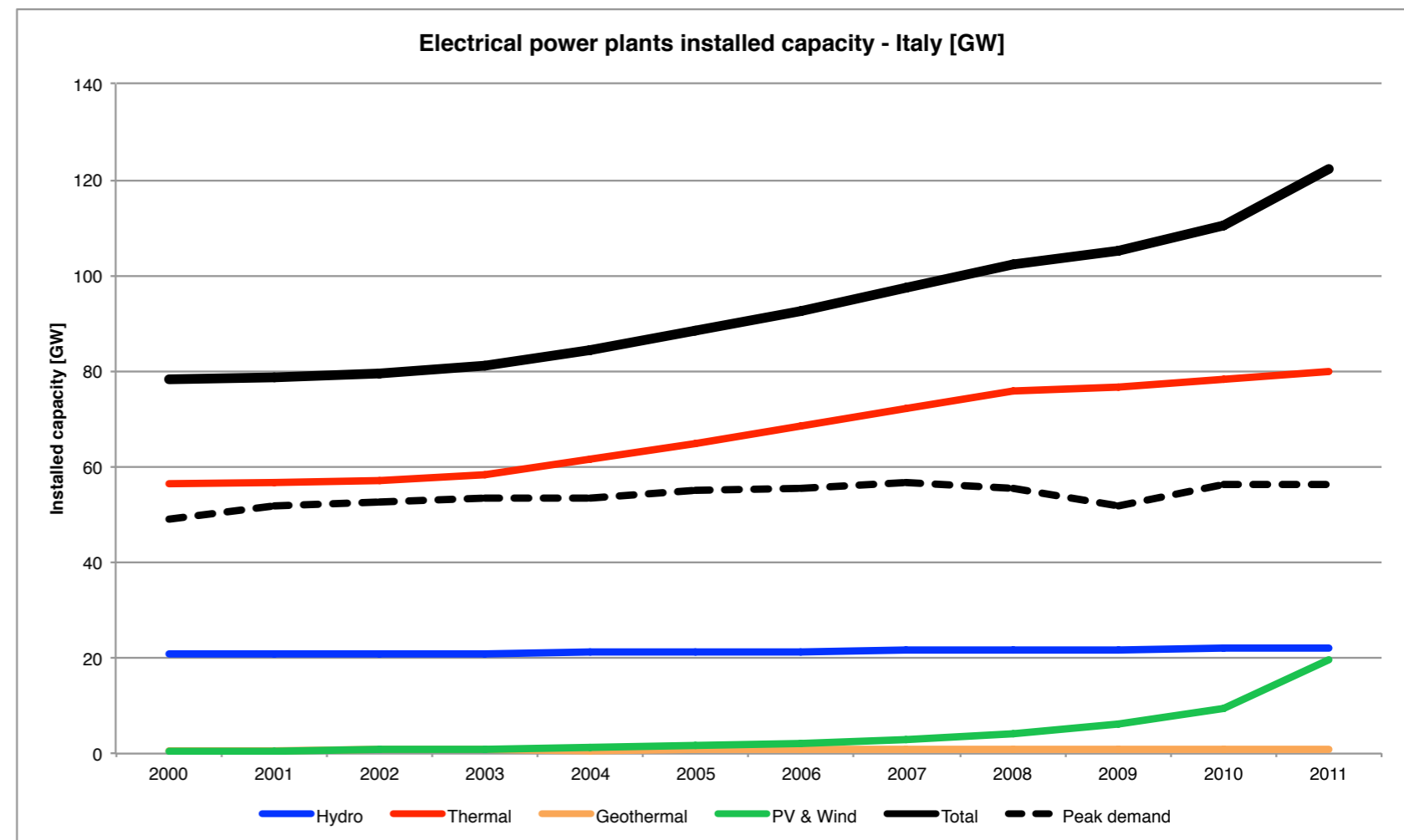
Energy forecasting: learning from the past

What is the effect of decisions taken based on this approach?

- **60%** electricity production overcapacity in EU-27 (2010)
- Overcapacity in Italy: CCGT plants used on average 2500-3000 h/year (2011)
- 5 CCGT plants never used in NL



Overcapacity implies cost!



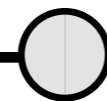
Intro & Literature



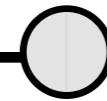
Model



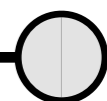
Uncertainty Classification



Robust Optimization



Post-sensitivity



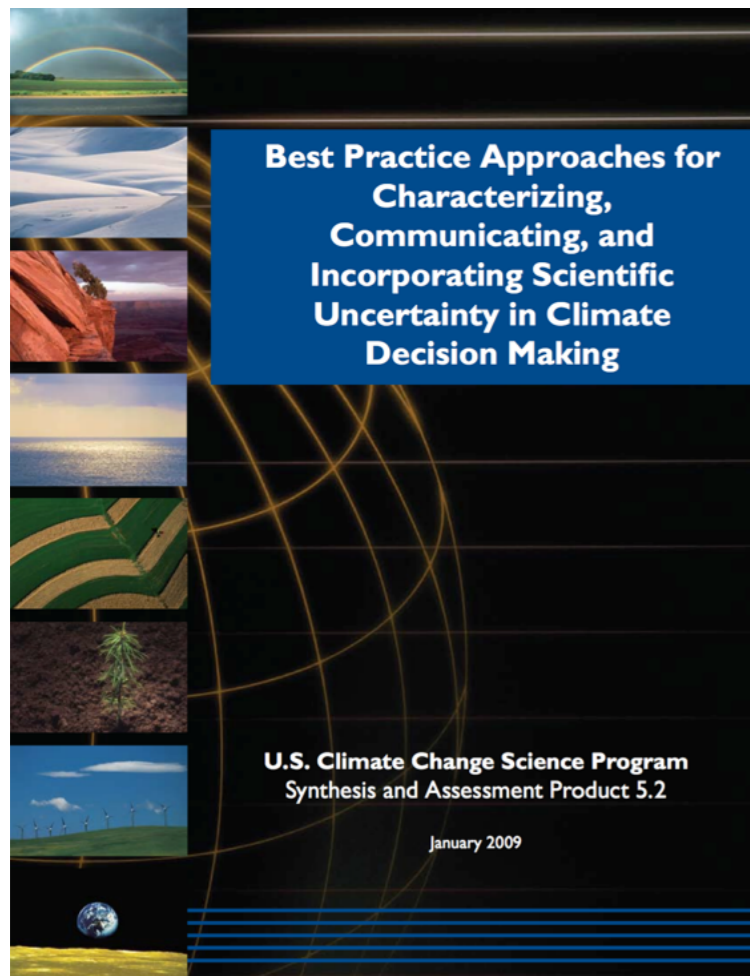
Conclusions

INTRODUCTION

The need of taking uncertainty into account

CRAG Conference (EPFL, 2013):

- Need of taking into account uncertainty in energy forecasting (Azevedo)
- flexible design, taking into account uncertainty, can lead to higher expected values (De Neufville)

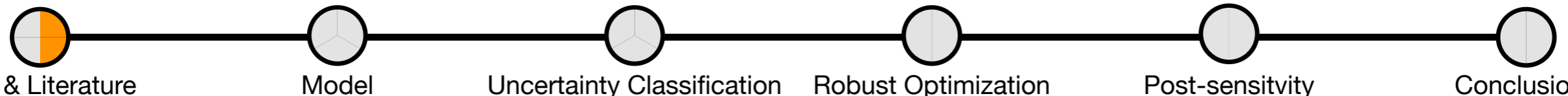


Key guidelines (Granger-Morgan):

- Uncertainty can be irreducible
- Probability is the language of uncertainty
- Not all quantities can be associated with a PDF
- Sometimes scenario analysis needs to be performed



Need of rigorous classification!



INTRODUCTION

Outline

The energy transition

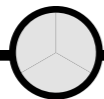
Energy systems forecasting
and uncertainty

Literature review

Goals & Approach



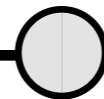
Intro & Literature



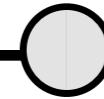
Model



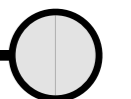
Uncertainty Classification



Robust Optimization



Post-sensitivity



Conclusions

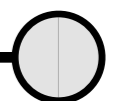
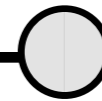
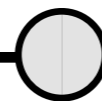
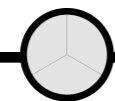
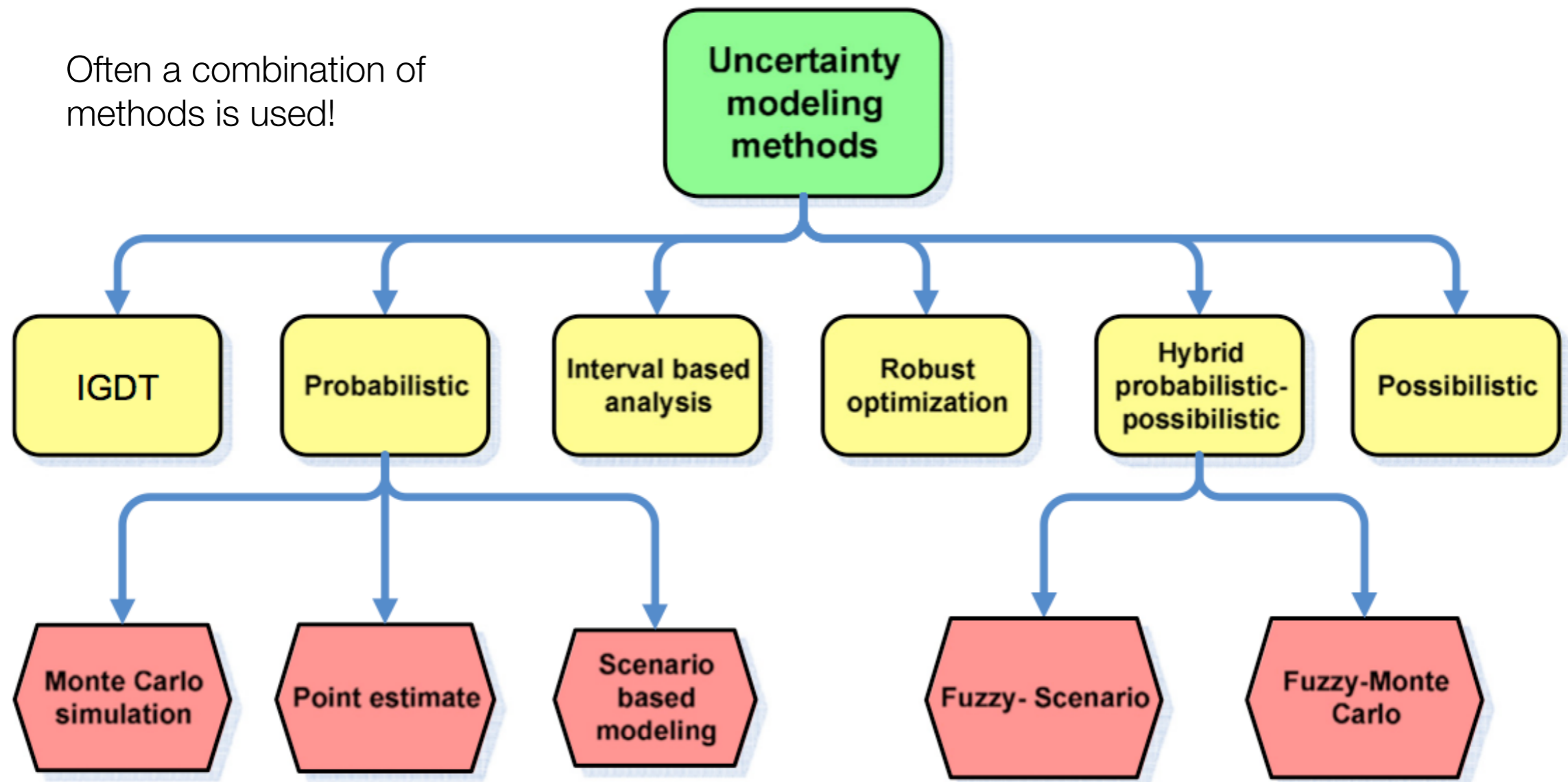
INTRODUCTION

Literature review

Robust optimisation: I can't define a PDF for my parameters, but a range of variation (worst-case)

Key applications: PHEV, renewables operations, electricity markets, electricity transmission/generation

Often a combination of methods is used!

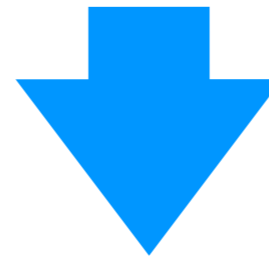


INTRODUCTION

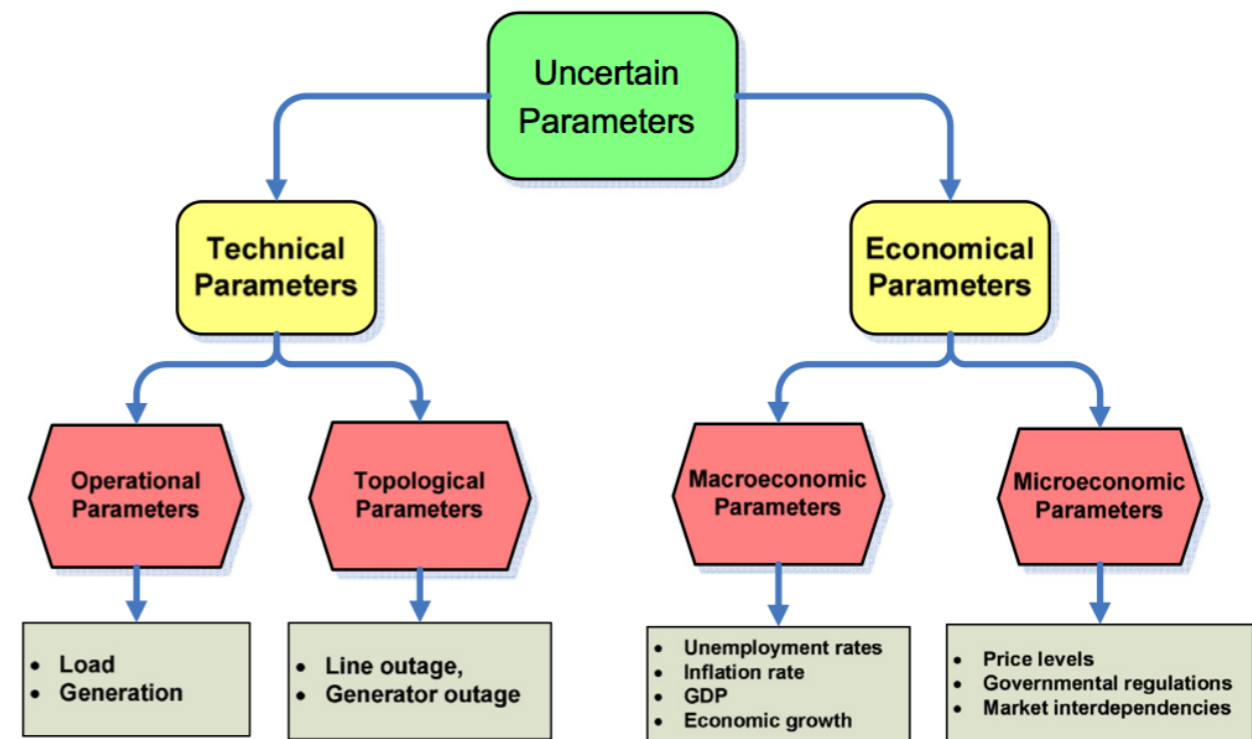
Literature review: uncertainty classification

- Alireza Soroudi and Turaj Amraee. Decision making under uncertainty in energy systems: State of the art. 2013
- Chris Marnay and Afzal S. Siddiqui. Addressing an uncertain future using scenario analysis. 2006
- M. Granger Morgan. CCSP, 2009: Best practice approaches for characterizing, communicating and incorporating scientific uncertainty in climate decision making. 2009
- Matthias Dubuis and François Maréchal. *Energy system design under uncertainty*. 2012.
- E. Loeken et al. Decision analysis and uncertainties in planning local energy systems. 2006

“An expected kWh output from a wind generator in a future year, which is not exposed to volatile and unpredictable fuel prices, should be truly worth more than an equivalent kWh from an alternative fossil fuel fired technology”



Uncertainty classification by type and degree

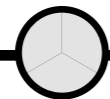


Key contributions:

- Generic classification of uncertainty (technical vs economic) (Soroudi)
- Internal VS External uncertainties (physical, economic, regulatory) (Loeken)
- Process design uncertainties (Dubuis)



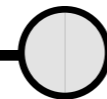
Intro & Literature



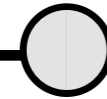
Model



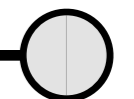
Uncertainty Classification



Robust Optimization



Post-sensitivity



Conclusions

INTRODUCTION

Literature review

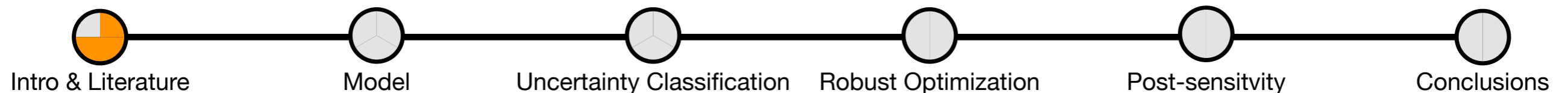
Some models have been extended to include uncertainties. Nonetheless (Marnay):

- The formalism of stochastic models sometimes hides very poor knowledge of distribution parameters
- Uncertainty might overcome the complexities of the models themselves

Key conclusion: Need of acknowledging uncertainty of the future!

Key gaps in research:

- **Uncertainty classification:** Rigorous classification missing, by type and degree.
- **Methods:** Various methods, often used in combination. No clear methodology defined.
- **Energy systems applications:** Most methods limited to single applications, or max. electricity market. Need of holistic view of the energy system (heating/cogeneration and transportation), electricity is only a part of the picture.



INTRODUCTION

Outline

The energy transition

Energy systems forecasting
and uncertainty

Literature review

Goals & Approach



Intro & Literature

Model

Uncertainty Classification

Robust Optimization

Post-sensitivity

Conclusions

INTRODUCTION

Goals & Approach

Renewables and/or innovative
(efficient) technologies



Lower resources
consumption



Lower emissions

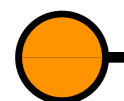
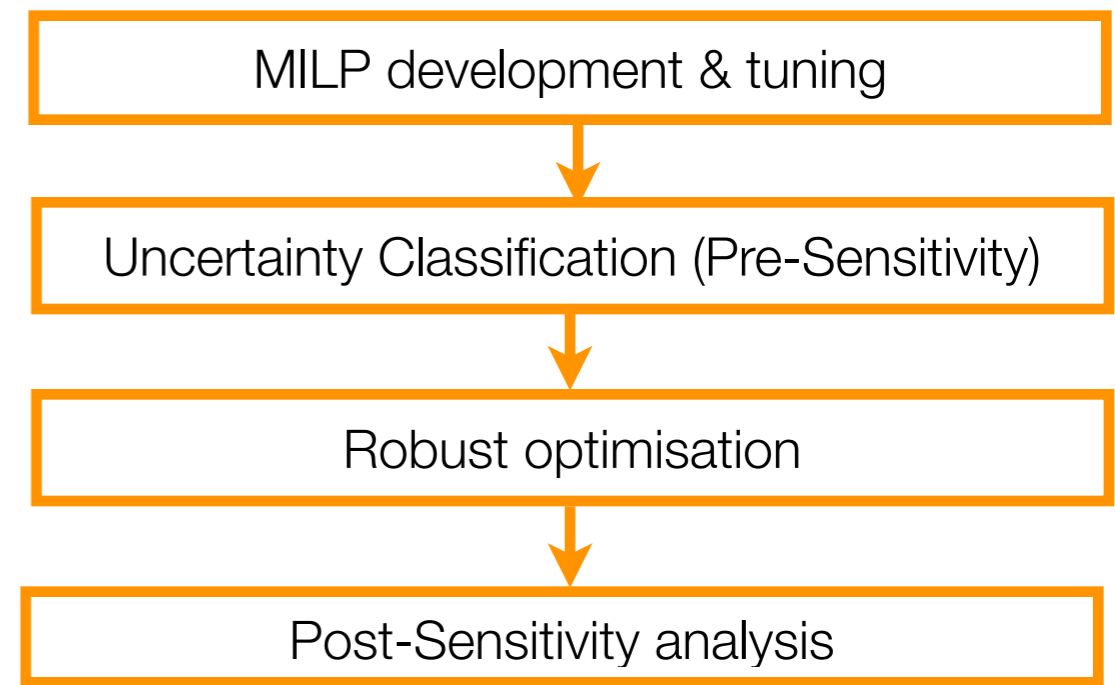


Higher investment
costs

*How does taking uncertainty into account influence
strategic energy planning?*

Key **goals**:

- Preliminary classification of uncertainty
- Robust optimisation for typical energy planning MILP
- Preliminary conclusions -> future work guidelines



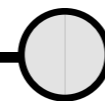
Intro & Literature



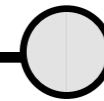
Model



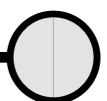
Uncertainty Classification



Robust Optimization



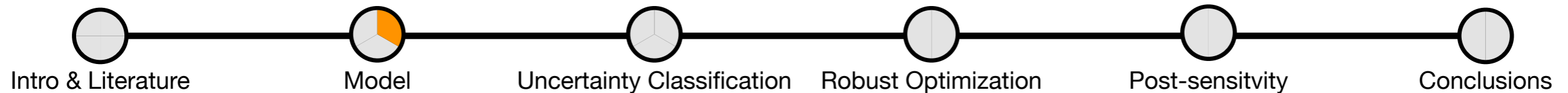
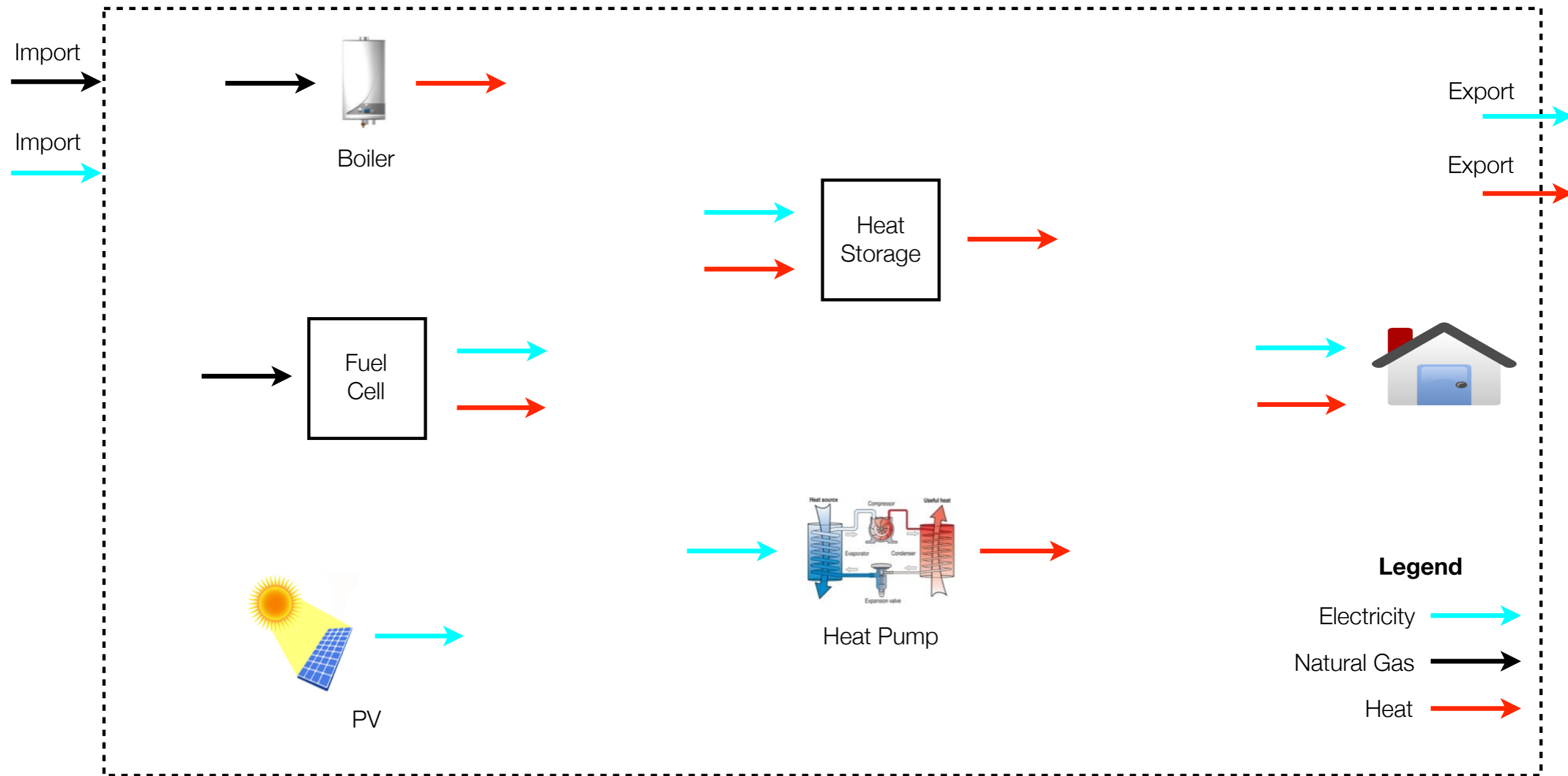
Post-sensitivity



Conclusions

OPTIMIZATION MODEL

Model description



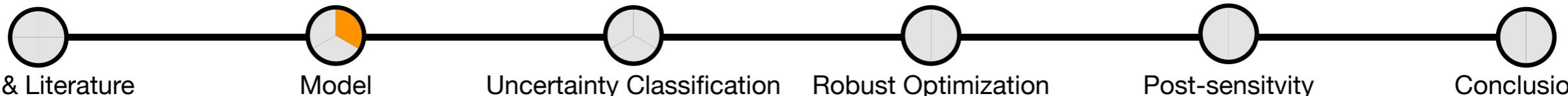
OPTIMIZATION MODEL

Model description

Key features:

- Typical, simplified MILP for energy planning: household -> urban/national scale
- Electricity and Heating yearly demand for SFH in Switzerland (SIA 380/1 compliant)
- multi-period problem: 12 times (monthly averages) + 1 peak period (sizing)
- Simplifying assumptions: day/night electricity balance managed by the grid
- Default average prices: 0.18 CHF/kWh_e, 0.097 CHF/kWh_{NG} (Switzerland)

Technology	Efficiency (total) [-]	Efficiency (electrical) [-]	Efficiency (thermal) [-]	Standard size	C_inv
Boiler	0.9	-	0.9	10 kW _{th}	4206
Fuel Cell	0.9	0.55	0.35	3 kW _e	20000
Storage	1	-	-	10 m ³	1500 (centr.)
PV	0.15	0.15	-	3 kW _e	10500
Heat Pump	4	-	4	10 kW _{th}	14167



OPTIMIZATION MODEL

MILP formulation

Implementation of the problem in the AMPL programming language

Sets

UNITS $u = \{1, \dots, U\} = \{BOIL, FC, STO, PV, HP\}$

TIMES $t = \{1, \dots, T\} = \{1, \dots, 13\}$

Key Variables

$y(u) \in \{0, 1\}$: binary variable, investment decision for unit u

$f(u, t)$: multiplication factor for each unit u at time t

$f_{size}(u)$: size of the units

Key Constraints

$$f(u, t) \leq f_{size}(u) \quad \forall t$$

$$C_{inv}(u) = C_{inv,1}(u) \cdot y(u) + f_{size}(u) \cdot C_{inv,2}(u) \quad \forall u$$

$$\dot{E}_{buy}(t) + \sum_u \dot{E}_{out}(u, t) - \sum_u \dot{E}_{in}(u, t) - \dot{E}_{demand}(t) \geq 0 \quad \forall t$$

$$\dot{E}_{buy}(t) + \sum_u \dot{E}_{out}(u, t) - \sum_u \dot{E}_{in}(u, t) - \dot{E}_{demand}(t) - \dot{E}_{sell}(t) = 0 \quad \forall t$$

Similar equations for Heating



OPTIMIZATION MODEL

MILP formulation

Objective Function: minimize Total Annual Cost (Annualised Investment + Yearly Operating cost)

Annualisation factor
($i = 5\%$, $n = 20$ years)

$$\tau = \frac{i(i+1)^n}{(1+i)^n - 1}$$

Prices of gas and
electricity import at t
[CHF/kWh]

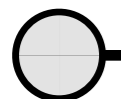
$0.4 * c_{el,buy}$

Operating time [h]

$$\left(\tau \sum_u C_{inv}(u) + \sum_t \left(\sum_u c_{ng}(t) \dot{Q}_{NG}(u, t) + c_{el,buy}(t) \dot{E}_{buy}(t) - p_{el,sell}(t) \dot{E}_{sell}(t) \right) \cdot t_{op}(t) \right)$$

Annualised investment

Yearly operating cost



Intro & Literature



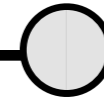
Model



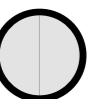
Uncertainty Classification



Robust Optimization



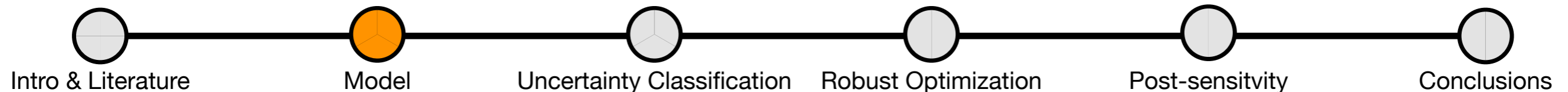
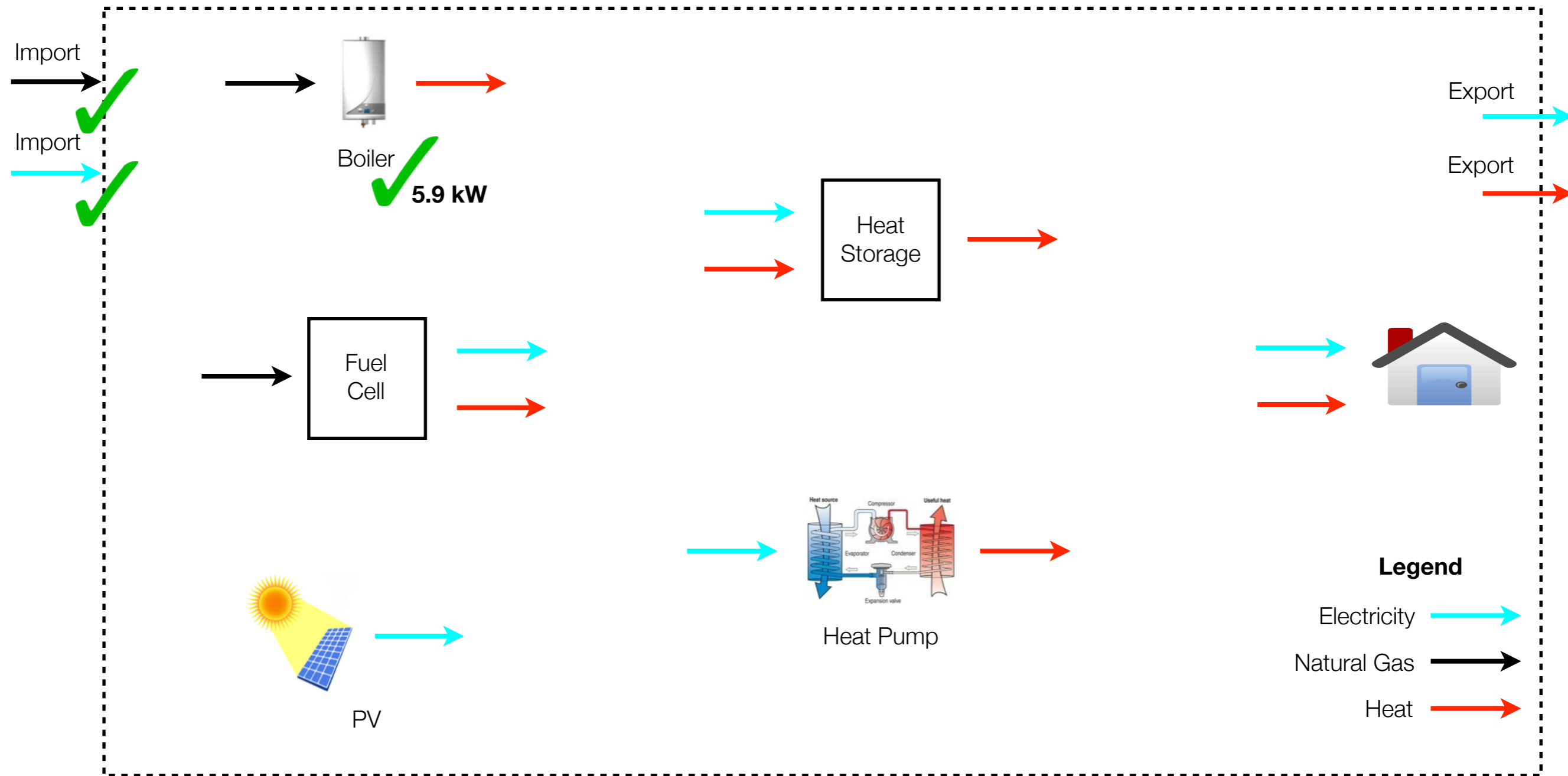
Post-sensitivity



Conclusions

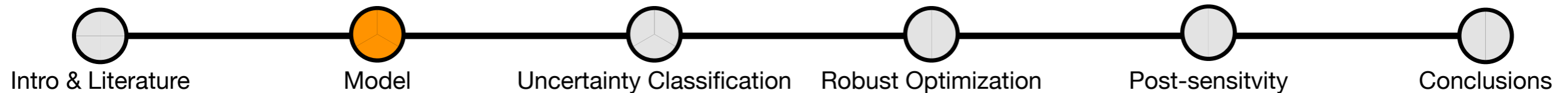
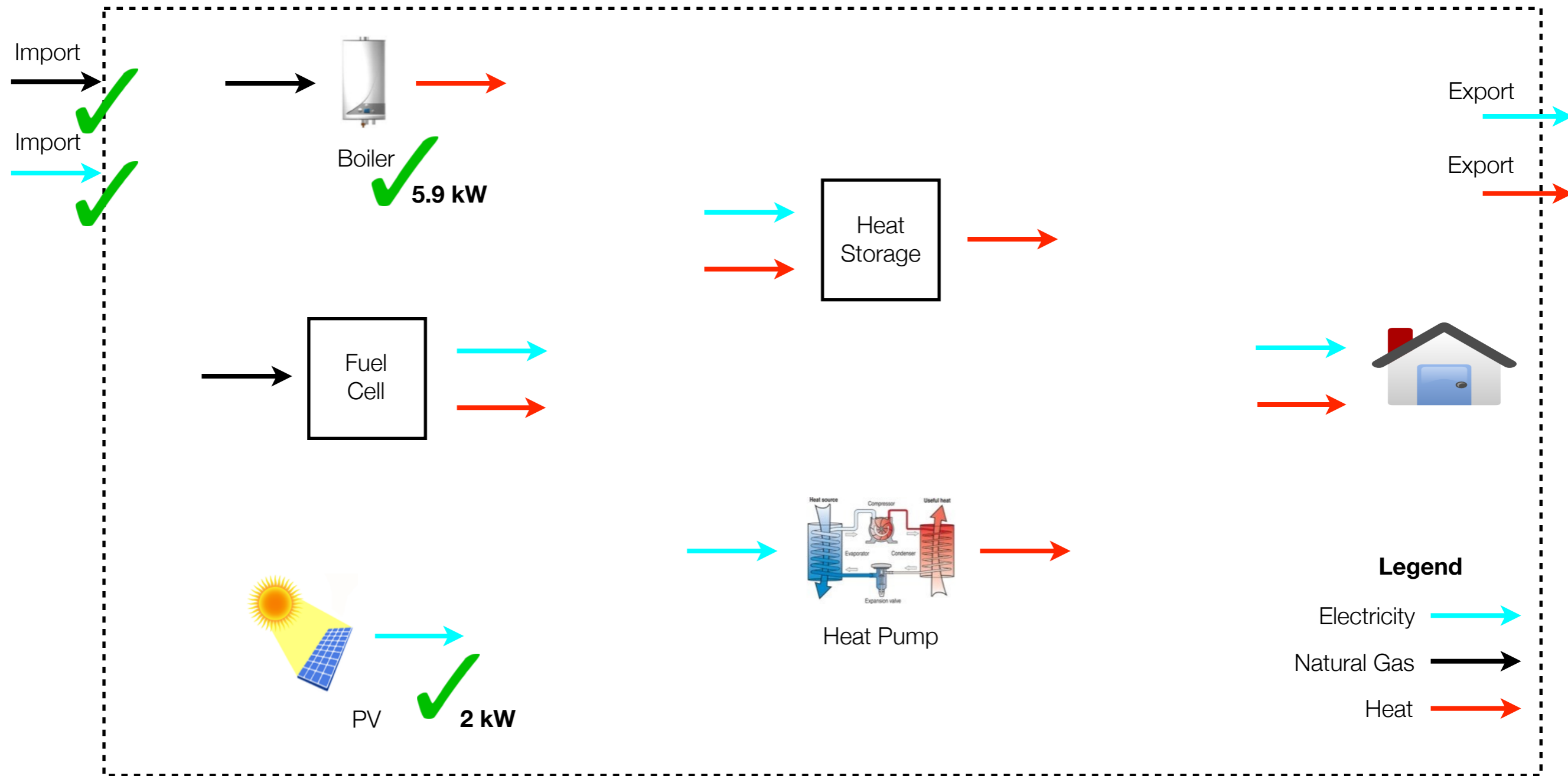
OPTIMIZATION MODEL

Obj = 1813. Case 1: $c_{el, buy}$ default, c_{ng} default



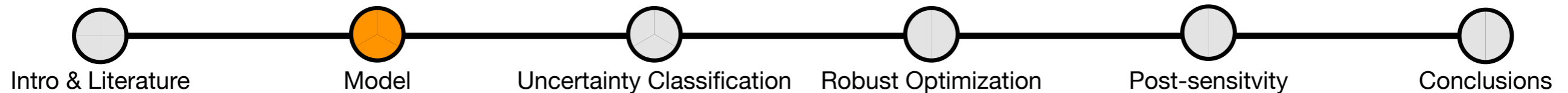
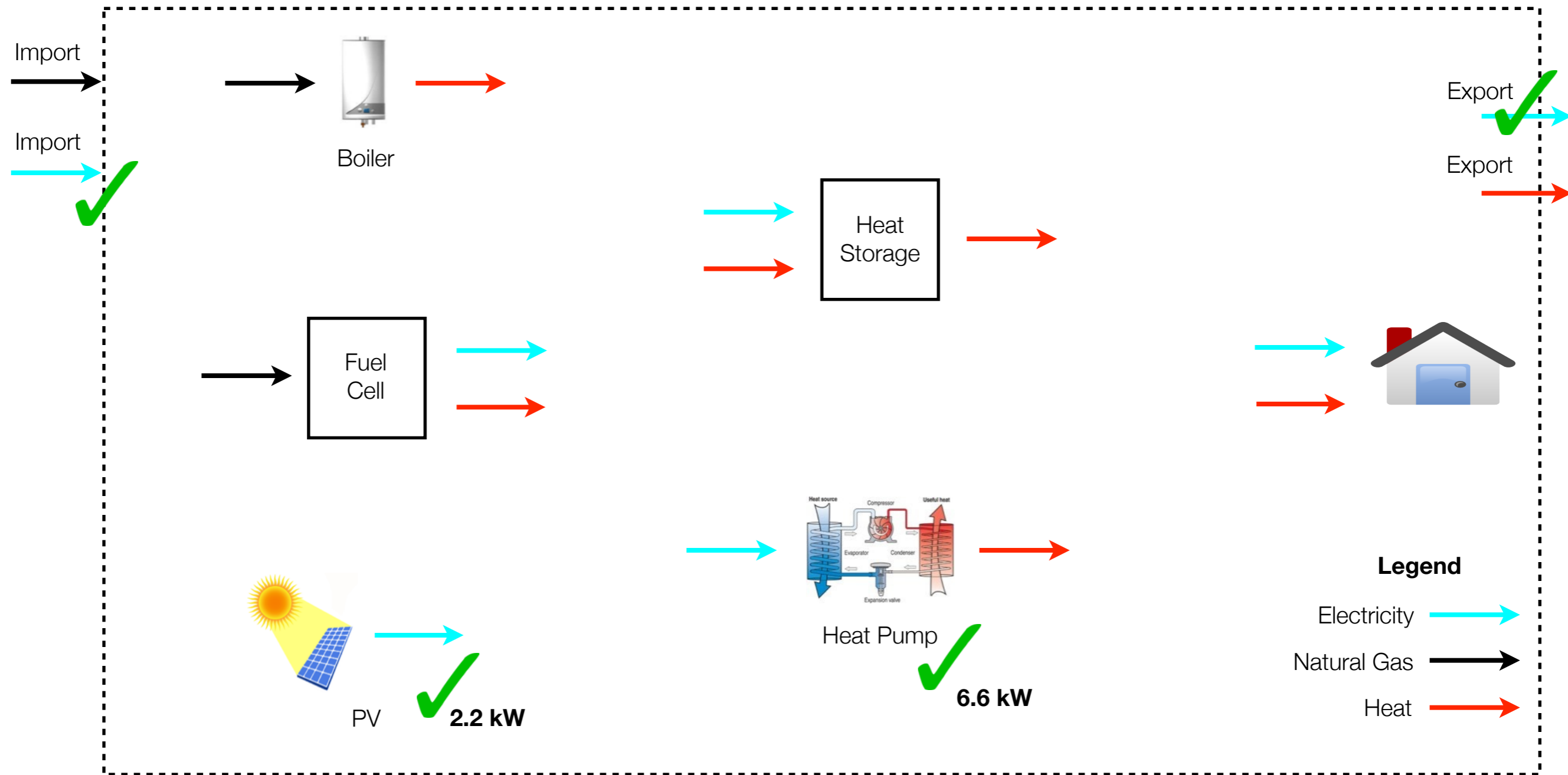
OPTIMIZATION MODEL

Obj = 2186. Case 2: $c_{el, buy}$ high, c_{ng} default



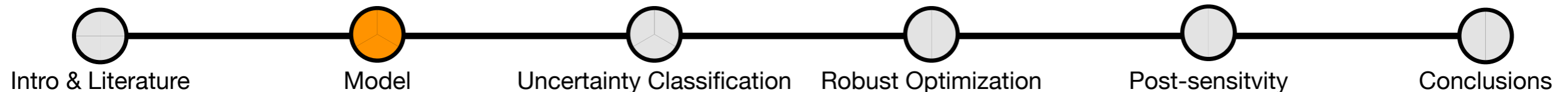
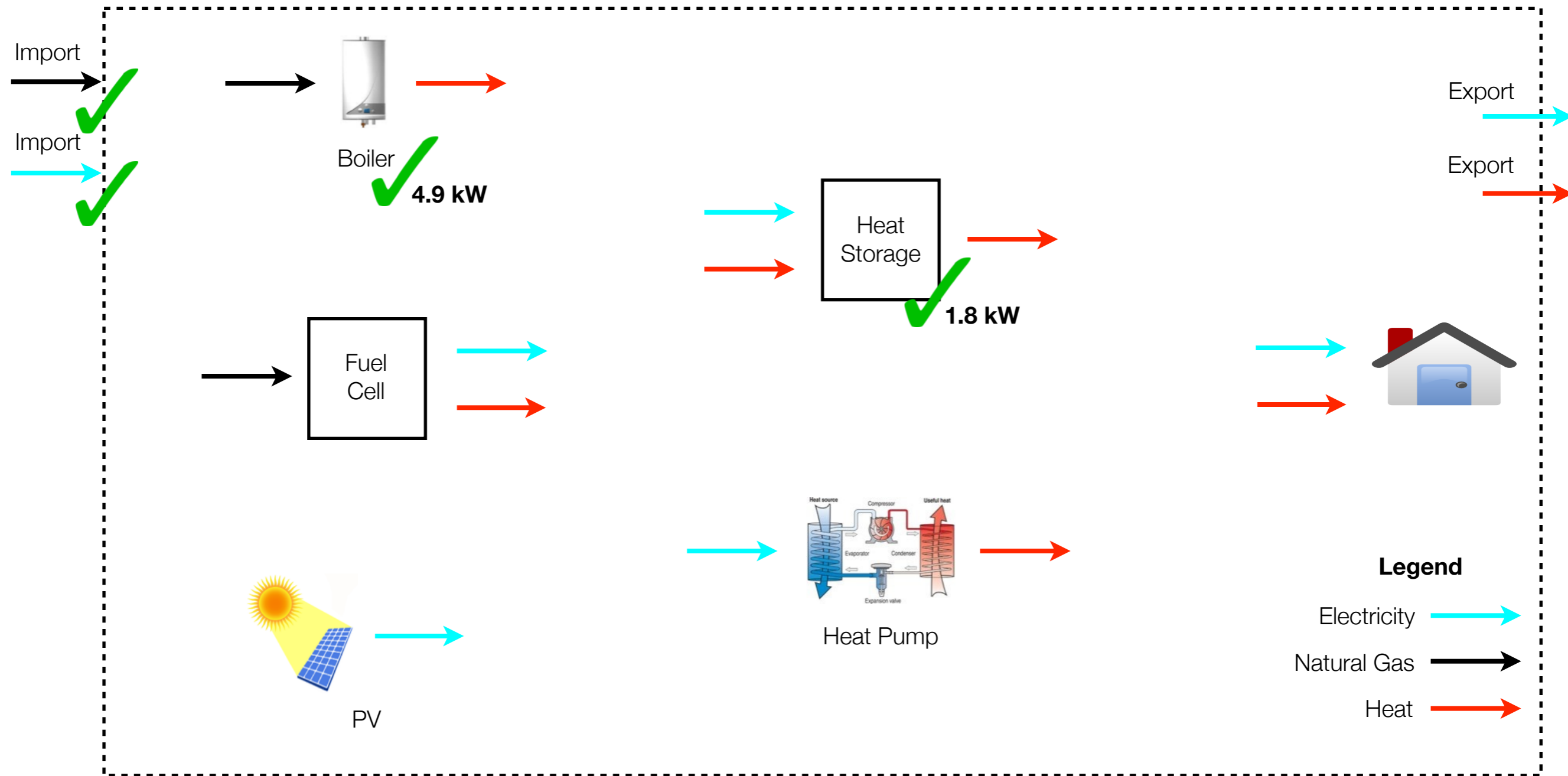
OPTIMIZATION MODEL

Obj = 2689. Case 3: $c_{el, buy}$ high, c_{ng} high



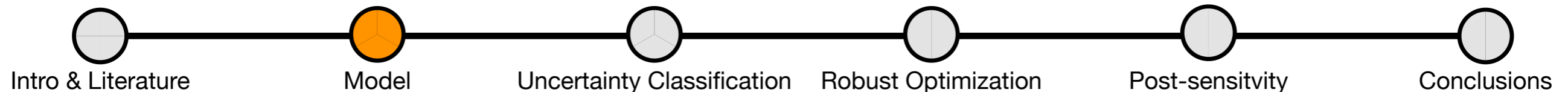
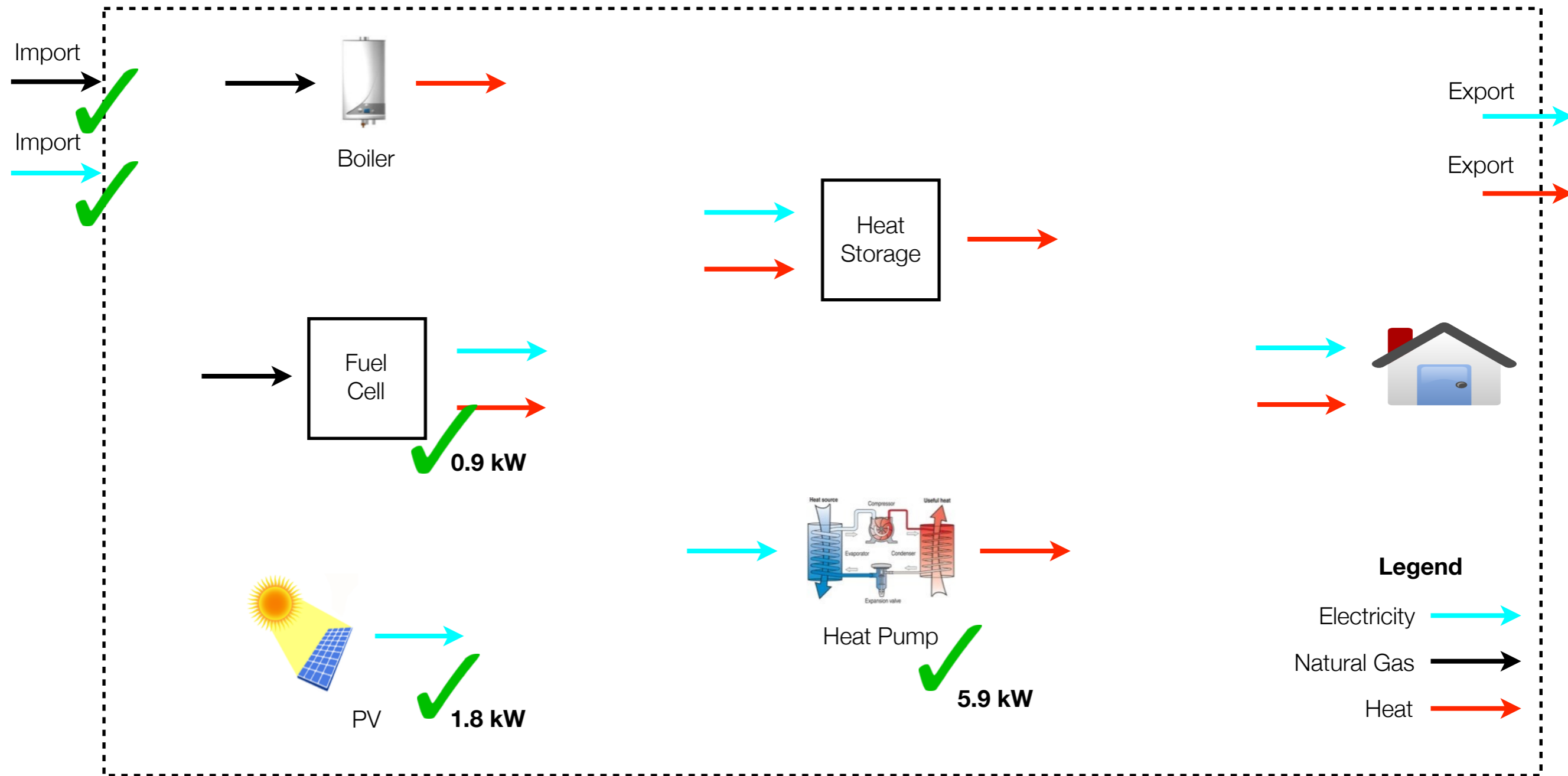
OPTIMIZATION MODEL

Obj = 1653. Case 4: $c_{el, buy}$ default, c_{ng} oscillating



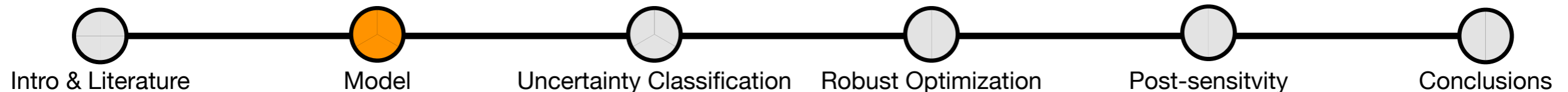
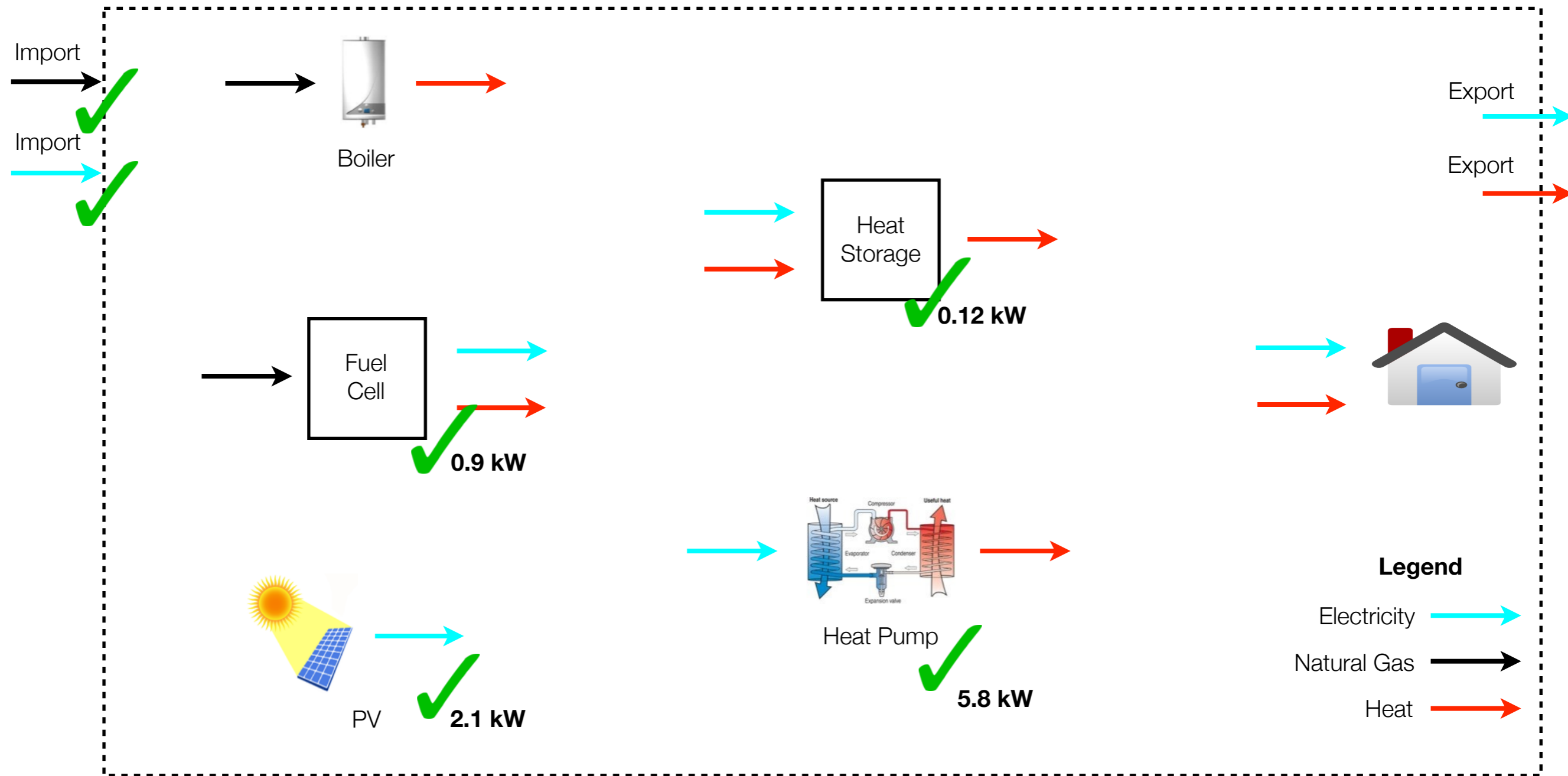
OPTIMIZATION MODEL

Obj = 2890. Case 5: $c_{el, buy}$ very high, c_{ng} high



OPTIMIZATION MODEL

Obj = 3020. Case 6: $c_{el, buy}$ very high, c_{ng} high & oscill.



UNCERTAINTY CLASSIFICATION

Methodology

All model parameters have an associated uncertainty, but which are the most important ones? The goal is identifying **priorities** for the uncertainty analysis

Parameters

i , interest rate

n , lifetime

BOIL: efficiency, $C_{inv}(2)$, $c_p(13)$

FC: efficiency, $C_{inv}(2)$, $c_p(13)$

STO: $C_{inv}(2)$, $c_p(13)$

PV: $C_{inv}(2)$, $c_p(13)$

HP: efficiency, $C_{inv}(2)$, $c_p(13)$

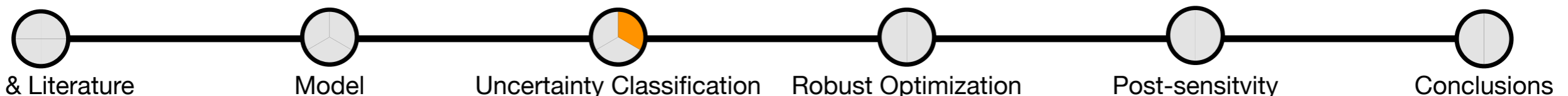
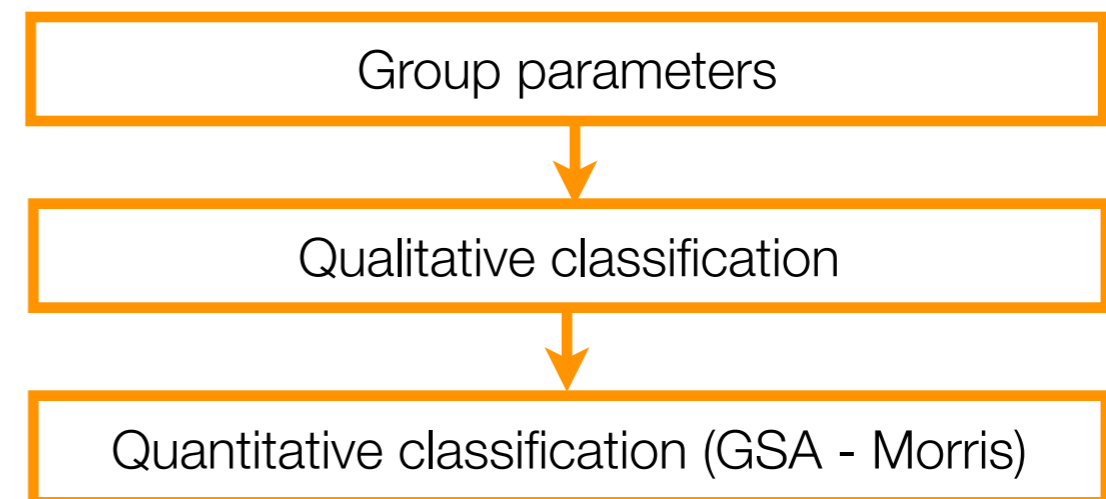
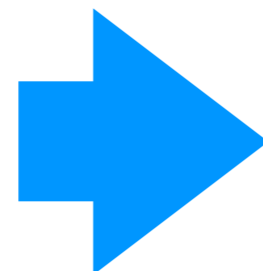
Q_{demand} (13)

E_{demand} (13)

$C_{el,buy}$ (13)

C_{ng} (13)

= **~130** parameters

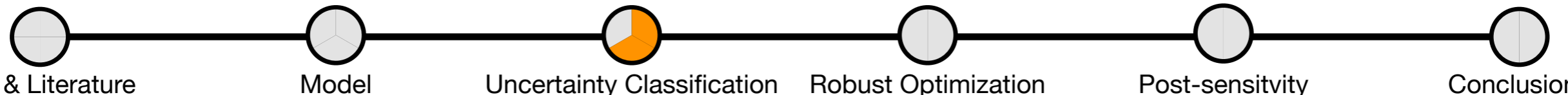


UNCERTAINTY CLASSIFICATION

Qualitative classification

To run a global sensitivity analysis we need to define plausible limits of variations for each parameter

#	Param. Group	Hic et nunc?	Formulas/models?	Historical data?	Choice?	Range
1	i (interest rate)	✓			✓	± 10%
2	n (lifetime)			✓		±15%
3	BOIL: efficiency		✓		✓	±5%
4	BOIL: C_inv	✓				±5%
5	FC: efficiency		✓		✓	±10%
6	FC: C_inv	✓				±10%
7	HP: efficiency		✓			±10%
8	HP: C_inv	✓				±5%
9	HP: c_p mult			✓		±5%
10	PV: C_inv	✓				±5%
11	PV: c_p mult			✓		±10%
12	Q_demand		✓	✓	✓	±20%
13	E_demand		✓	✓	✓	±20%
14	c_el,buy					±50%
15	c_ng mult					±50%
16	STO: C_inv	✓				±10%



UNCERTAINTY CLASSIFICATION

Global SA - Morris's EE method

Sources:

- Sin G et al., Good Modeling Practice for PAT Applications: Propagation of Input Uncertainty and Sensitivity Analysis. 2009
- Saltelli et al., Global Sensivity Analysis - The primer. 2008
- Pernet et al, Smart Heat Design - Urban Energy System Design under Uncertainty, Master Thesis EPFL, 2014 (Dir. J. Rager, F. Maréchal)

Global **S**ensitivity **A**nalysis "studies how variation (uncertainty) in the outputs of a model can be apportioned to different sources in the input of a model"

Model **f**: the output **Y** is function of a set of **k** uncertain parameter **X**

$$Y = f(X_1, X_2, \dots, X_k)$$

First order sensitivity effect for the **i**-th parameter:

$$S_i = \frac{V_{X_i}(E_{X_{\sim i}}(Y|X_i))}{V(Y)} \leq 1$$

Reduction of $V(Y)$ if fixing X_i
if $S_i \rightarrow 1$ then X_i is influential

Second order sensitivity effect:

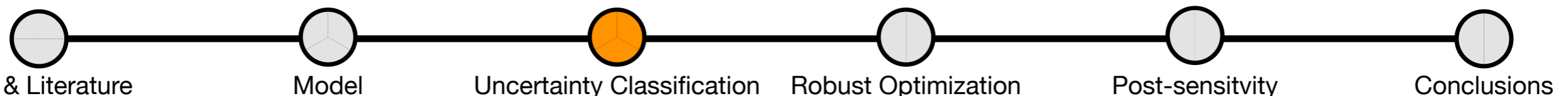
$$S_{ij} = \frac{V_{X_i, X_j}(E_{X_{\sim ij}}(Y|X_i, X_j))}{V(Y)}$$

if $S_{ij} \gg S_i + S_j$ then combination of X_i and X_j is influential

Total sensitivity effect for **i**-th input $S_{Ti} = S_i + S_{ij} + S_{im} + S_{ijm} + \dots$

if
$$S_{Ti} = \frac{E(V(Y|X_{\sim i}))}{V(Y)} = 0$$

then X_i non influential (necessary and sufficient condition)



UNCERTAINTY CLASSIFICATION

Global SA - Morris's EE method

S_{Ti} often unaffordable to calculate!

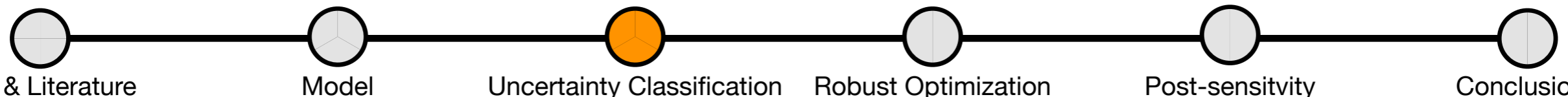
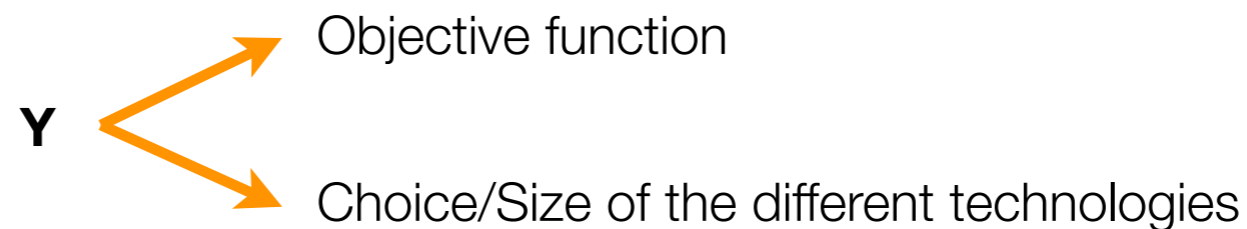
Elementary effect (Morris) method:

- One-at-a-time Global Sensitivity Analysis method
- Discrete sampling: r "trajectories" in which at every step only one of the k input varies of $\pm\Delta$
- Elementary Effect of the i -th input:

$$EE_i = \frac{[Y(X_1, X_2, \dots, X_{i-1}, X_i + \Delta, \dots, X_k) - Y(X_1, X_2, \dots, X_k)]}{\Delta}$$

$$\mu_i^* = \frac{1}{r} \sum_{j=1}^r |EE_i^j| \quad \longrightarrow \quad \text{Good proxy for } S_{Ti}$$

Idea: Application of Morris method to the optimization model in order to quantitatively classify uncertainty and distinguish between relevant and non-influential input parameters -> **factor fixing**

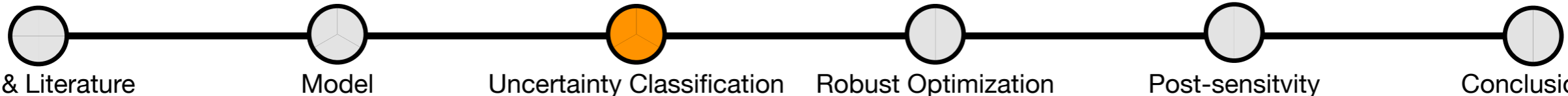
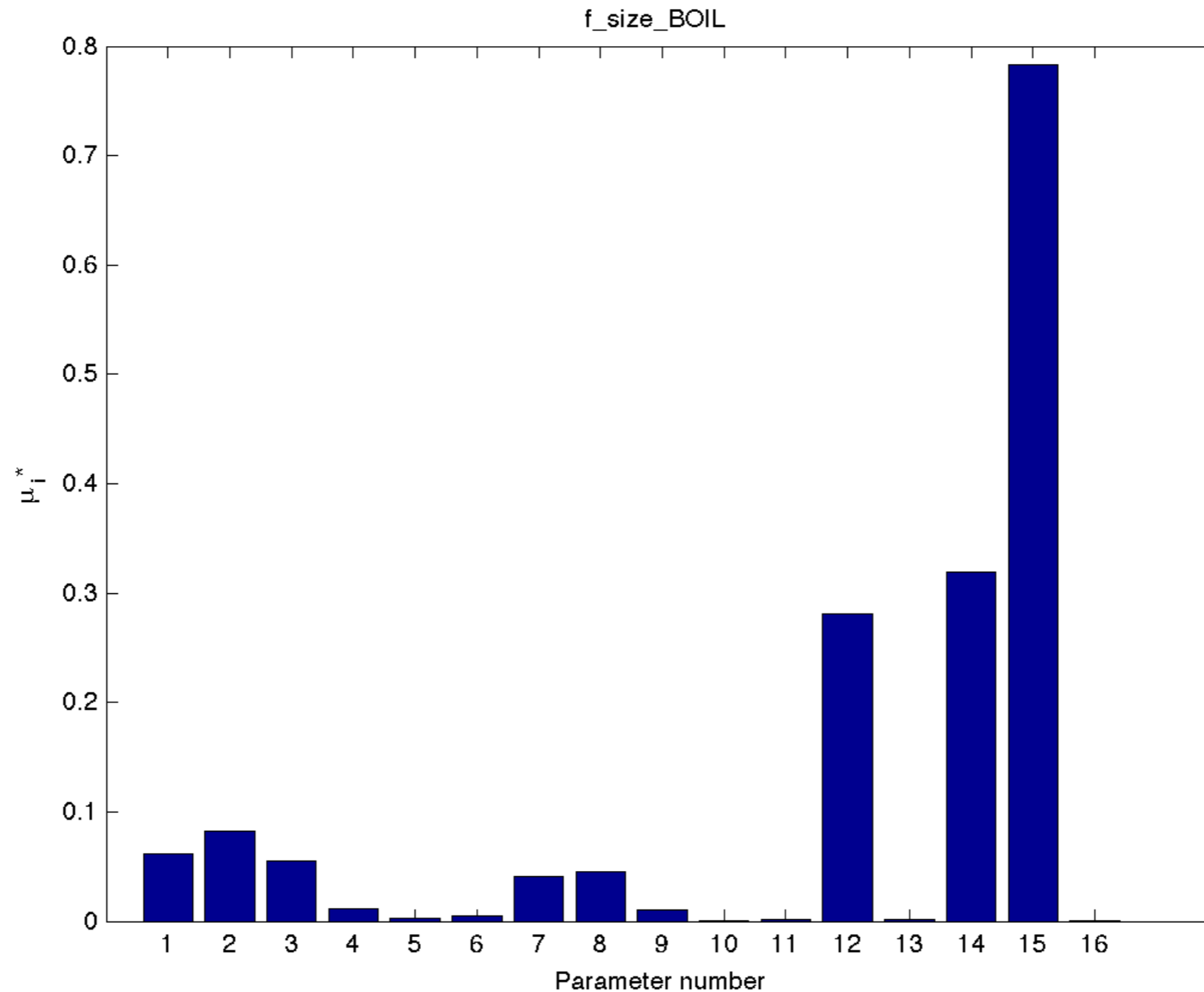


UNCERTAINTY CLASSIFICATION

Global SA - Morris's EE method

Sources:

- Sin G et al., Good Modeling Practice for PAT Applications: Propagation of Input Uncertainty and Sensitivity Analysis. 2009
- Saltelli et al., Global Sensivity Analysis - The primer. 2008
- Pernet et al, Smart Heat Design - Urban Energy System Design under Uncertainty, Master Thesis EPFL, 2014 (Dir. J. Rager, F. Maréchal)

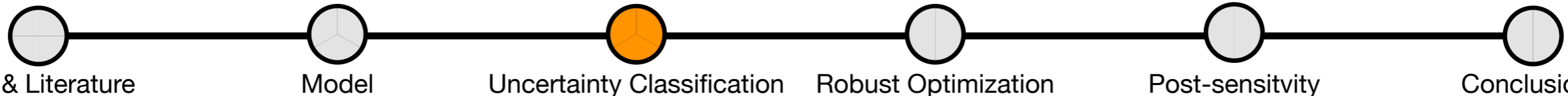
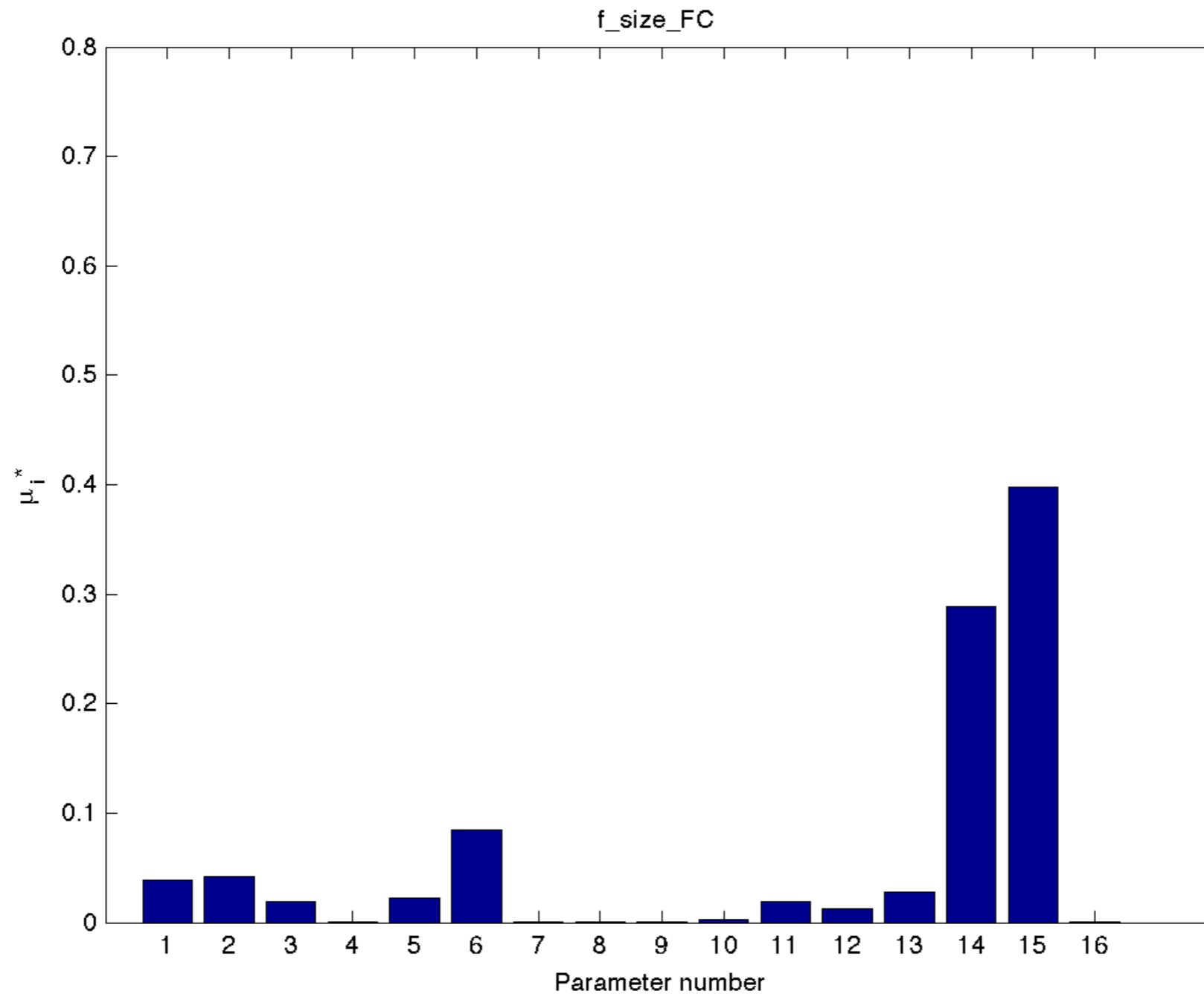


UNCERTAINTY CLASSIFICATION

Global SA - Morris's EE method

Sources:

- Sin G et al., Good Modeling Practice for PAT Applications: Propagation of Input Uncertainty and Sensitivity Analysis. 2009
- Saltelli et al., Global Sensivity Analysis - The primer. 2008
- Pernet et al, Smart Heat Design - Urban Energy System Design under Uncertainty, Master Thesis EPFL, 2014 (Dir. J. Rager, F. Maréchal)

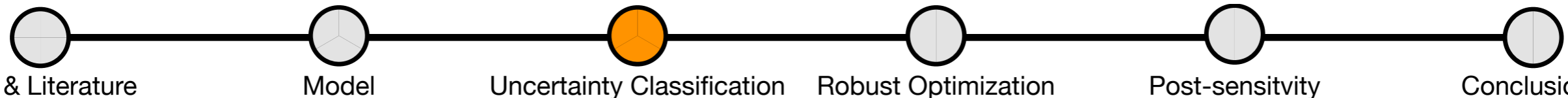
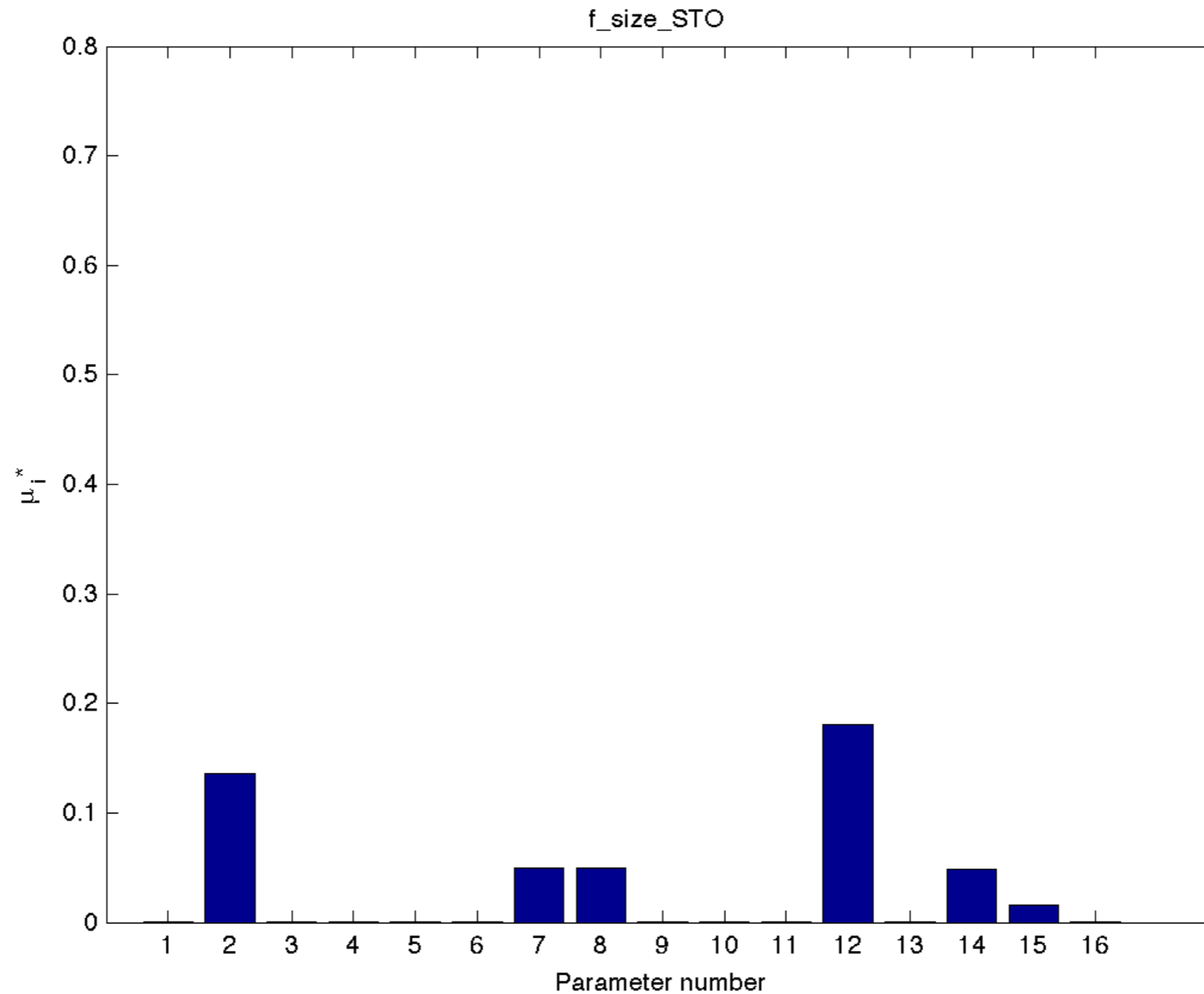


UNCERTAINTY CLASSIFICATION

Global SA - Morris's EE method

Sources:

- Sin G et al., Good Modeling Practice for PAT Applications: Propagation of Input Uncertainty and Sensitivity Analysis. 2009
- Saltelli et al., Global Sensivity Analysis - The primer. 2008
- Pernet et al, Smart Heat Design - Urban Energy System Design under Uncertainty, Master Thesis EPFL, 2014 (Dir. J. Rager, F. Maréchal)

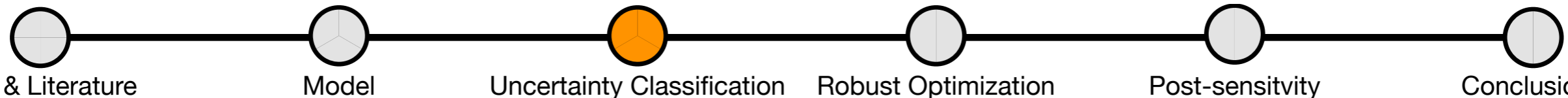
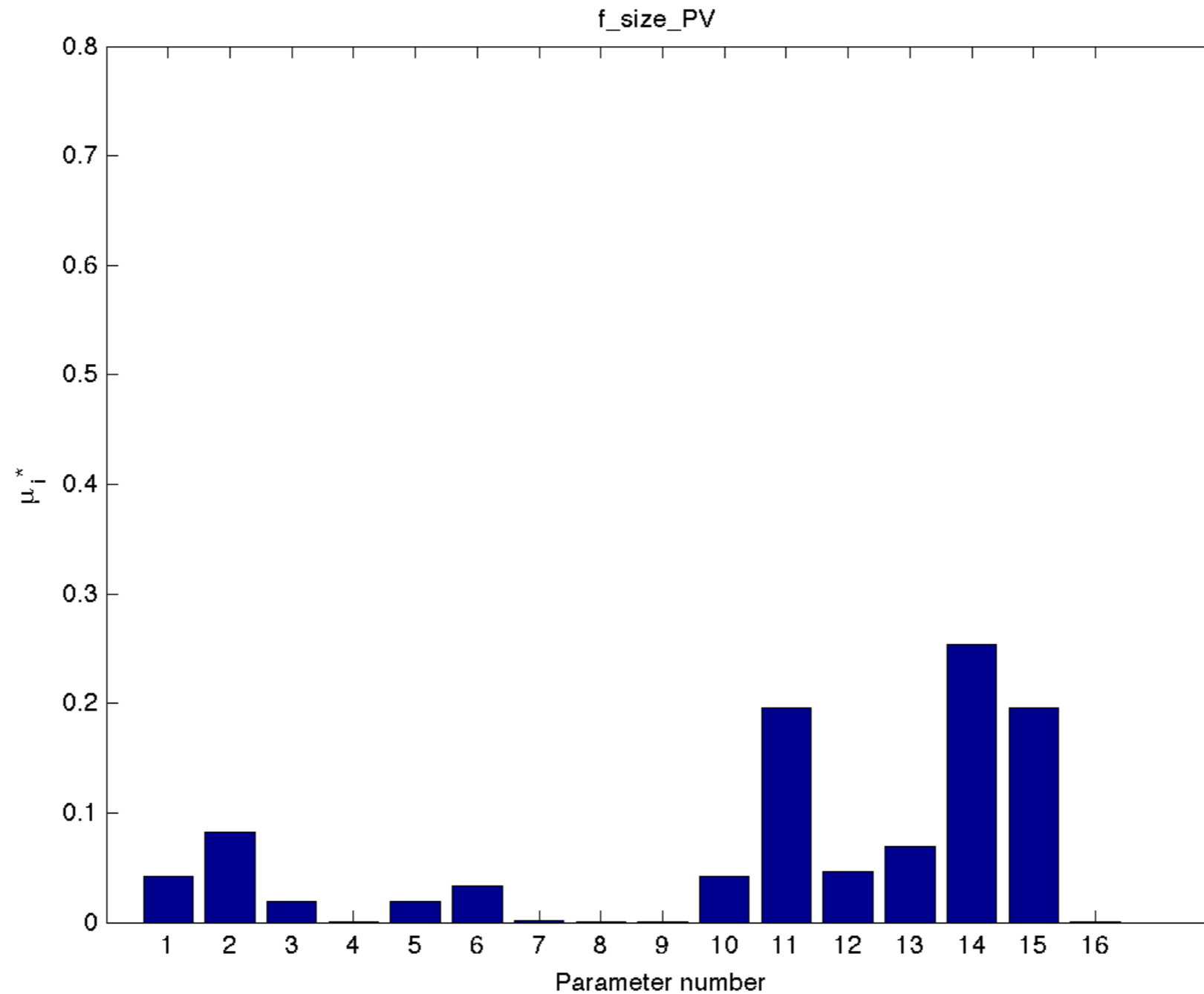


UNCERTAINTY CLASSIFICATION

Global SA - Morris's EE method

Sources:

- Sin G et al., Good Modeling Practice for PAT Applications: Propagation of Input Uncertainty and Sensitivity Analysis. 2009
- Saltelli et al., Global Sensivity Analysis - The primer. 2008
- Pernet et al, Smart Heat Design - Urban Energy System Design under Uncertainty, Master Thesis EPFL, 2014 (Dir. J. Rager, F. Maréchal)

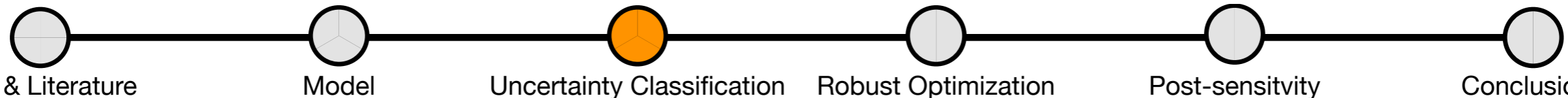
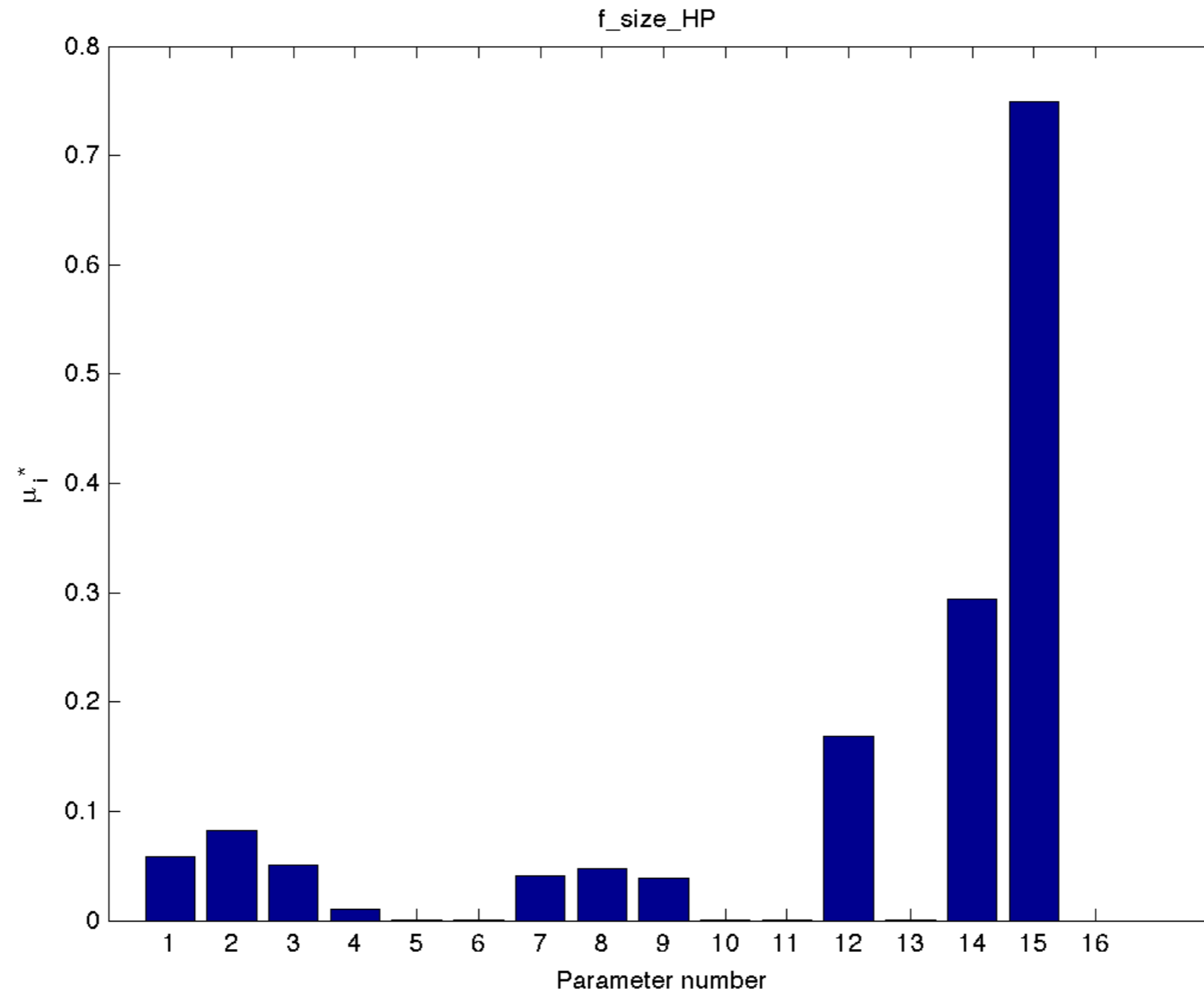


UNCERTAINTY CLASSIFICATION

Global SA - Morris's EE method

Sources:

- Sin G et al., Good Modeling Practice for PAT Applications: Propagation of Input Uncertainty and Sensitivity Analysis. 2009
- Saltelli et al., Global Sensivity Analysis - The primer. 2008
- Pernet et al, Smart Heat Design - Urban Energy System Design under Uncertainty, Master Thesis EPFL, 2014 (Dir. J. Rager, F. Maréchal)

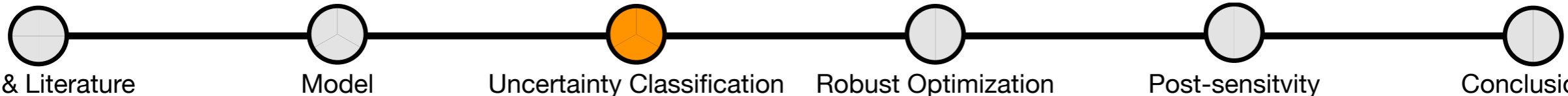
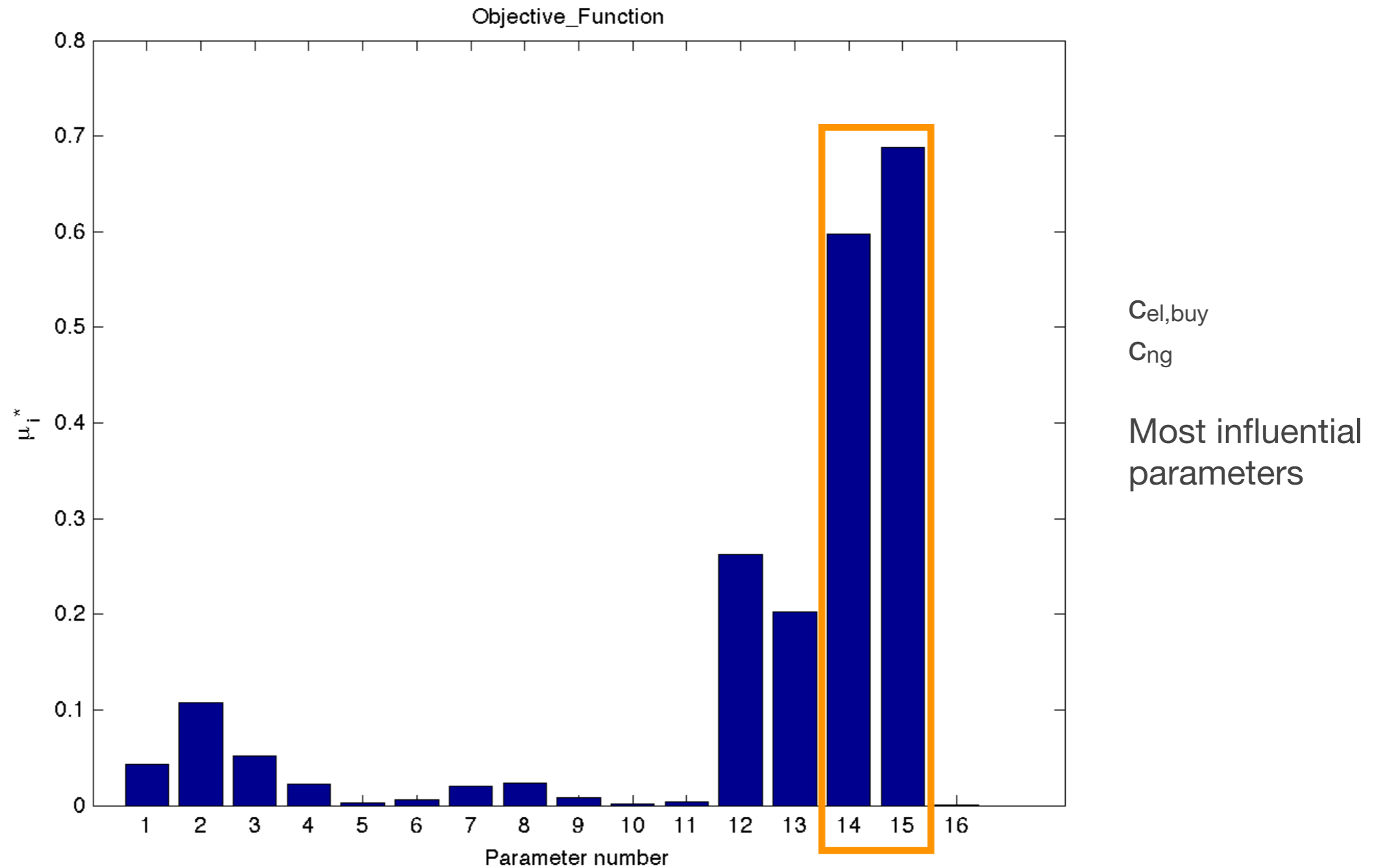


UNCERTAINTY CLASSIFICATION

Global SA - Morris's EE method

Sources:

- Sin G et al., Good Modeling Practice for PAT Applications: Propagation of Input Uncertainty and Sensitivity Analysis. 2009
- Saltelli et al., Global Sensivity Analysis - The primer. 2008
- Pernet et al, Smart Heat Design - Urban Energy System Design under Uncertainty, Master Thesis EPFL, 2014 (Dir. J. Rager, F. Maréchal)



ROBUST OPTIMIZATION

Problem formulation

Sources:

- Dimitris Bertsimas and Melvyn Sim. The price of robustness. 2004.
- Convex Programming with Set-Inclusive Constraints and Applications to Inexact Linear Programming. 1973

Soyster (1973): Protection against all uncertain parameters at worst case. Very conservative

Bertsimas and Sim (2004): reduction of the “**price of robustness**” through probabilistic approach

$$\text{minimize } \mathbf{c}^T \mathbf{x}$$

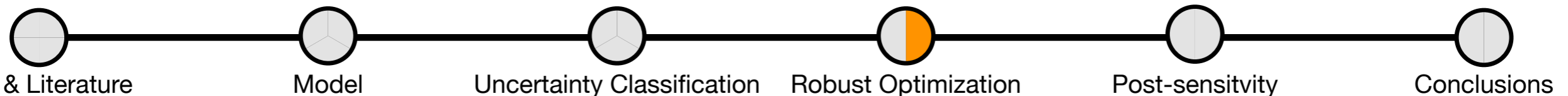
The vector \mathbf{c} (cost coefficients) has some uncertain elements belonging to the set \mathbf{J} . The j -th uncertain parameter can vary of a maximum value d_j

$$c_j = [c_j, c_j + d_j] \quad j \in J$$

The “protection parameter” controls the number of uncertain parameters at worst case:

$$\Gamma_0 = [0, |J|] \begin{cases} \Gamma_0 = 0 & \text{Deterministic MILP, no parameter at worst case} \\ \Gamma_0 = |J| & \text{All parameter at worst case (Soyster)} \end{cases}$$

26 uncertain parameters: $c_{el,buy}(t), c_{ng}(t) \quad \forall t$



ROBUST OPTIMIZATION

Problem formulation

Sources:

- Dimitris Bertsimas and Melvyn Sim. The price of robustness. 2004.
- Convex Programming with Set-Inclusive Constraints and Applications to Inexact Linear Programming. 1973

Robust formulation of our energy planning MILP

New parameters

Γ_0 : protection parameter

$d_{el} = [0.05, 0.5]$, $d_{ng} = \frac{1}{2}d_{el}$: variation from the nominal value of the cost

New Variables

$z_0, p_{0,1}(t), p_{0,2}(t), y_1(t), y_2(t)$: variables of the robust counterpart

New Constraints

$$z_0 + p_{0,1}(t) \geq d_{el}y_1(t) \quad \forall t$$

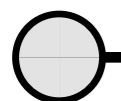
$$z_0 + p_{0,2}(t) \geq d_{ng}y_2(t) \quad \forall t$$

$$-y_1(t) \leq \sum_u \dot{Q}_{NG}(u, t) \cdot t_{op}(t) \leq y_1(t) \quad \forall t$$

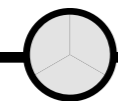
$$-y_2(t) \leq \dot{E}_{buy}(t) \cdot t_{op}(t) \leq y_2(t) \quad \forall t$$

New Objective

$$\min \left(\tau \sum_u C_{inv}(u) + \sum_t \left(\sum_u c_{ng}(t) \dot{Q}_{NG}(u, t) + c_{el,buy}(t) \dot{E}_{buy}(t) - p_{el,sell}(t) \dot{E}_{sell}(t) \right) \cdot t_{op}(t) \right) \\ + z_0 \Gamma_0 + \sum_t p_{0,1}(t) + \sum_t p_{0,2}(t)$$



Intro & Literature



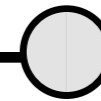
Model



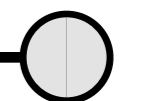
Uncertainty Classification



Robust Optimization



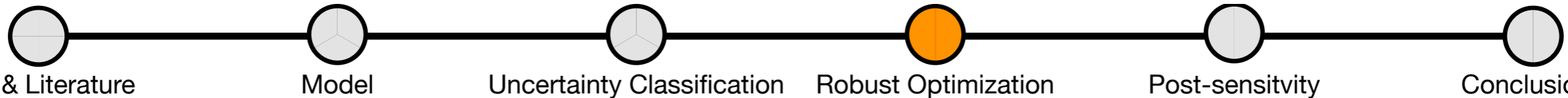
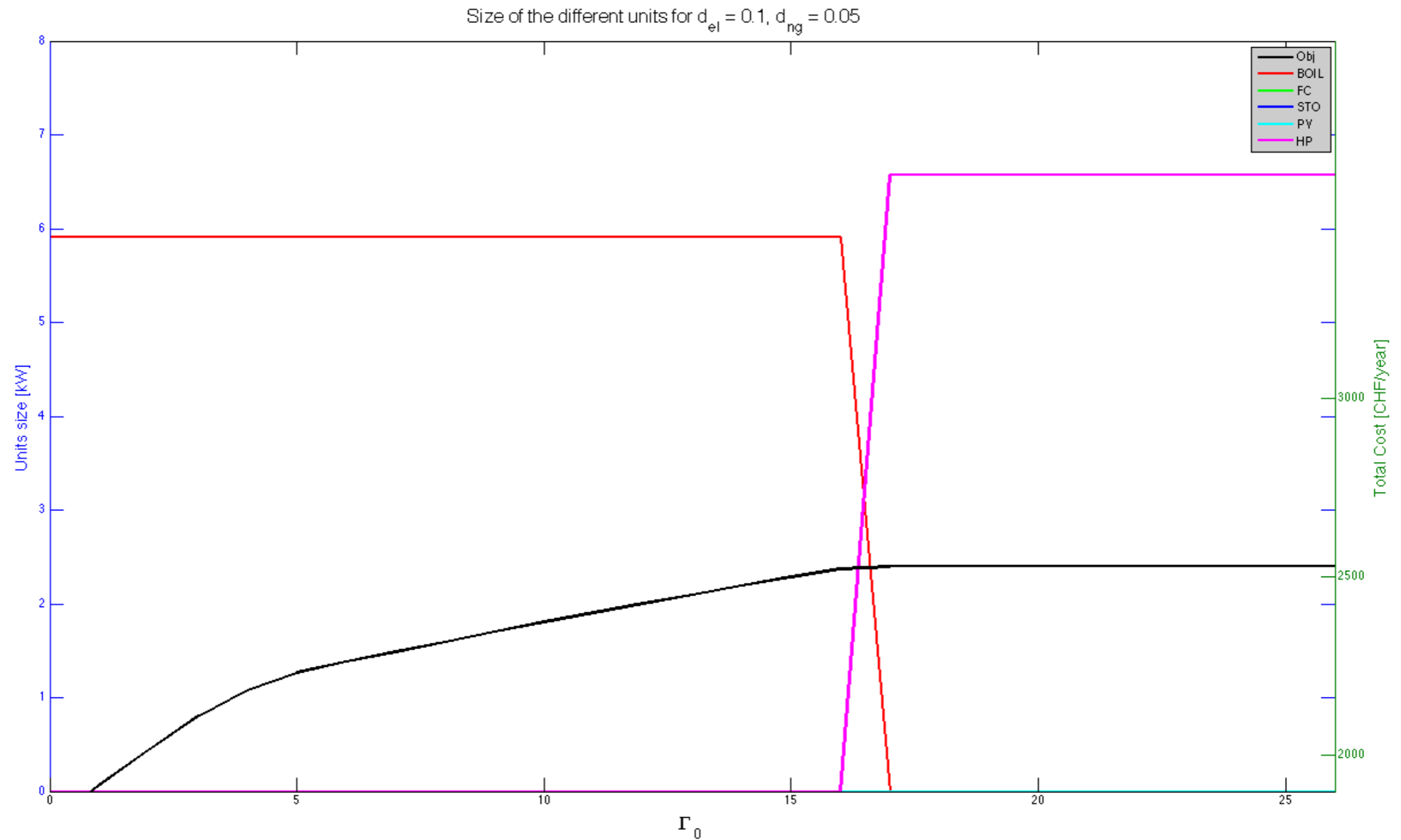
Post-sensitivity



Conclusions

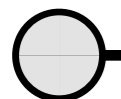
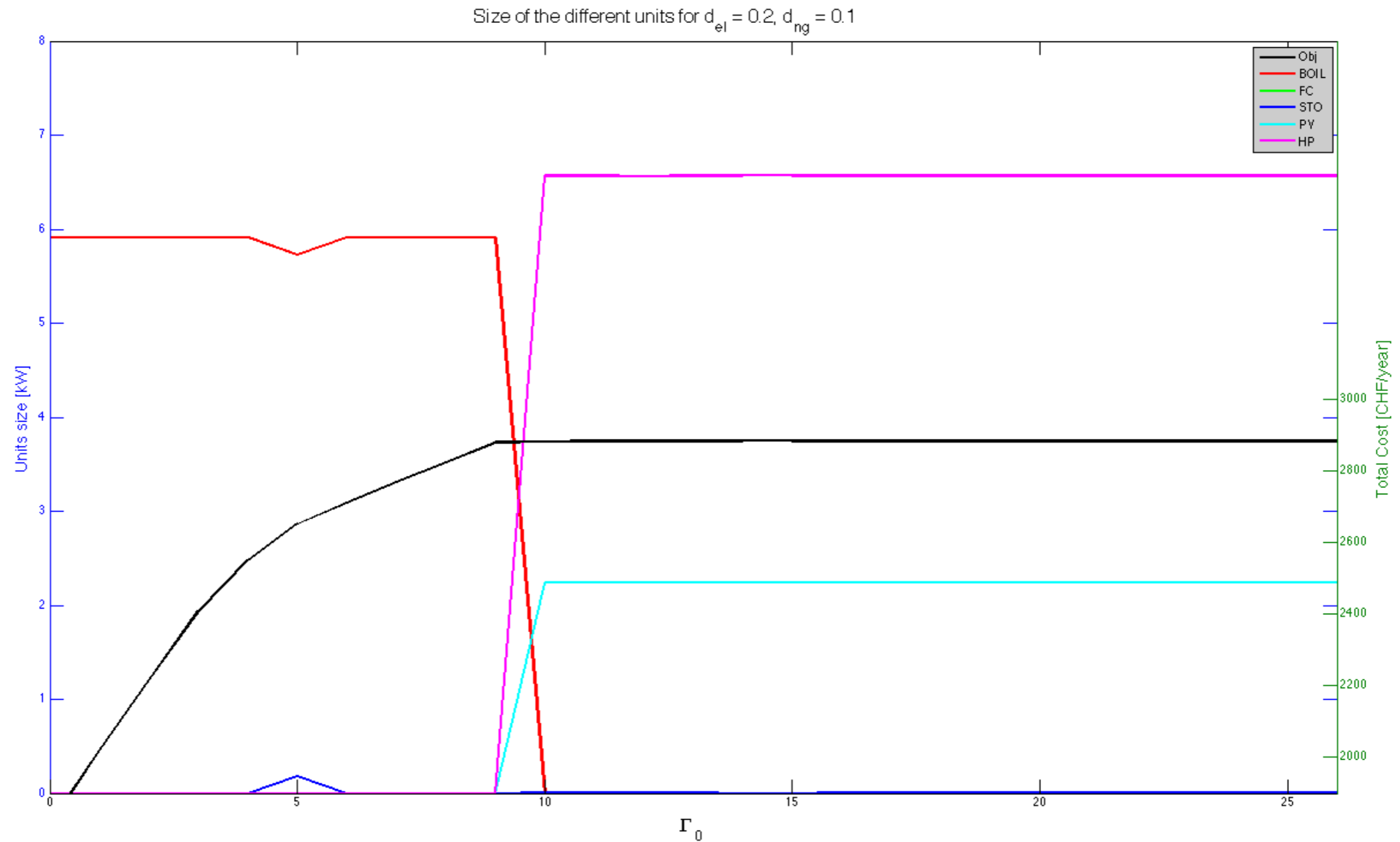
ROBUST OPTIMIZATION

Results ($d_{el} = 0.10$)



ROBUST OPTIMIZATION

Results ($d_{el} = 0.20$)



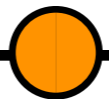
Intro & Literature



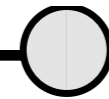
Model



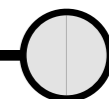
Uncertainty Classification



Robust Optimization



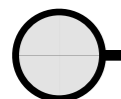
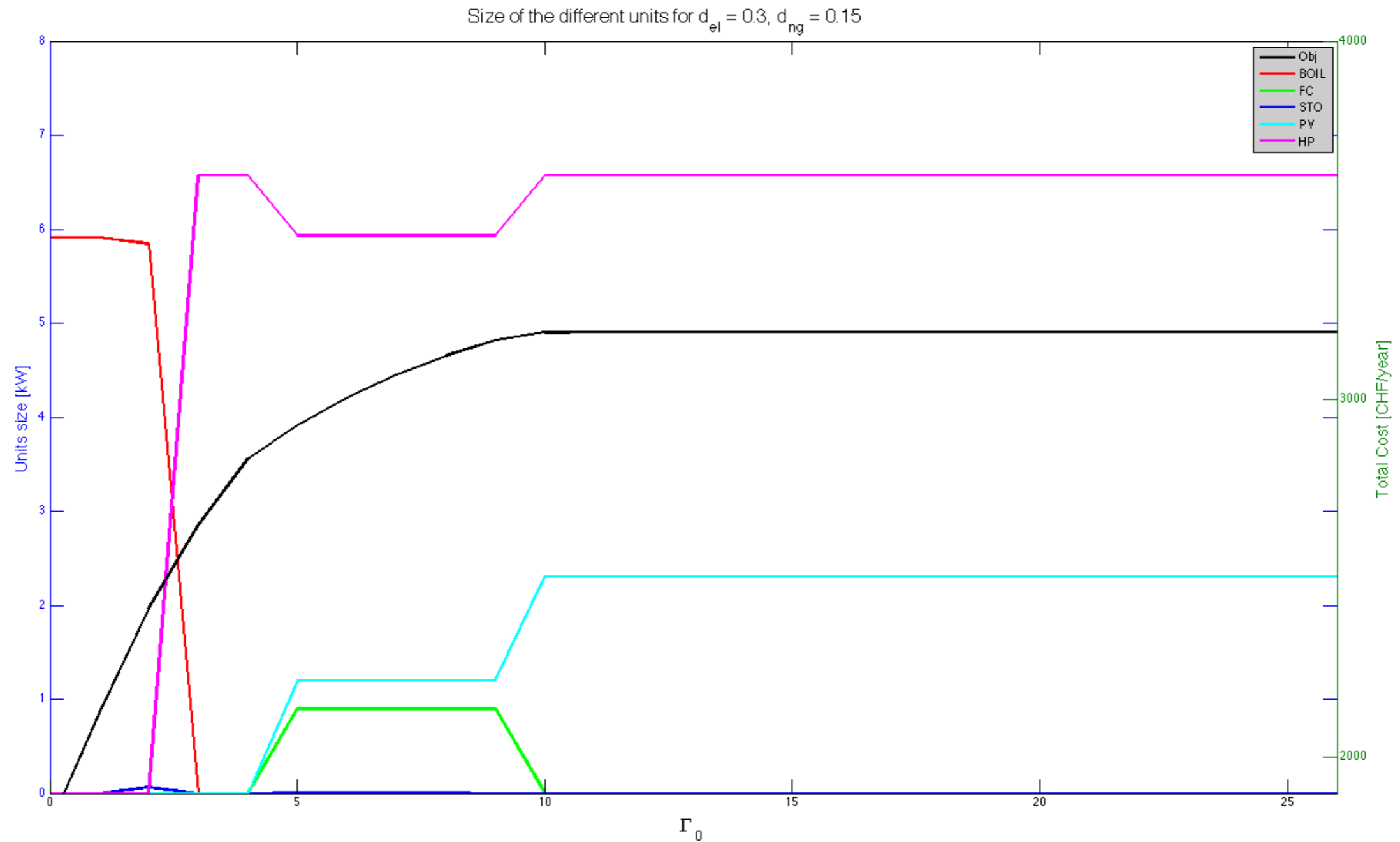
Post-sensitivity



Conclusions

ROBUST OPTIMIZATION

Results ($d_{el} = 0.30$)



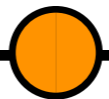
Intro & Literature



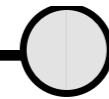
Model



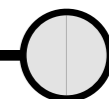
Uncertainty Classification



Robust Optimization



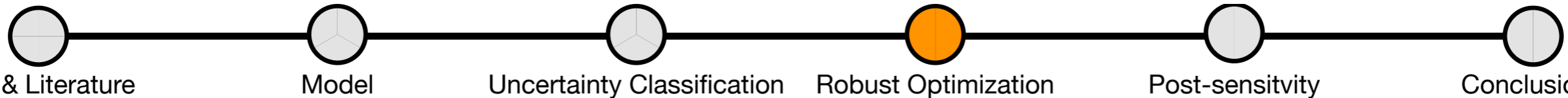
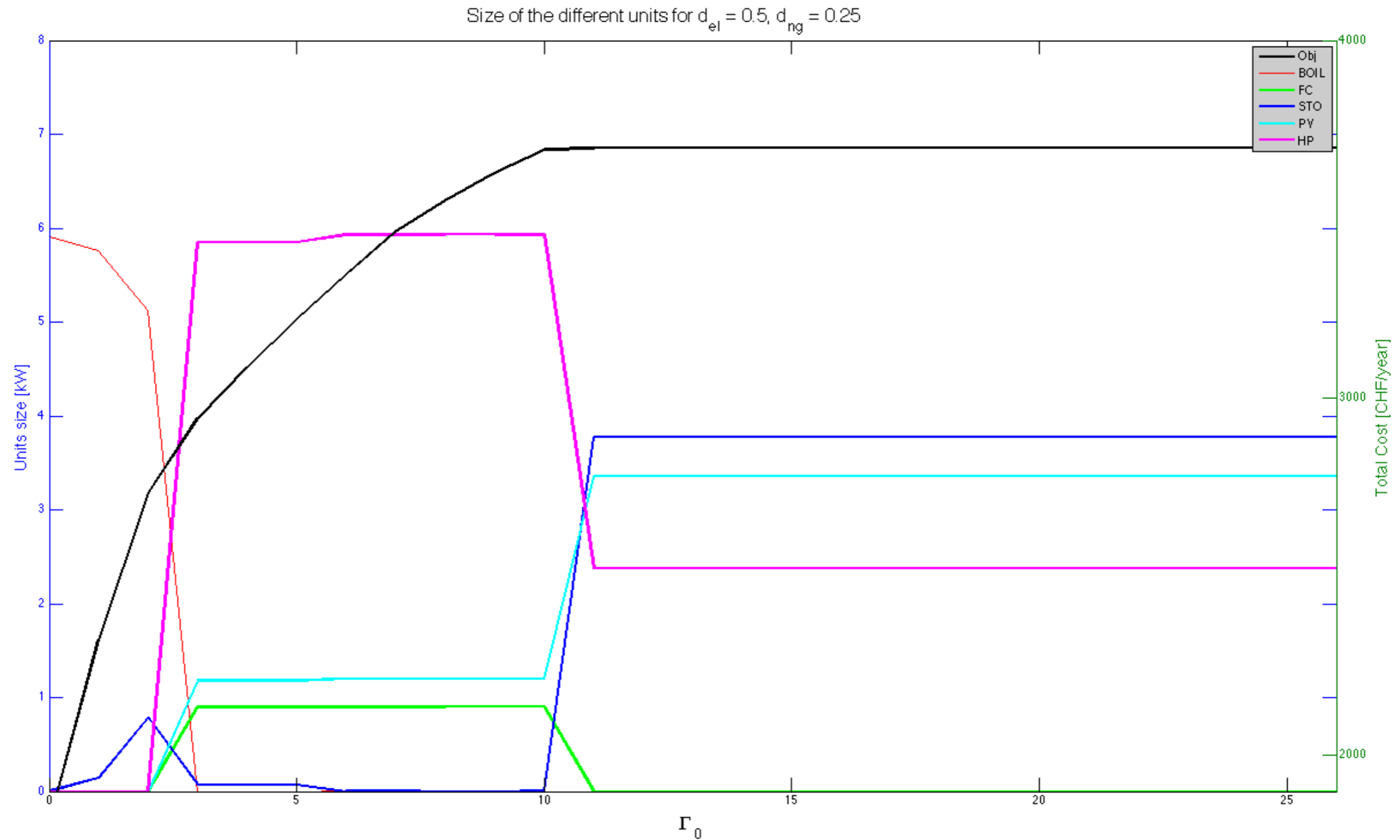
Post-sensitivity



Conclusions

ROBUST OPTIMIZATION

Results ($d_{el} = 0.50$)



ROBUST OPTIMIZATION

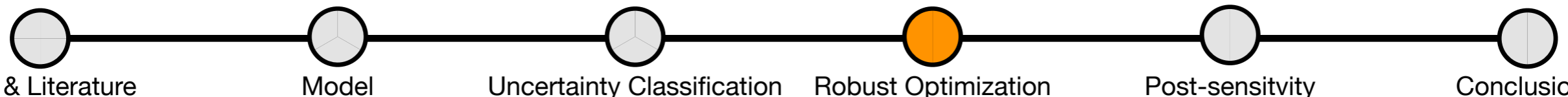
Results

Choice and size of the technologies:

- **Boiler**: deterministic case, when d increases is discarded even for low values of Γ_0
- **Fuel Cell**: chosen if $d_{el} \geq 0.25$, for medium values of Γ_0
- **Storage**: chosen if Γ_0 is either low (oscillations) either uncertainty is very high
- **PV**: natural replacement of E_{import} , size increases with increasing d and Γ_0
- **HP**: natural replacement of boiler, size increases with increasing d and Γ_0

Key preliminary conclusions:

- Model is very simple -> results should be taken as proof of concept
- Robust optimization implementation works correctly and shows interesting trade-offs
- Deterministic solution (Boiler + E_{import}) tends to be replaced by other technologies even with low Γ_0 (most parameters at their deterministic values)
- In the uncertain domain, investing on more efficient and renewable technologies can be **economically optimal**



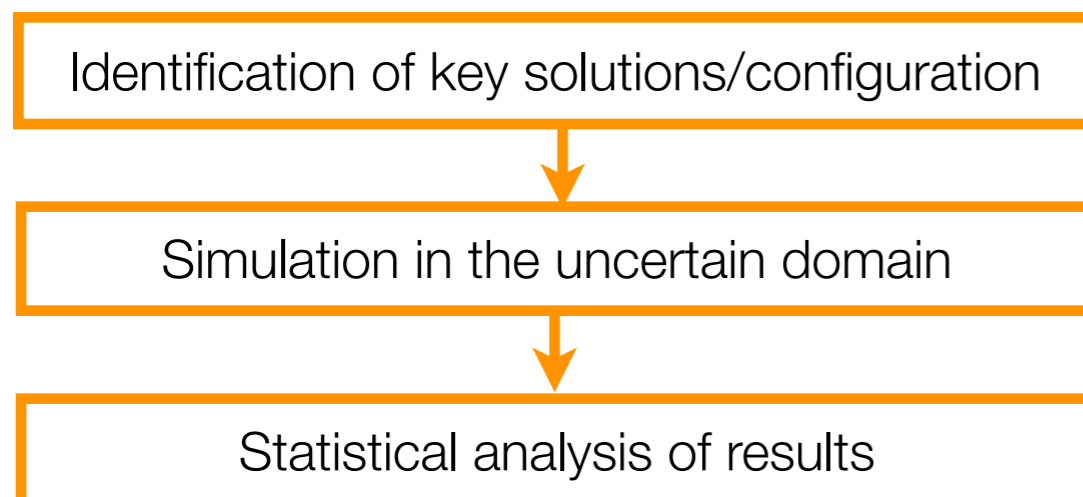
POST-SENSITIVITY

Methodology

Idea: how do the found robust solutions perform in the uncertain domain?

Investment decision is taken

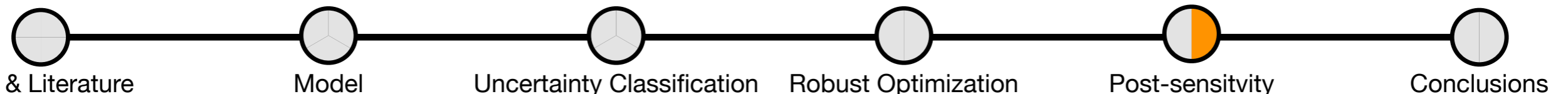
- \mathbf{y} (technology choice) and \mathbf{f}_{size} are now **parameters**
- \mathbf{f} (use, operation of the technology) is still a **variable**



Each solution is evaluated 2000 times
Parameters drawn from uniform distribution

$$c_{ng} \in [-0.0485, 0.25]$$

$$c_{el,buy} \in [-0.09, 0.5]$$



POST-SENSITIVITY Results

Legend

* All prices at worst case

* All prices at nominal value

*5731

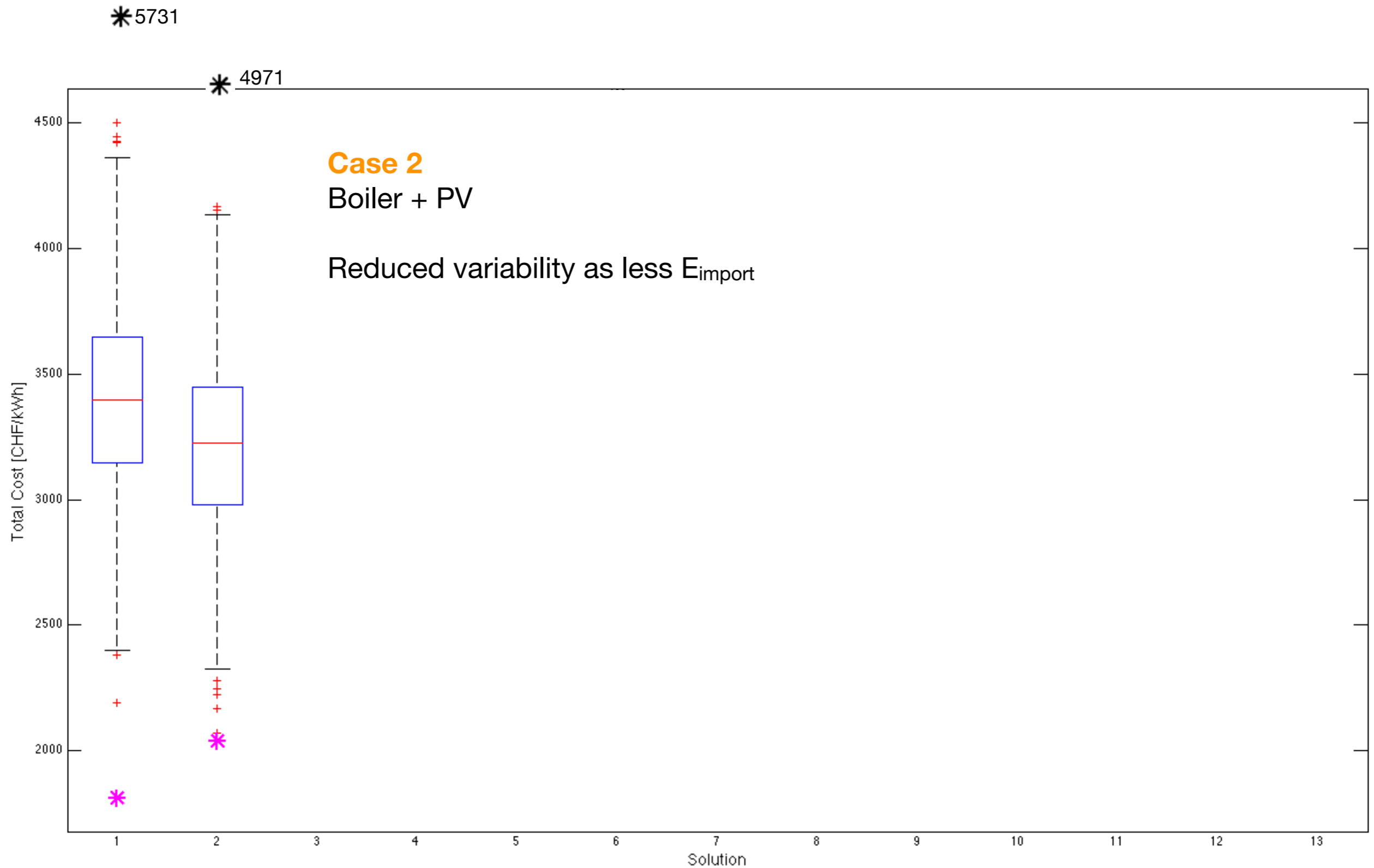


POST-SENSITIVITY Results

Legend

* All prices at worst case

* All prices at nominal value

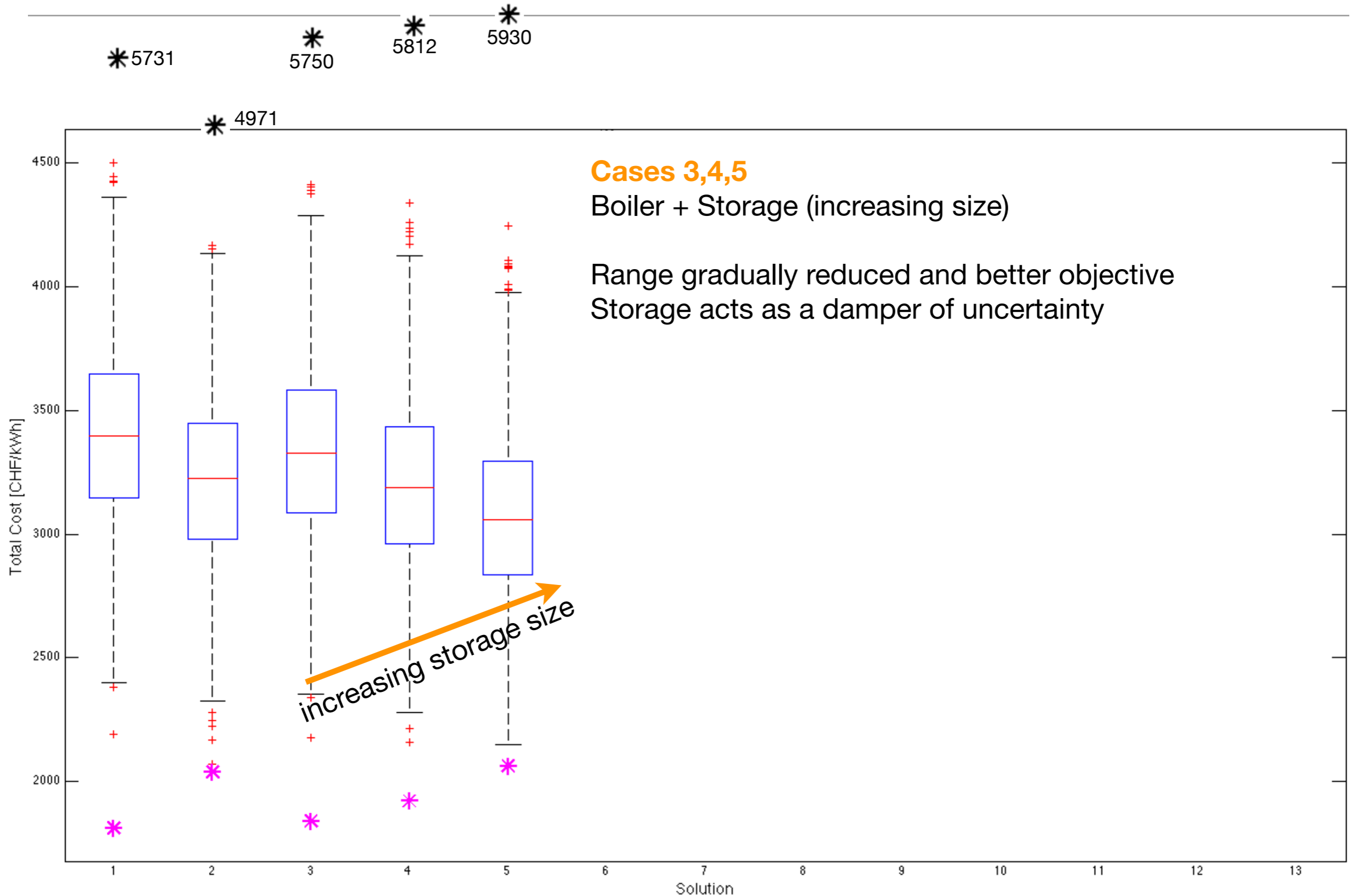


POST-SENSITIVITY Results

Legend

* All prices at worst case

* All prices at nominal value

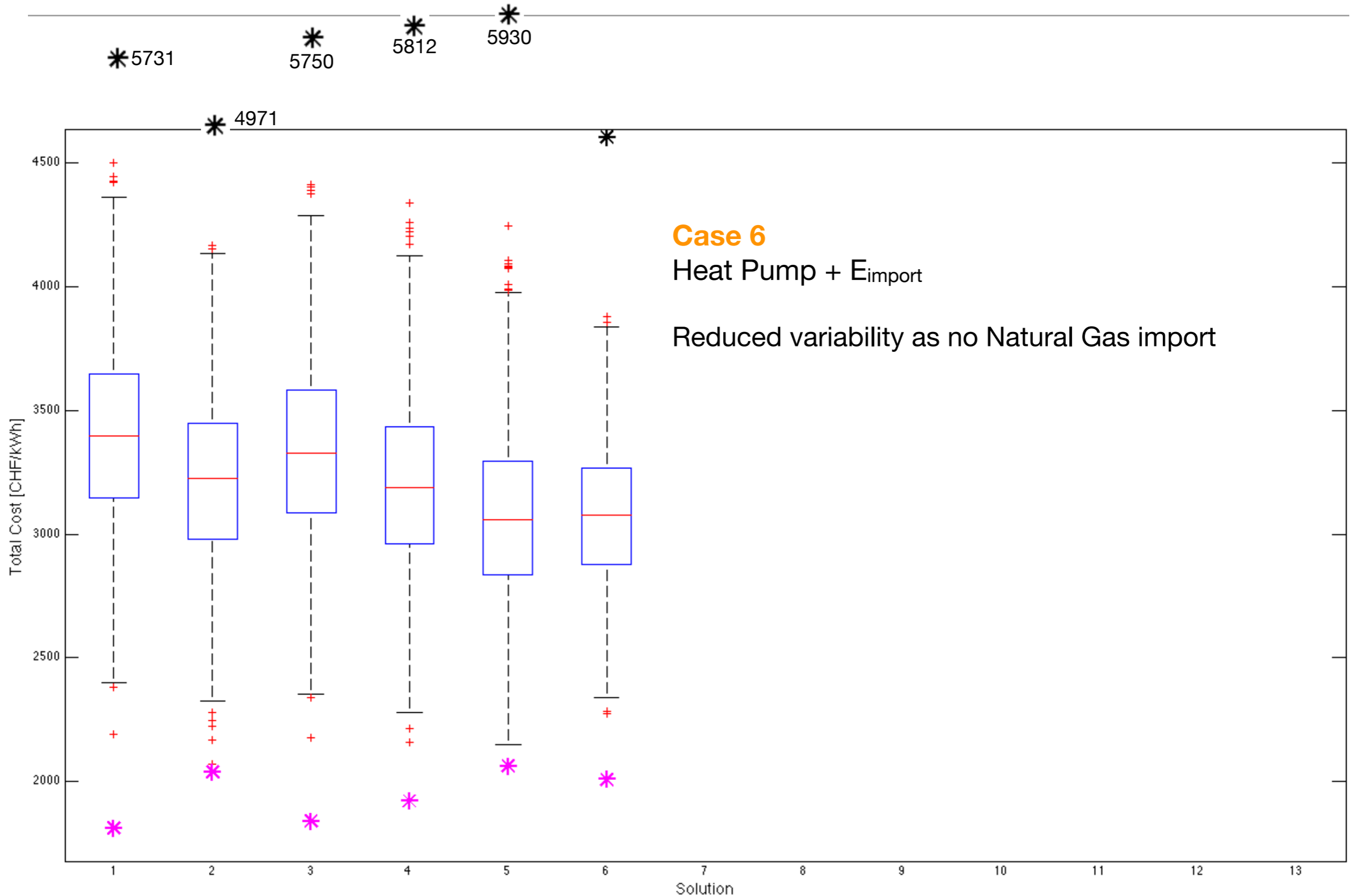


POST-SENSITIVITY Results

Legend

* All prices at worst case

* All prices at nominal value

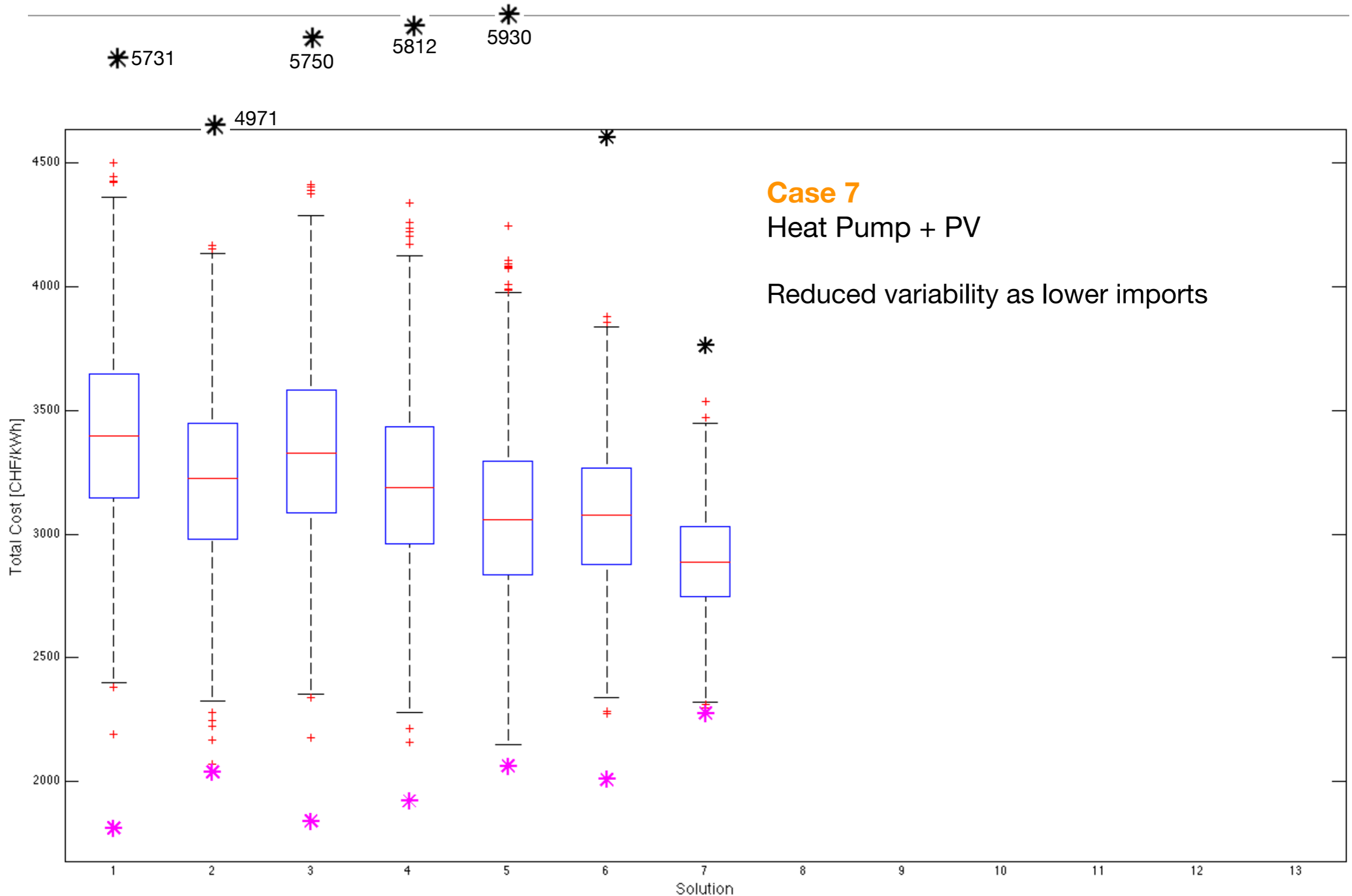


POST-SENSITIVITY Results

Legend

* All prices at worst case

* All prices at nominal value

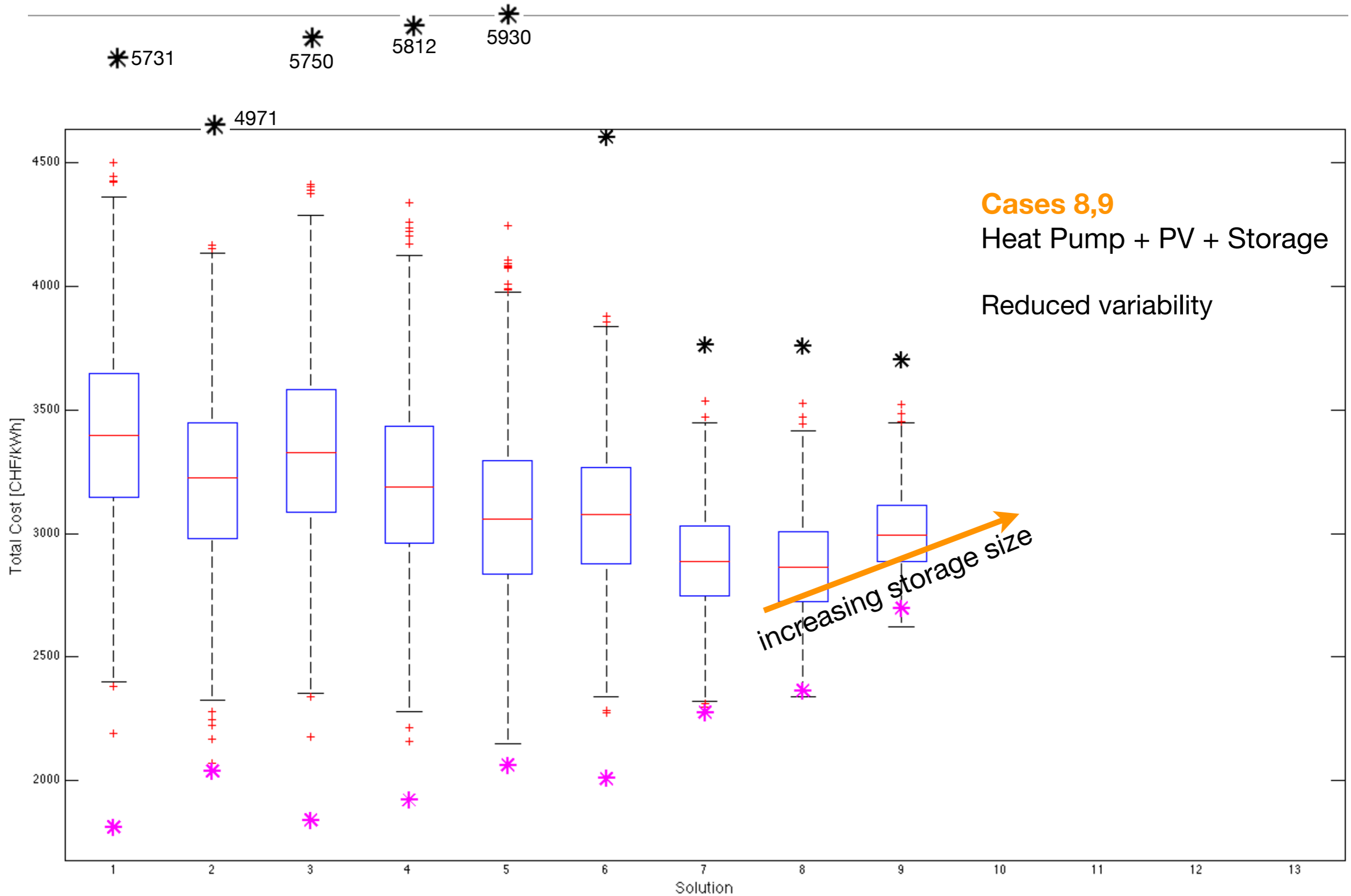


POST-SENSITIVITY Results

Legend

* All prices at worst case

* All prices at nominal value

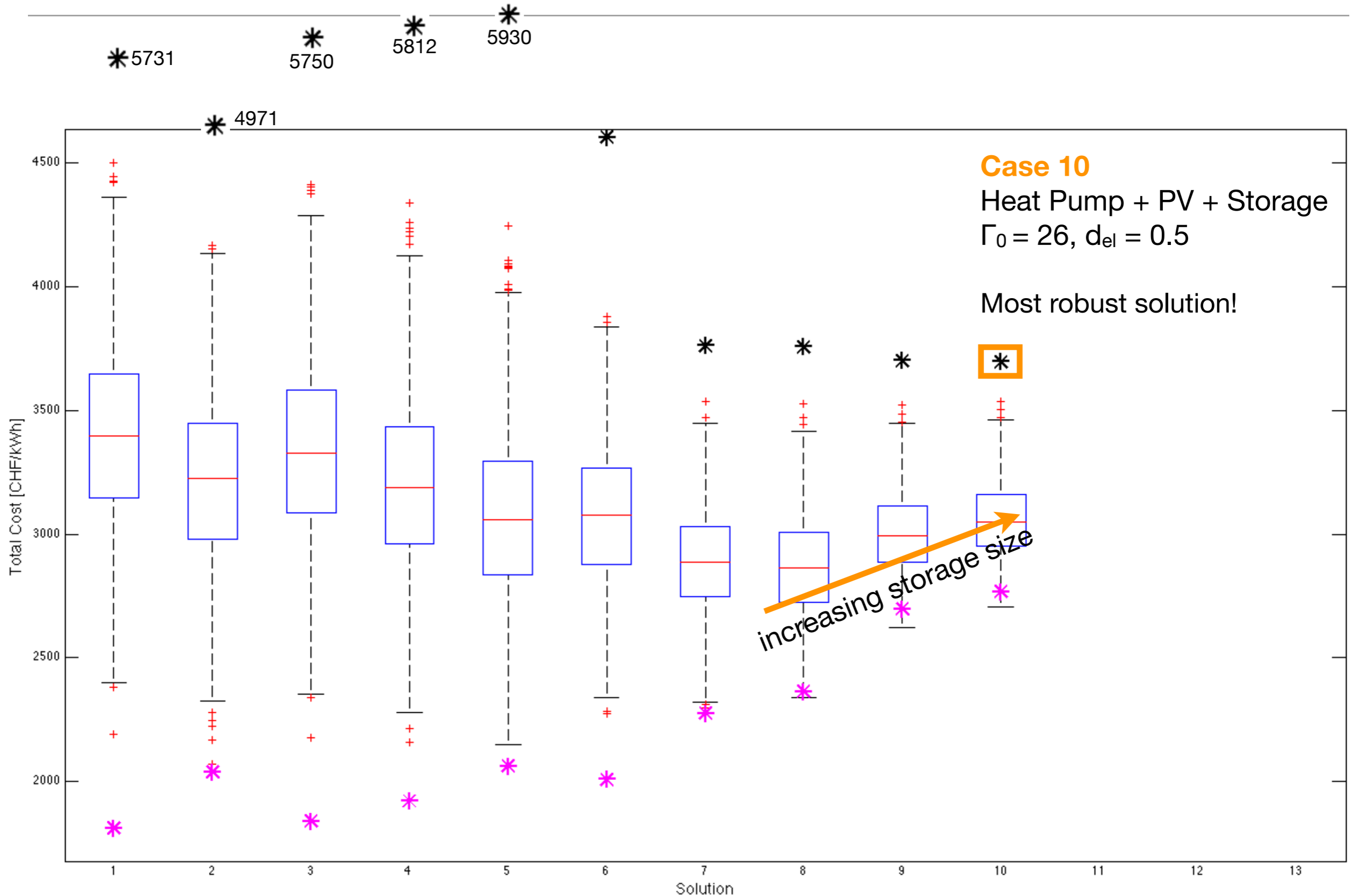


POST-SENSITIVITY Results

Legend

* All prices at worst case

* All prices at nominal value

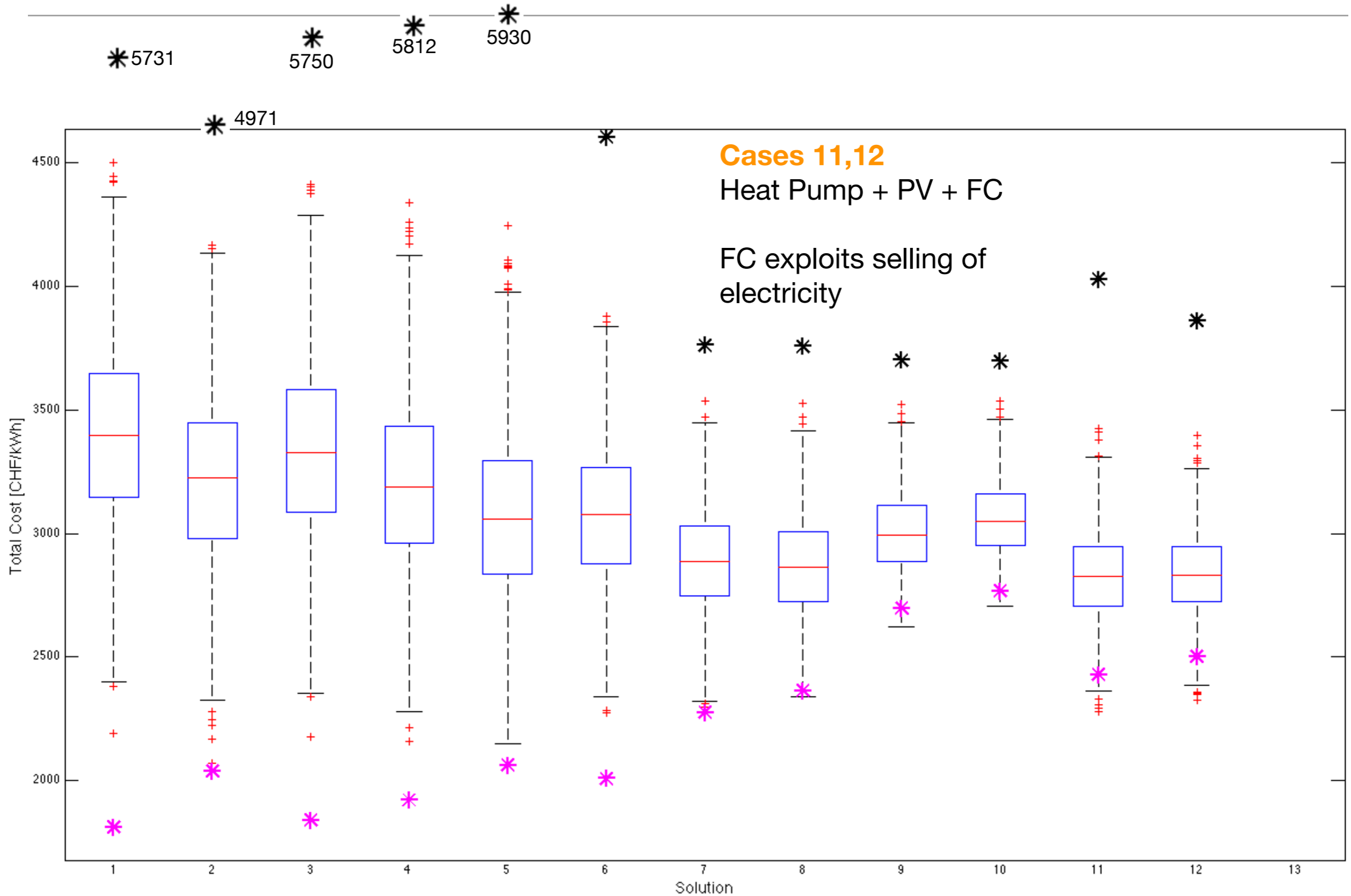


POST-SENSITIVITY Results

Legend

* All prices at worst case

* All prices at nominal value

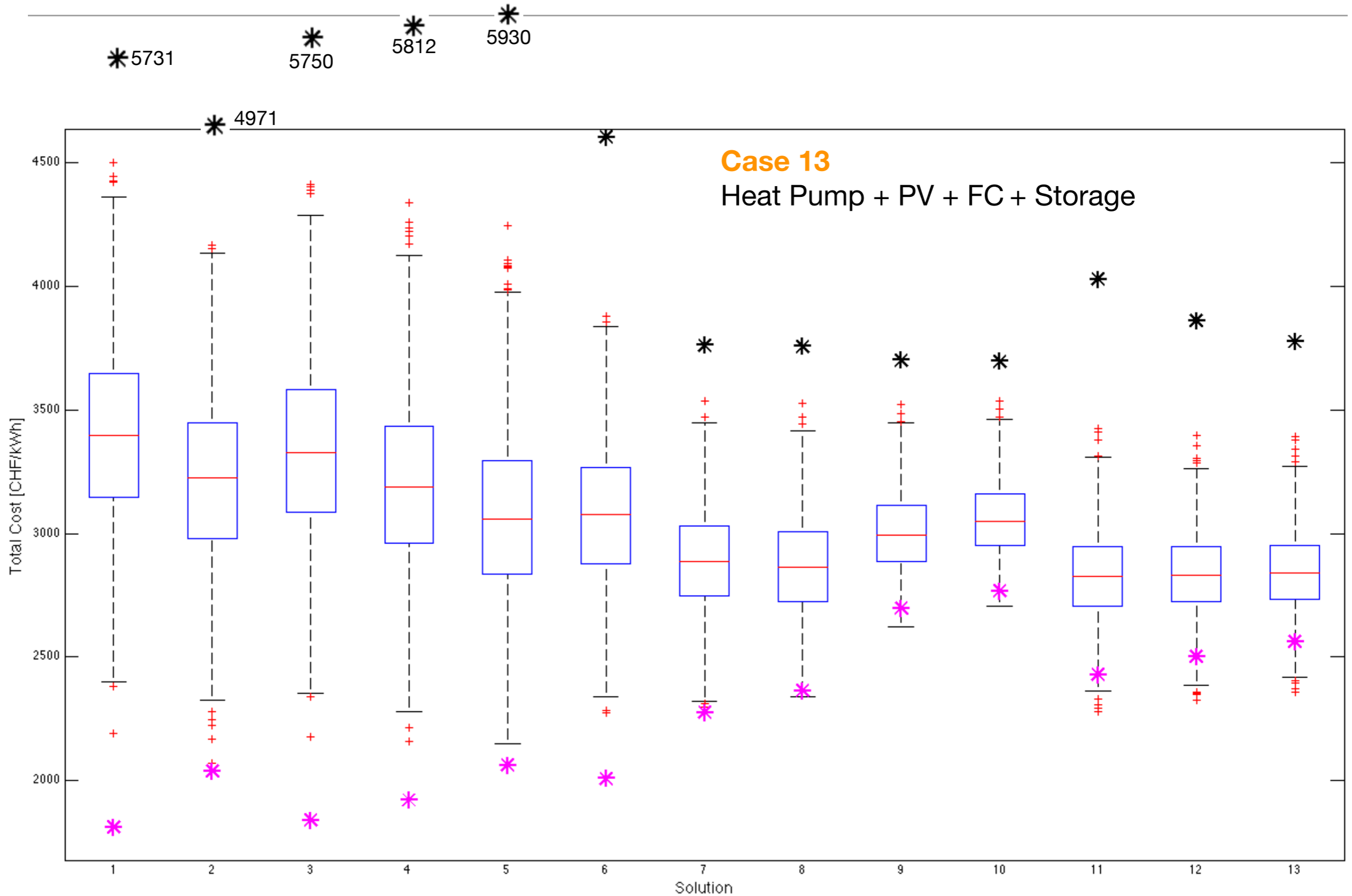


POST-SENSITIVITY Results

Legend

* All prices at worst case

* All prices at nominal value



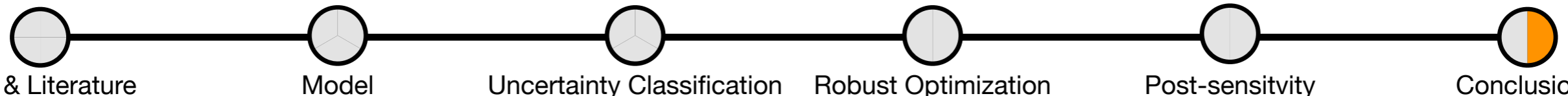
CONCLUSIONS

Key outcomes

- Efficient/renewable technologies (and Storage) can be uncertainty “**dampers**”
- Investment-intensive technologies reduce future cost oscillations
- Local, decentralised production (FC) can open room for profit
- Uncertainty is not the same for all parameters in a model
- Taking uncertainty into account highly impacts strategic energy planning (even with low Γ_0)



In the uncertain domain, investing on more efficient and renewable technologies can be **economically optimal**



CONCLUSIONS

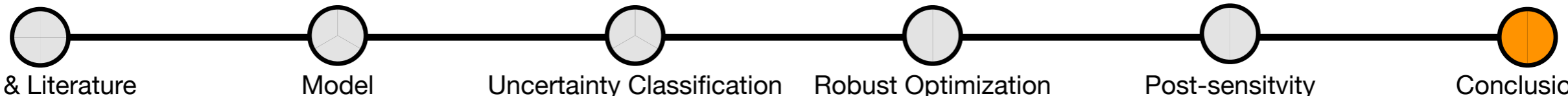
Next steps

Already achieved:

- Simple MILP showing typical trade-offs in strategic energy planning
- Qualitative/quantitative method to classify uncertainty
- First implementation of robust optimisation (no PDF needed!)
- Promising preliminary results, proof-of-concept

Next steps:

- More detailed model -> application to national energy system
- Rigorous methodology to classify uncertainty for strategic energy planning
- Application of two-stage programming -> uncertainty unfolding in the future
- Comparison with other decision-making approaches



THANK YOU!

Thank you for your attention!
Question/remarks?

