Unsicherheiten im Elektrizitätssystem: Welche Methoden für welche Herausforderungen?

lkDEU langfristige Planung und kurzfristige Optimierung des **Elektrizitätssystems in Deutschland** im europäischen Kontext

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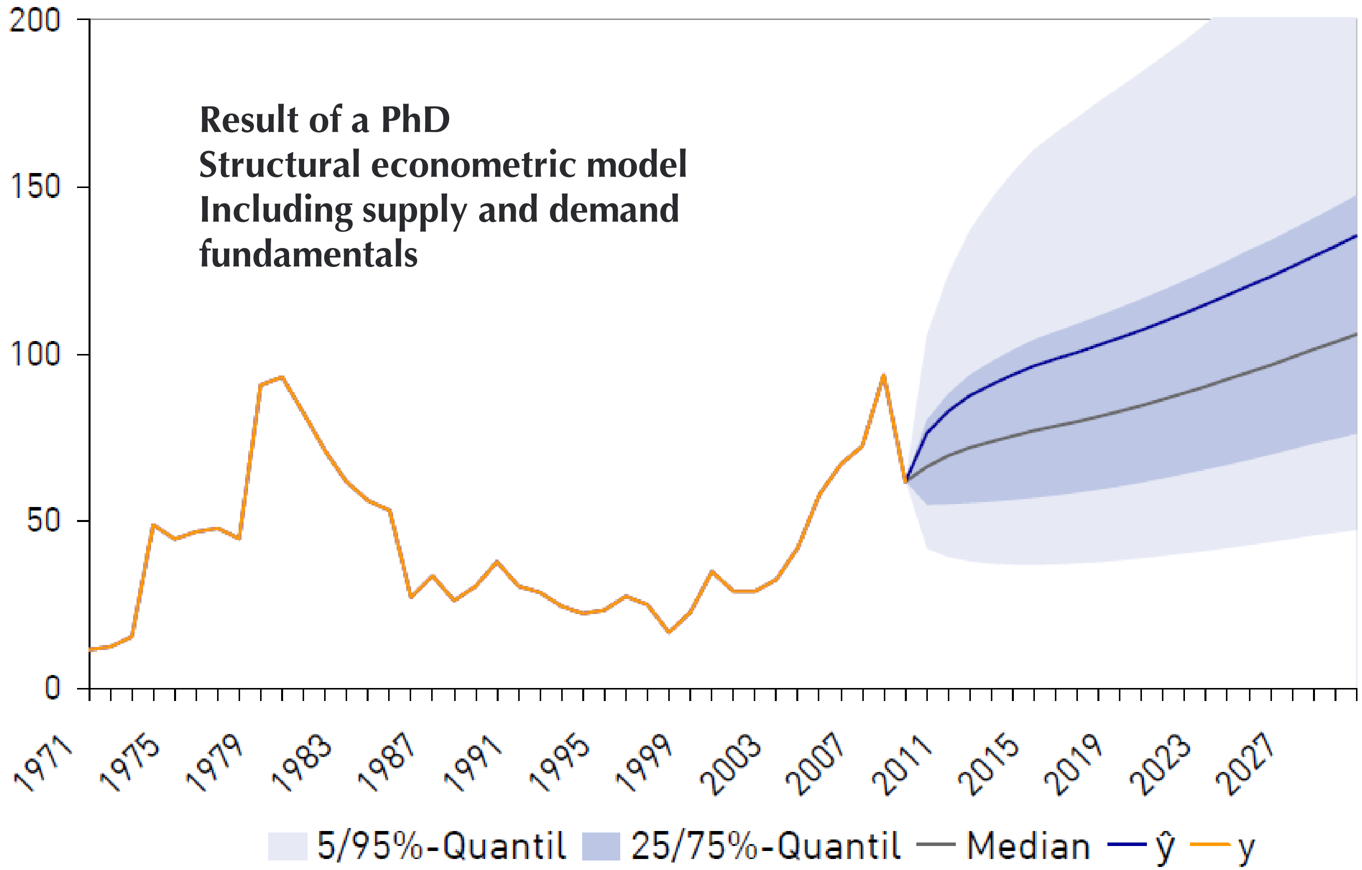
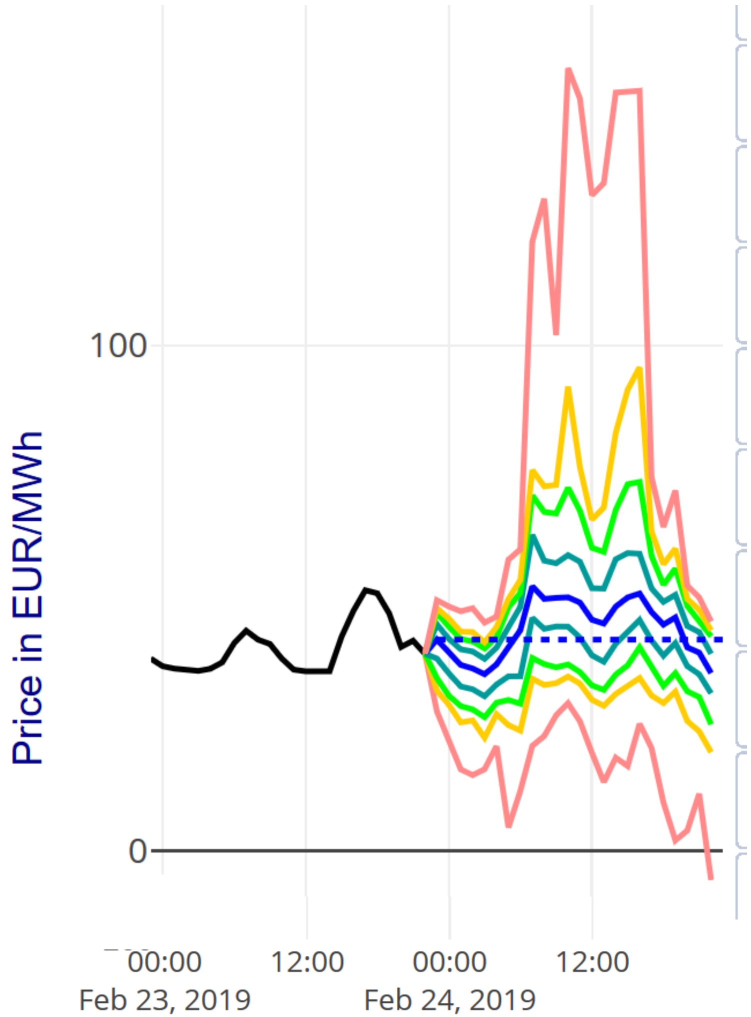
Energy has been a risky business…
Oil price forecast from 2009 onwards



Source: March, C. (2012)

… and will remain so: Electricity price forecasts from Friday 23 onwards



Probabilistic forecasts available online on

https://www.uee.wiwi.uni-due.de/forschung/prognose-von-strompreisen/

- Short-term forecasts
- Huge uncertainties
  - Red: 1%/99% quantiles
  - Green: 25%/75% quantiles

Source: Florian Ziel (2019)

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Dimensions of decisions under uncertainty

- What type of uncertainties is present?
  - Cf. next slide
- Who decides?
  - Individual vs. group
  - Policy makers vs. companies vs. households/citizens
- What is decided?
  - Operation
  - Investment
  - Regulation
- What interdependencies with other decisions are relevant?

Typology of energy decisions (bracketing "Who decides?" and "What is decided?")

Normative Decision Theory: Decision settings

- Decisions under certainty

- Decisions under risk

  Objective probabilities for events available

  ➢ Optimal decision rule: Bernoulli Principle, Maximization of expected utility

- Decisions under incertitude

  in the Anglo-Saxon literature frequently: "Knightian uncertainty"

  No objective probabilities

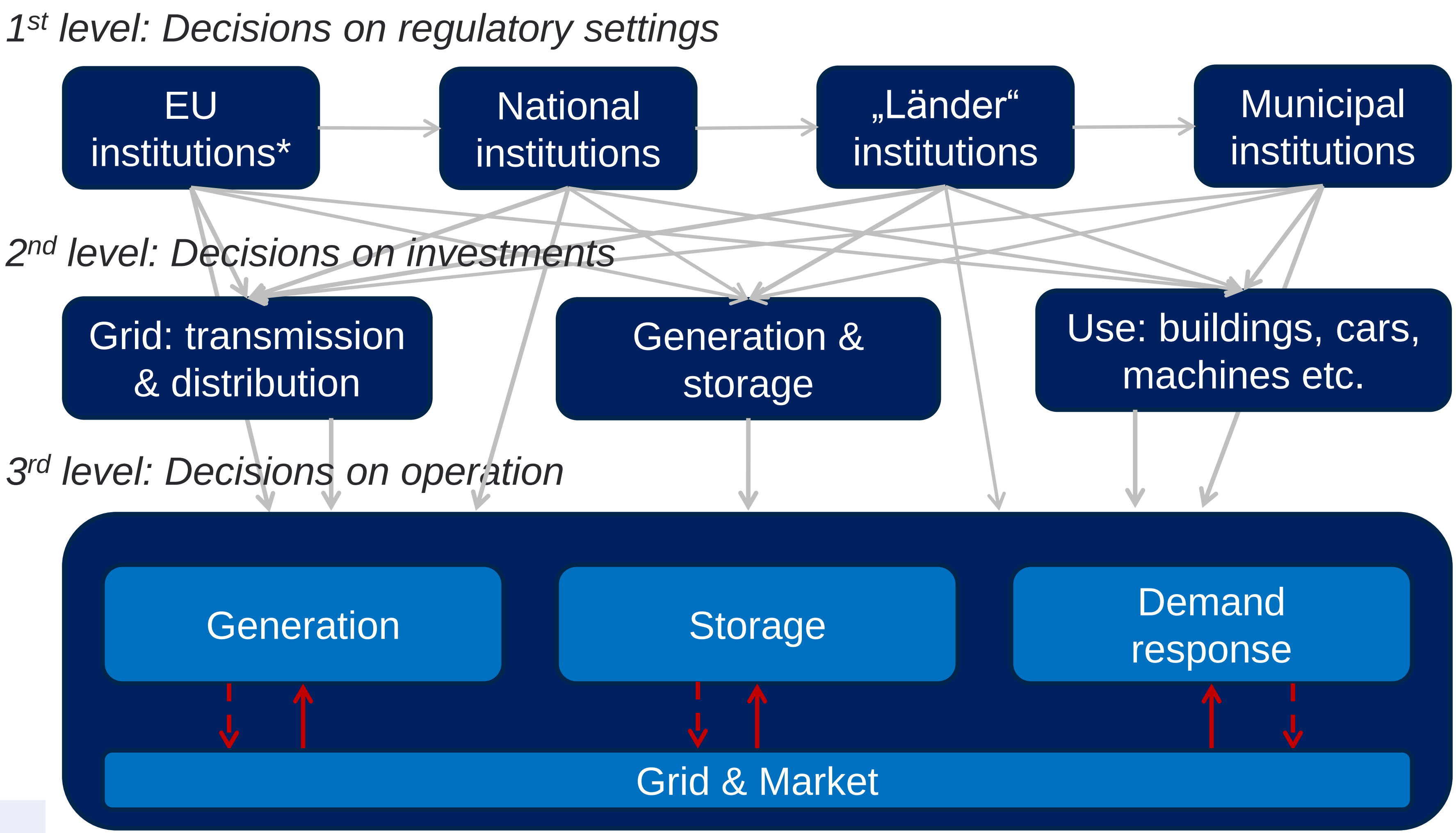
  ➢ Typical case for political uncertainty

  ➢ Savage (1954) and others use subjective (Bayesian) probabilities

  ➢ But also other, heuristic decision rules available: Maximin, minimum regret …

Decisions under uncertainty (risk and incertitude)

Decisions and decision makers in a national energy system perspective



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Characteristics of operational decisions

- Repeated decision making
- Varying circumstances, e.g.
  - Renewable infeed
  - Demand
  - Power plant & line availabilities
  - Fuel & CO_2 prices
- Considerable short-term uncertainty
  - Especially on first three factors
- Numerous situations rather standard
- But sometimes exceptional and critical situations occur

Examples of short-term decisions

- **Grid operators**
  - D-2: parameters for flow-based market coupling
  - D-1: procurement of secondary and tertiary reserve
  - D-1 & D: redispatch
  - D: operation of phase shifters and topology changes
  - D: activation of reserves
- **Power plant operators & portfolio marketers**
  - D-1: submission of bids to secondary and tertiary reserve markets
  - D-1: submission of bids to day-ahead trading (before DA auction)
  - D-1: day-ahead planning of power plant, storage and DSM operation (after DA auction)
  - D: submission of bids to intraday trading
  - D: intraday planning of power plant, storage and DSM operation

Methods for dealing with uncertainties

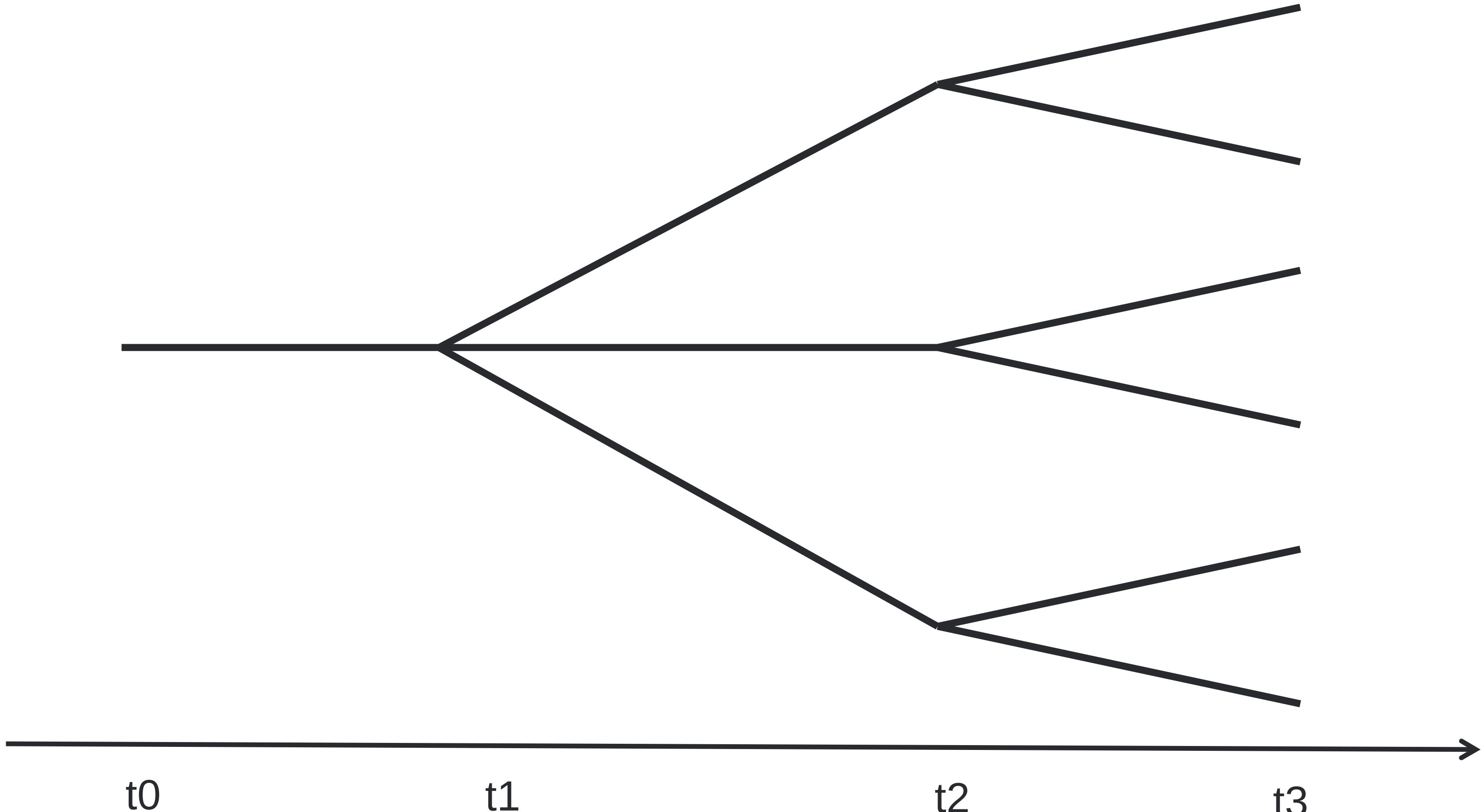
- **Linear and Mixed Integer Optimization using the deterministic equivalent**
- Sensitivity calculations
- **Stochastic optimization**
- Chance-constrained optimization
- **(Stochastic) (Dual) Dynamic Programming**
- **Robust optimization**
- Distributionally robust optimization
- Heuristic approaches
- …

Unit Commitment and Dispatch: Examples for dealing with uncertainties

- **Linear and Mixed Integer Optimization using the deterministic equivalent**
  e.g. Sheble & Fahd (1994), Baldick (1995), Tovar-Ramirez (2016)
- **Two-stage stochastic optimization**
  e.g. Caroe et al. (1997), Dentcheva et al. (2000)
- **Multi-stage stochastic optimization**
  e.g. Carpentier et al. (1996), Takriti et al. (2000), Meibom et al. (2011)
- **Stochastic Dynamic Programming**
  e.g. Wolfgang et al. (2009), Felix, Weber (2012),
- **Stochastic Dual Dynamic Programming**
  e.g. Pereira and Pinto (1991), Guiges and Römisch (2012)
- **Robust optimization**
  e.g. Jiang et al. (2012), Bertsimas et al. (2013), Zhao et al. (2013)

cf. also reviews by Zheng et al. (2015),
van Ackooij et al. (2018)

Tree as a representation of stochastic states



Stochastic Optimization Stochastic Programming vs. Stoch. Dynamic Programming

- Numerical Stochastic Optimization solves a deterministic equivalent of the original stochastic problem
- I.e. the branches and leafs of the tree are taken as given

Strategy 1:

Solve the entire problem at once → **Stochastic Programming**

→ Only feasible for a limited number of branches and leaves

Strategy 2:

Decompose the problem using the Bellmann Principle*

→ **Stochastic Dynamic Programming**

→ Only feasible if the number of decision states is limited

e.g. option exercised yes/no, plant on/off

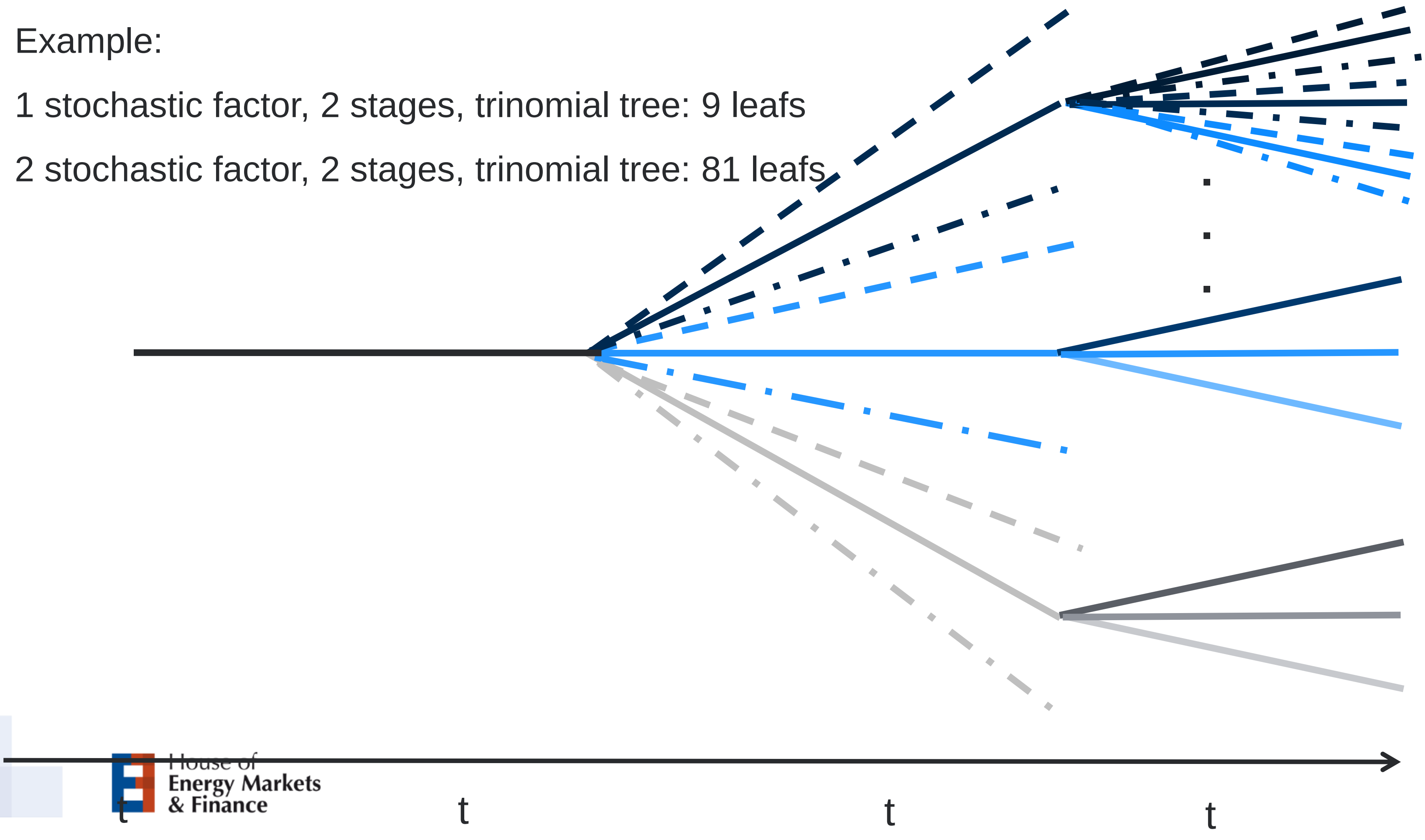
*loosely: each part of an optimal trajectory must be itself optimal

Challenges of stochastic programming
1) Multidimensional trees are really hard

Example:

1 stochastic factor, 2 stages, trinomial tree: 9 leafs

2 stochastic factor, 2 stages, trinomial tree: 81 leafs



Challenges of stochastic programming
2) Adequate determination of scenarios

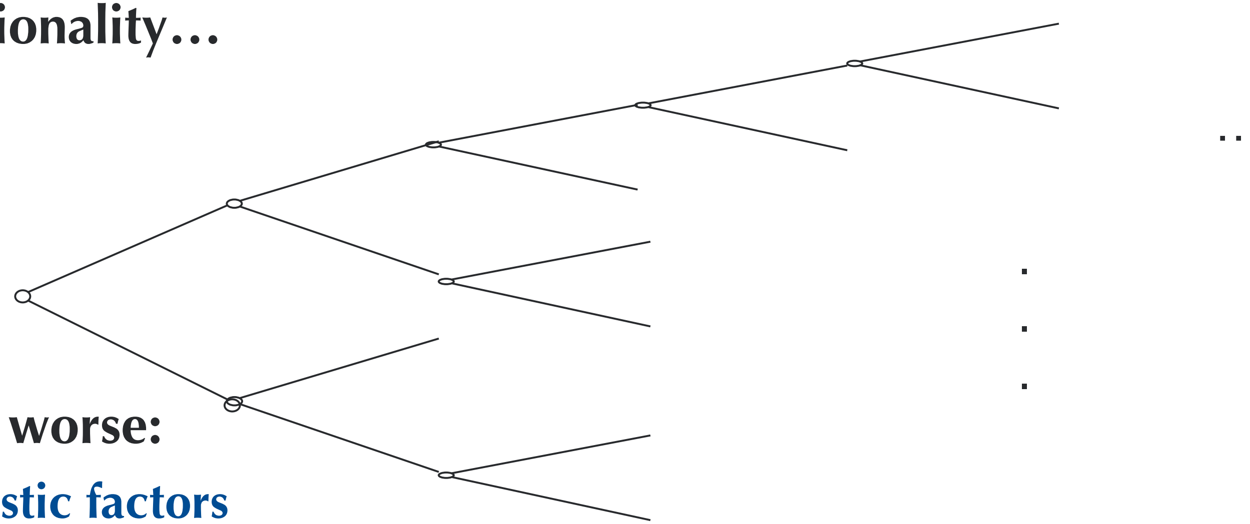
- Scenario reduction techniques have been repeatedly developed
  e.g. Dupacova, Römisch (2003), Hoyland, Wallace (2001), Rubasheuski et al. (2014)

- Yet the metrics used to determine the scenarios are generally not reflecting the cost differences

➢ Importance (in terms of cost impact) based sampling of scenarios is preferable
  Cf. Pöstges & Weber (2018) for time aggregation

Why not just doing it stochastically?

- **Curse of dimensionality…**



- **… and it is even worse:**
  - **Multiple stochastic factors**
    Power prices, fuel prices, inflows, temperatures…
  - **Multi-factor models for stochastic models**
    e.g. seasonal factor, long-term factor…
  - **Multiple decision states**
    several power plants with up/down times, large storages…
  - **…**

→ Making good stochastic models remains a challenge

Robust optimization

- Stochastic Optimization:
  - – Minimization of Expected Cost or
  - – Minimization of a Risk functional of Cost (Mean-Risk optimization), e.g. CVaR
  - ➢ Risk neutral or (mildly) risk averse approach

- Robust Optimization:
  - – Minimization of the worst outcome
  - – Minimax-strategy
  - ➢ Rather pessimistic approach
  - – Security constrained optimal power flow may be considered as an example of a robust optimization (N-1 criterion satisfied)
  - ➢ Robustness always measured again a set of possible events (contingencies)
  - ➢ "Milder" forms of robustness: local robustness, distributional robustness

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What is different with investments?

- Discrete decisions
- Long-lasting impacts
- Heavy financial impact

➢ Empirical foundations for stochastic (or robust) optimization weaker
  – Less independent observations
  – Likelihood of structural breaks higher
  ➢ Extrapolation of probabilities from the past to the future more dangerous

➢ More recourse actions
  – Modelling has to anticipate the multitude of operating decisions during lifetime

Coping with uncertainties in investment decisions (I)

Strategy 1:

Use of **high discount rates** (or low payback times)
& **deterministic equivalent**

- Implicit assumption: linear addition of uncertainty over time
- According to CAPM: uncertainty related to (market) systematic risk

Strategy 2:

Use of **scenarios**

e.g. Shell scenarios

- Reduction of multiple uncertainties to a limited number of scenarios (3 – 5)
- Focus on coherent and complementary world-views ("scenario family")
- In general no probabilities associated with scenarios

Coping with uncertainties in investment decisions (II)

Strategy 3:

Use of **stochastic optimization with subjective probabilities**

- Or if probabilities based on statistical model: unknown model risk
- Agreement on subjective probabilities difficult to reach in multi-person decision-making context

Strategy 4:

Focus on **mean scenario + risk assessment**

- Standard approach in corporate reporting
- Risks are frequently not quantified

A few remarks on scenarios (I)

Analysis

- Or rather a key question:

Why are we developing and using scenarios?

Answer – Version 1:

Analysis

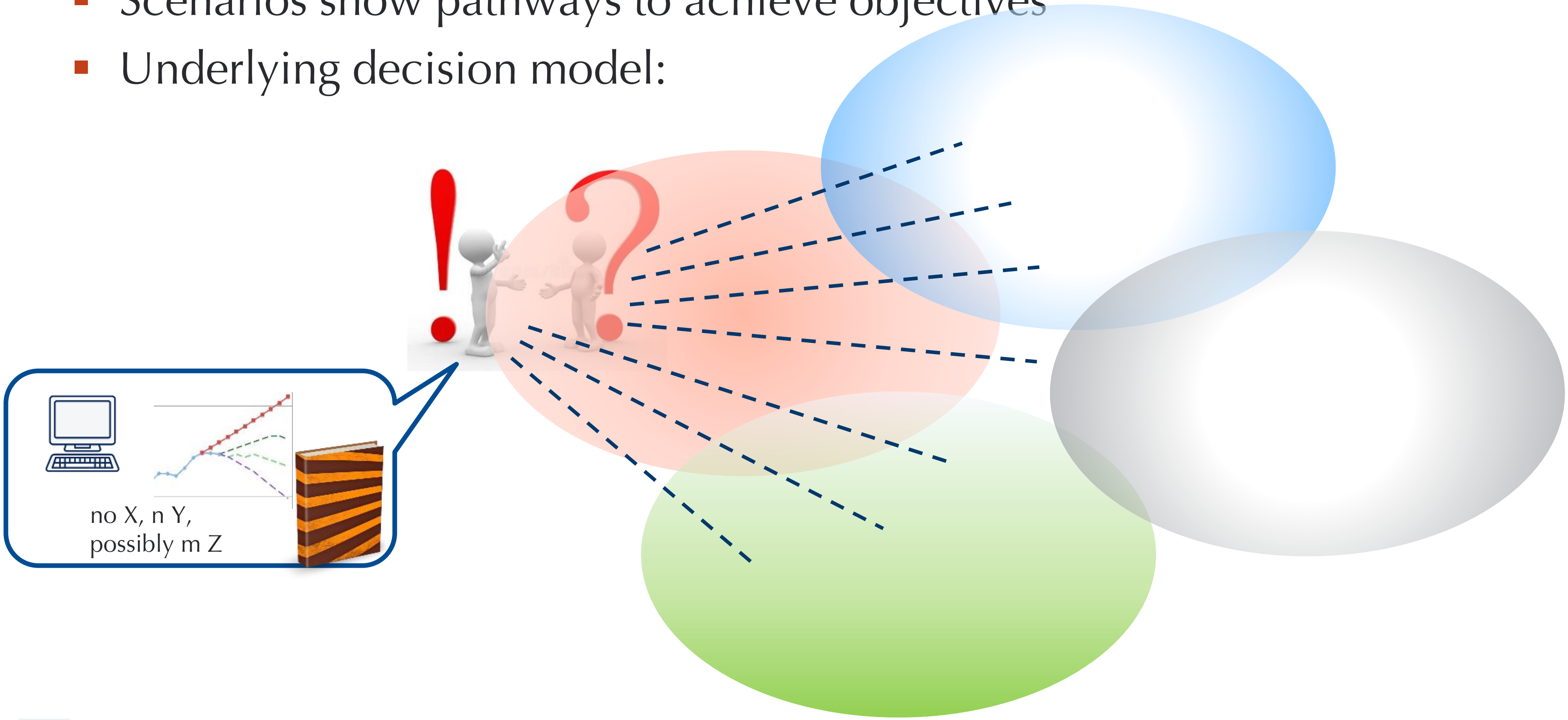
- Scenarios enable good decision making under uncertainty
- They structure the multiple uncertainties that decision makers are facing
- Underlying decision model: (as taught in 1st year business administration course)

Uncertainties ➢ Scenarios / ➢ Decision alternatives	s_1	s_2	. . .	s_n
a_1	$r_{11.}$	$r_{12.}$	. . .	$r_{1n.}$
a_2	$r_{21.}$	$r_{22.}$	. . .	$r_{2n.}$
⋮	⋮	Decision consequences (cost, emissions, …)		
a_m	$r_{m1.}$	$r_{m2.}$	. . .	$r_{mn.}$

→ ***Rule-based, rational decision making***

Answer – Version 2:

- Scenarios help to make the right decisions
- Scenarios show pathways to achieve objectives
- Underlying decision model:



decision making in political arenas
multi-level stakeholder interactions

A few remarks on scenarios (II)

If scenarios are focusing on **depiction of uncertainties**:

- They should capture **key uncertainties exogenous** to the **decision maker**

  E.g.

  – World market **prices for fossil fuels** and **renewable technologies**

  – **Global & European Climate Policy objectives** and **instruments** – if the decision maker is a company or a national government

- The same decisions should be evaluated against different scenarios

  Key questions:

  – Which decision yields the best outcome "on average"?

  – Is there a scenario where a decision leads to extremely negative consequences?

  ➢ A not (fully) formal way of implementing a mean-risk perspective on decisions

➢ The process of scenario construction and parameter selection is as important as the scenarios itself

  – Avoidance of "group think" key for appropriate dealing with risk

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What is different in political decision making?

- **Multiple objectives**
- **Multiple stakeholders**
- ➢ Advocating the own cause important
- ➢ Evoking the uncertainties may frequently be perceived as "not helpful" for the own cause
  - Scenarios rather used as in answer version 2

- **Cause-effect relationships** for many **policy instruments uncertain**
  - Not (as much) true for command & control type policies, e. g. schedule for coal phase out
  - But certainly true for price-based instruments and support mechanisms, e.g.
    CO_2 tax
    subsidies for electric vehicles or renewables
- **Multi-level decision hierarchy**

Decisions and decision makers in a national energy system perspective

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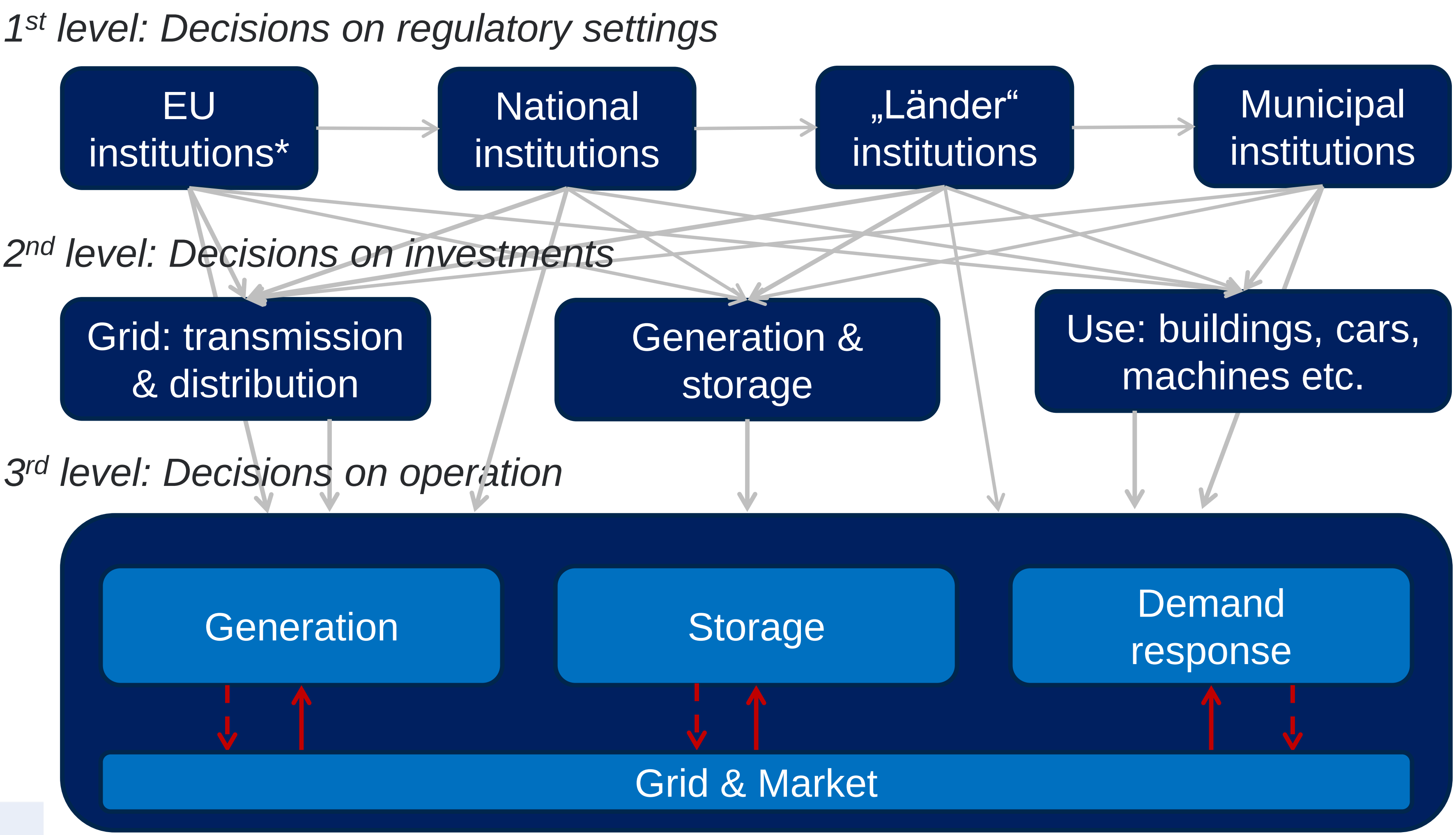

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Dealing with uncertainties in political decision support (I)

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- Use scenarios
  - Reflecting also truthfully exogenous uncertainties, e.g. technology cost
- Make sensitivity analyses
  - Notably on uncertain behavioural assumptions
    e.g. on uptake of flexibility provision through V2G for electric vehicles,
    on restrictions on land use for renewables due to limited acceptance
  - But also on technological assumptions

  cf. analyses by Wolf Schill

- ➢ Scenarios: many parameters are varied simultaneously
  - ➢ Enable an assessment of choices against contrasting world views
- ➢ Sensitivities: one parameter is at a time
  - ➢ Enable a transparent assessment of the impact of single parameter choices on results

Dealing with uncertainties in political decision support (II)

- Take into account behavioural heterogeneity among stakeholders:
  - Energy users, investors, governments

  cf. presentation by Sina Heidari

  - ➢ Take existing empirical evidence serious
  - ➢ Model behavioural uncertainty through parameter variations
  - ➢ Conduct further empirical studies on key behaviours of stakeholders (investors and users)

Dealing with uncertainties in political decision support (III)

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- Do not rely excessively on results from Linear programs

  Explicit assumptions:

  – one overarching, unique objective function

  – homogenous technology classes with known parameters

  ➢ False certainty

  ➢ Penny-switching

  ➢ Control illusion

  … or at least do sensitivity analyses

- Investigate operational risks induced by policy instruments in detail

  – Security of supply key challenge for energy transition

  – Modelling of operational uncertainties can build on established stochastic methods

  cf. presentation by Philip Hauser

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- There is no silver bullet to cope with uncertainties

- A major step is already taken when uncertainties/risks are thoroughly identified

- When you use an optimization model, adjust your shot well to hit your target:

  i.e. reflect carefully your choice of method and your representation of uncertainties (distribution)

Thank you.

Questions?

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