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Methodological Analysis of Investment Decision Making Algorithms in Long-term Agent-based Electricity Market Models

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KU Leuven

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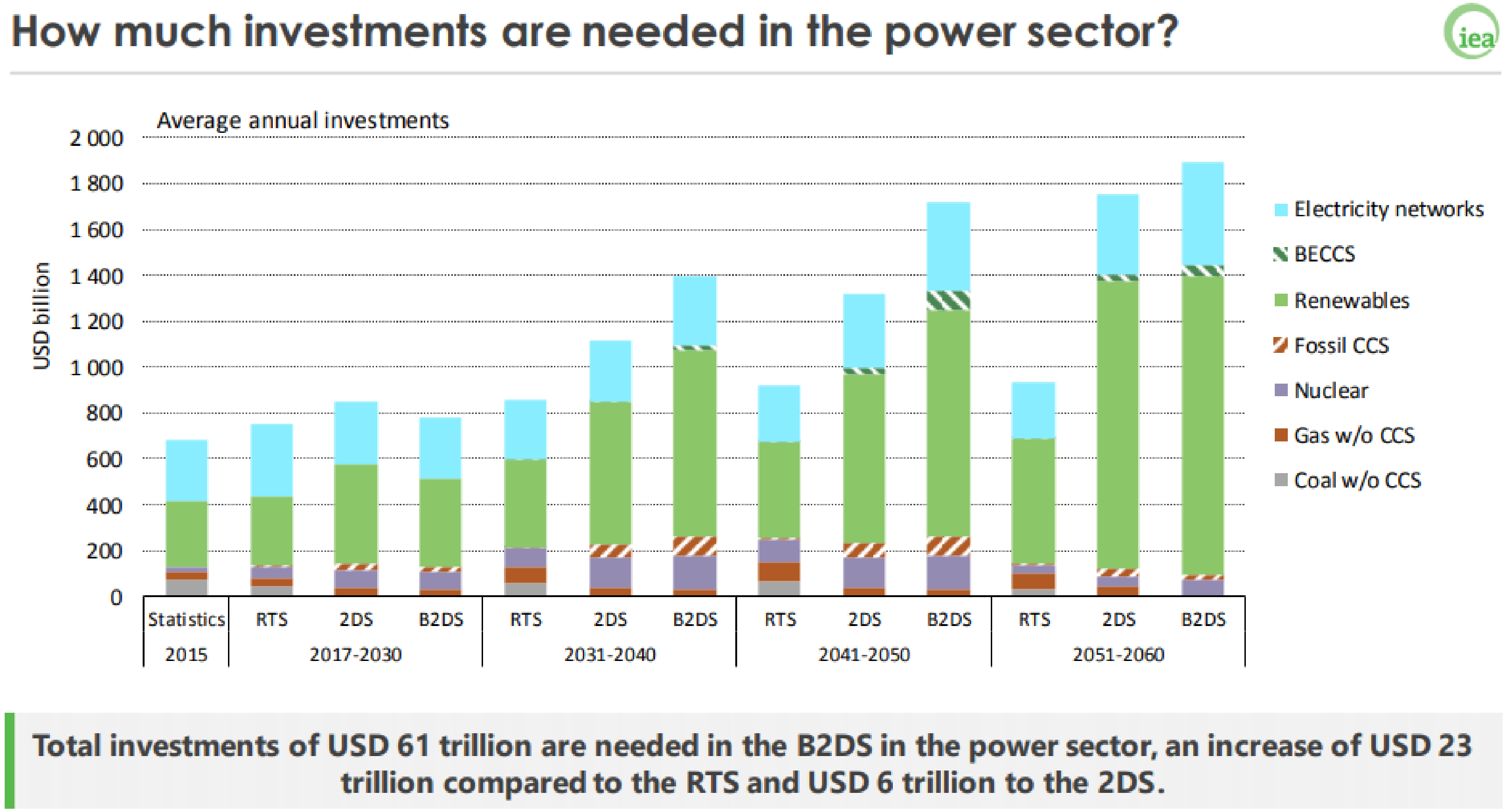
- Motivation
- Problem definition
- Literature review
- Proposed solution
- Proof of concept
- Conclusions

Energy system transition – Investment required



Total investment needed for different scenarios

International Energy Agency. Energy Technology Perspectives. Paris: IEA; 2017.

RTS =Reference Technology Scenario
(today’s commitment + pledged NDCs)

2DS = 2 Degree Scenario
(70% reduction)

B2DS = Beyond 2 Degree Scenario
(carbon neutral)

Long-term planning models in power systems

- **Optimization model**
  - A central system planner
  - Perfect information and perfect foresight
  - Total system cost minimization
- **Equilibrium model**
  - Explicit representation of agents
  - Agents are fully rational
  - Equilibrium is beforehand assumed to exist
- **Agent-based model**
  - Explicit representation of agents
  - Agents are not necessarily fully rational
  - Equilibrium is not pre-assumed to exist

Why agent-based modeling

- Electricity market is a complex adaptive system
  - Highly non-linear due to the interactions (e.g. crowd effect) and feedbacks (e.g. rivals' investment changes market price). Among agents and with environment
  - The system capacity mix and the agents' generator portfolio are constantly changing due to interactions and environmental change (e.g. policy landscape)
  - Generation companies / agents are heterogeneous and adapt to the change by alternating investment decisions
- Agents-based modeling can capture important factors that traditional models have difficulties with
  - Bounded rationality
  - Behavioral factors
  - Risk averseness

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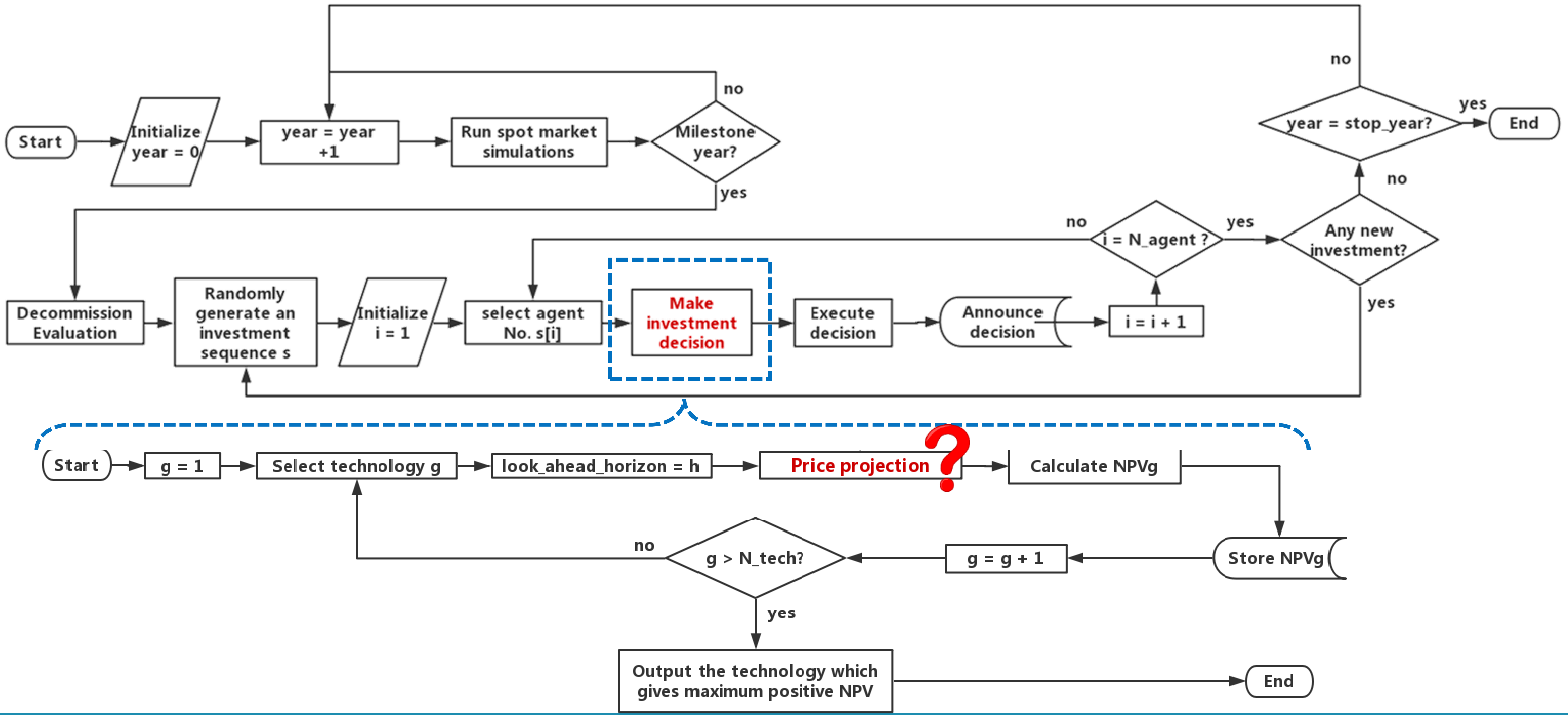
How can we get price projection properly?



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Existing price projection methods

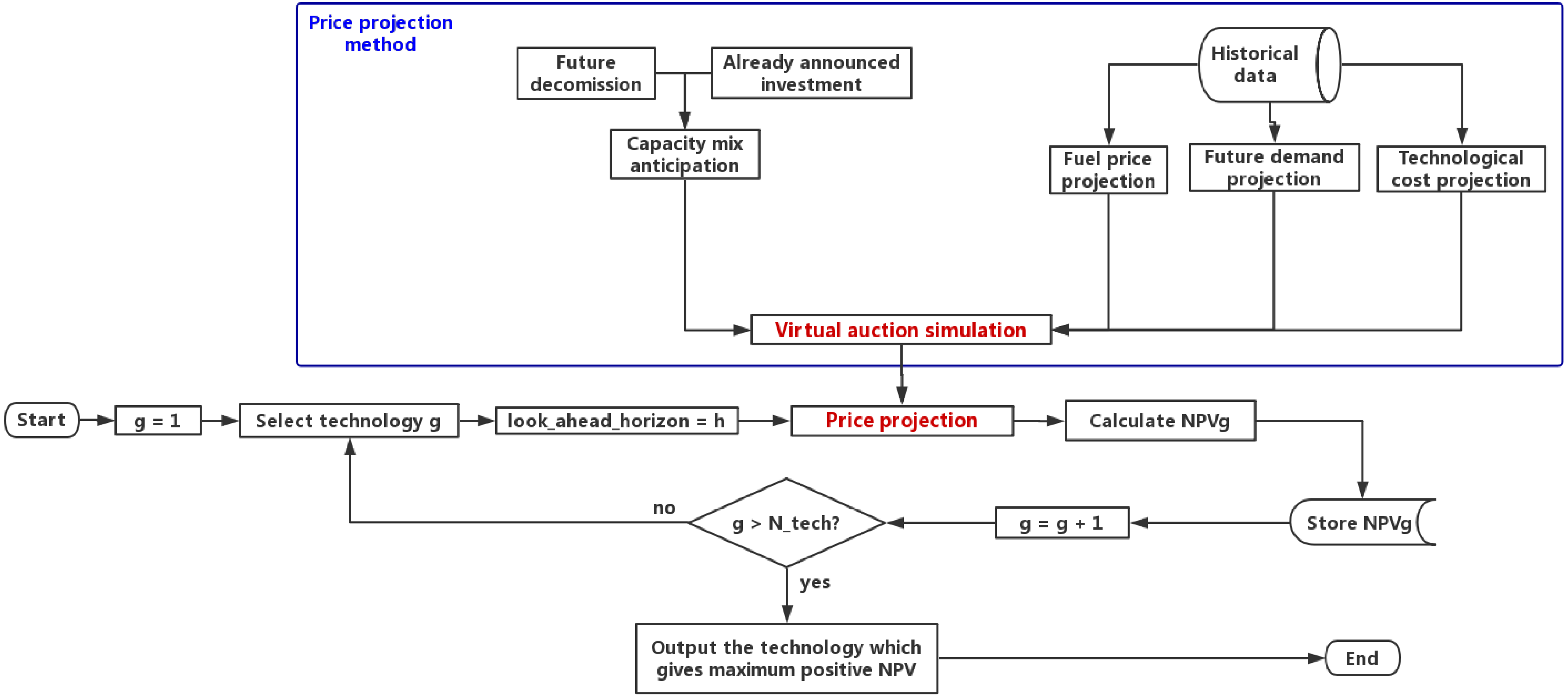
Classification	Name	Short description	Pros and cons
Direct predicting	Monotonously increasing	The electricity price will grow following a certain rate (risk-free interest rate).	• Easy implementation. • Price volatility ignored • Agents' investment influence ignored
	Stochastic time change	Based on financial theories originally used to predict stock price.	• Volatility included. • Long-term accuracy not guaranteed. • Agents' investment influence ignored
	Exogenous capacity mix	Based on capacity mix from existing literatures or reports	• Better transparency • Easy implementation • Agents' investment influence ignored
Fundamental predicting	Myopic agent	Consider existing capacity and planned decommissioning. Look at a limited look-ahead horizon.	• Easy implementation. • Part of future information lost.
	Scenario trees	Future rivals' investment is represented by scenarios	• Increased robustness facing look-ahead horizon change. • Results can change drastically as the probability associated with scenario changes. • Probabilities determination is difficult to justify

Borovkova, S. and Schmeck, M.D., 2017. Electricity price modeling with stochastic time change. Energy Economics, 63, pp.51-65.

Chappin, E.J., de Vries, L.J., Richstein, J.C., Bhagwat, P., Iychettira, K. and Khan, S., 2017. Simulating climate and energy policy with agent-based modelling: The Energy Modelling Laboratory (EMLab). Environmental modelling & software, 96, pp.421-431.

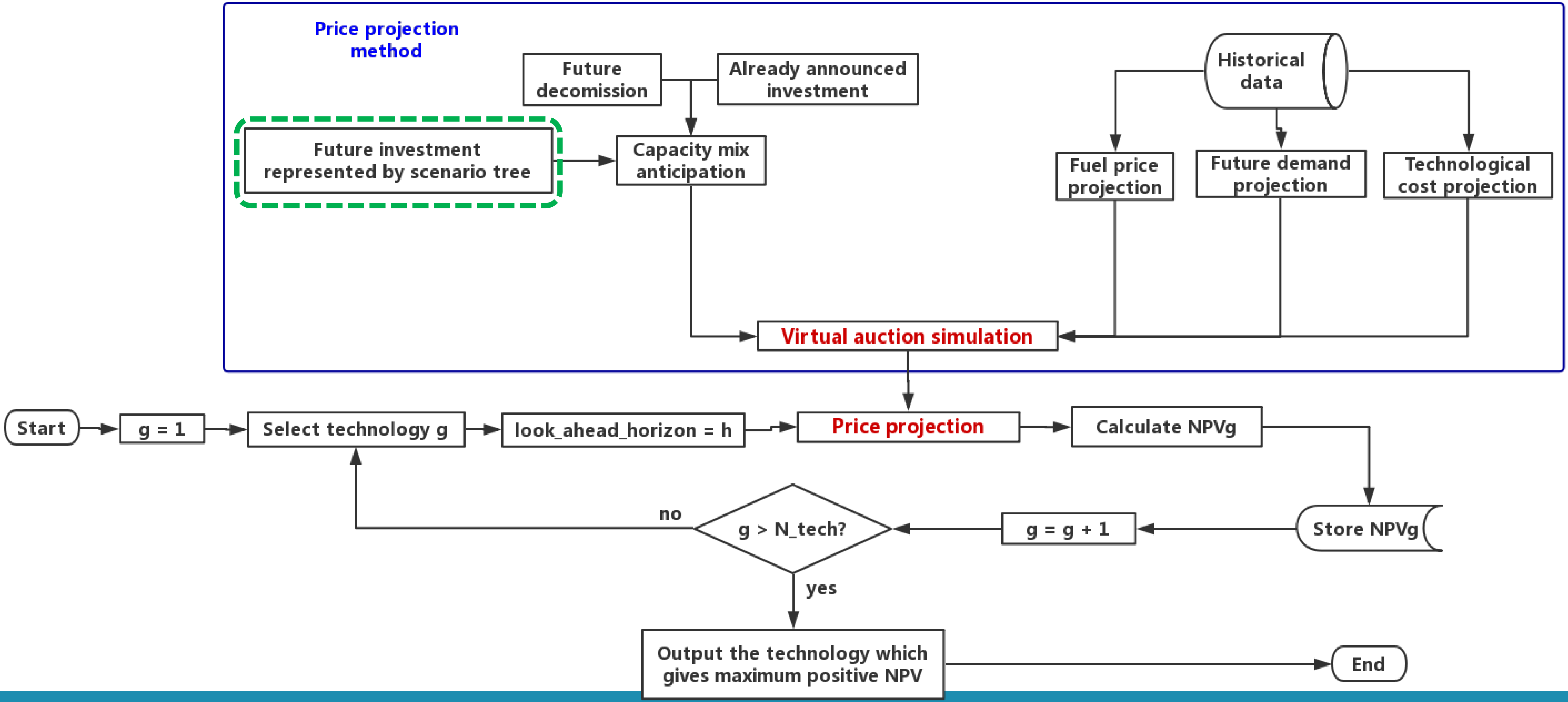
Conzelmann, G., Boyd, G., Koritarov, V. and Veselka, T., 2005, June. Multi-agent power market simulation using EMCAS. In IEEE Power Engineering Society General Meeting, 2005 (pp. 2829-2834). IEEE.

Fundamental predicting 1: myopic agent

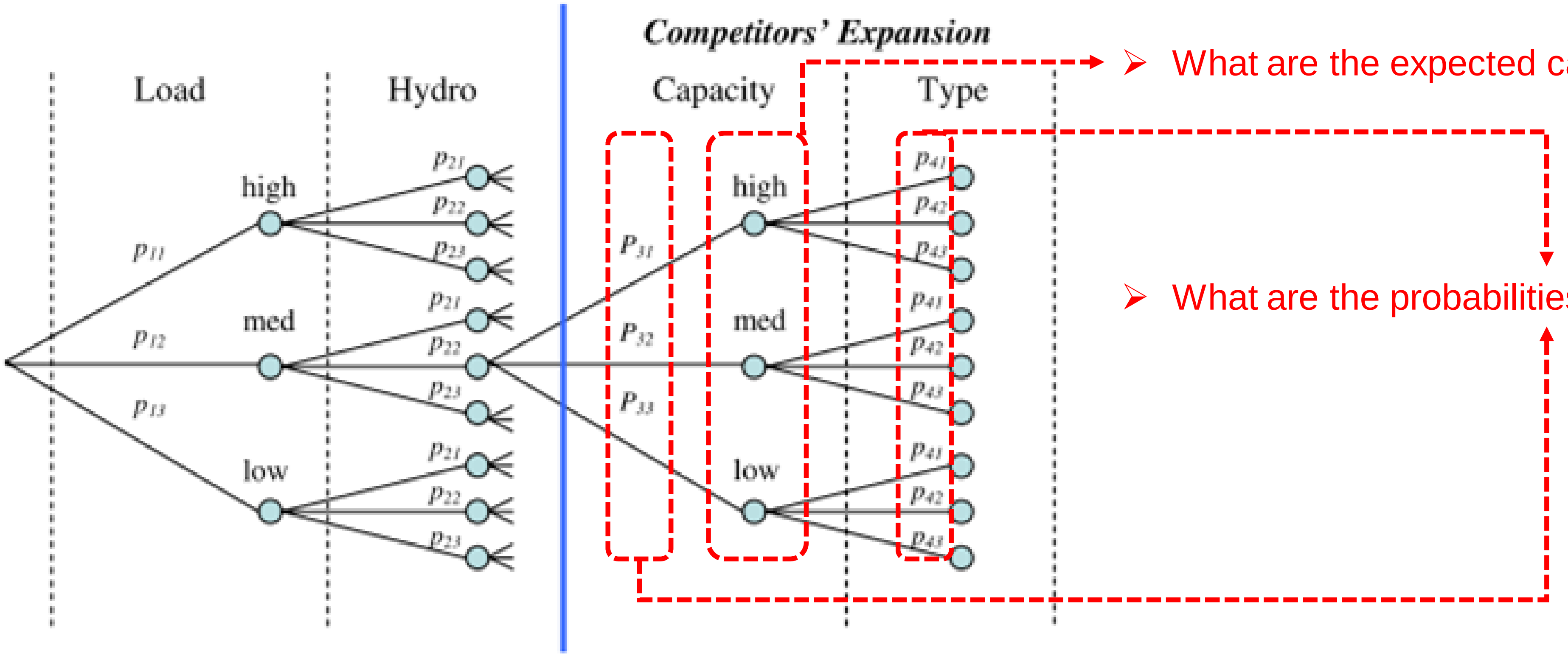


Future investment expectation is missing -> reduce the look-ahead horizon

Fundamental predicting 2: scenario tree



Fundamental predicting 2: scenario tree



- What are the expected capacity that they will build?
- What are the probabilities and technology types?

Scenario tree for uncertainties in load growth, hydro power conditions and competitors' expectations

Conzelmann, G., Boyd, G., Koritarov, V. and Veselka, T., 2005, June. Multi-agent power market simulation using EMCAS. In IEEE Power Engineering Society General Meeting, 2005 (pp. 2829-2834). IEEE.

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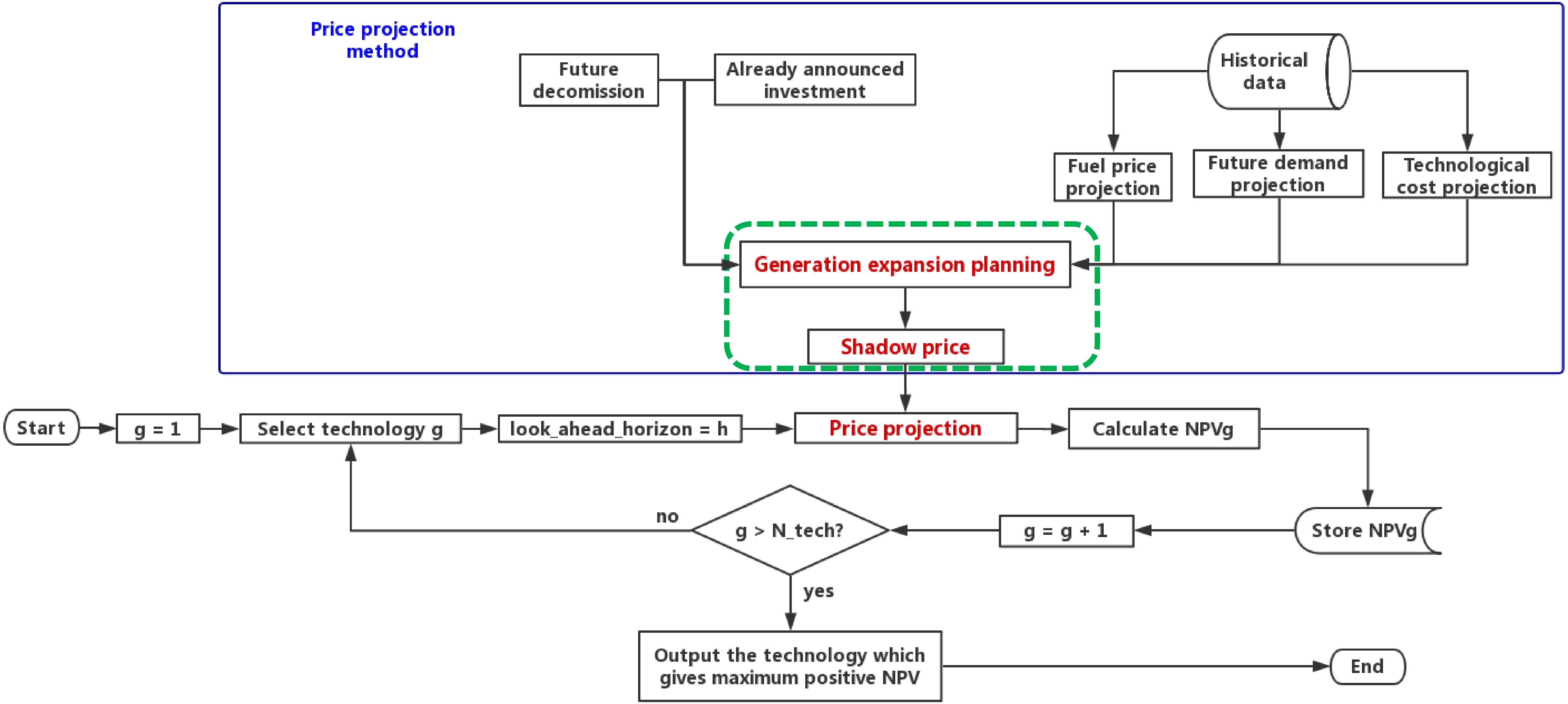
Fundamental predicting 3: GEP (as optimization model)



Fundamental predicting 3: The GEP

$$\text{Minimize} \sum_{y=1}^{Y}\sum_{j=1}^{J}\Big(\underbrace{f_{j,y}\cdot G_{j,y}}_{\text{Fixed cost}} + \underbrace{\sum_{d=1}^{D}\sum_{h=1}^{H} W_d \cdot \gamma_{j,h}\cdot v_{j,y,d,h}\cdot g_{j,y,d,h}}_{\text{Variable cost}}\Big) + \underbrace{\sum_{y=1}^{Y}\sum_{d=1}^{D}\sum_{h=1}^{H} W_d \cdot l_{y,d,h}\cdot VoLL}_{\text{Load shedding cost}}$$

j : *technology type*; y : *year*; d : *day*; h : *hour*
f : *fixed cost*; v : *variable cost*
g : *technology production*; l : *load loss*
W : *weight of representative days*; γ : *capacity factor*

s.t.

$$\sum_{j=1}^{J} g_{j,y,d,h} + l_{y,d,h} = D_{y,d,h}$$ Energy balance (of each time step)

$$G_{j,y} = G_{j,y} + inv_{j,y-1} - dec_{j,y-1}$$ Installed capacity

$$dec_{j,y} = inv_{j,y-n_j}$$ Decommission (n-> lifetime)

$$0 \leqslant g_{j,y,d,h} \leqslant G_{j,y}$$ Production

$$\sum_{j=1}^{J} inv_{j,y} \leqslant \overline{INV}_{round}, \quad \forall y = 1,2,\ldots,Y, \ \forall round = 1,2,\ldots$$ Investment constraints

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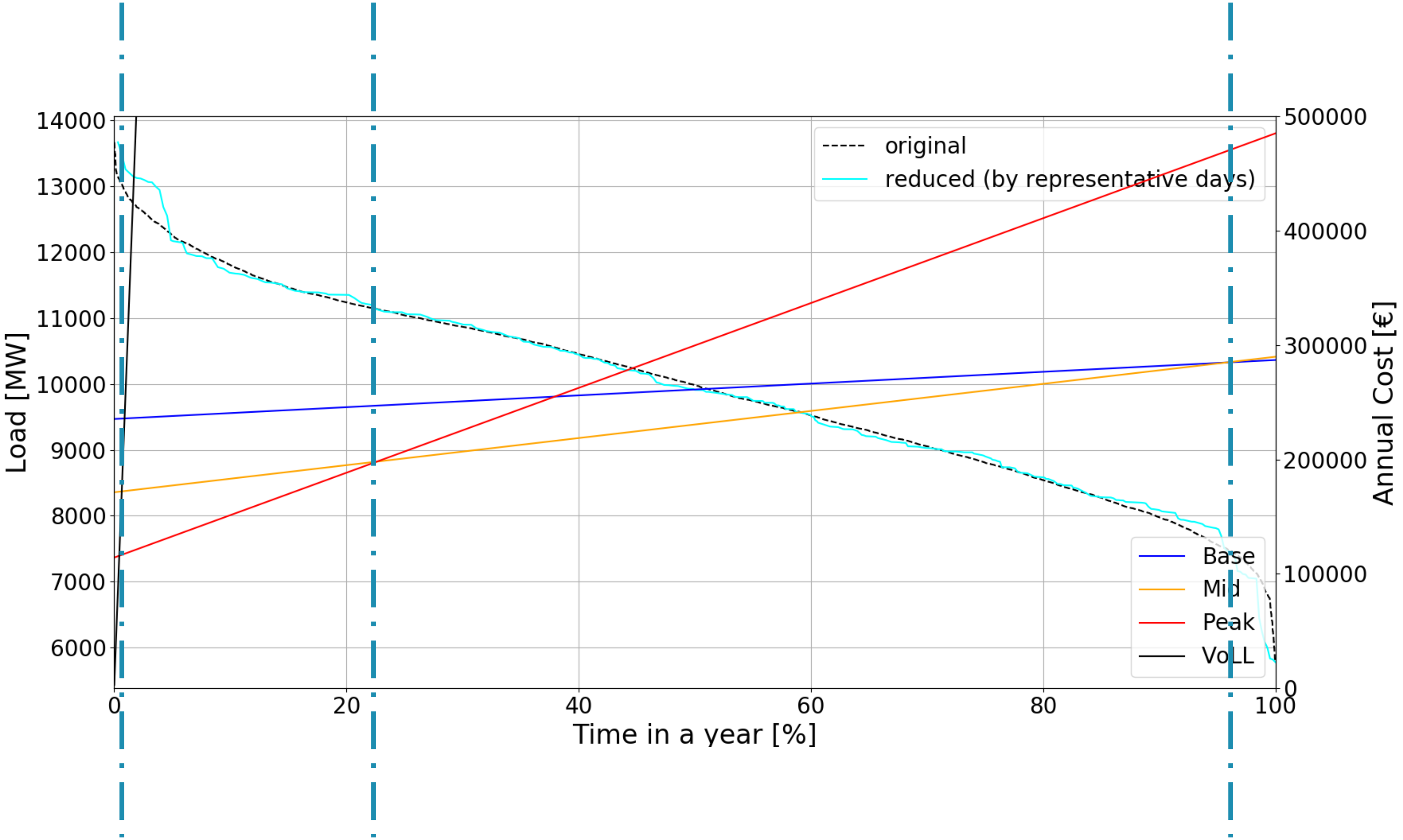
The long-run equilibrium



- Total installed: 13490.5 MW
- Maximum load: 13670 MW

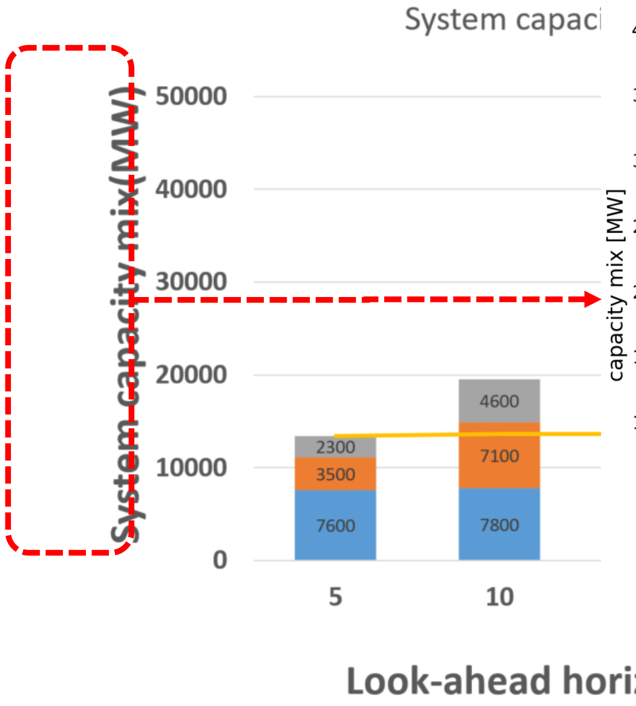
  - Base: 7472 MW
  - Mid: 3638.25 MW
  - Peak: 2380.25 MW
  - VoLL: 3000 €/MWh

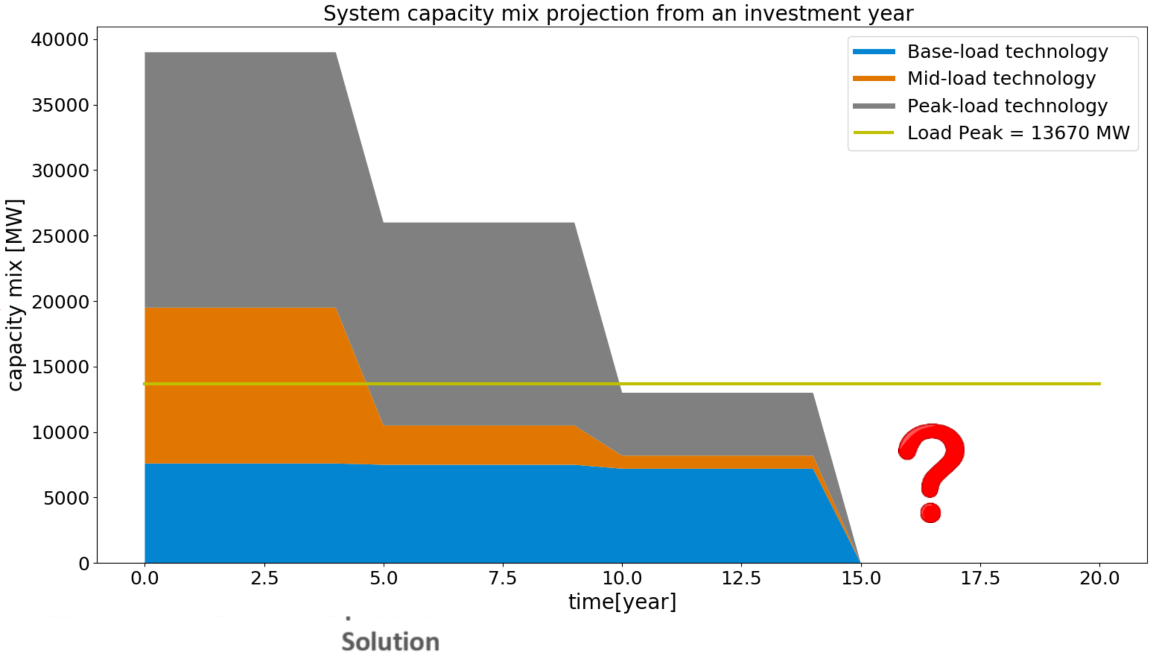
Expectations from agent-based model

- Agent-based model should reach long-run equilibrium as long as we don’t introduce bounded rational behaviors (e.g. a priori belief).
- In the following slides, we’ll compare the simulation results of myopic agent and GEP price projection method.

Faculty of Engineering Science, Department of Mechanical Engineering, Division TME

System capacity mix with agents' sight length



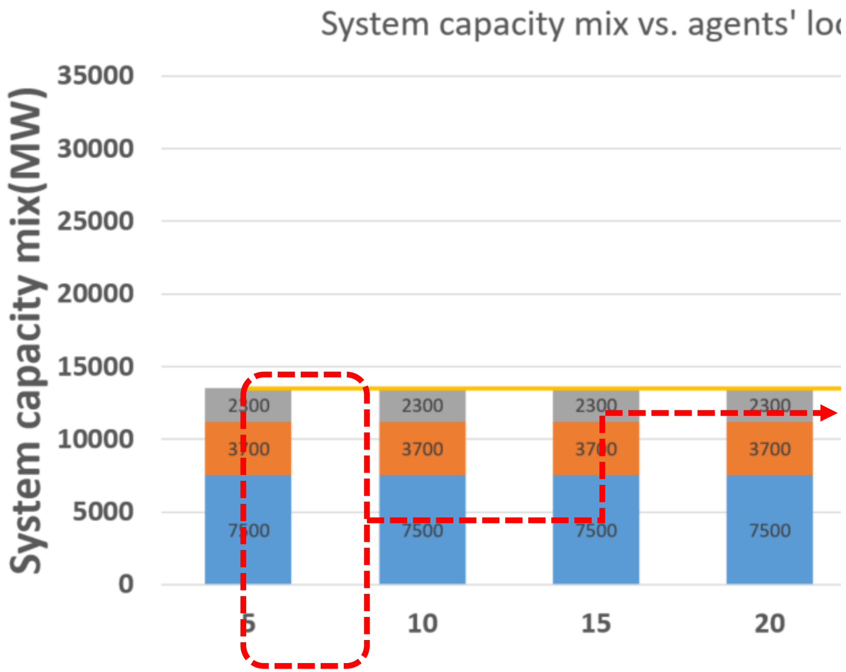


An example of capacity mix projection without considering future investment (look-ahead horizon = 20 years)

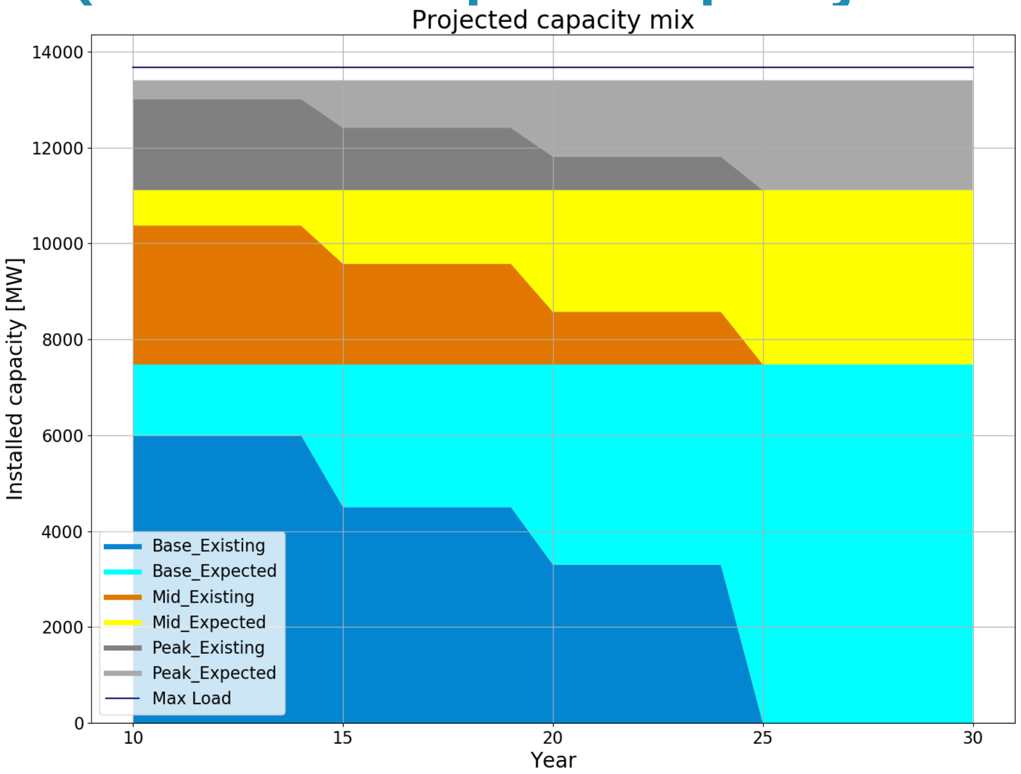
1. The longer the agents' sight length, the more overinvestment will be placed due to improper future capacity projection.

2. Mainly overinvestment in the peak-load technology

Simulation results – ABM+OPT (GEP for price projection)



Base/Mid/Peak: 7500/3700/2300 MW



An example of capacity mix projection considering future investment (look-ahead horizon = 20 years)

1. The simulation results are robust when agents' look-ahead horizon changes
2. Assuming rational agents and perfect foresight, the model can reach equilibrium

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Conclusions

- Results of existing ABMs are sensitive to the assumptions made in the price projection methods. Existing price projection methods are either non-transparent or introduce implicit biases.
- Our integrated ABM-OPT framework is transparent and preserves the flexibility of ABMs without introducing unintended biases.
- Agent-based framework can be used to compute the long-run equilibrium, but has more flexibility to also account for behavioral aspects.

Thank you for your attention

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Appendix

Appendix I - Modeling settings (deterministic)

- Load
  - Belgian load profile 2015, with hourly resolution. Assumed to be unchanged in the future.
- Agent properties
  - 5 homogeneous Agents (GenCos)
- Technologies

Technologies	Unit capacity (MW)	Life expectancy (y)	VOM(€/MWh) + Fuel price / efficiency	FOM(€/kWa)	Capital cost (€/kW)
Base	100	20	5 + 0.3/0.34	115	1500
Mid	100	20	4+4/0.42	75	1200
Peak	100	20	4 + 18.4/0.48	50	800

- Simulation horizon
  - 30 years
  - Representative days (1 year = 12 representative days)
  - Agents are allowed to invest every 5 years

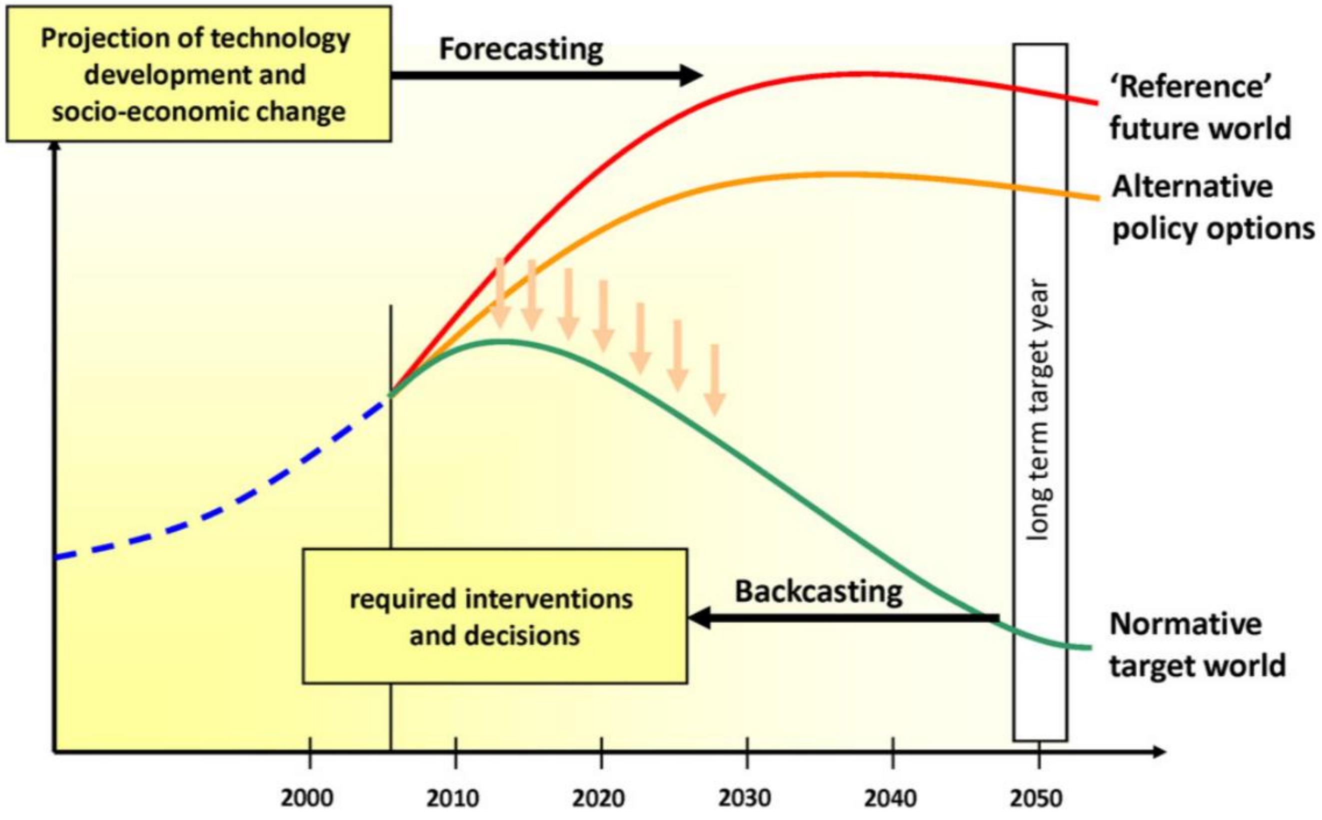
Appendix II - Mainstream normative approaches

- Optimization model
  - Minimized the total cost of the energy provision
  - Subject to constraints (e.g. system constraints, RES target, technical constraints)

Explicit representation of agents

- Equilibrium model
  - Maximize agent utility
  - Subject to constraints (e.g. market equilibrium, technical constraints)

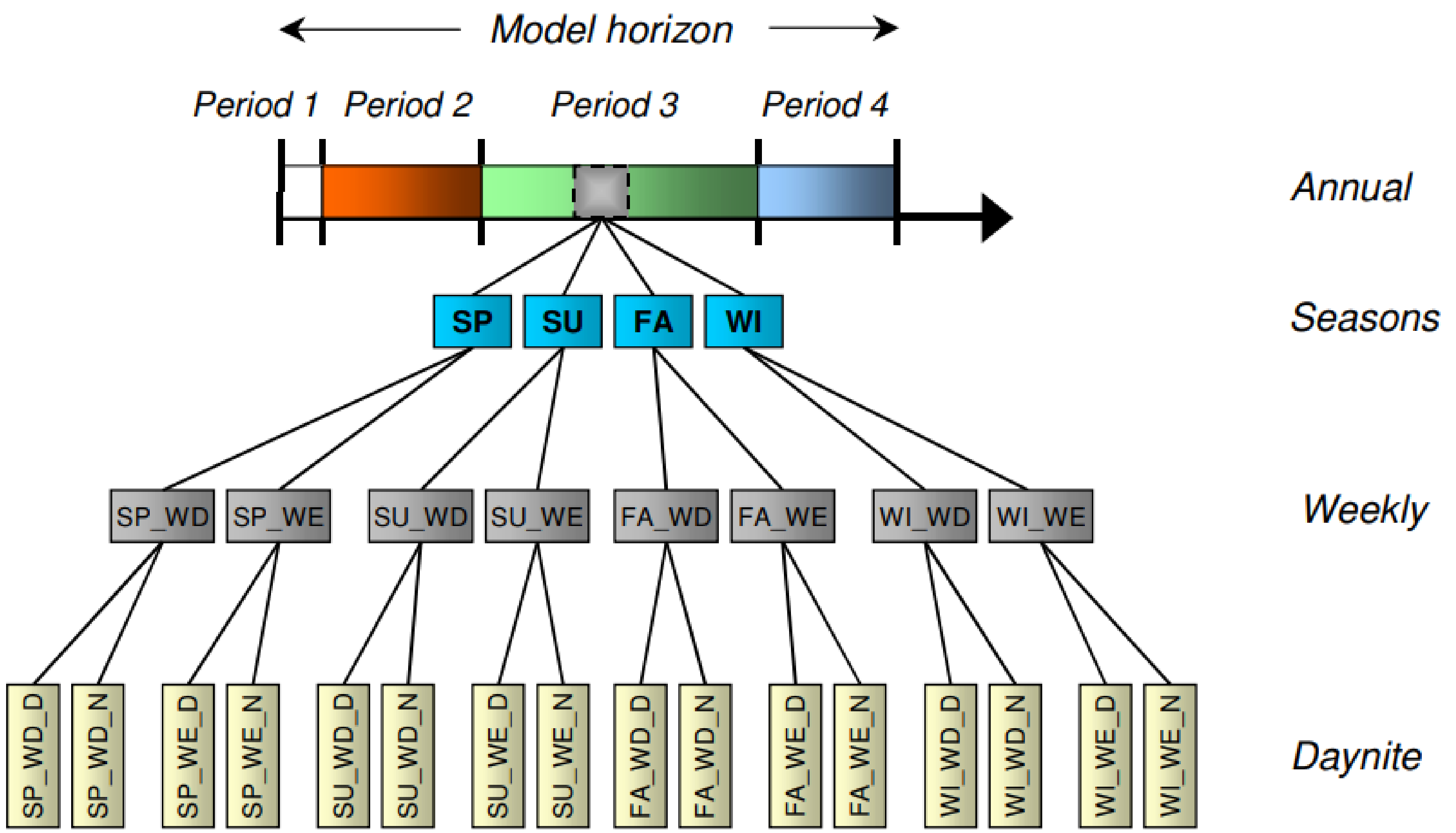
Appendix III - Normative vs. descriptive



Descriptive and normative

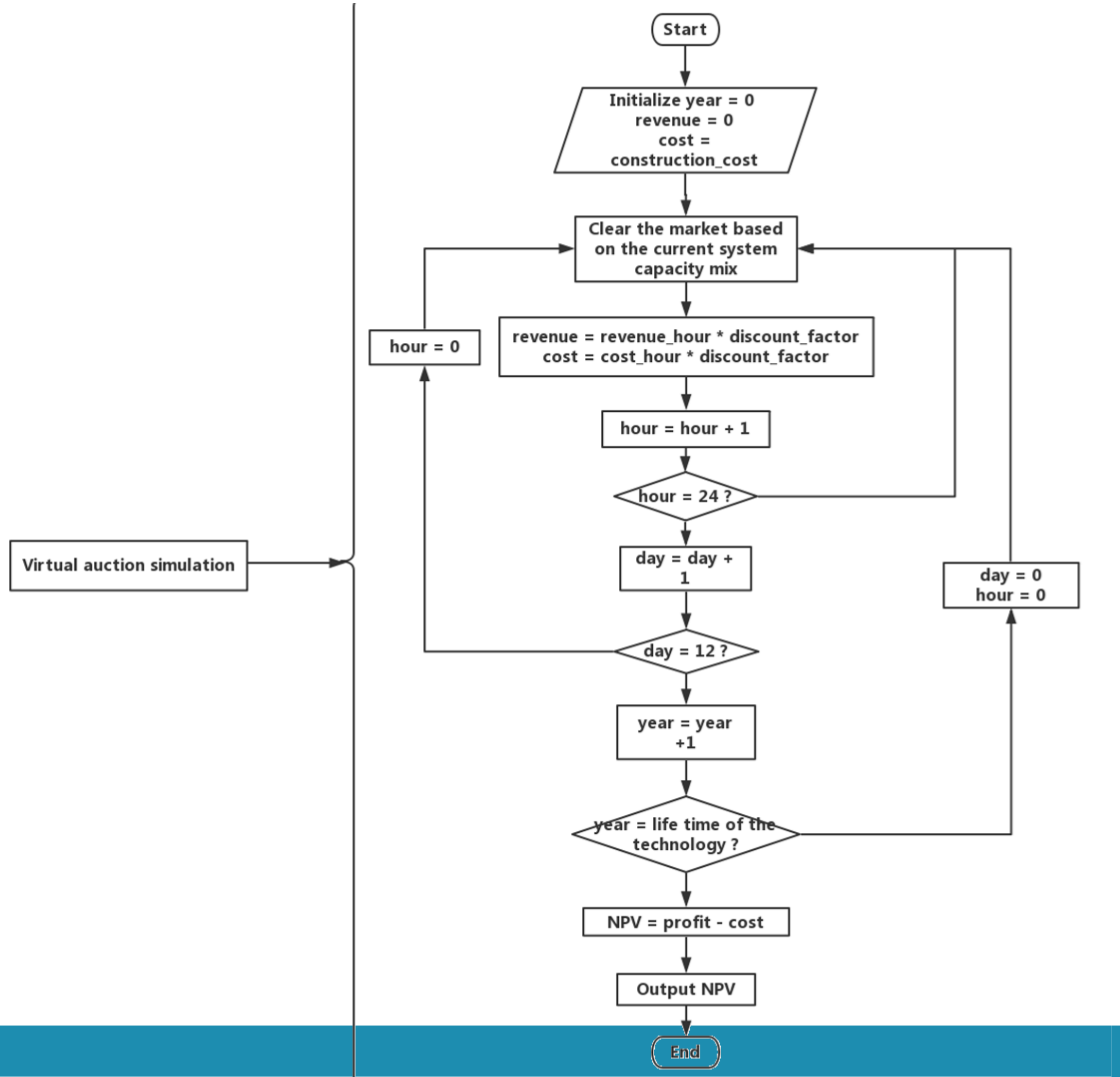
Macal, 2016 - Everything you need to know about agent-based modelling and simulation Journal of Simulation, 10, 144 – 156

Appendix IV – Representative days



An example of the representative days in TIMES model

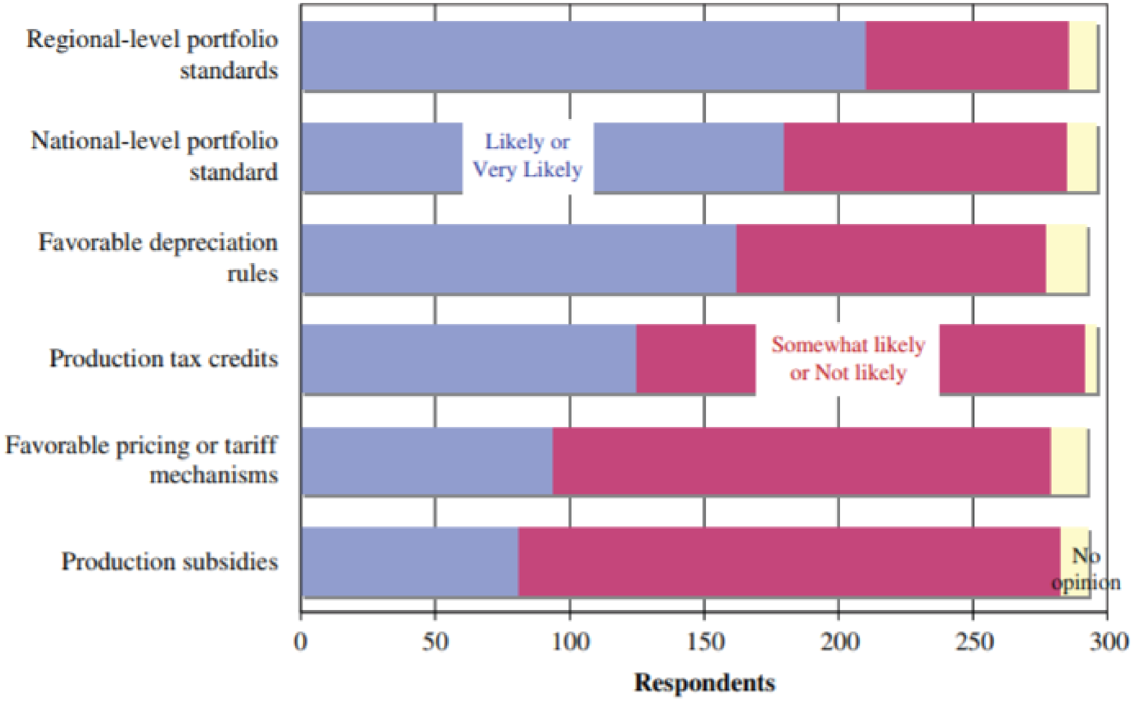
Appendix V – Virtual auction simulation



Appendix VI – Empirical findings on behavioral factors

Behavioral factors matters

- Evidence 1 – Perceived stability of various instruments



Exact question: How likely would you consider the following types of investment incentives, once enacted, to stay in effect long enough to influence long-term investment planning?

Barradale, M.J., 2010. Impact of public policy uncertainty on renewable energy investment: Wind power and the production tax credit. Energy Policy, 38(12), pp.7698-7709.

Behavioral factors matters

- Evidence 2 – Correlation between RE share and several behavioural factors

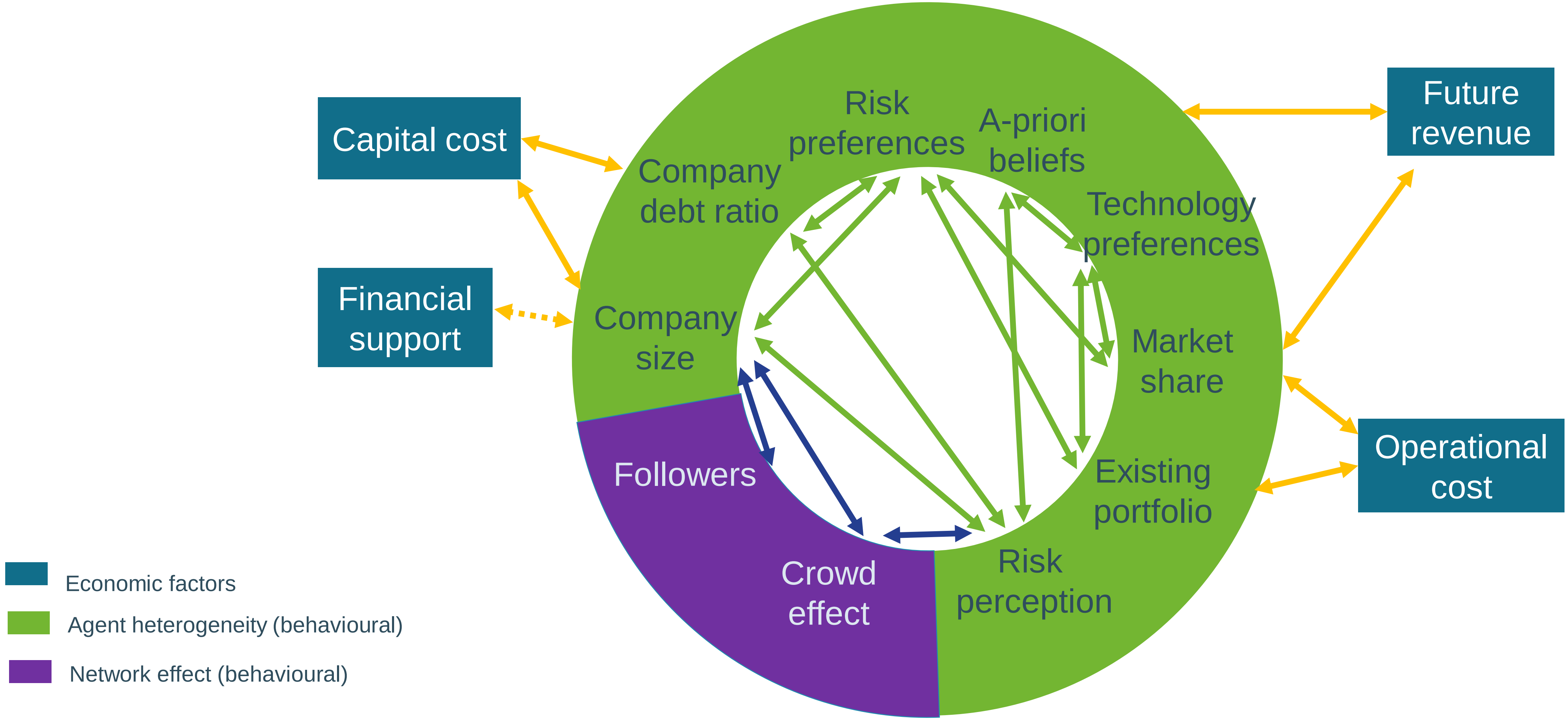
Impact of non-financial factors on RE share: results of the regression models.

	Dependent variable: RE share in the investment portfolio
	Parameter estimate
Confidence in the effectiveness of existing policies	0.16
Confidence in technological adequacy	0.49***
Attitude toward radical technological innovations	−0.33***
Investor's experience	0.42**
Knowledge of the RE operational context	0.63***
Institutional influence of peers	−0.15
Institutional influence of outside consultants	−0.23*
Influence of technical information	−0.05

* Significant at the 0.1 level.
** Significant at the 0.05 level.
*** Significant at the 0.01 level.

Masini, A. and Menichetti, E., 2013. Investment decisions in the renewable energy sector: An analysis of non-financial drivers. Technological Forecasting & Social Change Investment, 80, pp.510-524.

Factors that affect investment decisions

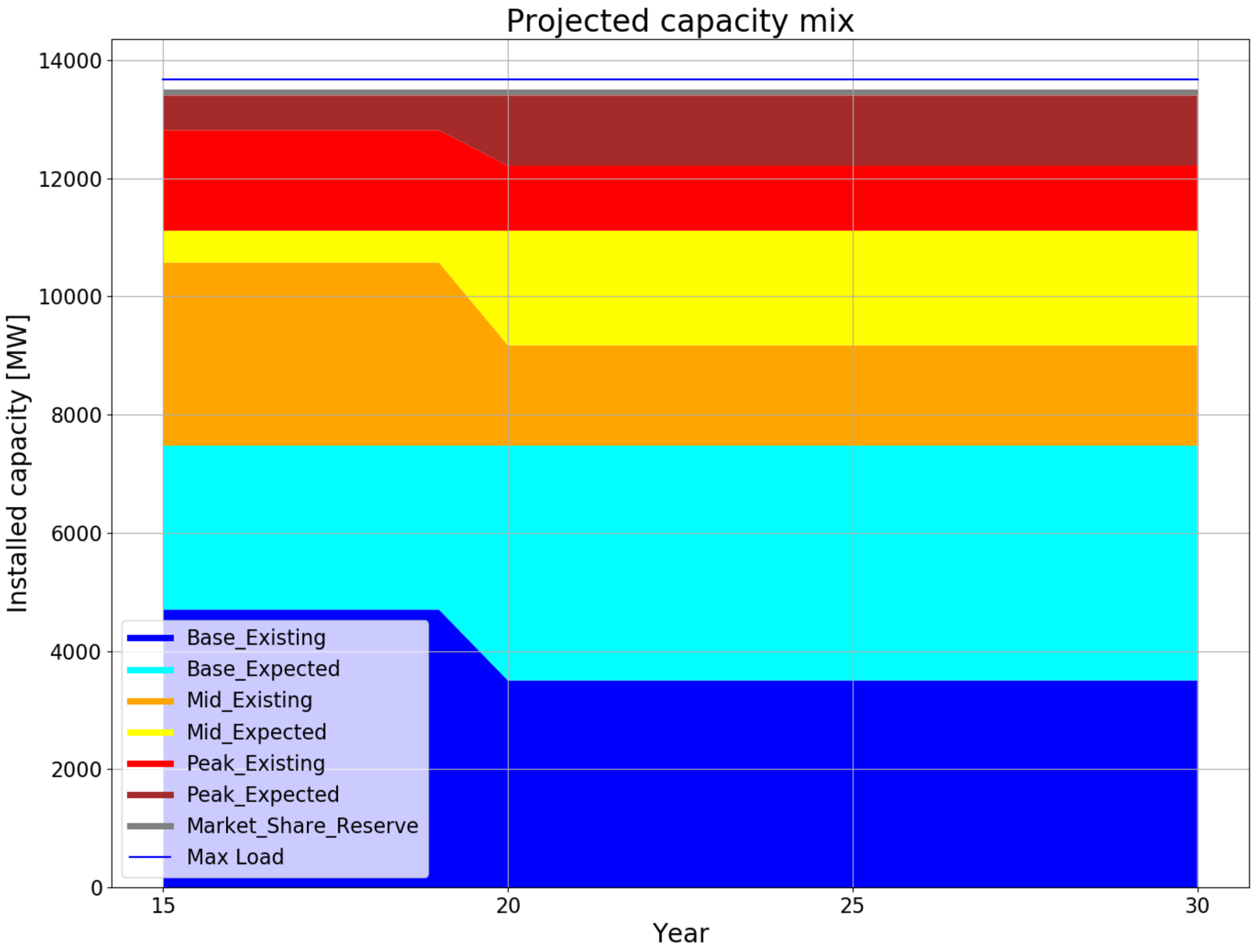


Appendix VII – Why we need investment constraints?

Appendix VII – Why we need investment constraints?

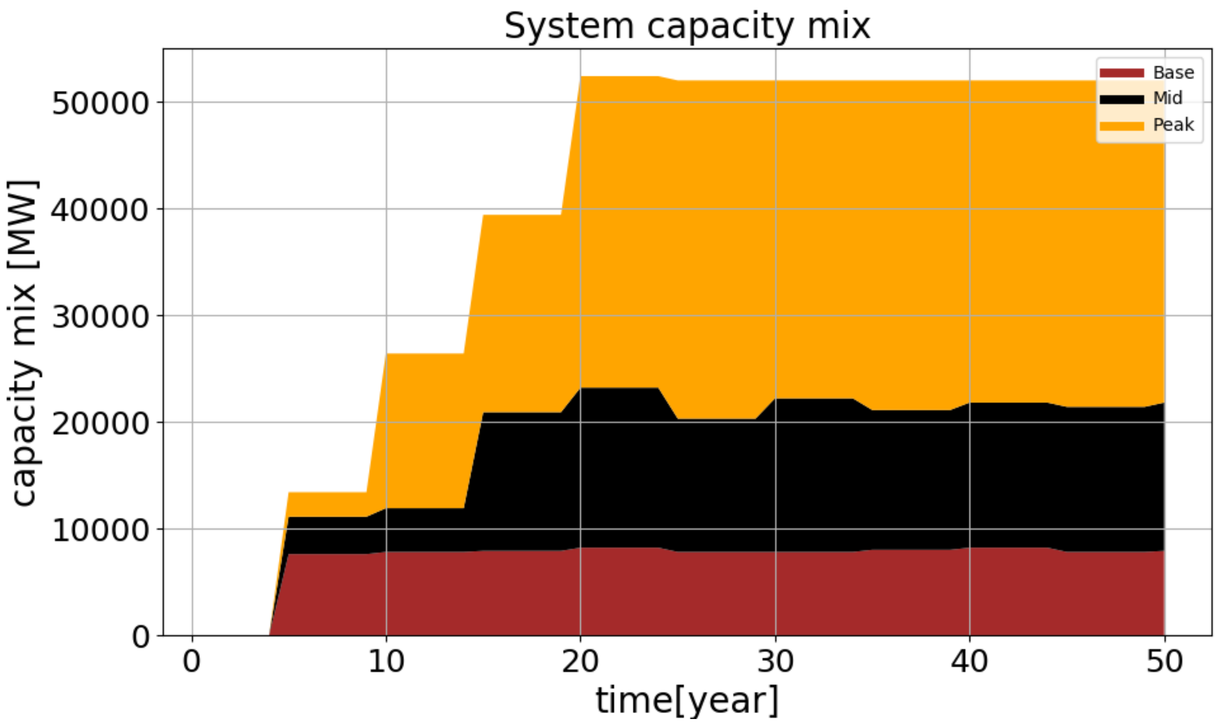
- In a already balanced system, all potential investment would not be profitable
- Investment constraints are used to incentivize agents to invest and this incentive should be as close to reality as possible
- So we keep a very small scarcity gap in the system so that agents are incentivized to invest.

Appendix VII – Why we need investment constraints?



Appendix VIII – Why overinvestment?

Look-ahead horizon = 20



The capacity mix projection can only expect zero scarcity when there is always 4 times the max load in the system which are build in year [-15,-10,-5,0]. (Present year = 0)

Year 5 Year 25

Year 10 Year 30

Year 15 Year 35

Year 20 Year 40

Year 25 Year 45

Projected capacity mix: [0 ,0 ,0 ,0] (4 milestone years) , inv. = 13490 MW, dec. = 0

Projected capacity mix: [13490, 13490, 13490,0] (4 milestone years) , inv. = 13490 MW, dec. = 0

Projected capacity mix: [26980, 26980, 13490,0] (4 milestone years) ,inv. = 13490 MW, dec. = 0

Projected capacity mix: [40470, 26980, 13490,0] (4 milestone years), inv. = 13490 MW, dec. = 0

Projected capacity mix: [40470, 26980, 13490,0] (4 milestone years), inv. = dec. = 13490 MW