



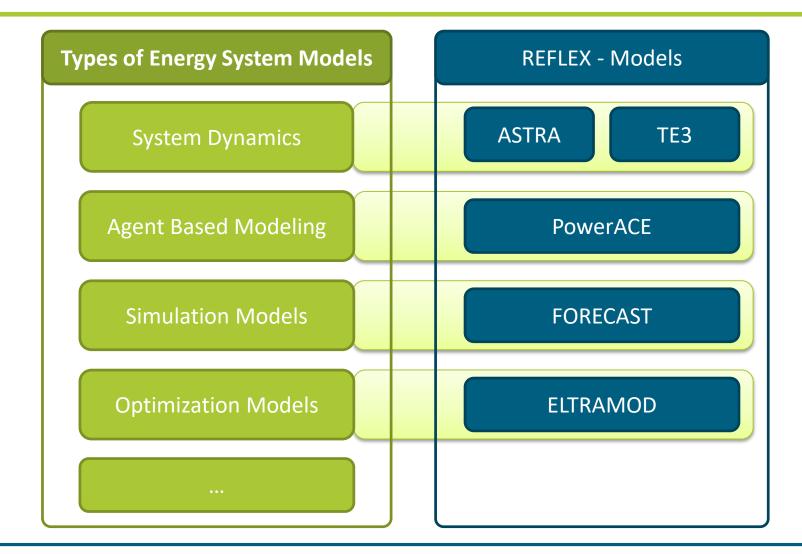
IMPLEMENTATION OF EXPERIENCE CURVES IN ENERGY MODELS

"Technological Learning in the Energy Sector"

Chair: Tobias Fleiter (Fraunhofer ISI)

REFLEX Expert Workshop Karlsruhe, 8th November 2017

Energy System Models





Presentations

Steffi Schreiber (TUD)

Implementing experience curves in an optimization model – the example of ELTRAMOD

Tobias Fleiter (Fraunhofer ISI)

Implementing experience curves in simulation models – examples from the buildings and industry sectors

Katrin Seddig (KIT-IIP)

Implementing experience curves in an system dynamics model using the example of TE3

Christoph Fraunholz (KIT-IIP)

Implementing experience curves in the electricity market simulation model PowerACE







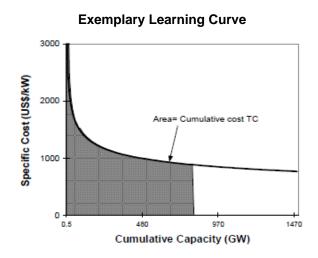
IMPLEMENTING EXPERIENCE CURVES IN AN OPTIMISATION MODEL

- THE EXAMPLE OF ELTRAMOD

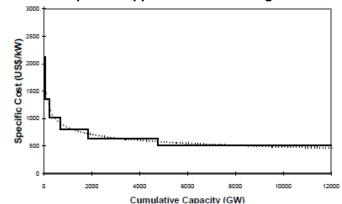
Theresa Müller & Steffi Schreiber TU Dresden

REFLEX Expert Workshop Session 2: Implementation of Experience Curves in Energy Models Karlsruhe, 8th November 2017

Challenges of Implementing Learning Curves in ELTRAMOD



Step-Wise Approximated Learning Curve



Source Figures: Barreto 2001



Challenges:

- ELTRAMOD is an optimization model
- To find an global optimal solution, the problem needs to be convex
- The characteristics of learning curves lead to a non-linear and non-convex optimization problem
 - Global optimal solution cannot be guaranteed

Solution:

- Linearization of the non-linear and non-convex problem
- Step-wise approximation of the cost curve
- Approach presented by Barreto, L. (2001): Technological Learning In Energy Optimization Models And Deployment Of Emerging Technologies, Diss., ETH Zürich.

Theresa Müller 08/11/2017



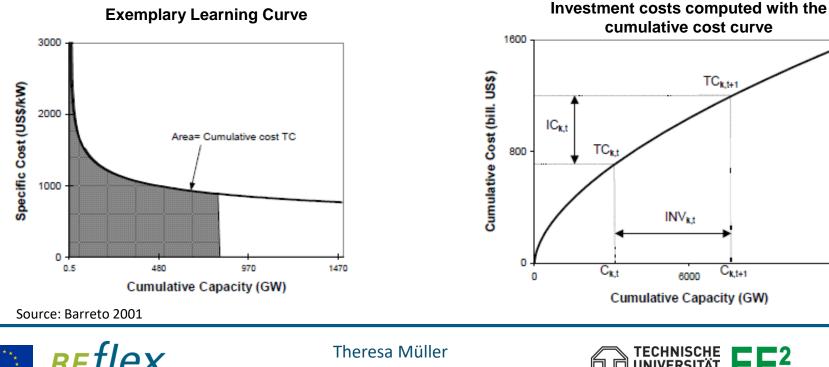
Step-Wise Approximation with the Help of Cumulative Cost Curve (1/3)

Definition of the Cumulative Cost Curve 1.

= integral of the specific cost curve

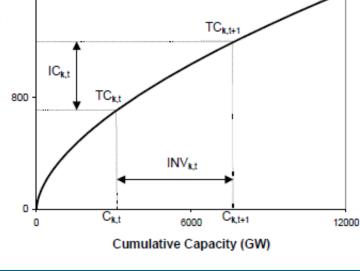
Definition of Investment Cost 2.

- Associated to the investments in a given learning technology k in period t
- Investment costs are discounted and included in the objective function





08/11/2017



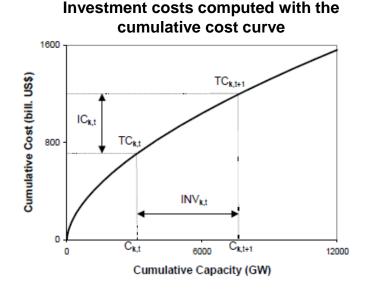
Step-Wise Approximation with the Help of Cumulative Cost Curve (2/3)

Theresa Müller

08/11/2017

2. Definition of Investment Cost

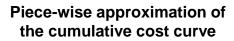
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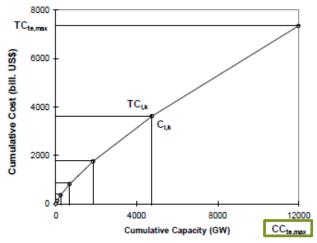


Source: Barreto 2001



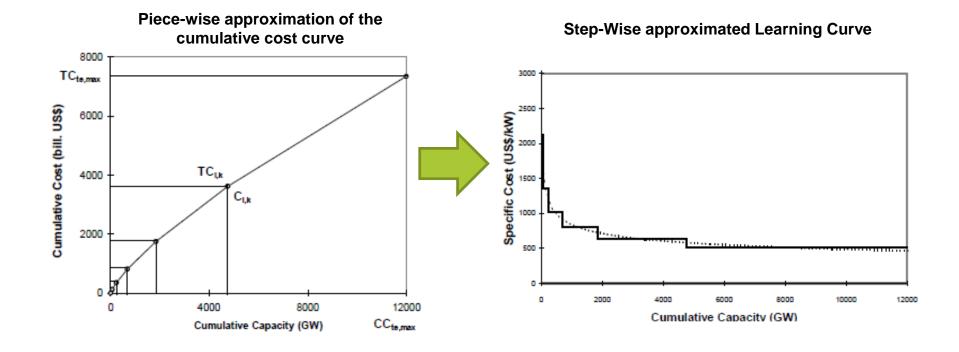
- 3. Interpolation of the Cumulative Cost Curve
 - Defining a maximum cumulative capacity CC_{max}
 - Specifying the number of segments
 - Computing the breakpoints using initial and final point as well as the number of segments







Step-Wise Approximation with the Help of Cumulative Cost Curve (3/3)





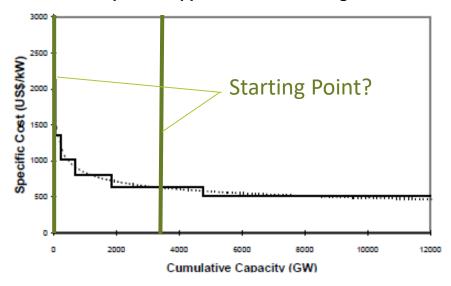
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Open Challenges

- How to consider technology investments in other continents? ("worldwide learning")
- What is the initial cumulative capacity of the learning curves?



Step-Wise Approximated Learning Curve



Theresa Müller 08/11/2017







THANK YOU!

Theresa Müller

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Steffi Schreiber steffi.schreiber@tu-dresden.de

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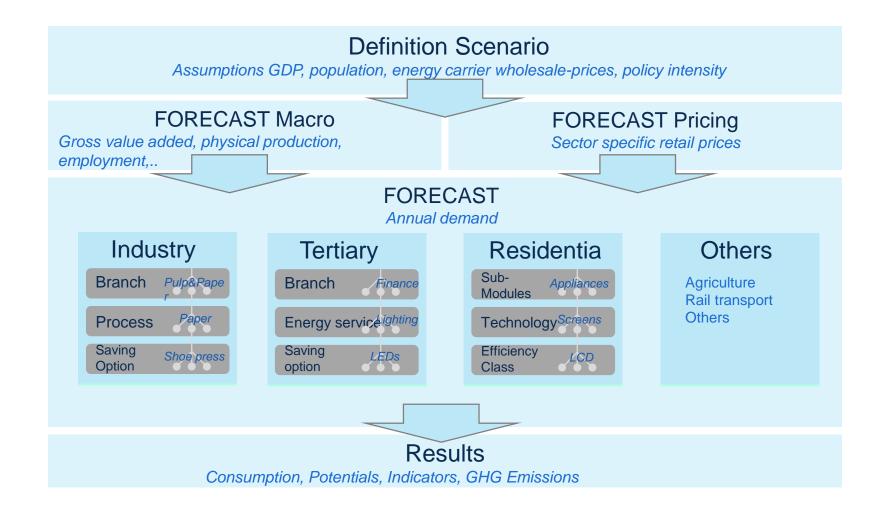




IMPLEMENTING EXPERIENCE CURVES IN DEMAND SIDE SIMULATION MODELS

REFLEX Experience Curve Workshop, 2017 November 8, Karlsruhe

The bottom-up model FORECAST

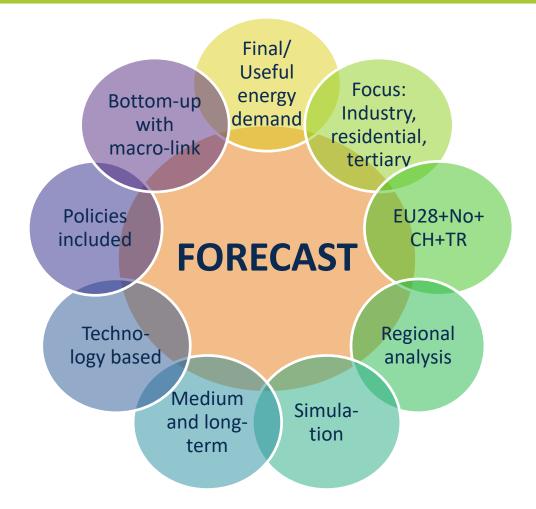




Fraunhofer ISI

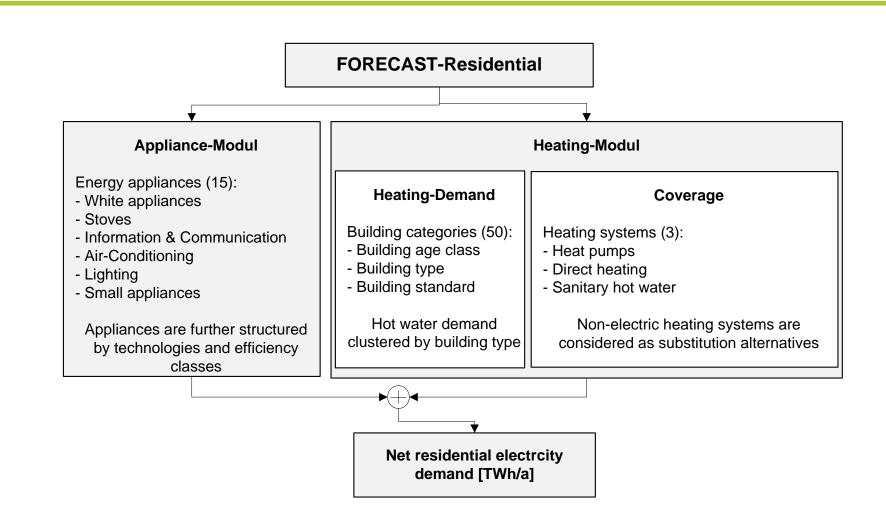
18/12/2017

Forecast: General characteristics





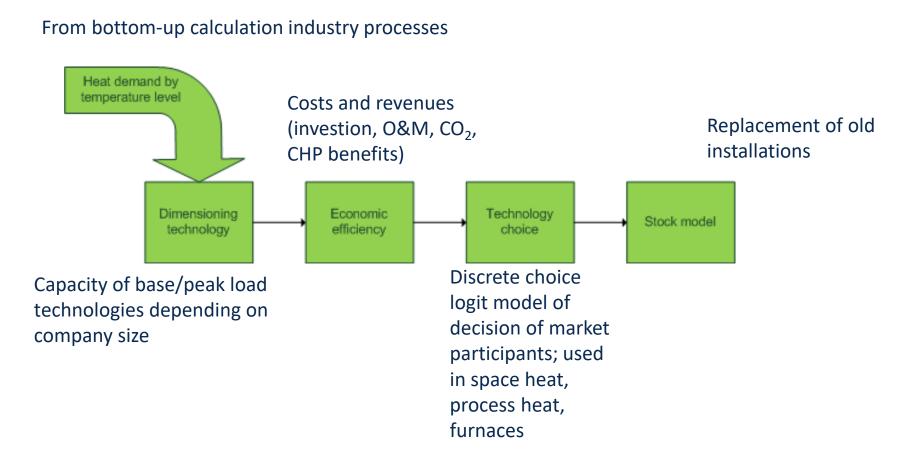
Technology detail: Example residential sector





Fraunhofer ISI

Modeling of technical change: Vintage stock model with discrete choice in industrial steam systems





Fraunhofer ISI

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The experience curve approach fits well to (discrete choice) bottom-up simulation models. Even more, technology diffusion models partly explain diffusion based on technical learning

Technology representation:

- Technology is explicit: Level of detail allows consideration of technology parameters
- Total costs of ownership (TCO) are a central element in decision making
- Parameters like CAPEX or efficiencies are specifically considered for individual technologies

Model algorithm:

- Technology diffusion in year t is a function of the diffusion in year t-1 plus additional parameters
- Less mathematical challenges compared to optimisation models



Assuming we have the learning curve in form:

```
specific cost = f(cumulative_quantity<sub>t-1</sub>)
```

Ideally, the models should implement such function directly to allow for endogenous modelling of technology costs



From a FORECAST model perspective, the following challenges occur:

- Models are used for **countries**, while learning is (partly) driven by global developments
- Models are sectoral, while learning is cross-sectoral for many technologies
 -> Part of the driving forces are outside the system boundaries
- Scarce empirical data for demand side technologies
 -> What is the value of a sophisticated methodology if input data is not available or very rough?
- Complexity of models: Understanding the dynamics of technology choice is already very complex with exogenous consideration of technology cost
 -> value the costs and the benefits carefully
- For energy efficiency, costs and performance of technologies are compared to a reference
 -> not the total costs matter, but the incremental costs (same for learning)



Proposed solution for FORECAST "Exogenous approach"

We propose an approach based on exogenous assumptions for the cumulative capacity:



- 1. Estimate projection of the cumulative capacity for a technology in line with scenario philosophy
- 2. Apply experience curve function to calculate specific costs time series and include in FORECAST as exogenous parameter
- 3. Run model to simulate future deployment based on TCO
- **4. Assess results** on cumulative capacity and annually installed units and compare with assumptions



Questions to discuss

- Is a rather "exogenous" approach justified?
- How to consider global learning when only national markets are modelled?
- How can we develop consistent assumptions on technical learning for a large number of technologies while empirical data is scarce?

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Thank you very much for your attention!

More about the FORECAST model: www.forecast-model.eu



Backup



FORECAST-Residential – status quo of experience curve modelling

- FORECAST-Residential is currently using a modified / simplified version of a one-factor experience curve
- <u>Approach</u>: As the production of products is outside the system boundary of the model, the experience curve is approximated by the difference between the current year and the first year of the ex ante analysis, which is a common approach in the case a constant production output is assumed.

$I_{i,t} = I_{i,t=0} \cdot \left(1 - LR_i \cdot ln(y_t - y_{t=0} + 1)\right)$ $\forall i \in EUM; \ TEC \subset EUM; \ EFF \subset TEC$				
Key:VariablesEFFEUMLRIITECy	Efficiency class Set of EUM end-uses Learning rate Investment sum Technology Projection year	Unit [none] [none] [€] [none] [none]	Indices i = Type of end-use t = Period	



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Empirical foundation?

• Huge number of demand side technologies important







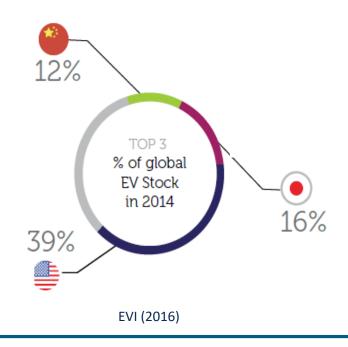
IMPLEMENTATION OF EXPERIENCE CURVES IN A SYSTEM DYNAMICS MODEL USING THE EXAMPLE OF TE3 **KIT-IIP, Katrin Seddig**

Workshop, Karlsruhe



Role of the TE3 model in REFLEX:

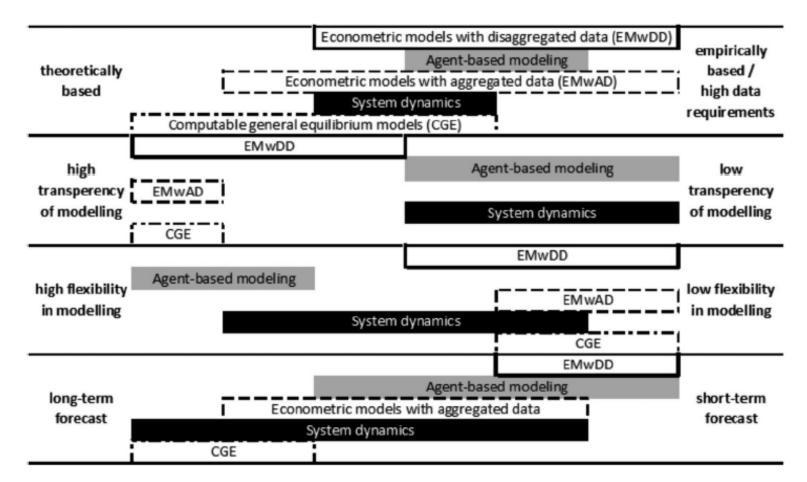
"It is not possible to come to a plausible estimation of electric vehicle (EV) market penetration in Europe without the explicit consideration of the global market dynamics related to electric vehicle battery (EVB) development and costs"





2

Evaluation of modelling approaches



Source: Jochem et al. (2017): Methods for forecasting the market penetration of electric drivetrains in the passenger car market, Transport Reviews



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Model Purpose

Model-based policy-making support in the context of oil demand reduction and GHG mitigation from car travel. This tool explores key impacts of future car technology market developments and provides an international perspective.

Modelling Approach is a mixed method combining econometrics and system dynamics.

System dynamics

- Approach to understand the behavior of complex systems
- Applied as a simulation model
- Represented through casual loop, stock and flow diagrams
- Equations to define the problem boundaries, estimate parameters

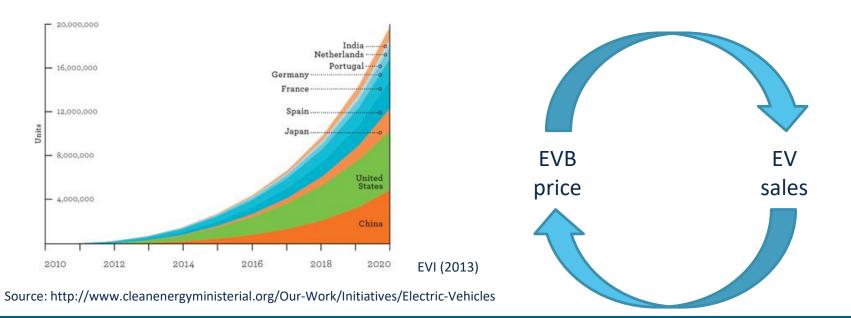




Equation: Y = a X ^ b

in which X is the cumulative volume of battery production b calculated with the formula $\log_2(1-l)$

 \rightarrow EVB cost is affected by the learning rate and the cumulative production of EVs

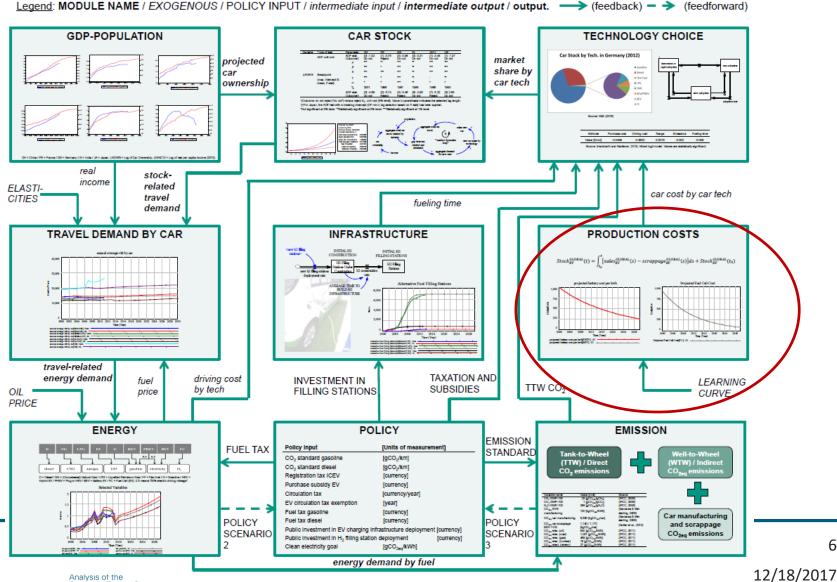




Katrin Seddig / KIT-IIP

The TE3 model - Overview

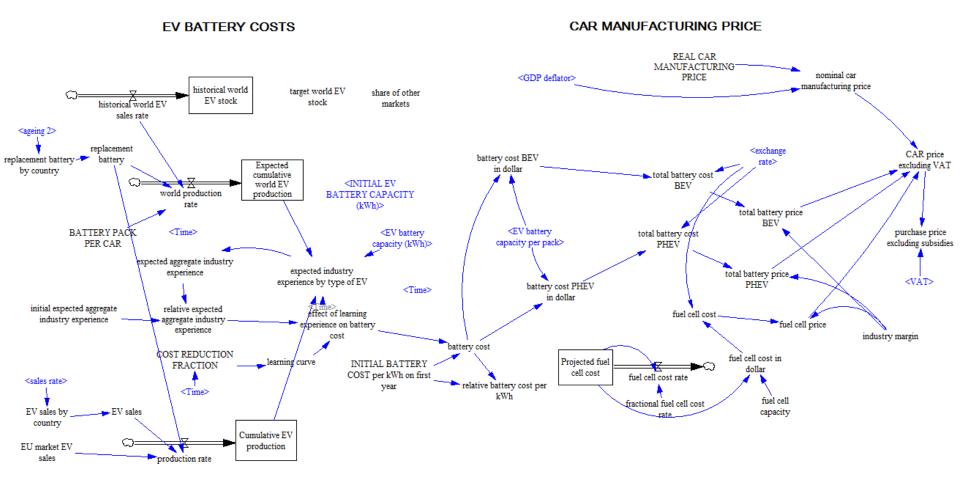




European Energy System

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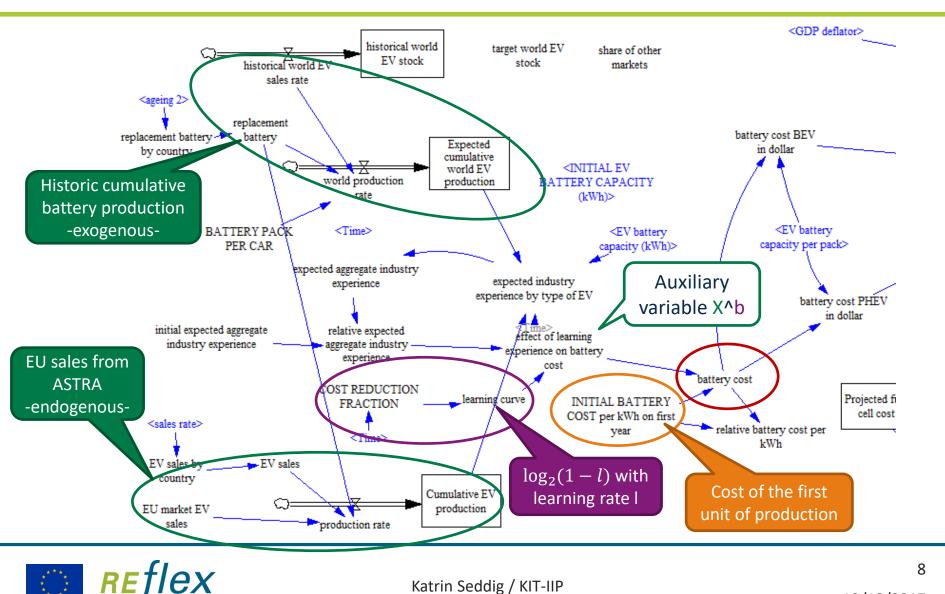
Katrin Seddig / KIT-IIP

7 12/18/2017

Experience Curve for EVB $\mathbf{Y} = \mathbf{a} \mathbf{X} \wedge \mathbf{b}$

European Energy System

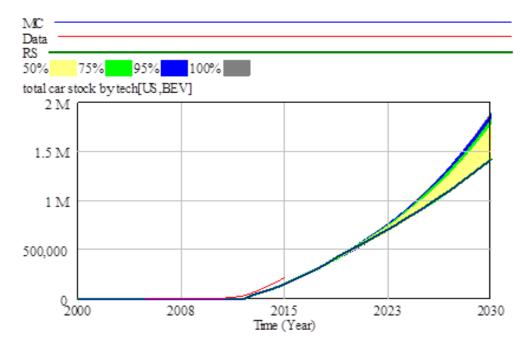






Monte Carlo simulation Effect of EVB cost reduction on US BEV stock

- Univariate sensitivity analysis for the variable learning rate
- Uniform probability distribution ranging from a minimum value of 0.05 to a maximum value of 0.2



By 2030 a possible divergence of almost 500,000 BEVs



Katrin Seddig / KIT-IIP

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REFIEX Analysis of the European energy system

Thank you

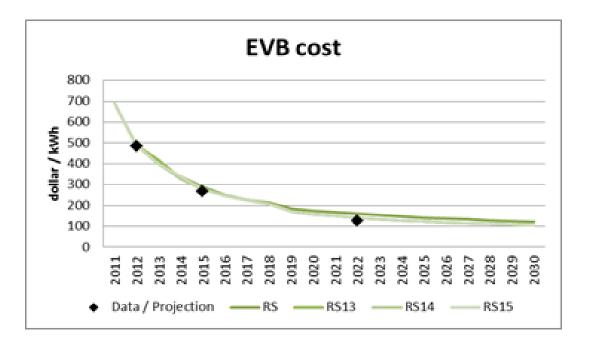
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Tel.: + 49 721 608- 44653 Katrin.seddig@kit.edu

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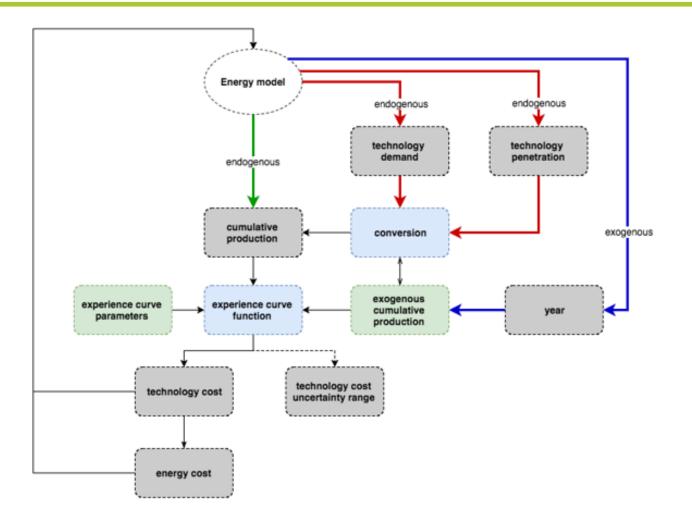
Partial endogenisation of the EVB cost

- Evolution of the EVB cost curve is higher in the RS, which rules out endogenization
- RS13, RS14 and RS15 refer to endogenisation for the years 2013, 2014 and 2015
- Experience curve no longer relies on historical data on cumulative EV production, but is instead based on the cumulative EV production simulated in the model





Schematic overview of possible model implementation routes for experience curves









IMPLEMENTATION OF EXPERIENCE CURVES IN THE ELECTRICITY MARKET SIMULATION MODEL POWERACE

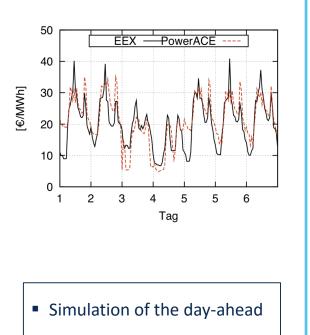
Karlsruhe Institute of Technology, Chair of Energy Economics, Christoph Fraunholz

Workshop on "Technological Learning in the Energy Sector", Karlsruhe, 8th November 2017

Agenda

- Model overview
- Investment planning methodology
- Implementation of experience curves
- Discussion





Agent-based simulation

market with hourly

- resolution (8760h/a)
- Yearly investment planning
- Time horizon until 2050



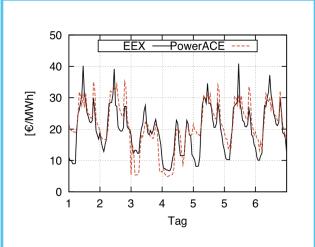
Input

- Fuel prices and CO₂ prices
- Investment options in flexible power plants
- Detailed power plant data with important technoeconomic parameters
- Hourly profiles for renewable feed-in
- Hourly profiles for electricity demand
- Net-transfer-capacities (NTC) between the market areas

European Energy System

 DSM parameters and potentials

Agent-based simulation



Simulation of the day-ahead

market with hourly

- resolution (8760h/a)
- Yearly investment planning
- Time horizon until 2050

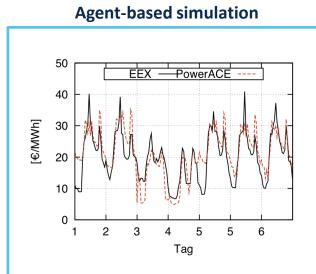


Input

- Fuel prices and CO₂ prices
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uropean Energy System

 DSM parameters and potentials



Simulation of the day-ahead

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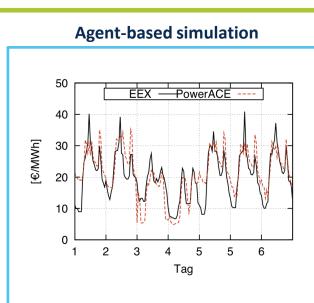
Output Market simulation Electricity production Emissions

 Spot-market prices and volumes



Input

- Fuel prices and CO₂ prices
- Investment options in flexible power plants
- Detailed power plant data with important technoeconomic parameters
- Hourly profiles for renewable feed-in
- Hourly profiles for electricity demand
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- DSM parameters and potentials



Simulation of the day-ahead

market with hourly

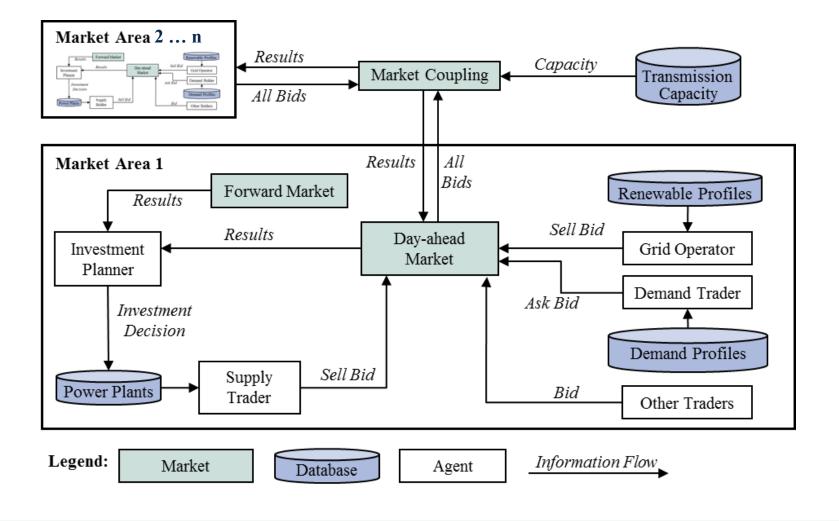
- resolution (8760h/a)
- Yearly investment planning
- Time horizon until 2050

Output Market simulation Electricity production Emissions Spot-market prices and volumes Investment module

- Development of conventional generation capacity
- Power plant investments

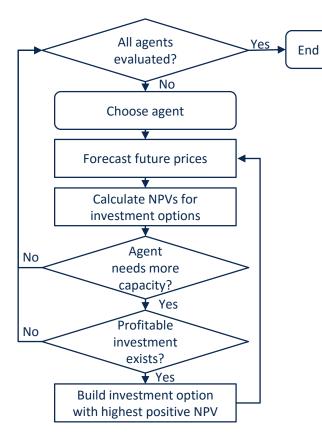
Power plant decommissions





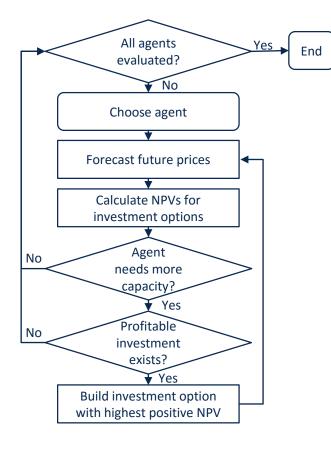


Investment planning methodology





Investment planning methodology

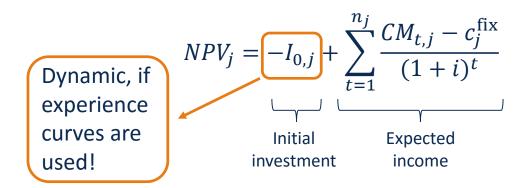


Calculation of Net Present Value

• Contribution margin *CM* in year *a* for technology option *j*

$$CM_{a,j} = \sum_{h=1}^{8760} (p_{a,h} - c_{a,h,j}^{\text{var}})$$

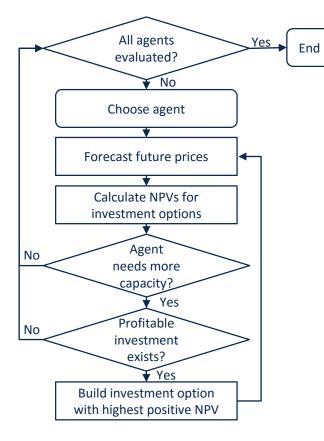
- ➔ Alternative calculation method for storage technologies
- Net present value NPV of technology option j





Christoph Fraunholz/KIT-IIP

Implementation of experience curves (1/3)



Modeling set-up

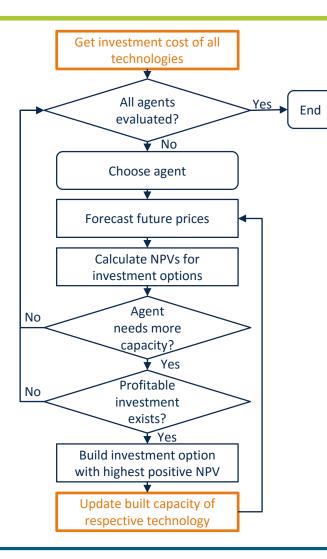
1) Regional scope

~10 countries simulated within PowerACE, in reality worldwide learning

2) Interdependencies between market areas/agents Investment planning in PowerACE performed individually for each market area and sequentially for all agents, in reality mutual influences?



Implementation of experience curves (2/3)



European Energy System

Modeling approach

1) Regional scope

Scaling factor or exogenous capacities for countries not modeled within PowerACE

2) Interdependencies between market areas/agents

- Same investment cost per technology j in all market areas m and for all agents
- Update of cumulative capacities for each simulation year *a*

$$cap_{a,j} = cap_{a-1,j} + \sum_{m} cap_{a-1,j,m}^{\text{built}}$$

Update of respective investment costs

$$I_{0,a,j}(cap_{a,j}) = I_{0,0,j} \cdot cap_{a,j}^{\log_2(1-l)}$$

 $I_{0,0,j}$: investment cost for first unit, l: learning rate

Challenges / Open issues

- Methodology for determining the scaling factor to account for countries not modeled? How to account for interdependencies?
- Due to the simulation-based approach, investments in technologies with high initial cost and fast learning rates might not occur and these technologies would never diffuse







DISCUSSION

Thank your for your attention! Any questions or comments?

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