



# From Experience Curves for Current Technologies to New and Emerging Technologies

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## Scenarios and Modelling

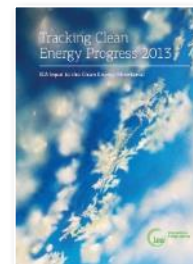
- Where do we need to go?

## Statistics and trends

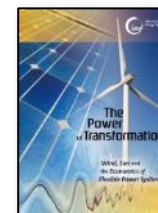
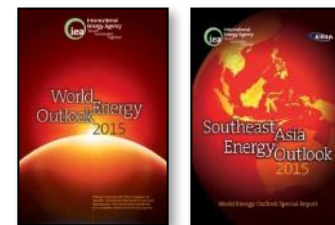
- Where are we today?

## Technology Roadmaps

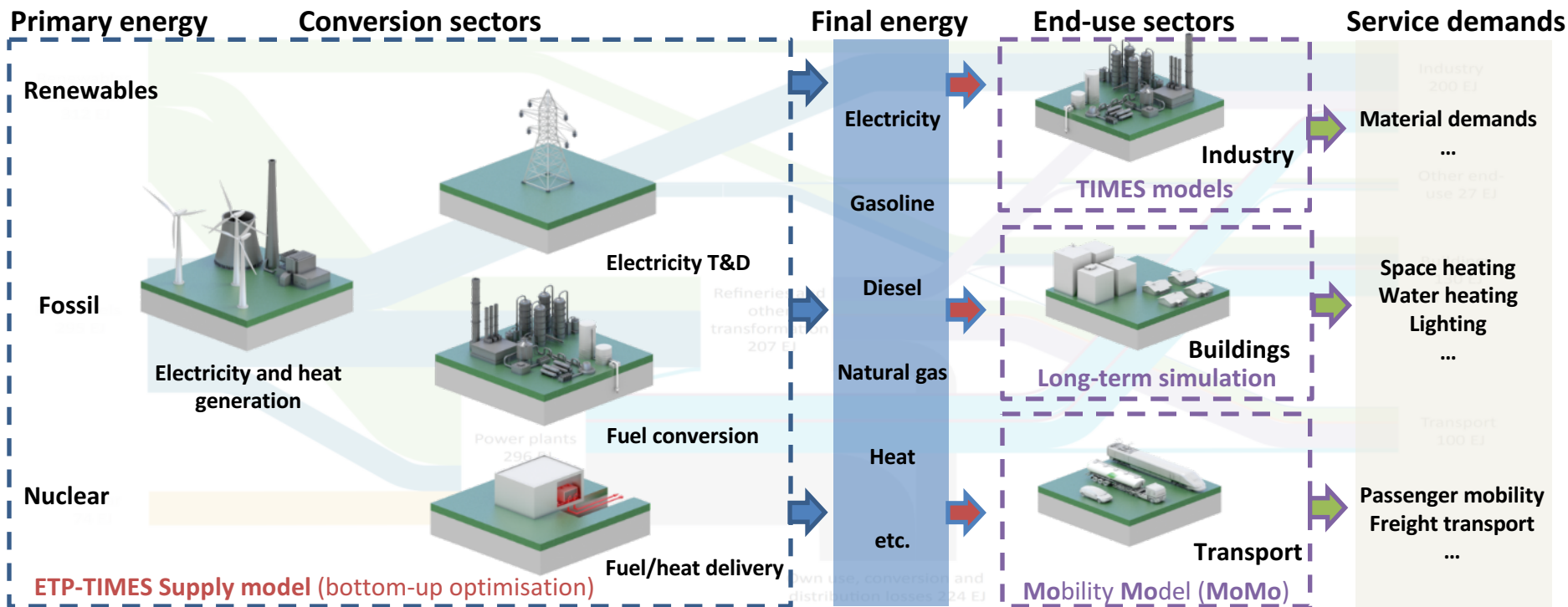
- How do we get there?



- **Forecasts (next 5 years) :** Medium-term Market Reports
- **Market-based scenarios (out to 2040):** World Energy Outlook
- **Long-term planning scenarios (out to 2060):** Energy Technology Perspectives
- **System Integration:** Analysis of flexibility resources/market design for vRE



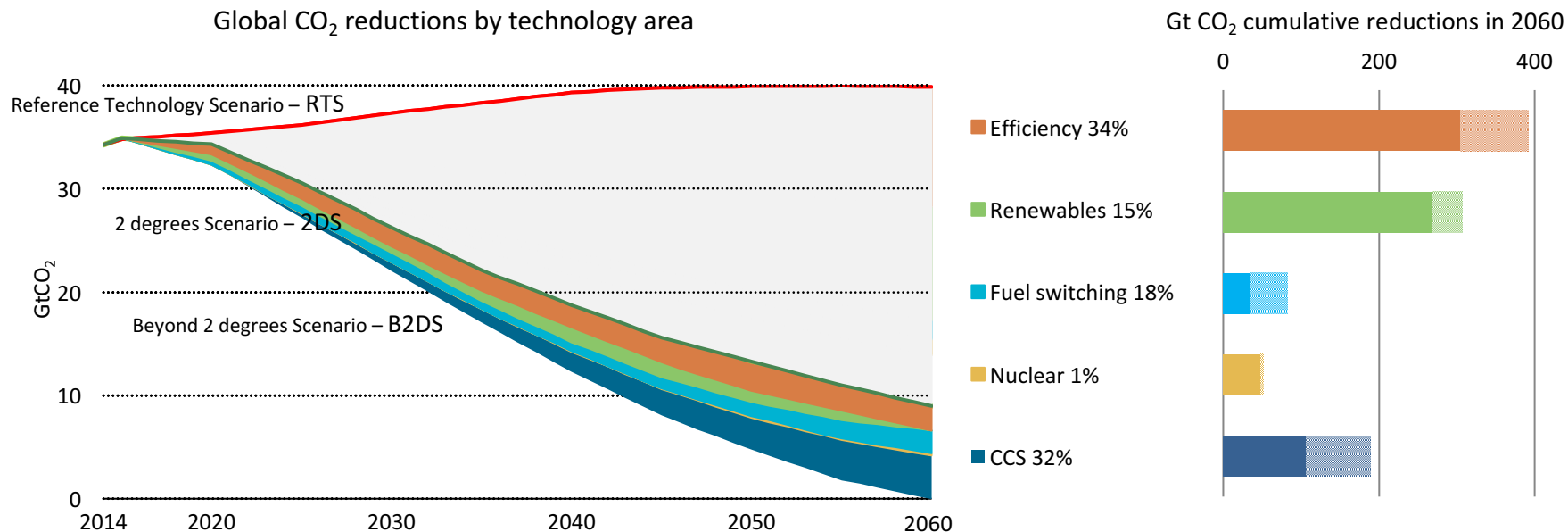
# ETP modelling framework



- Four soft-linked models based on simulation and optimisation modelling methodologies
- Model horizon: 2014-2060 in 5 year periods
- World divided in 28-42 model regions/countries depending on sector
- For power sector linkage with TIMES dispatch model for selected regions to analyse electricity system flexibility

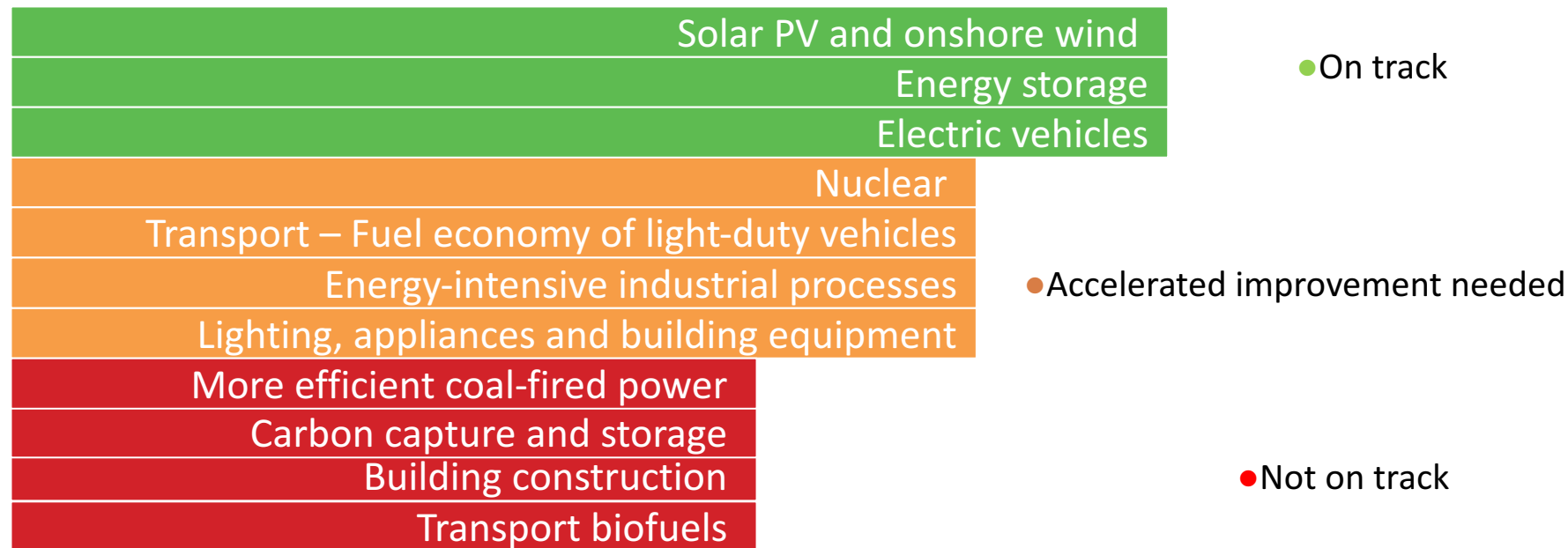
# How far can technology take us?

## Technology area contribution to global cumulative CO<sub>2</sub> reductions



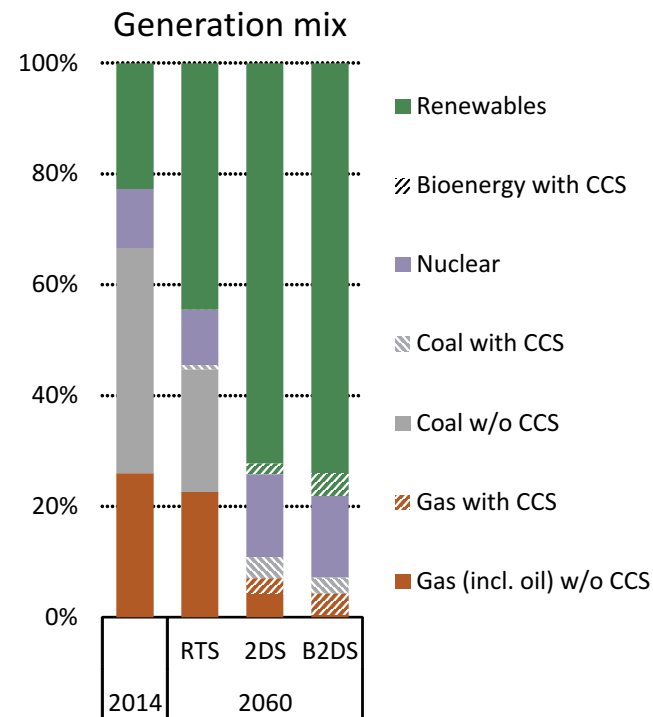
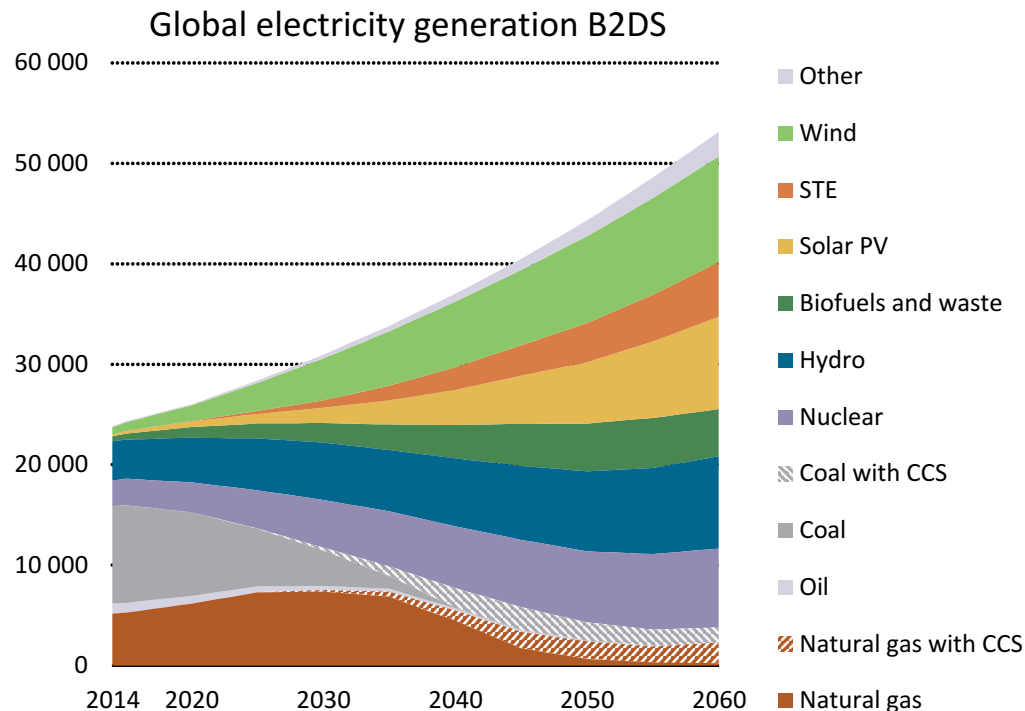
Pushing energy technology to achieve carbon neutrality by 2060 could meet the mid-point of the range of ambitions expressed in Paris.

# The potential of clean energy technology remains under-utilised



Recent progress in some clean energy areas is promising, but many technologies still need a strong push to achieve their full potential and deliver a sustainable energy future.

# Decarbonising electricity



**Renewables dominate electricity generation in the 2DS and B2DS, with wind and solar energy providing almost half of the global electricity demand in 2060 in the B2DS.**

# Work on experience curves at the IEA



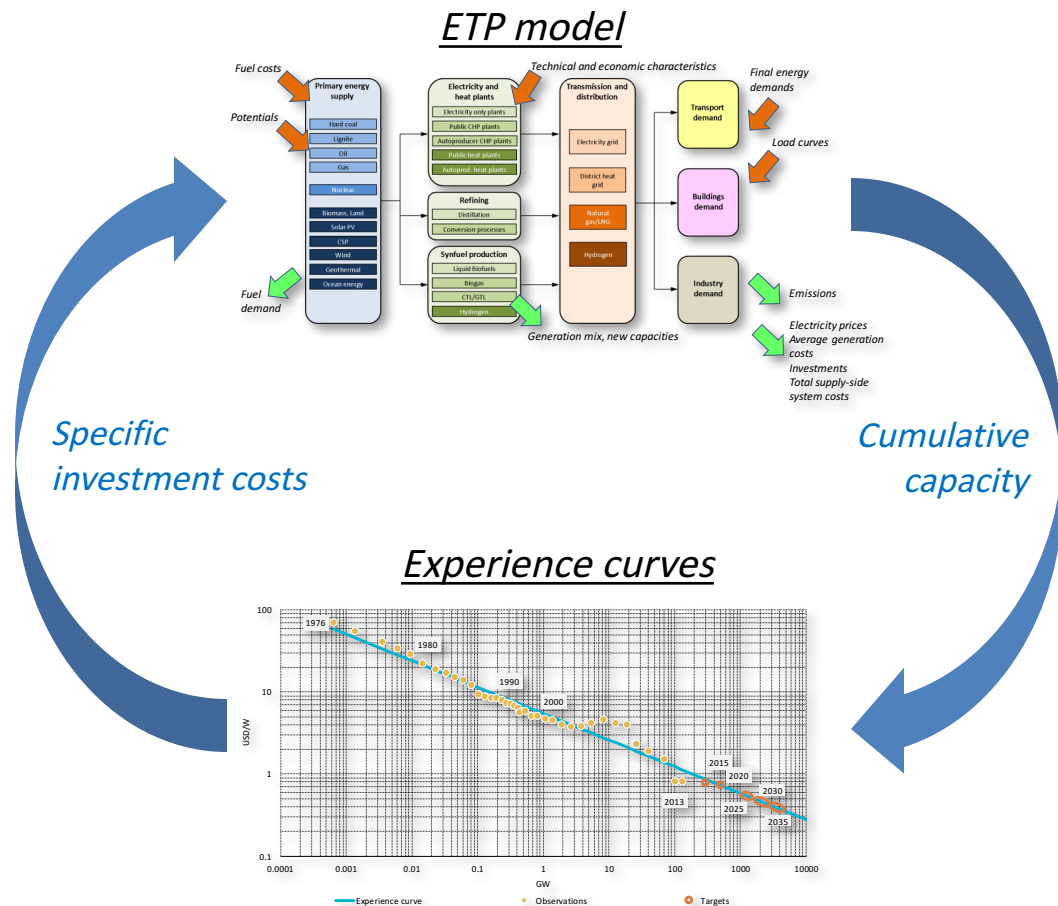
- Conceptual and methodological work on experience curves
- (Exogeneous) use of experience curves in ETP & WEO modelling
- Technology assessments, e.g. tracking clean energy progress, technology roadmaps, medium-term reports
- In the broader context of technology innovation and RD&D policy, e.g. ETP 2015, IEA's Experts' Group on R&D Priority Setting and Evaluation (EGRD)
- IEA's Technology Collaboration Programmes (TCPs), e.g. use of ETL in ETSAP's MARKAL/TIMES model



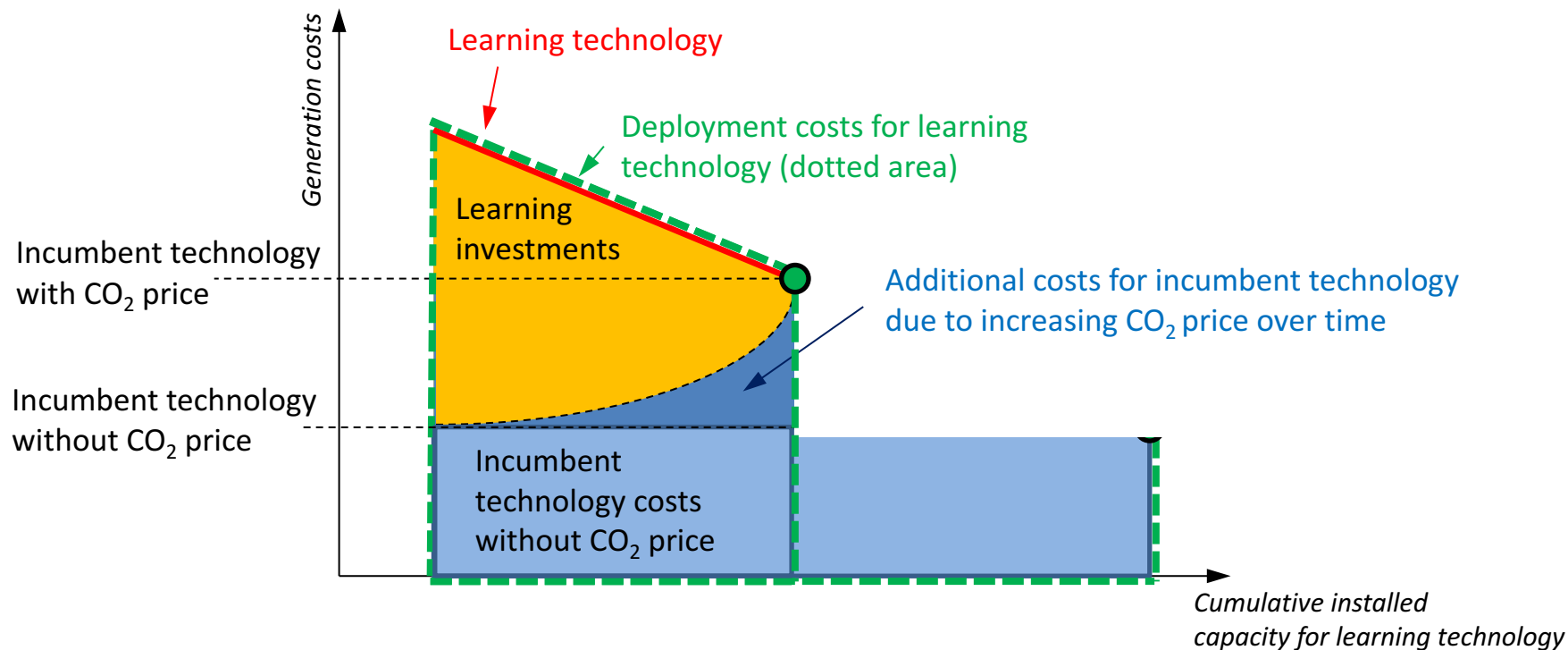


# Use of experience curves in ETP modelling

- Exogenous treatment of experience curves (1-FLC) using an iterative approach
- Driven by model size and computational limitations for using instead an endogenous approach based on MIP
- Additional growth constraints to avoid “wait-and-see/free-rider” behaviour by postponing deployment to later periods, partly influenced already through current policy support mechanism leading to early deployment (ETL may lead to opposite behaviour, i.e. too rapid, early deployment)
- Simplified model (in terms of model regions), but with ETL, could be a complementary approach to derive cost trajectories for larger model.



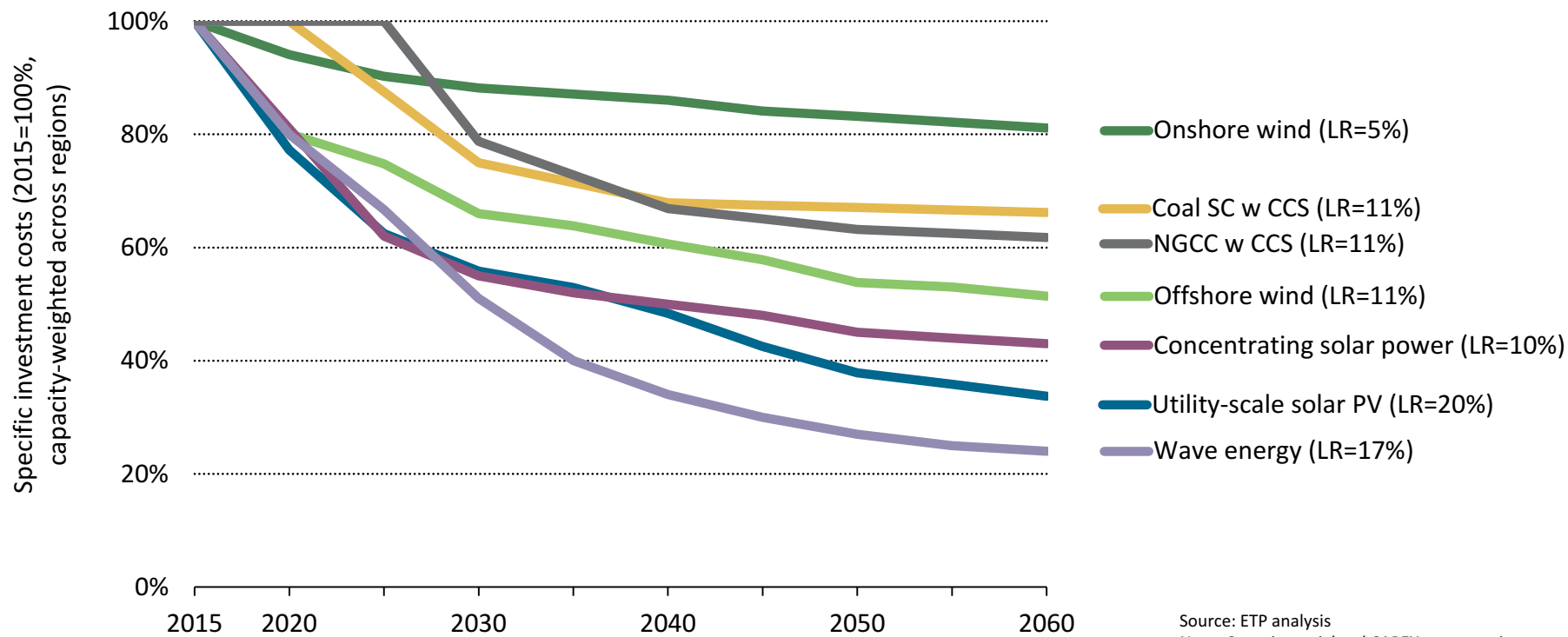
# Deployment costs and learning investments



## Example:

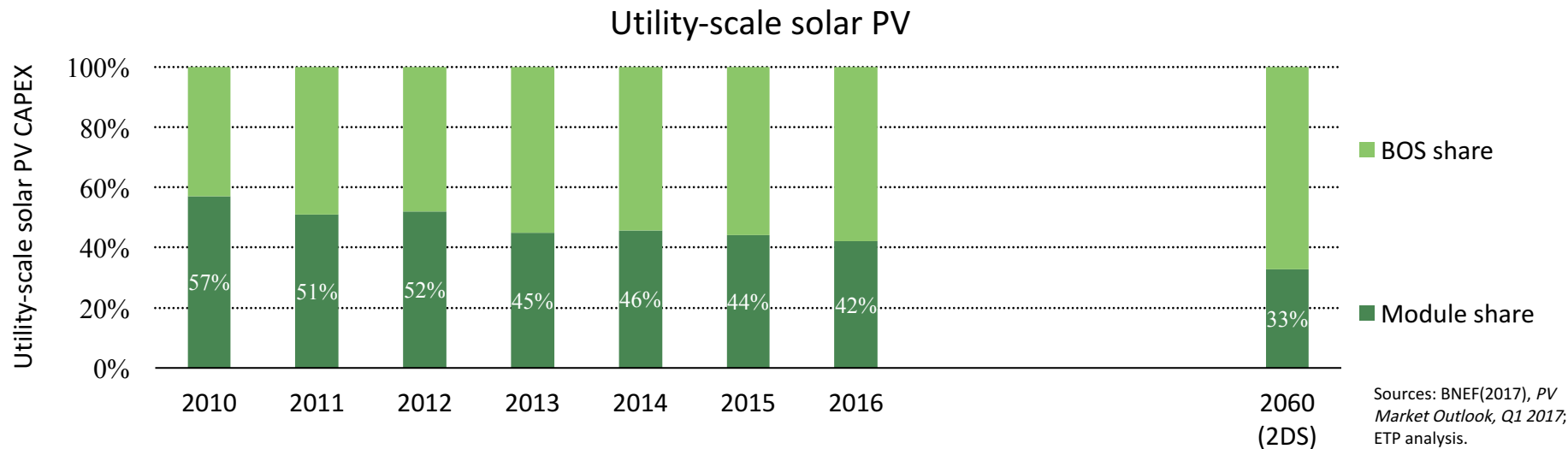
Global cumulative learning investments for solar PV fall from USD 1.9 trillion in the RTS to USD 1.2 trillion in the 2DS.

# Cost reductions for power generation technologies with experience curves in 2DS



- **Energy technologies often consist of various components**, with different drivers influencing their costs, e.g.:
  - Solar PV system: PV module + Balance-of-system (BOS)
  - Battery system: Battery pack + Power conversion system + Energy management system + BOS
  - CCS power plant: Conventional power plant + CO<sub>2</sub> capture equipment
- **Global versus local learning**

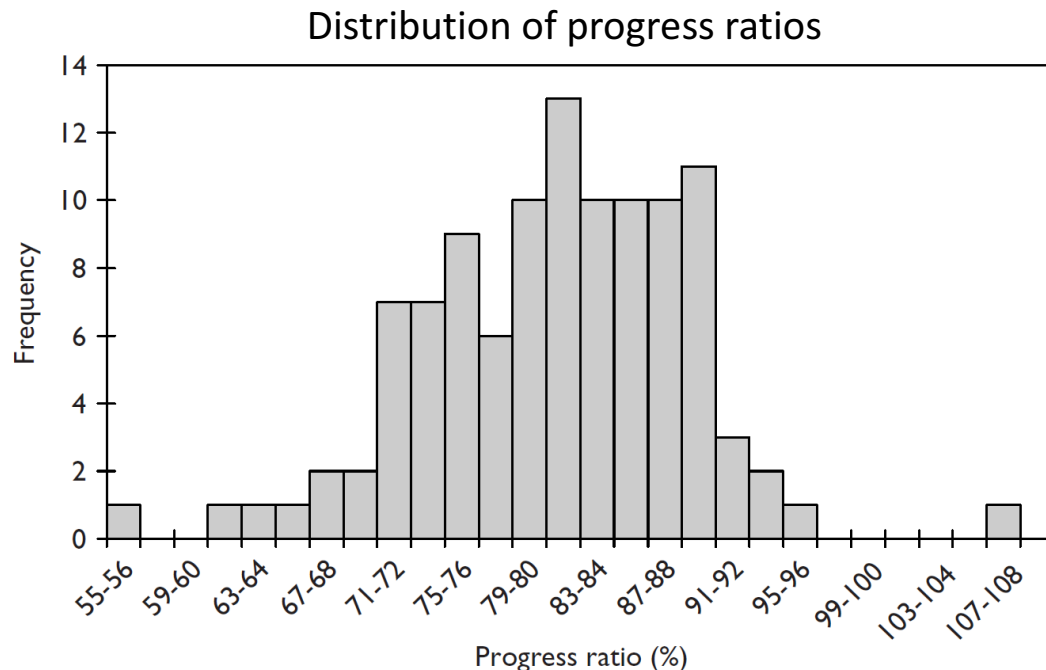
# Learning curve approach for solar PV: Separate learning for PV module and BOS



- Increasing share of BOS in total specific investment costs for PV systems
- Chosen approach:
  - PV module: global learning
  - BOS: regional learning
- Learning rate for BOS?
  - Current approach: same learning rate for module and BOS
  - Elshurafa et al. (2017) estimated learning rate of 11% for BOS of residential PV systems.

- **Energy technologies often consist of various components, with different drivers influencing their costs, e.g.:**
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- **Global versus local learning**
- **Experience curve formulation and model implementation**
- **Experience curve parameters for technologies, when only limited deployment so far (and hence few data points available):**
  - Expert elicitation
  - Drawing analogies from similar technologies

# Which learning rate, when only limited deployment so far?

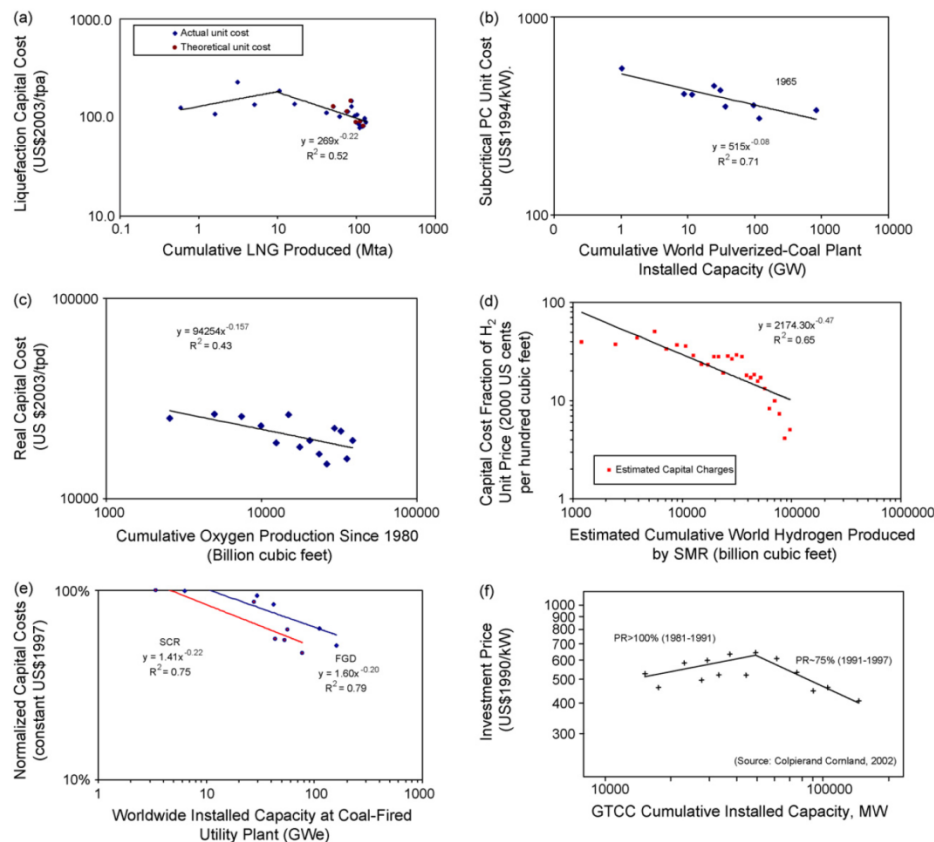


Source: Dutton, J.M. and Thomas, A. (1984), *Treating Progress Functions as a Managerial Opportunity* in IEA (2000), *Experience curves for energy technology policy*; McDonald and Schrattenholzer (2001), *Learning rates for energy technologies*.

- Review by Dutton and Thomas (1984) of manufacturing industries such as electronics, machine tools, system components for electronic data processing, papermaking, aircraft, steel, apparel, and automobiles shows 82% as most probable progress ratio (or 18% learning rate).
- McDonald and Schrattenholzer (2001) estimated around 14% as median for energy conversion technologies.

# Which learning rate, when only limited deployment so far? (2)

## Example: CCS power technologies



Technology	Learning rate <sup>a</sup>	
	Capital cost	O&M cost
Flue gas desulfurization (FGD)	0.11	0.22
Selective catalytic reduction (SCR)	0.12	0.13
Gas turbine combined cycle (GTCC)	0.10	0.06
Pulverized coal (PC) boilers	0.05	0.18
LNG production	0.14	0.12
Oxygen production	0.10	0.05
Hydrogen production (SMR)	0.27	0.27

<sup>a</sup> Fractional reduction in cost for each doubling of total production or capacity.

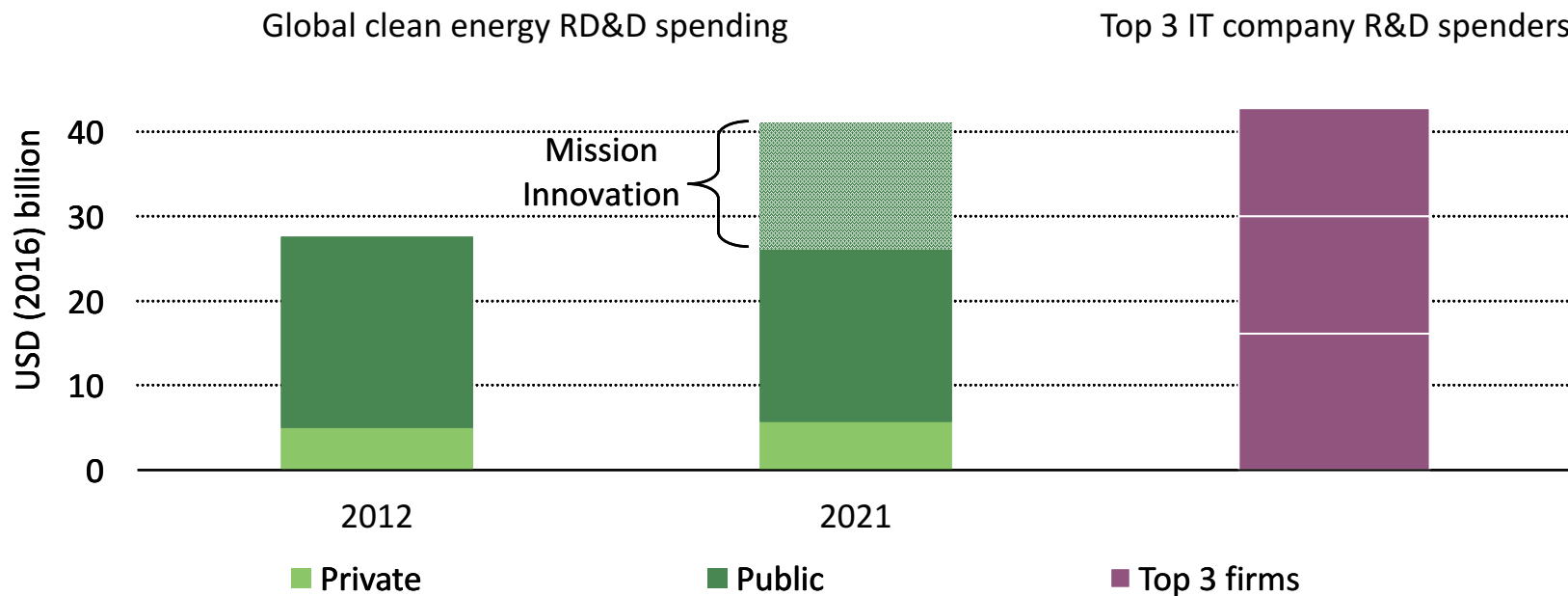
- Drawing analogies from similar technologies
- In ETP, learning curve approach used for additional CAPEX of capture equipment

Sources: Rubin et al. (2007), *Use of experience curves to estimate the future cost of power plants with CO<sub>2</sub> capture*; Van den Broeck et al. (2009), *Effects of technological learning on future cost and performance of power plants with CO<sub>2</sub> capture*.



- **Energy technologies often consist of various components**, with different drivers influencing their costs, e.g.:
  - Solar PV system: PV module + Balance-of-system (BOS)
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- **Global versus local learning**
- Experience curve formulation and **model implementation**
- **Experience curve parameters for technologies, when only limited deployment so far** (and hence few data points available):
  - Expert elicitation
  - Drawing analogies from similar technologies
- **Quantifying R&D impacts on technology costs and performance**

# Global clean energy RD&D spending needs a strong boost



Global RD&D spending in efficiency, renewables, nuclear and CCS plateaued at \$26 billion annually, coming mostly from governments.

Mission Innovation could provide a much needed boost.

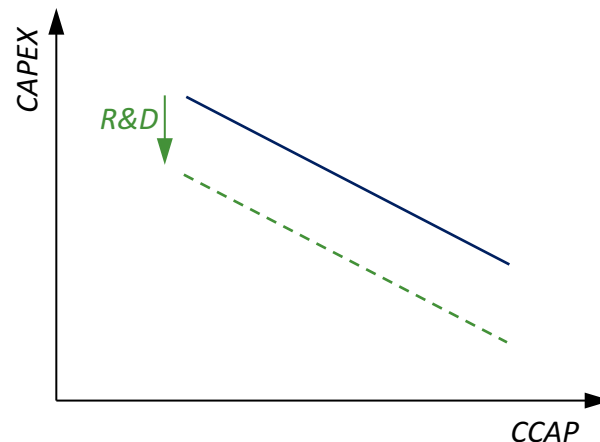
- Taking into account in addition to learning-by-doing (LBD) further drivers influencing learning. Notably learning-by-searching (LBS), i.e. R&D, resulting in 2-factor learning curve (2-FLC):

$$CAPEX_t = CAPEX_0 \left( \frac{CCAP_t}{CCAP_0} \right)^{-b} \left( \frac{R\&D_t}{R\&D_0} \right)^{-c}$$

$$LR_{LBD} = 1 - 2^{-b}$$

$$LR_{LBS} = 1 - 2^{-c}$$

- Some challenges in its use:
  - Interdependencies between LBD and LBS
  - No straightforward way of measuring effectiveness of R&D:
    - Expert elicitation
    - Statistical decomposition (if data available)
    - Mixed approaches
  - R&D spending data
  - Implementation in large-scale energy models



- Current work of IEA focussing on better tracking R&D spending on clean energy technologies

# Beyond individual energy technologies: Impact of digitalisation & learning on system level

- Dramatic performance improvements and cost reductions not only in computer hardware, but also numerical methods.
- Example: Improvements in Mixed Integer Programming solvers

## A Historical Comment

### ► Test set:

- Full library
  - 2791 MIP
- Removed:
  - 559 “Easy”
  - 348 “Difficult”
  - 22 “Hard”

### ► Parameter

- Pure default
- 30000 seconds

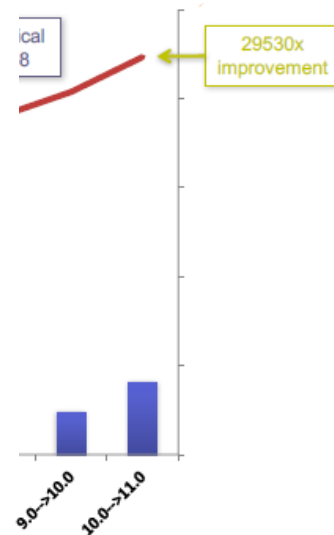
### ► Versions R

- CPLEX 1.2 (1989)

**Electrical Power Industry, ERPI GS-6401, June 1989:**  
Mixed-integer programming (MIP) is a powerful modeling tool, “They are, however, theoretically complicated and computationally cumbersome”

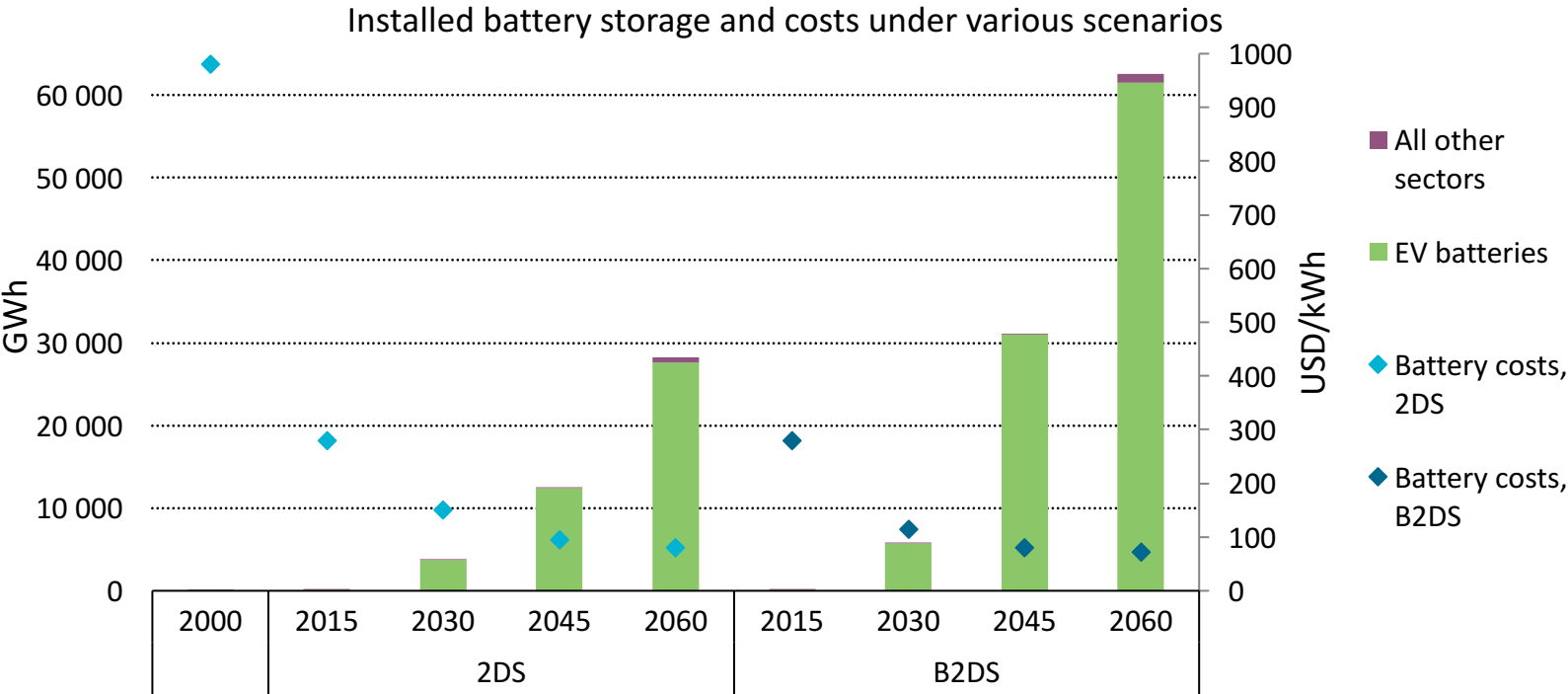
*In Other Words:* MIP is an interesting “toy”, but it just isn’t going to work in practice.

Improvements



CPLEX Version-to-Version Pairs

- Experience curves can be a powerful instrument for strategic analysis of technologies to understand their current progress and explore future deployment pathways.
- Still challenges in the use of learning curves for “established” technologies, such as learning for BOS or regional versus global learning.
- For emerging technologies with less empirical evidence, expert judgement or drawing analogies from similar technologies can be a way to estimate learning curve parameters.
- Uncertainty around the impact of R&D highlights the importance of sensitivity analysis to derive robust results through modelling.
- Endogenous representation of learning curves still numerically challenging in larger energy models; smaller “sandbox” models (e.g. less regions) may be an alternative approach to explore the impacts of endogenous learning and inform larger models.



Batteries experience a huge scale-up in the B2DS, with EV battery markets leading other sectors in size