Overview

One of the most complex and pivotal questions in power market modelling is the appropriate representation of technological change (TC). TC can be understood as the “increase in outputs for a given level of inputs through the process of invention, innovation, and diffusion” [1] and has a direct impact on models’ results, for example, the level of emissions abatement for a given cost. Hence, inadequate representation of TC can lead to biased environmental/climate policy recommendations. Earlier power market models treated TC as exogenous process – an autonomous function of time. Yet the last 20 years have seen a gaining momentum in endogenizing the TC in the models, thereby allowing for a more realistic consideration of the cost reduction as functions of distinct learning factors such as experience stocks through learning-by-doing (LBD) and knowledge stocks through learning-by-searching (LBS). Currently, there are several approaches to implement endogenous technological change (ETC) – the most frequently applied single-factor (only considering LBD or LBS), two-factor (LBS&LBD) and multi-factor learning (LBS&LBD&learning in specific components or materials) – each comes with its advantages and limitations. In this paper, based on the example of the EUREGEN power market model, we demonstrate how the application of various specifications of a single-factor approach to ETC affects outcomes of the model in terms of installed capacity, system costs and CO2 emissions. We add to current literature in the field a novel strategy of LBS implementation, in addition to developing and implementing a holistic metric allowing to include more sophisticated LBD features such as the integration of forgetting-by-not-doing. Associated with employee turnover, loss of routines, and technological obsolescence of experience, past experience has long been found less valuable than recent experience in the context of organizational forgetting [2,3,4]. Its representation as forgetting-by-not-doing in bottom-up power system models has therefore been pointed out as a relevant yet blank spot by researchers [5,6]. Our framework extensions will thus contribute to closing the research gap in enhanced implementation of ETC in complex power system models.

Methods

In order to demonstrate the impact of ETC on power market model outcomes, we apply our framework to the EUREGEN model as a case study. EUREGEN is a comprehensive partial-equilibrium model, which minimizes European power market system cost under CO2 emission reduction paths. The model intertemporarily optimizes dispatch and capacity investments into transmission, storage, and generation for 16 generation technologies. In a spatial resolution of up to 12 European regions the model makes investment decisions in 5-year cycles. The perfect foresight planning horizon runs from 2015 to 2050. We apply non-linear and piece-wise linear implementation strategies to represent single-factor learning curves for regional learning and learning with European spillovers. The implemented learning setting can be flexibly adjusted in three dimensions: the modeled learning regions, the number of modeled learning technologies, and the number of modeled line segments to approximate the learning curve. This enables us to analyze the energy system cost and respective price developments, the generation mix and share of specific technologies in installed capacity, and CO2 emissions in the given spatial and temporal resolution. The results under ETC are compared to exogenous TC as a function of time. We further analyze the effects of sophisticated learning features such as forgetting-by-not-doing, as opposed to perfect recall conditions. Comparing learning implementations in non-linear and linearized settings allows us to assess the trade-off between complexity and computational feasibility. The non-linear implementations are solved as a Non-Linear-Program and a Mixed-Integer-Quadratic Program. Piece-wise linear implementations are solved as a Mixed-Integer-Program. The learning implementations are further subjected to sensitivity checks.

Results

We find that the relative capacity cost of renewable technologies is sensitive to the learning mechanism applied and significantly influences the timing, extent, and regional distribution of capacity expansion of renewable energy technologies. Under exogenous TC the model is incentivized, due to perfect foresight, to postpone capacity investments to later periods with lower capacity cost. Instead, under endogenized learning we observe a dissipation of this incentive, leading to earlier capacity investments for some technologies. In addition to that, regional path-dependencies become apparent. Extending existing ETC implementation frameworks by depreciation of the experience stock, i.e. forgetting-by-not-doing, invokes new competitive dynamics among the learning technologies.
These dynamics stem from the trade-off between cost-degressions from early LBD on the one hand and depreciation of early learning progress due to forgetting-by-not-doing on the other hand. The implementation of forgetting-by-not-doing concentrates regional investments in the time-dimension because large regional expansion time gaps become inefficient. Figure 1 underlines these dynamics for onshore wind capacity in selected regions by visualizing the dissipation of multiple expansion peaks as soon as forgetting-by-not-doing is introduced.

![Figure 1: Added onshore wind capacity in selected regions under LBD – perfect recall vs. forgetting](image)

**Conclusions**

This paper provides a framework to implement LBD and LBS in the context of ETC in power market models. We show that implementing ETC in the models is essential to represent the well-acknowledged occurrence of path-dependencies and reasonable investment behavior. New expansion strategies exhibited by the model under endogenous learning conditions provide evidence for that. We observe that regional distribution and timing of capacity expansion follow different patterns under ETC as compared to exogenous time-dependent productivity increases. Not only is the mere consideration of ETC of importance but also the specific implementation design of learning features. While earlier work has focused on implementing forgetting and time lags for LBS only, it is likewise important to consider these sophisticated learning features for LBD. We see adjusted cost-optimized expansion strategies of the model as soon as these features are applied. It is therefore crucial to carefully consider ETC in power system models to make efficient environmental/climate policy recommendations based on cost-optimized investment paths. As the cost-optimized energy system is highly sensitive to the magnitude of learning parameters, we suggest that a careful calibration of the model with econometric estimations of learning parameters is vital.

**References**


