CHAPTER 3

Implementation of experience curves in energy-system models

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Abstract

To analyze the transition toward a low-carbon energy system and to develop appropriate policy measures toward this goal, large efforts are currently taking place to model future layouts of our energy system. In this context, it is important to consider the technological progress in energy-system technologies to take into account how this progress affects technology cost and deployment. In this chapter, we discuss the implementation of experience curves in energy modeling. Experience curves allow for endogenous modeling of cost reductions resulting from technological progress and are, therefore, widely applied in energy modeling. Several issues with implementation of experience curves in energy modeling are discussed, as well as possible solutions.

Chapter outline

Technological Learning in the Transition to a Low-Carbon Energy System.
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3.1 Introduction

In the past few decades the development of climate change mitigation and adaptation strategies are key issues of national and international discussions in policy, economy, and science. Therefore large efforts are currently taking place to model the energy transition and future pathways toward a low-carbon energy system across several sectors. In this context, assessing the impact of technological improvements is important to determine which technologies will increase their expansion and which technologies will be phased out in coming years (Louwen et al., 2018). Thus future cost developments of incumbent and new or premature technologies are influencing results of energy-system models significantly. To consider technology cost reductions with increased experience in energy models, mathematical formulations as learning curves or experience curves are implemented in the modeling code. The approach of incorporating the correlation between technology deployments and costs provides a framework for evaluating whole-system effects caused by and initiating further technology cost reductions (Heuberger et al., 2017). Hence, with consideration of technological learning in energy-system models through experience curves, scientists and policy makers can identify least-cost pathways and alternative pathways to encourage a low-carbon energy system and achieve CO_2 reduction levels at low costs. Furthermore, the consideration of cost-learning effects shifts periods for optimal investments to earlier planning years, which influences the competitiveness of technologies (Junginger et al., 2010). However, the implementation of experience curves in energy-system models still has some disadvantages and therefore chances and barriers encountered for modelers need to be discussed.

3.2 Energy modeling approaches: bottom-up versus top down

In general, energy-system models can be distinguished between top-down models (macroeconomic models) and bottom-up models (detailed techno-economic or process-oriented models). For both types of energy models, main aims are to examine deployment of energy technologies, the effects of energy policies, and the interplays between the economy, environment, and energy system.

Top-down models are applied to depict the whole economy on a national or regional level. Therefore effects of energy as well as climate change policies are generally assessed in monetary units. Further, macroeconomic models equilibrate market developments by maximizing consumer welfare, applying feedback loops between economic growth, employment, and welfare as well as by using production factors (Herbst et al., 2012). As shown in Fig. 3.1, a variety of modeling approaches exist under the umbrella of top-down models. Commonly in top-down modeling, general equilibrium modeling is applied (Junginger et al., 2010).

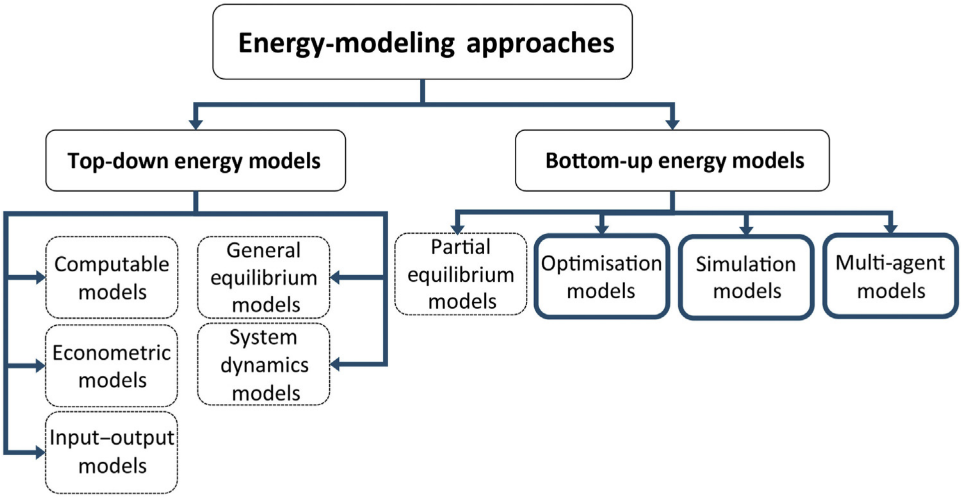

Figure 3.1
Overview of energy system modeling approaches. *Source: Based on Herbst et al. (2012). Credit: Steffi Schreiber.*

In contrast, bottom-up models are applied to depict energy sectors and the economy in an aggregated perspective by simulating economic developments, energy demand and supply as well as employment. Bottom-up models are much more detailed in terms of technological parameters, as compared to top-down models, and are often focused on separate sectors of the energy system. In the REFLEX project, bottom-up models separately model the transport sector, industry, and residential-energy demand, the electricity sector, and the heat sector. Bottom-up models can be generally distinguished into optimization models, simulation models, and multiagent or agent-based models.

Optimization models generally aim to minimize the cost of supplying some exogenous energy demand, while taking into account the available portfolio of energy technologies, including their technical and economic performance. Investment decisions are made based on, for example, total cost of ownership (TCO) or levelized cost of energy, but often, the whole timeframe of the modeling scope is optimized at once, meaning the models have perfect foresight.

Simulation models have a substantially different approach. Rather than finding a cost-optimal solution for a whole sector, over the whole modeling timeframe, simulation models attempt to more realistically capture behavior of actors in energy systems. Starting from a set of preexisting conditions, different actors in the modeled energy system make investment decisions based on TCO principles at each point in time. Often, these types of models employ algorithms that prevent technologies gaining a 100% market share, to ensure heterogeneity in market shares and simulate nonrational behavior (Herbst et al., 2012).

Finally, agent-based models, which can be considered a type of simulation model, are comprised of a set of autonomous "agents," who individually make decisions about deployment of technologies and their activities in the energy system. In contrast with other simulation models, there are several market players interacting in agent-based models, each making decisions and technology choices from a portfolio of available technologies, rather than an overall bottom-up simulation of an energy system as a whole. With this in mind, agent-based modeling is said to give a more natural description of (energy) systems, has the ability to include emergent phenomena, and should be more flexible compared to other modeling techniques (Bonabeau, 2002).

3.2.1 Integrated assessment models

A different category of models is the integrated assessment models (IAMs). These models, as their name indicates, integrate a variety of natural and economic processes. The aim of IAMs is to assess the effects of human activities on the Earth's system (van Sluisveld et al., 2018), with outcomes being effects on economy, greenhouse gas emissions, the energy system, and land use. IAMs are often applied to assess the effect of policy measures on climate change mitigation (Weyant, 2017; van Sluisveld et al., 2018). The models aim to inform policy makers about the requirements and consequences of limiting global-temperature increase (van Sluisveld et al., 2018).

IAMs, thus, extend their scope far beyond energy sectors, are often global models, and include representations of the economy, the land and climate system, and the energy system. Key model drivers include population growth, economic developments, policies, resources, and technological change. The prominent IMAGE model uses experience curves to model technological change in especially energy supply technologies (Stehfest et al., 2014), and many models incorporate technological learning endogenously (Stanton et al., 2009). Well-known models aside from IMAGE are (van Sluisveld et al., 2018): AIM/Enduse (Hibino et al., 2003), GCAM (Calvin et al., 2019), MESSAGE (Huppmann et al., 2019), REMIND (Luderer et al., 2015), and WITCH (Bosetti et al., 2006).

3.3 Implementation of experience curves in energy models

Modeling transitioning pathways for future energy systems requires precise cost estimations for several technologies across different sectors. The costs for technologies are changing over time regarding their technological improvements that can result in higher efficiency, reliability, or lower investment, operation, and maintenance costs (Junginger et al., 2010). By miscellaneous methods the decrease in technology costs due to learning mechanism as learning-by-doing, learning-by-researching, product upscaling (larger products), or production upscaling (economies of scales) can be estimated. One of these few methods are experience curves, which consist of empirical data that derive in mathematical functions to relate cumulative production experiences to cost decreases of technologies (Louwen et al., 2018). This chapter points out why it is necessary to implement experience curves into energy-system models. Further, the technical implementation of experience curves in energy models is described, followed by practical implications in different types of models. As experience curves have some limitations, the issues encountered for both endogenous and exogenous implementation are discussed at the end of this section.

3.3.1 Technical discussion on model implementation of experience curves

Costs are the key drivers for technology diffusion; however, estimating future costs is difficult and afflicted by uncertainties. Therefore experience curves are one of the few methods to allow evidence-based cost projections. In order to devise experience curves, two empirical datasets need to be gathered: data about the development of technology-production costs and about the development of cumulative production of the technology over a certain period (Louwen et al., 2018). The unit of the datasets depends on different types of applications. For instance, the production-cost data for energy supply technologies are given per unit of electrical capacity (e.g., EUR/MW_{el}) and the cumulative production in terms of total capacity (e.g., MW_{el}). According to these gathered data, the devised experience curves are the reduction of total product costs as a function of cumulative production (Boston Consulting Group, 1970).

$$C(Q) = C_1 \cdot Q^b \tag{3.1}$$

where $C(Q)$ is the cost C of a technology at cumulative production Q. Here, C_1 is the cost of the first unit produced and b is the experience curve parameter. The experience curve can be formulated in a linear equation by expressing it in a logarithmic form:

$$\log C(Q) = \log C_1 + b \cdot \log Q \tag{3.2}$$

The experience curve parameter b is the incline of the linear function represented in a double-logarithmic graph. The parameter b indicates at which rate the technology's costs decrease. Two parameters are connected to the experience curve parameter b: the learning rate (LR) and the progress rate (PR).

$$\mathrm{LR} = 1 - 2^b \tag{3.3}$$

$$\mathrm{PR} = 2^b \tag{3.4}$$

These two parameters are more meaningful than the experience curve parameter b since the LR ($= 1 - \mathrm{PR}$) describes the decrease in costs of a product for every doubling of cumulative production Q (Louwen et al., 2018).

The equations above describe *single-factor experience curves*. However, technology cost reductions are influenced by different learning mechanisms (e.g., learning-by-researching and economies of scales) as well as by multiple, independent input material prices. Consequently, single-factor experience curves have to be extended to *multifactor experience curves* to describe the cost developments of a technology in more detail and devise the learning curves accurately (Yu et al., 2011; Heuberger et al., 2017; Kittner et al., 2017). According to the consideration of multiple, independent input variables, the extension to multifactor experience curves requires more empirical data input compared to single-factor experience curves. Furthermore, technologies can consist of several components with different costs and LRs, which also lead to higher data requirements. Energy-system models generally do not supply the required input variables for multifactor experience curves and thus normally use only single-factor experience curves (Louwen et al., 2018).

The implementation of experience curves in energy-system models by including the equations mentioned above directly into the modeling code allows the endogenous modeling of technological progress. For the endogenous implementation the model needs to implement the development of cumulative production. However, the endogenous implementation of experience curves is not feasible for all types of energy-system models. Amongst others, possible reasons are that the mathematics or optimization approach of a model does not allow for endogenous implementation, another reason can be that the geographical scope is limited or that the model does not calculate the cumulative production data in the required unit (Louwen et al., 2018). For models that do not use experience curves for endogenous learning, the exogenous implementation of experience curves can be an alternative by taking future cost reductions into account. The technology costs are changing over time by following an autonomous and exogenous cost-decline path (Junginger et al., 2008).

The technical implementation of endogenous and exogenous experience curves in energy-system models is presented in Fig. 3.2 in a simplified overview, where the gray boxes with the dotted frame represent external data sources, the blue boxes illustrate the model functions, and the transparent boxes stand for model-produced data. The direct *endogenous implementation* (left) is indicated by calculating the required data of the cumulative production in the energy-system model. The data is transferred into the experience curve function. Consequently, the technology costs are calculated, feedback looped, and applied in the energy model. With the dotted arrows, alternative routes of endogenous implementation of experience curves are illustrated. The endogenous calculated technology demand or technology penetration is converted into the required data and unit of cumulative production and further transferred into the experience-curve function. This can be defined as a direct approximation that can still be considered as endogenous calculation. Following the *exogenous implementation* route (right), the model provides only the year for which the

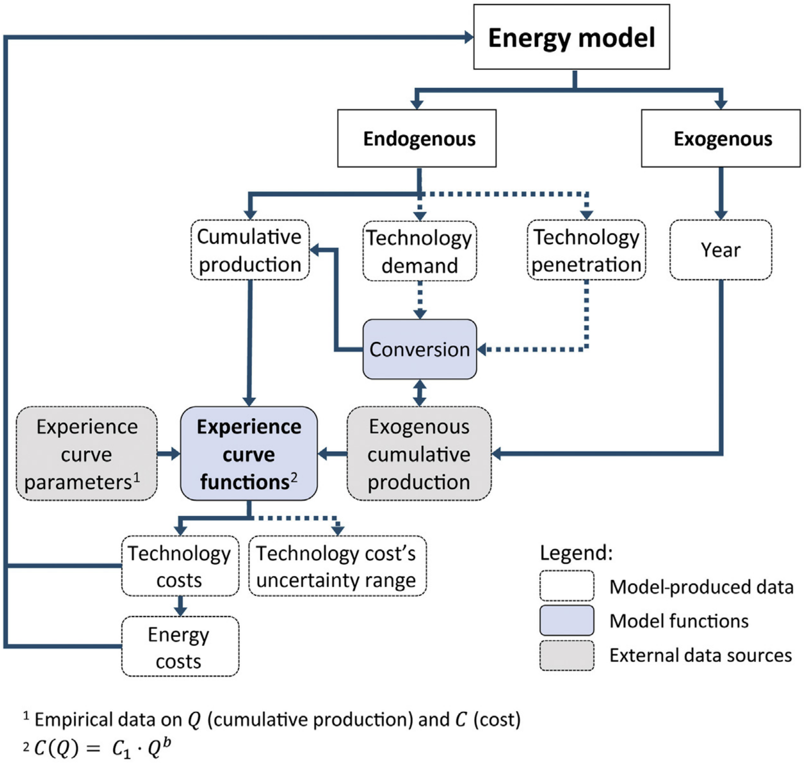

Figure 3.2
Overview of possible endogenous and exogenous experience-curve implementation routes in energy-system models. *Source: Based on Louwen et al. (2018). Credit: Steffi Schreiber.*

technology costs should be calculated, while external data are describing the cumulative production over time, which is converted into the right unit and implemented into the experience curve function.

3.4 Practical implications in different types of models

3.4.1 Endogenous technological learning

The importance of considering endogenous technological learning in energy-system models is addressed by Weyant and Olavson (1999). The authors highlight that the response of technological learning to economic incentives is of crucial importance for designing appropriate energy and environmental policy measures. A comprehensive review of large-scale models employing endogenous learning curves is given in the Fourth Assessment Report of the IPCC (2007) in Junginger et al. (2010) by Lensink et al. (2010). While energy-system models often display long-term perspectives, the effect of technological learning and innovation can have a large effect on the cost-competitiveness of different technologies and therefore a significant effect on the general model results. Endogenous technological learning is widely used in macroeconomic top-down models, for example, in RICE (Castelnuovo et al., 2005), MIND (Edenhofer et al., 2006), or E3MG (Barker et al., 2006) as well as in bottom-up energy models, for example, MESSAGE (Messner, 1997), MARKEL−TIMES (Loulou et al., 2004), or ESO−XEL (Heuberger et al., 2017). In general, two types of models can be defined that employ experience curves endogenously—the general equilibrium models (top-down model) and the partial equilibrium models (bottom-up model). In the case of top-down models, usually the general equilibrium models are used because of their simple representation of the energy sector including all other sectors of the economy. Hence, the general equilibrium models are able to estimate the relationship between research and development investments in energy technologies and their opportunity costs. The partial equilibrium models are appropriate because of their reasonable quantity of technological detail and as its mathematical formulation allows the incorporation of the nonlinear experience-curve function (Rubin et al., 2015).

The endogenous technological-learning model produces internally consistent technology-cost trajectories, which enables the evaluation of policy measures on realizable future cost reductions. However, with increasing complexity of a model, the interpretation of the model results becomes more difficult (Junginger et al., 2010). Thus the endogenous incorporation of technological learning in energy-system models has some threats to mention. While the relationship between investment costs and installed capacity is nonlinear, binary variables have to be implemented in energy models, which lead to a significant increase of computational burden. Furthermore, as technological learning occurs in almost all technologies, learning asymmetries have to be avoided by applying endogenous learning consistently among all relevant technologies (DeCarolis et al., 2017). Seebregts et al. (2000) and Anandarajah et al. (2013) are using clustering of technological learning for similar technology modules, whereas the learning is applied across a set of technologies with similar components. In addition, technological improvements can be driven by a modeled country or region, but indeed, technological learning is a global phenomenon. Therefore modelers and policy makers should be careful while structuring the model and interpreting its results that are influenced by endogenous experience curves (DeCarolis et al., 2017). Another caveat related to the implementation of endogenous learning is that LRs are not trivial to estimate and that they are not remaining constant over time (McDonald and Schrattenholzer, 2001). Further, LRs for a certain technology vary between studies as different datasets are used, for example, different gross domestic product (GDP) deflator rates (Rubin et al., 2015). The variation of LRs over time must also be faced by considering exogenous cost assumptions, as a small change in the assumptions leads to substantial different optimal investment decisions (DeCarolis et al., 2017). Energy-system models with perfect foresight assumptions can place enormous investments in nonmature technologies with high LRs without failure. Hence, the investment patterns can differ significantly from the probable reality.

Several studies indicate that models with endogenous learning curves demonstrate benefits from the early adoption of a new technology as it encourages greater cost reductions over the long term (Mattsson and Wene, 1997; van der Zwaan et al., 2002; Nordhaus, 2009). Hence, in models with endogenous experience curves the cost of delays in introducing a new or enhanced technology can be extremely high compared to models that are not considering technological learning (Bosetti et al., 2011). Applying the MESSAGE−MACRO model, Riahi et al. (2004) investigated the effect on the global carbon dioxide abatement levels with and without technological learning for carbon capture and storage (CCS) technologies. The findings show that in the scenario with endogenous technological learning, the overall CCS costs are lower, resulting in higher CO_2 abatement levels compared to other mitigation methods and in lower opportunity costs of global CO_2 abatement in contrast to the scenario without endogenous technological learning. Thus the results evince that CO_2 mitigation policies are less costly in models with endogenous technological learning than in models without learning. Divergent from the expected reality, CCS technologies are playing a crucial role in the future energy system when experience curves are implemented in the analyses (Heuberger et al., 2017).

To summarize, the implementation of endogenous learning curves in energy-system models is complex but of crucial importance and enables modelers to determine the effectiveness of technology improvements and the supporting policy measures. However, the interpretation of modeling results should be done carefully, as the models with endogenous experience curves are not predicting policy impacts but achievable outputs. Thus for some specific cases, it can be more transparent to identify changes in technology costs exogenously over time and verify it by sensitivity analyses (DeCarolis et al., 2017).

3.4.2 Exogenous technological learning

A large part of energy-system models are considering constant or exogenously driven technology-cost reductions as a time-dependent input parameter (Gillingham et al., 2008; Green and Staffell, 2016). Three ways exist to employ technology performance and cost trajectories exogenously. The first method changes future technology costs and/or the technology efficiency by an annual rate from a reference year, that is, $x\%$ per year decrease in capital costs and/or $y\%$ increase in technology efficiency. The second method would be to directly estimate the absolute technology costs or performance parameter over time, that is, in EUR per capacity and net plant efficiency (Rubin et al., 2015). As a third option, experience curves can be derived by empirical data and can emerge the future cost developments over a specific time period, followed by the exogenous implementation of the data in absolute values (e.g., EUR/kW$_{el}$) into the energy-system model. The exogenous implementation of experience curves by the first two methods with its assumed quantitative values implies the judgment of modelers that may derive from data analyses and/or expertise. Implementing the cost reduction and performance improvements as time-dependent variables lead to the fact that investments in new technologies are avoided until the costs are decreasing significantly and the technology becomes competitive. Thus policy implications are delayed to later time periods. In contrast, with endogenous technological learning, the early adoption of a technology helps to drop down costs and makes the deployment more attractive (Rubin et al., 2015). Hence, the choice of method to implement endogenous or exogenous learning can have substantially different policy implications.

The fundamental difference between exogenous and endogenous technological learning is that the exogenous technological change is only time dependent, while the endogenous technological improvements can be influenced in several ways from past, present, and/or future expected policies and prices (Gillingham et al., 2008).

3.5 Issues, caveats, and drawbacks of experience-curve implementation in energy models

The implementation of technological learning in energy-system models is complex, related to many uncertainties and, therefore, connected with some burden. In the following sections, we will discuss several issues that can be encountered when implementing experience curves in energy models.

3.5.1 Geographical scope of model

Only few models exist that are displaying worldwide developments. As the majority of energy-system models are limited in their geographical scale, the technological learning outside the system boundaries are not considered endogenously. But technological learning is a global process. In the REFLEX project, only the developments in the European Union are considered. However, technologies as CCS or battery storages are used and will be used in future years worldwide. Hence, to derive consistent and reliable experience curves, worldwide learning has to be taken into account. This could be realized by assuming that technological learning outside the system boundaries (e.g., outside the EU) advances with the same velocity as inside the EU. An alternative would be to base technological learning on global energy scenarios as the World Energy Outlook. In addition, the technological learning could partly be exogenized by modeling developments outside the model scope with a different global model. The learning curve function will, therefore, be enhanced by parameters as n_{glob}—the global cumulative developments in the global model and by $n_{glob_{in}}$—the cumulative developments in the global model for countries in the local model.

Hence, the experience curve function to project the model costs considering exogenous global learning in a local model is as follows (Louwen, 2018):

$$C(Q) = C_1 \cdot (Q_{\mathrm{in}} + Q_{\mathrm{glob}} - Q_{\mathrm{glob_{in}}})^b \tag{3.5}$$

where Q_{in} is the cumulative developments *in local model*, Q_{glob} is the global cumulative developments *in global model*, and $Q_{\mathrm{glob_{in}}}$ is the cumulative developments *in global model* for countries *in local model*.

However, this approach requires that the external global model has a compatible geographical subdivision. Further, the level of technology detail can be insufficient in a global model. Therefore the *S*-curve approach (Fleiter and Plötz, 2013; Schmidt et al., 2017) can be applied if the global model does not consider the required technology.

3.5.2 Technological learning in an energy modeling system

Considering technological learning in an energy modeling system, where several models are soft-linked with each other (e.g., as in the REFLEX project), can lead to model inconsistencies as some technologies are considered by different models (e.g., heat pumps) and thus each model represents the technology deployment individually. Hence, technology penetration is often modeled based on different settings and criteria in each model, sometimes even exogenously. As experience curves and cost reductions are a mathematical function of cumulative deployment, strategies are needed to keep the deployment levels and costs synchronized between the models (Louwen, 2018).

With the incorporation of endogenous experience curves in top-down or bottom-up models a cost floor may be implemented to prevent the technology costs from falling below a specific value. This would help to estimate a feasible solution and avoid that costs decrease in an extreme path where technologies become unrealistically cheap within a certain time period (Rubin et al., 2015).

3.5.3 Technical issues

Another issue encountered regarding learning curves in energy-system models is that especially optimization models are not compatible with the nonlinearity and nonconvexity of experience-curve functions. Nonconvexity can lead to local maxima or multiple global equilibria (Messner, 1997). Therefore a global optimum cannot be guaranteed as it is required for linear optimization problems. The development of a piece-wise linear approximation of the exponential experience-curve function can be a solution for optimization models as presented by Barretto (2001) and Heuberger et al. (2017).

Another issue, especially with optimization models, is the tendency of these models to prefer technologies with high LRs, as these models have "perfect foresight" due to their technical definition. On the other hand, technologies with high initial costs can hardly be overcome in simulation models, which can suffer from their myopic nature. Only when taking into account, for example, government subsidies or other incentives do they enter market deployment, and otherwise stagnate in end-consumer prices and thus do not enter the market.

Aside from these technical issues, implementation of experience curves in modeling also requires increased processing time, especially in endogenous implementations that create certain feedback loops in the modeling computations.

3.5.4 Technology deployment constrained by modeling scenario and policy targets

Furthermore, technology diffusion can be constrained by policy targets and assumptions set in the scenarios, which will lead to a prompt stoppage of technological learning in the energy models. If this is the case, an ex post check of the experience curves and the results should be performed to understand which assumptions have what influence on the experience curves (Louwen, 2018). Another threat can occur if models are not producing the data required for the needed input of experience curves (e.g., no calculation of cumulative capacity for a specific technology). If this is the case, a proxy method shall be used to convert the data into the desired input data, for example, data gathering on relation between TWh and TW, or the data shall be used from an external model with similar scenarios (Louwen, 2018).

3.5.5 Other issues

The most common caveat of deriving and implementing learning curves in energy-system models is the lack of empirical data, especially for innovations and new technologies as CCS. If empirical data is lacking proxy technologies, expert elicitations or a simplified estimation of LRs can be used. Further, cross-sectoral or spillover effects are difficult to take into account. Spillover effects can, for instance, describe how the technological learning of lithium-ion batteries influences the reduction in prices of electric vehicles, which for a large part depend on the battery system. Conversely, large deployment of battery electric vehicles could lead to sharp price declines in stationary battery-storage applications. To consider these effects the use of component-based experience curves are a possible solution. However, this approach is more complex, requiring models to produce a larger set of input parameters, and enlarging the threat of missing empirical data (Rubin et al., 2015).

Price developments of technologies can severely be affected by market dynamics, including among others, different levels of market diffusion (see Chapter 2), supply and demand balance, and input material prices. Multifactor learning curves can partly solve these issues of market dynamics. Multifactor experience curves can take factors such as policies, competition, R&D spending, and prices of input materials into account. Nevertheless, usually one model does not produce all of the required multiinput parameters and considering multifactor experience curves will thus increase modeling complexity rapidly (Louwen, 2018). Multifactor learning curves are not widely used; therefore further research is required in context of endogenous model implementation of multifactor experience curves.

Obviously, there exists a trade-off between increasing the accuracy of modeling results and limiting additional model complexity. Therefore each modeler should find a balance between modeling accuracy and complexity, and analyze as well as interpret modeling results very carefully.

3.6 Concluding remarks

Implementation of technological learning processes in energy modeling is an essential part in analyses of future energy systems. It is critical to take into account continuous development and improvement of new and incumbent energy-system technologies when designing policy measures and analyzing energy-transition pathways laid out to achieve climate targets. By using experience curves in energy modeling, technology-cost trajectories can be modeled endogenously, creating a direct feedback between technology deployment and associated learning processes and cost reductions.

That being said, model implementation of experience curves is not without its issues and drawbacks. As we have discussed, a variety of model characteristics can hamper endogenous implementation. Many energy models are restricted in geographical scope, while technological progress is most often considered a global process. In these cases, it is likely that an (at least partly) exogenous cost trajectory based on experience curves is necessary, but a feedback between development within the model under study and technological learning is in this case only possible to a limited extent. Other issues encountered relate to technical or practical considerations in energy modeling, such as the mathematical layout of the model, computation time, or the ability of models, to produce the required input parameters for endogenous (multifactor) experience curves.

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