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Reviewing the complexity of endogenous technological learning for energy system modeling

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ABSTRACT

Energy system components like renewable energy technologies or electrolyzers are subject to decreasing investment costs driven by technological progress. Various methods have been developed in the literature to capture model-endogenous technological learning. This review demonstrates the non-linear relationship between investment costs and production volume, resulting in non-convex optimization problems and discuss concepts to account for technological progress. While iterative solution methods tend to find future energy system designs that rely on suboptimal technology mixes, exact solutions leading to global optimality are computationally demanding. Most studies omit important system aspects such as sector integration, or a detailed spatial, temporal, and technological resolution to maintain model solvability, which likewise distorts the impact of technological learning. This can be improved by the application of methods such as temporal or spatial aggregation, decomposition methods, or the clustering of technologies. This review reveals the potential of those methods and points out important considerations for integrating endogenous technological learning. We propose a more integrated approach to handle computational complexity when integrating technological learning, that aims to preserve the model's feasibility. Furthermore, we identify significant gaps in current modeling practices and suggest future research directions to enhance the accuracy and utility of energy system models.

1. Introduction

In recent years, technological learning has become an important factor in energy system modeling as the cost of technologies such as solar PV, batteries, and fuel cells has decreased significantly [1]. The concept of technological learning was first outlined by Wright in 1936 [2] and describes the relationship between the produced quantity of a technology and the associated technology costs, and later became known as "learning-by-doing." More precisely, it states that every doubling of a produced quantity leads to a relative reduction in costs equal to the learning rate of the technology [2]. By integrating this concept into recent energy system models, researchers can gain a better understanding of how these effects influence current transformation pathways towards sustainable energy systems. An early and steady reduction of emissions, for example, could be more cost-effective than a later and rapid transformation path [3], and ambitious paths would be accompanied by a strong and difficult-to-implement ramp-up of solar and wind energy [4]. While major cost reductions have recently occurred for wind turbines [5], solar energy [6], and electricity storage [7], experts expect similar cost reductions for other technologies, such as direct air capture [8] or electrolysis [9]. Thereby, the timing of cost reductions heavily depends on learning rates and production numbers [10].

In general, various models can be used for energy system analysis, including simulations [11], agent-based models [12], and system dynamics models [13]. For these models, technological learning and its non-linear properties can be incorporated without significant increase in computational cost. While these models are useful for exploring potential system behavior, decentralized decision making, or the evolution of systems over time, they are typically not designed to identify optimal solutions. Optimization models, on the other hand, can be helpful in exploring cost-optimal system operations and designs. These models are therefore particularly useful for strategic decision support, as they provide robust support for the design of energy system transformation

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strategies [14].

However, due to the non-linear behavior of technological learning and the computational challenges that emerge with it, the cost reductions are usually formulated as exogenous quantities in energy system optimization models [15]. This can lead to a self-fulfilling prophecy in the modeling results, as the cost development for innovative technologies is based on exogenous cost assumptions, which are associated with certain developments in the produced quantity. A high predicted production quantity therefore usually leads to low technology costs, which in turn favors a strong expansion of the technology in the optimization model [16]. In addition, using exogenous cost assumptions reduces investment costs even without prior deployment and thus overestimates technological learning [17]. The energy system receives the benefits of technological learning "for free," as the system can simply wait until exogenously-set technology costs fall below a certain level and the use of a technology becomes economically-viable [18,19]. This problem can be overcome by endogenously calculating the cost development. A comprehensive summary of the fundamentals of endogenous technological learning in energy system models can be found in the Supplemental Information. While technological learning has been increasingly integrated into energy system models, existing approaches often fail to capture the full complexity of non-linear learning processes, leading to inaccuracies in system design projections. In this review, we critically examine these gaps and present methodologies that provide a more comprehensive approach to integrate endogenous technological learning and handle the increased computational complexity in order to ensure the model's feasibility while still preserving the model's accuracy.

Previous review papers on technological learning in energy system modelling offer an adequate summary of the fundamental concept of technological learning [18,20–24] as well as the rates at which different technologies learn [25,26]. In general, various studies focus on learning effects in technology assessments. The most prominent review in this regard was conducted by Rubin et al. [25] in 2015, which deals with the approximation of learning rates for learning-by-doing and learning-by-searching. The authors summarize various studies and provide a database for the learning rates of eleven electricity-producing technologies. This database was later extended and updated by Samadi [26] in 2018, who also provided learning rates for different major electricity-producing technologies, on the basis of which an estimate for future learning rate ranges was derived. In addition, Samadi [26] emphasizes that the cost development of a technology most likely does not depend solely on experience but also on several other factors, e.g., expenditures in R&D or the utilization of a technology.

When it comes to reviews dealing with endogenous technological learning within energy system optimization models, the number of existing review papers becomes a lot smaller. The most recent review in this area was conducted by Ouassou et al. [20] in 2021, who provided an overview of different approaches for implementing endogenous technological learning in energy system models. In addition to the methodological focus of the study on concepts for modeling floor costs, component-based learning, and declining learning rates, the authors also put an additional focus on hydrogen production technologies. They summarize studies that deal with learning by doing in hydrogen production and provide an overview of learning rates for selected technologies. Aside from the publication by Ouassou et al. [20], some earlier reviews deal with learning effects in energy system models. For example, Kram et al. [21] provided an overview of models that were part of the European Union funded "Energy Technology Dynamics and Advanced Energy System Modelling" (TEEM) project from 1998–1999. The main objective of this project was to enable energy system models to endogenously incorporate technological learning and therefore to compare different implementations and assess their advantages and drawbacks. The study provides an overview of how technological progress can be considered in energy system models and corresponding issues. The review was supplemented by the final report of the TEEM project by Seebregts et al. [18], which summarizes the overall findings and conclusions of the project. The report also provides an overview of the utilized models and their characteristics, how technological progress was considered, and the benefits and limitations identified during the project. In 2006, this work was extended by Berglund and Söderholm [22], who updated the overview and, amongst others, included publications created during the "System Analysis for Progress and Innovation in Energy Technologies" (SAPIENT) project from 2000–2002, which was a successor of the TEEM project [23,24]. The review analyzed various studies in terms of how they incorporated technological progress into their models and what the main findings of these were. Based on this analysis, they identified several problems of an endogenous consideration of technological progress in energy system models (e.g., uncertainties regarding learning rates or the incomplete representation of diffusion mechanisms) but also highlight the importance of such an implementation.

There is a shortage of literature that covers the concrete integration of technological learning into optimization models for energy systems as well as methods to handle the increased model complexity. To address this research gap, we conduct a systematic literature review that is focused on the various available implementations, studied technologies, and techniques for managing the increased model complexity. We also discuss common pitfalls and things to consider when dealing with technological learning such as the use of growth rates, parameter availability and quality, and the use of additional learning parameters to provide guidance on how to best integrate technological learning.

The remaining paper is structured as follows. Section 2 provides an explanation of the review methodology, including the search query, exclusion criteria, and a description of the concept matrix. The results of the review based on the concept matrix are presented in Section 3. A comprehensive discussion on the use of technological learning in energy system models can be found in Section 4. The paper is concluded in Section 5.

2. Review methodology

This section describes the methods used in this study to identify and analyze the relevant literature based on the guidelines by Webster & Watson [27]. First, a collection of relevant keywords was created and translated into a search string. The resulting search string was as shown below and resulted in a total of 422 matches in the Scopus [28] literature database on 01/10/2024:

TITLE-ABS-KEY((energy) W/3 (model* OR optimiz* OR analysis OR assessment) AND ("learning curve*" OR "learning rate*" OR "learning by doing" OR "experience curve*" OR "endogen* learn*" OR "techno* learn*" OR "techno* progress"))

In a second step, the titles and abstracts of the query results were analyzed, which led to the exclusion of 218 articles (see Fig. 1). We excluded publications that do not relate to energy economics, such as those that focus on physics or artificial intelligence methods, or only consider one specific technology without analyzing the full energy system. The remaining articles were then analyzed in depth, resulting in a further exclusion of 106 studies that did not focus on energy system models. Furthermore, 52 of the remaining articles did not rely on an optimization model or did not provide sufficient information about the optimization problem, as it made up only a small part of the study. This mainly occurred in studies that utilized large integrated assessment models (IAMs), which combine various simplified models. Articles containing IAMs were excluded from the methodological review approach. Instead, these articles were qualitatively considered in the discussion to provide the reader with important information for parameterizing and constraining endogenous technological learning. In addition, 15 articles were excluded in which technological progress was only considered in an exogenous manner. Therefore, the remaining database included 31 articles, which were complemented by eleven articles from a manual search and a backward citation search. This

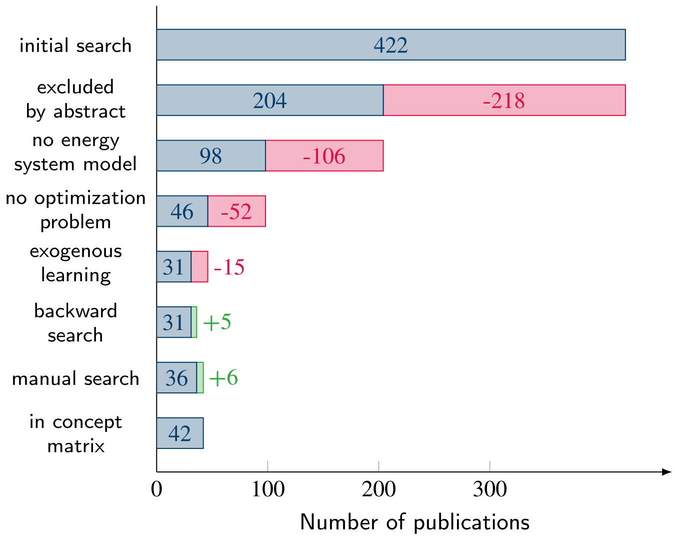

Fig. 1. Literature identification and exclusion.
The figure shows different inclusion and exclusion criteria. The blue bar depicts the number of remaining publications. The red and green bars indicate the number of excluded and included publications, respectively.

review methodology allows for a structured identification of relevant literature and helps to provide an unbiased overview of the research field. However, it is still possible that individual relevant articles are missed due to limitations in search terms or database coverage. The database analyzed in this study consisted of 42 articles that focused on endogenous technological learning in energy system optimization models. The articles were then analyzed using an all-encompassing concept matrix that contained the following categories:

2.1. Implementation of the experience curve

In this category, the studies were analyzed with regard to their implementation of the experience curve. Therefore, the optimization method (e.g., mix-integer linear programming, non-linear programming) and objective criteria within the optimizations were reviewed. Based on this information, we investigated if the authors used either a single- or multi-factor experience curve model and which explanatory variables they used. Furthermore, we examined how the experience curve model was implemented (e.g., piecewise linearization of the cost function or iterative approach) and whether the commissioning of technologies featuring endogenous technological learning was constrained. Finally, we assessed whether the authors analyzed the impact of including endogenous technological learning on the optimization results and whether they accounted for uncertainties in relation to the learning parameters.

2.2. Considered technologies

Next, we analyzed which technologies the authors considered in their studies and which technologies they applied endogenous technological learning to. Additionally, we also stated what demand sectors the studies focus on and whether the models incorporated a spatially resolved electricity or district heating grid.

2.3. Model complexity and reduction methods

The final category for this review is the complexity associated with the utilized models. To obtain an estimate of the complexity associated with the models considered herein, the models were evaluated with respect to the following three complexity dimensions:

- **Number of technologies:** Connected to the Considered technologies category, we determined how many technologies were represented in the studies and for how many of which endogenous technological learning was applied.
- **Spatial resolution:** In this dimension, we examined the spatial resolution and how many nodes were used in the optimization.
- **Temporal resolution:** The temporal resolution can be represented by two different variables. On the one hand, it is dependent on the number of investment periods, which can be derived from the length of an investment period and the considered time horizon. On the other hand, these investment periods are often divided into time steps to model the operation during that investment period. Additionally, we analyzed which foresight horizon and method was used in order to calculate how many total system states (#investment periods × #time steps) were simultaneously considered per optimization run.

Additionally, we examined whether, and if so which, complexity reduction methods were used by the authors. This could be any type of aggregation (e.g., temporal aggregation by using typical days) or decomposition methods (e.g., benders decomposition) to lower the model complexity and reduce the computational effort or computing time for solving the optimization models [14].

During the review process, we contacted all corresponding authors to ensure the correct interpretation of their study.

3. Results

3.1. Implementation of the experience curve

For the implementation of technological learning, the vast majority of the analyzed studies (88%) used a single factor learning function in combination with the installed capacity of a component as an explanatory variable. In contrast, Xu et al. [29], Miketa & Schrattenholzer [30], and Barreto & Kypreos [31] used a two-factor experience curve and thus also considered R&D expenditures a second explanatory variable. The authors employed non-linear models to account for this effect. De Feber et al. [24]. also incorporated this effect but, instead of using R&D spending as a second explanatory variable, they exogenously set specific R&D expenses and adjusted the learning rate accordingly. In addition to the experience-based endogenous learning effects, Straus et al. [32]. also considered an exogenously-modeled cost reduction to account for learning effects outside of their modeled region.

As shown in the section “Fundamentals of endogenous technological learning” in the Supplemental Information, cost functions of capacities which are subject to technological learning are concave, i.e., their marginal cost and thus their steepness decrease with deployment. Minimization problems with concave objective functions are non-convex which means that they can contain multiple local optima, even if their constraints are fully linear.

The direct implementation of this relationship allows modelers to most accurately represent all mathematical relationships of technological learning in a non-linear optimization model. However, the existence of multiple minima makes this kind of non-linear optimization problems (NLPs), illustrated in Fig. 2A, generally hard to solve. Simple optimization algorithms start somewhere within the feasible space and likely end up in a local optimum without proving that no better optimum exists. Thus, the direct solution of NLPs requires specialized solvers using multiple initialization and optimization algorithms such as particle swarm or genetic algorithms to guarantee a global optimum. These approaches are associated with high computing times, which, in turn, limit the maximum model size that can be solved. The representation of technological learning in a non-linear model is often found in models with low temporal resolution that focus more on capacity expansion than on plant operation [33], or in models that consider multifactorial learning [30].

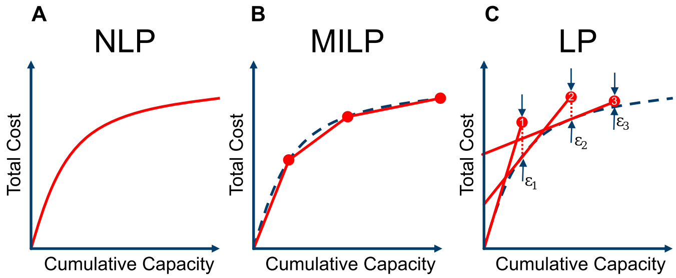

Fig. 2. Different optimization approaches for technological learning.
The figure shows the three most frequently used optimization approaches while including endogenous technological learning in energy system optimization models. This is done by presenting the total costs of a technology as a function of its cumulative capacity.
(A) Non-linear programming (NLP).
(B) Mixed integer linear programming (MILP) with piecewise linearization.
(C) Fully linear programming (LP) with an iterative approach, depicted by the numbered points. The slope of each red line represents the per unit costs for the corresponding iteration. The numbered points indicate the resulting cumulative capacity and total cost, which then determine the per unit costs of the next calculation (tangent of cost-capacity curve). The error for each iteration (deviation to cost-capacity curve) is depicted by the corresponding ε.

The optimizations using piecewise linearization, shown in Fig. 2B, replace the concave curves by a number of linear curve segments. Generally, they rely on additional binary variables that define which segment to choose. These additional binary variables turn the models into mixed-integer linear problems (MILPs). The first advantage of these models used by most articles are the broad availability of MILP solvers like Gurobi. Secondly, they can be solved to global optimality, e.g., using standard solving algorithms like the branch-and-bound algorithm. However, due to the use of piecewise segments to represent the learning curve, this method is only an approximation of the original learning curve and therefore does not solve with full accuracy. In addition, similar to NLPs, MILPs are known to be NP-hard as well, resulting in an exponential increase in solution time for larger models [34]. On the other hand, the popularity of MILPs, the resulting strong competition and high performance of state-of-the-art solvers, partially compensate for this drawback. The use of MILPs combined with a piecewise linearization of the learning curve is a common approach to represent technological learning, as it provides a global optimum for comparatively low computational effort.

Lastly, an iterative linearization of the concave objective function is the least computationally expensive approach and requires minimal adaptation of a linear optimization program (LP) neglecting technological learning. In this approach, an assumption about the capacity development of each learning component is made prior to the first optimization. This development is then translated into the cost development of the respective component using the corresponding learning curve which serves as an input for the first optimization. In each iteration, the cost curve is linearized at the abscissa of the previous optimization run by updating the cost gradient and y-intercept of the linearized cost curve. The iteration, which is shown schematically in Fig. 2C, terminates after a convergence criterion is met. This method is fast and simple to implement, but it is neither mathematically exact, because the quality of the solution depends on the convergence criterion, nor does it guarantee global optimality. This means that the final model solution depends on the initial assumptions about the expected capacities and cost gradients. For that reason, multiple initializations should be considered to ensure that the found local optima are close to the global optimum; an approach that is also well-parallelizable. This method is particularly useful for large linear energy system optimization models where the use of NLP or MILP solvers would lead to computational infeasibility. A limited number of learning technologies thereby may prevent the occurrence of local optima.

While the use NLPs offers the most accurate implementation of technological learning into the models, this also drastically limits the feasible model size and features, as the computational resources required to solve this type of problem are much higher as for other implementations. NLPs are used by 25% of the analyzed studies. In contrast, iterative LPs need much lower computational power and thus offer the possibility for larger and more comprehensive models. But these models do not guarantee to solve for global optimality and are therefore only useful for a very limited number of use cases. Within the analyzed database 10% of the studies utilized LPs. Lastly, MILPs offer a good compromise between the required computational resources and the provided accuracy and therefore are used by the majority (60%) of the analyzed studies. The remaining 5% of the studies either used a different optimization approach (e.g., dynamic programming), or defined models based on a combination of different optimization approaches. While the various models differ relatively strongly with respect to the optimization method used, there were only minor differences in their objective functions: all studies considered the energy system costs an objective value and differences could only be found in the specific formulations. For example, some articles added a carbon price by associating costs with the emission of greenhouse gases [35]. Other studies also included research and development costs in their objective function [30,31] or optimized the resulting cost of a particular product or energy carrier (e.g., the price per ton of steel or levelized cost of electricity) [29,36].

When fully linear optimization was applied in the analyzed articles, the investment periods were either optimized one at a time (myopic) and the learning effects considered between periods [37], or the investment periods were optimized all at once (perfect foresight) and the learning effects were applied in an iterative process until the learning converged to the optimization result [38,39]. In contrast, Rathi & Zhang [40] used a discretization of the experience curves that leaves only discrete commissioning possibilities to the optimization model, but allowed the authors to use uncertain learning rates.

A major drawback of energy system models that incorporate endogenous technological learning is that they favor the rapid ramp-up of a technology during the early optimization years. This frequently results in overestimated commissioning, which cannot be met considering resource availability or build-up times. Hence, 43% of the analyzed studies incorporated constraints to limit the capacity expansion of certain technologies featuring endogenous technological learning. This was done by either limiting the total capacity or the individual commissioning for each investment period and technology (growth rate). When applied, these growth rates are often binding in many models and thus determine the solution space. Historically, however, assumed possible growth rates have often underestimated the real growth [41].

Furthermore, only 55% of the studies present an analysis of how technological learning affects the model results. Most of these observed a fairly substantial influence of endogenous technological learning [38,42–44]. The observed effects include substantial changes in the energy supply [43,45,46,135,136], deviating commissioning dates [19,42], and increased competitiveness of technologies that incorporate technological learning [47,48]. Additionally, Barreto & Kypreos [31,49] found that the technologies incorporating endogenous technological learning tend to behave in an "all-or-nothing" manner. This means that the corresponding technology either gets built with its capacity expansion maximum or is not present in the energy system at all (the "lock-out" effect).

Another relevant aspect is the consideration of uncertainty, which only 35% of the articles considered. The authors either conducted sensitivity analyses [30–32,35,38,50,51], examined different scenarios [47,48,52,53], or used Monte Carlo simulations [24,33,132] to account for the uncertainties associated with the learning rates used. Additionally, Mattson [54] and Rathi & Zhang [40] performed a more in-depth analysis by introducing a stochastic optimization problem to account for different possible learning rates.

3.2. Considered technologies

Due to computational constraints, not all considered technologies were modeled with endogenous technological learning, leading to studies that mostly focused on specific technologies. PV and onshore wind were modeled with endogenous investment costs in almost all of the studies and showed no trend with respect to the year of publication (see Fig. 3 and Table 1). Offshore wind turbines were only considered in 15 newer studies with a mean publication year of 2015, of which 14 incorporated the investment costs endogenously. Only the study by Anandarajah et al. [47]. provides investment costs for offshore wind turbines exogenously, as they focus on the transportation sector. Most studies consider baseload renewables such as hydro, geothermal, or biomass power plants and conventional generation such as nuclear, coal, oil, or gas power plants. However, these technologies were only modeled with endogenous technological learning in a minority of the studies, unlike intermittent renewable energy technologies.

Other technologies such as Integrated Gasification Combined Cycle Coal (Coal IGCC) or Combined Cycle Gas Turbine (Gas CCGT) power plants, which were an area of focus during the beginning of the twenty-first century, were modeled with endogenous technological learning at that time. However, as these technologies emit greenhouse gases, they have rarely been modeled with endogenous technological learning in recent studies, which frequently focus on carbon-neutral energy systems. The focus therefore shifted away from these technologies, and they were primarily modeled with exogenous cost curves.

Recent publications have shifted from focusing on specific sectors or technologies to models that include multiple integrated sectors with a wide variety of technologies (see Table 1). Power-to-X technologies such as electrolysis, heat pumps, methanation, or Fischer–Tropsch plants are therefore more present in recent studies that address the need for greenhouse gas-neutral energy systems [47,55,56]. Furthermore, only a limited number of studies include short- or long-term energy storage options. The reason for this is the low temporal resolution within the individual investment periods in most of them, which means that the interactions of storage mediums in the energy system cannot be adequately represented. This especially holds true for short term storage technologies, which are only represented in models that use an hourly temporal resolution [38,50,57]. The only study that considers short-term storage with endogenous technological learning is that of Heuberger et al. (stationary battery storage) [50]. Long-term storage, such as pumped hydro or hydrogen, is only considered in models with three to twelve time slices per investment period [39,45,48,51,58], allowing the models to account for seasonality. Some of these studies endogenously consider components of long-term storage technologies by applying endogenous technological learning to renewable production technologies for hydrogen [38,51,53,57]. Road transport technologies are represented in ten different studies, of which six modeled them with endogenous technological learning [24,46,47,55,59,60] for analyzing the macroeconomic effects of technological learning in the transport sector. Lastly, carbon capture and storage (CCS) technologies are modeled in twelve articles, with eight of them modeling the investment costs of CCS technologies endogenously [43,46,50,61–65]. Our review results, presented in this section and depicted in Table 1, indicate that the analyzed studies used a wide range of methods to implement technological progress, focused on different technologies, and used different learning parameters. The articles also utilized completely different temporal and spatial scales, which makes a meaningful comparison of model results impossible.

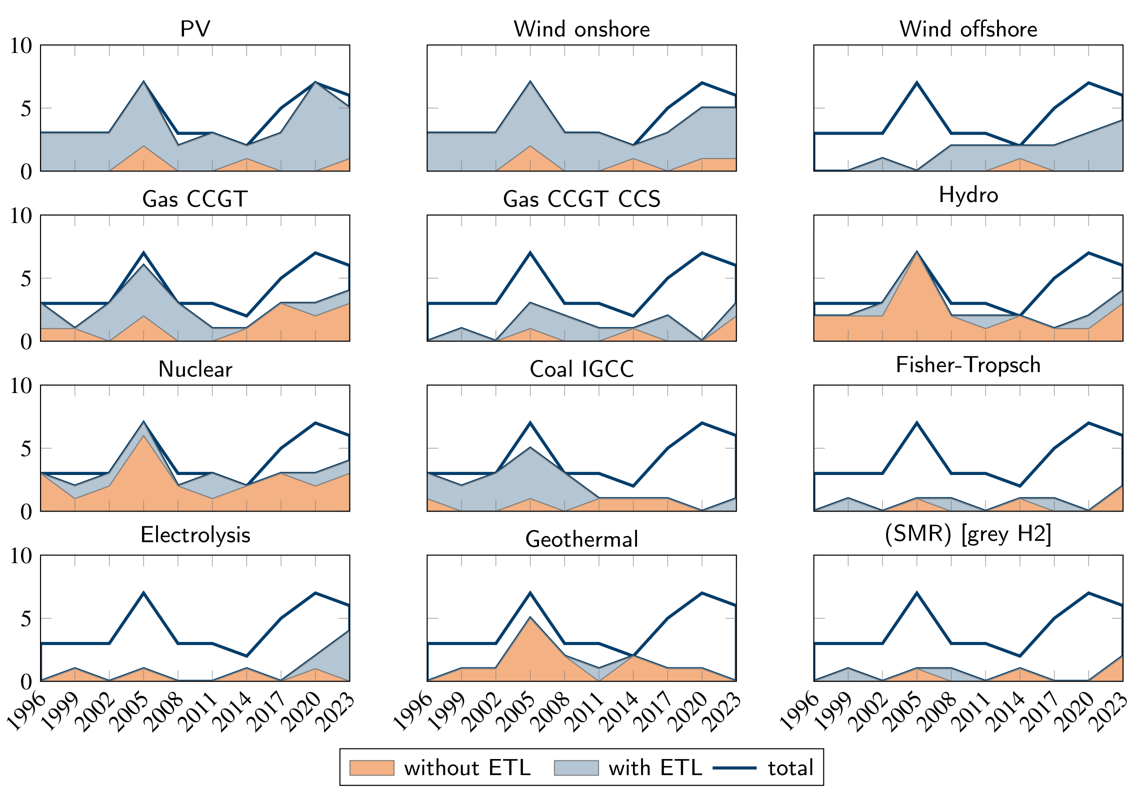

Fig. 3. Trends in technologies with and without endogenous technological learning (ETL) over time.
Number of publications, including specific technologies, with or without ETL. Publication years are shown on the x-axis, whereas the number of studies including a technology and the total number of publications for that year are shown on the y-axis of the corresponding subplot. A moving average of three years is used for the publication year.

Table 1
Considered technology classes, model formulations, and foresight horizons.
The table presents an overview of the analyzed studies. The corresponding studies are referenced in the first column. In the second column the different technologies were grouped into eight different categories, which are described in the legend. The color of the corresponding icon indicates whether all, some, or none of the technologies in that group are modeled with endogenous technological learning. If an icon is not present for a particular study, it means that none of the technologies in the group was addressed in that study. The third column reveals which models used growth rates to constrain technology diffusion. The fourth column shows the used model formulation, which is an indicator of how many investment periods were considered per optimization run (all investment periods: perfect foresight; all with optimal substructure: dynamic programming; multiple but not all: rolling horizon; one: myopic). Finally, the fifth column displays the time period used in the model (light blue) and the years in which investments in technologies and measures were possible (dark blue).

Study \ Criteria	Considered technology classes	Growth Rates	Model formulation	Foresight Horizon (1990 … 2100)
Gabrielli et al. (2024)	intermittend renewables, conventional generation, power to X, shortterm storage, longterm storage	×	perfect foresight	
Lerede et al. (2024)	intermittend renewables, baseload renewables, conventional generation, power to X, shortterm storage, longterm storage, road transport, CCS	×	perfect foresight	
Zeyen et al. (2023)	intermittend renewables, baseload renewables, conventional generation, power to X, shortterm storage, longterm storage, road transport, CCS	×	perfect foresight	
Seck et al. (2022)	intermittend renewables, baseload renewables, conventional generation, power to X, longterm storage, road transport, CCS	✓	DP, myopic foresight	
Lee et al. (2022)	not specified	×	myopic foresight	
Rathi and Zhang (2022)	intermittend renewables, conventional generation	✓	perfect foresight	
Felling et al. (2021)	intermittend renewables, baseload renewables, conventional generation, power to X, shortterm storage, longterm storage	✓	perfect foresight	
Straus et al. (2021)	intermittend renewables	✓	perfect foresight	
Tibebu et al. (2021)	intermittend renewables	n.a.	perfect foresight	
Xu et al. (2020)	intermittend renewables	✓	DP	
Kim et al. (2020)	intermittend renewables, conventional generation, longterm storage	n.a.	perfect foresight, myopic foresight	
Chapman et al. (2020)	intermittend renewables, baseload renewables, conventional generation, power to X, road transport	n.a.	perfect foresight	
Handayani et al. (2019)	intermittend renewables, baseload renewables, conventional generation, longterm storage	×	perfect foresight	
Heuberger et al. (2017)	intermittend renewables, baseload renewables, conventional generation, shortterm storage, longterm storage, CCS	✓	perfect foresight	
Hayward et al. (2017)	power to X, road transport	×	perfect foresight	
Karali et al. (2017)	not specified	×	perfect foresight	
Huang et al. (2017)	intermittend renewables, baseload renewables, conventional generation, CCS	n.a.	perfect foresight	
Choi et al. (2016)	intermittend renewables, baseload renewables, conventional generation	✓	perfect foresight	not specified (20 years)
Wu and Huang (2014)	intermittend renewables, baseload renewables, conventional generation, longterm storage	n.a.	perfect foresight	
Anandarajah et al. (2013)	intermittend renewables, baseload renewables, conventional generation, power to X, road transport, CCS	×	perfect foresight	
Kim et al. (2012)	intermittend renewables, baseload renewables, conventional generation	×	perfect foresight	
Hayward et al. (2011)	intermittend renewables, baseload renewables, conventional generation, CCS	✓	perfect foresight	
Rout et al. (2010)	intermittend renewables, baseload renewables, conventional generation, road transport	n.a.	perfect foresight	
Rout et al. (2009)	intermittend renewables, baseload renewables, conventional generation, power to X	✓	perfect foresight	
Turton and Barreto (2007)	intermittend renewables, baseload renewables, conventional generation, power to X, road transport, CCS	×	perfect foresight	
Rafaj and Kypreos (2007)	intermittend renewables, baseload renewables, conventional generation, CCS	×	perfect foresight	
Hedenus et al. (2006)	intermittend renewables, baseload renewables, conventional generation, power to X, longterm storage, road transport, CCS	✓	rolling horizon	
Rafaj et al. (2005)	intermittend renewables, baseload renewables, conventional generation, CCS	✓	perfect foresight	
Barreto and Kypreos (2004a)	intermittend renewables, baseload renewables, conventional generation	×	perfect foresight	
Miketa and Schrattenholzer (2004)	intermittend renewables, baseload renewables, conventional generation	×	perfect foresight	
Barreto and Kypreos (2004b)	intermittend renewables, baseload renewables, conventional generation	×	perfect foresight	
Barreto and Klaassen (2004)	intermittend renewables, baseload renewables, conventional generation	×	perfect foresight	
Riahi et al. (2004)	intermittend renewables, baseload renewables, conventional generation, CCS	n.a.	perfect foresight	
de Feber et al. (2003)	intermittend renewables, baseload renewables, conventional generation, road transport	✓	perfect foresight	
Mattsson (2002)	intermittend renewables, baseload renewables, conventional generation	✓	perfect foresight	
Barreto and Kypreos (2002)	intermittend renewables, baseload renewables, conventional generation	✓	perfect foresight	
Gritsevskyi and Nakicenovic (2000)	intermittend renewables, baseload renewables, conventional generation, power to X, road transport	n.a.	rolling horizon	not specified
Seebregts et al. (2000)	intermittend renewables, conventional generation	n.a.	perfect foresight	
Barreto and Kypreos (2000)	intermittend renewables, baseload renewables, conventional generation, CCS	✓	perfect foresight	
Mattsson and Wene (1997)	intermittend renewables, baseload renewables, conventional generation	✓	perfect foresight	
Messner (1997)	intermittend renewables, conventional generation	✓	perfect foresight	
Mattsson (1997)	intermittend renewables, baseload renewables, conventional generation	✓	perfect foresight	

intermittend renewables, conventional generation, shortterm storage, road transport, carbon capture and storage (CCS), baseload renewables, power to X, longterm storage, with ETL, without ETL, partly with ETL, myopic foresight, perfect foresight, rolling horizon, DP dynamic programming

3.3. Complexity and reduction methods

This review investigates the three dimensions of the spatial and temporal resolutions, as well as the number of technologies to estimate the complexity of the analyzed models, as endogenous technological learning may lead to unfeasible computation times. The first dimension (x-axis in Fig. 4) is the total number of time slices optimized in a single optimization run. For models with perfect foresight, this is the product of the number of investment periods and the number of time steps within these periods. This provides the optimization model with all available information from the outset and enables it to "know" the effects of technological progress. Based on this information, the model can calculate the most cost-effective design of the energy system for the entire observation period. Table 1 shows that this approach is used by the vast majority (36 out of 42) of the studies analyzed. To lower the total number of time slices optimized in a single optimization run, most models using perfect foresight consider fewer, but longer, investment periods to represent the optimization horizon. Most of these models consider between four and ten investment periods, representing five–ten years [43,49,65].

For myopic optimization models that were applied in three of the analyzed models [37,39,51], the number of time slices optimized in a single optimization run is equal to the number of time steps considered for one investment decision, as only one investment period is modeled per optimization run. In this approach, the model contains no information about subsequent investment periods, but only about the current one, and is therefore not able to consider the effects of technological progress within the optimization. Instead, technological learning is applied between optimization runs. Compared to perfect foresight models, this usually only leads to local optima. However, since the myopic approach only optimizes one of the investment periods at a time, the temporal complexity of these models is generally lower than that of models that use perfect foresight. This provides computational advantages over the perfect foresight approach and allows more investment periods to be considered in the model [66]. Two publications [42,45] used the rolling horizon approach, which, like the myopic one, divides the observation period into multiple optimization runs. However, instead of considering only one investment period per optimization run, multiple periods are considered. Thus, the considered investment periods overlap between the different optimizations and the foresight horizon changes. Our analysis shows that the use of myopic or rolling horizon approaches simplifies the computational demands of these models, but also inadequately accounts for long-term technological progress. In our view this underestimation of learning effects can lead to flawed system designs.

Furthermore, two studies used a dynamic programming approach [51,67], which is a frequently applied method in economic problems such as sequential (investment) decision problems or growth models [68–70]. Dynamic programming is applicable to optimization problems with an optimal substructure, which means that their solutions can be obtained by optimal solutions of their sub-problems. In sequential problems such as consecutive investment decisions, these models are solved via backwards induction, i.e., the final state of the decision problem defines the optimal solution of the last but one period, and the last but one state in turn defines the optimal solution of the last but two period, etc. As the investment periods can be recursively optimized, a computationally efficient "myopic" sequential optimization yields a global optimum, i.e., the same result as a joint and mathematically cumbersome perfect foresight optimization. While Xu et al. [67]. consider a pure investment model, Seck et al. [51]. couple their investment model, which is based on an earlier publication by Bakken et al. [71], with a linear bottom-up TIMES-type optimization model, and one for hydrogen import costs. As the authors point out, the complex interaction of operating costs and spatially resolved investment decisions would disrupt the optimal substructure in the investment model and thus the soft linkage between the models would only allow for the finding of local optima. At the same time, the limitation of dynamic programming models to very coarse technology representations and system operations is the main reason why this approach remains relatively unpopular amongst large-scale energy system models, as it resembles a top-down method.

To reduce the complexity based on the temporal resolution, some models attempt to identify representative time slices, e.g., one for each season and day/ night [52,56]. Others apply more accurate algorithms called time series aggregation to cluster the hourly time series of the components into typical periods and segments. As is shown in Fig. 4, Heuberger et al. [50] and Zeyen et al. [38] used this method to reduce the total number of time slices optimized in a single run by a factor of

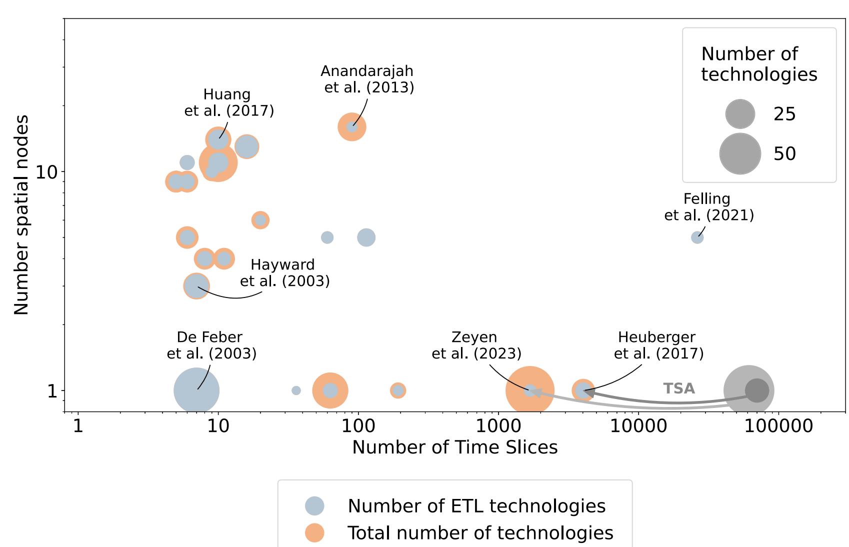

Fig. 4. Number of spatial nodes, time slices and technologies.
The complexity graph contains only studies that used a MILP. The gray arrows indicate complexity reduction through time series aggregation (TSA). The 'Number of Time Slices' refers to the number of time slices which were optimized within one optimization. For models which consider multiple investment periods per optimization run (perfect foresight, rolling horizon) the number of time steps per investment period therefore is multiplied by the number of investment periods per optimization run.

17.4 [50] and 36.5 [38], respectively. Both studies used the k-means approach for clustering time series to ensure the computational feasibility of their model. Heuberger et al. [50]. therefore used 11 and Zeyen et al. [38] 10 typical days, each containing 24 time slices, to represent the hourly time series. Meanwhile, Heuberger et al. [50] reported that the model's runtime decreased from 43 h to less than 5 min, while the objective values deviated by 2.5%. The technology-specific capacity deployment deviated by less than 8%.

The second complexity dimension (y-axis in Fig. 4) was estimated by the number of spatial nodes used in the models. Typically, multiple spatial nodes are used to account for regional effects and to represent the transfer of energy carriers between different regions, e.g., in electrical grids. As technological learning is considered a global phenomenon, most of the models analyzed in this review attempt to represent global, continental, or national energy systems. Modelers are thus confronted with a conflict between a good representation of regional effects and manageable model complexity. Of the analyzed studies, 23 focused on global and 15 on continental or national energy systems. These studies used an average of around seven spatial nodes for the global models and only around two for continental/national models. Only one of the analyzed studies focused on a region smaller than national, representing the Java–Bali energy system [48], in a single-node model.

The technological learning effects in publications that account for different regional nodes within their models are either defined as global or local learning [43,52,55]. Global learning thereby allows all regions to contribute and profit in the same way from the learning effects [43, 55]. In contrast, some publications have chosen to use a local learning approach that models technological progress for each spatial node individually and possibly with a local learning rate, resulting in different investment costs for each region [49,72,73,133]. This enables the models to depict spillover effects among regions, but also considerably increases the complexity of the models, as all required variables and constraints must be introduced for each region. Publications focusing on non-global energy systems typically accounted for global technological progress in two different ways [32]. They either approximated the global learning progress and applied it as exogenous cost reduction [51] or they assumed that the global capacity expansion would proportionally follow the modeled commissioning [35,57]. In some publications, both concepts were used depending on the technology [38] or scenario [50].

Finally, the third dimension (bubble size in Fig. 4) refers to the number of different technologies represented with or without endogenous technological learning in the models. Whenever the investment costs of a technology are considered via a piecewise linear function, this greatly increases the complexity of the model through the introduction of binary variables.It therefore is advisable to distinguish how many technologies are considered with or without endogenous technological learning. Some studies model the investment costs for nearly all considered technologies endogenously. For example, Hayward et al. [62] model technological learning endogenously for 16 of 20 considered technologies. Other studies only model cost reduction endogenously for certain technologies that are the focus of the study in order to reduce complexity [47]. In addition, it is also possible to implement clusters of technologies that are related to each other [134]. This accounts for spillover effects between different technologies and reduces the complexity, as different technologies can profit from the same knowledge stock. The corresponding (binary) variables must be introduced only once per cluster instead of per technology. This method is used by De Feber et al. [24], who assign all technologies to multiple clusters, which allows the authors to represent 60 different technologies while only introducing the binary optimization variables for 10 different technology clusters.

Most studies that include technological learning massively limit the temporal and spatial resolutions to ensure computational feasibility (see Fig. 4, lower left quadrant). An exception to this can be found in Felling et al. [57], who use an hourly resolution for three different years representing their investment periods, resulting in a total of 26,280 time slices, while still considering five spatial nodes. The authors are able to include this high number of time slices and spatial nodes by applying Benders decomposition and including binding constraints on the growth rates of the learning technologies. This method divides the optimization problem into one master- and several sub-problems, which can be solved in parallel, taking advantage of the resources of a high-performance computer and resulting in faster solution times. The authors show that this method is particularly suitable for models that utilize high temporal resolutions and piecewise linearization and are therefore defined as MILPs. In contrast, no time savings were observed for LP models and for those with low temporal resolutions. For further information, see the extensive reviews of application cases for decomposition in energy system optimization [74], on non-convex generalized Benders decompositions to mixed-integer nonlinear problems [75], and articles on the application of Benders decomposition to bottom-up energy system optimization models [76–81] for either enabling solvability or outperforming closed optimizations.

In addition to the presented methods of complexity reduction such as spatial aggregation, time series aggregation, the clustering of learning technologies, and decomposition approaches, there are also other techniques for ensuring the computational feasibility of energy system optimization models with endogenous technological learning. For example, Heuberger et al. [50] used a relaxed version of their model by transforming all integer variables into continuous variables, which can take any value between zero and one. Thereby, the model no longer represents the integer characteristics and so does not necessarily result in an optimal or even feasible solution. This method was reported to only result in a negligible change in the objective value [82]. However, the original model used by Heuberger et al. [50] was intractable with non-relaxed variables and the authors were unable to report the corresponding change in the objective value.

The model complexity and thereby its computation time can also be decreased by the implementation method of technological learning. For example, Kim et al. [39] and Zeyen et al. [38] utilized the iterative linearization approach presented above. They observed much faster computation times but also an overestimation of the total annualized costs by about 9% and delayed investments in emerging technologies. It should therefore be noted that this method does not necessarily yield a global optimum and that it depends heavily on the initial parameterization of the exogenous cost curves, especially if multiple learning technologies are included.

Fig. 4 reveals that more recent studies tend to integrate greater complexity within their models. These articles are located near the top right corner of the figure and include more technologies while preserving a high temporal and spatial resolution. Increasing computational power and improved solver performance enable more recent models to maintain feasibility [83]. In addition, novel methods such as stabilized Benders decomposition are emerging that could be applied to technological learning, allowing for increased model complexity [84].

4. Discussion

Despite the integration of endogenous technological learning in various studies, some still inadequately address the computational complexity associated with high spatial and temporal resolutions. This review highlights the need for a more sophisticated approach to model complexity, which we argue is crucial for the accurate forecasting of future energy system designs. In the following section we therefore critically discuss the before presented results and identify issues that have been inadequately addressed in the current literature and require further investigation.

4.1. Data availability and quality for parameters and constraints

The utilization of high-quality input data for parameters and constraints is a prerequisite for the successful implementation of endogenous technological learning. This applies for example for (regional) learning rates, costs, historically installed capacity (knowledge stock), potential growth rates, and floor costs. However, determining these data can be challenging, as they may need to be estimated (e.g. growth rates, floor costs) or determined statistically (e.g. learning rates, costs). Modelers are therefore often confronted with the challenging task of using empirically grounded data. This especially holds true for technologies which are up to the current date not economically feasible (i.e. carbon capture technologies, deep geothermal power plants, or power to X technologies) [85]. The uncertainty associated with these technologies is reasonably high and therefore needs to be considered carefully. The presented results indicate that 65% of articles did not indicate that they considered this uncertainty. The remaining studies applied different methods such as sensitivity analysis or Monte Carlo simulations to account for this issue. Apart from this, a broader availability of data could significantly increase the validity of the models, as the used parameters would be much more comparable, and modelers would not have to rely on individual data sources [86]. Modelers might also be able to address this uncertainty by using conservative predictions, apply sensitivity analyses, use the latest available data, and update their models accordingly to strengthen their results [87]. The use of exogenous cost curves also introduces significant uncertainties and might lead to an underestimation of a technology's potential. In these cases, a smaller and more focused model could be key to explore the potential of technologies and their role in future energy systems [41].

Many of the analyzed studies added additional constraints to the implementation of technological learning. The most frequently used constraint is the application of growth rates, which limit capacity expansion either based on absolute values or depending on the commissioning in prior periods. While this approach is widely used and validated in previous literature [88,89], there are also publications that reveal the dangers of careless use of growth rates [41,90]. In the past, the potential of solar energy was frequently underestimated. For example, PV deployment exceeded the expected maximal growth rates, and models failed to predict the role of solar PV within the energy system [90]. Whenever these constraints are utilized, modelers should carefully consider if and how growth rates are affected by additional factors such as advancements in skills, supply chains, or technology legitimacy which may allow for higher growth rates. Modelers should also check whether the growth rates can also be formulated based on the overall system design and not solely on the capacity development of one specific technology. For example, the commissioning of 10 GW of solar PV might be better achievable for a large country with good infrastructure and experience with other energy technologies than for a smaller country with less infrastructure and experience [63,89,91].

The same also holds true for the use of floor costs. Floor costs can be used to limit the marginal cost of a technology to a certain minimal value in order to avoid unrealistic low costs. Recent publications however show, that costs for solar PV have regularly fall below assumed floor costs [41]. For models using MILP formulations floor costs are endogenously following from their implementation. During the piecewise linearization the marginal costs a set to a fixed value within each segment. The marginal costs of the last segment therefore can be considered as the floor costs, as the implementation does not allow to build capacities beyond the last segment. As the definition of a bound is a necessary implication of this methodology, modelers should carefully select those bounds.

If modelers impose overly strict constraints on their models, they may inadvertently eliminate viable system designs, resulting in an insufficient exploration of the feasible solution space. Especially, methods that increase the mathematical stability of models, such as diminishing returns to scale, should only be used if they represent statistically proven correlations (e.g. diminishing returns to scale should only be used for resource-based industries) [92] and not for mathematical convenience. Modelers therefore should be careful when constraining the technological progress of technologies, especially when they are relying on expert elicitations in order to not omit feasible areas of the solution space that might include renewable energy system designs which are cheaper than the current system design [93]. This also applies for exogenous learning progress which is defined not by means of installed capacity but by the time a technology is available in a market (Moore's Law) [94]. Recent publications show that elicitations often fail to predict the future development of technologies [41,95]. Especially when constraints on growth rates or floor costs are binding, modelers should carefully consider the constraint parameters and perform sensitivity analysis in order to strengthen their results.

4.2. Consideration of parameters beyond costs

All analyzed studies consider the technology costs as the dependent variable. However, the basic concept of technological learning could also be applied to other technological properties. To the best of the authors' knowledge, this has not yet been applied in energy system optimization models. Amongst other factors, efficiency, lifetime, space requirements, and operational flexibility are affected by technological progress and should therefore be included in future research projects.

For efficiency, Weiss et al. [96] conducted a review and defined the learning rates for the specific energy consumption of several large household appliances such as washing machines and dishwashers. This learning process could be incorporated into energy system models using one of the approaches mentioned in Fig. 2. An increasing lifetime as a result of technological progress can be observed, for example, for lithium–ion batteries [97,98]. Furthermore, improvements in space requirements can be the result of new use cases for certain technologies. For example, the concept of agri-PV allows for the dual use of land for agriculture and electricity generation, thus reducing the required space [99]. Reduced space requirements can also occur as a side effect of other improvements, e.g., in efficiency, leading to a decrease in the area needed to produce the same amount of energy [100].

In addition, technological learning can also affect other technology-specific parameters. For example, as smart meters become more widespread, the system will increasingly be able to use demand-side management to increase the operational flexibility of various components. An increasing share of electric cars with vehicle-to-grid capability also contributes to increased operational flexibility by allowing storage capacity to be used for grid stabilization.

Finally, technological diffusion is not solely dependent on the manufacturing and installation of technical components, which is discussed throughout this paper, but also on numerous aspects of a greater socio-technical system [88,101]. These aspects, include various social effects such as consumer behavior, social acceptance, environmental pressure, or institutional learning [13,102]. While institutional learning might result in better regulations and thus enable a faster deployment of certain technologies, environmental pressure may lead to higher investments in research and development, which could lead to further technological improvements [13]. However, some other social factors may not be beneficial for the deployment of emerging technologies. For instance, the large-scale deployment of wind turbines might negatively affect the social acceptance and diffusion rates of the technology as house values in the proximity decrease [103] Furthermore, consumer behavior is especially important in sectors of the energy system where investment decisions are made by individuals rather than governmental institutions or companies. This applies for example to the passenger car sector, where the decision to invest in a specific type of vehicle is highly individual and not based solely on cost-effective considerations. Capturing these effects in energy system models is particularly challenging as consumer behavior depends on various uncertain factors and concepts [104].

To represent technological diffusion more realistically, researchers might include some of the presented social learning aspects into their analysis. However, as this is a computational and methodological challenge, modelers should carefully evaluate which concepts should be integrated to support policy makers in making informed decisions and effectively addressing challenges and opportunities [86].

4.3. Future research on emerging technologies

The analyzed literature of this review has predominantly explored the roles of wind and solar. Both are now well-established technologies that significantly contribute to the electricity supply in many countries [105,106]. As the EU sets political targets for net-zero emissions across all sectors [107], it becomes vital to expand the research scope beyond the power sector, to include emerging technologies in various domains. This future research is crucial for two reasons: firstly, it enables an analysis of the competition between established and emerging technologies. Secondly, it provides insights into the cost-optimal timeline of investments. For instance, addressing emissions in sectors that are challenging to decarbonize may require strategies such as direct air capture (DAC), bioenergy with carbon capture and storage (BECCS), or the use of fossil fuels in conjunction with carbon capture. Currently, these technologies are immature and their future costs and viability are uncertain [108–110]. As they compete with each other but also with other technologies that reduce emissions, it is important to model the respective technology's progress in an energy system model with a detailed technical representation [13,111]. Further studies are also needed regarding the question of whether low-emission hydrogen for sectors that are difficult to decarbonize will be provided by blue or green hydrogen [112]. In addition, there is growing interest in technologies with dispatchable energy and low emissions, such as enhanced geothermal systems [113], small modular nuclear reactors [114], and Allam Cycles with carbon capture and storage [115] for power and heat production. Similarly, advances in storage technologies, both in terms of new contenders and the evolving learning potential of existing ones, can significantly influence future energy system designs [116]. Future research on all these technologies in energy system models can not only provide information about a cost-optimal system design but can also offer political guidance, e.g., steering subsidies towards promising technological pathways.

4.4. Systematic complexity assessment

Mixed integer linear optimization problems combined with piecewise linear experience curves are the most commonly used approach to account for endogenous technological learning in energy system models. Our results show that 60% of the analyzed studies used this method in their model. Reasons for their popularity are that they are less computationally expensive than NLP approaches and, in contrast to iterative LP approaches, they still yield global optima. However, compared to conventional LPs, these models still have a massively increased model complexity, which is highly dependent on the specific implementation. Therefore, the trade-off between computational complexity and accuracy should be carefully evaluated. While the temporal and spatial resolutions in particular have been extensively studied in the literature [117,118], a far smaller number of publications has dealt with the cross-effects of varying model resolutions [119–122].

All of these studies come to the conclusion that feature resolutions must be carefully chosen given a limited complexity budget, i.e., a maximum mathematical model complexity for solving energy system models in a reasonable amount of time [123] and the decreasing marginal accuracy gains for higher resolutions, which, in turn, disproportionately increases complexity [122]. Simply put, it is not recommended to focus on a particularly high resolution of a single model feature such as temporal resolution while completely neglecting other model features – first, because they are likely relevant for an accurate solution, and second, because they may directly affect the accuracy of the highly-resolved model feature as well. For example, spatially aggregated demand profiles are smoother than spatially highly-resolved ones and may therefore seem appealing to an additional strong temporal aggregation, which is, however, misleading as the modeling errors made by spatial and temporal aggregation affect each other.

As discussed earlier, the studies on endogenous technological learning have thus far employed temporal aggregation techniques [50] and a cross-comparison of iterative LP and MILP solution strategies [38,39]. However, a large-scale sensitivity analysis of the optimal accuracy and runtime trade-off for varying numbers of investment periods, technologies considering endogenous technological learning, and linearized experience curve segments, remains a wide field of future research.

Lastly, as MILPs are solved by branch-and-bound routines that allow for aggressive pruning if good feasible starting solutions are provided. Future research could analyze the potential of warm starts (i.e. providing the solver with a feasible and, in the best case, near optimal starting point) on computational speedups for MILP-based energy system models considering endogenous technological learning. Although a number of application case-specific approaches for non-linear cost curves exist in the literature [124,125], their application to endogenous technological learning curves would open up a new field for these approaches. For example, local optima derived from an iterative linearized approach could serve as the upper bounds to a MILP formulation, which could help discard certain transformation pathways directly from the beginning.

4.5. Endogenous technological learning in integrated assessment models

Integrated Assessment Models (IAMs) commonly have a global coverage and frequently integrate technological learning into their frameworks. A wide range of articles have applied these frameworks to address the technological learning effects of one or more technologies [41,87,89,91]. However, this review focuses on bottom-up energy system models which often neglect the dynamics of technological learning, as this is difficult to integrate due to high spatial and temporal resolutions and the large diversity of considered technologies. Some challenges also apply to IAMs, such as too strict expansion rates [126], too high floor costs [41], and the absence of a comprehensive database for parameters [127]. The incorporation of technological learning into the optimization of IAMs gives rise to the same issues of increased complexity and uncertainty that have been previously discussed in the context of technological learning. Consequently, the measures presented earlier to reduce model complexity and address the associated uncertainty can also be applied to these models.

Furthermore, various literature reviews have summarized diverse implementations of technological learning in IAMs [128–131]. These reviews indicate that, unlike the studies analyzed in this review that mostly employed single-factor learning, IAMs are more likely to incorporate a wider range of technological learning [128–131]. A proportion of the studies on IAMs consider learning by searching, which links technological progress to research and development expenditures [130]. However, IAMs may not always be based on an optimization problem [130,131]. Instead, they can utilize various other methods (e.g. general equilibrium model, life cycle analysis, agent-based modeling). Incorporating these methods for modeling technological progress is often less computationally challenging and does not necessarily increase the model's complexity.

5. Conclusions

The accurate representation of technological learning in energy system models is of crucial importance for cost-optimized investment strategies. Previous predictions of technology costs and expansions have often failed because many energy system models neglect endogenous learning. Our study provides a comprehensive overview of the existing literature on endogenous technological learning in energy system models by performing a structured literature review. We present commonly used methods and concepts and provide practical information on how to implement technological learning by discussing the advantages and disadvantages of these methods. We also discuss several additional issues that are often neglected in the current literature but may be key to successful implementation. Our study highlights the crucial role of endogenous technological learning, especially for novel technologies such as carbon capture and storage, electrolysis, photovoltaics, and wind power, which often exhibit significant learning effects. Due to its computational complexity, the incorporation of technological learning requires a careful selection of appropriate methods to reduce model runtimes at constant accuracies. When using growth rates or floor costs, modelers must carefully consider how these parameters were determined to not omit feasible solution spaces. If growth rates are used, we recommend formulating them as relative growth rates (e.g., allowing only a doubling of capacity per period, but not setting a maximum capacity increase), explicitly stating whether they are binding, and, if so, performing a sensitivity analysis. Modelers might also use relative growth rates based on the already installed capacities or gross domestic product.

The inclusion of endogenous technological learning promises a more sophisticated understanding of the dynamics of energy systems and paves the way for more accurate predictions and informed decisions. Our overview presented here, together with the suggestions for complexity reduction, will enable researchers to integrate this crucial component into models and thus improve their validity and accuracy.

In the phase of energy system transformation, new technologies will play a crucial role, as they provide us with the opportunity to meet our energy needs without relying on fossil fuels. Having energy system models that accurately incorporate the technological learning of these components is key for cost-optimal policy and investment strategies.

CRediT authorship contribution statement

Johannes Behrens: Writing – review & editing, Writing – original draft, Visualization, Validation, Methodology, Investigation, Formal analysis, Data curation, Conceptualization. **Elisabeth Zeyen:** Writing – review & editing, Writing – original draft, Validation, Investigation. **Maximilian Hoffmann:** Writing – review & editing, Writing – original draft, Supervision, Data curation. **Detlef Stolten:** Writing – review & editing, Supervision, Project administration, Funding acquisition. **Jann M. Weinand:** Writing – review & editing, Writing – original draft, Validation, Supervision, Methodology, Conceptualization.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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Supplementary materials

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Data availability

Data will be made available on request.

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