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Introducing global learning in regional energy system models

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ABSTRACT

Energy system models are increasingly used to identify climate change mitigation measures. Crucially, such models require future cost estimates, which depend on both technological advancement and investments. In global models, which encompass the whole world, this can be implemented via *learning curves*. In regional models, which typically span a country or continent, it can however be challenging to reconcile global cost reductions with local investments. We propose a new approach to account for global cost developments in endogenous regional energy system models. Moreover, we show how this approach can be implemented using either a MILP formulation or discretized investment packages. Finally, we demonstrate and compare the proposed approach of implementing cost reductions to exclusively exogenous and endogenous approaches in a simple case study.

1. Introduction

Over the past 15 years, there has been a growing awareness of the anthropogenic climate change attributed to greenhouse gas emissions. Global temperatures will likely reach at least 1.5 °C above pre-industrial levels [1], but most nations have by now committed to limiting global warming to below 2.0 °C via the Paris Agreement [2]. As a concrete step towards that goal, the European Union has set its target to be net-zero emissions by 2050 [3]. Since a large fraction of the pertinent emissions come from the combustion of fossil fuels by the energy and transport sectors, fundamental changes to the energy system are required to achieve these objectives.

Realistically, energy system transformations of this magnitude must be guided by policy makers, which in turn require *energy system models* to make informed decisions. Energy system models come in many flavors and can be, *e.g.*, classified [4] as energy system optimization models (ESOMs) such as MARKAL/TIMES [5–7], MESSAGE [8], OSeMOSYS [9], and eTransport [10]; energy system simulation models (ESSMs) such as LEAP [11], NEMS [12], and PRIMES [13]; power-system /electricity-market models; and qualitative/mixed-method scenarios. Many of these models have roots in the models developed after the oil crisis in the 1970s and are now being used to plan a transition to a low-emission energy system. For more background, see *e.g.* Pfenninger et al. [4]. In this paper, we focus on ESOMs in particular, although the techniques may be appropriate for other models as well.

Energy system optimization models attempt to minimize the costs of constructing, maintaining, and operating an energy system, while satisfying the predicted societal needs: transport, heating, electricity, *etc*. Consequently, they can help identify realistic pathways to a zero-emission energy system [14], evaluate different technologies that satisfy the same societal needs [15], restructure the energy system into suitable regions [16], and not least, suggest cost-optimal strategies to achieve all these goals. Moreover, a *regional* energy system model is generally required to determine which technology investments are cost-effective within a geographical region, as different regions will have different natural resources, different industrial needs, and different existing infrastructure.

Based on the time scales proposed in current international treaties, modeling the full transition to a zero-emission energy system requires a model that spans decades. However, the costs of the energy system components are expected to change drastically on this time scale. One of the main factors behind this cost development is *technological learning*, which describes how, *e.g.*, a production process becomes increasingly optimized as more units are produced and deployed. To provide useful predictions, these *learning effects* must be accounted for. For example, the goal of an ESOM is to minimize costs. However, this requires an estimate of the cost, which for large-scale models requires a model for the cost reductions due to technological learning. Many scenarios of interest in energy systems analysis, such as the potential costs of flawed regulation or a lack of international coordination, may also yield different outcomes when learning effects are properly accounted for. For a recent review covering applications of learning effects in energy system models, see *e.g.* Ouassou et al. [17].

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List of notation

Sets

N	Investment periods with index $n \in N$
L	Line segments for piecewise linear implementation of cost reduction with index $l \in L$
P	Investment packages with index $p \in P$

Latin variables

x	Cumulative invested capacity
$x_{\text{inv},p}$	Capacity of investment package p
C	Unit costs
t	Time
y	Cumulative investment costs
$y_{\text{pre},n}$	Cumulative investment cost in investment period n with a total investment of x_{n-1}

Greek variables

α	Fraction of initial cost that experiences global learning
$\rho_{n,l}$	Binary variable for the piecewise linear approximation to assign a capacity to a given segment

Parameters

b	Exponential coefficient, calculated from the learning rate
LR	Learning rate
$X_{\text{lo},l}$	Lower cumulative capacity for a given line segment l
$X_{\text{up},l}$	Upper cumulative capacity for a given line segment l
$Y_{\text{lo},l}$	Lower cumulative investment cost for a line segment l
$Y_{\text{up},l}$	Upper cumulative investment cost for a line segment l
Slope_l	Cumulative investment cost slope for a line segment l

Subscripts

i	Inside the investigated model area
o	Outside the investigated model area, *i.e.*, exogenous input
0	Initial installed capacity and cost
s	Cumulative installed capacity at the start of an investment period, i.e. before purchasing new investment packages
f	Final installed installed capacity for an investment period, i.e. including investment packages purchased in that period

There are two ways to include cost developments due to learning effects in an energy system model [18]: *exogenous learning*, where the cost development over time is a predefined input to the model [19]; and *endogenous learning*, where the costs are dynamically updated as functions of the investments made by the model [20]. In the second approach, the final cost of a technology is notably an *output* from the model. In this paper, we focus on the latter, specifically via the concept of *learning-by-doing* [21]. Learning-by-doing was originally observed by Wright [22]; although only one of several known mechanism for technological learning [23], it is often the only one modeled [17,18,24]. Mathematically, such *one-factor learning curves* are formulated as follows [25]:

$$C(x) = C_0 \left(\frac{x}{x_0}\right)^b \tag{1}$$

Here, $C(x)$ corresponds to the capital costs of one unit after a cumulative capacity x has been installed, while C_0 is a reference cost at an installed capacity x_0. This equation is often parametrized in terms of a conventional *learning rate* $\text{LR} = 1 - 2^b$. In a full-scale energy system model, each relevant technology would be described by at least one such learning curve, where the learning rates are empirically determined by curve-fitting historical data.

Technologies are in general produced and deployed on a global scale. As an example, the deployment of renewable energy like wind power or photovoltaics is global with a large increase in recent years in Asia [26]. However, as discussed briefly above, most energy system models are regional. This causes difficulties in including learning effects stemming from regions outside the bounds of the energy system model. There are three main approaches to this problem, as discussed below.

The first approach is to ignore global capacity expansions, *i.e.*, to use a purely regional endogenous model. One example of such a model would be US EIA's National Energy Modeling System (NEMS) [12,27]. This approach may be acceptable for some scenarios (*e.g.*, forecasting local installation costs); but for many technologies, global learning effects can be expected to be as significant as local learning, which implies that this approach risks drastically overestimating future costs. In addition to the issues with applying endogenous learning models in a regional model specifically, their application to energy system modeling in general has been criticized in the literature; see *e.g.* Nordhaus [28]. This necessitates a careful analysis of the data and assumptions used for their implementation, as discussed in more depth by, *e.g.*, Samadi [29].

The second approach is to model the entire world, which avoids the problem by directly calculating global cost reductions. An example of this approach is CSIRO's Global And Local Learning Model (GALLM) [30]. They divide the world into three regions: AU (Australia), DV (developed world), and LD (less developed world). Technologies of interest are then grouped based on whether they primarily experience local learning (*e.g.*, PV BOS) or global learning (*e.g.*, PV modules). The former category is modeled using separate learning curves per region, while the latter category is modeled using a global learning curve. While this is clearly the most rigorous solution to the problem, it also significantly increases the computational effort and data requirements compared to the first approach discussed above. Moreover, as there is always a trade-off between model complexities along different dimensions for fixed modeling resources, this approach may require a reduced accuracy along other axes to make the optimization problem numerically tractable. Examples of other relevant dimensions one may need to sacrifice to implement this approach are the number of investment alternatives, the geographical and temporal resolutions, and the level of detail in energy infrastructure models (*e.g.*, for energy transmission and storage).

The third approach is to model only the region of interest fully endogenously and approximate the effects of global learning. Capacity expansions outside the region of interest are then estimated based on existing global models—either directly, or *via* references like the World Energy Outlook [31] or the Energy Technology Perspectives [32]. One may then use various mathematical approximations to subsume these global effects into the regional model. This provides an accuracy that is intermediate between the two conventional approaches above, while retaining the comparatively low computational requirements of the first approach. *This is the approach that we focus on in the present paper.*

One such strategy is to downscale the global capacity expansions to the modeled region, and use this to adjust the learning rates employed in the regional endogenous energy system model, as was performed by Heuberger et al. [25]. Note that in their model, they assume that the current ratio between capacity installed in the UK and globally will remain constant throughout the modeled time period. As the UK is a developed economy, this approach may lead to an overestimation of the learning rate for the UK as the scaling increases the learning rate. Hence, it corresponds to an optimistic scenario with respect to future cost reductions, as pointed out by the authors. The increased learning rate may result in an early investment in technologies in the chosen region resulting in an overestimation of the impact of global cost reductions. This overestimation can be caused by the model assuming implicitly that a certain capacity increase outside the investigated area is happening simultaneously. This may however not be the case. The approach can be further expanded with adjustments of the learning rates as a function of time due to a reduced share of capacity investments in the investigated region over time. This is similar to the approach reported by Handayani et al. [33].

Another uncertainty arises in this approach that certain aspects of cost reductions are associated to a regional and not a global effect. One example is the construction of wind turbines. Here, the foundation, the tower and the blades may have regional learning effects due to the transport costs and bulkiness of the components, while the turbine and gearbox may be more affected by global cost reductions. Correspondingly, it can be raised that utilizing endogenous learning effects does not deliver what it promises with respect to improved estimates of future costs, and hence, robustness of the model results. This concept is touched by Louwen, Schreiber [18], but unfortunately, no details regarding the implementation in an energy system model with time-depending global data was provided.

We propose a new methodology for approximating global learning effects in regional energy system models, which addresses some shortcomings of the previous implementations. Our approach treats the region of interest purely endogenously and the rest of the world purely exogenously, and we formulate a mathematical and numerical strategy to consolidate these two learning models into a hybrid model that is appropriate for regional learning model applications. Notably, this strategy could be used to retrofit existing regional energy system models with a learning model that accounts for both local and global learning effects—without requiring the implementation of a global energy system model.

The paper is structured as follows. Section 2 will present a generalized framework for the inclusion of global effects in a regional energy system model with a focus on the differentiation between learning caused by global and regional effects. Section 3 extends the concepts of learning-by-doing to a discrete investment model where the investments are bundled into packages. Section 4 illustrates the results with a small case study and compares them with purely endogenous and exogenous cost reductions. Section 5 discusses the inclusion of global effects in a regional model, how the approaches for including global effects differ, and what that the inclusion of global learning effects can imply for policies.

2. Implementing global learning with continuous investments

2.1. Combining endogenous and exogenous cost reductions

When employing a regional energy system model, it is possible to treat the regional learning effects endogenously. However, global learning effects should be exogenously defined as they are independent of the model results. Thus, combining regional and global effects into a regional energy system model results in a hybrid approach where both exogenous and endogenous cost reductions are present. In that respect, the capacities x and x_0 in Eq. (1) can be disaggregated as

$$\begin{aligned} x &= x_{\mathrm{o}} + x_{\mathrm{i}} \\ x_0 &= x_{\mathrm{o},0} + x_{\mathrm{i},0} \end{aligned} \tag{2}$$

in which the subscripts i and o correspond to capacity expansions inside and outside the investigated area. Consequently, the cost $C(x)$ is no longer a function of only the installed capacity x, but also a function of time, as is the case for exogenous cost developments. Eq. (1) can be then modified to

$$C(t) = C_0\left(\frac{x_{\mathrm{o}}(t) + x_{\mathrm{i}}(t)}{x_{0,\mathrm{o}} + x_{0,\mathrm{i}}}\right)^b \tag{3}$$

Hereby, $x_{\mathrm{o}}(t)$ is provided entirely exogenously to the model, while $x_{\mathrm{i}}(t)$ is a result of the model. Hence, it is necessary to obtain capacity expansion numbers for the regions of the world not considered in the energy system model. These can in general be obtained from global reports like World Energy Outlook [31] or the Energy Technology Perspectives [32]. As most energy system models utilize an approach using two different horizons, one for investments and one operational, time will normally not be modeled as a continuous variable. Instead, an integer variable is utilized, reducing Eq. (3) to

$$C_n(x_{n,\mathrm{i}}, x_{n,\mathrm{o}}) = C_0\left(\frac{x_{n,\mathrm{o}} + x_{n,\mathrm{i}}}{x_{0,\mathrm{o}} + x_{0,\mathrm{i}}}\right)^b \tag{4}$$

in which the index n corresponds to the n^{th} investment period. Note that the cost is in this representation both a function of the investment period n and the total installed capacity in all areas $x_{n,\mathrm{o}} + x_{n,\mathrm{i}}$. In practice, $x_{n,\mathrm{o}}$ is given exogenously to the model while $x_{n,\mathrm{i}}$ is an endogenous variable.

2.2. Inclusion of exclusive regional cost reductions

The advantage of the hybrid approach suggested in section 2.1 is the possibility to differentiate between factors affected by global capacity expansion (*e.g.*, battery cells or solar PV modules) and factors affected solely by regional capacity expansion (*e.g.*, construction or balance of plant). Although current implementations of endogenous cost reductions allow a differentiation in components with different learning rates using the concept of *composite learning curves* [34], the proposed approach allows to combine said exclusive local factors with global effects. To this end, we can extend Eq. (4) using composite learning curves to differentiate between the regional and global effects:

$$C_n(x_{n,\mathrm{i}}, x_{n,\mathrm{o}}) = \quad C_0\left[\alpha\left(\frac{x_{n,\mathrm{o}} + x_{n,\mathrm{i}}}{x_{0,\mathrm{o}} + x_{0,\mathrm{i}}}\right)^{b_{\mathrm{o}}} + (1-\alpha)\left(\frac{x_{n,\mathrm{i}}}{x_{0,\mathrm{i}}}\right)^{b_{\mathrm{i}}}\right] \tag{5}$$

Here, the total cost is divided into a fraction α that experiences global learning and a fraction $1-\alpha$ where only regional learning occurs. Fig. 1 illustrates this concept for capacity expansion of solar PV using the concept of iso-cost curves in which the investigated region is Europe. That is, each line corresponds to a constant curve in €/kW as shown on the lines. As we can see in subplot a), if we neglect regional learning ($\alpha = 1$), then there is not much to gain to include endogenous learning in the energy system model as the cost is dominated by the global investments. There is only a small benefit for investing in 2020–2025, as can be seen by the falling lines corresponding to cheaper investments in Europe at high invested capacities. In later investment periods, this benefit is reduced due to the large investments outside the investigated area as can be seen by the flatter (less steep) iso-cost curves. If we however assume that roughly half the cost comes from the balance of system, which is suggested to experience regional learning [35] ($\alpha = 0.5$, subplot b), then we can directly see the impact of global *vs.* regional learning: each contour curve now decreases significantly as a function of the European installed capacity, highlighting the importance of endogenous learning in the model. This is especially pronounced for high installed capacities in Europe as a significant fraction of the initial capital costs only experiences regional learning. The kinks in the contour plot are caused by the linear interpolation for the years not reported, resulting in non-continuous derivatives at the reported years. Furthermore, the overall cost reductions are reduced compared to the case with only global learning, as the balance of system costs are only affected by regional capacity expansion, hence reducing the number of doublings experienced by the system.

2.3. Implementation in energy system models

When modeling energy systems using Eq. (5), one challenge is how to handle the exogenous capacity $x_{n,\mathrm{o}}$. Should one use forecasted capacity

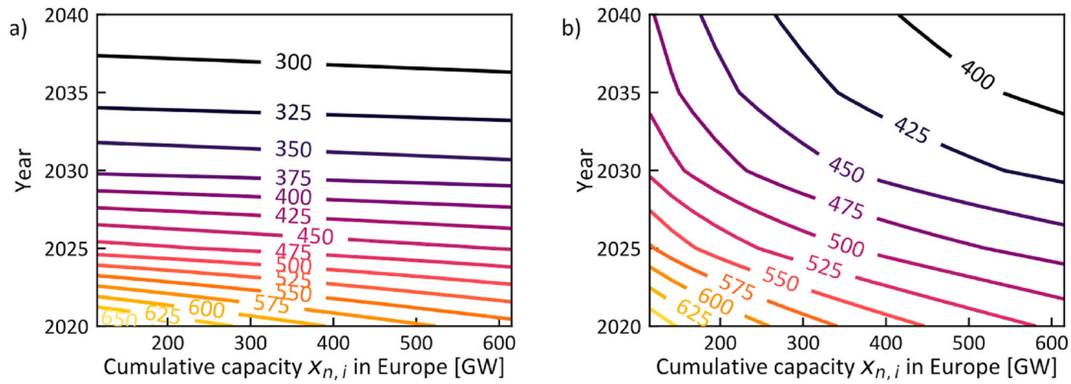

Fig. 1. Illustration of Eq. (5) using iso-cost curves (in €/kW) as a function of investment year and cumulative installed capacity in Europe. The data for the global capacity expansion is taken from the Net Zero by 2050 report [36]. The assumed global learning rate is $LR_o = 20\%$ and initial cost $C_0 = 671$ €/kW based on the costs reported by the Net Zero by 2050 report [36]. Subplot a) shows $\alpha = 1$ while b) uses $\alpha = 0.5$ and $LR_i = 13\%$ corresponding to BOS.

at the beginning of period n, which may last several years, at the middle year within period n, or for the final year of n? Using values for the beginning of n implies that the costs are not affected by forecasted investments outside the investigated area within the period n. There are two main ways to address this issue:

1. Use the initial external capacity $x_{n,o}$ in the first year within the investment period n, and neglect potential cost reductions stemming from investments in later years within that period n; or
2. Include global reductions for investment costs in period n that occur due to investments within that period.

The first alternative addresses the problem through using the external capacity $x_{n,o}$ at the first year of period n. However, the invested external capacity in period n will affect the investment costs in period $n+1$. Conceptually speaking, this approach corresponds to simultaneous investment in capacities without learning between the investment within an investment period. The cost reduction through learning is then only experienced in investment period $n+1$.

The second alternative is to include the cost reductions through investments outside the investigated area within an investment period n. This can be achieved by averaging the cost with respect to the international capacity expansions within that investment period. The average cost in each period is defined as an integral of the cost,

$$\overline{C}_n(x_{n,i}) = \frac{1}{x_{n+1,o} - x_{n,o}} \int_{x_{n,o}}^{x_{n+1,o}} C_n(x_{n,i}, x_o)\, dx_o \tag{6}$$

Note that this reduces a two-argument function C_n that depends on both the endogenous capacity $x_{n,i}$ and exogenous capacity $x_{n,o}$, to a one-argument function $\overline{C}_n$ that only explicitly depends on the endogenous capacity. Formally, the exogenous contribution is still there *via* the time index n, but this reformulation of the cost curve lets us treat the problem purely endogenously *within* a given investment period n. If we now substitute in Eq. (5) and perform the integration, we find the following analytical expression for the resulting cost function:

$$\overline{C}_n(x_{n,i}) = \frac{C_0 \alpha}{a_o} \frac{x_{rel,n+1}^{a_o} - x_{rel,n}^{a_o}}{x_{rel,n+1} - x_{rel,n}} + C_0(1-\alpha)\left(\frac{x_{n,i}}{x_{0,i}}\right)^{b_i} \tag{7}$$

where we defined $a_o = b_o + 1$ and the relative total capacities $x_{rel,n} = (x_{n,o} + x_{n,i})/(x_{0,o} + x_{0,i})$, $x_{rel,n+1} = (x_{n+1,o} + x_{n,i})/(x_{0,o} + x_{0,i})$.

Fig. 2 illustrates the implementation of discrete investment periods for both alternatives. The continuous contour lines correspond to Fig. 1 b) to simplify the understanding, while the color coding remains the same for the vertical, discontinuous contour lines. The discontinuous contour lines correspond here to the learning curves within an investment period. The discontinuous contour lines will approach the continuous contour lines in the limiting case in which the length of the investment periods approaches 0. Subplot a) shows the implementation, when the used capacity from outside the investigated area corresponds

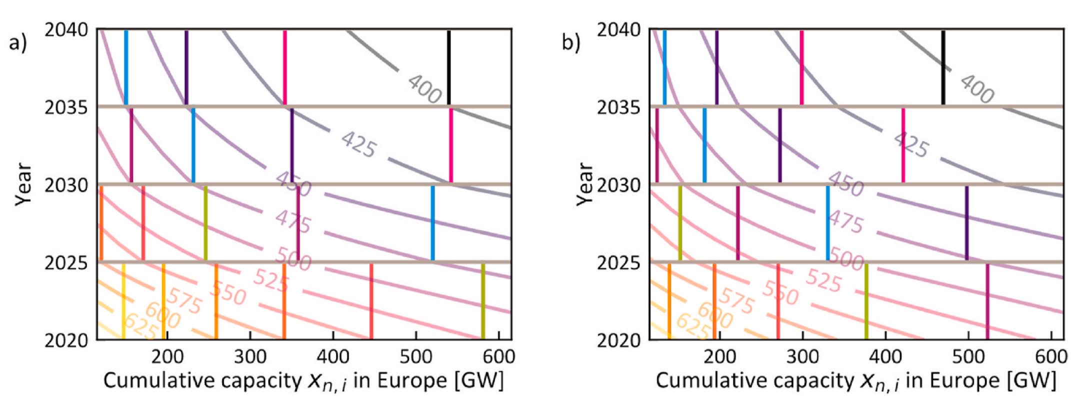

Fig. 2. Cost development using iso-cost curves (in €/kW) for an assumed constant cost in a 5 year investment period (indicated through grey boxes) as a function of the investment period and cumulative installed capacity in Europe. The vertical lines correspond to costs within an investment period when a) the initial capacity is used for calculating the impact of global capacity expansion [Eq. (5)] and b) the average price from global capacity expansion capacity is used for calculating the impact of global capacity expansion [Eq. (7)]. The vertical green line corresponds to a cost of 525 €/kW, the vertical light blue line corresponds to a cost of 475 €/kW, while the vertical pink line corresponds to a cost of 425 €/kW. The continouos contour lines in the background are the same as in Fig. 1 b).

to the initial year in the investment period using Eq. (5) for each investment period. This concept can also be verified as the vertical contour lines intersect with the continuous contour lines at the beginning of a new investment period. Subplot b) on the other hand utilizes Eq. (7) which corresponds to the average cost when considering the investments outside the investigated area through calculating the average investment cost. The vertical contour lines are in subplot b) shifted to the left and the leftmost vertical contour lines in subplot a) are not present. This is visualized for the individual years with the vertical green, light blue, and pink lines. Hence, using the average cost results in lower cost for the capacity expansion compared to using the initial cost. This is not surprising as the approach also considers cost reductions through learning outside the investigated area.

Due to the nonlinearity, learning curves are frequently implemented using piecewise linear approximations [25,37,38]. Here, it is preferred to utilize the cumulative cost instead of the unit cost to avoid a bilinear term in the cost function [25]. The inclusion of global learning effects would then result in the development of piecewise linear approximation for each investment period. Considering the implementation of Heuberger et al. [25] and based on the work of Gómez [37], we propose an extension for the inclusion of global learning. For simplification, we exclude the set *il* in our mathematical description below. This set corresponds to the technologies which experience learning effects. As we only consider technologies with learning in this approach, it is not necessary to include this index. However, that does not limit the approach to models in which all technologies experience technology learning. Furthermore, we consider investments in continuous capacity (MW) instead of number of units of a given capacity each. However, the approach could be also implemented when the model invests in units instead of capacity. Furthermore, we adjusted the notation to be consistent with the chosen notation in this paper. Fig. 3 reproduces Fig. 2b) from Heuberger et al. [25] with the adjusted notation. The cumulative capacity x_n corresponds in this representation to 10 GW, which results in line segment 3 being active. The corresponding upper and lower cumulative capacities $X_{\mathrm{up},3}$ and $X_{\mathrm{lo},3}$ as well as the cumulative costs $Y_{\mathrm{up},3}$ and $Y_{\mathrm{up},3}$ are highlighted in combination with the cumulative cost y_n.

Using the notation outlined in this paper, the implementation is then given by

$$\sum_l \rho_{n,l} = 1 \tag{8}$$

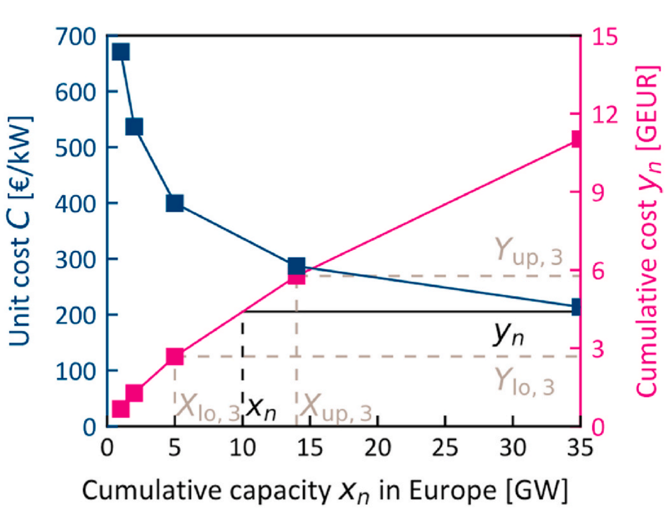

Fig. 3. Piecewise linear interpolation of the unit cost C and the cumulative cost y as a function of the cumulative capacity x, adopted from Heuberger et al. [25]. The figure also includes the breakpoints of the linear segments and highlights important parameters for line segment 3.

$$x_{n,l} \geq X_{\mathrm{lo},l}\rho_{n,l} \tag{9}$$

$$x_{n,l} \leq X_{\mathrm{up},l}\rho_{n,l} \tag{10}$$

$$x_n = \sum_l x_{n,l} \tag{11}$$

$$y_n = \sum_l \rho_{n,l}\, Y_{\mathrm{lo},l} + \mathrm{Slope}_l\left(x_{n,l} - \rho_{n,l}X_{\mathrm{lo},l}\right) \tag{12}$$

$$\mathrm{Slope}_l = \frac{Y_{\mathrm{up},l} - Y_{\mathrm{lo},l}}{X_{\mathrm{up},l} - X_{\mathrm{lo},l}} \tag{13}$$

Each line segment l generally spans multiple investment periods n, but the binary variables $\rho_{n,l}$ in Eq. (8) ensure that only one line segment l is active per investment period n. Consider Fig. 3: $\rho_{n,3} = 1$ while $\forall l \neq 3 : \rho_{n,l} = 0$. Eqs. (9) and (10) limit the capacity in each line segment to the lower and upper bound of that segment. Correspondingly, $x_{n,l} = 0$ if $\rho_{n,l} = 0$. Eq. (11) translates the cumulative capacities into the total capacity as introduced beforehand. Eq. (12) calculates the cumulated cost for all investments up to the investment period n using the slope calculated using Eq. (13). Note that the slope is a parameter, and hence, calculated beforehand. As this implementation is using the cumulative cost, that is all investments that happened up to the investment period n, it is important to subtract y_{n-1} from y_n in the cost function. Otherwise, it would not be possible to include discounting.

As can be noted from Eqs. 8–13, only the parameters describing the piecewise linear formulation are independent of the investment period. Introducing global cost reductions can hence be achieved through the introduction of time dependent parameters for describing the piecewise linear approximation, that is using, *e.g.*, $\mathrm{Slope}_{n,l}$ instead of Slope_l. However, this also requires modifications to the objective function as different piecewise linear approximations are used in the calculation of y_{n-1} and y_n. Instead, it is necessary to calculate the cumulative cost $y_{\mathrm{pre},n}$ corresponding to the cumulative investment cost in this period without any investments given by

$$y_{\mathrm{pre},n} = \sum_l \rho_{n-1,l}\, Y_{\mathrm{lo},n,l} + \mathrm{Slope}_{n,l}\left(x_{n-1,l} - \rho_{n-1,l}X_{\mathrm{lo},n,l}\right) \tag{14}$$

and subtract this value from y_n instead of y_{n-1}. One prerequisite of Eq. (14) is that the split in line segments is similar for all piecewise linear representations of the cost function. If this is not the case, it is possible to introduce further variables corresponding to the position of the cumulated installed capacity in the previous investment period $x_{n-1,l}$. Hence, constraints (8) to (10) have to be duplicated:

$$\sum_l \rho_{\mathrm{pre},n-1,l} = 1 \tag{15}$$

$$x_{\mathrm{pre},n-1,l} \geq X_{\mathrm{lo},n,l}\, \rho_{\mathrm{pre},n-1,l} \tag{16}$$

$$x_{\mathrm{pre},n-1,l} \leq X_{\mathrm{up},n,l}\, \rho_{\mathrm{pre},n-1,l} \tag{17}$$

3. A discrete approach for implementing global learning effects

3.1. General implementation of learning by doing for discrete investments

One alternative to the continuous implementation in the previous section is the implementation *via* investment packages. In this approach, operational and investment analyses are decoupled. The decoupling implies that it is possible to have a more complicated description in the operational analysis without problems associated with the computational cost. In addition, it allows non-linear, non-convex optimization problems for the investment analysis. As an example, Integrate (former name eTransport [10]) uses a (mixed-integer) linear programming approach for solving the operational problem and dynamic programming for the investment analysis [10]. To this end, it utilizes investment packages of a specific size (*e.g.*, 5 GW). Each investment package has a specific cost associated to invest into a technology. For each technology, there can exist several investment packages with a reduced cost associated to the subsequent investment package due to learning-by-doing. Integrate has a constraint implemented that avoids investment in subsequent investment packages before the initial investment packages, *e.g.*, it cannot invest in package 3 of a technology before it has invested in packages 1 and 2.

When using investment packages, learning effects can be incorporated through two different approaches:

1. The cost of an investment package p corresponds to the unit cost C_p before the investment multiplied with the size of the investment package. This approach implies that there is no learning within the package.
2. The cost of an investment package p corresponds to the average cost $\overline{C}_p$ within an investment package multiplied with the size of the investment package. Hence, learning can also occur within the package.

For a concrete example, consider a large investment in solar panels in 2020. The first option would then price every solar panel at their 2020 cost, corresponding to an instant purchase with no learning effects. This is a reasonable approach if the investment occurs on a short enough time scale (*e.g.*, 1–2 years). The second option is to assume that each solar panel purchased reduces the price of the next and include the associated learning effects into the cost estimates. This is more realistic for say a decade-long investment period that spans 2020–2030.

Let us define the capacity up until package p as $x_{p,\mathrm{s}}$, where the subscript s stands for *start*. In the first approach, Eq. (1) can be directly used with this capacity to calculate the corresponding cost C_p:

$$C_p = C_0 \left(\frac{x_{p,\mathrm{s}}}{x_0}\right)^b \tag{18}$$

However, if we choose the second approach, it is necessary to modify Eq. (18). The average cost of an investment package is calculated by integrating the traditional learning curve from the installed capacity at the beginning of an investment package, $x_{p,\mathrm{s}}$, to the end of an investment package, $x_{p,\mathrm{f}}$, and dividing it by the invested amount. This results in the following average cost $\overline{C}_p$ in an investment package p:

$$\overline{C}_p = \frac{1}{x_{p,\mathrm{f}} - x_{p,\mathrm{s}}} \int_{x_{p,\mathrm{s}}}^{x_{p,\mathrm{f}}} C_n \, dx_n = \frac{C_0}{a} \frac{\left(\frac{x_{p,\mathrm{f}}}{x_0}\right)^a - \left(\frac{x_{p,\mathrm{s}}}{x_0}\right)^a}{\left(\frac{x_{p,\mathrm{f}}}{x_0}\right) - \left(\frac{x_{p,\mathrm{s}}}{x_0}\right)} \tag{19}$$

with the helper variable $a = b + 1$. The installed capacity before and after purchasing an investment package p are then given by:

$$x_{p,\mathrm{s}} = x_0 + \sum_{k=1}^{p-1} x_{\mathrm{inv},k} \tag{20a}$$

$$x_{p,\mathrm{f}} = x_{p,\mathrm{s}} + x_{\mathrm{inv},p} \tag{20b}$$

Fig. 4 illustrates the concept of investment packages for a case study where the initial capacity x_0 corresponds to the installed solar PV capacity in Europe and 6 investment packages are applied for incorporating learning-by-doing-effects. Note that this corresponds to pure regional learning. The applied learning rate is LR = 20%. The green boxes correspond to using the initial cost C_p in each investment package, and hence, do not consider learning within an individual investment package. The blue boxes assume that each investment package is also affected by learning effects, corresponding to a reduction in the overall costs of an investment package through the utilization of an average cost $\overline{C}_p$. Neither of these two approaches considers the effect of global learning and may result in an overestimation of the learning effect in the early stage through investments into a technology in a European model.

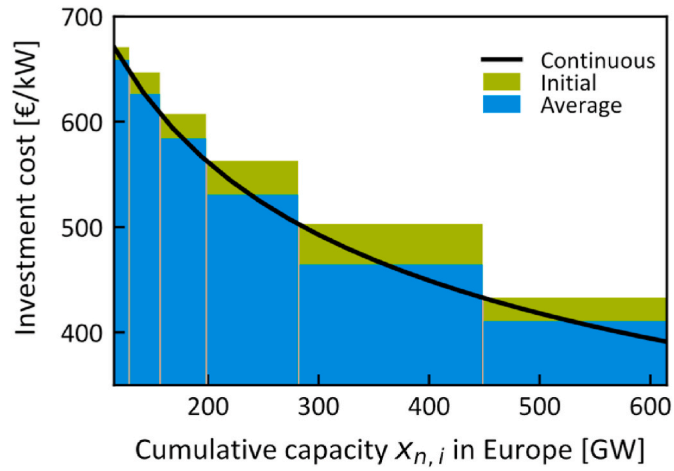

Fig. 4. Example for investment modules in Integrate for a learning rate of LR = 20% with the initial cost (green) and the average cost (light blue) used as the investment package cost. The initial cost C_0 = 671 €/kW is taken from the Net Zero by 2050 report [36] The continuous cost line illustrates the calculation of the average costs.

3.2. Inclusion of global learning effects

Global learning effects can be included in discrete investment models by making the investment package costs dependent on the investment period. This implies that if the model does not invest in a certain package in the first investment period, its price is decreased in the next period due to the learning that is happening in the rest of the world. It can be implemented using Eq. (4) and substituting $x_{n,\mathrm{i}}$ with $x_{p,\mathrm{s}}$.

$$C_{n,p} = C_0 \left(\frac{x_{n,\mathrm{o}} + x_{p,\mathrm{s}}}{x_{0,\mathrm{o}} + x_{0,\mathrm{i}}}\right)^b \tag{21}$$

It is also possible to calculate the average cost of an investment package based on the investments in Europe. This approach utilizes the same equation as in the regional learning implementation, see Eq. (19). However, for each investment period n and investment package p, both $x_{n,p,\mathrm{s}}$ and $x_{n,p,\mathrm{f}}$ include the global capacity at the start of the investment period $x_{n,p,\mathrm{s,o}}$:

$$x_{n,p,\mathrm{s}} = x_{n,p,\mathrm{s,o}} + x_{0,\mathrm{i}} + \sum_{k=1}^{p-1} x_{\mathrm{inv},k,\mathrm{i}} \tag{22a}$$

$$x_{n,p,\mathrm{f}} = x_{n,p,\mathrm{s}} + x_{\mathrm{inv},p,\mathrm{i}} \tag{22b}$$

Furthermore, it is possible to utilize the average costs occurring in the world within an investment period n. Here, $x_{n,p,\mathrm{f}}$ has to be further adjusted to account for the changes happening in the world in the investment period:

$$x_{n,p,\mathrm{f}} = x_{n,p,\mathrm{f,o}} + x_{0,\mathrm{i}} + \sum_{k=1}^{p} x_{\mathrm{inv},k,\mathrm{i}} \tag{23}$$

The latter will reduce the costs in each investment package even further.

Note that this approach can also incorporate exclusive regional cost reductions as outlined in Section 2.2. To this end, the cost function is split into two parts that can be integrated independently with different initial and end capacities:

$$\overline{C}_{n,p}(x_{n,i}) = \frac{C_0\alpha}{a_o}\frac{\left(\frac{x_{n,p,f}}{x_0}\right)^{a_o} - \left(\frac{x_{n,p,s}}{x_0}\right)^{a_o}}{\left(\frac{x_{n,p,f}}{x_0}\right) - \left(\frac{x_{n,p,s}}{x_0}\right)} + \frac{C_0(1-\alpha)}{a_i}\frac{\left(\frac{x_{p,f,i}}{x_{0,i}}\right)^{a_i} - \left(\frac{x_{p,s,i}}{x_{0,i}}\right)^{a_i}}{\left(\frac{x_{p,f,i}}{x_{0,i}}\right) - \left(\frac{x_{p,s,i}}{x_{0,i}}\right)} \tag{24}$$

with $x_0 = x_{0,o} + x_{0,i}$ and

$$x_{p,s,i} = x_{0,i} + \sum_{k=1}^{p-1} x_{inv,k,i} \tag{25a}$$

$$x_{p,f,i} = x_{p,s,i} + x_{inv,p,i} \tag{25b}$$

$x_{n,p,s}$ and $x_{n,p,f}$ are defined in Eqs. (22) and (23) and either way can be used for $x_{n,p,f}$.

The introduction of investment packages results in the cumulative installed capacities $x_{p,s,i}$ and $x_{p,f,i}$ being independent of the investment period. Fig. 5 shows the dependency of the package price as a function of both installed capacity in Europe and the investment year using the same parameters as in Fig. 2 b). It utilizes the average cost of the investment package as the continuous lines corresponding to the respective learning curves cross the investment packages in the center. In addition, it uses the average price from international investments, that is using Eq. (23) for the end capacity for the contribution from international capacity expansions. When comparing this Figure with Fig. 2 b), we can see that the costs of the investment packages in each year correspond to costs represented by the continuous description in this Figure and the vertical contour lines in Fig. 2 b). An investment algorithm is free to move both downwards (skip to next period) and to the right (purchase an investment package this period) within this plot.

4. Case study

4.1. Case study design

In a case study, we used Integrate for analyzing the impact of combining endogenous and exogenous cost reductions. To this end, we created a model with six investment packages each for onshore wind power and solar PV. In addition, there is unlimited electricity storage as well as a pre-defined demand for electricity. Fig. 6 illustrates the case study. The electricity demand and its profile is adapted from the work in the Hydrogen4EU study [14]. Hence, the investigated region corresponds to Europe. In addition, there is a node corresponding to other

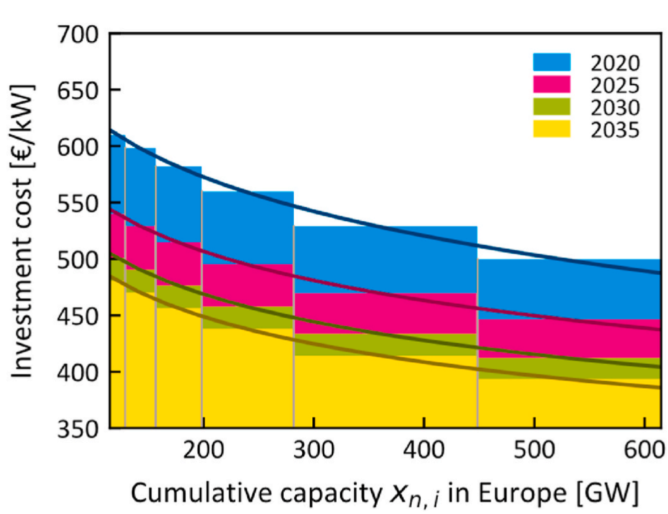

Fig. 5. Example for the development of the costs of individual investment packages. The assumed global learning rate is $LR_o = 20\%$, the initial cost $C_0 = 671$ €/kW, taken from the Net Zero by 2050 report [36], $\alpha = 0.5$, and $LR_i = 13\%$ corresponding to BOS.

power generation with a flat marginal electricity price. This “other” node is only able to satisfy 95%, 90%, 85% and 76% of the electricity demand in 2020, 2030, 2040, and 2050 respectively. Therefore, the model must invest in either onshore wind power, solar PV, or a combination of both. The chosen initial costs, learning rates, and production profiles for both onshore wind power and solar PV were also taken from the Hydrogen4EU study [14]. The total possible capacity investments for solar PV correspond to 2000 GW while for wind power they correspond to 1000 GW. With the given profiles, both capacity investments provide roughly the same amount of electricity as can be seen in Fig. 6. The distribution of total possible capacity between the six packages for each technology are given by the shares 1/36, 1/18, 1/12, 1/6, 1/3, and 1/3 respectively for package 1–6. This implies that the combined capacity of packages 1–4 equals the individual capacities if packages 5 and 6. The data for international capacity expansions for wind- and solar-power were taken from the Net Zero by 2050 report [36].

In total, three different approaches were compared:

1. purely exogenous cost reductions in which future costs are calculated using learning rates outside the model;
2. the proposed combination of exogenous and endogenous cost reductions;
3. and purely endogenous cost reductions.

The proposed approach utilized the initial global capacity for each investment period as starting point for optimization. As the aim of this case study is to highlight the differences in capacity investments depending on the chosen implementations of cost reductions, we had to scale the learning rate for both case 1 (exogenous, decrease to account for exclusive local learning) and case 3 (endogenous, increase, to account for global capacity expansions) so that the costs are comparable to case 2 (exogenous and endogenous). However, case 3 still utilizes the concept of composite learning rates for balance of system and module costs as this concept does not require the incorporation of global learning effects.

4.2. Results

The investment pathways of the three optimizations can be found in Fig. 7. From this figure, we can see that the different cost calculations result in significantly different chosen technologies, although the investment costs for the individual packages are comparable. In the exogenous case (Case 1), the model invests in wind power in the first three investment periods (2020–2040) followed by a heavy investment in solar PV in the final investment period (2050). On the opposite – using the purely endogenous approach (Case 3) results in exclusive investments in solar PV due to the higher learning rate. The proposed approach in case 2 keeps this balanced, as it invests in wind power in the first investment period (2020) and switches to investments in solar PV in the remaining investment periods.

Case 1 (only exogenous learning) can be explained by the initially high investment costs for solar PV which reduce significantly up to 2050 due to the large-scale capacity expansion outside of the modeled region. Before 2040, wind power is hence cheaper for investments. This investment pathway is typical for a model with significant decreases in costs for one technology over the simulation horizon. However, it fails to acknowledge that these cost reductions require investments in either R&D or capacity expansions where only the latter is implemented in the model. Similarly, case 3 (only endogenous learning) is not unsurprising as purely endogenous models tend to invest mostly into technologies having the highest learning rates to reduce the overall system costs. Hence, building rate constraints are frequently utilized to constrain models into more balanced solutions. This is in this case however not necessary, as the model instead chooses to invest only as much as required to satisfy the demand. Case 2 (the proposed method) however utilizes a more nuanced approach. As wind power is cheaper in 2020, it

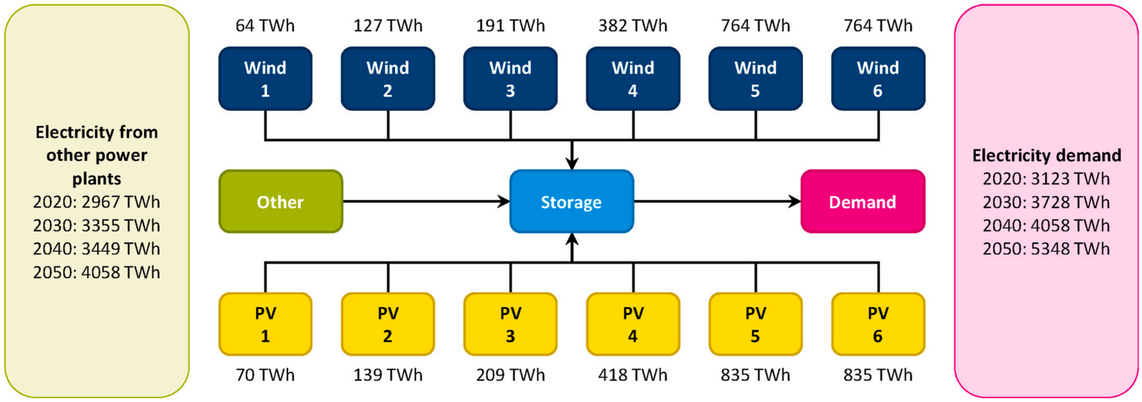

Fig. 6. Design of the simplified case study. The provided energy numbers correspond to the total energy/year that either can be provided by a given technology node or the energy demand/year.

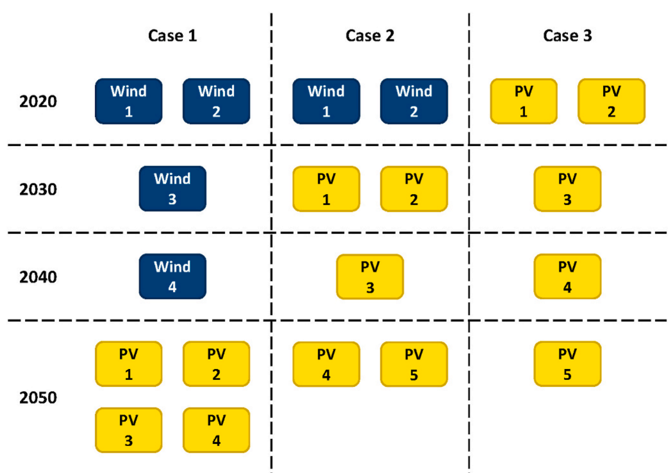

Fig. 7. Results of the simple case study showing the investments into the different packages in the three different learning models.

invests similarly to case 2. However, the cost reductions due to learning allow the model to invest in solar PV from 2030 onwards. In the context of the danger of applying endogenous cost reductions in energy system models as described by, *e.g.*, Nordhaus [28], we argue that comparing Case 2 and 3 illustrates how the proposed approach may avoid these pitfalls. As shown, including a time dependent part in the cost calculation avoids the favoring of single technologies to obtain high cost reductions.

Note, that this case study is purely illustrating the impact of the chosen strategy for calculating future costs. It neglects potential requirements of electricity storage, which would affect the chosen investment pathways.

5. Discussion

5.1. Inclusion of global learning

Global learning effects exist independently if they are included in a regional model or not. However, including global learning effects in a regional energy system model may still increase the uncertainties in the results. This is because one key input to such a model is a set of technology deployment predictions outside the investigated area, which is generally produced by another energy system model with potentially inconsistent assumptions and data. Hence, it may result in inconsistency in the results of the model. As an example, investment costs for electrolysers outside the considered area may correspond to 300 EUR/kW in 2050. If the inclusion of global effects will result in investment costs in the model area of 200 EUR/kW in 2050, we would implement a 33% reduction in investment costs compared to the source for global investments. If the investment costs in the global model would be 200 EUR/kW, it would correspondingly have a potentially larger investment in electrolysers, and hence, potentially larger investments within Europe. This is a common problem when models are linked in only one direction and could be solved by including two-way linking. However, this problem is not relevant if the global model uses endogenous cost reductions with the same learning rate assumptions.

Similarly, incorporating global learning effects into a local model assumes implicitly that there is no learning spillover from the investigated region to the global model as it uses a one-way linking. This can be considered as an extreme assumption. However, depending on the size of the investigated region, capacity investments in the investigated region may only marginally affect capacity investments outside of the investigated regions. As an example, the Net Zero by 2050 report [36] reports a weighted average of 75% for solar PV and 68% for wind power capacity expansions in *emerging markets and developing countries* while the remaining *advanced economies* correspond essentially to the OECD. In that respect, even when looking at the European Union, it may be assumed that the resulting feedback from the investigated region is small compared to the feedback from the rest of the world to the investigated region.

Another problem associated with this approach is that the implementation of piecewise linear constraints is more complex as the cost is both a function of installed capacity and time. The introduction of global effects does not necessarily increase the problem size significantly, as outlined in Sections 2.3 and 3.2, but it may increase the complexity of the problem. It can indeed be implemented with a single additional variable and constraint per technology and investment period, as shown in Section 2.3. Still, this approach may lead to a higher computational cost due to a more complex objective function. One solution to this problem is to limit inclusion of learning-by-doing effects (and global effects) to selected technologies, while continuing using exogenous costs for the remaining technologies. This would correspond to introducing subsets for which different cost descriptions are implemented. This approach is implemented in the ESO-XEL model [25] although without future cost reductions. One alternative is to use discrete investment packages as outlined in Section 3. However, then there may be still issues with a curse of dimensionality resulting in a potentially large investment problem.

One advantage of implementing global learning is the possibility to distinguish between global and regional effects. Certain factors of investment costs are mostly depending on regional cost reductions. As an example, it is suggested that the balance of system in solar PV is depending on regional effects [35], as used within the examples presented in this paper. The incorporation of regional learning may significantly affect the cost as shown in Fig. 1. Other factors that may affect regional costs are construction costs and regulations that affect the construction.

5.2. Different implementation of global investments

The combination of both exogenous and endogenous cost reductions as proposed in this paper has received little attention. To our knowledge, only Heuberger et al. [25] considered global cost reductions in the calculations of their learning rates while continuing to use Eq. (1). However, our approach differs significantly. We combined both endogenous and exogenous cost reductions instead of adjusting the learning rates for considering cost reductions from global investments. Correspondingly, the *form* of the learning curve changes as seen from the regional model. The second major difference is that there are several learning rates calculated for the piecewise linear interpolation, as highlighted in Section 2.3.

The key advantage of the proposed approach is that it avoids problems associated with scaling the learning rates. As mentioned in the introduction, scaling requires additional assumptions regarding the share of investments in the investigated area compared to the global investments. These may be based on previous data. However, using previous data may be especially problematic when modelling the future energy system of a developed economy as it is likely that developing countries will account for the majority of capacity investments in energy technologies. Furthermore, the approach of scaling implicitly assumes that the global capacity investments are occurring simultaneously with the investments in the regional model. This can be contradictory to the data source as it may result in a situation where the cost reductions would imply higher capacity investments in the world than the original data source predicts. Hence, this approach may lead to a significant overestimation of the cost reduction potential in early investment periods. Correspondingly, implementation speed constraints are crucial. Alternatively, it is necessary to iterate to adjust the fraction of investments. The proposed approach does not require any assumptions regarding the share of investments. It also allows investigating cost ranges in the different investment periods with the potential to identify overestimation of learning rates, and hence, a bias towards a technology. Furthermore, it is expected that implementation speed constraints are less crucial as the majority of the cost reductions may stem from global capacity investments.

5.3. Different options in implementation of learning-by-doing

In Section 3, we introduced 3 different approaches for quantifying the average cost for each investment package in the different investment periods:

1. The average unit cost of an investment package is calculated using the cost of the first unit in the investment package. Global capacities are included with the initial capacity at the beginning of the investment period.
2. The average unit cost of an investment package is calculated by the average cost of the units built in Europe excluding any changes in the worldwide deployment. Global capacities are included with the initial capacity at the beginning of the investment period.
3. The average unit cost of an investment package is calculated by the average cost of the sum of units built in the world and the capacity of the investment package without assuming a uniform global cost for the technology. This implies that only capacity expansions in the world are considered, while the costs are representing a regional cost.

Each approach has a different philosophy, and therefore, advantages and disadvantages. The implementation of approaches 2 and 3 in a continuous investment model was described in Section 2.3. Approach 1 could be implemented through a shift in the learning curve, if desired, to account for the omission of spillovers between investments.

The first approach can be considered as a conservative approach. It assumes that there is no learning within an investment package and the package cost is calculated using the initial costs without any capacity investments. The main reasoning for this approach is that technologies built simultaneously do not experience any cost reduction which may be based on learning in other constructions. As an example, consider the EPR nuclear reactor. There are currently constructions in Finland, France, and the United Kingdom while two units are finished in China. Utilizing approach 1 would therefore say that the learning obtained in the other construction sites do not affect the cost of a specific construction site. Any cost reductions in the construction in Finland does not affect the costs of the construction in the United Kingdom. One argument for this approach is that there may be no experience transfer with simultaneous constructions. However, it may be still feasible to reduce costs for simultaneous investments as cost reduction through improvements may be feasible, if the construction is slightly staggered.

Approach 2 assumes on the other hand, that there is a learning spillover within the investigated area for constructing technologies at the same time. Hence, the unit costs of an investment package are depending on the overall size of an investment package. This approach may be potentially useful for technologies where a lot of small-scale (kW and MW range) units are manufactured, *e.g.*, wind turbines or solar PV cells. Similarly, if the chosen length of the investment periods is rather long. Considering the cost reductions seen in both solar PV and wind power within the last 10 years, it would be surprising to assume a constant price within an investment period. Approach 2 for discrete investment packages tries to mimic the cost reductions given by the piecewise linear approach outlined in Section 2.3.

Approach 3 is an extension of approach 2. The global deployment in an investment period is taken into account when calculating an average unit price of an investment package. Again, the production of PV modules and wind turbines can be seen as an example for this approach as most of the PV modules are currently manufactured in China. That implies that the unit costs for solar modules are also depending on the unit costs in the global perspective in a given investment period. One can argue that the data sources for global capacity investments use the same investment periods as the chosen energy model. Hence, using the average cost results in an overestimation of the cost reduction through global investments. However, capacity expansions are not instantaneous as it is in general the case in energy system models. Using the average cost could then be seen as an improved approximation of the reality.

As shown in Sections 2.3 and 3.2, all approaches can be implemented in the same fashion in continuous and discrete investment models. Hence, the difference between the approaches is given through the chosen parameters. Therefore, we consider the different approaches to be complimentary and not exclusive. Due to the different nature of technologies within an energy system model, it may be therefore beneficial to combine the different approaches. Nuclear power plants as an example may not experience a learning spillover due to the long construction time, while solar PV cells will most likely experience spillover during an investment period, both from global and regional capacity investments. Consequently, we think that each approach may have its advantageous and may be beneficial in its applications.

5.4. Policy implications of learning effects

The existence of learning effects has several policy implications. Firstly, legislation, *e.g.*, on the EU-level, is typically based on systematic energy system analysis. It is therefore essential that the corresponding models include all important mechanisms, including an appropriate description of how future cost reductions are achieved through technology learning – at least when they are significant. In a global world, this requires accounting for learning stemming both from within and outside of the region, as it was shown for solar PV cost reductions through investments in Germany [39]. Secondly, private investors do not put any value on how others benefit from their investment through shared learning. As a result, the total learning typically becomes less than optimal for society in the absence of active governmental policy, *e. g.*, subsidies, support, or regulation.

6. Conclusion

In this paper, we presented a mathematical formulation for the inclusion of cost reductions through global capacity investments in a regional energy system model. Mathematically speaking, this approach corresponds to combining exogenous and endogenous cost reductions in a model. We show that the implementation is possible in both models with continuous and discrete capacity investments where the latter is represented through investment packages. The methodology may help to improve the estimation of future costs within an energy system model, and hence, increase the reliability of the results. Specifically, the inclusion of exclusive regional learning is becoming more and more important due to the change in cost distribution for technologies like solar PV and wind power. The mathematical formulations in Eqs. (7) and (24) furthermore allow the combination of purely time-dependent cost reductions with endogenous learning as the costs depend on the investment period n.

Credit author statement

Julian Straus: Conceptualization, Methodology, Software, Formal analysis, Investigation, Writing – original draft, Writing – review & editing, Visualization. Jabir Ali Ouassou: Conceptualization, Methodology, Validation, Formal analysis, Writing – original draft, Writing – review & editing. Ove Wolfgang: Conceptualization, Methodology, Software, Validation, Writing – review & editing. Gunhild Allard Reigstad: Validation, Writing – review & editing, Supervision, Project administration, Funding acquisition.

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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