Power Capacity Expansion Planning Considering Endogenous Technology Cost Learning

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Abstract

We present an power systems optimisation model for national-scale power supply capacity expansion considering endogenous technology cost reduction (ESO-XEL). The mixed-integer linear program minimises total system cost while complying with operational constraints, carbon emission targets, and ancillary service requirements. A data clustering technique and the relaxation of integer scheduling constraints is evaluated and applied to decrease the model solution time. Two cost learning curves for the different power technologies are derived: one assuming local learning effects, the other accounting for global knowledge spill-over. A piece-wise linear formulation allows the integration of the exponential learning curves into the ESO-XEL model. The model is applied to the UK power system in the time frame of 2015 to 2050. The consideration of cost learning effects moves optimal investment timings to earlier planning years and influences the competitiveness of technologies. In addition, the maximum capacity build rate parameter influences the share of power generation significantly; the possibility of rapid capacity build-up is more important for total system cost reduction by 2050 than accounting for technology cost reduction.

Keywords: power system modeling, capacity expansion planning, unit commitment, technology learning

1. Introduction

Climate change mitigation and adaptation strategies are influencing the debate in national and international politics, economies, and science. As a consequence, there is a marked increase in the number and diversity of climate and energy models developed for the analysis of future pathways. Despite inherent uncertainty in input parameters and unforeseeable events outside the typical modelling scope, such analyses have the value of being able to assess general feasibility, profitability, and effectiveness of relevant "real-world" actions. In the context of the electricity sector, assessing the implications of power technology improvement is crucial to assist a reasoned decision-making, especially when considering long time scales.

The observation of a reduction in technology cost with increased experience was first reported by Wright in 1936 for the case of aeroplane manufacturing [1]. Solow and Arrow later extended and formalised this observed trend as "learning by doing" [2, 3]. In the 1970s and 80s, Zimmerman, Joskow, Lieberman and others began studying learning effects on the cost of power plants and chemical processes [4–6].

Today the concept of technology cost reductions is embodied mathematically in the form of learning curves or experience curves, which are often used to project future technology cost trends [7–10]. Incorporating the correlation between technology deployment and cost into energy system models is an attempt to build a framework capable of evaluating whole-system effects caused by and inducing technology cost reduction.

The aim and contribution of this paper is to address the following questions: How can endogenous technology learning be integrated effectively in power system models? What is the impact on optimal capacity expansion and total system cost when considering technology learning effects? The paper is structured as follows:

Section 2: A brief discussion on technology cost reduction and an introduction to the concept of cost learning curves; a review of energy and power system models including technology cost learning effects.

Section 3: The development of a mixed-integer linear program (MILP) for cost-optimal capacity expansion of an power system considering endogenous technology learning curves as piecewise linear functions and accounting for operational detail.

Section 4: A presentation of case studies on the power system of the United Kingdom (UK) for optimal planning with and without technology cost learning; demonstration of the importance to consider cost reduction in long term system planning; an evaluation of system-wide and technology-specific effects on individual competitiveness and investment timing.

Section 5: Summary of findings and conclusions for future research.

2. Technological Learning and Cost Reduction

Three fields of research have dealt with the topic of technology cost reduction: the economic growth theory, the learning curve concept, and the innovation literature [11]. Explanations for the underlying reasons of technology cost reduction have provided different answers and insights, ranging from investment in research and development (R&D), to shared knowledge, and economies-of-scale. Although a classification is not straightforward, and effects are often correlated, we categorise the main cost reduction drivers following [12–15] in table 1.

Cost driver	Characteristics	Example
Market-push	competition, R&D investment	computer
Demand-pull	government policies, demonstration project, consumer adaptation	flue gas desulfurisation (FGD)
Process advancement	economies-of-scale, infrastructure, industry integration, components	photovoltaic (PV) panels
Technological change	functionality improvement, material, design, application	wind turbines

Table 1: Main technology cost reduction driver and their corresponding characteristics.

Market-push factors and governmental funding can result in non-incremental capacity deployment increase and abrupt cost reduction. Technologies that are being promoted by policies such as feed-in-tariffs often experience rather incremental changes in capacity additions [15]. Additionally, network effects can increase the value and rate of deployment of a technology [14]; an increased availability of the technology can be an enabler to a service, *e.g.* telephone for communication, high-voltage direct current (HVDC) cables for

power transmission. The aggregate effect of cost reductions in individual technology components, especially in the case of power stations, is known as compound learning [8, 9].

Information transfer is essential to the speed and extent of technological advancement and cost reduction. The phenomena of technology learning depends on the region of deployment. Differences in local and global technology diffusion across enterprises, industries, and countries has been studied empirically [16, 17] and within energy system models (section 2.2).

Obvious uncertainties exist in technology learning analyses. Besides the fundamental assumption that future trends can be extrapolated from historic ones, differences in data, the uniqueness of individual projects, and the fact that learning rates may change over time, are often overlooked [9, 11, 12]. The learning rate and the shape of the curve (exponential, s-shaped) can vary between different technologies [18].

Furthermore, not all technologies experience cost reduction with increasing deployment. Famously, the cost of nuclear power plants have increased due to the system complexity and more stringent safety regulations [19]. For mature technologies cost can temporarily increase if the market is short [15], or with fluctuations in commodity prices. Especially power generation technologies often experience a cost increase in the early phases of commercialisation due to difficulties in scale-up and cost underestimation based on demonstration projects or pilot plants [18]. Nemet highlights other limitations of the technology learning theory, which in the case of solar PV fails to account for factors such as module efficiency or the price of silicon [20].

A necessary and often overlooked point of discussion is how substantially a technology changes with deployment. Through manufacturing advances or disruptive scientific improvements, additional features can diversify potential applications of a technology. Depending on the significance of the technological transformation, the observed process might be considered the development of a new technology rather than improvement of an existing one. Changes in energy technology performance parameters, *e.g.*, efficiency, flexibility, or ability to provide ancillary services, should be studied alongside the effect of cost reduction. In the context of this paper, however, we focus one the effect of technological change reflected in cost reduction.

2.1. Learning Curve Model

The learning curve theory can be formalised in an exponential correlation between the unit cost, C_n (£/kW), and the cumulative capacity installed,

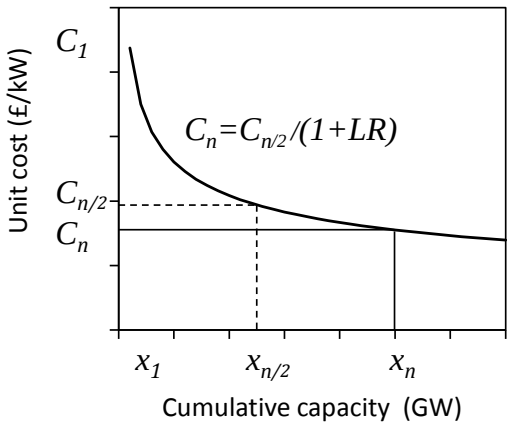

Figure 1: Illustrative cost learning curve.

x_n (kW), with the index $n \in \{1, 2..., N\}$, where $n = 1$ indicates the first-of-a-kind and $n = N$ an n$^{\text{th}}$-of-a-kind power plant. The unit cost of the n$^{\text{th}}$ capacity addition can then be determined via constraint 1. For each doubling of cumulative installed capacity the unit cost reduce by a factor LR. A schematic of a cost learning curve is visualised in figure 1. Equation 2 presents the learning rate LR as a function of the rate of cost reduction b_{LR}. The progress rate PR is defined as $1 - LR$.

$$C_n = C_1 \, x_n^{-b_{LR}} \tag{1}$$

$$LR = 1 - 2^{b_{LR}} \tag{2}$$

As an extension to this so called one-factor learning curve model, efforts have been made to include different learning effects into a similar form. The most prominent alternative is the two-factor learning curve model. This approach typically aggregates the "learning-by-doing" (b_{LR}) and "learning-by-research" effects (b_{RD}). Equation 3 outlines this approach, where in addition to the above y denotes the cumulative R&D investment and b_{RD} the rate of cost reduction due to research. Although the two-factor learning curve model promises greater accuracy and an explicit reflection of R&D driven technological advances, its application is limited due to data unavailability [18].

$$C_n = C_1 \, x_n^{-b_{LR}} \, y^{-b_{RD}} \tag{3}$$

The argument that technologies can be described as a combination of modular components which experience cost reduction individually, is the basis of the so called compound learning. Equation 4 summarises this approach by defining the unit cost of a technology as the sum of the standard cost reduction function (eqn. 1.) over all technology components i.

$$C_n = \sum_{i=1}^{I} C_{i,1}\, x_{i,n}^{-b_{LR}} \tag{4}$$

However, not all observed cost reduction trends match the exponential curve shape. In particular, technologies that are forced into the market, *e.g.*, promoted by governmental policies, show little time for cost reduction through competition [7, 21]. In these cases, costs initially reduce slowly, followed by a steeper cost decline and a final levelling out [22]. In exponential and s-shaped learning curves, there is a marked end point for cost reduction. This price floor is attained at market saturation or when the technology has reached complete maturity [21].

Rather than to provide a detailed review of learning rate data or to replicate existing reviews, we refer the interested reader to studies comparing learning rates of multiple power generation technologies by NREL [23], Rubin et al. [8, 17], Kahouli-Brahmi [24], McDonald and Schrattenholzer [25], and van der Broek [26]. Overall learning rates for energy technologies are reported to range between 3-34 % by Ferioli [9], and similarly between 9-27 % by Staffell [22], both with a mean of 20 %.

Junginger et al. report component-wise cost reduction for offshore wind farms [16, 27]; Staffell and Green study the learning of fuel cells [22]. Work on estimating future cost reduction for carbon capture and storage equipped power plants has been performed by Rubin et al. [8, 28], Knoope et al. [29], and van der Broek [30]. Cost reductions in the solar industry have been studied by van der Zwaan [31] and Nemet [20]. Matteson and Williams report learning rates for grid-scale lead acid battery [32]. The learning rate data used in this report is summarised in section 4.1, table 4.

2.2. Review of Energy System Models Including Technology Cost Learning

The ubiquitous trade-off in model building between breadth and depth has to be weighed according to the research questions asked. The integration of technological change adds to the challenge of balancing spatial, temporal, and complexity dimensions. The omission, however, of such effects in future

energy systems planning can lead to significant market failures in R&D, as Köhler et al. report [11]. Finally, Weyant et al. articulate the need to assess policy implications on technology cost learning [33].

Most models reported to date consider constant or exogenously driven cost reduction, as a time-dependent input parameter [34, 35]. However, economic causality analyses provide evidence that technological change and diffusion are indeed dependent variables [24, 36]. The endogenous consideration of technology learning effects as a function of capacity deployment requires an explicit integration of one of the learning curve models as introduced in section 2.1. Previous approaches including technology learning into large modelling frameworks have been reviewed for example by Grubb [13], Köhler [11], Seebregts [37], Gillingham [34], Kahouli-Brahmi [24], the Innovation Modeling Comparison Project [38], and the System analysis for progress and innovation in energy technologies (SAPIENT) project [39].

This paper reviews in particular energy system models based on mixed-integer linear programming (MIP) with endogenous technology learning (ETL) similar to the framework proposed in this work. To the best of our knowledge the models MESSAGE [40, 41], MARKAL-TIMES [42, 43], MERGE-ETL[1] [44, 45], NEMS [46, 47], ERIS [50], and GALLM [51, 52] fall into this category. The POLES [48, 49] model is based on partial equilibrium simulation. Due to its detailed modelling of technology learning it is included in the model comparison. Table 2 compares some salient model features with our Electricity System Optimisation - Expansion with Endogenous Technology Learning (ESO-XEL) formulation which is presented in detail in section 3. For a more extensive comparison including macroeconomic and computable general-equilibrium models (CGE) we refer to the aforementioned reviews.

[1]The Model for Evaluating the Regional and Global Effects of GHG Reduction Policies (MERGE) is now integrated into MESSAGE and therefore not listed individually in table 2.

[2]This refers to the integration of the Model for Energy Supply Strategy Alternatives and their General Environmental Impact (MESSAGE) and the MACRO model which details the energy demand side. The MERGE model with ETL function was developed by Bahn and Kypreos [44, 45] and built the basis for the MACRO model.

[3]NEMS is a large integrated model written in different programming lanuages. We here refer to the Electricity Market Module within NEMS.

[4]The costs projected by the Global And Local Learning Model (GALLM) function as input to CSIRO's Energy Sector Model (ESM) which preforms electricity generation capacity expansion based on leas-cost optimisation for 8 representative load blocks per

Name	ETL model	geographic region	time horizon / granularity	language / solver	source
MESSAGE-MACRO[2]	1F	global, 4-11 regions	1990-2011 / 5-10 yearly	C / CPLEX	[40, 41]
MARKAL-TIMES	1F	global, national, regional	2000-2110 / 4 seasons, 2 weekdays, 2 hours	GAMS / CPLEX	[42, 43]
NEMS	1F, 3 LR levels	national (US)	2000-2030 / yearly, multi-hour segments	GAMS[3] / Xpress	[46, 47]
POLES	2F	global, 57 countries	2005-2050 / yearly, 2 days, bi-houry	Vensim	[48, 49]
ERIS	1F, 2F, compound	global, 11 regions	2000-2100 / yearly	GAMS / CPLEX	[50]
GALLM[4]	1F, local, global	global, 9 regions	2010-2050 / yearly	in-house	[51–53]
ESO-XEL	1F	national + connectors	2015-2050 / 5 yearly, hourly	GAMS / CPLEX	this paper

Table 2: Comparison of energy and electricity system models with representation of endogenous technology cost learning. ETL: endogenous technology learning; 1F: one-factor learning curve; 2F: two-factor learning curve.

All models in table 2 which represent the cost reduction of technologies in one-factor learning curves apply these as piecewise linear approximations. This technique expresses a non-linear function as a convex combination of linear segments which can be integrated into an MIP framework. Depending on the degree of non-linearity, a sufficient number of linear segments is chosen to accurately represent the original function. The number of line segments increases the number of binary and continuous variables and constraints proportionally [37].

Barreto implements a dynamic segment generation such that in the early

year.

stages of capacity deployment segments are short, capturing the steep part of the curve more accurately. The segment length doubles for each following piece producing longer segments for the latter, more linear parts of the curve [54]. This approach is implemented for one-factor learning in the ERIS and MARKAL model with 6-20 segments [37, 50]. The ESO-XEL model applies 5 line segments of increasing but individual length per technology type. There is no explicit documentation on the number of line segments for the MESSAGE and NEMS model.

The NEMS model defines three distinct learning phases (revolutionary, evolutionary, conventional) with corresponding LRs of 10%, 5%, and 1%, which are rather low compared to the reported mean of LRs for all energy technologies at 20 % [9, 22]. Technologies pass through some or all of the phases according to their initial stage of development. After three doublings of cumulative installed capacity a technology moves from the revolutionary to the evolutionary phase, after five doublings it is classified as conventional. The NEMS documentation details the important choice of the starting capacity, the annual capacity growth rate, a minimum annual LR which is exogenous to the model, and a technology "optimism factor" which adjusts the initial price for "revolutionary" technologies upwards [46].

The two-factor learning curve in ERIS is modelled as non-linear program (NLP). Component-based learning can be applied to 26 different technologies, where the full cost reduction effects are aggregated from the individual component cost learnings (*e.g.*, gasifier, steam reformer, fuel cell) [50]. Also the POLES model implements the classical two-factor learning curve, accounting for R&D investment and "learning-by-doing" effects [49]. There is no information available on the number of linear segments in the POLES documentation.

3. The ESO-XEL Model Formulation

As introduced above, the ESO-XEL model is a mixed-integer linear program for cost-optimal electricity generation and storage capacity planning including endogenous treatment of technology cost learning. It builds on the model formulation presented in Heuberger et al. [55] and is extended to perform optimal capacity expansion on a national-scale while considering international electricity interconnectors.

The ESO-XEL model does not aim at being put on the same level with large-scale energy system models (a subset listed in table 2), which build

on a rich modelling history often dating back to the 1990's and which are mostly developed and maintained by multi-institutional and international research groups. The advantage of such models is their ability to cover multiple energy vectors (e.g., transport, industry, residential) from supply to end-use. However, the management of such model structures and large corresponding data sets can lead to difficulties in recognising the complex underlying effects, which for example promote the increased deployment of a power technology and evoke cost reductions.

The strength of the ESO-XEL model is to provide a transparent and flexible framework which enables us to scientifically observe interdependencies and determine the origin of whole-system effects caused by and leading to technology cost reduction. The distinguishing mark of the ESO-XEL model is its technical detail in the *operational* power plant behaviour, and high granularity in the representation of time. It simultaneously performs optimal capacity expansion in 5-yearly increments and unit commitment of the power plants on an hourly scale with a rigorous energy balance over time rather than "time slicing". A mathematically rigorous data clustering approach reduces the full hourly data sets from 8760 to 504 hours per year with a maximum deviation in results of 6.5 %. Section 4 will further expand on this point. The high time-wise granularity is essential in systems with a high penetration of power generation from intermittent renewable sources (iRES). System reliability and operability issues are decisive in system planning and can often not be addressed accurately if only a small subset of hours is considered.

We present the model formulation building on our previous work [55, 56] in section 3.2-3.7 while reviewing existing capacity expansion models without the representation of technology learning. In the relevant literature this concept is also referred to as generation expansion planning (GEP). Existing GEP models have been reviewed from both a conceptual [57] and a detailed modelling perspective [58–60]. The studies highlight two main categories of GEP models, the centralised/monopolistic and the decentralised/deregulated market view. Large centralised national-scale GEPs have been developed for example for the Greek [61] and Polish [60] power system, with a minimum time granularity of years or days. Murphy and Zou contribute modelling frameworks and case studies for GEP in imperfect markets [62, 63].

3.1. Assumptions and Simplifications

In the interest of minimising computational expense and to tackle the research questions outlined in section 1, we makes the following assumptions

in the context of the ESO-XEL model:

- We assume perfect foresight over the planning horizon.
- We take the perspective of a monopolistic system planner.
- We assume electricity demand and prices to be inelastic. Electricity demand is driven exogenously.
- Uncertainty in the input parameters is not considered. The model is deterministic.
- The national electric transmission system is represented as a single-node network. We do consider overall transmission losses.
- We assume that technological change is reflected in the capital cost of the power plant. Technology performance parameters remain exogenous.
- We assume that the learning effects for all power plants are based on global experience until today. This means that, *e.g.*, gas-fired power plants are considered to be a mature technology, and thus benefit marginally from deployment related cost reduction, whereas offshore wind power plants show significant learning potential. For future cost reduction we consider two scenarios; one based on national experience only, the second taking global knowledge spillover effects into account.
- We do not consider clustered learning where component-wise improvements impact the cost or performance of all affected technologies.

3.2. Power System Design and Expansion

The first set of constraints deals with the initial power generation and storage capacity design and the subsequent expansion, the investment and decommission plan. We refer to the nomenclature at the end of the manuscript for an explanation of the symbols. In the following all lower case symbols refer to decision variables, whereas all upper case symbols refer to parameters. Constraint 5 initiates the number of units of each technology type i for the first planning year a. In the subsequent years the number of new build units is constrained by the annual build rate BR_i multiplied by the planning time step width Δ_a in years (eqn. 6), and by the maximum capacity limitation in terms of space/availability/potential $DMax_i$ (eqn. 7).

Constraints 8-10 represent the capacity balances over the planning horizon. We differentiate between the lifetime of existing capacity stock 8 and new build units 9-10.

$$d_{i,a} = DIni_i \qquad \forall i, a = 1 \qquad (5)$$

$$b_{i,a} \leq BR_i \, \Delta_a \qquad \forall i, a > 1 \qquad (6)$$

$$d_{i,a} \leq DMax_i \qquad \forall i, a \qquad (7)$$

$$d_{i,a} = d_{i,a-1} - b_{i,a-\frac{LTIni_i}{\Delta_a}} + b_{i,a} \qquad \forall i, a \leq \frac{LTIni_i}{\Delta_a} + 1 \qquad (8)$$

$$d_{i,a} = d_{i,a-1} + b_{i,a} \qquad \forall i, \frac{LTIni_i}{\Delta_a} + 1 < a \leq \frac{LT_i}{\Delta_a} + 1 \qquad (9)$$

$$d_{i,a} = d_{i,a-1} - b_{i,a-\frac{LT_i}{\Delta_a}} + b_{i,a} \qquad \forall i, a > \frac{LT_i}{\Delta_a} + 1 \qquad (10)$$

Constraints 11-12 limit the number of power generation and storage units operating in each time period t to the installed number of units. The state variables for generation and storage technologies, $n_{ig,a,c,t}$ and $o_{is,a,c,t}$, respectively, represent the integer number of units of technology type ig or is which are operating/charging/discharging in year a at time t in time cluster c.

$$n_{ig,a,c,t} \leq d_{ig,a} \qquad \forall ig, a, c, t \qquad (11)$$

$$o_{is,a,c,t} \leq d_{is,a} \qquad \forall is, a, c, t \qquad (12)$$

3.3. System-wide Constraints

On the system-level, a range of energy and ancillary services need to be met for each planning year a and time period t. Equation 13 ensures sufficient electricity provision from generation (ig) and storage (ir) units. Unmet demand $slak_{a,c,t}$ is penalised monetarily in the objective function (eqn. 44).

$$\sum_{ig} p2d_{ig,a,c,t} + \sum_{is} s2d_{is,a,c,t} = SD_{c,t,a} \, (1 + TL) - slak_{a,c,t} \qquad \forall a, c, t \qquad (13)$$

$$\sum_{i} d_{i,a} \, Des_i \, TE_{i,Cmax} \geq PL_a \, (1 + CM) \qquad \forall a, t \qquad (14)$$

$$\sum_{ig} r_{ig,a,c,t} \, TE_{ig,RP} + \sum_{is} s2r_{is,a,c,t} \, TE_{is,RP} \geq SD_{c,t,a} \, RM + \sum_{ir} p2d_{ir,a,c,t} \, WR \qquad \forall a, c, t \qquad (15)$$

Constraints 14-15 represent reserve requirements (capacity margin CM) and regulation services as fixed (reserve margin RM) and dynamic factor balancing intermittent power output. Frequency control requirements are established by constraint 16 in form of a minimum level of system inertia[5]. System-wide annual carbon emissions are limited by SE_a (eqn. 17). The total amount of unsupplied electricity demand is limited by constraint 18.

$$\sum_{ig} n_{ig,a,c,t}\, Des_{ig}\, TE_{ig,IP} \geq SI \qquad \forall a,c,t \qquad (16)$$

$$\sum_{ig,c,t} e_{ig,a,c,t}\, WF_c \leq SE_a \qquad \forall a \qquad (17)$$

$$\sum_{c,t} slak_{a,c,t}\, WF_c \leq UD \sum_{t} SD_{c,t,a} \qquad \forall a \qquad (18)$$

3.4. Conventional and Intermittent Power Plant Operation

The operation of conventional thermal power plants ic is constrained by an upper (eqn. 19) and lower bound (eqn. 20). Power output from a generating unit is either feeds to the grid or charges a grid-connected energy storage (eqn. 21).

$$p_{ic,a,c,t} \geq n_{ic,a,c,t}\, Des_{ic}\, TE_{ic,Pmin} \qquad \forall ic,a,c,t \qquad (19)$$

$$p_{ig,a,c,t} + r_{ig,a,c,t} \leq n_{ig,a,c,t}\, Des_{ig}\, TE_{ig,Pmax} \qquad \forall ig,a,c,t \qquad (20)$$

$$p_{ig,a,c,t} = p2d_{ig,a,c,t} + p2s_{ig,a,c,t} \qquad \forall ig,a,c,t \qquad (21)$$

$$(22)$$

For the intermittent renewable power generators ir (excluding interconnectors "InterImp"), the upper (eqn. 23) and lower (eqn. 24) bound for power output is determined by the time-dependent availability factor $AV_{ir,c,t}$. Equation 25 summarised the carbon emission by generation technology.

$$p_{ir,a,c,t} \geq n_{ir,a,c,t}\, Des_{ir}\, TE_{ir,Pmin}\, AV_{ir,c,t} \qquad \forall ir^{\setminus} InterImp,a,c,t \qquad (23)$$

$$p_{ir,a,c,t} + r_{ir,a,c,t} \leq n_{ir,a,c,t}\, Des_{ir}\, AV_{ir,c,t} \qquad \forall ir^{\setminus} InterImp,a,c,t \qquad (24)$$

$$e_{ig,a,c,t} = (p_{ig,a,c,t} + r_{ig,a,c,t})\, TE_{ig,Ems} \qquad \forall ig,a,c,t \qquad (25)$$

[5]System inertia refers to the amount of kinetic energy stored in spinning generators connected to the grid which provides important frequency and voltage control services.

3.5. Up-time and Down-time Constraints

The switching behaviour of the power plants is reformulated from the typical unit-wise up-time and down-time constraints with binary variables per unit (*e.g.*, by Morales et al. [64, 65]) to integer variables per technology type. Inspired by the convex hull form presented by Takriti et al. [66], we generalise constraints 26-29 for a design problem where the number of generators is a variable itself (d_i instead of 1 in eqn. 29).

$$u_{ig,a,c,t} \geq n_{ig,a,c,t} - n_{ig,a,c,t-1} \qquad \forall ig, a, c, t \qquad (26)$$

$$w_{ig,a,c,t} \geq n_{ig,a,c,t-1} - n_{ig,a,c,t} \qquad \forall ig, a, c, t \qquad (27)$$

$$u_{ig,a,c,t} \leq n_{ig,a,c,\tau} \qquad \forall ig, a, c, \tau = t + t' - 1, t' \leq UT_{ig} \qquad (28)$$

$$w_{ig,a,c,t} \leq d_{ig,a} - n_{ig,a,c,\tau} \qquad \forall ig, a, c, \tau = t + t' - 1, t' \leq DT_{ig} \qquad (29)$$

3.6. Storage Operation

The operation of energy storage technologies is defined in constraints 30-37. The lower bound and upper bounds of service provision (electricity and revere depending on a technologies "reserve potential" $TE_{is,RP}$) are given in constraints 30-32. Equation 33 gives the initial state of charge per technology type is. The storage capacity is limited by the maximum and minimum state of charge (eqn. 34-35); grid electricity to be stored is assigned to the storage technologies (eqn. 36), maximum charging (eqn. 37), and charging and discharging electricity is balanced according to constraint 38.

$$s2d_{is,a,c,t} + s2r_{is,a,c,t} \geq o_{is,a,c,t}\, Des_{is}\, TE_{is,Pmin} \qquad \forall is, a, c, t \qquad (30)$$

$$s2d_{is,a,c,t} + s2r_{is,a,c,t} \leq o_{is,a,c,t}\, Des_{is} \qquad \forall is, a, c, t \qquad (31)$$

$$s2d_{is,a,c,t} + s2r_{is,a,c,t} \leq s_{is,a,c,t}\, SEta_{is} \qquad \forall is, a, c, t \qquad (32)$$

$$s_{is,a,c,t} = Des_{is}\, SOCIni_{is}\, SDur_{is} \qquad \forall is, a, c, t = 1 \qquad (33)$$

$$s_{is,a,c,t} \leq o_{is,a,c,t}\, Des_{is}\, SOCMax_{is}\, SDur_{is} \qquad \forall is, a, c, t \qquad (34)$$

$$s_{is,a,c,t} \geq o_{is,a,c,t}\, Des_{is}\, SOCMin_{is}\, SDur_{is} \qquad \forall is, a, c, t > SDur_{is} \qquad (35)$$

$$\sum_{ig} p2s_{ig,a,c,t} = \sum_{is} p2is_{is,a,c,t} \qquad \forall a, t \qquad (36)$$

$$p2is_{is,a,c,t} \leq o_{is,a,c,t}\, Des_{is} \qquad \forall is, a, c, t \qquad (37)$$

$$s_{is,a,c,t} = s_{is,a,c,t-1} - s2d_{is,a,c,t} + \sum_{is} p2is_{is,a,c,t}\, SEta_{is} \qquad \forall is, a, c, t > 1 \qquad (38)$$

In this version of the ESO-XEL model, the hourly time dependent input parameters are compressed into c clusters, each associated with a weighting factor WF_c. Hence, the maximum storage duration is limited by the cluster length $dim(c)$; we choose the continuous time period of 24 hours. We assume that at $t = 1$ of each cluster c the energy storages are empty. The data clustering approach is described in more detail in section 3.9.

3.7. Piecewise Linear Formulation of the Learning Curve Model

We develop a piecewise linear representation of the exponential cost learning curve as described in section 2. We follow the mixed-integer linear implementation based on Barreto [54]. The cost learning curve relates the technology unit cost to the amount of cumulative installed capacity, such that $CAPEX_i = f(d_{i,a})$. In the objective function this straightforward implementation would lead to non-linearities in $CAPEX_i \times b_{i,a}$. To avoid this problem, we convert the unit cost curve into a cumulative cost curve, such that $y_{il,a}$ represents the cumulative capacity cost of all assets of technology il in year a as visualised in figure 2.

$$\sum_{l} \rho_{il,a,l} = 1 \qquad \forall il, a \qquad (39)$$

$$xs_{il,a,l} \geq Xlo_{il,l}\, \rho_{il,a,l} \qquad \forall il, a, l \qquad (40)$$

$$xs_{il,a,l} \leq Xup_{il,l}\, \rho_{il,a,l} \qquad \forall il, a, l \qquad (41)$$

$$\sum_{a'=1}^{a} b_{il,a'} = \sum_{l} xs_{il,a,l} \qquad \forall il, a, a' \leq a \qquad (42)$$

$$y_{il,a} = \sum_{l} Ylo_{il,l} + \rho_{il,a,l} Slope_{il,l}\, (xs_{il,a,l} - Xlo_{il,l}\, \rho_{il,a,l}) \qquad \forall il, a \qquad (43)$$

Equation 39 ensures the selection of one segment, while constraints 40-42 determine the x-axis position on the segment. The breakpoints of the linear segments l are given as coordinates on the cumulative capacity versus cumulative cost curve , $Xlo_{il,l}, Xup_{il,l}, Ylo_{il,l}, Yup_{il,l}$. Via linear interpolation we then receive the cumulative cost $y_{il,a}$ by constraint 43, where $Slope_{il,l} = \frac{Yup_{il,l} - Ylo_{il,l}}{Xup_{il,l} - Xlo_{il,l}}$.

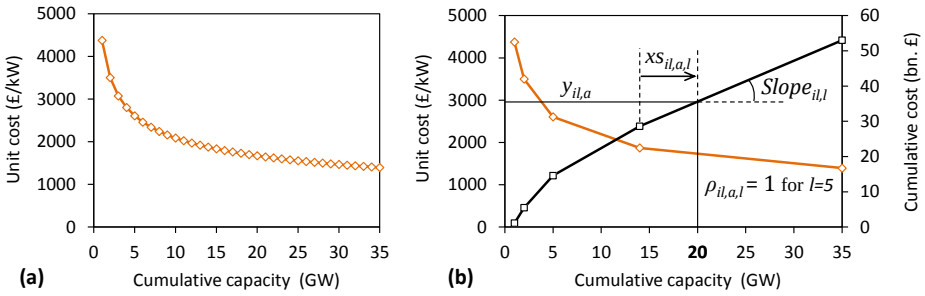

Figure 2: Illustrative technology cost learning curve as a continuous (a) and piecewise linear function (b) of cumulative capacity installed. The y-axis on the right hand side in graph (b) refers to the progressive cumulative cost curve. Symbol $y_{il,a}$ represents the unit cost of technology il in year a, which are determined via variables $xs_{il,a,l}$ and $\rho_{il,a,l}$ according to constraints 39-43.

3.8. Objective Function

We minimise the total cost of building and operating the power system over the observed time horizon. The first summand in constraint 44 represents the capital expenditures for each technology type $i \in I \backslash il$ not subject to technology cost learning, whereas the second factor adds the cost of each new build capacity increment which is modelled via the piecewise linear cost learning curve. We note that the capital expenses occur in the respective planning time step a in which the operation of the power generation or storage technology begins. The individual construction period for any new build capacity is considered monetarily via the interest during construction (IDC). The operational cost components consist of the start-up cost $OPEXSU_{ig}$, variable running cost ($OPEX_{ig,a}$ and $OPEX_{is,a}$), including fuel cost, operation and maintenance cost, carbon tax and carbon transport and storage cost where applicable, and fixed operation cost ($OPEXNL_{ig}$ and $OPEXNL_{is}$). The imported electricity is costed with the respective whole-sale market price $ImpElecPr_t$, and unmet electricity demand $slak_{a,c,t}$ is monetarily penalised with the Value of lost load[6] ($VoLL$).

[6]The so called Value of lost load is a monetary measure for the damaged caused to a society or economy by an electricity shortfall or outage. Estimated values are typically in the rage of £5,000-45,000/MWh, with a weighted average at £17,000/MWh [67, 68].

$$
\begin{aligned}
&minimise\{tsc\} \\
&tsc = \sum_{i \in I \setminus il,a} CAPEX_i \, b_{i,a} \, Des_i / Disc_a \quad + \sum_{il,a} (y_{il,a} - y_{il,a-1}) / Disc_a \\
&\quad + \sum_{ig,a,c,t} (u_{ig,a,c,t} \, OPEXSU_{ig} \, WF_c) / Disc_a \\
&\quad + \sum_{ig,a,c,t} (OPEX_{ig,a} \, p_{ig,a,c,t} \, WF_c + OPEXNL_{ig} \, n_{ig,a,c,t} \, WF_c) / Disc_a \\
&\quad + \sum_{is,a,t} (OPEX_{is,a} \, s2d_{ig,a,c,t} \, WF_c + OPEXNL_{is} \, o_{is,a,c,t} \, WF_c) / Disc_a \\
&\quad + \sum_{i=InterImp,a,t} ImpElecPr_t \, p2d_{i,a,c,t} \, WF_c / Disc_a \\
&\quad + \sum_{a,c,t} slak_{a,c,t} \, WF_c \, VoLL
\end{aligned}
\tag{44}
$$

Constraints 5-44 compose the ESO-XEL model. We refer to the Electricity System Optimisation model with capacity expansion but without technology learning (constraints 39-43) as ESO-X model.

3.9. Solution Strategies

In order to reduce the computational effort of solving the ESO-XEL MIP for each hour of the year over the course of several decades we apply two different solution strategies, individually and in conjunction:

(1) k-means data clustering, as presented in [69], with "energy-preserving" profiling
(2) relaxation of integer scheduling constraints, as shown in [70, 71].

Figure 3 visualises the k-means clustering approach. The size of a data set is reduced by matching each data point, or an array of consecutive data points, into k clusters such that the Euclidean distance between the data point and the cluster mean is minimised. For each cluster a representative profile is chosen and weighted according to the frequency of occurrence. Traditionally the cluster mean value is chosen as a representative profile. However, this can smoothen and distort the true data pattern which is particularly disadvantageous when dealing with data of intermittent renewable

energy sources, where power availability can vary starkly over short periods of time (see figure 3). To avoid this problem, we develop an "energy-preserving" profiling method, which chooses a specific profile for each cluster k such that the cluster average is preserved best. This enables us to retain the original profile's intermittency while accurately capturing the total available energy volume over the whole data set, here the course of a year.

We apply the k-means clustering and "energy-preserving" profiling to the normalised hourly data sets of annual electricity demand, onshore wind power availability, offshore wind power availability, solar availability, and the electricity import price, such that their hourly correlation is maintained.

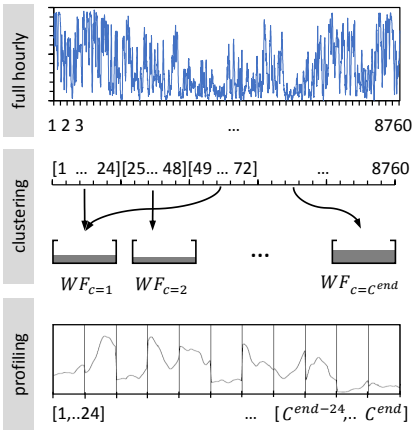

Figure 3: K-means clustering approach organising a full hourly data set into C^{end} clusters each with a length of 24 consecutive hours and a weighting factor WF_c; each cluster is then described by one representative profile. Wind and solar data is taken from Pfenninger and Staffell [72–74].

Increasing the solution speed by relaxing the integer scheduling constraints of the classic unit commitment formulation has been demonstrated successfully by Tran and Palmintier [70, 71]. In the presented formulation this is achieved by transforming the integer variables $n_{ig,a,c,t}$ and $o_{is,a,c,t}$ to continuous variables in $\mathbb{R}$. Palmintier reports a negligible sacrifice in accuracy for the objective function values from the relaxed model compared to the full MIP formulation. The presented capacity difference, however, ranges from 0-40 %, increasing in cases with a greater share of conventional power generation capacity where up- and down-time decisions matter. Wind capacity is observed to be underbuilt in the relaxed formulation, as it fails to capture the full (in)flexibility of conventional thermal power plants [71].

We conduct a detailed error analysis on the system-level and hourly operational results for the ESO-X model under the two outlined solution strategies. Table 3 presents the difference in the objective function value between the full hourly case with relaxed scheduling constraints FR and a scenario s as $\Delta_{tsc,s} = |\frac{tsc_{FR} - tsc_s}{tsc_{FR}}| \cdot 100$. The full hourly integer case FI is not tractable in solution times less than 200 hours. Hence, the error values shown for the integer clustered cases are in comparison to the full hourly relaxed model.

Scenario	8760 hours	21 cluster	11 cluster
integer	Full integer (FI) No. var.: $8.1 \cdot 10^6$ No. discrete: $1.1 \cdot 10^6$ *intractable*	$\Delta_{tsc} = -1.3$ %$^{\text{to } FR}$ No. var.: $4.5 \cdot 10^5$ No. discrete: $6.1 \cdot 10^4$ Sol. time: 3.1 h	$\Delta_{tsc} = 2.4$ %$^{\text{to } FR}$ No. var.: $2.4 \cdot 10^5$ No. discrete: $3.2 \cdot 10^4$ Sol. time: 0.78 h
relaxed	**Full relaxed (FR)** No. var.: $8.1 \cdot 10^6$ No. discrete: 240 Sol. time: 43 h	$\Delta_{tsc} = -1.7$ %$^{\text{to } FR}$ No. var.: $4.3 \cdot 10^5$ No. discrete: 240 Sol. time: 0.25 h	$\Delta_{tsc} = 2.5$ %$^{\text{to } FR}$ No. var.: $2.4 \cdot 10^5$ No. discrete: 240 Sol. time: 0.07 h

Table 3: Deviation in objective function value of scenarios deploying clustering and relaxation solution strategies from the full hourly model with relaxed scheduling constraints.

All presented results in table 3 are obtained for the ZET emission scenario, low build rates, and without technology cost learning. The clustered scenarios are solved on an Intel i7-4770 CPU, 3.4 Ghz machine with 8 GB RAM using 8 threads. The full hourly case with relaxed scheduling constraints is solved on a computer cluster composed of 32 machines with a total of 296 GB RAM (12 threads). All calculations are terminated at 3 % optimality gap. We implement the model in GAMS 24.8.3 [75] and apply the CPLEX 12.3 solver.

As outlined in table 3 the solution error in the objective function value Δ_{tsc} increases as the time dimension is reduced to 21 and 11 clusters. Accordingly, the solution time decreases significantly, such that the model version with relaxed scheduling variables and 11 clusters can be solved in less than 5 minutes. A technology-specific results, such as optimal capacity deployment, deviates on average -6 % to 0 % from the FR case. We find that CCGT power capacity is overestimated in the clustered scenarios by 8-12 %, for 11 and 21 clustered respectively. Interconnector and IGCC power capacity, however, is underestimated in the time clustered scenarios. Offshore wind

capacity deployment is underestimated by 18 % in the 21 cluster scenario, and overestimated by 2 % in the 11 cluster scenario. Remaining intermittent renewable power technologies, nuclear, and abated fossil fuel capacity expansion is determined in the clustered scenario without deviation from the full hourly model.

As the aim of this paper is the proof of the modelling concept rather than the performance of high accuracy optimal capacity expansion scenarios, we choose the 11 cluster scenario with relaxed scheduling variables for the following results.

4. Case Study on the UK Power System

The United Kingdom (UK) has enforced a legally binding carbon emission target, manifested as an 80% reduction by 2050 compared to 1990 levels [76]. This translates to a virtual decarbonisation of the UK power sector by mid-century [77]. In addition, the UK operates within the carbon emissions trading scheme and publishes short-term carbon trading values up to 2030 [78]. The baseline year for this study is chosen to be 2015. Much like today, the UK's power capacity mix was then composed of 12 % nuclear, 26 % coal, 40 % gas, 8 % wind, 2 % solar, 5 % hydro, and 7 % other types of power generating capacity [79]. The total annual power demand reached 303 TWh, with a peak of 53 GW [80].

Significant changes are expected in the capacity mix of the UK's power system. In the coming decades power station closures could amount to approximately 8.3 GW coal-fired, and 7.5 GW nuclear power plants [81]. The UK's electricity market regulator (Ofgem) argues that with supplemental balancing reserve and demand-side response mechanisms reliability standards could be maintained [82]. Nevertheless, a capacity compensation for the power plant retirements is indispensable. In the following sections we asses a cost-effective capacity expansion strategy while accounting for security of supply and environmental aspects. Demand-side management strategies, however, are beyond the scope of this study. Total electricity demand is considered to increase at 1 %/yr, in line with the average projection rate of National Grid [83].

4.1. Input Data and Scenario Definition

We consider fifteen different technology types, amounting to a total of 1722 individual power units in the first planning year of 2015. The tech-

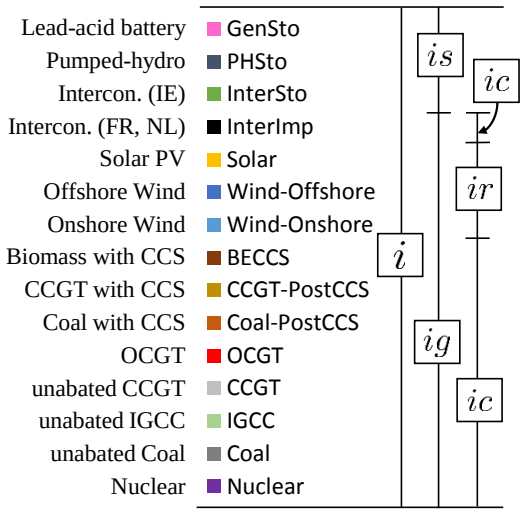

Figure 4: Technology types, corresponding acronyms, and allocation to subsets of I in ESO model formulation.

nologies are assigned to different subgroups of the set $i \in I$, according to figure 4. The existing capacity fleet has a lifetime $LTIni_i$ which is less than the lifetime LT_i of new-build capacity in years $a > 1$. The two grid-level storage technologies are lead-acid batteries at 100 MW/500 MWh (GenSto), and pumped-hydro storages at 300 MW/2.4 GWh (PHSto) per unit. Electric cross-boarder interconnectors are modelled in two ways. Firstly, as a storage system to which electricity excess can be "charged" and from which electricity can be "discharged" or imported (InterSto). This type of operation is common for the interconnectors between the British and the Irish power system. Secondly, interconnectors are modelled as a pure electricity import possibility, as it is the common mode of operation for the French and Dutch interconnector (InterImp). Projects are scheduled up to 2022 which could add up to 6.3 GW of additional interconnection capacity [84]. Wind and solar availability is based on temporally and spatially explicit simulation by Staffell and Pfenninger [73, 74], aggregated to the national level and retrieved from the online database [72].

Table 4 presents the input data relevant to the technology cost learning model. The initially installed capacity in 2015 for the UK ($DIni_i$) is complemented by the global-level values. We analyse the ESO-X model results under a low and a high capacity build rate scenario in section 4.2. Data underpinning the build rate scenarios is derived from historic capacity data

from 1980-2015 [79]. For conventional technologies (nuclear, unabated fossil fuel power plants, pumped-hydro) the historic maximum annual build rates are chosen for the high build rate scenario of this study. For renewable technologies historical values from the UK, Germany, and the Netherlands are compared [85, 86]. In Germany, solar PV capacity increased at a maximum rate of over 7 GW in 2012, and onshore wind capacity by 3.2 GW in 2002. In the UK and the Netherlands renewables power capacity types grew by less than 1 GW per annum. Anticipating an increasing effort to achieve the energy transition but remaining within the bounds of historic observations, we chose the low and high build rate values for renewables according to table 4. Little information on build rates for large-scale battery storage technologies and interconnector capacity is available. The values presented are chosen considering construction time and maturity of the technology.

The technology specific one-factor learning rates are chosen according to Rubin et al. [17]. Values are aggregated from country-specific and global learning rate estimates. The learning rate for HVDC interconnectors (InterImp and InterSto) is reported by Junginger et al. [27]; Matteson et al. quantify learning rates for large-scale lead-acid batteries [32]. The lower and upper values of learning rates shown in table 4 highlight the spread of available data and the uniqueness of learning effects in different countries and economies.

The trends for some crucial parameters are presented in figure 5. We analyse three different carbon reduction pathways: (1), a trajectory following DECC's 'reference scenario' up to 2035 and extrapolated to a zero-carbon emission target (ZET) in 2050; (2), a trajectory based on DECC's 'existing policy scenario' (ExPol) achieving an 88 % reduction of carbon emissions by 2050 compared to 2015 [90]; (3), a conservative emission target (CET) achieving a 52 % reduction in the same time frame. The carbon price is based on DECC estimates and extrapolated reaching £100/t_{CO_2} by mid-century [91]. We assume state-of-the-art efficiencies and carbon intensity values for the different power plant types rather than performance parameters of the existing capacity fleet. The full underlying data sets can be found in the supplementary documents provided.

Figure 6 illustrates the cost learning curves for the power technologies

[7] Referring to the nomenclature in the model formulation in section 3.

[8] Global capacity installed of HVDC interconnectors (InterImp and InterSto) amounteed to 195 GW in 2012 [88].

Technology	2015 capacity (GW)	Build rate (GW/year)		Learning rate (%)			Global capacity 2015 (GW)
Symbol[7]	$DIni_i$	BR_i		LR_i			-
		low	high	low	nom.	high	
Nuclear	9.6	0.6	3	-6	-1	6	385
Coal	21	0	0	6	8.3	12	1647
IGCC	0	0.25	0.5	3	9.25	16	7.6
CCGT	31.5	0.9	4.5	-1	14	34	1296
OCGT	4	0.5	0.5		15		
Coal-CCS	0	0.25	0.5	1	5.5	10	0.11
CCGT-CCS	0	0.375	0.75	2	4.5	7	0
BECCS	0	0.25	0.5	0	1.1	24	0
Wind-Onshore	10	1	2	-1	12	32	421
Wind-Offshore	5	1	2	5	12	19	12
Solar	9.5	1	3	10	23	47	200
InterImp	3	1	2		38		195[8]
InterSto	1	1	2		38		
PHSto	3	0.6	1.5		1.4		1055
GenSto	0	0.5	0.5		19		0.7
Totals	97.6	9.225	23.25		-		5,219.4

Table 4: Technology parameters related to the capacity expansion and cost learning curve model. Learning rate data can be found in [17, 27, 32], global capacity levels in [87–89].

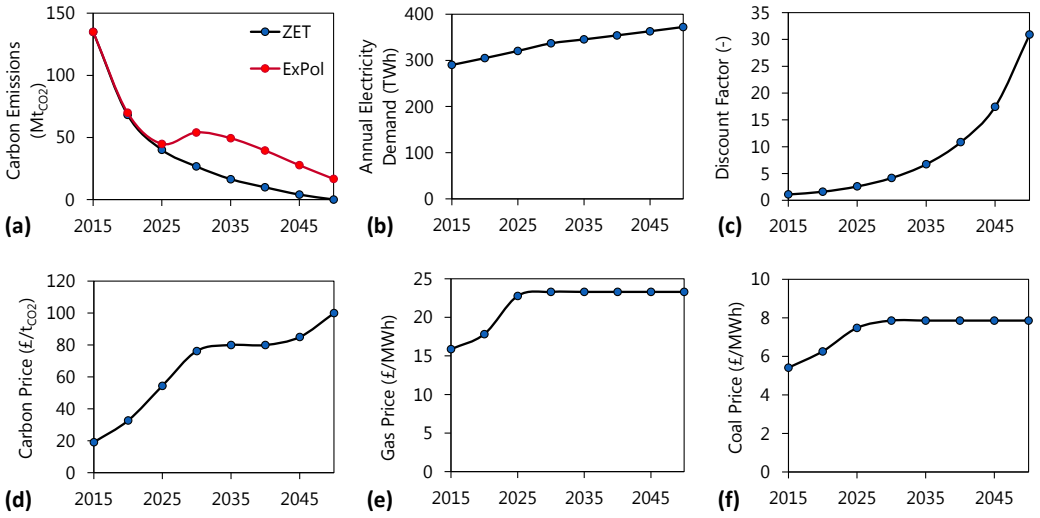

Figure 5: Input parameter trends over the planning time horizon. Scenarios in (a) refer to the zero emission target (ZET) extrapolated monotonously decreasing from 2035 in DECC's 'Reference scenario', the existing policy pathway (ExPol) extrapolated from DECC's 'Existing policy scenario' [90]. Carbon prices in (d) are reported in real 2015 values.

considered in this study. For comparison of the nominal learning rates as presented in table 4, figure 6 (a) depicts the current CAPEX values at 1 GW installed capacity experiencing a reduction for a capacity increase to 25 GW. In the context of global experience with power technologies, we present figure 6 (b) moving the learning curve starting points to the global level of installed capacity in 2015. Figure 6 (c) and (d) present two scenarios considered in this study, where the first is characterised by the assumption that only local (UK-wide) learning impacts the technology prices, whereas the latter accounts for cross-country spillover such that technology prices in the UK are affected more significantly. Based on the EIA and IEA global energy scenarios [87, 92] up to 2050 we derive a cost reduction curve for each technology according to their nominal learning rate presented in table 4. The global capacity increase is then rescaled to a UK-level applying the 2015 fraction between UK capacity and global capacity deployment per technology type. In cases where the technology is not yet deployed in the UK, the ratio is chosen such that a continuous build-up reflects current estimates for the UK capacity stock in 2050 [93]. Matching global cost reduction estimates with UK-level capacity additions leads to the optimistic learning curve scenario

in figure 6 (d). The simplification that the current scaling ratio between UK and global capacity stock remains constant until mid-century is a shortcoming of this method. Expecting a larger share of capacity additions coming from non-OECD countries, the presented global learning curves outline an optimistic scenario.

4.2. Optimal Capacity Planning without Technology Cost Learning

In order to validate the energy systems optimisation model for capacity expansion without technology cost learning (ESO-X) we present a set of scenarios examining the model's capabilities and limitations. Each scenario is defined by the choice of a time representation (full hourly, 21 clusters, 11 clusters), the scheduling formulation (integer, relaxed), the emission scenario (ZET, ExPol, CET), and the build rate (low, high). Remaining technology-specific and system-level parameters are unchanged between the scenarios. As discussed in section 3.9, the computational effort of solving the ESO-X model is significantly reduced by clustering the time sets and relaxing the scheduling constraints. The overall error incurred ranges from -1.7 % to 2.5 % for system-level results. All the following results are computed for the 11 cluster time compression and under the scheduling relaxation approach.

The feasible solution space of a scenario with a stringent emission target and a low build rate is tighter; the feasibility of such a scenario depends on the technologies available. If the full technology portfolio as listed in table 4 is accessible and capacity expansion is assumed at a low build rate the zero-emission target in 2050 (ZET) is achievable. However, we find that the same scenario is infeasible without the availability of the negative-emission technology bio-energy with carbon capture and storage (BECCS[9]). The emission target of 86 % reduction (ExPol), however, can be achieved without the deployment of BECCS technology.

We choose to present three scenarios in detail: the zero-emission target with low build rate (ZET_loBR), zero-emission target with high build rate (ZET_hiBR), and the existing policy emission reduction target with low build rate and no BECCS availability (ExPol_loBR_noBECCS). Figure 7 shows the energy output (a) and capacity stack with corresponding level of carbon intensity of total power generation (b) as a result of the ESO-X optimisation.

[9]We model a BECCS power plant combusting 25 % biomass and 75 % coal combined with a post-combustion monoethanolamine (MEA) CO_2 capture system operating at a 90 % capture rate [94].

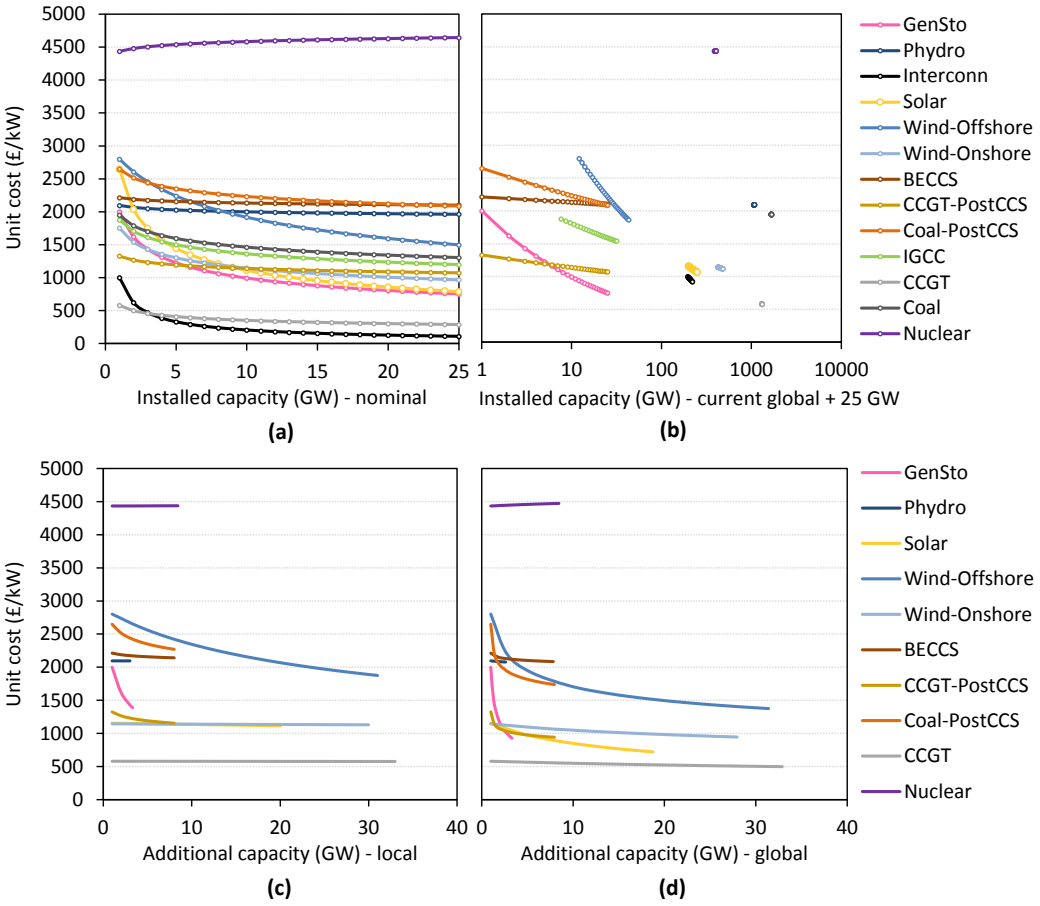

Figure 6: Learning curves for the capital cost (CAPEX) of various power technologies; (a) illustrative curve starting at today's CAPEX and applying respective learning rates over the addition of 25 GW; (b) as (a) but starting at the global level of installed capacity in 2015; (c) as (b) but shown for capacity additions up to 2050 on a UK-level [90]; (d) as (c) but accounting for global learning effects up to 2050 by considering expected global capacity additions [87, 92] converted to UK-equivalent capacity additions.

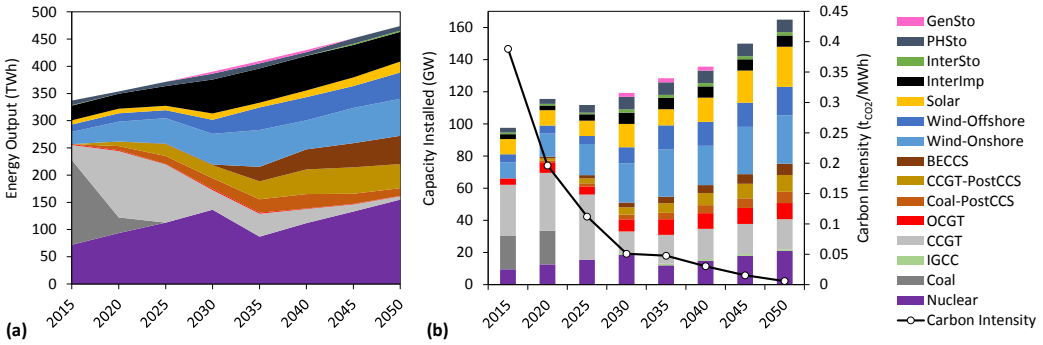

Figure 7: Energy output by technology type (a) and capacity stack (b) for the base case scenario with zero-carbon emission constraint by 2050 and without considering technology cost learning.

The largest carbon emission reductions happen in early planning years due to the switch in power generation from coal to gas. Coal capacity is scheduled to retire by 2025, accordingly power generation from coal power plants is phased out in the same time frame. The optimal mix of power generation up to 2050 involves an increase in zero-carbon nuclear and intermittent renewable power sources. In 2035, we observe a reduction in nuclear capacity and energy output due to the retirement of the existing capacity fleet from 2015. The share of electricity generation from CCS-equipped power plants increases while unabated CCGT power plants show low utilisation rates of below 26 % beyond 2035. Onshore wind proves to be the most valuable source of intermittent renewable power generation, growing at its maximum annual rate in each planning year from 2025 onwards. Large amounts of interconnection capacity are deployed which are operated to import electricity at 88 % of the time in 2050 and can be adjusted flexibly. The total capacity installed increases from 97 GW in 2015 to 165 GW in 2050, with the amount of firm capacity increasing form 73 GW to 92 GW, respectively.

The power plants' operational patterns change as we move from 2015 to a decarbonised power system. Figure 8 illustrates the hourly power output and storage charging operation for two sample days in 2015 and 2035. The annual average utilisation of nuclear power plants remains at a base load level of 85 %. The penetration of wind power increases significantly from 2015 to 2035. For the sample day on the right-hand side of figure 8 in 2035, all fossil fuel fired power plants except BECCS are shut down to accommodate wind power generation. CCS power plants run predominantly in base load

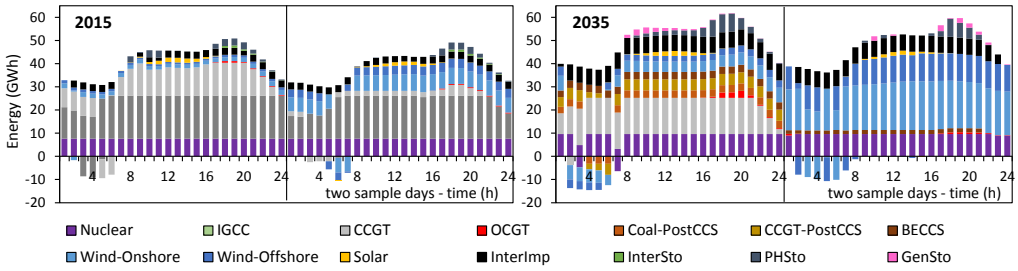

Figure 8: Power output and storage charging by technology type for the base case scenario in 2015 and 2035.

operation up to 2030/35. Thereafter, fossil fuel fired power plants are increasingly turned down and are forced to operate flexibly. BECCS utilisation rates, however, increase from 77 % in 2035 to 85 % in 2050. Being able to provide dispatchable electricity and ancillary services at zero-carbon emissions proves to be highly valuable despite operating cost exceeding those of the remaining CCS-equipped power plants. Up to 2020 the grid-level energy storage technologies are predominantly utilised to smoothen operation and reduce cycling of thermal power plants. As the share of intermittent capacity increases, onshore and offshore wind power plants charge short-term excess electricity to the storages to avoid curtailment. Their share in storage utilisation increases from 37 % to 80 %. In 2015, virtually no power generation from intermittent renewables (onshore and offshore wind, and solar) is curtailed due to supply-demand issues; in 2050, curtailment levels increase to 1 % of the intermittent power availability potential. Overall, electricity generation in 2050 is 31 % from intermittent renewables including storage operation, 25 % from CCGT and CCS-equipped power plants, 33 % from nuclear, and 11 % from imports.

Figure 9 panel (a) and (c) depict the high build rate scenario under otherwise equivalent parametrisation to the base case presented in figures 7 and 8. Since power plants can be built more quickly in this case, investment in new capacity is delayed and no substantial additions are necessary up to 2025. Nuclear capacity expansion is delayed until 2035. In the low and hight build rate scenario, the optimal starting point for the build-up of CCS-equipped power plants is in 2020. The greater degree of freedom in the annual capacity additions reveals CCGT-CCS as the more valuable CCS technology. Coal-CCS and CCGT-CCS could be deployed at the same rate, however, CCGT-CCS proves to be more cost-competitive. BECCS remains essential

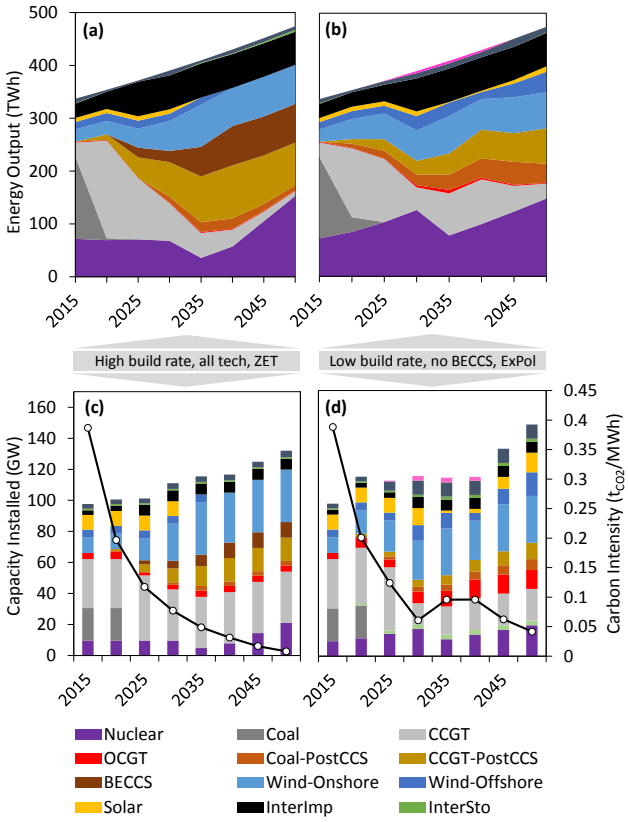

Figure 9: Energy output (a) and capacity stack (c) for the zero-emission scenario at high build rates, and (b)/(d) for the existing policy emission scenario at low build rates without the availability of bio-energy and carbon capture and storage (BECCS).

to achieve complete decarbonisation, 3 GW of additional capacity are deployed by 2050 compared to the low build rate case. Total system capacity by 2050 reaches 132 GW.

Since the zero-emission target is not achievable without carbon-negative BECCS technology, we present the case following the existing policy emission target at a low capacity build rate. Similar to the base case, CCGT, CCS, and onshore wind capacity is expanded continuously reaching the upper bound of annual capacity additions in most years. In 2050 total capacity installed amounts to 148 GW. CCGT remains a main source of power generation until 2040, whereas in the base case scenario including BECCS the utilisation of CCGT power plants plummets after 2035. As coal-CCS and CCGT-CCS power plants are able to run at higher capacity factors in 2045 and 2050,

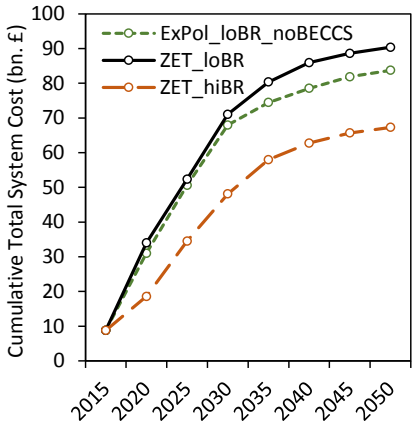

Figure 10: Comparison of cumulative total system cost as defined in equation 44) for the three scenarios shown in figure 7 and 9.

77 % and 67 % respectively, a larger amount of OCGT capacity is deployed to provide balancing and back-up capacity.

Figure 10 compares the cumulative total system cost for the three presented scenarios. As the initial power system design is predefined, the 2015 total system costs are equivalent in each scenario. The high build rate case is the least costly scenario, as capacity can be deployed effectively when it is required and can operate at high capacity factors. A level of 86 % decarbonisation without BECCS can be achieved at 7 % lower overall cost by mid-century compared to a complete decarbonisation with BECCS deployment. In both scenarios continuous expansion of low-carbon capacity increases total system cost until 2030 at a similar rate. The ensuing sections investigate how the optimal system design, operation, and cost are affected by considering technology cost learning.

4.3. Considering Cost Learning of Offshore Wind Capacity

The coastal areas surrounding the UK are among the locations with the highest potential electricity output from offshore wind power plants. However, the combination of high capital costs and low capacity factors, relative to dispatchable thermal power plants, acts to prevent the widespread deployment of this technology.

In the foregoing scenarios, offshore wind is part of the cost-optimal capacity mix in 2050 only under the low build rate assumption. Because it is a

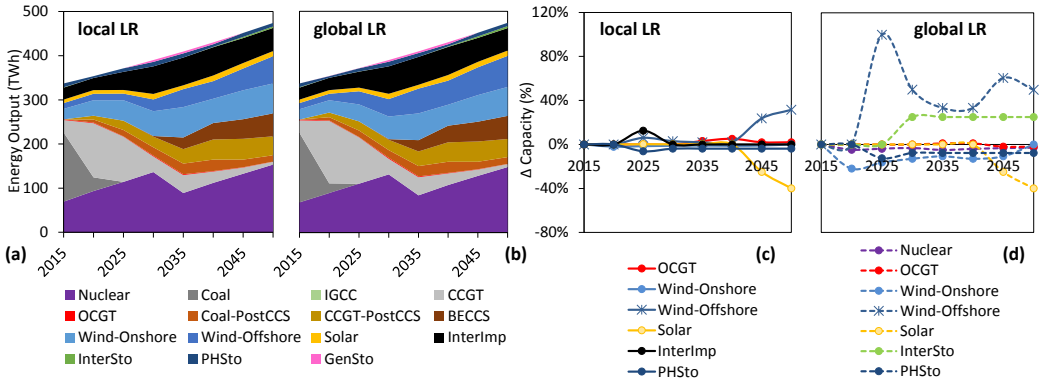

Figure 11: Share of power generation for the zero-emission scenario with low build rate and local technology cost learning for offshore wind capacity (a), and global learning (b), with LR data according to figure 6; difference in capacity installed between the base case without learning presented in figure 7 to the case with local cost learning (c) and global learning (d) of offshore wind capacity. Only technologies with a capacity deviation are shown.

low-carbon technology which does not prove to be robustly economical under the static cost assumptions, we apply the local and global cost learning curves as presented in figure 6 in section 4.1 to offshore wind capacity.

Moreover, we find that in scenarios assuming high capacity build rates, even under global cost reduction estimates offshore wind capacity expansion is not economical. Available low-carbon dispatchable sources, such as CCS-equipped coal, CCGT, and bio-energy power generators are more competitive. Figure 11 presents the power generation mix for the low build rate scenario with local (a) and global (b) learning, as well as the impact on the optimal capacity mix for the local (c) and global (d) learning case.

Offshore wind capacity deployment increases to 23.4 GW by 2050 in the local, and to 26.6 GW in global learning scenario, compared to 17.75 GW in the base case. The share of power generation increases to 13 % and 15 % respectively, compared to 10 % in the base case. The first capacity additions are profitable in 2025 as opposed to 2030 in the base case. Under local cost learning assumptions, a small amount (30 MW) is developed in 2025; under global learning assumptions, however, an additional 5 GW (a 100 % increase) are brought online in 2025. In the base case, offshore wind unit costs are £2800/kW, whereas in the global learning case after a capacity increase by 2 GW unit costs have reduced to £2458/kW, falling further to £1963/kW after 5 GW of deployment. Since, the ESO-XEL model assumes perfect fo-

resight, the anticipated cost reductions move the investment timing for the "learning" technology to earlier planning years.

System-level impacts of endogenous cost reduction of offshore wind capacity become apparent as capacity of other power technologies is displaced. Panels (c) and (d) illustrate a reduction in solar PV capacity by 40 % (15 GW vs. 25 GW in the base case) for both cost learning scenarios. In the global learning case, 25 % additional storage capacity (InterSto) is deployed, mainly being utilised by onshore and offshore wind power generators. From 2035 to 2050 grid-level storages are charged on average to 85 % by wind power. Nuclear power generation is affected marginally, however, a sufficient capacity mix with 600 MW less nuclear capacity (equivalent to one unit according to the ESO-XEL parametrisation) is achieved in the global LR case.

In addition to the optimal capacity mix, operational dispatch patterns are affected by the additional power generation from offshore wind power plants. The utilisation of CCGT-CCS power plants in 2050 falls to an average of 45 % as opposed to 50 % in the base case. In the global learning case, offshore wind power generation begins to be curtailed reaching 3 % of annual availability in 2050. Electricity is imported (InterImp) less frequently. The average utilisation falls from 88 % in the base case to 83 %; interconnectors remain an important source of electricity.

4.4. Considering Cost Learning for Multiple Technologies

We extend our analysis from a single technology to considering cost reduction for multiple technologies simultaneously. This results in a non-linear increase in computational effort following $il \times a \times l$. Hence, only technologies with measurable cost reduction relevant on a UK-scale, *i.e.*, a change >2 % over the considered capacity range, are included into the set il. The local learning curves according to figure 6 are applied to coal-CCS, CCGT-CCS, BECCS, onshore wind, offshore wind, solar PV, and battery storage under low and high build rate assumptions. Both scenarios follow the zero-emission trajectory as shown in figure 5.

In the case of low capacity build rates, illustrated in figure 12 (a), the share of power generation by mid-century and the corresponding optimal level of capacity deployment remains similar to the base case with static technology capital cost. Offshore wind capacity, however, stands out; in 2050 the amount of offshore wind capacity exceeds onshore wind (30 GW vs. 24 GW). New investments in onshore wind capacity move from 2025 to 2020, such that extensions in the following years benefit from the experience gained.

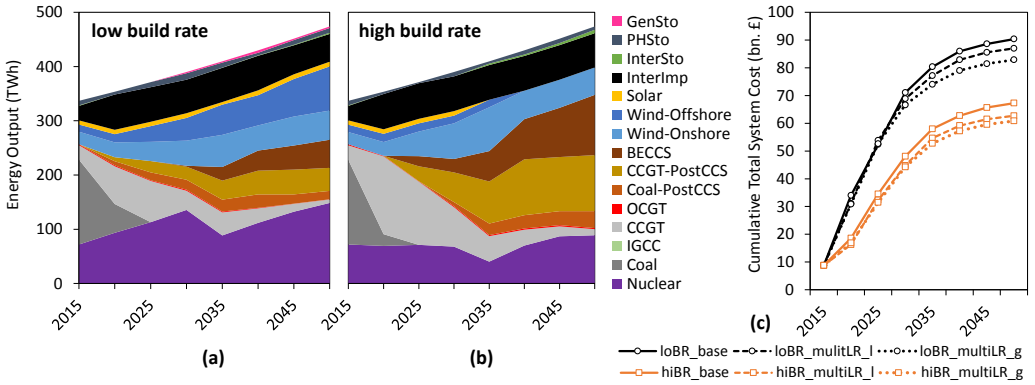

Figure 12: Energy output considering local endogenous cost reduction for coal-CCS, CCGT-CCS, BECCS, onshore wind, offshore wind, solar PV, and battery storage (GenSto) in a scenario with low build rates (a), and high build rates (b); comparison of cumulative total system cost (c).

Additional interconnector capacity (InterImp and InterSto) is developed in 2020, as opposed to 2030 in the base case, providing the system with extra resilience, although costs remain constant. Fitted with sufficient energy storage capacity in form of interconnectors and pumped-hydro, battery storage is deployed less heavily in 2025. From 2030 onwards, however, battery storage capacity is continuously expanded as the cost comes down, reaching 1.6 GW in 2050. The deployment of solar PV is not accelerated by the cost reduction potential considered here. Continuously low capacity factors in the UK means that large scale deployment is not economically viable.

Figure 12 (b) provides information on the optimal power generation mix under the high build rate scenario considering local cost learning for the mentioned technologies. In contrast to the high build rate scenario without learning (figure 9 (a)), nuclear capacity becomes less attractive while CCS-equipped power plants account for even larger shares of power generation. CCGT-CCS remains the most favourable low-carbon dispatchable source of electricity. Nevertheless, the influence of endogenous cost reduction increases the competitiveness of coal-CCS, diversifying the mix of main power producers in 2050. BECCS capacity is deployed more heavily than in the high build rate case with constant capital cost, amounting to 15 GW in 2050 (vs. 10 GW) and operating in a base load fashion. Despite the cost reduction potential, offshore wind and solar PV cannot compete against dispatchable low-carbon power generators in the high build rate scenario.

The annual cumulative cost comparison in figure 12 verifies the, perhaps intuitive, notion that overall total system cost decreases if endogenous technology cost reductions are considered. The observation that the effect of the capacity build rate per technology type on overall cost is more pronounced than the effect of technological learning is, perhaps, less intuitive. In the low build rate scenario, the optimal level of offshore wind capacity deployment is underestimated if learning effects are not recognised. Under high build rate assumptions, however, offshore wind is not part of the least-cost solution in 2050. Other technologies, such as onshore wind and BECCS, are robust against build rate variation in the presented range.

5. Conclusion

We have integrated endogenous technology cost learning into a mixed-integer linear power systems model. The technology cost learning curves are modelled in a piecewise linear fashion, relating cumulative investment cost to cumulative installed capacity. To improve model solutions times we have employed a k-means data clustering technique, and a relaxation of the integer power plant scheduling variables.

The consideration of technology cost learning impacts the optimal capacity mix, the share of power generation, and consequently the dispatch behaviour of individual power plants. In the case of offshore wind capacity, the omission of local (national) or global cost reduction effects leads to capacity estimates of 32 % or 50 %, respectively, below the optimal economic deployment level in 2050. The effects of simultaneous cost reduction assumptions for coal-CCS, CCGT-CCS, BECCS, onshore wind, offshore wind, solar PV, and battery storage vary under low and high capacity build rate scenarios. The economic deployment of offshore wind, solar PV, and battery storage units is not robust against build rate variations. All three technologies cannot compete against the low-carbon dispatchable power generators under high build rate assumptions.

We find that the model results are sensitive to both the integration of cost learning curves and the build rate parameter. The choice of the maximum build rate on the optimal capacity mix and the cumulative total system cost form 2015 to 2050 is more pronounced. However, a failure to account for learning effects in the low build rate scenario results in underestimating the value of offshore wind capacity, a technology then contributing to a system-wide least-cost pathways. Similarly, coal-CCS capacity, crowded out by less

costly low-carbon sources under static cost assumptions, becomes competitive and an attractive investment from a system perspective when cost reduction is taken into account.

The integration of technology cost learning in the presented power system model[10] moves the optimal investment timing of the technology experiencing cost reduction to earlier planning years. Early investments pay off and total system cost by mid-century are reduced. Unsupported technologies might undergo deployment delays although their early adoption could have contributed to cost reduction.

If the aim of power system models is to analyse possible future pathways, identify competitive technologies, and estimate their optimal investment timing, the integration of endogenous technology cost learning and realistic build rates is essential. A proactive strategy to support and incentivise early investment in promising technologies can lead to overall cost reductions owing to the development of an experience base, thus leading to technology cost reduction.

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Nomenclature

Sets		
a	yrs	planning periods, $a \in A = \{1, ..., A_{end}\}$
t	h	time periods, $t \in T = \{1, ..., T_{end}\}$
c	-	clusters of representative days of each year, $c \in C = \{1, ..., C_{end}\}$
i	-	technologies, $i \in I = \{1, ..., I_{end}\}$
ig	-	power generating technologies, $ig \subseteq I$

[10] This is likely to also be the case for other power system models based on cost optimisation and assuming perfect foresight over the planning time horizon.

ic	-	conventional generating technologies, $ic \subseteq I$
ir	-	intermittent renewable technologies, $ir \subseteq I$
is	-	storage technologies, $is \subseteq I$
il	-	technologies for which learning rate is applied, $il \subseteq I$
l	-	line segments for piecewise linear function
Parameters		
Δ_a	yrs	step width planning years
$DIni_i$	-	number of available units of technology i for $a = 1$
$DMax_i$	-	maximum number of available units of technology i for $a = 1$
Des_i	MW/unit	nominal capacity per unit of technology i
BR_i	unit/yr	build rate of technology i
$LTIni_i$	yrs	lifetime of initial capacity of technology i for $a = 1$
LT_i	yrs	lifetime of technology i
TL	%	losses in transmission network
$TE_{i,*}$	various	features of technology i,
where * is:		
$Pmin$	%-MW	minimum power output
$Pmax$	%-MW	maximum power output
$Cmax$	%-MW	maximum capacity provision
RP	%-MW	reserve potential, ability factor to provide reserve capacity $\in= \{0, 1\}$
IP	%-MW	inertia potential, ability factor to provide inertial services $\in= \{0, 1\}$
Ems	t_{CO_2}/MWh	emission rate.
$CAPEX_i$	£/unit	investment costs of technology i[11]
$OPEX_{i,a}$	£/MWh	operational costs of technology i in year a[12]
$OPEXSU_i$	£/MWh	start-up costs of technology i
$OPEXNL_i$	£/h	fixed operational costs of technology i when operating in any mode
$ImpElecPr_{c,t}$	£/MWh	electricity import price
UT_{ig}	h	minimum up-time for technology ig
DT_{ig}	h	minimum down-time for technology ig
$SEta_{is}$	%-MWh	storage round-trip efficiency
$SDur_{is}$	h	maximum storage duration
$SOCMin_{is}$	%-MW	minimum storage inventory level
$SOCMax_{is}$	%-MW	maximum storage inventory level

$AV_{ir,c,t}$	%-MW	availability factor of technology ir in cluster c at hour t
$SD_{c,t,a}$	MWh	system electricity demand in year a in cluster c at hour t
UD	MWh	maximum level of unmet electricity demand in any year a
PL_a	MW	peak load over time horizon T in each year a
CM	%-MW	capacity margin
RM	%-MW	absolute reserve margin
WR	%-MW	dynamic reserve for wind power generation
SI	MW.s	minimum system inertia demand
SE_a	t_{CO_2}	system emission target in year a
$VoLL$	£/MWh	Value of Lost Load
$Disc_a$	-	discount factor $(1+r)^a$ in year a
WF_c	-	weighting factor for clusters c
$Xlo_{il,l}$	MW	lower segment x-value of cumulative capacity of piecewise linear cost function
$Xup_{il,l}$	MW	upper segment x-value
$Ylo_{il,l}$	MW	lower segment y-value of cumulative CAPEX
$Yup_{il,l}$	MW	upper segment y-value
Variables		
tsc	£	total system cost
$e_{ig,a,c,t}$	t_{CO_2}/MWh	emission caused by technology ig in year a at hour t of cluster c
$u_{ig,a,c,t}$	-	number of units of technology ig starting up in year a at time t of cluster c
$w_{ig,a,c,t}$	-	number of units of technology ig turning down in year a at time t of cluster c
Positive Variables		
$p_{ig,a,c,t}$	MWh	energy output of technology i in year a in hour t of cluster c
$p2d_{ig,a,c,t}$	MWh	energy to demand
$p2s_{ig,a,c,t}$	MWh	energy to grid-level storage
$p2is_{is,a,c,t}$	MWh	energy to storage technology is
$r_{ig,a,c,t}$	MW	reserve capacity provided by technology ig
$s_{is,a,c,t}$	MWh	effective state of charge of technology is at the end of time period t
$s2d_{is,a,c,t}$	MWh	energy from storage to demand

$s2r_{is,a,c,t}$	MW	reserve capacity provided by technology is
$slak_{a,c,t}$	MWh	slack variable for lost load
$xs_{il,a,l}$	MW	position for technology i in year a on line segment l
$y_{il,a}$	£	cumulative CAPEX for technology i in year a
Integer Variables		
$b_{i,a}$	-	number of new built units of technology i in year a
$d_{i,}$	-	number of units of technology i operational in year a, cumulative
$n_{ig,a,c,t}$	-	number of units of technology ig operating in year a at hour t of cluster c
$o_{is,a,c,t}$	-	number of units of storage technology is operating in year a at hour t of cluster c
Binary Variables		
$\rho_{il,a,l}$	-	1, if cumulative CAPEX of technology il in year a on line segment l

7. Notes

The underlying technical and economic data for the considered power generation and storage technologies, as well as for system-level data on electricity demand, fuel prices, etc., are available online at: https://www.imperial.ac.uk/a-z-research/clean-fossil-and-bioenergy.

[10] including interest during construction (IDC) with a discount rate of 7.5% over the respective construction time period per technology type.

[11] including fuel cost, carbon tax, CO_2 transport and storage cost, fixed O&M cost per technology type.

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