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Power capacity expansion planning considering endogenous technology cost learning

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HIGHLIGHTS

- Endogenous technology learning can be integrated into MILP power system models.
- Efficient modelling reduces solution time by 95% with an average error of −1.7% to 2.5%.
- Disregarding technology learning distorts optimal capacity expansion planning.
- Early technology investments can reduce plant-level and total system costs.
- System design and cost results depend strongly on maximum new capacity build rate.

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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.

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.

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Nomenclature

Sets

a planning periods, $a \in A = \{1,...,A_{end}\}$ [yrs]
t time periods, $t \in T = \{1,...,T_{end}\}$ [h]
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, $ig \subseteq I$ [–]
ic conventional generating technologies, $ic \subseteq I$ [–]
ir intermittent renewable technologies, $ir \subseteq I$ [–]
is storage technologies, $is \subseteq I$ [–]
il technologies with endogenous learning, $il \subseteq I$ [–]
l line segments for piecewise linear function [–]

Parameters

Δ_a step width planning years [yrs]
$DIni_i$ 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 nominal capacity per unit of technology i [MW/unit]
BR_i build rate of technology i [unit/yr]
$LTIni_i$ lifetime of initial capacity of technology i for $a = 1$ [yrs]
LT_i lifetime of technology i [yrs]
TL losses in transmission network [%]
$TE_{i,*}$ features of technology i, where $*$ is: [various]
  $Pmin$ minimum power output [%-MW]
  $Pmax$ maximum power output [%-MW]
  $Cmax$ maximum capacity provision [%-MW]
  RP reserve potential, ability factor to provide reserve capacity $\in =\{0,1\}$ [%-MW]
  IP inertia potential, ability factor to provide inertial services $\in =\{0,1\}$ [%-MW]
  Ems emission rate. [t_{CO_2}/MWh]
  investment costs of technology i[1] [£/unit]
$OPEX_{i,a}$ operational costs of technology i in year a[2] [£/MWh]
$OPEXSU_i$ start-up costs of technology i [£/MWh]
$OPEXNL_i$ fixed operational costs of technology i when operating in any mode [£/h]
$ImpElecPr_{c,t}$ electricity import price [£/MWh]
UT_{ig} minimum up-time for technology ig [h]
DT_{ig} minimum down-time for technology ig [h]
$SEta_{is}$ storage round-trip efficiency [%]
$SDur_{is}$ maximum storage duration [h]
$SOCMin_{is}$ minimum storage inventory level [%-MW]
$SOCMax_{is}$ maximum storage inventory level [%-MW]
$AV_{ir,c,t}$ availability factor of technology ir in cluster c at hour t [%-MW]
$SD_{c,t,a}$ system electricity demand in year a in cluster c at hour t [MWh]
UD maximum level of unmet electricity demand in any year a [MWh]
PL_a peak load over time horizon T in each year a [MW]
CM capacity margin [%-MW]
RM absolute reserve margin [%-MW]
WR dynamic reserve for wind power generation [%-MW]
SI minimum system inertia demand [MW s]
SE_a system emission target in year a [t_{CO_2}]
$VoLL$ Value of Lost Load [£/MWh]
$Disc_a$ discount factor $(1 + r)^a$ in year a [–]
WF_c weighting factor for clusters c -
$Xlo_{il,l}$ lower segment x-value of cumulative capacity of piecewise linear cost function [MW]
$Xup_{il,l}$ upper segment x-value [MW]
$Ylo_{il,l}$ lower segment y-value of cumulative CAPEX [MW]
$Yup_{il,l}$ upper segment y-value [MW]

Variables

tsc total system cost [£]
$e_{ig,a,c,t}$ emission caused by technology ig in year a at hour t of cluster c [t_{CO_2}/MWh]
$u_{ig,a,c,t}$ 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

$p_{ig,a,c,t}$ energy output of technology i in year a in hour t of cluster c [MWh]
$p2d_{ig,a,c,t}$ energy to demand [MWh]
$p2s_{ig,a,c,t}$ energy to grid-level storage [MWh]
$p2is_{is,a,c,t}$ energy to storage technology is [MWh]
$r_{ig,a,c,t}$ reserve capacity provided by technology ig [MW]
$s_{is,a,c,t}$ effective state of charge of technology is at the end of time period t [MWh]
$s2d_{is,a,c,t}$ energy from storage to demand [MWh]
$s2r_{is,a,c,t}$ reserve capacity provided by technology is [MW]
$slak_{a,c,t}$ slack variable for lost load [MWh]
$xs_{il,a,l}$ position for technology i in year a on line segment l [MW]
$y_{il,a}$ 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 [–]

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

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

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