

A systems approach to quantifying the value of power generation and energy storage technologies in future electricity networks



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ABSTRACT

A new approach is required to determine a technology's value to the power systems of the 21st century. Conventional cost-based metrics are incapable of accounting for the indirect system costs associated with intermittent electricity generation, in addition to environmental and security constraints. In this work, we formalise a new concept for power generation and storage technology valuation which explicitly accounts for system conditions, integration challenges, and the level of technology penetration. The centrepiece of the system value (SV) concept is a whole electricity systems model on a national scale, which simultaneously determines the ideal power system design and unit-wise operational strategy. It brings typical Process Systems Engineering thinking into the analysis of power systems. The model formulation is a mixed-integer linear optimisation and can be understood as hybrid between a generation expansion and a unit commitment model. We present an analysis of the future UK electricity system and investigate the SV of carbon capture and storage equipped power plants (CCS), onshore wind power plants, and grid-level energy storage capacity. We show how the availability of different low-carbon technologies impact the optimal capacity mix and generation patterns. We find that the SV in the year 2035 of grid-level energy storage is an order of magnitude greater than that of CCS and wind power plants. However, CCS and wind capacity provide a more consistent value to the system as their level of deployment increases. Ultimately, the incremental system value of a power technology is a function of the prevalent system design and constraints.

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1. Introduction and background

In order to achieve a low-carbon electricity system, significant changes in the way electricity is generated, distributed, stored, and traded are necessary (Edenhofer et al., 2014). The electricity generation sector has been undergoing significant transformation over the past decade and is facing challenges of security of supply, affordability, and sustainability (Boston, 2013; E.ON UK, 2008). In addition to this energy trilemma, the increasing demand and changing patterns of electricity consumption and generation are further complicating the transition to a sustainable energy system (Holttinen et al., 2011; Boßmann and Staffell, 2015).

As electricity is increasingly generated from intermittent renewable sources, it can no longer be treated as a homoge-

neous product (Joskow, 2011). The amount and type of generating technologies have to ensure power system adequacy (amount of generating capacity), reliability (amount of operating capacity for reserve), and operability (amount of dispatchable capacity that can provide ancillary services and inertia). However, at the time of writing, power technologies based on intermittent renewable energy sources (iRES) which are increasingly being deployed, do not typically deliver essential power system services, such as frequency and voltage control.¹ The required reserve capacity increases by between 2 and 22% compared to a system without iRES as a function of the iRES penetration into the system (Gross et al., 2006; Heptonstall et al., 2017; Holttinen et al., 2011; Brouwer et al., 2014). Therefore, whilst the role of iRES technologies in the future

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¹ Inertia mimicking techniques, such as electronic controller on the wind power generator side which are able to restrain power output and increase rapidly if needed (synthetic inertia) are able to add to the service portfolio (National Grid, 2014b). In addition, regulatory and market incentives are needed to encourage the provision of such services.

electricity system as low-carbon technology is indisputable, the system-level impacts on reliability and operability of intermittent versus firm power generation technologies must be taken into consideration if we endeavour to implement a secure and sustainable power system.

1.1. Technology valuation

Existing decision-making tools and technology valuation metrics are mainly cost-based and focus on the individual technology. The Levelised Cost of Electricity (LCOE) is an intuitive metric for technology-specific cost, aggregating the investment and operational cost per unit of energy generated in £/MWh. This metric was practical in a 20th century electricity system, containing exclusively dispatchable power plants. Today however, the LCOE has lost its meaning as it does not account for price and production variability nor the impact that a plant's operation has on the electricity system in terms of reliability and operability (e.g., necessary back-up capacity, balancing and inertial services, reduced utilisation factors/increased emissions for other power plants) (Lew et al., 2013; Larsson et al., 2014). It is becoming clear that such services and technology features provide value to the power system but are not captured by existing valuation tools or market mechanisms.²

It is in an interconnected system, that power generating technologies depend on and influence each others services. In recent literature there are few approaches addressing the system-level implications in technology valuation. Ueckerdt et al. summarise the effects of a growing share of iRES on electricity market dynamics and try to capture these “integration costs” in a System LCOE (Ueckerdt et al., 2013). Providing some remedy, this metric reports the costs per unit of electricity calculated as a function of the deployment level of iRES. Nevertheless, it does not explicitly account for the characteristics of the prevalent capacity mix into which iRES are integrated, but rather makes use of theoretical benchmark technologies.

A recent approach by the U.S. Energy Information Administration presents a Levelised Avoided Cost of Electricity (LACE) as a complementary metric to the LCOE (Levelized Cost, 2015). Based on the U.S. national energy systems model NEMS, the LACE is derived as the system-wide avoided cost through a power sector specific project levelised by the projects lifetime power output.

Previous work by Lamont (2008) and Lamont (2013) and more recent work by Strbac et al. (2012), Pudjianto et al. (2014) have started the discussion on technology valuation through whole-system approaches based on rigorous mathematical optimisation. Both concepts make use of mixed-integer linear programming (MILP) techniques and identify an “economic value” or “system value” as a function of a technology's penetration into the system.³

1.2. Electricity system models

The centrepiece of value-based technology assessment methods are electricity system models which account for system integration effects and interrelated power plant behaviour. These optimisation-based formulations are part of a larger class of energy

system models, which also include simulation, energy market and qualitative analyses (Pfenninger et al., 2014). Within the past 30 years, the research community has created a significant number of energy system assessment tools ranging from small-scale applications (HOMER Energy LLC, 2015) to national scale models (Energy Information Administration, 2003; Loulou et al., 2005; IIASA, 2012; Lund, 2014), differentiated by the energy sectors covered (electricity, heat, transport, etc.), the spatial and temporal scope and granularity, their treatment of uncertainties (Aalborg University Denmark, 2008; SINTEF, 2009), and many other model characteristics. For more information on this point, the reader is directed to contributions of Connolly et al. (2010) and Bakirtzis et al. (2012) and references therein for further details.

Relevant for the model presented in this work are the aforementioned MILP-based electricity system models which share the most salient features with generation expansion planning (GEP) and unit commitment (UC) formulations (Bakirtzis et al., 2012; Koltsaklis et al., 2014; Morales-Espana et al., 2015). GEP models focus on determining the optimal system structure⁴ (the amount and type of power generating capacity), whereas UC models derive the optimal dispatch schedule (operation for each power generating unit), both subject to a range of system-wide and technical constraints.

The degree to which system reliability requirements, environmental targets, and technical variety and detail are present in the model formulation depends on the respective modelling aim and application. A key difference is often the observed time horizon and time step discretisation. These choices can be decisive, especially when including iRES, to capture short-term power plant operation on the one hand, and long-term system planning on the other hand. GEP models often show time steps of months, or years, or use load duration curves instead of hourly profiles (Bakirtzis et al., 2012; Wierzbowski et al., 2016). These approaches, however, are unable to capture the often minute-wise intermittency of iRES and the resulting impacts on the power system. Due to computational tractability the common trade-off between depth and scope of the model must be weighted according to the application.

Models which forfeit representing detailed power plant behaviour and system operability constraints, such as MOSSI by Green and Staffell (2016) or EMMA by Hirth (2016), however, succeed at determining the dispatch schedule alongside multi-decadal investment planning. Another branch of planning tools for energy systems include a spatial representation of the transmission infrastructure and operation by discretising space as nodes or cells. The WeSIM model by Pudjianto et al. (2014), and the STeMES model by Samsatli and Samsatli (2015) are such spatio-temporal models. The first focusses on short-term electricity grid dynamics over long-term design, whereas the latter enables system planning for multiple energy vectors besides electricity. The widely used MARKAL/TIMES model family additionally estimates end-user demands and addresses endogenous technology learning rates (Loulou et al., 2004, 2005).

A hybrid formulation of the GEP and UC model aims at representing a detailed technical level of power plant operation while determining optimal system design. Belderbos and Delarue describe such a set-up with an hourly discretisation and an observed horizon of one year (Belderbos and Delarue, 2015). The model, however, does not account for system operability or environmental constraints and presents only a limited variety of power generating technologies and their characteristics.

² Balancing services such as black-start support, Short-term operating reserve, or frequency services are remunerated under the National Grid Code (National Grid Electricity Transmission plc, 2015). The inherent inertia that a power plant provides to the electricity system, however, is not yet accounted for.

³ Lamont derives the system value as marginal value of the upper bound constraint on power generation which is limited by the amount of capacity installed. Strbac et al. derive the value of a technology as gross system benefits upon optimal technology capacity deployment. Both techniques are fundamentally equivalent, and based on the change in the objective function by installation and deployment of the respective technology.

⁴ Often GEP models are combined with transmission expansion planning which also determines the optimal network topology for power distribution or transmission (Papavasiliou and Oren, 2013).

1.3. Objectives and structure

In this work, we develop a modular mathematical and theoretical framework to value and compare power technologies within the electricity system. The system value (SV) metric is based on a hybrid GEP-UC formulation which tries to capture the challenges of the energy trilemma and 21st century energy systems planning. The SV aims to provide insight from a societal perspective to the power systems community, and can be used as a tool by policy and decision-makers to equitably assess the benefits and challenges of technology integration.

We extend existing GEP and UC model formulations by adding environmental, system reliability, and operability constraints. We increase the number of power technologies (e.g., coal post-combustion CCS, coal oxy-combustion CCS, CCGT post-combustion CCS, grid-level energy storage) and the level of modelling detail (e.g., unit-wise and modal operation, technical and economic parameters) in order to sufficiently capture the time scale of iRES intermittency and its impact on the system behaviour. This work aims to present a simple power systems model and its formal application as systemic technology valuation tool, rather than to cover many aspects of power systems modelling (e.g., transmission planning, technological learning, cross-sector integration).

The remainder of the paper is structured as follows. We introduce the system value (SV) concept and algorithm in Section 2, and present the electricity systems optimisation model (ESO) in Section 3. We conduct a case study comparing the SV of carbon capture and storage equipped power plants (in the following referred to as CCS), onshore wind power plants, and grid-level energy storage (i.e., compressed air energy storage (CAES)) in an electricity system, parametrised to match a future 2035 scenario for the United Kingdom (UK).

2. The system value

The system value (SV) concept and algorithm quantifies the value of a technology to the power system as the reduction in annual total system cost (TSC) caused by the deployment of the technology. Hence, the SV, measured in £/kW_{ann.}, of a power technology is a function of its installed capacity and the conditions and constraints on the system it is operating within, e.g., the other available power generating technologies, their operational and environmental characteristics, the overall system emission targets, and the amount of available capacity ($N_k(i)$) of the evaluated technology i . Consequently, it explicitly takes integration challenges and costs into account and addresses the value change from a first-of-a-kind (FOAK) to an n th-of-a-kind (NOAK) power plant.

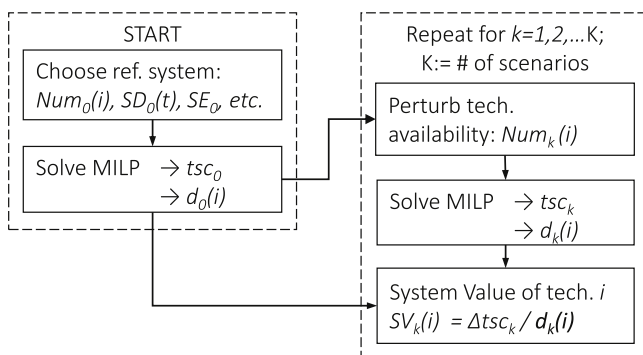


Fig. 1. The system value algorithm is based on the difference in total system cost. Mentioned parameters and variables in italic are described in detail in Section 3.

Fig. 1 summarises the SV procedure. The ESO analysis is performed for a chosen reference system o , resulting in an optimal system design $d_o(i)$ at minimal TSC tsc_o . The remaining model outputs, such as operational schedule, Carbon Intensity (CI), etc., are not listed in Fig. 1. $Num_o(i)$ for technology i is the available number of units to be installed (upper bound). In k iterations, we increase the upper bound $Num_k(i)$ in a stepwise fashion for the technology i and perform the analogous calculation for K perturbed systems. From K set of results the total system cost are compared between system k and the reference system o . This allows the evaluation of the marginal change in TSC by increasing the availability of the respective technology i taking the whole system effects into account.

3. Electricity systems optimisation model

The model formulation is based on GEP and UC formulations and extended to incorporate the features listed below. We differentiate between power generating technologies ig and energy storage technologies is (grid-level storage). A subset of ig are the conventional technologies ic (nuclear, coal, Combined Cycle Gas Turbine (CCGT), Integrated Gasification Combined Cycle (IGCC), Open Cycle Gas Turbine (OCGT), CCGT post-combustion CCS), and the power technologies without modal operational behaviour ir (onshore wind, offshore wind, solar, interconnector). The key features of the model are:

- Electricity system design is determined in terms of technology mix and number of installed units.
- Emission factors (tCO₂/MWh) are technology- and mode-specific. System target allows for temporary overshoot but constraints the total annual emissions.
- Spinning reserve requirements⁵ are defined as a fraction of peak demand plus a proportion of the instantaneous power output at every t to secure dynamically against failure of largest firm and intermittent unit or unexpected forecast error.
- Frequency control is integrated within the inertia constraint, ensuring system operability by a constant security level of system inertia. Generating technologies provide different levels of inertia (GW.s) depending on the operational mode.
- Operation of conventional power plants (nuclear, fossil-based) is modelled in detail by unit-wise switching between three different modes (off, start-up, bounded power output) and the respective power or reserve level provided.
- Intermittent renewables and interconnectors are modelled to operate in off, or continuous power output mode.
- Energy storage technologies can be continuously charged and discharged. The round-trip efficiency, minimum and maximum state of charge level, and its potential to provide reserve capacity are the salient technology performance parameter.

The key model assumptions are:

- There is perfect foresight over the time horizon.
- A monopolistic system planner aims at least-cost power supply and storage capacity planning and unit commitment.
- The model does not considering transmission grid planning, it can be classified as a so called copper plate model.
- Electricity demand is inelastic. The price for cross-boarder electricity import is given exogenously.

⁵ With regard to the British power system, the modelled reserve type refers to the Short-Term Operating Reserve (STOR) balancing services. This is a load independent reserve mechanism typically accounting for approximately 2.5 GW (Staffell and Rustomji, 2016).

- Heat rate curves for part-load efficiencies of fossil-fuel plants are not taken into account. Technology performance parameter vary between operational modes such that start-up behaviour is taken into account explicitly.
- The model structure and input parameters are deterministic.

3.1. Nomenclature

Sets		
i	–	technologies, $i \in I = \{1, \dots, I_{end}\}$
t	h	time periods, $t \in T = \{1, \dots, T_{end}\}$
m, m'	–	modes of operation, $m \in M = \{off, su, inc\}$, alias m'
k	h	set of all possible stay times, $k \in K = \{1, \dots, \max\{StayT_{i,m,m'}\}\}$
ig	–	power generating technologies, $ig \subseteq I$
ic	–	conventional technologies, $ic \subseteq I$
ir	–	intermittent renewable technologies, $ir \subseteq I$
is	–	storage technologies, $is \subseteq I$
$Trans_{m,m'}$	–	possible transitions from mode m to m' , 1 if transition allowed, 0 else
$ForbidT_{m,m'}$	–	forbidden transitions for mode m to m' , 1 if transition forbidden, 0 else
Parameter		
Num_i	–	number of available units of technology i
Des_i	MW/unit	nominal capacity per unit of technology i
$Pmin_{i,m}$	%-MW	minimum power output
$RP_{i,m}$	%-MW	reserve potential
$IP_{i,m}$	%-MW	inertia potential
$Ems_{i,m}$	tCO ₂ /MWh	emission rate.
$AV_{i,m,t}$	%-MW	availability factor of technology i in mode m at time step t
$StayT_{i,m,m'}$	h	minimum stay time of technology i in mode m' after transition from mode m to m'
$SEta$	%-MWh	storage round-trip efficiency
$SOCMax$	%-MW	maximum storage inventory level
$CAPEX_i$	£/unit	investment costs of technology i
$OPEX_{i,m}$	diff.	operational costs of technology i in mode m , in £/MWh for $m = \{inc\}$, in £/unit for $m = \{su\}$
$OPEXNL_i$	£/MWh	fixed operational costs of technology i when operating in any mode
SD_t	MWh	system electricity demand at time period t
PL	MW	peak load over time horizon T
RM	%-MW	reserve margin
WR	%-MW	reserve buffer for wind power generation
SI_t	MW.s	system inertia demand at time step t
SE	tCO ₂	system emission target
Integer variables		
d_i	–	number of units of technology i designed/installed
$n_{ig,m,t}$	–	number of units of technology ig in mode m at time t
$Z_{ic,m,m',t}$	–	number of units of technology ic switching from mode m to m' at time t
$o_{is,t}$	–	number of units of storage technology is operating at time t
Positive variables		
$p_{ig,m,t}$	MWh	power output of technology ig in mode m as time period t
$p2d_{ig,m,t}$	MWh	power of technology ig in mode m as time period t to demand
$p2s_{ig,m,t}$	MWh	power of technology ig in mode m as time period t to storage
$r_{ig,m,t}$	MW	reserve capacity provided by technology ig in mode m at time period t
$s_{is,t}$	MWh	effective energy stored by technology is at the end of time period t
$s2d_{is,t}$	MWh	power of technology is at time period t to demand
$s2r_{is,t}$	MW	reserve capacity provided by technology is at time period t
$e_{ig,m,t}$	tCO ₂ /MWh	emission caused by technology ig at time period t

3.2. Model formulation

The objective function (1) is the tsc decomposed into cost factors and operational modes aggregating annual construction and operation cost. We differentiate between “no load” costs (£/h), which occur for any power plant when being online, the incremental costs for providing power output or spinning reserve (£/MWh), and start-up costs (£/unit). Due to the different units of operational costs, the $OPEX_{i,m}$ term is split and multiplied by the respective decision variable.

$$\begin{aligned}
 \min \quad tsc = & \sum_{i \in I} CAPEX_i d_i Des_i \\
 & + \sum_{ic \in I, m = \{su\}} (OPEX_{ic,m} n_{ic,m,t} / StayT_{ic,m',m}) \\
 & + \sum_{ig \in I, m \in \{su, inc\}} OPEXNL_{ig} n_{ig,m,t} \\
 & + \sum_{ig \in I, m = \{inc\}} \sum_{t \in T} OPEX_{ig,m} p_{ig,m,t} + \sum_{is \in I, m \in \{inc\}} \sum_{t \in T} OPEX_{is,t} o_{is,t}
 \end{aligned} \quad (1)$$

The design constraint (2) limits the number of units of technology i to be installed (designed: d_i) by the upper bound Num_i . Eq. (3) ensures that each unit of generating technology ig can be in only one mode m (off , su : start-up, inc : incremental (running)) at any time period t . The number of energy storage technologies is cannot exceed the number of installed units, which is stated by constraint (4).

$$0 \leq d_i \leq Num_i \quad \forall i \quad (2)$$

$$\sum_{m \in M} n_{ig,m,t} = d_{ig} \quad \forall ig, t \quad (3)$$

$$o_{is,t} \leq d_{is} \quad \forall is, t \quad (4)$$

System-wide constraints (5)–(8) include power balances which ensure sufficient electricity supply, reserve, and inertia requirements in the system at every time period t . Reserve is provided as measured by a predefined reserve margin RM , a percentage of peak load demand $PL = \max_t SD_t$, plus a percentage of intermittent power output, denoted as “wind reserve” WR .

System inertia requirements are met if enough units with “inertia potential” $IP_{i,m}$ are on-line. Constraint (8) sets the environmental target for the electricity system by limiting the sum of emissions of all units i in every mode m at all time periods t by an emissions target SE . The dual variable for the power balance (5) represents marginal electricity price; dual variable for the reserve balance (6) the marginal price for reserve.

$$\sum_{ig \in I, m \in M} p2d_{ig,m,t} + \sum_{is \in I} s2d_{is,t} = SD_t \quad \forall t \quad (5)$$

$$\sum_{ig \in I, m \in M} r_{ig,m,t} + \sum_{is \in I} s2r_{is,t} \geq PL RM + \sum_{ir, m} p_{ir,m,t} WR \quad \forall t \quad (6)$$

$$\sum_{ig \in I, m \in M} n_{ig,m,t} Des_{ig} IP_{ig,m} \geq SI_t \quad \forall t \quad (7)$$

$$\sum_{i \in I, m \in M, t \in T} e_{i,m,t} \leq SE \quad (8)$$

Unit specific constraints define the detailed operation so as to comply with the technical abilities of each type of technology. With the mode-dependent availability matrix $AV_{i,m,t}$ we define the hourly available level of onshore wind, offshore wind, and solar power output. For the conventional power plants, we can model part-load behaviour by defining a different maximum power output in the start-up mode. Constraints (9)–(13) define the operational envelope for the power generating technologies ig , by the overall mode-dependent availability level (9); the upper and lower bounds of power output (10)–(11); the level reserve provision (12); and the technology power balance (13).

The provision of spinning reserve service is further constrained according to the mode-dependent “reserve potential” $RP_{i,m}$ which prohibits reserve offer in the *off* and *su* mode and assigns the possible amount of capacity provided for the *inc* mode. An exception are power plants that are able to start-up very quickly and are therefore eligible to offer reserve while being off. The only type of power plants that fall into this category and are considered in this model are OCGT power plants.

$$\sum_{m \in M} p_{ig,m,t} + r_{ig,m,t} \leq \sum_{m \in M} n_{ig,m,t} Des_{ig} AV_{ig,m,t} \quad \forall ig, t \quad (9)$$

$$p_{ig,m,t} \geq n_{ig,m,t} Des_{ig} Pmin_{ig,m} AV_{ig,m,t} \quad \forall ig, m, t \quad (10)$$

$$p_{ig,m,t} + r_{ig,m,t} \leq n_{ig,m,t} Des_{ig} AV_{ig,m,t} \quad \forall ig, m, t \quad (11)$$

$$r_{ig,m,t} \leq (n_{ig,m,t} Des_{ig} AV_{ig,m,t} - p_{ig,m,t}) RP_{ig,m} \quad \forall ig, m, t \quad (12)$$

$$p2d_{ig,m,t} + p2s_{ig,m,t} = p_{ig,m,t} \quad \forall ig, m, t \quad (13)$$

Constraint (14) can specify the type of generating technologies ig which are able to charge the energy storage. Since we consider grid-level energy storage, we initially enable all generating technologies ig to charge the energy storage.

$$p2s_{ig,m,t} = 0 \quad \forall ig = \emptyset, m, t \quad (14)$$

Constraint (15) determines the carbon emissions caused by each power generating technology ig by operation on in mode m in each time period t .

$$e_{ig,m,t} = Ems_{ig,m} (p_{ig,m,t} + r_{ig,m,t}) \quad \forall ig, m, t \quad (15)$$

The operation of the intermittent power generators $ir \in I$ is modelled with fewer operational modes. If wind speeds are sufficient and power output is possible, there is no start-up behaviour in wind power plants compared to thermal power plants. Hence, constraint (16) disables intermittent power generators from being in the *su* mode.

$$n_{ir,m,t} = 0 \quad \forall i, m = \{su\}, t \quad (16)$$

A set of integer constraints determines the optimal operational behaviour for the different units of the conventional technologies ic . Eqs. (17) and (18) define the switching between the operational modes as well as the region of allowed mode transitions by the set $Trans_{m,m'}$ and its inverse $ForbidTrans_{m,m'}$. Inequality (19) ensures that units stay in the operational mode m' for a minimum amount of time according to the set $StayT_{ic,m,m'}$ after transitioning from mode m to m' . The number of units $n_{ic,m',t}$ in mode m' has to be greater or equal than the number of units that switched into mode m' , $z_{ic,m,m',t}$, for the minimum stay time.

$$n_{ic,m,t} - n_{ic,m,t-1} = \sum_{m'} z_{ic,m',m,t} - \sum_{m'} z_{ic,m,m',t} \quad \forall ic, t, m \quad (17)$$

$$z_{ic,m,m',t} = 0 \quad \forall ic, m \in ForbidT_{m,m'}, t \quad (18)$$

$$n_{ic,m',t} \geq \sum_{k=t-StayT_{ic,m,m'}+1}^t z_{ic,m,m',k} \quad \forall ic, t, m \in Trans_{m,m'} \quad (19)$$

Energy storage technology constraints (20)–(24) specify the lower and upper bound for discharging (20) and (24); the upper bound on the storage inventory (22); the state of charge energy balance (23); the available reserve provided by the energy storage further constrained by the reserve potential $RP_{is,m}$ (24).

$$s2d_{is,t} \geq o_{is,t} Des_{is} Pmin_{is,m} \quad \forall is, m = \{inc\}, t \quad (20)$$

$$s2d_{is,t} + s2r_{is,t} \leq s_{is,t} * SEta \quad \forall is, m = \{inc\}, t \quad (21)$$

$$s_{is,t} \leq o_{is,t} Des_{is} SOCMax \quad \forall is, t \quad (22)$$

$$s_{is,t} = s_{is,t-1} - s2d_{is,t}/SEta + \sum_{ig \in I, m \in M} p2s_{ig,m,t} \quad \forall is, t \quad (23)$$

$$s2r_{is,t} \leq (s_{is,t} SEta - s2d_{is,t}) RP_{is,m} \quad \forall is, m = \{inc\}, t \quad (24)$$

The objective function (1) and constraints (2)–(24) define the final model formulation which provides the basis for the analyses and results presented in the following sections and is referred to as electricity systems optimisation (ESO) model. The optimisation problem is formulated as MILP, modelled in GAMS 24.6.1 and solved with CPLEX 12.3.

4. Comparative case study: wind, CCS, and energy storage

We conduct a case study to evaluate and establish the system value for different types of power generating technologies and grid-level energy storage. As a benchmark we choose a future 2035 reference scenario for the UK electricity system from the UK Department of Energy & Climate Change,⁶ including the estimated level of technology deployment (Department of Energy & Climate Change, 2014), emission constraint (80% reduction from a 1990 baseline to 16 MtCO₂/year) (Annual Statement of Emissions, 2014), and fuel prices (Department of Energy & Climate Change, 2015).

The underlying 2035 electricity system is characterised by a substantial increased contribution from iRES and interconnectors, amounting to 40.5% and 12% of a total capacity of 138.75 GW, respectively. The remainder is composed of 13% nuclear, 32.5% unabated and abated fossil fuels, and 2% of energy storage capacity. Annual electricity demand reaches 354 TWh, with a peak demand of 62 GW and a minimum demand of 22 GW. Hourly demand profiles from 2014 are scaled up by 22% according to National Grid's estimates (National Grid, 2014a). Hourly availability profiles for solar, onshore and offshore wind data is obtained from Staffell and Green (2014) and Pfenninger and Keirstead (2015).

As security requirements, we consider a de-rated capacity margin of 4% in addition to a dynamic reserve component of 15% of iRES power generation in each time step. Operability requirement is a constant minimum level of 100 GW.s of system inertia.

Table 1 summarises essential assumptions on the power system and the technologies which are investigated in the following. The full data sheet with the technology-specific data is provided as supplementary file in the online version of this paper.

4.1. Data clustering and profiling

For the analyses excluding grid-level energy storage we cluster the hourly input data (electricity demand, onshore wind, offshore wind, solar availability) via a k -means algorithm to reduce the computational effort and increase solution speed. The k -means clustering reduces the size of a raw data set by assigning each individual data point to a cluster such that the Euclidean distance between the data point and the cluster mean or centroid is minimal.

⁶ Now subsumed into the Department for Business, Energy and Industrial Strategy.

Table 1

Data assumptions for 2035 UK electricity system. We apply a discount rate of 7.5%; CAPEX includes interest during construction (IDC). In order to avoid double counting, the Carbon Intensity of electricity discharged from a storage is set to zero; the emissions are attributed to the charging power plants.

Parameter	Unit	Wind	CCS	Storage
Annualised CAPEX	£/kW-yr	104.38	119.11.	152.51
Full-load OPEX	£/MWh	5	43.9	3
Carbon intensity	tCO ₂ /MWh	0	0.041	0
Electricity demand	TWh/yr	354		
Peak demand	GW	62		
de-rated capacity margin	%-capacity	4		
System inertia	GW.s	100		
Emission target	MtCO ₂ /yr	16		
Coal price	\$/tonne / £/MWh		70.6/6.4	
Gas price	p/therm / £/MWh		46.1/15.7	
Carbon price	£/tCO ₂		70	

A number of $k=21$ clusters with a cluster size of 24 hourly time steps, was found to result in a reasonable trade-off between accuracy and computational tractability. We normalise the 4-dimensional data space such that each input vector (electricity demand, onshore wind, offshore wind, solar availability) is considered with equal weight. In this way, we reduce the full space from a length of 8760 to 504 clustered time steps and ensure that the day containing the annual electricity peak demand is included. A weighting factor according to the occurrence frequency of each cluster is applied to the model formulation. The output error between clustered and full data set (8760 vs. 504 time steps) is on average 0.6% for system-level results, and 4% for technology-specific results. This is in good accordance with findings by Green et al. who report an optimal number of 10 clustered days with a good accuracy-cost trade-off and a final error of $1.3 \pm 0.4\%$ (Green et al., 2014). On average, capacity installation levels are underestimated when time compression techniques are used compared to full hourly calculations. We also refer to Pfenninger where a detailed analysis of different data handling approaches in energy models are compared (Pfenninger, 2017).

Individual cluster profiles are typically obtained by choosing the cluster mean or average, which causes a smoothing effect of the original data profiles. To avoid this, we have developed a profiling technique which chooses the specific data profile which best preserves the cluster average energy. This ensures a consistent representation of the annual energy demand and availability while maintaining the realistic hourly profile intermittency. Fig. 2

visualises the clustering and profiling process for the case of offshore wind availability.

4.2. System value for on-shore wind, CCS, and energy storage

In order to understand the role and impact of a power technology on the system composition and the requirements in terms of cost, reliability, operability, and environment, we apply the SV approach to the presented ESO formulation. We choose two different types of power generating technologies, both of which are low-carbon or zero-carbon during their operation, but which are inherently distinct in their power generating patterns. Power generation from wind power plants is intermittent and dependent on region, season, and weather. CCS power plants provide firm capacity; they are referred to as dispatchable power generators, as their power output is adjustable and controllable. As additional power technology, we investigate grid-level energy storage (in the following referred to as storage).

4.2.1. System impact of wind capacity deployment

The upper bound of capacity installation for each technology is set to the 2035 UK reference scenario (Department of Energy & Climate Change, 2014). As we relax the capacity upper bound for onshore wind power plants, we observe the system-level impact on the optimal capacity mix and the total system cost. Fig. 3 illustrates these system changes depending on the level of available onshore wind capacity. The amount of deployed onshore wind capacity (limited by the amount of available onshore wind capacity) is shown as part of the capacity stack. The level at which wind capacity deployment stops increasing with wind capacity availability we call “economic deployment limit”. In this scenario, 85.5 GW of onshore wind capacity are economically deployed.

The annual TSC reduces as a larger proportion of electricity demand is met by iRES. Consequently, the utilisation of the nuclear and abated thermal power plants reduces by approximately 3%. OGCT and CCGT power plants show an increased utilisation level, as they balance larger amount of intermittent power due to their operational flexibility. Their annual start-up costs increase by 40% to just over £ 1 million. The utilisation rate of interconnectors is reduced, however, the capacity is still valuable, as is it modelled as being infinitely flexible and overseas emissions are not accounted for such as it is the accounting convention used in the UK emissions targets. Due to the limited ability of intermittent power generators to displace firm capacity the amount of nuclear and fossil capacity

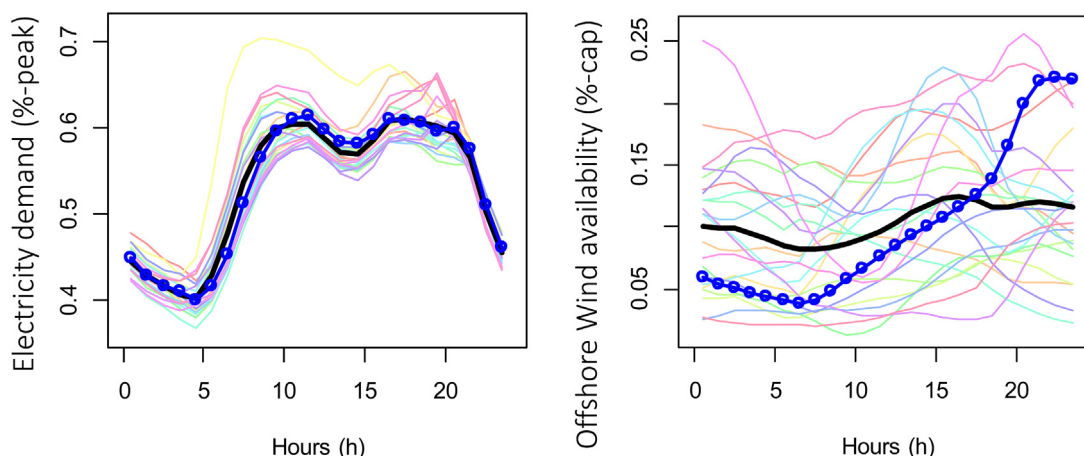


Fig. 2. Exemplary cluster ($k=11$) for electricity demand (left) and offshore wind availability (right); Original data profiles (rainbow coloured lines) are assigned via k -means algorithm to cluster k . The cluster mean (solid black line) is inherently smooth, whereas the chosen profile which best preserves the energy integral across the respective cluster (blue line with markers) represents the realistic nature of the underlying data. (For interpretation of the references to color in this figure legend, the reader is referred to the web version of this article.)

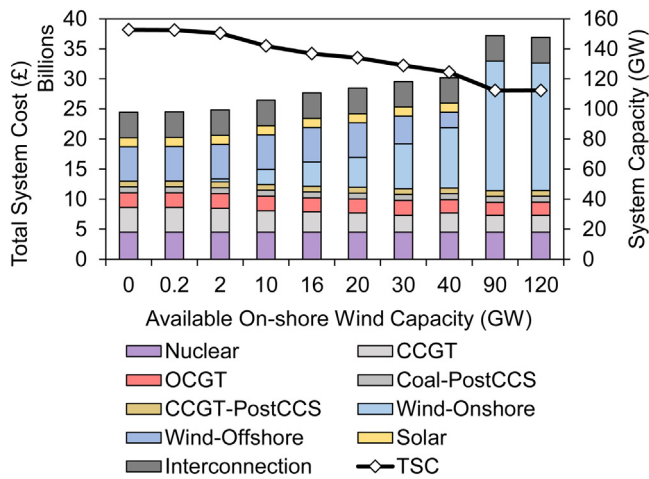


Fig. 3. Optimal capacity mix (right y-axis), and total system cost (left y-axis) under 2035 conditions depending on the level of onshore wind capacity availability.

is only reduced marginally. Off-shore wind being more costly, and solar power being less efficient, these technologies are gradually displaced at high onshore wind availabilities. In the given capacity mix and under the given system constraints, TSC decreases by 26% as the onshore-wind capacity reaches its maximum deployment rate of 85 GW. Despite higher availability, an increase in onshore wind capacity is non-optimal. We refer to this amount of capacity as economic deployment level. However, the total necessary capacity increases by 50% from 97.85 GW to 147.52 GW if the remaining technologies cannot be further deployed.

4.2.2. System impact of CCS capacity deployment

The change in optimal capacity mix as a function of CCGT-CCS availability reveals a reduction in total capacity installed from 119.2 GW to 97.95 GW. Accordingly, the TSC reduces by 30% at the maximum economic CCS deployment level of 52.5 GW.

Fig. 4 illustrates the significant reduction in energy dependency as the amount of necessary interconnection decreases. Off-shore wind and solar power plants become gradually uneconomical as the emissions target can be achieved with CCS; unabated CCGT is displaced, and at high CCS deployment rates a displacement of nuclear capacity is mathematically feasible and optimal. As unprofitable capacity is displaced, the utilisation rate for CCS increases

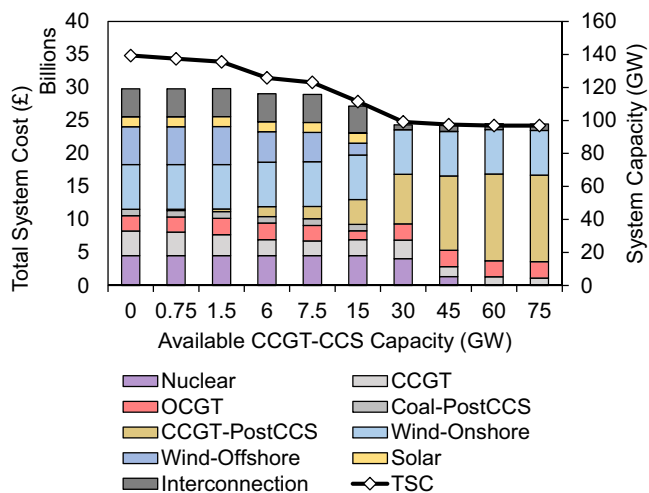


Fig. 4. Optimal capacity mix (right y-axis), and total system cost (left y-axis) under 2035 conditions depending on the level of CCGT post-combustion CCS capacity availability.

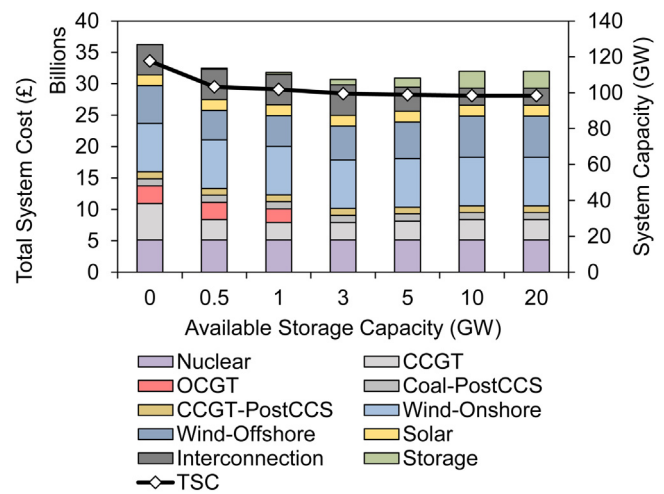


Fig. 5. Optimal capacity mix (right y-axis), and total system cost (left y-axis) under 2035 conditions depending on the level of grid-level energy storage capacity availability.

from 56% to 61%. The presence of iRES and the lack of interconnection induces higher cycling rates for all thermal power plants and increases start-up cost. The ESO model explicitly accounts for carbon dioxide emissions during start-up phases (constraint (15)). We do not, however, consider a possible long-term effect on the power plant performance that could be arise from increased cycling.

4.2.3. System impact of energy storage capacity deployment

The ESO model is solved for the scenarios including energy storage technology over the full time horizon of one year in hourly time discretisation without applying the aforementioned data clustering and profiling technique. The underlying energy storage model is parametrised as CAES-type grid-level energy storage with a round-trip efficiency of 70%, a storage duration of 48 hours, the ability to provide reserve capacity, and no carbon emissions during operation (RWE Power, 2010).

The deployment of the first capacity unit (1 GW) of energy storage causes an initial TSC reduction of 13%.⁷ The single largest contribution to this significant reduction is caused by the savings in operational (fuel) expenses from the thermal power plants. In comparison, the first gigawatt of onshore wind and CCGT-CCS capacity leads to a TSC reduction of 1.5% and 2.5%, respectively.

However, Fig. 5 indicates how the further increase of energy storage capacity deployment reduces TSC only marginally. A storage capacity of 9.5 GW is most economic to the power system under the given conditions. At this stage, TSC are reduced by 15%; total installed capacity decreases by 5%. The first three gigawatt of capacity are highly valuable, displacing CCGT capacity and substituting OCGT capacity entirely. The level of iRES integration is increased to the maximum available level of 50 GW.

Over the course of one year, 69% of the electricity charging the grid-level energy storage comes from onshore and offshore wind power plants. However, also nuclear and thermal capacity utilised the energy storage in order to maintain their most profitable operation levels and reduce shut-down times.

4.2.4. System value comparison

We apply the SV metric to the aforementioned technologies and obtain their SV functions depending on the level of capacity

⁷ The initial scenario at an available storage capacity of 0 GW, analogously to the analyses in Sections 4.2.1 and 4.2.2, omit hydro storage capacity of 2.75 GW currently installed in GB.

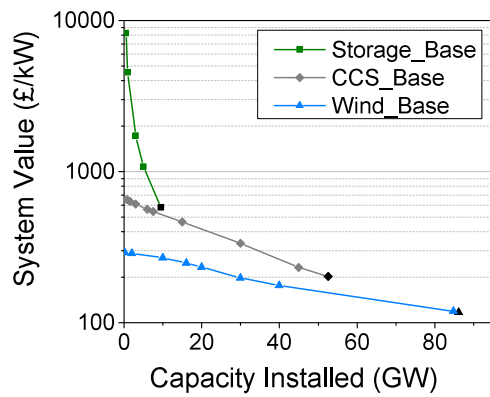


Fig. 6. System value for CCGT post-combustion CCS, and onshore wind without energy storage availability, and for energy storage with limited wind capacity availability (50 GW) as a function of the respective deployment level. The black markers indicate the economic level of capacity deployment for each technology as it is evaluated in its respective scenario.

Table 2
Technology comparison at different capacity availability levels.

Result	Unit	Wind 30 GW availability	CCS 30 GW availability	Storage 9.5 GW availability	Wind Maximum availability	CCS Maximum availability	Storage Maximum availability
Deployment	GW	30	30	9.5	85.5	52.5	9.5
TSC reduction	%	15.5	28.9	15	26.5	30	15
System value	£/kW	198	335	515	119	202	515

deployment. Fig. 6 illustrates a marked difference in the SV of the first capacity unit of energy storage compared to wind and CCS capacity. The initial storage availability causes a disruptive change in TSC, whereas the power generating technologies achieved a more gradual TSC reduction. At the economic storage capacity deployment level of 9.5 GW, the SV of energy storage and CCS capacity is on par; both technologies are equally valuable to the power system. The SV function of onshore wind capacity is consistently below the SV of CCS and energy storage capacity. However, large amounts of wind capacity are deployed due to a low average capacity factor and low operational cost.

Table 2 summarises the economic deployment level, TSC reduction, and system value for the three examined technologies.

The value of a power technology is not only a function of the level of capacity availability, but is furthermore dependent on the system design and system constraints such as carbon targets or security requirements, it is operating within.

4.2.5. The impact of power system conditions on the system value

In order to highlight the dependency of the value of a power technology to the system conditions, we repeat the above analysis under different capacity availability scenarios. All previously presented results are conducted with an estimated capacity availability defined by DECC's reference scenario for 2035 (Department of Energy & Climate Change, 2014), and are from now on referred to as base case ("Base").

Calculations analogous to the ones presented in Sections 4.2.1–4.2.3 are carried out for a "HiNuk" case with 50% higher nuclear capacity availability compared to the base case (27 GW vs. 18 GW). All other input parameters remain unchanged. In a "LoNuk" scenario the nuclear capacity availability is adjusted to 50% less than in the base case (9 GW vs. 18 GW). The "HiRes" and "LoRES" scenarios refer to a case with an 80% increase and 50% decrease in iRES availability (90 GW and 25 GW vs. 50 GW), respectively. The capacity adjustment for the iRES cases is distributed evenly among the onshore and offshore wind capacity.

We note that in the "LoNuk" and "LoRES" cases the amount of total available capacity at low installation levels of onshore wind, CCS, and energy storage capacity, respectively, is insufficient to meet system demands. In order to perform the system value analyses for these cases, we introduce a slack variable $\beta(t)$ on the overall electricity balance constraint (5) from Section 3.2. The objective function is penalised by the addition of the term ' $\beta(t) \cdot VoLL$ ', where $VoLL$ is the Value of Lost Load in £/MWh. The $VoLL$ monetarily quantifies the economic damage caused by electricity demand not being met. We choose a $VoLL$ value of £ 4000/MWh according to the UK Office of Gas and Electricity Markets (Ofgem) (Flamm and Scott, 2014). In all cases where the electricity balance constraint is relaxed, the percentage of electricity unmet is less than 0.8% of total electricity produced. Undoubtedly, such levels of power outage would lead to severe economy-wide implications. As a common modelling approach and for the limited number of cases it is applied to, we believe this modification to have a negligible impact on the results in this study.

Fig. 7 visualises the system value dependency of the three power technologies on the different system conditions. Each figure shows the base case scenario in the centre of the family of curves for the SV of onshore wind, CCS, and grid-level energy storage, respectively. In a power system which is constrained to achieve low-carbon targets alongside with a secure and stable electricity provision the value of a technology highly depends on the technologies composition of given the power system. For instance, a low nuclear capacity availability increases the SV of onshore wind from £ 290/kW to £ 370/kW reduction in total system cost upon deployment of onshore wind for the initial capacity unit of 200 MW. The lack of the firm and zero-carbon nuclear capacity makes zero-carbon power generation from onshore wind more valuable, despite its intermittent nature. A high availability of nuclear capacity devalues the contribution of wind power generation to the total system cost reduction. In the scenarios presented, the SV of onshore wind capacity is on average 40% greater with low nuclear availability and 40% lower with high nuclear availability.

Additionally, the availability of firm low-carbon nuclear capacity influences the optimal deployment level of onshore wind capacity. While in the base case onshore wind capacity reaches its economic deployment limit at 85 GW, the nuclear capacity availability reduces this level to 70 GW or increases it to 115 GW, respectively.

For the CCS capacity we make similar observations regarding the nuclear capacity availability. In the "LoNuk" case the SV of CCS increases on average by 140%. Due to its capacity firmness, CCS can provide ancillary services additionally to flexible power generation. The "HiNuk" case reduces the CCS SV on average by 40% compared to the base case. The iRES penetration in the given power system shows on average an increase in CCS SV of 40% and a decrease of 15% caused by low and high iRES capacity availability, respectively. The limit of optimal CCS capacity deployment is marginally influenced by the change in nuclear or iRES capacity availability.

The value of grid-level energy storage depends to an even greater extent than for power generating technologies on the design of and constraints of the energy system it is operating within. Only in the case of a temporary electricity generation excess from power generators, storage capacity can be charged and is able to perform a virtual time-shift in power production when it is discharged at a later point in time. This ability for power generators to decouple power production from load or price signals, or to adjust their production according to their optimal operation patterns (reduce cycling, shut-downs/start-ups), comes at the cost of electricity loss in the conversion process of the energy storage technology. Nevertheless, due to the discontinuous power production form iRES and the high costs associated with thermal power plant

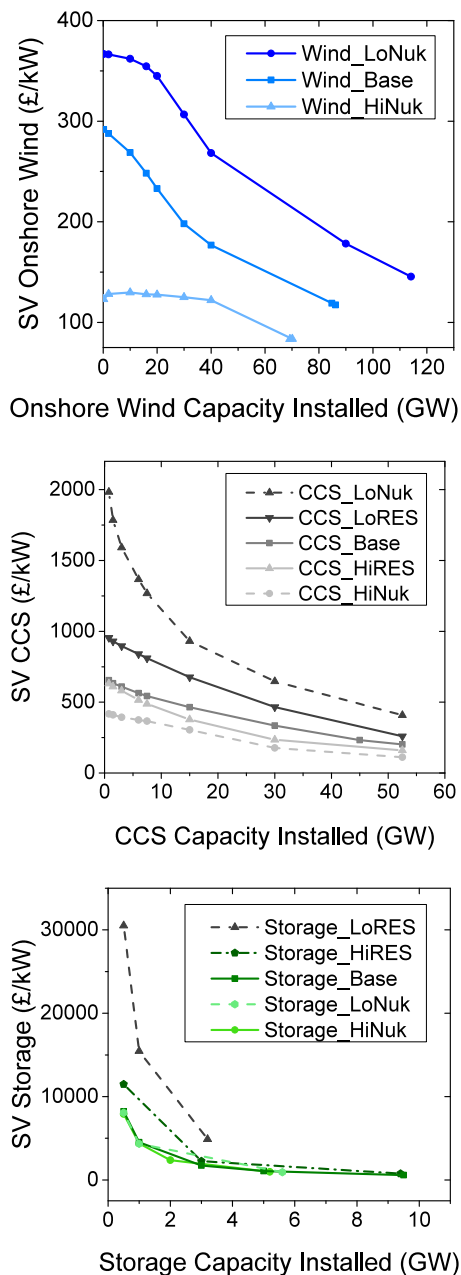


Fig. 7. Impact of different capacity availabilities on system value of onshore wind, CCS, and grid-level energy storage capacity. The “HiNuk” and “LoNuk” scenarios refer to a 50% increase and decrease in available nuclear capacity, respectively. Scenarios “HiRES” and “LoRES” are defined by a 80% increase and a 50% decrease of intermittent renewable (onshore and offshore wind) capacity.

shut-down and start-up, energy storage technologies are found to be highly valuable for overall system performance.

In Fig. 7 the energy storage SV shows a limited dependency on the level of nuclear capacity availability. As the main source of electricity charged to the storage is from iRES power production, the amount of wind capacity influences the value of a grid-level energy storage more significantly. However, although a low level of iRES capacity implies less available power to be charged to the storage, the SV of storage in the “LoRES” case is even higher than in the “HiRES” case. This is mainly due to the ability of grid-level energy storage to reduce the cycling and overall operational cost of thermal power plants. In the “LoRES” case, 66% of electricity charged comes from thermal power generation (nuclear, CCGT, coal and CCGT post-combustion CCS). The ability to store electricity and

optimise thermal power production according to the operational performance parameters reduces thermal start-up cost by 90% and fuel expenses by 25%.

In the “HiRES” case, the energy storage mostly operates to complement the intermittent power production from iRES. Electricity charged is to 65% from iRES and to 35% from thermal power plants. Operational expenses associated with cycling of thermal power plants are reduced by 30% through the integration of storage capacity (at the economic limit in the “HiRES” scenario of 9.4 GW). The initial total system cost reduction per amount of installed storage capacity to smoothen iRES electricity production (“HiRES” case) is less pronounced than the reduction in thermal cycling cost (“LoRES” case). However, we note that overall the savings in total system cost per amount of capacity installed for grid-level energy storage are more than 10 times higher than for CCS or onshore wind capacity. Furthermore, these savings can be achieved at one-tenth of capacity installation.

5. Concluding remarks

We have developed a conceptual and mathematical framework for systemic power technology valuation. The system value (SV) metric is based on an electricity systems optimisation model combining generation expansion and unit commitment formulations and taking detailed environmental, reliability and operability, and economic constraints into account. We demonstrate that the value of a given power generating technology is a function of the system constraints and composition of the system within which it is operating.

We find that the SV of onshore wind, CCGT post-combustion CCS, and grid-level energy storage capacity in a UK-type system is positive and indicates the actual savings in total system cost (TSC) caused by the deployment of the respective technology. The SV of the first available capacity unit of energy storage is an order of magnitude higher than the SV of wind and CCS capacity. However, the SV of energy storage declines rapidly from approximately £ 4500/kW to £ 500/kW as more capacity is deployed, reaching a common level with the SV of CCS at deployment rates of 9.5 GW. The SV of both CCS and wind capacity reduces gradually, however, the SV of wind remains well below CCS ranging from nearly £ 200/kW to £ 120/kW.

5.1. Future work

The presented analyses does not include cost learning rates as the technology capacity is deployed within the electricity system. The data clustering approach, which was applied only to scenarios excluding storage availability, leads to inconsistencies (sudden increase/decrease) in the data profiles causing potentially atypical power plant behaviour and possibly an overestimation of required flexible capacity. Furthermore, the ESO model does not include spatial granularity, hence does not account for electric transmission or distribution aspects. The modelled overseas interconnectors are represented as one-way electricity import mechanism without taking the overseas electricity market into account.

Future work aims at further investigating the mutual influence of power technologies within the power system and under changing system requirements. Additionally, we aim at addressing the aforementioned shortcomings by including endogenous technology learning rates into the model formulation, and adding modelling detail on interconnection and the distribution network.

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