

The EV-olution of the power system: A spatio-temporal optimisation model to investigate the impact of electric vehicle deployment

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Abstract

Power system models have become an essential part of strategic planning and decision-making in the energy transition. While techniques are becoming increasingly sophisticated and manifold, the ability to incorporate high resolution in space and time with long-term planning is limited. We introduce the ES-ONE model, a mixed-integer linear program, determining investment in power system generation and transmission infrastructure while simultaneously optimising operational schedule and optimal power flow on an hourly basis. Unique data clustering combined with model decomposition and an iterative solution procedure enable computational tractability. We showcase the capabilities of the ESONE model by applying it to the power system of Great Britain under CO₂ emissions reduction targets. We investigate the effects of a spatially distributed large-scale roll-out of electric vehicles (EVs). We find EV demand profiles correlate well with offshore and onshore wind power production, reducing curtailment and boosting generation. Time-of-use-tariffs for EV charging can further reduce power supply and transmission infrastructure requirements. Overall, spatially explicit power system modelling is key to assess increasingly distributed generation and demands.

Keywords: power systems modelling, transmission planning, optimisation, MILP, k-means, spatio-temporal clustering, electric vehicles, time-of-use-tariffs

1. Introduction

1.1. Motivation and aim of study

The rate at which energy systems around the world are changing is unprecedented. Aside from exceptions such as Iceland, New Zealand, or Denmark, countries which do not have access to an abundant source of complementary renewable energy sources struggle to find efficient pathways towards deep decarbonisation. In particular, the rapid increase in wind and solar power generation in the electricity sector has brought new challenges to the way existing power grids and assets have to be operated and managed. The intermittency of wind and solar power generation has precipitated a search for new ways to efficiently store energy, as well as to integrate different energy sector and processes. New technology and business solutions are being developed to address challenges of the energy transition, *e.g.*, balancing issues, transport of energy and resources, new supply and value chains, and the decentralisation of power generation. These trends will have to continue if governments and institutions are serious about their pledged greenhouse gas emission reduction targets.

In conjunction with the aforementioned energy system changes, an ever growing number of mathematical models are being used to investigate possible pathways in the increasingly complex decision space. The expectations for such models are high; having to capture technical detail, short and long-term time scale, supply and demand sides, political and societal requirements, market dynamics, granular spatial representation, uncertainties, optionality, and more. While it is obvious that models cannot - and do not need to - capture all described aspects in all cases, transparency of the models capabilities, assumptions, and data are essential.

However, despite this plethora of activity, a gap still exists in combining long-term power supply planning, based on technically detailed bottom-up models, with the ability to address location-dependent transitions such as transport electrification. Importantly, certain energy sources and sinks (*i.e.*, distributed solar generation, or electric vehicle (EV) charging) are highly site-specific. Today, transmission grid operators must anticipate generation expansion, increasing sector integration, and long permission processes [1]. Planning generation and transmission in conjunction is less costly than a sequential approach [2].

With regards to transport electrification, common research questions have been, for example, optimal charging/discharging of EV batteries, build-out of charging infrastructure, or vehicle-to-grid technologies for advanced grid management. In this work, the research questions of interest are: What type of power generation capacity should be built to meet future demands with/without considering passenger transport electrification? When is the optimal investment timing?

Where should the capacity be built - close to energy sources or demand centres? Where/when is additional transmission grid reinforcement necessary?

Our modelling and analysis intends to fill this research gap and provide an answer to the posed questions. In this paper we extend the Electricity Systems Optimisation (ESO) framework, a set of mixed-integer linear programs [3, 4, 5, 6] to include high spatial and temporal resolution. We introduce the ESONE model as part of the ESO framework. Further, we propose an efficient spatio-temporal data processing technique based on k-means clustering and specific profiling developed as part of this work, and a rolling-horizon solution technique to enable computational tractability of long-term planning combined with short-term operational detail. We showcase the ESONE model by assessing the impact of an EV revolution on the requirements for supply and transmission capacity scale-up, carbon emissions, and cost. The effect of an EV fleet under different charging strategies and regional load demand profiles is estimated and integrated exogenously to the ESONE model. Sub-optimal and optimal (*aka smart*) charging behaviour is compared by its impact on national scale electricity supply and transmission infrastructure.

The paper is structured as follows. In section 2, we discuss existing literature on spatio-temporal power system models, while section 3 reviews existing analysis of the effect of electric vehicles on the power system. In section 4 we develop the ESONE model. Section 5 introduces the underlying data sets and the developed data processing techniques. Section 6 discussed the results of our analysis, section 7 concludes, and section 8 outlines suggestions for future work.

2. Existing spatially and temporally detailed power system models

To briefly contextualise our work within the existing literature, we provide an overview of existing power system models with similar model structure and approach. Optimisation models, typically linear or mixed-integer linear programs, which are bottom-up, engineering-based, and with a techno-economic focus fall into this category. We combine the classical generation expansion planning (GEP) and transmission expansion planning (TEP) type models. While transmission planning and the corresponding optimal power flow are classical electrical engineering research questions, the process systems engineering and energy systems modelling community has produced many widely-used models, data processing, and solution techniques to tackle the combined GEP and TEP problem.

The ELMOD model (Spatial Optimization Model of the Electricity Sector) developed by DIW Berlin (Deutsches Institut für Wirtschaftsforschung) is a cost-minimizing or welfare-maximising spatial electricity systems optimisation model

considering power flow on high-voltage DC transmission lines performing power supply and infrastructure planning [7]. Applications have focussed on the European power system, including multi-period and rolling-horizon planning procedure [8]. ELMOD is written in GAMS and various model versions are available in public repositories [7]. ELMOD is also part of a larger group of models including e.g. DIETER for dispatch optimisation, and MultiMod for resource planning in a market equilibrium model [9, 10]. The URBS model performs GEP and TEP in a linear programming approach [11]. The Calliope model by Pfenninger is an object-oriented fully open-source and open-data energy systems model [12, 13]. A focus is set on flexible and high resolution spatio-temporal modelling, user-friendly model adjustment and data processing. Pfenninger studies the United Kingdom (UK) power system and transmission grid comparing different approaches to time series compression [12]. An extensive work by Krishnan et al. studies the advantages of co-optimised transmission and power supply capacity planning and provides a review of existing co-optimisation tools [2]. Krishnan et al. find that it is sub-optimal to plan supply and transmission independently, and point out that real-world transmission network and system operators consider both in conjunction. AC and DC optimal power flow (OPF) models are reviewed and mitigation approaches to the end effect or end-of-horizon effect are discussed. Others have proposed combined GEP and TEP models which are applied to the pan-European power grid such as the Dispa-SET model [14] as well as national power grids such as the PyPSA model by Hörsch, Brown, and Schlachtberger [15, 16]. With the SWTICH model such analyses are performed for the U.S. power system at a high spatial resolution of 124 transmission nodes and a medium temporal resolution of a total of 576 hours (*i.e.*, four investment periods from 2014-2029, 12 months, two days/month, six hours/day) [17]. The most prominent commercial model for GEP, TEP, and various other market simulation tools is PLEXOS [18].

Another group of models aims to capture the power or energy market uncertainties, combining GEP/TEP type models with stochastic optimisation approaches. Munoz, Hobbs et al. present a stochastic TEP and include detailed power flow representation considering Kirchhoff's law [19]. Another probabilistic GEP/TEP model is presented by Aghaei et al., considering voltage phase angles at each node and aimed at evaluating reliability requirements [20]. Also Riaz et al. analyse power system inertia and reactive power support capability by simulating the power market including unit commitment and KVDC power flow on the Australian grid [21]. A rolling horizon approach is applied to increase computational tractability. Sharifzadeh et al. develop a stochastic optimisation model based on DC flow for the UK power system to develop a robust design of future electrical grids given uncertainty on wind and solar availability [22]. Moreira et al. develop a novel robust optimisation GEP/TEP model in a two-stage min-max-min fashion accounting for uncertainty in renewable availability and demand, and high supply security standards, *i.e.*, $n-K$ criteria and loss of load

probability [23]. To increase tractability of the large-scale mixed-integer linear programs for the GEP/TEP problem, Bender's decomposition techniques are proposed for example by Munoz and Hobbs [24] increasing convergence speed and Lara et al. [25] allowing the solution of larger model instances.

3. Transport electrification: Impact of EVs on national-scale power systems

E-mobility has been identified by many countries as a medium-term priority, with the UK articulating particularly specific ambitions [26]. New sales of diesel and petrol cars are being banned from 2040 onwards, and charging infrastructure projects are being rolled out across the country. A necessary increase in electricity generation capacity due to transport electrification have been quoted to be low [27, 28]. In Germany, for example, a required capacity addition is estimated to 1% by 2030 and up to 4% by 2050 [28]. For the UK, analysis by AURORA Energy Research estimates an additional 19 TWh could be required annually by 2035 for 30% of the car fleet to be electrified [29]. UK's transmission grid operator, National Grid, projects in the highest consumption scenario and for 90% of car sales in 2050 to be EVs an additional annual demand of 46 TWh, or 11% national demand [30]. A comparison of high-level integrated assessment models shows that bio-energy, bio-energy with Carbon Capture and Storage (BECCS), and other fossil fuel based power generation with Carbon Capture and Storage (CCS) play a key role in providing the net-zero or net-negative electricity to an increasingly electrified fleet of vehicles [31]. Anable et al. provide an analysis of possible lifestyle changes and how these affect mode of transportation as well as distance travelled, vehicle ownership, and technology choice [32]. Final energy demand of the transport sector can be reduced if lifestyle changes are taken into account.

Perhaps more critical than the total capacity requirement is the effect a growing EV fleet could have on the shape of the daily load curve and the peak demand in particular. In high demand concentration areas, the peak demand could increase up to 20-30% [33, 28]. Local level peak demand (e.g., in residential areas) could increase significantly, affecting especially distribution level transformer load factors and potentially shortening the transformer lifetimes [34]. In the UK, estimates for 10 million EVs range from 0.5 GW under "smart" charging assumptions to 3 GW for unmanaged charging [29]. For 2040, the National Grid presents scenarios between 4-10 GW additional peak demand for a nearly fully electrified fleet [35]. Smart charging typically refers to shifting power draw from EVs to otherwise low demand or high supply hours, or specifically to time-of-use tariffs (TOU) framework; whereas unmanaged charging refers to a conventional "plug-and-charge" strategy. Similarly, Boßmann et al. model

energy demand and potential load curves in 2050 for Great Britain and Germany and find a substantial increase in peak demand for both countries (23% points in addition to change in annual demand) [33]. While minimum demand levels remain similar and the penetration of intermittent renewables increases, conventional power plants can expect higher ramp rates and overall lower asset utilisation. Pudijanto et al. assess the effect of increasing transport and heat sector electrification in various scenarios up to 2050 on the electricity distribution network¹ and identify a potential 2 to 3-fold increase in peak demand for the UK [36]. However, the coordinated deployment of “smart” appliances, such as EV charging or heat pump control, could significantly alleviate network reinforcement needs. Similarly, Dyke et al. show for load profiles across 27 EU member states how network investment costs can be managed by coordinated fixed and new variable location loads [37].

Much attention in the past years has been given to the opportunity of enabling variable location loads, such as EVs, to participate in ancillary service provision and capitalise on the ability to balance local networks. On a higher level, this can be done via an integrated scheduling approach of potentially intermittent supply (*i.e.*, renewable power generation) and variable loads [38, 39, 40]. On a lower level, explicit modelling and investigation of vehicle-to-grid technologies (V2G) allow the close linkage of power and transportation sector. The V2G potential was first described by Kempton and Letendre in 1997 and refers to the ability of power utilities and local networks to utilise the EV batteries for grid management and load balancing via a bi-directional charging points [41]. The authors postulated then that the benefit to power utilities would exceed the cost of installing the required infrastructure and the cost of increased battery degradation. More recently Kempton et al. suggest that a likely outlet for V2G technology will be the ancillary service market offering spinning reserve and short-term frequency and voltage control [42, 43]. Battery degradation is a direct function of the depth of discharge (DoD) [44]. It is assumed that for peak load balancing and spinning reserve services V2G batteries might experience deep cycling, whereas for power grid regulation shallow cycles are more likely [42]. Nevertheless, when providing V2G services, EVs will be likely to require multiple battery pack replacements over the vehicle lifetime[44].

Since then, a large body of literature has been created dealing with the integration of a V2G-able EV fleet into the power grid planning and management [45]. Charging control can reduce the need for grid reinforcement [46], and, for a large number of connected EVs for instance, other supply “peak-shaving” and “valley-filing” systems might become obsolete altogether [47]. The overall potential of load shifting from EVs, however, depends strongly on the maximum

¹This work focuses on the high-voltage transmission network only.

charging and discharging power [48]. Further, Hoogvliet et al. find that the participation of EVs in the secondary reserve market would have little effect on the owner's ability to travel [49]. EV owners participating with V2G technology in the ancillary service market (in particular voltage control) could see their owner's cost roughly halved, though without considering battery degradation or any additional charges to participate in the V2G service [50]. More conservative estimates for the UK show a benefit in the range of £150-400 per annum which is considered insufficient to incentivise EV adoption [38]. It is believed that the largest revenue generated by EV services could come from reduced curtailment of intermittent renewables [27]. Pavić et al. present reducing wind power curtailment levels as a function of increasing EV penetration providing ancillary services and system flexibility in the form of thermal power plants [51]. In a less flexible power system, total cost savings and curtailment reduction potential provided by EVs is greater (up to 85%) for high wind penetration levels.

Other research topics, however beyond the scope of this work, are the optimisation of EV charging infrastructure [52, 53], and the analysis of consumer behaviour (mode of transport, charging location/time, etc.) [54, 55, 56]. To date, such models are being deployed to inform real-world infrastructure design (e.g., BeWhere-bus by IIASA [57]).

4. ESONE - Electricity Systems Optimisation with high temporal and spatial resolution

ESONE is part of the ESO model family which have been developed in previous publications (ESO [58, 3], ESO-X and ESO-XEL [4, 59]). The ESO-X, ESO-XEL model and input data for perfect foresight and myopic planning are publicly available on the open access platform Zenodo [5, 6].

The key difference of the ESONE model (*Spatially granular Electricity Systems Optimisation model with capacity expansion*) to the remaining ESO models is the spatially explicit (e.g. multi-nodal representation of a country vs single-node representation) power supply and transmission capacity expansion. When the model is applied to the UK power system, unit commitment, economic dispatch, and optimal direct current power flow is optimised across a 29-node network. Similarly to the ESO-X and ESO-XEL models, we apply time compression techniques to reduce the computational expense and solution time. We develop a spatio-temporal k-means clustering algorithm and profiling approach to optimally represent full hourly time sets across the network nodes as 11 clusters with 24 hours each, in 5-yearly steps, *i.e.* 8 planning periods representing 35 years of planning and operation (2015-2050).

4.1. Key Assumptions and Salient Model Features

This section lists key underlying assumptions and important model features. The following section 4.3 introduces the mathematical form of the ESONE model in detail. Further information can be found in the supplementary online material.

- We take the perspective of a monopolistic system planner.
- We assume myopic foresight for 2 planning periods each (*i.e.*, 10 years) and solve the model iteratively in a rolling-horizon fashion. More information is provided in section 4.3.10 and 9.2.
- We assume electricity demand and electricity import prices to be perfectly inelastic.
- Uncertainty in the input parameters is not considered. The model is deterministic.
- We determine the optimal capacity expansion plan $b_{i,z,a}$, in terms of the number and type of power generation and storage technology i units in each zone z for each planning period a , transmission line capacity $bq_{z,z',a}$, and interconnection capacity (included in technologies i) to neighbouring networks. The lifetime of the capacity stack in the initial year (2015) is considered and appropriate capacity replacements/additions are determined.
- The space dimension is discretised into 29 zones in the UK case (see figure 3 or 4). Line capacity is modelled according to the base year (2015). Optimal grid reinforcement/expansion is determined simultaneously with power supply and energy storage capacity for all planning years.
- Power generation technologies and loads typically connected to the distribution grid are assumed to be grouped and accounted for on the transmission grid level at the respective node.
- Optimal power flow is modelled as direct current (DC) flow, assuming constant current, constant generator voltages, constant angles, and constant power factor (VAr/Watt ratio). Energy losses are considered as a function of power flow and distance.
- The time dimension is discretised into 5-yearly planning time steps a and hourly operational time steps t . The planning time horizon contains 8 planning period (2015-2050), the operational time horizon contains 11 hourly data clusters of 24 hours each. The optimal clusters are determined via k-means clustering and spatio-temporal profiling developed as part of this study and represent one year of operation. Time and space dependent data which is subject to this clustering and profiling algorithm are the power demand, onshore wind, offshore wind, and solar availability, and the import electricity price.

- We obtain the optimal operational schedule (e.g., dispatch, reserve provision, storage charging, discharging, DC power flow, electricity import/export) for each hourly time step t in each time cluster c for each planning time step a .
- We differentiate between conventional, i.e., thermal power plants ic and intermittent renewable power plants ir , which together compose the class of electricity generating power plants ig . Additionally, we model different grid-level energy storage technologies is .
- The operation of conventional power plants ic is modelled in a on/off fashion while considering minimum uptime and downtime constraints.
- The maximum power output of intermittent renewables ir is bound by hourly availability profiles.
- Two different types of international electric interconnectors are modelled: (1) as power generation technology, i.e., for connections mainly operated to import power; (2) as energy storage capacity where charging/discharging power is limited by the line capacity.²
- Energy storage technologies can be continuously charged and discharged. The storage efficiency is modelled as round-trip efficiency on the charging power flow, such that all stored energy is discounted. The storage level is constrained by the maximum amount of installed units. Discharging is bounded by operational limits. Reserve can be provided in form of storage capacity as the residual of storage inventory after energy discharge.
- CO₂ emissions from imported electricity via interconnection capacity are calculated based on the 2015 annual average carbon intensity levels for electricity generation in the connected power networks [61]. However, these “imported” emissions are not included in the national CO₂ emissions target, as a production based approach is the common accounting strategy in the UK.
- Carbon intensity of power generation (t_{CO_2}/MWh) is technology-specific. An overall system emission target allows for temporary overshoot but constrains the total annual emissions.
- Spinning reserve requirements are defined as a fraction of peak demand plus a proportion of the instantaneous power output to secure dynamically against failure of largest firm and intermittent unit or unexpected forecast error.

²Type (1) *InterImp* of the interconnectors model is applied to the existing UK-FRA, UK-NLD, UK-GB(NIR) (zone 27, 26, 5) and if chosen to the connection to zones 26, 27, 28, 29; type (2) *InterSto* is applied to the UK-IRE (zone 12) connection and if chosen to the connection to zones 1, 2, 5, 8, 11, 19, 29. These distinctions are based on historical power flow patterns [60].

- Frequency control ensures system operability and is modelled via a constant minimum security level of system inertia. Technologies provide different levels of inertia (GW.s).
- Unmet electricity demand is penalized by the Value of lost load (VoLL), which is set to £4,000/MWh. Additionally, the amount of unmet electricity demand is limited to a fraction of annual load.

4.2. Nomenclature

Symbol	Unit	Description
Sets		
a	years	planning periods, $a \in A = \{1, \dots, A_{end}\}$
t	h	time periods, $t \in T = \{1, \dots, T_{end}\}$
c	-	clusters for time set compression, $c \in C = \{1, \dots, C_{end}\}$
z	-	spatial zones, $z \in Z = \{1, \dots, Z_{end}\}$
i	-	technologies, $i \in I = \{1, \dots, I_{end}\}$
ig	-	power generating technologies, $ig \subseteq I$
ic	-	conventional generating technologies, $ic \subseteq I$
ir	-	intermittent renewable technologies, $ir \subseteq I$
is	-	storage technologies, $is \subseteq I$
iz	-	locationally constrained technologies, $iz \subseteq I$
$inoz$	-	locationally unconstrained technologies, $inoz \in \{I \setminus iz\}$
$Li_{z,z'}$	-	1, if zone z and z' connected, 0 else
$NoLi_{z,z'}$	-	1, if zone z and z' not connected, 0 else
Parameter		
Δ_a	years	step width planning years
$DIni_{i,z}$	-	number of available units of technology i for $a = 1$
$DMax_i$	-	maximum number of units of technology i
$DZMax_{i,z}$	-	maximum number of units of technology i by zone z
Des_i	MW/unit	nominal capacity per unit of technology i
BR_i	unit/year	build rate of technology i
$LTIni_i$	years	lifetime of initial capacity of technology i for $a = 1$
LT_i	years	lifetime of technology i
$TE_{i,*}$	diff.	features of technology i ,
where * is:		
$Pmin$	%-MW	minimum power output as percentage of nominal capacity
$Pmax$	%-MW	maximum power output as percentage of nominal capacity

C_{max}	%-MW	maximum capacity provision as percentage of nominal capacity
RP	%-MW	reserve potential as percentage of nominal capacity
IP	%-MW	inertia potential as percentage of nominal capacity
E_{ms}	tCO ₂ /MWh	emission rate
$UtilMin$	%-MW	minimum utilisation rate as percentage of nominal capacity
$MA_{i,a}$	-	maturity parameter for technology i - the years technology i is available for deployment
$CAPEX_i$	£/MW	investment costs of technology i
$OPEX_{i,a}$	£/MWh	operational costs of technology i in year a
$OPEXSU_i$	£/h/unit	start-up costs of technology i
$OPEXNL_i$	£/h/unit	fixed operational costs of technology i when operating in any mode
$TCAPEX$	£/MW/km	investment cost transmission line
$TOPEX$	£/MW	operational cost transmission line
$Dist_{z,z'}$	km	distance between zone z and z'
$TLDist$	%-MWh/km	transmission losses
$TDes$	MW	capacity unit size of transmission line
$TIni_{z,z'}$	MW	initial transmission capacity between zone z and z'
TBR	MW	transmission capacity build rate
$ImpElecPr_{c,t}$	£/MWh	electricity import price
UT_{ic}	h	minimum up-time for technology ig
DT_{ic}	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 as percentage of nominal storage capacity
$SOCMax_{is}$	%-MW	maximum storage inventory level minimum storage inventory level as percentage of nominal storage capacity
$AV_{ir,z,c,t}$	%-MW	availability factor of technology ir
$SD_{c,t,z,a}$	MWh	system electricity demand in year a at hour t
EVD_a	MWh	additional demand of EV fleet country wide in year a
$WFEVZ_{z,a}$	%	weighting factor for zonal demand share of EV fleet by zone z in year a
$EVDh_{c,t,a}$	MWh	hourly zonal demand of EV fleet at time t cluster c in year a
WF_c	-	weighting factor for time clusters c

$WFA_{i,a}$	-	weighting factor for CAPEX depending on life-time of technology i and year a
$PL_{a,z}$	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	tCO ₂	system emission target in year a
$UnDem$	%	level of tolerated unmet annual demand
$VoLL$	£/MWh	Value of Lost Load
$Disc_a$	-	discount factor $(1 + r)^a$ in year a
Variables		
tsc	£	total system cost
$e_{i,z,a,c,t}$	tCO ₂	emission caused by technology i in zone z in year a in time cluster c at hour t
Positive		
$p_{ig,z,a,c,t}$	MWh	energy output
$p2d_{ig,z,a,c,t}$	MWh	energy to demand
$p2s_{ig,z,a,c,t}$	MWh	energy to grid-level storage
$p2is_{is,z,a,c,t}$	MWh	energy to storage technology is
$p2x_{ig,z,a,c,t}$	MWh	energy of technology ig exported from zone z
$r_{ig,z,a,c,t}$	MW	reserve capacity provided by technology ig
$s_{is,z,a,c,t}$	MWh	effective state of charge of technology is at the end of time period t
$s2d_{is,z,a,c,t}$	MWh	energy from storage technology is to demand
$s2r_{is,z,a,c,t}$	MW	reserve capacity provided by storage technology is
$slak_{z,a,c,t}$	MWh	slak variable as lost load
$emslak_{a,c,t}$	tCO ₂	slak variable for emissions
$u_{ig,z,a,c,t}$	unit	number of units of technology ig starting up in year a at time t
$w_{ig,z,a,c,t}$	unit	number of units of technology ig turning down in year a at time t
$q_{z,z',a,c,t}$	MWh	energy flow from zone z to z'
$q2d_{z,a,c,t}$	MWh	energy flow into zone z to meeting demand in z
$q2s_{z,a,c,t}$	MWh	energy flow into zone z to storage in z
$q2is_{is,z,a,c,t}$	MWh	energy flow into zone z to storage technology is in z
$TotOPEX_a$	£/year	total operational expenses per planning period a
Integer		
$b_{i,z,a}$	unit	number of new built units of technology i

$d_{i,z,a}$	unit	total number of units of technology i installed in year a
$dq_{z,z',a}$	MW	operational transmission line capacity in year a
$bq_{z,z',a}$	MW	new build transmission line capacity in year a
$n_{ig,z,a,c,t}$	unit	number of units of technology ig operating
$ois_{z,a,c,t}$	unit	number of units of storage technology is operating

4.3. Model formulation

4.3.1. Objective function

The objective function 1 minimises total system cost, including capital expenses of power supply and transmission capacity expansion, total system OPEX where the years between the 5-yearly planning intervals a are approximated in a piecewise linear fashion (difference between OPEX in a and $a-1$). The end-of-horizon effect is addressed via introduction of the weighting factor $WFA_{i,a}$, which accounts for the fraction of a technologies lifetime compared to the modelled time horizon. More information is provided in the supplementary material [section 5](#).

$\min\{tsc\}$; where

$$\begin{aligned}
tsc = & \sum_{i,z,a} CAPEX_i b_{i,z,a} WFA_{i,a} Des_i / Disc_a + \sum_{a < 8} TotOPEX_a \Delta_a / Disc_a \\
& + \sum_{a > 1} (TotOPEX_a - TotOPEX_{a-1}) \left(\frac{\Delta_a}{2} - 1 \right) / Disc_a \quad (1) \\
& + \sum_{a=8} TotOPEX_a / Disc_a + \sum_{z,z' \in Li_{z,z',a}} TCAPEX_i Dist_{z,z'} bq_{i,z,a} / Disc_a
\end{aligned}$$

The total system operation cost $TotOPEX_a$ is defined in equation 2, comprising start-up cost $OPEXSU_{ig,a}$, running cost $OPEX_{ig,a}$ (incl. fuel cost, efficiency, variable OPEX, carbon price, cost of CO₂ transport and storage where applicable), fixed OPEX $OPEXNL_{ig}$, cost of energy storage operation $OPEX_{is,a}$ and $OPEXNL_{is}$, cost of power import, operation of the transmission grid, as well as a penalty term for possible power demand being unmet.

$$\begin{aligned}
TotOPEX_a = & \sum_{ig,z,a,c,t} u_{ig,z,a,c,t} OPEXSU_{ig} WFc \\
& + \sum_{ig,z,a,c,t} (OPEX_{ig,a} p_{ig,z,a,c,t} + OPEXNL_{ig} n_{ig,z,a,c,t}) WFc \\
& + \sum_{is,z,a,c,t} (OPEX_{is,a} s2d_{ig,z,a,c,t} + OPEXNL_{is} o_{is,z,a,c,t}) WFc \\
& + \sum_{i=InterImp,z,a,c,t} ImpElecPr_t p_{i,z,a,c,t} WFc \\
& + \sum_{z,z' \in Li_{z,z',a,c,t}} TOPEX q_{z,z',a,c,t} WFc + \sum_{z,a,c,t} slak_{z,a,c,t} WFc VoLL
\end{aligned} \tag{2}$$

4.3.2. Capacity expansion constraints

Constraints 3-11 define the power supply capacity expansion from the initial state in $a = 1$ (eqn. 3) via a maximum build rate (eqn. 4) and locationally dependent and independent upper bounds (eqn. 5-6). Life time constraints 7-9 determine the optimal build out, while constraints 10-11 ensure the number of operational units is limited by the number of units installed.

$$d_{i,z,a} = DIni_{i,z} \quad \forall i, z, a = 1 \tag{3}$$

$$\sum_z b_{i,z,a} \leq BR_i MA_{i,a} \Delta_a \quad \forall i, a > 1 \tag{4}$$

$$\sum_z d_{inoz,z,a} \leq DMax_{inoz} \quad \forall inoz, a \tag{5}$$

$$d_{iz,z,aa} \leq DZMax_{iz,z} \quad \forall iz, z, a \tag{6}$$

$$d_{i,z,a} = d_{i,z,a-1} - b_{i,z,a-\frac{LTIni_i}{\Delta_a}} + b_{i,z,a} \quad \forall i, z, a \leq \frac{LTIni_i}{\Delta_a} + 1 \tag{7}$$

$$d_{i,z,a} = d_{i,z,a-1} + b_{i,z,a} \quad \forall i, z, \frac{LTIni_i}{\Delta_a} + 1 < a \leq \frac{LT_i}{\Delta_a} + 1 \tag{8}$$

$$d_{i,z,a} = d_{i,z,a-1} - b_{i,z,a-\frac{LT_i}{\Delta_a}} + b_{i,z,a} \quad \forall i, z, a > \frac{LT_i}{\Delta_a} + 1 \tag{9}$$

$$n_{ig,z,a,c,t} \leq d_{ig,z,a} \quad \forall ig, z, a, c, t \tag{10}$$

$$o_{is,z,a,c,t} \leq d_{is,z,a} \quad \forall is, z, a, c, t \tag{11}$$

4.3.3. Transmission grid expansion constraints

Constraints 12-15 represent the transmission grid expansion; analogously to constraint 3 for power supply capacity starting from an initial transmission network (see figure 4) and expanding at a maximum build rate (eqn. 14). Retirement of existing transmission grid infrastructure is not considered (eqn. 15).

$$dq_{z,z',a} = TIni_{z,z'} \quad \forall z, z', a = 1 \quad (12)$$

$$bq_{z,z',a} = 0 \quad \forall z, z', a = 1 \quad (13)$$

$$bq_{z,z',a} \leq TBR \Delta_a \quad \forall z, z' \in Li_{z,z'}, a > 1 \quad (14)$$

$$dq_{z,z',a} = dq_{z,z',a-1} + bq_{z,z',a} \quad \forall z, z' \in Li_{z,z'}, a > 1 \quad (15)$$

4.3.4. System-wide requirements

The following constraints ensure compliance with the system-wide requirements on power systems adequacy, reliability, and operability via the power balance (eqn. 16), peak demand (eqn. 17), spinning reserve (eqn. 18), and system inertia (eqn. 19). Constraint 16 is visualised in appendix 9.1 figure 16 (a). Furthermore, constraint 20 sets the system-wide CO₂ emissions target and constraint 21 limits the amount of energy not being met by power supply via the Value of Lost Load *VoLL*.

$$\sum_{ig} p2d_{ig,z,a,c,t} + \sum_{is} s2d_{is,z,a,c,t} + q2d_{z,a,c,t} \quad (16)$$

$$= SD_{c,t,z,a} - slak_{z,a,c,t} \quad \forall z, a, c, t$$

$$\sum_{i,z} d_{i,z,a} Des_i TE_{i,Cmax} \geq \sum_z PL_{a,z} (1 + CM) \quad \forall a, c, t \quad (17)$$

$$\begin{aligned} \sum_{ig,z} r_{ig,z,a,c,t} TE_{ig,Rp} + \sum_{is,z} s2r_{is,z,a,c,t} TE_{is,Rp} \\ \geq \sum_z PL_{a,z} RM + \sum_{ir,z} p2d_{ir,z,a,c,t} WR \end{aligned} \quad \forall a, c, t \quad (18)$$

$$\sum_{ig,z} n_{ig,z,a,c,t} Des_{ig} TE_{ig,lp} + \sum_{is,z} o_{is,z,a,c,t} Des_{is} TE_{is,lp} \geq SI \quad \forall a, c, t \quad (19)$$

$$\sum_{ic \setminus InterImp, z, a, c, t} (e_{ic,z,a,c,t} - emslak_{z,a,c,t}) WF_c \leq SE_a \quad \forall a \quad (20)$$

$$\sum_t slak_{z,a,c,t} WF_c \leq UnDem \sum_{z,c,t} SD_{c,t,z,a} WF_c \quad \forall a \quad (21)$$

4.3.5. Technology-specific constraints

Constraints 22-26 define minimum and maximum power output, the generating technology-specific power balance (eqn. 24), as well as operational CO₂ emissions from power generation and imported power (technology type *InterSto* $\in is$). Constraint 24 is visualised in appendix 9.1 figure 16 (b). Constraint 27 enforces a minimum utilisation level for biomass fired power plants until planning time period 4, which is equivalent to the lifetime of the existing biomass fired assets.

$$p_{ic,z,a,c,t} \geq n_{ic,z,a,c,t} Des_{ic} TE_{ic,Pmin} \quad \forall ic, z, a, c, t \quad (22)$$

$$p_{ig,z,a,c,t} + r_{ig,z,a,c,t} \leq n_{ig,z,a,c,t} Des_{ig} TE_{ig,Pmax} \quad \forall ig, z, a, c, t \quad (23)$$

$$p2d_{ig,z,a,c,t} + p2s_{ig,z,a,c,t} + p2x_{ig,z,a,c,t} = p_{ig,z,a,c,t} \quad \forall ig, z, a, c, t \quad (24)$$

$$e_{ig,z,a,c,t} = p_{ig,z,a,c,t} TE_{ig,Ems} \quad \forall ig, z, a, c, t \quad (25)$$

$$e_{is,z,a,c,t} = s2d_{is,z,a,c,t} TE_{is,Ems} \quad \forall is, z, a, c, t \quad (26)$$

$$\sum_{c,t} p_{ic,z,a,c,t} \frac{WF_c}{8760} \geq TE_{ic,UtilMin} d_{ic,z,a} Des_{ic} \quad \forall ic = \{Bio\}, z, a \leq 4 \quad (27)$$

The minimum and maximum power supply from intermittent renewable energy sources, *i.e.*, onshore wind, offshore wind, and solar, are constrained via the respective availability profiles $AV_{ir,z,c,t}$ (eqn. 28-29).

$$p_{ir,z,a,c,t} \geq n_{ir,z,a,c,t} Des_{ir} TE_{ir,Pmin} AV_{ir,z,c,t} \quad \forall ir \setminus InterImp, z, a, c, t \quad (28)$$

$$p_{ir,z,a,c,t} + r_{ir,z,a,c,t} \leq n_{ir,z,a,c,t} Des_{ir} AV_{ir,z,c,t} \quad \forall ir \setminus InterImp, z, a, c, t \quad (29)$$

4.3.6. Up and down times for conventional generators

The on/off switching of conventional power plants *ic* is reformulated from the typical unit-wise up-time and down-time constraints with binary variables per unit (*e.g.*, by Morales et al. [62, 63]) to integer variables per technology type. Inspired by the convex hull formulation presented by Takriti et al. [64], we generalise constraints 30-33 for the design problem such that the number of generators is variable ($d_{ic,z,a}$ instead of 1 in eqn. 33).

$$u_{ic,z,a,c,t} \geq n_{ic,z,a,c,t} - n_{ic,z,a,c,t-1} \quad \forall ic, z, a, c, t > 1 \quad (30)$$

$$w_{ic,z,a,c,t} \geq n_{ic,z,a,c,t-1} - n_{ic,z,a,c,t} \quad \forall ic, z, a, c, t > 1 \quad (31)$$

$$u_{ic,z,a,c,t} \leq n_{ic,z,a,c,\tau} \quad \forall ic, z, a, c, \tau = t + t' - 1, t' \leq UT_{ig} \quad (32)$$

$$w_{ic,z,a,c,t} \leq d_{ic,z,a} - n_{ic,z,a,c,\tau} \quad \forall ic, z, a, c, \tau = t + t' - 1, t' \leq DT_{ic} \quad (33)$$

4.3.7. Energy storage constraints

The operation of energy storage technologies is defined in constraints 34-42. The lower and upper bound of electricity and reverse provision are given in constraints 34-36. Grid electricity to be stored $p2s_{ig,z,a,c,t}$ is assigned to the respective storage technologies $p2is_{is,z,a,c,t}$ (eqn. 37). Equation 38 defines the initial state of charge, while the storage inventory balance, and storage capacity limits are given in constraints 39-41; maximum charging is limited in constraint 42. Constraint 39 is visualised in appendix 9.1 figure 16 (d).

$$\begin{aligned} s2d_{is,z,a,c,t} + s2r_{is,z,a,c,t} + s2x_{is,z,a,c,t} \\ \geq o_{is,z,a,c,t} Des_{is} TE_{is,Pmin} \quad \forall is, z, a, c, t \end{aligned} \quad (34)$$

$$s_{is,z,a,c,t} \leq o_{is,z,a,c,t} Des_{is} SOCMax_{is} SDur_{is} \quad \forall is, z, a, c, t \quad (35)$$

$$s_{is,z,a,c,t} \geq o_{is,z,a,c,t} Des_{is} SOCMin_{is} SDur_{is} \quad \forall is, z, a, c, t > SDur_{is} \quad (36)$$

$$\sum_{ig} p2s_{ig,z,a,c,t} = \sum_{is} p2is_{is,z,a,c,t} \quad \forall z, a, c, t \quad (37)$$

$$s_{is,z,a,c,t} = Des_{is} SOCIni_{is} SDur_{is} \quad \forall is, z, a, c, t = 1 \quad (38)$$

$$\begin{aligned} s_{is,z,a,c,t} = s_{is,z,a,c,t-1} - s2d_{is,z,a,c,t} \\ - s2x_{is,z,a,c,t} + q2is_{is,z,a,c,t} SEta_{is} \\ + p2is_{is,z,a,c,t} SEta_{is} \quad \forall is, z, a, c, t > 1 \end{aligned} \quad (39)$$

$$s2d_{is,z,a,c,t} + s2r_{is,z,a,c,t} + s2x_{is,z,a,c,t} \leq o_{is,z,a,c,t} Des_{is} \quad \forall is, z, a, c, t \quad (40)$$

$$s2d_{is,z,a,c,t} + s2r_{is,z,a,c,t} + s2x_{is,z,a,c,t} \leq s_{is,z,a,c,t} \quad \forall is, z, a, c, t \quad (41)$$

$$p2is_{is,z,a,c,t} + q2is_{is,z,a,c,t} \leq o_{is,z,a,c,t} Des_{is} \quad \forall is, z, a, c, t \quad (42)$$

4.3.8. Transmission grid constraints

The final set of constraints 44-46 defines the DC power flow between zones z and z' . Power flow $q_{z',z,a,c,t}$ can meet instantaneous demand $q2d_{z,a,c,t}$, or be charged to energy storage units $q2s_{z,a,c,t}$ if these are present in zone z . Power flow between zones z incurs a distance dependent loss (eqn. 44). Constraint 44

is visualised in appendix 9.1 figure 16 (c). Constraint 46 ensures line capacity limits are maintained.

$$\sum_{ig} p2x_{ig,z,a,c,t} + \sum_{is} s2x_{is,z,a,c,t} + \sum_{z' \in Li_{z,z'}} q_{z',z,a,c,t} \quad (43)$$

$$= \sum_{z' \in Li_{z,z'}} q_{z',z,a,c,t} / (1 - Dist_{z,z'} TLDist) + (q2d_{z,a,c,t} + q2s_{z,a,c,t}) / (1 - TLDist) \quad \forall z, a, c, t \quad (44)$$

$$\sum_{is} q2is_{is,z,a,c,t} = q2s_{z,a,c,t} \quad \forall z, a, c, t \quad (45)$$

$$q_{z,z',a,c,t} \leq dq_{z,z',a} \quad \forall z, z' \in Li_{z,z'}, a, c, t \quad (46)$$

The ESONE model without considering transport electrification is described by the objective function 1 and constraints 2 to 46. Results generated with this model formulation are referred to as 'base case' in the following sections.

4.3.9. Modelling Electric Vehicles demand

As introduced in section 3, an increasing EV fleet can substantially impact the capacity and transmission requirements, and operation of a power system. With the ESONE model, we aim to investigate these effects by modelling the added demand of an EV fleet that is rolled out gradually across the UK. The modelling of V2G capable EV's is beyond the scope of this work. EV's are modelled as additional zonal demand, while simulating a specific load (*i.e.*, charging) profile. The data for annual energy demand increase as a function of EV fleet size as well as daily charging profiles is provided by National Grid [65]. In particular, we implement two different EV models in this work which are used to investigate three main scenarios including EV's. Data and scenarios are further discussed in section 5.4.

Option 1: Annual demand increase scaled up evenly across daily profiles, e.g. hourly constant charging

$$\sum_{ig} p2d_{ig,z,a,c,t} + \sum_{is} s2d_{is,z,a,c,t} + q2d_{z,a,c,t} \quad (47)$$

$$= SD_{c,t,z,a} + \mathbf{EVD}_a \mathbf{WFEVZ}_{z,a} - slak_{z,a,c,t} \quad \forall z, a, c, t$$

where

$$WFEVZ_{z,a} = \frac{EVZ_{z,a} pop_z}{\sum_z (EVZ_{z,a} pop_z)} \quad (48)$$

The parameter $EVZ_{z,a}$ is a matrix of $\{0,1\}$ indicating if a zone z contains EV demand in year a , and pop_z denotes the initial population in zone z for the baseline year. We do not consider population distribution changes over the planning time horizon. The weighting factor for zonal EV demand $WFEVZ_{z,a}$ is multiplied by the annual demand (TWh) associated with an increasing EV fleet EVD_a and added exogenously to the hourly demand profile of the individual zones.

Option 2: Hourly specific charging profiles

$$\begin{aligned} \sum_{ig} p2d_{ig,z,a,c,t} + \sum_{is} s2d_{is,z,a,c,t} + q2d_{z,a,c,t} \\ = SD_{c,t,z,a} + EVDh_{c,t,a} WFEVZ_{z,a} - slak_{z,a,c,t} \quad \forall z, a, c, t \end{aligned} \quad (49)$$

The weighting factor for zonal EV demand $WFEVZ_{z,a}$ is computed as shown in equation 48. Hourly charging profiles given as fleet percentage of daily charge in combination with annual EV demand (TWh) provide hourly (t) EV demand per year a and clustered time set c , $EVDh_{c,t,a}$.

4.3.10. Model implementation and solution procedure

The ESONE-X model is implemented in GAMS 25.0.3 and solved with CPLEX 12.8.0 on a x86_64 machine with 24 CPUs, typically using 6 threads. The model is decomposed along the planning time dimension a and solved in an iterative myopic rolling-horizon fashion. Each iteration contains two planning periods where in the first period $\tilde{a}$ system design decisions ($b_{i,z,a}$, $bq_{z,z',a}$) are fixed. The optimal solution for the latter time period are then used to initialise the next iteration. Appendix 9.2 table 3 formalises and presents the solution algorithm.

In each iteration, power supply and transmission capacity planning are solved simultaneously with hourly operation and power flow. We receive sup-optimal solutions compared to a full Bender's decomposition approach including forward and backward propagation [25]. Hence, the approach applied in this work is comparable to the upper bound solution based on the forward pass. With the outlined approach and hardware typical execution time is approximately 8-10 hours depending on the scenario.

5. Data Preparation and Processing

5.1. Data Processing Tools

Several software programs are used during our data preparation and processing. Python is used to extract solar and wind availability data from Renewables.ninja [66]. These raw hourly datasets are then fed into R [67] to pare down the number of days we model using a k-means clustering algorithm, described in further detail in section 5.3. The output is then sent to GAMS to be read as model inputs. ArcGIS for Desktop (version 10.5) is used extensively throughout data preparation, processing, and visualisation. ArcPy, a module in Python, is used to automate workflows within ArcGIS.

A schematic summarising these workflows and software links are shown in Figure 1, visualising the three main stages of the workflow: pre-optimisation (data preparation and processing), optimisation, and post-optimisation (data visualisation and analysis). In the data preparation and spatial data processing phase, data is transferred between Excel and ArcGIS to convert it into a usable form for ESONE.

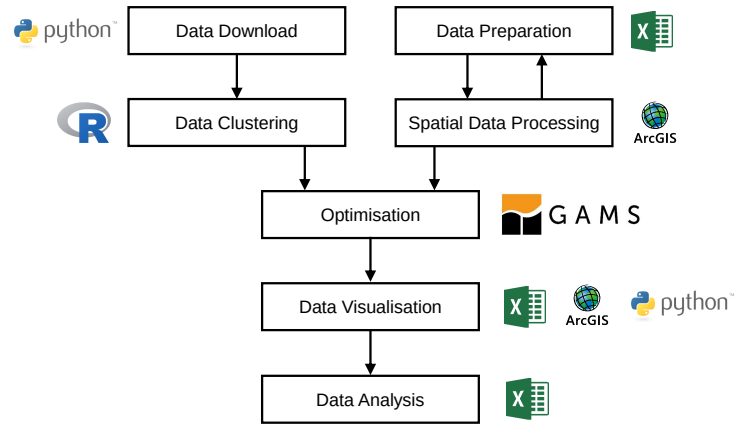


Figure 1: A representation of the workflow and software tools used with ESONE.

5.2. Spatial Data Preparation

Our spatial disaggregation of the UK is based on a 29-node structure proposed originally by Balvanis and Bell [68] and made available by University of Edinburgh [69] and Strbac [70] to approximate Great Britain's electricity transmission system. In addition to using the simplified transmission system, we

created zones by allocating each point within the UK to the closest node via the Thiessen Polygon method (see Figure 4). These zones set the basis for how all remaining spatial data are processed.

The baseline year for our analysis is chosen to be 2015. Figure 2 depicts the location and type of power plants available across the UK in 2015, giving a sense of distribution. On an aggregated level, the baseline power capacity mix consists of 9.8% nuclear, 21.5% unabated coal, 36.4% unabated natural gas, 9.7% solar, 15.3% wind and the remaining capacity composed of imported power and pumped hydro [71].

Maximum power plant capacities for each technology type are based on the projected reference scenario by the U.K. Department of Business, Energy and Industrial Strategy (BEIS) to 2035 and linearly extrapolated to 2050 [72]. Technologies which can be deployed only in certain locations (*i.e.*, nuclear, pumped-hydro, bio-energy, bio-energy with CCS, and international interconnectors) are modelled with a zone-specific upper bound on maximum deployment. For interconnectors the possible zones are chosen based on existing, contracted, and planned projects as reported by National Grid [73] (see [supplementary material section 3](#)). Bio-based technologies are made available according to the data and method described below.. New deployment of nuclear and pumped-hydro plants are assumed to be spatially limited to zones with existing nuclear and pumped-hydro facilities, respectively. The deployment of gas and coal-based technologies, intermittent renewables, and battery storage capacity are assumed to be less spatially constrained and instead limited by a national upper bound value [72]. Further, the annual build rate and resource availability inherent to each zone drive capacity deployment of different technologies.

Solar, onshore and offshore wind power availability data are provided by the renewables.ninja platform [66], developed by Pfenninger and Staffell [74, 75]. The availability determines what portion of a solar or wind plants nameplate power capacity would be available, or produced, at a given hour. In order to determine solar and wind availabilities that were representative for the entire zone, and to avoid local discrepancies, multiple points were sampled from each zone at 10 miles intervals and their availabilities were averaged. Although some smoothing will occur to the profiles due to this averaging, it mimics what the transmission-level grid would encounter from aggregating power from the distribution-level grid. For offshore wind resource availability, we sampled points up to 50 km from shore, a number chosen from the distances found in offshore wind plants currently under construction [76]. Figure 3 illustrates the average renewable resource available over 2015.

Biomass resource availability was calculated for each zone using bioenergy data provided by [77, 78, 79]. Bioenergy availability was averaged for each zone, and

divided by the U.K.'s total availability. The resulting proportionality factor was then used to allocate the U.K.'s maximum biomass power plant capacity into each zone.

Finally, we estimated energy demand distribution using 2015 electricity consumption data from BEIS [80] and total annual demand for 2015 (292 TWh). We assumed the hourly demand profiles for each zone were the same, and scaled based on the zones share of electricity consumption.

A more detailed listing of parameter values, data sources and methodology for each technology can be found in the supplementary material.

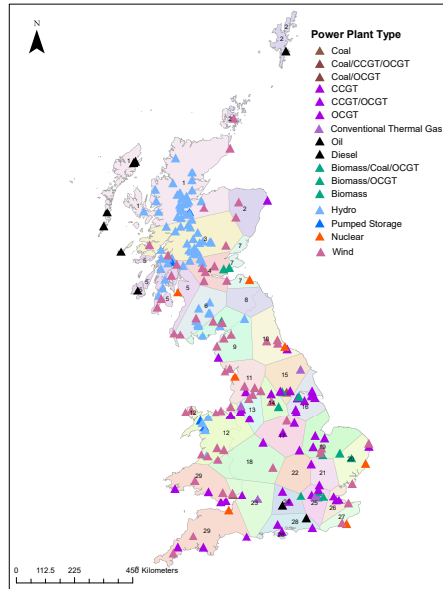


Figure 2: Spatial distribution of the U.K.'s power plants, based on data from CARMA and DUKES [81, 82]

5.3. Spatio-temporal data clustering

In addition to spatial representation, we also selected a temporal representation to make the optimisation problem tractable. Our hourly-based data sets include system demand, onshore wind, offshore wind and solar availability, and import electricity prices for the interconnectors modelled as power generators (e.g., *InterImp*). As discussed in previous work [3, 4], we selected 11 representative days to model, consisting of 10 days calculated using a spatio-temporal k-means clustering algorithm and 1 day representing the peak demand day. The novelty in our k-means clustering approach revolves around maintaining spatial as well as temporal relationships in the input data.

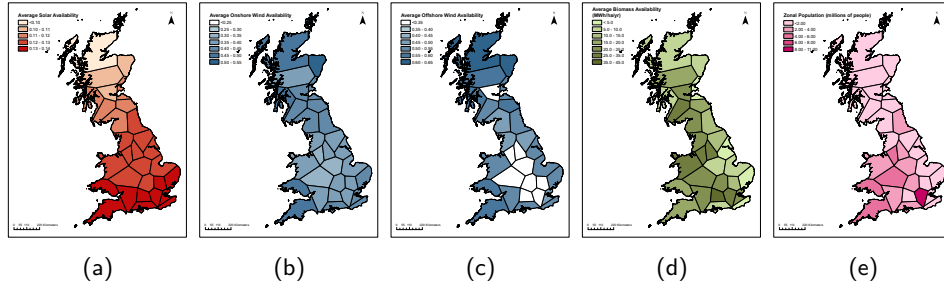


Figure 3: Representation of spatial input data for ESONE-X. (a) Annual average solar availability for each zone (b) Annual average onshore wind availability for 2015 (c) Annual average offshore wind availability for 2015 (d) Annual average biomass available, calculated from [77, 78, 79] (see section 2.1 in supplementary material) (e) Population of each zone for 2011. Data for resource availability is taken from [66]; the population data from [83]

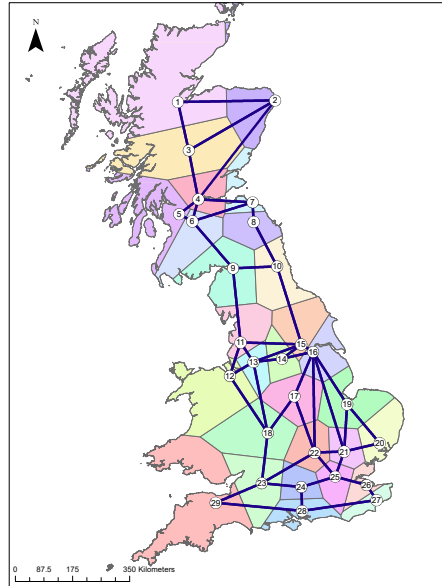


Figure 4: A representative transmission network for Great Britain, using a 29-node scheme presented by [70]. Zones are created using the Thiessen polygon method.

In k-means clustering, data points are allocated to a single cluster such that the Euclidean distance between the data point and the cluster's centroid is minimised. Previously [3, 4], only temporal associations were maintained, ensuring each cluster contained the same set of calendar days for each data set. In our current work, we are able to maintain both temporal associations (hourly and daily) as well as spatial (for each zone). This ensures each cluster not only includes the same set of calendar days, but also includes the full set of zones for each data set for each calendar day.

The clustering procedure was implemented in R [67]. The k-means clustering algorithm is as follows:

1. Prepare multi-dimensional hourly data set for one year, $8760 \text{ hours} \times 5 \text{ data types}$ (onshore wind $\in (0, 1)$, offshore wind $\in (0, 1)$, solar $\in (0, 1)$, power demand $\in \mathbb{R}^+$, electricity import price $\in \mathbb{R}^+$).
2. Divide data set into days ($365 \text{ days} \times (24 \text{ hours} \times 29 \text{ zones} \times 5 \text{ data types})$). This a-priori sets the cluster size to one day, a 24 hour sequence of data points across 29 zones.
3. Extract day with peak demand from all data type profiles.
4. Normalise data types which are not $\in (0, 1)$ (power demand, electricity import price) by its maximum value.
5. Specify the number of clusters k . Based on previous studies [84, 3], we implement a number of $k = 10$. Incurred errors for single-node model are reported in Heuberger et al. [4].
6. Apply k-mean clustering to multi-dimensional data set. This maintains the hourly and zonal correlation between the data types.
7. Receive allocation of daily profiles to k clusters (see figure 5).
8. Apply “energy preserving” profiling method to chooses a specific profile from the data subset in each cluster k . Choose the profile such that the mean value (of energy demand/power availability) across the profile is closest to the mean of the cluster. This enables us to retain the original profile’s intermittency while accurately capturing the total available energy volume over the course of a year.
9. Extract specific profiles for each cluster, data type and zone ($k \times 24 \text{ hours} \times 29 \text{ zones} \times 5 \text{ data types}$) and corresponding weighting factor WF_c (see Figure 5).
10. Add peak demand day back to profiles and assign weighting factor 1.
11. Receive full multi-dimensional clustered data set for all data types ($(k + 1) \times 24 \text{ hours} \times 29 \text{ zones} \times 5 \text{ data types}$).

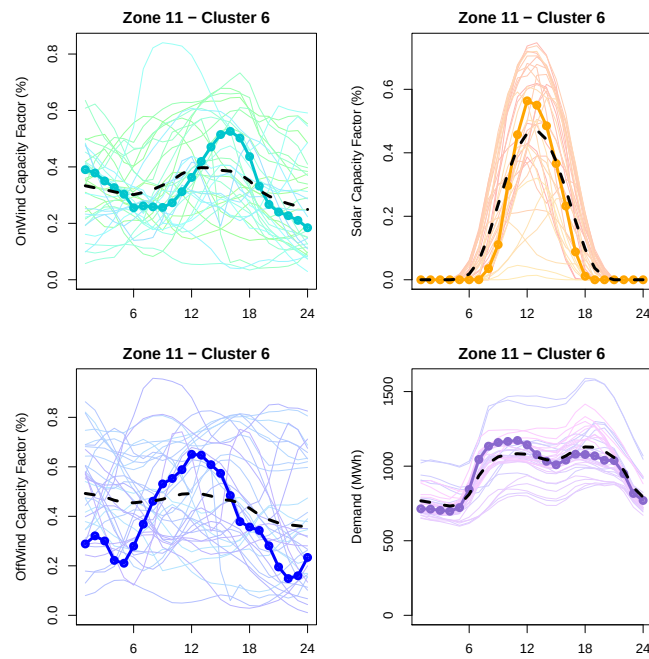


Figure 5: Example of clustered profiles ($k=11$) for power demand, onshore wind, offshore wind, and solar availability; Original data profiles (multicoloured thin lines) are assigned via k-means algorithm to cluster k . The cluster mean (dashed black line) is inherently smooth, whereas the chosen profile which best preserves the energy integral across the respective cluster (solid lines with markers) represents the realistic nature of the underlying data.

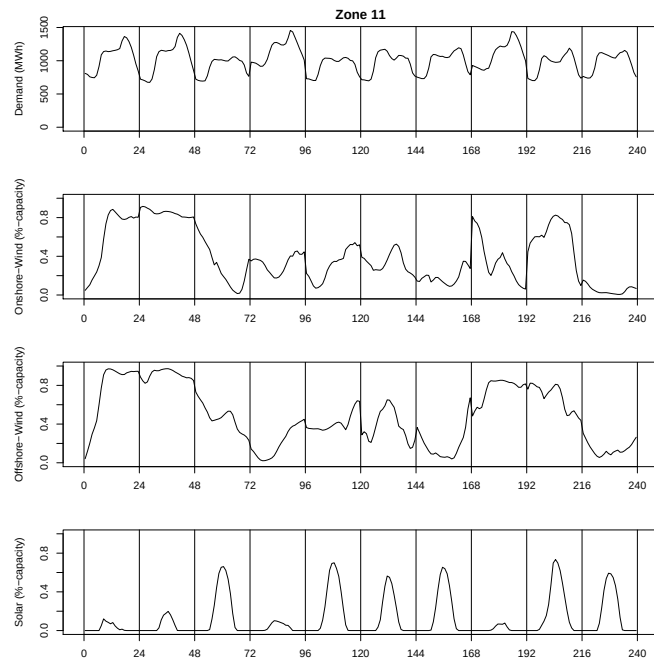


Figure 6: Example of chosen profiles using "energy preserving" profiling method for power demand, onshore wind, offshore wind, and solar availability

5.4. Data related to Electric Vehicles

As introduced in section 4.3.9, the underlying data is provided by National Grid's Future Energy Scenarios [65]. Assumptions are based on the Gone Green scenario, utilising annual data 2015-2040 for energy demand increase (TWh/year) as a function of EV fleet size (mio. vehicles) as well as hourly charging profiles (%) for a sample day (not differentiating between weekday and weekend). Annual data is linearly extrapolated from 2040 to 2050 based on the full given data set from 2015-2040. Key assumptions from National Grid for 2040 are 9.7 million EVs, leading to an annual demand increase of 23.7 TWh with a peak demand increase of 6.5 GW. Extrapolated data in 2050 reaches 14.6 million EVs, at an annual demand increase of 34.1 TWh, and a peak demand of 9.4 GW. Figure 7 (a) illustrates the national-level demand share due to base demand increase (*i.e.*, 1% p.a.) and due to road transport electrification. The zonal distribution of the base demand is based on electricity consumption statistics including industrial demand [80]³, while zonal distribution of EV demand is population-based [83] (see figure 7, b). Figure 8 visualises the EV roll-out via 3 snapshot years, 2020, 2035, and 2050, in which urban zones experience additional demand from EVs first, until subsequently all zones see some portion of EV demand by 2050.

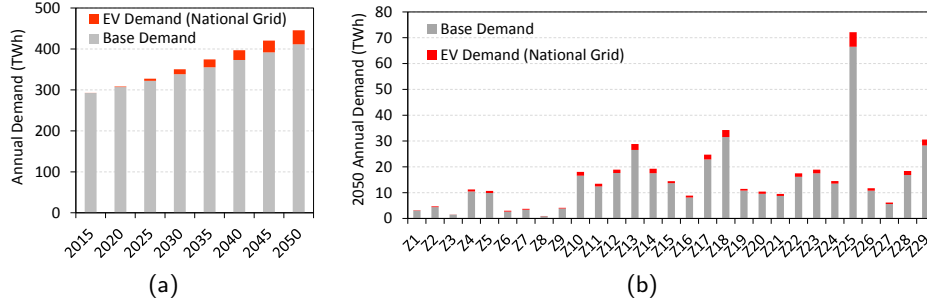


Figure 7: Electricity demand including in increasing electric vehicle (EV) fleet from 2015 to 2050 on a national-scale (a), and by zone (b)

Figure 9 shows the hourly demand profile of EV's under time-of-use-tariff (TOUT) and without TOUT. The TOUT incentivises moving charging further into the night hours where base electricity demand is lower. These charging profiles refer to model option 2 in section 4.3.9, while the hourly constant demand (also shown in figure 9) refers to model option 1. Further, we depict the peak demand hour for the base demand, which occurs around 17:00, while EV peak demand would occur at 21:00 according to the underlying data from National Grid [65].

³Underlying data sets are "MSOA domestic electricity 2015", and "MSOA non-domestic electricity 2015"

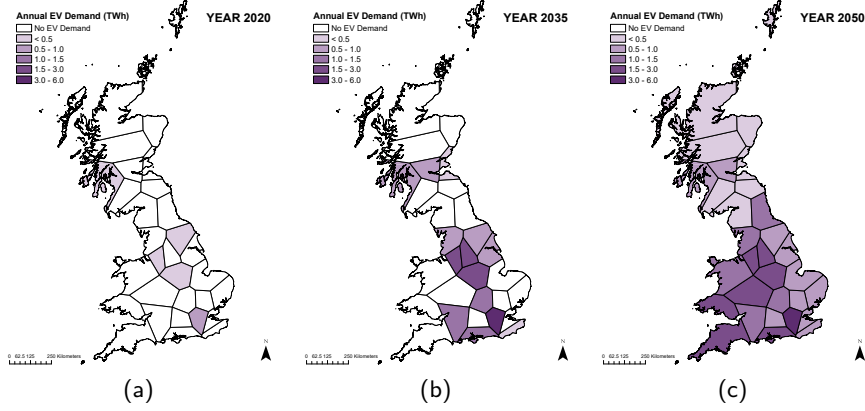


Figure 8: Snapshots of zonal demand increase due to electric vehicle (EV) fleet based on population distribution, (a) 2020, (b) 2035, (c) 2050.

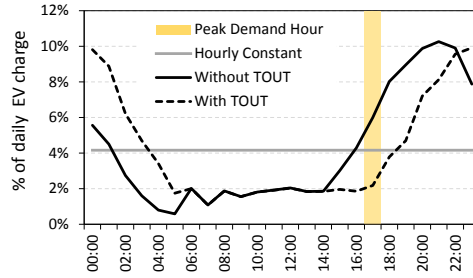


Figure 9: Hourly demand profiles for electric vehicles (EV) under time-of-use-tariff (TOUT) and without TOUT; and equivalent hourly constant demand. Indicated is also the peak demand hour for the base demand profile.

6. Results

6.1. Scenarios

In order to investigate the optimal spatial and temporal capacity and transmission expansion plan as determined with the ESONE model, we evaluate a set of scenarios which are listed with their key features in table 2. The scenarios are chosen such that their analyses can provide some insight into the importance of the time and space dimensions in power systems modelling. For example, the comparison of the ESONE-based scenarios *Base* and *EV-const* allows the assessment of the spatial element in demand distribution and the effect of the capacity requirements, transmission network, and operation. Further, the comparison with the *EV-no-TOUT* and *EV-TOUT* scenarios highlights the impacts of a high time granularity for distributed demands. Finally, we contrast the ESONE model with the previously developed ESO-X model [59], which neglects

Acronym	Key Features	Model	Section/Figure
Base	Base case without EV demand	ESONE	6.2, 10, 11
EV-const	Like Base, incl. EV demand as constant power demand addition equally distributed across all zones	ESONE	6.3
EV-no-TOUT	Like Base, incl. EV demand as hourly power demand without TOUT; with zonal EV roll-out	ESONE	6.3
EV-TOUT	Like EV-no-TOUT, but with TOUT	ESONE	6.3
ESO-X-my	Base case without EV demand, same underlying data to ESONE Base case	ESO-X	6.4, 15
ESO-X-my-EV	Like ESO-X-my, incl. EV demand as constant power demand addition	ESO-X	6.4, 15

Table 2: Key scenarios; TOUT: time-of-use-tariffs; my: myopic; the ESO-X-my model is solved via a myopic rolling horizon approach [59].

spatial granularity. Hereby we point out where caution is required when evaluating spatially aggregated models. A detailed model validation, especially of the transmission expansion and power flow, is performed and available in the [supplementary material section 6](#).

6.2. Power generation capacity and transmission expansion for the UK power system without transport electrification

The UK power system in 2015 is characterized by a large proportion of fossil-based capacity (60%, coal and gas), 11% nuclear capacity, 21% wind and solar combined (*i.e.*, 14% of power provided), 2% biomass, 3% interconnection capacity to overseas, 3% pumped-hydro storage [71]. The status quo of the UK power system in 2015 is shown in figure 10. Figure 10 (b) and (d) show a map with the share of power capacity installed per zone as defined in the ESONE model and power generated in 2015, respectively. Figure 10 (a) showcases for zone 23 the 5-yearly capacity expansion plan for the base case, and (c) depicts two sample days with hourly operation profiles for the power capacity in zone 23 in 2015. In this way, figure 10 demonstrates how the ESONE model simultaneously captures detailed spatial and hourly operation in long-term planning of power systems.

In the base case, the main drivers for generation capacity and transmission grid expansion are full decarbonisation by 2050, increasing electricity demand from the power sector (see figure 7 (a)), power plant retirements, maintaining reliable operation, technology cost reduction, and technology maturation (see eqn. 4). The full underlying data sets are provided as supplementary material in [section 1](#). Technology cost reduction is modelled exogenously, *i.e.*, as given input vector for

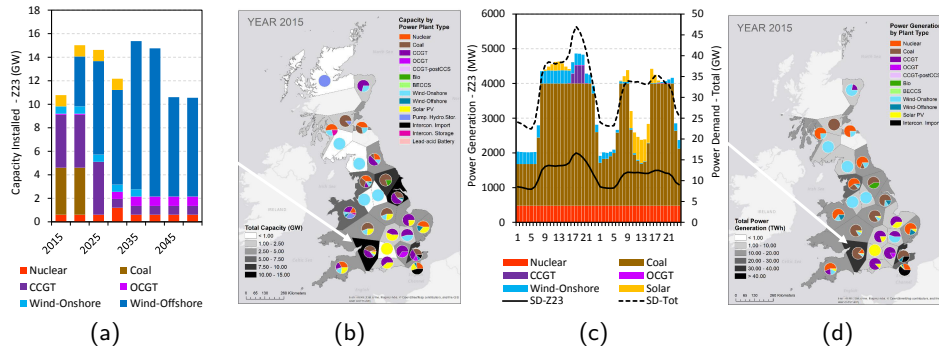


Figure 10: ESONE base case status quo in 2015; (a) capacity installed in zone 23, (b) map of capacity share, (c) hourly power generation profile for 2 sample days in 2015 in zone 23, (d) map of power generation share.

each planning time period and described in detail in the supplementary material [section 4](#). Scenarios considering increasing power demand due to transport electrification are discussed in [section 6.3](#).

Figure 11 shows the resulting UK power system in 2050 in terms of capacity installed (a), power generation (b), transmission capacity installed (c), and power flow on the transmission network (d). The [supplementary material figures 8 to 9](#) show the analogous maps for the years 2020 to 2045.

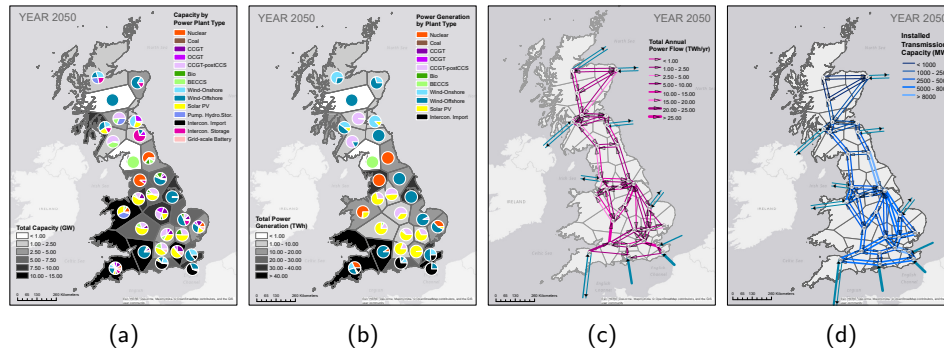


Figure 11: ESONE base case optimal generation capacity and transmission grid expansion in 2050; (a) capacity installed, (b) power generation, (c) transmission capacity installed, (d) power flow on transmission network.

From 2015 to 2050 the power capacity mix becomes more diverse (compare figures 10 (b) and 11 (a)). While in 2015, 17% of zones have more than 4 different types of power plants installed, in 2050 this number increases to 45% (see e.g., zone 13, 14, refer to figures 4 for the zone numbers). To a large extent, renewable power from offshore wind and solar replaces coal, gas, and nuclear (see East coast). Southern and coastal zones are dominated by power import

from overseas. Further, total share of power generation capacity installed per zone shifts from a rather even distribution across the UK to the coastal areas and the Southwest (indicated by the shaded grey background colour of each zone). CCGT-CCS and BECCS play a major role in providing power and system reserve at low and zero CO₂ emissions (see figure 11 (b)). Due to retirements of nuclear, onshore wind, and CCGT capacity between 2035 and 2045 (see supplementary figures 8 and 9 for analogous maps 2020-2045) and stringent CO₂ reduction target, power generation in 2050 relies to a large extent on CCGT-CCS in the Southern centre of the UK.

The transmission network requires expansion, especially in the South and in the Midlands (see figure 11 (c) compared to supplementary figures 8 and 9). In total, additional 10.8 GW of transmission capacity are needed in the base case scenario to transport electricity across the country from high supply to high demand areas. Total transmission capacity in 2015 amounts to 425.5 GW [69, 70]. The increasing inflow of power via interconnectors in the South requires reinforced connections lines to transport power inland (see also figure 13). Power flow along the connection between Scotland and England (zone 6 to 9) increase 3-fold between 2015 and 2050, existing transmission capacity, however, appears to be sufficient. Electricity demand increases further in densely populated areas (see figure 7), causing the hourly average power flow into London (zone 25) for example to rise from 3.9 GW to 4.5 GW (maximum flow in 2050 is 11.1 GW, see figure 11 (c) and (d)). Figure 13 (a) highlights the reinforced zonal connections across the entire planning period 2015 to 2050. Section 6.3 further discusses the effects on the regional transmission grid. The supplementary material section 7 shows the share of capacity installed, power generation, and transmission expansion by zone for each planning period.

6.3. The effect of transport electrification and time-of-use tariffs

We investigate the potential impact of an increasing fleet of electric vehicles on the optimal power generation and transmission expansion plan and operation with the ESONE model. The mathematical model with regards to EV demand is outlined in section 4.3.9, the underlying data on the spread and up-take of EV's across the UK is implemented according section 5.4. Three scenarios including EV's are modelled: (1) according to *option 1* in section 4.3.9 with a constant demand increase across the hours of each daily profile (EV-const), (2) according to *option 2* in section 4.3.9 with hourly charging (*i.e.*, demand) profiles without time-of-use-tariff (TOUT) (EV-no-TOUT), and (3) same as (2) with TOUT (EV-TOUT).

Figure 12 shows capacity mix installed by zone for 2015, 2030, and 2050 for the base case and the 3 different EV scenarios. Analogous figures for all years 2015 to 2050 in 5-yearly steps are shown in the supplementary material section 7.2.

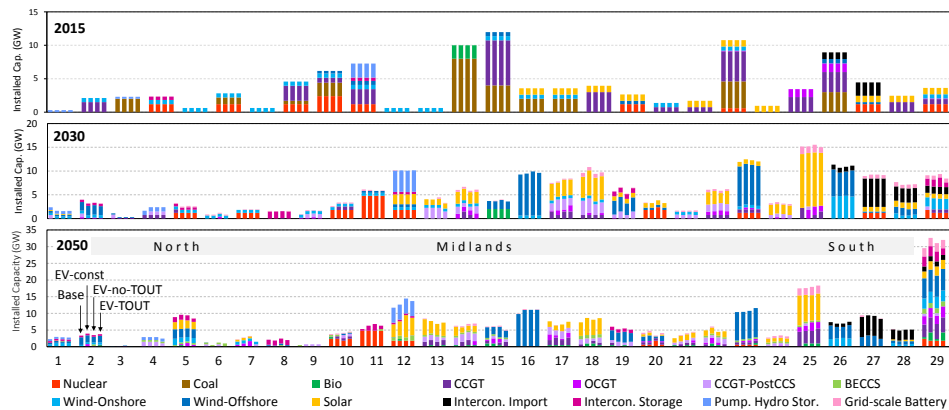


Figure 12: Installed capacity (GW) for 2015, 2030, and 2050 across all zones. Scenarios are, from left to right: base, EV constant, no TOUT, and TOUT. Note the different y-axis scale for 2050.

Similar to figure 11, we observe a general diversification of the capacity mix; most noticeably an increase in solar and offshore wind capacity and a spatial shift in where these resources are harvested. Since the build rate constraint for these technologies is set on a national level, deployment location is driven by resource availability and demand. Zones 23-29 (Southwest) have a relatively high availability of solar radiation and wind (see figure 3) and hence shows high build up of renewable capacity.

The power demand from a growing EV fleet accelerates the build-out rate in the 2030s and beyond. Between 2035 and 2050, an additional 4.4-9.5 GW of capacity is installed in the EV-no-TOUT case compared to the Base case, mostly in form of CCGT, OCGT, BECCS, and interconnector capacity (see e.g., zone 9 or 25). Total capacity requirements in 2050 are 8 GW greater in the EV-TOUT case and 9.2 GW for EV-const. Across all EV cases this is equivalent to an additional 4.2-5% increase compared to the Base case. The zonal shift in capacity deployment gives further insight into the effect of a distributed demand increase.

Cases considering power demand from EV's lead to an increase in offshore wind capacity deployment. Zones 16, 27, or 28 exhibit this effect which is, however, often less pronounced for the EV-TOUT case. Wind power, which is as opposed to solar, also available during night time correlates well with EV power demand which is highest during night time charging (see figure 9). Often wind speeds are even greater during the night than during the day which further creates a convenient supply-demand match-up. (For the underlying hourly offshore and onshore wind power profiles, however, this phenomena is only marginally present.) Further, zone 16 and 23, for example, shows how optimal offshore wind capacity deployment moves to earlier time periods (see 2030). Nevertheless,

increasing power demand in other zones, *e.g.*, 12, 13, 18, 25, is met by greater deployment of solar power. In London (zone 25), additional solar capacity, grid-scale battery storage, gas-fired power plants, as well as wind capacity in zones 26-29 meet the rising power demand.

We find that the utilisation of offshore wind and natural gas fired power plants (CCGT) increase in cases considering an EV demand. Offshore wind power curtailment reduces from a yearly average of 24.7% in the Base case to 20.6% in EV-const, 21.1% in EV-no-TOUT, and 19.9% in EV-TOUT. Conversely, total power generation from offshore wind in 2050 is 7% greater in the EV-TOUT case compared to the Base case. In certain zones, utilisation rates for offshore wind increase by up to 12 percentage points. Further, power generation from BECCS in 2050 increases two-fold in the EV-const case compared to the Base case, and 1.8-fold in the EV-no-TOUT and EV-TOUT case. Additionally, CCGT-CCS and OCGT power generation are 1.7-2.4 times greater in the EV cases than in the Base case. All three power generation technologies, however, show very low utilisation rates of less than 25% from 2030 onwards.

To probe the causes of implementing time-of-use-tariffs for EV's, we analyse the EV-TOUT and EV-no-TOUT scenarios in detail. TOUT incentives encourage demand to be distributed more evenly throughout the day, such that power generation capacity can be used more effectively. Despite the outcomes of the ESONE model being a result of many drivers (*e.g.*, plant retirements, demand, technology cost, CO₂ emission target), the EV-TOUT case consistently requires less total capacity additions compared to the other EV cases. Mainly balancing capacity such as OCGT and grid-scale battery storage can be reduced in the EV-TOUT case. Zone 20, for example, shows a decrease in solar capacity and increase in wind capacity being installed as TOUT shifts more demand into the night hours. In certain zones, *e.g.* 19, 27, also wind capacity requirements can be reduced as existing assets are utilised more efficiently. Across the whole time horizon, wind power curtailment rates are 1-5 percentage points lower in the EV-TOUT case compared to the EV-no-TOUT case. Onshore and offshore wind power curtailment rates reduce by 20% in the EV-TOUT case and 7-15% in the EV-no-TOUT case compared to the Base case.

Figure 13 visualises the requirements for transmission grid reinforcement. Build-up is observed around high demand areas, *e.g.* zone 13, 14, or to zone 18, while the power grid capacity into London (zone 25) is nearly sufficient. Furthermore, the transmission grid in the South (23, 27, 28, 29) requires reinforcements to distribute increasing power inflow from overseas. Grid connection 16 to 14, as well as 1 to 3 and 2 to 4, facilitate the distribution of wind power generation. Note that existing transmission grid capacity is not assumed to retire. The top chart of annual transmission capacity additions in figure 13 (b), allows us to observe a cyclic transmission build-out which matches the retirement and

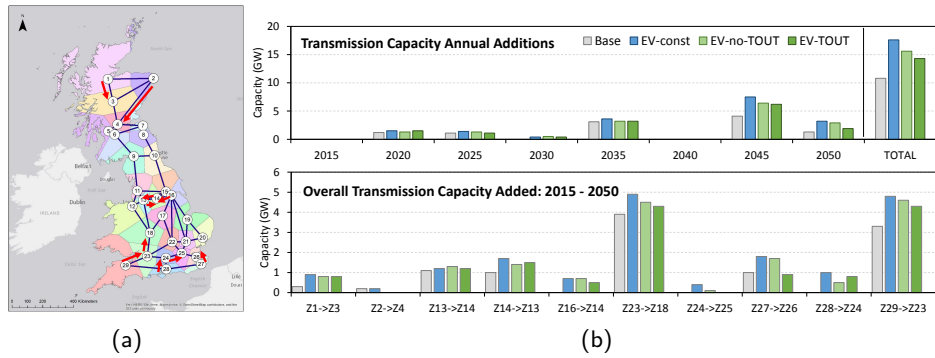


Figure 13: Transmission capacity expansion depending on uptake of electric vehicles; (a) most reinforced connections, (b) annual capacity additions and total additions by zonal connection.

expansion schedule of power generation capacity. In 2025 the existing stock of coal power plants, in 2035 nuclear power plants, and in 2045 onshore wind and CCGT capacity retires, all which correlate to an increase in transmission capacity to allow demand in each zone to be met. Again the EV-TOUT case outperforms the other EV scenarios with the lowest capacity additions necessary compared to the Base case.

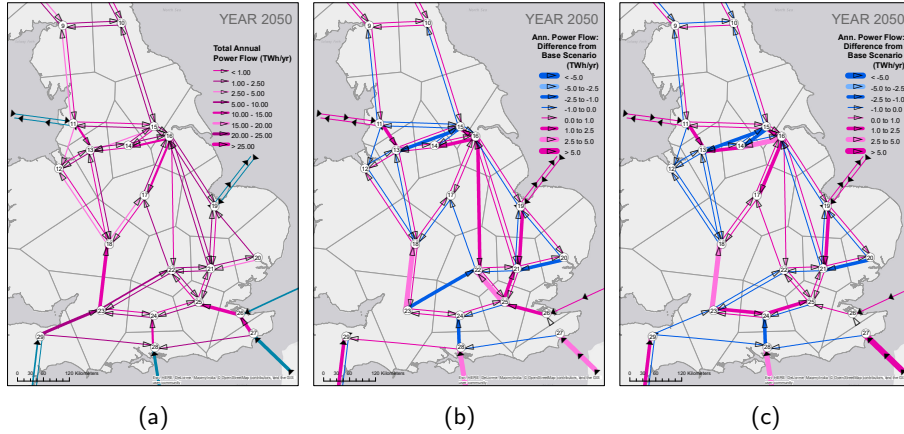


Figure 14: Power flow close-up of Southern region in 2050 for Base case (a), difference in power flow to Base case for EV-const (b), and EV-TOUT (c).

The close-up map of the South of the UK in figure 14 (a) depicts the total power transferred for the Base case in 2050. Figure 14 (b) and (c) visualise the difference in power flow compared to the Base case for the EV-const and EV-TOUT case, respectively. On figures 14 (b) and (c), the different colours refer to a positive or negative change in power flow. In the EV-const case, where additional power demand from EV's is added unregulated and across each zone simultaneously, we see an increase in power flow through London (26 to 25, 25

to 21, 22). Additionally there is an increased distribution of renewable power generation from coastal zones 16, 11, 19 towards the Midlands.

In the EV-TOUT case, where EV roll-out is assumed to correlate with population and base demand, pressure is taken off the power network around London. Power flow through the city is reduced (see 25 to 22), and more electricity is consumed within the city to meet the additional EV power demand. More power is transported from zone 24 to 25. In both EV cases, more power is sent South from Scotland along the “electric highways” 6-9-11 and 8-10-15 (6 and 8 are not shown in figure 14).

6.4. The importance of spatially detailed power system modelling

In order to investigate the effect of spatially granular power system modelling, we compare the capacity expansion plan for the ESONE model as developed in this paper with spatially aggregated modelling. Our point of reference is the myopic ESO-X-my model as presented in previous works [59]. Few modifications to the model as presented in Heuberger et al. [59] have been introduced. The objective function has been updated to reflect the operational expenses for the full time horizon (analogous to equation 1, see second to fourth summand). The parameter $WFA_{i,a}$ has been added to the ESO-X models (analogous to equation 1, see first summand). More information on the $WFA_{i,a}$ parameter is provided in the [supplementary material section 5](#). Additionally, the input data is updated such that for all possible entries the ESO-X models and the ESONE model are based on the same set of data. Note the ESONE model is solved via a myopic rolling horizon approach similar to the ESO-X-my model (see appendix 9.2).

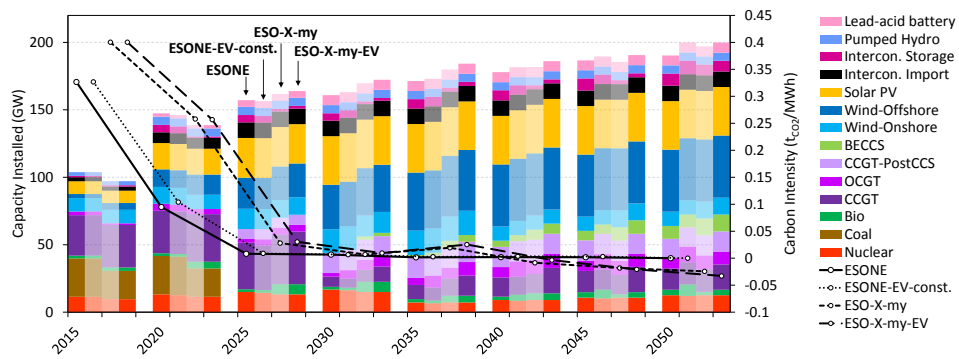


Figure 15: Power generation capacity expansion from 2015 to 2050 for the UK power system based on the ESONE (base case), ESONE-EV-const., the ESO-X-my, and the ESO-X-my model incl. EV demand (left axis); and system-wide carbon intensity (right axis).

Figure 15 presents a comparison of the optimal capacity expansion plan from 2015 to 2050 for the UK power system based on the ESONE and the ESO-X-

my model. For both models we compare the base case and a scenario including EV's as constant demand addition to the general power demand profile. The ESONE-EV-const case is based on an equally distributed roll-out across all zones and as such mimics the ESO-X-my-EV case where spatial disaggregation cannot be taken into account.

The projected capacity expansion plans (excl. EV demand) are in acceptable agreement on a national level with a maximum delta in total annual capacity installed of -6.4% to +7.5% for the ESO-X-my compared to the ESONE model. The ESO-X-my-EV scenario shows a deviation of -6.4% to +6.5% to the ESONE-EV-const case with the highest (6.5%) in 2035. The negative delta of -6.4% occurs in the start year 2015, and is an input to the optimisation models.

Initial installed capacity by zone is based on Strbac et al. [70]. In this data nuclear capacity exceeds historical installations of 9 GW in 2015 by 1.7 GW. However, in this way additional nuclear capacity substitutes for run-of river hydro power capacity (1.6 GW in 2015 [71] which is not modelled explicitly. Total installed capacity in ESONE amounts to 103 GW in 2015 compared to historically reported 100 GW [71]. The unit size per technology is the same for ESO-X-my and ESONE. Based on these inherent data discrepancies, for 2015 and 2020 ESONE sees higher total capacity installed than the ESO-X-my scenario. However, for all following planning periods, with the exception of 2045, the ESO-X-my scenario projects higher capacity requirements than ESONE. In 2040 and 2045, the ESONE model leads to greater deployment of interconnection capacity (Intercon. storage), which can balance supply and demand mismatch in high renewable penetration areas along the Northern coasts (e.g., zones 1, 2, 5, 8, 19). This spatial dimension is neglected in the ESO-X-my model which consequently underestimates the interconnection capacity deployment.

Biomass-fired power plants are deployed earlier and to a greater extend in the ESO-X-my scenarios, as low-carbon dispatchable capacity is required to meet increasing demand. Similarly, more CCGT-CCS and BECCS capacity is deployed sooner in the ESO-X-my scenarios. The maximum deployment rates for CCGT-CCS are reached between 2030 and 2045 for all four cases; in 2050, however, CCGT-CCS deployment in the ESONE cases are slightly lower (750 MW) compared to the ESO-X-my and ESO-X-my-EV case. The total increased power generation from low-carbon capacity leads to a greater reduction in CO₂ intensity levels for the ESO-X-my cases.

Overall, we find that spatially granular modelling (ESONE) yields lower requirements for dispatchable power capacity, and sees higher value in energy storage. A lack of spatial granularity (ESO-X-my) can overestimate CO₂ intensity reduc-

tion potential due to greater share of low-carbon power generation. Evidently, all geographical detail that was presented in sections 6.2 and 6.3 is neglected and unavailable in spatially aggregated models.

7. Conclusion

This work has set out to develop a spatially and temporally explicit power generation and transmission capacity expansion model, to assess the effect of high spatial resolution on optimal system planning. Further, we have analysed the impact of distributed demand for the case of an increasing fleet of electric vehicles (EV's) based on different modelling approaches and expected demands shapes (time-of-use-tariffs).

A large amount of data can be generated with the modelling framework in place, and many questions are still unexplored. We hope this work will stimulate further research; some ideas and ambitions for future work is outlined in section 8. Here, we focus our discussion on three main conclusions.

(1) Spatial disaggregation is key to accurately capture system behaviour and the increasing decentralization of power supply and demand. In line with a power system transition an evolution of tools and methodology is required to analyse the dominant effects and interactions. Spatially disaggregated models, such as ESONE, can give an indication for the optimal siting of power generation capacity and transmission line reinforcements which are key for a successful power system transition. For the spatially aggregated model ESO-X [59] and the here developed temporally and spatially explicit model ESONE, we find that on a national-scale (such as the UK power system) the total capacity requirements by 2050 for specific demand and CO₂ emission reduction scenarios are estimated to be up to 5% greater. This results from the fact that the transport of power across transmission network is not considered in the ESO-X model, neglecting the possibility of spatially balancing power supply and demand.

(2) Variable, distributed loads, such as demand from EV's, should not be neglected in power systems planning with regards to capacity building as well as transmission planning. For the case of the UK transmission grid, we have shown that there can be discernible differences in grid reinforcement requirements and power flow if the demand of EV's are taken into account. An increase or decrease in power flow between most of the 29 modelled zones is less than 2 TWh/year. Certain links, however, between high renewable capacity zones and those with growing demand requirements due to EV penetration can increase by above 5 TWh/year. Further, distributed demand from EV's changes optimal siting of renewable and dispatchable capacity. Trade-off between best resource

availability, demand location, distance, cost of transmission grid reinforcement has to be considered on a case-by-case basis.

(3) Offshore and onshore wind power production correlates well with EV demand profiles. A fleet of 14.6 million EV's by 2050 can reduce curtailment of offshore wind power generation on average between 2015-2050 by 5 percentage points, e.g. by from 11% to 7% in 2020 or 22% to 15% in 2050. Onshore wind and solar power curtailment rates are low, on average below 1%, but can be reduced further by 20-50% in scenarios including EV's. The value of time-of-use-tariffs (TOU) lays in moving more charging demand into night hours when general system demand is low. A boost in wind power utilisation between the EV-TOU and EV-no-TOU case is 2% in 2050. These observations are in line with previous studies reviewed in section 3 which describe an increase in wind power capacity and the improve usability of offshore wind by means of dedicated charging mechanisms, *i.e.* smart charging [85, 29].

8. Future Work

This work has addressed the impact of an EV fleet on power generation and transmission capacity expansion and operation. The presented model does not consider the power distribution level which is the crucial connection point for EV's. Vehicle-to-grid technology, which allows bi-directional connection of EV's to the power grid has also not been in the scope of this analysis. Both of these aspects should be addressed in future work.

Additionally, the modelling framework can be extended by further improving the solution procedure. A full Benders decomposition including forward and backward propagation or tri-level iterative approach could achieve performance improvement. The hourly data processing can be modified to allow for seasonal energy storage technologies by ordering the generated clusters, adjusting cluster size, or applying altogether different data compression techniques.

Acknowledgement

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9. Appendix

9.1. Power balances

Figure 16 visualises the power balances for constraint 16, 24, 44, and 39.

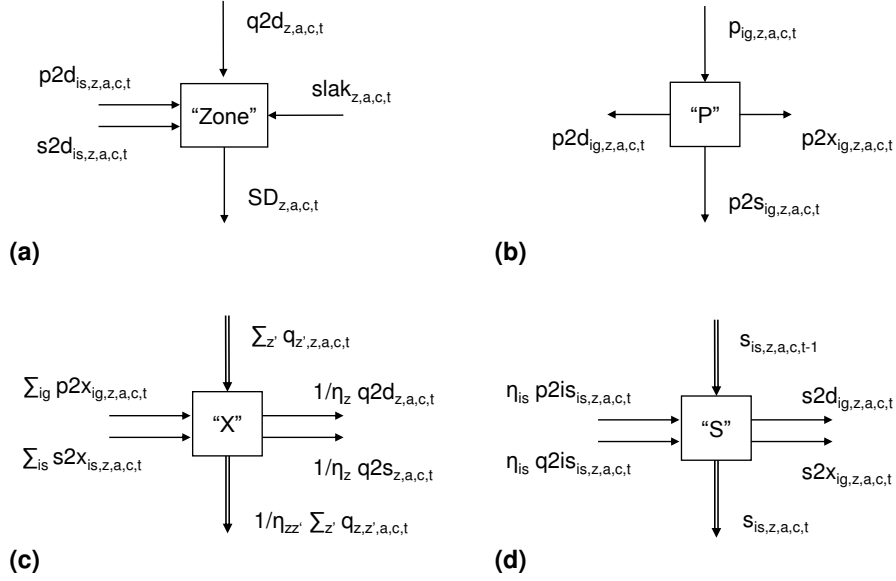


Figure 16: Schematic of power balance for (a) constraint ??, (b) 24, (c) 44, (d) 39

9.2. Solution procedure

Due to the model size and complexity (MILP), the model cannot be solved in its monolithic form. Apply convex hull reformulation of integer scheduling constraints, *i.e.*, variables $n_{ig,z,a,c,t}$, $z(ic, m, m', a, t)$, and $o_{is,z,a,c,t}$ are defined over $\mathbb{R}^+$ rather than $\mathbb{Z}$. Additionally, the model is decompose along the planning time dimension and solve in a rolling horizon fashion. The applied approach is comparable to the forward pass in a Bender's Decomposition [25]. The reduced models contain $2.2 \cdot 10^6$ variables, $2.8 \cdot 10^3$ of them discrete, and $2.9 \cdot 10^6$ constraints. Table 3 formally describes the developed solution procedure. Here, $\rho_{h,a}$ is defined to cover two planning years per iteration.

Algorithm: Solve ESONE-X in rolling horizon fashion.

- 1: define set of rolling horizon iterations $h \in H$
 - 2: define set of active planning periods a per iteration h as $\rho_{h,a}$
 - 3: **for all** $h \in H$
 - 4: assign $\rho_{h,a}$ to dynamic set aa of planning periods
 - 5: set $aa_f = \min\{\rho_{h,a}\}$ and $aa_l = \max\{\rho_{h,a}\}$
 - 6: **solve** MILP model ESONE minimising tsc
 - 7: assign $DIni_{i,z} = d_{i,z,aa} \forall aa = aa_l$, and
 $TIni_{z,z'} = dq_{z,z',aa} \forall aa = aa_l$ as starting point for next iteration
 - 8: fix variables in dynamic set aa to their current level value
 $b_{i,z,aa} = b_{i,z,a}$, $bq_{z,z',aa} = bq_{z,z',a}$, and
 $TotOPEX_{aa-1} = TotOPEX_{a-1}$
 - 9: **end for**
-

Table 3: Solution algorithm for ESONE model in a rolling horizon fashion. The procedure is implemented in GAMS 25.0.3.

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