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Slednev, Viktor and Bertsch, Valentin and Ruppert, Manuel and Fichtner, Wolf

Chair of Energy Economics, Karlsruhe Institute of Technology, Germany, Economic and Social Research Institute, Dublin, Ireland, Department of Economics, Trinity College Dublin, Ireland

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Viktor Slednev [1], **Valentin Bertsch** [2], **Manuel Ruppert** [1] and **Wolf Fichtner** [1]

1: Chair of Energy Economics, Karlsruhe Institute of Technology (KIT)

Hertzstr. 16, 76187 Karlsruhe, Germany

Email: viktor.slednev@kit.edu; manuel.ruppert@kit.edu; wolf.fichtner@kit.edu

2: Economic and Social Research Institute & Trinity College, Department of Economics

Dublin 2, Ireland

Email: valentin.bertsch@esri.ie

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Abstract

The system integration of an increasing amount of electricity generation from decentralised renewable energy sources (RES-E) is a major challenge for the transition of the European power system. The feed-in profiles and the potential of RES-E vary along the geographical and temporal dimension and are also subject to technological choices and changes. To support power system planning in the context of RES-E expansion and allocation planning required for meeting RES-E targets, analyses are needed assessing where and which RES-E capacities are likely to be expanded. This requires models that are able to consider the power grid capacity and topology including their changes over time. We therefore developed a model that meets these requirements and considers the assignment of RES-E potentials to grid nodes as variable. This is a major advancement in comparison to existing approaches based on a fixed and pre-defined assignment of RES-E potentials to a node. While our model is generic and includes data for all of Europe, we demonstrate the model in the context of a case study in the Republic of Ireland. We find wind onshore to be the dominating RES-E technology from a cost-efficient perspective. Since spatial wind onshore potentials are highest in the West and North of the country, this leads to a high capacity concentration in these areas. Should policy makers wish to diversify the RES-E portfolio, we find that a diversification mainly based on bioenergy and wind offshore is achievable at a moderate cost increase. Including solar photovoltaics into the portfolio, particularly rooftop installations, however, leads to a significant cost increase but also to a more scattered capacity installation over the country.

1 Introduction

To combat climate change, greenhouse gas emissions need to be reduced globally. In order to achieve this target, the decarbonisation of the energy sector is an important prerequisite [1,2]. The European Union (EU) plans to reduce carbon emissions to 80–95% below 1990 levels by 2050 and to realise the decarbonisation of the energy system mainly through energy efficiency and the expansion of renewable energy sources (RES). By 2030, the EU aims for a 27% share of RES in final energy consumption and by 2050, more than two-thirds of gross final European energy consumption shall be provided through RES, with a yet higher share for electricity [3].

The integration of the resulting increasing electricity generation from RES (RES-E) into the grid is a major challenge for the European power system. In order to provide structured support for long-term planning of the power system and RES-E integration on a European level, models are needed which allow for an assessment of where RES-E will most likely be allocated. The main requirements for such models include the following: *First*, a high granularity of temporal and spatial input data is important [4]. *Second*, these models need to be able to take into account the power grid's capacity and topology and its dynamic nature over the next decades according to national and European grid development plans [5]. The consideration of this dynamic nature is important because it has a major impact on where the RES-E generation will feed into the future transmission grid at a substation level which is highly relevant for long-term system planning. In short, the power grid can no longer be neglected in RES-E expansion and allocation planning as the mutual dependencies between RES-E and grid expansion planning need to be considered. *Third*, the models need to be able to consider technological changes and advances, which become manifest, for the example of wind power for instance, in repowering. This is important because, e.g. for wind, the same profile of wind velocities may result in a very different power generation profile which affects the way the grid will be used in future.

The first requirement is mainly challenging in terms of data availability. While data availability has improved in the past, some gaps will always remain, particularly when considering power systems of an entire continent such as Europe. Amongst others, we therefore address the big data problem of parameterising the existing and potential RES-E generation units in Europe in this paper. From a modelling point of view, the integration of renewables into systems of such a size constitutes a dimensionality problem when considering all possible combinations of suitable locations of different RES-E technologies along with the temporal dimension leading to a large-scale optimal RES-E allocation or positioning problem which requires computational efficiency.

The optimal allocation of distributed generation in general, as well as the optimal allocation and positioning of renewable generation as a more specific application, has been a widely discussed topic in literature. From a methodological point of view, a large variety of approaches have been applied, which can be distinguished into the three categories conventional techniques, artificial intelligence techniques and hybrid intelligent system techniques [6]. The focus of the vast majority of these approaches lays, however, on the integration of RES-E on the distribution grid level [7] and thus on smaller system sizes which do not require methods which are able to deal with big data problems of pan-national spatial horizons. While the vast majority of RES-E is connected on the distribution grid level, the additional stress on the transmission grid level also needs to be considered when investigating national or pan-national allocation problems. Approaches which deal with large-scale real-world applications of intermittent RES-E allocation require GIS-based data [8] and are today restricted to single energy sources such as solar [9], wind [10] or limited spatial scales when covering multiple RES types [11]. Overall, a number of real-world sized approaches are available that address the first requirement [12-14]. However, we are not aware of approaches combining all three requirements. While few existing approaches do consider the grid topology [15,16], they do not consider the restructuring of transmission grids, i.e. they assume a static assignment of RES-E generation sources to transmission grid busbars or substations. In order to address the expansion and dismantling of busbars within substations or even of entire substations over time as set out in many national grid development plans, however, a fixed assignment of RES-E generators to transmission grid buses is no longer adequate. On the contrary, an approach allowing for a variable grid connection of RES-E generators either connected directly to the transmission grid or indirectly through the distribution grid is required to assess how the future grid will be used and needs to be planned.

We therefore developed an approach for the optimal allocation of RES-E on a pan-national scale with a high spatial resolution which addresses all of the above three requirements for the European power system. In the context of a movement from feed-in tariff (FIT) based RES-E support schemes to more market-based RES-E support on a European level [17-19], adequate tools are needed to support decision making of regulators, investors or transmission system operators (TSOs) in this new environment. Assuming a tender-based RES-E support scheme, our approach is therefore aimed at translating national, long-term RES-E targets negotiated and agreed between individual countries and the EU into specific expansion targets for different technologies in different regions on the timeline. Specifically, we focus on the challenge of deriving representative greenfield investment RES-E generators in combination with the repowering of generators by computing a merit order of RES-E investment options.

We demonstrate our approach in the context of a case study in which we pursue two main objectives: *First*, we seek to support regulators or governments that wish to achieve a national RES-E target determined as percent share of energy demand in different years in a cost minimal way but may wish to auction RES-E expansion in a technology-specific and capacity-based way, e.g. for practicality reasons. *Second*, we aim to support long-term planning of grid operators by providing insight into the regional distribution of generation and demand in future and find that especially the repowering has a very high impact on the structure of the future RES-E generation.

The remainder of this paper is structured as follows. In section 2, we describe the data required for our approach and the essential sources. In section 3, we describe the large-scale optimisation problem itself focussing on the efficient handling of the large-scale data set. In section 4, we present the context and results of the case study. We conclude the paper in section 5.

2 Data handling

For a grid integration of renewables, the allocation of existing generators and loads with their specific characteristics and of representative investment options is a great challenge, especially in power systems with a changing grid topology. In the following, we first present an approach for parameterising the set of existing renewable generators following a three-step approach. Subsequently, we address the problem of deriving representative investment variables for the RES-E expansion planning problem with a variable grid topology.

For the interconnected European power system, the parameterisation of a consistent dataset of the existing assets in the power system is a non-trivial task, as no common source comprising all generators and operating resources for all countries is available due to their mainly proprietary nature. We, therefore, developed an approach based on three steps (see Figure 1). Focussing on generators from RES-E, the first step of our approach comprises a match of publicly available and commercial European and national databases. In the second step, the missing attributes of the merged database are matched. In both cases, a hierarchical multidimensional clustering approach is applied. In the third step, historical regional data for the installed RES-E capacities, their average technical lifetime and a ranking of the plant site conditions are used to deduce potentially remaining missing information about the commissioning dates of the units, which are of great importance for the (dis-) investment decisions.

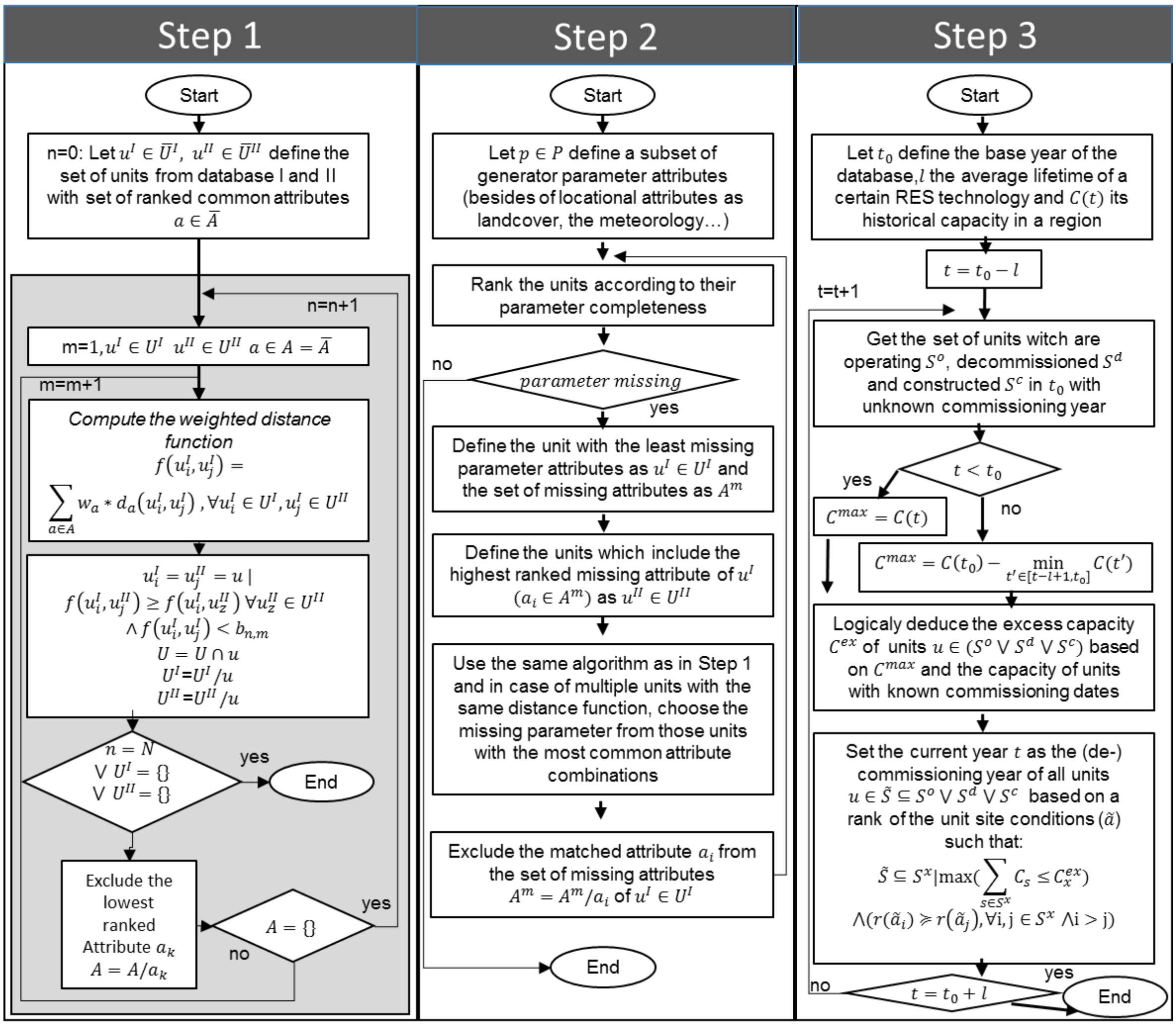

Figure 1: Conceptual structure of the proposed hierarchical, multidimensional clustering approach for parameterising the set of existing RES-E generators across Europe

In the first step, our main goal is to create an adequate database of each RES-E source by merging European databases with generally good technical parameterisations, such as The Wind Power[1] with generally good georeferenced databases such as OpenStreetMap (OSM)[2] for an exact regionalisation throughout all power ranges. For selected countries, additional national databases are used to improve the quality of the data. The main attributes for merging the data sets are the geo-coordinates, the plant, generator and operator names, the commissioning years as well as the installed power. Furthermore, turbine/module specific information, such as types, manufacturer names and its technical specifications, such as the hub heights, wind classes, etc. are utilised. While for some attributes, such as coordinates, commissioning years, and capacities the distance function is rather trivial we used a qualitative score function for other attributes such as names, which we analysed by specific string comparison functions. The varying importance of the attributes and the quality of their

[1] www.thewindpower.net
[2] www.openstreetmap.org

sources was taken into account by adjusting the attribute weights. By choosing a hierarchical approach, amongst others, varying geographical resolutions of the databases, ranging from exact generator coordinates, plant/ farm centroids to administrative areas (cities, postal codes etc.), can be taken into account by adjusting the minimum distance value $b_{m,n}$ for the mapping in each round.

In the second step, the missing parameters of the merged database, such as technical specifications are assigned, following the same hierarchical clustering approach as in step 1. The major idea for matching the parameters in step 2 is to start with units that are almost completely parameterised in order to maintain a high quality of the matching and to quickly increase the basis for parameterising the remaining ones. For instance, the missing information of the hub height of wind turbine might by easily found given the information of the site conditions (wind speed, roughness), the commissioning year and the turbine type etc. For the next unit, with a known hub height, but a missing further parameter, the previously parameterised unit might be taken as a reference and so on.

In the third step, potentially missing commissioning information, which is crucial for a correct modelling of the future investment cost, are derived on the basis of the known historical ramp-up curve of a RES technology in a region and the technical lifetime. Assuming, that the RES potential is first exploited in areas with the best site conditions (high resource availability, low resource cost etc.), the best-placed units with missing commissioning information are taken first to fill the gap to the historical ramp-up curve. Vice versa, these units are also decommissioned first in order to fill the gap the projected decommissioning of units based on their technical lifetime and the maximum capacity deduced from the ramp-up curve.

Finally, it might happen that the final set of parameterised existing units is insufficient to match the published cumulated capacities of historical years. In this case, the optimisation horizon for the RES expansion planning might be expanded to include historical years for calibrating the location of the RES generators and for fitting the age pattern.

Besides a well-calibrated database of existing or planned renewable units, the analysis of RES-E potentials in the context of a dynamic topology is a great challenge. While the introduction of grid restrictions requires a discretisation of potentials, which are typically referenced to an area, to the buses of the electricity grid, a restructuring of the grid also requires a reallocation of this potential. Focussing on RES-E integration into a variable transmission grid topology, we developed an approach for a consistent regionalisation of decentralised loads and generators based on Voronoi polygons over the substations of the distribution grid [5]. Assuming a static graph-based representation of the distribution grid, the solution of the shortest path problem over this graph to the next available substation with a transformation to the transmission grid allows a dynamic reallocation of demand and generation profiles and RES-E potentials. Furthermore, the Voronoi polygons define a consistent reference area, which might be overlaid with top-down and/or bottom-up modelled potentials and profiles. In this context, representative investment variables might be defined based on the overlay of polygons with equal conditions concerning the resource availability and suitability for specific RES-E technology options of a year with the Voronoi polygon of a substation. In Figure 2, the derivation of greenfield investment variables for the RES-E expansion planning is illustrated.

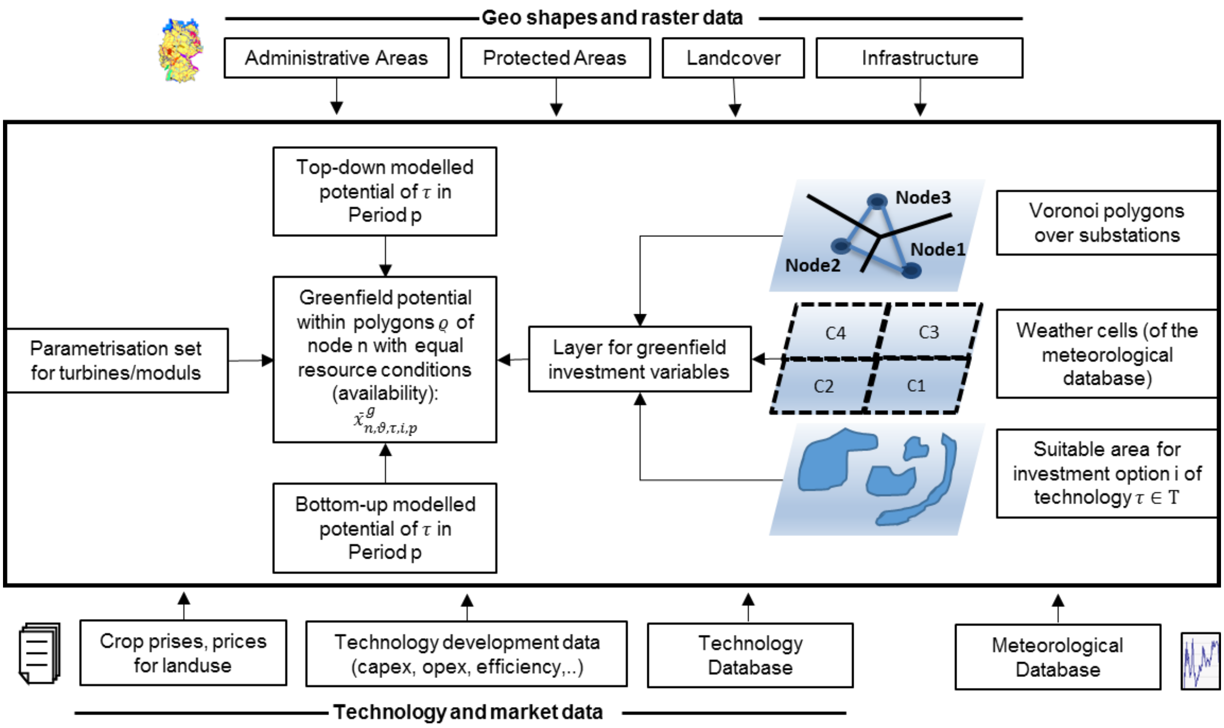

Figure 2: Approach to derive nodal greenfield investment variables from spatial potential

By intersecting the suitable area for an investment option i of a certain RES technology τ with the weather cells of the meteorological database and the Voronoi polygons over substations of the distribution grid (for decentralised investments) or the transmission grid for central units respectively, we gain a set of polygons which defines a layer for greenfield investment variables. Given a certain parameterisation of the investment option any top-down or bottom-up potential modelled for a certain technology investment option of a certain period, independent of its initial reference system (NUTS3, municipality, postal area, etc.), can now be easily transformed to a greenfield investment variable. Due to the implicit equality of all equally parameterised units lying within a polygon with equal site conditions concerning the resource availability, resource cost and site cost, our approach fulfils the general modelling requirement of including unique variables with respect to the objective function and constraint block. Furthermore, the information loss from the in-depth potential analysis of each RES-E technology to its modelling representation is kept at a minimum. Actually, the information loss might even reduce to zero, in case of a linear bottom-up potential analysis within the same reference system.

For the current modelling of greenfield investment options, we choose a bottom-up approach for wind onshore turbines and compute the suitable area for each investment option of our turbine database by excluding areas based on the land cover information from the Corine Land Cover (CLC2006) database[3], including minimum distance requirements to infrastructure derived from CLC2006 and excluding protected areas based on Natura 2000[4]. In order to keep the model linear, to allow a direct transformation of the potentials without information losses, we compute the best-fit turbine configuration of each polygon ϑ, based on a suitability factor for the land use and a linear space requirement per turbine [20], foregoing an integer turbine placement algorithm. For ground-mounted solar PV modules, a similar approach is chosen, with the addition of favouring or penalising specific sites based on the land use concurrence to agricultural usage. Rooftop PV potentials are modelled following [9] based on a statistical top-down approach on NUTS 3 level. For computing the intersection layer for greenfield investment the suitable areas are computed based on (CLC2006) and a statistical parameterisation of the module orientation is chosen. Biomass and biogas potentials are based on results of an external model (BioBoost[5]), which computed the potential for perennial, straw and forest residues on NUTS3 level. Due to the independency to short-term weather deviations, the layer for the weather cells is omitted and only a land use based redistribution is performed. For hydro and wind offshore, no greenfield investment variables are computed, restricting the capacity expansion to replacement decisions on existing plants or wind parks and to planned projects. The high specification and complexity of single large scale investment projects for this technologies as well as the large amount of announced project, at least for wind offshore, is the main reason for neglecting greenfield investment decisions in this case.

The modelling of the generation profiles is based on a bottom-up modelling from physical models for wind onshore and offshore as well as for ground-mounted and rooftop PV. Taking historical weather years from our database (ANEMOS), the generation profiles for each greenfield investment variable are computed with a 10-minute resolution. The same holds for all existing, planned, approved and constructed wind and photovoltaic generators, although the profile for generators lying within the same weather cell and sharing the same parameters is just computed once. For bioenergy and hydro profiles the specific national

[3] http://www.eea.europa.eu/data-and-maps/data/clc-2006-raster-4
[4] http://ec.europa.eu/environment/nature/natura2000/index_en.htm
[5] http://bioboost.eu/home.php

historical generation published by EEX[6] or ENTSOE[7] or from national sources is taken as far as available, while dynamic type profiles based on the profiles of available years for a country are taken for historical years without any information.

The regionalisation of demand profiles as well as the regionalisation of conventional power plants, which are not part of this paper, follows the same approach as published in [5]. The graph of the distribution grid is based on OSM data, while the transmission grid of selected European countries is modelled similarly to the approach published in [21].

3 Modelling and implementation

This section deals with the optimal allocation planning problem of RES-E with a focus on the efficient modelling of inter- and intra-technological dependencies of (dis-) investment decisions with respect to regional and (inter-) national capacity and energy targets and bounds. Being modelled as a linear problem with perfect foresight, the following equations might be used for a stand-alone analysis of RES expansion targets under grid restrictions, given an a priori known expansion plan of the transmission grid. Alternatively, the following problem might be included within a combined generation and transmission network expansion planning problem (GEP + TNEP) of a power system.

Analogously to the previously defined derivation of the potential for greenfield investments, we will first derive the brownfield potential for replacing existing or already planned renewable units within the polygon ϑ which lies within the Voronoi polygone of a substation node n and has equal conditions concerning the resource availability and suitability for specific investment option i of a RES-E technology τ for a period p. Let S^e define the set of all existing units, which in the base year t_0 (current year of the database), are operated, under construction or already decommissioned without a replacement. Let furthermore S^c define the set of all already known investment candidate units, which are currently in a planning state. The brownfield potential $\bar{x}^{be}$ for the replacement of existing and of candidate units $\bar{x}^{bc}$ is defined as follows:

$$\bar{x}^{be}_{n,\vartheta,\tau,i,p} = \sum_{s \in S^e} \max_{p' \in P}\left(\frac{1}{\alpha_{p',p}} * \tilde{x}^{e}_{n,\vartheta,\tau,p',s}\right) \qquad \forall n \in N, \vartheta \in \Theta_n, \tau \in \mathrm{T}, i \in I_\tau, p \in P \quad (1)$$

$$\bar{x}^{bc}_{n,\vartheta,\tau,i,p} = \sum_{s \in S^e} \max_{p' \in P}\left(\frac{1}{\alpha_{n,\vartheta,\tau,p',p}} * \tilde{x}^{c}_{n,\vartheta,\tau,p',s}\right) \qquad \forall n \in N, \vartheta \in \Theta_n, \tau \in \mathrm{T}, i \in I_\tau, p \in P \quad (2)$$

6 https://www.eex-transparency.com/
7 https://transparency.entsoe.eu/

where $\tilde{x}^{e}_{n,\vartheta,\tau,p',s}$ defines the maximum capacity of existing unit s of technology τ in period p' which is allocated within a polygon ϑ, lying within the Voronoi polygone of the grid node n. The possibility of a capacity increase on the same area between investment options of different periods, or the existing units and their replacement options is taken into account by introducing α. This parameter measures the average capacity increase of a technology within a certain polygon ϑ between the periods. For instance, α has a value of two in case that six 500 kW wind power turbines might be replaced by two 3000 kW turbines within the same polygon. Due to the definition of the replacement potentials as the absolute upper bound for a period, independent of the actual disinvestment decisions of the underlying units, the remaining greenfield potential $\bar{x}^{g,r}$ might be expresses as follows:

$$\bar{x}^{g,r}_{n,\vartheta,\tau,i,p} = \bar{x}^{g}_{n,\vartheta,\tau,i,p} - \bar{x}^{be}_{n,\vartheta,\tau,i,p} - \bar{x}^{bc}_{n,\vartheta,\tau,ip} \qquad \forall n \in N, \vartheta \in \Theta_n, \tau \in \mathrm{T}, i \in I_\tau, p \in P \qquad (3)$$

It should be noted that for each period p only one investment option is considered within a polygon ϱ for a certain technology as older technology options are assumed to be strictly dominated with regards to efficiency, and relative investment and variable cost etc.

Defining the level of a capacity as x^{lev} and its expansion/dismantling as $x^{exp}/\ x^{dis}$, the following restrictions apply to the expansion, dismantling and the level of a capacity variable:

$$0 \le x^{lev,y}_{n,\vartheta,\tau,i,p} \le \bar{x}^{y}_{n,\vartheta,\tau,i,p} \qquad \forall n \in N, \vartheta \in \Theta_n, \tau \in \mathrm{T}, i \in I_\tau, p \in P, y \in \{gr, be. bc\} \qquad (4)$$

$$0 \le x^{lev,y}_{n,\vartheta,\tau,s,p} \le \bar{x}^{y}_{n,\vartheta,\tau,s,p} \qquad \forall n \in N, \vartheta \in \Theta_n, \tau \in \mathrm{T}, s \in (S^e \vee S^c), p \in P, y \in \{e, c\} \qquad (5)$$

$$\bar{x}^{e}_{n,\vartheta,\tau,s,p} \le x^{lev,e}_{n,\vartheta,\tau,s,p} \qquad \forall n \in N, \vartheta \in \Theta_n, \tau \in \mathrm{T}, s \in S^e, p \in P|\ ord(p) \le ord(\tilde{p}) \qquad (6)$$

$$x^{exp,e}_{n,\vartheta,\tau,s,p} \le 0 \qquad \forall n \in N, \vartheta \in \Theta_n, \tau \in \mathrm{T}, s \in S^e, p \in P|ord(p) > ord(\tilde{p}) \qquad (7)$$

$$x^{lev,y}_{n,\vartheta,\tau,i,p} = x^{lev,y}_{n,\vartheta,\tau,i,p-1} + x^{exp,y}_{n,\vartheta,\tau,i,p} - x^{dis,y}_{n,\vartheta,\tau,i,p} \qquad \forall n \in N, \vartheta \in \Theta_n, \tau \in \mathrm{T}, i \in I_\tau, p \in P|ord(p) > 1, y \in \{gr, be. bc\} \qquad (8)$$

$$x^{lev,y}_{n,\vartheta,\tau,s,p} = x^{lev,y}_{n,\vartheta,\tau,s,p-1} + x^{exp,y}_{n,\vartheta,\tau,s,p} - x^{dis,y}_{n,\vartheta,\tau,s,p} \qquad \forall n \in N, \vartheta \in \Theta_n, \tau \in \mathrm{T}, s \in (S^e \vee S^c), \in P|ord(p) > 1, y \in \{e, c\} \qquad (9)$$

$$x_{n,\vartheta,\tau,i,p}^{dis,y} \geq \sum_{p'|d(p',p)>l_{\tau,i}} x_{n,\vartheta,\tau,i,p'}^{exp,y} - \sum_{p'|ord(p')\leq ord(p)} x_{n,\vartheta,\tau,i,p}^{dis,y} \qquad \forall n \in N, \vartheta \in \Theta_n, \tau \in \mathrm{T}, i \in I_\tau, p \in P, y \in \{gr, be. bc\} \tag{10}$$

$$x_{n,\vartheta,\tau,s,p}^{dis,y} \geq \sum_{p'|d(p',p)>l_{\tau,i}} x_{n,\vartheta,\tau,s,p'}^{exp,y} - \sum_{p'|ord(p')\leq ord(p)} x_{n,\vartheta,\tau,s,p}^{dis,y} + \sum_{p'|ord(p')=1 \wedge d(p',p)>l_{\tau,i}} x_{n,\vartheta,\tau,s,p'}^{lev,y} \qquad \forall n \in N, \vartheta \in \Theta_n, \tau \in \mathrm{T}, i \in I_\tau, p \in P, y \in \{e. c\} \tag{11}$$

$$x_{n,\vartheta,\tau,i,p}^{lev,be} \leq \sum_{p'|ord(p')\leq ord(p)} \sum_{s\in S^e} \frac{1}{\alpha_{n,\vartheta,\tau,p',p}} * x_{n,\vartheta,\tau,s,p'}^{dis,e} \qquad n \in N, \vartheta \in \Theta_n, \tau \in \mathrm{T}, i \in I_\tau, p \in P \tag{12}$$

$$x_{n,\vartheta,\tau,i,p}^{lev,bc} \leq \sum_{p'|ord(p')\leq ord(p)} \sum_{s\in S^c} \frac{1}{\alpha_{n,\vartheta,\tau,p',p}} * x_{n,\vartheta,\tau,s,p'}^{dis,c} \qquad \forall n \in N, \vartheta \in \Theta_n, \tau \in \mathrm{T}, i \in I_\tau, p \in P \tag{13}$$

$$\sum_{p'|ord(p')\leq ord(p)} x_{n,\vartheta,\tau,s,p'}^{dis,y} \leq \bar{x}_{n,\vartheta,\tau,s,p}^{y}\,, \qquad \forall n \in N, \vartheta \in \Theta_n, \tau \in \mathrm{T}, i \in I_\tau, p \in P, y \in \{e. c\} \tag{14}$$

$$\sum_{p'|ord(p')\leq ord(p) \wedge ord(p)>1} x_{n,\vartheta,\tau,s,p}^{exp,y} + \sum_{p'|ord(p')=1 \wedge d(p',p)>l_{\tau,i}} x_{n,\vartheta,\tau,s,p'}^{lev,y} \leq \bar{x}_{n,\vartheta,\tau,s,p}^{y} \qquad n \in N, \vartheta \in \Theta_n, \tau \in \mathrm{T}, i \in I_\tau, p \in P, y \in \{e. c\} \tag{15}$$

While restriction (4) and (5) define the potential bounds for the capacity of green and brownfield investment variables and the set of existing and candidate RES-E units, restriction (6) fixes the level of existing units prior to a reference period $\tilde{p}$. In this context, the reference period denotes the period including the base years of the underlying power plant database. By forbidding a capacity expansion for the set of existing RES units after the reference year (7), their possible replacement is shifted to the corresponding brownfield investment variable. The usual definition of a variable's level of a period as the sum of the previous level and the increase minus the decrease within the period is guaranteed by eq. (8) and (9). The dismantling restrictions (10) and (11) ensure that capacities are decommissioned if the difference between the period in which the capacity was expanded and the current period $d(p', p)$ exceeds their technical lifetime $l_{\tau,i}$ unless they where decommissioned in previous periods. The logical restriction that the capacity of replacement variables is limited by the dismantling of the underlying existing or candidate units adjusted by a factor for the technology development is set in eq. 12 and 13. Once existing and candidate units were fully expanded and afterwards dismantled, eq. (14) and (15) prevent any later replacement of existing/candidate units within the same variable.

Due to the large number of existing RES units, going into millions, and their highly diverse parameterisation, which increases the number of generation profiles, it might be of interest to reduce the number of variables. By decommissioning existing units at the end of their technical lifetime, or if the information is available, at their known decommissioning date, they can be handled as a parameter and added to the right-hand side.

Further restrictions on the capacity level, such as regional or national/international lower and upper bounds or targets can be easily added for each technology or any combination of technologies by a multiplication with the corresponding incidence matrix Π:

$$\Pi * x \leq b \tag{16}$$

Due to the nodal indices of all capacity variables starting at the distribution grid level and including selected pure transmission grid substations, introducing capacity constraints of the grid is an easy task, knowing the assignment of nodes to a topology of the transmission grid following the dynamic assignment approach presented in [5]. A quite rough but simple estimation of the upper bound of the grid capacity is to use the thermal limit of the adjacent lines of a bus m$\in M$ of the transmission grid of a period p. Summing up all variables which are either directly connected to this bus or indirectly based on the solution of the shortest path on the transmission grid is an easy task:

$$\sum_{n\in N_m}\sum_{\vartheta\in\Theta_n}\sum_{\tau\in\mathrm{T}}\left(\sum_{s\in S}x^{lev}_{n,\vartheta,\tau,s,p}+\sum_{i\in I_\tau}x^{lev}_{n,\vartheta,\tau,i,p}\right)\leq C_m \qquad \forall m\in M, p\in P \tag{17}$$

Here, N_m denotes the set of nodes of the distribution/transmission grid, which are assigned to bus m, and C_m denotes the capacity of the adjacent lines.

Modelling restrictions for RES-E generation is straightforward if, given the same site conditions, units of a technology are equally parameterised along the time axis. For generation variables g with an inter-period resolution $h \in H_p$, the a priory modelled profile vector v, when multiplied with the corresponding level of the capacity variable, defines an upper bound.

$$g_{n,\vartheta,\tau,i,p,h}\leq x^{lev,y}_{n,\vartheta,\tau,i,p} * v_{n,\vartheta,\tau,i,p,h} \qquad \forall n\in N, \vartheta\in\Theta_n, \tau\in\mathrm{T}, i\in I_\tau, p\in P, h\in H_p, y \in \{gr, be.bc\} \tag{18}$$

$$g_{n,\vartheta,\tau,s,p,h} \leq x^{lev,y}_{n,\vartheta,\tau,i,p} * \nu_{n,\vartheta,\tau,s,p,h} \quad \forall n \in N, \vartheta \in \Theta_n, \tau \in \mathrm{T}, s \in s \in (S^e \vee S^c), p \in P, h \in H_p, y \in \{e,c\} \tag{19}$$

In the event that the curtailment of RES is not allowed, eq. (18) and (19) are formulated as equality constraints. Imposing restrictions on the generation variables, such as the common minimal RES-E share constraint and lower and upper regional and national bounds, follow the same scheme as eq (15). From a computational point of view, it should be noted that in the case of missing generation restrictions with an inter-period time resolution, the number of variables might be highly reduced by summing up the profile parameter of a period to a capacity factor in advance and define the generation by variables with a period time resolution. Taking into account that technological changes influence the profiles of RES-E technologies along the time horizon, as well as degradation effects, might reduce the efficiency over time, modelling the generation becomes more complex. Given the comprehensive definition of capacity level variables as the combination of (dis-) investment of former periods with possible different profiles, the definition of the generation variable changes as follows:

$$g_{n,\vartheta,\tau,i,p,h} \leq \sum_{p'|d(p',p)\leq l_{\tau,i}} x^{exp,y}_{n,\vartheta,\tau,i,p'} * \nu_{n,\vartheta,\tau,i,p',p,h} - \sum_{p'|ord(p')\leq ord(p)} x^{dis,y}_{n,\vartheta,\tau,i,p'} * \nu_{n,\vartheta,\tau,i,p',p,h} \quad \forall n \in N, \vartheta \in \Theta_n, \tau \in \mathrm{T}, i \in I_\tau, p \in P, h \in H_p, y \in \{gr, be.bc\} \tag{20}$$

$$g_{n,\vartheta,\tau,s,p,h} \leq \sum_{p'|ord(p')=1} x^{lev,y}_{n,\vartheta,\tau,s,p'} * \nu_{n,\vartheta,\tau,s,p',p,h} + \sum_{p'|d(p',p)\leq l_{\tau,i} \wedge ord(p'>1)} x^{exp,y}_{n,\vartheta,\tau,s,p'} * \nu_{n,\vartheta,\tau,s,p',p,h} - \sum_{p'|ord(p')\leq ord(p) \wedge ord(p'>1)} x^{dis,y}_{n,\vartheta,\tau,i,p'} * \nu_{n,\vartheta,\tau,i,p',p,h} \quad \forall n \in N, \vartheta \in \Theta_n, \tau \in \mathrm{T}, s \in s \in (S^e \vee S^c), p \in P, h \in H_p, y \in \{e,c\} \tag{21}$$

Here, $\nu_{n,\vartheta,\tau,i,p',p,h}$ /$\nu_{n,\vartheta,\tau,s,p',p,h}$ defines the profile of existing units or investment options in period p with a commissioning in period p'. Forbidding RES curtailment analogously leads to fulfilling restrictions (19) and (20) to equality.

Finally, we define the objective function based on a minimisation of the discounted investment and variable cost:

$$
min \sum_{p \in P} \left[\begin{matrix} \tilde{d}(\mathrm{p}) * \sum_{n \in N} \sum_{\vartheta \in \Theta_n} \sum_{\tau \in \mathrm{T}} \sum_{h \in H_p} \lambda_{\tau,p} * \left(\begin{matrix} \sum_{s \in S^e} g_{n,\vartheta,\tau,s,p,h}^{lev,e} * c_{n,\vartheta,\tau,s,p}^{var} + \sum_{s \in S^c} g_{n,\vartheta,\tau,s,p,h}^{lev,c} * c_{n,\vartheta,\tau,s,p}^{var} + \\ \sum_{i \in I_\tau} \left(g_{n,\vartheta,\tau,i,p,h}^{lev,gr} + g_{n,\vartheta,\tau,i,p,h}^{lev,ge} + g_{n,\vartheta,\tau,i,ph}^{lev,gc} \right) * c_{n,\vartheta,\tau,i,p}^{var} \end{matrix} \right) + \\ \sum_{n \in N} \sum_{\vartheta \in \Theta_n} \sum_{\tau \in \mathrm{T}} \lambda_{\tau,p} * \kappa_\tau \left(\begin{matrix} \sum_{s \in S^c} \sum_{p' | d(p',p) \leq l_{\tau,i,}{}^{ec}} \min\left(d(p',p) - l_{\tau,i,}{}^{ec}, \tilde{d}(\mathrm{p}) \right) * x_{n,\vartheta,\tau,i,p'}^{exp,c} * c_{n,\vartheta,\tau,s,p'}^{inv,c} + \\ \sum_{i \in I_\tau} \sum_{p' | d(p',p) \leq l_{\tau,i,}{}^{ec}} \min\left(d(p',p) - l_{\tau,i,}{}^{ec}, \tilde{d}(\mathrm{p}) \right) * \left(\begin{matrix} x_{n,\vartheta,\tau,i,p'}^{exp,gr} * c_{n,\vartheta,\tau,s,p'}^{inv,gr} \\ + x_{n,\vartheta,\tau,i,p'}^{exp,ge} * c_{n,\vartheta,\tau,s,p'}^{inv,ge} \\ + x_{n,\vartheta,\tau,i,p'}^{exp,gc} * c_{n,\vartheta,\tau,s,p'}^{inv.gc} \end{matrix} \right) \end{matrix} \right) \end{matrix} \right] \tag{22}
$$

where $\lambda_{\tau,p}$ denotes the discount factor of period p and a duration of $\tilde{d}(\mathrm{p})$ and κ_τ the annuity factor for a technology τ with an economic lifetime of an investment of $l_{\tau,i,}{}^{ec}$.

It is important to mention that we differentiate the investment cost of candidate investment options based on the planning state (approved, proposed) and set different cost for greenfield and brownfield investments. For optimisation runs with restrictions addressing solely capacity variables, such as national capacity targets for RES-E technologies, all cost parameters are divided by the capacity factor of the corresponding variables, in order to run an optimisation based on the levelised cost of electricity (LCOE). This way, investments at preferable sites are incentivised. For technical reasons, we also include slack variables for certain restrictions and penalise them within the objective function. In the case of equality restrictions, the slack variable is furthermore split into its positive and negative part in order to penalise deviations in both directions. Common reasons for active slack variables are nationally defined combined capacity and generation targets for certain RES-E technologies which are either inconsistent to the short or long-term availability of RES-E potentials. Such inconsistency of the input data often occurs in the case of a linear scaling of generation per capacity values, ignoring profile changes due to technological evolutions, degradations effects, spatial potential exploitations by existing units or their actual age pattern.

The model is implemented in Matlab and solved using CPLEX. For typical applications such as the translation of national RES-E share targets up to 2050 with a yearly resolution the problem size lies in the range of 1e6 to 1e7 variables and constraints and is solved within a few minutes. In the event that inter-period resolved constraints are applied, such as the consideration of load flow constraints based on a direct current optimal power flow (DC-OPF) formulation, the problem size and complexity rapidly increases. Although the DC-OPF approach itself is a linear relaxation of the complex alternating current (AC) OPF, expressing the branch flow through the product of the bus injection vector and the power transfer distribution factor (PTDF) matrix, solving the RES-E allocation planning based on an hourly resolution for every year might lead to computational issues for large systems. A switch from yearly resolutions to periods representing multiple years and the choice of an adequate reduction of the time structure with respect to the constraint matrix [4] are possible strategies to keep the model computationally feasible.

4 Case study

We now demonstrate our approach in the context of a case study on RES-E expansion. While our approach is designed for the entire European continent, we focus on the island of Ireland in the case study for illustrative purposes. Ireland is well-suited as a case study because of its high RES-E targets. The case study is aimed at providing support to the regulatory authority and the government in achieving national RES-E targets in different years in a cost minimal way. Moreover, we study the regional distribution of future generation and demand to provide support to the transmission grid operator for its long-term planning processes. While our analysis below focuses on the Republic of Ireland, it is important to bear in mind that the Single Electricity Market (SEM), which will be replaced by the Integrated Single Electricity Market (I-SEM) in future, is the marketplace for trading electricity in the Republic of Ireland and Northern Ireland [22]. At the same time, however, renewables targets are negotiated and agreed with each member state, i.e. Northern Ireland contributes towards the UK target. In this context, the fact that Northern Ireland pursues the same relative renewable electricity target for 2020 has helped to minimise potential market distortions to date. While especially wind generation both onshore and offshore has been a subject of previous studies on the meteorological side [23], as well as on the generation side [24,25], no study covering the overall renewable targets of Ireland in the long-term (2050) including spatially differentiated generation or dynamic grid constraints has been performed yet.

4.1 Targets and assumptions

As is the case for many other European countries, the development of electricity generation capacities from renewable sources was based on a FIT scheme in Ireland. The Irish Renewable Energy Feed-in Tariff (REFIT) scheme is funded by the Public Service Obligation (PSO), i.e. it is paid for by all electricity consumers. The main purpose of REFIT was to ensure that Ireland meets its 2020 target of 40% of electricity coming from renewable sources. In 2015, the generation of RES-E increased to 27.3% of gross electricity consumption with wind onshore alone accounting for 22.8% (i.e. accounting for more than 80% of all RES-E) [26].

Unlike FIT schemes in many other countries, the Irish REFIT does not provide support for solar energy so far. However, REFIT closed as of the end of 2015 and the subsequent scheme is currently being prepared and discussed. While the exact details of the new scheme have not yet been decided, the Irish government in their energy white paper released in December 2015 [27] state that they envisage a diversification of renewable energy sources. While onshore wind is planned to continue to make a significant contribution, it is debated whether the new scheme should also support solar PV and further technologies including offshore wind and others. Moreover, the government envisages a more market-based support of RES-E.

At the same time, the Irish government negotiates the 2030 targets for RES-E with the EU. Together with the uncertain demand development, the yet unknown outcome of these negotiations creates a high uncertainty around the overall amount of RES-E required. In this uncertain context, our case study addresses the following two problems:

1. Provision of support to the regulatory authority and government in achieving their national RES-E target determined as % share of energy demand in different years in a cost minimal way. For practicality reasons, they may wish to auction RES-E expansion tranches in a technology-specific and capacity-based way. This procedure constitutes a major challenge and risk in terms of achieving a cost minimal solution. They will, therefore, require structured support as to how much capacity of which technology at what point in time should be auctioned.
2. Provision of support to the Irish TSO for long-term planning by providing insight into the future regional distribution of generation and demand for different scenarios.

In order to address the uncertainty in the demand development (from today's perspective driven to a large extent by the growth and connection of data centres according to the Irish TSO EirGrid) and in the 2030 targets, we consider two different demand development cases [28,29] and three different 2030 target scenarios for RES-E in Ireland (45%, 50%, 60%). By 2050, the corresponding target values for RES-E are assumed to increase to levels of 70% (for the 45% scenario in 2030), 80% (for the 50% scenario in 2030) and 90% (for the 60% scenario in 2030) respectively. As one of the demand cases is based on the EU Reference Scenario 2016 [28] using the PRIMES model and the other demand case is based on the Generation Capacity Statement by the Irish TSO EirGrid [29], we refer to the corresponding scenarios by PRIMES 45 – EirGrid 60 (see Figure 3). Note that our EirGrid demand case is based on EirGrid's 'Median' demand projection assuming the connection of 100% of data centres that are already in the connection process but no connection of additional data centres. Moreover, note that while this demand case only covers the period until 2025, we assume the same relative growth rates as in the PRIMES demand case for the period 2025-2050. In our analysis, the results of which are presented in the subsequent section 4.2, we further explore for each of these scenarios how the results differ between a pure cost minimal solution (Least Cost), a solution that assumes a predefined minimum level of diversification of RES-E sources (Diversify) and a solution that assumes a predefined minimum level of rooftop PV in addition (Diversify+PV). Thus, we consider a total of 18 scenarios. The assumptions for the Diversify scenario are that a minimum of 15% of the RES-E generation must come from sources other than wind onshore by 2030 increasing to 30% by 2050. In the Diversify+PV scenario we assume that, in addition to this, a minimum of 5% of the RES-E generation must come from rooftop PV by 2030 increasing to 10% by 2050.

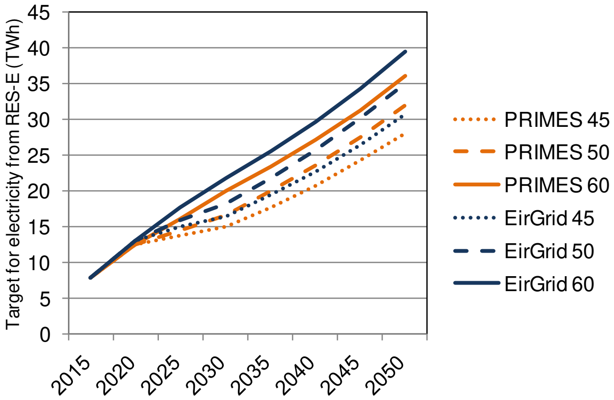

Figure 3: RES-E target scenarios for the Republic of Ireland

Concerning the parameterisation of RES-E investment cost, average 2015 investment values of 1560 €/kW for wind onshore, 4650 €/kW for wind offshore and 1810 €/kW for PV are taken from [30]. For biomass and biogas investments we assume 2250 €/kW and 3000 €/kW respectively on the basis of [31]. Based on this reference basis, investment cost for individual regional investment options are adjusted within a certain range in order to account for site and generator-type specific conditions such as the varying land-usage or turbine (module) specifications of different manufacturers. Furthermore, varying project costs for greenfield and brownfield investment options depending on their current project state are taken into account. For the future, cost reduction rates from 2015 to 2025 are taken from [30] and a moderate further reduction of 5% from 2025 to 2050 is assumed for all technologies except wind offshore, where we assumed a reduction of 15%. Moreover, we generally assume an interest rate of 6% for most technology investments with the exception of rooftop PV, where we assume a lower rate of 3% due to the main contribution of private households to the expansion of this technology. For an estimation of the upper bound of the grid capacity based on eq. (17) and a dynamic grid assignment approach following [5], we added up the thermal line limits of the existing or projected extra high voltage branches of the transmission grid substation for each year. The corresponding grid model is based on data from the All-Island Transmission Forecast Statement [32] by EirGrid[8].

[8] See: http://www.eirgridgroup.com/

4.2 *Results and discussion*

We now turn to the results of our model for the case study. We first describe the relevant results on a national level (section 4.2.1) before describing the results on a regional level (section 4.2.2).

4.2.1 RES-E expansion on a national level

Figure 4 shows the development of installed RES-E capacity until 2050 for the three scenarios 'Least Cost', 'Diversify' and 'Diversify+PV' for the highest (Eirgrid 60, left) and lowest (PRIMES 45, right) demand development case respectively. Figure 4 reveals that, unsurprisingly, in the Least Cost scenario, RES-E expansion basically happens through wind onshore only – regardless of the demand case. In the Diversify scenario, until 2030, the two preferred technologies beyond wind onshore are Wind Offshore and Bioenergy. After 2040, Figure 4 also shows expansion in ground-mounted solar PV for the Diversify scenario. Interestingly, however, this does only happen for the high demand case. For the Diversify+PV scenario, Figure 4 shows significant capacity expansion in Rooftop PV from 2030 onwards. In this scenario, however, there is no additional expansion in ground-mounted PV as in the Diversify scenario. By and large, the technology types that are expanded are the same for both demand cases, with the exception of ground-mounted PV. The amount of installed capacity by technology type, however, varies significantly between the two demand cases. For wind onshore, for instance, more than 12 GW will need to be installed by 2050 in the Least Cost scenario for the EirGrid 60 demand case while less than 9 GW will need to be installed in the PRIMES 45 demand case for the same scenario.

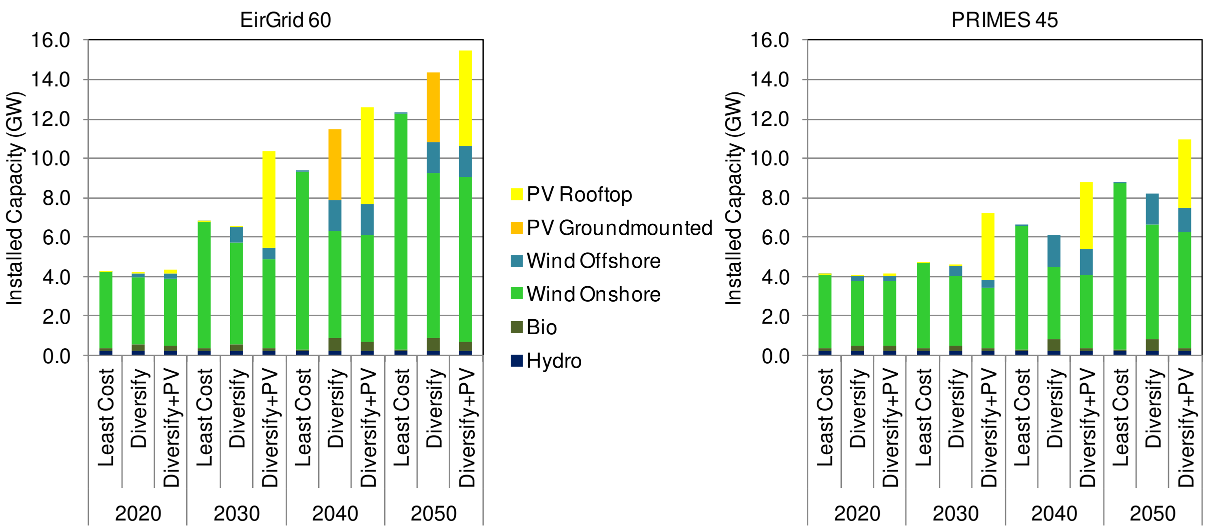

Figure 4: RES-E capacity expansion for 2 selected demand cases

Comparing capacity (Figure 4) and generation (Figure 5) by technology type, it can be observed that the three times higher capacity expansion in PV rooftop as compared to Wind

Offshore in the Diversify+PV scenario in 2050 yields lower RES-E generation levels. Of course, this is a direct consequence of the large differences in full load hours.

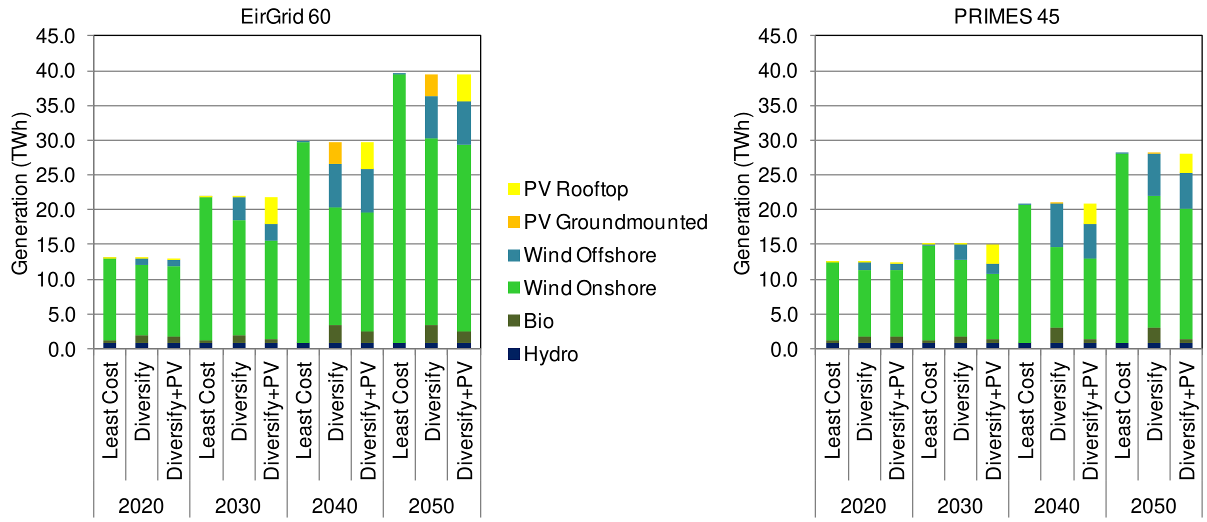

Figure 5: RES-E generation for 2 selected demand cases

Figure 6 shows the discounted costs for the same scenarios and demand cases. The figure reveals that the increase in discounted costs for the Diversify scenario (compared to the Least Cost scenario) is rather moderate varying between 7-9% in 2030 and around 6% in 2050 for both demand cases. The increase for the Diversify+PV scenario (again compared to the Least Cost scenario), however, varies between 60-70% in 2030 and around 20% in 2050.

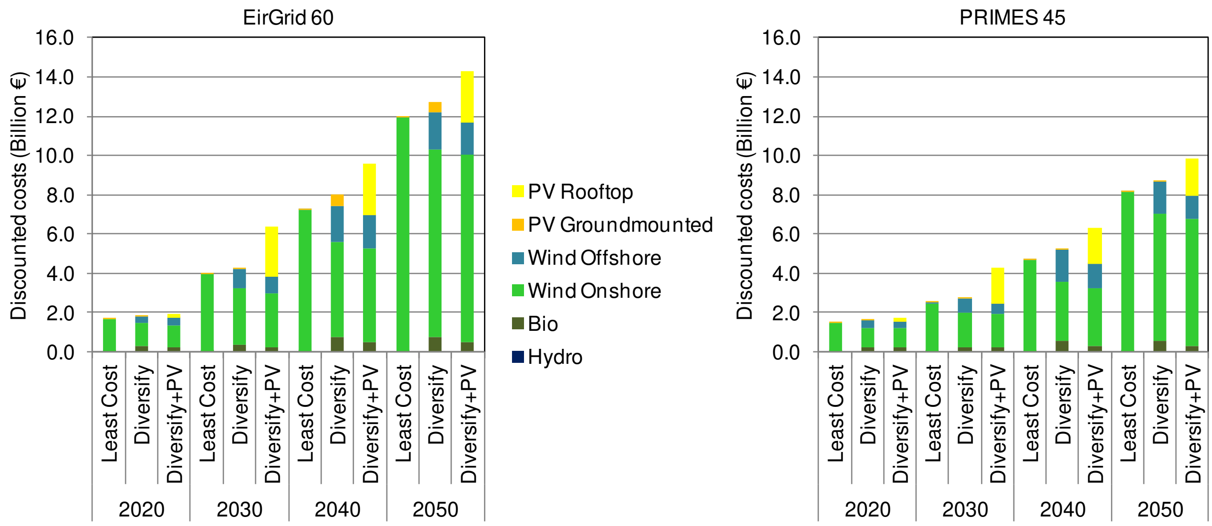

Figure 6: Discounted costs for capacity expansion for 2 selected demand cases

Overall, the above results show that the uncertain demand development, in the long run, creates enormous challenges for policy and planning in terms of compliance with RES-E policy targets defined as % shares of the overall electricity demand. This challenge has also been discussed by [33] in the context of climate variability. Moreover, our results show that, unsurprisingly, wind onshore proves to be the dominant technology across all scenarios. However, bearing the extremely high values of installed capacity in wind onshore in mind which are required to comply with EU targets in the long run, it should be noted that these imply enormous space requirements and will almost inevitably lead to problems in relation to public acceptance [34] but also in relation land-use planning in general.

It is interesting to see that, while the 10% minimum share for rooftop PV only comes into play for the Diversify+PV scenario in 2050, the capacity required to fulfil this requirement is already expanded in 2030. This can be explained as follows. Around 2030, a large cohort of installed wind onshore turbines reaches the end of its lifetime and needs to be repowered or decommissioned. Consequently, there is a large need for RES-E generation capacity in the 2030's. Moreover, please note that our model is a perfect foresight model as mentioned in section 3, i.e. it knows in 2030 already that the 10% solar share needs to be fulfilled by 2050. And expanding the PV capacity right away allows reducing investments into wind onshore (including repowering investments) and thus helps reduce the overall costs.

Another interesting result is that the (country-wide) average full load hours of wind onshore (which can be obtained by dividing the generation by the installed capacity) increase over time from approx. 3,000 h/y in 2020 to approx. 3,200 h/y in 2050, while at the same time the installed wind onshore capacity is expanded strongly. One would typically expect that the average full load hours decrease with increasing installed capacity on the basis of the assumption that the 'best' locations are usually exploited first. However, this trend is overcompensated by an increase in full load hours resulting from the repowering over time.

Finally, our results shed light on the tradeoff between different political targets, namely cost minimisation and diversification. While RES-E diversification may be desirable from a political perspective and may implicitly contribute to reducing concerns in relation to acceptance and land-use planning, it doesn't come for free. While diversification on the basis of solar PV leads to a significant cost increase, our results reveal that diversification per se (including wind offshore and bioenergy) only leads to a moderate cost increase. In particular, bioenergy seems to be often forgotten in the discussion concerning the future energy system while our results show that this technology can play an important role in diversifying RES-E generation. Moreover, biomass is synchronous electricity generation which brings further advantages in relation to grid operation which is not considered in this paper.

4.2.2 RES-E expansion on a regional level

Figure 7 shows the spatial distribution of the total installed RES capacities in Ireland under application of the energy constraints given by PRIMES 45 for the three investigated scenarios Least Cost, Diversify and Diversify+PV in the final year of the optimisation 2050.

The regional areas are consisting of the feed-in areas of the individual substations of the distribution and transmission grid level as described in the previous section. In all three cases, the results show a rather heterogeneous distribution of the installed capacities, which mainly stem from wind onshore (cf. Figure 4). In the Least Cost scenario, the most favourable locations of wind generation on the west coast and in the very North of the island are subject to the strongest expansion. These capacity hotspots change in both Diversify scenarios, as the introduction of wind offshore leads to new clustered generation on the landfall of the grid connection. Rooftop solar PV has its most preferable conditions in the South of Ireland and requires a sufficient amount of population in order to have the required roofs available, thus generation shifts southwards in the Diversify+PV case.

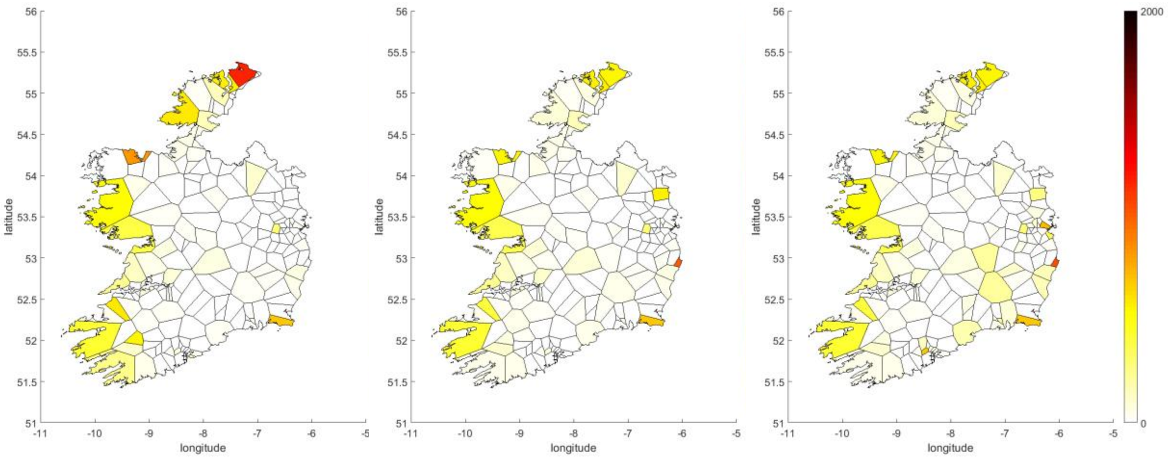

Figure 7: PRIMES 45 - Regional distribution in 2050 of installed RES-E capacities in Least Cost (left), Diversify (middle) and Diversify+PV (right) scenario in the Republic of Ireland

Figure 8 shows the spatial distribution of the total installed RES-E capacities in Ireland under application of the energy constraints given by the EirGrid60 scenario in 2050. The comparison to the installed capacities when applying the moderate RES-E energy goals in the PRIMES 45 scenario reveal a much stronger clustering of capacities. In the Least Cost scenario, the trend of clustered onshore wind generation in the west and north is intensified, with a single region reaching over 1,500 MW installed RES-E capacity. As in Figure 7, this effect is softened in the Diversify scenarios, as offshore wind and solar show a different spatial concentration. The introduction of larger amounts of ground-based solar capacities in the Diversify scenario is reflected in high capacity concentrations in locations in the southeast with the highest amount of solar irradiation available. As generation from solar shifts towards rooftop solar in the Diversify-PV case, the metropolitan area of Dublin becomes a major concentration of generation, as the overall available amount of rooftops in the more southern areas is too limited to ensure the required energy constraints given in this case. Overall, the Diversify scenarios lead, expectedly, to a more scattered generation due to the more diverse mix of technology types. Furthermore, the maximum capacity allocated to a single substation is decreasing, indicating that the additional constraints in the Diversify scenarios might result in less stress on the transmission grid, which might put the additional costs into perspective to the potential savings on the grid side (the quantification of which is outside the scope of this paper).

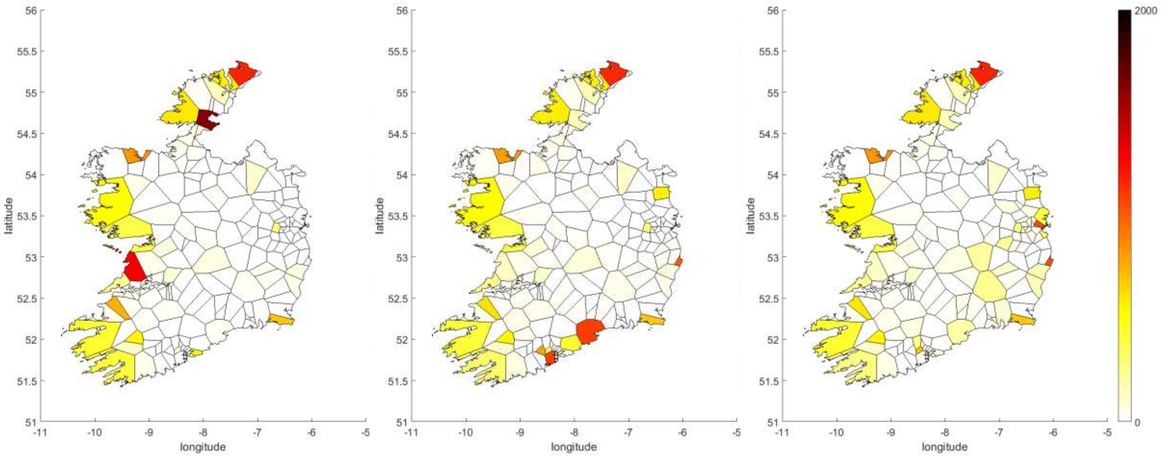

Figure 8: EirGrid 60 - Regional distribution in 2050 of installed RES-E capacities in Least Cost (left), Diversify (middle) and Diversify+PV (right) scenario in the Republic of Ireland

In addition to Figure 8, Figure 9 shows the resulting residual load curves for three illustrative Voronoi polygons under the three EirGrid 60 scenarios in 2050. The chosen Voronoi polygons include the polygon in the North with the highest wind onshore concentration across all scenarios, the polygon in the Southeast with the highest concentration of ground-mounted PV in the Diversify scenario and the polygon in Dublin with the highest rooftop PV concentration in the Diversify+PV scenario.

The residual load curves reveal that the area in the North of the republic will have a residual load of zero or below zero throughout the year across all scenarios because of the high wind onshore concentration across all scenarios. This implies that the area will be a net exporter of electricity throughout the year. Further grid analyses will need to be carried out to explore whether the existing grid capacities will be sufficient to transport these amounts of electricity to the demand centres. Moreover, Figure 9 shows that for Dublin, the residual load can be expected to remain positive throughout the year with the exception of the Diversify+PV scenario which involves the installation of a large amount of rooftop PV modules until 2050. However, even in the Diversify+PV scenario, the residual load is only expected to be negative in approximately 1,500 hours per year and the absolute level of negative residual load is much lower than for the area in the North. Finally, Figure 9 reveals that for the polygon in the Southeast, a residual load of approximately zero can be expected throughout the year with the exception of the Diversify scenario which involves the installation of ground-mounted PV in this area. Firstly, the residual load of around zero for two of the three scenarios implies that this is a rural area with very low electricity demand. Secondly, for the Diversify scenario, the curves show that the residual load can be expected to be negative in roughly 3,000 hours per year. Again, further grid analyses will be required to explore whether the grid capacities will allow for the resulting net export of electricity during these 3,000 hours.

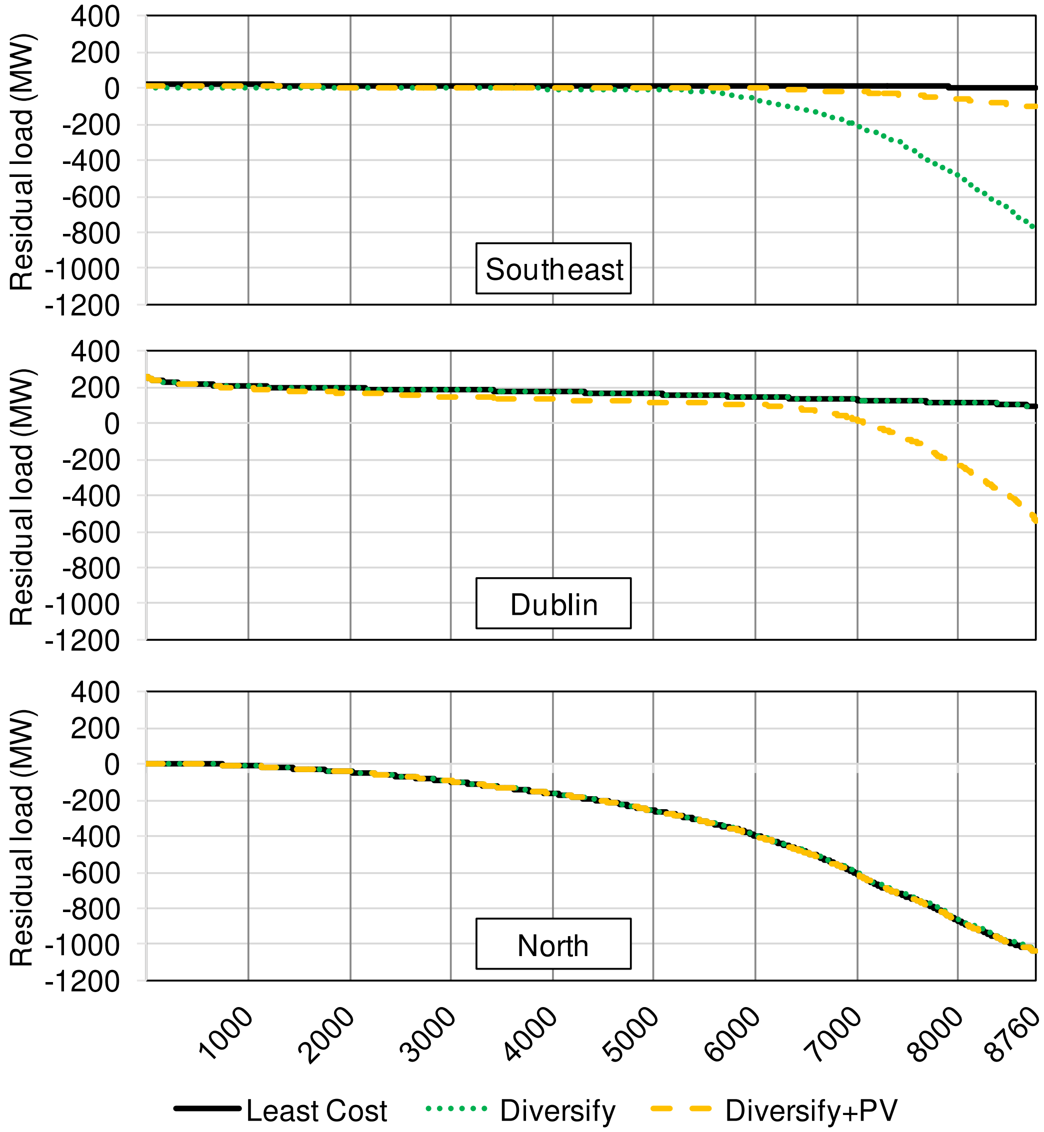

Figure 9: Residual load curves for 3 illustrative Voronoi polygons

5 Conclusions and outlook

In order to provide support in the context of long-term expansion and allocation planning of renewable electricity generation (RES-E) capacities, models are needed which enable an estimation of where RES-E capacities are likely to be allocated. To assess where the RES-E generation will feed into the transmission grid, these models need to be able to consider the capacity and topology of the power grid including their dynamic nature according to published grid development plans. Moreover, such models should be able to take technological advances into account.

In this paper, we therefore developed a model that meets these requirements. Different models existed before, which were targeted at a nodal RES-E expansion planning, mostly based on a fixed and given assignment of RES-E potentials to a node. However, our model goes beyond existing models by considering the assignment of RES-E potentials to grid nodes as a variable.

We demonstrated the model in the context of a case study on RES-E expansion planning in the Republic of Ireland. As part of the case study, we analyse a set of different scenarios, including a Least Cost scenario, a (RES-E) Diversify scenario and a Diversify+PV scenario requiring a predefined minimum amount of solar PV capacity to be expanded. Wind onshore proves to be the dominating technology across all scenarios and the Least Cost scenario is almost exclusively based on this technology. We also find that the Diversify scenario only leads to a moderate cost increase with bioenergy and wind offshore as the most preferred technologies after wind onshore. In contrast, the Diversify+PV scenario leads to a significant cost increase. We wish to emphasise, however, that our model does not include costs for grid expansion. In terms of the regional distribution of the RES-E generation, wind onshore potentials are highest in the West and North of the country leading to a high concentration of wind onshore capacities in these areas, particularly in the Least Cost scenario. In the Diversify scenarios, the RES-E generation is more scattered over the country, particularly in the Diversify+PV scenario, which requires a large amount of rooftop surface. However, since the rooftop PV capacities will mostly be installed in areas of high demand, the higher costs for PV are likely to be at least partially compensated by lower grid expansion costs.

The main limitation of our approach is the assumption of a perfect foresight for a problem with mainly stochastic weather driven variables. Furthermore, cross-sectoral interdependencies to related systems such as the gas, the thermal heating or the transportation sectors are neglected by focussing on the power system. Concerning the case study, our focus was to demonstrate our ability to combine GIS-based approaches for potential analysis of multiple RES-E technologies with the nodal representation of individual generators for solving the optimal allocation problem of RES-E in grid models. To allow for a comparison of different RES-E technologies under consideration of the grid-related cost components, an integration of the approach presented in this paper into a combined generation and transmission network expansion planning problem (GEP + TNEP) would be needed. Besides simply expanding the combined TNEP and GEP formulation to include the introduced constraints, the handling of the resulting problem complexity will be the major challenge for the next steps. While some approaches for an efficient handling of variables were presented within this paper, further problem reduction techniques such as decomposition approaches will be needed in order to solve such problems for large power systems. Finally, considerations of acceptance and opposition, as well as land use planning more generally should be given consideration in future research.

Acknowledgements

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