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Renewable electricity generation and transmission network developments in light of public opposition: Insights from Ireland

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Abstract: This paper analyses how people's attitudes towards onshore wind power and overhead transmission lines affect the cost-optimal development of electricity generation mixes, under a high renewable energy policy. For that purpose, we use a power systems generation and transmission expansion planning model, combined with information on public attitudes towards energy infrastructure on the island of Ireland. Overall, households have a positive attitude towards onshore wind power but their willingness to accept wind farms near their homes tends to be low. Opposition to overhead transmission lines is even greater. This can lead to a substantial increase in the costs of expanding the power system. In the Irish case, costs escalate by more than 4.3% when public opposition is factored into the constrained optimisation of power generation and grid expansion planning across the island. This is mainly driven by the compounded effects of higher capacity investments in more expensive technologies such as offshore wind and solar photovoltaic to compensate for lower levels of onshore wind generation and grid reinforcements. The results also reveal the effect of public opposition on the value of onshore wind, via shadow prices. The higher the level of public opposition, the higher the shadow value of onshore wind. And, this starkly differs across regions: regions with more wind resource or closest to major demand centres have the highest shadow prices. The shadow costs can guide policy makers when designing incentive mechanisms to garner public support for onshore wind installations.

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1. Introduction

Climate change concerns, among others, is leading to a paradigm shift in the electricity sector (Quéré et al., 2018), IPCC (2018). The conventional power system we know is largely based on centralised production and transportation of electricity over long distances before it reaches consumers. Such a centralised approach is economic due to the potential to exploit economies of scale. As a result, generation expansion planning has been mostly framed in this context. However, power systems have been experiencing several changes, particularly in the last few decades, due to increasing levels of electricity generation from renewable energy sources (RES). Wind and photovoltaic solar (PV) dominate renewable installations across many countries. These renewable power technologies have relatively unique characteristics. First, wind and solar PV power production heavily rely on meteorological conditions. This implies their power outputs are erratic, with high levels intermittency and variability. Second, wind and solar resources are spatially dispersed across a vast geographical area. Third, the power density of these energy sources, compared to conventional ones, is substantially lower. All this means their development requires considerable land area. In the presence of strong public support, large-scale renewable power development may prove least-cost. But this may in turn require substantial power system network upgrades (Guler et al., 2018), which is problematic because transmission lines are subjected to even greater public opposition. Renewable developments have been hindered in many cases by public opposition to energy infrastructure projects. This phenomenon has been noted throughout the literature in various jurisdictions (Rae and Bradley, 2012; Bell et al., 2005; Zoellner et al., 2008; Devine-Wright, 2011; Guo et al., 2015; Bertsch et al., 2017; Harold et al., 2018). Schumacher et al. (2019) provides a survey-based comparison of public acceptance of renewable development and attitudes towards energy autonomy in three countries.

Various policy initiatives have been proposed or used to alleviate public opposition to energy infrastructure. These include financial compensation (Hyland and Bertsch, 2018), part-ownership (Bauwens et al., 2016) or more stringent regulations, for example by increasing required set-back distances (Brennan and Van Rensburg, 2016). Highlighting the fact that regions can increase their energy self-sufficiency via locally-sourced energy has also gained traction as a potential mechanism for reducing public opposition to energy infrastructure (e.g. Engelken et al., 2016; Hicks and Ison, 2011). In line with this, the so-called "energy democracy" is emerging as a notable social movement in energy supply and demand (Burke and Stephens, 2017; Di Silvestre et al., 2018). Over the coming years, communities, municipalities and even ordinary citizens are generally expected to have greater control of decisions concerning a sustainable energy transition (Weinand et al., 2019). However, as noted above, economies of scale dictate that community-level, small-scale renewable development is likely to prove more costly than centrally-planned large-scale developments (McKenna, 2018). But continuously falling costs of renewable technologies and storage systems may render local power production and use economically viable (Lai and McCulloch, 2017), and if network reinforcements can be avoided, may be preferable from a systems perspective.

From a planning context, the existing literature has not sufficiently regarded the consideration of public opposition to certain generation technologies in the planning and development of power systems. This gap provides the primary motivation for the current work. The paper performs a case study of Ireland's future power system, with renewable generation and grid reinforcement developments facing social acceptance hurdles. The Irish power system provides a particularly interesting case study due to its high current and planned levels of renewable power, as well as its limited interconnection to other power systems. Ireland has made slow progress towards meeting its climate and renewable energy targets, which has prompted new and demanding policy targets for the year 2030 and beyond. In particular, the Irish Government's 2019 Climate Action Plan (DCCAE, 2019) targets 70% of electricity to be generated by renewables in 2030.

To carry out the aforementioned analysis, we undertake a joint Generation and Transmission Expansion Planning (GTEP) optimisation incorporating public preferences for such infrastructures, using a power systems generation and transmission investment model (Fitiwi et al., 2019). The optimisation model determines the least-cost generation capacity expansion, while respecting a number of technical and policy constraints including public acceptance of energy infrastructure.

The remainder of this paper is structured as follows. Section 2 explores further the existing literature. A description of the methodology, highlighting how the public acceptance information is incorporated into a generation and transmission investment model and the cases under consideration, is provided in section 3. Section 4 presents relevant data and assumptions pertaining to the analysis. Section 5 presents the results and includes a broader discussion. Section 6 concludes.

2. Literature Review

This paper contributes to two areas of literature, one on power systems modelling under high levels of renewable energy integration, a second on public acceptance of energy infrastructure.

2.1. Power System Planning

Power systems expansion planning is a widely researched topic, given its high relevance to modern economies. The planning model determines (ideally) the optimal investment levels of both generation and network-related infrastructure to meet an increasing demand for electricity. Various mathematical models (including commercial ones) are used to perform such optimisation. In addition to the quantities, power system planning models should answer questions related to when and what sorts of investments are required over a predefined horizon, preferably in a dynamic manner and under various technical, economic and environmental constraints.

The literature on power system expansion planning spans several decades. Extensive reviews of the existing literature can be found in recently published works (Gacitua et al., 2018; Chen et al., 2018; Koltsaklis and Dagoumas, 2018; Oree et al., 2017). From a methodological perspective, power system planning models can be broadly categorised into three areas. The first category deals only with supply side investment optimisation (e.g. Rashidaee et al., 2018; Pereira et al., 2017; Fitiwi et al., 2019). This is denoted as Generation Expansion Planning (GEP). The second one is Transmission Expansion Planning (TEP), which optimises only network-related investments in the face of uncertain power generation portfolios that are exogenously fed to the TEP model (e.g. Fitiwi, 2016; Zhan et al., 2017a; Moreira et al., 2018; Zhang et al., 2013, 2018). The third category (often abbreviated as GTEP) optimises GEP and TEP problems simultaneously, (e.g. Aghaei et al., 2014; Pozo et al., 2013; Roh et al., 2007; Hemmati et al., 2016; Seddighi and Ahmadi-Javid, 2015; Zhang et al., 2017; Guerra et al., 2016). The literature review in the current work is therefore framed mainly from the GTEP context, consistent with the analysis we carry out.

As mentioned above, GTEP models determine optimal generation and transmission portfolios ideally considering relevant sources of uncertainty, emanating from policy, infrastructural and demand growth related issues. Given the paradigm changes happening in power systems, network and spatial effects have become more relevant as some of the key determinants of generation investment portfolios (Fitiwi et al., 2019). However, these effects are largely neglected in existing models, reviewed here. In particular, most GEP models in the extant literature are mostly formulated without taking account of network effects, often ignoring the network altogether by essentially collapsing the entire system into a single node (e.g. Palmintier and Webster, 2016; Rashidaee et al., 2018; Saboori and Hemmati, 2016; Luz et al., 2018; Bracht and Moser, 2017; Peker et al., 2018; Pereira et al., 2017; Park and Baldick, 2016; Slednev et al., 2018; Pereira and Saraiva, 2011; Zhan et al., 2017b). Needless to say, such models are incapable of accounting for the increasingly important spatial aspects of the generation expansion planning problem. In particular, ignoring network and spatial effects may render generation investment decisions that are infeasible from an operational standpoint. Otherwise, the decisions may lead to massive and costly network reinforcements. A few other models represent transmission lines as pipelines (e.g. Pineda and Morales, 2018; Sarid and Tzur, 2018; Koltsaklis and Georgiadis, 2015). In some other studies, a lossless Direct Current Optimal Power Flow (DC-OPF) is used to consider network effects (Aghaei et al., 2014; Pozo et al., 2013; Roh et al., 2007; Zhang et al., 2016; Guerra et al., 2016). However, this modelling technique overly simplifies the physical characteristics of complex power systems. This is because a DC-OPF based GEP model implicitly assumes uniform voltage across the considered system, and does not take account of reactive power flow constraints, which are critically important especially in insular systems such as the Irish one.

GTEP models can also be employed for other purposes, such as impact assessments pertaining to new technology deployment, a new operational scheme and/or an unprecedented system evolution. Examples include carbon capture and storage (Saboori and Hemmati, 2016), energy storage systems (Pineda and Morales, 2018), renewable integration (Bhuvanesh et al., 2018; Luz et al., 2018), power-to-gas (Bracht and Moser, 2017), demand response (Zhang et al., 2017), electric vehicles (Sarid and Tzur, 2018; Ramírez et al., 2016), distributed generation (Sarid and Tzur, 2018), endogenised technology learning (Heuberger et al., 2017) and unit commitment (Koltsaklis and Georgiadis, 2015), among others.

The GEP problem in the literature is either formulated under a static planning framework, in which decisions are made for a target year (e.g. Hemmati et al., 2016; Guerra et al., 2016; Peker et al., 2018; Pereira et al., 2017) or a dynamic framework (e.g. Slednev et al., 2018; Fathtabar et al., 2018; Pereira et al., 2017). Given the nature of the problem, the dynamic framework is a more orthodox approach. However, it is rarely implemented in existing studies, mainly due to computational limitations. Some researchers approach this challenge by a hybrid of static and dynamic approaches. For example, the work in Pozo et al. (2013) is originally formulated under a static planning framework, but with the capability of performing year-by-year dynamic analysis. Others resort to sequential static planning or the rolling horizon approach, especially when dealing with long-term planning horizon (Seddighi and Ahmadi-Javid, 2015).

Power systems are exposed to various sources of uncertainty, both from the supply and demand sides (Zhan et al., 2017b). Variable renewable generation, whose power output is characterised by limited predictability, is experiencing robust growth across many countries. This further exacerbates uncertainty (particularly, operational uncertainty). As a result, stochastic modelling is becoming increasingly important in GTEP studies (e.g. Seddighi and Ahmadi-Javid, 2015; Fitiwi et al., 2019). Poncelet et al. (2017) incorporate uncertainty from renewable power sources by selecting representative days. Hemmati et al. (2016) resort to a Monte Carlo Simulation (MCS) approach to account for uncertainty in wind power generation. Other studies have also included uncertainty pertaining to reliability issues in power system planning optimisations. For example Aghaei et al. (2014) consider generator and transmission line outages in a GTEP optimization. Seddighi and Ahmadi-Javid (2015) perform an in-depth stochastic GTEP exercise with uncertainty in future electricity demand, fuel prices, costs of greenhouse gas emissions and supply disruptions, while also taking into account carbon emissions, noise impacts and social acceptance. Moreover, the prospects of robust optimisation (Jornada and Leon, 2016) and risk-based planning (Gitizadeh et al., 2013) form part of the extensive approaches used for managing uncertainty in power systems planning.

Other measures proposed in the literature to mitigate the negative effects of variable power generation include increasing the flexibility of power systems. Increased flexibility better deals with operational uncertainty that may otherwise unfold unfavourably, resulting in detrimental effects to power systems. Along these lines, highlighting the importance of developing flexible power systems, Palmintier and Webster (2016) investigate ways of improving operational flexibility within a GEP framework, under renewable and emission reduction targets.

Despite the huge body of literature on power system planning, network and spatial effects are largely neglected or insufficiently accounted for in existing models. The current work addresses this limitation by employing a more suitable optimisation model based on a linearised Alternating Current Optimal Power Flow (AC-OPF). Furthermore, uncertainty pertaining to public preferences are not factored in any of the reviewed existing planning models, with the exception of Rodgers et al. (2018), which incorporates health and societal damages into the planning framework.

However, the study does not account for public attitudes towards and personal judgement about energy infrastructures.

This paper builds on Fitiwi et al. (2019), which employs a constrained GTEP optimisation model. This approach estimates a cost-optimal electricity generation expansion and operation plan on the island of Ireland considering a set of different generation technologies in a time horizon up to 2030. The work by Fitiwi et al. (2019) is carried out under a range of demand and policy scenarios, and subject to several constraints, but excluding public preference constraints. A more realistic consideration of locals' views and preferences regarding diverse types of technologies like wind farms and transmission lines is required for a more effective design of energy policies and infrastructure. The contribution of this paper is an extension of the model in Fitiwi et al. (2019) to include constraints representing public preferences for energy infrastructure.

2.2. Public Preferences on Energy Infrastructure

The second strand of literature, distinct from power systems, examines public preferences to large scale infrastructure, including energy. Several papers have analysed public acceptance with respect to wind farms. In the context of France and Germany, Jobert et al. (2007) explored factors important for winning acceptance of wind-energy parks at different stages. Among those factors, the authors identify institutional conditions (e.g. economic incentives and regulations), as well as territorial factors e(.g. local economy, geography, actors and project management). Wolsink (2000) suggests that institutional factors have a greater impact on the siting of wind energy infrastructure, beyond the common argument that locals suffer from the "Not-In-My-Backyard" (NIMBY) syndrome. Hence, this may explain why strong overall public support for wind power clashes with attitudes towards specific wind projects.

The existing literature shows that distance to dwellings is an increasingly relevant factor to take into account for the development of wind energy. Van Rensburg et al. (2015) focus on factors influencing the planning approval of wind farms in Ireland, highlighting among them the duration of local appeal processes, decisions of local authorities, identities of the appellants and projects that conflict with strategic development plans or generate visual externalities. Interestingly, the authors find that proximity to dwellings, towns or protected habitats does not influence planning outcomes. However, Guo et al. (2015) find that distance is a relevant factor shaping public acceptance of existing wind power infrastructure in China, describing locals' behaviour as "not in my backyard, but not far away from me", since people's acceptance is lowest when the wind farm is located in their village, highest when located in the county and city, and decreases when it is further away. In the case of Germany, Bertsch et al. (2016) also remark that distance between places of residence and places of energy infrastructure is crucial. Nevertheless, they emphasise that acceptance or rejection of technologies will never be fully tangible or explicable, especially for new technologies.

Further works on Ireland provide insights on other factors driving people's opinions on electricity generation and transmission technologies. Bertsch et al. (2017) identify among them socio-demographic factors, technology-specific perceptions and energy policy preferences. Just like other studies, the authors find that Irish citizens have positive views of Renewable Energy Sources (RESs) and agree to move towards cleaner electricity sources, but far from their place of residence. They particularly point out the importance of tradeoffs people make between economic and environmental policy objectives as drivers of public acceptance. Brennan et al. (2017) go even further and analyse public acceptance of wind energy export from Ireland to the UK, concluding that significant public and private investment is required to provide better information, build trust, internalise wind farm externalities for Ireland to fully capture the benefits of this process.

A parallel literature examines the role of community involvement mechanisms in shaping the public views of wind farms and other renewable technologies. In the context of Ireland, Hyland and Bertsch (2018) find preferences in favour of schemes in which people receive financial compensation without sharing the ownership or associated risks of project development. They also mention other socio-economic factors and policy goal trade-offs as main drivers of people's acceptance of energy infrastructure. In the case of south-west Scotland, Warren and McFadyen (2010) find that people residing or visiting an area where a community-owned wind farm is installed were consistently more positive about wind power than in other surrounding areas where private-owned farms operate. Furthermore, in a German study, Musall and Kuik (2011) consider the role of co-ownership schemes, finding that people are more positive towards energy infrastructure in community co-ownership schemes rather than schemes that are fully community-owned.

Brennan and Van Rensburg (2016) quantify the compensation required to permit wind farms to be built in Ireland, finding that most respondents are willing to make monetary trade-offs to allow for wind power initiatives. Such compensation will be lower if the project allows for a community representative and the distance to dwellings is increased. By contrast, Ek and Persson (2014) consider the option of residents bearing a monetary cost expressed as an additional electricity certificate fee. Thus, consumers in Sweden are willing to accept a higher fee if wind farms in recreational areas are avoided, if the farm is totally or partially community-owned, and if locals are involved in the planning and implementation process. By making a policy simulation, Ek and Persson (2014) find that residents would pay a higher fee to avoid privately-owned wind farms in mountainous areas. Few studies actually incorporate that valuable information quantitatively in power systems planning models, which is a gap this study aims to bridge.

This paper also contributes to an existing literature on public acceptance of transmission lines specifically. Analysing EU-27 countries, Cohen et al. (2016) argue that auxiliary information regarding the positive impact of a grid development project can substantially reduce the opposition to transmission lines by local stakeholders. Indeed, emphasising the potential carbon reduction in the long run and the economic benefits of a project can reduce opposition by 10%. In the specific case of southern Finland, Soini et al. (2011) confirm that transmission lines are generally perceived as negative landscape elements, both when long-established and when new. However, perceptions are heterogeneous among residents, which is explained by environmental attitudes, leisure activities, knowledge and land ownership. Additionally, in the UK context, Devine-Wright and Batel (2013) surveyed residents on their preferences on high voltage pylon designs, finding that a new "T-pylon" design has the best perceived fit for a rural landscape, but this design is less supported than burying new powerlines underground and routing pylons away from homes and schools.

The contribution of this paper is twofold: the inclusion of a social constraint in a power systems planning model, which accounts for public acceptance to power technologies like onshore wind and overhead transmission lines; and the quantification of the impact of public attitudes towards onshore wind power and overhead transmission lines on the cost-optimal development of a power system with high levels of renewable energy integration.

3. Methodology

3.1. Model Description

The Electricity Network and Generation INvEstment (ENGINE) model, employed in the current work, is a stochastic optimisation tool, designed to simultaneously determine optimal investments in transmission and generation infrastructures (i.e. GTEP) that minimise system-wide cost while respecting a number of technical, economic, spatial and environmental constraints (Fitiwi et al., 2019). The objective function of the ENGINE model, expressed in Equation 1, constitutes a sum of the net present values (NPV) of five terms related to investment, reliability, operation, maintenance and emission costs.

$$MinTC = TInvC + TMC + TEC + VOLL + TEmiC \tag{1}$$

$TInvC$ denotes the NPV of total investment costs in new generation capacity, transmission and storage installations. The second term, TMC, represents the NPV of fixed maintenance and operation costs of (new or existing) generators and of network components. TEC refers to the total cost of producing electricity in the system using both new and existing generators. In other words, TEC denotes the variable costs of meeting the electricity demand, i.e. the cost of power generation. The fourth term, $VOLL$, represents the total cost of unserved power in the system, i.e. the value of lost load or reliability cost. Finally, the term $TEmiC$ gathers the total carbon emission costs in the system, given by the sum of costs of emissions emitted by existing and new generators when producing electricity.

The constraints included in the ENGINE model can be broadly classified as technical, economic, spatial and environmental constraints. Within the technical constraints, the model deploys Kirchnoff's current and voltage laws. Kirchnoff's current law states that the sum of all incoming flows to a node must equal the sum of all outgoing flows at any given time. Kirchnoff's voltage law, unlike the current law, is nonlinear and states that the sum of all voltages around a closed loop is equal to zero. This paper, however, linearises the non-linear expression of this law (Fitiwi, 2016; Fitiwi et al., 2017). The technical constraints also include boundary conditions of relevant system variables. Within this group, the model considers flow limits, whereby power flows in each line should not exceed its maximum transfer capacity, as well as constraints related to network losses, active power production and reactive power sources.

Economic constraints include logical constraints related to the irreversibility of investment and budget constraints. Investment planning is also subject to spatial constraints, depending on either the availability of resources, space or both. One example in this case is wind power, which requires the availability of both the primary energy resource, wind, and space to exploit it. Such constraints are critical in power system planning, and are incorporated into the ENGINE model. Environmental constraints emanate from climate policy targets to abate greenhouse emissions. For a detailed description of the algebraic formulation of the ENGINE model, see Fitiwi et al. (2019).

An innovation in this paper is the inclusion of a social constraint in the power systems expansion planning model, which accounts for public acceptance of power technologies like onshore wind and overhead transmission lines. A detailed description of this constraint is given in Section 3.4.

3.2. Uncertainty Management

Electricity systems have several sources of uncertainty and variability. Short-term or operational uncertainty includes variable power production sources (such as wind and solar), electricity demand and forced outages of conventional generators. Long-term uncertainty includes policy measures, demand composition and growth, and carbon and fuel prices. Any robust solution to the generation expansion problem must account for these sources of uncertainty.

To address short-term uncertainty, we use historical wind speed and solar radiation data at hourly resolution spanning 35 years for different regions of the island of Ireland (Bertsch et al., 2018). The dataset therefore has a total of 306,762 operational time points, each of which contains wind speed and solar radiation for each region. The data are obtained from Bosilovich et al. (2016). The regional wind speed and solar radiation data are then converted into power production factors using appropriate power curves of the respective technology (Santos et al., 2017b). Further details on the data acquisition and processing can be found in Qazi and Flynn (2016). An hourly demand series for a length of five years from 2011 is downloaded from EirGrid, the Irish transmission system operator EirGrid (2018), and is duplicated to match the length of wind and solar power output series. The rationale for this approach is that 35 years of historical wind and solar data are representative of the wind and solar that can be expected today, however, in the case of electricity demand, more recent data are required.

Computational constraints prohibit solving the expansion problem with the entire dataset described above and so a reduced dataset is obtained by means of clustering. We employ the *k-means clustering algorithm* (Hartigan and Wong, 1979). The performance of the clustering process is recorded by varying the number of clusters, leading to a trade-off curve. The number of clusters to use in the final analysis is then decided according to the Elbow method (Thorndike, 1953). In our case, this number is between 300 and 500. Beyond this range, the trade-off curve is more or less flat, i.e. changes in the objective function value of the clustering algorithm are not significant. We thus set the number of clusters to 300. A representative snapshot is then selected from each cluster, with the objective of accurately representing the system's operational status.

The ENGINE model considers four potential future demand scenarios, each with a specific probability, which represent a realisation of the relevant sources of long-term uncertainty such as demand growth, carbon prices and fuel prices. The demand growth projections are primarily driven by different potential growth rates of datacentres in Ireland, as projected by the transmission system operator, EirGrid (EirGrid, 2017). A collection of hourly realisations of demand and actual renewable power generation models the operational uncertainty pertinent to the power system expansion planning problem. The optimisation model is formulated as a multi-stage problem, dividing the entire planning horizon into multiple decision periods. At each stage, the model determines optimal values of all control variables, considering all probability-weighted scenarios. A stochastic expansion solution is obtained at each stage, i.e. a solution that is optimal for the combination of all probability-weighted scenarios.

3.3. Solution Strategy

Despite clustering a large number of snapshots and using a relatively small number of scenarios (four in our current study), the problem cannot be directly solved without significant computational effort. Hence, we employ a solution strategy that is based on a combination of problem decomposition and rolling-horizon approaches. The solution strategy employed in this work uses only two phases; the first being a relaxed version of the model presented in Fitiwi et al. (2019). This phase involves a continuous relaxation of all discrete variables. A less-detailed network model is also used. The second phase uses the model in its entirety, and polishes the solutions obtained in the first phase. This means the expansion problem is solved in a series of iterations. The model is coded in the general algebraic modelling system (GAMS) GAMS (2018), and solved using CPLEX™12.0 IBM (2015). All simulations are carried out on a server with Intel Xeon E5-2630 dual processor clocking at 2.2 GHz and with 256 GB RAM.

3.4. Public Acceptance: Constraint in ENGINE Model

The way public acceptance of electricity infrastructures enters into the ENGINE model is twofold. Firstly, as a factor diminishing the maximum wind capacity per region. Secondly, as a threshold value above which a new overhead transmission line can be constructed in a region or set of regions.

3.4.1. Onshore wind turbines

The ENGINE model considers a spatial constraint determining the maximum capacity of onshore wind power that can be feasibly developed in each geographical region. This constraint is expressed as follows:

$$\sum_{g\in\Omega^{onsh}} \sum_{i\in\Omega^{i};(g,i)\in\Omega^{reg}} x_{g,i,t} \leq \omega_{reg}\xi_{reg}. \tag{2}$$

where $x_{g,i,t}$ represents the investment variable associated with power generation technology g, connected to a transmission node i, in planning stage t, located within a region reg. Equation 2 implies that the total sum of these investments made in region reg should not exceed the maximum onshore wind potential of the same region ξ_{reg}. This is adjusted by a factor ω_{reg} accounting for public acceptance in the same region reg. Ω^{onsh} denotes the set of potential onshore wind farms, whereas Ω^{reg} represents the set of regions where the power infrastructure is allocated.

Based on the public survey results which are detailed in Section 5, we estimate for each region the factor ω_{reg}, the regional weight of public acceptance of wind turbines, which derates the maximum wind capacity per region. Overall, as will be demostrated later, there is a positive judgement on wind turbines across the Irish regions. However, the willingness to accept such infrastructure near homes is not as high. Therefore, in order to control for actual public acceptance of wind turbines, we only consider the regional shares of respondents judging this technology as "positive" or "somewhat positive", as well as the regional shares of people willing to accept a wind farm up to 5 km from their dwellings. We compute the regional weight of public acceptance of wind turbines, ω_{reg}, expressed by the following function:

$$\omega_{reg} = k_l(1 - e^{\alpha_l W_{1,reg}} e^{\beta_l W_{2,reg}}), \tag{3}$$

where $W_{1,reg}$ denotes the share of respondents in region reg reporting a positive personal judgment of wind turbines, whereas $W_{2,reg}$ represents the share in that region of respondents willing to accept a wind turbine up to 5 km away from their place of residence. The rationale behind this function is that, in case all respondents are happy with wind turbines, i.e. $W_{1,reg} = W_{2,reg} = 1$, the regional weight will be equal to one, reflecting full acceptance. This explains the inclusion of the factors α_l, β_l and k_l in the formula, which make the function converge to unity.

We assign different values of α_l, β_l and k_l to account for a set of four public acceptance scenarios which are described afterwards. Table A.1 in the Appendix shows how regional weights of public acceptance of wind turbines are computed, by using the aforementioned inputs, considering a value k_l of 1.156 and $\alpha_l = \beta_l = 1$. It is evident from those figures that, even though there is not so much variability of weights across regions, the Border region exhibits the largest degree of wind turbine approval, according to this approach.

3.4.2. Overhead Transmission Lines

To account for public acceptance of overhead (above-ground) transmission lines, we first calculate for every potential transmission line a public acceptance weight. Subsequently, we set a threshold weight at the national average acceptance level, which helps us determine which potential transmission lines are publicly acceptable for construction.

In order to compute the public acceptance weight for each above-ground transmission line, we follow a similar approach as for wind turbines. From each region, we extract the shares of positive personal judgement and willingness to accept a transmission line up to 5 km from residents' homes. However, one single transmission line may pass through up to three regions in Ireland. This characteristic must be taken into account in the weights' calculation. Hence, the function for the public acceptance weight per transmission line, according to their respective courses, is expressed as follows:

$$\omega_{i,j} = k_l\left[1 - \left(\frac{\sum_{reg=1}^{n} e^{\alpha_l W_{1,reg}} e^{\beta_l W_{2,reg}}}{n}\right)\right]. \tag{4}$$

where $\omega_{i,j}$, the weight computed for transmission line between power system nodes i and j, is a function of the average public acceptance of all the regions through which the line in question passes, with n ranging from 1 to 3. The factor k_l is set to 1.156 so that the function value converges to unity in case of full public acceptance per region.

Table A.2 in the Appendix displays the weights computed for transmission lines lying within one single region. Overall, the small weights obtained reflect the low levels of acceptance, both in terms of personal judgement and willingness to accept a transmission line near respondents' homes and in opposition to wind turbines. Tables A.3 and A.4 present the corresponding weights for the transmission lines covering two and three regions, respectively, by applying Equation 4. These tables only show the weights for the geographically possible combinations.

As a next step, a threshold weight is computed, meaning that in those regional combinations obtaining a weight above that threshold, an above-ground transmission line is permitted for construction. In regional combinations with a weight below the threshold, no transmission line can be installed due to public opposition.

To set the threshold weight, we use the one-region weights presented in Table A.2 and the number of existing above-ground transmission lines passing through each of the eight areas analysed, regardless of the number of regions per line (see Table A.5). The threshold weight is calculated as the average of one-region weights, weighted by the number of existing lines per region. The 0.452 threshold obtained from this approach is applied in the public acceptance scenarios described later. This value implies that new above-ground transmission lines cannot be constructed if they do not go beyond regions like the Border (0.424), the Mid-East (0.362), the Mid-West (0.411) and the South-West (0.447). Nevertheless, it will be publicly acceptable to install a transmission line in the Border, for instance, if it starts or finishes in the Midland area or the West, or if the line involves these three regions.

3.4.3. Formulation of the cases

As stated earlier, the main focus of this paper is to investigate the system-wide impacts of public preferences pertaining to renewable energy technologies like wind turbines and transmission grid developments. To this end, based on the regional weights computation presented earlier, we construct four different scenarios depending on the level of social acceptability to these infrastructural developments. These are labelled as *Full Acceptance*, *High Acceptance*, *Moderate Acceptance*, and *Low Acceptance*.

Table 1 lists the regional weights of public acceptance of wind turbines, for each of the four scenarios introduced above. As mentioned earlier, a regional weight and threshold of 1 corresponds to a scenario of full acceptance. This is reflected in the second column for all regions. The wind turbines' regional weights assigned to the high acceptance scenario are the same weights computed in Table A.1, by applying $k_l = 1.156$ and $\alpha_l = \beta_l = 1$. For the construction of weights in the moderate and low acceptance scenarios, we set $k_l = 1.431$ and 3.034, respectively.[1] Likewise, α_l and β_l are set to 0.6 and 0.2 in the moderate and low acceptance scenarios, respectively. Figure 1 graphically shows the functions used to compute the regional weights attributed to wind turbines under the high, moderate and low acceptance scenarios. Table 2 provides some example weight calculations based on values for minimum distance accepted and public judgement and the parameter values noted above.

Table 1: Public Acceptance Scenarios: Wind Turbines' Regional Weights

	Scenarios			
	Full Acceptance	High Acceptance	Moderate Acceptance	Low Acceptance
Border	1.000	0.809	0.736	0.649
Midland	1.000	0.700	0.613	0.516
West	1.000	0.792	0.716	0.626
Dublin	1.000	0.792	0.715	0.626
Mid-East	1.000	0.761	0.680	0.587
Mid-West	1.000	0.743	0.660	0.565
South-East	1.000	0.791	0.714	0.624
South-West	1.000	0.780	0.701	0.610
Northern Ireland	1.000	1.000	1.000	1.000
k_l		1.156	1.431	3.034
$\alpha_l = \beta_l$		1.000	0.600	0.200

k_l, $alpha_l$ and β_l are described in section 3.4.1

Regarding the thresholds for overhead transmission lines per scenario, once again we assign a value 1 to the full acceptance case. The 0.452 threshold presented in Table A.5 is assigned to the moderate acceptance scenario, seeking to reflect the degree of approval to transmission lines observed in the survey of preferences. For the high acceptance scenario, we arbitrarily assign a threshold value of 0.35, so that all possible regional combinations for a transmission line are publicly accepted and hence included in the ENGINE model estimation. Similarly, for the low acceptance case, we arbitrarily set a 0.6 threshold which makes all regional combinations unacceptable. Thus, under the low acceptance scenario the ENGINE model outputs does not include any new transmission lines.

4. Data and Assumptions

The analysis is performed using the 2017 power system of the island of Ireland, described in detail in Fitiwi et al. (2019). The system includes a transmission network aggregated at 110 kV or higher for the whole island. Data and

[1]These values are obtained by making each joint weight function (i.e. equation 3) converge to 1, for a given shape parameter value and full acceptance levels for both personal judgement and minimum distance attributes.

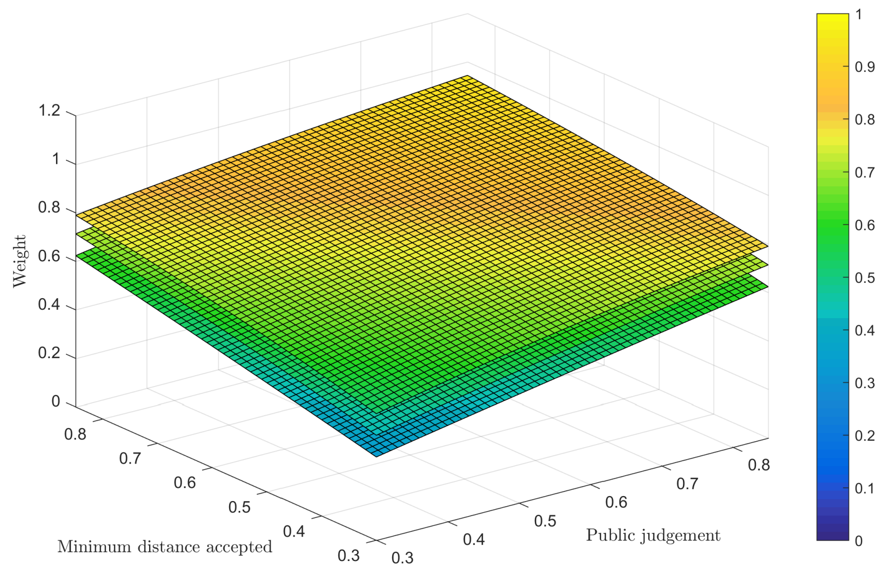


Figure 1: Weight transforming functions

Table 2: Example weight calculations based on equation (3), values for minimum distance accepted, public judgement, and parameter values described in section 3.4.3

			Weights:		
Example	Personal judgement	Minimum distance accepted	Low acceptance	Moderate acceptance	High acceptance
1	0.797	0.407	0.649	0.736	0.809
2	0.655	0.276	0.515	0.612	0.700
3	0.786	0.369	0.626	0.716	0.792
4	0.789	0.366	0.625	0.715	0.792
5	0.731	0.343	0.587	0.680	0.761
6	0.720	0.310	0.565	0.660	0.743
7	0.784	0.368	0.624	0.714	0.791
8	0.769	0.354	0.610	0.701	0.780

further details of this system can be found in EirGrid (2016).

The planning horizon is 12 years long, with two intermediate decision stages coinciding with 2021 and 2025. We assume carbon prices of €25/tCO_2 for 2025 and €30/tCO_2 2030, in line with the projections in Carbon Tracker (2018). The renewable integration (RES-E)[2] target for 2030 is assumed to be 70%, which is 30 percentage points higher than the mandatory 40% RES-E target in 2020. This is consistent with Irish government policy (DCCAE, 2019). An intermediate RES-E target of 55% for 2025 is imposed. Investments in new thermal power plants, including carbon capture and storage (CCS), are assumed to be in brown field sites. A retirement plan of existing thermal generation assets is assumed to be a policy decision. Hence, the model does not provide endogenous decommissioning of existing old, inefficient power plants. A 75% system non-synchronous penetration (SNSP) limit, defined as the ratio of generation from variable renewable power sources plus HVDC imports to demand plus HVDC exports, is imposed[3]. We do not include current HVDC interconnections with England and Scotland, or any planned future interconnection. This is because we are interested in examining the impacts of renewable generation in an isolated system.

The optimisation model also considers investments in battery energy storage technology. The transmission system operator's projections for battery storage range between 100 MW and 1700 MW by 2030 (EirGrid, 2017), which are used as the basis for our storage installations. We assume a four-hour duration battery energy storage facility of 30 MW rating (O'Dwyer et al., 2017; IRENA, 2019). We impose the constraint that no more than four storage systems of this type can be built at each candidate node, or demand node, shown in Figure 2.

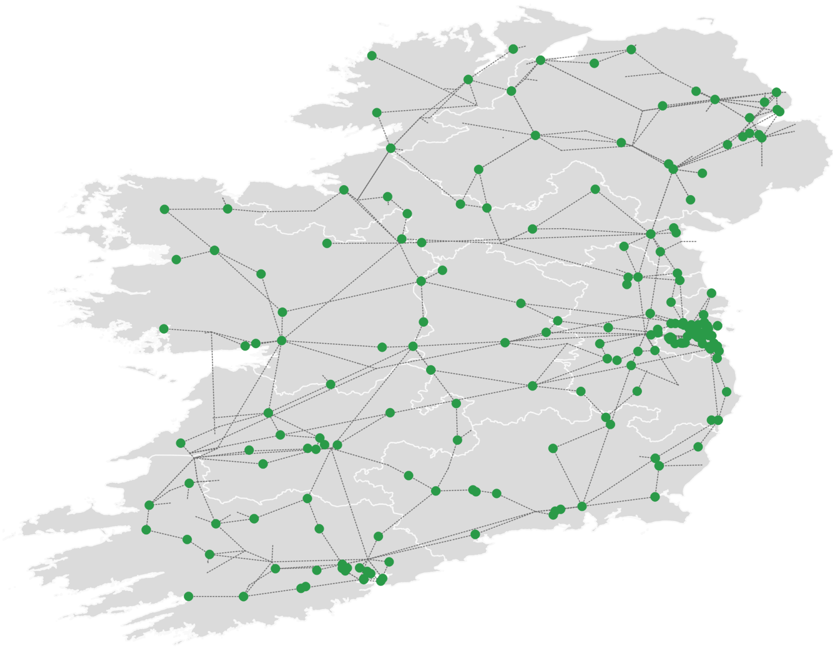


Figure 2: Candidate connection nodes of renewable and storage investment

To ensure problem tractability, integer constraints related to storage investments (due to lumpiness) are relaxed. This means the optimal storage installations can be fractions of the above nameplate capacities. As battery-based storage systems tend to be modular in nature (similar to wind and solar PV power production technologies), this assumption is not unreasonable. Further assumptions for storage include a 90% round-trip efficiency, a 10 year lifetime

[2]RES-E: Renewable Energy Sources -Electricity.

[3]Further definition and derivation of the SNSP limit can be found in EirGrid (2010).

and an 80% depth of discharge (DoD) (Zakeri and Syri, 2015; Santos et al., 2017a; O'Dwyer et al., 2017).

The optimal location of renewable power generation assets depends on a number of technical, spatial and environmental factors, such as demand, electrical connectivity and proximity to primary energy resources, as well as socio-economic factors. In order to ensure that renewable power expansion is not unrealistically concentrated in one or two geographical regions, we impose a maximum installed capacity at a regional level that can be feasibly built by 2030. This maximum is based on existing and planned levels of installed capacity and scaled up according to population density and available space in the regions in question. The resulting maximum wind installations per region are shown in Table 3. The table also shows the number of demand nodes as well as the percentage share of demand of each region.

Table 3: Maximum onshore wind capacity and demand share by region

Region	Feasible onshore wind potential (MW)	Number of demand nodes	Demand share (%)
Mideast	289	23	9
Midland	1096	5	2
West	742	15	7
Midwest	316	14	6
Southeast	674	15	6
Southwest	736	29	10
Border	905	16	6
Northern Ireland	450	27	20
Dublin	0	45	34

Additional parameter assumptions regarding generator and storage technologies are presented in Table A.6.

4.1. *Public Acceptance: Data*

To incorporate public acceptance by Irish households on electricity generation technologies, we use data from a representative survey of Irish adults administered in May 2016 by a professional survey company. Hyland and Bertsch (2018) documents the survey, which was undertaken to examine community involvement in the development of energy project. Table 4 shows the number of respondents per region, and a comparison with population shares for the census of population, indicating that the completed survey is broadly representative by region.

Table 4: Survey respondents by region

Region	N° Respondents	Percent	Population Share 2016
Border	118	11%	8%
Midland	58	6%	6%
West	103	10%	9%
Dublin	298	28%	28%
Mid-East	108	10%	15%
Mid-West	100	9%	10%
South-East	125	12%	9%
South-West	147	14%	15%
Total	1057	100%	100%

The questionnaire covers a wide range of subjects related to public judgement and attitudes towards several types of technologies such as wind turbines, above-ground electrical transmission lines, solar generation technologies, coal-fired, gas-fired and biomass power plants, among others. For this research, we focus on attitudes towards the first two.

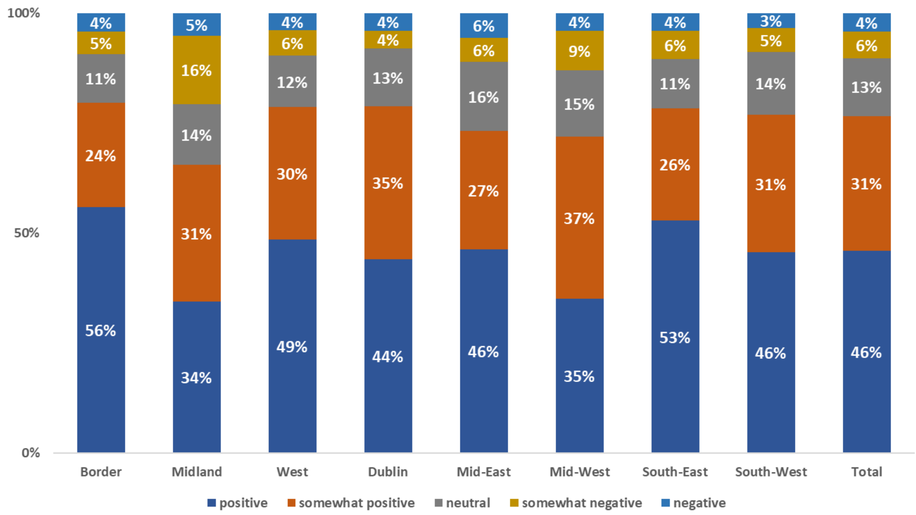
More specifically, from the survey, we have extracted the personal judgment by respondents on these technologies, as well as the minimum distance from their place of residence they are willing to accept for their potential construction.

5. Results and Discussion

5.1. Public Acceptance: Survey Results

Among the electricity generation technologies considered in the survey, wind turbines enjoy one of the largest degrees of public acceptance. When asked about their overall personal judgement of each technology, 77% of the respondents in Ireland gave a positive assessment of wind turbines, which was reported as either "positive" (46%) or "somewhat positive" (31%). Figure 3 plots the statistics on personal judgment on wind turbines by region, showing that the Border, West, Dublin and South-East regions each report larger acceptance to wind turbines than the country average. On the other hand, the Midland reports the greatest rejection level (21%).

Figure 3: Personal Judgement on Wind Turbines by Region



Nonetheless, when it comes to accepting the installation of a wind turbine near their dwellings, households do not give clear approval. Figure 4 presents the results to the question on minimum acceptable distance to wind turbines accepted by region. Overall, despite the high positive judgement, 40% of Irish respondents are willing to accept a wind turbine, but greater than 5 km from their dwellings. Only 36% are happy to have up to 5 km away, whereas 13% will not accept any wind turbine regardless of the distance.

The regions with above average willingness to accept that infrastructure nearby are the Border, the West, Dublin, South-East and the South-West, while the Midland region is the most negative towards energy infrastructure regardless of the distance (21%). It is necessary to point out that many respondents did not answer this question. Indeed, 11% in Ireland gave a "don't know" response. That share jumps to 17% in regions like the Midland and the Mid-West, and 16% in the Mid-East.

Respondents were informed of the necessity to install electrical transmission grids in order to transport the electricity generated by the different types of technologies. They were also informed that these networks could be installed either above or under the ground. Figure 5 features the results of the question on personal judgement on above-ground electrical transmission line expansions, which is complementary to the construction of wind turbines.

Figure 4: Minimum Distance to Wind Turbines Accepted by Region

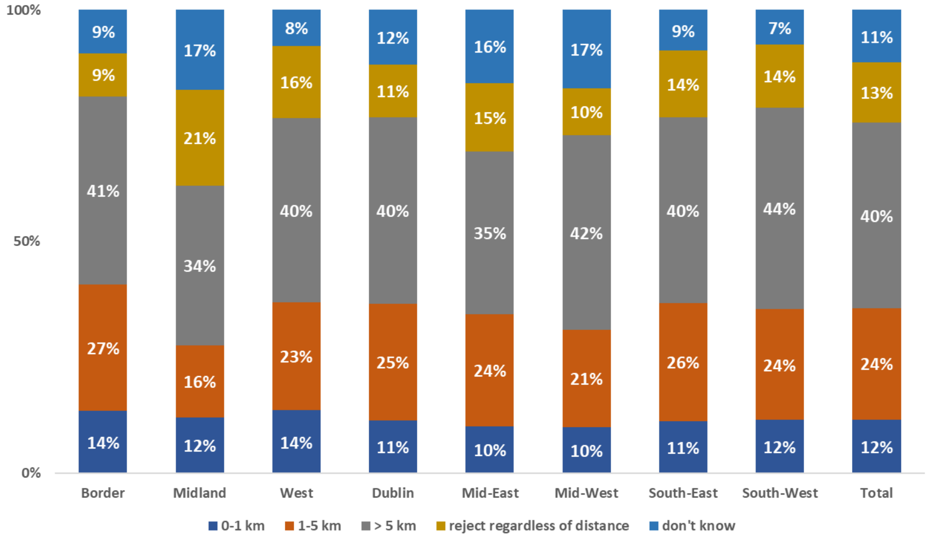
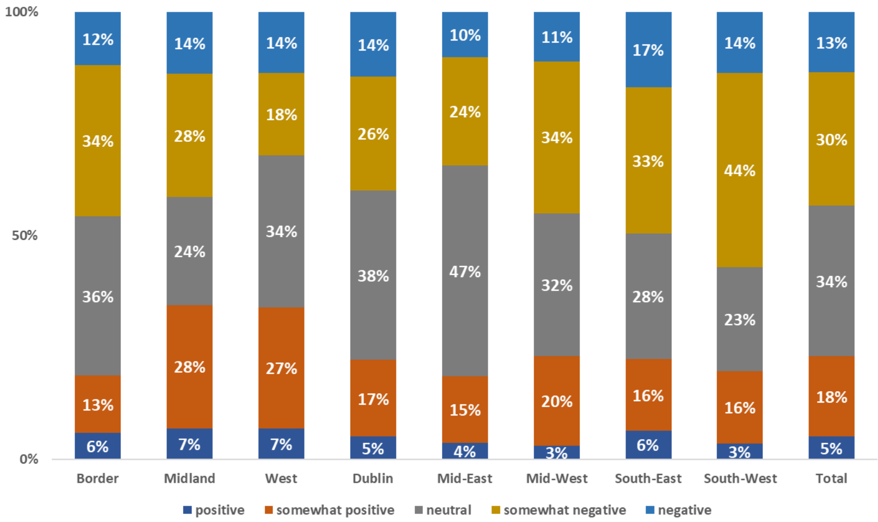


Figure 5: Personal Judgement on Transmission Lines by Region

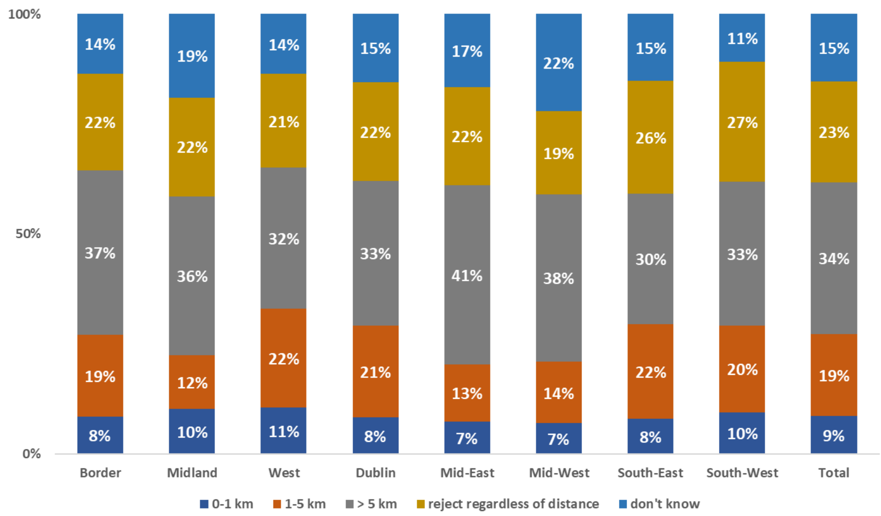


These results reveal a large degree of rejection to above-ground transmission lines, as well as a high level of neutrality. Overall, 43% of respondents in Ireland provided a negative judgement on this technology, whereas 34% reported being neutral to it. Only 23% clearly approve this infrastructure. Surprisingly, the Border and the South-East, two of the regions with the largest acceptance to wind turbines, report larger levels of negative judgement than the country average, together with the Mid-West and the South-West. By contrast, the Midland and the West give the largest degree of positive judgement, whereas the Mid-East reports the largest level of neutrality (47%).

Only 28% in the Republic of Ireland are happy to accept above ground transmission lines up to 5 km away, 34% will only accept it further than 5 km from their dwellings, and 23% will never approve it regardless of the distance, as shown in Figure 6. Regions like the South-East (26%) and the South-West (27%) report rejection levels above the country average. However, these two regions, along with Dublin and the West, also reveal a higher willingess than the

Irish average to accept transmission lines near their place of residence. There is also a high share of respondents not able to give their preferences. Overall, 15% responded "don't know" to this question.

Figure 6: Minimum Distance to Transmission Lines Accepted by Region



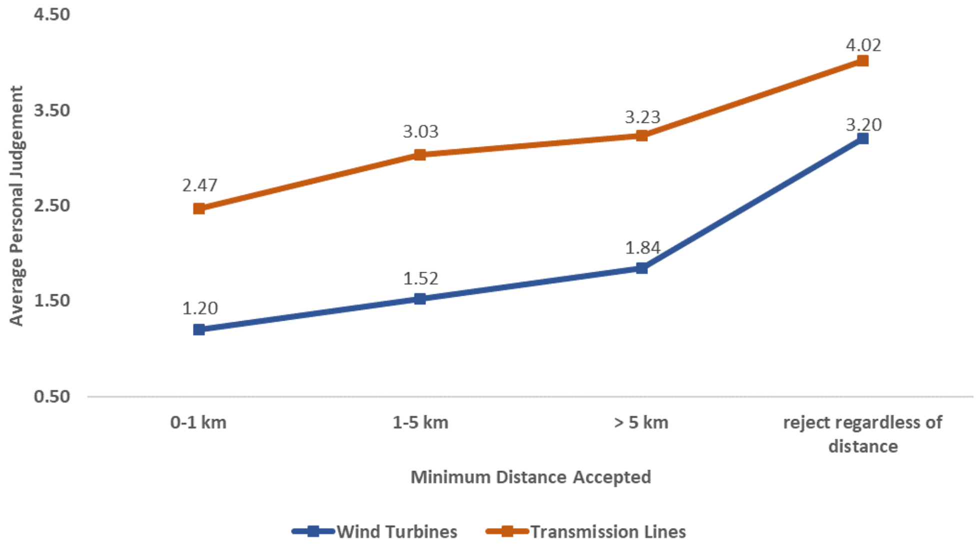
The survey results presented so far unveil a problem if we intend to incorporate public acceptance into the design of a cost-optimal electricity generation mix in the island of Ireland. That is, despite the high positive judgement on wind turbines, not so many people want them near their homes. Furthermore, wind turbines operate along with an above-ground transmission grid, which is mostly viewed negatively by households and rejected near their homes. This limitation can be seen graphically by correlating negative judgement and mininum distance accepted for these two technologies. In the personal judgement question, the answers provided by households were ranked from 1 (positive) to 5 (negative). Hence, the larger the figure is, the more skeptical a household is. Figure 7 plots the relation between negative judgement and minimum distance accepted for both wind turbines and transmission lines. It is evident that both technologies follow similar patterns, i.e. the more negative judgement, the larger the minimum distance; although transmission lines obtain a higher rejection level than wind turbines across all distances. For both technologies, the negative judgement sharply climbs for respondents who reject them regardless of the distance.

5.2. Power Systems: Expansion Planning Results

5.2.1. System and shadow costs

We first examine the system-wide costs in comparison to those of the "Full acceptance" case. Table 5 presents system costs in net present value (NPV) under the four scenarios, while Figure 8 shows the change in total system costs relative to the "Full acceptance" case. As expected, the "Full acceptance" case exhibits the lowest NPV among all cases. System-wide costs are 2.3% higher in the "High acceptance" scenario and 4.3% higher in the "Low acceptance" scenario relative to the "Full acceptance" scenario. The difference in cost is reflects different generation mixes and network upgrades. For example, in the "High acceptance" case new onshore wind capacity installations are 21% lower than in the "Full acceptance" scenario, which has lower off-shore wind installations. These different mixes are reflected in investment costs. Total additional investment, including wind and other technologies, is €89m higher in the "High acceptance" scenario relative to the "Full acceptance" scenario. In the "Low acceptance" scenario, it is €159m higher. In the scenario with the highest level of public opposition to energy infrastructure, investment costs are 15% higher over the planning horizon, compared to the case with no opposition. The increase in costs with decreasing public acceptance levels is mainly driven by the compounded effects of the decrease in onshore wind installations and network reinforcements, and the increase in more expensive power production technologies such as offshore wind and

Figure 7: Negative Judgement of Electricity Technologies vs. Minimum Distance Accepted



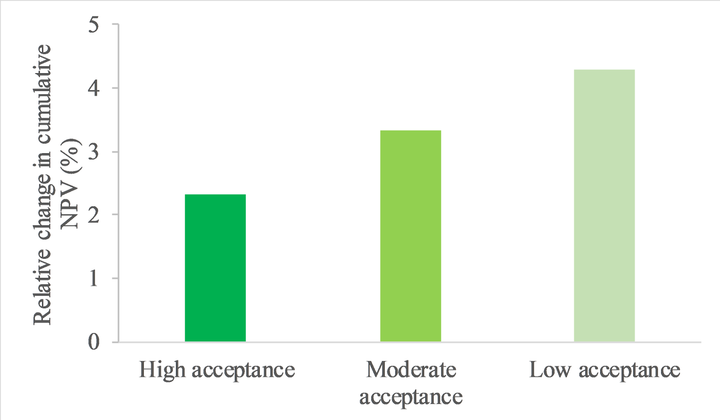
solar PV to compensate the shortfall. Emission costs are broadly similar across the four scenarios, which reflects a largely unchanged fossil power generation in the system, and renewable generation expanding to meet growing system load.

Table 5: Net present value of power system costs, m€

	Full Acceptance	High Acceptance	Moderate Acceptance	Low Acceptance
Total Investment Costs	1085	1174	1204	1243
Total Variable Costs	3036	3056	3073	3080
Total Emission Costs	606	607	606	606
Total System-wide Costs	4727	4836	4884	4930

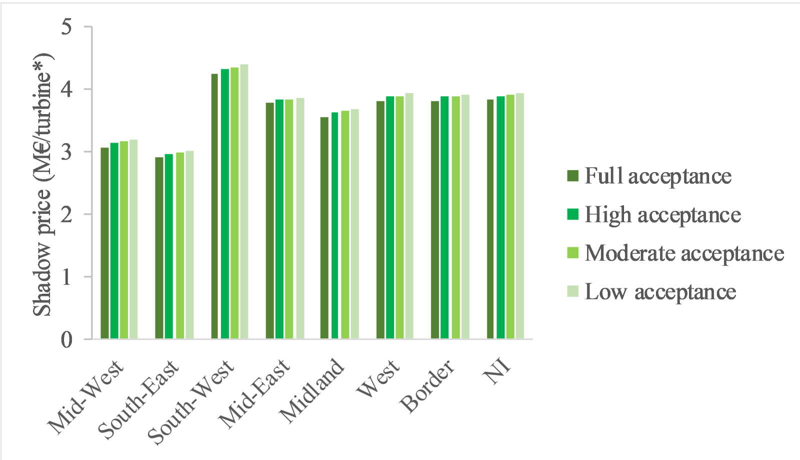
We also quantify the shadow price of marginally increasing onshore wind installations in each region, as depicted in Figure 9. The shadow price measures the change in objective function value as a result of marginally increasing onshore wind capacity (represented by an additional 3MW turbine). Hence, the shadow price in Figure 9 roughly estimates the value to the operation of the entire power system of building one more turbine in each region. We can see some heterogeneity across regions. For instance, shadow prices are the highest in the South-West region. The wind resource available in this region is relatively high compared to elsewhere on the island of Ireland, which partly explains the high shadow prices. The entire power system benefits from marginal wind generation capacity due to the high capacity factor of wind in this region. The Mid-East, West and Border regions as well as Northern Ireland also see relatively high shadow prices, while South-East record the lowest values. Among all regions, the Mid-East region has the lowest wind capacity factor and has relatively high shadow prices. The high shadow prices for this region are because of its proximity to major demand centres and network congestion, both of which increase the value of onshore wind installation in the same region. Average electricity prices by region are presented in Figure 10. Within each region there are multiple demand nodes, hence the multiple data plots for each of the acceptance scenarios by region. What is clear from this figure is the direct impact of public acceptance on wholesale electricity prices, with roughly €5/MWh difference between the maximum and minimum values. The difference in electricity price levels across regions reflects features of the power network, particularly congestion. For instance, under the full acceptance scenario, the Dublin region has the highest electricity prices, which is explained by the relatively high demand and

Figure 8: Changes in expected NPV relative to the "Full acceptance" case



high network congestion in this region relative to elsewhere. Both network congestion and demand drive electricity prices higher.

Figure 9: Shadow costs of public acceptance constrained onshore wind development for 3 MW wind turbine

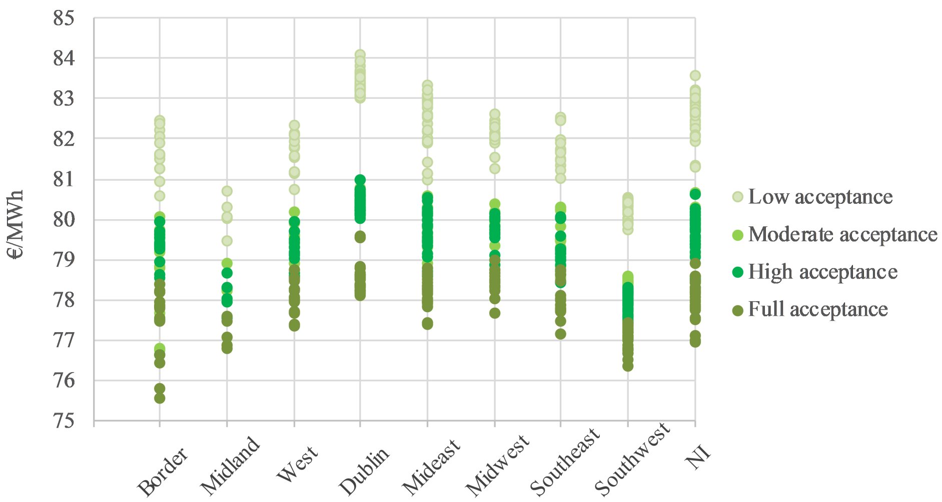


5.2.2. *Generation and network expansion outcomes*

Figure 11 shows the optimal mix of newly installed power generation and storage capacities for each case. Several results are of note here. First, the optimal generation expansion outcome consists of only a few power production technologies: combined cycle gas turbine (CCGT), solar PV, onshore and offshore wind. In particular, an assumed 20% cost reduction in the installation cost of carbon capture and storage (CCS) technology by 2030 is not sufficient to justify its investment at the assumed carbon price levels. The almost complete exclusion of conventional generation options, i.e. CCGT, from the expansion solution is a result of the high 70% RES-E targets.

The "Full acceptance" case sees slightly higher total installed capacity than any other case. Offshore wind has a higher capacity factor than onshore wind, and the slightly higher storage reduces curtailment, increasing the effective capacity factor in the generation system even further. The "Full acceptance" case has the lowest levels of both offshore wind and solar PV, with investment in both occurring in 2030 only. In the other cases, however, investments in these technologies happen well before the final year of the planning horizon. This is partly to compensate for the reductions in onshore wind installations as a result of the public acceptance constraint. The more stringent this constraint is,

Figure 10: Average locational marginal electricity prices by region



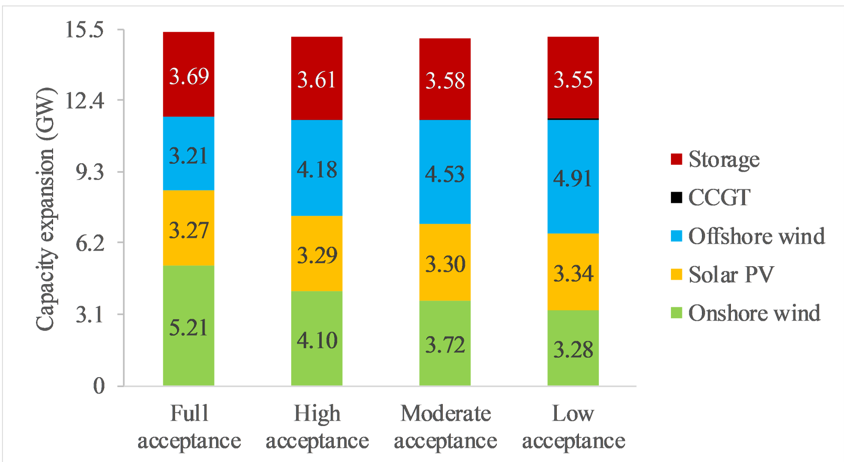


Figure 11: Optimal mix of new generation and storage investments under each case

the lower investment in onshore wind gets. The reduction in onshore wind capacity relative to the “Full Acceptance" scenario ranges from 21% in the “High acceptance” case to 37% in the “Low acceptance” case.

The spatial distribution of generation and storage investments are also of relevance. Figure 12 shows by location the difference in onshore wind investment by 2025 between the “High” and “Low acceptance” cases. When the public acceptance constraint is binding, more regions are affected in terms of onshore wind investment.

Figure 12: Optimal location and size (MW) of onshore wind installations by 2025: “Low” relative to “High acceptance”

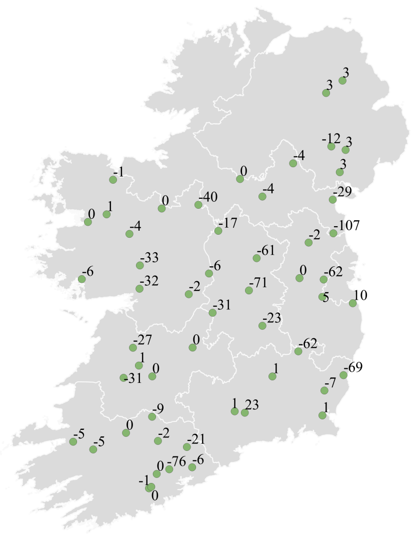
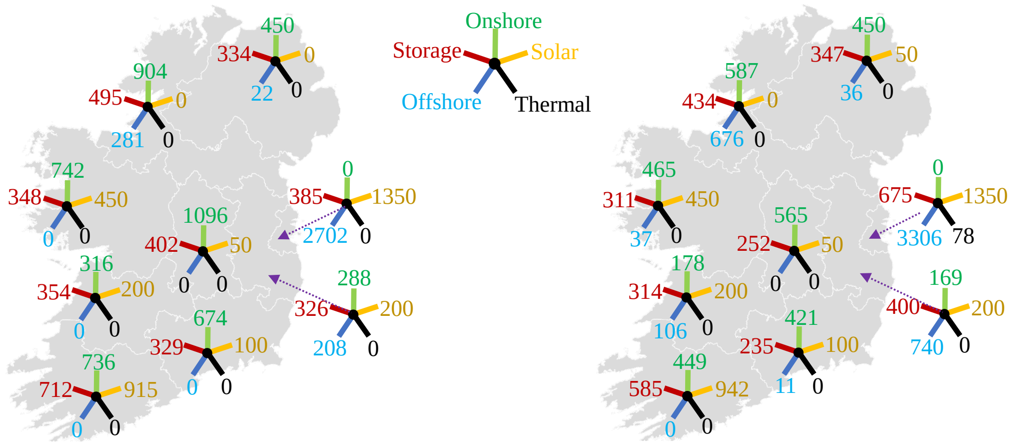


Figure 13 shows the total generation capacity investment over the entire horizon at the regional level, for the “Full” and “Low acceptance” cases. The major differences between these two cases mainly lie in storage, onshore and offshore wind installations. First, the “Full acceptance” case sees a more spatially distributed installation of storage than the “Low acceptance” one, even though the total storage investments are comparable for both cases. Under the “Low acceptance” case, more storage is built around Dublin, compared to the "Full acceptance" case. Moreover, the offshore wind installations are also mainly located close to Dublin.

The “Low acceptance” case leads to a slightly higher solar PV installation than the “Full acceptance” case, partly due to the reduction in onshore wind investment. The analysis does not explicitly model acceptance of PV so it is relative investment costs that are driving this result rather than a higher level of public acceptance of PV relative to other energy infrastructure. However, in practice there is substantial solar PV investment in the Dublin region, where demand and network congestion are the highest. Both of these effects likely drive the location of solar PV in this region. These results highlight the importance of spatial modelling as the regional effects of different policies may vary widely even if the system-wide figures are comparable under each policy.

Another striking observation in Figure 13 is related to the CCGT investment, which happens only under the “Low acceptance” case. This investment is located in Dublin (where most datacentres are located), making the phenomenon even more interesting. One plausible reason driving this investment is the reduction of involuntary load shedding, which would otherwise happen due to network congestion. The other scenarios do not see on-site CCGT investments, because the network congestion in the Dublin area is removed by reinforcing the grid. In those cases, reinforcing the grid turns out to be much cheaper than investing in an on-site power generation system such as CCGT. But under the “Low acceptance” case, re-enforcement of congested transmission lines is precluded due to public opposition, leaving on-site generation investment as the only option to minimise involuntary load curtailment. The model assumes that



(a) Full acceptance (b) Low acceptance

Figure 13: Optimal MW generation and storage capacity installations aggregated by region.

the new CCGTs are built at the transmission nodes, where datacentres are also connected.

We also compare the cases in terms of network expansion outcomes. The “Full acceptance” case leads to network reinforcements, with additional transmission transfer capacity of 3400 MW over the planning horizon. The other scenarios see a much reduced number of network upgrades, e.g. fewer new transmission lines. These reductions stand at 24%, 35% and 82% on a capacity basis under the "High", "Moderate" and "Low acceptance" cases relative to the "Full acceptance" scenario.

6. Conclusion and Policy Implications

There is an increased awareness of the necessity to expand renewable electricity generation technologies. However, there is also limited consideration of public knowledge and acceptance of technologies such as onshore wind power and transmission networks. This paper contributes to the literature by incorporating into a power system model information on people’s judgement of these technologies and their willingness to accept that infrastructure near their homes. In particular, we determine how people’s attitudes towards onshore wind power and transmission lines affect the cost-optimal development of future electricity generation mixes, under a high renewable energy policy. We use a realistic power system representing the entire island of Ireland as a case study. This system is expanded under a range of scenarios and public acceptance levels.

We highlight four key results here. First, survey results on public acceptance show that there is an overall positive judgement by respondents on wind turbines at 77%. However, fewer households are actually willing to accept the development of wind farms within 5 km of their homes at 36%. Acceptance levels are even lower for overhead transmission lines.

Second, low acceptance levels have a considerable effect on the design of a cost-optimal electricity generation mix: the higher public opposition is, the higher the overall cost of power system expansion planning becomes. This has been clearly observed when comparing the different scenarios considered, relative to a case of full public acceptance. For the case study, the optimal expansion results, obtained by taking account of public acceptance constraints, system-wide costs increase by 4.3% or €203m when the lowest public acceptance scenario is considered in the GTEP optimisation. These additional costs comprise higher investment and operational costs, roughly in a 3:1 ratio. Public opposition to wind farm and transmission infrastructure leads to substantial capital and operating cost increases in the power system, some of which will ultimately be absorbed by the public in terms of higher electricity prices.

Third, the incremental cost due to opposition to onshore wind power and transmission lines is primarily driven by the increased capital costs of offshore wind and solar PV infrastructure. Investments in these technologies increase with lower levels of public acceptance to onshore wind farms and overhead transmission lines. For the Irish system, numerical results show that considering those constraints leads up to a 37% decrease in the optimal onshore wind installations by 2030. The Midlands region experiences the largest reductions, followed by the West and the Border regions. That shortfall is compensated by further installations of offshore wind and solar PV generation technologies. The modelling did not consider investment in underground transmission lines.

Fourth, the effect of public opposition to onshore wind power and overhead transmission lines differs across regions on the island of Ireland. Indeed, the shadow costs of onshore wind development, i.e. the value of building one more turbine, tend to be highest in regions closest to big demand centres and/or with the greatest wind resource. These shadow prices are a guide to policy makers to design spatially differentiated financial incentives to garner support for onshore wind developments.

Appendix.

Table A.1: Wind Turbines - Regional Weights of Public Acceptance

Region	$W_{1,reg}$	$W_{2,reg}$	ω_{reg}
Border	0.797	0.407	0.809
Midland	0.655	0.276	0.700
West	0.786	0.369	0.792
Dublin	0.789	0.366	0.792
Mid-East	0.731	0.343	0.761
Mid-West	0.720	0.310	0.743
South-East	0.784	0.368	0.791
South-West	0.769	0.354	0.780

$k_l = 1.156$; $\alpha_l = \beta_l = 1$

Table A.2: Overhead Transmission Lines - Public Acceptance Weights (one-region lines)

Region	$W_{1,reg}$	$W_{2,reg}$	$W_{i,j}$
Border	0.186	0.271	0.424
Midland	0.345	0.224	0.501
West	0.340	0.330	0.564
Dublin	0.221	0.292	0.464
Mid-East	0.185	0.204	0.372
Mid-West	0.230	0.210	0.411
South-East	0.224	0.296	0.468
South-West	0.197	0.293	0.447

Table A.3: Overhead Transmission Lines - Public Acceptance Weights (two-region lines)

Region 1	Region 2	$W_{i,j}$
Border	Midland	0.463
Border	West	0.494
Border	Mid-East	0.398
Midland	West	0.533
Midland	Mid-East	0.437
Midland	Mid-West	0.456
West	Mid-West	0.488
Dublin	Mid-East	0.418
Mid-East	South-East	0.420
Mid-West	South-East	0.440
Mid-West	South-West	0.429
South-East	South-West	0.458

Table A.4: Overhead Transmission Lines - Public Acceptance Weights (three-region lines)

Region 1	Region 2	Region 3	$W_{i,j}$
Border	Midland	West	0.496
Border	Midland	Mid-East	0.432
Border	Midland	Mid-West	0.445
Border	Midland	South-East	0.465
Border	West	Mid-West	0.466
Border	Dublin	Mid-East	0.420
Border	Mid-East	South-East	0.422
Midland	West	Mid-East	0.479
Midland	West	Mid-West	0.492
Midland	West	South-East	0.511
Midland	Dublin	Mid-East	0.446
Midland	Mid-East	Mid-West	0.428
Midland	Mid-East	South-East	0.447
Midland	Mid-West	South-East	0.460
Midland	Mid-West	South-West	0.453
Midland	South-East	South-West	0.472
West	Mid-West	South-East	0.481
West	Mid-West	South-West	0.474
Dublin	Mid-East	South-East	0.435
Mid-East	Mid-West	South-East	0.417
Mid-East	South-East	South-West	0.429
Mid-West	South-East	South-West	0.442

Table A.5: Overhead Transmission Lines - Calculation of Threshold Weight

Region	$W_{i,j}$	N° Existing Lines
Border	0.424	48
Midland	0.501	8
West	0.564	47
Dublin	0.464	87
Mid-East	0.372	50
Mid-West	0.411	36
South-East	0.468	34
South-West	0.447	86
	Total Lines	396
	Threshold	0.452

Table A.6: Parameter assumptions of generator and storage technologies (SEAI, 2016; IRENA, 2017, 2019; IEA, 2015)

Technology	Operation cost* (€/MWh)	Emission rate (tCO2/MWh)	Investment cost (M€/MW)	Cumulative cost reductions (%) 2020	2025	2030
Offshore wind	22.80	0.02	3.65	0.05	0.10	0.20
Onshore wind	13.00	0.02	1.40	0.05	0.10	0.20
Solar PV	11.40	0.05	1.50	0.05	0.10	0.20
Biomass	54.00	0.23	2.25	0.02	0.05	0.10
Coal	34.00	0.93	0.90	0.05	0.08	0.10
Coal with CCS	38.00	0.19	4.40	0.05	0.08	0.10
CCGT	40.00	0.37	0.90	0.05	0.08	0.10
CCGT with CCS	55.00	0.04	2.40	0.05	0.08	0.10
Hydro	10.50	0.01	-	-	-	-
Gas oil fired	80.00	1.04	-	-	-	-
Heavy fuel oil fired	100.00	0.77	-	-	-	-
Storage	5.00	0.00	1.00	0.00	0.05	0.10

* *includes fuel costs but excludes emission costs.*

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