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Putting wind and solar in their place: Internalising congestion and other system-wide costs with enhanced contracts for difference in Great Britain

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Abstract

The large-scale deployment of renewable energy assets can create system-wide costs due to the impact on congestion management and reserve provision, and may have a limited effect on carbon emissions if subject to curtailment. We show how the successful UK incentive scheme for renewable energy, termed Contracts-for-Difference (CfD), can be further enhanced by introducing three new cost components to internalise these system-wide externalities. The proposed scheme can help: (i) incentivise more efficient investments by signalling where renewable assets can offer more value from a whole system perspective, (ii) promote fairer competition between renewable energy technologies with different levels of intermittency, and (iii) reduce actual carbon emissions by accounting for the effect of grid redispatch. The developed case studies show that one additional MWh of renewable generation in the northern regions of Great Britain (GB) increases congestion management cost by £5.61/MWh (14% of the CfD_{2019} price), and that the potential carbon emission abatement is reduced by 9% (23.52 kgCO2/MWh) due to grid redispatch. By contrast, deployment in southern regions can decrease congestion cost by £4.04/MWh, and can increase potential carbon abatement by 17% (44.33 kgCO2/MWh). Finally, one additional MWh of intermittent wind generation in GB can increase reserve provision cost by £6.58/MWh, while a perfectly predictable technology would decrease reserve cost by £2.44/MWh.

Keywords: carbon emission; network constraint; uncertainty; externality; incentive scheme; renewable energy;

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1. Introduction

More than 130 countries are already committed to reaching net zero emission in 2050 (Hale et al., 2021). This implies that significant investments in low-carbon technologies are required in coming years (Bistline & Blanford, 2021). The International Energy Agency (2021) estimates that the global share of electricity generation from renewable energy assets will increase from 29% in 2020 to 90% in 2050, with an annual deployment of wind and solar power capacity five-times greater than current levels. Delivering these investments in new capacity requires effective incentive mechanisms, which ensure the lowest cost for consumers, avoid market distortions, and maximise decarbonisation.

In this work, we focus on the Contract-for-Difference (CfD) scheme, which is the main mechanism for supporting low-carbon technologies in Great Britain since 2014 (BEIS, 2014), and has recently been introduced in both Poland (European Commission, 2021a) and Denmark (European Commission, 2021b). In particular, we address the problem of the additional costs this scheme may create at the system level, which can be divided into (i) costs for managing congestion due to the deployment of renewable energy assets in network-constrained regions, (ii) costs for reserve provision caused by the presence of intermittent generation, and (iii) the carbon emissions impact of grid redispatch in constrained networks (Heptonstall et al., 2017). A detailed review of these issues is reported in Section 3.2. The fundamental problem affecting the current CfD scheme is that these system-wide costs are not borne by those who cause them, but are socialized through a use of system charge and ultimately paid by consumers, leading to negative externalities.

The aim of this paper is to show how these system-wide costs could be internalised through an enhanced CfD (eCfD) scheme to address the problem of negative externalities. This will be achieved by introducing three additional cost components into the current CfD mechanism. Accounting for these system-wide costs can help: (i) increase efficiency, signalling where renewable assets would be most beneficial from a whole system perspective, while ascribing the additional system-wide costs to those who cause them; (ii) promote fairer competition among renewable energy technologies with different degrees of uncertainty, such as wind power with or without energy storage; and (iii) account for the actual carbon emissions reduction that will be achieved, which is the ultimate objective of CfDs as a renewable incentive policy. The main contributions of this work can be summarized as:

- Proposing a novel incentive scheme for low-carbon technologies, which enhances the current CfD to better account for system-wide costs;
- Demonstrating the potential value of the proposed scheme and the relevance of the externality problem through a detailed case study based on the electricity system of Great Britain (GB);
- Developing a high-fidelity and open-source transmission network of GB, and modelling approaches to show how these system-wide costs can be determined. The network and data are accessible at (Savelli & Morstyn, 2021a).

The remaining sections are structured as follows. Section 2 reviews the literature on incentive schemes and system-wide costs caused by the deployment of renewable assets. Section 3 describes the current CfD implemented in GB, highlights the problem of negative externalities, and introduces the proposed scheme. Section 4 describes the methodology used to compute congestion management costs, carbon emissions, and the costs for reserve provision. Section 5 reports the results obtained, showing (i) the additional congestion management costs for deploying renewable energy assets in different regions of GB, (ii) the carbon emission changes due to grid rebalance, and (iii) the additional costs for reserve provision due to the usage of different renewable energy technologies. Finally, Section 6 concludes and outlines some policy implications.

2. Literature review

Internalising system-wide costs into incentive schemes for renewable energy technologies is a relatively new area of academic investigation. Bjørnebye et al. (2018) analysed the Norwegian electricity system, showing that grid reinforcement costs to accommodate renewable energy assets can be up to 55% higher when the decision to locate these assets is based on an incentive scheme paying a uniform tariff compared with geographically differentiated tariffs, which highlights the importance of providing proper locational signals through incentive schemes. Pechan (2017) analyses the effect of different subsidy schemes and market designs on the spatial distribution of wind energy investments. Both feed-in tariffs and feed-in premium schemes, as well as uniform and nodal pricing designs are compared. The results show that uniform pricing (such as the one adopted in GB) leads to greater wind power concentration at sites with the most favourable weather conditions compared to nodal pricing, which instead fosters a wider spatial distribution. Eicke et al. (2020) review the instruments that twelve major power systems use to provide economic signals to affect the location of generation investment. These instruments are clustered in five groups defined as connection charges, usage charges, market pricing schemes, capacity mechanisms and subsidies for renewable energy technologies. They discuss the properties of these instruments and their strength. Oggioni et al. (2014) compare a real-time nodal market design and a zonal day-ahead market architecture with subsequent rebalancing operations, under different priority dispatch policies for wind power. Priority dispatch means that the system operator has to accommodate all wind generation at the expense of conventional power plant production. Their results show that without a priority dispatch rule both nodal and zonal markets perform reasonably well. By contrast, if a priority dispatch rule is enforced, the nodal design significantly outperforms the zonal one as the wind penetration increases. Höfer and Madlener (2021) developed an econometric model based on a spatial regression analysis to investigate congestion costs in Germany. They estimate that one additional MWh of wind generation increases renewable energy curtailment costs by up to 8.10 €/MWh in the most congested areas located in the northern regions. These additional costs are socialised and paid by German consumers. They suggest that these costs should be fully internalised to enable a welfare-enhancing deployment of renewable energy assets, and propose the introduction of a regional pricing system accounting for network congestion. In the UK, Newbery (2021) proposed a new capacity-based[2] CfD scheme with a specific term to provide locational signals, given by the difference between an average capacity factor at the national scale and a reference factor for the region where the renewable asset is built. This is to incentivise the deployment of renewable generation in areas where it has low correlation with existing renewable energy output. However, this model does not account for demand patterns, and neither reserve costs nor the effect of grid redispatch on emissions are considered. Recently, the Department for Business, Energy & Industrial Strategy (BEIS, 2020) estimated an average system wide cost for Great Britain by computing the average discounted cost impact that power plants commissioned in 2025 could have on wholesale, capacity and balancing markets up to 2050. The results show that these additional system costs can range between £1/MWh and £10/MWh for offshore wind generation, and between £6/MWh and £13/MWh for large-scale solar generation.

Carbon emissions can be significantly affected by network constraints, as the system operator may be forced to curtail low-carbon generation to manage congestion. To analyse this problem, Hitaj (2015) used a 30-node test network to simulate the potential effect that siting renewable energy assets in different locations would have on carbon emissions, showing that actual carbon emissions can change by up to a factor of 7 due to congestion for this test network. Amor et al. (2014), using data obtained from the electricity system operator in Ontario (Canada), showed that the carbon emission reduction due to one additional MWh of wind generation can be up to 393.68 kg/MWh if the network is not congested, but it reduces to 283.49

[2] See Appendix A (in the Supplementary Material) for a description of the most common price-based, quantity-based, investment-based, and capacity- based schemes.

kg/MWh when the network is congested, i.e. a detrimental effect of 28%. More recently, Fell et al. (2021) analysed both the Texas electricity system and the one encompassing the central regions of the United States, which is operated by the Midcontinent Independent System Operator (MISO). They designed a location-based index of environmental damage accounting for greenhouse gas emissions and other pollutants. Their results showed that wind generation is 30% more environmentally valuable in Texas when the network is not congested, and 17% more valuable in the MISO area without congestion.

Intermittent generation, such as solar and wind power, can impose additional costs for reserve provision, and inaccurate weather forecasts (instead of the largest power plant outage) may become the greatest contingency in the near future (O'Neill, 2020). Indeed, despite recent advances in forecasting methods, large forecast errors, for example relating to wind power, are becoming more common (Holttinen et al., 2019), and are critical for grid stability. Brouwer et al. (2014) reviewed 19 studies focusing on both European countries (e.g. Germany, the Netherland, Ireland) and the USA (e.g. Texas, Minnesota, Arizona). They report that with a wind power penetration rate of around 20%, the average increase in reserve requirements is around 8.6% of the installed wind capacity, with additional costs of up to €6/MWh per MWh of wind generation. Bunn and Muñoz (2016) remark on the importance of internalising these additional costs for reserve provision into renewable energy incentive schemes and argue that investment-based incentives that account for these externalities could be more effective than other mechanisms such as green certificates.

Finally, it is important to note that some metrics, such as the levelized cost of energy (LCOE), may be inappropriate for comparing intermittent resources (such as wind and solar) and dispatchable ones. In particular, Joskow (2011) shows that the LCOE can overvalue intermittent generation, and it also likely overvalues wind power compared to solar. He suggests that additional factors should be considered, such as differences in generation profiles and the associated variations in market prices. Indeed, the presence of renewable technologies can significantly affect market prices, which in turn can impact the market value of renewable investments. On this point, Hirth (2013) discusses the market value of wind and solar investments as their penetration increases. These renewable technologies have near-to-zero marginal costs and can receive subsidies for their metered output (e.g., through a CfD). Therefore, they can bid zero or even negative prices in wholesale markets, reducing the clearing price due to the merit-order effect. This is known as price cannibalisation, and the price drop increases as more renewable capacity is installed. As the market prices decline, the market value of generation investments decreases as well. The paper shows that the value of wind power falls from 110% of the average power price to 50-80% as wind penetration reaches 30%. For solar, these levels are reached with a 15% penetration. Price cannibalisation of solar power is also reported in Simshauser (2018), which analyses the effect of progressively adding intermittent renewable generation in an energy-only market where price caps are substituted with capacity charges.

A review of the most widely adopted incentive schemes for renewable energy assets, including green certificates, feed-in tariff, feed-in premium, and both investment and capacity-based mechanisms is reported in Appendix A (in the Supplementary Material). For ease of reading, the CfD scheme currently implemented in GB and the problem of negative externalities that motivates this work are described in detail in Section 3.1 and Section 3.2, respectively.

3. Motivation for a new incentive scheme

3.1. How the current CfD works

The current CfD scheme implemented in GB is a feed-in scheme with a sliding premium, structured as a two-sided obligation[3]. It was introduced through the Electricity Market Reform issued in 2013 (UK Parliament, 2013). Legally, the CfD is a private-law contract between a generator and the Low Carbon Contracts Company (LCCC), which is an independent government-owned company. The CfD's payoff Φ_t (in £) at time t is defined as:

$$\Phi_\mathrm{t} = M_t(s - p_t),$$

where M_t is the generator metered output (MWh), s is the fixed strike price (£/MWh) received by the investor, and p_t is a reference market price (£/MWh). If the reference price p_t is greater than the strike price s, the amount $M_t(s - p_t)$ is negative, and the generator must pay the LCCC. If the amount is positive, the LCCC pays the generator. The LCCC recovers payment costs through a levy paid by all licensed electricity suppliers in GB, who ultimately pass these costs on their customers through bills (LCCC, 2021a).

For intermittent technologies (e.g. solar and wind), the reference price p_t coincides with the day-ahead hourly market price[4] (LCCC, 2019a). This means that for these assets, which sell their energy M_t in the market and collect the market price, this scheme yields the same incentive as a feed-in tariff with a fixed tariff equal to the strike price s[5]. This provides price certainty to renewable energy investors for the length of the contract (usually 15 years in GB[6]), which helps lower financing costs, facilitating the project's funding and bankability (Grubb & Newbery, 2018). These contracts are allocated through competitive auction rounds[7] that are held every two years, in which investors bid their requested strike price and project power capacity, then the lowest strike prices are accepted until either a target capacity or a maximum budget is reached (LCCC, 2019b). The last accepted bid determines the auction clearing price (i.e. pay-as-clear approach), which becomes the actual strike price paid by the CfD contracts (Welisch & Poudineh, 2020).

3.2. The problem of additional system-wide costs

The CfD is a successful scheme, which significantly supported the deployment of renewable energy technologies in GB, with almost 6 GW of capacity allocated in 2019 (BEIS, 2019). However, this incentive mechanism may increase system-wide costs (Heptonstall et al., 2017), which are then socialized, leading to a

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[3] See Appendix A (in the Supplementary Material) for details on the general structure of feed-in premium incentives.

[4] For baseload technologies (e.g. biomass with combined heat and power) the reference price is computed on a seasonal basis (winter and summer) as a volume weighted average price based on the data received from the London Energy Brokers' Association (LCCC, 2021b).

[5] Mathematically, the final payoff including both the CfD and market revenues is $M_t(s - p_t) + M_t p_t = M_t s$, assuming that the metered power is equal to the quantity sold in the day-ahead market.

[6] In Denmark, the maximum duration is 20 years (European Commission, 2021b), and 25 years in Poland, but with a limit of 100GWh per each MW of installed capacity (European Commission, 2021a).

[7] Each auction round (AR) is further divided in "pots", where technologies with similar maturity can compete with each other. For example, in the fourth AR the first pot included established technologies (such as onshore wind and solar), the second pot less established technologies (such as floating offshore wind, tidal stream, and wave), and the third pot only offshore wind. Each pot usually has its maximum budget and an administrative strike price cap.

negative externality problem. In this work, we focus on three[8] of these system-wide costs, described as follows.

1. **Cost of congestion management**. In a CfD, assets deployed in different areas receive the same fixed strike price. Therefore, renewable energy investors are incentivised to locate their power plants in regions with lower project costs (e.g. land costs), and more favourable weather conditions (to maximize their power output), without reference to the location of demand or system costs[9] (Newbery, 2021). For example, wind power investors prefer regions with high wind speed, such as Scotland, which is far from the largest sources of demand in the southern areas of GB. A CfD does not provide any locational signal to address this problem, and this effect leads to significant system-wide costs due to transmission constraints. To resolve network congestion, the system operator uses balancing services to start plants in importing zones, while reducing power in exporting ones. The cost of these activities is termed constraint management cost and amounted to around £0.5 billion in 2020. Constraint management costs are projected to increase, reaching between £1 and £2.5 billion/year before 2030 (National Grid, 2020b). These costs are recovered through the Balancing Services Use of System (BSUoS) charge[10], which is a flat tariff levied on both generators and suppliers by the GB electricity system operator (Joos & Staffell, 2018b), currently National Grid ESO (National Grid, 2022a).
2. **Cost of uncertainty**. The deployment of weather-dependent renewable technologies forces the system operator to reserve additional capacity to deal with uncertainty (Dowell et al., 2016). This translates into additional system-wide costs, which are also recovered through the BSUoS in GB (Competition and Markets Authority, 2018). The CfD scheme does not consider the level of uncertainty of power delivered by renewable technologies. For example, wind power plants with or without energy storage devices currently receive the same strike price. However, the presence of a storage device can significantly reduce uncertainty, which can decrease the reserve required, translating into lower system-wide costs. Ignoring this effect reduces the incentives to invest in more predictable renewable projects, e.g. coupling wind power plants with batteries, selecting less variable technologies like tidal stream power, developing better forecast methods, or building in a wider area to average out power fluctuations (Lewis et al., 2019). Neglecting the cost of uncertainty has the potential to hinder competition among renewable technologies, as the benefit of lower reserve costs is not realised by generators, and increased reserve costs are socialized through the BSUoS charge.
3. **Emission due to redispatch**. The ability of renewable energy technologies to abate carbon emissions can be severely compromised if these are located in congested areas. Technologies such as wind and solar power have near-to-zero marginal costs, which can push more expensive marginal assets out of the market, particularly in a single-zone market such as GB. Marginal units are predominantly carbon-emitting dispatchable power plants (Lane Clark & Peacock, 2014). Ideally, each MWh provided by a renewable asset would reduce carbon emissions by an amount equal to the emission of the displaced marginal units. However, when renewable energy assets are deployed in a region where export is limited by congestion, the transmission system operator can curtail low-carbon generation to manage the constraint, while dispatching other assets to rebalance the grid, as described in point 1. If the dispatched assets are fossil-fuel power plants, then the final effect is that the actual carbon emission abatement can be significantly

[8] Additional system-wide costs can be due to e.g. system adequacy, i.e. the ability of the system to supply peak demand. This because renewable energy technologies do not necessarily provide the same level of equivalent firm capacity as dispatchable assets (Madaeni et al., 2013). This effect is not considered in this work.

[9] This is a common problem affecting generation-based schemes (Meus et al., 2021), where payments depend on the actual power output. On this point, see Appendix A (in the Supplementary Material) and Newbery (2021).

[10] Note that congestion management costs are not included in the Transmission Network Use of System (TNUoS) charges, which are separate charges used to recover the allowed revenue for transmission owners for the activity of building and maintaining the transmission infrastructure.

smaller compared to the case in which the deployment of the renewable asset does not cause a grid redispatch.

3.3. The proposed scheme

Incentive schemes should account for externalities and stimulate renewable energy investment at the least system cost. This implies that the right technology should be deployed in the correct place from a whole system perspective. Therefore, to internalise the system-wide costs described in the previous section, we propose an enhanced CfD (eCfD), obtained by adding three components to the current CfD payoff Φ_t, as follows:

$$\Phi_t = M_t\left(s - p_t - \alpha_z - \beta_m - \gamma_z\right)$$

where (i) the term α_z (£/MWh) represents the additional system-wide cost for managing transmission network congestion due to the deployment of a renewable energy asset in the location z; (ii) the term β_m is the additional system-wide cost in £/MWh for reserve provision due to the usage of the technology type m; and (iii) the term γ_z is the carbon emission cost (in £/MWh = tCO2/MWh x £/tCO2) due to grid rebalancing after deployment in location z. Note that in GB, carbon-emitting power plants that are started up in the BM already pay a carbon price, which is determined through the UK Emission Trading System (ETS). The term γ_z allows regulators to introduce an uplift if they believe that the carbon price is not representative of the true carbon cost, which can also be useful in countries that do not have a carbon market. The values of these parameters are estimated in Section 5, and should be fixed by the auctioneer before each CfD auction to provide the right economic signal. Moreover, these parameters could be indexed to new estimates, so that at each new auction existing contracts can be automatically adjusted, and a cap on each readjustment could be introduced by the regulator to limit the risk for investors.

4. Modelling system-wide costs in Great Britain

To demonstrate the value of the proposed scheme and the magnitude of the system-wide costs described in Section 3.2, we develop a detailed case study based on the electricity system of Great Britain. The following sections describe how both congestion management and reserve requirement costs due to the deployment of renewable energy assets in GB can be estimated.

4.1. BM rebalancing costs

Generators and consumers producing or consuming at least 50MW in England and Wales, 30MW in South Scotland, or 10MW in North Scotland must submit their expected generation and demand for each half-hour settlement period to the Electricity System Operator[11] (ESO), with a time resolution of one minute[12] (Elexon, 2020a). Smaller units are not obliged to communicate this data, however small generators usually provide these values as well, as this allows them to participate in the balancing mechanism (BM). At gate closure, i.e. one hour before the beginning of a settlement period, these values become the final physical notification

[11] In Great Britain, this role is currently performed by National Grid ESO.

[12] In this work, we will use the value of the final physical notification at the beginning of each half-hour settlement period $t \in T$ as the reference value for that period.

(FPN). The FPNs, as well as the expected demand and generation imbalances are used by the ESO to compute power injections at each node. If these injections satisfy all network constraints and the scheduled generation matches the expected demand, then no actions are required to rebalance the grid, and both congestion and energy imbalance cost in that settlement period are zero. However, if any transmission line constraint is violated or an energy imbalance is detected, then the power injections have to be adjusted to ensure the simultaneous fulfilment of all transmission network constraints, while considering expected power imbalances at each node and network losses. This is performed by the ESO through the BM[13] by accepting offer orders to increase power injections, and bid orders to decrease power injections (Elexon, 2020a).

In detail, each unit $\mathrm{k} \in \mathcal{K}_t$ can submit up to five bid orders and five offer orders[14], for each settlement period $t \in T$. An offer order h with offer price $c_{t,k,h}^{up}$ = 50 £/MWh and offer quantity $p_{t,k,h}^{up}$ = 100 MW implies that at time t the balancing unit k can increase the power injection by 100 MW, raising its power output (generators) or decreasing its consumption (energy suppliers or directly connected large consumers), while *receiving* 50 £/MWh from the system operator. By contrast, a bid offer with bid price $c_{t,k,h}^{down}$ = 50 £/MWh and bid quantity $p_{t,k,h}^{down}$ = 100 MW means that the unit can help reduce the power injection by 100 MW, decreasing its power output or increasing its consumption, while *paying* 50 £/MWh to the system operator. This payment by the generator to the system operator would normally be related to the fuel cost savings. In the case of large shut-down/start-up costs the bid price can be negative, implying that the unit wants to be paid for reducing its power output. Wind and solar power plants have near-to-zero marginal costs, but receive a subsidy (either as renewables obligation certificates or a strike price in a CfD) which is paid for each MWh produced. Therefore, they want to be compensated for curtailing their power, and ask a (negative) bid price equal to the value of the lost subsidy[15]. The ESO clears the market finding the lowest cost set of bids and offers which addresses the network constraints and energy imbalance. The optimization problem used to estimate the BM rebalancing costs is detailed in Appendix B (in the Supplementary Material). Note that at the imbalance settlement phase, generators that have produced less than expected (or suppliers that have consumed more) have to pay the System Buy Price, as if they were buying electricity from the system, and generators that have produced more than expected (or suppliers that have consumed less) receive the System Sell Price, as if they were selling electricity to the system (Elexon, 2019). Since November 2015, these two prices have both been set at the same imbalance price (also termed "cash-out" price), and therefore these monetary flows aim to cancel each other[16]. The fundamental point is that the imbalance settlement is a mechanism to incentivise units to be in balance by penalising them with an unattractive price, but balancing costs are not recovered and instead are socialised through the BSUoS charge (Joos & Staffell, 2018a).

[13] Non-BM actions are allowed if economically advantageous, however the volume of these transactions is usually small.

[14] All *bid* orders also include an "offer" price, which is the cost sustained by the system operator to undo the trade once accepted. Similarly, *offer* orders also include a "bid" price that the system operator will be paid to undo the acceptance. Undo trades are often used by the system operator to return the unit's output to the final physical notification scheduled at the end of the settlement period, to avoid inducing imbalances in the next settlement period (Elexon, 2019). This means that all BM orders actually include two prices, i.e. a bid-offer price pair. For each unit k, an *offer order* to increase power injection is uniquely identified through a *positive* bid-offer pair number h, ranging from 1 to 5, i.e. $\mathrm{h} \in \mathcal{H}_{t,k}^{up} = \{1, \dots, 5\}$, whereas a *bid order* to decrease power injection is identified through a *negative* bid-offer pair number h, ranging from -1 to -5, i.e. $\mathrm{h} \in \mathcal{H}_{t,k}^{down} = \{-1, \dots, -5\}$. In this work, undo trades are not considered.

[15] Note that only generators participating in the balancing mechanism are compensated for curtailment, which are usually large power plants connected to transmission network, while distributed renewable resources connected to distribution networks do not receive compensation for curtailment. However, they pay lower network access charges for their non-firm connection (Joos & Staffell, 2018).

[16] Note that a generator that is correlated with the overall imbalance will be more likely to trade at an unattractive price than an attractive one, creating an incentive to be less correlated, which may contribute to reducing the amount of reserve that must be procured.

4.2. Reserve requirements

Unexpected changes in generation and demand force the ESO to maintain operating reserves[17]. Reserves are used to deal with the differences between the expected power output of each unit $p_{t,k}^{exp}$ and their actual metered output $p_{t,k}^{act}$ (National Grid, 2016). In the following, we focus on both positive and negative reserves. Positive reserve (also termed upward reserve) is used to provide additional power in time periods when generation is smaller than demand. In contrast, negative (downward) reserve is used to decrease power injections when power generation is greater than the demand. Formally, demand forecast errors and unexpected generation changes for each unit k and time t can be represented as the amount $\varepsilon_{t,k}$ defined as:

$$\varepsilon_{t,k} = p_{t,k}^{act} - p_{t,k}^{exp}$$

For ease of exposition, demand is treated as negative injection (i.e. $p_{t,k}^{act} < 0$ and $p_{t,k}^{exp} < 0$ if k is a consumer). Positive values of $\varepsilon_{t,k}$ mean that the unit is producing more (or consuming less) than expected, and negative values imply that the unit is producing less (or consuming more) than expected. This means that positive values of $\varepsilon_{t,k}$ must be offset with negative (downward) reserve, and negative values of $\varepsilon_{t,k}$ with positive (upward) reserve. ESOs usually maintain an amount of both positive and negative reserves capable to offset these aggregate power errors within a given confidence level (Dowell et al., 2016), which is equal to 99.7% in the case of the UK (National Grid, 2016).

For each half-hour time period t, the aggregate distribution of the sum of the errors, labelled as $\phi_{\mathrm{t}}^{\Sigma}$, can been computed by convolving each distribution $\phi_{t,k}$ of the errors $\varepsilon_{\mathrm{t,k}}$ (i.e. $\varepsilon_{t,k} \sim \phi_{t,k}$) for the units $\mathrm{k} \in \mathcal{K}_t = \{1, \dots, \mathrm{m}\}$ operating in time t, as follows:

$$\phi_{\mathrm{t}}^{\Sigma} = \phi_{t,1} * \dots * \phi_{t,m}$$

where the symbol "$*$" represents the convolution operator. Then, the distributions $\phi_{\mathrm{t}}^{\Sigma}$ can be used to estimate the reserve requirement at time t with a given confidence level. An example of the distribution $\phi_{\mathrm{t}}^{\Sigma}$ for the settlement period ranging from 9:30 am to 10:00 am is depicted in Figure 1.

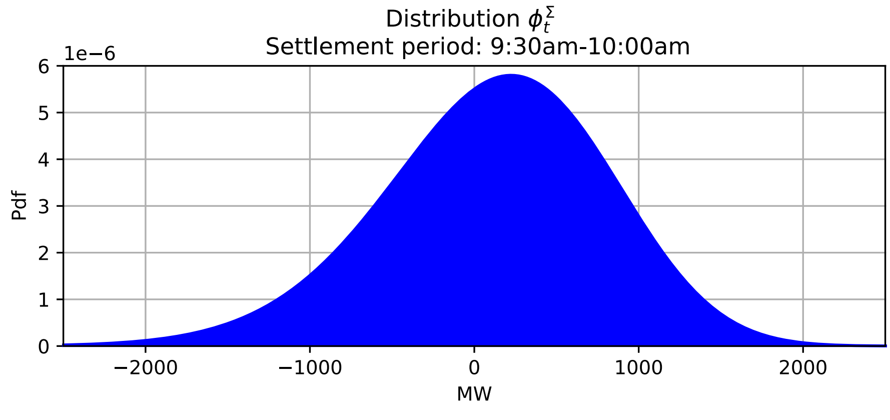

Figure 1: The figure shows an example of distribution ϕ_t^{Σ} for the settlement period $t = 20$, ranging from 9:30am to 10:00am, obtained by convolving the probability density functions (PDFs) $\phi_{t,k}$ of the errors of the 740 units k operating at time t. For each unit k and time period t, the PDF $\phi_{t,k}$ has been determined by using the errors $\varepsilon_{t,k}$ for each day in the months of August 2020 and January 2021. The data was collected from the Elexon's SAA-I014 settlement data files (Elexon, 2021c).

[17] Reserve requirements for intermittent generation, such as wind power, are explicitly accounted into operating reserve (National Grid, 2016). Therefore, other ancillary services are not considered in this work (Morstyn et al., 2021; Savelli et al., 2020; Savelli & Morstyn, 2021b, 2021c).

5. Results and discussion

This section reports the results obtained by applying the methods described in Section 4. In particular, we estimate (i) the additional congestion management costs due to the deployment of renewable energy assets in different regions of GB, (ii) the effect on carbon emission due to grid redispatch, and (iii) the additional reserve requirement due to the deployment of intermittent power generation.

5.1. Data description

The data used in this section refers to both August 2020 and January 2021, i.e. a total of 2,976 half-hour settlement periods have been used. Bid and offer orders h have been collected from the data provider EnAppSys (EnAppSys Ltd., 2021). The FPNs $p_{t,k}^{fpn}$ and energy imbalances $p_{t,k}^{imb}$ have been gathered from the Elexon's SAA-I014 raw settlement files (Elexon, 2021c), where the values of $p_{t,k}^{imb}$ are defined as the difference between the metered and the scheduled power output. The electrical transmission network for Great Britain has been adapted from the National Grid Electricity Ten-Year Statement (ETSY) (National Grid, 2020a). Figure 2 outlines the resulting grid, which comprises 1882 nodes ranging from 400 kV to 33 kV, 2744 electric elements including alternating-current lines and transformers, as well as two high-voltage direct-current lines, and 38 extra lines manually added (e.g. to connect offshore wind farms to the nearest substation). This GB network with a description of how the ETSY data has been adapted[18], and the values of parameters $b_{k,n}$ are freely accessible at (Savelli & Morstyn, 2021a). The model (reported in Appendix B in the Supplementary Material) has been implemented in Python 3.8 using Pyomo (Bynum et al., 2021), and solved with CPLEX 12.9 (Nickel et al., 2021) on a 4-core CPU with 16 GB of RAM, with an average computation time for each day (which comprises 48 half-hour settlement periods) of 8 minutes. Each half-hour settlement period includes 847 bid-offer orders, on average. The proposed approach has been validated by comparing the BM costs estimated by our model in the time periods considered (i.e. August 2020 and January 2021). For our model, the BM costs amounted to £50M, while the BM costs reported by National Grid were £54M (National Grid, 2022b).

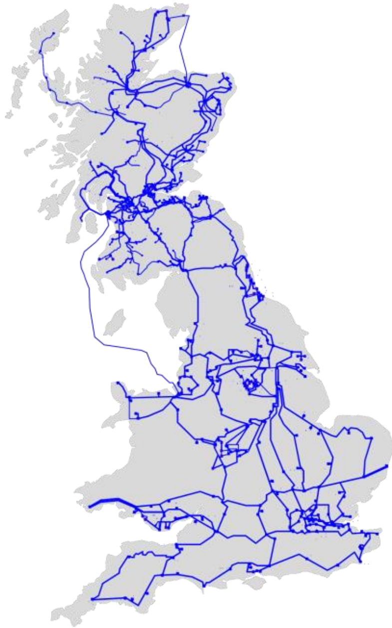

Figure 2 The developed GB network, adapted from National Grid (2020a).

Marginal generators have been identified by selecting the units with the highest offer price that have been actually accepted in the BM by the ESO. The list of these orders has been collected from Elexon's Indicative System Price Stack (ISPSTACK) files (Elexon, 2021b), after removing undo trades (i.e. offer orders with negative bid-offer pair number) and considering only entries referring to BM units. Table 1 shows the technology type and the percentage of time intervals that power plants have been identified as marginal

[18] For example, power control devices such as Thyristor Series Capacitor and pairs of series resistor/capacitor have been considered as elements of the set $\mathcal{L}^{\mathcal{DC}}$ to prevent infeasibility due the negative reactance $x_{i,j}$ of the capacitor (Ding et al., 2019; Gruenbaum et al., 2012). Moreover, five links have been added to prevent infeasibilities due to the demand from embedded units whose connection points were not provided in the data reported from Elexon in (Elexon, 2020b).

units in the months of August 2020 and January 2021. Energy storage systems in GB are assumed to be zero marginal carbon emission technologies. However, this assumption is worth further research.

Marginal Units	
Technology type	**Occurrence**
Combined Cycle Gas Turbines	52.49%
Pumped-Storage Hydro	30.28%
ESS/DSR/Embedded Renewable	5.17%
Coal	3.69%
Biomass	2.77%
Hydro	2.50%
Open Cycle Gas Turbines	1.57%
Other	1.36%
Wind	0.17%

Table 1: Type of technology and percentage of times that power plants have been identified as marginal units in the months of August 2020 and January 2021. In the computation of the percentages, when a settlement period has two or more marginal units, their weights have been equally shared. The label "ESS/DSR/Embedded Renewable" refers to energy storage system, demand side response and small renewable energy assets embedded into distribution networks.

5.2. Additional BM costs caused by the deployment of renewable technologies in different locations

This section shows how the location where renewable energy technologies are deployed can affect BM costs at the system level. The introduction of assets with near-to-zero marginal cost can put more expensive marginal generators out of the market. As a consequence, a different rebalancing in the BM may be required, leading to an increase or decrease of the system costs. For example, suppose that the marginal generator is a power plant located close to a demand centre. Due to merit order, this unit can be put out of the market by renewable energy technologies (e.g. wind and solar) with near-to-zero marginal cost which may be located in distant and congested areas[19]. Therefore, the latter may not provide the same amount of power due to network constraints. As a result, the ESO may be forced to accept offer orders $h \in \mathcal{H}_{t,k}^{up}$ to provide missing power, with an increase of the overall BM costs.

[19] We recall that the GB electricity market is a self-dispatch *single* zone market that ignores the physical location of participants up to gate closure, i.e. one hour before real time. At gate closure, the ESO takes BM actions to manage constraints and to offset energy imbalances between generation and demand.

To highlight this problem, first we have computed the BM costs (for managing both thermal constraints on transmission lines and energy imbalances) by simulating the rebalancing actions performed by the ESO at gate closure, using the method reported in Section 4.1 and the data described in Section 5.1. This represents our *reference* case[20]. Then, we have removed 1 MW from the marginal units, and added a renewable energy asset providing 1 MW in a DNO area[21] (e.g. North Scotland). We have repeated this for each one of the 14 DNO areas that divide GB, obtaining 14 different *test* cases. The difference of the BM costs between each test case and the reference case gives an estimate of how the location where a renewable energy asset is deployed can affect BM costs at the system level.

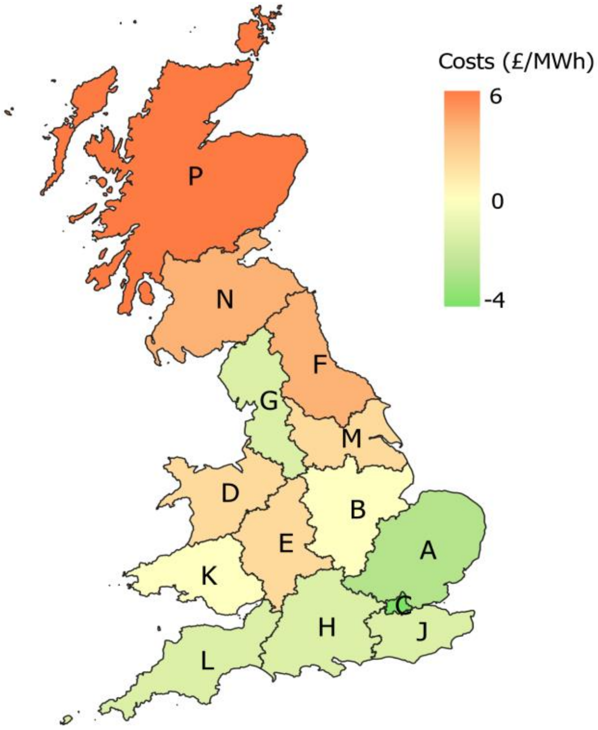

Figure 3: The map visually shows the change of BM costs reported in Table 2. We can observe an increase of BM costs as a result of deploying renewable energy assets in the northern regions, particularly North Scotland. The opposite effect is obtained if these assets are built in the southern regions, where the greater benefit is achieved if the units are located in the London area.

Table 2 shows the DNO labels, the corresponding region name, and the average change of the BM costs. Figure 3 visually shows these values through a heat map and depicts the 14 DNO areas. These results show that the deployment of a renewable energy asset in the northern regions of GB lead to an increase in BM costs at the system level, where the greatest increase is measured when the renewable energy technology is deployed in North Scotland (labelled as “P” in Figure 3), which increases the overall costs in the BM by £5.61/MWh (see the last row in Table 2). In contrast, BM costs decrease if renewable energy units are deployed in the southern regions, particularly in the London area (labelled as “C”), where the decrease is equal to £4.04/MWh. Note that adding renewable generation in the north-west zone of England helps relieve the Anglo-Scottish boundary, which contributes to decreasing the overall congestion management costs.

DNO Area	Region	Average cost change (£/MWh)	Avg. cost as % of the AR3 CfD's strike price
A	Eastern	-2.23	-5.62%
B	East Midlands	-0.49	-1.23%
C	London	-4.04	-10.19%

[20] For the two months considered (August 2020 and January 2021), the absolute difference between the actual metered national demand and the one resulting by simulating the rebalancing activities of the ESO with the proposed model in the reference case is equal to 0.39%, on average.

[21] For each DNO area, the additional power has been split among its grid supply points proportionally to the parameter $b_{k,n}$ for embedded units in that area (see Appendix B). The effect of adding renewable assets in a specific node i can be assessed by setting $b_{k,n} = 1$ if $i = n$, and zero otherwise.

D	Merseyside & N. Wales	0.31	0.79%
E	Midlands	0.77	1.94%
F	Northern	1.76	4.43%
G	North Western	-1.84	-4.63%
H	Southern	-1.56	-3.93%
J	South Eastern	-1.89	-4.78%
K	South Wales	-0.90	-2.28%
L	South Western	-1.17	-2.95%
M	Yorkshire	0.55	1.39%
N	South of Scotland	1.30	3.29%
P	North of Scotland	5.61	14.15%

Table 2: The table reports the DNO labels, their corresponding region name, and the average increase or decrease of BM costs w.r.t. the reference case as a result of deploying renewable energy assets in that DNO area, while removing the same power from marginal generators. The last column shows the same value reported as percentage of the strike price of the CfD auction in 2019 (round 3) (BEIS, 2019)*, for projects with delivery 2023/24, whose strike price is £39.65/MWh.*

Table 3 reports a sensitivity analysis to assess whether deploying a larger amount of renewable generation could affect the BM costs reported in Table 2, or not. This is obtained by running the same computations described previously, but considering 100MW instead of 1MW. The average change in BM cost in the 100MW case, for each DNO area, is shown in the fourth column of Table 3. For North Scotland, this increases from 5.61 £/MWh in the 1MW case (third column) to 6.03 £/MWh. This can be explained by the fact that the more capacity is built in a congested area, the more additional lines can become constrained, further increasing balancing costs. However, the difference between the 100MW and the 1MW cases (reported in the last column of Table 3) shows that this effect is relatively small. It is also interesting to observe that it is still beneficial adding resources in the London area, although the benefit is lower. This can be explained by noting that the 1MW case can be regarded as estimating benefits at the "margin", which decreases for larger changes. This highlights that the system impacts are nonlinear and worth further research.

DNO Area	Region	Average cost change with 1MW (£/MWh) (A)	Average cost change with 100MW (£/MWh) (B)	Difference (£/MWh) (B - A)
A	Eastern	-2.23	-2.18	0.05
B	East Midlands	-0.49	-0.44	0.04
C	London	-4.04	-2.49	1.56
D	Mers. & N. Wales	0.31	0.37	0.06
E	Midlands	0.77	0.82	0.05
F	Northern	1.76	1.82	0.07
G	North Western	-1.84	-1.64	0.20
H	Southern	-1.56	-1.51	0.05
J	South Eastern	-1.89	-1.84	0.05
K	South Wales	-0.90	-0.86	0.04
L	South Western	-1.17	-1.13	0.05
M	Yorkshire	0.55	0.60	0.05
N	South of Scotland	1.30	1.37	0.06
P	North of Scotland	5.61	6.03	0.42

Table 3 The table reports in the fourth column the average change in BM costs if 100MW are considered instead of 1MW. The last column shows the difference between these values in the 100MW and the 1MW cases, where the latter are reported in the third column (from Table 2) for ease of reading.

Finally, Table 4 reports a sensitivity analysis obtained by running the same computations used to create Table 2, but assuming that the capacity of all lines is increased by 5% (i.e., 88 GW of new transmission capacity). The last column of Table 4 reports the difference between the original average cost change detailed in Table 2, and the average cost change in the transmission expansion case, showing that the difference is relatively small. The maximum variation is in the London area (1.91 £/MWh), as the increased transmission capacity reduces the beneficial effect of adding renewable generation locally.

DNO Area	Region	Average cost change in Table 2 (£/MWh) (A)	Average cost change with all line capacity +5% (£/MWh) (B)	Difference (£/MWh) (B - A)
A	Eastern	-2.23	-2.17	0.06
B	East Midlands	-0.49	-0.54	-0.06
C	London	-4.04	-2.13	1.91
D	Merseyside & N. Wales	0.31	0.21	-0.10
E	Midlands	0.77	0.63	-0.14
F	Northern	1.76	1.52	-0.24
G	North Western	-1.84	-1.43	0.41
H	Southern	-1.56	-1.54	0.02
J	South Eastern	-1.89	-1.85	0.04
K	South Wales	-0.90	-0.93	-0.03
L	South Western	-1.17	-1.18	-0.01
M	Yorkshire	0.55	0.41	-0.14
N	South of Scotland	1.30	1.10	-0.20
P	North of Scotland	5.61	4.75	-0.86

Table 4 reports a sensitivity analysis, similar to Table 3, but obtained assuming that all lines (both AC and DC) are expanded by 5%.

5.3. Carbon emissions caused by the deployment of renewable technologies in different locations

Section 5.2 showed that the deployment of renewable energy technologies may induce a change in the BM activities, which can increase or decrease the system costs. Another consequence of this different grid rebalance is that it can induce unintended carbon emissions, as shown in this section. Here, we demonstrate how the deployment of renewable energy technologies may result in actual carbon emissions that are significantly different than the ones expected by displacing marginal units, due to the effect of grid redispatch, as described in Section 3.2.

Following the same approach used in Section 5.2, the change in carbon emission has been estimated by comparing (i) a *test* case (where 1 MW of power is produced by a renewable energy asset, while removing 1 MW from marginal generators), and (ii) a *reference* case (where no power is added or subtracted).

Technology	kgCO2/MWh
Coal	937
Open Cycle Gas Turbine	651
Combined Cycle Gas Turbine	394

Biomass	120
Nuclear	0
Non-pumped storage hydro	0
Wind	0
Pumped storage	0
ESS/DSR/Embedded Renewables	0
Other	300

Table 5: Carbon emission intensity of different technologies. These values have been collected from (Staffell, 2017)*, except the entries in the last three rows. The values for "pumped storage" and "other" are from* (National Grid, 2021a) *and (Rogers & Parson, 2019), where the latter includes BM units whose technology type was not reported in the Elexon's data set* (Elexon, 2021a)*.The carbon emission for energy storage systems, demand side response, and small renewable energy assets embedded into distribution networks has been assumed equal to zero.*

Given the carbon intensities listed in Table 5, a reduction of 1 MW of electrical power from the portfolio of marginal units reported in Table 1 should lead to a decrease of carbon emissions equal to 259 kgCO2 per hour. This is the carbon emission abatement that would be expected due to the displacement of marginal units described in Section 3.2. However, this is true only if the BM activities do not affect these carbon emissions. To assess this, for each BM unit we computed the power output difference between the test and the reference cases. Then, using the carbon intensities reported in Table 5, we determined how these power output differences translate into greater or smaller carbon emissions.

DNO Area	Region	Effect of Grid Redispatch on Emission w.r.t. Ref. Case (kgCO2/MWh) (a)	Total Emission Abatement (c) Including Impact of Marginal Unit Displacement (b) (kgCO2/MWh) (c = a + b)	Multiplier Total/Expected Abatement (c/b)
A	Eastern	-4.58	-264	1.02
B	East Midlands	-30.90	-290	1.12
C	London	-7.93	-267	1.03
D	Mers. & N. Wales	-35.14	-294	1.14
E	Midlands	-3.60	-263	1.01
F	Northern	-3.13	-262	1.01
G	North Western	1.53	-257	0.99
H	Southern	-4.12	-263	1.02
J	South Eastern	-4.35	-263	1.02
K	South Wales	-3.74	-263	1.01
L	South Western	-44.33	-303	1.17
M	Yorkshire	-4.16	-263	1.02
N	South of Scotland	-4.92	-264	1.02
P	North of Scotland	23.52	-235	0.91

Table 6: The table shows the effect of deploying renewable energy technologies in different DNO areas. The columns report in order (i) the DNO area where the renewable energy asset is deployed, (ii) the corresponding region name, (iii) the change of carbon emission caused by the grid redispatch in the test case compared to the reference case, (iv) the total carbon emission abatement, given by the sum of the reduction due to the marginal units' displacement (i.e. -259 kgCO2/MWh) and the change of carbon emission due to grid redispatch, and (v) a "multiplier" given by the ratio between the total emission abatement and the ones that would be expected if the deployment of the renewable asset did not cause a grid redispatch (i.e. the emission reduction due to the marginal unit displacement).

Table 6 reports the results obtained. The first two columns list DNO labels and the corresponding region names. The third column reports the change of carbon emission due to the grid redispatch in the test case compared to the reference case, caused by the deployment of renewable energy technologies in the region.

The fourth column shows the total carbon emission abatement, given by the sum of the reduction due to the marginal unit displacement (i.e. -259 kgCO2/MWh) and the change in carbon emissions caused by BM redispatch (third column). Finally, the last column reports a "multiplier", computed as the ratio between the total emission abatement (fourth column) and the one that would be observed if the deployment of the renewable asset did not cause grid redispatch (i.e. the expected emission reduction due to the marginal unit displacement). If the value of the multiplier in a region is greater than 1, then deploying renewable energy assets in that area has an amplifying effect in terms of carbon reduction. By contrast, if the multiplier is smaller than 1, then the BM activities have a detrimental effect in terms of carbon reduction.

Figure 4 depicts the values listed in the fourth column of Table 6, reporting the total carbon emission reduction including the effect of the grid redispatch. The map shows that deploying renewable energy technologies is beneficial in all regions. However, the actual reduction can be significantly affected by the grid redispatch. In particular, the map highlights that change in carbon emission in the BM has an amplifying (beneficial) effect in terms of carbon reduction in the southern regions. The opposite effect is obtained if assets are deployed in North Scotland. The beneficial effect in East Midlands is due to the presence of the last British coal-fired stations, where changes in renewable generation have a relatively large impact on their output and hence emissions.

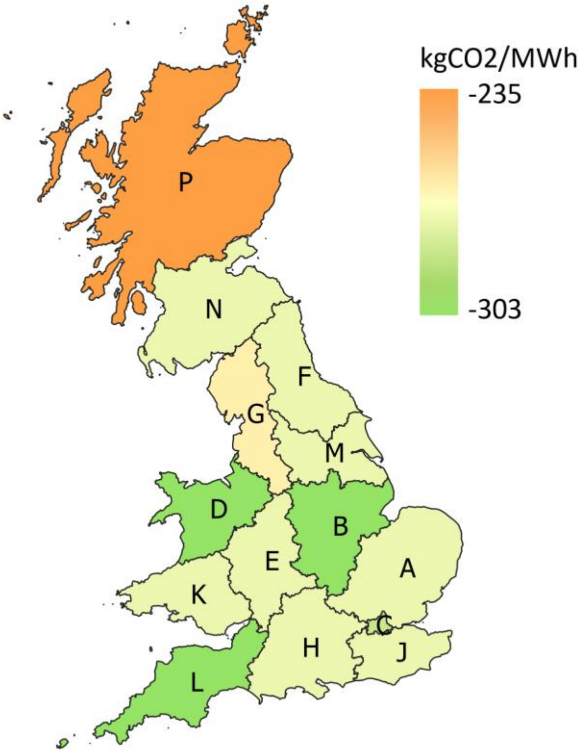

Figure 4: The figure depicts the total carbon emission reduction (including the change in emissions due to the grid redispatch) caused by the deployment of 1MW of renewable energy in a region, and the simultaneous reduction of 1MW from the marginal units.

5.4. Change in reserve requirements due to the deployment of renewable energy assets

Data and parameters

The data referring to the expected power output $p_{t,k}^{exp}$ and the actual metered output $p_{t,k}^{act}$ has been collected from the Elexon's SAA-I014 settlement data files[22] (Elexon, 2021c). Currently, in GB the amount of *upward* reserve for wind power is determined as a function of the expected wind power output, but this function is not disclosed. Therefore, for all units, including wind power plants, we use the approach described in section 4.2 consistently with the method reported by National Grid in (National Grid, 2011). Moreover, National Grid does not procure *downward* reserve for wind power, as excess wind power can be curtailed (National Grid,

[22] We only considered units providing BM data, identified as those units with non-zero FPNs. Some suppliers reported an expected power withdraw significantly greater than their maximum demand capacity reported in the Elexon's BM register (Elexon, 2020c). These values have been considered as data errors and replaced with their maximum demand capacity.

2016). For this reason, we included in our computations only the negative values of the forecast errors $\varepsilon_{t,k}$ for wind power plants. For all other units, we considered both positive and negative forecast errors. The total reserve requirement is given by the sum of both upward and downward reserves. Each settlement period involved 724 units, on average. The convolution of the probability density functions of the forecast errors $\varepsilon_{t,k}$ of these units has been computed with Python 3.8 and SciPy 1.6 (Virtanen et al., 2020) by resorting to the overlap–add method (R. G. Lyons, 2011) and solved in 55 seconds for each settlement period, on average, by using an 8-core AMD Ryzen 7 4800H CPU with 16 GB of RAM. In 2020, the wind penetration level[23] in GB was 28%.

Reserve requirements

This section reports the results obtained by using the approach described in Section 4.2 to estimate the additional reserve requirement due to the deployment of renewable energy assets. As in the previous sections, we compare a base case (where no generation is added or subtracted), with different test cases, obtained by removing 1MW of power from the marginal units[24] and adding 1MW of power provided by renewable energy assets. We tested two types of renewable energy technologies. The first is wind power, which was the technology with the largest share of capacity assigned in the CfD auction in 2019 (BEIS, 2019). The second one is a perfectly predictable renewable energy technology, which can be regarded as a wind power plant coupled with a sufficiently large energy storage device used to offset forecast errors.

To estimate the forecast errors in the test cases, where 1MW of power is removed from the marginal units and 1MW is added to renewable energy assets, we assume that for marginal variations of power, the forecast errors $\varepsilon_{t,k}$ described in Section 4.2 scale linearly with the change of the expected output. That is, for each marginal unit $\mathrm{k} \in \mathcal{K}_t^m$, where $\mathcal{K}_t^m = \{1, \ldots, n_t\}$ is the set of the marginal units at time t, the new error $\bar{\varepsilon}_{t,k}$ for the marginal unit $\mathrm{k} \in \mathcal{K}_t^m$ after 1MW of power is jointly reduced from the units in $\mathcal{K}_t^m$, is given by:

$$\bar{\varepsilon}_{\mathrm{t,k}} = \frac{p_{t,k}^{exp} - \frac{1}{n_t}}{p_{t,k}^{exp}} \varepsilon_{\mathrm{t,k}}$$

where $p_{t,k}^{exp}$ is the expected power and $\varepsilon_{\mathrm{t,k}}$ is the original forecast error. Similarly, for each reference[25] wind power plant $\mathrm{k} \in \mathcal{K}_t^{\mathcal{W}}$, with $\mathcal{K}_t^{\mathcal{W}} = \{1, \ldots, n_t\}$, the new error $\bar{\varepsilon}_{t,k}$ for $\mathrm{k} \in \mathcal{K}_t^{\mathcal{W}}$ after 1MW of power is jointly increased from the units in $\mathcal{K}_t^{\mathcal{W}}$, is given by:

$$\bar{\varepsilon}_{\mathrm{t,k}} = \frac{p_{t,k}^{exp} + \frac{1}{n_t}}{p_{t,k}^{exp}} \varepsilon_{\mathrm{t,k}}$$

Figure 5 reports the results obtained, showing the change in the total reserve requirements with respect to the base case. The first column in the figure shows that adding 1MW of wind power requires 0.105MW of additional power as reserve, on average. The second column highlights that if the displacement of marginal units is considered, then the net requirement reduces to 0.089MW. By contrast, the third column

[23] Computed as the ratio between the total wind generation (BEIS, 2022) and the total electricity consumption (excluding network losses) in England, Scotland and Wales (BEIS, 2021).

[24] We have considered only marginal units providing at least 1MW of power. If a settlement period has no marginal unit providing such amount, then we used those with the second highest price in the Elexon's ISPSTACK files, as described in section 5.1.

[25] For each settlement period, we have considered as reference wind power plants those with $p_{t,k}^{exp}$ greater than or equal to 100MW. If in a settlement period there was no unit providing such amount, the unit with the greatest expected output has been used.

shows that if wind power was perfectly predictable, for example thanks to the usage of energy storage devices to offset forecast errors, then the change in reserve requirements would be negative instead, decreasing the overall reserve requirements of 0.016MW.

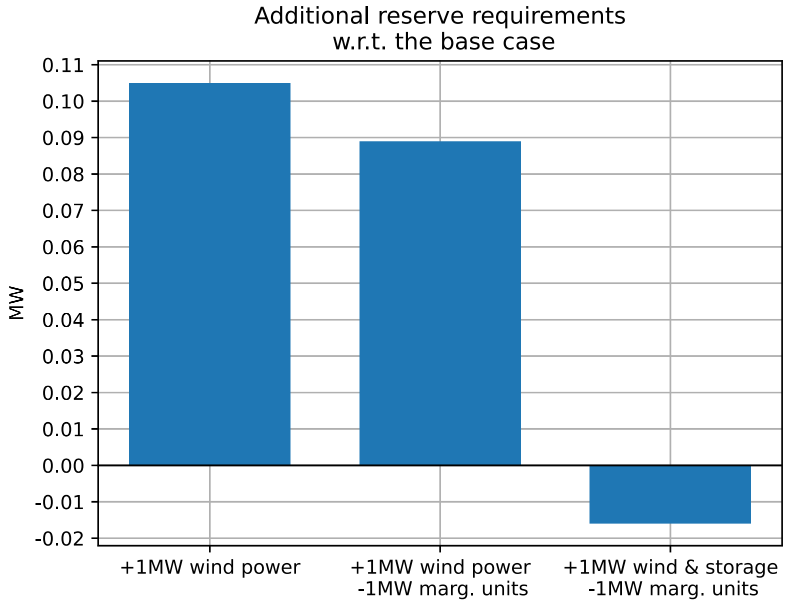

Figure 5: The figure shows the change in the total reserve requirement with respect to the base case. The addition of 1MW of wind power requires 0.105MW of additional power reserve, on average. If the displacement of marginal units is considered, then the net increase is 0.089MW. A perfectly predictable renewable energy asset would instead reduce the reserve requirement of 0.016MW.

Table 7 reports the details of (i) positive (upward) reserve, (ii) negative (downward) reserve, (iii) total reserve, which is given by the sum of both positive and negative reserves, and (iv) the change of the total reserve requirement with respect to the base case (see Figure 1) for the test cases considered.

	Positive Reserve (MW)	Negative Reserve (MW)	Total Reserve (MW)	Difference w.r.t. base case (MW)
Base case	1,814.03	1,792.91	3,606.94	
+1MW wind & storage -1MW marg. units	1,813.91	1,793.01	3,606.92	-0.016
+1MW wind power -1MW marg. units	1,814.36	1,792.66	3,607.02	0.089
+1MW wind power	1,814.48	1,792.57	3,607.04	0.105

Table 7: the table reports the amount of (i) positive (upward) reserve, (ii) negative (downward) reserve, (iii) the total reserve, and (iv) the change with respect to the base case for the test cases considered. Following (National Grid, 2016)*, the amount of positive and negative reserve has been determined by selecting the value at the 0.3 percentile for both the left and right tails of the distribution* ϕ_t^{Σ}*, obtained as described in Section 4.2.*

Table 8 reports in the last column the change in the total costs with respect to the base case for each test case. Computation details are reported in the table caption. The increase of 1MW of wind power output raises the costs for reserve provision by £9.02/h. If the simultaneous displacement of marginal units is considered, the total cost would increase by £6.58/h. By contrast, if the wind power plant was able to provide power with no forecast error, e.g. due to the presence of a suitable energy storage device, then the cost for reserve would *decrease* by £2.44/h. Given these additional system-wide costs for reserve requirements, the ESO could charge wind power plants by up to £6.58/h per MW produced, on average, whereas a perfectly predictable unit could receive up to £2.44/h per MW, on average[26].

	Positive (upward) Reserve			Negative (downward) Reserve			Change in total cost (£/h) per 1MW wind
	Average $E[\varepsilon_t \mid \varepsilon_t < 0]$ (MW)	Difference w.r.t. base case (MW) (A)	Average Price (£/MWh) (B)	Average $E[\varepsilon_t \mid \varepsilon_t > 0]$ (MW)	Difference w.r.t. base case (MW) (C)	Average Price (£/MWh) (D)	(A*B+C*D)
Base Case	518.77			606.31			
+1MW wind & storage -1MW marg. units	518.73	-0.04	72.34	606.35	0.04	4.69	-2.44
+1MW wind power -1MW marg. units	518.87	0.10	72.34	606.18	-0.14	4.69	6.58
+1MW wind power	518.91	0.14	72.34	606.14	-0.18	4.69	9.02

Table 8: For both positive (upward) and negative (downward) reserve, the table reports the average conditional expected values of the possible overall error $\varepsilon_t \sim \phi_t^{\Sigma}$, where ϕ_t^{Σ} is the distribution of the sum of the forecast errors and unexpected generation changes described in Section 4.2. The amount $E[\varepsilon_t \mid \varepsilon_t < 0]$ is used as an estimate of the positive (upward) reserve utilization, and the amount $E[\varepsilon_t \mid \varepsilon_t > 0]$ as an estimate of the negative (downward) reserve utilization at time period t. The table also shows the difference of these conditional expected values with respect to the base case, and the average price paid by National grid for positive reserve (£72.34/MWh) and negative reserve (£4.69/MWh) in the financial year 2020/2021, ranging from April 2020 to March 2021 (National Grid, 2021b). *The price for negative reserve is usually lower than the one for positive reserve, as reducing power allows generators to save fuel costs. The last column shows the change in total costs per each MW of power output, for each test case, with respect to the base case.*

5.5. A comparison of the auction results using both the CfD and eCfD schemes

This section compares the results obtained by running an auction using both the proposed eCfD and the CfD scheme currently implemented in GB. We assume that there are four wind farm projects, and the auction has to select only two of them. For ease of exposition, we assume that these candidate wind farms have the same capacity and expected load factor. Table 9 reports: (i) the project number; (ii) the location where the wind farm will be built; (iii) the corresponding DNO area; (iv) whether the wind farm will be coupled with a battery (large enough to offset the wind power forecast errors) or not; and (v) the bid price that investors will submit to the auction under the CfD scheme currently implemented in GB. We assume that investors are price-takers and truth-telling, i.e. their bids reflect their true preferences and costs.

Project Number	Location	DNO Area	Battery	CfD Bid Price (£/MWh)
I	North Scotland	P	No	45.00
II	Yorkshire	M	No	48.00
III	Yorkshire	M	Yes	55.00
IV	South Western	L	No	50.00

[26] Notice that the data about the forecast errors inferred from the Elexon's SAA-I014 settlement files refers to one hour ahead of real time. Instead, the National Grid uses data referring to 4-hour ahead when it schedules the reserve requirements, to give enough time to thermal units to start up. However, the 4-hour ahead forecast errors are usually larger than those one hour ahead. This means that the amounts reported here should be regarded as lower bounds, as the actual benefits and costs could be greater.

Table 9: Data referring to four candidate wind farm projects. The table reports in order (i) the project number, (ii) the location where the wind farm will be built, (iii) the corresponding DNO area, (iv) whether the wind farm will be coupled with a battery or not, and (v) the bid price that investors will submit to the auction under the CfD scheme currently implemented in GB.

Given the bid prices reported in the last column in Table 9, the CfD auction will select the two projects with the lowest prices, accepting the project number one and two. The market clearing price (which becomes the strike price paid in the CfD) is equal to the bid price of the last accepted order, i.e. £48/MWh.

If we assume that the carbon price determined in the UK ETS (which is paid by the carbon emitting plants started in the BM) fully internalises the carbon externality due to grid rebalance, then the remaining externalities to consider are (i) the BM cost to manage network constraints, and (ii) the cost for reserve provision, computed in Section 5.2 and Section 5.4, respectively. For ease of reading, these costs are reported in the fourth and fifth columns in Table 10. Note that the value of the reserve cost for project number three is negative (i.e. the asset reduces this cost) due to the presence of the storage device. Finally, the last column shows the total system-wide cost, given by sum of these two externalities.

Project Number	Location	Battery	BM Cost Change (£/MWh) (A)	Reserve Cost Change (£/MWh) (B)	System-wide Cost (£/MWh) (A + B)
I	North Scotland	No	5.61	6.58	12.19
II	Yorkshire	No	0.55	6.58	7.13
III	Yorkshire	Yes	0.55	-2.44	-1.89
IV	South Western	No	-1.17	6.58	5.41

Table 10: The table reports for each project: (i) the BM costs to rebalance the grid (fourth column) due to the deployment of the wind farm in the location specified in the second column; (ii) the costs due to the additional reserve required to deal with the intermittency of wind power (fifth column); and (iii) the sum of these two costs in the last column.

Under the proposed enhanced CfD (eCfD), investors have to pay for the system-wide costs they cause (through the terms α_z, β_m and γ_z in the payoff). This means that an estimate of the price they will bid in the eCfD auction can be obtained by adding the amount they have to pay to the price they would have bid under the CfD scheme. This value is reported in the last column of Table 11. Given these bids, the eCfD auction accepts the two orders with the lowest bid price, which are the projects number two and three. The clearing price (strike price) is £55.13/MWh, i.e. the highest bid price of the accepted orders.

Project Number	Location	Battery	CfD Bid Price (£/MWh) (A)	System-wide Costs (£/MWh) (B)	Bid Price in eCfD Auction (£/MWh) (A + B)
I	North Scotland	No	45.00	12.19	57.19
II	Yorkshire	No	48.00	7.13	55.13
III	Yorkshire	Yes	55.00	-1.89	53.11
IV	South Western	No	50.00	5.41	55.41

Table 11: For each project, the table reports in the last column the price that the investor would bid in the eCfD. This is given by the sum of the CfD price (fourth column) and the cost of externalities that investors have to pay (fifth column).

Table 12 reports the cleared strike price (£48/MWh), and the system-wide costs associated with the accepted projects under the current CfD scheme. We recall that in this case the system-wide costs are socialised through the BSUoS charge. Therefore, as a reference, an all-encompassing system-wide strike price can be computed as the cleared strike price plus the average of the system-wide costs associated with each project weighted according to their power outputs (assumed the same in this example). This value is equal to £57.66 per MWh, and reported in the last column of Table 12.

Current CfD scheme

Accepted Project	Location	Cleared Strike price (£/MWh)	System-wide Costs (£/MWh)	Average System-wide Strike Price (£/MWh)
I	North Scotland	48	12.19	57.66
II	Yorkshire		7.13	

Table 12: the table summarises the results of the auction under CfD scheme currently implemented in GB. The last column shows the actual average strike price including system-wide costs, which is equal to £57.66 per MWh of wind generation.

The payoff Φ_t of the proposed eCfD (defined in Section 3.3) is given by $\Phi_t = M_t(s - p_t - \alpha_z - \beta_m - \gamma_z)$. In this example, $\gamma_z = 0$, as we assume that the UK ETS carbon price correctly internalise the carbon cost. If the values of α_z and β_m coincide with the true system-wide costs for managing network constraints and providing reserve, then the payments α_z and β_m, and the system-wide costs cancel each other (i.e. the sum of values in the fifth and sixth columns in Table 13 is equal to the value in the seventh column). Therefore, in this case the average all-encompassing system-wide strike price (reported in the last column of Table 13) exactly coincides with the eCfD strike price (fourth column), and is equal to £55.13 per MWh, i.e. £2.53/MWh lower than the one under the current CfD scheme (equal to £57.66/MWh, see Table 12, last column). In a 15-year eCfD contract, awarded to a 100 MW wind farm with a load factor of 25%, this difference translates into £8M lower costs for consumers.

Proposed Enhanced CfD (eCfD) scheme							
Accepted Project	Location	Battery	eCfD Cleared Strike Price (£/MWh)	BM Cost Change (£/MWh)	Reserve Cost Change (£/MWh)	System-wide Costs (£/MWh)	Average System-wide Strike Price (£/MWh)
II	Yorkshire	No	55.13	0.55	6.58	7.13	55.13
III	Yorkshire	Yes		0.55	-2.44	-1.89	

Table 13: This table reports in the last column the average all-encompassing strike price under the eCfD (similarly to the one reported in Table 12 for the CfD). If the externalities are fully internalised, this value coincides with the eCfD strike price (fourth column).

In countries that do not have a carbon market (or if the carbon price is not representative of the actual carbon cost), the regulator can impose an (additional) carbon price to internalise the carbon cost caused by the emissions due to grid rebalancing (shown in Section 5.3). The results reported in Table 14 are obtained assuming that a regulator imposes an additional carbon price equal to £30/tCO2. In this case, the bid prices that would be submitted to the eCfD auction by the four investors are listed in the last column. Given these bids, the eCfD auction will accepts the two orders with the lowest prices, which are projects number three and four. The clearing price (strike price) in the eCfD auction is therefore £54.08/MWh. By contrast, the auction using the CfD scheme would still accept projects one and two (as in the case with $\gamma_z = 0$), as it does not consider any system-wide costs. However, now the actual cost per MWh (considering the CfD strike price and all system-wide costs) would increase to £57.95/MWh, due to the presence of the carbon externality. This means that adopting the proposed eCfD scheme could lead to a cost savings equal to 57.95 - 54.08 = 3.87 pounds per MWh of wind generation.

ID	Location (z)	Battery (m)	CfD Bid Price (£/MWh) (A)	BM Cost Change (£/MWh) (α_z)	Reserve Cost Change (£/MWh) (β_m)	Carbon Cost (£/MWh) (γ_z)	Bid Price in eCfD Auction (£/MWh) (A + α_z + β_m + γ_z)
I	North Scotland	No	45.00	5.61	6.58	0.71	57.90
II	Yorkshire	No	48.00	0.55	6.58	-0.12	55.01

III	Yorkshire	Yes	55.00	0.55	-2.44	-0.12	52.99
IV	South Western	No	50.00	-1.17	6.58	-1.33	54.08

Table 14: This table reports the same values of Table 10 and Table 11 with the difference that here the system-wide costs include the carbon cost due to the grid rebalance. The last column shows the bid price that investor would submit to the eCfD auction.

6. Conclusion and policy implications

Incentive schemes to support renewable energy investments are fundamental policy instruments to help achieve net-zero carbon emissions. However, if not properly designed, they can create additional system-wide costs. This can lead to a negative externality problem if these costs are not borne by those who cause them, but are socialised and ultimately paid by consumers, as in the case of the UK. In this work, we focused on three system-wide costs, classified as (i) the cost for managing transmission network congestion due to the deployment of renewable assets, (ii) the cost for reserve provision due to intermittent generation, and (iii) the carbon emission caused by grid rebalance in constrained network. To address these issues, we proposed an enhanced contract-for-difference (eCfD) scheme, which internalises these system-wide costs through the addition of three components, each representing one of the described problems. The obtained results show that these system-wide costs can be substantial. The addition of one MWh of renewable energy generation in the northern regions of GB can increase congestion management cost by £5.61/MWh (14% of the CfD strike price in 2019, here labelled CfD_{2019}), and can reduce carbon emission abatement by 9% (23.52 kgCO2/MWh) due to the effect of grid rebalance in constrained network. By contrast, the deployment in the southern regions of GB can reduce congestion management costs by £4.04/MWh (10% of CfD_{2019}), and can amplify carbon abatement by 17% (44.33 kgCO2/MWh). Finally, one additional MWh of intermittent wind generation in GB can increase reserve provision cost by £6.58/MWh (17% of CfD_{2019}), whereas a perfectly predictable unit would reduce those costs by £2.44/MWh (6% of CfD_{2019}).

From a policy perspective, these results demonstrate that the cost of externalities can be significant, and therefore that the decision to invest in renewable energy technologies should be driven by a least system cost approach. This can be achieved through incentive schemes which internalise the cost of externalities, such as the proposed eCfD, which ensures that these costs are paid by investors, rather than being socialized. Moreover, internalising these system-wide costs can help level the playing field, fostering competition among different low-carbon technologies by recognizing the additional benefit derived from deploying more predictable energy assets, which impose lower reserve requirements. This could support the business case for the deployment of emerging technologies and projects coupled with clean flexible assets, such as batteries and demand response. The eCfD scheme can provide additional revenues to investors in these technologies, while also reducing system-wide costs. The adoption of the proposed eCfD can also help policymakers and regulators incentivise more efficient renewable energy investments, thanks to the locational signals provided by the scheme. Indeed, the locational cost component (linked to network congestion) highlights where renewable energy assets can offer more value, and where they may instead be detrimental, from a whole system perspective.

In conclusion, the eCfD can be a useful tool for policymakers, because it internalises system-wide externalities associated with particular projects. However, these cost components are not the only investment drivers, since other factors (e.g. favourable weather conditions, low land prices) will still be reflected in project bids. Furthermore, it should be noted that wind power is amongst the cheapest source of electricity in the UK, and will likely remain the cheapest in the coming years. The proposed eCfD can help incentivise the deployment of new wind farms closer to demand centres, as well as the development of more predictable low-carbon technologies. Further research includes (i) the design of an overarching mechanism encompassing all units that accounts for the costs of reserve at each point in time according to the predictability of generators and demand, and (ii) an assessment of the possible carbon emissions from storage devices in GB.

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CRediT authorship contribution statement

Iacopo Savelli: Conceptualization; Methodology; Data curation; Formal analysis; Software; Writing - Original Draft. **Jeffrey Hardy**: Conceptualization; Writing - review & editing; Funding acquisition. **Cameron Hepburn**: Conceptualization; Writing - review & editing; Funding acquisition. **Thomas Morstyn**: Conceptualization; Methodology; Writing - Review & Editing; Supervision; Project administration; Funding acquisition.

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