Strategic Decision-Making for Power Network Investments with Distributed Renewable Generation

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ABSTRACT

Deregulated power systems with high renewable penetration often involve complex decision-making by self-interested private investors. In this work, we study the setting of privately developed and shared network capacity, where the power grid infrastructure, renewable generation and storage units are built by profit-driven investors. Specifically, we consider a case where demand and generation sites are not co-located, and a private investor installs generation capacity and a power line between the two locations providing also access to rival competitors (local generators and storage investors) against a fee. We show such a setting leads to a bilevel Stackelberg-Cournot game between the line investor (leader) and local investors (followers) and develop a data-driven solution to derive the profit-maximising capacities installed by players at equilibrium, based on analysis of a large-scale empirical dataset from a grid upgrade project in the UK. Our method provides a realistic tool to analyse decision-making of private investors in such games and subsequently encourage further adoption of renewable generation.

KEYWORDS

Energy storage, Game theory, Network expansion, Renewable generation, Stackelberg-Cournot game

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1 INTRODUCTION

Recent years have seen increasing adoption of renewable energy sources (RES), in order to reduce CO2 emissions and combat climate change. The sustainability agenda has led to research efforts not only in power systems, but also in the multi-agent and artificial intelligence communities [9, 25, 34–36]. Variable RES generation has led to operational challenges in power systems [8, 14] and undesirable energy *curtailment*, i.e. the wastage of RES energy so that power system's operation is safeguarded. Typically, curtailment happens when existing grid infrastructure is insufficient and RES generation cannot be transported where required [7, 10, 17] entailing high costs for energy end-users. This issue is especially critical in remote areas, such as in windy islands, where resources are abundant, and installation of wind turbines is preferred.

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Curtailment can be partially reduced by smarter operation of electricity grids, however, a long-term solution is increasing the transmission network capacity, usually a costly investment supported by public funding. Against this background, recent debates have focused on attracting private funding in network investments [15], such as from RES generation companies [19]. A key knowledge gap faced by energy policy makers is how to incentivise such projects, that could prove beneficial, especially in cases where several RES generators can share the privately developed grid infrastructure, against payment of a transmission fee.

One solution attracting significant attention is for all newly developed power lines to be shared by private investors under *'common access'* line rules. This means that a private investor may be granted a license to build a line under the obligation to allow third-party access (local generators or energy storage projects), by setting a payment mechanism per unit of energy transported through the line. The interplay of competing rival investors accessing demand through the shared transmission line however, raises strategic behaviour issues, especially as the line and local rival local investors may have conflicting underlying goals. In this paper, a game-theoretic model is developed to allow a systematic study of these interactions. Our model allows incentivising of private line investments and line access fees determination, such that desirable game equilibria (from a public policy perspective) are achieved, and in which all stakeholders can benefit.

In more detail, motivated by a realistic case of a network investment from the UK, we consider a two-location model, where excess RES generation and demand are not co-located, and where a private RES investor constructs and shares access of a power line with local investors of renewable energy and storage. This leads to a two-stage *Stackelberg-Cournot game* between the line investor (leader), who builds the line and RES generation capacity, and investors in local generation and storage (followers). Stackelberg game equilibria are classified as solutions to sequential hierarchical problems where a dominant player (here the line investor) has the market power to impose their strategies to smaller players and influence the equilibrium. Cournot games describe structures where rival investors independently and simultaneously decide production output quantities (here RES generation and storage capacities). Agents act to maximise their own profits and optimal investor strategies of transmission, generation and storage capacities are interdependent and affect the resulting curtailment and profitability of projects.

Several works considered strategic issues raised by private grid capacity investments [5, 11, 21, 22, 24]. A simplified analytical solution to a stylised deterministic model of a Stackelberg game between a line investor and local generators was shown in [1], while subsequent work [2] developed a formal model that considered stochastic

RES resources and demand. Work in [2] showed that, due to the large and continuous action sets, an analytical solution of the game equilibrium could not be found. Moreover, work in [2] did not consider *energy storage* players, which not only introduce additional non-linearities and time dependencies in the optimisation, but lead to a secondary Cournot game between local generators and storage investors. Building on previous work, this paper presents a new game-theoretic decision framework, which additionally includes energy storage players. In the Stackelberg-Cournot game analysis, payoff enumeration is derived not by simplified (smooth) mathematical functions, but from realistic energy system control algorithms that emerge from real data of RES generation and demand and from a concrete application. In more detail, our contributions are:

- *First*, we formulate a Stackelberg-Cournot game to model strategic decision-making on optimal investments in distributed energy systems, where energy assets are privately developed and access to network capacity is shared. In the first stage, a private investor (leader) constructs the network capacity required to access areas of high demand, and own generation capacity. Next, local investors (followers) compete on installing additional generation and storage capacity, using the infrastructure installed by the leader, against a transmission fee. Local investors play a Cournot game, conditioned on the line investment decision made by the Stackelberg leader.

- *Second*, we develop an algorithmic solution approach where agents' payoffs are derived from large-scale datasets of historical observations and simulations that realistically represent operation and control in energy systems. Moreover, we establish a technique for finding equilibrium, despite agents exhibiting continuous and multi-dimensional strategy sets.

- *Finally*, the practical application of the Kintyre-Hunterston grid project in the UK is studied for validation and parametric exploration of the game dynamics. The analysis proposes a mechanism for setting fees that ensure the line gets built, but local investors can also benefit from investing in RES energy and energy storage. Our work provides a decision support tool for investors and energy policy makers facing the problem of funding costly grid upgrades and enabling alternative market structures for RES generators.

The structure of the paper is: Section 2 discusses relevant literature, Section 3 presents the Stackelberg-Cournot game model, Section 4 presents the equilibrium solution analysis, Section 5 introduces the case study, Section 6 presents results from explorative scenarios and Section 7 concludes and discusses future work.

2 RELATED WORK

Following the deregulation of the electricity sector and proliferation of variable RES technologies, power network expansion and planning requires adoption of optimisation techniques [13, 27] and modelling of strategic behaviour of market participants [11]. In this context, game-theoretic and agent-based modelling are becoming highly relevant for efficient planning and achieving desired outcomes. Strategic behaviour can be analysed by agent-based approaches, such as in Baringo & Conejo [5], where renewable and network capacity investment are jointly considered or in Motamedi et al. [22] where the effect of generation capacity on network planning is examined. Maurovich-Horvat et al. [21] compare network capacity undertaken by system operators or private investors, and

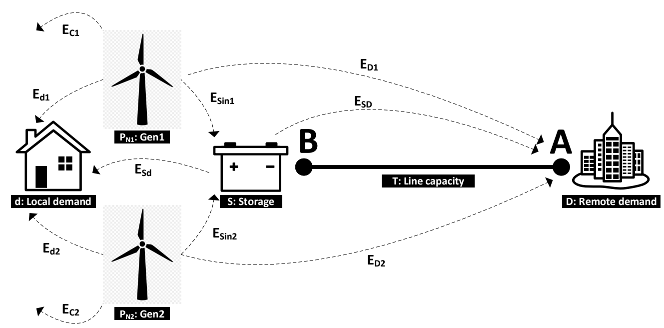


Figure 1: Energy flows in Stackelberg-Cournot game

show that different ownership models may lead to significantly different optimal results. Perrault & Boutilier [24] also consider private grid upgrades and use coalition formation to enforce coordination, reduce inefficiencies and transmission losses. Instead, our work uses non-cooperative game theory to study strategic interactions of investors in constrained areas of the grid. Other works consider transmission expansion at power network areas with congestion, such as the work from Joskow and Tirole [16] that analysed a two-node system and studied market behaviours of players exerting market power and allocation of transmission rights. Our work derives optimal capacity decisions at areas with curtailment by consideration of a Stackelberg-Cournot game.

In the context of network expansion, Stackelberg games were utilised in several works, which considered analysis with social welfare [28], locational marginal pricing [29] or highlight uncertainties introduced by stochastic renewable generation [33]. More recent works on the renewable energy domain, use Stackelberg game analysis to model energy trading between microgrids [4, 20], peer-to-peer energy trading [3, 32] or the development of electric vehicles infrastructure [37]. In the security domain, efficient strategies for attacker-defender problems [18, 23] and poaching prevention [12] are often modeled as Stackelberg games.

3 PROBLEM FORMULATION

Two locations were considered, location A of high energy demand D, representing a large city or mainland, and a high RES generation location B, such as a windy island, with local demand d (see Fig. 1). Three investor or agent types were assumed:

- Player 1 or the *'line investor'* is building RES generation capacity of P_{N_1} at B and a transmission line of capacity T between A and B, which is crucially also used by rival players to access remote demand D against a transmission payment.
- Player 2 or *'local generators'* represent all small-scale producers at B installing generation capacity of P_{N_2}.
- Player 3 or the *'storage investor'* builds storage capacity S at B and purchases renewable energy at times of RES oversupply. In other words, storage utilises energy that would prior to its installation have been curtailed.

Players are self-interested and aim to maximise their own utility (profit). The main research question of this work is the *determination of optimal strategies or capacities built by players* $\langle P_{N_1}, T, P_{N_2}, S\rangle$

so that profits are maximised. Estimation of optimal agents' actions is studied as a *Stackelberg-Cournot game*. The line investor is the *leader*, as he moves first by building the transmission line T and renewable generation capacity P_{N_1} at B, intending to maximise his own profit. The leader is typically a larger investor who has the capital and technical expertise to build the line enabling also local investors to export their energy surplus. Profits however, depend also on the investment capacity decisions (action sets) of local generators and the storage. Local investors share available capacity at B by playing a Cournot game. Local investors' optimal action sets consists of finding P_{N_2} and S so that profits are maximised. Analytically, the game equilibrium can be found by *backward induction.* At the first stage, the leader estimates the Cournot game equilibrium, determined by the joint actions of local investors, for every strategy of the leader $\langle P_{N_1}, T\rangle$. For a given $\langle P_{N_1}, T\rangle$, the Cournot game equilibrium can be found by the intersection of the local investors best responses. Next, the line investor selects from the set of Cournot game equilibria to build the profit-maximising $\langle P_{N_1}, T\rangle$.

A model schematic of the game is shown in Fig. 1 along with the energy flows between energy system components owned by players. Without loss of generality wind and battery storage capacities were assumed in this work, as shown in Section 3.1.

3.1 Models of energy system components

3.1.1 Wind generation model. Wind generation depends on the rated capacity installed P_{N_i} and wind speed at the project's location w_i. Power output from wind generators is modelled as a sigmoid function of wind speed, as in other works in the literature [26]:

$$x_{G_i}^{(t)} = \frac{1}{1 + e^{-\alpha(w_i^{(t)} - \beta)}} \tag{1}$$

where x_{G_i} is the normalised power generated by player i and α, β are the sigmoid function parameters [1]. Time series data of wind power output can be created by the product of $P_{N_i} x_{G_i}^{(t)}$.

3.1.2 Energy storage model. A generic battery storage model is assumed based on Lithium-ion batteries (e.g. Tesla Powerwall). Formally stated, energy stored in the storage device at time t, $E_{S,t}$, depends on energy stored in the previous storage state $E_{S_{t-\delta t}}$:

$$E_{S,t} = E_{S,t-\delta t} + r_t \eta \delta t \tag{2}$$

where r_t is the power charged or discharged from storage, i.e. when $r_t > 0$ then $r_t = P_{ch,t} > 0$, else when $r_t < 0$ then $r_t = -P_{dch,t} < 0$, η represents the efficiency during charging $\eta = \eta_{ch}$ or discharging $\eta = 1/\eta_{dch}$. Moreover, storage follows operational constraints, such as dynamic restrictions of power charged to or discharged from the device. In addition, to prevent battery lifetime degradation, the operation of storage is usually bounded between a safe minimum and a maximum state of charge SOC, which represents the maximum capacity reached $SOC_{max} = 100\%$:

$$SOC_{min} \leq SOC_t = \frac{E_{S,t}}{S} 100\% \leq SOC_{max} \tag{3}$$

[1] A generic wind turbine model assumed in this paper was based on a 2.05 MW Enercon E82 yielding $\alpha = 0.3921$ s/m and $\beta = 16.4287$ m/s http://www.enercon.de/en/products/ep-2/e-82/

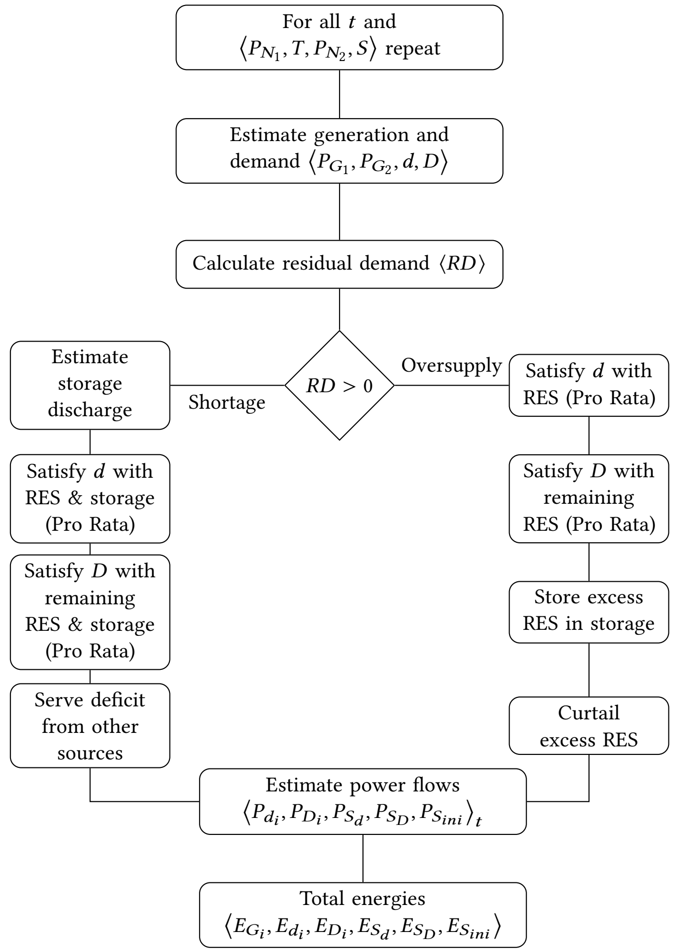


Figure 2: Control algorithm for energy flows estimation

3.1.3 Demand model. Demand follows a typical electricity load behaviour P_L with a morning and an afternoon peak. Local demand d is a smaller portion of P_L, while remote demand D at location A, represents the demand that can be served, after the transmission line capacity T is taken into account:

$$D = \begin{cases} P_L, & \text{if } P_L < T \\ T, & \text{otherwise} \end{cases} \tag{4}$$

3.2 Power and energy flows

Energy flows and dispatch priority in the two-location system is determined by the control scheme shown in Fig. 2. In summary, for every t, the residual demand RD (total demand minus potential RES production) is estimated. When there is a *shortage of renewable supply*, the control algorithm estimates the storage discharge, while respecting power constraints and SOC_{min}. Next, available supply from agents serves the local demand in an equal or proportional way (Pro Rata). Local demand is prioritised over remote demand due to reduced energy losses, but also because of transmission charges imposed to local generators and the storage investor. Any remaining renewable or storage supply then serves the remote demand. The deficit to fully satisfy demand is supplemented by other sources in the system. On the other hand, when there is an *oversupply of renewable production*, RES generators serve both local and remote demand on a Pro Rata basis. Excess is stored in the storage system, as long as the $SOC \leq SOC_{max}$ and maximum charging power constraints are not violated. Any excess generation that cannot be stored in the storage unit is curtailed. Power flows are estimated for all t, while energy flows for a larger duration such as the project lifetime, are computed as the summation of power flows for each t over the project lifetime horizon.

Renewable generators have an energy production of E_{G_i} and can serve either local demand E_{d_i} at B or remote demand E_{D_i} at A via the transmission line. In addition, RES generators can sell any excess energy that cannot be absorbed locally or transferred through the line to storage at B. The energy sold to storage by i player is denoted as $E_{S_{ini}}$. Any excess that doesn't serve the demand and cannot be stored is curtailed E_{C_i}. Taking all possible energy flows for renewable energy production, the following must hold for the line investor and local generators, respectively:

$$E_{G_i} = E_{d_i} + E_{D_i} + E_{S_{ini}} + E_{C_i} \tag{5}$$

where $i = 1$ denotes the line investor and $i = 2$ the local generators.

Energy stored that serves local demand d and remote demand D are denoted as E_{S_d} and E_{S_D}, respectively. Demand can be served either directly from RES generators or from storage or other external sources in the system:

$$E_d = E_{d_1} + E_{d_2} + E_{S_d} + E_{d_{oth}} \tag{6}$$

$$E_D = E_{D_1} + E_{D_2} + E_{S_D} + E_{D_{oth}} \tag{7}$$

Eq. (5) - (7) hold for a larger time period and for each t. For profit (payoff) estimation however, aggregate energy flows are required.

3.3 Profit or payoff functions

Players' profits or payoffs depend on aggregate energy quantities, tariff prices and costs for capacity installation. RES production is remunerated with a price of p_G in £/MWh of energy used to serve demand. Energy traded with storage is sold for a tariff price of p_S and energy transported through the line stemming from either one of local investors is charged with p_T. With regards to costs, RES generation capacity is assumed to cost c_{G_i} in £/MWh of expected generation installed E_{G_i}, the power line costs c_T in £/MW per unit of transmission capacity installed and storage costs c_S in £/MWh per unit of storage capacity installed. The costs reflect both capital required and operation and maintenance costs.

Taking these into consideration the players' profits are equal to:

$$\Pi_1 = (E_{d_1} + E_{D_1})p_G + (E_{D_2} + E_{S_D})p_T + E_{S_{in1}}p_S - c_{G_1}E_{G_1} - c_T T \tag{8}$$

$$\Pi_2 = (E_{d_2} + E_{D_2})p_G + E_{S_{in2}}p_S - c_{G_2}E_{G_2} - E_{D_2}p_T \tag{9}$$

$$\Pi_3 = (E_{S_d} + E_{S_D})p_G - (E_{S_{in1}} + E_{S_{in2}})p_S - E_{S_D}p_T - c_S S \tag{10}$$

Line investor's revenues (see Eq.(8)) stem from serving the demand (d or D), rewarded with p_G, from energy transmitted through the line charged with p_T, and from energy sold to storage, charged with p_S. Costs represent RES capacity c_{G_1} and transmission capacity c_T installation. Similarly, local generators earn p_G per unit of demand served and p_S for the energy sold to storage. The costs incurred by local generators are RES capacity costs c_{G_2}, and the cost for energy transmitted through the line p_T (Eq.(9)). Finally, the storage investor earns p_G when serving the local and/or remote demand, while paying p_S for the energy purchased from renewable generators, p_T for the energy transported through the transmission line and c_S for installing energy storage capacity of S (Eq.(10)). Note here that the energy purchased by storage from RES generators would otherwise have been curtailed, meaning that the storage investor can negotiate a low tariff price p_S, hence increasing the profitability of storage investments in the region.

Algorithm 1 PROFIT ESTIMATION

p_G, p_T, p_S ▷ feed-in tariff, transmission fee, storage fee
c_T ▷ transmission capacity cost
c_{G_i} ▷ i player's generation cost
for all $\langle P_{N_1} \in \{0, ..., P_{Nmax}\}, T \in \{0, ..., T_{max}\} \rangle$ **do**
    for all $P_{N_2} \in \{0, ..., P_{Nmax}\}$ **do**
        for all $S \in \{0, ..., S_{Nmax}\}$ **do**
            $\Pi_1 \leftarrow (E_{d_1} + E_{D_1})p_G + (E_{D_2} + E_{S_D})p_T + E_{S_{in1}}p_S - c_{G_1}E_{G_1} - c_T T$
            $\Pi_2 \leftarrow (E_{d_2} + E_{D_2})p_G + E_{S_{in2}}p_S - c_{G_2}E_{G_2} - E_{D_2}p_T$
            $\Pi_3 \leftarrow (E_{S_d} + E_{S_D})p_G - (E_{S_{in1}} + E_{S_{in2}})p_S - E_{S_D}p_T - c_S S$
        end
    end
end
return $\langle \Pi_1, \Pi_2, \Pi_3 \rangle$

Payoff enumeration and the continuous and multi-dimensional nature of agents' action sets, highlight the high complexity of the analysis task. In addition, there are interdependencies with regards to the curtailment incurred, time dependencies introduced by storage and complex rules in the priority of dispatch (analysed in Section 3.2). Hence, an analytical solution of the game equilibrium is not feasible. For this reason, we propose an algorithmic solution that relies on payoff enumeration directly from simulation analysis. The methodology is described in detail in the following section.

4 EQUILIBRIUM ANALYSIS

The methodology utilises time series data for payoffs and equilibrium estimation. In particular, wind speed and demand data inform the models presented in Section 3.1 and energy flows computation (see Section 3.2). The game is restricted by considering a discretised action set of $\langle P_{N_1}, T, P_{N_2}, S \rangle$ that represents the continuous payoff game. Following computation of energy flows, profits are estimated for various financial parameters as in Alg. 1. Profits represent the players' expected payoffs, hence the game equilibrium can be found by estimation of the normal form of the game shown in Fig. 3.

The game equilibrium is found by backward induction as in the algorithmic procedure summarised in Alg. 2 and illustrated in Fig. 3. Each plane in Fig. 3 illustrates the Cournot game played by local investors for a given strategy of the leader. First, the line investor moves in order to maximise his profit, however he needs to anticipate the reaction of other investors to building the transmission line and P_{N_1} at B. The leader estimates for every possible strategy $\langle P_{N_1}, T \rangle$, the equilibrium solution of the Cournot game played

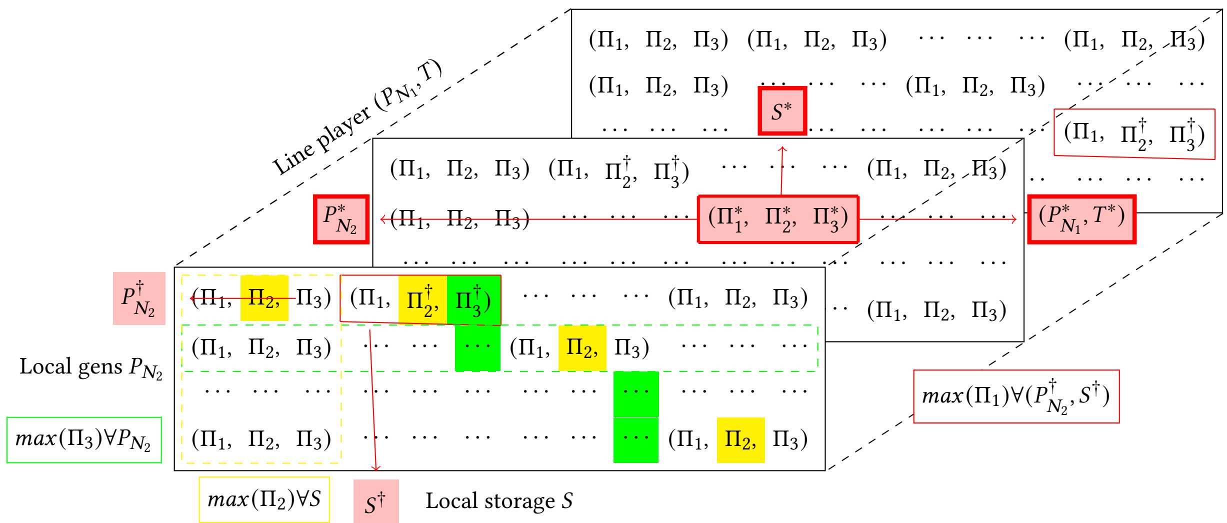


Figure 3: Stackelberg-Cournot game equilibrium estimation: each plane illustrates the Cournot game played by local investors for any given action of the leader, who then selects the profit-maximising Cournot game equilibrium

Algorithm 2 STACKELBERG-COURNOT EQUILIBRIUM ESTIMATION

for each $\langle P_{N_1}, T\rangle \in \langle\{0, ..., P_{Nmax}\}, \{0, ..., T_{max}\}\rangle$ **do**
  for each $S \in \{0, ..., S_{max}\}$ **do**
    $\Pi_2^{\#} \leftarrow \max_{P_{N_2}} \Pi_2(P_{N_2}, S)|_{\langle P_{N_1}, T\rangle}$ ▷ local generators best response
    $P_{N_2}{}^{\#} \leftarrow \arg\max_{P_{N_2}} \Pi_2(P_{N_2}, S)|_{\langle P_{N_1}, T\rangle}$
  end
  $BR_2 \leftarrow (P^{\#}_{N_2}, S)|_{\langle P_{N_1}, T\rangle}$
  for each $P_{N_2} \in \{0, ..., P_{Nmax}\}$ **do**
    $\Pi_3^{\#} \leftarrow \max_{S} \Pi_3(P_{N_2}, S)|_{\langle P_{N_1}, T\rangle}$ ▷ storage best response
    $S^{\#} \leftarrow \arg\max_{S} \Pi_3(P_{N_2}, S)|_{\langle P_{N_1}, T\rangle}$
  end
  $BR_3 \leftarrow (P_{N_2}, S^{\#})|_{\langle P_{N_1}, T\rangle}$
  $(P_{N_2}, S)^{\dagger} = intersect(BR_2, BR_3)|_{\langle P_{N_1}, T\rangle}$ ▷ Cournot game equilibrium
end
$\Pi_1^* \leftarrow \max_{(P_{N_1}, T)} \Pi_1(P_{N_1}, T, (P_{N_2}, S)^{\dagger})$ ▷ line investor best response
$(P_{N_1}, T, P_{N_2}, S)^* \leftarrow \arg\max_{(P_{N_1}, T)} \Pi_1(P_{N_1}, T, (P_{N_2}, S)^{\dagger})$
$(P_{N_1}, T, P_{N_2}, S)^* = (P^*_{N_1}, T^*, P^*_{N_2}, S^*)$ ▷ game equilibrium
return $\langle \Pi_1^*, \Pi_2^*, \Pi_3^*, P^*_{N_1}, T^*, P^*_{N_2}, S^*\rangle$

between local investors. An illustration of the Cournot game equilibrium estimation is shown for clarity in the first plane in Fig. 3. The Cournot game is analysed as follows. For every $\langle P_{N_1}, T\rangle$, local generators estimate their best response for all possible strategies of the storage player. In other words, local generators estimate the renewable capacity they need to install $P_{N_2}{}^{\#}$ for every possible storage capacity S (and for every $\langle P_{N_1}, T\rangle$). In Fig. 3 this corresponds to finding the maximum Π_2 at each column (yellow color). Simultaneously, the storage investor estimates his best response to the RES capacity built by local generators i.e. for every possible P_{N_2}, the storage investor estimates the profit-maximising capacity $S^{\#}$ to be built. In Fig. 3, this is equal to finding the maximum Π_3 at every row of the payoff matrix (green color). The Cournot game equilibrium between local investors is given by the intersection of their best responses $(P_{N_2}, S)^{\dagger}$ (pink color). The Cournot game analysis is repeated for all possible strategies of the line investor and the corresponding line investor's profits Π_1 are recorded (red square). From the set of Cournot game equilibria, the leader selects the strategy that maximises Π_1 i.e. the Stackelberg-Cournot game equilibrium $\langle P^*_{N_1}, T^*, P^*_{N_2}, S^*\rangle$ (red box filled with pink color). This concludes the optimal strategy backward induction process followed by the line investor. The line investor then installs $(P^*_{N_1}, T^*)$. Local investors (local generators and storage investors) observe the leader's strategy and respond by installing the Cournot game equilibrium capacities $P^*_{N_2}$ and S^*, as anticipated by the leader. Results from methodology application are discussed in the next section.

5 CASE STUDY ANALYSIS

The methodology was applied to the practical application of the Kintyre-Hunterston network upgrade project in the UK. Located in western Scotland, the Kintyre peninsula is one of most favourable wind generation sites in the UK, however grid infrastructure originally built to serve a typical rural area of low demand, was inadequate to integrate high RES volumes developed in the region. This led to a £230m network upgrade project connecting the Hunterston substation, partially through a sub-sea link, to the Kintyre creating headroom for 150 MW additional RES capacity [31] with an estimated net lifetime benefit of £520m [30]. Based on this project figures, we consider a two-node network of a location A of high demand (mainland) and a location B of high wind generation (Kintyre). Historical observations of hourly mean wind speed data over a 17-year period (MIDAS dataset from UK Met Office) and hourly demand data over the 2006-2015 period (UK National Demand) were collected to inform generation and demand models. Demand follows a similar pattern to the UK demand profile with local demand equal to about 20% of remote demand. Energy flows were computed for an hourly simulation analysis over a year, accounting for hourly and seasonal variations of generation and demand. Installation cost parameters were adjusted to represent annual costs. Transmission cost c_T was based in cost figures of the Kintyre-Hunterston project i.e. £230m/150 MW of T installed. A useful lifetime of 10 years was assumed for storage, after which the system is replaced. Energy storage system parameters were based on typical values for Lithium-ion batteries, with SOC_{min} = 20%, SOC_{max} = 100% and a charging and discharging efficiency of $\eta_{ch} = \eta_{dch}$ = 90%.

Continuous action sets were discretised as $P_{N_i} = [0:1:500]$ MW, $S = [0:1:300]$ MWh and $T = [0, 75, 100, 125, 150, 175]$ MW leading to $501 \times 301 \times 3006$ or 450million potential strategy combinations. This results in a restricted game that represents the continuous payoff game. For each combination, hourly energy flows were estimated (vectors of 8760 magnitude) and profits calculated for at most 51 values of cost parameters per scenario, increasing the computational intensity required for the analysis. Hence, simulations were executed in a high-performance computing facility (Cirrus UK National Tier-2 HPC Service at EPCC http://www.cirrus.ac.uk) in a MATLAB environment with 36 parallel workers.

Discrete action sets mean that agents' best responses are vectors of pair elements (or arrays), which lead to a challenge observed with regards to the *intersect* function (Alg. 2 Line 12), which returns as output the common data found in best responses BR_2 and BR_3. The *intersect* function does not exhaustively search the payoff space for estimation of the Cournot game equilibrium, but only in feasible areas where intersections can occur. If the search for intersection returns exactly one intersection point $(P_{N_2}, S)^\dagger$ then this is the Cournot game equilibrium (e.g. see Fig 4). In the case of multiple intersection points, the equilibrium is the mean of the intersection points. If the intersection lies between the best response data recorded, the Cournot game equilibrium is taken at the intersection between the line segments formed by the local investors' best response curves. The two latter cases above only occur due to the discrete strategy space and large-scale data analysis, as opposed to other works where profits/costs are mathematical functions and the equilibrium is found analytically.

6 SCENARIO RESULTS

This section explores the game dynamics and equilibrium properties by varying the cost parameters of the game. Five scenarios were considered in which, the value of the tested parameter varies, while other parameters remain fixed (parameter values are shown in Table 1). Transmission, generation and storage capacities installed and agents' profits at equilibrium are shown in Fig. 5-6.

In Scen. 1-3, total generation capacity decreases as the tested parameter value increases. RES investors, i.e. the line investor and local generators, install less capacity, as their own generation cost c_{G_i} increases. Reduction in capacity installed by a RES investor

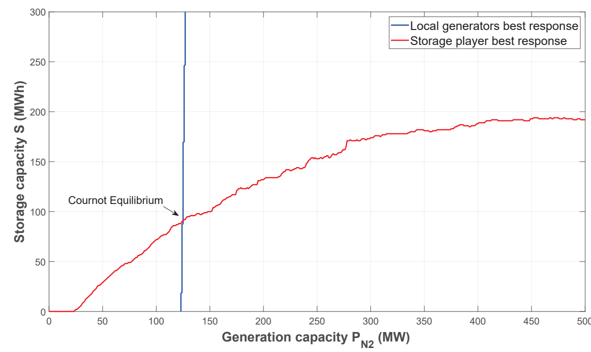


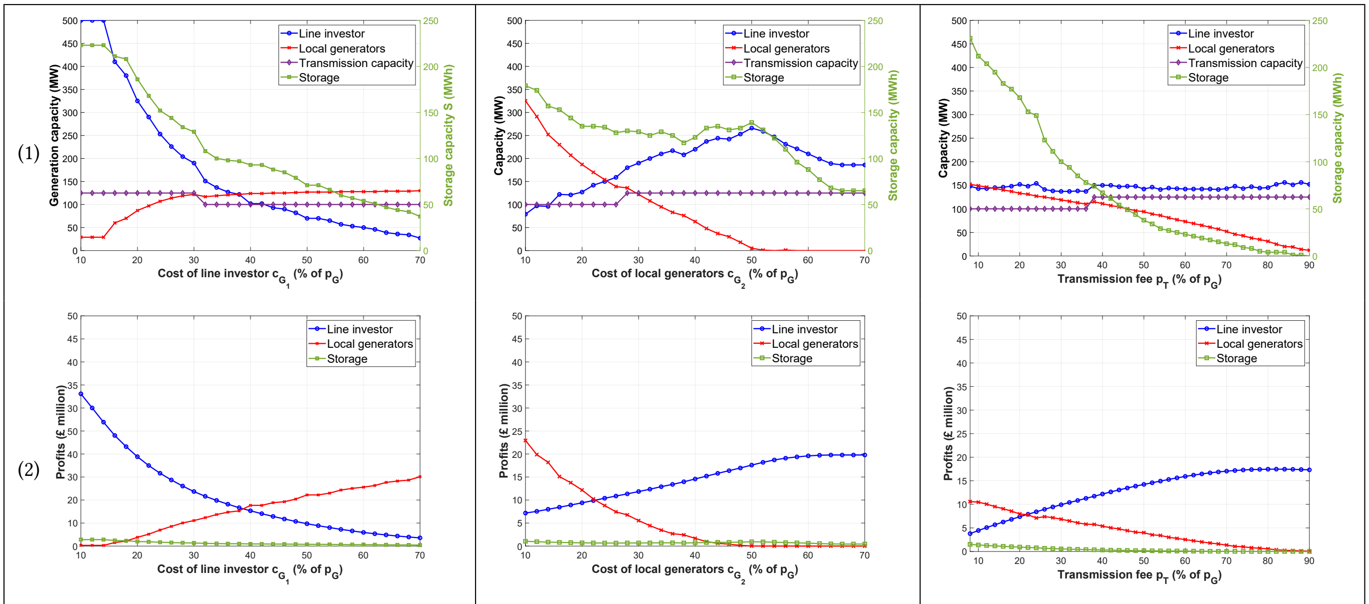
Figure 4: Local investors best responses in Cournot game for $\langle P_{N_1}, T\rangle = \langle 100, 100\rangle$ and $c_{G_1} = c_{G_2} = p_T = 0.30p_G$, $p_S = 0.10p_G$

benefits the rival RES investor (Scen. 1-2). In Scen. 3, P_{N_1} is relatively constant (small increase is observed for large p_T), while P_{N_2} decreases. Lower S capacity is installed as p_S or c_S increase (Scen. 4-5). In Scen. 1-3, S decreases along with P_{N_1}, leading also to a decrease of the total RES capacity installed. Transmission capacity remains largely unchanged, with some step changes observed (in Scen.1 & 5 T decreases, in Scen. 2 & 3 increases, and in Scen. 4 is constant). Profits exhibit similar behaviour to the capacity installed. In all scenarios, storage's profits are significantly lower than profits by RES investors. This is attributable to high storage costs c_S and fees of p_S and p_T. Storage has limited market power, as it purchases energy only when there is RES oversupply and serves demand at times of RES deficit. Scen. 3 shows that high transmission fees p_T inhibit the uptake of RES generation and storage. Low p_T can deliver line investor's profits, as the line is crucial for accessing remote demand and generating revenue from rival investors. Suitable p_T determines a feasible range that allows transmission, generation and storage capacity investments to be profitable. Scen. 4 showed that p_S effect on P_{N_i} and T installed is not significant, however if $p_S \geq 0.4p_G$, no storage capacity is built. Storage can negotiate a low p_S as energy stored would otherwise have been curtailed. Scen.5 displays a sensitivity analysis to the storage cost c_S with (c_S = 100% represents current state of battery costs \$200/kWh). As c_S increases, S installed decreases, however the reduction is not linear. Future reduction in storage costs (at the range of c_S = 30% − 35% of current prices) could lead to massive adoption of storage devices leading also to higher RES and transmission capacity.

In addition to optimal strategies installed, we also investigated the value that storage brings to the energy system by comparing operation with and without storage. When storage is removed, the game reduces in a Stackelberg game between the line investor and local generators. A significant beneficiary when storage is introduced is the line investor. In all scenarios (Scen. 1-3), the line investor is able to achieve larger profits, when storage is deployed (see Fig. 7-(a)), for two main reasons: the leader installs more RES capacity and revenue is generated by storage (energy sold at p_S and transferred with p_T). Note this result is not obvious, as in the case of a RES shortage, storage and RES generators compete for serving the demand on equal terms (Pro Rata). On the other

	Scenario 1 (varying c_{G_1})	Scenario 2 (varying c_{G_2})	Scenario 3 (varying p_T)	Scenario 4 (varying p_S)	Scenario 5 (varying c_S)
c_{G_1}	$0.10p_G : 0.02p_G : 0.70p_G$	$0.30p_G$	$0.36p_G$	$0.36p_G$	$0.36p_G$
c_{G_2}	$0.30p_G$	$0.10p_G : 0.02p_G : 0.70p_G$	$0.30p_G$	$0.30p_G$	$0.30p_G$
p_T	$0.30p_G$	$0.30p_G$	$0.10p_G : 0.02p_G : 0.90p_G$	$0.30p_G$	$0.30p_G$
p_S	$0.10p_G$	$0.10p_G$	$0.10p_G$	$p_S = 0 : 0.02p_G : p_G$	$0.10p_G$
c_S	$15,000$	$15,000$	$15,000$	$15,000$	$0.30c_S : 0.05c_S : 1.60c_S$

Table 1: Cost parameter assumptions for scenario analysis (in all scenarios $p_G = \$74.3/\text{MWh}$ and $c_t = \$76,666.67/\text{MW}$)



(a) Scenario 1 **(b) Scenario 2** **(c) Scenario 3**

Figure 5: Scenarios 1-3 results: effects of c_{G_1}, c_{G_2} and p_T on capacities installed and profits at Stackelberg-Cournot equilibrium

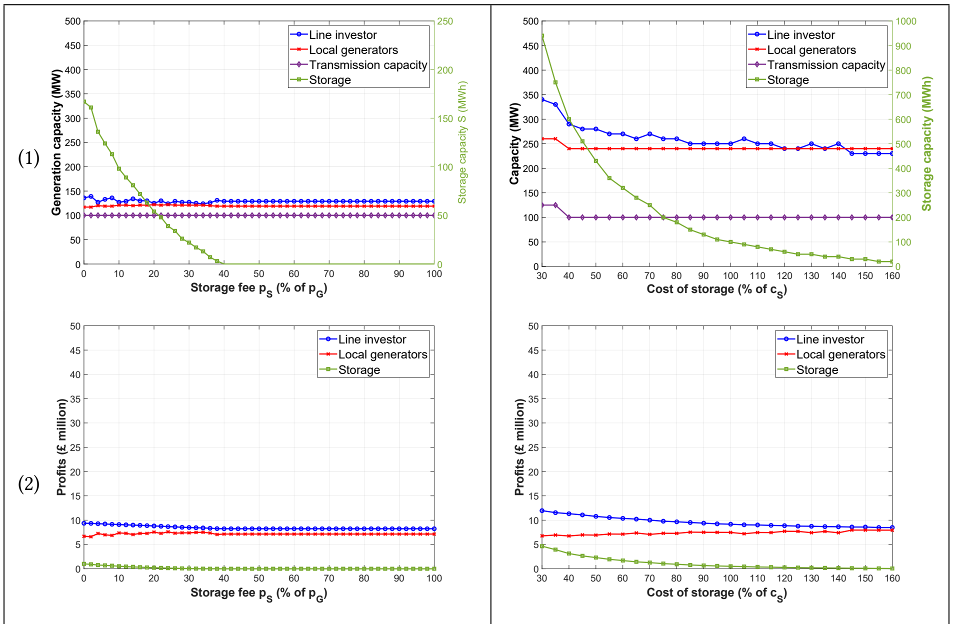
hand, in the majority of cases, local generators are marginally worst off when storage is deployed (see an example shown for Scen. 1 in Fig. 7-(a)). In Scen. 1 & 3, local generators install less RES capacity when storage is introduced and achieve marginally lower profits. In Scen. 2, storage brings higher profits for local generators, only if they have a lower generation cost than the line investor. A potential reason for the behaviour observed for local generators is the competitive game between local investors. Local generators can generate additional revenue by trading energy surplus with the storage system, however, they also compete with storage when there is a RES generation shortfall. The competitive behaviour manifests in a reduction of profits for local generators. On the contrary, the line investor is able to exploit his competitive advantage and reap the benefits from the introduction of storage.

Additional benefits that storage brings are observed in increased RES penetration, as demand served by other sources and curtailment are reduced (see Fig. 7-(b) and (c) respectively). A significant decrease was observed in the remote demand served, as high levels of local demand served by RES are already achieved before storage is introduced. Storage increases the RES capacity and reduces the remote energy demand served by other sources in the grid achieving larger penetration of renewable generation. Despite storage entering the market, RES generation curtailment is not fully eliminated and it is still required when storage capacity is exceeded. Eradication of RES curtailment would require a massive storage capacity installed, a situation not profitable with current cost prices. Simulation results showed a reduction of curtailment reaching savings up to 7% (see Fig. 7-(c)).

Finally, a general observation is that results may fluctuate and may not be monotonic. The main reason for this behaviour is that the solution approach for payoffs and equilibrium estimation stems from large-scale simulation analysis, as opposed to analytical solutions considered in other works. In fact, the large space of agents' action sets was restricted by assuming a discrete strategy space, that allowed a restriction of the game that made finding equilibrium computationally tractable, but without losing the ability to gain insights to the original game. This combined with non-linearities introduced by storage led to approximations of the Cournot game equilibrium in the cases of multiple or in-between intersections, discussed in Section 5, which contributes to non-monotonicity.

7 CONCLUSIONS & FUTURE WORK

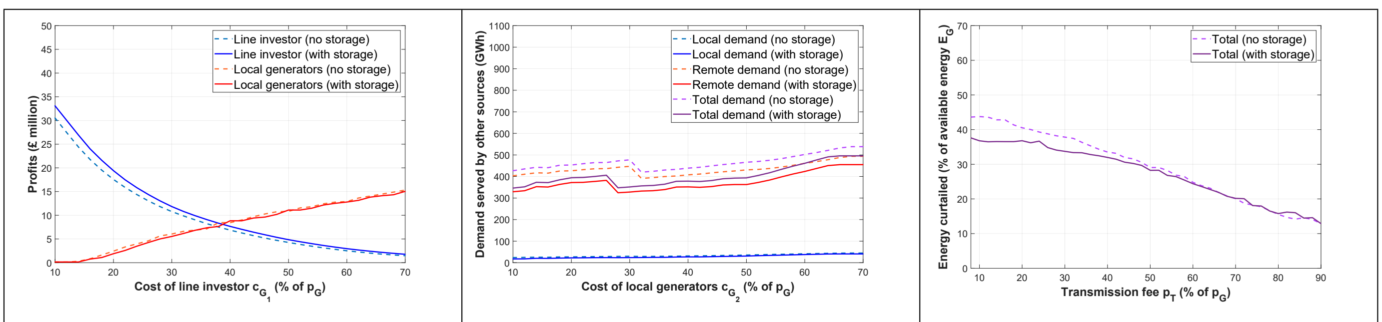
A game-theoretic analysis is developed in this work to model strategic decision-making of low-carbon capacity investments, including



(a) Scenario 4

(b) Scenario 5

Figure 6: Scenarios 4-5 results: effects of p_S and c_S on capacities installed and profits at Stackelberg-Cournot equilibrium



(a) Scenario 1: Agents' profits

(b) Scenario 2: Demand by others

(c) Scenario 3: Curtailed energy

Figure 7: Comparison of profits, demand served by other sources and RES curtailment with and without storage

RES generation, energy storage and network upgrades, undertaken by self-interested and profit-maximising private investors. Specifically, we model a setting where network access is shared among investors leading to a two-stage Stackelberg-Cournot game. Agents' payoff functions and equilibrium estimation are based on simulations and a large-scale data-driven analysis and game dynamics was studied for a wide range of cost parameters enabling RES investors, network operators and energy policy makers to explore suitable market structures and charging fees for transmission and storage, and to encourage profitable low-carbon technology investments. A key finding is that by introducing storage, lower curtailment and higher RES integration can be achieved, with the line investor benefiting most from storage, while local generators are marginally worst due to the competitive nature of the game. Future work will focus on alternate market structures with regards to storage ownership. For example, RES investors could decide to invest in their own storage capacity or they can jointly invest in a common storage system. Fair allocation of profits generated by co-owned storage system is of interest in this setting, especially as RES generators may have invested in dissimilar generation capacities. Game equilibrium estimation required significant computational resources, due to the enumeration of payoffs for a large size of agents' action sets. Hence, future work will focus on efficient equilibrium estimation, as in the work by Basilico et al [6]. and will investigate machine learning techniques for fitting an approximate payoff function to the agent's strategy space.

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