Analysis of Strategic Renewable Energy, Grid and Storage Capacity Investments via Stackelberg-Cournot Modelling

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ABSTRACT With increasing decarbonisation and accessibility to our energy systems and markets, there is a need to understand and optimise the value proposition for different stakeholders. Game-theoretic models represent a promising approach to study strategic interactions between self-interested private energy system investors. In this work, we design and evaluate a game-theoretic framework to study strategic interactions between profit-maximising players that invest in network, renewable generation and storage capacity. Specifically, we study the case where grid capacity is developed by a private renewable investor, but line access is shared with competing renewable and storage investors, thus enabling them to export energy and access electricity demand. We model the problem of deducing how much capacity each player should build as a non-cooperative Stackelberg-Cournot game between a dominant player (leader) who builds the power line and renewable generation capacity, and local renewable and storage investors (multiple followers), who react to the installation of the line by increasing their own capacity. Using data-driven analysis and simulations, we developed an empirical search method for estimating the game equilibrium, where the payoffs capture the realistic operation and control of the energy system under study. A practical demonstration of the underlying methodology is shown for a real-world grid reinforcement project in the UK. The methodology provides a realistic mechanism to analyse investor decision-making and investigate feasible tariffs that encourage distributed renewable investment, with sharing of grid access.

INDEX TERMS Data analysis, energy storage, game theory, leader-follower game, network upgrade, optimisation, renewable generation, Stackelberg-Cournot game.

NOMENCLATURE

Subscripts

i	for players or agents
max	maximum value
min	minimum value
t	time interval/data sample

Roman symbols

A	mainland location of remote demand
B	renewable location of local demand
BR	best response
c_G	generation cost
c_S	storage cost
c_T	transmission cost
D	power demand at location A (remote demand)
d	power demand at location B (local demand)
E_C	energy curtailed
E_D	remote energy demand
E_d	local energy demand
$E_{D_{oth}}$	remote demand served by the main grid or other sources

$E_{d_{oth}}$	local demand served by the main grid or other sources
E_G	expected energy produced without curtailment
E_S	energy stored in storage
E_{S_D}	remote demand served by storage
E_{S_d}	local demand served by storage
$E_{S_{in}}$	energy input to storage
I_G	capital cost (initial investment) for generation capacity
I_T	capital cost (initial investment) for transmission capacity
M_G	operation and maintenance cost for generation capacity
M_T	operation and maintenance cost for transmission capacity
N	total number of players
n	number of samples
P_C	power curtailed
P_{ch}	charging power
P_D	remote power demand
P_d	local power demand
$P_{D_{oth}}$	remote power demand served by other sources
$P_{d_{oth}}$	local power demand served by other sources
P_{dch}	discharging power
P_G	expected power produced without curtailment
p_G	generation tariff price
P_L	generic demand profile
$P_{L_{h,s}}$	power demand distribution per hour and season
P_N	rated power of generation capacity
P_{S_D}	remote power demand served by storage
P_{S_d}	local power demand served by storage
$P_{S_{in}}$	power input to storage
r	power charged/discharged to/from storage
RD	residual demand
S	storage capacity
s_{dch}	self-discharge rate of energy storage
SOC	state of charge
T	transmission line capacity
t_{burn}	burn-in period for Gibbs sampling
w	wind speed
x_G	normalised power generation
z_h	wind turbine hub height

Greek symbols

α	Sigmoid function parameter
β	Sigmoid function parameter
δ	increment capacity in strategy space
δt	duration between two consecutive time intervals
η	efficiency of storage system
η_{ch}	charging efficiency of storage system
η_{dch}	discharging efficiency of storage system
Π	profit or payoff
σ	strategy

I. INTRODUCTION

Energy systems are becoming increasingly complex in response to the need to support decarbonisation of energy, with increasing integration of multi-vector energy services and adoption of variable renewable energy sources (RES). Furthermore, there is the additional challenge of decarbonisation of interdependent services, such as transport. As well as increasing decentralisation of energy systems, to support tailoring systems to specific community needs, such as enabling more active participation in energy choices, increasing self-consumption and resilience, there is also progressive deregulation of energy markets to encourage more equitable access and market competition, which has gradually led to the introduction of multiple self-driven actors shaping the operation and management of energy systems. Optimal and efficient operation of energy systems relies increasingly on autonomous and often competitive actions performed by multiple actors that are often driven by their own utility-maximising objectives, hence, studying of strategic interactions is to an increasing extent important. Game theory is a mathematical framework for studying conflict and cooperation between rational agents, where an agent represents a smart entity, such as an investor or a computer program that acts on behalf of an entity, and is able to initiate actions, including optimisation, cooperation and negotiation, in order to perform a task or achieve an objective. Therefore, game-theoretic models represent a promising approach to analyse strategic interplay between self-driven and self-interested energy system stakeholders. Prominent examples of research works from the literature that showcase the use of agents and game theory can be found in [2]–[6].

In this work, we study a power network investment problem through the lens of game theory. Profit-maximising agents or players invest in network, renewable generation and storage capacity. Specifically, we study the case where grid infrastructure is developed by a private renewable investor, but line access is shared with rival players investing in renewable and storage capacity, which enables them to export energy and access additional electricity demand. We consider settings of privately developed and shared grid access.

Traditionally, grid projects are performed by transmission and distribution network operators and grid access is allocated via market-based rules or specified in commercial arrangements between generating units and network operators. However, attracting private investment [7], possibly from RES developers [8], is a critical enabler to reduce costs associated with network upgrades required for RES integration and further decarbonisation. In the EU alone, the sustainable transition is estimated to require an investment of €200b per year for generation, network and energy efficiency development [9], while $2t in electricity network upgrades will be required by 2030 in the US [10]. Energy policy makers and network operators face a key knowledge gap on how to incentivise private investment and shared grid access market models and have trialed several

strategies to stimulate the market aiming at the reduction of connection costs and times. To address these challenges, they are considering novel commercial arrangements, such as in the Orkney islands Active Network Management (ANM) scheme (https://www.ssen.co.uk/ANMGeneration/) and the 'Accelerated Renewable Connections' (ARC) project [11] in Scotland. The latter investigated commercial techniques to couple demand with distributed generation. These techniques include physical private wire systems (connection between the generation and demand site is achieved through a privately-owned grid connected to the main distribution network through a single connection point), virtual private wire systems (connection between generation and flexible demand is achieved through the main distribution network but operation is managed behind a point of constraint), demand aggregators and local markets.

A relevant business model to make line investment profitable to private investors is the concept of a *'common access'* private line, built or supported by funds from a RES investor, but with shared access. Traditionally, a RES generator builds and pays for a 'single access' line (or reinforcement) with a capacity large enough to meet his own needs. Instead, under 'common access', RES investors are incentivised to build larger capacity lines and may grant access to third-party rival investors, by setting a payment mechanism for third-party line usage. This would create a new revenue stream for RES investors, especially as other renewable financial incentives are being removed. However, the interplay of investors competing to get access to demand through the shared transmission line raises strategic behaviour issues, because decisions on the level of investment and capacities installed depend on opponent actions. Research works that studied strategic issues raised by private grid capacity investments can be found in [12]–[16]. Often, preferred locations for RES project development are remote areas where primary renewable resources are favourable and yield high returns for investors. For example, in the UK such areas are windy islands or coastal areas, where wind resources are remarkable, albeit usually local grid capacity cannot accommodate more renewables. Connection of variable and intermittent RES generation, such as wind power, has led to multiple challenges with regards to the safe operation and management of power systems [17], [18]. An important consequence is excess RES generation *curtailment*, i.e., discarding excess renewable energy in order to guarantee safe operation of the power system, which entails high costs for RES developers and energy end-users. Typically, curtailment happens when existing grid infrastructure is insufficient and energy generated by RES cannot be transported to areas of high demand [19]–[21], therefore dealing with this issue is of great importance to support RES investment. Although, short and middle-term solutions to RES integration exist, such as smart grid techniques and energy storage, arguably, the long-term solution is grid reinforcement, usually publicly funded, but, potentially also supported by private means.

Motivated by the specific techno-economic challenges experienced in developing smart local energy systems (SLES) in remote and distributed communities, this paper considers a two-location model, where excess RES generation and demand are not co-located, and where a private RES investor builds and shares access of a power line with local investors of renewable energy and storage, who are charged for using the line. This leads to a noncooperative *Stackelberg-Cournot game* between the line investor (single-leader), who builds the line and RES generation capacity, and rival investors of local generation and storage (multi-followers), who react to the installation of the line by increasing their own capacity built. A Stackelberg game is a mathematical framework for analysis of sequential hierarchical problems where a dominant player (leader) plays first and followers play after observing the leader's strategy. In contrast, a Cournot game describes problems where independent rival investors decide simultaneously their output quantities. The analysis of this game and computation of optimal and profit-maximising capacity decisions present significant challenges.

This paper builds on the authors prior research in several key ways. Andoni *et al.* [22] presents an analytical solution to a simpler stylised deterministic model of a Stackelberg game between a line investor and local generators. In subsequent work, Andoni *et al.* [23] develops a formal model that considers stochastic RES resources and demand. This work shows how, due to large players' action sets, a closed-form solution of the game is not feasible. However, both these works do not consider the crucial issue of *storage*, which not only introduces additional non-linearities, time dependencies and complexity in the optimisation, but leads to a secondary Cournot game between local investors (local generators and storage). Building on previous results, this paper presents a game-theoretic decision framework, which includes energy storage players and where payoff enumeration is derived not by simplified explicit mathematical functions, but from large-scale, data-driven analysis and simulation that capture realistic operation and control of the energy system under study. In detail, the main contributions of the work to the state of the art are:

- *First*, we provide a formulation of a single-leader-multi-follower game that studies strategic decisions on capacity investments in energy systems, where network, renewable and storage capacity are privately developed and grid access is shared.

- *Second*, we develop an empirical solution for equilibrium finding where players' payoffs are directly computed from large-scale datasets of historical observations and simulations that realistically represent operation and control in energy systems. This is an important contribution as according to the literature survey, very few works deal with techniques for solving bi-level optimisation and single-leader-multi-follower games [24].

- *Third*, we demonstrate the underlying methodology to a practical application based on the UK Kintyre-Hunterston grid project [25]. Based on project figures, we perform a

sensitivity analysis on financial parameters that affect the game equilibrium and we determine the value of adding energy storage to the mix of investors.

In summary, our research provides a decision support tool for investors and energy policy makers that seek to incentivise private grid capacity projects and explore tariff charges for energy trading between stakeholders that achieve profitable investment equilibria.

The remainder of the paper is structured as follows: Section II discusses relevant literature on network upgrades, game-theoretic modelling and leader-follower games used in this work, Section III presents the game formulation and methodology for finding equilibrium, Section IV demonstrates the underlying methodology in a real-world application, Section V presents the sensitivity analysis and parametric exploration results, Section VI discusses the main findings and Section VII concludes and elaborates on future work.

II. RELATED WORK

Network upgrades may refer to reinforcement of existing grid infrastructure or installation of new power lines, and are usually accomplished by transmission or distribution network operators. In recent years, adoption of RES technologies has also introduced private or merchant investors in grid capacity projects, leading to different and often conflicting investor objectives depending on their type [26]. Network operators, which are typically regulated monopolies, aim to maximise social welfare, while private investors are driven by self-interest and profit maximisation [16].

The effects of grid capacity increase, include financial and technical benefits, such as the mitigation of congestion, reduction of energy curtailment and increasing competition in electricity markets. With interconnection, generating units can increase their efficiency [27] and uncertainty in generation and demand forecasting can be reduced, leading to cost reduction, lower electricity prices and enhancement of energy security. Reliability of the power system can also improve as the probabilities of unserved load or generation breakdown decrease with interconnections. Future uncertainties such as varying fuel or carbon prices, costs for transmission or installation of renewable capacity, demand growth and potential changes in markets and regulation [28] can add significant value to grid capacity projects [29], on top of strategic, environmental and social value [30].

Utility companies employ long-term load forecasting and generation capacity planning to efficiently design network upgrades with the aim to minimise financial and environmental costs, while ensuring safe and reliable operation. Decisions are typically supported by simulation analyses and load-flow models [28]. In parallel, research has focused in game-theoretic models, as a tool to demonstrate and simulate deregulated energy markets and strategic interplay between private investors [14]. Game theory is a promising method to assess market behaviour of energy players in a more realistic way [31]. An overview of game-theoretic modelling

is presented in [32] including Stackelberg [33] and Cournot game [34] formulations used in this work.

Techniques based on Stackelberg games have been utilised in several network upgrade modelling works. In detail, these works focused on designing network upgrades with social welfare [27], modelling networks with locational marginal prices [35] or focused on uncertainties instigated by the progression of variable renewables [36]. Stackelberg game analysis has also been used to study energy trading between microgrids [37], [38], while other works pursued objectives that minimised power line losses [39] or generation and transmission costs [40]. More recent works on the renewable energy domain, use Stackelberg game analysis to model peer-to-peer energy trading [41]–[43] and demand response [44], [45]. Lu *et al.* (2019) modelled residential demand response as a Nash-Stackelberg game between two leaders and two followers [46]. Bruninx et al (2020) utilised Stackelberg game formulations to model the interplay between residential consumers and aggregators providing demand response and flexibility services in the day-ahead electricity market [47]. Feng *et al.* (2020) model the interaction between an electricity utility company and an aggregator as a leader-follower game and compute via bilevel optimisation optimal price signals for demand response [48]. Wei *et al.* (2017) studied trading between distributed generators and consumers as a multi-leader-multi-follower game [49]. Ma *et al.* (2018) modelled interactions between an energy provider and energy consumers with demand response potential as a hierarchical leader-follower game [50]. Li *et al.* (2018) [51] focused on optimal bidding strategies for forward and spot electricity markets for demand response and renewable generators characterised under a Stackelberg-Cournot-Nash game. The majority of the aforementioned works followed an analytical approach for solving the game equilibrium, often based on well-defined (smooth) cost functions. Instead, our work determines the equilibrium results by virtue of a data-driven simulation analysis, which considers realistic energy flows derived by control management schemes of the energy system under consideration, hence leading to more operationally compliant and robust model refinement.

Game-theoretic modelling and Stackelberg games have also been used by several researchers to model optimal capacity investment decisions, similar to the approach undertaken in this work. For example, Huang *et al.* (2020) studied storage capacity investment undertaken by a profit-maximising merchant and a regulated social-welfare-maximising entity under Stackelberg competition [52]. Zheng *et al.* (2015) [6] propose a novel, crowdsourced funding model for renewable energy investments, using a sequential game-theoretic approach. Xu *et al.* (2020) determine the optimal sizing of residential PV panels, while considering uncertainty parameters [53], while work presented in [54] studied the development of electric vehicles infrastructure. Similarly, the work presented in this paper aims to model optimal investment capacity decisions, but we consider in one model renewable generation, energy storage and grid capacity investments.
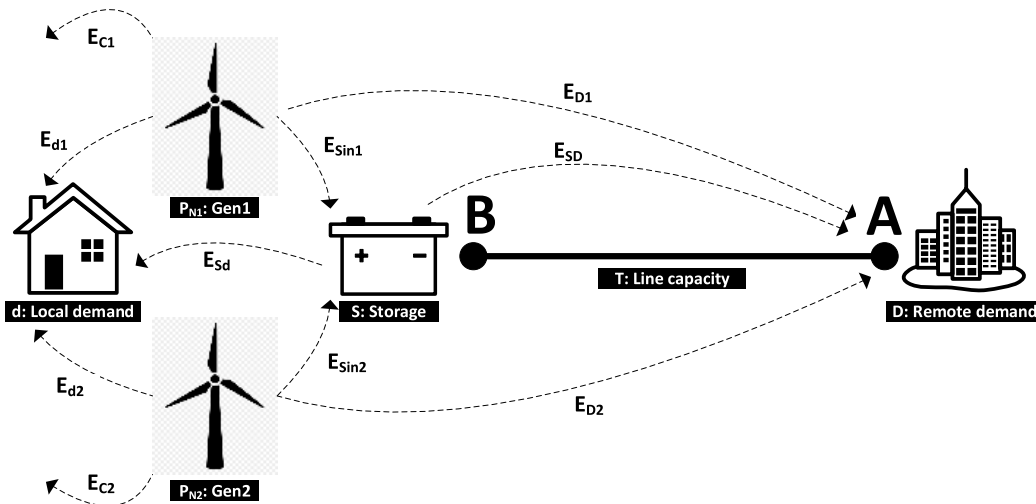
FIGURE 1. Simplified model schematic of the three-player, two-location game: Remote demand D is located at A, local demand d, RES generation capacity P_{N_1} built by the line investor, P_{N_2} by local generators and storage S are located at B, while locations A and B are connected with a power line of T capacity built by the line investor.

Several network upgrade works considered optimisation including bilevel optimisation [16], [36], stochastic optimisation [13], [30], three-level optimisation with social welfare [26], [27] and a three-stage Nash game that aimed to model grid capacity expansion at a national level [55]. Other works focused on the expansion of the distribution grid and incorporated multi-objective optimisation [56], [57], multi-level optimisation [58] and Monte-Carlo simulations [59]. Research works [60], [61] studied distributed generation planning with game theory and probabilistic modelling, respectively. Some works considered an integrated model for both generation and transmission capacity [13], [62], while [15] studied how generation capacity decisions impact network planning.

Several works focused on network upgrades undertaken by private investors. Work in [63] introduced incentives for private transmission investment, while [16] compared investments undertaken by network operators or private investors and showed that social welfare is maximised under the operator, as private investors benefit from withholding capacity to increase congestion rents. Coalitional game theory was used in [12] to coordinate private grid investments and it was found that if the process is not controlled by the regulator or network operator, there is a risk of decreasing the power system efficiency due to an increase in transmission losses.

Several early works considered transmission congestion management protocols for independent system operators [64] and compared transmission costs in a pool model based on nodal pricing and a game-theoretic bilateral model [65]. Other works considered network planning at congested areas, such as in [66], where a two-node network was studied and players' market behaviours and equilibrium prices were analysed. Paper [67] developed a methodology for designing dynamic tariffs imposed to generators participating in demand response schemes. These tariffs considered network costs, computed as a trade-off between congestion and

investment costs. Our work uses non-cooperative game theory to study strategic interactions of investors in constrained areas of the grid, where a network upgrade is required. Moreover, the work presented in this paper focuses on the estimation of optimal transmission, generation and storage capacity investment decisions, as opposed to deriving operational, market strategies or price formulation in areas where curtailment occurs.

In summary, prior works have predominantly focused on optimum investment planning of renewable generation or network capacity. The area of modelling joint investment decisions that are undertaken by private investors is underrepresented. In particular, to our knowledge, few works consider private network investment with shared grid access to rival investors and follow a game-theoretic approach to study the underlying problem.

III. MODEL AND METHODOLOGY

In this section, we present the game for determination of optimal capacity decisions and the methodology developed for finding equilibrium.

A. GAME FORMULATION

To investigate the problem of deducing optimal decisions on capacity investments undertaken by private investors, we consider a mathematical framework based on game theory. Formally, the *game* consists of a set of $N = 3$ *players*. Each player i is characterised by a set of actions or *strategies* Σ_i and a specification of their utilities or *payoffs* $\Pi_i\left((\Sigma_i)^3 \rightarrow \mathbb{R}\right)$, which is a mapping from the combination of strategies Σ for all players to the set of real numbers. Players act in a two-node energy system shown in Fig. 1. In detail:

- **Location A** is a net consumer node, with a net power demand D and net energy demand E_D. Meeting the demand at A in practice requires energy produced or imported from other locations. In addition, generation

TABLE 1. Summary of players acting in the game, their strategies and relevant financial parameters.

Players	Strategies	Financial parameters
Player 1: Line investor (leader)	P_{N_1}: Renewable generation capacity at B T: Transmission line linking A-B	c_{G_1}: generation cost c_T: transmission cost p_G: revenue earned when serving demand p_T: revenue earned from line usage p_S: revenue earned when selling to storage
Player 2: Local generators (follower)	P_{N_2}: Renewable generation capacity at B	c_{G_2}: generation cost p_G: revenue earned when serving demand p_T: tariff paid for line usage p_S: revenue earned when selling to storage
Player 3: Energy storage (follower)	S: Energy storage capacity at B	c_S: storage cost p_G: revenue earned when serving demand p_T: tariff paid for line usage p_S: tariff paid when buying from renewables

may also be present at A, in which case the net demand D would be equal to the demand minus generation at A. Location A can be thought of as an area of high demand with significant population density and industry, which can be supplied by generation at location B.

- **Location B** is a net energy producer node with local demand d that is significantly lower than remote demand D at A. Location B can be thought of as a region with considerable potential for RES development. Due to substantial gains and advantageous RES resources, B is favoured among RES investors, especially if a connection line is built to give access to remote demand.

In addition, we consider three investors or type of players distinguished by the admissible capacity investment decision (strategy) that falls under their control (brief summary of players and actions is shown in Table 1):

- *Player 1* is a private investor willing to install:
  (i) a *new power line* with transmission capacity T linking locations A-B with a per-unit transmission cost of $c_T = (I_T + M_T)/T$, where I_T represents the costs related to building the power line or initial investment, and M_T the costs related to operation and maintenance of the line over a larger time horizon. (ii) *renewable generation capacity* of P_{N_1} at B with a per-unit generation cost of $c_{G_1} = (I_{G_1} + M_{G_1})/E_{G_1}$, where I_{G_1} is the initial investment required to build the RES generation capacity, M_{G_1} the costs related to operation and maintenance, and E_{G_1} the generation or energy that can be produced by P_{N_1} over a large time horizon. RES production can supply demand at locations A and B and earn a revenue of p_G in £/MWh of loads supplied.
  Here, we refer to player 1 as the **'line investor'** with a strategy $\sigma_1 = \langle P_{N_1}, T \rangle$, who can be thought of as a private or utility company that has the funds and know-how to install new network capacity in the form of the line. Crucially, T provides access to demand at location A, not only to the line investor, but also to other investors who must pay an agreed charge for transmission denoted with p_T in £/MWh of energy transported through the line.
- *Player 2* represents all local renewable capacity investors at B other than the line investor, who are

willing to install *generation capacity* of P_{N_2} with a generation capacity cost of c_{G_2}. This second player with a strategy $\sigma_2 = \langle P_{N_2} \rangle$, also called **'local generators'**, can be thought of as investors from the local community at B, who do not have the technical/financial capacity to build a line, but may have access to cheaper land, might get an easier community approval to build RES capacity, hence may have a lower generation capacity cost c_{G_2}. Individual behaviour of local RES investors is considered negligible and too small to have a considerable effect in the emerging game. Instead, local generators' actions come from a single entity with a cost c_{G_2}, which is the weighted average cost of all local generators. Aggregate actions of local generators are capable to exert market power and have an impact on the outcome of the game.

- *Player 3* is a private investor who installs energy storage of capacity S at B with a per storage unit cost of $c_S = (I_S + M_S)/S$, where I_S represents the initial capacity investment and M_S the operation and maintenance costs. Storage purchases excess energy from the RES producers at B at a price of p_S in £/MWh of energy traded, and discharges when there is a shortage of RES supply. Player 3 with a strategy of $\sigma_3 = \langle S \rangle$ is called the **'storage investor'** and makes use of RES production that would otherwise have been curtailed.

All players follow a rational economic behaviour model and act accordingly to maximise their payoffs. From a strategic interaction viewpoint, the line investor's position in the marketplace dominates other players, as only they can build the line. However, access to the privately built line is also granted to rival investors at B, who can use the line to transport their energy production and supply remote demand at location A. In other words, the line provides 'common access' to all investors located at B, thereby provides an opportunity for rival local investors (generators and energy storage at B) to increase their capacity and the energy exported. In turn, capacity installed by local investors affects the line investor, as all players compete to serve the electricity demand. This leads to a *Stackelberg-Cournot game* formed between the line investor (leader) and local investors (followers), who in turn play a Cournot game between them by determining

simultaneously how much capacity to install. A Stackelberg game is a mathematical framework for analysis of sequential hierarchical problems where a dominant player (leader) plays first and followers play after observing the leader's strategy. In contrast, a Cournot game describes problems where independent rival investors decide simultaneously their output quantities, here RES generation capacity built by local generators and storage capacity by the storage investor. Overall, in the game formed, capacity investment quantities are the strategic variables that need to be determined by players, so that their profits are maximised. The solution to the game is formalised in the following section.

B. STACKELBERG-COURNOT GAME EQUILIBRIUM SOLUTION

Computing the equilibrium of the Stackelberg-Cournot game amounts to solving the following bilevel programming problem with the leader acting in the first level and followers acting in second level:

$$\max_{(\sigma_1, \sigma_2, \sigma_3) \in \Sigma_1 \times \Sigma_2 \times \Sigma_3} \Pi_1 \tag{1}$$

$$\text{subject to: } \sigma_2 \in \arg\max_{\sigma_2 \in \Sigma_2} \Pi_2 \tag{1a}$$

$$\sigma_3 \in \arg\max_{\sigma_3 \in \Sigma_3} \Pi_3 \tag{1b}$$

where Π_i is the payoff of player i. Constraints (1a)-(1b) applied in the second-level call for a pair (σ_2, σ_3) of local investors' (followers') strategies for each strategy σ_1 played by the line investor. These strategies are the solutions that achieve the Cournot equilibrium between local investors, induced by the strategy chosen by the line investor (leader). The Cournot equilibrium is also a Nash equilibrium, as local investors have no incentive to deviate from their selected strategy, if their opponent action remains unchanged. For each σ_1, σ_2 maximises the payoff Π_2 over the subset σ_3 of the third player strategies. Respectively, for each σ_1, σ_3 maximises the payoff Π_3 over the subset σ_2 of the second player. Subject to these constraints, the first level calls for a triple $(\sigma_1, \sigma_2, \sigma_3)$ that maximises the leader's payoff function.

Solving the single-leader-multi-follower optimisation problem stated in Eq. (1) can be challenging. Moreover, as stated by Basilico et al. [24], leader-follower games with multiple followers have not been extensively investigated in the literature, and in addition not many computationally affordable techniques are available for the analysis task. A well-known technique for solving the problem is based on *backward induction*, i.e., a solution is first derived for the second-level problem by taking as a given the strategy of the leader (process is repeated for all possible σ_1), then the leader selects the strategy that maximises her payoff/profit. Assuming that payoffs can be expressed as multivariate functions of players' strategies, then the game equilibrium can be found analytically by the partial derivatives of players' payoffs and backward induction. The feasibility of the analytical solution however relies on the ability to express payoffs as functions of players' strategies and the computation of

the partial derivatives. A closer look at payoffs or profits functions (as shown below), shows that this is not feasible in practical, large-scale games such as ours, hence we estimate payoffs by a data-driven approach. Simplification of payoff functions was not considered due to the complexity of the power system operation and because it would not lead to a realistic representation of the system under study.

C. PAYOFF FUNCTIONS

Player's payoffs are functions of revenues earned by energy trades and costs that each investor incurs. Revenue is generated from demand supply and rewarded with a price of p_G. Local demand served by the i-th RES producer is denoted as E_{d_i}, and remote demand as E_{D_i}, where $i = 1$ is the line investor and $i = 2$ the local generators. Similarly, demand served by storage is denoted as E_{S_d} and E_{S_D}, for local and remote demand, respectively. RES producers also generate income when trading excess energy with storage $E_{S_{in,i}}$ (energy in storage from RES producer i) with a tariff of p_S. The line investor earns revenue from local investors using the power line with a charge of p_T. Finally, players incur the costs for installation of additional capacity c_{G_1}, c_T, c_{G_2} and c_S:

$$\Pi_1 = \overbrace{\underbrace{(E_{d_1} + E_{D_1})p_G}_{\text{demand}} + \underbrace{(E_{D_2} + E_{S_D})p_T}_{\text{transmission}} + \underbrace{E_{S_{in,1}}p_S}_{\text{storage}}}^{\text{revenue}}$$
$$- \overbrace{\underbrace{c_{G_1}E_{G_1}}_{\text{gen. capacity}} - \underbrace{c_T T}_{\text{trans. capacity}}}^{\text{cost}} \tag{2}$$

$$\Pi_2 = \overbrace{\underbrace{(E_{d_2} + E_{D_2})p_G}_{\text{demand}} + \underbrace{E_{S_{in,2}}p_S}_{\text{storage}}}^{\text{revenue}} - \overbrace{\underbrace{c_{G_2}E_{G_2}}_{\text{gen.capacity}} - \underbrace{E_{D_2}p_T}_{\text{trans. capacity}}}^{\text{cost}} \tag{3}$$

$$\Pi_3 = \overbrace{\underbrace{(E_{S_d} + E_{S_D})p_G}_{\text{demand}}}^{\text{revenue}}$$
$$- \overbrace{\underbrace{(E_{S_{in,1}} + E_{S_{in,2}})p_S}_{\text{RES trading}} - \underbrace{E_{S_D}p_T}_{\text{transmission}} - \underbrace{c_S S}_{\text{stor. capacity}}}^{\text{cost}} \tag{4}$$

As shown by Eqs. (2)-(4), players' payoffs are functions of energy quantities and financial parameters over the time horizon of the study, which can be equal to the project lifetime e.g. 20 years or normalised over the course of a year. For energy quantities or *energy flows*, shown in Fig. 1, the following constraints must hold:

$$E_{G_i} = E_{d_i} + E_{D_i} + E_{S_{in,i}} + E_{C_i} \tag{5}$$

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

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

where E_{C_i} is player's i curtailed energy, $E_{d_{oth}}$ and $E_{D_{oth}}$ the local and remote demand supplied from other sources in the grid, E_{G_i} player's i RES generation supplying local

demand E_{d_i} at B or remote demand E_{D_i} at A via the line. Moreover, RES generators can sell excess energy to storage, as indicated by $E_{S_{in,i}}$. Any further RES production that exceeds the demand needs and cannot be stored is curtailed E_{C_i} (Eq. (5)). Local demand (Eq. (6)) and remote demand (Eq. (7)) are served by the RES generators, storage or other sources in the grid.

In realistic settings, energy quantities in Eqs. (2-7) also depend on complex rules associated with the power system operation, such as priority of dispatch, energy trading arrangements between players and market access rules. For this reason, it is difficult to determine realistic representations or mathematical formulas for determination of the energy quantities and payoff estimation that could be used for solving the game equilibrium analytically. Other challenges for finding equilibrium analytically are related to non-linearities introduced by the energy storage system and large action sets of players. For these reasons, we follow an empirical and data-driven approach that utilises time-series simulation analysis to compute the energy flows. The methodology developed to identify the Stackelberg-Cournot game equilibrium is described in Section D.

D. EMPIRICAL SOLUTION OF STACKELBERG-COURNOT GAME

The empirical solution approach proposed in this paper follows the steps below:

- *Step 1*: We select to analyse the game for a suitable time horizon H (e.g. one year or larger time horizon of 20 years) and an appropriate time step t used for the time series analysis.
- *Step 2*: We utilise real renewable production and demand data to inform modelling of the energy system under study.
- *Step 3*: Financial parameters are determined for the estimation of payoffs under different scenarios.
- *Step 4*: We discretise the players action sets, i.e., we determine the incremental step that capacities can increase, as in real-world settings investment options are often discrete and non-continuous. This means that instead of solving the general game we instead solve a reduced game where players have a finite number of actions they can play.
- *Step 5*: For every t and discretised action set of players $\langle P_{N_1}, T, P_{N_2}, S \rangle$ we compute the power and energy flows, according to the RES production, demand and control rules that apply to the energy system under study, as shown in Fig. 2.
- *Step 6*: Energy quantities for each t are aggregated for the whole time period H.
- *Step 7*: Payoffs or profit functions are computed from energy quantities determined in Step 5.
- *Step 8*: An algorithmic approach is developed to find the Stackelberg-Cournot game equilibrium based on backward induction and optimisation techniques, as shown in Algorithm 1.
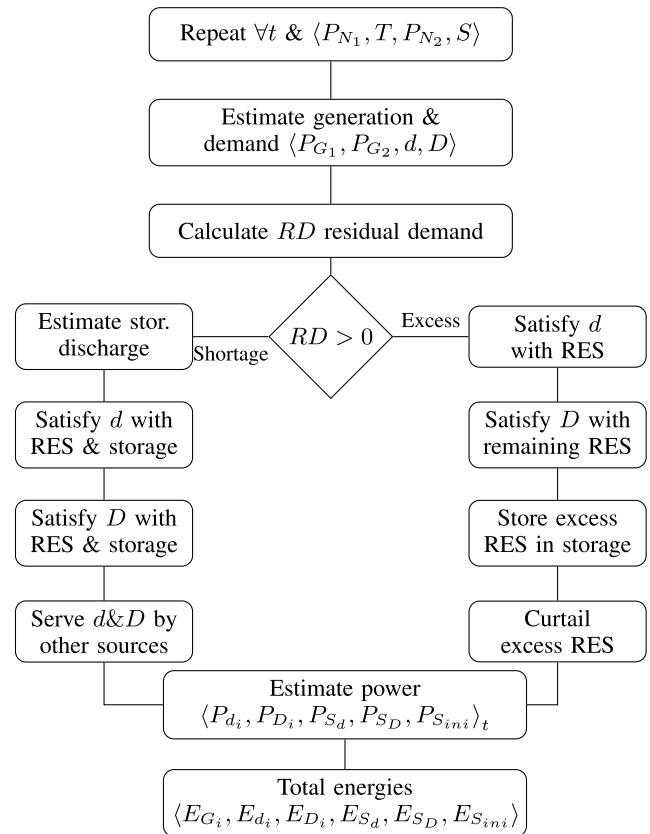

FIGURE 2. Control algorithm for estimation of aggregate energy flows (Steps 1-6).

The control rationale and rules for priority of dispatch from Steps 1-6 are summarised in Fig. 2. For every t and combination of players' strategies $\langle P_{N_1}, T, P_{N_2}, S \rangle$, RES production and demand are computed from primary renewable resource and demand data. Next, we estimate the residual demand RD, which is equal to the total demand minus potential RES production. When there is a *shortage of RES supply*, the control algorithm estimates how much energy should be discharged from storage, while honouring technical constraints of the energy storage system. RES production is firstly used to serve local demand d and then any remaining energy is used to serve the remote demand D at A. This is justified by the energy losses reduction, but also by the fact that transmission charges are imposed to local investors. Any deficit is covered by other sources in the system or imports from the main grid. When there is an *oversupply of RES production*, RES generators serve and share the demand equally. Excess energy from renewables is stored, as long as the storage capacity and technical constrained are not violated. Finally, any excess generation that cannot be stored is curtailed. This provides a methodology to estimate power quantities for every t. Energy quantities are then computed as the summation of power quantities over a larger time horizon (Step 6).

Next, energy quantities computed at Step 6 are plugged into Eqs.(2-4) to estimate the players' payoffs. From this, we develop an algorithmic approach to estimate the equilibrium of the single-leader-multi-follower game. The search
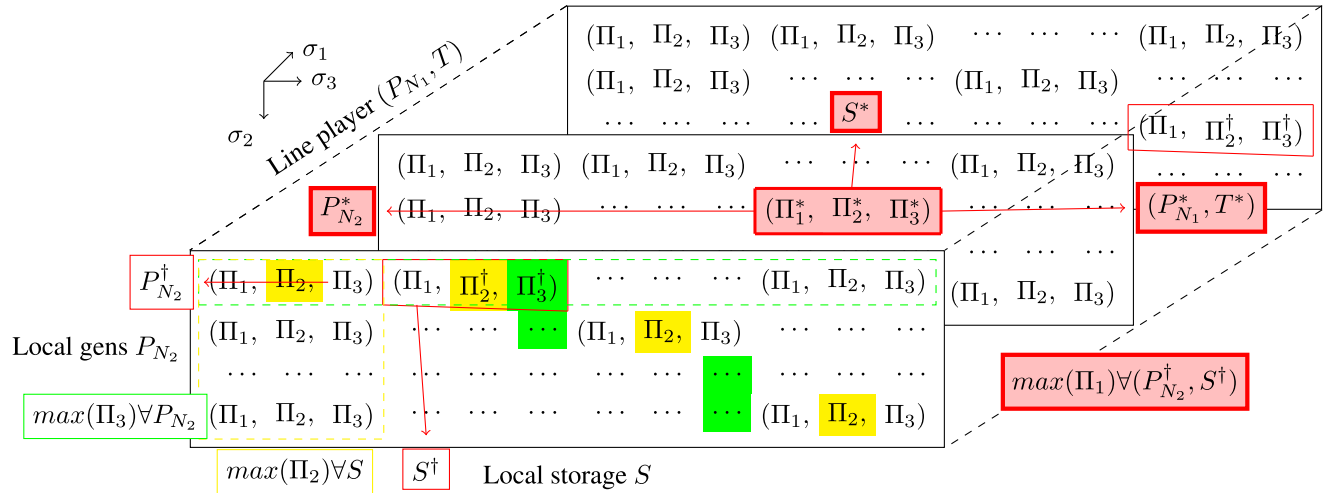
FIGURE 3. Stackelberg-Cournot game equilibrium estimation: each plane illustrates the Cournot game played by local investors for any given action of the leader, who then selects the profit-maximising Cournot game equilibrium.

Algorithm 1 Empirical Game Equilibrium Solution

1: **for each** $\langle P_{N_1}, T \rangle \in \langle\{0, \ldots, P_{Nmax}\}, \{0, \ldots, T_{max}\}\rangle$ **do**

2:      **for each** $S \in \{0, \ldots, S_{max}\}$ **do**

3:          $\Pi_2^{\#} \leftarrow \max\limits_{P_{N_2}} \Pi_2(P_{N_2}, S)|_{\langle P_{N_1}, T\rangle}$

4:          $P_{N_2}{}^{\#} \leftarrow \arg\max\limits_{P_{N_2}} \Pi_2(P_{N_2}, S)|_{\langle P_{N_1}, T\rangle}$

5:      **end**

6:      $BR_2 \leftarrow (P_{N_2}^{\#}, S)|_{\langle P_{N_1}, T\rangle}$ ▷ Player 2 BR

7:      **for each** $P_{N_2} \in \{0, \ldots, P_{Nmax}\}$ **do**

8:          $\Pi_3^{\#} \leftarrow \max\limits_{S} \Pi_3(P_{N_2}, S)|_{\langle P_{N_1}, T\rangle}$

9:          $S^{\#} \leftarrow \arg\max\limits_{S} \Pi_3(P_{N_2}, S)|_{\langle P_{N_1}, T\rangle}$

10:      **end**

11:      $BR_3 \leftarrow (P_{N_2}, S^{\#})|_{\langle P_{N_1}, T\rangle}$ ▷ Player 3 BR

12:      $(P_{N_2}, S)^{\dagger} = intersect(BR_2, BR_3)|_{\langle P_{N_1}, T\rangle}$ ▷
Cournot game equilibrium

13: **end**

14: $\Pi_1^{*} \leftarrow \max\limits_{(P_{N_1}, T)} \Pi_1(P_{N_1}, T, (P_{N_2}, S)^{\dagger})$ ▷ Player 1 BR

15: $(P_{N_1}, T, P_{N_2}, S)^{*} \leftarrow \arg\max\limits_{(P_{N_1}, T)} \Pi_1(P_{N_1}, T, (P_{N_2}, S)^{\dagger})$ ▷
Stackelberg-Cournot game equilibrium

16: **return** $\langle \Pi_1^{*}, \Pi_2^{*}, \Pi_3^{*}, P_{N_1}^{*}, T^{*}, P_{N_2}^{*}, S^{*} \rangle$

---

for equilibrium is summarised in Alg. 1 and illustrated in a polymatrix (normal form) in Fig. 3. The σ_1 axis represents the strategy played by the line investor $\langle P_{N_1}, T \rangle$ (the two-dimensional action set is collapsed into one-dimensional vector of combined strategies), σ_2 the strategy played by local generators $\langle P_{N_2} \rangle$ and σ_3 the strategy of the storage investor $\langle S \rangle$. The approach is an approximation of the analytical solution of the game discussed in Section III-B and is based on backward induction. First, for every strategy

$\sigma_1 = \langle P_{N_1}, T \rangle$ of the leader, the Cournot game equilibrium between local generators and storage is computed as the intersection of local investors' best responses (a Cournot game exists for every given σ_1, i.e., every $\langle \sigma_2, \sigma_3 \rangle$ plane formed; three planes are shown in Fig. 3). The best response of local generators for strategy choice S of the storage investor is denoted as $P_{N_2}{}^{\#}$, i.e., the RES generation capacity they need to install so that Π_2 is maximised (see Alg. 1). For the first plane in Fig. 3, this is highlighted in yellow and corresponds to finding the maximum Π_2 for each S column (for clarity the first column is shown in yellow dashed line). Respectively, the best response of storage for strategy choice P_{N_2} of local generators is denoted as $S^{\#}$, i.e., the storage capacity they needs to be install for Π_3 to be maximised (see Alg. 1). For the first plane in Fig. 3, this is highlighted in green and corresponds to finding the maximum Π_3 for each P_{N_2} row (for clarity the first row is shown in green dashed line). The Cournot game equilibrium is given by the intersection of best responses $(P_{N_2}, S)^{\dagger}$, i.e., the row and column location where the best responses simultaneously occur. The red arrows in the first plane in Fig. 3 point at the Cournot game equilibrium capacities found by the intersection of the followers' best responses. The process is repeated for all $\langle \sigma_2, \sigma_3 \rangle$ planes across the σ_1 axis (Cournot game equilibria). The leader chooses $(P_{N_1}^{*}, T^{*})$ strategy that maximises Π_1, leading to the determination of the Stackelberg-Cournot game equilibrium $\langle P_{N_1}^{*}, T^{*}, P_{N_2}^{*}, S^{*} \rangle$ shown in a thick red square and highlighted in pink colour. The red arrows dictate the capacities that need to be installed to achieve the Stackelberg-Cournot game equilibrium $\langle \Pi_1^{*} \Pi_2^{*}, \Pi_3^{*} \rangle$. Next, we demonstrate how the search methodology can be applied to practical settings.

IV. PRACTICAL APPLICATION OF UNDERLYING METHOD
This section demonstrates the equilibrium estimation methodology in a practical application inspired by the Kintyre-Hunterston grid reinforcement project in the UK

(see Fig. 4). To accommodate remarkable interest from renewable developers in the Kintyre peninsula located in western Scotland, a £230m network upgrade project was undertaken that led to the connection of the Kintyre, one of the richest wind regions in the UK, to the Hunterston substation located in the Scottish mainland, which enabled 150 MW of additional RES generation being connected [25] with an estimated net lifetime benefit for UK consumers of £520m [68].

FIGURE 4. Hunterston-Kintyre project map [25].

This project forms the real-world setting laid out to study the strategic decision-making game. Hunterston represents the mainland region where demand is located (Location A) and the Kintyre peninsula represents the region with favourable renewable resources (Location B). We consider a private investor (player 1 or line investor) installing wind generation capacity P_{N_1} at B and a power line linking the two regions T. As access to remote demand is established, local investors at B react to the installation of the line by constructing wind generation capacity P_{N_2} (player 2 or local generators) and storage capacity S (player 3 or storage investor). Optimal decisions on players' capacity investments correspond to the equilibrium of the Stackelberg-Cournot game, computed using real data.

A. DATA COLLECTION AND PROCESSING
To enable accurate estimation of energy quantities and players' payoffs, real measurements of wind speed and demand data were collected. Specifically, we gathered hourly mean wind speed data from two weather stations in the wider Kintyre area and from a publicly available dataset (MIDAS dataset-UK Met Office[1]), the first station with database ID of 908 representing wind resources in the location of the line investor and the second with ID 23417 representing wind resources in the area of local generators. Wind speed data consist of hourly averages over a 17-year period for which common data was available. Half-hourly UK national demand data was also collected for a 10-year period (2006-2015)[2] that data was available. National demand data was substituted with the hourly average and scaled down to generate a generic demand profile P_L. Local demand d was assumed to be

[1] https://catalogue.ceda.ac.uk/uuid/220a65615218d5c9cc9e4785a3234bd0
[2] https://www.nationalgrideso.com/balancing-data

Algorithm 2 Gibbs Sampling

1: w_1, w_2, P_L ▷ wind speed 1,2, power demand
2: n ▷ number of samples
3: t_{burn} ▷ burn-in period (samples ignored)
4: $\langle w_1^{(k)}, w_2^{(k)}, P_L^{(k)} \rangle, k \in \{1, 2, \ldots, k_{max}\}$ ▷ historic data
5: $F(w_1, w_2)$ ▷ wind distribution from data
6: $G(P_{L_{h,s}})$ ▷ demand distribution (hour-season)
7: $t \leftarrow 1$
8: $\langle w_1^{(t)}, w_2^{(t)} \rangle \leftarrow sample(w_1, w_2)$ ▷ initialise wind
9: $\langle P_L^{(t)} \rangle \leftarrow sample(P_{L_{h,s}})$ ▷ initialise demand
    $(h = 1, s = 4)$
10: **repeat**
11:     $w_1^{(t+1)} \leftarrow sample\ F(w_1 \mid_{w_2^{(t)}})$
12:     $w_2^{(t+1)} \leftarrow sample\ F(w_2 \mid_{w_1^{(t+1)}})$
13:     $P_L^{(t+1)} \leftarrow sample\ G(P_{L_{h,s}})$
14:     $t \leftarrow t + 1$
15: **until** $t > T$
16: **return** $\langle w_1^{(t)}, w_2^{(t)}, P_L^{(t)} \rangle, t \in \{t_{burn}, t_{burn} + 1, \ldots, n\}$

---

about 20% of P_L, while remote demand D at A was considered equal to the demand that can be served by the investors after the transmission line capacity T is taken into account.

B. DATA SAMPLING
While historical observations can be directly used as inputs to the simulation analysis, this does not consider uncertainty of future values of RES production and energy demand. In this section, we present a data sampling tool based on Gibbs sampling, a Markov Chain Monte Carlo (MCMC) technique [69]. The importance of the tool developed is twofold, first it enables the capability to draw multiple data samples and hence generate multiple future scenarios that can be used for quantifying uncertainty, and second it helps dealing with data quality issues, such as data gaps or missing data. Overall, the tool reinforces the investors' confidence with regards to taking optimised capacity decisions.

Gibbs sampling uses the conditional probability distributions as proposal distributions with acceptance probability equal to 1 [70] and can be used to generate data observations that are interdependent and form a Markov chain (MC). In our case, the method enables sampling of cross-correlated wind speed and demand data $\langle w_1, w_2, P_L \rangle$ for use in the simulation analysis. With Gibbs sampling, the obtained Markov Chain converges to the real distribution, it is ergodic, i.e., all possible states of the MC are reachable with non-zero probability and are independent of the starting state, for a sufficiently large number of samples [70]. Moreover, the method provides a computationally efficient way to generate a lot of samples from the underlying distribution.

The process is described in detail in Alg. 2. In summary, wind speed data were grouped into bins with a step of 1 knot $[0, 1), \ldots, [47, 48)$. Data that reside in common time periods were identified and used to construct the joint wind

speed probability distribution of the line investor and local generators. From the joint distribution, we then estimated each player's conditional probability distribution of wind speed for every wind speed value of their opponent. For every w_1 (respectively w_2), the corresponding w_2 (w_1) values were recorded resulting in 48 subsets that contain w_2 (w_1) wind speed data conditional on w_1 (w_2). A more detailed analysis is presented in [71]. Demand data was classified into hour-season distributions (e.g. $G(P_{L_{h=1,s=4}})$) represents the demand distribution from $0:00 - 00:59$ in Winter) to capture daytime and seasonal variations of demand.

Sampling is initialised by randomly selecting a pair of wind speeds and demand (Lines 8-9), which form the initial state of the MC produced. Subsequent states of the MC $w_i^{(t+1)}$ were generated by replacing the value of the wind speed by a randomly selected value from the conditional $F(w_i |_{w\_i^{(t)}})$. While, demand sampling followed a procedure that preserved the daytime dependency alternating the values of h and s to form a time series of demand data that contains n samples. For example, if a random sample is drawn from the demand distribution for $h = 1$, $s = 4$, i.e., 1am winter time, then the consecutive sample was drawn for $h = 2$ and $s = 4$. Finally, a burn-in period was adopted to ensure that sampling is independent of the starting condition, leading to the first 20% of the data generated not included in the simulation procedure. The process in Alg. 2 can be repeated to create multiple MCs, hence multiple future scenarios.

C. SYSTEM ASSETS MODELLING
For every t, the power generated by wind can be expressed as the product of the rated capacity that a player installs P_{N_i} and the per unit (normalised) wind power generated x_{G_i}, given by a sigmoid function of the wind speed at the project's location w_i:

$$P_{G_i}^{(t)} = P_{N_i} x_{G_i}^{(t)} = P_{N_i} \frac{1}{1 + e^{-\alpha(w_i^{(t)} - \beta)}} \tag{8}$$

Parameters α, β of the sigmoid function are determined by the power curve and wind turbine characteristics. In this paper, we assumed a generic wind turbine based on a 2.05 MW Enercon E82[3] with a hub height of $z_h = 85$ m and a rated wind speed of 13 m/s, yielding parameter values of $\alpha = 0.3921$ s/m and $\beta = 16.4287$ m/s.

For energy storage, we assume a generic model based on Li-ion batteries, one of the most promising electrochemical technologies for energy storage [72]. The subscript t is used to denote variables referring to time step t. Hence, for each t, the energy stored in the battery $E_{S,t}$ is given by:

$$E_{S,t} = E_{S,(t-\delta t)}(1 - s_{dch}) + \left(P_{ch,t}\eta_{ch} - \frac{P_{dch,t}}{\eta_{dch}}\right)\delta t \tag{9}$$

where:

$E_{S_{(t-\delta t)}}$ is the energy stored in storage device at time $(t - \delta t)$ (in the previous state or simulation step)

[3]http://www.enercon.de/en/products/ep-2/e-82/

δt is the duration of time between two consecutive time intervals used in the analysis

s_{dch} is the storage system's self-discharge rate

$P_{ch,t}$ is the charging power at t

$P_{dch,t}$ is the discharging power at t

η_{ch} is the charging efficiency, which accounts for the energy losses during the charging process, and

η_{dch} is the discharging efficiency, which accounts for the energy losses during the discharging process.

At each t, the storage device can either be in a charging ($P_{ch,t} > 0$ and $P_{dch,t} = 0$) or discharging mode ($P_{ch,t} = 0$ and $P_{dch,t} > 0$). Assuming negligible energy losses due to self-discharge $s_{dch} = 0$ and by substitution of charging/discharging efficiencies with the round-trip efficiency η_{rt}, Eq.(9) can be further simplified:

$$E_{S,t} = E_{S,t-\delta t} + r_t \eta \delta t \tag{10}$$

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 $\eta = 1/\eta_{dch}$. Dynamic restrictions result in constraints of the power charged or discharged from the storage device:

$$0 \le P_{ch,t} \le P_{ch_{max}} \tag{11}$$

$$0 \le P_{dch,t} \le P_{dch_{max}} \tag{12}$$

Moreover, for reasons of capacity retention and prevention of battery degradation, storage operation is bounded within a safe range of state of charge SOC:

$$SOC_{min} \le SOC_t = \frac{E_{S,t}}{S}100\% \le SOC_{max} \tag{13}$$

In the simulations, we assumed an operational range of $SOC_{min} = 20\%$ and $SOC_{max} = 100\%$ and a round-trip efficiency of $\eta_{rt} = 0.81$. Finally, the useful lifetime for generation and grid capacity was considered to be 20 calendar years, while for storage, 10 calendar years. Considering the useful lifetime of each asset, capacity costs for transmission c_T and storage c_S were normalised for a single year analysis. Energy system assets were assumed to be fully depreciated at the end of their useful lifetime, although for several components, such as the transmission line, there is significant value remaining after the 20 years considered for the analysis.

D. MODEL ASSUMPTIONS AND CHALLENGES
A step-by-step overview of the equilibrium search is shown in Fig. 5. To enable a thorough and detailed exploration
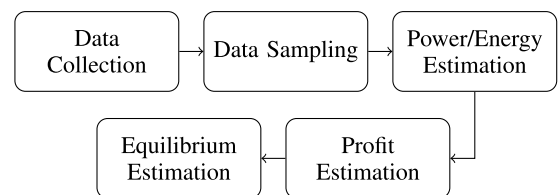

FIGURE 5. Workflow for empirical equilibrium estimation.

(a) Empirical equilibrium estimation: single intersection point for $\langle P_{N_1}, T \rangle = \langle 100, 100 \rangle$ and $c_{G_1} = c_{G_2} = p_T = 0.30 p_G$, $p_S = 0.10 p_G$

(b) Empirical equilibrium estimation: multiple intersection points for $\langle P_{N_1}, T \rangle = \langle 181, 100 \rangle$ and $c_{G_1} = c_{G_2} = p_T = 0.30 p_G$, $p_S = 0.10 p_G$

(c) Empirical equilibrium estimation: no intersection point (illustration based on $\langle P_{N_1}, T \rangle = \langle 100, 100 \rangle$ and $c_{G_1} = 0.28 p_G$, $c_{G_2} = p_T = 0.30 p_G$, $p_S = 0.10 p_G$)
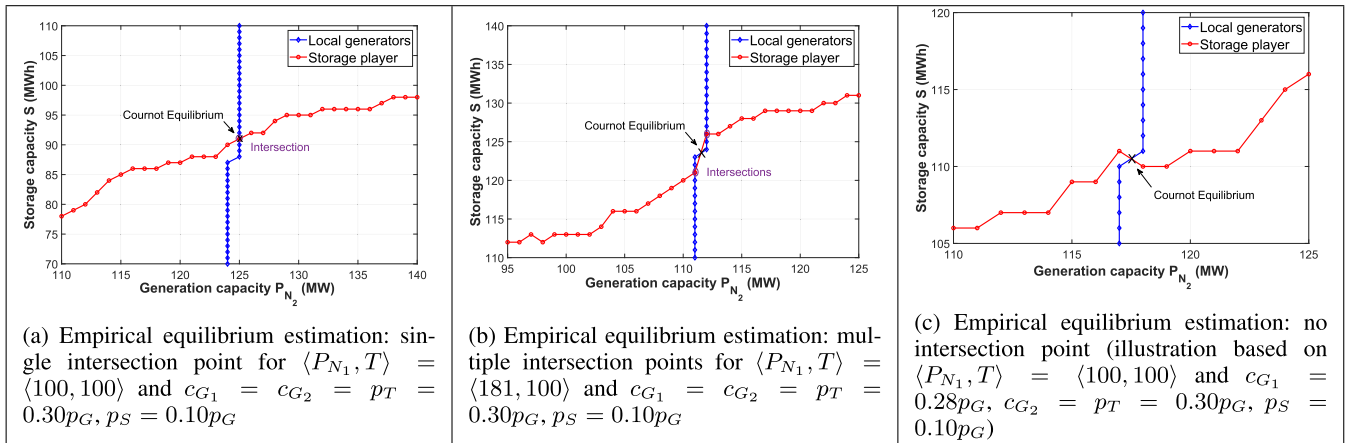
FIGURE 6. Challenges observed regarding the intersection points and Cournot game equilibrium.

of the equilibrium space, the search was realised for all possible combinations of players' strategies $T = [0, 75, 100, 125, 150, 175]$ MW, $P_{N_i} = [0 : 1 : 500]$ MW, and $S = [0 : 1 : 300]$ MWh leading to $301 \times 501 \times 3006$ or 450 million strategy combinations. Hourly energy values were estimated for the duration of $H = 1$ year, leading to a 8760 magnitude vector for each strategy combination. In addition to computations above, we performed a sensitivity analysis on the impact that several financial parameters (prices, costs) have on the payoff estimation, as explained in Section V. This analysis required the calculation of profits for at most 51 values of the financial parameters per case, increasing even further the computational intensity required. 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. Once payoffs were enumerated, we estimated the game equilibrium following the process described in Algorithm 1. We note that while the computational burden of the analysis is not negligible, in practical settings a complete exploration of the strategy space may not be required, as investment decisions of players may be restricted to fewer options in real-world applications. Similarly, while financial cost parameters constitute private information, market conditions may reveal to a significant extent cost parameters to rival investors, who are then required to perform the analysis within smaller regions of underlying parameters and thus improving the tractability of the problem.

The data-driven approach for payoff estimation followed in this work meant that a formal proof that shows the existence of the game equilibrium is not feasible. In reality, the game consists of continuous action spaces, and in general it is difficult to solve for an exact equilibrium. The approach adopted in this work was to discretise the players' action sets, however this meant that agents' best responses are not continuous, but vectors of pair elements (or arrays), which in turn lead to a challenge observed with regards to the *intersect* function (Line 12 of Algorithm 1). The *intersect*

function returns the common data found in best responses BR_2 and BR_3, however it does not exhaustively search the payoff space for estimation of the Cournot game equilibrium, but only in feasible areas where intersections can occur. This intersection will be a single point in the theoretical case when the functions are perfectly smooth or when the computation of profits is performed in the continuum space. However, due to the discretised and data-driven approach, the following occurrences were observed. In the majority of cases, the search for intersection returned exactly one intersection point $(P_{N_2}, S)^{\dagger}$, which represents the Cournot game equilibrium (see Fig 6a). In a few cases, multiple (two) intersection points occurred, hence the equilibrium was assumed to be the mean of the intersection points (see Fig. 6b). 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 (see Fig. 6c). It is worth noting that the two latter cases above only occur due to the discretised strategy space and large-scale data analysis, as opposed to other works looking at equilibrium computation, where profits/costs are mathematical functions and the equilibrium can be derived analytically, as a closed-form solution.

V. ANALYSIS OF RESULTS
In this section, we perform a sensitivity analysis of the effect of financial parameters on capacity built and profits. This is achieved by changing one parameter at a time, while keeping other parameters fixed. First, we analyse the effect that capacity installation costs have on the equilibrium (Case I-III), and next the effect of varying trading tariffs agreed among investors (Case IV and V). Finally, we investigate the value of coupling RES production with energy storage, we compare the equilibrium results with and without storage. Results below are shown for a single MC with a duration of a year.

A. VARIATION OF CAPACITY COSTS AND EQUILIBRIUM
This section studies how the capacities installed by investors and their underlying profits vary in the light of varying
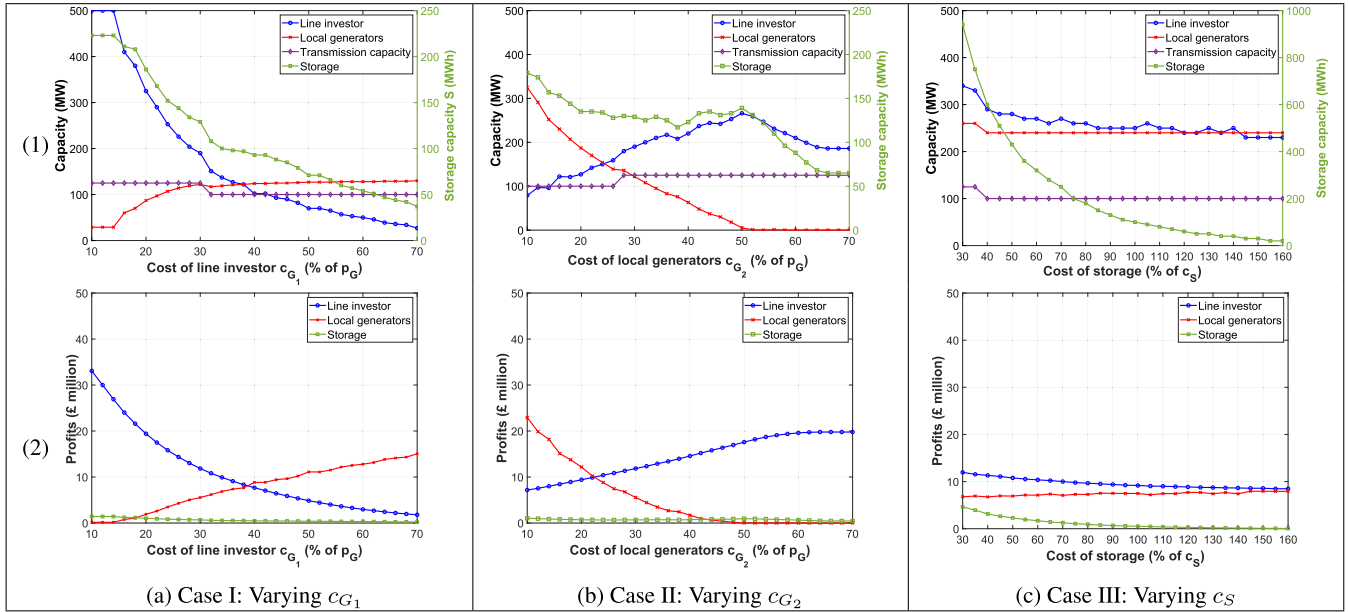
FIGURE 7. Cases I-III: effects of c_{G_1}, c_{G_2} and c_S on capacities installed (first row) and profits (second row) at Stackelberg-Cournot game equilibrium.

TABLE 2. Financial parameter assumptions for sensitivity analysis, Case I-III (capacity costs), Case IV-V (trading tariffs costs): in all scenarios revenue from serving the demand is $p_G = \$74.3/MWh$ and cost for building transmission capacity $c_t = \$76,666.67/MW$ based on a 150 *MW* transmission line with a cost of $\$230m$ and a project lifetime of 20 years. For the energy storage a cost of $\$200/kWh$ of capacity installed was assumed with a useful lifetime of 10 years leading to $c_S = \$15,000/MWh$ of storage capacity installed.

	Case I (varying c_{G_1})	Case II (varying c_{G_2})	Case III (varying c_S)	Case IV (varying p_T)	Case V (varying p_S)
c_{G_1}	$\mathbf{0.10p_G : 0.02p_G : 0.70p_G}$	$0.30p_G$	$0.36p_G$	$0.36p_G$	$0.36p_G$
c_{G_2}	$0.30p_G$	$\mathbf{0.10p_G : 0.02p_G : 0.70p_G}$	$0.30p_G$	$0.30p_G$	$0.30p_G$
c_S	$15,000$	$15,000$	$\mathbf{0.30c_S : 0.05c_S : 1.60c_S}$	$15,000$	$15,000$
p_T	$0.30p_G$	$0.30p_G$	$0.30p_G$	$\mathbf{0.10p_G : 0.02p_G : 0.90p_G}$	$0.30p_G$
p_S	$0.10p_G$	$0.10p_G$	$0.10p_G$	$0.10p_G$	$\mathbf{0 : 0.02p_G : p_G}$

capacity costs, i.e., the generation capacity costs c_{G_1} and c_{G_2} built by the line investor (Case I) and local generators (Case II), respectively, and the cost incurred by the storage player c_S for installing storage capacity (Case III). A summary of the underlying cost parameter assumptions is shown in Table 2. Parameters are shown as a percentage of p_G for easier interpretation of results.

Case I investigates how investment decisions of capacity built (Fig. 7-1a) and profits (Fig. 7-2a) depend on varying line investor's generation cost c_{G_1}. The cost for building transmission capacity c_T and other parameters were assumed constant (see Table 2). Results in this case show that the line investor's cost c_{G_1} increases, her profits and generation capacity installed decrease. This reduction in the line investor's generation capacity is partly replaced by the increase of generation capacity from the local generators, that also increases their profits, and even leading to higher profits than the line investor when c_{G_1} is high. As a consequence, the storage capacity decreases.

Case II studies the evolution of the game equilibrium as the generation capacity cost of local generators c_{G_2} increases, while other parameters remain constant (see Table 2). Results are as follows: similar to *Case I*, the increase of c_{G_2} leads to a decrease of the local generators profits and capacity

installed. In the proposed simulations, the capacity installed decreases until it is not profitable any more to invest in renewable generation, which happens for a cost $c_{G_2} > 0.5p_G$ in our simulations. Reduction of local generators' capacity is replaced by an increase of the generation capacity by the line investor and profits. Storage capacity follows the total generation capacity installed at location B. As the reduction in the local generators' capacity is greater than the increase of the line investor, the storage capacity decreases overall, along with the the storage investor's profits. An interesting observation is that in the region of $c_{G_2} = 0.50 - 0.66p_G$, while $P_{N_2} = 0$, P_{N_1} and S decrease gradually and converge to constant values only for $c_{G_2} \geq 0.66p_G$. This is a result of the methodology followed, as for every $\langle P_{N_1}, T \rangle$, the Cournot game equilibrium is the intersection of the local investors' best responses, which depends on profits Π_2 and Π_3. Increasing c_{G_2} makes Π_2 decrease, essentially leading to a different intersection and Cournot game solution, affecting also the Stackelberg-Cournot game equilibrium.

Case III studies the effect of the storage capacity cost c_S on optimal capacity investment decisions (Fig. 7-1c) and profits (Fig. 7-2c), while other parameters remain fixed, as shown in Table 2. The value of $c_S = 100\%$ represents current costs for grid-scale Li-ion batteries. A sensitivity analysis on storage costs was performed in the range of $30\% - 160\%$
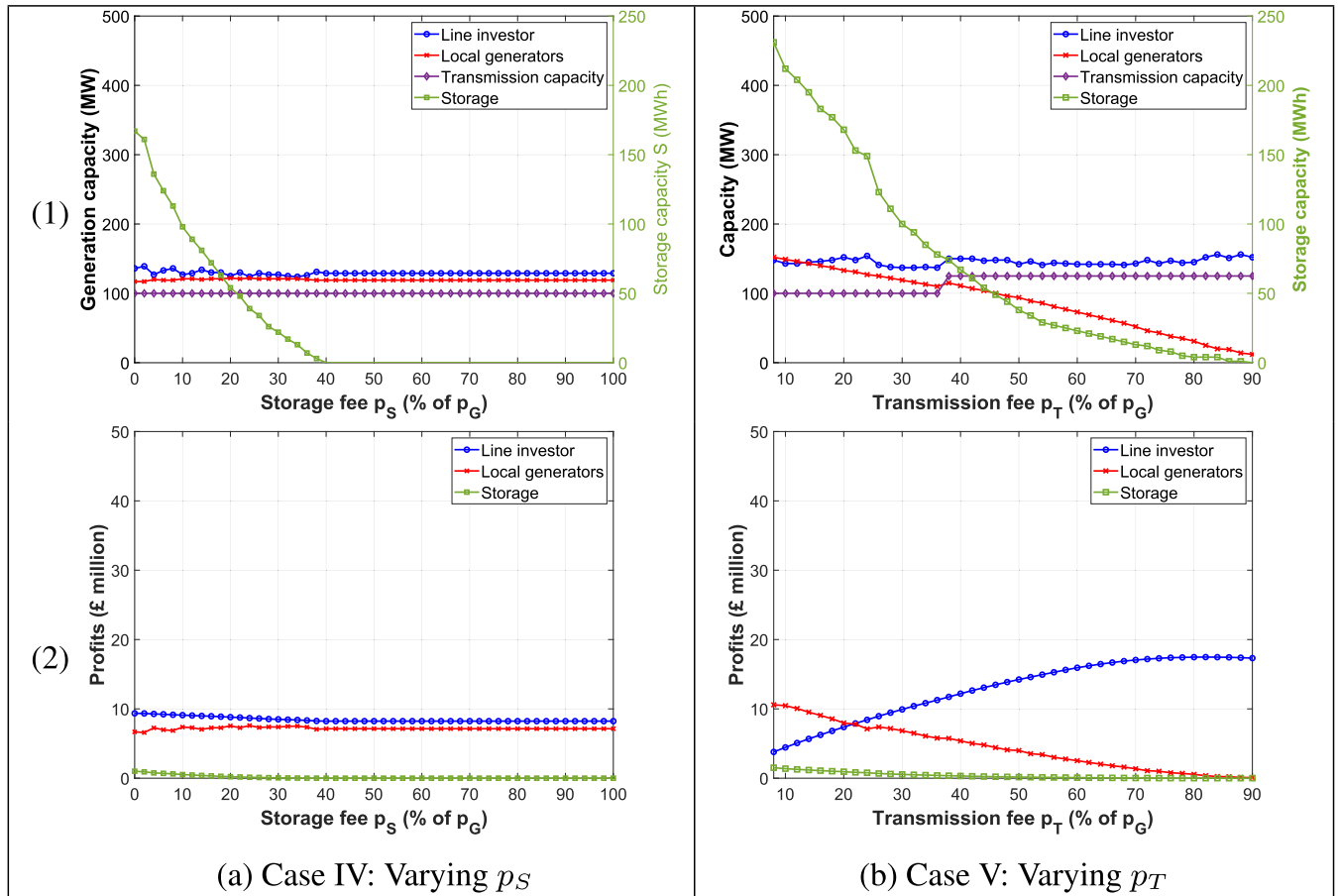
FIGURE 8. Cases IV-V results: effects of p_S and p_T on capacities installed (first row) and profits (second row) at Stackelberg-Cournot game equilibrium.

of the present value, to capture further drop of costs in the future and other storage technologies that are currently more expensive. Similar to other cases, storage capacity and profits decrease as c_S increases, although the reduction is not linear indicating that further drop in c_S could lead to massive adoption of storage devices. Generation capacity of the line investor decreases as c_S increases, while P_{N_2} remains unchanged. Line investor's profits decrease, while on the contrary, the profits for local generators increase slightly when S decreases, despite P_{N_2} remaining constant, due to more demand being served by local generators, as less capacity is built by the line investor.

In all cases, the transmission line capacity T remains largely unchanged and storage's profits are significantly lower than theirs opponents, mostly due to current costs of storage. Next, we study how equilibrium results depend on energy trading tariffs between investors.

B. VARIATION OF TARIFF CHARGES AND EQUILIBRIUM
This section shows a sensitivity analysis on energy trading tariffs between RES producers and storage p_S, and energy transmitted through the line p_T.

Case IV investigates how investment decisions on capacity (Fig. 8-1a) and profits (Fig. 8-2a) depend on varying storage charges p_S, i.e., cost of energy stored and purchased by RES

producers, while other cost parameters remain constant (see Table 2). The effects of p_S on the generation and transmission capacity built are not significant (only small changes observed for P_{N_1} and P_{N_2}). However, S and Π_3 decrease as p_S increases, until storage investment is no longer profitable ($p_S > 40\%p_G$). However, the storage investor purchases energy that would otherwise have been curtailed, therefore in real-world settings, very low values of p_S can be reached. With regards to profits, Π_1 display a slight reduction, while Π_2 a slight increase with p_S.

Case V studies the evolution of the game equilibrium results, as transmission fee charges p_T increase. The capacity and profits of local generators decrease considerably due to the increasing cost of the transmission line access, until is no longer profitable for local generators to invest in RES generation. On the contrary, the line investor maintains the same capacity, but his profits increase as long as the local investors use the transmission line. Finally, the transmission line capacity is mostly not impacted by the increase in access fee charges p_T. Similar to previous cases, the storage capacity follows the overall generation capacity installed at location B, and thus decreases with the transmission line access fee charges. Results from Case V show that low p_T could incentivise the deployment of renewable generation, although it would reduce the profitability for the line investor.
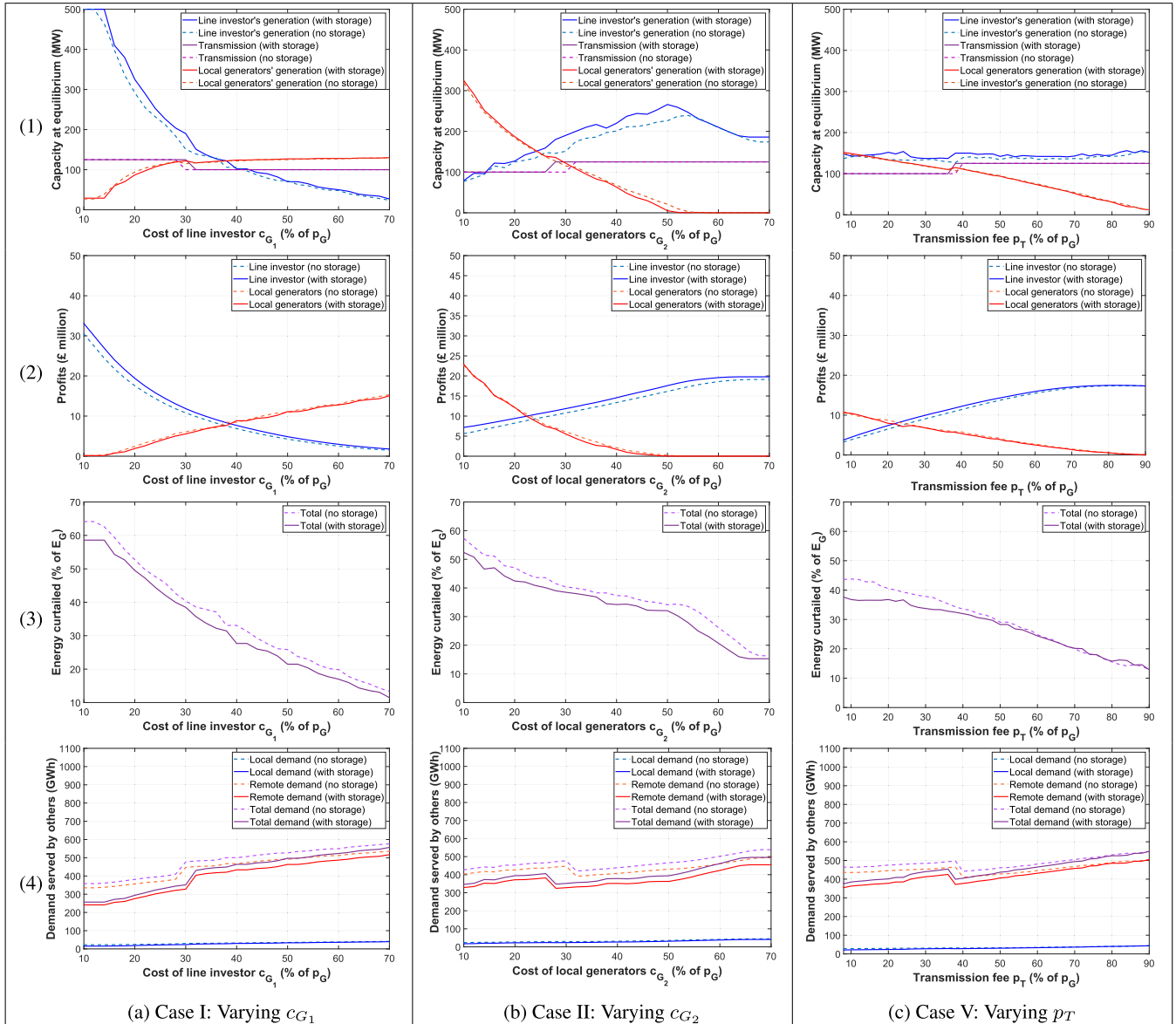
FIGURE 9. Cases I,II and V comparison of game equilibrium results with and without energy storage: effects on capacity installed-row (1), on profits-row (2), on curtailment-row (3) and demand served by other sources-row (4) at Stackelberg-Cournot game equilibrium for varying c_{G_1} column (a), varying c_{G_2} column (b) and varying p_T column (c) .

In the following section, we turn our attention to the role of energy storage in the investment game.

C. THE ROLE OF STORAGE IN EQUILIBRIUM RESULTS

In this section, we study the special role that energy storage holds in the underlying investment game and its impact on the evolution of the game equilibrium. In our previous research [23], we presented a Stackelberg game between the line investor and local generators, hence it would be useful to compare how the game evolves with the introduction of storage, which transforms the game into a considerably more complex, Stackelberg-Cournot game, since it creates a new revenue stream for RES investors. Hence, we wish to investigate how storage affects the capacities installed by investors, their profitability, the underlying curtailment

and participation of RES generators in serving the demand. Note here that, when there is no storage the game reduces into a simpler case of a Stackelberg game between the line investor and the local generators. The comparative results are shown in Fig. 9 for Case I,II and V.

Fig. 9-1 showcases the capacities built by investors at the equilibrium of the game with and without storage for varying c_{G_1}, c_{G_2} and p_T. Introduction of energy storage leads to larger total RES capacity installed at location B, as storage can absorb excess renewable energy and generate additional revenue for RES investors. However, the growth observed is not equally distributed between the RES investors. When there is sufficient RES supply, RES generators take priority when serving the load. On the contrary, when there is a shortage of RES supply, RES producers and storage compete

and share in equal terms the demand served according to the control algorithm introduced in Fig. 2. In all cases where storage investment is profitable, RES capacity (Fig. 9-1) and profits (Fig. 9-2) achieved by the line investor are larger with the introduction of storage, who seems to be able to capitalise on their competitive advantage over other players and benefit from the introduction of storage. This might give an incentive for the line investor to invest in storage capacity along with the transmission line.

Results in the third row of Fig. 9, show the curtailed RES energy as a percentage of the maximum energy E_G that could have been achieved given the wind resource at location B. The introduction of storage has not eliminated curtailment, which is still required when storage reaches its maximum capacity, however, curtailment is reduced by 5% in average on all scenarios where investment in storage was profitable.

Finally, results displayed in the fourth row of Fig. 9 show a significant decrease in both local and remote demand served by other sources or the main grid. In all cases under study, introducing energy storage leads to larger penetration of RES production clearly showing that energy storage can be utilised for further integration of renewable generation.

VI. DISCUSSION OF RESULTS
Section V presented in detail results from the simulation and parametric analysis applied to a practical application of a grid reinforcement project in the UK. The main findings of the study on the evolution and dynamics of the game are discussed here.

As shown in Section V, the higher the cost for installing additional capacity, the less profitable it is to invest in renewable generation, leading to a reduction of the installed capacity. Additionally, RES investors compete with each other to match the optimal RES capacity given the investment costs and trading fees. In fact, reduction in capacity built by one RES investor leads to increase in capacity by the rival RES investor (see Case I-II). Storage capacity follows a similar trajectory to the total RES capacity installed, as the storage system relies on the practice of trading excess RES production that cannot be absorbed. Generally, transmission capacity remains unaffected by changes in financial parameters with the exception of a few step-size increases or decreases that are aligned with the line investor's RES capacity trend. This indicates that the search for optimal T can be reduced in a smaller region, crucially leading to a significant dimensionality reduction with regards to the leader's strategy.

Charges for transmission p_T play a significant part for the viability of storage and renewable generation built by local generators (Case V). If p_T is set too high, local investors build less RES capacity and storage, which can inhibit further adoption of renewable generation. If p_T is set low, the leader can still achieve a profitable investment, as the power line opens up access to remote demand at location A and generates new revenue streams from rival investors also using the line. Negotiation of p_T between the line investor and other investors allows for determination of a suitable range of p_T

when transmission, generation and storage capacity investments are profitable and all investors can mutually benefit from the installation of the line.

The most disadvantaged player with regards to profitability appears to be the storage investor, whose profits are consistently lower than profits of other investors in all the cases under study. This can be assigned to a combination of factors, including high costs for building storage capacity at the present time c_S (a cost of $200/kWh was assumed in this study), charges for purchasing energy from RES producers p_S, fees that need to be paid to access remote demand through the power line p_T and priority of dispatch. Recall here that storage has limited market power, as it purchases energy only when there is RES oversupply and serves demand only at times of RES deficit. However, results from Case III indicate that energy storage may become more profitable as c_S continues to fall in the future, leading also to massive uptake of energy storage. Moreover, a significant advantage for storage is the position to negotiate low charges for energy purchased from RES producers p_S. As the RES energy traded between RES investors and storage would otherwise have been wasted, RES producers would be willing to accept a low value of p_S, which still allows them to improve their profits and even increase the RES capacity that can be built. To improve the profitability of energy storage in real world applications, storage investors need to explore additional revenue streams, such as increasing their profitability by participating in flexibility markets and provision of grid services such as frequency regulation or voltage management, services which not considered in the present work. Another, solution could be that the line investor also invests in storage, which would lead to a new Stackelberg game with two players that would increase the profits for the line-storage investor.

Introducing storage can bring about technical benefits to the energy system operation. Specifically, as indicated by results in Fig. 9-3, storage can increase the part of RES in the energy consumption, as demand served by other sources or the main grid is reduced. Larger penetration of RES generation manifests foremost in the remote demand served by RES producers, as high levels of local demand served by RES are already achieved before storage is introduced. As shown in Fig. 9-4, despite a reduction in curtailment observed, RES curtailment is not fully eradicated and still happens at times when profitable storage capacity is too small to store all the excess production. Complete elimination of curtailment can only be achieved by massive adoption of storage, which is not feasible at current cost levels for large-scale electrical battery storage.

An important question is who benefits from the introduction of storage. Results displayed in Fig. 9-1 and Fig. 9-2 reveal that the beneficiary is predominantly the line investor, as in all cases considered in the study the line investor achieves higher profits. Revenues are increased due to larger capacity being installed by the line investor, but also due to additional revenue streams generated by selling surplus energy to storage and charges for transmission. Despite the

increased competitiveness from storage when there is a shortage of supply, the line investor is able to exploit his leader's market power to his own advantage. On the contrary, local generators are susceptible to the competition introduced by energy storage and market power from the leader, thereby they achieve lower profits with storage. This is a key finding caused by the strategic behaviour of investors and trading rules determined in the game.

Finally, an important observation is that game equilibrium results are not always monotonic, the main cause being that game equilibrium estimation relies on large scale and data-driven simulation analysis, instead of an analytical solution that would necessarily have to assume payoff functions with properties that make such solution achievable. Discretised strategy space and cost parameters search space were largely dictated by computational limitations. This combined with non-linearities introduced with storage, had also a significant impact on the results observed.

VII. CONCLUSION AND FUTURE DIRECTIONS

This work utilised game-theoretic modelling and optimisation techniques to study the strategic interaction between self-interested and profit-maximising investors. Investors or players differ according to their financial and technical capability to perform investment decisions and increase their market power. Specifically, the first player (line investor) can invest in RES generation and transmission capacity that links a location favourable for RES development to a location of high electric demand. Crucially, access to the power line is granted to rival investors for a fee, hence the capacity of the power line installed reflects RES and storage capacities installed by local generators (second player) and by a storage investor (third player), respectively. Players' decisions on how much capacity to install are intertwined and co-dependent on their opponent actions. We modelled such behaviours as a bilevel Stackelberg-Cournot game between the leader (line investor), who has the market power to build the line, and multiple followers (local generators and storage), whose competitive behaviour is studied as a Cournot subgame. The complexity of this real application setting means that the resulting game cannot simply be analysed by determining analytical expressions of the equilibrium capacity decisions and underlying profits. Consequently, we developed a novel empirical and algorithmic approach for game equilibrium estimation where players' payoff functions are directly computed from large-scale and data-driven simulation analysis that is informed by realistic energy system models and operation rules. A demonstration of the methodology was shown for a practical application based on data from a network upgrade project in the UK. However, our method could also be applied to other settings and locations where shared grid access would be beneficial and where demand and generation are not co-located leading to large curtailment rates.

In addition, we studied the dynamic behaviour and evolution of the equilibrium results by performing a sensitivity analysis of the financial parameters that largely determine the players' payoff functions. The analysis can assist private investors and energy system stakeholders to determine suitable tariffs for energy trading and transmission so that profitable investments can be attainable by all investors. As results show, this can be achieved if a relatively low fee is set for transmission line access. By comparative analysis of the game equilibrium results with and without storage, we were able to demonstrate the added value that storage brings in the system operation, although the profitability for the storage investor is considerably lower than for other investors. Our findings indicate that introducing storage can increase the maximum RES capacity that can be installed at a particular location, can reduce curtailment and can be utilised to increase RES adoption.

Future work will focus on extending the model to account for energy transmission losses, other storage technologies and their control management and exploring how alternative ownership models and market structures would affect the underlying strategic game. For example, RES investors could build their own storage capacity or cooperate to invest in a large community storage system [73]. Another extension is to consider multiple local investors (local generators and energy storage devices), where each is modelled as an independent separate entity, leading to new formulations of the game. One challenge identified with the present work was tractability and computational cost of estimating the equilibrium of the game, based on empirical data. Therefore, future work will focus on finding more efficient ways to compute the equilibrium [24], including finding an efficient algorithm for game equilibrium estimation, investigation of machine learning techniques to approximate the players' payoff functions and reduction of their strategy space.

REFERENCES

[1] M. Andoni, V. Robu, W.-G. Fruh, and D. Flynn, "Strategic decision-making for power network investments with distributed renewable generation," in *Proc. 19th Int. Conf. Auton. Agents Multi-Agent Syst. (AAMAS)*, Auckland, New Zealand, 2020, pp. 52–60.

[2] G. Chalkiadakis, V. Robu, R. Kota, A. Rogers, and N. R. Jennings, "Cooperatives of distributed energy resources for efficient virtual power plants," in *Proc. 10th Int. Conf. Auto. Agents Multi-Agent Syst. (AAMAS)*, Taipei, Taiwan, 2011, pp. 787–794.

[3] S. D. Ramchurn, P. Vytelingum, A. Rogers, and N. R. Jennings, "Putting the 'smarts' into the smart grid: A grand challenge for artificial intelligence," *Commun. ACM*, vol. 55, no. 4, pp. 86–97, Apr. 2012.

[4] M. Vasirani, R. Kota, R. L. Cavalcante, S. Ossowski, and N. R. Jennings, "An agent-based approach to virtual power plants of wind power generators and electric vehicles," *IEEE Trans. Smart Grid*, vol. 4, no. 3, pp. 1909–1916, Sep. 2013.

[5] P. Vytelingum, T. D. Voice, S. D. Ramchurn, A. Rogers, and N. R. Jennings, "Agent-based micro-storage management for the smart grid," in *Proc. 9th Int. Conf. Auto. Agents Multi-Agent Syst. (AAMAS)*, Toronto, ON, Canada, 2010, pp. 39–46.

[6] R. Zheng, Y. Xu, N. Chakraborty, and K. Sycara, "A crowdfunding model for green energy investment," in *Proc. 24th Int. Joint Conf. Artif. Intell. (IJCAI)*, Buenos Aires, Argentina, 2015, pp. 52–60.

[7] P. Joskow and J. Tirole, "Merchant transmission investment," *J. Ind. Econ.*, vol. 53, no. 2, pp. 233–264, 2005.

[8] T. Kristiansen and J. Rosellón, "Merchant electricity transmission expansion: A European case study," *Energy*, vol. 35, no. 10, pp. 4107–4115, Oct. 2010.

[9] Energy Union Package. (2015). *A Framework Strategy for a Resilient Energy Union With a Forward-Looking Climate Change Policy.* Accessed: Jun. 30, 2017. [Online]. Available: https://eur-lex.europa.eu/legal-content/en/TXT/?uri=COM%3A2015%3A80%3AF%

[10] P. Bronski, J. Creyts, M. Crowdis, S. Doig, J. Glassmire, and L. Guccione. (2015). *The Economics of Load Defection: How Grid-Connected Solar-Plus-Battery Systems Will Compete With Traditional Electric Service-Why it Matters, and Possible Paths Forward.* Accessed: 20 Nov. 20, 2017. [Online]. Available: https://www.rmi.org/wp-content/uploads/2017/04/2015-05_RMI-TheEconomics%OfLoadDefection-FullReport-1.pdf

[11] S. Gill, M. Plecas, and I. Kockar, "Coupling demand and distributed generation to accelerate renewable connections: Options for the accelerating renewable connections project," Univ. Strathclyde, Glasgow, U.K., Tech. Rep., 2014. [Online]. Available: https://www.spenergynetworks.co.uk/userfiles/file/ARC_Learning_Report_Coupling_Demand_and_Distributed_Generation_to_Accelerate_Renewable_Connections_April_2014.pdf

[12] A. Perrault and C. Boutilier, "Efficient coordinated power distribution on private infrastructure," in *Proc. 13th Int. Conf. Auton. Agents Multi-Agent Syst. (AAMAS)*, Paris, France, 2014, pp. 805–812.

[13] L. Baringo and A. J. Conejo, "Transmission and wind power investment," *IEEE Trans. Power Syst.*, vol. 27, no. 2, pp. 885–893, May 2012.

[14] C. J. Day, B. F. Hobbs, and J.-S. Pang, "Oligopolistic competition in power networks: A conjectured supply function approach," *IEEE Trans. Power Syst.*, vol. 17, no. 3, pp. 597–607, Aug. 2002.

[15] A. Motamedi, H. Zareipour, M. O. Buygi, and W. D. Rosehart, "A transmission planning framework considering future generation expansions in electricity markets," *IEEE Trans. Power Syst.*, vol. 25, no. 4, pp. 1987–1995, Nov. 2010.

[16] L. Maurovich-Horvat, T. K. Boomsma, and A. S. Siddiqui, "Transmission and wind investment in a deregulated electricity industry," *IEEE Trans. Power Syst.*, vol. 30, no. 3, pp. 1633–1643, May 2015.

[17] A. S. Brouwer, M. van den Broek, A. Seebregts, and A. Faaij, "Impacts of large-scale intermittent renewable energy sources on electricity systems, and how these can be modeled," *Renew. Sustain. Energy Rev.*, vol. 33, pp. 443–466, May 2014.

[18] H. Holttinen, P. Meibom, A. Orths, B. Lange, M. O'Malley, J. O. Tande, A. Estanqueiro, E. Gomez, L. Söder, G. Strbac, J. C. Smith, and F. van Hulle, "Impacts of large amounts of wind power on design and operation of power systems, results of IEA collaboration," *Wind Energy*, vol. 14, no. 2, pp. 179–192, Mar. 2011.

[19] K. Bell, R. Green, I. Kockar, G. Ault, and J. McDonald, "Academic review of transmission charging arrangements," Univ. Strathclyde Birmingham, Birmingham, U.K., Tech. Rep., 2011. [Online]. Available: https://www.ofgem.gov.uk/sites/default/files/docs/2011/05/project_transmit_final-report_strath_birm_0.pdf

[20] R. Currie, B. O'Neill, C. Foote, A. Gooding, R. Ferris, and J. Douglas, "Commercial arrangements to facilitate active network management," in *Proc. 21st Int. Conf. Electr. Distrib. (CIRED)*, Frankfurt, Germany, 2011, pp. 1–4.

[21] L. Kane and G. W. Ault, "Evaluation of wind power curtailment in active network management schemes," *IEEE Trans. Power Syst.*, vol. 30, no. 2, pp. 672–679, Mar. 2015.

[22] M. Andoni and V. Robu, *Using Stackelberg Games to Model Electric Power Grid Investments in Renewable Energy Settings*, vol. 10002. New York, NY, USA: Springer, 2016, pp. 127–146.

[23] M. Andoni, V. Robu, W.-G. Früh, and D. Flynn, "Game-theoretic modeling of curtailment rules and network investments with distributed generation," *Appl. Energy*, vol. 201, pp. 174–187, Sep. 2017.

[24] N. Basilico, S. Coniglio, N. Gatti, and A. Marchesi, "Bilevel programming methods for computing single-leader-multi-follower equilibria in normal-form and polymatrix games," *EURO J. Comput. Optim.*, vol. 8, no. 1, pp. 3–31, 2019.

[25] SSE. (2015). *Kintyre-Hunterstone.* Accessed: Aug. 01, 2015. [Online]. Available: https://www.ssepd.co.uk/KintyreHunterston

[26] E. E. Sauma and S. S. Oren, "Economic criteria for planning transmission investment in restructured electricity markets," *IEEE Trans. Power Syst.*, vol. 22, no. 4, pp. 1394–1405, Nov. 2007.

[27] E. E. Sauma and S. S. Oren, "Proactive planning and valuation of transmission investments in restructured electricity markets," *J. Regulatory Econ.*, vol. 30, no. 3, pp. 358–387, Dec. 2006.

[28] B. F. Hobbs, "Optimization methods for electric utility resource planning," *Eur. J. Oper. Res.*, vol. 83, no. 1, pp. 1–20, May 1995.

[29] J. McGarvey, "Transmission investment: A primer," *Electr. J.*, vol. 19, no. 8, pp. 71–82, Oct. 2006.

[30] J. M. Chamorro, L. M. Abadie, R. de Neufville, and M. Ilić, "Market-based valuation of transmission network expansion. A heuristic application in GB," *Energy*, vol. 44, no. 1, pp. 302–320, Aug. 2012.

[31] A. G. Kagiannas, D. T. Askounis, and J. Psarras, "Power generation planning: A survey from monopoly to competition," *Int. J. Electr. Power Energy Syst.*, vol. 26, no. 6, pp. 413–421, Jul. 2004.

[32] C. Ruiz, A. J. Conejo, J. D. Fuller, S. A. Gabriel, and B. F. Hobbs, "A tutorial review of complementarity models for decision-making in energy markets," *EURO J. Decis. Processes*, vol. 2, nos. 1–2, pp. 91–120, Jun. 2014.

[33] H. von Stackelberg, *Market Structure and Equilibrium.* Berlin, Germany: Springer, 2010.

[34] A. A. Cournot, *Researches Into the Mathematical Principles of the Theory of Wealth.* New York, NY, USA: Macmillan, 1897.

[35] G. B. Shrestha and P. A. J. Fonseka, "Congestion-driven transmission expansion in competitive power markets," *IEEE Trans. Power Syst.*, vol. 19, no. 3, pp. 1658–1665, Aug. 2004.

[36] A. H. van der Weijde and B. F. Hobbs, "The economics of planning electricity transmission to accommodate renewables: Using two-stage optimisation to evaluate flexibility and the cost of disregarding uncertainty," *Energy Econ.*, vol. 34, no. 6, pp. 2089–2101, Nov. 2012.

[37] G. E. Asimakopoulou, A. L. Dimeas, and N. D. Hatziargyriou, "Leader-follower strategies for energy management of multi-microgrids," *IEEE Trans. Smart Grid*, vol. 4, no. 4, pp. 1909–1916, Dec. 2013.

[38] J. Lee, J. Guo, J. K. Choi, and M. Zukerman, "Distributed energy trading in microgrids: A game-theoretic model and its equilibrium analysis," *IEEE Trans. Ind. Electron.*, vol. 62, no. 6, pp. 3524–3533, Jun. 2015.

[39] W. Saad, Z. Han, and H. V. Poor, "Coalitional game theory for cooperative micro-grid distribution networks," in *Proc. IEEE Int. Conf. Commun. Workshops (ICC)*, Kyoto, Japan, Jun. 2011, pp. 1–5.

[40] J. Matamoros, D. Gregoratti, and M. Dohler, "Microgrids energy trading in Islanding mode," in *Proc. IEEE 3rd Int. Conf. Smart Grid Commun. (SmartGridComm)*, Tainan, Taiwan, Nov. 2012, pp. 49–54.

[41] K. Anoh, S. Maharjan, A. Ikpehai, Y. Zhang, and B. Adebisi, "Energy peer-to-peer trading in virtual microgrids in smart grids: A game-theoretic approach," *IEEE Trans. Smart Grid*, vol. 11, no. 2, pp. 1264–1275, Mar. 2020.

[42] W. Tushar, T. K. Saha, C. Yuen, T. Morstyn, Nahid-Al-Masood, H. Vincent Poor, and R. Bean, "Grid influenced peer-to-peer energy trading," *IEEE Trans. Smart Grid*, vol. 11, no. 2, pp. 1407–1418, Mar. 2020. [Online]. Available: https://ieeexplore.ieee.org/author/38275372700

[43] S.-W. Park, Z. Zhang, F. Li, and S.-Y. Son, "Peer-to-peer trading-based efficient flexibility securing mechanism to support distribution system stability," *Appl. Energy*, vol. 285, Mar. 2021, Art. no. 116403.

[44] M. Sheha, K. Mohammadi, and K. Powell, "Solving the duck curve in a smart grid environment using a non-cooperative game theory and dynamic pricing profiles," *Energy Convers. Manage.*, vol. 220, Sep. 2020, Art. no. 113102.

[45] M. Tavakkoli, S. Fattaheian-Dehkordi, M. Pourakbari-Kasmaei, M. Liski, and M. Lehtonen, "Bonus-based demand response using Stackelberg game approach for residential end-users equipped with HVAC system," *IEEE Trans. Sustain. Energy*, vol. 12, no. 1, pp. 234–249, Jan. 2021.

[46] Q. Lu, S. Lü, and Y. Leng, "A Nash–Stackelberg game approach in regional energy market considering users' integrated demand response," *Energy*, vol. 175, pp. 456–470, May 2019.

[47] K. Bruninx, H. Pandzic, H. L. Cadre, and E. Delarue, "On the interaction between aggregators, electricity markets and residential demand response providers," *IEEE Trans. Power Syst.*, vol. 35, no. 2, pp. 840–853, Mar. 2020.

[48] C. Feng, Z. Li, M. Shahidehpour, F. Wen, and Q. Li, "Stackelberg game based transactive pricing for optimal demand response in power distribution systems," *Int. J. Electr. Power Energy Syst.*, vol. 118, Jun. 2020, Art. no. 105764.

[49] F. Wei, Z. X. Jing, P. Z. Wu, and Q. H. Wu, "A Stackelberg game approach for multiple energies trading in integrated energy systems," *Appl. Energy*, vol. 200, pp. 315–329, Aug. 2017.

[50] T. Ma, J. Wu, L. Hao, H. Yan, and D. Li, "A real-time pricing scheme for energy management in integrated energy systems: A Stackelberg game approach," *Energies*, vol. 11, no. 10, p. 2858, Oct. 2018.

[51] C. Li, C. Liu, X. Yu, K. Deng, T. Huang, and L. Liu, "Integrating demand response and renewable energy in wholesale market," in *Proc. 27th Int. Joint Conf. Artif. Intell.*, Stockholm, Sweden, Jul. 2018, pp. 382–388.

[52] Q. Huang, Y. Xu, and C. Courcoubetis, "Stackelberg competition between merchant and regulated storage investment in wholesale electricity markets," *Appl. Energy*, vol. 264, Apr. 2020, Art. no. 114669.

[53] X. Xu, J. Li, Y. Xu, Z. Xu, and C. S. Lai, "A two-stage game-theoretic method for residential PV panels planning considering energy sharing mechanism," *IEEE Trans. Power Syst.*, vol. 35, no. 5, pp. 3562–3573, Sep. 2020.

[54] L. Zhu, Q. Zhang, H. Lu, H. Li, Y. Li, B. McLellan, and X. Pan, "Study on crowdfunding's promoting effect on the expansion of electric vehicle charging piles based on game theory analysis," *Appl. Energy*, vol. 196, pp. 238–248, Jun. 2017.

[55] D. Huppmann and J. Egerer, "National-strategic investment in European power transmission capacity," *Eur. J. Oper. Res.*, vol. 247, no. 1, pp. 191–203, Nov. 2015.

[56] A. A. Foroud, A. A. Abdoos, R. Keypour, and M. Amirahmadi, "A multi-objective framework for dynamic transmission expansion planning in competitive electricity market," *Int. J. Electr. Power Energy Syst.*, vol. 32, no. 8, pp. 861–872, Oct. 2010.

[57] A. Soroudi and M. Ehsan, "A distribution network expansion planning model considering distributed generation options and techo-economical issues," *Energy*, vol. 35, no. 8, pp. 3364–3374, Aug. 2010.

[58] B. Zeng, J. Wen, J. Shi, J. Zhang, and Y. Zhang, "A multi-level approach to active distribution system planning for efficient renewable energy harvesting in a deregulated environment," *Energy*, vol. 96, pp. 614–624, Feb. 2016.

[59] T. Akbari, A. Rahimikian, and A. Kazemi, "A multi-stage stochastic transmission expansion planning method," *Energy Convers. Manage.*, vol. 52, nos. 8–9, pp. 2844–2853, Aug. 2011.

[60] A. S. Fini, M. P. Moghaddam, and M. K. Sheikh-El-Eslami, "An investigation on the impacts of regulatory support schemes on distributed energy resource expansion planning," *Renew. Energy*, vol. 53, pp. 339–349, May 2013.

[61] S. Kamalinia, M. Shahidehpour, and L. Wu, "Sustainable resource planning in energy markets," *Appl. Energy*, vol. 133, pp. 112–120, Nov. 2014.

[62] N. Gupta, R. Shekhar, and P. K. Kalra, "Computationally efficient composite transmission expansion planning: A Pareto optimal approach for techno-economic solution," *Int. J. Electr. Power Energy Syst.*, vol. 63, pp. 917–926, Dec. 2014.

[63] J. Contreras, G. Gross, J. M. Arroyo, and J. I. Muñoz, "An incentive-based mechanism for transmission asset investment," *Decis. Support Syst.*, vol. 47, no. 1, pp. 22–31, Apr. 2009.

[64] R. S. Fang and A. K. David, "Transmission congestion management in an electricity market," *IEEE Trans. Power Syst.*, vol. 14, no. 3, pp. 877–883, Aug. 1999.

[65] H. Singh, S. Hao, and A. Papalexopoulos, "Transmission congestion management in competitive electricity markets," *IEEE Trans. Power Syst.*, vol. 13, no. 2, pp. 672–680, May 1998.

[66] P. L. Joskow and J. Tirole, "Transmission rights and market power on electric power networks," *Rand J. Econ.*, vol. 31, no. 3, pp. 450–487, 2000.

[67] C. Gu, X. Yan, Z. Yan, and F. Li, "Dynamic pricing for responsive demand to increase distribution network efficiency," *Appl. Energy*, vol. 205, pp. 236–243, Nov. 2017.

[68] SKM. (2004). *Technical Evaluation of Transmission Network Reinforcement Expenditure Proposals by Licensees in Great Britain–Draft Report*. Sinclair Knight Merz. [Online]. Available: http://www.ofgem.gov.uk/temp/ofgem/cache/cmsattach/8259_19604_tirg_skmreport.pdf

[69] C. Fox and A. Parker, "Convergence in variance of Chebyshev accelerated Gibbs samplers," *SIAM J. Sci. Comput.*, vol. 36, no. 1, pp. A124–A147, Jan. 2014.

[70] C. J. Geyer, "Practical Markov chain Monte Carlo," *Stat. Sci.*, vol. 7, no. 4, pp. 473–483, Nov. 1992.

[71] M. Andoni, V. Robu, D. Flynn, and W.-G. Friuh, "Gibbs sampling for game-theoretic modeling of private network upgrades with distributed generation," in *Proc. IEEE PES Innov. Smart Grid Technol. Conf. Eur. (ISGT-Europe)*, Sarajevo, Bosnia and Herzegovina, Oct. 2018, pp. 1–6.

[72] BloombergNEF. (2019). *A Behind the Scenes Take on Lithium-Ion Battery Prices*. Accessed: Aug. 14, 2019. https://about.bnef.com/blog/behind-scenes-take-lithium-ion-battery-prices/

[73] S. Norbu, B. Couraud, V. Robu, M. Andoni, and D. Flynn, "Modelling the redistribution of benefits from joint investments in community energy projects," *Appl. Energy*, vol. 287, Apr. 2021, Art. no. 116575.

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