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Game theory approaches to hydrogen infrastructure investment planning in Great Britain: A comparative analysis of competitive and cooperative frameworks

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ABSTRACT

Achieving Great Britain's 2050 net-zero target requires coordinated integration of electricity, gas, and hydrogen systems. This paper presents a game-theoretic optimisation framework that evaluates competitive and cooperative investment and operational strategies within a bi-level structure combining long-term planning and short-term operational constraints. The competitive scenario is modelled through a Nash–Cournot equilibrium, while the cooperative scenario applies the Shapley value to ensure a fair allocation of costs and benefits among technologies.

Results show that both approaches enable decarbonisation, but cooperation delivers superior economic efficiency at the 2050 peak demand, achieving a 57% reduction in operational costs and complete decarbonisation, compared to residual emissions of 8161 tonnes under competition. Competitive strategies favour flexibility technologies such as Power-to-Gas (P2G) (11.7%) and Battery Energy Storage (BESS) (11.4%), whereas cooperative planning utilises lower flexibility (P2G 3.4%, BESS 4.5%) and greater nuclear baseload (20%–26%). Shapley value analysis quantifies each technology's marginal contribution, identifying hydrogen technologies as major value drivers, while gas-to-hydrogen reforming with carbon capture and storage (G2G-CCS), biomass, and combined heat and power (CHP) require policy support. When market conditions are not favourable, electricity technologies require between £0.82 and 2.16 million in financial support.

The paper findings offer quantitative insights to guide policy development that incentivises collaboration and coordinated planning, supporting a resilient, fair, and economically efficient pathway to a net-zero energy system for Great Britain.

1. Introduction

The United Kingdom (UK) plans to cut emissions by 80% by 2035 and reach net-zero by 2050 [1]. Meeting these targets will require major changes and investments in the UK's energy system. Recent reports [2,3] point to hydrogen as a key part of this transition. National Grid's Future Energy Scenarios for 2023 outline four possible paths to net-zero [3]. The most ambitious scenario, called Leading the Way, expects hydrogen demand to reach 100 to 150 TWh per year by 2050. In this scenario, about 55 to 65% of hydrogen would come from green sources, 30 to 40% from blue hydrogen, and 5 to 10% from new turquoise methods [3]. These projections highlight the scale of investment and coordination challenges facing the UK energy system.

1.1. Background and motivation

This pathway raises key challenges for investment in the UK's liberalised energy market. One important consideration is whether independent investors and competition should drive hydrogen infrastructure, or whether the complexity of the hydrogen value chain requires coordinated planning among stakeholders. The uncertainty surrounding the optimal capacity allocation strategy adds another layer of complexity. Investment could be distributed across all technologies or concentrated on maximising both renewables and hydrogen. Otherwise, the focus could be on prioritising renewables with limited hydrogen expansion, or on making hydrogen the primary long-term flexibility source, thereby reducing reliance on battery energy storage systems (BESSs).

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Nomenclature

Abbreviations

ATR	Autothermal Reforming for hydrogen production
BECCS	Bioenergy with Carbon Capture and Storage
BESS	Battery Energy Storage System
CapEx	Capital Expenditure
CCGT	Combined Cycle Gas Turbine
CCS	Carbon Capture and Storage
CGT	Cooperative Game Theory
CHP	Combined Heat and Power
CO2	Carbon Dioxide Emissions
DNO	Distribution Network Operator
Fuel Cell	Fuel Cell Power Generation
G2G	Gas-to-Gas
G2P	Gas-to-Power
GB	Great Britain
H2	Hydrogen as an energy vector
H2-CCGT	Hydrogen-fired Combined Cycle Gas Turbine
H2-OCGT	Hydrogen-fired Open Cycle Gas Turbine
OCGT	Open Cycle Gas Turbine
OpEx	Operational Expenditure
OPGF	Optimal Power and Gas Flow
P2G	Power-to-Gas
PHS	Pumped Hydropower Station
PV	Photovoltaic
RES	Renewable Energy Sources
ROI	Return on Investment
ROR	Run-of-River Hydropower
Shapley	Shapley Value (for cooperative allocation)
VCS	Vector-Coupling Storage

Indices

N	Number of players in the game theory model
N_c	Number of gas mixture components
t	Index of time
Z, z	Set and indices of energy technologies

Parameters

η_{P2G}	Efficiency of the P2G conversion process (%)
λ_i	Economic lifetime of player i (year)
ϕ_i	Fixed cost fraction of player i (%)
ρ_{air}	Density of air at Standard Temperature and Pressure (STP) condition (kg/m^3)
emis_i	Emission factor of player i (tCO_2/MWh)
ε_i	Capital expenditure of player i (£/MW)
AF	Annuity Factor
c_i	Cost of player i (£/MW/year)
Cap_{vcs}	Total storage capacity (m^3)
CO_t	Carbon emissions cost at time t (£)
D	Pipe diameter (m)
f	Friction factor
GCV_i	Gross calorific value of component i (kJ/m^3)
h_z	Emission intensity of technology z (tCO_2/MWh)
$I_i^{\max}$	Maximum allowed investment for player i (MW)
k_i	Maximum power capacity of player i (MW)
L	Pipeline length (m)
LoG_{vcs}^{min}	Minimum permissible storage level (%)
LoG_{vcs}^{max}	Maximum permissible storage level (%)
p_E	Energy price (£/MWh)
p_n	Reference pressure (MPa)
Q_e	Total power demand
$q_{i,j}^{elec,active,max}$	Maximum active power transfer limit between nodes i and j (MW)
$q_{i,j}^{elec,reactive,max}$	Maximum reactive power transfer limit between nodes i and j (MVAR)
$q_{i,j}^{gas,max}$	Maximum allowable gas flow between nodes i and j (m^3)
r	Discount rate
R_{air}	Gas constant for air
T	Gas temperature (K)
T_n	Reference temperature (K)
v_{max}^b	Upper voltage limit at bus b (p.u.)
v_{min}^b	Lower voltage limit at bus b (p.u.)
X_i	Mole fraction of component i

Variables

$v(S)$	Value (characteristic function) of coalition S
α_i	Shadow price of market clearing for player i (£/MWh)
δ_i	Shadow price of investment constraint for player i (£/MW)
μ_i	Dynamic viscosity of the component i in the gas mixture.
μ_{mix}	Dynamic viscosity of the gas mixture (Pa s)
σ_i	Shadow price of generation constraint for player i (£/MWh)
C_t	Operational cost at time t (£)
GCV_{mix}	Gross calorific value of gas mixture (kJ/m^3)
I_i	Investment by player i (MW)
LoG_{vcs}	Level of stored gas in the VCS (%)
NPV	Net Present Value (£)
p_i	Pressure at node i (Pa)
q_i	Power production by player i (MW)
q_k	Gas flow through pipeline k (m^3)
$q_{(i,j),t}^{elec,active}$	Active power transmitted between nodes i and j at time t (MW)
$q_{(i,j),t}^{elec,reactive}$	Reactive power transmitted between nodes i and j at time t (MVAR)
$q_{j,in}$	Gas inflow to node j from adjacent branches (m^3)
$q_{j,out}$	Gas outflow from node j to connected branches (m^3)
$q_{L,j}$	Gas demand at node j (m^3)
q_{max}^{ccgt}	Maximum power output of the CCGT unit (MW)
q_{max}^{ez}	Maximum electrical input to the electrolyser (MW)
q_{max}^{p2g}	Maximum power input to the Power-to-Gas unit (MW)

q^{z}_{max}	Maximum generation output from technology z at time t (MW)
q^{ccgt}_{min}	Minimum power output of the CCGT unit (MW)
q^{ez}_{min}	Minimum electrical input to the electrolyser (MW)
q^{p2g}_{min}	Minimum power input to the Power-to-Gas unit (MW)
q^{z}_{min}	Minimum generation output from technology z at time t (MW)
R_t	Revenue from energy sales at time t (£)
S_{mix}	Relative density of gas mixture
v^b	Voltage magnitude at bus b at time t (p.u.)
$V^{available}_{vcs}$	Available storage volume (m^3)
Z_{air}	Compressibility factor of air at STP condition
Z_{mix}	Compressibility factor of gas mixture

Traditional planning models often assume that a central planner makes all investment decisions to minimise costs or maximise social welfare. But this does not match how the UK energy market works, since independent generators, hydrogen producers, network operators, renewable developers, and infrastructure investors all act on their own. These groups make investment choices based on what they expect others will do, market prices, regulations, and the advancement of new technologies. It is still unclear whether competitive or coordinated planning is more effective for reaching net-zero targets. It is also not yet clear which approach is more cost-effective, fairer, or comprehensive for decarbonisation.

This paper addresses these questions by using game-theoretic methods to compare competitive and cooperative investment planning for hydrogen-integrated energy systems in Great Britain (GB). The focus is on the Leading the Way scenario from National Grid's 2023 outlook. The approach combines a non-cooperative Nash–Cournot game, where investors act independently to maximise profits, with cooperative models based on the Shapley value. This allows stakeholders to work together for the best system outcome and share the benefits fairly.

1.2. Related work

The integration of multiple energy vectors, electricity, hydrogen, gas, and heat, into unified energy systems demonstrates substantial technical, economic, and environmental benefits. The analysis, presented in [4–8] shows that operational integration across gas, electricity, and heating sectors achieves significant cost reductions, enhances system flexibility through cross-vector resource shifting, and reduces carbon emissions through optimised dispatch coordination. An integrated multi-vector system can also achieve technical benefits such as higher renewable energy penetration, improved system flexibility [9], and enhanced overall system efficiency, reliability, and resilience [10]. Quantified technical, economic, and environmental benefits compared to single-vector approaches have also been reported in [4,8–10].

Building on these observed benefits, researchers have explored centralised optimisation approaches to systematically capture and maximise these gains. Substantial research has developed centralised optimisation models for coordinated energy system investment planning. These models assume a single planner, making simultaneous investment decisions across all technologies and sectors to minimise total system costs or maximise social welfare while being subject to technical and policy constraints. The centralised models capture technical constraints (capacity factors, ramping limits, storage dynamics), economic parameters (capital costs, operating costs, discount rates), and policy requirements (emissions targets, renewable mandates) [11]. Additionally, centralised optimisation-based planning models of integrated energy systems can achieve more economic and environmental outcomes than sequential, sector-by-sector planning [12]. Generally speaking, the centralised models provide valuable insights for long-term decarbonisation pathways [13]; however, they underrepresent market structures and the strategic behaviour of entities involved in the market [11,13], assume perfect information [11], and consequently tend to overestimate coordination feasibility and underestimate investment barriers arising from information asymmetries and misaligned incentives [13]. They also struggle with computational tractability for national-scale systems with high temporal and spatial resolution [14]. The models assume cooperative coordination across all stakeholders and perfect information about technology costs and demand [12]. These assumptions are violated in competitive, liberalised markets where investors hold private information and make independent strategic decisions.

The limitations of centralised models naturally motivate exploration of decentralised methods that can capture independent decision-making and strategic interactions. Two decentralised approaches, which are widely used, are the multi-agent systems (MAS) and game-theoretic models (GTM). An agent-based modelling (ABM) paradigm for optimising planning and operation in complex energy systems was discussed in [15]. Each stakeholder (generator, consumer, network operator, aggregator) is represented in the ABM as an autonomous agent with individual objectives, constraints, and decision rules. Agents interact through markets, negotiations, or coordination protocols, enabling bottom-up emergence of system-level outcomes from individual agent behaviours. The ABM captures realistic information constraints and stakeholder autonomy; however, it shows lower system efficiency compared with centralised optimisation models [16]. Additionally, ABM approaches face major limitations in characterising equilibrium outcomes and stability properties [15,16]. To overcome these limitations and provide a more rigorous representation of strategic behaviour, game-theoretic frameworks have been proposed.

Game-theoretic approaches address MAS limitations by providing mathematical frameworks for representing interactions between investors and the market with well-defined equilibrium concepts and stability properties for the market. The Stackelberg mechanism is used in [17] for a coordinated multi-energy trading framework. A Stackelberg–Cournot game-theoretic model is used in [18] for strategic renewable energy and grid infrastructure investments, incorporating incomplete information in which investors have private knowledge of costs and capabilities, and analysing how information asymmetries affect equilibrium investment. A Cournot game-theoretic model for capacity investment in the context of the liberalised energy market is developed in [19]. The model captures the strategic behaviour of market participants through the Cournot mechanism, considers carbon pricing as a policy instrument, and demonstrates the efficacy of the Nash equilibrium concept for market settlement. The Nash equilibrium concept effectively characterises stable market outcomes in game theory applications to integrated energy systems, as shown in [20].

Non-cooperative game theory analyses competitive equilibria, while cooperative game theory examines outcomes when players can form binding agreements and coordinate decisions. Additionally, cooperative game theory provides mechanisms for fair benefit and cost allocation among players, which are absent in centralised optimisation [21]. Shapley value has been applied to distribution network cost allocation [22] and shared battery storage planning [23]. These studies showed that Shapley value guarantees individual rationality (each participant receives at least their standalone value) and collective rationality (total allocated benefits equal total coalition value), while increasing stakeholder willingness to participate in shared infrastructure by 40%–60% compared to arbitrary cost allocation rules [23]. Beyond fairness, cooperative games enable system-wide optimisation, which is not possible in competitive games, in which players act independently [24]. Nash bargaining-based cooperative model for wind–hydrogen–heat systems demonstrates that cooperative planning reduces system costs compared to competitive Nash–Cournot equilibria, achieving both efficiency and equity. Review of the game-theoretic methods in power system [21] and the applications in energy systems [25] show that cooperative approaches extend beyond cost sharing to inform market rule design, pricing mechanisms, and regulatory strategies, offering insights into how policies such as carbon pricing or renewable mandates influence equilibrium outcomes. Additionally, a game-theoretic model demonstrated the ability to capture coordination failures arising from circular dependencies in hydrogen systems [26].

On the other hand, energy system planning faces significant uncertainty, including rapid technological changes, shifts in demand patterns, evolving policies, and fluctuations in fuel prices. While game-theoretic models capture strategic interactions, investment planning must also account for uncertainties in technology, demand, and policy, which motivates scenario-based approaches. The scenario-based planning methodology is valuable for evaluating investment robustness across different possible futures. Let us take the UK, for example. In the analysis presented in [27], the scenarios for energy pathways through 2050 showed hydrogen demand could be as low as 20 TWh/year or as high as 450 TWh/year. It all depends on how well electrification goes, how technology costs change, and which policies take hold. Some investments stay profitable no matter what scenario happens. Others are profitable if a specific future unfolds.

Future Energy Scenarios (FES) developed by National Grid, lay out four distinct pathways [3]. Each pathway captures critical uncertainties in technology costs, sectoral electrification rates, policy ambition, and public acceptance. DNV's Energy Transition Outlook takes this further [28]. Their scenario analysis suggests that investment planning under uncertainty requires explicit consideration of adaptation strategies, in terms of how today's investment choices will affect the system's ability to adapt later: which early investments create flexibility for future adjustment versus which create lock-in to specific technological pathways. Their analysis showed that hydrogen infrastructure investments face particular uncertainty regarding optimal scale and technology choice (electrolysis versus reforming with CCS), requiring a scenario-based approach to weigh those options. The planning of renewable energy, storage, and demand-side management integration for the Danish case study in [29] showed that scenario-based planning identifies investment strategies robust across multiple futures (renewable energy, grid reinforcement) versus strategies optimal only under specific scenarios (large-scale hydrogen, biomass with CCS).

This review of scenario-based investment planning [3,27,28] reveals that existing studies employ centralised optimisation frameworks, evaluating the impacts of scenarios on optimal central plans rather than analysing how scenarios affect strategic competitive or cooperative equilibria. This represents a significant gap, as scenario-based game-theoretic analysis evaluates how strategic equilibria vary across plausible future scenarios.

As shown, policy instruments can be adjusted across different energy scenarios, thereby shaping the investment planning of energy systems. In this context, the design and interaction of policy instruments play a critical role in influencing strategic investment outcomes under varying scenarios. The impact of carbon pricing, capacity markets, and renewable support mechanisms on the investment planning of CCS systems has been demonstrated in [30]; however, only the impact of carbon pricing on the investment planning of low-carbon technologies, such as CCS systems, was also investigated in [31]. Two critical carbon price thresholds were defined in [30] to incentivise CCS deployment: below £50/tCO_2, CCS deployment is not economically viable, whereas above £100/tCO_2, carbon pricing alone effectively incentivises competitive investment.

Additionally, it has been demonstrated that carbon pricing creates strategic asymmetries by reducing the profitability of high-carbon technologies and increasing the competitiveness of low-carbon technologies, potentially triggering rapid technology transitions when carbon prices cross critical thresholds [32]. The role of the carbon price in investment planning for low-carbon technologies, such as CCS systems, was also investigated in [31]. The analysis of UK and European CCS projects showed that carbon price volatility prevented final investment decisions for multiple proposed CCS facilities. The complementarity between policy instruments (carbon pricing) and coordinated planning approaches, as demonstrated for the Danish energy system, has been highlighted in [32]. Furthermore, the impact of policy instruments on strategic investment equilibria using game-theoretic models was investigated in [18]. Results show that subsidies, contracts for difference, and carbon pricing mechanisms alter Nash equilibrium investment levels, and poorly designed subsidies can create perverse incentives, leading to overinvestment in subsidised technologies and underinvestment in complementary flexibility resources.

The review of the role of policy instruments in investment planning in the energy system reveals a gap in how policy instruments should be designed within cooperative planning frameworks using game-theoretic benefit-sharing mechanisms (Shapley values, core solutions). Specifically, there remains an open question on how policy support should be targeted when Shapley value analysis identifies technologies with negative contributions to system-wide coalitions—technologies necessary for reliability or diversity, but economically unattractive without support.

1.3. Research gaps and questions

The literature review on multi-vector energy systems, centralised optimisation, decentralised methods, scenario analysis, and policy instruments identifies significant gaps that this paper addresses.

- Comparative analysis of competitive and cooperative planning frameworks: Existing research analyses either competitive game-theoretic equilibria or cooperative optimisation, but does not compare both frameworks within a unified analysis for the same energy system. The analysis presented in [17,18,20] focuses on competitive equilibria and the analysis presented in Ma et al. [22–24] focuses on cooperative frameworks. However, systematic comparison quantifying efficiency differences, cost implications, emissions outcomes, and technology mix variations between competitive and cooperative planning for national-scale hydrogen-integrated systems remains absent. This gap is critical because GB's liberalised market structure creates competitive dynamics; however, hydrogen's coordination requirements suggest cooperative planning advantages without quantitative comparison; policymakers lack evidence for optimal market design choices.
- Application of Shapley value fair benefit-sharing to national-scale hydrogen infrastructure: While Shapley value applications exist for distribution networks [22] and battery storage [23], applications to national-scale hydrogen-integrated multi-vector energy systems are absent. Hydrogen brings some unique characteristics: circular dependencies, plus a mix of technologies (electrolysis versus reforming with CCS). However, there are no answers yet on how to use the Shapley value to fairly split costs and benefits between hydrogen production options and storage infrastructure.
- Policy support quantification using game-theoretic frameworks: Existing policy instrument literature [30,31,33] proposes qualitative policy recommendations without a quantitative game-theoretic derivation of required support levels. Critical questions remain: Which technologies require policy support to participate in cooperative frameworks? What financial support magnitudes ensure participation? How does required support vary with commodity prices (electricity, hydrogen, natural gas, CO_2)? Game theory provides tools (Shapley values indicating marginal contributions) for quantifying policy support, but this application is underdeveloped.

- Capacity allocation strategy evaluation under competitive and cooperative paradigms for different planning scenarios: Energy system planning requires strategic choices about capacity allocation across technologies: Should investment be balanced uniformly across all technologies? Should renewables and hydrogen scale simultaneously? Should renewables dominate with minimal hydrogen? Or should hydrogen provide primary flexibility with constrained battery storage? Existing literature evaluates such capacity allocation questions using centralised optimisation [11,12] but not through comparative game-theoretic analysis. Whether optimal capacity allocation strategies differ between competitive and cooperative planning paradigms remains unexplored. There is no answer to whether the best capacity allocation strategy changes depending on whether a competitive or cooperative approach is used.
- Investment sensitivity to commodity prices and economic assumptions: While scenario-based planning literature [3,27] evaluates technology cost uncertainty, sensitivity analysis of investment outcomes to commodity prices (electricity, hydrogen, natural gas, CO_2) under game-theoretic frameworks is limited. Specifically, how does competitive versus cooperative planning robustness differ under commodity price volatility? Which technologies remain economically viable under price stress? How much policy support is required under unfavourable price conditions? These questions are critical for investment risk assessment but are inadequately addressed.

The remainder of the paper will be organised as follows: Section 2 will explain the design methodology and the structure of the game-theoretic investment planning models. Section 3 will describe the case study and the considered scenarios, and Section 4 will show and discuss the analysis results. Finally, the conclusion will be presented in Section 5.

2. Methodology

The methodology is built on a bi-level framework that connects long-term investment planning with short-term operational decisions for a multi-vector energy system, including electricity, gas, and hydrogen networks. The two levels interact in an iterative manner, as shown in Fig. 1. In the first level, the investment model estimates future capacities, the expected energy mix, planned investments, and projected carbon emissions. These outputs are then passed to the operational model, which evaluates short-term performance. Conversely, the results from the operational model—covering costs, hourly dispatch, and emissions—are used to refine the long-term plans, making them more aligned with actual system behaviour. Details of the simulation settings and iterative solution procedure are provided in Appendix A of the Supplementary Material.

Key players in the system include investors and operators of electricity generation units, hydrogen production facilities, and energy storage systems, such as batteries (BESS) and bidirectional hydrogen-based vector-coupling storage (VCS). Each actor makes decisions based on economic rationality, either competing or cooperating, depending on the chosen game-theoretic framework. Policy instruments are incorporated by defining technology types, their expected contributions to the energy mix, capacity constraints, and projected energy and carbon prices.

For the short-term, the framework applies optimal power and gas flow (OPGF) calculations, capturing hourly variations in demand, renewable generation, and cross-network interactions through coupling devices. This allows for a detailed assessment of the system's performance over time, providing insights that feed back into long-term planning. The following sections present the mathematical details of the models, including competitive and cooperative investment approaches (Sections 2.1 and 2.2) and the operational interactions between electricity and gas networks (Section 2.4).

2.1. Competitive game-theoretic model

In this model, the investors in the liberalised energy market compete to maximise their returns in a dynamic environment [19].

Each player i in the game (competitive or cooperative) is characterised by a set of decision variables and parameters that represent their operational, investment, and environmental attributes. It should be noted that the Nash–Cournot equilibrium is inherently sensitive to the number of strategic players. In our framework, each player represents an aggregated technology-level decision-maker, with assets within the same technology class assumed to act in a coordinated manner. This abstraction is commonly used in national-scale energy system models to focus on inter-technology competition rather than firm-level rivalry. Disaggregating a technology group into multiple independent firms would progressively converge the equilibrium towards a perfectly competitive outcome, reducing the potential for strategic market power.

The decision variables include the power production q_i, capacity investment I_i, and the associated dual variables σ_i, δ_i, and α_i for the generation, investment, and market-clearing constraints, respectively. The model also incorporates several parameters: the cost coefficient C_i, the specific capital expenditure ε_i, fixed cost fraction ϕ_i, economic life λ_i, and maximum power capacity k_i. Environmental and market factors are captured through the emission factor emis_i, total power demand Q_e, energy price p_E, and the carbon emissions cost CO_t. Additional global parameters include the discount rate r (assumed 5%), the number of years until the target year, the maximum allowable investment $I_i^{\max}$, and the total number of players in the cooperative set $|N|$.

2.1.1. Objective function

The core objective of the investment model is to maximise the Net Present Value (NPV) of future cash flows from energy operations, for each player. The detailed NPV equation can be expressed in Eq. (1).

$$NPV = AF\left(\sum_{t=0}^{T}\left(R_t - C_t - CO_t\right) - FC\right) - NI \tag{1}$$

In Eq. (1), R_t is the revenue from energy sales at time t and C_t is the operational cost, which includes fuel costs, variable costs, and fixed costs related to technology z.

Under the assumption of a uniform annual cash flow, the operational profit is annualised using the annuity factor (AF), as shown in Eq. (2).

$$AF = \frac{(1+r)^n - 1}{r(1+r)^n} \tag{2}$$

In Eq. (2), r is the discount rate and n is the number of years in the planning horizon.

In Eq. (2), CO_t refers to the carbon emissions cost at time t and can be calculated using Eq. (3), where h_z is the emission intensity of technology z and c_{emis} is the cost per ton of emissions.

$$CO_t = \sum_{z} q_z \cdot h_z \cdot c_{\text{emis}} \tag{3}$$

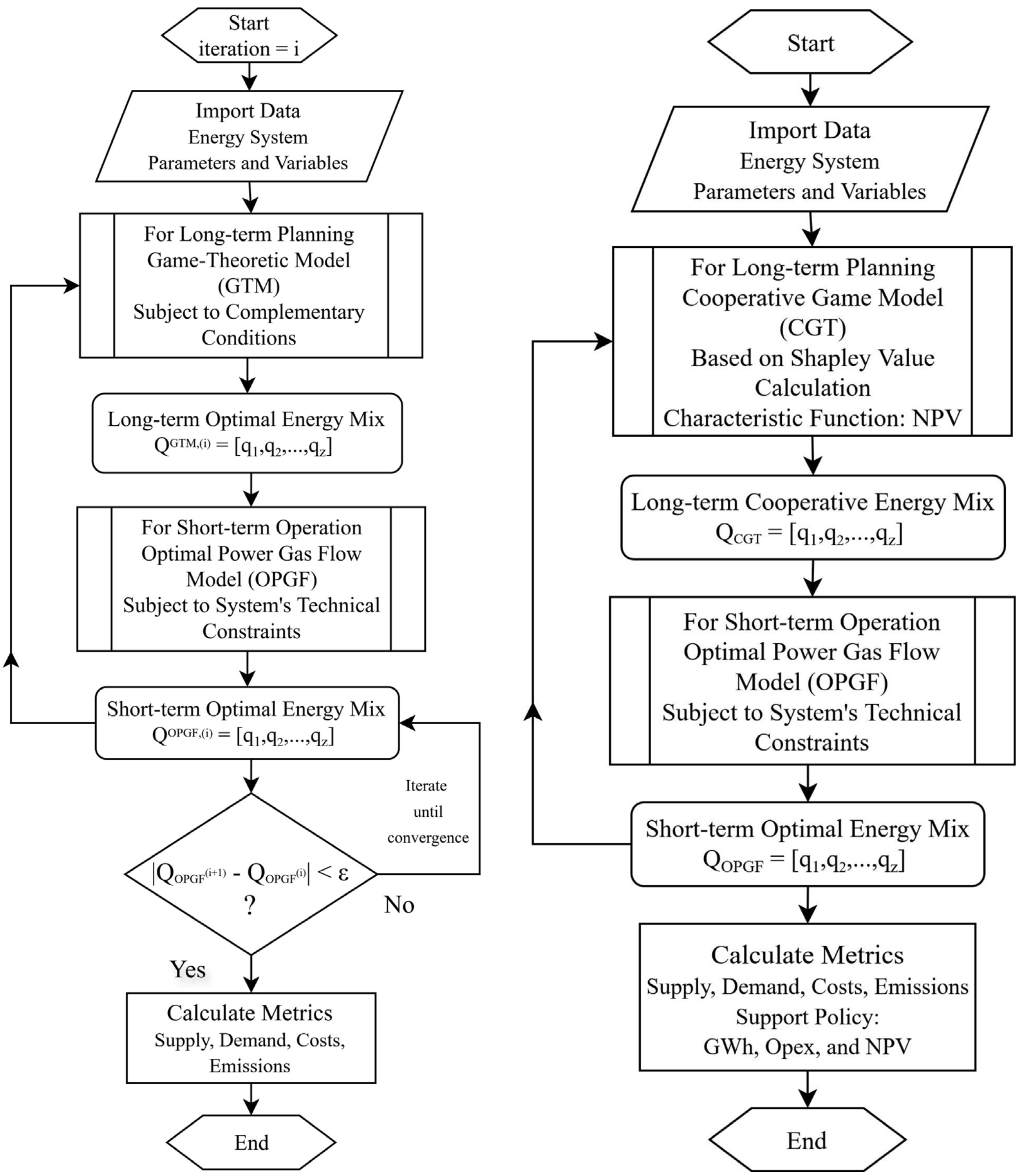
FC in Eq. (1) represents the total fixed costs of the energy system, which are calculated using Eq. (4). Here, K_z denotes the total installed capacity of technology z at the end of the year, I_z represents the investment in that capacity, ε_z is the specific capital expenditure, and ϕ_z is the fixed cost fraction associated with technology z.

$$FC = \sum_{z\in Z}\left(\phi_z \cdot \varepsilon_z \cdot (k_z + I_z)\right) \tag{4}$$

NI in Eq. (1) represents the net investment outlay for all technologies, which are calculated using Eq. (5). Here, λ_z is the economic lifetime of the technology z.

$$NI = \sum_{z\in Z}\left[\varepsilon_z \cdot I_z \cdot \left(1 - \frac{\lambda_z - n}{\lambda_z(1+r)^n}\right)\right] \tag{5}$$

This expanded NPV equation, given in Eq. (1), considers both operational profits and investment costs, while maximising returns across multiple time periods.



(a) Competitive approach (b) Cooperative approach

Fig. 1. Framework flowcharts for the competitive and cooperative approaches.

2.1.2. *Competitive game constraints and market clearing conditions*

The objective function incorporates various cost components related to energy production, including operational costs and carbon emissions. The technical constraints and market-clearing conditions are formulated in this section in the form of complementarity conditions. In the following paragraphs, these conditions are explained.

2.1.3. *Generation capacity*

The first condition to consider is the generation capacity, expressed in Eq. (6):

$$q_z \geq 0 \quad \perp \quad AF\,[p_e - c_z(qz)] - \sigma_z - \alpha_z \leq 0 \tag{6}$$

In Eq. (6), the symbol $\perp$ denotes the complementarity condition, where q_z represents the electricity generation from technology z, p_e is the market price of electricity, σ_z is the shadow price associated with the generation capacity constraint, and $c_z(qz)$ is the cost function for technology z. The cost function is typically quadratic and is given by Eq. (7):

$$c_z(q_z) = a_z q_z^2 + b_z q_z + c_z \tag{7}$$

where a_z, b_z, and c_z are the corresponding cost coefficients. Specifically, this condition implies that:

- if $q_z > 0$ (i.e. the technology produces electricity), then $p_e - c_z - \sigma_z - \alpha_z = 0$, meaning the constraint is active; or
- if $q_z = 0$ (i.e. the technology does not produce electricity), then $p_e - c_z - \sigma_z - \alpha_z \leq 0$, meaning the constraint is non-binding.

Thus, the complementarity condition ensures that for each technology z, either production is positive and the profit condition holds exactly, or no production occurs when generation is not economically justified.

2.1.4. *Generation investment*

The model also incorporates a generation investment condition, expressed in Eq. (8). In this equation, I_z denotes the investment in technology z, ϕ_z represents the fixed cost fraction, ϵ_z is the specific capital expenditure, and λ_z corresponds to the economic lifetime of the technology.

$$I_z \geq 0 \quad \perp -AF \cdot \phi_z \cdot \epsilon_z - \epsilon_z \cdot \left(\frac{1-\lambda_z - n}{\lambda_z(1+r)^n}\right) + \sigma_z - \delta_z \leq 0 \tag{8}$$

This complementarity condition ensures that investment in each technology z occurs only when it is economically justified. This occurs when the marginal benefit, represented by the shadow prices (σ_z and δ_z), offsets the associated capital and fixed costs.

Together with the generation capacity condition in Eq. (6), this constraint guarantees that both production and investment levels remain non-negative and consistent with the Nash–Cournot equilibrium framework, balancing profitability with market and capacity limitations.

2.1.5. Generation and investment limits

To ensure that the generation and investment decisions are optimised within the capacity and financial limits of the system, the following two complementarity conditions have been considered to enforce the generation and investment limits for each technology.

Generation capacity limits:

$$0 \leq q_z \leq q_z^{\max} \quad \perp \quad \sigma_z \geq 0 \tag{9}$$

where $q_z^{\max}$ is the maximum generation capacity for technology z.

Generation investment limits:

$$0 \leq I_z \leq I_z^{\max} \quad \perp \quad \delta_z \geq 0 \tag{10}$$

where $I_z^{\max}$ is the maximum investment allowed for technology z and δ_z is the shadow price for investment constraints.

2.1.6. Market clearing conditions

The market-clearing conditions for the electricity and gas markets ensure that the total supply from all generation sources matches the demand. These conditions can be expressed as:

$$q_e = \sum_z q_z \quad \text{(Electricity)} \tag{11}$$

$$q_g = \sum_j q_j \quad \text{(Gas)} \tag{12}$$

where q_e and q_g represent the total electricity and gas supplied, respectively. Eqs. (11) and (12) ensure that the electricity generation or gas import or production from all sources is balanced with the corresponding energy demand. In this investment model, it is assumed that there are no losses in the electricity, gas, or hydrogen networks, as such losses are considered in the short-term operational model.

2.2. Cooperative game-theoretic model

The cooperative approach employs Cooperative Game Theory (CGT) to fairly allocate the NPV among players according to their marginal contributions. In particular, the Shapley value is used as an equitable NPV-sharing mechanism, ensuring that each player is rewarded in proportion to their contribution to the overall system [34]. The flowchart in Fig. 1(b) illustrates the cooperative approach applied in this paper.

2.2.1. Shapley value calculation

The total NPV of a coalition of players is used as the characteristic function $v(S)$, where $S \subseteq N$ and N is the set of all players. The Shapley value $\text{Shapley}_i(v)$ for player $i \in N$ is calculated using Eq. (13), where $v(S)$ represents the NPV of coalition S (as in Eq. (1)), $|S|$ is the size of the coalition, and $|N|$ is the total number of players.

$$\text{Shapley}_i(v) = \sum_{S \subseteq N \setminus \{i\}} \frac{|S|!\,(|N|-|S|-1)!}{|N|!} \left[v(S \cup \{i\}) - v(S)\right], \tag{13}$$

This formulation ensures a fair allocation of the total value based on each player's average marginal contribution across all possible coalition permutations. Positive Shapley values indicate players who enhance coalition profitability, whereas negative values identify those whose participation reduces collective value. Generation allocation is guided by these Shapley values, and policy mechanisms—such as operational expenditure support or NPV-based subsidies—can be applied to players with negative contributions to maintain overall system viability.

2.2.2. Generation and investment limits in the cooperative approach

In the cooperative optimisation framework, each player's generation or storage decisions are constrained by physical and financial limits. Here, a player $i \in Z$ may represent an electricity generation unit, a hydrogen production/storage unit, or an energy storage system. These constraints are incorporated directly into the coalition-level optimisation problem, ensuring that total system operation remains feasible and consistent with capacity bounds.

Generation capacity limits. The output of each player is limited by its existing installed capacity k_i and any additional investment I_i:

$$q_i \leq k_i + I_i, \quad \forall i \in N. \tag{14}$$

Investment limits. Investment in new capacity is restricted by a maximum allowable limit $I_i^{\max}$ or each player, as illustrated in Eq. (15), where q_i is the energy quantity generated by player i, and $I_i^{\max}$ is the upper bound on investment for player i.

$$I_i \leq I_i^{\max} \quad \forall i \in N. \tag{15}$$

Global energy balance for electricity, gas, and hydrogen is enforced through the market-clearing conditions in Eqs. (11) and (12). Unlike competitive models, where limits are enforced via complementarity conditions and dual pricing, the cooperative approach embeds these constraints directly in the optimisation. The system maximises joint NPV while respecting technical limits and allocates the resulting value fairly among players using the Shapley value, as illustrated in Fig. 1(b).

2.3. Benchmark: central planning approach

The benchmark planning approach represents a centrally optimised system, consistent with standard centralised optimisation models such as PyPSA, which has been applied to several national-scale energy systems [35,36]. Unlike the game-theoretic approaches, it assumes a single planner that simultaneously optimises long-term generation investment and short-term system operation across electricity and hydrogen networks, subject to network, technical, and operational constraints.

The benchmark shares a similar structure to the competitive approach (Fig. 1) but is formulated as a standard non-linear programming (NLP) problem, without complementarity conditions. All investment and dispatch decisions are determined centrally, without strategic interactions between market actors.

Objective function. The benchmark maximises overall system net present value (NPV), as defined in 2.1.1, but with generation dispatch and investment decisions (q_z, I_z) jointly determined by a central planner rather than strategic agents. The resulting objective is given by:

$$\max_{\{q_z, I_z\}} NPV = AF\left(\sum_{t=0}^{T}\left(R_t(q_z) - C_t(q_z) - CO_t(q_z)\right) - FC\right) - NI(I_z), \tag{16}$$

where parameters AF, C_t, CO_t, FC, and NI follow the same definitions as in the game-theoretic formulation (see 2.1).

Benchmark capacity and investment constraints. While the competitive model relies on complementarity conditions and associated dual variables, the benchmark formulation determines generation and investment decisions directly through standard non-linear programming (NLP) constraints, without strategic interactions or complementarity conditions. All feasibility requirements are enforced directly on the primal decision variables (q_z, I_z).

Generation capacity constraint. For each technology $z \in Z$, electricity generation is bounded by the available installed capacity and new investment:

$$0 \leq q_z \leq k_z + I_z \quad \forall z \in Z. \tag{17}$$

Investment constraint. Investment decisions are restricted by an upper bound on allowable capacity expansion:

$$0 \leq I_z \leq I_z^{\max} \quad \forall z \in Z. \tag{18}$$

No dual feasibility conditions with shadow prices are introduced, as the decision variables are determined centrally to minimise total system cost.

Market balance. System-wide market-clearing conditions for electricity and gas remain identical to those in Eqs. (11) and (12), with analogous expressions for gas and hydrogen where applicable.

Network and technical constraints. All generation, network flow, and storage limits described in 2.4.1–2.4.3 are enforced directly in the optimisation.

The benchmark serves as a reference approach for evaluating the impacts of strategic behaviour and cooperation within our game-theoretic framework. For each scenario, it provides metrics such as total system cost, net present value (NPV), generation mix, operational dispatch, and CO_2 emissions (see Table 3). Further implementation details are provided in Appendix A of the Supplementary Material.

2.4. Short-term operational model capturing electricity–gas interactions

A short-term operational framework is formulated to capture the dynamic interactions between electricity and gas systems. The model integrates steady-state representations of AC power flow for the electricity grid and gas flow equations for the gas network. Both systems are solved iteratively using the Newton–Raphson method to ensure numerical convergence.

The short-term operational objective, shown in Eq. (19), minimises total system costs at each time step. The structure of this function parallels the investment cost expression introduced in Eq. (1).

$$\min C_t = \sum_{z \in Z} c^z(q_t^z) \cdot q_t^z \qquad \forall z \in Z \tag{19}$$

The following subsections describe the mathematical representations for the electricity network, gas network, and vector coupling elements that link the two energy domains.

2.4.1. Electricity network model

The active and reactive power flow equations, given by Eqs. (20) and (21), define the steady-state operation of each bus in the electrical network. The electricity system is implemented using the `pandapower` Python library.

$$P_{G_i} - P_{L_i} - \sum_i |V_i| \left|V_j\right| \left(G_{ij}\cos(\delta_i - \delta_j) + B_{ij}\sin(\delta_i - \delta_j)\right) = 0 \tag{20}$$

$$Q_{G_i} - Q_{L_i} - \sum_i |V_i| \left|V_j\right| \left(G_{ij}\sin(\delta_i - \delta_j) - B_{ij}\cos(\delta_i - \delta_j)\right) = 0 \tag{21}$$

The operational constraints of each technology are expressed through Eqs. (22)–(24). Eq. (22) defines the permissible operating range for each technology z. The upper limit, q^z_{max}, is obtained from the investment model and represents the optimised installed capacity. The actual dispatch q_t^z is computed from the short-term optimisation of power, gas, and hydrogen flows.

$$q^z_{min} \leq q^z_t \leq q^z_{max} \qquad \forall z \in Z \tag{22}$$

Examples of such bounds for key technologies (electrolysers, CCGTs, and P2G units) are given in Eqs. (23)–(25).

$$q^{ez}_{min} \leq q^{ez}_t \leq q^{ez}_{max} \tag{23}$$

$$q^{ccgt}_{min} \leq q^{ccgt}_t \leq q^{ccgt}_{max} \tag{24}$$

$$q^{p2g}_{min} \leq q^{p2g}_t \leq q^{p2g}_{max} \tag{25}$$

Power flow limits between buses i and j are imposed through Eqs. (26) and (27).

$$0 \leq q^{elec,active}_{(i,j),t} \leq q^{elec,active,max}_{i,j} \tag{26}$$

$$0 \leq q^{elec,reactive}_{(i,j),t} \leq q^{elec,reactive,max}_{i,j} \tag{27}$$

The permissible voltage range for each bus b is expressed by Eq. (28).

$$v^b_{min} \leq v^b_t \leq v^b_{max} \tag{28}$$

2.4.2. Gas network model

Gas flow continuity at each node j is expressed as:

$$\sum_j q_{j,in} - \sum_j q_{j,out} - q_{L,j} = 0 \qquad \forall j \tag{29}$$

The steady-state gas flow through branch k is estimated via Eq. (30):

$$q_k = \pi \sqrt{\frac{R_{air}}{8}\frac{T_n}{p_n}} \sqrt{\frac{(p_i^2 - p_j^2)D^5}{f\, S_{mix} L T Z_{mix}}} \tag{30}$$

The friction factor f depends on the Reynolds number, Re, defined as:

$$Re = \frac{D\, v\, \rho_{mix}}{\mu_{mix}} \tag{31}$$

The calculation of ρ_{mix}, μ_{mix}, v, which represent respectively, the density of gas mixture, the dynamic viscosity of the component i in the gas mixture, and the velocity of the gas flow, follow standard gas network formulations described in [19,37,38]. The iterative solution updates f, Re, and q_k until convergence.

The upper bound on pipeline gas flow is enforced as:

$$0 \leq q^{gas}_{i,j} \leq q^{gas,max}_{i,j} \tag{32}$$

2.4.3. Vector coupling components

Vector coupling systems (VCS), such as Power-to-Gas (P2G) units and gas storage, interlink the electricity and gas networks. Their operation follows charging under electricity surplus and discharging during shortfalls, particularly in high-renewable conditions. Gas generation from P2G units is determined via Eq. (33).

$$q_{P2G} = \frac{\eta_{P2G} \cdot P_{P2G}}{GCV_{mix}} \tag{33}$$

The mixture's calorific value is obtained using Eq. (34):

$$GCV_{mix} = \frac{\sum_{i=1}^{N_c}(X_i \times GCV_i)}{Z_{mix}} \tag{34}$$

The gas storage state in VCS units is described by the level-of-gas (LoG) in Eq. (35):

$$LoG_{vcs} = \frac{V^{available}_{vcs}}{Cap_{vcs}} \times 100 \tag{35}$$

Its operational range is bounded as:

$$LoG^{min}_{vcs} \leq LoG_{vcs} \leq LoG^{max}_{vcs} \tag{36}$$

Methodological details and supplementary figures are provided in the Supplementary Material.

3. Case study description

The modelling framework captures the Great Britain (GB) energy system as a multi-vector network linking electricity, gas, hydrogen, and heat infrastructures. It accounts for conventional (e.g., nuclear and gas-fired power plants, potentially equipped with carbon capture and storage (Gas+CCS)) and renewable electricity generation such as wind and solar PV, green hydrogen production via electrolysis, blue hydrogen from reforming with CCS, and bio-based hydrogen from biomass gasification with CCS. The gas network, supplied by gas providers, meets direct gas demand and fuels gas-fired power generation. It also serves as a primary feedstock for hydrogen production via reforming technologies. Hydrogen is stored and subsequently used for electricity generation, heating, or industrial demand. The interactions between the different energy networks are illustrated in Fig. 2. Flexibility is provided by energy storage systems, including BESS, pumped hydropower stations (PHS), and vector coupling storage(VCS). The geographical layout of the case study system is shown in Fig. 3, where Fig. 3.a depicts the electricity transmission network, and Fig. 3.b illustrates the gas/hydrogen network expected by 2050. The system co-optimises investment and operation decisions to achieve cost-effective decarbonisation while meeting technical constraints.

The system's economic assumptions for all generation and hydrogen technologies, sourced from [39–42], are presented in Table 1.

In addition, carbon pricing is explicitly represented by applying a CO_2 price trajectory consistent with Great Britain's *Leading the Way* pathway to fossil-fuel-based technologies [3,43]. This ensures that investment and operational decisions reflect policy-aligned carbon cost signals when assessing system performance under uncertain market conditions.

To explicitly account for market volatility and uncertainty, the analysis distinguishes between profitable and unprofitable planning conditions. Profitable planning corresponds to market price assumptions under which the net present value (NPV), defined in Eq. (1), is positive, reflecting economically viable investment outcomes. Unprofitable planning represents adverse market conditions in which the NPV becomes negative due to unfavourable combinations of commodity prices and revenues. These conditions are identified through a sensitivity analysis of electricity, hydrogen, and natural gas prices, as illustrated in Fig. 8.

All simulations are evaluated under peak demand hour conditions, corresponding to an electricity peak demand of 102.17 GWh and a hydrogen peak demand of 14.27 GWh. Profitable planning is obtained for electricity, hydrogen, and gas prices of £100/MWh, £150/MWh, and £75/MWh, respectively, whereas unprofitable planning corresponds to lower price levels of £40/MWh, £50/MWh, and £15/MWh. The CO_2 price is held fixed at £163/tCO_2 in line with the Leading the Way pathway. By evaluating system performance under both regimes, the framework quantifies the impact of price uncertainty on investment viability and demonstrates the relative robustness of competitive, cooperative, and benchmark planning strategies under volatile energy market conditions.

In the game-theoretic formulation, the system comprises 18 players, each representing a distinct technology group that makes independent investment and operational decisions. These players include hydrogen technologies (P2G, G2G, G2P), renewable generation (onshore wind, offshore wind, solar PV), firm low-carbon generation (nuclear, hydropower), storage technologies (BESS and VCS), and fossil or dispatchable units (Gas+CCS, biomass, CHP). The defined set of players corresponds directly to the technology categories presented in Table 1.

The simulation framework developed in this study is designed to assess optimal decarbonisation strategies for GB's energy system, focusing specifically on the energy generation mix for peak demand in 2050. The demand profiles are based on the Future Energy Scenarios (FES) 2022, specifically the Leading the Way scenario [44].

The demand remain fixed across the four scenarios. The scenarios therefore differ not in demand assumptions, but in the limits placed on the installed capacities of generation, storage, and hydrogen technologies used to meet that demand.

Several key scenarios are considered to evaluate the potential impacts of various factors on the energy system, with a particular emphasis on hydrogen integration, as summarised in Table 2. The table outlines the assumed installed capacities for 2050 relative to the 2025 baseline across all scenarios. These capacity limits are treated as scenario-specific inputs rather than outputs of the optimisation. The model subsequently determines the cost-optimal utilisation and operational strategy within these limits. Each scenario modifies the upper bounds of deployable technologies to test different strategic directions for meeting the Leading the Way demand. For example, in the High RES–Low H_2 scenario, the allowable capacity for renewable generation and BESS is increased, while the maximum hydrogen production and storage capacity is reduced. This reflects a system that prioritises renewables and short-duration storage over hydrogen infrastructure.

These scenarios reflect varying levels of renewable energy deployment, alongside storage and hydrogen technologies, in pursuit of decarbonisation targets. Specifically, the four investment scenarios are as follows:

(i) *Uniform +25 GW*: This scenario assumes a balanced increase in capacity across all technologies. The aim of this scenario is to distribute investment evenly and reduce dependency on any single energy source.

(ii) *High RES–High H_2*: This scenario focuses on strong expansion of renewable generation, battery storage, and hydrogen infrastructure. This configuration seeks to push forward decarbonisation while enhancing system flexibility through joint deployment of these complementary assets.

(iii) *High RES–Low H_2*: this scenario places emphasis on rapid growth in renewables and battery systems, with only modest investment in hydrogen. It represents an energy system that relies mainly on batteries for short-term balancing and reserves hydrogen for a minimal supporting role.

(iv) *High H_2–Low BESS*: This scenario prioritises investment in hydrogen production and storage as the main flexibility solution for the long term, while keeping the expansion of battery energy storage systems relatively limited.

These scenarios allow for a comparative assessment of techno-economic and environmental implications under different strategic directions for future capacity development, revealing fundamental differences in cost-effectiveness, emissions outcomes, energy mix composition, and technology viability between competitive and cooperative planning paradigms, providing actionable insights for policymakers regarding optimal market design and policy support mechanisms.

4. Results and discussion

The game-theoretic framework is applied to analyse strategic investment and operational decisions for GB's energy system transition by 2050. The analysis compares outcomes under both competitive (Nash–Cournot) and cooperative (Shapley value-based) planning paradigms across four distinct investment scenarios. These scenarios, detailed in Table 2, are designed to probe the system's response to varying levels of investment in renewable energy sources, battery energy storage systems, and hydrogen infrastructure.

All reported results correspond to the 2050 peak-demand hour. The optimisation uses the peak electricity and hydrogen demands (102.17 GWh and 14.27 GWh), so all quantitative comparisons reflect system behaviour at this peak demand.

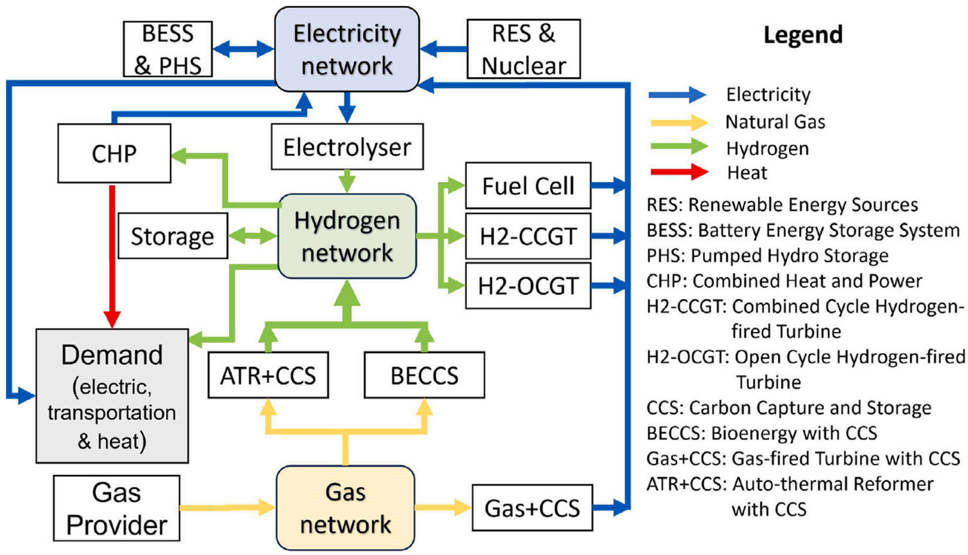


Fig. 2. Integrated multi-vector energy system framework for GB, illustrating the coupling between electricity, gas, hydrogen, and heat networks, including various generation, conversion, and storage technologies.

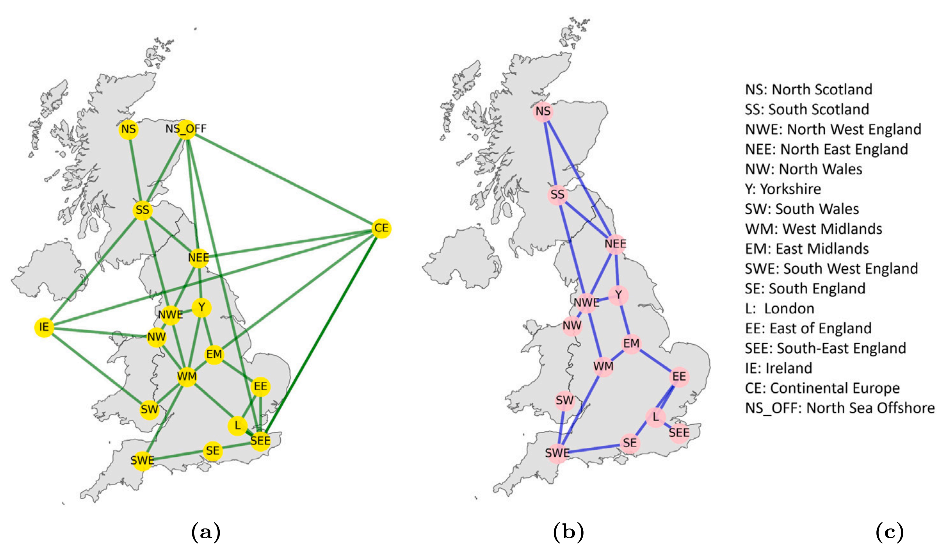


Fig. 3. GB's future energy networks: (a) electricity network, (b) gas/hydrogen network, (c) Legend for distribution network operators (DNO) and interconnections.

4.1. Comparative analysis of energy mix and system performance

Table 3 provides a quantitative comparison of the competitive and cooperative planning for an investment span of 25 years at the 2050 peak demand. A primary finding is that cooperative planning leads to a more efficient system when hydrogen integration is high, evidenced by lower total energy supply and significantly lower total operational costs across scenarios of high hydrogen integration. This efficiency gain stems from the coordinated dispatch of generation and storage assets, which minimises system-wide operational expenses and avoids the suboptimal outcomes of players acting solely in their own interest. The largest cost saving is observed in the (High H_2–Low BESS) scenario, where the total operational cost decreases from £3.40 million under competitive planning to £1.47 million under cooperative planning.

Interestingly, the (*High RES–Low* H_2) scenario, which restricts hydrogen infrastructure development, exhibits the smallest difference in operational cost between the two planning models. This result indicates that when the system has limited reliance on interlinked energy vectors such as hydrogen, the advantages of coordinated, cooperative planning are less pronounced. In this case, the reduced hydrogen infrastructure constrains the degrees of freedom available to the cooperative model, thereby limiting its potential efficiency gains. Moreover, while the competitive planning model includes no nuclear generation (0%), the cooperative model allocates approximately 22.2% to nuclear, which contributes to its lower cost-effectiveness under this configuration. In the (*High* H_2*–Low BESS*) scenario under competitive planning, 8161 tonnes of CO_2 emissions remain. These residual emissions arise under competitive planning because limited economically rational flexibility options lead to the allocation of some fossil-based generation to meet demand.

In contrast, the cooperative planning framework attains complete decarbonisation in every scenario, including this case, underscoring the value of system-wide coordination in driving emissions to zero. The non-zero CO_2 emissions and higher operational costs under competitive planning indicate that market signals alone may fail to internalise cross-vector interactions, system-wide flexibility requirements, and coordination risks in a liberalised system. This outcome highlights that, while both approaches target net-zero emissions, they rely on fundamentally different economic pathways with distinct implications for

Table 1
Techno-economic assumptions for generation and hydrogen technologies. CapEx in £/kW, OpEx in £/MWh, CO_2 in kg/MWh.

Electricity generation						
Technology	CapEx (£/kW)	O&M (%)	Discount rate	Life (yrs)	OpEx (£/MWh)	CO_2 (kg/MWh)
Nuclear	5191	83.4	9.5	40	5	0
CCGT	617	15.6	8.9	25	45.8	339
OCGT	440	10.9	8.9	25	66.8	548
Gas-CCS	2361	41.6	13.8	25	33.1	32
Coal-CCS	3403	82.0	13.5	25	35.4	81
H_2-CCGT	830	15.5	10.5	25	0	0
H_2-OCGT	440	10.9	10.5	25	0	0
Biomass	3446	119.8	11.2	25	14	89
Geothermal	4800	140.0	8.5	30	15	35
Gas CHP	910	24.9	8.9	15	69	185
Hydropower	3475	48.3	7.2	80	0	0
Wind (Onshore)	1017	25.5	7.9	25	0	0
Wind (Offshore)	1578	42.1	8.9	30	0	0
PV (Utility-scale)	457	5.6	6.9	35	0	0
Hydrogen production						
Technology	CapEx (£/kW)	O&M (%)	Discount rate	Life (yrs)	CO_2 (kg/MWh)	Efficiency (%)
Electrolyser	465	48.5	10	30	0	74
ATR-CCS	384	24.4	10	40	21.9	84

Table 2
Installed capacity settings for different investment scenarios in 2050, with 2025 baseline capacities. All values in GW. The electric peak demand is 102.17 GWh, while the hydrogen peak demand is 14.27 GWh.

Technology	Installed capacities (GW)				
	2025	Uniform +25 GW	High RES–High H_2	High RES–Low H_2	High H_2–Low BESS
Electricity generation					
Nuclear	6.8	31.8	25	25	50
Wind (offshore, onshore)	31	81	100	100	80
Solar (PV)	17	42	70	70	50
BESS	3	28	60	60	5
Others	>25	>25	>25	>25	>25
Hydrogen technologies					
G2P (H2-CCGT)	0	25	10	0.5	20
G2P (H2-OCGT)	0	25	10	0.5	20
G2P (Fuel Cell)	0	25	10	0.5	20
P2G (Electrolyser)	0.5	25.5	15	0.5	30
G2G (ATR+CCS, BECCS)	0	25	15	0.5	30

system efficiency. Moreover, the influence of hydrogen integration on system cost and efficiency becomes particularly evident when examining how different planning paradigms shape the overall energy generation structure. In scenarios with higher hydrogen integration, cooperative planning demonstrates greater cost reductions and enhanced system efficiency. This relationship is further illustrated in Figs. 4 and 5, which compare the energy generation mix under competitive and cooperative planning, respectively.

Under competitive planning (Fig. 4), wind consistently remains the dominant generation source across all scenarios, covering between 18.9% and 58.9% of the energy mix. Photovoltaics (PV) account for 7.9–18.8% in the scenarios, showing their noticeable but secondary role compared to wind. Nuclear energy, however, is more variable: for instance, in Scenario (*High RES–Low H_2*), nuclear contributes nothing (0%) to the total generation, whereas in Scenario (*High H_2–Low BESS*) it reaches 24.49%, highlighting the scenario-dependent nature of nuclear integration under competitive planning. Flexible technologies under competitive planning show notable utilisation differences across scenarios. For instance, P2G, G2P, and G2G+CCS reach up to 11.7%, 13.5%, and 6.7% of the energy mix, respectively, while BESS reaches up to 11.4%. This higher deployment of flexibility resources reflects the profit-driven nature of competitive planning, which seeks to cover flexibility gaps rather than optimising system-wide resource use.

In contrast, cooperative planning (Fig. 5) is characterised by wind consistently dominating the generation mix, contributing 35.6–46.7%, while PV accounts for 8.5–13.4%. Nuclear plays a more stable role compared with competitive planning, ranking as the second most utilised generation source in all scenarios, with a share of 20.2%–26%. Hydrogen-related technologies and BESS are reduced under cooperative planning. Across scenarios, P2G, G2P, and G2G+CCS account for up to 3.4%, 4.6%, and 2.8% of the energy mix, respectively, while BESS does not exceed 4.5%. This lower deployment reflects system-wide coordination, which reduces reliance on flexibility resources compared to competitive planning. A key driver is that cooperative planning increases the share of nuclear while reducing variable renewables, thereby lowering the need for such flexibility technologies.

In summary, these quantitative comparisons highlight that competitive planning encourages higher utilisation of flexible and variable resources, including PV, storage, and hydrogen conversion technologies, whereas cooperative planning stabilises nuclear integration, optimises storage deployment, and reduces reliance on flexibility resources to achieve a more balanced and cost-effective energy mix. In high hydrogen integration scenarios, cooperative planning further reduces operational costs, residual CO_2 emissions, and hydrogen demand by coordinating generation, storage, and conversion assets system-wide. These results suggest that policies promoting integrated, coordinated planning can enhance efficiency and cost-effectiveness in multi-vector energy systems.

Taken together, across scenarios with high hydrogen integration, cooperative planning consistently delivers lower operational costs and zero CO_2 emissions, demonstrating superior system efficiency relative to both competitive and benchmark approaches. In contrast, when

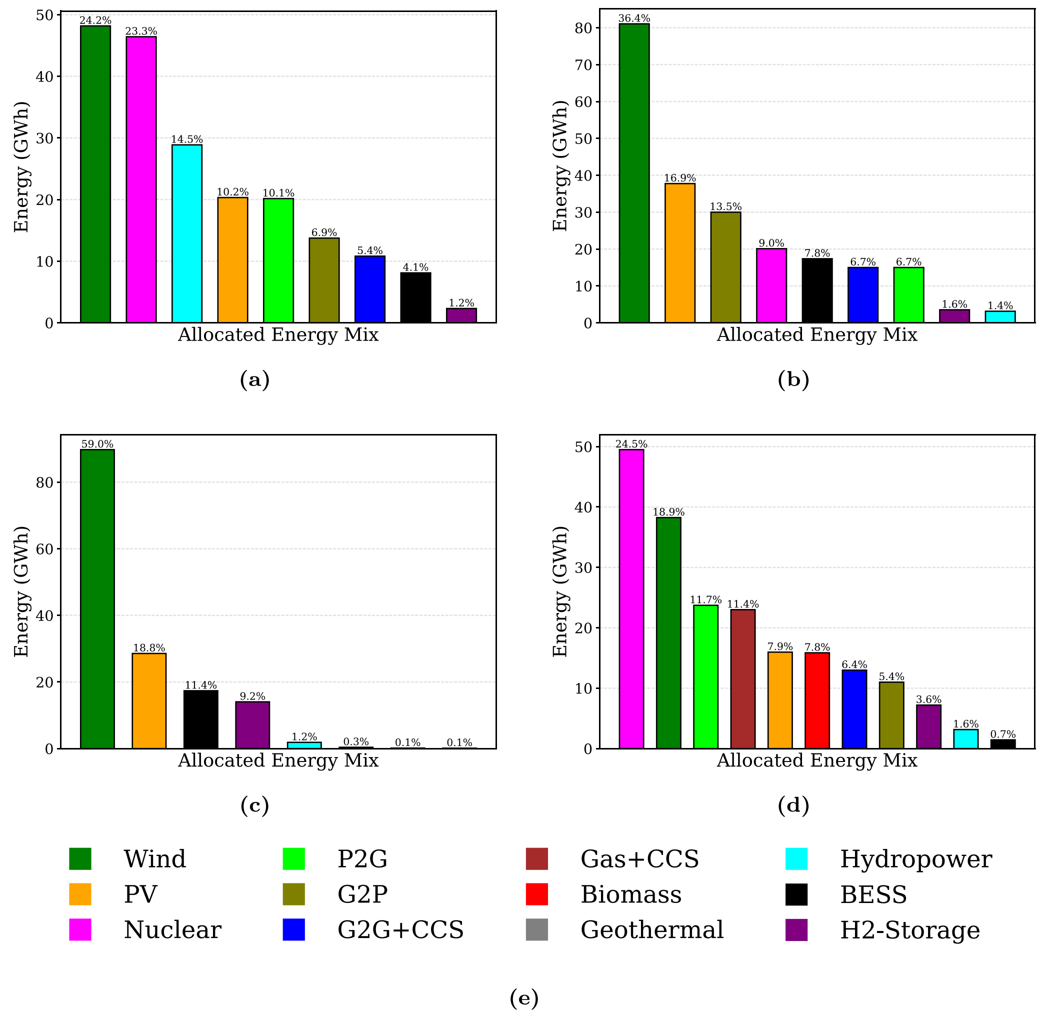


Fig. 4. Competitive planning of energy generation mix (GWh) for 2050 peak demand under four investment scenarios: (a) Uniform +25 GW, (b) High RES–High H_2, (c) High RES–Low H_2, (d) High H_2–Low BESS. (e) Legend for Technology Types.

hydrogen deployment is limited, these efficiency gains diminish, indicating that the benefits of cooperation are closely tied to effective hydrogen integration. This finding exposes structural gaps and coordination risks in competitive and centrally optimised planning when hydrogen plays a dominant role, highlighting the importance of coordinated decision-making in highly coupled electricity–hydrogen systems.

Fig. 6 illustrates the energy generation mix under Benchmark planning across the four investment scenarios. Across all cases, centrally optimised planning favours large-scale deployment of low-cost, low-emission technologies, with wind and nuclear forming the backbone of electricity supply. Wind is the dominant contributor in all scenarios, ranging from approximately 27% to 54%, while nuclear consistently contributes around 18%–27% of total generation. PV generation provides a secondary but stable contribution, accounting for roughly 9%–24% across scenarios. Flexible technologies, including power-to-gas (P2G), gas-to-power (G2P), hydrogen storage, and BESS, play a supporting role, with their combined contribution varying by scenario. In the (*Uniform +25 GW*) and (*High H_2–Low BESS*) scenarios, flexibility options collectively represent a non-negligible share of the mix, reflecting the system's need to balance variable renewable output under uniform capacity expansion. Under the (*High RES–High H_2* and *High RES–Low H_2*), the reliance on hydrogen-based flexibility technologies decreases markedly. In comparison, the (*High H_2–Low BESS*) scenario exhibits a more diversified mix, with increased contributions from gas-based generation and conversion technologies due to limited BESS. This results in a modest share of fossil-based generation and corresponding non-zero CO_2 emissions, consistent with the benchmark results reported in Table 3. Overall, the benchmark energy mixes highlight how central optimisation prioritises high-capacity, low-marginal-cost generation while deploying flexibility and gas-based resources only when system constraints—such as reduced storage availability or elevated hydrogen demand—necessitate their use.

Across all scenarios, Benchmark planning provides a centrally optimised reference that highlights the techno-economic limits of system-wide coordination. While Benchmark planning does not always achieve the lowest operational costs compared to the cooperative planning, but it maintains intermediate and stable cost levels across all scenarios. Operational CO_2 emissions remain zero in most cases; however, in the (High H_2–Low BESS) scenario, 4285 tonnes of CO_2 emissions remain due to increased reliance on gas-based generation under constrained system flexibility. Overall, the Benchmark results illustrate how centralised optimisation balances operational efficiency, emissions reduction, and technology deployment, providing a consistent baseline against which the trade-offs associated with decentralised and cooperative planning approaches can be evaluated under profitable investment conditions.

Comparison of Net Present Value (NPV) across the three planning approaches reveals distinct economic trade-offs. Competitive planning achieves the highest NPV in several scenarios, particularly under high hydrogen deployment, reflecting strong private investment incentives, but this is often accompanied by higher operational costs and, in some

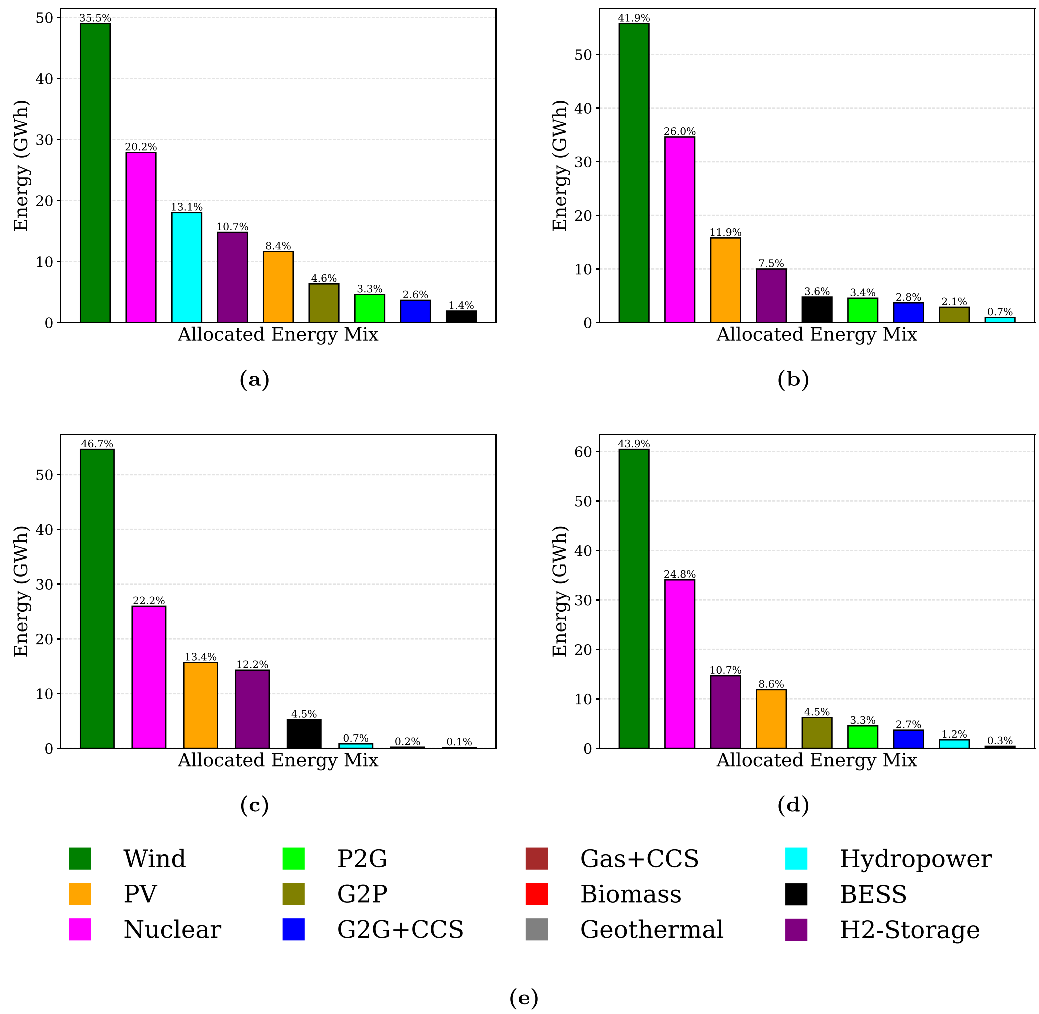


Fig. 5. Cooperative planning of energy generation mix (GWh) for 2050 peak demand under four investment scenarios: (a) Uniform +25 GW, (b) High RES–High H_2, (c) High RES–Low H_2, (d) High H_2–Low BESS. (e) Legend for Technology Types.

cases, residual CO_2 emissions. Cooperative planning yields more moderate yet comparatively stable NPV (+) outcomes across all scenarios, demonstrating the economic benefits of coordinated investment and operation while consistently achieving full decarbonisation. Benchmark planning delivers intermediate NPV (+) outcomes: higher than cooperative planning but generally lower than competitive planning in scenarios of high hydrogen integration, reflecting centrally optimised investment and dispatch decisions that internalise system-wide costs without strategic behaviour.

Furthermore, the deviation between NPV (+) and NPV (−) is notably smaller for the cooperative planning scenarios, indicating higher robustness of this approach under unprofitable planning and suggesting that cooperative strategies better mitigate financial risks and uncertainties in long-term energy system planning.

The corresponding NPV (−) and other associated performance metrics under unprofitable planning are reported in Appendix B of the Supplementary Material.

4.2. Fair cost allocation and policy support via cooperative planning

A central feature of the cooperative framework is fairness, specifically, how costs and benefits can be split up among all different technologies in the energy system. The Shapley value measures exactly what each player contribute to the overall system cost, hence it can be used to figure out the players requiring support. Consequently, it provides a robust basis for designing incentives and support mechanisms. To assess fairness in a neutral and unbiased way, we focus on the (Uniform +25 GW) scenario, which represents a balanced capacity allocation across technologies. Unlike scenarios with concentrated investments in hydrogen, storage, or renewables, this scenario avoids over-reliance on any single technology, enabling a systematic evaluation of each technology's contribution to the coalition. Table 4 presents the calculated Shapley values under this scenario, highlighting which technologies are the most valuable contributors and which may require policy support to participate effectively in a decarbonised, cooperative energy system.

Table 4 presents the calculated Shapley values for various technologies under the (Uniform +25GW) scenario. The results show that hydrogen technologies, particularly G2G and P2G, have the highest positive Shapley values, indicating they are the most valuable contributors to the system-wide coalition. This is followed by renewable sources like onshore and offshore wind. Conversely, technologies such as Gas CCS, Biomass, and both industrial and micro CHP exhibit negative Shapley values. This implies that, from a system-wide cost perspective, their inclusion increases the total cost of the coalition, even if they are necessary for reliability or other constraints. Such players would be unwilling to participate in a cooperative market without financial support. The model, therefore, identifies these technologies as prime candidates for policy support, such as subsidies or other incentives, to ensure their economic viability and continued participation in the

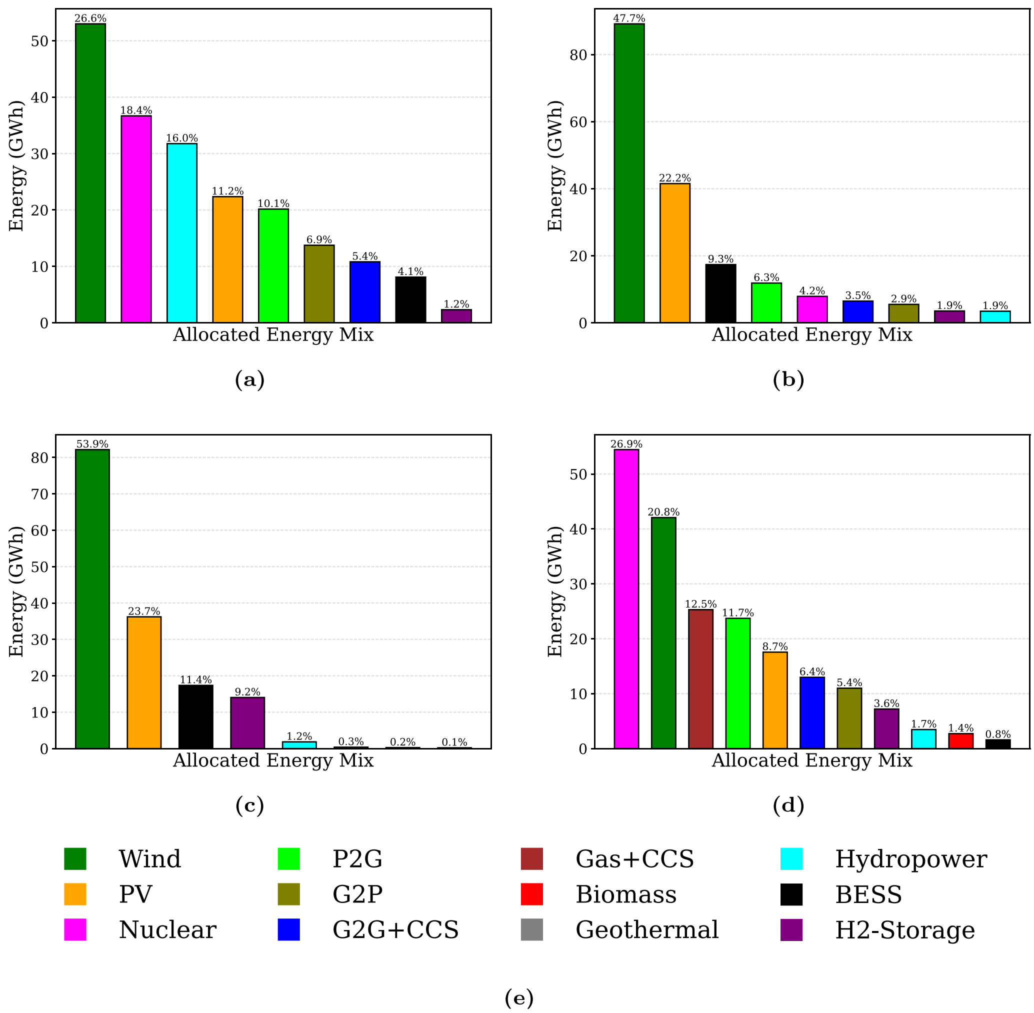


Fig. 6. Benchmark planning of energy generation mix (GWh) for 2050 peak demand under four investment scenarios: (a) Uniform +25 GW, (b) High RES–High H_2, (c) High RES–Low H_2, (d) High H_2–Low BESS. (e) Legend for Technology Types.

decarbonised energy system. This provides a quantitative, model-driven rationale for targeted policy interventions.

It is important to note that the normalised Shapley values, as shown in the table, are calculated separately by technology category and by sign (i.e., positive and negative), rather than across the entire system. For instance, the hydrogen technologies (G2G and P2G) are normalised within their own category such that their contributions sum to 100% of the hydrogen-related value. Likewise, technologies with positive electricity-related Shapley values are normalised separately from those with negative values.

These normalised values are subsequently used in the cooperative allocation mechanism for each energy vector. The allocation follows a merit-order approach, where energy resources with positive Shapley values are prioritised to meet demand. If the demand cannot be fully met by positively contributing technologies, the remaining supply is sourced from technologies with negative Shapley values. This approach ensures a transparent and economically grounded method for distributing energy contributions within the cooperative framework, while also highlighting where policy support is required to maintain system adequacy.

4.3. Sensitivity analysis and investment viability

To assess the robustness of this paper's findings, a sensitivity analysis is conducted on key economic parameters. Fig. 7 examines the impact of the investment planning horizon on the Net Present Value (NPV) and Return on Investment (ROI) for different technologies. The Return on Investment is defined as:

$$\mathrm{ROI}(\%) = \frac{\text{NPV [£]}}{\text{Investment Cost [£]}} \times 100 \tag{37}$$

where NPV is as defined in Eq. (1), and investment cost refers to the capital expenditure (CapEx) required to build the technology capacity (see Table 1). ROI quantifies the economic attractiveness of each technology relative to its investment cost.

The analysis shows that under profitable planning (Fig. 7(a)–(b)), hydrogen production technologies, G2G and P2G, offer the highest long-term NPV and ROI, underscoring their economic attractiveness in a decarbonised system. Conversely, technologies such as Gas-CCS and Biomass exhibit negative NPV over the entire 50-year horizon, reinforcing the Shapley value analysis that they would require financial support to remain viable. Most renewable technologies, while having lower ROI than hydrogen, demonstrate positive and stable returns, making them dependable long-term investments.

Under unprofitable planning conditions (Fig. 7(c)–(d), as described in Section 3), the NPV and ROI trends remain similar to the profitable planning, but values decrease overall, with many technologies showing negative returns.

Furthermore, the sensitivity of investment decisions is analysed to commodity prices. Fig. 8 illustrates the NPV's response to fluctuations in electricity, hydrogen, natural gas, and CO_2 prices. The NPV of

Table 3
Comparison of simulation results for competitive, cooperative, and benchmark planning (Investment span: 25 years). Electric peak demand is 102.17 GWh, and hydrogen peak demand is 14.27 GWh. The Benchmark planning follows a centralised optimised approach. NPV (+) denotes the Net Present Value under profitable planning, while NPV (−) denotes the Net Present Value under unprofitable planning; complete results for unprofitable planning are provided in Appendix B of the Supplementary Material.

Competitive planning	Investment scenarios 2025–2050			
	Uniform +25GW/Tech.	High RES–High H_2	High RES–Low H_2	High H_2–Low BESS
Total demand [GWh]	182.75	152.05	117.75	187.67
Electric demand [GWh]	149.44	130.17	103.10	158.17
Hydrogen demand [GWh]	33.31	21.88	14.65	29.50
Total energy supply [GWh]	182.75	152.05	117.75	187.67
Total operational cost [m£]	2.22	2.09	1.13	3.40
Total CO_2 emissions [tonnes]	0	0	0	8161
NPV (+) [bn£]	589	975	689	521
NPV (−) [bn£]	−334	−184	−120	−293
Cooperative planning	**Investment scenarios 2025–2050**			
	Uniform +25GW/Tech.	High RES–High H_2	High RES–Low H_2	High H_2–Low BESS
Total demand [GWh]	137.81	132.95	116.99	137.63
Electric demand [GWh]	114.76	114.73	102.50	114.73
Hydrogen demand [GWh]	23.05	18.23	14.50	22.91
Total energy supply [GWh]	137.81	132.95	116.99	137.63
Total operational cost [m£]	1.47	1.41	1.14	1.47
Total CO_2 emissions [tonnes]	0	0	0	0
NPV (+) [bn£]	424	485	442	492
NPV (−) [bn£]	−69	−133	−86	−118
Central planning (Benchmark)	**Investment scenarios 2025–2050**			
	Uniform +25GW/Tech.	High RES–High H_2	High RES–Low H_2	High H_2–Low BESS
Total demand [GWh]	182.75	152.06	117.75	187.67
Electric demand [GWh]	149.44	130.17	103.10	158.17
Hydrogen demand [GWh]	33.31	21.88	14.65	29.50
Total energy supply [GWh]	182.75	152.06	117.75	187.67
Total operational cost [m£]	2.14	1.56	1.13	3.22
Total CO_2 emissions [tonnes]	0	0	0	4285
NPV (+) [bn£]	606	824	700	562
NPV (−) [bn£]	−301	−171	−107	−363

Table 4
Shapley values for technologies in the cooperative 'Uniform +25GW' scenario, indicating their marginal contribution to the system. Values are normalised within their respective groups.

Technology	Shapley value	Normalised Shapley (%)
G2G[a]	1.71E+11	59.19
P2G[a]	1.18E+11	40.81
Onshore wind	1.02E+11	17.46
Offshore wind	9.37E+10	16.08
G2P (H2-CCGT)	8.73E+10	14.98
G2P (Fuel Cell)	6.58E+10	11.29
PV	4.29E+10	7.37
Hydropower	4.09E+10	7.02
Storage	3.73E+10	6.40
Nuclear	3.47E+10	5.95
Other RES	2.87E+10	4.93
Hydro ROR	2.71E+10	4.65
G2P (H2-OCGT)	2.25E+10	3.86
Gas CCS[b]	−3.23E+09	1.05
Geothermal[b]	−1.29E+10	4.22
Biomass[b]	−6.47E+10	21.11
Industrial CHP[b]	−8.63E+10	28.15
Micro CHP[b]	−1.39E+11	45.47

[a] Indicates hydrogen technologies.
[b] Indicates electricity-related technologies with negative contributions.

renewable sources (wind, solar) and nuclear power is largely insensitive to commodity price volatility, making them low-risk investments from a market perspective. In stark contrast, the profitability of Gas CCS is highly sensitive to both natural gas and CO_2 prices, exposing it to significant market risk. Hydrogen-related technologies (P2G, G2P) are, as expected, highly dependent on the relative prices of electricity and hydrogen, highlighting the need for stable policy and market frameworks to de-risk these crucial investments.

Finally, Table 5 synthesises these insights by quantifying the policy support required under different economic conditions. As indicated in this table, the support is expressed in terms of energy quantities (GWh) and financial support as an operational expenditure (opex) when the system is operating at its peak demand.

The table clearly shows that under markets with unprofitable planning, significant financial support is necessary to ensure technologies participate cooperatively, as illustrated in Fig. 7(c)–(d) and detailed in Appendix B of the Supplementary Material. It is important to note that all other results are produced under profitable planning unless otherwise specified.

To ensure the robustness of our findings to assumptions on technology capacities, we conducted a targeted sensitivity analysis varying key capacity limits (renewables, nuclear, hydrogen, and storage) by ±20% (see Appendix C of the Supplementary Material). The results indicate that the main conclusions are largely unaffected by these variations, with only minor changes in operational costs under tightened limits.

The Shapley value analysis highlights that hydrogen technologies (G2G and P2G) are the largest positive contributors to system efficiency, while Gas CCS, Biomass, and CHP technologies increase system costs and would require policy support to participate. Sensitivity

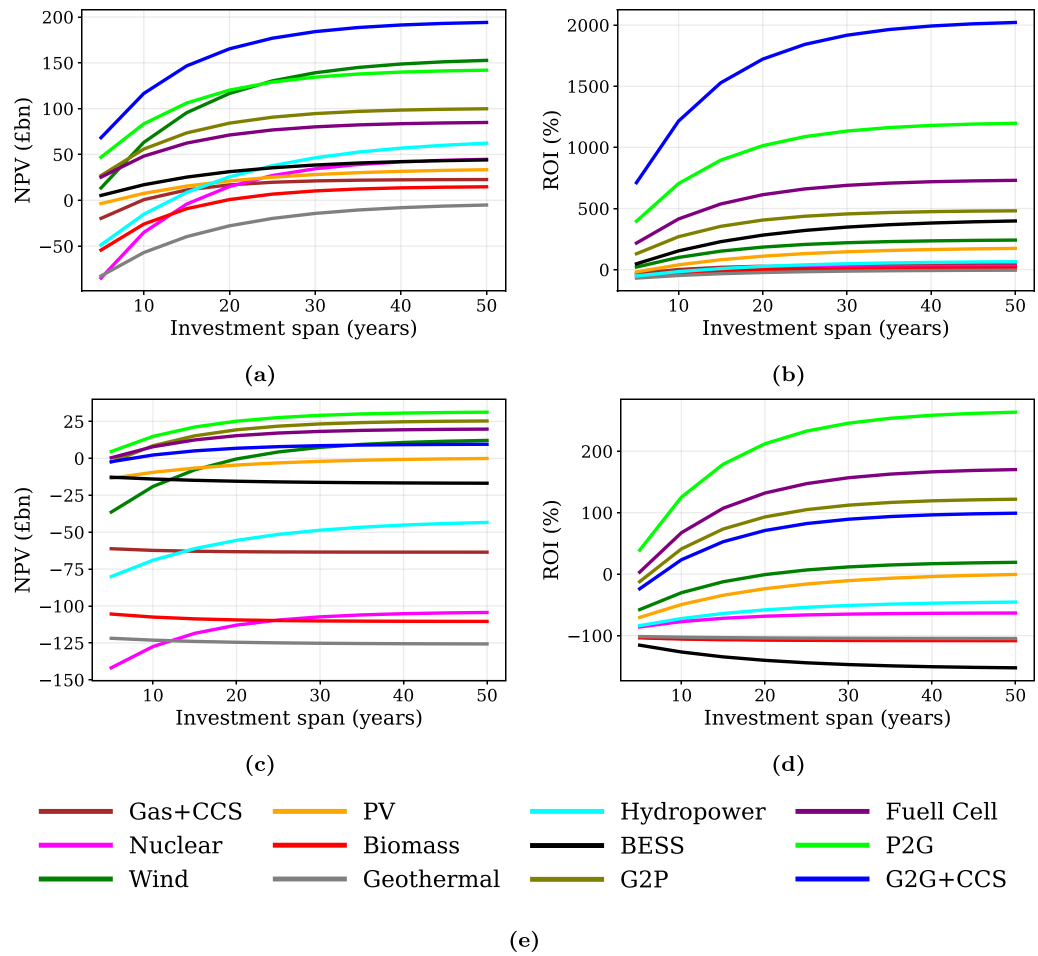


Fig. 7. Sensitivity of Net Present Value (NPV) and Return on Investment (ROI) to the investment span for different energy technologies. (a)–(b) show NPV and ROI under the profitable planning, (c)–(d) correspond to the unprofitable planning, and (e) provides the legend for technology types.

analysis confirms the economic robustness of hydrogen, nuclear, and renewables under varying investment horizons and commodity prices, while technologies like Gas CCS remain highly exposed to market volatility. Policy support, quantified in terms of energy supply and operational expenditure, is necessary under unprofitable market conditions to maintain system adequacy and equitable participation. Overall, cooperative, system-level planning reduces operational costs, residual CO_2 emissions, and hydrogen demand, stabilises the energy mix, and prioritises resources based on their system-wide value. By integrating these insights, the framework provides actionable guidance for policymakers, ensuring a cost-effective, resilient, and equitable pathway to decarbonisation in Great Britain.

5. Conclusion

This paper demonstrates the value of cooperative approaches in the strategic planning of Great Britain's integrated electricity–hydrogen system under the 2050 net-zero pathway. We hypothesised that while competitive markets drive individual efficiency, the complex, cross-vector nature of hydrogen and electricity infrastructures requires a cooperative game-theoretic framework to overcome coordination risks and market misalignments. The significant innovation of this work lies in the development of a bi-level game-theoretic framework that integrates competitive Nash–Cournot and cooperative Shapley value-based interactions, providing a more realistic representation of liberalised markets than traditional centralised optimisation approaches.

Our key findings show that under low hydrogen integration, both competitive and cooperative planning frameworks are technically feasible for achieving net-zero system design. However, in highly hydrogen-integrated energy systems, cooperative planning consistently delivers superior economic and environmental outcomes. At the 2050 peak demand hour, cooperative planning achieves a 57% reduction in operational costs and full decarbonisation under high hydrogen integration scenarios, whereas competitive planning leaves residual emissions of 8161 tonnes of CO_2. Cooperative outcomes also exhibit greater financial robustness, reflected by smaller deviations between profitable NPV (+) and unprofitable NPV (−). Under adverse market conditions, cooperative strategies therefore incur lower NPV losses and require reduced policy support compared to competitive strategies. These outcomes reflect that cooperative planning delivers a more coordinated energy mix shaped by system-wide optimisation across electricity and hydrogen vectors, whereas competitive planning produces a more fragmented mix driven by individual profit-seeking behaviour.

From a methodological perspective, the central hypothesis underpinning this work, that explicitly modelling strategic investment behaviour is essential for accurately assessing hydrogen infrastructure deployment, provides new insights for policymakers. The cooperative framework offers a transparent mechanism for distributing costs and benefits among heterogeneous technology stakeholders, helping align private incentives with system-wide decarbonisation objectives. It also identifies technologies requiring policy support and evaluates

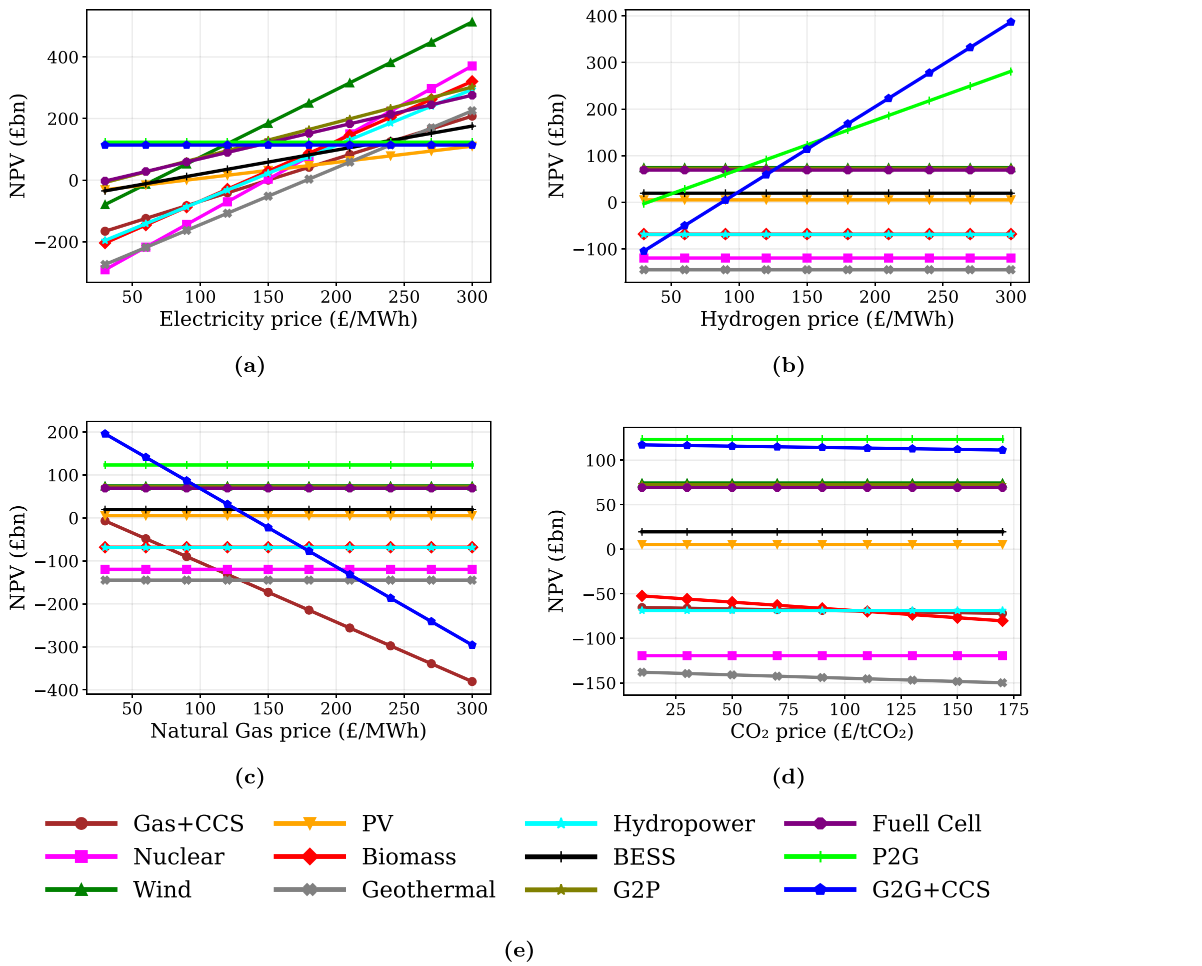


Fig. 8. Sensitivity of net present value (NPV) to prices of (a) electricity, (b) hydrogen, (c) natural gas, and (d) CO_2. (e) Legend for technology types.

Table 5
Policy support by cooperative planning under a 25-Year investment span with different price cases. Electric peak demand is 102.17 GWh, and hydrogen peak demand is 14.27 GWh. Profitable prices: Electricity = 100 £/MWh, Hydrogen = 150 £/MWh, Gas = 75 £/MWh, CO_2 = 163 £/tCO_2; Unprofitable prices: Electricity = 40 £/MWh, Hydrogen = 50 £/MWh, Gas = 15 £/MWh, CO_2 = 163 £/tCO_2.

Case of profitable prices	Investment scenarios			
	Uniform +25GW/Tech.	High RES–High H_2	High RES–Low H_2	High H_2–Low BESS
Support for electricity technologies [GWh]	0	0	0	0
Support for hydrogen technologies [GWh]	0	0	0	0
Opex-based support for electricity [m£]	0	0	0	0
Opex-based support for hydrogen [m£]	0	0	0	0
Case of unprofitable prices	**Investment scenarios**			
	Uniform +25GW/Tech.	High RES–High H_2	High RES–Low H_2	High H_2–Low BESS
Support for electricity technologies [GWh]	20.54	54.06	18.20	32.49
Support for hydrogen technologies [GWh]	0	0	0	0
Opex-based support for electricity [m£]	0.82	2.16	0.73	1.30
Opex-based support for hydrogen [m£]	0	0	0	0

their financial viability under both profitable and unprofitable market conditions, providing actionable guidance for policy design.

This study provides several advances over previous research, which primarily assumes centralised optimisation or considers competitive and cooperative formulations in isolation. First, it endogenises strategic behaviour among technology investors in a multi-player setting, capturing interactions that influence investment and operational decisions. Second, it applies cooperative game theory with Shapley value allocation at a national scale, quantifying each technology's marginal contribution to system-wide net present value and identifying G2G and P2G hydrogen technologies as primary value drivers. Third, it explicitly evaluates financial support requirements, ranging from £0.82 to 2.16 million, to maintain stakeholder participation under adverse market conditions. Finally, the framework enables controlled comparisons between competitive, cooperative, and benchmark planning approaches, all conducted under identical system conditions, quantifying differences in costs, emissions, and technology deployment.

Looking forward, future work will focus on expanding the framework to incorporate policy instruments such as Contracts for Difference (CfD) and Marginal Abatement Cost (MAC), evaluating seasonal energy storage coordinated with hydrogen technologies, and applying the framework to other regional and national energy systems.

CRediT authorship contribution statement

Mohamed Abuella: Writing – review & editing, Writing – original draft, Visualization, Supervision, Software, Resources, Methodology, Investigation, Formal analysis, Data curation, Conceptualization. **Adib Allahham:** Writing – review & editing, Validation, Supervision, Resources, Project administration, Methodology, Investigation, Funding acquisition, Conceptualization. **Sara Louise Walker:** Supervision, Project administration, Funding acquisition.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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Appendix A. Supplementary data

This material contains additional details on the simulation settings, unprofitable planning results, and sensitivity analysis results.

Supplementary material related to this article can be found online at https://doi.org/10.1016/j.ijhydene.2026.154064.

Data availability

This paper utilises a dataset enabling national-scale energy system modelling and planning for Great Britain (GB), supporting scenario analyses and optimisation studies to identify optimal pathways for integrating hydrogen into the energy system. The dataset ensures consistency, scalability, and accuracy in assessing decarbonisation strategies. The data used to construct the model are available at: https://github.com/MohamedAbuella/GB_IES.

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