Renewable and Sustainable Energy Reviews 225 (2026) 116147

Contents lists available at ScienceDirect

Renewable and Sustainable Energy Reviews

journal homepage: www.elsevier.com/locate/rser

Local energy community with a power-to-gas system: A feasibility case study and performance analysis

Amin Amin [a,*], Ioan Petri [a], Simon Minett [b]

[a] School of Engineering, Cardiff University, Cardiff, CF24 3AA, United Kingdom
[b] Challoch Energy Ltd., Bridgend, CF31 1BE, United Kingdom

HIGHLIGHTS

- Power-to-gas system potential for achieving net-zero carbon communities.
- Predicting determinants of power-to-gas systems using machine learning approaches.
- Neural networks perform more efficiently in predicting energy and weather parameters.
- Hybrid power-to-gas systems provide high-cost savings equal to the capital cost.

ARTICLE INFO

Keywords:
Decarbonisation
Net-zero
Renewable energy
Environmental impact
Energy forecasting
Hydrogen energy
Carbon emission
Energy community

ABSTRACT

The transition to local renewable energy communities offers a promising route to decarbonisation, energy security, and system decentralisation. Achieving high renewable shares necessitates highly integrated flexibility through combining multiple energy carriers and storage systems to manage variability and ensure reliability. This study explores the technical, economic, and environmental performance of a hybrid power-to-gas (P2G) system in a UK rural community, incorporating wind and solar generation, battery storage, and hydrogen production. A machine learning-based framework was developed for forecasting key energy system determinants. Among four approaches tested, artificial neural networks (ANN) and random forest (RF) demonstrated high accuracy, with ANN elected for real-time operation due to lower computational requirements. System simulations indicated that 92 % of the community's annual electricity demand could be supplied by renewables, yielding average electricity cost savings of 54.3 %. Hydrogen blending at a 20 % volume-based scenario reduced gas demand by 6.3 %, while surplus hydrogen produced offered additional revenue potential. Over a 25-year lifetime, total revenues were approximately equal to the capital investment, with a 15-year payback period. These findings highlight the potential of hybrid P2G systems to support net-zero targets at the community level, considering supportive policy and system integration.

1. Introduction

The energy landscape is undergoing a profound transformation, characterised by the rapid integration of renewable energy sources (RES) and the growing deployment of distributed energy systems (DES). This shift is primarily driven by the urgent need to mitigate climate change through comprehensive decarbonisation strategies across all energy sectors. These advancements offer promising opportunities to enhance energy efficiency, reduce greenhouse gas emissions, and accelerate the transition towards a low-carbon economy [1,2]. Furthermore, they contribute to decentralising energy markets, empowering local governance of energy production and consumption, and enabling greater participation of individual prosumers in energy-related decisions [3–5]. However, the pace of RES deployment is anticipated to be insufficient to meet the projected rise in global energy demand [6]. In response, the United Nations Climate Change Conference (COP27) has advocated for ambitious mitigation actions, calling for significant reductions in carbon emissions and a full transition to renewable energy by 2050 [7].

Consequently, many nations have set ambitious targets to increase the share of renewable energy and reduce greenhouse gas (GHG) emissions, while maintaining a stable and secure energy supply [8].

* Corresponding author.
Email addresses: amina8@cardiff.ac.uk (A. Amin), petrii@cardiff.ac.uk (I. Petri), simon.minett@challoch-energy.com (S. Minett).

https://doi.org/10.1016/j.rser.2025.116147
Received 4 August 2024; Received in revised form 22 July 2025; Accepted 28 July 2025
Available online 31 August 2025

Nomenclature

Acronyms

AC	Alternating current
ANN	Artificial neural network
BESS	Battery energy storage system
CEC	Citizen energy community
CHP	Combined heat and power system
DC	Direct current
DER	Distributed energy resource
DES	Distributed energy system
DR	Demand response
EMS	Energy management system
EU	European Union
EV	Electric vehicle
FC	Fuel cell
GHG	Greenhouse gas
IES	Integrated energy system
LCA	Life cycle assessment
LCOE	Levelised cost of energy
LEC	Local energy community
LEM	Local energy market
LES	Local energy system
LSTM	Long short-term memory
LV	Low voltage
MAE	Mean absolute error
MBE	Mean bias error
MES	Multi energy system
ML	Machine learning
P2G	Power-to-gas
P2P	Power-to-power
P2X	Power-to-product
PCA	Principal component analysis
PV	Photovoltaic
R^2	Coefficient of determination
REC	Renewable energy community
RES	Renewable energy source
RF	Random forest
RNN	Recurrent neural network
UK	United Kingdom
UN	United Nations

Units

%	Percentage
°C	Degree celsius
£	British Pound Sterling
kg	Weight in kilograms
kg CO_2-eq/kWh	Kilogram of carbon dioxide equivalent per kilowatt-hour
kg/d	Kilogram per day
km	Kilometre
kW	Kilowatt
kWh	Kilowatt-hour
kWh/kg	Kilowatt-hour per kilogram
M	Million
m	Meter
m/s	Meter per second
MW	Megawatt
MWh	Megawatt-hour
MWh/y	Megawatt hour per year
tonne	Weight in tonnes
tonne/y	Tonne per year
W	Watt
W/m^2	Watt per square metre

Variables

DBT	Dry-bulb temperature
GHI	Global horizontal irradiance
H2	Hydrogen
WS	Wind speed

For example, the European Union (EU) achieved its 2020 Renewable Energy Directive target by reaching a 22 % share of renewables in total energy consumption and a 31 % reduction in emissions in 2022 [9]. However, the European Commission has proposed raising the renewable energy target to 40 % by 2030 to facilitate a 55 % reduction in GHG emissions [10]. The United Kingdom (UK) has also demonstrated leadership by enacting a binding target to achieve net-zero GHG emissions by 2050, and announced an interim goal in 2021 of a 78 % emissions reduction by 2035, compared to 1990 levels [3,11].

A central objective of the United Nations Sustainable Development Goals (SDGs) is to ensure inclusive access to affordable and sustainable energy [12,13]. However, increasing penetration of RES introduces critical challenges, particularly due to the inherent intermittency and uncertainty associated with solar and wind power [14]. Key challenges include (i) power fluctuations and system instability arising from variable weather conditions [15]; (ii) imbalances between periods of peak energy demand and renewable energy availability [16]; and (iii) curtailment of generation as a result of network constraints and the high cost of export reinforcements required to accommodate surplus production [17]. Addressing these issues necessitates the integration of high-flexible energy systems and the adoption of novel operational strategies to manage intermittency and support system stability [18,19]. This imperative extends to both urban and rural areas, ensuring inclusive progress towards decarbonisation and the achievement of net-zero targets.

In this context, hydrogen (H_2) energy technologies have attracted considerable interest as a low-carbon energy carrier, due to their long-term storage capability, high energy density, and versatility in conversion to other energy forms [15]. Such attributes can facilitate increased self-consumption of renewable energy, support decarbonisation objectives, and promote further decentralisation of energy systems [19–21]. Hydrogen-based systems, including Power-to-Product (P2X) [21,22], Power-to-Gas (P2G) [23,24], and Power-to-Power (P2P) [25,26], enable the absorption of surplus or non-flexible electricity generation for hydrogen production, which can subsequently be stored, converted into other gas products, or used for electricity generation [19,27].

Local DES communities are likely to involve diverse RES technologies, with renewable electricity contributing more than 80 % of generation in some scenarios [28]. In the UK, photovoltaic (PV) and wind installations are widely deployed, occasionally accompanied by electrolysers for converting excess electricity into hydrogen for on-site storage [15]. However, high levels of renewable generation may exceed conventional load capacities, necessitating enhanced flexibility measures within electricity networks, including balancing and scalable storage solutions [29]. Therefore, future energy systems must be designed, developed, and validated to ensure secure, efficient, and reliable value-added energy services within an increasingly complex and dynamic energy landscape. Such systems should incorporate capabilities for simulation, prediction, and optimisation, enabling informed decision-making for stakeholders by leveraging data analytics and machine learning tailored to specific technological needs.

This research presents an integrated forecasting and assessment framework for local renewable energy communities, with a focus on hybrid P2G systems that combine electricity and hydrogen pathways. The aim is to evaluate the technical, economic, and environmental performance of such systems in achieving net-zero carbon goals, while supporting energy security, decentralised market structures and lower energy costs for communities. By managing surplus renewable electricity—primarily from wind and solar—through battery storage and hydrogen production, the proposed system offers flexibility without requiring extensive customer-level retrofits.

The scope of this study encompasses two main contributions: (i) the development of machine learning-based models to predict key drivers of multi-energy system operation, including energy demand and weather-related generation variability; and (ii) a scenario-based performance analysis of a hybrid P2G system implemented in a real UK community, considering both conventional and renewable-dominant conditions. The novelty of this study lies in developing a more holistic approach, incorporating uncertainty analysis, system operation assumptions, and policy-relevant hydrogen blending scenarios. The study aims to bridge practical and analytical gaps by demonstrating the feasibility and system-level benefits of integrating P2G technologies into community-scale renewable energy systems.

The remainder of this paper is structured as follows. Section 2 reviews determinants of local distributed energy systems and recent advancements in hydrogen energy integration. Section 3 presents the key components of the proposed multi-energy system, alongside the modelling workflow and implementation in a pilot community. The main findings and results of the life-cycle assessment are detailed in Section 4. Finally, Section 5 provides concluding remarks and future research directions.

2. Distributed energy systems

The transition towards sustainable, low-carbon, and decentralised energy systems is increasingly underpinned by distributed energy resources (DERs), which promote local control of energy production, management, and consumption. Such systems aim to increase the flexibility of energy networks through the integration of diverse energy generation, conversion, and storage technologies, as summarised in Table 1, thereby meeting local community demand, reducing energy costs, enhancing energy security and resilience, and minimising carbon emissions [30–33].

Distributed energy systems (DES) encompass a wide range of energy localisation approaches, including local energy community (LEC) [8], local energy system (LES) [3], multi-energy system (MES) [34], integrated energy system (IES) [35], renewable energy community (REC) [31], local energy market (LEM) [36], and citizen energy community (CEC) [37]. Each concept addresses specific priorities, ranging from system optimisation and multi-carrier integration (as in LES, MES, and IES), to maximising renewable energy use (REC), and fostering community participation and local governance (LEC, REC, CEC). The performance scope of these systems spans community engagement, system integration, market mechanisms, and renewable energy targets. For instance, LEMs specifically focus on the economic trading of locally generated energy between producers and consumers, while REC models emphasise the exploitation of local renewable resources [1,31,32,36].

Table 1
A classification of energy systems incorporated in locally distributed energy systems.

Category	System
Generation	Electricity: Photovoltaic, wind turbine, hydro, tidal, wave Bioenergy: Biogas, biomass, biofuel Thermal: Solar thermal collector, geothermal
Conversion	Electrical generator, electrolyser, heat pump, combined heat and power, combined cooling, heat and power
Storage	Batteries, thermal, thermochemical energy storage

Table 2
Community benefits and performance metrics for distributed energy systems.

Criteria	Metric
Technical	Maximise RES self-consumption and self-sufficiency, minimise traditional energy network dependency, reduce losses and peak loads, increase demand and supply flexibility, enhance system modularity and energy synergies
Environmental	Reduce carbon emissions and conventional fuel dependency
Economic	Reduce energy costs, enhance payback period, localising energy generation and operation (decentralising energy networks)
Social	Community engagement, local investment and ownership, energy autonomy and security

The deployment and effectiveness of local DESs depend on a variety of interrelated and sensitive determinants [14,38,39]:

- **Energy demand patterns** include the characteristics of end-users (residential or commercial) and their daily and seasonal variability.
- **Resource availability** depends on the diversity and accessibility of local renewable energy resources and system components.
- **Weather and climate conditions** are crucial in performance forecasting and controlling of smart energy systems [74].
- **Network flexibility** is achieved through the integration of demand- and supply-side technologies, including electric vehicles (EVs), energy storages, and other conversion systems.
- **Network reliability** refers to the system's capacity to maintain a stable and secure energy supply under varying conditions.
- **Economic incentives** cover the impact of energy prices on system design and the affordability of supply for end-users.
- **System efficiency and stakeholder benefits** include not only techno-economic and environmental outcomes but also broader social impacts, as summarised in Table 2.

The implementation of DESs broadens the range of actors engaged in local energy markets, extending beyond the conventional roles of utility grids, system operators, retailers, and consumers. New participants include DER operators, prosumers, community shareholders, local system operators, EVs, energy storage providers, and those responsible for district heating/cooling and hydrogen technologies [40]. A key challenge is configuring systems to align with community needs, while managing significant upfront investments and deploying novel, community-based energy management systems (EMS) for optimal operation. The development of an effective EMS depends on the integration of reliable and accurate forecasting of both generation and demand, whether in real-time or for day-ahead planning. Such capabilities increase energy efficiency, enhance self-consumption, and maintain system stability and synchronisation for local economic benefits [1,19,41–43].

Several studies have examined the techno-economic potential of power-to-gas (P2G) systems to address the intermittency challenges of renewable energy sources and maximise their local value, as summarised in Table 3. Hybrid generation systems integrating hydrogen storage have been modelled with a variety of approaches, spanning different energy carriers (electricity, gas, heat), temporal resolutions (annual to sub-hourly), and objectives (planning and operational management). Common configurations include solar, wind, or combined PV-wind systems for meeting local demand and supporting hydrogen production. In many cases, hydrogen is further converted into electricity via fuel cells or injected into local gas networks. Additional system services, such as the integration of heat pumps and combined heat and power

Table 3
A summary of research applications on hydrogen production incorporated with renewable energy systems.

Production	Energy sort			Conversion		Battery	Model	
	Electricity	Blended gas	Thermal	FC	CHP		Simulation	Mathematic
Solar	[8,16,27,35,44–50]	[45]	[8,35,44–47,49]	[8,16,27,35,46–50]	[8,44,46,49]	[8,16,27,44–46]	[27,44,48,49]	[16,35,45–47,50]
Wind	[51]							[51]
PV-wind	[15,34,52–61]	[54]	[34,55–58]	[52–54,56–59,61]	[34,56]	[34,58]	[15,59,60]	[34,52–57,61]
Hydro	[46,62]		[46]	[46,62]	[46]	[46]	[62]	[46]
Wave	[34]		[34]		[34]	[34]		[34]
Heat pump	[8,46,58]		[8,46,58]	[8,46,58]	[8,46]	[8,46,58]		[46]

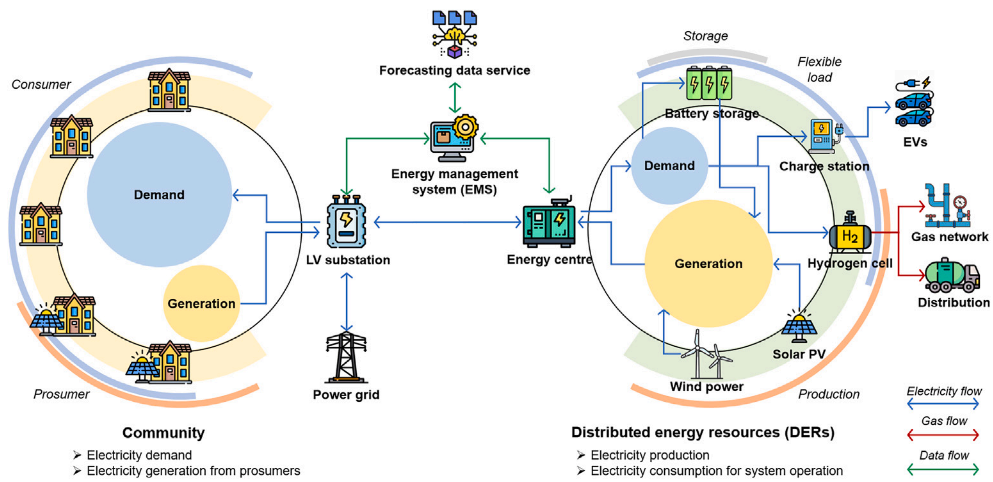

Fig. 1. A general scheme of the energy and data flows in the proposed hybrid P2G system, including wind turbine, solar PV, hydrogen production, and battery storage systems.

(CHP) units, extend the provision of heating and cooling for local thermal loads, while battery storage is employed to enhance system stability during intermittent generation periods.

3. Methodology

3.1. Hybrid local P2G system

Building on the multi-energy system challenges and opportunities discussed previously, this study examines the integration of local energy community projects with power-to-gas (P2G) systems. A key challenge is determining effective approaches for integrating electricity and hydrogen to accelerate the deployment of hydrogen energy as a practical energy vector. The proposed framework combines hybrid renewable energy, hydrogen, and storage technologies to support the UK's net-zero emissions target by 2050, as shown in Fig. 1. The design focuses on delivering innovative solutions that minimise the need for major upgrades to available distribution infrastructure or customer installations, making the renewable transition more accessible and flexible.

The framework considers two main aspects of electricity flow, each with two segments: (i) the community side, covering dwelling demand and prosumer generation; and (ii) the distributed energy system (DES) side, which comprises the production and consumption of DESs. To address local demand and system flexibility, the framework incorporates a wind turbine, solar PV system, electrolyser with hydrogen storage, and a battery energy storage system (BESS). Surplus electricity is stored in the BESS for short-term balancing or used to produce green hydrogen locally. This hydrogen can then be blended into the natural gas network or used as a local energy carrier.

The implementation of the local multi-energy system relies on developing robust forecasts for both internal and external system determinants. In this work, a forecasting module is developed to predict key weather and energy variables, supporting optimal sizing and configuration of system components, and enabling the anticipation of demand and generation patterns. This module is integrated into a real-time operational framework, managing energy flows across the low-voltage network over a day-ahead time horizon. The focus is on coordinated control of battery storage, electrolyser operation, PV generation, and wind output.

3.2. Pilot community

This study is demonstrated in South Cornelly, a rural village in South Wales comprising approximately 200 dwellings, all connected to a central low-voltage substation, as shown in Fig. 2. The village is part of a community-led energy initiative aiming to promote low-carbon, decentralised energy systems through shared renewable infrastructure. The initiative facilitates participation in a local energy market (LEM) by offering collective access to solar PV generation and battery storage, enabling residents to benefit from lower-cost electricity without requiring excessive household-level retrofitting. Unlike decentralised approaches where each household owns its own PV and storage, the centralised model enhances energy sharing, system resilience, and operational simplicity.

The proposed hybrid P2G system reflects the configurations defined by the community and comprises a 1 MW wind turbine, a 1 MW solar PV system connected to a 98 % efficient inverter, a 1 MWh BESS, a 1 MW electrolyser, and a 5-tonne hydrogen storage tank. The electrolyser operates in load-following mode, automatically adjusting hydrogen production in response to surplus renewable electricity. The BESS is constrained by technical limits typical of lithium-ion systems, with a maximum charge rate of 2 C, a discharge rate of 3 C, and an operational window between 20 % and 100 % state of charge. The battery is rated for 6,000 full charge-discharge cycles across its lifespan. These

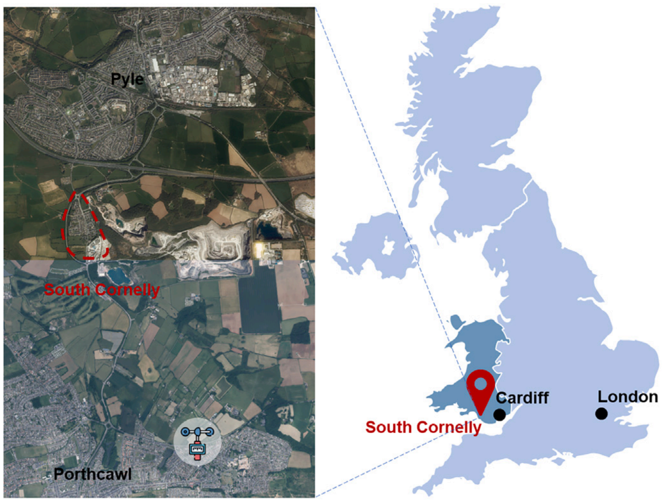

Fig. 2. Pilot community location: South Cornelly, Wales, UK.

parameters ensure safe and efficient system operation while providing sufficient flexibility to handle short-term variability in generation and demand. Further details on component lifespans, cost assumptions, and system boundaries are provided in Section 3.5.

The local energy system is designed to meet the village's electricity demand primarily through hybrid renewable sources. Surplus electricity is either stored in the BESS or directed to hydrogen production via the electrolyser, as illustrated in Fig. 3. The generated hydrogen can be stored on-site or injected into the natural gas network. Blending hydrogen in the natural gas network must consider technical and regulatory limits, as hydrogen has a lower volumetric energy density than methane [63,64]. In the UK, the current blending volume-based guideline is limited to a maximum of 20 % as outlined in the UK Government's strategy [65]. Therefore, three blending scenarios are evaluated: 10 %, 20 % (base case), and 30 % by volume.

The community-led energy initiative aims not only to meet local electricity needs but also to leverage surplus renewable generation for green hydrogen production. A key objective is to sell excess hydrogen to nearby commercial and agricultural users, where there is growing interest in hydrogen as a clean fuel—particularly for fleet transport and industrial applications. Given this outward-facing ambition, the system component sizes have been predefined by the community to maximise local and external impact, rather than optimised for internal self-sufficiency alone. Accordingly, this study does not seek to optimise system sizing. Instead, it evaluates the technical feasibility, economic performance, and environmental implications of the proposed configuration under realistic operational conditions.

3.3. Local energy asset modelling

3.3.1. Wind turbine

Wind power is a key contributor to overall system efficiency and capacity factor. The output depends on both the characteristics of the turbine and the local wind profile. As wind measurements are typically taken near ground level, wind speed is adjusted for hub height using the logarithmic wind profile, as shown in Eq. (1) [66–70]. Power output from the wind turbine (P_{wt}) is estimated using Eq. (2) [15,52,53]:

$$V_{wt}(t) = V_{aws}(t) \cdot \frac{\ln\left(\frac{H_{wt}}{Z_{wt}}\right)}{\ln\left(\frac{H_{aws}}{Z_{aws}}\right)} \tag{1}$$

where $V_{wt}(t)$ and $V_{aws}(t)$ are wind velocity (m/s) at the wind hub (H_{wt}) and anemometer (H_{aws}) heights, respectively. Z_{wt} and Z_{aws} are surface roughness coefficients.

$$P_{wt}(t) = \begin{cases} 0, & V_{wt}(t) < V_{in} \text{or } V_{wt}(t) > V_{out} \\ P_{\max}, & V_r \le V_{wt}(t) < V_{out} \\ P_{\max} \cdot \left(\frac{V_{wt}^3(t) - V_{in}^3}{V_r^3 - V_{in}^3}\right), & V_{in} \le V_{wt}(t) < V_r \end{cases} \tag{2}$$

where V_{in}, V_{out}, and V_r are the cut-in, cut-out, and rated wind speeds (m/s), respectively. $P_{\max}$ is the rated power capacity (kW).

3.3.2. Photovoltaic array

PV output is primarily driven by incident solar radiation. The PV power output (P_{pv}) is given by Eq. (3) [15,59,71]:

$$P_{pv}(t) = P_{\max} \cdot \left(\frac{G(t)}{G_{st}}\right) \cdot T_{pv} \cdot \eta_{invert} \tag{3}$$

where $P_{\max}$ is the PV capacity (W), $G(t)$ is the solar irradiance (W/m^2) at time t, G_{st} is standard irradiance (1000 W/m^2), T_{pv} is module temperature (°C), and η_{invert} is inverter efficiency.

3.3.3. Hydrogen production

The electrolyser converts electricity into hydrogen by splitting water, with the produced hydrogen either stored or injected into the gas network (see Fig. 4). The hydrogen production rate (H) in kg is calculated using Eq. (4) [50,54,72,73]:

$$H(t) = \frac{P_{el}(t) \cdot \eta_{invert} \cdot \eta_{el}}{\text{LHV}_H} \tag{4}$$

where P_{el} is the power consumed by the electrolyser (kW), η_{invert} is inverter efficiency, η_{el} is electrolyser efficiency, and LHV_H is the lower heating value of hydrogen (33.3 kWh/kg).

3.4. Machine learning prediction

Accurate forecasting of both internal and external factors is crucial for the optimal operation of distributed energy resources [74]. In this study, the performance of four widely used machine learning models in

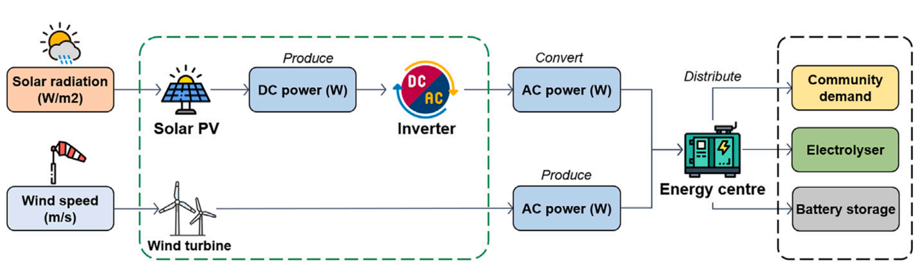

Fig. 3. A schematic diagram of electricity flows in the proposed P2G multi-energy system.

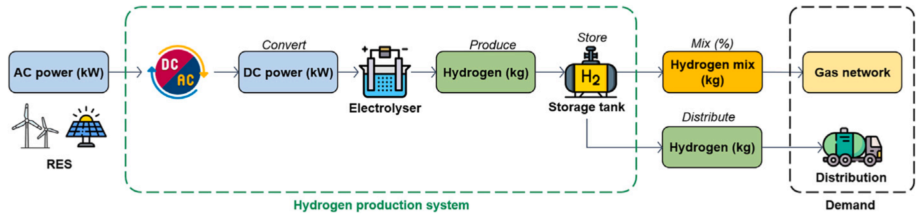

Fig. 4. A schematic diagram of hydrogen production from hybrid renewable energy.

Table 4
Technical and environmental features of energy components incorporated into the proposed P2G system.

System	Lifetime [y]	Degradation [%/y]	Emissions [kg CO^2-eq/kWh]	Investment	Replacement [% Inv.]	O&M [%/y Inv.]	Reference
Solar PV	25–30	1	0.014–0.073	730£/kW	70£/kW (10 y)[1]	1.5	[87–89]
Wind turbine	25–30	1.6	0.004	1050£/kW	NA	3	[90–92]
Battery	10	0.5	0.08–0.10[2]	500£/kWh	100	2	[93–95]
Electrolyser	30	1	0.01–0.02[3]	860£/kW	35 (9 y)[4]	3	[91,96,97]
Hydrogen tank	30–50	NA	NA	430–520£/kg	NA	2	[91,98]
Engineering cost				20 % Inv.			[87]

[1] Costs for inverter replacement with a lifetime of 10 years.
[2] Carbon emissions per kWh of the battery storage capacity over its lifecycle.
[3] Carbon emissions per kg of hydrogen produced.
[4] Replacement costs every 9 years.

weather and energy prediction research was evaluated [75–82], including artificial neural network (ANN), long short-term memory (LSTM), recurrent neural network (RNN), and random forest (RF). Then, the feasible model was selected for short-term forecasting of energy and weather determinants. The models were evaluated on their capacity to predict day-ahead profiles for five key variables: community electricity demand, community gas demand, wind speed, air temperature, and solar radiation. These weather parameters were directly used to estimate power output from solar PV and wind turbine assets.

- **Data collection:** Energy and weather data for the pilot community were collected over a continuous one-year period (2022), including aggregated electricity and natural gas demand at the low-voltage substation (30-min resolution). Additionally, air temperature, solar radiation, and wind speed data (5-min resolution) were obtained from the nearest automatic weather station, via the WeatherUnderground Personal Weather Station Network [83].
- **Model design:** All models were structured with similar input features. For weather variables, the previous two-day data points of the three parameters, plus time of day, day, month, and season indicators. For energy variables, historical two-day data of the target variable and the three weather variables, and temporal indicators are used, as well as next-day weather data points. The output for each model was a vector of 48 predicted values of the target variable, corresponding to each half-hour interval of the next day.
- **Training and validation:** Each model was trained and tested using 17,520 half-hourly records of energy and weather datasets. The data were split into 60 % training, 20 % validation, and 20 % testing. Preprocessing included outlier removal, forward-filling of missing values for gaps under one hour, omitting larger gaps, variable reduction, data transformation, and min-max normalisation. Hyperparameters such as learning rate, batch size, and epochs were tuned by grid search.
- **Feature selection and importance:** Principal component analysis (PCA) and feature importance metrics were employed to identify the most influential variables, confirming that recent historical values, key weather variables, and temporal indicators had the greatest impact on predictive performance.

Table 5
Economic factors considered in assessing the proposed P2G system.

Factor	Rate	Unit	References
Energy price			
Electricity	0.29	£/kWh	[99]
Electricity standing charge	0.53	£/day	[99]
Gas	0.07	£/kWh	[99]
Gas standing charge	0.3	£/day	[99]
Other			
Discount rate	3	%	[100]
Energy tariff growth	5	%	[100]

- **Performance metrics:** Model accuracy and reliability were evaluated using wide error metrics [84–86], such as mean absolute error (MAE), mean bias error (MBE), and the coefficient of determination (R^2). Both cross-validation and out-of-sample testing were used to ensure robust assessment.

3.5. Economic and environmental analysis

The economic and environmental implications of the proposed hybrid P2G system were assessed using clearly defined system boundaries that include all major components: wind turbine, solar PV, BESS, electrolyser, and hydrogen storage. The analysis considers a 25-year operational horizon and uses the annual community energy demand as the functional unit. Technical and financial assumptions of system components —including capital expenditure, component lifespans, replacement cycles, and operation and maintenance (O&M) costs—are drawn from published literature and summarised in Table 4.

Table 5 presents the main economic parameters used in the evaluation. The cost of renewable electricity was estimated at £0.08/kWh, while the hydrogen production cost was estimated at £2.27/kg (equivalent to £0.07/kWh), both calculated using the Levelised Cost of Energy (LCOE) [101] according to Eq. (5). This approach accounts for total investment, operational and maintenance costs, replacement cycles and potential revenues from energy sales over the system's lifetime.

$$\mathrm{LCOE} = \frac{I_c + \sum_{i=1}^{n} \frac{O_i + M_i - R_i}{(1+r)^i}}{\sum_{i=1}^{n} \frac{E_i}{(1+r)^i}} \tag{5}$$

Table 6
Statistical analysis of the effectiveness and performance of machine learning models in predicting the next 24-h key system determinants.

Model	Metric*	Determinant					Computational time	
		Energy[1]		Weather			Training [min]	Forecast [s]
		Electricity	Gas	WS[2]	GHI[3]	DPT[4]		
ANN	MAE	2.92	49.85	0.49	51.47	1.23	12–21	1–2
	MBE	−0.38	7.3	0.03	−2.98	−0.22		
	R^2	0.98	0.94	0.56	0.76	0.94		
RNN	MAE	2.98	52.93	0.8	55.05	1.65	20–35	3–5
	MBE	−0.47	10.32	0.03	−3.29	−0.46		
	R^2	0.98	0.92	0.53	0.74	0.93		
LSTM	MAE	3.59	52.48	0.94	56.42	1.73	35–45	5–8
	MBE	0.22	8.42	−0.17	3.87	0.33		
	R^2	0.97	0.93	0.53	0.7	0.92		
RF	MAE	1.18	19.04	0.49	41.9	0.97	6–13	90–120
	MBE	0.05	−0.24	0.02	−1.8	−0.01		
	R^2	1.0	0.99	0.57	0.81	0.94		

* MAE and MBE provide the average absolute and bias error with the same variable unit, while R^2 provides a statistical value between 0.0 and 1.0 for the relationship between the actual and predicted data.
[1] Energy in kWh.
[2] Wind speed in m/s.
[3] Global horizontal irradiance in W/m^2.
[4] Dry-bulb temperature in °C.

where I_c is investment cost, O_i and M_i are annual operation and replacement costs, R_i is revenue from energy sales, E_i is expected energy production, and r is the discount rate.

To assess long-term economic benefits, the Total Saving Flow (TSF) was estimated using Eqs. (6) and (7), reflecting the net difference in energy-related costs with and without the system. This includes electricity and gas tariffs, inflation, and sales revenue.

$$\mathrm{TSF} = -I_c + \sum_{n=1}^{LT} \left[(C_o - C)(1 - r) \right] \tag{6}$$

$$\begin{aligned}
C_o &= E_d \cdot T_{elec}(1+i) + G_d \cdot T_{gas}(1+i) \\
C &= (C_{elec} + C_{gas}) + O(1+r) + M - R \\
C_{elec} &= E_{res} \cdot LCOE_{elec} + E_i \cdot T_{elec}(1+i) \\
C_{gas} &= G_{H2} \cdot LCOE_{H2} + G_i \cdot T_{gas}(1+i)
\end{aligned} \tag{7}$$

where I_c is capital cost, C_o and C are energy costs without and with the system, r is discount rate, and LT is system lifetime. E_d and G_d are electricity and natural gas demand (kWh), T_{elec} and T_{gas} are electricity and natural gas tariffs (£/kWh), and i is the energy tariff increase (%). C_{elec} and C_{gas} are electricity and natural gas costs with the developed system (£), O is annual operation costs (£), M is replacement costs (e.g., inverter and battery replacement), and R is revenues of selling the surplus hydrogen (£). E_{res} and G_{res} are electricity and blended gas purchased from the developed system (kWh), while E_i and G_i are electricity and natural gas purchased from the grid (kWh).

In terms of environmental assessment, the analysis focuses on both operational emissions and embodied carbon. Although renewable electricity generation is emission-free at the point of use, upstream carbon emissions are considered based on emission factors for manufacturing and installation of PV panels, wind turbines, batteries, and hydrogen systems [102]. Carbon intensity values of 0.207 kg CO_2-eq/kWh for grid electricity and 0.182 kg CO_2-eq/kWh for natural gas were applied, consistent with current UK benchmarks [103]. Embodied emissions associated with major system components are summarised in Table 4.

While this study does not conduct a formal life-cycle assessment, we recognise that material sustainability and resource depletion play a growing role in assessing the long-term environmental impact of clean energy systems. Future research should incorporate midpoint indicators to evaluate the trade-offs between decarbonisation and material sustainability.

4. Results and discussion

This section presents the results in three main parts, corresponding to the research workflow. First, the performance of the forecasting models is evaluated, highlighting the capability of different machine learning (ML) techniques for predicting energy demand and key weather parameters. Next, the operational performance of the proposed hybrid power-to-gas (P2G) system is assessed. Finally, a techno-economic and environmental feasibility analysis evaluates the local P2G system's impact within the pilot community.

4.1. Prediction of system determinants

Reliable forecasting models are crucial for managing local energy systems, as they underpin both operational control and strategic planning. Four ML techniques—artificial neural network (ANN), recurrent neural network (RNN), long short-term memory (LSTM), and random forest (RF)—were compared for half-hourly day-ahead prediction of the community's electricity and natural gas demand, wind speed (WS), global horizontal irradiance (GHI), and air temperature (DBT). All models were developed and tested using similar datasets to ensure comparability, and hyperparameters for the neural networks were standardised across all variables. Model training and validation were performed on a standard personal computer (Intel Core i7, 3.40 GHz, 16 GB RAM).

Table 6 summarises the performance metrics for each ML technique. Both ANN and RF achieved higher prediction accuracy than RNN and LSTM, particularly for energy demand and air temperature. Fig. 5 illustrates model performance for representative winter and summer days. While RNN and LSTM captured general trends, they struggled with peak prediction, often missing critical fluctuations. In contrast, ANN closely followed daily variations and demonstrated improved peak prediction, whereas RF achieved the best overall performance for most variables, due to its ensemble approach and reduced risk of overfitting [104,105].

Electricity demand in the community showed less seasonality than natural gas demand, reflecting the reliance of most UK homes on gas for space heating [43]. This resulted in relatively stable daily demand profiles, simplifying next-day forecasting. Predictions for electricity and gas demand were more accurate than those for weather variables, as aggregation smooths individual fluctuations. Air temperature forecasts benefited from their relationship with other weather parameters, notably solar radiation, which introduces time-lagged effects. Conversely, wind speed and solar irradiance remained more challenging to predict

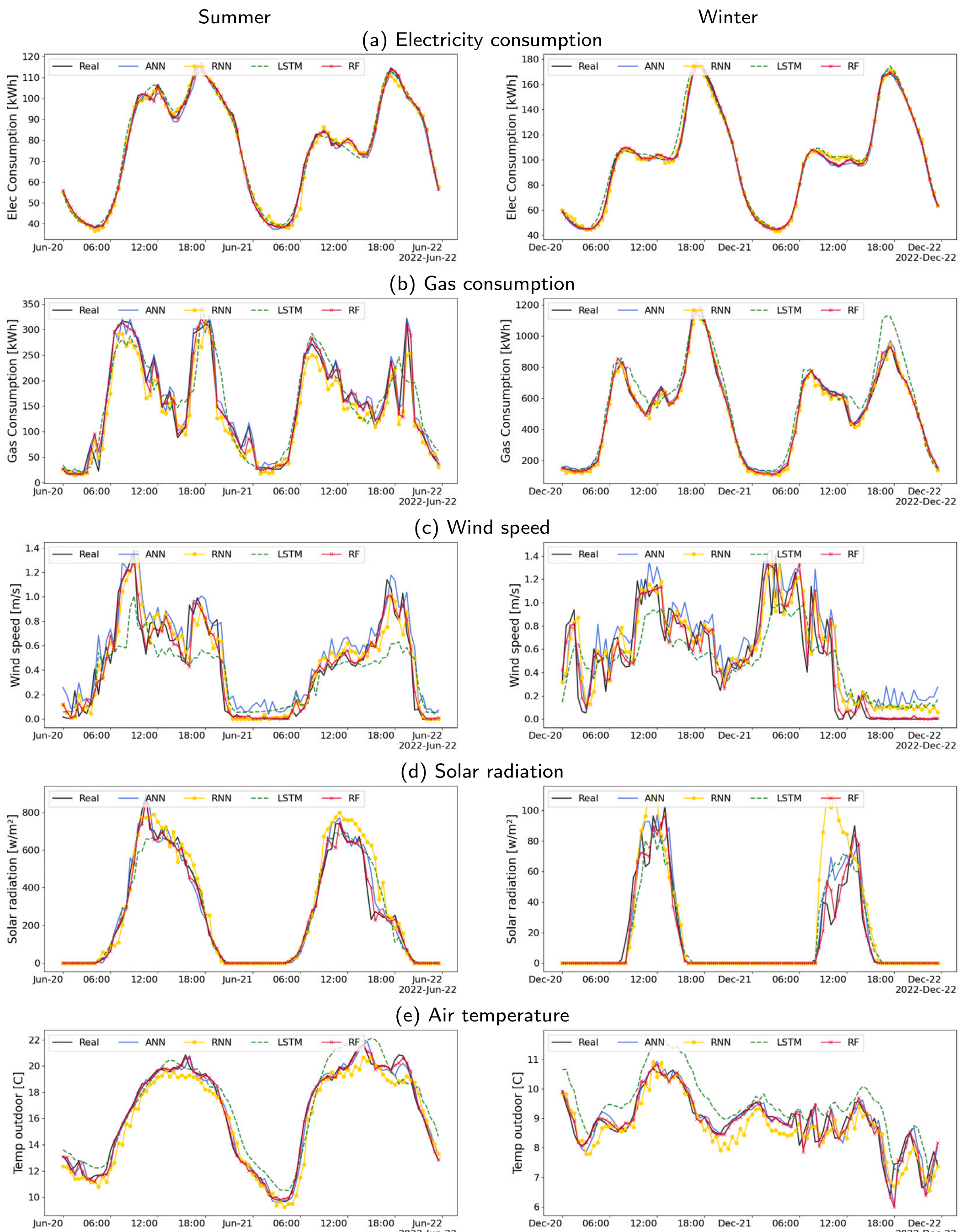

Fig. 5. Daily performance of forecasting models in estimating the next 24-h predictions for key weather and energy parameters over summer and winter.

due to their high variability, local terrain influence, and cloud cover dynamics.

Overall, both ANN and RF showed strong performance in forecasting day-ahead profiles of energy and weather determinants. In addition to predictive accuracy, computational requirements are an important consideration. Although RF offers high accuracy, it is more computationally demanding and slower to establish compared to ANN, which trains faster and is better suited for advanced optimisation over practical time horizons. Thus, ANN is recommended for real-time energy management applications in this context. Since wind and solar predictions directly inform energy generation estimates, uncertainties propagate into the output of the hybrid system. Therefore, wind power output has an expected fluctuation range of 44 % and solar PV output ±24 %, while ±2 % for electricity and ±6 % for gas.

4.2. Hybrid P2G system performance

Final fine-tuned ANN models were used to simulate annual energy demand and renewable generation for the community. Fig. 6 shows the daily electricity demand and renewable generation over a typical year, as well as the flows to system components and the grid. As most households use gas for heating, daily electricity demand is relatively steady, ranging from 1.7 MWh (±2 %) in summer to 2.7 MWh (±2 %) in winter. The wind turbine provides higher output between November and May, aligning with periods of low solar irradiance in the UK. The high wind resource at the pilot site ensures persistent generation throughout the year, with the PV array contributing most during spring and summer.

Fig. 7 illustrates annual shares of electricity production and use. The community's annual electricity demand is 759 MWh (±15 MWh). The

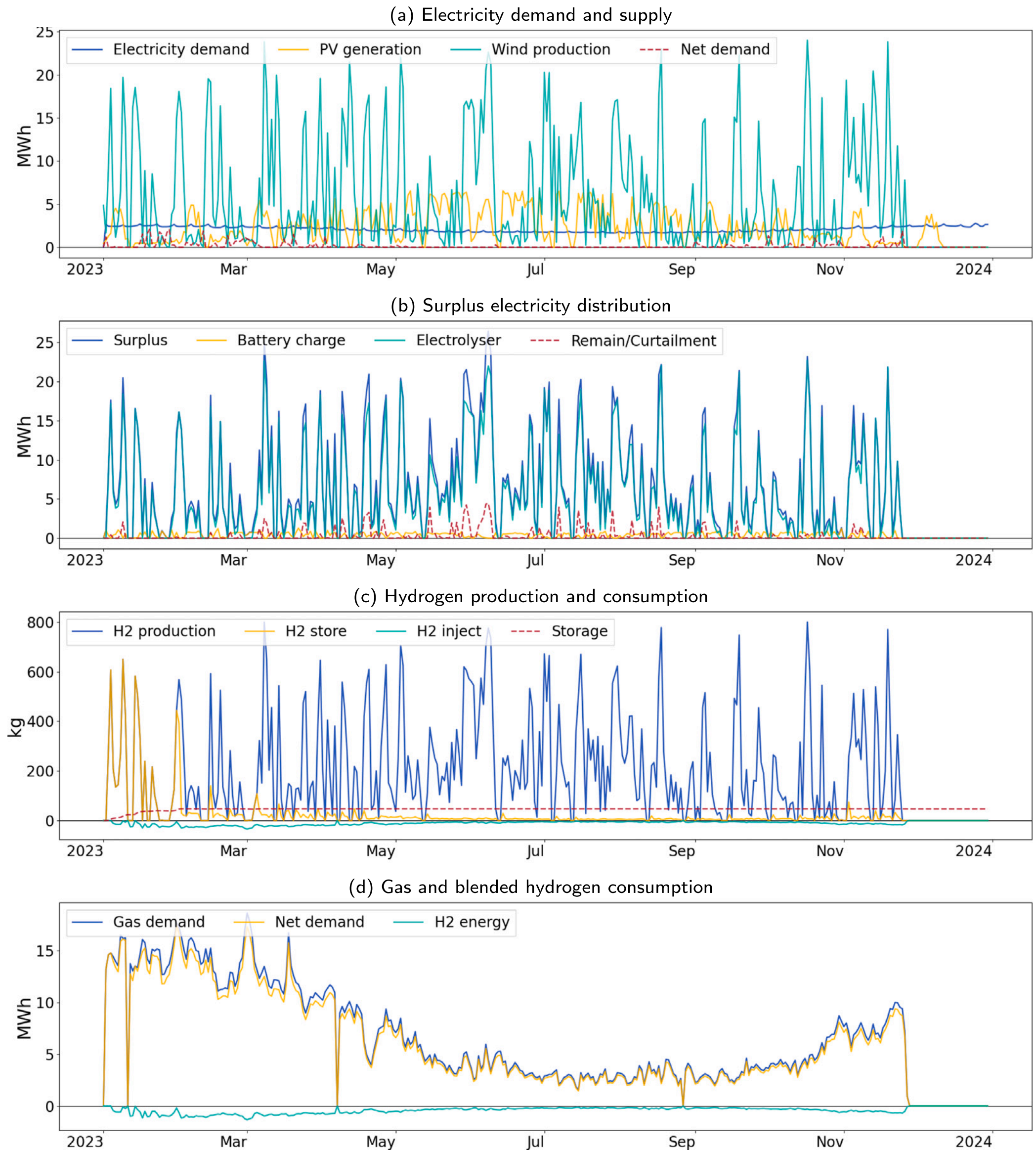

Fig. 6. Annual daily community energy demand and renewable production, as well as daily hydrogen production, delivered, and storage.

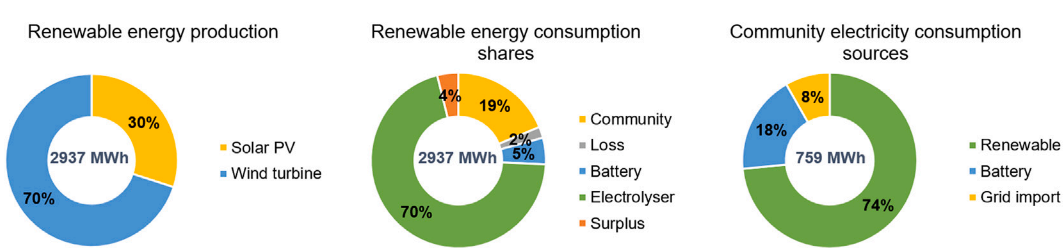

Fig. 7. Annual electricity generation and usage distribution in the hybrid P2G system.

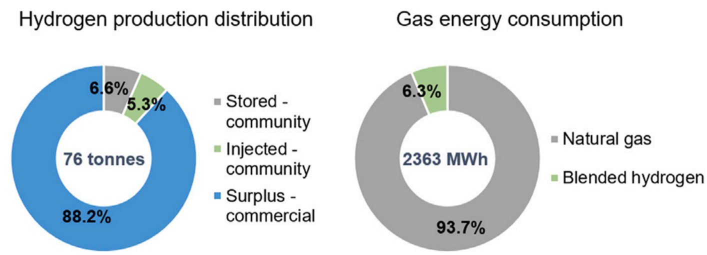

Fig. 8. Annual hydrogen production and distribution by the proposed P2G system, and the gas energy consumption for a 20 % blending scenario.

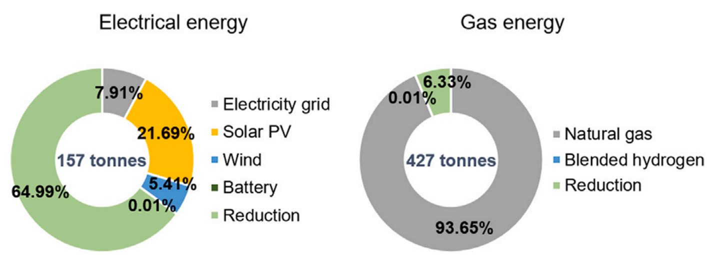

Fig. 9. Annual carbon emissions and reduction achieved by the proposed P2G system.

renewable system generates 2937 MWh/y, comprising 882 MWh (±211 MWh) from solar PV (30 % of renewable energy) and 2055 MWh (±904 MWh) from wind (70 % of renewable energy). Around 552 MWh/y (19 %) of renewable energy directly supplies the community, with the remainder either stored, used for hydrogen production, or exported. The battery system absorbs 143 MWh/y (5 %) to balance daily fluctuations, while the electrolyser consumes 2068 MWh/y (70 %) of renewable electricity for hydrogen production. Conversion losses account for 65 MWh/y (2 %), and 110 MWh/y (4 %) is surplus energy that cannot be used or stored. Overall, the local renewable system, coupled with battery storage, meets 92 % of the community's annual electricity needs—74 % (552 MWh/y) from hybrid renewable and 18 % (137 MWh/y) from the battery, leaving just 8 % (62 MWh/y) to be imported from the grid.

The electrolyser utilises renewable-mix electricity to produce 76 tonne/y of green hydrogen, with average and maximum daily rates of 192 kg and 794 kg, respectively. Fig. 6 shows the daily system behaviour where hydrogen storage reaches full capacity early in the year, with surplus production available for external use.

Fig. 8 presents the annual hydrogen balance. At 20 % blending, 4 tonnes are blended into the gas network, contributing 149 MWh/y (6.3 % of gas delivered) to the community's gas demand (2363 MWh/y). Another 5 tonnes are stored, while the remainder (67 tonnes, 88 %) is available for commercial sale. Although hydrogen per mass has high energy containment, the higher heating value (HHV) per volume of hydrogen is about three times lower than that of methane due to the low density of hydrogen. This means blended gas has a lower energy content and decreases with higher hydrogen mixtures [106].

4.3. Environmental implications

Without intervention, annual carbon emissions from electricity and gas are estimated at 157 tonnes (±3 tonnes) and 427 tonnes (±26 tonnes), respectively. Annual electricity supplied by the P2G system yields a 102-tonne (65 %) reduction in emissions, as shown in Fig. 9. Hydrogen production introduces a small additional emission (1 tonne), but blending at 20 % reduces gas demand by 6.3 %, yielding a further 27-tonne reduction. Overall, integrated hydrogen blending offers the potential for a 22 % reduction (128 tonnes) of total annual carbon reduction. Varying the blending ratio revealed a trade-off between hydrogen utilisation and infrastructure compatibility, with higher ratios offering greater emissions reductions but increasing technical and economic challenges.

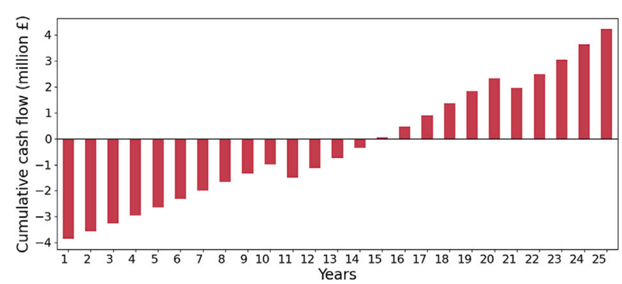

Fig. 10. Cumulative energy savings and payback period analysis for the hybrid P2G system.

While carbon emissions are a primary metric in evaluating the environmental performance of energy systems, they are not the only relevant indicator. Future research should incorporate midpoint indicators and assess the trade-offs between decarbonisation and material sustainability.

4.4. Economic system feasibility

Economic aspects of the developed P2G system were evaluated at the community scale, regarding cost savings, payback period, and revenue from renewable and hydrogen sales. The high and persistent wind resource at the pilot site provides most of the annual renewable output. Coupled with solar PV and battery storage, it further increases flexibility and resilience, particularly in spring and summer.

System degradation and component replacement cycles increase overall lifecycle costs; however, the integration of hydrogen production, along with rising energy tariffs and inflation, contributes to a faster investment payback period [107]. Additional financial returns from surplus hydrogen sales further strengthen the system's economic viability. As shown in Fig. 10, the cumulative cash flow trajectory indicates a break-even point post the mid-lifecycle period (within 15 years). Over the 25-year lifespan, the system reduces electricity usage by around 50.7 %, delivering an average annual electricity cost saving of 36.4 %. Although blending hydrogen reduces natural gas demand by around

Table 7
Impact of hydrogen blending scenarios on community gas demand, cost savings, and system payback.

Blending rate [%]	H_2 Injected [tonne/year]	Energy delivered [MWh/year]	Gas saving [%]	Energy cost saving [%/year]	Payback [years]
10 %	1.8	71	3.0	33.6	15
20 %	4.0	149	6.3	33.7	15
30 %	6.0	237	10.0	33.9	15

Table 8
Sensitivity analysis of selected techno-economic parameters.

Parameter	Baseline	Variation	Energy cost saving [%/year]	Payback [years]
Energy tariff growth	5 %/year	2–8 %	30–36	19–13
Electricity demand growth	5 %/year	0–10 %	49–24	12–22
Gas demand reduction	5 %/year	0–10 %	31–36	15–14
Discount rate	3 %	2–5 %	35–31	15–17
Renewable electricity price	£0.08/kWh	£0.06–0.10	33.7–33.8	15–14
Hydrogen sale price	£2.20/kg	£1.60–4.40	30–46	17–12

6.3 %, the average gas cost savings are approximately 2.5 % over time. The total net present cost of the system is estimated at £6.8 million, comprising £4.2 million in capital expenditures (CAPEX) and £2.6 million in operational and maintenance costs (OPEX). Cumulative revenues, primarily from hydrogen sales and electricity savings, are projected at £4.2 million, contributing to an average total energy cost reduction of 33.7 % over the system's lifetime.

4.5. Scenario-based and uncertainty analysis

In this exercise, the impact of varying hydrogen blending levels on gas savings, energy cost reductions, and investment returns was evaluated. Three volume-based blending scenarios—10 %, 20 %, and 30 %—were analysed, with the 20 % case aligned with the UK Government's current policy guidance [65]. Table 7 summarises the outcomes for each scenario.

The results indicate that increasing the hydrogen blending rate has a consistent impact on reducing natural gas consumption. A 10 % blend displaces 3 % of community gas demand, while a 30 % blend achieves a 10 % reduction. However, average energy cost savings marginally increase from 33.6 % to 33.9 % annually. The variation in blending scenarios has no visible impact on the payback period, which remains within 15 years. Nevertheless, higher hydrogen injection levels may require infrastructure upgrades or enhanced safety protocols due to hydrogen's lower volumetric energy density and combustion characteristics. Moreover, increased internal hydrogen consumption for blending reduces the availability of surplus hydrogen for commercial sale, affecting overall system revenue.

To enhance the robustness and transparency of the techno-economic and environmental results, a basic uncertainty and sensitivity analysis was conducted on key parameters influencing system performance. Given that the system configuration is predefined by the community initiative and the model has been intentionally simplified for feasibility assessment, the exercise was focused on understanding how fluctuations in critical input assumptions affect average annual energy cost savings and the investment payback period. Table 8 summarises the tested parameters, baseline assumptions, and resulting variations in performance. The selected parameters reflect both technical and market uncertainties likely to evolve over the system's 25-year operational lifespan.

- Energy tariff growth, set at a 5 % annual baseline, reflects general energy inflation, which has shown volatility in recent UK markets. A modest tariff escalation (2–8 %) affects financial outcomes by 6 % in cost savings and shifts the payback period from 19 to 13 years.
- Electricity demand growth is one of the most influential factors. It is assumed to be 5 % per year, considering potential drivers such as population growth in the village, increased uptake of EVs, and household heating electrification (e.g., air-source heat pumps). Higher electricity demand intensifies the value of local renewable generation and shortens the payback period, with savings reaching 49 % and payback reducing to 12 years.
- Gas demand reduction is also tested, ranging from 0 % to 10 % annually. The baseline 5 % decline anticipates progressive electrification of heating systems, as well as household energy efficiency improvements. A higher rate of gas displacement improves cost savings with a slight reduction in the payback period, whereas low demand shifts financial returns.
- The discount rate, varied from 2 % to 5 %, reflects alternative social or private discounting scenarios often used in public energy assessments. The outcomes are relatively insensitive to this range, resulting in a 4 % variation in cost savings and a two-year swing in the payback period.
- The renewable electricity cost was assumed to fluctuate between £0.06 and £0.10 per kWh. This variation had minimal impact, as electricity from the hybrid PV-wind system remained cheaper than the grid supply across all cases.
- Finally, the hydrogen sale price—varied from £1.60 to £4.40 per kg—emerged as a highly sensitive factor. Surplus hydrogen sold to nearby commercial or agricultural consumers represents a potential revenue stream. At higher market prices, annual savings reach 46 % with a 12-year payback, while lower prices extend the period to 17 years.

Overall, this analysis demonstrates the importance of local demand growth and hydrogen market development in determining the system's long-term economic viability. It also reinforces the system's resilience to energy price volatility, underlining its potential as a robust pathway for rural energy decarbonisation.

5. Conclusion

This study investigated the feasibility and performance of a community-scale hybrid power-to-gas (P2G) energy system combining wind, photovoltaic (PV), battery energy storage (BESS), and hydrogen technologies. Grounded in a real-world rural village case study in the UK, the research evaluated the technical, economic, and environmental implications of deploying a predefined renewable system configuration proposed by a local energy initiative. Rather than optimising system size, the focus was on assessing the benefits and trade-offs under realistic operating and policy conditions.

A robust machine learning-based forecasting framework was developed to support day-ahead energy management. Among the four models tested—ANN, LSTM, RNN, and RF—the ANN and RF delivered superior accuracy, particularly in forecasting electricity and gas demand. However, uncertainty in weather forecasting—most notably wind speed and solar irradiance—introduces downstream variability in system outputs, with wind energy subject to ±44 % uncertainty and solar ±24 %.

Simulation results showed that the proposed hybrid system could directly supply 92 % of the community's annual electricity demand. Battery storage significantly maintained around of 18 % community demand, highlighting its crucial role in increasing system flexibility and resilience. Surplus electricity was directed to hydrogen production, yielding 76 tonnes per year, of which 4 tonnes were blended into the local gas supply following a 20 % volume-based scenario, displacing 6.3 % of natural gas demand. The majority (88 %) of hydrogen remained available for commercial sale, particularly targeting nearby agricultural and fleet users.

Economic analysis showed that the system could reduce annual energy costs by 33.7 %, with projected lifetime savings nearly equal to the initial capital expenditure. Hydrogen sales emerged as a key revenue stream, and scenario-based analysis indicated that higher blending rates (up to 30 %) or improved hydrogen prices could further enhance financial viability, reducing the payback period to 12 years. A basic sensitivity analysis confirmed that energy demand growth, tariff inflation, and hydrogen market prices have the strongest influence on system economics.

Environmentally, the system enables substantial carbon emission reductions from both renewable electricity substitution and partial hydrogen blending. The study accounted for both operational and embodied emissions, including indicative estimates for critical materials. The results emphasise that hydrogen blending alone cannot fully decarbonise gas use but can act as a transitional strategy alongside broader electrification.

In conclusion, the findings demonstrate that hybrid community energy systems with P2G integration offer significant potential for local decarbonisation and cost savings. However, realising these benefits at scale will require clear hydrogen blending regulations, improved market structures, and long-term policy support. Future work will focus on integrating real-time optimisation, demand response, and peer-to-peer energy trading to enhance system flexibility and community engagement.

CRediT authorship contribution statement

Amin Amin: Conceptualisation, methodology, software, investigation, resources, data curation, validation, writing – original draft, visualisation, writing – review and editing. **Ioan Petri:** Conceptualisation, methodology, supervision, investigation, resources, data curation, writing – original draft, validation, writing – review and editing. **Simon Minett:** Supervision, resources, writing – review and editing.

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.

Acknowledgment

This work was supported by the Local Energy Operating System (LEOS) project, funded through Smart Partnerships, Welsh Government grants.

Data availability

Data will be made available upon request.

References

[1] Amin A, Kem O, Gallegos P, Chervet P, Ksontini F, Mourshed M. Demand response in buildings: unlocking energy flexibility through district-level electro-thermal simulation. Appl Energy 2022;305:117836.
[2] Ma W, Fang S, Liu G, Zhou R. Modeling of district load forecasting for distributed energy system. Appl Energy 2017;204:181–205.
[3] Revesz A, Dunham C, Jones P, Bond C, Fenner R, Mody S, et al. A holistic design approach for 5th generation smart local energy systems: project greenscies. Energy 2022;242:122885.
[4] Van Der Schoor T, Scholtens B. Power to the people: local community initiatives and the transition to sustainable energy. Renew Sustain Energy Rev 2015;43:666–75.
[5] Petrucci A, Barone G, Buonomano A, Athienitis A. Modelling of a multi-stage energy management control routine for energy demand forecasting, flexibility, and optimization of smart communities using a recurrent neural network. Energy Convers Manag 2022;268:115995.
[6] Ang YQ, Polly A, Kulkarni A, Chambi GB, Hernandez M, Haji MN. Multi-objective optimization of hybrid renewable energy systems with urban building energy modeling for a prototypical coastal community. Renew Energy 2022;201:72–84.
[7] Locke J, Dsilva J, Zarmukhambetova S. Decarbonization strategies in the uae built environment: an evidence-based analysis using cop26 and cop27 recommendations. Sustainability 2023;15(15):11603.
[8] Bartolini A, Carducci F, Muñoz CB, Comodi G. Energy storage and multi energy systems in local energy communities with high renewable energy penetration. Renew Energy 2020;159:595–609.
[9] European Environment Agency. Climate change mitigation: reducing emissions; 2024. https://www.eea.europa.eu/en/topics/in-depth/climate-change-mitigation-reducing-emissions. [Accessed: 2024-05-02].
[10] European Parliament. Proposal for a directive of the European parliament and of the council amending directive (EU) 2018/2001 of the European parliament and of the council, regulation (EU) 2018/1999 of the European parliament and of the council and directive 98/70/EC of the European parliament and of the council as regards the promotion of energy from renewable sources, and repealing council directive (EU) 2015/652 of 14 july 2021, com (2021) 557 final; 2021.
[11] GOV.UK. UK enshrines new target in law to slash emissions by 78 % by 2035; 2021. https://www.gov.uk/government/news/uk-enshrines-new-target-in-law-to-slash-emissions-by-78-by-2035. [Accessed:2023-11-25].
[12] Norbu S, Couraud B, Robu V, Andoni M, Flynn D. Modeling economic sharing of joint assets in community energy projects under LV network constraints. IEEE Access 2021;9:112019–42.
[13] Hendawy M, Junaid M, Amin A. Integrating sustainable development goals into the architecture curriculum: experiences and perspectives. City Environ Interact 2024:100138.
[14] Koirala BP, Koliou E, Friege J, Hakvoort RA, Herder PM. Energetic communities for community energy: a review of key issues and trends shaping integrated community energy systems. Renew Sustain Energy Rev 2016;56:722–44.
[15] Gul E, Baldinelli G, Farooqui A, Bartocci P, Shamim T. AEM-electrolyzer based hydrogen integrated renewable energy system optimisation model for distributed communities. Energy Convers Manag 2023;285:117025.
[16] Marocco P, Ferrero D, Martelli E, Santarelli M, Lanzini A. An MILP approach for the optimal design of renewable battery-hydrogen energy systems for off-grid insular communities. Energy Convers Manag 2021;245:114564.
[17] Wang H, Good N, Mancarella P. Modelling and valuing multi-energy flexibility from community energy systems. In: 2017 Australasian universities power engineering conference (AUPEC), IEEE; 2017. p. 1–6.
[18] Nyeche EN, Diemuodeke EO. Modelling and optimisation of a hybrid PV-wind turbine-pumped hydro storage energy system for mini-grid application in coastline communities. J Clean Prod 2020;250:119578.
[19] Bukar AL, Tan CW. A review on stand-alone photovoltaic-wind energy system with fuel cell: system optimization and energy management strategy. J Clean Prod 2019;221:73–88.
[20] Mirzaei MA, Habibi M, Vahidinasab V, Mohammadi-Ivatloo B. Chapter three - concept, environmental benefits and working mechanism of power-to-gas (P2G) technology. In Mirzaei MA; Habibi M, Vahidinasab V, and Mohammadi-Ivatloo B, editors. Power-to-gas. Academic Press; 2023. pp. 29–46. https://doi.org/10.1016/B978-0-323-90544-2.00001-4, Hybrid Energy Systems, ISBN 978-0-323-90544-2. https://www.sciencedirect.com/science/article/pii/B9780323905442000014.
[21] Wan Y, Kober T, Schildhauer T, Schmidt TJ, McKenna R, Densing M. Conditions for profitable operation of P2X energy hubs to meet local demand with energy market access. Adv Appl Energy 2023;10:100127.
[22] Dahiru AR, Vuokila A, Huuhtanen M. Recent development in power-to-x: part IA review on techno-economic analysis. J Energy Storage 2022;56:105861.
[23] Gondal IA. Hydrogen integration in power-to-gas networks. Int J Hydrog Energy 2019;44(3):1803–15.
[24] Mehrjerdi H, Saboori H, Jadid S. Power-to-gas utilization in optimal sizing of hybrid power, water, and hydrogen microgrids with energy and gas storage. J Energy Storage 2022;45:103745.
[25] Shahid Z, Santarelli M, Marocco P, Ferrero D, Zahid U. Techno-economic feasibility analysis of renewable-fed power-to-power (P2P) systems for small French islands. Energy Convers Manag 2022;255:115368.
[26] Crespi E, Colbertaldo P, Guandalini G, Campanari S. Design of hybrid power-to-power systems for continuous clean PV-based energy supply. Int J Hydrog Energy 2021;46(26):13691–708.
[27] Gandiglio M, Marocco P, Bianco I, Lovera D, Blengini GA, Santarelli M. Life cycle assessment of a renewable energy system with hydrogen-battery storage for a remote off-grid community. Int J Hydrog Energy 2022;47(77):32822–34.

[28] Mendes G, Ioakimidis C, Ferrão P. On the planning and analysis of integrated community energy systems: a review and survey of available tools. Renew Sustain Energy Rev 2011;15(9):4836–54.

[29] Busch S, Kasdorp R, Koolen D, Mercier A, Spooner M, et al. The development of renewable energy in the electricity market. European Commission Discussion Paper, vol. 187; 2023.

[30] Capotosto T, Di Fazio AR, Perna S, Conte F, Iannello G, De Falco P. Day-ahead forecast of PV systems and end-users in the contest of renewable energy communities. In: 2022 AEIT international annual conference (AEIT), IEEE; 2022. p. 1–6.

[31] Rana R, Berg K, Degefa MZ, Löschenbrand M. Modelling and simulation approaches for local energy community integrated distribution networks. IEEE Access 2022;10:3775–89.

[32] Orehounig K, Evins R, Dorer V. Integration of decentralized energy systems in neighbourhoods using the energy hub approach. Appl Energy 2015;154:277–89.

[33] Hargroves K, James B, Lane J, Newman P. The role of distributed energy resources and associated business models in the decentralised energy transition: a review. Energies 2023;16(10):4231.

[34] Chen Y, Chen J, Liu C, Liu G, Ferrari M, Sundararajan A. Integrated modeling and optimal operation of multi-energy system for coastal community. In: 2023 IEEE international conference on electro information technology (eIT); IEEE; 2023. p. 211–16.

[35] Wang J, Xue K, Guo Y, Ma J, Zhou X, Liu M, et al. Multi-objective capacity programming and operation optimization of an integrated energy system considering hydrogen energy storage for collective energy communities. Energy Convers Manag 2022;268:116057.

[36] Xiao Y, Wang X, Pinson P, Wang X. A local energy market for electricity and hydrogen. IEEE Trans Power Syst 2017;33(4):3898–908.

[37] Dorahaki S, Rashidinejad M, Ardestani SFF, Abdollahi A, Salehizadeh MR. An integrated model for citizen energy communities and renewable energy communities based on clean energy package: a two-stage risk-based approach. Energy 2023;277:127727.

[38] Fouladvand J, Ghorbani A, Sarı Y, Hoppe T, Kunneke R, Herder P. Energy security in community energy systems: an agent-based modelling approach. J Clean Prod 2022;366:132765.

[39] Cuesta MA, Castillo-Calzadilla T, Borges CE. A critical analysis on hybrid renewable energy modeling tools: an emerging opportunity to include social indicators to optimise systems in small communities. Renew Sustain Energy Rev 2020;122:109691.

[40] Bekirsky N, Hoicka CE, Brisbois MC, Camargo LR. Many actors amongst multiple renewables: a systematic review of actor involvement in complementarity of renewable energy sources. Renew Sustain Energy Rev 2022;161:112368.

[41] AhmadiAhangar R, Rosin A, Niaki AN, Palu I, Korõtko T. A review on real-time simulation and analysis methods of microgrids. Int Trans Electr Energy Syst 2019;29(11):e12106.

[42] Swan LG, Ugursal VI. Modeling of end-use energy consumption in the residential sector: a review of modeling techniques. Renew Sustain Energy Rev 2009;13(8):1819–35.

[43] Amin A, Mourshed M. Community stochastic domestic electricity forecasting. Appl Energy 2024. 355:122342. ISSN 0306-2619. https://doi.org/10.1016/j.apenergy.2023.122342. https://www.sciencedirect.com/science/article/pii/S0306261923017063.

[44] Byun J, Go J, Kim C, Heo Y. Reliability, economic, and environmental analysis of fuel-cell-based hybrid renewable energy networks for residential communities. Energy Convers Manag 2023;284:116964.

[45] Shi M, Vasquez JC, Guerrero JM, Huang Y. Smart communities-design of integrated energy packages considering incentive integrated demand response and optimization of coupled electricity-gas-cooling-heat and hydrogen systems. Int J Hydrogen Energy 2023.

[46] Jin L, Rossi M, Ferrario AM, Alberizzi JC, Renzi M, Comodi G. Integration of battery and hydrogen energy storage systems with small-scale hydropower plants in off-grid local energy communities. Energy Convers Manag 2023;286:117019.

[47] Fan G, Liu Z, Liu X, Shi Y, Wu D, Guo J, et al. Energy management strategies and multi-objective optimization of a near-zero energy community energy supply system combined with hybrid energy storage. Sustain Cities Soc 2022;83:103970.

[48] Temiz M, Dincer I. Development and analysis of a solar-based offshore energy system for sustainable island communities. Int J Energy Res 2022;46(14):20357–68.

[49] Caramanico N, Di Florio G, Baratto MC, Cigolotti V, Basosi R, Busi E. Economic analysis of hydrogen household energy systems including incentives on energy communities and externalities: a case study in Italy. Energies 2021;14(18):5847.

[50] Ghenai C, Salameh T, Merabet A. Technico-economic analysis of off grid solar PV/fuel cell energy system for residential community in desert region. Int J Hydrog Energy 2020;45(20):11460–70.

[51] Garmsiri S, Rosen MA, Smith GR. Integration of wind energy, hydrogen and natural gas pipeline systems to meet community and transportation energy needs: a parametric study. Sustainability 2014;6(5):2506–26.

[52] Raimondi G, Spazzafumo G. Exploring renewable energy communities integration through a hydrogen power-to-power system in Italy. Renew Energy 2023;206:710–21.

[53] Ahangar HG, Yew WK, Flynn D. Smart local energy systems: optimal planning of stand-alone hybrid green power systems for on-line charging of electric vehicles. IEEE Access 2023;11:7398–409.

[54] Çiçek A. Multi-objective operation strategy for a community with RESs, fuel cell EVs and hydrogen energy system considering demand response. Sustain Energy Technol Assess 2023;55:102957.

[55] Temiz M, Dincer I. Development of solar and wind based hydrogen energy systems for sustainable communities. Energy Convers Manag 2022;269:116090.

[56] Wang S, Qi Y, Xu K, Ai D, Zhang L, Liu H. Medium-term and long-term optimal scheduling for community integrated energy system with high proportion of renewable energy and multi-type energy storage. In: 2022 IEEE international conference on power systems and electrical technology (PSET), IEEE; 2022. p. 389–96.

[57] Erdemir D, Dincer I. A new solar energy-based system integrated with hydrogen storage and heat recovery for sustainable community. Sustain Energy Technol Assess 2022;52:102355.

[58] Temiz M, Dincer I. Development and assessment of an onshore wind and concentrated solar based power, heat, cooling and hydrogen energy system for remote communities. J Clean Prod 2022;374:134067.

[59] Ayodele TR, Mosetlhe TC, Yusuff AA, Ogunjuyigbe ASO. Off-grid hybrid renewable energy system with hydrogen storage for South African rural community health clinic. Int J Hydrog Energy 2021;46(38):19871–85.

[60] Liu J, Yang H, Zhou Y. Peer-to-peer energy trading of net-zero energy communities with renewable energy systems integrating hydrogen vehicle storage. Appl Energy 2021;298:117206.

[61] Naughton J, Wang H, Riaz S, Cantoni M, Mancarella P. Optimization of multi-energy virtual power plants for providing multiple market and local network services. Electr Power Syst Res 2020;189:106775.

[62] Magtibay M, Wong D. Design of a hybrid renewable energy system for a northern Ontario community. In: 2013 IEEE global humanitarian technology conference (GHTC), IEEE; 2013. p. 23–28.

[63] Vaccariello E, Trinchero R, Stievano IS, Leone P. A statistical assessment of blending hydrogen into gas networks. Energies 2021;14(16):5055.

[64] Cristello JB, Yang JM, Hugo R, Lee Y, Park SS. Feasibility analysis of blending hydrogen into natural gas networks. Int J Hydrog Energy 2023;48(46):17605–29.

[65] DESNZ. Hydrogen blending into GB gas distribution networks; 2023. https://www.gov.uk/government/consultations/hydrogen-blending-into-gb-gas-distribution-networks.

[66] Kiehbadroudinezhad M, Merabet A, Rajabipour A, Cada M, Kiehbadroudinezhad S, Khanali M, et al. Optimization of wind/solar energy microgrid by division algorithm considering human health and environmental impacts for power-water cogeneration. Energy Convers Manag 2022;252:115064.

[67] Walton RA, Takle ES, Gallus WA. Characteristics of 50–200-m winds and temperatures derived from an IOWA tall-tower network. J Appl Meteorol Clim 2014;53(10):2387–93.

[68] Chaichan W, Waewsak J, Nikhom R, Kongruang C, Chiwamongkhonkarn S, Gagnon Y. Optimization of stand-alone and grid-connected hybrid solar/wind/fuel cell power generation for green islands: application to Koh Samui, southern Thailand. Energy Rep 2022;8:480–93.

[69] Bañuelos-Ruedas F, Angeles-Camacho C, Rios-Marcuello S. Analysis and validation of the methodology used in the extrapolation of wind speed data at different heights. Renew Sustain Energy Rev 2010;14(8):2383–91.

[70] Axaopoulos PJ, Tzanes GT. Wind energy potential (measurements, evaluation, forecasting); 2022.

[71] Sorrenti I, Zheng Y, Singlitico A, You S. Low-carbon and cost-efficient hydrogen optimisation through a grid-connected electrolyser: the case of Greenlab Skive. Renew Sustain Energy Rev 2023;171:113033.

[72] El-Taweel NA, Khani H, Farag HE. Hydrogen storage optimal scheduling for fuel supply and capacity-based demand response program under dynamic hydrogen pricing. IEEE Trans Smart Grid 2018;10(4):4531–42.

[73] Su W, Zheng W, Li Q, Yu Z, Han Y, Bai Z. Capacity configuration optimization for green hydrogen generation driven by solar-wind hybrid power based on comprehensive performance criteria. Front Energy Res 2023;11:1256463.

[74] Amin A, Mourshed M. Weather and climate data for energy applications. Renew Sustain Energy Rev 2024;192:114247. ISSN 1364-0321. https://doi.org/10.1016/j.rser.2023.114247. https://www.sciencedirect.com/science/article/pii/S136403212301105X.

[75] Voyant C, Notton G, Kalogirou S, Nivet M-L, Paoli C, Motte F, et al. Machine learning methods for solar radiation forecasting: a review. Renew Energy 2017;105:569–82.

[76] Meenal R, Michael P, Pamela D, Rajasekaran E. Weather prediction using random forest machine learning model. Indones J Electr Eng Comput Sci 2021;22(2):1208.

[77] Svennevik H, Riegler MA, Hicks S, Storelvmo T, Hammer HL. Prediction of cloud fractional cover using machine learning. Big Data Cognit Comput 2021;5(4):62.

[78] Baran Á, Lerch S, El Ayari M, Baran S. Machine learning for total cloud cover prediction. Neural Comput Appl 2021;33(7):2605–20.

[79] Han JM, Ang YQ, Malkawi A, Samuelson HW. Using recurrent neural networks for localized weather prediction with combined use of public airport data and on-site measurements. Build Environ 2021;192:107601.

[80] Hewage P, Trovati M, Pereira E, Behera A. Deep learning-based effective fine-grained weather forecasting model. Pattern Anal Appl 2021;24(1):343–66.

[81] Kuster C, Rezgui Y, Mourshed M. Electrical load forecasting models: a critical systematic review. Sustain Cities And Soc 2017;35:257–70. ISSN 2210-6707. https://doi.org/10.1016/j.scs.2017.08.009. https://www.sciencedirect.com/science/article/pii/S2210670717305899.

[82] Ahmad MW, Mourshed M, Rezgui Y. Trees vs neurons: comparison between random forest and ann for high-resolution prediction of building energy consumption. Energy Build 2017;147:77–89. ISSN 0378-7788. https://doi.org/10.1016/j.enbuild.2017.04.038. https://www.sciencedirect.com/science/article/pii/S0378778816313937.

[83] Weather Underground. Weather underground PWS network; 2023. https://www.WeatherUnderground.com/wundermap. [Accessed:2023-10-02].

[84] Pepe D, Bianchini G, Vicino A. Model estimation for solar generation forecasting using cloud cover data. Sol Energy 2017;157:1032–46.

[85] Perez R, Cebecauer T, Šúri M. Semi-empirical satellite models. Solar Energy Forecast Resour Assess 2013:21–48.
[86] Urquhart B, Ghonima M, Nguyen D, Kurtz B, Chow CW, Kleissl J. Sky-imaging systems for short-term forecasting. Solar Energy Forecast Resour Assess 2013:195–232.
[87] Sajid MU, Bicer Y. Comparative life cycle cost analysis of various solar energy-based integrated systems for self-sufficient greenhouses. Sustain Prod Consum 2021;27:141–56.
[88] Department for Business, Energy and Industrial Strategy. Solar PV cost data: 2019/20; 2020. https://www.gov.uk/government/statistics/solar-pv-cost-data-201920.
[89] Tawalbeh M, Al-Othman A, Kafiah F, Abdelsalam E, Almomani F, Alkasrawi M. Environmental impacts of solar photovoltaic systems: a critical review of recent progress and future outlook. Sci Total Environ 2021;759:143528.
[90] Staffell I, Green R. How does wind farm performance decline with age? Renew Energy 2014;66:775–86.
[91] Marocco P, Ferrero D, Gandiglio M, Ortiz MM, Sundseth K, Lanzini A, et al. A study of the techno-economic feasibility of H_2-based energy storage systems in remote areas. Energy Convers Manag 2020;211:112768.
[92] Xie J-B, Fu J-X, Liu S-Y, Hwang W-S. Assessments of carbon footprint and energy analysis of three wind farms. J CleanProd 2020;254:120159.
[93] Han X, Garrison J, Hug G. Techno-economic analysis of PV-battery systems in Switzerland. Renew Sustain Energy Rev 2022;158:112028.
[94] Robert Rapier. Estimating the carbon footprint of utility-scale battery storage; 2020. https://www.forbes.com/sites/RobertRapier/2020/02/16/estimating-the-carbon-footprint-of-utility-scale-battery-storage/?sh=6bd230077adb. [Accessed: 2023-12-25].
[95] Rahman MM, Gemechu E, Oni AO, Kumar A. The greenhouse gas emissions' footprint and net energy ratio of utility-scale electro-chemical energy storage systems. Energy Convers Manag 2021;244:114497.
[96] Ginsberg MJ, Venkatraman M, Esposito DV, Fthenakis VM. Minimizing the cost of hydrogen production through dynamic polymer electrolyte membrane electrolyzer operation. Cell Rep Phys Sci 2022;3(6).
[97] Tenhumberg N, Büker K. Ecological and economic evaluation of hydrogen production by different water electrolysis technologies. Chem Ing Tech 2020;92(10):1586–95.
[98] Shin HK, Ha SK. A review on the cost analysis of hydrogen gas storage tanks for fuel cell vehicles. Energies 2023;16(13):5233.
[99] DESNZ. Domestic energy price statistics; 2021. https://www.gov.uk/government/collections/domestic-energy-prices. [Accessed: 2024-01-30].
[100] Office for National Statistics (ONS). Inflation and price indices; 2022. https://www.ons.gov.uk/economy/inflationandpriceindices/timeseries/l55o/mm23. [Accessed: 2023-12-20].
[101] Guo C, Sheng W, De Silva DG, Aggidis G. A review of the levelized cost of wave energy based on a techno-economic model. Energies 2023;16(5):2144.
[102] Wies RW, Johnson RA, Agrawal AN, Chubb TJ. Simulink model for economic analysis and environmental impacts of a PV with diesel-battery system for remote villages. IEEE Trans Power Syst 2005;20(2):692–700.
[103] Bramwell R, Brown P, Galatioto F, Ingledew D, Karagianni E, MacCarthy J, et al. 2023 government greenhouse gas conversion factors for company reporting: methodology paper. Department For Energy Security And Net Zero; 2023.
[104] Ahmad MW, Mourshed M, Rezgui Y. Trees vs neurons: comparison between random forest and ann for high-resolution prediction of building energy consumption. Energy Build 2017;147:77–89.
[105] Papantoniou S, Kolokotsa D-D. Prediction of outdoor air temperature using neural networks: application in 4 European cities. Energy Build 2016;114:72–79.
[106] National Research Council and others. The hydrogen economy: opportunities, costs, barriers, and R&D needs. National Academies Press; 2004.
[107] Mohamed AAR, Best RJ, Liu X, Morrow DJ. Residential battery energy storage sizing and profitability in the presence of PV and EV. In: 2021 IEEE Madrid PowerTech, IEEE; 2021. p. 1–6.