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Author(s)	Bopaiah, Arjun;Monaghan, Rory F. D.
Publication Date	2025-06-13
Publisher	Elsevier
Repository DOI	https://doi.org/10.1016/j.ijhydene.2025.03.416

International Journal of Hydrogen Energy 142 (2025) 739–751

Contents lists available at ScienceDirect

International Journal of Hydrogen Energy

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

Is one year enough? The impact of availability of wind data on optimal wind-to-hydrogen system design

Arjun Bopaiah [a,b,c,*], Rory F.D. Monaghan [a,b,c]

[a] School of Engineering, University of Galway, Galway, Ireland
[b] Ryan Institute for Marine, Environmental and Energy Research, University of Galway, Galway, Ireland
[c] MaREI, the SFI Centre for Energy, Climate and Marine Research, Ireland

A R T I C L E I N F O

Handling Editor: Ibrahim Dincer

Keywords:
Interannual weather variability
Hydrogen system design
Near-optimal solutions
System reliability
System cost variability

A B S T R A C T

Decreasing prices of renewable energy sources (RES), like wind and solar, in recent years have led to numerous studies on the optimal design of RES for hydrogen production in an off-grid system. RES are intermittent and vary from year to year. Yet, most of the studies still consider only a random single weather year for system design, often ignoring the impact of input weather data on system design and its performance. This study evaluates, for a gaseous hydrogen system, the impact of input weather data on optimal system design, system reliability and system costs. Random single-year, averaged, and multiple years of weather data from 1994 to 2021 are considered. Further, multiple years of weather data are considered using a novel method of near-optimal solutions and a maximum of near-optimal solutions. The results show that using the maximum of near-optimal solutions method improves system reliability by as much as 96 % when used in other weather years. The system costs are reduced to 0.1 €/kgH_2 in other weather years at the expense of an oversized system design. Meanwhile, a wind-to-hydrogen system (WHS) designed using randomly selected single-year weather data results in a significantly undersized system with lower reliability (3.5 %) and higher cost variability (up to 4.7 €/kgH_2) in other weather years. On the other hand, averaging the weather data smoothens the weather fluctuations and always results in a WHS design with lower reliability and higher cost variability than a WHS designed using multi-year weather data values. The results reveal that the size of input weather dataset significantly impacts the system design and its performance. The maximum of near-optimal solutions method proposed in this study provided significantly lower computational time with improved system performance (reliability and cost variability) in comparison to solving the WHS using multiple years of weather data outright.

Nomenclature

Acronyms		M	Mass, kg
agl	Above ground level	Δp	Pressure drop, barg
CAPEX	Capital expenditure	p	Pressure, barg
EMU	Energy management unit	P	Nominal power, MW_e
H_2	Hydrogen	r	Discount rate, %
HVAC	High voltage alternating current	t	Time, hour
HVDC	High voltage direct current	$temp$	Temperature, $^{\circ}C$
Kg	Kilogram	T	Time, year
Km	Kilometer	v	Wind speed, m/s

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This article is part of a special issue entitled: EHEC-2024(Barrio) published in International Journal of Hydrogen Energy.

* Corresponding author. School of Engineering, University of Galway, Galway, Ireland.
E-mail address: A.Bopaiah1@universityofgalway.ie (A. Bopaiah).

https://doi.org/10.1016/j.ijhydene.2025.03.416
Received 31 May 2024; Received in revised form 21 March 2025; Accepted 29 March 2025
Available online 11 April 2025

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LCOH	Levelised cost of hydrogen		
LHV	Lower heating value	*Subscripts*	
MW	Megawatt	Comp	Compressor
MWh	Megawatt hour	Elec	Electricity
NOpD	Near optimal design	Eng	Engineering
OWF	Offshore wind farm	H_2O	Water
OPEX	Operational and maintainence expenditure	HP	Hydrogen production
RES	Renewable energy source	HS	Hydrogen system
WHS	Wind to hydrogen system	HSS	Hydrogen storage sytem
		HT	Hydrogen transportation
Symbols		IAC	Interarray cable
ρ	Density, kg/m^3	IC	Interconnection
η	Efficiency, %	Inst	Installation
f_D	Friction factor	Max	Maximum
u_o	Gas velocity, m/s	OC	Other cost
τ	Lifetime, year	OffCable	Offshore cable
π	Pi	OffSub	Offshore substation
$\in$	Pipe roughness	OM	Operation and maintenance
R_e	Reynolds number	OnCable	Onshore cable
μ	Specific energy consumption, kWh/kg_{H2}	OnSub	Onshore substation
α	Wind power coefficient	PD	Project development
		Pipe	Hydrogen pipeline
Parameters		Ref	Reference
C	Total cost, €	SC	Hydrogen salt cavern
D	Diameter, meter	SR	Electrolyser stack replacement
E	Energy, kWh	WE	Water electrolyser
h	Turbine hub height, meter	WT&S	Wind turbine and substructure
L	Length, meter		
$\dot{m}$	Mass flow rate, kg/s		

1. Introduction

Current energy systems are heavily dependent on fossil fuels, which result in greenhouse gas emissions and global warming. The energy transition, which is shifting away from fossil-based towards renewable-based energy systems is essential in achieving the EU's climate neutrality target of 2050 [1]. Large-scale deployment of renewables, like wind and solar power, is gaining momentum globally and is vital for decarbonising the electricity system. However, limited grid expansion capacity has led to offshore wind farm developers facing significant delays and challenges in integrating their electricity into the electricity system. Alternative routes to market like hydrogen production are a potential solution with benefits in three ways: (i) storage of variable renewable energy, (ii) reducing project delays due to the availability of grid connection and (iii) creation of an economic opportunity in the hard-to-abate sectors like transport, heat and chemicals where direct electrification is challenging. Hard-to-abate sectors in modern economies and societies heavily depend upon a reliable and secure supply of energy [2,3]. The fluctuating and intermittent behaviour of renewable energy supply means that a completely new approach is required to optimally plan, design, and operate a wind-to-hydrogen system far different from the existing fossil-based system. Further, the year-to-year weather variability (interannual) poses a major risk to the system's reliability when designed based on a single year of weather data. The system design and reliability aspects become even more relevant for off-grid systems with no backup source. Yet, most of the literature has been devoted to determining the design of hydrogen systems based on single weather years [4] and the development of novel economic [5] and environmental optimisation methods [6]. The impact of long-term weather data on hydrogen system design, system reliability, and system costs has received little attention.

1.1. Single weather year-based system design

A single year of weather data is commonly used to design and simulate the operation of power-to-hydrogen system. Gunawan et al. [6] optimally designed a wind-PV-battery-electrolyser system to decarbonise the city bus network in Ireland. According to the study, the optimised system design based on weather data from 2017 can meet the fuel demand of the entire network of city buses. Samsatli et al. modelled a wind-hydrogen-electricity system for decarbonising the domestic transport sector of Great Britain [7]. The complete system optimisation model for determining the optimal size, location and technology for electricity and hydrogen transport that minimises the total cost of the network was based on single year weather data from 2014. A study performed by Kikuchi et al. [8] using weather data from 2016 found that the optimal design of a battery storage system improved the electrolyser capacity factor and reduced the overall production cost for solar-to-hydrogen facilities. In another study, Burhan et al. investigated the optimal design of a concentrated photovoltaic hydrogen system which provided a least cost system and zero power supply failure for customers in Singapore [9]. The study highlights the system benefits offered by hydrogen, which can be produced, stored, and reused through fuel cells to generate electricity during nighttime to meet the demand. Zero power supply failure and reduced system cost and energy storage size were observed based on a specific weather profile from September 2014 to June 2015. For a renewable energy-based system design, Dominkovic et al. [10] conducted a feasibility study for a 100 % renewable, zero-carbon energy system in 2050 for southeast Europe. The study found that a wide variety of renewable generation technologies based on 2008 as the base weather year are required for achieving a cheap zero-carbon system. From the above studies, it is observed that weather years are mostly randomly selected for designing a power-to-hydrogen system without any explanation for selecting the specific year. Moreover, studies by Gökçek [11,12], Hemmati [13] and Gunawan [14] do not even specify the weather years used for conducting their analysis. Single-year weather data cannot capture interannual weather variability. The design of power-to-hydrogen systems based on a single weather year might result in an optimal design for one specific weather year while being suboptimal for other weather years, resulting in increased costs due to capacity shortages and unserved demand.

Sensitivity analysis is another typical approach considered in power-to-hydrogen studies based on single weather years. In this approach, input parameters like wind/solar time series, equipment cost, efficiency, emission factors and discount rates are varied to evaluate the change in systems technical, economic, and environmental performance. Gunawan et al. [14] analysed the change in carbon abatement cost for trucks due to variation in technical, economic and environmental parameters for on and off-grid fuel systems. The study found that for off-grid fuel system, the variation in wind capacity factor, electrolyser efficiency and diesel emissions have a significant impact on the overall system design, costs, and lifecycle emissions. Ghussain et al. [15] conducted a sensitivity analysis for a renewable energy system with different energy storage types for a microgrid in Cyprus. In this study, the optimal system configuration was tested with different years of weather data. It was found that the variation in weather patterns amongst different weather years significantly affects the techno-economic feasibility of renewable energy based microgrids. Further, Robertson et al. [16] found that natural variability in renewable energy output in different weather years increases system costs and emissions due to increased dependence on diesel power to manage the supply-demand mismatch. The study highlights the need to investigate a wide variety of historical and future weather years when designing a renewable energy system for remote communities. In another study, Toke et al. [17] found that the optimal design and profit margin of an onsite renewable-based hydrogen system are very sensitive to the renewable production profiles. It is well recognised from the sensitivity analyses of the above studies that, for off-grid systems, varying the input weather data has major impacts on the cost, reliability, and robustness of the system. Methods to reduce the off-grid system design's sensitivity to changes in input weather data have received limited attention. The availability of long-term weather data is often considered one of the major reasons to limit the analysis to single weather years. Single weather years might considerably undersize the system design, as a result, system design based on a single weather year might not be optimal for other weather years. It is essential to design a system using multiple years of weather data since the system might experience a wide variety of weather patterns, such as prolonged periods of weather droughts. Thereby, requiring a larger system design for off-grid systems in order to prevent blackouts.

1.2. Multiple weather years-based system design

Numerous studies have considered multiple years of weather data for the optimal design of future energy system and wind-to-hydrogen system. A review by Prina et al. [18] highlights the wide range of modelling tools used at different space and time resolutions to model the energy system at island and national scales. Some of the modelling tools like TIMES [19] and OSeMOSYS [20] are based on multi-year time horizons and are extensively used for wind-to-hydrogen and energy system capacity planning. However, TIMES and OSeMOSYS models are typically focused more towards solving techniques like linear programming and mixed integer linear programming while less attention has gone towards novel ways to use multi-year weather data. Instead in TIMES and OSeMOSYS models, multi-year weather data time series are aggregated into time slices to reduce the computational burden of simulating the energy system model. Novo et al. [21] showed that each year can be divided into time slices based on the seasons (e.g. summer, winter), day types (e.g. week, weekend) and daily time bracket (e.g. morning, night). The optimal choice for the number of time slices to accurately represent each year chronologically depends upon the mathematical structure of the energy system optimisation model [22]. Increasing the number of time slices improves the accuracy of the model but at the expense of increased computational time and model complexity. This highlights the significant trade-off that exists between model accuracy and computational time to solve multi-year energy system models. Furthermore, representing each year with time slices restricts the ability to model storage behaviour accurately and capture its long-term effects. The impact of storage becomes even more pronounced where time series gains more importance i.e. in isolated systems (off-grid), which might lead to an underestimation of total system cost and installed capacity. Particularly, the long-term energy storage benefit offered by hydrogen during prolonged periods of wind drought is often underestimated.

Another common approach for designing energy and power-to-hydrogen systems while considering multiple years of weather data is by averaging the weather data over multiple months and years. Heide et al. [23,24] considered the monthly average of wind and solar generation over 8-year period (2000–2007) to optimally design a fully renewable future European power supply system. Further, Gunawan et al. [25] optimally designed a photovoltaic-battery-electrolyser system for hydrogen injection in a long-distance transmission line in Libya. The study used an average hourly PV generation profile based on 10 years of solar data from 2005 to 2015. A study by Marocco et al. [26] investigated the role of batteries and hydrogen storage in a 100 % renewable energy system. The study considered all the time-related input profiles values as the average value of the original time series in their TRAD method. Meanwhile, Ganter et al. [27] analysed the cost-optimal planning of near-term infrastructure for low-carbon hydrogen supply chains in Europe. The study highlights the importance of spatial resolution on the cost of hydrogen, while on a temporal resolution, time-dependent wind and solar capacity factors are approximated by their average values. Similarly, studies by Poncelet [28], Byers [29] and Ludig [30] used averaged hourly wind and solar generation profiles as input parameters for designing future energy systems. By averaging the weather data, the weather fluctuations are smoothed out, leading to an underestimation of weather variability, which has a considerable impact on the overall design of the system.

Weibull distribution is another widely used approach in power-to-hydrogen studies. Dinh et al. [31] developed a geospatial model to assess the economic viability of hydrogen production from offshore wind farms in Irish waters. The model estimated annual wind energy generation from offshore windfarms using two parameter Weibull probability distribution function based on 10 years (2001–2010) of wind speed data. The estimated annual wind energy generation is directly used alongside electrolyser conversion efficiency to calculate the annual hydrogen production capacity of each location and the power-to-hydrogen configuration. In another study, Fragiacomo et al. [32] considered 3 years of wind speed data to obtain Weibull factors for estimating annual wind energy generation for an onshore site in southern Italy. The estimated annual wind energy is then uniformly distributed across each day to design a hydrogen production facility for power-to-gas application. Chrysochoidis-Antsos et al. [33] evaluated an on-site wind-powered hydrogen-producing refuelling stations for a case study in the Netherlands. The study found that the technical potential of hydrogen refuelling stations is directly related to the hydrogen production capability at the site. Weibull distribution curve based on 5 years of wind speed data was used to estimate the annual wind energy generation and hydrogen production capacity. Similarly, studies by Iqbal [34], Ahmad [35] and Idriss [36] designed a power-to-hydrogen system based on Weibull distribution of monthly wind speed data. Most of the above-mentioned studies on power-to-hydrogen system design have utilized Weibull distribution functions at coarse time resolutions (monthly or yearly) or down sampled to uniform daily generation, which fails to depict and capture the actual hourly mismatch that exists between renewable supply and demand. Therefore, in this paper Weibull distribution method is not considered to design a wind-to-hydrogen system.

1.3. Near-optimal solutions-based system design

When designing a renewable energy system, a variety of decisions need to be made regarding production, storage, and transmission capacities. Energy system optimisation models are commonly used in energy system planning for making informed decisions about renewable energy mixes and technologies. However, their focus on the pursuit of a single cost minimisation result limits their ability to address alternative factors such as real-world political feasibility, environmental sustainability, and social acceptability. Moreover, focusing on just a single system configuration (global optimum) overlooks the range of equally feasible diverse system configurations. Consequently, the global optimum solution becomes less versatile in other diverse real-world situations. Additionally, global optimal solutions might prevent consensus among different stakeholders as it is very difficult to meet multiple stakeholder objectives with a single optimisation problem. By employing approaches such as near-optimal solution analysis, energy system modelers have the flexibility to choose from a wide range of system configurations and make more informed decisions.

Near-optimal solutions are a range of solutions which are close to the optimal, meaning the solutions are within a pre-defined threshold from the optimal. Near-optimal solutions increases the degree of freedom in designing a system and are preferable compared to a single optimal solution, which are sometimes difficult to capture due to computational restrictions. Trutnevyte [37] found a range of near-optimal solutions for UK energy system by varying the electricity generation mix, electricity import from interconnectors and pumped hydropower storage. Similarly, Neumann [38] and Pederson [39] systematically explored a wide range of similarly costly but diverse technology mixes for the European power system. These near-optimal solutions helped in identifying the multitude of technologically diverse alternatives to keep the system cost within a pre-defined range. Nacken [40] and Berntsen [41] introduced modelling-to-generate-alternatives methodology to systematically explore optimal and near-optimal solutions for German and Swiss energy systems, respectively. The near-optimal solutions were calculated based on the Euclidean distance from the optimal solution using the distance-to-selected algorithm. Following the above studies on energy system design, it is observed that near-optimal solutions are obtained by varying the electricity generation mix, storage types, cost and emission values. Further, the maximally different near-optimal solution is calculated based on the largest squared Euclidian distance from the cost-optimal solution. Most of the studies identify near-optimal solutions (generation, storage and transmission capacities) by iterative modification of the cost-minimizing objective function by multiplying a slack value to the previously obtained optimal solution. Existing studies [38,39,42] map out near-optimal solutions only based on costs, and a complete understanding of the reliability and cost variability of the near-optimal solution when employed in different weather years has not been explicitly investigated. In addition, the concept of near-optimal solutions for designing a wind-to-hydrogen system by varying the input weather data has not been adequately investigated as suggested in this study. In this work, we present a novel approach to optimally design a wind-to-hydrogen system by considering multiple years of input weather data in order to improve the reliability of the system in the face of interannual weather variability. The method builds on recent advancements in modelling techniques like Modelling to Generate Alternatives [40,43] and Modelling All Alternatives [39] and provides new insights into a parallelised approach for working with large wind datasets for system design.

In our study, the input weather data is varied, which results in a range of near-optimal solutions for each weather year. Combining all the near-optimal solutions from each weather year (union of results) and taking the maximum of all the near-optimal solutions results in a system configuration that should satisfy all the weather years under consideration. Unlike previous studies [40,41], which use Euclidean distance for selecting among near-optimal solutions, the maximum value of all near-optimal solutions is used. This is because, to evaluate Euclidean distance, the optimal solution needs to be calculated, which requires solving the system using multiple years of weather data outright, which is the core problem; it is computationally prohibitive. Solving each weather year individually, generating near-optimal solutions, and combining them to find the system configuration helps in reducing the computational time drastically compared to solving the system using multiple years of weather data outright. Therefore, a large multiple-year optimisation problem can be approximated and solved using smaller single-weather-year-based optimisation. Other methods like global sensitivity analysis [44], stochastic programming [45], and scenario analysis [46] offer lower computation time but are more focused on parametric uncertainty, i.e., how variation in costs impacts investment choices. The near optimal solution method proposed in this work provides higher degree of freedom and increased dimensional flexibility, i.e., choosing from a wide range of capacity choices both in terms of investment and dispatch when designing the final system. Furthermore, the proposed method helps address other computational factors affecting the model, such as software (license availability and software proficiency), and hardware capabilities (computational capacity). As a result, this work adds to the existing modelling techniques and complements them rather than substituting them.

1.4. Contribution, objectives & outline of the paper

The literature review shows that most of the prior studies on wind-to-hydrogen system design are based on single weather years that are randomly selected. The reliability of the system design when evaluated with other weather years and the system costs due to undersized or oversized system design has not been examined. The multiple years of weather data are mainly considered in the form of average values or aggregations of time slices of each year chronologically to reduce the computational burden. The available studies have not evaluated the consequence of averaging the weather data on the overall system design and the designed systems operational performance when employed with original weather dataset. Further, instead of aggregating multiple years into time slices, a systematic approach to selecting a representative weather year amongst the multiple weather years for system design, as a trade-off to solving the wind-to-hydrogen model with multiple years of weather data outright has not been thoroughly explored. In addition, there is a lack of literature studies that evaluate the potential of using near-optimal solutions for wind-to-hydrogen system design. In summary, research gaps exist in the (1) reliability and cost variation of system designed based on a randomly selected single weather year, (2) impact of averaged weather data on system design and its performance, (3) systematic approach to choosing a representative weather year for system design and (4) near-optimal solutions for system design. This study contributes to the literature by developing a detailed modelling method to account for weather variability while designing a wind-to-hydrogen system thereby improving the system reliability and minimizing cost variation. The objectives of this study are (1) to determine the impact of different input weather data methods (single, averaged, representative weather year and near-optimal solutions) on wind-to-hydrogen system design, (2) to compare the performance (reliability and cost variation) of wind-to-hydrogen system design based on different input weather data methods against computationally prohibitive multiple years based system design, and (3) to evaluate which of the input weather data methods presented in this work would provide a suitable computational trade-off compared to solving the system using multiple years of weather data outright.

The rest of the paper is structured as follows: Section 2 covers the detailed methodology used to model the wind-to-hydrogen system while accounting for various input weather data. In Section 3, the results of the various input weather data methods on the system design and its performance are presented and discussed. Finally, in Section 4, conclusions are drawn, and future areas of work are discussed.

2. Method and data

2.1. System description & scenario

In this study, an offshore wind farm (OWF) is used to generate hydrogen. The OWF is located in the north channel of the Irish sea, off the northeast coast of the island of Ireland, near the town of Larne,

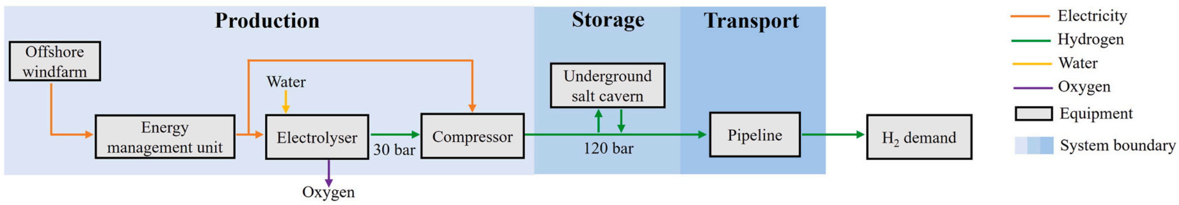

Fig. 1. The components for the wind-to-hydrogen system with underground salt cavern.

Northern Ireland [47]. The OWF project is currently under the planning and scoping stage of development, which gives the project the opportunity to finalise the project design for selling electricity to the grid or finding an alternative route to market to sell their electricity due to lack of grid connections like in the form of hydrogen. The OWF location benefits from enormous untapped wind potential alongside electricity and gas interconnector with Great Britain and nearby salt caverns for hydrogen storage. The city of Belfast is located nearby which represents a large potential demand centre for hydrogen from different end use applications like heavy-duty road transport and hydrogen blending in natural gas network. The hydrogen is assumed to be produced and stored onshore and transported to a network of hydrogen refuelling stations located within a 20-km radius. The hydrogen system configuration considered in this study is shown in Fig. 1. The impact of input weather data is evaluated for the system configuration. In the configuration, electricity generated by the OWF is supplied to the electrolyser through the energy management unit. Hydrogen produced by the electrolyser is compressed, stored in the nearby underground salt cavern, and delivered to a network of hydrogen refuelling stations through a dedicated hydrogen pipeline. The OWF provides electricity required for hydrogen compression, and no grid electricity is used hydrogen production and compression. The use of grid electricity for the production of renewable liquid and gaseous transport fuels of non-biological origin, which includes hydrogen, and its derivatives must adhere to strict spatial, temporal, and greenhouse gas emission reduction threshold compared to fossil fuels [48]. From 2030 onwards, hydrogen produced using grid electricity will be required to follow renewable energy output on an hour-by-hour basis, which will have an impact on the overall design and cost of hydrogen systems. The focus of this work is primarily on an off-grid hydrogen production system and the impact of grid electricity and grid electricity rules on the system design and the levelised cost of hydrogen is considered as a future opportunity. In this study, we assume that 25,000 tonnes of hydrogen must be delivered annually. The hourly demand is calculated by dividing the annual hydrogen demand by the total number of hours in a year. For this study, the hourly hydrogen demand profile is fixed and constant across all weather years. This is done to offer a fair comparison of results for the different input weather data methods considered in this study. As the main focus of this work is on the importance of multiple years of input weather data for hydrogen system design. Considering a varied hydrogen demand profile would alter the mismatch between hourly supply and demand, and would change the storage requirements, but it would not fundamentally alter the study's findings.

2.2. Input weather data and offshore windfarm electricity generation

In this study, 28 years (1994–2021) of hourly wind speed (100 m above ground level (a.g.l)), temperature (2 m a.g.l) and pressure (2 m a.g.l) data were obtained from Copernicus ERA5 reanalysis dataset, available at https://cds.climate.copernicus.eu [49]. The wind speed data was converted from 100 m (h_{ref}) to 150 m (h_i) hub height based on power law with exponent coefficient (α) of 1/7 as shown in Equation (1) [50]. Temperature, pressure and gas constant of air (287 J/kg.K) were used to calculate the density of air at 2 m a.g.l (ρ_{ref}). Further, density of air at 150 m hub height was estimated using Equation (2) [51]. Finally, using the wind speed and density data at hub height, representative hourly wind power for each year was generated, considering 15 MW turbine specifications from the International Energy Agency [52]. The electricity generated by OWF is transferred through the components: inter-array cables, high voltage alternating current (HVAC) offshore substation, HVAC offshore & onshore cables, onshore substation, and energy management unit (EMU) to onshore electrolyser as shown in Fig. 2. The total electrical energy losses due to these components is assumed to be 6.35 % of the electricity transmitted [53–55]. The impact of wind wake is included in the total electrical energy loss from the wind farm. Other issues like the wind turbine downtime due to technical problems, planned/unplanned maintenance and its overall impact on the hydrogen system design is considered an area of potential future work. High voltage direct current (HVDC) cables are used onshore from EMU to electrolyser. The electricity generated by OWF is dedicated to hydrogen production and no surplus electricity is sold to the grid. This is done in order to avoid profit maximisation from selling surplus electricity to the electricity market, which is not the objective of this study.

$$v_i = v_{ref} * \left(\frac{h_i}{h_{ref}}\right)^{\alpha} \tag{1}$$

$$\rho_i = \rho_{ref} - 1.194 * 10^{-4} * h_i \tag{2}$$

2.3. Hydrogen production

Hydrogen production ($M_{H2,t}$) depends upon the hourly electricity supply from the OWF to the water electrolyser ($P_{OWF,WE,t}$) and the specific energy consumption of the water electrolyser ($\mu_{WE,t}$) as expressed in Equation (3). The specific energy consumption of the water electrolyser is further a function of the (1) electrolyser load ($P_{OWF,WE,t}/P_{WE}$) that fluctuates based on the hourly electricity input to the water electrolyser and the (2) efficiency of the water electrolyser ($\eta_{WE,t}$) at the given electrolyser load as shown in Equation (4). The electrolyser load vs

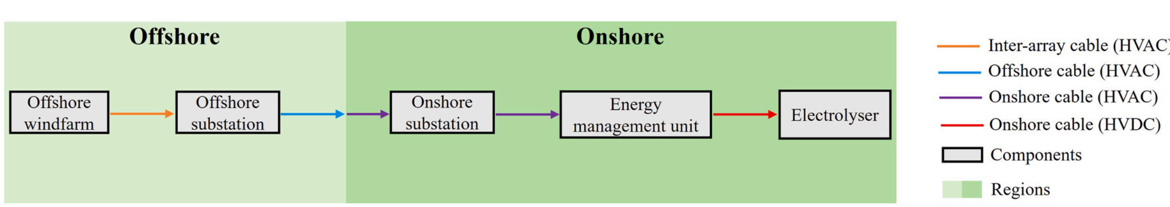

Fig. 2. Schematic representation of offshore windfarm with onshore electrolyser.

efficiency curve was considered to represent the dynamic behaviour of the water electrolyser [56]. LHV_{H2} represents the lower heating value of hydrogen.

$$M_{H2,t} = \frac{P_{OWF,WE,t} * \Delta t}{\mu_{WE,t}} \tag{3}$$

$$\mu_{WE,t} = LHV_{H2} * \left(\eta_{WE,t} \left(\frac{P_{OWF,WE,t}}{P_{WE}} \right) \right)^{-1} \tag{4}$$

The energy flow to the electrolyser and compressor depends upon the energy supply from OWF ($E_{OWF,t}$, result of $P_{OWF,t}$ multiplied by time step Δt). When $E_{OWF,t}$ is greater than the maximum energy input to the electrolyser ($E_{WE,t}$) and compressor ($E_{Comp,t}$). Then, the OWF electricity supply to the electrolyser ($E_{OWF,WE,t}$, result of $P_{OWF,WE,t}$ multiplied by time step Δt) is equal to the maximum electricity input capacity of the electrolyser as expressed in Equation (5). The OWF energy supply to the compressor ($E_{OWF,Comp,t}$) can be calculated using Equation (6). The energy demand for compressing hydrogen ($E_{Comp,t}$) can be calculated using Equation (7). $E_{Comp,t}$ depends upon the hydrogen mass flow from the electrolyser ($M_{H2,WE,t}$) at time t and the specific energy consumption of the compressor ($\mu_{Comp,t}$). The surplus electricity generated by OWF ($E_{Surplus,OWF,t}$) can be calculated using Equation (8). $E_{Surplus,OWF,t}$ is generated when the electricity supply from OWF is larger than the maximum electricity demand from the electrolyser and compressor. However, during times when the electricity supply from OWF is lower than the maximum capacity of the electrolyser and compressor. $E_{OWF,t}$ is iteratively distributed between the electrolyser and compressor such that the energy balance between electricity supply from OWF and the energy consumed by the electrolyser and compressor is equal to zero, as shown in Equation (9). There is no surplus electricity generated during times when the electricity supply from OWF is lower than the maximum capacity of the electrolyser and compressor.

$$E_{OWF,WE,t} = \min\left(E_{WE,t}, E_{OWF,t}\right) \tag{5}$$

$$E_{OWF,Comp,t} = \min\left(\left(E_{OWF,t} - E_{OWF,WE,t}\right), E_{Comp,t}\right) \tag{6}$$

$$E_{Comp,t} = M_{H2,WE,t} * \mu_{Comp,t} \tag{7}$$

$$E_{Surplus,OWF,t} = E_{OWF,t} - E_{OWF,WE,t} - E_{Comp,t} \tag{8}$$

$$E_{OWF,t} = E_{WE,t} + E_{Comp,t} \tag{9}$$

In terms of sizing, the optimal size of OWF and electrolyser is calculated iteratively such that all the hourly demands are met for the minimum levelised cost of hydrogen. The levelised cost of hydrogen subsection 2.6 provides further details on cost calculations. Equipment sizing intervals of 1 MWe are considered for both OWF and electrolyser. Compressor sizing depends upon the optimal electrolyser size.

2.4. Underground hydrogen storage

Most of the studies have focused on gaseous hydrogen storage, especially compressed tank storage [6,11,26]. Compressed tanks have high specific capital costs. Storing large quantities of hydrogen in compressed tanks results in significantly more expensive hydrogen fuel costs. Thereby making hydrogen fuel cell trucks uneconomical for replacing diesel trucks [14]. Large-scale underground storage of hydrogen, where available, would be the most cost-effective form of hydrogen storage [57]. As described in section 2.1, the onshore electrolyser considered in this study is located near a salt cavern that can store hydrogen, making it an ideal storage option. Hydrogen is stored at 120 barg in underground salt caverns.

Hydrogen is stored in underground salt caverns ($M_{H2,SC,t}$) when hydrogen production ($M_{H2,WE,t}$) is greater than the hourly hydrogen demand ($M_{Demand,t}$), as expressed in Equation (10). During times when hourly hydrogen production is lower than the demand, the hydrogen stored in the salt cavern is released to meet the demand as shown in Equation (11). The maximum amount of hydrogen stored among all the hours (time t) of the year determines the optimal storage size.

$$M_{H2,SC,t} = M_{H2,SC,t-1} + \left(M_{H2,WE,t} - M_{Demand,t} \right) \tag{10}$$

$$M_{H2,SC,t} = M_{H2,SC,t-1} - \left(M_{Demand,t} - M_{H2,WE,t} \right) \tag{11}$$

2.5. Hydrogen transportation

Once produced, hydrogen is transported to a network of hydrogen refuelling stations located near the port of Larne within a 20-km radius. In gaseous form, hydrogen is transported through a dedicated hydrogen pipeline. Austenitic stainless steel pipes are assumed in this study due to their higher resistance to hydrogen embrittlement [58]. The required inner diameter (D) of the pipeline can be calculated based on mass flow rate ($\dot{m}_{H2,t}$), gas velocity (u_o), and the density of hydrogen ($\rho_{H2}(temp,p)$), as shown in Equation (12). The maximum hourly hydrogen demand at the network of hydrogen refuelling stations determines the $\dot{m}_{H2,t}$ of hydrogen through the pipe. Gas velocity is assumed to be 15 m/s [59], while the density of hydrogen at 25 °C and 120 barg is 9.09 kg/m^3 [60]. The pressure drop (Δp) in the pipeline was calculated using the Darcy-Weisbach equation as mentioned in Equation (13) [61]. The Colebrook-White model was used for estimating the friction factor (f_D), as expressed in Equation (14) [61]. The friction factor depends upon the pipe roughness ($\in$) and the Reynolds number of the gas flow (R_e).

$$\dot{m}_{H2,t} = u_o * \rho_{H2}(temp, p) * \pi \frac{D^2}{4} \tag{12}$$

$$\frac{\Delta p}{L} = f_D * \frac{\rho_{H2}(temp, p)}{2} * \frac{{u_o}^2}{D} \tag{13}$$

$$\frac{1}{\sqrt{f_D}} = -2 \log\left(\frac{2.51}{R_e \sqrt{f_D}} + \frac{\epsilon}{3.7D} \right) \tag{14}$$

2.6. Levelised cost of hydrogen

The levelised cost of hydrogen ($LCOH$) represents the total discounted capital, operation, and maintenance cost of a hydrogen system per discounted total mass of hydrogen produced, stored, and transported over a year (T). $LCOH$ is calculated as the sum of the levelised costs of production ($LCOH_P$), storage ($LCOH_S$) and transportation ($LCOH_T$) as shown in Equation (15). The hydrogen system is assumed to operate (τ_{HS}) for 20 years with a discount rate (r) of 6 % [62].

$$LCOH = LCOH_P + LCOH_S + LCOH_T \tag{15}$$

The $LCOH_P$ is calculated using Equation (16). $C_{Capex,HP}$ represents the capital costs of hydrogen production (HP) equipment such as water electrolyser (C_{WE}), compressor (C_{Comp}), energy management unit (C_{EMU}), onshore substation (C_{OnSub}), engineering (C_{Eng}), interconnections (C_{IC}) and other costs (C_{OC}) as expressed in Equation (17). $C_{Opex,HP}$ represents the operational and maintenance (C_{OM}) cost of water electrolyser ($C_{OM,WE}$), stack replacement ($C_{OM,SR}$), compressor ($C_{OM,Comp}$), EMU ($C_{OM,EMU}$), onshore substation ($C_{OM,OnSub}$), water costs (C_{H2O}), energy penalty cost ($C_{Energy\ penalty}$) and electricity cost (C_{Elec}) as expressed in Equation (18). $C_{Energy\ penalty}$ also known as the cost of gas supply disruption, refers to the economic damage caused by gas demand not being met [63]. $C_{Energy\ penalty}$ has a wide range of values varying from 100 to 1100 €/MWh based on the affected consumer [63]. For this study, $C_{Energy\ penalty}$ is assumed to be 300 €/MWh (10 €/kgH_2).

$$LCOH_P = \frac{\sum_{T=0}^{T=\tau_{HS}} \frac{C_{Capex,HP}}{(1+r)^T} + \sum_{T=0}^{T=\tau_{HS}} \frac{C_{Opex,HP}}{(1+r)^T}}{\sum_{T=0}^{T=\tau_{HS}} \frac{M_{H2,HP}}{(1+r)^T}} \quad (16)$$

$$C_{Capex,HP} = C_{WE} + C_{Comp} + C_{EMU} + C_{OnSub} + C_{Eng} + C_{IC} + C_{OC} \quad (17)$$

$$C_{Opex,HP} = C_{OM,WE} + C_{OM,SR} + C_{OM,Comp} + C_{OM,EMU} + C_{OM,OnSub} + C_{H20} + C_{Energy\ penalty} + C_{Elec} \quad (18)$$

The electricity cost (C_{Elec}) is calculated using Equation (19), which is the sum of the capital costs ($C_{Capex,OWF}$) and operation and maintenance costs ($C_{Opex,OWF}$) of offshore wind farm components. The component costs included are the wind turbine & substructure ($C_{WT\&S}$, $C_{OM,WT\&S}$), inter-array cable (C_{IAC}, $C_{OM,IAC}$), offshore cable ($C_{OffCable}$, $C_{OM,OffCable}$), offshore substation (C_{OffSub}, $C_{OM,OffSub}$), onshore cable ($C_{OnCable}$, $C_{OM,OnCable}$), project development (C_{PD}), and installation costs of inter-array cable ($C_{IAC,Inst}$) and offshore ($C_{OffCable,Inst}$) as shown in Equation (20) and Equation (21). The length of the offshore and onshore cables is assumed to be 20 km and 2 km, respectively. The length of the inter-array cable is modelled using the method explained in Ref. [64].

$$C_{Elec} = C_{Capex,OWF} + C_{Opex,OWF} \quad (19)$$

$$C_{Capex,OWF} = C_{WT\&S} + C_{IAC} + C_{OffCable} + C_{OffSub} + C_{OnCable} + C_{PD} + C_{IAC,Inst} + C_{OffCable,Inst} \quad (20)$$

$$C_{Opex,OWF} = C_{OM,WT\&S} + C_{OM,IAC} + C_{OM,OffCable} + C_{OM,OffSub} + C_{OM,OnCable} \quad (21)$$

The $LCOH_S$ is calculated using Equation (22) where $C_{Capex,HSS,SC}$ and $C_{Opex,HSS,SC}$ represents the capital, operational and maintenance costs of an underground salt cavern (*SC*) hydrogen storage system (*HSS*).

$$LCOH_S = \frac{\sum_{T=0}^{T=\tau_{HS}} \frac{C_{Capex,HSS,SC}}{(1+r)^T} + \sum_{T=0}^{T=\tau_{HS}} \frac{C_{Opex,HSS,SC}}{(1+r)^T}}{\sum_{T=0}^{T=\tau_{HS}} \frac{M_{H2,HP}}{(1+r)^T}} \quad (22)$$

The annual hydrogen production ($M_{H2,HP}$) used in $LCOH_P$ and $LCOH_S$ is calculated based on the total amount of hourly hydrogen produced as explained in the hydrogen production subsection 2.3.

The $LCOH_T$ is calculated using Equation (23) where $C_{Capex,HT,Pipe}$ and $C_{Opex,HT,Pipe}$ represents the capital, operational and maintenance costs of hydrogen transportation (*HT*) by a dedicated hydrogen pipeline (*Pipe*). The annual hydrogen transported ($M_{H2,HT}$) represents the total annual hydrogen demand from a network of hydrogen refuelling stations.

$$LCOH_T = \frac{\sum_{T=0}^{T=\tau_{HS}} \frac{C_{Capex,HT,Pipe}}{(1+r)^T} + \sum_{T=0}^{T=\tau_{HS}} \frac{C_{Opex,HT,Pipe}}{(1+r)^T}}{\sum_{T=0}^{T=\tau_{HS}} \frac{M_{H2,HT}}{(1+r)^T}} \quad (23)$$

All the techno-economic component costs considered in this study are listed in Tables S3–S8 in the supplementary, assumed for the year 2030.

2.7. Overall model

This study evaluates the impact of different input weather data methods (single, averaged, representative weather year and near-optimal solutions) on the optimal design of the wind-to-hydrogen system as shown in Fig. 3. First, a single weather year (I) is randomly selected from 28 years (1994–2021) of weather data. The optimal design of the wind-to-hydrogen system is iteratively calculated by varying different equipment combinations such that all hourly hydrogen demands are met for the minimum levelised cost of hydrogen (*LCOH*). Then, the obtained optimal wind-to-hydrogen system design is fixed and tested in terms of reliability and cost variation, using the other 27 weather years individually. The term "reliability" here refers to the ability of the system design to meet all the hourly hydrogen demands when employed with other weather years, as shown in Table S2. The term "cost variation" here refers to the change in system cost (*LCOH*) that an optimal system design based on one weather year would face while operating in other weather years due to capacity shortages and unmet demand. An energy penalty cost is assumed for unmet demand as mentioned in levelised cost of hydrogen subsection 2.6.

In the averaged weather year method (II), the original 28 years (1994–2021) of weather data is averaged over multiple years at an hourly resolution. For instance, 2 years of averaged weather data means averaging hourly weather data from 1994 to 1995, 5 years of averaged weather data means averaging hourly weather data from 1994 to 1998, going up to averaging 28 years of hourly weather data. The averaged hourly weather data is used to determine the optimal design of the wind-to-hydrogen system by varying different equipment combinations such that all the hourly demands are met for the minimum LCOH. Further, the

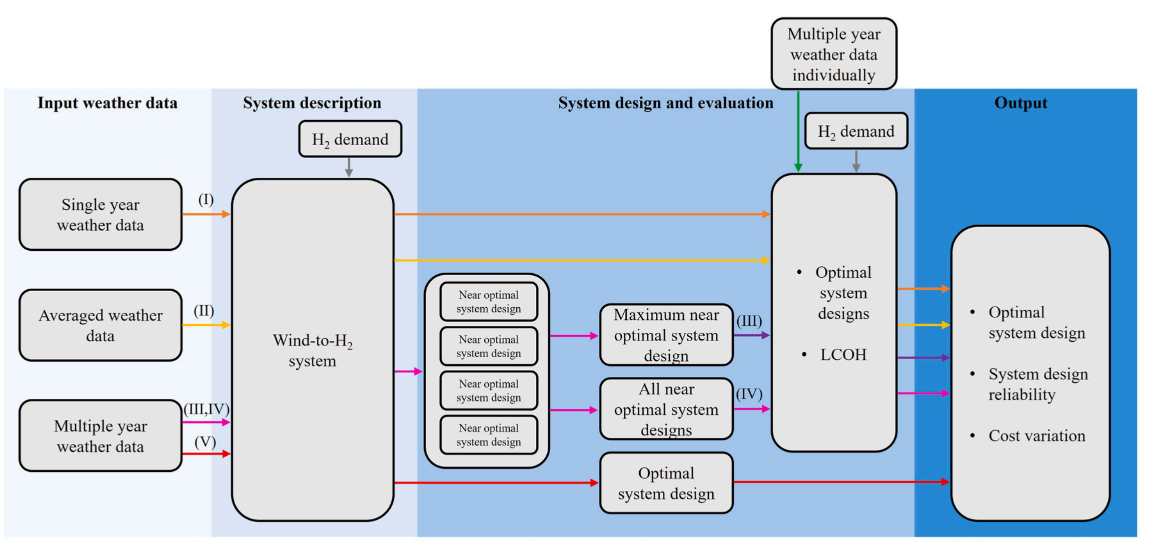

Fig. 3. Overall model to compare the impact of (I) single, (II) averaged, (III) Maximum near optimal and (IV) All near optimal solutions method on optimal system design, system reliability and cost variation compared to (V) ideal system design method (Full 28 years of weather data solved outright).

obtained optimal design of the wind-to-hydrogen system from averaged weather data is fixed and tested against original 28 years of weather data individually, in terms of reliability and cost variation as highlighted above.

In the near-optimal solutions method, each weather year is solved individually to obtain a wind-to-hydrogen system design that meets all the hourly demands for the minimum LCOH. All the near-optimal solutions (system designs) from each weather year are combined, i.e., the union of results and the maximum of all near-optimal designs (max NOpD) is considered as the optimal solution (III). This max NOpD configuration is tested against 28 years of weather data individually, in terms of reliability and cost variation.

Based on the near-optimal solutions method, 28 different optimal wind-to-hydrogen system designs are obtained for each weather year (IV). Each optimal system design is evaluated with the other 27 weather years in terms of reliability and cost variability. The system design with the highest reliability and lowest cost variability in other weather years is considered the final optimal system design. The corresponding year is the representative single weather year suitable for designing a wind-to-hydrogen system among the other 27 weather years. Representative here refers to a weather year that results in a system design that closely matches the system design and performance of an ideal system (28 years of weather data solved outright). This representable weather year could be a high renewable generation year (strong weather year), low renewable generation year (poor/extreme weather year) or some other peculiar characteristic weather year.

Finally, each of the four methods (I-IV) mentioned above is compared with designing a wind-to-hydrogen system by solving all the 28 years of weather data outright ("ideal system") (V). The comparison is based on optimal system design, system reliability and cost variation in operating the system.

The electricity generated from an offshore wind farm was calculated using MATLAB 2023b [65], using the input weather data from the Copernicus ERA5 reanalysis dataset [49] and a 15-MW turbine model from the International Energy Agency [52]. Electricity generated from offshore wind farms and other input parameters defining the hydrogen supply chain are defined in Excel. The optimal size of the components in the hydrogen supply chain are calculated iteratively through the use of Excel data tables such that all the hourly hydrogen demand are met at all times for each of the weather years at minimum LCOH. Finally, the reliability and cost variations of the system design are post-processed in MATLAB and visualized in Excel. Further details explaining the sizing of the hydrogen supply chain can be found in the previous work [66]. All simulations were performed on an 11th Gen Intel$^{(R)}$ Core$^{(TM)}$ i7-1165G7 machine with 32 GB RAM.

3. Results and discussion

The results are discussed in four parts. In the first part, the impact of four input weather data methods on hydrogen system design is compared with solving 28 years of weather data outright ("ideal system"). The comparison is to observe how far the system design results from each input weather data method are from the ideal system design. The second and third parts explore the reliability and cost variation of system designs from each input weather data method when employed with other weather years. Lastly, the impact of wind dataset size on the hydrogen system design is discussed, along with the limitations of this study.

3.1. Impact of different weather data methods on optimal wind-to-hydrogen system design

The results (see Table S1) from the ideal system design (28 years solved outright) show that an increase in weather data leads to an increase in the system design. The importance of large-scale energy storage becomes apparent during long periods of wind drought, with hydrogen storage meeting 33.9 % of total hydrogen demand. The use of large-scale storage increases the flexibility of the system design since it

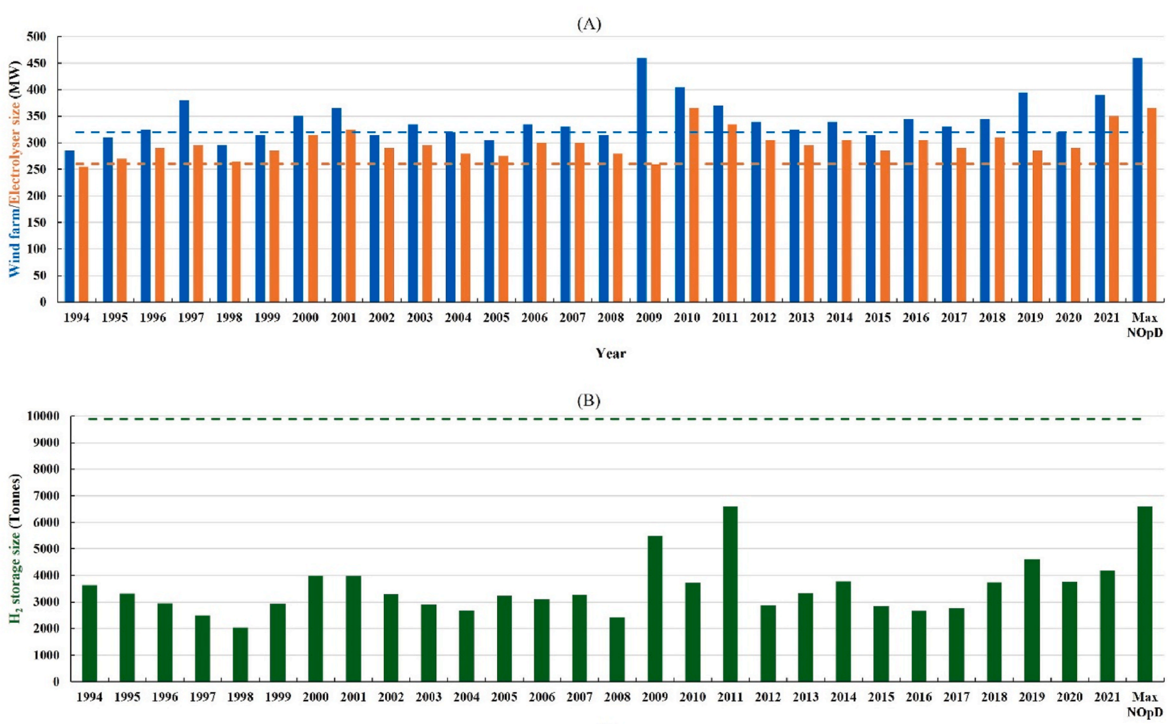

Fig. 4. Optimal wind farm, electrolyser (both in A) and storage (B) sizes for each weather year (1994–2021) for gaseous hydrogen system with underground salt cavern storage. Results can be interpreted for single weather year design, maximum near-optimal design (Max NOpD) and all near-optimal designs. The dashed line represents the ideal system design (Full 28 years of weather data solved outright).

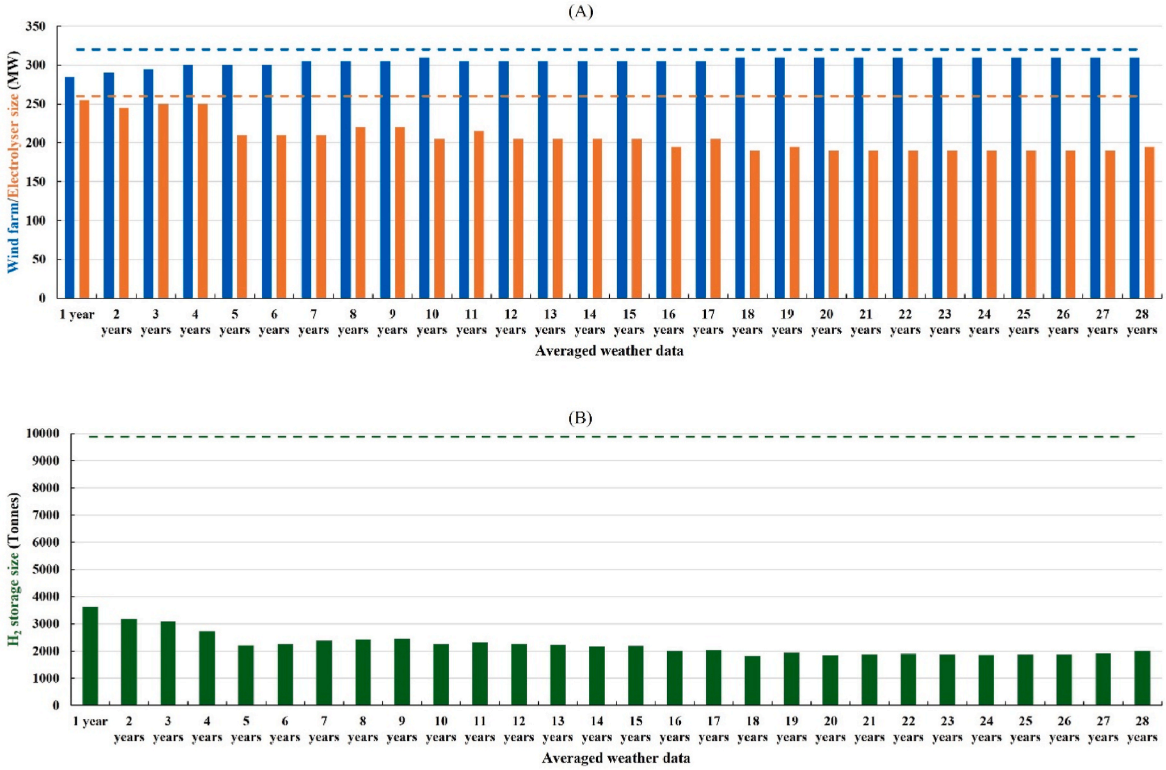

Fig. 5. Optimal wind farm, electrolyser (both in A) and storage (B) sizes for gaseous hydrogen system with underground salt cavern storage for different lengths of averaged weather data. The dashed line represents the ideal system design (Full 28 years of weather data solved outright).

reduces the need to oversize the wind farm and electrolyser during periods of low wind generation. The optimal size of large-scale storage can only be captured by solving with multiple years of weather data outright. Fig. 4 shows the optimal system design of wind farm, electrolyser, and storage for each weather year from 1994 to 2021 for a gaseous hydrogen system with underground salt cavern storage. The dashed line represents the ideal system design of each system component highlighted with different colour patterns. In the gaseous hydrogen system design (Fig. 4a), the optimal wind farm and electrolyser size for each weather year is close to the ideal system design. The variation in wind farm and electrolyser size is observed for weather years with strong wind generation like 1994 and 1998. Strong weather years generate wind consistently, resulting in smaller wind farm and electrolyser sizes that meet the demand. On the other hand, weather years with poor wind generation, like 2010 and 2021, result in significantly bigger wind farm and electrolyser sizes that meet the demand. It is evident from Fig. 4a that randomly selected weather years return a single optimal solution (undersized/oversized) for the wind farm and electrolyser system. On the contrary, individually analysing each weather year yields a range of near-optimal wind farm and electrolyser sizes, which could be chosen based on reliability and cost variation as discussed in sections 3.2 and 3.3. The maximum of near-optimal designs (Max NOpD) results in an oversized wind farm and electrolyser system. Hydrogen storage (Fig. 4b) is always undersized for any randomly selected weather year and all near-optimal storage designs for each weather year, compared to the ideal storage design (9880 tonnes). This is because the ideal storage size is iteratively calculated on an hourly resolution over 28 years, whereas, for a single weather year and all near-optimal designs, only individual weather years are solved on an hourly resolution over one-year periods. The results show that the optimal storage size based on a single weather year is underestimated and that the size would not be adequate to cover the hydrogen production-demand mismatch that occurs during

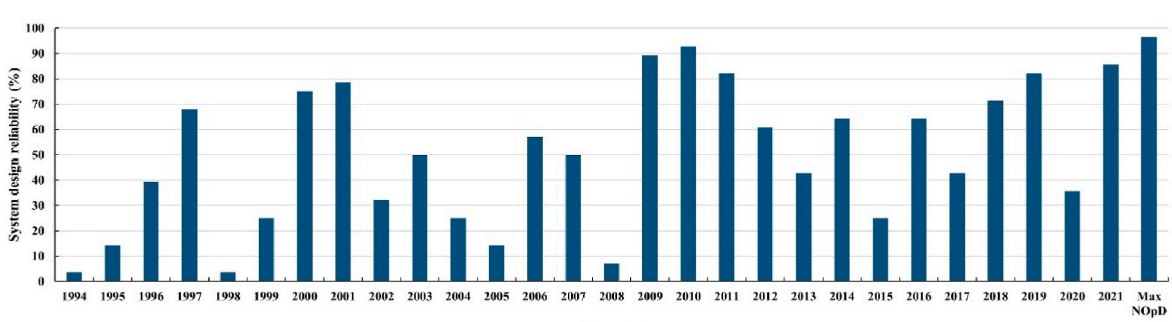

Fig. 6. System design reliability of gaseous hydrogen system with underground salt cavern storage when employed with other input weather years. Optimal system design capacities of each year are fixed, and input weather years are varied. System design reliability shows the total number of years out of 28 years where all the hourly demands are met. The reliability results can be interpreted for single weather year design, maximum near-optimal design (Max NOpD) and all near-optimal designs.

prolonged periods of wind drought. Storage size based on max NOpD is the most conservative approach to estimating storage design, reducing the scale of storage size (6596 tonnes) underestimation to 1.5 times compared to the ideal storage size.

Fig. 5 shows the optimal system design for a gaseous hydrogen system with underground salt cavern storage based on averaged weather data. The optimal system design of a wind farm, electrolyser and hydrogen storage is significantly undersized over averaged weather years compared to the ideal system design. This is because averaging the weather data (wind power output) smooths the peaks and troughs (variability) of the weather data (see Fig. S4). The smoothening of weather data dilutes the effect of poor weather years, thereby resulting in a consistent hourly time series of wind generation. Consistent hourly wind generation results in a smaller system design to meet the demand and, hence, an undersized system. Further, as the averaging time horizon increases, the size of the weather data over which averaging is performed increases, resulting in minimal changes to the system design over time. shows that the optimal wind farm and electrolyser size varies until 17 years and is constant thereafter. In terms of storage (Fig. 5b), similar to wind farm and electrolyser, the storage size is significantly undersized compared to the ideal storage design, and it does not vary after a certain averaging time horizon. This highlights that averaging the weather data always leads to an undersized system design due to the underestimation of weather variability and is an inaccurate method of designing a system. Considering the inaccuracy and for the sake of brevity, the averaging method is not discussed further in this article.

3.2. Impact on system design reliability

Fig. 6 shows the reliability of optimal system designs from each weather year when tested against the other 28 years of weather data. The results show that optimal system designs based on randomly selected single weather years are not suitable for other weather years. In the gaseous hydrogen system, the primary reasons for lower reliability among weather years are due to the combination of undersized production (wind farm and electrolyser) and storage. System design based on strong weather years results in an undersized wind farm and electrolyser that fail to meet all the hourly demand during poor weather years, resulting in lower reliability. In fact, system design based on strong weather years (1994) results in the lowest reliability (3.5 %) among all the analysed weather years. Individually analysing all the near-optimal designs from each weather year with the other 28 years of weather data shows that system design based on the year (2010) provides higher system reliability (92 %). This is because 2010 was a poor weather year with a bigger optimal system design than the ideal system design. From all the near-optimal system design reliability, we understand that a system designed based on the worst weather year increases system reliability at the expense of a bigger system design. Further, the maximum of near-optimal designs (Max NOpD) provides the highest system reliability (96 %) as a consequence of an oversized system design.

3.3. Impact on system costs

Fig. 7 shows the impact on system cost when the optimal system design from each weather year is evaluated against the other 28 years of weather data. The results illustrate that an optimal system design based on a single weather year can result in a wide range of costs when analysed for other weather years. This is due to two main factors: (i) energy penalty costs for unmet demand and (ii) wind farm electricity curtailment due to filled storage. Undersized system design faces energy penalty costs for not meeting the demand in other weather years. Particularly, the system design based on the strong weather year (1994) suffers from significant energy penalty costs, contributing to the system's operating expenses. The system cost can range from 5.6 to 10.3 €/kgH_2 for a system design based on weather data from 1994, as shown in Fig. 7. This variation in system cost by 4.7 €/kgH_2 clearly highlights the sensitivity of weather years to optimal system design and its system cost. Cost results from all the near-optimal designs from each weather year show that bigger system designs suffer from electricity curtailment in strong weather years. For instance, weather data from 2010 resulted in a bigger system design than the ideal system. When this system design from 2010 is fixed and analysed with weather data from 1994, the system produces large quantities of hydrogen, which is more than the demand. The storage rapidly fills up and reaches the point where storage is nearly full, and the electricity going to the electrolyser needs to be curtailed as shown in Fig. S5. While electricity dumping increases the system cost, bigger systems are already expensive to operate in any weather year. As a result, larger systems have smaller variations in costs between different weather years. This shows that poor weather year-based system design (e.g., 2010) lowers the cost variation of the system between different weather years at the expense of selling hydrogen at a higher price compared to the ideal system. This is particularly evident for poor weather year like 2010 (7.1–7.25 €/kgH_2) and max NOpD (7.2–7.3 €/kgH_2) based system, which are expensive to operate compared to ideal system design (6.7 €/kgH_2). Poor weather year-based system design (2010) suffers from higher electricity curtailment in other weather years due to smaller storage size, resulting in slightly higher cost variation compared to max NOpD. Max NOpD results in the lowest cost variation for gaseous hydrogen systems, while randomly selected

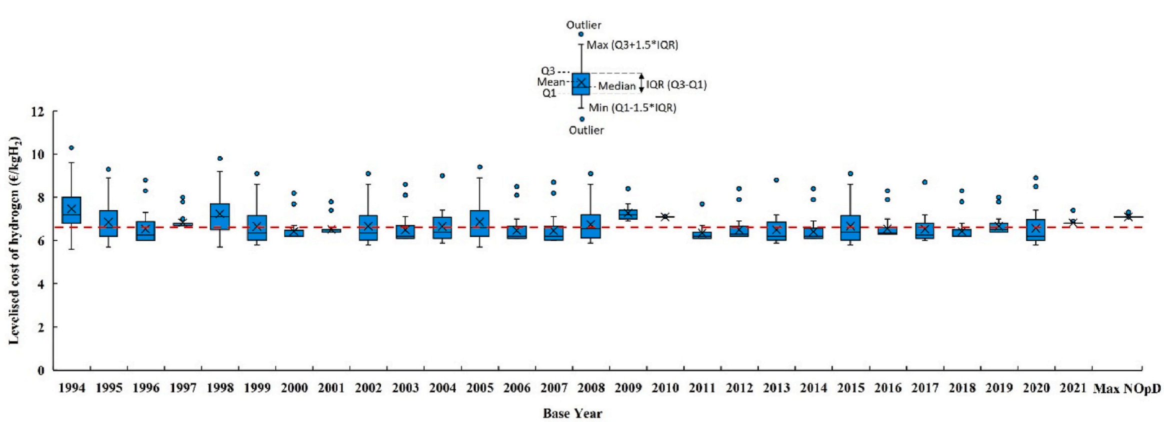

Fig. 7. System cost variation of gaseous hydrogen system with underground salt cavern storage when employed with other input weather years. Optimal system design capacities of each year are fixed, and input weather years are varied. The cost variation shows the range of costs the system must bear in other weather years due to either capacity shortage or wind farm electricity curtailment. The cost results can be interpreted for single weather year design, maximum near-optimal design (Max NOpD) and all near-optimal designs. The dashed line represents the ideal system cost (Full 28 years of weather data solved outright).

single weather year designs suffer from significant energy penalty costs due to undersized systems. Therefore, it can be observed that for gaseous hydrogen systems, the lower the system design reliability, the higher the cost variation in operating the system in other weather years.

3.4. Impact of wind dataset size on system design

The large inter-annual weather variability as well as the lack of dispatchable generation technologies make it necessary to access a wide range of input weather data in order to optimally size the off-grid wind-to-hydrogen system. When solving using multi-year weather data outright, it was observed that as the size of the input weather dataset increased, the optimal design and reliability of the corresponding design changed. For instance, a study with 9 years of weather dataset (1994–2002) had a different and smaller system design than a study with 28 years of weather dataset (1994–2021), as shown in Table S1. This is because as the size of the input weather dataset increased, the number of rare/extreme weather events both in terms of duration and frequency of occurrence substantially affected the system design, resulting in the need for a larger system design for improved system reliability. Hydrogen energy storage size is highly sensitive to the size of the input weather dataset, and a significantly larger storage size is required when the input weather dataset size increases. Due to the flexibility offered by increased storage size, offshore wind farms and electrolysers have smaller variation in size for increased input weather dataset. Increased storage capacity prevents overbuilding of offshore wind farms and electrolysers while reducing load curtailment substantially. This results in a small increase in LCOH with increased input weather dataset, as shown in Table S1. Moreover, as size of the input weather dataset increases, the dependence on hydrogen storage also increases, as a greater amount of hydrogen demand is met by hydrogen supplied by storage. Extended period of wind drought, lasting for days or weeks, were identified as the primary cause of increased hydrogen supply from storage. Hydrogen energy storage at large scale and at low costs is crucial for mitigating the impacts of wind droughts and ensuring a reliable hydrogen supply.

More pronounced weather variability was observed for the weather dataset from 2000 to 2021 compared to 1994–2000, significantly impacting the reliability of the wind-to-hydrogen system. Our study highlights that more than 20 years of input weather dataset, starting from the weather year 2000 and onwards, is required to improve system reliability. Ideally, a wind-to-hydrogen system should always be designed based on the maximum number of years of weather data available for the site. Planning a wind-to-hydrogen system by computationally solving multiple years of weather datasets outright is ideal. However, it is much more computationally expensive. The computational time increases exponentially with the increase in the size of the input weather dataset, the number of system operational constraints and complex long-term energy planning models. The max NOpD method proposed in this study provided significantly lower computational time with improved system performance and could be an effective approach for designing a wind-to-hydrogen system with multiple years of input weather datasets.

Despite the numerous insights gained from our study, there are some limitations that could impact the results, which are acknowledged and discussed in the following paragraph. Variation in renewable generation is highly dependent on location. Future research should investigate how renewable sources at different specific geographical locations influence the performance of the maximum near-optimal solutions method for wind-to-hydrogen system design. These would be particularly relevant for islands and off-grid energy communities, which have isolated energy systems and lack access to national energy grids. The analysis presented in this work showed that the size and cost of hydrogen storage can significantly impact the design, reliability and cost of the system. Further research is needed to evaluate the performance of the maximum near-optimal solution method over single weather years when different hydrogen storage systems are considered, such as high pressure tanks, liquid hydrogen tanks, liquid organic hydrogen carriers, ammonia, and methanol. Another aspect is that the model does not consider using grid electricity or energy imports from neighbouring countries. In reality, grid electricity and international energy trade could enhance the system's reliability and robustness. During times of reduced grid electricity prices, electricity may be stored in the form of hydrogen, or hydrogen could be imported and stored as a long-term energy reserve in order to mitigate the impact of wind droughts. The impact of integrating grid electricity and international energy trade on the design and performance of the system should be investigated in future work. Throughout the study, hydrogen demand is assumed to be constant and perfectly inelastic. It should be noted that the demand for hydrogen is determined by market conditions, policies, and regulations. There is a need for further investigation of the impact of grid electricity rules, and demand elasticity on wind-to-hydrogen system design.

4. Conclusion

Inter-annual weather variability poses a significant challenge in planning a wind-to-hydrogen system (WHS), which is different from the existing grey hydrogen system design based on dispatchable generation technologies. This paper illustrates how different input weather data methods impact the optimal size, cost and reliability of the WHS. The WHS is designed for supplying gaseous hydrogen to a network of refuelling stations. The input weather data methods evaluated are: Randomly selected single-year weather data (I), weather data averaged over multiple years (II), and multi-year weather data from 1994 to 2021. The multi-year weather data is evaluated using the concept of near-optimal system design in two ways: maximum of near-optimal designs (max NOpD) (III) and all the near-optimal designs (IV) for a WHS located on the island of Ireland. The optimal WHS design obtained from the input weather data methods (I-IV) is evaluated in terms of (i) variation in WHS design, (ii) reliability and levelised cost of hydrogen (LCOH) variation when employed with other weather years, and (iii) the computation time compared to designing the WHS using multiple years of weather dataset outright (ideal system) (V).

The results show that the input weather dataset significantly impacts the system configuration, reliability and cost of the WHS. The study showed that WHS designed using randomly selected single-year weather dataset results in a significantly undersized system design with lower reliability (3.5 %) and higher cost variability (up to 4.7 €/kgH_2) in other weather years. This behaviour is particularly evident when a high renewable generation year (strong weather year) is randomly considered for WHS system design, for instance, 1994. On the other hand, averaging weather data over multiple years smoothens the weather fluctuations, resulting in more consistent hourly wind generation. Averaging weather data is a misrepresentation and an inaccurate way of using weather dataset to design a WHS. Furthermore, with an increase in the averaging time horizon, the scale of undersizing the system increases. A WHS designed using strong single-weather year or averaged weather data values always has an undersized system design, a lower reliability, and a higher cost variability than a WHS designed using multi-year weather dataset values.

When multi-year weather dataset is solved outright, the optimal WHS design increases as the input weather data size increases. The hydrogen energy storage size was more sensitive to the size of the input weather dataset and always increased in size as the input weather dataset increased. In contrast, the offshore wind farm and electrolyser had smaller size variations with increased input weather dataset. In designing a WHS, it is essential to incorporate multi-year weather dataset in order to accommodate rare/extreme weather events both in terms of duration, and frequency of occurrence, which have a considerable impact on the system's reliability and costs. However, using multiple decades of weather data outright for WHS design is computationally prohibitive. Compared to solving multiple years of weather data outright, the max NOpD method proposed in this study provided significantly lower computation time with improved system performance (reliability and cost variability). The Max NOpD method has two main advantages: (i) parallelizing the solving process for multiple years of weather data, thereby reducing computation time, and (ii) improved system performance over other methods (I, II, IV). Max NOpD method results in the highest reliability (96 %) and lowest cost variability (0.1 €/kgH_2) for gaseous hydrogen systems at the expense of an oversized system design. Our results suggest that the reliability of the WHS design is directly related to the number of years of input weather data considered. A WHS should be designed considering more than 20 years of input weather dataset (2000–2021). Ideally, the maximum number of years of weather data available for the site. When multi-year weather dataset is not available for the site or the weather data cannot be used in a specific energy planning model, it would be beneficial to design the WHS based on low renewable generation weather years (extreme weather years). Analysing weather dataset from 1994 to 2021, 2010 was identified as an extremely poor weather year. A WHS design based on 2010 weather dataset resulted in a high level of reliability (92 %), and low-cost variability (0.14 €/kgH_2) in other weather years. For sites in Ireland, where long-term weather data is not available, planning a WHS with gaseous hydrogen storage using the 2010 weather data would provide nearly comparable system performance to the ideal system.

Future studies could compare the performance of the near-optimal methodology proposed in this work against other input weather data methods like a typical meteorological year and multiple weather years considered as time slices. A thorough analysis of the effects of varying the geographical region, storage type (batteries, hydropower), introducing grid electricity and technology mix (solar energy alongside wind energy) can assist in coping with future uncertainties and improving the adaptability, flexibility, and generalizability of the proposed maximum near-optimal solution method. Further, the impact of trading surplus electricity in the electricity market and and its influence on the overall wind-to-hydrogen system design needs to be investigated. Liquid hydrogen systems are constrained by liquefiers operational flexibility. The effect of liquefier constraint on system design and reliability needs to be investigated. Also, the impact of relaxing the liquefier system constraints on the system design and system reliability could be another interesting avenue to investigate.

CRediT authorship contribution statement

Arjun Bopaiah: Writing – original draft, Visualization, Validation, Software, Methodology, Investigation, Formal analysis, Data curation, Conceptualization. **Rory F.D. Monaghan:** Writing – review & editing, Supervision, Resources, Project administration, Investigation, 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.

Acknowledgement

The authors acknowledge funding support from MaREI Funded Investigator PhD Scholarship, Science Foundation Ireland through MaREI, the SFI Centre for Energy, Climate, and Marine research, [Grant number 12/RC/2302_P2] and the 26 industry partners of the HyLIGHT collaborative project. The authors acknowledge support from the Ryan Institute and University of Galway. The authors would like to thank Cian Moran and Ahmad Rafiee for sharing their technical knowledge.

Appendix A. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.ijhydene.2025.03.416.

References

[1] European Commission. The European green deal. https://commission.europa.eu/strategy-and-policy/priorities-2019-2024/european-green-deal_en. [Accessed 17 May 2024].
[2] SEAI. Energy in Ireland report. 2023, https://www.seai.ie/publications/Energy-in-Ireland-2023.pdf. [Accessed 17 May 2024].
[3] Ayop R, Isa NM, Tan CW. Components sizing of photovoltaic stand-alone system based on loss of power supply probability. Renew Sustain Energy Rev 2018;81:2731–43. https://doi.org/10.1016/j.rser.2017.06.079.
[4] Mati A, Ademollo A, Carcasci C. Assessment of paper industry decarbonization potential via hydrogen in a multi-energy system scenario: a case study. Smart Energy 2023;11:100114. https://doi.org/10.1016/j.segy.2023.100114.
[5] Superchi F, Mati A, Carcasci C, Bianchini A. Techno-economic analysis of wind-powered green hydrogen production to facilitate the decarbonization of hard-to-abate sectors: a case study on steelmaking. Appl Energy 2023;342:121198. https://doi.org/10.1016/j.apenergy.2023.121198.
[6] Gunawan TA, Williamson I, Raine D, Monaghan RFD. Decarbonising city bus networks in Ireland with renewable hydrogen. Int J Hydrogen Energy 2021;46(57):28870–86. https://doi.org/10.1016/j.ijhydene.2020.11.164.
[7] Samsatli S, Staffell I, Samsatli NJ. Optimal design and operation of integrated wind-hydrogen-electricity networks for decarbonising the domestic transport sector in Great Britain. Int J Hydrogen Energy 2016;41(1):447–75. https://doi.org/10.1016/j.ijhydene.2015.10.032.
[8] Kikuchi Y, Ichikawa T, Sugiyama M, Koyama M. Battery-assisted low-cost hydrogen production from solar energy: rational target setting for future technology systems. Int J Hydrogen Energy 2019;44(3):1451–65. https://doi.org/10.1016/j.ijhydene.2018.11.119.
[9] Burhan M, Chua KJE, Ng KC. Sunlight to hydrogen conversion: design optimization and energy management of concentrated photovoltaic (CPV-Hydrogen) system using micro genetic algorithm. Energy 2016;99:115–28. https://doi.org/10.1016/j.energy.2016.01.048.
[10] Dominković DF, Bačeković I, Ćosić B, Krajačić G, Pukšec T, Duić N, et al. Zero carbon energy system of south east Europe in 2050. Appl Energy 2016;184:1517–28. https://doi.org/10.1016/j.apenergy.2016.03.046.
[11] Gökçek M, Kale C. Techno-economical evaluation of a hydrogen refuelling station powered by Wind-PV hybrid power system: a case study for İzmir-Çeşme. Int J Hydrogen Energy 2018;43(23):10615–25. https://doi.org/10.1016/j.ijhydene.2018.01.082.
[12] Gökçek M, Kale C. Optimal design of a hydrogen refuelling station (HRFS) powered by hybrid power system. Energy Convers Manag 2018;161:215–24. https://doi.org/10.1016/j.enconman.2018.02.007.
[13] Hemmati R, Mehrjerdi H, Bornapour M. Hybrid hydrogen-battery storage to smooth solar energy volatility and energy arbitrage considering uncertain electrical-thermal loads. Renew Energy 2020;154:1180–7. https://doi.org/10.1016/j.renene.2020.03.092.
[14] Gunawan TA, Monaghan RFD. Techno-econo-environmental comparisons of zero- and low-emission heavy-duty trucks. Appl Energy 2022;308(October 2021):118327. https://doi.org/10.1016/j.apenergy.2021.118327.
[15] Al-Ghussain L, Samu R, Taylan O, Fahrioglu M. Sizing renewable energy systems with energy storage systems in microgrids for maximum cost-efficient utilization of renewable energy resources. Sustain Cities Soc 2020;55:102059. https://doi.org/10.1016/j.scs.2020.102059.
[16] Robertson B, Bekker J, Buckham B. Renewable integration for remote communities: comparative allowable cost analyses for hydro, solar and wave energy. Appl Energy 2020;264:114677. https://doi.org/10.1016/j.apenergy.2020.114677.
[17] Tőke PM, Hortay O. Simulation-based sensitivity analysis of an on-site hydrogen production unit in Hungary. Int J Hydrogen Energy 2021;46(7):4881–9. https://doi.org/10.1016/j.ijhydene.2020.11.010.
[18] Prina MG, Groppi D, Nastasi B, Garcia DA. Bottom-up energy system models applied to sustainable islands. Renew Sustain Energy Rev 2021;152:111625. https://doi.org/10.1016/j.rser.2021.111625.
[19] Loulou R, Goldstein G, Kanudia A, Remme U. Documentation for the TIMES model Part I: TIMES concepts and theory. https://iea-etsap.org/docs/Documentation_for_the_TIMES_Model-Part-I_July-2016.pdf. [Accessed 17 May 2024].
[20] Howells M, Rogner H, Strachan N, Heaps C, Huntington H, Kypreos S, et al. OSeMOSYS: the open source energy modeling system: an introduction to its ethos, structure and development. Energy Policy 2011;39(10):5850–70. https://doi.org/10.1016/j.enpol.2011.06.033.
[21] Novo R, Minuto FD, Bracco G, Mattiazzo G, Borchiellini R, Lanzini A. Supporting decarbonization strategies of local energy systems by de-risking investments in renewables: a case study on pantelleria island. Energies 2022;15(3):1103. https://doi.org/10.3390/en15031103.
[22] Gabrielli P, Gazzani M, Martelli E, Mazzotti M. Optimal design of multi-energy systems with seasonal storage. Appl Energy 2018;219:408–24. https://doi.org/10.1016/j.apenergy.2017.07.142.
[23] Heide D, von Bremen L, Greiner M, Hoffmann C, Speckmann M, Bofinger S. Seasonal optimal mix of wind and solar power in a future, highly renewable

Europe. Renew Energy 2010;35(11):2483–9. https://doi.org/10.1016/j.renene.2010.03.012.
[24] Heide D, Greiner M, von Bremen L, Hoffmann C. Reduced storage and balancing needs in a fully renewable European power system with excess wind and solar power generation. Renew Energy 2011;36(9):2515–23. https://doi.org/10.1016/j.renene.2011.02.009.
[25] Gunawan TA, Cavana M, Leone P, Monaghan RFD. Solar hydrogen for high capacity, dispatchable, long-distance energy transmission – a case study for injection in the Greenstream natural gas pipeline. Energy Convers Manag 2022;273:116398. https://doi.org/10.1016/j.enconman.2022.116398.
[26] Marocco P, Novo R, Lanzini A, Mattiazzo G, Santarelli M. Towards 100% renewable energy systems: the role of hydrogen and batteries. J Energy Storage 2023;57:106306. https://doi.org/10.1016/j.est.2022.106306.
[27] Ganter A, Gabrielli P, Sansavini G. Near-term infrastructure rollout and investment strategies for net-zero hydrogen supply chains. Renew Sustain Energy Rev 2024;194:114314. https://doi.org/10.1016/j.rser.2024.114314.
[28] Poncelet K, Delarue E, Six D, Duerinck J, D'haeseleer W. Impact of the level of temporal and operational detail in energy-system planning models. Appl Energy 2016;162:631–43. https://doi.org/10.1016/j.apenergy.2015.10.100.
[29] Byers C, Levin T, Botterud A. Capacity market design and renewable energy: performance incentives, qualifying capacity, and demand curves. Electr J 2018;31(1):65–74. https://doi.org/10.1016/j.tej.2018.01.006.
[30] Ludig S, Haller M, Schmid E, Bauer N. Fluctuating renewables in a long-term climate change mitigation strategy. Energy 2011;36(11):6674–85. https://doi.org/10.1016/j.energy.2011.08.021.
[31] Dinh QV, Dinh VN, Mosadeghi H, Todesco Pereira PH, Leahy PG. A geospatial method for estimating the levelised cost of hydrogen production from offshore wind. Int J Hydrogen Energy 2023;48(40):15000–13. https://doi.org/10.1016/j.ijhydene.2023.01.016.
[32] Fragiacomo P, Genovese M. Technical-economic analysis of a hydrogen production facility for power-to-gas and hydrogen mobility under different renewable sources in Southern Italy. Energy Convers Manag 2020;223:113332. https://doi.org/10.1016/j.enconman.2020.113332.
[33] Chrysochoidis-Antsos N, Escudé MR, van Wijk AJM. Technical potential of on-site wind powered hydrogen producing refuelling stations in The Netherlands. Int J Hydrogen Energy 2020;45(46):25096–108. https://doi.org/10.1016/j.ijhydene.2020.06.125.
[34] Iqbal W, Yumei H, Abbas Q, Hafeez M, Mohsin M, Fatima A, et al. Assessment of wind energy potential for the production of renewable hydrogen in sindh province of Pakistan. Processes 2019;7(4):196. https://doi.org/10.3390/pr7040196.
[35] Ahmad J, Imran M, Ali S, Adnan M, Ashraf S, Hussain Z, et al. Wind-to-Hydrogen production potential for selected sites in Pakistan. IEEE Access 2021:1. https://doi.org/10.1109/ACCESS.2021.3116259.
[36] Idriss AI, Ahmed RA, Atteyeh HA, Mohamed OA, Ramadan HSM. Techno-economic potential of wind-based green hydrogen production in Djibouti: literature review and case studies. Energies 2023;16(16):6055. https://doi.org/10.3390/en16166055.
[37] Trutnevyte E. Does cost optimization approximate the real-world energy transition? Energy 2016;106:182–93. https://doi.org/10.1016/j.energy.2016.03.038.
[38] Neumann F, Brown T. The near-optimal feasible space of a renewable power system model. Elec Power Syst Res 2021;190:106690. https://doi.org/10.1016/j.epsr.2020.106690.
[39] Pedersen TT, Victoria M, Rasmussen MG, Andresen GB. Modeling all alternative solutions for highly renewable energy systems. Energy 2021;234:121294. https://doi.org/10.1016/j.energy.2021.121294.
[40] Nacken L, Krebs F, Fischer T, Hoffmanna C. Integrated renewable energy systems for Germany–A model-based exploration of the decision space. In: 16th international conference on the European energy market (EEM), ljubljana, Slovenia; 2019. p. 1–8. https://doi.org/10.1109/EEM.2019.8916442.
[41] Berntsen PB, Trutnevyte E. Ensuring diversity of national energy scenarios: bottom-up energy system model with Modeling to Generate Alternatives. Energy 2017;126:886–98. https://doi.org/10.1016/j.energy.2017.03.043.
[42] Neumann F, Brown T. Broad ranges of investment configurations for renewable power systems, robust to cost uncertainty and near-optimality. iScience 2023;26(5):106702. https://doi.org/10.1016/j.isci.2023.106702.
[43] Lombardi F, Pickering B, Colombo E, Pfenninger S. Policy decision support for renewables deployment through spatially explicit practically optimal alternatives. Joule 2020;4(10):2185–207. https://doi.org/10.1016/j.joule.2020.08.002.
[44] Moret S, Codina Gironès V, Bierlaire M, Maréchal F. Characterization of input uncertainties in strategic energy planning models. Appl Energy 2017;202:597–617. https://doi.org/10.1016/j.apenergy.2017.05.106.
[45] Yue X, Pye S, DeCarolis J, Li FGN, Rogan F, Bó Gallachóir. A review of approaches to uncertainty assessment in energy system optimization models. Energy Strategy Rev 2018;21:204–17. https://doi.org/10.1016/j.esr.2018.06.003.
[46] DeCarolis J, Daly H, Dodds P, Keppo I, Li F, McDowall W, et al. Formalizing best practice for energy system optimization modelling. Appl Energy 2017;194:184–98. https://doi.org/10.1016/j.apenergy.2017.03.001.
[47] North Channel Wind. Public consultation 2023. https://northchannelwind.com/. [Accessed 28 February 2025].
[48] European Union Commission. Delegated regulation on the union methodology for renewable fuels of non-biological origin. https://energy.ec.europa.eu/delegated-regulation-union-methodology-rfnbos_en. [Accessed 3 March 2025].
[49] Hersbach H, Bell B, Berrisford P, Biavati G, Horányi A, Muñoz Sabater J, et al. ERA5 hourly data on single levels from 1940 to present. Copernicus Climate Change Service (C3S) Climate Data Store (CDS) 2023. https://doi.org/10.24381/cds.adbb2d47.
[50] Raab M, Körner R, Dietrich RU. Techno-economic assessment of renewable hydrogen production and the influence of grid participation. Int J Hydrogen Energy 2022;47(63):26798–811. https://doi.org/10.1016/j.ijhydene.2022.06.038.
[51] Martinez J. Modelling and control of wind turbines. London, UK: Imperial College; 2007. Master thesis, https://www.academia.edu/32048722/Modelling_and_Control_of_Wind_Turbines.
[52] Gaertner E, Rinker J, Sethuraman L, Anderson B, Zahle F, Barter G. Definition of the IEA 15-Megawatt Offshore Reference Wind. National Renewable Energy Laboratory. NREL/TP-5000-75698. https://www.nrel.gov/docs/fy20osti/75698.pdf.
[53] Crivellari A, Cozzani V. Offshore renewable energy exploitation strategies in remote areas by power-to-gas and power-to-liquid conversion. Int J Hydrogen Energy 2020;45(4):2936–53. https://doi.org/10.1016/j.ijhydene.2019.11.215.
[54] Jiang Q, Li B, Liu T. Tech-economic assessment of power transmission options for large-scale offshore wind farms in China. Processes 2022;10(5):979. https://doi.org/10.3390/pr10050979.
[55] Barelli L, Pelosi D, Ciupageanu DA, Ottaviano PA, Longo M, Zaninelli D. HESS in a wind turbine generator: assessment of electric performances at point of common coupling with the grid. J Mar Sci Eng 2021;9(12):1413. https://doi.org/10.3390/jmse9121413.
[56] Uchman W, Kotowicz J. Varying load distribution impacts on the operation of a hydrogen generator plant. Int J Hydrogen Energy 2021;46(79):39095–107. https://doi.org/10.1016/j.ijhydene.2021.09.166.
[57] Gabrielli P, Poluzzi A, Kramer GJ, Spiers C, Mazzotti M, Gazzani M. Seasonal energy storage for zero-emissions multi-energy systems via underground hydrogen storage. Renew Sustain Energy Rev 2020;121:109629. https://doi.org/10.1016/j.rser.2019.109629.
[58] Liu J, Zhao M, Rong L. Overview of hydrogen-resistant alloys for high-pressure hydrogen environment: on the hydrogen energy structural materials. Clean Energy 2023;7(1):99–115. https://doi.org/10.1093/ce/zkad009.
[59] The Future of Hydrogen. International energy agency G20 hydrogen report: assumptions. https://iea.blob.core.windows.net/assets/a02a0c80-77b2-462e-a9d5-1099e0e572ce/IEA-The-Future-of-Hydrogen-Assumptions-Annex.pdf. [Accessed 23 May 2024].
[60] Lemmon EW, Bell IH, Huber ML, McLinden MO. NIST standard reference database 23: reference fluid thermodynamic and transport properties-REFPROP, version 10.0. Gaithersburg: National Institute of Standards and Technology, Standard Reference Data Program; 2018. https://doi.org/10.18434/T4/1502528.
[61] Thawani B, Hazael R, Critchley R. Assessing the pressure losses during hydrogen transport in the current natural gas infrastructure using numerical modelling. Int J Hydrogen Energy 2023;48(88):34463–75. https://doi.org/10.1016/j.ijhydene.2023.05.208.
[62] Gunawan TA, Singlitico A, Blount P, Burchill J, Carton JG, Monaghan RFD. At what cost can renewable hydrogen offset fossil fuel use in Ireland's gas network? Energies 2020;13(7):1798. https://doi.org/10.3390/en13071798.
[63] Agency for the Cooperation of Energy Regulators. Study on the estimation of the cost of disruption of gas supply (CoDG) in europe. https://documents.acer.europa.eu/en/Gas/Infrastructure_development/Pages/Study-on-the-estimation-of-the-Cost-of-Disruption-of-Gas-Supply-(CoDG)-in-Europe.aspx. [Accessed 29 May 2024].
[64] Singlitico A, Østergaard J, Chatzivasileiadis S. Onshore, offshore or in-turbine electrolysis? Techno-economic overview of alternative integration designs for green hydrogen production into Offshore Wind Power Hubs. Renew Sustain Energy Transit 2021;1(September):100005. https://doi.org/10.1016/j.rset.2021.100005.
[65] The MathWorks inc. MATLAB. https://uk.mathworks.com/products/matlab.html. [Accessed 4 March 2025]. 2023.
[66] Moran C, Moylan E, Reardon J, Gunawan TA, Deane P, Yousefian S, et al. A flexible techno-economic analysis tool for regional hydrogen hubs – a case study for Ireland. Int J Hydrogen Energy 2023. https://doi.org/10.1016/j.ijhydene.2023.04.100.