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Advancements in hydrogen production through the integration of renewable energy sources with AI techniques: A comprehensive literature review

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HIGHLIGHTS

- The review paper covers integration of artificial intelligence (AI) with various renewable energy sources (RES), including biomass, solar, algae power, geothermal, and wind.
- Exploration of AI techniques, including machine learning (ML) and deep learning (DL), for improving green hydrogen production (GH2).
- Identification of gaps in existing research on AI-enabled hydrogen production from algae, ocean, hydroelectric, and tidal energy sources. Continued research, collaboration, and investment are crucial for overcoming challenges and fully harnessing AI-enabled GH2 production.
- Addressing the importance of water management in GH2, especially in arid regions, and AI's potential solutions.
- AI methods and optimisation algorithms show promise in enhancing GH2.

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ABSTRACT

Hydrogen possesses the ability to produce energy with minimal greenhouse gas emissions when sustainably produced, making it a promising renewable energy carrier. Moreover, recent advancements in Artificial Intelligence (AI) can further enhance cleaner hydrogen production in a more optimised way. The main objective of this review paper is to comprehensively examine the current state-of-the-art in the integration of AI techniques with Renewable Energy Sources (RES), such as biomass, solar, algae power, geothermal, and wind to advance various hydrogen production methods, including electrolysis, biological, and photovoltaic processes. Furthermore, we aim to explore how AI optimisation can enhance sustainability, reliability, and commercial viability of Green Hydrogen (GH2) systems. These processes are crucial for reducing greenhouse gas emissions and meet the world's growing energy needs. The integration of RES with hydrogen production technologies has been recognised as a key strategy to attain a sustainable and environmentally friendly energy future, and the incorporation of AI can optimise efficiency and cost-effectiveness. This review found that there is a growing interest in the development of AI techniques to optimise GH2 production. While most of the studies focus on utilising wind and solar energy sources, this review found minimal existing research applying AI to GH2 production from algae, ocean, intermittency, and hybrid RES. Moreover, no works exploring AI to optimise GH2 production from sources like tidal and hydropower were found. Thus, prioritising AI-enabled system development to integrate and optimise these resources for GH2 production can help progress renewable generation capabilities towards a more sustainable, cleaner, carbon-free future for industry, transport, and societal sectors. Further extensive research is essential to fully harness the promise of AI in transforming diverse RES for clean hydrogen.

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1. Introduction

Urbanisation and a growing human population have significantly heightened global energy needs, leading to environmental issues such as ecosystem degradation, acid rain, air pollution, global warming, and energy resource depletion. These concerns make it imperative to investigate renewable resource-based alternative energy sources. The integration of RES, such as solar, wind, biomass, and geothermal, with AI techniques has led to significant advancements in hydrogen production. These advancements have not only addressed the challenges associated with fluctuating renewable energy production but also facilitated efficient and sustainable hydrogen generation to meet the growing demand for clean fuel alternatives. By harnessing the power of AI, renewables can be optimised for hydrogen production, leading to increased efficiency and reliability in the transition towards a greener future [81]. AI's role extends significantly to renewable energy, particularly in optimising electrolysis processes for hydrogen production [1]. Through real-time monitoring, adaptive control strategies, and predictive maintenance, these AI-driven optimisations contribute to heightened efficiency and cost-effectiveness in hydrogen production. The potential of AI-driven frameworks improves energy systems, control mechanisms, and automation, ultimately supporting a sustainable energy transition [2]. Researchers and engineers analyse, and process massive amounts of data using AI to find similarities and optimise energy production processes, increasing overall efficiency and lowering hydrogen production costs. A combination of density functional theory calculations and Machine Learning (ML) algorithms such as Support Vector Regression (SVR), Gradient Boosting (GB), Random Forest (RF), AdaBoost, Multi-layer Perceptron (MLP), and Ridge Regression have demonstrated significant advancements in optimising hydrogen evolution reaction catalysts for enhanced hydrogen production efficiency [3]. The symbiotic relationship between AI and RES, as exemplified by innovative technologies, facilitates advancements across the entire hydrogen production life cycle, encompassing production, distribution, and utilisation [4]. These advancements align with the principles of a circular economy and contribute to developing comprehensive policy frameworks that address evolving energy demands and technological advancements [5]. Despite these developments, the integration of RES with AI still encounters challenges related to water scarcity and the need for pure water in electrolysis processes, particularly in arid regions [6]. However, AI technologies continue to encourage the transition to a more sustainable and decarbonised energy system while enabling the renewable energy industry to grow. This integration not only enhances the overall efficiency and reliability of hydrogen production but also accelerates the transition towards a sustainable and decarbonised energy system.

There are several clean and sustainable sources that can be used to produce hydrogen through electrolysis, as illustrated on the left side of Fig. 1. Solar panels directly generate electric energy, while wind turbines and hydroelectric dams use rotational generators, geothermal produces electric energy by splitting water (H_2O) into hydrogen (H_2) and oxygen (O_2), and biomass can be used to generate hydrogen through gasification, feedstock, etc. To generate hydrogen, electrolysers simply need water and electricity. The resulting hydrogen can then be used for various applications, as shown on the right side of the figure. Fuel cells can convert the hydrogen back into electric energy to power transportation. Hydrogen is also used directly in industrial applications or injected into natural gas pipelines. Additionally, hydrogen provides a method to store energy from renewable sources that are intermittent such as solar and wind power. Therefore, GH2 represents a clean and sustainable energy carrier that can facilitate the transition to a decarbonised energy system. AI can also help address the challenges of

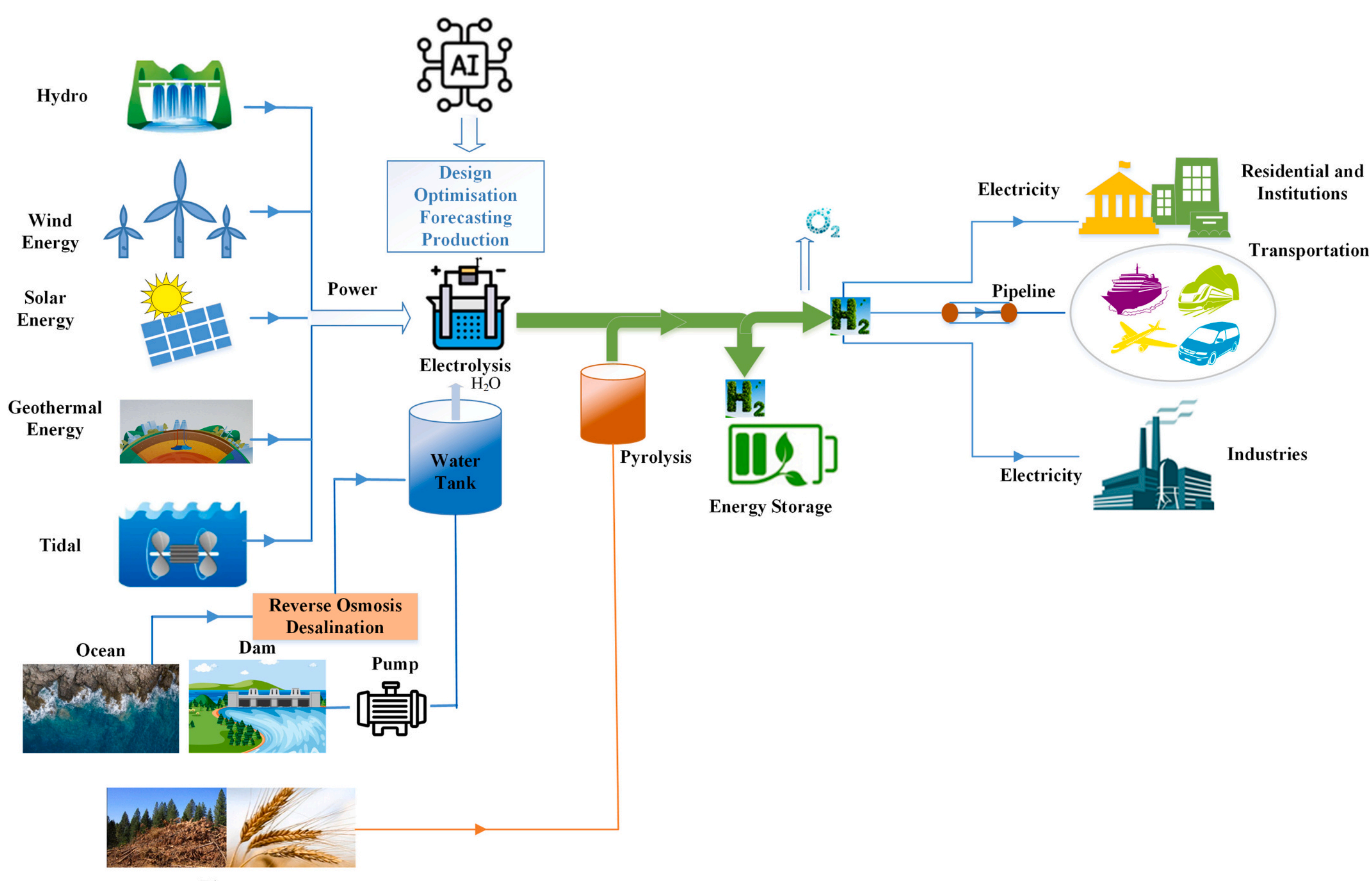

Fig. 1. Integration of renewable energy and AI for hydrogen production.

intermittency and storage by optimising the integration of RES with GH2 production systems. This can be achieved by predicting weather patterns and adjusting the production of hydrogen accordingly. In continuation to the production of hydrogen in 2030, a solar-driven steam-autothermal hybrid reforming system was proposed to capture the carbon emissions generated during hydrogen extraction [7]. The forecast hydrogen demand is shown in Fig. 2, for 2030 and 2050. The demand of hydrogen is increasing fivefold for China reaching 200 MmT (million metric tons), whereas for North America and Europe it increases from 25 and 20 to 95. For Japan and Korea, it rises from 10 to 35 MmT, and for the rest of the world it reaches 235 MmT (McKinsey & Company @ Statista 2023).

Large volumes of hydrogen are produced using fossil fuels; however, these processes are not sustainable due to their negative environmental effects [8]. The review explored various hydrogen production methods, evaluating both renewable and non-renewable sources, with a focus on costs, environmental impact, and technological advancements. Predominantly, traditional methods rely on natural gas and coal, which pose considerable environmental challenges. In contrast, renewable-based approaches like water electrolysis and thermochemical cycles powered by clean energy sources such as wind, solar, and nuclear present promising alternatives. The studies emphasise the need to transition towards these sustainable methods while adopting innovations like Proton Exchange Membrane (PEM) electrolysis, biomass gasification, and microbial hydrogen production to achieve long-term sustainability and reduce environmental impacts. Increasing global population, economic growth, and technological progress have driven a rise in primary energy consumption, which remains heavily reliant on fossil fuels. Although RES currently contribute only a small fraction to GH2, ongoing research has been focused on generating environmentally friendly and pollution-free hydrogen by integrating AI with these sources.

Achieving truly sustainable hydrogen production demands requires a careful balance between efficiency and cost-effectiveness. As the global energy landscape shifts towards cleaner alternatives, researchers and stakeholders are actively exploring and evaluating diverse production methods to find the optimal pathway that aligns with environmental, economic, and operational priorities. Selecting the most suitable hydrogen production approach requires a thorough analysis of efficiency and cost trade-offs to ensure a viable and sustainable energy future. This intricate relationship is illustrated through a profile analysis, as depicted in Fig. 3. Steam Reforming (SR) boasts an impressive 85 % efficiency, substantially higher than Electrolysis and Dark Fermentation (DF) which each have 80 % efficiency. However, Photo Fermentation (PF) and Photolysis exhibit remarkably low efficiencies of just 0.1 % and 0.06 %, respectively. In terms of cost, SR is at \$2.27/kg, followed closely by Partial Oxidation (PO) and Autothermal Reforming (AR) at \$1.48/kg. Electrolysis remains by far the most expensive option at \$10.3/kg. With these efficiency and cost profiles in mind, stakeholders face a critical decision whether to prioritise the high efficiency of SR or the cost-effectiveness of methods like PO, AR, and Gasification (G). Striking the right balance will be key to maximising the viability and potential of hydrogen production.

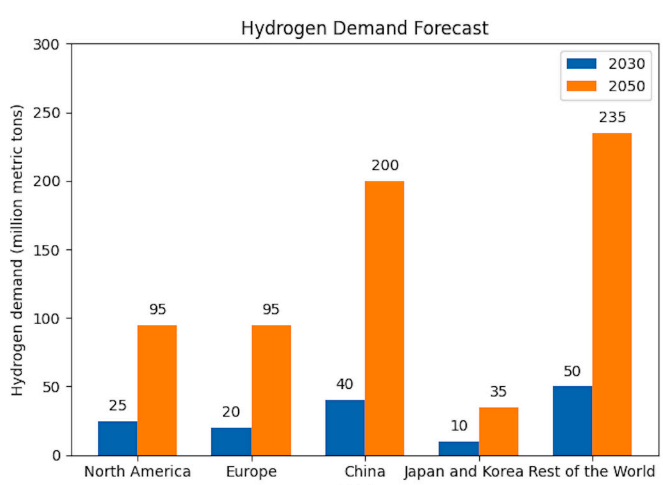

Fig. 2. Forecast hydrogen demand worldwide in 2030 and 2050 (source Hydrogen Council, McKinsey & Company @ Statista 2023).

Moreover, the International Energy Agency data on global energy investments from 2015 to 2023, presented in Fig. 4, reveals increasing capital allocation towards diversifying the world's energy sources. Total investments grew steadily from \$2392 billion in 2015 to \$2791 billion in 2023, representing a growing focus on energy diversity.

Therefore, the overall objective of this work is to provide a comprehensive analysis of the current state-of-the-art in the integration and development of AI techniques for optimising GH2 production methods. We have outlined the following main objectives of our literature review:

1. To analyse the current state-of-the-art integration of AI techniques with various RES for optimising GH2 production methods, including electrolysis, biological, and photovoltaic processes.
2. To identify the current gaps in the existing research literature related to the application of AI in hydrogen production from algae, ocean, hydroelectric, and tidal energy sources, and highlight the need for prioritising AI-enabled systems for these underutilised resources.
3. To review the role of AI algorithms in improving electrolysis processes and their potential to develop adaptive control strategies for greater efficiency and cost-effectiveness in hydrogen production.
4. To analyse the critical importance of addressing water scarcity challenges for hydrogen production from water electrolysis, with a particular focus on the pressing water issues faced by arid regions.

This literature review paper is structured as follows: In Section 2 we provide a background of theoretical foundation, and in Section 3 we outline the research methodology and highlight the process of searching, focusing on the topic. Section 4 delves into the examination of results, encompassing efficiency, cost analysis, various electrolysis processes for hydrogen production, and methodologies integrating AI for GH2 production using RES. Section 5 engages in a discussion of the advancements, challenges, and opportunities in hydrogen production. Lastly, Section 6 presents the conclusion and offers suggestions for further research.

2. Theoretical foundation

2.1. Techniques of hydrogen production incorporating AI techniques

2.1.1. Electrolytic processes

ML techniques have significantly advanced the field of electrolytic hydrogen production [10]. Hydrogen can be produced through electrolysis, which utilises electricity to split H_2O molecules into H_2 and O_2. In this electrochemical process, H_2O is broken down into its basic components of H_2 and O_2 by passing an electric current through it [83]. The reaction takes place in an electrolyser which contains a cathode and an anode separated by an electrolyte medium. As current passes between the electrodes, the H_2O molecules are split, resulting in H_2 gas collecting at the cathode and O_2 at the anode. The ML algorithms can precisely analyse electrode surface interactions, predicting optimal electrolyte compositions and membrane performance with unprecedented accuracy. Deep Learning (DL) techniques excel at modelling complex electrochemical reactions, identifying subtle variations in current efficiency, and recommending material modifications that enhance hydrogen generation. AI-powered predictive models can simulate electrical current distributions, voltage losses, and potential degradation mechanisms across different electrolyses technologies like PEM and alkaline systems.

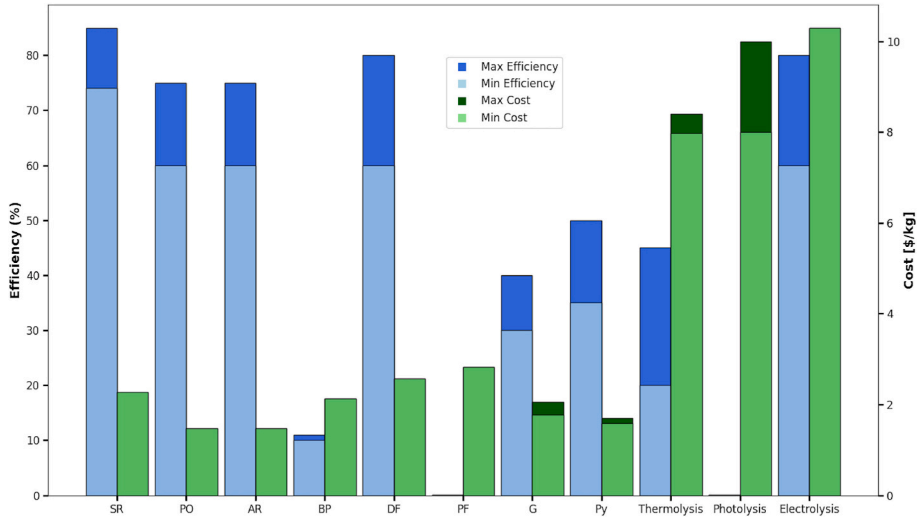

Fig. 3. Hydrogen production methods for efficiency and cost [9].

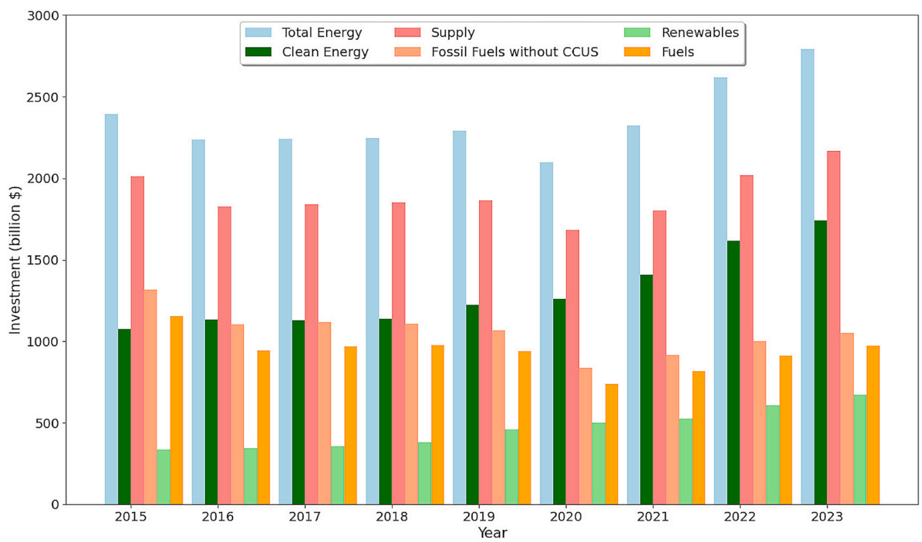

Fig. 4. World energy investment data 2023 (source IEA).

By integrating advanced ML techniques, AI facilitates more detailed understanding of electrolytic hydrogen production, accelerating technological improvements and supporting the development of more robust and efficient electrochemical hydrogen generation systems.

The equations given by Ivy [11] outline basic reactions, with Eq. (1) representing water decomposition. The subsequent Eqs. (2)–(5) delve into electrode reactions within PEM and Alkaline systems.

$$H_2O \rightarrow \frac{1}{2}O_2 + H_2 \tag{1}$$

In a PEM hydrogen production at cathode and anode, the electrode reactions are as follows:

$$2H^{+} + 2e^{-} \rightarrow H_2 \tag{2}$$

$$H_2O \rightarrow \frac{1}{2}O_2 + 2H^{+} + 2e^{-} \tag{3}$$

In an Alkaline system, the electrode reactions for Hydrogen production at Cathode and O_2 production at Anode are as follows:

$$2H_2O + 2e^{-} \rightarrow H_2 + 2OH^{-} \tag{4}$$

$$2OH^{-} \rightarrow \frac{1}{2}O_2 + 2H_2O + 2e^{-} \tag{5}$$

2.1.2. Photovoltaic processes

The PV industry is increasingly adopting AI techniques to optimise and improve various aspects of PV processes. AI techniques have the potential to significantly enhance electrolytic hydrogen production by improving process efficiency, predicting performance, and optimising system parameters. For instance, ML models such as Recurrent Neural Network (RNN), XGBoost, and LightGBM have been successfully applied to predict and optimise hydrogen production from electrolysis processes, demonstrating high predictive accuracy and the ability to identify optimal configurations [12]. PV processes directly harness solar energy to generate hydrogen through photocatalytic water splitting. These methods use solar cells or semiconducting materials to absorb sunlight and use the energy to break H_2O molecules into H_2 and O_2 [84]. Ultimately, PV hydrogen production provides a renewable approach to generate H_2 gas directly from sunlight and H_2O without any carbon emissions [13]. The H_2 and O_2 evolution reactions in a PEM system are expressed through Eqs. (6)-(8) for PEM system electrode reaction, hydrogen evolution reaction, and oxygen evolution reaction emphasising the electrochemical aspects of hydrogen production [14].

$$2H_2O + photons \rightarrow 2H_2 + O_2 \tag{6}$$

$$2H_2O + 4e^- \rightarrow H_2 + 2OH^- \tag{7}$$

$$4OH^- \rightarrow O_2 + 2H_2O + 4e^- \tag{8}$$

2.1.3. Biological processes

AI techniques, particularly supervised ML algorithms, are transforming biological hydrogen production through sophisticated computational modelling approaches. ANN emerge as the most dominant technique, capable of modelling complex biochemical reactions and handling nonlinear biological processes with exceptional precision. By integrating Artificial Neural Networks Inference Fuzzy Systems and combining Neural Network (NN) capabilities with fuzzy logic, uncertainties inherent in biological systems are effectively managed. SVM provide robust predictive modelling by handling high-dimensional data and performing advanced classification and regression tasks. Ensemble learning techniques like GB and RF further enhance computational intelligence by improving prediction accuracy, reducing model overfitting, and generating critical feature importance insights. These advanced AI techniques require extensive datasets and offer significant advantages over traditional first-principle models, enabling dynamic time-invariant and time-variant modelling of microbial metabolic processes. These AI approaches are revolutionising our understanding and optimisation of biological hydrogen production technologies. Biological process employs microorganisms or enzymes for hydrogen production through fermentation or biological H_2O splitting. In anaerobic conditions, mixed microbial cultures can break down glucose, glucose isomers like other hexoses, and polymers such as starch, glycogen, and cellulose [15]. This microbial degradation produces hydrogen along with various metabolic by-products. Eqs. (9)-(11) introduce acidogenesis reactions linking hydrogen yield to metabolic products, showcasing the importance of metabolic pathways in achieving high hydrogen productivity ([85], [17,18]). The hydrogen yield can be stoichiometrically correlated with the final metabolic products through specific acidogenesis reactions:

$$C_6H_{12}O_6 + 2H_2O \rightarrow 2CH_3COOH + 2CO_2 + 4H_2 \tag{9}$$

$$C_6H_{12}O_6 \rightarrow CH_3CH_2CH_2COOH + 2CO_2 + 2H_2 \tag{10}$$

$$C_6H_{12}O_6 + 2H_2 \rightarrow 2CH_3CH_2COOH + 2H_2O \tag{11}$$

2.2. AI techniques for optimising hydrogen production

2.2.1. Machine learning

AI, particularly ML, has the potential to change hydrogen generation from RES. ML can analyse complicated datasets involving renewable energy inputs and system performance, imitating human-like learning by using methods like logic, deduction, and statistical inference to create prediction models [19]. This data-driven strategy increases the efficiency and scalability of hydrogen generation technologies, allowing for autonomous decision-making and adaptive responses to changing conditions. The integration of RES such as solar and wind, which are fundamentally unpredictable and weather-dependent, can be optimised using ML to maximise hydrogen yield. ML models analyse both historical and real-time data, allowing for better management of energy fluctuations and increasing the reliability of hydrogen generation operations. For example, SVMs can be utilised for classification, regression, or other tasks; Linear Regression (LR) models can be used to predict energy production patterns; and k-Nearest Neighbor ($k-$NN) can estimate energy outputs by evaluating similar previous conditions, allowing for more effective energy supply and demand management [20]. Whereas RF classifier is a prominent ensemble method of classification used in ML and data science for a wide range of applications [21]. These models can autonomously identify and optimise essential factors in electrolysis, such as temperature, pressure, and voltage, to increase efficiency. By continuously learning from operational data, ML systems may make real-time adjustments to ensure optimal hydrogen yield with minimal energy use. Furthermore, AI's capacity to integrate heterogeneous RES helps to build a more robust and sustainable energy ecosystem for hydrogen generation, addressing issues such as variability and optimising performance metrics [86].

2.2.2. Artificial neural network

ANN is a form of ML model influenced by the human nervous system consisting of neurons and designed to learn and make assessments based on data. Fig. 5 depicts a simplified ANN structure that includes an input layer, hidden layers, and an output layer. The data is first introduced in the input layer, with each neuron representing a distinct aspect of the input data. This data is then passed via hidden layers, which use mathematical functions and algorithms to detect complicated patterns. These layers are essential for learning the correlations in the data and are optimised to achieve high predictive accuracy. Various activation functions are utilised within these layers to introduce nonlinearity to the model, allowing it to learn more complex patterns. The output layer produces the outcome based on the learnt patterns, which could be a prediction or classification, depending on the objective. [22]. ANNs are especially useful for jobs involving big datasets and complicated interactions, such as image recognition, classification, and predictive modelling. By carefully choosing training approaches, ANNs may effectively mimic the complicated interactions between input factors and output results. Furthermore, hybrid systems that combine ANNs and optimisation algorithms, such as evolutionary methods, improve network efficiency and reduce errors. These advanced models are critical for forecasting how environmental changes affect hydrogen production and making real-time adjustments to maintain maximum performance, thereby promoting sustainable resource management. A Feed-Forward Neural Network (FFNN) is a similar type of ANN in which the connections between the nodes do not form cycles, allowing data to flow in only one direction from source to output, making it especially helpful for tasks such as pattern recognition and function approximation [23].

2.2.3. Deep learning

DL is at the cutting edge of AI technology, providing a specialised technique within ML in which models learn to do tasks like classification directly from raw data such as audio signals, pictures, or text. This method is based on advanced NN designs inspired by the human nervous system, which comprise of numerous interconnected layers. The name 'deep' refers to the large number of layers in these networks, generally in the hundreds, as opposed to regular NNs, which typically have fewer

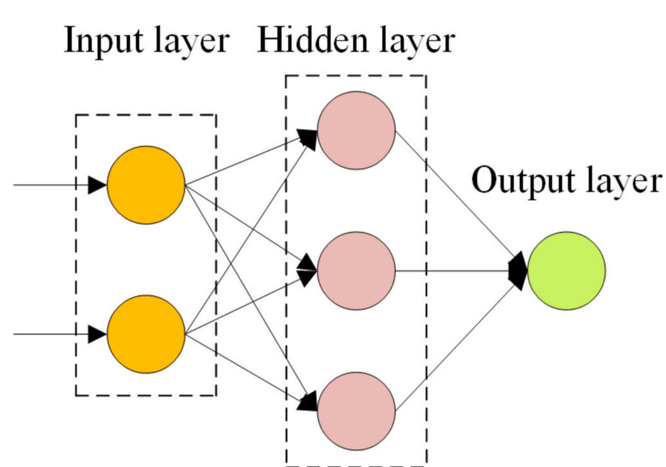

Fig. 5. Basic ANN framework.

than five layers. These networks are built using an input layer, several hidden layers, and an output layer, with each hidden layer processing the output of the preceding one. This broad infrastructure is useful for complicated applications like facial recognition, language translation, speech recognition, and advanced safety features. Unlike standard ML, which involves human feature extraction, DL allows networks to learn features automatically, improving adaptability and performance [19]. As a subset of AI, DL can significantly increase hydrogen production by effectively analysing massive and complicated datasets, modelling detailed nonlinear relationships, and making real-time predictions. In hydrogen production methods such as electrolysis, thermochemical processes, or other advanced approaches, DL models such as CNNs and RNNs can optimise and drive efficiency. These models use historical and real-time data to identify the optimal operational settings, increasing hydrogen yield while decreasing energy usage. Furthermore, DL algorithms constantly learn from data, allowing them to adapt to changing conditions and automatically modify system parameters, resulting in greater production efficiency. In addition, DL improves predictive maintenance in hydrogen facilities, increasing dependability by proactively addressing possible issues and reducing failures. RNNs are one of the major models utilised in these applications, as they process sequential data by storing hidden states containing information from prior steps [24]. The advanced subset of RNNs is Long-Short Term Memory (LSTM) networks, that use gates and memory cells to handle the vanishing gradient problem, making it easier to simulate long-term dependencies than simple RNNs [87]. However, the more complicated internal framework of LSTM networks makes them more difficult to train, necessitating larger computer resources and longer training cycles [25]. Gated Recurrent Units (GRUs) are another type of RNN that simplifies the LSTM architecture by reducing the number of gates to maintain learning performance while cutting computational cost [26].

3. Methods

The research methods for this study involve a systematic and interdisciplinary approach to explore the integration of AI techniques with renewables for efficient hydrogen production. The following key steps were undertaken to achieve this goal:

- Conducting an extensive review of academic journals, conference proceedings, and relevant publications to understand the current state of research in AI-enabled hydrogen production from renewable sources.
- Identifying and evaluating various RES to assess their potential for hydrogen production. Analysing the characteristics and environmental impact of each source to determine suitability for integration with AI.
- Exploring different AI techniques, such as ML and DL algorithms, for optimising hydrogen production, investigating the role of AI in predicting optimal operating conditions for electrolysers, addressing intermittency challenges, and optimising energy generation.
- Examining real-world case studies showcasing successful integration of AI with renewable energy for hydrogen production.
- Analysing the impact of AI on electrolysis processes, smart grids, and energy management systems.
- Analysing the importance of addressing water scarcity challenges, particularly in regions like the Middle East and Western Australia (Perth), through the integration of AI. Exploring AI's role in ensuring sustainable hydrogen production in water-scarce environments.
- Suggesting widening the focus of AI techniques for GH2 production to harness tidal and hydro energy in conjunction with other RES, such as solar and wind.

Through the literature review, the following research questions arose:

Q1. What is the current state-of-the art for hydrogen production enabled with AI and RES? Numerous studies highlight the integration of AI with RES to optimise hydrogen production processes. The methodologies involve systematic reviews, economic assessments, and advancements of AI in renewable energy sectors. These studies collectively contribute valuable insights into the current state-of-the art for AI-enabled hydrogen production within the realm of RES.

Q2. What challenges arise due to the intermittency of RES, and how can AI contribute to overcoming these issues?

AI, utilising ML, will elevate GH2 production by optimising processes, ensuring heightened efficiency and sustainable output. This technological advancement enables precise resource utilisation, thereby contributing to a more effective and environmentally friendly approach to hydrogen production.

Q3. In what ways will AI contribute to the generation, distribution, and transportation aspects of hydrogen production in conjunction with RES?

AI is poised to enhance hydrogen production by playing a pivotal role in optimising processes related to generation, distribution, and transportation integrated with RES. Through advanced algorithms and data-driven insights, AI can improve efficiency and reliability, and optimise the utilisation of RES and overall sustainability in various stages of hydrogen production.

The filtering analysis presented in Table 1 outlines the meticulous process undertaken to refine the literature search. By leveraging the extensive databases of Google Scholar and Web of Science, relevant research papers exploring the integration of AI in hydrogen production methods were identified. This rigorous selection process forms the foundation for our comprehensive literature review. By using Boolean operators to connect keywords on hydrogen production, renewables, AI, and electrolysis, the most relevant articles on this topic were identified.

Fig. 6 provides a visual representation of the comprehensive literature search conducted across Google Scholar and Web of Science databases to identify relevant research papers focusing on the keywords of AI in hydrogen production methods. The initial database search yielded a substantial number of 2970 results (Filter 1). Subsequently, through the incorporation of specific keywords, the selection was refined to a more

Table 1
Filtering analysis of scholarly documents on hydrogen production, artificial intelligence, and renewable energy sources using Boolean operators.

Filter	Search String and Filtering Procedure	Objective	Documents
1	"Hydrogen production" AND "Artificial Intelligence" AND "Renewable Energy Sources"	To review the comprehensive examination for generating hydrogen through the integration of RES with AI techniques	2970
2	"Hydrogen production" AND "Artificial Intelligence" AND "Renewable Energy Sources" AND "Artificial Neural Network" AND "Machine Learning" AND "Deep Learning"	To review the latest methods for generating hydrogen through the integration of AI techniques and electrolysers	265
3	Thorough analysis to further refine those papers aligned to this literature review	To identify the approach for generating hydrogen through the integration of solar, wind, algae, biomass, tidal, hydro, fuel cell with AI-driven optimisation techniques and electrolysers including the PEM, Solid Oxide Electrolysis (SOEL), Solid Oxide Electrolysis Cell (SOEC), Alkaline Water Electrolysis (AWE) and Alkaline Electrolysis (AEL) methods assessments	62

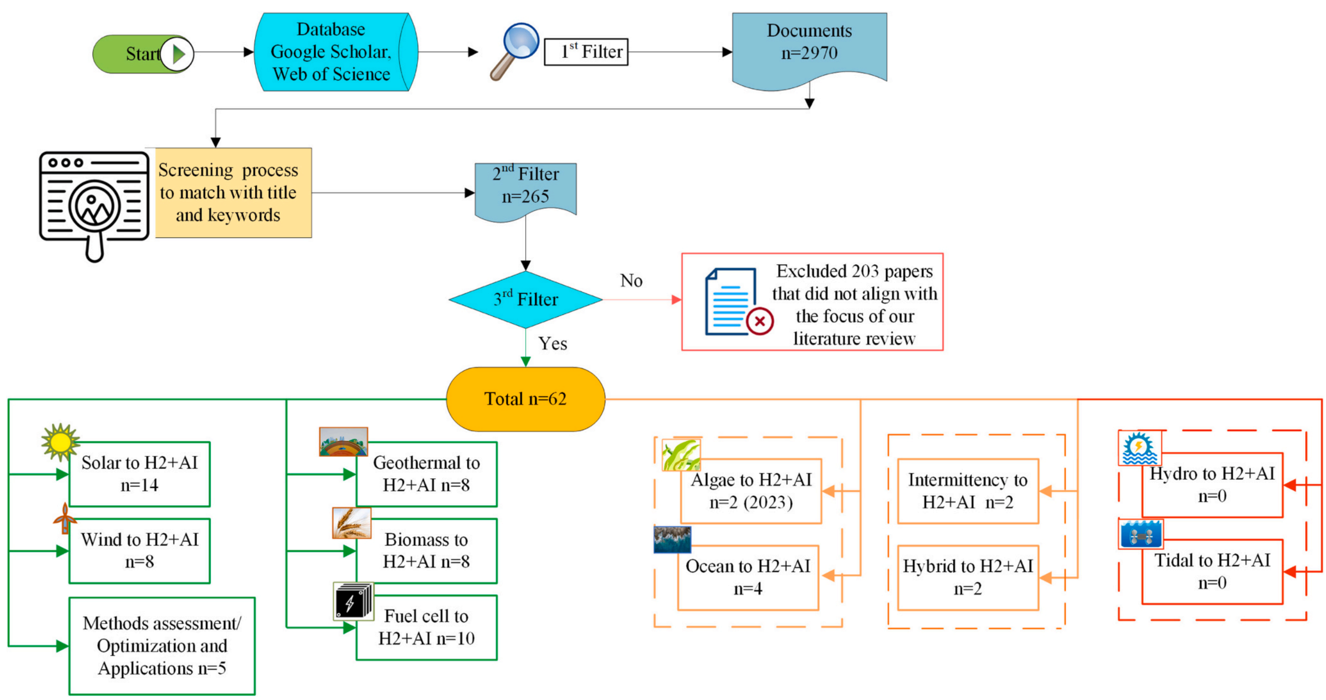

Fig. 6. Flow chart of literature searches and screening results.

manageable set of 265 relevant papers (Filter 2). Further curation was performed to exclude 203 papers that did not directly align with the specified keywords, culminating in a thorough review of the remaining 62 papers (Filter 3). This refined selection process guides the direction and focus of our comprehensive literature review, ensuring a targeted and in-depth exploration of the subject matter.

The analysis revealed limited research on applying AI to some hydrogen production methods. As highlighted in the box in the lower right corner of the figure, only two papers examined AI for hydrogen generation from algae and four from ocean sources. This suggests these are promising areas for impactful AI-focused research. Additionally, there currently appear to be no studies investigating the potential of AI technologies for hydrogen production from hydroelectric and tidal energy. To progress renewable hydrogen generation, more research could prioritise exploring how AI could aid these underexplored production approaches including algae, ocean, hydroelectric, and tidal sources.

4. Results

In this section, we present and analyse 62 carefully selected papers out of 265, which are detailed in Tables 2 to 10. These papers explore the methods, advantages, and disadvantages associated with the production of hydrogen facilitated by AI using RES. The results are organised into two subsections: one focusing on different processes of electrolysis for production of hydrogen with AI using RES, and the other with efficiency and cost-effectiveness.

4.1. Hydrogen technologies enhanced by AI using renewable energy sources

4.1.1. Solar to hydrogen

Solar energy presents a promising renewable pathway for GH2 production through PV electrolysis and photo-electro chemical cells. In PV electrolysis, solar panels or concentrated solar power systems capture sunlight to generate electricity that splits H_2O into H_2 and O_2, as depicted in Fig. 7. Researchers have employed various AI methods to enhance hydrogen production from RES. For instance, Su et al. [81] utilised ANN for prediction, achieving a R^2 of 0.99952 and a relative error below 3 %. However, their approach was limited by data dependency and complexity. Meanwhile, Krzos et al. [27] explored how AI can improve energy efficiency and optimise GH2, supporting energy transformation in Poland. Nonetheless, overcoming infrastructure costs, fossil fuel reliance, and workforce impacts remain key challenges to scale and adopt these solutions.

In optimisation efforts Assareh and Ghafouri [29] employed the Non-Dominated Sorting Genetic Algorithm (NSGA-II) for Multi-Objective Optimisation (MOO), providing a trade-off between efficiency and costs. However, optimising only for exergy and costs is limited, and other objectives like emissions could be considered. The study by Elaziz et al. [32] optimised an AI method Random Vector Functional Link (RVFL) network and Mayfly Optimisation (MO) algorithm to predict the performance of a Photovoltaic/Thermal Collector (PVTC) system that produces electricity and hydrogen simultaneously, but the system is complex and requires multiple components. Senthilraja et al. [34] employed the Adaptive Neuro-Fuzzy Inference System (ANFIS) technique, which is cost-effective but has limited generalisation. Haider et al. [37] explored ML algorithms (Prophet, SARIMAX, SGD) for forecasting, achieving high accuracy but facing seasonal dependency challenges. Finally, the study by Sareen et al. [35] found that the Complete Ensemble Empirical Mode Decomposition with Adaptive Noise-Bidirectional Long Short-Term Memory (CEEMDAN-BiDLSTM) algorithm accurately forecasted GH2 production potential at Fatehgarh ($0.017\ kg/m^2$) and Bhadla ($0.016\ kg/m^2$), outperforming other methods with an MAE of $2.987\ W/m^2$, RMSE of $3.129\ W/m^2$, and R^2 of 0.988 at the Bhadla site. This demonstrates the algorithm's effectiveness in optimising hydrogen production based on solar energy, supporting scalable and efficient GH2 generation. The information provided in Table 2 outlines the methods, advantages, and disadvantages of solar to hydrogen production enabled with AI and electrolysis.

4.1.2 Wind to Hydrogen

Wind energy offers a viable renewable pathway for sustainable hydrogen production, as depicted in Fig. 8, where wind turbines generate electricity used to electrolyse water for hydrogen generation. In the quest to optimise GH2 from RES, researchers have explored

Table 2
The methods, advantages, and disadvantages of solar to produce hydrogen using AI techniques.

S·No	Authors	Methods	Advantages	Disadvantages
1.	[81]	The AI methods employed for prediction include Swarm Biological Algorithms, Non-swarm Biological Algorithms, Physical or Chemical Heuristic Algorithms, and Hybrid Optimisation Algorithms, with ANN being utilised	Prediction accuracy for correlation coefficient of 0.99952 and a relative error below 3 %	Data dependency and complexity
2.	[27]	AI to enhance energy efficiency and optimise hydrogen production, and by leveraging AI to facilitate the integration of hydrogen technologies and RES in the Polish energy sector	Hydrogen and AI can support energy transformation in Poland	Overcoming infrastructure and technology costs, fossil fuel reliance, and workforce impacts remain key challenges to scale and adopt these solutions
3.	[28]	ML algorithms (Prophet, SARIMAX, SGD, LSTM, SVR)	Statistical methods are simpler but may lack the sophistication for accurate short-term forecasts	Require careful tuning and large datasets, may not capture nonlinear relationships
4.	[29]	NSGA-II Algorithm	MOO using NSGA-II provides trade-off between efficiency and costs	Optimising for only exergy and costs is limited. Could consider other objectives like emissions.
5.	[30]	DL models such as Fully Connected Neural Networks (FCNs) and CNNs	In capturing complex patterns	Data dependency
6.	[31]	ANN, neuro-fuzzy systems, multiple regression, and DL	Effective in modelling, high predictivity	Data scarcity challenges
7.	[32]	Optimised AI method (RVFL network and MO algorithm) to predict performance of PVTC	The system produces electricity and hydrogen simultaneously	The system is complex and requires multiple components
8.	[33]	ANN, Cultural Algorithm-Artificial Neural Network (CA-ANN) hybrid method	The CA-ANN hybrid method provided more accurate prediction of solar PV output power compared to ANN alone	Solar PV panels alone are insufficient to provide uninterrupted energy throughout the day, necessitating integration with energy storage systems (ESS) like hydrogen production
9.	[34]	ANFIS technique	Cost-effectiveness	Limited generalisation
10.	[35]	CEEMDAN-BiDLSTM	Accurate prediction of GH2 production	Not been validated for other hydrogen production methods like steam reforming
11.	[36]	ANN, RNN, DL algorithms	Eco-friendly framework for hydrogen production	Optimising and refining challenges
12.	[37]	ML algorithms (Prophet, SARIMAX, SGD)	Forecast accuracy	Seasonal dependency
13.	[38]	CNN, Gated Recurrent Unit, CatBoost, Multi-objective grey wolf optimiser (MOGWO)	Enabling efficient prediction and performance enhancement of the system	Requires careful tuning of hyper parameters and model selection which is time-consuming and complex
14.	[39]	SVM, FbProphet	Accurate prediction of GH2 production	Challenges in algorithm assessment and selection

Table 3
The methods, advantages, and disadvantages of wind to hydrogen production using AI techniques.

S·No	Author	Methods	Advantages	Disadvantages
1.	[40]	AI method like GDHS	Improved GDHS optimisation	Limited comparison metrics
2.	[41]	AI-enhanced MPC, PSO with a BPNN	Economic viability	Simulation environment limitation
3.	[42]	PSO, Tabu Search, Simulated Annealing, and Harmony Search	The total annual cost of $18,798.05 achieved using PSO for the PV/wind/FC system was the lowest among all the algorithms evaluated	It requires efficiency improvements in fuel cells and electrolysers to become competitive
4.	[43]	Bayesian networks	Accurate probabilistic analysis	Dependency on local conditions
5.	[44]	ANN, SVM Metaheuristic algorithms, GA, PSO, GWO	Cost-effective production and maintenance	Focused on short-term horizons
6.	[45]	NSGA-II optimisation algorithm	NSGA is efficient approach for optimisation	Limited details
7.	[46]	Levenberg-Marquardt algorithm	Efficient prediction of system performance.	Limited sustainability criteria
8.	[47]	LSTM	Provides a reliable estimation of the site's potential for producing hydrogen	The model may not be able to generalise to new data

various AI techniques. Zhang et al. [40] employed AI optimisation techniques, like the Global Dynamic Harmony Search (GDHS), introducing three improved versions to enhance the efficiency of off-grid Hybrid Renewable Energy Systems (HRES) comprising wind turbines, fuel cells, and hydrogen storage. Among these, the GDHS-II algorithm demonstrated superior convergence speed, robustness, and accuracy compared to the original GDHS. The simulation results revealed that GDHS-II effectively balances exploration and exploitation, achieving better fitness values and system reliability. This optimisation approach not only improves the cost-effectiveness and reliability of hybrid systems

Table 4
The methods, advantages, and disadvantages of geothermal to produce hydrogen using AI techniques.

S·No	Reference	Methods	Advantages	Disadvantages
1.	[88]	ANN with GA	Achieved optimal values for hydrogen production rates	Economic model not provided
2.	[49]	4E analysis, ML coupled with GA optimisation	ML method reduces calculation time	LINMAP is not explained
3.	[50]	MLP with imperialist competitive algorithm	The hybrid system is suitable for remote area regions	The method can be expensive and difficult to implement
4.	[51]	ANN coupled with GA	Optimal solution, hydrogen production	Initial cost is high
5	[52]	Four different ANN models to predict (cumulative electricity generation, injection pressure at the well bottom, temperature of produced water and average electrical power generation) and Differential Evolution (DE) algorithm, FFNN	Surrogate model has high precision	Complexity during training
6.	[53]	Real-time ANN was employed on a Field Programmable Gate Array (FPGA) and FF-ANN	The FPGA-based ANN model was more accurate	It is expensive and complex to implement
7.	[54]	Conventional SMOA	It is a promising approach	The system not investigated for different climatic regions

but also shows potential for adaptation to other hybrid energy schemes by adjusting key variables. Meanwhile, Chen et al.'s [41] framework combines Model Predictive Control (MPC) with AI to enhance power management in an integrated wind-hydrogen-fuel cell network connected to a smart grid. The system employs a hybrid forecasting approach using PSO with Back-Propagation Neural Networks (BPNN) to predict wind energy generation across 24-h intervals. Power flow optimisation is achieved through GA iterations that continuously adjust the state space model. The integrated energy infrastructure encompasses wind generation facilities, hydrogen and oxygen storage systems, and multiple fuel cell units. Implementation of this advanced MPC strategy successfully improves supply-demand balance by significantly increasing local wind power utilisation from 45 % to 90 %, thereby minimising grid power exchanges.

Further exploration by Maleki and Askarzadeh [42] delved into AI optimisation techniques and heuristic algorithms, with PSO showing promising results, although economic considerations were not fully addressed. Similarly, Abisoye et al. [44] combined ANN, SVM, and metaheuristic algorithms, enabling cost-effective production and maintenance but focusing primarily on short-term horizons. In another study, Zhang et al. [45] employed the NSGA-II optimisation algorithm, demonstrating its efficiency for optimisation tasks, although the study lacked detailed information. In estimating GH2 production, Javaid et al. [47] utilised LSTM networks, providing a reliable estimation of a site's potential for producing hydrogen, although the model's ability to generalise to new data was not discussed. Collectively, these studies

Table 5
The methods, key findings, and advantages of biomass to produce hydrogen using AI techniques.

S·No	Reference	Methods	Key findings	Advantages
1.	[89]	ANN model developed for two-stage biomass with Single Hidden Layer, FFNN	Accuracy in prediction	Time efficient and cost-effective
2.	[55]	ML models (LR, k-NN, SVMR) Decision Tree Regression (DTR))	Gasification experiments, higher heating value, model accuracy	Reduced time and costs
3.	[56]	An ANN-based model featuring a single hidden layer with 13 neurons, trained using a backpropagation algorithm	$R^2 > 0.999$ and MSE < 0.25	Versatility
4.	[80]	SVM with ABC optimiser	$R^2 = 0.9464$ and correlation $= 0.9751$	High accuracy
5	[57]	ML models (RF, ANN, SVM)	$R^2 = 0.9782$ and hydrogen reaction efficiency 45.6 %	High accuracy
6.	[58]	Palm Kernel Shell (PKS) and fuzzy logic models	Optimal values obtained	Higher H_2 and syngas production
7.	[59]	ML model, Bayesian Regularisation (BR) and Scaled Conjugate Gradient (SCG)	$R^2 = 0.99$	Clean energy production
8.	[60]	ML integrated with GA	Enhances prediction accuracy and model performance using GA	Requires effective implementation and tuning

highlight the diverse range of AI techniques and methodologies used to enhance GH2 production from RES, each with its own strengths and limitations. Table 3 outlines the methods, advantages, and disadvantages of wind to hydrogen production enabled with AI and electrolysis.

4.1.3 Geothermal to hydrogen

Harnessing the Earth's natural heat reservoirs in an environmentally sustainable manner, by converting geothermal energy into hydrogen, offers a compelling avenue for clean and renewable energy solutions. This process involves tapping into the Earth's internal heat through a combination of geothermal resources, allowing the production of hydrogen without dependence on traditional fossil fuels. Mehrenjani et al. [88] integrated ANN with a GA, achieving optimal values for hydrogen production rates, although an economic model was not provided. It presents a geothermal-driven multi-generation system designed for power, cooling, and hydrogen production using geothermal energy as a heat source and a liquefied natural gas stream as a heat sink. The system supplies generated power to a PEM electrolyser for hydrogen production and utilises a Claude cycle for the liquefaction process. Through a comprehensive energy, exergy, and economic analysis, it was determined that the system could produce 106.8 kg/h of hydrogen when all available power is utilised. Optimal performance was achieved with a hydrogen production rate of 154.95 kg/h, an exergy efficiency of 23.34 %, and a total cost rate of $291.36/h. Meanwhile, Khosravi and Syri [50] proposed a hybrid geothermal-solar system optimised using MLP and NN combined with an imperialist competitive algorithm. This system,

Table 6
The methods, key findings, and advantages of electrolysis to produce hydrogen using AI techniques.

S·No	Reference	Methods	Key findings	Advantages
1.	[61]	AI (Fuzzy logic system, MPC, GA) and ML (supervised learning, unsupervised learning, semi supervised learning)	Flexibility, cost-effectiveness	Real-time adaptability, reducing H_2 consumption
2.	[62]	AI methods (GA, PSO, RF, k-NN, SVM, and ANN)	Optimisation of HRES	Development in hydrogen economy
3.	[63]	AI-MOO framework	Comprehensive coverage of studies utilising AI-MOO	Improves efficiency
4.	[64]	AI, DL and GA	NN achieved an excellent correlation coefficient of 0.9998	Cost-effectiveness
5.	[65]	MLP-ANN, ML	Model demonstrated high accuracy	Accurate prediction and optimisation
6.	[66]	Hybrid intelligent approach, SVR, MLP	Performance validation, H_2 consumption	Predictive accuracy
7.	[19]	FFNN, LR	Accurate results with less than 1 % error	Efficient fuel economy assessment
8.	[67]	ANFIS modelling, JO	Improved modelling accuracy with ANFIS	Increased H_2 production
9.	[68]	GPR and GA optimisation.	Power efficiency reaches 60 %	ML optimisation enhances accuracy and low LCOE
10.	[69]	MLP and polynomial regression algorithms	Adaptive-predictive control system	Accurate prediction of the H_2 flow variation

Table 7
The methods, advantages, and disadvantages of algae to produce hydrogen using AI techniques.

S·No	Reference	Methods	Advantages	Disadvantages
1.	[90]	AI with GA	Cost-effective and efficient	High initial investment
2.	[91]	RF, ANN, SVM, and regression algorithms	ML techniques demonstrate effectiveness	Model overfitting

designed to address challenges like low geothermal well temperatures and limited operating lifetimes, integrates solar thermal collectors, a desalination unit, and a hydrogen storage system to enhance energy efficiency, achieving a payback period of around eight years with a 3 % interest rate.

For optimal solutions in their integrated geothermal-solar system, Balali et al. [51] combined an ANN with a GA to achieve MOO of hydrogen production, energy efficiency, and cost rates. The system demonstrated the potential to produce GH2 alongside electricity and freshwater, although it was noted that the initial investment costs were relatively high due to the complexity of the set-up and the inclusion of advanced components like parabolic trough solar collectors and thermoelectric generators. Additionally, Sohani et al. [54] explored the conventional Static Multi-objective Optimization Approach (SMOA) method, which demonstrated promising results in optimising electricity, heat, hydrogen, and freshwater production in solar-geothermal multi-generation systems. However, due to its static nature, SMOA was limited in its adaptability to varying operational conditions, as the study did not account for dynamic factors or explore its performance across different climatic regions. This limitation suggests that while SMOA can achieve notable gains in efficiency and production, it may not fully leverage the system potential under changing environmental conditions. Fig. 9 illustrates the process flow for utilising geothermal energy to produce hydrogen.

Table 8
The methods, advantages, and disadvantages of ocean-to-hydrogen production using AI techniques.

S·No	Reference	Methods	Advantages	Disadvantages
1.	[72]	LSTM, MLP	Leverages ocean wave energy for sustainable hydrogen generation	Limited information provided in the given context
2.	[92]	CNN, RNN	AI techniques can improve the efficiency of RES by optimising their design, operation, and maintenance processes	AI techniques in renewable energy require large amounts of high-quality data
3.	[73]	MPC	Improved system stability	MPC requires computational power
4.	[74]	MLP-ANN, SVM, ANFIS, GA-ANFIS	High accuracy, efficient optimisation	Risk of overfitting

These studies collectively demonstrate the diverse range of AI and ML techniques employed to enhance hydrogen production from RES, each with its unique advantages and limitations, ranging from improved optimisation and accuracy to cost considerations and implementation complexities. Table 4 shows the methods, advantages, and disadvantages of geothermal to hydrogen production enabled with AI techniques.

4.1.4 Biomass to hydrogen

In the pursuit of harnessing biomass for hydrogen production, previous studies have employed various AI and ML techniques. Hannah et al. [89] developed an ANN model for a two-stage biomass process, demonstrating high accuracy in prediction while being time-efficient and cost-effective. The model exhibited high prediction accuracy with a correlation coefficient ($R^2 > 0.99$), effectively simulating gas yield and composition while reducing the need for extensive experimental trials, thereby saving both time and costs. The ANN was able to optimise operating conditions, such as temperature and steam-to-carbon ratio, to achieve high hydrogen yields and minimal carbon emissions. Similarly, Safarian et al. [56] proposed an ANN model that exhibited outstanding performance, with high correlation ($R^2 > 0.999$) and a low mean square error (MSE < 0.25), indicating its strong predictive capability and adaptability across various biomass feedstocks and operating conditions. By effectively capturing the influence of key parameters such as gasifier temperature, steam-to-biomass ratio, and feedstock moisture content, this model underscores its potential for optimising biohydrogen production and identifying suitable biomass types for efficient gasification-based hydrogen production systems. A combined SVM with an Artificial Bee Colony (ABC) optimiser studied by García-Nieto et al. [80], demonstrated high predictive accuracy in estimating hydrogen gas production from biomass. The model achieved an R^2 of 0.9464 and a correlation of 0.9751, highlighting its effectiveness in capturing the complex relationships between physicochemical parameters and hydrogen yield.

The investigation by Zhao et al. [57] on supercritical water gasification and ML models, achieved an R^2 of 0.9782 and a hydrogen reaction efficiency of 45.6 %, further demonstrating the high accuracy of

Table 9
Performance characteristics and cost estimates of different electrolysis methods for hydrogen production.

No	Reference	Methods	Temperature (°C)	Pressure (bar)	Efficiency %	Cost /kW	Current density (A/cm^2)	Hydrogen production (m^3/h)
1.	[8]	PEM	50–90	15–30	67–84	~$750	1–2	30 N
		AEL	60–90	2–10	62–82	~$600	0.2–0.5	760 N
		SOEL	500–1000	<30	81–86	~$200	0.3–1	–
2.	[75]	PEM	50–90	<30	70–80	€250–1700		400
		AEL	30–80	<30	73	€370–900		1000
		SOEC	900–1000	<30	85–100	€570–730		–
3.	[76]	AWE	60–90	2–10	62–82	~$600	0.2–0.5 m	–
		PEM	50–90	15–30	67–84	~$750	1–2	–
		SOE	500–1000	<30	90	~$200/ch	0.3–1 m	–

Table 10
Methods, advantages, and disadvantages for addressing intermittency in HRES with hydrogen production.

S·No	Reference	Methods	Advantages	Disadvantages
1.	[77]	ANN, CNN, RNN	It will handle complex data and improve accuracy	Using ANN for predicting renewable energy generation includes the challenge of intermittency inherent in RES, such as wind power, which can affect the accuracy of predictions and require sophisticated modelling techniques to account for variability over time
2.	[93]	Predicting solar irradiance: the ASHRAE clear sky model and NNs	Better accuracy, increased battery capacity	Impact of solar energy intermittency
3.	[95]	AI-based optimisation methods, PSO, GA	Hybrid algorithms can improve efficacy and reliability by combining strengths of different techniques	Prioritise comprehensive investigations to develop efficient AI methods
4.	[78]	MILP	Integrating RES and non-RES considering weather intermittency	AI/metaheuristic methods are more complex, requiring tuning of many parameters
5.	[79]	ANN, CEEMDAN–CNN–LSTM, computer vision	AI techniques enhance real-time monitoring, reduce false alarms, and improve safety measures in hydrogen-related applications	Challenges include data scarcity, model optimisation, and integration into existing systems
6.	[94]	ANN, supervised learning, unsupervised learning, RL	Improvements in energy management	Difficulties in model predictions

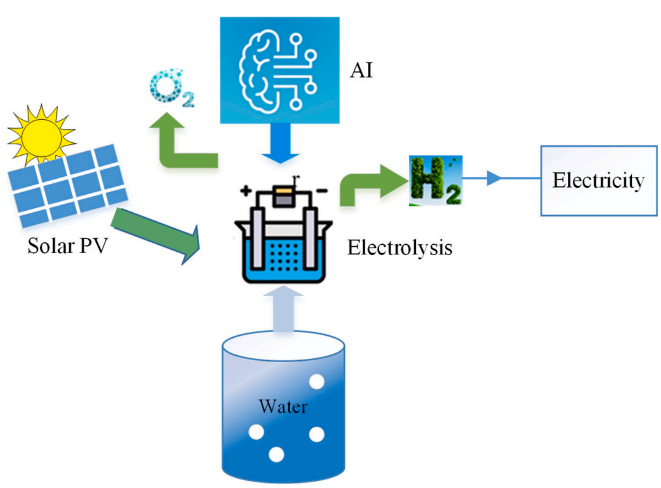

Fig. 7. The techniques for harnessing solar energy to drive hydrogen production.

these approaches. Biomass gasification has emerged as a viable path for hydrogen generation by exploring studies on feedstocks and catalyst. The biomass gasification process for hydrogen production is illustrated in Fig. 10. These studies collectively demonstrate the diverse range of AI and ML techniques, as well as innovative processes and catalysts, employed to enhance hydrogen production from biomass, addressing challenges such as tar formation, optimising conversion efficiencies, and ensuring cost-effectiveness and environmental sustainability. Table 5 presents the techniques, main discoveries, and benefits associated with utilising biomass for hydrogen production.

4.1.2. Hydrogen production through electrolysis

Sustainable hydrogen production can be achieved through electrolysis, a process involving the use of an electric current to split H_2O into H_2 and O_2. Powered by renewable sources like wind and solar energy, electrolysis offers an environmentally friendly method for hydrogen production. Distinguished by its lack of greenhouse gas emissions, electrolysis is well-suited for large-scale hydrogen generation compared to alternative production methods. The recent advancements highlighted by Al-Othman et al.'s [62] utilisation of AI methods, include GA, PSO, RF, k-NN, SVM, and ANNs for the optimisation of HRES, contributing to the development of the hydrogen economy. This integration of AI not only enhances the efficiency and reliability of energy management but also significantly contributes to advancing the hydrogen economy by maximising power production and addressing technical, economic, and environmental challenges in fuel cell-integrated systems. Fig. 11 illustrates a basic schematic of water electrolysis, where the water molecules undergo a splitting reaction at the electrodes, producing hydrogen gas at the cathode and oxygen gas at the anode, driven by an external electric current.

Furthermore, the integration of AI-based MOO frameworks, as proposed by Feng et al. [63], offers a flexible approach to optimising multiple performance metrics in PEM fuel cells. This integration allows for more precise design, control, and operational adjustments, addressing both technical and economic challenges while improving overall system efficiency. By simultaneously balancing objectives such as power output, cost, and thermal management, AI-MOO frameworks enhance the adaptability of PEM fuel cell systems under diverse operating conditions and evolving requirements. Fathy et al. [67] demonstrated the effectiveness of coupling innovative methodologies like ANFIS modelling and the Jellyfish Optimiser (JO), showcasing significant strides in improving the accuracy of predictive models and enhancing hydrogen production efficiency in microbial electrolysis cells (MECs). This integrated strategy not only reduced prediction errors but

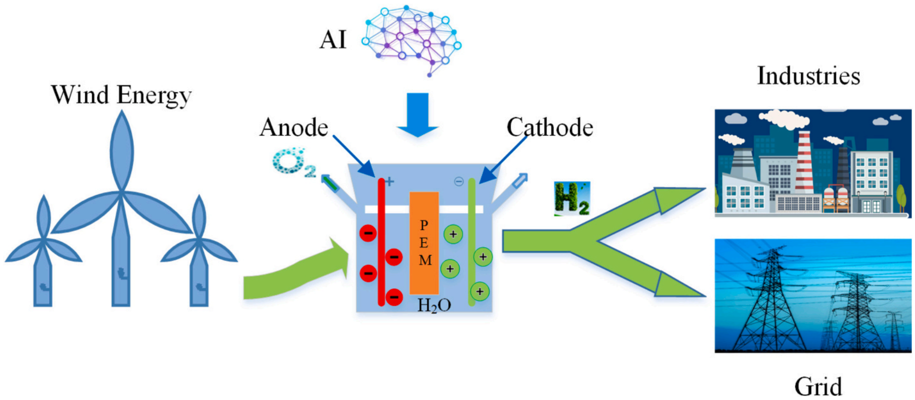

Fig. 8. Efficient green hydrogen production through wind energy integration. (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

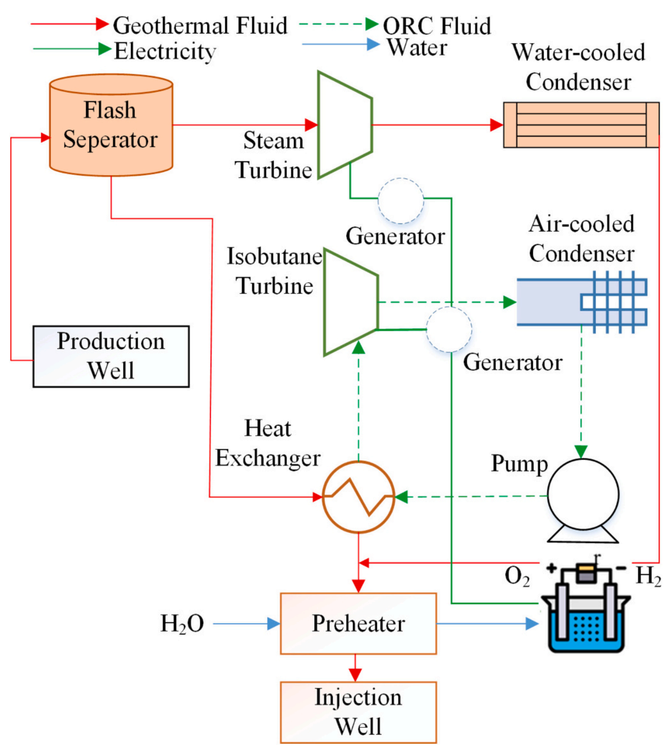

Fig. 9. The procedure for utilising geothermal energy to produce hydrogen [48].

also optimised critical operational variables, leading to a measurable increase in bio-hydrogen yield. Furthermore, the combination of these advanced techniques successfully outperformed traditional approaches, providing a more robust framework for maximising hydrogen output in wastewater treatment applications. The amalgamation of Gaussian Process Regression (GPR) with GA optimisation, as exemplified by Shboul et al. [68], not only enhances power efficiency but also reduces the LCOE, highlighting the potential for ML optimisation to revolutionise sustainable energy solutions. This study focuses on a robust techno-enviro-economic (3E) analysis of a hybrid PV-FC system for green hydrogen and electricity production, using MATLAB/Simulink® for performance evaluation. The integration of AI methods such as GPR and GA optimisation demonstrated a high degree of reliability, achieving an LCOE below $2/kWh for solar radiation levels above 250 W/m^2 and optimal fuel cell efficiency reaching 60 % at operational temperatures between 40 °C and 55 °C. Such advancements showcase the potential of hybrid energy systems in reducing carbon footprints while optimising cost-effectiveness and system performance for future energy landscapes. These studies collectively illustrate the diverse range of AI and ML techniques employed to enhance various aspects of hydrogen production, including process optimisation, predictive modelling, efficiency improvements, and cost-effectiveness. The integration of these techniques with established methods and frameworks has contributed to advancements in the hydrogen economy and the pursuit of sustainable energy solutions. Table 6 provides an overview of the techniques, main discoveries, and benefits associated with electrolysis technology for hydrogen production.

4.1.5 Hydrogen from Algae

Algae play a crucial role in the production of hydrogen through photo-biological H_2O splitting, where water serves as the electron source and light energy drives the process. The intricate mechanism involves electron transfer from water to the electron transport chain in the thylakoid membrane, facilitated by plastoquinone oxidoreductase and Ferredoxin-by-Ferredoxin oxidoreductase. Ferredoxin [Fe] transfers electrons to hydrogenase, initiating the reaction that yields hydrogen, with oxygen produced as a by-product and protons ($H+$) released during the process. Guodao et al. [90], delves into the application of AI methods in GH2, emphasising their cost-effectiveness and efficiency. Despite these advancements, the study emphasises the substantial initial costs that could pose barriers to the widespread implementation of these technologies. Furthermore, the research illustrates how AI approaches can address various technical and environmental challenges, suggesting a promising direction for enhancing the sustainability and efficiency of GH2 production processes. Similarly, Sobri et al. [91] utilised ML algorithms to enhance various aspects of hydrogen production processes, showcasing effectiveness while cautioning against model overfitting risks that may impact model generalisability and robustness. Furthermore, the research suggests integrating advanced techniques, such as regularisation or ensemble learning, to mitigate overfitting and enhance the adaptability of ML models in GH2 production. These studies collectively emphasise the potential of AI and ML in advancing RES-based hydrogen production, offering avenues for cost-effective and efficient solutions. However, they also underscore the importance of addressing obstacles like high initial investments and guarding against model overfitting to ensure seamless integration and scalability of these technologies. Fig. 12 visually represents the methodology for hydrogen production utilising algae as a sustainable resource, highlighting the innovative approach towards sustainable energy solutions.

Ongoing research efforts are focused on overcoming these limitations by exploring innovative approaches, optimising resource allocation, and developing robust and generalisable models. By addressing these challenges, the integration of AI and ML techniques could pave the

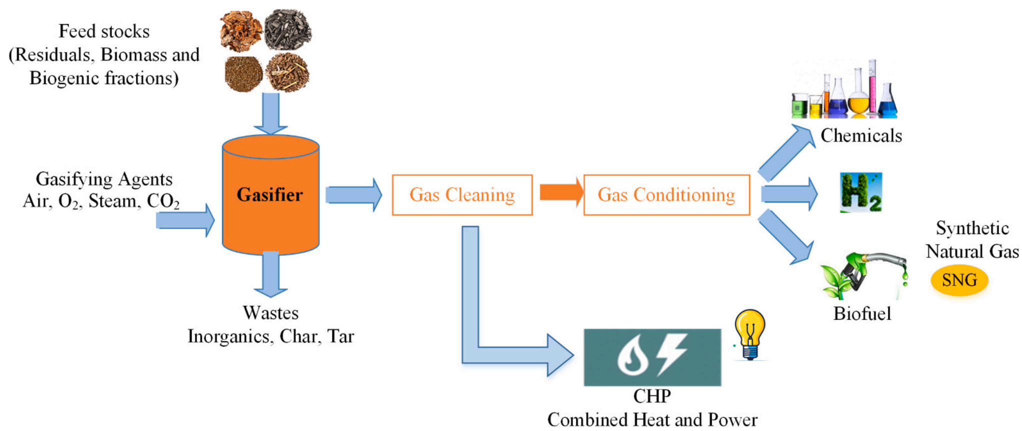

Fig. 10. Hydrogen manufacturing process using gasification of biomass.

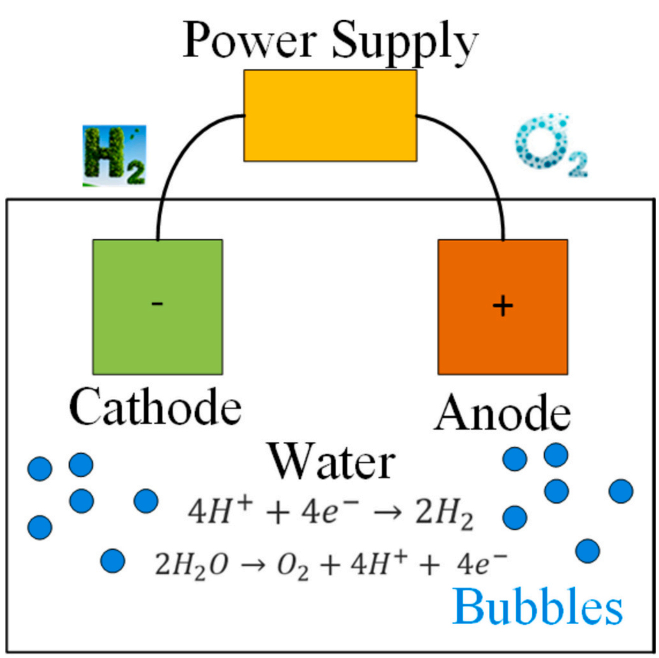

Fig. 11. Sustainable hydrogen production from electrolysis.

way for more sustainable and economically viable hydrogen production systems, contributing to the global transition towards a cleaner and more renewable energy future. Table 7 provides an overview of the techniques, advantages, and disadvantages of algae hydrogen production.

4.1.6 Hydrogen from the Ocean

The vast potential of the world's oceans presents a promising frontier for sustainable hydrogen production, driving researchers to explore innovative methods for harnessing this abundant resource and shaping a cleaner, renewable energy landscape. One such avenue involves tapping into ocean wave energy for hydrogen generation. Mirshafiee et al. [72], introduced a data-driven approach to leverage the power of ocean waves, utilising advanced analytical techniques to optimise this renewable pathway. Their study compared AI-based prediction methods, the LSTM algorithm, and MLP to traditional numerical solutions, demonstrating that the MLP algorithm outperformed LSTM in prediction accuracy, reducing the average squared error to 0.49. This comparison highlighted the efficiency, speed, and cost-effectiveness of the AI approach, emphasising the potential of combining simulation and AI to enhance energy management technologies and encourage investment in ocean-based renewable energy systems. Similarly, Sunil et al. [92], delved into extracting hydrogen directly from seawater, using CNN and RNN techniques, with improved efficiency, operation, and maintenance. Their study demonstrated the effectiveness of these AI techniques in optimising the extraction process, highlighting potential improvements in performance and reliability. By integrating AI with renewable energy systems, the research emphasises the importance of advanced computational methods in advancing sustainable energy solutions. Moreover, their findings underline the versatility of AI in addressing complex challenges in resource management, showcasing its potential to refine operational models and achieve higher yields with minimal environmental impact. This work provides valuable insights into the role of intelligent algorithms in driving innovation within the renewable energy sector, particularly for hydrogen production from seawater, paving the way for scalable and cost-effective clean energy technologies. Zhou [73] implemented advanced AI techniques, particularly MPC, to enhance the stability, reliability, and efficiency of ocean energy systems. Their work focused on optimising multi-energy synergies and managing energy storage solutions such as ocean hydrogen-based storage, aiming to overcome challenges like power intermittency and grid fluctuations.

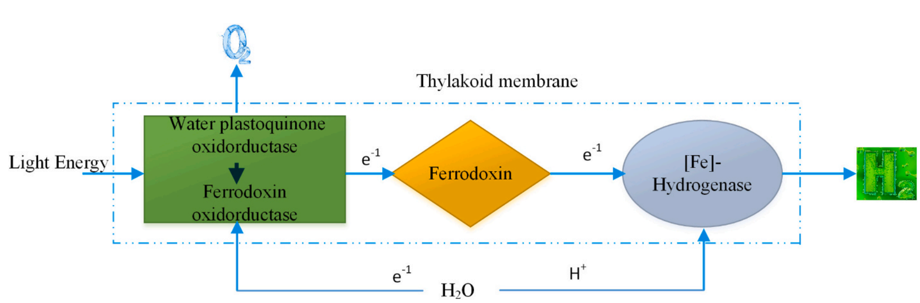

Fig. 12. Innovative methodology for efficient hydrogen production utilising algae as a sustainable resource (Source: [70]).

It also highlighted the advantages of AI-based controls in terms of reducing power losses and improving system robustness, while acknowledging the high computational demands and investment requirements for deploying such sophisticated AI approaches effectively. Table 8 provides a comprehensive overview of the techniques, advantages, and disadvantages associated with ocean-to-hydrogen production pathways, as reported in the literature. The desalination process mirrors techniques commonly employed in arid regions like the Middle East and relies on high-pressure equipment. These advancements are particularly crucial in water-scarce regions like the Middle East, as illustrated in Fig. 13, showcasing the importance of optimising operations and incorporating AI with RES to improve the efficiency and sustainability of desalination processes in arid environments.

4.2. Sustainable hydrogen production, efficiency, and cost-effectiveness

Assessing the operational temperature ranges of various hydrogen production technologies provides crucial insights into their performance and applicability. The methods (AEL, PEM and SOEL) are used to validate the concert of these systems, including temperature, cost, and efficiency. Fig. 14 provides a visual representation of the temperature ranges associated with three hydrogen production technologies by water electrolysis [8]. The light coral bars indicate the minimum operating temperatures, ranging from 50 °C to 60 °C for PEM and AEL, while SOEL operates at a higher minimum temperature of 500 °C. The red extensions denote the maximum temperature range, revealing significant variations between technologies reaching up to 1000 °C for SOEL, in contrast to the narrower ranges for AEL and PEM. This visualisation facilitates a clear comparison of the operational temperature diversity among these technologies, offering insights into their respective applications and potential advantages in hydrogen production.

Moving forward to 2030, Fig. 15 shows the efficiency analysis of hydrogen production. This bar chart offers a visual insight into the efficiency range anticipated for three distinct hydrogen production technologies in the year 2030. The chart reveals that the SOEC method is significantly more efficient than AEL and PEM. While AEL demonstrates a minimum efficiency of 73 %, PEM ranges from 70 % to 80 %. In contrast, SOEC exhibits an impressive efficiency range of 85 % to 100 %, making it a particularly promising technology for hydrogen production from electrolysis. Fig. 16 visually depicts the cost range analysis for hydrogen production technologies in 2030, featuring AEL, PEM and SOEC. Notably, SOEC exhibits a broader cost range of €570–730/kW^{-1}, indicating potential efficiency advantages compared to the respective ranges of €370–900/kW^{-1} for AEL and €250–1700/kW^{-1} for PEM [75].

Table 9 provides a comprehensive summary and assessment of several hydrogen production methods, focusing on temperature, pressure, efficiency, cost-effectiveness, current density, and hydrogen production rates. The data reveals that the SOE method stands out as the most efficient, boasting an impressive 90 % efficiency rate closely follows, with an efficiency range of 81–86 % for SOEL with pressure < 30 bar. These technologies demonstrate remarkable potential for achieving

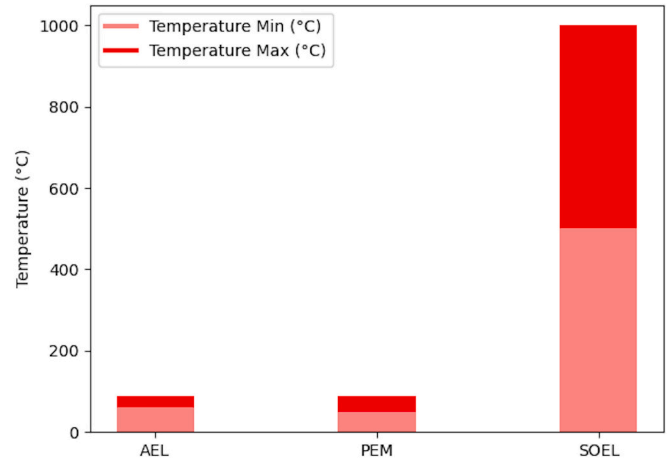

Fig. 14. Temperature analysis.

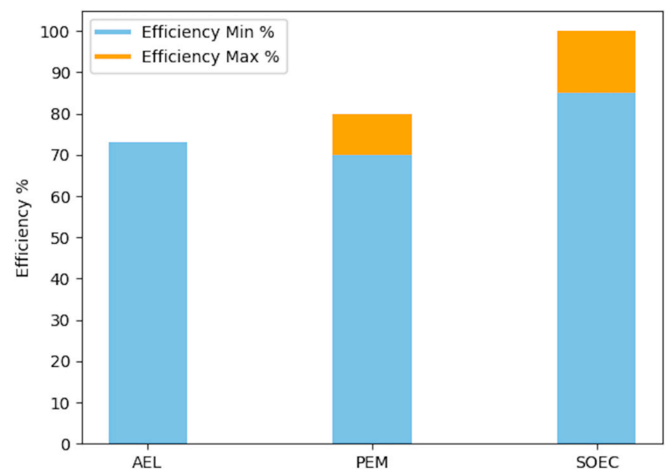

Fig. 15. Efficiency analysis.

high conversion rates in hydrogen production processes. When it comes to cost-effectiveness, the PEM method emerges as the frontrunner, with an estimated cost of approximately $750/kW. This positions PEM as an attractive option for stakeholders seeking a balance between efficiency and economic viability. In terms of current density, PEM again takes the lead, reaching 1–2 A/cm^2. This high current density indicates PEM's ability to handle larger electrical currents, potentially contributing to enhanced productivity in hydrogen production operations. Lastly, AEL method excels in hydrogen production, generating an impressive 760 Nm^3/h. This remarkable output underscores AEL's capability to produce substantial quantities of hydrogen, making it a notable candidate for applications with high demand.

Fig. 13. Map of Western Australia and Middle East region (Source: [71]).

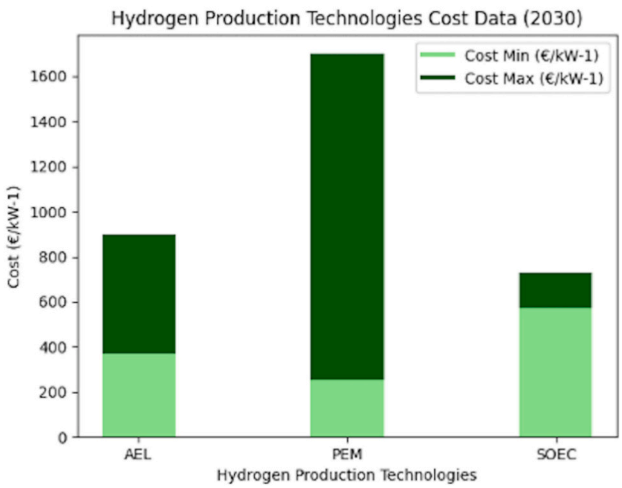

Fig. 16. Cost analysis.

4.3. Optimising GH2 from hybrid and intermittent RES using AI and its applications

Hydrogen's role as a clean energy carrier and industrial resource has led to its growing use across a variety of sectors. This role is further elevated by the integration of AI, which is driving significant improvements in hydrogen-based systems. By leveraging advanced techniques like computer vision and sensor fusion, AI improves leak detection and enhances overall safety in hydrogen production, storage, and distribution [79]. AI is enhancing these manufacturing processes through predictive maintenance, quality control, and process optimisation. ML models analyse sensor data to predict issues in hydrogen systems or optimise its use in various steps, leading to improved efficiency and product quality. Hydrogen is also essential in the chemical and refining industries, particularly in petroleum refining where it is used for processes such as hydrocracking and hydrotreating. ML can forecast renewable energy output and optimise hydrogen production and storage, making it easier to integrate variable RES into the grid. AI is also enhancing safety and monitoring in hydrogen systems [94]. The combination of hydrogen and AI technologies is also being applied in smart cities and intelligent transportation systems, depicted in Fig. 17. AI-powered platforms are helping optimise the deployment of hydrogen-powered public transport, manage charging infrastructure, and integrate hydrogen systems with RES to create more resilient urban environments. So, as both hydrogen technologies and AI evolve, their potential to support decarbonisation and energy security will expand, leading to new innovations and future applications. The integration of hydrogen systems with AI is shaping a smarter, more efficient, and sustainable energy future.

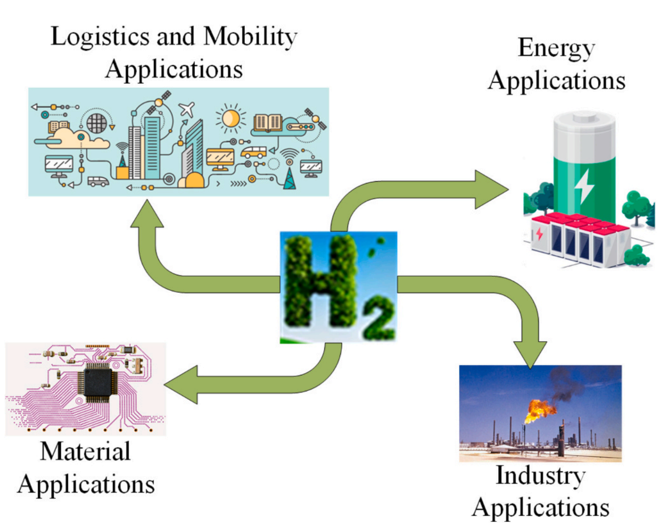

Fig. 17. Hydrogen's multifaced applications in different sectors.

The importance of efficient energy storage systems, especially for addressing the intermittency of RES, highlights hydrogen-based storage as a viable solution to overcome the limitations of battery storage systems. It reviews recent advancements in sizing and optimising HRES with hydrogen storage using various classical, soft computing, and hybrid metaheuristic optimisation techniques to improve sustainability and address challenges like intermittency and high costs [95]. In continuation to previous studies, an innovative Mixed-Integer Linear Programming (MILP) model is required that integrates RES and non-RES, accounting for weather intermittency, demand uncertainties, and green chemical processes like hydrogen production and methanation [78]. Table 10 presents a comparative analysis of various methods utilised to tackle intermittency in hybrid renewable energy systems coupled with hydrogen production.

5. Discussion

The findings from this review highlight the growing interest and efforts in integrating AI techniques with RES for optimising GH2 production. Several studies have explored the application of AI models, such as ANNs, SVMs, and DL approaches like LSTM networks, for forecasting and optimising various GH2 pathways from solar, wind, biomass, geothermal, and other RES. For solar-based hydrogen production, techniques like ANNs (Su et al.[81]; [27]), LSTM networks, and SVR by Javaid et al. [28] have been employed. While these models can capture complex nonlinear relationships and provide accurate predictions, they often require large datasets and careful tuning for optimal performance [31]. Similarly, Elaziz et al. [32] optimised an AI method RVFL and MO algorithm to evaluate the performance of PVTC system and Senthilraja et al. [34] employed ANFIS with limited generalisation. Sareen et al. [35] found the CEEMDAN-BiDLSTM algorithm to predict GH2 production. Nikulins et al. [30] developed DL model FCNs and CNNs to capture complex patterns. Some studies have highlighted the need to consider multiple objectives beyond efficiency and costs, such as emissions or energy consumption [29]. The development of photo-electro chemical and PVE systems as promising avenues for cheaper GH2 from solar energy introduces new opportunities for AI-based optimisations. Adeli et al. [36] proposed an eco-friendly framework for hydrogen production using ANN and DL algorithms to refine key challenges. Haider et al. [37] and Cheng et al. [39] employed various ML models, including Prophet, SARIMAX, SVM, and FbProphet, to enhance forecast accuracy and address seasonal dependencies, while emphasising the importance of algorithm selection. Salari et al. [38] leveraged CNN, GRU, CatBoost, and MOGWO to improve system efficiency, noting the complexity of hyperparameter tuning and model selection. Additionally, Ateş [33] demonstrated that a CA-ANN hybrid method outperformed ANN alone in predicting solar PV output, emphasising the need for integrating energy storage systems, such as hydrogen production, to ensure uninterrupted energy supply. However, these technologies face challenges related to component costs, and durability, and the need for further optimisation to realise their potential cost advantages over traditional methods.

To produce hydrogen through wind, Zhang et al. [40] demonstrated the effectiveness of GDHS optimisation using AI, despite having limited comparison metrics. Similarly, Chen et al. [41] combined AI-enhanced MPC with PSO and BPANN to improve economic viability, though constrained by simulation environment limitations. Maleki and Askarzadeh [42] achieved the lowest annual cost using PSO in a PV/wind/FC system but highlighted the need for efficiency improvements in fuel cells and electrolysers for competitiveness. Additionally, Dudziak et al. [43] and Abisoye et al. [44] emphasised cleaner and cost-effective production through Bayesian network and AI-based metaheuristics, acknowledging challenges like high costs, quality data needs, and short-term planning. Zhang et al. [45] presented NSGA-II as an efficient optimisation method, while Dehshiri and Bahar Firoozabadi [46] and Javaid et al. [47] explored wind-based hydrogen production and the reliability of the Levenberg-Marquardt algorithm and LSTM models, noting significant costs and generalisation issues. For geothermal-based hydrogen production, several approaches have demonstrated promising outcomes using AI and ML techniques. Mehrenjani et al. [88] achieved optimal hydrogen production rates with an ANN-GA hybrid but lacked an economic model. Sangesaraki et al. [49] combined 4E analysis with ML and GA optimisation, reducing calculation time, although LINMAP was not fully explained. Similarly, Khosravi and Syri [50] and Balali et al. [51] utilised hybrid systems of MLP and GA, emphasising their suitability for remote areas and optimal hydrogen production, despite challenges related to cost and implementation. Xue et al. [52] applied multiple ANN models with a DE algorithm and FFNN, achieving high precision, albeit with training complexity. Yilmaz et al. [53] employed a real-time FPGA-based ANN model, which proved more accurate but came with higher costs and implementation complexity. Sohani et al. [54] explored SMOA as a promising approach but did not address different climatic regions.

For hydrogen production from biomass, Hannah et al. [89] developed a two-stage ANN model that provided accurate predictions while being time-efficient and cost-effective. Ozbas et al. [55] utilised ML models like LR, k-NN, SVMR, and DTR, achieving model accuracy in gasification experiments and higher heating values with reduced time and costs. Safarian et al. [56] emphasised the versatility of their ANN model, and Nieto et al. [80] combined SVM with an ABC optimiser to achieve high prediction accuracy. Zhao et al. [57] employed SCWG with ML models, focusing on optimising hydrogen reaction efficiency. Rezk et al. [58] used PKS and fuzzy logic models to obtain optimal values, increasing hydrogen and syngas production. Tahir et al. [59] applied ML with Bayesian Regularisation and SCG to produce clean energy efficiently. Haq et al. [60] integrated ML with GA to enhance prediction accuracy and model performance, though it required careful tuning. For hydrogen production through fuel cell electrolysis, AI techniques have demonstrated significant potential in optimising and modelling various fuel cell technologies. Al-Othman et al. [62] showcased the effectiveness of diverse AI methods in optimising HRES, marking important progress in hydrogen economy development. Building on this foundation, Fayyazi et al. [61] integrated various AI and ML approaches, including fuzzy logic systems and GAs, demonstrating enhanced real-time adaptability and reduced hydrogen consumption. The implementation of advanced optimisation frameworks has shown promising results. Feng et al. [63] proposed AI-MOO frameworks that significantly improved system efficiency. This work was complemented by Sousa et al. [66], who developed hybrid intelligent approaches focusing on performance validation and hydrogen consumption optimisation. Further advancements in simulation methodologies were achieved by Peksen [19], who combined multi-physics simulation with ML to enhance fuel economy assessment. Recent innovations have focused on improving modelling accuracy and production efficiency. Fathy et al. [67] demonstrated the effectiveness of ANFIS modelling coupled with JO in increasing hydrogen production efficiency. Shboul et al. [68] explored the combination of GPR with GA optimisation, achieving significant improvements in power efficiency and cost reduction. These developments were further supported by Mansir et al. [64], who utilised AI, DL, and GAs to achieve excellent correlation in their predictions. The integration of NN-based approaches has shown promise in prediction accuracy. Zaferani et al. [65] employed MLP-ANN and ML techniques to demonstrate high accuracy in system predictions, while Casteleiro-Roca et al. [69] successfully developed adaptive-predictive control systems using ANN and polynomial regression algorithms, enabling accurate prediction of hydrogen flow variations. These collective advancements show the significant potential of AI and ML techniques in advancing fuel cell technology for sustainable hydrogen production.

In the context of algae-based hydrogen production through photobiological H_2O splitting, AI methods have been investigated for their cost-effectiveness and efficiency. However, the previous studies have also acknowledged potential barriers like high initial investment costs by Guodao et al. [90] and the risk of model overfitting, which could compromise generalisability and robustness [91]. The adoption of AI-driven approaches has significantly advanced the optimisation of renewable energy pathways, including ocean wave power and seawater-based hydrogen extraction. Mirshafiee et al. [72] introduced a data-driven approach to harness ocean wave energy through advanced analytical techniques. This methodology effectively optimised power extraction, enhancing the efficiency and viability of ocean waves as a RES. Similarly, Sunil et al. [92] explored the use of DL techniques, specifically CNN and RNN, to extract hydrogen directly from seawater. Their approach led to improved efficiency, streamlined operations, and reduced maintenance efforts, demonstrating the utility of ML models. The studies by Zhou [73] applied advanced AI techniques, particularly MPC, to enhance the stability and efficiency of ocean energy systems by optimising multi-energy synergies and managing ocean hydrogen storage. The study highlighted the benefits of AI in reducing power losses and improving system robustness, while noting the high computational and financial costs involved. Additionally, Iqbal et al. [74] highlighted the integration of ML techniques, such as SVM, MLP-ANN, and GA-ANFIS, as key contributors to optimising electrochemical hydrogen production by improving catalyst design, reactor efficiency, and data-driven modelling.

Efficient energy storage systems are vital for mitigating the challenges posed by the intermittency of RES, and hydrogen-based storage stands out as a promising alternative to traditional battery solutions. Advancements in the sizing and optimisation of HRES incorporating hydrogen storage have shown potential in improving sustainability and addressing issues such as variability and high costs through classical, soft computing, and hybrid metaheuristic techniques Modu et al. [95]. The distinctions among electrolyser technologies, as examined by Domalanta et al. [75], reveal essential trade-offs in efficiency, operating temperature, and cost, emphasising the need for optimisation strategies. Hosseini and Wahid [76] further underscored the importance of understanding variations in efficiency, pressure, and cost to enhance system performance and ensure practical application. The effective management of complex and variable data is critical in renewable energy forecasting. Rahman et al. [77] leveraged advanced models like ANN, CNN, and RNN to improve prediction accuracy, addressing the inherent challenges of resource intermittency. In a similar way, Daniel et al. [93] demonstrated the effectiveness of NNs combined with the ASHRAE clear sky model for better solar irradiance predictions, ultimately enhancing the reliability and performance of energy systems. Building upon previous studies, an innovative MILP model has been proposed to integrate RES and non-RES, accounting for weather intermittency, demand uncertainties, and green chemical processes like hydrogen production and methanation [78]. The assessment of hydrogen production technologies through AEL, PEM, and SOEL have been extensively analysed for their suitability in different applications, with findings highlighting variations in efficiency and cost-effectiveness under different operational conditions (Mengdi et al. [8]).

The integration of AI with hydrogen technologies is revolutionising various sectors, particularly in energy systems optimisation. In the energy sector, AI is proving transformative by deploying ML algorithms to forecast energy demand, enhance fuel cell performance, and effectively manage hydrogen production and distribution networks. Advanced techniques such as computer vision and sensor fusion are being utilised to enhance safety measures through improved leak detection in production, storage, and distribution processes [79]. For instance, AI-driven platforms are optimising real-time operations at hydrogen fuelling stations by refining refuelling schedules and maintaining inventory levels to ensure seamless functioning with minimal downtime. AI enhances these manufacturing processes through predictive maintenance, quality control, and process optimisation. ML models analyse sensor data to predict system issues and optimise hydrogen usage, resulting in improved efficiency and product quality. Hydrogen's applications extend significantly into the chemical and refining industries. It is essential in petroleum refining processes such as hydrocracking and hydrotreating. AI's capabilities in forecasting renewable energy output and optimising hydrogen production and storage are facilitating the integration of variable RES into the grid while enhancing safety and monitoring capabilities (Martinez et al.,[94]) AI is also driving innovation in GH2 production through the development of more efficient electrolysis systems.

Despite the promising results, some common challenges emerge across various hydrogen production pathways. Data availability and quality remain critical factors, as many ML and DL models require large, high-quality datasets for accurate training and generalisation. Additionally, the economic viability of these AI-integrated systems is often influenced by factors like component costs, infrastructure requirements, and the potential impact of workforce changes or fossil fuel reliance. As the global focus on energy diversification intensifies, the integration of AI techniques with RES for optimised GH2 presents a promising pathway towards a sustainable energy future. These technologies are transforming various sectors, from energy systems to manufacturing processes. AI-driven platforms are optimising operations through advanced techniques like computer vision and sensor fusion for improved safety, while ML models are enhancing process efficiency and system performance across different applications. Furthermore, a comprehensive analysis of efficiency and cost trade-offs is crucial for selecting the optimal GH2 method. While processes like SR boast high efficiency but higher costs, methods like PO, AR, and gasification offer relatively lower costs but lower efficiencies. Stakeholders must carefully weigh these trade-offs to maximise the viability and potential of sustainable hydrogen production.

6. Conclusion

The integration of AI techniques with RES presents a promising pathway towards optimising GH2 production processes. This comprehensive literature review has highlighted the significant potential of AI-optimisation methods and its applications, such as ML and DL, in enhancing the efficiency, cost-effectiveness, and overall viability of various hydrogen production methods. Previous studies have explored a wide range of AI techniques, including LR, RF, ANNs, LSTM, FFNN, MLP, SVR, SVMs, CNN, ANFIS, RL, DNN, Bayesian network and optimisation algorithms like GA, PSO, POA, MO-PSO, SMOA, ABC and NSGA-II. These approaches have demonstrated remarkable accuracy, adaptability, and optimisation capabilities across various RES, such as solar, wind, geothermal, and biomass. While significant progress has been made, several challenges persist, including data availability and quality, high initial costs, and the need for comprehensive optimisation frameworks that consider multiple objectives, such as emissions, energy consumption, and environmental impact. The assessment of hydrogen production technologies through AEL, PEM, and SOEL has been extensively analysed for their suitability in different applications. Findings highlight variations in efficiency and cost-effectiveness under different operational conditions, emphasising the need to select appropriate technologies for specific applications.

Furthermore, findings from research in ocean-based hydrogen production emphasise the importance of integrating multi-energy synergies and employing advanced AI-based control strategies to optimise system efficiency and stability, although high computational demands remain a barrier. Moreover, AI-driven advancements have significantly improved hydrogen production systems, enhancing their adoption across various sectors such as transportation, manufacturing, and power generation. Hydrogen fuel cells are being widely adopted in vehicles, heavy-duty transportation, and backup power solutions, providing a zero-emission alternative to traditional combustion engines. The combination of AI and hydrogen technologies is driving significant transformations across various industries. Through sophisticated AI methods such as computer vision and sensor fusion, operational safety and efficiency have improved, while ML implementations have enhanced system performance and process optimisation in numerous applications. The combination of AI techniques with RES for optimised GH2 generation offers an avenue to a sustainable energy future as the world's focus shifts to energy diversification. However, a comprehensive analysis of efficiency and cost trade-offs is crucial for selecting the optimal GH2 method, as processes like SR boast high efficiency but higher costs, while methods like PO, AR, and gasification offer relatively lower costs but lower efficiencies.

The following are recommendations and areas for future research that can be considered from this thorough literature review:

- The development of comprehensive AI frameworks that integrate MOO techniques must be the main goal of future research. Such frameworks should aim to improve efficiency in addition to addressing emissions reduction, environmental effects, and economic viability. Better understanding of how various AI models perform in many scenarios and how effectively they adapt to emerging RES technologies is needed for this purpose.
- The efficiency and cost-effectiveness of electrolysis technologies such as SOEL, PEM, and AEL vary depending on the application. Future studies should concentrate on lowering operating costs, increasing efficiency, and resolving issues related to water shortages to maximise these technologies by utilising AI-driven approaches.
- Further investigation and analysis are required to integrate AI with underutilised resources including tidal, hydropower, intermittency, algae, the ocean, and hybrid energy sources. The efficiency and economy of hydrogen production depend on AI's capacity to optimise electrolysis processes, real-time monitoring, and adaptive control strategies. Water scarcity must be addressed for water electrolysis technologies to be used sustainably, particularly in desert areas.
- To enhance accuracy in forecasting, lower costs, and optimise multi-energy systems, future research should investigate innovative combinations of AI models with optimisation algorithms like GA, PSO, and deep reinforcement learning.

Overall, the integration of AI and RES for GH2 production is a rapidly evolving field with significant potential for enabling a transition towards a more sustainable and renewable energy landscape. Continued research, collaboration, and investment in this domain are crucial for overcoming existing challenges and unlocking the full potential of AI-enabled GH2 production.

CRediT authorship contribution statement

Mohammad Abdul Baseer: Writing – original draft, Visualization, Resources, Methodology, Formal analysis, Data curation, Conceptualization. **Prashant Kumar:** Writing – review & editing, Supervision, Investigation. **Erick Giovani Sperandio Nascimento:** Writing – review & editing, Supervision, Conceptualization.

Declaration of competing interest

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

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Data availability

Data will be made available on request.

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