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Review

AI Empowering Green Hydrogen: Innovating for A Sustainable Energy Future

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Abstract- Finding green hydrogen has become essential in the request for a cleaner energy source and as a means of achieving a net-zero carbon economy. The following concepts for enhancing green generation have been spread due to the current study focuses on offering suggestions for a literature evaluation in AI and RE (renewable energy). Therefore, based on the proportion and potential to modify specific phases of hydrogen production, such as water cleaving, or to enhance the dependability and efficiency of systems that use renewable energy, including solar, wind, and so on. The current literature review includes an examination of AI technologies. The proposed model also describes primary neural networks and machine learning approaches, as well as the primary predictive maintenance-based application domains for them. These insights also have significance for improving the use of sustainable energy, addressing ambiguous prior energies, and presenting AI's approach to the revival of green hydrogen technology.

Keywords- Artificial intelligence; Green hydrogen production; Renewable energy sources; Sustainable energy technologies; Water electrolysis

1. INTRODUCTION

Clean hydrogen production, often referred to as green hydrogen, is characterized by environmentally friendly technologies that produce hydrogen using renewable energy sources, including sunlight and wind. In contrast to conventional hydrogen production methods that use fossil fuels and release large amounts of carbon dioxide CO_2. Green hydrogen is produced by water electrolysis, a process that uses an electric current to split water molecules H_20 into hydrogen H_2 and oxygen O_2, without emitting any greenhouse gases [1].

The hydrogen thus produced has multiple potential applications, including in fuel cells for vehicles, domestic energy storage systems, and various industries, as well as a reagent for the synthesis of numerous chemicals. Its use extends to the electrification of sectors that are difficult to decarbonize, such as heavy industry, aviation and long-distance transport. In addition, green hydrogen offers a viable solution for the storage and transport of renewable energy, alleviating the problems associated with the intermittency of solar and wind power sources [2]. Clean hydrogen is essential to the shift to a low-carbon, sustainable economy. Lowering reliance on fossil fuels and lowering CO_2 emissions, it helps achieve global climate goals as an energy transporter [3]. The purpose of this literature review is to examine artificial intelligence (AI)-driven advancements in green hydrogen generation, emphasizing the technology's significance for the energy transition and evaluating how AI can enhance the technologies' economic feasibility and efficiency. The conversation will also focus on the climate goals that different nations have set and how green hydrogen may achieve these goals. This research will also draw attention to the difficulties and potential applications of this exciting technology.

The significance of using AI to generate green hydrogen generation methods has already been emphasized in several publications. For instance, research has been conducted on the latest developments and difficulties in incorporating AI into battery and hydrogen technologies [4]. A study on the recent developments in hydrogen energy technology was also conducted, which included the contributions of AI and machine learning techniques [5].

With an emphasis on scientific advancements and policy approaches, a review of hydrogen technologies and policies required for a sustainable future was given [6]. Lastly, a study of recent developments in the Power-to-Hydrogen (P2H) concept—which generates hydrogen using renewable energy sources, was conducted [7].

1.1. Role of AI in green hydrogen production

Artificial intelligence (AI) is essential for the generation of green hydrogen because it optimizes several parts of the process, increasing productivity, cutting expenses, and lowering carbon emissions.

- ***Enhancing electrolyzer performance***: Green hydrogen generation requires electrolyzers, that use renewable electricity to convert water into hydrogen and oxygen. According to Mohammad Ali Abdelkareem et al., artificial intelligence (AI) can optimize operations by modifying a variety of parameters in real time, including temperature, pressure, water and gas flow rates, voltage, and current intensity [8]. This approach minimizes energy consumption and operating expenses while optimizing hydrogen production efficiency. Continuous sensor data analysis using machine learning algorithms finds the best operating conditions and automatically modifies the parameters. Production is dependable and extremely efficient thanks to this dynamic optimization.

- ***Simulations and feasibility studies***: AI significantly speeds up simulations and feasibility studies for green hydrogen projects, claim E. Crespi et al. Numerous intricate elements are considered in these simulations, including models for the production of renewable energy (wind, solar, hydro), weather forecasts, both short- and long-term, fluctuating electricity market prices, and plant investments and operating expenses [9]. These simulations can precisely ascertain the ideal electrolyzer size, usage rate, geographic dispersion, storage and distribution infrastructure needs, and overall carbon footprint because of sophisticated optimization techniques. These sophisticated assessments help decision-makers create green hydrogen initiatives that are both feasible and lucrative.
- ***Renewable energy generation***: AI is also essential for enhancing the layout and functionality of renewable energy production plants that supply power to electrolyzers. Zghaibeh, Ben Belgacem, and colleagues observed that real-time data from sensors at wind and solar power plants are analyzed by machine learning algorithms. As a result, it is able to anticipate weather-related production changes, optimize the alignment and orientation of turbines and panels, and continually modify the operational settings to achieve the optimum yield. A constant and dependable power supply for electrolyzers is ensured by the clever handling of renewable resources, which is essential for large-scale hydrogen-green production [10].
- ***Digital twins for asset management***: Digital twins are defined as digital representations of real physical systems, whether living or not, that integrate technology, decision support, and complex systems analysis [11]. They facilitate scenario simulations to optimize the efficiency and reduce costs [12]. Integrating real-time data, improves asset management and decision-making. Finally, they contribute to sustainability by optimizing processes to minimize emissions and maximize the use of renewable energies.
- ***Intelligent energy management systems***: The use of AI-enabled management systems (EMS) play a crucial role in integrating hydrogen production with renewable energies and power grids [13]. Predictive control algorithms optimize the energy consumption in real time, reduce operating costs, and maximize green hydrogen production. This will contribute to more efficient and sustainable energy management.
- ***Government initiatives for green hydrogen***: Various nations have initiated worthwhile projects in recognition of the advantages of AI for green hydrogen production [14]. Germany, for example, has allocated 9 billion € to become a world leader in this field, while China has set a goal of 6.5 GW of installed electrolyzer capacity by 2023, or 50% of the worldwide capacity (Figure 1). These expenditures and ambitious targets highlight green hydrogen’s strategic significance in the energy transition [14].

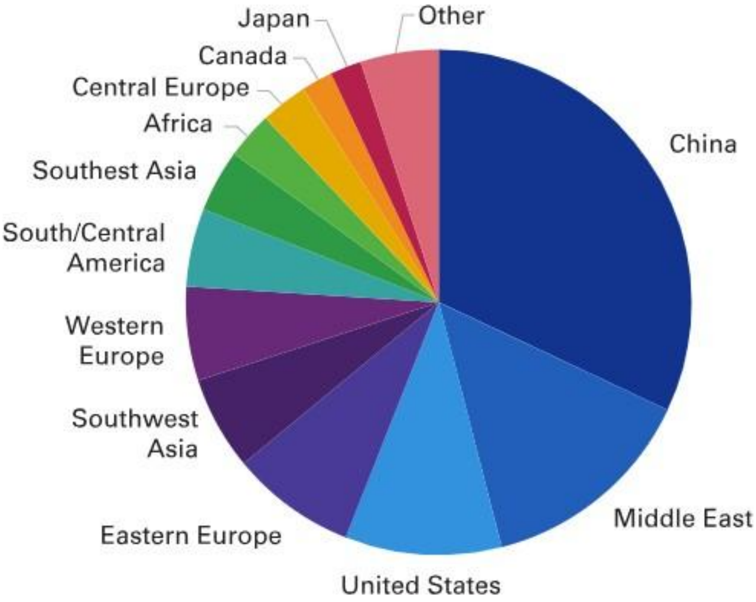

Figure 1. Distribution of hydrogen use by regions, Source: IHS Markit

1.2. Purpose of the review

The purpose of this literature review is to discuss the potential application of artificial intelligence in enhancing the efficiency of green hydrogen generation, specifically focusing on AI solutions as methods of increasing the reliability and scalability of green hydrogen generation processes based on renewable energy sources. For this kind of review, it is proposed to introduce one of the biggest and most recent collections of the literature, identification of key AI approaches and their application in this field, as well as the assessment of the current developments' trends and perspectives in this field. The field also encompasses examining the opportunities in production, forecasting, and averting maintenance, energy consumption, and costs related to green hydrogen within the sphere of renewable resources in the aspects of solar and wind. AI incorporation into hydrogen technologies offers a game-changing chance to solve technical issues and streamline the hydrogen value chain. Within this framework, the current review was designed to examine the various facets of hydrogen's contribution to global energy transition. This study investigates cutting-edge hydrogen technologies and their integration difficulties and the prospects for their widespread deployment with the aim of closing research gaps.

2. METHODOLOGY

This literature review highlights innovations based on artificial intelligence for the production of green hydrogen from renewable energy sources. The proposed methodology is based on several key steps. First, research objectives and questions were determined, including identifying technological breakthroughs in the field of AI, assessing the field's effects on efficiency and costs, and identifying some of the challenges and opportunities ahead. Second, a systematic search of sources was carried out on academic databases such as Google Scholar, ScienceDirect, Scopus, and IEEE Xplore, using keywords such as “AI in green hydrogen production” and “machine learning for water electrolysis” and focusing on publications from the last decade to ensure relevance.

Articles were selected on the basis of specific criteria, such as peer-reviewed publications and studies on AI applications in green hydrogen production, and excluded redundant or off-topic articles. Data from the selected articles were critically analyzed and reviewed, focusing on emerging trends and identifying recent innovations. They identified gaps in the current literature, as well as new topics and advances suggesting a possible move toward AI-enabled green hydrogen production (Table 1).

Table 1. Research approach adopted in the current study

Type of analysis	**Publication period**	**Keywords**	**Search engines**	**Papers**
Qualitative	2000-2023	- Artificial intelligence - Green hydrogen production - Renewable energy sources - Sustainable energy technologies - Water electrolysis	- Science Direct - Springer - Taylorandfrancais - Wiley - Scopus - EBSCO - Emrald insight	- Articles - Books - Thesis

3. RESULTS AND DISCUSSION

3.1. Publication trend

The general information is used to provide an overview of the number of publications per year from 2000 to 2023 [15]. According to the data, there were scarce of research publications on the three general themes of H2 production. During the first five years of the study, the pattern was largely unchanged. However, the researchers noted a significant exponential increase in the number of articles at the beginning of 2005 (Figure 2). The same authors reported that more than 150 articles were published, and the number of authors continued to increase. Figure 3 presents the five most trending themes in terms of publication percentage. The largest proportion is devoted to energy, accounting for 38.8% of the total. The Scopus database is the world’s largest source of academic information; it covers most of the academic participation fields [16]. In this research, we conducted a bibliographic analysis (BA). BA searched for machine learning (ML) applications in predicting feasible H_2 production technologies from the wastewater recycling industry (WRI) for CREs [17]. To perform our research, Scopus advanced search instruction was used with the “title-abs-key (hydrogen and production) and title-abs-key (machine and learning) or title-abs-key (circular and economy) or title-abs-key (water and industry)” query, marked “no” in all the prior filters, and the “2000-2024” period was set. The database was last updated on 22nd February 2023, and we retrieved 1810 documents.

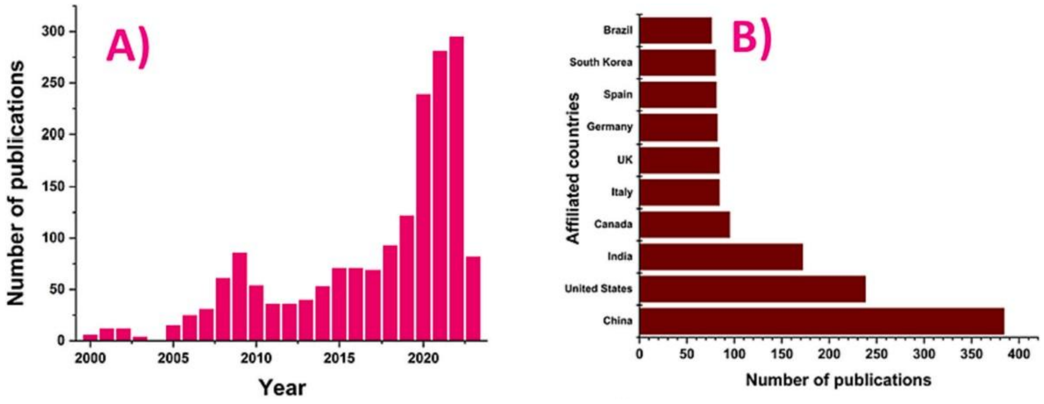

Figure 2. A) The annual number of publications over the period 2000-2023 B) Top 10 countries publishing the most papers in the same period

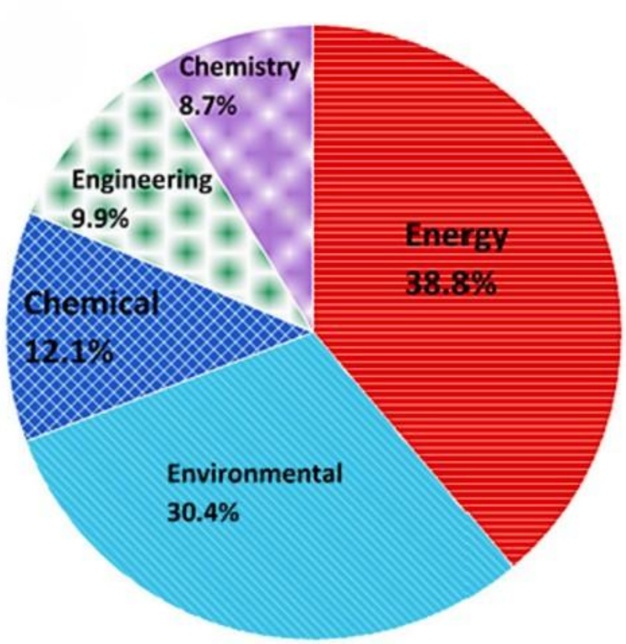

Figure 3. Top 5 fields by percentage of publications

3.2. AI in green hydrogen production

3.2.1. AI techniques used

Optimization techniques, neural networks, machine learning, and reinforcement learning are widely used to produce hydrogen. Optimization algorithms, including genetic algorithms and PSO particle swarm optimization are used to maximize the efficiency of hydrogen production systems by identifying the most appropriate solutions for complex parameters [18].

A neural network can be used to model and optimize electrolysis processes to increase hydrogen production. Machine learning for real-time electrolyzer performance can lead to improved sustainability and profitability of hydrogen production systems [18]. Artificial intelligence can help to solve the challenges of renewable energy prices and promote sustainable and profitable hydrogen production [19].

3.2.2. Applications in production processes

3.2.2.1. Machine learning

Machine learning is a branch of artificial intelligence in which systems can learn independently by learning from experience. What's more, machines, like humans, use data and experience to make predictions and decisions. This system fires without outside help; it does not need to be customized for each separate task [20]. This approach is advantageous given the many complex aspects of production and consumption. Consequently, integrating machine learning into this sphere is likely to generate savings and rationalize production.

First, machine learning algorithms can analyze large quantities of data from different sources, such as electrolyzer data, energy management systems, renewable energy sources, etc., in a very powerful way [21]. In the case of electrolyzer data, for example, these algorithms can be used to identify consumption patterns and conditions that maximize hydrogen production efficiency. These algorithms can be used to find optimal operating parameters based on the analysis of thousands or even millions of data points. In this way, they can increase hydrogen production and reduce the energy consumed in its production, which is absolutely crucial to the development of this process from the point of view of its economic and environmental viability.

In addition, machine learning can predict hydrogen demand and supply very accurately. Algorithmic procedures can predict hydrogen demand and supply using predictive procedures to anticipate aggravations and increased demand for external reasons such as weather, electricity market factors, or the customer demand model [22]. A case in point: at times of low electricity demand, the company believes it makes sense to step up hydrogen production to obtain and retain the surplus. Thanks to the previous forecast, production allows employers to make the most of the capital on offer and minimize production costs, ensuring that production continues in a more orderly direction [23]. Finally, machine learning enables advanced predictive maintenance detection. By examining the equipment's operating data in real time, the algorithms can detect the warning signs of potential failures. For example, abnormal operating temperatures or unusual vibrations could indicate that part of the chlorinator is about to fail. By detecting these signs early, companies can plan maintenance before failure occurs, thereby reducing unplanned downtime and last-minute repair costs [24]. This continuous approach ensures that equipment is always available and production is uninterrupted, which is crucial for an appropriate response to changing demand levels in the market.

3.2.2.2. Neural networks

The production of green hydrogen is possible thanks to neural networks [25]. They reduce energy consumption and increase efficiency by optimizing processes such as water electrolysis [26]. These networks can help identify and optimize catalysts for photocatalysis and dry methane reforming, leading to higher yields and greater stability (Figure 4 [27]. Solar and wind energy generation also contribute to the efficient management of renewable energy. Neural networks can be used to identify efficient and energy-saving production methods through accurate simulations, leading to a sustainable energy transition [28].

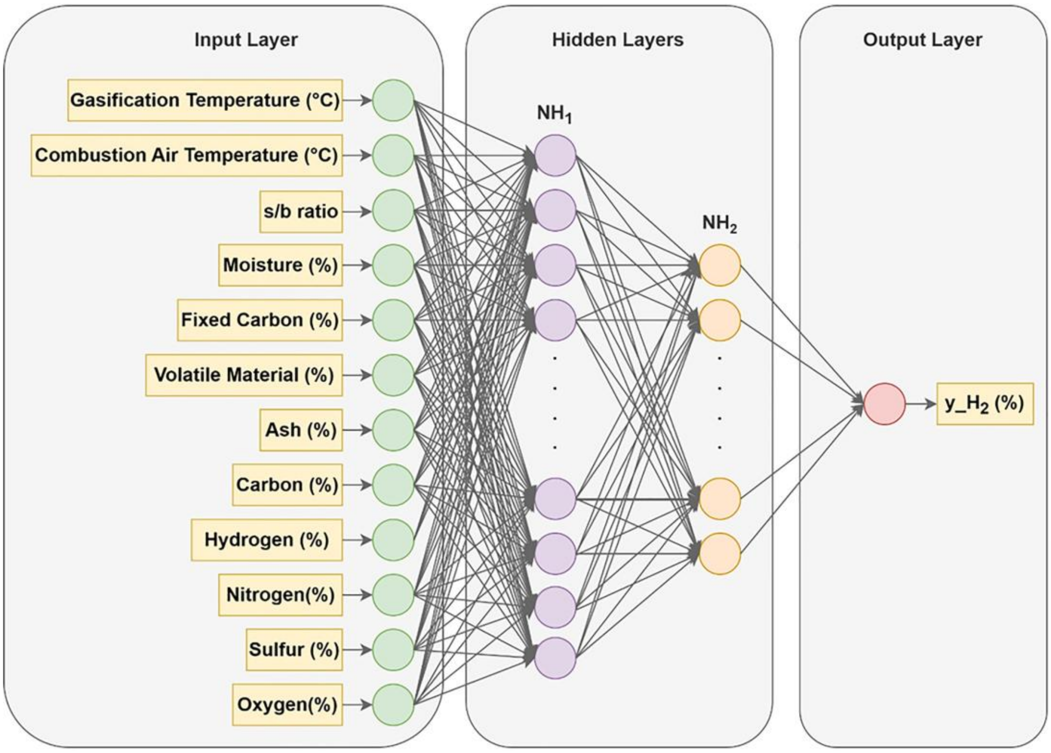

Figure 4. Artificial neural networks

3.2.2.3. Optimization algorithms

Optimization algorithms are mathematical algorithms that evaluate a set of possibilities to identify the optimal solution, by either reducing or increasing the objective function. Green hydrogen is produced and handled by these algorithms [29]. They help in the planning of hydrogen production to account for both the demand and supply (Figure 5) [30], particularly by optimizing the use of electrolyzers and managing hydrogen reserves to meet changing demand and production conditions. Renewable energy is made possible by optimizing wind turbines and solar panels using algorithms, which is crucial for developing environmentally friendly hydrogen. Wind patterns, solar irradiation, and geographical constraints are the best places to go [31]. Hydrogen production facilities can be improved by reducing operational costs and losses, especially in terms of energy management, by implementing these algorithms.

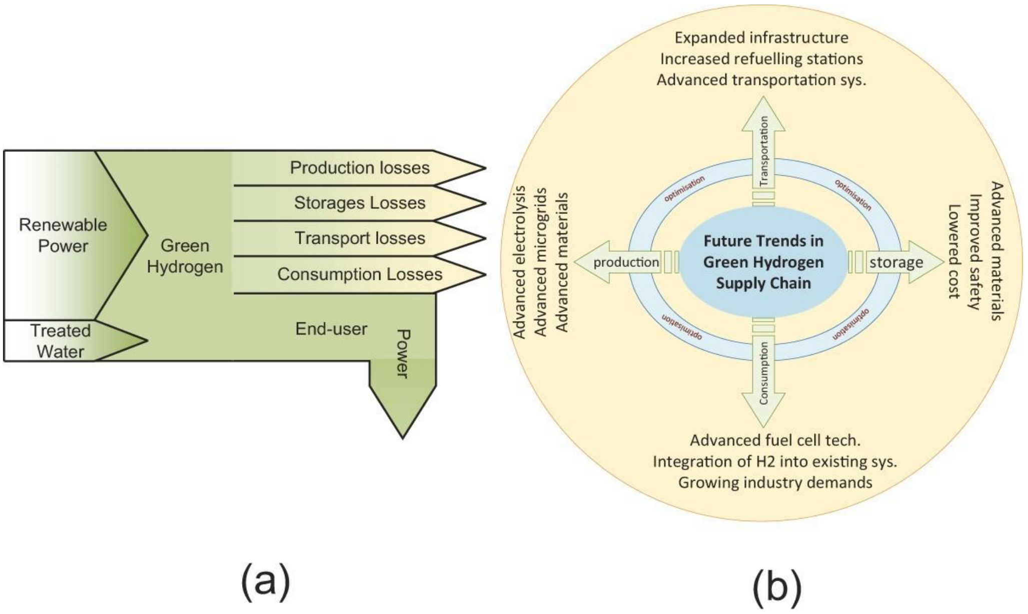

Figure 5. Optimization green hydrogen supply chain

3.3. Renewable energy sources for green hydrogen

The production of green hydrogen by electrolysis of water using renewable energy represents a significant technological advance in the decarbonization and improvement of air quality. The large-scale deployment of this technology is contingent on advancements in both technology and economics, which have been the subject of numerous recent research studies. In their study, Hoising and Sakaushi [32,33] examine the requirements for dimensionally stable electrodes for large-scale, long-term hydrogen production. Mazzeo et al., present an analysis of the performance of various hydrogen production modes, including approaches related to solar photovoltaics and wind power generation, as well as an investigation of the impact of geographical factors on hydrogen production [34]. In their analysis, Guerra et al., determined that the optimal configuration in terms of operational and financial costs was a 165 MW stack [35].

3.3.1. Electrolysis unit

The alkaline electrolysis technology proposed for use in hydrogen filling station electrolysis units is both highly economical and well developed. The demonstrated size module has the capacity to produce 23 m3/h (50 kg/d) of hydrogen at a pressure of 10 bar and an AC energy consumption of 5.1 kW h/m3. The module has a daily water consumption of 560 L [32]. The system can be configured with a higher production capacity through the use of multiple modules. For instance, a 100 kg/d system requires two modules and consumes 1120 L of water per day, while a 200 kg/d system requires four modules and consume 2240 L per day.

3.3.2. Compression and Storage unit

The piston compressor in the hydrogen compressor station serves to elevate the hydrogen pressure from 10 bar (the pressure at which electrolysis is conducted) to 820 bar. The high-pressure storage is conducted in an arrangement of several tanks at varying pressures, with the tanks being filled in a cascading manner. The specific work (kJ/kg) of the compressor station was determined by the following equation [32].

$$L_{is,c} = \frac{k}{k-1} \times R_{H2} \times T_{in} \times \left(\left(\frac{p_{out}}{p_{in}} \right)^{\frac{k-1}{k}} - 1 \right)$$

Where:

k = 1.4 (ratio of specific heats)
R_{H2} = 4.12 kJ/(kg K) (hydrogen gas constant)
T_{in} = 298 K (25 °C, hydrogen inlet temperature)
p_{in} = 10 bar (inlet pressure)
p_{out} = 820 bar (outlet pressure)

3.3.3. Hydrogen cooling and distribution unit

The hydrogen dispensing system incorporates a refrigeration unit for the purpose of pre-cooling the hydrogen prior to dispensing (Figure 6), in accordance with the SAE J2601 refueling procedure. The hydrogen pre-cooling temperature range is between −40 ◦C to −17.5 ◦C. The cooling power required for the dispenser during vehicle refueling is calculated using the following formula [32]:

$$P_{cool} = \dot{m}_{H2,D} \times (h_{storage} - h_{dispenser})$$

Where:

$\dot{m}_{H2,D}$ = 16,7 g/s (hydrogen flow to distributor)
$h_{storage}$ = enthalpy at storage conditions (900 bar and 25°C)
$h_{dispenser}$ = enthalpy at distributor outlet conditions (900 bar and -40°C)

The electrical power supplied to the refrigeration unit is specified by:

$$P_{ref\ refrigerator} = P_{cool}/COP$$

COP = coefficient of performance is 1.0.

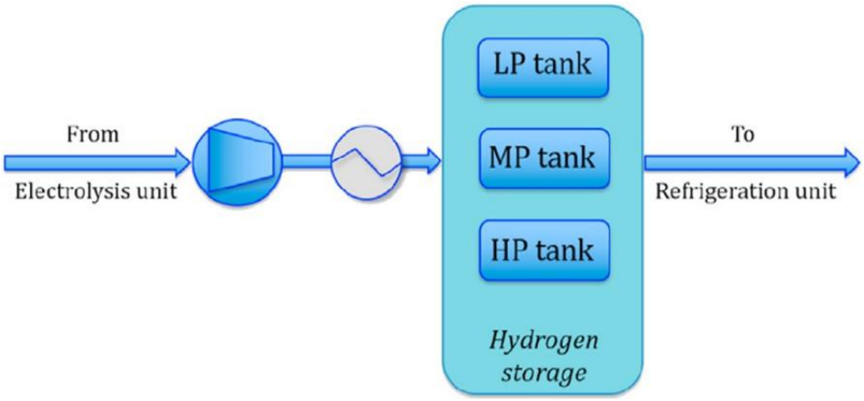

Figure 6. Hydrogen compression and storage unit

3.3.4. Hybrid system cost

The expenses of producing hydrogen in Poland, including onshore and inland waterway facilities, were thoroughly examined by Komorowska et al.[36] . The feasibility of offshore hydrogen production using wind power, as well as the cost and technical efficiency of production and transport alternatives, was examined by Franco et al [37]. The economic viability of small-scale hydrogen supply systems for zero-emission transport in Norway and the associated techno-economic benefits were presented by Ulleberg and Hancke [38]. Bhandari and Shah evaluated the economic viability of decentralized hydrogen production in Germany[39], while Minutillo et al., conducted a comprehensive cost analysis of hydrogen production at on-site electrolysis refueling stations in Italy (Figure 7) [39]. Milani et al. presented an analysis of hydrogen production pathways in Australia [40].

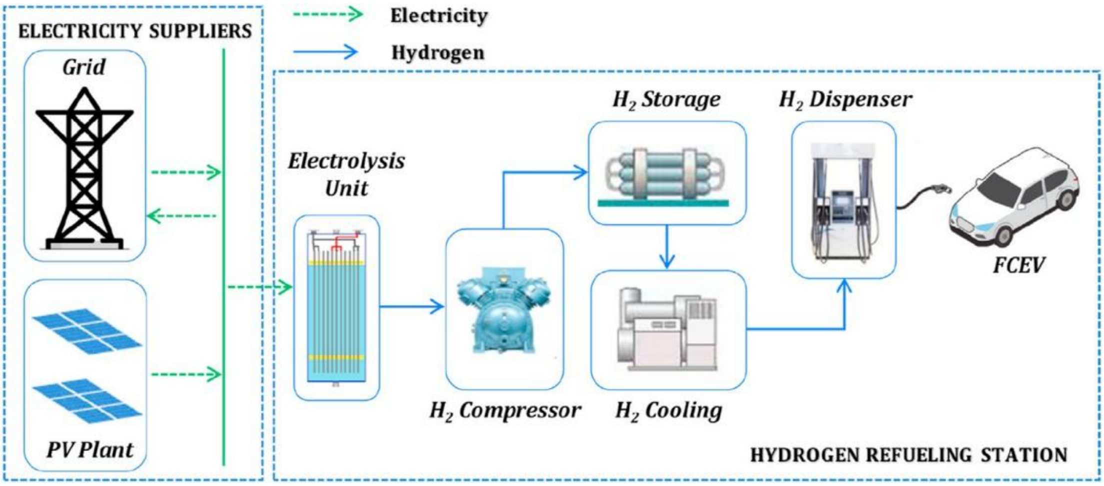

Figure 7. Scheme of the proposed on-site hydrogen filling station

Mosca et al. presented a novel approach for large-scale hydrogen production utilizing transmembrane transformers, accompanied by an analysis of the associated time-based costs

[41]. In their studies, Lee et al., conducted techno-economic assessments of green hydrogen production from solar and hybrid energy sources, respectively [42,43]. Their findings emphasize the pivotal role of electricity costs in determining the competitiveness of electrolysis. In conclusion, Weidner et al. examined various pathways for the large-scale deployment of hydrogen production, emphasizing that production rates may be constrained by global factors, regardless of the source of hydrogen [44]. This work is in alignment with the conclusions published by the International Renewable Energy Agency (IRENA), which indicated that, in addition to lowering the price of electricity, the price of electrolyzers needed to be reduced in order to make green hydrogen competitive. Furthermore, financial mechanisms, such as credits, needed to be put in place. Moreover, an analytical study published in the Chemical Engineering Journal in 2020 examined the performance of green hydrogen in substantially reducing GHG emissions and its contributions to sustainable development goals [45]. Another analytical study indicated a downward trend in production costs with technological development and scale effects by 2030 [46]. A comprehensive overview of the technologies pertinent to the various stages of water electrolysis was presented, elucidating recent advancements and the current obstacles to the complete production of hydrogen.

3.4. Critical Analysis of Artificial Intelligence Approaches Applied to Green Hydrogen Production

3.4.1. Machine Learning

Supervised machine learning techniques are extensively employed in green hydrogen production systems for production forecasting, energy demand estimation, and electrolyzer performance modeling based on environmental parameters (e.g., solar irradiation, temperature, pressure) (Table 2). These techniques include linear and non-linear regression, random forest (RF), support vector machine (SVM), and Bayesian networks. For instance, Machine learning algorithms have been widely applied to optimize hydrogen production, especially in wastewater treatment contexts [22]. Their study demonstrated that random forests, combined with sensitivity analysis, could identify key influencing factors (e.g., pH, temperature, flow rate) while minimizing root-mean-square error.

The effectiveness of machine learning in solar-hydrogen systems has also been demonstrated, with approaches like polynomial regression combined with variable selection techniques improving the prediction accuracy of hydrogen production under high solar irradiance conditions [21]. These findings provide new avenues for the precise control of PV–electrolyzer hybrid systems in real-world settings.

3.4.2. Neural networks

Artificial neural networks (ANNs) and deep learning models are particularly effective at capturing non-linear and dynamic relationships in energy systems (Table 2). These models are well suited for modeling electrolyzer kinetics, performing long-term forecasting, and enabling predictive maintenance. Common architectures include multilayer perceptions (MLP), convolutional neural networks (CNN), and recurrent neural networks (RNN/LSTM). A systematic review of ANN applications in hydrogen production via dry catalytic reforming has shown that ANN models outperform conventional regression approaches in both accuracy and computational efficiency [25]. In a different application, Deep learning models, such as CNNs, have also been used to predict hydrogen production from complex waste streams, demonstrating high precision even under uncertain and variable conditions [24].

3.4.3. Optimization algorithms

Metaheuristic optimization algorithms represent a powerful class of AI tools used to manage complex, multi-objective problems in hydrogen production systems (Table 2). These algorithms were inspired by natural and social processes, including genetic evolution (GA), swarm intelligence (PSO), and ant colony behavior (ACO). They are widely applied in system sizing, cost reduction, environmental impact minimization, and operational planning. Improvements in particle swarm optimization algorithms have enabled better management of renewable energy volatility in PV-coupled hydrogen systems, achieving faster convergence and more effective energy-system trade-offs [29]. Likewise, Metaheuristic optimization techniques have been applied to optimize various aspects of the green hydrogen supply chain, such as site selection, transportation, and storage under fluctuating market conditions [30]. These algorithms provide a robust framework for developing economically viable and scalable hydrogen infrastructure.

3.4.4. Hybrid AI–Physics Models

Hybrid approaches that combine AI with physical modeling are emerging as a highly promising direction (Table 2). Physics-informed machine learning (PIML) refers to a class of models that embed physical laws, thermodynamic principles, and electrochemical behaviors into AI algorithms to enhance their accuracy and generalizability. A hybrid model combining dynamic optimization with supervised learning has shown promise for forecasting hydrogen production, even under noisy or incomplete datasets, while maintaining physical consistency [19]. These approaches are particularly effective for modeling hybrid configurations, such as PV-electrolyzer–battery systems, in which strong interdependencies and non-linear dynamics must be managed. However, implementing these systems remains complex and requires expertise in both AI and physical system modeling from multiple disciplines.

3.4.5. Identified Methodological Gaps

Despite considerable advancements, several critical gaps hinder the operational deployment of AI in green hydrogen systems:

- Limited industrial validation: Many studies are based on simulations or lab-scale data, which restricts the generalization and scalability of the results. It is essential to conduct field-level validation using real-world, industrial-scale hydrogen systems.
- Inadequate uncertainty modeling: Current models often neglect variability in solar radiation, energy pricing, or grid stability. Integrating probabilistic modeling techniques (e.g., Bayesian inference, Monte Carlo methods) can improve robustness.
- Lack of interoperability and cybersecurity readiness: Few models are designed for seamless integration with real-time industrial platforms such as SCADA or EMS, and even fewer incorporate safeguards against cybersecurity risks inherent in smart energy systems.
- Scarcity of open-access datasets: The absence of standardized and publicly available datasets hinders reproducibility, benchmarking, and collaborative progress across research groups.

Table 2. Comparative Overview of AI Approaches

AI Approach	Main Objectives	Required Data	Key Advantages	Limitations	Representative Applications
Machine Learning (ML)	Production prediction Performance modeling Energy demand forecasting	Structured historical data (temperature, irradiance, consumption)	Fast training High accuracy Moderately interpretable	Sensitive to data quality Risk of overfitting	[21,22]
Neural networks	Non-linear system modeling Predictive maintenance Noisy data processing	Large-scale, multidimensional, possibly unstructured data	Handles complexity Strong time-series prediction capabilities	Black-box nature Requires extensive data and computation	[23–25]
Optimization algorithms	System sizing multi-objective planning Cost and emission minimization	Simulated scenarios or system models	Solves complex multi-objective problems Less data-dependent	May converge locally Sensitive to initial conditions non-deterministic	[29,30]
Hybrid AI–Physics Models	Enhance robustness Integrate physical constraints Improve generalization	Combination of empirical data and physical equations	Better generalizability Physical consistency Works with sparse data	Implementation complexity Lack of industrial-scale case studies	[19]

3.5. Challenges and limitations

3.5.1. Technical barriers to integrating AI with green hydrogen production

There are significant technological barriers to integrating AI into green hydrogen generation. When gas compressors are not used, high-pressure proton exchange membrane electrolyzes exhibit better cost-performance ratios. However, they are unable to achieve the 350 or 700 bar pressures required for cost-effective performance because of technological limitations (Figure 8) [47,48].

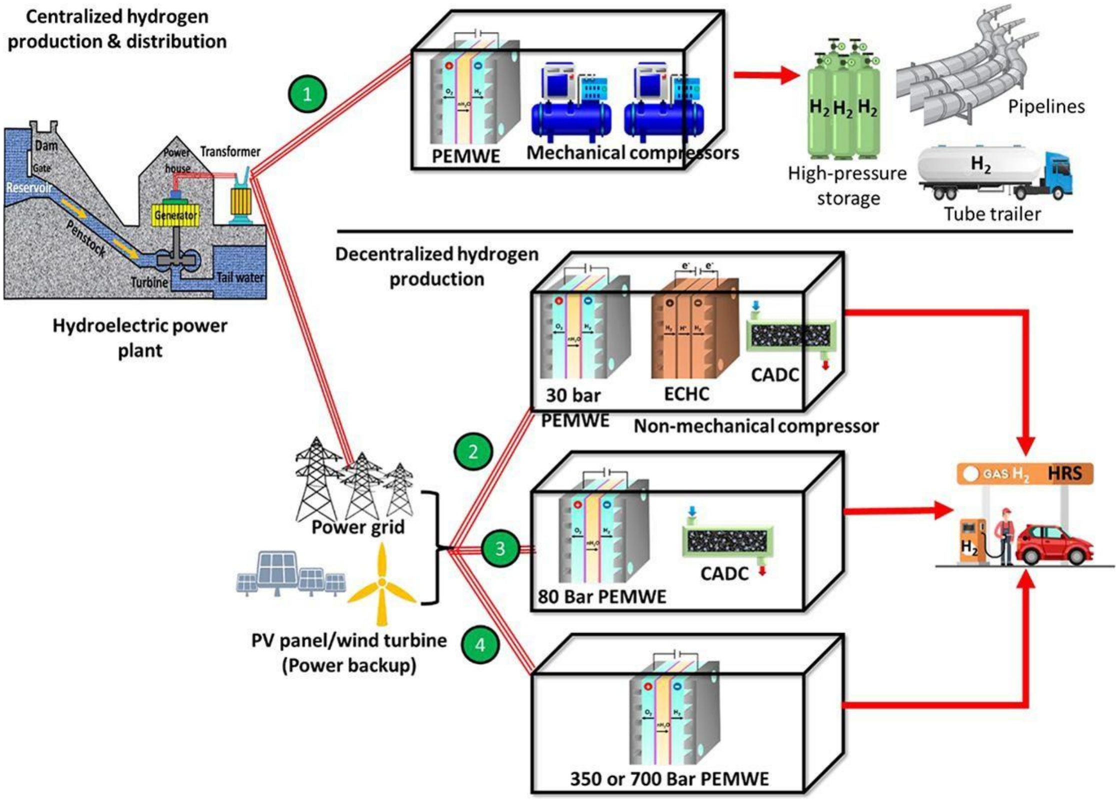

Figure 8. Scheme of the proposed on-site hydrogen filling station

Furthermore, water availability represents an additional challenge. Although, the desalination of seawater is entirely feasible and entails only marginal additional costs to produce hydrogen, this will require the development of appropriate infrastructure and adaptations that are well integrated into existing infrastructure [49].

In addition, AI enhances the efficiency of the electrolysis process by employing machine learning software to assess the impact of input variables, including electricity levels, water quality and temperature [50]. This enables the prediction of optimal operating conditions that maximize hydrogen production while minimizing the cost [51]. Ultimately, the advancement of highly efficient, cost-effective catalysts is of paramount importance for enhancing the yield of chemical reactions in water separation technologies. Nevertheless, this remains a significant research and development challenge [52].

3.5.2. Economic feasibility and environmental impact

Green hydrogen production through renewable energy infrastructure has recently been shown to be a favorable and economically feasible sustainability solution (Figure 9). The incorporation of windfarms and electrolyzers into industrial segments that are challenging to decarbonize is a potential solution [53].

Bouzas et al., reported that 97% of Uruguay's energy generation in 2020 was from renewable sources, thanks to its geographical position, which enhanced the transition to green hydrogen [54]. Green energy was shown to be a feasible alternative for commercial buildings in the United Arab Emirates [55]. In a similar vein, Sayed et al., put forth a proposal for a plant powered by solar and wind energy as the most optimal solution for curbing greenhouse gas emissions and meeting peak load demand [56]. Additionally, a comparative study of large-scale green hydrogen production between Europe and the Middle East was conducted by Jasczur et al., [57]. The latter region emerged as a leader due to its low production costs and abundance of solar and wind resources.

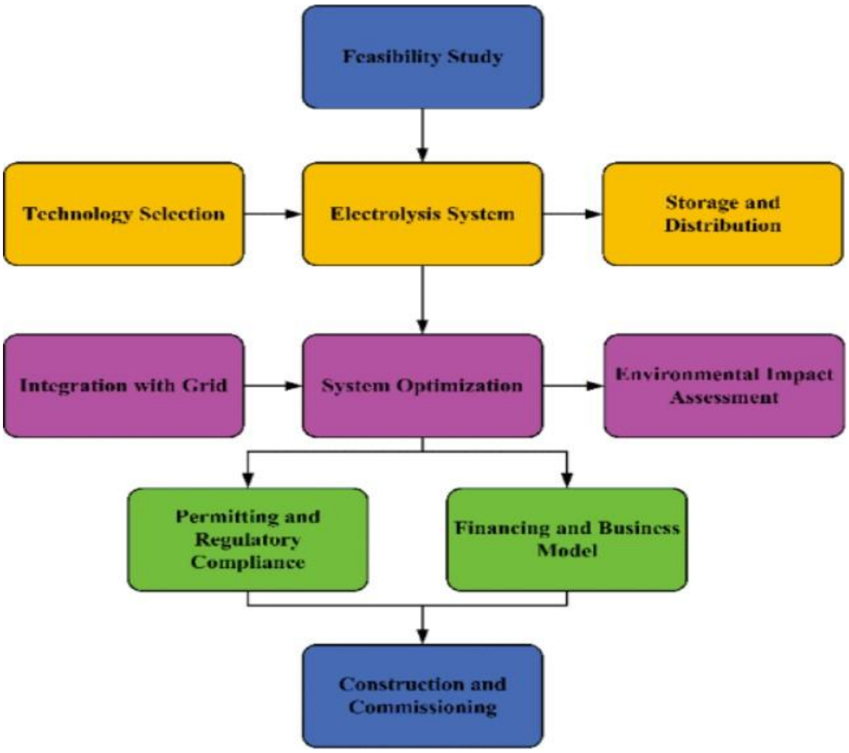

Figure 9. The following is a block diagram of the design steps for a PV/wind-powered hydrogen production plant

On the other hand, the integration of AI into the production of green hydrogen can significantly reduce CO_2 emissions. In fact, Sajid et al., demonstrated that an AI optimized hybrid microgrid energy system, powered by solar, wind, and battery energy, could reduce CO_2 emissions of 2.278 tons with a daily production capacity of 150 kg of hydrogen [58].

Farah et al., introduced an AI-based long-term planner for green hydrogen production in a grid-connected renewable energy system [59]. This planner simultaneously minimizes costs and CO_2 emissions, enabling significant reductions in emissions with only minor increases in cost(Figure 11)[60,61].

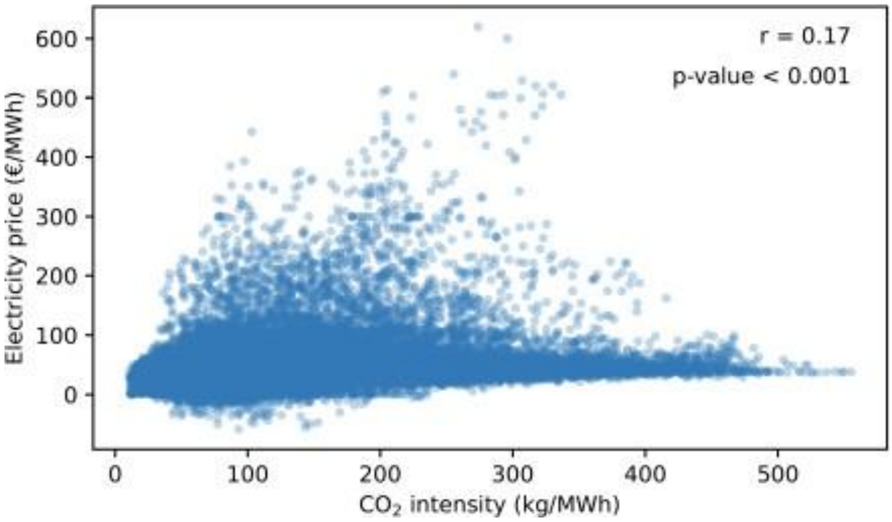

Figure 10. Correlation of electricity price [60] and CO_{2eq} intensity[61] in Denmark

In a recent study, Lan and Yao investigated the potential of artificial intelligence in the production of green hydrogen via the gasification of mixed plastic waste [62]. Their findings suggest that compared with traditional stream plastics, this approach could significantly reduce greenhouse gas emissions.

4. CONCLUSION

Driven by algorithmic optimization, neural networks, and machine learning, artificial intelligence (AI) enables efficient, cost-effective, and low-carbon production of green hydrogen. The provided use cases provide sufficient evidence of the potential for AI to be implemented in order to optimize production, demand, and yield. The use of AI in the production of green hydrogen represents a significant advancement in the technological arsenal employed in the pursuit of a sustainable energy transition. The review of the existing literature included the applications of AI for electrolyzer optimization, modeling, feasibility studies and simulations, and intelligent energy management. To enable the global deployment of this technology, international cooperation must be promoted, and more research must be conducted to tackle the remaining challenges.

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Declarations of interest

The authors declare no conflict of interest in this reported work.

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