International Journal of Applied Mathematics
Volume 38 No. 9s, 2025
ISSN: 1311-1728 (printed version); ISSN: 1314-8060 (on-line version)

AI-ENABLED OPTIMIZATION OF SOLAR PHOTOVOLTAIC–HYDROGEN ELECTROLYSER SYSTEMS FOR SUSTAINABLE ENERGY TRANSITION

Aishwarya Shinde[1,2], Anita Agrawal[1*]

[1]K K Birla Institute of Technolgy, Pilani-Goa, 403726, Goa, India.

[2]KIT's college of engineering Kolhapur, 416234, Maharashtra, India.

dandekar.aishwawrya@kitcoek.in

***Correspondence:**

Anita Agrawal,

[1]K K Birla Institute of Technolgy, Pilani-Goa, 403726, Goa, India. aagrawal@goa.bits-pilani.ac.in

Email: p20230071@goa.bits-pilani.ac.in , aagrawal@goa.bits-pilani.ac.in

Abstract

Green hydrogen that is produced through the process of electrolysis with renewable energy is already considered one of the linchpins of the global energy switchover. Even with a rapid technological development, operational inefficiencies as well as intermittency of renewable supply and safety issues still continue to hinder large scale deployment. The paper under study explores how artificial intelligence (AI) and machine learning (ML) can be utilized to transform solar photovoltaic (PV)-hydrogen systems into sustainable energy integration. We also provide a comparative analysis of AI-based algorithms such as supervised learning models, random forests, genetic algorithms, reinforcement learning, and fuzzy logic controllers with their corresponding strengths in predicting the availability of renewable energy, improving the efficiency of electrolyser, predicting maintenance requirements, and allowing dynamic grid integration. In addition to technical optimization, we touch on important regulatory, ethical, and safety issues related to AI-based hydrogen production, including data governance, transparency, and operational risks. By summarizing the findings of recent studies and defining the current methods deficiencies, this paper suggests a model to apply AI to hydrogen systems, which will be efficient, safe, and sustainable. The results emphasize opportunities of AI to expedite the process of green hydrogen infrastructure deployment and help in building resilient low-carbon energy networks.

Keywords: Green hydrogen; hydrogen production; energy policy; renewable energy technologies; energy transition; electrolysis

1. Introduction

The decarbonization of the world energy system is the issue of primary concern in the 21 st century. As the demands to achieve the targets established by the Paris Accord and the further international climate agreements grow, the world is actively investing in renewable energy sources and green fuels. Green hydrogen has become one of them, being a general-purpose

Received: August 10, 2025

International Journal of Applied Mathematics
Volume 38 No. 9s, 2025
ISSN: 1311-1728 (printed version); ISSN: 1314-8060 (on-line version)

energy carrier that can be utilized to maintain grid stability, to provide long-term storage, and to decarbonize those sectors, which are hard to decarbonize, including steelmaking, chemicals, and heavy transport. As compared to hydrogen generated using fossil fuels, green hydrogen is made using an electrolysis of water that is solely energized by renewable energy, including solar and wind.[1] The process will guarantee almost zero greenhouse gas emissions hence, hydrogen production will be in line with climate neutrality goals. Although it has potential, three recurring challenges, namely, limit the roll out of green hydrogen: Liquidity bottlenecks in electrolysis operations especially when operating within dynamic conditions that are associated with fluctuating renewable energy sources. Complexities of integrating hydrogen generation with variable solar and wind generation. Economicaly the levelized cost of hydrogen is still higher than the fossil-fuel-based options. [2]These barriers may be overcome with the help of artificial intelligence (AI) and machine learning (ML), which provide the possibility to optimize hydrogen systems in real-time. In contrast to conventional control methods, AI techniques are able to process high-dimensional data, acquire non-linear relationships, and evolve dynamically to uncertain working conditions. They have found application in predicting the renewable energy generation, predictive maintenance of electrolysers, optimization of processes and grid integration decision support. The initial results indicate that AI-based solutions can save up to 20 percent of energy during the electrolysis process, increase the lifecycle of equipments and enhance safety measures.[3] Recent literature has worked on applying various AI techniques to hydrogen systems, such as regression models, neural networks, genetic algorithms, reinforcement learning and fuzzy logic. Most of the studies are however, disjointed either in terms of developing algorithms or doing pilot projects on a small scale. The scientific analysis of AI methods in solar PV-hydrogen integration, in particular, is not carried out thoroughly and comparatively. Moreover, although the technical potential of AI is well-known, ethical and regulatory aspects, including data privacy, accountability and adherence to the hydrogen safety standards, have been insufficiently studied by scholars. The following paper will fill these gaps by: Survey of the state of the art in AI-based optimization of green hydrogen generation. Performance, scalability and applicability Comparison of major algorithms to PV-hydrogen systems. Looking at the ethics, safety, and policy implications of the deployment of AI. Offering a road map of future research that will combine AI with digital twins, hybrid physics-ML models, and regulatory innovation. Placing AI in the context of the energy transition discourse, this paper will add to the current discussion on how the advanced digital technologies can make green hydrogen commercially viable and sustainable. The presented insights are especially useful to scholars, policymakers, and industry stakeholders to essentialize the role of hydrogen in the next-generation energy systems.

PV Integration and Green Hydrogen Production.

Green hydrogen can be utilized in the energy transition process in various ways.The vision of a net-zero emission environment has placed the concept of green hydrogen as one of the essential elements in the future energy mix.[4] Green hydrogen is a renewable hydrogen which is produced by electrolyzing water by using renewable electricity as compared to grey or blue hydrogen which uses fossil fuels and capturing of carbon. [5]This allows the decarbonization of other industries that are outside of the immediate access of renewable electricity, such as

Received: August 10, 2025

heavy industry, aviation, and long-haul transport.[6] Hydrogen can equally serve as a energy vector that can store any surplus renewable energy, intermittency reduction and enhancement of stability of the entire grid. According to the International Energy Agency, hydrogen might be used to meet close to 10 percent of the global energy demand in 2050, should large-scale and cost-competitive green hydrogen infrastructure exist.[7], [8], [9]

2. Methodology

2.1 Electrolysis Technologies

Electrolysis is the key to green hydrogen generation, and in it, hydrogen and oxygen are formed by dividing the water molecules with the help of electricity.[10], [11] Some of the commercialized or developing technologies in electrolyser include: The most developed technology is the alkaline Electrolyser (AEL): using aqueous alkaline solutions (KOH or NaOH). AELs are less efficient in variable renewable inputs and are not as effective in dynamic response, although they are cost-effective.

Proton Exchange Membrane (PEM) Electrolyser: Has increased efficiency, fast load-following and can be smaller. PEMs are appealing to be coupled with solar PV and wind but are expensive with platinum and iridium as catalysts.

Solid Oxide Electrolyser (SOE): It is a high temperature operation (600-800 degC), and it has high efficiencies by way of utilizing heat energy. SOEs have potentials of integrating the industries but still at the initial stages of commercialization.

Anion Exchange Membrane (AEM) Electrolyser: A comparatively new type that integrates the features of PEM and alkaline systems and can be characterized by the low material costs and quite good dynamic performance.

These electrolysers are highly sensitive to the operating conditions because their efficiency is greatly affected by current density, temperature, pressure and purity of water.[12] With the rise in the scale of renewable-powered hydrogen plants, the characteristics of the operating conditions will vary considerably, which is why highly-developed optimization tools, including AI, will be necessary to sustain high performance.

2.2 Problems with Hydrogen Production with Renewable energy sources.

Even though the decision to produce hydrogen and renewable energy simultaneously gets rid of emissions, it also presents a number of operational and financial issues. Renewable Generation intermittency: Solar PV and wind power are variable in nature and hence, have fluctuating input electricity. [13], [14]Electrolysers will have to operate dynamically without the need to trade off lifetime and efficiency.

Partial Load Operation: Intensive ramping and partial load operation heightens the degradation rate, which impacts the stack durability and cost increment.

Grid Integration: The large scale implementation needs co-ordination with grid demand, peak shaving and storage.

Received: August 10, 2025

Economic Competitiveness: Levelized cost of hydrogen (LCOH) is currently higher than fossil-based options, which restricts its short-term use without subsidies or regulation.

To respond to such issues, it is not only necessary to engage in technological advances in the design of electrolyser but also to have operational intelligence based on the data that AI can be especially important in the future.

2.3 System Architecture of PV-Hydrogen Integration.

A conventional PV-hydrogen system is a system comprising three subsystems:

Solar PV Generation Photovoltaic modules, DC-DC converters, and maximum power point tracking (MPPT).

Energy Storage and interrelation to the grid: Hydrogen storage tanks, batteries and direct grid interconnection as balancing options are possible. There must be real-time control amongst these subsystems in order to achieve effective integration. Indicatively, variations in the amount of sun radiation can be evened with MPPT algorithms, which will result in the highest PV production. [15]Nevertheless, electrolysers should also be used in safe current density and pressure ranges. The real-time implementation of these goals is computationally expensive, which opens opportunities to AI-based solutions.

The operations of the electrolyser have been controlled by conventional control methods, including proportional-integral-derivative (PID) controllers. In the same way, there is the application of heuristic methods of scheduling to handle renewable intermittency. Although these methods work with small-scale systems, they are limited when scaled. Rules-based controls do not perform well in highly variable and multi-objective operating environments. General traditional models do not easily adapt to new patterns of data or evolving environmental conditions. Reactive management is associated with inefficiencies and increased cost of maintenance.[16] Conversely, AI and ML solutions exploit historical and real-time data to understand the best reaction and consequently allow predictive and adaptive control policies. This data-driven paradigm shift to the deterministic one is a paradigm shift in the management of a hydrogen system.

With the above-presented challenges, AI technologies are becoming more and more used to combat them. Key opportunities include predicting Solar Irradiance and Load Profiles by using ML algorithms (e.g., recurrent neural network) used to forecast PV generation and hydrogen demand on a high-temporal basis. Efficiency Improvement in Electrolyser by using real time current density, temperature and pressure optimization to optimise the hydrogen yield at the lowest possible degradation. The predictive maintenance predicts the failure of components in PV modules, inverters or electrolyser stack to minimize downtime. Hybrid Energy Management by integrating PV, batteries and hydrogen storage to achieve maximum system efficiency[17]. All these abilities highlight the fact that AI can help make the process of PV-hydrogen integration not only technically possible but also a viable and profitable energy solution.

Received: August 10, 2025

International Journal of Applied Mathematics
Volume 38 No. 9s, 2025
ISSN: 1311-1728 (printed version); ISSN: 1314-8060 (on-line version)

2.4 Artificial Intelligence in Hydrogen Systems.

Modern energy systems have been transformed by artificial intelligence (AI) and machine learning (ML) to offer predictive control, adaptive control, and optimization-based control, which are not limited to rule-based approaches. In the green hydrogen production setting, AI technologies can be used as key facilitators in tackling the issue of renewable variability, the efficiency of electrolysers, and the cost competitiveness.[18] In contrast to conventional algorithms that rely on the established assumptions to a large extent, AI systems are able to learn based on past and current data, identify concealed trends, and keep enhancing the quality of decisions when there is uncertainty.

The applications made to AI in PV-hydrogen systems have been divided into four areas, Projection and estimation (renewable availability, hydrogen demand, equipment degradation),optimization of the processes (real-time electrolyser, optimization of the efficiency), fault diagnosis and predictive maintenance, system level integration and energy management. The following section is a detailed discussion of the aspects as a whole, showcasing the algorithms, approaches, and practical implementations that characterize the transformative nature of AI in hydrogen systems.

2.5 Prediction of availability of Renewable energy.

Among the greatest obstacles to the integration of PV and Hydrogen generation is the intermittent nature of the solar generation. Effective prediction of solar irradiance and temperature is needed to make sure that the operation of the electrolyser stays within the optimal levels. Data-driven models are AIs that have been demonstrated to be superior to either physical or statistical models.[19]

Time-Series Models: Recurrent Neural Networks (RNNs) and Long Short-Term Memory (LSTM) networks are usually employed in short-term PV power prediction. These models are a representation of the time dependencies in irradiance and load patterns.

Hybrid Models: Physics-informed ML models combine both weather forecast data and AI predictions so that it is more accurate in extreme conditions, like cloud transients.

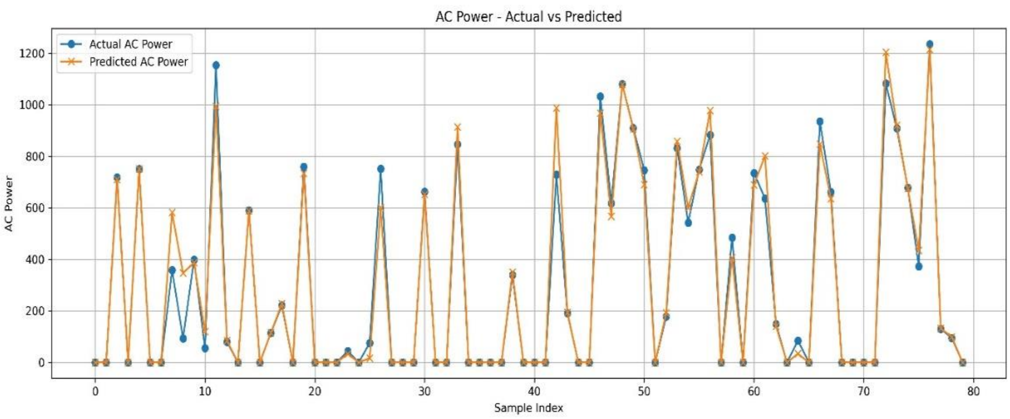


Table 1: AC Power(Actual vs Predicted)

Received: August 10, 2025

International Journal of Applied Mathematics
Volume 38 No. 9s, 2025
ISSN: 1311-1728 (printed version); ISSN: 1314-8060 (on-line version)

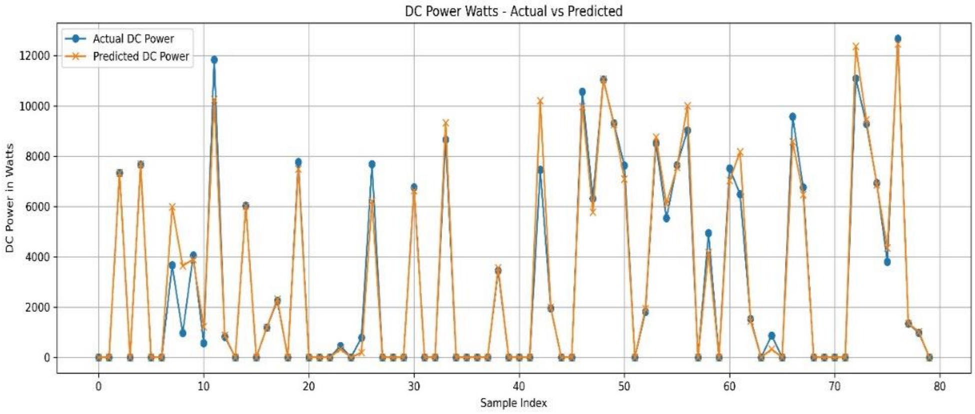


Table 2: DC Power(Actual vs Predicted)

Use in Hydrogen Systems AI can predict PV generation to schedule loads in an electrolyser, hydrogen storage process, or load import of auxiliary grid electricity. This ensures that there is a slight number of start-stop cycles, and this lowers wear and tear. Research indicates that AI-based solar forecasts in hydrogen plants can boost the utilization rate of electrolyser by 15-20, which has a direct impact on cost competitiveness.The predictive and actual Output of AC and DC power can be seen in table1 and table 2 respectively.

2.5 Maintenance Prognostics and Fault Diagnostics.

Unplanned downtime of hydrogen systems may cause massive financial losses particularly on a utility scale. Artificial intelligence has the ability to forecast maintenance through sensor data analysis which helps in identifying anomalies and forecasting failures before they transpire.

Anomaly Detection: Unsupervised learning algorithms like k-means clustering or autoencoders detect abnormalities in normal operation (e.g., abrupt voltage spikes or unusual temperature increase).

Remaining Useful Life (RUL) Prediction: RNNs and survival analysis models are used to predict the remaining useful life of electrolyser stacks or PV inverters.

Type of Fault: Random Forests and Support Vector Machines (SVMs) determine the type of faults to avoid confusion during the identification of the maintenance crews of the most important tasks.

Case studies indicate that predictive maintenance made possible by AI has the potential to cut unforeseen downtimes by 30-40% of the case with significant cost savings and safety improvement.

2.6 System Level Integration and Energy Management.

In addition to the component level, AI will be one of the key components in the overall control of PV-hydrogen systems at the system level, especially when combined with storage and the electrical grid.

Received: August 10, 2025

ISSN: 1311-1728 (printed version); ISSN: 1314-8060 (on-line version)

Energy Scheduling: AI based optimization systems optimize the distributions of electricity between PV output, electrolyser load, hydrogen storage, and grid exports.

Demand Response: AI has the potential to optimise cost by predicting price signals of electricity using AI, and also predicting the demand of hydrogen to ensure production does not exceed its cost limits, but meets demand reliably.

Hybrid Energy Management: Batteries and hydrogen storage need to be managed together. The AI methods that may be used to dynamically assign energy flows include Fuzzy Logic Controllers (FLCs), and reinforcement learning.

As an illustration, an AI-controlled hybrid PV-battery-hydrogen system recorded 20-25 percent cheaper LCOH than those controlled through other heuristic methods.There are various algorithmic strategies in the implementation of AI in hydrogen systems with strengths and weaknesses:

Machine Learning (ML): Regression and supervised ML techniques are ideal at making predictions of forecasts and yields and usually need massive datasets that are high quality.

Neural Networks (NN): Good at finding the complicated nonlinear relationships, but tends to overfit without sufficient data.

Random Forests (RF): The RFs are strong, interpretable, and do not easily overfit which means that they can be used to analyze feature importance (e.g. which input variables have the strongest impact on hydrogen yield).

Genetic Algorithms (GA): Effective in multi-objective optimization although is computationally expensive.

Fuzzy Logic Controllers (FLC): Are useful in uncertain situations, and allow the creation of decisions based on rules, when the precise models were not possible.

Reinforcement Learning (RL): Adaptive and scalable, especially when training long-term optimization, but can be very resource-demanding.

All the algorithms have shown their difference in application- to schedule electrolyser processes given varying PV supply or detect faults in gas separator units. The most important lesson to draw is that there is no consensus on the best algorithm; hybrid and ensemble methods, in most cases, are more useful than single models.

The use of AI in the form of an integration has several real advantages at the technical, economic, and ecological levels. Enhanced efficiency of electrolyser, low degradation rates, enhanced stability of systems. Decreased cost of operation due to predictive maintenance, optimal scheduling, and energy wastage decrease. The early fault detection reduces the risks related to the leakage of hydrogen or component failure. A high level of renewable integration will maximize the yield of hydrogen and minimize the intensity of carbon. According to modeling research, AI plants in hydrogen will be able to cut costs by up to 30 percent relative to traditional control approaches, and this is the transformative value of digitalization.[20]

Received: August 10, 2025

International Journal of Applied Mathematics
Volume 38 No. 9s, 2025
ISSN: 1311-1728 (printed version); ISSN: 1314-8060 (on-line version)

Although AI has promised immensely, its use in hydrogen systems is not an easy task.Given below are the drawbacks:

Hackers Data Scarcity: The data of electrolyzer especially the data of operation and failure is usually proprietary and scarce. This limits the training of models.

Computational Requirements: State-of-the-art models like deep RL require massive amounts of computation, which is not necessarily possible with smaller operators.

Generalization Problems: Models that have been trained in a certain condition do not perform very well when used in other climates, type of electrolyser, or scale of electrolyser.

Transparency and Interpretability: Black-box models like deep neural networks are associated with accountability issues, especially with safety-critical systems like hydrogen production.

These issues demonstrate the necessity of the hybrid strategies (the integration of data-driven AI and physics-informed models) and the creation of explainable AI (XAI) to enhance credibility and regulation acceptance.

2.7 Comparison of AI Algorithms of PV-Hydrogen Systems.

Regression / ML Hydrogen yield, efficiency prediction Simple, interpretable, low computation Poor behavior of nonlinear dynamics, poor scalability Small-scale forecasting, scholarship studies.

Random Forest (RF) Predictive maintenance, feature importance, diagnostics Robust, can predict large numbers of variables, interpretable Slower to real-time control, must be tuned Diagnostics, maintenance optimization

Neural Networks (NN) PV forecasting, electrolyser modelling, RUL prediction Nonlinearities, high accuracy, data-hungry, risk of overfitting, black-box, real time prediction, forecasting.

Reinforcement Learning (RL) Energy scheduling, electrolyser lifetime optimization Adaptive, long-term optimization, scalable High computational need, needs a training environment Real-time control, advanced plants.

Genetic Algorithms (GA) System design optimization, hybrid system scheduling large solution space, multi-objective Computationally expensive, risk of early convergence Planning and design optimization

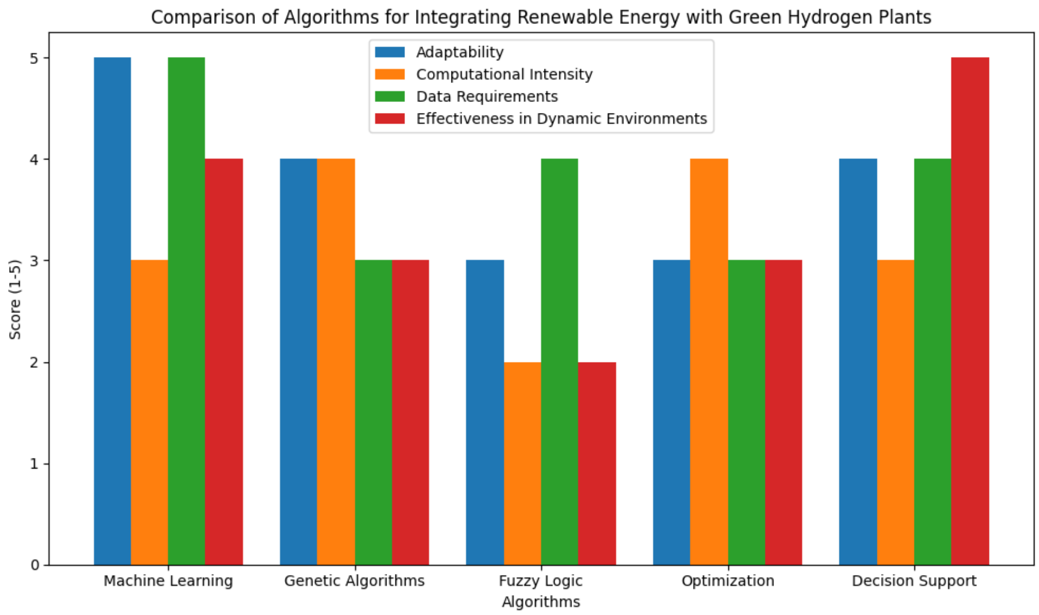
Fuzzy Logic Systems Uncertain control in electrolyser, hybrid control, easy to understand, low data, difficult to scale up Less adaptive, difficult to scale up Pilot plants, uncertain, hard to manage environments

Ethical, Safety and Regulatory.

Received: August 10, 2025

International Journal of Applied Mathematics
Volume 38 No. 9s, 2025
ISSN: 1311-1728 (printed version); ISSN: 1314-8060 (on-line version)

Introduction of Artificial Intelligence (AI) in hydrogen production systems has an unlimited potential of optimization, cost saving, and stability. Nevertheless, it creates new ethical, safety, and regulatory issues. Hydrogen is an energy carrier that has inherent dangers, flammability, high-pressure storage, and explosive dangers. Introduction of AI-controlled decision-making points to the issues of accountability, transparency and compliance in safety-critical scenarios. The paragraph examines the moral obligation, safety measures, and legal provisions that must be in place to use AI ethically in PV-hydrogen systems.



2.8 Ethical Considerations

The approach to transparency and explainability is ensured to a high level.

Transparency and Explainability.

A large number of AI algorithms, especially deep neural networks are black boxes and it is hard to understand how decisions are made. Explainability is unimportant in safety-critical hydrogen usage, as it leads to mistrust within the stakeholder group and legal ambiguity.

Issue: In case of one of the electrolyzer controlled by AI, where a failure occurs resulting in an accident, the operators should be able to prove how and why the AI took the specific decisions.

Solution: Transparency can be enhanced by adopting Explainable AI (XAI) frameworks that can identify important features that are driving AI decisions, including SHAP (SHapley Additive Explanations) or LIME (Local Interpretable Model-agnostic Explanations).

Data Privacy and Ownership

Hydrogen systems based on AI depend on operational sensor information, weather predictions, and grid interactions greatly. Gathering and sharing such data provokes the concerns of privacy and ownership.It is advisable to implement data-sharing protocols with ownership rights and

Received: August 10, 2025

anonymization criteria to make sure that it not only generates innovation but also keeps it confidential.

Ethical Use of Resources

The AI models are usually demanding of large datasets and high-performance computing, which consume indirectly more carbon footprints through the training. The utilization of AI needs to be ethically deployed by weighing between the efficiency benefits and the environmental price of its computer infrastructure. Such strategies as edge computing and lightweight AI models can decrease unnecessary computation.

Safety Considerations

Hydrogen is inflammable, colourless and odourless. The control systems based on AI used to control the system might fail to predict the occurrence of abnormal conditions like leaks, overpressure, or cooling failures, thus increasing the risk. Thus, integration of AI should not be used instead of already implemented engineering safety standards. Predictive Safety Management: This involves implementing preventive measures for safety concerns that are anticipated to occur within a specific timeframe. This is the use of preventive measures against safety issues that are expected to happen in a given time.

AI will help in enhancing safety by early leak detection using Artificial Intelligence based on the anomaly detection algorithms trained on pressure and gas concentration data. Overpressure Prevention by Reinforcement learning systems which dynamically control working pressures. Safety Shutdown Systems using Fuzzy logic based controllers that give interpretable, rule based decisions in cases of emergency. As a system that allows predicting risks in real-time, AI can significantly minimize the number of accidents, although it should be subject to a supervisory layer that ensures a correction to a minimum.

Human-AI Collaboration

Hydrogen safety is an area that cannot be fully replaced through automated decision-making. The system must have a human-in-the-loop structure, and AI is able to make suggestions but the final decision made by trained operators. These frameworks are accountable and enhance safety in operation since they combine human judgment with the accuracy of computations.

Regulatory Considerations

Currently available hydrogen safety standards, e.g., the ISO 19880 of hydrogen fueling stations, are mainly mechanical, electrical and process oriented. They are yet to reliably deal with AI-informed decision-making in hydrogen plants. This ambiguity poses a risk to developers and operators of AI-based control systems due to this regulatory lag.

AI-Specific Standards Requirement.

The policymakers should increase regulatory frameworks to consider algorithmic Transparency, declarations of AI models, training data, and validation outputs.Cybersecurity Measures as hackers can attack hydrogen plants in a cyber-physical attack, AI systems should be resistant to adversarial interference. Accountability Structures to establish liability in case

Received: August 10, 2025

International Journal of Applied Mathematics
Volume 38 No. 9s, 2025
ISSN: 1311-1728 (printed version); ISSN: 1314-8060 (on-line version)

of system failures caused by AI errors. The project should be integrated with renewable policies to boost the project's viability and sustainability.

Renewable Policies Integration as the project is supposed to be coupled with renewable policies to enhance the viability and sustainability of the project. Artificial intelligence hydrogen systems should also be in line with the bigger renewable energy strategies. As an example, the National Green Hydrogen Mission (2023) of India promotes the use of AI in enhancing production efficiency but has not yet outlined how ethical deployment of AI should be. To speed up the adoption and at the same time provide safety, harmonizing renewable energy incentives and AI governance frameworks will be necessary.

2.9 Case Studies and Lessons Learned.

European Union Approach

EU has been active in preparing the Artificial Intelligence Act (2021) that categorises AI in critical infrastructure (including energy) as high-risk. Under this category, AI that is used in hydrogen facilities would be tested, documented, and certified before it is released into the market. This method creates the precedent of AI regulation in hydrogen safety standards.

Japan's Hydrogen Roadmap

The Hydrogen plan in Japan is focused on design with safety-first. Although the concept of AI is not explicitly regulated yet, there are demonstration projects that indicate the ways that predictive maintenance algorithms can minimize operational risk in PEM electrolysers. It is a case study that technology generally outpaces the policy, yet practical pilots could guide the changes in regulation.

India's Regulatory Gap

The hydrogen regulatory environment in India is still on its early stages. Although there are safety codes of storage and transport, there are no clear specifications of AI deployment. Such a gap gives India a chance to build on integrated digital safety regulations as part of its National Green Hydrogen Mission which may become an international standard.

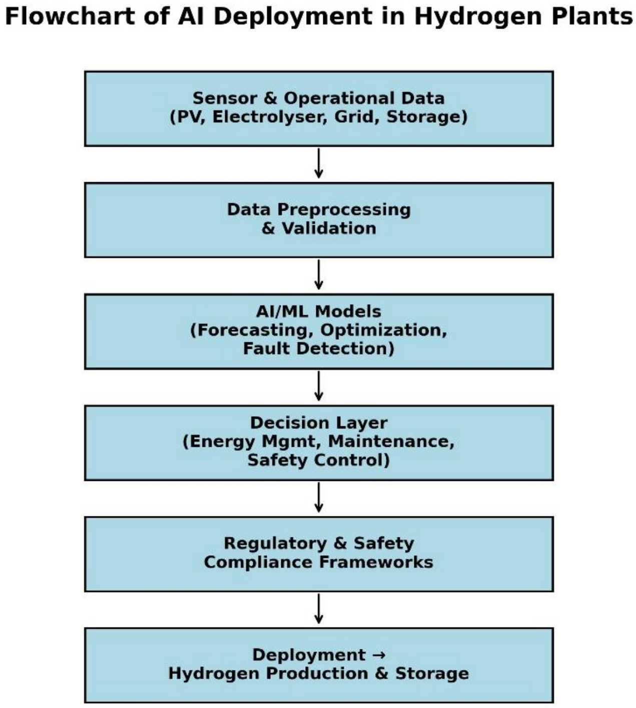
Ethical AI Framework Proposal in Hydrogen Systems.

In accordance with the discussion above we suggest a five-layered structure of ethical and safe AI implementation in PV-hydrogen plants (as shown in Figure 5):

Figure 5: Flowchart of AI Deployment in Hydrogen Plants

Received: August 10, 2025

International Journal of Applied Mathematics
Volume 38 No. 9s, 2025
ISSN: 1311-1728 (printed version); ISSN: 1314-8060 (on-line version)



Data Layer: Make sure that operational data is collected in a manner that is privacy compliant and secure.

AI Processing Layer: Use intelligible and transparent models where feasible.

Decision Layer: Have human control, and AI should not be the ultimate decision-maker but offer suggestions instead.

Regulatory Layer: Implement adherence to hydrogen safety measures, AI ethics, and cybersecurity regulations. Deployment Layer: constant track of AI-driven decision-making in terms of safety KPIs and ethical standards. This is a stratified strategy that will guarantee the use of AI as an efficiency and safety facilitator and not a genesis of novel risks.

AI implementation in the hydrogen production provides unparalleled prospects of efficiency, predictive safety, and affordability. Nevertheless, in the absence of effective ethical, safety and regulatory frameworks, these technologies might bring about unacceptable risks. Industry, policymakers, and researchers should ensure that they work to develop AI-specific standards, expand the already present hydrogen safety codes and make it mandatory that the human-in-the-loop decision-making framework is implemented.

Although AI-based optimization of PV-hydrogen systems is a relatively new research area, a number of pilot projects, demonstration plants, and research show how these technologies are implemented in the real world. These examples indicate the variety of the AI application - forecasting and scheduling to predictive maintenance and reveal the possible advantages and challenges of the digitalized hydrogen infrastructure. Notably, geography influences the use of AI in green hydrogen, as seen in that regional policies, energy resources, and industrial needs

Received: August 10, 2025

affect both the growth of AI in energy and its use in green regions like Europe, Japan, and India.

Europe: Hydrogen Valleys with AI.

Some of the Hydrogen Valley projects spearheaded by the European Union combine the generation of renewable, the production of hydrogen, and inclusion in the ecosystem of the regions. The HEAVENN project in Northern Netherlands is an integration of wind, solar and electrolysis plants along with hydrogen storage and distribution. AI models are deployed for:

Energy forecasting: The PV and wind output are predicted to improve the scheduling plans of the electrolyser.

Load balancing: Reinforcement learning algorithms identify when the energy should be redirected on hydrogen production or grid export.

Predictive maintenance: Predictive maintenance involves the use of machine learning to predict failures of inverter and electrolyser stacks.

The findings show that there is a 15 percent decrease in operation downtime and enhancement in the rate of utilization of the electrolyser, which highlights the contribution of AI on the project economics.

Japan: AI to Manage PEM Electrolyser.

To date, the Fukushima Hydrogen Energy Research Field (FH2R) is one of the largest Hydrogen demonstration facilities in the world which is mainly solar powered with PV. The plant employs AI for:

Predicting the solar irradiance to predict the PV output.

Coordinating the production of hydrogen with mobility and industrial demand.

The optimization of the electrolyser working efficiency on the basis of neural networks modifying the operating parameters in time.

The incorporation of AI has enabled FH2R to stabilize the hydrogen production despite the weather conditions that are very unpredictable. According to the system, up to 20 percent efficiency gains were observed over the ability to operate the system without AI.

America: AI in Hydrogen Microgrids with PV-Battery.

Experiments have been conducted in California with a few micro grid projects trying to combine PV, battery storage and hydrogen into a single system to provide grid stability. The title implies that AI algorithms, especially fuzzy logic controllers are used to deal with variability and uncertainty:

PV is given priority of the short term demand.Unutilized energy is actively used to charge the batteries (short-term storage) and hydrogen (long-term storage).The AI scheduling is the most effective at minimizing costs and taking into consideration the electricity tariffs and demand-response incentives.The results of these pilot systems demonstrate that levelized cost of hydrogen (LCOH) can approach a 20 to 25 percent reduction with the use of hybrid energy

Received: August 10, 2025

management and AI, and that can serve as a model region with a high level of renewable penetration.

Middle East: AI in Solar-to-Hydrogen in Arid Areas.

Large scale PV-hydrogen projects are being motivated by the presence of large quantities of solar resources in the Middle East and ambitious hydrogen export policies. An example of this is the NEOM hydrogen project of Saudi Arabia, which will deploy AI to:Prediction of dust and temperature effects on the PV performance.The optimization of the cooling systems of electrolyser under severe conditions.The water desalination and purification with the hydrogen production.

Through AI prediction and optimization of hardware, the project expects to save up to 30 percent of the operational costs, which is essential to establish green hydrogen as a competitive export product.

Case Insights from India

The National Green Hydrogen Mission of India.

The National Green Hydrogen Mission (NGHM) was launched in 2023 to transform India into a global centre of green hydrogen production. AI is the key aspect in the technological roadmap of the mission, with special focus on:

Predicting renewable variability: How to use the large base of solar resources in India to schedule electrolyser optimally.

Resource allocation: AI-site selection models are being deployed to find the best hydrogen hubs based on such criteria as solar irradiance, land availability and water access.

Reduction of costs: AI has been applied in the techno-economic studies to maximize the settings of PV-hydrogen systems.

AI-enabled predictive control strategies on electrolysers that are part of solar PV farms are piloted in NGHM, especially in Gujarat and Rajasthan.

AI in PV-Hydrogen Microgrids to rural electrification.

Decentralized PV-hydrogen microgrids are being considered in remote parts of India as one way of access to energy and rural electrification. AI applications include:

Load forecasting: The prediction of the patterns of the demand of electricity in rural regions which tend to be irregular.

Hybrid management: The reduction of PV supply and hydrogen production with the restricted battery storage to serve continuously.

Safety monitoring: AI-based anomaly detection to track leaks or pressure variations of hydrogen in low-resource environments.

Received: August 10, 2025

The field tests in Maharashtra and Karnataka in villages have demonstrated that AI-upgraded microgrids may be used as reliable sources of power with minimum curtailment to enhance the social acceptability of hydrogen systems.

Indian Industry Initiatives

Indian firms like NTPC, Reliance and Adani are engaged in massive investments in green hydrogen projects. Artificial intelligence applications are being introduced in, Plant digital twins, supply chain optimization, water resource management. The virtual models of the PV-hydrogen plants based on the AI that simulates and forecasts the performance of the plant in various operating conditions. AI-based models predict the demand of hydrogen in refinery plants, steel mills, and fertilizer plants, make production consistent with consumption. India faces the problem of water scarcity and AI is being used to ensure the optimization of using the recycled and desalinated water in electrolysis. These programs show that India is planning to not only roll out green hydrogen at scale, but also integrate AI as a fundamental driver of efficiency and sustainability.

Global and Indian Applications Lessons Learned.

Technical Lessons

AI increases efficiency and exploitation within hydrogen systems, yet the effectiveness of the use is highly determined by the quality of information and system design. Hybrid systems based on AI algorithms tend to be more effective than single plans, particularly in more complicated systems such as PV-hydrogen microgrids. Combining AI with digital twin platforms have strong capabilities of prediction both in operational optimization and long-term planning.

Economic Lessons

Predictive maintenance and scheduling implemented by AI always save operational expenses, which can be 20-30 percent. The cost of the first implementation of AI systems (software, sensors, computing infrastructure) is still an obstacle, especially in developing countries. Cost reductions are highly dependent on the size of the system, which implies that large industrial or export-driven hydrogen development is the area of AI implementation.

Policy Lessons

There are still regulatory loopholes in the regulation of AI applications, especially in the area of accountability in safety-critical systems. Examples of countries that have been at the forefront in the adoption of hydrogen (EU, Japan) indicate that pilot projects could provide feedback on regulation, developing a feedback loop between technology and policy. The policy framework offered by India NGHM is robust but should include AI-related guidelines to make the deployment safe and ethical.

Regulatory and Policy Innovation

Existing regulations of hydrogen systems deal with physical and process safety mainly, including the standards of storage of high-pressure systems on the high-pressure storage, pipeline transport, and refueling systems. As an example, ISO 19880 provides the technical

Received: August 10, 2025

recommendations of hydrogen fueling stations, whereas national standards of Japan and the EU are focused on the safety of materials and procedures. Nonetheless, all these frameworks do not consider properly the digital aspect brought by AI. The lack of AI-specific guidelines induces the uncertainty of three paramount domains liability, Transparency, Cybersecurity. In case of an accident that was caused by a malfunctioning decision of an AI system, the question of who bears the responsibility such as the developer, operator, or regulator is unclear. Black-box AI models are non-auditable and therefore make it difficult to verify compliance. AI-controlled hydrogen facilities are prone to cyber-physical attacks whereby the attackers can interfere with sensor data to promote undesirable operations.

AI Certification Protocols: This is similar to the certification of mechanical equipment and before the AI model can be installed in the hydrogen facilities, it must go through intensive validation and stress testing.

Cybersecurity Standards: The rules should stipulate encryption, intrusion detection, and AI-specific intrusion detection systems.

Explainability Requirements: AI systems used in safety-constrained scenarios must be able to have interpretable outputs, which are then regulators able to determine conformity.

International Harmonization: The creation of the international standards, which will be carried out by organizations like ISO, IEC, or IEA, will enable the cross-border hydrogen trade and investment to happen seamlessly.

Policy Experimentation

Hydrogen projects managed by AI could have a sensible way of innovation by regulatory sandboxes, which are controlled milieus where the new rules can be lax but controlled. These settings allow policy makers to obtain experience through real life deployments as well as reducing systemic risks. India, through its National Green Hydrogen Mission can be the first to take such experimental regulatory structures.

3. Results

Future Research Directions

Implementation of artificial intelligence (AI) in photovoltaic-hydrogen (PV-hydrogen) systems is still largely experimental, and the majority of deployments have been on pilot developments, laboratory experiments or small scale demonstrations. The initial evidence indicates improvements in productivity, cost reduction, and reliability; however, there are still strong research gaps. Specifically, AI models need to be subject to immediate review in terms of their scalability, interpretability, and governance before such technologies can be introduced into the industry or across the country safely. In this section, three key research directions of digital twins, hybrid AI -physics -informed, and regulatory innovation are outlined, and a roadmap to resistant, reliable, and sustainable AI-based hydrogen systems is outlined.

Hydrogen System Digital twins.

Received: August 10, 2025

International Journal of Applied Mathematics
Volume 38 No. 9s, 2025
ISSN: 1311-1728 (printed version); ISSN: 1314-8060 (on-line version)

A digital twin is a computer-based depiction of a real-world system, which develops in real time along with its real-world counterpart. Unlike the traditional simulations, digital twins are dynamic in nature: the hydrogen production facilities are simulated, which absorbs the real-time sensor data, the historical records of the performance, and predictive analytics to create a living image of the facility. Digital twins can bridge the gap between theory and practice in PV-hydrogen operation using simulations of electrolysers, PV arrays, storage vessels, grid interfaces, and other physical devices operating under a variety of conditions by simulating the whole system.

PV Hydrogen Integration Applications.

Performance Monitoring: Digital twins allow operators of photovoltaic generation to have a constant understanding of the efficiency of photovoltaic generation, kinetics of electrolyser degradation, as well as hydrogen purity measurements.

Fault Prediction: Integrated AI in the twin is able to identify warning signs of upcoming malfunctions and thus reduce unexpected downtime.

Scenario Testing: Digital twins can be used to simulate dangerous weather patterns, unstable demand curves or new operation strategies, and in doing so safely experiment with them without risking actual production.

Lifecycle Optimization Digital twins are able to evaluate the influence of operational decisions (e.g. oscillatory ramping and steady-state operation) on long-term electrolyser life and economic feasibility.

The nature of electrochemical processes in electrolysers is nonlinear; studies are necessary to reveal twins models of suitable tradeoff between accuracy and calculability. Digital twins have to accept heterogeneous data originating with PV sensors, electrolyser stack and storage containers which requires advanced data fusion algorithms. Absence of common interoperability standards means that twins of different manufactures will be isolated, and hence optimization of the system will be suppressed. The rural microgrids should have lightweight and edge-calculable twins, but more specific twins might be suitable in massive industrial hydrogen hubs. Digital twins, when properly developed, may serve as decision-support systems, which allows real-time optimization, predictive protection, and planning. They represent the shift of the reactive to the proactive management of plants, and they are core components of the PV-hydrogen integration in the next generation.

The drawbacks of Data-driven AI alone are modern AI hydrogen system models are strongly data-driven, in which correlations are deduced between input and output variables. Although effective in many settings, the models are faced by three major limitations:

Data Scarcity: Quality data on the degradation of electrolyser, fault cases, and dynamic hydrogen production is in many cases scarce or proprietary.

Over fitting: The models can be able to capture statistical patterns that do not have physical meaning, thus making it unstable in generalizing.

Received: August 10, 2025

Black-Box Concerns: AI can priorize the strategies of operation that are either unsafe or do not comply with the thermodynamic limitations.

Hybrid AI models combine predictive power of machine learning with the appeal of physics-based models. Researchers can achieve interpretability and precision equally by instantiating basic principles, namely energy conservation, electrochemical kinetics, and gas laws, into AI architectures. PV-Hydrogen System Applications include electrolyser modelling, real time control, degradation prediction. It is possible to use neural networks to predict the behaviour of a stack with electrolyte has been trained using physics based loss functions that respect electrochemical constraints. It is possible to use reinforcement learning agents together with physics-based simulators, which allows safe training of the agent before it can be deployed on real plants. Hybrid models have the ability to combine empirical with mechanistic models of membrane wear, catalyst poisoning and electrode corrosion to predict Remaining Useful Life.

The future work should be focused on prioritizing framework development having systematic ways of putting neural network components along with differential equations together. Transferability to assure hybrid models between electrolyser modalities (PEM, AEM, SOE) and geographic settings. Computational Efficiency spar the load of heavy processing of hybrid models to allow real-time implementation. Explainability to take advantage of the interpretability provided by physics constraints in achieving regulatory and stakeholder confidence.Hydrogen optimization Hybrid AI models are set to turn out to be the standard in optimizing hydrogen systems. Combining domain knowledge and machine learning, they bring together efficiency, reliability, and trustworthiness, which are critical to the protection of energy infrastructure with safety-related concerns.

4. Discussion

There are various measures that can be suggested regarding the potential of AI-powered hydrogen systems. In order to come up with technically sound, ethically responsible and regulatory-compliant AI models, co-disciplinary efforts must be undertaken by engineers, data scientists, and policymakers. The idea of scaling pilot to scale has to do with prioritisation of scaling of pilot knowledge into industrial deployments and such that AI benefits can be converted into the reduction of costs and global competitiveness. Hydrogen cross-border trade will be possible because AI standards can be developed through international collaboration and, as a result, interoperability among hydrogen hubs will be realized. AI is not only to be built in hydrogen plants but, it can be also oriented to connect the sector such as electric mobility, industrial decarbonisation, and smart grid integration.

Green hydrogen has the potential to be a foundation of the low-carbon energy system. This transition can be quickened by using AI in a responsible way, maximising efficiency, upholding safety, and reducing expenses. Nonetheless, AI is unified, its success will be determined by enough powerful datasets, transparent algorithms, human controls, and flexible regulatory frameworks. The implementation of these needs will enable the synergy between AI and hydrogen to trigger the development of a resilient, sustainable, and globally scalable energy infrastructure. The future will not be filled with small adaptations but a total change of the

Received: August 10, 2025

system that is digital intelligence and renewable hydrogen working together to alter the overall situation on the energy front.

5. Conclusions

It has been studied that Artificial Intelligence (AI) could be used to transform solar photovoltaic (PV) systems in terms of integrating them with hydrogen electrolysers with specific emphasis on efficiency and reliability improvements and sustainability. By reviewing existing technologies, discussing the functions of AI in optimisation, and comparing the essential algorithms, this paper has demonstrated the possibility to solve some of the most acute issues in green hydrogen implementation, such as efficiency constraints, variability in the functioning, and high costs of production. The paper has also been keen on the need to have responsible adoption of the technology by stressing on the ethical, safety, and regulatory considerations in addition to technical optimisation. AI has shown rather obvious benefits in the field of forecasting, optimization of the processes, predictive maintenance, and integration at the system level. Models like LSTM and regression-based forecasting are helpful to enhance the predictability of renewable energy as well as to synchronise the activities of electrolysers with the output of PV. Reinforcement learning and genetic algorithm optimisation algorithms actively modify electrolyser parameters and so minimise energy usage as well as increase the life span of stacks. Predictive maintenance technologies reduce unplanned maintenance, and it may help reduce operational expenses by 30-40 percent. System-level energy management systems combine hydrogen with batteries and the grid bringing the levelised cost of hydrogen (LCOH) down to as low as 25.

There are weaknesses and strengths of each algorithm. Simple and interpretable regression and supervised machine-learning models have limited scalability. Random forests are also robust and provide interpretability, which would be especially beneficial in the case of diagnostics. Nonlinear environments are the most precise with neural networks which labor intensively with large datasets. Although reinforcement learning offers flexibility and scaling, it is also expensive to compute. Genetic algorithms have a specific advantage in system design optimisation but less useful in the context of a real- time result. Fuzzy logic systems are well able to cope with uncertainty, but are not adaptive. The analysis indicates that hybrid and ensemble schemes, which had used combination of different algorithms, was the best performer in complex PV-hydrogen systems.

The present paper makes its contribution to the existing literature on green hydrogen and AI in a number of ways. It provides a comparative analysis of AI algorithms in the context of PV-hydrogen systems in particular, which is an area that is seldom covered by the existing reviews. It combines technological, moral, and legal aspects, hence offering a comprehensive approach to AI implementation in the sphere of hydrogen generation. It situates global learning in the context of India policy framework and dwells on the opportunities to develop AI-powered hydrogen within the framework of the National Green Hydrogen Mission. Lastly, it specifies a multi-tiered model, which consists of data, AI processing, decision, regulation, and deployment levels, to adopt ethical and safe AI usage in hydrogen plants.

Received: August 10, 2025

.References

[1] P. T. Borges *et al.*, "Photosynthetic green hydrogen: Advances, challenges, opportunities, and prospects," 2024. doi: 10.1016/j.ijhydene.2023.09.075.

[2] R. W. Makepeace, A. Tabandeh, M. J. Hossain, and M. Asaduz-Zaman, "Techno-economic analysis of green hydrogen export," *Int J Hydrogen Energy*, vol. 56, 2024, doi: 10.1016/j.ijhydene.2023.12.212.

[3] Z. Allal, H. N. Noura, O. Salman, and K. Chahine, "Machine learning solutions for renewable energy systems: Applications, challenges, limitations, and future directions," *J Environ Manage*, vol. 354, Mar. 2024, doi: 10.1016/j.jenvman.2024.120392.

[4] T. Yarally, L. Cruz, D. Feitosa, J. Sallou, and A. Van Deursen, "Uncovering Energy-Efficient Practices in Deep Learning Training: Preliminary Steps Towards Green AI," in *Proceedings - 2023 IEEE/ACM 2nd International Conference on AI Engineering - Software Engineering for AI, CAIN 2023*, Institute of Electrical and Electronics Engineers Inc., 2023, pp. 25–36. doi: 10.1109/CAIN58948.2023.00012.

[5] Q. Hassan, S. Algburi, A. Z. Sameen, H. M. Salman, and M. Jaszczur, "Green hydrogen: A pathway to a sustainable energy future," *Int J Hydrogen Energy*, vol. 50, 2024, doi: 10.1016/j.ijhydene.2023.08.321.

[6] M. Nasser, T. F. Megahed, S. Ookawara, and H. Hassan, "A review of water electrolysis–based systems for hydrogen production using hybrid/solar/wind energy systems," *Environmental Science and Pollution Research*, vol. 29, no. 58, pp. 86994–87018, Dec. 2022, doi: 10.1007/s11356-022-23323-y.

[7] M. Awad *et al.*, "A review of water electrolysis for green hydrogen generation considering PV/wind/hybrid/hydropower/geothermal/tidal and wave/biogas energy systems, economic analysis, and its application," 2024. doi: 10.1016/j.aej.2023.12.032.

[8] M. Zghaibeh *et al.*, "Optimization of green hydrogen production in hydroelectric-photovoltaic grid connected power station," *Int J Hydrogen Energy*, vol. 52, 2024, doi: 10.1016/j.ijhydene.2023.06.020.

[9] D. Rodríguez-Fontalvo, E. Quiroga, N. M. Cantillo, N. Sánchez, M. Figueredo, and M. Cobo, "Green hydrogen potential in tropical countries: The colombian case," *Int J Hydrogen Energy*, vol. 54, 2024, doi: 10.1016/j.ijhydene.2023.03.320.

[10] X. H. Nguyen and M. P. Nguyen, "Mathematical modeling of photovoltaic cell/module/arrays with tags in Matlab/Simulink," *Environmental Systems Research*, vol. 4, no. 1, Dec. 2015, doi: 10.1186/s40068-015-0047-9.

Received: August 10, 2025

[11] G. K. Karayel and I. Dincer, "Green hydrogen production potential of Canada with solar energy," *Renew Energy*, vol. 221, 2024, doi: 10.1016/j.renene.2023.119766.

[12] M. Saberiabkouhi Simone Mancin, C. Lars Jürgensen, and F. Kuhnen Hochschule Bremen, "Integrating AI and AEM Electrolyzer for Green Hydrogen Production: Optimization of Solar-Powered Electrolysis in Residential Energy Management Master Candidate Supervisor."

[13] J. Park, S. Kang, S. Kim, H. S. Cho, S. Heo, and J. H. Lee, "Techno-economic analysis of solar powered green hydrogen system based on multi-objective optimization of economics and productivity," *Energy Convers Manag*, vol. 299, 2024, doi: 10.1016/j.enconman.2023.117823.

[14] R. Tawn and J. Browell, "A review of very short-term wind and solar power forecasting," *Renewable and Sustainable Energy Reviews*, vol. 153, p. 111758, Jan. 2022, doi: 10.1016/j.rser.2021.111758.

[15] A. Irham, M. F. Roslan, K. P. Jern, M. A. Hannan, and T. M. I. Mahlia, "Hydrogen energy storage integrated grid: A bibliometric analysis for sustainable energy production," *Int J Hydrogen Energy*, vol. 63, pp. 1044–1087, Apr. 2024, doi: 10.1016/j.ijhydene.2024.03.235.

[16] M. Wadi, A. Shobole, W. Elmasry, and I. Kucuk, "Load frequency control in smart grids: A review of recent developments," Jan. 01, 2024, *Elsevier Ltd*. doi: 10.1016/j.rser.2023.114013.

[17] M. Swarnkar, M. Chopra, V. Dhote, N. Nigam, K. Upadhyaya, and M. Prajapati, "Use of AI for development and generation of renewable energy," in *2023 IEEE Renewable Energy and Sustainable E-Mobility Conference, RESEM 2023*, Institute of Electrical and Electronics Engineers Inc., 2023. doi: 10.1109/RESEM57584.2023.10236136.

[18] Kelvin Edem Bassey and Chinedu Ibegbulam, "MACHINE LEARNING FOR GREEN HYDROGEN PRODUCTION," *Computer Science & IT Research Journal*, vol. 4, no. 3, pp. 368–385, Dec. 2023, doi: 10.51594/csitrj.v4i3.1253.

[19] T. Liang, L. Chai, X. Cao, J. Tan, Y. Jing, and L. Lv, "Real-time optimization of large-scale hydrogen production systems using off-grid renewable energy: Scheduling strategy based on deep reinforcement learning," *Renew Energy*, vol. 224, Apr. 2024, doi: 10.1016/j.renene.2024.120177.

[20] Faisal Ghazi Bishaw, "Review Artificial Intelligence Applications in Renewable Energy Systems Integration," *Journal of Electrical Systems*, vol. 20, no. 3, pp. 566–582, Apr. 2024, doi: 10.52783/jes.2983.

Received: August 10, 2025