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Secure Hydrogen Production Analysis and Prediction Based on Blockchain Service Framework for Intelligent Power Management System

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Abstract: The rapid adoption of hydrogen as an eco-friendly energy source has necessitated the development of intelligent power management systems capable of efficiently utilizing hydrogen resources. However, guaranteeing the security and integrity of hydrogen-related data has become a significant challenge. This paper proposes a pioneering approach to ensure secure hydrogen data analysis by integrating blockchain technology, enhancing trust, transparency, and privacy in handling hydrogen-related information. Combining blockchain with intelligent power management systems makes the efficient utilization of hydrogen resources feasible. Using smart contracts and distributed ledger technology facilitates secure data analysis (SDA), real-time monitoring, prediction, and optimization of hydrogen-based power systems. The effectiveness and performance of the proposed approach are demonstrated through comprehensive case studies and simulations. Notably, our prediction models, including ABiLSTM, ALSTM, and ARNN, consistently delivered high accuracy with MAE values of approximately 0.154, 0.151, and 0.151, respectively, enhancing the security and efficiency of hydrogen consumption forecasts. The blockchain-based solution offers enhanced security, integrity, and privacy for hydrogen data analysis, thus advancing clean and sustainable energy systems. Additionally, the research identifies existing challenges and outlines future directions for further enhancing the proposed system. This study adds to the growing body of research on blockchain applications in the energy sector, specifically on secure hydrogen data analysis and intelligent power management systems.

Keywords: blockchain; IoT; hydrogen production; secure data-driven analysis; historical data management

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1. Introduction

Green hydrogen, produced from renewable sources such as wind, solar, and hydropower, has emerged as a promising solution to decarbonize the global energy system. It can potentially reduce greenhouse gas emissions, create new job opportunities, and contribute to energy security. However, effective management and analysis of the production and consumption data is crucial to achieve its full potential. This requires multiple data analytics techniques to extract valuable insights from the large amounts of data generated by green hydrogen production and consumption [1].

The analysis of green hydrogen production and consumption data can provide valuable insights into the production process's efficiency, the equipment's performance, and the impact of external factors such as weather and demand fluctuations. By employing data analytics techniques such as machine learning, statistical analysis, and optimization algorithms, patterns and correlations in the data can be identified, future trends can be predicted, and the production and consumption process can be optimized [2].

Furthermore, analyzing green hydrogen consumption data offers insights into the performance and efficiency of equipment that uses hydrogen, such as fuel cells, hydrogen turbines, and hydrogen engines. The data can be used to optimize equipment operation, improve performance and reliability, and reduce costs. Data analytics techniques also help identify potential issues and prevent equipment failures [3].

The effective management and analysis of green hydrogen production and consumption data can also contribute to developing policies and regulations that support the growth of the green hydrogen industry. The insights gained from data analysis can inform decision making, set targets and standards, and allocate resources effectively [4].

One of the primary challenges in managing green hydrogen production and consumption is the need for efficient data analytics techniques. The sheer volume of data generated from various sources, such as weather data, production logs, and consumption patterns, can be overwhelming. Various data analytics techniques such as correlation analysis, feature extraction, and pattern recognition are used to manage and analyze these data effectively. These techniques enable the identification of trends, patterns, and anomalies that aid in improving the efficiency of green hydrogen production and consumption [5].

Correlation analysis is an essential data analytics technique in green hydrogen production and consumption management. It examines the relationships between wind speed, solar irradiation, and hydrogen production variables. Correlation analysis helps identify the factors that influence green hydrogen production and consumption, enabling the development of better predictive models [6].

Feature extraction is another important data analytics technique used in green hydrogen management. It involves identifying relevant features from large datasets. Features such as wind speed, solar irradiation, and temperature in green hydrogen production and consumption provide valuable insights into the system's performance. By extracting these features, data analysts can identify patterns and trends that inform decisions related to system optimization and maintenance [7].

Pattern recognition is also a key data analytics technique in green hydrogen management. It involves identifying patterns or anomalies in datasets. In green hydrogen production and consumption, pattern recognition aids in detecting abnormal system behavior, such as a sudden drop in hydrogen production or consumption. By detecting and responding to these patterns, operators can improve the efficiency and reliability of the system [8,9].

Furthermore, blockchain technology plays several essential roles in green hydrogen production. It ensures the traceability and transparency of green hydrogen production by recording and verifying each step of the production process on a decentralized ledger [10]. Blockchain-based platforms facilitate the certification and verification of green hydrogen production according to specific standards, such as renewable energy sourcing or carbon intensity limits [11]. Additionally, blockchain enables the peer-to-peer trading of green hydrogen, eliminating the need for intermediaries. Through smart contracts, producers and consumers can directly trade hydrogen and settle transactions securely and efficiently [12,13]. Moreover, blockchain technology facilitates the integration of renewable energy sources into green hydrogen production, enabling the real-time monitoring of energy generation, consumption, and storage as well as optimizing the use of renewable energy sources [14].

Overall, the effective management and analysis of green hydrogen production and consumption data are crucial for harnessing the full potential of green hydrogen as a clean energy source. By utilizing various data analytics techniques and integrating blockchain technology, the intelligent power management system can optimize production and consumption, improve efficiency, and contribute to a sustainable and decarbonized energy future.

- In this paper, blockchain is applied for secure hydrogen data analysis, ensuring data integrity, transparency, and immutability, to enhance the security and trustworthiness of the hydrogen data analysis process.
- The paper proposes integrating intelligent power management systems with blockchain technology. It highlights the benefits of combining these two domains to optimize hydrogen generation, storage, and consumption, leading to more efficient and sustainable power management practices.
- The paper presents various data analysis techniques specifically tailored for hydrogen data analysis. These include correlation analysis, box plot analysis, feature ranking, and predictive analytics, enabling valuable insights and informed decision making.
- The paper addresses the security and privacy challenges associated with hydrogen data analysis. It proposes using encryption, access control mechanisms, and secure data handling protocols to safeguard sensitive information and ensure secure data management throughout the analysis process.
- The paper discusses the practical implementation aspects of the proposed system. It includes details on the architecture, algorithms, protocols, and technologies employed to realize the secure hydrogen data analysis system based on blockchain and intelligent power management.

The rest of the paper is organized as follows: Section 2 presents a literature review wherein contemporary state-of-the-art on green hydrogen production is explained. The system overview of the proposed model is described in Section 3. Section 4 presents the implementation details of the architecture along with a blockchain-based secure data analysis case study. Section 5 analyzes the performance of the proposed green hydrogen production platform. Section 6 discusses the limitations of the proposed method, and Section 7 concludes the paper with possible future dimensions.

2. Literature Review

This section will explore recent advancements in green hydrogen as a promising energy carrier for decarbonization across sectors. Numerous research studies have focused on managing and analyzing green hydrogen production and consumption using various data analytics techniques. Analyzing historical data offers valuable insights into system performance, enabling improvements in efficiency and sustainability. This paper presents a comprehensive review of the literature on green hydrogen production, historical data management and analysis, diverse data analytics techniques, the role of blockchain in data analysis, and trend prediction derived from historical data analysis.

Toshiba Corporation (Tokyo, Japan), Tohoku Electric Power Co., Inc. (Sendai, Japan), and Iwatani Corporation (Osaka, Japan) collaborate to advance hydrogen energy technology, focusing on innovative solutions such as advanced electrolysis systems, efficient storage and transportation methods, and establishing hydrogen refueling stations and power plants. This aligns with the global shift toward cleaner and more sustainable energy sources, as hydrogen offers high energy density and produces only water vapor when utilized. Their investment aims to contribute to the growth of the hydrogen economy and promote its adoption as a viable energy solution [15].

Shimizu specializes in hydrogen infrastructure development, including planning, designing, and constructing hydrogen production facilities, storage systems, and distribution networks. They also integrate hydrogen energy systems into construction projects and offer smart energy management systems that optimize hydrogen utilization with other renewable energy sources [16].

ENEOS Corporation (Tokyo, Japan) focuses on technologies for efficient and sustainable hydrogen production, storage, and distribution. They explore hydrolysis, steam methane reforming, and biomass gasification to generate hydrogen. ENEOS also integrates hydrogen energy with renewable sources like solar and wind power, enhancing sustainability and carbon neutrality for hydrogen production. They incorporate advanced energy management systems into their hydrogen initiatives, optimizing energy usage by integrating smart grid networks and demand–response systems [17].

PCI energy solutions accelerate decarbonization by integrating hydrogen assets into energy systems. Hydrogen plays a crucial role in energy storage, utilizing excess renewable energy through electrolysis for later use. This enables sector coupling across transportation, industrial processes, and power generation, creating new markets and stimulating the development of hydrogen production technologies, infrastructure, and distribution networks [18].

A framework aims to evaluate the feasibility and potential of green hydrogen production projects, utilizing open-source software tools and integrating Geographic Information Systems, Life Cycle Assessment, Techno-Economic Analysis, and Optimization Algorithms. This systematic approach supports decision-making processes and optimizes the design of hydrogen production systems [19].

The primary objective of this research is to demonstrate the feasibility and potential of using hydrogen as an energy carrier for power generation. It follows a power-to-X-to-power concept, where renewable electricity is converted into hydrogen through electrolysis and later utilized to generate power in a gas turbine [20]. This work address challenges related to integrating renewable energy sources into the power grid, enhancing grid flexibility, improving energy storage capabilities, reducing carbon emissions, and promoting renewable energy integration [21].

Historical data analysis plays a crucial role in understanding the performance of green hydrogen production and consumption systems and predicting future trends. Numerous studies have focused on utilizing historical data analysis to forecast trends in the field [22]. Blockchain technology holds significant promise for managing and analyzing historical data in green hydrogen systems. Its decentralized and secure nature makes it an ideal platform for storing and sharing historical data. Research has explored the potential of blockchain in this regard. For instance, blockchain enables the traceability and transparency of green hydrogen production by recording and verifying each production step on a decentralized ledger [23]. This transparency fosters trust among stakeholders and simplifies the verification of hydrogen's green credentials. Additionally, blockchain-based platforms facilitate the certification and verification of green hydrogen production [24], enhancing credibility and marketability. Furthermore, blockchain eliminates the need for intermediaries, enabling peer-to-peer trading of green hydrogen [25]. This decentralized trading system reduces costs, improves market efficiency, and promotes the wider adoption of green hydrogen. Moreover, blockchain technology aids in integrating renewable energy sources into green hydrogen production [26]. By aligning hydrogen production with the availability of renewable energy, blockchain-based systems help balance the grid and maximize the utilization of green energy.

Historical data management and analysis are crucial for improving the efficiency and sustainability of green hydrogen production and consumption systems. Several research studies have focused on historical data management and analysis using various data analytics techniques. The article [27] focuses on the analysis of smart meter data in power systems. The primary role of clustering analysis, time-series analysis, and pattern recognition in this article is to enable the interpretation and utilization of smart meter data for applications such as demand response, load profiling, energy-efficiency analysis, and anomaly detection. Similarly, in [28], the article reviews the application of data analytics techniques for the predictive maintenance of power transformers. The main aim of this article's statistical analysis and support vector machines is to analyze transformer data, including sensor readings, historical maintenance records, and other relevant information, to predict the health condition and remaining useful life of power transformers. Moreover, in [29], various data analysis techniques are applied to wind power forecasting. It explores using historical weather data, wind turbine data, and other relevant variables to develop accurate wind power forecast models. The article applies time series and regression analyses to understand the relationship between weather patterns and wind power output.

Furthermore, in another research article [30], data analysis techniques for demand response in smart grids, such as clustering analysis, pattern recognition, and regression analysis, are used to explore the use of data analysis to analyze energy consumption patterns, customer behavior, and grid conditions for effective demand response programs.

We have curated a collection of 10 diverse research methods (in 2023) as shown in Table 1, each applied to distinct application areas, showcasing the evolving landscape of blockchain-based data analysis. These methods explore cutting-edge solutions, addressing various industries' specific challenges and opportunities. Here is a summary of methods with diverse application areas based on blockchain-based data analysis:

In summary, the related work acknowledges the importance of historical data analysis in understanding the performance of green hydrogen systems and predicting future trends. It explores the potential of blockchain technology in managing and analyzing historical data, including its role in traceability, transparency, certification, and the peer-to-peer trading of green hydrogen. The use of blockchain-based systems aligns hydrogen production with renewable energy availability and aids in balancing the grid and maximizing the utilization of green energy. In addition, the related work also provides a comprehensive review of green hydrogen production, historical data management and analysis, diverse data analytics techniques, the role of blockchain, and trend prediction derived from historical data analysis. It highlights the efforts of various companies and research projects in advancing hydrogen technology. It emphasizes the significance of data analysis in improving the efficiency and sustainability of energy generation and delivery systems.

Table 1. Critical summary of the existing blockchain-based data analysis applications.

Application Area	Ref.	Method Summary	Advantageous	Dis-Advantageous
Bibliometric Analysis	[31]	Emerging trends in the field of blockchain and machine learning are analyzed for the development of new blockchain-based machine learning platforms and data analysis frameworks. It enables federated learning that allows multiple parties to train a shared model and create decentralized marketplaces for bibliometric analysis.	In the method, blockchain provides a decentralized and immutable ledger, which helps to improve the security and privacy of data with better transparency and traceability. ML-based methods can be used to develop new automation tools and processes.	Blockchain and machine learning are both complex technologies; combining them can be challenging, slow, and expensive to scale.
Health Care	[32–34]	A private blockchain network is built based on Hyperledger Fabric for health care to support the sharing and management of patient records between different health-care providers.	The method improves the security and privacy of patient records by providing a decentralized and tamper-proof ledger. Automated many manual processes in the health-care system, such as patient registration and record sharing.	The lack of standardization of blockchain technology. Blockchain implementations must adhere to the health-care regulations where achieving compliance can be complex and time-consuming
Supply Chain Management	[35,36]	The authors use a structural equation modeling approach to analyze data from a survey of 300 retail supply chain employees in India to adopt blockchain technology.	The authors perceived the benefits of blockchain technology, such as improved transparency, traceability, and efficiency, are positively associated with employees' intentions to adopt blockchain.	The perceived risks of blockchain technology, such as complexity and cost, are negatively associated with employees' intentions to adopt blockchain.
Construction Industry	[37,38]	The authors investigate the barriers and mitigation strategies to blockchain technology implementation in the construction industry. The authors use an interpretive structural modeling (ISM) approach to analyze data from a survey of 10 construction experts.	A systematic and rigorous method for identifying the root causes of problems and to develop effective mitigation strategies in the construction industry to communicate complex information in a clear and concise manner for blockchain-based data analysis.	ISM can be time consuming and complex to implement as it requires a high degree of expertise from the researcher. It can be subjective, and the results may vary depending on the researcher's interpretation of the data.
Social Network Analysis	[39,40]	A social network analysis (SNA) framework for modeling and handling cross-blockchain ecosystems. A multi-dimensional and multi-view SNA framework is designed for modeling cross-blockchain ecosystems. The framework considers different dimensions of the ecosystem, such as the network's topology, the flow of transactions, and the behavior of wallets and users.	SNA is a powerful tool for analyzing complex networks, such as cross-blockchain ecosystems that allow it to capture the different aspects (multi-dimensional and multi-view) of cross-blockchain ecosystems. It can be used to identify important wallets in cross-blockchain ecosystems and to develop strategies for handling common challenges.	SNA is complex and computationally expensive to implement. The framework proposed in the paper is still in its early stages of development, and more research is needed to evaluate its effectiveness in real-world cross-blockchain ecosystems.

Table 1. *Cont.*

Application Area	Ref.	Method Summary	Advantages	Disadvantages
Finance and Insurance Industry	[41,42]	The blockchain platform provides a secure and transparent ledger for storing and managing insurance data. Smart contracts automate many manual processes in insurance claims processing and underwriting.	Decentralized applications offer a variety of services to insurance customers, such as policy comparison, claims processing, and risk assessment. Blockchain-based data analysis can help to reduce fraud in the insurance industry by providing a secure and tamper-proof ledger for storing and managing insurance data.	Several assumptions, such as the assumption that all parties involved in the insurance process are honest and trustworthy. The framework could be vulnerable to fraud and attacks if these assumptions are unmet. The framework is not yet widely adopted by the insurance industry. This could make it difficult to find other insurance companies and organizations that are willing to participate in the blockchain network.
Smart Automotive Diagnostic	[43,44]	The system is designed to improve the efficiency, transparency, and security of automotive diagnostics and performance analysis, where the OBD device collects data from the vehicle's sensors and sends it to the blockchain network. The cloud platform provides a variety of services to users, such as data visualization, analytics, and reporting.	The system uses cryptography to protect vehicle data from unauthorized access and tampering. This can help to improve the security of vehicles and prevent fraud. Blockchain helped to automate many of the manual processes involved in automotive diagnostics and performance analysis.	Many challenges are associated with implementing and managing blockchain technology in the automotive industry. More research and testing are needed to evaluate the effectiveness of the system in real-world automotive applications.
Smart Livestock Farming	[45]	The blockchain network stores and manages livestock data in a secure manner in which IoT sensors are used to collect data from livestock, such as their health, location, and activity levels. Smart contracts are used to automate animal feeding and vaccination.	It has automated many of the manual processes involved in livestock farming and provided a secure and transparent way to store and manage livestock data. It can lead to increased efficiency, reduced costs, improved food safety traceability, and trust between consumers and farmers.	Blockchain networks are slow and expensive to scale, which could limit the applicability of the framework to large-scale livestock farms.
Tourism Industry	[46]	The study uses qualitative and quantitative data collection methods for a blockchain-based framework to enhance the integrated blue economy on smart islands. Qualitative data are gathered from scientific journal publications and analyzed using VOS viewer. Quantitative data are obtained through a questionnaire survey of 150 blue economy industry players in the Seribu Islands.	The authors identify several potential benefits of blockchain as well as the challenges of implementation. They also provide a case study of the Seribu Islands in Indonesia to illustrate the potential of blockchain in a real-world setting.	Findings are specific to the Seribu Islands and may not fully apply to other regions or contexts. Implementing blockchain technology can be complex, and the study does not delve deeply into the technical challenges and potential barriers faced during implementation.

Table 1. *Cont.*

Application Area	Ref.	Method Summary	Advantages	Disadvantages
Data Protection	[47]	Blockchain-based biomedical document protection (BBDP) uses cryptography to secure biomedical documents and protect their privacy. The algorithm allows authorized users to retrieve biomedical documents from the blockchain in a secure and privacy-preserving manner.	The blockchain-based framework is transparent and auditable. This means that all transactions are recorded on the blockchain and can be viewed by anyone. BBDPF offers a holistic approach to safeguarding biomedical documents, addressing data integrity, non-repudiation, and smart contract support.	The study focuses on specific blockchain technologies and may not fully generalize to all health-care contexts. Blockchain operations, especially on public blockchains, can consume substantial computational resources.

3. Methodology

This section comprehensively overviews the proposed green hydrogen production and consumption history management and analysis scheme. The scheme provides information regarding the green hydrogen production steps, elements data analysis, data security, and prediction of the trends obtained from the history management framework.

3.1. Proposed Scenario of Blockchain Based Secure Hydrogen Data Analysis

Figure 1 represents the scenario diagram of the proposed secure hydrogen production and management network. The scenario involves multiple participants: the operational in charge, maintenance in charge, data analyst, and supply management. Each participant has specific requests and interactions within the hydrogen power management system.

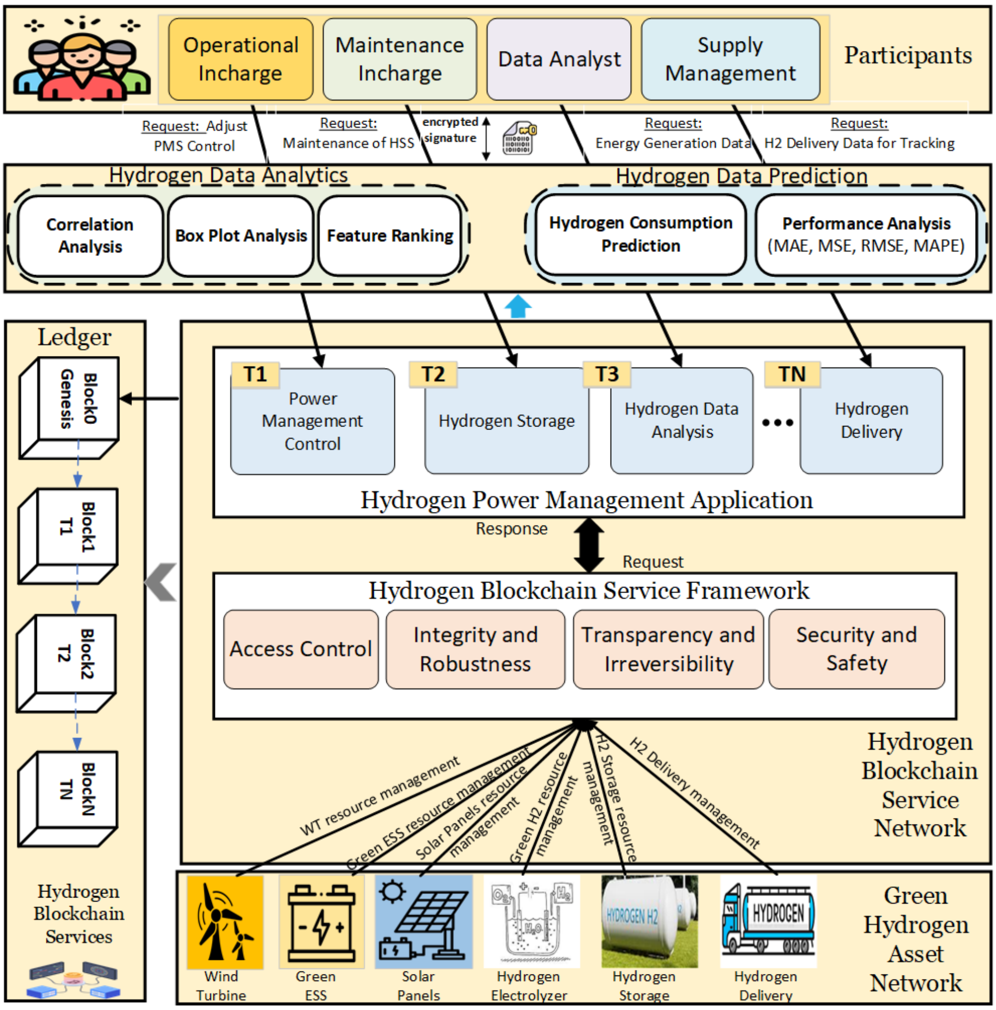


Figure 1. Proposed blockchain-based secure hydrogen data analysis architecture aims to improve the efficiency of the green hydrogen asset network's performance and optimize hydrogen production and distribution.

The operational in charge requests the blockchain framework to adjust power management system control. This represents transaction 1 in the hydrogen power management application. The maintenance in charge requests the maintenance of the hydrogen storage system. This represents transaction 2 in the hydrogen power management application. The data analyst requests the energy generation data for analysis. This involves performing correlation analysis, box plot analysis, and feature ranking in the data analysis module. This represents transaction 3 in the hydrogen power management application. The supply management requests hydrogen delivery data tracking. This represents an nth transaction in the hydrogen power management application. All these transactions are recorded and stored in the hydrogen blockchain ledger. The hydrogen power management application communicates with the hydrogen blockchain service framework through a REST API server, following a request and response fashion.

This article discusses the impacts of blockchain adoption on data access performance within the context of hydrogen production and management. Blockchain enhances data security by cryptographically securing data and reducing the risk of unauthorized access and tampering. It improves data transparency, making information easily accessible to authorized parties. The technology also streamlines data traceability, ensuring a clear history of data changes. With decentralized data access, participants can directly retrieve relevant data, eliminating delays from centralized systems. Smart contracts automate access control, and data immutability guarantees integrity. Lastly, efficient compliance reporting is facilitated, reducing the time and resources needed for regulatory tasks. These improvements collectively create a more robust and efficient data access framework for hydrogen production management.

Figure 2 showcases how each blockchain adoption impact improves data access performance in hydrogen production. The technology secures data and streamlines access, enhances transparency, and automates various aspects of data management, ultimately bolstering data access efficiency and reliability.

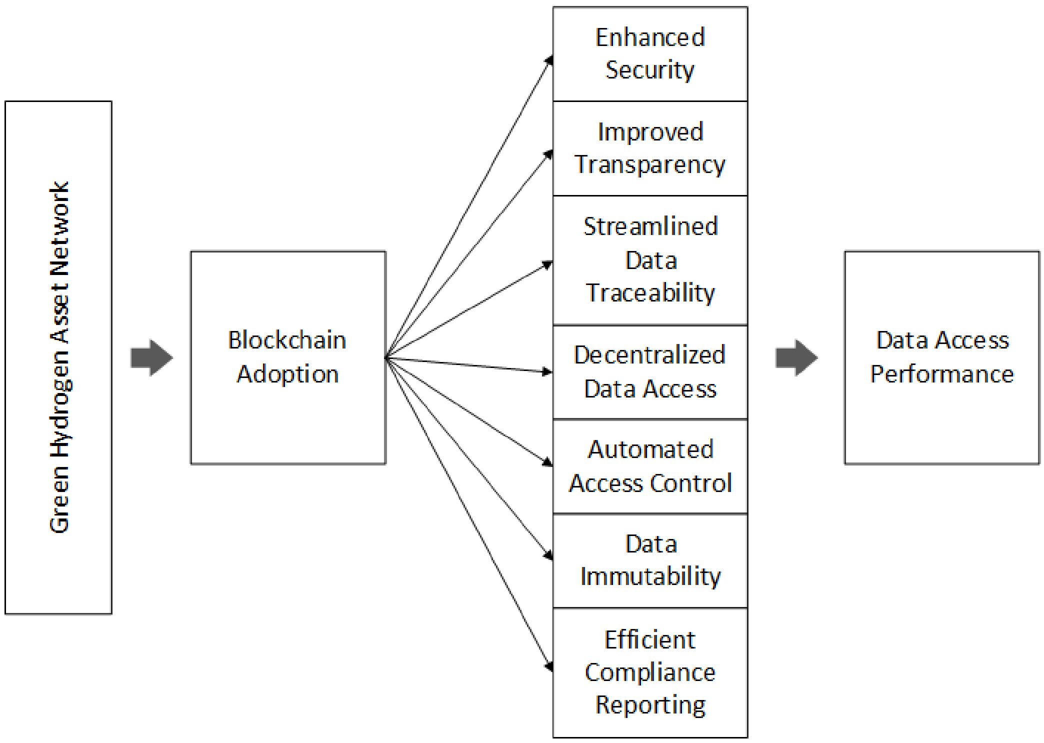


Figure 2. Impacts of blockchain on data access performance in hydrogen production.

The hydrogen blockchain service framework ensures access control, integrity, robustness, transparency, irreversibility, security, and safety. It acts as the intermediary for communication between the hydrogen power management application and the physical assets in the green hydrogen asset network, including wind turbines, green ESSs (energy storage systems), solar panels, hydrogen electrolyzers, hydrogen storage tanks, and hydrogen delivery units. Each asset, such as the wind turbine, green ESS, solar panels, hydrogen electrolyzer, hydrogen storage, and hydrogen delivery, has its management within the hydrogen blockchain framework.

The scenario diagram illustrates the interactions and transactions within the hydrogen power management system, highlighting the role of blockchain technology in securing hydrogen data analysis and enabling intelligent power management.

3.2. Proposed Layered Architecture Design

Figure 3 explains the layered architecture for the secured data analysis (SDA) and intelligent power management system (PMS) to investigate hydrogen data using blockchain technology.

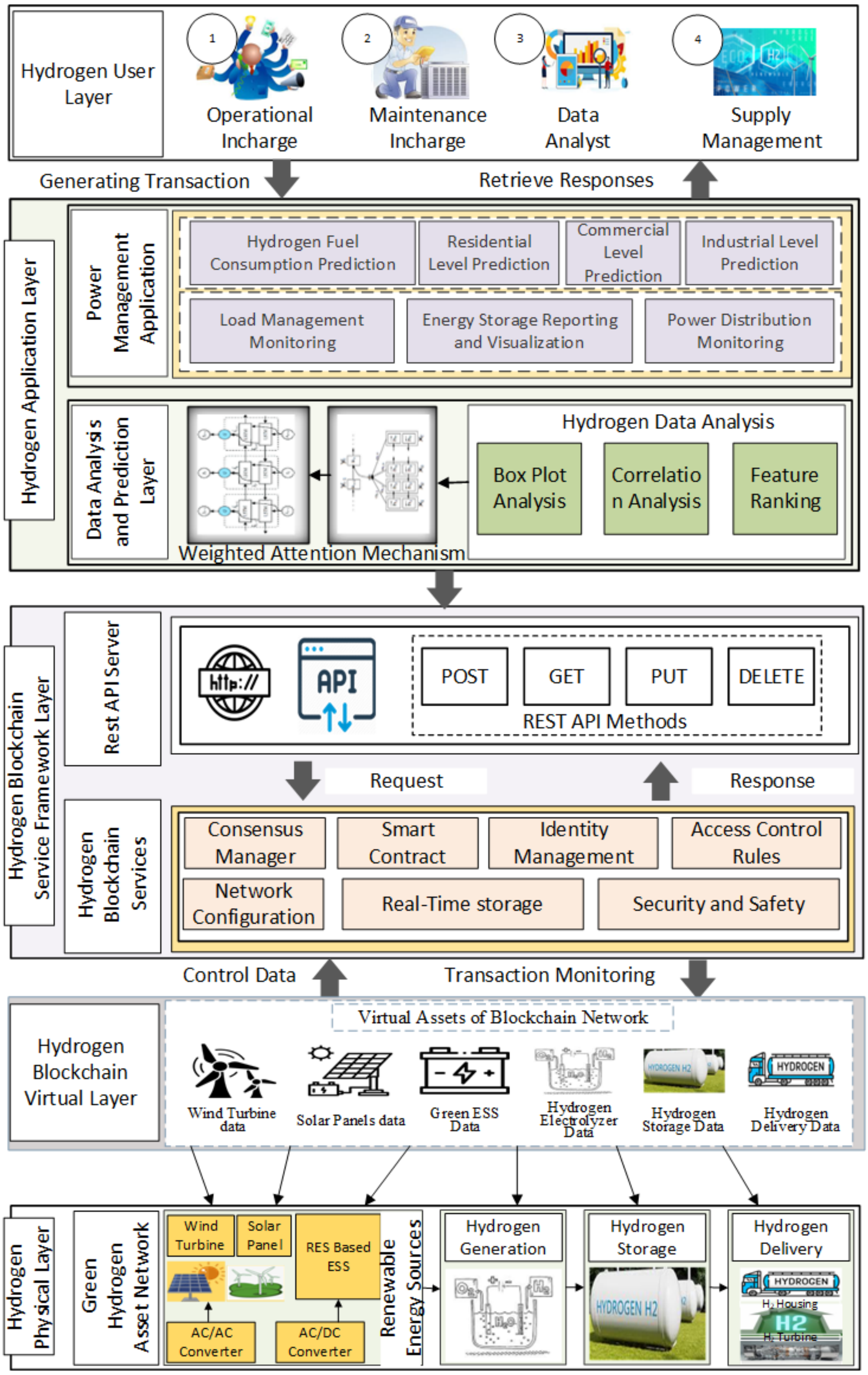


Figure 3. Layered architecture for secure hydrogen data analysis and intelligent power management system using blockchain technology.

- Layer 1: Hydrogen Physical Layer. The bottom-most layer represents the system's physical components, including renewable energy sources, power converters, and energy storage systems. It incorporates an electrolyzer for green hydrogen production through electrolysis. The produced hydrogen is compressed, stored in a hydrogen tank, and distributed to various destinations within the green hydrogen asset network, such as hydrogen housing, hydrogen turbines, and hydrogen pumps.

- Layer 2: Hydrogen Blockchain Virtual Layer. The virtual representation of each physical asset's data resides in this layer. It includes the virtual assets of the blockchain network, such as wind turbine data, solar panel data, green ESS (energy storage system) data, hydrogen electrolyzer data, and hydrogen delivery data.
- Layer 3: Hydrogen Blockchain Service Framework Layer. Sitting atop the Hydrogen Blockchain Virtual Layer is the Hydrogen Blockchain Service Framework Layer. This layer is further divided into two sub-layers: the Hydrogen Blockchain Services sub-layer and the REST API Server sub-layer. The Hydrogen Blockchain Services sub-layer comprises components such as a consensus manager, smart contracts, identity management, access control, network configuration, real-time storage, and security. The REST API Server sub-layer includes HTTP, API, and REST API methods for communication, including POST, GET, PUT, and DELETE. This layer facilitates the connection between the above layers and the hydrogen blockchain services.
- Layer 4: Hydrogen Application Layer. In this layer, two sub-layers are introduced. The first sub-layer is the Power Management Application Layer, which includes functionalities such as hydrogen fuel consumption prediction, residential level prediction, commercial level prediction, industrial level prediction, load management monitoring, energy storage reporting and visualization, and power distribution monitoring. The second sub-layer focuses on hydrogen data analytics, including the use of a weighted attention mechanism for hydrogen data predictive analytics and modules for box plot analysis, correlation analysis, and feature ranking analysis.
- Layer 5: Hydrogen User Layer. The topmost layer represents the hydrogen user layer, which includes the operational in charge, maintenance in charge, data analyst, and supply management. These users interact with the system by generating transactions and retrieving responses from the hydrogen blockchain service framework using the REST API server.

The layered architecture provides a structured and organized approach to secure hydrogen data analysis and intelligent power management. Each layer contributes to the overall functionality and security of the system.

3.3. Hydrogen Power Management Architectural Based on Data Analysis Using Blockchain Framework Overview

Figure 4 illustrates the architecture and data flow within the system. The participants, including operational in charge, maintenance in charge, data analyst, and supply management, are connected to the system through a REST API that ensures secure communication using encrypted signatures. The blockchain network, built on Hyperledger Fabric, consists of multiple peers that maintain the same chain codes and ensure the integrity of the data. Within the blockchain network, there are MSP (Membership Service Provider) definitions and organization certificate authorities (CAs) that facilitate the authentication and authorization of participants. The network is connected to an off-chain data lake that stores various data related to wind turbines, green ESS, solar panels, hydrogen production electrolyzers, hydrogen delivery, and hydrogen storage. This off-chain data lake acts as a repository for the data used in the analysis.

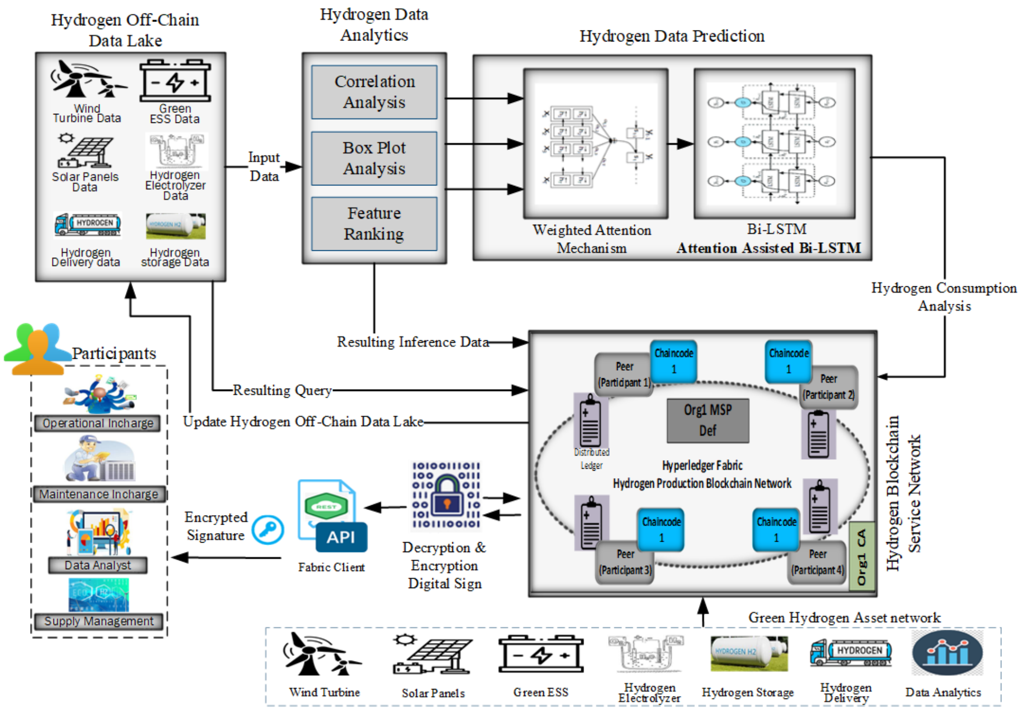


Figure 4. Development model and data flow of blockchain-based secure hydrogen data analysis and intelligent power management system.

The data from the off-chain data lake are then passed as input to the data analytics module, which includes correlation analysis, box plot analysis, and feature-ranking techniques. These analytics techniques help derive insights and patterns from the data. The output of the data analytics module is then fed into the predictive data analytics module, which employs a weighted assisted BI-LSTM (Bidirectional Long Short-Term Memory) prediction algorithm. This algorithm uses historical data and weighted factors to predict future hydrogen-related parameters. Finally, the output of the predictive analytics module is incorporated back into the blockchain network, ensuring the secure and transparent storage of the prediction results. The architecture presented in the figure demonstrates how blockchain technology is leveraged to securely analyze hydrogen-related data and support intelligent power management within the system.

The figure provides an overview of the system's components, including the participants, blockchain network, off-chain data lake, data analytics module, and predictive analytics module. It showcases how the secure analysis of hydrogen data is integrated into the blockchain-based power management system. The proposed blockchain-based framework used the Practical Byzantine Fault Tolerance (PBFT) consensus algorithm. PBFT is a consensus mechanism that ensures consensus among a set of nodes in a network even if some nodes are malicious or faulty. It provides a high level of fault tolerance and ensures that the agreed-upon transactions are added to the blockchain consistently and securely.

3.4. *Blockchain Framework for Secure HDA*

In this paper, we propose a hydrogen history management blockchain-based framework for analyzing green hydrogen data securely. The proposed Single-Channel Blockchain Framework for Secure Hydrogen Data Analysis is designed to manage and analyze historical data in a green hydrogen asset network. This network comprises various physical assets, such as wind turbines, solar panels, green energy storage systems (ESSs), hydrogen electrolyzers, hydrogen storage units, and hydrogen delivery units, which play vital roles in green hydrogen production, storage, and distribution.

The Single-Channel Blockchain Framework consists of three key components: the Green Hydrogen Asset Network, the Hydrogen Blockchain Service Network, and the

Hydrogen Off-Chain Data Lake. The Green Hydrogen Asset Network forms the foundation for green hydrogen operations. At the same time, the Hydrogen Blockchain Service Network ensures the secure and confidential management of hydrogen data using a single-channel blockchain. The Hydrogen Off-Chain Data Lake acts as a centralized repository, housing historical data from each asset in the network enabling valuable insights into the system's performance.

The functioning of the Single-Channel Blockchain Framework follows a systematic process. Physical assets in the green hydrogen network continuously generate data on their operations and performance, which is integrated and stored in the off-chain data lake. The hydrogen data analytics and prediction modules utilize this data lake to conduct various data analysis techniques, extracting insights and predicting future trends. These modules interact securely with the hydrogen blockchain service network through encrypted channels and chain-code, accessing data from the off-chain data lake and storing analysis results on the distributed ledger.

Furthermore, the hydrogen blockchain service network facilitates interactions with hydrogen user participants, including the operational in charge, maintenance in charge, data analyst, and supply management. Each user's role is defined in the organization MSP, granting specific access rights and permissions for conducting transactions on the blockchain network.

Several essential components play vital roles in the Hyperledger Fabric-based hydrogen production blockchain network. The chain-code acts as the "smart contract," governing interactions between the hydrogen data analytics module, hydrogen data prediction module, and the distributed ledger. The organization certificate authority ensures user authentication, allowing only authorized participants to access specific data. The distributed ledger serves as an immutable record of all transactions and analysis results, promoting transparency and security. This framework guarantees secure, reliable, and authorized operations in hydrogen data analysis and prediction, facilitating intelligent power management in green hydrogen systems.

3.5. Interection Model of the Proposed Blockchain-Based HMA of Green Hydrogen Production and Consumption

This section outlines the workflow of our proposed blockchain and ML-based RIVHPMA (Renewable Integrated Virtual Hydrogen Power Management Application). The platform serves as both a technical infrastructure and a user service framework, offering a smart contract and blockchain ledger as services to the front-end application. Figure 5 illustrates the workflow diagram of our RIVHPMA, building upon the integrated IoT and blockchain flow model .

The front-end application provides a user-friendly interface to interact with the blockchain system. Users can access intuitive services like enrolling and authenticating their identities, requesting data, managing participant profiles, and generating data analytics reports. Our RIVHPMA operates on a permissioned chain of networks, necessitating user enrollment and authentication to generate private keys used for transaction signing. Transactions involve reading and writing hydrogen production and prediction analysis data to/from the blockchain ledger across the entire network. Hydrogen user participants can submit requests related to power management control, hydrogen storage, hydrogen data analysis, and hydrogen delivery to hydrogen power management applications.

An integrated inference engine analyzes and discovers hidden knowledge from renewable energy generation, green hydrogen production, hydrogen storage, and hydrogen delivery data fetched from the ledger, with data analytics results stored back to the distributed ledger. A predictive analytics module also builds a prediction model based on mined patterns, fetching input data from the data analytics module and storing prediction results in the ledger.

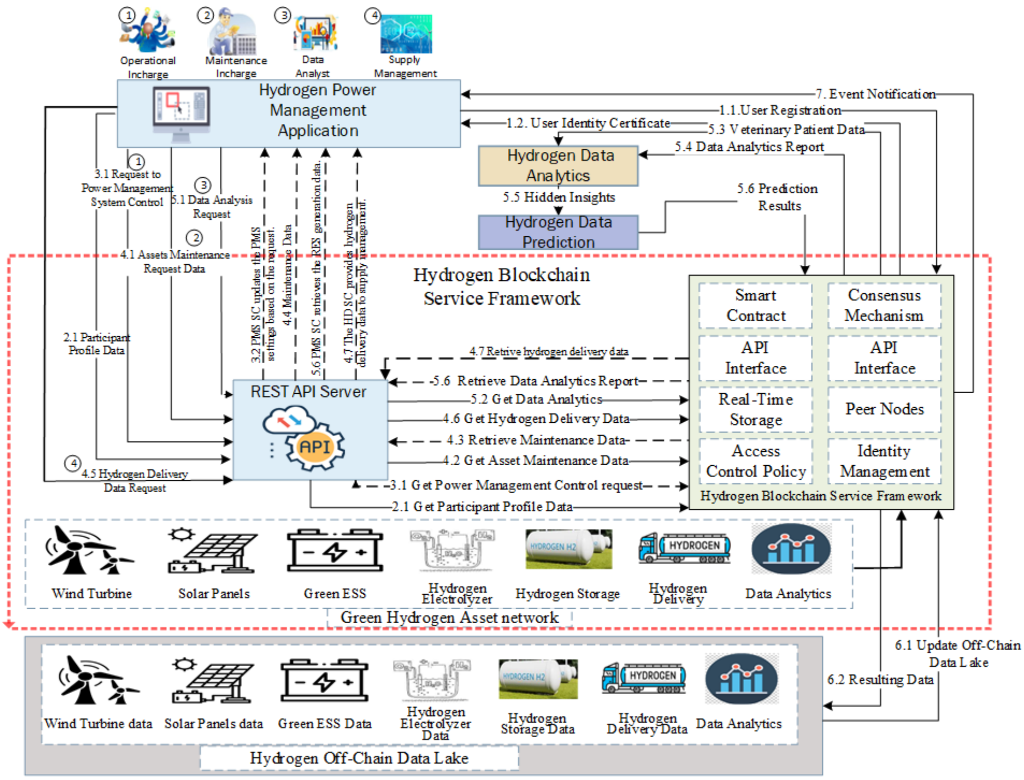


Figure 5. Digital flow of transactions in blockchain-based secure hydrogen data analysis and intelligent power management system.

We utilize an off-chain data lake to ensure the efficient storage and retrieval of the current values of participants and assets from the blockchain ledger. This independent data storage maintains up-to-date sets of various data, such as the latest records of renewable energy generation, green hydrogen production, hydrogen storage, and hydrogen delivery data.

Lastly, an event manager sends notification alerts to the client application, informing users about the successful execution or status of their submitted transactions. Our proposed blockchain and ML-based RIVHPMA streamline green hydrogen production and consumption operations, providing secure and transparent access to data analytics and predictive insights for efficient intelligent power management in green hydrogen systems.

3.6. TPM of the Proposed Blockchain-Based HMA of GHP and Consumption

Figure 6 depicts the transaction process management of the proposed HDA for Intelligent PMS. The participants include the Operational in Charge, Maintenance in Charge, Data Analyst, and Supply Management. Blockchain smart contracts are utilized, namely the Power Management System Smart Contract, Hydrogen Storage Smart Contract, and Hydrogen Data Analysis Smart Contract. The assets involved are Solar Panels, Wind Turbines, a Hydrogen Electrolyzer, Hydrogen Storage, a Green Energy Storage System, and Hydrogen Delivery Data. The sequence diagram showcases the interactions and message flow between participants, blockchain smart contracts, and asset involvement. The diagram provides an overview of the process steps and interactions. The Operational In Charge initiates a power management system control request, which is verified by the Power Management System Smart Contract. The Solar Panels and Wind Turbines interact with the Power Management System Smart Contract to collect energy generation data. The Data Analyst retrieves these data for analysis from the Secure HDA Based on Blockchain For Intelligent PMS Power Management System Smart Contract. The Data Analyst then generates insights from the analysis and shares them with the Operational in Charge for decision making. The Maintenance in Charge initiates a request for asset maintenance, interacting with the Hydrogen Storage Smart Contract to assess storage status and maintenance needs. Similarly, the Supply Management initiates a request for hydrogen delivery data, and the Hydrogen Data Analysis Smart Contract verifies the authority of the Supply Management before retrieving relevant information from the Hydrogen Delivery Data.

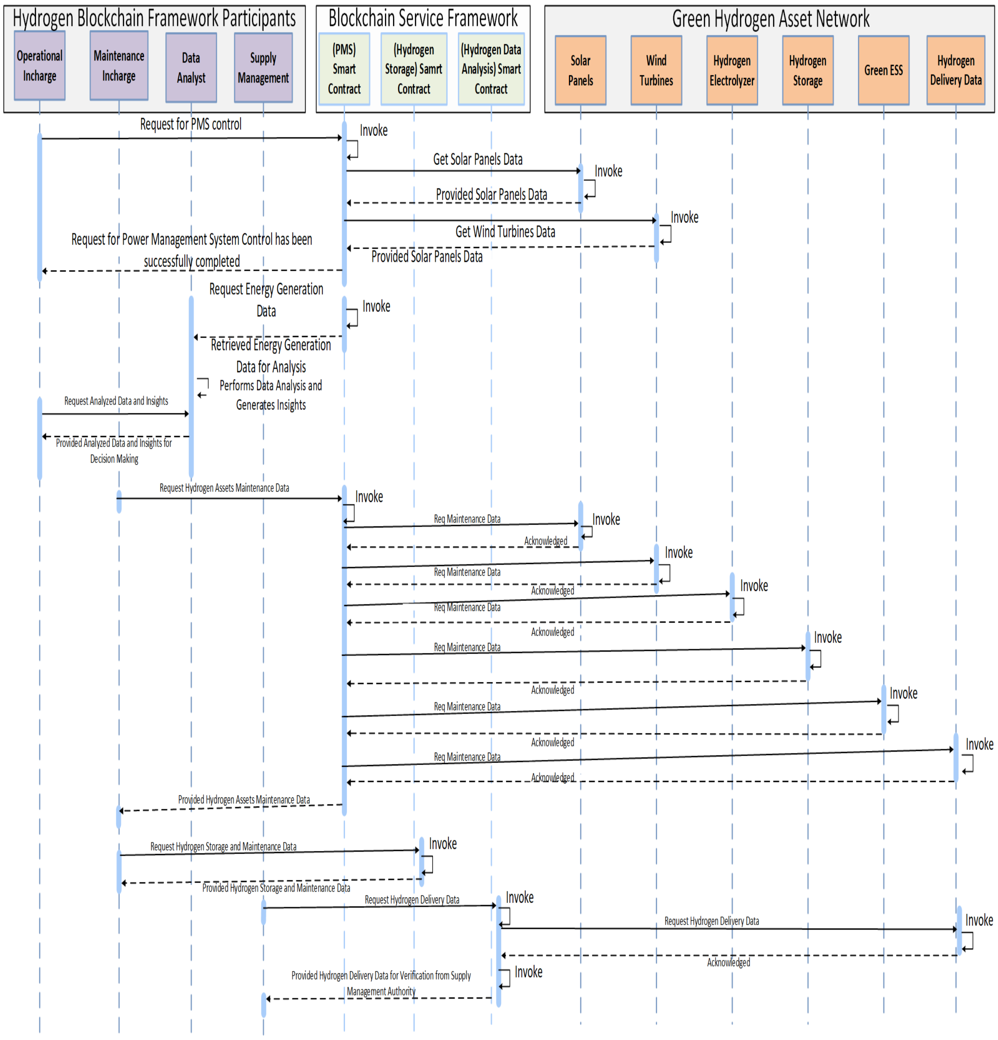


Figure 6. Sequence diagram of the proposed blockchain-based HDA for intelligent PMS.

3.7. Hydrogen Consumption Data Prediction

This section presents an overview of our proposed weighted Bidirectional Long Short-Term Memory (BILSTM) scheme for hydrogen consumption prediction data in the context of the "Secure Hydrogen Data Analysis Based on Blockchain for Intelligent Power Management System" paper. Our scheme utilizes an attention-assisted BI-LSTM model, which combines the power of Bidirectional LSTM (BILSTM) with an attention mechanism to capture long-term dependencies and enhance prediction accuracy. The attention mechanism allows the model to focus on the most relevant features within the hydrogen consumption data, dynamically assigning weights to different elements based on their importance. By incorporating this attention-assisted BI-LSTM model into our framework, we aim to improve the precision and reliability of hydrogen consumption predictions, enabling more effective power management and resource optimization in the intelligent power management system.

In this paper, we present the model flow of the suggested weighted BILSTM-CNN algorithm, as depicted in Figure 2, for hydrogen consumption prediction in the context of the "Secure Hydrogen Data Analysis Based on Blockchain for Intelligent Power Management System". The weighted BILSTM model is a deep learning architecture that analyzes sequential data. It builds upon the classic LSTM model by enabling bidirectional analysis, incorporating forward and backward hidden states to enhance performance. The proposed model utilizes a weighted sum of the forward and backward hidden states at each time step, leading to improved feature extraction and increased prediction accuracy for hydrogen consumption. The model architecture consists of three main components: the input, BILSTM, and output layers.

The input layer receives data from various sensors, including temperature, humidity, and hydrogen consumption, which are categorized accordingly. For hydrogen consumption prediction, the input data are structured as a sequence of vectors with each vector representing a specific time step in the sequence. Each vector contains features used for predicting the output.

The BILSTM layer processes the input sequence in forward and backward directions. At each time step, the BILSTM layer produces a concatenated vector that combines the forward and backward hidden states. A weighted attention mechanism is employed to enhance the model's performance further. This mechanism assigns varying importance to specific hidden states based on their relevance to the prediction task at hand. In the weighted BILSTM model, the forward hidden state is denoted as $hf(t)$, and the backward hidden state is denoted as $hb(t)$.

The concatenated vector at each time step, represented as $h(t)$, is computed by combining $hf(t)$ and $hb(t)$. This process ensures that the model captures information from both past and future time steps, facilitating a comprehensive understanding of the sequential data and enabling accurate hydrogen consumption predictions.

By adopting the weighted BILSTM-CNN algorithm and incorporating attention mechanisms, our proposed model offers a robust approach to analyzing sequential data and accurately predicting hydrogen consumption. This model architecture, comprising the input layer, BILSTM layer with bidirectional analysis, and attention mechanism, forms the foundation of our research in secure hydrogen data analysis for intelligent power management systems.

$$h(t) = [h_{f(t)}; h_{b(t)}] \tag{1}$$

where $[;]$ denotes vector concatenation.

The concatenated output $h(t)$ is subjected to the attention mechanism, which functions as follows:

$$u(t) = tanh[W_h * h(t) + b_h] \tag{2}$$

The intermediate vector $u(t)$ is used to compute the attention vector $e(t)$ by applying the softmax function as follows:

$$e(t) = softmax[w_u * u(t) + b_u] \tag{3}$$

$$c(t) = \sum[e(t) * h(t)] \tag{4}$$

The intermediate vector $u(t)$ is used to compute the attention vector $e(t)$, with W_h and b_h representing the weight matrix and bias vector for the hidden state $h(t)$, respectively. The attention mechanism's weight matrix and bias vector are denoted as w_u and b_u, respectively. The resulting attention vector $e(t)$ is then used to calculate the context vector $c(t)$ from the output of the BILSTM layer at each time step. The intermediate vector $u(t)$ is normalized and assigned weights to each hidden state based on its relevance to the task by applying the softmax function to compute the attention vector $e(t)$. The context vector $c(t)$ is calculated as a weighted sum of the hidden states. The attention vector $e(t)$ determines the weights assigned to each hidden state. The summary of the hidden states at time step t is represented by the context vector $c(t)$, which assigns higher weights to the more relevant hidden states through the attention mechanism.

The output of the attention mechanism passed to the 1D-CNN to learn the essential spatial features from enhanced temporal features data efficiently. The 1D-CNNs can identify patterns in the time-series data regardless of location. This is because the convolution operation slides a filter over the entire time series, capturing patterns at all time steps. The layerwise explanation of the 1D-CNN is discussed below.

Zero padding layer: The zero padding layer adds zeros to the beginning and end of the input sequence to ensure that the convolutional layer can process the entire sequence. The output of this layer is the padded sequence. Let x be the input sequence of length L, and let p be the amount of padding applied to each end of the sequence. Then, the output of the zero padding layer follows:

$$x_{(padded)} = [0, \ldots, 0, x_1, \ldots, x_L, 0, \ldots, 0] \; with \; 2p + L \; elements. \tag{5}$$

The purpose of the batch normalization layer is to standardize the input data so that the mean and variance of the input features remain uniform across all the samples in a batch. Assuming x is a sequence of input data with a length of L and μ and σ are the mean and standard deviation of the input features across the entire batch, the batch normalization layer transforms the input data to ensure the mean and variance of the input features are consistent across all samples in the batch. The output of the batch normalization layer can be expressed as shown below:

$$x_{(norm)} = \frac{(x - \mu)}{\sqrt{(\sigma^2 + \epsilon)}} \tag{6}$$

To ensure numerical stability, the equation is modified with a small constant *epsilon*.

The 1D convolutional layer utilizes a set of learned filters to process the input data, enabling it to extract local features from the input sequence. Let W be the set of filters, each with a length of K, and let b be the bias term. Then, the output of the convolutional layer follows:

$$z = W * x_{norm} + b \tag{7}$$

where $*$ represents the convolution operation, and the output z is a sequence of length $L - K + 1$.

The output of the convolutional layer is processed by the ReLU activation layer, which applies the rectified linear unit (ReLU) activation function. The ReLU function sets all negative values in the output to zero, which introduces non-linearity into the model and helps to prevent overfitting. The output of the ReLU layer is shown below:

$$a = max(0, z) \tag{8}$$

The output of the second batch normalization layer is obtained by normalizing the output of the ReLU activation layer in the same manner as the input data. The resulting output is given by the following:

$$a_{(norm)} = \frac{(a - \mu)}{\sqrt{(\sigma^2 + \epsilon)}} \tag{9}$$

During training, the dropout layer randomly drops out a fraction of the output units from the previous layer. Let $p_{dropout}$ be the probability of dropping out each unit. Then, the output of the dropout layer is shown below:

$$a_{(dropout)} = a_{(norm)*d} \tag{10}$$

where d is a dropout mask, which is a binary matrix of the same shape as a_{norm} with values of 1 with probability $1 - p_{dropout}$ and 0 with probability $p_{dropout}$.

The purpose of the average pooling layer is to decrease the dimensionality of the previous layer's output by computing the average value of each feature map. If the size of the pooling window is denoted as k, then the output of the average pooling layer can be expressed as follows:

$$y = [mean(a_{dropout[i:i+k]})foriinrange(0, L - K + 1, k)] \quad (11)$$

where *mean* is the mean function, and the output y is a sequence of length $(L - K + 1)/k$. Overall, the 1D-CNN architecture allows the model to extract informative features from the enhanced temporal features data and increase the HDL activity classification accuracy. The training of the BILSTM model employs the Adam optimizer, which is a variation of the stochastic gradient descent algorithm. For multiclass classification, the categorical cross-entropy loss function is utilized as the loss function. Using backpropagation, the loss function is optimized by minimizing the difference between the predicted and true output.

The output layer is responsible for producing the final output of the model. The output layer includes a fully connected layer with a softmax activation function for recognizing the activity in HDL's multiclass time-series data. The output obtained from the softmax layer denotes the probability of each class concerning the given input sequence.

The model for contextual and local feature extraction, i.e., the weighted BILSTM-CNN model, is a highly capable and adaptable machine learning model for sequential data-processing tasks such as HDL activity recognition, which offers significant advantages over other models in terms of accuracy and flexibility.

4. Experiment and Implementation

The Power Management Smart Contract in Table 2 is the main smart contract controlling power. It interacts with the asset data to handle the physical assets in the green hydrogen asset network. The Participants' data represent the participants in the green hydrogen blockchain framework. The Transactions data structure defines the different types of transactions that can be performed for power management, and the corresponding functions (updatePowerGeneration, updatePowerConsumption, calculatePowerBalance, distributePower, and transferPower) handle the specific actions for power management. Additionally, there are functions to retrieve specific assets' current power balance, power consumption, and power generation data (getPowerBalance, getTotalPowerBalance, getPowerConsumption, and getPowerGeneration). These functions enable participants to access relevant information for decision-making and analysis.

Furthermore, the experimental setting for the proposed blockchain-based green hydrogen production and consumption history management is expressed in Table 3.

Table 4 shows the services offered using PyCharm and Python-based programming implemented using the TensorFlow framework and the Flask web server application platform. The following core Python libraries are utilized: Keras 2.6, TensorFlow 2.6, Flask 2.2.2, Numpy 1.19.5, Request 2.28, Seaborn, and MatplotLib. Additionally, MS Excel is utilized to store both the raw and final hydrogen production and consumption data analysis data. Moreover, 11th Gen Intel(R) hexa-Deca-Core (TM) i9-11900 @ 2.50 GHz, 64-bit OS, and 63.8 GB usable random access memory to perform experiments.

Table 2. Smart contract modeling for proposed blockchain-based green hydrogen production and consumption history management.

Type	Component	Description
Assets	Wind Turbines	Wind turbines are REAs that convert wind energy into electrical power. Wind turbines are essential for harnessing wind power and generating green energy.
	Solar Panels	Solar panels are a key asset in the green hydrogen asset network, as they utilize solar energy to produce clean and sustainable electrical power.
	Green Energy Storage System	The green energy storage system is a crucial asset that stores excess renewable energy generated by wind turbines and solar panels. It helps balance energy supply and demand, ensuring a stable and reliable power output.
	Hydrogen Electrolyzer	The hydrogen electrolyzer is a critical asset used for the production of green hydrogen through the process of electrolysis.
	Hydrogen Storage	Hydrogen storage units are responsible for storing the produced green hydrogen securely. They ensure that the hydrogen is readily available for utilization during peak demand or when renewable energy generation is low.
	Hydrogen Delivery Units	Hydrogen delivery units are involved in transporting hydrogen to various destinations such as hydrogen housing, hydrogen turbines, and hydrogen fuel pumps. These units facilitate the distribution of hydrogen throughout the system.
Participants	Operational in Charge	The operational in charge is responsible for overseeing and managing the day-to-day operations of the power management system. They have the authority to request adjustments to the power management system control and initiate transactions related to the system's operation and performance.
	Maintenance in Charge	The maintenance in charge is in charge of monitoring and maintaining the various assets in the green hydrogen asset network. They can request maintenance for the assets as needed and interact with the hydrogen storage smart contract to check the status and maintenance requirements of the hydrogen storage units.
	Data Analyst	The data analyst plays a vital role in the power management system as they are responsible for performing data analysis on the energy generation data obtained from wind turbines and solar panels. They use various data analysis techniques to extract insights and patterns that can aid in decision making and optimization of the power management system.
	Supply Management	The supply management participant is involved in tracking and managing the delivery of hydrogen to various destinations within the system, such as hydrogen housing, hydrogen turbines, and hydrogen fuel pumps.
Transactions	Adjust Power Management System Control	The operational in charge initiates this transaction to request adjustments to the power management system control. This could involve optimizing the power distribution, adjusting energy storage settings, or managing renewable energy sources based on real-time data and system requirements.
	Retrieve Energy Generation Data	The power management system smart contract interacts with wind turbines and solar panels to retrieve real-time energy generation data. These data are crucial for making decisions regarding power distribution and storage.
	Perform Data Analysis	The data analyst requests energy generation data from the power management system smart contract to perform data analysis. This transaction involves extracting insights, identifying patterns, and generating data analytics reports.
	Request Maintenance	The maintenance in charge initiates this transaction to request maintenance for specific assets in the green hydrogen asset network. The smart contract verifies the maintenance requirements and schedules necessary maintenance activities.
	Retrieve Hydrogen Delivery Data	The supply management participant requests hydrogen delivery data from the hydrogen data analysis smart contract. This transaction provides information on hydrogen delivery to various destinations within the system.
	Approve or Cancel Maintenance Request	After receiving the maintenance request, the smart contract allows the operational in charge or maintenance in charge to approve or cancel the maintenance request based on the system requirements and priorities.
	View Data Analytics Report	The operational in charge and data analyst can view the data analytics report generated by the data analyst through this transaction. The report includes insights on energy generation, power distribution, and system performance.
	Hydrogen Consumption Prediction	The power management system smart contract may include a transaction for hydrogen consumption prediction. This involves leveraging the hydrogen data prediction module to forecast hydrogen usage for various applications, such as hydrogen housing, turbines, or fuel pumps.

Table 3. Experimental setting of the proposed blockchain-based green hydrogen production and consumption history management.

Component	Description
CPU	Intel Core i9-8500 @ 3.00 GHz
Memory	20 GB
Operating System	Ubuntu Linux 18.04.1 LTS
Docker Engine	Version 18.06.1-ce
Docker-Compose, Simulink	Version 1.13.0, Version 10.7
Node	v8.11.4
Python, Matlab	v2.7.15, R2023a
Hyperledger Fabric	v1.2
IDE	composer-playground
CLI Tool	composer-cli, composer-rest-server
DBMS	CouchDB
Programming Language	JavaScript

Table 4. Implementation environment of the proposed approach.

Component	Description
Operating System	Windows 10 Professional
Hardware	Anemometers, Temperature Sensors, IMU-6050, and Humidity sensors
CPU/Memory	Intel(R) Core(TM) i5-5800 CPU @ 3.00 GHz, 32 GB
External Libraries	geodesy-2.0.0, slf4j-api-1.7.2, achartengine-1.1.0, EJML-core-0.26, and MidasconSDK_android_1.0.0.
Programming Language	Java, Python (for pre-trained LSTM model)
Integrated Development Toolkit	PyCharm

In the experimental setting of the proposed blockchain-based green hydrogen production and consumption history management system, the components and descriptions are as follows. The system utilizes an Intel Core i9-8500 @ 3.00 GHz CPU with 20 GB of memory, running on Ubuntu Linux 18.04.1 LTS. Docker Engine (Version 18.06.1-ce) and Docker Compose (Version 1.13.0) are used for containerization. Node.js (v8.11.4) and Python (v2.7.15) are the programming languages employed, while Hyperledger Fabric (v1.2) serves as the blockchain framework. The development environment is facilitated by Composer-Playground IDE, and Composer-CLI acts as the command–line interface tool. The database management system employed is CouchDB, and JavaScript is used for implementing various functionalities within the system.

Figure 7 illustrates a hybrid energy system with voltage signals from both the battery and the grid represented on the x-axis. The hybrid energy system integrates two energy sources, the battery and the grid, to optimize energy utilization and enhance overall efficiency. The x-axis represents the voltage levels of both energy sources, which can vary over time depending on factors such as energy demand and supply. The hybrid energy system is designed to work seamlessly by intelligently switching between the battery and the grid as needed. When the energy demand is low, the system may draw power from the battery, which is typically charged during off-peak hours or when renewable energy sources like solar panels generate excess electricity. This helps reduce reliance on the grid and allows for more efficient energy utilization.

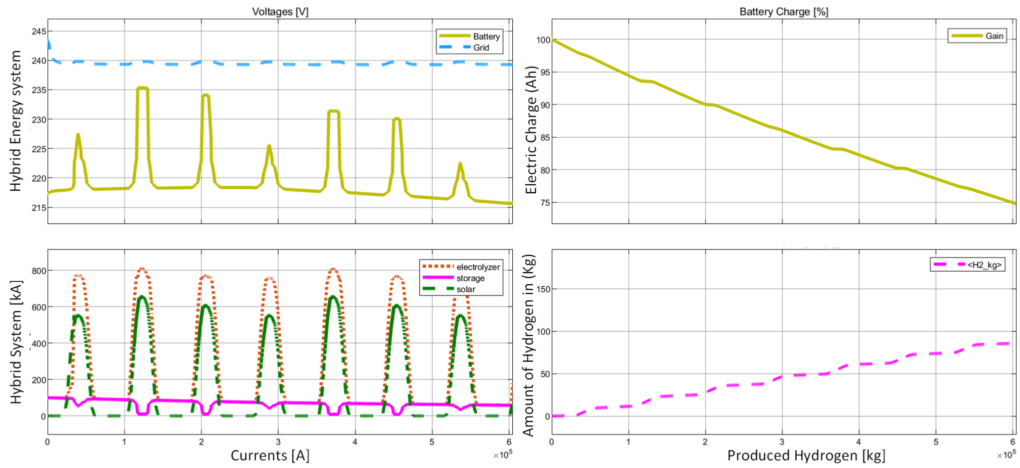


Figure 7. Green hydrogen production from the hybrid green renewable energy system.

Furthermore, the figure depicts a comprehensive view of the hybrid energy system, including various current measurements and battery charge status, which are crucial for understanding and optimizing the system's performance.

On the y-axis, the currents (in amperes) for different system components are represented. Specifically, these include the following.

- Solar Current: This line indicates the current generated by the solar panels, which convert sunlight into electricity.
- Energy Storage System Current: This line represents the current flowing to or from the energy storage system (e.g., batteries), which stores excess electricity generated by the solar panels or other renewable energy sources.
- Electrolyzer Current: This line shows the current used by the electrolyzer, which is a critical component responsible for producing hydrogen through electrolysis.

On the x-axis, the timeline is displayed, indicating different time intervals during which the system operates.

Additionally, the figure includes a plot of the battery charge (in ampere-hours) over time. The battery charge indicates the amount of electricity stored in the battery at a given moment. When renewable energy sources produce more electricity than needed, the excess power is used to charge the battery, increasing its charge level. Conversely, when energy demand exceeds the renewable energy generation, the battery discharges to meet the demand.

By analyzing the current and battery charge status over time, system operators and energy managers can gain insights into the efficiency and performance of the hybrid energy system. They can identify periods of peak energy generation, monitor the battery charge level, and assess the overall energy utilization to optimize the system's operation and ensure a reliable and sustainable energy supply.

Similarly, Figure 8 shows the standalone energy system based on solar arrays. It also shows the required voltage for the electrolyzer and the produced voltage from renewable energy sources. Moreover, the figure also expressed the pressure bar of produced hydrogen and the consumed energy of the electrolyzer.

In a blockchain-based green energy production history management system, the identification of organization members or participants can be updated using various methods. One approach is utilizing cryptographic keys, such as public–private key pairs, to uniquely identify and authenticate network participants. Each member would possess their private key, which is securely stored and used for cryptographic operations, while their corresponding public key serves as their identifier on the blockchain. Figure 9 in the blockchain-based framework shows the data of three participants. The Figure 9a–c shows the various participants. When a new organization member joins the network, they can go through a registration process where the network administrators verify their identity and credentials.

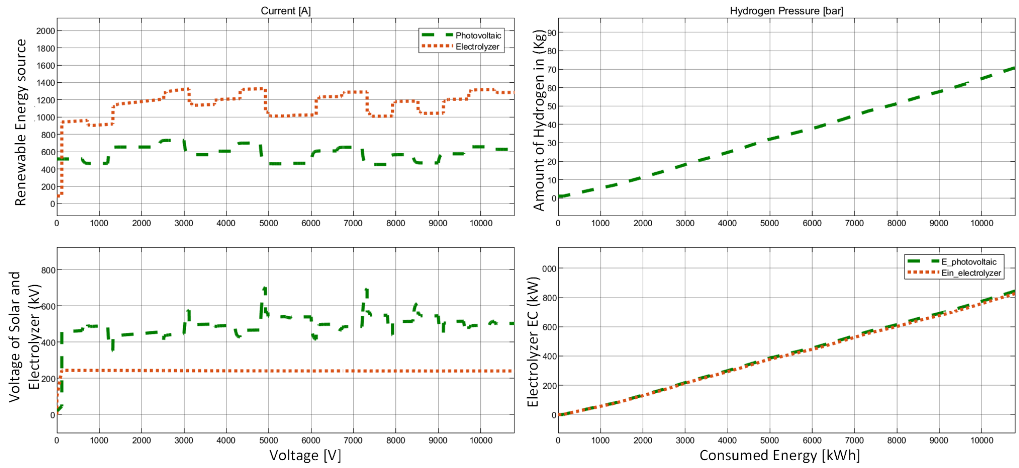
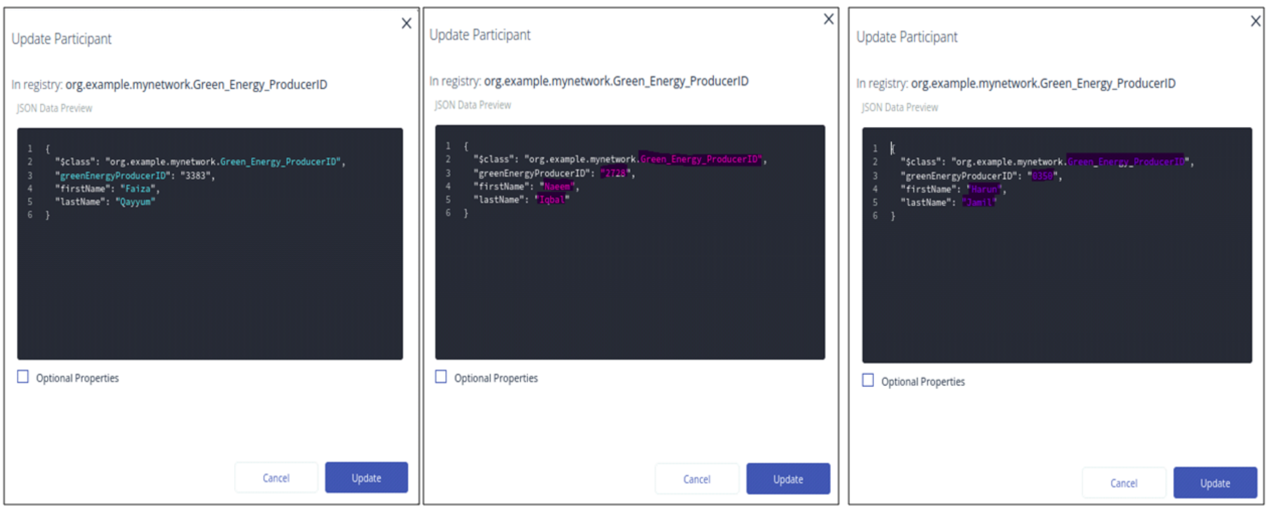


Figure 8. Green hydrogen production from green renewable energy system.

This verification process may involve providing relevant information, such as legal identification documents or certificates, to establish trust and compliance with the organization's rules and regulations. Once verified, the new member's public key can be added to the blockchain, linking their identity to their cryptographic key pair.

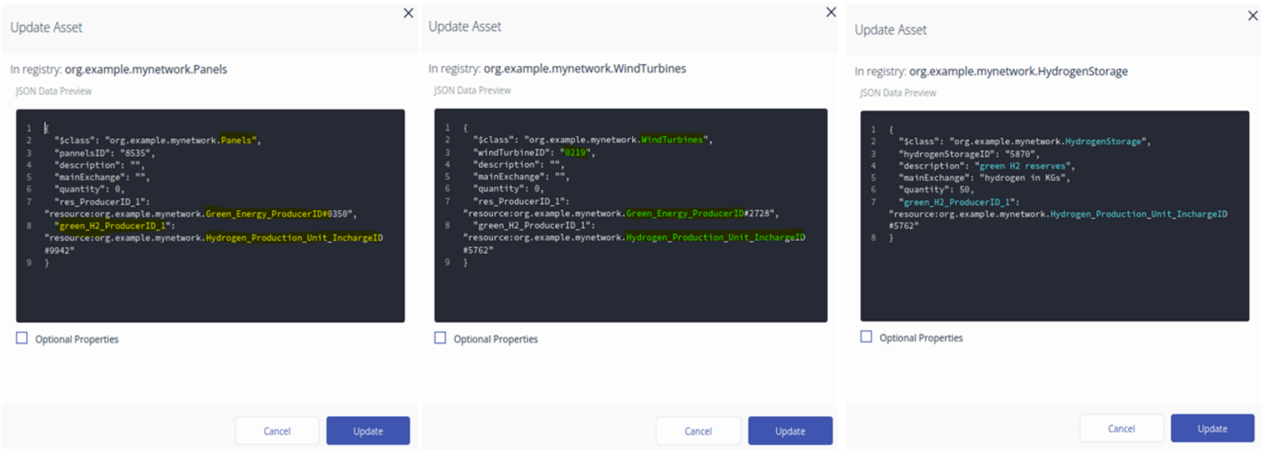


(**a**) Participant 1 (**b**) Participant 2 (**c**) Participant 3

Figure 9. Representation of participants in hydrogen production unit based on blockchain service framework.

In a blockchain-based green energy production history management system, the identification of organization assets can be updated using various methods. Assets in this context refer to the different components involved in producing and managing green energy, such as solar panels, wind turbines, energy storage systems, and more.

A unique identifier can be assigned to each asset within the blockchain network to update asset identification. This identifier can be a digital token, a smart contract, or a specific code representing the asset, as shown in Figure 10. When a new asset is added to the network, it goes through a registration process where its identity and relevant information are recorded on the blockchain.



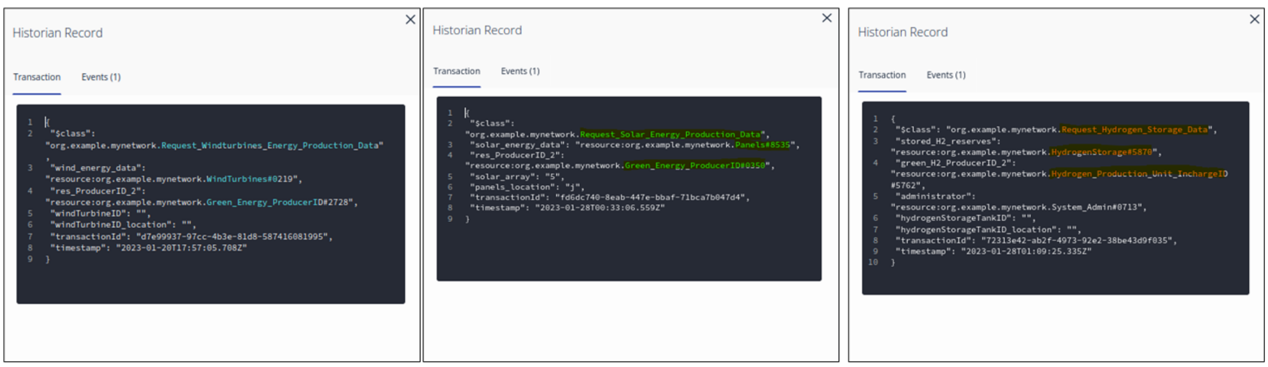
(**a**) Asset 1 (**b**) Asset 2 (**c**) Asset 3

Figure 10. Blockchain-based green hydrogen production history management organization assets (configuration) identification.

Changes to the asset's information, ownership, or status can be made during asset updates. This can include modifications to technical specifications, maintenance records, operational data, or other relevant details. Like participant identification updates, asset identification updates require a consensus among the network participants to validate and approve the changes.

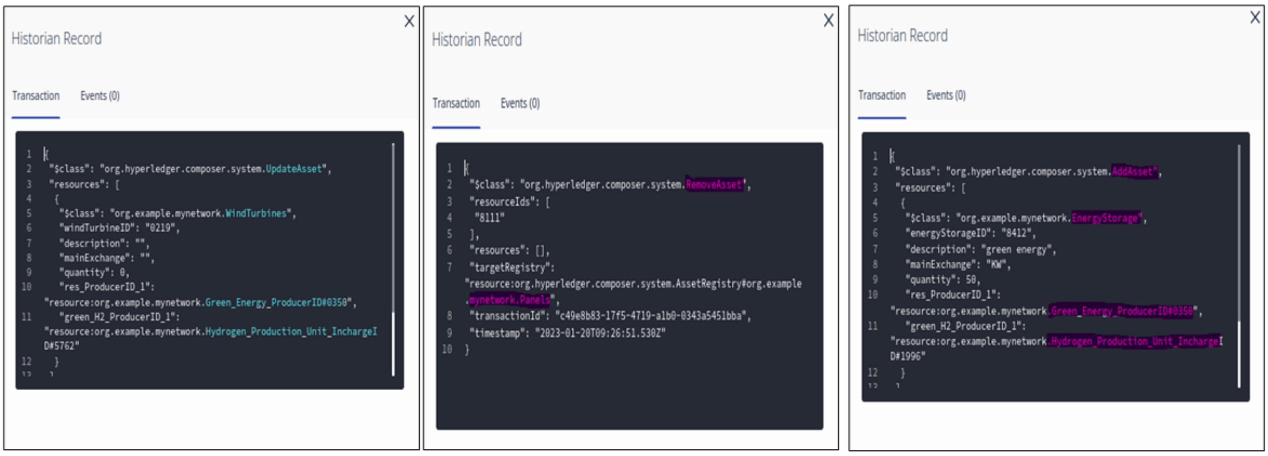
A unique identifier can be assigned to each record within the blockchain network to update historian record identification. This identifier can be generated based on the timestamp, transaction ID, or a combination of both to ensure uniqueness and traceability. When a new historian record is added to the network, it is assigned a unique identification that serves as a reference for future updates or retrieval.

Updating historical records involves making changes or additions to existing records. This can include updating energy generation data with new readings, adding maintenance records for equipment, or modifying consumption data based on real-time measurements. Like participant and asset identification updates, updating historian records requires consensus among the network participants to validate and approve the changes. In this regard, Figures 11 and 12 show any events in the hydrogen blockchain service framework and all the requests originated from the participants recorded in the form of transactions. Also, Figure 13 refers to the transaction data in the green hydrogen blockchain service framework. This figure is the ledger of the blockchain network. The content in the figure showed the changes in the ledger.



(**a**) Event 1 (**b**) Event 2 (**c**) Event 3

Figure 11. Blockchain-based green hydrogen production history management organization event identification.



(**a**) Transaction 1 (**b**) Transaction 2 (**c**) Transaction 3

Figure 12. Blockchain-based green hydrogen production history management organization historian record update (configuration) transactions identification.

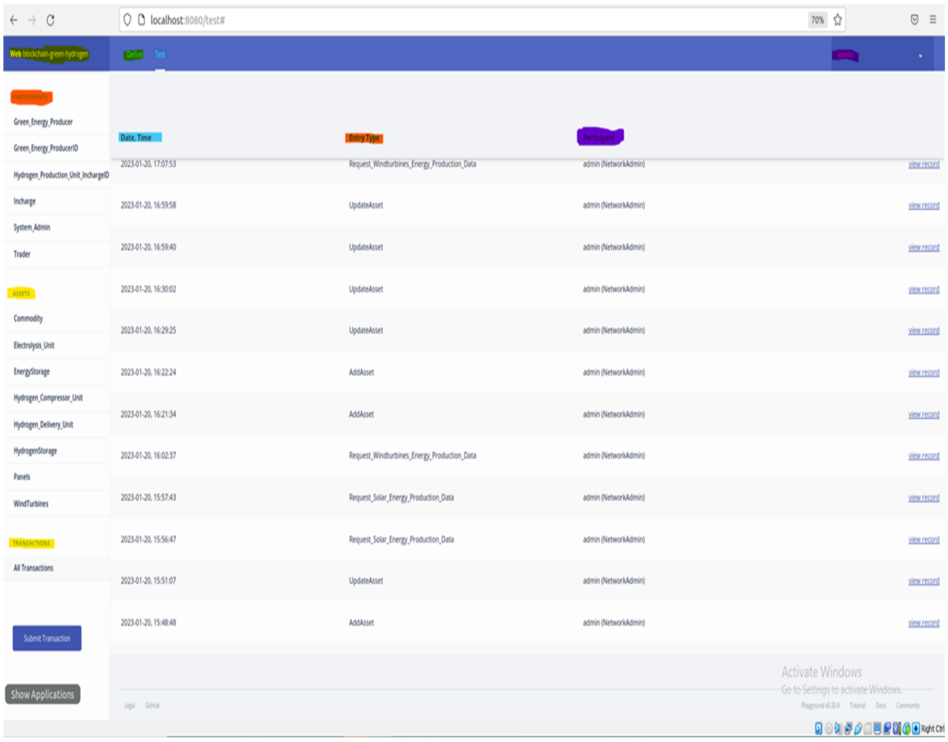


Figure 13. Blockchainmanager/user development plan for managing green hydrogen production history).

5. Performance of Secure Data-Driven History Management Analysis

Heatmap analysis of the hydrogen dataset involves visualizing the data using a color-coded matrix representation, where different colors indicate the intensity or value of a particular variable. In the context of the provided dataset, a heatmap analysis can provide insights into the relationships and patterns between the different variables, such as Date/Time, Temperature, Wind Speed, General Diffuse Flows, Diffuse Flows, and Hydrogen Commercial Building consumption. Plotting the variables on the heatmap makes it possible to observe correlations, trends, and variations within the dataset. For example, the intensity of colors in the Temperature column can indicate temperature fluctuations over time, with warmer colors representing higher temperatures and cooler colors representing lower temperatures. Similarly, the Wind Speed column can show high or low wind intensity areas. Heatmap analysis allows for a quick visual identification of patterns, such as high hydrogen fuel pump consumption periods coinciding with specific temperature or wind speed conditions. It helps identify any dependencies or interactions between the variables in the dataset.

The correlation heatmap analysis is a graphical representation of the correlation matrix, which quantifies the relationships between variables in a dataset, as shown in Figure 14. It helps to visualize the strength and direction of the linear relationship between pairs of variables.

The correlation coefficient, often denoted by "r", measures the strength and direction of the linear relationship between two variables. It ranges between -1 and 1, where -1 represents a strong negative correlation, 0 represents no correlation, and 1 represents a strong positive correlation. To calculate the correlation coefficient between two variables, you can use the following mathematical formula:

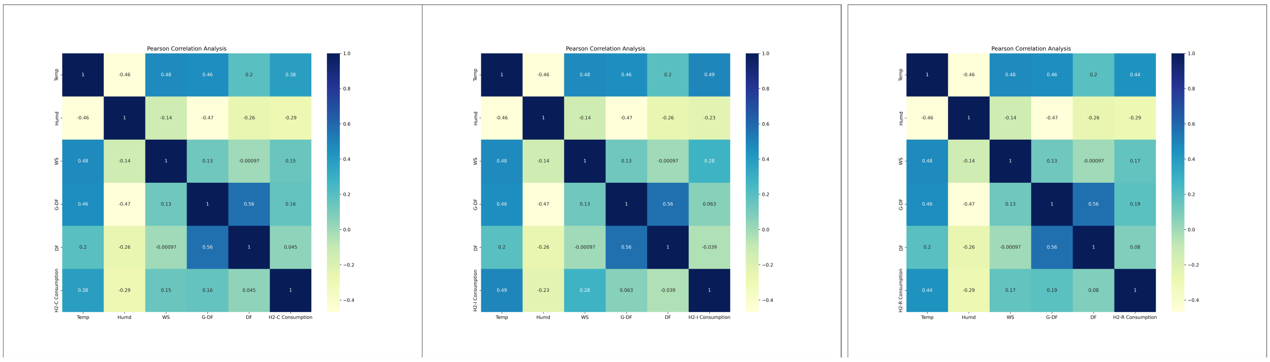
$$r = \frac{\sum((X - \bar{X})(Y - \bar{Y}))}{\sqrt{\sum(X - \bar{X})^2} \cdot \sqrt{\sum(Y - \bar{Y})^2}} \tag{12}$$

where X and Y are the values of the two variables. $\bar{X}$ and $\bar{Y}$ are the means of X and Y, respectively. $\sum$ denotes summation.

The resulting correlation coefficient ranges between -1 and 1, where a value close to -1 or 1 indicates a strong correlation and a value close to 0 indicates no or weak correlation. This formula quantifies the degree and direction of the linear relationship between the variables X and Y.

In the context of the correlation heatmap analysis, this calculation is performed for each pair of variables in the dataset, and the resulting correlation coefficients are visualized in a heatmap, with colors representing the strength of the correlation.

Heatmap analysis provides an intuitive and visually appealing representation of the dataset, enabling users to gain insights into the relationships and trends between the variables. It can aid in identifying patterns, making data-driven decisions, and optimizing the performance of the green hydrogen power management system.



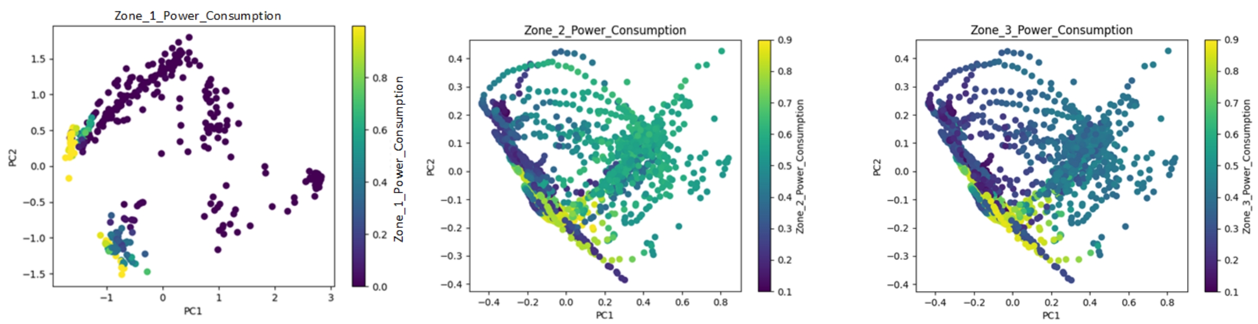
(**a**) Correlation analysis for commercial consumption of hydrogen

(**b**) Correlation analysis for industrial consumption of hydrogen

(**c**) Correlation analysis for residential consumption of hydrogen

Figure 14. Correlation analysis of hydrogen consumption in different sectors for optimizing hydrogen production, distribution, and utilization strategies for each sector. (**a**) Correlation analysis for commercial consumption of hydrogen. (**b**) Correlation analysis for industrial consumption of hydrogen. (**c**) Correlation analysis for residential consumption of hydrogen.

Autocorrelation and partial autocorrelation are two important statistical tools used in time-series analysis to identify the patterns and relationships between consecutive data points. In this paper, we conducted experiments where PCA is applied to a hydrogen fuel consumption dataset with nine features and six principal components retained. In the given figure, we can analyze the dimensionality of the data of applying PCA. The analysis computed the proportion of the total variance in the data that is explained by each principal component, which is called the explained variance ratio. This provides insight into the relative contribution of each component toward the overall variance of the data. Finally, the model performance was evaluated using the R2 score, and it was observed that the score improved from 86.5 to 87.5 after applying Principal Component Analysis (PCA). PCA is a dimensionality reduction technique that transforms a dataset into a lower-dimensional space while preserving the data's most important information or patterns. The mathematical formulation for PCA suggests that the reduced-dimensional representation captured by PCA was informative for the predictive task. Figure 15 shows the PCA analysis for three considered factors.



(**a**) PCA analysis for commercial consumption of hydrogen

(**b**) PCA analysis for industrial consumption of hydrogen

(**c**) PCA analysis for residential consumption of hydrogen

Figure 15. Principal Component Analysis on hydrogen consumption data to facilitate more effective decision making in optimizing hydrogen production, distribution, and utilization strategies for each sector. (**a**) PCA analysis for commercial consumption of hydrogen. (**b**) PCA analysis for industrial consumption of hydrogen. (**c**) PCA analysis for residential consumption of hydrogen.

Consider a dataset X with n samples (data points) and m features (variables), where X is an $n \times m$ matrix. Compute the mean of each feature, represented as a column vector μ, by taking the average of the values across all samples. Center the data by subtracting the mean vector from each sample in X, resulting in a centered data matrix Z, where $Z = X - \mu$. Compute the covariance matrix C of the centered data Z. The covariance matrix measures the pairwise relationships between the different features.

$$C = \frac{1}{(n-1)) * Z^T * Z} \tag{13}$$

where Z^T represents the transpose of the centered data matrix Z. Perform eigenvalue decomposition on the covariance matrix C to obtain its eigenvectors and eigenvalues.

$$C = V * \wedge * \ V^T \tag{14}$$

V is a matrix of eigenvectors, and $\wedge$ is a diagonal matrix of eigenvalues.

Sort the eigenvalues in descending order and select the top k eigenvectors corresponding to the largest eigenvalues to form a projection matrix P.

$$P = V1, V2, \ldots, Vk \tag{15}$$

where $V1, V2, \ldots, Vk$ represent the top k eigenvectors. Project the centered data Z onto the new lower-dimensional space by multiplying Z with the projection matrix P.

$$Y = Z * P \tag{16}$$

where Y represents the transformed dataset with reduced dimensions; the resulting transformed dataset Y captures the most important information or patterns in the original data with the dimensions ordered by the significance of their contribution to the overall variance.

Feature density analysis is a statistical technique used to identify important features in a dataset, as shown in Figure 16. The goal of feature density analysis is to find a set of features that can best explain the variation in the data. The following steps are used to perform feature density analysis.

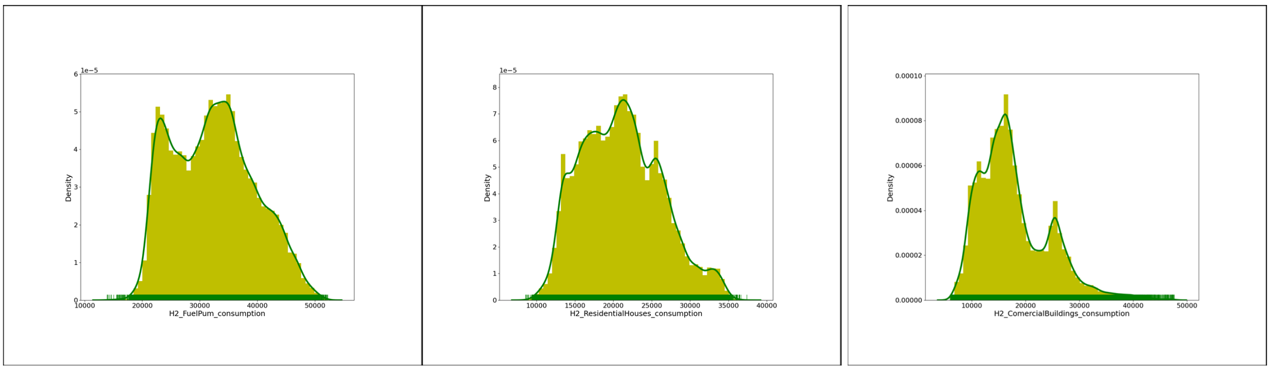
Density analysis can be used to understand the distribution of hydrogen production data over time. It can provide insights into the concentration or variability of hydrogen production rates within a given timeframe. The kernel density estimation (KDE) method estimates the hydrogen production data's probability density function (PDF) based on observed values. It assigns a density value to each data point, representing the likelihood of finding other hydrogen production values nearby.

Here, KDE(x) is the estimated density at value x of hydrogen production, n is the number of data points, h is the bandwidth parameter that determines the width of the kernel function, xi represents the individual hydrogen production data points, and $K()$ is the kernel function, which specifies the shape of the kernel. The choice of the kernel function, such as the Gaussian (normal) distribution, Epanechnikov, or triangular kernel, can affect the shape and characteristics of the density estimation.

$$\mathrm{KDE}(x) = (1/(n^*h)) * \Sigma[K((x - xi)/h)] \tag{17}$$

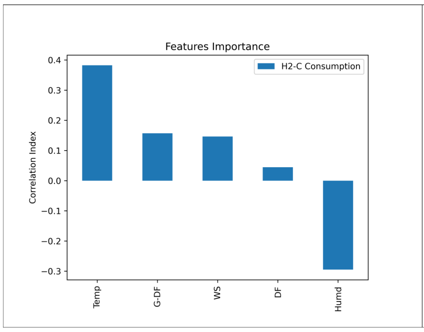
Moreover, the benefit of applying feature importance analysis on hydrogen consumption data in different sectors in this paper is identifying the most influential features that significantly contribute to hydrogen consumption variations within each sector. Feature importance analysis, often conducted using techniques like feature ranking, can help understand the relative importance of different variables or factors affecting hydrogen consumption. Figure 17 shows the result of feature importance for different sectors.

This paper performs prediction analysis on the hydrogen dataset by applying various machine learning models to predict hydrogen consumption data in different sectors, as shown in Figures 18 and 19. The significance of this analysis lies in its potential to offer precise and dependable forecasts of future hydrogen consumption patterns. Machine learning models are robust tools capable of analyzing historical data and recognizing intricate relationships between variables, enabling accurate predictions based on the patterns they have learned. By harnessing machine learning models for prediction analysis on hydrogen consumption data, the paper aims to achieve numerous benefits, including improved decision making, resource planning, risk mitigation, informed investment decisions, sustainable growth, and real-time decision support.

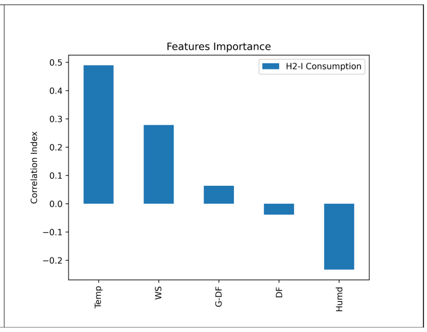


(**a**) Density analysis for commercial consumption of hydrogen
(**b**) Density analysis for industrial consumption of hydrogen
(**c**) Density analysis for residential consumption of hydrogen

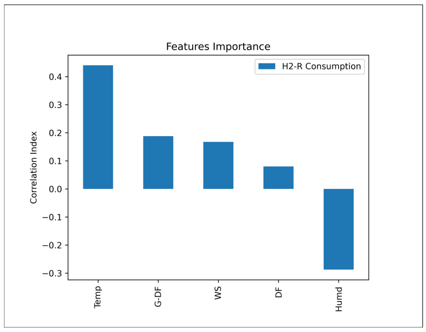
Figure 16. Density analysis of hydrogen consumption data to gain insights into the distribution and concentration of hydrogen consumption within each sector. (**a**) Density analysis for commercial consumption of hydrogen. (**b**) Density analysis for industrial consumption of hydrogen. (**c**) Density analysis for residential consumption of hydrogen.



(**a**) Feature importance for commercial consumption of hydrogen data.

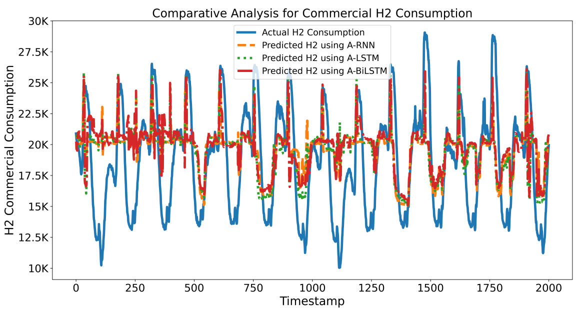


(**b**) Feature importance for industrial consumption of hydrogen data.

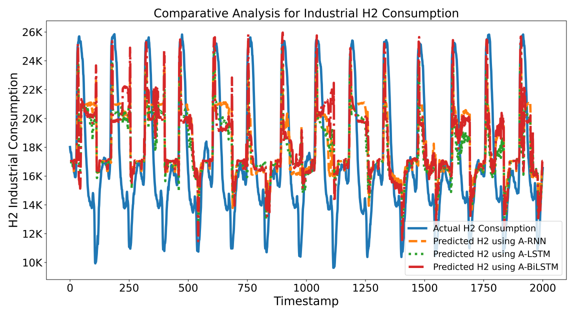


(**c**) Feature importance for residential consumption of hydrogen data.

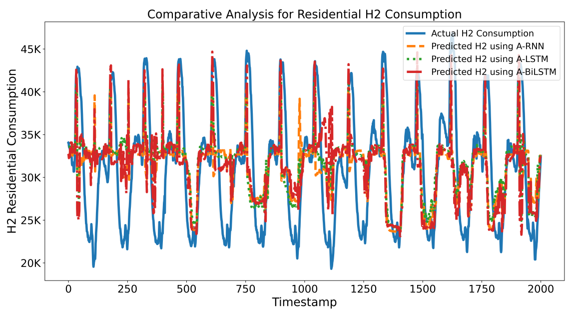
Figure 17. Feature importance analysis to identify the most influential features that significantly contribute to hydrogen consumption variations within each sector. (**a**) Feature importance for commercial consumption of hydrogen data. (**b**) Feature importance for industrial consumption of hydrogen data. (**c**) Feature importance for residential consumption of hydrogen data.



(**a**) Prediction results for commercial consumption of hydrogen data.

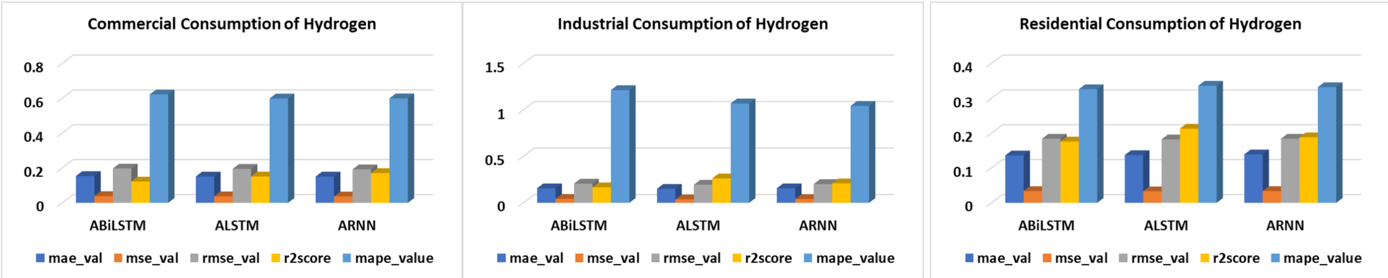


(**b**) Prediction results for industrial consumption of hydrogen data.



(**c**) Prediction results for residential consumption of hydrogen data.

Figure 18. Prediction analysis to provide accurate and reliable forecasts of future hydrogen consumption patterns. (**a**) Prediction results for commercial consumption of hydrogen data. (**b**) Prediction results for industrial consumption of hydrogen data. (**c**) Prediction results for residential consumption of hydrogen data.



(**a**) Prediction error analysis for commercial consumption of hydrogen data.

(**b**) Prediction error analysis for industrial consumption of hydrogen data.

(**c**) Prediction error analysis for residential consumption of hydrogen data.

Figure 19. Prediction error result evaluation of future hydrogen consumption patterns. (**a**) Prediction analysis for commercial consumption of hydrogen data. (**b**) Prediction analysis for industrial consumption of hydrogen data. (**c**) Prediction analysis for residential consumption of hydrogen data.

Three models—ABiLSTM, ALSTM, and ARNN—were used to assess the prediction outcomes for the three scenarios of hydrogen consumption—commercial, industrial, and domestic. All models had low prediction errors in the commercial scenario; ALSTM had the highest R2 score, and ABiLSTM had the lowest MAE. With the lowest MAE and RMSE, ABiLSTM performed better for industrial consumption than the other models, indicating reliable predictions. All models performed similarly in the residential environment with low MAE and RMSE values. With the greatest R2 value, ALSTM appears to provide a more effective explanation for variance. Ultimately, the selection of a model could depend on the particular scenario. For example, ALSTM demonstrated promise in commercial and residential scenarios due to greater R2 scores, indicating better data variation, whereas ABiLSTM excelled in industrial forecasts.

6. Discussion, Comparison, and Limitations

To forecast future hydrogen requirements, systems for analyzing and predicting hydrogen production gather information on hydrogen production, use, and storage. Without blockchain, several security problems can arise in systems that analyze and anticipate hydrogen production. The security risks related to hydrogen production analysis and prediction systems without blockchain technology are outlined below:

- The possibility of data tampering, in which nefarious individuals try to alter the information gathered about hydrogen production, use, and storage. This could cause erroneous forecasts and interfere with the system's functionality [48].
- The manufacturing and storage systems for hydrogen are becoming more and more vulnerable to hackers. These kinds of assaults can be used to harm equipment, interfere with operations, or even steal data. Because blockchain creates a dispersed, decentralized network that is more resilient to attacks, it can improve cybersecurity. Additionally, it can be used to safeguard login information and prevent unauthorized changes [49].
- Security and safety risks might arise from supply chain weaknesses, such as tampering with the transportation and storage of hydrogen. A supply chain-wide immutable ledger can be produced using blockchain technology. It lowers the possibility of tampering by guaranteeing the traceability of hydrogen generation, transmission, and storage [50].
- Sensitive information may be present in predictive maintenance systems. Unauthorized entry may result in data breaches and possibly harm essential equipment. Predictive maintenance data can be secured using blockchain technology by encrypting it and limiting access via smart contracts. Authorized personnel can access data while security and privacy are preserved [2].
- Systems for energy trading and billing can be subject to fraud and conflicts in hydrogen production. Blockchain-based smart contracts can automate energy trade and billing,

guaranteeing tamper-proof and transparent transactions. Settlements become more open and safer [51].
- Penalties, both monetary and legal, may arise from breaking environmental and safety standards. Blockchain technology can securely store data on emissions, safety precautions, and other regulatory requirements, which can automate compliance reporting. Transparency and compliance are thus guaranteed [52].

Furthermore, the paper should address the limitations of the research. This includes acknowledging any constraints or challenges faced during the implementation of the proposed system, potential biases in the data collected, or limitations in the analytical methods employed. By acknowledging these limitations, the authors demonstrate a critical understanding of the study's scope and provide directions for future research to overcome these limitations.

Overall, the paper's discussion, comparison, and limitations sections contribute to a comprehensive understanding of the research, its implications, and its potential for real-world applications. They provide researchers, practitioners, and policymakers with valuable insights in secure hydrogen data analysis and intelligent power management systems.

7. Conclusions and Future Directions

The proposed research uses blockchain technology to present a four-layer architecture for safe and effective green hydrogen data analysis. It highlights blockchain's function in maintaining data integrity and transparency within intelligent power management systems and specializes in historical data analysis. By incorporating renewable energy sources, applying statistical approaches, closely monitoring data, and facilitating power management, this design substantially contributes to creating and distributing clean and sustainable energy. Making decisions is further improved by the addition of machine learning prediction models. With mean absolute error (MAE) values of 0.154 for commercial consumption, 0.157 for industrial consumption, and 0.136 for residential consumption, the prediction models specifically showed noteworthy accuracy, demonstrating the efficacy of the suggested approach in forecasting hydrogen consumption. These findings endow power management systems with the capacity to predict hydrogen requirements precisely.

Prospective avenues for development encompass enhancing scalability, tackling pragmatic implementation obstacles, and investigating interoperability. Potential technical difficulties and the requirement for scalability and processing efficiency are limitations. As a result, this study provides a strong foundation for safe blockchain-based hydrogen data analysis, promoting improved power control, the integration of green energy sources, and accurate hydrogen consumption forecasting. More research should concentrate on optimization and useful implementation to fully realize the promise.

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