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Deep Learning for Wind and Solar Energy Forecasting in Hydrogen Production

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Abstract: This research delineates a pivotal advancement in the domain of sustainable energy systems, with a focused emphasis on the integration of renewable energy sources—predominantly wind and solar power—into the hydrogen production paradigm. At the core of this scientific endeavor is the formulation and implementation of a deep-learning-based framework for short-term localized weather forecasting, specifically designed to enhance the efficiency of hydrogen production derived from renewable energy sources. The study presents a comprehensive evaluation of the efficacy of fully connected neural networks (FCNs) and convolutional neural networks (CNNs) within the realm of deep learning, aimed at refining the accuracy of renewable energy forecasts. These methodologies have demonstrated remarkable proficiency in navigating the inherent complexities and variabilities associated with renewable energy systems, thereby significantly improving the reliability and precision of predictions pertaining to energy output. The cornerstone of this investigation is the deployment of an artificial intelligence (AI)-driven weather forecasting system, which meticulously analyzes data procured from 25 distinct weather monitoring stations across Latvia. This system is specifically tailored to deliver short-term (1 h ahead) forecasts, employing a comprehensive sensor fusion approach to accurately predicting wind and solar power outputs. A major finding of this research is the achievement of a mean squared error (MSE) of 1.36 in the forecasting model, underscoring the potential of this approach in optimizing renewable energy utilization for hydrogen production. Furthermore, the paper elucidates the construction of the forecasting model, revealing that the integration of sensor fusion significantly enhances the model's predictive capabilities by leveraging data from multiple sources to generate a more accurate and robust forecast. The entire codebase developed during this research endeavor has been made available on an open access GIT server.

Keywords: sustainable energy systems; renewable energy sources; hydrogen production; deep learning; weather forecasting; fully connected neural networks; convolutional neural networks; energy management; wind power; solar power

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1. Introduction

The imperative of transitioning to sustainable energy systems, given escalating environmental concerns and diminishing fossil fuel reserves, has led to a heightened focus on renewable energy sources, particularly in the context of hydrogen production. This shift is emphasized by several studies and reports that have explored the dynamics and implications of this transition.

The World Energy Transitions Outlook 2023 report highlights that renewable energy, clean hydrogen, and sustainable biomass, along with electrification and energy efficiency, are critical drivers of this transition. The report highlights the necessity of a rapid and systemic transformation of the energy system away from its current reliance on fossil fuels, emphasizing that achieving the 1.5 °C climate target is made feasible by using a range of policies and technical strategies, which include a significant scale-up of renewables in the power sector, coupled with major efficiency upgrades and a shift to direct renewable use across all end use sectors [1].

Further, the research presented in *Nature Energy* delves into the social and economic aspects of the energy transition, examining the impact of transitioning from fossil fuels to renewable energy sources like solar and wind on communities and job markets [2]. It particularly focuses on the implications for regions and communities historically dependent on coal and other fossil fuels, assessing how the transition affects local economies and employment.

1.1. State of the Art

In the domain of hydrogen production, studies have shown the integration of green hydrogen into renewable energy systems, particularly for residential and electric vehicle (EV) applications [3]. This integration is aimed at addressing the challenges of intermittency in solar and wind power, showcasing adaptability to remote areas. The research also highlights the economic and environmental sustainability of such systems, emphasizing their role in enhancing energy accessibility and stability.

At the heart of this integration is the need for precise and reliable forecasting of wind and solar energy outputs [4,5]. Currently, deep learning techniques have surfaced as transformative tools, revolutionizing the approach to energy forecasting [6,7]. These advanced computational methods offer unprecedented capabilities in handling the complexity and variability inherent in renewable energy systems, thereby significantly enhancing forecasts' accuracy and reliability [8].

Recent strides in the field have seen the emergence of sophisticated multivariate forecasting models. These models, as stated in the works of Sørensen et al. [9], employ state-of-the-art techniques in multivariate analysis to predict wind and solar power production. The emphasis on probabilistic forecasting within these models marks a significant evolution in the field of electrical engineering, allowing for more nuanced and informed decision-making processes in energy management. Concurrently, time-series methodologies have gained prominence for their efficacy in improving the forecasting precision, as evidenced by the comprehensive analysis presented by Ghofrani and Alolayan [10]. These methods offer a granular view of prediction techniques, paving the way for more accurate and actionable insights into wind and solar power generation trends.

In the broader landscape of sustainable energy research and development, the application of deep learning techniques to forecasting for solar energy represents a monumental stride forward. This area of study, as expounded upon in the pivotal research by Alkhayat et al. [11], not only identifies the existing gaps in solar energy forecasting but also underscores the immense potential that artificial intelligence holds in refining the accuracy of these predictions. Such advancements are critical in navigating the challenges posed by the inherent variability and unpredictability of solar energy, thereby enhancing the reliability and efficiency of solar power systems.

The significance of this research is further amplified by the initiatives of major governmental bodies, such as the U.S. Department of Energy. Their sponsorship of projects aimed at advancing wind and solar power forecasts, as detailed in the comprehensive studies of Orwig et al., reiterates the critical importance of accurate variable generation forecasting [12]. This is not only vital for the optimization of the power system but also for ensuring the stability and resilience of the energy grid in the face of fluctuating renewable energy sources. Additionally, the exploration of deep learning architectures in wind time-series forecasting, as demonstrated by Manero et al., marks a significant advancement in the

field [13]. The application of sophisticated algorithms like recurrent neural networks and convolutional networks has opened up new avenues in accurately predicting wind patterns, a factor crucial for the efficient harnessing of wind energy. This aspect of renewable energy research is pivotal in addressing challenges such as wind power curtailment and enhancing the overall utilization of wind resources.

The role of hydrogen production technology, particularly when powered by wind energy, as illustrated in the research by Li et al., stands out as a key solution in the renewable energy domain [14]. This technology not only augments the efficiency of wind energy utilization but also presents a sustainable method for integrating renewable sources into the energy grid. The ability to convert wind energy into hydrogen effectively mitigates the issues related to an intermittent energy supply, thus reinforcing the role of hydrogen as a versatile and clean energy carrier.

The scope of deep learning applications in the realm of sustainable energy extends far beyond the conventional domains of wind and solar energy forecasting, encompassing innovative areas such as bio-hydrogen production technology. This expansion reflects a concerted effort within the scientific community to harness the full potential of artificial intelligence in revolutionizing various facets of renewable energy production and management. Different studies exemplify this trend, showcasing how deep learning can facilitate the automation and optimization of bio-hydrogen production processes [15,16]. This technological advancement is not merely an incremental improvement; it represents more efficient and sustainable hydrogen production methods, leveraging the power of artificial intelligence (AI) to enhance the process control and production rates. In parallel, the field of computer vision, an integral part of deep learning, has made significant inroads in the energy sector. As elucidated in the studies by Bosma and Nazari, computer vision techniques are being employed to refine the forecasting of regional energy outputs, particularly in the context of renewable energy sources [17]. This approach underscores the multifaceted nature of deep learning applications, extending beyond numerical data analysis to include visual data interpretation, thereby broadening the horizon for more accurate and comprehensive energy forecasting models. Moreover, the application of deep learning transcends the technicalities of energy production, venturing into the intricate dynamics of energy markets. The research by Dumas et al. highlights the use of probabilistic forecast-driven strategies, enabled by deep learning models, in the capacity firming market [18]. This approach exemplifies how AI can contribute to more informed and risk-aware decision-making in energy trading and management. By generating quantile forecasts of renewable energy generation, these models provide crucial insights into the uncertainties inherent in renewable energy markets, facilitating more robust and resilient energy trading strategies.

Complementing these engineering advancements, the field of renewable energy forecasting has witnessed a surge in the application of machine learning and deep learning techniques. Benti et al. provide a comprehensive review of the current state and future prospects in this domain [19]. Their analysis sheds light on the transformative impact of these technologies on predicting renewable energy outputs, which is integral to planning and optimizing energy systems. The potential of machine learning and deep learning in this context represents a substantial enhancement of how energy forecasting is approached, offering more accurate, reliable, and dynamic predictions. Further enhancing the predictive capabilities in renewable energy forecasting, attention mechanisms, as explored by Brahma et al., have been identified as a promising frontier in improving the accuracy of wind speed and solar irradiance models [20]. These mechanisms, part of the broader suite of advanced deep learning techniques, bring a nuanced understanding of the temporal and spatial dependencies in weather patterns, which are crucial for precise energy forecasting. The introduction of such sophisticated methodologies signifies a leap forward in our ability to predict and harness renewable energy, directly contributing to the efficiency and reliability of renewable energy systems.

Collectively, these developments in turbine optimization, energy forecasting, and advanced predictive models represent a rapidly evolving field, where interdisciplinary approaches are converging to address the multifaceted challenges of sustainable energy generation. This broader and more comprehensive perspective not only highlights technological innovations but also emphasizes the interconnected nature of these advancements in contributing to a sustainable and climate-resilient future. The synergy between engineering advancements, predictive analytics, and environmental foresight is setting the stage for a new era of renewable energy, characterized by efficiency, sustainability, and a deep commitment to combating climate change.

Another important factor in terms of forecasting is data privacy, which is crucial to the development of deep-learning-based wind and solar energy forecasting models. The use of federated-learning-based methods has been proposed as a novel approach to addressing privacy concerns in the context of wind power forecasting [21,22]. This decentralized collaborative modeling method allows the training of a single model on data from multiple wind farms without compromising the privacy or security of the data. Similarly, in the field of solar energy forecasting, there is recognition of the importance of addressing privacy concerns, as evidenced by the identification of the key research gaps in deep-learning-based solar energy forecasting methods.

Furthermore, the application of deep learning methods to power load and renewable energy forecasting in smart microgrids has been the subject of extensive research, highlighting the significance of privacy-preserving techniques in this domain [23]. Additionally, the availability of solar and wind generation data from on-site sources has been acknowledged as beneficial to the development of data-driven forecasting models, emphasizing the importance of ensuring the privacy and security of such data [8]. The potential for geographically distributed time-series data to enhance the forecasting skills for wind and solar energy has been recognized, underscoring the need for privacy-preserving mechanisms in handling such data [24]. Additionally, the robustness of privacy-preserving distributed learning methods for renewable energy forecasting has been demonstrated, further emphasizing the importance of protecting privacy in this context [25].

In summary, these references highlight the critical role of data privacy in the development of deep-learning-based wind and solar energy forecasting models. The use of federated-learning-based approaches, privacy-preserving distributed learning methods, and the identification of research gaps in the context of solar energy forecasting all underscore the significance of addressing privacy concerns in this domain.

1.2. Objectives of This Work

The novelty of this research is underscored by its focus on the development of a deep learning (DL) system designed specifically for forecasting short-term weather conditions (1 h ahead) at a highly localized level. This represents a significant advancement in meteorological modeling, particularly in its application to regions with solar or wind energy installations. The current weather prediction models typically do not provide such immediate and localized forecasting capabilities, making this approach a novel contribution to the field. Moreover, the operational costs of hydrogen production facilities are drawing attention to more precise predictions of available solar and wind energy. Therefore, in this publication, fully connected neural network (FCN) and convolutional neural network (CNN) forecasting systems are considered. The implementation of such systems aims to enhance the efficiency of load balancing in smart power grids, facilitating the feasibility of storing surplus energy in the form of hydrogen. To explore this deep-learning-based approach, a specific use case is explored, and the AI deep learning model is trained on open access data from 25 weather monitoring stations located in the Republic of Latvia (Latvia). The concept of the smart power grid load-balancing system and the results of the available renewable energy forecasting system are reported further in the publication.

The variety of sensors used in the training of deep learning models can be expanded by incorporating additional sensors, such as sky-viewing sensors. This area of investigation requires additional research [26].

The usage of fully connected neural network and convolutional neural network models enhances the efficiency of renewable energy source (RES) utilization. The 1 h ahead weather forecasting system functions primarily as a real-time monitoring tool and relies on a precise sensor network for data collection, as can be seen in Figure 1. Surplus energy from renewable sources, such as wind, presents an optimal opportunity for hydrogen production through electrolysis, where excess electricity facilitates the conversion of water into hydrogen and oxygen, thereby storing renewable energy in a form that is transportable and usable across various sectors. Advanced weather forecasting plays a critical role in managing wind energy production, enabling more precise prediction of wind patterns and thus optimizing the scheduling of hydrogen production during periods of anticipated energy surplus, enhancing both the efficiency and sustainability of renewable energy systems. This approach promises to revolutionize sustainable hydrogen production by harnessing renewable energy more efficiently.

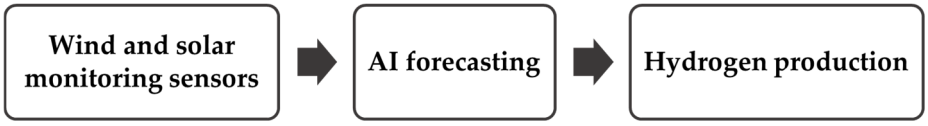

Figure 1. Deep learning control for H_2 production.

2. Materials and Methods

The methodology is structured into distinct subsections for clearer exposition and detailed articulation of this research's key components:

2.1. Communication Protocol

Figure 2 shows the required protocol for integrating parameter monitoring with the RES production module control. This illustration outlines how all the modules have to be interconnected to implement a cohesive smart energy system.

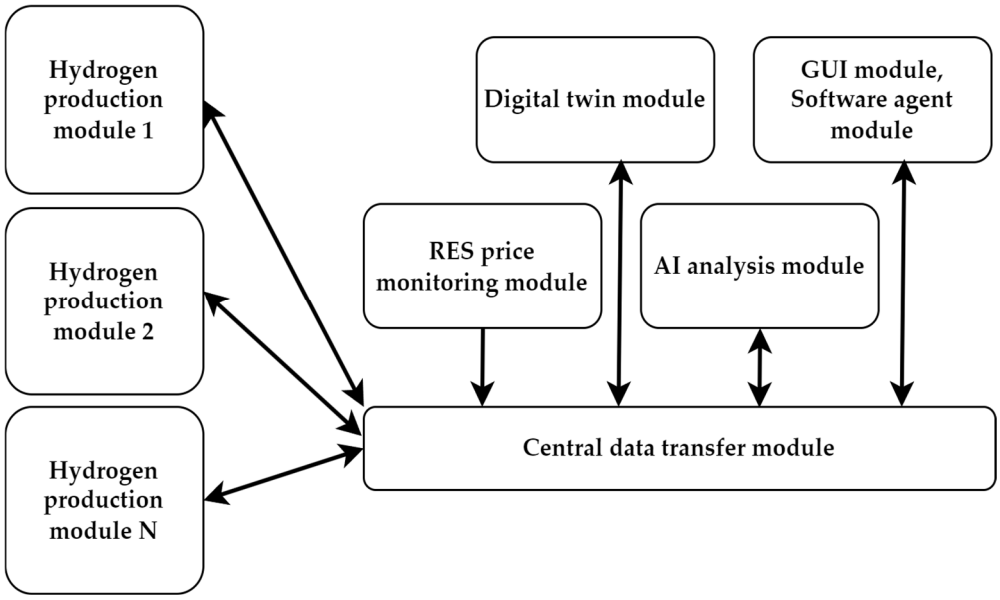

Figure 2. Hydrogen production system data transfer scheme.

In our research, the ZeroMQ communication system is employed for the data transfer from sensors to the server, capitalizing on its Python library compatibility given that the AI system operates within a Python environment. Utilizing the Transmission Control Protocol

(TCP), ZeroMQ serves as the backbone for server–client interactions, facilitating efficient, cross-platform data transmission between operating systems like Windows and Linux (alternative solutions: MQTT messaging or the OPC UA standard). The system is designed to be lightweight and scalable, capable of supporting a variety of messaging patterns and handling large data volumes without the risk of loss or congestion [27].

A Python code snippet exemplifying the minimal steps to establish a ZeroMQ connection between the server and client is included in the documentation on implementation guidance (Algorithm 1).

Algorithm 1: Server and client Python scripts

The script for the server side	The script for the client side

import zmq
# create a ZeroMQ context 	
context = zmq.Context()
# set up a server socket 	
server_socket = context.socket(zmq.REP)
server_socket.bind(f"tcp://*:5555")
# receive the message on the server 	
message = server_socket.recv()
print (message)
# send a reply from the server to the client 	
server_socket.send(b"Hello, client!")
	import zmq
	# insert your computer ip
	serverIP = "192.0.2.X"
	# create a ZeroMQ context
	context = zmq.Context()
	# set up a client socket
	client_socket = context.socket(zmq.REQ)
	client_socket.connect(f"tcp://{serverIP}:5555")
	# send a message from the client to the server
	client_socket.send(b"Hello, server!")
	# receive the replay on the client
	reply = client_socket.recv()
	print (reply)

Once the data have been appropriately pre-processed to meet the neural network input requirements, they are directly fed into the specified neural network model. A link to the GIT site is available in the data availability statement at the end of this manuscript.

2.2. Data

Weather condition monitoring is an ongoing endeavor. For the purposes of training and testing the neural networks, the data are sourced from the Latvian Open Data Portal [28] uploaded by the Latvian Environment, Geology and Meteorology Centre [29]. It is essential that the neural network be localized and fine-tuned to align with the unique climatic and environmental characteristics of the region in which it will operate.

Global training of the neural network allows the model to recognize generic weather patterns and relationships that are universally applicable. Subsequent fine-tuning for the local area enables the model to adapt to region-specific nuances. In our development, we used historical data [29] from twenty-five weather monitoring stations located in Latvia, as shown in Figure 3.

The dataset contains 4211 hourly measurement instances for each weather station, starting from 00:00 11 January 2023. Every measurement instance stores 10 parameters, giving 250 parameters total for each time instance (Table 1).

In our study, we selectively focused on the wind speed data parameter, specifically designated as WNS10, for the training and refinement of our deep learning models. The sourced data originate from the Madona weather station. For solar energy scenarios, a comparable dataset needs to be downloaded from the weather stations.

In the case of real-time monitoring, an example code snippet for data scraping is provided as Algorithm 2.

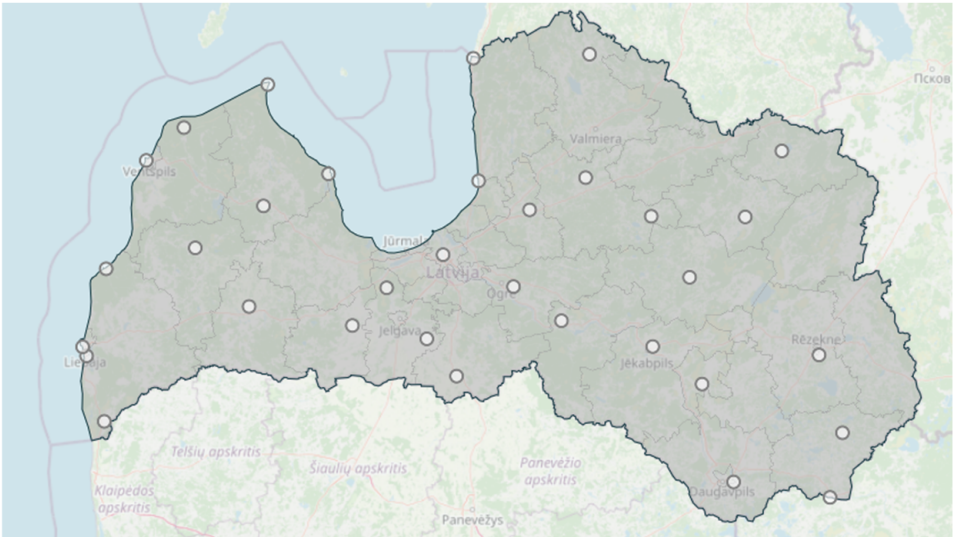

Figure 3. Weather monitoring stations in Latvia [29].

Table 1. The parameters collected from each station.

Parameter Code	Description
HPRAB	Precipitation amount, hourly sum, mm
HWDMX	Wind direction, hourly maximum speed, 0–360 degrees
HWSMX	Wind speed, hourly maximum, m/s
PRSS	Atmospheric pressure at station level, actual QFE, hPa
RLH	Relative humidity, actual, %
SNOWA	Snow depth, actual, cm
TDRY	Air temperature actual, Celsius degrees
VSBA	Visibility meteorological, actual, m
WNDD10	Wind direction, actual, 0–360 degrees
WNS10	Wind speed, actual, m/s

Algorithm 2: Example of Python code for real-time data scraping to extract specific parameters (e.g., wind power) from a meteorological station in Latvia

```
import urllib.request
url = "https://data.gov.lv/dati/api/3/action/datastore_search?resource_id=17460efb-ae99-4d1d-8144-1068f184b05f&limit=5%E2%80%9D
with urllib.request.urlopen(url) as response:
html = response.read()
print(html)
```

2.3. AI Module

To develop an AI-based weather forecasting system, various methodologies are possible. In the paper, we employed fully connected neural network (FCN) and 1D convolutional neural network (CNN) architectures to tackle the problem. These selected models offer distinct advantages in capturing complex patterns and relationships in the data.

To train the deep learning models, we used the data described before. We split the dataset, consisting of 4211 time instances, into a training set and a test (or validation) set at a ratio of 70:30 and we used a 24 h time window and data from 25 monitoring stations simultaneously to forecast 1 parameter (wind speed) 1 h ahead at specific location. We used 1 random station (Madona) from 25. Thus, the system has a 6000 $\times$ 1 input vector (24 h $\times$ 10 parameters $\times$ 25 stations) and 1 output value.

For training the deep learning model, a sequence-to-sequence approach was utilized, wherein the model predicts the next value in the sequence. This eliminates the need for specific data labeling or an annotated dataset.

2.3.1. AI Module Based on an FCN

In this research, an FCN is utilized for predicting the available RES energy. In our study, while the hyperparameters, such as layer sizes, remain subjects for further optimization, it was observed that specific deep neural networks (DNNs) configured for the 6000 × 1 input dimension have not yet been explicitly identified in the current literature. The details governing this neural network can be seen in Table 2.

Table 2. Data dimensionality at each layer in the employed fully connected neural network architecture.

Layer (Type)	Output Shape	Param Count
Input	[−1, 1, 6000]	0
Linear-1	[−1, 1, 500]	3,000,500
Linear-2	[−1, 1, 500]	250,500
Linear-3	[−1, 1, 500]	250,500
Linear-4	[−1, 1, 500]	250,500
Linear-5	[−1, 1, 1]	501

The AI model for hydrogen production incorporates 3,752,501 trainable parameters, with no non-trainable parameters, indicating a fully adaptable architecture for the training process.

2.3.2. AI Module Based on a CNN

Additionally, within this research, we employed a 1D convolutional neural network model to forecast the required parameters. The 1D CNN architecture is particularly well suited to time-series data, where a fixed time window is considered. It excels in capturing local patterns and dependencies, discerning them across various signal areas. This makes it highly appropriate for tasks involving data processing with time series, such as time-series forecasting, speech recognition, and signal processing. Weather data are inherently sequential, consisting of parameters like temperature, humidity, wind speed, and pressure recorded over time in a given local area. The specifics of the utilized CNN are given in Table 3.

Table 3. Data dimensionality at each layer in the employed convolutional neural network architecture.

Layer (Type)	Output Shape	Param Count
Input	[−1, 1, 6000]	0
Conv1d-1	[−1, 500, 1999]	3000
MaxPool1d-2	[−1, 500, 999]	0
Conv1d-3	[−1, 500, 332]	1,250,500
MaxPool1d-4	[−1, 500, 166]	0
Conv1d-5	[−1, 500, 81]	1,250,500
MaxPool1d-6	[−1, 500, 40]	0
Conv1d-7	[−1, 500, 18]	1,250,500
MaxPool1d-8	[−1, 500, 17]	0
Conv1d-9	[−1, 500, 7]	1,250,500
MaxPool1d-10	[−1, 500, 6]	0
Flatten-11	[−1, 3000]	0
Linear-12	[−1, 500]	1,500,500
Linear-13	[−1, 1]	501

The AI model for hydrogen production incorporates 6,506,001 trainable parameters, with no non-trainable parameters, indicating a fully adaptable architecture for the training process.

3. Results

AI Module

The observed forecasting performance makes our CNN/FCN approaches suitable for controlling H_2 electrolysis according to the available renewable power. The interface to the actual electrolyzer plant can be realized by means of ZeroMQ, as proposed in Section 2.1. In terms of the data format, predictions using a set of different forecasting horizons can be made in order to allow for fine-grained electrolyzer control as well as allowing for sufficient advance notice when a plant has to be shut down completely. A sample data structure for controlling hydrogen electrolysis is given in Table 4.

Table 4. Example of a control message to the hydrogen production operators.

T = 0 s; 25 kW; +0 kW −0 kW; 100% certain
T = 600 s; 21 kW; +1 kW −1 kW; 95% certain
T = 1200 s; 18 kW; +3 kW −1 kW; 92% certain
T = 1800 s; 11 kW; +1 kW −1 kW; 84% certain
T = 2700 s; 2 kW; +0 kW −2 kW; 60% certain
T = 3600 s; 22 kW; +2 kW −1 kW; 90% certain

The FCN and CNN models were evaluated using wind speed data, leading to the results specified subsequently. The performance metrics and insights drawn from this evaluation serve to validate the model's efficacy and reliability in wind speed prediction tasks. In Figure 4, the progressive convergence of the AI-predicted values toward the actual values is evident, as measured using the mean squared error (MSE) or L2 loss.

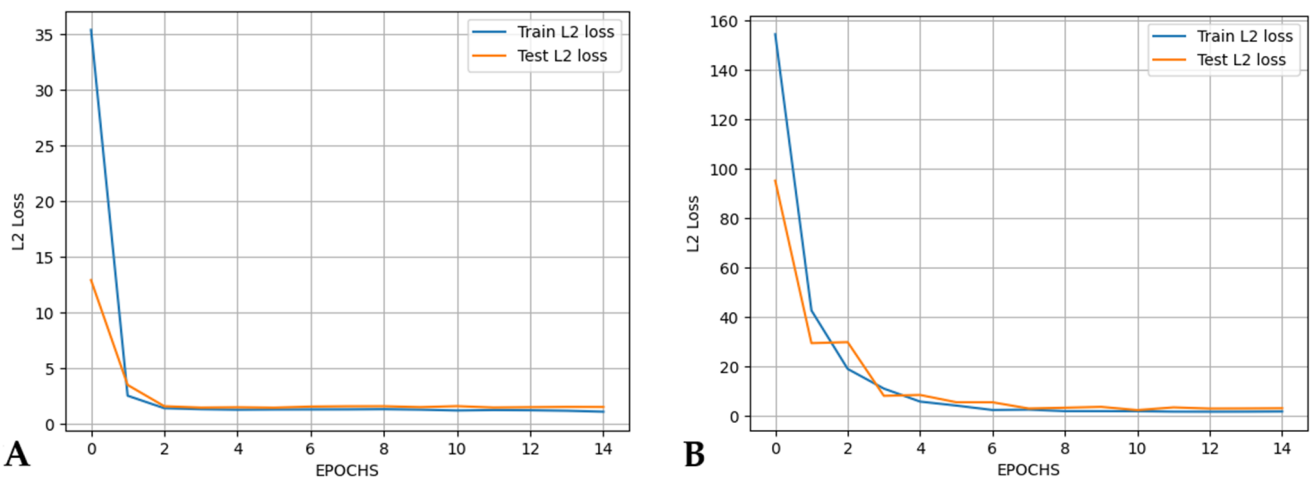

Figure 4. Comparative analysis of training and test L2 losses over epochs for the CNN-based (**A**) and FCN-based (**B**) AI prediction systems.

The network is optimized using the adaptive moment estimation optimizer (Adam optimizer) with a learning rate of 0.00001 throughout the experiment. The training and test sets were described before in the paper. The source code of the experiments is publicly available on the official Git server. The link to the Git site is available in the data availability statement at the end of this manuscript.

The FCN model yields a mean squared error (MSE) or L2 loss of 1.61 for wind speed estimation on the training set and 1.77 on the validation set. In comparison, the CNN model yields an L2 loss of 1.10 on the training set and 1.36 on the validation set (after 14 epochs). The dataset for wind speed from the used station in the experiments has a mean value of

2.25 [m/s] and a standard deviation of 1.3. A comparable performance will be anticipated for the other parameter predictions.

4. Discussion

In the manuscript, we present a deep-learning-based prediction system engineered to enhance hydrogen (H_2) production control. This system is pivotal in the context of renewable energy management, particularly for its integration with the smart energy grid concept. The core of our research involves an exploration of two deep neural network architectures: fully convolutional networks (FCNs) and convolutional neural networks (CNNs). Our empirical investigations employed these neural network models in the context of wind speed data analysis. The findings, as elucidated in this paper, are significant in affirming the models' effectiveness and reliability in wind speed prediction tasks. Figure 4 in our manuscript provides a graphical representation of the models' performance, particularly illustrating the progressive convergence of the AI-predicted values toward the actual wind speed values. This convergence is quantitatively measured using the mean squared error (MSE) or L2 loss, a standard metric in the assessment of predictive precision.

The optimization of the neural network models was achieved using the adaptive moment estimation (Adam) optimizer, employed with a learning rate of 0.00001. This optimization strategy was critical in refining the models' learning efficacy. The performance metrics, as detailed in the manuscript, reveal a distinctive advantage of the CNN model over its FCN counterpart. Specifically, the CNN model demonstrates a lower MSE, with values of 1.0488 on the training set and 1.1662 on the validation set after 14 epochs, in comparison to the FCN model, which exhibits an MSE of 1.61 on the training set and 1.77 on the validation set. Considering the wind speed dataset's characteristics, specifically a mean value of 2.25 m/s and a standard deviation of 1.3, the CNN model's precision closely approximates the range within 1 standard deviation. The observed level of precision achieved using the CNN model in our study, which is approximately an MSE of 1.36, is commendable and stands in favorable comparison to similar research in the field [30–32]. This level of performance, particularly when assessed in the context of wind speed forecasting, underscores the efficacy of the CNN architecture in capturing complex spatial and temporal patterns inherent in meteorological data. The superior performance of the CNN over the FCN model in our study corroborates the findings from the existing literature, where CNNs are often reported to outperform FCNs in tasks that require the analysis of intricate data patterns [33,34].

The prospective enhancements to the forecasting system emphasize the integration of a more diverse array of monitoring sensors and the inclusion of data from various weather forecasting sources. These improvements are expected to not only refine the precision of the predictions but also broaden the model's applicability beyond just wind speed estimation. A key limitation identified in the study is the availability of data, particularly the scarcity of local sources with open access retrospective forecasting data. This is crucial, as machine learning heavily depends on the quality and quantity of data provided. Additionally, the study acknowledges the sensitivity of deep neural network configurations, especially in wind and solar energy forecasting for hydrogen production. Citing Kuzle et al., the manuscript underscores the challenges in optimizing the network architecture to ensure accurate and reliable forecasting, a critical aspect of deep learning applications in this field [35].

Author Contributions: Conceptualization, K.S.; methodology, A.R., K.S., V.K., A.Z., A.K. and I.N.; software, A.N. and K.S.; validation, K.S.; formal analysis, K.S.; investigation, K.S.; resources, K.S.; data curation, K.S.; writing—original draft preparation, E.E. and K.S.; writing—review and editing, E.E., K.S., K.O., V.K., A.Z. and A.K.; visualization, K.S.; supervision, K.S.; project administration, K.S.; funding acquisition, K.O. All authors have read and agreed to the published version of the manuscript.

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Data Availability Statement: https://pubgit.edi.lv/kaspars.sudars/hydrog-re-energy-env-project (accessed on 29 January 2024).

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