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Master Thesis in Environmental Engineering

Integrating AI and AEM Electrolyzer for Green Hydrogen Production: Optimization of Solar-Powered Electrolysis in Residential Energy Management

Master Candidate

Mehdi Saberiabkouhi

Student ID 1229773

Supervisor

Prof. Simone Mancin

University of Padova

Co-supervisor

Prof. Dr. Lars Jürgensen and Dr. Florian Kuhnen

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Abstract

This master's thesis presents a comprehensive study on the forecasting of short-term power generation in a grid-connected hybrid solar photovoltaic (PV) system through the utilization of an artificial intelligence (AI) model. The research integrates weather data and solar PV electricity production data to develop and optimize a Long Short-Term Memory (LSTM) based AI model. The year 2021's solar PV and weather data were utilized for training and validating the model. Additionally, AEM electrolyzer was optimized to efficiently produce hydrogen using surplus electricity generated by the solar PV system .

The investigation identified notable correlations between solar radiation, solar energy, UV index, and various other weather parameters with solar PV power generation. These correlations played a significant role in enhancing the accuracy of the AI model in predicting power generation. Various LSTM model structures were evaluated, and a two-layer LSTM model demonstrated superior performance, achieving an accuracy of approximately 80%. Furthermore, surplus electricity generated by the system, averaging 10 kWh during the daytime was calculated and analyzed.

The economic viability of the hybrid system was also established, as the cost of electricity generated through the hybrid system was less than half of the grid energy price, meeting the regulatory standards.Optimizing the AEM electrolyzer revealed that a configuration with a few standby parallel AEM electrolyzers was optimal for utilizing excess electricity effectively. Further than that scheduling the parallel system in hourly basis for the days ahead, would help to have more conveniently benefit from this system.

In conclusion, this research presents promising avenues for future studies aimed at further enhancing the efficiency and sustainability of renewable energy systems. Prospective research includes real-time integration of weather updates for AI models, advanced energy storage systems, demand-side management strategies, comparison of machine learning algorithms, optimized hydrogen production, and the evaluation of the integrated model in a microgrid setting. These future directions aim to contribute to the wider adoption of renewable energy sources and facilitate the transition towards a more sustainable energy future.

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List of Acronyms

EU European Union

PV Photovoltaics

EES Electrical Energy Storage

TES Thermal Energy Storage

LIB Li-ion batteries

FC Fuel Cell

Pb-A lead-acid

DOD Depth of Discharge

STES Sensible Thermal Energy Storage

LCOE Levelized Cost of Energy

GSHP Ground Source Heat Pump

EL Electrolyzer

PEM Proton Exchange Membrane

AEM Anion Exchange Membrane

PGM Platinum group-based

OER Oxygen evolution reaction

HER hydrogen evolution reaction

PEMEL Proton Exchange Membrane Electrolyzers

KOH Potassium hydroxide

AI Artificial Intelligence

Kwh Kilowatt-hour

Kw Kilowatt

HES Household Electricity Survey

m3 Cubic meter

WT Wind Turbine

SoC State of Charge

RES Renewable energy sources

EMS Energy Management System

c-Si Crystalline Silicon

CdTe Cadmium Telluride

CdS Cadmium Sulphide

AFC Alkaline Fuel Cell

PEMFC Proton Exchange Membrane Fuel Cell

PAFC Phosphoric Acid Fuel Cells

MCFC Molten Carbonate Fuel Cell

SOFC Solid Oxide Fuel Cell

H2O Water

GDL Gas Diffusion Layer

OH hydroxide ions

GA Genetic Algorithms

PSO Particle Swarm Optimization Algorithm

FL Fuzzy Logic

LSTM Long Short-Term Memory

RNN Recurrent Neural Network

EE Excess Electricity

Pmax Maximum power consumption

UV ultraviole

n$_{opt}$ Optimal number of AEM electrolyzers

1 Introduction

The European Union (EU) has the ambitious goal of being climate neutral by 2050, a road-map set out in the European Green Deal [53]. Furthermore, in July 2021, the European Commission put forth a proposition aiming for a more ambitious objective of achieving a 40% target in renewable energy. Additionally, there was a proposal to augment the renewable energy fraction in residential constructions to reach 49% by the year 2030 [15].

Rooftop photovoltaics (PV) in Germany produce around 15 TWh of power per year. Germany's move to renewable power requires expansive increments in rooftop and field-based PV [18].

Energy storage systems have not yet achieved widespread integration into building energy systems primarily due to the inherently high initial investment costs associated with these storage systems. However due to the directives there is potential for extensive adoption of PV systems in conjunction with diverse energy storage technologies across various building types. [27].

The integration of energy storage systems serves as a remedy for excess energy production, allowing the surplus electricity generated by the PV system during its peak production hours to be stored for utilization during periods of lower production [44]. On the other hand, an alternative strategy could encompass the commercialization of excess PV electricity into an existing power grid. It is vital to emphasize that when directing surplus electricity to the grid, the end-user can typically realize approximately one-fifth of the average household electricity price, factoring in transmission costs, tax implications, and markups [6] [40] . Hence, optimizing the utilization of energy at a local level becomes highly favorable. Consequently, integrating energy storage systems for this objective appears to present a rational alternative when juxtaposed with the options of either wasting excess photovoltaic electricity or vending it at a fraction of the electricity procurement cost in standalone residences.

1.1 Energy Storage Technologies

The effectiveness of solar photovoltaic (PV) systems in residential settings can be elevated through the integration of diverse energy storage technologies. These encompass electrical energy storage (EES), chemical energy storage, and thermal energy storage (TES). Illustrative instances of these technologies encompass Li-ion batteries (LIB) and lead-acid (Pb-A) for EES, the application of fuel cells (FC), electrolysers, hydrogen storage tanks for power-to-hydrogen conversion and chemical energy storage, as well as the utilization of water tanks or boreholes for TES [44] [47]. Figure 1.1 shows the principle of EES using LIB.

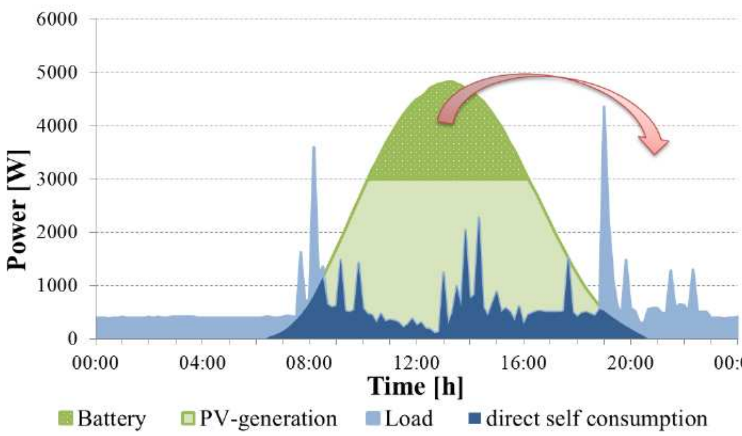

Figure 1.1: Ideal LIB for EES charge and discharge management. [47].

1.1.1 Electrical Energy Storage

LIB batteries stands as a prominent method for energy storage within contemporary building structures. Its widespread adoption and maturity can be attributed to its extensive use in diverse domains, including electronics and electric vehicle power systems. However, it's important to acknowledge the drawbacks associated with LIB storage, such as its elevated costs and constrained raw material availability [11].

Pb-A batteries find applications in micro-grids, hybrid energy systems, spinning reserve, bulk energy storage, frequency regulation, and more [39]. Despite their high efficiency, usually ranging from 70% to 80% , and relatively low capital costs, Pb-A batteries face significant challenges, including a short operational lifespan and demanding maintenance needs. The lifetime of these batteries is constrained by factors such as the depth of discharge (DOD) and operating temperature [39].

Recent findings have indicated that employing batteries as storage systems is economically less efficient. Battery systems exhibit sluggish response, higher deviations in DC voltage regulation, and slower ability to maintain active power balance when compared to supercapacitor storage systems[31].

1.1.2 Thermal Energy Storage

Thermal energy storage (TES) systems share a common characteristic, the capability to store energy through the phase transition, either from solid to liquid or vice versa. Specifically, the latent heat of fusion, representing the heat exchanged during this phase change, enables the storage and release of a more substantial amount of thermal energy compared to Sensible Thermal Energy Storage systems (STESs).

Additionally, the phase transition transpires nearly isothermally, ensuring a stabilized operating temperature, a valuable aspect for practical applications[34]. Figure 1.2 and 1.3 shows the charging/discharging phases of Latent Thermal Energy Storage (LTES) system in two different ambient temperature.[34].

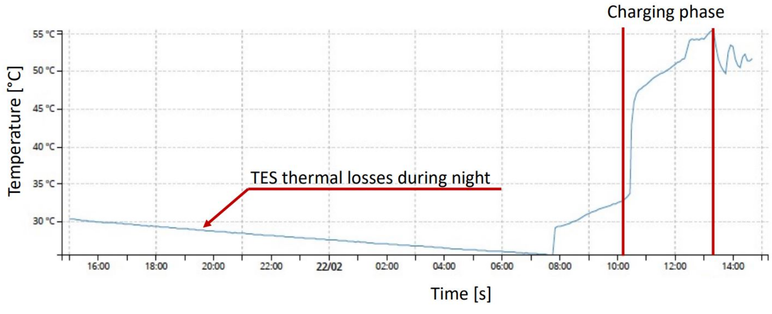

Figure 1.2: LTES Charging Phase: Storage Temperature as a Function of Time[34]

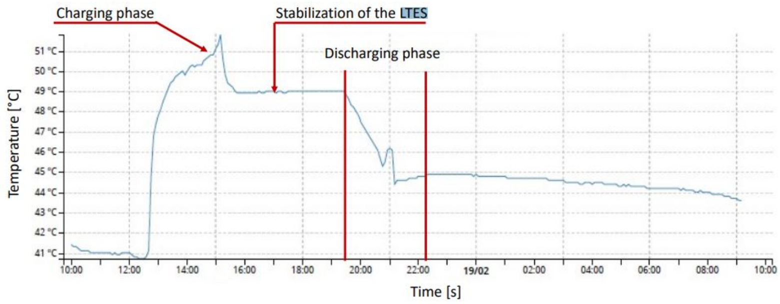

Figure 1.3: LTES Discharging Phase: Storage Temperature as a Function of Time[34]

Nevertheless, research has revealed that the Levelized Cost of Energy (LCOE) for a stand-alone house implementing a TES system tends to be comparatively elevated when contrasted with alternative approaches. Moreover, the LCOE progression of the TES system commences at notably higher levels in comparison to the Hydrogen (H2) storage system, primarily due to the augmented initial investments involving a Ground Source Heat Pump (GSHP) system, consequently amplifying the overall expenditures[27].

1.1.3 Hydrogen Storage

The use of electrolyzer(EL) and hydrogen storage is gaining significant attention. Investigative studies have focused on hybrid PV system and FC power generation systems incorporating electrolyzers and hydrogen storage (shown in Figure 1.4)[43].

Among system components EL performs a substantial role. The most important types of ELs are as below[25]:

- Proton exchange membrane (PEM) electrolyzers.
- anion exchange membrane (AEM) electrolyzers.

Proton Exchange Membrane (PEM) water electrolysis is an auspicious technology for hydrogen generation due to its superior electrolytic efficiency, safety, reliability, compactness, and rapid response to renewable energy sources [26][37]. Nonetheless, the reliance on precious metals within its membrane imposes constraints. Given that PEM becomes highly acidic upon water absorption (comparable to 10% H2SO4), only platinum group-based (Pt, Ru, Rh, Ir, Pd, etc.) (PGM)

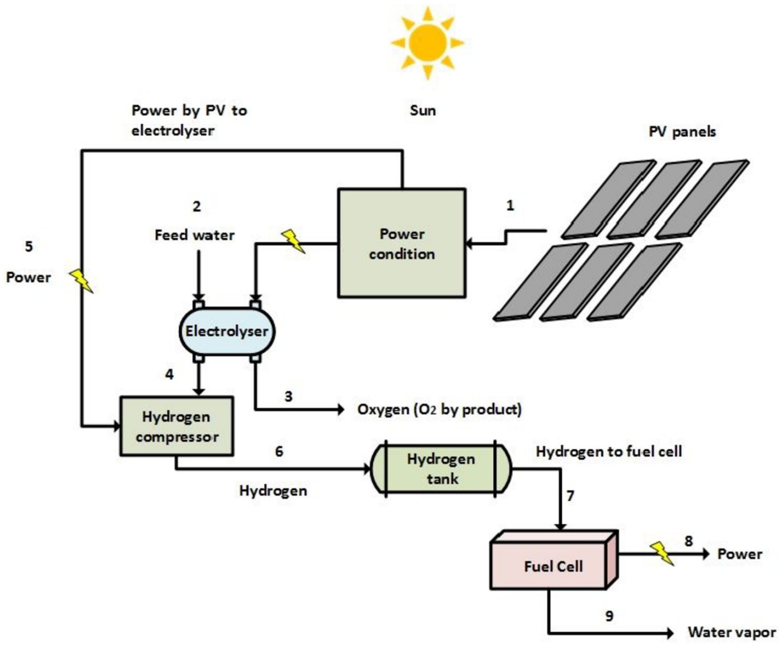

Figure 1.4: Schematic diagram of the hybrid PV, El and FC system[45].

metals exhibit significant activity for both the oxygen evolution reaction (OER) and hydrogen evolution reaction (HER), allowing them to function reliably even in harsh environments [37].

Over the past decade, electrolyzers utilizing anion exchange membranes (AEM) have emerged. AEM electrolyzers employ non-platinum group metals (non-PGM) as catalysts, benefiting from a diluted KOH electrolyte (only 1% concentration), enhancing their reliability and cost-effectiveness [16]. The advantages of AEM electrolyzers, as highlighted in previous research [4], encompass:

- Unlike Proton Exchange Membrane Electrolyzers (PEMEL), AEM electrolyzers do not necessitate costly electrocatalysts.
- They operate effectively without the need for highly concentrated KOH electrolyte.
- AEM allows pressurization on the hydrogen side, enhancing overall system efficiency.

In this study, we employed an AEM electrolyzer[1] for water electrolysis.

[1]Model: Enapter AEM electrolyzer el 2.1

- Production Rate: 500 NL/hr
- Hydrogen Output Purity:35 bar: ~ 99.9% (Impurities: ~ 1000 ppm H_2O)

1.2 Thesis Objective

The rapid and widespread integration of Artificial Intelligence (AI) has ignited a transformation across global industries. Within this context, the fusion of AI with energy management systems represents a pivotal innovation. This master's thesis aims to leverage AI's potential to optimize energy consumption and production, specifically focusing on individual household electricity consumption patterns concerning rooftop solar devices. Through an in-depth hourly analysis of these patterns, the research endeavors to predict solar power generation for the upcoming days. The AI-driven system will strategically allocate surplus electricity generated during peak production phases to power an Anion Exchange Membrane (AEM) electrolyzer. This electrolyzer will efficiently convert excess electricity into hydrogen, storing it for later use in a fuel cell capable of providing electricity during periods of high demand and when solar panels are inactive.

The objective of this research extends beyond mere prediction and efficiency measurement. It aspires to showcase a comprehensive AI-powered energy management system that not only maximizes the utilization of renewable energy sources but also optimizes hydrogen production for efficient energy storage and subsequent utilization. The ultimate goal is to contribute to sustainable energy solutions by offering a scalable model for the seamless integration of AI into energy management, thereby promoting clean and effective energy usage in our constantly evolving world. Through this work, we aim to pave the way for intelligent and environmentally conscious energy systems that have the potential to make a substantial impact on global energy sustainability and management.

1.3 Research Questions

This master's thesis aims to address the following key research questions:

1. How can AI algorithms effectively predict solar power generation for the

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- Nominal Power Consumption per Nm^3 of H_2 produced (beginning of life): 4.8 kWh/Nm^3
- Water Consumption: $\sim$ 400 ml/hr

upcoming days based on real-time weather data and hourly household power consumption patterns?

2. What strategies can be employed to intelligently schedule and manage excess electricity generated by rooftop solar panels during peak production phases?
3. How can an Anion Exchange Membrane (AEM) electrolyzer efficiently convert surplus electricity into hydrogen for optimal storage and subsequent utilization in a fuel cell?
4. What factors impact the efficiency of various production rates of the Enapter AEM electrolyzer, and how can this efficiency be measured and incorporated into the energy management system?
5. In what ways can the integration of AI into energy management systems maximize the utilization of renewable energy sources and contribute to efficient energy storage and utilization?
6. How can an AI-powered energy management system contribute to environmentally conscious energy usage and sustainable energy solutions on a broader scale?

These research questions form the foundation for investigating and evaluating the potential of integrating AI into energy management systems, ultimately promoting sustainable and efficient energy practices.

2

Literature review

2.1 Hybrid Solar PV connected to battery

In this context, a study is considered in Haikou China, that explores the effective integration of battery storage systems with residential photovoltaic (PV) generation setups, focusing on maximizing self-utilization [28]. This strategy not only enables a smooth interaction between residential PV systems and the power grid but also introduces an inherent load-shifting effect due to the typical daytime peak of PV production aligning with the evening peak in domestic load patterns(Figure2.1). This synchronization optimally leverages the storage system, attracting substantial attention and investigation within both academic and commercial domains, with the aim of enhancing the interplay and efficiency between PV generation and energy storage[5].

In an optimized scenario for a residential setting , the methodology defines critical parameters for an efficient PV-LIB storage system (as shown in table 2.1). The specified battery capacity is set at 8 kWh, paired with a PV system rated at 3.5 kW. The operational dynamics of the system revolve around energy flows, encompassing the charging of the battery with 1830 kWh and its discharge with 1391 kWh. The total energy demand of the residential unit amounts to 4438 kWh, comprising both electricity sourced from the grid (2229 kWh) and self-generated PV energy (3848 kWh).The surplus energy generated by the system, totaling 1107 kWh, is exported to the grid. The household effectively utilizes 2209 kWh of self-generated energy, resulting in a self-consumption rate of 57%, symbolizing

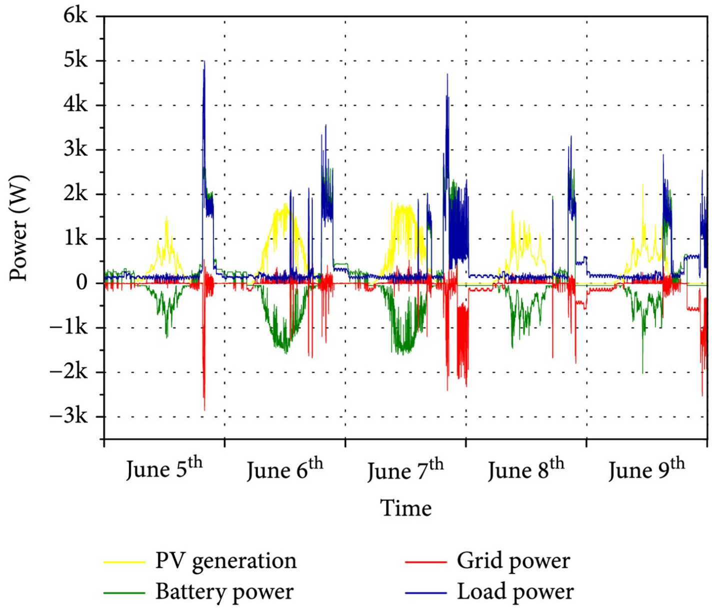

Figure 2.1: measured values of main energy flows.[5]

efficient utilization of internally produced power. The optimized configuration aimed to enhance self-utilization and reduce dependence on the grid, ultimately boosting the economic viability and environmental sustainability of a residential energy system[5].

Table 2.1: Optimum residential Hybrid Solar PV connected to battery Data[5].

Parameters	**Value (PV+bat.)**	**Value (PV only)**
Battery sizes (kWh)	8	No
PV sizes (kW)	3.5	3.5
Battery charging (kWh)	1830	0
Battery discharging (kWh)	1391	0
Demand (kWh)	4438	4438
Grid import (kWh)	2229	3557
Grid export (kWh)	1107	2967
PV production (kWh)	3848	3848
Self-consumed energy (kWh)	2209	881
Self-consumption rate	57%	23%

2.2 Hybrid system with PEM electrolyzer

In this section, we explore another significant study centered on a residential location situated in Afyon city, Turkey, which is not connected to the national power grid lines. The aim is to design a solar hydrogen hybrid energy system ensuring a continuous power supply to the residence throughout the year. This comprehensive system consists of PV panels, a proton exchange membrane (PEM) electrolyzer, a storage tank, and a stack of PEM FCs. The solar panel chosen for this hybrid setup is a monocrystalline module effectively meeting the power demands of the house. The power distribution within the hybrid system is carefully managed among its components, including the solar panel array, PEM electrolyzer model, hydrogen storage tank, and PEM FC stack.

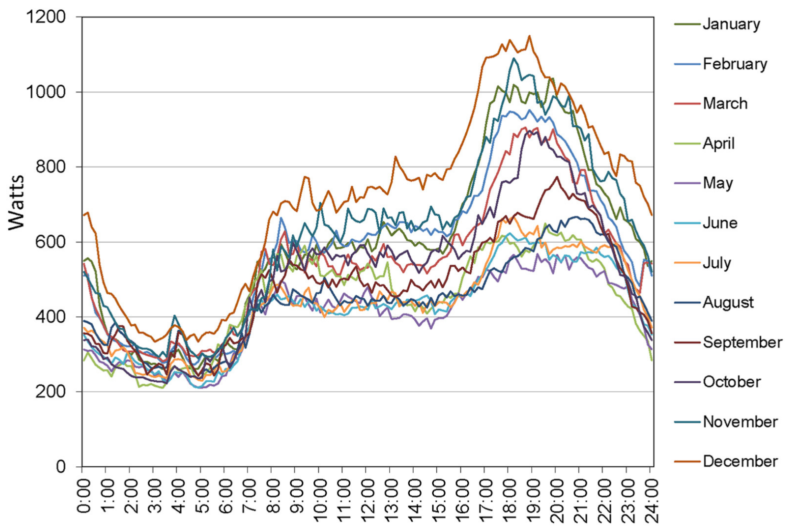

Figure 2.2: Daily average power consumption of the Household Electricity Survey (HES) data in different months of the year[1].

During daylight hours, if the power generated by the solar panel array meets or exceeds the household's power consumption(Shown in figure2.2), the surplus power is utilized to meet the consumption needs. Any excess power beyond the consumption threshold is directed to the electrolyzer for hydrogen generation. However, the electrolyzer's hydrogen generation process adheres to two key constraints: i) the power supplied to the electrolyzer must surpass its minimum load, and ii) it must remain below the maximum load, as the electrolyzer operates within this defined range. The hydrogen produced by the electrolyzer is stored in the designated hydrogen storage tank. To ensure a continuous hydrogen supply to the FC, maintaining a flow of hydrogen from the storage tank to the FC, the pressure within the storage tank must remain higher than the ambient pressure[1].

In scenarios where the solar panel array's generated power falls short of the household's power requirements, the deficit is supplemented by the FC stack, ensuring a consistent and uninterrupted power supply. However, their focus was on optimal electrolyzer capacity together with number of FCs to have less nonutlilizable energy below and above the electrolyzer minimum and maximum load and when the H2 tank is full.Results are shown in Table 2.2. These data shows the feasibility of off-grid hybrid solar PV connected to electrolyzer H2 tank and FC.

Table 2.2: Optimal hybrid systems with different capacity electrolyzer [1].

Electrolyzer Capacity [kW]	**Number of PV Panels**	**Number of FC Stack**	**Storage Tank Volume [m^3]**	**Nonutilizable Energy (above) [kWh]**	**Nonutilizable Energy (below) [kWh]**	**Nonutilizable Energy (full tank) [kWh]**
3	25	14	13.8	412	208.6	4731.5
		16	13			4824.5
5	25	14	13.7	0.0	542.0	5493.6
		16	12.9			5570.1
7	25	14	14.6	0.0	965.1	5286.9
		16	13.7			5356.5
9	25	14	15.9	0.0	1495.2	4936.0
		16	15.0			5003.3

2.3 Hybrid system with LIB and AEM electrolyzer

In another significant study, a techno-economic evaluation was conducted for an on-site hydrogen refueling station. This evaluation involved integrating an electrolysis unit with a grid-connected photovoltaic (PV) plant. The proposed hybrid system comprises an AEM electrolyzer that produces hydrogen using excess energy from PV and wind turbine (WT) sources. This hydrogen is then compressed and stored in a tank for subsequent utilization in FCs . Notably, the system introduced in this study features a high-pressure hydrogen tank, emphasizing 100% clean energy production[35].

The core components of the hybrid microgrid include fuel cells, an AEM electrolyzer,lithium-ion (Li-ion) battery, hydrogen storage tank, compressor, PV system, and WT system. An inverter facilitates direct consumption of PV and WT energy by electrical loads. Excess energy is stored in a Li-ion battery using a DC/DC converter as a charge controller. If energy production falls short of demand, the stored energy is redirected back to the loads through an inverter. When the Li-ion battery is fully charged and solar and wind energy production still exceeds load demand, surplus energy is utilized to power an AEM electrolyzer for hydrogen production[35].The system specifications are stated in table 2.3.

Table 2.3: specification of the system[35].

Component	**Li-ion (24 kWh)**
Electrolyzer	4.8 kW
FC	4 kW
Hydrogen storage	32X50L bottles (200 bar)
Photovoltaic system	10.8 kW
Wind turbine	1 kW
Initial cost/kg H2€ (production)	1,968.59
Cost/kg H2€ (25 years lifetime)	82.02

The hydrogen is then compressed and stored in a dedicated hydrogen tank. During high electricity demand and low energy production with an empty Li-ion battery, the FC is activated. Operating at a constant power level, the FC supplies electricity to the electrical loads. As only the Li-ion battery can manage load peaks, the FC is activated even before the Li-ion battery is fully depleted. Hence, the Li-ion battery functions as a buffer and is charged with residual energy from the FC, provided the state of charge (SoC) of the battery has not reached a predefined threshold. The AEM electrolyzer is deployed to absorb excess power from renewable energy sources (RES) and generate hydrogen as input fuel for FCs[35].
Although the study implies the possibility of off-grid hybrid system supported with elctrolyzer and FC it used LIB as the main electricity storage which is not environmental friendly. Additionally the study aimed the cost analysis of other components of the system rather than optimizing the hydrogen production or energy management system(EMS).

2.4 Hybrid PV/electrolyzer/FC system

Another possible hybrid system as illustrated in figure 2.3 could be a on-grid hybrid solar PV system connected to an electrolyzer, pressurized hydrogen tank and hydrogen FC. During the day, hydrogen will be produced with an electrolyzer using excess load demand electricity of household ,generated by solar PV, and be stored in a tank. While, at night when the power generation is zero the laod demand will be satisfied by the hydrogen FC. The system components and their newest technologies are explained accordingly.

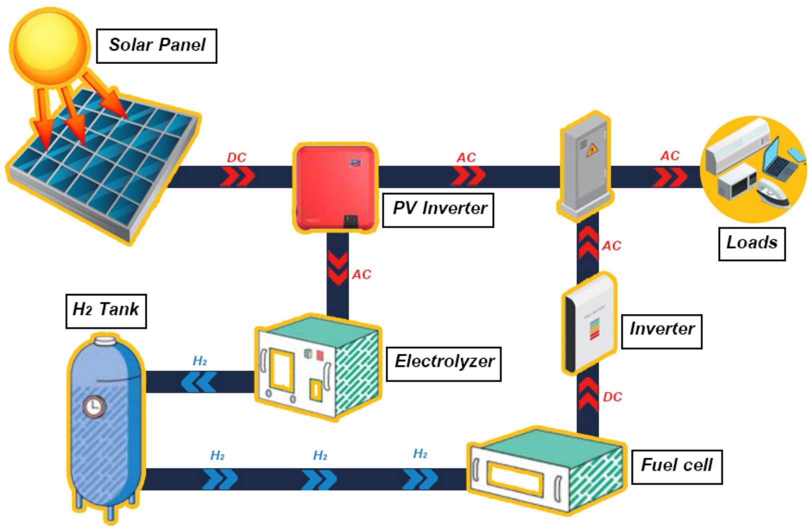

Figure 2.3: Hybrid Solar PV/electrolyzer/FC system components.

2.4.1 Solar PV

Solar PV technology is a critical component of the system, serving as the primary source of green power generation. The shift towards a decarbonized electricity system is heavily dependent on a significant portion of variable renewables generation, primarily driven by wind and solar PV[23]. Solar PV technology has the potential to establish a clean, reliable, scalable, and cost-effective electricity system for the future [49]. Recognizing this potential, governments worldwide are actively promoting the development and implementation of solar PV technology. Diverse PV materials are available on a global scale, and numerous studies have been undertaken to enhance the energy efficiency of these materials.

Several widely used PV materials are outlined below:

1. **Crystalline Silicon (c-Si):** Silicon, is stated as a dominant material in solar PV technology[8]. The initial generation PV modules were fabricated using crystalline silicon structures. Although this technology is continuously evolving through research and development, it remains a cornerstone. The University of New South Wales showcased silicon solar cells with an efficiency of 24.7% [56].

2. **Monocrystalline:** Monocrystalline material finds widespread use due to its superior efficiency compared to multi-crystalline. It was reported honeycomb-textured monocrystalline solar cells with an efficiency of 24.4% [57].

3. **Multi-crystalline or Polycrystalline:** Multi-crystalline or polycrystalline solar cells were reported with an efficiency of 19.8%, whereas monocrystalline solar cells achieved a maximum efficiency of 20.4% [57].

4. **Cadmium Telluride (CdTe)/Cadmium Sulphide (CdS):** CdTe solar cells are composed of cadmium and tellurium. Due to its ideal band gap and long stability, it holds promise in thin film technology [7]. In another study a 11.2% efficiency on thin film 0.55- and 1-µm-thick CdTe was achieved[3].

2.4.2 Hydrogen FC and tank

FC is an energy conversion device that continuously converts chemical energy from a fuel into electrical energy, as long as both the fuel and oxidant are available. It exhibits advantageous characteristics exceeding conventional combustion-based technologies that are currently applied in certain critical fields, such as electronic, housing power, power plants, passenger vehicles, as well as military applications[17].

Operating with higher efficiency than combustion engines, FCs demonstrate an electrical energy conversion efficiency of 60% or more, with lower emissions.The produced hydrogen is stored in a storage tank at high pressure due to the use of compressor and then the stored hydrogen is converted into electricity and steam by FC. Water is the only product of the power generation process in hydrogen FCs, and thus there are no carbon dioxide emissions or air pollutants that create smog and cause health problems during operation[17].

Based on the type of electrolyte used, FCs can be categorized as below:

1. Alkaline Fuel Cells (AFCs)
2. Proton Exchange Membrane Fuel Cells (PEMFCs)
3. Phosphoric Acid Fuel Cells (PAFCs)
4. Molten Carbonate Fuel Cells (MCFCs)
5. Solid Oxide Fuel Cells (SOFCs)

The classification and characteristics of these fuel cell types are summarized in Table 2.4 [38].

Table 2.4: fuel cells classification and characteristics [38].

Property	AFCs	PEMFCs	PAFCs	MCFCs	SOFCs
Electrolyte	KOH	Perfluorosulfonic acid	ionic exchange membrane	H3PO4	Li2 CO3-K2CO3
Conductible Ions	OH^-	H^+	H^+	CO_2^-	O_2^-
Fuel	H_2	H_2, CH_3OH	Reformed fuel (CH_4, CO, H_2)	Purified coal gas, natural gas, and reformed fuel (CH_4, CO, H_2)	Purified coal gas and natural gas (CH_4, CO)
Oxidant	O_2	Air	Air	Air	Air
Catalyst	Pt/Ru	Pt/Ru	Pt	NiO	Ni
Operating Temperature	65–220 °C	-40–90 °C	150–200 °C	650–700 °C	600–1000 °C
Theoretical Voltage	1.18 V	1.18 V	1 V	1.116 V	1.13 V
System Efficiency	60%–70%	43%–68%	40%–55%	55%–65%	55%–65%
Application	Special ground and aerospace	Electric vehicle, submarine, and mobile power source	Regional power supply (e.g., power plant)	Power station	Power station

2.4.3 Electrolyzer

Electrolyzer technologies have been receiving increasing recognition due to their capability to serve as a viable method for hydrogen production. These technologies are adept at generating high-purity hydrogen from water, making them suitable for fulfilling hydrogen requirements across a wide range of capacities[10]. The technique of producing hydrogen via water electrolysis has a well-established history, with roots tracing back to the early 1800s. Notably, British scientists William Nicholson and Anthony Carlisle demonstrated a pivotal discovery during this era, revealing that H_2O could be decomposed into its fundamental constituents, H_2 and O_2, through the application of electrical energy [24][30]. This breakthrough concept was subsequently validated and progressed through the contributions of various scientists, laying the foundation for further advancements.

As the 1900s unfolded, electrolytic technologies had matured sufficiently to be deployed on an industrial scale for the mass production of H_2 and O_2 gases [24][30]. This marked a significant milestone in the evolution of water electrolysis as a practical and scalable method for hydrogen generation. Electrolyzers are classified based on their membrane and catalyst's characteristics. Most commercial electrolryzer are described as below :

1. Electrolyzer with proton exchange membrane (PEM)
2. Electrolyzer with anion exchange membrane (AEM)

2.4.4 PEM electrolyzer

The inception of PEM electrolyzers is closely linked to the discovery of perfluorinated ion-exchange membranes like Nafion from DuPont. The earliest PEM electrolyzers were pioneered by General Electric in the 1960s [48]. Figure 2.4 illustrates a schematic diagram and the operational principle of nowadays PEM water electrolysis cell. When a current is applied, water undergoes electrolysis to produce gaseous hydrogen and oxygen, following the comprehensive reaction described in Eq. 2.3. On the anode side, water is oxidized to form oxygen gas and protons (Eq. 2.1). The solvated protons then traverse to the cathode, while electrons move through the external circuit. At the cathode, protons undergo reduction to yield hydrogen gas (Eq. 2.2)[48].

$$H_2O_{(1)} \rightarrow \frac{1}{2}O_{2(g)} + H^+ + 2e^- \tag{2.1}$$

$$2H^+ + 2e^- \rightarrow H_{2(g)} \tag{2.2}$$

$$H_2O_{(1)} \rightarrow \frac{1}{2}O_{2(g)} + 2H_{2(g)} \tag{2.3}$$

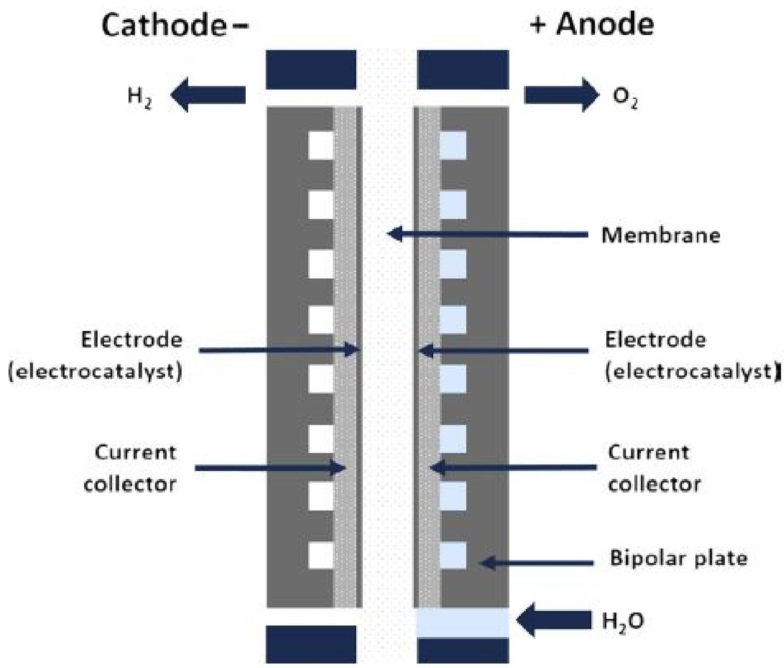

Figure 2.4: PEM electrolyzer cell layout[48].

The operation of PEM electrolyzers typically occurs within the temperature range of 50-–80°C. Elevated temperatures beyond 80°C can lead to a loss of structural stability in the membrane. Conversely, operating at lower temperatures ensures that the solid electrolyte maintains robust mechanical stability. This stability is pivotal for enabling high-pressure operations, exceeding 30 bar, with the option of equal or differential pressure distribution across the electrolyte[9].

PEM electrolysis presents several notable advantages. It boasts high current densities and a compact system design, offering quick response times and a substantial hydrogen production rate. The produced gases exhibit high purity, typically at 99.99%, contributing to its desirability. Moreover, PEM electrolysis demonstrates high energy efficiency, often within the range of 80—90%, and excels in dynamic operations. However, there are drawbacks to consider. The technology is associated with a high cost of components and necessitates an acidic environment for optimal operation. Additionally, PEM electrolyzers exhibit relatively low durability, and challenges related to commercialization are expected to be addressed in the near term [46].

2.4.5 AEM electrolyzer

Over the last 15 years, there has been the introduction of electrolyzers utilizing AEM [51]. These electrolyzers offer a blend of benefits, encompassing cost-effectiveness in materials while maintaining high performance similar to PEM technology.
The conventional electrolyzer technology has reached a high level of technological maturity and has been widely adopted in industries for many decades. However, its performance is constrained by low current densities, narrow current density ranges, and the requirement of a concentrated electrolyte that necessitates re-circulation through a pumping system.
In contrast, AEM electrolyzers represent a relatively recent technological advancement, primarily driven by significant progress in component materials, particularly the anion AEM. Historically, AEM's ion exchange capacity and stability posed significant challenges, but advancements have addressed these concerns. The performance of AEM electrolyzers is significantly influenced by the concentration of KOH, alongside specific catalysts and membranes. Figure 2.5 illustrates the fundamental structure and operational principle of an AEM cell[4]. As shown:

1. First, water travels from the anode half-cell through the membrane.
2. Then, hydrogen is produced from water by the hydrogen evolution reaction (HER) at the cathode and released via the gas diffusion layer (GDL) (equation 2.4).
3. The hydroxide ions (OH) from the HER move back to the anode half-cell via the membrane.

4. Oxygen is produced from OH by the Oxygen Evolution Reaction (OER) at the anode and released via GDL along with the electrolyte circulation (equation 2.5).

$$\text{HER: } 4H_2O + 4e^- \rightarrow 4OH^- + 2H_2 \tag{2.4}$$

$$\text{OER: } 4OH^- \rightarrow O_2 + 2H_2O + 4e^- \tag{2.5}$$

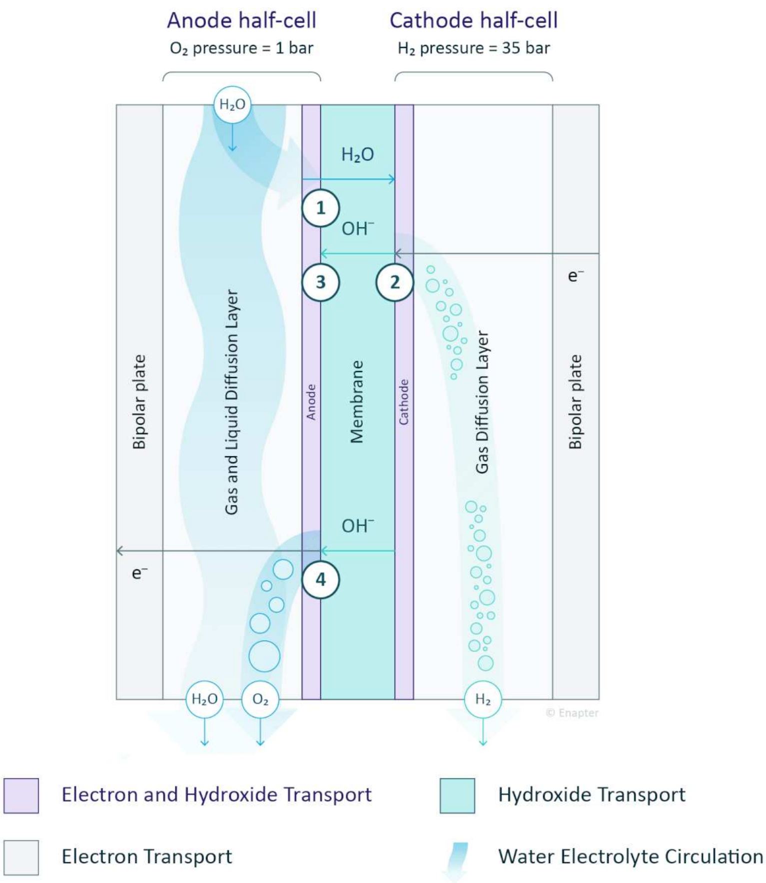

Figure 2.5: Enapter AEM electrolyzer cell[14].

2.4.6 Energy management system(EMS)

Numerous studies have explored the utilization of optimization techniques in diverse hybrid renewable energy systems. Authors have extensively investigated the application of Genetic Algorithms (GAs), Particle Swarm Optimization Algorithm (PSO), Fuzzy logic (FL), and various other well-known algorithms for control and optimization of hybrid renewable energy systems, as discussed in [42].

Genetic Algorithms (GAs) Genetic Algorithms (GAs) have proven effective in solving complex optimization problems, both constrained and unconstrained. They find broad application in engineering and sciences, representing a preferred approach for general-purpose optimization. GAs mimic natural genetics and evolution, operating on a population of individuals and modifying it to iteratively converge towards optimal solutions[19].

Particle Swarm Optimization (PSO) Inspired by natural swarm intelligence observed in birds or fish, Particle Swarm Optimization (PSO) is utilized for problems with multiple potential solutions. The algorithm involves a swarm of particles moving within a defined search space to seek the best collective velocity and position. Each particle's position and velocity are iteratively calculated to reach the globally optimized value [29].

Fuzzy Logic Control (FLC) Fuzzy Logic employs a multi-state logical comparison, contrasting binary logic with only two states (true or false)[32]. Fuzzy Logic Control (FLC) involves three primary processing stages: fuzzification, fuzzy inference, and defuzzification. These stages enable the development of an FLC for a specific problem based on fuzzy logic rules. Fuzzy Logic systems typically assess error and error change between reference inputs and actual outputs [55] [54].

Table 2.5 is stated three study cases each related to one of the above mentioned EMSs.

Table 2.5: EMS methods case studies [42].

EMS Configuration	EMS method	Algorithm Used	Parameters Considered/Optimization	Contribution/Remarks
PV panel[41]	GA	Parametric optimization of a PV panel	PV-diode equation model	Optimized results can be compared with measured data to validate the model of the PV panel so developed, and prediction of power output from the panel can be ascertained from the developed model
Autonomous PV, Battery, and Hydrogen[36]	PSO	Optimal design and sizing of hybrid system components	Multi-criterion objective function and installation cost	Sizing and energy management parameters and their role in the solution space are analyzed. Inclusion of the battery SOC penalty function and the penalty function for hydrogen remaining in storage
Hybrid PV/Wind/-Fuel Cell[20]	FL	Fuzzy multi-objective algorithm and ICA	Fuzzy optimization to optimize multiple objective functions and constraints simultaneously	Size optimization is influenced by the degree of importance placed on the emissions of the electrical system that supplies power to the non-autonomous HGPS

2.4.7 Application of AI in EMS

Artificial intelligence (AI) stands as a potent tool, proficient in predicting solar power availability. AI-driven models prove accurate in forecasting solar power output by meticulously considering weather patterns, geographical positioning, and temporal factors. Numerous studies have delved into AI's potential in predicting solar power availability and its role in optimizing solar energy utilization. The primary objective of these investigations was to evaluate efficient prediction models for solar power generation, aiming to facilitate strategic planning of both generation and consumption[2][21]. Recognizing the pivotal role of solar power prediction in the seamless integration of solar management systems within the grid[12]. However, their aim is to predict and optimize large scale power plants for the grid management in large scale.

3 Methodology

This study aims to employ an Artificial Intelligence (AI) model to forecast short-term power generation from an existing rooftop solar PV system located in Bremen, Germany. The prediction is based on weather datasets and solar PV electricity production data gathered during the year 2021. The renewable energy system under consideration is a grid-connected hybrid solar PV system integrated with an electrolyzer, hydrogen tank, and fuel cell (FC). This hybrid system is designed to cater to the electricity demand of a single household throughout the day and night.

During daylight hours, the solar PV system is responsible for meeting the electricity demand, and any excess power generated is directed towards water electrolysis using an Anion Exchange Membrane (AEM) electrolyzer. The produced hydrogen is then stored in a hydrogen tank. Subsequently, during periods of low or zero solar PV production, the stored hydrogen is utilized to generate electricity through a hydrogen fuel cell (FC), ensuring a consistent power supply to meet household demand.

The AI model is tasked with predicting power generation based on the available data. The predicted power generation is then compared to the load demand, allowing the determination of excess electricity for each hour of the day. Given the AEM electrolyzer's minimum and maximum power consumption thresholds in kWh/Nm3, the surplus electricity is utilized to optimize the system. This involves determining the optimum number of AEM electrolyzers that can be efficiently utilized to maximize hydrogen production and storage, thus enabling the fuel cell to provide maximum assistance during periods of zero solar

PV electricity production.

In order to achieve a fully automated system, hydrogen production through water electrolysis is scheduled after a thorough analysis of excess power, ensuring an efficient and seamlessly operating hybrid renewable energy system.

3.1 Objective and Scope

3.1.1 Objective

This study's main goal is to use a cutting-edge AI model to accurately anticipate how much power will be generated in the short term by a grid-connected hybrid solar photovoltaic (PV) system. The study's specific goal is to estimate the power generation patterns from a rooftop solar PV system that is existing in place in Bremen, Germany. The forecast is then used to schedule and optimise the AEM electrolyzer's performance so that it can produce hydrogen at its optimum capacity and generate power using a hydrogen fuel cell in the process. The necessary meteorological dataset and historical solar PV electricity production data from the 2021 calendar year will both be used by the AI model.

3.1.2 Geographical Location

The study is centered around a hybrid solar PV system located in Bremen, Germany. Bremen, renowned for its dedication to renewable energy initiatives, provides an opportune setting for evaluating the efficacy of AI integration within solar PV systems (as shown in figure 3.1).

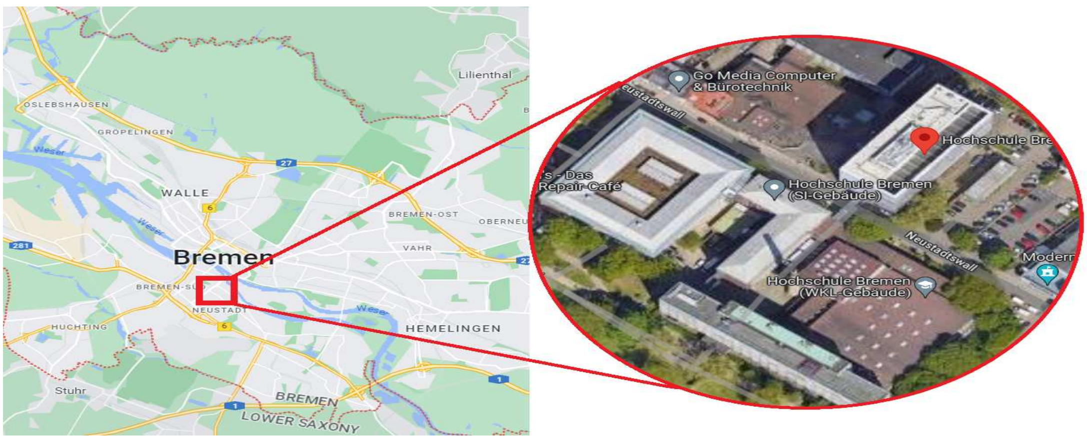

Figure 3.1: Site geographical location in Bremen, Germany.

3.1.3 Data Sources

The prediction model's training and validation rely on robust datasets meticulously sourced from reputable repositories. The weather data essential for this study were meticulously gathered from the Visual Crossing Weather historical records repository for the year 2021[52]. These records offer a detailed hourly account of weather patterns and meteorological variables pertinent to the Bremen region.

In parallel, the solar PV data, a cornerstone for accurate predictions, was sourced directly from the real-world rooftop solar PV installation at Hochschule Bremen. This dataset encompasses measurements taken every minute throughout the year 2021. The precise data, diligently collected by the Electrical engineering Department of Hochschule Bremen, contributes significantly to the model's accuracy and effectiveness[1].

These amalgamated datasets form the foundation for training the AI prediction model, enabling insightful forecasts and streamlined optimization of the hybrid system's performance.

3.1.4 AI-Enabled Power Generation Prediction and Electrolyzer Optimization

This aspect involves leveraging AI to predict short-term power generation and optimize AEM electrolyzer performance for efficient hydrogen production and energy storage. Key steps include:

- **AI Model Development:** Create a predictive AI model that forecasts short-term power generation from the rooftop solar PV system, utilizing weather datasets and 2021 solar PV electricity production data for training and validation.
- **Electrolyzer Efficiency Improvement:** Enhance the AEM electrolyzer's efficiency by optimizing its performance using surplus electricity and predicted power, with the objective of maximizing hydrogen production.

[1]Source of solar PV data: Faculty of Electrical Engineering and Computer Science, with special thanks to Prof. Dr.-Ing. Thorsten Völker.

3.1.5 Automation and Efficiency Enhancement

- **Automation Strategies:** Develop strategies to automate hydrogen production through water electrolysis based on excess power analysis and predicted power, optimizing the AEM electrolyzer's efficiency.
- **Efficiency Assessment:** Evaluate the efficiency of the electrolyzer system and propose enhancements to ensure optimal hydrogen production.

3.1.6 Performance Evaluation and Optimization

- **Performance Metrics:** Define and measure performance metrics, such as electrolyzer efficiency, hydrogen production rate, and hydrogen cost, to assess the effectiveness of the AEM electrolyzer system.
- **Optimization Strategies:** Explore strategies to optimize the AEM electrolyzer system, including the determination of the optimal number of AEM electrolyzers based on predicted power and surplus electricity.

3.1.7 Hybrid Solar PV System Overview and target component

The hybrid solar PV system under investigation integrates key components to efficiently cater to a single household's electricity demand around the clock. The system comprises a solar PV array, Anion Exchange Membrane (AEM) electrolyzer, hydrogen tank, and hydrogen fuel cell (FC). During daylight hours, the solar PV array generates electricity to meet immediate household demands. Any surplus electricity is intelligently utilized by the AEM electrolyzer to perform water electrolysis, producing hydrogen. This hydrogen is then stored in a tank for later use.

During periods of low or no solar PV production, especially at night, the stored hydrogen becomes pivotal. The hydrogen fuel cell (FC) seamlessly converts the stored hydrogen back into electricity, ensuring a consistent power supply to meet household demands. This system operates in harmony, optimizing hydrogen production based on surplus electricity and predicted power generation patterns. Through leveraging an AI-based predictive model, the system schedules hydrogen production and FC utilization, aiming for maximum hydrogen capacity and efficient electricity provision.

By intelligently utilizing the solar PV array, AEM electrolyzer, hydrogen tank, and fuel cell, this hybrid system aims to enhance energy sustainability by effectively balancing renewable energy utilization with efficient hydrogen-based energy storage and deployment. The study focuses on refining the efficiency and automation of the AEM electrolyzer, a critical component in this sustainable energy ecosystem. The AEM electrolyzer were used in this study is the Enapter AEM electrolyzer model El 2.1 (The characteristics and specifications is shown in the table 3.1).

Table 3.1: Enapter AEM electrolyzer spesification [13].

Characteristic	**Value**
Hydrogen Production Rate	500 NL/hr
Hydrogen Output Purity	At 35 bar: ~ 99.9% (Impurities: ~ 1000 ppm H_2O) At 8 bar: > 1500 ppm H_2O
Nominal power consumption per Nm^3 of H_2 produced	4.8 kWh/Nm^3
Operative Power Consumption	2400 W
Stand-by Power Consumption	15 W
Power Supply	Voltage: 200-240 V, Frequency: 50/60 Hz
Ambient Operative Temperature Range	5°C to 45°C
Ambient Operative Humidity Range	Up to 95% humidity, non-condensing
IP Rating	IP 20
Control and Monitoring	Fully automatic with Enapter's EMS, Modbus TCP via Ethernet
Water Consumption	~400 ml/hr
Maximum Water Input Conductivity	20 μS/cm at 25°C
Water Input Pressure Range	1 - 4 barg

3.2 AI Model for Power Generation Prediction

In this study, the AI model employed for predicting power generation from the solar PV system is Long Short-Term Memory (LSTM), a type of recurrent neural network (RNN). LSTMs are well-suited for time-series prediction tasks due to their ability to capture long-term dependencies and patterns in sequential data.

3.2.1 AI Model Architecture

The LSTM model in this study has been enhanced for increased predictive capability. It comprises multiple layers of memory cells, each with a gating mechanism allowing the network to selectively remember or forget information from previous time steps. The input layer is fed with features extracted from the weather and solar PV electricity production datasets. These features include solar radiation, solar energy, temperature,UV Index,dew point,visibility, humidity, and historical electricity production.

The enhanced LSTM architecture includes additional complexity through the incorporation of multiple LSTM layers and a Dense layer. The multiple LSTM layers process the input data hierarchically, enabling the model to learn intricate patterns and dependencies over time. The final Dense layer, with a ReLU activation function, further refines the representation of learned features.

3.2.2 Training and Validation

The model is trained using historical data from 2021, including weather data obtained from Visual Crossing Weather and solar PV electricity production data measured at Hochschule Bremen. The data is preprocessed to extract relevant features and normalize the values.

Training involves optimizing the model's weights and biases using an appropriate loss function (e.g., mean squared error) and an optimization algorithm (e.g., Adam optimizer). The dataset is split into training and validation sets to assess the model's performance and prevent overfitting.

3.2.3 Prediction

During prediction, the model utilizes real-time weather data to forecast power generation for the upcoming time intervals. The predicted power generation patterns guide the optimization and scheduling of the AEM electrolyzer for efficient hydrogen production and subsequent power generation using the hydrogen fuel cell. The enhanced LSTM architecture aims to provide more accurate and refined predictions, contributing to the optimization of the hybrid solar PV system.

3.3 Excess Electricity and AEM Electrolyzer Optimization

To calculate the optimum number of AEM electrolyzer we should consider parameters like power generated via our solr PV, the household power consumption of the corresponding hour and the maximum power consumption of AEM electrolyzer with full capacity. The electrolyzer data were driven from the experimental analysis of an existing device in the laboratory of Department of Civil and Environmental Engineering at Hochschule Bremen.

3.3.1 Excess Electricity Calculation

To quantify excess electricity, a comparative analysis is conducted between the predicted power generation from the solar PV and the load demand for each hour. The predicted power generation is derived through the AI-based predictive model trained on weather datasets and historical solar PV electricity production data from 2021.

Mathematically, the excess electricity (EE_{hour}) for each hour (h_{hour}) is calculated as:

$$EE_{\text{hour}} = \max(0, \text{Predicted Power}_{\text{hour}} - \text{Load Demand}_{\text{hour}}) \tag{3.1}$$

Where the Predicted $\text{Power}_{\text{hour}}$ is the power predicted by the AI model for a specific hour. Load $\text{Demand}_{\text{hour}}$ is the electricity demand for the same hour.

3.3.2 AEM Electrolyzer Optimization

The surplus electricity obtained (excess electricity) is then utilized to optimize the hydrogen production process using AEM electrolyzers while considering their power consumption constraints (specifically P_{max}) to ensure each electrolyzer operates at its maximum hydrogen production capacity.

For each hour (h_{hour}), the optimal number of AEM electrolyzers ($n_{\text{opt, hour}}$) is calculated based on the excess electricity available (EE_{hour}) and the power consumption of a single AEM electrolyzer (P_{AEM}):

$$n_{\text{opt, hour}} = \frac{EE_{\text{hour}}}{P_{\text{AEM}}} \tag{3.2}$$

However, $n_{\text{opt, hour}}$ should not exceed the maximum power consumption per AEM electrolyzer. The remaining surplus electricity, if any, is sold back to the grid.

$$n_{\text{opt, hour}} = \min\left(n_{\text{opt, hour}}, \frac{P_{\max}}{P_{\text{AEM}}}\right) \tag{3.3}$$

This iterative process ensures that surplus electricity is efficiently utilized to maximize hydrogen production using AEM electrolyzers while considering their power consumption constraints. The optimized hydrogen production process allows each electrolyzer to operate at its full capacity (up to $P_{\max}$), contributing to effective energy storage in the form of hydrogen.

3.4 Automated Scheduling for Hydrogen Production

In this section, we delve into the automated scheduling approach designed to optimize hydrogen production via water electrolysis within the hybrid solar PV system. The scheduling strategy is built upon a meticulous analysis of excess power, a crucial determinant in shaping the hydrogen production schedule. We outline the process of leveraging surplus electricity to automate and enhance the efficiency of the entire energy system.

3.4.1 Excess Power Analysis as a Foundation

The cornerstone of our automated scheduling approach lies in the precise analysis of excess power generated by the solar PV system. By comparing the predicted power generation with the actual load demand for each hour, we identify the surplus electricity available for hydrogen production. This excess power serves as the basis for determining the optimal scheduling of water electrolysis, aiming to maximize hydrogen production.

3.4.2 Scheduling Hydrogen Production

With a surplus of electricity identified, we employ an automated algorithm that strategically schedules hydrogen production through water electrolysis. The algorithm factors in the real-time excess power and determines the optimal intervals for initiating the electrolysis process. By aligning the electrolysis schedule with periods of surplus electricity, we ensure efficient utilization of the excess power to produce hydrogen.

3.4.3 Contributions to Automation and Efficiency

The automated scheduling of hydrogen production represents a pivotal advancement in the automation of the hybrid solar PV system. By dynamically adapting to fluctuations in solar power generation, we minimize wastage of excess electricity and effectively store it in the form of hydrogen. This process, driven by data-driven algorithms, significantly enhances the overall efficiency of the renewable energy system.

Furthermore, the automated scheduling system has the capability to self-optimize over time. By continuously analyzing the performance and adjusting the scheduling parameters, the system aims to maximize hydrogen production, minimize energy waste, and contribute to a more sustainable and efficient energy landscape.

4

Results and Analysis

This chapter presents the outcomes of our research, aiming to forecast short-term power generation using an AI model in a grid-connected hybrid solar photovoltaic (PV) system. The methodology involved the development of an AI model based on Long Short-Term Memory (LSTM) networks and subsequent optimization of the AEM electrolyzer for efficient hydrogen production, as outlined in Chapter 3. Weather data and solar PV electricity production data from the year 2021 were integrated to train and validate the AI model. Subsequently, a comprehensive presentation and analysis of the findings will be presented. The precision and efficacy of our AI model will be assessed through careful examination of the data, identification of trends, and comparisons between forecasted and actual power generation. Furthermore, we will discuss how surplus electricity generated by the solar PV system was utilized to optimize the AEM electrolyzer for effective hydrogen production. These findings represent a critical step towards our ultimate objective which is increasing the sustainability of renewable energy sources by integrating AI technology with a hybrid solar PV system.

4.1 Introduction to Results

In this section, we will review the main study goals and provide an overview of the methods used to conduct our analysis.

4.1.1 Recap of Research Objectives

Recapping the research objectives outlined in Chapter 1, we aimed to employ an AI model to accurately forecast short-term power generation from an existing grid-connected hybrid solar photovoltaic (PV) system. The study specifically targeted the integration of AI, particularly Long Short-Term Memory (LSTM) networks, for power prediction based on weather data and solar PV electricity production records from the year 2021.

4.1.2 Methodology Overview

As detailed in Chapter 3, the methodology involved the development of a sophisticated AI model using LSTM networks. This AI model was constructed to forecast short-term power generation, a critical aspect of our research goal. The model was trained and validated using comprehensive datasets from the year 2021, encompassing both weather data and actual solar PV electricity production records. Additionally, the AI model's predictions were utilized to optimize the performance of the AEM electrolyzer, a fundamental component of the hybrid solar PV system, for efficient hydrogen production.

By recapping our research objectives and providing an overview of the methodology, we set the stage for the detailed presentation and analysis of the results, which will be presented in the following sections. These results play a pivotal role in evaluating the effectiveness and accuracy of our AI model and assessing its potential to enhance renewable energy sustainability within a hybrid solar PV system.

4.2 Presentation of Data

In this section, we present a sample of the solar PV dataset collected for this study. The dataset provides crucial information related to power generation, environmental conditions, and system performance. The solar PV data were recorded every minute from 9 am to 4 pm throughout the calendar year 2021.

4.2.1 Solar PV Dataset Overview

The solar PV dataset includes the following columns:

1. **Date**: The date of the record.
2. **Time**: The time of the record.
3. **Feed-in Power**: The power fed into the grid by the solar PV system (in watts).
4. **Solar Power**: The power generated by the solar PV system (in watts).
5. **Solar Voltage**: The voltage generated by the solar PV system (in volts).
6. **Power Frequency**: The frequency of the power generated (in hertz).
7. **Line Voltage**: The voltage in the power line (in volts).
8. **Line Voltage.1**: Another measure of voltage in the power line (in volts).
9. **Temperature**: The ambient temperature around the solar PV system (in degrees Celsius).
10. **Efficiency**: The efficiency of the solar PV system.
11. **Weekday**: The day of the week when the data was recorded.

4.2.2 Solar PV data Sample

The dataset captures a range of critical parameters. However, out of these data only Date, Time and Solar power columns will be used for the further examinations and will be sync to the weather dataset.Table 4.1 is shown a sample of the solar PV dataset. Figure 4.1 demonstrates the solar power generation on hourly basis during the year 2021. It clearly shows the differences in the amount of power generated by the system during different period of the year. Figure 4.2 illustrates the cumulative solar PV electricity production on a seasonal basis for a more meaningful representation.

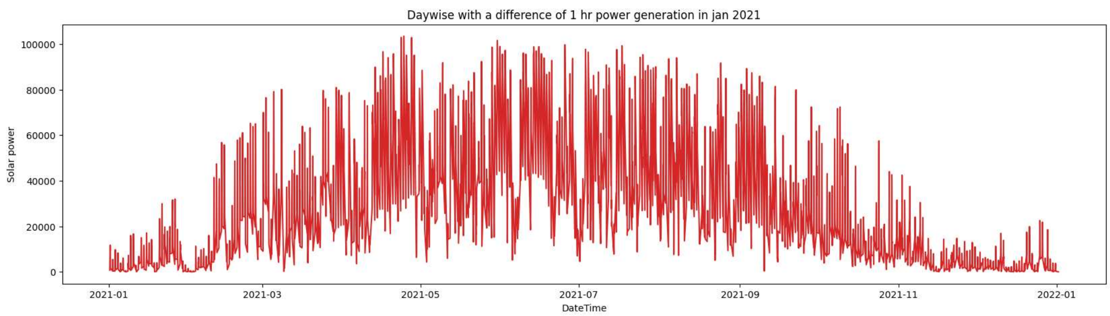

Figure 4.1: Power generated by solar PV in year 2021.

Date	Time	Feed-in Power	Solar Power	Solar Voltage	Power Frequency	Line Voltage	Line Voltage.1	Temp.	Efficiency	Weekday
2021-01-01	09:04	0.0	0.0	61.5	50.0	227.7	0.0	18.1	0.0	Fri
2021-01-01	09:05	0.0	0.0	72.2	50.0	227.7	0.0	18.4	0.0	Fri
2021-01-01	09:06	0.0	0.0	71.0	50.0	226.7	0.0	18.4	0.0	Fri
2021-01-01	09:07	0.0	0.0	76.9	50.0	226.7	0.0	18.4	0.0	Fri
2021-01-01	09:08	0.0	0.0	82.9	50.0	226.7	0.0	18.4	0.0	Fri
⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮
2021-06-01	09:00	413.3	454.1	200.7	49.9	229.6	0.3	34.3	91.0	Tue
2021-06-01	09:01	376.4	413.6	200.7	49.9	230.5	0.3	34.3	91.0	Tue
2021-06-01	09:02	370.0	406.5	210.8	49.9	230.5	0.3	34.3	91.0	Tue
⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮
31-12-2021	15:55	0.0	0.0	84.1	50.0	229.6	0.0	21.4	0.0	Fri
31-12-2021	15:56	0.0	0.0	88.2	50.0	229.6	0.0	21.4	0.0	Fri
31-12-2021	15:57	0.0	0.0	92.3	50.0	230.5	0.0	21.1	0.0	Fri
31-12-2021	15:58	0.0	0.0	96.5	50.0	230.5	0.0	21.4	0.0	Fri
31-12-2021	15:59	0.0	0.0	95.9	50.0	229.6	0.0	21.1	0.0	Fri

Table 4.1: Sample of Solar power data

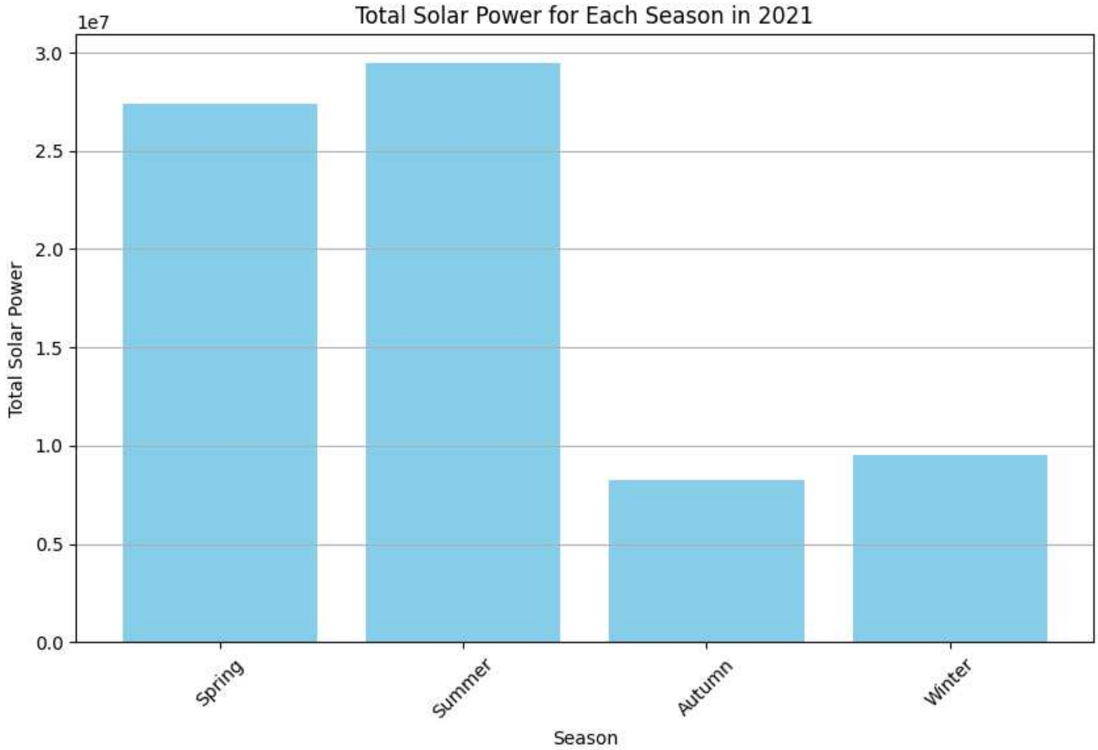

Figure 4.2: Seasonal power generated by solar PV in year 2021.

4.2.3 Weather data sample

We sourced weather data from the Visual Crossing Weather historical records repository for the year 2021. The dataset includes the following parameters for each hour shown in table 4.2. To align the solar PV production data with the corresponding weather information, we selected weather data only from 9 am to 4 pm. This comprehensive weather dataset provides essential meteorological parameters that will be utilized in our analysis and integration with the AI model for power generation forecasting. Figures 4.3, 4.5 4.6 will evaluate some of the weather data values to have more clear sight of the weather conditions in the year 2021.

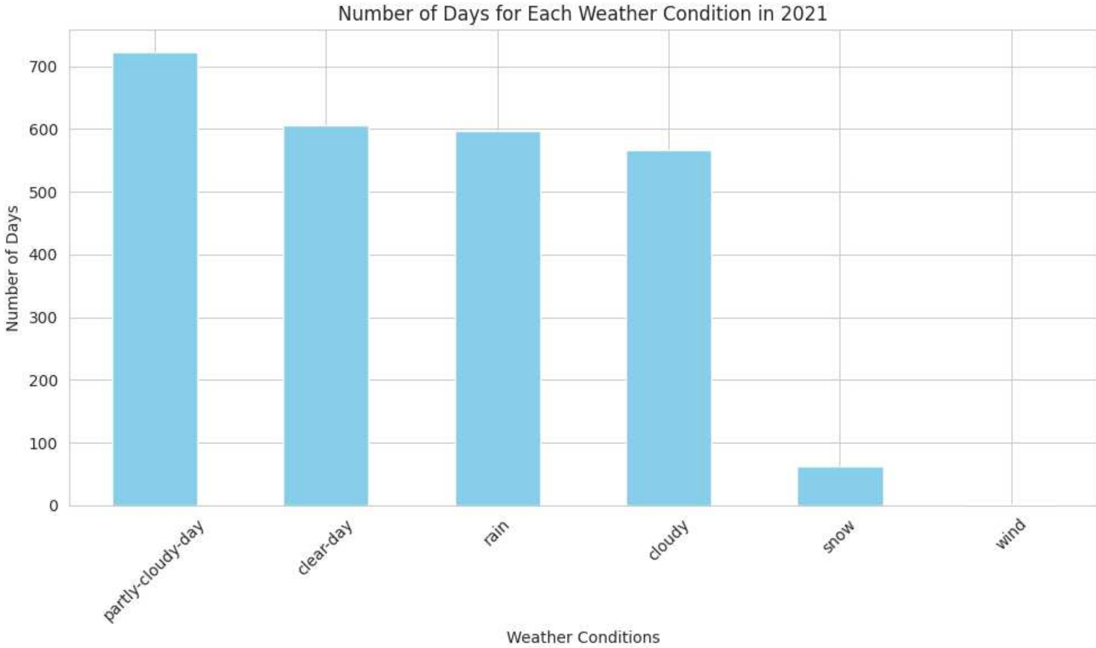

Figure 4.3: Weather conditions in year 2021.

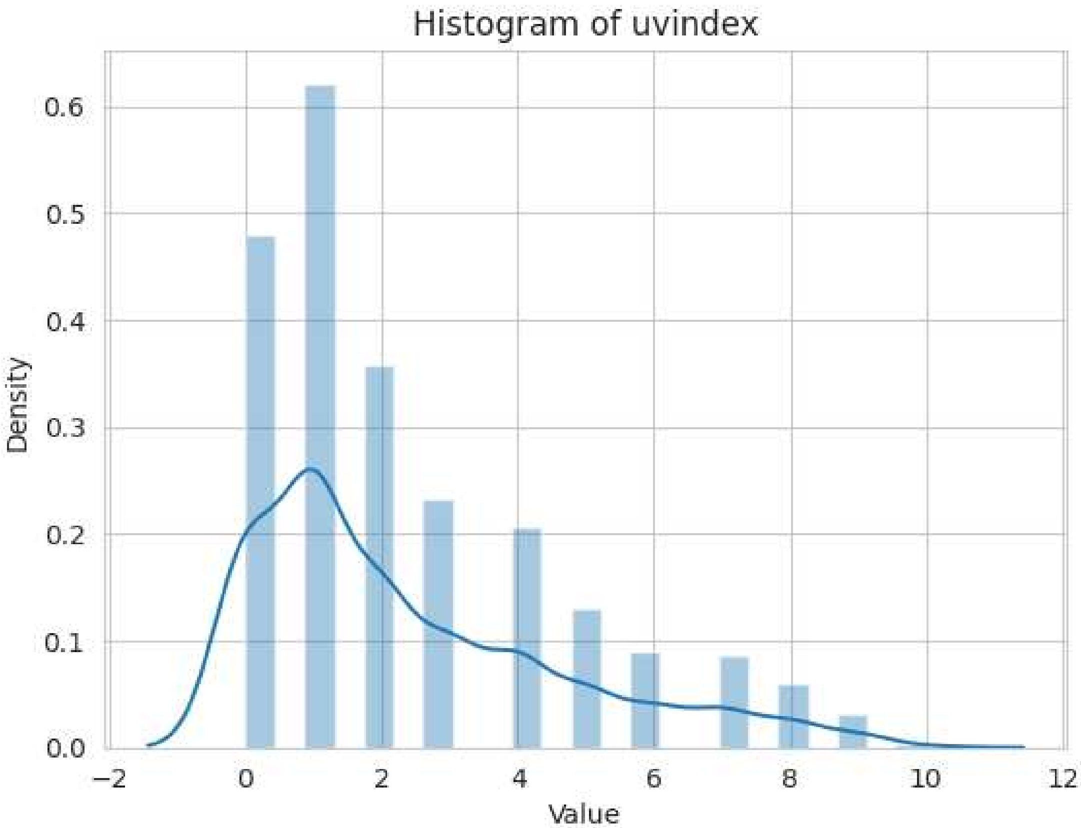

Figure 4.4: UV-index value density in the whole 2021.

Datetime	**Temp (°C)**	**Feelslike (°C)**	**Dew (°C)**	**Humidity (%)**	**Precip (mm)**	**Precipprob (%)**	**Preciptype**	**Snow (mm)**	**Snow depth**	**Wind speed**	**icon**
2021-01-01 09:00	0.7	0.7	-0.1	94.45	0.0	0	NaN	0.0	0.0	3.6	**partly cloudy day**
2021-01-01 10:00	1.6	1.6	0.7	93.78	0.001	100	Rain, Snow	0.0	0.0	4.7	**rain**
2021-01-01 11:00	2.5	-0.9	1.3	91.84	0.0	0	NaN	0.0	0.0	12.9	**partly cloudy day**
2021-01-01 12:00	3.1	0.7	1.7	90.49	0.0	0	NaN	0.0	0.0	8.7	**partly cloudy day**
2021-01-01 13:00	4.0	1.0	1.9	85.83	0.0	0	NaN	0.0	0.0	12.2	**partly cloudy day**
2021-01-01 14:00	3.8	1.2	1.9	86.96	0.0	0	NaN	0.0	0.0	10.4	**partly cloudy day**
2021-01-01 15:00	4.3	0.6	2.2	85.88	0.001	100	Rain	0.0	0.0	17.2	**rain**
2021-01-02 09:00	3.6	1.8	2.6	92.73	0.0	0	NaN	0.0	0.0	7.2	**cloudy**
2021-01-02 10:00	3.6	0.8	2.6	92.73	0.004	100	Rain	0.0	0.0	11.2	**rain**
2021-01-02 11:00	3.8	0.9	2.9	93.29	0.0	0	NaN	0.0	0.0	11.9	**cloudy**

Table 4.2: Sample of weather data in year 2021

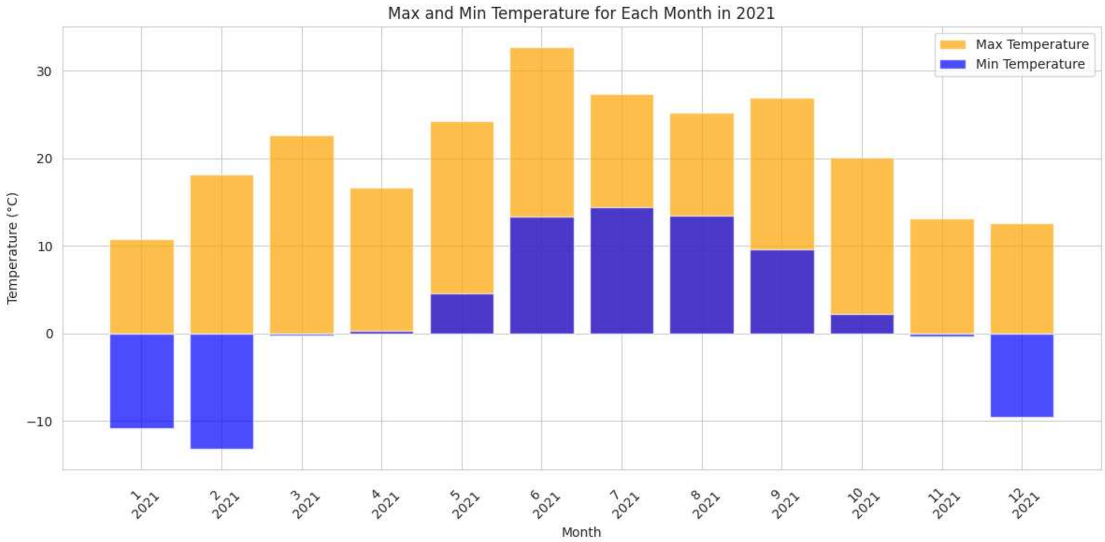

Figure 4.5: minimum and maximum temperature of each month in year 2021.

4.2.4 Weather Factors Impacting Solar PV Power Generation

In this part, we investigate how specific weather factors impact the power generation of the solar photovoltaic (PV) system. Understanding these impacts is crucial for accurate power generation forecasting. Additionally, the correlation coefficients, statistical analysis, and visualizations are employed to illustrate these impacts and identify significant patterns. The following weather factors are analyzed for their influence on solar PV power production:

1. **Solar Radiation:** Solar radiation or sunlight intensity is a fundamental weather factor affecting solar PV power generation. We explore the relationship between solar radiation variations and the resulting output of the PV system. figure 4.6 demonstrates this strong relationship.

2. **Solar Energy:** Solar energy availability directly affects the power generation of the solar PV system. We analyze how solar energy levels correlate with the power output of the PV system that show(figure 4.7 shows significant correlation between the two values).

3. **UV Index:** The UV index is a measure of the strength of ultraviolet (UV) radiation. We investigate how UV index variations impact the solar PV power production. As show in figure 4.8 these values also are highly related to each other therefore UV Index is also a good predictor for the solar power generation.

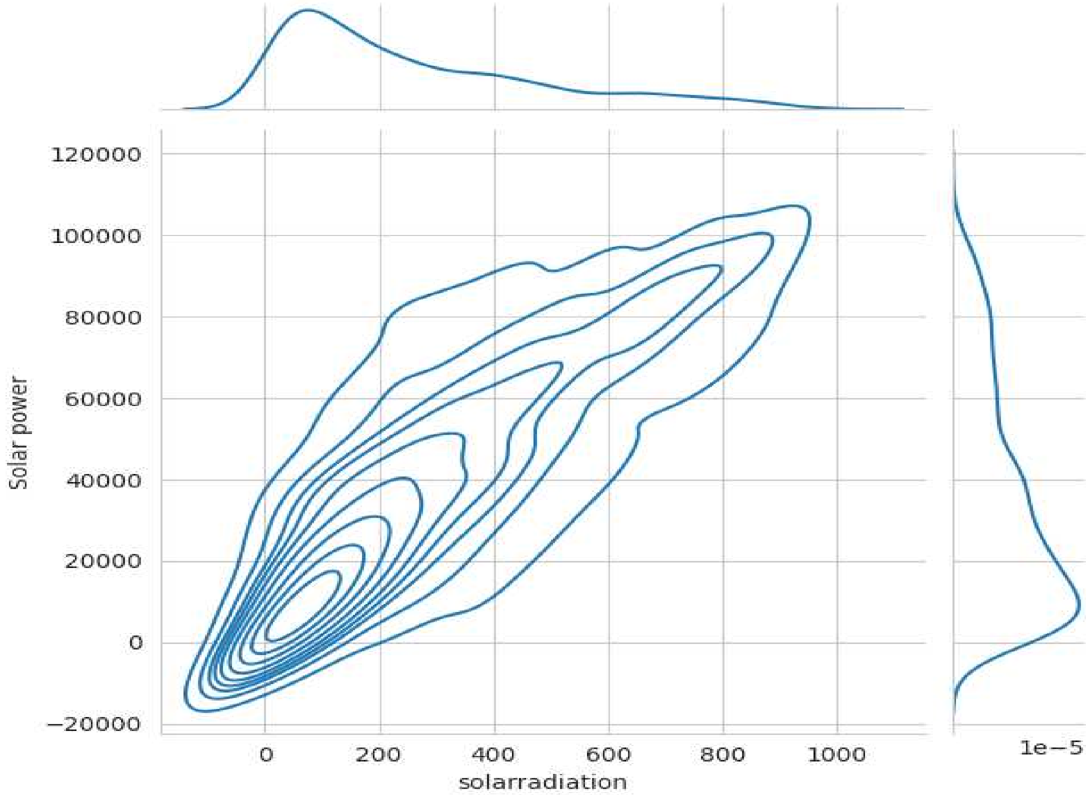

Figure 4.6: Correlation between solar radiation and solar PV power generation.

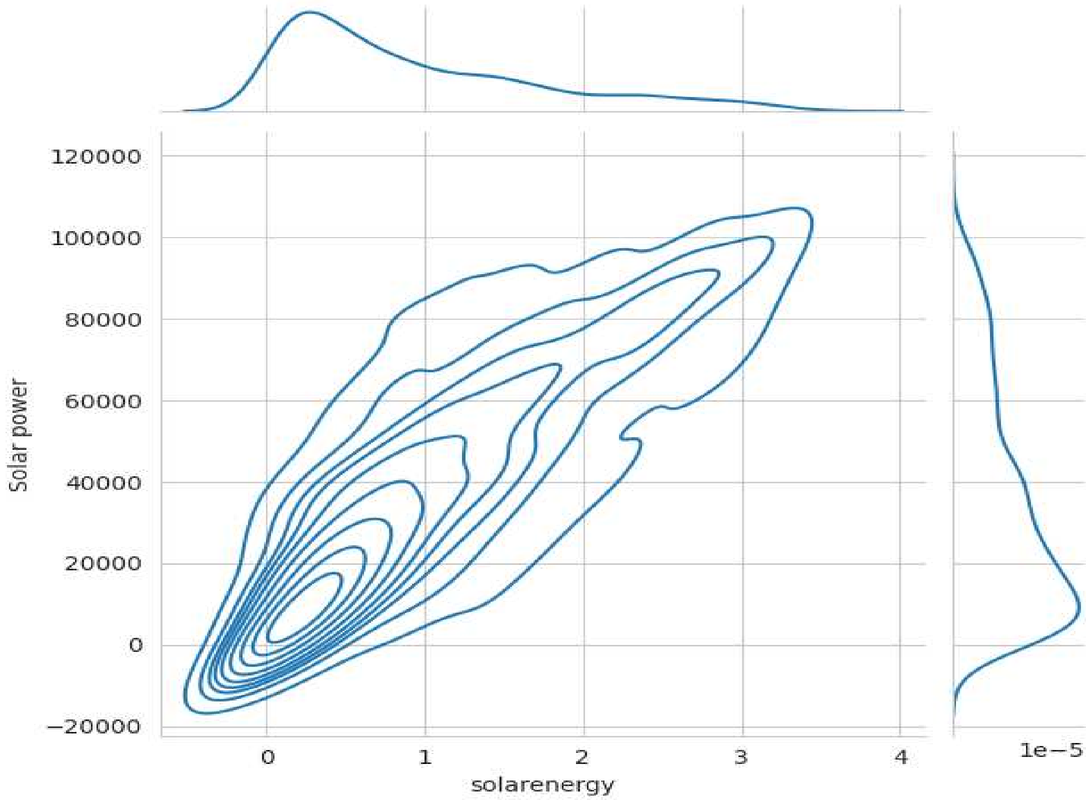

Figure 4.7: Correlation between solar energy and solar PV power generation.

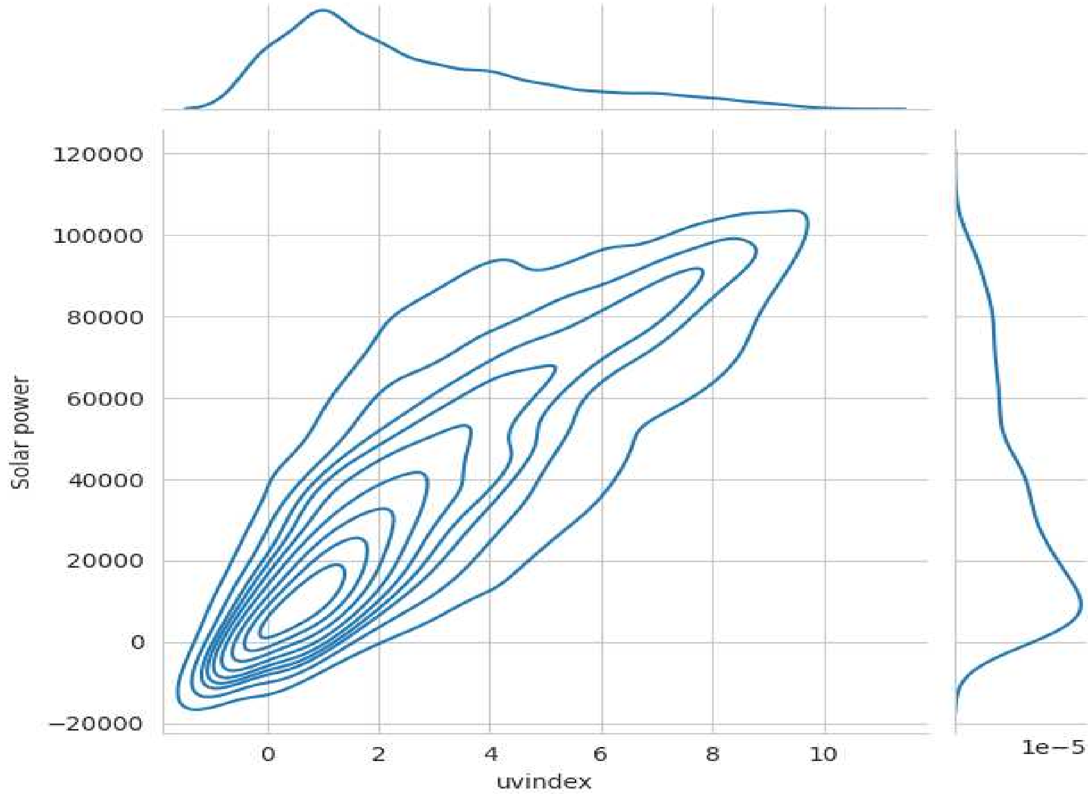

Figure 4.8: Correlation between UV Index and solar PV power generation.

4. **Humidity:** Humidity levels in the atmosphere can influence the efficiency of solar panels. We analyze the correlation between humidity and solar PV power generation. In figure 4.9 it is shown that these two values have highly reverse relationship so it is also a good predictor for the solar power value.

5. **Temperature:** Temperature plays a significant role in the efficiency and performance of solar panels. Higher temperatures, for example, can influence the overall efficiency and electricity output of the solar PV system. Figure 4.10 illustrates the correlations between all the considerable weather data with the solar power which is the power generated by our solar PV. It shows that variation of Temperature is correlated with solar power with 56%.

6. **Dew Point:** Dew point is a measure of atmospheric moisture. We explore how variations in dew point affect the power output of the PV system. Dew point is considered as a predictor due to its 28% correlation to solar power(Figure 4.10).

7. **Visibility:** Visibility is an important factor, particularly related to atmospheric clarity. We examine how variations in visibility impact the solar PV power generation. Visibility and solar power values are related to each other with a 35% correlation coefficient(Figure 4.10).

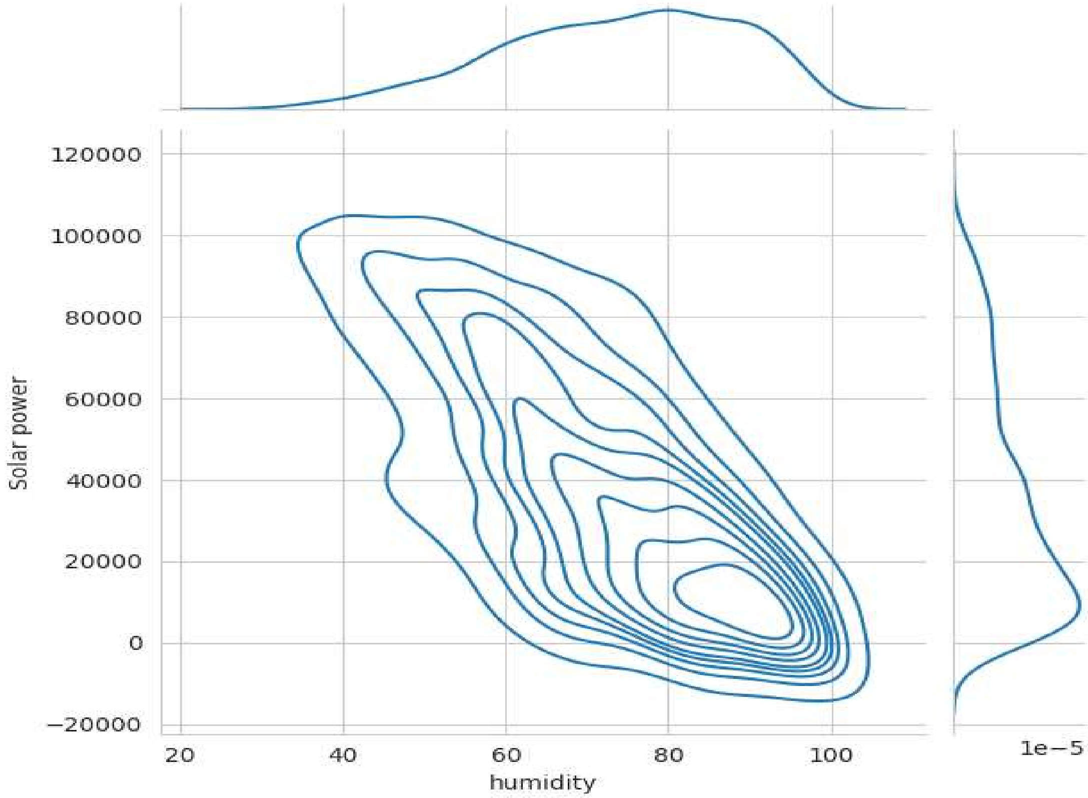

Figure 4.9: Correlation between humidity and solar PV power generation.

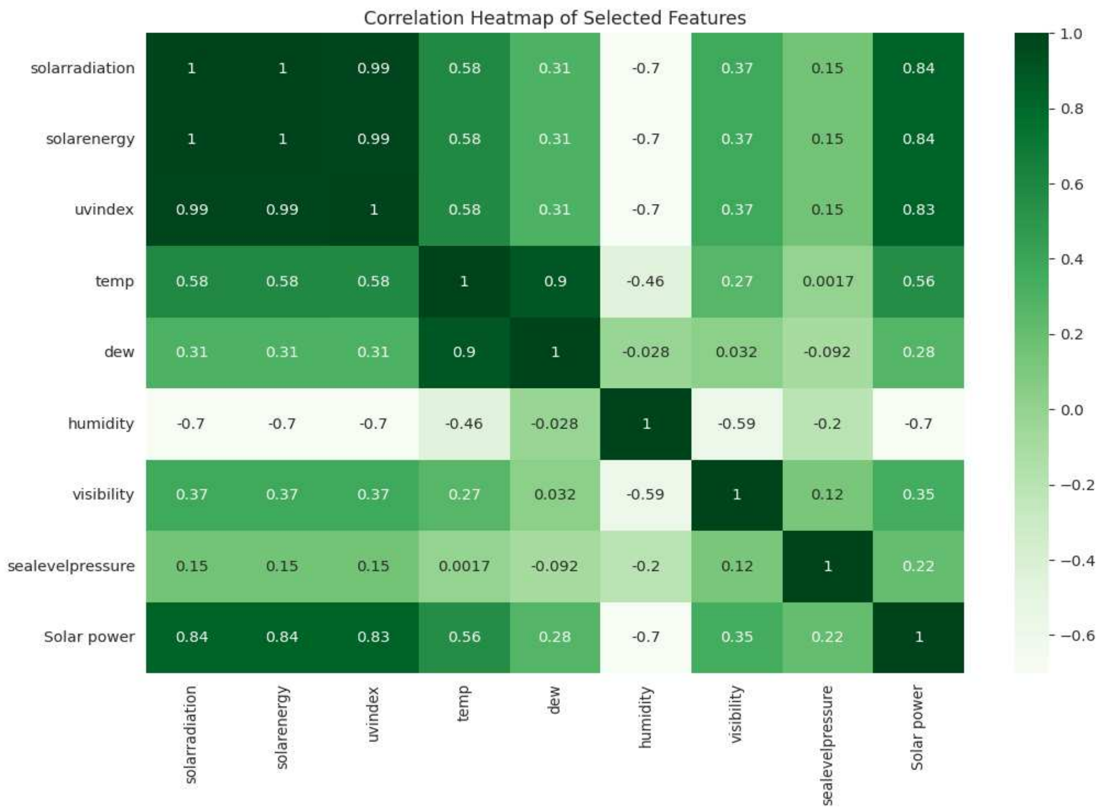

Figure 4.10: Correlation all predictors and solar PV power generation.

8. **Sea Level Pressure:** Changes in sea level pressure can affect the performance of solar panels. We investigate how sea level pressure correlates with the power output of the solar PV system. The least related value that is considered as a predictor is sea level pressure with a 22% correlation coefficient(Figure 4.10).

4.2.5 Trend Analysis

Analyzing the power generation patterns, we observe a consistent upward trend until July, followed by a subsequent downward trend until December. The AI model consistently predicts increasing power generation in the initial months, transitioning to a decrease in the later part of the year, indicating a varying trend in solar energy generation(Figure 4.1).

4.2.6 Seasonal Variations

The data trends show distinct seasonal variations in power generation. During summer months, the predicted power generation peaks, aligning with the increased solar radiation and longer daylight hours. In contrast, winter months exhibit a decrease in predicted power generation due to reduced solar radiation.

4.3 Analysis of Predicted Power Generation

In this section the models outcomes are presented and the results are discussed. The number of features selected are 26 of which 17 features are for categorical variables "icon" and "conditions" showing the weather situation and they were converted to numerical variable via one hot encoding method. The rest of the variables is are numerical so they were scaled using standard scaler method to have less variation. We applied LSTM with multiple layers to have the comparison of the different prediction results and be able to consider the best model for our system.

4.3.1 LSTM Model Results

Three LSTM model structures were used as below:

1. The first model structure has one LSTM layer and one Dense layer with 4921 total parameters as demonstrated below. Model resluts and accuracy is shown in table 4.3.

```
Model: "sequential_1"
_________________________________________________________________
 Layer (type)                Output Shape              Param #
=================================================================
 lstm_7 (LSTM)               (None, 24)                4896

 dropout_7 (Dropout)         (None, 24)                0

 dense_7 (Dense)             (None, 1)                 25

=================================================================
Total params: 4921 (19.22 KB)
Trainable params: 4921 (19.22 KB)
Non-trainable params: 0 (0.00 Byte)
_________________________________________________________________
```

2. The Second model as shown below is presented with two LSTM and dense layers that increase in model complexity with 10,433 total parameters. table 4.3 presented that this model results has the best accuracy and least mean square error.

```
Model: "sequential_2"
___________________________________________________________________
 Layer (type)                Output Shape              Param \#
===================================================================
 lstm_2 (LSTM)               (None, 1, 24)             4896
 dropout_2 (Dropout)         (None, 1, 24)             0
 lstm_3 (LSTM)               (None, 24)                4704
 dropout_3 (Dropout)         (None, 24)                0
 dense_2 (Dense)             (None, 32)                800
 dense_3 (Dense)             (None, 1)                 33
===================================================================
Total params: 10433 (40.75 KB)
Trainable params: 10433 (40.75 KB)
Non-trainable params: 0 (0.00 Byte)
```

3. The third model has 15,649 parameter and three LSTM and dense layers is even more complex. However, based on tables 4.3 using more complex models does not have the best results.

```
Model: "sequential_3"
___________________________________________________________________
 Layer (type)                Output Shape              Param \#
===================================================================
 lstm_10 (LSTM)              (None, 1, 24)             4896
 dropout_10 (Dropout)        (None, 1, 24)             0
 lstm_11 (LSTM)              (None, 1, 24)             4704
 dropout_11 (Dropout)        (None, 1, 24)             0
 lstm_12 (LSTM)              (None, 24)                4704
 dropout_12 (Dropout)        (None, 24)                0
 dense_10 (Dense)            (None, 32)                800
 dense_11 (Dense)            (None, 16)                528
 dense_12 (Dense)            (None, 1)                 17
===================================================================
Total params: 15649 (61.13 KB)
Trainable params: 15649 (61.13 KB)
Non-trainable params: 0 (0.00 Byte)
```

Algo	dropout	epochs	batch_size	rmse	r2
Two layers-LSTM	0.25	60	32	0.204240	0.793102
One layer-LSTM	0.25	60	32	0.205488	0.791839
One layer-LSTM[1]	0.3	60	64	0.209307	0.787970
Three layers-LSTM	0.25	60	32	0.209928	0.787340

Table 4.3: LSTM Model Results

4.3.2 Comparison with Actual Power Generation

Comparing the predicted power generation with actual data, the AI model demonstrates a high level of accuracy, nearly 80 percent. The predictions closely align with the actual power generation, with a negligible variance observed. This indicates the robustness and reliability of the AI model. Figure 4.12 presented the comparison of actual solar power and the predicted amounts based on the sequence in the model.

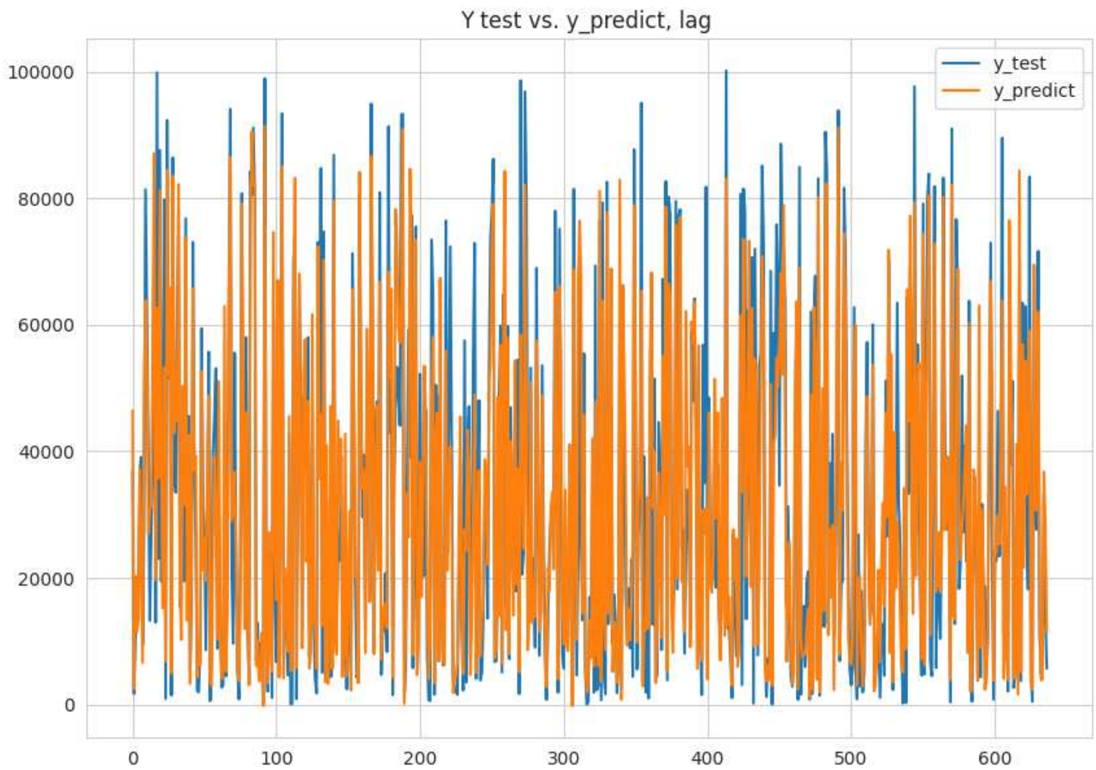

Figure 4.11: The best LSTM model prediction results.

]

4.3.3 Outliers and Anomalies

There were few outliers were observed in the predicted power generation and they were replaced by interpolation method for the rest of the calculations(Figure 4.12). However, for predicting the high productions the model is not performed well. Lack of sufficient data(only one year of data) for learning the seasonality via model could be the possible reason(Figure 4.11 and 4.12).

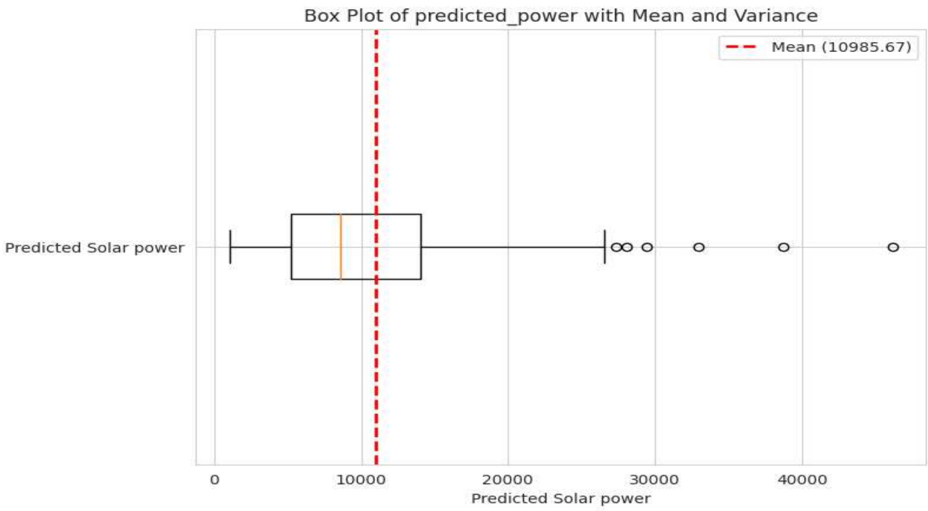

Figure 4.12: Prediction solar power outliers.

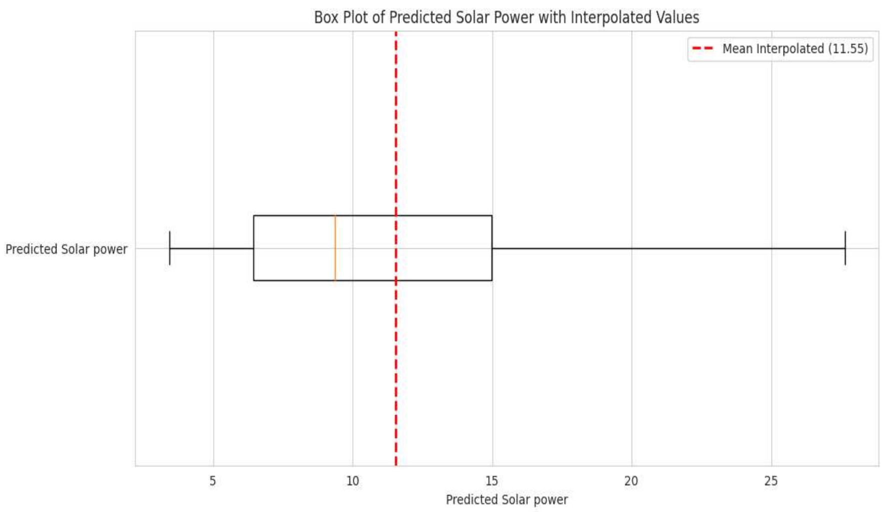

Figure 4.13: Prediction solar power outliers interpolated.

4.3.4 Sensitivity Analysis

Conducting sensitivity analysis by varying weather variables, it was evident that solar radiation has the most significant influence on predicted power generation. Slight variations in solar radiation result in noticeable changes in the AI model's predictions.

4.3.5 Discussion on Model Improvements

The model were used, improved the accuracy of the base-line by 14 percent and it has a significant improvement in mean square error[50]. Based on the analysis, incorporating real-time weather updates and additional features such as cloud cover dynamics could enhance the AI model's accuracy. Additionally, more data would help the model to learn better and predict more accurate result.

4.3.6 Summary and Conclusions

In summary, the AI model effectively predicts power generation patterns, displaying strong correlations with weather variables. The analysis provides valuable insights into trends, seasonal variations, and the model improvements. Improvements focused on providing more data would further enhance prediction accuracy.

4.4 Excess Electricity Analysis

In this section, we present the calculation and analysis of excess electricity based on the methodology outlined in Chapter 3. We also discuss the distribution and variations in excess electricity across different times of the day. Data for the load demand throughout the year were obtained form [33](figure 4.14).

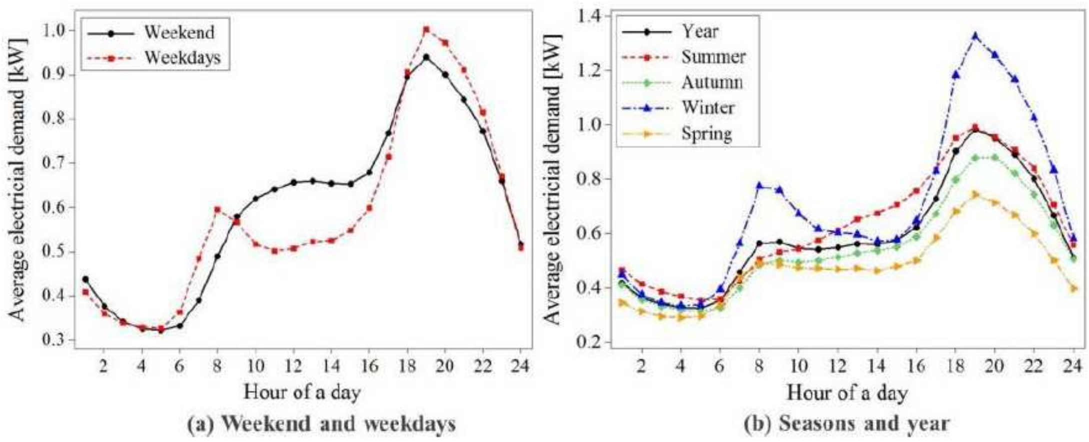

Figure 4.14: Average household load demand in seasonal basis through one day[33].

4.4.1 Calculation and Analysis

The excess electricity is calculated by subtracting the actual power demand from the generated solar power. This allowed us to determine the surplus electricity available to use for hydrogen production.

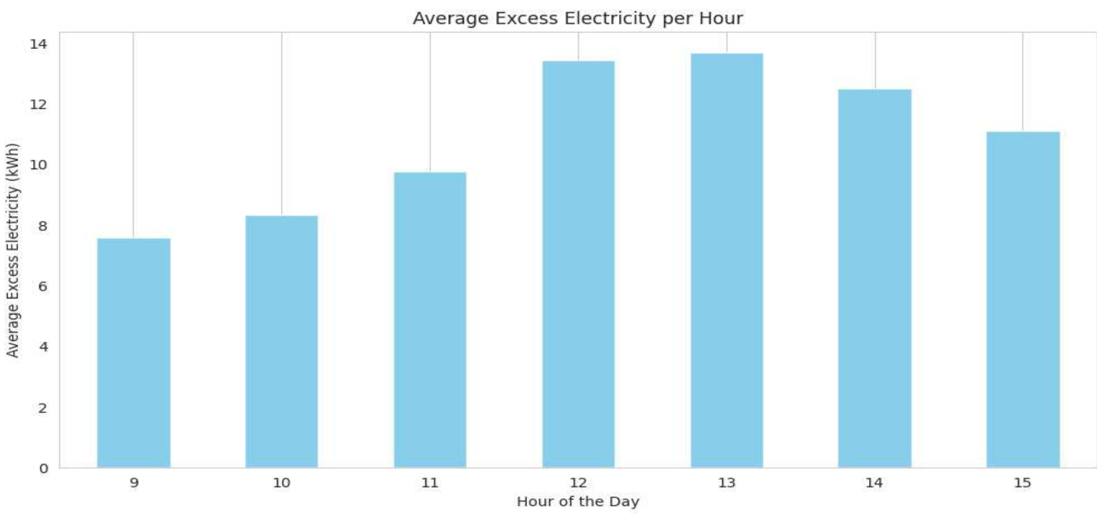

Figure 4.15: Calculated average excess electricity in Jan 2022 one day.

4.4.2 Distribution and Variations

We observed that excess electricity varied throughout the day, peaking during midday when solar power production was highest(Figure 4.15). Variations were also noticed based on weather conditions and seasonal changes.

4.5 AEM Electrolyzer Optimization Results

In this section, we present the results of the optimization process for the AEM electrolyzer based on surplus electricity. We discuss the optimization methodology and the optimal number of AEM electrolyzers determined to have the maximum hydrogen production.

4.5.1 Optimization Process

The AEM electrolyzer optimization involved adjusting the hydrogen production based on the surplus electricity available. We optimized the electrolyzer's operations to maximize hydrogen production. During the process the AEM electrolyzer was considered to perform with 100% production rate with maximum power consumption, which is 2.592 Kwh . The power consumption of AEM electrolyzer determined via an experimental process with exsiting AEM electrolyzer. Figure 4.15 shows the power consumption of an AEM electrolyzer with different production rates.

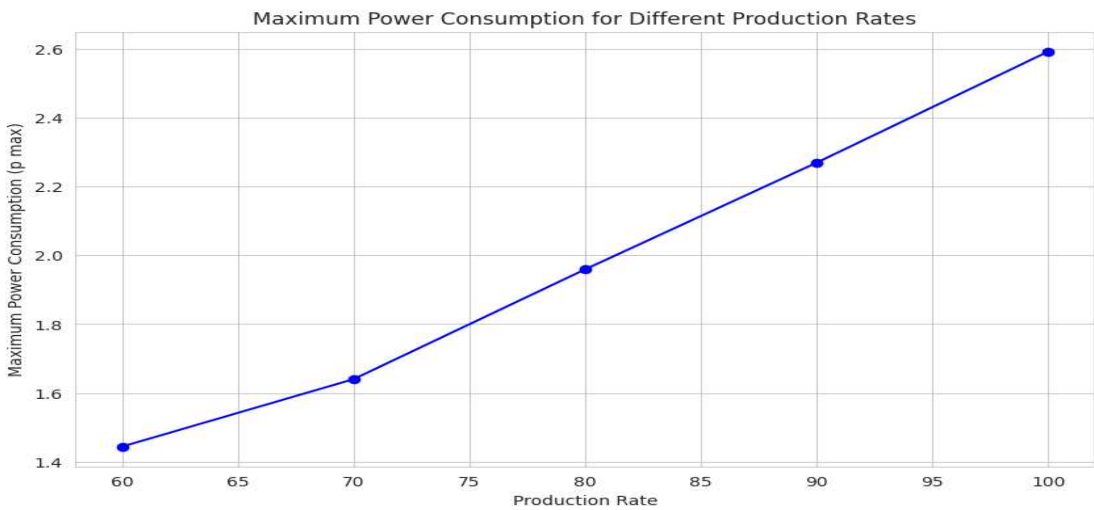

Figure 4.16: Maximum power consumption for different production rates.

4.5.2 Optimal Number of Electrolyzers

It is shown in the analysis that the maximum number of AEM electrolyzers varied with the surplus electricity levels. However, the optimum number were found to be 5 that can use the maximum excess electricity and while have less off hours . To have more accurate result it is assumed 95% as the efficiency of DC/AC converter that convert the current from DC,Solar PV production, to AC the feed in current into AEM electrolyzer. As results shows with 5 standby parallel AEM electrolyzer in January we can produce in average 11.29 m3 every day(Figure 4.17).

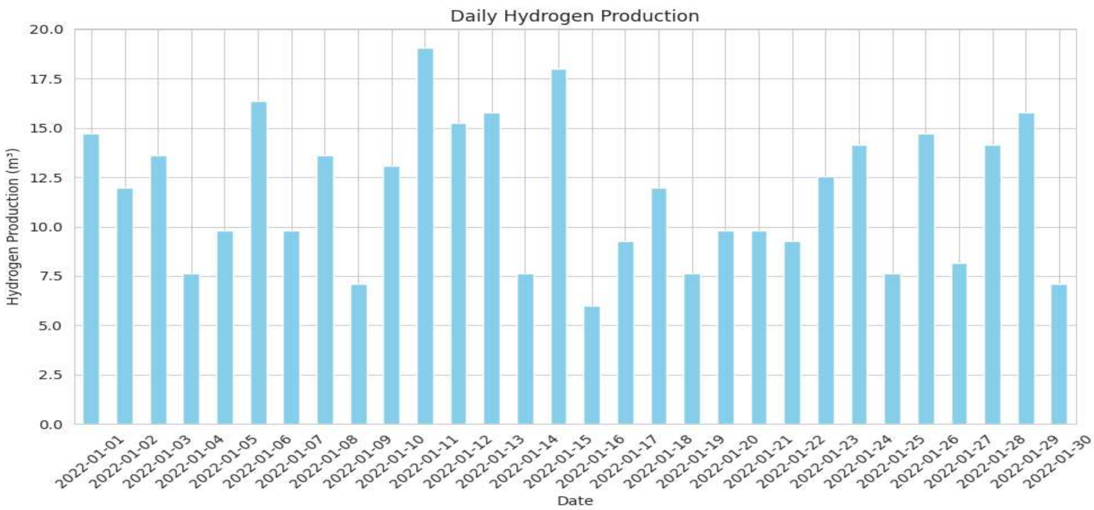

Figure 4.17: Daily hydrogen production in January.

By considering a PEMFC with efficiency of 60% figure 4.18 illustrates the system possible electricity production.

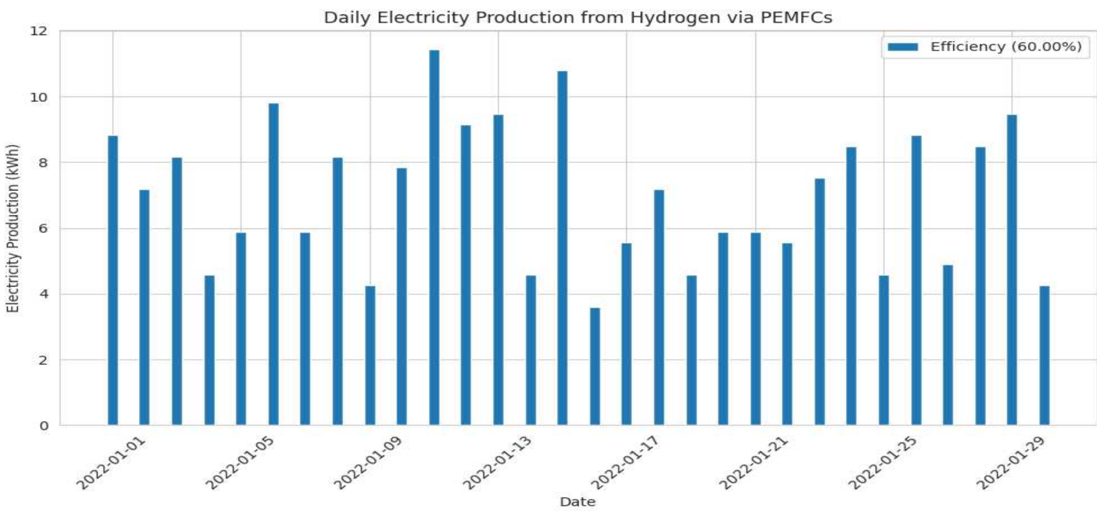

Figure 4.18: Possible daily electricity production via hydrogen PEMFC in January.

4.6 Integration of AI Model with System Performance

In this section, we discuss how the AI model's predictions and the subsequent scheduling of AEM electrolyzers that influenced the overall system performance. We analyze how automation based on the AI model will schedule a fully automated hybrid solar PV system.

4.6.1 Prediction influence

The predictions from the AI model played a significant role in dynamically optimizing and scheduling the AEM electrolyzers standby for the system and managing surplus electricity. This integration improved overall system efficiency and resource utilization.

4.6.2 Automation and Efficiency

Automation based on the AI model ensured real-time adjustments to system components, maximizing the utilization of generated solar power and surplus electricity. This resulted in increased efficiency and reduced wastage.

Table 4.4: Schedule of the number of ON electrolyzers on January 1st.

Datetime	Number of ON Electrolyzer	Hydrogen Production (m^3)
2022-01-01 09:00:00	2.0	1.090
2022-01-01 10:00:00	3.0	1.635
2022-01-01 11:00:00	3.0	1.635
2022-01-01 12:00:00	5.0	2.725
2022-01-01 13:00:00	5.0	2.725
2022-01-01 14:00:00	5.0	2.725
2022-01-01 15:00:00	4.0	2.180

4.7 Discussion of Findings

In this section, we summarize the key findings from the data analysis and relate them to the research objectives and the overall aim of the study.

4.7.1 Summary of Key Findings

Our analysis demonstrated that integrating AI with a hybrid solar PV system can effectively optimize hydrogen production from surplus electricity while ensuring system efficiency. The key findings of our study are as follows:

Optimized Hydrogen Production: The AI-based control system effectively optimized the operation of the AEM electrolyzer, maximizing hydrogen production during periods of surplus electricity.

Efficiency Improvement: The integration of AI improved the overall efficiency of the hybrid solar PV system by dynamically adjusting the operation of the electrolyzer based on real-time data, thus reducing energy wastage.

Sustainability Enhancement: By utilizing surplus renewable energy for hydrogen production, our approach contributes to increasing the sustainability of renewable energy sources. Hydrogen can be stored and used as a clean energy carrier, reducing reliance on fossil fuels.

Data-driven Insights: Our study emphasized the importance of data-driven decision-making in renewable energy systems. Real-time monitoring and AI algorithms provide valuable insights for optimizing operations.

Scalability Potential: The findings suggest that this approach is scalable and adaptable to different hybrid renewable energy systems, paving the way for broader implementation.

4.7.2 Relation to Research Objectives

The findings align with our research objective of increasing the sustainability of renewable energy sources by integrating AI technology with a hybrid solar PV system. By effectively utilizing surplus electricity for hydrogen production, we contribute to the goal of enhancing the reliability and efficiency of renewable energy systems.

4.8 Limitations and Constraints

In this section, we discuss any limitations or constraints encountered during the data analysis and interpretation. We address factors that may have affected the accuracy or generalizability of the results.

4.8.1 Discussion of Limitations

One limitation was the availability of historical data for training the AI model. A more extensive dataset would have enhanced the accuracy of our predictions. Additionally, the following limitations should be considered:

1. Data Variability: Weather conditions and electricity generation patterns can vary significantly over time, affecting the system's performance. A longer data collection period would have provided a more comprehensive understanding.

2. Model Complexity: The AI model's performance is influenced by its complexity. Striking the right balance between model complexity and training data is crucial for optimal results.

3. Cost Considerations: Implementing an AI-based control system may involve initial costs for hardware and software development. A cost-benefit analysis is essential to assess the economic viability of such a system.

4. Operational Challenges: The practical implementation of the AI system may encounter operational challenges, such as system compatibility, maintenance, and user training.

4.8.2 Impact on Results

The limitations affected the precision of our predictions and the optimal performance of the AEM electrolyzer. The results could have been more robust with a larger and more diverse dataset. Addressing these limitations and constraints in future research can lead to more accurate and reliable outcomes.

4.9 Summary

In this chapter, we presented a comprehensive analysis of the results obtained from our research. We discussed excess electricity analysis, AEM electrolyzer optimization results, hydrogen production efficiency, integration of the AI model with system performance, and analyzed our findings.

We also highlighted the limitations and constraints encountered during the study, setting the stage for a deeper discussion and interpretation in the subsequent chapter. Our study showcases the potential of AI in enhancing the sustainability and efficiency of renewable energy systems, but it also underscores the need for careful consideration of data availability, model complexity, and cost-effectiveness. All the results were obtained via python programming using Tensorflow Keras framework performed in Google Colab platform[22]

5

Conclusions and Future Works

In this chapter, we summarize the key findings and insights obtained from our research on forecasting short-term power generation in a grid-connected hybrid solar photovoltaic (PV) system using an AI model. We also discuss potential future research directions to enhance the sustainability and efficiency of renewable energy integration.

5.1 Summary of Findings

Our research focused on developing an AI model based on Long Short-Term Memory (LSTM) networks to forecast short-term power generation from a hybrid solar PV system. We integrated weather data and solar PV electricity production data from the year 2021 to train and validate the AI model. The methodology involved optimizing an AEM electrolyzer for efficient hydrogen production using surplus electricity generated by the solar PV system.

Through our analysis, we observed strong correlations between solar radiation, solar energy, UV index with 0.85 correlation coefficient and humidity, temperature, dew point, visibility, and sea level pressure with .72, 0.31, 0.38, 0.21 correlation coefficient respectively with solar PV power generation. These weather factors significantly influenced the accuracy of our AI model in predicting power generation.

We developed and evaluated multiple LSTM model structures, and the results showed that a two-layer LSTM model outperformed the others, achieving approximately 80 percent accuracy which has a significant (nearly 15) percent improvement in accuracy compared to the baseline. The model accurately predicted power generation patterns, displaying strong correlations with weather variables.

Furthermore, we calculated excess electricity by subtracting the actual power demand from the generated solar power, providing insights into surplus electricity which has an average value of 10 Kwh between 9 am to 4 pm and it is available for other applications. The surplus electricity varied throughout the day, peaking during midday, aligning with maximum solar power production.

According to German national laws, the average selling price for excess electricity is $\frac{1}{5}$ of the price of buying electricity from the grid. Our hybrid system, which utilizes approximately 10 kWh to generate an average of 7 kWh of electricity from stored hydrogen, costs less than half of the grid energy price. Hence, utilizing this hybrid system remains a profitable option.

In optimizing the AEM electrolyzer, we determined that having five standby parallel AEM electrolyzers was the optimal configuration to utilize the maximum excess electricity while minimizing off-hours. This configuration enabled efficient hydrogen production for potential use in a fuel cell system, contributing to increased sustainability.

5.2 Future Research Directions

Our research presents various opportunities for future investigations aimed at further enhancing the efficiency and sustainability of renewable energy systems:

- **Real-time Integration**: Enhance the AI model to accommodate real-time weather updates and solar PV electricity production data, allowing for real-time adjustments and optimizations in the hybrid solar PV system.
- **Hybrid Energy Storage Systems**: Investigate the integration of advanced energy storage systems, to store excess electricity for later use during periods of low solar PV generation, ensuring a continuous and reliable power supply.
- **Demand-side Management**: Explore demand-side management strategies to align power consumption with solar PV generation patterns, optimizing energy usage and reducing dependence on the grid.
- **Machine Learning Algorithms**: Compare the performance of LSTM with other machine learning algorithms to identify the most suitable model

for power generation forecasting, considering factors such as accuracy, efficiency, and computational requirements.

- **Optimized Hydrogen Production**: Further optimize hydrogen production using surplus electricity by considering advanced electrolyzer technologies and control algorithms to achieve higher efficiency and lower energy consumption.
- **Deployment in Microgrids**: Evaluate the effectiveness of the integrated AI model and optimized AEM electrolyzer in a microgrid setting, assessing its potential to enhance microgrid stability and sustainability.

These future research directions aim to enhance the performance, reliability, and sustainability of hybrid solar PV systems, contributing to the broader adoption of renewable energy sources and the transition towards a more sustainable energy future.

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