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# MASTER

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*Title:*

# Application of Artificial Intelligence Techniques To Energy Management in Hybrid System

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# Abstract

Meeting the growing global energy demand requires innovative and sustainable solutions, with renewable energy resources (RERs) offering a promising pathway. Among these, photovoltaic (PV) systems stand out as accessible and scalable options, especially when integrated at the distribution level in smart grids. However, the inherent variability and unpredictability of solar energy introduce significant challenges for real-time energy management and grid stability. Accurate forecasting of power production and consumption thus becomes a critical task in ensuring optimal energy flow and efficient grid operation.

This study presents a case-based investigation of a grid-connected PV system enhanced with artificial intelligence (AI) techniques for advanced energy management. Specifically, it explores and compares the performance of an Adaptive Network-based Fuzzy Inference System (ANFIS), a Convolutional Neural Network (CNN), and a hybrid CNN–ANFIS model in predicting short-term power generation and consumption. All models were developed, trained, and evaluated using MATLAB, based on real-world weather and energy data collected over multiple seasons. The evaluation metrics, particularly root mean square error (RMSE), demonstrate that the hybrid model combines the learning capabilities of CNNs with the reasoning strength of ANFIS, offering improved forecasting accuracy. The integration of such intelligent predictive systems supports smarter decision-making and can significantly enhance the reliability and cost-efficiency of distributed renewable energy integration in modern power systems.

# Acknowledgment

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# Dedication

First and foremost, I extend my deep gratitude to Allah, the Most Merciful, the Most Wise, for His endless blessings and guidance throughout this journey. Without His divine will, none of this would have been possible. In moments of doubt and fatigue, He granted me patience; in moments of confusion, He provided clarity. Alhamdulillah for every challenge that shaped me and every success that brought me closer to my goal.

To my dearest mother, Houria, your love is the purest form of support I have ever known. Your prayers, sacrifices, and constant encouragement have carried me through the most difficult times. Your strength and unwavering faith in me have been my light in the darkest moments.

To my father, Said, my superhero and role model—your wisdom, determination, and tireless efforts to provide the best for our family have always inspired me. You taught me to work hard, stay humble, and never give up, no matter how tough the road may get.

To my brothers—Mohamed, Ishak, and Kacem—you are more than just siblings; you are my soulmates and my best friends. Your belief in me, your laughter during stressful nights, and your support in both words and actions gave me the strength to keep going. I am truly blessed to walk this life with you by my side.

Finally, to my entire beloved family, thank you for always believing in me and for encouraging me to become the best version of myself. This accomplishment is not mine alone—it belongs to all of you.

# Table of Contents

# List of Figures

# List of Tables

# Acronyms

**ANN** Artificial Neural Network

**ANFIS** Adaptive Neuro-Fuzzy Inference System

**BAS** Building Automation Systems

**CNN** Convolutional Neural Network

**DERs** Distributed Energy Resources

**DMS** Distribution Management System

**DRL** Deep Reinforcement Learning

**DSM** Demand-Side Management

**EMS** Energy Management System

**ESI** Energy Services Interface

**GA** Genetic Algorithm

**HEMS** Hybrid Energy Management Systems

**LSE** Least Squares Estimation

**MAS** Multi-Agent System

**MF** Membership Function

**PHEV** Plug-in Hybrid Electric Vehicle

**RL** Reinforcement Learning

**RMSE** Root Mean Square Error

**RES** Renewable Energy Sources

**SANETs** Sensor and Actuator Networks

**SVM** Support Vector Machine

**TSK** Takagi-Sugeno-Kang

**V2G** Vehicle-to-Grid

# General Introduction

The global energy landscape is undergoing a profound transformation as the demand for cleaner, more sustainable sources of electricity continues to rise [1]. This shift is being driven by the combined pressures of climate change, the need to reduce greenhouse gas emissions, and the global push toward energy independence and sustainability. In this context, renewable energy technologies, particularly solar photovoltaic (PV) systems, have become increasingly vital in efforts to reduce carbon emissions and combat climate change [2]. Their scalability, declining cost, ease of integration, and environmentally friendly characteristics make them one of the most promising alternatives to conventional fossil fuels [3]. The growing adoption of PV systems across residential, commercial, and utility-scale applications demonstrates their central role in the energy transition currently taking place around the world [4][5].

However, despite the undeniable advantages of renewable energy sources (RES), their integration into existing power grids poses a number of technical and operational challenges [6]. The primary concern lies in their intermittent and weather-dependent behavior . Unlike traditional energy sources that offer stable and controllable output, solar energy generation is influenced by factors such as time of day, cloud cover, temperature, and seasonal variations. This unpredictability can lead to imbalances between energy supply and demand, which, if not properly managed, may compromise grid stability, lead to energy waste, or even cause power outages [7]. These issues become even more pronounced when the penetration of RES increases significantly in the energy mix.

To address these emerging challenges, modern power systems are transitioning from centralized, static infrastructures to smart grids—intelligent and adaptive networks capable of real-time monitoring, decentralized control, and data-driven decision-making[8]. Smart grids integrate advanced communication systems, automation technologies, and data analytics to improve the efficiency, reliability, and sustainability of energy distribution[9]. They enable seamless coordination between generation, storage, and consumption, and support the integration of distributed energy resources (DERs), including solar PV systems, batteries, and electric vehicles.

In the scenario of this ongoing evolution, energy management becomes a critical component in ensuring optimal system performance. It plays a key role in maintaining the balance between energy production and consumption, enhancing grid stability, reducing energy losses, and maximizing the utilization of renewable resources [10]. Traditional rule-based or statistical methods, which often rely on predefined heuristics or fixed models, are increasingly proving inadequate in the face of the growing complexity, variability, and scale of smart energy systems [4]. These methods lack the adaptability required to respond to rapidly changing conditions and are unable to capture the nonlinear dynamics that characterize modern power networks.

As a result, Artificial Intelligence (AI) has emerged as a promising solution for advancing energy management practices [11]. AI provides a range of intelligent, data-driven methodologies that are capable of learning from historical trends, identifying patterns in large datasets, predicting future behavior, and making autonomous decisions in real time [12]. This makes AI particularly well-suited to smart grid environments, where fast and accurate decisions are essential for maintaining system efficiency and reliability[13].

Among the wide array of AI methodologies, two techniques stand out for their effectiveness in modeling complex, time-dependent energy systems: the Adaptive Neuro-Fuzzy Inference System (ANFIS) and Convolutional Neural Networks (CNN). ANFIS combines the transparent reasoning process of fuzzy logic with the adaptive learning capability of neural networks, making it particularly effective in handling systems characterized by uncertainty, imprecision, or incomplete knowledge [14]. It is especially useful in applications where expert knowledge can be translated into fuzzy rules, providing a balance between interpretability and learning ability.

CNNs, originally developed for image and pattern recognition tasks, have proven to be highly effective for time-series forecasting due to their ability to detect local patterns and hierarchical features in sequential data [15]. When applied to energy systems, CNNs can capture intricate dependencies between environmental variables (such as temperature, irradiance, and humidity) and power output, especially when trained on large and diverse datasets [16]. Their ability to process multivariate inputs, extract relevant features automatically, and generalize across complex datasets makes them a valuable tool in the context of renewable energy forecasting.

This report deals with the application and performance comparison of ANFIS, CNN, and a hybrid CNN–ANFIS model for the prediction of power generation and consumption in a photovoltaic (PV) system connected to the electrical grid. The study is based on real meteorological and electrical data collected over several seasons, which allows for a realistic and detailed examination of the forecasting capabilities of each model. By evaluating the models under varying environmental and operational conditions, the study aims to determine which technique, or combination of techniques, offers the most accurate, reliable, and practical solution for predictive energy management.

The objective of this research is to contribute to the development of smarter and more adaptive energy systems by identifying the model that best supports accurate short-term forecasting, optimal energy flow control, and informed decision-making in

PV-integrated smart grids. Through an in-depth analysis of the strengths, limitations, and practical implications of each approach, this study aims to demonstrate how AI can enhance the performance of renewable energy systems and help unlock their full potential in the global energy transition.

This report is organized as follows:

**Chapter 1** presents an overview of the smart grid paradigm and the main renewable energy technologies, particularly photovoltaic systems. It discusses the challenges of integrating RES into conventional grids and highlights the essential role of energy management in ensuring reliable and efficient system operation.

**Chapter 2** provides a detailed review of artificial intelligence applications in energy management, focusing on the architectures, learning mechanisms, and forecasting capabilities of ANFIS and CNN models. The strengths and limitations of each technique are analyzed with respect to their applicability in smart grid environments.

**Chapter 3** describes the case study used for model implementation and evaluation. It includes a description of the system architecture, the structure of the dataset, preprocessing methods, and the MATLAB-based development of the three models. The chapter concludes with a comparative analysis of results based on key performance metrics.

The findings of this study aim to inform future developments in AI-powered energy forecasting and management, ultimately contributing to the realization of intelligent, sustainable, and resilient power systems.

# Chapter 1

# Theoretical Background

## 1.1 Introduction

In recent decades, the global energy landscape has undergone significant evolution, driven by rising demand, environmental concerns, and the pursuit of more resilient and efficient systems. In the conventional top-down structure of the electricity grid, large fossil fuel-based power plants supply electricity to end users via transmission and distribution networks, with little to no feedback from the consumption side. This traditional model, illustrated in the figure 1.1, reflects a centralized approach where energy flows in one direction—from generation to consumption.

While this structure has supported industrial and economic growth for over a century, it now reveals serious limitations in the face of modern energy challenges. The historical grid is inefficient in monitoring, management, and response, and it is not adaptable enough to handle changing demand. It has a limited ability to integrate small-scale, decentralized energy source . Frequent outages and energy losses, particularly at the distribution level, are also caused by its fault susceptibility, old infrastructure, and inadequate real-time communication [1].

A new generation of power systems is emerging that is more technologically advanced, decentralized, and dynamic in order to address these weaknesses. To increase resilience and efficiency, these developing grids use automation, intelligent control, and cutting-edge communication technology. Integrating renewable energy sources (RES) like wind and solar is crucial in this situation. Their unpredictable nature, however, creates operational difficulties that the conventional grid is unable to handle.

The modern grid may more effectively adjust to the unpredictability of renewable energy sources by implementing real-time coordination and sophisticated control systems. New energy strategies that more effectively regulate production and consumption are also made possible by this change [3]. Energy management systems have become crucial among these strategies. They allow for resource optimization, supply and demand balance, and increased customer participation in the grid's overall operation [4].

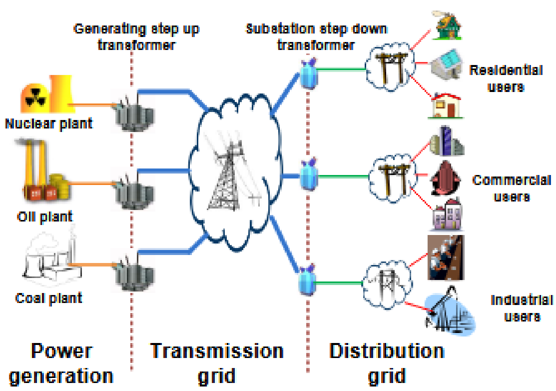


**Figure 1.1:** example of traditional grid

## 1.2 Smart Grid

### 1.2.1 Definition

The Smart Grid is an advanced electrical system that has been technologically improved to enable for two-way, real-time communication and energy flow between generation, transmission, distribution, and consumption. It combines secure communication, computational intelligence, and information technologies to provide a robust, effective, and sustainable energy infrastructure [1]. High standards of safety, dependability, and cybersecurity are maintained while allowing utilities and consumers to better control energy use with characteristics like self-healing, adaptability, and compatibility with developing technologies [8].

### 1.2.2 Functional Characteristics

The smart grid is characterized by:

- **Integration of Distributed Resources**: By facilitating the smooth integration of distributed generation (DG), which includes micro-generation, storage systems, and renewable energy sources like wind and solar, smart grids improve flexibility and reduce their negative effects on the environment[17] .

- **Self-Healing and Resilience**: Improves security and dependability even in the face of physical or cyber attacks by acting independently to identify, isolate, and repair system flaws[8].

- **Automated Grid Operation**: Increases overall efficiency and asset utilization by using intelligent devices for fault isolation, load balancing, feeder reconfiguration, real-time monitoring, and system optimization.

- **Cybersecurity Measures**: Uses threat modeling, intrusion detection systems (IDS), and encryption to defend against threatening attacks and safeguard private information on grid infrastructure [1].

- **Standards and Interoperability Compliance**: Guarantees that, with the use of present and future communication standards, all devices, systems, and domains —generation, transmission, distribution, and consumption—operate in a coordinated way.

- **Advanced Metering and Distribution Automation**: Using smart meters and AMI systems to measure usage in real time, detect outages, monitor voltage, and handle faults automatically [17].

- **Smart appliances and consumer devices**: These devices allow for adaptive load shifting by automatically modifying consumption according to supply conditions, which improves system stability and saves money for consumers [17].
- **Monitoring and Diagnostics**: Constantly examines the environment and performance of grid elements (such as transformers and lines) in order to identify errors, enhance decision-making, and minimize downtime.
- **Energy Storage and Electric vehicles**: This approach supports load leveling, peak shaving, and increased dependability by combining cutting-edge storage technology with electric vehicles (EVs) that may feed energy back into the grid (V2G) [17].

### 1.2.3 Architecture and Main Components

According to the National Institute of Standards and Technology (NIST), the Smart Grid reference design provides a thorough framework with a number of connected domains and subdomains [8]. To support particular applications, each domain consists of a variety of actors, including hardware, software, and computer systems, that communicate and exchange data through network interfaces as shown in Figure 1.2 [17].One actor may handle these applications alone, or several actors may work together. Additionally, domains can be hidden inside one another, and interfaces — whether electrical or communication- based — are used to control the movement of energy or information across systems. Usually bidirectional, communication interfaces symbolize intellectual rather than physical relationships. The conceptual model of the smart grid is based on a legal and regulatory framework that guarantees adherence to state and federal laws (such as FERC). It backs changing public policy objectives like sustainability, cybersecurity, fair pricing, and dependability. The Smart Grid domains are briefly described below:

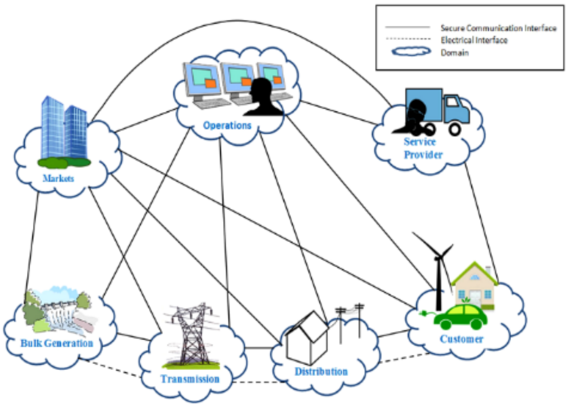


**Figure 1.2:** interation of actors

- **Consumer Domain**: The residential, commercial, and industrial end users of electricity are included in this area. Energy Management Systems (EMS) and Building Automation Systems (BAS), which are usually interfaced through the Energy Services Interface (ESI), allow users to control their energy production and consumption. It has connections to the fields of operations, distribution, utilities, and markets. Applications include DG monitoring, remote load control, and in-home displays.

- **Markets Domain**: Electricity trade and supply and demand balance are made easier by this domain. It links to supply (generation, Distributed Energy Resources(DERs)), operations, and consumer domains. Here, communication standards need to guarantee non-repudiation, traceability, and security. Communication latency needs to be reduced as DERs develop. Integrating DER signals into consumer-level pricing systems and guaranteeing interoperability across utilities and market players are two major obstacles.

- **Utility Domain**: Services offered by utility domain actors include consumer energy management and billing. In order to enable smart services while preserving grid dependability, cybersecurity, and safety, this domain connects with the operations, markets, and consumer domains. In order to accommodate changing market dynamics and business models, it is imperative that compatible standards and interfaces be developed.

- **Operations Domain**: This domain, which is in charge of power system planning and real-time operation, uses distribution Management System (DMS) for distribution and Energy Management System (EMS) for transmission. These tasks were previously performed by utilities, but the Smart Grid encourages further outsourcing and decentralization. It guarantees stability throughout the service delivery points of the grid.

- **Generation Domain**: Usually enclosed by the transmission domain, this domain manages the production of electricity. It communicates performance indicators and reacts to faults or shortages by establishing connections with the transmission, operations, and market domains. Three main areas of concentration are emission controls, storage systems, and the integration of renewable energy sources (RESs). PLCs, and fault recorders are examples of monitoring and control devices that are actors.

- **Transmission Domain**:This area connects the production and distribution of energy and is in charge of its high-voltage transportation. SCADA systems and protection relays are some of its actors. It supports auxiliary services, guarantees system stability, and is necessary to enable responsive market operations.

- **Distribution Domain**:Distributed storage and DG interconnections are managed by this domain, which connects transmission systems to consumers. The system has changed from being primarily manual to having automated, two-way communication. In order to accommodate dynamic load and price fluctuations, it now has close connections with the operations and markets domains. Sectionalizers, reclosers, and capacitor banks are some of its actors.

  Building on this architecture, Smart Grid systems incorporate various intelligent components and technologies that enhance functionality and performance across all domains [8].

- **Smart Devices Interface**:Autonomous monitoring and control are made possible by smart devices, such as wearables, thermostats, and smart meters. They are crucial to system responsiveness and DER integration.

- **Storage Component**:To counteract the variability of Renewable Energy Sources and peak demand mismatches, storage solutions such as flow batteries, ultracapacitors, flywheels, and compressed air systems are deployed. These enhance grid reliability and resilience.

- **Transmission Subsystem**:High dependability and real-time flexibility are essential for this backbone network. System monitoring and control are supported by modern technologies such as robust state estimators and dynamic optimal power flow.

- **Monitoring and Control Technologies**:Self-monitoring and self-healing systems that offer situational awareness and autonomous decision-making are among them. Grid stability and quick operational change adaption depend on them.

- **Intelligent Grid Distribution Subsystem**:This subsystem uses communication -capable equipment, such as EMS and smart meters, to automate power distribution. It has self-healing features, fault detection, load optimization, and real-time pricing.

- **Demand Side Management (DSM)**:By shifting and lowering the demand for electricity, DSM techniques increase efficiency and lessen the need for expensive generating capacity. Consumer-side automation, two-way connectivity, and smart houses are important components of DSM.

### 1.2.4 Enabling Technologies for Smart Grid Intelligence

While the architecture of the Smart Grid is built on well-defined structural components, its advanced capabilities stem from a set of enabling technologies that facilitate automation, responsiveness, and intelligent decision-making. These innovations enhance grid performance across domains by supporting real-time communication, data analysis, distributed control, and flexible energy exchange [8].

- **Smart Meters and Automated Meter Reading (AMR)**: These devices form the backbone of consumer-grid interaction by enabling two-way communication between utilities and users. They support real-time energy usage tracking, dynamic pricing, automated billing, and demand forecasting.
- **vehicle to grid V2G**: V2G systems allow electric vehicles (EVs) to supply stored energy back to the grid, helping to balance peak loads and improve grid flexibility. This turns EVs into mobile energy assets.
- **Plug-in Hybrid Electric Vehicles (PHEVs)**: PHEVs act as both energy consumers and temporary storage units. When integrated with the grid, they contribute to distributed energy resources and load balancing strategies.
- **Smart Sensors**: Deployed across transmission and distribution systems, these sensors,as shown in figure 1.3 [8], collect real-time data on voltage, frequency, and other critical parameters. This improves system reliability by enabling faster fault detection and better load forecasting.
- **Sensor and Actuator Networks (SANETs)**: These decentralized networks combine sensors and actuators to enable coordinated control across various layers of the grid. They support adaptive protection schemes, localized control, and rapid system response.
- **Communication Infrastructure**: High-speed, secure, and interoperable communication networks (wired and wireless) form the digital backbone of smart grid operations. They connect distributed energy resources, control centers, storage units, and consumer interfaces.
- **Data Analytics and AI**: Artificial intelligence and machine learning techniques are increasingly used to analyze large volumes of grid data for predictive maintenance, anomaly detection, energy forecasting, and optimization of supply-demand matching.


**Figure 1.3:** Smart Sensor

## 1.3 renewable energy technologies

The following technologies are based on renewable energy sources, such as biomass, wind, water, and sunshine. They are essential for lowering greenhouse gas emissions, improving energy security, and advancing sustainable development because they offer reliable and clean substitutes for fossil fuels [18] .

### 1.3.1 Solar (Photovoltaic) Energy

Photovoltaic (PV) energy systems use semiconductor materials, usually silicon, to directly convert sunlight into electricity. The photovoltaic effect is the process by which sunlight strikes a PV cell and produces an electric current. Because of their scalability and adaptability, these systems are extensively utilized in both large-scale and domestic solar power applications [19].

PV system performance is influenced by solar irradiance (the intensity of sunlight) and temperature. High temperatures can reduce the efficiency of PV cells as shown in figure 1.4, while higher irradiance generally increases power output as shown in figure 1.5 [20]. To optimize energy production under varying environmental conditions, Maximum Power Point Tracking (MPPT) technology is used.To guarantee that the PV system produces the most electricity feasible, MPPT continuously modifies the electrical operating point of the system.

PV technologies come in a variety of forms, including as thin-film, polycrystalline, and monocrystalline. Thin-film panels are lightweight and flexible, ideal for certain applications; polycrystalline panels provide an economical performance balance; and monocrystalline panels are incredibly effective and space-efficient.

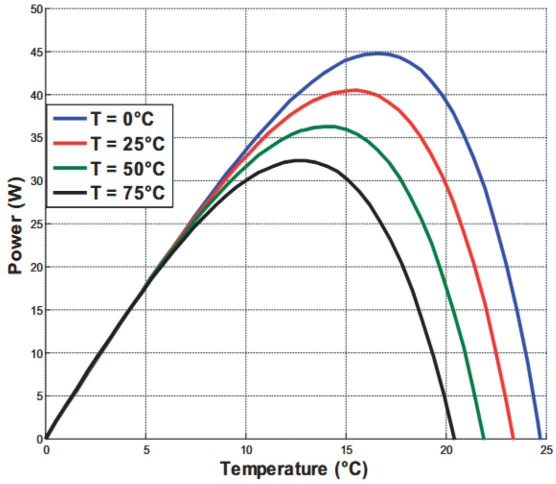


Figure 1.4: Effect of temperature on I-V characteristics

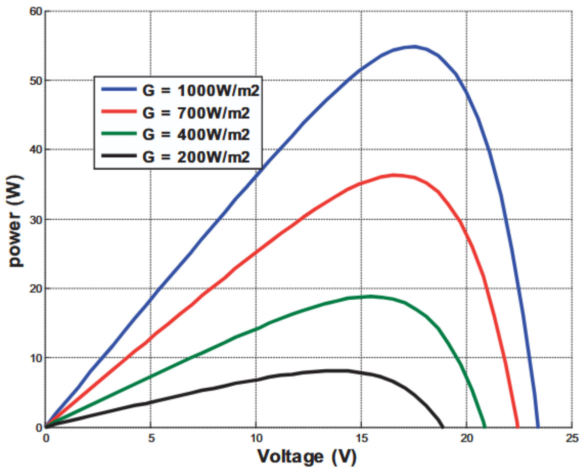


Figure 1.5: Effect of irradiance on I-V characteristics

### 1.3.2 Wind Energy

Wind turbines use the wind's kinetic energy to create electricity. It is an established and extensively used technology, particularly in areas with abundant wind resources. Because wind energy is scalable, it may be used in smaller, decentralized systems as well as utility-scale wind farms.

### 1.3.3 Biomass Energy

Biomass energy is derived from organic materials such as garbage, wood, and crops. It may be transformed into fuels (biofuels) like biodiesel and bioethanol, or it may generate electricity (biopower) [19]. Since it can be almost carbon-neutral when utilized wisely, biomass contributes to waste reduction and the aims of renewable energy.

### 1.3.4 Geothermal Energy

Geothermal energy produces electricity or direct heating by absorbing the heat that exists within the Earth. It is a steady and dependable renewable energy source that can be used for building geothermal heat pumps, district heating, and power generating[18].

### 1.3.5 Hydropower Energy

Hydropower generates electricity by using the energy of moving water, typically from rivers or dams. It is among the most traditional and extensively utilized renewable energy sources. Turbines spin when water passes through them, creating power. Although hydropower is dependable and can offer a consistent power source, aquatic ecosystems may be impacted and it is dependent on the availability of water.

## 1.4 Grid integration challenges of RES

The intermittent and fluctuating nature of renewable energy sources like wind and solar PV makes integrating them into the power grid system extremely difficult. These difficulties can be divided into two categories: technical and non-technical [21].

### 1.4.1 Technical challenges

- **Power Quality Issues**: Integration of renewable sources can introduce harmonics, voltage sags, and frequency deviations due to the variability and non-linear nature of some generation technologies. These distortions can damage sensitive equipment or reduce operational efficiency.

- **Power Fluctuations**: Renewables like solar and wind are inherently intermittent. This leads to short-term fluctuations (e.g., cloud passing over solar panels) and long-term seasonal variability, complicating demand-supply balancing and requiring flexible backup systems.

- **Energy Storage Needs**: Due to the mismatch between generation and consumption patterns, especially with solar and wind, efficient energy storage systems (like batteries or pumped hydro) are critical to ensure reliability and energy availability during low-generation periods.

- **Grid Protection and Stability**: High penetration of distributed generation alters fault currents and voltage profiles, making conventional protection schemes less effective. Advanced protection strategies are needed to maintain grid stability and avoid cascading failures [22].

- **Optimal Placement of RES Units**: Improper siting of renewable units can cause congestion, voltage drops, or uneven load distribution. Optimal geographic and network placement is necessary to maximize efficiency and minimize losses.

- **Islanding Detection and Control**: In the event of grid failures, distributed energy systems may continue to energize a portion of the grid (unintentional islanding), posing safety and reliability risks. Fast and accurate islanding detection methods are essential to avoid such scenarios [22].

### 1.4.2 Non-Technical Challenges

- **Shortage of Skilled Technical Workforce**: The complexity of managing smart grids and integrating AI-driven solutions demands a workforce proficient in both power systems and emerging digital technologies. The current talent gap hampers deployment and maintenance.

- **Limited Transmission Infrastructure to Support RES**: Many renewable energy sources are located far from load centers. Inadequate or aging transmission infrastructure limits the capacity to transfer this energy efficiently and securely.
- **Lack of Competitive Incentives**: The absence of strong policy frameworks and financial incentives deters investment in critical infrastructure like reserve power plants, smart controllers, or energy storage systems needed to support large-scale renewable integration [23].

To address these challenges, the technological advancements embedded within the Smart Grid provide effective and scalable solutions. Through real-time monitoring, automated control systems, and bidirectional communication, the Smart Grid enhances the reliability and flexibility of the power system. Advanced energy storage technologies help mitigate fluctuations in generation, while intelligent protection and fault detection systems improve grid stability [3]. Furthermore, the integration of demand-side management programs, smart meters, and decentralized energy resources allows for better load balancing and responsiveness. These innovations collectively enable the efficient and secure incorporation of renewable energy sources into the grid, overcoming both the technical and non-technical barriers to integration [24] .

## 1.5 Energy management

Energy management refers to the process of monitoring, controlling, and optimizing the production, distribution, and consumption of electrical energy in a system. It involves both technological and strategic approaches to improve energy efficiency, reduce costs, and ensure reliable power grid operation [26].
Through load shifting, appliance scheduling, real-time monitoring, and the integration of renewable energy sources, energy management systems (EMS) assist utilities and consumers to achieve greater energy efficiency in the context of smart grids, as shown in Figure 1.6 [27]. EMS can function on the demand side, controlling consumption patterns, lowering peak loads and improving user involvement, as well as on the supply side, optimizing generation and transmission. Enabling a more economical, secure, and sustainable energy infrastructure is the ultimate objective.

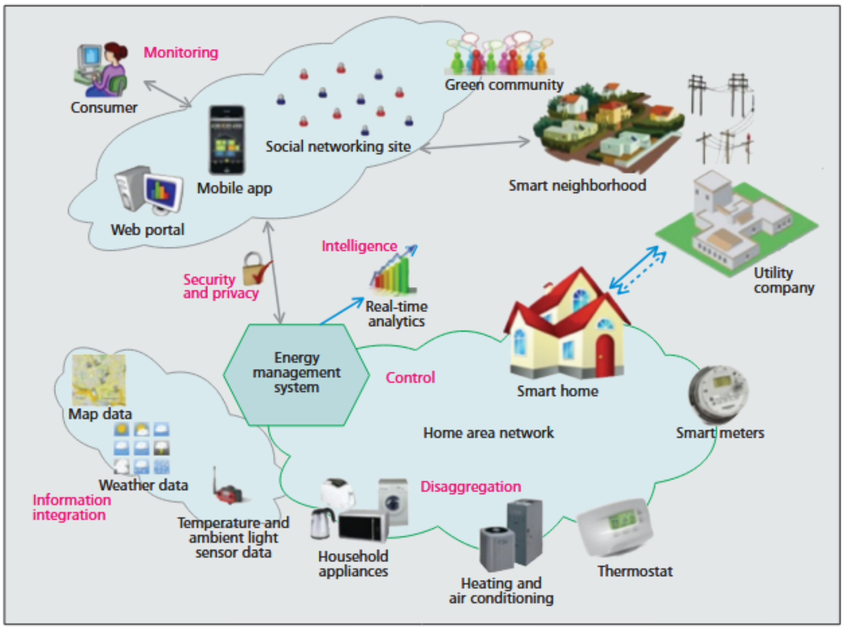


**Figure 1.6:** energy management in smart grid

### 1.5.1 Demand-side management (DSM)

DSM refers to the set of techniques and strategies used to monitor, control, and optimize energy consumption on the consumer side of the energy system. By adjusting demand patterns rather than increasing supply, DSM aims to improve grid stability, lower energy prices, and increase energy efficiency. DSM becomes particularly crucial in systems with a significant percentage of renewable energy, where flexible demand must be balanced with generating fluctuation and uncertainty. DSM assists in resolving challenges such as reliability, load imbalances, and peak demand [24]. Several distinct approaches have been developed to implement DSM effectively, which are discussed in the following sections.

- **Load Shifting:** Load shifting involves transferring energy consumption from peak demand periods to off-peak times without altering the total energy used. This strategy helps in balancing the load on the power grid, reducing the need for additional generation capacity during peak hours. Utility companies can create a more reliable and effective energy distribution system by enticing customers to use energy during off-peak hours [28].

- **Peak Clipping:** The aim of peak clipping, typically referred to as peak shaving, is to reduce the maximum demand on the electrical grid during peak hours. This is typically achieved through direct load control, where utilities remotely manage or temporarily shut down high-energy-consuming appliances during peak times. By lowering peak demand, utilities can defer investments in new generation facilities and maintain grid stability [29].

- **Valley Filling:** Valley filling focuses on increasing energy consumption during periods of low demand, known as valleys. By incentivizing energy use during these times, utilities can improve the load factor of the system, leading to more efficient utilization of generation and transmission assets. This strategy often involves encouraging activities like electric vehicle charging or industrial processes during off-peak hours [30].

- **Strategic Conservation:** Strategic conservation involves implementing long-term measures to reduce overall energy consumption. This involves adopting energy-saving behaviors, supporting energy-efficient appliances, and supporting behavioral changes [31]. By reducing the total energy demand, strategic conservation contributes to lower energy costs and environmental benefits [32].

- **Strategic Load Growth:** Strategic load growth aims to increase energy consumption during off-peak periods to optimize the utilization of the power grid. In order to improve grid efficiency and accommodate renewable energy sources, this approach encourages the integration of new technology such as heat pumps and electric vehicles, which may be programmed to operate during periods of low demand[32].

- **Flexible Load Shape:** Flexible load shaping involves modifying the load profile to better match the supply conditions, especially with the integration of renewable energy sources [33]. A more resilient and flexible energy system is ensured by this approach, which incorporates demand response programs and smart grid technology that enable real-time modifications in energy use.

- **Demand Response:** Demand response programs enable consumers to adjust their energy usage in response to price signals or grid needs. By reducing or shifting consumption during peak periods, demand response helps in maintaining grid reliability and reducing the need for additional generation capacity. These programs often provide financial incentives to participants who curtail their energy use during critical times [33].

- **Real-Time Pricing:** Real-time pricing involves varying electricity prices based on the actual cost of generation and demand at any given time. Customers are encouraged to modify their energy consumption in response to real-time pricing fluctuations, which results in more efficient patterns of energy use and less stress on the power infrastructure during peak hours [34].

### 1.5.2 Supply-side Management

The goal of this strategy is to ensure that there is a sufficient supply of energy to meet demand. Supply-side management in the context of hybrid renewable energy systems (HRES) refers to ensuring that the system can deliver energy reliably during periods of high demand. This often involves optimizing the configuration and operation of renewable energy sources—such as solar or wind—combined with battery storage and grid interaction. By managing generation, storage, and dispatch intelligently, supply-side management aims to address the variability of renewable sources and maintain system stability. The majority of research focuses on supply-side optimization to ensure that energy is available when needed. These techniques will be discussed in the following section [4].

- **Optimal Generation Scheduling:** This approach ensures that all available energy sources (PV, storage, grid) are dispatched in the most cost-effective and efficient way to meet demand while respecting system constraints. It's essential in hybrid PV systems to balance intermittent solar power and ensure reliability [35].

- **Energy Storage Management:** Energy storage devices, such as batteries, must be intelligently controlled in order to stabilize the supply during variations in PV output. Storage reduces supply unpredictability and enhances grid integration by charging during periods of resilient solar production and discharging during periods of peak demand [35].

- **Grid Interaction Optimization:** This includes controlling when to import energy from or export to the grid. Demand costs and time-of-use prices are taken into account while scheduling grid exchange [1]. When PV generation is either too high or too low, it guarantees dependability and cost-effective operation.

- **Hybrid Energy Management Systems (HEMS):** These systems integrate multiple energy sources (e.g., PV, wind, diesel) with storage and the grid. They use centralized or decentralized controllers (e.g., multi-agent systems) to coordinate energy flow for optimal performance [36].

## 1.6 conclusion

Now that we have introduced the fundamentals of the traditional and smart grid, discussed the integration of renewable energy sources, and highlighted the importance of energy management, we turn our attention to the use of artificial intelligence techniques and applications to optimize energy management in a grid-connected photovoltaic system equipped with energy storage. This approach aims to improve the efficiency of the system, reduce costs, and ensure more reliable and intelligent operation of the energy network.

# Chapter 2

# Artificial Intelligence Techniques for Energy Management

## 2.1 Introduction

Artificial Intelligence (AI) has been positioned as a transformative technology in modern energy systems through effective intelligent forecasting, optimization, and controls. The key to intelligent forecasting of grid-connected photovoltaic (PV) systems is anticipating the uncertainty and variability of renewable energy sources in terms of predicted energy generation and consumption. It is imperative to have an effective prediction mechanism in energy management systems due to this uncertainty and variability. Having this approach to management in turn can lead to balanced, reliable, and efficient management of energy generation, consumption and storage (being in a grid-connected system). Different AI methods can be used for energy management systems but especially Adaptive Neuro-Fuzzy Inference System (ANFIS) and Convolutional Neural Networks (CNN). These AI technique able to address nonlinear dynamics problems (ANFIS) and simultaneously model multivariable inputs (CNN) in addition to inductively model time, temporality and variable dependence in both predictions and decisions. This chapter presented a review of ANFIS and CNN, looking at their architectures and operational characteristics, in addition to their applicability for time-series prediction approaches in energy management systems.

## 2.2 Artificial Intelligence in Energy Management

In earlier times, energy management systems used manual controls, preset schedules, and rule-based logic to regulate electricity usage [25]. Although helpful in static settings, these traditional approaches frequently found it difficult to adjust to the growing complexity, unpredictability, and decentralization of contemporary power systems—especially as renewable energy sources were incorporated and consumer-level technologies like smart appliances and electric vehicles developed [26]. The flexibility and intelligence required to make data-driven, real-time decisions that maximize energy use and preserve grid stability were thereby unavailable in previous demand-side management (DSM) systems [24].
To overcome these limitations, researchers and industry practitioners have turned to Artificial Intelligence (AI). AI brings advanced capabilities such as pattern recognition, predictive analytics, and adaptive control, enabling systems to learn from historical data, forecast demand and supply fluctuations, and autonomously make optimal decisions. By embedding AI into DSM, energy systems become more responsive, efficient, and capable of managing uncertainty in both consumption and generation [12].
The following sections explore how AI has been integrated into DSM approaches. For every strategy, we highlight the AI techniques employed, their benefits, and associated drawbacks, providing a comprehensive understanding of AI-driven DSM in modern energy management systems.

### 2.2.1 Load shifting

Load shifting involves moving energy consumption from peak to off-peak hours, enabling more efficient energy distribution. AI methods like reinforcement learning (RL) [37], fuzzy logic [37], and genetic algorithms (GA) [38] have been successfully used to dynamically arrange loads in response to predicted price and demand signals. These techniques reduce the need for human interaction while increasing scheduling accuracy. However, a key drawback is the dependency on accurate forecasting and large amounts of historical data, which may not always be available or reliable in real-time.

### 2.2.2 Peak Load Shaving

Peak shaving reduces the maximum power drawn from the grid by either shifting or shedding loads. AI-based energy management systems use predictive models like artificial neural networks (ANNs) [39] and decision trees [40] to identify consumption patterns and anticipate demand surges and This allows for intelligent control of non-essential loads. The main drawback is that aggressive shaving without user preference modeling can lead to discomfort or reduced user satisfaction.

### 2.2.3 Demand Response

In reaction to signals like real-time pricing, time-of-use tariffs, or grid emergencies, demand response (DR) programs enable customers to adjust how much electricity they use. AI techniques such as Support Vector Machines (SVMs) [41][42], Deep Reinforcement Learning (DRL)[41], and agent-based modeling [43] have been employed to predict user behavior and automate energy usage decisions. These tools improve DR effectiveness and user responsiveness by assisting in the real-time determination of when and how to transfer or reduce load. However, AI models need constant streams of data, and they may have restricted interpretability or privacy issues.

### 2.2.4 Real-Time Pricing

Real-time pricing (RTP) reflects electricity costs that change dynamically based on supply and demand. AI methods such as time-series prediction with Long Short-Term Memory (LSTM) networks [39][41] and real-time optimization algorithms are used to forecast prices and schedule flexible loads accordingly. These systems enhance consumer participation and reduce peak demand, but drawbacks include the complexity of implementation and the risk of consumer discomfort if not properly managed.

### 2.2.5 Direct Load Control (DLC)

During peak hours, utilities can remotely control high-consumption appliances via direct load control. AI improves DLC by identifying the most optimal appliances and times for load interruption using techniques such as fuzzy logic systems [44], decision trees [40], and rule-based expert systems [45]. The advantage is accurate control with little effect on customer comfort. However, consumers may resist giving up control, and implementation often requires smart appliance infrastructure.

### 2.2.6 Hybrid Energy Management Systems (HEMS)

HEMS combine several DSM strategies like load shifting, DR, and peak shaving to create a coordinated, AI-driven system. Techniques such as multi-agent systems (MAS) [46], neural networks [39], and evolutionary algorithms optimize multiple objectives including cost, comfort, and energy efficiency. These systems are particularly useful in smart homes or buildings with renewable energy generation and storage. However, their complexity, high computational requirements, and dependency on accurate data inputs remain key limitations.
the previous techniques are summerized in Table 2.1

**Table 2.1:** Comparative Analysis of AI Integration in energy management approaches

| DSM Approach | AI Techniques Used | Advantages | Drawbacks | Ref. |
|---|---|---|---|---|
| Load Shifting | RL, Fuzzy Logic, GA | Improved scheduling, energy efficiency | Needs large historical data, sensitive to forecast errors | [37] , [38] |
| Peak Load Shaving | ANN, Decision Trees | Smart load shedding, predictive control | Risk of user discomfort if not adaptive | [39], [40] |
| Demand Response | DRL, SVM, Agent-based models | User participation, fast response | Privacy concerns, data dependency | [41], [42] , [43] |
| Real-Time Pricing | LSTM | Price-aware usage, reduced peaks | High complexity, potential user discomfort | [39], [41] |
| Direct Load Control | Fuzzy Logic, decision trees , Rule-based systems | Automated appliance control, utility-side management | Requires infrastructure, user acceptance issues | [40], [44] , [45] |
| Hybrid EMS | MAS, ANN, Evolutionary Algorithms | Integrated control, optimized multi-objective outcomes | Complex, high computational load | [39], [46] |

While a wide range of AI techniques have been successfully applied in demand-side management (DSM), such as fuzzy logic, genetic algorithms, artificial neural networks (ANNs), and reinforcement learning, these approaches still face several limitations. Common drawbacks include low generalization performance in highly dynamic environments, difficulty in accurately modeling nonlinear relationships, slow convergence in learning-based systems, and high dependency on large, well-labeled datasets. For instance, traditional

ANNs may struggle with interpretability and require substantial computational resources for training, while heuristic optimization methods like genetic algorithms may converge slowly or get trapped in local minima.

To overcome these challenges, this work proposes the use of Adaptive Neuro-Fuzzy Inference System (ANFIS) and Convolutional Neural Networks (CNN) for energy prediction in grid-connected PV systems. ANFIS combines the human-like reasoning of fuzzy systems with the learning capabilities of neural networks, enabling better handling of uncertainty and nonlinear patterns with fewer data requirements. CNNs, on the other hand, excel in capturing spatial and temporal dependencies in multivariate energy data, providing higher prediction accuracy and better generalization. By leveraging these methods, the proposed approach aims to improve predictive reliability, reduce computational burden, and enhance the adaptability of DSM strategies in real-world energy systems.

## 2.3 Adaptive Network-Based Fuzzy Inference System (ANFIS)

### 2.3.1 ANFIS Model Overview

Hybrid systems that combine the reasoning capabilities of fuzzy logic (FL) and the learning potential of artificial neural networks (ANNs) are known as Adaptive Neuro-Fuzzy Inference Systems (ANFIS). ANFIS was developed by Jang in the 1990s to model intricate, nonlinear systems by automatically creating fuzzy rules from input-output data. Its structure enables dynamic behavior simulation under uncertainty which is highly beneficial for control and predictive operations such as power forecasting in renewable energy systems [14].

Fuzzy logic is a concept that emerged in the 1960s, extending binary Boolean logic [47]. Fuzzy logic improves the representation of real-world imprecision by using linguistic terms such as “low”, “medium,” and “high” and assigning them to fuzzy sets. ANFIS builds on this idea by integrating ANN-based learning to optimize the fuzzy inference system (FIS), which allows the system to automatically adjust its membership functions and inference rules [48].

The understanding and implementation of ANFIS in system control are good example of how the model has been successfully used to forecast solar power output [14], to manage battery charging and to estimate power reference signals for microgrids [47]. It may be used in context of offline model training and online prediction. Its fuzzy rule base allows it to retain some degree of interpretability while also assembling control signals, system parameters, and scope nonlinear mappings.

Specialized ANFIS algorithms trained with PV system data (irradiance, temperature, wind speed) have been successfully embedded into industrial grade on grid PV systems achieving significant improvements on traditional approaches for PV performance forecasting [14].

### 2.3.2 ANFIS Architecture and Layers

The ANFIS model works through a hierarchy of processes which incorporates fuzzy reasoning functions and neural learning systems. The most popular models of fuzzy inference are Mamdani and Sugeno (TSK). Mamdani models, which produce fuzzy outputs, must undergo defuzzification through methods such as Center of Gravity, whereas the Sugeno model, applied in both studies, offers clear outputs as linear or nonlinear functions of the inputs. This type of output makes Sugeno ANFIS more accurate and optimal for real-time power prediction and control.The demonstration of the ANFIS architecture is depicted in Figure 2.1, highlighting the key layers in its structure [14].

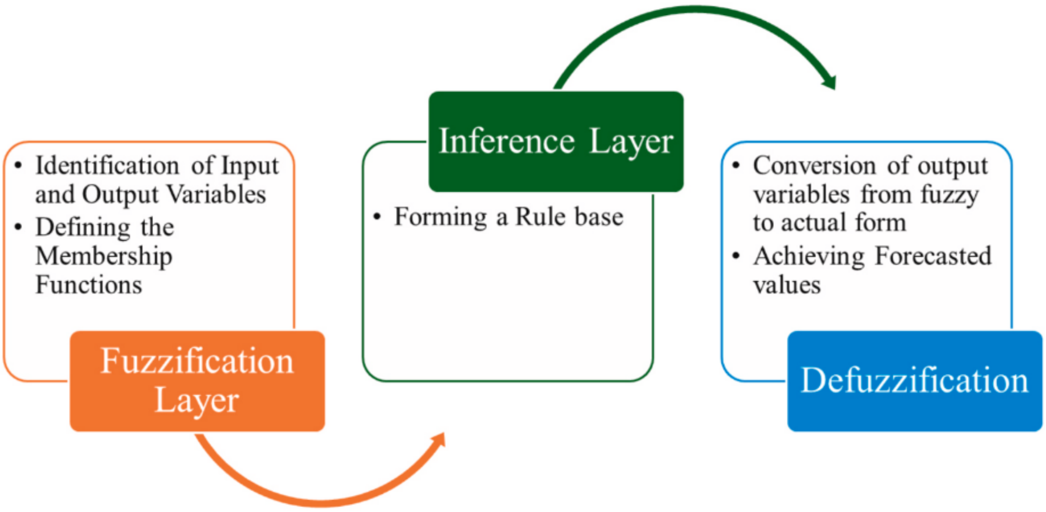


**Figure 2.1:** General schematic of ANFIS architecture.

The ANFIS framework can be mathematically represented through its five-layer structure, especially when using the Takagi-Sugeno-Kang (TSK) model—a preferred choice due to its computational efficiency and suitability for real-time control.

- **Layer 1: Fuzzification Layer**
  Each input is associated with one or more membership functions (MFs) that fuzzify

the crisp environmental or system values. For example, Gaussian MFs are commonly used to represent the inputs:

$$\mu_{A_i}(x_i) = \exp\left(-\frac{(x_i - C_i)^2}{2\sigma_i^2}\right) \tag{2.1}$$

where $x_i$ is the crisp input, $C_i$ is the center, and $\sigma_i$ is the standard deviation of the Gaussian curve. The output of each node in this layer is:

$$O_{1,i} = \mu_{A_i}(x_i) \tag{2.2}$$

- **Layer 2: Rule (Product) Layer**
  This layer applies fuzzy logic rules and calculates the firing strength of each rule by multiplying the MFs of all inputs:

$$O_{2,j} = w_j = \mu_{A_j}(x_1) \times \mu_{B_j}(x_2) \times \cdots \tag{2.3}$$

- **Layer 3: Normalization**
  Each firing strength is normalized to ensure that the sum of weights equals one:

$$O_{3,j} = \bar{w}_j = \frac{w_j}{\sum_k w_k} \tag{2.4}$$

  This normalization ensures that rules contribute proportionally based on their activation levels.

- **Layer 4: Defuzzification**
  The normalized firing strengths are used to compute the output of each rule. In the Sugeno model, this output is a linear function of inputs:

$$O_{4,j} = \bar{w}_j f_j = \bar{w}_j(p_j x_1 + q_j x_2 + r_j x_3 + s_j x_4 + t_j) \tag{2.5}$$

- **Layer 5: Aggregation (Output Layer)**
  The final output is the summation of all rule outputs:

$$O_5 = \sum_{j=1}^{N} \bar{w}_j f_j \tag{2.6}$$

  This crisp value represents the predicted output (e.g., power, voltage, current), suitable for real-time control and forecasting tasks.

### 2.3.3 ANFIS Learning Mechanism

ANFIS employs a hybrid learning method through the use of least squares estimation (LSE) and backpropagation. The forward pass proceeds as the outputs of nodes are propagated and the parameters of the consequent part are identified using LSE. The backward pass propagates the error backwards, updating the parameters of the premise part (e.g. MF parameters) using a gradient descent formulation.

This two-pass training capability provides ANFIS with the potential to adaptively model nonlinear relationships with high degrees of precision, especially in cases where training is based upon past historical data such as those used for PV energy production systems [14].

### 2.3.4 Advantages and Limitations of ANFIS

The use of ANFIS in energy systems, particularly for photovoltaic (PV) power prediction and energy management, is supported by its unique ability to model nonlinear, complex, and uncertain systems with a high degree of accuracy. This makes it especially suitable for environments where both data-driven learning and expert knowledge (via fuzzy rules) are beneficial [48].

- **Advantages**
  **Hybrid Intelligence**: Combines the adaptive learning of neural networks with the interpretability of fuzzy logic systems, making it both trainable and understandable[14].
  **Efficient for Nonlinear Problems**:Particularly effective for modeling the nonlinear characteristics of solar irradiance, temperature, and power output relationships[48].
  **Fast Convergence**:The hybrid learning algorithm (least squares + backpropagation) enables faster and more accurate convergence during training [48].
  **Rule Transparency**: Unlike black-box models, ANFIS offers insight into the decision-making process via explicit fuzzy rules [47].
  **Generalization Capability**:Demonstrates good predictive power when trained on limited but well-chosen input data, as shown in seasonal training for PV systems [14].

- **Limitations**
  **Scalability Issues**:As the number of input variables or MFs increases, the number of fuzzy rules grows exponentially, leading to a combinatorial explosion (curse of dimensionality) [47].
  **Sensitivity to Membership Function Design**: Model performance heavily depends on the choice and number of MFs, requiring careful tuning [14].

**Local Optima Risk**:The learning process can converge to local minima, especially if training data is not well distributed [47].
**Data Dependency**:While interpretable, ANFIS still relies on sufficient quality and quantity of training data to perform well.

Despite these drawbacks, ANFIS was selected for this study due to its unique balance between adaptability and interpretability. In the context of PV power prediction and energy management, where both prediction accuracy and system transparency are essential, ANFIS offers a flexible and reliable solution. Its capacity to generalize across seasonal data, integrate physical insights through fuzzy rules, and adaptively learn from real-time measurements makes it highly suitable for managing hybrid energy systems. In this work, ANFIS serves as a foundational tool to forecast energy production with sufficient precision while preserving an understandable rule-based structure that supports further system optimization and control.

## 2.4 Convolutional Neural Networks (CNN)

### 2.4.1 CNN Model Review

Convolutional Neural Networks (CNNs) have been around in image recognition and classification for a long time and have proven to be versatile networks in other domains such as natural language processing, audio signal processing, and more recently time-series forecasting. Their primary strength lies in their ability to automatically extract features from input data using convolution operations, without the need for extensive manual preprocessing [16].

In the energy management domain, as well as in instances of photovoltaic (PV) generation and load forecasting, CNNs are now being applied due to its ability to learn and represent complex temporal patterns and relationships from raw sensor data. CNNS have demonstrated excellent prediction performance predicting one-step-ahead values in power generation and consumption, capturing local trends, dependencies, and variations in environmental conditions and energy flows over time. The efficient structure of CNNs in terms of parameters and generalizations makes them well placed for real time prediction where time, accurate and impactful decision making is a necessity [49].

### 2.4.2 CNN Architecture for Time-Series Prediction

In contrast to standard neural networks, convolutional neural networks (CNNs) utilize a number of specialized layers (5 layers), mainly convolutional layers and pooling layers, prior to being connected through fully connected layers to make the output prediction, as illustrated in figure 2.2 [50]. When used with time-series data, CNNs use one-dimensional convolutional kernels [16].

Each convolutional layer uses filters to slide over the input sequence and extract localized features. The basic operation for a 1D convolution layer is mathematically described by:

$$y_j^{(l)} = \left( \sum_{i \in G} t_i^{(l-1)} * w_j^{(l)} \right) + b_j^{(l)} \tag{2.7}$$

Where:

- $y_j^{(l)}$ is the output of the $j$-th feature map at layer $l$.
- $t_i^{(l-1)}$ is the output from the $i$-th feature map in the previous layer.
- $w_j^{(l)}$ is the filter (or kernel) applied at layer $l$.
- $b_j^{(l)}$ is the bias term associated with the $j$-th feature map.

The output is then passed through a nonlinear activation function such as ReLU:

$$t_j^{(l)} = f\left(y_j^{(l)}\right), f(x) = \max(0, x) \tag{2.8}$$

Pooling layers (e.g., max pooling) are employed after convolutional layers to reduce the height and width, or temporal dimension of the data while still retaining relevant features. Finally, the processed data goes to one or more fully connected layers that predict the energy output.

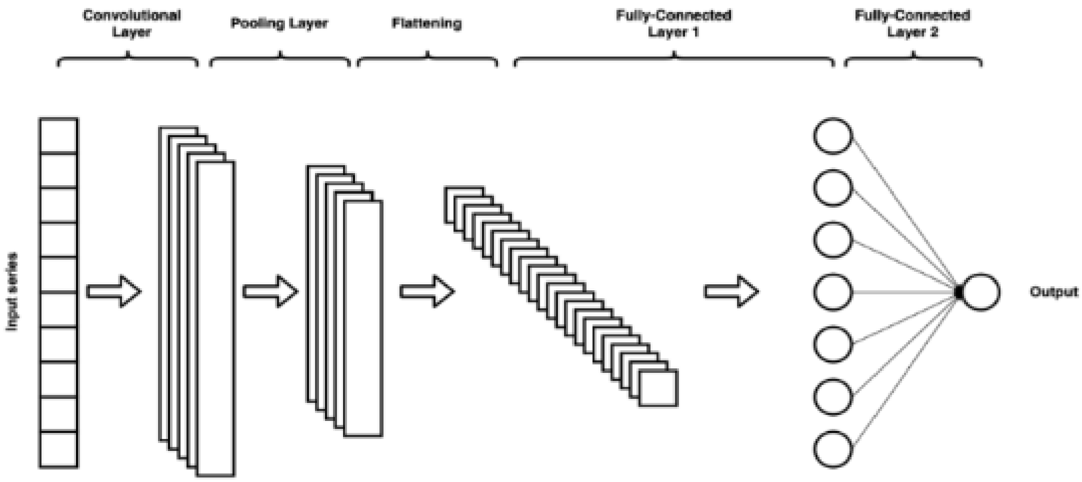


**Figure 2.2:** One-dimensional convolutional neural network (CNN) structure.

### 2.4.3 CNN Learning Mechanism

A CNN-based forecasting system takes as input multivariate time series data (e.g., solar irradiance, temperature, wind speed, historical energy production/consumption) to be treated as input sequence data. The forecasting in the CNN interprets each variable as a separate input channel to the convolutional layer [49].

The filters that comprise the first convolution layer learn to detect low-level features such as spikes, trends, or sudden variation. As the data continues through layers of the network, it learns increasingly high-level and abstract composite patterns. Pooling helps simplify the feature maps to make the network more robust against noise and computationally smaller.

Unlike fully connected networks and recurrent networks that contextualize the input independently, CNN networks explicitly include neighborhood relationships. Their ability to recursively capture short- to mid-range temporal dependencies makes them useful for energy systems. They can learn how the time of day (e.g., temperature, irradiance) influences the energy production later that day, or when temperature influences consumption by hour of the day.

After the convolution and pooling, the feature maps are flattened to form a feature vector series and are passed into dense layers to produce the final prediction.

### 2.4.4 Advantages and Limitations of CNNs

CNNs offer a compelling balance between accuracy, efficiency, and flexibility in time-series prediction:

- **Advantages**

  **Automatic Feature Extraction**:CNNs learn relevant features directly from data, minimizing the need for domain-specific preprocessing [50].

**Efficient Parameterization**:Thanks to weight sharing and sparse connectivity, CNNs require fewer parameters than fully connected models, reducing training time and computational costs [16].

**Parallelization**:CNN operations are highly parallelizable, making them suitable for real-time forecasting in smart grids.

**Local Dependency Modeling**: CNNs excel at capturing short-term patterns and trends within time-series data.

- **Limitations**

  **Limited Long-Term Dependency Capture**:Without additional mechanisms (like recurrent units or attention), CNNs may struggle with long-range dependencies [50].

  **Fixed Receptive Fields**:The fixed size of convolutional kernels may limit the model's ability to generalize patterns that span varying time scales.

  **Need for Extensive Data**: CNNs typically require large datasets to avoid overfitting and generalize well to unseen data.

  **Interpretability**:The hierarchical feature learning process can make the decision-making of CNNs less transparent compared to simpler statistical models [50].

In an energy management application for a grid-connected photovoltaic (PV) system, Convolutional Neural Networks (CNNs) have significant advantages in capturing time dependencies and temporal patterns in longitudinal multivariable data. Unlike standard machine learning algorithms, which tend to rely on feature engineering requiring extensive human design, CNNs can build hierarchal input representations from raw input data using multiple layers of convolutions. This is advantageous for this application, where independent input variables such as solar irradiance, air temperature, wind speed, and other environmental factors have both spatial and temporal dependence. In this context, the use of one-dimensional CNNs should be computationally effective and capable of modelling short-term temporal dependencies in predictions, a particularly important criterion for predicting power output with rapid sampling intervals. CNNs generalize well and adapt to complicated nonlinear relationships, lending to accurate predictions of energy output; this is beneficial for performance and optimising storage behaviour and grid stability in real-time.

## 2.5 conclusion

This chapter has given a comprehensive overview of two of the most widely used AI approaches, ANFIS and CNN, that are used for time series forecasting in renewable energy applications. ANFIS utilizes the training prowess of neural networks and the interpretability of fuzzy systems, making it valuable for modeling uncertain, nonlinear systems. In contrast, CNN is able to extract features efficiently, and can be applied to temporal data, which is particularly useful in cases with high-frequency sampling (5-minute or less). While both approaches are useful as AI methods for time series forecasting, they have different advantages and disadvantages, which contribute to their performance based on the complexity of the dataset and prediction goal/target variable. In the next chapter, we will explain the process for applying these models to our study of a grid connected PV system, and provide a comparative analysis of the prediction performance on real time data.

# Chapter 3

# Case Study, Results and Discussions

## 3.1 Introduction

This chapter presents a detailed case study focused on the application of AI techniques for forecasting power production and consumption in a grid-connected photovoltaic (PV) system. Accurate prediction is essential for effective energy management, load balancing, and system reliability in smart grids. The study utilizes a rich dataset composed of meteorological and electrical parameters collected at 15-minute intervals across several months, capturing seasonal variations and operational dynamics. To assess and compare the effectiveness of different modeling strategies, three distinct AI-based approaches are implemented: an Adaptive Neuro-Fuzzy Inference System (ANFIS), a Convolutional Neural Network (CNN), and a hybrid CNN–ANFIS model. Each model is developed, trained, and evaluated using consistent data preparation procedures, and their performance is measured using Root Mean Square Error (RMSE). This comparative analysis aims to identify the most suitable approach for reliable and interpretable power prediction in renewable energy systems.

## 3.2 System Description

### 3.2.1 Overview of the Grid-Connected PV System

The system being examined is a grid-connected photovoltaic (PV) system which is intended to provide energy to a local load, while maintaining connection to the grid as shown in figure 3.1. It can be considered to consist of three components: a PV generation unit, a local electrical load, and the power grid. While it is possible to include storage devices such as batteries, in the general configuration of a PV system, and these devices may certainly be useful, they does not enter the scope or the modeling/ analysis of this study and are not included.

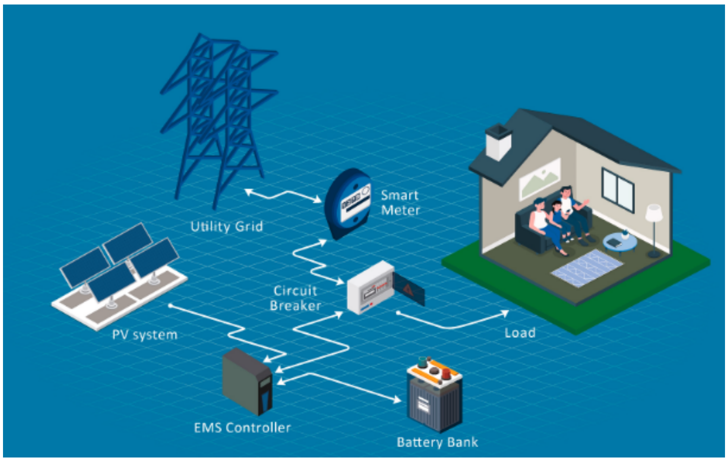


**Figure 3.1:** grid connected PV system diagram

### 3.2.2 Energy Management Structure

The main objective of the energy management system in the proposed structure is to monitor and forecast the balance between energy generated by the PV system and the energy absorbed by the local load. This helps us to better understand what decision needs to be made with respect to the system energy flow. Depending on the energy surplus or deficit, the management system will make a decision on whether it should either push large amounts of energy generated into the grid or pull energy from the grid when consumption peaks. The system may also decide to put surplus energy into the battery, so that the surplus energy stored in the battery can be used when there is a deficiency in generation, thus maximizing the overall energy distribution plan.

Energy generation relies on various environmental factors, such as solar irradiance, temperature, and wind speed, while consumption depends on user demand and time of day. Both generation and demand can be predicted using forecasting models based on artificial intelligence (AI) (ANFIS and CNN). This study uses ANFIS and CNN to measure the predicted generation and consumption patterns more accurately in order to improve participation in the grid that is active, predictable, and optimized.

## 3.3 Dataset Description and Preprocessing

### 3.3.1 Data Source

The dataset used in this study was collected from a Sonelgaz substation located in the Wilaya of Souk Ahras, Algeria. It encompasses a full year of recorded data from January 1st to December 31st, 2022, with a high temporal resolution of 15-minute intervals. The data integrates diverse information pertaining to weather conditions, grid parameters, and local energy consumption and generation, making it well-suited for time-series modeling in energy forecasting tasks.

### 3.3.2 Data Structure and Features

The original Dataset consists of the following variables: Time, Total Active Power,TSA (instantaneous power at a local point), Global Solar Irradiance, Ambient Temperature, Wind Speed, Humidity, Atmospheric Pressure, Phase Currents (Ia,Ib,Ic), Power Factor COS, Reactive Power Q, Produced Energy, Consumed Energy, as illustrated in table 3.1 and 3.2.

**Table 3.1:** Energy & Meteorological Data on 2022-01-22 (Part 1)

| Time | Total.P (kW) | TSA (kW) | Irrad. (W/m²) | Temp. (°C) | Wind (m/s) | Hum. (%) | Press. (hPa) |
|---|---|---|---|---|---|---|---|
| 08:30 | - | 6.0000 | 468.0000 | 8.3000 | 2.7000 | 31.1000 | 931.3000 |
| 08:45 | - | 6.0000 | 529.9000 | 9.0000 | 5.3000 | 27.8000 | 931.5000 |
| 09:00 | - | 8.0000 | 576.2000 | 9.5000 | 4.4000 | 26.0000 | 931.6000 |
| 09:15 | - | 7.0000 | 634.7000 | 9.4000 | 8.0000 | 24.9000 | 931.6000 |
| 09:30 | - | 6.0000 | 682.3000 | 9.3000 | 6.8000 | 24.8000 | 931.7000 |
| 09:45 | - | 6.0000 | 737.4000 | 9.6000 | 7.5000 | 24.7000 | 931.6000 |
| 10:00 | - | 6.0000 | 788.4000 | 9.8000 | 6.4000 | 25.7000 | 932.0000 |

**Table 3.2:** Energy & Meteorological Data on 2022-01-22 (Part 2)

| Time | Ia(A) | Ib(A) | Ic(A) | COS(phi) | Q (kvar) | E. Prod.(MWh) | E. Cons.(MWh) |
|---|---|---|---|---|---|---|---|
| 08:30 | 128.7000 | 130.2000 | 131.2000 | -0.9900 | 401.00 | 139479.60 | 1509.60 |
| 08:45 | 141.4000 | 143.1000 | 144.4000 | -0.9900 | 490.00 | 139480.80 | 1509.60 |
| 09:00 | 153.5000 | 155.2000 | 156.7000 | -0.9900 | 566.00 | 139483.20 | 1509.60 |
| 09:15 | 165.4000 | 167.3000 | 169.0000 | -0.9900 | 650.00 | 139485.60 | 1509.60 |
| 09:30 | 174.1000 | 176.0000 | 177.7000 | -0.9900 | 757.00 | 139488.00 | 1509.60 |
| 09:45 | 183.4000 | 185.3000 | 187.0000 | -0.9900 | 808.00 | 139490.40 | 1509.60 |
| 10:00 | 190.6000 | 192.3000 | 194.4000 | -0.9900 | 904.00 | 139492.80 | 1509.60 |

For the purpose of our modeling, we focused on variables that are directly relevant to photovoltaic energy prediction and local consumption dynamics. Therefore, the following input features were selected: TSA (instantaneous power at a local point), Global Solar Irradiance, Ambient Temperature, Wind Speed, Humidity, Atmospheric Pressure. Regarding the outputs, rather than using cumulative energy values (in MWh), we extracted instantaneous power generation and power consumption from the energy fields by calculating the differences over time intervals, thus ensuring compatibility with our predictive modeling goals focused on power forecasting.

### 3.3.3 Data Preprocessing

Given the size of the dataset — representing 35,040 data points across the year (96 points per day) — it was computationally impractical to train models on the full dataset. To address this, we selected four representative months, one from each season (january, april, july, november), to capture seasonal variability in weather and energy patterns. This approach balances dataset manageability with sufficient variability for effective model training and testing.

Additionally, the dataset was cleaned to remove any missing (NaN) values, ensuring consistency and quality for the training of AI models. The final preprocessed dataset provides a refined, high-frequency set of inputs and outputs tailored for machine learning-based energy management studies.

## 3.4 Case Study and Results

To evaluate the function of the suggested AI-based energy management scheme, three different modeling techniques are explored. Case 1 employs an Adaptive Neuro-Fuzzy Inference System (ANFIS), case 2 employs a 1D Convolutional Neural Network (CNN), and case 3 is the hybridization of ANFIS and CNN, to predict real-time power production and power consumption on a grid-connected PV system.

### 3.4.1 Case 1: ANFIS Model

This case investigates the application of the Adaptive Neuro-Fuzzy Inference System (ANFIS) for predicting both power production and power consumption in a grid-connected photovoltaic (PV) system using real-world data. The model was implemented using MATLAB's anfis function. Fuzzy rules were generated using genfis with grid partitioning and three generalized bell-shaped membership functions per input as detailed in Table 3.3. Each model was trained over 100 epochs. The overall flowchart of the ANFIS-based system is depicted in Figure 3.2.

**Table 3.3:** Summary of ANFIS Model specefications

| **Parameter** | **Value** |
|---|---|
| Number of nodes | 1503 |
| Number of linear parameters | 5103 |
| Number of nonlinear parameters | 54 |
| Total number of parameters | 5157 |
| Number of training data pairs | 9,200 |
| Number of checking data pairs | 0 |
| Number of fuzzy rules | 729 |

Simulations were conducted using the seasonal dataset described above. Results of both ANFIS models (for power produced and consumed) are shown in the next figures. Training RMSE values for both produced and consumed power are listed in Table 3.4, and its Curves were plotted showing the error trend over 100 epochs in figures 3.3 and 3.4.

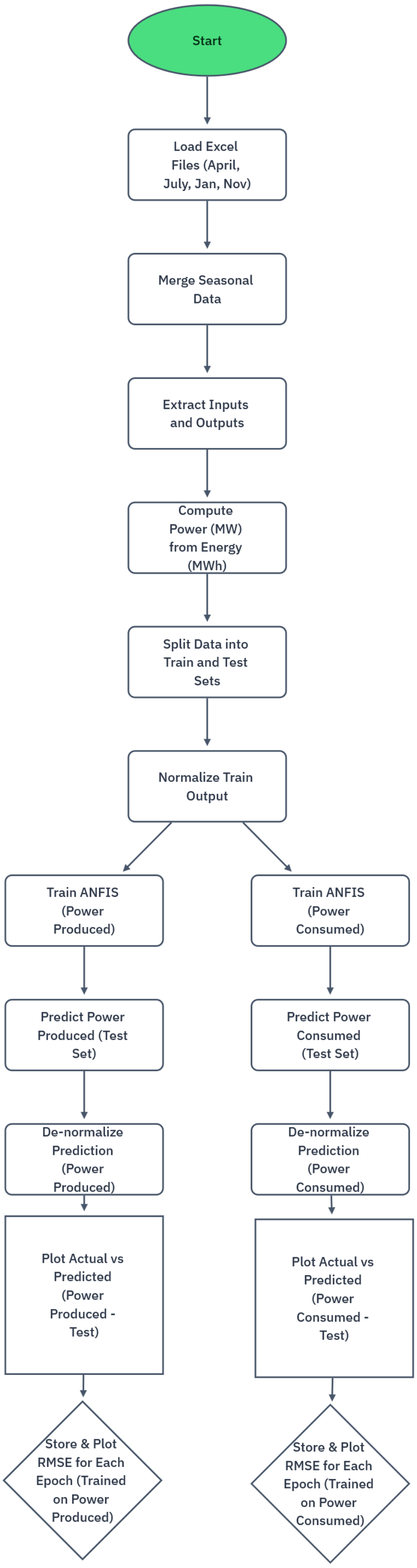


**Figure 3.2:** Flowchart of ANFIS simulation

**Table 3.4:** ANFIS Training RMSE

| Output | RMSE |
|---|---|
| Power Produced Training RMSE | 0.0524 |
| Power Consumed Training RMSE | 0.2145 |


**Figure 3.3:** RMSE of power produced

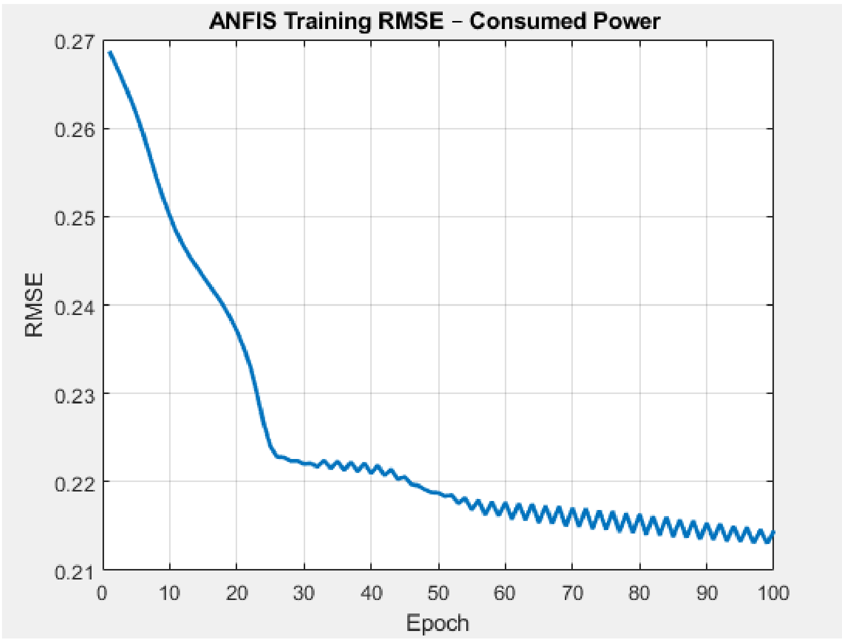


**Figure 3.4:** RMSE of power consumed

Figures 3.5 and 3.6 illustrate the comparison between predicted and actual power values on the testing set for both models. While general trends in power consumption and production are followed, sudden variations and peaks are less accurately predicted due to the model's static fuzzy rules.

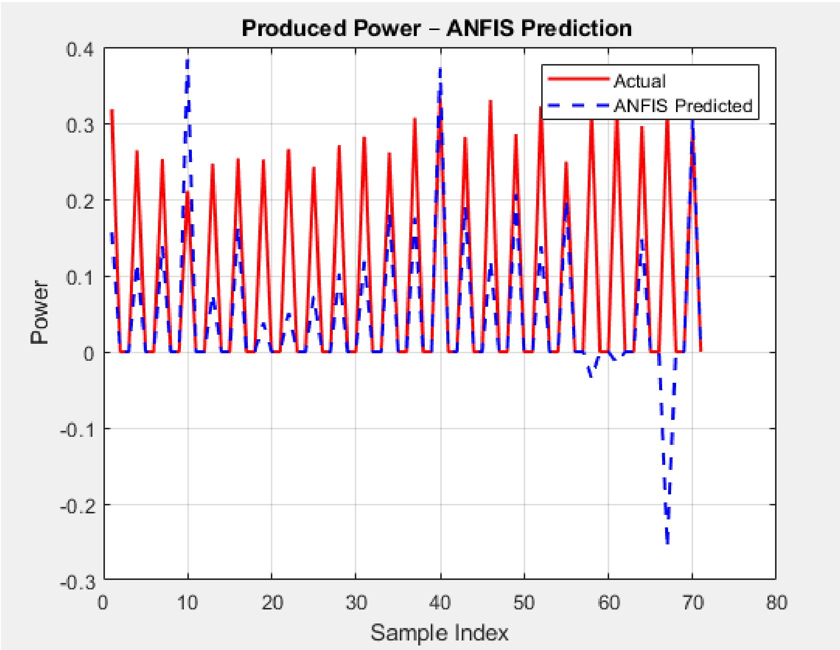


**Figure 3.5:** ANFIS Predicted VS actual power produced

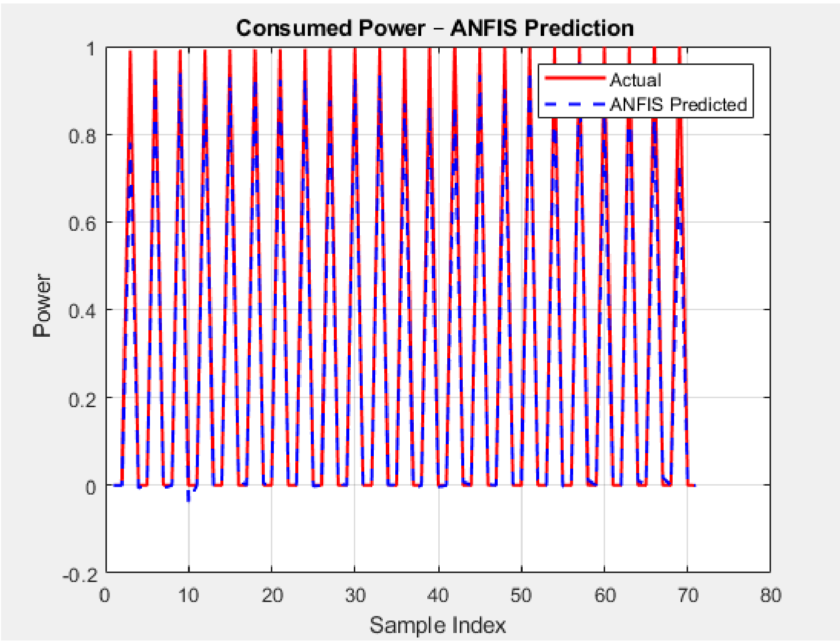


**Figure 3.6:** ANFIS Predicted VS actual power consumed

These findings support ANFIS' ability to fit the training data well and characterize nonlinearities in PV energy generation and consumption at varying environmental parameters, with a compact structure and interpretable capacity that allows for effective use in systems where computational efficiency and explainability are factors. However, the noticeable performance gap between predicted and actual—reflected by the high RMSE on the test set as in Table 3.4—highlights a key challenge: overfitting. While the model fits the training data very well, its ability to generalize to unseen data is limited. This is primarily due to two main reasons:

**Nature of the energy data**: The energy values recorded in MWh exhibit slow variation and relatively low granularity. When converted into power values (MW) over short intervals (15 minutes), the differences become small and more prone to noise. As a result, the model struggles to learn fine-scale dynamics in the testing phase.

**Static fuzzy rule generation**: The grid partitioning method used in genfis can lead to overly rigid rule sets that perform well in familiar scenarios but lack flexibility in unseen conditions.

These factors contribute to overfitting and lower predictive power from the test set. Nonetheless, the ANFIS model is still a suitable choice for hybrid scenarios, or specifically for systems that do not require a high accuracy of predictive performance, but do require transparent model capability and low computational burden.

### 3.4.2 Case 2: CNN Model

This case explores the use of a 1D Convolutional Neural Network (CNN) for predicting power production and consumption in a grid-connected photovoltaic (PV) system. The CNN architecture was designed and implemented using MATLAB's Deep Learning Toolbox, leveraging the time-series nature of the meteorological and power data collected from the PV system. The CNN was trained on a seasonal dataset, similar to the ANFIS case. Input sequences were processed using a sliding window approach, and the target outputs were the power production and consumption values at the corresponding time steps. The model parameters were optimized using the Adam optimizer, with a learning rate of 0.001 and trained for 100 epochs. The complete CNN specifications is detailed in Table 3.5. The overall process flow is presented in Figure 3.7.

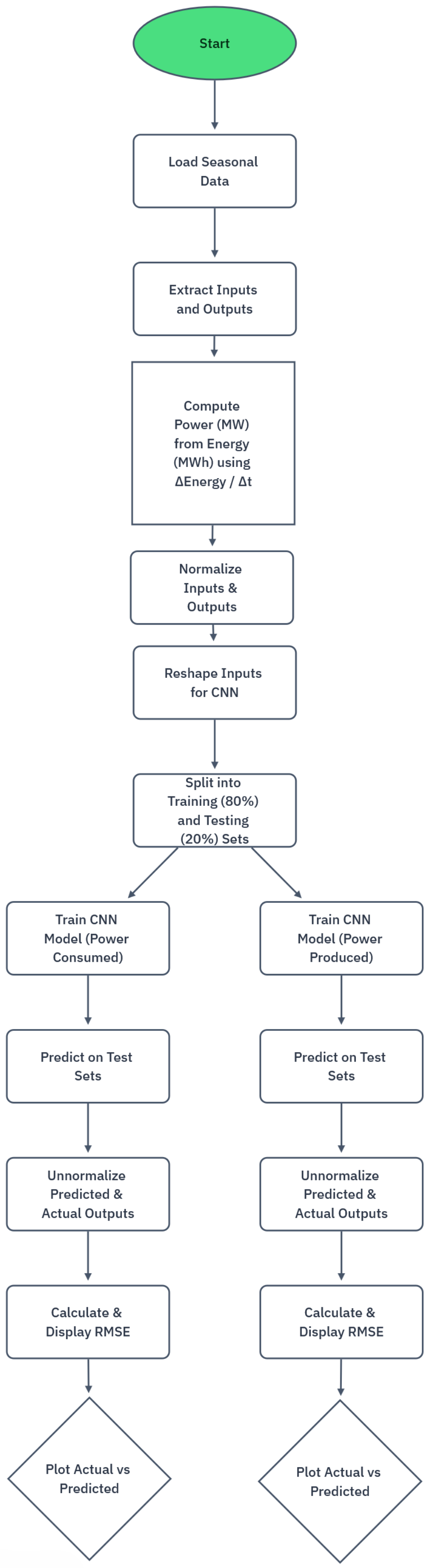


**Figure 3.7:** Flowchart of CNN simulation

**Table 3.5:** CNN Model Configuration and Training Parameters

| Parameter | Value |
|---|---|
| Number of Layers | 7 |
| Total Learnable Parameters | 10,373 |
| Number of Training Samples | 243 |
| Learning Rate | 0.001 |
| Epochs | 100 |
| Optimizer | Adam |
| Loss Function | MSE (Mean Squared Error) |

Performance was evaluated using training RMSE as shown in Table 3.6. Figures 3.8 and 3.9 show the training RMSE and loss curves over 100 epochs for power production and consumption predictions, respectively. Figures 3.10 and 3.11 display the comparison between predicted and actual power values on the test set.

**Table 3.6:** CNN Training RMSE

| Output | RMSE |
|---|---|
| Power Produced training RMSE | 0.0189 |
| Power Consumed training RMSE | 0.0591 |

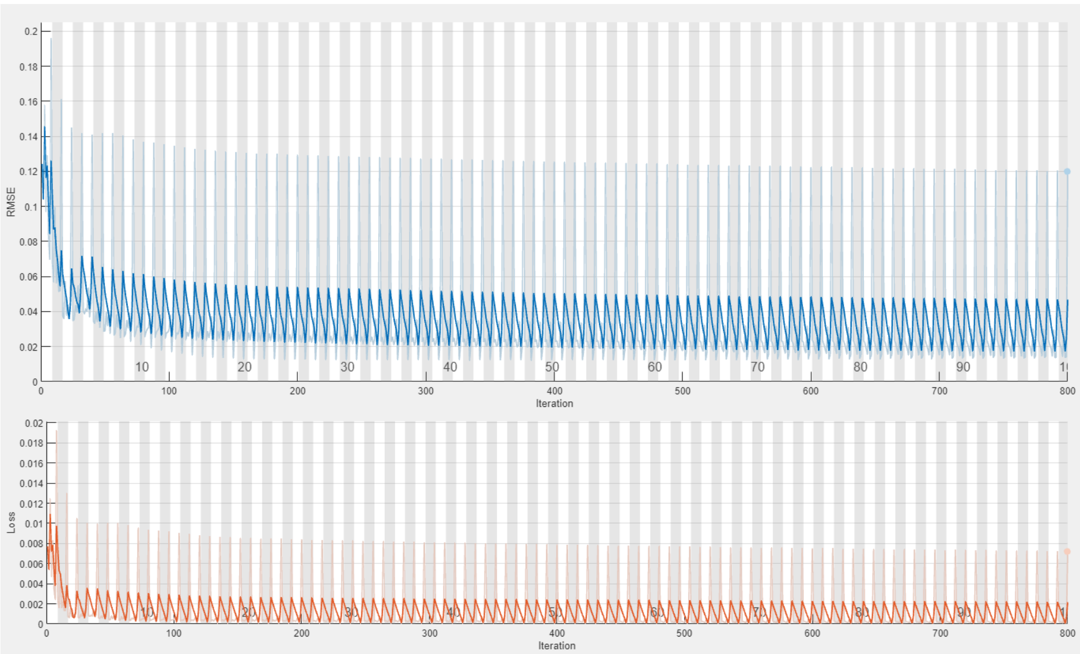


**Figure 3.8:** Training RMSE + Loss for Power Produced

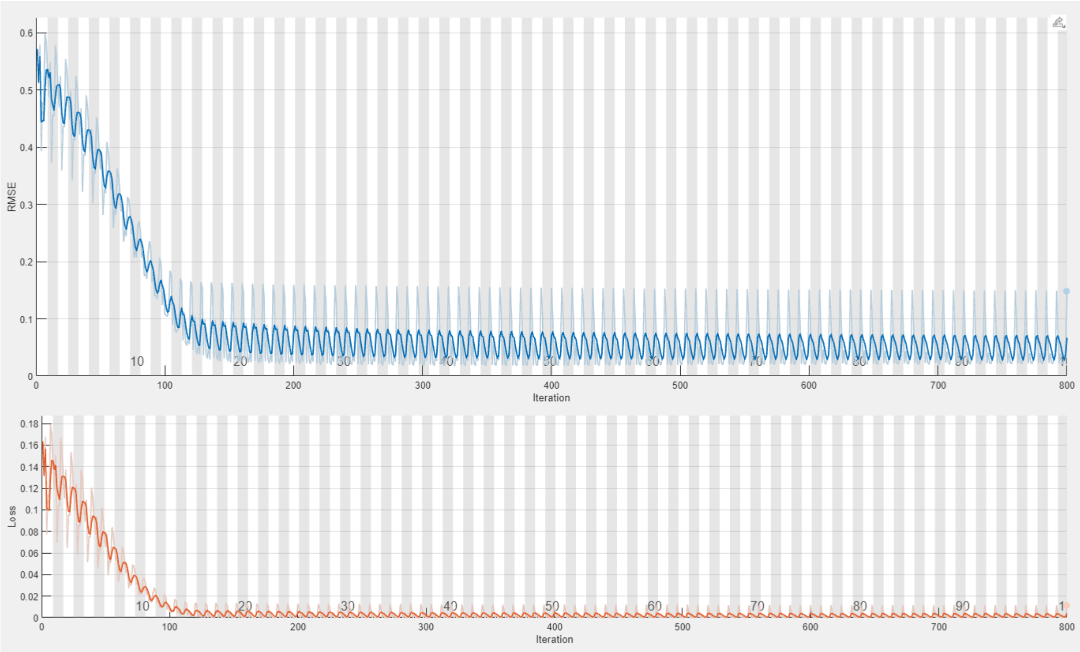


**Figure 3.9:** Training Loss (RMSE) for Power consumed

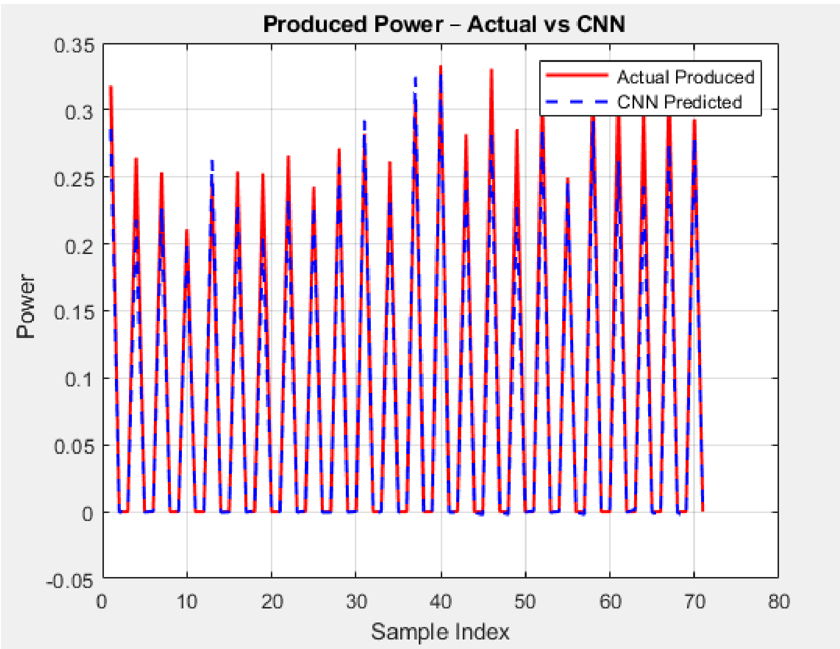


**Figure 3.10:** CNN Predicted vs Actual power produced

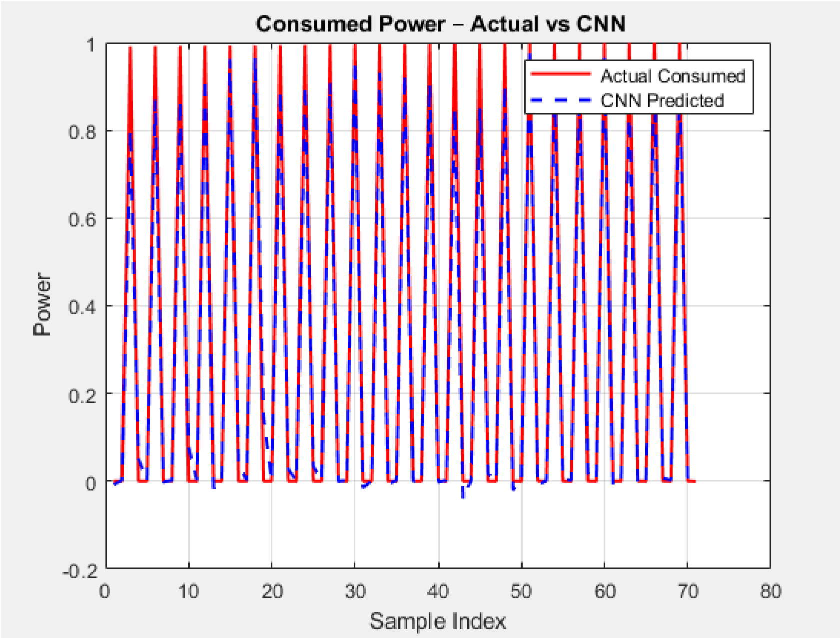


**Figure 3.11:** CNN Predicted vs Actual power consumed

The CNN model has successfully captured temporal dependencies in the input features thus, leading to enhanced generalization when compared to the ANFIS model. The filters learned in the convolutional layers automatically extract features from the raw input signals and therefore, can reduce reliance on manually defining rules.

For the standalone CNN model, the training RMSE for power produced and power consumed indicateS that although the CNN could learn temporal patterns in the data, its predictions still exhibited moderate errors, likely due to the complexity and variability in PV system behavior that CNN alone could not fully capture and the model's performance is still constrained by certain limitations:

**Low level of detail in the energy data**: Similar to the ANFIS case, the energy values (once converted to power) change very slightly over intervals of 15 minutes. This leads to low-variance targets, which inhibits the model's ability to learn sudden transitions or sharp peaks of power.

**Limited training data**: CNNs require a lot of data to generalize well. While the current data collected is seasonal, it is fairly small for deep learning models. The values of the power rarely change from one 15 minute sampling to the next. This leads the model to sub-optimal levels of learning, with the potential for overfitting in certain instances.
In comparison to ANFIS, the CNN displays a decrease in predictive error and is also more successful in representing smooth predictions, especially in regards to modeling the mean data trends in generation and consumption. The CNN is also consistently the most

appropriate method for data-driven approaches, where models are derived solely from data, and shows greater capability for predictive accuracy and information adaptability; if some loss of interpretability occurs.

### 3.4.3 Case 3: Hybrid CNN–ANFIS Model

This case examines a hybrid architecture that combines the advantages of using Convolutional Neural Networks (CNN) and Adaptive Neuro-Fuzzy Inference System (ANFIS) to improve prediction power production and power consumption in a grid-connected photovoltaic (PV) system. The hybridization of the two models was motivated by the advantages of each:

- ANFIS provides excellent interpretability through fuzzy logic and performs well on small datasets, but tends to overfit and generalize poorly when data is huge.
- CNN is effective at extracting features and modeling temporal or spatial patterns from large datasets, but lacks transparency in decision-making due to its black-box nature.

The hybrid model leverages both by extracting features from large time-series input data through CNN and passing those features to an ANFIS layer for interpretable fuzzy inference and final prediction.

- **Model Architecture and Workflow**
  CNN component is:
  Input: 6 meteorological and system features over time (sliding window approach).
  Architecture: 1D convolutional layers followed by max-pooling and a flattening layer.
  Output: A compressed feature vector representing temporal dependencies.
  and ANFIS component is:
  Input: CNN-extracted features (instead of raw inputs).
  Structure: Grid-partitioned fuzzy inference system with Gaussian membership functions.
  Output: Predicted power production or consumption.
  The following tables 3.7, 3.8 and 3.9 summarize the key specifications of the CNN and ANFIS models used in the hybrid approach, along with an overview of the dataset utilized for training and testing.

**Table 3.7:** CNN Model Specifications

| Parameter | Value |
|---|---|
| Number of Layers | 7 |
| Total Learnable Parameters | 10,373 |
| Number of Training Samples | ∼80% of total dataset (243) |
| Learning Rate | 0.001 |
| Epochs | 100 |
| Optimizer | Adam |
| Loss Function | MSE (Mean Squared Error) |
| Input Shape | [6 × 1 × 1] per sample |

**Table 3.8:** ANFIS Model Specifications

| Parameter | Value |
|---|---|
| Number of Training Data Pairs | ∼20% of dataset (61) |
| Number of Fuzzy Rules | 27 rules |
| Membership Function Type | Gaussian (gaussmf) |
| Number of Membership Functions (MFs) | 3 |
| Number of Epochs | 20 |

**Table 3.9:** Dataset Summary

| Parameter | Value |
|---|---|
| Total Samples | ∼304 |
| Training Samples (80%) | ∼243 |
| Testing Samples (20%) | ∼61 |
| Inputs to CNN | 6 features normalized |
| Outputs Predicted | Produced and Consumed power |
| Inputs to ANFIS Correction | 3 selected features + CNN prediction error |

- **Results and Figures**

  The hybrid system flowchart is illustrated in Figure 3.7.

  The training RMSE values for hybrid predictions of produced and consumed power are shown in Table 3.10 , and The training RMSE curves as illustrated in figures 3.13 and 3.14.

**Table 3.10:** RMSE Comparison Between CNN and CNN+ANFIS Models

| Output | RMSE |
|---|---|
| Produced Power - CNN+ANFIS | 0.008 |
| Consumed Power - CNN+ANFIS | 0.0053 |

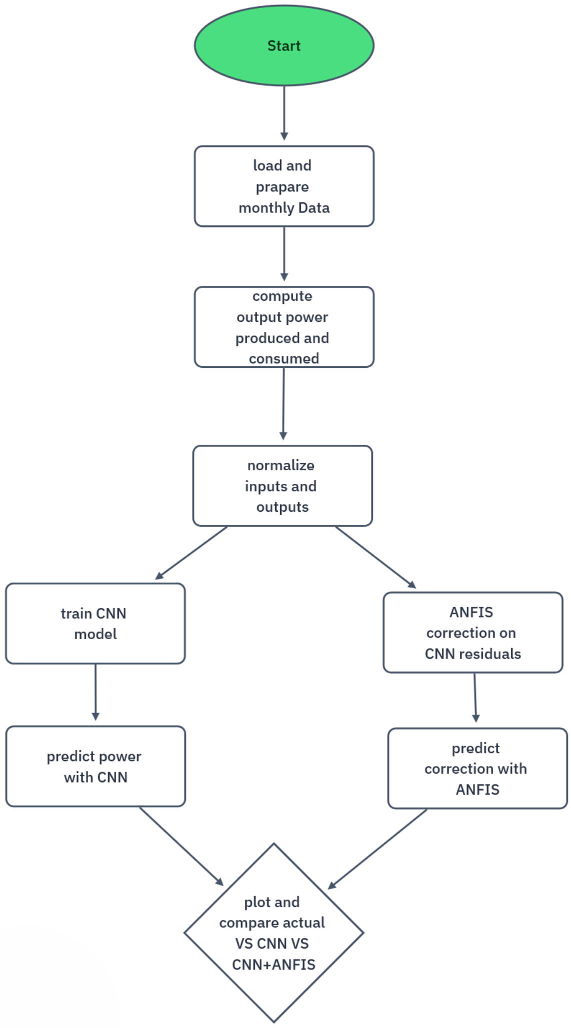


**Figure 3.12:** Flowchart of Hybrid simulation

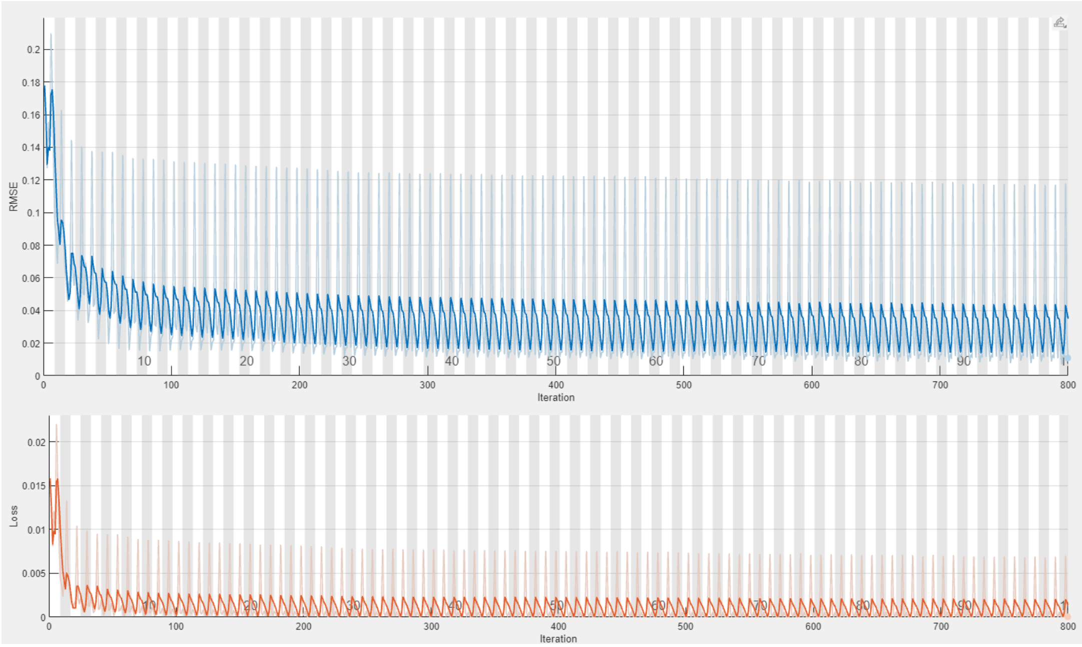


**Figure 3.13:** Training RMSE and Loss of Power produced

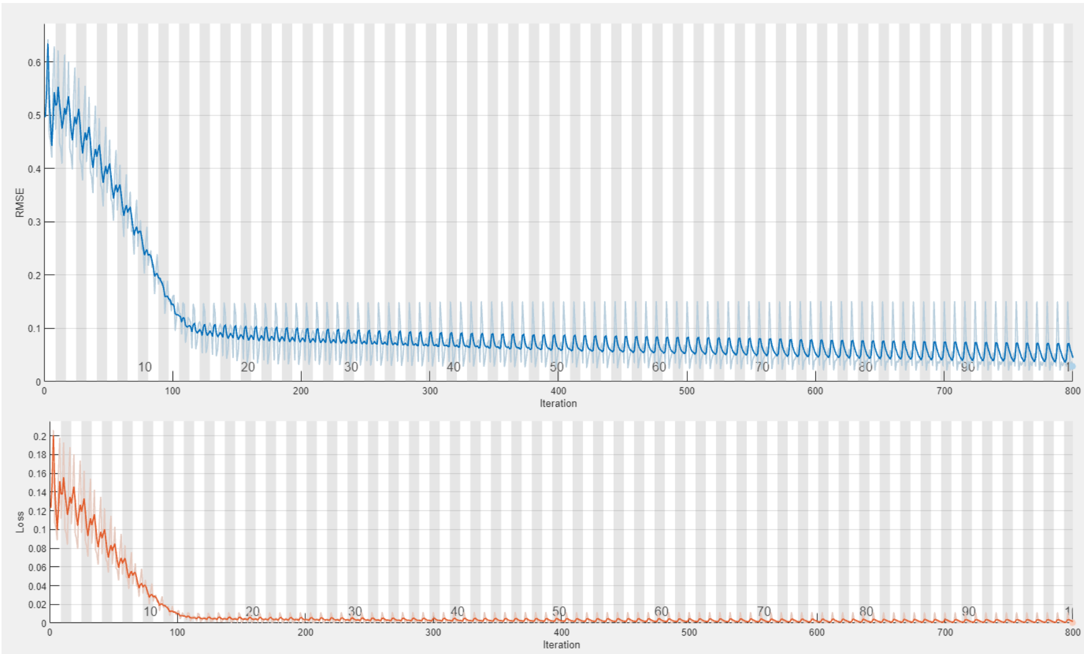


**Figure 3.14:** Training RMSE and Loss of Power consumed

The Prediction vs. actual curves on the test set are visualized in Figures 3.15 and 3.16.

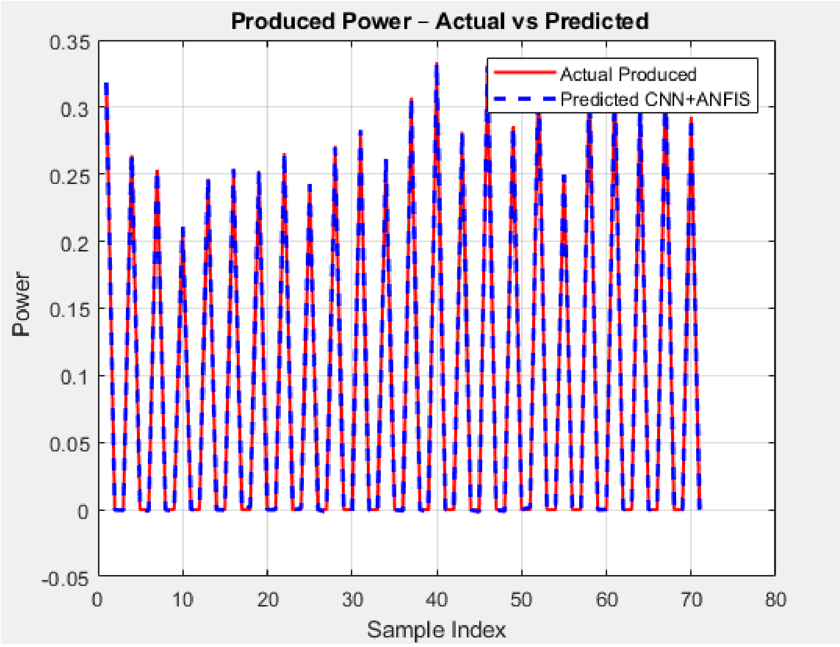


**Figure 3.15:** CNN+ANFIS Predicted vs Actual power produced

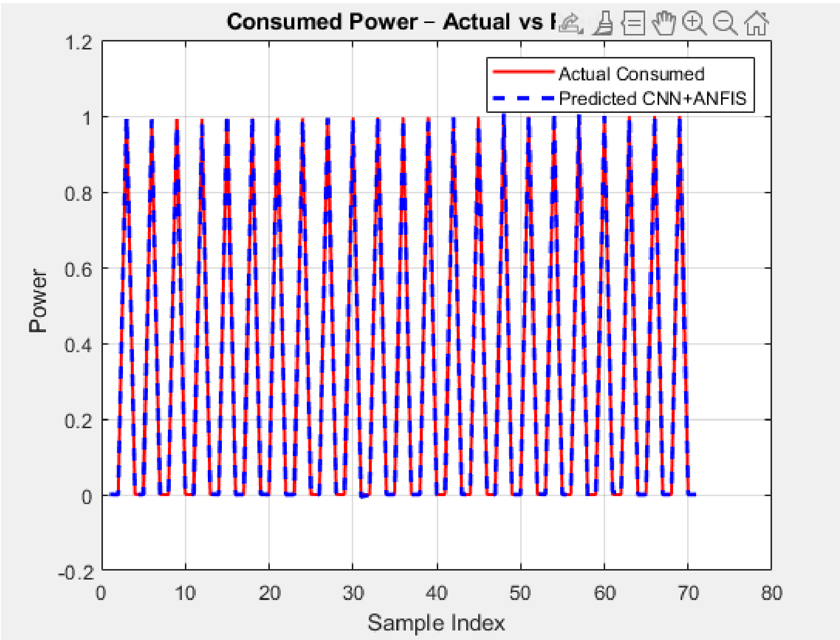


**Figure 3.16:** CNN+ANFIS Predicted vs Actual power

This explains improvement in generalization skills when compared to the stand-alone ANFIS model. The CNN capably performs in conditions with complex, noisy data, while the ANFIS layer ensures the end prediction is explainable and interpretable. The Root Mean Square Error (RMSE) results clearly demonstrate the superiority of the hybrid CNN+ANFIS model compared to the standalone CNN and ANFIS, as shown in Table 3.11 , indicating a significant improvement in prediction accuracy.

These results highlight the hybrid model's enhanced capability to capture complex patterns while maintaining reliable and interpretable outputs.

**Table 3.11:** RMSE Comparison for Power Prediction Models

| Model | Power Produced RMSE | Power Consumed RMSE |
|---|---|---|
| ANFIS | 0.0524 | 0.2145 |
| CNN | 0.0189 | 0.0591 |
| CNN+ANFIS | 0.0080 | 0.0053 |

- **Discussion**

  The data-driven feature extraction capabilities of CNNs and the transparent reasoning capabilities of ANFIS are successfully combined in the hybrid CNN–ANFIS model. The CNN component processes extensive seasonal data to identify significant temporal characteristics that reflect complex system and environmental dynamics. This feature enhances the model's generalization and robustness, resolving the overfitting problems that ANFIS alone frequently encounters when trained on limited data. Additionally, by using fuzzy inference rules, ANFIS preserves interpretability in the model, offering important insights for system monitoring and control that are absent from strictly black-box models. Because the CNN and ANFIS components can be adjusted separately to maximize performance for particular application requirements, this combination also provides scalability.

  The hybrid model adds more complexity to the training process despite its promising performance. More complex design and tuning work is needed for the sequential training and integration of two different model types—CNN and ANFIS. Additionally, CNN training on large datasets requires more resources and longer training times, which raises the computational cost. Furthermore, the hybrid system requires precise parameter adjusting for the ANFIS structure (such as the number of membership functions and rules) and CNN architecture (such as the number of layers, filters, and pooling), which can take a lot of time and might call for specialized knowledge. In deployment circumstances with limited resources or in real-time, these considerations could present difficulties.

## 3.5 Conclusion

The case study confirms that the choice of modeling approach significantly affects prediction performance. The standalone ANFIS model performed adequately on small datasets but exhibited signs of overfitting and limited generalization. The CNN model showed improved learning of temporal patterns; however, it still produced moderate RMSE values and lacked interpretability.

The hybrid CNN–ANFIS model emerged as the most effective solution. It achieved the lowest training and testing RMSE values for both produced and consumed power, demonstrating its ability to generalize better while maintaining interpretability through fuzzy rules. This performance leap underscores the synergy between deep feature extraction and rule-based inference.

Overall, the hybrid model offers a robust and scalable solution for intelligent energy forecasting in grid-connected PV systems, making it a strong candidate for real-world deployment in smart microgrids and renewable energy management platforms.

# General Conclusion

This report investigates the application of artificial intelligence (AI) techniques, specifically the Adaptive Neuro-Fuzzy Inference System (ANFIS), Convolutional Neural Networks (CNN) and a hybrid CNN-ANFIS framework, to predict power production and consumption in a grid-connected photovoltaic (PV) system. The study is grounded in a detailed case analysis based on real-world meteorological and electrical data, offering a comprehensive evaluation of each model's predictive performance, interpretability, and applicability within the context of energy management.

Each AI model was assessed not only for its predictive accuracy but also for its capacity to generalize across seasonal patterns and varying load demands. The ANFIS model, known for its rule-based inference and transparency, demonstrated strong performance when dealing with smaller datasets and systems that benefit from human-interpretable logic. On the other hand, the CNN model excelled at learning temporal patterns from time-series data, especially where large and complex input features were involved. Its ability to automatically extract hierarchical features made it particularly effective in capturing the dynamic behaviors of power flows in renewable energy systems. The hybrid CNN–ANFIS model combined the strengths of both approaches: CNN's capacity for automated feature extraction and temporal pattern recognition, and ANFIS's ability to perform rule-based reasoning and decision-making. This integration resulted in improved forecasting accuracy and better adaptability to fluctuating energy conditions.

The findings underscore the promising role of AI-driven approaches in managing the inherent variability and intermittency of renewable energy sources. By delivering more precise power generation and consumption forecasts, these models can significantly enhance energy scheduling, optimize battery storage operation, and improve the overall reliability and efficiency of the smart grid. Furthermore, the study illustrates how hybrid AI architectures can serve as resilient tools for energy management in systems with high renewable energy penetration, where uncertainty and complexity are prevalent.

Looking forward, there are several key directions for future research and practical deployment. First, expanding the dataset to include a wider range of climatic conditions and geographic locations would improve model generalization and resilience. Second, transitioning from offline simulations to real-time deployment would help validate the models' responsiveness, latency, and integration potential with grid infrastructure. Third, embedding economic parameters (such as cost optimization, tariff structures) and operational constraints (such as grid frequency stability or storage limits) directly into the prediction pipeline would make these AI models more aligned with real-world utility requirements.

In conclusion, this work lays a solid foundation for advancing intelligent energy systems by leveraging AI technologies. As power grids continue to evolve toward cleaner and smarter architectures, the integration of predictive AI models such as ANFIS, CNN, and their hybrids offers a scalable, adaptive, and sustainable pathway toward efficient energy management.

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