MULTIVARIATE TIME SERIES ANALYSIS OF SOLAR IRRADIANCE FOR PHOTOVOLTAIC SYSTEMS: THE HYBRIDIZATION OF NARX AND LSTM MODELS

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CHAPTER 2

LITERATURE REVIEW

2.1 Introduction

The literature reviewed in this chapter is an effort to provide an in-depth review of research related to solar irradiance forecasting and the integration of renewable energy sources into microgrids. It includes an exploration of the emergence of forecasting models and analyzes the evolution from traditional methods to advanced machine learning techniques. The chapter also discusses the multifaceted challenges involved in the integration of renewable sources, such as solar energy, into microgrid systems. Through a critical examination of the existing literature, the chapter aims to offer a comprehensive understanding of the current state of technology, highlight the challenges faced in the integration of renewable energy, and identify potential solutions. The development of the hybrid NARX-LSTM model is placed in the context of a thorough literature review, thus providing a reasonable basis for the contributions offered by the model towards the increase in the efficiency and reliability of solar energy forecasting and microgrid management.

2.2 Microgrid and Renewable Energy Integration

2.2.1 Basic Principle of Microgrids

Recently, due to heightened environmental concerns and an exacerbated global energy crisis, the conventional centralised power supply has shown several drawbacks. Concurrently, the highly efficient and less polluting distributed generation (DG) has garnered growing interest [Lasseter and Paigi, 2004]. The idea of microgrids is not new. Nonetheless, the emergence of innovative methods for harnessing renewable energy, alongside more efficient electricity generation techniques and the adaptability of power electronics, is fostering the development of a new industry aimed at promoting these innovations and integrating them into microgrids to optimise benefits for the power grid.

Microgrids, primarily known for their localized power generation and distribution capabilities where it consist of micro-sources, energy storage devices, loads, and control and protection systems, are the most efficient conduits for distributed generation (DG). When a microgrid is connected to the utility grid, it functions as a regulated load or generator, therefore mitigating the power quality and safety issues associated with the direct connection of distributed generators. Microgrids may function in islanded mode, hence enhancing system resilience and power supply availability [Lei et al., 2023].

At its core, an intelligent control system manages power generation and distribution from all energy sources present in the microgrid. It can refer to from renewable sources like solar or wind even traditional fossil-fuel based generators [Logenthiran et al., 2015]. The stability of the electrical power generated is balanced by the control system supporting the maintaining of power output.

Effective control is essential for the steady and effective functioning of microgrids. The comprehensive control needs arise from several factors, including voltage and frequency regulation, as well as power flow optimization [Guo and Mu, 2016]. Consequently, if well administered, it may function as a singular controlled entity, operating either in conjunction with the electric grid or in an isolated mode. Despite the multiple advantages microgrids provide to end users, their integration into existing distribution networks is impeded by several challenges mostly associated with their operation, protection, and control [Cagnano et al., 2020].

Microgrids are, overall, a localized power solution that can help to offset damages to the bigger grid. Microgrids achieve a more resilient and more stable power infrastructure at the local level through diversifying power sources, serving the islanding capabilities, including the resilience features, allowing quick recovery, optimising the load management, and integrating the renewable energy sources.

2.2.1.1 Microgrid Architecture

The distribution generators differ, therefore, their microgrid architecture. The structure of microgrid consists or characterized by five major as is illustrated in Figure 2.1 : (a) microsources or distributed generators, (b) flexible loads, (c) distributed energy storage devices, (d) control systems, and (e the point of common coupling components linked to a low voltage distribution network and capable of operation in a coordinated, regulated fashion in both the service to the utility grid and service to themselves or landed modes [Shahgholian, 2021]. Different forms of renewable energy resources are included as the power generators in a microgrid.

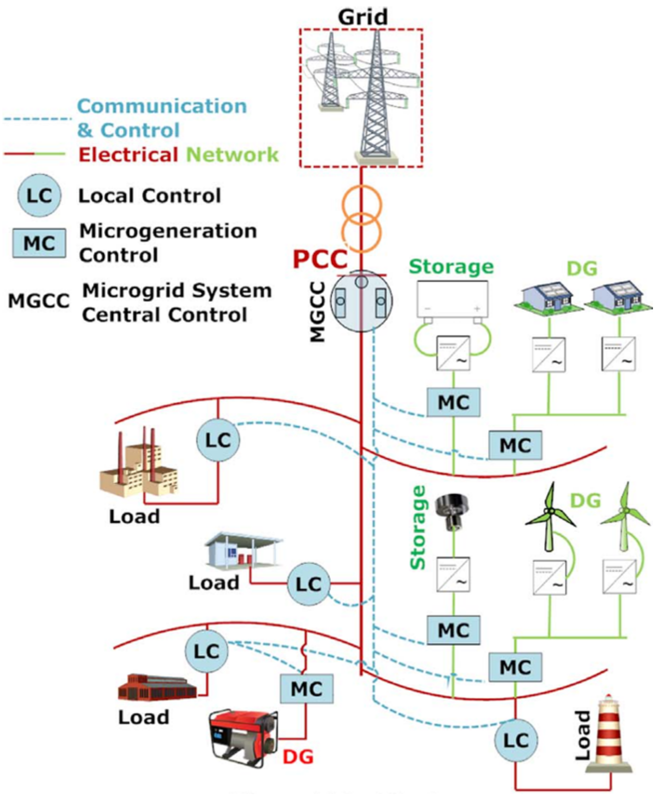

Figure 2.1 Architecture of Microgrid [Mariam et al., 2016].

The distribution system is the main body of the microgrid, providing the electricity from the power source to all connected loads. It includes physical infrastructure and power lines, cables and transformers that help make efficient use of this within a microgrid [Shahgholian, 2021].

DG sources are the local power generation units within the microgrid. Sources may be conventional generators, renewable energy such as solar panels or wind turbines - or indeed one on this 'small privileges of nature' [Alsaidan et al., 2017]. These DG sources are an integral part in meeting the overall electricity demand of the microgrid and can suit themselves to both need and resource available locally.

Power storage devices (batteries) are an absolutely essential part of microgrids. Where the Storage units may balance reserves between short-term to long-term use range. The microgrid is linked to the upstream network, which may receive the full or partial electricity by the main grid. When linked to a grid, it can both receive or inject electricity into the main grid, suggesting that it may increase the grid efficiency and address energy crises to a certain degree [Shahgholian, 2021].

The control and communications modules are the brain of the microgrid system [Albarakati et al., 2022]. This includes control systems, monitoring equipment, and communication networks, which allows real-time monitoring, optimization of power flow, as well as it is aimed at establishing communication among several microgrid components in order to monitor and control in the real-time the overall microgrid [Gungor et al., 2011]. Therefore, these modules help manage the load efficiently and keep the system stable and integrated with the main grid or other microgrids.

The categorisation of microgrid systems is largely dependent on the selection of the aforementioned components and the integration with the main electrical grid network [Mariam, 2018]. Figure 2.2 depicts the fundamental structure of this categorisation. With reference to grid integration, the microgrid system may be grid linked or isolated. Microgrid may be operated as AC or DC distribution networks. Based on DG sources, both AC and DC microgrid may further be classified into three types- entirely conventional, partly conventional/renewable and totally renewable [Mariam et al., 2013]. Both AC and DC systems may have energy storage devices installed. The AC microgrid may further be classed as line frequency or high frequency AC (HFAC) microgrid systems.

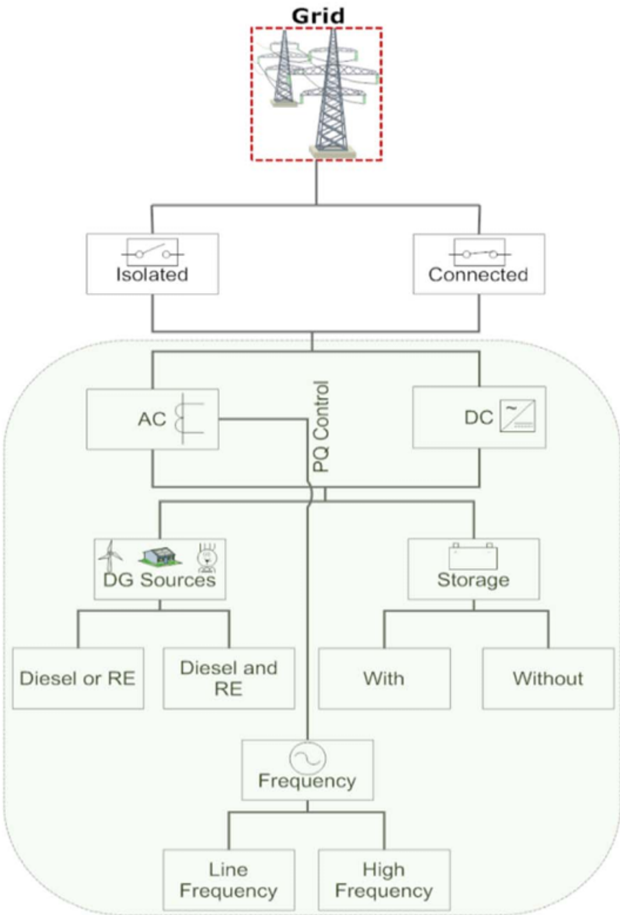

Figure 2.2 Structure of Microgrid [Mariam et al., 2016].

2.2.2 Integrating Renewable Energy into Microgrids

An important first step toward achieving sustainability and resilience in the energy system is integrating renewable energy into microgrids.[Kiehbadroudinezhad et al., 2023]. This integration is part of keeping sustainable development running and winning for the environment and the economy, in terms of the savings in costs and emission reductions [Saeed et al., 2021].

Solar and wind power as renewable energy are directly implementable in local communities and substantially reduce the dependence on conventional fossil fuels. The large majority of these resources can meet energy demand at location by aggregating these resources in a microgrid which will improve grid resilience and security [Lu et al., 2016, Hussain et al., 2019].

While renewable integrated into microgrids is not without risks. The power output from solar and wind resources tends to fluctuate, and is therefore seldom fully reliable [Saeed et al., 2021]. Besides, high penetration of renewable may cause power quality issues, as with voltage fluctuation [Kalakotla and Korra, 2023]. The following section gives a bit more detail on these challenges.

2.3 Challenges in Microgrid Operation

Microgrids have many advantages but integrating renewable energy sources within them brings with it its own set of hurdles. While benefits like greater reliability, local level grid resilience and opportunities for renewable integration are enticing, the complexities inherent in these same benefits will need to be carefully managed. The challenges span over issues related to technical such as stability in microgrids, power quality issues, voltage fluctuations and voltage sag and swell Voltage sag and swell with unique aspects associated with each [Shahzad et al., 2023].

A fundamental operational challenge of microgrids is the variability and intermittency inherent in renewable energy sources such as wind and solar power. These energy sources may generate variable energy outputs, depending upon the time of day and meteorological circumstances [Choudhury, 2020]. The unpredictability in power generation poses a significant problem for power regulation and achieving balance within the microgrid.

2.3.1 Stability in Microgrids

This section elucidates critical elements influencing the stability of the power system and the complications arising from the diverse operational behaviors of microgrids and their dispersed generating sources. The challenges can be broadly grouped under three key aspects, namely, lower system inertia (limited spinning reserves in power generation), reduced voltage stability (lower energy distribution support), and low frequency oscillations in power [Choudhury, 2020, Gopakumar et al., 2014].

Firstly, reduced system inertia results to cascading effects where angular stability leads to voltage and frequency swing [Gopakumar et al., 2014]. This instability can lead to some major operating hassles, which can compromise energy delivery and cause breakdowns or failures at any one time.

The deficiency in energy distribution support leads to a reduction in voltage stability margins. This is particularly pertinent during peak demand periods, when sustaining a constant voltage is crucial for activating the microgrid and the associated appliances appropriately [Energy, 2016].

Finally, the low frequency oscillating power is an effect of the changes in the power sharing ratio between the distributed generations [Energy, 2016]. Such fluctuation can significantly disturb the delicate equilibrium of power sharing in the microgrid, resulting in decreased efficiency and operational issues.

Within the domain of microgrid operations, stability is defined as how well a system can respond to disturbance, and its ability to revert to normal operation after being perturbed. Stability in a microgrid definition is categorized into two major categories- steady state stability and dynamic stability.

Steady-state stability refers to the ability of a microgrid to maintain a stable voltage and frequency within defined limits under normal and abnormal conditions. This type of stability is vital in the daily usage of a microgrid; stability is required to keep all the connected appliances up and running and to avoid variations that can result in a shutdown or further damage [Choudhury, 2020].

In contrast, dynamic stability refers to the ability of the system to return itself to its operating point following a disturbance. These disturbances may arise from differences in load or generation capable of displacing the system from equilibrium [Shahzad et al., 2023]. So, dynamic stability is a reflection of the microgrid's resiliency in response to disturbances and the capacity to maintain reliable energy delivery of the highest quality, post-adversity.

2.3.2 Power quality Issues

Power quality, an essential factor, significantly influences the optimal and harmonious performance of the microgrid system [Bandeiras et al., 2020]. Owing to the decentralized architecture of microgrids and the incorporation of diverse renewable energy sources. Power quality issues significantly impact system performance [Kalakotla and Korra, 2023].

2.3.2.1 Voltage fluctuations

Voltage fluctuations, commonly referred to as ”flicker,” are swift alterations in voltage magnitude that occur within the regulatory confines of typical gradual voltage variations (±5% of the nominal value). In accordance with the IEEE standards, it signifies a recurrent variation in voltage magnitude that falls within a range of 0.9 to 1.1 per unit [Shafiullah et al., 2010]. This condition is usually induced by power sources whose output oscillates over time.

As a salient power quality issue, voltage fluctuation frequently manifests when renewable energy sources are merged with the grid. The primary cause for these fluctuations is the high penetration of renewable energy sources which are inherently unpredictable and unregulated. Factors such as irregular solar irradiance due to cloud cover, geographic variation in PV installation, and temporal changes in wind speed all contribute to voltage instability [Mohamed et al., 2015].

One of the major repercussions of these voltage fluctuations is an effect known as voltage flicker. In the past, assessments of voltage fluctuations relied on measures such as the peak-to-peak RMS voltage, its energy spectrum, and duration. However, contemporary characterization of voltage fluctuations is primarily based on two parameters: short-term flicker severity (P_{ST} index) and long-term flicker severity (P_{LT} index) [Bajaj and Singh, 2020]. A typical voltage fluctuation waveform is depicted in Figure 2.3.

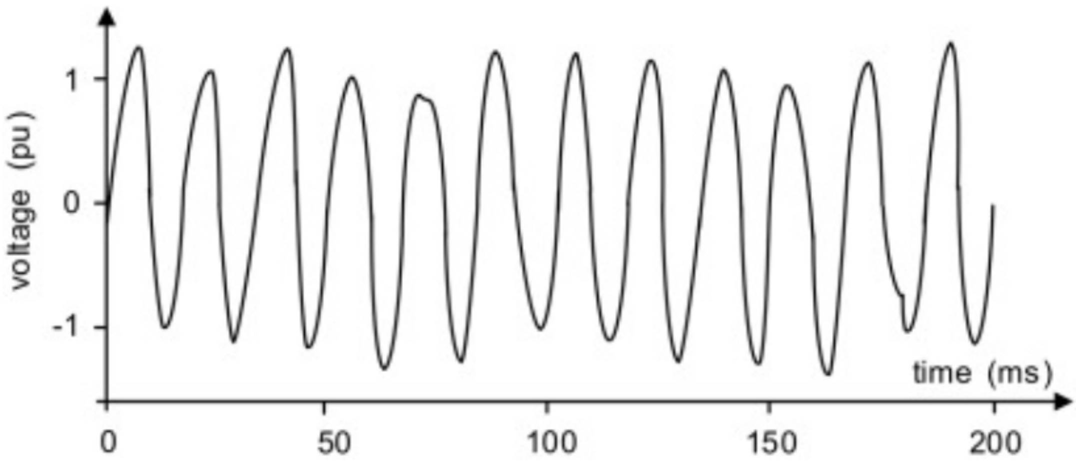

Figure 2.3 A typical voltage fluctuation waveform. [Bajaj and Singh, 2020]

2.3.2.2 Voltage sag and swell

Voltage sag and swell are prominent power quality issues, particularly notable when integrating renewable energy sources into the grid. Manifesting as transient reductions or surges in voltage levels, these phenomena are provoked by alterations in the load, or the power produced by the microgrid especially those incorporating renewable energy sources. Voltage sag and swell are graphically depicted in Figure 2.4, respectively. Voltage sag and swell can spawn an array of complications, encompassing equipment damage, diminished system efficiency, and power outages [Adefarati and Bansal, 2019]. Furthermore, they can adversely affect the lifecycle and performance of sensitive electrical equipment connected to the microgrid. The rapid progression of power electronics technology has now made it feasible to mitigate issues related to voltage stability [Bajaj and Singh, 2020].

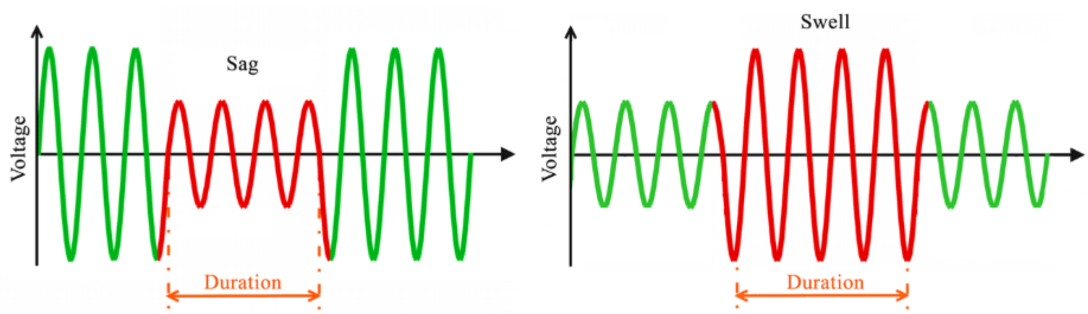

Figure 2.4 voltage sag and voltage swell representation. [Mattar et al., 2024]

Voltage Sag: also referred to as a voltage drop, can be ascribed to fluctuations in the load or problems associated with the network, including short-circuiting or voltage interruptions. With more renewable source of energy such as solar and wind-based electricity, voltage sag is one of the direct effects pertained by varying and unstable climatic nature. For example, reduced wind speed or amount of light would cut the flow of electricity from windmills or solar cells leading to brief fluctuation in the voltage [Mattar et al., 2024]. Recognizing that the IEC 610004-30 is the industry standard governing the definition of voltage sag, the latter is widely understood as a short-term RMS voltage excursions below 10% the value of the rated system voltage, expected to last between a half a cycle and one minute. These sags can be caused by constant fluctuations in the load such as starting up of a motor or a short circuit.

Voltage swell typically occurs due to a decrease or removal of load, as well as the disconnection of a significant power component within the electrical power system. Renewable energy sources, sourced from natural resources like wind or sun, experience fluctuations in production during peak power generation while consumption remains minimal. For example, during a sunny day or a windy night, a renewable energy system is likely to generate excess energy beyond the grid's requirements, perhaps leading to a temporary increase in voltage levels [Mattar et al., 2024]. The IEC 61000-4-30 standard defines voltage swells as intentional or unintentional increases in the RMS voltage at the system voltage or more by 10% over a duration ranging from half a cycle to one minute [Dhoke et al., 2018].

Therefore, voltage quality issues need to be addressed in microgrids including renewable energy sources in order to maintain stable and reliable operation. This can be achieved through different methods such as using power electronic, energy storage systems. achieving this should involve the use of converters, and effective demand response strategies. Moreover, accurate renewable energy generation forecasting has a key role in resolving these power quality issues [Kaushal and Basak, 2020].

As a result, integrating weather forecasting with microgrid operations benefits in minimizing system efficiency and reliability, as well as various stability and power quality problems.

2.4 Weather (Solar) Forecasting in Microgrid

Solar power generation is directly influenced by local weather conditions [Mishra and Ramesh, 2009]. It is essential to recognize that solar electricity is inherently diurnal and fluctuates throughout the day in accordance with variations in sun irradiation levels. A calculation of future power generation from this type of source is essential for achieving a balanced system.Nonetheless, these prospective power computations necessitate an understanding of the forthcoming meteorological variables that influence these technologies [Rodríguez et al., 2018].

Forecasting weather variables for energy generation assessments is a well-established endeavor, with numerous methodologies documented in the literature. Various models and influential characteristics, including cloudiness and irradiance, have been employed [Lara-Fanego et al., 2012]. Nonetheless, other authors advocate for the prediction of renewable generation as a means to attain this objective. Forecasting entails projecting future trends derived from historical data. The application of this approach may lead to a significant decrease in ambiguity regarding the utilization of clean energies.

2.4.1 Importance of Accurate Forecasting

This section contends that the necessity for accurate forecasting is crucial for microgrids incorporating a significant proportion of solar or other renewable energy sources. The uncertainty stemming from renewable energy generation, especially owing to climatic and environmental changes, can substantially impact power balance and system stability [Ahmad et al., 2023]. Consequently, precise weather forecasting has critical importance, since it is essential for predicting Renewable Distributed Generation (DG) and load power profiles. Such forecasts facilitate efficient power production planning and are essential for island microgrids with limited dispatchable power sources or microgrids aiming to effectively implement grid-connected flexibility services [Alamo et al., 2019].

Power fluctuations of Renewable Energy Sources (RES), such as photovoltaic (PV), are primarily determined by two factors: It is a deterministic factor related to revolution of the Earth about the Sun, and a stochastic factor depending on atmospheric conditions such as cloudiness, dust, pollution, or local shadows on PV modules [Nespoli et al., 2019]. The uncertainty associated with renewable power sources and end users, however, poses a major challenge for the robustness, security and reliability of the integrated electricity systems. Accurate forecast of power production from RES within this context can significantly assist the management and operation of modern energy system such as microgrids.

Microgrids, whether functioning independently or connected to the main grid, generally consist of a diverse set of generation resources (including photovoltaic, wind, and conventional sources), loads (both manageable and unmanageable), and various Energy Storage Systems (ESS) such as batteries, fuel cells, flow batteries, and thermal storage. This varied composition presents new problems to load and renewable energy source forecasting [Dutta et al., 2017]. Given these obstacles, a critical objective is to determine the appropriate dispatch strategy via a centralized Energy Management System (EMS) [Moretti et al., 2019], in which renewable energy source forecasting is essential.

These systems must equilibrate the use of electricity from controlled resources, like energy storage systems (ESS), diesel generators, micro-turbines, or gas turbines, while considering demand and production from renewable sources [Ma and Ma, 2018]. Accurate forecasting methods are essential for this equilibrium, as seen in Table 2.1, which delineates how accurate forecasting improves microgrid management by maximizing resource use, assuring dependability, and promoting efficient operation in renewable-integrated grids.

In addition, maintaining a constant and reliable power supply to local customers becomes more difficult when distributed generators have high penetration due to their intermittent, time varying outputs from weather conditions. Similarly, electricity consumption is not constant as it due to seasonal effects and the user behavior to changes in electricity tariff [Vincent et al., 2020]. As a result, forecasting of power generation and load demand can be tackled accurately to solve unit commitment and to optimally schedule the operation of energy storage devices.

Apart from balancing power supply and demand, accurate forecasting is imperative in microgrid management and plays a role in several other operational, economic and reliability facades. They are especially pronounced when the microgrid is composed of renewable energy sources, the unpredictability of which greatly exacerbates the need for forecast accuracy.

Significant improvements in operational efficiency are possible as a result of power demand and supply close to match up forecasts. As an example, an accurate estimation of peak renewable generation periods allows for optimal use of costly technologies, such as diesel generators or battery storage [Vincent et al., 2020]. This is an optimization which, in addition to reducing the operational cost of the system, avoids the usage of fossil fuel resources, and hence results in environmental sustainability of the grid operation.

Furthermore, adequate load forecasting improves maintenance planning. The periods of reduced renewable power generation due to weather condition are also anticipated to schedule preventive maintenance tasks. As a result, during high generation periods, the operational disruption is minimized, and this helps in the improvement of the grid's reliability [Ma and Ma, 2018].

The exact forecasting ensures the proactive stance towards risk management. However, these unexpected power surges or drops can inflict a lot of damage to sensitive electrical equipment [Sone et al., 2013]. Such events can, however be anticipated with accurate forecasting. Such events can be foreseen with accurate forecasting and can take some protective measures in advance to protect the infrastructure and to continue supplying the power.

Energy markets are frequently used by microgrids to purchase or sell excess power. Accurate forecasting enables operators to make cost effective decisions about when to sell excess power or about when to buy power from the grid operations.

Moreover, in the presence of multiple power sources, economic dispatch decisions can be made according to forecasting to operate the most economic [Dudek et al., 2023].

An important component of a renewable integrated microgrid is the energy storage that can serve as a buffer between the intermittency of renewable generation. Optimization of charging and discharging schedules of the storage systems can prolong their life, reduce costs, and produce more accurate load and renewable power forecasting prediction [Vincent et al., 2020].

Essentially, the need for accurate forecasting creates many challenges, but If achieved, it can shed significant light on improving some of the operational, economic and reliability aspects of microgrid management, particularly those with high renewable energy penetration.

Table 2.1 Summary of different ways in which accurate forecasting impacts microgrid management.

Impact Area	**Description**
Operational Efficiency	Forecasts made with high accuracy enable usage of resources in an optimized manner while decreasing operational costs and dependency on fossil fuels.
Maintenance Planning	By means of forecasting, preventive maintenance tasks can be scheduled during periods of reduced power generation so as to improve grid reliability.
Risk Management	Power surges or drops can be predicted, enabling advance implementation of protective measures that will protect infrastructure, as well as maintaining uninterrupted power supply.
Economic Dispatch and Energy Trading	Energy trading decisions and market operations are optimized and costs are reduced with forecasting, allowing for efficient energy dispatch.
Energy Storage Management	The forecasting of load and the generation of renewable power helps optimize the charging and discharging schedules of energy storage systems.

2.4.2 Solar Forecasting Approaches

Meteorology is an important field and weather forecasting, a key part of meteorology has a great significance in many branches of human activity such as agriculture, disaster management, aviation, energy sector (especially in the energy generation from renewable sources). The demand for accurate, reliable, and timely weather forecasts has led to the development of a variety of methodologies, broadly grouped into three categories: physical, statistical, and hybrid methods. Each with their special strengths, weaknesses and applicability, these approaches are the product of scientists, mathematicians and engineers spending decades trying to decode the patterns of Mother Nature.

2.4.2.1 Physical Approaches

The earliest attempts to formalize weather forecasting, physical methods use physical laws to explain or predict what happens in the atmosphere. It is a method where data about physical variables like temperature, pressure, humidity, and are processed and modelled. All these variables are fed into models, from which the model can predict the weather prediction based on the interplay of these variables. The method is regarded as a theoretically grounded method, based on the scientific understanding of the processes in the atmosphere for weather prediction. Nevertheless, these models may be tedious as well as computationally demanding and are not able to fully account for the inherent uncertainty and complex non-linearity in atmospheric systems [Sobri et al., 2018].

The physical forecasting approach requires two separate models: Solar radiation, and the Photovoltaic (PV) system [El Hendouzi and Bourouhou, 2016]. As a result, the PV power generation is a function of weather parameters and PV system data that result in forecasted output of the PV system.

Figure 2.5 shows how PV power generation can be predicted. It appears that this prediction is mostly determined by weather parameters (Global Horizontal Irradiance (GHI) and Ambient Temperature (AT)). Other variables may also be considered, for example the aerosol index (AI) [Marinelli et al., 2014]. The second major factor in PV power forecasting is PV system data. As even minor microclimatic changes are important but it is very important system location parameter. It can however affect the power generated by the panels [El Hendouzi and Bourouhou, 2016]. Furthermore, manufacturer specifications provide another avenue for poor PV power forecasting. Both these factors help estimate how much irradiance to fall on PV plane or lam orientation These fields include the array (POA) irradiance, the back-of-module temperature (Tm), to make it easier to predict PV power [Yang et al., 2014].

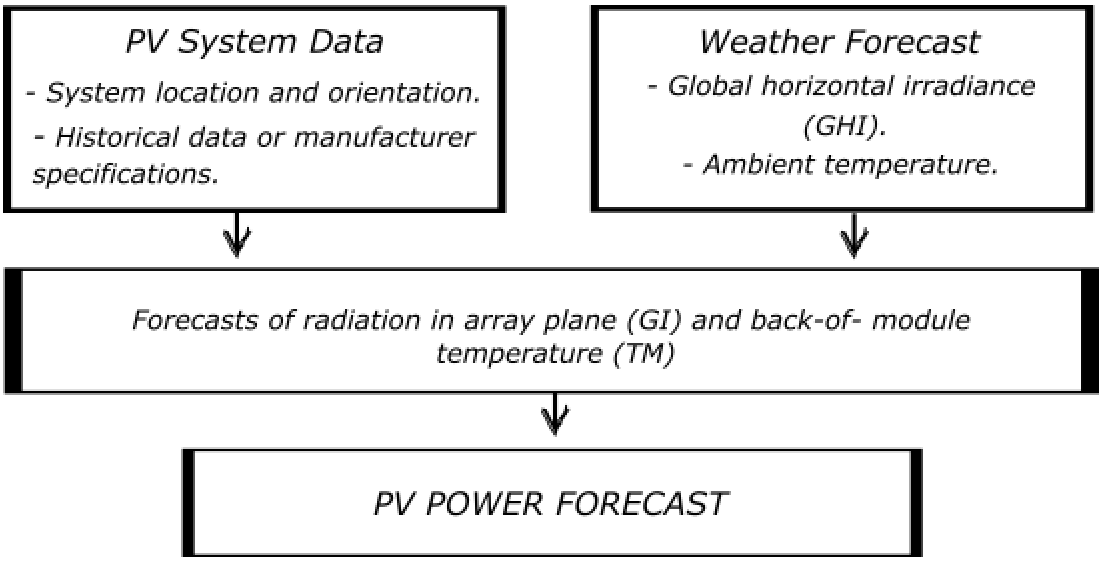

Figure 2.5 Typical physical model.

Two techniques are predominantly utilized: Numerical Weather Prediction (NWP) and Total Sky Imagery (TSI), both classified as physical approaches:

Numerical Weather Prediction (NWP) is a weather prediction strategy based on the dynamic equations of the atmosphere [Pelland et al., 2013], using complex algorithms to predict various meteorological variables such as temperature, pressure, wind, and rain.

On the other hand, according to the Solar Electric Power Association (SEPA) report [El Hendouzi and Bourouhou, 2016], Cloud Imagery, also known as Total Sky Imagery (TSI), ranks second among physical techniques. This method uses sky imaging to predict cloud movement with high resolution (10 to 100 m), providing greater prediction accuracy for very short-term horizons (0 to 6 hours or intra-day). TSI allows for real-time PV power prediction, up to 30 minutes in advance (Intra-hour) and can detect every 30 minutes the presence of clouds that may impact a site [Pelland et al., 2013]. However, Total Sky Imagers have limited applicability in island regions due to their specific weather conditions.

2.4.2.2 Statistical and Hybrid Approaches

The statistical approach to weather forecasting leverages both mathematical models and stochastic strategies. This encompasses a broad range of techniques such as Artificial Neural Networks (ANNs), Machine Learning (ML), Adaptive Models (AM), and Data Mining (DM) [Ren et al., 2015].

These methods, detailed in Table 2.2, typically rely on historical data of solar irradiance and power production to predict future trends. They are primarily divided into two categories: Artificial Intelligence (AI)-based methods and regression methods [Vincent et al., 2020]. Regression techniques include seasonality analysis, Auto Regressive Integrated Moving Average (ARIMA), multiple regressions, and exponential smoothing. On the other hand, AI paradigms involve fuzzy inference systems, genetic algorithms, and neural networks.

A widely recognized model in the realm of statistical forecasting is the persistence technique, noted for its prevalence in various reports on PV power forecasting, including those by the International Energy Agency (IEA) and the Solar Electric Power Association (SEPA). This technique serves as a reference model and is used to compare various PV power forecasting techniques [El Hendouzi and Bourouhou, 2016]. The data utilized for these forecasts typically include time series or historical datasets. However, one inherent drawback of statistical methods lies in the accuracy of historical datasets used to train forecasting models.

Table 2.2 Statistical models summarized

Category	**Sub-category**	**Description**
Statistical Models	**Linear Models (Time Series Models)**	Linear statistical methods derive relations between predictors and the variable to be predicted through statistical analysis. Direct time series modeling has seen success in several studies.
	Persistence Model	A common reference model in solar or wind forecasting for short-term forecasting. It serves to check if the forecast model provides results better than any trivial reference model. A complex forecasting tool is only worth implementing if it outperforms these trivial models.
	Preprocessing of Input Data	This process deals with non-stationary series to transform them into an appropriate form for analysis. Statistical time series analysis requires dealing with stationary series (no trend or seasonality, homoscedastic), so preprocessing of data becomes necessary.
	ARMA Model	The ARMA model, typically applied to autocorrelated time series data, is an effective tool for understanding and predicting the future value of a time series. Comprising two parts: the autoregressive (AR) and moving average (MA), this model can represent several different types of time series using different orders.
	CARDS Model	This model involves the use of Fourier Series techniques for deseasoning. The residual series, obtained by subtracting the Fourier series component from the original series, is then modeled. This model can effectively deal with peaks in the series and provides a superior fit for the residual series.
Learning Models	**Non-linear Models**	These models use Artificial Intelligence (AI) techniques for forecasting and various applications such as control, data compression, optimization, pattern recognition, and classification.
	Artificial Neural Network (ANN)	A computing system inspired by the human brain, used for pattern recognition and prediction tasks.
	Wavelet Neural Network	A type of neural network that uses wavelet transformation.
	Recurrent Neural Network (RNN)	Recurrent Neural Networks, a type of neural network designed to recognize patterns in sequences of data.
	ANN and Classical Time Series Models Comparison	Both ANN and classical time series models have been compared in several studies. These studies found that the error of a simple regression model can be reduced significantly (by a factor in the range of 0.6 – 0.8) when using advanced models.

Furthermore, these datasets include more than just irradiance and module temperature; they may also comprise other variables such as Numerical Weather Prediction (NWP) output parameters and ground station measurements. Despite the advantages of statistical methods, the hybrid approach is emerging as a modern methodology. Hybrid approaches employ advanced statistical techniques to correct known inaccuracies associated with different forecasting methods through model bias adjustments or automated learning techniques [AlKandari and Ahmad, 2024]. Physical models generate forecasts for irradiance and module temperature, which are then used to simulate the solar plant model. The output of these simulations is subjected to statistical post-processing to enhance accuracy [Pu and Kalnay, 2019].

Apart from homogeneous or heterogeneous model combinations within the same approach, hybrid models can also be a mix of different approaches for instance, the combination of Satellite Images and ANNs. These hybrid models aim to achieve higher forecasting accuracy, and the most widely accepted example is the adaptive neural fuzzy inference system (ANFIS) [Singla et al., 2021].

A Physical Hybrid Artificial Neural Network (PHANN) based methodology, which has been homed in various research studies, was developed [Diagne et al., 2013], [Soman et al., 2010]. Figure 2.6 illustrates its essential structure. This forecasting tool integrates an Artificial Neural Network (ANN) trained on historical weather forecasts and clear-sky condition solar radiation (CSRM) to generate a precise hourly profile of expected PV plant output for the upcoming seven-day period [Nespoli et al., 2019]. Following the creation of this output, a post-processing step is required for validation, ensuring the reliability of the data. Consequently, it's crucial to correct any nonsensical values (whether negative or positive) of the output power during the night, setting them to zero.

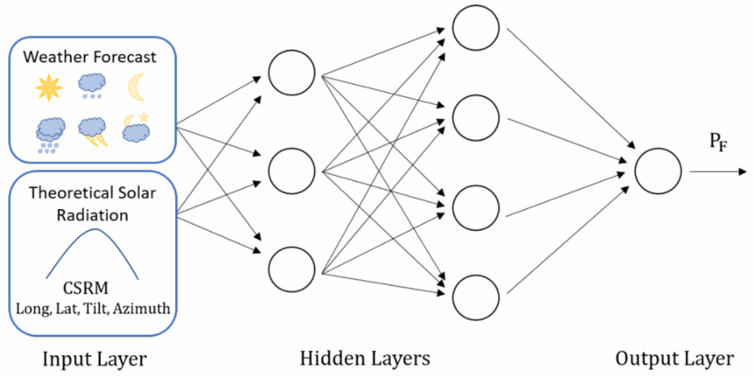

Figure 2.6 PHANN, a physical hybrid artificial neural network, was developed to anticipate output power [Nespoli et al., 2019]

It's worth noting that statistical methods operate under the premise that the forecasted value has a linear correlation with historical data within a specified time duration. Prominent statistical methods include autoregression (AR), moving average (MA), autoregressive moving average (ARMA), and autoregressive integrated moving average (ARIMA). Techniques such as the Box-Jenkins approach and the Kalman filter are effective tools for identifying components and parameters in time series [Ma and Ma, 2018].

In contrast, AI approaches bypass the physical process from input variables and output performance, replacing it with a 'black box' model. These models can either be single models such as fuzzy logic, artificial neural network (ANN), support vector regression (SVR), wavelet transform (WT), genetic algorithm (GA), and expert systems or hybrid models [Ma and Ma, 2018], which integrate one or more algorithms to pursue higher forecasting accuracy. In Figure 2.7, a summary of the forecasting methods is shown.

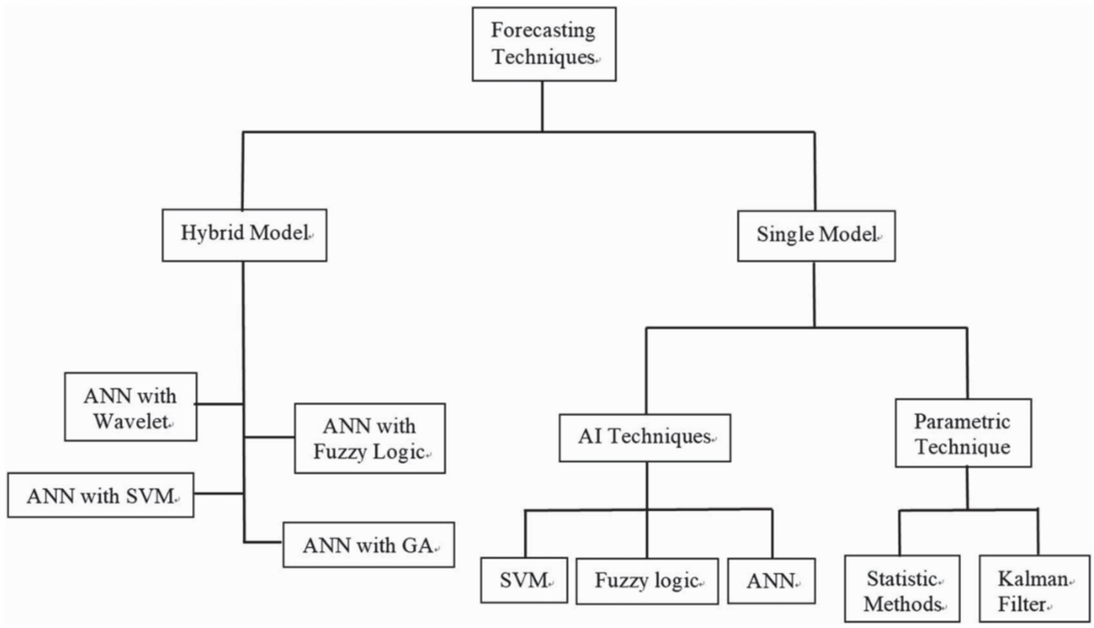

Figure 2.7 An overview of forecasting methods[Ma and Ma, 2018]

A classification of solar irradiance forecasting methods in terms of the type of data used as input is carried out and presented in Table 2.3 . We lay out physical methods, which are based on meteorological data, versus statistical methods that are based on historic data to use for predicting future trends. RNN, MLP, ANN and ARIMA are examples of statistical models. Their predictive capabilities makes these methods necessary, however, the challenges of increased accuracy as a function of the quality of historical data used to train the model remains.

Table 2.3 classification of solar irradiance forecasts based on approach. [Diagne et al., 2013]

Approach	Input	Q Examples
Physical	Meteorological data	TSI, NWP
Statistical	Historical data	RNN, MLP, ANN, ARIMA

Solar irradiance forecasting is described across a variety of time horizons from a very short term (less than 30 minutes) to long term (1–7 days) in Table 2.4. This is necessary for forecasting model tailored to operational needs which differ in scale along temporal axis (depending on if they are used for immediate grid management or long term planning) [Soman et al., 2010]. The table shows that the choice of forecasting models is important, and that it depends on the time interval and purpose of application in the energy sector.

Table 2.4 classification depending on the temporal horizon for predicting. [Soman et al., 2010]

Time Horizon	Interval
Very short term	< 30 min
Short term	0.5 – 6 h
Medium term	6 – 48 h
Long term	1–7-day

Table 2.5 summarizes the effectiveness of various solar irradiance forecasting models using diverse approaches as measured by different performance metrics. As an illustrative example, we combine numerous ANN techniques into a Bagging ANN model and benchmark it against MLP, RBFNN, and RNN methods, with MAE of 17.4% and a surprisingly low MAPE of only 2.3%, indicating substantial accuracy over a short-term horizon. A similar MAE is echoed by the Multi-stage ANN model, showing the capabilities of such layered NN architectures to deal with the solar irradiance patterns' complexity.

On the contrary, models based on non-linear regression and pattern recognition techniques, which provide a resolution of 1 hours forecast, have higher MREs of 40% and 33.3% for 1 and 3 hours forecast respectively. This suggests that there might be a resolution vs. accuracy trade off for these models. Finally, a high MAE and MRE are noted in the Wavelet-RBPNN model with its day-long horizon, implying that although it may predict daily trends, its performance is very unreliable which is perhaps due to its sensitivity to the non-linear and volatile nature of solar irradiance data.

2.5 Machine Learning in Weather Forecasting

Recently, machine learning has been used heavily in the field of weather forecasting because of its inherent ability to develop new patterns from large, complex

Table 2.5 Summary of the forecasting models for solar irradiance that were examined.

Approach	Horizon	Benchmark methods	Results
Bagging ANN [Choi and Hur, 2020]	1 day	MLP, RBFNN, RNN	17.4% (MAE), 2.3% (MAPE)
Multi-stage ANN [Gheouany et al., 2023]	1 day	ANN	17.43% (MAE)
Non-linear regression and PR [Alizamir et al., 2020]	1 h, 3 h	Regression, ARIMA, ANN	40% (MRE, 1 h), 33.3% (MRE, 3 h)
Wavelet-RBPNN [Zayed et al., 2022]	1 day	RBPNN	74.5% (MAE), 77.61% (MRE)

datasets. This is also an ability to deal and learn from messy, and multi faceted data. This is a rapidly developing area of meteorological research weather, as ML is such a powerful tool for predicting the weather patterns.

As in [Khan et al., 2020], machine learning algorithms can detect subtle patterns in historical weather data which can, in turn, be used to predict how future weather will be. These algorithms are very complex and consider hundreds of variables such as temperature, humidity, wind speed and wind direction, atmospheric pressure and many, many more. So they can train ML models with past meteorological data, and have it learn to accurately predict future weather conditions. Moreover, machine learning can be used to enhance the accuracy of weather simulation as model parameter optimization and calibration [Sharifzadeh et al., 2019].

2.5.1 Types of Machine Learning Algorithms

In weather forecasting, several types of machine learning algorithms are used, each with its (own) strengths and weaknesses.Supervised, unsupervised and deep learning are the main categories of ML methods [Diagne et al., 2013].

Supervised Learning Algorithms: Such algorithms are built using a training dataset and used to estimate results using the acquired patterns. Field including Linear Regression, Decision Trees, Random Forest, Support Vector Machines also fall under this category. Models that integrate decision trees and therefore nonlinear relationships and interactions among variables, like Random Forest, might accurately handle the present study's patterns.

Unsupervised Learning Algorithms: They can be used to discover structure in data that hasn't been pre-tagged or categorized in any way. K-Means and Hierarchical Clustering are the examples of machine learning methods which help Meteorology find groups of similar weather patterns.

Deep Learning Algorithms: Applications of CNN and RNN are for handling large data structures along with complex structures. They have been applied in domains of image recognition to classify the clouds pattern, and sequence prediction in time-series meteorological data.

2.5.1.1 Deep Learning for Time-Series Forecasting

This branch of machine learning, called deep learning, is oriented towards so called artificial neural networks, but in particular its 'deep' networks (cf Figure 2.8) where each layer consists of several nodes between the input and output. The layers are able to capture complex, high level features [Patterson and Gibson, 2017], and join these relating to the data. As deep learning is able to deal with large amount of high dimensional data and learn very complex temporal dependencies [Tomin et al., 2019], it can be particularly effective at time series forecasting.

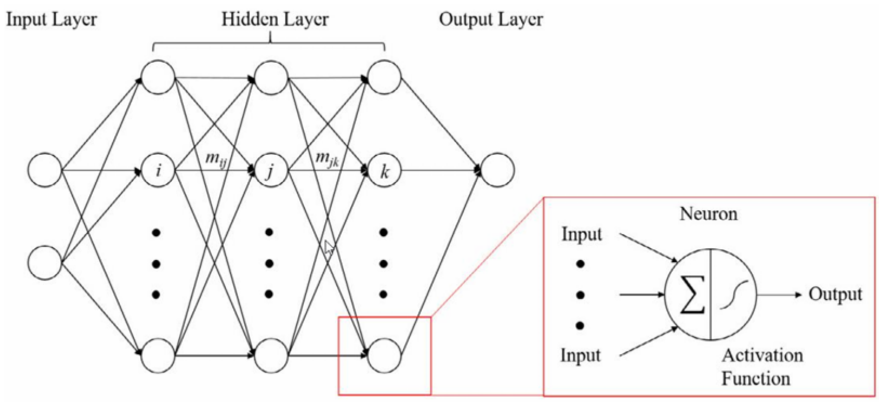

Figure 2.8 Deep learning general structure. [Chen et al., 2019]

2.5.1.2 Neural Network Models

Radial Basis Function Neural Network: Radial Basis Function Neural Networks (RBFNNs) have been effectively applied in a variety of practical scenarios, outperforming Multi-Layer Perceptron Neural Networks (MLPNNs) due to their lesser demand for computational resources and time. Some of these applications encompass the prediction of chaotic time-series, speech recognition, and categorization of data [He et al., 2019]. This capability is exemplified in Figure 2.9, showcasing the RBFNN's architecture.

It's worth highlighting that, given a sufficient volume of hidden units, an RBFNN stands out as a universal estimator, capable of approximating any type of continuous functions [Adcock and Dexter, 2021].

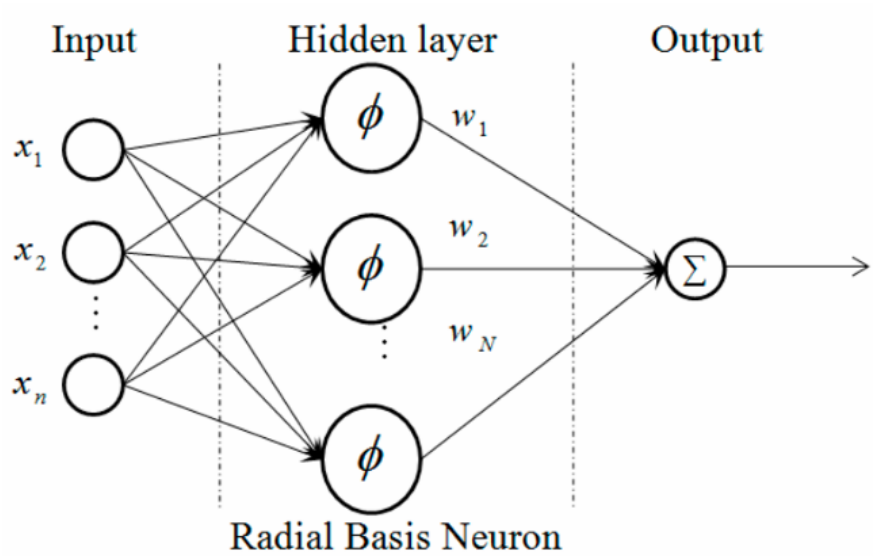

Figure 2.9 RBFNN's architecture. [He et al., 2019]

Multi Layered Perceptron Neural Network: Multi-layer Perceptron's (MLPs) have proven to be efficacious in addressing a wide array of complex and distinct problems. This is achieved through an initial supervised training phase that leverages the error back propagation algorithm and an error correction learning rule [Desai and Shah, 2021]. Multi-layer Perceptron's have proven to be efficacious in addressing a wide array of complex and distinct problems. This is achieved through an initial supervised training phase that leverages the error back propagation algorithm and an error correction learning rule.

The backward pass is characterized by the adjustment of synaptic weights in alignment with an error correction rule. The error signal, calculated as the difference between the actual output and the desired value, is then disseminated backward through the network, against the flow of synaptic connections [Wani and Thagunna, 2024].

While MLPNNs can have multiple hidden layers as in Figure 2.10, K.M. Hornik's research [Hornik et al., 1989], suggests that even a neural network with a solitary hidden layer possesses the capability to approximate a function of arbitrary complexity.

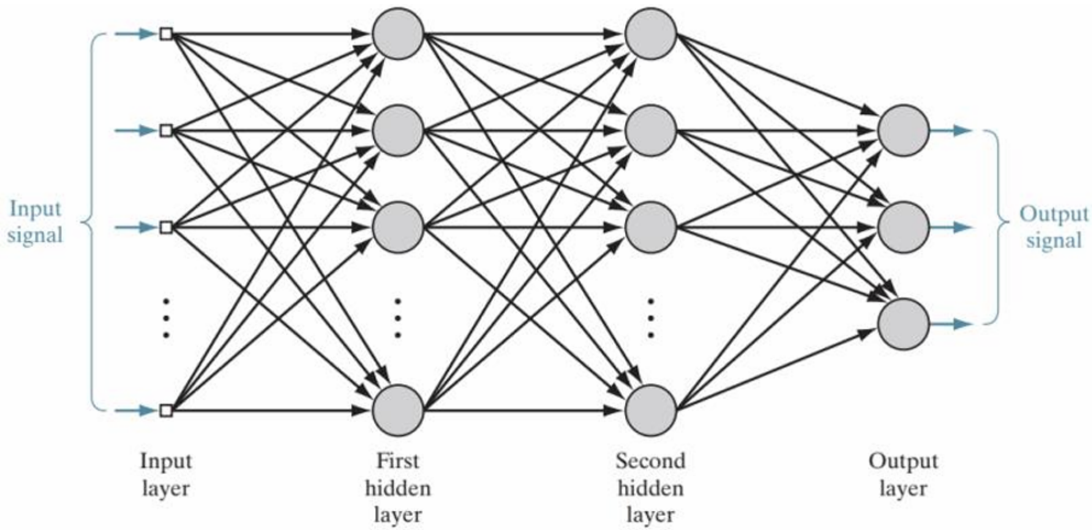

Figure 2.10 Architecture of a multilayer perceptron with three outputs and two hidden layers [Wani and Thagunna, 2024]

Neural Network Ensemble: A Neural Network Ensemble, often referred to as an ensemble, is a learning paradigm where multiple neural networks are trained to solve the same problem. The main idea behind this approach is to exploit the diversity among the networks to get a more robust and better generalizing model [Chen et al., 2019].

Ensemble methods leverage the fact that a group of ’weak learners’ can come together to form a ’strong learner’. Each neural network in the ensemble makes a prediction (or vote), and the ensemble combines these predictions to make a final forecast [Lee et al., 2009], typically by simple averaging or voting. The intention is to improve the predictive performance and robustness over a single model.

Neural network ensembles can be particularly effective when the individual models in the ensemble are significantly different or independent from each other [Desai and Shah, 2021]. This diversity can be induced by using different architectures or learning algorithms, training on different subsets of the training data, or using different initial random weights.

The architecture of a Neural Network Ensemble (NNE) is a set-up where multiple neural networks are grouped together to solve a problem as shown in Figure 2.11. The individual networks, or ”ensemble members,” operate in parallel and independently from each other. They are typically trained on the same problem but may have different initial conditions, structures, or training data subsets, creating a diversity of predictions.

The ensemble’s final output is typically obtained by aggregating the individual predictions of its members, often through simple techniques such as voting, averaging, or weighted averages [Desai and Shah, 2021]. This setup allows the ensemble to take advantage of the diverse predictive capabilities of its members, often leading to better performance compared to a single network.

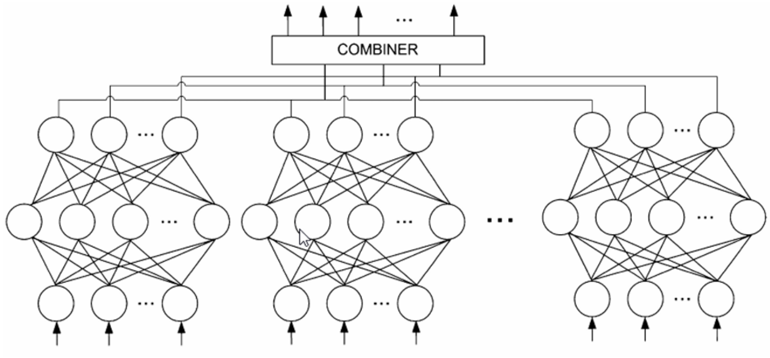

Figure 2.11 Architecture of the neural network ensemble [Lee et al., 2009]

Recurrent Neural Network: Recurrent Neural Networks (RNNs), while being a subset of feed-forward neural networks, stand apart due to their distinctive ability to transmit information across temporal intervals [60]. RNNs support both parallel and sequential computations, essentially embodying the computational ability of conventional computers. However, these networks are more akin to the human brain, a vast feedback network of interconnected neurons [Mienye et al., 2024], which translates continuous sensory input into a sequence of beneficial motor responses. The human brain serves as an exceptional model, resolving numerous challenges that present machines struggle to overcome.

RNNs process each vector from a sequence of input vectors one by one, allowing the network to maintain its state while modeling each input vector across the input vector window. This hallmark ability to model the time dimension sets RNNs apart [Hewamalage et al., 2021].

Expanding upon this unique architecture, RNNs introduce the notion of recurrent connections, which these connections (or recurrent edges) span across consecutive time-steps (e.g., from a previous time-step) as shown in Figure 2.12, providing the model with a sense of time. Traditional connections in RNNs do not form cycles. However, recurrent connections can create cyclical paths, including those looping back to the original neurons at future time-steps [Reza et al., 2022].

As input is transmitted through a recurrent network at each time-step, nodes receiving input along recurrent edges process input activations from both the current input vector and the network's previous state's hidden nodes. The output is computed based on the hidden state at that specific time-step [Hewamalage et al., 2021]. Thus, the previous input vector at the last time-step can influence the current output at the present time-step, facilitated by the recurrent connections.

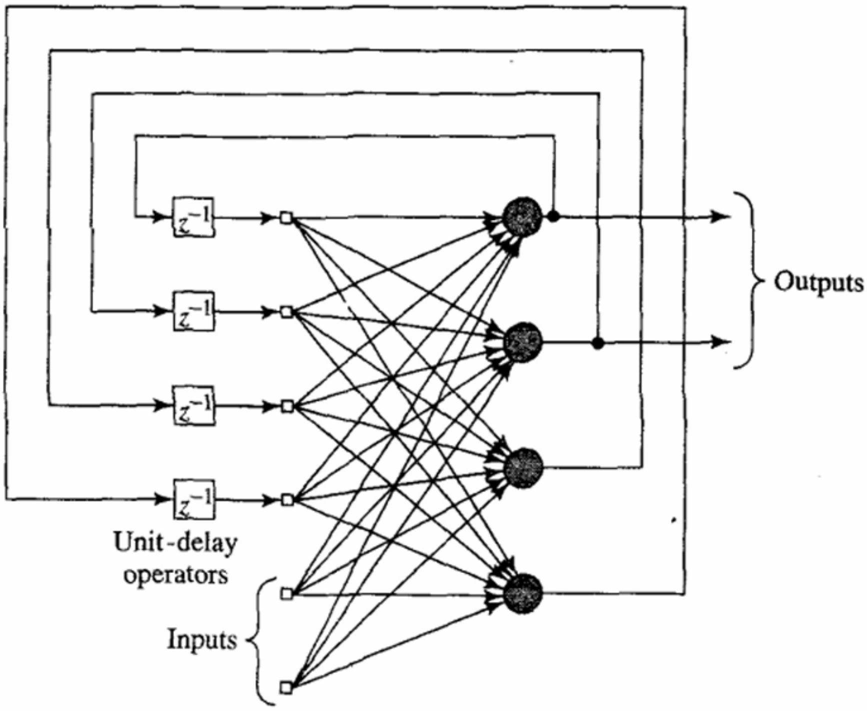

Figure 2.12 Architecture of the neural network ensemble[Lee et al., 2009]

Recurrent Neural Networks (RNNs) are neural networks that have at least one feedback loop in essentially. We classify these feedback mechanisms as local or global. The structure of RNN usually begins as shown in Figure 2.13 with a neural network of the type Multi Layer Perceptrons Neural Network (MLPNN) and the feedback can take many forms. Taking feedback out of the output neurons to the input layer, or giving feedback from the hidden neurons in the network back to the input layer, is just one example. And both scenarios can co-exist. In the case of MLPNN with two or more hidden layers the potential number of feedback forms increases correspondingly. RNNs are able to evolve state representations, making them a great nonlinear prediction and modeling framework [Hewamalage et al., 2021], due to the inclusion of feedback mechanisms.

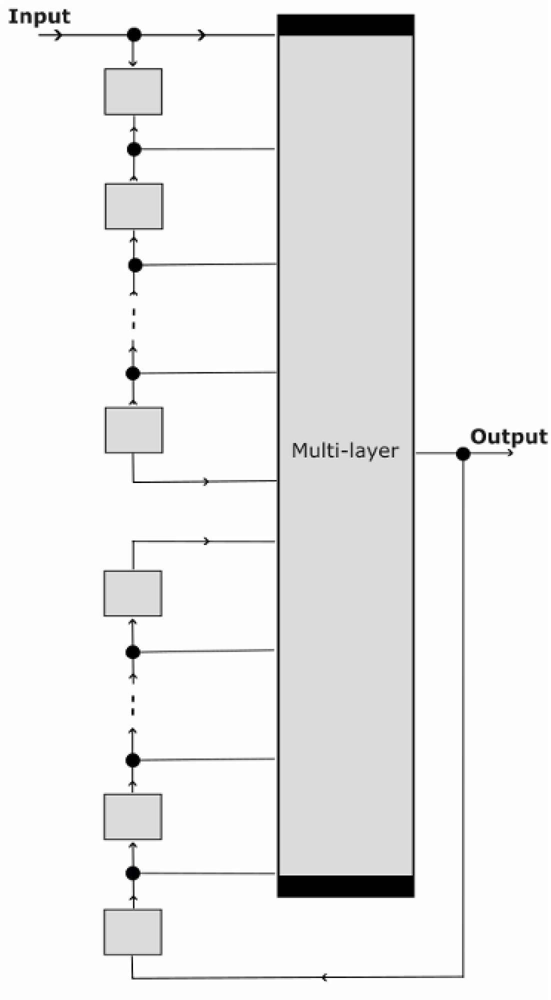

Figure 2.13 structure of NARX-RNN

Table 2.6 summarizes different neural network models with architectures and possible applications. This compares with the Radial Basis Function Neural Network (RBFNN) for its three layer architecture excellent for function approximation, and in turn with the Multi-layer Perceptron Neural Network (MLPNN) rich in the hidden layers and capable of building complex data interactions. Recurrent Neural Networks (RNNs) are also described in the table; RNNs are able to process sequential data, due to the recurrent connections which allow information to persist. In the thesis, the architecture of each model informs which forecasting tasks are appropriate for which models.

Table 2.6 Neural Network Models

Neural Network Type	Architecture
Radial Basis Function Neural Network (RBFNN)	RBFNN structure is composed of three layers. The input layer connects the network to the external environment. The hidden layer, which is the only hidden layer in the network, applies a nonlinear transformation from the input space to the hidden space, which is often high dimensional. The output layer is linear, supplying the response of the network to the pattern applied to the input layer.
Multi-layered Perceptron Neural Network (MLPNN)	MLPNNs have an input layer, one or more hidden layers, and an output layer. The input layer receives the input vector, and its effect propagates through the network layer by layer to produce an output. During the training phase, synaptic weights are adjusted in accordance with an error correction rule. In general, MLPNNs can have several hidden layers.
Artificial Neural Network Ensemble (ANNE)	ANNEs are a collection of multiple individual neural networks. Each network is trained independently, and their predictions are later combined. They provide a way to mitigate the instability of single neural network models. Changes in the architecture of the networks in the ensemble, or changes in the training data, can affect the performance of the ensemble.
Recurrent Neural Network (RNN)	RNN architecture introduces the concept of recurrent connections. These connections span adjacent time-steps, giving the model the concept of time. At each time-step of sending input through a recurrent network, nodes receiving input along recurrent edges receive input activations from the current input vector and from the hidden nodes in the network's previous state. The output is computed from the hidden state at the given time-step.

A comprehensive comparison of recent advancements in solar irradiance (SI) forecasting techniques with previous work is reported in Table 2.7 in order to assess the SI forecasting landscape. It encapsulates a range of methodologies from LSTM based models to support vector machines (SVM) with their lowest error rates, along with their largest drawbacks, presenting a tradeoff between accuracy and complexity.

Compared to the LSTM-TCM and LSTM-RNN models, for example, which achieved normalized root mean square error (nRMSE) rates of 6.29% and 3.89%, respectively, these models also offer higher complexity and difficulties in handling dynamic parameters, limiting their use in real time forecasting situations. Secondly, simpler models like the ANN cited in ref. [Chung, 2020] produce a respectable RMSE of 2.70 kWh/m², but the fact that they require current weather observation data, which may not make good enough estimation of future values, is a complicating factor.

Although the SVM approach is very complex to calculate, in fact the RMSE achieves a 2.78 MJ/m², indicating that the approach is in fact, highly suitable for accurate forecasting. On the other hand, the hSBFM model with the lowest nRMSE of 1.43 is critiqued for not taking into account the future weather or solar conditions that could be important for long term accuracy of prediction.

In addition, although the SVM-BAT and EMD-SCA-ELM are highly efficient, they consume a lot of computation and training, which is not practical for direct deployment.

At 6.34 nRMSE, the CNN-LSTM model also suffers from computational complexity, butthat is avoidable since optimization is required. Although the nRMSEs of 21.2 and 11.81 are achieved by using Deep ConvNets and NAR respectively, their nonlinear complexity and parameter sensitivity, which may affect the adaptability to different conditions of solar irradiance, limit them.

The analysis highlights continued effort as well as challenges in the world of SI forecasting and suggests a healthy trade off between model complexity, computational efficiency, and the forecast precision. The strengths of each method as well as limitations are unique, rendering an informed selection of the most appropriate model for practical solar energy management applications essential.

Table 2.7 A comprehensive analysis contrasting SI forecasting techniques with prior studies.

Method	Ref.	Year	Country	Lowest Error	Limitation
LSTM-TCM	[Wang et al., 2020]	2020	Australia	nRMSE = 6.29%	High Complexity
LSTM-RNN	[Zafar et al., 2021]	2021	United States	nRMSE = 3.89%	Difficult to heal with dynamic parameters
ANN	[Chung, 2020]	2020	South Korea	RMSE = 2.70 kWh/m^2	The model estimates solar insolation based on current weather data, not future forecasts.
SVM	[Sutarna et al., 2023]	2021	Brazil	RMSE = 2.78 MJ/m^2	High Complexity
hSBFM	[Sangrody et al., 2020]	2020	United States	nRMSE = 1.43%	It doesn't account for upcoming changes in weather or solar conditions.
SVM-BAT	[Feng et al., 2020]	2020	China	RMSE = 1.694 MJ/m^2	Computational Complexity
EMD-SCA-ELM	[Behera and Nayak, 2020]	2020	India	nRMSE = 1.88%	Need for heavy training
CNN-LSTM	[Qu et al., 2021]	2021	China	nRMSE = 6.34%	Computational Complexity
Deep ConvNets	[Wen et al., 2020]	2020	United States	nRMSE = 21.2%	Nonlinear complexity
NAR	[Takilalte et al., 2022]	2022	Algeria	nRMSE = 11.81%	Parameter Sensitivity

2.5.2 Challenges and Limitations

Nonetheless, emerging with the application of machine learning in weather forecasting there are several challenges and limitations. One of the critical factors defining the model's accuracy is the extent to which the training dataset is informative and large enough [Patterson and Gibson, 2017]. Lack of or incorrect data results in wrong predication. However, these algorithms are complex, especially, in terms of the amount of computational work involved particularly when large data sets are in use. Moreover, it is necessary to mention that despite the fact that machine learning models improve the forecast precision, commonly, they act as black boxes [Murphy, 2012]. The problem with this situation is that it becomes very difficult to understand how they came up with such predictions and this may pose a lot of challenges especially when their application is very important and the details of their thinking must be brought to light.

Furthermore, it is essential to acknowledge that weather patterns exhibit intricate behavior, shaped by several interacting elements. This implies they may continue to have difficulty properly forecasting the subsequent number. To forecast future occurrences in instances when these occurrences are influenced by variables not represented in the training data.

Extreme weather events, more prevalent due to climate change, are often caused by uncommon combinations of elements not represented in historical data. Consequently, such catastrophes may be inadequately forecasted by machine learning algorithms, leading to extensive ramifications for disaster prevention and management.

In addition, even though machine learning models deal well with high dimensional data, choosing the proper features (variables) to predict would require a daunting task. However, inclusion of extraneous characteristics in the data set may cause a suboptimal model performance [James, 2013]. On the other hand, dropping characteristics thought of as insignificant can cause the removal of essential predictive info.

A significant issue in using machine learning for weather forecasting is overfitting. This transpires when a model overfits the training data, resulting in poor performance on novel data. An overfitted model has a greater number of parameters than the quantity of data. Ultimately, it identifies the noise in the training data that may adversely impact its capacity to generalize from previously encountered data to novel data [Murphy, 2012].

In the context of weather forecasting, an overfitted model might predict past weather patterns with remarkable accuracy but fail miserably when asked to predict future weather. This is because the model has not truly 'learned' the underlying patterns in the weather data; instead, it has merely 'memorized' the training data [Murphy, 2012]. Therefore, the model becomes unable to make accurate predictions when faced with new data or scenarios that differ from what it has seen during training.

Techniques such as cross-validation, regularization, early stopping, and pruning can be used to prevent overfitting. Also, it is always essential to have a holdout validation or test dataset to evaluate the model's performance on unseen data [Patterson and Gibson, 2017]. This helps ensure that the developed model can generalize well and provide accurate forecasts on new data.

2.6 Chapter Summary

Research in solar irradiance forecasting has seen a variety of approaches. Traditional methods, including statistical and rule-based models, often fall short in accurately predicting solar energy due to the intricate and dynamic nature of weather patterns affecting solar irradiance. Recognizing these limitations, recent studies have shifted towards more sophisticated techniques. This project specifically explores the integration of machine learning algorithms, notably a hybrid model combining Nonlinear Autoregressive with Exogenous Inputs (NARX) and Long Short-Term Memory (LSTM) networks, to enhance daily solar irradiance forecasting accuracy in microgrids.

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