SEMARAK ILMU PUBLISHING

Semarak Engineering Journal

Journal homepage:
https://semarakilmu.my/index.php/sej/index
ISSN: 3036-0145



Photovoltaic Systems for Sustainable Energy: A Comprehensive Review with Neural Network-Based Prediction and A Utility-Scale Case Study

Esraa M. Abd Elsadek[1,*], A. H. Abdelbaky Elbatran[1], Ayman Samy Abdel-Khalik[2], Hossam Kotb[3]

[1] Construction and Building Engineering, Arab Academy for Science, Technology & Maritime Transport, Heliopolis, Cairo, Egypt
[2] Civil & Environmental Engineering, University of Waterloo, Waterloo, Canada
[3] OPTEAM Technologies Inc., UAE
[4] Construction and Building Engineering, Arab Academy for Science, Technology & Maritime Transport, Smart Village Campus, Giza, Egypt

ARTICLE INFO

Article history:
Received 3 July 2026
Received in revised form 10 September 2026
Accepted 10 October 2026
Available online 22 November 2026

Keywords:
Photovoltaic systems; Renewable energy; Neural networks; MPPT; Power forecasting; Smart grids

ABSTRACT

This study reviews recent advances in photovoltaic (PV) systems, focusing on building-integrated photovoltaics, maximum power point tracking, and performance enhancement through shading control, cooling, and thermal management. It also examines the integration of PV systems with hybrid and smart energy systems under diverse climatic conditions. To address solar energy uncertainty, a data-driven predictive model based on artificial intelligence is developed and evaluated using four years of operational data from the Benban Solar Park in Aswan, Egypt, one of the largest PV installations in the Middle East. A neural network model was developed to predict PV performance, achieving high accuracy, with a mean squared error of 0.056 and a correlation coefficient exceeding 0.98. The findings demonstrate the potential of AI-based prediction to improve PV system performance and provide valuable directions for future research.

1. Introduction

1.1 Background and Motivation

Renewable energy sources include solar, hydropower, wind, geothermal, biomass, and tidal energy [1]. These sources can be converted into electricity, heat, and fuels. Solar energy is derived directly from the Sun [2]. It also drives natural processes such as the hydrological cycle and wind generation, as solar heating of the troposphere induces air movement. Building-applied photovoltaics (BAPV) have attracted considerable attention in recent years as an effective means of harnessing solar energy [3].

In densely populated urban residential areas, limited space and shading constraints can restrict photovoltaic installations. Innovative approaches are therefore required to meet urban energy demands and support sustainable communities. The integration of renewable energy systems is a key feature of net-zero energy buildings (NZEBs), which promote sustainable development. In the

* *Corresponding author.*
E-mail address: hossam.kotb@alexu.edu.eg, esraasadek@egypt.aast.edu

https://doi.org/10.37934/sej.17.1.80115

building sector, standalone hybrid photovoltaic/thermal (PV/T) systems have gained attention for their potential to meet electricity and thermal energy demands [4]. However, a comprehensive assessment of the feasibility of integrating renewable energy into existing energy infrastructure remains necessary.

The electrical conversion efficiency and reliability of photovoltaic modules are influenced by operating temperature. For every 1°C increase in solar cell temperature, the relative efficiency of crystalline silicon solar cells decreases by approximately 0.45%. Both passive and active cooling techniques have been employed to reduce solar cell temperatures. However, active cooling methods that use fans or pumps to circulate air or water around PV modules present additional operational challenges [5].

Previous studies have reviewed the development of building-integrated photovoltaic/thermal (BIPV/T) systems, focusing on numerical and experimental investigations of their advantages, limitations, and operational efficiency. These studies have also examined the application of BIPV/T systems to external walls and evaluated their thermal and electrical performance, building energy consumption, and potential contributions to space heating and cooling [6].

Buildings account for approximately 20–40% of total energy consumption across different sectors [7]. Under a reference scenario that considers improvements in existing technologies, building energy consumption is projected to increase by approximately 0.4% between 2017 and 2050. Heating, ventilation, and air conditioning (HVAC) systems account for approximately 40% of building energy consumption, highlighting the need to address the environmental impacts of conventional energy sources.

Near-zero-energy buildings offer a practical approach to meeting the growing demand for reliable, sustainable, and environmentally friendly energy systems. Extreme weather conditions, particularly in hot and humid regions, increase thermal loads and air-conditioning energy requirements. Meanwhile, fossil fuels remain a major energy source supporting global development [8].

Energy demand has increased due to rapid population growth, rising living standards, and the expansion of energy-intensive activities. This has accelerated the depletion of conventional energy resources and contributed to global warming through increased greenhouse gas emissions, particularly carbon dioxide and methane. Therefore, the effective utilization of clean, economically feasible renewable energy sources is essential for mitigating climate change and global warming [9–10].

1.2 Building-Integrated Photovoltaics (BIPV)

Building-integrated photovoltaic (BIPV) systems are incorporated into building structures to generate electricity for on-site consumption while minimizing environmental impacts. These systems can be classified as standalone, grid-connected, or hybrid configurations. BIPV systems generate and distribute electricity according to building energy requirements and can incorporate energy storage systems (ESS) to provide power when needed. This study classifies BIPV systems using a comprehensive framework that includes simulation and optimization approaches, as illustrated in Figure 1 [11].

Solar shading devices play an important role in energy-efficient building design and regulations. Common solar control and shading strategies include external fins, light shelves, low-shading-coefficient glazing, adjustable louvers for indoor glare control, and landscape elements such as trees and windbreaks [8]. These approaches can reduce cooling energy consumption while improving glare

control. However, their application may be limited by structural and economic constraints, particularly when modifications to existing buildings are required.

BIPV systems offer an alternative to conventional building façades by combining solar shading functions with electricity generation. This dual functionality can improve building energy performance while reducing dependence on conventional energy sources [12, 13].

Further improvements are necessary to enhance overall energy conversion efficiency and reduce installation and operating costs. Recent developments in BIPV systems for window insulation have demonstrated their potential to improve building energy performance [14].

The present study examines the thermal efficiency of BIPV systems and their influence on indoor thermal comfort. Thermal calculations and experimental investigations will consider both indoor and outdoor environmental conditions across a range of operating scenarios. In addition, a structural assessment will be conducted to evaluate the effects of installing BIPV panels on the building structure [15].

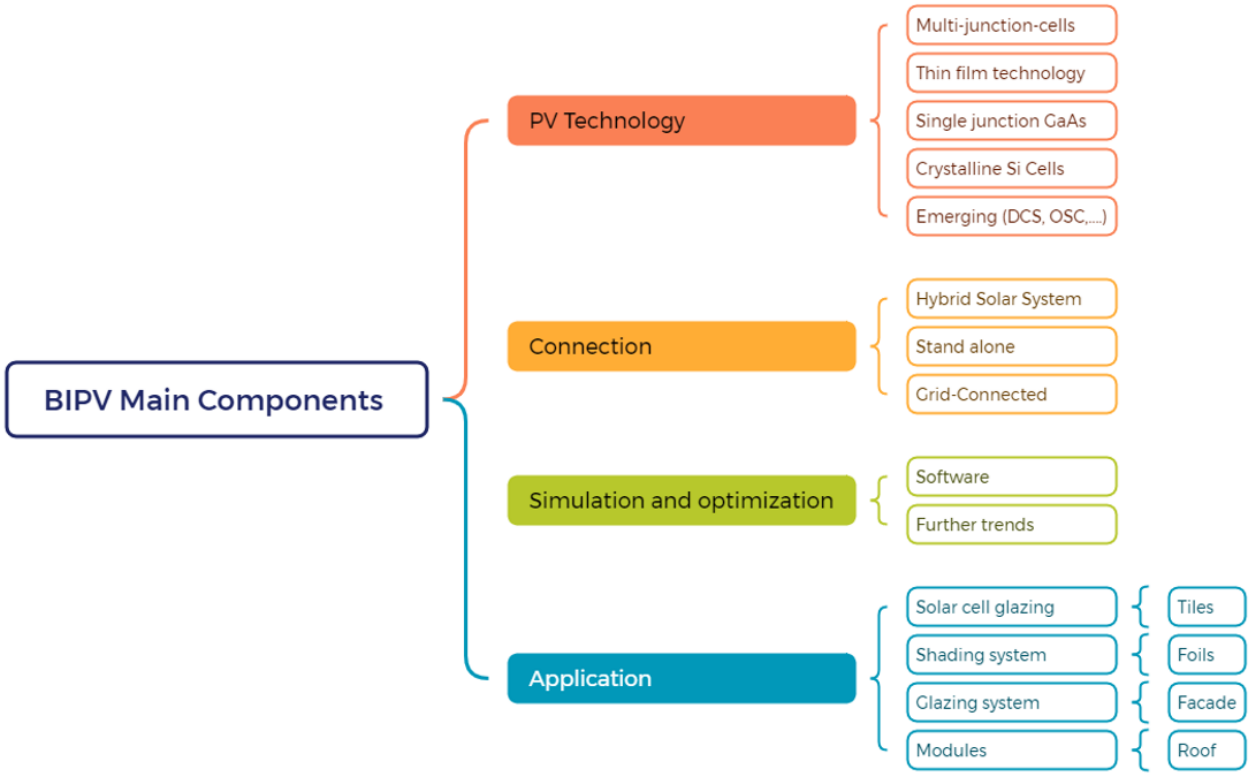


Fig. 1. Organizing BIPV Systems

A building's façade can be equipped with solar collectors and photovoltaic (PV) panels to generate thermal and electrical energy. Consequently, these systems can reduce heating and cooling loads while improving solar energy utilization. A comprehensive analysis of thermal BIPV applications has been conducted, covering their performance, efficiency, nominal power, energy generation, and evaluation methods [11]. In solar thermal systems, a receiver containing a heat-transfer fluid absorbs solar radiation and converts it into thermal energy. This energy can be used to generate steam that drives a turbine to produce electricity. Thermal energy can also be stored for later use when sunlight is unavailable [16].

The analysis of energy-related characteristics of BIPV systems can contribute to improvements in existing modeling and simulation technologies. The electrical and thermal performance of BIPV systems is interconnected and directly influences building energy performance and occupant comfort. Several studies have examined the effects of BIPV systems on buildings. The magnitude and distribution of energy savings depend on system characteristics, regional climatic conditions, building location, building type, and usage patterns.

Nevertheless, a comprehensive simulation tool that integrates all relevant aspects of BIPV performance has not yet been developed. Figure 2 provides an overview of the thermal and electrical models currently employed in commercially available BIPV systems.

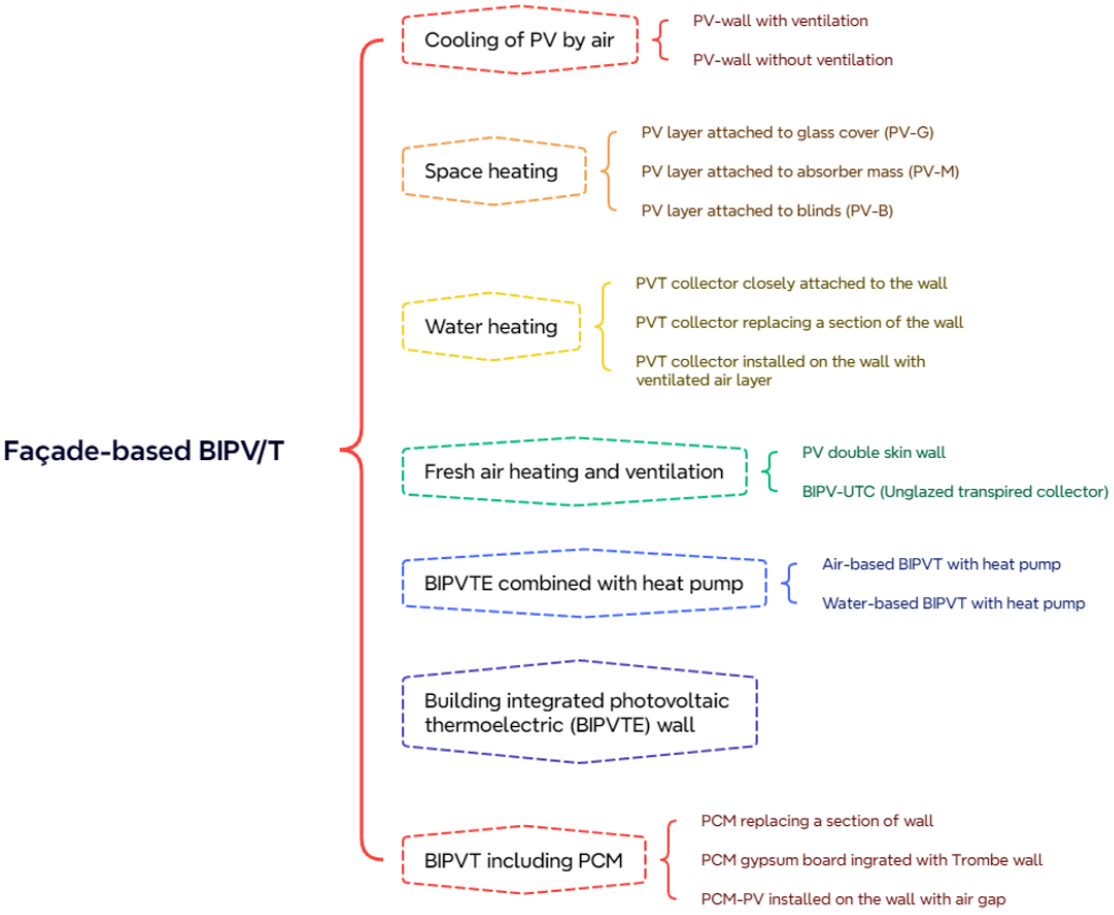


Fig. 2. Solar thermal systems installed on building facades are classified according to their type

2. Major Areas for Improving PV Power Output

Photovoltaic cells with a fixed orientation exhibit limited efficiency because of changes in the Sun's position throughout the day. Solar tracking devices can improve energy capture by adjusting the orientation of PV modules according to the Sun's movement [17].

Solar tracking systems have been extensively studied to address the limited efficiency of conventional solar modules and improve electricity generation. Previous studies have demonstrated that integrating tracking devices into conventional PV systems can significantly enhance energy production. Three main approaches have been developed to improve PV performance: solar tracking systems, concentrating photovoltaic (CPV) systems, and hybrid photovoltaic/thermal (PV/T) systems.

Each approach incorporates specific components and operating principles to increase energy output [18].

Although each approach offers distinct advantages, previous studies have not identified a comprehensive system that integrates the key characteristics of all three technologies. Researchers continue to investigate methods for combining their beneficial features to develop more efficient and cost-effective PV tracking systems. Additional government incentives may also be necessary to encourage the wider adoption of solar tracking technologies.

Conventional fixed PV systems remain more widely used because of their simpler installation and lower system complexity. However, solar tracking systems offer potential benefits that may justify their additional costs under suitable operating conditions. Their application in buildings may provide an alternative to fixed PV installations where sufficient space and appropriate structural conditions are available [19].

Solar tracking systems can be classified according to several criteria, including control mechanisms, driving systems, tracking methods, and degrees of freedom. As illustrated in Figure 3, these classifications reflect differences in system operation, actuation mechanisms, and tracking capabilities [20].

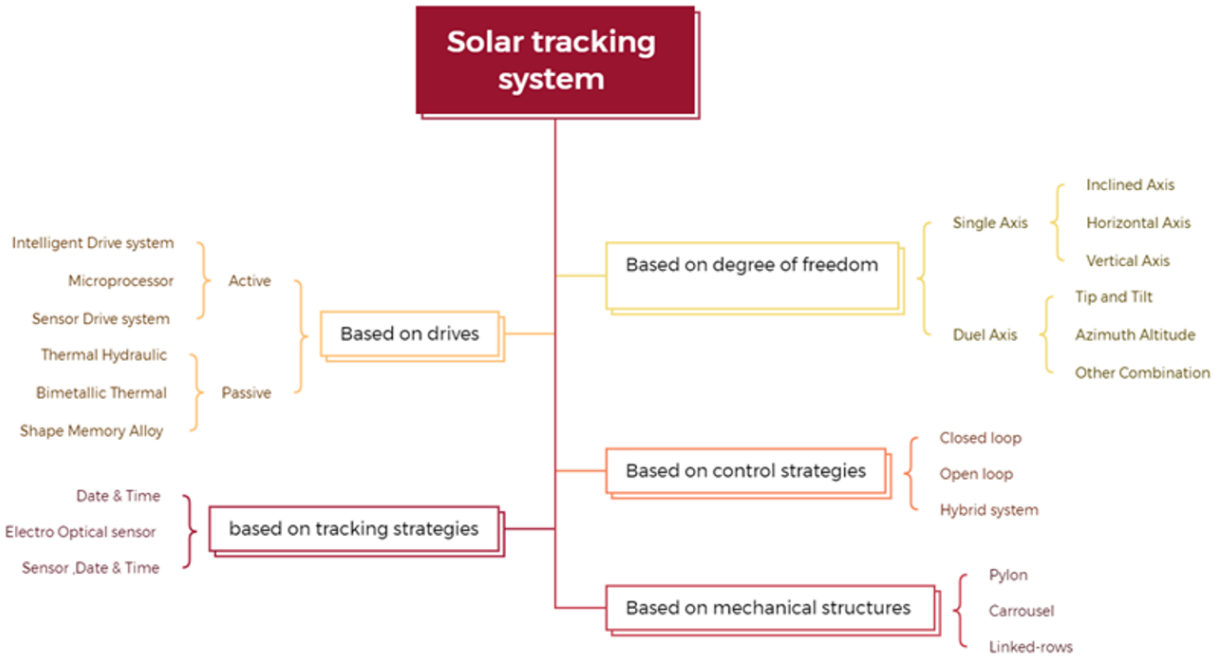


Fig. 3. Grouping solar tracking devices

The classification of photovoltaic tracking systems is determined by their driving mechanisms, degrees of freedom, and control methods. Based on preliminary research, the following discussion focuses on the most critical aspects of these systems [21].

The most widely used and practical control approaches combine microprocessor-based controllers with sensors. Active tracking systems employ electric motors to control the movement of the tracking axes. However, these systems may consume significant electrical energy if not properly regulated. To improve the efficiency of electrical drives, it is essential to minimize the frequency of motor movements. Brushless DC motors with permanent magnets are widely used because of their

low maintenance requirements. Advanced monitoring systems may incorporate real-time weather forecasting and utilize air or water cooling techniques to improve PV system performance [22].

2.1 Effect of Shading on PV Panels

Solar energy can be harnessed by directly converting sunlight into electrical energy using photovoltaic (PV) cells. These cells are the primary components responsible for converting incident photons into electrical energy through the photovoltaic effect. Because individual PV cells generate relatively low voltage and power, they are connected in series or parallel configurations. Series connections increase the overall voltage, whereas parallel connections increase the total current [23]. A PV system can therefore be configured using combinations of series and parallel connections to achieve the required voltage and power levels.

However, partial shading can prevent a PV array from achieving its maximum power output. Under these conditions, bypass diodes may conduct to protect shaded cells, resulting in multiple peaks in the power–voltage (P–V) characteristics of the array. These multiple peaks complicate the maximum power point tracking (MPPT) process and may reduce the overall power output of the PV system [24].

2.2 Maximum Power Point Tracking (MPPT)

The MPPT algorithm is used to optimize power extraction from a photovoltaic system and deliver the maximum available power to the load. However, PV system performance is influenced by environmental conditions, particularly solar irradiance and temperature. Consequently, the maximum power point changes with variations in these conditions. The optimal operating voltage and current of the PV module therefore fluctuate according to the surrounding environment [25].

Figure 4 illustrates the schematic diagram of a DC–DC converter integrated into a PV system, where *Rin* and *Ro* represent the converter's input resistance and output (load) resistance, respectively. The figure also indicates the location of the MPPT controller within the PV system [26].

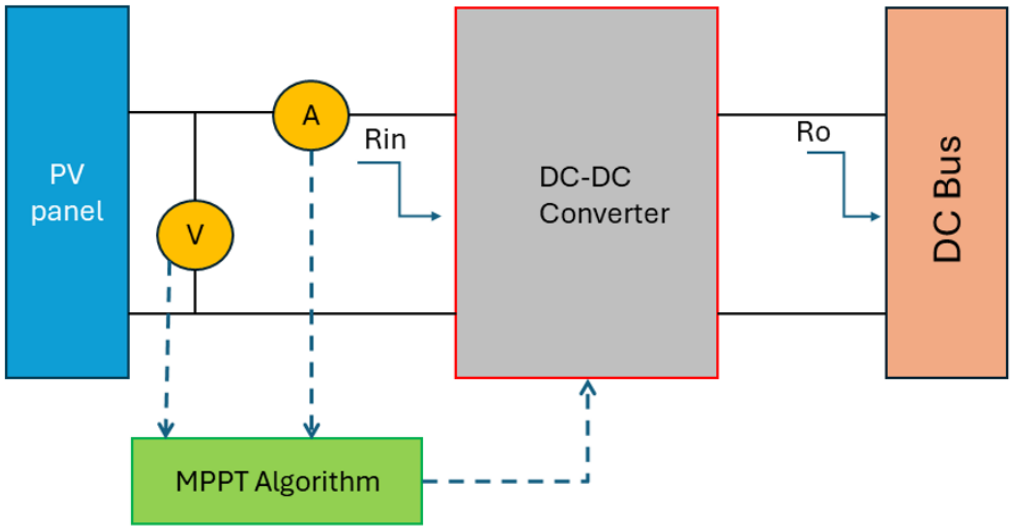


Fig. 4. Illustration of the PV system schematically

For photovoltaic (PV) systems, the Incremental Conductance (IC) method is a maximum power point tracking (MPPT) algorithm used to optimize power extraction from solar panels. The method iteratively adjusts the operating voltage of the PV panel by comparing the incremental conductance

(dI/dV) with the negative instantaneous conductance (−I/V). At the maximum power point (MPP), these values are equal. When the operating point is to the left of the MPP, the voltage is increased, whereas it is decreased when the operating point is to the right of the MPP. This iterative approach maintains operation close to the MPP and enables the system to respond to changes in solar irradiance and temperature, thereby improving energy extraction. The flowchart of the IC technique is presented in Figure 5.

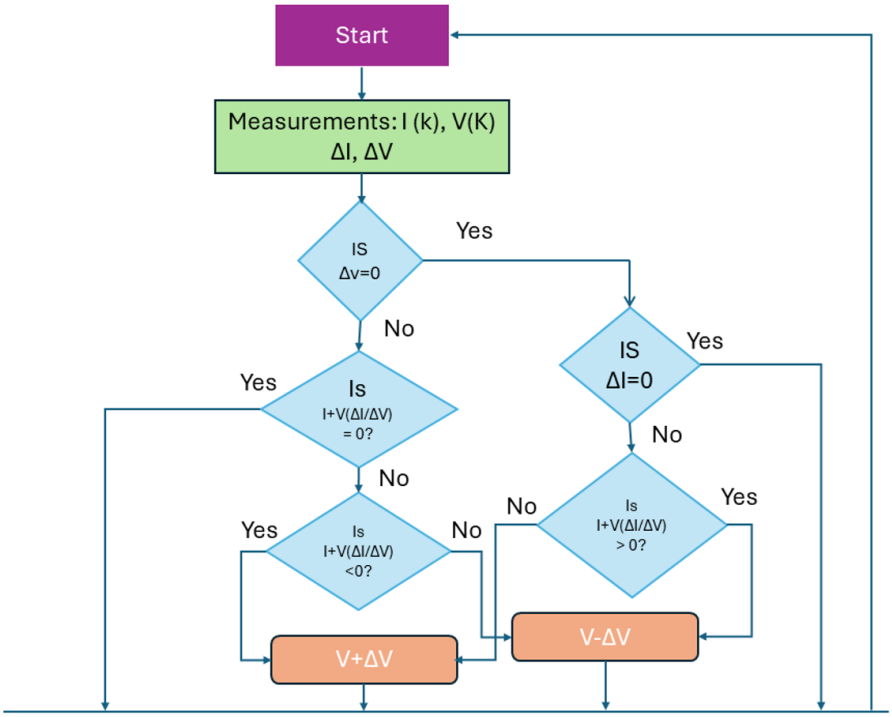


Fig. 5. PV MPPT technique flow chart

Partial shading is a common phenomenon that significantly reduces the efficiency of PV systems. Under partial shading conditions, the power–voltage (P–V) characteristics may exhibit multiple peaks. Therefore, a reliable tracking technique is required to accurately identify the global maximum power point (GMPP) [24, 27]. Conventional MPPT methods, such as Perturb and Observe (P&O) and Incremental Conductance (INC), may fail to identify the GMPP under these conditions because they can become trapped at local maximum power points, resulting in reduced PV system performance. Various MPPT techniques and alternative approaches have been proposed in the literature to accurately identify the GMPP among multiple local maximum power points [23, 28–30]. Figure 6 illustrates the classification of various MPPT techniques.

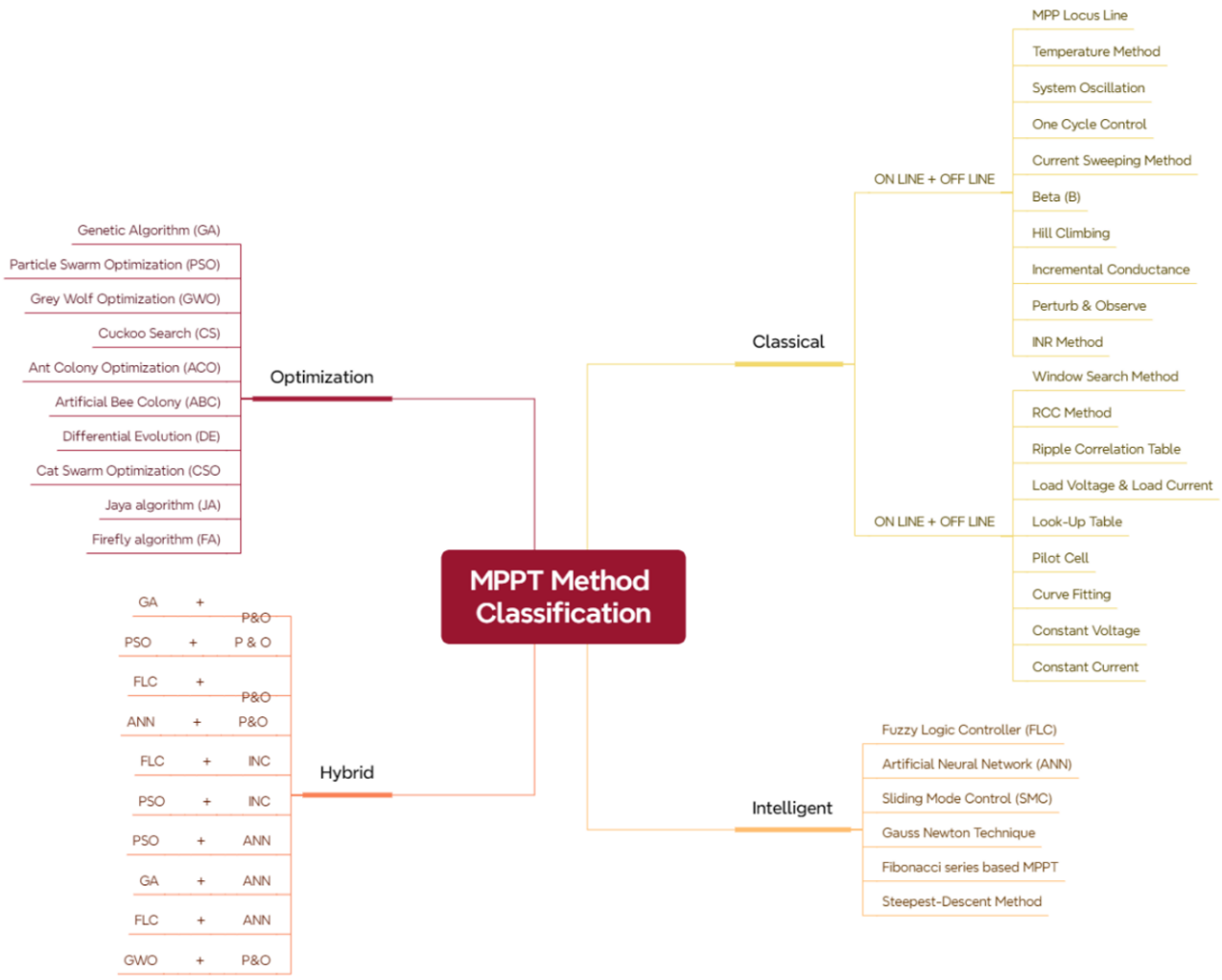


Fig. 6. Classification of Various MPPT Techniques

2.3 Cooling Systems for PV Modules

Photovoltaic (PV) modules absorb solar radiation, part of which is converted into heat, resulting in an increase in their surface temperature. The electrical efficiency of a PV module is determined by the ratio of its electrical power output to the incident solar power. Various cooling techniques have been developed to mitigate the adverse effects of elevated temperatures and improve the performance of PV panels operating under conditions that differ from Standard Test Conditions (STC) [31, 32].

To improve the competitiveness of PV-generated electricity compared with conventional non-renewable energy sources, considerable research has focused on minimizing the adverse effects of high operating temperatures on PV module electrical efficiency. The various PV cooling techniques are reviewed in the following subsections and summarized in Figure 7.

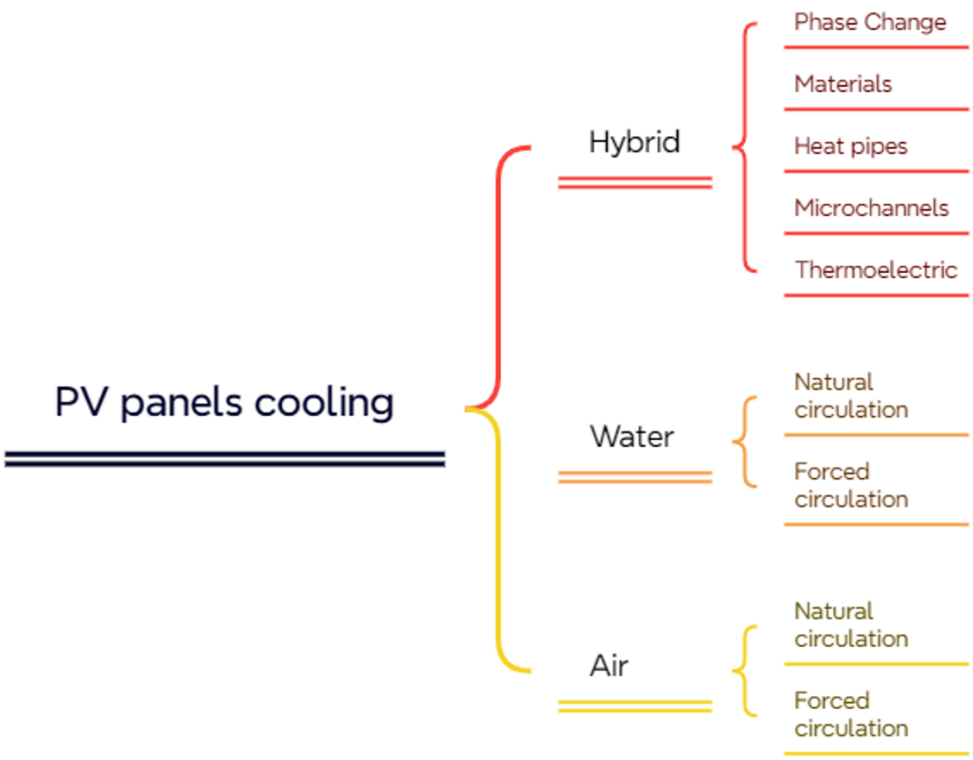


Fig. 7. There are several methods of cooling

To improve the performance of solar panels, this review examines various cooling technologies, including the Floating Tracking Concentrating Cooling System (FTCC), heat sinks, forced water circulation, phase-change materials, water immersion cooling, photonic crystal cooling, forced air circulation, and thermoelectric cooling [33]. Numerous research papers have been reviewed and classified according to their specific focus, contributions, and technological approaches to cooling photovoltaic panels. The findings were analyzed by considering the advantages, limitations, applicability, and techno-economic aspects of each cooling technology [34].

These cooling techniques can improve the electrical efficiency of PV modules, while the extracted heat can be utilized for various applications, thereby increasing overall energy utilization. Several innovative approaches to liquid cooling of photovoltaic modules have been investigated to achieve a more uniform cell temperature, including the use of converging channels. Figure 8 illustrates the proposed channel geometry. According to the principle of mass conservation, a reduction in the channel's cross-sectional area increases fluid velocity, potentially enhancing forced convective heat transfer and improving temperature uniformity. The figure also illustrates various cooling components, including heat exchangers, heat sink fins, water storage reservoirs, and air-cooling pumps [35].

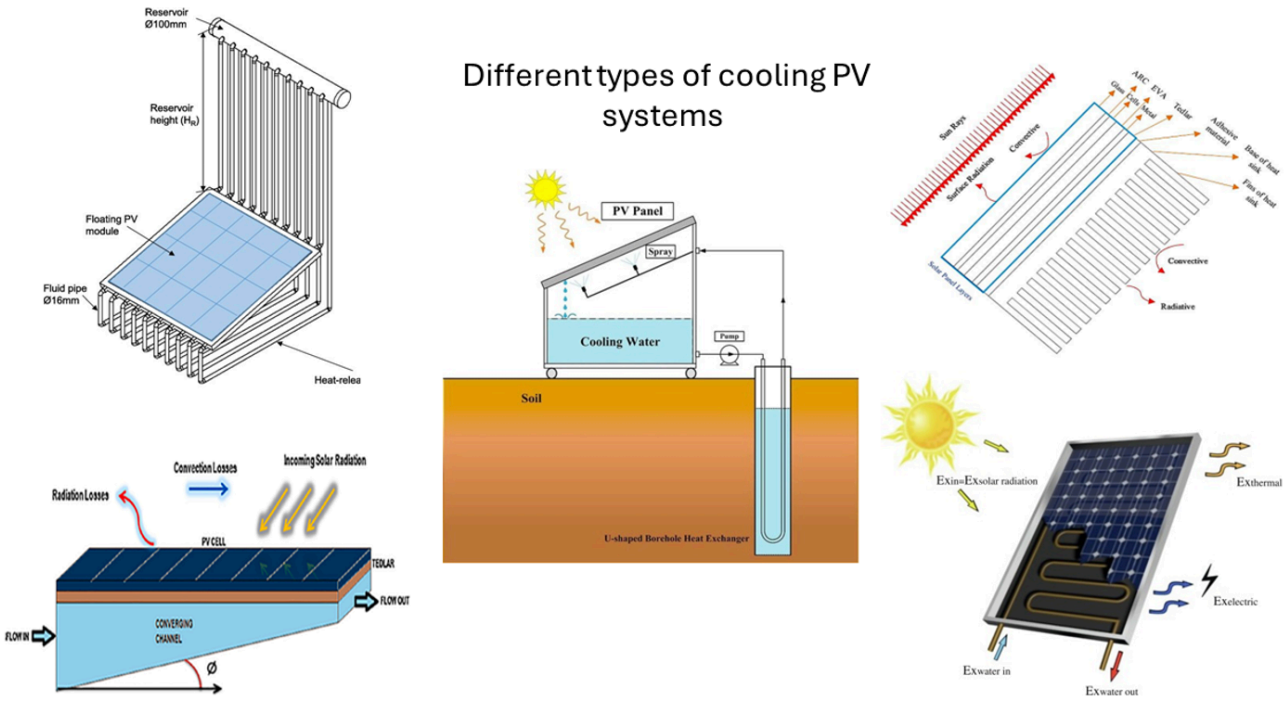


Fig. 8. Various PV system cooling options

Multiple publications from various academic disciplines have been reviewed and categorized according to their research focus, contributions, and technological approaches to improving cooling performance and maximizing PV panel efficiency. Future research should prioritize efficient heat extraction from PV module surfaces and the development of more accurate and reliable cooling systems [36].

The following equation can be used to evaluate the effect of temperature on the electrical efficiency of PV modules:

$$\eta_{pv} = \eta_{TR}[1 - \beta_R(T_C - T_R) + \gamma log_{10} I_{PV}] \quad (1)$$

where η_{pv} is the electrical efficiency of the PV module, T_R is the reference efficiency at the reference cell temperature T_R (25 °C), and β_R is the temperature coefficient of cell efficiency, typically ranging from 0.004 to 0.005 °C^{-1}. I_{PV} represents the incident solar irradiance on the PV module, while T_C is the PV module temperature. The parameter ϒ represents the irradiance-dependent efficiency coefficient. When ϒ is assumed to be zero, Equation (1) simplifies to [35]:

$$\eta_{PV} = \eta_{TR}[1 - \beta_R(T_C - T_R)] \quad (2)$$

By incorporating the ambient temperature, **TA**, into the temperature-related terms, the following expression is obtained:

$$\eta_{PV} = \eta_{TR}[1 - 0.9\beta\left(\frac{I_{PV}}{I_{PV,NT}}\right)(T_{C,NT} - T_{A,NT}) - \beta(TA - TC)] \quad (3)$$

where $\mathbf{T_{C,NT}}$ and $\mathbf{T_{A,NT}}$ represent the cell and ambient temperatures under nominal operating conditions, typically 45 °C and 20 °C, respectively. $I_{PV,NT}$ denotes the solar irradiance under nominal

operating conditions. Equation (3) is intended to describe the influence of irradiance and operating temperature on PV module efficiency. In general, an increase in cell temperature reduces the electrical efficiency of PV modules.

The evaluation of various PV cooling technologies has primarily focused on their advantages, limitations, applications, and techno-economic characteristics. The reviewed technologies include floating tracking concentrating cooling sprinklers, hybrid solar photovoltaic/thermal (PV/T) systems, heat sinks, hydrostatic pressure-based cooling, phase-change materials (PCMs), immersion cooling, transparent coverings, forced air circulation, and thermoelectric cooling systems.

Floating tracking concentrating cooling sprinklers have a limited coverage area, potentially resulting in inefficient water utilization and wastage [37]. Hybrid solar PV/T systems can improve overall energy efficiency; however, their performance may be affected by unstable airflow conditions. Forced water circulation can enhance cooling performance, although a constant flow rate may not provide optimal efficiency under varying operating conditions [38].

Phase-change materials can improve PV panel efficiency, although their effectiveness may vary under extreme hot and cold weather conditions. Water immersion cooling reduces PV module temperatures and improves electrical efficiency, but its applicability may be limited by environmental and operational conditions. Transparent coverings designed to address temperature-related issues may offer potential applications in residential buildings. Furthermore, forced air circulation may provide better cooling performance in colder environments than in hot climates. Thermoelectric cooling systems can provide active temperature control; however, their practical application may be constrained by low conversion efficiency and relatively slow technological development [39].

2.4 Optimization and Simulation Work

Soft computing (SC) techniques have emerged as practical alternatives to conventional methods for solving complex nonlinear optimization problems in partially shaded photovoltaic (PV) systems. Several optimization algorithms have been proposed, including Glowworm Swarm Optimization (GSO), the S-Jaya algorithm, Ant Colony Optimization (ACO), Modified Ant Colony Optimization, Particle Swarm Optimization (PSO), and the Bat Algorithm [29].

These algorithms have demonstrated promising performance in addressing the multiple-peak global maximum power point tracking (GMPPT) problem. Various hybrid MPPT techniques have also been investigated, including Perturb and Observe with Artificial Neural Networks (P&O–ANN), Fireworks Optimization with P&O, Grey Wolf Optimization with P&O, Bat Algorithm with P&O (Bat–P&O), and Particle Swarm Optimization with P&O (PSO–P&O) [30]. Other hybrid approaches combine intelligent optimization algorithms, including Simulated Annealing, Particle Swarm Optimization, and the Shuffled Frog Leaping Algorithm (SFLA), to improve tracking performance under complex operating conditions [40].

The Hybrid Optimization of Multiple Energy Resources (HOMER) software is widely used to simulate and evaluate hybrid energy systems based on their technical and economic performance. HOMER has been extensively applied to both off-grid and grid-connected systems for system design, feasibility assessment, operational planning, and analysis of energy system inputs.

The software enables the identification of optimal system configurations that support sustainable energy supply. Different configurations are evaluated and ranked using economic indicators, particularly the levelized cost of energy (COE) and net present cost (NPC). The HOMER Optimizer uses predefined system parameters and search spaces to identify suitable configurations for different energy system designs [37, 40–44].

Table 1
Summary of Studies on Solar Photovoltaic Tracking Systems

Ref.	Research Aim	Key Findings	Methods Used	Efficiency / Performance
[45]	Investigate the application of Honey Badger Optimization (HBO) for MPPT systems.	HBO outperformed conventional MPPT algorithms in terms of power loss, accuracy, oscillations, and iterations.	HBO algorithm evaluated using five PV module configurations under real-time operating conditions.	Reported performance exceeding 97%.
[46]	Compare conventional MPPT algorithms with modern metaheuristic approaches.	Artificial Rabbit Optimization (ARO) performed better under standard test conditions.	Perturb and Observe (P&O), Incremental Conductance (INC), ARO, and Most Valuable Player (MVP) algorithms.	ARO achieved 99.86% efficiency under unshaded conditions.
[47]	Review time-based solar tracking systems and identify future research opportunities.	Examined tracking configurations according to driving mechanisms and axis rotation.	Comparative review of time-based tracking systems and drive mechanisms.	Maximum incident solar power is obtained when sunlight is perpendicular to the panel surface.
[48]	Develop the Offshore Solar Irradiance Calculator (OSIC) to investigate the effects of wave motion on offshore PV systems.	Evaluated wave-induced motion and its influence on offshore solar tracking performance.	OSIC simulation and annual parametric analysis of wave characteristics and tracking configurations.	Not reported.
[49]	Evaluate solar tracking systems using technical, economic, and environmental criteria.	Two-axis tracking generated the highest electricity output, while fixed-tilt systems achieved the lowest LCOE.	SWARA, WASPAS, EDAS, and ARAS multicriteria decision-making methods.	Two-axis tracking produced 31.8% more electricity than fixed-tilt systems; horizontal tracking had an 8.8% higher LCOE.
[50]	Review deep learning approaches for PV tracking systems.	Hybrid deep learning models were identified as commonly preferred approaches.	Review of datasets, preprocessing methods, feature extraction, and deep learning models.	Quantitative efficiency not reported.
[51]	Investigate Support Vector Machine Regression (SVMR) for PV maximum power point tracking.	The proposed SVMR controller improved MPP tracking performance.	SVMR-based control and a perceptron-type Artificial Neural Network (ANN) model.	Reported MPP tracking performance exceeding 94%.
[52]	Review and classify MPPT algorithms for solar PV applications.	Summarized the advantages and limitations of different MPPT methods.	Classification into conventional, intelligent, optimization-based, and hybrid techniques.	Comparative review; no specific efficiency reported.
[53]	Simulate a 3 MWp solar PV facility in Nigeria and compare energy generation configurations.	Bifacial PV systems demonstrated higher energy yields under the evaluated configurations.	Simulation comparing monofacial, bifacial, fixed-tilt, and tracking PV systems.	Bifacial gain of 12%; tracked bifacial systems achieved an 8.9% gain relative to tracked monofacial systems.
[54]	Identify an effective solar tracking control strategy using mathematical and electrical models.	Proposed a control strategy intended to maximize solar power generation.	Mathematical modeling of variable-orientation PV panels and electrical performance.	Quantitative efficiency not reported.
[55]	Apply the Search and Rescue Algorithm (SRA) to improve MPPT performance.	SRA improved power generation, energy yield, and tracking response compared with other MPPT techniques.	Comparison with GHO, GWO, PSO, Cuckoo Search, and PSO–Gravitational Search methods.	Up to 99.93% steady-state efficiency; reported improvements of 8% in power and 5% in energy.

[56]	Evaluate a 1.5-axis tracking (1.5AT) configuration for utility-scale PV systems.	Proposed a benchmarking approach for evaluating shading and energy performance across locations and seasons.	Feasibility assessment, shading analysis, and energy performance evaluation.	Potential improvement in investment returns; quantitative efficiency not reported.

3. Forecasting and Prediction in PV Systems

3.1 Introduction and Literature on Prediction Systems

Artificial intelligence (AI) is transforming various fields, with machine learning (ML) emerging as one of its key techniques. ML models are widely used to predict energy demand, electricity prices, and solar energy generation. In photovoltaic (PV) systems, ML is also applied to model PV panel performance and optimize energy conversion efficiency. Several studies have explored the applications of ML in solar energy systems, highlighting recent developments and promising approaches across different areas [57].

A neuro-fuzzy system has been developed to classify daily solar irradiance profiles and predict the performance of photovoltaic installations. The system employs fuzzy logic to classify irradiance profiles in a linguistically interpretable manner. Additionally, a relatively simple yet accurate classifier was developed using data mining and supervised learning techniques [58].

Another study investigated the application of ensemble numerical weather prediction (NWP) to solar power forecasting. The study introduced an archived dataset from the European Centre for Medium-Range Weather Forecasts (ECMWF) Ensemble Prediction System for probabilistic solar power estimation. It emphasized the importance of ensemble forecasting in generating multiple plausible trajectories of future weather conditions. However, producing such forecasts requires expertise in atmospheric science and substantial computational resources, which are typically provided by meteorological centers [59].

Another study aimed to identify the research directions necessary to achieve dispatchable PV electricity and increase PV penetration in global power systems. It addressed challenges associated with the intermittent nature of solar power generation and the resources required for integrating PV systems into existing power infrastructure. The study emphasized the importance of improving system flexibility while reducing uncertainty and variability in PV power generation. It concluded that dispatchable PV power, supported by advancements in energy storage, forecasting, and curtailment strategies, is both necessary and feasible for achieving high PV penetration [60].

Machine learning techniques have also been investigated for predicting electricity generation from building-integrated PV systems. Different algorithms were evaluated in terms of forecasting accuracy and practical applicability. The random forest algorithm demonstrated high prediction accuracy with relatively limited training data. The study also examined the influence of feature selection and meteorological parameters on forecasting performance [61].

A comprehensive review examined the application of machine learning and deep learning algorithms to solar irradiance and PV power forecasting across different temporal and spatial scales. The review discussed existing challenges, influencing factors, forecasting methodologies, and potential research directions. It also identified suitable prediction algorithms and approaches to assist engineers and researchers in optimizing solar energy applications [62].

Another study investigated commonly used machine learning approaches and existing research gaps in solar power forecasting. It highlighted the challenges associated with unpredictable weather conditions and uncertainties in PV system operation. The study emphasized the importance of incorporating climatic variations into forecasting models and discussed the limitations of certain ML techniques. It also provided recommendations for future research [63].

Quantile regression techniques have been widely investigated for probabilistic forecasting in various fields, including energy systems and building engineering. A comprehensive review presented different quantile regression algorithms and evaluation criteria for assessing forecasting performance [64].

Short-term probabilistic forecasting of PV power output remains challenging because of fluctuations in weather conditions and solar irradiance. One study examined the limitations of conventional linear prediction models and the potential advantages of deep learning approaches, particularly the Minimal Gated Memory (MGM) network. The study incorporated Quantile Regression (QR) for interval prediction and Fuzzy C-Means (FCM) clustering into a proposed QR-BiMGM model. The results demonstrated improved prediction interval coverage and width compared with other models, indicating enhanced accuracy and reliability in probabilistic PV power forecasting [65].

The Bui Power Authority generates grid-connected solar electricity, which is sold to Ghana Grid Company Limited (GRIDCo) through bilateral contracts. However, forecasting solar power generation remains challenging because of variations in weather and climatic conditions. A study employing random forest and gradient boosting regression algorithms developed deterministic and probabilistic forecasts of solar electricity generation. The random forest model demonstrated improved forecasting accuracy, achieving a normalized mean absolute error of 1.18%. The study highlighted the potential contribution of accurate solar power forecasting to reliable renewable energy generation and the objectives of the African Union's Agenda 2063 [66].

Accurate PV power forecasting is essential for managing energy flows as photovoltaic generation becomes increasingly integrated into electrical networks. One study investigated regional PV power forecasting by comparing six prediction models over one year across six electricity bidding zones in Italy. The results indicated that forecasting accuracy was strongly influenced by the selected model and the associated data preprocessing and postprocessing techniques. Performance differences of approximately 30% were observed among the evaluated approaches. Furthermore, irradiance forecasting accuracy had a smaller influence on regional PV power predictions than on forecasts for individual PV plants. The impact of the forecasting area on prediction accuracy also decreased as the geographical aggregation increased [67].

Another study proposed a short-term solar power forecasting approach for an 89.6 kWp solar PV power plant in India. The model employed the Autoregressive Integrated Moving Average (ARIMA) method to predict electricity generation. The proposed approach was relatively simple, reliable, and adaptable to varying environmental conditions. The ARIMA model demonstrated improved root mean square error (RMSE) and forecast score values for 15-minute and 30-minute forecasting horizons compared with the benchmark persistence-based methods [68].

Several studies have also compared advanced machine learning techniques for short-term PV power forecasting. One investigation evaluated ten ML methods and proposed a hybrid forecasting approach combining the best-performing models. MATLAB simulations demonstrated that seasonal variations significantly influenced the forecasting accuracy of the evaluated techniques [69, 70].

Because PV systems exhibit nonlinear characteristics, the relationship between environmental parameters and electrical power output is complex. To improve prediction accuracy, a hybrid approach combining K-Means++ clustering with a deep neural network featuring adjustable input and output structures (K-IAOA-DNN) was proposed. The model integrated clustering and deep learning techniques to address variations in weather conditions and PV system degradation [71].

A forecasting tool incorporating four deep learning predictors was also developed to facilitate PV power participation in Day-Ahead Market (DAM) and Intra-Day Market (IDM) electricity auctions. The

proposed tool was evaluated using five PV systems and their aggregated electricity generation, considering the geographical distribution of the installations [72].

3.2 Key Determinants Affecting Prediction Accuracy

Data-driven models have been extensively investigated for forecasting solar photovoltaic power generation. One study evaluated an alternative approach to operational PV forecasting by using numerical weather prediction (NWP) data to assess an artificial neural network (ANN) trained on historical weather observations.

The study compared the performance of an ANN trained using observational data from three locations in eastern Finland with models trained using historical NWP data. The results indicated that the ANN trained on observational data performed less accurately than models trained on NWP forecasts. Nevertheless, the ANN demonstrated better forecasting performance than a conventional physical model.

The study concluded that historical NWP forecasts should preferably be used for training and evaluating data-driven forecasting models when such data are available. However, historical weather observations may serve as a suitable alternative when NWP data are limited [73].

3.2.1 Effects of Changing Weather Parameters on Prediction Accuracy

One study investigated the verification of numerical weather prediction models for solar irradiance forecasting, which is an essential component of PV power prediction. Various verification techniques and case studies were employed, including seasonal verification, point-based versus area-based verification, variance ratio analysis, and Murphy–Winkler decomposition.

The findings indicated that irradiance forecasting accuracy does not always directly reflect the accuracy of PV power forecasts, contrary to common assumptions. The study provided valuable insights into how errors in solar irradiance predictions influence PV power forecasting performance [74].

3.2.2 Forecasting Horizons

Forecasting horizons are generally classified into three categories: short-term, medium-term, and long-term forecasting. Some researchers have proposed an additional category, referred to as very short-term or ultra-short-term forecasting, which primarily supports operational decision-making in smart grids and microgrids. However, no universally accepted classification criteria have been established for these forecasting horizons [75].

Various forecasting techniques used to predict solar PV power generation are classified and illustrated in Figure 9. To achieve accurate forecasting results, an appropriate prediction method should be selected based on the available data, forecasting objectives, and required time horizon. The following section discusses commonly used forecasting models and the proposed prediction approach.

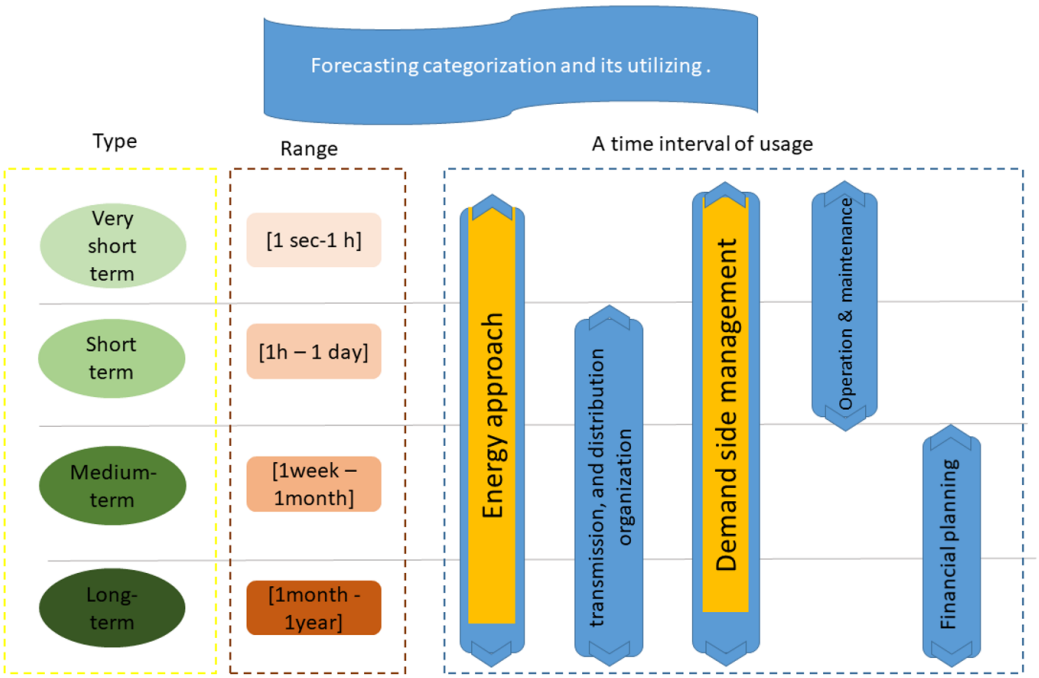


Fig. 9. Classification of Solar Photovoltaic Power Forecasting Based on Forecasting Horizons

As illustrated in Figure 10, various forecasting methods have been developed in the literature to predict solar photovoltaic (PV) power generation. These methods can be broadly classified into several categories. Selecting an appropriate forecasting method based on the available data and the desired forecasting horizon is essential for achieving accurate predictions. The following section reviews commonly used forecasting models and the proposed model.

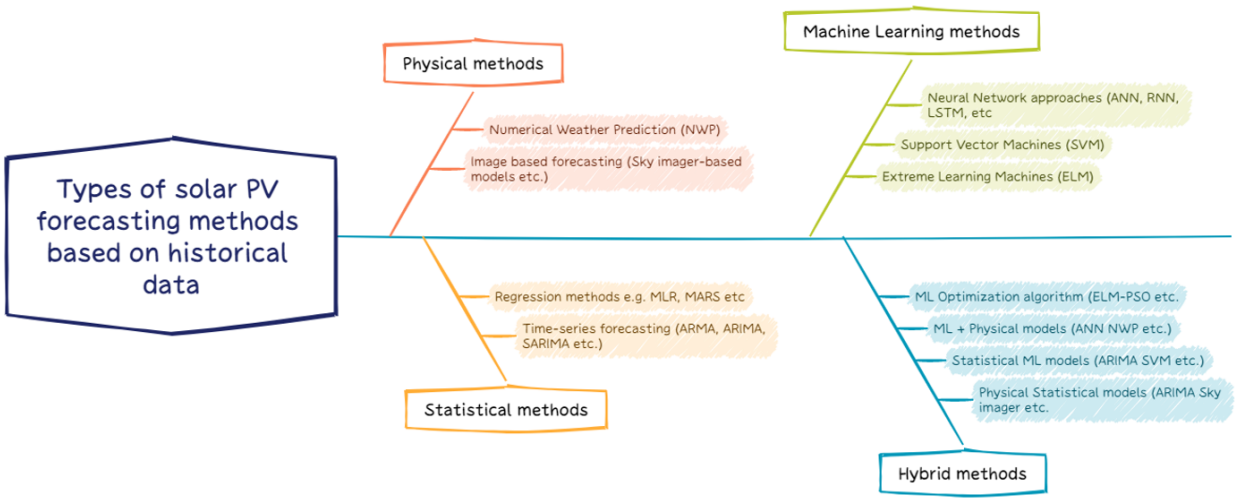


Fig. 10. Classification of Solar Photovoltaic Forecasting Methods Based on Historical Data Analysis

3.3 Forecasting Models and Techniques

3.3.1 Neural Networks

Various models and methodologies have been investigated for predicting photovoltaic (PV) power generation, including artificial neural networks (ANNs) and deep learning algorithms. Previous

research has emphasized the importance of considering multiple factors, such as solar irradiance, weather conditions, and cloud movement, to improve the accuracy of PV power forecasting [75].

A study proposed an optimal generation scheduling and operating reserve management strategy for standalone PV-integrated microgrids. A two-stage recurrent neural network-based model was employed to forecast solar irradiance and cloud cover. The proposed approach also incorporated weather-based PV operating reserve management and an optimal power output scheduling model. The results demonstrated improved performance compared with conventional approaches, reducing the required PV operating reserve to 30% of the power output under clear-sky conditions and achieving cost savings exceeding 5.5% [76].

Figure 11 illustrates the simplified architecture of a Multilayer Perceptron Neural Network (MLPNN), consisting of eight input nodes for solar power prediction.

Another study proposed a two-stage training framework for probabilistic forecasting using deep learning and Quantile Regression (QR). The framework was developed to address the challenges associated with non-differentiable loss functions during the training of Quantile Convolutional Neural Networks (QCNNs).

In the first stage, a Convolutional Neural Network (CNN) was trained using a deterministic forecasting approach. In the second stage, a linear programming method was employed to train the quantile regression component. By avoiding the direct optimization of non-differentiable loss functions, the proposed approach enabled QCNNs to generate the required probabilistic forecasts.

The results demonstrated that QCNNs trained using this framework achieved improved forecasting accuracy and reliability compared with alternative methods, indicating their potential for applications requiring probabilistic predictions [77].

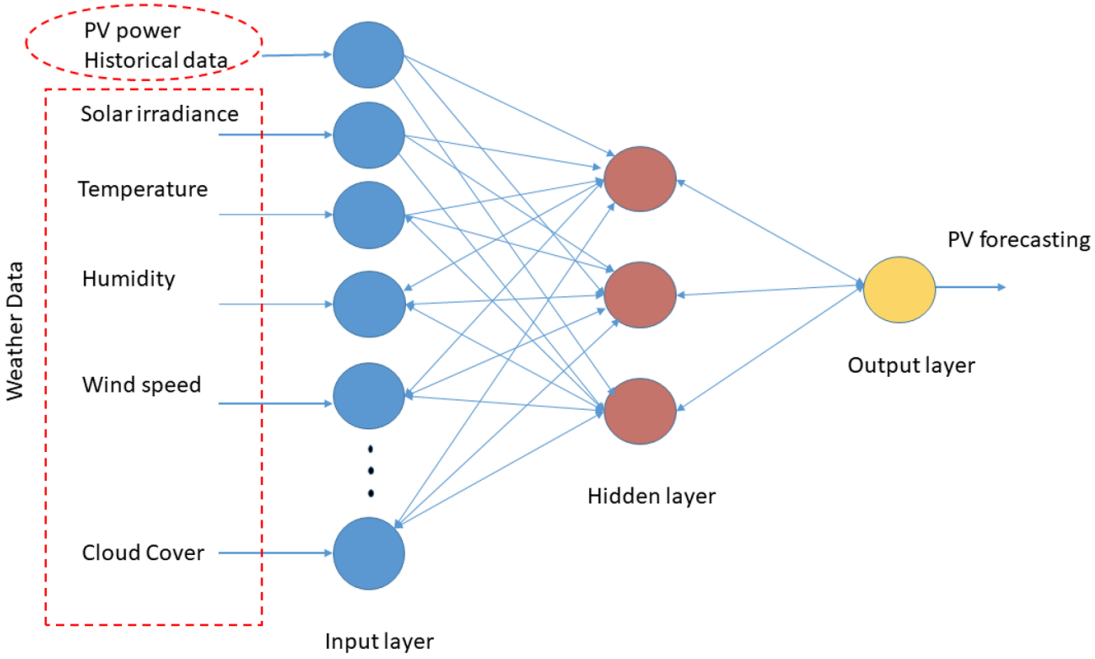


Fig. 11. Basic Structure of a Multilayer Neural Network for PV Power Forecasting

Among the various types of Artificial Neural Networks (ANNs), Recurrent Neural Networks (RNNs) are distinguished by their ability to model complex interdependent relationships and dynamic temporal patterns. The activation of a neuron in an RNN is calculated by summing the weighted inputs and recurrent feedback signals, together with a bias term. This relationship can be mathematically expressed using the following activation function [75]:

$$S_K(t) = \sum_{p=1}^{p+1}(W_{ik}X_p(t))\sum_{q=1}^{q} V_{kq}Y_q(t) \quad (4)$$

where the activation function represents the output of processing node (k) at time (t), the connection weights represent the influence of signals from connected nodes, the weight vector contains the corresponding weights for processing node (k), and the bias term adjusts the activation threshold. Figure 12 illustrates the relationships between these components.

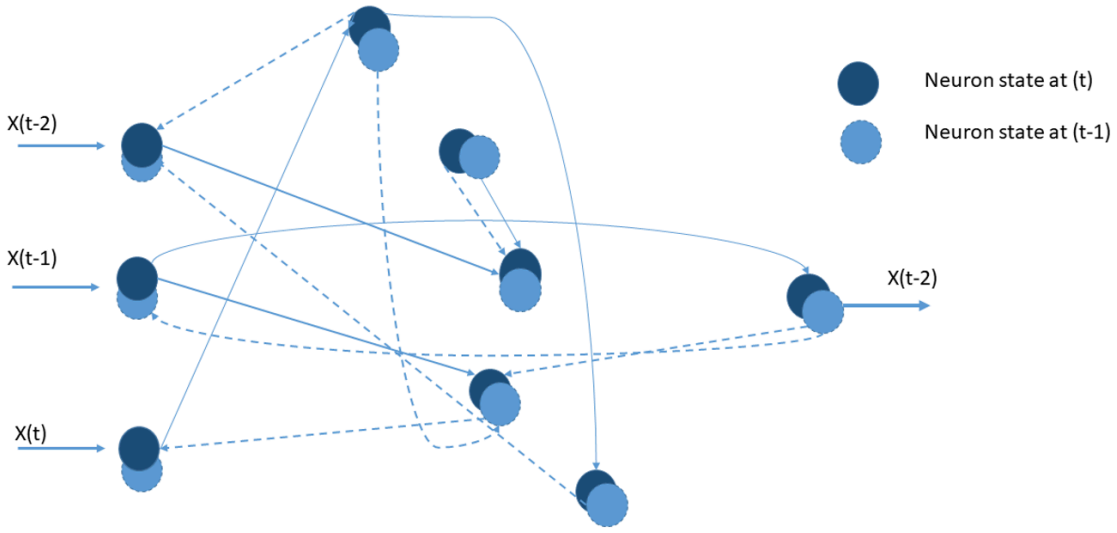


Fig. 12. Fundamental Structure of a Recurrent Neural Network

In 2006, a revised version of the Extreme Learning Machine (ELM) algorithm was introduced. Figure 13 illustrates the comprehensive architecture of the improved ELM. The network structure consists of three main layers: the input layer, the hidden layer, and the output layer.

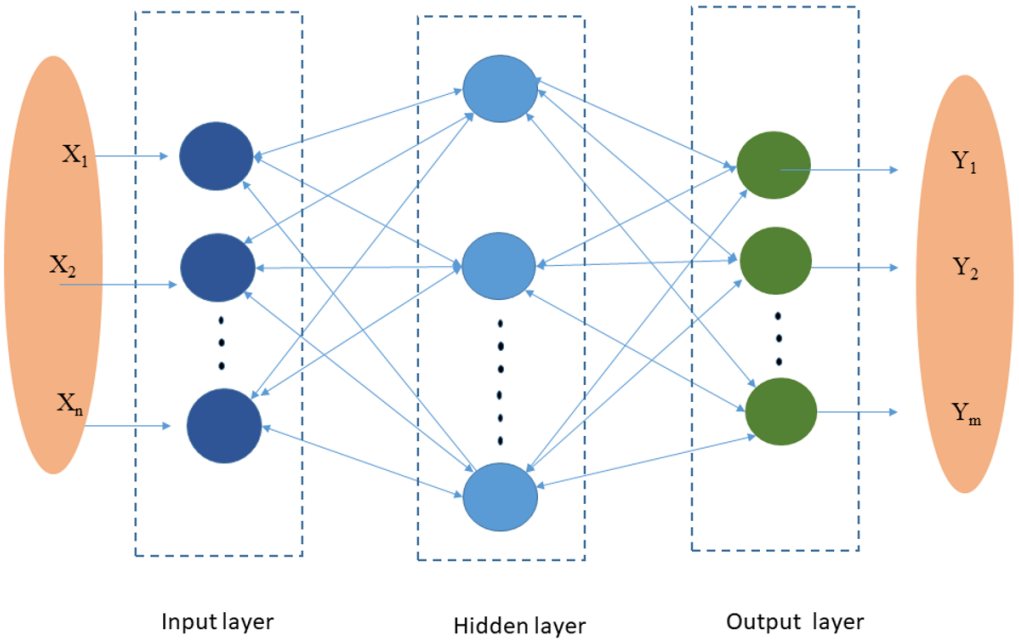


Fig. 13. Structure of the Extreme Learning Machine (ELM) Model

The network output is calculated using (N) training samples, (K) hidden neurons, and an activation function, as expressed in Equation (5) [75].

$$y_i = \sum_{i=1}^{K} \beta_i g(w_i . x_i + b_i) , j = 1,2, \ldots . , N \quad (5)$$

where (w_i) and (\beta_i) represent the connection weight vectors between the input and hidden neurons and between the hidden and output neurons, respectively, while (b_i) denotes the bias of the (i)th hidden neuron.

3.3.2 Long Short-Term Memory (LSTM)

A study reviewed machine learning techniques for photovoltaic (PV) power forecasting, focusing on grid sustainability and achieving the United Nations Sustainable Development Goals by 2030. The findings indicated that grouping datasets based on feature similarity improved forecasting accuracy, while Long Short-Term Memory (LSTM) models demonstrated superior performance across different forecasting horizons. A novel deep learning network model was also proposed to address complex data patterns [78].

Another study proposed an LSTM-based forecasting algorithm to predict photovoltaic power generation. The algorithm employed K-means clustering and historical solar irradiance data to generate simulated weather forecasts for the target PV plant location. The proposed approach significantly improved forecasting accuracy, achieving improvements of up to 33% compared with hourly sky-condition forecasts and 44.6% compared with daily sky-condition forecasts. Comparisons with other machine learning approaches, including Recurrent Neural Networks (RNNs), Generalized Regression Neural Networks (GRNNs), and Extreme Learning Machines (ELMs), further demonstrated the superior performance of the proposed model [79].

One of the major challenges associated with photovoltaic systems is their nonlinear power output characteristics. LSTM-based models are particularly effective in capturing nonlinear relationships between input and output parameters in time-series datasets. Consequently, LSTM models have been widely applied to investigate the influence of meteorological conditions on solar power generation.

Figure 14 illustrates the schematic structure of a typical LSTM cell. The memory cell stores information over successive time steps, while three primary gates regulate the flow of information. These gates are the input gate, forget gate, and output gate. The input gate controls the incorporation of new information into the cell state, the forget gate determines which information should be retained or discarded, and the output gate regulates the information transferred to the hidden state. Together, these mechanisms control the cell state and hidden state, enabling the network to capture long-term dependencies in sequential data.

A Bidirectional Long Short-Term Memory (BiLSTM) neural network has been effectively applied to solar energy forecasting to predict short-term solar irradiance using meteorological data. The proposed model demonstrated superior forecasting accuracy and learning speed compared with the Multilayer Perceptron (MLP) model. It also addressed challenges associated with the intermittent and variable nature of solar energy generation in multi-energy systems. Future research directions include the development of cloud-based computing infrastructure for efficient data processing. The potential applications of the model in anomaly detection and real-time monitoring were also discussed [80].

The BiLSTM architecture was employed to overcome the limitations of conventional neural networks by capturing information from both past and future contexts within a given input sequence,

as illustrated in Figure 15. Compared with the feedforward MLP model, BiLSTM offers several advantages. Its recurrent connections enable information to be retained across successive time steps, while its gating mechanisms help mitigate the vanishing gradient problem and improve the learning of long-term dependencies. Furthermore, its memory cells allow the network to capture complex temporal relationships and adapt to variations in sequential data.

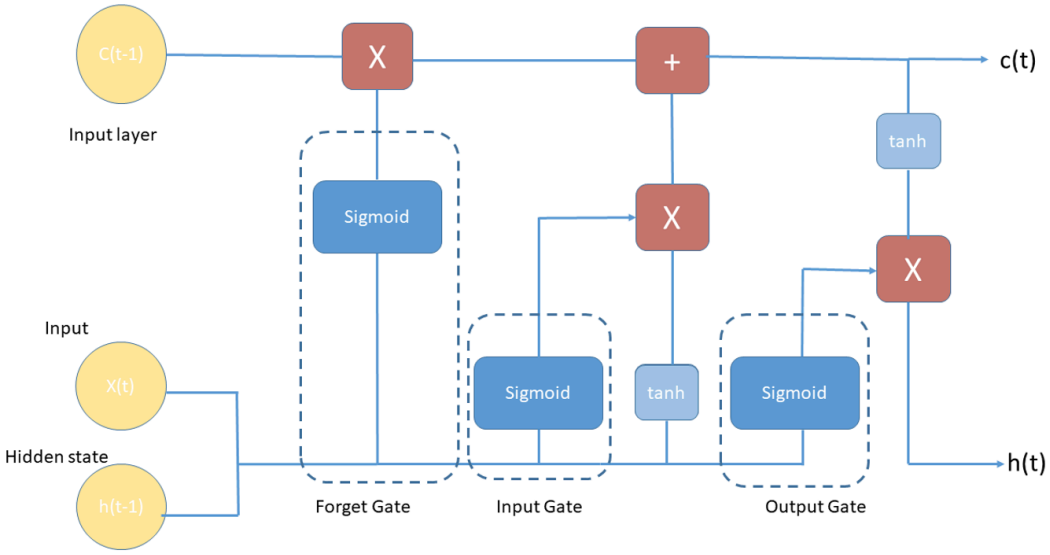


Fig. 14. Standard Long Short-Term Memory (LSTM) Cell Architecture

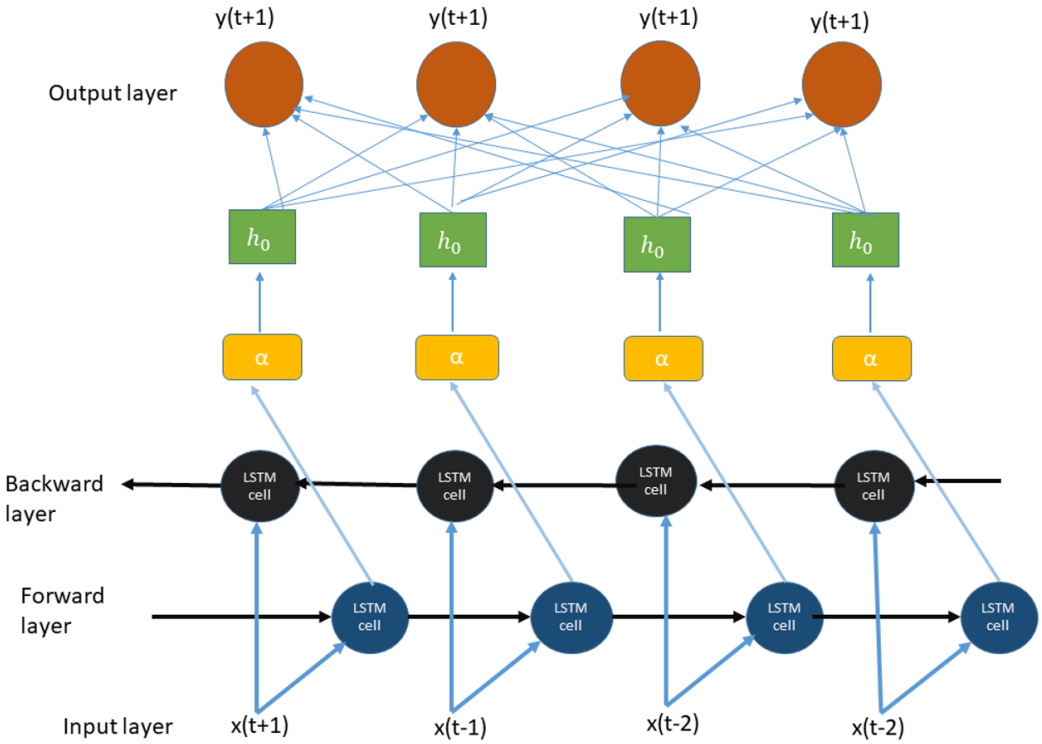


Fig. 15. Schematic Representation of a Bidirectional Long Short-Term Memory (BiLSTM) Network

Traditional Recurrent Neural Networks (RNNs) have limitations in capturing long-term dependencies because of the vanishing and exploding gradient problems. Long Short-Term Memory (LSTM) networks address these limitations by incorporating memory cells and gating mechanisms

that retain relevant information over extended time sequences. In conventional unidirectional RNNs, predictions are generated using information from preceding time steps. In contrast, Bidirectional Long Short-Term Memory (BiLSTM) networks process sequential information in both forward and backward directions, enabling the model to capture past and future contextual relationships within an input sequence.

The hidden state, h_t, represents the output of an LSTM cell at time step (t) and is calculated using the cell state and output gate [80].

$$h_t = \tanh(c_t) * o_t \quad (6)$$

$$i_t = \sigma(x_t U^i + h_{t-1} w^i) \quad (7)$$

$$f_t = \sigma(x_t U^f + h_{t-1} w^f) \quad (8)$$

$$o_t = \sigma(x_t U^o + h_{t-1} w^o) \quad (9)$$

$$\bar{\bar{C}}_t = \tanh(x_t U^g + h_{t-1} w^g \quad (10)$$

$$c_t = \sigma(f_t * c_{t-1} + i_t * \bar{\bar{C}}_t) \quad (11)$$

The forward and backward hidden states of the BiLSTM network are expressed as:

$$h_t^f = \tanh(x_t U_{xh}^f + h_{t-1}^f W_h^f \quad (12)$$

$$h_t^f = \tanh(x_t U_{xh}^f + h_{t-1}^f W_h^f \quad (13)$$

Finally, the forward and backward hidden states are combined to obtain the output:

$$y_t = h_t^b + h_t^f \quad (14)$$

3.3.3 Hybrid Techniques

A Cascaded Multi-Fidelity Deep Learning (CMF-DL) framework was proposed to address the challenges associated with day-ahead photovoltaic power (PVP) forecasting. The framework can incorporate different deep learning architectures, including Long Short-Term Memory (LSTM) and Gated Recurrent Unit (GRU) models. Two forecasting models, namely CMF-LSTM and CMF-GRU, were developed and evaluated using actual PV plant data. The results demonstrated that the proposed models achieved improved forecasting accuracy and noise reduction compared with conventional baseline models [81].

Another study introduced a hybrid cascaded forecasting network that integrates several techniques, including LSTM, Nonlinear Autoregressive Networks with Exogenous Inputs (NARX), Extreme Learning Machines (ELM), MRIG-based feature selection, and Wavelet Transform (WT). The proposed approach aimed to improve the accuracy and efficiency of solar power generation forecasting (SPGF) over a 24-hour prediction horizon, particularly in developing countries [82].

A novel attention-based Bayesian Sequence-to-Sequence (Seq2Seq) model was also developed for short-term solar power generation forecasting. The model integrates a decomposition-ensemble framework, influential factor analysis, and an attention mechanism to improve forecasting

performance. Through case studies and comparative analyses, the proposed approach demonstrated superior prediction accuracy compared with alternative methods. The study also emphasized the importance of solar energy in addressing environmental challenges [83].

Another study proposed a hybrid model for short-term PV power forecasting by integrating a Transformer Neural Network (TransNN) with a Convolutional Neural Network (CNN). Variational Mode Decomposition (VMD) was employed during the data preprocessing stage to enhance forecasting accuracy. The proposed model was evaluated using two real-world datasets and compared with five benchmark models. The results indicated that the hybrid VMD–CNN–TransNN approach achieved higher forecasting accuracy than the benchmark methods [84].

3.4 Forecasting Error Evaluation

Performance evaluation is essential for assessing the accuracy and reliability of forecasting models. Commonly used evaluation metrics include Mean Absolute Error (MAE), Root Mean Square Error (RMSE), and Mean Absolute Percentage Error (MAPE).

MAE measures the average absolute difference between actual and predicted values, while RMSE calculates the square root of the mean squared differences. RMSE assigns greater weight to larger prediction errors, making it particularly sensitive to substantial deviations and outliers.

Normalized Root Mean Square Error (nRMSE) provides a relative measure of forecasting error, facilitating comparisons across datasets with different scales. Both MAE and RMSE range from zero to infinity, with lower values indicating better forecasting performance.

MAPE expresses the average absolute prediction error as a percentage of the actual values, providing an interpretable measure of relative forecasting accuracy. Similarly, normalized Mean Absolute Percentage Error (nMAPE) can be used to evaluate prediction errors relative to the average observed value. The mathematical expressions for these evaluation metrics are presented in Equations (15)–(19) [75].

$$\mathrm{MAE} = \frac{1}{\mathrm{N}}\sum_{\mathrm{i}=1}^{\mathrm{N}} \left|\mathrm{y}_{\mathrm{j}-\mathrm{t}_\mathrm{j}}\right| \tag{15}$$

$$\mathrm{RMSE} = \sqrt{\frac{1}{\mathrm{N}}\sum_{\mathrm{i}=1}^{\mathrm{N}}(\mathrm{y}_\mathrm{i} - \mathrm{t}_\mathrm{i})^2} \tag{16}$$

$$\mathrm{nRMSE} = \frac{\sqrt{\sum_{\mathrm{i}=1}^{\mathrm{N}}(\mathrm{y}_\mathrm{i}-\mathrm{t}_\mathrm{i})^2}}{\sqrt{\sum_{\mathrm{i}=1}^{\mathrm{N}}\mathrm{y}_\mathrm{i}{}^2}} \tag{17}$$

$$\mathrm{MAPE} = \frac{1}{\mathrm{N}}\sum_{\mathrm{i}=1}^{\mathrm{N}} \frac{|\mathrm{y}_\mathrm{i}-\mathrm{t}_\mathrm{i}|}{\mathrm{y}_\mathrm{i}} \times 100\% \tag{18}$$

$$\mathrm{nMAPE} = \frac{1}{\mathrm{N}}\sum_{\mathrm{i}=1}^{\mathrm{N}} \frac{\left|\mathrm{y}_{\mathrm{i}-\mathrm{t}_\mathrm{i}}\right|}{\frac{1}{\mathrm{N}}\sum_{\mathrm{i}=1}^{\mathrm{N}}\mathrm{y}_\mathrm{i}} \times 100\% \tag{19}$$

where y_i and t_i represent the measured and predicted PV power values, respectively, and N denotes the total number of test samples.

A study investigated the influence of meteorological conditions on power system planning and forecasting, particularly in solar power generation. It examined the use of horizontal pyranometers and the potential inaccuracies associated with estimating electricity generation. A novel forecasting

approach applied to a photovoltaic solar facility in Peru reduced the Mean Absolute Percentage Error (MAPE) from 12.14% to 5.93%. The study also discussed various solar irradiance prediction techniques, including Artificial Neural Networks (ANNs) and Recurrent Neural Networks (RNNs) [85].

Another study proposed an approach to improve one-hour-ahead deterministic PV power forecasting by dynamically combining the predictions of multiple deep learning models. Four baseline models with different long- and short-term memory architectures were employed to predict PV power generation without relying on numerical weather prediction data. The results indicated that the forecasting performance of individual models varied across different PV plants [86].

A novel deep learning approach, referred to as SSA-RNN-LSTM, was proposed to forecast the hourly power output of three different solar photovoltaic systems. The proposed method was compared with GA-RNN-LSTM, PSO-RNN-LSTM, and conventional RNN-LSTM models. The results demonstrated improved forecasting accuracy, with lower Root Mean Square Error (RMSE), Mean Square Error (MSE), and Mean Absolute Error (MAE) values compared with the benchmark methods [87].

Machine learning techniques have been widely employed to improve the accuracy of photovoltaic power forecasting. These methods analyze historical data to identify patterns and relationships that influence future power generation. Various machine learning approaches have been investigated, including Extreme Gradient Boosting (XGBoost), Recurrent Neural Networks (RNNs), Convolutional Neural Networks (CNNs), and Decision Trees [88, 89].

Transfer learning has also been applied to address the limitations associated with insufficient historical data by transferring knowledge from related domains with more extensive datasets. Overall, machine learning approaches have demonstrated promising potential for improving PV power forecasting accuracy, even under conditions of limited data availability. The key findings of these studies are summarized in Table 2.

Table 2
Summary of Machine Learning Techniques for Improving Photovoltaic Power Forecasting

Ref.	Methods Used	Key Findings	Practical Outcomes	Accuracy / Performance
[63]	Review and classification of 100 publications on machine learning techniques for PV power forecasting.	Identified commonly used forecasting approaches and existing research gaps.	Highlighted the limitations of current ML methods and areas requiring further improvement.	Identified gaps in forecasting accuracy; no specific numerical results reported.
[90]	Recurrent Neural Networks (RNN), Convolutional Neural Networks (CNN), Decision Trees (DT), and ensemble machine learning methods.	Ensemble learning models achieved the highest prediction accuracy among the evaluated approaches.	Improved the accuracy and reliability of PV power forecasting.	RMSE = 0.4477.
[91]	Physical, statistical, and machine learning approaches for solar power forecasting.	Physical forecasting methods are comprehensive but computationally complex.	Demonstrated the importance of accurate solar power forecasting for improving PV system reliability and efficiency.	Emphasized high-quality forecasting; no numerical accuracy reported.
[61]	Random Forest (RF), Neural Networks (NN), Support Vector Machines (SVM), and Linear Regression (LR).	RF achieved the lowest average prediction error compared with the other evaluated algorithms.	Demonstrated the effectiveness of RF for forecasting PV electricity generation.	Lowest reported RMSE = 32 (unit not specified).

[92]	Lasso Regression, Random Forest Regression (RFR), Gradient Boosting Regression (GBR), Support Vector Regression (SVR), and Extremely Randomized Trees Classification for weather classification.	Lasso, RFR, GBR, and SVR demonstrated favorable forecasting performance.	Improved forecasting under stable meteorological conditions.	Relatively high prediction accuracy during October, November, and December; numerical values not reported.
[93]	Extreme Gradient Boosting (XGBoost) and Artificial Neural Networks (ANN).	Both models were trained to predict PV power output, with ANN demonstrating better performance.	Demonstrated the applicability of ML models for accurate PV power prediction.	ANN achieved lower RMSE values than XGBoost; numerical values not reported.
[94]	Ensemble stacking using an RNN meta-learner, integrating ANN, Deep Neural Networks (DNN), Support Vector Regression (SVR), LSTM, and CNN.	The proposed ensemble approach improved forecasting performance compared with individual learning models.	Enhanced PV power forecasting through the integration of multiple learning algorithms.	Mean Relative Error (MRE) = 4.29%.
[95]	Review of physical, statistical, machine learning, and hybrid forecasting approaches incorporating optimization and postprocessing methods.	Approximately 42% of the reviewed studies employed hybrid forecasting methodologies.	Identified short-term forecasting as the dominant approach in solar resource prediction.	83% of reviewed studies focused on short-term forecasting; no specific accuracy metric reported.

4. Real Case Study of PV Power Prediction Using Neural Networks

4.1 Case Study Description

The Benban Solar Energy Park, located in the Aswan Governorate of Egypt, is considered one of the world's largest solar photovoltaic (PV) facilities. The park covers an area of more than 37 square kilometers and was developed to utilize Egypt's abundant solar energy resources. The facility has a total installed capacity of approximately 1.65 gigawatts (GW). The project plays an important role in Egypt's renewable energy development strategy, which targeted generating 20% of the country's electricity from renewable sources by 2022. It also contributes to energy diversification and the reduction of greenhouse gas emissions.

In addition to its environmental benefits, the park has contributed to regional economic development by attracting foreign investment and creating employment opportunities. Figure 16 illustrates the geographical location of the case study using Google Earth imagery and provides an overview of the Benban Solar Energy Park. The present case study focuses on a selected PV installation operated by one company within the park.

The experimental data were collected from a solar PV installation at Benban Solar Energy Park, one of the major renewable energy facilities in Egypt and the Middle East. The dataset covers the period from April 2019 to November 2023 and was divided into training and testing datasets for the power prediction process.

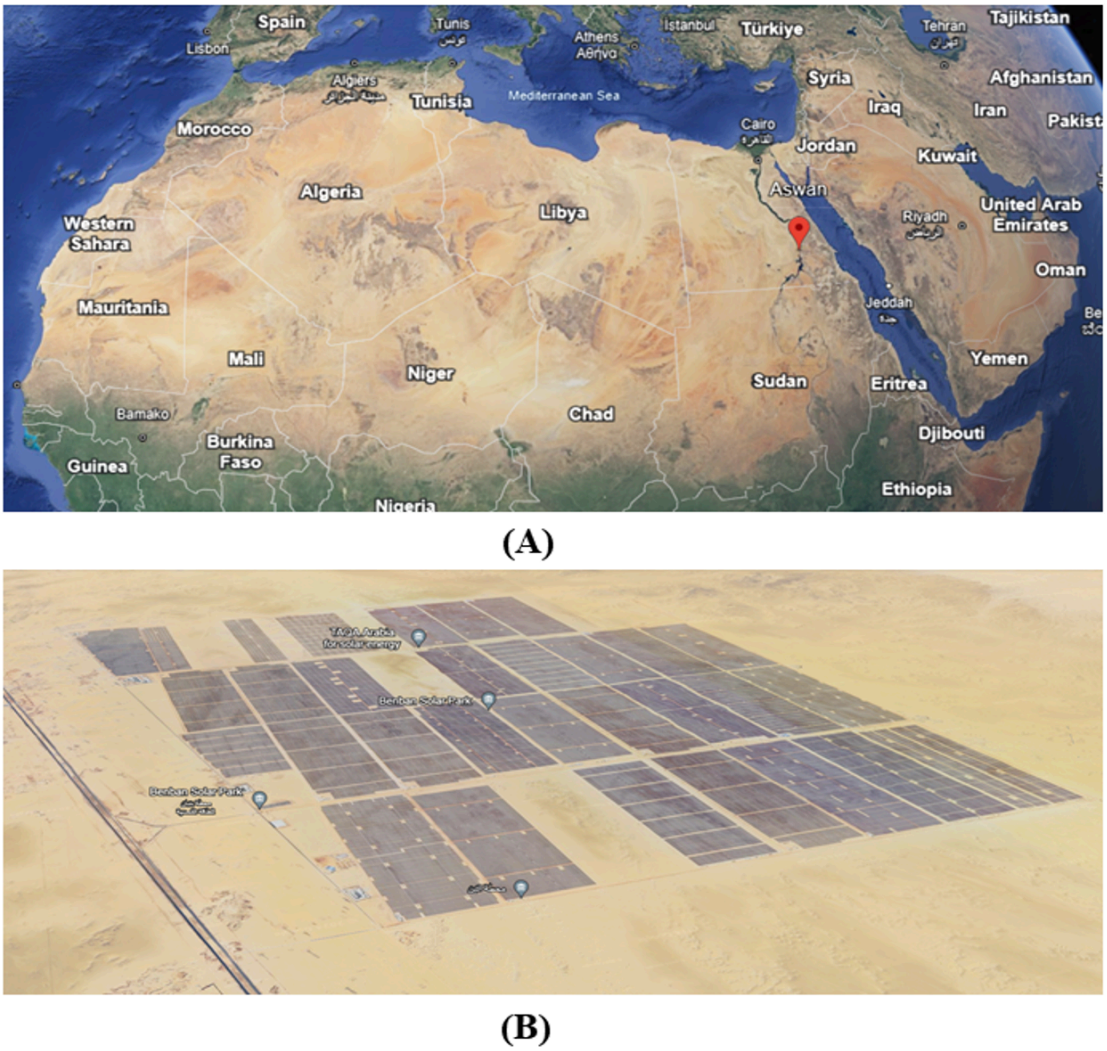


Fig. 16. (A) Geographical location of the experimental case study obtained from Google Earth; (B) Benban Solar Energy Park in Aswan, Egypt

Figure 17 presents the variations in the main meteorological parameters over the study period. The primary input parameters include Global Horizontal Irradiance (GHI), ambient temperature, and solar irradiance, represented by blue, red, and green curves, respectively. The plotted ranges are maintained consistently across the figures, with GHI ranging from 0 to 10, ambient temperature from 0 to 50 °C, and solar irradiance from 0 to 1200 W/m².

Analysis of the data indicates that the meteorological profiles exhibit similar seasonal patterns, with some variations between years. Solar irradiance generally increases during the summer months, particularly July, August, and September, before decreasing during the winter months. The figures demonstrate recurring seasonal variations throughout the observation period.

In Figure 17(A), GHI values from April to July are relatively lower than those recorded during the corresponding periods in the other years. Furthermore, the temperature difference between summer and winter appears more pronounced during the final two years of the study.

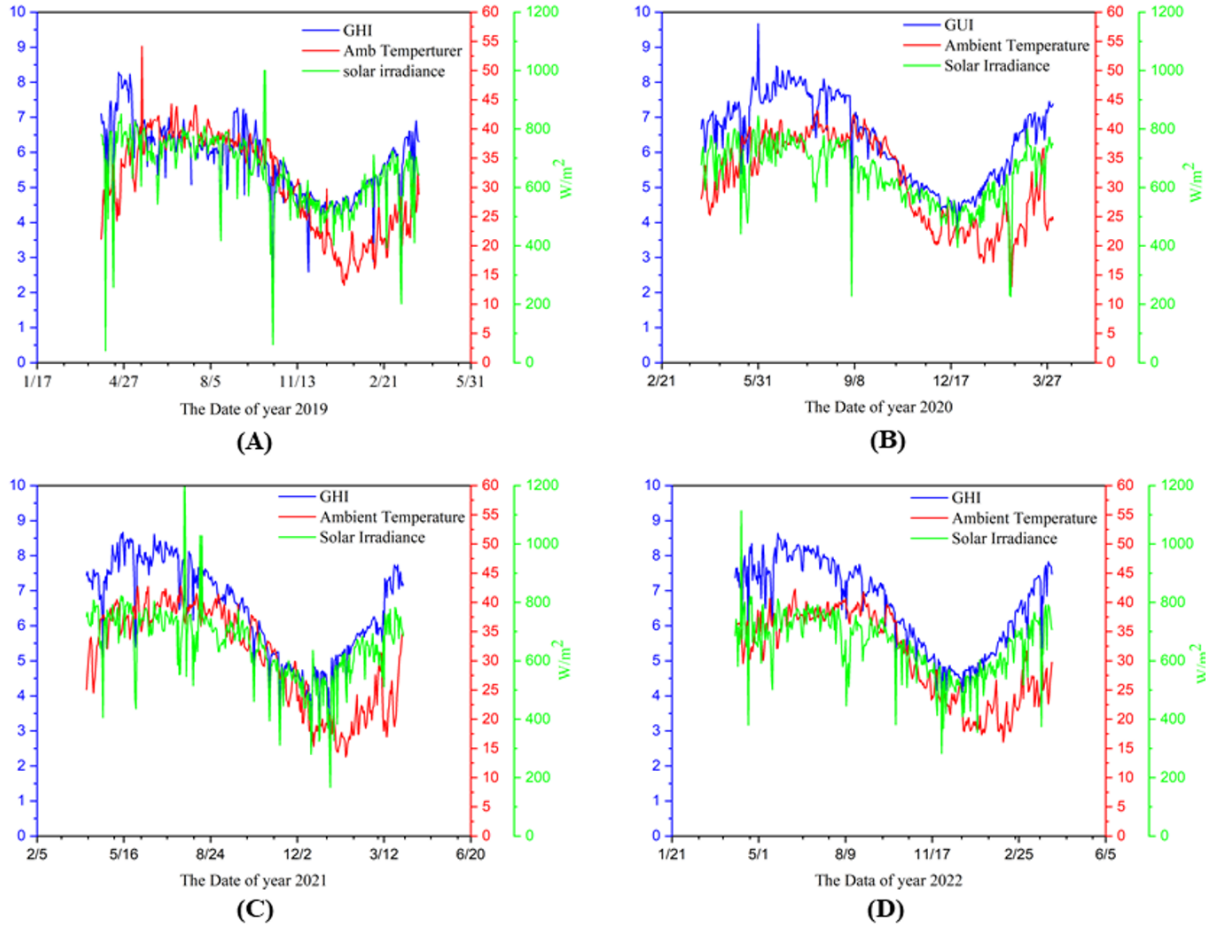


Fig. 17. Main input parameters for PV power prediction obtained from the experimental case study

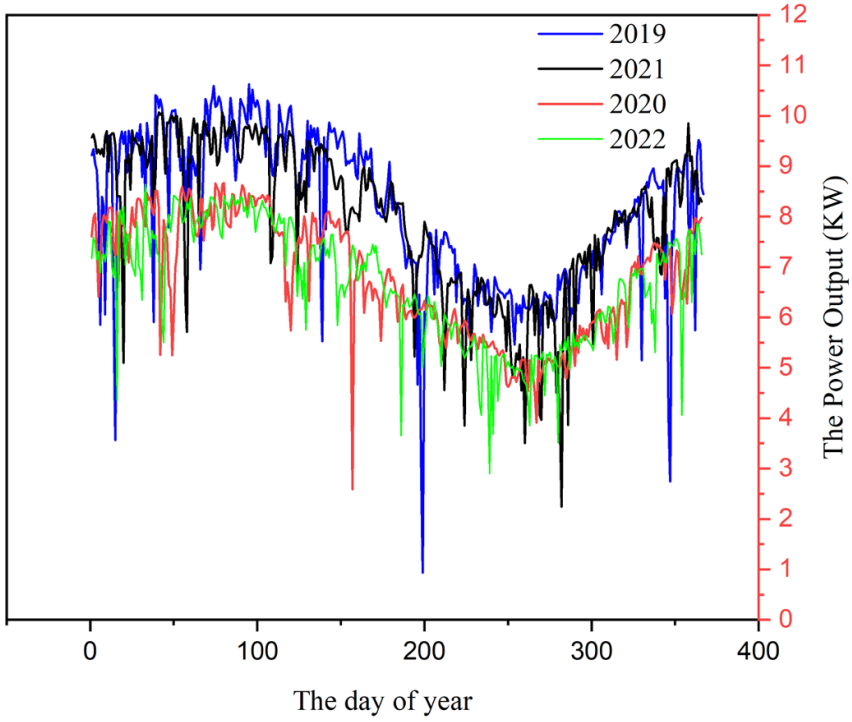


Fig. 18. PV power generation profiles obtained from the experimental data over the study period

The measured PV power generation data were used to train the neural network prediction model, as illustrated in Figure 18. The power generation profiles exhibit generally similar trends across the observation period. However, the power output during the final two years appears slightly lower than that recorded in the earlier years. This variation may be associated with changes in PV module performance, environmental conditions, and other operational factors.

4.2 Methodology of the Case Study

The development of an Artificial Neural Network (ANN) for PV power prediction involves several important stages, including data collection, preprocessing, network architecture design, training, validation, and testing.

The first stage involves collecting relevant historical data and preprocessing the input variables to ensure consistency and suitability for network training. Data normalization is commonly applied to reduce differences in the numerical scales of input parameters.

The second stage involves designing the neural network architecture by specifying the number of input variables, hidden layers, neurons, and output variables. The selected architecture determines how the network processes input information and captures relationships between meteorological conditions and PV power generation.

The network is subsequently trained using historical data to establish relationships between the input parameters and the corresponding power output. During forward propagation, the input data pass through the network to generate predicted values. Backpropagation is then used to update the network weights and biases based on the differences between predicted and actual outputs.

Following training, the network undergoes validation and hyperparameter tuning to improve its forecasting performance. Parameters such as the learning rate, number of hidden layers, and number of neurons may be adjusted to achieve suitable prediction accuracy. Finally, the trained network is evaluated using previously unseen data to assess its generalization capability. The main stages involved in developing an ANN-based prediction system are illustrated in Figure 19.

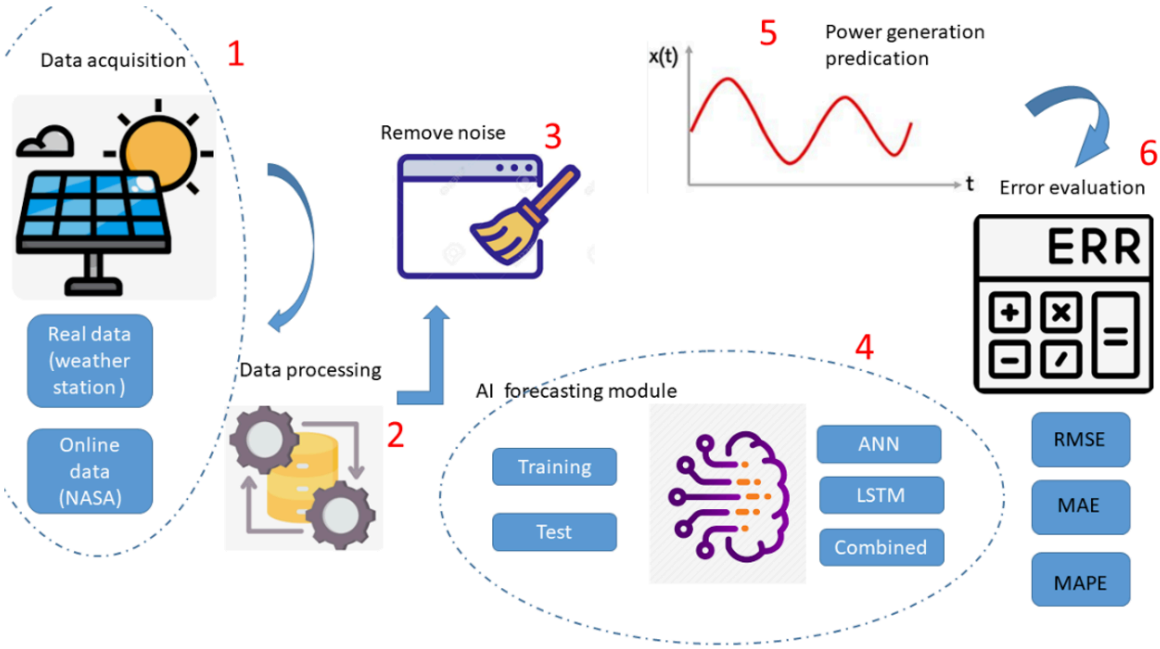


Fig. 19. Schematic diagram illustrating the main stages of Artificial Neural Network development

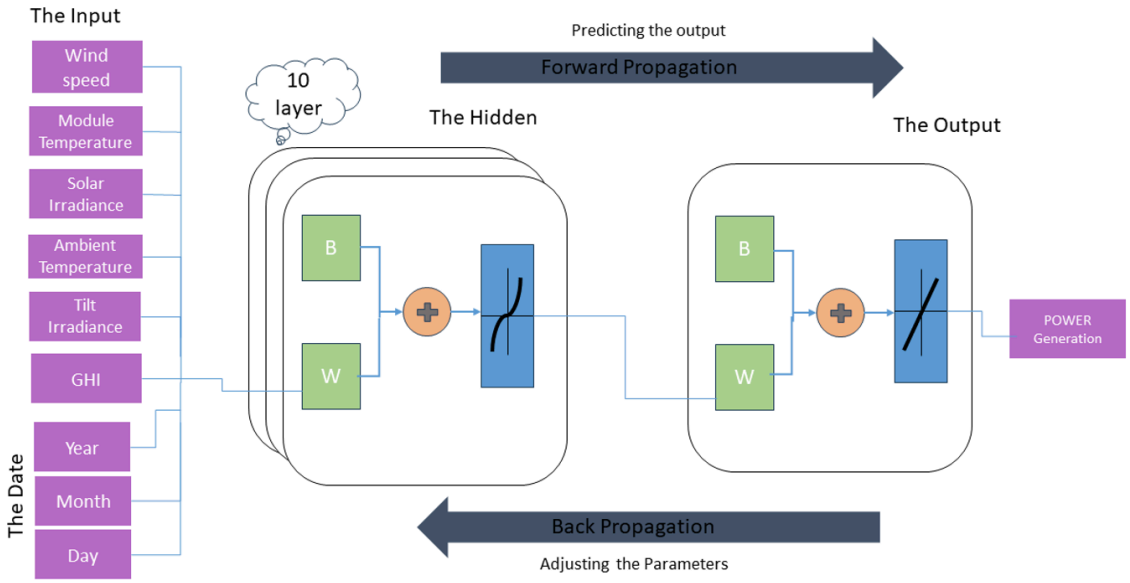


Fig. 20. Neural network architecture for PV power prediction developed using MATLAB

The proposed forecasting network was developed using MATLAB and the experimental data collected from Benban Solar Energy Park. As illustrated in Figure 20, the network consists of nine input parameters, which can be categorized into date-related and meteorological variables. The network has a single output representing the predicted electrical power generation of the solar PV system.

Solar power forecasting can involve several stages. The first stage is weather forecasting, for which meteorological information may be obtained from online databases and services, such as NASA POWER. The second stage involves predicting PV power generation based on the available meteorological parameters. Additional optimization stages may include predicting or adjusting the orientation angles of PV panels in single-axis or dual-axis tracking systems.

The hidden layers establish nonlinear relationships between the input and output variables through adjustable weights, biases, and activation functions. The proposed network is described as having ten hidden layers to process the input information and generate PV power predictions.

4.3 Validation and Results

The performance of the proposed neural network was evaluated by comparing the predicted PV power output with the corresponding measured values. Figure 21 illustrates the prediction results obtained using MATLAB. The agreement between the predicted and actual values indicates the effectiveness of the proposed forecasting model. Prediction accuracy is influenced by several factors, including the amount and quality of training data and the selected network architecture.

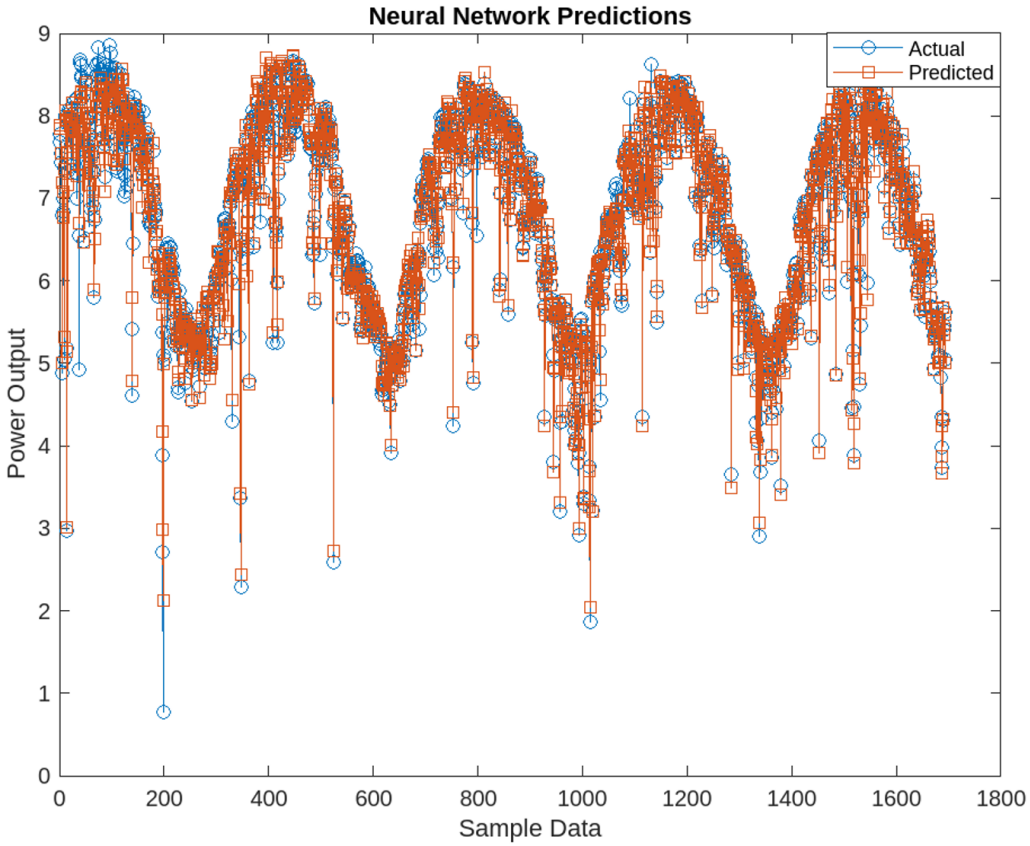


Fig. 21. Results of PV power prediction using the MATLAB neural network model

Figure 22 illustrates the variation in the best fitness value with the number of generations during the optimization process. The optimal fitness value decreases rapidly during the initial generations, indicating improvements in the optimization performance. After approximately 14 generations, the fitness value becomes relatively stable, suggesting that further improvements are limited. Consequently, the optimization process is terminated after 20 generations.

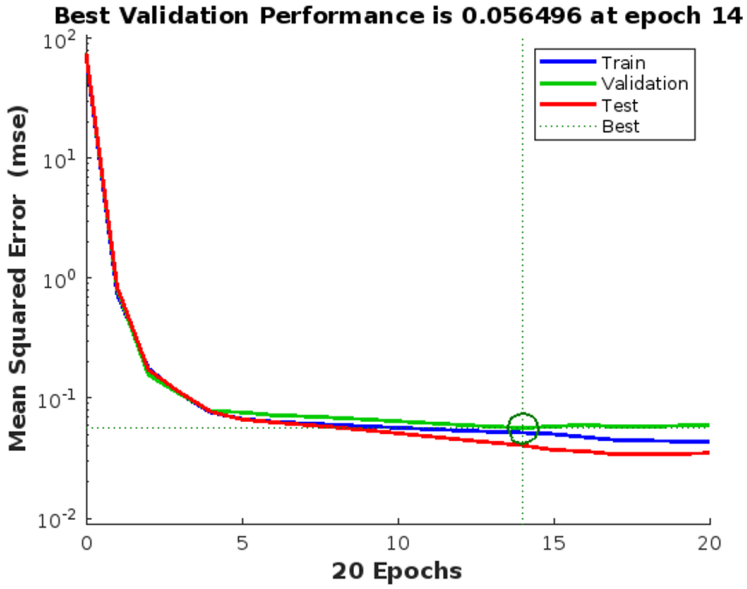


Fig. 22. Neural network performance during the optimization process

The optimized weights and biases were subsequently used to initialize and train the neural network.

The available dataset was divided into training, validation, and testing subsets, with proportions of 70%, 10%, and 20%, respectively. The training dataset was used to update the network weights and biases, while the validation dataset was employed to monitor model performance during training and support the selection of appropriate network parameters. The testing dataset was then used to evaluate the predictive performance of the trained neural network using previously unseen data.

To reduce the risk of overfitting, the training process was stopped at epoch 20.

Figure 23 presents the comparison between predicted and reference values for the training, validation, and testing datasets. Most data points are distributed close to the (y=x) line, indicating good agreement between the predicted and reference values. The correlation coefficients, (R), exceed 0.98, demonstrating a strong positive correlation between the predicted and reference PV power values.

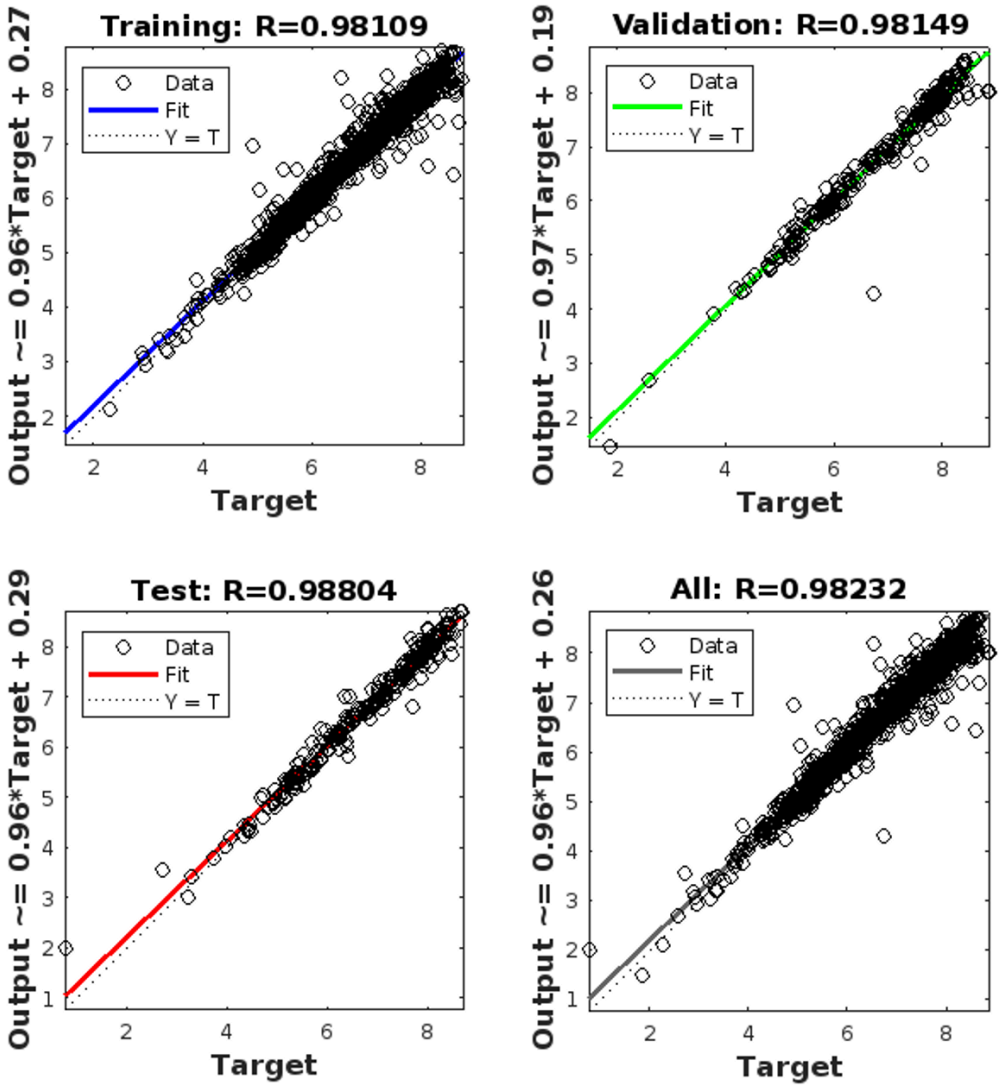


Fig. 23. Comparison of predicted and reference values for the training, validation, and testing datasets

5. Conclusions

Renewable energy sources, including solar, wind, hydropower, biomass, geothermal, and tidal energy, play an important role in sustainable energy generation. These resources can be converted into electricity, heat, and fuels for various applications. Building-Applied Photovoltaic (BAPV) systems have attracted increasing attention as a means of integrating renewable energy technologies into urban environments. Innovative approaches are required to meet growing energy demands and support the development of sustainable communities.

Optimization and Artificial Intelligence (AI) techniques can improve the efficiency and control of renewable energy systems, while forecasting methods help address the variability and uncertainty associated with renewable power generation. Accurate forecasting contributes to improved grid management, energy scheduling, and operational planning. Ensemble Numerical Weather Prediction (NWP) techniques, including those based on the ECMWF Ensemble Prediction System, provide multiple plausible future weather scenarios to support probabilistic solar power forecasting. This review highlights recent developments and applications of these technologies in photovoltaic systems.

In addition, a case study was conducted using experimental data from Benban Solar Energy Park in Aswan, Egypt, one of the largest solar PV facilities in the Middle East. Approximately four years of operational data were used to develop and evaluate a Neural Network (NN)-based PV power prediction model. The proposed approach represents a potential component of an AI-based control and forecasting system for solar energy applications.

The prediction model demonstrated strong performance, achieving a Mean Squared Error (MSE) of 0.056 and correlation coefficients, (R), greater than 0.98. These results indicate good agreement between predicted and reference PV power values and demonstrate the potential of neural network techniques for improving solar power forecasting.

6. Recommendations for Future Work

1. **Integration of complementary renewable energy technologies:** Future research should investigate the integration of photovoltaic systems with other renewable energy resources, such as geothermal and wind energy, according to regional environmental conditions and energy requirements. Such integration could improve energy system flexibility and mitigate the intermittent nature of solar power generation. For example, Building-Integrated Photovoltaic/Thermal (BIPV/T) systems could be combined with ground-source and air-source heat pumps to recover and utilize waste heat from PV modules according to building energy demands. Further investigation is also required to address variations in thermal performance under different weather conditions.
2. **Application of simulation tools:** Appropriate simulation tools should be employed before designing and implementing renewable energy systems. These tools can support the generation, evaluation, and optimization of site-specific data based on geographical location, meteorological conditions, and system operating requirements.
3. **Implementation of AI-based forecasting and optimization:** Artificial intelligence and advanced forecasting techniques should be incorporated into different stages of renewable energy system planning and operation. Accurate forecasting is essential for developing sustainable energy infrastructure and can support demand-side management, operation and maintenance, transmission and distribution planning, and financial decision-making.

4. **Development of supplementary thermal management systems:** Additional thermal management technologies should be investigated to improve PV system efficiency. Effective cooling solutions can reduce the thermal load on photovoltaic modules, while recovered waste heat may be utilized for building heating, cooling, and air-conditioning applications.

Reference

[1] Alshibil, A. M. A., I. Farkas, and P. Víg. "Sustainability contribution of hybrid solar collector towards net-zero energy buildings concerning solar cells wasted heat." Energy for Sustainable Development 74 (2023): 185–195. https://doi.org/10.1016/j.esd.2023.04.001

[2] Md Khairi, N. H., Y. Akimoto, and K. Okajima. "Suitability of rooftop solar photovoltaic at educational building towards energy sustainability in Malaysia." Sustainable Horizons 4 (2022). https://doi.org/10.1016/j.horiz.2022.100032

[3] Mehmood, A., J. Ren, and L. Zhang. "Achieving energy sustainability by using solar PV: System modelling and comprehensive techno-economic-environmental analysis." Energy Strategy Reviews 49 (2023). https://doi.org/10.1016/j.esr.2023.101126

[4] Panicker, K., P. Anand, and A. George. "Assessment of building energy performance integrated with solar PV: Towards a net zero energy residential campus in India." Energy and Buildings 281 (2023). https://doi.org/10.1016/j.enbuild.2022.112736

[5] Alshammari, A. A., E. M. Salilih, E. Almatrafi, and M. Rady. "Polymeric coatings for passive radiative cooling of PV modules in hot and humid weather: Design, optimization, and performance evaluation." Case Studies in Thermal Engineering 57 (2024). https://doi.org/10.1016/j.csite.2024.104341

[6] Cao, X., N. Li, Y. Li, L. Che, B. Yu, and H. Liu. "A review of photovoltaic/thermal (PV/T) technology applied in building environment control." Energy and Built Environment (2023). https://doi.org/10.1016/j.enbenv.2023.12.003

[7] El Hammoumi, A., S. Chtita, S. Motahhir, and A. El Ghzizal. "Solar PV energy: From material to use, and the most commonly used techniques to maximize the power output of PV systems: A focus on solar trackers and floating solar panels." Energy Reports 8 (2022): 11992–12010. https://doi.org/10.1016/j.egyr.2022.09.054

[8] Herrando et al, M.. "A review of solar hybrid photovoltaic-thermal (PV-T) collectors and systems." Progress in Energy and Combustion Science 97 (2023). https://doi.org/10.1016/j.pecs.2023.101072

[9] Zdyb, A. and S. Gulkowski. "Performance Assessment of Four Different Photovoltaic Technologies in Poland." Energies 13, no. 1 (2020). https://doi.org/10.3390/en13010196

[10] Sharma, P., M. Kolhe, and A. Sharma. "Economic performance assessment of building integrated photovoltaic system with battery energy storage under grid constraints." Renewable Energy 145 (1901): 1901–1909. https://doi.org/10.1016/j.renene.2019.07.099

[11] Abojela, Z. R. K., M. K. M. Desa, and A. H. Sabry. "Current prospects of building-integrated solar PV systems and the application of bifacial PVs." Frontiers in Energy Research 11 (2023). https://doi.org/10.3389/fenrg.2023.1164494

[12] Marques Lameirinhas, R. A., J. P. N. Torres, and J. P. de Melo Cunha. "A Photovoltaic Technology Review: History, Fundamentals and Applications." Energies 15, no. 5 (2022). https://doi.org/10.3390/en15051823

[13] Vassiliades et al, C.. "Building integration of active solar energy systems: A review of geometrical and architectural characteristics." Renewable and Sustainable Energy Reviews 164 (2022). https://doi.org/10.1016/j.rser.2022.112482

[14] Sun et al, Y.. "Integrated semi-transparent cadmium telluride photovoltaic glazing into windows: Energy and daylight performance for different architecture designs." Applied Energy 231 (2018): 972–984. https://doi.org/10.1016/j.apenergy.2018.09.133

[15] Martín-Chivelet et al, N.. "Building-Integrated Photovoltaic (BIPV) products and systems: A review of energy-related behavior." Energy and Buildings 262 (2022). https://doi.org/10.1016/j.enbuild.2022.111998

[16] Ullah et al, A.. "Techno-economic and GHG mitigation assessment of concentrated solar thermal and PV systems for different climate zones." Energy Reports 9 (2023): 4763–4780. https://doi.org/10.1016/j.egyr.2023.03.109

[17] Al Bartamani, B. K. and A. A. El-Saleh. "Development of a Smart Solar Tracking (SST) system as a green renewable energy solution." In Journal of Physics: Conference Series, vol. 1812, no. 1, 012009. 2021.

[18] Awasthi et al, A.. "Review on sun tracking technology in solar PV system." Energy Reports 6 (2020): 392–405. https://doi.org/10.1016/j.egyr.2020.02.004

[19] Seme, S., B. Štumberger, M. Hadžiselimović, and K. Sredenšek. "Solar Photovoltaic Tracking Systems for Electricity Generation: A Review." Energies 13, no. 16 (2020). https://doi.org/10.3390/en13164224

[20] Li, G., S. Shittu, T. M. O. Diallo, M. Yu, X. Zhao, and J. Ji. "A review of solar photovoltaic-thermoelectric hybrid system for electricity generation." Energy 158 (2018): 41–58. https://doi.org/10.1016/j.energy.2018.06.021
[21] Svetozarevic et al, B.. "Dynamic photovoltaic building envelopes for adaptive energy and comfort management." Nature Energy 4, no. 8 (2019): 671–682. https://doi.org/10.1038/s41560-019-0424-0
[22] Sayed, M. A. A. E. D. A. and M. A. Fikry. "Impact of glass facades on internal environment of buildings in hot arid zone." Alexandria Engineering Journal 58, no. 3 (2019): 1063–1075. https://doi.org/10.1016/j.aej.2019.09.009
[23] Belhachat, F. and C. Larbes. "A review of global maximum power point tracking techniques of photovoltaic system under partial shading conditions." Renewable and Sustainable Energy Reviews 92 (2018): 513–553. https://doi.org/10.1016/j.rser.2018.04.094
[24] Wasim, M. S., M. Amjad, S. Habib, M. A. Abbasi, A. R. Bhatti, and S. M. Muyeen. "A critical review and performance comparisons of swarm-based optimization algorithms in maximum power point tracking of photovoltaic systems under partial shading conditions." Energy Reports 8 (2022): 4871–4898. https://doi.org/10.1016/j.egyr.2022.03.175
[25] Kumar, M., K. P. Panda, J. C. Rosas-Caro, A. Valderrabano-Gonzalez, and G. Panda. "Comprehensive Review of Conventional and Emerging Maximum Power Point Tracking Algorithms for Uniformly and Partially Shaded Solar Photovoltaic Systems." IEEE Access 11 (2023): 31778–31812. https://doi.org/10.1109/access.2023.3262502
[26] Yang, B., R. Xie, J. Duan, and J. Wang. "State-of-the-art review of MPPT techniques for hybrid PV-TEG systems: Modeling, methodologies, and perspectives." Global Energy Interconnection 6, no. 5 (2023): 567–591. https://doi.org/10.1016/j.gloei.2023.10.005
[27] Singh, B. P., S. K. Goyal, and S. A. Siddiqui. "Maximum power point estimation of MSX-60 poly-crystalline standalone solar PV system." Materials Today: Proceedings 79 (2023): 424–429. https://doi.org/10.1016/j.matpr.2022.12.268
[28] R.-M. Chao, A. Nasirudin, I. K. Wang, and P.-L. Chen. "Multicore PSO Operation for Maximum Power Point Tracking of a Distributed Photovoltaic System under Partially Shading Condition." International Journal of Photoenergy 2016 (2016): 1–19. https://doi.org/10.1155/2016/9754514
[29] Belay Kebede, A. and G. Biru Worku. "Comprehensive review and performance evaluation of maximum power point tracking algorithms for photovoltaic system." Global Energy Interconnection 3, no. 4 (2020): 398–412. https://doi.org/10.1016/j.gloei.2020.10.008
[30] Ahmed, S., S. Mekhilef, M. B. Mubin, and K. S. Tey. "Performances of the adaptive conventional maximum power point tracking algorithms for solar photovoltaic system." Sustainable Energy Technologies and Assessments 53 (2022). https://doi.org/10.1016/j.seta.2022.102390
[31] Kumar, P., N. Pal, and H. Sharma. "Optimization and techno-economic analysis of a solar photo-voltaic/biomass/diesel/battery hybrid off-grid power generation system for rural remote electrification in eastern India." Energy 247 (2022). https://doi.org/10.1016/j.energy.2022.123560
[32] AlAmri, F., G. AlZohbi, M. AlZahrani, and M. Aboulebdah. "Analytical Modeling and Optimization of a Heat Sink Design for Passive Cooling of Solar PV Panel." Sustainability 13, no. 6 (2021). https://doi.org/10.3390/su13063490
[33] Fosso Tajouo, G., P. Tiam Kapen, and F. L. Djanna Koffi. "Techno-economic investigation of an environmentally friendly small-scale solar tracker-based PV/wind/Battery hybrid system for off-grid rural electrification in the mount bamboutos, Cameroon." Energy Strategy Reviews 48 (2023). https://doi.org/10.1016/j.esr.2023.101107
[34] Chiang, W., I. Permana, F. Wang, H. Chen, and M. Erdenebayar. "Experimental investigation for an innovative hybrid photovoltaic/Thermal (PV/T) solar system." Energy Reports 8 (2022): 910–918. https://doi.org/10.1016/j.egyr.2022.10.264
[35] Sharaf, M., M. S. Yousef, and A. S. Huzayyin. "Review of cooling techniques used to enhance the efficiency of photovoltaic power systems." Environ Sci Pollut Res Int 29, no. 18 (2022): 26131–26159. https://doi.org/10.1007/s11356-022-18719-9
[36] Siecker, J., K. Kusakana, and B. P. Numbi. "A review of solar photovoltaic systems cooling technologies." Renewable and Sustainable Energy Reviews 79 (2017): 192–203. https://doi.org/10.1016/j.rser.2017.05.053
[37] Kumar, A. and S. Vadhera. "Design and Simulation of Hybrid Microsystem and Its Effect on the Environment Using Homer Software." In Intelligent Manufacturing and Energy Sustainability, (Smart Innovation, Systems and Technologies, 257–265. 2022.
[38] Seedahmed et al, M. M. A.. "Optimal sizing of grid-connected photovoltaic system for a large commercial load in Saudi Arabia." Alexandria Engineering Journal 61, no. 8 (2022): 6523–6540. https://doi.org/10.1016/j.aej.2021.12.013
[39] Gonzalez Lopez, J. M., R. O. Jimenez Betancourt, J. M. Ramirez Arredondo, E. Villalvazo Laureano, and F. Rodriguez Haro. "Incorporating Virtual Reality into the Teaching and Training of Grid-Tie Photovoltaic Power Plants Design." Applied Sciences 9, no. 21 (2019). https://doi.org/10.3390/app9214480

[40] Vadhera, S.. "Design and Simulation of Hybrid Solar PV-Fuel-Cell-Battery System to supply in the Nit Kurukshetra Campus and its effect on the Environment using Homer Software." In Journal of Physics: Conference Series, vol. 2062, no. 1, 012030. 2021.
[41] Elnajjar, H. M., A. S. Shehata, A. H. A. Elbatran, and M. F. Shehadeh. "Experimental and techno-economic feasibility analysis of renewable energy technologies for Jabel Ali Port in UAE." Energy Reports 7 (2021): 116–136. https://doi.org/10.1016/j.egyr.2021.08.102
[42] Taghavifar, H. and Z. S. Zomorodian. "Techno-economic viability of on grid micro-hybrid PV/wind/Gen system for an educational building in Iran." Renewable and Sustainable Energy Reviews 143 (2021). https://doi.org/10.1016/j.rser.2021.110877
[43] Shahzad, M. K., A. Zahid, T. ur Rashid, M. A. Rehan, M. Ali, and M. Ahmad. "Techno-economic feasibility analysis of a solar-biomass off grid system for the electrification of remote rural areas in Pakistan using HOMER software." Renewable Energy 106 (2017): 264–273. https://doi.org/10.1016/j.renene.2017.01.033
[44] Konneh et al, K. V.. "Optimal Design and Performance Analysis of a Hybrid Off-Grid Renewable Power System Considering Different Component Scheduling, PV Modules, and Solar Tracking Systems." IEEE Access 9 (2021): 64393–64413. https://doi.org/10.1109/access.2021.3075732
[45] Chandrasekharan, S., S. Subramaniam, and V. Veerakgoundar. "Honey badger optimization algorithm based maximum power point tracking for solar photovoltaic systems." Electric Power Systems Research 221 (2023). https://doi.org/10.1016/j.epsr.2023.109393
[46] Ravi, S., M. Premkumar, and L. Abualigah. "Comparative analysis of recent metaheuristic algorithms for maximum power point tracking of solar photovoltaic systems under partial shading conditions." International Journal of Applied Power Engineering (IJAPE) 12, no. 2 (2023). https://doi.org/10.11591/ijape.v12.i2.pp196-217
[47] Musa, A., E. Alozie, S. A. Suleiman, J. A. Ojo, and A. L. Imoize. "A Review of Time-Based Solar Photovoltaic Tracking Systems." Information 14, no. 4 (2023). https://doi.org/10.3390/info14040211
[48] Bugeja, R., L. Mule' Stagno, and L. Dexarcis. "An Offshore Solar Irradiance Calculator (OSIC) Applied to Photovoltaic Tracking Systems." Energies 16, no. 9 (2023). https://doi.org/10.3390/en16093735
[49] Hosseini Dehshiri, S. S. and B. Firoozabadi. "Comparison, evaluation and prioritization of solar photovoltaic tracking systems using multi criteria decision making methods." Sustainable Energy Technologies and Assessments 55 (2023). https://doi.org/10.1016/j.seta.2022.102989
[50] Phiri, M., M. Mulenga, A. Zimba, and C. I. Eke. "Deep Learning Techniques for Photovoltaic Solar Tracking Systems: A Systematic Literature Review." 2023. https://doi.org/10.21203/rs.3.rs-2539961/v1
[51] Mahesh, P. V., S. Meyyappan, and R. Alla. "Support Vector Regression Machine Learning based Maximum Power Point Tracking for Solar Photovoltaic systems." International journal of electrical and computer engineering systems 14, no. 1 (2023): 100–108.
[52] Kumar, M., K. P. Panda, J. C. Rosas-Caro, A. Valderrabano-Gonzalez, and G. Panda. "Comprehensive Review of Conventional and Emerging Maximum Power Point Tracking Algorithms for Uniformly and Partially Shaded Solar Photovoltaic Systems." IEEE Access (2023).
[53] Yakubu, R. O., L. D. Mensah, D. A. Quansah, and M. S. Adaramola. "Improving solar photovoltaic installation energy yield using bifacial modules and tracking systems: An analytical approach." Advances in Mechanical Engineering 14, no. 12 (2022). https://doi.org/10.1177/16878132221139714
[54] Palomino-Resendiz, S. I., F. A. Ortiz-Martínez, I. V. Paramo-Ortega, J. M. González-Lira, and D. A. Flores-Hernández. "Optimal Selection of the Control Strategy for Dual-Axis Solar Tracking Systems." IEEE Access 11 (2023): 56561–56573. https://doi.org/10.1109/access.2023.3283336
[55] Hamza Zafar et al, M.. "A novel meta-heuristic optimization algorithm based MPPT control technique for PV systems under complex partial shading condition." Sustainable Energy Technologies and Assessments 47 (2021). https://doi.org/10.1016/j.seta.2021.101367
[56] Wong, J., F. Bai, T. K. Saha, and R. H. G. Tan. "A feasibility study of the 1.5-axis tracking model in utility-scale solar PV plants." Solar Energy 216 (2021): 171–179. https://doi.org/10.1016/j.solener.2020.12.035
[57] Tina, G. M., C. Ventura, S. Ferlito, and S. De Vito. "A State-of-Art-Review on Machine-Learning Based Methods for PV." Applied Sciences 11, no. 16 (2021). https://doi.org/10.3390/app11167550
[58] Gersnoviez, A., J. C. Gámez-Granados, M. Cabrera-Fernández, I. Santiago, E. Cañete-Carmona, and M. Brox. "Neuro-fuzzy systems for daily solar irradiance classification and PV efficiency forecasting." Alexandria Engineering Journal 79 (2023): 21–33. https://doi.org/10.1016/j.aej.2023.07.072
[59] Wang, W., D. Yang, T. Hong, and J. Kleissl. "An archived dataset from the ECMWF Ensemble Prediction System for probabilistic solar power forecasting." Solar Energy 248 (2022): 64–75. https://doi.org/10.1016/j.solener.2022.10.062
[60] Liu, Z. and Y. Du. "Evolution towards dispatchable PV using forecasting, storage, and curtailment: A review." Electric Power Systems Research 223 (2023). https://doi.org/10.1016/j.epsr.2023.109554

[61] Scott, C., M. Ahsan, and A. Albarbar. "Machine learning for forecasting a photovoltaic (PV) generation system." Energy 278 (2023). https://doi.org/10.1016/j.energy.2023.127807
[62] Tian, J., R. Ooka, and D. Lee. "Multi-scale solar radiation and photovoltaic power forecasting with machine learning algorithms in urban environment: A state-of-the-art review." Journal of Cleaner Production 426 (2023). https://doi.org/10.1016/j.jclepro.2023.139040
[63] A. Alcañiz, D. Grzebyk, H. Ziar, and O. Isabella. "Trends and gaps in photovoltaic power forecasting with machine learning." Energy Reports 9 (2023): 447–471. https://doi.org/10.1016/j.egyr.2022.11.208
[64] Xu, C., Y. Sun, A. Du, and D.-c. Gao. "Quantile regression based probabilistic forecasting of renewable energy generation and building electrical load: A state of the art review." Journal of Building Engineering 79 (2023). https://doi.org/10.1016/j.jobe.2023.107772
[65] Ma, X., H. Du, K. Wang, R. Jia, and S. Wang. "An efficient QR-BiMGM model for probabilistic PV power forecasting." Energy Reports 8 (2022): 12534–12551. https://doi.org/10.1016/j.egyr.2022.09.077
[66] Abdulai, D., S. Gyamfi, F. A. Diawuo, and P. Acheampong. "Data analytics for prediction of solar PV power generation and system performance: A real case of Bui Solar Generating Station, Ghana." Scientific African 21 (2023). https://doi.org/10.1016/j.sciaf.2023.e01894
[67] Pierro et al, M.. "Progress in regional PV power forecasting: A sensitivity analysis on the Italian case study." Renewable Energy 189 (2022): 983–996. https://doi.org/10.1016/j.renene.2022.03.041
[68] Das, S.. "Short term forecasting of solar radiation and power output of 89.6kWp solar PV power plant." Materials Today: Proceedings 39 (1959): 1959–1969. https://doi.org/10.1016/j.matpr.2020.08.449
[69] Bektas, S. C., R. Cakmak, and I. H. Altas. "Design of a MATLAB GUI for Day Ahead Forecasting of PV Panel Power." In presented at the 2019 Innovations in Intelligent Systems and Applications Conference (ASYU). 2019.
[70] Su, D., E. Batzelis, and B. Pal. "Machine learning algorithms in forecasting of photovoltaic power generation." In 2019 International Conference on Smart Energy Systems and Technologies (SEST), 1–6. 2019.
[71] Lu, X.. "Day-ahead photovoltaic power forecasting using hybrid K-Means++ and improved deep neural network." Measurement 220 (2023). https://doi.org/10.1016/j.measurement.2023.113208
[72] Kothona, D., K. Spyropoulos, C. Valelis, C. Koutsis, K. C. Chatzisavvas, and G. C. Christoforidis. "Deep learning forecasting tool facilitating the participation of photovoltaic systems into day-ahead and intra-day electricity markets." Sustainable Energy, Grids and Networks 36 (2023). https://doi.org/10.1016/j.segan.2023.101149
[73] Brester, C., V. Kallio-Myers, A. V. Lindfors, M. Kolehmainen, and H. Niska. "Evaluating neural network models in site-specific solar PV forecasting using numerical weather prediction data and weather observations." Renewable Energy 207 (2023): 266–274. https://doi.org/10.1016/j.renene.2023.02.130
[74] Mayer, M. J., D. Yang, and B. Szintai. "Comparing global and regional downscaled NWP models for irradiance and photovoltaic power forecasting: ECMWF versus AROME." Applied Energy 352 (2023). https://doi.org/10.1016/j.apenergy.2023.121958
[75] Ahmed, R., V. Sreeram, Y. Mishra, and M. D. Arif. "A review and evaluation of the state-of-the-art in PV solar power forecasting: Techniques and optimization." Renewable and Sustainable Energy Reviews 124 (2020). https://doi.org/10.1016/j.rser.2020.109792
[76] Vu, B. H. and I.-Y. Chung. "Optimal generation scheduling and operating reserve management for PV generation using RNN-based forecasting models for stand-alone microgrids." Renewable Energy 195 (2022): 1137–1154. https://doi.org/10.1016/j.renene.2022.06.086
[77] Huang, Q. and S. Wei. "Improved quantile convolutional neural network with two-stage training for daily-ahead probabilistic forecasting of photovoltaic power." Energy Conversion and Management 220 (2020). https://doi.org/10.1016/j.enconman.2020.113085
[78] Chandel, S. S., A. Gupta, R. Chandel, and S. Tajjour. "Review of deep learning techniques for power generation prediction of industrial solar photovoltaic plants." Solar Compass 8 (2023). https://doi.org/10.1016/j.solcom.2023.100061
[79] Hossain, M. S. and H. Mahmood. "Short-Term Photovoltaic Power Forecasting Using an LSTM Neural Network and Synthetic Weather Forecast." IEEE Access 8 (2020): 172524–172533. https://doi.org/10.1109/access.2020.3024901
[80] Liu et al, Q.. "A cloud-based Bi-directional LSTM approach to grid-connected solar PV energy forecasting for multi-energy systems." Sustainable Computing: Informatics and Systems 40 (2023). https://doi.org/10.1016/j.suscom.2023.100892
[81] Luo, X. and D. Zhang. "A cascaded deep learning framework for photovoltaic power forecasting with multi-fidelity inputs." Energy 268 (2023). https://doi.org/10.1016/j.energy.2023.126636
[82] Memarzadeh, G. and F. Keynia. "Solar power generation forecasting by a new hybrid cascaded extreme learning method with maximum relevance interaction gain feature selection." Energy Conversion and Management 298 (2023). https://doi.org/10.1016/j.enconman.2023.117763

[83] Xiao, F., X.-k. Wang, W.-h. Hou, X.-y. Zhang, and J.-q. Wang. "An attention-based Bayesian sequence to sequence model for short-term solar power generation prediction within decomposition-ensemble strategy." Journal of Cleaner Production 416 (2023). https://doi.org/10.1016/j.jclepro.2023.137827

[84] Nguyen Trong, T., H. Vu Xuan Son, H. Do Dinh, H. Takano, and T. Nguyen Duc. "Short-term PV power forecast using hybrid deep learning model and Variational Mode Decomposition." Energy Reports 9 (2023): 712–717. https://doi.org/10.1016/j.egyr.2023.05.154

[85] Arias Velasquez, R. M.. "A case study of NeuralProphet and nonlinear evaluation for high accuracy prediction in short-term forecasting in PV solar plant." Heliyon 8, no. 9 (2022). https://doi.org/10.1016/j.heliyon.2022.e10639

[86] Sarmas, E., E. Spiliotis, E. Stamatopoulos, V. Marinakis, and H. Doukas. "Short-term photovoltaic power forecasting using meta-learning and numerical weather prediction independent Long Short-Term Memory models." Renewable Energy 216 (2023). https://doi.org/10.1016/j.renene.2023.118997

[87] Akhter et al, M. N.. "A hybrid deep learning method for an hour ahead power output forecasting of three different photovoltaic systems." Applied Energy 307 (2022). https://doi.org/10.1016/j.apenergy.2021.118185

[88] Tang, Z., Y. Tang, A. Qiao, J. Liu, and J. Gao. "Transfer Learning Based Photovoltaic Power Forecasting with XGBoost." In 2023 Panda Forum on Power and Energy (PandaFPE), 1781–1785. 2023.

[89] Borunda, M., A. Ramírez, R. Garduno, G. Ruíz, S. Hernandez, and O. A. Jaramillo. "Photovoltaic Power Generation Forecasting for Regional Assessment Using Machine Learning." Energies 15, no. 23 (2022). https://doi.org/10.3390/en15238895

[90] Zhou et al, Q.. "Ensemble Machine Learning Method for Photovoltaic Power Forecasting." In 2023 26th International Conference on Computer Supported Cooperative Work in Design (CSCWD), 332–337. 2023.

[91] Patel, A. and O. Gnana Swathika. "Day-Ahead Solar Power Forecasting Using Statistical and Machine Learning Methods." Integrated Green Energy Solutions Volume 2 (2023): 71–101.

[92] Wang, X., Y. Sun, D. Luo, and J. Peng. "Comparative study of machine learning approaches for predicting short-term photovoltaic power output based on weather type classification." Energy 240 (2022). https://doi.org/10.1016/j.energy.2021.122733

[93] May, S. I., P. Bokoro, L. Pratt, and K. Roro. "Modelling photovoltaic power output using machine Learning techniques." 2022 IEEE PES/IAS PowerAfrica (2022): 1–5.

[94] Lateko et al, A. A. H.. "Stacking Ensemble Method with the RNN Meta-Learner for Short-Term PV Power Forecasting." Energies 14, no. 16 (2021). https://doi.org/10.3390/en14164733

[95] Carneiro, T. C., P. C. M. de Carvalho, H. Alves dos Santos, M. A. F. B. Lima, and A. P. d. S. Braga. "Review on Photovoltaic Power and Solar Resource Forecasting: Current Status and Trends." Journal of Solar Energy Engineering 144, no. 1 (2021). https://doi.org/10.1115/1.4051652