



AI-Based Solar Power Forecasting for Utility-Scale Photovoltaic Plants: A Review

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Article Info	Abstract
Article history: Received Feb 25 th , 2026 Revised Aug 25 th , 2026 Accepted Sep 7 th , 2026 Published Sep 30 th , 2026	Solar photovoltaic (PV) energy has experienced substantial expansion in electricity generation, with a considerable number of PV systems integrated into grid-connected networks in recent years. However, solar PV power generation is highly intermittent and volatile due to its reliance on solar irradiance and other weather conditions. This variability poses challenges to power systems and become a major constraint on the operation of utility-scale PV plants. As a result, accurate forecasting and effective operational strategies are essential for ensuring the safe and stable integration of utility-scale PV system into the grid. Research on Artificial Intelligence (AI) algorithms, such as machine learning, artificial neural networks and deep learning has been widely reported in different perspectives. Nevertheless, forecasting research on utility-scale PV system applications remains limited compared with research on small-scale PV systems. This paper reviews AI-based forecasting methods for utility-scale PV plants, highlights key forecasting challenges and national grid code requirements, aiming to support future development of reliable solar forecasting solutions.
Index Terms: Solar Power Forecasting Artificial Intelligence Utility-scale Large-scale Solar	

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I. INTRODUCTION

Renewable energy (RE) offers a sustainable alternative to conventional fossil-fuel-based power generation by providing cleaner and potentially inexhaustible sources of electricity. Among the available RE technologies, solar photovoltaic (PV) systems have experienced rapid growth because of declining costs, supportive policies, and continuous technological advances. Despite temporary setbacks caused by the COVID-19 pandemic, global PV capacity increased from 400 GW in 2017 to 1.6 TW in 2023 and projected to exceed 4,500 GW by 2050 [1][2]. Figure 1 illustrates the global potential for solar energy, particularly in emerging economies where solar power deployment is expanding rapidly. This growing is further encouraged by national legislations and regulatory frameworks that encourage the transition from conventional fossil-fuel and nuclear energy sources toward large-scale RE deployment.

However, power generation from solar PV plants is highly dependent on meteorological and environmental conditions, resulting in inherent uncertainty and variability. Fluctuations in solar irradiance, temperature, cloud cover, wind speed, and

other environmental variables can produce substantial variations in PV output, creating challenges in balancing electricity generation and load demand [3], [4]. The intermittent nature of PV generation can consequently affect the economic operation, reliability, and stability of the main grid. Therefore, the increasing penetration of solar PV systems makes power-system scheduling dispatch more complex and difficult [5][6]. Accurate solar power forecasting is thus essential for mitigating these uncertainties. Reliable forecasts support the planning, management, and operation of power systems and enable plant operators to minimise penalties arising from deviations between scheduled and actual power generation [7].

PV systems can generally be classified into three categories according to their installed generation capacity: small-scale, medium-scale and large-scale systems, with the latter commonly referred to as utility-scale PV systems. Small-scale PV systems typically have capacities of up to 250 kW and are primarily used for localized or single applications. Medium-scale systems generally range from 250 kW to less than 1 MW and are suitable for larger commercial or community-level applications. In this review, utility-scale PV systems are defined as centralized, grid-connected

installations with capacities of 1 MW or greater that are primarily designed to supply electricity to the power grid. These facilities typically have substantial generation capacities, occupy extensive geographical areas, and contributing significantly to regional and grid-level electricity supply.

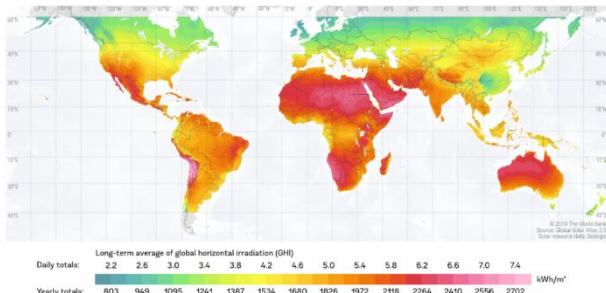


Figure 1. World Global Horizontal Irradiation Map [8]

In recent years, solar power forecasting, including solar power, solar irradiance and solar energy forecasting, has attracted considerable research attention. This interest corresponds with the rapid expansion of grid-connected PV systems at both distributed and utility-scale. The growing number of publications in this field reflects the importance of solar forecasting for energy planning, grid reliability, power-system operation, and electricity-market participation. Accordingly, researchers have focused on developing new forecasting models and optimization techniques, and evaluating the performance and limitations of existing approaches under different forecasting conditions [9]. Numerous review studies have consequently been published to assess the available forecasting methodologies, identify research gaps, and recommend directions for future research.

Table 1 summarizes previous studies on solar forecasting. The reviewed literature demonstrates a gradual transition from conventional forecasting to approaches toward artificial intelligence (AI)-based methods, particularly machine learning (ML) and deep learning (DL). Earlier studies mainly reviewed general solar power and irradiance forecasting methods, whereas more recent reviews have increasingly focused on data-driven approaches because of their ability to capture nonlinear relationships and temporal dependencies in PV generation. Nevertheless, these reviews remain predominantly methodology-oriented, with limited consideration of PV plant scale, operating conditions, spatial characteristics, and grid-integration requirements.

Utility-scale PV systems present additional forecasting challenges that are either absent or less significant in smaller PV installations. These challenges include spatial heterogeneity caused by nonuniform topography, variations in module orientations, localized shading, geographical dispersed meteorological conditions, and limitations in the coverage and availability of monitoring sensors. Moreover, forecasting models for utility-scale plants must satisfy practical grid-operational requirements, including forecasting horizons, temporal resolutions and accuracy levels specified by national grid codes. Most existing reviews examine forecasting approaches primarily from algorithmic and performance-based perspectives but rarely integrate the spatial and operational characteristics of utility-scale PV plants with grid-code-driven forecasting requirements. Emerging approaches, including micro-level forecasting for spatially nonuniform PV plants and probabilistic forecasting

for uncertainty quantification, have also received comparatively limited attention.

To the best of the authors' knowledge, no existing review has comprehensively integrated AI-based forecasting methodologies, utility-scale spatial and data-related issues, grid-code requirements, and emerging forecasting needs and challenges for large-scale PV applications. Therefore, the uniqueness of this review is not restricted to the capacity classification of utility-scale PV system capacity. This study presents an integrated assessment of AI-based solar power forecasting for utility-scale PV plants by addressing forecasting challenges, reviewing relevant AI methods and applications, comparing national grid-code forecasting requirements, and identifying future research directions, including micro-level and probabilistic forecasting. This integrated perspective aims to provide a more application-oriented understanding of the current constraints and future requirements for reliable utility-scale PV forecasting.

Table 1
Review of solar power forecasting in utility-scale PV systems

Ref	Year	Solar Power	Irradiance	Energy	ML	DL
[10]	2020				x	x
[11]	2020	x			x	x
[12]	2020	x			x	x
[13]	2020	x	x		x	
[14]	2020	x			x	
[5]	2020	x			x	x
[15]	2020	x				x
[16]	2020		x			x
[9]	2021	x	x	x	x	x
[17]	2021	x			x	x
[18]	2021				x	x
[19]	2021			x		x
[20]	2021		x		x	
[21]	2021			x		x
[22]	2023	x	x			x
[23]	2023	x	x		x	
[24]	2023	x	x		x	
[25]	2023	x			x	
[26]	2024	x	x		x	x

II. FORECASTING CHALLENGES IN UTILITY-SCALE PV SYSTEMS

Accurate forecasting of the power output of utility-scale PV systems is remains a complex problem. One of the main issues is meteorological variability, which is caused by rapid changes in atmospheric conditions, such as the cloud movement, that contribute to sudden fluctuations in solar irradiation. Such variability primarily affects short-term forecasts, for which a high temporal resolution is needed to capture these rapid changes [27].

Moreover, utility-scale PV systems are installed across large, non-uniform areas by varying topography, different panel orientation, localized shading, and varying module degradation rates. These spatial heterogeneities present a considerable modelling challenges, especially for conventional forecasting frameworks that assume homogeneous system behavior throughout the plant. Thus, a measurement at one location may not be representative of conditions at other locations within the solar plant, thereby reducing forecasting accuracy.

Data quality and granularity also remain important limitations. Measurement-instruments failures, calibration faults, and communication problems, often lead to incomplete records of variables such as solar irradiance, ambient temperature, and module temperature. These abnormalities compromise the temporal consistency and completeness of historical datasets, which are crucial for the effective training and validation of forecasting models. In particular, missing data for highly influential variables, including irradiance and temperature, may substantially affect model accuracy and forecasting robustness [28].

The integration of utility-scale PV systems into the power grid becomes increasing difficult, particularly when forecasts are inaccurate. Discrepancies between forecasted and actual power generation may cause dispatch inefficiencies and potentially contribute to grid-frequency instability. Although these systems generally operate reliably within dispatch parameters, their intermittent nature may still contribute to small but significant power imbalances [29]. These observations highlight the need for sophisticated, spatially responsive, and adaptable AI-based forecasting methods to effectively address the multi-faceted difficulties associated with complex topography, data limitations, and operational uncertainty in utility-scale PV deployment.

III. ARTIFICIAL INTELLIGENCE SOLAR POWER FORECASTING IN UTILITY-SCALE PV SYSTEMS

ML has emerged as a powerful AI approach that enables computers to learn patterns from data and generate accurate predictions. In the context of PV power forecasting, ML models have demonstrated strong predictive capabilities. Their performance largely depends on the quality and quantity of input data, as well as the selection of an appropriate algorithm [13][17]. Compared with traditional physical and statistical approaches, ML models benefit from superior data-processing and feature-extraction capabilities, especially with the continued growth in computational power. Commonly used ML models in solar power forecasting include support vector machines (SVM), k-nearest neighbors (kNN), artificial neural networks (ANN), extreme learning machines (ELM), naive Bayes, and random forests (RF).

With advances in computational capabilities and the increasing availability of high-resolution PV and meteorological data, deep learning (DL), a subset of ML, has gained considerable attention. DL architectures can automatically learn complex features from large datasets and are particularly useful for sequential and time-series forecasting. Recurrent neural networks (RNN), long short-term memory (LSTM), gated recurrent units (GRU), bidirectional LSTM (Bi-LSTM), and convolutional neural networks (CNN) have therefore been increasingly applied to PV forecasting. In particular, recurrent architectures such as LSTM and GRU are well suited to short-term forecasting because they can capture temporal dependencies in historical PV power and meteorological data. However, these advantages are generally accompanied by greater computational requirements, larger training datasets, and sensitivity to architecture and hyperparameter selection.

Table 2 summarizes a comparative review of forecasting studies applied to utility-scale PV systems with capacities of 1 MW or greater. The reviewed studies demonstrate considerable methodological variation, ranging from traditional regression and statistical approaches to ANN-

based models, recurrent DL models, decomposition-based hybrid methods, optimized DL models, Transformer architectures and spatio-temporal forecasting frameworks. The forecasting horizons also vary greatly, ranging from 1-min nowcasting and 5-min very-short-term forecasting to several hours, day-ahead and even multi-week and monthly forecasts. The wide variation suggests that the model selection should be closely aligned with the intended operational timescale and grid application.

The conventional ML methods presented in [30] and [31], such as multilayer perceptron (MLP), support vector regression (SVR), linear regression (LR), random forest (RF) and feed-forward neural networks (FFNN) offer relatively simple forecasting frameworks and enable different algorithms to be compared using similar datasets and forecast horizons. Their major advantages are relatively low model complexity and computational requirements. However, conventional feed-forward models do not explicitly retain temporal information from previous time steps and may be less effective in capturing long-term sequential dependencies in PV generation.

In contrast, recurrent DL models such as Bi-LSTM [32], LSTM, and LSTM-RNN [33] and GRU-RNN [34] are designed to learn temporal dependencies in sequential data. These characteristics make them particularly suitable for short-term utility-scale PV forecasting, in which current power output is strongly influenced by prior irradiance, climatic conditions, and historical generation trends. Their applicability to utility-scale has been demonstrated using plants with capacities ranging from 20 MW to 75 MW. More recent studies have further confirmed the usefulness of recurrent architectures. For example, LSTM forecasting was used to an operational 25 MWac PV plant in Malaysia [35], while a Bi-LSTM model paired with Bayesian optimization was evaluated using a 10 MW PV project in the United Arab Emirates [36]. These findings suggest that recurrent DL represents a viable option for utility-scale forecasting in practical applications, although its performance differences remain dependent on data quality, input variable selection, and model tuning.

Hybrid forecasting methods attempt to overcome the limitations of individual approaches by combining complementing models, optimization procedures, or signal-processing techniques. Earlier approaches include EEMD-SE-RVM [37] and EEMD-SOA-BPNN [38], which use decomposition methods to divide non-stationary PV power signals into simpler components before forecasting, and ARIMA-ANN [39], which integrates statistical time-series modelling with nonlinear ANN learning. This concept has been extended in more recent studies using hybrid ML and optimized DL frameworks. For instance, the study involving the 50-MWp Bui PV plant [40] examined conventional ANN, RF, XGBoost and several hybrid combinations over forecast horizons ranging from one day to one month. Such hybrid systems may improve flexibility and predictive capability, but typically at the cost of greater computational and methodological complexity.

Recent literature also indicates a trend toward more advanced systems capable of addressing the temporal, spatial, and non-stationary features of utility-scale PV generation. The study of the 26 MW Kom-Ombo [41] employed actual meteorological and historical plant data to compare linear regression, decision tree, random forest and LSTM models, thereby demonstrating the real-world forecasting capabilities

of both traditional ML and recurrent DL methods. More sophisticated Transformer-based forecasting methods are also emerging. A hierarchical frequency-aware Transformer was validated using two grid-connected PV facilities with capacities of 23.92 MWp and 10 MWp in Algeria [42]. The approach combined frequency decomposition with Transformer modelling to represent non-stationary PV behavior across short-term and multiple forecasting horizons. Although these models provide stronger temporal representation, their more sophisticated architectures require greater computational resources, which may limit their practical application, when such resources are constrained.

Another major recent advancement is spatially resolved forecasting. In 2026, cloud-motion vectors were estimated and used to enable plant- and sub-plant-level nowcasting based on 1-min string-level observations from a utility-scale PV plant with a capacity exceeding 150 MWp [43]. This strategy is particularly important for very large PV plants because rapidly moving clouds may affect different areas of a plant at different times. The study represents a transition from conventional aggregated forecasting toward spatially sensitive forecasting frameworks that can account for intra-plant variability. However, these approaches require extensive sensing, transmission, and high-resolution data infrastructure.

Table 2 also demonstrates that forecasting performance cannot be compared solely according to the AI architecture employed. Reported forecasting accuracy can be significantly influenced by differences in plant capacity, geographical location, climatic conditions, sampling resolution, input variables, training datasets, forecasting horizons, and evaluation metrics. Consequently, a model that performs effectively for a particular plant or forecasting horizon cannot be universally regarded as superior for all utility-scale PV

applications. Standardized or normalized performance metrics, consistent forecasting horizons, identical evaluation periods, and common datasets are therefore necessary for meaningful benchmarking.

From an application perspective, conventional ML and FFNN approaches remain viable when computational simplicity and relatively short training time are important. LSTM-, GRU-, and Bi-LSTM- based models are more suitable when temporal dependencies are dominant and sufficient sequential data are available. Hybrid decomposition- and optimization-based approaches may improve the representation of nonlinear and non-stationary PV output, although at the cost of greater modelling complexity. Transformer architectures offer greater capacity for long-range temporal and multi-horizon forecasting. Spatio-temporal and cloud-motion-based methods are especially promising for very large and spatially heterogeneous PV plants.

Overall, no single forecasting method can be considered optimal for all utility-scale PV applications. Conventional ML models generally offer lower computational requirements, recurrent DL models provide stronger temporal modelling capabilities, hybrid approaches improve the representation of nonlinear and non-stationary behavior, Transformer architectures support more complex temporal dependencies, and spatially resolved methods are increasingly relevant to very large heterogeneous plants. Therefore, model selection should consider not only forecasting accuracy, but also the forecasting horizon, plant capacity, data availability and quality, computational requirements, model complexity, spatial characteristics, and the intended grid-operational application.

Table 2
Solar power forecasting in utility-scale PV system application

Ref	Year	Model	Capacity/Location	Forecast Horizon	Advantage	Limitation	Utility-Scale Suitability
[30]	2020	MLP, SVR, LR, RF	1.22MW, Brisbane	3 h	Enables comparison of several conventional ML approaches using the same forecasting problem	Limited explicit representation of long temporal dependencies compared with recurrent models	Suitable for benchmarking conventional ML approaches and applications where computational simplicity is important
[32]	2020	Bi-LSTM	20MW, China	1-3 h	Captures temporal dependencies in both forward and backward directions during model training	Higher computational and training complexity than conventional ML models	Suitable for short-term forecasting with sufficiently large sequential datasets
[37]	2020	EEMD-SE-RVM	30MW, China	1 h	Decomposition can reduce non-stationarity and separate complex PV power patterns before prediction	Multi-stage processing increases model complexity	Suitable for highly variable and nonlinear short-term PV generation
[70]	2020	LSTM	2.8MW	Not reported	Effective in capturing temporal dependencies in sequential PV data	Requires adequate historical data and careful hyperparameter configuration	Suitable for time-series-based forecasting where historical temporal information is important
[33]	2021	LSTM	68.8MW, Vietnam	Not reported	Demonstrates application of recurrent DL to a relatively large utility-scale PV plant	Training complexity and dependence on data quality	Highly relevant to large-scale PV applications because the model was evaluated on a 68.8 MW plant

Ref	Year	Model	Capacity/Location	Forecast Horizon	Advantage	Limitation	Utility-Scale Suitability
[34]	2021	FFNN, LSTM-RNN, GRU-RNN	75MW Northern Cape	1-6 h	Direct comparison of feed-forward and recurrent DL architectures across multiple forecast horizons	Model performance may vary considerably with forecast horizon and input configuration	Highly relevant because it evaluates multiple architectures on a 75 MW utility-scale plant
[60]	2021	ARMA	54MW, Australia	Not reported	Relatively simple statistical time-series implementation	Limited capability for representing complex nonlinear relationships compared with AI-based models	Useful as a statistical benchmark for large-scale PV forecasting
[71]	2021	GBNN	20MW, China	Not reported	Combines data-driven learning with a neural-network-based forecasting structure	Performance depends strongly on model configuration and representative training data	Applicable to medium-to-large utility-scale PV forecasting
[38]	2021	EEMD-SOA-BPNN	1.8MW, Australia	1 h	Combines decomposition, optimization, and nonlinear neural-network forecasting	Increased computational and methodological complexity	Suitable for nonlinear and non-stationary short-term PV forecasting, although demonstrated on a smaller plant
[39]	2021	ARIMA-ANN	9.9MW, Romania	1 h	Combines linear temporal modelling with nonlinear ANN learning	Requires multiple modelling stages and parameter configuration	Suitable when both linear temporal behavior and nonlinear relationships are present
[31]	2021	FFNN	1.22MW, Brisbane	5 min-3 h	Can evaluate model behavior across very-short- to short-term horizons	Does not explicitly retain temporal states as recurrent models do	Useful for examining the influence of forecast horizon on a conventional neural-network architecture
[72]	2022	ANN	50MW, Malaysia	30 min	Demonstrates ANN forecasting on a large Malaysian utility-scale PV plant	Conventional ANN may have limited explicit representation of sequential dependencies	Highly relevant to very-short-term forecasting for a 50 MW utility-scale PV application
[35]	2023	LSTM	25 MWac, Malaysia	5 min	Compares univariate and multivariate LSTM forecasting using actual utility-scale PV data	Performance depends on input-variable availability and data quality	Directly relevant because the model was validated on an operating 25 MWac utility-scale PV plant
[36]	2024	Deep learning / hybrid PV forecasting	10 MW, UAE	Short and medium term	Combines deep learning forecasting with practical PV project performance assessment	Site-specific validation and relatively complex model structure	Directly relevant because it was evaluated on a real 10 MW utility-scale PV project
[40]	2025	ANN, RF, XGBoost, XGBoost-ANN hybrid	50 MWp, Ghana	1 day, 1 week, 2 weeks, 1 month ahead	Compares single and hybrid ML models across multiple horizons; hybrid and ensemble methods show strong performance	Performance remains site- and climate-dependent	Highly relevant because models were validated on an operating 50 MWp utility-scale plant
[41]	2025	Nonparametric ML	26 MW, Egypt	Not stated	Uses real meteorological and historical plant data and demonstrates scalability of ML for large-scale plants	Conventional ML may have weaker long-range temporal modelling than advanced sequence models	Direct real-world application on a 26 MW utility-scale solar plant
[42]	2026	Hierarchical frequency-aware Transformer	23.92 MWp, El Bayadh and 10 MWp, Tindouf, Algeria	Short- and multi-horizon	Captures non-stationary PV behavior through frequency-aware Transformer	More complex than conventional ML/DL models; validated under arid climatic conditions	Strong utility-scale evidence because two grid-connected plants above 10 MW were used

Ref	Year	Model	Capacity/Location	Forecast Horizon	Advantage	Limitation	Utility-Scale Suitability
[43]	2026	Spatio-temporal cloud-motion forecasting	>150 MWp	1-min nowcasting	modelling and tests multiple horizons Uses string-level power measurements to estimate cloud motion and supports sub-plant forecasting	Requires highly granular plant-level measurements and communication infrastructure	Particularly relevant to very large heterogeneous PV plants and cloud-movement forecasting

IV. GRID CODE GUIDELINE FOR UTILITY-SCALE FORECAST

As the penetration of PV systems continues to increase globally, regulatory agencies have introduced specific grid codes (GCs) and compliance requirements for utility-scale PV plants. These grid codes aim to maintain grid reliability, stability, and operational efficiency by defining standards for forecasting, communication, and real-time response capabilities of utility-scale PV systems [44]. Forecasting requirements is one of the key components of these grid codes, particularly in power systems with high shares of variable RE. In practice, the plant operators are required to submit forecasts of expected power output according to the relevant GC requirements, together with periodic updates.

A comparative summary of the forecasting requirements for utility-scale PV plants across selected countries is presented in Table 3. The table compares the required forecasting horizons and the corresponding forecast-performance requirements, where specified. Accuracy refers to the forecast-error tolerance, allowable deviation, or minimum forecasting-performance requirement stated in the respective national grid code or regulatory guideline. Since different countries adopt different definitions, criteria, and performance measures, the reported accuracy values are presented according to the terminology used in the original regulatory sources and should not be interpreted as directly comparable metrics.

Germany was the first country to develop a technical GC specifically for solar power plants connected to medium-voltage (MV) and high-voltage (HV) networks [45][46]. This pioneering GC provided a comprehensive framework of technical standards and regulatory requirements for integrating PV systems into low- and medium-voltage networks, addressing key issues such as power quality and anti-islanding protection. Several other countries, particularly in Asia including Indonesia, Malaysia, Cambodia, Singapore, Thailand, Vietnam, Philippines, have established their own national GCs. Meanwhile, Myanmar, Brunei and Laos are reported to have internal GC documents that are applied selectively through bilateral agreements between utilities and applicants [47].

The Malaysia government has introduced specific guidelines and GCs for connecting utility-scale PV systems to the power grid. These requirements were established and published by the Energy Commission Malaysia (ECM) in 2016 [48]. According to the guidelines, the PV plant is required to submit a forecast of its expected output to be delivered to the grid system at the Interconnection Point. This forecast must be provided at 15-minute intervals for the subsequent 24-hour period. Similarly, the Philippine GC assigns forecasting responsibility to the System Operator [49]. The System Operator is responsible for producing and submitting an aggregated generation forecast to the Market Operator. To comply with the obligations stated in the GC,

the System Operator must develop or procure solar power forecasting software with expected forecast errors below 18% for short term forecasting and 30% for medium-term forecasting.

In India, the Indian Electricity Grid Code (IEGC), implemented by the Central Electricity Regulatory Commission, requires solar operators to submit generation forecasts at 15-minute intervals for the subsequent 24-hour period [50]. The GC stipulates a forecast-accuracy threshold of 70%, requiring actual generation to remain within $\pm 30\%$ of the scheduled forecast. Deviations beyond this range result in the imposition of unscheduled interchange (UI) charges in accordance with the relevant regulatory provisions.

In addition, Egypt has established two specific GCs for integrating solar power facilities into the national electricity grid. The first code specifies the technical criteria for connecting small-scale PV systems with capacities below 500 kW to low-voltage distribution networks. The second is the Solar Energy Grid Connection Code (SEGCC), which defines grid-integration standards for medium-scale PV systems, ranging from 500 kW to less than 20 MW, and large-scale systems with capacities of 20 MW and above. Importantly, the SEGCC requires solar plant operators to provide day-ahead and week-ahead forecasts of hourly active power output to the grid operator. This requirement indicates a clear emphasis on improving near-term operational coordination and mid-term grid planning to support reliable integration of variable solar energy.

In South Africa, the National Energy Regulator has approved a GC that requires solar plant owners to submit solar power generation forecasts 24 hours and seven days in advance [51]. The forecasts must be submitted daily at 10:00 am, for each 1-hour interval over the subsequent 24 hours and seven-day periods. The differences illustrated in Table 3 reflect the variations in national electricity-market structures, grid-operational methods, renewable-energy penetration levels, and regulatory requirements.

V. FUTURE RESEARCH DIRECTIONS

With the fast growth of utility-scale solar PV systems globally, there is an increasing need for highly accurate forecasting models that offer robustness, scalability, and adaptation across a wide range of operational conditions. Despite significant advances in AI-based forecasting approaches in recent years, persistent difficulties and knowledge gaps continue to prevent their widespread implementation at the utility scale. These limitations highlight the need for future research to develop more reliable, flexible and uncertainty-aware forecasting frameworks suited to the complex characteristics of large-scale solar power systems.

A. Focus on Large-Scale Solar Forecasting

Most PV forecasting studies continue to focus on small- and medium-scale installations. Studies involving large utility-scale plants remain relatively scarce. This represents a significant knowledge gap because forecasting performance obtained from smaller PV systems may not accurately reflect the behavior of utility-scale plants. Large PV facilities may cover extensive areas and comprise thousands of modules installed across diverse terrains, orientations, electrical zones and localized meteorological conditions. Therefore, the assumption that an entire plant behaves as a spatially homogeneous generation source becomes increasingly difficult to justify as plant size increases.

Another limitation is the evaluation of forecasting models using single site data. Such evaluations demonstrate model effectiveness under specific climatic and operational conditions, but provide limited evidence of model scalability and robustness across different utility-scale environments. Therefore, future studies should verify the applicability of AI-based forecasting models across several large PV plants and diverse climatic regions. Benchmarking should also consider normalized performance indicators, comparable forecasting horizons, and standardized validation procedures to enable more meaningful comparisons across different plant capacities and operating conditions.

Table 3
Forecasting requirements for utility-scale PV plants in selected countries

Country	Short-term	Medium-term	Long-term	Accuracy
Malaysia [48]	1 hour ahead and day ahead	9 days ahead	4 months ahead	
India [50]	24 hours ahead	-	-	$\pm 30\%$, 70%
Philippine [49]	1 hour ahead	4 to 36 hours	-	18% to 30%
South Africa [51]	24 hours ahead	7 days ahead	-	-
Malawi [52]	24 hours ahead	7 days ahead	-	-
Germany [53]	15 min to 1 hour ahead	Day-ahead	Week-ahead	-
Spain [54]	1 hour and day-ahead	2 days ahead	7 days ahead	$\sim 10\text{--}20\%$ mean error
Italy [55]	15-min, day-ahead	48 hours ahead	-	-
Australia [56]	5-min, 30-min ahead, day-ahead	Rolling forecast up to 2 days	-	-
China [57]	15-min to 1-hour ahead	Day-ahead	Week-ahead	$< 30\%$
Japan [58]	1-hour ahead and day-ahead	3 to 7 days ahead	-	-

Recent studies have begun to consider operational forecasting requirements rather than focusing solely on prediction accuracy. For instance, Tao et al. proposed a Transformer based day-ahead PV forecasting framework [59]. In particular, the system considers the timing and

accuracy requirements of real-world grid-connected forecasting applications. Therefore, future utility-scale forecasting studies should consider not only conventional error metrics, such as RMSE and MAE, but also computational efficiency, robustness to missing data, scalability, and suitability for practical grid operation.

B. Forecasting Data, Meteorological Resolution, and Cloud Movement

Meteorological variability is one of the dominant sources of uncertainty in utility-scale PV forecasting. Most studies are based on either direct forecasting using historical PV-production data or indirect forecasting using meteorological variables. Researchers generally recognize that integrating meteorological data can improve forecasting accuracy. However, utility-scale PV plants often extend across vast and uneven landscapes. Consequently, a measurement obtained at one location may differ significantly from measurements obtained in other areas of the same plant [34] [60].

Solar irradiance is strongly affected by cloud formation and movement, which can cause substantial changes in PV generation over a short period. For utility-scale facilities, this issue becomes more complex because cloud cover may affect different parts of the plant at different times. Therefore, one zone may experience cloud cover and reduced irradiance, while another zone may receive direct solar radiation, resulting in considerable spatial variation in power generation.

Most forecasting methods rely on historical PV power data, on-site meteorological measurement, numerical weather prediction (NWP), or a combination of these sources. However, measurements obtained from a single meteorological station may not adequately represent conditions across a geographically extensive PV plant. Future studies should thus investigate the integration of spatially distributed irradiance and temperature measurements, multiple meteorological stations, all-sky images, satellite observations, and high resolution NWP data.

Advanced AI technologies are increasingly being applied to represent the spatial and temporal variability of weather conditions. Recently, transformer-based techniques have been developed for solar-energy nowcasting utilizing geostationary satellite data, demonstrating the ability of satellite observations and attention-based models to represent rapidly changing atmospheric conditions [61]. These techniques are particularly relevant to utility-scale PV facilities because the spatial movement of clouds across different sections of a plant can produce substantial ramp events. Future forecasting frameworks should therefore move beyond single-point meteorological measurements and investigate spatiotemporal modelling that combines local sensors, remote sensing data, and AI-based cloud-motion analysis.

C. Forecasting Horizon and Grid-Code Alignment

The required data resolution, input variables, forecasting architecture and intended operational application depend directly on the forecasting horizon. Ultra-short-term forecasting may rely heavily on recent power measurements, local irradiance observations, and cloud movements, whereas day-ahead forecasting typically incorporates meteorological forecasts such as NWP. Medium- and long-term forecasts have different uncertainty characteristics and serve distinct operational and planning objectives.

Moreover, there is no consistent classification of ultra-short-, short-, medium-, and long-term forecasting horizons, making comparison across studies problematic [48]. More importantly, utility-scale PV forecasting is typically required to satisfy national grid-code requirements related to scheduling, dispatch, balancing and electricity-market participation. As shown in Table 3, different regulatory frameworks prescribe varying forecasting horizons, temporal resolutions, submission frequencies, and acceptable forecast errors.

Recent work on operational day-ahead forecasting demonstrates the importance of developing forecasting models according to real-world application requirements. Tao et al. proposed a Transformer-based model capable of generating multi-step forecasts at a 15-min resolution and explicitly examined the forecasting horizons required for actual grid-connected PV systems [59]. Therefore, future forecasting models should not be developed independently of their intended practical application. Instead, the model architecture, input data, temporal resolution and evaluation criteria, should be aligned with the relevant grid-code requirements.

D. Micro-Level Forecasting for Non-Uniform Terrain

Utility-scale PV plants are typically modelled as a single aggregation of generation units. This simplifies forecasting but can obscure crucial geographical differences within the plant. Non-uniform terrain, localized shading, different module orientations, temperature gradients, inverter operating conditions, and spatial variations in irradiance can produce different power-generation patterns across individual sections of the plant [34].

This limitation becomes more important as plant size increases because the probability of experiencing different meteorological and operating conditions across the site also increases. Micro-level or zonal forecasting therefore represents an important future research direction. Under this approach, a large PV plant can be divided into electrically or spatially meaningful zones, with the power output of each zone forecast independently before the individual forecasts are aggregated to obtain total plant power output.

Future studies should investigate hierarchical forecasting, clustering, graph-based neural networks, attention mechanisms, and other spatiotemporal models capable of representing relationships among different sections of a PV plant. However, improvements in forecasting performance should also be evaluated against the additional sensing, communication, data-storage, and computational requirements introduced by micro-level forecasting. This is particularly important for determining whether spatially distributed forecasting is economically justified for real-world utility-scale deployment.

E. Probabilistic Forecasting

Most existing PV forecasting studies rely on deterministic point forecasts. Although point forecasting provides an expected generation value, it does not indicate the uncertainty associated with that prediction. This is a major challenge for utility-scale operation because forecast uncertainty can affect reserve allocation, dispatch decisions, market bids and balancing costs.

Probabilistic forecasts provide additional information in the form of prediction intervals, probability distributions or forecast scenarios. Recent studies have shown the potential of

these techniques for PV applications. Massidda et al. [62] evaluated several probabilistic forecasting approaches in a day-ahead setting and found conformalized quantile regression deliver strong probabilistic forecasting performance, while also highlighted the crucial influence of weather forecast quality. These results suggest that uncertainty modelling should be considered together with the quality of meteorological inputs when developing probabilistic PV forecasts.

The practical relevance of uncertainty information has also been demonstrated in electricity-market applications. Visser et al. demonstrated that stochastic market-bidding techniques based on probabilistic solar power forecasts can result in higher revenues and lower energy imbalances [63]. Therefore, the economic and operational value of probabilistic forecasting should be considered in addition to its statistical accuracy measures.

Future utility-scale investigations should therefore augment deterministic metrics like RMSE and MAE with probabilistic measurements such as prediction interval coverage probability, interval width, calibration, sharpness and continuous ranking probability score. More importantly, probabilistic forecasts should be integrated into practical grid-operation and market-decision frameworks to determine whether improved uncertainty representation leads to measurable operational benefits.

F. Transfer Learning and Model Generalization

A key practical limitation of AI-based PV forecasting is that models are usually trained and validated using data from a single PV site. When such models are relocated to another site, their performance may deteriorate due to differences in temperature, PV capacity, terrain, module orientation and design, sensor availability, and operating conditions. Developing and re-training a separate forecasting model for each new utility-scale PV project may also require substantial historical data and computational resources.

Transfer learning and domain-adaptation methods offer a potential solution by reusing knowledge obtained from existing sites at new locations. Recent studies have investigated the use of transfer learning for solar irradiance forecasting, demonstrating that it can enhance forecasts when the target region has limited historical measurements [64]. Although these methods were not specifically developed for the utility-scale PV facilities, their basic notion is very relevant for large scale forecasts especially for the newly commissioned plants with limited historical operational data.

Future research should therefore explore transfer learning, domain adaptation, continual learning, and adaptive retraining across utility-scale PV plants. Particular attention should be given to identifying which model components can be transferred between plants and which require local recalibration. Model generalization should also be examined across different climates, seasons, plant capacities and operating conditions rather than assuming that performance achieved at one site can be replicated at another.

G. Emerging Transformer and Hybrid AI Approaches

Recent advances in artificial intelligence have produced novel forecasting architectures that may improve the accuracy, scalability and robustness of PV power forecasting. In this respect, Transformer-based models have attracted more attention because their attention mechanisms can capture long-range temporal dependencies and interactions

among different meteorological variables and historical power data. Recently, Hanif and Mi [65] reviewed the growing application of Transformer architecture in solar-energy forecasting across different forecasting horizons, while also emphasizing challenges related to computational requirements, data quality and model standardization.

In addition, Transformer models have been evaluated in real-world PV forecasting scenarios. Tao et al. [59] proposed an operational day-ahead PV power forecasting framework based on a Transformer variant that integrates historical measurements and numerical weather prediction data. The model generates multi-step forecasts at a 15-min resolution and was designed to satisfy practical day-ahead grid-connected forecasting requirements. These characteristics indicate that Transformer architectures have potential for utility-scale applications requiring long input sequences, multiple meteorological variables, and multi-step forecasting. However, their relatively high computational requirements and dependence on large, representative datasets should be considered before real-world deployment.

Graph neural networks (GNNs) represent another promising direction because they can explicitly model spatial relationships among geographically distributed PV systems or different sections of a large PV installation. Verdone et al. [66] developed an explainable spatio-temporal GNN framework for multi-site PV energy forecasting that combines spatial and temporal information while also providing explanations for the resulting predictions. More recently, Yang et al. [67] proposed the DEST-GNN model for multi-site intra-hour PV power forecasting, in which adaptive graph convolution and spatiotemporal attention are used to capture relationships among different PV sites. These approaches are particularly relevant to utility-scale PV plants because individual zones, inverter groups, or sensor locations can potentially be represented as interconnected nodes, allowing spatial variability within the plant to be incorporated into the forecasting process. Nevertheless, further research is required to validate GNN-based forecasting using data from heterogeneous, real-world utility-scale PV plants.

Physics-informed machine learning and hybrid physical-AI approaches also represent important research direction. These approaches incorporate physical knowledge of PV conversion, irradiance, temperature and system behavior into data-driven forecasting models rather than depending solely on historical data. De Oliveira Santos et al. [68] examined hybrid methods for PV estimation and forecasting and classified them into three categories: physics-informed machine learning methods, optimized physical models, and physics-guided methods. They found that integrating physical knowledge with machine learning can improve generalization, interpretability and physical consistency while also addressing some of the limitations of purely data-driven models. These approaches are particularly beneficial for utility-scale PV facilities because forecasting models must be robust under operating conditions that may not be fully represented by the training dataset.

Another emerging issue is the ability of AI forecasting models to generalize across different PV sites and operating conditions. Wang et al. [69] proposed a graph-based domain-adaptation approach for ultra-short-term PV forecasting under data-scarce conditions, enabling forecasting-related knowledge to be transferred from data-rich PV sites to sites with limited historical data. Although this study focused on distributed PV systems, the underlying concept is relevant to

utility-scale forecasting, particularly for newly commissioned plants where extensive historical datasets may not yet be available. Similar transferability approaches may reduce the need to develop a completely independent forecasting model for each utility-scale PV plant.

Overall, these emerging developments indicate a transition from standalone AI forecasting models toward more integrated frameworks that combine temporal learning, spatial modelling, physical knowledge, and model transferability. Future research should therefore evaluate the use of Transformer architecture, GNNs, physics-informed machine learning, foundation models and hybrid physical-AI techniques using real-world utility-scale PV datasets. Their performance should be evaluated not only in terms of forecasting accuracy, but also computational efficiency, interpretability, generalization, scalability and adaptability to operational grid requirements.

VI. CONCLUSION

The integration of utility-scale photovoltaic systems into modern power grids require accurate and robust forecasting mechanisms to mitigate the challenges associated with the intermittency and meteorological dependence of solar energy. Although AI techniques such as ML, DL and hybrid approaches have shown promising performance in solar power forecasting, their application in large-scale PV contexts remains underdeveloped compared to small-scale systems. Utility-scale forecasting challenges, spatial variability, high-resolution data requirements, and the need to comply with evolving regulatory standards underscores the critical demand for technically advanced and regulation-aligned forecasting solutions. Future research should prioritize the development of AI models that are not only scalable and adaptable across diverse operating conditions but also capable of accurately quantifying and managing forecasting uncertainty. Reliable forecasting is essential for maintaining grid stability, reducing balancing costs, and supporting the continued global expansion of solar power.

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CONFLICT OF INTEREST

Authors declare that there is no conflict of interests regarding the publication of the paper.

AUTHOR CONTRIBUTION

The authors confirm contribution to the paper as follows: Conceptualization, Noor Hasliza Abdul Rahman, Shahril Irwan Sulaiman.; literature search and data curation, Noor Hasliza Abdul Rahman.; formal analysis and synthesis of reviewed studies, Noor Hasliza Abdul Rahman, Mohamad Zhafran Hussin.; visualization, Ezril Hisham Mat Saat.; writing original draft preparation, Noor Hasliza Abdul Rahman.; editing, Muhammad Asraf Hairuddin. All authors have read and agreed to the published version of the manuscript.

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