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Review Article

State-of-the-Art Probabilistic Solar Power Forecasting: A Structured Review

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ABSTRACT

In recent years, the installed capacity increment with regard to solar power generation has been highlighted as a crucial role played by Photovoltaic (PV) generation forecasting in integrating a growing number of distributed PV sites into power systems. Nevertheless, because of the PV generation's unpredictable nature, deterministic point forecast methods struggle to accurately assess the uncertainties associated with PV generation. This paper presents a detailed structured review of the state-of-the-art concerning Probabilistic Solar Power Forecasting (PSPF), which covers forecasting methods, model comparison, forecasting horizon and quantification metrics. Our review methodology leverages the Preferred Reporting Items for Systematic Reviews and Meta-Analyses (PRISMA) approach to systematically identify primary data sources, focusing on keywords such as probabilistic forecasting, Deep Learning (DL), and Machine learning (ML). Through

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an extensive and rigorous search of renowned databases such as SCOPUS and Web of Science (WoS), we identified 36 relevant studies (n=36). Consequently, expert scholars decided to develop three themes: (1) Conventional PSPF, (2) PSPF utilizing ML, and (3) PSPF using DL. Probabilistic forecasting is an invaluable tool concerning power systems, especially regarding the rising proportion of renewable energy sources in the energy mix. We tackle the inherent uncertainty of renewable generation, maintain grid stability, and promote efficient energy management and planning. In the end, this research contributes to the development of a power system that is more resilient, reliable, and sustainable.

Keywords: Deep learning, machine learning, photovoltaic, probabilistic forecast, solar power

INTRODUCTION

Solar power has emerged as a highly promising and environmentally sustainable renewable energy source. It holds the potential to address escalating global energy demands while simultaneously mitigating the negative impacts of greenhouse gas emissions (Panagiotopoulou et al., 2022; Shafiullah et al., 2022). Due to the high solar radiation, global Photovoltaic (PV) development has been increasing and is expected to reach 4,500 GW by 2050 (Chowdhury et al., 2020). Global photovoltaic (PV) capacity experienced substantial growth in 2022, reaching a cumulative capacity of 1,185 GW, as reported by the International Energy Agency (IEA) (International Energy Agency, 2023). However, integrating solar energy into the grid system presents a few challenges, primarily due to its intermittent and unpredictable nature (Zafar et al., 2022). The intermittency stems from several factors, such as the diurnal sunlight cycle, cloud cover, and weather conditions. Conventional fossil fuel power plants generate a consistent and manageable output, while solar power generation fluctuates throughout the day and halts during nighttime. Moreover, the variability poses significant challenges for grid operators and energy planners tasked with ensuring a reliable power supply.

Traditional forecasting methods typically utilize deterministic approaches, providing a single-point forecast of expected solar generation (Maraggi et al., 2021). However, the application of Artificial Intelligence (AI) methods, particularly Machine Learning (ML), has garnered widespread attention in a multitude of recent research (Mellit et al., 2020; Pazikadin et al., 2020). In the current status quo, the ML method has become a focal point for numerous researchers. ML-based models leverage their ability to predict PV power with precision dependent on the volume and quality of data and the selected learning algorithm. Random Forest (RF), Support Vector Regression (SVR), Support Vector Machine (SVM), and Artificial Neural Network (ANN) are also some of the prominent ML models with regard to forecasting in the PV system application.

Nevertheless, conventional ML model learning typically offers limited depth for long-term sequence data (Wang et al., 2019). Since ML models learn from input data, they struggle to familiarize themselves with environmental changes. Other than that, the complexity with regard to weather conditions as well as the massive input data required with respect to large-scale solar applications. It indicates that shallow models may not fully capture the corresponding deep non-linear characteristics as well as time-series dynamic characteristics regarding the dataset (Yu et al., 2020).

Deep Learning (DL) refers to a subset of machine models. It attracted significant attention because of its capability to tackle complex problems with massive as well as unstructured data volumes utilizing deep neural networks (Chen et al., 2019). Compared to ML, DL adapts to environmental changes by continuously receiving input and improving its models. Note that the main application scenario for DL models is sequential or time-series data. These comprise Recurrent Neural Networks (RNN), Long Short-Term Memory (LSTM), Gated Recurrent Units (GRU), and Convolutional Neural Networks (CNN). The hierarchical relationship between AI, ML, and DL is illustrated in Figure 1.

Recently, there have been significant advancements in solar power forecasting. It marks a notable shift towards improving the accuracy and dependability of forecasting regarding solar power generation (Li et al., 2022; Thaker & Höller, 2022). This progress stems from acknowledging that traditional deterministic forecasts are inadequate for the modern energy landscape. It is defined by the unpredictable and intermittent nature of solar power generation since traditional deterministic methods forecast the power generation future relying on a single value without considering the associated uncertainty.

Probabilistic Solar Power Forecasting (PSPF) utilizes advanced techniques to generate forecasts that predict the most probable future solar power output and quantify the associated uncertainties (Abuella & Chowdhury, 2019; Wen et al., 2020). This approach is especially critical in variable solar generation, as it enables decision-makers to make well-informed choices based on a comprehensive understanding of the projected outputs and the inherent risks involved. By assigning probabilities to different scenarios, this method fosters a deeper understanding of the potential range of outcomes and their associated uncertainties. Hence, this information is invaluable for decision-makers, enabling them to assess the risks and make well-informed choices considering the likelihood of various outcomes.

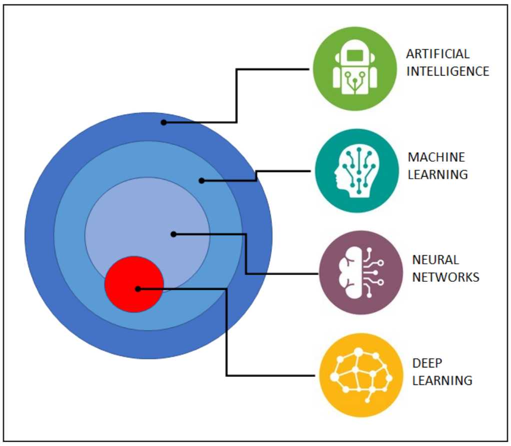

Figure 1. The relationship exists between ML, AI, Neural Networks (NN), and DL

Note that a significant number of research papers have reviewed the deterministic solar power forecast in ML and DL methods. The research on ML and DL models in PSPF may be established new as well as lacking in comparison to deterministic forecasting (Ahmed et al., 2020; Chu et al., 2021; Devaraj et al., 2021; Feng et al., 2021; Kumari & Toshniwal, 2021; Mittal et al., 2022; Rajagukguk et al., 2020; Wang et al., 2019). PSPF has not yet been broadly adopted in PV fields. Nonetheless, its applications are progressively applied to other decision-making challenges under uncertainty. For instance, PSPF techniques are utilized in wind forecasting (Bazionis & Georgilakis, 2021) and domains beyond energy forecasting. It includes weather predictions (Kirkwood et al., 2021) and applications in economics and finance (Salisu et al., 2021). Solar power forecasting may benefit advancements in wind forecasting. However, it has challenges, such as high weather variability and increased penetration of PV systems into the grid.

Considering these developments, this structured review aims to furnish a comprehensive overview of the state-of-the-art in PSPF. One notable exclusion from the present literature is adopting the ML and DL models in probabilistic forecasting. It encourages us to examine cutting-edge forecasting approaches in their entirety, as well as the most current advancements in the PSPF field.

This research's contributions are given below:

- A comprehensive review of the impact of forecasting horizon and model performances.
- A comparative evaluation of ML and DL in probabilistic forecasting model advancement.
- A comprehensive review of uncertainty quantification metric.

MATERIAL AND METHODS

Identification

The structured review consists of three key stages in choosing pertinent articles for this research. Note that the first stage involves recognizing keywords and searching for related terms utilizing thesauruses, previous research, encyclopedias, and dictionaries. Once all the relevant keywords were decided, search strings were generated regarding the SCOPUS and Web of Science (WoS) databases (Table 1). Before the structured review process's initial phase, this study project acquired 165 papers from both databases.

Screening

As part of the screening process, extensive measures are needed to ensure the utmost accuracy and reliability of findings. In the initial stage of the study, 39 articles were meticulously screened using the scholars' inclusion and exclusion criteria. The main focus was on literature, specifically research articles and conference papers, as they are the primary sources. Only publications in the English language were reviewed to ensure

Table 1
The search string

Database	Descriptions
Scopus	**TITLE-ABS-KEY** (("probabilistic forecast*" AND ("deep learning" OR "deep neural network" OR deep OR "machine learning" OR "artificial intelligence") AND ("solar power" OR photovoltaic OR pv OR "large scale solar" OR "utility-scale"))) AND PUBYEAR > 2019 AND PUBYEAR < 2025 AND (LIMIT-TO (DOCTYPE , "ar") OR LIMIT-TO (DOCTYPE , "cp")) AND (LIMIT-TO (LANGUAGE , "english")) Access Date: 12 March 2024
WoS	"probabilistic forecast*" AND ("deep learning" OR "deep neural network" OR deep OR "machine learning" OR "artificial intelligence") AND ("solar power" OR photovoltaic OR pv OR "large scale solar" OR "utility-scale") (**Topic**) and 2024 or 2023 or 2022 or 2021 or 2020 (Publication Years) and Article or Proceeding Paper (Document Types) and English (Languages) Access Date: 12 March 2024 "probabilistic forecast*" AND ("deep learning" OR "deep neural network" OR deep OR "machine learning" OR "artificial intelligence") AND ("solar power" OR photovoltaic OR pv OR "large scale solar" OR "utility-scale") (**Title**) and 2023 or 2022 or 2020 (Publication Years) and Article or Proceeding Paper (Document Types) and English (Languages) Access Date: 12 March 2024

consistency and clarity in findings. Consequently, it is important to note that the study focused on the past six years (2019–2024). For the second round, 39 articles were rejected to eliminate any duplicates. In total, 88 publications were eliminated based on our rigorous selection criteria.

Eligibility

The third phase resembled the eligibility assessment. A total of 77 articles were compiled. During this stage, a comprehensive evaluation of both article titles and essential content was conducted to verify their adherence to the inclusion criteria and alignment with the current research objectives of the study. Consequently, 41 reports were deemed ineligible for being outside the scope, featuring irrelevant titles, having abstracts unrelated to the study's objectives, or full text not being accessible. Finally, 36 articles were deemed eligible for review, as tabulated in Table 2.

Table 2
Searching selection criterion

Criterion	Inclusion	Exclusion
Language	English	Non-English
Timeline	2019–2024	<2019
Literature type	Journal article and conference proceeding	Book chapter, review, data paper

Data Abstraction and Analysis

As a part of this study, an integrative analysis was utilized to assess a range of research designs, including quantitative, qualitative, and mixed methods. The study aimed to identify relevant topics and subtopics by utilizing a meticulous approach that commenced with data collection. Figure 2 illustrates the analysis of 36 articles to extract information related to the study's topics. Correspondingly, the studies related to probabilistic forecasting were assessed, carefully considering each study's research methods and findings. Subsequently, the authors collaborated to develop themes based on the evidence presented in the study's context. A comprehensive log was diligently maintained throughout the entirety of the data analysis process, meticulously documenting all pertinent analyses and perspectives relevant to the interpretation of the data. Once the themes were developed, the authors compared them to ensure consistency. The produced themes were then fine-tuned to establish consistency. In securing the findings' validity, two experts were interviewed, one having expertise in solar power forecasting as well as statistical analysis. These experts reviewed each sub-theme to ensure its clarity, importance, and adequacy by determining domain validity. Consequently, the author adjusted corresponding to the feedback and comments by experts.

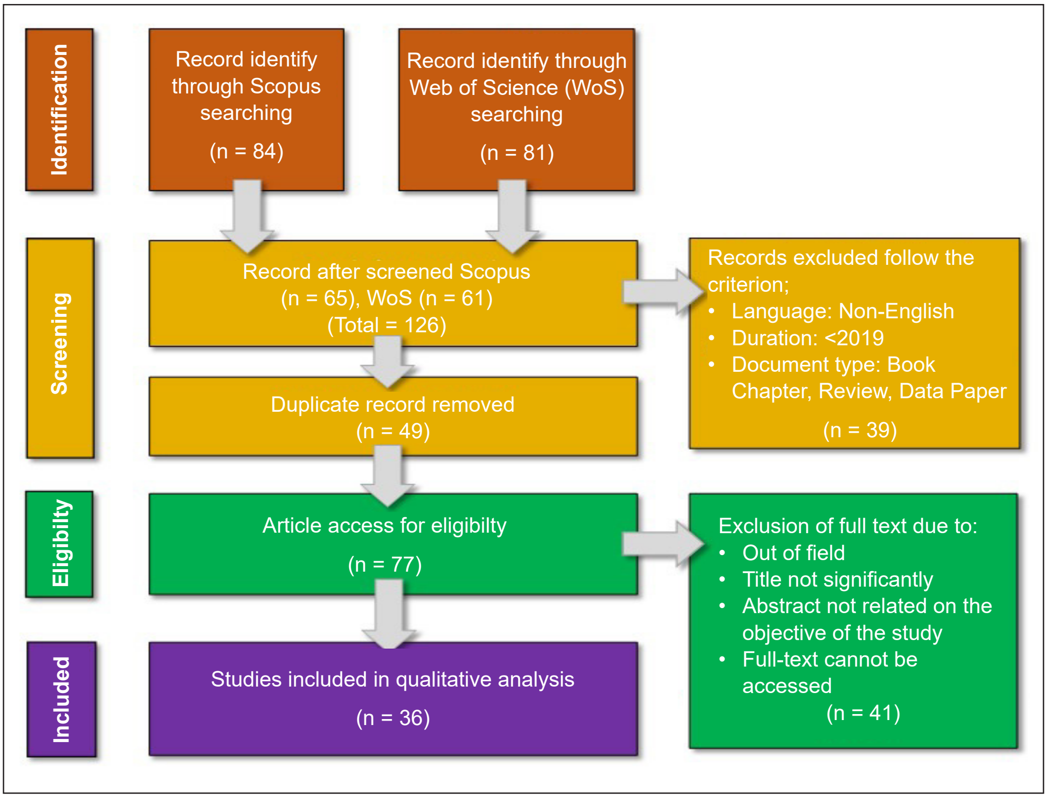

Figure 2. Flow diagram of the proposed search study (Mustafa, 2022)

RESULTS AND DISCUSSION

Accurate forecasts of solar power generation are vital for effective grid management and integrating renewable energy sources. Researchers have developed various solar power forecasting techniques, including probabilistic approaches, ML, and DL.

Throughout the most recent six years, the total number of publications per year from 2019 to 2024 is illustrated in Figure 3. The development of the PSPF study that is being presented demonstrates a steady rise in the number of publications for the WoS and SCOPUS databases. By 2020, there were twice as many documents available as in 2019. Note that a total of 12 documents were published. The years 2022 and 2023 saw the highest peak publishing numbers, with 36 papers published annually overall. Whether they are small- or large-scale solar systems, this spike probably reflects the increased interest in grid-connected PV systems. However, with just seven papers produced in 2024, there was a noticeable decline in the overall number of publications. Instead of a true decline in interest, this decline could be attributed to missing data or database updates. The data that has been presented indicates a distinct preference for publishing in the SCOPUS database over WoS. This preference could result from factors including citation metrics evaluation or accessibility. Other than that, these publications demonstrate the increasing interest in and significance of precise PSPF in renewable energy published in several scholarly journals and conference proceedings.

An extensive literature review was conducted, and 36 relevant articles were analyzed. It categorized them into three themes: probabilistic forecasting (eight articles) in Table 3, PSPF with ML (9 articles) in Table 4, and PSPF with DL (19 articles) in Table 5. The analysis has covered a significant state-of-the-art trend, providing a comprehensive overview of the

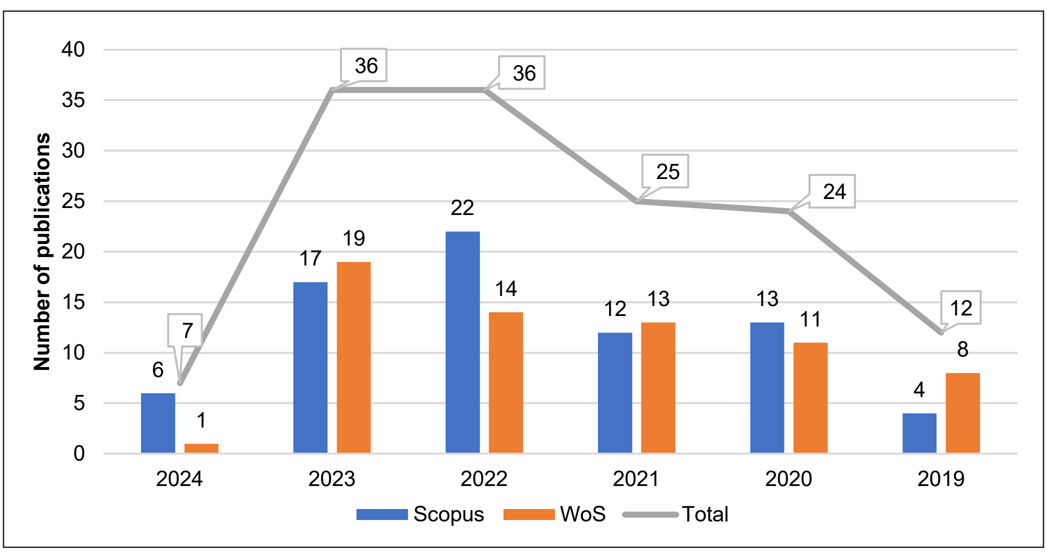

Figure 3. Publication trend analysis of PSPF

present research status of PSPF, as exhibited in Tables 3 to 5. Moreover, the analysis has disclosed the existence of forecasting models based on day-ahead and hour-ahead forecasting horizons, as depicted in Figure 4. The term day ahead resembles a forecasting horizon enveloping the next day (Andrade et al., 2017). Conversely, an hour ahead generally pertains to the formulation of forecasting that covers the next hour from the current moment (Wang et al., 2020). The number of articles published on hour-ahead forecasting in 2022 has significantly increased compared to prior years. It indicates an increasing attraction to this field of study. Conversely, the number of articles published on day-ahead forecasting peaked in 2020 and has relatively maintained over the following four years.

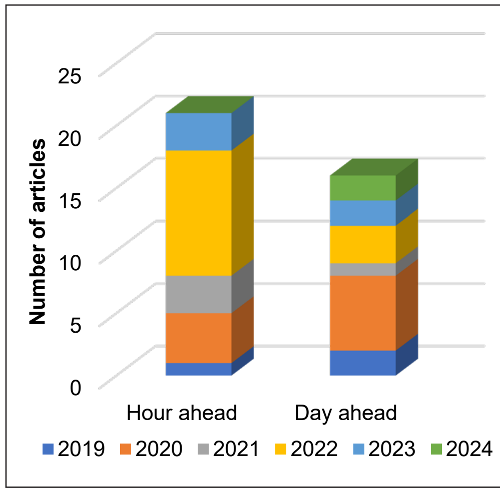

Figure 4. The probabilistic forecasting is based on the forecasting horizon from 2019 to 2024

Impact of Forecasting Horizon and Model Performances

The accuracy and reliability of PV power forecasting are achieved for a limited period called forecasting horizon. The selection of appropriate time horizons allows grid operators, utility companies, and energy managers to effectively strategize and enhance the operation of the grid and balance the supply and demand while maintaining the accuracy of forecasting output (Ahmed et al., 2020). Depending on the application for which forecasting is employed, the classification can vary significantly, involving very short, short-term, medium-term, or long-term horizons. However, there is no standard on horizon classifications, and the categories may overlap in some applications. Table 6 shows the type of forecasting horizon for the application in PV fields.

Based on the results from Tables 3 to 5, the majority of papers address short-term forecasting, focusing on horizons ranging from intra-day (hour ahead to day-ahead) (Bai et al., 2023; Mitrentsis & Lens, 2022; Phan et al., 2024). According to Mpfumali et al. (2019), “day ahead” pertains to a forecasting horizon that spans the entirety of the subsequent day. On the other hand, the term “hour ahead” typically refers to the development of a forecast that encompasses the subsequent hour from the present moment (Wang et al., 2020).

The field of probabilistic forecasting has yielded significant insight. Research reveals that forecasting models display varying performance levels based on the evaluation time horizon. Moreover, recent research has demonstrated the significance of employing short-term (hour ahead) forecasting methodologies when integrating PV power generation into

Table 3
Conventional Probabilistic Solar Power Forecasting (PSPF)

Authors	Title	Source Title	Method	Forecasting Horizon	Dataset & Case Study Location	Results
Bai M., Zhou Z., Chen Y., Liu J., Yu D. (Bai et al., 2023)	Accurate four-hour-ahead probabilistic forecast of PV power generation based on multiple meteorological variables-aided intelligent optimization of numeric weather prediction data.	Earth Science Informatics	NWP and Kernel Density	4 hours ahead	3 years, Brussels	MAE ranging from: 25.04% to 48.12% for 1–4 steps 14.80% to 21.27% for 5–8 steps 6.40% to 11.10% for 9–12 steps 2.18% to 4.45% for 13–16 step
Doelle O., Klinkenberg N., Amthor A., Ament C. (Doelle et al., 2023)	Probabilistic Intraday PV Power Forecast Utilizing Ensembles of Deep Gaussian Mixture Density Networks	Energies	Gaussian mixture density networks	Intra-day	20 months, Germany	Multiple Gaussian Distribution Skill score= 20.5% Ensembles Gaussian Distribution Skill score= 19.5%
Zhou N., Xu X., Yan Z., Shahidehpour M. (Zhou et al., 2022)	Spatio-Temporal Probabilistic Forecasting of PV Power Based on Monotone Broad Learning System and Copula Theory	IEEE Transactions on Sustainable Energy	Quantile Regression Monotone broad Learning System (QRMBLS) and Copula theory.	Hour ahead	Australia and USA	Pinball Loss (kW) 5 min = 1.7640 1 h = 2.7674 Wrinkle Score (kW) 5 min = 25.7535 1 h = 39.3493
Van Der Meer D., Camal S., Kariniotakis G. (Meer et al., 2022)	Generalizing Renewable Energy Forecasting Utilizing Automatic Feature Selection and Combination	2022 17th International Conference on Probabilistic Methods Applied to Power Systems, PMAPS 2022	Analogue Ensemble (AnEn)	7 hours ahead	21 months	Mean ± Standard Deviation = 0.274 ± 0.06, 0.277 ± 0.065 and 0.227 ± 0.032

Table 3 *(continue)*

Authors	Title	Source Title	Method	Forecasting Horizon	Dataset & Case Study Location	Results
Wang W. T., Yang D. Z., Hong T., Kleissl J. (Wang et al., 2022)	An archived dataset from the ECMWF Ensemble Prediction System for probabilistic solar power forecasting	Solar Energy	NWP model (model chain)	90 hours ahead	4 years, Europe and North America	MAE = 1.27 RMSE = 2.24
Yagli G. M., Yang D., Srinivasan D. (Yagli et al., 2020)	Reconciling solar forecasts: Probabilistic forecasting with homoscedastic Gaussian errors on a geographical hierarchy	Solar Energy	Hierarchical forecasting and reconciliation	Day ahead and hour ahead	California and Arizona	PINAW = 93.10 CRPSSS = 61.55% PICP = 44.03
Alessandrini S., McCandless T. (Alessandrini & McCandless, 2020)	The Schaake Shuffle technique combines solar and wind power probabilistic forecasting	Energies	Analogue Ensemble (AnEn) + Schaake Shuffle (SS)	Hour ahead	26 months, Kuwait	CRPS = 182 Reliability = 8.74
Mpfumali P., Sigauke C., Bere A., Mulaudzi S. (Mpfumali et al., 2019)	Day ahead hourly global horizontal irradiance forecasting—application to South African data	Energies	Quantile Regression	Day ahead	South Africa (August 2009–April 2010)	CRPS =151.57 Pinball loss = 8.82 PICP = 98.82%

Table 4
Probabilistic Solar Power Forecasting with regard to ML

Authors	Title	Source Title	Method	Forecasting Horizon	Dataset & Case Study Location	Results
Polo J., Martín-Chivelet N., Alonso-Abella M., Sanz-Saiz C., Cuenca J., de la Cruz M. (Polo et al., 2023)	Exploring the PV Power Forecasting at Building Façades Using Gradient Boosting Methods	Energies	Deterministic: XGBoost + Random Forest. Probabilistic: XGBoost + Bootstrap	Hour ahead	2 years, BIPV Spain	MAE: 40% (south array) MAE: 30% (East array

Table 4 *(continue)*

Authors	Title	Source Title	Method	Forecasting Horizon	Dataset & Case Study Location	Results
Thaker J., Höller R. (Thaker & Höller, 2022)	A Comparative Study of Time Series Forecasting of Solar Energy Based on Irradiance Classification	Energies	Ensemble ML	72 hours ahead	9 months	rMAE = 20.9% rRMSE 32.4% skill score = 0.48
Mitrentsis G., Lens H. (Mitrentsis & Lens, 2022)	An interpretable probabilistic model for short-term solar power forecasting utilizing natural gradient boosting	Applied Energy	NGBoost	Hour ahead	20 months, Southern Germany	MAE (pu) = 0.0367 RMSE (pu) = 0.0617 MBE (pu) = −0.0007 PICP (–) = 0.8882 PINAW (pu) = 0.1732 CRPS (pu) = 0.0274
Cui W., Wan C., Song Y. (Cui et al., 2022)	Hybrid Probabilistic Forecasting of PV Power Generation Considering Weather Conditions	IEEE Power and Energy Society General Meeting	Extreme learning machine-based quantile regression, as well as the Hidden Markov Model (HMEQR)	3 hours ahead	-	Skill score = -0.0258 Average Coverage Deviation (ACD) 90% = -1.48 80% = 0.33
Mitrentsis G., Liu M., Lens H. (Mitrentsis et al., 2022)	Open-Source Tool for Probabilistic Short-Term PV and Wind Power Forecasting	2022 17th International Conference on Probabilistic Methods Applied to Power Systems, PMAPS 2022	NGBoost	Day ahead	-	Spring CRPS (pu) = 0.03 RMSE (pu) = 0.07 Summer CRPS (pu) = 0.02 RMSE (pu) = 0.05 Autumn CRPS (pu) = 0.01 RMSE (pu) = 0.03 Winter CRPS (pu) = 0.01 RMSE (pu) = 0.02

Table 4 *(continue)*

Authors	Title	Source Title	Method	Forecasting Horizon	Dataset & Case Study Location	Results
Bhavsar S., Pitchumani R., Ortega-Vazquez M. A. (Bhavsar et al., 2021)	ML-enabled reduced-order scenario generation for stochastic analysis of solar power forecasts	Applied Energy	Clustering-based ML	Hour ahead	California ISO	Reduced uncertainty estimation 2–4.5%
Qiao J., Pu T. J., Wang X. Y. (Qiao et al., 2021)	Renewable Scenario Generation Using Controllable Generative Adversarial Networks with Transparent Latent Space	IEEE	Generative Adversarial Networks	Hour ahead		-
Liu W., Xu Y. (Liu & Xu, 2020)	Randomized learning-based hybrid ensemble model for probabilistic forecasting of PV power generation	IET Generation, Transmission and Distribution	Randomized Learning-based Hybrid Ensemble (RLHE)	Day ahead	2 years, Australia	RMSE = 10.03% MAE = 6.19%
Lauret P., David M., Pinson P. (Lauret et al., 2019)	Verification of solar irradiance probabilistic forecasts	Solar Energy	Quantile Regression Forest Gradient Boosting	Hour ahead	United States and La Réunion Island	USA, CRPS = 6.97% Reunion Island, CRPS = 23.1%

Table 5
Probabilistic Solar Power Forecasting with regard to DL

Authors	Title	Source Title	Method	Forecasting Horizon	Dataset & Case Study Location	Results
Phan Q. T., Wu Y. K., Phan Q. D. (Phan et al., 2024)	Enhancing One-Day-Ahead Probabilistic Solar Power Forecast With a Hybrid Transformer-LUBE Model and Missing Data Imputation	IEEE Transactions on Industry Applications	Transformer-LUBE	Day ahead	Taiwan	PI 90%: PINAW = 10.93 PI 80%: PINAW = 8.57 PI 70%: PINAW = 7.01
Bai M., Zhou Z., Li J., Chen Y., Liu J., Zhao X., Yu D. (Bai et al., 2024)	Deep graph gated recurrent unit network-based spatial-temporal multi-task learning for intelligent information fusion of multiple sites with application in the short-term spatial-temporal probabilistic forecast of photovoltaic power	Expert Systems with Applications	Gated Recurrent Unit (GRU) – Kernel Density Estimation (KDE)	Day ahead	Belgium and China	PI 90%: PINAW = 93.3% PI 80%: PINAW = 87.6% PI 70%: PINAW = 83.8%
Liu Y., Liu Y., Cai H., Zhang J. (Liu et al., 2023)	An innovative short-term multi-horizon PV power output forecasting method based on variational mode decomposition and a capsule convolutional neural network	Applied Energy	Two-stage hybrid Variational Mode Decomposition (VMD) as well as Innovative Capsule CNN (ACCNet)	Day ahead	DKASC Australia	Highest Coefficient of Determination (R^2) values for the six forecast horizons 5 min = 0.9640 15 min = 0.9647 30 min = 0.9655 1 h = 0.9607 6 h = 0.9637 1 d = 0.9617

Table 5 *(continue)*

Authors	Title	Source Title	Method	Forecasting Horizon	Dataset & Case Study Location	Results
Jonler J. F., Brunolottrup F., Berg B., Zhang D., Chen K. (Jonler et al., 2023)	Probabilistic Forecasts of Global Horizontal Irradiance for Solar Systems	IEEE Sensors Letters	Transformer model	Hour ahead	Groningen (Netherlands) Brighton (United Kingdom)	MASE Netherlands = 0.846 United Kingdom =0.807
Shi J., Wang Y., Zhou Y., Ma Y., Gao J., Wang S., Fu Z. (Shi et al., 2023)	Bayesian Optimization - LSTM Modeling and Time-Frequency Correlation Mapping Based Probabilistic Forecasting of Ultra-short-term Photovoltaic Power Outputs	IEEE Transactions on Industry Applications	Bayesian-LSTM		North China	PI 80% = 0.08 PI 90% = 0.10 PI 95% = 0.13
Sansine, V Ortega, P Hissel, D Hopuare, M (Sansine et al., 2022)	Solar Irradiance Probabilistic Forecasting Using Machine Learning, Metaheuristic Models and Numerical Weather Predictions	Sustainability	PSO-LSTM-Gaussian PSO-LSTM-Laplacian	Day ahead	Tahiti	PI 38%: CWC = 6.3% PI 68%: CWC = 14.68% PI 95%: CWC = 59.13% PI 99%: CWC = 40.1%
Lin F., Zhang Y., Wang K., Wang J., Zhu M. (Lin et al., 2022)	Parametric Probabilistic Forecasting of Solar Power with Fat-Tailed Distributions and Deep Neural Networks	IEEE Transactions on Sustainable Energy	Laplace and DeepAR (LSTM)	Hour ahead	10 months	Sharpness = 0.2147 CRPS = 0.0523
Sun M., He L., Zhang J. (Sun et al., 2022)	DL-based probabilistic anomaly detection for solar forecasting under cyberattacks	International Journal of Electrical Power and Energy Systems	Convolution Neural Network - LSTM -Gaussian CNN-LSTM-Gaussian	Hour ahead	4 years, Texas	True Positive Rate (TPR) = 0.94 False Positive Rate (FPR) = 0.21 F-1 Score = 0.86

Table 5 *(continue)*

Authors	Title	Source Title	Method	Forecasting Horizon	Dataset & Case Study Location	Results
Afrasiabi S., Allahmoradi S., Salimi M., Liang X., Chung C.Y. (Afrasiabi et al., 2022)	Nonparametric Maximum Likelihood Probabilistic PV Power Generation Forecasting based on Spatial-Temporal DL	Canadian Conference on Electrical and Computer Engineering	CNN – Gated Recurrent Unit - Nonparametric Smooth Band Limit Maximum Likelihood CNN-GRU-NSBML	Hour ahead	-	CRPS = 1.0963 MAPE = 2.4634 CE = 0.0357 NRMSE = 0.0633
Dumas J., Wehenkel A., Lanaspeze D., Cornélusse B., Sutera A. (Dumas et al., 2022)	A deep generative model for probabilistic energy forecasting in power systems: normalizing flows	Applied Energy	Variational AutoEncoders (VAE), Generative Adversarial Networks (GAN), and Normalizing Flow (NF)	Hour ahead	Global Energy Forecasting Competition 2014	NF outperformed GAN and VAE CRPS = 2.35 QS = 1.19 MAE-r = 2.66 AUC = 0.950 ES = 23.08 VS = 4.68
Cheng L. L., Zang H. X., Wei Z. N., Zhang F. C., Sun G. Q., (Cheng et al., 2022)	Evaluation of opaque DL solar power forecast models toward power-grid applications	Renewable Energy	LSTM - Analogue Ensemble LSTM-AE	Day ahead	2 years, GEFCOM 2014	MAE = 0.050 ± 0.002 RMSE = 0.098 ± 0.003
Kodaira D., Tsukazaki K., Kure T., Kondoh J. (Kodaira et al., 2021)	Improving forecast reliability for geographically distributed PV generations	Energies	Neural Network-Naïve Bayes Classifier - LSTM	Day ahead	1 year, Japan	Cover Rate = 87% - 98.1% PI Width = 0.78kW – 4.051kW MAPE = 12.1% - 81.6% RMSE = 0.113kW – 0.939kW
Lin Y., Koprinska I., Rana M. (Lin et al., 2021)	Temporal Convolutional Attention Neural Networks for Time Series Forecasting	Proceedings of the International Joint Conference on Neural Networks	Temporal Convolutional Attention Neural Network (TCAN)	Hour ahead	6 years, Australia	MAPE = 0.062 – 0.068 MAE = 0.031 – 0.035

Table 5 *(continue)*

Authors	Title	Source Title	Method	Forecasting Horizon	Dataset & Case Study Location	Results
Dumas J., Cointe C., Fettweis X., Cornelusse B. (Dumas et al., 2021)	DL-based multi-output quantile forecasting of PV generation	2021 IEEE Madrid PowerTech, PowerTech 2021 - Conference Proceedings	MLP, LSTM, Encoder-Decoder (ED), Gradient Boosting Regression (GBR)	Day ahead and intra-day	5 months, Belgium	NMAE MLP= 7.9 LSTM = 7.7 GBR = 9.0 NRMSE MLP= 9.7 LSTM = 9.4 GBR = 10.9 CRPS MLP= 6.2 LSTM = 4.4 GBR = 6.3
Mashlakov A., Kuronen T., Lensu L., Kaarna A., Honkapuro S. (Mashlakov et al., 2021)	Assessing the performance of deep learning models for multivariate probabilistic energy forecasting	Applied Energy	DeepAR (LSTM), DeepTCN, LSTNet (GRU), and DSANet	-	2 years	Error Sensitivity DeepAR = 0.24 ± 0.099 DeepTCN = 0.32 ± 0.281 LSTNet = 0.33 ± 0.141 DSANet = 0.16 ± 0.070
Huang Q., Wei S. (Huang & Wei, 2020)	Improved quantile CNN with two-stage training for daily-ahead probabilistic forecasting of PV power	Energy Conversion and Management	Quantile CNN (QCNN)	Day ahead	Australia	Quantile 0.05 RMSE = 0.43kW MAPE = 19% Quantile 0.95 RMSE = 0.49kW MAPE = 23.9%
Kharlova E., May D., Musilek P. (Kharlova et al., 2020)	Forecasting PV Power Production using a DL Sequence to Sequence Model with Attention	Proceedings of the International Joint Conference on Neural Networks	LSTM Sequence to Sequence	Day ahead	-	Skill scores = 42.5-46%

Table 5 *(continue)*

Authors	Title	Source Title	Method	Forecasting Horizon	Dataset & Case Study Location	Results
Zang H., Cheng L., Ding T., Cheung K.W., Wei Z., Sun G. (Zang et al., 2020)	Day-ahead PV power forecasting approach based on deep CNN and meta-learning	International Journal of Electrical Power and Energy Systems	Novel CNN - Residual network (ResNet) and dense convolutional network (DenseNet)	Day ahead	10 years, DKASC Australia	MAEs ResNet = 0.152kW DenseNet = 0.180 kW Coverage error = 1% - 5%
Park S., Park S., Hwang E. (Park et al., 2020)	Normalized residue analysis for DL-based probabilistic forecasting of PV generations	Proceedings - 2020 IEEE International Conference on Big Data and Smart Computing, BigComp 2020	Auto-regressive recurrent neural network (DeepAR)	Hour ahead	2 years, Korea	RMSE = 50.7338 MAE = 37.8768
Toubeau J. F., Bottieau J., Vallee F., De Greve Z., (Toubeau et al., 2019)	Deep Learning-Based Multivariate Probabilistic Forecasting for Short-Term Scheduling in Power Markets	IEEE TRANSACTIONS ON POWER SYSTEMS	Bi-LSTM-Gaussian Bi-LSTM-Quantile	Day ahead		Quantile Loss Bi-LSTM-Gaussian = 42MW Bi-LSTM-Quantile = 41MW

Table 6
Solar Power Forecasting horizon classification and application (Mishra et al., 2020; Perera et al., 2022)

Forecasting Classification	Horizon	Horizon Range	Application
Very-short term	Intra hour	1 min–30 min	Real-time control, ramp rate control, variability management
Short-term	Intra day	1–24 h	Demand response scheduling, grid operation
Medium-term	Intra week	1–7 days	Transmission scheduling and maintenance, economic dispatch
Long-term	Intra month	1 month–1 year	Energy procurement, economic feasibility, optimal design of renewable power plant

the electricity grid. Shi et al. (2023) have proposed an innovative method for predicting PV power outputs in the short term, focusing on time intervals ranging from minutes to hours. The researchers employ LSTM networks in combination with Bayesian optimization to provide probabilistic predictions. These predictions have prediction ranges of 80%, 90%, and 95%, resulting in accuracies of 0.08, 0.10, and 0.13, respectively. Jonler et al. (2023) have proposed a methodology that utilizes ensemble modeling and QR techniques to generate probabilistic predictions of Global Horizontal Irradiance (GHI) within a short-term horizon. The proposed approach provides probabilistic predictions encompassing the whole spectrum of conceivable GHI values, resulting in a predicted Mean Absolute Scaled Error (MASE) as minimal as 0.807.

Accuracy is of utmost importance in short-term forecasting when the level of uncertainty is comparatively smaller than that of longer forecasting horizons. Although advanced forecasting approaches are valuable, conventional XGBoost (Polo et al., 2023) may also be enough for short-term forecasting. The utilization of advanced forecasting methodologies is paramount in successfully integrating solar PV power generation into the power grid, guaranteeing efficient and dependable management of energy resources.

In solar power forecasting, day-ahead forecasting is significant for power system planning and market operations. The research conducted by Dumas et al. (2022; Zang et al., 2020) demonstrates the significance of day-ahead forecasting in these scenarios. Consequently, their study's findings indicate that this method improves forecasting precision while maintaining computing efficiency. It presents it as appropriate for incorporation into intraday decision-making tools for effective optimization. Other researchers, Huang and Wei (2020) and Kharlova et al. (2020), also explore day-ahead forecasting but propose innovative approaches to improve precision and reliability. The proposed techniques achieved skill scores ranging from 42.5% to 46% utilizing normalized root mean square error (RMSE) based on forecast skill records as a performance metric. However, challenges escalate with increasing uncertainty over longer forecasting horizons (Liu et al., 2023).

As the forecasting horizon increases, there is an increasing demand for complex models that can effectively manage increased levels of uncertainty. PSPF is preferable for longer-term horizons since it provides a more reliable representation of possible solar power generation. Furthermore, the increasing length of the forecasting horizon highlights the need for reliable probabilistic forecasting methods, such as advanced DL models, to enable efficient decision-making in power systems, given the inherent uncertainty associated with solar power generation. The latest research by Bai et al. (2024) and Phan et al. (2024) employs the DL method for day-ahead forecasts. The advancement of AI techniques, specifically DL algorithms, has shown significant effectiveness in PSPF.

The significance of the forecasting horizon is apparent in numerous aspects of power system operations, market dynamics, and the incorporation of renewable energy sources. Day-ahead and hour-ahead forecasting are vital to decision-making since they serve different purposes regarding planning horizons and operational requirements. The accuracy level generally tends to decrease as the duration of the forecasting period increases. Nevertheless, selecting these forecasting horizons depends on the distinct requirements and objectives. The adaptability of forecasting approaches to correspond with expected forecasting timeframes is crucial to ensure accurate, reliable, and effective decision-making in power system management and planning.

Comparative Evaluation of Machine Learning and Deep Learning in Probabilistic Model Advancement

Two methods can be used to create a probabilistic forecast: (1) parametric, calculating the parameters of the prediction distribution, and (2) nonparametric, which requires developing a predictive distribution with a limited amount of data observations. Many scholars prefer the parametric approach, a straightforward technique for creating predictive distributions that is well-known for its simplicity and low computational cost. After comparing probabilistic predictions made with parametric and nonparametric methods, Bakker et al. (2019) discovered that the nonparametric approaches perform significantly. The use of parametrics in the probabilistic forecast is restricted since they are the least dependable compared to nonparametric methods.

With the nonparametric method, the distribution is created using a variety of observable models rather than assuming its shape. One significant benefit of the nonparametric method is its flexibility. The input data are used to directly compute the output value distribution, reducing the number of estimating errors brought on by false assumptions concerning a specific distribution.

Initially, parametric and nonparametric methods were considered conventional probabilistic methods. These conventional methods traditionally relied on statistical approaches such as Autoregressive Moving Averages (ARMA), Autoregressive Integrated Moving Averages (ARIMA), Bayesian, Gaussian Distribution (Doelle et al., 2023), Quantile Regression (QR) (Zhou et al., 2022) (Mpfumali et al., 2019), Kernel Density Estimation (KDE) (Bai et al., 2023) and bootstrapping. The straightforward conventional modeling approaches that require fewer computational resources and expertise give an advantage to this method. Due to this, conventional probabilistic forecasting methods frequently offer interpretable models, facilitating comprehension of the fundamental assumption (Doelle et al., 2023). However, conventional probabilistic forecasting might encounter difficulties when dealing with big datasets based on multiple meteorological variables (Bai et al., 2023). Conventional probabilistic forecasting techniques, QR, Bayesian models, and Gaussian methods frequently encounter difficulties in effectively capturing the associated complexity. Handling a massive dataset may require significant resources and time to train the model and tune complexity, thus making it unfeasible for certain applications.

In recent years, a significant increase in research has highlighted the ML models' incorporation within the domain of PSPF. The increasing interest in ML models arises from recognizing their enhanced efficacy in handling the inherent complexities of solar power forecasting, exceeding conventional approaches (Liu et al., 2023; Polo et al., 2023; Qiao et al., 2021). Their proficiency in employing advanced algorithms and computational techniques enables them to discern complex patterns, enhancing forecasting accuracy. Implementing ML, particularly decision tree-based methods such as XGBoost and Random Forest, allows the inclusion of exogenous parameters, leading to improved forecasting accuracy. This flexibility enables the model to capture additional information that may influence solar power generation (Polo et al., 2023). Besides that, the availability of implementation tools, such as the forecast library in Python, facilitates the implementation of different deterministic and probabilistic forecasting schemes by using ML models. These transparency implementation tools enable reproducibility and accelerate experimentation with different methodologies (Mitrentsis et al., 2022).

Hybrid ensemble models, which integrate multiple ML algorithms, exhibit the potential to enhance the accuracy of PSPF by offering enhanced prediction intervals essential for capturing the inherent uncertainty in solar power output (Liu & Xu, 2020). According to Bhavsar et al. (2021), ML techniques effectively handle uncertainty, decreasing the number of scenarios needed for analysis and simplifying the forecasting process. Mitrentsis and Lens (2022) proposed an advanced study that researched a two-stage probabilistic forecasting framework for PV power forecasting. It utilizes Natural Gradient Boosting (NGBoost) and Shapley additive explanation. Compared to state-of-the-art algorithms, the framework improved performance and accuracy, allowing for detailed analysis of complex non-linear relationships and interaction effects.

Since ML methods learn from the input data, they struggle to adapt to environmental changes. It could potentially lead to the models not fully capturing the corresponding deep non-linear characteristics under varying environmental conditions. On top of that, ML methods may encounter scalability issues that require extensive computational resources for data training, especially when dealing with time series utility-scale PV system applications (Mitrentsis & Lens, 2022).

In the age of computer hardware, software, and big data technology advancements, a notable and expanding emphasis exists on DL networks. It draws inspiration from the human brain's functions and structure. These networks have evolved into a vital component of contemporary AI and ML owing to their remarkable capacity to autonomously identify and grasp intricate patterns and representations from extensive datasets. Among DL-based models, LSTM is widely used in PSPF due to its ability to model time series data and capture long-term temporal dependencies (Sun et al., 2022). (Sansine et al., 2022; Shi et al., 2023) evaluated various DL models based on LSTM and emphasized that the LSTM model is the most reliable in terms of its practicality for applications inside the energy market.

Notably, a two-stage hybrid approach combining Variational Mode Decomposition (VMD) and Innovative Capsule CNN (ACCNet) achieves high Coefficient of Determination (R^2) values for different forecast horizons, indicating strong predictive performance (Liu et al., 2023). Other models, such as Laplace and DeepAR (LSTM) (Lin et al., 2022), demonstrate good calibration and accuracy, while CNN-LSTM-Gaussian showcases robust binary classification performance. Normalizing Flow (NF), Generative Adversarial Networks (GAN), as well as Variational AutoEncoders (VAE), reveal that NF outperforms others in probabilistic forecasting (Dumas et al., 2022). LSTM-AE excels in point forecasting with low MAE and RMSE, while DSANet exhibits low error sensitivity (Mashlakov et al., 2021). However, some methods show room for improvement, such as the Auto-regressive recurrent neural network (DeepAR) (Park et al., 2020), which yields relatively high RMSE and MAE. These findings offer a detailed analysis of DL methods with regard to solar power forecasting, assisting in selecting appropriate models based on specific forecasting requirements.

The present study on Transformer architectures for probabilistic DL forecasting has revealed higher accuracy than alternative AI models. Transformers utilize parallel processing capabilities and excel over traditional methods in dynamic forecasting contexts (Phan et al., 2024). DL algorithms greatly improve the accuracy and efficiency of PSPF, providing scalable and flexible solutions for dynamic situations. Note that probabilistic DL techniques have the advantage of being extremely scalable due to their ability to leverage the parallel processing capabilities of Graphics Processing Units (GPUs) as well as Tensor Processing Units (TPUs). Other than that, they adapt to diverse data sources and changing conditions, making them more flexible in dynamic forecasting environments.

Nevertheless, the development and implementation of DL models inherently incur costs associated with hardware resources like GPUs and TPUs. DL models also need sufficient data to train for accurate probabilistic forecasting (Jonler et al., 2023). Compared to conventional probabilistic forecasting methods, pre-processing and data imputation need to be implemented in the DL model to help improve convergence, prevent vanishing or exploding gradients, and enhance the model's ability to learn relevant patterns from the data (Phan et al., 2024).

Table 7 summarizes PSPF's strengths and weaknesses. However, the advancement of ML and DL models holds great promise for enhancing the accuracy and reliability of probabilistic solar power forecasting in the future, thereby facilitating the integration of solar energy into the power grid and supporting the transition to renewable energy sources. As a result, probabilistic ML and DL techniques are advantageous in improving forecasting performance compared to conventional methods.

Table 7
Strengths and weaknesses of the PSPF Model

Model category	Strength	Weakness
Conventional PSPF	• Simplicity modeling approaches • Low computational cost	• Difficulties in capturing the complexity associated. • Requires significant resources and time to train and tune the model. • Not feasible in handling massive datasets and complex application
ML PSPF	• Ability to adapt to dynamic and uncertain environments. • Availability of open-source tools. • Allows the inclusion of exogenous parameters.	• Difficulty in capturing long-term temporal dependencies. • Requiring extensive computational resources • Require a large dataset.
DL PSPF	• Ability to capture long-term temporal dependencies. • Adapt to diverse data sources and uncertain environments. • Ability to leverage parallel processing capabilities.	• High cost associated (GPU and TPU) • Requiring extensive computational resources • Require a large dataset.

Uncertainty Quantification Metric

Probabilistic forecasts, frequently depicted as interval or scenario predictions, present further complexity in contrast to deterministic forecasts due to incorporating a range of possible outcomes compared to a single-point prediction. The measurement of uncertainty in PSPF implies assessing the reliability and sharpness of these forecasts. Note that reliability is related to the probabilistic calculation, the forecasting model's accuracy that aligns with the actual probabilities. At the same time, sharpness quantifies the dispersion of the predicted distributions and evaluates the forecasts independently, indicating the forecast model's usefulness (Doubleday et al., 2020).

The utilization of metrics to assess reliability and sharpness offers valuable insights into the quality and accuracy of forecasting. Prediction Interval Coverage Probability (PICP) and Average Coverage Error (ACE) are often utilized reliability metrics that assess the extent to which prediction intervals correspond to observed data. Lower ACE values indicate better reliability, as the prediction intervals are closer to the desired coverage probability. An elevated PICP, as illustrated by (Mpfumali et al., 2019) attaining 98.82%, indicates superior reliability, whereas reduced ACE values indicate enhanced reliability.

The optimization of sharpness while maintaining reliability is crucial in probabilistic forecasting since it helps to reduce uncertainty. Sharpness analysis often uses metrics such as Coverage Width-based Criterion (CWC), Prediction Interval Normalized Average Width (PINAW), and CRPS. The PINAW metric evaluates the mean width of prediction intervals concerning the variability observed in the data, where smaller values indicate more precise forecasts. Nevertheless, the capability to compare studies may be constrained when employing distinct metrics, as outlined by Phan et al. (2024) and Bai et al. (2024). The CWC technique assesses the difference between predicted and observed cumulative distribution functions, where lower values indicate superior performance. It is demonstrated by the research undertaken by Sansine et al. (2022) with 38%, 68%, 95%, and 99% with regard to prediction interval. CWC values are 6.3, 14.68, 59.13, and 40.1, respectively.

CRPS is a robust metric that combines reliability and sharpness evaluation. The key advantage of this approach is its ability to facilitate the comparison between probabilistic and point forecasts. Consequently, it has the potential to establish itself as an established method for validating probabilistic forecasts, as proposed by Lauret et al. (2019). CRPS has become popular in academic research because it maintains unit consistency with the projected variable. Studies conducted by Yang (2020), Alessandrini and McCandless (2020), Mpfumali et al. (2019) and Lin et al. (2022) have consistently shown that lower scores are indicative of higher accuracy. For example, Dumas et al. (2021) compared CRPS values among several forecasting models. LSTM had the lowest CRPS of 4.4, lower than MLP and GBR. Furthermore, a study conducted by Mitrentsis et al. (2022) examined the CRPS across various seasons, revealing that the winter season exhibited the lowest CRPS value of 0.01. The investigation of spatial distribution in the United States and Reunion Island revealed disparate values of CRPS, with the United States exhibiting lower scores in comparison to Reunion Island, with 6.97 and 23.1, respectively.

ML and DL models routinely demonstrate superior performance compared to conventional methods. Mitrentsis et al. (2022) demonstrated that the ML model attained a CRPS value of 0.01, whereas Lin et al. (2022) reported that the DL model achieved a CRPS value of 0.0523. As Yagli et al. (2020) described, the conventional approach exhibited a CRPS value 0.615. Furthermore, significant research highlights the effectiveness of ML methods in enhancing solar power forecasting accuracy. ML methodologies have exhibited a capacity to adjust to changing circumstances, providing precision of solar power (Bai et al., 2024; Jonler et al., 2023; Sansine et al., 2022). Additionally, ML-based offers probabilistic forecasts and prediction intervals, which hold significant value in the context of grid management and decision-making procedures.

Beyond the CRPS method, the pinball loss function and the Winkler score account for reliability and sharpness, making them particularly suitable for quantile forecasting. A low pinball score and Winkler score signify an accurate probabilistic prediction. Zhou et al. (2022) conducted an assessment 5 minutes ahead; forecasting indicates a minimum Pinball loss of 1.76kW in contrast to 2.767kW observed 1 hour ahead. For the Winkler score, the lowest 25.75kW was observed 5 minutes ahead of forecasting compared to 39.94kW obtained 1 hour ahead of forecasting. Overall, these uncertainty quantification metrics serve a valuable role in optimizing the use of PSPF to evaluate accuracy and reliability, facilitating informed decisions regarding integrating renewable energy and managing power grids.

CONCLUSION

In conclusion, integrating ML and DL methods has resulted in remarkable advancements in PSPF. Researchers have explored various models and evaluation metrics to improve PSPF reliability and accuracy. Note that forecasting horizons significantly impact the performance of solar power forecasting models. The increasing length of the forecasting horizon highlights the need for reliable probabilistic forecasting methods such as the ML and DL models. Day-ahead and hour-ahead forecasting are both vital components of the decision-making process since they serve different purposes in terms of planning horizons and operational requirements. ML ensemble and hybrid models show promise in improving the accuracy of PSPF by providing improved prediction intervals with low relative MAE and RMSE values and high accuracy scores. The advancement of the latest DL Transformer architecture, leveraging their ability to discover intricate patterns in large datasets, has revealed higher accuracy. The uncertainty quantification metric, CRPS's robust metric that combines reliability and sharpness evaluation, assists in selecting the best probabilistic forecasts due to its ability to maintain unit consistency with the projected variable. These research findings provide valuable insights for stakeholders in solar power generation, enabling informed choices about forecasting methods, horizons, and uncertainty metrics. As the field evolves, integrating the ML and DL methods is crucial in improving efficiency and reliability regarding solar power forecasting, ultimately contributing to the growth and sustainability of renewable energy sources. Future work could extend a comprehensive review of a hybrid probabilistic model method for utility-scale PV systems known as large-scale solar.

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