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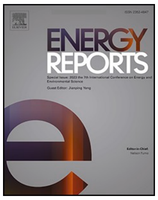

Review article

Renewable energy forecasting: Engineering foundations, AI-driven approaches, current challenges, and future research directions

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ABSTRACT

The rapid advancement in global energy demand, driven by industrialization and technological expansion, underscores the necessity for efficient renewable energy integration into smart grids. Power generation forecasting (PGF) plays a significant role in improving and supporting microgrids, energy storage, and smart grid planning, particularly due to the intermittent nature of renewable resources. While AI and deep learning (DL) models have emerged as effective solutions for real-time PGF, existing reviews often lack a comprehensive analysis of methodologies, datasets, and evaluation strategies. This survey makes several key contributions: first, it presents a new taxonomy of AI-driven PGF methods, categorizing the latest literature across machine learning, DL, fuzzy logic, and hybrid approaches. Second, it integrates an in-depth discussion of edge intelligence in PGF, highlighting its potential to enable real-time decision-making at the point of energy generation. Third, this survey provides a comprehensive overview of the datasets used in PGF, addressing gaps in existing reviews by offering a detailed analysis of the challenges and best practices. Finally, we propose an integrated framework for evaluating PGF methods, comparing performance metrics and identifying key challenges for researchers. By consolidating these areas, this work offers a unique and detailed perspective on the current state and future directions of intelligent PGF, guiding researchers and practitioners in advancing PGF solutions.

1. Introduction

The rapid increase in industrialization, populace growth, and economical progressing has tremendously surge the energy demand worldwide and projecting 30% upsurge by 2040 with the rise in commercial (Antonopoulos et al., 2020; Shahbaz et al., 2021) and residential sectors (Krarti and Aldubyan, 2021; Barros et al., 2024; Tomašević et al., 2025). In (Antonopoulos et al., 2020), authors reviewed about 160 articles in the 2009 and 2019 period database with 40 companies and 71 large projects for AI trends in energy sector. This work has developed their focus towards AI impact, however, they lack the latest advancement and generative nature of AI while in (Shahbaz et al., 2021), the financial development and its impact on renewable power consumption is discussed with consideration of economic growth. Though, these methods are limited to financial and economic discussions only. The ever-growing energy demand leads towards vital need of power generation, better sustainability (Mikulčić et al., 2022; Liu et al., 2025a), and its safe distribution to the community. Globally, reliance is based on non-renewable sources such as pollution causing fossils fuels for power generation to fulfill electricity needs. About two-thirds of carbon dioxide emission is from these fuels to produce electricity, if maintained, it will inexorably lead to significant rise in global warming. These methods are rise in global temperature is correlated to the extreme weather conditions namely: violent storms, heavy snowfalls, and floods (Varotsos et al., 2019; He et al., 2025; Luo et al., 2025). Filling this gap, the renewable energy resources present a tremendous potential for solving worldwide energy crisis founding a clean environment leading to green technology (Seyam, 2019; Ellabban et al., 2014). The renewable energy resources are clean energy source such as solar, hydropower, wave energy, and wind power technologies that are mostly crucial drivers towards energy conversion and sustainability (Ghenai et al., 2020; Deng et al., 2025; Al-Mahrouqi et al., 2025). Meanwhile, renewable energy production-based distributed energy supply has developed a progressive step in energy field. Similarly, sustainability meets the current

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generation's demands without affecting the resources for next generation and protects the natural environment to meet the urgent needs. From a sustainable development goals (SDG) perspective, improving renewable power generation forecasting (PGF) supports SDG action including affordable and clean energy and climate action by enabling cleaner and more reliable electricity generation and supporting emissions reduction, while also contributing to SDG's Industry, Innovation and Infrastructure action by strengthening data-driven smart-grid infrastructure and innovation. However, the continuous fluctuation and intermittences of solar energy, wind energy, and other renewable energy resources gradually sharpen the contradiction between the grid and new energy. In the interim, failure of big grid stress the crucial requirement of energy power supply to a large-scale and efficient energy storage system (ESS) technology (Liu et al., 2025a; Asija and Choudekar, 2021). Relying on ESS technology for wind and solar generated energy power storage and its stable transmission can offer a rapid and active power support, enhancing the grid capacity in terms of frequency modulation. Also, it enables large-scale solar and wind power to be reliably and conveniently integrated into regular grids. Therefore, ESS technology has also become a core technology for large-scale applications of energy power generation.

Worldwide high temperature for the last five years shows the level of global warming where the largest contributor is CO_2 emissions which is peaked at about 34,169 million tons in 2019 (BP, 2021). Regarding the intergeneration theory, ensuring the sustainability of environment is a commitment with the morality and ethics towards future generations (Yu et al., 2020) that cannot be obtained without switching into renewable energy resources (Jebli et al., 2019). It is argued that about 1000 instruments have been executed for water mitigation and air pollution internationally (Khan et al., 2020). Though, nothing is effective in them due to government non-seriousness and lack of consumer awareness towards consequences created by the non-renewable energy sources. Tabrizian et al (Tabrizian, 2019) warned that the governmental bodies cannot achieve their environmental sustainability without greening the businesses that can be performed through encouraging the industries for renewable energy usage (Khan et al., 2019). However, renewable energy generation requires forecasting strategy to overcome energy wastage and provide proper infrastructure by matching the power energy supply and demand. Several articles in the forms of surveys and reviews came into being to deliver a thorough direction for PGF. Inspired by this, we deliver a comprehensive survey on intelligent PGF and cover its overall working flow, current challenges, and power generation datasets.

Retrieving PGF literature, we visited different search engines such as Google, Google Scholar, Science direct, etc. The search procedure is performed for each year separately in each search engine. Initial search engines includes Google and Google Scholar for a single year followed by the Science direct and then other search engines. For fair retrieval of literature, we queried numerous sets of keywords that are given in Table 1 while the overall abbreviations used throughout the survey are provided in Table 2. Each word subsequently applied in each engine. It is important to note that preprint repositories such as arXiv were not considered in this study to ensure the inclusion of peer-reviewed and quality-assured research. Furthermore, only conference papers published in high-impact venues or those having significant citation counts were considered to maintain the credibility and scholarly value of the selected literature. Searching procedure prevailed a greater increase in

Table 1
Keywords applied to fetch PGF literature.

#	Word	#	Word
1	Energy production forecasting	5	Energy power production forecasting
2	Energy generation forecasting	6	Energy power generation forecasting
3	Energy production Prediction	7	Energy power production Prediction
4	Energy generation Prediction	8	Energy power generation Prediction

Table 2
Nomenclature applied throughout the paper.

Word	Description	Word	Description
AB	Adaptive Boosting	LOGR	Logarithmic Regression
ANEN	Analog Ensemble	LLLR	Lasso Lars Linear Regression
ANN	Artificial Neural Network	MME	Multi-Model Ensemble
ARIMA	Auto-Regressive Integrated Moving Average	MLP	Multi-Layer Perceptron
ARMA	Auto-Regressive Moving Average	MLR	Multiple Linear Regression
ANFIS	Adaptive Neuro-Fuzzy Inference Systems	MLFF-ANN	Multi-Layered Feed-Forward ANN
ANF	Adaptive Neuro-Fuzzy	MSE	Mean Square Error
ARMAX	Autoregressive Moving-Average Model	MAE	Mean Absolute Error
ARCA	Adaptive Residual Compensation Algorithm	MAPE	Mean Absolute Percentage Error
AHP	Analytic Hierarchy Process	MBE	Mean Bias Error
AN	Attention Mechanism	MRE	Mean Relative Error
AWNN	Adaptive Wavelet Neural Network	NRMSE	Normalized Root Mean Square Error
BA	Bat Algorithm	MAXAE	Maximum Absolute Error
CNN	Convolutional Neural Network	NN	Neural Network
CFD	Computational Fluid Dynamics	NB	Naïve Bayes
CBEA	Cloud-Based Evolutionary Algorithm	NMAE	Normalized Mean Absolute Error
CL	Conventional Learning	PAR	Polynomial Auto regression
DL	Deep Learning	PGF	Power Generation Forecasting
DIRMS	Double-Input-Rule-Modules	PHANN	Physical Hybrid Artificial Neural Network
DBN	Deep Belief Networks	PLSR	Partial Least-Squares Regression
DNN	Deep Neural Network	PRL	Polynomial Regression Lasso
DFM	Deep Fuzzy Model	PV	Photovoltaic
DCN	Deep Convolutional Network	PR	Polynomial Regression
DT	Decision Tree Regression	PCA	Principal Component Analysis
DFF	Deep Feed Forward	PLSR	Partial Least Squares Regression
EEMD	Ensemble Empirical Mode Decomposition	PSOA	Particle Swarm Optimization Algorithm
EMD	Empirical Mode Decomposition	RBF	Radial Basis Function Neural Network
ELM	Extreme Learning Machine	RF	Random Forest
EOT	Evolutionary Optimization Technique	RR	Ridge Regression
ESN	Echo State Networks	R	Correlation Coefficient
ELI5	Explain Like I'm 5	R^2	Coefficient of Determination
FF-ANN	Feedforward ANN	RMSE	Root Mean Square Error
FFNN	Feedforward Neural Network	RNN	Recurrent Neural Network
GFF	Generalized Feedforward Networks	SHAP	Shapley Additive Explanations
GA	Genetic Algorithm	SOM	Self-Organizing Map
GB	Gradient Boosting	SVM	Support Vector Machine
GRNN	Generalized Regression Neural Network	SM	Statistical Model
GM	Grey Model	SAM	System Advisor Model
GRF	Generalized Random Forest	SVR	Support Vector Regression
HA	Heuristic Approach	STPN	Spatiotemporal Pattern Network
HIMOVE	Hybrid Improved Multi-Verse Optimizer Algorithm	SOFM	Self-Organizing Feature Maps

(*continued on next page*)

Table 2 (*continued*)

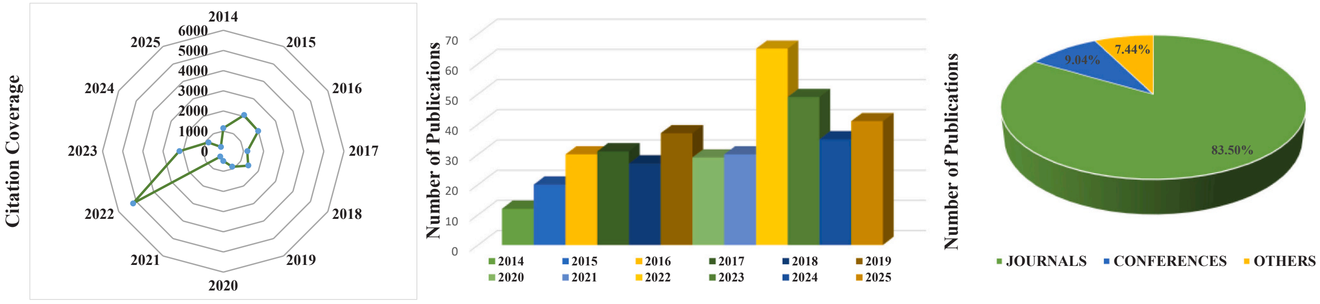
Word	Description	Word	Description
ISM	Interpretative Structural Modeling	SO-CSLN	Self-Organizing Cosine Similarity Learning Network
IoT	Internet of Thing	SCADA	Supervisory Control and Data Acquisition
KNN	K-Nearest Neighbors	TFM	Transfer Function Model
LR	Lasso Regression	TNN	Tailored Neural Network
LS-SVM	Least Square Support Vector Machine	US	United States
LUBE	Lower Upper Bound Estimation	VR	Voting Regression
LSTM	Long-Short Term Memory	WPD	Wavelet Packet Decomposition
LMA	Levenberg-Marquardt Algorithm	WPFUA	Uncertainty Analysis of Wind Power Forecasting
LIME	Local Interpretable Model-Agnostic	WPPF	Wind Power Probabilistic Forecasting
LSSVM	Least Squares Support Vector Machine	WMAE	Weighted Mean Absolute Error
LoGRM	Logarithmic Regression Model	EEMD	Ensemble Empirical Mode Decomposition
VMD	Variational Mode Decomposition	WTD	Wavelet Threshold Denoising
TFT	Temporal Fusion Transformer	GCN	Graph Convolutional Network
ML	Machine Learning	ESS	Energy Storage System
DeepTCNs	Deep Temporal Convolutional Network	GRU	Gated Recurrent Unit
BiGRU	Bidirectional Gated Recurrent Unit	GA-SVM	Genetic Algorithm Support Vector Machine

number of publications in leading year reflecting the growth and interest in PGF arena. Fig. 1(b) witnesses the visual representation of annual PGF publications number. A gradual increase towards renewable sources found with time passage as shown in Fig. 2. Nevertheless, the hallmarks for quality research needs deep investigation with the ability to acquire worthy research. Citing articles increases the impact of work and journals, for instance, high cited scores are the indication of positive influence of articles on the research community. Warming the mind, we categorized all the literature based on each article's citations and computed each single year citation score delivering a positive visualization of PGF attentions. This categorization is in Fig. 1(a). Likewise, Fig. 1(c) describes the overall PGF coverage in terms of journals, conferences, and other sources. The other sources include the book chapters and the literature from the quality competitions. From these statistics, a reader can easily follow up the journals to retrieve more information about the PGF.

A considerable progress towards PGF techniques can be found and its distribution using different machine learning, fuzzy logics, and DL techniques. Numerous challenges and problems are faced by the researchers due to diverse nature of PGF techniques. The main aim of this survey is the composition of a compact PGF representation into single platform with varied range of paper coverage focusing on sustainable energy systems, distributed power generation, and renewable energy resources in terms of machine learning, DL, fuzzy logics, and hybrid approaches. Existing surveys lack coverage of significant articles, PGF datasets, the challenges and issues in PGF faced by the researchers. There are no explanations of neural networks, DL, fuzzy concepts, consideration of hybrid networks and machine learning-based PGF methods. To overcome such challenges and limitations, we propose a reader-friendly PGF survey that gives a prestigious and fetching direction to data scientist and research community to assist them easily sorting out the PGF methods and data formation. For better representation and understanding, the working flow of the survey is given in Fig. 3.

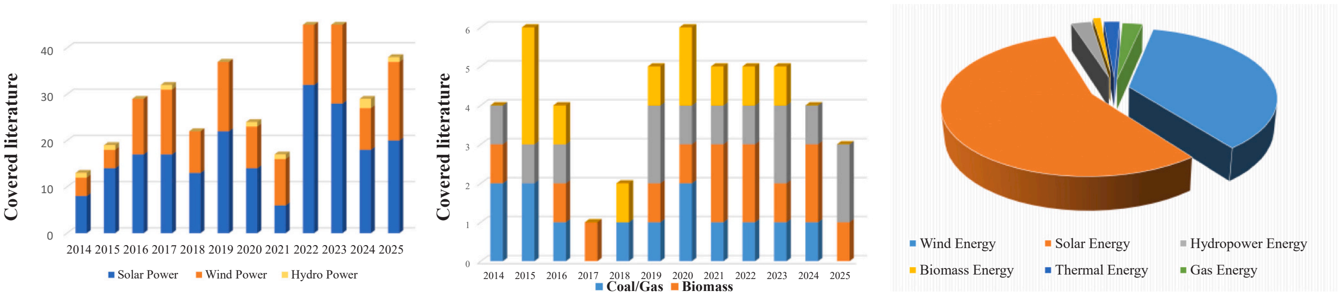
The main contributions of the proposed survey are given as follows:

1. ***New Taxonomy***: To the best of our knowledge, this survey for the first time, delivers a new taxonomy of the most recent PGF literature in terms of AI analyzing the nature of distributed power generation system with both DL, fuzzy logics, hybrid approaches, and CL establishing a compact representation. We include the bibliometric analysis of peer-reviewed and non-peer reviewed PGF articles that convey broader understandings of intelligent PGF literature.
2. ***Extensive Review***: We cover the comprehensive review of each intelligent PGF method, their portals/publishers, citation coverage, conference/journal details, and acknowledge PGF domains. Next, we surpass the existing surveys/reviews through deep examination by their comparison to overcome the limitations present in them.
3. ***Adequate Coverage:*** Unlike mainstream PGF surveys, we comprehensively discuss power generation datasets abundantly used for PGF in real-world scenarios and highlight the challenges confronted by the researchers dealing PGF derived from the deep investigation. Next, we forward numerous types of intelligent PGF methods division with categorical distribution of tracked algorithms, learning procedure established for PGF. To attain fair conclusion from PGF methods, we deliberately explain their implementation and performance details. Based on this analysis, readers can easily identify the advantages and limitations of employed methods to utilize those working strategies for their problems. Also, the pros and cons of renewable energy sources are investigated that assist the energy scientists to choose the cleanest energy form.
4. ***Research Advice and Future Directions:*** For the first time, we deliver future insights and recommendations to address challenges faced by researchers in the PGF domain, providing a thorough research guideline. These directions are explicitly linked to our guiding research questions, which highlight open issues in datasets, model design, evaluation protocols, and real-time deployment. We believe that the proposed survey supports PGF researchers and practitioners



(a) (b) (c)

Fig. 1. Detailed overview of the PGF statistical analysis through overall literature. **(a)** Delivers the annual citations score of published literature, showing significance of PGF techniques. **(b)** Provides the number of annual PGF publications, displaying a thorough upsurge in researchers' interest. **(c)** Shows the categorized division of PGF in each module.



(a) (b) (c)

Fig. 2. Overview and visual analysis of statistics of renewable and non-renewable resource used by the researchers for PGF. **(a)** Expresses the detailed annual investigation of renewable energy sources' division. **(b)** Reflects the statistics of other sources such as Coal/Gas, Biomass, etc. **(c)** Shows the division of PGF literature based on the energy sources that reveals that the solar energy is the most prominently used renewable source.

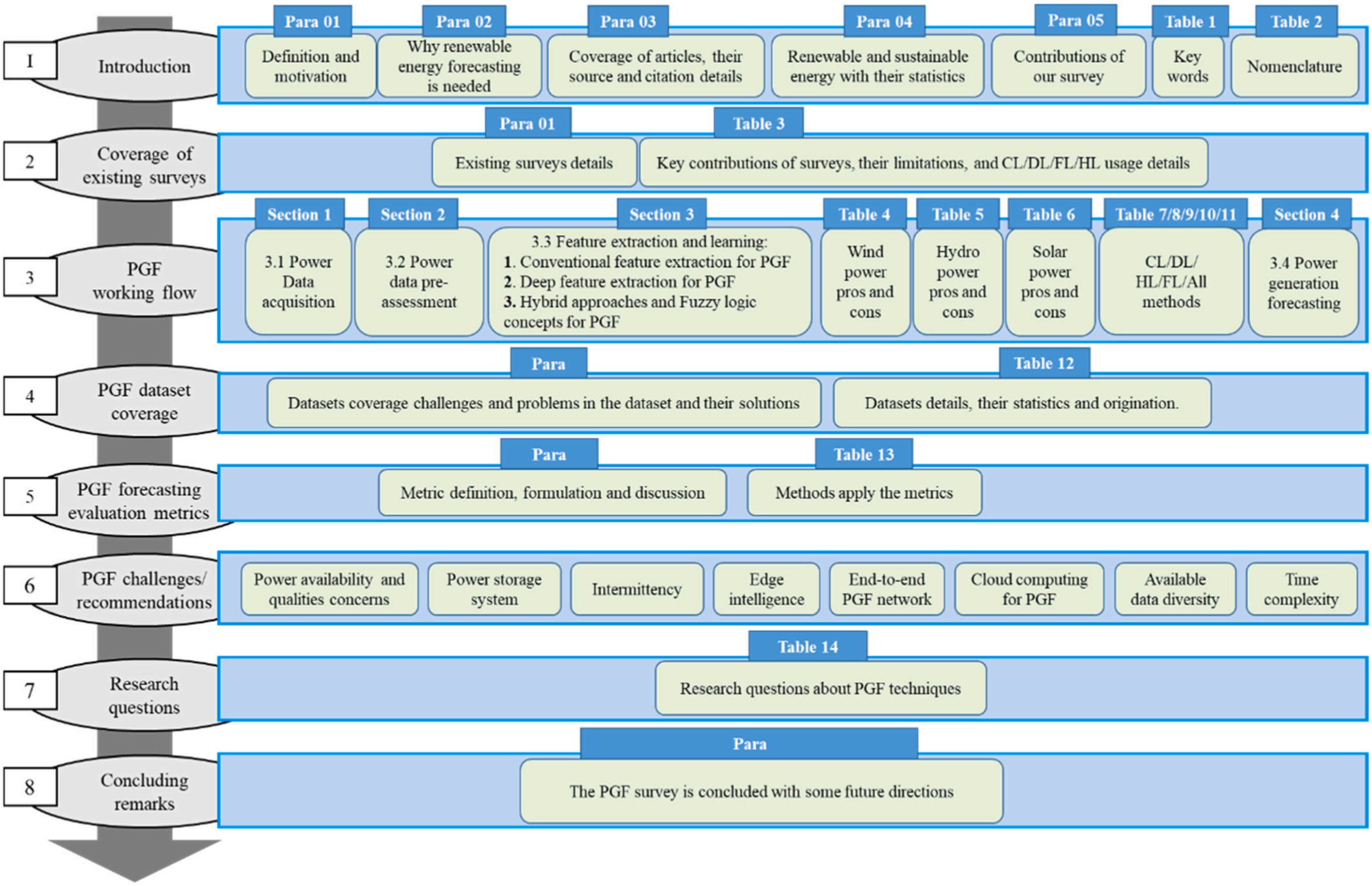


Fig. 3. A quick overview showing the structure of the working flow of the proposed PGF survey.

by improving their understanding of model selection, architecture design, and optimization.

The rest of survey is organized as follows: Section 2 covers the existing power generation reviews and their limitations. Section 3 provides the working flow mechanism for intelligent PGF while Section 4 explores the power generation datasets and their statistics. Section 5 delivers the PGF evaluation strategies, Section 6 outlines challenges, solutions, and future research directions; and Section 7 consolidates the research questions for clarity and ease of recommendations.

2. Coverage of Existing Surveys

This section discusses the contributions and downsides of existing power generation surveys. We focus and target the most recently high-quality published articles on power generation. The same searching procedure is applied to retrieve the articles and examine each article for their contributions and limitations. Regarding the surveys, we also focus on covering the reviews and surveys based on energy system management in terms of forecasting procedure. We deliver the initial review proposed by Ahmad et al (Ahmed and Khalid, 2019)., where authors surveyed the forecasting models applicable for renewable power systems. With regard towards applications, accurate forecasting optimality in terms of economics is emerging phenomena where the applications include dispatching of optimal power system, optimal ESS sizing, determining the reserve size in power system, and reliability assessment. Based on these applications regarding solar and wind energy forecasting, they collected the articles. Their conclusion delivered the idea of influence and applicability of uncertainty in forecasting performed for micro grid planning. Similarly, Deng at al (Deng et al., 2020)., and Khouili et al (Khouili et al., 2025) attempted to provide deep investigation of methods analysis based on DL, transfer learning, and enforcement learning for wind speed and power forecast modeling. The forecasting frameworks based on DL, selection of multi-and single features is discussed. The DL-based literature comparison, advantages and disadvantages of relevant methods are covered. Though, this paper is only based on 26 papers from a set of 155 that is fairly a small figure. Also, it lacks standardization amongst the studies, and the reviews differ in many aspects such as data sources, forecasting horizon, or feature engineering. This wide variation makes it harder to compare the results and draw the conclusion. Another survey introduced by Rangu et al (Rangu et al., 2020) where they reviewed several deterministic and probabilistic approaches, different optimization strategies, and stochastic programming are covered to address the uncertainties present in energy resources. They considered the optimal scheduling of resources of micro grid and provided a review of optimization models. Additionally, they discussed the control and demand response strategies for economic benefits of grids. This work is dated and has not captured recent advances in reinforcement learning, data-driven control, cybersecurity or multi-agent coordination-aware power management after 2020, and more analysis is based on qualitative lacking standardized comparisons. Another reviewed article by Mahmud et al (Mahmud et al., 2021) provided machine learning-based short and long-term PGF methods. Several machine learning methods such as linear regression, DT, PR, SVM, RF, MLP, and LSTM, are considered in their study. The main limitation in this survey is their focus on short-term operational metrics such as cost, power balance, or energy efficiency and does not consider long-term aspects including equipment degradation, battery lifetime or maintenance, or changes in generation in different seasons. The summarized representation of the comparison of the surveys is provided in Table 3.

The aforementioned surveys delivered a rough direction with diverse range of applications and strategies for power generation. There is no single review that holds a thorough investigation on PGF and explains its working flow and mostly based on single covered sources of energy such as solar, wind, etc. To overcome all these challenges, we deliver a compact survey comprises of detail investigation of DL, fuzzy logics, machine learning, and hybrid methods covered from high quality research articles. We also provide a compact form of existing PGF literature, providing a detailed working flow and their visual representation for PGF. Additionally, we provide a compact review of existing PGF literature, presenting a detailed working flow and visual representation of PGF. We also cover the datasets used in PGF studies and the challenges researchers face when conducting forecasting.

Table 3
Comparative analysis of the proposed PGF survey with existing power generation surveys with division into CL, Fuzzy Logic (FL) concepts, Hybrid Learning (HL), DL, and coverage of datasets.

#	Year	CL	FL	HL	DL	Data	Main Contributions	Remarks
Ahmad et al (Ahmed and Khalid, 2019).	2019	×	×	×	×	×	• Role of forecasting models has been focused on renewable power system planning. • The generation scheduling, forecasting uncertainties and their impact in market are investigated. • Applications for forecasting are studied.	• Block to cover the future research directions and recommendations is missing. • Challenges exist in wind and solar power generation forecasting are not given.
Deng et al (Deng et al., 2020).	2020	×	×	×	✓	×	• In this article, methods based on DL are stabled that forecast the wind power.	• This article focusses on wind power generation only. • No coverage of all renewable resources.
Rangu et al (Rangu et al., 2020).	2020	✓	×	×	×	×	• Deterministic and probabilistic approaches are discussed along with stochastic programming and optimization strategies. Problems with distributed sources are covered.	• There is no discussion based on evaluation strategy. • The contribution of their survey is not clearly highlighted.
Mahmud et al (Mahmud et al., 2021).	2021	✓	×	×	×	×	• The methods based on machine learning are surveyed. • Power generation of PV is considered in Alice Springs.	• The survey is based on machine learning techniques only. There is no coverage for DL, AI, etc. • The survey is carried out for energy generation for only single region.
Markovics et al (Markovics and Mayer, 2022).	2022	✓	×	×	×	×	• Compared 24 ML models for day-ahead PV power forecasting with NWP inputs and engineered features. • Identified KR and MLP as top models; hyperparameter tuning and feature engineering reduced RMSE significantly.	• No deep learning models included. • Focused on deterministic day-ahead forecasting, no probabilistic intervals. • Limited to Hungarian PV plants; generalization not assessed.
Tian et al (Tian et al., 2023).	2023	✓	✓	×	×	✓	• Reviewed ML-based studies on solar forecasting at meso-, micro-, and building-scales in urban environments. • Discussed inputs, models, forecasting horizons, and challenges by scale.	• Narrative review; no unified performance benchmarks. • Limited quantitative comparison: some scales (micro/building) have sparse data coverage.
Gupta et al (Gupta and Singh, 2025).	2025	×	×	✓	✓	×	• Comprehensive review of PV power forecasting techniques. • Analyzes correlations between solar irradiance and PV output, highlighting importance of weather classification and cloud motion analysis.	• Focused solely on PV forecasting; excludes other renewable energy sources. • Mostly qualitative comparisons; lacks unified benchmark datasets. • Emphasis on short-term horizons in reviewed literature.
Khouili et al (Khouili et al., 2025).	2025	✓	×	×	✓	×	• Systematic review dedicated solely to DL for solar PV forecasting (26 papers, 2015–2024). • Shown dominant architectures (LSTM, CNN), preprocessing (Wavelet Transform), and common inputs (temperature, pressure, humidity).	• No performance meta-analysis: comparisons are qualitative. • Focused on PV; excludes other renewables.
Ours	2026	✓	✓	✓	✓	✓	• New taxonomy for PGF in terms of AI is presented and PGF techniques investigation in terms of CL, FL, HL, and DL with their Origination. • Investigation of pros and cons of renewable energy sources. • Solutions to problems and future research directions are given.	• Detailed and thorough coverage to PGF techniques and research directions for practitioners and AI.

3. Working Flow of Intelligent PGF

This section discusses step-by-step procedure and working flow of intelligent PGF methods. The detail of each step along with their visual representation is given in Fig. 4 where step 1 holds the data acquisition process from different renewable resources. Step 2 is responsible for the pre-assessment and arrangement of the acquired power data while step 3 performs features collection from the refined data sequence. In the same step, the power data sequence is learnt. In the final step, the output forecasting is provided, and the method evaluation is performed. The detail of each step is covered in the following sections.

3.1. Power Data Acquisition

The most significant and vital step in PGF is data acquisition where the data are obtained from different renewable/sustainable resources such as wind, hydro, solar, coal, petroleum, fuel, gas, etc. From decades, the practice of acquiring the energy from these sources remained a challenge due to different environmental conditions and their impacts. Some of these resources are pollution-friendly, which badly affects the environment. In this regard, researchers and practitioners are investigating novel ways for smooth production of power energy that ensure the clean environment. The most common resources of clean energy are wind, hydro, and solar power that are abundantly used nowadays, and their details are covered in the coming sections.

3.1.1. Wind Power Generation and its Data Acquisition

The electricity generation from wind power has significantly grown in few decades and has widely decreased the production cost (Electricity generation from wind, 2021) and is one of the most fast-growing renewable energy technologies. Its usage is on rise globally. The capacity of installed wind generation worldwide onshore and offshore has peaked by almost 75 in two decades jumping from 7.5 GW in 1997–564 GW by 2018 (IRENA, 2021). Its production between 2009 and 2013 doubled while in 2016, it was accounted for as 16% of electricity generated from the renewable source. Electric energy is obtained from wind power generation where the wind energy is converted into rotating energy via blades. Rotated energy is converted into electrical energy through generators. With the cube of wind speed, the wind energy is increased. Therefore, turbine for wind generation system is installed in the area with high wind speed. The wind turbines contain the blades for wind's kinetic energy collection. These blades connected to drive shaft turn the electric generator to produce electricity. Regarding wind energy for clean energy, it has few pros and cons that are given in Table 4. For instance, regarding pros side, wind is cleaner renewable energy source and is mostly cost-effective source while on cons side, wind turbines can be aesthetically unappealing and noisy and sometimes impact the physical environment adversely. Wind power is intermittent too where the turbines rely on weather and become incapable of generating electricity 24/7.

3.1.2. Hydro Power Generation

Hydro power is one of the most abundant renewable energy resources that produces energy using a barrier/dam, or diversion structure to change the water flow. Large reservoir used to control water flow that drives a turbine to generate electricity. Hydropower source is more reliable than wind or solar, in the case when it came from tidal rather

Table 4
The advantages and dis-advancement of wind power.

Pros	Cons
Clean and renewable energy source	Intermittent
Lower operating cost	Visual and noise pollutant
Land space usage	Few adverse environmental impact

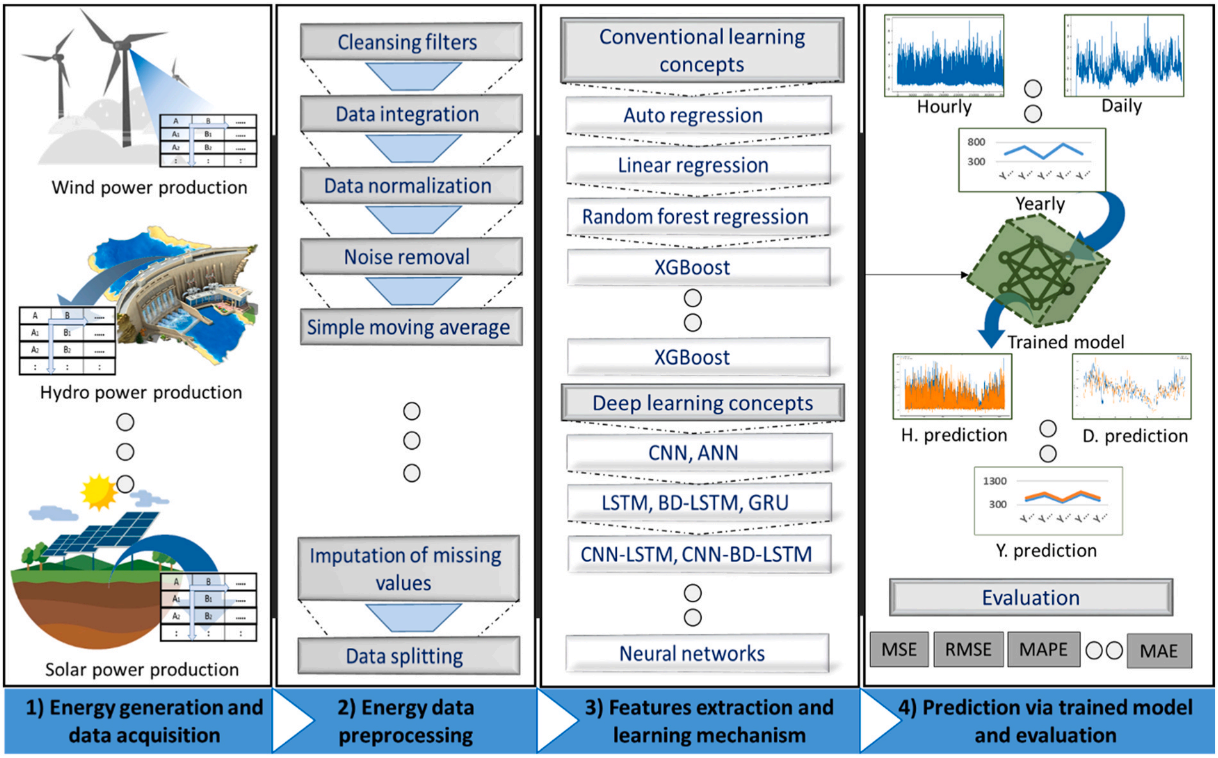


Fig. 4. Detailed overview of the basic working steps of PGF where at first, the data acquired from any renewable sources such as solar, hydro, or wind, is recorded and arranged in an appropriate format. Next, the acquired data is fed into pre-assessment step for outliers and noise removal and data arrangement for network. The sequence from the refined data in particular format is given as input to the features extraction and learning step to extract the deep knowledge and important information. The final phase evaluates the method's effectiveness and its performance using defined metrics.

than river. It allows electricity for use when the demand is increased. Hydropower uses generators and turbines that convert the kinetic energy into electricity which is fed to electric grid for powering the houses, industries, and businesses. The energy obtained from movement of water widely depends on the volume of water flow and elevation change that is known as head. The higher the head and greater the flow, the more electricity will be generated. Similar to wind power, hydro power has some pros and cons that are given in Table 5. On the pros side, hydropower is also a clean renewable energy source which is well paired with other renewable energy technologies. In few cases, it can be used to meet the peak energy demand. However, hydropower can also adversely impact the surrounding environment and is very expensive to build. Also, the optimal places are limited to be suitable for hydroelectric plants and reservoirs.

3.1.3. *Solar Power Generation*

Solar is most common and cleaner form where the sunlight and heat is used to for green power generation. It is harnessed through PV cells or solar panels. In PV stations, these panels are arranged edge-to-edge capturing the light in larger fields. These PV cells are manufactured from semiconductors. When the light rays hit these cells, the electrons become loosen from their atoms, which allows electrons to flow via the cell and produce electricity. The total solar energy incident globally is wider than world’s expected and current energy needs. If suitability harnessed, this source keeps the potential of satisfying all future power needs. Solar energy is expected to be the more attractive renewable energy source due to its inexhaustible supply and nonpolluting character in contrast to fossil fuels, coal, petroleum or natural gas. The sun is extremely the most powerful energy source and is by far the largest energy source obtained by the earth but its intensity reaching the ground surface is quite low, which is essentially due to enormous radial spreading from distant sun. Additional minor loss occurs due to clouds and earth atmosphere that scatters or absorbs 54% of incoming sunlight (Ashok, 2021). Potential towards solar energy is enormous as 200,000 times global daily electric-production capacity received by the earth every day in solar form. Like wind and hydropower, solar power has also various Pros and Cons that are given in Table 6. Regarding its advantages, it reduces the carbon footprint, making lower electric bills, and increasing the home value. It also helps in combatting the rise in electricity costs and earning the money invested back. Despite these advantages, solar system does not work for every type of roof and is not ideal if movement takes place.

3.2. *Power Data Pre-Assessment*

One of the most significant steps in forecasting power generation before the feature’s extraction or information collection, is the pre-assessment of the data from renewable resources. Initially, this data, after measurement through different sensors and meters, has noises and outliers due to different anomalous conditions such as short-circuits, improper wire management, and transmission infrastructure. Direct processing of such data creates abnormality in PGF, which affects the overall balance between the smart grid and consumer side. To avoid such types of issues and problems, the pre-assessment terminology is applied. This step enrolls different filters for data refinement such as cleansing filters, data normalization, etc. After the refinement, the data are ready for training and its processing. However, before training, the data are converted into several phases for validation purposes. Numerous ways of cross validation are applied in time series data processing, but two basic cross-validation methods that are widely in practice: Holdout and K-fold method. In holdout method, the data are converted into training, validation, and testing set while in k-fold method, k-fold validation is used where k value is chosen such as k = 5 or k = 10. For instance, choosing k = 10 will divide the whole dataset into 10 sets, and the training is performed for k-1 sets while the remaining k is used as testing.

Table 5
Advantage and downsides of hydro power.

#	Pros	Cons
1	Renewable energy source	Few adverse environmental impact
2	Well pair with other renewable sources	Expensive
3	Capable of meeting electricity demand	Lack of reservoirs

Table 6
Advantages and disadvantages of solar power.

#	Pros	Cons
1	Reduction of carbon	Expensive to buy panels
2	Lower electricity bill	Location dependent
3	Home value improvement	Not ideal if movement occur
4	Investment can be back	Difficult to find local solar installers
5	Rising costs of electricity can be combated	Lower savings
6	Environmentally friendly	Does not work at night
7	Sustainable	Space constraints

3.3. *Feature Extraction and Learning Mechanism*

This section explains features extraction techniques that are worthy in their applications to PGF. Features extraction from the large-scale data is the core step towards meaningful information collection for processing that are used to solve numerous computer vision and time series problems such as activity analysis, energy consumption prediction (Ullah et al., 2021a; Hussain et al., 2021), etc. In machine learning or data mining literature, the feature extraction refers to the procedure of creating features from the initial set of data. Such features encapsulate central properties of data and give it a low-dimensional space which facilitates the learning. It is the practice to enhance the learning capability where the learning models always hunt for the extraction of useful characteristics and act as primary step in time series data analysis. Distinct algorithms are used that are somehow significant for generation forecasting such as SVM (Leone et al., 2015; Martin et al., 2016; Li et al., 2016), PHANN (Dolara et al., 2015), LoGRM (Aydin, 2015), ARIMA (Wan et al., 2015; Yadav et al., 2015; Barbosa de Alencar et al., 2017), PLSR (Li et al., 2015), and MLR (Abuella and Chowdhury, 2015a). These works include forecasting techniques ranging from classical models and SVM to NN, but they are highly dependent on good quality local weather or its predictions, which makes the accuracy sensitive to errors. Most of these uses limited generalizability while some of them use simple standalone or statistical ML models which struggle with weather dynamics due to non-linearity, uncertainty quantification, and rapid irradiance fluctuations. One of the main points in these methods is that hybrid and ensemble-based works will aim to improve accuracy but usually increase computational complexity, making real-time deployment challenging. We categorize the features extraction techniques into traditional features extraction and DL-based features extraction. Each type is discussed as follows:

3.3.1. *Traditional Features Extraction for PGF*

Over the recent years, the growing amount of timestamped data collection has brought an explosion of interest to apply the machine learning techniques to the timestamped data. There exist several features descriptors that are developed to understand the nature of variables in time series sequence data. Though, the time series pertains to observations sequence collected in certain time intervals to be minutely, hourly, daily, weekly, monthly, or yearly. So, the analysis includes development of such models that are applied to define and observe the series. Forecasting in this case makes the use of fitting the model essential for the future observation prediction based on current and previous data processing. Traditional features extraction techniques also

Table 7
Collection of conventional/traditional PGF methods, where the origin and source of renewable energy is also considered. The BN represents Baseline Network.

Ref	BN	Contributions	Origin	Resource
(Xiong et al., 2014)	GM	They developed integrated forecasting and modeling framework for consumption and production. Optimized GM is applied to model power production and consumption. Their method helped policymakers to access energy and support decision-making.	China, Iran, Argentina	N/A
(Rathnayaka and Seneviratne, 2014)	GM (1,1)	Grey system based on GM (1,1) to forecast annual power generation, is proposed. It is computationally simple method and useful for planning and scenarios with dataset.	Sri Lanka	Solar, Wind, Biomass
(Tascikaraoglu et al., 2014)	Linear Model, CFNN, EMD	Economic operation-based strategy is proposed that can be adapted in real-time measurement of solar and wind production.	Turkey	Solar, Wind
(Hernández et al., 2014)	SOM, K-means	Short-term forecasting is performed based on SOM, clustering via K-means, and demand is computed through MLP.	Spain	N/A
(Zamo et al., 2014)	SM	Different SM are applied for forecasting based on hourly production, giving systematic comparison which helped identify most effective ways in diverse conditions. Practical insights are given to select the model for forecast.	France	Solar
(Li et al., 2014)	SVM, GA	SVM is applied for power generation forecasting while GA is used to identify the effective parameters.	China	Hydropower
(Ma et al., 2014)	N/A	A model for simulation of PV power generation forecasting is proposed where review of solar PV modeling techniques and prediction with comparison are given. Key modeling parameters are synthesized along with system behavior and environmental factors.	Hong Kong	Solar
(Xie et al., 2015)	TFM	The TFM is used to forecast power energy production. This method provides the policymakers with clear insights into supply/demand dynamics.	Italy	Solar
(Xie et al., 2015)	Markov approach	GM is employed to forecast energy production and consumption while the Markov approach based on quadratic programming model is used to forecast the power production	China	Oil, Gas
(Leone et al., 2015)	SVM	SVM is used to forecast energy production using historical data and environment temperature.	Italy	Solar
(Aydin, 2015)	Linear Regression, LoGRM	SM are applied to forecast the production of natural gas, and comparative analysis which helps to identify the suitable model is provided to capture trends and improve planning accuracy.	Britain	Natural Gas
(Yadav et al., 2015)	Persistence model, ARIMA, Regression model	Broad spectrum regarding solar power forecasting at centralized and distributed level, are discussed.	N/A	Solar
(Abuella and Chowdhury, 2015a)	MLR	MLR model is used to forecast solar energy. They demonstrate the provision of valuable insights by the traditional statistical ways in renewable energy.	N/A	Solar
(Zhang and Wang, 2015)	KNN	KNN is modified to identify the days with same weather conditions and kernel density estimator is employed to derive the probability density from the KNN.	N/A	Solar
(Kazem et al., 2016)	SVM	SVM is designed and implemented for energy generation management based on their experimental procedure.	N/A	Solar
(Pierro et al., 2016)	MME	Comparison of several data-driven models with weather prediction data is performed where the MME is built up. In this way, statistical, hybrid, and stochastic machine learning algorithms are developed	Italy	Solar
(Martin et al., 2016)	SVM, GB	Several machine learning algorithms such as SVM and GB are used with different features, selection techniques including linear, local information analysis etc. are used.	N/A	Solar
(Ahmed Mohammed and Aung, 2016)	Ensemble model, ARIMA	Three different methods for ensemble probabilistic forecasting are proposed that are derived from seven machine learning models.	N/A	Solar
(Verma et al., 2016)	MLR, LR, PR, ANN	This method proposed several models such as MLR, LR, PR, and ANN, to forecast solar power generation.	N/A	Solar
(Zhang and Wang, 2016)	KNN	Framework for probabilistic forecasting of renewable energy generation is presented.	N/A	Wind
(Wang et al., 2017a)	GA, SVM	Model based on environmental factors is developed where SVM model is used optimized by GA.	N/A	Solar
(Zhong et al., 2017)	PSOA	Short-term power generation forecasting technique is developed where the prediction accuracy of GM is improved using PSOA.	China	Solar
(Alfadda et al., 2017)	SVM, PRL	SVR and PRL are applied to forecast hour ahead power.	Virginia	Solar
(Zhang et al., 2017)	LS-SVM	LS-SVM is used to forecast wind power generation.	China	Wind
(Karakuş et al., 2017)	PAR	PAR is employed to forecast one-day ahead wind power through previously used hourly average wind speed.	Turkey	Wind
(Bayindir et al., 2017)	NB	Daily power generation is forecasted using NB.	Turkey	Solar
(Kazem and Yousif, 2017)	GFF, MLP, SOFM, SVM	Models such as GFF, MLP, SOFM, and SVM are used to forecast and simulate output of solar energy.	Oman	Solar
(Yesilbudak et al., 2017)	KNN	Model based on KNN for short-term wind power forecasting is proposed with the usage of wind speed, its direction, the barometric pressure, and air temperature	N/A	Wind
(Kim and Hur, 2018)	PR	Enhanced ensemble method is developed for short-term wind forecasting where the ensemble methods are gathered into two groups such as spatial and temporal ensemble method.	Korea	Wind
(Wang et al., 2018d)	EEMD	EEMD and variable-weight combination forecasting are utilized where EEMD decomposes the power data into components which are combined to form three groups.	N/A	Solar
(Huertas Tato and Centeno Brito, 2019)	RF	Smart persistence algorithm that integrates irradiance and production data via RF, is proposed.	Portugal	Solar
(Shabbir et al., 2019)	SVM	SVM-based regression algorithm is applied to forecast wind power generation for one day ahead.	N/A	Wind

(continued on next page)

Table 7 (*continued*)

Ref	BN	Contributions	Origin	Resource
(Atique et al., 2019)	ARIMA	Well-known statistical method such as ARIMA is applied to forecast daily solar power generation.	Texas	Solar
(Scher and Molinder, 2019)	RF	SM based on RF regression is developed that assists the model to forecast production loss.	Sweden	Wind
(Harrou et al., 2019)	MLR, SVM, PCA, PSR	Bagging ensembles DT is adopted for wind power forecasting.	N/A	Wind
(Pawar and TarunKumar, 2020)	PSO	PSO-based SVM regression model is proposed to forecast hourly and day ahead energy production.	Mangalore	Solar
(Zhang et al., 2020)	GA	Variation mode decomposition algorithm and wind speed prediction based on GA-ANN model is proposed	China	Wind
(Lee et al., 2020)	BT, RF, GRF	Based on ensemble learning methods combined with multiple learners, wind power energy is predicted.	Turkey	Wind
(Lin et al., 2020)	SVM	The Cauchy mutation operator and inertia weighting techniques are introduced to improve the optimization algorithm for the prediction of power generation using SVM.	Australia	Solar
(Rushdi et al., 2020)	VR, NN, GB, DT, NR, LoGR, RR, LR, ElasticNet regression, AB	A kite system is presented and demonstrated for training regression models.	N/A	Wind
(Davide et al., 2022)	Caputo-derivative	A Caputo fractional-derivative method is presented for real-time PV power forecasting	N/A	Solar
(Liu et al., 2025b)	WTD, VMD	A PV power prediction method is proposed using wavelet denoising and VMD-based IMF features.	China	Solar
(Sopeña et al., 2023)	EEMD	Wavelet threshold denoising method is used for PV power prediction that is used with VMD to create IMF features	China	Solar

proved to be effective to capture the patterns in sequence of both structured and unstructured series data. Techniques such as AR (Sobri et al., 2018), ARIMA and SARIMA (Barbosa de Alencar et al., 2017; Korprasertsak and Leephakpreeda, 2019; Atique et al., 2019; Chang et al., 2016), GM (Xiong et al., 2014; Rathnayaka and Seneviratne, 2014), LM (Abuella and Chowdhury, 2015a; Harrou et al., 2019; Theocharides et al., 2020), RF (Huertas Tato and Centeno Brito, 2019), and some other SM (Aydin, 2015; Sobri et al., 2018; Korprasertsak and Leephakpreeda, 2019; Atique et al., 2019; Zamo et al., 2014; Graditi et al., 2016; Wan et al., 2016a; Pearre and Swan, 2018; Scher and Molinder, 2019). In these models, the ARIMA is one of the popular and widely used forecasting methods. However, most of these mentioned algorithm's struggle for capturing nonlinearity, abrupt changes in weather, and long-term dependencies in wind and solar energy generation. Next, GM and LM are lightweight, easy to implement but mostly oversimplify the complex relationship between the variables and output power while RF and other ML methods improve prediction, however, require high-quality data and might lack interpretability across climatic regions. Overall, they offer significant baseline, their performance acts to be limited through linear assumptions, poor handling of variability, uncertainty and data dependences compared to more advanced deep learning approaches.

Over the years, the ARIMA models dominated several areas in times series forecasting such as power load forecasting, generation forecasting, etc. ARIMA is a class of statistical algorithms capturing the standard dependencies that are unique in series data. Though, to obtain complete handy skills on ARIMA, its integral part such as auto regressive model is analyzed. In ARIMA model, the future variable value is linear function of past observations and random errors. So, underlying process which generates time series with mean μ given in Eq. (1).

$$\phi(\mathrm{B})\nabla^{d}(y_t-\mu) = \quad \theta(B)a_t \tag{1}$$

Here, y_t indicates the actual value while a_t represents random error at time t, $\phi(\mathrm{B}) = 1 - \sum_{i=1}^{p}\varphi_i B^i,\ \theta(B) = 1 - \sum_{j=1}^{q}\theta_j \mathrm{B}^j$ are polynomials in B having degree p and q, $\phi_i(i = 1,2,3,\ldots p)$ and $\phi_j(i = 1,2,3,\ldots q)$ indicate the model parameters. Next, in $\nabla = (1 - B)$, B represents the operator such as backward shift, p and q are the integers that are referred to as models' orders while d is the integer refers as differencing order. The random error a_t are distributed identically and independently with the zero mean and constant variance σ^2.

In PGF, the most important concern is related to limited data samples and inadequate information. Dealing such problem, the grey theory approach is advised that is used in the construction of the model with limited samples which is worthy for the short-term forecasting (Bilgil, 2021). The grey forecasting models play a significant role in grey system theory introduced by Deng and are successfully applied in several fields such as industry, energy consumption, etc. Though, they generally assume simplified system dynamics and exponential trends that lead to high error when it comes to highly nonlinearity or volatile procedure such as wind power or solar irradiance. Recently, several extended forms of grey forecasting models (Cui et al., 2013; Wang et al., 2018a) are proposed based on GM (1,1) due to its prediction accuracy and practicality. Other algorithms include linear regression (Abuella and Chowdhury, 2015a), LL (Tang et al., 2018; Wang et al., 2018b), RR (Massaoudi et al., 2020), HR (Papalexopoulos and Hesterberg, 1990), LLLR (He et al., 2019), Passive Aggressive Regression, and Stochastic Gradient Descent Regression (Persson et al., 2017). All these forecasting models are linear in nature which usually improve accuracy through features engineering, nonlinear relations, and probabilistic outputs. In numerous cases, they require sufficient high-quality data, proper tuning of the hyper parameters, and extensive computational efforts for ensemble and hybrid models. Furthermore, hybrid models such as LASSO-LSTM can extract more complex patterns, they aim to be less interpretable and make efforts in generalization to extreme weather events or unseen sites while non-linear algorithms include KNN (Wang et al., 2018c), DT (Massucco et al., 2019; Hambali et al., 2016), Extra Tree Regression (Ahmad et al., 2018a, 2018b), and SVR (Alfadda et al., 2017). In these algorithms, the linear regression is the simplest approach applied to show the correlation between the input and output variables represented by Eq. 3 where a is the interception, b represents line slope while e is the error. Eq. 2 is functional for the prediction of target variable value based on the predictor variable. Similarly, logistic regression is used to understand the relation between binary dependent variable and nominal, or ratio-level independent variable. Another forecasting model is PR where a regression equation is polynomial equation if power of independent variable is above the 1. Its formulation is given in Eq. 2. RR is mostly suitable to analyze multiple regression data which suffers from multi-collinearity. The offer discussed traditional PGF give a rough direction to ensure their suitability in smart grid and consumer management. Further details on these methods are out of scope of paper. The PGF methods based on traditional features extraction are presented in Table 7.

$$y = a + bX + cX2 \tag{2}$$

$$y = a + bX + e \tag{3}$$

3.3.2. Deep Features Extraction for PGF

DL plays a significant role in several data science domains such as video analysis, law-enforcement, and time series analysis (Khan et al., 2021). Similarly, growing data availability and computing power, the DL became a fundamental portion of generating new PGF models and achieving excellent results. In machine learning models, features engineering is manually performed, and the optimized parameters consider the domain knowledge. DL-based networks learn the features directly from the data, this way the data preparation is speed up and become able to learn more complex sequence patterns.

PGF researchers used DL-based technologies such as NN (Dolara et al., 2015; Mellit et al., 2014; Rashkovska et al., 2015; Abuella and Chowdhury, 2015b; Liu et al., 2015) (Ceci et al., 2016), LSTM (Gensler et al., 2016; Chen et al., 2018; Wang et al., 2019a; Gao et al., 2019; Harrou et al., 2020a; Stefenon et al., 2020), CNN (Zhu et al., 2017; Ni and Ma, 2018; Koprinska et al., 2018; Wang et al., 2019a), etc. These techniques comprised of highlighting PGF achievements, are comprehensively provided in Table 8. Apart from these, the traditional PGF methods are comparatively less computational, but they are not effective enough to manage the smart grid and its operation for production. Several latest neural network terminologies are less explored to achieve the desired goals. Therefore, researchers are motivated towards DL comprised of complex neural architectures that are effective in smart grids management. Similarly, the PGF techniques are still hunting for high robustness and efficiency to deal with complex smart grid infrastructure to smoothly operate between the generation and consumption edge. Several models, for instance, RNNs and their numerous flavors, deal with the time-series sequential data effectively, however, at the same time, it has downsides. For instance, RNNs are deficient to handle long-term series forecasting. To this purpose, enhancements are desired for DL-based PGF in terms of precise learning and effective power data time-series representation.

3.3.3. Hybrid Approaches and Fuzzy Logic Concepts for PGF

Mainstream PGF techniques from recent literature are widely based on DL or its variants. If the PGF literature is overviewed, a limited amount of research contributions via unexplored techniques such as hybrid approaches or fuzzy logic, can be observed. To obtain desired output, the hybrid schemes integrate different learning mechanisms such as CNN, LSTM, auto encoders, etc., for accurate and precise output forecasting. Hybrid approaches are an advancement towards better performance where different algorithms, procedures, or processes are seamlessly combined with the objective to complement each other. As there is no single cap to fit all the heads, there is no single machine learning method applicable to solve all the problems. Some methods perform better to handle noisy data while might not be able to handle high-dimensional input space. Similarly, few methods might scale well on high dimensional input scale but will not be capable of handling sparse data. Such conditions are well-precise to apply hybrid approach to complement the candidate method and apply one method to overcome weakness of the other. Table 9 shows PGF methods based on hybridization strategy while the fuzzy logic-based PGF techniques are highlighted in Table 10. Possibilities to hybrid the machine learning methods are endless and can be made for single one building a new hybrid model in distinct ways.

The fuzzy logic and fuzzy set theory provide a general way to handle vague and uncertain information that are unavoidable in several PGF methods. This vague and uncertain information is where the decision making needs to be done with the relatively inconsistent, unverifiable, and obsolete information. The PGF methods nowadays consider the applications of fuzzy logic-based concepts such as ANFIS, fuzzy systems, etc., for different purposes such as smart grid management, energy systems and so on. Several fuzzy logic-based PGF methods are comprehensively highlighted in Table 10.

Throughout the PGF literature, we examined that there also exist such methods that are based on the combination of DL, hybrid approaches, and CL to obtain their most desired results and performance. The primary goal of these methods is the uncertainties removal and consideration of different scenarios in complex and variable conditions. They used several forms of network structure to achieve short-, medium-, or long-term PGF results. Table 11 highlights such methods with their source of energy and origination.

3.4. Power Generation Forecasting

This section discusses the final and the desirable step to reach the final goal of forecasting power. Once the PGF model from the learning stage is obtained, a sequence from any horizon such as minutely, hourly, or daily is given as input to achieve the forecasting in terms of visual representation that shows the given and predicted power. The final prediction is in practitioner's hands so that where the model needs to be deployed or used. The trained model is based on the duration of forecasting such as short-term, very short-term, or long-term forecasting for one-hour, one-day, or one-month ahead. Similarly, the model assessment is performed in the same step to evaluate and confirm the method effectiveness. This evaluation is performed through error metrics such as MSE, RMSE, etc., that are widely used to check model performance and analyze the method accurateness. The lower error rate represents the closeness of the model towards better performance.

3.5. Trends and PGF Methodological Evolution

The early approaches to PGF were based on traditional statistical models such as ARIMA, LR, and Multiple Linear Regression (MLR). These methods were widely used due to their simplicity and interpretability, providing a foundation for early studies on power generation forecasting. However, these models faced significant limitations, particularly in their inability to handle non-linear relationships and temporal dependencies that are characteristic of renewable energy sources. As Ahmad et al (Ahmed and Khalid, 2019) and Bayindir et al (Bayindir et al., 2017) highlighted, while these models provided useful baselines, they struggled with the variability and complexity of renewable energy data, which led to the development of more advanced techniques in the following years. With the increasing complexity of renewable energy systems and the need for more accurate forecasts, ML methods such as SVM, RF, and GB began to dominate PGF applications. These methods were capable of modeling non-linear relationships and handling larger datasets more effectively than traditional statistical models. Works conducted by researchers such as Li et al (Li et al., 2015) and Suanpang, Jamjuntr (2024) demonstrated the improved performance of these ML methods, especially in forecasting wind and solar power. While these models offered better accuracy, they still faced challenges in capturing long-term dependencies and were computationally expensive, which hindered their real-time deployment in large-scale energy systems. The introduction of DL methods, particularly LSTM networks and Transformer architectures, marked a significant breakthrough in PGF. These models were specifically designed to handle time-series data and capture long-term dependencies, which made them well-suited for forecasting renewable energy production. Gensler et al (Gensler et al., 2016) and Harrou et al (Harrou et al., 2020b) demonstrated the power of LSTM networks in solar power forecasting, achieving state-of-the-art results by learning complex temporal patterns in renewable energy data. The emergence of Transformer-based models, as explored by Vaswani et al (Vaswani et al., 2017) and used by Kim et al (Kim et al., 2024)., further advanced the field by offering enhanced scalability, efficiency, and accuracy in multi-step and multi-variable forecasting scenarios. These models became dominant due to their ability to process large datasets efficiently and make highly accurate predictions. Despite their advantages, DL models are computationally

Table 8
DL-based PGF methods with their source of energy usage and the origination. BN represents the Baseline Network.

Ref	BN	Contributions	Origin	Resource
(Mellit et al., 2014)	ANN	Three distinct ANNs applied for power production forecasting in large-scale grid connected to PV plant for short-term is provided.	Southern, Italy	Solar
(Rashkovska et al., 2015)	ANN	The features analysis is performed by the short-term ANN model.	Slovenia	Solar
(Dolara et al., 2015)	PHANN	ANN-based hybrid method known to be PHANN and curve of PV plant clear sky is proposed.	N/A	Solar
(Abuella and Chowdhury, 2015b)	ANN	ANN-based model is used to forecast the solar power production.	N/A	Solar
(Liu et al., 2015)	ANN	The back propagation ANN approach is employed for next 24-hour forecasting.	China	Solar, Hydro, Wind, Thermal
(Ceci et al., 2016)	ANN	This paper is the comprehensive representation of a single day forecasting of power energy production.	Italy	Solar
(Sperati et al., 2016)	NN	This method used two years' power data from solar panel farms located at different parts of Italy with distinct weather conditions. The ensemble members from meteorological variables are retrieved to build power probability density function. The NN is applied to reduce the model bias and generate probability density function of power.	Italy	Solar
(Gensler et al., 2016)	DBN, AE, LSTM	Several power DL algorithms such as DBN, AE, and LSTM are introduced.	Germany	Solar
(Sarshar et al., 2017)	ANN	ANN is used for power forecasting, and the wavelet decomposition is applied to the wind power, and its results are fed to ANN.	N/A	Wind
(Zhu et al., 2017)	CNN	CNN model is used to predict wind power generation.	Belgium	Wind
(Al-Dahidi et al., 2017)	ANN	Method based on ANN is proposed to forecast wind power production using weather forecasting information.	N/A	Wind
(O'Leary and Kubby, 2017)	ANN	ANN is applied for forecasting.	California	Solar
(Dolara et al., 2017)	FF-ANN	The FF-ANN is used to obtain wind power forecasting.	N/A	Wind
(Dumitru and Gligor, 2017)	ANN	Architecture based on FF-ANN is proposed for wind power forecasting.	N/A	Wind
(Díaz–Vico et al., 2017)	DNN	DNN is applied for wind and solar energy forecasting where the input is derived from the weather prediction system.	N/A	Wind, Solar
(Gligor et al., 2018)	FFNN	A solution to provide electricity production is proposed based on current historical solar data.	Romania	Solar
(Rodríguez et al., 2018)	ANN	ANN is proposed to predict solar power generation.	Euskadi	Solar
(Ni and Ma, 2018)	CNN	CNN is used to predict the energy produced by the marine wave energy.	China	Wave
(Chen et al., 2018)	RNN, LSTM	RNN with LSTM is adopted to predict solar energy generation.	N/A	Solar
(Alomari et al., 2018)	ANN	ANN is applied to examine the correlations between solar power and solar irradiance that are used for real-time prediction of generated power.	Jordan	Solar
(Koprinska et al., 2018)	CNN	CNN is employed and is deeply investigated to produce solar power for next day.	Australia	Solar
(Raffán et al., 2019)	ANN	This method is based on ANN that uses data filtered via environmental variables.	Argentina	Solar
(Ceci et al., 2019)	ANN	An ANN is employed in this method that performs adaptive training online and enriches measuring the entropy via data spatial information to take spatial autocorrelation into account.	Italy	Solar
(Aineto et al., 2019)	RNN	The influence of energy production on electricity prices is analyzed in Iberian market that helps to identify forecasts as explanatory variables based on RNN.	Iberian	Solar, Wind
(Ma and Zhai, 2019)	FF-ANN	A dual-step machine learning model based on wavelet transform hybridization, colony optimization algorithm and FFANN is proposed that is devised for 24 h-ahead energy production forecasting.	China	Wind
(Raffán et al., 2019)	ANN	Day ahead solar irradiation curve165165 via extreme meteorological phenomena is presented that is based on ANN which gives the forecast of generated power.	Argentina	Solar
(Wang et al., 2019a)	LSTM-Convolutional Network	A hybrid connection of CNN and LSTM (LSTM-Convolutional Network) is developed for solar power prediction. The temporal features are extracted through LSTM while CNN extract spatial features.	Australia	Solar
(Gao et al., 2019)	LSTM	One hour-ahead solar power forecasting is performed based on LSTM network.	China	Solar
(Al-Dahidi et al., 2019a)	ANN	Along with other 10 learning algorithms, ANN is proposed for power production forecasting.	Jordan	Solar
(Al-Dahidi et al., 2019b)	ANN	An ensemble approach proposed via diversified and optimized ANN to improve 24 h ahead solar power forecasting.	Jordan	Solar
(Vaitheeswaran and Ventrapragada, 2019)	LSTM	LSTM-based prediction model is proposed for short-term wind power generation forecasting.	N/A	Wind
(Han et al., 2019)	LSTM	A mid-to-long-term solar and wind power generation forecasting method is proposed that use copula function and LSTM network for effective extraction of meteorological factors.	China, US	Solar, Wind
(Brodny et al., 2020)	ANN	ANN is used for renewable energy production forecasting until 2025 in Poland	-Poland	Biofuels
(Harrou et al., 2020a)	LSTM	LSTM-based solar power generation forecasting is proposed.	N/A	Solar
(Hu et al., 2020)	ESN	Deep ESN, a stacked reservoirs hierarchy for wind power generation forecasting, is developed through adding deep framework into ESN.	China	Wind
(Sewdien et al., 2020)	ANN	Different parameters are investigated that influence the forecasting algorithms' performance.	N/A	Wind
(Barrera et al., 2020)	ANN	Different factors affecting the prediction of energy production are analyzed through ANN using IoT sensors distributed across Europe.	N/A	Solar
(Akbaş and Özdemir, 2020)	ANN	A data driven optimization and prediction model to improve and analyze energy production is presented.	N/A	Thermal Energy
(Zamee and Won, 2020)	ANN	Mode adaptive ANN algorithm is proposed using Spearman's rank correlation, population-based algorithm and ANN to forecast renewable energy power generation	N/A	Wind, Solar
(Kim et al., 2020)	LSTM	Multi-scale LSTM is proposed to forecast short-term solar power.	South Korea	Solar

(*continued on next page*)

Table 8 (*continued*)

Ref	BN	Contributions	Origin	Resource
(Nielson et al., 2020)	ANN	ANN is applied for multi-parameter input model's generation to estimate wind power production.	US	Wind
(Shahid et al., 2020)	LSTM	A paradigm exploiting the strength of RNN based on LSTM is presented with wavelet kernels. The Wave nets utilizing LSTM (WN-LSTM) with Morelet, Ricker, and Gaussian for wind power prediction	Europe	Wind
(Mishra et al., 2020)	DFF, DCN, RNN, LSTM	Five models are investigated for wind power generation prediction.	Estonia	Wind
(Elsaraiti and Merabet, 2022)	LSTM	A short-term PV power prediction method is presented using LSTM.	Canada	Solar
(Tian et al., 2022a)	Self-attention	Proposed feature decomposition and a dual-stage self-attention mechanism	Spain	Wind
(Arora et al., 2022)	NGOA-DeepAr	A probabilistic wind power forecasting model, NGOA-DeepAR, is proposed using an auto-regressive DNN with hyper-parameters optimized by an improved grasshopper optimization algorithm	Australia	Wind
(Wang et al., 2022a)	GCN	An ultra-short-term wind farm forecasting method is proposed using dynamic spatio-temporal correlations and a hierarchical directed graph to improve prediction accuracy	China	Wind
(Zhang et al., 2022a)	GCN	A short-term PV forecasting method is proposed using an optimally constructed graph with GCN to capture spatio-temporal correlations.	China	Solar
(Ye et al., 2022)	LSTM with Attention	A short-term wind power forecasting model is proposed combining wave division, improved grey wolf-optimized FCM, and attention-based Seq2Seq LSTM.	China	Wind
(Netsanet et al., 2022)	VMD, ANN	VMD-ACO-2NN model is proposed for day-ahead PV power forecasting, combining VMD decomposition, ANN prediction, and ant colony-optimized weights	China	Solar
(Ahmadi et al., 2022)	LSTM	A federated learning-based wind power forecasting model is proposed, enabling collaborative training across multiple farms with high accuracy while preserving data privacy.	Iran	Wind
(Shi et al., 2022)	GLFFNet	A four-stage space-time hybrid method using GLFFNet and Copula-based correlation is proposed for distributed PV power forecasting	Australia	Solar
(Tian et al., 2022b)	Transformer	A Transformer model is proposed for ultra-short-term PV power forecasting, outperforming GRU and DNN	China	Solar
(Aslam et al., 2023)	LSTM-attention	Dual-attention LSTM sequence-to-sequence model with Bayesian-optimized hyperparameters is proposed for multi-step wind power forecasting	South Korea	Wind
(Dai et al., 2023)	SANN	Self-attention-based neural network (SANN) is proposed for online wind power forecasting, capturing temporal relations without recurrence.	China	Wind
(Liu et al., 2023)	Time-GGAN	A dual-dimensional time series adversarial network is proposed to enhance low-value-density PV data	China	Solar
(Li et al., 2023)	EMD-Transformer	Proposed for wind power forecasting, using EMD decomposition and a convolutional attention mechanism	China	Wind
(Huang et al., 2023a)	DeepTCNs	DeepTCNs, and MVO-NNCT optimization is proposed for short-term PV power prediction	Australia	Solar
(Tian et al., 2025)	Transform	This study presents a transformer-based wind power forecasting system using feature selection, attention mechanisms, and transfer learning to improve predictions for new wind farms with limited data	China	Wind
(Zhou et al., 2025)	Attention-DCC-BiLSTM-AR	The ADBA model combines Attention, DCC-BiLSTM, and AR to capture both linear and nonlinear PV power patterns	Australia	Solar

intensive and require substantial hardware resources for training, which remains a barrier to their widespread use, particularly in real-time forecasting applications.

As the field has evolved, there has been a clear trend towards increasing model complexity, with DL methods offering the most accurate forecasts for renewable energy generation. However, this advancement has come with trade-offs. While accuracy has improved, computational efficiency remains a significant concern, as DL models require considerable computational resources, limiting their real-time applicability in large-scale energy systems. Moreover, these models are highly dependent on large, high-quality datasets for effective training, which can be a challenge in regions with limited data.

4. PGF Datasets

There exists plenty of power generation datasets abundantly used in forecasting and relevant applications, recorded from various energy generation sources such as solar, wind, hydro, etc. The most abundant and widely considered energy source is sunlight obtained through solar panels and is comparatively a cleaner source of energy. Majority of the collected literature discovered in earlier sections are based on confidential data usage that has made those methods incapable for comparison by other researchers. Table 12 witnesses the power generation datasets with their sources. The datasets with published paper are included along with a reference. The first dataset known to be Wind Turbine Scada Dataset is collected from a wind turbine's Scada system found and generating power in turkey. This dataset consists of five attributes such as date/time, active power, wind speed, theoretical power curve, and wind direction. Similarly, the PV Italy dataset is collected from a power generation system found in Italy in the duration of 1st January 2012–4 May 2014. The data in this dataset is collected in 15 min' horizons. Next, the EPEX SPOT dataset is recorded from the German electricity market in 2014 and organized in 15 min' resolution with the total samples and attributes of 34944 and 8, respectively. Another dataset, EPEX is the EU power exchange dataset that include solar, and wind power obtained from German energy market, comprise of data in 2010–2014 duration, and consists of 31464 instances and 7 attributes. The Korean solar dataset is obtained from Yeongam F1 stadium situated in Korea. The duration of this dataset is from January 2015-October 2018 making three years and ten months' data. There is total 11 attributes such as plant place, plant capacity, year, month, day, day, hour, plant output power, inclined irradiance, horizontal insolation, surface temperature, and surrounding temperature. Furthermore, the NREL Wind dataset is collected in 2012 year, near new kirk, United States, in 5 min' resolution making total 105120 samples. This dataset consists of 8 attributes such as date, time, power, wind direction (deg), wind speed (m/s), air temperature (K), surface air pressure (Pa), and density at height (kg/m^3).

5. PGF Evaluation Metrics

This section describes the abundantly applied performance evaluation metrics practiced in PGF. Generally, the evaluation strategies and metrics usage depend on the applications area. For instance, regarding classification problems, the accuracy, recall, sensitivity, precision, and specificity are drastically used. However, as the PGF is the regression problem, most of the researchers apply MSE, RMSE, MAPE, MAE, etc. This analysis helps the practitioner for better comparison of their techniques through considered metrics. Eq. 4 is MSE, which is the most used metric and is a basic metric for evaluation of a regression problem. Here, y_i is the actual output while $y_i^{\sim}$stands for the predicted values. MSE computes squared prediction errors and measures the squared difference between the actual and predicted value. Similarly, Eq. 5 represents the RMSE values that are computed by taking square root of MSE and makes the errors scaled to be identified as targets scale. Similarly, MAE is given in Eq. 6 that computes the error through calculation of absolute difference between the predicted and target values. MAE is better for error penalization while MSE fails for error suppression. Next, metric given Eq. 7 is the MAPE that average the forecast percentage error.

To compute the MAPE, the percentage errors are sum up and provide errors in percentage. For forecast error local deviation, the MaxAE is utilized which is given in Eq. 8. This metric is significant for the evaluation of short-term forecasting in power systems. Similarly, MBE shows average forecasting bias, so that the all the forecasting bias allows power systems operations for resource allocation to compensate forecast error during dispatch process. MBE metric is formulated in Eq. 9 while Eq. 10 represents R^2 assesses the model ability to predict the outcome in regression settings. Particularly, R^2 represents the proportion of variance in variable Y predicted by the regression model and predictor. Further details are out of scope of the paper. Table 13 illustrates the PGF methods along with the metrics used by them to evaluate their forecasting. This analysis helps the readers to easily find the most desired metric and perform comparison in detail.

$$MSE = \frac{1}{n}\sum_{i}^{n}(y_i - y_i^{\sim})^2 \tag{4}$$

$$RMSE = MSE = \sqrt{\frac{1}{n}\sum_{i}^{n}(y_i - y_i^{\sim})^2} \tag{5}$$

$$MAE = \frac{1}{n}\sum_{i=1}^{n}|y_i - y_i^{\sim}| \tag{6}$$

$$MAPE = \frac{100\%}{n}\sum_{i=1}^{n}\left|\frac{y_i - y_i^{\sim}}{y_i}\right| \tag{7}$$

$$\mathrm{MaxAE} = \quad \mathrm{max}_{i=1,2,\ldots,N}|y_i - y_i^{\sim}| \tag{8}$$

$$\mathrm{MBE} = \frac{1}{N}\sum_{i=1}^{N}(y_i - y_i^{\sim}) \tag{9}$$

$$R^2 = 1 - \sqrt{\frac{\sum_{i=1}^{n}(y_i - y_i^{\sim})^2}{\sum_{i=1}^{n}{y_i^{\sim}}_i^2}} \tag{10}$$

6. PGF Recommendation and Research Directions

A thorough investigation into PGF literature concludes numerous limitations in the current literature that need its solution in the upcoming research. This section delineates research advises for future research and for policy attempts. The limitations exit in PGF are explained below while discussed in subsequent sections individually.

Table 9
Hybrid learning-based PGF techniques with the considered sources of energy and their origination.

Ref	BN	Contributions	Origin	Resource
(Gandelli et al., 2014)	PHANN	Energy generation forecasting is performed for PV plant using PHANN. This method integrates NN with analytical approaches for efficient prediction.	N/A	Solar
(Ramsami and Oree, 2015)	MLR, ANN, GRNN, FFNN	Based on weather forecast, the next 24-hours stochastic solar energy is forecasted. Three single stage models such as GRNN, FFNN and MLR. Next, a hybrid approach of combing these models is adopted	United Kingdom	Solar
(Saleh et al., 2016)	Fuzzy C-Means	A hybrid neuro-fuzzy-based wind power forecasting model is proposed where the wireless sensor network measures the required parameters and transmits them for prediction model	N/A	Wind
(Kassa et al., 2016a)	MLFF-ANN, GA	A MLFF-ANN network that is optimized by GA is presented that is trained by back propagation algorithm.	N/A	Wind
(Wu and Peng, 2016a)	LSSVM, CBEA	A hybrid approach comprised of CBEA and LSSVM is presented to forecast wind power generation.	China	Wind
(Wu and Peng, 2016b)	EEMD, PCA, LSSVM, BA	This method develops hybrid model for wind power generation forecasting where the EEMD is applied to decompose the generation series into sub-series. PCA is applied to reduce input without reducing the forecasting accuracy	N/A	Wind
(Chang et al., 2016)	ARIMA, ANN	The hybrid approach of ARIMA and ANN is applied for wind power generation and speed forecasting.	Taiwan	Wind
(Barbosa de Alencar et al., 2017)	ANN, ARIMA, Hybrid Model	A short, ultra-short, medium, and long-term forecasting of wind power generation is performed using	Brazil	Wind

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Table 9 (*continued*)

Ref	BN	Contributions	Origin	Resource
		ANN, ARIMA and Hybrid model.		
(Abedinia et al., 2018)	NN, Metaheuristic algorithm	A forecasting approach based on combined NN and metaheuristic algorithm has been proposed	US	Solar
(Santhosh et al., 2018)	EEMD, AWNN	This method uses EEMD as a preprocessing step. The wind speed data is decomposed where the decomposed signal is utilized to forecast future wind through AWNN.	India	Wind
(Serttas et al., 2018)	Mycielski-Markov	Mycielski-Markov is utilized for short-term solar power generation forecasting. The method is based on hybrid connection of Mycielski-Markov and probabilistic Markov chain.	Turkey	Solar, Wind
(Wu and Gao, 2018)	SVM, GM	A hybrid method comprised of SVM and GM (SVM-GM) is proposed where SVM is used to forecast the wind direction and speed via different weights computed through gray correlations. The GM is then utilized to forecast the wind power generation	N/A	Wind
(VanDeventer et al., 2019)	GA, SVM	An SVM based on GA (GA-SVM) is proposed for short-term solar power forecasting. GA-SVM classifies weather data via SVM which is optimized by GA via ensemble method	N/A	Solar
(Li et al., 2019)	HIMOVE	A hybrid approach of HIMOVE is proposed that optimizes SVM for solar power prediction	Australia	Solar
(Kong et al., 2020)	Hybrid models	A series of approaches based on deep whole sky image learning are proposed for short-term solar power generation forecasting.	N/A	Solar
(Sun et al., 2020)	ANN	A hybrid data-driven, mechanism, and event-prediction model is proposed where furnace operational event is considered to predict the blast furnace gas generation.	China	Gas
(Li et al., 2020a)	WPD, LSTM	A hybrid approach of WPD and LSTM network is proposed for one-hour power forecasting	Australia	Solar
(Stefenon et al., 2020)	LSTM	A combination of LSTM and Wavelet as wavelet LSTM is proposed to forecast power energy production in solar trackers.	N/A	Solar
(Zhang et al., 2022b)	VMD-CNN-BiGRU	A VMD-CNN-BiGRU model is proposed for PV power forecasting, decomposing power series into sub-modes and using meteorological variables.	South Korea	Solar
(Ren et al., 2022)	QK_CNN, CNN_LSTM	Proposed for intra-hour PV power forecasting, using multiple kernel sizes to extract features	Australia	Solar
(Wang et al., 2022a)	Model chain	An archived ECMWF ensemble NWP dataset is presented for solar power forecasting, demonstrating post-processing and machine learning applications for improved probabilistic predictions	Europe	Solar
(Wang et al., 2022b)	AL-MCNN-BiLSTM	Proposed for wind power forecasting, using multi-scale CNN features, BiLSTM temporal extraction, and an asymmetric Laplace loss for accurate predictions and reliable uncertainty intervals	Ireland	Wind
(Rayi et al., 2022)	ELM, Autoencoder	A hybrid VMD–Deep MKELM-AE model is proposed for short-term wind power forecasting, using SCWCA-optimized decomposition and kernel parameters	Spain, US	Wind
(Alkabbani et al., 2023)	ANN, LSTM	Regional wind power forecasting, found LSTM is more accurate for multi-step ahead forecasting	Canada	Wind
(Huang et al., 2023b)	FCM	Hybrid method using FCM clustering and a	N/A	Wind

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Table 9 (*continued*)

Ref	BN	Contributions	Origin	Resource
		three-stage hierarchical framework is proposed for wind power forecasting		
(Li et al., 2024)	CNN-BiLSTM	A hybrid CNN-BiLSTM model with attention mechanism is proposed for PV power forecasting	China	Solar
(Li et al., 2025)	ConvLSTM, Transformer	Proposes SolarFormer, a large-scale GHI nowcasting model using satellite data, GRU, and a space-time transformer to provide 3-hour-ahead forecasts	N/A	Solar
(Barros et al., 2024)	RNNs	This study uses RNN to improve initial conditions for solar wind simulations	N/A	Wind, Solar

Advance technologies of machine and DL are applied in different data science domains to obtain the desired outcomes and applications where they input the raw data to generate the results. Concluding results are obtained after the data is passed through several DL layers that process for decisive output. Such end-to-end DL models are missing in PGF literature to intelligently process it and generate outcomes with precision in results. Also, there is lack of PGF methods that process the data at the same point where its generation is held, that is known to be edge intelligence. Similarly, IoT is vastly applied in several real-life applications linking light and agile devices to share information.

6.1. Power Availability and Qualities Concerns

One of the biggest challenges in renewable energy is the dependence of generation on natural resources, which are uncontrollable by humans. For instance, solar power is generated when the sunshine is available that turns off during darkness. Similarly, wind power also depends on wind availability, lower wind speed cause in turbine stoppage that results in zero power flow towards the grid (Liu et al., 2025a; Kochtcheeva, 2016). However, high speed winds may damage generators. Such uncertainty in power generation technologies make integration more complex. To this purpose, an intelligent balancing strategy need to be applied for consistent power generation (Abaka et al., 2017). Similarly, consistent high-quality power ensures the efficiency and stability of the network, enabling the system to operate with lower costs and higher reliability (Stram, 2016). On the contrary, poor quality can lead to adverse effects on power grid and industrial processes leading to equipment’s failure and high cost. Other major concerns include voltage variation, frequency disorder, and current/voltage harmonics (Ouedraogo, 2019).

6.2. Power Storage System

Lack of proper storage system at affordable cost and condition is another big challenge. Renewable energy sources produce power at definite time of the day, and it does not match peak hours. Intermittency of wind and sun do not produce on-demand power. The intermittent generation of power from renewable sources requires an efficient energy storage system that can store surplus energy for future use.

Table 10
Fuzzy logic-based PGF techniques with the sources of energy and their origination.

Ref	BN	Contributions	Origin	Resource
(Sáez et al., 2014)	Fuzzy Logics	The fuzzy prediction intervals are generated by the proposed model that ensure representation of future prediction	Chile	Solar, Wind
(Geng et al., 2015)	Fuzzy grey–Markov prediction model	This method improves the precision of the conventional prediction approaches through dynamic fuzzy grey-Markov model that divides random time series into change trend and fluctuation sequence.	China	Biofuel
(Kassa et al., 2016b)	ANFIS	ANFIS-based approach is used to develop the prediction model for wind power	N/A	Wind
(Rosato et al., 2017)	NN, ANF	Three techniques based on neural and fuzzy NNs such as ANF, redial basis function, and high-order neuro-fuzzy, are proposed to forecast the solar power energy	Italy	Solar
(Sivaneasan et al., 2017)	ANN, FL	A feedforward model having three layers with back-propagation is proposed where fuzzy logic is applied as pre-processing step.	Singapore	Solar
(Sujil et al., 2019)	ANFIS	A forecasting agent for solar and wind power generation forecasting has been proposed for energy management systems. To this purpose, ANFIS is proposed that is used for development of solar and wind power generation forecasting.	China	Solar, Wind
(Vosoogha and Addeh, 2019)	Fuzzy systems	A method based on fuzzy systems for wind power generation forecasting is proposed. The method consists of forecasting and optimization module	N/A	Wind
(Baptista et al., 2020)	ANN, SVM, Neuro-FIS	ANN, SVM, and ANF inference system are used to predict wind energy production.	Spain	Solar, Wind

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Table 10 (*continued*)

Ref	BN	Contributions	Origin	Resource
(Li et al., 2020a)	DIRMs	DIRM-DFM is proposed to strengthen the data-driven models' interpretability for power prediction	China	Solar
(Lim et al., 2022)	CNN-LSTM	PV power forecasting, with CNN classifying weather and LSTM used for predicting Power.	South Korea	Solar
(Lu et al., 2022)	CNN-LSTM	A day-ahead wind power forecasting model is proposed using VMD-WPE for feature decomposition and a CNN–LSTM network with optimized parameters	China	Wind
(López Santos et al., 2022)	TFT	A TFT model is proposed for hourly day-ahead PV power forecasting.	Germany, Australia	Solar
(Xu et al., 2022)	FNN	A correlation-based neuro-fuzzy Wiener model is proposed for wind power forecasting	Turkey	Wind
(Zhai et al., 2025)	VMD-SSA-Transformer-LSTM	Proposed MD-SSA-Transformer-LSTM model accurately forecasts PV power with high reliability	China	Solar

6.3. *Intermittency*

Integration of variable or intermittent resources, for instance, solar and wind could be difficult for usage that are built to accommodate the reliable and predictable power generation sources. Next, although peak of solar power generation syncs with peak demand, a large amount of its capacity is generated by the wind during off-peak hours. Such challenges can be mitigated via natural gas sources that complement variable power generation. Moreover, the storage system capacity joined with generation, but compressed energy storage and batteries help to provide predictable and some fixed output.

6.4. *On-Device Intelligence*

Edge intelligence has gotten increasing attention in PGF research due to its wide range of applications, such as reducing latency, increasing efficiency, and preserving privacy in forecasting systems (Shah et al., 2021). With the rise of IoT-based applications, edge intelligence enables real-time decision-making by processing data at the point where it is generated. Edge intelligence refers to connected devices and systems that collect, cache, process, and analyze data locally, rather than relying on centralized cloud systems. This approach enhances data processing speed and reduces reliance on cloud resources, thus enabling quicker and more efficient decision-making. Furthermore, edge intelligence improves data privacy and user security, as sensitive data does not have to be transmitted to central servers (Lee et al., 2019). One promising approach in this area is the development of lightweight models, such as TinyML (Abadade et al., 2023), that can be deployed on resource-constrained devices. TinyML offers the potential for low-latency predictions for solar and wind forecasting, particularly in remote or off-grid locations where computational resources and connectivity may be limited. The application of TinyML to PGF could enable edge devices, such as solar inverters or wind turbine controllers, to make forecasting decisions without relying on cloud-based systems. This would significantly enhance the real-time applicability of PGF, especially in areas where network connectivity is limited or intermittent. However, there are communication constraints in edge-based PGF systems that need to be addressed. Given the limited bandwidth and network reliability in certain areas, future research should focus on communication-efficient algorithms that can ensure the timely and accurate transmission of forecasting data. Data compression techniques and low-latency communication protocols could be explored to minimize the data transmitted from edge devices to central control systems, thus improving the efficiency and scalability of PGF systems. Furthermore, federated learning (Li et al., 2020b) offers a promising direction in edge intelligence for PGF. By enabling decentralized model training, federated learning allows multiple edge devices to collaborate on model building without sharing sensitive data, which is crucial for protecting privacy and reducing data transmission overhead. This approach could enable more accurate and collaborative PGF models across distributed energy generation sites, such as solar farms and wind turbines, without compromising data security or privacy.

6.5. *Integrated PGF Network*

Learning via end-to-end network is a hot topic in DL, taking the advantages of NNs comprised of several layers for solving complex problems. Conventional networks have several stages of data processing and comparatively make the network more complex in terms of parameters and model size. Similarly, forecasting through these networks is questionable for time wastage to load the forecasting models. In these procedures, multiple models are independently trained to obtain the desired results which are obtained after passing the data from various learning layers. However, practicing end-to-end models for forecasting will further boost the system performance where learning through the network is optimized by considering the input and output directly.

6.6. *Cloud/Fog Enabled Forecasting*

Fog and Cloud are extensive dispersed networks functional and much faster than solo computers. They are considered as the most sophisticated place where the data is efficiently analyzed and instantly distributed. Cloud setup is extensively used in different AI-based methods for effective outcomes. For instance, research presented in (Boveiri et al., 2019) proposed a development approach utilizing cloud-based setup. Likewise, Ullah et al (Ullah et al., 2021b) proposed IoT-based network with connection to cloud module for activity analysis in surveillance scenarios. Therefore, cloud-based PGF methods will further boost the performance of generation forecasting and provision of instant services (Ahmed et al., 2020).

6.7. *Data Diversity*

There exist numerous PGF benchmark datasets used in different research techniques and most of that research used confidential data details that are not publicly reachable for the researchers. In this way, several benchmarks in PGF field are sought that pose a lotss of challenges including missing values and remain publicly available with their details. Data collected in real-world scenarios from generation system is mainly required to efficiently deal with the nature of forecasting and characteristics of data. Similarly, researchers in PGF areas need to provide full access to the data in their publications that will open the ways for more sophisticated research.

6.8. *Time Complexity*

An open challenge and trend in data science fields and PGF research community is the race towards improvement in the employed methods

Table 11
PGF methods consist of approaches comprised of combination of different DL, CL, and hybrid connections.

Ref	BN	Contributions	Origin	Resource
(Orwig et al., 2014)	N/A	Trends and technologies related to solar and wind power generation forecasting are investigated.	US	Solar, Wind
(Wan et al., 2015)	ARIMA, ARMAX, ANN	Comprehensive review of forecasting methodologies for solar resources is explained.	N/A	Solar
(Yan et al., 2015)	WPFUA, WPPF	Uncertainties sources of wind power are analyzed.	N/A	Wind
(Alessandrini et al., 2015)	AnEn	AnEn is proposed to forecast wind power where its prediction is constituted through past measurements set.	Italy	Wind
(Tuohy et al., 2015)	N/A	The solar forecasting state is focused and the key issues relevant to its application and development	N/A	Solar
(Zhang et al., 2015)	N/A	Different scenarios are considered presented as a suite of value-based metrics for improved forecasting.	US	Solar
(Li et al., 2015)	PLSR	An ensemble method comprises of neural network, wavelet transform, and PLSR is proposed for wind power generation forecasting.	US	Wind
(Pascual et al., 2015)	N/A	An energy management system is developed for a micro grid of solar panels and wind turbines where the grid is connected to the main grid that allows the exchange of control over battery system.	N/A	Solar
(Zhang et al., 2016)	N/A	Variation mode decomposition is applied to process wind power data. Next, the differential evolution algorithm is employed to adjust the weights.	China	Wind
(Graditi et al., 2016)	MLP, MLR	A comparative analysis of three methods to estimate power production of solar power plant is proposed which is installed at research center located at South Italy. A phenomenological model and two SM such as MLP neural network and regression approach are compared.	Italy	Solar
(Seme et al., 2016)	N/A	A method to maximize energy production of solar tracking system is proposed and to determine orientation and tilt of modules for sun tracking system is introduced	N/A	Solar
(Capellaro, 2016)	N/A	Method to predict the value factor and market value of wind production, is presented, which allows this method to estimate the economic viability of turbine.	N/A	Wind
(Li et al., 2016)	ANN, SVM	Two commonly used methods such as SVM and ANN are compared for the energy production prediction.	Florida	Solar
(Gulin et al., 2016)	N/A	A static model is developed and verified for the power production prediction from PV array through manufacturers and online data integration.	N/A	Solar
(Niayifar and Porté-Agel, 2016)	N/A	The primary goal of this method is the development and testing of analytical models for wind prediction and associated power in wind farms.	N/A	Wind
(Wan et al., 2016b)	Direct quantile, ELM	A direct quantile regression approach is presented in this method, which generates non-parametric wind power generation forecasting by combining quantile regression and ELM.	Denmark	Wind
(Tang et al., 2016)	ELM, GRNN, RBF	The entropy and ELM are combined for short-term power generation forecasting where the data is initially processed through entropy method.	Oregon	Solar
(Li and Chiang, 2016)	N/A	The best point forecasting problem is studied that works under cost-oriented loss function. The theoretical points of optimal forecasting with different losses are studied	N/A	Wind
(Wan et al., 2016a)	ELM	A linear programming-based prediction model is presented for power generation forecasting where the model is based on ELM and quantile Regression	Denmark	Solar
(Golestaneh et al., 2016)	ELM	This method relies on ELM as fast regression model that is trained in varied ways for quantile and point forecast of power generation	Singapore	Solar
(Haupt and Kosović, 2016)	N/A	NA	N/A	NA
(Sheng et al., 2017)	GR	This study employs a weighted Gaussian regression approach for short-term power forecasting.	Singapore	Solar
(Ni et al., 2017)	LUBE, ELM	An ensemble approach of LUBE combined with ELM is proposed for short-term power forecasting.	Singapore	Solar
(Kim et al., 2017)	Self-adaptive model	A model for daily prediction based on weather information is proposed based on self-adaptive model.	South Korea	Solar
(Wang et al., 2017b)	ELM	A short-term power generation forecasting model is proposed using online sequential ELM with forgetting mechanism (FOS-ELM).	Oregon, US	Solar
(Jiang et al., 2017)	STPN	STPN framework is developed that not only captures the characteristic of individual system, but the pair-wise dependencies are also captured. Based on STPN, the energy prediction approach is developed	US	Wind
(Kosunalp, 2017)	N/A	An approach to predict wind power for energy harvesting-wireless sensor network.	Turkey, US	Wind
(Safari et al., 2017)	Chaotic Time Series Analysis, Singular Spectrum Analysis	A decomposition approach that takes chaotic nature of wind power, is proposed where the wind power time series is separated into few components with distinct frequency scales through ensemble mode decomposition	Canada	Wind
(Gulin et al., 2017)	N/A	A predictor-corrector technique is developed to forecast day ahead solar power production.	N/A	Solar
(Touati et al., 2017)	N/A	The main purpose of this research is the investigation of PV performance where a wireless system is developed for critical parameters recording including solar irradiance, humidity, dust, wind speed etc.	Qatar	Solar

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Table 11 (*continued*)

Ref	BN	Contributions	Origin	Resource
(Wasilewski and Baczynski, 2017)	MLP	This method proposes the optimization of MLP model for short-term wind power forecasting.	N/A	Wind
(Mavrigiannaki et al., 2017)	NN	24 h forecasting is examined for excess production of power in existing micro-grid where the prediction is used to schedule charging process of storage.	Italy	Hydropower
(Mason et al., 2018)	Evolutionary Algorithm	An evolutionary optimization algorithm and covariance matrix evolution procedure is proposed to predict short term wind power generation. This method also aimed to predict the power demand and level of carbon dioxide intensity in two months	Ireland	Wind
(Sobri et al., 2018)	ANN, SVM, Markov chain, Autoregressive, Regression	This paper classifies solar power forecasting into statistical methods, physical, ensemble methods.	N/A	Solar
(Geng et al., 2018a)	ELM, ISM, AHP	A production prediction method based on ELM integrated with ISM and AHP is proposed where the productivity affecting factors are divided by ISM. The attributes obtained from each layer are fused through AHP.	N/A	N/A
(Bleeg et al., 2018)	N/A	N/A	N/A	Wind
(Rosato et al., 2018)	ESN	The technique developed in this method is distributed centralized technique based on ESN, which is a type of RNN.	N/A	Solar
(Wang et al., 2018e)	N/A	A dynamic system is proposed to forecast the change of coal production.	China	Coal
(Morshedizadeh et al., 2018)	SCADA	An algorithm to impute data values that are missing or out of range, is developed where the combination of mean value and DT improves the data analysis and performance.	Canada	Wind
(He et al., 2018)	ELM	A sample generation technique based on nonlinear interpolation combined with ELM is proposed.	China	N/A
(Geng et al., 2018b)	SO-CSLN	SO-CSLN is proposed that obtain stable structure and parameters where the sample covariance matrix rank is applied to determine hidden layers' nodes in SO-CSLN. The method aims to build the model to predict ethylene production in petro industry	China	Petroleum
(Labati et al., 2018)	Decision Support System	A decision support system is developed to predict the wind power production for long-term power prediction.	N/A	Wind
(Yang and Huang, 2018)	N/A	Issue regarding ultra-short-term power prediction is considered to reduce the effects of stable and safe operation in power systems	N/A	Solar
(Pearre and Swan, 2018)	N/A	Four months of wind speed from 36 wind energy converters are used to compute the corrections for wind power generation forecasting	Canada	Wind
(Agoua et al., 2018)	Spatio-temporal model	A probabilistic spatio-temporal model is developed to forecast power production and provides complete future probability density of production for short-term	France	Solar
(Awan et al., 2018)	RNN, LMA	RNN is used to forecast solar power generation by incorporating LMA.	Pakistan	Solar
(Anagnostos et al., 2019)	TNN	Based on Sky-imager details and TNN, the energy production is forecasted where thermal effects are included.	NA	NA
(Su et al., 2019)	ARCA, EOT	Improved ensemble framework is proposed for solar power generation forecasting that is based on adaptive residual compensation and evolutionary optimization algorithm	N/A	Solar
(Kaab et al., 2019)	ANN, ANFIS	This method employs AI-based methods such as ANN and ANFIS model to predict sugarcane energy production and the life-cycle environmental impacts	Iran	Sugarcane
(Alonso-Montesinos et al., 2019)	SAM	Energy forecasting analysis is performed in solar plants through combined short-term forecasting scheme via SAM as a modeling tool to compute plant production.	N/A	Solar
(Khandakar et al., 2019)	Multiple regression model, ANN	The effects of environmental parameters including humidity, temperature, irradiance, wind speed, and solar plant surface temperature, are analyzed for power generation forecasting. Multiple regression models and ANN-based models are applied to forecast hourly power.	N/A	Solar
(Tabas et al., 2019)	CFD	The CFD software WindSim is analyzed for its ability to predict the wind power production forecasting in complex terrain.	Switzerland	Wind
(Zhang et al., 2019)	GM	GM (1,1) is applied to improve wind speed prediction through background value optimization. So, to clear the inherent uncertainty of wind speed, the fractional order grey system is constructed.	China	Wind
(Hao et al., 2019)	GRNN	Prediction model based on dilation and erosion clustering algorithm is proposed for wind power generation forecasting.	China	Wind
(Korprasertsak and Leephakpreeda, 2019)	ARIMA, ANN, GP model	Weight method is proposed that systematically combine the values of prediction of three models over time based on forecasting performance.	Spain	Wind
(Wang et al., 2019b)	GM	Differential evolution algorithm and rolling mechanisms are developed to improve GM prediction accuracy.	China	Thermal
(Matyjaszek et al., 2020)	HA	HA is applied to optimize the predictor variables in ANN while forecasting the price for energy forecasting.	Colombia, Europe, Australia	Coal, Natural Gas, Coal
(Theocharides et al., 2020)	ANN, K-means clustering, Linear regressive correction method	Proposed framework is comprised of data-driven approaches such as ANN, K-means clustering and linear regressive correction method that are applied for individual tasks in the process of hourly- and day-ahead forecasting.	US	Solar
(Wang et al., 2020)	ELM	ELM based on Monte Carlo algorithm is presented for energy production prediction.	N/A	Hydropower
(Kuzlu et al., 2020)	LIME, SHAP, ELI5	Several cases for solar energy forecasting are used via XAI tools including LIME, ELI5, and SHAPE giving complete insight of prediction model.	N/A	Solar

Table 12
List of power generation datasets that are worthy to be used in PGF.

#	Dataset	Instances	Active Power statistics			Year/Duration	Horizon	Provider	Source link
			Min	Avg	Max				
1	Wind Turbine Scada Dataset	50530	-2.47 kW	1307.68 kW	3618.73 kW	2018/1 year	10 M	Kaggle	https//www.kaggle.com/berkerisen/wind-turbine-scada-dataset
2	PV Italy (Ceci et al., 2016)	N/A	982.80 kW	995.71 kW	999.99 kW	2012.01.01–2014.05.04	15 M	NREL	https://www.nrel.gov/
3	EPEX SPOT	34944	0.0	3756.32	24243.7	2014/1 year	15 M	Mendeley	https://data.mendeley.com/datasets/3z8pwhxj5r/1
4	EPEX	31464	29201.0	3756.32	79884.0	2010–2014/5 years	1 H	Mendeley	https://data.mendeley.com/datasets/wr3zm9d7n9/1
5	Solar (Martin et al., 2016)	~677082	N/A	N/A	N/A	1994–2007	12–24 H	Kaggle	https://www.kaggle.com/c/ams-2014-solar-energy-prediction-contest.
6	Solar generation dataset (Kim et al., 2019)	4380	N/A	N/A	N/A	2013–01–01–2015–12–3	1 H	Government	http://www.data.go.kr/
7	Korean Solar PV Dataset	17251	0.40	920.02	2859.8	2015–2018/4 years	1 H	Korea's public data website	https://www.data.go.kr/data/15025486/fileData.do
8	NREL Wind	105120	0.00	6.78	16.00	2012/1 year	5 M	NREL	https://maps.nrel.gov/wind-prospector/?aL=sgVvMX%255Bv%255D%3Dt&bL=groad&cE=0&lR=0&mC=41.983994270935625%2C-98.173828125&zL=5
9	Solar Energy Generation	40896	0.00	N/A	N/A	2015–2019/5 year	1 H	Korea's public data website	https://www.data.go.kr/
10	Eco-Kinetics, 26.5 kW, mono-Si, Dual, 2010	1144324	0.00	N/A	52.98	2010.08.24–2021.08.03	5 M	DKA Solar Centre	http://dkasolarcentre.com.au/download?location=alice-springs

Table 13
Collection of PGF methods and the metric used by each method.

#	Metric	Evaluated methods
1	RMSE	(Mellit et al., 2014), (Tascikaraoglu et al., 2014), (Zamo et al., 2014), (Li et al., 2014), (Sáez et al., 2014), (Ma et al., 2014), (Dellino et al., 2015), (Leone et al., 2015), (Wan et al., 2015), (Golestaneh et al., 2016), (Wu and Peng, 2016b), (Chang et al., 2016), (Li and Chiang, 2016), (Yadav et al., 2015), (Zhang and Wang, 2016), (Abuella and Chowdhury, 2015b), (Zhang et al., 2015), (Abuella and Chowdhury, 2015a), (Zhang and Wang, 2015), (Ahmed Mohammed and Aung, 2016), (Kassa et al., 2016a), (Ramsami and Oree, 2015), (Saleh et al., 2016), (Kassa et al., 2016b), (Pierro et al., 2016), (Gulin et al., 2016), (Graditi et al., 2016), (Li et al., 2016), (Gensler et al., 2016), (Barbosa de Alencar et al., 2017), (Zhong et al., 2017), (Alfadda et al., 2017), (Al-Dahidi et al., 2017), (Gulin et al., 2017), (Kazem and Yousif, 2017), (O'Leary and Kubby, 2017), (Yesilbudak et al., 2017), (Touati et al., 2017), (Dumitru and Gligor, 2017), (Gligor et al., 2018), (Mason et al., 2018), (Abedinia et al., 2018), (Rosato et al., 2018), (Labati et al., 2018), (Rodríguez et al., 2018), (Ni and Ma, 2018), (Santhosh et al., 2018), (Yang and Huang, 2018), (Alomari et al., 2018), (Koprinska et al., 2018), (Serttas et al., 2018), (Wu and Gao, 2018), (Huertas Tato and Centeno Brito, 2019), (Shabbir et al., 2019), (Anagnostos et al., 2019), (Ceci et al., 2019), (Su et al., 2019), (Sujil et al., 2019), (VanDeventer et al., 2019), (Kaab et al., 2019), (Ma and Zhai, 2019), (Raffán et al., 2019), (Alonso-Montesinos et al., 2019), (Wang et al., 2019a), (Gao et al., 2019), (Koster et al., 2019), (Al-Dahidi et al., 2019a), (Al-Dahidi et al., 2019b), (Khandakar et al., 2019), (Vaitheeswaran and Ventrapragada, 2019), (Harrou et al., 2019), (Tabas et al., 2019), (Zhang et al., 2019), (Korprasertsak and Leephakpreeda, 2019), (Matyjaszek et al., 2020), (Harrou et al., 2020a), (Dupré et al., 2020), (Hu et al., 2020), (Pawar and TarunKumar, 2020), (Kong et al., 2020), (Samadi et al., 2020), (Wang et al., 2020), (Akbaş and Özdemir, 2020), (Zhang et al., 2020), (Li et al., 2020a), (Li et al., 2020a), (Stefenon et al., 2020), (Kuzlu et al., 2020), (Lee et al., 2020), (Lin et al., 2020), (Mishra et al., 2020), (Dai et al., 2023), (Li et al., 2024)
2	MAE	(Tascikaraoglu et al., 2014), (Orwig et al., 2014), (Sáez et al., 2014), (Zhang et al., 2017), (Dellino et al., 2015), (Xie et al., 2015), (Rashkovska et al., 2015), (Wan et al., 2015), (Yesilbudak et al., 2017), (Kazem and Yousif, 2017), (Golestaneh et al., 2016), (O'Leary and Kubby, 2017), (Barbosa de Alencar et al., 2017) (Gensler et al., 2016), (Wu and Peng, 2016b), (Safari et al., 2017), (Yadav et al., 2015), (Al-Dahidi et al., 2017), (Tuohy et al., 2015), (Zhang et al., 2015), (Ramsami and Oree, 2015), (Kassa et al., 2016b), (Pierro et al., 2016), (Martin et al., 2016), (Li et al., 2016), (Kassa et al., 2016a), (Wu and Peng, 2016a), (Ahmed Mohammed and Aung, 2016), (Yesilbudak et al., 2017), (Touati et al., 2017), (Díaz–Vico et al., 2017), (Gligor et al., 2018), (Mason et al., 2018), (Abedinia et al., 2018), (Morshedizadeh et al., 2018), (Labati et al., 2018), (Ni and Ma, 2018), (Santhosh et al., 2018), (Wang et al., 2018d), (Ceci et al., 2019), (Sujil et al., 2019), (Ma and Zhai, 2019), (Elmouatamid et al., 2019), (Wang et al., 2019a), (Gilbert et al., 2019), (Al-Dahidi et al., 2019a), (Al-Dahidi et al., 2019b), (Khandakar et al., 2019), (Harrou et al., 2019), (Zhang et al., 2019), (Brodny et al., 2020), (Matyjaszek et al., 2020), (Harrou et al., 2020a), (Dupré et al., 2020), (Hu et al., 2020), (Pawar and TarunKumar, 2020), (Barrera et al., 2020), (Zamee and Won, 2020), (Sun et al., 2020), (Zhang et al., 2020), (Li et al., 2020a), (Stefenon et al., 2020), (Nielson et al., 2020), (Lee et al., 2020), (Shahid et al., 2020), (Rushdi et al., 2020), (Dai et al., 2023),
3	MAPE	(Xiong et al., 2014), (Rathnayaka and Seneviratne, 2014), (Mellit et al., 2014), (Hernández et al., 2014), (Wang et al., 2017b), (Zhang et al., 2017), (Kazem and Yousif, 2017), (Orwig et al., 2014), (Li et al., 2014), (Xie et al., 2015), (Leone et al., 2015), (Aydin, 2015), (Wan et al., 2015), (Li et al., 2015), (Kassa et al., 2016b), (Graditi et al., 2016), (Kassa et al., 2016a), (Wu and Peng, 2016a), (Tang et al., 2016), (Wu and Peng, 2016b), (Chang et al., 2016), (Barbosa de Alencar et al., 2017), (Zhong et al., 2017), (Wang et al., 2017b), (Yesilbudak et al., 2017), (Sivaneasan et al., 2017), (Mason et al., 2018), (Kim and Hur, 2018), (Abedinia et al., 2018), (He et al., 2018), (Santhosh et al., 2018), (Serttas et al., 2018), (Wang et al., 2018d), (Wu and Gao, 2018), (Aineto et al., 2019), (VanDeventer et al., 2019), (Kaab et al., 2019), (Ma and Zhai, 2019), (Wang et al., 2019a), (Gao et al., 2019), (Li et al., 2019), (Han et al., 2019), (Zhang et al., 2019), (Wang et al., 2019b), (Brodny et al., 2020), (Theocharides et al., 2020), (Hu et al., 2020), (Pawar and

(continued on next page)

Table 13 (*continued*)

#	Metric	Evaluated methods
		TarunKumar, 2020), (Kong et al., 2020), (Zhang et al., 2020), (Li et al., 2020a), (Shahid et al., 2020), (Lin et al., 2020)
4	MSE	(Rathnayaka and Seneviratne, 2014), (Tascikaraoglu et al., 2014), (Rashkovska et al., 2015), (Wan et al., 2015), (Kazem et al., 2016), (Kassa et al., 2016b), (Kassa et al., 2016a), (Wu and Peng, 2016a), (Zhang et al., 2017), (Zhu et al., 2017), (Jiang et al., 2017), (Kazem and Yousif, 2017), (Yesilbudak et al., 2017), (Touati et al., 2017), (Gligor et al., 2018), (Mason et al., 2018), (Geng et al., 2018a), (Santhosh et al., 2018), (Koprinska et al., 2018), (Serttas et al., 2018), (Wang et al., 2018d), (Sujil et al., 2019), (Kim et al., 2019), (Elmouatamid et al., 2019), (Khandakar et al., 2019), (Li et al., 2019), (Wang et al., 2019b), (Barrera et al., 2020), (Stefenon et al., 2020), (Mishra et al., 2020)
5	NRMSE	(Gandelli et al., 2014), (Dolara et al., 2015), (Zhang et al., 2015), (Li et al., 2015), (Zhang et al., 2016), (Ceci et al., 2016), (Graditi et al., 2016), (Karakuş et al., 2017), (Wang et al., 2017b), (Safari et al., 2017), (O'Leary and Kubby, 2017), (Wasilewski and Baczynski, 2017), (Dolara et al., 2017), (Wasilewski and Baczynski, 2017), (Dolara et al., 2017), (Abedinia et al., 2018), (Huertas Tato and Centeno Brito, 2019), (Hao et al., 2019), (Theocharides et al., 2020), (Sewdien et al., 2020), (Akbaş and Özdemir, 2020)
6	MBE	(Orwig et al., 2014), (Ma et al., 2014), (Wan et al., 2015), (Yadav et al., 2015), (Ramsami and Oree, 2015), (Pierro et al., 2016), (Gulin et al., 2016), (Gulin et al., 2017), (O'Leary and Kubby, 2017), (Sujil et al., 2019), (Li et al., 2020a)
7	NMAE	(Gandelli et al., 2014), (Dolara et al., 2015), (Zhang et al., 2016), (Wasilewski and Baczynski, 2017), (Dolara et al., 2017), (Wasilewski and Baczynski, 2017), (Dolara et al., 2017), (Labati et al., 2018), (Sewdien et al., 2020)
8	R^2	(Kaab et al., 2019), (Su et al., 2019), (Kim et al., 2019), (Al-Dahidi et al., 2019a), (Harrou et al., 2019), (Harrou et al., 2020a), (Lee et al., 2020), (Lin et al., 2020)
9	MRE	(Zhong et al., 2017), (Yang and Huang, 2018), (Sujil et al., 2019), (Wang et al., 2020)
10	WMAE	(Al-Dahidi et al., 2017), (Dolara et al., 2017), (Dolara et al., 2017), (Labati et al., 2018)
11	MaxAE	(Dellino et al., 2015), (Orwig et al., 2014)
12	R	(Zhang et al., 2016), (O'Leary and Kubby, 2017)

Table 14
Popular research questions considered in PGF techniques.

RQ#	Research Questions	Inspiration
RQ1	How can TinyML models be optimized for PGF to run on edge devices with limited computational resources?	Accentuate latest AI-based smart technologies and their struggling for efficient PGF
RQ2	What evaluation strategies are worthy and effective to be used to verify the experiments?	Check what diverse types of evaluation metrics are used in the PGF literature.
RQ3	What are the conditions that affect the PGF?	Find all the possible related conditions.
RQ4	Which datasets are used in the PGF studies?	Underline the studies buoyed by experiments and what data they used in the experiments.
RQ5	What renewable source of energy are they using in PGF?	Check the data patterns and find the data attributes.
RQ5	Which countries participate in PGF research?	Highlights the originations of renewable resources and indicates the countries that are actively working in PGF.

in certain perspectives such as perfection in accuracy, method preciseness, and reduction in the computational complexity. In the field of PGF, computational complexity is not considered at large level and is almost eliminated. This is an important aspect that is less focused on by researchers. Therefore, it is strongly recommended to include complete set of details about the running time of the engaged framework. Adding this aspect into consideration will further open the ways to speed up the forecasting mechanism.

6.9. Policy and Regulatory Considerations

Practical deployment of PGF is strongly influenced by policy and regulatory frameworks, since forecasting performance is tied to grid reliability requirements and renewable market participation (Papadaki et al., 2025). Grid codes and operator rules may impose scheduling and operational constraints (e.g., dispatch-aligned horizons, ramping considerations, reserve planning), while electricity-market regulations (day-ahead/intraday bidding, settlement intervals, and imbalance penalties) determine which forecast horizons and update frequencies are most valuable. In addition, data governance policies (access, sharing, ownership) and cybersecurity/privacy requirements for critical smart-grid data can restrict centralized data use and motivate secure and privacy-aware implementations. Therefore, PGF research should increasingly report market- and regulation-consistent experimental settings and complement accuracy metrics with operational and cost-oriented indicators to improve real-world adoption.

7. Research Questions

The primary question which leads the survey is what the areas are, datasets, technologies, evaluation metrics, etc. are used in development of PGF models. To efficiently pipeline the systematic mapping, the key questions are categorized into five research questions that are given Table 14 that will help the readers by clearly portraying the roadmap of PGF study and in grasping the desired insights.

8. Concluding Remarks

PGF recorded major advancements towards its development and applications over the last few years. They play a vital role in power management within wide range of applications. These methods contribute to the proper energy production planning, its demand management, and schedule to confirm a stable and reliable operation in grids systems. These days, there is a greater increase in energy consumption and in this regard, copious amounts of energy are wasted. To tackle such issues and avoid copious amounts of energy wastage, PGF techniques are obligatory to provide smooth operation of energy generation and its management with the supply. Therefore, we deliver a comprehensive survey of existing state-of-the-art PGF methods from the literature ranging from 2014 to 2025. In this survey, we provide a comprehensive survey of existing intelligent PGF techniques, highlight the advantages and their downsides, and briefly prove the working flow of employed literature. Next, we widely debate on power generation datasets for their features and briefly overview the challenges defied by the researchers while practicing these datasets. Apart from existing power generation survey papers, the performance evaluation strategies are concretely overviewed, and comparison of methods employed for PGF, thereby concluding the need of effective, efficient, and adoptable intelligent PGF approaches functional for real-world settings. Finally, the recommendation for intelligent PGF is emphasized in future research guidelines which aid this arena with trending research endeavors.

In future, we intend to further investigate power generation and its consumption in terms of their matching strategies. We also aim to provide comparative analysis of distinct PGF approaches.

CRediT authorship contribution statement

Fath U Min Ullah: Writing – original draft, Visualization, Validation, Software, Methodology, Investigation, Formal analysis, Data curation, Conceptualization. **Muhammad Munsif:** Visualization, Validation, Formal analysis, Data curation. **Khan Muhammad:** Writing – review & editing, Investigation, Formal analysis. **Sung Wook Baik:** Supervision, Project administration.

Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Data availability

No data was used for the research described in the article.

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