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Federated learning and non-federated learning based power forecasting of photovoltaic/wind power energy systems: A systematic review

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HIGHLIGHTS

- Accurate PV and WP forecasting aids grid management, sustainability, and low impact.
- Traditional methods face privacy, centralised, and data sharing challenges, needing upgrades.
- Paper explores FL in PV/WP forecasting, detailing methods and encryption for challenges.
- Paper reviews methods, comparing non-FL and FL forecasting for renewable integration.

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ABSTRACT

Renewable energy sources, particularly photovoltaic and wind power, are essential in meeting global energy demands while minimising environmental impact. Accurate photovoltaic (PV) and wind power (WP) forecasting is crucial for effective grid management and sustainable energy integration. However, traditional forecasting methods encounter challenges such as data privacy, centralised processing, and data sharing, particularly with dispersed data sources. This review paper thoroughly examines the necessity of forecasting models, methodologies, and data integrity, with a keen eye on the evolving landscape of Federated Learning (FL) in PV and WP forecasting. Commencing with an introduction highlighting the significance of forecasting models in optimising renewable energy resource utilisation, the paper delves into various forecasting techniques and emphasises the critical need for data integrity and security. A comprehensive overview of non-Federated Learning-based PV and WP forecasting is presented based on high-quality journals, followed by in-depth discussions on specific non-Federated Learning approaches for each power source. The paper subsequently introduces FL and its variants, including Horizontal, Vertical, Transfer, Cross-Device, and Cross-Silo FL, highlighting the crucial role of encryption mechanisms and addressing associated challenges. Furthermore, drawing on extensive investigations of numerous pertinent articles, the paper outlines the innovative horizon of FL-based PV and wind power forecasting, offering insights into FL-based methodologies and concluding with observations drawn from this frontier.

This review synthesises critical knowledge about PV and WP forecasting, leveraging the emerging paradigm of FL. Ultimately, this work contributes to the advancement of renewable energy integration and the optimisation of power grid management sustainably and securely.

1. Introduction

The persistent advancement of technology has precipitated a dramatic surge in energy demand, leading to the rapid depletion of conventional energy reservoirs. This trend not only aggravates environmental

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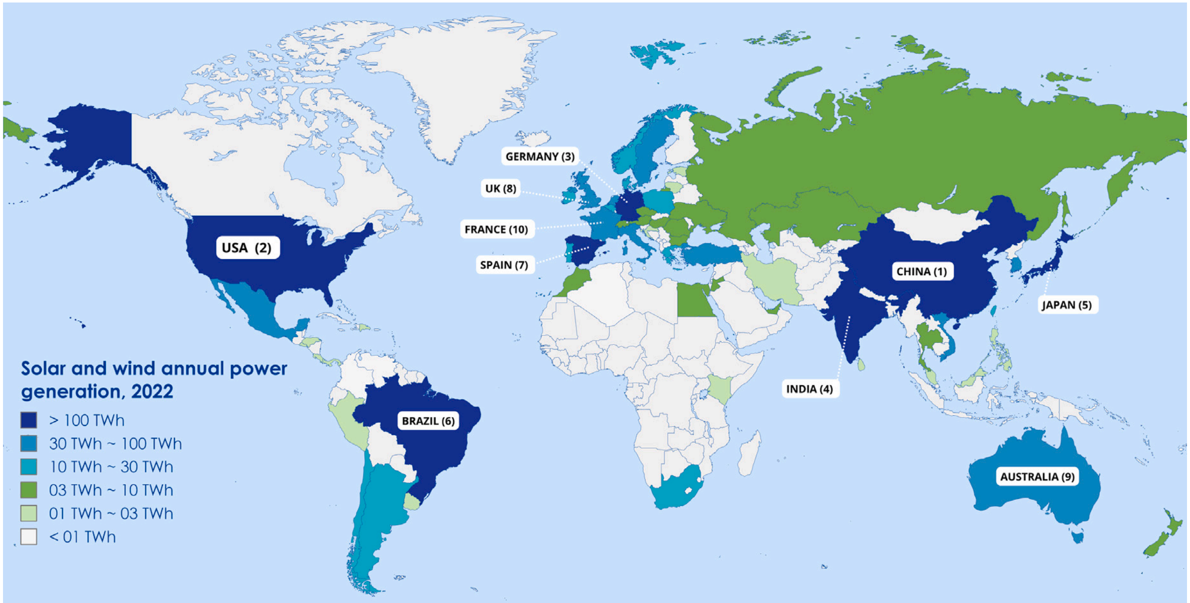

Fig. 1. Map representation depicting the top countries leading in solar and wind annual power generation during the year 2023; Measured in terawatt-hours. [Figure created using WORLD MAP online software].

degradation but also engenders significant socio-economic repercussions, accentuating the exigent for an expeditious transition towards cleaner and sustainable energy modalities. Within this context, renewable energy emerges as a pivotal remedy, promising multifaceted advantages [1]. Solar energy, notably, has ascended to preeminence as the most economically viable source of carbon-neutral energy on a global scale [2], with further potential for cost reductions through technological advancements and economies of scale [3]. Photovoltaic (PV) and wind power (WP), as stalwarts of the renewable energy paradigm, offer compelling solutions to the dual imperatives of climate mitigation and societal progress including the proliferation of gainful employment opportunities across the energy value chain. These renewable sources also encourage the move towards improved local energy autonomy and a decentralised energy infrastructure [4,5].

In the pursuit of sustainable energy solutions, examining recent achievements is essential. The year 2022 witnessed significant advancements, with several countries setting benchmarks in solar and wind power generation. As depicted in Fig. 1, the top ten countries leading in annual solar and wind power generation in 2023 include China, the United States, and Germany, which generated 1470.02, 663.35, and 198.85 terawatt-hours respectively. This underscores their commitment to harnessing renewable energy sources. Additionally, Fig. 2 provides a geographical representation of countries ranked by annual solar and wind power generation per capita, highlighting Denmark, Sweden, and Australia as leaders with 3812, 3505, and 3027 kiloWatt-hours per person in 2023. Further emphasising this progress, Fig. 3 identifies the top ten countries achieving the highest integration of solar and wind energy within their national grids. Luxembourg, Denmark, and Lithuania lead this category with integration levels of 67.5%, 67%, and 57.2% respectively, a feat facilitated by their relatively small geographical areas. In contrast, larger countries such as the USA, China, and Canada achieve notable integration levels of 15.6%, 15.5%, and 7.2% respectively, reflecting the challenges larger nations face in scaling renewable energy integration across vast areas. Russia, however, has not surpassed 0.5% renewable energy integration, indicating significant room for improvement [6].

The paradigm shift in energy sources has therefore gained significant academic attention, particularly emphasising the seamless integration strategies of renewable energy sources into the global electrical infrastructure [7–9]. Analysing this growing phenomenon highlights various impacts related to the inherent intermittency of these sources on the power system, affecting voltage regulation, protection mechanisms, frequency stability, angular stability of generators, harmonics, flexibility, and overall stability requirements [10,11]. This intermittency complicates the alignment of real-time consumption with grid production [12,13]. For example, the frequency of the current grid is directly affected by the rotational speed of traditional synchronous generators [14–16], which are controlled to maintain the frequency within the prescribed limits set by the National Grid Electricity System Operator [17]. Consequently, the kinetic energy produced by these generators is essential in constraining the initial rate of frequency control during load-generation instabilities. In contrast, PV technology does not include rotating machinery, which traditionally provides inherent inertial support. This, coupled with solar variability, results in a higher rate of frequency change (ROCOF) [14], power generation losses [18], and an increased complexity control process [19].

Therefore, the integration of large-scale PV and wind power plants into the power transmission grid necessitates the provision of additional frequency support services to ensure grid stability, as proposed in [20–22], and is contingent upon the ability to predict and manage its fluctuations [11,23,24]. Such forecasts and predictions are indispensable for ensuring system stability, reserve allocation, mitigating market risks, optimising energy distribution, and catering to the diverse needs of stakeholders ranging from power plant operators to policymakers [25–27]. For instance, in the event of a forecast predicting optimal weather conditions, reliance on non-renewable energy sources can be scaled back, maximising the input from renewable systems. Conversely, during anticipated periods of low renewable output due to suboptimal weather patterns, backup energy reserves can be readied proactively.

Beyond operational logistics, forecasting has profound implications for the economic dynamics of the energy market. In a domain where financial equilibrium is intrinsically tied to the ebb and flow of supply and demand, a surge in predicted yields from renewables could catalyse a drop in energy prices. Such predictive acumen enables energy traders to strategise effectively, potentially curtailing significant financial repercussions [28]. Moreover, system stability, which is paramount for the seamless integration of intermittent renewable sources, stands to gain immensely from precise forecasting. By tuning in to forecasted outputs, the robustness of the grid can be enhanced, curtailing potential disturbances. This proactive approach ensures a consistent electricity

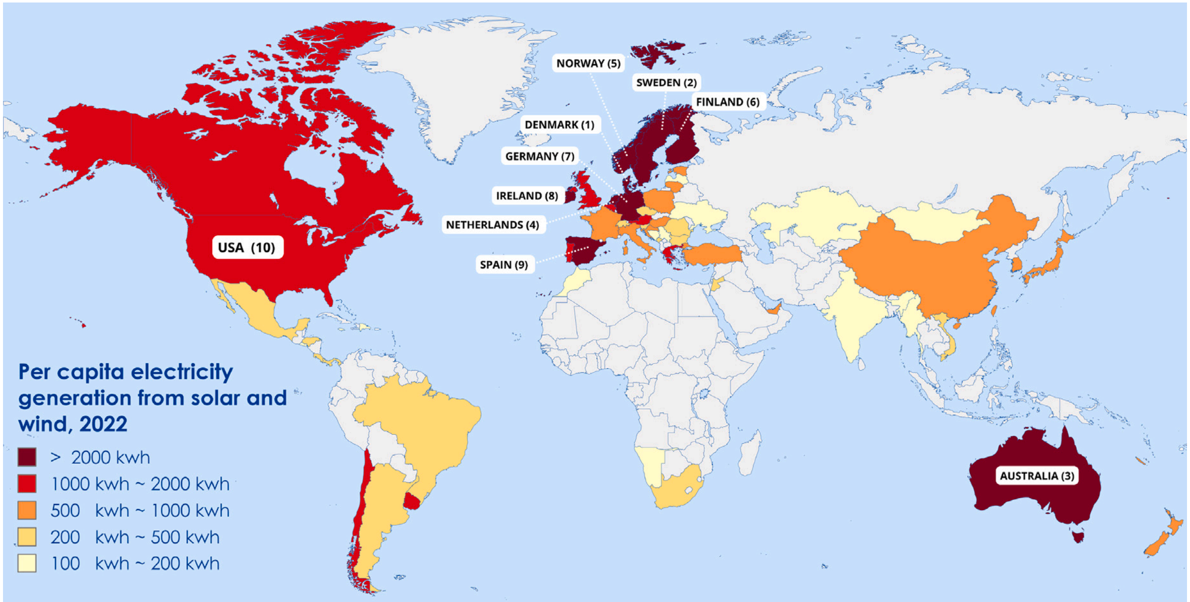

Fig. 2. Map representation highlighting regions that lead in solar and wind generation per capita; Measured in kilowatt-hours per person, during 2023.[Figure created using WORLD MAP online software].

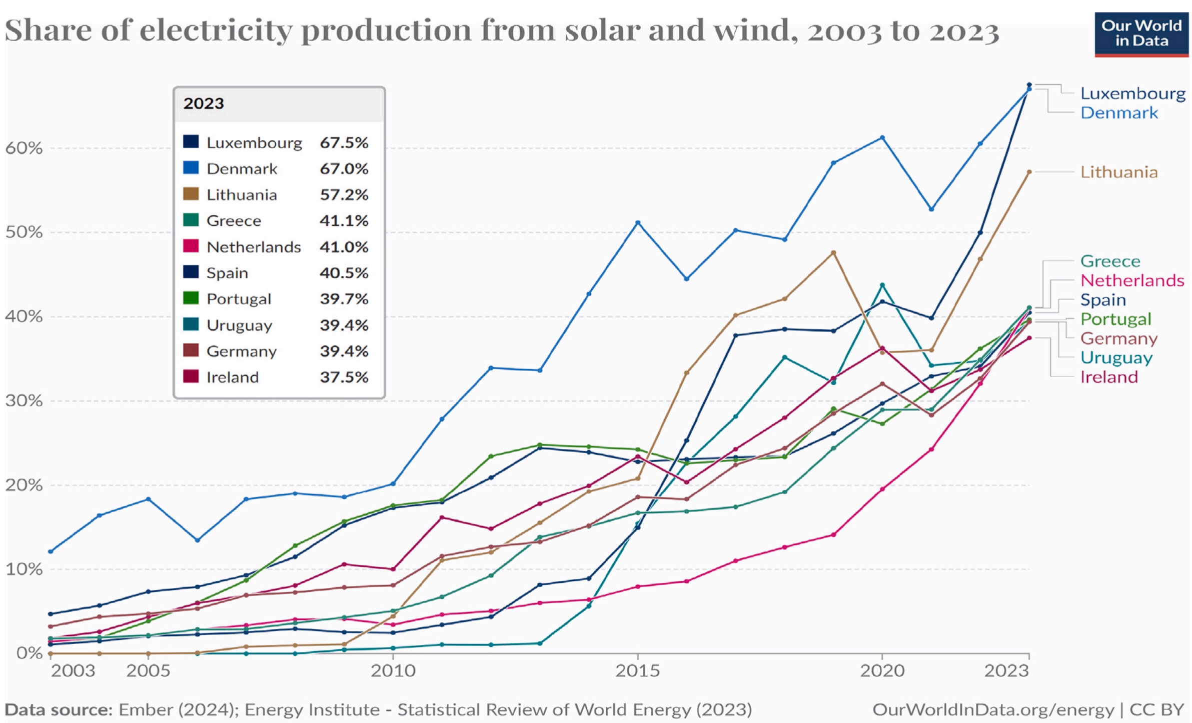

Fig. 3. Line plot visualising the trend of the top ten countries that lead in the integration of solar and wind energy within their respective national electricity grids from 2003 to 2023. This visualisation underscores the steady or accelerated growth rates in certain nations, indicating proactive policy implementations and technological adoption.

supply, an aspect deemed indispensable in our modern world. With nations globally setting forth stringent renewable energy benchmarks, the effective harnessing of PV and wind energy takes centre stage. Besides, in some electricity markets, solar producers can face penalties when deviations between targeted and produced energy exceed a tolerance band [29]. As these benchmarks evolve from broad aspirations to granular, quantifiable targets, the indispensability of accurate forecasting becomes even more pronounced. In essence, within the overarching narrative of renewable energy proliferation, forecasting is not just beneficial, but essential [30]. As global discourse pivots increasingly towards eco-friendly energy alternatives, the imperative for pinpoint forecasting methodologies becomes all the more salient.

Plenty of reviews related to the role of machine learning in forecasting methods can be found in the literature. For instance, R. Ahmed et al. [8] presented contemporary forecasting techniques and standardised comparisons of different forecast models by focusing on data length, quality, and resolution. They have been able to impart insights, especially using hybrid artificial neural networks and evolutionary algorithms. Voyant et al. [31] summarise all the methods of solar irradiation forecasting using machine learning approaches. The study of Akhtar et al. [32] provides a systematic and critical review, focusing mainly on metaheuristic and machine learning methods for PV power forecasts. The characteristics of each technique are described based on historical data along with forecasting horizons and input parameters. The reviews by Wang et al. [33], and Mellit et al. [34] present taxonomy research on the existing solar power forecasting models based on AI algorithms, the challenges, as well as the future trends. In wind forecasts, Liu et al. [35] give a broad literature survey of the intelligent predictors, including both shallow and deep learning-based categories. The paper by Marugan [36] presents the state-of-the-art artificial neural networks (ANN) applied to wind energy systems, as well as an extensive compilation of methods, algorithms, and models. More reviews of PV and Wind forecasts from specialised journals, including Elsevier, Springer, IEEE, Wiley, and MDPI, are listed in Table 1.

Surprisingly, federated learning (FL) has not been cited or has not received as much attention in current studies. This lack of focus is worrying, especially considering the distributed nature of renewable energy systems and the growing importance of data privacy and security today. FL, which allows decentralised datasets to collaborate in machine learning, presents a valuable approach to address modern data privacy challenges. This manuscript addresses an important gap in the existing literature, spotlighting the potential and complexities of FL methodologies specifically tailored for PV and WP forecasting. At its core, our research seeks to unravel the myriad advantages, inherent challenges, and evolving trajectories of federated learning within the ambit of renewable energy forecasting.

Table 1
A comparative analysis of previous reviews on photovoltaic (PV) and wind power (WP) forecasting.

Citation	Year	ML/DL	Wind	Solar	Federated Learning
[31]	2017	✓	X	✓	X
[36]	2018	✓	✓	X	X
[32]	2019	✓	X	✓	X
[33]	2020	✓	X	✓	X
[34]	2020	✓	X	✓	X
[8]	2020	✓	X	✓	X
[39]	2020	✓	✓	X	X
[40]	2021	✓	X	✓	X
[41]	2022	✓	✓	✓	X
[42]	2022	✓	✓	X	X
[43]	2022	✓	✓	✓	X
[44]	2022	✓	X	✓	X
[45]	2022	✓	X	✓	X
[46]	2023	✓	✓	X	X
[47]	2023	✓	X	✓	X
[48]	2023	✓	X	✓	X
[49]	2023	✓	X	✓	X
[50]	2024	✓	X	✓	X
[51]	2024	✓	X	✓	X
[52]	2024	✓	X	✓	X
Our paper	2024	✓	✓	✓	✓

2. Non-federated learning based PV/wind forecasting methods: an overview

The accuracy of forecasting is challenged by the unpredictable nature of solar and wind behaviour, as well as weather unpredictability. Addressing these challenges has encouraged the development of a plethora of methodologies, each of which has advantages and disadvantages [7,27,37]. Table 2 offers a concise spectrum of forecasting methodologies pertinent to PV and WP. Dominating the heart of such forecasts are physical models, with a particular focus on Numerical Weather Prediction (NWP). These models, rooted in mathematical formulations, emulate atmospheric behaviours by integrating variables like pressure, temperature, and humidity to forecast forthcoming atmospheric conditions. For solar power forecasting, the anticipated presence or absence of sunlight is paramount. Consequently, cloud forecasts, which significantly influence solar power output, are an essential component of these physical models. For WP, the emphasis shifts to predicting wind velocities at heights relevant to wind turbines. NWP are generally reserved for long-term predictions due to their computational demands [38].

Conversely, statistical models may be limited in their ability to capture the complicated non-linearities inherent in weather patterns [7]. It is within this context that artificial intelligence, especially deep learning, has carved a niche, given its adeptness at managing complex and non-linear interactions [7,26,53]. Concurrently, the field of statistical and machine learning (ML) has witnessed a suite of methodologies that are fundamentally grounded in historical datasets. Drawing from past records approaches like neural networks (NN), support vector machines (SVM), and linear regression (LR) are fine-tuned to predict future energy outputs. The expanding significance of ML and Deep Learning (DL) in this domain stems from their proficiency in decoding non-linear data correlations and their inherent ability to enhance predictions through continuous data assimilation. Beyond standalone physical and statistical models, there is growing interest in hybrid forecasting. These models seek to amalgamate the virtues of both physical and statistical paradigms, aiming to furnish forecasts that harness the strengths of both, potentially culminating in heightened accuracy.

Centralised machine learning models require the collection of a large amount of data on a central server. They present distinct benefits, notably in their simplicity, uniformity, and direct governance over data and processes. On the other hand, decentralised machine learning refers to the preservation of local client data and training on-site instead of being shared with a central server, which can enhance privacy and security but often increases the complexity of algorithms and reduces overall efficiency due to the need for coordination between distributed clients [54]. Fig. 4 illustrates the fundamental differences between centralised and decentralised learning, focusing on five critical parameters: data location, algorithmic complexity, data privacy, efficiency, and security. As the renewable energy sector deliberates between decentralising or maintaining centralised forecasting strategies, Federated learning emerges as a promising solution to preserve all local clients' data and the forecasting model's robustness. This section offers an exhaustive examination of non-federated learning models, their methods, effectiveness, and pertinence in the current dynamic energy context.

Table 3 addresses key forecasting aspects documented in the literature such as the horizon, which defines the temporal step ranging from ultra-short (1 s to 1 min minute ahead) to medium and long term (several hours to several days or months). The data distribution distinguishes between continuous data (e.g., time series) and discrete variables (e.g., images). The preprocessing stage represents the first step following data collection and involves removing aberrant values and outliers, as well as performing scale adjustments, particularly when different units are used (a process known as normalisation). In certain deep learning algorithms, this step may also include preliminary filtering to retain only meaningful data through feature selection. A forecasting technique refers to the practical application of algorithms such as Artificial Neural Networks (ANNs), Long Short Term Memory (LSTM), Support Vector Machines (SVM), Convolutional Neural Networks (CNN), and Decision Trees. On the other hand, an approach defines how uncertainty is addressed in predictions: deterministic approaches produce fixed outcomes, while probabilistic approaches incorporate uncertainty, providing a confidence interval around the forecast. Optimisation algorithms are employed to determine the optimal solution for achieving accurate predictions. Finally, evaluation techniques are used to assess the accuracy of the forecast by comparing it against real-world outcomes.

2.1. Non-federated learning-based PV power forecasting

Photovoltaic solar energy, with its significant capability to harness solar power, has become an indispensable pillar in the pursuit of sustainable energy solutions. Due to the variable and intermittent nature

Table 2
Modelling in PV and WP forecasting.

Modelling in PV and WP Forecasting	Physical Models	These Models are built upon the principles of physics. They describe the physical process governing the behaviour of systems.	Numerical Weather Prediction (NWP) Wake Models (For Wind) Radiative Transfer Learning (For Solar)
	Statistical Models	These models make predictions based on historical data, finding patterns or relationships in past observations. They encompass both traditional models, such as ARIMA and linear regression, as well as advanced artificial intelligence techniques, including machine learning and deep learning algorithms.	Time-Series Analysis (ARIMA, Exponential Smoothing) Regression Models (Linear/Logistic Regression) Stochastic Models (Randomness) ANN, SVM, RNN, LSTM, GRU, CNN, GA, etc.
	Hybrid Models	Combines the principles of physical and statistical models to leverage the strengths of both approaches	Physical–Statistical Models Machine Learning Enhanced Physical Models Model Stacking or Ensembling

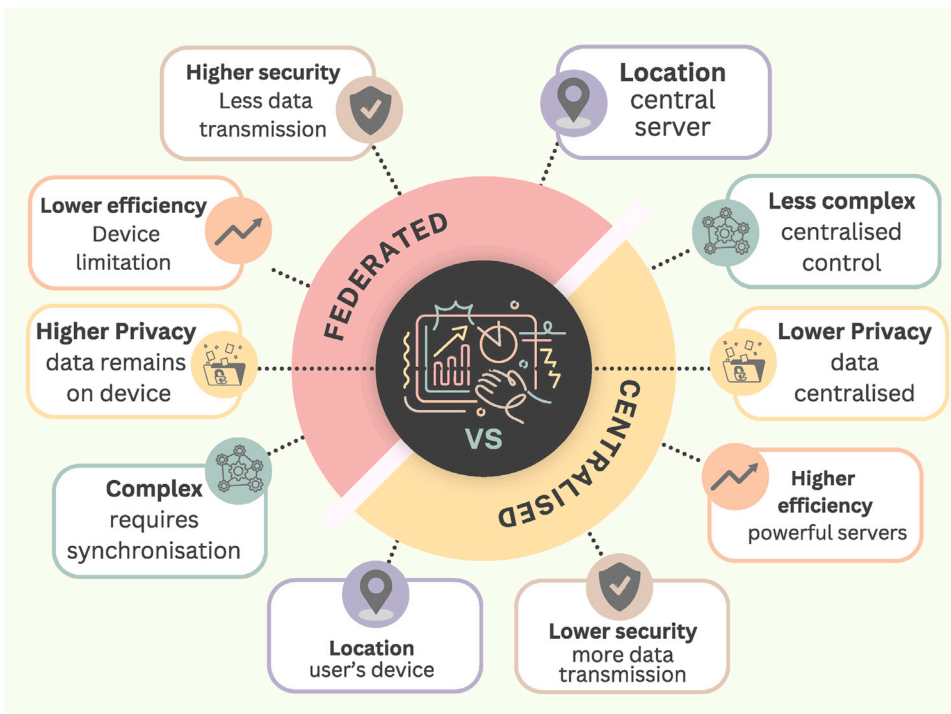

Fig. 4. Main differences between Federated Learning and Centralised Learning.

of solar irradiation, precise forecasting is essential for the seamless integration of PV systems into the electricity grid. Traditional non-federated learning models, relying on vast centralised data sets, have been at the forefront of PV forecasting, offering accurate predictions. This section delves into the progress and enhancements realised in non-FL PV forecasting, laying the foundation for exploring the potential of emerging decentralised methodologies. A summary of the research undertaken in this arena to date is presented in Table 4.

Renewable energy systems' mathematical modelling is an active research area, with considerable attention given to artificial neural networks (ANNs). ANNs have consistently shown superior solar forecasting capabilities when compared to traditional statistical methods [75]. Particularly in noisy data scenarios, the Long Short-Term Memory (LSTM) model has surpassed the Autoregressive Integrated Moving Average model (ARIMA) in accuracy [76]. Deep learning algorithms, primarily due to their adaptability through supervised learning, excel in classification and regression tasks [77]. Extensive research has explored the prediction and optimisation of artificial intelligence (AI) methods in the renewable energy sector [78]. Modern AI techniques are increasingly applied in modelling and simulating solar energy systems [79].

This review emphasises the primary methodologies and neural models used, highlighting ANNs' pivotal role in forecasting environmental variables and assessing various alternative energy systems [80]. Recent developments spotlight LSTM's dominance in short-term wind speed forecasting within ANNs [77,81]. LSTM's capabilities were investigated in 24-hour wind farm scenarios, outshining Multi-Layer Perceptron (MLP), deep MLP, and traditional methods in accuracy [82]. For solar radiation tasks, neural network-based deep learning techniques are predominantly applied. Evaluations show that the MLP model outperformed decision trees and linear regression in solar energy estimation, with outstanding coefficient of determination indicators (R^2 at 97.7) and Root Mean Squared Error (RMSE) at 0.033 [83]. The SVM model, using a direct approach, also demonstrated impressive results [84]. An MLP network, when combined with iterative strategies, provided a robust mechanism for long-term forecasting. LSTMs, with their capacity to manage extensive data and strong generalisation

Table 3
Fundamental concepts and general overview of photovoltaic and wind power forecasting techniques.

Forecasting Techniques	Categorisation	
Horizon	UltraShort [55]	
	Short [56]	
	Medium [57]	
	Long [58]	
Data Distribution	Satellite Images	
	Spatial	
	Time Series	Meteorological
		Wind Speed [59]
		Wind Power [60]
		Solar Irradiance [61]
		Solar Power [8]
Preprocessing	Normalisation	MinMax
		Standard
	Cleaning	Data Imputation
		Outliers Treatment
	Changing Resolution	
	Transformation /Augmentation	
	Clustering	
	Correlation Analysis	
	Feature Selection	
Forecasting Models	Machine Learning	ARIMA [62]
		ARMAX [63]
		FBPROPHET [64]
		CNN [65]
		RNN - LSTM [65]
		RNN - GRU [66]
Approach	Deterministic	Multistep [67]
		One step [68]
	Probabilistic	Multistep [69]
		One step [69]
Optimisation	Hyperparameter Tuning [70]	
	Parameter Adjustments [70]	
	Overfitting [71]	
	Enhanced Training	
Evaluation Techniques	Metrics [72]	
	Runtime [70]	
	Statistical Testing [70]	
	Benchmark Testing [73]	
	Input time steps [74]	
	Data Fusion [74]	

capabilities, surpassed SVM-based models [85]. LSTM-RNN has been endorsed for accurately predicting annual solar PV system outputs [86]. Comparisons with MLR, Bagged Regression Trees (BRT), and traditional NNs showed LSTM networks to have lower prediction errors. LSTMs, when employed, showcased superior mid and long-term forecasting for wind and solar power, with error rates significantly below SVM and persistence models [58]. In place of conventional solar irradiation measurement techniques, ANNs have been validated as effective. The MLP structure is the most common neural network, with an MLP approach recommended for forecasting solar radiation in the subsequent 24 h using real-time data from Italy [87,88].

Recent advancements in PV forecasting for 2022 highlight a surge in innovative methodologies and approaches. Hybrid models combining various techniques have gained traction. One notable method is the integration of Particle Swarm Optimisation (PSO) with deep learning, which effectively marries the strengths of swarm intelligence and artificial intelligence [92]. There is also a growing emphasis on merging physical data with computational strategies, as seen with hybrid physical and AI irradiance-to-power conversion models tailored for day-ahead forecasting in PV plants [93]. In the same vein, the synergy of LSTM with models like Nonlinear Auto-Regressive Neural Networks with Exogenous Input (NARXNN) is paving the way for more robust forecasting tools. A study showcasing this blend utilised hierarchical learning and the Tabu search method to create a comprehensive forecasting system [91].

While deep learning techniques, especially LSTM, are proving invaluable in handling intricate data structures for solar power forecasting [95], traditional machine learning approaches remain relevant. For instance, methods such as SVM and Gaussian Process Regression (GPR) have accentuated the importance of pivotal input variables like solar flux and panel temperature in achieving precision [94].

Local challenges have also encouraged customised solutions. At Deakin University, researchers established a local weather station in conjunction with their PV system to address discrepancies from remote weather data acquisitions. Their innovative GASVM model showcased a marked improvement in forecasting over the traditional SVM [89]. Similarly, a unique study aimed at leveraging PV power generation and Electrical vehicles charging load output from the forecasting model highlighted enhanced algorithm efficiency using real data from China's Aifeisheng PV power station and EV charging stations in the UK [90].

Lastly, geographical specificity remains a focal point in research. An investigation centred on Alice Springs, Australia, a region known for its abundant solar energy, deployed machine learning methodologies to provide both short-term and long-term predictions for PV power generation, factoring in diverse environmental variables [106].

The range of techniques presented illustrates a diverse spectrum of non-federated learning strategies applied to PV power forecasting, paving the way for future innovations in the sector. By integrating the advantages of decentralised learning methods with tailored forecasts for renewable energy, a novel perspective emerges for the industry. Tapping into the predictive prowess of intricate AI models, such as FL, becomes imperative as the renewable energy sector continues its expansion. Beyond their immediate contribution to mathematical modelling, these methodologies signify the synergy between technological advancement and sustainable growth.

2.2. Non-federated learning based wind power forecasting

Wind energy, derived from unpredictable atmospheric currents, is a pivotal component of our renewable energy portfolio. Accurately harnessing this fluctuating power source requires forecasting techniques capable of managing the intricate nature of wind patterns. Traditional non-federated learning algorithms, capitalising on centralised data repositories, have led the charge in predicting wind energy outputs. As this exploration delves into the intricacies of wind power prediction, it will shed light on the achievements and challenges associated with non-FL wind forecasting. This sets the stage for discussions on decentralised modelling strategies. Table 5 offers an encapsulated view of the research progress in this domain until now.

The evolution of wind power prediction highlights the ongoing efforts of researchers to use advanced methods for accurately understanding this unpredictable renewable energy source. The inclusion of deep learning techniques has considerably amplified the capacity of deep NNs to represent data, distil pertinent features [107,108], and address the limitations of traditional methods—particularly their struggle with grasping the non-stationary attributes of wind power-related time series data [109,110]. Deep learning models, whether singular or hybrid, excel at recognising the nonlinearity inherent in wind power data [111–113]. LSTM, GRU, and Bi-LSTM have been at the vanguard of this endeavour. These RNN-based models particularly

Table 4
Detailed comparison of publications for non-federated PV power forecast.

Citation	Year	Methodology	Summary
[58]	2019	LSTM	Predicts medium and long-term performance of wind and solar power using LSTM
[89]	2019	GASVM	Assesses the GASVM model's forecasting accuracy based on MAPE and RMSE
[90]	2020	PFM	Uses PFM's PV power generation and EV charging to enhance GA performance
[91]	2021	LSTM-NARXNN	Combines LSTM with NARXNN for a hierarchical PV power forecasting method
[92]	2022	Hybrid Deep Learning Model with PSO	Uses a hybrid system integrating signal decomposition, AI, and swarm intelligence for predictions
[93]	2022	Irradiance to Power (Physical + AI)	Proposes a hybrid irradiance-to-power conversion and compares it for 14 PV plants in Hungary
[94]	2022	SVM and GPR	Considers SVM and GPR for estimating solar PV power considering various input variables
[95]	2022	LSTM	Assesses the ability of LSTM for predicting solar power data
[96]	2022	ML deterministic Model	Compares 24 ML models for power forecasting using datasets from 16 PV plants in Hungary
[97]	2022	ANT colony optimiser with ANN	Integrates ANN with data processing and other techniques to predict PV system output
[98]	2023	LSTM with Grid Search Algorithm	Proposes precise hyperparameters for the LSTM network for improved performance prediction
[99]	2023	MLFFNN,NARXNN and RNN	Applies an upscaling methodology for forecasting regional solar PV power
[100]	2023	EEMD with LSTM and SVM	Develops an approach based on Ensemble Empirical Mode Decomposition and LSTM model for PV power prediction minute-hour-day output
[101]	2023	TVF-EMD-ElM	Uses hybrid method to deal with the fluctuation of PV power data by splitting it into a series of more stable and constant subseries
[102]	2024	VMD-IF-FSRA-CNN	Indicates that the proposed combination mechanism (Variational Mode Decomposition, Iterative Filter, Forward stepwise regression algorithm, and Convolutional NN) is more suitable for multi-site time series forecasting
[103]	2024	GPR-WD	Presents a novel hybrid ML model that combines Gaussian process regression with wavelet packet decomposition to fore cast PV power half an hour ahead.
[104]	2024	BiLSTM, 1D-CNN, and GRU	Evaluates the performance of the three models for one hour ahead PV forecasts
[105]	2024	SSA-BiLSTM	Proposes a short-term PV power prediction method based on meteorological similarity day and sparrow search algorithm and Bidirectional LSTM network combination

shine in discerning temporal dependencies—a pivotal aspect of wind power data. Both LSTM and GRU address a persistent challenge that traditional RNNs grappled with: the vanishing gradient problem. They exhibit proficiency in unravelling forward temporal nuances, with Bi-LSTM pushing the envelope by also considering backward temporal characteristics [114–117]. The bidirectional modus operandi of Bi-LSTM provides it with a panoramic view of the data, both historically and in terms of future instances. The resultant rich contextual information significantly bolsters the learning capacity of the neural networks. Recent studies affirming Bi-LSTM's superiority over LSTM in certain scenarios underline its potential [118]. Its nascent yet notable success in wind power prediction showcases the immense prospects the method holds [60,112,119–124]. Simultaneously, the foray of CNNs, typically hailed for image processing, into wind power prediction has brought about intriguing results. By leveraging convolutional operations, CNNs adeptly identify interrelationships across variables, focusing on more localised features within time series data.

On the other hand, one of the most promising developments is the introduction and fine-tuning of hybrid deep-learning models. By amalgamating multiple deep neural networks, these hybrid architectures strive to encapsulate the multifaceted nature of wind power time series data. Such a combinatorial approach is not just a redundant addition of different networks, but rather an orchestrated attempt to exploit the strengths of individual networks. The crux here is to extract features optimally, and the advantage of hybrid models lies in their ability to synergise the benefits of the individual deep neural networks they are comprised of. To culminate, the innovative incorporation of architectures like sequence-to-sequence [125] into hybrid models underlines the ongoing experimental spirit of researchers. The horizon of wind power prediction is ever-expanding, and the relentless amalgamation of deep learning techniques promises an era of more precise and reliable forecasts. Hybrid deep learning models, by their synergistic combination of distinct neural networks, have ushered in a new era of enhanced feature extraction and representation for wind power datasets. Their multidimensional approach leverages the strengths of individual networks, culminating in more precise and dependable predictions. The versatility and breadth of deep learning have been optimally harnessed in these models, offering a richer, more nuanced understanding of the complex dynamics governing wind power. This advancement underscores the transformative potential of hybrid architectures in leveraging the full might of deep learning, resulting in an evolutionary leap in wind power forecasting.

The combination of CNN and RNN models has been observed in several studies. An example can be seen in the work by Liu et al. [126], where CNN and GRU were integrated for wind speed forecasting. Similarly, Yin et al. [111] paired CNN and LSTM to derive meteorological and temporal data. To offer a comprehensive wind speed prediction, Chen et al. [109] combined the spatial feature extraction potential of CNN with LSTM's temporal feature extraction capabilities, bearing in mind the spatiotemporal attributes of wind power-related data.

An intriguing approach merged the capabilities of the Discrete Wavelet Transform (DWT), Seasonal Autoregressive Integrated Moving Average (SARIMA), and LSTM to manage the power time series of an offshore wind turbine [132]. The creation of an advanced short-term wind power forecasting technique named the WD-IGFCM-LSTMS model hinged on deep learning, enriched further by Wave Division, Grey Wolf Optimiser, and Seq2Seq models [133]. Subsequent exploration into neural network architectures led to the conception of a comprehensive

Table 5
Comparison of publications for non-federated wind power forecast.

Citation	Year	Methodology	Summary
[127]	2019	ML Models	Proposes an accurate forecasting strategy based on ML
[128]	2019	Q-Learning	Uses a deterministic Q-learning technique for specific farms estimates
[109]	2019	CNN-LSTM	Combines CNN's spatial feature with LSTM's temporal extractions
[125]	2020	AGRU	Uses a sequence-to-sequence model using the Attention-based GRU
[107]	2021	DNN	Highlights the increased data representation and feature extraction capabilities of deep neural networks
[129]	2021	Genetic LSTM	Employs LSTM for feature learning and GA to optimise window size and number of neurons
[130]	2022	probabilistic lidar	Advects an observer-based power forecast of individual and aggregated offshore wind turbines
[131]	2022	MSIN	Proposes a Multi-step Informer network to forecast wind power generation
[132]	2022	DWT, SARIMA, LSTM Hybrid	Uses a hybrid model on a power time series of a wind turbine in Scotland
[133]	2022	WD-IGFCM-LSTMS	Integrates Wave division, enhanced grey wolf optimiser, and Seq2Seq model
[134]	2022	Deep Learning with Attention Mechanism	Proposes a forecasting system with multiple modules including self-attention
[135]	2022	Hybrid Attention-based Deep Learning	Suggests a hybrid attention-based technique
[136]	2022	AMC-LSTM	Advocates a multi-dimensional model, AMC-LSTM
[137]	2022	Ensemble Learning with ES Models	Explores ensemble learning models and various predicting performances of hyperparameters
[138]	2023	CNN-MMoE	Combines a CNN-WaveNet with a multigate mixture-of-experts architecture
[139]	2023	NWP/Reconciliation	Implements a spatial hierarchy for one day-ahead forecasts
[140]	2023	MCC	Adopts a Maximum Correntropy Criterion for forecasts optimisation
[141]	2023	ANN-k-means-PSO	Introduces a novel hybrid forecasting model for wind power generation.
[142]	2024	Bagged-CNN	Combines the strengths of the Bagging ensemble technique and CNN
[143]	2024	BiLSTM-GAN-VMD/CNN-BiGRU	Suggests a novel two-stage hybrid forecasting approach
[144]	2024	XGBoost-LSTM	Offers an ultra-short-term forecasting relying on feature engineering

wind power forecasting system encompassing modules for feature decomposition, self-attention, forecasting, optimisation, and performance evaluation [134]. An innovative stride was the formulation of a hybrid attention-centric deep learning method, underscoring the importance of attention mechanisms in augmenting prediction precision [135]. The advent of the AMC-LSTM, or multi-dimensional extended features fusion model, further signals progress in LSTM-centric wind power forecasting techniques [136]. Contrasting the prevailing deep learning trend, ensemble learning models, particularly boosted and bagged trees, were employed to probe the predictive proficiencies of machine learning techniques such as GPR, SVR, and Bayesian optimisation [137]. Collectively, these methods showcased a centralised data processing and model training approach, inherent to non-federated learning strategies. The overarching theme from these investigations underscores the symbiotic relationship between deep learning and machine learning in refining wind power forecasting methodologies.

In the study presented by Niu et al. [125], a groundbreaking sequence-to-sequence model is introduced, which employs the Attention-based Gated Recurrent Unit (AGRU) to bolster forecasting procedures. This model facilitates the connection of various forecasting stages via concealed GRU block activations. To further refine the model's accuracy, an attention mechanism serves as a feature selection technique, identifying pivotal input variables for the forecasting process. In another investigation by Demolli et al. [127], five distinct machine learning techniques are employed to predict long-term wind power based on daily wind speed data. This research proposes a methodology centred on machine learning algorithms for enhancing the accuracy of wind power forecasts. Sun et al.'s work [128] integrates a Q-learning enhanced method aimed at generating deterministic wind power predictions for designated wind farms. The core of this approach is a joint distribution model founded on copula theory, which mirrors the spatiotemporal correlation between individual wind farms and the cumulative wind power output. To sculpt the marginal distributions of both the genuine consolidated wind power and the projected power from the member wind farms, Gaussian mixture models are utilised.

Centralised learning methodologies have unmistakably echoed throughout the domain of renewable energy forecasting, spanning from photovoltaic solar to wind power. Sophisticated neural networks and hybrid deep learning models have emerged as pivotal instruments in navigating the intricacies of these renewable energy forms, thereby enhancing predictive capabilities. Employing these strategies, forecasting protocols have been devised that not only uphold precision but also exhibit adaptability to the dynamic nature of renewable energy resources.

In the centralised model's workflow that is shown in Fig. 5, the process starts with data collection, where data from various sensors that belong to one specific power station is gathered. This raw data is then subjected to preprocessing, involving cleaning and transforming it into a suitable format for analysis. Following preprocessing, the data is divided into training and testing sets. The training set is utilised to train the models, allowing them to learn patterns and relationships within the data. Once trained, the models are evaluated using the testing set to assess their predictive performance, ensuring they generalise well to unseen data. Finally, validation techniques are applied to refine the models and enhance their accuracy.

Recognising these centralised forecasting frameworks sheds light on the burgeoning innovation within this sphere, poised at the threshold of a renewable renaissance. While their milestones warrant commendation, the pursuit for increasingly efficient, decentralised, and privacy-centric models persists, heralding the commencement of a new epoch in renewable energy prediction.

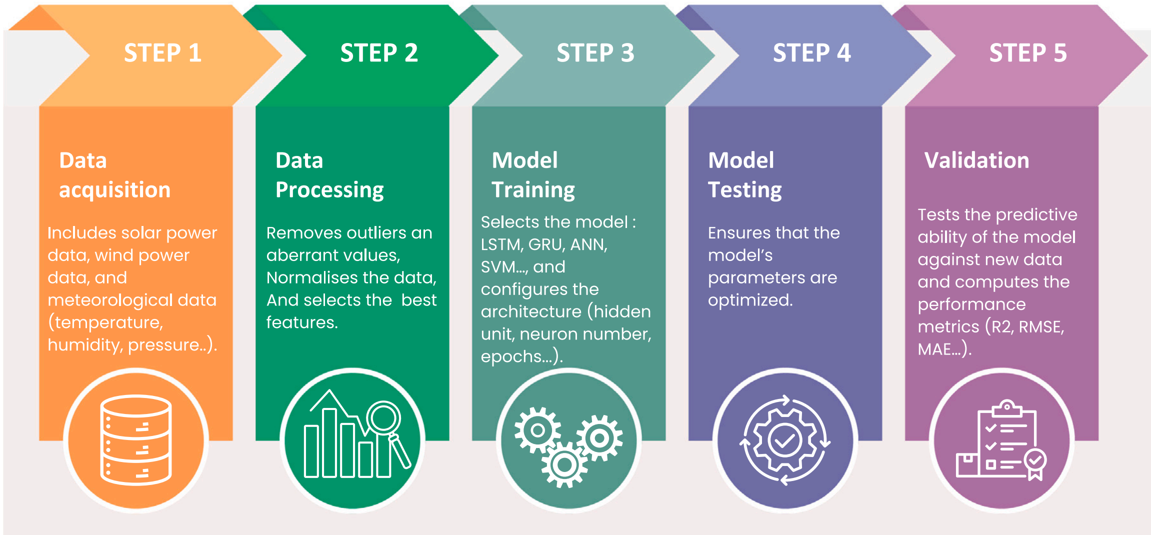

Fig. 5. Work flow of centralised models (including traditional and DL-based models).

3. Federated learning: A descriptive presentation

3.1. Upholding data integrity and security in forecasting

In the specific field of PV and PW forecasting, maintaining data integrity and ensuring robust security are paramount. Data integrity guarantees the consistent accuracy and reliability of data throughout its life cycle. For PV and wind forecasting, this signifies safeguarding meteorological and energy generation data from unwarranted alterations. Preserving such integrity translates into dependable and accurate forecasts, which in turn pave the way for optimised energy production, financial prudence, and minimised operational hazards. However, any compromises in data integrity could lead to flawed storage and dispatch strategies, resulting in considerable financial and operational repercussions.

As the digital transformation progresses, PV and wind forecasting systems increasingly intertwine with vast interconnected networks. This interconnectivity, while enhancing operational efficiency, inadvertently amplifies system vulnerabilities. Unguarded systems can become susceptible to cyber-attacks, jeopardising not only the accuracy of the forecasts but also risking precious operational, financial, and strategic datasets. Such breaches could potentially destabilise extensive energy infrastructures. Given these profound risks, an unwavering commitment to robust data security is imperative. This calls for the implementation of stringent security measures, encompassing advanced encryption standards, multi-level authentication schemes, and regular security assessments. These measures fortify not just the confidentiality and availability of data, but also its integrity, reinforcing the resilience of the forecasting systems against potential adversities. In essence, the focus on data integrity and security in PV and wind forecasting surpasses the mere accuracy of predictions. It represents a cornerstone of public confidence in renewable energy initiatives and supports the global stride toward a sustainable energy future.

As observed in Table 6, the diversity of approaches in forecasting for renewable energy is vast. While some papers focus on traditional or physical models, others delve into advanced computational techniques. This variance underscores the richness of research in this domain and highlights the numerous strategies employed by researchers. The table serves not only as a comparative tool but also as an indicative roadmap for researchers and professionals aiming to gain insights into the current state of forecasting techniques in renewable energy.

3.2. Federated learning approach

Distributed across an expansive network of servers or devices, FL emerges as a pivotal tool in domains such as PV/WP forecasting, where data accrues from diverse locales. This methodology sidesteps the pitfalls of centralisation and honours the regional nuances inherent in each dataset [157,158]. By doing so, it promises a more nuanced and accurate prediction model that delivers discerning insights while meticulously observing data protection regulations. With the rapid advancement of FL [159], its deployment in the PV/WP sector has been demonstrated to achieve comparable success to traditional centralised models, with the added advantage of preserving data confidentiality, as illustrated in Fig. 4. Such a capability proves invaluable in a domain where real-time adjustments, informed by substantial data volumes, significantly influence predictions and energy efficiency. The mechanism of an FL process can be summarised as follows [160–162]:

- **Initialisation:** From a coordinating body, or a central grid manager, each participating wind farm or PV installation receives a preliminary model.
- **Localised Training:** Each installation uses its local data to train and improve its model rather than transferring sensitive or large amounts of raw data. This might involve modifications depending on regional weather patterns, machinery efficiency, or other regional characteristics impacting the generation of PV and wind energy.
- **Model Aggregation:** After compiling these locally trained models, the central server updates the models, creates an updated global model using this compiled information, and then distributes it to each user or installation. This model is an improved version that takes into account observations from all involved parties without ever having access to the specific data. In this context, the optimal global model, θ, is achieved by minimising the aggregated loss function, $f_a(\theta^a)$, across all participating clients:

$$\text{minimise} \quad \theta\left(\sum_{k=1}^{C\times A} \frac{n_a}{n} f_a(\theta^a)\right) \tag{1}$$

with:

  - C : Indicates the participation ratio, indicating the assumption that not every local client engages in each round of model updates. This summation calculates the cumulative data samples from all participating clients, giving the total number of data samples involved in a particular round of FL.

Table 6
Reviewed paper analysis.

Citation	Horizon/Forecasting Model	Solar	Wind	ML	DL	FL	Non-FL	RF
[58]	Medium/Long term	✓			✓		✓	
[89]	Short term	✓		✓			✓	
[90]		✓			✓		✓	
[91]		✓			✓		✓	
[92]	Short term	✓			✓		✓	
[93]	Physical Model	✓					✓	
[94]	Short/Medium/Long term	✓		✓			✓	
[95]	Short/Medium/Long term	✓			✓		✓	
[96]	Deterministic Model	✓		✓			✓	
[97]	Short term	✓			✓		✓	
[127]	Long term		✓	✓			✓	
[128]	Deterministic Model		✓		✓		✓	✓
[109]			✓		✓		✓	
[125]	Short term/Multi Step		✓		✓		✓	
[107]	Long term	✓			✓		✓	
[132]	Short term		✓	✓	✓		✓	
[133]	Short term		✓		✓		✓	
[134]			✓		✓		✓	
[135]			✓		✓		✓	
[136]	Short term		✓	✓			✓	
[137]	Short/Medium/Long Term		✓	✓			✓	
[145]	Short term	✓		✓		✓		
[146]		✓		✓		✓		
[147]	Medium/Short term	✓		✓		✓		
[148]		✓		✓		✓		
[149]	Short term	✓		✓		✓		
[150]			✓		✓	✓		
[151]	Short term		✓		✓	✓		
[152]	Image Based		✓		✓	✓		
[153]			✓	✓		✓		
[154]	Short term		✓		✓	✓		✓
[155]	Short term		✓		✓	✓		
[156]			✓		✓	✓		

– k : Is the index associated with each client.
– n_a : Denotes the size of local data.
– n : Is the total number of sample pairs across all clients, given in Eq. (2) :

$$n = \sum_{k=1}^{C\times A} n_a \tag{2}$$

– $f_a(\theta^a)$: Represents the local loss function, given in Eq. (3):

$$f_a(\theta^a) = \frac{1}{n_a}\sum_{i=1}^{n_a} l(x_i, y_i; \theta^a) \tag{3}$$

– l : Stands for the loss function.
– x_k : Shows the data feature.
– y_k : Symbolises the data label.

• **Iteration:** This cycle repeats until the model reaches an ideal state or the required number of iterations has been reached. Reduced communication overhead is a benefit of the client–server design, which is fundamental, for large-scale renewable energy networks. The FL approaches may be illustrated as shown in Fig. 6.

A deeper exploration into its diverse categories can be undertaken after a thorough understanding of the foundational concepts underlying FL. Yang et al. [163], Liu et al. [164], and Kaur et al. [165] classified FL into three distinct types, determined by the manner in which data is distributed among the participating clients:

1. Horizontal FL
2. Vertical FL
3. Transfer FL

3.3. Types of federated learning

3.3.1. Horizontal federated learning

In datasets from multiple renewable energy sources or locations with limited user (or source) overlap but substantial feature overlap, horizontal federated learning (HFL) has been identified as particularly promising for PV/WP predictions. This characteristic is essential in the renewable energy domain, as data can be categorised by source or location yet display common features, such as wind speed or solar irradiance levels. Consider the scenario of two energy corporations harnessing wind energy in distinct geographical areas. Even though the data may be sourced from various wind farms, the features recorded, such as wind speed, humidity, and temperature, might exhibit similarities. An option for these corporations is to engage in collaboration via an HFL platform, which allows for the joint training of a unified model using the amalgamated datasets. It has been observed that this collective strategy can markedly improve forecasting accuracy. In a typical HFL process, local gradients are computed and forwarded by each participating entity (in this context, each energy company or wind farm). These gradients are subsequently integrated by a central server to establish a comprehensive global forecasting model. While this decentralised method offers advantages, concerns regarding energy data privacy arise. Smooth and secure gradient exchanges have been facilitated by methods such as homomorphic encryption [166], differential privacy [167], and secure aggregation [168].

In 2016, a data federated modelling scheme was proposed by Google for updates to Android phone models [169–171]. In this scheme, when an Android phone is used by an individual, the model parameters are continuously updated locally. These parameters are then uploaded to the Android cloud, enabling data owners with matching feature dimensions to form a federated model. Safe aggregation and differential privacy techniques are employed in this system [167], marking a

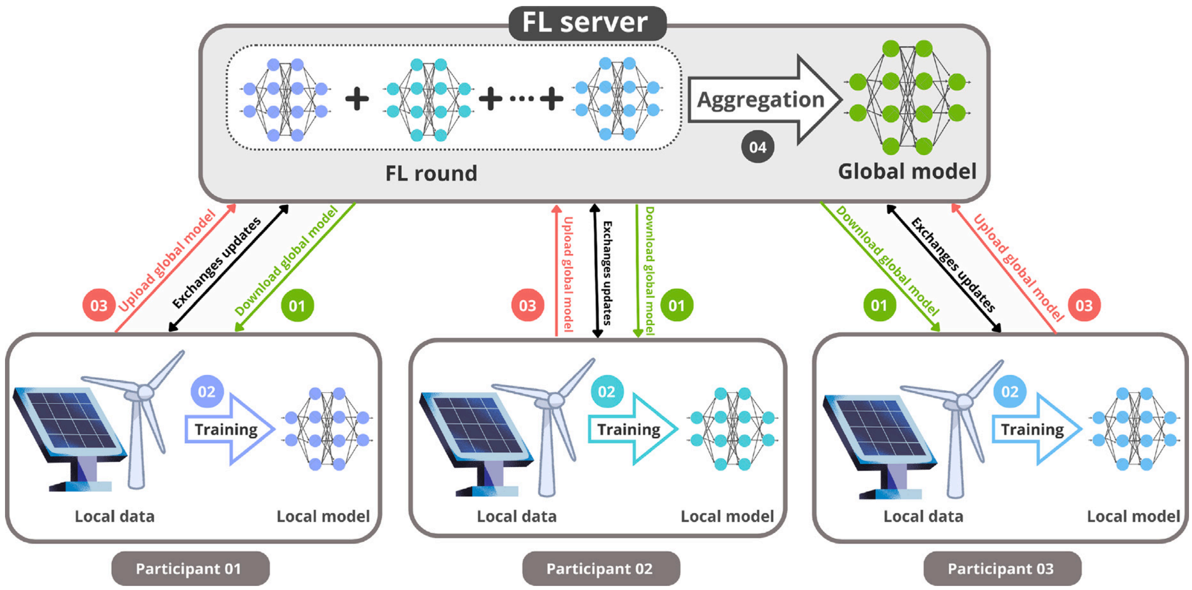

Fig. 6. Federated Learning-based Design Architecture for Photovoltaic and Wind Energy Units.

standard application of horizontal federated learning. Drawing a parallel, the methodology introduced by Google can be applied to PV/WP forecasting. An HFL system, where local forecasting models at each wind farm or solar PV installation are updated based on real-time data, could serve as a representative model for this concept in renewable energy. Through these localised updates, a federated forecasting model encompassing the insights of all participating entities can be formed when data is relayed to a centralised cloud system.

When adapted to PV/WP scenarios, the BlockFL approach by Kim et al. [172] could allow individual energy installations to autonomously update their local forecasting models over a blockchain network. Similarly, a system akin to MOCHA [173] could enable multiple energy sites to collaborate, aiming to enhance forecasting accuracy while ensuring data integrity. Research [159,174] that segments data specific to individual energy installations has been contextualised in the renewable energy realm. By transmitting only the requisite gradient data to a centralised entity for holistic model adjustments, the confidentiality of proprietary energy data is ensured.

3.3.2. *Vertical federated learning*

When datasets exhibit minimal feature overlap yet considerable user similarity, vertical federated learning (VFL) is considered an appropriate method for exploration. In VFL, data is segmented vertically according to user attributes. Consequently, while the identity of each user remains consistent across all data fields, the attributes associated with each user are distinct. Such a process has been observed to augment the feature dimension of the training data. Take, for instance, a bank and an online shopping platform operating within the same region. The local population might constitute a significant portion of the user bases for both entities, yet the nature of their data varies considerably. E-commerce platforms are known to document customer behaviours, such as browsing patterns and purchasing histories, whereas banks generally record financial profiles, encompassing aspects like income, expenditure, and credit scores. The potential of VFL is realised here: by integrating these diverse variables in an encrypted format, the predictive capacity of the resultant model is enhanced.

The diversity of data across various sources is increasingly observed in sectors such as PV/WP forecasting. Such information might be derived from multiple sensors, instruments, or platforms, each registering distinct attributes of the same entity, be it a wind turbine or a solar panel. In this context, VFL is recognised as crucial for amalgamating these varied features into a holistic dataset, which is fundamental for accurate prediction. For the generation of robust prediction models in PV/WP forecasting, the inherent data structure often necessitates sophisticated partitioning strategies. The vertical splitting of data has been facilitated by numerous machine-learning methodologies. Techniques such as classification [175], statistical analysis [176], gradient descent [177], secure linear regression [178,179], and data mining [180] have been employed successfully for vertical data delineation. Such methods are posited to discern intricate patterns within PV/Wind energy data streams, contributing to enhanced prediction accuracy. Certain models are recognised for their significant contributions to the broader field of VFL. For instance, SecureBoost [170] represents a pivotal VFL system that amalgamates numerous user attributes, with the objective of enhancing decision-making precision through its lossless training approach. The methodology it employs is posited to be invaluable for the integration of diverse data streams originating from varied renewable energy sources.

Notable contributions to the field also come from specialised models, such as that introduced by Hardy et al. [181]. A profound emphasis is placed on privacy preservation in their VFL-based logistic regression model, a consideration of paramount importance given the sensitive nature of energy grid information. Distributed logistic regression and pipelined entity analysis, underpinned by Paillier additive homomorphic encryption [182], are incorporated in their model. Such an approach is believed to not only bolster data confidentiality but also enhance classifier precision, thereby positioning it as essential for secure and accurate PV/Wind energy production forecasting. It is inferred that VFL presents a promising avenue for the burgeoning realm of PV/WP forecasting, facilitating comprehensive data representation while safeguarding data privacy and security.

3.3.3. *Transfer federated learning*

Owing to the non-overlapping characteristics of user attributes across multiple datasets, a challenge is observed in certain scenarios within the renewable energy sector, especially in PV/WP forecasting. This challenge manifests when datasets are sourced from regions with distinct geographical or climatic conditions, diminishing the effectiveness of traditional learning methods. In such contexts, Federated Transfer Learning (FTL) is considered an appropriate solution [183]. Envision datasets of wind and PV electricity derived from Scandinavian coastal areas and a dry region in the Middle East. Given the geographical variations and inherent differences in the data features tied to their specific renewable energy sources, the user groups (or data providers) from these regions exhibit distinct attributes. The overlap of features between these datasets might be minimal. To address this disparity and generate a cohesive forecasting model, transfer learning is employed, bridging the data divide and enhancing the predictive model's accuracy. Such a technique proves beneficial when the aim is to augment a model's efficacy with limited specific data [184]. For illustration, in a hospital's radiology department facing challenges in amassing sufficient X-ray scans to develop a dependable diagnostic tool, the method of transfer learning, which shifts knowledge from one domain to another – such as from general image recognition to radiological diagnostics – becomes pertinent. In the realm of PV/WP forecasting, FTL is posited to mitigate the scarcity of specialised data, facilitating the application of models from related domains to primary forecasting tasks, all while preserving data privacy.

Federated learning comes in different types, each offering unique benefits based on specific algorithms. HFL improves prediction accuracy by using similar features from different datasets without needing to centralise the data. It employs secure aggregation and differential privacy techniques to protect sensitive energy information during collaboration. VFL enhances the feature set by merging different data sources. This allows for the development of comprehensive models from datasets that share common user identities but have different features, such as weather sensors and regional power output data, all while ensuring data privacy. FTL enables knowledge transfer between geographically or climatically diverse datasets. This helps in optimising renewable energy forecasting in situations where data is limited or fragmented, as it improves model performance by applying learned knowledge from one region to another. Collectively, these types of federated learning offer tailored solutions for the challenges of decentralised and privacy-sensitive energy forecasting, each with specific advantages based on the available data.

3.4. Cross device federated learning

In contexts such as PV/WP forecasting, where data is often sourced from an array of sensors, IoT devices, and monitoring systems spanning diverse geographical landscapes, the need for cross-device FL is underscored. Devices ranging from solar irradiance sensors to wind speed meters generate a plethora of real-time data points. Considering the vast array of devices in play, challenges associated with efficient client selection become more pronounced, ensuring that only the most relevant and informative devices contribute to the model's learning process. Techniques like client selection and incentive designs, as referenced in [185], are employed to guarantee proactive and efficient participation from these disparate devices. Through these methods, consistent and premium data inputs from devices are encouraged, while also ensuring the most representative data is incorporated in each FL cycle. By adopting this approach, it is posited that Cross-Device FL can augment the accuracy and reliability of PV/WP forecasting models, all the while ensuring data remains decentralised.

3.5. Cross silo federated learning

In scenarios where the integration and processing of data from a limited set of significant entities, such as major energy utility providers or renewable energy farms, are required, the relevance of cross-silo FL is accentuated. In such contexts, each entity, be it a PV or wind farm, might possess a wealth of data and participate consistently throughout the iterations. Depending on the features and user attributes, data in these systems can be federated in either a horizontal or vertical manner. This type of FL is posited to be instrumental in the domain of PV/WP forecasting, especially when multiple energy entities, each safeguarding their distinct data trove and insights, collaborate to refine forecasting precision without revealing the underlying raw data. Such an approach not only ensures data privacy but also elevates the collective predictive models. Demonstrated success in employing the cross-silo FL methodology can be found in studies such as [186], where models are crafted by integrating concepts from diverse entities without compromising the sanctity of individual data sets.

Cross-Device and Cross-Silo FL offer unique benefits for forecasting renewable energy at different operational levels. Cross-Device FL is best suited for situations with various IoT devices and sensors. It effectively manages large amounts of real-time data while keeping the information decentralised. Methods such as efficient client selection and incentive structures help incorporate high-quality, relevant data, improving the accuracy and speed of forecasts. On the other hand, Cross-Silo FL is advantageous for a smaller number of large organisations, like energy utility companies or significant renewable energy farms. This approach allows these organisations to work together to create models without centralising their data, thus maintaining privacy and security. By sharing data across silos, Cross-Silo FL enhances forecasting models while respecting proprietary data limitations. Together, these methods offer strong solutions for both large-scale and specialised renewable energy forecasting challenges, ensuring privacy and accuracy in decentralised settings.

3.6. Federated learning specifications and requirements

3.6.1. Encryption mechanism

In the realm of PV/WP forecasting, the protection of data privacy becomes paramount due to the decentralised nature of data collection. A vast array of sensors and IoT devices continuously contribute data. A primary advantage of FL for predicting renewable energy is highlighted: data can be retained privately by companies, while only model knowledge is exchanged to enhance the collective prediction model [187]. There exists a potential risk that certain details in the shared model information could inadvertently disclose private details. This is especially concerning in the energy sector, where revealing specific data might expose proprietary methods or technologies. Despite these concerns, there are measures in place to ensure the privacy of such data. Techniques such as model aggregation [168], homomorphic encryption [166,188], and differential privacy [167] are commonly employed to bolster federal privacy.

Several encryption techniques have gained popularity in order to strengthen data security in PV/WP forecasting:

- **Model Aggregation:** Model aggregation, recognised as a pivotal element of federated learning, ensures that contributions to a comprehensive model in PV/WP forecasts can be made without transmitting raw data. This technique is deemed valuable, particularly when data from multiple geographic regions is amalgamated to predict overarching trends without revealing specifics from individual data sources.
- **Homomorphic Encryption:** While conventional encryption methods might render encrypted data unsuitable for computation, homomorphic encryption permits calculations on the encrypted data itself. This capability is considered vital for immediate analyses, ensuring that the security of the foundational data remains uncompromised.
- **Differential Privacy:** As the renewable energy sector evolves to be more reliant on data, inadvertent disclosure of details pertaining to installations, technological advancements, or strategies via aggregate statistics remains a concern. Differential privacy mitigates this concern by confirming that the presence or absence of specific data points, for instance, the output of a particular wind farm, does not influence the comprehensive statistical results. While this approach facilitates the observation of overarching trends, it also safeguards against potential threats attempting to pinpoint the origins of specific data inputs.

In the PV/WP forecasting sector, the harmonisation of federated learning's collective advantages with stringent data privacy measures can be achieved through the deployment of these encryption methodologies.

Table 7
Comparison of publications in FL-based PV power forecasting.

Citation	Year	Methodology	Summary	Privacy-Preserving
[145]	2022	CNN-LSTM with FL	Proposes a semi-asynchronous FL framework for forecasting short-term solar power using CNN-LSTM	✓
[146]	2022	STANN with FL	Introduces a distributed solar forecasting framework using a spatial and temporal attention-based neural network in conjunction with federated learning	✓
[147]	2023	BTM-FL	FL method for PV power forecasting, training a unified model on data from several BTM sites	✓
[148]	2023	FedZero	Describes an FL system powered by renewable excess energy and spare compute infrastructure capacity	✓
[149]	2023	FL-EncoderDecoder	Presents a paradigm for interpretable deep learning using FL to estimate short-term residential load	✓
[189]	2023	LSTM-BPNN	Uses a hybrid prediction model based on FL	✓
[190]	2023	RNN	Explores regression models in the FL	✓
[191]	2024	HFF-SA-CNN-LSTM	Constructs a hybrid Horizontal Federated Framework, Self-Attention mechanism, CNN, and LSTM to assess model performance under different conditions	✓
[192]	2024	Orchard-optimized Conv-SGRU	Accentuates the performance of the predictive model using hybrid FL-CNN with Stacked GRU and an orchard gardening optimiser	✓
[193]	2024	FL-CNN	Proposes a global solar radiation forecasting approach tested for eight regions located in Iran	✓

4. Federated learning based PV/WP forecasting: A new frontier

In the domain of PV and WP forecasting, the rise of FL is observed as a reflection of the sector's commitment to innovation and adaptability. Being a decentralised machine learning approach, FL is seen to surpass traditional boundaries defined by centralised training models. The training of algorithms across multiple devices or nodes is facilitated, leveraging localised data while ensuring privacy and minimising data transfer overheads. Given the unique challenges presented by PV and wind energy generation – from source variability to the extensive geographical distribution of installations – an avenue for leveraging detailed, location-specific data without centralising this information is provided by FL. In this section, a deep exploration into the nuances of FL-based forecasting in the renewable energy sector is undertaken, detailing its methodologies, benefits, potential hurdles, and the profound influence it is anticipated to bring to the field of PV and WP predictions.

4.1. Federated learning-based PV power forecasting

Given the distributed nature of PV systems, the decentralised design of FL is believed to ensure model robustness without sacrificing data privacy. The objective of this section is to scrutinise significant contributions to FL-based PV power forecasting. Although numerous studies exist, the focus is directed toward fundamental works that are deemed to provide a comprehensive overview of the approach, its advancements, and its efficacy in addressing the unique challenges posed by PV power forecasting. A comparative analysis of literature in this domain is also presented in Table 7.

A semi-asynchronous FL framework for short-term solar power forecasting has been proposed [145], with the framework's efficacy evaluated using a CNN-LSTM model. It is believed that the proposed federated forecasting solution incorporates a personalisation method and a semi-asynchronous aggregation mechanism for enhanced efficiency. Comprehensive evaluations using a real-world dataset suggest that the semi-asynchronous aggregation and personalisation technique might enhance the resilience of the forecasting framework in practical situations. Furthermore, these evaluations indicate that federated models might outperform purely local models in forecasting accuracy while safeguarding data privacy. A flexible distributed solar forecasting framework, based on a novel spatial and temporal attention-based neural network (STANN) in tandem with FL approach, has been presented [146]. This framework aims to address the deficiencies observed in AI forecasting models, focusing on multi-horizon forecasting scenarios ranging from 5 to 30 min. Within the proposed structure, the STANN model comprises a feature extractor and a forecaster, both of which are trained on distinct local datasets for improved localisation. These components are updated through global parameter aggregation to further elevate forecasting precision. The effectiveness of the proposed approach has been evaluated using comprehensive tests on real-world datasets and juxtaposed against other notable forecasting techniques.

Given that a majority of distributed PV plants operate behind the meter (BTM) and remain undetected by utilities, forecasting their collective output encounters three challenges. Firstly, standard centralised prediction algorithms, which were employed in earlier research, might be deemed inappropriate due to privacy concerns. As a result, decentralised forecasting techniques, such as FL, have been identified as essential to ensure data privacy. Secondly, the delicate balance between prediction accuracy and data privacy has not been thoroughly explored, and no comparative studies between localised, centralised, and decentralised forecasting methods for BTM PV generation are currently available. Lastly, the computational duration of data-driven prediction methodologies remains unexamined. An FL power forecasting approach for PVs, which employs FL as a decentralised collaborative modelling technique, has been introduced in this research [147]. By training a single model utilising data from multiple BTM locations, this approach proposes a solution for BTM PV forecasting. A multi-layered perceptron machine learning network was utilised in the development of this FL-based BTM PV forecasting model, ensuring data security and privacy.

To effectively reduce operating carbon emissions from training to zero, FedZero, an FL system, is proposed to operate solely on renewable excess energy and surplus compute infrastructure capacity [148]. The spatiotemporal availability of excess energy is utilised by FedZero, with clients being selected based on energy and load estimates to ensure rapid convergence and equitable participation. In a study presented in [149], a paradigm for interpretable deep learning combined with FL is proposed for short-term residential load forecasting. A novel automated relevance determination network for feature interpretation is introduced to achieve interpretable multi-step load prediction. This network is designed to work in tandem with an encoder–decoder architecture. The adopted training method, underpinned by FL, avoids sharing the original data within the edge computing network, thereby maintaining data privacy.

The rapid growth in the renewable energy market has underscored the pressing need for enhanced forecasting methods. An examination of FL-based PV power forecasting reveals the transformative potential of decentralised prediction methodologies, especially within the photovoltaic domain. The essence of FL, which prioritises retaining data at its source while crafting comprehensive models, aligns seamlessly with the distributed, detailed nature of PV systems. From this analysis, it can be inferred that the shift towards federated learning-based PV power forecasting is more than a fleeting academic trend; it represents a genuine endeavour to integrate sustainability with technological advancement. The innovations showcased in the aforementioned research bolster the belief that PV power forecasting will embrace greater accuracy, decentralisation, and privacy in the forthcoming years. Continued refinement, evaluation, and expansion of the understanding of FL's role in this pivotal industry are imperative as this future trajectory is pursued.

4.2. Federated learning-based wind power forecasting

Federated Learning allows for the adaptation to the evolving demands of wind power forecasts by facilitating training on decentralised data, all while maintaining data privacy. There is a rich body of literature detailing the intricacies of FL as applied to wind power. This section delves into an in-depth analysis of pertinent seminal papers, highlighting the evolution of FL-based methodologies, their achievements, and the challenges addressed in the realm of WP forecasting. A comparative review of these works can be found in Table 8.

Forecasting wind power is crucial for managing fluctuations, ensuring supply–demand balance, and enhancing system reliability. The spatial and temporal interdependence of numerous wind farms necessitates sharing comprehensive datasets to derive models that offer enhanced accuracy and generalisability. However, complex regulatory procedures, stiff industry competition, and data privacy and security concerns hinder data aggregation across wind farms dispersed nationally. The paper by Ahmadi et al. [150] introduces an FL-based approach for wind energy forecasting. This decentralised collaborative method facilitates training a unified model on data from multiple wind farms without compromising data security or privacy. It achieves this by securely exchanging local model parameters, obviating the need to transfer sensitive data.

In the study by Zhang et al. [151], a CNN-Attention-LSTM model is presented, leveraging federated learning as a means to forecast the multi-energy load of IEMs. This approach seeks to enhance data variety, strengthen model generalisation, and ensure data privacy. The global model relies on the CNN-Attention-LSTM structure for feature extraction. Through FL, IEMs can train the forecasting model in a decentralised manner without the need to share their local datasets. The research rigorously evaluates four distinct FL methodologies, contrasting them with individual, centralised, and federated models. Furthermore, the study delves into the potential vulnerabilities of FL to fake data injection attacks (FDIA), given its reliance on communication technologies. The results underscore that federated models while surpassing individual models in accuracy, can achieve a performance akin to the centralised model. Notably, FedAdagrad emerged as the top-performing prediction methodology.

Centralised forecasting methods have historically raised concerns regarding data privacy and potential data isolation. In response to these challenges, Li et al. [154] introduced the federated deep reinforcement learning (FedDRL) approach, which marries federated learning with deep reinforcement learning (DRL) to address ultra-short-term WP forecasting. This work utilises the deep deterministic policy gradient (DDPG) method to enhance forecasting precision. By integrating the DDPG forecasting model within the federated learning framework, the study achieves accurate predictive modelling in a decentralised fashion. Crucially, this approach prioritises the exchange of model parameters over raw data, sidestepping sensitive privacy issues.

Recent research emphasises the application of FL in the WP forecasting domain, especially in regions with distinct geographic and climatic patterns like Iran. In one such effort, Moayyed et al. [152] proposed a cyber-resilient hybrid model combining FL and CNN. Notably, this model is designed for generalisability, data independence, the ability to forecast in regions without prior training data, and, crucially, to ensure data confidentiality and privacy. A different approach is presented by Yang et al. [155], who introduced the VMD-FK-SecureBoost method. This method fuses variational mode decomposition (VMD), federated k-means clustering, and SecureBoost. By first decomposing the raw data into multiple sub-sequences via VMD, it allows for characteristic extraction and individual sub-sequence forecasting, thereby enhancing prediction accuracy. Following this, the federated k-means clustering groups the sub-sequences based on shared attributes. SecureBoost, in its final step, implements FL, ensuring privacy protection based on the clustering results.

Furthermore, Liu et al. [153] delved into a nuanced scenario where distributed power estimation is derived from disparate external features. Their innovative hybrid federated learning framework, grounded on XGBoost, addresses situations characterised by features scattered across localised, heterogeneous entities and samples distributed across various geographic regions. The fusion of horizontal and VFL with the introduction of boosted trees presents a commendable advancement in enhancing both model accuracy and interpretability. Jenkel et al. [156] underscore the efficacy of enhanced normal behaviour models, especially for turbines with minimal representative training data, through the lens of federated fleet-wide learning. The research further accentuates that, in scenarios where the monitored target variable is sporadically distributed across the fleet, adapting the global federated model to individual turbines proves optimal for fault detection accuracy.

Fl approach, as showcased by the selected studies, emphasises that the future of WP forecasting lies in decentralised learning combined with rigorous data privacy. In essence, FL emerges as a transformative tool for WP forecasting, promising enhanced accuracy while respecting data sanctity. As the renewable sector evolves, embracing such innovative techniques will be paramount.

4.3. Conclusions from FL-based forecasting for PV and wind systems

Photovoltaic and wind power sources are at the vanguard of the world's shift to renewable energy, which is accelerating. They are crucial to contemporary energy matrices, which emphasises how important good forecasting is. This examination of forecasting using FL for the PV and wind energy industries provides enlightening insights into the significant changes in predictive approaches.

- **PV Power Systems:** About PV power systems, the decentralised nature of the energy systems and FL algorithms perfectly synergises to provide reliable forecasting models that are sensitive to the intricacies of the actual world. Through the studies mentioned, it is clear that FL skillfully tackles the two issues of data privacy and the irregular nature of PV generation. FL-based models not only increase forecasting accuracy but also protect sensitive data by placing an emphasis on local data storage and allowing model training across many platforms.
- **Wind Power Systems:** The complex dynamics of wind patterns on the frontier of wind energy demand sophisticated forecasting methods. The research discussed highlights the several benefits of using FL to forecast wind generation. The FL decentralisation concept offers a suitable response to the problems that come up naturally in WP forecasts, such as data islands and privacy issues. FL provides a potential method for comprehensive WP forecasting that takes into consideration the various geographical and temporal aspects of wind farms through collaborative, decentralised modelling.

Table 8
Comparison of publications in FL-based wind power forecasting.

Citation	Publication Year	Methodology	Summary	Privacy-Preserving
[150]	2022	Hybrid DL using FL	Presents FL-based wind energy forecasting, enabling model training on multiple wind farm data without compromising data privacy	✓
[151]	2022	CNN-Attention-LSTM with FL	Proposes a FL-based CNN-Attention-LSTM model to anticipate multi-energy load of IEMs, ensuring data privacy	✓
[152]	2022	FL-CNN	Introduces a hybrid, cyber-resilient forecasting approach combining FL and CNN	✓
[153]	2022	FL-XGBoost	Recommends an FL architecture using XGBoost to predict distributed power from live external characteristics	✓
[154]	2023	DDPG with FeDRL	Presented federated deep reinforcement learning (FedDRL), a forecasting method for ultra-short-term WP forecasting	✓
[155]	2023	VMD-FK-SecureBoost	Combines variational mode decomposition, federated k-means clustering, and SecureBoost into the VMD-FK-SecureBoost method	✓
[156]	2023	Federated-Fleet-Wide Learning	Suggests that federated fleet-wide learning can enhance accuracy for turbines with limited training data	✓
[194]	2024	FL-TL	Proposes two-stage framework consisting of FL-based pre-training and personalised fine-tuning	✓
[195]	2024	FL-BiLSTM	Merges a hybrid FL-BiLSTM with a Geometric median-based federated aggregation scheme	✓

Federated Learning emerges as a beacon of innovation in renewable energy forecasting. Its application in both PV and wind energy sectors exemplifies its transformative potential, particularly in ensuring data privacy. As we look to the future, it is evident that renewable energy forecasting will lean more toward federated techniques rather than purely centralised or localised methods. As access to datasets grows and technology evolves, the role of FL in PV and WP forecasting will only become more vital, heralding a new epoch of efficient and secure renewable energy management.

5. Necessary tools for federated learning applications

5.1. Online free data

Having reliable and diverse datasets is crucial, particularly for federated learning (FL) in the domain of renewable energy. To complement the practical side of this review, a glossary of relevant websites and publicly available datasets focused on photovoltaic (PV) and wind energy is presented and organised in Table 9. Each data source listed offers essential information such as geographical location, weather data, recording period, granularity, and system capacity. These datasets cover a wide range of parameters, making them invaluable for researchers and analysts working in this field. By accessing the datasets via the provided hyperlinks, users can easily compare and validate their findings, enhancing the robustness and reliability of FL models in energy-related applications.

This glossary serves as a foundational resource for advancing the development of FL in renewable energy. It offers a gateway for data acquisition that can lead to more accurate and diverse model training, driving forward the frontier of FL research and implementation in PV and wind energy systems.

5.2. Evaluation metrics

Several independent variables affect the precision of power generation predictions. The forecasting error arises from a complex function that integrates these various elements. Although formulating a precise mathematical expression for this function is challenging, examining the influence of specific variables on the magnitude of the error is possible. It is within this context that different evaluation metrics, also called performance metrics, are essential for evaluating the accuracy and reliability of the predictive models. In machine learning, performance metrics are crucial for understanding how well a model generalises to new data and optimises its performance. These metrics also enable forecasters to compare models quantitatively and make informed decisions based on their performance.

Evaluation metrics are different kinds of statistical indicators, such as Mean squared error (MSE), Mean Absolute Error (MAE), correlation coefficient (r), and Skill Score (SS), etc. Each one of them can give insightful information related to the performance of the developed model. Table 10 presents a set of widely used statistical metrics, mainly conceived for analysing and interpreting the forecasting accuracy by computing the differences between the reel and predicted values through different formulas [41,196–199].

6. System challenges and research perspectives

Federated learning methodologies offer substantial advantages in the realm of photovoltaic and WP forecasting, where rapid data collection and immediate analysis are paramount. Nevertheless, this field presents challenges. The following discussion addresses the three primary issues encountered in an FL environment, while Fig. 7 explicitly illustrates the locations of these challenges.

- **Edge devices' dependability in renewable energy systems:** Edge devices are frequently used in PV/WP projects to monitor and report data from the machinery [200]. These devices, when subjected to continuous data transmission, might face fast energy consumption, impacting their lifetime and dependability, just like real-time communication has an impact on a smartphone's battery. A solar panel's monitoring gadget, for instance, can experience data reporting delays if its battery runs out quickly from frequent data transmission. The study of Yan, Chen, Feng, and Qin [201] focused on reducing communication to improve energy efficiency, a strategy that edge devices in renewable energy systems may use. To make these devices live longer in such contexts, energy-efficient model training procedures, like the one in [202], are essential.
- **Data Unbalance in Distributed Energy Systems:** Because renewable energy sources are decentralised, data will inevitably be spread out unevenly among many installations [203]. For

Table 9
Glossary of online available data.

	PV	Wind	Weather	Category	Recorded year	Granulation	Capacity	Link
All regions	X	X	✓	Satellite	2004 to 2006	1 to 60 min	–	SoDa
All regions	X	X	✓	Satellite	2001- to date	1 h,1d,1M	–	
USA	✓	✓	✓	Simulated	2006	5 min	–	NREL
EU	✓	✓	X	Simulated	PV : 1985–2016 Wind : 1980–2016	1 h	–	Renewables.ninja
Different Regions	✓	✓	X	Real	2010 - to date	multiple	variable	PVoutput
Different Regions	✓	✓	✓	Real	2011 - to date	multiple	variable	IEEE
China	✓	✓	✓	Real	2019–2020	15 min	08 PV farms: 30–130 MW 06 Wind farms: 36–200 MW	GitHub
	✓	X	✓	Real	07/2018–06/2019	15 min	10 PV farms: 6.6–35 MW	PVOD
Peru	✓	X	X	Real	05/2019 – 01/2022	15 min	285 MW	Peru
Italy	✓	X	✓	Real	2017	1 min	245 W	Italy
USA	✓	X	X	Real	2000–2023	5 min	–	USA
Australia	✓	X	✓	Real	2008 - to date	5 min	38 PV farms 2 kW–26.5 kW	

instance, a wind farm near the shore could record distinct patterns than one near the mountains. The accuracy of the global model may be negatively impacted by such inequalities, which would cause it to favour overrepresented data while ignoring under-represented patterns. Pre-trained networks for improved feature extraction in less labelled data, as shown in [204], might be useful in resolving these inconsistencies in the field of energy forecasting.

- **Communication Cost in Dispersed Installations:** When several renewable energy sources are linked to a grid, communication between a central server and the numerous installations becomes frequent. This can increase communication costs and cause network congestion, particularly during periods of high data transfer. PV/WP forecasting is relevant to the general concerns of communication costs in FL as discussed in [205]. Federated networks for energy forecasting may become more effective if these issues are addressed using techniques designed for renewable energy systems.

Combining methodological, computational, and system-level improvements is necessary to tackle these problems. Many of these problems are being actively addressed by researchers, and as the field develops, it is hoped that many of them will be successfully resolved.

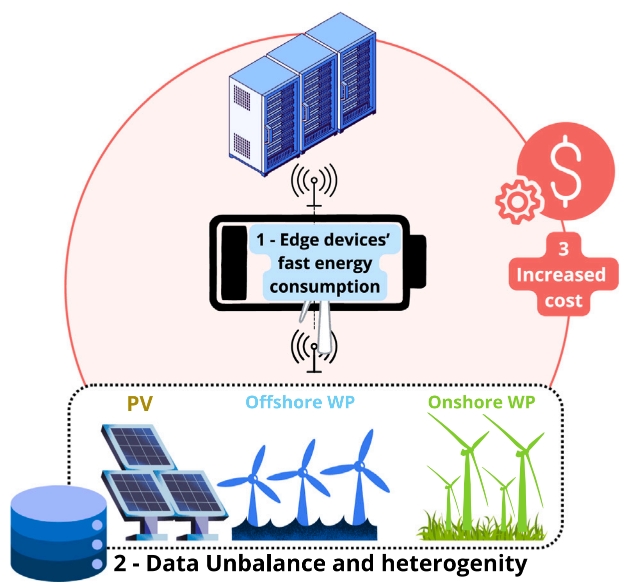

Fig. 7. Key challenges in FL process.

Conclusion

As the world struggles with the challenges of climate change and energy sustainability, the relevance of renewable energy sources, particularly photovoltaic (PV) and wind power (WP), has never been more profound. This research initiated a comprehensive examination of the advancements and complexities in the domain of power forecasting for these renewable sources. Although traditional machine learning and deep learning techniques are effective for forecasting PV and WP, they face concerns related to scalability and data privacy. Federated Learning is a paradigm shift that promotes global model training and emphasises the importance of local data privacy. While the preliminary investigations into the applications of FL for PV and WP forecasting underscore its transformative potential, it is evident that the incorporation of FL into renewable energy is still nascent, grappling with challenges such as data heterogeneity and communication bottlenecks.

The presented review delineates the tangible advantages and disadvantages of precise power forecasting, providing a pragmatic perspective on the implementation of these methodologies. These challenges catalyse upcoming research avenues, emphasising that technological advancements will lead to an evolution in our proficiency in harnessing renewable energy. In essence, despite commendable strides in PV and WP forecasting, the journey ahead remains expansive. The prudent amalgamation of non-FL and FL methodologies, coupled with addressing inherent obstacles, positions the renewable energy sector on a promising course to meet global energy requirements in a sustainable and efficacious manner.

CRediT authorship contribution statement

Ferial ElRobrini: Writing – review & editing, Writing – original draft, Software, Investigation, Formal analysis, Conceptualization. **Syed Muhammad Salman Bukhari:** Writing – review & editing, Writing – original draft, Resources, Formal analysis, Data curation. **Muhammad Hamza Zafar:** Writing – review & editing, Writing – original draft, Visualization, Resources, Data curation. **Nedaa Al-Tawalbeh:** Writing

Table 10
Commonly used evaluation metrics for wind and solar power forecasts.

Metric	Formulas	description
Root Mean Squared Error	$\mathrm{RMSE} = \sqrt{\frac{1}{n}\sum_{i=1}^{n}(y_i - \hat{y}_i)^2}$ Ideal = 0	A good metric for detecting extreme error values because of the squaring parameter: can be biased if the data is not clean (outliers)
Mean Squared Error	$\mathrm{MSE} = \frac{1}{n}\sum_{i=1}^{n}(y_i - \hat{y}_i)^2$ Ideal = 0	Penalises larger errors more severely
Mean Absolute Error	$\mathrm{MAE} = \frac{1}{n}\sum_{i=1}^{n}\lvert y_i - \hat{y}_i\rvert$ Ideal = 0	Estimates actual situation of forecasting error; Positive and negative errors cannot cancel each other out because deviations are measured absolutely.
Normalised RMSE	$\mathrm{nRMSE} = \frac{\mathrm{RMSE}}{y_{\max} - y_{\min}}$ Ideal = 0	The normalisation facilitates the comparison between datasets or models with different scales
Normalised MAE	$\mathrm{nMAE} = \frac{1}{n}\sum_{i=1}^{n}\left(\frac{\lvert y_i - \hat{y}_i\rvert}{\max - \min}\right)$ Ideal = 0	
Mean Bias Error	$\mathrm{MBE} = \frac{1}{n}\sum_{i=1}^{n}(y_i - \hat{y}_i)$ Ideal = 0	Used to determine if the predicted value is : underestimated <0 or overestimated >0
Mean Relative Error	$\mathrm{MRE} = \frac{1}{n}\sum_{i=1}^{n}\left\lvert\frac{y_i - \hat{y}_i}{y_i}\right\rvert$ Ideal = 0	determines the extent of the discrepancy between forecasted and observed values
Mean Absolute Percentage Error	$\mathrm{MAPE} = \frac{100}{n}\sum_{i=1}^{n}\left\lvert\frac{y_i - \hat{y}_i}{y_i}\right\rvert$ Ideal = 0	Determines the percentage error relative to the true value. Used for comparison; Susceptible to small values appearing in its denominator, resulting in an infinite value.
Symmetric Mean Absolute Percentage Error	$\mathrm{sMAPE} = \frac{200\%}{n}\sum_{i=1}^{n}\frac{\lvert y_i - \hat{y}_i\rvert}{\lvert y_i\rvert + \lvert\hat{y}_i\rvert}$ Ideal = 0	Fixes the issue of the infinite upper bound present in MAPE.
Prediction Interval Normalised Average Width	$\mathrm{PINAW} = \frac{1}{n}\sum_{i=1}^{n}\frac{U_i - L_i}{\max(y_i) - \min(y_i)}$ Ideal = 0	Measures the width of the PIs for a given length of the PI
Prediction Interval Coverage Probability	$\mathrm{PICP} = \frac{1}{n}\sum_{i=1}^{n}\rho_i \left\{ \begin{array}{ll} 1 & \text{if } y_i \in [L_i, U_i] \\ 0 & \text{otherwise} \end{array} \right\}$ Ideal = 100%	Measures the PIs' ability to cover target values. Ideal values mean all targets are covered by PIs.
Skill Score (SS_{MAE} or SS_{RMSE})	$1 - \frac{\mathrm{nMAE}_{\mathrm{forecast}}}{\mathrm{nMAE}_{\mathrm{reference}}}$ or $1 - \frac{\mathrm{nRMSE}_{\mathrm{forecast}}}{\mathrm{nRMSE}_{\mathrm{reference}}}$	SS = 0 : no skill using the historical average as the forecast. SS<0 : the average is better than the forecast. SS = 1 : perfect skill (no error in the forecast).
Coefficient of determination	$R^2 = 1 - \frac{\sum_{i=1}^{n}(y_i - \hat{y}_i)^2}{\sum_{i=1}^{n}(y_i - \bar{y})^2}$ Ideal = 1	Measures how closely predicted values match target values based on the distance to the 1:1 line. Closer points mean a higher R^2, indicating model strength.
Pearson Correlation Coefficient	$r = CC = \frac{\sum_{i=1}^{n}(x_i - \bar{x})(y_i - \bar{y})}{\sqrt{\sum_{i=1}^{n}(x_i - \bar{x})^2 \sum_{i=1}^{n}(y_i - \bar{y})^2}}$ Ideal = 1	Measures the linear dependence between predicted and actual based on distance from the best-fit line

y_i and x_i : are actual values, $\hat{y}_i$ and $\hat{x}_i$: are predicted value , $\bar{y}$: is the average of actual values n: is the number of samples, ρ_i :Probability, L_i and U_i: are the lower bound and the upper bound of the PIs.

– review & editing, Validation, Software. **Naureen Akhtar:** Writing – review & editing, Writing – original draft, Resources, Formal analysis. **Filippo Sanfilippo:** Writing – review & editing, Writing – original draft, Validation, Supervision, Project administration.

Declaration of competing interest

NONE

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Data availability

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

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