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Wind speed and solar irradiance forecasting techniques for enhanced renewable energy integration with the grid: a review

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Abstract: Power generation from renewable energy resources is on the increase in most countries, and this trend is expected to continue in the foreseeable future. In an effort to enhance the integration of renewable power generation from solar and wind into the traditional power network, there is need to address the vulnerabilities posed to the grid as a result of the intermittent nature of these resources. Variability and ramp events in power output are the key challenges to the system operators due to their impact on system balancing, reserves management, scheduling and commitment of generating units. This has drawn the interest of utilities and researchers towards developing state of the art forecasting techniques for forecasting wind speeds and solar irradiance over a wide range of temporal and spatial horizons. The main forecasting approaches employ physical, statistical, artificial intelligence and hybrid methodologies. This study provides the rationale for forecasting in power systems, a succinct review of forecasting techniques as well as an assessment of their performance as applied in the literature. Also, techniques for improving the accuracy of forecasts have been presented together with key forecasting issues and developing trends.

1 Introduction

There has been unprecedented growth in the amount of renewable energy generation over the past decade. With the exception of hydro power, the two leading renewable energy sources are wind and solar. At the end of 2014, the World's total wind power generation reached a capacity of 369.579 GW and solar power capacity stood at 177 GW [1, 2]. The IEA projects that by 2050, about 15–18% of global electricity will be generated from wind with solar photovolatic (PV) contributing as high as 16% [3, 4]. Despite its numerous attractions, increased renewable power generation is not without vicissitudes; it does pose grid integration challenges once the levels exceed 10% of the total energy mix and therefore the attendant economic and technological concerns need redress. These concerns largely emanate from the intermittent nature of the resources which leads to large variability and uncertainty in the power output. This makes it extremely challenging to dispatch wind and solar-based power generation plants. Concentrating solar power plants with storage do offer the possibility of dispatching, but the cost of thermal energy storage is still prohibitive for most power producers [5].

The primary purpose of forecasting intermittent renewable generation is to determine as accurately as possible the power output of the generation plants in the near term (15, 30 min or hour-ahead) and day-ahead time periods. The amalgamated utilisation of renewable resources notably solar and wind energy has become increasingly attractive; studies have shown that the reliability of a hybrid wind and solar PV system is twice as much as for either technology used independently [6]. Solar has several characteristics that are quite different from wind, such as difference in self-correlation and strong production in the middle of the day. For optimal performance of hybrid solar PV/wind systems, the inherent variability of these two resources should be adequately studied and modelled. The need for balancing energy can be significantly reduced and power generation scheduling and dispatch decisions optimally realised through the use of forecasts [7, 8]. Furthermore, reliable forecasts can help to keep the costs competitive by reducing the need for power curtailments as well as imbalancing penalties, thereby increasing the power plant's revenue in electricity market operations [9]. The simplest forecasting technique is persistence; this is regarded as a basic approach since it assumes that the solar irradiance or wind speed at the current time step is the same as that in the previous time step. The other approaches can broadly be classified into two main categories; physical and statistical. In recent years, the focus has been on building forecasting tools that can be used for short term predictions ranging from minutes to a few days ahead, mainly due to the importance of this data to grid operation. This is reinforced by the adverse impact of cloud motion on solar irradiance and great deviations in wind speeds which usually result in ramps that must be dealt with on a daily basis at the operation level. Day-ahead predictions are paramount for system operators to execute tasks such as scheduling, unit commitment, load following, congestion management, reserves allocation and other functions [10, 11]. Fig. 1, which is a modification from [12] shows various applications of forecasts with respect to their spatial resolution and temporal horizon.

Although vast resources do exist on the topics of solar irradiance and wind speed forecasting, papers with a compelling and well-organised review of the existing research are scarce. Effort has been made to present this paper in a concise and effective manner, to enable the reader to get a refined appreciation of the subject matter. The remainder of the paper is organised as follows. In Section 2, a review of the various forecasting techniques has been carried out according to different classifications and their application in the literature. Section 3 presents a critique of the performance of the different techniques and an examination of the challenges in forecasting. Section 4 is devoted to a compendium of ways in which forecasting accuracy could be improved and finally, Section 5 is a discourse of the paper's concluding remarks.

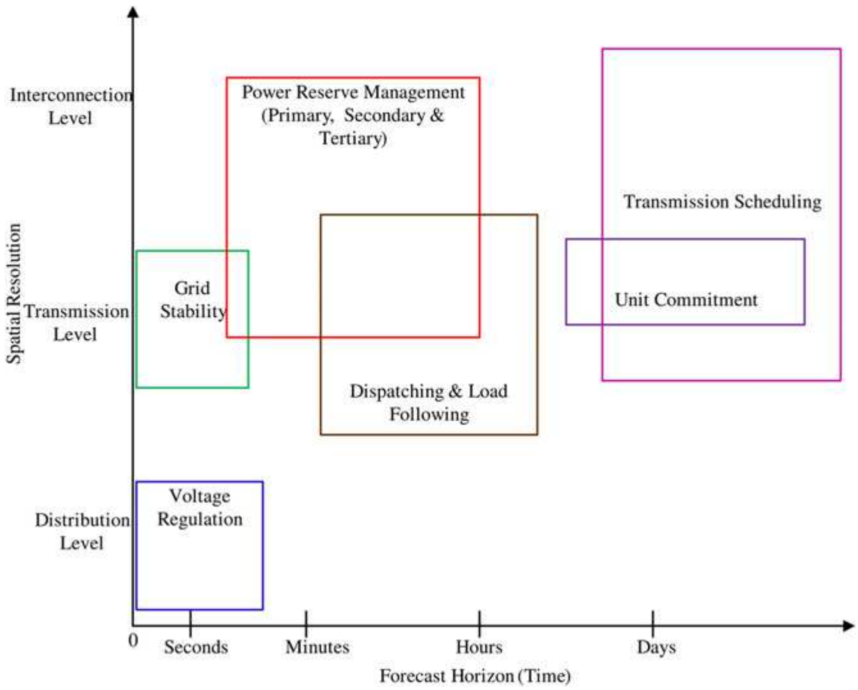

Fig. 1 *Applications of forecasts with respect to spatial resolution and temporal horizon*

2 Rationale for forecasting and overview of prediction techniques

This section presents the rationale of forecasting for power systems applications and a review of both wind speed and solar irradiance prediction techniques. It is imperative to note that fundamental considerations such as solar irradiance components, airmass, Linke turbidity, clear sky models and clearness's indices have not been presented here since the reader can easily find a detailed review of the same in [13]. Furthermore, the methods presented here deal with Global Horizontal Irradiance (GHI) which is applicable to solar PV systems and not concentrating solar systems for which the direct component is the most relevant. A comprehensive review of parametric and decomposition models relating to both direct and diffuse solar radiation can be found in [14]. In addition, Kleissl [15] provides a detailed analysis of solar energy forecasting and resource assessment. The mathematical formulations pertaining to the techniques presented can be found in the in-text references under each technique.

2.1 Rationale for forecasting in power systems applications

The importance of accurate wind speed and solar irradiance forecasts to power systems operations cannot be overemphasised. The fact that wind turbine power curves are highly non-linear and the cubic relationship between wind speed and wind power means that a small error in wind speed prediction corresponds to a very large error in predicted power output. The main use of forecasting renewable power output (solar and wind) in power systems is balancing of the network. The low capacity factors and output variability of these plants means that the transmission system operator must grapple with ensuring that enough reserves are available to account for shortfalls in wind and or PV power production, other factors such as forecast of congestion, network losses, electricity market participation and so on are also significant [16]. Accurate forecasts result in enormous technical and economic benefits. In [17], it is reported that the Western Electricity Coordinating Council (WECC) system would save up to $28 million annually for a 10% reduction in wind speed forecasting errors at 14% renewable power penetration. These savings significantly rise with increasing levels of renewable energy penetration. In summary, the forecasts aid the power system operators in preparing the system for oncoming high ramp rates of renewable generators for optimal dispatching to ensure supply reliability, plan for ancillary services market to mitigate against intermittent generation, enable dispatching of quick-start generators in advance as well as ensuring optimal operation scheduling to enable dispatch of available renewable generation.

2.2 Persistence method

Persistence forecasts are hinged on extrapolation of prevailing conditions into future horizons. The persistence method is the simplest type of forecast and is the most common reference model for short time horizon forecasts [18]. For solar irradiance prediction, the model assumes clear sky conditions and that irradiance, I at a given time t (lag0) will be the same as that at the previous time step $t-1$ (lag1), i.e. I at lag1 is considered as the forecast for I at lag0

$$I_t = I_{t-1} \tag{1}$$

A similar approach is applicable to wind. The wind speed in a given time step is assumed to be the same as that in the previous time step. Persistence could thus be suitable for intra-day forecasts (0–6 h ahead), but not for long term horizon planning as its accuracy rapidly declines with an increase in forecast horizon since cloudiness and wind speed are highly variable.

2.3 Physical techniques

Physical prediction techniques can be grouped under two main categories; those based on numerical weather prediction (NWP) and those that are satellite based (cloud imagery).

2.3.1 NWP for wind: NWPs are developed by modelling the relationship between physical variables such as wind speed, temperature, pressure, humidity, dew point, surface roughness, topography and the specifications of the wind turbines and so on [19, 20]. The typical structure of NWP-based prediction schemes for wind is presented in Fig. 2. These models consist of an

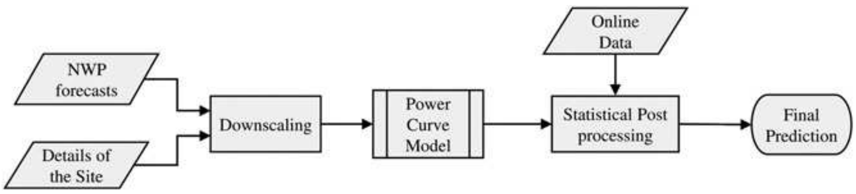

Fig. 2 *General schematic diagram for NWP-based predictions*

ensemble of sub-models, such that each sub-model represents a different grid point. Each of these sub-models solves the complex physical equations involving the aforementioned variables at the lower atmospheric boundary layer of the grid points [21]. The distance between the grid points is referred to as the spatial resolution of the model. The output of the sub-models is then utilised to calculate the wind speed and direction on the site. Subsequently, these values need to be downscaled to the physical specifications of the wind farm which include the layout of the farm, hub-heights, surface roughness, obstacles, wake effect and so on [22]. These downscaled values are then used to calculate the predicted wind power output based on the wind power curves of the individual turbines. Some statistical post-processing may also be involved in order to reduce the error of the NWP forecasts. Various NWP-based prediction models have been presented in the literature. They are typically commercial and are developed and operated by utilities, meteorological stations and private companies. [23].

2.3.2 NWP for solar irradiance: There are about 14 operating global NWP models worldwide that can be used in solar irradiance forecasting [24]. The two most well-known ones are the Global Forest System (GFS) and the Integrated Forecast System (IFS). The GFS is run by the US National Oceanic and Atmospheric Administration (NOAA) while the IFS is operated by the European Centre for Medium Range Weather Forecasts (ECMWF). ECMWF forecasts have been used in both wind and solar power predictions. The model outputs include solar irradiance, cloud parameters and so on and are up to 15 days ahead. In the work of Lorenz *et al.* [25], the T799 version of the ECMWF model with a spatial resolution of 25 km × 25 km was used. The most recent version of the model is T1279/L137 with a horizontal resolution of 16 km × 16 km. The temporal resolution of the forecasts is 3 h for the first 3 days of the forecasts which adequately covers the period most critical to PV power forecasting.

2.3.3 Irradiance forecasting using cloud motion vectors, satellites and sky images: Other than the explicit daily and seasonal variations of solar irradiance, cloud cover and cloud optical depth have the most dominant effect on the variability of solar irradiance at the surface level. Therefore, the assessment of clouds at a specified time for a given location is pertinent for irradiance forecasting and modelling. The use of satellites and sky images for solar irradiance forecasting is based on the evaluation of cloud structures in the previous time steps and extrapolating the clouds' motion to be able to predict their position and magnitude in future time steps and hence the solar irradiance. A typical structure for obtaining solar irradiance predictions based on sky imaging and cloud motion is shown in Fig. 3. A detailed review of forecasting schemes based on cloud motion vectors can be found in [26, 27].

2.4 Linear statistical approaches

Linear statistical models belong to the class of time-series prediction methods. They are the most widely implemented and traditional methods present in the literature as alternatives to the physical techniques. These models are based on utilising historical time series data in order to develop relationship between several explanatory variables to obtain an estimate of future values. Conventional statistical techniques include autoregressive (AR), moving average (MA), AR MA (ARMA) and other variants of similar models. The general form of such a model is given by

$$x_t = \sum_{i=1}^{p} \varphi_i x_{t-1} + \sum_{i=1}^{q} \theta_i \varepsilon_{t-1} + k + \varepsilon_t \tag{2}$$

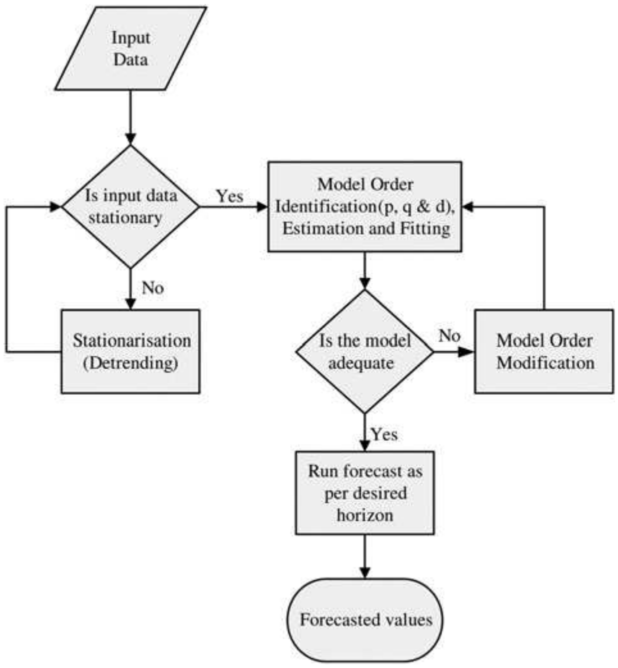

Fig. 4 *General schematic diagram for ARMA-based predictions*

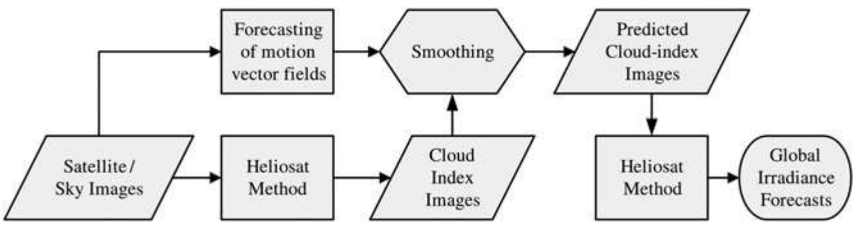

Fig. 3 *Typical structure of prediction models-based on sky imaging*

where x_t is the forecasting parameter at time instant t, φ represents the AR parameter, θ is the moving average parameter, k is a constant and ε_t models the random white noise. p and q are the orders of the AR and MA models, respectively. The order of the model, i.e. the values of p and q are determined using the sample auto-correlation function (ACF) and the partial ACF of the time series, respectively [28]. A general schematic diagram of ARMA-based forecasting methodology is shown in Fig. 4.

2.4.1 Linear statistical approaches in wind prediction: The AR method has been implemented for prediction of wind speeds in [29]. In addition, the AR model was modified using second-order blind identification (SOBI) technique and the results showed that the modified AR-SOBI model achieved better forecast performance as compared to the persistence and individual AR model. In [30], AR and AR exogenous (ARX) models were developed to forecast wind power. The structure of ARX is similar to that of the AR model, but the difference lies in the inclusion of an externally determined (exogenous) input in ARX. The exogenous input used in this study was the wind speed modulus in the point of the grid, which is close to the wind farm. The performance of both these models was compared to the persistence method for time horizons of 6–24 h for independent and aggregated wind farms. The analysis reveals that both these methods are superior to the persistence approach and ARX achieves slightly more accurate results than the AR model. However, it must be noted that the performance of the models depends significantly on the selected parameters.

AR integrated MA (ARIMA) and limited ARIMA (LARIMA) models, which are slight variations of ARMA, have been developed in [31] to obtain point forecasts and probability density distribution of wind speeds. Based on the given dataset, it was concluded that the LARIMA demonstrated better performance in estimating the wind speed probability density distribution as compared to both ARIMA and first-order transition matrix-based discrete Markov model. A fractional ARIMA was introduced in [32] which was shown to be able to improve the forecasting accuracy over a 48 h forecast horizon as compared to the persistence method. Seasonal ARIMA (SARIMA) is also gaining scholarly attention for developing wind speed prediction models. SARIMA takes into account the observed seasonality in historic wind data, thereby, presenting a possibility of increase in the accuracy of the traditional ARIMA model [33].

Four different ARMA models have been developed in [34] to forecast both wind speed and direction. The models include the traditional ARMA, traditional-linked ARMA, vector AR (VAR), and restricted VAR. Based on the differences in mean absolute error (MAE) of the models, it was concluded that traditional ARMA out-performed the traditional-linked model for wind direction prediction, but not for wind speed forecasting. Both vector-based models showed almost equivalent performance and resulted in lower values of MAE for wind direction as compared to the univariate traditional models.

Other statistical methods such as AR Conditional Heteroscedastic (ARCH) have been employed. The typical process for developing an ARCH or a GARCH model includes three main steps. The first is to approximate a best-fitting autoregressive model; the second is to calculate the values of autocorrelations of the error term and he last is to test for statistical significance. Taking into account the heteroscedastic nature of wind speed can help in reducing the errors as compared to the individual ARIMA model.

2.4.2 Linear statistical approaches in solar irradiance prediction: Most of the linear statistical techniques applied to wind are applicable to solar irradiance forecasting. Usually, the inputs to the models are not stationary yet ARMA requires stationary time series (see [35]), therefore a form of de-trending is performed to obtain appropriate values of p and q, this often necessitates the use of ARIMA models. The authors of [36] by removing the annual periodicity and seasonal variation of solar irradiance developed multiplicative ARMA models to generate instantaneous series of global radiation. The prediction results showed a good match with the measured values. In some studies, the focus has been on forecasting the power output from a PV plant based on similar techniques for irradiance forecasting. In a study by Bacher *et al.* [37], both AR and AR with exogenous input (ARX) models were to predict the hourly values of solar power for horizons up to 36 h. The efficacy of SARIMA models and their potential for short-term solar irradiance prediction was investigated by Craggs *et al.* [38] using measured solar irradiance as the model input for a site in Newcastle upon Tyne, UK. Results showed that the model accounted for at about 82 and 85% of the total variation in the 10 min averaged horizontal and vertical irradiances, respectively.

Another statistical approach is the Coupled AR and Dynamical System (CARDS) model developed by Boland *et al.* [39] to forecast solar radiation time series for one-step-ahead at the hourly and sub hourly time scales. Since solar radiation exhibits seasonality, the solar radiation data was deseasoned using Fourier series and power spectrum analysis as presented in Boland [40]. AR is effective at mean reversion which makes it inefficient to model the peaks of the resulting residual series formed by subtracting the Fourier series from the original series. A much superior fit was obtained by the introduction of Lucheroni's resonating model to account for the dynamical system portion and the perceptive use of a proxy for curvature (see [41]). The discretised version of the deseasoned solar radiation time series R_t is given in (3) and (4) where ω_t and a_t are noise terms, Δ_t is the time step. The parameters k, λ, ϵ, γ and b are estimated using the ordinary least squares method

$$R_{(t+1)} = R_t + z_t \Delta t + \omega_t \tag{3}$$

$$z_{(t+1)} = z_t + [k(z_t + R_t) - \lambda(3R_t^2 z_t + R_t^3 - \epsilon z_t - \gamma R_t - b)] \cdot \frac{\Delta_t}{\epsilon} + a_t \tag{4}$$

The results of the CARDS model had a normalised root mean square error (NMRSE) of 16.5 for all days, which is agreeable with the findings in [42] which showed the best performing model having a NRMSE of 17% for mostly clear days and 32% for mainly cloudy days, at the 1 h time step.

Statistical models can provide reasonably accurate performance for the short-term forecast horizon and have the capability of correcting local trends in the data. However, statistical approaches require significant volume of historical time series data. In addition, they do not show satisfactory performance for medium and long-term prediction horizons and cannot be easily used to model non-linear trends.

2.5 Artificial neural networks (ANNs)

ANNs are inspired by the natural intelligence and the ability of the human brain to adapt its cognitive process to solve complex problems. The design of ANNs enables them to learn from experience and to demonstrate strong generalising capabilities. These models are data-driven techniques which can represent a complex non-linear relationship and are capable of extracting the dependence between the input and output variables through the training and learning process [43]. In addition, they have the ability of self-organisation, learning and adaptation [44], hence, they are a powerful and flexible tool for forecasting. ANNs are classified in two structures: feed-forward neural networks (FFNNs) and recurrent neural networks (RNNs) [45]. The general structures of FFNN and RNN are shown in Figs. 5*a* and *b*.

FFNNs are the most widely implemented class of neural networks (NNs). In FFNN architecture the computations proceed only in the forward direction (from input nodes to output nodes). These networks typically have layers of input and output neurons with one or more hidden layers. The function of the hidden neurons in the hidden layers, is to develop meaningful connections between the external inputs and the network outputs. On the other hand, RNNs are characterised by the presence of backward connections

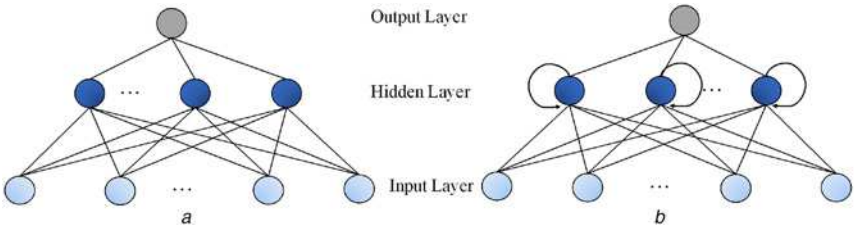

Fig. 5 *Simple representations of ANNs*
a FFNN
b RNN

providing feedback loops. This makes RNNs particularly useful in the modelling of dynamic systems [46].

2.5.1 ANN applications in wind speed forecasting: In [47], a FFNN structure is implemented with four input nodes, eight hidden layer nodes and one output node to estimate wind power. The inputs are the measured data for wind speeds and directions from two meteorological towers. The model demonstrated reasonably good forecast performance. The effect of wind speed and direction on wind power generation was also evaluated and it was shown that direction has much less influence on wind turbine power generation than wind velocity. The authors of [48] compared SARIMA with Adaptive Linear Element (ADALINE) NN to forecast wind speeds in Mexico. The results depicted that SARIMA predictions had lower statistical errors than that of ADALINE. Radial basis function NN (RBFNN) and Elman recurrent NN (ERNN) have been implemented to predict wind speeds in [49]. The accuracies of both these networks with different architecture parameters were compared in terms of mean square error (MSE). It was concluded that for the given dataset, RBFNN gives less error as compared to ERNN in all the architectures. A comprehensive comparison of three ANNs [RBFNN, feed-forward back propagation (FFBP) and ADALINE] has been presented in [50]. The comparison revealed that different model parameters and architectures can result in different forecast accuracies for the same test data.

Many techniques involving ANNs present in the literature implement various mathematical procedures to improve the training and learning process of the networks. In [51], a unique genetic NN (GNN) was proposed for the prediction of wind speeds. The weights and biases of NN layers were determined during the training process using genetic algorithm (GA) instead of the typically used back propagation (BP). It was shown that BP has tendency of converging to local optima and thus the GNN had a better prediction performance. Similarly, particle swarm optimisation (PSO) has been used in [52, 53] in order to enhance the training process of the ANN for short-term wind power prediction. Significant improvement in forecast accuracy was noticed as compared to the methods involving training without PSO. A multi-agent system has been implemented to enhance the performance of the BPNN in [54]. The interactions between the self-learning agents were used to facilitate the continuous modification of the BPNN model, thereby increasing the accuracy of the model. Similar to ANNs, SVMs can model the non-linear trends in data and can effectively carry out pattern recognition. In [55] the authors compared SVM to multi-layer perceptron (MLP) NNs for wind forecasting. SVMs demonstrated superior prediction performance to the MLP NNs.

2.5.2 ANN applications in solar irradiance forecasting: A detailed review on the different artificial intelligence techniques for photovoltaic applications such as modelling and prediction of solar irradiance, temperature, clearness index and humidity among others, is presented in [56, 57]. In a study by Mellit *et al.* [58], an ANN model based on the MLP structure (see [59]) was developed to forecast the solar irradiance on a base of 24 h (day ahead) for a site in Trieste, Italy that has a grid-connected PV (GCPV) plant. The model uses values of mean daily solar irradiance, air temperature and the day of the month as inputs to output day-ahead forecasts of solar irradiance. Training of the model is based on the Levenberg–Marquardt BP learning algorithm (see [60]). The model performance prediction had a correlation coefficient of 98% for sunny days and 94% for cloudy days. The MAE and MBE in the forecasted and actual GCPV plant power output were 3.21 and 8.54%, respectively.

Wavelet networks which are a result of a combination of wavelet theory and NNs have also been implemented in forecasting solar irradiance. They are basically feed-forward networks utilising wavelets as activation functions. In [61], an adaptive wavelet-network architecture was used to develop a prediction model for forecasting daily total solar radiation in Algeria. The model's MAPE was below 6% and its performance was considerably good when compared to other NN structures and classical models. The key advantage of the wavelet networks is the fast convergence time and the ability of the models to fill in missing data points. Using the NARX architecture, Negash *et al.* [62] developed a model to predict the next day's PV generation using the forecasted GHI values.

In conclusion, the advantage of ANNs and SVMs lies in their ability to model complex non-linear relationships. They are generally easy and simple to develop. The training and learning processes help these methods to discern the trends in historic data and hence provide good short term forecasts without the need of specifying any mathematical model a priori.

2.6 Fuzzy logic models

Fuzzy logic can be conceptualised as a generalisation of classical logic. This method involves non-linear mapping of input variables to the output using soft linguistic variables and a continuous range of membership functions in the range [0, 1] [63]. The usefulness of fuzzy logic models is particularly prominent in situations where the exact model of the system is not available or inadequate, or when the problem formulation involves uncertainty or ambiguity [64]. A generalised flowchart for developing fuzzy logic predictions models is given in Fig. 6.

2.6.1 Fuzzy-based approaches in wind forecasting: A wind speed prediction model based on probabilistic fuzzy system was presented in [65]. The proposed method shows the capability of modelling stochastic and deterministic uncertainties owing to the introduction of the third probability dimension in the model. The simulation results show that the proposed system is robust and can achieve satisfactory prediction performance in complex stochastic environment. A wind power prediction method based on fuzzy modelling derived from raw data of wind farm has been developed in [66]. The optimal rule numbers of the model are determined using fuzzy C-means and the membership functions are tuned using a BP algorithm. The model shows accurate prediction performance for the short term forecast horizon for the given wind speed data from Mongolia.

The performance of fuzzy logic models has been enhanced using different techniques including wavelet transform (WT) and

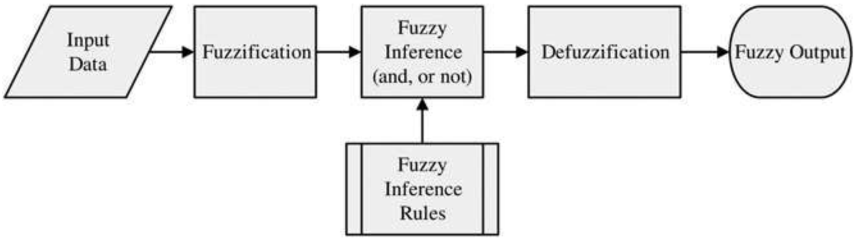

Fig. 6 *General flowchart for fuzzy logic prediction models*

optimisation techniques. The authors of [67] have implemented a combined fuzzy ARTMAP (FA) and WT for forecasting wind power using meteorological information such as wind speed, wind direction and temperature. The spikes and chaotic variations in wind power are filtered by WT and non-linear nature of wind power fluctuations is modelled by the FA. As a result, the performance of the proposed technique is significantly superior to the persistence method and various ANNs for short-term wind power prediction.

2.6.2 Fuzzy-based approaches in solar irradiance forecasting: Various studies have utilised fuzzy approaches in the forecasting of solar irradiance and PV power production. In [68], the authors used forecasted temperature and irradiance to obtain fuzzy logic models. Interval type-2 fuzzy models are used to account for the uncertainty inherent in the solar irradiance prediction. The key advantage of using interval type-2 fuzzy models is that the model gives both an uncertainty range as well as a forecasted value which is helpful in determining prediction intervals (PIs). Fuzzy logic based methods can help in achieving non-linear mapping for the complex wind speed and solar irradiance time series even without requiring large volumes of historical data (see [69] for an overview of this approach).

3 Performance evaluation of different prediction techniques

This section presents a defined set of performance criteria for the different prediction techniques and the major challenges associated with forecasting.

3.1 Performance criteria

The efficacy of the prediction models discussed in Section 2 is dependent on the forecasting methodology employed as well as the forecast horizon being considered. Following is a presentation of the pertinent performance parameters which often need to be considered during the selection of forecasting techniques.

3.1.1 Data requirement and dependence: The volume of data required depends on the technique being employed. NWP requires a huge volume of data in comparison to the other techniques. As expected, the persistence method requires the least volume of data. The majority of the statistical techniques and ANNs rely on meteorological data which is sometimes not available for some locations and this poses a major hindrance in determining the data to be used in such scenarios.

3.1.2 Computational requirements: Computational requirements comprise both the amount of time required to train a model and to carry out predictions for the intended horizon as well as the actual hardware requirements. NWP is by far the most computationally intensive due to the volume of data required, they are followed by ANNs and statistical approaches while persistence has the least computational requirements. The computational requirements of statistical and ANNs methods are quite moderate, but the demand changes depending on the type of technique employed. Also, hybrid models tend to be more computationally intensive due to the combination of different techniques that may require different sets of data.

3.1.3 Forecast horizon and accuracy: For model accuracy and forecast horizon, different aspects need to be analysed when evaluating the model's performance. These include the purpose of the forecast, the temporal and spatial horizon being considered as well as the integrity of the raw data used, among others. From the forecast user's (power producer's) point of view, accuracy metrics should be able to pinpoint the aspects of forecast performance relevant to the application or technology employed (solar or wind).

In the evaluation of solar and wind power forecasts, the conventional approach is to use the root MSE (RMSE) as the basic measure for assessing the prediction model's accuracy. For comparing the accuracy of different models, the RMSE of each individual model is usually normalised. However, no consistent agreement of RMSE normalisation can be found in the literature, but the common practice is to normalise using either the range or mean of the measurements (data points) under consideration. The other commonly used statistical error metrics are the mean absolute error (MAE), mean absolute percentage error (MAPE), and the mean bias error (MBE) [70].

$$\mathrm{RMSE} = \sqrt{\frac{1}{N}\sum_{k=1}^{N}\left(I_{\mathrm{pred},k} - I_{\mathrm{actual},k}\right)^2} \tag{5}$$

$$\mathrm{MAE} = \frac{\sum_{k=1}^{N}\left|I_{\mathrm{actual},k} - I_{\mathrm{pred},k}\right|}{N} \tag{6}$$

$$\mathrm{MAPE} = \frac{100}{N} X \sum_{k=1}^{N}\left|\frac{I_{\mathrm{actual},k} - I_{\mathrm{pred},k}}{I_{\mathrm{actual},k}}\right| \tag{7}$$

$$\mathrm{MBE} = \frac{\sum_{k=1}^{N}\left(I_{\mathrm{pred},k} - I_{\mathrm{actual},k}\right)}{N} \tag{8}$$

where N is the number of evaluated data points, $I_{\mathrm{pred},k}$ denotes the predicted values and $I_{\mathrm{actual},k}$ is the measured or actual value.

The key advantage of the RMSE is that large deviations between the predicted and measured values are weighted more strongly than small deviations which is suited for power generation applications. This is attributed to the fact that big forecast errors have a high negative impact on the grid operation and management [26].

In [71], Marquez and Coimbra proposed a different way of determining the forecast skill of a given model. The quality of the forecast model is evaluated by taking into account both the uncertainty and variability associated with the forecast. This has been shown to be well approximated by the ratio of the model's RMSE (RMSE_m) to that of the persistence model (RMSE_p) as given in (8). The higher the value of s, the better the quality of the forecast.

$$s = 1 - \frac{\mathrm{RMSE}_m}{\mathrm{RMSE}_p} \tag{9}$$

Fig. 7 depicts the classification of different prediction models based on the spatial resolution of input data and the forecasting horizon of

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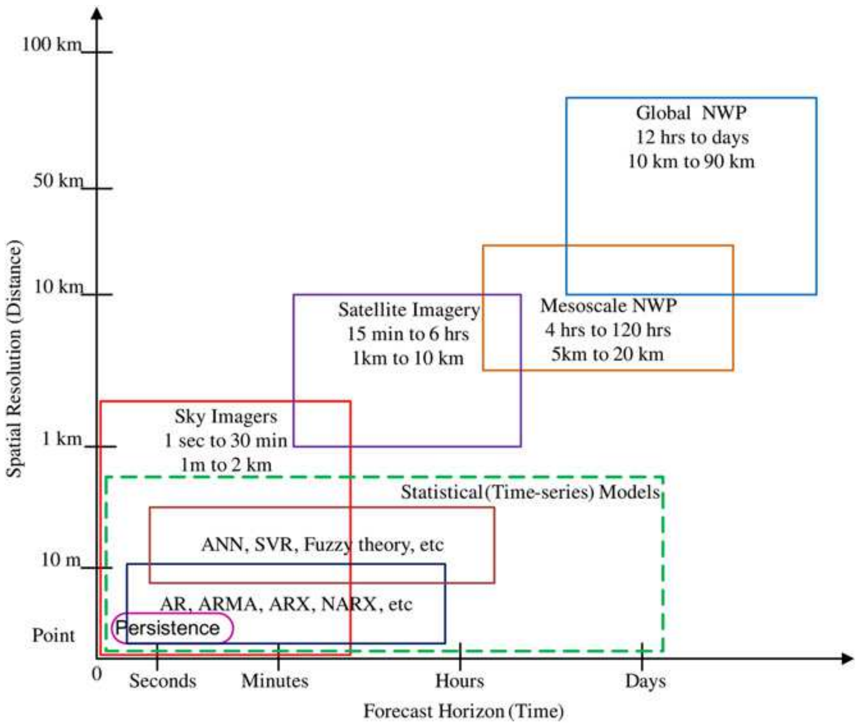

Fig. 7 *Classification of prediction methods based on spatial and temporal resolution*

the output and Table 1 provides a summary of the strengths and drawbacks of the different forecasting techniques.

Another pertinent consideration is the issue of ramps characterisation for both wind and solar. This is perhaps one of the major concern whenever a large amount of installed power from these resources is being integrated into the grid. Extreme weather and cloud events are not easily predictable yet are the main cause of large ramp events in wind and solar power output, respectively. Different spatial and temporal scales also do influence ramps which could either be up-ramps or down-ramps and with varying levels of severity [72]. Ramp identification could be carried out using different techniques such as the swinging door algorithm signal compression and heat maps, see [73].

3.2 Major challenges in forecasting solar irradiance and wind speeds

Intermittency is the bane to effective integration of solar and wind power resources into the grid. It comprises of two separate elements; variability and unpredictability. It is imperative to note that the output of a plant may conceptually be highly variable, but 100% predictable. Conversely, it could be very steady, but highly unpredictable. Perez-Arriaga [74] notes that to a certain extent, although the power output of any actual power plant is variable and unpredictable, wind and solar power generation exhibit both phenomena to a level that justifies their classification as 'intermittent' resources. For solar power forecasts, the amount of cloud cover and its variability is a key factor which impacts on the effective solar energy available for power generation. Also, the lack of thermal inertial in PV systems implies that rapid changes in the PV system output are bound to happen. Intermittency can be dealt with in various ways such as use of forecasting and management algorithms with a high level of accuracy, employment of energy storage and cycling of traditional power plants, among others. Although significant progress has been made in the advancement of both solar irradiance and wind speed forecasting over the past decade, the major challenge still remains the level of accuracy of the predictions which is tightly linked to the objective of the forecast horizon, frequency of predictions and the variability conditions. Most methodologies utilise historical meteorological data to carry out predictions. This implies that the dearth of meteorological data in many places poses a key challenge to the implementation of forecasting algorithms in such areas. The quality of data used in forecasts is sometimes poor resulting in highly inaccurate predictions. Also, the high cost of obtaining real time data is a bottleneck.

Wind and solar variability are sometimes correlated and sometimes independent of each other. Since the output of solar and wind power plants is highly variable, high accuracy of the predictions over different horizons including ramps is pertinent to the efficient and reliable operation of power system networks with high penetration of these resources. Reports by the authors [75, 76] indicate that large forecast errors may compromise reliability, increase operating costs, and require greater ancillary service procurement. In particular, large over forecasts can lead to under-commitment of flexible generation units resulting in contingency reserve shortfalls, while severe under forecasts can result in wind/solar generation curtailment. In comparison to wind power, solar PV power output is roughly more predictable due to a low level of forecast errors on clear days, and the ability to use satellite data to track the direction and speed of impending clouds [74].

4 Improvements in forecasting accuracy

In light of the challenges in forecasting wind and solar energy discussed in the previous section, this section presents some of the proposed techniques, presented in literature, for improving the forecasting performance of the techniques presented in Section 2. In addition, the potential of such methods in shaping the future of forecasts is discussed.

4.1 Hybrid models

As discussed in the previous section, the performance of the individual forecasting methods depends on the forecast horizon, input data and terrain complexity and so on. As a result, some of the methods might be superior to others depending on the location and application of the forecast. The notion behind the development of hybrid forecasting techniques is to utilise the superior features

Table 1 Comparison of the key techniques employed for wind speed and solar irradiance forecasting

Forecasting approach	Strengths	Drawbacks
NWP techniques	NWPs are the most suitable for long time horizon forecasts (several hours to days ahead)	Difficulty in acquiring the physical input data, due to the complexity and volume of calculations involved in these models, they require a significant amount of computational and time resources, the models are weak at handling smaller scale phenomena and are not suitable for short term forecast horizons.
satellite and sky images	Satellite and sky images have excellent temporal and spatial resolution making them excellent for short-term forecast horizons.	The derivation of cloud motion vectors requires expert knowledge; this approach is not applicable for wind speed forecasting.
time series models (persistence, AR, ARMA, ARX, ARIMA etc.)	Use of readily available meteorological data, no expert knowledge is required as the models have a basic structure, local trends in data can be easily corrected, confidence intervals for the predictions are easily defined.	These techniques require a big volume of historical data, they are poor at modelling/capturing the non-linear nature of wind speed and solar irradiance and exhibit low accuracy for long-term forecast horizons.
ANN-based techniques	ANNs do not need explicit mathematical expressions which are required in the physical and statistical approaches, ability to model the nonlinear behaviour of wind speeds solar irradiance, and the models gain knowledge about the data to be forecasted through the training process, they exhibit a high data error tolerance, they do have a higher adaptability to online measurements.	An optimal training method must be specified, a large amount of training data is required to enhance the accuracy of the predictions, some training algorithms require a huge amount of computational and time resources.
SVR/SVM-based models	These models exhibit good generalization capabilities irrespective of the location under consideration	The models comprise a complex optimisation structure and require longer training time, model accuracy depends on proper tuning of the parameters.
fuzzy logic models	These are relatively less complex and suitable for systems that are difficult to model exactly, they enhance accuracy of the forecasts via creation of robust models	The models have a weak learning ability and if many fuzzy rules are specified, it increases model complexity, processing time and the required computational resources.

of these individual prediction methods, and more importantly, to reduce the impact of limitations of these individual methods. As a result, hybrid methods have the potential of not only improving the forecast accuracy irrespective of the location and application of the forecast, but also help in saving a substantial amount of time and computation resources which would have been consumed in determining the most suitable individual method.

4.1.1 Hybrid wind forecasting techniques: One of the commonly implemented hybrid techniques for wind speed prediction is the combination of ANNs and fuzzy systems. This is because these methods naturally complement each other and their union can potentially provide the benefits of both approaches [77]. NNs are essentially low-level computational models which can deal with imprecise data. On the other hand, fuzzy systems have higher level cognitive attributes which can help in developing approximate reasoning and inference, however, they lack the learning capabilities of ANNs. Hence, the unification of these methods can yield improved forecasting performance for the short term horizon. ANNs and FL can also be combined to form adaptive neuro-fuzzy inference systems (ANFISs) for obtaining wind forecasts. ANFIS is essentially a NN which can achieve the functionality of fuzzy inference systems. It can integrate the fuzzy if-then rules and the parameters of the membership functions can be fine-tuned through the learning process to reduce the measurement errors [78]. The typical ANFIS architecture is shown in Fig. 8.

In [79], the ANFIS approach was applied to forecast very short-term wind power in Tasmania. The authors implemented different formats for the ANFIS model and the prediction performance was compared against the persistence approach. The analysis revealed that the ANFIS model significantly outperformed persistence as the mean absolute percentage error of ANFIS remained under 4% as compared to 30% for persistence. Another widely implemented approach for developing hybrid prediction models is based on assigning weights to the outputs of the individual prediction schemes to obtain the final prediction. The notion behind developing weighting-based hybrid prediction methods is to increase the accuracy by ascribing an appropriate value to each individual model in the hybrid. The weight coefficients for the individual models are determined taking into consideration their relative prediction accuracy. Although the inputs to the models may be kept different depending on the structure of the models, yet, most of such proposed hybrid methods prefer to keep the inputs same for all the individual schemes. The generic structure of the weight-based hybrid models is presented in Fig. 9.

Hybrid prediction models can also be developed in the form of hierarchical multiple step methods, whereby each individual model is assigned to accomplish a different task. Generally, such models involve modelling linear characteristics of the wind time series using conventional statistical methods and subsequently fitting the non-linear residue series using advanced intelligent schemes. The general structure of these residue based models in depicted in Fig. 10. In [80], the combination of ARIMA with ANN for forecasting wind speeds has been presented. ARIMA is used to model the linear characteristics of the time series while the ANN models the non-linear behaviour. The proposed hybrid model produced lower statistical errors for all the different test sites as compared to the individual ARIMA and ANN models.

4.1.2 Hybrid solar irradiance forecasting techniques: The common approach in hybrid solar irradiance models is to combine linear statistical approaches with ANNs. Benmouiza and Cheknane [81] combined ARMA with non-linear AR NNs (NAR-NNs) to carry out multi-hour (915 h) forecasting of hourly global horizontal radiation as well as one day ahead forecasts for a site in Ghardaia, Algeria using measured meteorological solar radiation. The hybrid model had the best results with a NRMSE of 0.2034 in comparison to the NAR-NN and ARMA model with a NRMSE of 0.2634 and 0.3241, respectively. The ARMA–NAR-NN hybrid model improved the forecasting accuracy as it takes advantage of the goodness of ARMA for linear problems and NAR for non-linearity. In [82], a hybrid support vector machine–firefly optimisation algorithm (SVM-FFA) model was proposed to estimate monthly mean horizontal global solar radiation for Bandar Abbass, Iran. Model inputs for the best results were a combination of relative sunshine duration, difference between maximum and minimum temperatures, relative humidity, water vapour pressure, average temperature, and extra-terrestrial solar radiation. SVM-FFA showed better performance with a MAPE of 3.2924% when compared with other ANN, Genetic Programming (GP) (see [83]) and ARMA, which had a MAPE (%) of 8.1721, 8.0227 and 8.2399, respectively. Despite the advantages of hybrid models, determining the optimal hybrid model can be a challenge as there exists no universal standard for an unbiased comparison of prediction performances. Complex hybrid approaches, although generally more accurate, are more computationally intensive than the individual models which limit their application in the very

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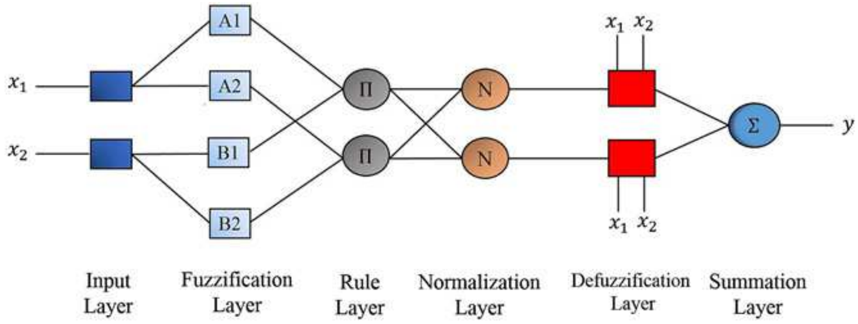

Fig. 8 *Typical ANFIS architecture*

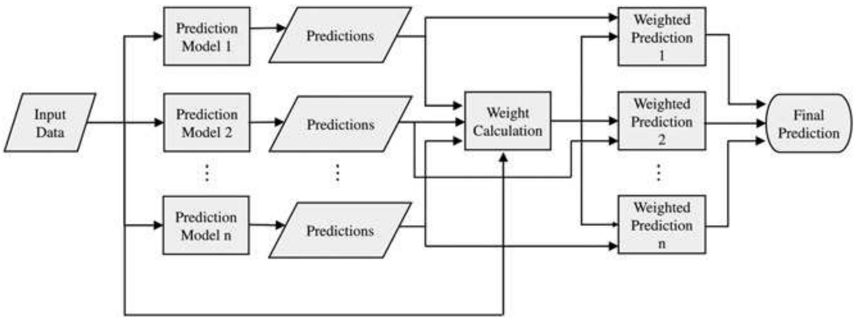

Fig. 9 *Typical structure of weight-based hybrid models*

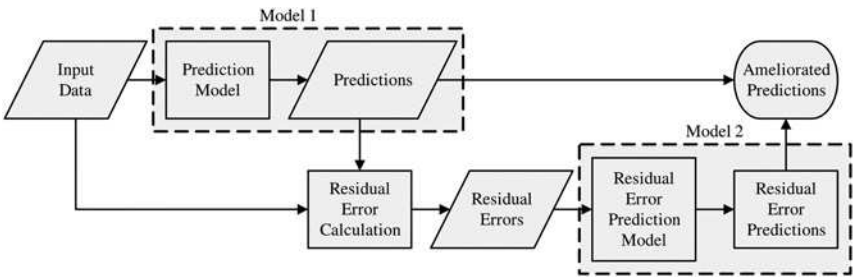

Fig. 10 *General structure of residue-based hybrid models*

short-term wind forecasts. Moreover, it was also shown in some of the studies that if not tuned appropriately, hybrid models may even deteriorate the prediction performance.

4.2 Prediction intervals

Conventionally, weather predictions are provided as point forecasts. Owing to the chaotic nature of the weather related variables, errors in wind speed forecasting are simply inevitable and can usually be very substantial. Consequently, there are always inherent uncertainties in predictions which represent the lack of complete knowledge of the physical processes that affect weather phenomena. In addition, errors related to model structure selection and parameter estimation add to the uncertainty of the predictions. PIs can be very helpful for quantifying these uncertainties of predicted values. A PI is comprised of upper and lower bounds, U_i^t and L_i^t, respectively, that bracket a future unknown value with a prescribed probability called a confidence level $(1-\alpha)\%$ [84]. Given a set of N finite pairs of inputs and corresponding output $\{(\boldsymbol{x}_i, t_i)\}_{i=1}^{N}$, where $\boldsymbol{x}_i \in \Re_m$ is the input vector with m real-number components and $t_i \in \Re$ is the corresponding target, a PI of nominal coverage rate $100\ (1-\alpha)\%$, I_i^t, of the measured target is a stochastic interval expressed as

$$I_i^t = [L_i^t, U_i^t] \tag{10}$$

such that

$$P(t_i \in I_i^t) = 1 - \alpha \tag{11}$$

The performance of PIs in estimating the uncertainty in predictions can be evaluated in terms of two important parameters; PI coverage probability (PICP) and PI nominal average width (PINAW) [85]. PICP is the measure of the reliability of the PIs. It basically is the probability of the targets actually being covered by the PI and is calculated as

$$\text{PICP} = \frac{1}{N}\sum_{i=1}^{N} a_i \tag{12}$$

where

$$a_i = \begin{cases} 1 & t_i \in I_i^t \\ 0 & t_i \notin I_i^t \end{cases} \tag{13}$$

For the developed PIs to be reliable, the values of PICP should be close to its prescribed nominal coverage rate. PINAW is the measure of the sharpness of the PI. As narrower PIs are more informative than wider ones, PINAW describes the average nominal width of the PI as follows

$$\mathrm{PINAW} = \frac{1}{NR}\sum_{i=1}^{N}(U_i^t - L_i^t) \tag{14}$$

where R is the range of the targets and is calculated as the difference between the minimum and maximum values. Lower values of PINAW imply that the PIs are sharper and more informative.

Methods for constructing PIs can be divided into two distinct classifications; parametric and non-parametric. Parametric techniques are developed based on an underlying assumption regarding the distribution of the errors in prediction. Conversely, no such assumptions are made for non-parametric (or 'distribution-free') approaches [86].

Simplistic parametric calculations of PIs can be made based on the Box and Jenkins method [87] and by assuming a Gaussian error distribution. Such a basic approach has been implemented in [88] for the construction of PIs. However, usage of techniques based on Box-Jenkins for non-linear time series (such as that for wind speeds) will inherently give poor results. This limitation was demonstrated in detail in [89]. Instead of implementing a Gaussian distribution, a β-distribution is considered, which is bounded and its shape is determined by functions of mean and variance. It was shown that β-distribution can potentially offer significant improvement as compared to the Gaussian assumption. Parametric PIs can also be constructed using the Bayesian method. According to this method, the parameters of prediction method assume a priori distributions. The predictive density of these model parameters are then described and updated using the Bayes' rule. These density functions are subsequently used to calculate the upper and lower prediction bounds. The most widely implemented parametric technique for construction of PIs is known as Bootstrapping. It is a statistical inference method based on data resampling. The concept behind this technique is that an ensemble of prediction models will produce a less biased estimate of the true regression of the targets. Several prediction models are used for making point forecasts of the targets and then based on their outputs, the mean and variances of both the model misspecification and data noise are estimated. Bootstrapping based PIs have been developed in [90–92]. In addition, this method has been specifically used to develop PIs for ANN-based wind speed forecasts in [93]. It was found that as bootstrapping can flexibly estimate the non-constant variance, it can help in constructing satisfactory PIs. However, the most important limitation of this approach is its heavy computational cost. An important limitation of using parametric techniques is that the assumed forecast error distribution can have a significant effect on the performance of the constructed PIs. While most studies conclude that Gaussian distributions can be used to model wind speed forecast errors, the power forecast error distributions depict both skewness and excess kurtosis. This non-normality of power forecast error distributions has resulted in an increased interest in modelling and fitting error distributions of wind power prediction. In [94], the unsymmetric wind power prediction error is modelled by first evaluating the Gaussian conditional wind speed error probability density function (pdf) and subsequently transforming this conditional pdf using wind power curve to determine the error distribution of wind power. This technique lends itself well to wind power forecasting applications where wind power measurement data is not available. Bludszuweit *et al.* [95] present the modelling of the power forecast error of the persistence model using β-distribution with variable parameters to fit the variable kurtosis values at different time scales. However, the β-distributions were not 'fat-tailed' enough for forecasts up to 24 h. So, the β-function was implemented to size an energy storage system for smoothing wind power output. Also, the authors of [96] identified the variable characteristic of kurtosis and skewness of wind power forecast error distributions over different forecasting time horizons. Subsequently, Cauchy, Weibull and β-distributions were compared as model distribution for the forecast errors. These distribution models were fitted to the observed data using a maximum-likelihood optimisation. The log-likelihood values for the fitted distributions demonstrate that the Cauchy distribution is a better fit for the wind power forecast error distributions for a majority of the wind plants at all timescales. In addition, the authors then compared the confidence intervals constructed using normal and the fitted Cauchy distributions. The results indicate that not only does the sharpness of the intervals depends on the type of distribution, but also the quality of the intervals varies with different confidence levels. These factors point to the limitations of using parametric distributions and emphasise the need for careful selection and model fitting of the assumed distribution.

Non-parametric methods can be more valuable in developing reliable and sharper PIs for wind and solar forecasts because they do not have a priori assumptions regarding the distribution of the error-generating process and hence can be used for quantifying the uncertainties for all of the different types of forecasting methods [97]. In addition, typically a Gaussian distribution is assumed in parametric methods which is generally not true for wind and solar generation forecasting errors. Quantile regression based techniques have been implemented in the literature to develop non-parametric PIs [98]. These models provide robust estimates of the coefficients of linear regression. Forecast in quantile regression can be considered a local measure, relative to the specific quantile under investigation. Recently, these methods have been implemented to construct PIs for wind forecasts [99, 100]. However, the disadvantage of these methods is that dedicated models have to be trained for each specific quantile and for each different site.

Another non-parametric method for construction of PIs is the lower and upper bound estimation (LUBE) method. The LUBE method uses a feedforward NN to estimate lower and upper bounds of a PI. Two NNs are trained to output the point forecasts of the upper and lower bounds of the PI separately. Hence, this method eliminates the need for assuming a parametric distribution for the forecast errors. As the upper and lower bounds of PIs are not available when LUBE NN models are trained, indirect training methods can be implemented [101]. A combined LUBE method based on the combination of several NNs for constructing wind speed PIs has been proposed in [85]. The combination of NNs aims to reduce the uncertainties and inconsistencies associated to individual NNs and thereby improving the reliability of the PIs. The results demonstrated that the combined approach yielded significantly improved performance of the constructed PIs. However, traditional NNs employed in the LUBE method would cause several inevitable limitations, such as overtraining, high computation burden and so on. In addition to this, the performance criterion for PIs is not taken into account during the model developments. In order to solve these problems, several optimisation techniques have been proposed to enhance the quality of LUBE-based PI construction methods. An extreme learning machine (ELM)-based LUBE method has been implemented in [102], whereby the objective function is defined based on the reliability and sharpness criterion of PIs. Subsequently, PSO is applied to directly optimise the ELM with respect to the objective function. The proposed scheme was compared to other benchmark methods such as climatology, persistence and quantile regression. The results showed that quantile regression could also produce similar reliability results, yet the PSO-based LUBE method outperformed all the other methods when both sharpness and reliability performance was taken into account. The above analysis highlights the importance and the methods for developing high quality PIs for forecasting renewable energy. The nature of wind and solar forecasts deem non-parametric schemes to be generally more suitable for construction of PIs, however, other factors should also be considered. For example, a comparison of Bootsrapping and LUBE methods revealed that bootstrap PIS are more suitable for shorter forecasting horizon, while the LUBE method PIs show a better performance for longer forecasting

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periods [103]. Hence, a detailed comparison using the same datasets is mandatory for a more justified comparison.

4.3 Additional input parameters

Inclusion of exogenous inputs and parameters in the prediction models can also assist in improving the forecasting performance. These additional inputs, if selected carefully, can capture the time variations of the forecasting parameters, thereby, yielding accurate results. Inclusion of various meteorological parameters such as temperature, pressure and relative humidity can aid in improving the accuracy of wind and solar prediction models. In [104], it was shown that enhanced prediction performance of global solar radiation using temperature and relative humidity as additional input parameters can be achieved for ANN-based prediction models. In addition to these weather parameters, spatial information from remote measurement has been used in the literature to improve the forecasts of wind speeds at a given location. These methods implement spatial correlation of different parameters at various distances such as topographical elevation, wind turbulence and wind direction and so on to enhance wind speed predictions [105]. Aerosol index which is a measure to indicate the amount of particulate matter in the atmosphere has strong linear correlation with solar radiation attenuation which could have potential influence on PV power generation. Although additional input parameters could enhance wind and solar forecasts, it must be mentioned that the selection of these parameters is highly subjective and depends on the site of interest and local weather profile.

4.4 Model output statistics (MOS)

As discussed in the previous sections, many prediction models are based on the processing of weather data input from NWPs and hence the accuracy of the NWPs plays a vital role in the forecast accuracy of the final predictions. MOS is basically a statistical adjustment of NWP model predictions to account for processes below the NWP model resolution and correct for systematic errors caused by model bias. One of the key MOS techniques is the use of filtering algorithms, such as Kalman filtering, which is usually applied to improve the accuracy of the data input from NWPs. The Kalman filtering algorithm provides the statistically optimal estimate recursively by combining recent weighted observations which minimise the corresponding biases [106]. Third-order polynomial functions are implemented in the Kalman filtering algorithm [107] for wind speed forecast improvement. The proposed scheme is evaluated using two different NWPs and the simulation results depict that significant improvements in forecasting accuracy can be obtained using the proposed filtering technique. Similarly, Kalman filtering has been applied for neuro-fuzzy based model for short term and medium term predictions of solar irradiance and temperature [108]. The results validate the potential of Kalman filtering in improving the forecast performance. Similar filtering methods have been employed in [109] for enhancing the performance of forecasts.

4.5 Detrending

In recent years, detrending techniques have been applied to wind speed data to study persistence and non-stationarity of various wind time series. The most widely implemented detrending algorithm is the 'Detrending Fluctuation Analysis (DFA)', which can systematically eliminate trends in the time series and thus reveal intrinsic dynamical properties such as scaling, distributions and long-range correlations which are often masked by non-stationarities. This method is essentially based on the computation of the fluctuation function $F(s)$ for time scale s. For long-term correlated data, $F(s)$ can be modelled like a power law, such that $F(s) \sim s^{\alpha}$, where α is called the scaling exponent. In [110], the authors implemented DFA to detect long-term correlations in wind speed data form 20 wind generation stations located in Turkey. The results revealed that for short time scales, the data resembled Brownian noise, but shows persistent long-term correlations. In addition, geographical factors such as elevation, roughness height, orography and so on do not affect the temporal structure of wind speeds. Similarly, in [111], DFA was applied to average and maximum hourly wind speeds measured at four stations in Brazil, and the results indicated that the fluctuations can be categorised by power-law behaviour, with two different scaling regimes and their corresponding scaling exponents. In contrast to the mono-fractal DFA conducted in the aforementioned studies, a multi-fractal DFA was implemented on 10-min averages of six wind speed time series measured in Switzerland at different altitudes and geomorphic conditions in [112]. In addition to the similar conclusions regarding long-term correlation of wind speeds as indicated in [110, 111], the multi-fractal analysis revealed that at wind speed in significantly monofractal at short timescales while multifractal at larger timescales. This implies that wind speeds have a more heterogeneous and dynamic structure at larger time scales and thus different scaling exponents need to be calculated for the fractal subsets of the original series. The authors of [113] highlighted the need of applying detrending to obtain a reasonable degree of stationarity required for ARMA and VAR models. Therefore, the wind speed data was first detrended using harmonic analysis (identifying seasonal and diurnal trends) for 14 sites in UK and subsequently a common concurrent period was selected for which to calculate the detrended series. The detrended time series for the different sites was then modelled by VAR process. The results validated the implementation of this approach in terms of improvement in RMSE as compared to persistence forecasting for 3 and 6 h ahead intervals.

4.6 Spatial correlation

The vast body of research on wind and solar resources suggests that the groups of power plants exhibit spatial correlation in terms of the power output depending on the nature of the resource, distance between the plants, time resolution of measurement and topographical features of the locations. The correlation typically decreases with increasing distance, higher time resolution and, for solar irradiance, lower cloud speed. In [114], the authors statistically analyse the hourly irradiance data at 12 locations and wind power data at 56 wind farms across Sweden. The analysis reveals that the correlation in wind power is strong between neighbouring wind farms, but for distances greater than 500 km, the correlation coefficient is only between 0.2 and 0.4, and around 0.1 for distances over 1000 km. However, the correlation of solar irradiance is consistently higher and the coefficient is still close to 0.8 even for distances spanning 1500 km. This strong correlation in solar irradiance can be attributed to the fact that all the stations follow similar seasonal and diurnal insolation patterns. The high value of correlation between neighbouring wind plants and solar stations can be of crucial importance in enhancing the resource forecasts and, therefore, using data from multiple observation points and applying spatial correlation for predicting wind and solar resources has gained scholarly attention. Out of the several techniques adopted for spatial correlation forecasting, measure-correlate-predict (MCP) method has been most commonly used. The MCP method has been implemented in [115] to forecast long-term wind speeds at Kwangyang Bay, South Korea using data from a measurement tower located ~15 km away. Analysis of the data showed that the correlation decreases with increasing time resolution and lower wind speeds. The MCP method was followed by Monte Carlo-based simulation to use the probability models at the target location. The results depicted that the method can be used to effectively estimate the annual wind energy production at the site. In [116], a Bayesian hierarchical model was implemented to characterise the wind speeds using the spatial correlation from four weather stations and the target site's auto correlation. The hierarchical structure contains two modelling levels in which at the first level, the wind speed data from the reference weather stations is defined as the sum of a temporal, a spatial and an unstructured error component. In the second level, the temporal part is modelled as a first order random walk with a zero-mean random term, and the spatial part is modelled as a multivariate normal distribution. Based on the comparison of the predictions with actual measurements, the authors concluded that Bayesian inference presents great potential for spatial correlation forecasting. A multilayer perceptron (MLP)-based ANN approach was adopted to predict wind speeds in [117] using recorded data at 22 neighbouring measuring stations as signals to the input layer of the MLP. The analysis conducted in this study was to quantify the effects of a number of reference sites, degree of correlation, and inclusion of wind direction on accuracy of prediction (in terms of mean absolute relative error) of wind speed, wind power density and power output. The results indicated that prediction errors tend to decrease with increased number of correlated reference stations. In addition, if input signals include angular wind direction together with wind speeds, then the number of reference stations required to achieve a certain prediction performance is reduced. The application of a fuzzy model using spatial correlation for prediction of wind speeds is investigated in [118]. The model inputs included both wind speed and wind direction data from neighbouring stations within a 30 km radius. GA has been employed for training the TSK fuzzy model. The authors compared the results of their prediction model to the persistence method and found that their proposed scheme performed better at all stations considered. Spatial correlation forecasting has also been applied for solar irradiance prediction. In [119], PV output under cloudy sky conditions was predicted using measurements from 80 locations distributed over a 50 km × 50 km area. Kalman filtering was used to model the clearness index. Subsequently, the spatial correlation properties of clouds in the geographical region was taken in to account to make the final predictions for forecast horizons ranging from 30 up to 90 min. The results revealed the importance of including spatio-temporal correlations for reducing the RMS forecasting errors of PV output. Based on the above discussion, it can be concluded that multiple point forecasts using spatial correlations and introducing wind direction in the model inputs can yield better prediction performance for both solar and wind resources. However, the extent of such improvement is dependent on the regional topographic and weather features. In addition, accurate and computationally efficient use of data from multiple neighbouring reference sites might require the determination of the optimal number and location of these reference sites.

4.7 Key research issues and developing trends in forecasting

The challenge with wind and solar power utilisation emanate from the intermittent nature of the resources. According to industry, the key issues are variability and non-dispatchability of the resources. Furthermore, if integration with the grid is carried out, power system network reconfiguration is sometimes required to handle the requisite system operation such as bi-directional power flows. As a result, accurate prediction of both wind speed and solar irradiance (in both the short and long-term horizons) is at the heart of research focusing on renewable power output integration with power systems.

It is well known that a forecast is only as good as the information used to generate the predictions. However, even with accurate historical data, it is not possible to predict the future solar irradiance or wind speed with 100% certainty. As already noted, the scarcity of historical data in most locations is a major problem in the design phase of projects which has often led to over sizing of renewable power plants due to large forecast errors that accrue when data from a given site is used to determine that of a similar site that lacks historical records. This is because each site has unique characteristics. Many system operators still consider power output from wind and solar as unscheduled generation. This implies that they contribute to system unbalance and thus require ancillary services which increases the system complexity and operation costs. Therefore, issues considered when designing a forecasting model vary. They include most importantly, the objective of the forecast; is it for expected energy output or for detecting extreme weather events. This impacts on the model methodology and selection of input parameters. Characterising and estimating the accuracy of the developed model is also an issue [120]. It is not an easy task to compare performance of different forecast models since their performance varies with many factors such as forecast time horizon, quality of data used, sensitivity of forecasts to initialisation errors, distribution of wind speeds and topography of area for which the forecast is carried out. Major issues identified by researchers and industry experts pertain to the unpredictable and steep ramps, accounting for the forecasting errors, intra-hour variability of the resources and usually over generation by wind plants in the middle of the night. Storage and demand response have been proposed as possible mitigation measures against these challenges but these too, have their own limitations.

Reliable forecasts are the first step towards optimal integration of renewable power generation into the traditional power networks. Therefore, in a bid to repugnant the adverse impacts of renewable power integration with the grid, researchers have recently focused more on developing techniques that provide predictions with an accuracy that could enable the operation of such plants like conventional ones. Also, intra-hour forecasts of fast ramp rates in solar irradiance or wind speeds is pertinent for intra-day electricity market participation. Thus, the need to develop real-time accurate forecasts has become the main focus for researchers engaged in this field. This has also led to a shift from single step ahead predictions to multi-step ahead predictions as required in some electricity markets. The current trend to enhance forecast accuracy is the combination of several different models to exploit the strengths and minimise the weaknesses of each model under different scenarios. Also, forecasts are being customised to the real needs of grid operators; a case in point is ramp forecasting. This has necessitated development of models for real-time forecasting (nowcasting) due to its importance for grid operators in guaranteeing grid reliability. These predictions comprise the detailed description of the current weather together with forecasts up to 3–4 h ahead and require a high-up temporal resolution (a forecast every 10 or 15 min) [16]. It is imperative to highlight that multi-step ahead predictions are more accurate if the number of steps is kept low, for example three steps ahead (which is sufficient for most electricity markets), otherwise the accumulation of errors from previous predictions downgrades the accuracy of the subsequent forecasts. Also, new data pre-processing and learning techniques for NNs are being studied as they offer potential for improving the accuracy of forecasts [121]. Other approaches to enhance forecasts include model improvement, higher resolution and more frequent runs of NWP models, better data assimilation techniques, use of ensemble forecasting, and acquisition of more and higher quality weather data.

5 Conclusions

A broad number of existing forecasting techniques have been reviewed. Performance comparison has been carried out for the different approaches and techniques for improving forecasting accuracy presented. There is continuing increase in wind and solar power integration with the grid due to the complementary nature of the two resources. However, the challenges posed by this increased penetration necessitates that more accurate predictions be carried out to not only make the plants more economically viable, but also to enable power system operators deal with their power output variability. This paper has given prominence to detailing techniques useful in improving forecasting accuracy as this is the key forecasting research direction. The use of confidence intervals and hybrid techniques have gained more approval than other approaches. Reliable confidence intervals make it possible to schedule renewable energy-based power plants so that they are more able to favourably participate in the electricity markets' bidding process. If well designed, hybrid approaches outperform individual techniques as they maximise the strengths of each individual technique whilst minimising its weaknesses. The procedure of developing confidence intervals or hybrid techniques is critical since the assumptions made must be relevant to the technology or application being considered. Pre-processing techniques are relevant for long term predictions and dealing with complex input data; they are thus mainly applied in NWP-based techniques. Conversely, data pre-processing is unsuitable for statistical techniques or short time horizon predictions in general due to their slow adaptation to new sets of data. In such scenarios, decomposition techniques could be explored. Comparably, weighting-based approaches do have a long response time despite being intrinsically adaptive to time-varying data sets. For techniques based on this approach, the forecasting accuracy and speed increase significantly with an optimal weight assignment scheme. Ultimately, especially noteworthy in forecasting, is the exigency for continued research on improving prediction accuracy especially for ramp forecasts so that power output from intermittent resources could become almost as certain as that from conventional power plants.

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