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# Time Series and Renewable Energy Forecasting

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## Abstract

Renewable energy generation has been constantly increasing during recent years. Wind and solar have had the most significant growths among all renewable resources. Wind and solar resources are highly intermittent and dependent on meteorological parameters and climatic conditions. The power output of wind turbines is subject to various meteorological parameters, such as wind speed, wind direction, air temperature, relative humidity, etc., among which the wind speed is the most direct and influential factor in wind power generation. Solar photovoltaic (PV) power is a function of solar radiation. Wind speed and solar radiation time series data exhibit unique features which complicate their prediction. This makes wind and solar power forecasting challenging. Accurate wind and solar forecasting enhances the value of renewable energy by improving the reliability and economic feasibility of these resources. It also supports integrating solar and wind power into electric grids by reducing the integration and operation costs associated with these intermittent generation sources. This chapter provides an overview of the time series methods that can be used for more accurate wind and solar forecasting.

**Keywords:** forecasting, renewable energy, solar, time series, wind

## 1. Introduction

Power generation forecasting is the fundamental basis in managing existing and newly constructed power systems. Without having accurate predictions for the generated power, serious implications such as inappropriate operational practices and inadequate energy transactions are inevitable. High penetrations of intermittent renewable energy sources such as wind and solar significantly increase uncertainties of power systems which in turn, complicate the system operation and planning. Accurate forecasting of these intermittent energy sources provides a valuable tool to ease the complication and enable independent system operators (ISOSs) to more efficiently and reliably run power systems.

There are three major methods for wind and solar forecasting; classical statistical techniques, computational intelligent methods, and hybrid algorithms. Each category includes several methods.

Time series methods are one of the most commonly used statistical techniques for forecasting. Time series can be defined as "the evolution of a set of observations sampled at regular intervals along time. The specificity of time series models, compared to other statistic methods, is that it introduces 'time' as one of its explicative variables" [1]. Time series develop mathematical models that can forecast future observations on the basis of available data. Section below provides definitions and explanations for time series methods commonly in use for forecasting.

## 2. Time series methods

This section provides an overview of the most commonly used time series methods for solar and wind forecasting. A brief description is provided for each method along with its mathematical representation.

### 2.1. Autoregressive (AR)

The autoregressive (AR) model presents a process whose current value can be represented as a linear combination of the past values and a signal noise $\omega_t$. The AR model of order $m$, AR($m$), is described by [2]:

$$\tilde{x}_t = \sum_{i=1}^{m} \Phi_i \, x_{t-i} + \omega_t = \Phi_1 \, x_{t-1} + \Phi_2 \, x_{t-2} + \ldots + \Phi_m \, x_{t-m} + \omega_t \tag{1}$$

where $x_t$ is the time series values, $\omega_t$ is the noise, $\Phi = (\Phi_1, \Phi_2, \ldots, \Phi_m)$ is the vector of model coefficients and $m$ is a positive integer.

### 2.2. Moving average (MA)

Unlike the AR model that uses a weighted sum of past values ($\tilde{x}_{t-i}$) to provide a time-series representation, the moving average (MA) model combines $n$ past noise values ($\omega_t, \omega_{t-1}, \omega_{t-2}, \omega_{t-n}$) to develop a time-series process. The MA model of order $n$, MA($n$), is describes as, is describes as [3]:

$$\tilde{x}_t = \sum_{j=0}^{n} \theta_j \, \omega_{t-j} = \omega_t + \theta_1 \, \omega_{t-1} + \theta_2 \, \omega_{t-2} + \ldots + \theta_n \, \omega_{t-n} \tag{2}$$

where $\theta = (\theta_1, \theta_2, \ldots, \theta_n)$ is the vector of model coefficients and $\theta_0 = 1$.

### 2.3. Autoregressive moving average (ARMA)

The autoregressive moving average (ARMA) model is developed by combining AR and MA terms to provide a parsimonious parametrization for a process. The ARMA model of orders $m$ and $n$, ARMA$(m, n)$ is given by [3]:

$$\tilde{x}_t = \sum_{i=1}^{m} \Phi_i x_{t-i} + \sum_{j=0}^{n} \theta_j \omega_{t-j} \tag{3}$$

where $\Phi_i$ and $\theta_j$ are the autoregressive and moving average coefficients of the ARMA model.

### 2.4. Autoregressive moving average model with exogenous variables (ARMAX)

The auto regressive moving average model with exogenous variables (ARMAX) provides a multivariate time-series representation to enhance the accuracy of the univariate ARMA model by including relevant information in addition to the time-series under consideration. For example, climate information such as cloud cover, humidity, wind speed and direction can be included as exogenous variables in an ARMA model to develop an ARMAX for more accurate forecasting of solar radiation time series. The ARMAX model of orders $m, n$ and $p$, ARMAX $(m, n, p)$, is defined as [3]:

$$\tilde{x}_t = \sum_{i=1}^{m} \Phi_i x_{t-i} + \sum_{j=0}^{n} \theta_j \omega_{t-j} + \sum_{k=1}^{p} \lambda_k e_{t-k} \tag{4}$$

where $\Phi_i$, $\theta_j$ and $\lambda_k$ are the autoregressive, moving average and exogenous coefficients of the ARMAX model, and $e_t$ is the exogenous input term.

### 2.5. Autoregressive integrated moving average (ARIMA)

The autoregressive integrated moving average (ARIMA) model is used for non-stationary time series. Despite representing differences in local trend or level, different sections of non-stationary processes exhibit certain levels of similarity. A stationary ARMA $(m, n)$ process with the $d$th difference of the time-series develops an ARIMA $(m, d, n)$ model. The ARIMA $(m, d, n)$ model is represented by [4]:

$$\tilde{x}_t = \sum_{i=1}^{m} \Phi_i S^d x_{t-i} + \sum_{j=0}^{n} \theta_j \omega_{t-j} \tag{5}$$

where $S = 1 - q^{-1}$ and $\Phi_m(q)$ is a stationary and invertible AR$(m)$ operator; $x_t$, $\omega_t$, $\Phi_i$ and $\theta_j$ are the observed time series values, error, AR and MA parameters, respectively; $d$ is the number of non-seasonal differences; $m$ is the number of autoregressive terms, and $n$ is the number of lagged forecast errors.

### 2.6. Autoregressive fractionally integrated moving average (ARFIMA)

The autoregressive fractionally integrated moving average (ARFIMA) model is used for long-memory forecasting. ARFIMA generalizes ARIMA by allowing the differencing to take fractional values. An ARFIMA model is given by [5]:

$$\left(1 - \sum_{i=1}^{m} \Phi_i L^i\right)(1-L)^d \tilde{x}_t = \left(1 + \sum_{j=1}^{n} \theta_j L^j\right) \omega_t \tag{6}$$

where powers of $L$ indicate a corresponding number of shifts backward in the time series, and $(1-L)^d$ is the fractional differencing operator.

### 2.7. Autoregressive integrated moving average with exogenous variables (ARIMAX)

The autoregressive integrated moving average with exogenous variables (ARIMAX) includes the previous values of an exogenous time-series in the ARIMA to enhance its performance and accuracy. It is more applicable to time-series with sudden changes in trends. An ARIMA $(m, d, n)$ process including the past $p$ values of an exogenous variable $e_t$ develops an ARIMAX process of order $(m, d, n, p)$. The ARIMAX $(m, d, n, p)$ model is represented by [3]:

$$\tilde{x}_t = \sum_{i=1}^{m} \Phi_i S^d x_{t-i} + \sum_{j=0}^{n} \theta_j \omega_{t-j} + \sum_{k=1}^{p} \lambda_k e_{t-k} \tag{7}$$

where $\omega_t$ is the white noise. $\Phi_i$, $\theta_j$ and $\lambda_k$ are the coefficients of the autoregressive, moving average and exogenous inputs, respectively.

### 2.8. Vector autoregressive (VAR)

The vector autoregressive (VAR) model characterizes linear dependences between two or more time-series. VAR model uses multiple variables to generalize the univariate autoregressive model (AR model). A $k$-dimensional VAR model of order $L$ is given by [6].

$$\tilde{x}_t = v + \sum_{i=1}^{L} A_i x_{t-i} + \omega_t = v + A_1 x_{t-1} + \ldots + A_L x_{t-L} + \omega_t \tag{8}$$

where $x_t$ and $v$ are $k \times 1$ vectors of variables and constants, respectively. $L$ is the maximum lag in the VAR model, $A_i$ is a $k \times k$ matrix of lag order parameters, and $\omega_t = (\omega_{1t}, \ldots, \omega_{kt})$ is the vector of white noise [6, 7].

### 2.9. Autoregressive conditional heteroscedasticity (ARCH)—generalized ARCH (GARCH)

The autoregressive conditional heteroscedasticity (ARCH) is used for time series with specific variances for the error terms [7].

Estimated values are calculated using the following equations [8]:

$$x_t = \varepsilon_t \, \sigma_t \tag{9a}$$

$$\sigma_t = \sqrt{a_0 + \sum_{i=1}^{q} a_i \, x_{t-i}^2} \tag{9b}$$

where $x_t$ is the observed time series values; $\varepsilon_t$ is the error; $\sigma_t$ is the conditional standard deviation; and $a_0$ is the constant added to the model.

The generalized ARCH (GARCH) model estimates the values by:

$$x_t = \varepsilon_t \, \sigma_t \tag{10a}$$

$$\sigma_t = \sqrt{a_0 + \sum_{i=1}^{p} a_i \, x_{t-i}^2 + \sum_{i=1}^{q} \beta_j \, \sigma_{t-i}^2} \tag{10b}$$

By setting $p = 0$, the GARCH model reduces to an ARCH process with parameter $q$.

# 3. Performance metrics

The performance of the forecast methods is measured by various metrics related to the forecast error. Higher values of errors correspond to less forecast accuracies. This section provides the definitions and equations for performance metrics which are commonly used to calculate the forecast error. Note that $x$ represents the observed value, $\tilde{x}$ is the predicted value (forecast) and $n$ is the total number of samples.

### 3.1. MSE

Mean square error (MSE) is calculated by:

$$\text{MSE} = \frac{1}{n} \sum_{i=1}^{n} (\tilde{x}_i - x_i)^2 \tag{11}$$

### 3.2. NMSE

Normalized mean square error (NMSE) is calculated by normalizing the MSE as:

$$\text{NMSE} = \frac{n \sum_{i=1}^{n} (\tilde{x}_i - x_i)^2}{\sum_{i=1}^{n} x_i \sum_{i=1}^{n} \tilde{x}_i} \tag{12}$$

### 3.3. RMSE

Root mean square error is given by calculating the square root of the MSE as:

$$\text{RMSE} = \sqrt{\frac{1}{n}\sum_{i=1}^{n}\left(\tilde{x}_i - x_i\right)^2} \tag{13}$$

### 3.4. NRMSE

Normalized root mean square error (NRMSE) is calculated by normalizing the RMSE as:

$$\text{NRMSE} = \frac{\sqrt{\frac{1}{n}\sum_{i=1}^{n}\left(\tilde{x}_i - x_i\right)^2}}{\frac{1}{n}\sum_{i=1}^{n}x_i} \tag{14}$$

### 3.5. MAE

Mean absolute error is calculated by:

$$\text{MAE} = \frac{1}{n}\sum_{i=1}^{n}\left|\tilde{x}_i - x_i\right| \tag{15}$$

### 3.6. NMAE

Normalized mean absolute error (NMAE) is calculated by normalizing the MAE as:

$$\text{NMAE} = \frac{1}{n}\sum_{i=1}^{n}\frac{\left|\tilde{x}_i - x_i\right|}{\max(x_i)} \tag{16}$$

### 3.7. MRE

Mean relative error (MRE) is calculated by:

$$\text{MRE} = \frac{1}{n}\sum_{i=1}^{n}\frac{\left|\tilde{x}_i - x_i\right|}{x_i} \tag{17}$$

### 3.8. MBE

Mean bias error (MBE) is calculated by:

$$\text{MBE} = \frac{1}{n}\sum_{i=1}^{n}\left(\tilde{x}_i - x_i\right) \tag{18}$$

### 3.9. MAPE

Mean absolute percentage error is calculated by:

$$\text{MAPE} = \frac{1}{n} \sum_{i=1}^{n} \left| \frac{\tilde{x}_i - x_i}{x_i} \right| \times 100\% \tag{19}$$

### 3.10. MASE

Mean absolute scaled error is calculated by:

$$\text{MASE} = \frac{\sum_{i=1}^{n} |\tilde{x}_i - x_i|}{\frac{n}{n-1} \sum_{i=2}^{n} |x_i - x_{i-1}|} \tag{20}$$

### 3.11. MSPE

Mean square percentage error is calculated by:

$$\text{MSPE} = \frac{1}{n} \sum_{i=1}^{n} \left( \frac{\tilde{x}_i - x_i}{x_i} \right)^2 \times 100\% \tag{21}$$

## 4. Time series methods for solar energy/wind power forecasting

Time series methods have been extensively used to forecast solar radiation/power and wind speed/power. Typically, solar and wind data exhibit features such as non-linearity and non-stationarity which cannot be captured by most of the time series methods. To address this limitation, these methods are used in combination with other computational intelligent or data processing methods to take advantage of their capabilities to better characterize wind and solar data for more accurate forecasting. These combinations are referred to as hybrid methods which are proven effective for renewables forecasting.

### 4.1. Time series methods for solar energy forecasting

This section provides a review of the articles that use time series methods individually or in hybrid algorithms for solar radiation/power forecasting. The literature review provides a summary of the solar-related variable that is predicted, the horizon for which the variable is predicted, the performance metrics in use to calculate the forecast error, the time series methods and data in use, and the research findings of each article. **Table 1** provides the summary.

### 4.2. Time series methods for wind power forecasting

This section provides a review of the articles that use time series methods individually or in hybrid algorithms for wind speed/power forecasting. The literature review provides a summary of the wind variable that is predicted, the horizon for which the variable is predicted, the performance metrics in use to calculate the forecast error, the time series methods and data in use, and the research findings of each article. **Table 2** provides the summary.

| References | Forecast variable | Forecast horizon | Error metric | Time series method | Data | Finding |
|---|---|---|---|---|---|---|
| [9] | 5, 15, 30, and 60 min averaged global horizontal irradiance (GHI) | 5 min to several hours | MAPE | Regressions in logs, ARIMA, and hybrid (ARIMA and ANN) | 4 years of hourly GHI data for three locations in USA | ARIMA can obtain better results if used in logs with time varying coefficients |
| [10] | Daily GHI | 1 day | RMSE, NRMSE, MAE, and MBE | AR, ARMA | 19 years of daily GHI from the metrological station of Ajaccio, France | AR and ANN models perform better than other prediction methods (ARMA, k-Nearest Neighbors, Markov Chains, etc.), if the time-series data is not pre-processed |
| [11] | Hourly GHI | 1 h | MBE and RMSE | ARIMA | Meteorological data including GHI, diffuse horizontal irradiance (DHI), direct normal irradiance (DNI) and cloud cover from two weather stations in USA (Miami and Orlando) | Cloud cover information yields to more accurate forecasting |
| [12] | Half daily values of GHI | Up to 3 days | NRMSE | AR | Hourly GHI measurements from stations of the Spanish National Radiometric Network | Neural network models obtain better results for almost all stations except for Lerida station where the clearness index-based models outperform |
| [13] | Hourly solar irradiance | 1 h | RMSE, and NRMSE | Naive, ARMA | 144 months of hourly solar irradiance of the Paris suburb of Alfortville | ARMA model has competitive results as compared to similarity method (SIM), support vector machine (SVM) and neural network (NN) |
| [14] | Hourly solar radiation | 1 h | RMSE, and NRMSE | Hybrid (ARMA and time delay neural network (TDNN)) | 10 months of solar radiation data from the observation station in Nanyang Technological University | The combination of the ARMA and TDNN provides more accurate results than each individual forecaster |
| [15] | Daily average of solar irradiance | 1–15 h | MAPE | ARIMA | Solar irradiance data from a 4.0 kW PV panel in the city of Awali, Kingdom of Bahrain | ARIMA models are proved to effectively capture the auto-correlative structure of the solar irradiance |
| [16] | Daily solar irradiance | 1 day | NA | ARIMA | Solar irradiance and surface air temperature | Various climate time series are dependent on |

| References | Forecast variable | Forecast horizon | Error metric | Time series method | Data | Finding |
|---|---|---|---|---|---|---|
| | and surface air temperature | | | | data from 10 meteorological stations in Europe and 4 stations in Asia | long-range variability of solar irradiance |
| [17] | Hourly solar power from PV systems | 1 h up to 36 h | RMSE | AR, AR with exogenous input (ARX), RX (regressive model with no endogenous variables) | 1 year of solar power observations from 21 PV systems in Denmark | ARX model with both solar power observations and numerical weather predictions (NWPs) as the input outperforms the AR model for forecast horizons longer than 2 h ahead |
| [18] | Hourly GHI, DHI and DNI | 1 h | RMSE, and MBE | AR | 5 min GHI data from Jeddah, Saudi Arabia for a five-year interval | Using sunshine duration, relative humidity and air temperature as the inputs result in the most accurate forecast by the developed adaptive model |
| [19] | Monthly average solar radiation | 1 month | RMSE | Linear regression (LR) | Daily GHI and meteorological data in Darwin, Australia from 2000 to 2011 | LR obtains the best predictions compared to Angstrom-Prescott-Page (APP) and ANN models |
| [20] | Hourly PV power | 1 and 2 h | MAE, MBE, RMSE, and NRMSE | ARIMA | Hourly average power of a 1 MW PV power plant located in Merced, California collected between November 2009 and August 2011 | ANN-based forecasting models including the ANN and GA-optimized ANN obtain better predictions than Persistent, ARIMA and k-NN models |
| [21] | Hourly GHI | 1 h | NRMSE | Hybrid (ARMA and ANN) | 6 years of hourly solar radiation and meteorological data from five locations in the Mediterranean area in France | Combining ARMA and ANN enhances the forecast accuracy |
| [22] | Hourly solar irradiation | 24 h | NRMSE | ARMA | 2 years of meteorological data from Ajaccio, France | ANN outperforms the ARMA by 1.3 points reduction in the error estimate |
| [23] | Daily GHI | 1 day | RMSE, NRMSE, MAE, and MBE | AR, ARIMA | 30 min global solar radiation data in Corsica Island, France from January 1998 to December 2007 | An ANN with exogenous and endogenous data outperforms univariate forecasters such as ARMA models |
| [24] | Solar irradiance | 12 h | | Hybrid (ARIMA-Back Propagation) | Hourly solar irradiance observations from | |

| References | Forecast variable | Forecast horizon | Error metric | Time series method | Data | Finding |
|---|---|---|---|---|---|---|
| | | | RMSE, and MASE | | National Solar Radiation Data Base (NSRDB) site between 2008 and 2009 | The hybrid ARIMA-BP does not outperform ARIMA |
| [25] | Solar power | 1 min | MAE, MSE, and MAXE | Hybrid (Wavelet, ARMA, and Nonlinear Autoregressive model with exogenous variables (NARX)) | 1 min solar power data from the solar panel at UCLA for nearly 200,000 observations | Capability of the ARMA process to model the linear features of the data and the NARX advantage to compensate the error of Wavelet-ARMA enhances the forecast accuracy of the hybrid Wavelet-ARMA-NARX method |
| [26] | Solar generation | 1–5 h | MAE, and MSE | ARMA | 14 years of hourly solar radiation data from SolarAnywhere | ARMA outperforms the persistence model for short and medium term solar predictions |
| [27] | Hourly solar irradiance | 1 h and 3 h | RMAE | Hybrid (non-linear regression and PR) | Solar radiation data from sensors, and National Digital Forecast Database, as well as the meteorological measurements from local airports in Los Angeles region | The hybrid method excels the benchmark methods including the regression, ARIMA and ANN by 40% and 33.33% for 1-h and 3-h ahead, respectively |

**Table 1.** Summary of the articles with time series methods (individual or hybrid) for solar radiation/power forecasting.

| References | Forecast variable | Forecast horizon | Error metric | Time series method | Data | Finding |
|---|---|---|---|---|---|---|
| [28] | Hourly average wind Speed | 1 h | NA | ARMA | 2 years of wind speed data from Quetta in Pakistan | ARMA is more appropriate for prediction intervals and probability forecasts |
| [29] | Wind power density | 1–10 days | MAE, and RMSE | AR-GARCH, ARFI-GARCH | Daily midday wind speed measurements from 1995 to 2004, as well as weather ensemble predictions from 1997 to 2004 for five wind farms in UK | Weather ensemble-based forecasters are shown to perform better than time series models and atmospheric-based models |
| [30] | Mean hourly wind speed | 1 h | RMSE | AR, and ARIMA | 744 hours of wind speed measurements in Odigitria of the Greek island of Crete in March 1996 | The neural logic-based models perform better than the time series methods |

| References | Forecast variable | Forecast horizon | Error metric | Time series method | Data | Finding |
|---|---|---|---|---|---|---|
| [15] | Daily average of wind speed | 1–15 h | MAPE | ARIMA | Wind speed data from a 1.7 kW wind turbine in the city of Awali, Kingdom of Bahrain | ARIMA models are proved to effectively capture the auto-correlative structure of the wind speed |
| [31] | Wind speed | 3 h | RMSE | AR | Wind speed data measured every 3-h in three Mediterranean sites in Corsica | AR is sufficient to simulate 3-h wind speeds |
| [32] | Wind speed | 1, 2 and 3-step(s) | MAE, MAPE and MSE | Hybrid (Wavelet Packet-ARIMA-BFGS (Broyden-Fletcher-Goldfarb-Shanno)) | Half-hourly wind speed measurements from 20 December 2011 to 5 January 2012 in Chinese Qinghai wind farm | The ARIMA models have better time performance than the ANN models in approximating wind speed time series while providing a little lower accuracy |
| [33] | Hourly mean wind speed and direction | 1 h | MAE | ARMA, and VAR | Hourly average wind data from May 1 to October 21, 2002 in two wind sites in North Dakota, USA | ARMA forecasts the wind speed better than the component model whereas the opposite is observed for wind direction forecasting |
| [34] | Wind power | 3 h | MAPE, and NMAE | ARIMA | Wind power data in Portugal | The ARIMA model is used as a benchmark to evaluate the performance of the proposed hybrid Wavelet-PSO-ANFIS forecasting method |
| [35] | Wind speed | 1–24 h | MAE, and RMSE | AR, ARX, ARX-GARCH, Hybrid (ARX-TN (truncated normal), ARX-GARCH-TN) | 3 years of hourly wind speed observations from a meteorological station in Denmark, as well as wind speed predictions based on a NWP model from the Danish Meteorological Institute | The time series models are used as benchmark methods to evaluate the performance of the developed stochastic differential equation for probabilistic wind speed forecasting |
| [36] | Wind speed/power | 1–24 h | MAE, MBE, RMSE, MASE NMBE, NMAE, and NRMSE | AR, ARMA, and ARIMA | Wind speed, wind direction, humidity, solar radiation, temperature, atmospheric pressure, and heat radiation data from two anemometric measuring towers in La Ventosa, Mexico | Results show that the developed method based on support vector regression is more accurate than the persistence and autoregressive models |
| [37] | Wind speed/power | 1 and 2 day(s) | Daily mean | fractional-ARIMA (f-ARIMA) | 4 weeks of hourly average wind speed data from four wind | The proposed f-ARIMA is more accurate than the persistence method |

| References | Forecast variable | Forecast horizon | Error metric | Time series method | Data | Finding |
|---|---|---|---|---|---|---|
| | | | error (DME) | | monitoring sites in North Dakota | |
| [38] | Average hourly wind speed | 1 h | ME, MSE, and MAE | Hybrid (ARIMA-ANN) | 1 month of wind speed measurements in three regions of Mexico | The combination of ARIMA and ANN predicts the wind speed with more accuracy than the individual ARIMA and ANN |
| [39] | Wind speed | 1 day | MAPE | Hybrid (KF-ANN model based on ARIMA) | Daily wind speed observations from two meteorological stations in Mosul, Iraq and Johor, Malaysia | The ARIMA model provides inaccurate wind speed forecasts due to its limitation to capture the nonlinearity of the wind speed patterns |
| [40] | Wind speed | 1, 2 and 3-step(s) | MAE, MSE, and MAPE | Hybrid (ARIMA-ANN and ARIMA-Kalman) | Hourly wind speed measurements from a station | Both hybrid methods can obtain accurate forecasts and are appropriate for non-stationary wind speed datasets |
| [41] | Wind speed | 1 h | NA | ARMA-GARCH | 7 years of hourly wind speed data from an observation site in Colorado, USA | The ARMA-GARCH model is proved efficient in capturing the trend change of wind speed mean and volatility over time |
| [42] | Hourly average wind speed | 1 h up to 10 h | RMSE | ARMA | 9 years of hourly wind speed data of five locations in Navarre, Spain | For longer term forecasting, the ARMA models with transformed and standardized data perform better than the persistence model |
| [43] | Wind speed | 1 month | MSE, MAE, and MAPE | ARIMA | 7 years of wind speed measurements from the South Coast of Oaxaca, Mexico | ARIAM models provide more sensitivity than the ANN methods to the adjustment and prediction of the wind speed |
| [44] | Win speed | 1–6 min (s), and 1–6 hour (s) | MAE, and MAPE | Hybrid (Empirical mode decomposition (EMD)-Least squares support vector machines (LSSVM)-AR) | 1 year of wind speed data measurements in Beloit, Kansas, USA | The proposed hybrid approach is proved more accurate than the existing forecasting approaches |

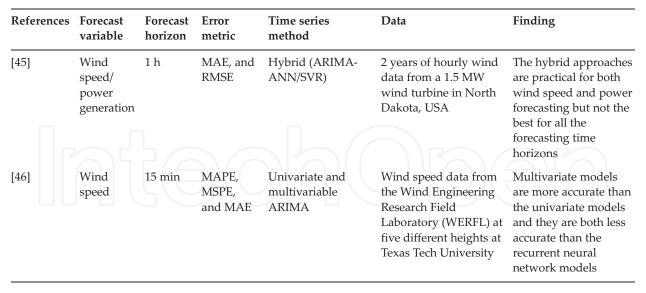| References | Forecast variable | Forecast horizon | Error metric | Time series method | Data | Finding |
|---|---|---|---|---|---|---|
| [45] | Wind speed/ power generation | 1 h | MAE, and RMSE | Hybrid (ARIMA-ANN/SVR) | 2 years of hourly wind data from a 1.5 MW wind turbine in North Dakota, USA | The hybrid approaches are practical for both wind speed and power forecasting but not the best for all the forecasting time horizons |
| [46] | Wind speed | 15 min | MAPE, MSPE, and MAE | Univariate and multivariable ARIMA | Wind speed data from the Wind Engineering Research Field Laboratory (WERFL) at five different heights at Texas Tech University | Multivariate models are more accurate than the univariate models and they are both less accurate than the recurrent neural network models |

**Table 2.** Summary of the articles with time series methods (individual or hybrid) for wind speed/power forecasting.

# 5. Conclusion

This chapter provides a comprehensive literature review to demonstrate the application of time-series methods for renewable energy forecasting. In spite of recent developments in intelligent methods and their extensive applications for more accurate solar energy/wind power forecasting, our literature review concludes that time-series methods, individually or in combination with intelligent methods, are still viable options for short-term forecasting of intermittent renewable energy sources due to their less computational complexities.

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