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ABSTRACT

Accurate forecasting of renewable energy resources has a deep societal and environmental impact. In this work, we investigate the efficacy and applicability of the Window-Sliding ARIMA (WS-ARIMA) method for daily and weekly forecasting of wind speed. The WS-ARIMA technique with a fixed or variable window length belongs to the class of adaptive models. Particularly, the sliding windows of fixed length are popular in the areas of finance, energy, and traffic management, where the dataset of necessity exhibits a seasonal pattern. To carry out the proposed analysis, the following processes were done: (1) we first perform a stationarity test on the wind speed data and observe weak stationarity; (2) we then apply a grid search method to obtain the optimal parameters of the ARIMA model; (3) we implement the WS-ARIMA method for both daily and weekly wind speed data and compare the results with the conventional ARIMA model, and (4) finally, we perform a residual analysis as a post processing step to examine any systematic bias in the implemented models. The experimental results based on 15 years (2000–2014) of daily and weekly wind speed data collected at four different locations in India reveal that the WS-ARIMA method consistently outperforms the conventional ARIMA method. The inclusion of window sliding in ARIMA has resulted in the overall RMSE reduction up to 75% in daily wind speed data and 50% in the weekly data. Therefore, we recommend the WS-ARIMA model as one of the potential techniques in wind speed forecasting at daily and weekly time horizons.

I. INTRODUCTION

Renewable energy resources are regarded as the most pollution-free, abundant, and safest resources of energy. Solar and wind power are the major contributors among various types of green energy. India holds third position for the largest renewable energy production and fourth position for the installed wind power capacity globally.[1] As of July 2022, India has produced about 160 GW of renewable energy, in which the wind energy contributes to 40.79 GW. In addition, the country is pacing up rapidly toward more wind energy development with an ambitious target of 60 GW by the end of 2022. For this, public–private partnerships are being promoted throughout the country to understand the mutable behavior of the wind speed and associated wind energy potential to cater the nationwide energy demand.

With the growing focus on wind energy due to environmental concerns, analysis and forecasting of wind energy are of great importance. As wind is a site-specific resource of energy that heavily depends on climatic variations, such as temperature, pressure, humidity, and other seasonal changes, reliable assessment of the wind speed is the key for many practical applications, including renewable energy integration, operational planning, sustainable maintenance, and potential site identification.[2–4] As a consequence, reliable forecasting of the wind speed is the need of the hour to manage uncertainties in wind energy production and its integration with existing thermal energy storage. The present study contributes to this endeavor by proposing a relatively new Window-Sliding ARIMA (WS-ARIMA) technique for wind speed forecasting.

In the literature, the wind speed forecasting methods are broadly categorized into three types, namely, numerical weather predictions, time series methods, and artificial intelligence techniques. Among these, time series based approaches are the most reliable ones to study the temporal effects in historical data.[5] In this context, various time scales, such as hourly, daily, weekly, monthly, and yearly, are utilized to characterize the underlying data variability and thereby to serve a variety of end user applications.

Among time series models, the most popular approach for wind speed or wind power forecasting is the Auto-Regressive Moving Average (ARMA) model. Some variants of ARMA include Auto-Regressive Integrated Moving Average (ARIMA), Seasonal-ARIMA (SARIMA), Fractional-ARIMA (F-ARIMA), and ARMA with exogenous input (ARMAX or ARX).[2] In 1991, the ARMA method was first used for hourly averaged wind speed forecasting in Jamaica.[6] Karakus *et al.*[7] highlighted the efficacy of the polynomial auto-regressive model and compared the results with several other time series models for daily wind speed and wind power predictions in Turkey and USA. Shukur and Lee[8] developed a hybrid Kalman Filter-Artificial Neural Network (KF-ANN) based ARIMA for daily wind speed data from Iraq and Malaysia. Cadenas and Rivera[9] implemented the SARIMA model and Adaline neural network model to forecast wind speed in Mexico to demonstrate that SARIMA closely follows the actual wind speed pattern. Cadenas *et al.*[10] compared a univariate ARIMA model and a multivariate nonlinear ARX model for the wind speed prediction at two different locations in Mexico. Pasari and Shah[11] considered daily and monthly wind speed forecasting using univariate ARIMA (2,1,2) model based on Akaike Information Criterion (AIC) and Bayesian Information Criterion (BIC). Recently, Sheoran *et al.*[12] demonstrated the application of several statistical methods, such as AR, MA, ARMA, ARIMA, SARIMA, and Holt Winter's technique for the wind speed forecasting at hourly, daily, and monthly time horizons at a location in Madhya Pradesh, India. In their work, they have provided a generic guideline for the applicability of different statistical models in wind speed forecasting at desired time horizon. In a similar effort, Saima *et al.*[13] have summarized the strengths and drawbacks of statistical, hybrid, and machine learning models in the area of weather forecasting. A comprehensive review on the statistical modeling of the wind speed is available in Refs. 2, 3, 14, and 15.

From the above-mentioned literature review, we note that the ARIMA model is inadequate to deal with seasonal variations present in the wind speed data. To overcome this limitation, several variants of ARIMA have been proposed, with SARIMA as the most prominent one. However, as the implementation of SARIMA $(p, d, q)(P, D, Q, S)$ requires estimation of seven parameters, it is quite cumbersome to deal with longer time series data. As a potential alternative, one may consider the WS-ARIMA method as a variant of the ARIMA model for wind speed forecasting. The WS-ARIMA model has widely been used in the areas of finance, energy, and traffic management, where the dataset of necessity exhibits a seasonal pattern. Reikard in Ref. 16 and Reikard and Hansen in Ref. 17 presented the WS-ARIMA method as an efficient technique for solar energy prediction. Alberg and Last[18] developed the WS-ARIMA model for load forecasting in smart meters to balance the demand and supply of electricity. The predicting power of the WS-ARIMA model in forecasting equity returns was highlighted in Ref. 19. Yu *et al.*[20] showed that the inclusion of sliding windows has significantly improved the efficacy of the ARIMA model in traffic anomaly detection. Recently, in 2022, Mehdi *et al.*[21] mentioned that sliding windows on a fuzzy ARIMA provide the best accuracy in cloud traffic prediction. Similarly, Sheoran *et al.*[22] highlighted the effectiveness of the WS-ARIMA model for daily and weekly solar irradiance prediction. Based on the results of two selected study locations from Gujarat and Rajasthan, India, their study has demonstrated that the WS-ARIMA model provides the best performance in comparison to the SARIMA and machine learning methods for daily and weekly data. Motivated by the efficacy of the WS-ARIMA method in previous works, here, we implement both ARIMA and WS-ARIMA methods for daily and weekly wind speed forecasting and compare their relative performance through Root Mean Square Error (RMSE) values.

The article is organized as follows. After a generic introduction in this section, Sec. II briefly describes the dataset, along with their descriptive measures. The formulation of the WS-ARIMA method and the proposed methodology are presented in Sec. III, whereas the experimental results are provided in Sec. IV. Finally, we summarize the article and bring out notable conclusions in Sec. V, followed by a list of references.

II. DATASET DESCRIPTION

The wind speed data for the present analysis is obtained from the National Solar Radiation Database (NSRDB) maintained by the U.S. Department of Energy. We have collected 15 years (January 1, 2000 to December 31, 2014) of hourly wind speed data from four selected locations in India, one each from Rajasthan, Gujarat, Karnataka, and Telangana. Along with the wind speed (m/s), the features in the dataset include Direct Horizontal Irradiance (DHI), Direct Normall Irradiance (DNI), Global Horizontal Irradiance (GHI), and other environmental variables, such as temperature, pressure, relative humidity, and solar zenith angle. The descriptive measures of the daily and weekly data are summarized in Table I. For the sake of observation, we also provide two time series plots corresponding to daily and weekly wind speed data of one location (Pokhran, Rajasthan) in Figs. 2 and 3, respectively. We observe yearly seasonal pattern in both the time series plots.

III. FORMULATION AND METHODOLOGY

A. The WS-ARIMA model

Before we provide a description for the WS-ARIMA model, it is important to understand the basic formulation of the conventional ARIMA model.

ARIMA (*p, d, q*) model: As an extension of the ARMA model, the expression for the ARIMA model is given as

$$\phi(B)(1-B)^d X_t = \theta(B) Z_t. \tag{1}$$

At $d = 0$, the above-mentioned formulation represents an ARMA (p, q) model, as mentioned in the following equation:

$$\begin{gathered} X_t - \phi_1 X_{t-1} - \cdots - \phi_p X_{t-p} = Z_t + \theta_1 Z_{t-1} + \cdots + \theta_q Z_{t-q}, \\ \phi(B) X_t = \theta(B) Z_t. \end{gathered} \tag{2}$$

Here, $\{X_t\}$ is a time series of forecast variable and Z_t denotes the random noise; B is the backshift operator. The parameters p, d, and q represent the number of autoregressive terms, the order of differencing that must be performed to stationarize the time series, and the number of terms in moving average, respectively. Since the present dataset is observed to be stationary (details are provided in Sec. IV), no differencing was applied, resulting $d = 0$. Thus, the final model turns out to be an ARMA (p, q) model.

As mentioned before, the ARMA model is inadequate to deal with seasonal variations. In such cases, the SARIMA model is often recommended. However, as the SARIMA $(p, d, q)(P, D, Q, S)$ model includes seven parameters, the model is quite complex to deal with

TABLE I. Descriptive statistics of the dataset from four study sites.

Study site	Time scale	Data count	Mean	Standard deviation	Minimum	Maximum
Pokhran, Rajasthan	Daily	5475	3.01	1.24	0.56	8.27
(26.65°N, 71.65°E)	Weekly	783	3.01	0.96	1.27	6.75
Bitta, Gujarat	Daily	5475	3.53	1.27	0.56	8.43
(23.25°N, 69.05°E)	Weekly	783	3.53	1.08	1.22	7.22
Pavagada, Karnataka	Daily	5475	3.17	1.38	0.59	8.18
(14.15°N, 77.25°E)	Weekly	783	3.17	1.27	1.13	7.12
Ramagundam, Telangana	Daily	5475	2.34	1.04	0.30	6.50
(18.75°N, 77.25°E)	Weekly	783	2.33	0.91	0.89	5.30

longer time series data. The complexity of such models can be significantly reduced by the inclusion of sliding windows, where the size of the window is fixed through a complete nested loop.[16,22]

The general procedure of the sliding window technique is as follows. (i) First, find the size of the required window based on data characteristics; (ii) then, obtain the result corresponding to the 1^{st} window, and (iii) finally, use a loop to slide the window to compute results window by window. A simple demonstration of the process is provided in Fig. 1.

As the present wind speed data show a high positive autocorrelation peak at an interval of one year (yearly seasonal pattern as viewed from Figs. 2 and 3), a sliding window of 365 days is applied to make predictions for the next day. The results are consequently accumulated for three years of test dataset. Similarly, a sliding window of 52 weeks is considered for the weekly dataset.

B. Step-by-step procedure of implementation

The methodology is presented in a threefold manner as detailed below.

1. Data pre-processing

The entire data are initially split into training and testing sets, with a training period from January 1, 2000 to December 31, 2011 and the testing period from January 1, 2012 to December 31, 2014. Then, the hourly wind speed data are sampled according to the desired time horizon. For instance, the daily and weekly wind speed data are obtained from the hourly data through "resampling time series" based on mean values.[23] For this, we have used the Python's inbuilt resample function "df.resample('D',on='Date').mean()" for daily and "df.resample('W').mean()" for weekly dataset. Various descriptive measures, such as sample mean, standard deviation, and quartiles, are computed based on the training data (Table I). We then perform the Augmented Dickey Fuller (ADF) test to check for stationarity in the time series. The hypotheses are as follows:

- H_0: The series has a unit root.
- H_1: The series has no unit root.

If the null hypothesis (H_0) is rejected, it implies that the time series does not have a unit root, indicating its stationary behavior.

2. Model selection and validation

We implement the ARIMA and WS-ARIMA models on the test data. For the WS-ARIMA model, a sliding window of 365 and 52 is used for daily and weekly data. The minimum values of AIC and RMSE are considered while performing a grid search procedure to obtain optimal parameters of the studied models. For computation, we have used ARIMA and autoarima functions from the open-source "statsmodels" and "pmdarima" python libraries. The efficacy of the forecasting models is assessed on the basis of the RMSE error metric that uses the sum of squared differences between the actual and the predicted values. The formula for RMSE is given as

$$RMSE = \sqrt{\sum_{t=1}^{t=N} \frac{(X_t - \hat{X}_t)^2}{N}}, \tag{3}$$

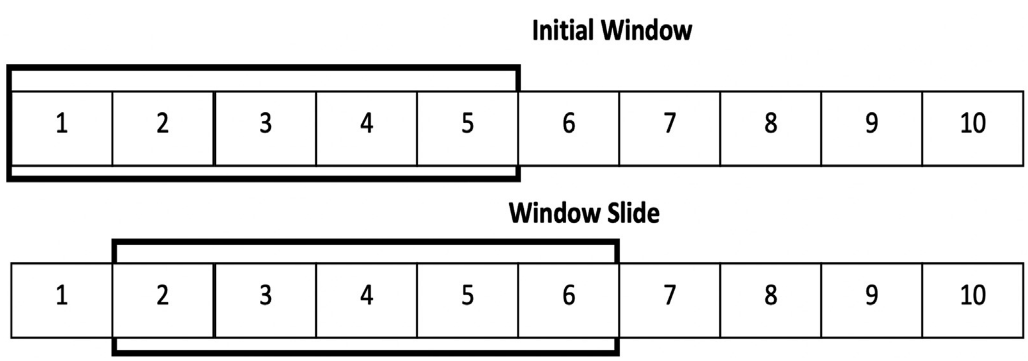

FIG. 1. A visual representation of the window sliding process.[25]

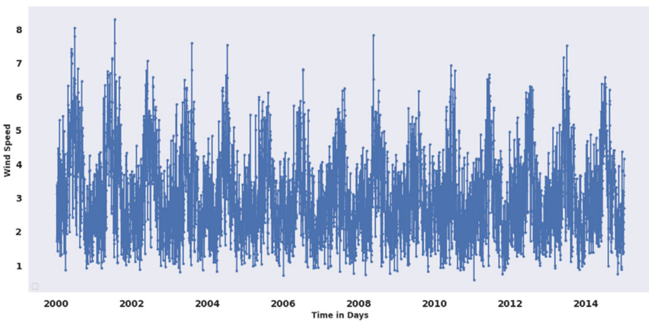

FIG. 2. Average daily wind speed (m/s) in Pokhran.

where X_t is the forecast variable, $\hat{X}_t$ is the corresponding forecast value, and N is the length of time series of the forecast variable. Lower the error values, the better is the forecast.

To summarize, for the daily and weekly forecasting, the wind speed data were split into training and testing data. Consequently, the best-fit ARIMA model (with the minimum AIC) for the training data were applied onto the sliding window model to forecast the results for the testing data.[16]

3. Residual analysis

Carrying out a residual analysis is a standard practice to check for any systematic bias in the implemented models. As the residuals of a forecast model should exhibit Gaussian distribution with zero mean and a constant variance, we analyze residual plots and corresponding P–P plots (Secs. 14.8 and 14.9 in Ref. 24) of the standardized residuals. The results are discussed at a later section.

IV. RESULTS

The results are presented in three subsections corresponding to three primary steps of the methodology.

A. Results of data pre-processing

The time series plots of daily and weekly averaged wind speed from Rajasthan are shown in Figs. 2 and 3, respectively. We observe a yearly seasonal pattern in both time series plots. Similar observations are made for the other three locations. The order of seasonality guides

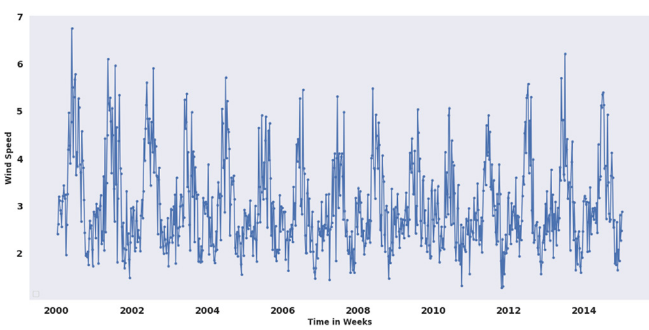

FIG. 3. Average weekly wind speed (m/s) in Pokhran.

TABLE II. Results of the ADF test for daily and weekly data.

Study site		Daily	Weekly
Rajasthan	ADF statistic	−6.3609	−7.8903
	p-value	2.4753×10^{-8}	4.4541×10^{-12}
Gujarat	ADF statistic	−5.9226	−8.6577
	p-value	2.4853×10^{-7}	4.9156×10^{-14}
Karnataka	ADF statistic	−7.2096	−9.6200
	p-value	2.2527×10^{-10}	1.7190×10^{-16}
Telangana	ADF statistic	−6.1220	−8.9989
	p-value	8.8069×10^{-8}	6.5754×10^{-15}

us to choose appropriate window lengths for the implementation of the sliding window technique.

The results of the ADF test, which was applied to check for stationarity in the dataset, are summarized in Table II. It is observed that the values of ADF statistic are significantly less than the critical values −2.8620 and −2.8653 for daily and weekly data, respectively. Consequently, the p-value in each case is much less than the considered significance level, $\alpha = 5\%$. Therefore, we reject the null hypothesis at $\alpha = 5\%$ and confirm that the series is stationary for both time scales.

B. Results of model implementation

The results in terms of optimal parameters and corresponding RMSE values are listed in Table III. The actual vs forecast values corresponding to four study regions and two time horizons are plotted in Figs. 4 and 5.

From Table III and Figs. 4 and 5, we note the following points: (i) The WS-ARIMA consistently outperforms the ARIMA model at different time horizons across all four locations. In fact, the inclusion of window sliding in ARIMA has resulted in the overall RMSE reduction up to 75% in daily wind speed data and 50% in the weekly data. (ii) As we move from weekly to daily, the RMSE of the conventional ARIMA model increases, probably due to more seasonal variability in the daily wind speed data in comparison to weekly data. (iii) However, for the WS-ARIMA model, the RMSE values decrease when we move from

TABLE III. Optimal parameters and RMSE values of daily and weekly wind speed forecasting models.

		Daily		Weekly	
Study site	Model	(p,d,q)	RMSE	(p,d,q)	RMSE
Rajasthan	ARIMA	(1,0,3)	1.3178	(3,0,2)	0.8018
	WS-ARIMA		0.3724		0.4837
Gujarat	ARIMA	(2,0,3)	1.1264	(4,0,5)	0.6573
	WS-ARIMA		0.2823		0.4536
Karnataka	ARIMA	(2,0,2)	1.1195	(2,0,4)	0.8680
	WS-ARIMA		0.1278		0.3939
Telangana	ARIMA	(2,0,2)	0.9266	(2,0,5)	0.6370
	WS-ARIMA		0.2321		0.3774

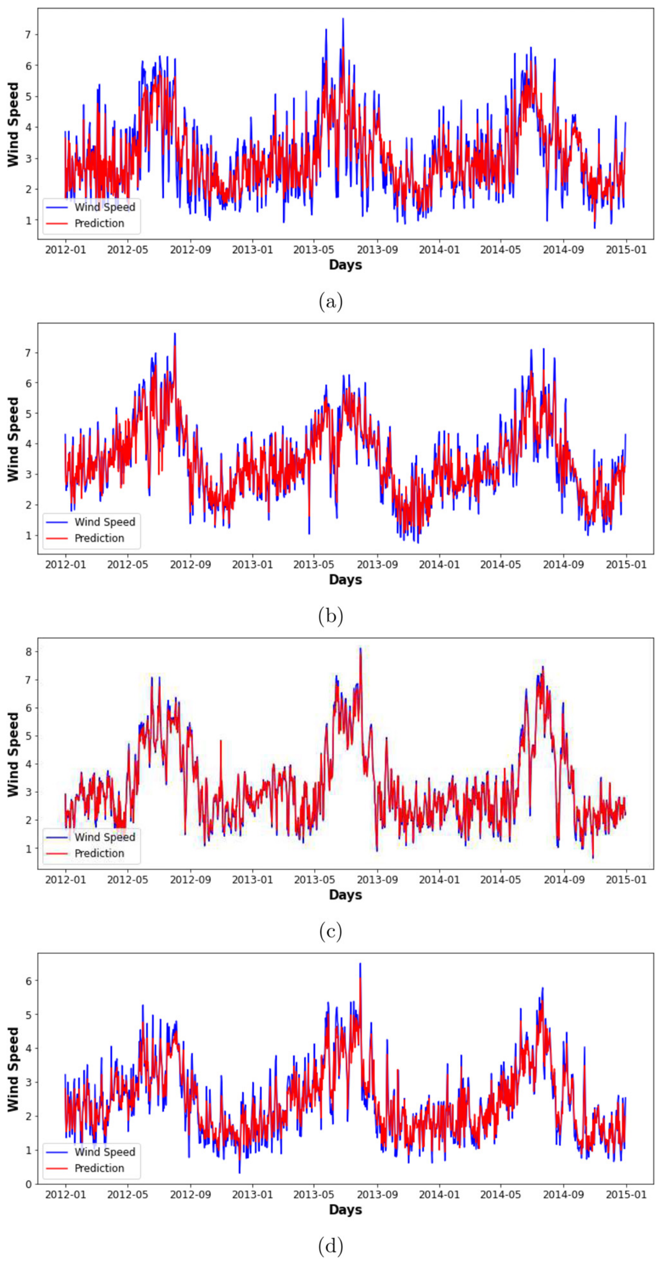

FIG. 4. Daily wind speed forecasting from the WS-ARIMA model for (a) Rajasthan, (b) Gujarat, (c) Karnataka, and (d) Telangana.

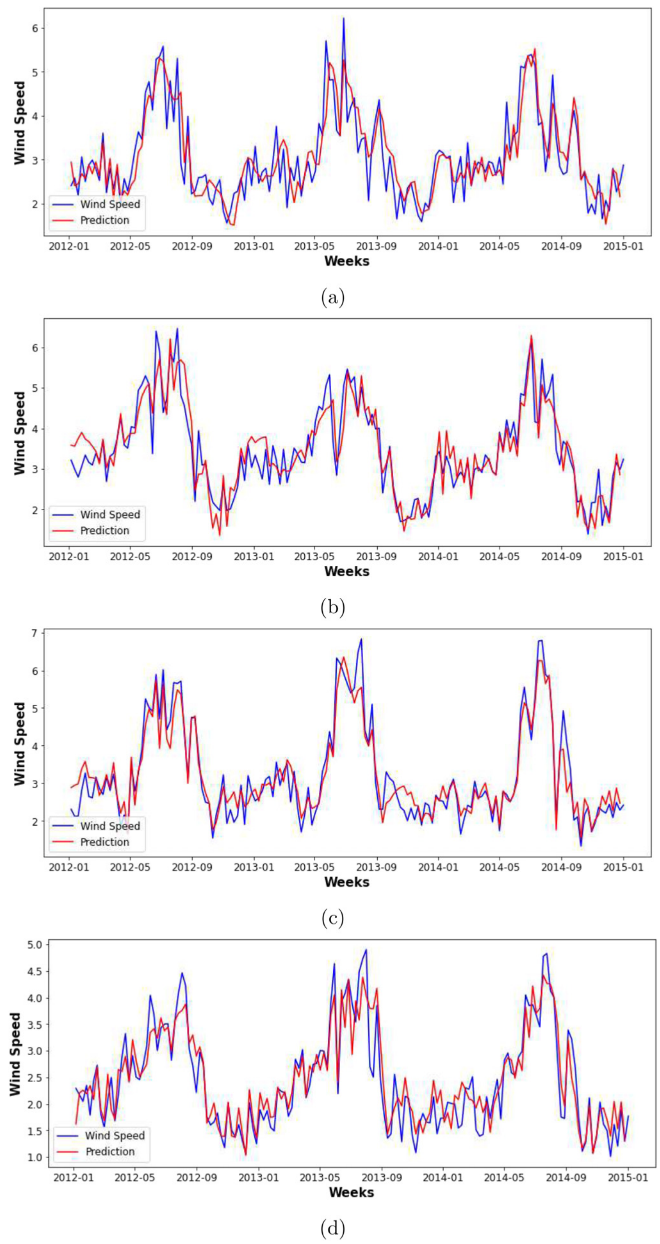

FIG. 5. Weekly wind speed forecasting from the WS-ARIMA model for (a) Rajasthan, (b) Gujarat, (c) Karnataka, and (d) Telangana.

weekly to daily prediction. This is due to the fact that the inclusion of sliding windows has captured seasonal variation more effectively for both data types, while a large number of observations in daily wind speed data have led to its better prediction accuracy.

C. Results of residual analysis

As mentioned earlier, we have performed the residual analysis through standardized residual plots and P–P plots corresponding to the fitted models at chosen time horizons. Figures 6 and 7 represent residual plots, whereas Figs. 8 and 9 represent P–P plots of the standardized residuals. From these plots, we observe that the residuals are symmetric about zero, exhibiting the characteristics of an unbiased model.

V. SUMMARY AND CONCLUSIONS

Reliable forecasting of wind energy is crucial for strategic planning in energy management. In this work, our aim was to introduce a

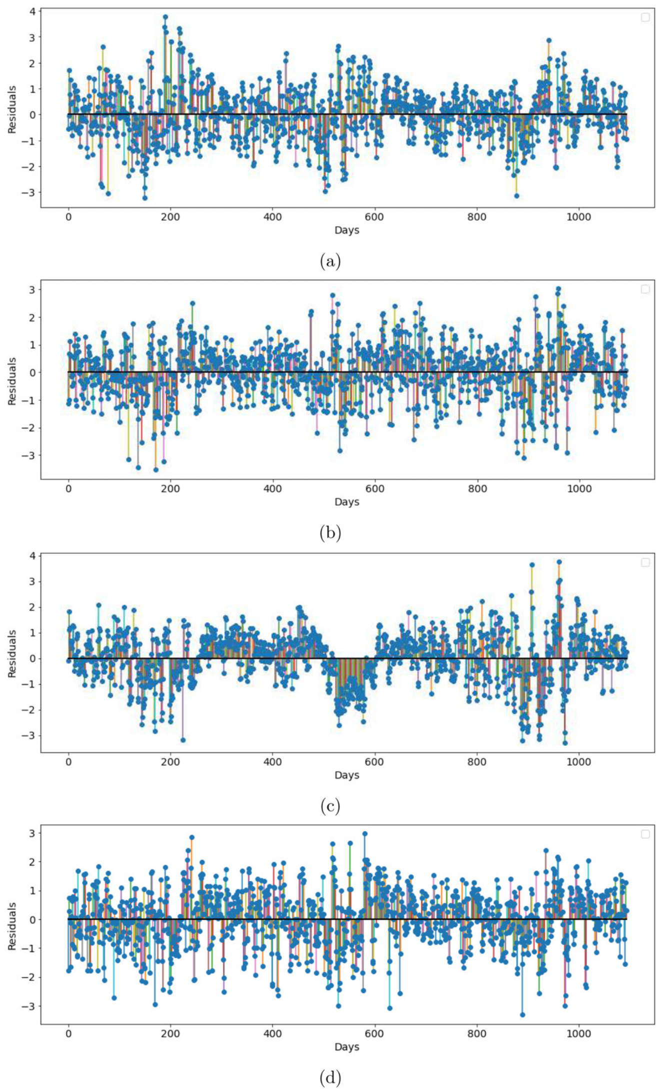

FIG. 6. Residual plot of the standardized residuals of the ARIMA-WS model for daily data at (a) Rajasthan, (b) Gujarat, (c) Karnataka, and (d) Telangana.

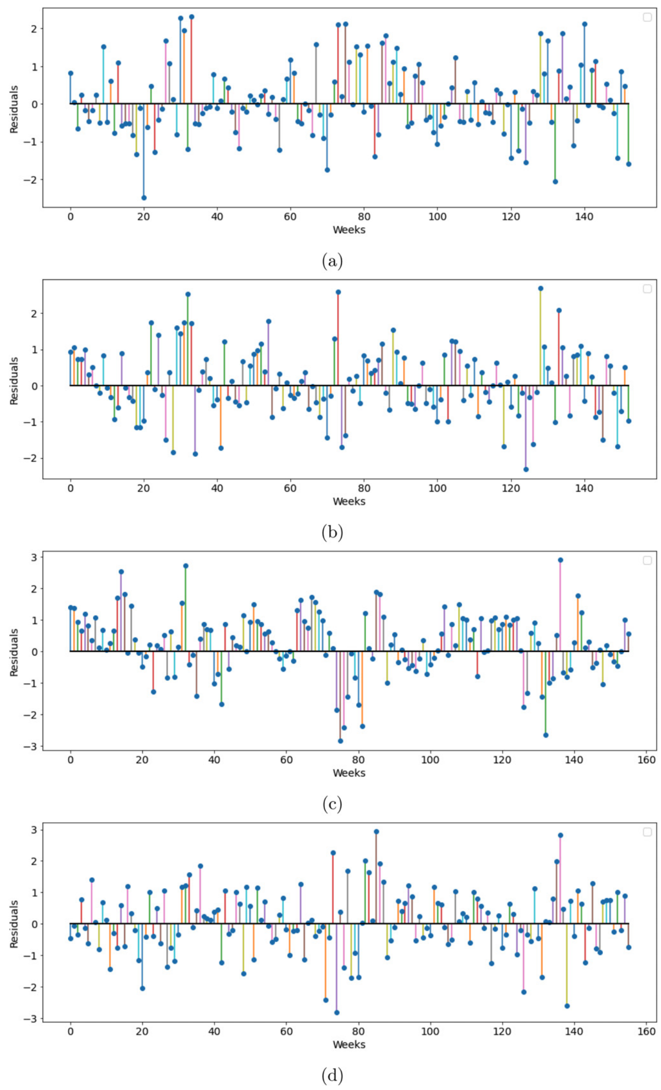

FIG. 7. Residual plot of the standardized residuals of the ARIMA-WS model for weekly data at (a) Rajasthan, (b) Gujarat, (c) Karnataka, and (d) Telangana.

relatively new WS-ARIMA model and test its efficacy in daily and weekly wind speed forecasting at four selected locations in India. For this, first, we collected 15 years (2000–2014) of the wind speed data from publicly available NSRDB database. We then carry out data pre-processing including a stationarity test and data resampling at daily and weekly time scales. Using a grid search method, we obtained the optimal parameters of the ARIMA model, and consequently, we implemented the WS-ARIMA model with window lengths 365 (daily) and 52 (weekly). We compared the relative performance of WS-ARIMA and ARIMA models through RMSE values. We also performed the residual analysis as a post processing strategy to examine any systematic biases in the implemented models. The emanated results lead to the following key observations:

1. The wind speed data at the selected four sites exhibit a stationary behavior. Therefore, neither differencing nor detrending was required, and the ARIMA model turns out to be a simple ARMA model across time and space.
2. The WS-ARIMA model, in comparison to the conventional ARIMA method, yields RMSE reduction up to 75% in daily wind speed data and 50% in weekly data.
3. Unlike conventional ARIMA model, the WS-ARIMA shows that the RMSE decreases when one moves from weekly to daily prediction.

In conclusion, the present study demonstrates that the inclusion of window sliding in ARIMA has resulted in significant accuracy improvement in the wind speed analysis. Therefore, we strongly

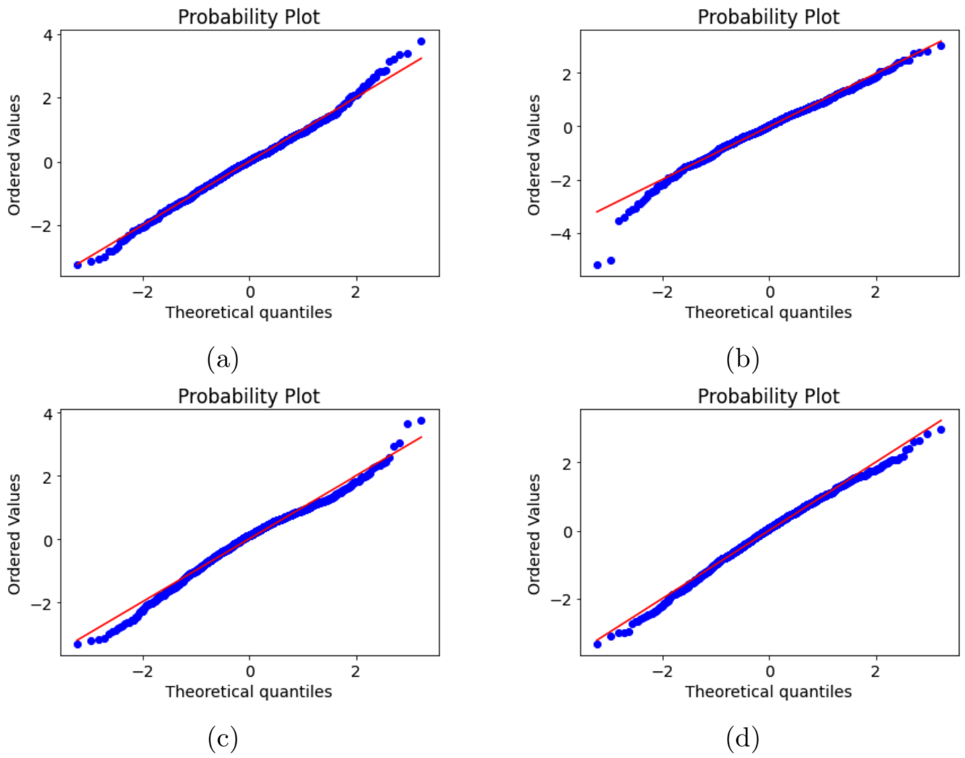

FIG. 8. Probability plots of the standardized residuals of the ARIMA-WS model for daily dataset at (a) Rajasthan, (b) Gujarat, (c) Karnataka, and (d) Telangana.

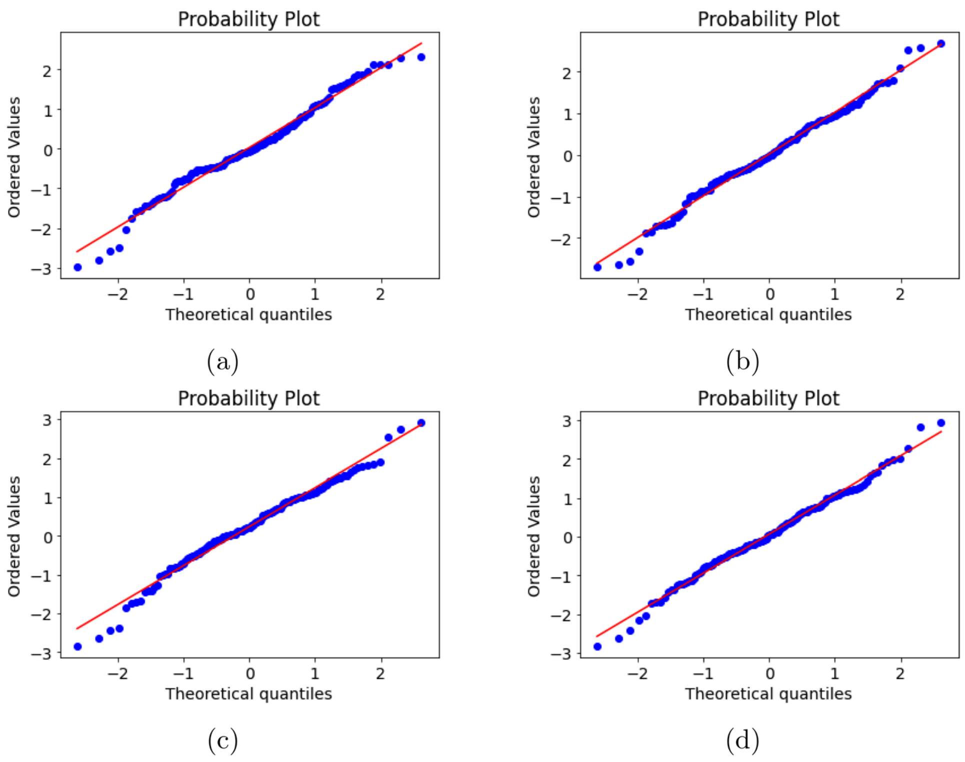

FIG. 9. Probability plots of the standardized residuals of the ARIMA-WS model for weekly dataset at (a) Rajasthan, (b) Gujarat, (c) Karnataka, and (d) Telangana.

recommend the WS-ARIMA model as one of the potential techniques in wind speed forecasting at daily and weekly time horizons.

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AUTHOR DECLARATIONS

Conflict of Interest

The authors have no conflicts to disclose.

Author Contributions

Sarita Sheoran: Formal analysis (equal); Methodology (equal); Software (equal); Writing – original draft (equal). **Sumanta Pasari:** Conceptualization (equal); Data curation (equal); Formal analysis (equal); Methodology (equal); Supervision (equal); Writing – review & editing (equal).

DATA AVAILABILITY

The data for the present study are publicly available in the National Solar Radiation Database (NSRDB) maintained by the U.S. Department of Energy (https://nsrdb.nrel.gov/). The website was last accessed in July 2022.

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