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A Novel and Alternative Approach for Direct and Indirect Wind-Power Prediction Methods

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Received: 9 October 2018; Accepted: 24 October 2018; Published: 26 October 2018

Abstract: Wind energy is a variable energy source with a growing presence in many electrical networks across the world. Wind-speed prediction has become an important tool for many agents involved in energy markets. In this paper, an approach to this problem is proposed by means of a novel method that outperforms results obtained by current direct and indirect wind-power prediction procedures. The first difference is that it is not strictly a direct or indirect method in the conventional sense because it uses information from both wind-speed and wind-power data series to obtain a wind-power series. The second difference is that it smooths down the wind-power series obtained in the first stage, and uses the resulting series for predicting new wind-power values. The process of smoothing is based on the label sequence generation process discussed in the pattern sequence forecasting algorithm and the Naive Bayesian method-based matching process. The result is a less chaotic way to predict wind speed than those offered by other existing methods. It has been assessed in multiple simulations, for which three different error measures have been used.

Keywords: wind speed; wind power; prediction; indirect prediction approach; power curve

1. Introduction

Renewable energy sources, such as solar and wind, are gaining more importance and attention because of the depletion of conventional energy sources, such as fossil fuels, and pollution generated by the combustion of such fuels. Wind power is a clean and sustainable source of energy, and it does not lead to any environmental hazards. Hence, energy generation with wind power has become the main goal of many countries. However, effective power generation with wind energy is quite an uncertain process because of the chaotic and intermittent nature of wind-power availability. This uncertainty in wind power can imperil power availability, quality, and stability. Eventually, this can lead to a huge loss in the energy market. Hence, precise prediction of wind power is a critical task with deep impact and large benefits for humanity.

There are various approaches to forecasting wind power and these can be classified broadly into three categories: (1) model-driven approaches, (2) data-driven approaches, and (3) hybrid approaches [1]. Model-driven approaches require abundant meteorological knowledge and information of various physical factors affecting wind power [2]. In data-driven approaches, on the other hand, data-driven statistical models are used for forecasting. With the advancement in the artificial-intelligence and data-science fields, more accurate prediction results can be achieved with this approach [3]. Historical data are the only requirement for such models. Many research articles describe the performance of distinct data-driven models, such as the basic persistence model [4], and complex models, including support vector machines (SVM) [5,6], neural networks (NN) [7,8], and autoregressive integrated moving average (ARIMA) [9]. However, due to the highly stochastic and intermittent nature of wind-power time series, it is difficult to predict within a significantly accurate range.

Wind-power prediction studies are broadly classified into direct and indirect approaches. In direct approaches, wind-power data are directly predicted by various methods. The advantage of this kind of approach is that there is no need to study the relations between wind-power and wind-speed parameters. However, the prediction accuracy of a direct approach is not always good enough since wind-power data usually show high levels of randomness and a chaotic nature. Such wind-power data are very difficult to efficiently process with the prediction methods.

To overcome this difficulty, another part of the available studies focused on indirect prediction approaches. In this kind of approach, wind-speed data are firstly forecasted, and then the predicted data converted into wind-power data by means of various techniques. However, in practice, while transforming wind-speed into wind-power data, further errors are made in prediction accuracy because of inaccuracies in nonlinear power curve analysis. Generally, wind power and wind speed are related in terms of cubic or higher-order powers. Hence, a small change in wind speed leads to larger and significant deviations in wind power. The success of an indirect approach is in how it evaluates the nonlinear dependence between wind-power and wind-speed data. Such error evaluations lead to a rise in learning accuracy and comprehensibility. Instead of manufacturer power curves, statistical techniques seem to be a better option to describe the nonlinear relationship between wind power and wind speed. Higher-order polynomial equations, exponential, fitted power, regression, logistic, and many other models are used to estimate wind power by using explanatory wind-speed datasets.

While reviewing the literature related to short-term wind-power prediction, there is a large number of articles that are focused on direct wind-power as well as wind-speed predictions [10–12].

However, there are very few articles that have compared the performance of direct and indirect approaches. Most of them have evidenced that the best prediction accuracy comes with direct approaches [10,11], whereas Reference [12] concluded that an indirect approach performed better than the alternative.

In this paper, a novel approach is presented in order to eliminate the drawbacks of both direct and indirect prediction methods used in wind-power predictions. The proposed method cannot be classified into any of the commented groups because it uses combined information from wind-speed and wind-power series. In this sense, it is an alternative method and behaves as a direct–indirect hybrid that does not directly or indirectly predict power. It starts by smoothing down a wind-power time series by keeping respective wind-speed data as a reference. The process of smoothing down is based on the label sequence generation process discussed in the PSF algorithm and the Naïve Bayesian method-based matching process following the next procedure. Wind-speed and wind-power data are converted into a sequence of labels. Then, these labels are mapped and their best combination is estimated. Keeping these combinations as a reference, the wind-power labels are smoothed down and further predicted with the steps involved in the PSF method. After following this procedure, an important consequence is to reduce the degree of chaos contained in the resulting predicted series.

Multiple simulations have been carried out with the aim of collecting a contingent of results. Three different error measures have been used in order to quantify how much the proposed method outperforms existing ones.

The rest of the paper is organized as follows: Section 2 describes the steps involved in the PSF algorithm. Section 3 introduces the proposed methodology and the description of the prediction methodology for wind-power forecasting. Section 4 shows the results obtained by the proposed approach in predicting wind power, including their quality measurements. Comparisons between the proposed method and other techniques are also provided. Finally, Section 5 summarizes the conclusions achieved with regard to wind-power predictions.

2. Conventional PSF Methodology

The PSF algorithm is one of the most popular types of univariate time-series prediction methodology, proposed in Reference [13] and further analyzed in Reference [14]. The basic principle behind predictions with the PSF algorithm is an optimum search of pattern sequences present in a time series. This methodology consists of several processes that operate in two steps. During the first step, data are clustered, and during the second, the forecasting process is carried out based on the previously clustered data, as shown in Figure 1. The novelty of the PSF algorithm is the utilization of labels for respective pattern sequences present in a time series, instead of the use of the original time-series data.

The clustering step consists of various tasks, including data normalization, the selection of an optimum number of clusters, and the application of k-means clustering. The ultimate aim of this step is to discover clusters of time-series data and accordingly label them. This starts with a normalization process, in which the time series is normalized with Equation (1) in order to remove the redundancies present in it.

$$X_j = \frac{X_j}{\frac{1}{N}\sum_{i=1}^{N} X_i} \tag{1}$$

where X_j is the jth value of each cycle in the input time series, and N is its size in time units. Secondly, the normalized series is assigned with the labels according to different patterns present in it with the help of clustering methods. In PSF, a k-means clustering method is used because of its popularity, simplicity, and fast computing nature. However, it requires prior knowledge of a number of centers so that the series can be clustered in respective numbers of clusters. Reference [13] utilized the Silhouette index [15] to decide the number of clusters in PSF methodology, whereas Reference [14] suggested the 'best among three' policy to decide the optimum number of clusters, in which three different indices (the Silhouette index [15], Dunn index [16], and Davies–Bouldin index [17]) are used. In this policy, the cluster size is finalized with the use of multiple statistical tests to ensure efficiency in the clustering process. Further, References [18–20] used a single index (Silhouette index [15]) to simplify computation complexity in the clustering process.

Then, with respect to cluster heads (K) generated with the k-means clustering method, the values in the original time series are transformed into label series. These label series are further used for the prediction procedure. This prediction procedure consists of window-size selection, pattern sequence matching, and an estimation process.

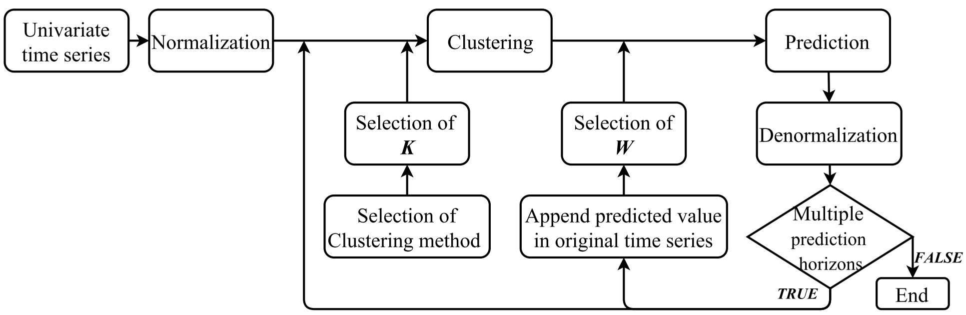

Figure 1. Steps involved in PSF method.

Consider that $x(t)$ is the vector of time-series data of length N, such that $x(t) = [x_1(t), x_2(t), ..., x_N(t)]$. After clustering and labeling, the vector is converted into $y(t) = [L_1, L_2, ..., L_N]$, where L_i are labels representing the cluster centers to which data in vector $x(t)$ belongs. Then, during the process, the last W labels are searched in vector $y(t)$. If this sequence of the last W labels is not found in $y(t)$, then the search process is repeated for the last $W - 1$ labels. In PSF, the length of this label sequence of size W is denoted as the window size. Therefore, window size can vary from W to 1, although this is not usual. In the window-size selection process, the sequence of labels of length size W were picked from the backward direction, and this sequence was searched in the label series. The selection of optimum window (W) is one of the most challenging processes in prediction with PSF in order to minimize the prediction errors. The mathematical expression for an optimum window size is the minimization of Equation (2):

$$\sum_{t \epsilon TS} \left\| \hat{X}(t) - X(t) \right\| \tag{2}$$

where $\hat{X}(t)$ is a predicted value at time t, $X(t)$ is the measured data at same time instance, and TS represents the time series under study. Practically, the estimation of an optimum window size is done by means of errors validation. However, while searching a sequence W in the label series, if this sequence is not found, then the size of W is reduced by one unit. Again, this process continues until a new window sequence repeats itself in the label series at least once. This confirms that at least one sequence appears more than once in the label series. Once the optimum window size is obtained, the available pattern sequence in the window is searched in $y(t)$, and the label present just after each discovered sequence is noted in a new vector ES. Finally, the future time-series value is predicted by averaging the values in vector ES as in Equation (3).

$$\bar{X} = \frac{1}{size(ES)} \times \sum_{j=1}^{size(ES)} ES(j) \tag{3}$$

where $size(ES)$ is the length of vector ES. Finally, the predicted labels are replaced with the appropriate value in a range of an original measured time series with a denormalization process. However, in order to predict future values for multiple time indices, the current predicted value is appended to the original time series, and this procedure continues until the desired number of prediction values are obtained. The usability and superior performance of the PSF method for distinct univariate time-series prediction applications are discussed in References [20–24].

3. Proposed Methodology

The conventional PSF algorithm has gained popularity because of its superior and promising prediction performance for univariate time series. Also, PSF has shown its capability in wind-power and wind-speed predictions in [25]. The methodology proposed in this paper is focused on predicting wind-power data samples framed in a time series with the assistance of corresponding wind-speed data. The prediction concept is based on the PSF algorithm. This novel methodology is proposed as an alternative to direct and indirect wind-power prediction approaches. In this methodology, the wind-power time series is predicted with modifications in conventional PSF and dataset smoothing. In contradiction to state-of-the-art methods and approaches, the significant difference in the proposed approach is the utilization of both wind-power and wind-speed datasets to achieve better accuracy in wind-power predictions.

Usually, researchers have used indirect wind-power prediction approaches due to the highly chaotic nature of wind-power time series. In comparison to wind-speed time series, the nature of respective wind-power time series is more chaotic and intermittent. Hence, it is difficult to predict them more accurately. Contrary to this, indirect approach methods are associated with additional errors accumulated by the curve fitting of power curves. The proposed approach attempts to reduce the prediction errors associated with both direct and indirect approaches. Firstly, this approach smooths down wind-power time series with the help of wind-speed time series by using the same labeling sequence technique as the one used in the conventional PSF algorithm. Secondly, it predicts the future values of wind-power time series with PSF principles.

Given wind-speed and wind-power values recorded in the past at a specific interval (5, 15, 30, and 60 min) up to the day $(d-1)$, the prediction of future values of wind power is expected at the next few intervals (of same precision) for day d. Consider that TS_P and TS_S are the time series composed of 'n' samples of wind power and wind speed, respectively, as follows:

$$TS_P = [x_1, x_2, \ldots, x_n] \tag{4}$$

$$TS_S = [y_1, y_2, \ldots, y_n] \tag{5}$$

Similar to the procedure followed in PSF, TS_P and TS_S are converted into label sequence LS_P and LS_S, respectively.

Let $L_i,\ i \in \{1, ..., K\}$ be the labels of day i obtained in the labeling step of the PSF method, where K is the number of clusters. LS_P and LS_S are the label sequence of W consecutive days, as follows:

$$LS_{P,W}^{t-1} = [L_{P,t-W}, L_{P,t-W+1}, \ldots, L_{P,t-1}] \tag{6}$$

$$LS_{S,W}^{t-1} = [L_{S,t-W}, L_{S,t-W+1}, \ldots, L_{S,t-1}] \tag{7}$$

The next step is to map the LS_P sequence with the LS_S sequence. This mapping is done with decision matrix (M) that uses the Naïve Bayesian method. The motive of this matrix is to represent the pair of each label in LS_S with all corresponding labels from LS_P with respective occurrence probabilities of each pair. The formulation of decision matrix (M) is done with four parameters: labels from LS_S at t and $t-1$, labels from LS_P at t, and the probability of occurrence of respective combinations, where t is the label sequence index (LS_P and LS_S).

$$M = f(LS_S(t-1), LS_S(t), LS_P(t), PO) \tag{8}$$

where PO stands for probability of occurrence.

Table 1 shows a sample decision matrix, where the first three columns are the combinations of labels of $LS_S(t-1)$, $LS_S(t)$, and $LS_P(t)$, and the fourth one is the probability of occurrence of a combination of labels. It can often be possible in a decision matrix that each label in LS_S has multiple alternatives in respective labels in LS_P, with different probabilities of occurrence. In such cases, the Naïve Bayesian method is used to map the most suitable pairs in LS_P and LS_S. This mapping of labels generates a look-up table (LUT), as shown in Table 2, which is referred further to smooth down the TS_P sequence as indicated in Equation (9):

$$LUT = f(NB(LS_P, LS_S)) \tag{9}$$

where NB is the Naïve Bayesian function.

The next process is the smoothing of the TS_P series. This process is performed with the consideration of the above-mentioned look-up table. Firstly, all labels in LS_S are compared with the respective labels in LS_P. The ideal cases are considered wherever these matching pairs follow the pairs, as mentioned in the look-up table as shown in Equation (10):

$$[L_{S,t}, L_{S,t-1}, L_{P,t}] \in LUT \tag{10}$$

Whereas for mismatched cases, the labels in LS_P are replaced with the labels corresponding to the respective LS_S in the look-up table, as shown in Equation (11):

$$[L_{S,t}, L_{S,t-1}, L_{P,t}] \leftarrow [L_{S,t}, L_{S,t-1}, L_{P,LUT,t}] \tag{11}$$

where $[L_{S,t}, L_{S,t-1}, L_{P,t}] \notin LUT$, $L_{S,t}$, $L_{P,t}$ are the labels in LS_P and LS_S, respectively, and $L_{P,LUT,t}$ is a replacement of $L_{P,t}$ from the look-up table at nonideal cases.

Table 1. Decision matrix.

$LS_S(t-1)$	$LS_S(t)$	$LS_P(t)$	Probability of Occurrence (%)
L_2	L_1	L_3	63.15
L_2	L_1	L_2	27.66
L_2	L_1	L_4	09.19
L_3	L_1	L_3	65.78
L_3	L_1	L_4	11.05
$\vdots$	$\vdots$	$\vdots$	$\vdots$
L_3	L_2	L_5	58.33
L_3	L_2	L_4	23.27
$\vdots$	$\vdots$	$\vdots$	$\vdots$
L_4	L_2	L_6	41.66
L_4	L_2	L_5	38.03
$\vdots$	$\vdots$	$\vdots$	$\vdots$
L_1	L_3	L_1	70.12
L_1	L_3	L_2	17.32
L_1	L_3	L_4	12.56
L_2	L_3	L_1	80.67
L_2	L_3	L_2	19.33
L_4	L_3	L_2	100.00
L_5	L_3	L_7	35.50
$\vdots$	$\vdots$	$\vdots$	$\vdots$

Table 2. Look-up table.

$LS_S(t-1)$	Matching of Labels						
L_1	$LS_S(t)$	L_1	L_2	L_3	L_4	L_5	$\cdots$
	$LS_P(t)$	-	-	L_1	L_2	L_7	$\cdots$
L_2	$LS_S(t)$	L_1	L_2	L_3	L_4	L_5	$\cdots$
	$LS_P(t)$	L_3	-	L_1	L_2	L_7	$\cdots$
L_3	$LS_S(t)$	L_1	L_2	L_3	L_4	L_5	$\cdots$
	$LS_P(t)$	L_3	L_5	-	L_2	L_7	$\cdots$
L_4	$LS_S(t)$	L_1	L_2	L_3	L_4	L_5	$\cdots$
	$LS_P(t)$	-	L_6	L_2	L_2	-	$\cdots$
$\vdots$	$\vdots$	$\vdots$	$\vdots$	$\vdots$	$\vdots$	$\vdots$	$\ldots$

Eventually, this leads to the removal of labels in LS_P responsible for making the wind-power time series more chaotic and intermittent, and to generate a smoother sequence of wind-power labels ($\overline{LS}_P$). This new sequence series ($\overline{LS}_P$) possesses a positive but much smaller Maximum Lyapunov Exponent (MLE) compared to that of LS_P, as shown in Section 4.3. The correlation coefficient between $\overline{LS}_P$ and LS_S is also smaller than the one between LS_P and LS_S. This assures that the $\overline{LS}_P$ sequence is smoother and more favorable for future values prediction than LS_P. The procedure of the proposed methodology is illustrated in graphical form and a block diagram in Figures 2 and 3, respectively. It is also expressed in terms of pseudocode in Figure 4.

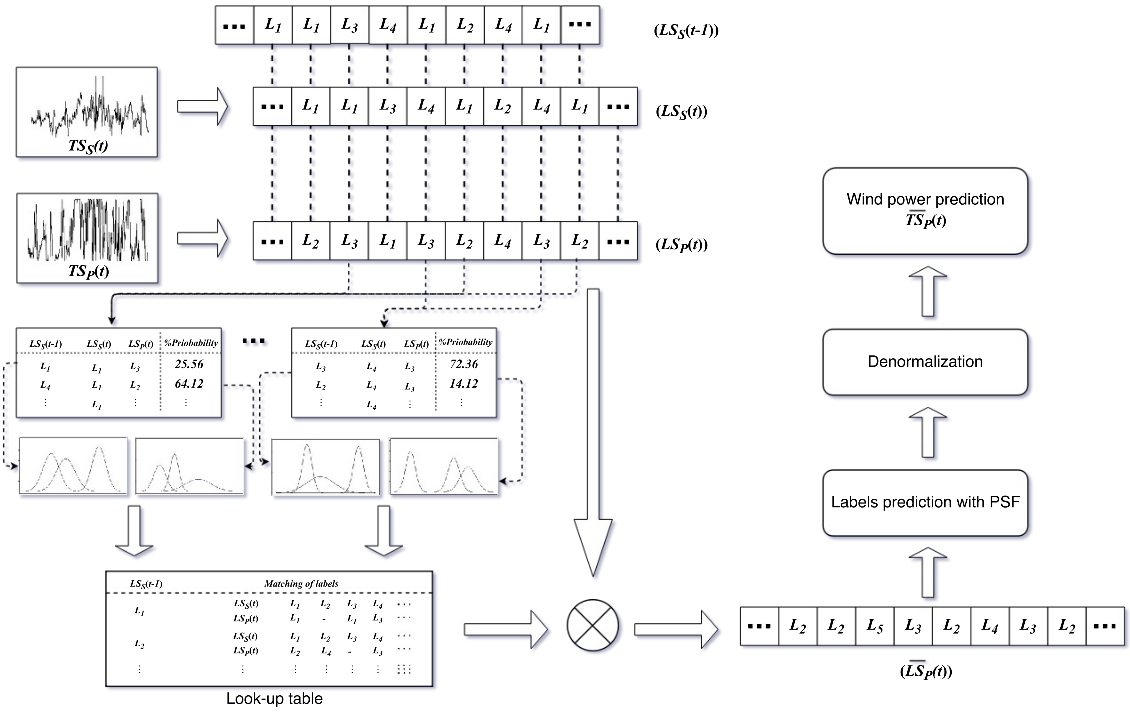

Figure 2. Steps involved in the proposed methodology.

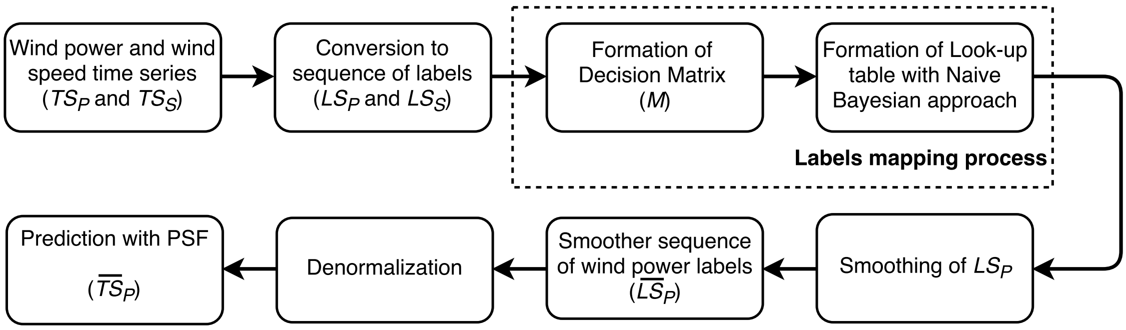

Figure 3. Block diagram of the proposed methodology.

Furthermore, the prediction process after smoothing LS_P is adopted from a conventional PSF algorithm. It starts with the calculation of optimum window (W) selection. Similar to the conventional PSF algorithm, the last W-sized label sequences in $\overline{LS}_P$ are searched for in the whole $\overline{LS}_P$ series. The mean of the very next label of each repetition of this window (W) sequence is noted as the future value of $\overline{LS}_P$, and it is again replaced with a value within the range of TS_P with the denormalization process.

Input: Dataset D, number of clusters K, labeled dataset $[L_1, L_2, ..., L_{t-2}, L_{t-1}]$
Variables: Label sequence of power $LS_{P,W}$ and speed $LS_{S,W}$ data, length of window W, test set T, decision matrix M, and look-up table LUT
Output: Forecasts $\overline{TS}_P(t)$ for all time intervals of T

Proposed Methodology()
$ES_t \leftarrow \{\}$
$\overline{TS}_P(t) \leftarrow 0$
for each time index $t \in T$
  $LS^{t-1}_{P,W} \leftarrow [L_{P,t-W}, L_{P,t-W+1}, \ldots, L_{P,t-1}]$
  $LS^{t-1}_{S,W} \leftarrow [L_{S,t-W}, L_{S,t-W+1}, \ldots, L_{S,t-1}]$
  $M \leftarrow \text{mapping}(LS^{t-1}_{P,W}, LS^{t-1}_{S,W})$
  $LUT \leftarrow \text{Neive\_Bayesian}(M)$
  $\overline{LS}^{t-1}_{P,W} \leftarrow \text{smoothing}(LS^{t-1}_{P,W}, f(LUT))$
  for each j such as $TS_P(j) \in D$
    $S^j_W \leftarrow [L_{j-W+1}, L_{j-W+2}, \ldots, L_{j-1}, L_j]$
    if$(S^j_W = S^{t-1}_W)$
      $ES_t \leftarrow ES_t \bigcup j$
  for each $j \in ES_t$
    $\overline{TS}_P(t) \leftarrow \overline{TS}_P(t) + TS_P(j+1)$
  $\overline{TS}_P(t) \leftarrow \overline{TS}_P(t)/size(ES_t)$
  $D \leftarrow D \triangleright \overline{TS}_P(t)$
  $[L_1, L_2, ..., L_{t-1}, L_t] \leftarrow \text{clustering}(D, K)$
  $t \leftarrow t + 1$
return $\overline{TS}_P(t)$ for all time intervals of T

Figure 4. Pseudocode for the proposed methodology.

4. Case Study

4.1. Description of Experimental Data

The proposed methodology can be better understood if it is accompanied by a numerical example. This section aims at proving that the proposed method can outperform results obtained by only using a PSF algorithm without involving the smoothing process. In this study, the performance of the proposed prediction approach was evaluated using wind-power and wind-speed datasets collected from the website of the National Renewable Energy Laboratory (NREL), USA [26]. The wind data were measured in 2012 at a time interval of 5 min. With the same resolution of 5 min, the wind-speed and -power datasets were segmented for a week from the four seasons (winter, spring, summer, and autumn). Both wind power and wind speed were measured at the same time interval at the same location. The basic statistical parameters of these datasets are discussed in Table 3. The mean, median, minimum, and maximum values of all datasets are shown, which express the variation and deviation in wind data with respect to the change in seasonal conditions.

4.2. Observations

The proposed methodology has been tested by checking three error performance measures. These are Root Mean Square Error (RMSE), Mean Absolute Error (MAE), and Mean Absolute Percentage Error (MAPE), which are as given in Equations (12)–(14).

$$RMSE = \sqrt{\frac{1}{N}\sum_{i=1}^{N}\left|X_i - \hat{X}_i\right|^2} \tag{12}$$

$$MAE = \frac{1}{N}\sum_{i=1}^{N}\left|X_i - \hat{X}_i\right| \tag{13}$$

$$MAPE = \frac{1}{N}\sum_{i=1}^{N}\frac{|X_i - \hat{X}_i|}{X_i} \times 100\% \tag{14}$$

where X_i and $\hat{X}_i$ are the measured and predicted data at time t, respectively. N is the number of data for prediction evaluation.

Table 3. Statistical characteristics of datasets.

Season		Min	Median	Mean	Max
Winter	Power	0.000	2.995	3.604	12.784
	Speed	0.204	6.251	6.191	11.011
Spring	Power	0.000	9.049	8.601	14.000
	Speed	0.164	9.274	12.203	21.100
Summer	Power	0.000	2.883	3.806	14.000
	Speed	0.161	6.397	6.215	22.740
Autumn	Power	0.000	1.549	2.699	13.987
	Speed	0.061	5.212	5.294	13.483
One Year	Power	0.000	3.411	4.985	14.000
	Speed	0.036	6.655	6.998	30.367

The RMSE and MAE values indicate sample standard deviation and variation between measured and predicted data, respectively, whereas MAPE values show accurate sensitivity measurements for minute changes in the predicted data.

Further, the prediction accuracy of the proposed method is compared with seven distinct state-of-the-art methods used for short-term wind-power prediction applications with similar time horizons. The performance of the proposed method is compared with ARIMA [11,27], Persistence Model (PM) [28,29], Nonlinear AutoRegressive eXogenous model (NARX) [30], SVM [31,32], and Multilayer Perceptron neural network (MLP) [33], Extreme Learning Machine neural network (ELM) [34], and PSF [25] models for each week's dataset from all four seasons, as well as for the one-year dataset. All comparisons are performed for 5, 15, 30, and 60 min ahead of value prediction.

Since the proposed method is presented as an alternative to direct and indirect prediction approaches, its comparison is done with both direct and indirect approaches. In the direct approach, wind-power datasets are directly predicted with all methods under study, whereas in the indirect prediction approach, wind-speed datasets are predicted with prediction methods and then transformed into wind-power data with the use of power curves. In this study, four different power curve fitting techniques are used, these being the fourth-order polynomial, exponential, fitted-power, and regression models. The corresponding seasonwise equations are discussed in Appendix A. These equations are derived by fitting the power curves of datasets of each season as illustrated in Figure 5. Further in Appendix B, Tables A5 and A6 show the prediction results of state-of-the-art methods with direct prediction approaches, and those of indirect approaches are tabulated in Tables A5b and A6a–c for the fourth-order polynomial, exponential, fitted-power, and regression models, respectively. On the same comparison platform, the prediction results of the proposed approach are shown in Table 4.

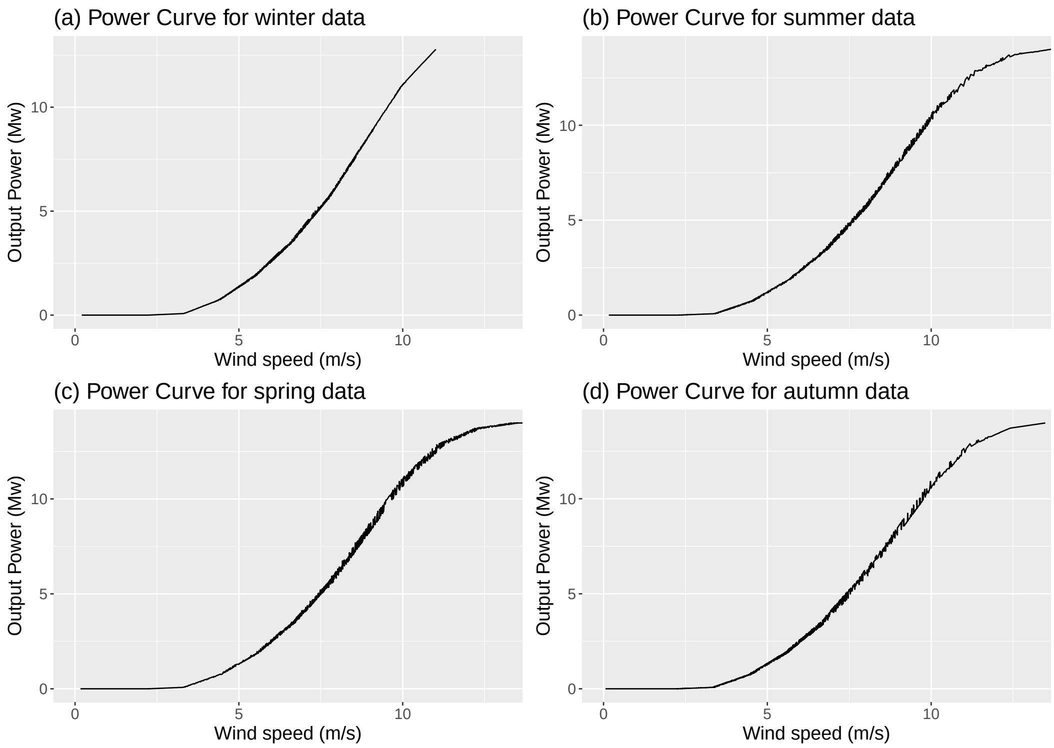

Figure 5. Power curves for datasets from (**a**) winter, (**b**) summer, (**c**) spring, and (**d**) autumn.

Table 4. Performance of proposed methodology for wind power predictions.

Seasons	Prediction Horizon (in Minutes)	5	15	30	60
Winter	**RMSE**	0.005	0.054	0.077	0.127
	MAE	0.005	0.050	0.072	0.108
	MAPE	0.16	0.776	1.321	2.033
Spring	**RMSE**	0.032	0.124	0.127	0.116
	MAE	0.032	0.094	0.109	0.097
	MAPE	1.972	5.586	7.671	6.577
Summer	**RMSE**	0.07	0.172	0.356	0.388
	MAE	0.07	0.156	0.310	0.333
	MAPE	7.772	22.131	37.117	43.49
Autumn	**RMSE**	0.051	0.146	0.213	0.316
	MAE	0.051	0.125	0.168	0.251
	MAPE	1.524	3.456	4.475	6.523

However, by primarily observing these tables, the lower RMSE, MAE and MAPE values in the case of the proposed approach indicates its better prediction accuracy and usability. A more detailed comparative analysis of the case study is discussed below.

4.3. Discussion

Tables A5 and A6 provide a comparison between distinct prediction models in terms of three statistical measures for different datasets at different prediction horizons. By simply observing this table, it can be stated that none of the methods shows superior performance in any cases. Hence, it is extremely difficult to make a generalized statement regarding any model that could provide the best prediction method for any wind-power time series. Furthermore, it can be observed that the methods' performance varies with changes in the prediction horizon. In other words, It does not necessarily happen that the method performing the best very short-term prediction horizon is also the best one for short-term horizon prediction. It is even difficult to generally state which method is superior between direct or indirect approaches.

In order to address this ambiguity, the results in Tables A5 and A6 were further analyzed in a different format, as shown in Tables 5 and 6. Table 5 indicates the performance of all methods excluding the proposed method, collectively for all datasets (one-week data for all four seasons). Each value in this table represents the percentage of the respective methods that outperformed all other methods in the comparison. The overall comparison shows that ARIMA, SVM, and PSF showed the best performance in most cases. These methods outperformed other methods in 16.25%, 22.50%, and 26.25% of cases, respectively. However, if the comparison is done on the basis of prediction horizons, prediction-method performance significantly varied. In this study, for a 5 min ahead prediction horizon, PSF showed the best performance in 45% of cases, whereas such dominant performance was not observed by any method in the 15, 30, and 60 min ahead prediction horizons. Nearly similar and mixed performance was achieved with most of the methods. It is important to note that the performance of the ELM models was better in most cases, but while representing the best-performing methods in Table 5, it only reflected 7.5%. Such misleading results are reflected because prediction accuracy associated with ELM was very near but quite larger than the best-performing methods. Contrary to this, the PM method showed the worst prediction accuracy in almost all cases.

Table 5. Percentages of best performance of state-of-the-art methods for different prediction horizons.

Prediction Horizon (in Min.)	5	15	30	60	Overall
ARIMA	0	20	25	20	16.25
PM	5	5	10	20	7.50
NARX	15	15	15	15	15
SVM	25	25	15	25	22.50
MLP	10	20	20	10	15
ELM	0	10	5	10	6.25
MLP	45	15	20	25	26.25

Interestingly, the best performance percentage in Table 5 changed significantly with the inclusion of the proposed method, because the errors corresponding to the proposed method were lesser than the contemporary methods. The prediction errors for all seasons with the proposed methods are tabulated in Table 4. The proposed method showed the best performance in almost all cases. This quantified comparison shows the superiority of the proposed method for wind-power predictions. Additionally, this case study examined and compared the performance of direct and indirect prediction approaches with the proposed approach as shown in Table 6. This table presents the percentage of cases at which the corresponding technique (direct or indirect) performed best among other techniques with all prediction methods in the dataset study from all seasons. These techniques are compared for different prediction horizons (5, 15, 30, and 60 min). In this study, the direct prediction approach has outperformed all indirect techniques for all four prediction horizons. Eventually, the direct approach performed best in overall situations for all seasons. By comparing the performance of indirect approach techniques, the regression model showed better prediction accuracy in more cases than other techniques for all prediction horizons.

So far, the comparative study explained the superior performance of the proposed methodology for week-sized datasets collected from the different seasons in a year. However, it would be interesting to observe its performance during a whole one-year dataset, and to know the effects of seasonal variations on prediction accuracy. Figure 6a,b illustrates the wind-speed and wind-power time series (initial 5000 samples) of the whole one-year dataset, respectively. The power curve between these time series is also shown in Figure 6c. As discussed in Section 3, the proposed methodology smooths down the wind-power time series as shown in Figure 6d. The changes in amplitudes of smoother time series ($\overline{TS}_P$ as shown in Figure 6d) at various samples are clearly visible as compared to measured wind power time series (TS_P). These significant changes in amplitudes of $\overline{TS}_P$ remove the chaotic components in it, so that maximum Lyapunov exponent, which was 0.9898 for TS_P is reduced to 0.9221 for $\overline{TS}_P$. It was also observed that $\overline{TS}_P$ was more correlated to the TS_S time series (Correlation coefficient was 0.981) than to that of TS_P (correlation coefficient was 0.9421). This makes time series more favorable for prediction with PSF methodologies.

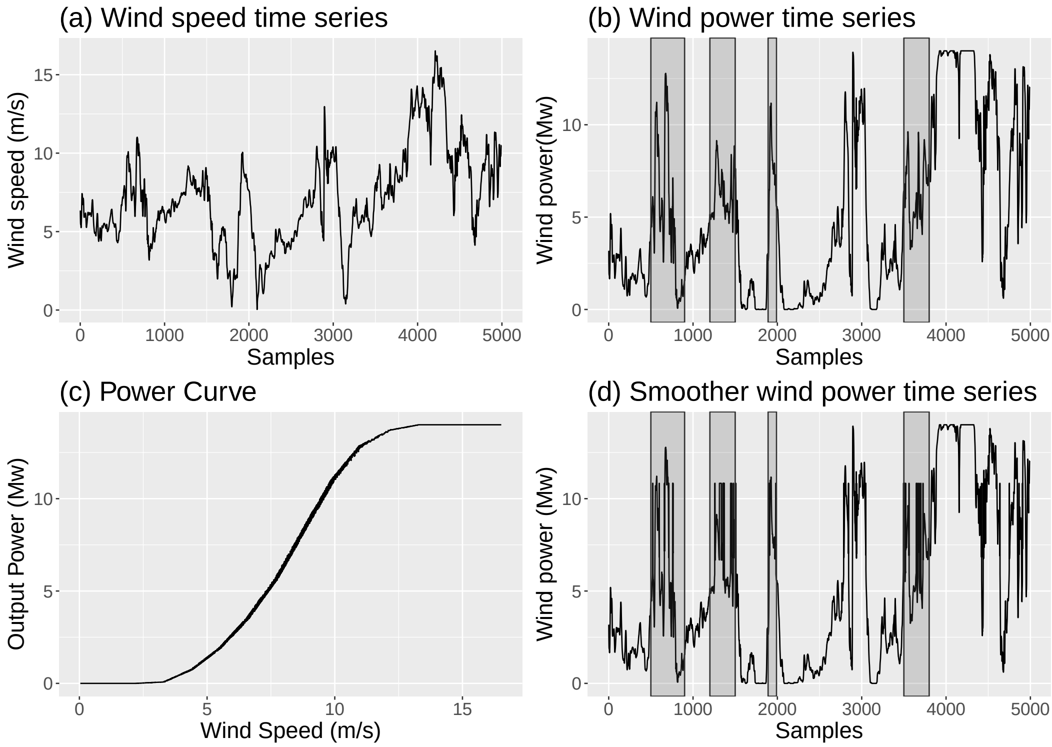

Figure 6. Illustrations of a whole one-year dataset used in the study: initial 5000 samples of (**a**) wind-speed and (**b**) wind-power time series; (**c**) power curve; (**d**) smoother wind-power time series with the proposed method.

Further, Figure 7 shows the prediction comparison of the initial 100 samples of the observed and predicted values respective to the validating time series. The comparison of prediction error values for the whole one-year dataset for distinct time horizons for the proposed and other contemporary methods is also shown in Table 7. Similar to earlier comparisons for datasets from different seasons, Figure 7 and Table 7 reflect the superior prediction performance of the proposed methodology.

Table 6. Percentages of best performance of direct and indirect prediction approaches for different prediction horizons.

Prediction Horizon (in Minutes)	5	15	30	60	Overall
Direct Approach	67.84	42.85	32.14	28.57	42.85
Forth order polynomial	0	7.14	10.71	10.71	7.14
Exponential models	10.71	7.14	7.14	20.42	11.60
Fitted power model	3.57	14.28	17.85	17.85	13.39
Regression model	17.85	35.71	32.14	20.42	26.78

Last four rows are curve-fitting techniques used for indirect approaches.

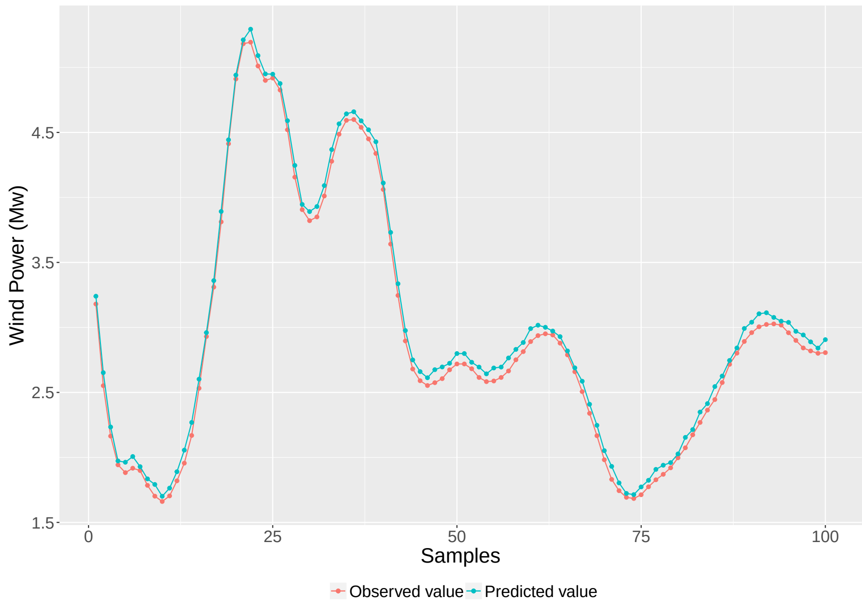

Figure 7. Comparison of observed and predicted values of a whole one-year dataset (initial 100 samples).

Table 7. Comparison of proposed methodology with contemporary methods for a whole one-year dataset.

Errors	Time (min)	ARIMA	PM	NARX	SVM	MLP	ELM	PSF	Proposed Method
RMSE	5	0.227	0.508	0.186	0.742	0.170	0.182	0.221	0.134
	15	0.365	1.203	0.912	1.016	0.621	0.364	0.371	0.289
	30	1.991	3.94	2.758	2.593	2.159	1.908	1.836	1.178
	60	1.952	7.301	2.727	2.549	2.036	1.842	1.935	1.210
MAE	5	0.227	0.508	0.186	0.742	0.120	0.182	0.221	0.134
	15	0.319	1.203	0.700	0.966	0.450	0.291	0.358	0.267
	30	1.515	3.94	2.217	2.216	1.693	1.445	1.733	1.059
	60	1.553	7.301	2.330	2.234	1.634	1.451	1.860	1.180
MAPE	5	3.841	7.904	2.756	12.547	2.339	3.081	3.791	2.127
	15	5.054	19.61	10.953	15.475	6.989	4.569	5.117	3.969
	30	17.91	56.72	26.777	27.499	20.231	17.042	17.552	15.238
	60	18.68	99.49	28.827	27.924	19.741	17.410	18.734	15.688

5. Conclusions

In this paper, a wind-power forecasting algorithm has been proposed, which can be considered an alternative method to direct and indirect approaches. While a direct approach directly predicts power, and an indirect approach does so with the help of power curves after previous predictions of wind speed, the proposed method combines both wind-speed and wind-power data, smooths down the resulting wind-power series, and uses them for predicting wind power in a clearly less chaotic way than existing methods do.

Multiple simulations were carried out with the aim of collecting a contingent of results. Three different error measures were used in order to quantify how much the proposed method can be said to outperform existing ones. Our conclusions are outlined in the next few paragraphs.

Direct prediction approaches show more accuracy in forecasts in comparison to indirect approaches in terms of all three error measures. The crucial reason behind these observations is that power curves are only based on the average deterministic relationships between wind-speed and -power datasets. However, such relationships are actually stochastic in nature. Power-curve variability is the significant factor to reduce wind-power prediction accuracy. In contrast, in the proposed method, all time instances in a wind-power time series are handled and modified individually on a case-by-case basis. This smooths down the time series and removes stochastic patterns in it up to an extent.

As shown in Table 6 and discussed in the corresponding section, between the contemporary methods, ARIMA, SVM, and PSF showed the best performance for both direct and indirect approaches of wind-power predictions. However, Table 5 shows how much the proposed methodology outperforms ARIMA, SVM, PSF, and other methods for all seasons. It shows, on average, 22.79%, 24.65%, and 17.26% improvement of the proposed method compared to ARIMA, SVM, and PSF, respectively, for collectively all seasons and time horizons. Similar improvement is observed for the whole one-year data.

There is scope for future developments. For instance, in this paper, the method used only values at time instants t and $t-1$. A possibility is to use more time instants, such as $t-2, t-3, \ldots, t-n$. In a way, this presents certain similarities with Markov processes, where several-order Markov chain matrices could be established, regarding whether data of one or more previous states are taken into account when the probability of a state must be calculated.

Author Contributions: Conceptualization, N.B. and A.F.; methodology, N.B. and A.F.; software, N.B.; validation, N.B., A.F., and D.V.; formal analysis, D.V.; investigation, A.F.; resources, N.B., K.K., and A.F.; data curation, N.B. and A.F.; writing—original draft preparation, A.F., K.K., and N.D.; writing—review and editing, D.V. and K.K.; visualization, N.B.; supervision, A.F. and D.V.; project administration, A.F. and K.K.

Funding: This research received no external funding.

Acknowledgments: Neeraj Bokde was supported by the R and D project work undertaken under the Visvesvaraya PhD Scheme of the Ministry of Electronics and Information Technology, Government of India, implemented by the Digital India Corporation.

Conflicts of Interest: The authors declare no conflict of interest.

Abbreviations

The following abbreviations are used in this manuscript:

ARIMA	Autoregressive integrated moving average
ELM	Extreme-learning machine
LUT	Look-up table
MAE	Mean absolute error
MAPE	Mean absolute percentage error
MLP	Multilayer perceptron
NARX	Nonlinear autoregressive exogenous
NB	Naïve Bayesian
NN	Neural networks
NREL	National Renewable Energy Laboratory
PM	Persistence model
PSF	Pattern sequence based forecasting
RMSE	Root mean square error
SVM	Support vector machine

Appendix A. Power Curve Fitting Equations

Generally, the indirect wind-power prediction approach starts with the prediction of wind-speed time series, and the predicted values are converted with power-curve equations of the turbines. However, the practical power curves obtained with the measured wind-power and wind-speed datasets are different from the turbine power-curve equations provided by turbine manufacturers. The environmental and seasonal parameters are the factors that significantly affect the power curves. In this paper, four curve-fitting techniques were used to derive the power-curve equations for four different seasons (winter, spring, summer, and autumn). These curve-fitting techniques are the fourth-ordered polynomial equation, exponential, fitted-power, and regression models. The seasonwise equations used for these models are shown in Tables A1–A4.

Table A1. Fourth-order polynomial equations.

Seasons	Power Curve Fitting Equations
Winter	$y = -0.1027 + 0.2359 \cdot x - 0.01907 \cdot x^2 + 0.5247 \cdot x^3 - 0.0024 \cdot x^4$
Spring	$y = +3.8504 - 3.8539 \cdot x + 0.9158 \cdot x^2 - 0.0585 \cdot x^3 + 0.0011 \cdot x^4$
Summer	$y = +2.4992 - 2.3994 \cdot x + 0.5681 \cdot x^2 - 0.0305 \cdot x^3 + 0.0004 \cdot x^4$
Autumn	$y = -0.0462 + 0.2038 \cdot x - 0.1927 \cdot x^2 + 0.0537 \cdot x^3 - 0.0025 \cdot x^4$

Table A2. Exponential model equations.

Seasons	Power Curve Fitting Equations
Winter	$y = e^{(-1.0995+0.3544 \cdot x)}$
Spring	$y = e^{(0.1369+0.0932 \cdot x)}$
Summer	$y = e^{(0.3780+0.1525 \cdot x)}$
Autumn	$y = e^{(-0.7418+0.2908 \cdot x)}$

Table A3. Fitted-power model equations.

Seasons	Power Curve Fitting Equations
Winter	$y = x^{(0.7992+/-0.0051)}$
Spring	$y = x^{(0.2342+/-0.0019)}$
Summer	$y = x^{(0.8713+/-0.0044)}$
Autumn	$y = x^{(0.8138+/-0.0065)}$

Table A4. Regression model equations.

Seasons	Power Curve Fitting Equations
Winter	$y = -4.7922 + 1.3561 \cdot x$
Spring	$y = -4.3794 + 1.0761 \cdot x$
Summer	$y = -3.6410 + 1.1980 \cdot x$
Autumn	$y = -3.8480 + 1.2370 \cdot x$

Appendix B. Performance of State-of-the-Art Methods

The comparison of various state-of-the-art methods for wind-power prediction is shown in Tables A5 and A6. It compares the performance of the ARIMA, PM, NARX, SVM, MLP, ELM, and PSF methods for direct and indirect prediction approaches for different prediction horizons.

Table A5. Comparison of wind-power prediction results with (**a**) direct prediction approach and indirect prediction approach with curve-fitting techniques: (**b**) fourth-order polynomial model.

(a) Direct Approach

Errors	Time (min)	ARIMA				PM				NARX				SVM				MLP				ELM				PSF			
		Win	Spr	Sum	Aut	Win	Spr	Sum	Aut	Win	Spr	Sum	Aut	Win	Spr	Sum	Aut	Win	Spr	Sum	Aut	Win	Spr	Sum	Aut	Win	Spr	Sum	Aut
RMSE	5	0.016	0.114	0.106	0.028	0.018	0.167	0.112	0.151	0.022	0.049	0.094	0.015	0.087	0.129	0.27	0.044	0.0177	0.061	0.113	0.011	0.016	0.148	0.106	0.12	0.006	0.032	0.129	0.065
	15	0.012	0.272	0.255	0.11	0.043	0.451	0.66	0.423	0.037	0.076	0.297	0.061	0.185	0.287	0.236	0.039	0.031	0.127	0.281	0.061	0.024	0.319	0.287	0.223	0.061	0.158	0.477	0.098
	30	0.079	0.335	0.385	0.437	0.148	0.618	0.873	1.094	0.041	0.163	0.484	0.0558	0.227	0.388	0.32	0.318	0.041	0.118	0.462	0.353	0.041	0.386	0.462	0.342	0.087	0.251	0.753	0.417
	60	0.219	0.261	0.461	0.648	0.23	1.033	1.585	1.632	0.11	0.786	0.667	0.477	0.324	0.867	0.415	0.39	0.103	0.474	0.635	0.516	0.102	0.304	0.606	0.511	0.128	0.224	0.946	0.591
MAE	5	0.016	0.114	0.106	0.028	0.018	0.167	0.112	0.151	0.022	0.049	0.094	0.015	0.087	0.129	0.27	0.044	0.017	0.061	0.113	0.011	0.016	0.148	0.106	0.12	0.006	0.032	0.129	0.065
	15	0.012	0.25	0.198	0.091	0.043	0.451	0.66	0.423	0.035	0.074	0.233	0.054	0.185	0.283	0.213	0.032	0.029	0.119	0.221	0.047	0.023	0.298	0.226	0.196	0.048	0.132	0.372	0.085
	30	0.054	0.318	0.34	0.338	0.148	0.618	0.873	1.094	0.038	0.122	0.425	0.045	0.225	0.38	0.299	0.281	0.037	0.107	0.405	0.259	0.035	0.369	0.406	0.293	0.077	0.225	0.662	0.322
	60	0.173	0.225	0.415	0.566	0.23	1.033	1.585	1.632	0.091	0.582	0.611	0.288	0.319	0.851	0.381	0.352	0.087	0.358	0.58	0.441	0.086	0.26	0.556	0.457	0.118	0.201	0.838	0.516
MAPE	5	0.289	6.511	12.014	0.868	0.325	9.216	12.698	4.76	0.406	2.909	10.502	0.478	1.76	1.531	17.47	11.798	0.321	3.578	12.868	0.36	0.291	8.303	11.961	3.82	0.18	1.983	2.905	1.941
	15	0.218	14.411	22.786	2.697	0.774	27.283	26.33	12.808	0.64	4.832	25.12	1.53	2.757	6.103	29.053	18.584	0.529	7.558	24.495	1.36	0.421	16.642	24.768	5.407	0.881	8.283	31.672	2.512
	30	0.962	18.341	39.267	9.79	2.666	39.778	49.21	36.15	0.697	10.122	43.45	1.319	3.129	14.3	39.689	17.444	0.675	7.261	42.612	7.281	0.64	20.661	42.685	8.04	1.428	13.706	51.537	9.255

(b) Indirect Approach (Forth order polynomial)

Errors	Time	ARIMA				PM				NARX				SVM				MLP				ELM				PSF			
	(min)	Win	Spr	Sum	Aut	Win	Spr	Sum	Aut	Win	Spr	Sum	Aut	Win	Spr	Sum	Aut	Win	Spr	Sum	Aut	Win	Spr	Sum	Aut	Win	Spr	Sum	Aut
RMSE	5	0.026	0.12	0.208	0.175	0.063	0.191	0.254	0.202	0.041	0.058	0.125	0.027	0.231	0.155	0.404	0.136	0.033	0.085	0.262	0.036	0.037	0.212	0.26	0.138	0.019	0.055	0.21	0.104
	15	0.059	0.21	0.218	0.148	0.159	0.538	0.694	0.526	0.076	0.086	0.347	0.18	0.247	0.341	0.498	0.168	0.059	0.136	0.326	0.095	0.059	0.849	0.225	0.297	0.08	0.223	0.686	0.191
	30	0.152	0.28	0.165	0.259	0.231	0.717	0.951	1.235	0.124	0.252	0.609	0.273	0.31	0.75	0.561	0.779	0.073	0.279	0.607	0.404	0.104	1.48	0.295	0.397	0.121	0.329	0.925	0.643
	60	0.302	0.221	0.195	0.402	0.339	1.341	1.725	1.824	0.197	0.891	0.757	0.765	0.538	1.47	0.824	1.04	0.217	0.703	0.828	0.684	0.193	2.35	0.363	0.611	0.174	0.421	1.317	0.813
MAE	5	0.026	0.12	0.208	0.175	0.063	0.191	0.254	0.202	0.041	0.058	0.125	0.027	0.231	0.155	0.404	0.136	0.033	0.077	0.262	0.036	0.037	0.212	0.26	0.138	0.019	0.055	0.209	0.104
	15	0.023	0.17	0.2	0.143	0.159	0.538	0.694	0.526	0.072	0.078	0.313	0.176	0.244	0.34	0.497	0.167	0.054	0.127	0.308	0.093	0.051	0.738	0.205	0.291	0.069	0.234	0.664	0.187
	30	0.157	0.25	0.131	0.218	0.231	0.717	0.951	1.235	0.119	0.198	0.467	0.271	0.297	0.654	0.535	0.765	0.069	0.254	0.688	0.381	0.096	1.32	0.278	0.306	0.119	0.308	0.922	0.624
	60	0.297	0.18	0.159	0.353	0.339	1.341	1.725	1.824	0.186	0.734	0.675	0.603	0.529	1.44	0.8	1.01	0.199	0.671	0.793	0.625	0.187	2.13	0.328	0.531	0.167	0.422	1.309	0.809
MAPE	5	0.47	7.28	25.303	5.034	0.73	11.54	17.37	5.74	0.712	2.69	13.76	0.663	2.371	2.03	22.82	10.14	0.571	8.03	15.87	0.57	0.503	11.43	35.48	4.001	0.27	2.665	36.11	1.32
	15	0.73	10.34	31.64	4.016	1.61	28.8	38.4	16.14	0.855	5.31	37.92	2.685	3.589	9.12	36.82	18.87	0.773	10.12	28.68	2.35	0.711	31.05	28.19	6.62	0.987	9.95	33.02	4.12
	30	1.02	15.108	22.49	5.926	2.9	42.4	58.05	34.92	0.903	20.28	52.8	3.786	4.84	22.24	44.74	29.5	0.912	12.24	48.92	8.81	0.931	44.71	38.03	8.706	1.93	21.8	64.14	15.68
	60	5.59	11.09	43.51	9.361	6.08	68.14	61.85	45.66	1.87	33.35	68.55	12.097	6.287	33.91	53.73	31.12	2.35	43.91	58.83	16.44	2.02	54.41	44.64	15.09	3.04	25.01	79.73	28.07

Table A6. Comparison of wind-power prediction results with (**a**) exponential model; (**b**) fitted-power model; and (**c**) regression model.

(a) Indirect Approach (Exponential models)

Errors	**Time**	**ARIMA**				**PM**				**NARX**				**SVM**				**MLP**				**ELM**				**PSF**			
	(min)	Win	Spr	Sum	Aut	Win	Spr	Sum	Aut	Win	Spr	Sum	Aut	Win	Spr	Sum	Aut	Win	Spr	Sum	Aut	Win	Spr	Sum	Aut	Win	Spr	Sum	Aut
RMSE	5	0.036	0.125	0.119	0.135	0.026	0.262	0.12	0.122	0.026	0.224	0.12	0.116	0.067	0.119	0.17	0.037	0.028	0.245	0.12	0.125	0.029	0.184	0.12	0.155	0.01	0.48	0.1	0.141
	15	0.056	0.242	0.428	0.227	0.059	0.395	0.43	0.177	0.043	0.394	0.43	0.148	0.193	0.213	0.48	0.041	0.045	0.394	0.43	0.197	0.047	0.496	0.43	0.282	0.096	0.64	0.41	0.263
	30	0.073	0.35	0.597	0.553	0.153	0.44	0.59	0.34	0.05	0.448	0.6	0.33	0.24	0.339	0.65	0.072	0.063	0.445	0.6	0.499	0.068	0.623	0.6	0.644	0.112	0.71	0.58	0.308
	60	0.174	0.441	0.688	0.779	0.237	1.356	0.68	0.46	0.187	0.348	0.69	0.348	0.39	0.788	0.74	0.12	0.091	0.348	0.69	0.706	0.128	0.6	0.69	0.896	0.287	0.615	0.68	0.504
MAE	5	0.036	0.125	0.119	0.135	0.026	0.262	0.12	0.122	0.026	0.244	0.12	0.116	0.067	0.119	0.17	0.037	0.028	0.245	0.12	0.125	0.029	0.284	0.12	0.155	0.009	0.48	0.1	0.141
	15	0.056	0.241	0.364	0.215	0.057	0.384	0.36	0.172	0.041	0.38	0.36	0.145	0.172	0.204	0.42	0.04	0.043	0.38	0.36	0.188	0.044	0.474	0.36	0.264	0.091	0.631	0.406	0.26
	30	0.07	0.348	0.546	0.472	0.152	0.432	0.54	0.308	0.049	0.436	0.55	0.289	0.224	0.328	0.16	0.071	0.061	0.434	0.54	0.423	0.061	0.601	0.54	0.556	0.109	0.703	0.53	0.304
	60	0.168	0.376	0.645	0.707	0.229	1.325	0.64	0.3431	0.133	0.301	0.65	0.307	0.353	0.755	0.7	0.099	0.087	0.3	0.65	0.639	0.116	0.586	0.65	0.819	0.285	0.592	0.64	0.497
MAPE	5	0.54	6.61	10.73	4.27	0.24	13.75	10.8	3.82	0.41	12.92	10.8	3.62	1.197	7.822	15.31	13.112	0.68	12.99	10.79	3.92	0.34	14.73	10.79	4.91	0.249	22.86	9.42	4.6
	15	0.61	16.62	32.76	6.63	0.87	20.52	32.9	5.23	0.76	20.31	32.89	4.39	2.295	6.85	36.21	19.03	0.91	20.33	32.86	5.76	0.66	23.96	32.86	8.3	0.98	29.69	31.87	4.49
	30	1.62	20.55	49.18	14.31	2.701	23.39	49.1	8.76	0.92	23.54	49.62	8.16	3.194	18.51	51.76	20.02	1.62	23.46	49.3	12.59	0.98	29.53	49.3	17.4	1.795	33.12	48.6	15.92
	60	4.36	24.71	58.29	21.28	4.725	37.6	58.17	11.8	1.79	16.41	58.62	8.11	3.689	20.49	60.29	32.62	2.7	16.34	58.48	18.77	1.75	27.69	58.48	25.65	3.96	27.85	58	18.46

(b) Indirect Approach (Fitted power model)

Errors	**Time**	**ARIMA**				**PM**				**NARX**				**SVM**				**MLP**				**ELM**				**PSF**			
	(min)	Win	Spr	Sum	Aut	Win	Spr	Sum	Aut	Win	Spr	Sum	Aut	Win	Spr	Sum	Aut	Win	Spr	Sum	Aut	Win	Spr	Sum	Aut	Win	Spr	Sum	Aut
RMSE	5	0.062	0.156	0.188	0.15	0.064	0.155	0.19	0.145	0.062	0.162	0.19	0.143	0.057	0.134	0.26	0.041	0.043	0.181	0.18	0.146	0.023	0.147	0.18	0.156	0.011	0.084	0.158	0.13
	15	0.071	0.177	0.487	0.282	0.071	0.105	0.491	0.267	0.069	0.113	0.492	0.258	0.166	0.22	0.55	0.054	0.076	0.113	0.491	0.273	0.047	0.128	0.491	0.3	0.037	0.131	0.465	0.26
	30	0.14	0.234	0.659	0.62	0.148	0.115	0.652	0.575	0.139	0.12	0.66	0.571	0.234	0.371	0.73	0.083	0.148	0.119	0.665	0.619	0.145	0.168	0.66	0.664	0.094	0.178	0.641	0.381
	60	0.19	0.273	0.75	0.88	0.208	0.17	0.804	0.752	0.163	0.195	0.768	0.74	0.381	0.615	0.82	0.21	0.185	0.29	0.761	0.86	0.194	0.152	0.75	0.919	0.184	0.169	0.742	0.67
MAE	5	0.056	0.155	0.188	0.15	0.064	0.155	0.19	0.145	0.062	0.162	0.19	0.143	0.057	0.134	0.26	0.041	0.043	0.181	0.18	0.146	0.023	0.147	0.18	0.156	0.011	0.084	0.158	0.12
	15	0.07	0.165	0.432	0.264	0.07	0.101	0.436	0.251	0.069	0.091	0.436	0.243	0.166	0.198	0.5	0.052	0.073	0.09	0.43	0.256	0.047	0.114	0.43	0.28	0.036	0.12	0.406	0.25
	30	0.12	0.215	0.613	0.54	0.147	0.091	0.608	0.501	0.136	0.104	0.621	0.496	0.233	0.331	0.68	0.079	0.146	0.103	0.61	0.535	0.144	0.155	0.61	0.576	0.091	0.165	0.592	0.374
	60	0.18	0.271	0.711	0.807	0.205	0.136	0.702	0.788	0.15	0.154	0.729	0.678	0.37	0.559	0.78	0.14	0.177	0.251	0.72	0.786	0.138	0.134	0.72	0.842	0.176	0.143	0.7	0.61
MAPE	5	1.1	8.52	15.85	4.74	1.13	10.43	16.04	4.6	0.103	10.93	16.05	4.53	1.188	2.642	20.99	8.6	0.415	4.89	16.03	4.63	0.224	9.87	16.03	4.95	0.97	5.43	3.75	5.08
	15	2.27	16.63	36.66	8.3	2.26	5.942	36.86	7.84	1.22	6.18	36.84	7.57	2.04	5.25	40.49	9.72	0.93	6.14	36.81	8.017	0.535	7.56	36.81	8.84	1.44	7.71	35.16	5.68
	30	3.77	18.14	52.09	17.16	2.79	6.804	52.01	15.33	2.56	7.09	52.36	15.14	3.512	10.15	55	11.03	1.077	7.01	52.28	16.6	0.817	10.16	52.28	18.17	2.17	10.61	51.12	6.94
	60	6.59	19.85	60.62	25.14	2.99	9.267	60.44	22	3.844	10.68	61.12	20.17	4.203	20.51	62.96	12.89	1.74	10.39	60.93	24.31	1.623	8.65	60.89	26.56	2.33	19.57	60.16	9.03

(c) Indirect Approach (Regression model)

Errors	**Time**	**ARIMA**				**PM**				**NARX**				**SVM**				**MLP**				**ELM**				**PSF**			
	(min)	Win	Spr	Sum	Aut	Win	Spr	Sum	Aut	Win	Spr	Sum	Aut	Win	Spr	Sum	Aut	Win	Spr	Sum	Aut	Win	Spr	Sum	Aut	Win	Spr	Sum	Aut
RMSE	5	0.037	0.145	0.186	0.12	0.034	0.126	0.32	0.156	0.037	0.237	0.932	0.148	0.066	0.071	0.024	0.575	0.036	0.228	0.119	0.096	0.035	0.105	0.121	0.1007	0.068	0.166	0.282	0.181
	15	0.032	0.133	0.239	0.25	0.033	0.153	0.63	0.184	0.037	0.181	1.221	0.247	0.071	0.161	0.168	0.589	0.029	0.177	0.289	0.112	0.028	0.495	0.284	0.223	0.137	0.281	0.294	0.195
	30	0.071	0.165	0.317	0.47	0.063	0.259	0.98	0.298	0.104	0.226	1.492	0.396	0.159	0.361	0.191	0.692	0.074	0.242	0.379	0.402	0.067	0.68	0.36	0.588	0.163	0.349	0.46	0.253
	60	0.14	0.16	0.487	0.68	0.078	0.321	0.804	0.564	0.26	0.665	1.87	0.487	0.204	0.49	0.469	0.903	0.174	0.396	0.748	0.592	0.138	0.731	0.474	0.683	0.266	0.257	0.809	0.487
MAE	5	0.037	0.145	0.186	0.17	0.034	0.126	0.32	0.156	0.037	0.237	0.932	0.148	0.066	0.071	0.024	0.575	0.036	0.228	0.119	0.096	0.035	0.105	0.121	0.1007	0.068	0.166	0.282	0.181
	15	0.031	0.12	0.227	0.23	0.033	0.15	0.68	0.179	0.037	0.175	1.196	0.241	0.071	0.159	0.166	0.586	0.028	0.172	0.278	0.102	0.026	0.489	0.26	0.203	0.136	0.278	0.284	0.193
	30	0.059	0.154	0.307	0.38	0.056	0.239	0.94	0.271	0.084	0.21	1.458	0.393	0.154	0.36	0.189	0.689	0.059	0.226	0.356	0.319	0.053	0.64	0.34	0.491	0.163	0.345	0.409	0.25
MAPE	5	0.673	9.73	16.57	3.3	0.614	8.31	18.29	3.73	0.676	16.84	48.39	3.47	1.217	18.05	13.48	11.93	0.647	16.09	18.04	3.86	0.628	8.19	18.11	3.93	0.954	11.48	30.67	4.06
	15	0.57	7.95	28.28	4.13	0.592	11.52	31.6	5.4	0.661	13.16	61.41	4.4	1.302	16.3	18.4	18.81	0.508	12.95	26.78	5.045	0.476	19.22	20.87	6.24	1.264	16.14	39.37	4.98
	30	1.065	10.13	36.96	11.21	1.015	21.97	42.84	7.87	1.493	17.92	71.62	7.143	2.99	18.32	30.28	21.34	1.063	19.98	40.52	9.149	0.965	22.55	26.47	15.08	2.3	18.67	45.17	6.79
	60	2.166	9.18	50.31	17.69	1.325	25.77	61.4	7.92	3.731	20.33	78.91	10.44	4.657	17.48	42.52	26.06	2.569	26.2	56.55	14.72	2.111	31.09	35.84	23.12	2.75	14.82	60.21	8.04

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