Received October 15, 2020, accepted October 23, 2020, date of publication October 30, 2020, date of current version November 12, 2020.

Digital Object Identifier 10.1109/ACCESS.2020.3035121

A New Hybrid ARAR and Neural Network Model for Multi-Step Ahead Wind Speed Forecasting in Three Regions of Pakistan

MIRZA NAVEED SHAHZAD[1], SAIQA KANWAL[1], AND ABID HUSSANAN[2,3]

[1]Department of Statistics, University of Gujrat, Gujrat 50700, Pakistan
[2]Division of Computational Mathematics and Engineering, Institute for Computational Science, Ton Duc Thang University, Ho Chi Minh City 700000, Vietnam
[3]Faculty of Mathematics and Statistics, Ton Duc Thang University, Ho Chi Minh City 700000, Vietnam

Corresponding author: Abid Hussanan (abidhussanan@tdtu.edu.vn)

ABSTRACT Wind is one of the most essential sources of clean, environmental friendly, socially constructive, economically beneficial, and renewable energy. To intuit the potential of this energy in a region the accurate wind speed modeling and forecasting are crucially important, even for planning, conversion of wind energy to electricity, energy trading, and reducing instability. However, accurate prediction is difficult due to intermittency and intrinsic complexity in wind speed data. This study aims to suggest a more appropriate model for accurate wind speed forecasting in the Jhimpir, Gharo, and Talhar, regions of Sindh, Pakistan. Therefore, the present study combined the Autoregressive-Autoregressive (ARAR) and Artificial Neural Network (ANN) models to propose a new hybrid ARAR-ANN model for better prediction by precisely capturing different patterns of the wind speed time-series data sets. The proposed hybrid model is efficient in modeling, reducing statistical errors, and forecasting the wind speed effectively. The performance of the proposed hybrid ARAR-ANN model is compared using three error-statistics and Nash-Sutcliffe efficiency-coefficient. The empirical results of the four performance indices fully demonstrated the superiority of the hybrid ARAR-ANN model than persistence model, ARAR, ANN and SVM. Indeed, the proposed model is an effective and feasible approach for wind speed forecasting.

INDEX TERMS Artificial neural network, ARAR model, forecasting, hybrid model, Pakistan, wind speed.

ABBREVIATIONS

ANFIS	Adaptive Neuro Fuzzy Inference System
ANN	Artificial Neural Network
ANN-SFLA	Artificial Neural Network-Shuffled Frog-Leaping Algorithm
ARAR	Autoregressive-Autoregressive
ARARMA	Autoregressive-Autoregressive Moving Average
ARIMA	Autoregressive Integrated Moving Average
BDS	Brock-Dechert-Scheinkman test
GW	Giga Watt
ITSM-R	Interactive Time Series Model-R
KF-ANN	Kalman Filter-Artificial Neural Network
km/h	Kilometer per hour
MAE	Mean Absolute Error
MAPE	Mean Absolute Percentage Error
MSE	Mean Square Error
MW	Mega Watt
NSEC	Nash-Sutcliffe efficiency coefficient
RBF	Radial Basis Function
ReLu	Rectified Linear Units
SARIMA	Seasonal ARIMA
SVM	Support Vector Machine
WN	White Noise

NOMENCLATURE

Y_t	Long-memory time series
$\tilde{Y}_t$	Transformed into short-memory time series
$\widehat{\varphi}\left(\hat{k}\right)$	Coefficients in the autoregressive model that transform long-memory series into short-memory series
Y_t^s	Memory-shortened series
$\overline{Y}^s$	Sample mean of memory shortened series
Z_t	Mean corrected memory shorted series

The associate editor coordinating the review of this manuscript and approving it for publication was Frederico Guimarães.

c_i	Lag length (i=1,2,3)
φ_j	Coefficients in the autoregressive model that transform moderately long-memory series into short-memory series
σ^2	Variance of white noise error term
ε_t	White noise error term
$\psi(B)$	Backshift operator of memory shortening filter
$\varphi(B)$	Backshift operator of autoregressive model
$\xi(B)$	Backshift operator of ARAR model
ω_{lk}	Synaptic weights for the input nodes in the input layer of ANN
ω_k	Synaptic weights for the hidden nodes in the hidden layer of ANN
$g(y)$	Activation Function in ANN
w	Vector of parameters
y_t	Original time series
L_t	Labeled as linear part
N_t	Labeled as nonlinear part
$\hat{L}_t$	Predicted values by linear model
e_t	Residual at time t
$\hat{N}_t$	Predicted values by nonlinear model
K	Number of predicted observations
N_{tr}	Training set sample size
$\hat{y}_t$	Estimated values
$\overline{y_t}$	Mean of the observed time series

I. INTRODUCTION

Electricity is a great source of economic growth and development in many other sectors of a country, as the household appliances to major industrial processes heavily rely on electricity. The population of the world is rapidly increasing and almost every facility is converted to an electrical mechanism that increased electricity consumption. It is a serious challenge to balance the demand and supply of electricity, especially for developing countries. Globally, almost 68% of electricity is generated from fossil fuels [1]. The use of fossil fuels is harmful to the environment, the greatest threats form human health [2] and also become the cause of global warming. A source that proved environmentally friendly with tremendous continuous growth and economical is the wind energy [3], which depends on atmospheric waves. It is a predominant alternative source that has been industrialized rapidly over the last two decades all over the world [4].

In energy generation, wind power has become an important source and global capacity is now approaching 600 GW [5]. The wind energy sector employed at least 1.1 million people in 2018 [6]. Then, it is beneficial for the environment and in the employment sector. In Pakistan the total power generation capacity by wind is about to 22800MW but currently producing 1237MW by installing 12 different wind projects [7]. Currently, the share of wind power in energy is only 6%. In Pakistan, the summer season is enormously hot. Sometimes, in summer maximum temperature hit the 54°C, as observed in 2016 in Larkana, Sindh. Heatstroke and other temperature-related circumstances can result in human mortalities, mostly when the shortage of power occurs. There is an energy crisis in Pakistan and it became crucial to facilitate more than 210 million populations in severe winter and summer. In recent years, researchers pay attention to utilize wind energy as it is a renewable and clean source of power. Fortunately, the coastal area in Southern Sindh, Pakistan is blessed with immense wind energy resources. Therefore, authorizes have been focused on wind energy because of environment spoliation and conventional resource reduction. Pakistan's emerging wind industry needs to predict the wind speed and to explore the new most potential regions there to erection wind parks.

Wind speed fluctuates continuously, thus the prediction of wind power is highly important before the power generation and distribution. Therefore, modeling and forecasting of wind speed variability and intermittency are vital for planning, producing, and operating the wind-power generation. Nevertheless, it is most challenging to model and forecast the wind speed due to haphazard fluctuations in its historical data. In general, wind speed predictions classify into short-term (minute, hour, and day, time zone) and long-term (week, month, and year, time zone) predictions. Accuracy in long-term prediction is vital for site selection, windmill preparation, optimal wind machine size selection, and for performance forecast for a particular site [8]. The focus of this study was also on long-term wind speed prediction.

A. BACKGROUND

To obtain accurate wind speed forecasting many approaches and models are proposed in the literature, those are categories in physical, statistical, mathematical, and artificial intelligence models [9]. A more recent method for accurate modeling and prediction for time series datasets is the hybrid approach, which performs better in this perspective in many fields. As the traditional models perform better only in their own linear or nonlinear domain. In the linear domain, it is possible to highlight works that used time-series univariate ARIMA models for prediction of wind speed, such as [10]–[12]. Another methodology, especially for nonlinear datasets is the artificial intelligence that has been studied to predict the wind speed, by Guo *et al.* [13], Azad *et al.* [14], Li and Shi [15], Cao *et al.* [16] and Santamaría-Bonfil *et al.* [17].

The support vector machine (SVM) is another suitable technique for non-linear characteristics of wind speed series and confirmed better accuracy ([18], [19]). The SVM has also been extensively studied for the prediction of the wind speed ([20], [21]). For example, Ahmed, Khalid and Akram [22] used the SVM to predict the wind speed time-series data for some areas of Sindh, Pakistan. Natarajan and Nachimuthu [23] applied the SVM with the combination of other models to predict wind speed accurately. Zhu *et al.* [24] utilized SVM for the short-term wind speed investigation. The SVM has been also considered here to assess its performance along with ANN and to suggest a better model for the prediction of the wind in the selected regions. In literature, various studies also compared the performance of these techniques in wind speed prediction, few of them are, [18], [20], [25]–[29]. The performance accuracy of SVM and ANN for wind speed data equally vetted as one of them not always produced outstanding results from the other.

It is much better to deal with the datasets using the combination of the time series and artificial intelligence models, which are called hybrid models. These models can capture both nonlinear and linear patterns of the data and provide outstanding forecasting results than individual models. In recent years, Okumus and Dinler [31] combined ANFIS and Artificial Neural Network (ANN) to predict one hour ahead wind speed forecasts. Shukur and Lee [32] presented a hybrid KF-ANN model and claimed the most accurate forecasts of the daily wind speed data for Malaysia and Iraq. Multi-Step ahead Wind Speed of Brazil was forecasted by Alencar *et al.* [33] using hybrid SARIMA-ANN. Mostafaeipour *et al.* [34] observed the prediction accuracy of different hybrid algorithms on wind speed behavior and concluded the hybrid ANN-SFLA model performed well for the monthly data of the city of Abadeh.

Santhosh *et al.* [35] utilized the hybrid approach and developed the hybrid TLBO-ANN for a day-ahead wind. Qin [36] proposed a hybrid model by combining Elman ANN and time series smoothing technique and the proposed hybrid model indicated notable performance for the Hebei wind farms of China. Jafarian-Namin *et al.* [37] forecasted the wind power generation values for Likak, Iran by the hybridization of ANN and genetic algorithm with better results. The ANN is also combined with many other linear time series models in many fields other than wind speed prediction and superior results achieved.

Wind speed has seasonal patterns with trend variations as it is a weather-driven phenomenon [38]. However, seasonal patterns are frequently ignored in the predictions of the wind speed series, which in result produce large prediction errors. Deseasonalization of seasonal series can affectedly increase the prediction accuracy. The ARAR time series model was developed to capture the seasonal and trend components of the time series. Thus in this study, the ARAR was used as an initial model to wind speed data. The trend component often comprises linear and nonlinear characteristics. Thus, the individual use of a statistical time series or artificial intelligence models are inadequate to predict the series that contains both linear and nonlinear patterns [8]. However, to improve the prediction accuracy hybrid models have been established [31]–[34].

In this paper, the time series technique, ARAR was combined with ANN to predict the complex and noisy wind speed time series. The focus of this study falls into the long-term forecasting of the mean monthly wind speed in the regions Jhimpir, Gharo, and Talhar, all located in Sindh, Pakistan. The wind speeds seasonally fluctuate and the ARAR algorithm is the most reliable model to explain such fluctuations as compared to many seasonal models in forecasting context [39]. The ARAR method has been used to address the linear and seasonal components and ANN has been used to model the nonlinearity in the error term of wind speed datasets. Numerical results show that the proposed hybrid ARAR-ANN model has better forecasting performance compared with forecasting models such as ARAR and ANN individually.

The rest of the paper is organized as follows: Section II introduces the methodology of ARAR, ANN, and hybrid models with the proposed model. Section III discusses the performance evaluation criteria. The considered study regions are explained in Section IV. Section V presents the empirical results with in-sample forecasting and multistep ahead forecasting. Finally, the last section summarizes the conclusion.

II. PREDICTION METHODS

This study developed a hybrid model to predict the wind speed in the three most windy regions of Pakistan, that is the combination of the ARAR and ANN model. The individual and hybrid models are described as follows.

A. ARAR ALGORITHM

The ARAR algorithm was explained in detail by Brockwell and Davis [40]. It was adapted from the ARARMA model that was introduced by Parzen [41] in which the series transformed from long memory to short memory if needed. The ARAR algorithm already used for electricity load forecasting [42] and tourism demand forecasting [39] and in many other studies but none of the articles is found which tries the ARAR approach to model and forecast wind speed. The ARAR algorithm consists of the following three steps in the time series (Y_t) modeling, those are explained in short here, for detail see [39].

1) *Memory-shorting process*: This process is used to determine either series contain long, moderate, or short-memory. And also it is a looping process that works continuously until the long-memory series transformed as short-memory and stationary. The process follows the following memory-shortened series

$$\widetilde{Y}_t = Y_t - \widehat{\varphi}\big(\widehat{k}\big)Y_{t-\widehat{k}} \tag{1}$$

and

$$\widetilde{Y}_t = Y_t - \widehat{\varphi}_1 Y_{t-1} - \widehat{\varphi}_2 Y_{t-2} \tag{2}$$

The $\widetilde{Y}$ in (1) and (2) are the series that is evaluated for memory status (long, moderate or short), t is $1, 2, \ldots, T$ and $\varphi_0, \varphi_1, \ldots, \varphi_k$ are the coefficients of memory-shortening series. Finally, the memory-shorting process transforms the Y_t series into memory-shortened series and denoted by Y_t^s for the next step.

2) *Fitting a subset auto-regressive*: Let Y_t^s be the memory-shortened series and $\overline{Y}^s$ be the sample mean of $Y_{k+1}^s, Y_{k+2}^s, \ldots, Y_T^s$, then the mean corrected series computed in (3) as given below

$$Z_t = Y_t^s - \overline{Y}^s \tag{3}$$

In this step, fit an auto-regressive process to the mean corrected series (Z_t) as the auto-regressive model is given below,

$$Z_t = \varphi_1 Z_{t-1} + \varphi_{c_1} Z_{t-c_1} + \varphi_{c_2} Z_{t-c_2} + \varphi_{c_3} Z_{t-c_3} + \varepsilon_k \tag{4}$$

where c_1, c_2 and c_3 are lags value, the coefficients φ_j, $\{\varepsilon_t\} \sim WN(0, \sigma^2)$ and σ^2 is the white noise (WN).

3) *Forecasting*: The third and last step for the ARAR algorithm is the forecasting. It uses the combination of the memory-shortened equation obtained from the first step and fitted auto-regressive model on the mean corrected series in the second step. The memory-shortening filter with $\psi(B)$ denoted by the back-shift operator that can be expressed as:

$$Y_t^s = \psi(B) Y_t = Y_t + \psi_1 Y_{t-1} + \ldots + \psi_k Y_{t-k} \tag{5}$$

The auto-regressive model achieved in the second step can be expressed as,

$$\varphi(B)\, Z_t = \varepsilon_t, \tag{6}$$

where $\varphi(B)$ is $1-\varphi_1 B-\varphi_{c_1}(B^{c_1})-\varphi_{c_2}(B^{c_2})-\varphi_{c_3}(B^{c_3})$. Finally, by the combination of (5) and (6) the ARAR model is obtained as forecasting, such as

$$\xi(B)\, Y_t = \varphi(B)\, \overline{Y}^s + \varepsilon_t \tag{7}$$

where $\xi(B) = \psi(B)\varphi(B)$.

B. ARTIFICIAL NEURAL NETWORK

The ANN is the most popular artificial intelligence technique that has been recommended as an alternative to time series forecasting and has many distinctive characteristics [43]. One of the significant features of the ANN over other nonlinear models is a universal approximation which can approximate any nonlinear continuous function with a high degree of accuracy. Furthermore, there is no prior information required for the modeling process.

ANN structure consists of three layers of the network; an input, a hidden, and an output layer connected via acyclic link [44]. The mathematical representation of inputs $(y_{t-1}, y_{t-2}, y_{t-3}, \ldots, y_{t-p})$ and output (y_t) is given in (8) as below;

$$y_t = \omega_0 + \sum_{k=1}^{q} \omega_k g\left(\omega_{0k} + \sum_{l=1}^{p} \omega_{lk} y_{t-l}\right) + \varepsilon_t. \tag{8}$$

where $\omega_{lk}(l = 1, 2 \ldots, p; k = 1, 2, \ldots, q)$ and $\omega_k(k = 1, 2 \ldots, q)$ are the parameters of the model often known as synaptic weights, p and q are the numbers of input nodes in the input layer and hidden nodes in the hidden layer, ε_t are WN error term and $g(.)$ is an activation function that used as a hidden layer transfer function. There are different transfer functions such as tanh, sinh, ReLu (rectified linear units) and logistic (sigmoid). In this study, sigmoid activation function used as a hidden layer transfer function, that is,

$$g(y) = \frac{1}{1+e^{-y}}.$$

Thus, the ANN model in (8) performs as the non-linear mapping from past observations to the future value (y_t), that is,

$$y_t = f(y_{t-1}, y_{t-2}, y_{t-3}, \ldots, y_{t-p}, w) + \varepsilon_t,$$

where the vector of parameters is represented by w, and the function $f(.)$ is fixed by connection weights and network structure.

Hence, the ANN structure similar to the non-linear auto-regressive model. The neural network has a powerful capability to perform well as the number of the hidden layers increased, but sometimes with the small number of hidden layers, it generates the best results for out-of-sample prediction due to the over-fitness effect. There is no hard and fast rule that used to decide the number of appropriate hidden nodes, it typically depends on data nature.

To get the best model for ANN with higher accuracy, the trial-error method was used by varying the number of input and hidden nodes. If the optimal number of the hidden layer, input, and hidden nodes obtained by the model with a minimum value of error then the model is used next for forecasting purpose. Back-propagation is the learning algorithm is used for selecting weights. There are several ways to optimize the weights using back-propagation such as Gauss-Newton and conjugate gradient. These learning algorithms used to train the weights and try to minimize the sum of square error.

C. THE PROPOSED HYBRID ARAR-ANN MODEL

A model rarely captures the characteristics of time-series data successfully in all circumstances. Sometimes, both linear and nonlinear patterns exhibited in data so the approximations by the linear model may provide bad results because it has no ability to detect the non-linearity in data, and vice versa. To overcome this problem, Zhang [45] introduced the idea of the hybrid model which provides a great accuracy level that used to form the additive link between linear and nonlinear components of data, as given below.

$$y_t = f(L_t, N_t) = L_t, N_t. \tag{9}$$

where L_t is labeled as linear part while N_t is labeled as a nonlinear part.

In this study, we proposed the hybrid ARAR-ANN model by following the methodology of Zhang [45], assuming that this model will be flexible and able to capture the different patterns of the wind speed data for accurate forecasting. The proposed hybrid model is based on the combination of the ARAR and the ANN models and these models have different competencies to express the characteristics of data in linear and nonlinear domains. First, the ARAR model was used to model the data to estimate the predicted values $(\widehat{L_t})$ of the wind speed data and for the computation of the residual. Let the residuals at time t are denoted by e_t and calculated by the (10).

$$e_t = y_t - \widehat{L}_t. \tag{10}$$

where y_t is the original time-series and $\widehat{L}_t$ is the forecasted values obtain by linear model.

Second, model the residuals (obtained from the best ARAR model) by the ANN model. The relationship between p input nodes and output node work as discussed in Section II-B to produce the predicted values of residuals ($\widehat{N}_t$). Finally, merged the predicted values in the first and second step to expand the overall modeling performance for accurate forecasting. It is observed, in the wind speed prediction the hybrid methods always perform better than the single models [46]. This algorithm is also described in a flowchart and illustrated in Figure 1.

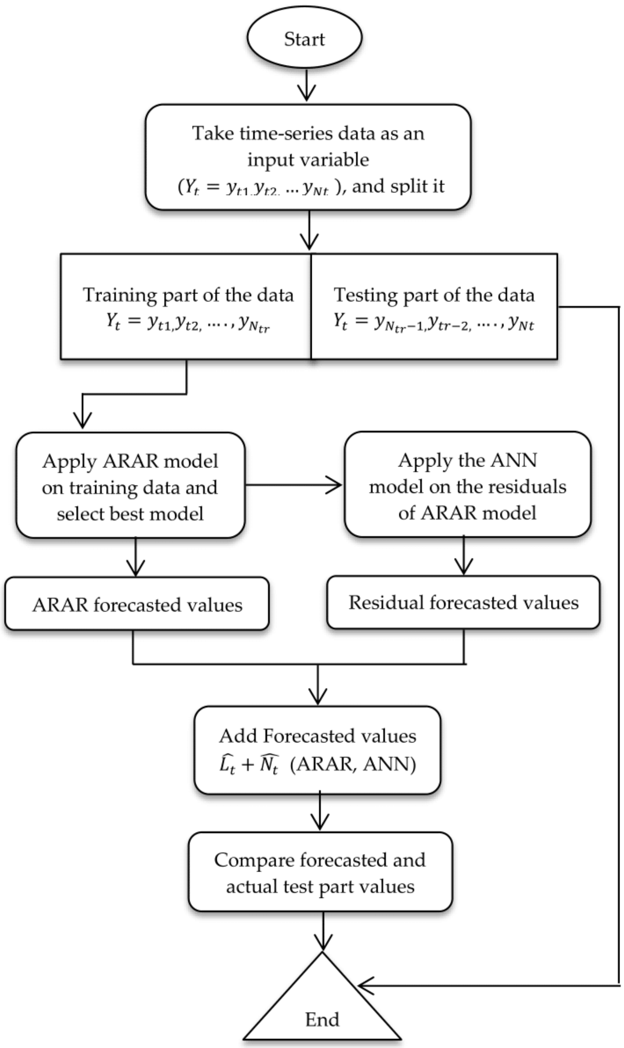

FIGURE 1. **Flowchart for proposed hybrid ARAR-ANN model.**

III. EVALUATION CRITERIA

To evaluate and compare the ARAR, ANN, and proposed hybrid ARAR-ANN models four criteria were used, to identify the best model quantitatively. In the first two criteria, the mean-absolute error (MAE) and the mean-square error (MSE) that represents the quadratic differences, were employed. These measures can be interpreted as the higher value indicate a poor fit and the value close to zero indicate a near to perfect fit. Both measures depend on the observed and fitted wind speed observations and measured in the kilometer per hour (km/h) unit of measurement with the following mathematical representation.

$$MAE = \frac{1}{K} \sum_{t=N_{tr}+1}^{N_{tr}+K} |e_t|,$$

and

$$MSE = \frac{1}{K} \sum_{t=N_{tr}+1}^{N_{tr}+K} e_t^2.$$

where e_t is the error term obtained from the difference between observed (y_t) and fitted ($\widehat{y}_t$) values, N_{tr} is the training set sample size of each dataset and K is the number of forecast observations.

Two other measures the mean absolute-percentage error (MAPE) and Nash-Sutcliffe efficiency-coefficient (NSEC) was also used for a quick and easy understanding. The MAPE express results in percentages (%) and the value of NSEC lies in-between $-\infty$ to 1, the value lower than 0.36, 0.36 to 0.75, and higher than 0.75 indicate that the model is unacceptable, acceptable and perfect fit, respectively [47]. The expression used to compute the MAPE and NSEC is given by

$$MAPE = \frac{1}{K} \sum_{t=N_{tr}+1}^{N_{tr}+K} |\frac{e_t}{y_t}| \times 100,$$

and

$$MSEC = 1 - \frac{\sum_{t=N_{tr}+1}^{N_{tr}+K} e_t^2}{\sum_{t=N_{tr}+1}^{N_{tr}+K} (y_t - \bar{y}_t)^2},$$

respectively, where the $\bar{y}_t$ denotes the mean of the observed time series.

IV. STUDY AREA AND DATASETS

The Gharo-Keti Bandar wind corridor in Northeast Singh, Pakistan has superabundant wind speed due to its geographical location. Three selected regions, Jhimpir (25.02°N and 68.01°E), Gharo (24.74°N and 67.58°E), and Talhar (24.88°N and 68.82°E) are located in the Gharo-Keti Bandar wind corridor at the Arabian Sea and have been shown in Figure 2. These study regions are potentially valuable wind farm sites. The wind energy development is the bigger power density, long-lasting, climatic friendly, and low costs for investment construction. In this study, the available mean monthly wind speed historical data were selected in Jhimpir (from January 2009 to May 2020), Gharo (from January 2009 to May 2020) and Talhar (from January 2010 to May 2020) to evaluate the performance of the proposed hybrid ARAR-ANN model. Figure 3 shows the pattern of the mean monthly wind speed in the three study regions and graphical patterns show the strong seasonal variations in the datasets.

FIGURE 2. Map of Pakistan with highlighted study regions: Jhimpir, Gharo and Talhar.

In order to validate the performance of ARAR, ANN, and hybrid ARAR-ANN models, the datasets were partitioned into the training and testing groups. The dataset from the starting month to December 2018 was used as a training group for the construction of the model, and from January 2018 to May 2020 as a testing group to evaluate the trained models accuracy.

V. RESULTS AND DISCUSSIONS

In this section, we discuss the data of the study regions, along with the results of forecasting models. All the numerical results and graphical representations were produced by the software Python and R, which have been widely used for such purposes.

The monthly behavior of the wind speed observed in Jhimpir, Gharo, and Talhar as shown in Figure 3. The strongest winds appeared in the month of June and July, and weakest in the month of November mostly of every year and the seasonal behaviors observe in the time series. In this study, nine years of data were used to train the model using training sample set, and the last two and half years data have been reserved as a testing sample set to observe the accuracy of the fitted and proposed hybrid models.

A. ARAR MODEL

The ARAR model performed as discussed in Section II-A. To apply this ARAR memory-based model, first of all, the memory of data was verified. If long memory notice in data 'gentle transformation' is needed to transform the data into short memory, the process continued until the short

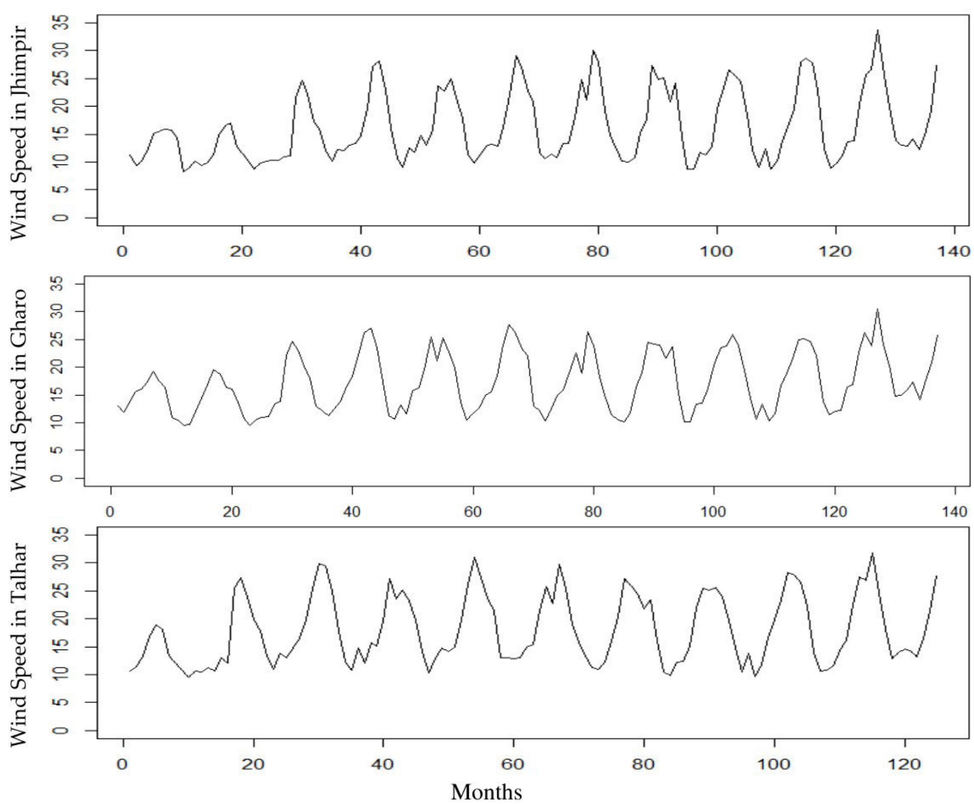

FIGURE 3. The mean monthly wind speed (km/h) in Jhimpir, Gharo, and Talhar.

TABLE 1. ARAR model estimation for wind speed data.

Estimates	Wind Speed Datasets		
	Jhimpir	Gharo	Talhar
$ERR(\widehat{\tau})$	0.0322	0.0202	0.0301
$8/n$	0.0740	0.0740	0.0833
$\widehat{\varphi}_{\tau}$	0.0740	1.0184	1.0225
$\widehat{\tau}$	12.000	12.000	12.000
Lagged AR filter	$(1-0.0740B^{12})$	$(1-1.0184B^{12})$	$(1-1.0225B^{12})$

TABLE 2. Coefficients of overall whitening filter for Jhimpir wind speed.

1.0000	-0.3292	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
0.0000	0.0000	0.0000	0.0000	-0.5244	-0.0819	0.0000	0.0000
0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
-0.3299	0.4277	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	-1827

memory achieved. According to the Adhoc rule a long-memory series exhibit $ERR(\widehat{\tau}) < 8/n$, $\widehat{\varphi}_{\tau} \geq 0.93$ and/or $\widehat{\tau} > 2$. The results in Table 1, indicated that long memory present in all considered datasets. Therefore, the memory-shortening filter was applied and short-memory achieved for all datasets. The coefficients of the memory-shortening filter were obtained for each station and reported for the Jhimpir station in Table 2 and results for other stations are not reported here for reasons of brevity but will get-at-able from the authors on request. The next step is to fit the subset AR model on the mean corrected series, as here AR model is applicable only on short memory data, zero mean, and variance constant. Therefore, the shortened series were mean corrected in order to achieve the above assumption. In this study, the maximum lag set equal to either 13 or 26 has been used to minimizing WN variance. The optimal lags, optimal coefficients, and minimum WN variance obtained from the Yule-Walker equation. The ITSM-R package was used to execute the ARAR models. As it is a very attractive package that applies the memory shortening filter automatically and estimates the best non-stationary autoregressive lag which shorts the memory, then subset AR model apply and most significant coefficients highlighted and other coefficients become zero which is not significant or in other words which coefficients maximize the WN variance.

The four optimal lags and optimal coefficients for Jhimpir (1, 12, 13, 24; 0.3292, −0.4977, 0.4184, -0.1788). Gharo (1, 12, 13, 15; 0.4154, −0.4974, 0.4698, −0.1499) and Talhar (1, 12, 13, 15; 0.4474, −0.4943, 0.4811, −0.1837) were estimated which minimize the WN variance.

B. SUPPORT VECTOR MACHINE REGRESSION MODEL

The purpose of the applicability of the SVM on the data of selected regions was to investigate and compare the results with the proposed hybrid ARAR-ANN model. The Radial Basis Function (RBF) kernel has been selected as it is considered the best kernel for SVM in the case of time series analysis [48]. Table 3 shows the comparison of testing and forecasting accuracy among the models based on the five measures. Empirical results of four error based indices clearly reveal that the hybrid, ANN, and ARAR models performed better than the SVM model, even the values of the NSEC for SVM were negative. It was observed that all the datasets in hand were seasonal and the SVM model does not perform better in forecasting the seasonal data [50]. Some literature ([49], [51], [52]) indicated that the ANN provides better results in seasonal and trend data forecasting than SVM. On the other hand, the SVM took lower computational time as compared to other models. The objective of accurate modeling and forecasting not achieved by the SVM. Therefore, it not reasonable to carry this technique further in this study.

C. ARTIFICIAL NEURAL NETWORK MODEL

To obtain the best ANN model for mean monthly wind speed datasets, several ANN models were developed for the aforementioned datasets using two hidden layers with varying 2 to 20 nodes in the first hidden layer, and 2 to 6 nodes in the second hidden layer. By varying the number of nodes in the first and second hidden layers, a total of 95 models were developed, whereas each model is trained 50 times. Due to the space limitation. From these models, the best models were selected based on minimum MAE and MSE. Consequently, we obtained ANN($8 \times 6 \times 1$), ANN($9 \times 4 \times 1$) and ANN($7 \times 6 \times 1$) for Jhimpir, Gharo, and Talhar wind speed datasets, respectively.

D. HYBRID ARAR-ANN MODEL

The hybrid approach mainly consisted of two steps as discussed earlier. In the first step, an ARAR model is fitted to analyze the mean monthly wind speed and to obtain the residuals from the best fitted ARAR model. The nonlinearity in the residuals is checked by using the BDS test as suggested by Broock *et al.* [53]. The results of the BDS test lead to the rejection of the null hypothesis of the linearity of the series at 5% level of significance. This shows that the residuals from ARAR models exhibit a nonlinear trend. This implies that only ARAR models are not enough to fit the data well. We, therefore, need to implement nonlinear models such as ANN to deal with this nonlinearity. In the second step, the residuals were analyzed by ANN. Finally, the predicted values of the optimal ARAR and ANN models combined to obtain the results of hybrid ARAR-ANN models for the wind speed in the selected study regions. The summary results were presented in Table 3 for the comparison with the other models.

TABLE 3. Error-statistics to observe the accuracy in the fitted models.

MODELS	MAE(km/h)	MSE(km/h)	MAPE(%)	NSEC	Time(s)
Jhimpir Wind Speed Data					
ARAR	1.8225	5.8216	10.2126	0.8821	0.605
SVM	6.0492	64.8020	42.4060	-0.3128	0.504
ANN($8 \times 6 \times 1$)	2.1196	6.6694	12.6533	0.8649	1.051
Hybrid ARAR-ANN	1.5560	4.0086	9.2127	0.9188	1.728
Gharo Wind Speed Data					
ARAR	1.8607	5.3178	11.4795	0.8117	0.542
SVM	4.7465	34.3382	23.8305	-0.2156	0.841
ANN($9 \times 4 \times 1$)	1.6931	4.8167	10.7671	0.8295	1.109
Hybrid ARAR-ANN	1.2531	2.3172	7.4307	0.9180	1.327
Talhar Wind Speed Data					
ARAR	1.8495	4.8096	9.8455	0.8853	0.424
SVM	5.7427	51.8032	36.1759	-0.2358	0.697
ANN($7 \times 6 \times 1$)	2.8901	13.8659	16.5460	0.6692	0.961
Hybrid ARAR-ANN	1.5775	3.9007	9.5079	0.9069	1.203

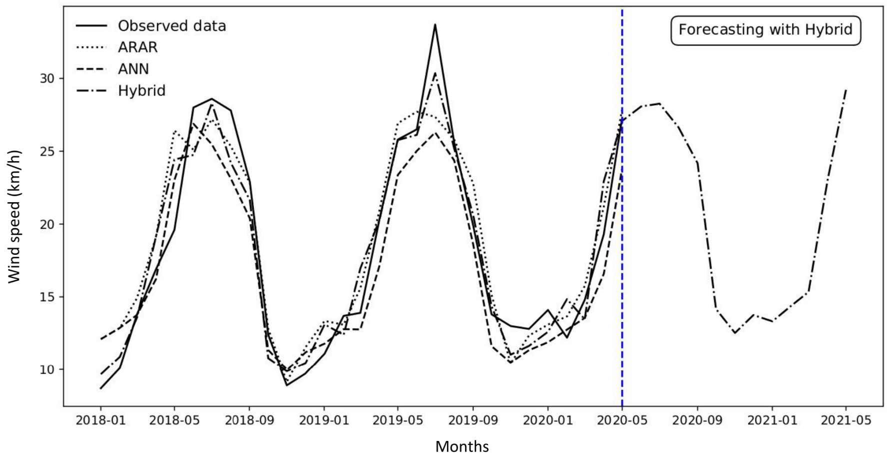

FIGURE 4. The in-sample and out-sample mean monthly wind speed forecast of Jhimpir based on the best-fitted models on the training set sample.

E. COMPARATIVE ANALYSIS OF IN-SAMPLE FORECASTING

To compare the in-sample forecasting of the proposed new hybrid ARAR-ANN model with the other models, four error-statistics were calculated for evaluation and comparison, the MAE, MSE, MAPE, and NSFC. The visual representation is also employed to observe the pattern of the forecasted series with the observed series.

It is important to note that the smallest values of the first three error-statistics provide a more accurate model for the in-sample forecasting. Table 3 shows the results of the four considered evaluation criteria. Comparatively, the hybrid ARAR-ANN model generated the lowest values of MAE in Jhimpir, Gharo, and Talhar datasets, like 1.5560, 1.2531, and 1.5775 km/h, respectively. The second error-statistics, MSE also indicates that the hybrid models are better for all the study regions as its values are 4.0086, 2.3172, and 3.9007 km/h and minimum for all study regions. The third error-statistics, MAPE also specifies that the hybrid models for the three cities are better than the ARAR and ANN, with the minimum values for hybrid models are 9.2127%, 7.4307%, and 9.5079%. The NSFC values for the three models are displayed in Table 3 and the closest values to the 1 were provided by the hybrid model those are 09188, 0.9180, and 0.9069. Comparatively, the proposed hybrid model is better in in-sample forecasting than the individual models for all three regions, Jhimpir, Gharo, and Talhar.

The graphical representation of in-sample forecasting in Figure 4 shows the mean monthly wind speed of the time series in Jhimpir (Figure 4), Gharo (Figure 5) and Talhar (Figure 6) with the observe data. The observed data represented by the solid line, forecasted values of ARAR by the dotted line, predicted values of ANN by dashes line, and the predicted value of hybrid model by dotted and dashes mixed line. The forecasted values by hybrid model following the almost same existing pattern of the series with seasonality. Hence, the investigational results indicated that the proposed hybrid model was able to capture both linear and non-linear features of the mean monthly wind speed series.

F. COMPUTATIONAL TIME OF THE ALGORITHMS

Indeed, in recent years, hybrid approaches have been developed by combining different models for representing a complex system. The interest in developing hybrid methods is to obtain an accurate prediction. However, modeling and predicting this way brings computational time complexity that must also be addressed. Therefore, the algorithms

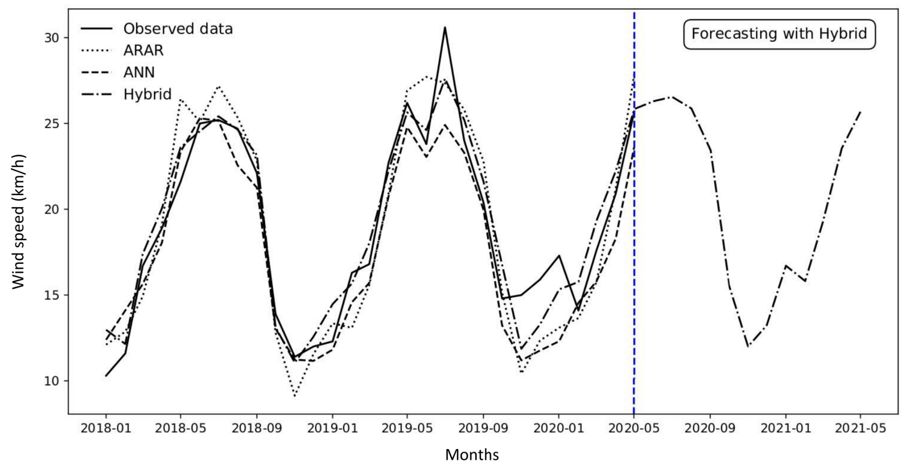

FIGURE 5. The in-sample and out-sample mean monthly wind speed forecast of Gharo based on the best-fitted models on the training set sample.

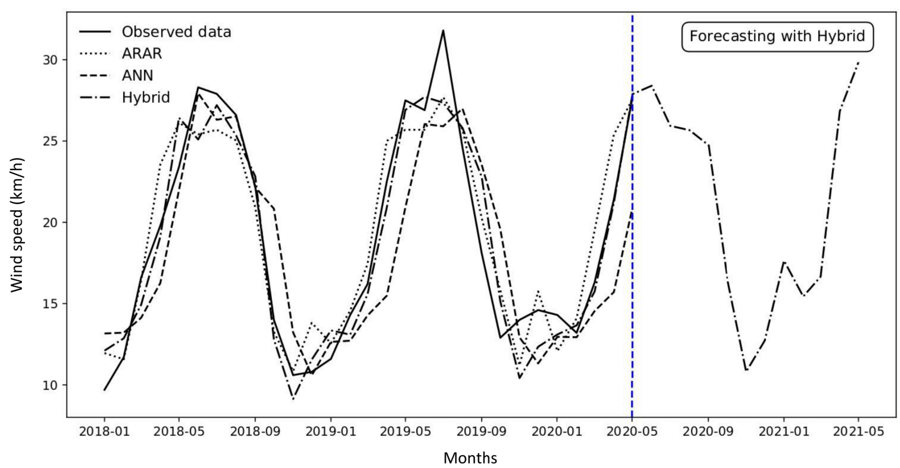

FIGURE 6. The in-sample and out-sample mean monthly wind speed forecast of Talhar based on the best-fitted models on the training set sample.

computational time for each model and each city were measured. But it depends on CPU performance and the operating system of the machine. In this study, all the algorithms were performed using Python on a machine with a Core i7-7500U GHz processor with 16-GB-RAM running Windows 10. The algorithms computational time in seconds (including training, testing, and prediction time) has been reported in Table 3. The values of computation time are found to be very small and in the vicinity of each other. The hybrid model consumed very few seconds but relatively more time in execution. This is because hybrid performed two models one after another. The SVM took lower computational time but produced fitting and prediction accuracy also very low. Intuitively, the proposed scheme was the better choice according to convergence fitness criteria.

G. RESULTS OF WILCOXON SIGNED-RANK TEST

This study also commenced the Wilcoxon-signed-rank test [54] using absolute error of each model and denoted by $|E|_{ARAR}$, $|E|_{ANN}$, $|E|_{SVM}$ and $|E|_{hybrid}$, to determine the best model among ARAR, ANN, SVM, and hybrid ARAR-ANN model. To ensure that the difference in the results of the different models was statistically significant and not by statistical chance. The use of the Wilcoxon-signed-rank test is preferred as it does not rely on the restriction of the normality. This test tests the null hypothesis that the two models perform equally well and their results are not significantly different. Otherwise, the significance difference between the models indicated. The null hypothesis is rejected if the p-value is less than the common level-of-significance (0.05). The null hypothesis rejection specifies that the hybrid models were superior to the other considered model. The results of the three cities were summarized in Table 5. It can be observed from Table 4 that the p-values between hybrid ARAR-ANN and ARAR and between hybrid ARAR-ANN and ANN models are all much small and much less than the value of 0.05. The hybrid ARAR-ANN was also paired with SVM, as shown in Table 4. On the base of results the Wilcoxon-signed-rank test yield a

TABLE 4. The results (p-values) of the Wilcoxon-signed-rank test.

Dataset	Hybrid-ARAR	Hybrid-ANN	Hybrid-SVM
H_O : Null hypothesis	$H_O : \|E\|_{hybrid} = \|E\|_{ARAR}$	$H_O : \|E\|_{hybrid} = \|E\|_{ANN}$	$H_O : \|E\|_{hybrid} = \|E\|_{SVM}$
H_1 : Alternative hypothesis	$H_1 : \|E\|_{hybrid} < \|E\|_{ARAR}$	$H_1 : \|E\|_{hybrid} < \|E\|_{ANN}$	$H_1 : \|E\|_{hybrid} < \|E\|_{SVM}$
Jhimpir	0.0205	0.0016	0.0000
Gharo	0.0058	0.0104	0.0000
Talhar	0.0121	0.0010	0.0000

p-value less than the threshold level-of-significance. These results suggested the rejection of the null hypothesis for all comparative models. Taken together, the data presented here provide evidence that the hybrid ARAR-ANN model was a statistically better model than ARAR, ANN, and SVM model.

H. MULTISTEP AHEAD FORECASTING

The accurate model that capable of predicting wind speed was the proposed hybrid ARAR-ANN model for Jhimpir, Gharo, and Talhar. It was decided to use the hybrid models for out-of-sample forecasting, to further illustrate the quality of the hybrid ARAR-ANN model. The out-of-sample forecasting was computed for multistep head from June 2020 to May 2021 and sketched in Figure 4, 5 and 6, with the extended dotted and dashes lines for all three study regions with the only hybrid model.

VI. CONCLUSION

Wind power generation is essential for economic and environmental benefits than the other energy resources. Obtaining accurate wind speed predictions become vital for wind farm management and the research work for improving this aspect attracted intensive attention. The ARAR model became popular for the time series data with periodic pattern and the ANNs has shown much flexibility in modeling the nonlinear data. The ARAR and ANN can only perform efficiently on their premises. Hence, based on these models hybrid ARAR-ANN model has been proposed for mean monthly wind speed forecasting, with the purpose to achieve exceedingly accurate and stable forecasting results. To demonstrate the adequacy of the proposed hybrid model, the mean monthly wind speed data of Jhimpir, Gharo, and Talhar, Pakistan were obtained as three case studies. As compared with the individual models, the proposed hybrid model significantly improves the accuracy of forecasting as shown by the reduction of statistical errors. The hybrid model forecasting accuracy is also justified by the NSEC that is above 0.90 for the studied regions, which represents an excellent performance. Indeed, the proposed hybrid ARAR-ANN model can be deemed as credible alternatives when modeling and forecasting wind speed. Twelve-step ahead wind speed forecasting has been also computed and observed the same periodic pattern in the out-of-sample forecasting. Finally, it is important to highlight that this work can serve to explore the wind potential, wind speed prediction, and thus to plan the electricity generation from wind energy for decision-makers.

REFERENCES

[1] A. Mengal, N. H. Mirjat, G. Das Walasai, S. A. Khatri, K. Harijan, and M. A. Uqaili, "Modeling of future electricity generation and emissions assessment for Pakistan," *Processes*, vol. 7, no. 4, p. 212, Apr. 2019.

[2] J. Kotcher, E. Maibach, and W.-T. Choi, "Fossil fuels are harming our brains: Identifying key messages about the health effects of air pollution from fossil fuels," *BMC Public Health*, vol. 19, no. 1, p. 1079, Dec. 2019.

[3] L. Xiang, Z. Deng, and A. Hu, "Forecasting short-term wind speed based on IEWT-LSSVM model optimized by bird swarm algorithm," *IEEE Access*, vol. 7, pp. 59333–59345, 2019.

[4] P. Liu, F. Meng, and C. Y. Barlow, "Wind turbine blade end-of-life options: An eco-audit comparison," *J. Cleaner Prod.*, vol. 212, pp. 1268–1281, Mar. 2019.

[5] A. Sayigh and D. Milborrow, *The Age of Wind Energy: Progress and Future Directions From a Global Perspective*. Cham, Switzerland: Springer, 2019.

[6] International Renewable Energy Agency (IRENA), *Renewable Energy and Jobs, Annual Review*. Abu Dhabi, United Arab Emirates, 2019. [Online]. Available: https://www.irena.org/publications/2019/Jun/

[7] M. Ahmed, M. N. Ali, and I. A. Memon, "A review of wind energy potential in Sindh, Pakistan," in *Proc. ICPA*, Tallahassee, FL, USA, 2018, Art. no. 020017.

[8] J. Wang, W. Zhang, J. Wang, T. Han, and L. Kong, "A novel hybrid approach for wind speed prediction," *Inf. Sci.*, vol. 273, pp. 304–318, Jul. 2014.

[9] E. Cadenas and W. Rivera, "Wind speed forecasting in three different regions of mexico, using a hybrid ARIMA–ANN model," *Renew. Energy*, vol. 35, no. 12, pp. 2732–2738, Dec. 2010.

[10] E. Grigonytė and E. Butkevičiūtė, "Short-term wind speed forecasting using ARIMA model," *Energetika*, vol. 62, nos. 1–2, pp. 45–55, Jul. 2016.

[11] E. Erdem and J. Shi, "ARMA based approaches for forecasting the tuple of wind speed and direction," *Appl. Energy*, vol. 88, no. 4, pp. 1405–1414, Apr. 2011.

[12] E. Cadenas, W. Rivera, R. Campos-Amezcua, and C. Heard, "Wind speed prediction using a univariate ARIMA model and a multivariate NARX model," *Energies*, vol. 9, no. 2, pp. 1–15, Feb. 2016.

[13] Z.-H. Guo, J. Wu, H.-Y. Lu, and J.-Z. Wang, "A case study on a hybrid wind speed forecasting method using BP neural network," *Knowl.-Based Syst.*, vol. 24, no. 7, pp. 1048–1056, Oct. 2011.

[14] H. B. Azad, S. Mekhilef, and V. G. Ganapathy, "Long-term wind speed forecasting and general pattern recognition using neural networks," *IEEE Trans. Sustain. Energy*, vol. 5, no. 2, pp. 546–553, Apr. 2014.

[15] G. Li and J. Shi, "On comparing three artificial neural networks for wind speed forecasting," *Appl. Energy*, vol. 87, no. 7, pp. 2313–2320, Jul. 2010.

[16] Q. Cao, B. T. Ewing, and M. A. Thompson, "Forecasting wind speed with recurrent neural networks," *Eur. J. Oper. Res.*, vol. 221, no. 1, pp. 148–154, Aug. 2012.

[17] G. Santamaría-Bonfil, A. Reyes-Ballesteros, and C. Gershenson, "Wind speed forecasting for wind farms: A method based on support vector regression," *Renew. Energy*, vol. 85, pp. 790–809, Jan. 2016.

[18] C. Zhang, H. Wei, J. Zhao, T. Liu, T. Zhu, and K. Zhang, "Short-term wind speed forecasting using empirical mode decomposition and feature selection," *Renew. Energy*, vol. 96, pp. 727–737, Oct. 2016.

[19] A. Zendehboudi, M. A. Baseer, and R. Saidur, "Application of support vector machine models for forecasting solar and wind energy resources: A review," *J. Cleaner Prod.*, vol. 199, pp. 272–285, Oct. 2018.

[20] M. A. Mohandes, T. O. Halawani, S. Rehman, and A. A. Hussain, "Support vector machines for wind speed prediction," *Renew. Energy*, vol. 29, no. 6, pp. 939–947, May 2004.

[21] J. Zhou, J. Shi, and G. Li, "Fine tuning support vector machines for short-term wind speed forecasting," *Energy Convers. Manage.*, vol. 52, no. 4, pp. 1990–1998, Apr. 2011.

[22] S. Ahmed, M. Khalid, and U. Akram, "A method for short-term wind speed time series forecasting using support vector machine regression model," in *Proc. 6th Int. Conf. Clean Electr. Power (ICCEP)*, Jun. 2017, pp. 190–195.

[23] Y. J. Natarajan and D. S. Nachimuthu, "New SVM kernel soft computing models for wind speed prediction in renewable energy applications," *Soft Comput.*, vol. 24, pp. 11441–11458, Dec. 2019.

[24] Z. Zhu, D. Zhou, and Z. Fan, "Short term forecast of wind power generation based on SVM with pattern matching," in *Proc. IEEE Int. Energy Conf. (ENERGYCON)*, Apr. 2016, pp. 1–6.

[25] H. Bouzgou and N. Benoudjit, "Multiple architecture system for wind speed prediction," *Appl. Energy*, vol. 88, no. 7, pp. 2463–2471, Jul. 2011.

[26] V. Nikolić, S. Motamedi, S. Shamshirband, D. Petković, S. Ch, and M. Arif, "Extreme learning machine approach for sensorless wind speed estimation," *Mechatronics*, vol. 34, pp. 78–83, Mar. 2016.

[27] C. Zhang, H. Wei, X. Zhao, T. Liu, and K. Zhang, "A Gaussian process regression based hybrid approach for short-term wind speed prediction," *Energy Convers. Manage.*, vol. 126, pp. 1084–1092, Oct. 2016.

[28] A. H. Haghiabi, H. M. Azamathulla, and A. Parsaie, "Multiple architecture system for wind speed prediction," *ISH J. Hydraulic Eng.*, vol. 23, no. 1, pp. 102–110, Jul. 2017.

[29] A. Parsaie, A. H. Haghiabi, S. Emamgholizadeh, and H. M. Azamathulla, "Prediction of discharge coefficient of combined weir-gate using ANN, ANFIS and SVM," *Int. J. Hydrol. Sci. Technol.*, vol. 9, no. 4, pp. 412–430, 2019.

[30] L. B. Ferreira, F. F. da Cunha, R. A. de Oliveira, and E. I. F. Filho, "Estimation of reference evapotranspiration in Brazil with limited meteorological data using ANN and SVM—A new approach," *J. Hydrol.*, vol. 572, pp. 556–570, May 2019.

[31] I. Okumus and A. Dinler, "Current status of wind energy forecasting and a hybrid method for hourly predictions," *Energy Convers. Manage.*, vol. 123, pp. 362–371, Sep. 2016.

[32] O. B. Shukur and M. H. Lee, "Daily wind speed forecasting through hybrid KF-ANN model based on ARIMA," *Renew. Energy*, vol. 76, pp. 637–647, Apr. 2015.

[33] D. B. Alencar, C. M. Affonso, R. C. L. Oliveira, and J. C. R. Filho, "Hybrid approach combining SARIMA and neural networks for multi-step ahead wind speed forecasting in brazil," *IEEE Access*, vol. 6, pp. 55986–55994, 2018.

[34] A. Mostafaeipour, A. Goli, M. Rezaei, M. Qolipour, H. R. Arabnia, H. Goudarzi, and E. Behnam, "Performance of different hybrid algorithms for prediction of wind speed behavior," *Wind Eng.*, vol. 11, no. 2, Oct. 2019, Art. no. 0309524X19882431.

[35] M. Santhosh, C. Venkaiah, and D. V. Kumar, "A hybrid forecasting model based on artificial neural network and teaching learning based optimization algorithm for day-ahead wind speed prediction," in *Intelligent Computing Techniques for Smart Energy Systems*. Singapore: Springer, 2020, pp. 455–463.

[36] S. Qin, J. Wang, J. Wu, and G. Zhao, "A hybrid model based on smooth transition periodic autoregressive and Elman artificial neural network for wind speed forecasting of the Hebei region in China," *Int. J. Green Energy*, vol. 13, no. 6, pp. 595–607, May 2016.

[37] S. Jafarian-Namin, A. Goli, M. Qolipour, A. Mostafaeipour, and A. M. Golmohammadi, "Forecasting the wind power generation using Box–Jenkins and hybrid artificial intelligence: A case study," *Int. J. Energy Sector Manage.*, vol. 13, no. 4, p. 1038–1062, Nov. 2019.

[38] R. G. Kavasseri and K. Seetharaman, "Day-ahead wind speed forecasting using f-ARIMA models," *Renew. Energy*, vol. 34, no. 5, pp. 1388–1393, May 2009.

[39] F.-L. Chu, "Analyzing and forecasting tourism demand with ARAR algorithm," *Tourism Manage.*, vol. 29, no. 6, pp. 1185–1196, Dec. 2008.

[40] P. J. Brockwell and R. A. Davis, *ITSM: An Interactive Time Series Modelling Package for the PC*. New York, NY, USA: Springer, 2012.

[41] E. Parzen, "ARARMA models for time series analysis and forecasting," *J. Forecasting*, vol. 1, no. 1, pp. 67–82, Jan. 1982.

[42] N. H. Miswan, N. H. Hussin, R. M. Said, K. Hamzah, and E. Z. Ahmad, "ARAR algorithm in forecasting electricity load demand in Malaysia," *Glob. J. Pure Appl. Math.*, vol. 12, no. 1, pp. 361–367, 2016.

[43] A. Dutsarak and J. Liangrokapart, "A study of the hybrid model performance for time series forecasting," *Kasem Bundit Eng. J.*, vol. 8, pp. 151–163, Aug. 2018.

[44] X. Wang and M. Meng, "A hybrid neural network and ARIMA model for energy consumption forecasting," *J. Comput.*, vol. 7, no. 5, pp. 1184–1190, May 2012.

[45] G. P. Zhang, "Time series forecasting using a hybrid ARIMA and neural network model," *Neurocomputing*, vol. 50, pp. 159–175, Jan. 2003.

[46] H. Liu, H.-Q. Tian, and Y.-F. Li, "Comparison of two new ARIMA-ANN and ARIMA-Kalman hybrid methods for wind speed prediction," *Appl. Energy*, vol. 98, pp. 415–424, Oct. 2012.

[47] O. O. Ajayi, O. D. Ohijeagbon, C. E. Nwadialo, and O. Olasope, "New model to estimate daily global solar radiation over Nigeria," *Sustain. Energy Technol. Assessments*, vol. 5, pp. 29–36, Mar. 2014.

[48] S. Ruping, "SVM kernels for time series analysis," in *Proc. Tagungsband Der GI-Workshop-Woche Lernen Lehren (LLWA)*, Dortmund, Germany: Adaptivitt, Univ. Dortmund, 2001, pp. 43–50.

[49] R. Samsudin, A. Shabri, and P. Saad, "A comparison of time series forecasting using support vector machine and artificial neural network model," *J. Appl. Sci.*, vol. 10, no. 11, pp. 950–958, Nov. 2010.

[50] P.-F. Pai, K.-P. Lin, C.-S. Lin, and P.-T. Chang, "Time series forecasting by a seasonal support vector regression model," *Expert Syst. Appl.*, vol. 37, no. 6, pp. 4261–4265, Jun. 2010.

[51] K. Nam and T. Schaefer, "Forecasting international airline passenger traffic using neural networks," *Logistics Transp. Rev.*, vol. 31, no. 3, pp. 239–251, Sep. 1995.

[52] P. F. Pai and W. C. Hong, "An improved neural network model in forecasting arrivals," *Ann. Tourism Res.*, vol. 32, no. 4, p. 1138–1141, 2005.

[53] W. A. Broock, J. A. Scheinkman, W. D. Dechert, and B. LeBaron, "A test for independence based on the correlation dimension," *Econ. Rev.*, vol. 15, no. 3, pp. 197–235, Jan. 1996.

[54] I. C. Anaene Oyeka and G. U. Ebuh, "Modified Wilcoxon signed-rank test," *Open J. Statist.*, vol. 2, no. 2, pp. 172–176, Apr. 2012.

MIRZA NAVEED SHAHZAD received the master's degree in statistics from the University of the Punjab, Lahore, Pakistan, the M.Phil./M.S. and Ph.D. degrees in statistics from Quaid-i-Azam University, Islamabad, Pakistan, in 2008 and 2016, respectively. He is currently an Assistant Professor with the Department of Statistics, University of Gujrat, Pakistan. He published more than 25 scientific research papers in journals and conferences. He has supervised 37 B.S., M.Sc., and M.Phil. students. He is also Co-PI in a project and also completed a project as PI, funded by HEC Pakistan. His keen interests include probabilistic theory, applied statistics, Bayesian statistics, time-series analysis, and hybrid models.

SAIQA KANWAL received the B.S. (Hons.) and M.Phil. degrees in statistics from the University of Gujrat, Pakistan, in 2017 and 2020, respectively. Her current research interests include time series analysis and extreme value frequency analysis.

ABID HUSSANAN received the M.S. degree from the University of Technology Malaysia, Malaysia, in 2014, and the Ph.D. degree in applied mathematics from University Malaysia Pahang, Malaysia, in 2017. From 2017 to 2020, he was a Postdoctoral Research Fellow with University Malaysia Pahang, and Shenzhen University, China, respectively. He is currently working as a part-time Researcher in Applied Mathematics with Ton Duc Thang University, Ho Chi Minh City, Vietnam. He has more than 30 scientific research articles published in prestigious international journals. He also presented his research findings at ICIAM 2019, Spain. He is an international journal reviewer for Elsevier, Springer, Emerald, Taylor & Francis, MDPI, Begell House, IEEE Access, and some other publishers. In 2018, he got the China Postdoctoral Science Foundation Research grant. He has co-supervised two Ph.D. degree students at University Sultan Zainal Abidin, Malaysia. His research interests include fluid mechanics, Newtonian and non-Newtonian fluids, heat and mass transfer analysis, entropy generation, nanofluids flow, exact, and numerical solutions.