IEEE Access
Multidisciplinary : Rapid Review : Open Access Journal

Received September 7, 2020, accepted September 18, 2020, date of publication October 1, 2020, date of current version November 12, 2020.

Digital Object Identifier 10.1109/ACCESS.2020.3028259

One-Month-Ahead Wind Speed Forecasting Using Hybrid AI Model for Coastal Locations

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ABSTRACT Wind speed forecasts can boost the quality of wind energy generation by increasing the efficiency and enhancing the economic viability of this variable renewable resource. This work proposes a hybrid model for wind energy capacity for electrical power generation at coastal sites by utilizing wind-related variables' characteristics. The datasets of three coastal locations of Kuwait validate the proposed method. The hybrid model is a merger of Artificial Neural Network (ANN) and Particle Swarm Optimization (PSO) and predicts one-month-ahead wind speed for wind power density calculation. The neural network starts its performance evaluation with a variable number of hidden-layer neurons to finally identify the optimal ANN topology. Comparisons of statistical indices with both expected and observed test results indicate that the ANN-PSO based hybrid model with the low root-mean-square-error and mean-square-error values outperforms ANN-based trivial models. The prediction model developed in this work is highly accurate with a Mean Absolute Percentage Error (MAPE) of approximately (3-6%) for all the sites.

INDEX TERMS Electrical energy, wind energy, power density, artificial neural network, particle swarm optimization.

NOMENCLATURE

ANN	Artificial Neural Network
PSO	Particle Swarm Optimization
MAPE	Mean Absolute Percentage Error
WASP	Wind Atlas Analysis and Application Program
LSTM	Long-short term memory
SVM	Support Vector Machines
BPNN	Backpropagation neural network
MLH	Maximum likelihood method
WPD	Wind power density
RMSE	Root-mean-square error
v_i	wind speed at time instant i
c	Weibull scale parameter
k	Shape factor
$f(v)$	Weibull distribution function
P_{best}	Particle's best fitness in PSO space
G_{best}	Global best fitness in PSO space

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

I. INTRODUCTION

Renewable energy sources have received considerable scientific attention due to the rapid depletion in fossil fuel resources. Global energy demand has accelerated due to industrialization; this is the primary cause of the depletion of the oil and gas reserves [1]–[4]. Energy generation currently uses a range of renewable energy sources, including solar PV systems, wind-based energy systems, tidal energy extraction schemes, biomass-based generation, to name a few [4]. Wind and solar photovoltaic (PV) energy are among the most promising options for generating electricity. In particular, wind energy has attracted significant attention from researchers as it can be harvested year-round at any time. In contrast to other renewable sources, the other anticipated advantages of wind energy include its abundant availability and one of the most economical options among renewable energy sources. These factors have made wind energy a rapidly growing source in developing countries like Kuwait [5]. Kuwait is known as a country that produces high amounts of oil. The extensive use of fossil fuels

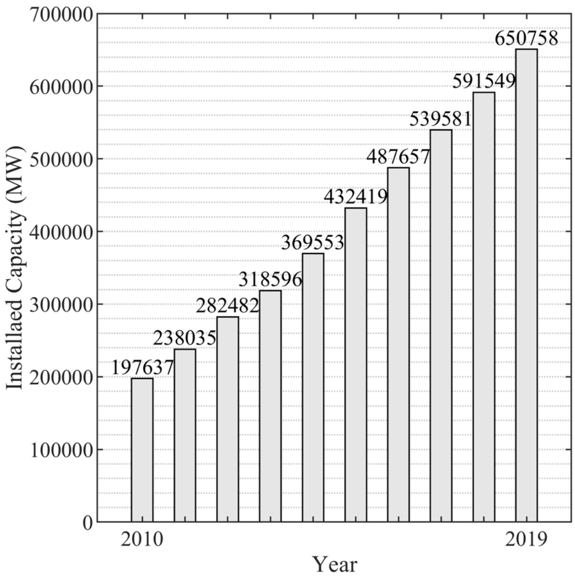

FIGURE 1. The total installed capacity of wind energy of the world from 2010 to 2019 [11].

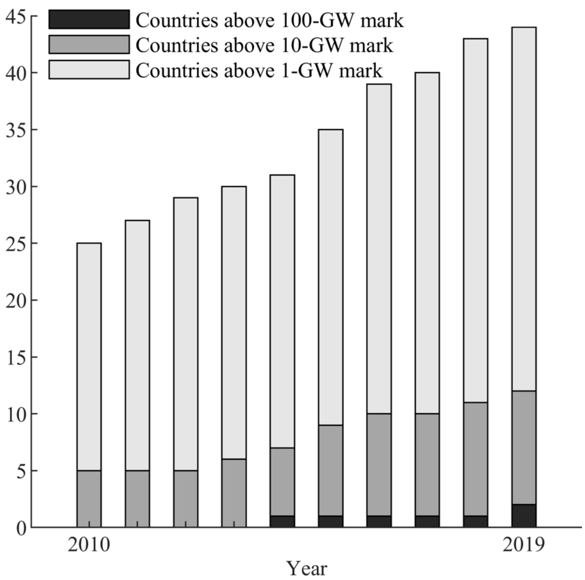

FIGURE 2. Growing number of gigawatt markets in the world from 2010 to 2019.

and manufacturing activities has exacerbated environmental and elevated health issues in Kuwait's residential areas. Therefore, to improve control over polluting emissions, fossil fuel dependence of power generations needs to be reduced.

The wind energy potential of a location can be determined using wind-related variables such as wind speed at a certain height, direction, and continuity [3], [4]. Researchers have used multiple methods to analyze these wind characteristics. Application programs such as Wind Atlas Analysis and Wind Atlas Analysis and Application Program (WASP) frequently use Rayleigh and Weibull methods [3]. Many time scales, including monthly, quarterly, and annual time scales, are considered to evaluate wind speed data characteristics.

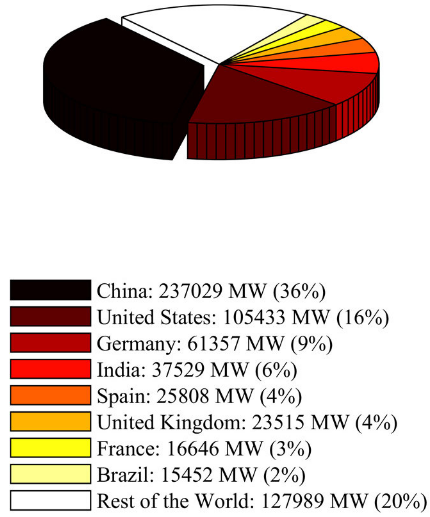

FIGURE 3. Top countries by cumulative capacity in 2019.

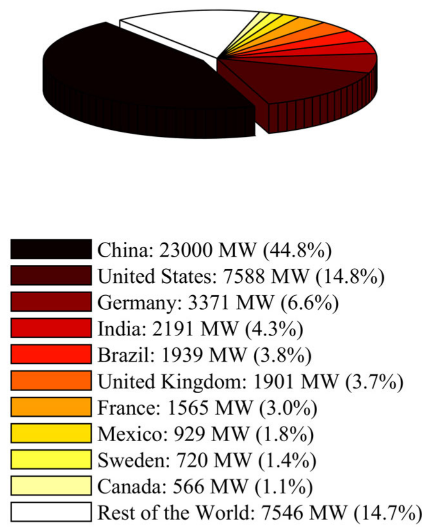

FIGURE 4. Top countries by added wind capacity in 2018.

Since the beginning of the third millennium, the total cumulative electricity capacity generated from wind energy observes a rapid increase, reaching 650.8 GW by the end of 2019. In 2019, 59,667 MW were installed, significantly higher than 50,252 MW of 2018 [6]. All completed wind turbines at the end of 2019 will cover 6 % of the world's electricity market. More than half of the new wind power installation has been added outside Europe and North America's traditional markets since 2010, mainly due to the continued boom in China and India [7]. China installed 145 GW of wind turbine-based generation at the end of 2015 [8]. By 2015, China had installed nearly half of the world's additional wind capacity. With 27.5 GW, corresponding 9.1 GW of new installations, both China and the United States have shown strong years, in both cases of the highest market volume of the previous five years [6]. Commercial wind power is being implemented in more than half of the world's nations [4]. The upcoming wind development market is expected to be driven by emerging markets such as Latin America and

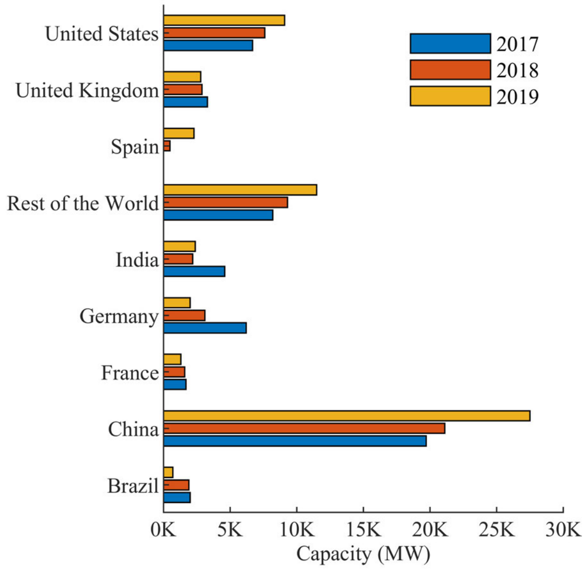

FIGURE 5. The total installed added capacity.

South-East Asia. Further policy funding and reforms in these areas would make for more substantial business development. Global production of renewable energy continues to expand with the growing cost-effectiveness of renewables technologies [9].

As of 2020, the current Coronavirus crisis is predicted to impact wind power market growth globally. Like most other sectors in 2020, the wind sector is being hampered by disrupted foreign supply chains and by national lockdown legislation. Many governments have started to draw up plans and stimulus programs to restore their businesses after the corona crisis [9].

The wind energy potential for power generation was evaluated at Binalood, Iran by Mostafaeipour *et al.* in [10], and it was investigated that the site offered a vast potential for a sizeable grid-connected system. Alamdari *et al.* [10] has investigated the characteristics of Iran at 68 locations. Their study analyzed annual, seasonal, and diurnal variations in wind speed. It revealed the importance of the economic evaluation from an investment perspective of renewable energy projects and their technical assessments. An evaluation based on economic and technical considerations of renewable energy sources for different applications has been performed at multiple locations of the world [12]–[14]. Analysis of the cost incurred in wind energy resources in different regions has been presented in past literature [15]–[21]. An economic evaluation of a few Turkey locations is presented by Vardar and Çetin [21] and Celik [22]. Rehman *et al.* [23] provide a cost analysis of 20 locations of Saudi Arabia. An analysis of small wind power electric generations is done by Nouni *et al.* [24]. However, most past studies have never been implemented in real practical applications.

A. RELATED WORK

There are already several wind-power prediction methods available in the literature. The physical model-based method develops thermodynamic and kinetic equations which describe the evolution of the atmosphere in layers. Wind speed and wind power are predicted, taking into account the limits and constraints. This method's prediction model is highly dynamic and very sensitive to initial erroneous information [25]–[27].

Machine learning models are used with bio intelligence to estimate the wind forecast problem [28]–[32]. These techniques include a fuzzy logic algorithm [33]–[36], a long-short term memory (LSTM) networks [37]–[40]. In [41], authors have developed a new prediction method using a regularized pseudo-inverse neural network. In [42], a two-layer machine learning system is created, which can progressively improve accuracy. In [43], a novel hybrid architecture designed to estimate extreme learning machines with composite regression and feature selection was introduced. Some more complex models combine different predictive methods and are discussed in [44]–[49].

Recent initial conditions and a high-resolution model are not always performance improvers. A probabilistic forecast was studied, and more detailed information on the associated uncertainty was provided [50]. The interval description has been checked for wind speed [51] and wind power [52], [53]. Hybridization of the numerical weather forecast and the wind speed prediction algorithm [54]–[57] was implemented. A system model with varying initial parameters produces the data diversity. The model's final output is handled with a wise, non-linear approach that allows the use of the system's diversity.

The machine learning approach has been increasingly employed to derive internal patterns from data published in Nature in 2019 [58]. The machine learning model and the physical model have specific (data-driven) paradigms. The former has strong extrapolation capability. That is more robust, with the prospect of new legislation. Combining the two methods would improve the parameters and replace the master-learning process with the physical sub-model [59].

Neural networks have become increasingly popular for forecasting wind speeds due to their non-linear nature and evolving network structure. Models can be used to resolve the question of an unknown intrinsic mechanism and to establish a non-linear relationship between the vectors of input and output. However, the algorithm's robustness requires tuning of parameters and large training data. Also, a more extensive computation is needed for model training and estimation of parameters.

This paper investigates three different coastal locations of Kuwait that are considered for the wind data accumulation: its speed, direction, and frequency distribution. The investigation of potential wind energy is based on a thorough assessment of the statistics of the wind characteristics of frequency distribution and average wind speed. For estimation of wind energy potential at higher altitudes, Weibull distribution function is an acceptable tool employed to fit the wind speed frequency along with its time series [60], [61]. Since vertical deviations in wind velocities are pivotal in the assessment of wind energy potential, the power-law expression is employed to evaluate the wind parameters from heights of 10 m to 70 m. Weibull's parameters are finally determined using the Windographer software, which analyzes the data to estimate the Wind Power Density (WPD) [62], [63]. The effect of seasonal variations on the wind power potential at the suggested locations is thoroughly analyzed through all four seasons' seasonal data. The prediction of the wind power density on short-term bases, one-day-ahead forecast models based on an artificial neural network (ANN) Support Vector Machines (SVM), and a hybrid model that combines ANN and PSO is developed and implemented. It involves three input variables, including the wind speed, generation hours and relative humidity, and one variable-energy output of the wind farms. The modeling was performed in MATLAB®/Simulink environment. The model's efficacy was validated by comparing the results with the values measured at the wind farms. Based on the data analysis and these prediction models' results, the ANN-PSO model was found to be much more accurate than the other two models.

II. FRAMEWORK OF METHODOLOGY

A. QUANTITATIVE DATA ANALYSIS

The data set was analyzed from three different Kuwait locations, including Al Wafrah, Abadaly, and Al Asimah, composed of regular sampled meteorological variables linked to winding. Such variables include wind velocity, wind direction, maximum wind speed, and maximum wind rate. The data's complexities were analyzed by a detailed statistical and quantitative study of the data. These studies have given the maximum, minimum, mean, median, and standard deviation values. The data examination also highlights the numbers of second-standard deviations, third-standard deviations, and forth-standard deviation outliers, which can be eliminated from the training data to ensure the useful estimation of wind potential.

B. PARAMETRIC ANALYSIS AND CALCULATIONS

The density of wind power at a specific location is considered a reliable measure of the potential generation of wind power relative to wind speed or direction. The average annual wind speed of all sites was calculated individually at a standard height of 10 meters. The Weibull distribution function was used to determine the power density and Weibull parameters of each location. Typically, the Weibull distribution function is used to adjust the probability distribution of the measured wind speed at a specific location over a given period. The probability density function of the Weibull wind speed 'v' is defined as f(v) at a specific time interval, and is calculated as:

$$f(v) = \left(\frac{k}{c}\right)\left(\frac{V}{c}\right)^{k-1} \exp\left(-\left(\frac{V}{c}\right)^{k}\right) \tag{1}$$

In this equation, 'c' is the Weibull scale parameter, 'k' is the shape factor, and(V/c) is the dimensionless Weibull parameter. The maximum likelihood method (MLH) was

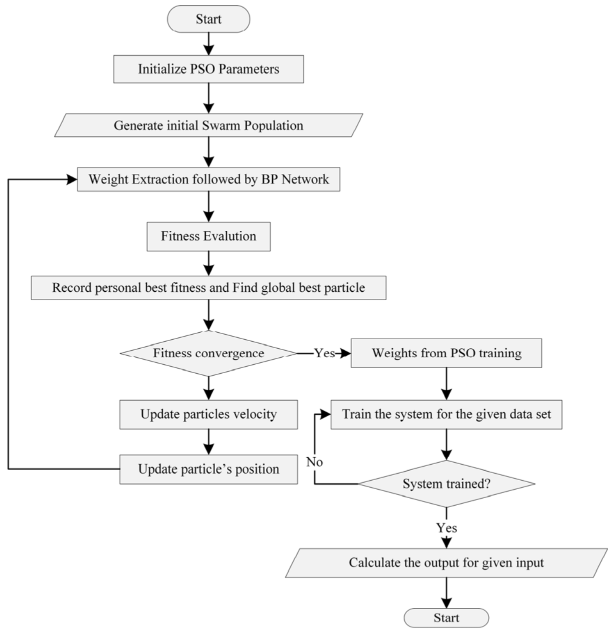

FIGURE 6. Proposed hybrid algorithm for wind prediction.

applied to estimate the shape and scale parameters as:

$$k = \left(\frac{\sum_{i=1}^{n} v_i^k \ln(v_i)}{\sum_{i=1}^{n} v_i^k} - \frac{\sum_{i=1}^{n} \ln(v_i)}{n}\right)^{-1} \tag{2}$$

$$c = \left(\frac{1}{2}\sum_{i=1}^{n} v_i^k\right)^{1/2} \tag{3}$$

In this equation, 'V_i' is the wind speed in the time stage 'i', and 'n' is the number of non-zero wind data points. By extrapolation of data at10 meters using the Power-Law, the wind data at heights of 20, 30, 40, and 70 meters was obtained. Finally, the data obtained from all three locations were analyzed to examine the effect of seasonal variations on wind power density.

C. VERTICAL EXTRAPOLATION USING POWER LAW

A power law is defined as a functional relationship of two quantities in which deviation in one quantity produces a relative proportional change in the other quantity. Moreover, the initial size and state of these quantities are not relevant; one quantity varies with each other's power. The wind data measurements used in this study have been performed at a standard height of 10 m. A 1/7 power law analyzed the effect of wind speed on WPD at different heights [62]. This law was used to extrapolate the wind speed at different heights. The mathematical notation of the power-law is written as:

$$V_2 = V_1\left(\frac{Z_2}{Z_1}\right)^{\alpha} \tag{4}$$

In this equation, V_1 represents the real wind speed at height 'Z_1'. 'V_2' is the calculated wind speed at the desired

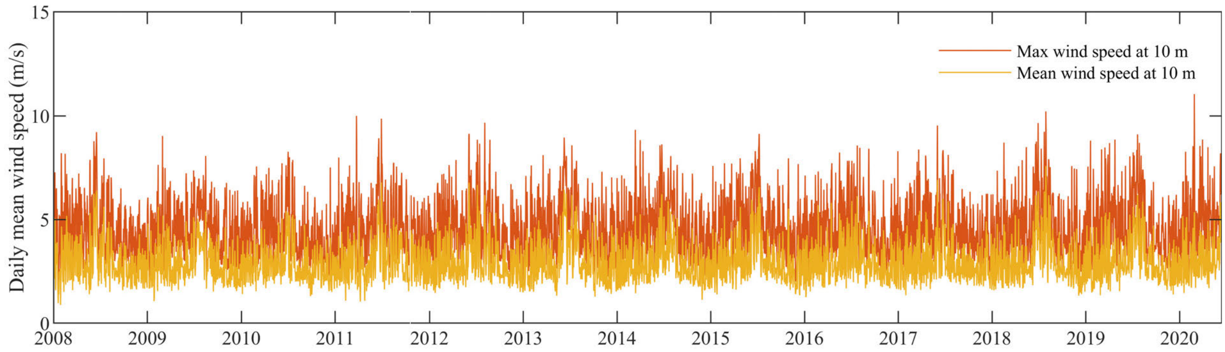

FIGURE 7. Time series plot of wind speed Al Wafrah.

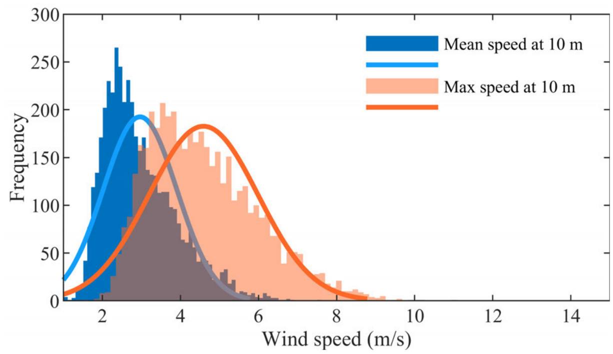

FIGURE 8. Wind speed Distribution Analysis (Al wafrah).

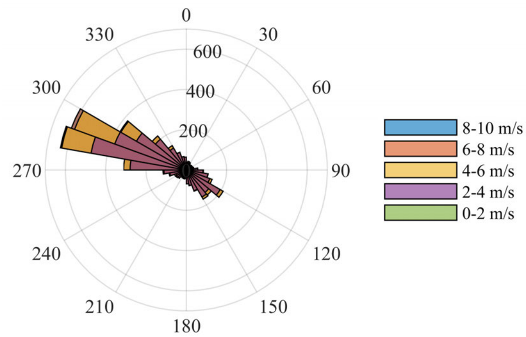

FIGURE 9. Wind direction and mean speed rose chart (Al Wafrah).

(extrapolated) height Z_2. Here, 'α' is an exponent alpha that relates to the surface's roughness; a typical value of 0.142 is generally used for normal and well-exposed locations.

By implementing this extrapolation technique, the wind speed at different heights from 10 m to 70 m, with a difference of 5 meters, was calculated.

D. WEIBULL DISTRIBUTION

Weibull distribution is a function based on two wind parameters to calculate wind speed. It can be expressed mathematically in (1). As a cumulative distribution function, the Weibull function can be described as:

$$F(v) = 1 - \exp\left(-\left(\frac{V}{c}\right)^k\right) \tag{5}$$

As already described,'V' and 'c' are calculated through Windographer software and both have the same units of m/s. By implementing the double logarithmic transformation on equation (5), it can be reproduced as follows:

$$\ln\{-\ln(1 - F(v))\} = k \ln(v) - k \ln(c) \tag{6}$$

Eq. (6) is equivalent to $y = ax + b$. If $\ln(v)$ is plotted against $\ln\{-\ln[1 - F(v)]\}$, then a straight-line result has gradient k and a y –intercept of $-k*ln(c)$. WPD is expressed in W/m^2. While calculating the wind power density, the wind speed frequency distribution, the wind power depends on the air density, and the cube-root of the wind speed. Therefore, the WPD is normally regarded as a superior pointer of the wind parameter in comparison to wind speed. By using the wind speed as a primary variable, the average wind power density can be calculated as:

$$WPD = \sum_{i=1}^{N} \frac{1}{2N}\left(\rho v_i^3\right) \tag{7}$$

In this equation, I and N indicate the wind speed and the total number of data samples used for the period of five years, respectively. It should be noted that N of a particular month is the accumulation of the data of that specific month over five years.

III. PROPOSED HYBRID ARTIFICIAL NEURAL NETWORK PREDICTION MODEL FOR WIND POWER DENSITY

The conventional backpropagation neural network (BPNN) uses the weight update rule of gradient and a decent technique to determine the system's weights under investigation by minimizing the error criterion. However, this technique primarily gets stuck in a local minimum. On the other hand, Particle swarm optimization (PSO) is a robust search and optimization technique. PSO can effectively overcome the problem of local minima of BPNN. In PSO algorithm, each particle searches its space to find the best local fitness, called P_{best}. Every particle cannot achieve globally best fitness, called G_{best}. Every single particle track and memorize its current best fitness in the swarm [64]. In this proposed hybrid model,

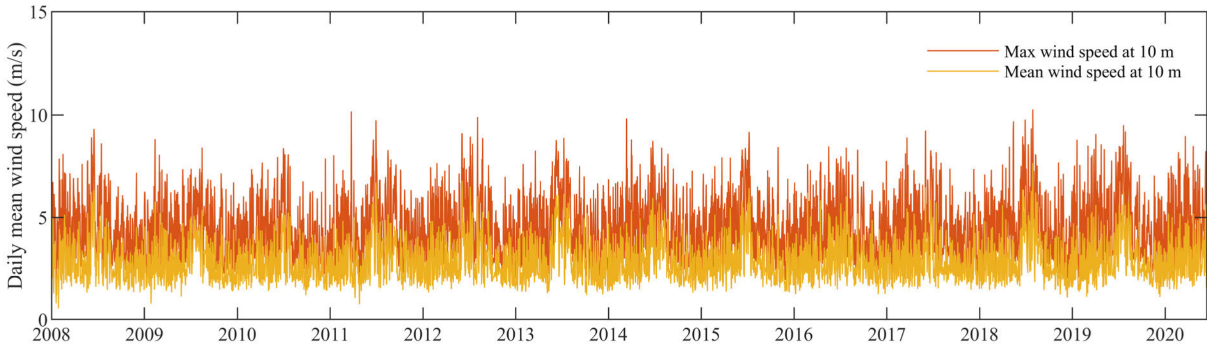

FIGURE 10. Time series plot of wind speed Abadaly.

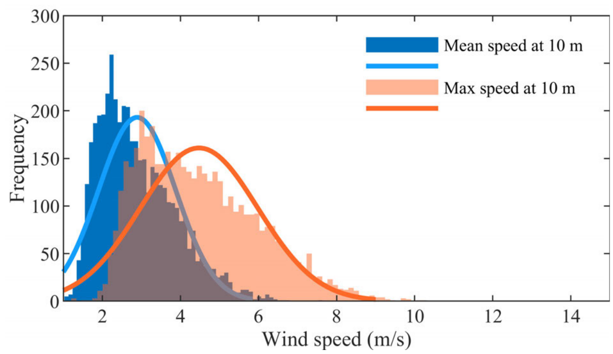

FIGURE 11. Wind speed Distribution Analysis (Abdaly).

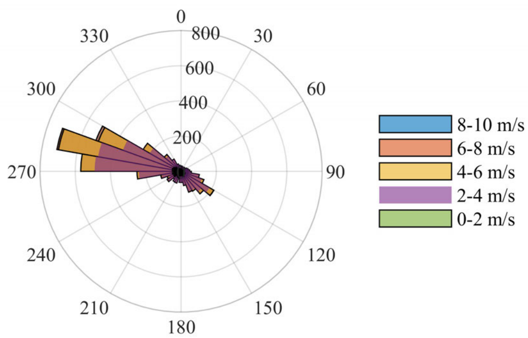

FIGURE 12. Wind direction and mean speed rose chart (Abadaly).

the solution vector of PSO consists of weights and biases of ANN model. For best training of ANN, weights and biases are predicted by PSO algorithms.

In this hybrid model, PSO improves the architecture of the Artificial Neural Network (ANN) as its training is based on trial and error [64]. In the PSO algorithm, each particle is accelerated in each time step toward P_{best} and G_{best} by using random weights. In this PSO-ANN hybrid model, fitness function depends on input, hidden layer size, bias and output. The position and velocity of a particle characterize its search space. Equation (9) and (10) show how a particle adjusts its position and velocity.

$$X_i^{k+1} = X_i^k + V_i^k \tag{8}$$

$$V_i^{k+1} = W * V_i^k + c_1 * r_1(G_{best}^k - X_i^k) + c_2 * r_2(P_{best}^k - X_i^k) \tag{9}$$

where, X_i^k and V_i^k position and velocity of k^{th} particle at i^{th} iteration. W is the inertiaweight of particles. c_1 and c_2 are acceleration coefficients having a value of 2 and r_1, r_2 are normalized random numbers. Figure 6 depicts the algorithm of the modified PSO-BP model. As PSO-BP methodology is well-known for its accuracy and performance, the fitness evaluation was formulated to obtain the minimum value of the MAPE. MAPE fitness function is formulated as:

$$Fitness = \frac{100}{N} \frac{\sum_{i=1}^{N} (V_i^{\wedge} - V_i)}{\bar{V}} \tag{10}$$

$$\bar{V} = \frac{\sum_{i=1}^{N} V_i}{N} \tag{11}$$

Weights and biases are chosen as the PSO selection parameters, while the length of the selection parameter vector, containing the weights and biases, depends on hidden numbers of layers.

A feed-forward ANN with a BP training algorithm was used to develop a one-month-ahead prediction model for wind speed, which will calculate power density. Before presenting data to the model, it was normalized in the range of 0 to 1 because the variables used in this research had different units. Twelve years of data (from 2008 to 2020) was used in the experimentation. The dataset was divided into two sets: The data from 2008 to 2018 was implemented for the training of the neural network-based models, whereas the data from 2019 to 2020 was used for testing and validation of the model results. The selection of the most appropriate number of hidden layer neurons is vitally important since the ANN-based models' prediction accuracy widely depends upon neural network architecture. For selecting the ideal ANN topology, the network was tested for its performance with a varying number of hidden layer neurons. After conducting these tests comprehensively, it has been observed that the ANN with one hidden layer containing eight hidden layer neurons produces the best results. Logarithmic sigmoidal function and

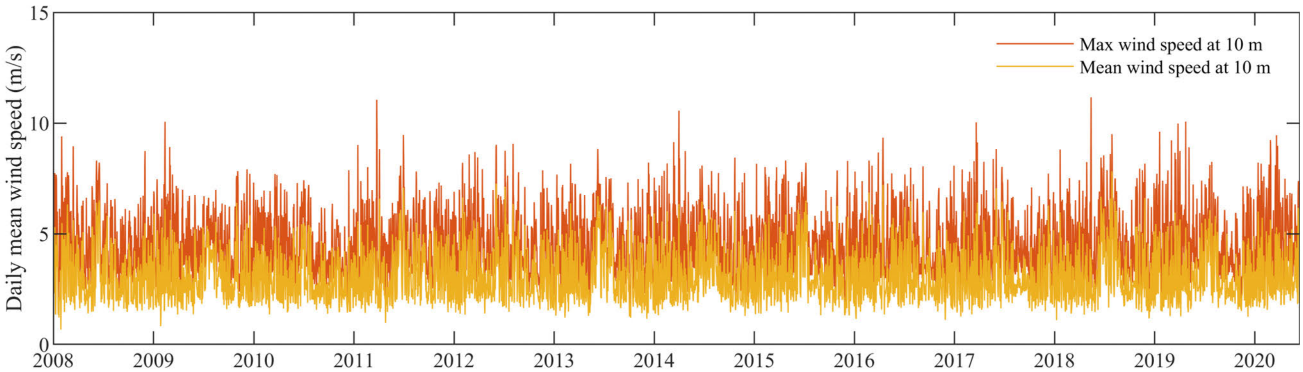

FIGURE 13. Daily time series plot of wind speed Al Asimah.

linear activation function were used for the hidden and the output neurons, respectively. The optimized neural network structure has been determined to be 4-8-1 (4 input neurons, 8 hidden neurons, and 1 output neuron) by trial. MAPE is used as the performance evaluation measure.

IV. RESULTS AND DISCUSSION

A. WIND POWER DENSITY

This study has investigated the characteristics of wind-related variables at three locations in Kuwait to explore wind energy potential for electrical power generation. The trained network's accuracy was tested against the available wind speed output data for a period of one year. The accuracy was assessed by using the root-mean-square error (RMSE) and MAPE as a performance index. RMSE is calculated using the following relation.

$$RMSE = \sqrt{\frac{1}{N}\sum_{i=1}^{N}(t_i - V_i)^2} \tag{12}$$

The overall average MAPE obtained from tested results of all locations of the PSO-BP model was measured as about (3-6%). Table 1 indicates the locations, elevations, and wind parameters of the sites. The analysis and evaluation were performed using the meteorological data of the wind energy characteristics and determining the location of the highest wind energy.

One of the critical parameters that influence the wind-generated electricity is the WPD. According to Alamdari *et al.* [10], WPD is defined as the energy in the region per unit rotor area and time, and it is a function of the distribution of wind and its velocity in the region. Table 1 shows the formulated wind power density at different heights for the three locations. It can be observed from Table 1 that, If the wind speed is regarded as the target variable, its correlation analysis with the other wind variables is summarized in Table 2 . The results demonstrate that the wind direction exerts the highest impact on wind speed because of the maximum positive correlation value of 0.8745.

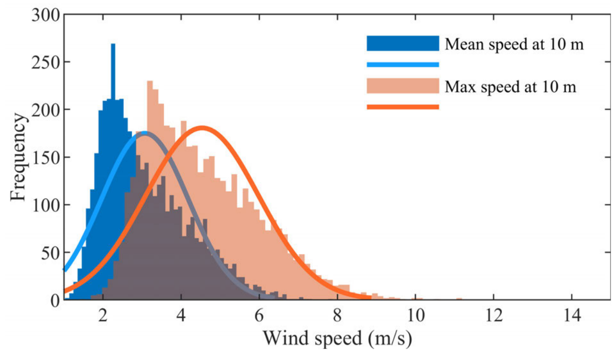

FIGURE 14. Wind speed Distribution Analysis (Al Asimah).

Similarly, the maximum wind speed and maximum wind direction also have a positive correlation with the wind speed.

The essential statistical and quantitative details of all the wind-related meteorological variables are presented in Tables 3.

Figure 7 illustrates the time series plot of wind speed over the span of 2008 to May 2012 for the location of Al Wafrah, while Figure 8 presents a histogram of samples occurring in particular wind speed ranges for the location of Al Wafrah. Figures 7 and 8 both indicate that most of the daily winds mean speed samples occur in the wind speed range from 1 m/sec to 6 m/sec. The wind speed pattern observed in Figure 7 suggests that there are no uncertain variations in the wind speed throughout the year; however, it is slightly higher during June and July. Wind speed and the direction analysis in this zone of time demonstrate the northwest direction of the principal wind in Al Wafrah at an average velocity of 4-6 m/s, Figure 9. The plots present 4542 samples at a sampling rate of one sample per day, all the samples are collected at a standard height of 10 meters. The arguments presented above can also be extended for the other two locations of this study, with the wind data of the location of Abdaly is represented in Figures 10-12 and wind data at the location of Al Asimah is represented in Figures 13-15.

B. WIND SPEED PREDICTION

This section describes results and their one-month-ahead prediction at all three locations by implementing the SVM,

TABLE 1. Wind power density at different heights for the three locations.

Station Name	*WPD at 10 m height*	*WPD at 20 m height*	*WPD at 30 m height*	*WPD at 40 m height*	*WPD at 70 m height*
Wafra	50.45	74.34	98.36	156.87	238.12
Abdaly	11.28	34.22	45.98	94.23	145.23
Al Asimah	28.38	44.23	67.56	103.70	174.19

TABLE 2. Correlation analysis of wind-related variables.

S. No.	*Wind variables*	*Correlation*
1	Wind direction	0.8745
2	Maximum wind speed	0.7143
3	Maximum wind direction	0.7112
4	Wind power density	0.8923

TABLE 3. Locations of the three sites and average wind parameters.

Station Name	*Latitude*	*Longitude*	*Average wind speed (m/s)*	*Average wind direction (Deg)*	*Average wind max. speed (m/s)*
Wafra	29^0 36` 35``	47^o 34` 36``	2.96	230.70	4.58
Abdaly	30^0 03` 57``	47^o 41` 27``	2.88	230.67	4.47
Al Asimah	29^0 33` 42``	47^o 98` 12``	3.07	220.90	4.53

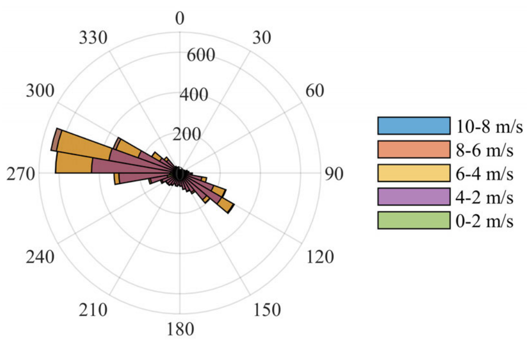

FIGURE 15. Wind direction and mean speed rose chart (Al Asimah).

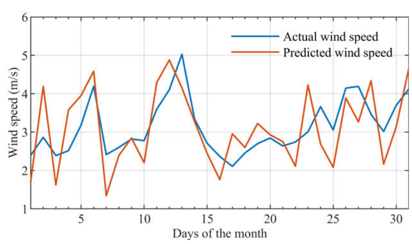

FIGURE 16. One month-ahead prediction results based on SVM model at Wafra.

ANN, and hybrid ANN-PSO based models. ANN, SVM, and hybrid ANN-PSO-based results of Wafra are represented in Figures 16, 17, and 18, respectively. A comparison of SVM, ANN, and ANN-PSO-based wind speed predictions at all locations is provided in Table 4 power potential, and electricity demand remains at their peaks during the summer season in Kuwait. At the Wafra location, the SVM-based

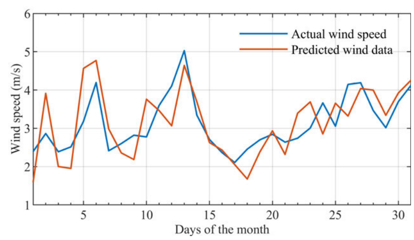

FIGURE 17. One month-ahead prediction results based on ANN model at Wafra.

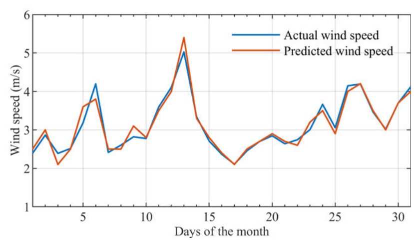

FIGURE 18. One month-ahead prediction results based on ANN-PSO model at Wafra.

model was predicted with a MAPE of 21.12%; ANN model reached a value of16.78% of MAPE, while ANN-PSO produced a MAPE of 3.78%.

At the Al Asimah and Abdaly locations, the SVM-based model predicted the MAPE values of 21.37% and 17.51%, respectively. In contrast, ANN-based model reached a MAPE of17.45% and 16.57% at the Al Asimah and Abadaly locations, respectively. However, the accuracy is again found to be better in ANN-PSO model, producing MAPE values of

TABLE 4. A comparison of ANN and ANN-PSObased wind speed prediction.

Location	*SVM Model*		*ANN Model*		*ANN-PSO Model*	
	MAPE (%)	*RMSE*	*MAPE (%)*	*RMSE*	*MAPE (%)*	*RMSE*
Wafra	21.12%	0.72	16.78%	0.61	3.78%	0.17
Al Asimah	21.37%	0.73	17.45%	0.73	5.36%	0.18
Abdaly	17.51%	0.57	16.57%	0.68	5.61%	0.19

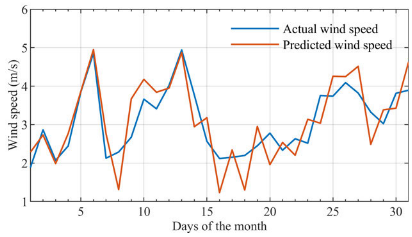

FIGURE 19. One month-ahead prediction results based on SVM model at Abadaly.

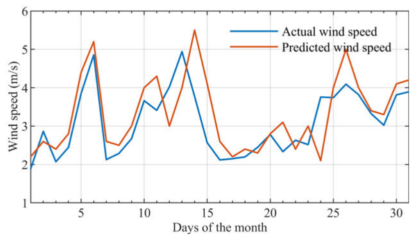

FIGURE 20. One month-ahead prediction results based on ANN model at Abadaly.

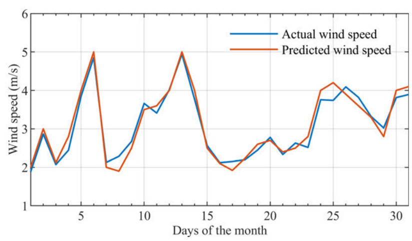

FIGURE 21. One month-ahead prediction results based on ANN-PSO model at Abadaly.

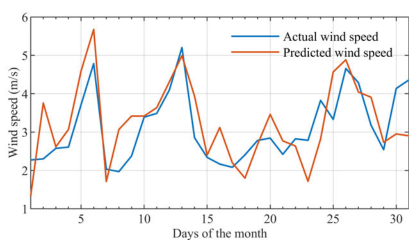

FIGURE 22. One month-ahead prediction results based on SVM model at Al Asimah.

5.36% and 5.61% at the Al Asimah and Abadaly locations, respectively (Figures 19-24). Power potential and electricity demand remain at their peaks during the summer season in Kuwait.

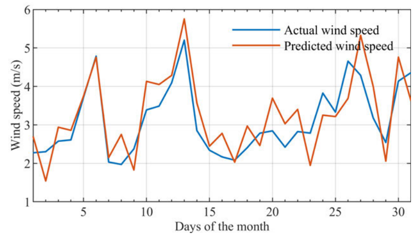

FIGURE 23. One month-ahead prediction results based on ANN model at Al Asimah.

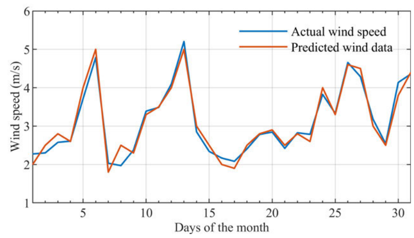

FIGURE 24. One month-ahead prediction results based on ANN-PSO model at Al Asimah.

Based on the results of the wind power density at different heights at all locations, it appears that at the height of 70 m at the Wafra location, the maximum WPD is a demonstration of the location strength for maximum power generation. The ANN-PSO model, on the other hand, can be applied effectively to forecast wind speed a month ahead. The average wind velocity at these sites remained between 3 m/s and 6 m/s over the period of one year. The mean wind power density is determined using Weibull distribution, ranged from 70 W/m^2 to 179 W/m^2 at a standard height of 10 meters.

It was observed that at the height of 70 m from the ground, the wind power density remained between 160 W/m^2, and power potential and electricity demand remain at their peaks during the summer season in Kuwait was 293 W/m^2, which demonstrates an average increase of 82%.

The ANN parameters are tuned by using gradient descent, while the proposed approach uses PSO to modify the network parameters. Local minimum levels influence the convergence of neural network training. On the other hand, the proposed PSO approach ensures that the global optimum for tuning parameters is achieved. Quadratic programming (QP) trains SVMs, and training time is found to be faster in SVM compared to ANN and the proposed ANN-PSO technique. With ANN and ANN-PSO, the computational time obtained in this work is almost the same, with a small reduction of time taken by the PSO network. On the other hand, SVM is found to be reducing the computational time by almost 8 % in the study of wind predictions.

V. CONCLUSION

In this study, the one-month-ahead forecast of wind density is done by exploiting the data of wind speed, its direction, and its frequency distribution at the coastal locations. The data at three different Kuwait locations were utilized to determine the annual WPD by evaluating the Weibull parameters of the wind distribution function. The wind speed was predicted at all the locations by implementing the SVM, ANN, and hybrid ANN-PSO models for one-month-ahead prediction. Annual average wind speed at the standard height of 10 m was found in the range of 3.7 to 5.5 m/s. It was concluded that at the height of 70 m from ground, the wind power density increases by an average of 82%. The proposed ANN-PSO-based hybrid prediction model is applied to predict the wind power density one month ahead. The results of the prediction model indicated reasonably high prediction accuracy. These prediction results can help the power system managers determine the capacity of this renewable source in advance to integrate into the power grid by reducing the thermal generation. The prediction model results demonstrated relatively high precision in prediction at all locations.

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