Wind Power Prediction Using a Hybrid Approach with Correction Strategy Based on Risk Evaluation

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Abstract- With the rapid increase of renewable-energy capacities, the management of grid-connected wind farms is becoming more and more important. In this paper, a very short-term wind power prediction (VSTWPP) method with hybrid strategy based on risk evaluation is proposed. The VSTWPP is essential for both producers and consumers in the electricity market, because it can reduce uncertainties of wind power fluctuation and thus maintain power balance, security and quality of the system. This paper focuses on a hybrid approach with correction (HWC) strategy for the VSTWPP method, in which the Gaussian model is applied to calculate the probability distributions of wind power value and its error during different time periods and different methods. The WPP process includes: 1) Wind power ratios are predicted using the hybrid approach of multiple linear regression and least squares; 2) Transformation of these ratios is performed to obtain predicted wind power values; 3) Correction strategy is implemented to obtain the final results of WPP. Besides, in order to observe the prediction performance, WPP model with HWC, with the hybrid approach without correction (HWoC), with autoregressive moving average (ARMA) and with autoregressive integrated moving average (ARIMA) are examined respectively. The results confirm the accuracy and validity of the proposed HWC-based VSTWPP method, and show great promise for the prediction within intricate time series, which are highly volatile, irregular and uncertain. The obtained results confirm an observable accurate for the prediction validity of the proposed hybrid approach with correction strategy.

Keywords- wind power prediction, hybrid approach, normal distribution, correction strategy.

Nomenclature

WPP	wind power prediction
VSTWPP	very-short-term wind power prediction
MLR	multiple linear regressions
LS	least square
HWC	hybrid approach with correction strategy
HWoC	hybrid approach without correction
R	risk evaluation index
Δt	length of prediction or time period (minute)
T	width of prediction time window (minute)
ARMA	autoregressive moving average
ARIMA	autoregressive integrated moving average
ANN	artificial neural network
BP	back propagation
RBF	radial basis function
NWP	numerical weather prediction
PDF	probability density function
CDF	cumulative density function
RMSE	root mean square error
MAPE	mean absolute percent error
MSE	mean square error

1. Introduction

Wind power generation has effects on power system operation reliability and efficiency. These effects are apparent in three aspects of power system: the security, stability and power quality. However, connecting wind power plants to an existing electricity network may lead to increased uncertainty in the operation of the energy system. In this paper, we evaluate the HWC-based WPP performance by comparing simulation results using different methods.

Wind power is considered as one of the most attractive renewable-energy sources because of its high-efficiency and low pollution. However, the penetration of wind power in power grid brings several challenges to system stability. In terms of power system operation, accurate prediction of wind power can reduce the unreliability of electricity supply, and increase wind power penetration [1, 2, 25]. An unexpected variation of wind power output may increase uncertainty for the electricity system, which requires high-accuracy prediction of wind energy properties. In addition, accurate WPP plays an essential role in the balancing of power system. One of the most important priorities of wind power research is to improve the performance of prediction method [2], such as improvements of WPP techniques by a number of scientific hypotheses [3].

Connecting wind power farm to power network increases the variability and uncertainty of power grid. Therefore, applying accurate prediction techniques, such as time series prediction, combined prediction, multi-step-ahead and single-step prediction, is essential to assure system stability [4, 27]. Nowadays, some other approaches are developed to predict wind power. For instance, the hourly level of WPP data can be calculated by Gray Correlation Analysis [5]; a novel of VSTWPP approach based on numerical weather prediction and error correction method is an effective way to overcome the challenge in WPP [6]. While data of wind power have very strong non-linearity and non-stationary, and the traditional approach just focuses on solving the non-linear problem, the combining approach of atomic sparse decomposition and artificial neural network (ANN) could solve the non-stationary problem as well [7].

The proposed works for VSTWPP are generally based on the prediction horizon from several minutes to one hour. The horizon in this paper is carried out by the hybrid approach with correction strategy, which is more accurate than other models used in this work. The application of the hybrid approach based on the combination of particle swarm optimization intended to reduce WPP's error [8, 28]. The accurate prediction can be achieved by a new hybrid technique for VSTWPP with real-time [9]. In addition, the prediction accuracy of WPP by the new hybrid short-term WPP based on the combination of neural network and imperialistic competitive algorithms are analyzed in [10]. The hybrid method of WPP, with novel time-series based on K-means clustering, enhances the value of wind energy by improving the reliability and increasing economic feasibility [11].

The ARMA model is one of the most popular methods for prediction. It can be effectively used to predict the behavior of a time series just from past values, especially in wind power prediction where it is suggested to be effective as compared to those obtained from other models. The ARIMA model is a popularization of ARMA model, and is applied in some cases to historical data with evidence of non-stationary. The statistical methods used in WPP, including ARMA and ARIMA models, which are used to find out the inherent structure within the measured wind power data [4, 26, 30]. It is important to reveal and improve the fluctuation of wind power, by use of the ultra-short WPP based ARMA model [12]. The hybrid ARIMA-ANN model is to be used to facilitate an increase in the forecasting accuracy of a linear and a nonlinear component of a time-series data [13, 29]. The ARIMA model and time series based on Markov Residual Correction to perform accurate WPP and reduce error values [14]. The numbers of the approaches have been introduced to improve WPP, such as ARMA and Generalized Autoregressive Conditional Heteroskedasticity [15].

In recent years, some new technologies such as neural networks are often used for WPP. ANN is used to reduce uncertainty from wind power [16]. Meanwhile, BP neural network is used to improve the generalization ability of ANN and prediction accuracy [17, 18, 24]. ANN techniques were used with NWP models to get the accurate WPP [19]. Recently, some of WPP approaches that include short-term WPP method is based on RBF neural network, multi-layered feed-forward ANN, the new Imperialistic Competitive Algorithm Neural Network (ICA-NN) method with NWP; wavelet transform are used to predict wind power [20-23].

This paper, extending the application of the risk evaluation index, aims to show a detailed mathematical model of the wind power plant connected to the power grid. The system contains other generations, which causes wind power uncertainties in the power grid. However, the effects of the uncertainty can be reduced by the accurate calculation. This study proposed a new efficient approach with correction strategy for pattern feature vector structure, probabilistic distribution of power and power error. In this work, risk evaluation index for VSTWPP errors has been proposed to achieve stable and economic operation of the power system. Risk evaluation index can be directly accumulated as risk operating of VSTWPP error on security, and economy cost.

The contribution of this work is to propose a new hybrid approach, MLR & LS with correction strategy, for VSTWPP in Northeast China. Meanwhile, this paper introduces several indexes for HWC accuracy evaluation, including the root mean square error value (RMSE), the mean absolute percentage error (MAPE), the mean square error (MSE) and the linear correlation coefficient (r). The first three indexes are well-known and used to evaluate prediction accuracy with the smaller but more accurate index value. The last one measures, the strength and the direction of a linear relationship between actual and predicted values with the higher r being of more accurate.

2. Methods for VSTWPP

This section introduces several methods with the width of prediction time window ≤ 1 h. Firstly, the proposed approach, HWC, is generally explained; then, the details of the HWC algorithm steps and HWoC model are introduced; lastly, ARMA and ARIMA approaches are presented. In addition, the evaluation of the prediction performance is also discussed.

2.1. Description dataset and the region

Wind power data is collected by SCADA systems of wind farm; the data in this paper is averaged into time intervals, 5 minutes, which are suitable for various applications. The data used in this study was collected at every one-minute intervals (called 1's data) at a wind farm for a period of hour, day, and month up to one year. The proposed approach is tested on 5-minute mean wind power data provided by the Northeast China of wind farm power generation at eight wind farms.

Data from one year are available comprising at each site. The wind farm location in Northeast China. Some of the data are used as a training set on which the implementation of the fitting procedure is optimized by cross validation, and using data processing step is chosen. The other data are then used to evaluate the performance of the prediction approach, and the results confirmed that.

2.2. HWC model

The proposed approach is based on the hybrid of multiple linear regressions and least square (MLR & LS) with correction strategy (HWC). The MLR & LS are used to calculate the coefficients for minimizing the error and to improve the performance of the HWC. It can be used to predict wind power of a time series from historical values alone. The HWC is most accurate with lower expected error.

The general form of the MLR models is as follows:

$$\hat{W}(k)=\beta_0+\sum_{i=1}^{\lambda}\beta_i w_i(k)+\varepsilon \tag{1}$$

Where, $\hat{W}(k)$ is the predicted variable; $w_i(k)$ is the historical wind power (predictor variables); β_i is regression coefficient to be computed; λ is the maximal order of regression; k=1~N, N is the length of the prediction variable; ε is regression error.

In order to estimate regression coefficients, we take the least squares approach in simple linear regression case that it is minimized as:

$$L=\sum_{k=1}^{N}[\hat{W}(k)-\beta_0-\sum_{i=1}^{\lambda}\beta_i w_i(k)]^2 \tag{2}$$

To minimize L, β should be as Eq. (3):

$$\hat{\beta}=(w^{\mathrm{T}}w)^{-1}w^{\mathrm{T}}\hat{W} \tag{3}$$

For the proposed approach, the ratio to total wind power is used in the following steps for improving the performance of WPP:

1- Ratio to total WPP is defined as following:

$$X_i=w_i\big/\sum w \tag{4}$$

Where, w_i is the wind power from the i^{th} wind farm, and $\sum w$ is the total wind power of the farm cluster including the i^{th} wind farm.

2- After getting ratio X_i and total wind power $\sum w$, the WPP of i^{th} wind farm is as following:

$$W_i=X_i\times\sum w \tag{5}$$

3- Use correction strategy to calculate the correction ratios as following:

$$X_i^{Corr}=X_i\Big/\sum_{i=1}^{n}X_i \tag{6}$$

4- Finally predict wind power by using correction ratios and total wind power from the wind farm cluster:

$$\hat{W}_i^{Corr}=X_i^{Corr}\times\sum w \tag{7}$$

Algorithm steps of the proposal approach for WPP in Matlab code are as follows:

- Input data:

$w_a^{(0)}=(w^0(1),w^0(2),w^0(3),\ldots\ldots,w^0(n))$ — time series of sample data;

$X^{(0)}=(X^0(1),X^0(2),X^0(3),\ldots\ldots,X^0(n))$ — time series of ratios;

$T^{(0)}=(t^0(1),t^0(2),t^0(3),\ldots\ldots,t^0(n))$ — sample time (per minute).

- Output data:

$\hat{X}^{(0)}=(\hat{X}^0(1),\hat{X}^0(2),\hat{X}^0(3),\ldots\ldots,\hat{X}^0(n))$ —time series of prediction ratios;

$W_p^{(0)}=(\hat{w}^0(1),\hat{w}^0(2),\hat{w}^0(3),\ldots\ldots,\hat{w}^0(n))$ —sequence of prediction values.

- Coefficients:

n − number of time series data;

w_a − actual wind power;

X — ratio of wind power;

W_p — predicted wind power.

- Procedure of the HWC code:

1: Read the historical data;

2: Evaluate the transformation of the time series data to ratios;

3: Check the ratios from i=1 up to n (i, n) = 0 where i=1=w size;

4: End of this, and start loop of WPP (i, n) = 0 where i=1=W size;

5: Check the prediction winds, and then go through correction;

6: Start for i=1: correction size;

7: End of that, and calculate the sum of correction must be equal to 1, then;

8: Calculate WPP according to the correction values.

In view of the uncertainty resulting from wind energy, we introduced the method of multiple linear regressions and the least square analysis based on the correction process. Calculation steps are as follows: preliminary analysis of data processing; observation of the change in the behavior of the data or graphically shape; comparison of results; reprocessing of the abnormal values. Therefore, the historical wind power data sequence tends to be stable, as illustrated in Fig.1.

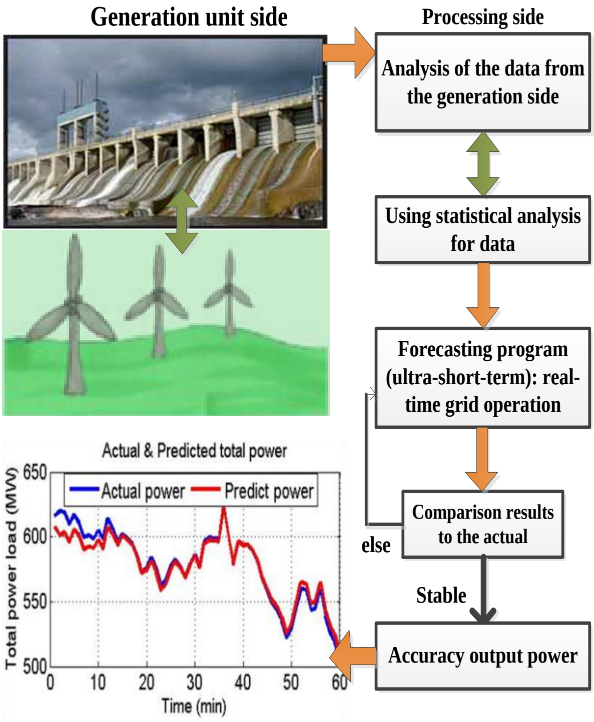

Fig.1. The process of the diagram on proposal approach.

2.3. HWoC model

Multiple linear regressions and least square are used without correction strategy as Eq. (4) and (5). In this case, the output power of WPP will be determined by historical data, directly through hybrid time series model.

2.4. ARMA model

The predicted wind power time series $\{W_t\}$ is modeled using the ARMA model as shown in Eq. (8):

$$W_t = \sum_{i=1}^{p} \varphi_i w_{t-i} - \sum_{j=1}^{q} \theta_j a_{t-j} + a_t \tag{8}$$

Where, p is the order of autoregressive parts; q is the order of moving average; φ_i is the autoregressive part of the parameters model (i=1~p); θ_j is the model parameters of the moving average (j=1~q); w is the historical wind power time series; a is error terms.

2.5. ARIMA model

The ARIMA model is one of the most popular and frequently used stochastic time series model in prediction. ARIMA model using for non-stationary time series becomes stationary values, however, ARIMA model is the general form of ARMA model.

3. Risk evaluation of WPP method with different Δt

The power grid integration of renewable resources can significantly improve energy security of power systems as primary sources are diversified and renewable-energy resources are available locally. However, the penetration level of renewable energy in the system can bring operational security concerns and risks. The challenges can lead to a variety of instability and operational security problems, and the proposed risk evaluation procedure can be summarized in the following.

3.1. Different evaluation risk of error values

A- Suppose that $t^0(n)$ in the input data is the current time and $\hat{t}(i)$ in the output is future time instant to be predicted. With the measured value of wind power $w_a^{(0)}$ as the criterion for comparison, the error e_i of the prediction value $\hat{W}_p$ before using correction strategy is defined as:

$$e_i = \hat{W}_p - w^{(0)}{}_a \tag{9}$$

Wind power is overrated when e_i is greater than zero while it is underestimated when e_i less than zero in different time periods. The positive or negative error values have different impact on the reliability of the power grid.

B- Assume (n) as the number of output WPP values within range of investigation, and then the error value after using correction strategy is E that consists of every relevant error e_i as it appears in the Eq. (10).

$$E = [e_i \therefore i = 1,2,\ldots..,n] \tag{10}$$

The total E reflects the predictive quality. The above Eq. can be extended to wide range statistical results. The probability $(p_j(e_j))$ of predict error e_j whose probability distribution function is $P(e)$ can be obtained from statistics methods. A normal PDF and CDF probabilistic method is proposed to coordinate the WPP between predict values and risk events with high error's probability. The risk evaluation index R for the wind power is defined as an integration of the probability of a power instable status caused by WPP error is defined as

$$R = \int_{-\infty}^{\infty} P(t) \times e(t)dt \tag{11}$$

The application of the risk evaluation index can be expanded from the post-evaluation of WPP to selection the accurate VSTWPP method using for the wind power connected to the power grid. The framework of the risk evaluation based VSTWPP method is shown in Fig.2. The process evaluation is divided into four parts: first processing data and checking the software method; second using technical model and simulation values; then arranging output of the simulation and finally comparing output results with different methods.

Our aim in the present section is to focus on the wind-power predictability only. For this purpose, we introduce prediction risk evaluation indices that can be used as skill forecasts, the forecasts of the distributions of expected prediction wind power values and errors. In the power system with wind farm connection, the proposed process computes first data initialization, then using technical simulation to checked data, and finally comparison results through probability distribution. In this case, the prediction period and horizon will have a significant impact on the wind power predict error. For T = 60, Δt = 5-minute scales, wind power variation and predict error is smallest and can be seen into the following Fig. (3, 5 and 14), it confirms that larger time period and horizon up to several hours can lead to higher prediction errors due to the higher probability of wind power output changes for longer predict horizon. The risk evaluation index for wind power prediction is proposed in Fig.2. This index can be used for quantitative evaluation of the largest wind power prediction error at any confidence level.

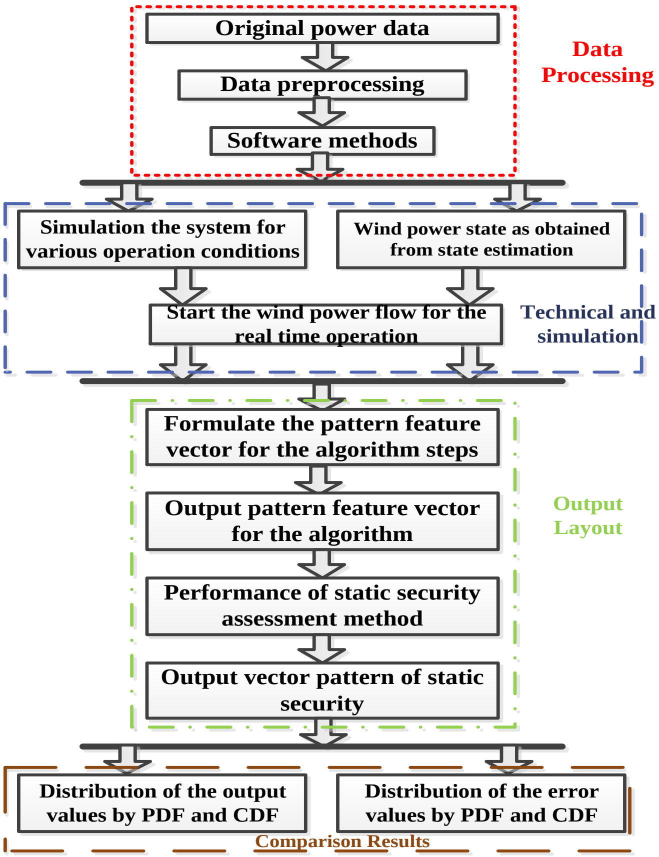

Fig.2. Process of risk evaluation.

The power generated from wind power farm depends on many factors, such as wind speed, direction, temperature and pressure. These factors lead to the generation of random fluctuations. It needs accurate methods to predict wind power for a different time. This paper proposes a correction method in hybrid with multiple linear regressions and least square for VSTWPP in Northeast China taking as an example.

3.2. Comparison of prediction PDF with different Δt

The wind-power variability was represented by the normal (Gaussian) probability distribution, a PDF of two parameters (μ & σ). The parameters were used to correlate the Gaussian function with the min average wind power, the variance of the wind power and mean density.

The main purpose of this paper is to calculate the accurate wind power in Northeast China: 1) identification of the historical records of wind power data (using statistical characteristic of wind power); 2) Gaussian probability distribution investigated by examining the effect of the assumed shape of the wind power value probability distribution on the predicted wind power; and 3) calculating the wind power density by the proposed method and evaluating different methods to find, which has the smallest error.

The data set is comprised of a different length of the prediction which will be assigned to 5 and 10 minutes with time window being within an hour. The historical records of wind power from an offshore region are the input, and the target output is total WPP. Correction strategy performance was estimated by PDF between the actual and predicted wind power values with the different time period. For an independent evaluation of the HWC method, the results of the verification are presented in Fig.3. The comparison results are also shown graphically in Fig.3.

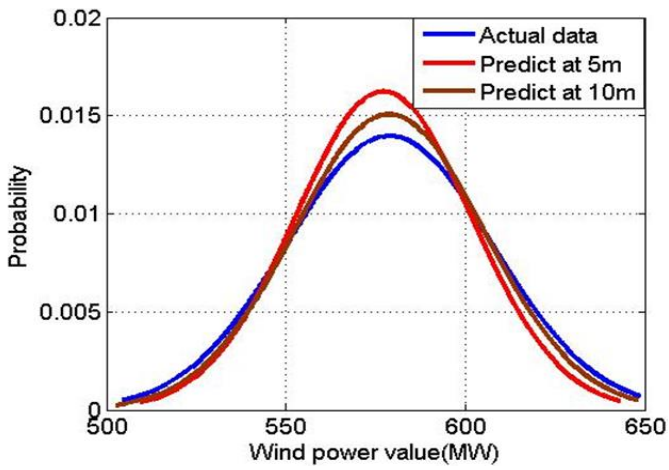

Fig.3. Comparison of PDF of simulated wind power value at different Δt with HWC method.

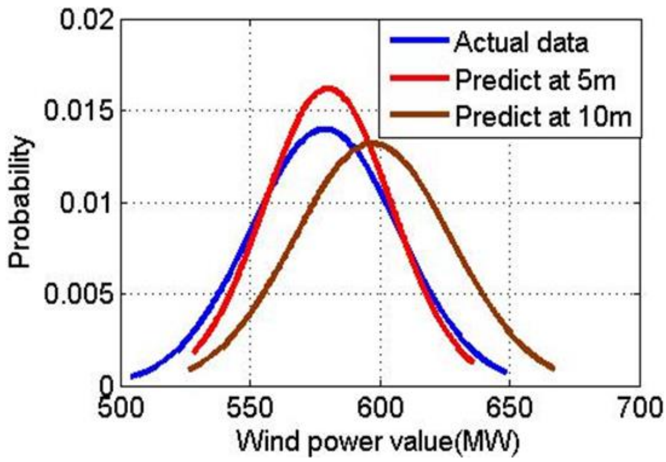

Fig.4. Comparison of PDF of simulated wind power value at different Δt with HWoC method.

According to the hybrid approach with and without correction strategy for the above PDF shapes at two different sampling intervals of wind power prediction, the prediction values of two kinds of methods with different Δt =5, 10 minutes and the same T = 60 minutes. The numerical values of WPP are shown in Table 1. Fig.3 and 4 show results of prediction wind power in distribution by normal PDF. Clearly, the two groups of prediction value show the stable result, but the first one by proposal method shows more accurate and closer to the actual value with different time periods.

3.3. Comparison of HWoC and HWC errors with different Δt

From Table1, the results show that the 5-minutes time period of HWC model have the best performance for WPP than 10-minutes time period at the same model. Error assessment indexes by HWC prediction results decreases values with the increasing of the time period, and the evaluation risked based index (R), HWC model shows more accuracy than HWoC model.

Table 1. Errors for different methods and time periods

Time Period	5 minute		10 minute	
Error/Model	HWoC	HWC	HWoC	HWC
RMSE	18.19	5.65	27.41	9.42
MAPE	2.45	0.69	3.95	1.36
MSE	3.30	0.32	7.52	0.88

For more accurate evaluation of the HWC and HWoC methods, the following absolute percentage error is used:

$$Error = \frac{W_a - W_p}{W_a} * 100 \qquad (12)$$

The maximum percentage errors of WPP at T = 60, Δt =5 minute are 8.57% for HWoC method and 2.97% for HWC method.

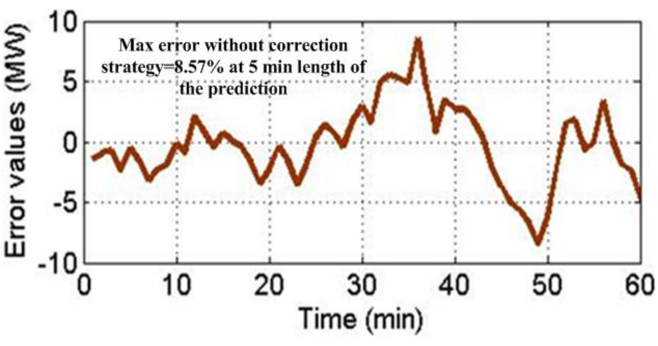

Fig.5. Error of WPP for HWoC at (T = 60, Δt = 5 minute).

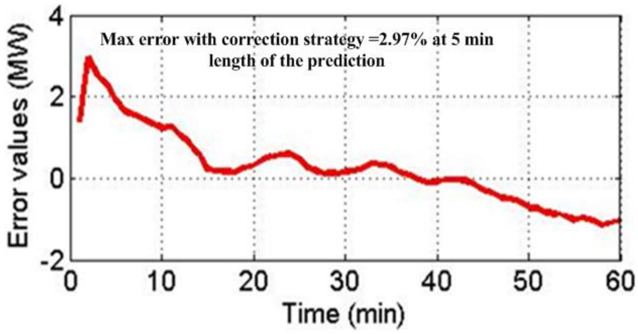

Fig.6. Error of WPP for HWC at (T = 60, Δt = 5 minute).

Fig.7 illustrate the comparison error of WPP for HWoC and HWC at T= 60, Δt= 5 minute. It is shown that the proposed method reduced maximum percentage error comparing with another method.

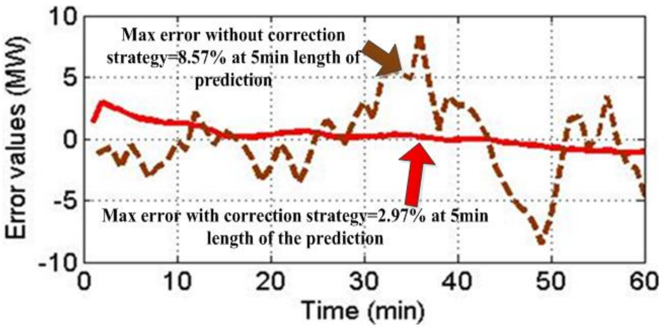

Fig.7. Comparison error of WPP for HWoC and HWC at (T= 60, Δt= 5 minute).

4. Simulation and results of WPP

In this part, simulations are carried out for the VSTWPP using a time series with a hybrid approach. The test of WPP values includes three parts and divided into two issues: The first one is the result comparison, and the second one is the result confirmation.

4.1. WPP values by HWC with different Δt

Fig.8 and 9 respectively are WPP results with the HWC at different Δt. The prediction accuracy in Fig.8 with Δt= 5 minute is higher than that in Fig. 9 with Δt= 10 minute, and its overall predict the curve is closer to the actual curve. Obviously, the HWC approach can predict the wind-power output more accurately than HWoC approach in Fig.10 & 11.

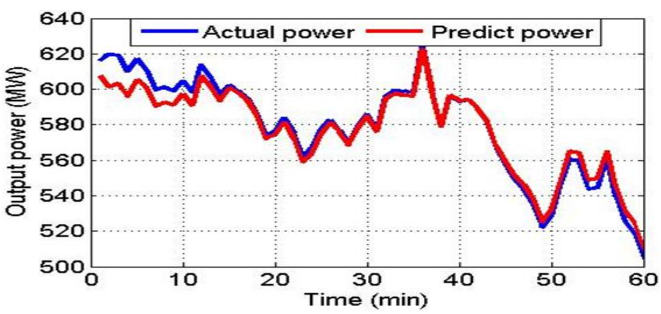

Fig.8. Actual and predicted total wind power values by HWC at (T = 60, Δt = 5 minute).

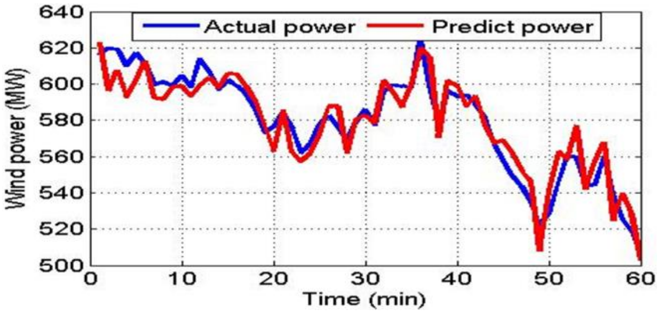

Fig.9. Actual and predicted total wind power values by HWC at (T = 60, Δt = 10 minute).

4.2. WPP values by HWoC with different Δt

Fig.10 and 11 shows the actual and predicted outputs of wind power by HWoC approach at T = 60 and Δt = 5, 10 minutes. The shape clearly shows that the performances of the HWoC approach are not close to the actual values at different Δt when compared with HWC at the same period.

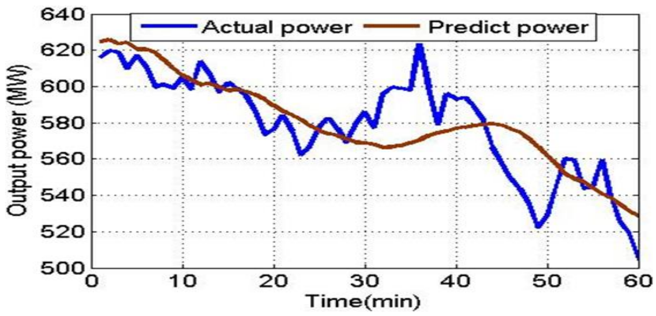

Fig.10. Actual and predicted total wind power by HWoC at (T = 60, Δt = 5 minute).

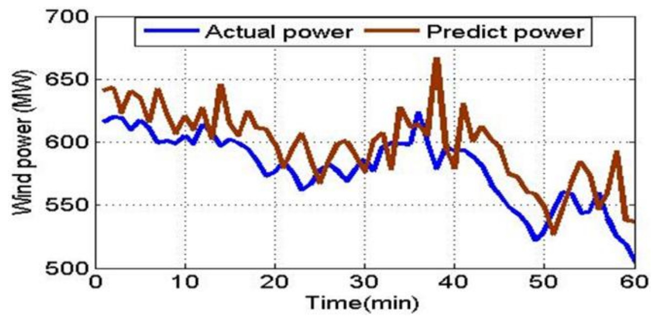

Fig.11. Actual and predicted total wind power by HWoC at (T = 60, Δt = 10 minute).

4.3. Comparison between HWC and HWoC of WPP values, PDF, CDF distribution

Table 2 lists the comparison between actual, predicted WPP and error values by HWoC and HWC, which is from one hour. The numerical results confirm the accuracy of the proposed method.

Table 2. Comparison between actual, predicted and error values with different methods

Time Min	Without correction		Error (%)	With correction		Error (%)
	Actual	Predict		Actual	Predict	
1	616.10	624.84	1.42	616.10	607.51	1.39
2	619.80	625.88	0.98	619.80	601.38	2.97
3	618.99	623.45	0.72	618.99	603.29	2.53
4	609.74	624.20	2.73	609.74	595.68	2.30
…	…	…	…	…	…	…
58	525.23	535.15	1.89	525.23	531.26	1.14
59	519.01	531.46	2.40	519.01	524.72	1.10
60	504.31	528.35	4.77	504.31	509.50	1.02

Fig.12 illustrates a comparison between WPP values with correction and without correction approach. For better comparison, the shape of depicting the WPP by HWoC before using correction strategy, and the shape of depicting the WPP by HWC after using correction strategy are illustrated. It is clear that the proposed approach (HWC) followed the actual wind power data better than HWoC approach. Additionally, the errors of both approaches are listed in Table 2. The error of HWC is smaller than that of HWoC.

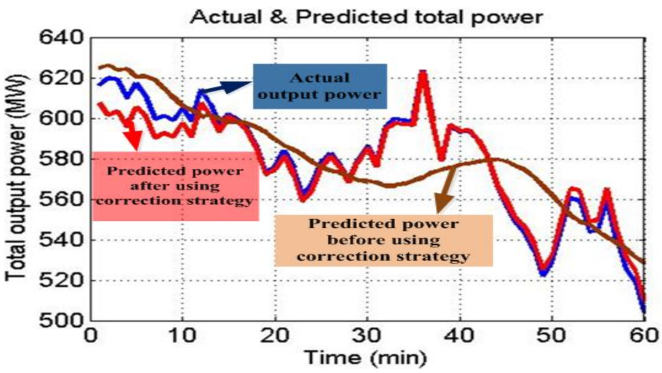

Fig.12. Comparison of WPP with and without correction at (T = 60, Δt = 5 minute).

4.4. Variability of WPP

It is very important to take the variability of wind power value into account in a right way while connected to the power grid. Generally, the variability of wind power decreases as there are more wind turbines and wind power plants distributed over the area. Larger areas of wind power also decrease the number of hours of zero output power, in this work using eight wind power plants. The variability as well decreases as the time period scale decreases; in this paper, we used minute scale (Δt = 5&10 minute) that's why it was variability of large-scale wind power is generally small. However, the most important variability and uncertainty occurring in the minima time window scales (T = minute up to an hour). In case of this work, Fig. 13. shows an example of the variability and uncertainty of wind power prediction by HWC proposed approach and comparison with HWoC method. The contributions of this paper are in two main parts: accurate prediction of wind power for the power system grid and evaluation of the system security risk with wind power predicted errors; this also reduces the variability and uncertainty of wind power.

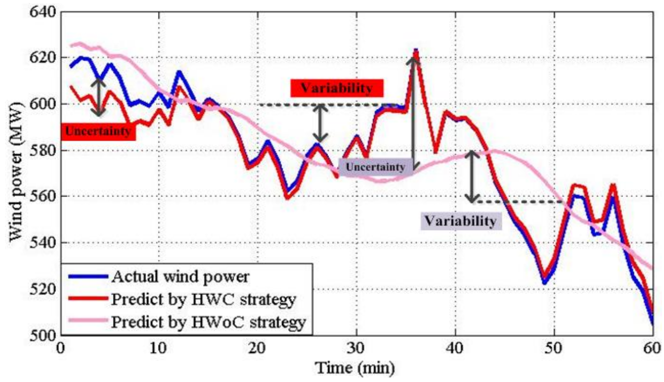

Fig. 13. Example of wind power prediction variability and uncertainty with different approach.

4.5. Comparison of PDF, CDF distribution of WPP error

The normal distribution describes a special class of the distributions that are symmetric and can be described by two parameters, which are, the mean (μ) and the standard deviation (σ).

The probability density function (PDF) of the normal distribution is called Gaussian. The PDF is a very common continuous distribution in wind power. Normal distributions are important to describe the natural and characteristics to represent real-valued predicted variables whose distributions are not known, using the PDF as shown in Eq. (13) as the following:

$$f(e) = \frac{1}{\sigma\sqrt{2\pi}} \exp\left(\frac{-(e-\mu)^2}{2\sigma^2}\right) \tag{13}$$

The cumulative distribution function (CDF) returns the cumulative probability of WPP error from 0 up to 1 input value of predicted variable error. Technically, it returns the percentage of area under a continuous distribution curve from large negative values to large positive error values. The below formula for the CDF of the standard normal distribution as Eq. (14) used in this work:

$$f(e) = \int_{-\infty}^{e} \frac{1}{\sigma\sqrt{2\pi}} \exp\left[\frac{-(t-\mu)^2}{2\sigma^2}\right] dt \tag{14}$$

PDFs of the normalized WPP errors for two models are shown in Fig. 14. Clearly error distributions, depending on the prediction approach are significantly different. Obviously, the uncertainty for these various prediction methods must be different. As shown, for proposed method (HWC), the percentage of WPP errors is concentrated between -17% and 17% in T = 60, Δt = 5 minutes, and for HWoC method, the larger percentage of WPP errors is concentrated between -48 and 48.

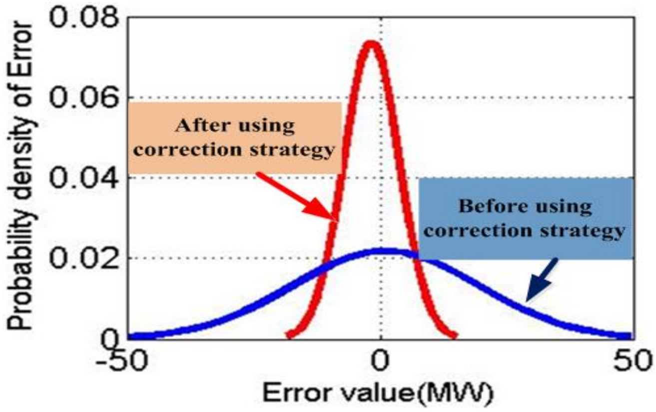

Fig. 14. PDFs of WPP error with and without correction at (T = 60, Δt = 5 minute).

The Gaussian distribution in Fig.15 represents the WPP errors by HWC and HWoC respectively. HWC has more pronounced peak and slimmer shoulders than HWoC. It is also seen that the distribution of the WPP error by HWoC covers for most of the plot. Similar phenomenon can also be seen from the CDF distribution and plot in Fig. 15. The distribution of HWC mirrors the observed errors very carefully and small deviations. On the contrary, the error distribution of HWoC has large deviations.

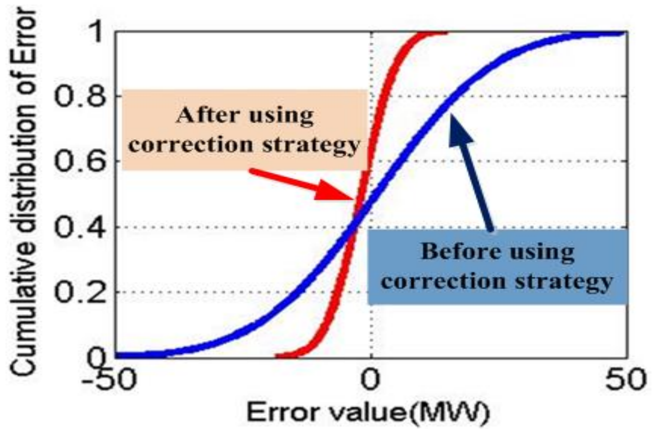

Fig.15. CDFs of WPP error with and without correction at (T = 60, Δt = 5 minute).

The numerical results and shapes indicate that in every case, the proposed approach is better than the other models, i.e., the prediction error is the smallest.

5. Evaluation indexes

Three indexes are used to evaluate the hybrid approach with correction strategy. These indexes are described as follows.

5.1. The Root Mean Square Error (RMSE)

The root means square error value (RMSE) can be used for a variety of statistic's applications. It can be expressed as the following:

$$Error = Wa_m - Wp_m \tag{15}$$

$$RMSE = \sqrt{1/60 \sum_{m=1}^{60} (Wa_m - Wp_m)^2} \tag{16}$$

Where, m is the flowed minutes of the hour, Wa_m is the measured value (actual), and Wp_m is the predicted value of the minutely predict. The smaller RMSE indicates more accurate.

5.2. The mean absolute percentage error (MAPE)

The mean absolute percentage error (MAPE) can be defined as:

$$MAPE = \left[\frac{1}{60} \sum_{m=1}^{60} \frac{[Wa_m - Wp_m]}{|Wa_m|} \right] * 100 \tag{17}$$

A smaller MAPE indicated that the forecasted values are close to the actual values and the method is more accurate.

5.3. The mean Square error (MSE)

The mean square error (MSE) can be written as the following:

$$MSE = 1/60 \sum_{m=1}^{60} (Wa_m - Wp_m)^2 \tag{18}$$

MSE is the always non-negative. Values of MSE closer to zero are better and perfect accuracy.

5.4. Linear correlation coefficient (r)

The mathematical formulation for computing the linear correlation coefficient r is:

$$r = \frac{\sum_{i=1}^{N} [(w_i - \overline{w})(W_i - \overline{W})]}{\sqrt{\left(\sum_{i=1}^{N} (w_i - \overline{w})^2 \right) \left(\sum_{i=1}^{N} (W_i - \overline{W})^2 \right)}} \tag{19}$$

Where, N is the number of point data, w_i, $\overline{w}$ is the actual and means power values, and W_i , $\overline{W}$ is the predict and means power values, $r \in$ [-1, 1], means positive and negative linear correlations.

Positive correlation: if actual value w_i and predicted value W_i have a strong positive linear correlation, r is close to +1. Positive values indicate the good prediction method and a relationship between actual and predicted variables such as values for actual w_i increases, values for predict W_i also increases.

Negative correlation: if actual value w_i and predicted value W_i have a strong negative linear correlation, r is close to -1. Negative values indicate that the prediction method not accurate and a relationship between actual and predicted variables such that as values for actual w_i increases, values for predicted W_i decreases, and vice versa.

Table 3. Comparison between errors with different models

Model Errors	Prediction Models			
	HWoC	ARMA	ARIMA	HWC
RMSE	18.19	18.13	18.03	5.65
MAPE	2.45	2.47	2.45	0.69
MSE	3.30	3.29	3.25	0.32
r	0.78	0.79	0.78	0.98

Table 3 shows a comparison between the HWC and three other approaches (HWoC, ARMA, and ARIMA), regarding the RMSE, MAPE, MSE, criterion and linear correlation coefficient. The proposed HWC approach presents better prediction accuracy with RMSE =5.65. MAPE and MSE of HWC are as so less when compared to other methods. The correlation coefficient of HWC is higher than those of other methods. All indexes show that HWC is the most accurate prediction method.

5.5. General comparison

A general comparison of four methods (HWoC, ARMA, ARIMA and HWC) is carried out for total power prediction. Their actual and predicted values and error values are computed in Table 4. Prediction is done for one hour.

Table 4. Comparison between predicted values and errors for 4 methods

Time Min	HWoC Predict	Error (%)	ARMA Model	Error (%)	ARIMA Model	Error (%)	HWC Predict	Error (%)
1	624.8	1.4	616.0	0.003	616.0	0.001	607.5	1.3
2	625.9	0.9	619.1	0.005	619.5	0.007	601.4	2.9
3	623.5	0.7	618.9	0.004	618.9	0.003	603.3	2.5
4	624.2	2.7	613.1	0.551	609.7	0.007	595.7	2.3
…	…	…	…	…	…	…	…	…
58	535.2	1.9	540.9	2.992	537.6	2.345	531.3	1.1
59	531.5	2.4	535.3	3.714	538.6	3.768	524.7	1.1
60	528.4	4.8	549.5	8.957	549.9	9.048	509.5	1.0

Table 4 shows the efficiency of the proposed method (HWC) and indicates that the proposed method can predict the VSTWPP better than other methods.

6. Conclusions

This paper evaluates the impacts of wind power prediction by using a hybrid approach with correction strategy. By using the historical wind power data, the numerical values are determined using 4 methods, and comparison were determined using 2 methods with different time periods. Performance comparison for the WPP has been done with five statistical tools. Risk evaluations based correction strategy for VSTWPP framework is detailed in this paper to check improved prediction approaches and reflect different preferences on WPP methods of a practical operation system. The efficacy of the proposed method is verified by simulation's results.

The simulation results show that the HWC is the most accurate method for WPP while compared to HWoC, ARMA and ARIMA. The HWoC is suggested to provide less accurate prediction and is not efficient for the longer time period (Δt). In contrast, the HWC is with less error and is applicable for different time periods. Other methods such as ARMA and ARIMA are the least accurate methods to fit the numerical values in this paper.

An HWC based power prediction with input historical data selected by a hybrid MLR & LS method is able to produce a good prediction and constantly with correction values. The developed HWC approach improves the prediction, especially after using the correction ratios in the input values to predict total wind power. This study will be the first step to evaluate the high penetration of wind power distribution connected with power system impact on the stability system. The future study includes determining the impact of the distributed total power generation and load providing voltage, and how this will impact transmission system and outage.

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