Ultra-Short-Term Wind Power Prediction Using a Hybrid Model

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Abstract. This paper aims to develop and apply a hybrid model of two data analytical methods, multiple linear regressions and least square (MLR&LS), for ultra-short-term wind power prediction (WPP), for example taking, Northeast China electricity demand. The data was obtained from the historical records of wind power from an offshore region, and from a wind farm of the wind power plant in the areas. The WPP achieved in two stages: first, the ratios of wind power were forecasted using the proposed hybrid method, and then the transformation of these ratios of wind power to obtain forecasted values. The hybrid model combines the persistence methods, MLR and LS. The proposed method included two prediction types, multi-point prediction and single-point prediction. WPP is tested by applying different models such as autoregressive moving average (ARMA), autoregressive integrated moving average (ARIMA) and artificial neural network (ANN). By comparing results of the above models, the validity of the proposed hybrid model is confirmed in terms of error and correlation coefficient. Comparison of results confirmed that the proposed method works effectively. Additional, forecasting errors were also computed and compared, to improve understanding of how to depict highly variable WPP and the correlations between actual and predicted wind power.

1. Introduction

Wind power prediction (WPP) is one of the most important issues of wind-power grid integration. An accurate WPP is suggested to be practical to operators in power systems. From the applied time-series data analysis, ultra-short-term WPP (USTWPP) is very important and contributes to the stability to the power system. The accurate prediction is not only useful for ensuring operation security for the power system, but also for enhancing the economic feasibility and performance of the power system [1].

In this paper, we developed and applied a modern hybrid method to predict high resolution by applied time-series analysis in data for wind power system, which focus on understanding the current methods to forecast on different time series (different time window and different length of prediction sample). The developed method is multiple linear regressions, and least square (MLR&LS) based a hybrid model which utilizes a new principle. As a proposal is a concern, there are two main ways to predict wind power. The first way is data transformation: convert raw data of wind power into some ratio and use this ratio as the value to be predicted. The second way is data inverse-transformation: convert the predicted ratio value into actual value and then predict total wind power. In many studied cases, there are sets of alternative forecast strategies. Forecast with a single model or method (SF) may not always lead to fitting values, while the forecast with hybrid model or method (HF) is more...
appropriate because the hybrid strategy can take the advantages of each SF and is more likely to get better results.

In recent years, wind power as one of the most important renewable-energy sources is growing fast. Utilization of wind energy showed rapid growth in the latest years which span many regions around the world [2, 3]. In China, the growth of wind power is revealed to be faster than accounting for a growth rate of 21.2% in 2012 [4]. Most of the wind-power projects are achieved based on national goals of reducing an emission, and producing high-output electricity.

It has been shown that, wind power output has been strong fluctuating by characteristics and only is partly controllable in nature [5, 6]. Short-term or ultra-short-term WPP is required for controlling and scheduling of power generation, for self-dispatching of power transmission market [7] and for rating improvement of the overhead line [8].

High penetrated wind power to the power grid brings many challenges to power system operators [9] if not managed properly. Accurate load forecasting is more important for electric utilities planning for the future [10]. More research on wind power technology is then necessary to supplement the conventional energy sources. However, wind power is a highly fluctuating resource. The fluctuations at large wind farms have the impact to the control and management strategies of their power output in the power grid [5].

Several studies have investigated the accuracy of short-term WPP through three approaches: physical numerical weather prediction models, statistical models based historical data and statistical models with numerical weather prediction data as additional exogenous inputs [4]. Estimating wind power output through accurate forecasting could significantly reduce the uncertainty of system operators by using incorporated meteorological data. Short-term WPP and USTWPP are required for monitoring and scheduling of power grid [7].

Power forecasting has become one of the major areas of research in engineering, particularly for short-term and ultra-short-term forecasting that increasingly become important since the rise of the competitive power system in markets. Although power forecasting is the important, great challenge is expected due to influence of several exogenous variables of the power [11]. The main purposes of ultra-short-term and short-term forecasting that ranges from minutes to hours are for real time control, operation and security evaluation of the power system [12].

2. Related work and model

2.1. Time series models in forecasting

Time series is the sequence of data points, typically measured at sequential times, predominantly with uniform time intervals [13]. There are many different modern and traditional approaches to time series modeling. In this paper, the time-series analysis is performed using the autoregressive moving average(ARMA) model, autoregressive integrated moving average(ARIMA) model and MLR&LS model.

There are two types of goals for time-series analysis. The first goal is to identify the nature of the phenomenon represented by the sequence of observations, and the second one is to forecast by predicting future values of the time-series variable. Both goals require identifying and more or less formally describing the pattern of observed time-series data. Time-series data of wind power is developed on understanding the behavior of wind power signals at different time scales. As it is well known, output power of wind farm is high variable and only partial controllable [14]. In the time-series analysis, it is assumed that, the data consist of a systematic pattern (usually a set of identifiable components) and noise (error) which usually makes the pattern difficult to be identified. Most time series analytical techniques involve some form of filtering out of noise to make the pattern more salient [11, 14-16].

2.2. ARMA model
ARMA model is considered as a basic sequential method and a practical model for comprehensive time series [17]. ARMA model is a kind of time-series analysis statistical model, historically suggested by the American G. Box and British G. Jenkins of statisticians [18]. For the random and dynamic wind power data, ARMA model with time series reflects a larger advantage. The problem for this model is to determine the order [16].

ARMA model uses autocorrelation or persistence in a time-series. The general form of ARMA model is as following:

\[ w_t = c + \sum_{i=1}^{p} \varphi_i w_{t-i} + \sum_{j=1}^{q} \theta_j \varepsilon_{t-j} \]  

(1)

Where, \( t \) is the time to be forecasted; \( w_t \) represents the forecasting value at time \( t \); \( w_{t-i} \) represents the historical sample data at time \( t-i \); \( \varphi_i \) is the autoregressive coefficient; \( \theta_j \) is the moving average coefficient; \( c \) is the constant value; \( \varepsilon_{t-j} \) represents error at time \( t-j \), is a random variable; \( p \) is the order of the autoregressive terms; \( q \) is the order of the moving-average process.

Forecast the future values; they predict future values can be using the realized ARMA model, in equation (2) is applied to predict the minutes ahead forecasting values (\( m = 1; 2; 3 \) minutes).

\[ w_{t+m} = \sum_{i=1}^{p} \varphi_i w_{t-i} + \sum_{j=1}^{q} \theta_j \varepsilon_{t-j} \]  

(2)

Where, \( w(t+m) \) is the predict wind power generation at time \( t+m \).

2.3. ARIMA model

ARIMA model is one of the most popular and frequently used stochastic time series models in forecasting. ARMA model is used only for stationary time series, but ARIMA model could be used in cases of non-stationary time series. Applying generalized mathematical formulation with parameters such as \( p,d,q \), ARIMA model can make a non-stationary time series become stationary. ARIMA model is based on the assumption of linearity of the predicted values [19].

The general form of ARIMA model is as following:

\[ (1 - \sum_{i=1}^{p} \varphi_i L^{i})(1-L)^d w(t+m) = (1 + \sum_{j=1}^{q} \theta_j L^{j}) \varepsilon_t \]  

(3)

Where, \( L \) represents the lag operator, and \( d \) is the order of the difference.

2.4. ANN Model

Artificial neural network (ANN) model is considered an advanced technology of short-term forecasting, so it becomes an alternative technique to time series forecasting, and gained immense popularity in last few periods. ANN has a flexible structure to model a wide variety of nonlinear problems. The advantage of ANN model is that it has the potential to approximate a large class of functions with a high degree of accuracy [19]. The ANN with multi-layer structure is very adaptable because it can incorporate several levels in a single model [20]. The goal of use ANN is to find the neural network weights that reduce the model errors.

In this paper, ANN structure used is a three-layer feed-forward back propagation neural network which includes input layer, hidden layer and output layer. Actual input data in the following simulation used two variables, recorded wind power and time for the forecasted horizon. Recorded data obtains from the historical records of offshore region wind farms. The composition of the sample set is as follows: training, validation and testing samples account for 70%, 15% and 15% respectively.

In general, ANN forecasting model can be written as follows:

\[ W = F[H_1(w), H_2(w), ..., H_q(w)] + \varepsilon \]  

(4)

Where, \( W \) represents the dependent output variables (forecasted wind power values); \( w \) represents a set of input variables (historical wind power data); \( F \) represents output layer activation functions, \( H_i \)
represents hidden layer activation functions; \( \varepsilon \) is the error term; forecasted power will be calculated by equation (5) with time series values:

\[
W(t + m) = \sum_{j=1}^{q} \theta_j \cdot g(C_{0,j} + \sum_{i=1}^{p} \varphi_{q,i} \cdot W_{i-1}) + \varepsilon_i
\]  

(5)

Where, \( \varphi_q \) \((i=0,1,2,\ldots, p, j=1,2,\ldots, q)\) \( \theta_j \) \((j=1,2,\ldots, q)\) are connected weights, \( p \) is the number of input neurons and \( q \) is the number of hidden neurons.

2.5. Multiple Linear Regressions
MLR analysis in WPP technique used the weighted least square estimation method, based on statistical analysis, can calculate the relationship between other factors [21]. The least square method is a wide-range used parameter estimating method in the MLR. The basis of this method is that it can lead to the least mean square error between the actual value and the estimated value [17].

3. Methods for USTWPP
In this section, we will describe the detail procedure of USTWPP with maximum width of the prediction time window no more than 60min. The output power of a wind farm or multiple wind farms in a power grid will be determined by historical wind power data through hybrid time series model.

3.1. Procedure of USTWPP
Wind power has a random and intermittent nature characteristic, and the output power of wind represents this characteristic. Hence it is very vital to reduce these influences for improving the accuracy of WPP. This issue will be discussed from the following aspects:

- For different width of the prediction time window, what is the most appropriate length of prediction?

  In this paper, the width of the prediction time window will be assigned to 20, 30 and 60min; the length or step of prediction will be assigned to 5 and 10min.

- What's the performance difference between SF and HF?

  In this paper, SF is implemented by ARMA, ARIMA and ANN respectively; HF is implemented by the MLR&LS model.

- What's the performance difference between single-point prediction and multi-point prediction?

  In this paper, single-point prediction is to forecast the power or power ration of the next one length, and multi-point prediction is to forecast the power or power ration of the next few lengths within the width of the prediction time window.

- For single wind farm, what's the performance difference between direct prediction for single wind power and indirect prediction for power ration to total wind power?

  Power ratio to total wind power is defined as equation (6):

\[
w_i = \frac{P_i}{P_{total}}
\]  

(6)

Where, \( P_i \) is the wind power of the \( i^{th} \) wind farm, and \( P_{total} \) is the sum of wind power of multiple wind farms including the \( i^{th} \) wind farm.

After predicting power ratios \( w_i \) and total power \( P_{total} \), the WPP of the \( i^{th} \) wind farm is as following:

\[
P_{i}^{pred} = w_i \times P_{total}
\]  

(7)

- For multiple wind farms, what's the performance difference between direct prediction for total wind power and indirect prediction for single wind power?

  For indirect prediction, first predict the wind power of each wind farm, and then sum them to obtain the total wind power of multiple wind farms. The wind power of each wind farm can be from the direct WPP.
Figure 1 shows the detail procedure of USTWPP designed in this paper. In figure 1, the procedure of USTWPP collects data from SCADA systems of wind farms, and power grid dispatch center, and predicts WPP of single wind farm, total WPP of multiple wind farms, and power rations of different wind farms at different prediction conditions and with different prediction ways. The predicted value of the box② can be obtained from the box③ and ④ according to the formula (14), and the predicted value of the box⑤ can be obtained from the sum of the box①.

This paper will observe and compare the error of USTWPP respectively from the above aspects.

3.2. Forecasting framework by MLR & LS hybrid model
MLR is a new analysis tool, and has the statistical learning mechanism to explain the behavior of one of the dependent variables as a function of many other predictor variables. MLR allows finding the best linear prediction equation between dependent and other predictor variables. The basic idea of the hybrid model in this paper is to combine MLR and LR, which retains advantages to each approach and access to the largest combination advantages. The main goal of doing so is to improve the forecast accuracy.

Next, we will review the hybrid model forecasting method. The general form of MLR model is as following:

$$
\beta_0 + \sum_{j=1}^{p} \beta_j w_j + \varepsilon_i = W_i
$$

(8)

Where, $w_i$ is the variable to be predicted; $w_j$ is the predictor variable; $p$ is the number of predictor variables; $\varepsilon$ is the regression error; $\beta$ is the regression coefficient that reflects the weight of each predictor variable denotes the regression error.

The regression coefficients are calculated by using the least square function according to the following formulas:

$$
\sum_{i=1}^{n} (W_i - \beta_0 - \sum_{j=1}^{p} \beta_j w_j)^2 \rightarrow \min
$$

(9)

The optimal solution of $\beta$ is:

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

(10)
The fitted values are $\hat{W} = w\hat{\beta}$, the residuals are $\hat{E} = W - \hat{W}$.

Equation (8) can be represented by the following matrix to estimate the regression coefficients. 

$$
\begin{bmatrix}
1 & w_{i1} & w_{i2} & \ldots & w_{ip} \\
1 & w_{i1} & w_{i2} & \ldots & w_{ip} \\
\vdots & \vdots & \vdots & \ddots & \vdots \\
1 & w_{i1} & w_{i2} & \ldots & w_{ip}
\end{bmatrix}
\begin{bmatrix}
\beta_0 \\
\beta_1 \\
\beta_2 \\
\vdots \\
\beta_p 
\end{bmatrix}
+ 
\begin{bmatrix}
\varepsilon_1 \\
\varepsilon_2 \\
\varepsilon_3 \\
\vdots \\
\varepsilon_p 
\end{bmatrix} = 
\begin{bmatrix}
W_1 \\
W_2 \\
W_3 \\
\vdots \\
W_n
\end{bmatrix}
$$

(11)

When MLR model is used to WPP, the first part to the left of equation (11) showed the historical wind power or power ration data matrix with $n \times (p+1)$ dimensions, the right of the equation (11) show the predicted wind power or power ration (response vector) with $n$ dimension. Equation (11) above can be simplified to: $w\beta + \varepsilon = W$

From equation (6) and (7), one can find that following equation holds in the matrix of equation (11). The summation of power ration values $w_{i,t}$, must be equal one, as equation (12)

$$
\sum_{t=1}^{n} w_{i,t} = 1
$$

(12)

Since $[W_1, W_2, \ldots, W_n]$ is a predicted vector, the summation of $W_i$ might not be equal to 1. Thus, a correction is needed, as in equation (13)

$$
P_{i, pred} = \frac{W_i}{\sum_{i=1}^{n} W_i}
$$

(13)

After predicting the total power $P_{total}$, and power ratio by correction equation $P_{i, pred}$, the indirect WPP of the $i^{th}$ wind farm is as following:

$$
\hat{P}_i = P_{i, pred} \times P_{total}
$$

(14)

Where, $\hat{P}_i$ is the indirect WPP of the $i^{th}$ wind farm which satisfies $\hat{P}_{total} = \sum_{i=1}^{n} \hat{P}_i$.

Figure 2 shows the process of combine method for direct and indirect of USTWPP.

4. Simulation and results
In this section, simulations are carried out for USTWPP using the time-series analysis. The test data is divided into two sets: one is the comparing results, and the other is the confirmed results.

4.1. Comparisons between single-point prediction and multi-point prediction
The prediction accuracy is a function for the difference between the predicted value and actual values. In this section, the comparison of a numerical result of the single-point and multi-point prediction ways will be displayed on the table 1. In this table, data is taken from the actual wind power data, and the width of prediction time window $T$ is assigned to 60, 30 and 20 min; the length of prediction $\Delta t$ is assigned to 5 and 10 min. MAPE is the mean absolute percentage error, and MSE is the mean square error.
Table 1. MAPE and MSE comparisons of two ways.

| Error | Single-Point | Multi-Point | Single-Point | Multi-Point |
|-------|--------------|-------------|--------------|-------------|
|       | $T=60\text{min}, \Delta t=5\text{min}$ | $T=60\text{min}, \Delta t=10\text{min}$ | $T=30\text{min}, \Delta t=5\text{min}$ | $T=30\text{min}, \Delta t=10\text{min}$ |
| MAPE  | 2.01         | 2.18        | 2.18         | 2.45        |
| MSE   | 2.09         | 2.61        | 2.61         | 3.30        |
|       | $T=20\text{min}, \Delta t=5\text{min}$ | $T=20\text{min}, \Delta t=10\text{min}$ |
| MAPE  | 1.41         | 1.52        | 1.52         | 2.27        |
| MSE   | 1.09         | 1.45        | 1.45         | 2.32        |
|       | $T=30\text{min}, \Delta t=5\text{min}$ | $T=30\text{min}, \Delta t=10\text{min}$ |
| MAPE  | 0.97         | 1.13        | 1.13         | 1.40        |
| MSE   | 0.51         | 0.69        | 0.69         | 1.02        |

Table 1 show that the single-point prediction way will give the better results, and is slightly more prone to MSE. This way could outperform others if fewer period data sets were used and fewer time intervals ahead were predicted.

Figure 3 gives the total WPP comparison of the two prediction ways, at $T = 60 \text{ min}, \Delta t = 5\text{min}$.

![Figure 3. Total WPP with single-point & multi-point predictions.](image)

From figure 3, the WPP curve with the single-point prediction way is closer to the actual wind power curve, and correlation coefficient between the two curves is about 0.874; while the WPP curve in the multi-point prediction way is less accurate with correlation coefficient being about 0.844.

4.2. Comparisons of multi-point USTWPP and its errors with different time

The graphical view about the multi-point USTWPP for three cases, anyone at different $\Delta t$ with the same $T$ is shown in figure 4 - 6. From these figures, it is seen that the total WPP curve accurately follows the actual curve at the smaller time horizon, and at the end of $T$, only minor deviations are seen for $\Delta t = 10\text{ min}$.

![Figure 4. Multi-point USTWPP curve at $\Delta t = 5$ and 10min with $T = 60\text{min}$.](image)

![Figure 5. Multi-point USTWPP curve at $\Delta t = 5$ and 10min with $T = 30\text{min}$.](image)

![Figure 6. Multi-point USTWPP curve at $\Delta t = 5$ and](image)

![Figure 7. Multi-point USTWPP error curve at](image)
To illustrate the performance of the multi-point USTWPP in a short run, the predicted result up to 60 min are shown in table 1, and the corresponding error curves are shown in figure 7 - 9. From these cases, the better accuracy for the USTWPP corresponds to the short width of prediction time window $T$ and sampling time period.

As shown in figure 9, the multi-point USTWPP error is quite low and is the smallest one, which concentrates within the prediction range.

### 4.3 Comparisons of two wind farms at WPP by direct and indirect prediction types

This part will show the comparisons between single WPP at two wind farm by direct and indirect prediction types. According to the values of WPP in figure 10&11, direct and indirect WPP of two wind farms respectively, WPP of two wind farms by direct type of prediction at $\Delta t=5$ min and $T=60$ min. The actual and prediction curves at two wind farm powers are shown in figure 10. It was observed that the predicted values by the direct prediction are not close to the actual values.

The WPP of two wind farms by indirect type of prediction at $\Delta t=5$ min and $T=60$ min, as it can be seen from figure 11, the predictive power result at two wind farm is more satisfactory than the direct predict type.

As part of the comparison between direct and indirect WPP, to find out, why the prediction by the indirect type it is the high-accuracy value, in the case of indirect WPP, using the correction values to prediction wind power, causing him to better than direct prediction.

### 4.4 Comparisons between proposed method & ARMA, ARIMA and ANN methods

This paper studies USTWPP using four methods: ARMA, ARIMA, ANN, and MLR&LS. In this part, the simulation results for USTWPP using the statistical methods are presented.

Figure 12 gives the comparison procedures of the four methods.
Wind Power Data (Input)

- MLR & LS Model (Proposal Method)
- ARMA Model
- ARIMA Model
- ANN Method

- Total WPP with Power Ratio
- Order (p,q) Selection
- Order (p,d,q) Selection
- Training
- Transform Ratio into Total WPP
- Total WPP by ARMA
- Total WPP by ARIMA
- Validating and Testing

**Figure 12.** Comparison procedures among four methods.

The ARMA model is known to have good results, so it is used as the benchmark in this paper. Figure 13 with using the ARMA model shows that the predicted values are almost close with the actual values in the previous stage of the width of the prediction time window, and the error is very small.

**Figure 13.** Actual & predicted total WP by ARMA.

**Figure 14.** Actual & predicted total WP by ARIMA.

Figure 14 with using the ARIMA model shows that the predicted curve is different from the actual one. The predicted values by ARIMA model depend upon the parameter.

Simulation results of ANN model are demonstrated after many experiments with various network architectures based on BP algorithm as shown in figure 15. The accurate predicted values and the correlation between the actual values and the predicted values indicate high prediction accuracy. Devaluation expected error also indicates high prediction accuracy. ANN has been successfully used to forecast integrated wind power.

**Figure 15.** Actual & predicted total WP by ANN.

**Figure 16.** Actual & predicted total WP by MLR&LS.

The proposed MLR&LS hybrid model for USTWPP has been successfully implemented in this paper. Figure 16 shows a time series of WPP that is closest to the time series of actual wind power. In this study, the final predicted value by MLR&LS is more accurate than that by ARMA or other models.

4.5. **Comparison of the predicted results**
Comparison of ARMA, ARIMA, ANN and MLR&LS model is depicted in table 2. From table 2 and figure 13 - 16, it can be clearly observed the WPP accuracy level with ARIMA compared with ARMA is not quite significant. It can be said both methods achieved a good forecast response as errors of them are low. This result is consistent with most of previous studies. Moreover, we observed the WPP accuracy level with ANN compared with ARIMA is not quite significant. However, it is observed, the MLR & LS has a more high-accuracy level for total WPP, compared with other methods in this paper. Numerical results in table 2 and figure 17 showed the MLR&LS is best than other methods. We also noted the pattern of ARMA, and ARIMA shows the linear pattern. This finding is consistent with a majority of the studies. Finally, all analysis and simulation results prove the proposed approach gives better performance.

4.6. Forecasting accuracy comparisons of the four approaches
The forecasting accuracy is a function as the difference between the predicted values and the actual values. Table 2 gives the error of predicted values compared to actual values for the four methods. It can be inferred that the predicted values are close to the actual values when used MLR&LS. In these calculations, it is also shown that there is high correlation between the actual curve and predicted curve in all models, but the proposed hybrid model gives the better result.

Table 2. Error and correlation coefficient of the 4 methods for USTWPP at $\Delta t= 5$ min and $T= 60$ min.

| Model     | MAPE | MSE  | $\rho$ |
|-----------|------|------|--------|
| ARMA      | 2.01 | 2.09 | 0.86   |
| ARIMA     | 3.09 | 5.63 | 0.65   |
| ANN       | 1.89 | 1.67 | 0.90   |
| MLR & LS  | 1.36 | 0.88 | 0.95   |

It is observed from table 2 above. That WPP by the proposed hybrid model outperformed all other models. The hybrid model has both the lowest error and the maximum correlation coefficient. Compared with ARMA, ARIMA and ANN, the hybrid model has the superiority of high USTWPP accuracy. Through table 2 and figure 13-16, we evaluated the predictive performances of the four models in details. In the total WPP of multiple wind farms, it is shown that the hybrid model is better than ANN, ARMA and ARIMA.

Figure 17. Simulation chart of comparison between four methods to total WPP of multiple wind farms.

Based on the simulation training about the historical data of eight wind farms, the USTWPP is reasonable. To avoid volatility due to the use of the MLR & LS hybrid model, all the forecasting were
repeated with $T = 60$ min. From table 2 and figure 17, the hybrid model clearly performs much better than ARMA, ARIMA and ANN model for single-point prediction and multi-point prediction. More accurately, in calculation of total WPP with ARMA, ARIMA, ANN and hybrid model, MAPE and MSE of the hybrid model are reduced, and $\rho$ of the hybrid; models are increased.

5. Conclusion
For USTWPP, this paper compared the performances of four methods, including the MLR & LS hybrid model. The WPP obtained from ANN, and ARMA are accurate compared against the ARIMA model. Broadly, the hybrid model is the best one than ANN and ARMA. In the case of WPP, wind power pursues the peak and valley of actual power components of the patterns. The shape of WPP obtained from the hybrid model is more accurate than that obtained from the other methods for this study. And the USTWPP by the proposed method is close to the actual power. So, we can easily conclude that the forecasting accuracy with the combination method performs better than the individual ones in general. Our simulation results show that the proposed method has best performance than the same method for individual forecasting process and contributes for a reasonable improvement in the final WPP. After several experiments with different width as the prediction time window on the MLR & LS hybrid model, the smallest MSE was noted to give the best prediction accuracy for the test and validity data. The MSE recorded during the experiment is presented in table 2 and figures17 to show that.

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7. References
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