Medium and long term wind power generation forecast based on OWA combined model and Markov chain

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Abstract. Wind energy, as one of the renewable energies with the most potential for development, has been widely concerned. At the same time, the medium and long term wind power prediction is easily affected by many factors. In order to avoid the instability of a single model, this paper first builds a self-adaptive filtering model and a gray model with parameter optimized by teaching learning-based optimization (TLBO), then uses ordered weighted averaging (OWA) to assign weights to two single models, and finally uses Markov chain to modify the prediction results to further improve the prediction accuracy.

1. Introduction
Wind energy is a kind of clean energy with great potential for development. Increasing the proportion of wind energy in energy supply is an important measure to reduce greenhouse gas emissions and deal with climate change. However, with the continuous expansion of scale, Large amount of wind power integration into power system may affect the quality of power supply and the safe operation of the power system. And accurate forecast of wind power generation will provide data analysis basis for power industry and related industry planning, and play an important guiding role in power system operation safety, development, formulation of planning schemes, and energy plans [1-3].

At present, the forecasting methods of wind power generation mainly include artificial intelligence methods[4-6], time series method[7], gray model[8] and their improvements and combination methods[9-10]. Wind power is intermittent, volatile, and random, and is related to many factors, such as geographic location and climate. Therefore, a single model cannot be used to predict the medium and long term wind power generation well. Ke et al. [11] predicted the power generation of wind turbines well through the long and short term memory network, but the effect is not good for the medium and long term power generation forecast with less data. Chang et al. [12] realized the prediction of wind power generation through the entropy weight combination of three prediction algorithms: unit matching, data expansion, and time series, but this method still requires a lot of data. Zhao et al. [13] used the kernel density estimation method to predict wind power in the medium and long term, but this method has problems with kernel function selection and optimal bandwidth. Meng et al. [14] used the gray model of metabolism to predict the annual power generation capacity. But this method is more dependent on the data sequence. And the length of the original data used in the model has a great impact on the prediction results. Li et al. [15] optimized the background value of the gray model. At the same time, in view of the problem that the curve fitted by the model must pass through the first point of the data, the least square method improves the accuracy of the original model, but this
method still belongs to the category of a single model. Therefore, the requirements for the shape and
general trend of the data sequence are relatively high, and Sun et al. [16] used a combination of
improved gray model and back propagation neural network (BP) to predict wind power generation.
Compared with the single model before the improvement, it has higher accuracy.

Considering that the background value structure is one of the reasons for the error of gray model
[17], this paper first optimizes the parameter of the background value construction through the TLBO
algorithm to improve the prediction accuracy, and then introduces the OWA operator to combine the
improved gray model and the self-adaptive filtering method to improve the stability and prediction
accuracy problems of a single model. To further improve the prediction accuracy, the error is
compensated through the Markov chain.

2. Markov modified OWA combination prediction model
In this paper, the gray model optimized by TLBO algorithm and the self-adaptive filtering method are
used to predict separately, then the OWA operator is used for weighting combination model, and the
final predicted value is obtained by correcting the error through Markov chain. The prediction process
is shown in Figure 1.

![Figure 1. Flowchart of overall structure of prediction model](image)

2.1. Gray Model
The gray model (GM) is a model for studying the uncertain small sample system with "some
information is known and some information is unknown". It is suitable for medium and long term
power generation forecasting with less data. It is established by the first-order ordinary differential
equation, and it is recorded as the GM(1,1). Let the sample sequence be \(x(0) = (x(0)(1), x(0)(2), \ldots, x(0)(n))\),
the randomness and volatility of the sequence are reduced by the first-order accumulation
\(x(1) = (x(1)(1), x(1)(2), \ldots, x(1)(n))\). It's calculated as follows:

\[ x(1)(n) = \sum_{i=1}^{n} x(0)(n) \]  \hfill (1)

The gray differential equation of the model is as follows:

\[ \frac{dx^{(1)}}{dt} + ax^{(1)} = b \]  \hfill (2)
where $a$ is the development coefficient, $b$ is the endogenous control coefficient. The basic form of the gray model corresponding to Equation (2) is:

$$x^{(0)}(k) + az^{(1)}(k) = b$$  \hspace{1cm} (3)

where $z^{(1)}(k)$ is the adjacent generation sequence of $x^{(1)}(k)$:

$$z^{(1)}(k) = 0.5(x^{(0)}(k) + x^{(1)}(k-1))$$  \hspace{1cm} (4)

The weights of the elements in Equation (4) are the same. Equation (3) is obtained by integrating and discretizing Equation (2). The use of an equal weight is an important cause of errors in the gray model. According to Lagrange’s theorem, we can find a parameter $\rho$, $\rho \in [0,1]$ which satisfies Formula (5).

$$z^{(1)}(k) = \rho x^{(1)}(k) + (1-\rho) x^{(1)}(k-1)$$ \hspace{1cm} (5)

where $a$ and $b$ are calculated by the least square method, and the parameter $\rho$ are optimized by the TLBO algorithm. The prediction equation of gray GM(1,1) can be obtained, as shown in Equation (6).

$$\hat{x}^{(0)}(k+1) = x^{(1)}(k+1) - \hat{x}^{(1)}(k) = (x^{(0)}(1) - \frac{b}{a}) (1 - e^{-ak})$$ \hspace{1cm} (6)

2.2. Optimization of parameter based on TLBO algorithm

TLBO algorithm is an intelligent optimization algorithm, which has higher search efficiency than the grid method. Therefore, this paper uses the TLBO algorithm to find the parameter in Formula (5).

The parameters to be optimized are called students. In the solution space, the parameters to be optimized are initialized randomly. TLBO tries to update the fitness value through two stages. The first stage is "Teacher Stage", the second stage is the "Learner stage". In the first stage, learners improve their average grades through the teaching of teacher (the best student). The fitness value of the $i$-th student is $X_i=(x_{i1},x_{i2},...,x_{im})$, and the candidate solutions are as follows [18-19]:

$$newX_i = X_i + rand \ast (T - T_f \ast M)$$ \hspace{1cm} (7)

where $rand$ is a random number generated between $[0,1]$, $T_f$ is the teaching factor that determines the value of $M$, and is given by

$$T_f = round[1 + rand(0,1)]$$ \hspace{1cm} (8)

where the $round[]$ is a rounding function. In the second stage, each learner uses another random learner to improve his own performance. The candidate solutions are:

$$newX_i = \begin{cases} X_i + rand \times (X_j - X_i) & f(X_i) < f(X_j) \\ X_i + rand \times (X_j - X_i) & otherwise \end{cases}$$ \hspace{1cm} (9)

where $j$ is randomly selected from the population, and $f()$ is the fitness function. When the fitness function of the candidate scheme is better than the original scheme, the original scheme is updated.

2.3. The model of self-adaptive filtering method

The adaptive filtering method is based on the weighted average of historical time series observations. According to the principle of mathematical optimization, The weights in the moving average model are adjusted to reduce forecast errors. The prediction formula of this model is as follows:

$$\hat{y}_{t+1} = w_1 y_t + w_2 y_{t-1} + \cdots + w_n y_{t-n+1}$$ \hspace{1cm} (10)

The steps of prediction are as follows:

1. The order $n$ of the model is determined
2. The appropriate filtering parameter $k$ is selected, which is generally shown in Equation (11).

$$k = \frac{1}{\sum_{i=1}^{\rho} x_i^2_{\text{max}}}$$ \hspace{1cm} (11)

3. We calculate the residual $e$ of each time, and then calculate the weight of the next round
according to Equation (12), and iterate until the appropriate weight is obtained.

\[ \phi'_i = \phi_i + 2ke_{t-i+1}y_{t-i+1} \] (12)

2.4. OWA operator combination model

Let OWA:R^n→R[20], if

\[ OWA(a_1, a_2, \cdots, a_i, \cdots, a_n) = \sum_{j=1}^{n} w_j b_j \] (13)

where w is the weighted vector associated with the function OWA, \( w_j \in [0,1] \), \( \sum_{j=1}^{n} w_j = 1 \), \( b_j \) is the jth largest element in the set\( \{a_1, a_2, \cdots, a_i, \cdots, a_n\} \), R is the set of real numbers, then the function OWA is called the ordered weighted average operator.

In this paper, the prediction results obtained by the improved gray model and the self-adaptive filtering method are rearranged through the OWA operator. According to different decisions, different calculation methods are selected to obtain the weights, and then the combined prediction model is obtained according to the weights.

The steps of model establishment are as follows:

Step1: The predicted sequences\( \{a_1, a_2, \cdots, a_i, \cdots, a_n\} \) obtained from each single model are rearranged into new sequences\( \{b_1, b_2, \cdots, b_i, \cdots, b_n\} \) according to the above rules.

Step2: The weight of the OWA operator is determined according to the focus of the decision maker. The index for determining the weight in this paper is the minimum sum of average relative error.

\[ \min \sum_{t=1}^{n} \frac{\sum_{i=1}^{m} w_i x_{i, t} - y_t}{y_t} \] (14)

where \( x_{i, t} \) is the i-th largest value at time \( t \) of each predicted sequence, and \( y_t \) is the actual value at time \( t \).

In order to keep the combination model unbiased, the weighting coefficient should satisfy:

\[ \sum_{i=1}^{m} w_i = 1 \quad i = 1, 2, \cdots, m \]

Step3: Combine the prediction results of each single model to get the combined prediction value, which is described as follows:

\[ \hat{x}(t) = w_1 x_{1, t} + w_2 x_{2, t} + \cdots + w_m x_{m, t} \] (15)

where \( \hat{x}(t) \) is the predicted value of the combined model at time \( t \), \( x_{i, t} \) is the i-th largest single model value arranged in accordance with the above rules at time \( t \).

2.5. Correcting errors by using Markov chain

Medium and long term wind power generation is a discrete-time random process, and the prediction error is also a discrete-time random process. This process can be described by a Markov chain. If each state transition is only related to the state at the previous moment, and has nothing to do with the state in the past, then such a process is called a "Markov process", which is expressed as follows:

\[ P = \{P_{n+1} = E_{n+1} | P_n = E_n \} \] (16)

The sample satisfies the non-negative time integer set \( T = \{0, 1, 2, \cdots, n\} \), and the state \( E = \{E_0, E_1, E_2, \cdots, E_n\} \) satisfies Equation (16) at any time. The possibility of transition from a certain state to the next state is described by the state transition probability, and \( P_{ij} \) is the conditional probability of transition from state \( E_i \) to state \( E_j \).

\[ P_{ij} = P(E_i \rightarrow E_j) = P(f_{ij} / f_i) \] (17)

where \( f_{ij} \) is the frequency of state \( i \) transitioning to state \( j \) after one step, \( f_i \) is the frequency of
appearance of state $i$. The state transition probability satisfies:

$$\sum_{j=1}^{n} P_{ij} = 1 \quad j = 1,2,\ldots,i,\ldots,n$$  \hspace{1cm} (18)

where $P_{ij} \in [0,1], i,j=1,2,\ldots,n$. According to the known initial state $R(0)$, the next state is $R^{(1)} = R(0)P_{ij}$. Markov's state division can generally be divided into relative error division or compensation value division. This paper uses relative error division. Suppose the predicted value of the combined model at time $t$ is $\hat{x}(t)$, the state at time $t$ is $E_j$, and the upper and lower bounds of state $E_j$ are $[N_j-, N_j+]$, then the final predicted value is given by:

$$\hat{y}(t) = (1 \pm 0.5(N_j- + N_j+))\hat{x}(t)$$  \hspace{1cm} (19)

And the sign in Equation (19) is selected according to the state interval.

3. Case study

3.1. Modifying Combined model by Markov chain

In order to verify the model proposed in this paper, the wind power generation in Region A of certain country from January 2011 to January 2019 was selected as the basic data, and the wind power generation data for January 2020 was used for prediction verification. The specific data are shown in Table 1.

| Year | Jan | Feb | Mar | Apr | May | Jun | Jul | Aug | Sep | Oct | Nov | Dec |
|------|-----|-----|-----|-----|-----|-----|-----|-----|-----|-----|-----|-----|
| 2011 | 23.23 | 29.88 | 26.10 | 30.14 | 32.20 | 24.60 | 15.50 | 14.45 | 17.78 | 31.20 | 35.29 | 32.49 |
| 2012 | 38.54 | 28.90 | 35.29 | 34.81 | 34.58 | 29.43 | 19.76 | 20.72 | 24.45 | 37.02 | 37.28 | 22.81 |
| 2013 | 44.30 | 36.37 | 38.81 | 42.15 | 37.29 | 32.70 | 26.36 | 22.24 | 34.91 | 40.46 | 47.35 | 37.41 |
| 2014 | 53.58 | 40.69 | 49.21 | 50.52 | 38.24 | 34.16 | 30.82 | 21.27 | 33.94 | 43.87 | 55.67 | 38.51 |
| 2015 | 50.35 | 43.11 | 47.30 | 48.58 | 45.55 | 29.66 | 27.46 | 31.25 | 40.58 | 45.80 | 55.81 | 51.23 |
| 2016 | 48.85 | 53.83 | 56.76 | 64.56 | 43.54 | 41.93 | 35.84 | 31.00 | 48.53 | 58.12 | 58.16 | 70.09 |
| 2017 | 58.30 | 65.62 | 75.17 | 70.27 | 63.20 | 54.30 | 37.88 | 31.62 | 54.22 | 73.79 | 68.49 | 72.54 |
| 2018 | 76.44 | 61.98 | 71.68 | 69.63 | 52.61 | 61.73 | 37.36 | 45.69 | 59.34 | 60.28 | 61.42 | 70.91 |
| 2019 | 67.36 | 56.07 | 77.37 | 78.48 | 64.30 | 53.69 | 53.47 | 60.27 | 74.72 | 86.28 | 79.81 | 82.01 |
| 2020 | 77.09 | 85.89 | 86.21 | 86.12 | 78.08 | 73.32 | 58.97 | 66.40 | 78.33 | 80.16 | 78.27 | 95.50 |

The prediction process of the combined model modified by Markov chain is as follows:

(1) The data in January of each year in Region A in Table 1 are taken to establish gray model. The parameters of TLBO algorithm are set as follows: The number of students is 10; The number of learning rounds is 50; The upper and lower limits of the optimization range are 1 and 0 respectively; The minimum fitting average relative error was taken as the fitness function.

Through numerical calculation, the optimal parameter $\rho$ is 0.8521, the development coefficient $a$ is -0.0804, and the endogenous control coefficient $b$ is 35.5868. So the prediction equation is:

$$\hat{x}_i(t) = 35.9884e^{0.0804(t-1)} \quad t = 2,3,\ldots,n$$  \hspace{1cm} (20)

(2) Similarly, the annual wind energy generation data in Region A in Table 1 is used to build the model, where the order of $p$ is 2. After calculation, the coefficients $w_1$ and $w_2$ of Formula (10) are 0.6460 and 0.6004, respectively. Therefore, the prediction equation of the model is:

$$\hat{x}_p(t) = 0.6460x_{p-1} + 0.6004x_{p-2} \quad t = 3,\ldots,n$$  \hspace{1cm} (21)

Substituting the power generation in January 2018 and January 2019 into Equation (21), the predicted power generation in January 2020 is 89.41 hundred GWh.
Table 2. January status interval division

| State | Interval  |
|-------|----------|
| E1    | (0.01, 0.11) |
| E2    | (-0.09, 0.01) |
| E3    | (-0.19, -0.09) |

According to the steps in Section 2.4, the prediction sequence is arranged according to the rules, and the weights \( w_1=0, w_2=1 \) can be obtained. Then the prediction model is:

\[
\hat{x}(t) = x_{21}(t) \tag{22}
\]

The results of the combined prediction are shown in Table 1. Equation (20) indicates that the smaller predicted value of the gray prediction model and the self-adaptive filtering model is used as the predicted value of the combined model, that is, the predicted value of the OWA combined model is 74.20 hundred GWh.

Table 3. Predicted value (100GWh) and relative error of each method in 2020

| Month | Actual value | Improved GM(1,1) Predicted | Relative Error | Self-adaptive filtering method Predicted | Relative Error | OWA Combined model Predicted | Relative Error | After Markov correction Predicted | Relative Error |
|-------|--------------|-----------------------------|----------------|----------------------------------------|----------------|-------------------------------|----------------|----------------------------------|----------------|
| Jan   | 77.09        | 74.20                       | -3.75%         | 89.41                                  | 15.98%         | 74.20                         | -3.75%         | 77.17                            | 0.1%           |
| Feb   | 85.89        | 68.90                       | -19.78%        | 69.46                                  | -19.13%        | 69.10                         | -19.55%        | 77.74                            | -9.49%         |
| Mar   | 86.21        | 89.00                       | 3.24%          | 83.13                                  | -3.57%         | 87.40                         | 1.38%          | 87.40                            | 1.38%          |
| Apr   | 86.12        | 87.06                       | 1.09%          | 90.38                                  | 4.95%          | 87.06                         | 1.09%          | 87.06                            | 1.09%          |
| May   | 78.08        | 70.42                       | -9.81%         | 62.21                                  | -20.33%        | 70.42                         | -9.81%         | 72.36                            | -7.33%         |
| Jun   | 73.32        | 66.05                       | -9.92%         | 55.25                                  | -24.65%        | 66.05                         | -9.92%         | 70.34                            | -4.06%         |
| Jul   | 58.97        | 53.62                       | -9.07%         | 46.66                                  | -20.88%        | 53.62                         | -9.07%         | 54.69                            | -7.26%         |
| Aug   | 66.40        | 64.13                       | -3.42%         | 54.93                                  | -17.27%        | 64.13                         | -3.42%         | 67.34                            | 1.42%          |
| Sep   | 78.33        | 83.17                       | 6.18%          | 81.86                                  | 2.12%          | 83.17                         | 6.18%          | 80.67                            | 2.99%          |
| Oct   | 80.16        | 94.36                       | 17.71%         | 80.04                                  | -0.85%         | 94.36                         | 17.71%         | 82.09                            | 2.41%          |
| Nov   | 78.27        | 85.00                       | 8.60%          | 88.80                                  | 13.45%         | 85.00                         | 8.60%          | 76.08                            | -2.80%         |
| Dec   | 95.50        | 94.03                       | -1.54%         | 95.20                                  | -0.31%         | 94.71                         | -0.83%         | 95.18                            | -0.34%         |
| Ave   |              | 7.84%                       | 11.96%         | 7.61%                                  | 3.39%          |

According to the relative errors of the combined model, the relative errors are arranged according to the size, the upper and lower limits of the relative errors are found, and the state interval is reasonably divided. The specific division of the relative error state in January in area A is shown in Table 2. According to the above division, a state transition matrix is:

\[
H = \begin{bmatrix}
0 & 1 & 0 \\
1/2 & 0 & 1/2 \\
1/3 & 1/3 & 1/3
\end{bmatrix}
\]

Since it is in state E1 in 2019, it is known from the one-step state transfer matrix \( H \) that the state will be transferred to state E2 in 2020. According to Formula (19), the revised value of wind power generation in January 2020 is 77.17 hundred GWh by weighted average of the state interval. Through the same method, the predicted values of each model in other months of 2020 can be obtained, and the results are shown in Table 3.
Through the above method, the forecast value of the model and average relative error of each month in 2020 can be obtained. The comparison is shown in Figure 2 and Figure 3, and the specific values are shown in Table 1. From Figure 2 and Figure 3, we can see that the relative error from the single model to the OWA combined model decreased by 2.93%, and after the correction from the combined model to the Markov chain, the relative error decreased by 55.45%. In summary, the OWA combined forecasting model modified by Markov chain has higher accuracy in the application of medium and long term power generation forecasting.

4. Conclusions
This paper studies the modeling process of gray model. In view of the limitations of gray theory, the following improvements have been made: The background value structure is improved to make the prediction more reasonable, and the fitting accuracy of the gray model is improved. The TLBO algorithm for fast searching and finding the global optimal ability optimizes the background value construction parameter. The improved gray model and the self-adaptive filtering model are combined through OWA operator to increase the scope of application of the model. Finally, the Markov chain is used for error compensation to further reduce the prediction error. The results in area A show that the
model proposed in this paper effectively reduces the prediction error, and the model is a scientific and reasonable medium and long term wind energy generation forecasting method. Its prediction accuracy is higher than the improved gray model, self-adaptive filtering model and combined model.

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