Wind Water and Solar Complementary Power Generation System Based on Particle Swarm Optimization and Neural Network Algorithm

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Abstract. Wind and light energy are volatile and need to be predicted to provide the basis for the next control strategy. This system uses the neural network algorithm to carry on the short time forecast to the wind energy, the solar energy, under the condition of high accuracy and based on the predicted results, particle swarm optimization (PSO) is adopted to make decisions. In this way, it can decide how to do today, like when should it charge/discharge the battery to maintain the stability of system rather than just analysis feasibility of system only bases on the history data. By regulating each energy use strategy at different times, the purpose of complementary output is achieved, and the output is guaranteed to be stable as far as possible.

1. Introduction
Wind power and solar energy are ideal clean energy; however, they are volatile and difficult to be directly used as stable energy. While wind energy and solar energy have complementary characteristics. At the same time, the water storage machine can provide more stable water and electricity. Wind, solar and water can form a distributed generation system. In this system, rather than only focus on getting more energy from the wind and solar, it uses two algorithms to predict the data from the history so as to find out a way to control the system that can get more energy while the stability of the output is guaranteed. The difference between this system and other systems is that it needs to predict today's wind speed and solar light intensity based on historical data to regulate the complementary utilization of solar energy and wind energy, water energy and the time of battery charging and discharging, so as to achieve more stable output than other complementary systems.

2. Back-Propagation Artificial Neural Network
The classic model of Back-Propagation artificial neural network is a three-layer neural network structure, namely: Input Layer, Hidden Layer and Output Layer. The figure is as Figure 1. The input and output of the BP neural network is a highly nonlinear mapping relationship. If the number of input nodes is N and the number of output nodes is M, the network is a mapping from N-dimensional Euclidean space to M-dimensional Euclidean space. [1]By adjusting the connection weight and network scale of the BP neural network, any nonlinear function can be approximated with arbitrary precision.[2]
In Back-Propagation neural network, designing the topology of the neural network is a very important issue. It not only greatly affects the performance of the established neural network model, but also can cause "overfitting" phenomenon. There are too few hidden nodes in the network. Then the learning process may not converge. While if there are too many hidden layer nodes, it will not converge for a long time, and the fault-tolerant performance of the network will be reduced due to overfitting. However, there is no scientific method to determine the number of nodes in the hidden layer Methods. In order to avoid the phenomenon of "overfitting" during training, to ensure high enough network performance and generalization ability, the most basic principle for determining the number of hidden layer nodes is to take the structure as compact as possible on the premise of meeting the accuracy requirements. [3] That is, take as few hidden layers as possible.

3. Neural Network Data for Wind Power and Solar Radiation Forecasting

Wind power and solar radiation forecasting model uses back-propagation neural network algorithm to predict short-term result. The data of the neural network prediction are as follows:

3.1. Data Acquisition

The data used in this study were derived from National Earth System Science Data Center. The specific data is the daily 24h data of 31d Changbai Mountain in January 2018. The data is authentic, reliable, and there is no missing or invalid data. For Wind Water and Solar Complementary Power Generation System, the solar radiation at night can be ignored. So, in this model, wind power to generate electricity will be used after sunset. This study mainly studies and predicts wind speed and solar radiation during the day, and excludes the effects of extreme special weather on the forecast.

3.2. Selection of Indicators

For the selection of sample features, if it is too small, it does not have the ability to generalize and cannot traverse all weather modes. Although the network is easy to converge, the prediction error is large; if too much data is selected, the training time becomes longer and the network is not easy to converge. At the same time, the generalization ability cannot be improved significantly. When selecting a data set, the strong correlation and similarity principles must also be met. Select wind power and solar radiation curves similar to the predicted day in history, and obtain similar curve sets for network training.

3.2.1. Wind Power Forecast. For the wind power prediction model, suppose to predict the wind power on the L day. Note the real-time wind power for the t hour of day L-1 and day L-2 are Mt and Nt , and the data from 6 am to 18 pm is used as the feature values, which are substituted into the neural network model for each time period corresponding to day L, and the data from 6 am to 18 pm is used as the feature values as an input to predict wind power from 6 am to 18 pm on day L. At the same time, considering that the air pressure will also affect the prediction of wind power, the real-time air
pressure for the t hour of day L-1 and day L-2 are recorded as \( W_t \), \( V_t \). \( t \) ranges from \([6,18]\). The feature values are as Table 1.

### Table 1. Wind power forecast data

| Date    | Time | Wind power (level) | Air pressure (mmHg) |
|---------|------|--------------------|---------------------|
| 2018-1-1 | 6:00 | 0.3                | 933.3               |
| 2018-1-1 | ...  | ...                | ...                 |
| 2018-1-1 | 18:00| 2.8                | 933.2               |
| 2018-1-2 | 6:00 | 0.4                | 935                 |
| ...     | ...  | ...                | ...                 |
| 2018-2-1 | 18:00| 3.2                | 935.2               |

#### 3.2.2. Solar Radiation Forecast
For the prediction model of solar radiation, suppose to predict solar radiation on day L, and record real-time solar radiation value as \( S_t \), the ultraviolet radiation intensity as \( U_t \), and PAR flux density as \( H_t \) on day L-1. Considering the data was tested on January, the sunrise time in Changbai Mountain area is 8:00 am, and the sunset time is 17:00 pm, so the range of \( t \) is \([8,17]\). The 30 data from the day before the prediction day are used as feature values, and Back-propagation neural network model is used to predict the total solar radiation value at 10 times of the day. The feature values are as Table 2.

### Table 2. Solar radiation forecast data

| Date    | Time | Ultraviolet Radiation W/m² | PAR flux density mol/m²/s | Solar Radiation W/m² |
|---------|------|-----------------------------|--------------------------|----------------------|
| 2018-1-1 | 8:00 | 0.9                         | 17.0                     | 2018-1-1             |
| 2018-1-1 | ...  | ...                         | ...                      | 2018-1-1             |
| 2018-1-1 | 17:00| 0.2                         | 9.7                      | 2018-1-1             |
| 2018-1-2 | 8:00 | 1.0                         | 21.4                     | 2018-1-2             |
| ...     | ...  | ...                         | ...                      | ...                 |
| 2018-2-1 | 17:00| 1.5                         | 8.4                      | 2018-2-1             |

### 4. Architecture of the Forecast Model

#### 4.1. Data Preprocessing
According to the characteristics of the collected detection data, in order to improve the model processing effect, a simple normalization method is adopted. There are lots of methods that can transform the original data to MATLAB data. The widely used transform method is as [4]:

\[
x_{\text{normalization}} = \frac{x - \text{Min}}{\text{Max} - \text{Min}}
\]

#### 4.2. Topology of Back-propagation Neural Network Model
Due to the characteristics of the problems involved in this study, the Back-Propagation neural network with one hidden layer was selected. Therefore, the network consists of three layers. According to the actual application, after repeated verification, the rules for setting the topology of this network are as follows:
4.2.1. Wind Power Forecast. Input layer feature vector and the output layer feature vector of the neural network are:

\[
\text{Input} = (M_{t-8}, ..., M_{t-18}, N_{t-6}, ..., N_{t-18}, W_{t-6}, ..., W_{t-18}, V_{t-6}, ..., V_{t-18})^T
\]
\[
\text{output} = (M_{t-6}, M_{t-7}, M_{t-8}, M_{t-9}, M_{t-10}, M_{t-11}, ..., M_{t-15}, M_{t-16}, M_{t-17}, M_{t-18})^T
\]

Set 11 nodes in the hidden layer, 26 nodes in the input layer, and 12 nodes in the output layer. The structure is as Figure 2.

![Figure 2: The structure of wind power forecasting neural network](image)

4.2.2. Solar Radiation Forecast. The input layer feature vector and the output layer feature vector of the neural network are:

\[
\text{Input} = (S_{t-8}, ..., S_{t-17}, U_{t-8}, ..., U_{t-17}, H_{t-8}, ..., H_{t-17})^T
\]
\[
\text{output} = (S_{t-6}, S_{t-7}, S_{t-8}, S_{t-9}, S_{t-10}, S_{t-11}, S_{t-12}, S_{t-13}, S_{t-14}, S_{t-15}, S_{t-16}, S_{t-17})^T
\]

Set 11 nodes in the hidden layer, 30 nodes in the input layer, and 10 nodes in the output layer. The structure is as Figure 3.

![Figure 3: The structure of Solar Radiation forecasting neural network](image)

5. Prediction Process of Back-Propagation Neural Network

The prediction based on Back-Propagation neural network is to use the good nonlinear processing ability of BP artificial neural network to continuously fit the expected values of wind power and solar radiation. Therefore, a prediction model capable of predicting the non-linear variation law of the wind speed and the total solar radiation value is established. The specific process is as follows:
6. Forecast Results and Analysis

In the wind prediction model, for the 32 sets of data in Table 2, the first 26 sets are training samples and the last six sets are test samples. The data processing method of this network is the real-time wind forecast one day after the real-time data corresponding to the previous two days.

The prediction result can be denormalized to obtain the simulation result of model prediction.

In solar radiation prediction, for the 22 sets of data in Table 3, the first 16 sets are training samples and the last 6 sets are test samples. The data processing method of this network is the real-time solar radiation one day after the real-time data corresponding to the previous day.

Comparing the prediction result with the actual value, the resulting image as shown in Figure 4 can intuitively reflect the relationship between the predicted value and the actual value.

![Comparison of wind power prediction results on the test set](image1)
![Comparison of solar radiation prediction results on the test set](image2)

**Figure 4.** Comparison of results on the test set
7. Improved Chaos Particle Swarm Optimization

7.1. Particle Swarm Optimization

Particle swarm optimization is a swarm based intelligent optimization algorithm based on the idea of imitating the foraging behavior of birds. Suppose the problem is in the \( d \)-dimensional space, the velocity vector and the position vector are defined as:

\[
V_i = \{V_{i1}, V_{i2}, \ldots, V_{id}\} \\
X_i = \{X_{i1}, X_{i2}, \ldots, X_{id}\}
\]

Then the update equation of velocity and position can be expressed as

\[
V_{id}(t+1) = \phi V_{id}(t) + c_1 * rand_1(pBest_{id}(t) - X_{id}(t)) + c_2 * rand_2(gBest_{id}(t) - X_{id}(t))
\]

\( \phi \) is the linear decline of inertia weight coefficient, \( c_1 \) and \( c_2 \) are acceleration coefficient, \( rand_1 \) and \( rand_2 \) are respectively in \([0, 1]\) two random numbers. \( PBest_{id} \) represents the best location (individual best) for the \( i \)th particle found so far, \( gBest \) is the best location found in the entire population (global best).

7.2. Chaotic Particle Swarm Optimization

A group of chaotic variables are generated by chaotic mapping, which are introduced into the variables to be optimized. The chaotic optimization variables become chaotic state, and the range of chaotic motion is extended to the range of optimization variables, and then the range is carried out by using the chaotic variables. Internal optimization is characterized by ergodicity, internal randomness, high sensitivity, fractal dimension and universality.

7.3. An improved scheme of chaos particle swarm

Chaos particle swarm optimization algorithm has the characteristics of ergodicity and internal randomness, which makes particles search continuously in the global scope and avoids the early convergence problem. Its improvement on standard particle swarm optimization mainly includes three aspects:

7.3.1. Using logistic chaos map to improve the initial position and velocity of particles.

7.3.2. The inertia weight is improved by logistic, and the random constant is updated by Henon mapping:

7.3.3. Chaos theory is used to iterate chaos for the optimal particle searched by PSO.

In the third method, the combination of chaos theory and particle swarm optimization algorithm is embedded, which can greatly improve the global search ability of particle swarm optimization algorithm. The local chaos iteration is carried out for the optimal particle after one or several iterations of particle swarm optimization algorithm with chaos idea. The chaos iteration and particle swarm optimization algorithm iteration are carried out alternately. Every time particle swarm optimization algorithm searches, the chaos iteration is carried out for the optimal particle it searches. When the current solution searched by chaos system is better than the original solution, the current solution is used to replace the original solution. The main contents of chaos are as follows:

\[
y^k = \frac{p_{i1}^k - p_{min}}{p_{max}^k - p_{min}}
\]
7.3.4. Mapping the optimal value of individual particle to the domain of logistic mathematical equation. The optimal value of individual particle is mapped to the domain (0, 1) of logistic mathematical equation, and the formula is as follows:

7.3.5. Logistic map

\[ y_{i+1}^{k} = \mu y_{i}^{k} (1 - y_{i}^{k}) \]

\( i = 1, 2, ..., d; \quad k \) is the number of iterations. \( \mu \) is the control parameter, which is generally 4.

7.3.6. The inverse mapping

The mathematical equation of Logistic mapping is used to carry out chaotic iteration, and the inverse mapping is made to the original after the iteration. In the spatial domain of the solution, we get a new solution. The formula is as follows:

\[ p_{gm}^{k} = (p_{\text{max}}^{k} - p_{\text{min}}^{k})g_{m}^{k} + p_{\text{min}}^{k} \]

7.4. The Step of Chaotic Particle Swarm Optimization

The main idea of the combination of chaos thought and particle swarm optimization (PSO) is to utilize the initial position, initial velocity and random constant of the particles in the chaotic particle swarm of chaos theory. The main flow is as follows.

7.4.1. Set parameters in the particle swarm optimization algorithm.

Including: random number \( r_1, r_2 \); Learning factors \( c_1, c_2 \); Population number \( m \); The inertia weight in the standard particle swarm \( \omega = 0.65 \), in the improved particle swarm, \( \omega_{\text{max}} = 0.9, \omega_{\text{min}} = 0.4 \), Maximum iteration number \( k_{\text{max}} \), chaotic maximum iteration steps \( M_c \) etc.

7.4.2. Produces the initial state of the particle randomly.

7.4.3. Update the position and speed of particles. Define the fitness function, calculate the fitness value of particles, and calculate the individual extreme value / st and the global extreme value of particles.

7.4.4. Mapping the individual extremum of particles to (0, 1) by using Logistic mapping to perform chaotic iteration. After the iteration, returns to the spatial range of the original solution.

7.4.5. When the new solution is better than the old one, the new solution is output.

7.4.6. Judge whether the iteration result meets the end condition, otherwise return to step (3) to continue the iteration.

8. Operation Model of Wind Water Solar storage complementary System

8.1. The structure of Independent Wind, Water and Solar Complementary Power Generation System

The typical microgrid structure is shown in Figure 5, including various distributed generation, load and energy storage devices. Among them, the distributed generation includes wind power, photovoltaic, hydropower Battery is selected as energy storage device.
8.2. Objective Function

On the basis of ensuring the security and stability of the system, this paper selects daily scheduling, one hour a period, the maximum daily power obtained by the system is the objective function.

In the day, wind power, solar power, water storage machine supply the power to the system,

$$\max F = P_{wdt} + P_{phdt} + P_{pdt} + P_{te}$$

At the same time, we need to keep the output as state as possible at the same time. It takes the most stable daily output obtained by the complementary system as the objective function. We (same) choice the minimum of variance of the whole output of system per time during the day and night as the objective function.

$$\min S^2$$

Among them, $P_{wd}$, $P_{pdt}$ and $P_{phdt}$ are wind power output, photovoltaic output and hydropower output of the load at time $t$ respectively. $P_{bt}$ is the charge (discharge) power of the battery at time $t$ (positive value is discharge, negative value is charge).

8.2.1. Constraint Condition. Daily power balance constraint:

$$P_{lt} = P_{pt} + P_{nt} + P_{wt} + P_{ht} + P_{gt}$$

Water balance constraint:

$$V_{t+1} = V_t + (q_t - Q_t) \Delta t$$

Generation reference flow constraint:

$$Q_{min} \leq Q_t \leq Q_{max}$$

Output constraint of the water storage machine:

$$P_{hmin} \leq P_{ht} \leq P_{hmax}$$

Battery capacity constraint:

$$W_{min} \leq W_t \leq W_{max}$$

Battery capacity balance constraint:

$$W_{t+1} = W_t + P_{ht} \Delta t$$

Power transmission constraint:

$$P_{gmin} \leq P_{gt} \leq P_{gmax}$$

$P_{lt}$ is the load power at time $t$.
8.2.2. Rule of scheduling. Priority will be given to wind and photovoltaic power generation, because they are uncontrollable, highly dependent on natural conditions, and not schedulable. In order not to waste, they must be fully loaded. On the other side, they do not directly consume fuel and have no environmental pollution, and national policies also focus on supporting clean and renewable energy power generation, so priority should be given to them.

In the case of strong solar energy during the day, wind energy, light energy and water energy to provide stable power output. In the case of no solar energy at night, the system utilizes the complementary power generated by wind energy and water storage machine to generate electricity.

The difference between this system and other systems is that it needs to predict today's wind speed and solar light intensity based on historical data to regulate the complementary utilization of solar energy and wind energy, water energy and the time of battery charging and discharging, so as to achieve more stable output than other complementary systems.

9. Example Analysis

The data of wind and solar has been predicted in part II.

![Figure 6. The data of solar](image1.png)

![Figure 7. The data of windpower](image2.png)

The basic parameters of the selected reservoir are: the total storage capacity is $103.43 \times 10^6$ m$^3$, the normal water level of the reservoir is 1179.6 m, the corresponding storage capacity is $29.9 \times 10^6$ m$^3$, the limited water level in flood season is 1177.1 m, the flood control storage capacity is $9.3 \times 10^6$ m$^3$, and the dead water level is 1177.8 m. The installed composition and total capacity of the hydropower station is $800 \times 3 + 400 = 2800$ kW, which is a small hydropower station. The maximum flow of single unit power generation is $3.56 \text{ m}^3 / \text{s}$. It is assumed that the daily initial storage capacity of the reservoir is $7.03 \times 10^6$ m$^3$. In general, the power generation of hydropower station in one day is basically stable, and a typical small hydropower station in one day is selected as the data of this example.

![Figure 8. The data of hydropower](image3.png)
Using the model, algorithm and data established in this paper, the power generation situation of various power sources is obtained through simulation calculation. The figure shows the wind power, photovoltaic power generation, battery charging and discharging power and hydropower station output directly supplying the load, as well as the power exchange between the wind water storage complementary micro grid and the large grid.

**Figure 9. The results of mode**

**Figure 10. The results of PSO**

Figure 10 shows the results only use the traditional PSO. We (same) can find from the picture that the output remains from 400KW to 800KW, which is very unstable compare to the improved PSO.

10. Conclusion
In this paper, a mathematical model for the optimal operation of wind solar hydro power generation is established. By using the neural network algorithm, the data used is predicted form the history
data. Then we (same) use improved PSO to deal with these data, so that it can know how to dispatch those energy, because it can’t decide how much should we (same) export and how much should we (same) send to the battery to keep the output as stable as possible when we (same) don’t know the trend of data.

The operation model of wind water storage complementary microgrid proposed in this paper gives priority to wind power, photovoltaic power generation and hydropower. The regulation can increase the utilization ratio of wind and photovoltaic, and make the best use of water energy resources, which has a high application value.

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