The Application of Simulated Annealing Particle Swarm Algorithm in the Short-term Wind Speed Prediction

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Abstract. In view of the low prediction accuracy of short-term wind speed, a forecasting method based on simulation annealing particle swarm optimization BP neural network (SAPSO-BP) was proposed. The simulation results showed that the average absolute error and mean squared error of the proposed prediction model were better than several other optimization algorithms, and had better robustness, could be used for short-term wind forecasting.

Introduction

Wind speed has the randomness and other features, resulting in wind farm output power volatility and intermittent, thus endangering the safety and stable operation of the power grid. Therefore, reliable forecasting wind speed has important practical implications for the economic dispatch of the grid. Currently seen in the literature of wind prediction methods are neural network [1], support vector machines [2], wavelet analysis [3] as well as some optimization algorithms [4,5]. However, due to the wind speed is affected by temperature, pressure and other natural environmental factors, leading to the prediction accuracy of a single model was often low, the error was usually 25% to 40%.

Since the neural network has unique advantages in data processing, this paper introduces neural network model. By weakening the original wind speed random sequence, to improve the robustness and fault tolerance of the model. Meanwhile, BP neural network is easy to fall into local minima, difficult to guarantee global optimization and other defects, the researchers combine genetic algorithms, particle swarm algorithm with BP algorithm to improve the performance of BP network. Genetic algorithm exist crossover and mutation, and the more complex encoding. Although the particle swarm algorithm is simple, but still easy to premature convergence phenomenon. Simulated Annealing Particle Swarm Optimization (SAPSO) Integrated global particle swarm optimization capabilities and the ability of simulated annealing algorithm to escape from local optimal solution [6], this paper constructed neural network model based on simulated annealing Particle Swarm Optimization, and forecasted wind farm short-term wind speed, effectively improved the prediction accuracy of the model.

Model Implementation Process

Realization of Simulated Annealing Particle Swarm Optimization. Simulated Annealing Particle Swarm full used of particle swarm's rapid convergence and the simulated annealing algorithm's global convergence, SAPSO optimization BP neural network algorithm (SAPSO-BP) was usually used to optimize BP network weights, threshold parameters, and to adapt function to a minimum. The algorithm steps were as follows [7, 8, 9]:

(1) Determined the topology of BP neural network

(2) Initialized the particle swarm

(3) Determined the fitness function, selected the neural network mean square error indicators as particle group fitness function

(4) Fitness evaluation, the position and fitness of current each particle stored in each particle p_i, the globally optimal solution p_{best} best individual's location and fitness stored in p_g

(5) Determined the initial temperature, $t_0 = f(p_g)/\ln 5$

(6) Determined adaptation value, using the Eq.1 to determine the adaptation value of the current temperature of each p_i

$$TF(p_i) = \frac{e^{-(f(p_i)-f(p_g))/t}}{\sum_{i=1}^{N} e^{-(f(p_i)-f(p_g))/t}} \quad (1)$$

(7) Roulette strategy determined the global optimal alternative value p_g from all p_i, Eq.2 updated the velocity and position of each particle

$$v_{id}(k+1) = \varphi\{v_{id}(k) + c_1 r_1 (p_{id}(k) - x_{id}(k)) + c_2 r_2 (p_{gd}(k) - x_{id}(k))\} \quad (2)$$

$$x_{id}(k+1) = x_{id}(k) + v_{id}(k+1)$$

Where: v_{id}, x_{id} respectively represented the current particles velocity vector and the position vector, k was the current iteration number, c_1, c_2 were learning factors, φ was the shrink factor, $\varphi = 2/\left|2 - c - \sqrt{c^2 - 4c}\right|$, $c = c_1 + c_2$, r_1, r_2 were two random numbers.

(8) Extreme update, updated value p_i of each particle and value p_g of populations

(9) Annealing operation, annealing mode selected $t_{k+1} = \lambda t_k$, λ was the annealing constant

(10) Stop searching. If the stop condition was satisfied, the search was stopped, output result, then the corresponding value of p_g was the BP neural network right and threshold parameter. Otherwise, go to step (6).

Simulations

With an offshore wind farm in an area as an example to verify the analysis, the wind farm composed of 200 linear array wind turbines, unit capacity was 2.5 MW. According to 120 groups of average hourly wind speed sample data for 5 d[10], mapped out short-term wind speed time series of curve (Fig. 1).

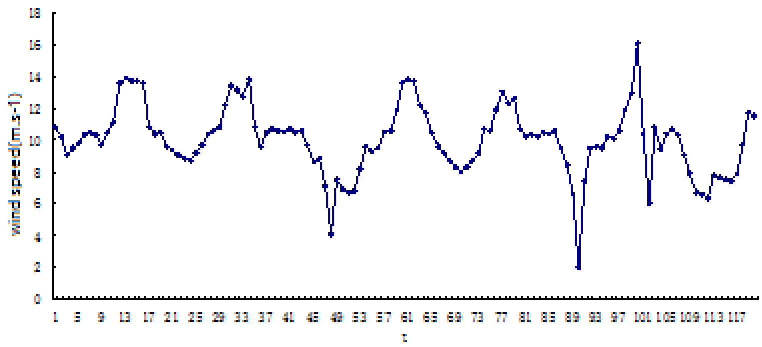

Figure 1. The actual wind speed sequence

Based on experience algorithm, set SAPSO-BP model main parameters: population size of 50, learning factor $c_1 = 2.8$, $c_2 = 1.3$, annealing constant $\lambda = 0.5$. In the MATLAB programming environment, get training error curve of SAPSO-BP algorithm (Fig. 2).

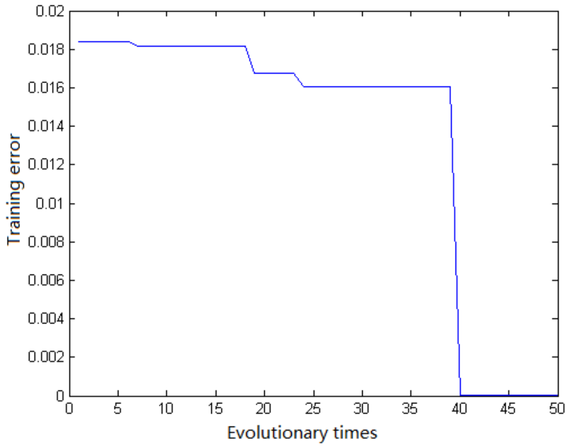

Figure 2. Training error curve of SAPSO-BP algorithm

In order to verify the feasibility of the method, used day 24 h average wind speed time series data for comparative analysis, and separately used gray GM (1,1) modeling method, BP network and SAPSO-BP network for validation. According to GM (1,1) modeling idea, get the prediction model $\hat{x}^{(0)}(k+1)=2348.825(1-e^{-0.004})e^{0.004k}$, Wherein k was the hour number of wind speed sequence. Prediction results of different models were shown in Table 1.

Table 1 The comparison of forecasting results [m/s]

Hour Number	Actual Value	Predictive Value		
		GM(1,1)	BP	SAPSO-BP
1	7.5	9.3765	7.2146	7.6892
2	6.9	9.4141	7.0180	7.2890
3	6.7	9.4518	7.0220	6.5481
4	6.8	9.4897	7.0268	7.0889
5	8.2	9.5278	7.6323	8.6763
6	9.4	9.5660	8.4333	9.6710
7	9.3	9.6043	8.7781	9.3222
8	9.5	9.6428	9.7594	9.2681
9	10.5	9.6814	10.6373	10.3145
10	10.6	9.7202	11.4606	10.4595
11	11.9	9.7592	12.5194	12.2718
12	13.7	9.7983	14.4571	13.3173
13	13.8	9.8376	12.1162	13.8533
14	13.7	9.8770	12.0373	14.2396
15	12.2	9.9166	11.0330	12.4463
16	11.7	9.9563	11.0328	12.0138
17	10.5	9.9963	10.1432	10.6700
18	9.6	10.0363	10.6654	9.3685
19	9.2	10.0765	10.6374	9.5695
20	8.7	10.1169	9.1091	8.4264
21	8.3	10.1575	7.5396	7.9534
22	8.0	10.1982	8.7518	7.5653
23	8.3	10.2391	8.6292	8.6009
24	8.7	10.2801	9.4142	8.9216

Seen from Table 1, the prediction results of SAPSO-BP algorithm was closest to the actual value of wind speed, the error was relatively stable, followed by BP algorithm, gray GM (1,1) model was the worst. According to the predicted value of each model were calculated their average absolute error (MAE), mean square error (MSE) and root mean square error (RMSE) (Table 2).

Table 2 Error analysis of forecasting results [%]

Error	GM(1,1)	BP	SAPSO-BP
MAE	175.4	68.8	27.5
MSE	272.5	66.8	9.28
RMSE	16.51	8.17	3.05

As can be seen from Table 2, GM (1,1) model mean square error reached 272.5%, 175.4% of the average absolute error, simply couldn't fit a nonlinear trend of short-term wind speed. Due to the presence of BP network falling into local minima and other defects, although the prediction accuracy was higher than GM (1,1) model, but its prediction error was still large, the mean square error of 66.8%, hadn't much practical value. SAPSO-BP model optimized the BP network's right and threshold parameters through the use of simulated annealing particle swarm algorithm, improved the generalization ability of the network, the average absolute error was 27.5%, the mean square error down to 9.28%, significantly improved short-term wind speed forecast accuracy, and the error was relatively small fluctuations, fully demonstrated the feasibility and effectiveness of this method.

Conclusions

In this paper, SAPSO-BP optimization algorithm had good ability to build a short-term forecasting model for wind farm wind speed prediction, mean square error of 9.28%. In several predictive model presented in this paper, this method was the minimum prediction error, robust and fault tolerance, was an effective reference model.

Rapid change in wind speed of time, predictions of several models volatility would be larger, the prediction error was significantly increased, which was the short-term prediction of wind farms Winds difficulty presence.

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