Short-term prediction of wind power based on self-adaptive niche particle swarm optimization

Hong Zhang[1, 2*]

[1] *Department of Electrical Engineering, Southeast University, Nanjing, Jiangsu 210096 China*

[2] *Key Laboratory of Technical and Device of Smart Grid, Nanjing, Jiangsu 210096 China*

Received 12 May 2014, www.tsi.lv

Abstract

Connecting wind power to the power grid has recently become more common. To better manage and use wind power, its strength must be predicted precisely, which is of great safety and economic significance. Speed sensors are widely applied, it make prediction of wind power more accurate. In this paper, the short-term prediction of wind power is based on self-adaptive niche particle swarm optimization (NPSO) in a neural net. Improved PSO adopts the rules of classification and elimination of a niche using a self-adaptive nonlinear mutation operator. Compared with the traditional method of maximum gradient, NPSO can skip a local optimal solution and approach the global optimal solution more easily in practice. Compared with the basic PSO, the number of iterations is reduced when the global optimal solution is obtained. The method proposed in this paper is experimentally shown to be capable of efficient prediction and useful for short-term power prediction.

Keywords: Speed sensor, PSO, Niche, Short-term power prediction, Neural net

1 Introduction

Wind power is a renewable energy source that is becoming increasingly popular for application in the grid because of its environmentally friendly and low-cost properties. However, because the power fluctuates with the wind strength, connecting wind power to the grid is challenging. To make the use of wind power reasonable and reduce its negative effects on the power grid, scientists in many countries have been working to develop methods to predict the power of the wind generators, which is of great importance to the economical distribution and operation of the power grid. Advanced wind speed sensor makes it possible to accurately predict short-term wind power and plays an important role in the wind power prediction. Denmark was among the first countries to develop a system of power prediction for wind power [1]. Prediktor is the wind power work prediction system developed by Ris National Laboratory of Denmark, which mainly applies physical models [2]. ANEMOS, a research project sponsored by the European Union, combines physical and statistical methods [3, 4]. The eWind is a system developed by AWS Truewind in America [5]. The highly precise mathematical models of atmospheric physics and adaptive statistical models are combined; the velocity of the wind and the power of the wind power plants have been investigated in studies based on time serials and neural networks [6-8]. At present, quite some few PSO alternatives such as Wang et al (2012) [9], Pousinho et al (2010) [10] or Pratheepraj et al (2011) [11] for short-term wind power prediction, and so on.

The back propagation (BP) neural network is the mostly widely used neural network. The classic BP learning law is typically used in BP neural networks to determine net-work connection weights. However, this technique is slow in practice and may lead to a local optimal solution. In this paper, the short-term power prediction of the wind power is based oneself-adaptive niche particle swarm optimization (NPSO) in a neural network. Improved PSO adopts the rules of classification and elimination of a niche and uses a self-adaptive nonlinear mutation operator. Compared with the traditional method of maximum gradient, NPSO can skip a local optimal solution and approach the global optimal solution more easily in practice. Compared with the basic PSO, the number of iterations is reduced when the global optimal solution is obtained. The method proposed in this paper is experimentally shown to be capable of efficient prediction and useful for short-term power prediction.

2 The principle of prediction of wind power based on speed data from mechanical sensors

In 1926, Betz proposed general theory of Betz about aerodynamic action of the wind. From this theory, we get the formula related to the power output of wind turbines and wind speed as shown in Equation 1.

$$P_1=8/27\rho SV^3C_P, \tag{1}$$

* ***Corresponding author*** e-mail: hazh0216@163.com

ρ is the density of air, S is cross-sectional area of airflow through wind turbine fan. V is the average wind speed through the fan. C_P is the actual utilization of wind turbine efficiency.

$$n=2NV/D \tag{2}$$

$$N=½ρAra_m \tag{3}$$

$$D=2πρr^2Ab_m \tag{4}$$

The wind speed measured by cup anemometer is based on the formula 2-4. In Equations (2), (3) and (4), n is the rotational speed of cup anemometer; A is the cross sectional area of the cups; am and bm are intrinsic parameters of cup anemometer. From the formula (1)-(4), we can obtain the wind turbine power from the wind speed measured by wind speed sensor. When we want to know the wind power of sometime later in the future, we can use hybrid swarm intelligence theory based on speed data from speed sensors. It is described the prediction of wind power as shown Figure 1

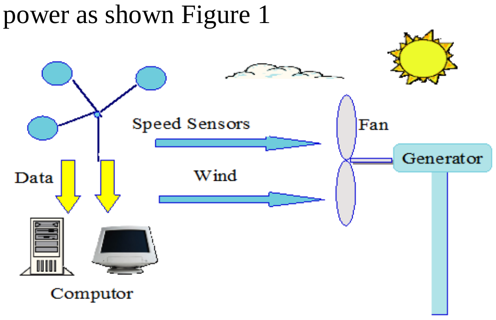


FIGURE 1 Schematic diagram for the prediction of wind power

3 Theoretical basis for improved self-adaptive PSO

3.1 THEORETICAL BASIS FOR BASIC PARTICLE SWARM OPTIMIZATION

In 1995, J. Kennedy and R. C. Eberhart developed PSO [12, 13], which aims to simulate a simple social system, such as a bird flock searching for foods, to study and explain complex social behaviour. In basic PSO, every candidate solution is compared to a bird searching the space and is called a particle. The position and velocity of a particle is denoted as $X_i = (x_{i1}, x_{i2},...,x_{iD})$ and $V_i = (v_{i1}, v_{i2},...,v_{iD})$, respectively. At the initial stage, a swarm of particles is randomly selected. Then, the swarm is updated according to the best known positions of individual particles and the entire swarm. The equations defining the position and velocity of the particles are shown below:

$$\begin{aligned} v_{id}(k+1) &= wv_{id}(k) + c_1r_1(p_{id}(k) - x_{id}(k)) \\ &\quad + c_2r_2(g_{id}(k) - x_{id}(k)) \\ x_{id}(k+1) &= x_{id}(k) + v_{id}(k) \end{aligned} \tag{5}$$

In Equations (5) and (6), p is the best known position of a particle and g is the best known position of the entire swarm; i = 1,2·n; D is the dimension of a particle; k is the k-th iteration; d is the d-th dimension; k_{max} is the maximum number of iterations; w is the inertia weight; w_{ini} is the initial inertia weight; w_{end} is the final inertia weight; c_1 and c_2 are learning factors; and r_1 and r_2 are uniform random numbers in the range [0, 1].

3.2 ADAPTIVE NICHING PARTICLE SWARM OPTIMIZATION

Basic PSO may lead to premature convergence to a local optimum, thus affecting the quality of the solution. The probability of prematurity can be reduced by mixing basic PSO with other algorithms or by adopting a comprehensive strategy. Niche technology simulates ecological balance, i.e., a species evolves to establish a surviving niche in a larger environment, which reflects the evolutionary rule of survival of the fittest. Goldberg and Richardson described niche technology based on a sharing mechanism in [14], and Brits et al., described NPSO in [15, 16]. The following formulae are based on adaptive NPSO:

$$\begin{aligned} v_{id}(k+1) &= wv_{id}(k) + c_1r_1(p_{id}(k) - x_{id}(k)) + \\ &\quad c_2r_2(g_{id}(k) - x_{id}(k)) + c_3r_3(\bar{p}_{id}(k) - x_{id}(k)) \\ x_{id}(k+1) &= x_{id}(k) + v_{id}(k) \end{aligned} \tag{7}$$

$$w = (w_{ini} - w_{end})\exp(-1/[1+(1+\frac{k}{k_{max}})] + w_{end} \tag{8}$$

In Equations (7) and (8), $\bar{p}_{id}$ is the best known position of a sub-swarm; c_3 is the learning factor; and r_3 is a uniform random sequence in the range [0, 1].

The diversity selection of the swarm regulates the adaptability of individual particles by reflecting the sharing functions among them, upon which the later evolutionary process is selected, to create an evolved environment and to realize swarm diversity.

The adaptive mutation operator adopts an adaptive non-linear decreasing inertia weight function [17]. The decreasing velocity of the inertia weight is accelerated in the first iteration of the algorithm to achieve a more efficient solution.

3.3 THE MAIN STEPS OF THE IMPROVED PSO ALGORITHM

The main steps of the improved PSO algorithm are as follows:

Step 1 Start.

Step 2 Generate the initial population by chaotic iteration.

Step 3 Initialize parameters.

Step 4 Select a particle randomly and divide all of the particles evenly into m small niche subpopulation based on adaptive functions.

Step 5 Establish the initial velocity of the particles randomly.

Step 6 Set the initial position of the present particle as the individual historical optimal value, pbx; set the historical optimal value of the optimal individual in each subpopulation as the population historical optimal value, $\overline{p}$ bx; and set the historical optimal value of all of the particles as the overall historical optimal value, gbx.

Step 7 When k is less than the maximum number of iterations, the following cycle of operations is performed for each subpopulation:

I) Calculate the inertia weight, threshold value, and calibration coefficient.

II) Update the velocity and position of every particle within each subpopulation.

Step 8 Adopt a niche elimination strategy.

Step 9 Determine whether the convergence conditions are met; if so, stop the calculation and output the results; if not, go to Step 6.

Step 10 End.

3.4 TESTING THE IMPROVED PSO ALGORITHM USING STANDARD TEST FNCTIONS

To test the performance of the improved PSO algorithm, two standard testing functions are selected: the 2-D Rosenbrock function and 2-D Rastrigin function. Standard testing functions are commonly employed in the optimization literature to evaluate the efficiency of new algorithms [18, 19]. The two standard testing functions have numerous local optima and a global minimum that is very difficult to locate.

3.4.1 The 2-D Rosenbrock Function

The 2-D Rosenbrock function is given by Equation (9):

$$f(x_1,x_2)=100(x_2-x_1^2)^2+(1-x_1)^2 \tag{9}$$

For the 2-D Rosenbrock function in this paper, the global minimum is fglobal = 0 as x = (1,1), but the valley in which the minimum lies has steep edges and a narrow ridge. The tip of ridge is also steep. Figure 2 illustrates the main characteristics of the 2-D Rosenbrock function.

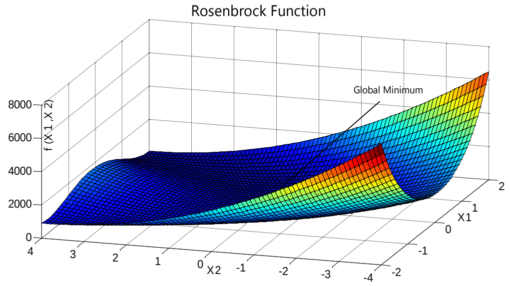


FIGURE 2 Graph of the Rosenbrock function

3.4.2 The 2-D Rastrigin function

The 2-D Rastrigin function is given by Equation (10):

$$g(x_1,x_2)=x_1^2+x_2^2-10[\cos(2\pi x_1)+\cos(2\pi x_2)]+20 \tag{10}$$

For the 2-D Rastrigin function employed in this paper, the global minimum is $f_{global}=0$ when x = (0,0). There are many local minima arranged in a lattice configuration, as shown in Figure 3. Figure 3 illustrates the main characteristics of the 2-D Rosenbrock function.

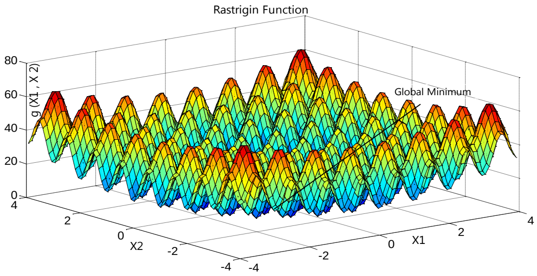


FIGURE 3 Graph of the Rastrigin function.

The global minima of the 2-D Rosenbrock function and 2-D Rastrigin function can be located by simulation computation based on the improved PSO algorithm. Thus, the model based on the improved PSO can be used in practice.

4 Neural Network Model Based on Self-Adaptive Niche PSO

4.1 THERORETICAL BASIS FOR THE BASIC NEURAL NETWORK

Since the insightful study of the neural network in the 1980s [20, 21], neural networks have been widely applied to the industrial field. The artificial intelligence neural network is a complex nonlinear system. The artificial neural network is also a nonlinear mapping system with good self-adaptability and can be used to identify any complicated state or process.

Figure 4 describes a simple artificial intelligence neural network. The basic principle of the neural network model to process information is that the input signal X(i) acts on the intermediate node (the hidden layer), leading to a result from the output node, which utilizes a non-linear transformation and generates an output signal Y(k) by adjusting W(ij), the value relating to the input nodes and hidden layer nodes. T(jk), the value relating to the hidden layer nodes, the output node, and their respective values, is reduced by repetitive learning training; the network parameters (weights and threshold values) relating to the minimum error are determined. The training continues until the error reaches the threshold value. The BP neural network model is expressed in Equation (11):

$$
\begin{aligned}
O_j &= f(\sum W_{ij} \times X_i - q_j) \\
Y_k &= f(\sum T_{jk} \times O_j - q_k
\end{aligned} \tag{11}
$$

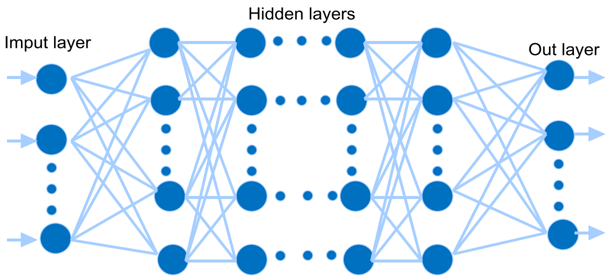


FIGURE 4 Artificial intelligence neural network

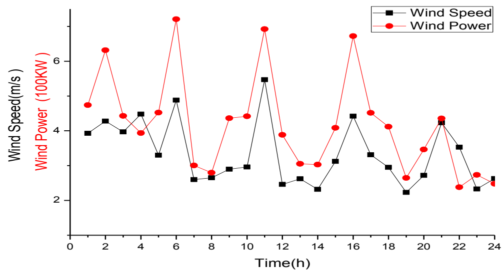
4.2 THE STEPS OF THE PREDICTION ALGORITHM BASED ON SELF-ADAPTIVE NPSO NEURAL NETWORK

The main steps of prediction algorithm based on the self-adaptive NPSO neural network are as follows:

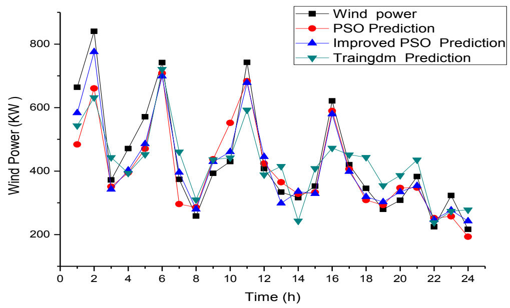
Step 1 Start.
Step 2 Input the initial values and target values of the samples.
Step 3 Initialize the coupling weight values and thresholds.
Step 4 Convert connection weights and thresholds to particles.
Step 5 Divide the initial population into several small niche subpopulations.
Step 6 Calculate the adaptive values of the particle swarm.
Step 7 Determine the best known positions of the individuals, sub-populations, and overall population.
Step 8 Adjust the adaptability and inertia weight and update the velocity and position of the particles.
Step 9 Judge whether the niche update conditions are met. If not, go to Step 6.
Step 10 Run the niche optimization rules.
Step 11 Judge whether the maximum time is reached. If not, go to Step 6.
Step 12 Determine the coupling value and threshold.
Step 13 End.

5 Predictive Analysis of the Neural Network Based on Self-Adaptive NPSO

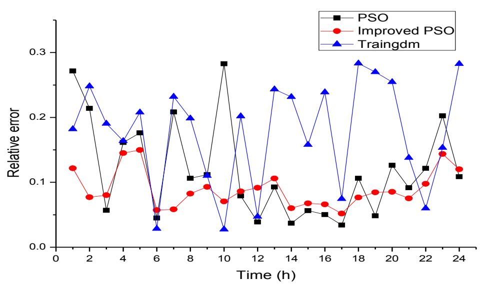
The power prediction model is established by the neural network based on self-adaptive NPSO (improved PSO). The power of a wind generator in Dongtai (Jiangsu, China) was predicted in 2008 based on the meteorological data and data for the power generated by the wind generator in the previous months. The predictive models for the neural network are based on PSO, NPSO, and Traingdm. First, the original data related to wind speed and wind power must be processed and normalized by advanced mathematical methods [22, 23]. For example, the model will observably decrease systematic error when the origin data have been processed by the Kalman filter described in the literature [24, 25]. All predictive models are trained beforehand. Figure 5 illustrates the main characteristics obtained from different prediction models 3 h ahead. Figure 5(a) illustrates that higher wind powers generally correspond to higher wind speeds. Figure 5(b) presents the measured power and forecasted power based on PSO, improved PSO, and Traingdm. Comparing the results of the three methods, the forecasted wind power curve based on the improved PSO is the closest to the measured power in Figure 5(b). Figure 5(c) presents the relative error from different predictions. The minimum relative error of the forecast wind power is obtained by the improved PSO method. Figure 5(d) illustrates the frequency and probability from different prediction models based on PSO, improved PSO, and Traingdm. The probability of a relative error of less than 0.1 for the improved PSO method is greater than those of PSO and Traingdm. Thus, the prediction accuracy of the improved PSO method is better than those of PSO and Traingdm. The absolute error, relative error, means absolute error, mean relative error, standard deviation, and relative standard



(a)



(b)



(c)

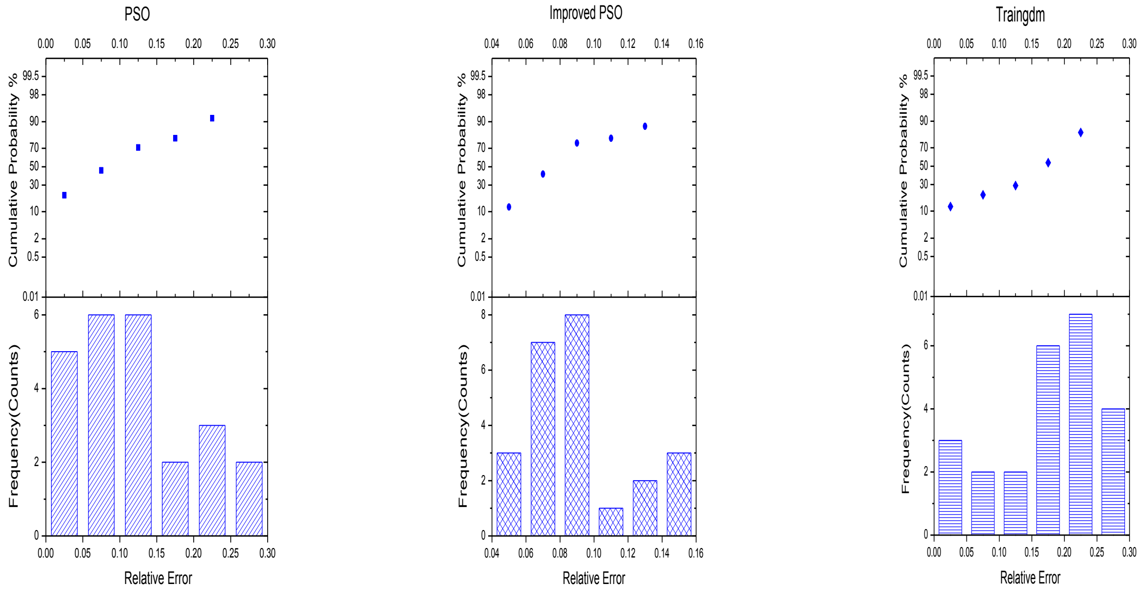


FIGURE 5 Main characteristics obtained from the three different predictions

(a) Wind speed and wind power. (b) The measured power and forecasted power based on PSO, improved PSO, and Traingdm. (c) Relative error from different prediction models based on PSO, improved PSO, and Traingdm. (d) Frequency and probability from different prediction models based on PSO, improved PSO, and Traingdm.

Deviation and interval probability in this paper are illustrated by Equation (12) [26]. From this data of Figure 5(d), we can determine the best method of the three based on PSO, improved PSO, and Traingdm.

$$\begin{aligned}
&\text{absolute error} = |\,\text{forecast}\ (i)\text{-measure}\ (i)| \\
&\text{mean absolute error} = \frac{|\,\text{forecast}\ (i)\text{-measure}\ (i)|}{n} \\
&\text{relative error} = \frac{|\,\text{forecast}\ (i)\text{-measure}\ (i)|}{\text{measure}\ (i)} \\
&\text{mean relative error} = \frac{\text{relative error}}{n} \\
&\text{standard deviation} = \sqrt{\frac{\sum_{i=1}^{n}\left(\text{forecast}\ (i)\text{-}\frac{1}{n}\sum_{i=1}^{n}\text{forecast}\ (i)\right)^2}{n-1}} \\
&\text{relative standard deviation} = \frac{\text{standard deviation}}{\frac{1}{n}\sum_{i=1}^{n}\text{forecast}\ (i)} \\
&\text{interval probability} = \frac{\text{frequency(counts)}}{n}
\end{aligned} \tag{12}$$

6 Conclusions

In this paper, a predictive model for neural networks based on self-adaptive NPSO is established. Using model analysis, experiments, and comparison with predictive models based on other algorithms, the model is shown to be more precise than the other two models considered; furthermore, it has the lowest absolute variance, demonstrating its effectiveness. The reliability of the model is significantly related with the precision of the weather forecast, but by combining with the weather predictive model, the dependence will be lowered. With computers becoming increasingly powerful, the predictive method of the neural network based on hybrid multi-algorithms will be useful in the future.

Acknowledgments

The author gratefully acknowledges Prof. Xueliang Huang School of Electrical Engineering, Southeast University. This paper is partly supported by the National High Technology Research and Development Program (863 Program) (2011AA05A107).

References

[1] Landberg L, Watson S J 1994 Short-term prediction of local wind conditions *Bound.-Lay. Meteorol* **70** 171-95
[2] Landberg L, Giebel G, Nielsen H A, et al. 2003 Short-term prediction-an overview *Wind Energy* **6** 273-80
[3] Martí I, Kariniotakis G, Pinson P, et al. 2006 Evaluation of Advanced Wind Power Forecasting Models–Results of the Anemos Project *In Proceedings of the European Wind Energy Conference, EWEC 2006, Athens, Greece, February-March 2006.*
[4] Kariniotakis G, Halliday J, Brownsword R, et al. 2006 Next Generation Short-Term Forecasting of Wind Power–Overview of the ANEMOS Project. *In Proceedings of the European Wind Energy Conference, EWEC 2006, Athens, Greece, February-March 2006.*
[5] Porter K, Rogers J 2010 Status of Centralized Wind Power Forecasting in North America; NREL/SR-550-47853; National Renewable Energy Laboratory: Golden, CO
[6] Yang X, Xiao Y, Chen S 2005 Wind speed and generated power forecasting in wind farm *Proceedings of the CSEE* **25** 1-5

[7] Ding M, Zhang L, Wu Y 2005 Wind speed forecast model for wind farms based on time series analysis *Electric Power Automation Equipment* **8** 32-4

[8] Xiao Y, Wang W, Huo X 2007 Study on the time-series wind speed forecasting of the wind farm based on neural networks *Energy Conserv. Technol.* **2** 2

[9] Wang H, Hu Z, Hu M, et al. 2012 Short-Term Prediction of Wind Farm Power Based on PSO-SVM *Power and Energy Engineering Conference (APPEEC) Asia-Pacific, 2012; IEEE: 2012* 1-4

[10] Pousinho H, Catalão J, Mendes V 2010 Wind power short-term prediction by a hybrid PSO-ANFIS approach *MELECON 2010-2010 15th IEEE Mediterranean Electrotechnical Conference, 2010; IEEE: 2010* 955-60

[11] Pratheepraj E, Abraham A, Deepa S N, et al. 2011 Very Short Term Wind Power Forecasting Using PSO-Neural Network Hybrid System *In Advances in Computing and Communications, Springer* 503-11

[12] Eberhart R, Kennedy J 1995 A New Optimizer Using Particle Swarm Theory *In Proceedings of the Sixth International Symposium on Micro Machine and Human Science, Nagoya, Japan, 4-6 October 1995* 39-43

[13] Kennedy J, Eberhart R 1995 Particle Swarm Optimization. *In Proceedings of the IEEE International Conference on Neural Networks, 27 November-01 December 1995* 1942-8

[14] Goldberg D E, Richardson J 1987 Genetic Algorithms with Sharing for Multimodal Function Optimization *In Proceedings of the Second International Conference on Genetic Algorithms and Their Application, Cambridge, MA, USA* 41-9

[15] Brits R, Engelbrecht A P, Van den Bergh F 2002 A Niching Particle Swarm Optimizer *In Proceedings of the 4th Asia-Pacific Conference on Simulated Evolution and Learning, Singapore* 692-6

[16] Brits R, Engelbrecht A P, Van Den Bergh F 2003 Scalability of Niche PSO *In Proceedings of the 2003 IEEE Swarm Intelligence Symposium, April 2003* 228-34

[17] Gao Y, Ren Z 2007 Adaptive Particle Swarm Optimization Algorithm with Genetic Mutation Operation *In Third International Conference on Natural Computation, Haikou, Japan, August 2007* 211-5

[18] Faerman M, Birnbaum A, Berman F, Casanova H 2003 Resource allocation strategies for guided parameter space searches *Int. J. High Perform. C* **17** 383-402

[19] Potter M A 1997 *The design and analysis of a computational model of cooperative coevolution* PhD. dissertation, George Mason University, Fairfax, VA, USA

[20] McClelland J L, Rumelhart D E 1986 PDP Research Group *Parallel Distributed Processing, Explorations in the Microstructure of Cognition, 2nd ed.; The MIT Press: Cambridge, MA, USA*

[21] Hopfield J J, Tank D W 1986 Computing with neural circuits- a model *Science* **233** 625-33

[22] Ogasawara E, Martinez L C, de Oliveira D, et al. 2010 Adaptive Normalization: A Novel Data Normalization Approach for Non-Stationary Time Series *In The 2010 International Joint Conference on Neural Networks (IJCNN), Barcelona, Spain, 18-23 July 2010* 1-8

[23] Sola J, Sevilla J 1997 Importance of input data normalization for the application of neural networks to complex industrial problems *IEEE Trans. Nuclear Sci.* **44** 1464-8

[24] Louka P, Galanis G, Siebert N, et al. 2008 Improvements in wind speed forecasts for wind power prediction purposes using Kalman filtering *J. Wind Eng. Ind. Aerod.* **96** 2348-62

[25] Libonati R, Trigo I, DaCamara C C 2008 Correction of 2 m-temperature forecasts using Kalman filtering technique *Atmos. Res.* **87** 183-97

[26] Spiegel M 1998 Schaum's Outline of Probability and Statistics; McGraw-Hill: New York, NY, USA 157-77

Authors

Zhang Hong, born on February 16, 1971, Huai'an City, Jiangsu Province, China

Current position, grades: Fujian Normal University until 2009. Since 2009, has been studying a doctoral program at Southeast University.
University studies: electrical engineering from Huaiyin Institute of Technology in 1992. M.Eng in electrical engineering from Southwest Jiaotong University in 2006.
Scientific interest: power system computation and simulation.