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Singular Value Detection of Genetic Algorithm Optimizing RBF Neural Network

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Abstract: Due to the improper choosing of network weight, the center vector and the initial value of sound stage width vector of Gaussian function, when using RBF neural network to detect the singular value of the grid signal, it would lead to the decline of detection accuracy even to the RBF network divergent. Basing on the genetic algorithm, this study proposes a grid signal singular value detecting algorithm which is a genetic algorithm that can optimize RBF neural network and provides the mathematical model as well as detecting and analyzing the singular values of these conditions such as depression, heave, interruption and high frequency transient vibration in grid signals. The simulation results show that the proposed algorithm can detect the start and end time of various mutation singular values and it has certain application value in the power quality analysis of distributed generation synchronizing.

Key words: Distributed generation, singular value, genetic algorithm, RBF neural network

INTRODUCTION

Distributed generation technology such as wind power generation and photovoltaic power generation has become the most potential renewable energy sources power technology. In order to guarantee the maximum utilization rate of renewable energy, the power generating system of synchronizing new energy sources all adopt proper controlling strategy to ensure the maximum output of active power as much as possible (Hou *et al*., 2008; Jiasheng *et al*., 2012a). As the wind speed of wind power station fluctuates dynamically, there exists great random fluctuation in the output power of new energy synchronizing generation. Intermittent power fluctuation usually leads to grid signal distortion (Shuchun *et al*., 2011) which will cause negative influence on the power quality of the big grid. Currently, new energy source synchronizing generation is being promoted greatly. How to detect the grid signal distortions effectively and eliminate or control them which have extensive application value in new energy source synchronizing generation (Qin *et al*., 2010; Lin and Fan, 2007). To overcome the problem of detection accuracy decline or even RBF network divergence when detecting the grid signal singular value for the reason of improper choosing of network weight, the central vector and the initial value of sound stage width vector of Gaussian function (Babu and Rao, 2006), this study proposes a grid signal singular value detecting algorithm which is a genetic algorithm that can optimize RBF neural network, to do some research on the singular value detection when grid signal distorts, Good results were obtained. It provides a new method and important evidences for evaluating the safety and reliability of new energy source synchronizing generation systematically and for the controlling and managing of new energy source generation synchronization (Yedjour *et al*., 2011; Sharma and Agarwal, 2012).

PRINCIPLE OF GENETIC ALGORITHM OPTIMIZING RBF NEUTRAL NETWORK

Genetic algorithm principle: Genetic algorithm is a random search algorithm which is based on biology natural selection and genetic mechanism and it starts searching from the initial solution of a group of random generated "population". Each individual in this population is a solution to the question and is called chromosome (Amiri *et al*., 2008). Chromosome is a string of signs such as a binary system character string. These chromosomes evolve continuously in the follow-up iteration which is named heredity. In each generation, "fitness" is used to measure the quality of the chromosome. The generated younger chromosome is called offspring. Offspring is formed by crossover or mutation calculating the older chromosome (Mahi and Izabatene, 2011).

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In the forming process of the younger generation, according to the size of the fitness to choose part of the offspring and to weed out the others. Thus the size of the population is a constant. Those chromosomes whose fitness is higher are more likely to be chosen. After several generations like this, the algorithm can collect the best chromosome and it is probably the optimal or suboptimum solution to the problem (Sinha and Chande, 2010; Li *et al*., 2003). It includes the following five steps: coding, generation of the initial colony, evaluation and test of adaptability value, selection, crossover and mutation.

Structure of RBF neural network model: RBF (Radial Basis Function) neural network is a three-tier feed-forward network with single hidden layer. As it simulates the human neural network structure which can locally adjust and mutually cover acceptance domain (or is called Receptive Field), therefore, RBF network is a local approximation network. The mapping of its input to output is nonlinear while the mapping of hidden layer space to output space is linear. As a result, it can accelerate learning speed greatly and avoid local minimum problems. Its structure diagrammatic figure is shown in Fig. 1 (Shifei *et al*., 2011). Its structure chart of RBF network approximating an object is shown in Fig. 2.

In Fig. 1 and 2, $X = [x_1, x_2, \cdots, x_n]^T$ is the network input vector. Suppose the radial base vector of RBF network to be $H = [h_1, h_2, \cdots h_j, \cdots h_m]^T$. In this expression, h_j is Gaussian primary function:

$$h_j = \exp(-\frac{\|X-C_j\|^2}{2b_j^2}), j=1,2,\cdots m \quad (1)$$

The center vector of the j node in the network is:

$$C_j = [c_{1j}, c_{2j} \cdots c_{ij} \cdots c_{nj}]^T \text{ and } I = 1, 2, \ldots n \quad (2)$$

Suppose the sound stage width of the network is:

$$B = [b_1, b_2 \cdots, b_m]T \quad (3)$$

where, b_j is the sound stage width of the node and is a number bigger than zero. Then the weight vector of the network is:

$$W = [w_1, w_2 \cdots w_j \cdots w_m]^T \quad (4)$$

The network output in the moment of k is:

$$W = [w_1, w_2 \cdots w_j \cdots w_m]^T \quad (5)$$

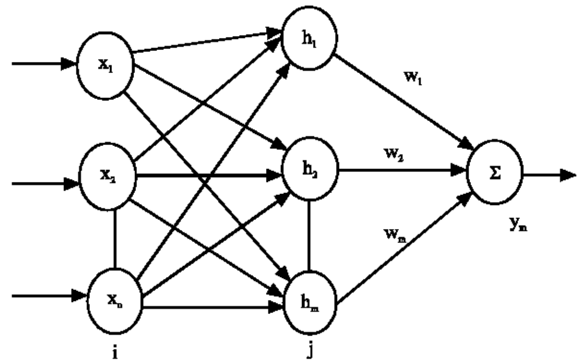

Fig. 1: Structure diagram of RBF neural network

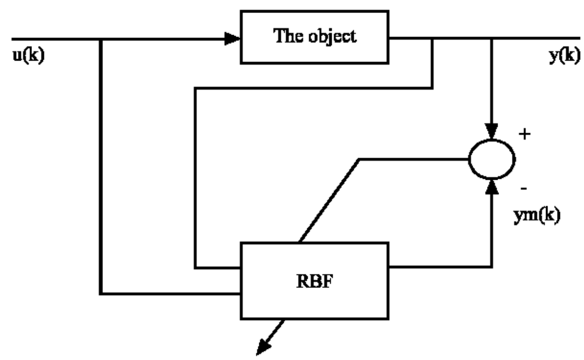

Fig. 2: Structure chart of RBF network approximating an object

Suppose the ideal output to be y (k), then the performance index function is:

$$E(k) = \frac{1}{2}(y(k)-y_m(k))^2 \quad (6)$$

According to the gradient descent, the iterative algorithms of output weight, node center and node sound stage width parameter are as follows:

$$w_j(k) = w_j(k-1)+\eta(y(k)-y_m(k))h_j+\alpha(w_j(k-1)-w_j(k-2)) \quad (7)$$

$$\Delta b_j = (y(k)-y_m(k))w_j h_j \frac{\|X-C_j\|^2}{b_j^3} \quad (8)$$

$$b_j(k) = b_j(k-1)+\eta\Delta b_j+\alpha(b_j(k-1)-b_j(k-2)) \quad (9)$$

$$\Delta c_{ji} = (y(k)-y_m(k))w_j \frac{x_j-c_{ji}}{b_j^2} \quad (10)$$

$$c_{ij}(k) = c_{ij}(k-1)+\eta\Delta c_{ij}+\alpha(c_{ij}(k-1)-c_{ij}(k-2)) \quad (11)$$

In these expressions, η is the learning speed and α is the factor of momentum.

The algorithm of *Jacobian* Array (the sensitivity information of object output to controlled input) is:

$$\frac{\partial y(k)}{\partial u(k)} \approx \frac{\partial y_m(k)}{\partial u(k)} = \sum_{j=1}^{m} w_j h_j \frac{c_{1j} - x_1}{b_j^2} \quad (12)$$

In this expression, x_1 = u (k).

APPLICATION IN SINGULAR VALUE DETECTION

When RBF neural network is singular detecting signals (Yu, 2005), the network weight value, the center vector of Gaussian function and the initial value of sound stage width vector are hard to determine. If these parameters are improperly selected, it would lead to the decline of detection accuracy and even the divergence of RBF network (Wang and Meng, 2010). In order to get satisfying detecting results, the genetic algorithm can be adopted to optimize the initial value of RBF network parameters. Figure 3 is the initial value block diagram of genetic algorithm optimizing RBF neural network controller. After adopting genetic algorithm to optimizing the initial value of neural network, then the optimized initial value will be brought to the RBF neural fuzzy control system. Presume the parameter setting of genetic algorithm is: the sample amount is Size = 25; the terminal evolution algebra is 180; the crossover probability is 0.6; the mutation probability is 0.001-[1:1:size]*0.001/size. The neural network structure of RBF is 2-3-1. The value range of network weight w_j is [-1, +1]. The value range of Gaussian function's sound stage width vector b_j is [0.1, +3]. The value range of Gaussian function center vector c_{ij} is [-3, +3]. Additionally, assume p = [b_1 b_2 b_3 c_{11} c_{12} c_{13} c_{21} c_{22} c_{23} w_1 w_2 w_3], after 180 generations genetic algorithm optimization of the 12 parameters to get result p = [2.7959 9.1714 7.4308 -2.2493 4.9824 13.5161 -1.2757 9.2463 1.8446 -0.2395 3.2444 3.6784]. The evolution process of genetic algorithm cost function is as shown in Fig. 4. Then the result Gaussian function parameters after optimizing are applied to RBF neural network, suppose momentum factor α = 0.05 and learning speed η = 0.85 in the RBF neural network.

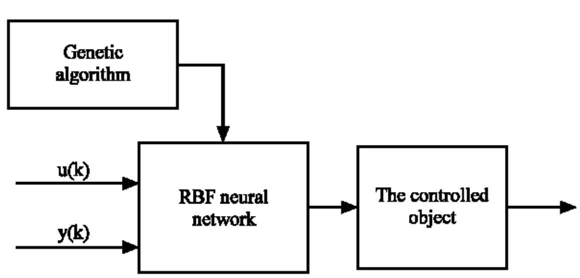

Fig. 3: Initial value block diagram of genetic algorithm optimizing controller

SIMULATION AND RESULTS ANALYSIS

In order to illustrate the effectiveness of this algorithm in this study, it is applied to signals with mutation conditions such as depression, heave, interruption or high frequency transient vibration in Matlab 7.0 to be detected and analyzed.

Simulation example 1

Detection on grid signal with depression: If there is a grid signal u (t) which is a depressed signal, then its mathematical model is:

$$u(t) = A[1-b(u(t-t_2)-u(t-t_1))]\sin(\omega t) \quad (13)$$

In this expression, B is the signal mutation range, t_2-t_1 is the duration time, t_1 is the mutation starting time and t_2 is the end time. Suppose A = 1, b = 0.5, t = t-0.5, t_1 = t_2 = 0.04, ω = 5π, the optimized network parameters are taken as the RBF network initial value, then the operation procedure is shown in Fig. 5. In the upper half part, red represents the controlled object output *y* and the blue part represents the network output y_m. The below half part is the D-value chart of e = y-y_m. From the figure it can be seen that there is signal depression during 0.5-0.04 and 0.5+0.04 sec, correspondently, obvious mutation from 0.5-0.04-0.5+0.04 sec can also be seen clearly. The

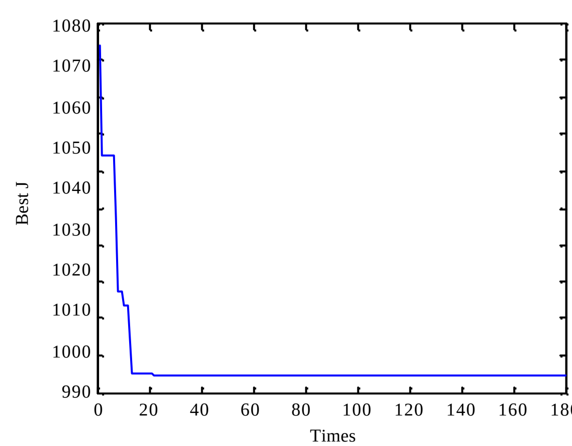

Fig. 4: Evolution process chart of genetic algorithm cost function

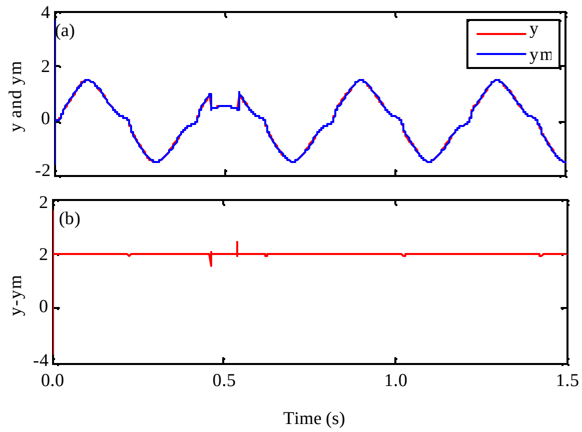

Fig. 5(a-b): Singular value detection chart of grid signal with depression

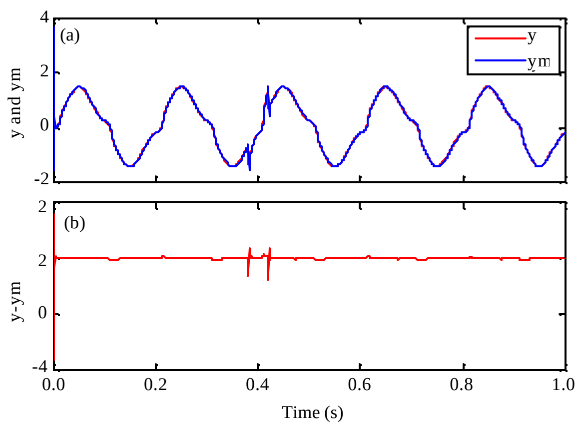

Fig. 6(a-b): Singular value detection chart of grid signal with heave

simulation results show that when there is depression in grid signal, the algorithm mentioned in this study can make accurate detection on starting time and end time successfully.

Simulation example 2

Detection on signal with heave: If the input signal u (t) is a signal with heave, its mathematical model is the same as that of Genetic Algorithm. Suppose A = 1, b = 0.7, t = t-0.4, $t_1 = t_2 = 0.02$, taking the optimized network parameters as RBF network initial value, then the operation procedure is as shown in Fig. 6. The representation meaning of each curve is the same as Genetic Algorithm. From the figure it can be seen that there is signal heave during 0.4-0.02 and 0.4+0.02 sec, correspondently, obvious mutation from 0.4-0.02 to 0.4+0.02 sec can also be seen clearly. The simulation results show that when there is heave in grid signal, the algorithm mentioned in this paper can make accurate detection on starting time and end time successfully.

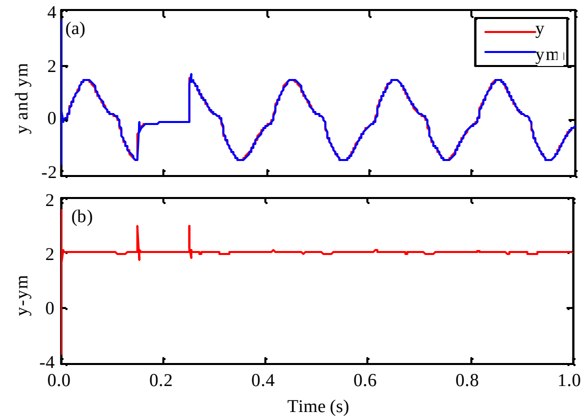

Fig. 7(a-b): Singular value chart of grid signal with instant interruption

Simulation example 3

Detection on signals with instant interruption: If the input signal u (t) is a signal with instant interruption, its mathematical model is the same as that of Genetic Algorithm. Suppose A = 1, b = 0.995, t = t-0.2, $t_1 = t_2 = 0.05$ sec, $\omega = 10\pi$, taking the optimized network parameters as RBF network initial value, then the operation procedure is as shown in Fig. 7. The representation meaning of each curve is the same as Genetic Algorithm. From the figure it can be seen that there is signal instant interruption during 0.2-0.05 and 0.2+0.05 sec, correspondently, obvious mutation from 0.2-0.05 to 0.2+0.05 sec can also be seen clearly. The simulation results show that when there is instant interruption in grid signal, the algorithm mentioned in this study can make accurate detection on starting time and end time successfully.

Simulation example 4

Detection on signal with high frequency transient vibration: If the input signal u (t) is a signal with high frequency transient vibration, its mathematical model is:

$$u(t) = \sin(5\pi t)+0.3*\exp((t-0.1+0.015)/4)\times\sin(100\pi(t-0.1+0.015))\times(\text{heaviside}(t-0.1-0.015)-\text{heaviside}(t-0.1+0.015)) \quad (14)$$

Taking the optimized network parameters as RBF network initial value, then the operation procedure is as shown in Fig. 8. The representation meaning of each

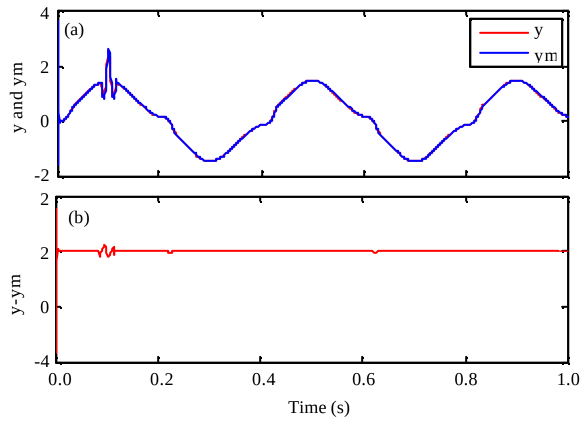

Fig. 8(a-b): Singular value detection chart on grid signal with high frequency transient vibration

curve is the same as Genetic Algorithm. From the figure it can be seen that there is signal high frequency transient vibration during 0.1-0.0015 and 0.1+0.0015 sec, correspondently, obvious mutation from 0.1-0.0015 to 0.1+0.0015 sec can also be seen clearly. The simulation results show that when there is high frequency transient vibration in grid signal, the algorithm mentioned in this study can make accurate detection on starting time and end time successfully.

In conclusion, The algorithm mentioned can make accurate detection successfully the start and end time of various Singular value.

CONCLUSION

In order to improve the detection accuracy on grid signal singular value, in this paper it utilizes the complex controlling strategy of genetic algorithm optimizing RBF neural network to detect grid signal when there is odd mutation. Simulation researches on grid signal mutation conditions such as depression, heave, interruption and high frequency transient vibration are made by using this complex controlling strategy (Jiasheng *et al*., 2012b) The experiment results show that this strategy can detect the mutation starting time and end time effectively and provide effective help for solving the power quality problems in new energy source synchronizing generation. In application, this method has many advantages. Its waveform is very clear and direct; its analysis and calculation is simple and fast; the calculated data amount is small- all these make it have great popularity in all kinds of signal singular value detection.

The assumed controlled object in this study is nonlinear model. If it can be changed into linear model, the effect would be better. Additionally, the signals studied in this paper are simulated signals; they have certain disparity from real signal. How to detect real signal would be the next research issue.

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