TELKOMNIKA Indonesian Journal of Electrical Engineering
Vol.12, No.4, April 2014, pp. 2448 ~ 2457
DOI: http://dx.doi.org/10.11591/telkomnika.v12i4.4302

The Power Load Prediction Based on Improved Genetic Neural Network

Dong Dai*, Lin-Chao Ma
Henan Mechanical and Electrical Engineering College, Xinxiang City, Henan Province , China 453003
*Corresponding author, e-mail: dong_dai01@163.com

Abstract

There exist nonlinear and high redundancy between the power load factors, and the traditional methods in neural network can not eliminate the redundancy in the prediction data and capture the nonlinear characteristics, resulting in lower prediction precision of the power load. In order to improve the prediction precision of the power load, a power load prediction method based on improved genetic algorithm optimization neural network (IGA-BP) is put forward. First, the power load is reconstructed using the correlation function, and then performed the normalization processing. Secondly, the power load training sample is input into the BP neural network for learning, and then the initial connection weights and thresholds of the BP neural network are selected using the improved genetic algorithm. Finally, the power load prediction model is established. Simulation results show that the improved neural network can reflect the trend of complex non-linear power load, achieve higher power load fitting and prediction precision, and is an effective load prediction method for power system.

Keywords: *power load, prediction precision, neural network, improved genetic algorithm*

1. Introduction

The power load prediction plays key role on ensuring safe operation of power grid and improving the power quality. Thus, the prediction of the power load has important practical value [1].

With the power load prediction problem, the main current traditional methods are the statistical method and the nonlinear modeling method. The traditional statistical methods include the multivariate linear regression, sliding average, moving average and so on [2-4]. They have the features of fewer parameters, simple calculation, fast prediction speed, and high prediction precision for the linear power load [5]. However, the power load varies according to the weather, seasons, holidays and economic factors which are nonlinear and chaotic [6]. The prediction precisions of the traditional statistics methods are low. Nonlinear prediction methods use artificial intelligence theory for modeling and predicting. They are mainly the hidden Markov, gray model, neural network, support vector machines and other machine learning methods which assumes the power load is nonlinear variation coinciding with the actual power load variation and they have the adaptive, self-learning abilities which do not need to know the accurate mathematical models of the power load to predict [7, 8]. They overcome the disadvantage of the traditional statistical method, that is, the poor nonlinear prediction ability [9]. In all of the nonlinear prediction methods, BP neural network does not require priori knowledge which is a feedback mechanism widely used in the non-linear power load prediction. When apply BP neural network in practical applications, the prediction precisions are relative to the BP neural network parameters (initial connection weights and thresholds). If these parameters are selected improperly, it is easy to appear to the slow convergence, trapped in a local optimum, and over-fitting which affects the application areas of the BP neural network in power load prediction [10]. In order to solve the defects, some scholars put forward using genetic algorithms, particle swarm optimization algorithm, ant colony algorithm, evolutionary algorithm, and simulated annealing algorithm to determine BP neural network parameters in which the load prediction results can be improved [11]. However, these algorithms are heuristic algorithms all of which have a different degree of defects. Therefore how to find the better parameter optimization algorithm for BP network parameters selection to further improve the accuracy of load prediction has become a hot spot for current research [12].

Received August 2, 2013; Revised October 13, 2013; Accepted November 8, 2013

In order to improve the power load prediction precision, the basic genetic algorithm is improved and an improved genetic algorithm optimized neural network power load prediction method (IGA-BP) is proposed, and the performance of the IGA-BP in predicting the power load is verified through simulation experiments.

2. Principle on Power Load Prediction

Power system load prediction is to use a set of mathematical methods which can process the past and future load systematically to determine the load value of a particular time in the future with a certain precision requirement, while taking full account of some important factors, such as the system operating characteristics, capacity increase decision-making, natural conditions and social confluence [13-15]. Because the power load represents high degree of nonlinear when influenced by a variety of factors such as the climate, weather and so on, and serious redundancy exists between the factors, so the traditional methods can not predict accurately for complex power load system, resulting in low prediction precision. Only to find out an appropriate set of power load impact factors, can the trend of the power load be captured effectively, so as to perform accurate prediction on the power load.

In this paper, the impact factors with large contribution on the predicted results are selected using the principal component analysis method firstly to eliminate the highly redundancy among the data. Then, the learning modeling and prediction are carried out to the selected factors using the neural network which has the excellent nonlinear predictive performance to achieve the final prediction results. The proposed algorithm not only combines the characteristic extraction capacity of the PCA, but also makes full use of the excellent nonlinear function approximation ability of the neural network, thereby improving the accuracy of the model prediction and the generalization ability. The prediction principle is shown in Figure 1.

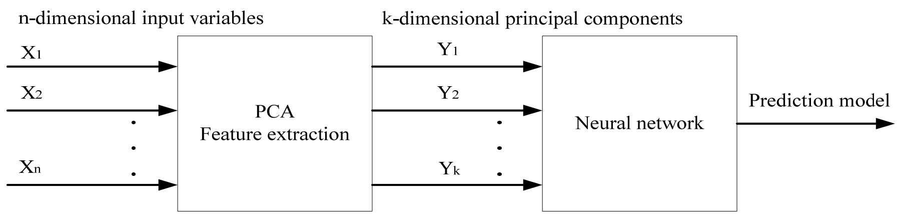

Figure 1. Power Load Prediction Schematic

2.1. Principal Component Analysis

In the research of power load prediction problem, there are a lot of factors affecting the prediction of the power load and the influence degrees of the factors are different, and some of the factors may cause negative impact. Therefore, these negative factors must be removed and a relatively small number of unrelated factor variables be used to reflect most of the information provided by all the factors, and fulfill the objective of the problem solution through the analysis of the selected factors.

As one kind of the statistical correlation analysis technologies for input data dimensionality reduction and revealing the linear correlation between the variables, principal component analysis (PCA) method extracts information from the observable explicit variables to form the implicit variables which can not be observed directly, and then to perform the dimensionality reduction on high-dimensional variable space on the basis of the principle of ensuring that the information data loss is the least to make the principal component variables in the low dimensional feature vector maintain the characteristic information of the original variables, while eliminating the redundant information. The artificial neural network based on principal component analysis carries out the principal component analysis by the neural network training sample set to improve the number of input factors of the samples, remove the correlation between the network inputs, reduce the number of network inputs, and simplify the network structure, so as to improve the network performance. The main steps of the algorithm are as follows:

(1) Standardize the $N \times P$ raw data of the original P indicators to eliminate the compact between the variables caused by different magnitudes, so that the average value of each variable is 0 and the variance is 1;

(2) Calculate the covariance matrix σ according to the standardized matrix,

$$\sigma = \frac{1}{N}[Y - \overline{Y_l})[Y - \overline{Y_l}]^T \tag{1}$$

Here, $\overline{y_i} = \frac{1}{N}\sum_{k=1}^{N} y_{ik}$, $\overline{Y} = [\overline{Y}_1, \overline{Y}_2, \cdots, \overline{Y}_m]$.

(3) Find the characteristic roots λ_i and unit eigenvectors of the covariate matrix R.

(4) Determine the primary components. The number of the selected principal components depends on the cumulative variance contribution rate.

In practical applications, m <p is usually selected to make the cumulative contribution rate of the fore-m main components achieve a higher proportion of generally 80% to 90%, so that the first m main components Y1, Y2, ..., Ym are used to replace the original variables X1, X2, ..., XP. The algorithm can not only reduce the dimensionality of the variable, but also lose not too much information of the original variables, and the m principal components are taken as the input of the neural network model.

2.2. BP neural Network

If the power load data is $X(t)=(x(t),x(t+\tau),\cdots,x(t+(m-1)\tau))^T$, and the output is $y(i)$, then the number of nodes in the input layer of the BP neural network is the number of power load embedded dimensions m, p for the hidden layer, and the output is the power load expectation. BP neural network completes the mapping $f: R^m \rightarrow R^1$, and the input of each node in the hidden layer is as follows:

$$S_j = \sum_{i=1}^{m} w_{ij} x_i - \theta_j \tag{2}$$

Wherein, wij is connection weight of the input layer to the hidden layer and θj is the threshold of the node in the hidden layer.

The Sigmoid function is taken as the transfer function of BP neural network, that is,

$$f(x) = \frac{1}{1+e^{-x}} \tag{3}$$

The output of the node in the hidden layer of BP neural network is as follows:

$$b_j = \frac{1}{\left(1+\exp\left(\sum_{i=1}^{m} w_{ij} x_i - \theta_j\right)\right)}, \; j = 1, 2, \cdots, p \tag{4}$$

Similarly, the input and output of the nodes in the output layer are shown respectively, as follows:

$$\begin{cases} L = \sum_{j=1}^{p} w_{jk} b_j - \theta_k \\ x_{i+1} = \dfrac{1}{\left(1+\exp\left(\sum_{j=1}^{p} v_j b_j - \gamma\right)\right)} \end{cases} \tag{5}$$

Here, vj is connection weight of the hidden layer to the output layer and y is the threshold of the node in the output layer.

Before the BP neural network to start training, the most appropriate connection initial weight (wij) and initial threshold need to be selected, and the values are usually initialized randomly, resulting in slow convergence of BP neural network and being easy to fall into the local optimal solution. Moreover, some scholars have optimized the connection weight and threshold, but all of them have their respective defects. In this paper, the genetic algorithm is improved, and then the parameters of the BP neural network are optimized, so as to further improve the precision of power load prediction.

3. Power Load Prediction Model

3.1. Basic Genetic Algorithm

The genetic algorithm simulates the duplication, crossover and mutation phenomenon in the natural selection and heredity. From any initial population, after random selection, crossover and mutation operations, the new adaptive population will be generated which lead the group evolutes to much better regions in the searching space. After generations of evolution, finally they will converge to the individuals that are more suitable to the environment to obtain the solution. The normal steps of the genetic algorithm are as shown in Figure 2.

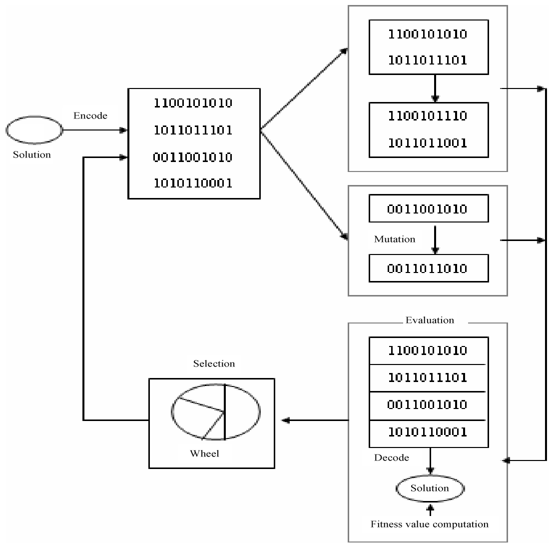

Figure 2. Genetic Algorithm Operation Flow Chart

The genetic algorithm is composed by the following components, that is, chromosome coding, methods for initializing the population, individual fitness settings, genetic manipulation (selection operator, crossover operator, mutation operator) and the algorithm terminate conditions. Using genetic algorithms to solve optimization problems, each part of the design is critical.

3.2. Fitness Function

Fitness is a quantitative reflection of the pros and cons of individuals in the population, and its structure has a direct impact on the efficiency of problem solving. The fitness is used in genetic algorithm to measure the merits of the individual, and the principle of survival of the fittest is adopted to decide which individuals to breed and which individuals to be eliminated.

3.3. The Basic Operations of the GA

The three basic operations of the genetic process are selection, crossover and mutation.

(1) Selection operator

Selection operator is not only the process that the individual bit strings (chromosome) with high fitness are selected from the parent population to generate new populations, but also the process that the individuals copy according to their own survival abilities, which reflects the law of natural selection, that is, survival of the fittest.

(2) Crossover operator

The crossover operation are divided into two steps. In the matching pool consisted by the bit strings obtained from the selection operator, the new individuals generated from the copy are matched pairwisely first. Then the cross-point is selected randomly, and the paired individuals are carried out the crossover operation, so as to generate new individuals.

(3) Mutation operator

The design idea of the mutation operator comes from the gene mutation on chromosome in the nature, The gene mutation can generate features in species, which the ancestors have never had. Then through the natural selection, new species with full of vitality survive and continue. Mutation operator in GA make certain gene bits in the bit string generate random changes with smaller probability. Crossover operator as well asand mutation operator are the main reasons of the organic evolution.

The running process of GA is shown in Figure 3.

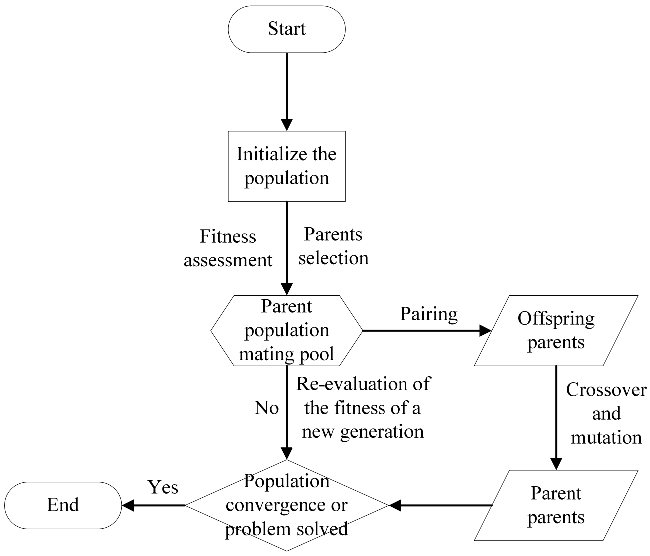

Figure 3. The GA Flowchart

3.4. Disadvantages of the Genetic Algorithm

The genetic algorithm has a strong global search ability, and the algorithm can find the global optimal solution from any initial population theoretically. However, it is often found in practical applications that the algorithm will converge to a local optimum value and no longer continue to evolve, or that groups can no longer produce the offsprings whose performance exceed the parent generation, and individuals of the same group are very similar with each other, that is the so-called early convergence phenomenon. Overcoming the premature phenomenon of the genetic algorithm has aroused the interest of many scholars. However, due to the complexity of the problem, no remarkable theoretical results has achieved.

4. Improved Genetic Algorithm

4.1. Selection Operation Improvement

In the standard genetic algorithm, the roulette wheel selection strategy is used according to the individual fitness value. Although the strategy is simple, it’s easy to lead to the problems of premature convergence and slow search. The effective solution is to apply conditional optimal reservation strategy, namely pass the optimal generation to the next generation or at least equivalent to the previous generation, which can prevent the problem of premature convergence.

4.2. Improved Crossover and Mutation Operations

The Crossover and mutation operations are two important operators in genetic algorithm. Through the crossover and mutation, the search abilities will rapidly increase. The cross effect is combining the intersection of valuable information in the two individuals to produce new offspring which can significantly speed up the search in the evolution period. The mutation operation is to maintain the population genetic diversity which plays a supporting role. In the computation procedure of the improved genetic algorithm, the crossover and mutation probability are adaptively changed according to the specific situation of the individual to divide the evolution procedure into two stages- progressive and mutation stages. The progressive stage is strong cross and weak mutation; mutation stage is weak crossover and strong mutation. It increases the computation speed and efficiency of the algorithm. The adaptive parameter adjustment scheme is as follows.

$$\delta = f_{\max} - \overline{f} \tag{6}$$

In the equation, $f_{\max}$ is the optimal fitness value in some generation. $\overline{f}$ is the mean fitness value of the generation. The flow chart of the improved genetic algorithm is as shown in Figure 4.

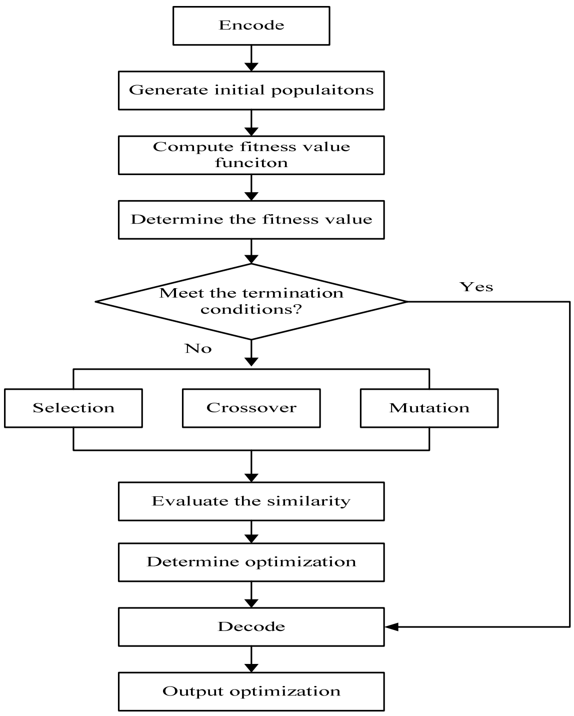

Figure 4. The Improved Genetic Algorithm Flow Chart

4.3. IGA-BP Neural Network Power Load Prediction Procedures

Step 1: Collect the historical power load data and pre-process them.

Step 2: Initialize the populations. A group of individuals are randomly generated in which each individual contains the initial connection weights and initial threshold of the BP neural network.

Step 3: Decode the individuals. τ, m are determined by association functions and the power load data are reconstructed. The initial connection weights and threshold are used as the BP neural network parameters to train the power load. The individual prediction results are used to compute the individual fitness value. The fitness function f(x) is defined as:

$$f(x) = \frac{1}{n}\sum_{i=1}^{n}(y_i - \hat{y}_i)^2 \tag{7}$$

In the equation, y_i is the prediction value of the BP neural network, $\hat{y}_i$ is the actual power load, n represents the amount of training samples.

Step 4: The Optimum reservation strategy and roulette wheel selection are used to choose the optimal individual to the next generation.

Step 5: The crossovers probabilities are used to crossover operate the two individuals to select the optimal individual to the next generation.

Step 6: The mutations probabilities are used to mutation operate the two individuals to select the optimal individuals to the next generation.

Step 7: Judge the algorithm termination conditions. If the conditions are met, return the global optimal individuals. If not, the evolution generation adds 2 and return to step 3 keeping optimization.

Step 8: The optimal individual is decoded to the initial connection weights and threshold of the BP neural network.

Step 9: The power load data are reconstructed and the optimal power load prediction model is built according to the initial connection weights and threshold.

5. Practical of the Power Load Prediction

5.1. Power Load Data

In order to testify the validity and superiority of the IGA-BP neural network in power load prediction, the power data from 03/01/2010 to 03/30/2010 in some Chinese place are used to do the simulation experiments. The power load time sequences of the data samples are shown in Figure 5.

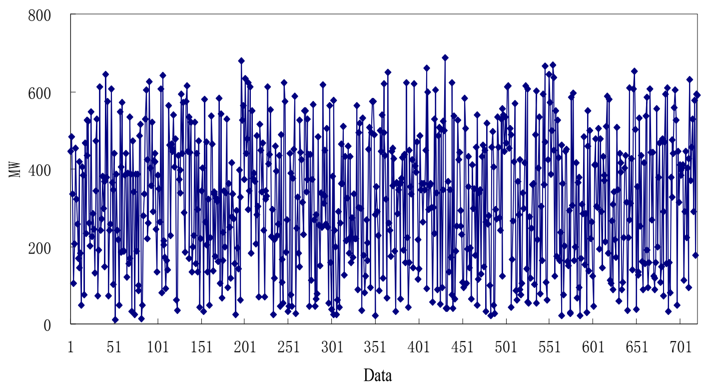

Figure 5. Collected Power Load Data

5.2. Comparison Model and Evaluation Indexes

In order to make the IGA-BP neural network prediction results more persuasive, the basic genetic algorithm optimized BP neural network (GA-BPNN) is used as the comparison model. The evaluation indexes are Mean Average Relative Error (MARE) and Root Mean Square Error (RMSE). Their definitions are as follows.

$$MAPE = \frac{1}{n}\sum_{i=1}^{n}\left|\frac{y_i - \hat{y}_i}{y_i}\right| \times 100\% \tag{8}$$

$$\mathrm{RMSE} = \sqrt{\frac{1}{n}\sum_{i=1}^{n}\left(\frac{y_i - \hat{y}_i}{y_i}\right)^2} \tag{9}$$

In the equations, y_i and $\hat{y}_i$ are actual value and prediction value of the short-term power load, n is amount of samples.

5.3. Data Normalization

Before modeling, the original power load data are normalized in order to make them have the same scale. The details are as follows:

$$\begin{cases} X(n,i) = \dfrac{X(n,i) - M\_X(n)}{D\_X(n)} \\ Y(n) = \dfrac{Y(k) - M\_Y(n)}{D\_Y} \end{cases} \tag{10}$$

In the equation, M_X(n), D_X(n) are the mean and variance of the nth column of the input vector X respectively. M_Y(n) and D_Y(n) are the mean and covariance of the output vector Y respectively.

5.4. Results and Analysis

First, the basic genetic algorithm and improve genetic algorithm are used to optimize the initial connection weights and threshold of the BP neural network to build the power load prediction model. Then, the established power load prediction model is fitting the training sets and the obtained fitting results are shown in Figure 6. The average errors of the fitting results are in Table 1.

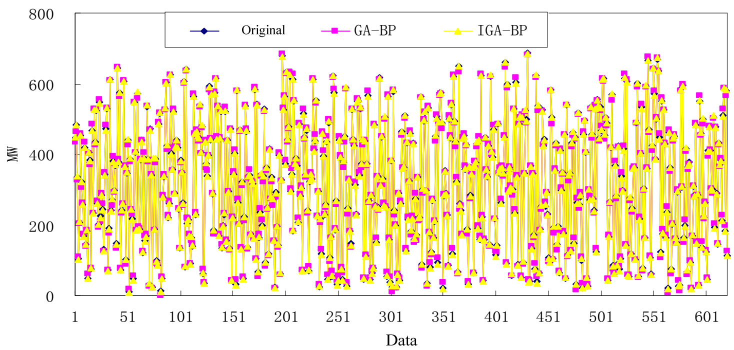

Figure 6. Fitting Results Comparison of IGA-BP and GA

Table 1. The Fitting and Prediction Errors Comparisons of IGA-BP and GA

Errors	A-BP	GA-BP
Fitting RMSE	0.28	.43
Fitting MAPE	.25%	.55%
Predictive RMSE	0.35	5.99
Predictive MAPE	7.14%	1.04%

Then, the established power load prediction model is used to predict the test sets and the prediction results are shown in Figure 7. The average prediction errors are shown in Table 1.

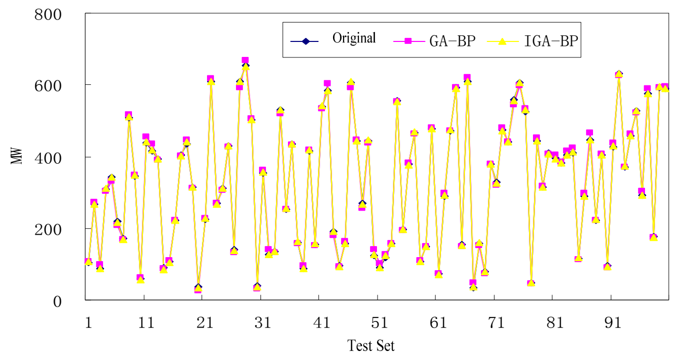

Figure 7. Prediction Results Comparison of IGA-BP and GA

By analyzing the power load fitting and prediction results of the two models in the Figure 6~7 and Table 1, conclusions can be drawn as follows.

(1) The fitting results for the training samples by IGA-BP neural network are better than GA-BP neural network. The fitting values are more close to the actual power load and the fitting errors are quite small. The comparison results illustrate IGA-BP neural network is a kind of effective power load prediction model. IGA can optimize the BP neural network parameters to build more optimal power load prediction model. The improvement for the basic genetic algorithm in this paper is effective and feasible.

(2) The prediction results for the test set by the IGA-BP is more better than that of GA-BP neural network, which illustrates the power load data prediction model built by IGA-BP neural network has better generalization capabilities. It can solve the shortcomings of slow convergence speed, falling into local optimization, over-fitting in the BP neural network. It can precisely describe the complex nonlinear feature of the power load which is a nonlinear power load prediction model with high prediction precisions and better generalization capabilities.

6. Conclusion

To address the problem of parameters optimization for BP neural network problem and overcome the shortcomings of the basic genetic algorithm, a power load prediction model based on the improved genetic algorithm optimized BP neural network is proposed in this paper. Experimental results show that, compared with the power load prediction model, the IGA-BP neural network can describe the complex chaotic and nonlinear characteristics of the power load more accurately, and achieve higher precisions of the fitting and prediction.

References

[1] Zhang Li-Ping, Wang Yi. An ID-Based Authenticated Key Agreement Protocol for Wireless Sensor Networks. *Journal of Communications*. 2010; 5(8): 620-626.
[2] Li Ruixue, Fang Zhiyi. LLA: A New High Precision Mobile Node Localization Algorithm Based on TOA. *Journal of Communications*. 2010; 5(8): 604-611.
[3] Alam, Muhammad Mahfuzul, Rajib, Md Majharul Islam, Biswas, Sumon Jumar. Design and Performance Analysis of Smart Antenna System for DECT Radio Base Station in Wireless Local Loop. *Journal of Communications*. 2010; 5(8): 593-603.
[4] ZHANG Ren-shang. Network Intrusion Detection System Based on Expert System and Neural Network. *Computer Simulation*. 2012; 29(9): 162-165.
[5] U Mitra, HV Poor. Adaptive receiver algorithm for near-far resistant CDMA. *IEEE Transactions on Communication*. 1995; 43(4): 1713-1724.
[6] MJ Juntti. *Genetic Algorithms for Multiuser Detection in Synchronous CDMA.* Proc. of. IEEEE International Symposium on Inform Theory. 1997; 42(1): 492-495.

[7] K Yen, L Hanzo. Antenna Diversity Assisted Genetic Algorithm Based multiuser detection schemes for synchronous CDMA systems. *IEEE Transactions on Communications.* 2003; 3(2): 366-370.
[8] WANG Hai-feng, LU Jun. Research and Simulation on Complex Electric Power Equipment Sudden Fault Diagnosis. *Computer Simulation*. 2013; 30(3): 127-129.
[9] Rahila Patel, MM Raghuwanshi, Anil N. Jaiswal. Modifying Genetic Algorithm with Species and Sexual Selection by using K-means Algorithm. WEE International. *IJECE.* 2008; 35(3): 114-119.
[10] Petra Kudov´a. Clustering Genetic Algorithm 18th International Workshop on Database and Expert Systems Applications. *Journal of Communications*. 2007; 65(5): 138-142.
[11] Zhenguo Tu, Yong Lu. A robust stochastic genetic algorithm (StGA) for global numerical optimization. *IEEE Transactions on Evolutionary Computation*. 2004; 8(5): 456-470.
[12] D Marcano, F Duran, O Chang. Synthesis of multiple beam linear antenna arrays using genetic algorithms. *Antennas and Propagation Society International Symposium.* 1995; 5(3): 938-941.
[13] Tao Su, Hao Ling. Array Beamforming in the Presence of a Mounting Tower Using Genetic Algorithms. *IEEE Transactions on Antenna and Propagation.* 2005; 53(6): 2011-2019.
[14] Keen-Keong Yan, Yilong Lu. Sidelobe reduction in array-pattern synthesis using genetic algorithm. *IEEE Transactions on Antennas and Propagation*. 1997; 45(7): 1117-1122.
[15] Hoga Saragih, Indra Sulistyo Wibowo, Wisnu Darjono Tulodo Utomo, Rusdianto Roestam. Design Simulation Program of Runway Capacity Using Genetic Algorithm at Soekarno-Hatta. *International Journal of Electrical and Computer Engineering*. 2011; 1(2): 202-212.