Asian Journal of Research in Computer Science

2(2): 1-13, 2018; Article no.AJRCOS.45375

A Method for the Dynamic Distribution of Special Population Prediction Based on GA-BP

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Authors' contributions

This work was carried out in collaboration between all authors. All authors read and approved the final manuscript.

Article Information

DOI: 10.9734/AJRCOS/2018/v2i228741

Editor(s):
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Complete Peer review History: http://prh.sdiarticle3.com/review-history/27923

Original Research Article

Received 25 September 2018
Accepted 07 December 2018
Published 22 December 2018

ABSTRACT

In order to predict the dynamic distribution of special population effectively, it is very necessary to establish an early warning population system. In this paper, a Back Propagation (BP) neural network quantitative prediction optimization model based Genetic Algorithm (GA-BP model) is proposed. Firstly, the initial weight and the thresholds of the BP network are optimized by GA. Then, the BP network starts training the related data of special population, which will be used to predict the distribution of special population. Finally, some standard errors are used to verify the proposed GA-BP model, and the simulation results demonstrate that GA-BP model outperforms the GA both in prediction accuracy and convergence. According to the average value of the M_{SE} index numerical results of the defined function, the following numerical results are obtained: for the model established, the average value of the GA-BP function is 10.3273 compared with the average of

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20.8815 of the BP model, and has better performance and more stable performance. In addition, the improved model can be adopted to show the early warning of the population distribution, which has a certain reference value for urban traffic managers.

Keywords: GA-BP model; back propagation neural network; genetic; algorithm special population prediction convergence; early warning.

1. INTRODUCTION

With the rapid growth of the population, the issue of urban population security has become increasingly prominent, especially the threat of special populations, which refers to those who are potentially dangerous and have a criminal record. Moreover, special population forecast has increasingly attracted the researchers' attention. Special population issues are closely related to the harmonious development of the city. Special population distribution is a complex phenomenon that depends on several factors, such as weather, temperature, date type etc. Thus, special population prediction model stability is extremely necessary. In order to more accurately predict the dynamic distribution of special population, a model based on Back Propagation (BP) neural network quantitative prediction optimization model and Genetic Algorithm (GA) is proposed.

Recently, numerous prediction models have been proposed to apply in various scenes. For instance, in order to reduce the waiting times at gas station, Zhang et al. [1] showed a refueling behavior model and proposed an improved system. During the each day for gas station, the waiting times and the most crowded times were calculated to reduce the flow of traffic. Witayangkurn et al. [2] proposed the hidden Markov model to predict the urban population change within a week. In [3], Chan et al. proposed Bayesian Poisson regression model to predict the number of urban populations. Dai et al. [4] showed multivariate linear regression to predict traffic flow. Regression model can predict the future by relevant external factors. The dynamic distribution of special population is non-linear; however, a simple linear regression model is not applicable. To predict accurately the position of the future population, some scholars adopted the method of machine learning [5-7]. In recent years, neural network, particularly BP neural network as the core algorithm, has been widely used in many fields [8-10].

BP is essentially a non-linear function, and not clear about the connection between data. By using the mathematical theory, it was proved that any complicated non-linear function can be expressed with precise approximate [11,12]. However, because of both the slow convergence rate and easy to produce local extremum of BP algorithm, it also has several inherent disadvantages, thus further affect processing efficiency of BP algorithm to some certain degree. Because BP algorithm has the characteristics of being ease to fall into local optimum, GA has the ability of global search. This advantage obviously overcomes the shortcomings of BP algorithm [13]. Hence, this method can be applied in many fields, including plenty of these fields [14-17]. In recent years, evolutionary algorithms have played an important role in improving the learning process of feed-forward neural networks. Improved forward feedback networks are used in these areas, such as GPS height conversion [18], prediction of river water quality [19] and so on. Partha [20] showed a hybrid training algorithm for fuzzy neural networks. This paper proposes a prediction model of the dynamic distribution of special populations based on GA-BP, which mainly focuses on addressing the problem of local extremum and slow convergence. The theory on how to use GA is conveyed by the studies [21]. It discussed the factors influencing the performance of GA, such as, mutation rate, the population, and crossover rate [22], respectively.

2. BP NEURAL NETWORK AND GENETIC ALGORITHM

This chapter introduces the advantages and disadvantages of BP neural networks and genetic algorithm (GA) and how they work. BP neural network is a multi-layer feed-forward neural network with supervised learning. Its working process is divided into two steps. The first step forwards the input signal along the constructed network and passes it through the hidden layer to the output layer. The main features of genetic algorithm are group search strategy and information exchange between individuals in the group. Search does not depend on gradient information. It is especially suitable for dealing with complex and nonlinear problems that traditional search methods are difficult to solve. The genetic algorithm can converge to the global optimal solution.

2.1 BP Neural Network

Neural network is a processing data mode that is enlightened the biological nervous system (such as brain, procedural information). The most important key of paradigm is the originality framework of the system for processing information. In the human brain, there are interconnected neurons that can availably handle with information, with a similar processing model to this paradigm. In biological systems, it is learning to fine-tune the synaptic connections that exist between neurons, in order to achieve the purpose of processing information, neural networks are also so. For the proof procedure, neural network follows the human brain function and provides much proof about the existence of neural networks. Neural networks have obtained notable results in human perception, cognition and control tasks, which are composed of a great deal of processing units. It has different levels of input layer, hidden layer, and output layer. The different layers are connected in a tightly connected way, in order to cooperatively work for solving the specific problem [23,24]. In recent years, the BP algorithm has attracted the interest of a constant research work. Based on the error back propagation, BP algorithm adds one or several hidden layers in the middle of an input and output layer, which successfully solves the adjustment weight problem of multi-layer feed-forward neural networks. According to the application requirement in reality, there has always been a difference between the number of input layers and the amount of hidden layers. Non-linear raw data is referred to the network as input data, and the hidden layer uses the excitation function or transfer function to calculate the input weight. Application-based excitation functions can be linear, sigmoid or tangential. The different algorithms can be used to train the BP neural network, which will produce correspondingly diverse effects.

It is supposed that the input parameters are the influencing factors that affect the dynamic distribution of the special population, was placed in the first layer. Based on various neurons and the number of the inner layers and the output layers, the weight is randomly assigned. Assuming that the output result is equal to the number of population. Thus, the functional structure is illustrated in Fig. 1.

Based on the above analysis, we design an experiment to verify the prediction accuracy of the above BP neural network. As shown in Fig. 2, it can be observed that the search is terminated after 2 iterations, and the mean squared error is 0.13108 at epoch 2. The horizontal coordinates represent the number of iterations, and the vertical coordinates represent the errors. With the increase of the number of iterations, the errors gradually decrease and finally reach the stable error value.

Neural network optimizes the weight and thresholds along the gradient descent direction. Before the parameters optimizing, BP will initialize a group of the weight and thresholds that can be situated with any position in the searching field. It searches in the direction of the fastest descent. As a result, the iteration disappears to the local optimal solution and stops to shift to an earlier date, i.e. 86.892%.

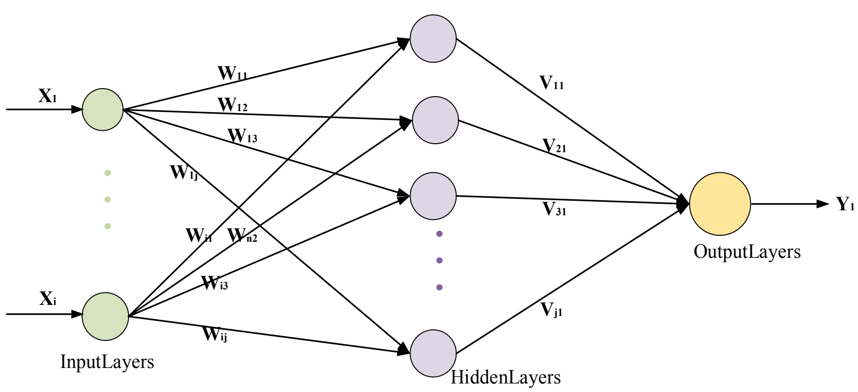

Fig. 1. The BPNN structure for population prediction

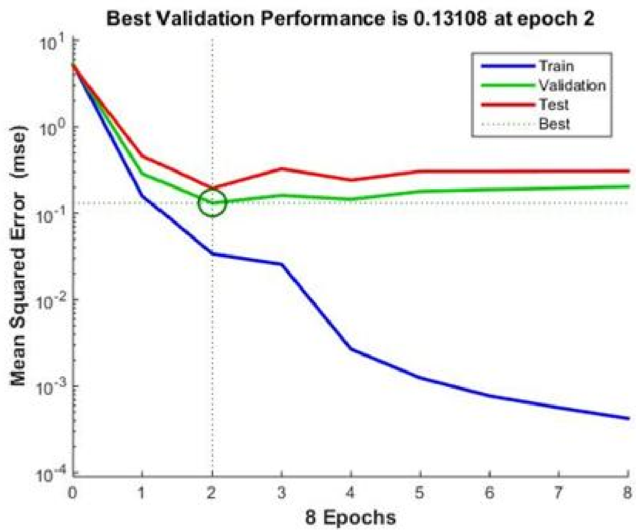

Fig. 2. The BP training curve

2.2 Genetic Algorithm

Genetic algorithm (GA) has the ability of the global search that can search from one point to another point. It searches for the best solution area by far, as the algorithm continues to search the space of the parameter. GA has a powerful function, which is to get the global optimal solution in complex nonlinear functions [25]. John Holland firstly proposed the mathematical form of GA [26], which is the most widely used to solve various problems, in many random search methods. y analyze a large of amount of the simulation results, the performance of GA is superior to the other random search methods [27]. It can be also known as the binary strings. Population is simply the amount of data-in and its population should not make obscured with the value of parameters. The fitness value for those particular strings can be calculated by an evaluating function, which represents the relationship between binary strings.

2.2.1 The structure of genetic algorithms

The following part is a brief account of the main components of GA [28]:

Chromosome: In GA, the chromosome indicates the point in searching field, which is a probable answer of the problem. In addition, a method of expressing a chromosome has a binary code, a floating-point number code, a character code, and so on, in which, the binary code is a common method for expressing a chromosome.

Population: The unique population is made up a group of chromosomes, and by the genetic manipulations, the same number of chromosomes will form new populations.

Fitness function: In GA, a fitness function should be designed to solve each problem. In evolution theory, the degree of adaptation is the ability of an individual to adapt to the environment, as well as the ability of the individual to reproduce offspring. The fitness function of GA, i.e., the evaluation function, is used to judge the level of the individual in the group, which is based on the objective function of the problem to be evaluated.

Genetic operators: The key function of genetic operators is to generate offspring, and the main operators of genetic algorithms includes in selection, crossover and mutation. In addition, the operation of genetic operators will influence the birth of the next generation.

2.2.2 A brief introduction of genetic operators

These are referred to the operator of the selection, crossover and mutation of GA, in front of the prior chapter. In this chapter, each of the above operations is listed, separately, giving a brief overview [29].

Operators of the selection: The nature of survival the fittest is that individuals with higher fitness are more likely to be inherited in the next generation, thus the smaller individuals with smaller adaptation are less likely to be inherited in the next generation, and ultimately accelerate the convergence of GA. One of the main aspects of the optimization algorithm is the process of selecting individuals. In fact, there are multiple strategies of selection strategies, including roulette selection, tournament selection, selection based on ranking and so on. If it selects a better chromosome, the population will be quite abundant and numerous.

Operators of the crossover: Crossover, also known as recombination, refers to the operation of replacing the two parts of a parent with a new individual. The function of crossover operation is to combine new individuals to search efficiently in string space, while decreasing the failure probability to guarantee the effective patterns. Crossover plays a central role in GA, a distinct characteristic of GA, which is obviously different from the others algorithms.

Of course, it is worth noting that the crossover process does not appear on the selected chromosome. If the process of crossover is on such a pair of chromosomes, will be no new chromosomes. However, the child will produce by repeating its parent.

Operators of the mutation: According to the probability, the mutation operation is to change the gene value at a certain gene position. It is also an operation method to generate a new individual. The basic bit variation method is used to carry out the mutation operation. The specific operation process is firstly, each individual is determined. The position of the genetic mutation, and then reverse the original gene of the mutation point according to a certain probability. The specific operation process is as follows; firstly, determine the location of the genetic variation of each individual, and then reverse the original gene of the mutation point according to a certain probability. One iteration is completed and the same process is started again by the fitness function of evaluation the population.

The key difference between the operator of selection and the operator of crossover is whether a new individual is generated, where the crossover probability usually varies between 0.3 and 0.9. It is worth noting that the probability of mutation usually varies between 0.1 and 0.9.

3. HYBRID BP NEURAL NETWORK AND GENETIC ALGORITHM

Due to the superior capabilities of BP, the meaning can be derived from complex or inaccurate data, and be used in cross-disciplines in many fields [30-33], such as neuroscience, noetic science, artificial intelligence, and computer science. BP has some important assumptions, for example, the work of processing data is done by what are called neurons. The exchange of information will be accomplished through connections between neurons. The connection between the two nodes is gone by the name of weight, which stands for describe as the weighted value of a signal connection, which is amount to the memory of the neural network. According to the weight and the excitation of the function, the output of the neural network has some different. However, the neural network is essentially an approximation to some algorithms or function in nature, and it may be the logical expression. The number of BP neural networks is unrestricted. It is characterized by the using nonlinear systems for modeling, fast speed, and adaptability. Fig. 3 illustrates the structure that combines neural networks and GA.

In now available study, GA has been bestowed to improve the practicing process of BP neural network. Adopting to the optimal values of weight and deviations train the network and simulate the results. Afterwards, the network will train itself in order to present the model by considering errors.

The modeling and training process of GA-BP neural network is:

i) Create a suitable structure of BP network and normalize the experimental data.
ii) Define the number of different input levels and excitation function in BP.
iii) Initialize randomly a group of weight and thresholds.
iv) Initialize the population in GA, the characteristics of the first generation individual are chosen by weight.
v) Set the individual's fitness function. According to the smallest fitness value, the best individuals in the population will be transferred to the next generation.
vi) Pick the best parents to produce the next generation, by using GA operators.
vii) Repeat the above process and within the cycle specified by the algorithm.
viii) After the above variables are trained by GA, BP will enter.
ix) Until the M_{SE} minimum is reached or any other parametric condition is met, for example, if the momentum reaches the set threshold, the training is stopped, ultimately generating the best solution.

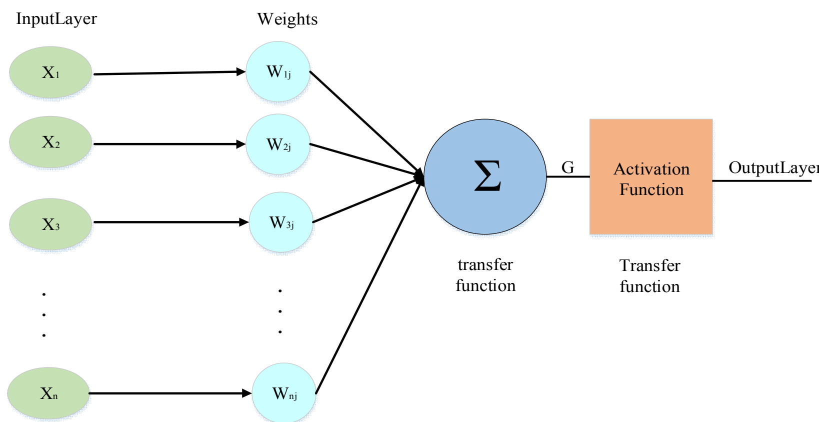

Fig. 3. Structure combining BP and GA

The Fig. 4 illustrates the operation of the computational flowchart of modeling and predicting the dynamic distribution of special population, as follows.

3.1 GA Optimization Neural Network Weight and Threshold

BP is susceptible to both the initial connection weight and threshold between the inner layer and the output layer. If the initial value of these parameters is set unreasonably, the convergence rate will slow down, so far as to drop down to the local minima. GA has the ability of global search and can screen individuals through the selection, crossover, and mutation of genetic processes, in biological evolution. It retains individuals with the best fitness, eliminates individuals with poor fitness, and repeats cycles, thus, individuals satisfying the condition are obtained [34]. Therefore, GA optimizes the initial parameters of BP neural network [35], improving the convergence speed of BP, reducing the possibility of BP algorithm into the local minima. Using data training BP to predict the output of the system, the specific steps are as follows [36].

Step 1 Encode method

The weight learning of BP can be regards as a complex optimization problem about the continuous parameter. The main coding methods are binary and real number. Due to the use of binary, the code string may be too long. Therefore, this article adopts real number. Each weight of the neural network is cascaded into a long string in a certain order. Each position on the string corresponds to a weight of the network. The order of the encoded strings is arranged in sequence from input to output.

Step 2 Calculate the fitness function

The error represents the absolute value between the predicted value and the required value, denoted by the fitness value F, which is given as follows:

$$F = k\left(\sum_{i=1}^{n} abs(Y_i - O_i)\right) \tag{1}$$

Where k is the coefficient, n is the amount of output nodes of the network, Yi is the required value of the ith node of BP, and Oi is the predicted value of the ith node.

Step 3 Select operation

The selection of GA has many methods, such as roulette and tournament method. When selected the roulette method, which is the selection strategy based on fitness ratio, and the probability of selection for individual Pi is given by:

$$f_i = \frac{k}{F_i} \tag{2}$$

$$p_i = \frac{f_i}{\sum_{j=1}^{N} f_j} \tag{3}$$

Where Fi is the fitness value of the ith individual. Since the fitness values are as small as possible, before individual selection, the fitness value should be reciprocal, and N is the individual number of the population.

Step 4 Cross operation

For each individual, the real number coding method is employed, correspondingly, the real number crossover method is used in the crossover operation, the crossover method for the k chromosome and the l chromosome in place is given by:

$$a_{kj} = a_{kj}(1-r) + a_{lj}r \tag{4}$$

$$a_{lj} = a_{lj}(1-r) + a_{kj}r \tag{5}$$

Where r is a random number and $r \in [0,1]$.

Step 5 Mutation operation

There is selecting the jth gene aij of the ith individual to perform the mutation.

$$a_{ij} = \begin{cases} a_{ij}r + (a_{ij} - a_{\max}) * f(g) & r > 0.5 \\ a_{ij}r + (a_{\min} - a_{ij}) * f(g) & r <= 0.5 \end{cases} \tag{6}$$

$$f(g) = r'\left(1 - \frac{g}{G_{\max}}\right)^2 \tag{7}$$

Among them, a_{max} and a_{min} are the upper and lower bounds of the gene, respectively, g is the current iteration times, G_{max} is the maximum iteration times $r' \in [0,1]$.

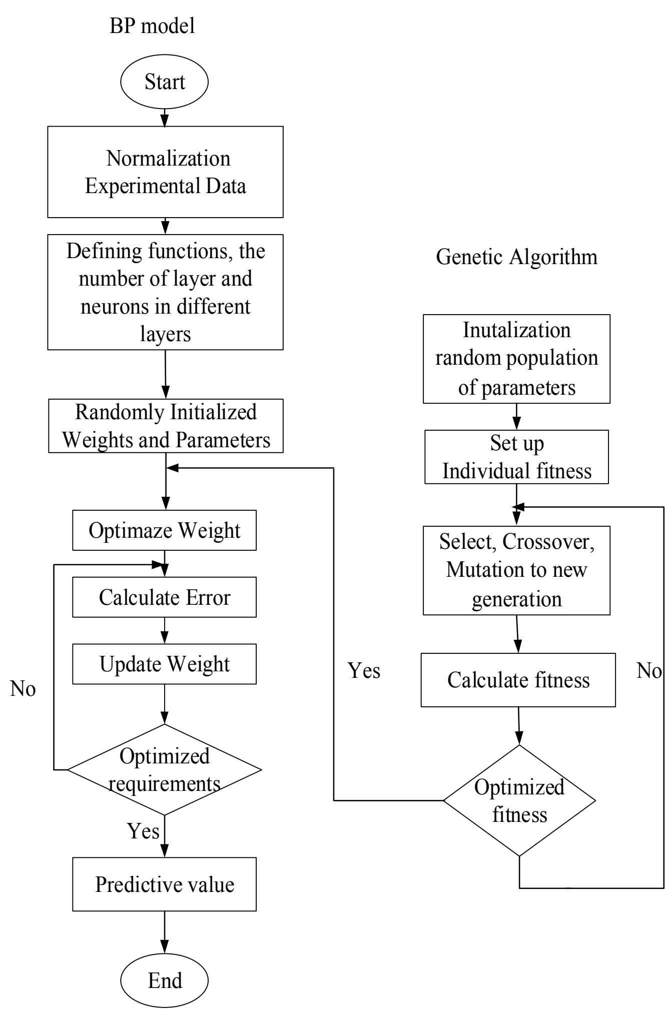

Fig. 4. Computational flowchart for the distribution of special population

3.2 Statistical Analysis

In order to evaluate the performance of the modeling and predicting the dynamic distribution of special population in a comprehensive and accurate way, it uses the following methods as evaluation indicators, such as, Root Mean Square Error (M_{SE}), Mean Absolute Error (M_{AE}) and Mean Absolute Percentage Error (M_{APE}). In the study of accuracy and functionality, M_{APE} and M_{SE} can be used. The M_{AE} is an accurate method of the accuracy of the model. Therefore, when the values of these indicators get closer to zero, this shows that this model is a valid model. As for the formulas of several evaluation models mentioned above, the following concrete calculation methods are given below:

$$M_{AE} = \frac{1}{N}\sum_{i=1}^{N} abs(Y_i - O_i) \tag{8}$$

$$M_{APE} = \frac{1}{N}\sum_{i=1}^{N} \frac{abs(Y_i - O_i)}{Y_i} \tag{9}$$

$$M_{SE} = \sqrt{\frac{1}{N}\sum_{i=1}^{N} (Y_i - O_i)^2} \tag{10}$$

Among them, *Yi* is the predictive value; *O*i is the expected value; *N* is test sample set number.

4. EXPERIMENT AND DISCUSSION

It is well known that weather conditions and traffic conditions have an important influence on the dynamic distribution of special population. In addition, the results of the dynamic distribution of special population are also affected by the date and previous data. Therefore, the factors that the weight affecting is larger, are as the input of the BP, such as weather conditions, traffic status, date type, temperature, humidity, wind speed, age, gender, whether owns vehicles, etc. The prediction result is output as a network. Since the nature of data is non-linear, the method presented in this paper is more applicable.

As for the experiment implementation platform settings, the algorithm program is implemented on the MATLAB 2014b platform. The computer CPU is Intel(R) Core(TM) i7-8550U 2.90GHZ and the memory is 8G. Because of the sensitive problem of real data, 730 simulation data were used in the experiment, and these data retained the same characteristics of real data. Among them, 670 pre-processed data were used as training samples and another 60 were used as test data. In the process of running different algorithms, training data and testing data can adjust the value of each parameter repeatedly. Tansig was chosen as the excitation function for hidden layer neurons. A linear function was selected as the output layer neurons. The initial parameters of GA adopted in this paper are shown in Table 1.

Table 1. The initial parameters of GA

Parameters	Values
Population size	50
Maximum number of iterations	100
Crossover probability	0.7
Mutation probability	0.3

The amount of hidden layers will affect the accuracy of the prediction. The following analyzes the error size from the number of different hidden layers. Fig. 5, Fig.6, and Fig. 7 show the comparison between the prediction error of BP model and GA-BP model, where Fig. 5 uses the 13-7-1 network structure diagram, Fig. 6 uses 13 -15-1 network structure diagram, and Fig. 7 uses 13-30-1 network structure diagram.

When the point of the curve is approximated to 0, the predicted value of the algorithm will become very precise. As can be seen from Fig. 5, Fig. 6, and Fig. 7, the accuracy of the BP prediction is less than that of the GA-BP. The prediction error curve of the BP is often high, indicating that the prediction is not stable enough so that it cannot accurately predict the dynamic distribution of special population. Therefore, the GA-BP model proposed in this paper is more accurate and stable in predicting the distribution of special populations.

The BP algorithm and GA-BP algorithm are applied to the predicting the dynamic distribution of special population. According to the flowchart of Fig.4, modeling is preformed by means of BP and GA. In each modeling, the results of the dynamic distribution of specific populations are predicted by changing the model or network structure to find out which model or network structure or combination thereof is more suitable for this scenario. In order to evaluate accurately the prediction ability of the algorithm, Mean Absolute Error (M_{AE}), Mean Absolute Percentage Error (M_{APE}) and Root Mean Square Error (M_{SE}) under the same training error were used to evaluate the algorithm. Then model the results of statistical indicators are recorded in Table 2.

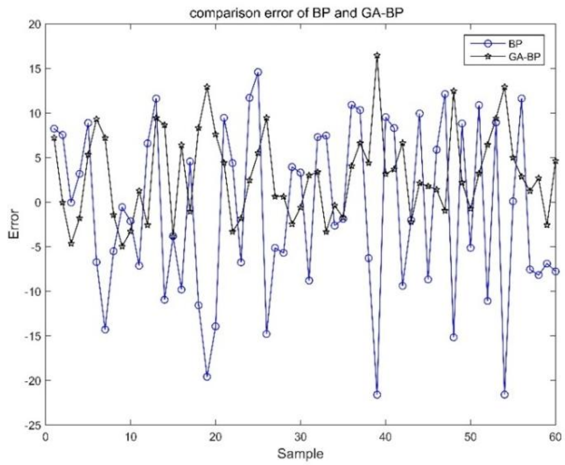

Fig. 5. The network structure of 13-7-1

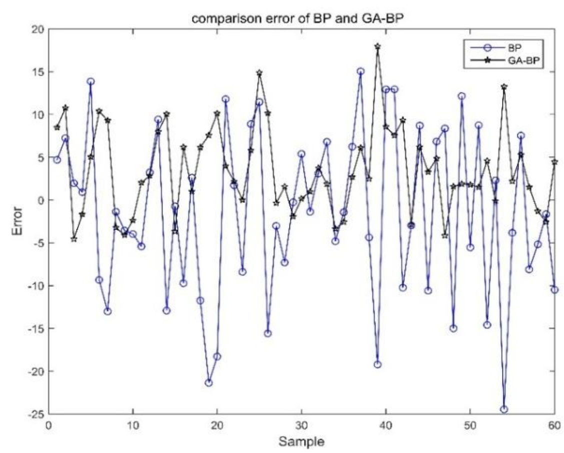

Fig. 6. The network structure of 13-15-1

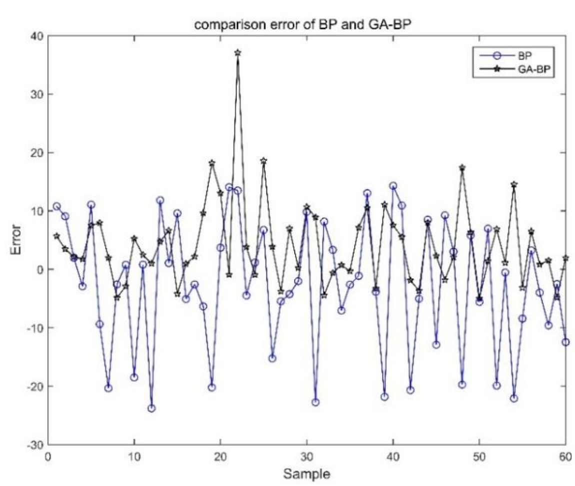

Fig. 7. The network structure of 13-30-1

Table 2. The results of measurement indicators by considering different conditions

Model	Network structure	M_{AE}	M_{APE}	M_{SE}
BP	13-7-1	19.0616	0.0583	21.2204
BP	13-15-1	18.6148	0.0570	20.7829
BP	13-30-1	17.8375	0.0549	20.5513
GA-BP	13-7-1	8.0523	0.0256	9.4095
GA-BP	13-15-1	8.5296	0.0271	9.9094
GA-BP	13-30-1	9.1950	0.0293	11.6630

In order to understand the impact of GA on the optimization results of BP, M_{SE} index has been explained by each of the models in Fig. 8. The closer the index number is to 0, the better the prediction result is. Because the three samples are predicted by the BP model, and the index number is relatively high. The last three samples are predicted by the GA-BP model, and the index values are obviously much lower. According to the average value of the M_{SE} index numerical results of the defined function, the following numerical results are obtained: for the model established, the average value of the GA-BP function is 10.3273 compared with the average of 20.8815 of the BP model, and has better performance and more stable performance. As shown in Fig. 8, the amount of neurons selected will not adhere to certain rules, and only random selection can achieve the desired results.

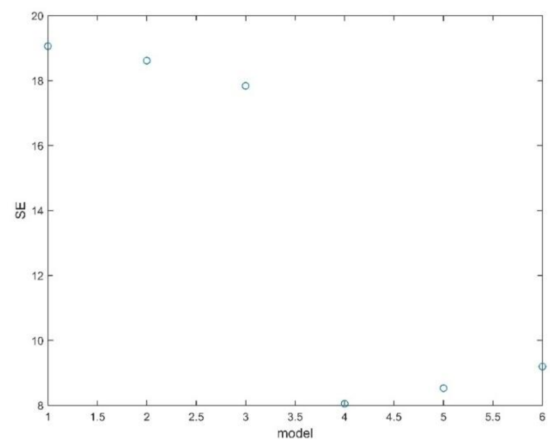

Fig.8. Results of calculating the index of M_{SE}

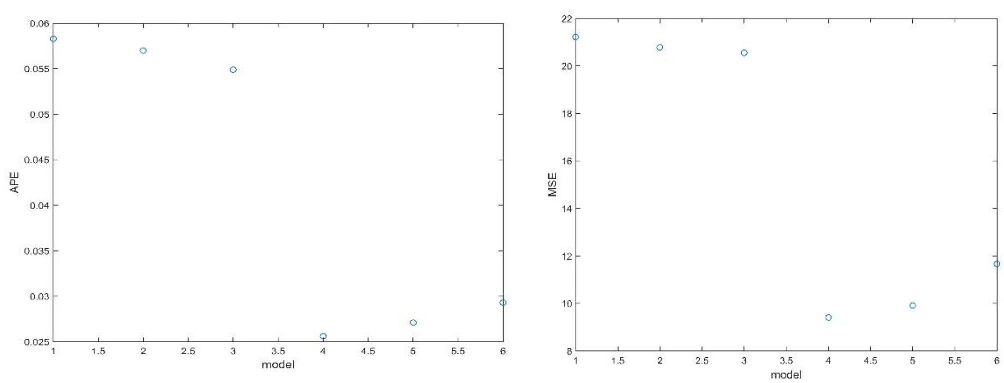

Fig. 9. The results of surveying statistical indicators

In general, accuracy is the focus of all establishing model way. It is possible for the model to be applied only when the estimation error of the prediction sample data is low and the accuracy of the prediction sample is high.

All without exception is the method of GA-BP neural network used for special population prediction in this study. If it provides the data sample that are not enough comprehensive, in other words, it has lost its rationality and excessive fitting, the neural network can also be a comprehensive test of these samples, and then good results are output. GA ensures the accurate operation of the model proposed in this study.

5. CONCLUSIONS AND FUTURE WORKS

In this paper, a BP neural network quantitative prediction optimization model based genetic algorithm is developed by combing the GA and BP, in which the desired prediction accuracy and convergence are achieved. Combining the advantages of both BP with self-learning and adaptability and GA with quickly global search capability, BP-GA model can effectively predict the dynamic distribution of special population. By optimizing the initial weight and thresholds according to the GA algorithm, the trained data of special population becomes more accurately predict the distribution of special population. The simulation results demonstrate that the proposed GA-BP model is flexible, accurate and efficiency. It is also verified that the proposed GA-BP model outperforms GA algorithm both in prediction accuracy and in convergence. It is worth noting that the framework of the GA-BP model can be widely used because of its flexible and easily implemented. In addition, the improved model can be used to show the early warning of the population distribution, which has a certain reference value for urban traffic managers.

ACKNOWLEDGEMENT

The authors would like to be grateful for all anonymous reviewers who give insightful comments and constructive advises to polish this paper in high quality. This research was supported by Shanghai Science and Technology Innovation Action Plan Project (16111107502, 17511107203) and Shanghai key lab of modern optical system. As well, as support from National Natural Science Foundation of China (No.61502220), and the project for tackling key problems in Henan science and technology (No.172102310636) for funding.

COMPETING INTERESTS

Authors have declared that no competing interests exist.

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