A.J. Tallón-Ballesteros (Ed.)

doi:10.3233/FAIA230203

Prediction of Litter Size of Sows Based on PSO Optimized RBF Neural Network

Xuzhao YANG[1]
School of Electronic Information Engineering, Xi'an Technological University, Shaanxi 710021, China

Abstract. In view of the research status of low accuracy in the prediction of litter number in pig breeding, the new method is proposed, which is based on PSO optimal RBF neural network. The litter number of sows is affected by various factors such as breed, strain, genetic gene, nutrition level, enclosure environment, feeding management level, birth age, different birthtimes, breeding management, epidemic disease and so on. According to the pig breeding information, the breeding model is established and the breeding information database is used as the input information source of neural network. In the experiment, particle swarm optimization (PSO) algorithm is used to train radial basis function (RBF) neural network. The neural network structure of 20-15-1 is established to fit the complex relationship between many indexes affecting litter size and prediction results. The experimental result shows that the error between the predicted litter number and the actual litter number is less than 5% and the prediction of litter size by PSO-RBF is in the best agreement with the actual production value. The conclusions show that the prediction method can accurately predict the litter size of sows and meet the new requirements of the development of livestock and poultry precision breeding. The research can be applied to the prediction of Litter Number in pig farm, which is helpful to improve the efficiency of pig reproduction and provide economic decision for the users.

Keywords. Pig breeding, PSO-RBF neural network, sow litter size, mean square error, precision breeding

1. Introduction

The pig breeding industry is one of the important supporting industries for the state to implement a series of policies to benefit farmers and improve agriculture, such as rural revitalization and targeted poverty alleviation [1]. China is the world's largest pig breeding country, among which the sow reserve and the pig output have exceeded half of the world's total [2]. Sows will develop healthy and healthily in the optimal growth environment, which is beneficial to improving the body performance; conversely, under excessive temperature, biting rack, catching up, slip, whipping, scare and other on [3-8]. The litter size of pig sows effectively characterized the reproductive performance and productivity of pigs, which are closely related to the economic benefits of breeding farms. The key to improve the productivity level of pig breeding is to steadily improve the reproductive performance of sows, and expecting the price increase of pigs is only expedient [9]. Sow litter performance is the key factor that determines the production

[1] Xuzhao Yang, School of Electronic Information Engineering, Xi'an University of Technology, Shaanxi 710021, China; E-mail: 414792038@qq.com.

efficiency and economic benefits of breeding farms and has a huge impact on pig quality breeding work [10].

The total litter size of reserve sows is one of the key indicators to measure the overall performance of the pig farm, and the delivery rate of reserve sows is regarded as a prediction indicator of the future performance of the pig farm. This is a good indicator to predict the future performance of pig farms. The performance of the total litter size of the reserve sows is also a good indicator, but it is lower than the delivery rate. The artificial intelligence neural network algorithm at home and abroad theory has matured, and more universities and research institutions will neural network technology is widely used in the field of livestock and poultry breeding, but few neural network algorithms applied to livestock and poultry litter number analysis, at the same time it is also artificial intelligence neural network algorithm in livestock and poultry production prediction blank [11-17]. In recent years, some large-scale livestock and poultry farms in China have gradually introduced BP neural network or RBF technology to predict the yield number of livestock and poultry, but these traditional neural network algorithms have problems such as falling into local optimal solution and local minimum value, slow convergence speed, or even unable convergence [18-25]. Therefore, the livestock and poultry breeding industry urgently need to use an objective and practical test method, namely the Radical Basic Function (RBF) based on Partical Swarm Optimization (PSO), to solve the above problems, so as to accurately predict the litter size of sows, and also to provide a basis for scientific evaluation of sow reproductive performance.

2. Materials and Methods

2.1. Sow Litter Size Influences Factor Selection

The number of livestock and poultry litter yield in rural areas generally mainly depends on the accumulated experience of breeding personnel all the year round, with strong subjectivity and low prediction accuracy [26]. Sow litter size will be pig breeding varieties, strains, genetic genes, nutrition level, season, housing environment climate, feeding management (feed type, breeding before short-term optimal feeding, pregnancy feeding amount), sow age, parity, with boar management (breeding, delivery), disease factors (disease, vaccine), herd rate, embryo survival rate of multiple factors influence and restrict [27-28]. The correlation degree between the above various elements is complex and non-linear, difficult to establish the model, and the existing evaluation methods are highly subjective and random. In order to accurately predict the litter size of live pigs, there should be a comprehensive and reasonable litter size prediction model of strong sows.

Based on early visit a large-scale pig farms, research a city animal husbandry and veterinary departments effective MoPai work, according to the influence of the existing livestock and poultry farms sow litter size factors are divided into primary influence factor and secondary influence factor, as shown in table 1, the secondary influence factor respectively using X1, X2, X3 (and so on) X20 representation.

Table 1. Influences on gilts litter size.

Impact factors	
Level 1 impact factors	Level 2 impact factors
Breeding varieties	1. Variety (sow X1)
	2. The strain (hybrid X2)
	3. Genetic factors (genetic genes are mainly X3)
Pig age parity	1.1~2 fetuses with low reproductive performance and low litter (X4)
	2.3~5 The best reproductive performance is more litter (X5 above 7 months of age)
	3. Lower reproductive performance above 6 fetuses (fatigue X6)
Poultry house environment	Temperature, humidity, illumination, and CO2、H2S、NH3Concentration (X7)
	1. Nutrition full price feed (moldy and spoiled feed is strictly prohibited) (X8)
	2. Appropriate health additives (X9)
Feed management	3. Weaning sows receive vitamins (X10)
	4. Breeding weight, age and fat condition of gilts (X11)
	5. Short-term optimal feeding for weaned sows and short-term optimal feeding before breeding (X12)
	6. Feeding amount of sows during pregnancy (restricted feeding and fat feeding X13)
Grow boars and semen	Breeding performance (3 to 5 for adults, 2 to 3 for youth, X14)
Disease situation	1. Time of vaccination (vaccine X15 during pregnancy)
	2. Blue-ear disease, swine fever, pseudo-rabies, parvovirus, swine flu, JE, swine erysipelas, etc. (X16)
	3. Serum examination (X17)
climatic factor	Spring, summer (the temperature is too high), autumn and winter (low temperature) (X18)
Piggy delivery	Pigs breathing, prevent cold and avoid suspended death (X19)
All kinds of stress	Sow slip, scare, catch up, bite and whip (X20)
comprehensive evaluation	Comprehensive prediction of sow litter size

2.2. Methods for Sow Litter Size Prediction

The PSO particle swarm biomimetic algorithm is characterized by strong global optimal search ability and good local search ability, which originates from a stochastic search model based on group intelligence collaboration designed by humans to simulate the foraging behavior of birds. The RBF feedforward neural network relies on its adaptive ability, outstanding learning ability, and is good at processing and fitting multi-dimensional data, and can achieve the consistent convergence and consistent approximation effect of any nonlinear continuous function. However, a single RBF neural algorithm is prone to fall into the local optimal solution when predicting the yield number of livestock and poultry, which will lead to certain prediction error. Therefore, the PSO particle swarm biomimetic algorithm is used to optimize the RBF feedforward neural network to improve the convergence speed and self-learning performance, so as to accurately and quickly find the global optimal solution.

2.2.1. Partical Swarm Optimization (PSO)

Partical Swarm Optimization (PSO) is an iterative research algorithm derived from the natural bird flock foraging behavior. Assuming that birds randomly search for food in an area and have only one piece of food in this area, all the birds in the flock do not know where the food is, and also do not know how far away they are from the food. When the flock catches food, the most effective way is to find as soon as possible to the surrounding area of the bird closest to the food as soon as possible. Each bird in the search area is equivalent to a possible solution to each optimization problem in the PSO algorithm, also known as a "particle".

There are several possible solutions in the problem to be found and solved by the PSO algorithm. Each possible solution represents a particle in the algorithm, and each particle corresponds to a fitness value solved based on the fitness function solution. The main characteristics of each particle are the particle fitness value, particle velocity, and particle position, where the particle velocity determines the flight direction and distance of birds. In each new iteration, the particle will independently and dynamically determine the next capture direction and position of the foraging area according to its own unique speed and position and the flying experience of other particles, so that the particle can search for the optimal solution in several possible solutions.

Specifically, each particle is self-updated by tracking the global extreme gbest and the individual extreme pkibest. When the particle searches for the above two optimal solutions, its motion rule will follow the following formula to update its own flight speed and experience position in real time:

$$\mathrm{V}_{\mathrm{i}}^{\mathrm{k+1}} = wV_i^k + c_1 rand_1()[p_{ibest}^k - x_i^k] + c_2 rand_2()[g_{best} - x_i^k] \tag{1}$$

$$\mathrm{x}_{\mathrm{i}}^{\mathrm{k+1}} = x_i^k + v_i^{k+1} \tag{2}$$

In the formula: w is the inertial weight factor affecting the particle motion velocity; $rand_1()$ and $rand_1()$ are random constant values in the interval [0,1]; c_1 and c_2 are learning factors (also known as acceleration coefficient, non-negative constant value), causing each particle to accelerate to p_{ibest}^k and g_{best}; k is the current iteration number; respectively is the flight velocity vector and experience position vector after iteration $k+1$; p_{ibest}^k is the best particle searched after iteration k; and g_{best} is the best location for the entire particle population.

2.2.2. Radical Basic Function neural network (RBF)

RBF neural network is a three-layer feed-forward analysis network with input layer, hidden layer and output layer, which can handle multi-input nonlinear function relationship. General RBF contains n input layers, m hidden layers, and 1 output layer, which can approximate any continuous nonlinear function with any accuracy. The conversion of the input to the output of the RBF network is a nonlinear relationship, while the conversion of its hidden layer to the output layer is a linear relationship. The input layer and hidden layer of RBF are connected based on Gaussian radial basis function, while the output layer and hidden layer are connected by inertial weight factor. The k-th output layer is represented by the following equation:

$$y_k = \sum_{j=1}^{n} w_{jk} \exp\left(-\frac{1}{2\delta_j^{\ 2}} \| x - c_j \|^2\right) \tag{3}$$

In the formula: w_{jk} is the weight of the j th hidden layer node to the k th output layer; the c_j is the data center of the j th node radial base Gaussian function; δ_j is the width of the j th node radial base Gaussian function in the hidden layer.

Wi(i=1~m) is the corresponding weight of each layer of network. Because RBF generally only adjusts and changes the network weight, its algorithm has a short operation period and high execution efficiency. However, if the training of Wi parameters is not sufficient and the optimization is not careful, the output accuracy of a single RBF neural network will inevitably be low. Considering that the PSO particle swarm algorithm can optimize the weight factor of the RBF neural network, the organic combination of the two is adopted to solve the above problems. The factors X1~X20 in Table 1 was selected as the input parameter (20), and the sow litter number Y was selected as the output parameter. Therefore, the basic topology of multi-input single output of RBF neural network is shown in Figure 1.

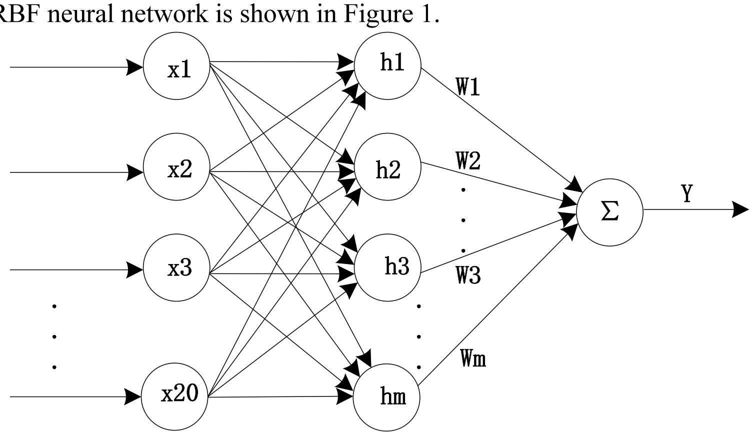

Figure 1. Basic Topology of the radial basis function RBF neural network.

2.2.3. The PSO-Optimized RBF Neural Network

The global optimization search ability of PSO algorithm is used to optimize the three important performance parameters of RBF neural network, namely, the center point cj of the radial basis function, the radial basis function width (variance), and the weight w, and determining the specific number of hidden layer nodes is also an important link in the realization of the network function. Generally, the number of nodes in the hidden layer is directly proportional to the approximation ability and output accuracy of the RBF neural network, but the more the number of nodes in the hidden layer will increase the algorithm training time, reduce the convergence ability, fault tolerance ability, generalization ability and approximation ability of the neural network, thus damaging the RBF performance. The specific number of hidden layer nodes is generally shown by the following formula. We know that the number of hidden layer nodes in the regularized PSO-RBF neural network is 6~16 (m=20, n=1 according to the actual situation of this paper).

$$k = \sqrt{m+n} + c \tag{4}$$

In the formula:c is 1 to 10; n is the output variable; m is the input variable.

The performance of the neural network is measured by training the particle fitness of the sample data. The smaller the general particle fitness value is, the closer the particle is to the best position. In the PSO-RBF optimization algorithm, its fitness function equation can be characterized by the following equation:

$$\text{Fit}ness = \sqrt{\frac{1}{n}\sum_{t=1}^{n}(train_t - y_t)^2} \tag{5}$$

In the formula: Fitness is the fitness function; n is the total sample amount of the training data; t is the t th training sample data; $train_t$ is the expected output value after the training; y_t is the actual output value.

2.3. Prediction Steps of the PSO-RBF Neural Network Algorithm

The flowchart of the sow litter size prediction by the PSO optimized RBF neural network algorithm designed according to the actual production requirements of the pig farms is shown in Figure 2.

The specific execution steps of the algorithm are as follows:

According to the practice of livestock and poultry breeding, the important influence factors X1~X15 affecting the sow litter size were selected as the input variable, and the sow litter size Y was selected as the output variable. After normalizing the training samples, the input-output non-linear correspondence of the neural network is established;

The three major parameters to be optimized in the regularized radial base neural network (center point, variance, the weights connecting the hidden layer and the output layer) are composed into each dimensional vector of the individual particle in the particle swarm optimization algorithm, and the whole PSO particle population is initialized simultaneously;

The fitness value of each particle is calculated according to Equation (6), and the Fitness value is used to determine the location of the current search area, and then the best location of the individual particle pkibest and the population particle gbest are updated based on Equation (2) and Equation (3);

According to the output value of the neural network, check whether it meets the maximum number of iterations or task completion conditions, and then the particle search process is finished and the best particle position is given in real time;

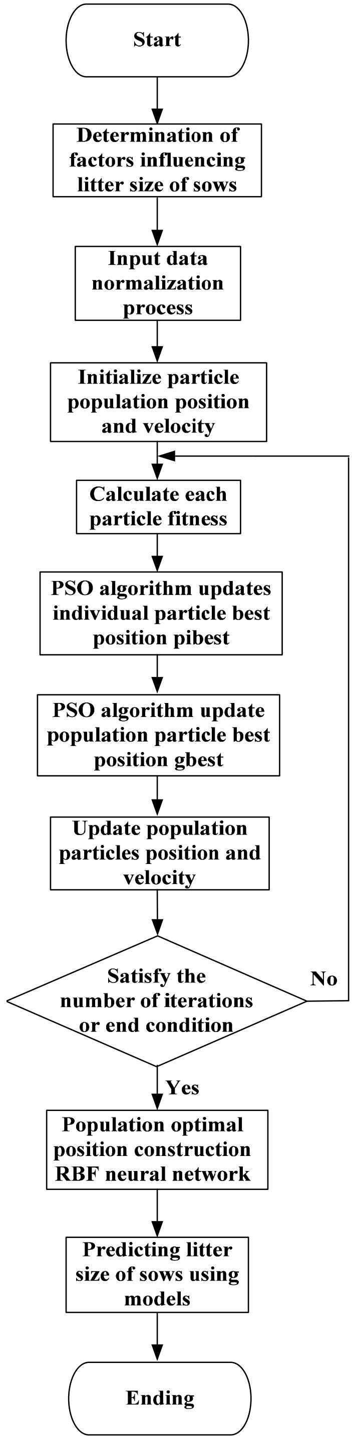

Figure 2. Flow chart of PSO-RBF neural network for predicting litter size of sows.

The best particle position obtained in (4) was taken as the optimization result to form the PSO-RBF neural network model, in which the input variable sample data was transmitted to the model to obtain the predicted value of sow litter size.

Considering that there are many input variables in this design and the inertial weight factor w will affect the motion speed and search accuracy of individual particles in the above optimization process, the convex function decreasing weight method is adopted to improve it (the particle optimization process is first fast and then slow nonlinear treatment):

$$w = (w_{\max} - w_{\min})\left(\frac{a}{a_{\max}} - 1\right)^2 + w_{\min} \tag{6}$$

In the formula: $a_{\max}$ is the maximum number of iterations; a is the current number of iterations; $W_{\max}$ is the maximum weight value; $W_{\min}$ is the minimum weight value.

3. Interpretation of Result

In order to ensure the accurate prediction characteristics of the PSO-RBF algorithm, in this paper, the number of nodes in the hidden layer from 6 to 16 are sequentially trained for the experiments, and it has been verified that different nodes and their corresponding experimental correlation coefficients R are shown in Figure 3. From Figure 3, it can be seen that the correlation coefficient value is the largest when the number of nodes in the implicit layer is 15, so node 15 is chosen as the number of nodes in the implicit layer for the training network. Therefore, a PSO-RBF neural network with a network structure of 20-15-1 is established.

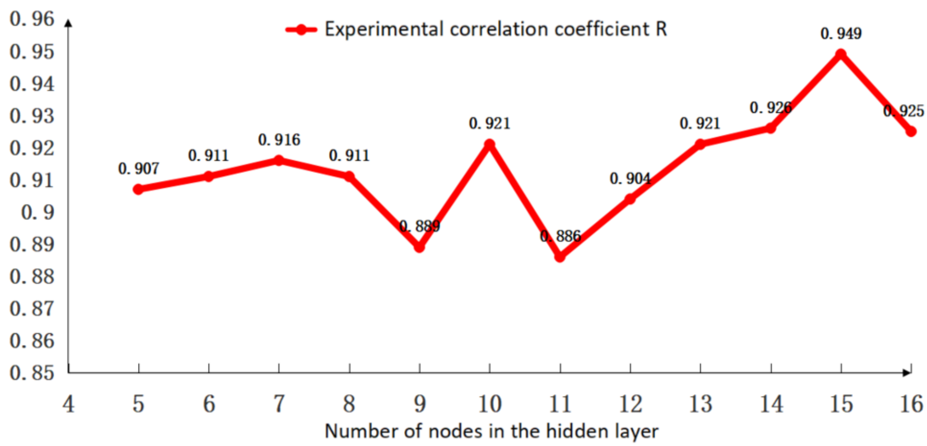

Figure 3. Different nodes and their corresponding experimental correlation coefficients.

The 20 influencing factors such as sow age and litter size, sow and gilt breed and strain, gilt semen, shed environmental information (see Table 1 for specific indexes), feed management, epidemic disease, and climatic factors were used as input variables, and only the sow environmental information could not be directly input into the PSO-

RBF neural network, while the other factors could be directly input; the output variable was one, i.e., sow litter size. According to the above analysis, the factors influencing the litter size of sows are multiple in nature. Considering that the magnitude and order of magnitude criteria are different among the influencing factors, all the above input parameters need to be normalized and pre-processed before using the neural network algorithm, and the formula is shown below:

$$P = (P_{\max} - P_{\min})Q + P_{\min} \tag{7}$$

As shown in the formula: P is the sample value; Q is the normalized value; $P_{\max}$ and $P_{\min}$ are the maximum and minimum values of the specific column where the sample is located.

3.1. Training Mean Square Error Results of Algorithms with Different Inertia Weight Control Methods

The 335 sets of breeding parameters stored in a pig farm breeding information upper computer database were used as sample data, of which 327 sets of sample data were used as learning samples and the remaining 8 sets of data were used as test evaluation samples. The prediction step using PSO-RBF neural network requires training of the neural network, and at the same time, in order to verify and compare the feasibility and effectiveness of the strategy proposed in this paper, different inertia weight factor control methods are selected to optimize the PSO network, and the specific training mean square error data are shown in Figure 4. Among the three different weight control methods, after 50 iterations, the mean square error of the algorithm based on the PSO optimized RBF neural network with inertial weight convex function decreasing strategy is less than 5%; as the number of iterations increases from 100 to 300, the mean square error of the algorithm is The mean square error of the algorithm decreases as the number of iterations increases from 100 to 300, and its prediction effect is good; it overcomes the disadvantage that the simple BP neural network algorithm is easy to fall into the local optimal solution and local minimum, and the convergence speed is slow.

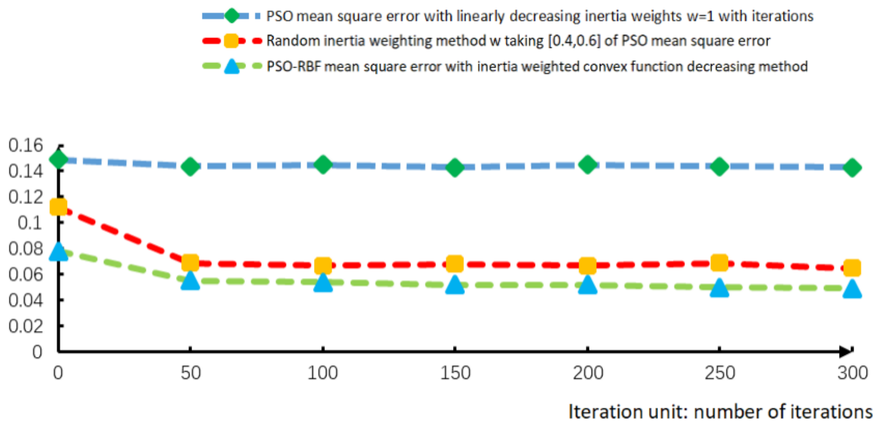

Figure 4. Mean square error corresponding to different inertia weighting factor control methods.

3.2. Analysis of PSO-RBF Neural Network for Predicting Litter Size of Sows

In order to further test the effectiveness of PSO-optimized RBF neural network, eight sets of experimental data were input into BP neural network, traditional RBF neural network and PSO-RBF neural network after in-depth training, and the prediction accuracy and working reliability of the three algorithms for litter size of sows can be compared. The distribution of prediction results and comparison of prediction curves of litter size of 64 sows in a farm by three different neural network algorithms are shown in Figure 5(a) and Figure 5(b).

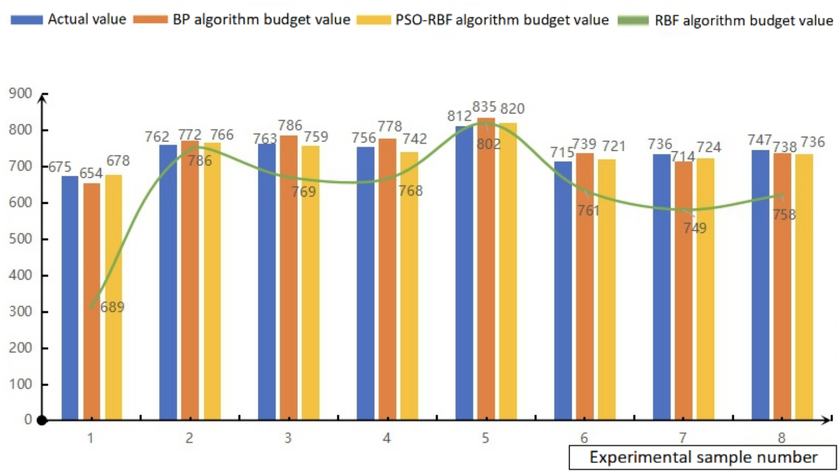

Figure 5 (a). Distribution diagram of the prediction results.

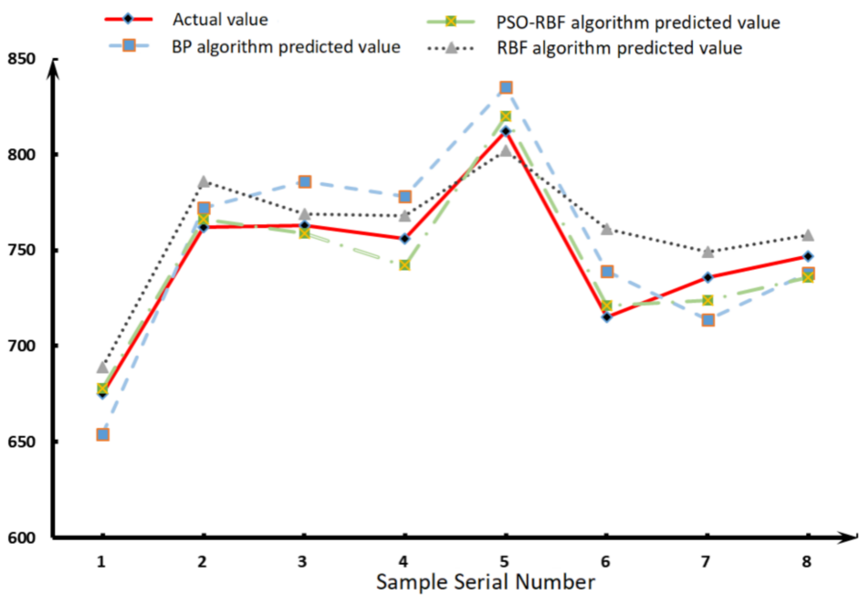

Figure 5 (b). Comparison of the prediction curves.

According to Figure 5, the prediction curve of sow litter size based on PSO optimized RBF neural network algorithm has the highest agreement with the actual situation, which also verifies the high prediction accuracy of this algorithm from the side, and has more superior convergence than the traditional pure BP neural network or RBF neural network.

4. Conclusion

In this study, the sows of a large-scale pig farm in Shaanxi Province were selected as the experimental object, which is based on the demand for accurate prediction of litter size of sow population, and 335 groups of breeding parameters were selected as the sample data. RBF neural network algorithm is used to predict the litter size of sows in this farm based on PSO optimization. When the number of hidden layer nodes is 15, the correlation coefficient value is the largest. After training with a large number of data samples, the algorithm determines the prediction neural network structure of 20-15-1 and adopts the convex function weight control strategy. Under the premise of increasing the number of iterations from 100 to 300, the prediction mean square error gradually decreases. The mean square error of PSO-RBF in predicting litter size of sows is less than 5% and the highest coincidence with the actual output value. At the same time, PSO-RBF algorithm can effectively improve its prediction accuracy and convergence speed, so this prediction method has certain practical significance and application value.

5. Future work

In the previous studies on sow breeding and production, there are few reports on how to predict the litter size of sows by establishing mathematical models. However, this study proposes an optimized neural network modeling method based on learning the traditional regression analysis method. However, due to the limited number of samples in this study, the accuracy and universality of the prediction model constructed by the new method need to be further verified; Secondly, the factors affecting litter size of sows in this study are limited, and there are few key factors that significantly affect litter size; In addition, this study is only a preliminary exploratory study using the neural network method, without in-depth parameter adjustment of the model. Therefore, the next research will focus on expanding the data volume that affects the litter size of sows, adding key factors, and gradually optimizing the prediction model. In the future sow breeding, the use of PSO-RBF neural network algorithm can provide a more objective and accurate scientific prediction of the litter size of sows in pig farms. In view of the prediction error of this neural network, the generalization ability of this measurement method should be further improved and more influencing factors should be considered in the modeling process of this study. In the future, the research focus will be on the establishment of classification standards for high and low yield sows.

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