Prediction Model for Piggery Ammonia Concentration Based on Genetic Algorithm and Optimized BP Neural Network

Kunhua Zhu, Shuyan Wu, Qian Li

Department of Automation and Control, Henan University of Animal Husbandry and Economy, ZhengZhou 450000, Henan, China

Abstract

In the large-scale farming, piggery environment has a direct impact on the health of swine and its production capacity. In order to predict the ammonia concentration in the large-scale piggery accurately and overcome the shortcomings of the existing prediction models, we combine the genetic algorithms and BP neural networks method to predict the concentration of ammonia. In this paper, piggery environmental factors mainly include wind speed, temperature, humidity and ammonia concentration. The gray relational analysis method is used to determine the input layer factor and output layer factor, while the 3-7-1 BP neural network model of the three-layer structure based on GA(Genetic Algorithm) and L-M (Leven berg-Marquardt) optimal algorithm was built to predict the piggery ammonia concentration. The prediction model can optimize the initial value and the threshold value of neural networks, so the optimized values can be more in line with the requirements. At the main time, the training process can avoid falling into local minima. In this paper, the prediction model is based on the global optimization of genetic algorithm, the initial weights and thresholds value of the neural network are optimized, and then the L-M algorithm is used to speed up the training speed of the neural network. By using the continuous monitored data, the neural network is trained and used to predict piggery ammonia concentrations through the resulting neural network model. Training results show that the method is precise enough, and it can be applied to predict piggery ammonia concentrations.

Key words: AMMONIA CONCENTRATION, GENETIC ALGORITHMS, BP NEURAL NETWORK, L-M ALGORITHM, PREDICTION MODEL, WEIGHT OPTIMIZATION, THRESHOLD OPTIMIZATION.

1. Introduction

Ammonia concentration is an important indicator for reflecting piggery environment. The ammonia concentration in piggery should be controlled at 25 mg/m3 or less. When the ammonia concentration exceeds a certain limit value continuously, it will harm the central nervous system and respiratory system of pigs, and it will also affect the productive and reproductive performance of boar, as well as feed efficiency. Research shows that the optimum temperature inside the piggery is 8 ~ 20 ℃.In terms of humidity, depending on the type of individual quality of pigs, the relative humidity is generally required between 65% to 85% [1].

At present, in domestic and foreign, many gas measurement feature extraction methods have been proposed [2]. N, et al measured ammonia distributed and establish ammonia distributed model [3]. These methods can be classified into two categories: The first category is extracting basic statistical feature of the signals. Such as the basic characteristics of the signal average value, maximum value, and so on. The biggest advantage of such method is that extraction method is simple and intuitive， and it only requires a small amount of calculation. Its disadvantage is that the extracted features are rougher, and selection of feature points is more subjective and has poor anti-noise ability; the second category is taking mathematical transformation of original signal first and then extracting corresponding feature. Such as those methods that based on principal component analysis, methods of GA feature extraction and BP neural network prediction. Such methods only take steady state value or several feature points on the curve of the output signal of the sensor. The time factor which is the chemical reaction process is not considered. Relying on BP neural network only will be extremely easy falling into local minimum, so it cannot be forecast accurately.

For the reason that the ammonia concentration in the piggery is affected by temperature, humidity and ventilation and other environmental factors, it is difficult to establish an accurate prediction model. The ammonia concentrations can be obtained by equipment monitoring, only but there are regulatory lag problem. That is why we can‘t establish an effective ammonia concentrations prediction model.

In this paper, we collect the environmental parameters of piggery in the large-scale livestock farms, and combine genetic algorithms and BP neural networks to predict the gas concentration according to the collected data. Basing on the excellent global searching capability of GA, it optimizes the network initial weights. By using GA method, it can approach the characteristic of on algorithm to accelerate the convergence of neural networks in the small space, while avoiding neural network training fall into a local minimum. This article established a method that based on genetic algorithms and LM optimization neural network prediction model which used GA to predict piggery ammonia concentration.

2. GA (Genetic-Algorithm)

Genetic algorithm is an intelligent algorithm which is based on the nature of Bio-genetic [4] , evolutionary mechanisms and process background to stimulate biological evaluation. It introduced the concept of reproduction, crossover, mutation, competition and selection in the algorithm. By maintaining a set of feasible solutions and regrouping the feasible solution, we will improve feasible solution within the multidimensional space of movement trajectory or trend, and result in optimal solution. It overcomes the shortcomings of traditional optimization method, which is falling into local optimum, and it is a global optimization algorithm. The Achievement of the genetic algorithm contains three main elements: the individual series (solution) code design, the individual evaluation fitness function design, and population genetic of genetic operator design.

3. BP Neural Network

BP neural network is a multilayer feed forward network that based on back propagation algorithm training, which is proposed by Rumelhart and McCellandin 1986. It is one of the most widely used neural network model. BP neural network can learn and store large amount of input - output mode mapping without prior revealing mathematical equations that describe this mapping. Its learning rule is to use the steepest descent method. By using reverse spread [5], it constantly adjusts the network weights and thresholds, so that the deviation sum of Squares achieves the minimum. Figure 1 shows the network topology of single hidden layer former feed forward BP neural network model [6]. It is generally regarded as the three-tier feed forward or three-tier perception network, namely: an input layer, a hidden layer (also called intermediate layer) and an output layer.

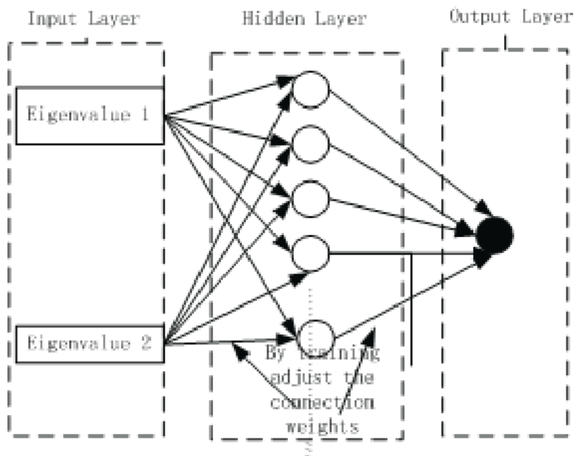

Figure1. BP neural network topology

It is characterized by: each layer neurons only fully connected to neurons of adjacent layers, no connection between neurons in the same layer, and no feedback connection between neurons of the layers, and constitute feed forward neural networks having hierarchical structure [6-8].

Information forward propagation and deviation back-propagation process constitute BP neural network. Each input layer neurons is responsible for receiving input information from the outside world and transmit to each neuron of the intermediate layer; The intermediate layer is internal information processing layer, according to demand information capacity changing, the intermediate layer can be designed as a single hidden layer or multi-layer structure hidden; Finally, the information transmitted from the hidden layer to the output layer each neuron, after further processing export results from the output layer to the outside world to complete a study of the forward propagation process. When the actual output does not compatible expected output, the algorithm enters into the deviation back-propagation. According to the deviation gradient descent, approach correct weights of each layer, then back propagate to the hidden layer and input layer. Information forward propagation and deviation back propagation process are repeated again and again, which is the process of constantly adjusting the weights of each layer, as well as training of the neural network learning process. This process continues until the network output error is reduced to an acceptable level, or reaches a predetermined number of learning.

Initialization weights strongly influence the final solution in neural networks. Therefore, the traditional genetic algorithm optimize BP neural network so that the initial value and the threshold value of the network is more reasonable and beneficial to further processing.

4. L-M Algorithm

Because of its simple, easy, less computation, parallelism and other advantages, BP algorithm is the one of the most widely used and most mature algorithms in neural network training adoption. Because that BP algorithm uses Nonlinear Programming steepest descent methods, the weights are modified according to the direction of the negative gradient of the error function. The usual problems are:

(1) Learning efficiency is low, and convergence rate is slow;

(2) From the mathematical point of view, BP algorithm is based on gradient descent method based nonlinear optimization methods. It is easy to fall into local minimum, and there may not be a global minimum;

(3) Poor numerical stability, the parameter is difficult to adjust, and inconvenience to apply;

(4) Network generalization and adaptability is poor.

Due to these deficiencies of BP algorithm, the paper decided to use Leven-berg - Marquardt algorithm to train the network (the L-M method). When solving the iterative nonlinear process, the Gauss-Newton iteration has second order convergence rate, but an iterative process may become singular Hessian matrix array. So it can‘t be a situation of iterations, which is less stable. L-M algorithm is between the Gauss-Newton method and the steepest descent method to smooth harmony, and switch to the Gauss-Newton method while it is away from the minimum gradually. The weight correction formula is:

$$\Delta x = -[J^T(x)J(x) + \mu I]^{-1}J^T(x)e(x) \quad (1)$$

In formulas 'Δx' is the network weights when an iteration occurs; The 'J' is the error Jacobian matrix of weight values differentiated; The 'μ' is an adaptive tuning parameters， which is a scalar greater than zero, and it is adaptive. When μ is large enough, the formula would close the steepest descent method. When μ is small, the formula becomes Gauss-Newton method; the 'e' is the error; the 'I' is the identity matrix.

5. Establish Piggery Ammonia Concentration Prediction Model

5.1. Collect sample data

Data acquisition is the basis of the monitoring and early warning. To collect piggery environmental date， sensor nodes is reasonable arranged in the piggery [9], and the nodes collect current environmental data value by data integration. Since the ammonia concentration is influenced by environmental factors such as temperature and humidity inside the piggery, ventilation, pig structure, so the article select the temperature, humidity and ammonia concentration as environmental monitoring factors, and we establish an environmental early warning model. There are a variety of environmental factors that are influencing with time and space, and they are related among teach other, which means it is non-linear systems. By using LM optimization algorithm, BP neural network can effectively mapping the contained rule in nonlinear models between the input and output, and it has arbitrary precision that can approach any function.

In this paper, environmental monitoring data are come from a large-scale pig farms, and it is 30 consecutive days monitoring record. There are six data collection points in piggery, each data collection point collect temperature, humidity, wind speed and ammonia concentration at the same time. The interval is 10min.

Setting one of six samples of a node is x_i (t_i, h_i, s_i, n_i, w_i), where: t_i, h_i, s_i, n_i, ω_i denote temperature, humidity, wind velocity and ammonia concentration and sensor weights value of the node x_i at a moment,. According to the distance from the sensor to the entrance of piggery differently, values of weights ω_i is as shown in Equation (2), and mi is sensor distance from the pig house entrance.

$$\omega_i = \frac{m_i}{\sum_{i=1}^{n} m_i} \ (i=1,2,3,\cdots,6) \quad (2)$$

The temperature is 'T', humidity is 'H', wind speed is 'S', ammonia concentration is 'N'. Then

$$T = \sum_{i=1}^{6} t_i \times \omega_i \quad (3)$$

$$H=\sum_{i=1}^{6} h_i \times \omega_i \quad (4)$$

$$N=\sum_{i=1}^{6} n_i \times \omega_i \quad (5)$$

The value of 'T', 'H', 'S' and 'N' are considered as an environmental value of a certain time of pig house into the database, 'T', 'H', 'S' as input data of environmental prediction model, 'N' as the output layer predicted value of the control data. We selected 30 days of temperature; humidity, wind velocity and ammonia concentration data, and average these environmental data every 60 min. The part data presented in Table 1.In the table 1,'ST' is 'Sampling Time', 'T' is 'Temperature', 'H' is 'Humidity' ,'WV' is 'Wind Velocity', 'AC' is 'Ammonia Concentration'.

Table 1. Data Collection Form

ST	T(℃)	H(%)	WV (m/s)	AC (mg/l)	ST	T(℃)	H(%)	WV (m/s)	AC (mg/l)
0:00	20.25	67.80	0.41	4.25	0:00	21.48	62.96	0.44	5.12
1:00	20.97	63.22	0.31	4.18	1:00	21.55	63.71	0.40	5.77
2: 00	21.84	61.36	0.32	4.05	2: 00	21.33	64.35	0.40	5.79
3:00	21.77	61.96	0.56	3.42	3:00	21.14	65.58	0.51	5.95
4:00	21.58	62.01	0.57	3.42	4:00	21.26	66.28	0.47	7.32
5:00	21.62	63.27	0.53	3.46	5:00	21.27	66.63	0.48	7.65
6:00	21.33	61.95	0.42	4.01	6:00	21.48	66.84	0.44	7.79
7:00	21.27	53.98	0.53	1.19	7:00	21.53	69.31	0.49	4.89
8:00	21.35	50.13	0.54	1.09	8:00	21.68	67.22	0.53	3.19
9:00	22.42	46.79	0.57	1.01	9:00	21.99	59.24	0.56	2.19
10:00	23.66	40.38	0.46	1.02	10:00	22.94	48.81	0.65	1.39
11:00	24.30	32.74	0.52	0.04	11:00	22.97	46.45	0.67	1.09
12:00	24.32	32.76	0.51	0.90	12:00	23.17	46.56	0.64	1.27
13:00	24.33	32.88	0.68	1.02	13:00	23.19	46.75	0.55	1.37
14:00	24.38	33.11	0.65	1.24	14:00	23.22	45.93	0.53	1.37
15:00	24.41	33.98	0.62	1.31	15:00	23.28	43.22	0.57	1.38
16:00	24.39	35.63	0.64	1.46	16:00	23.35	43.29	0.52	1.39
17:00	24.42	38.98	0.66	1.67	17:00	23.36	42.59	0.61	1.33
18:00	24.45	43.87	0.55	2.76	18:00	20.67	63.83	0.38	6.38
19:00	24.58	45.11	0.58	2.94	19:00	23.13	59.26	0.49	3.78
20:00	24.62	45.35	0.56	3.44	20:00	20.09	67.56	0.61	6.01
21:00	24.67	49.98	0.43	4.68	21:00	20.68	69.08	0.55	6.01
22:00	21.22	50.13	0.46	4.99	22:00	20.02	67.19	0.54	5.19
23:00	21.20	51.38	0.46	5.02	23:00	20.11	67.88	0.42	4.33

5.2. Pre-treatment predict model data

Before training network model, we first need to normalize networks sample data. The data is converted into interval values between (0, 1), normalizing using the max-min method, as shown in equation (6).

$$\bar{x}=\frac{x_i-x_{min}}{x_{max}-x_{min}} \tag{6}$$

Where, the 'x_i' represents the input data, the 'x_{min}' represents the minimum data, the 'x_{max}' represents the maximum value of the data.

5.3. Determine the structure of BP neural network

In this article, we designed the BP network structure, in Figure 2shown.

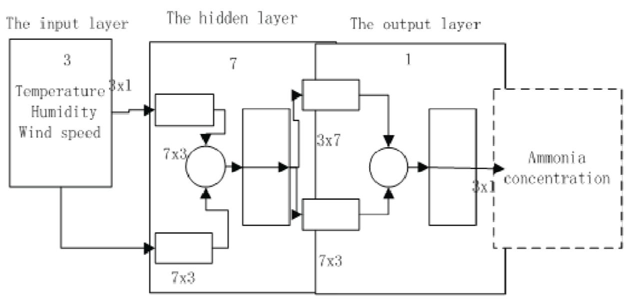

Figure2. Model structure

Node input layer is the main factor affecting the quality of the environment, namely temperature, humidity and wind speed. The number of neurons of the input layer is 3; According to Hecht-Nielsen proof: Only one hidden layer neurons multilayer neural network can approximate any continuous function arbitrary precision; we take the S-type tangent hidden layer activation function, and we take the S-type logarithmic activation function in the output layer. For the determination of hidden layer neuron, this article uses empirical formula $k=\sqrt{s+m}+a$, within a certain range. Where, the 'k' is the number of output neurons; the's' for the input number of cells; the 'a' is a constant between [110]. After trying calculation, 7 hidden layer neurons can reach the best approximation effect. Thereby, it establishes a 3-7-1network prediction model. Three-layer structure of BP neural network is established by Mat lab, using L-M optimization algorithm to train the network, training steps is 1000, the performance target error is 0.001, learning rate is 0.05, Momentum of constant is 0.9.

5.4. Using genetic algorithm to optimize the initial weights and thresholds

In Mat Lab environment, we use genetic algorithm toolbox. In this paper, we use real coding to encode the original weights and threshold values, forming an initial population; We use the training sample to train each individual, learning error is calculated for each individual to determine the fitness value . Learning error is:

$$E=\frac{1}{2}\sum\sum(y_i-t_i)^2 \tag{7}$$

Where, 'E' learning error function; 'y_i' output as an output layer node; 't_i' is the desired output of the network. This is a learning error function adapted to a single output.

Fitness function:

$$F=2-P_m+2(P_m-1)\frac{x_i-1}{N-1} \tag{8}$$

Where, the 'P_m' is offset determination parameters between [1.12.0]; the 'x_i' is position in the order for the individual of' 'i' in the population;' N' is the population size.

The chosen method is roulette method, crossover operator choose uniform crossover operator, and mutation operator use multi-point non-uniform mutation operator.

The process of genetic algorithm to optimize neural network weights is as follows:

1) Identify genetic algorithm and BP network parameters, including community capacity GA, crossover rate, mutation rate, BP network configuration parameters and accuracy [10]; Based on the sample in the training process, we take 50 initial population, crossover probability is 0.7, mutation rate is 0.01, terminate evolution generation is 200, the initial weight and threshold value is in the range of (1, 1), and the neural network learning rate is 0.05, error is 0.0001.

2) Randomly generating a set of weights and thresholds distribution (chromosomes), optimizing the weights and thresholds by genetic algorithm. By the neural network generate network weights and thresholds conventional approaches to generate initial weights and thresholds, any of the set of weights and thresholds equivalent to a chromosome, which is the parent individual. Chromosome adopts real number coding. Calculate individual fitness, if individual fitness condition is satisfied, skip to step 4), otherwise, go to Step 3);

3) Genetic manipulations produce a new generation of individuals, eliminate parent individuals, go to step 2). Genetic operators are the choice, the inheritance, and crossover these three common operators. This step is to optimize the network weights and thresholds using genetic algorithms;

4) BP algorithm fine tune until the condition ends.

Flow chart is shown in Figure 3.

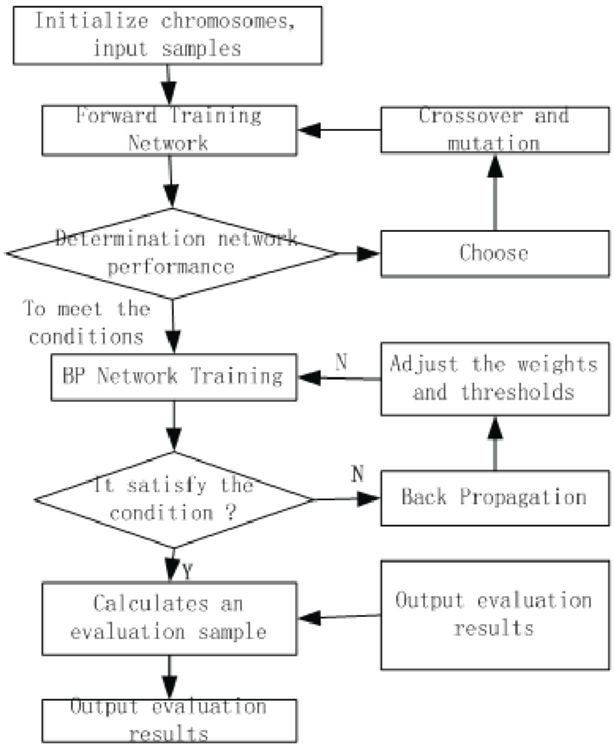

Figure3. Genetic Algorithm optimization BP neural network processes

5.5. BP network training and test results

Setting the resulting network weights and thresholds to be the initial weights and thresholds, L-M optimization algorithm is used to the training process. Prediction results are acquired by using Mat Lab and select part of the continuous data (Table 2). Where 'M' represents Found, 'F' for predictions, 'E' denotes an error. Upon examination, the average error of the test samples meet the requirements, it can be used to predict ammonia concentration of piggery. In table 2,'ST' is 'Sampling Time'.

Table2. Use of genetic algorithm and L-M optimization of neural network predictive value and relative error

ST	M	F	E	ST	M	F	E
0:00	4.24	4.12	0.12	13:00	1.01	0.81	0.20
1:00	4.17	4.20	0.13	14:00	1.23	1.34	0.11
2:00	4.04	4.20	0.16	15:00	1.30	1.42	0.12
3:00	3.46	3.46	0	16:00	1.45	1.59	0.14
4:00	3.41	3.20	0.21	17:00	1.67	1.51	0.16
5:00	3.46	3.47	0.01	18:00	2.76	2.61	0.15
6:00	4.01	4.01	0	19:00	2.93	3.036	0.106
7:00	1.19	1.28	0.09	20:00	3.34	3.34	0
8:00	1.08	1.26	0.18	21:00	4.68	4.523	0.157
9:00	0.9	0.815	0.085	22:00	4.99	4.88	0.11
10:00	0.92	0.92	0	23:00	5.01	5.31	0.60
11:00	0.07	0.05	0.02	0:00	5.12	5.118	0.002
12:00	0.9	0.80	0.10	1:00	5.78	5.760	0.02

Line chart measured and predicted values of visual comparison, shown as Figure 4.

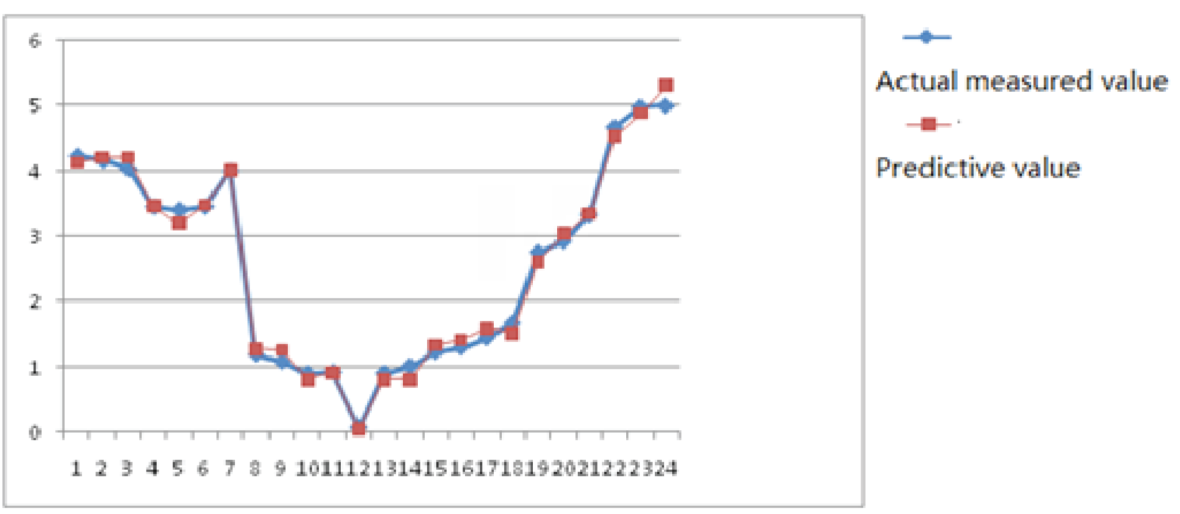

Figure 4. Ammonia concentrations measured and predicted values of a line visual comparison chart

6. Conclusions

In this paper, aiming at solving the problem that the traditional BP neural network convergence is slow and it is easy to fall into local minimum point, ithas proposed BP neural network model optimization algorithm based on genetic algorithm and L-M. The model has been used to predict the concentration of ammonia pig house. Experimental results showed that the maximum error of neural network model is 0.56; the smallest error is zero, which is generally close to the measured value. Within the allowable error range, it has good precision, and with the continuous supplementary learning samples, prediction accuracy and generalization ability of the network will be further enhanced. Therefore, the application of optimization based on genetic algorithm and LM BP neural network combining methods to predict piggery ammonia concentration is entirely feasible.

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Intelligent Solar Power Management Based on Fuzzy Logic Control

Lei Feng, Chunhui Liang

School of Electrical and Information Engineering,
Changchun Institute of Technology, Changchun, 130012,
China

Suli Zhang

School of Computer Technology and Engineering,
Changchun Institute of Technology, Changchun, 130012,
China

Abstract

This paper presents the intelligent charging and discharging management method for the solar power management circuitry based on fuzzy logic control theory. The mathematical model of DCDC circuit is established, and through Matlab theoretical derivation the feasibility of the maximum power point tracking by the method of obtaining the maximum output current through control is proven. And the experimental results confirm the theoretical rationality and correctness of the tracking of the maximum power point through the method of by sampling the maximum output current, to achieve the optimal solar charging