Study on Water Production Function of Rice Based on RAGA-BP Neural Network Model

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Abstract

The water production function model of rice based on RAGA-BP neural network model is established by taking the advantages of RAGA-BP neural network model (high ability in solving nonlinear problem, high rate of convergence, etc.). Compared with traditional Jensen model, this method is featured by high flexibility and intelligence, avoiding the inconvenience caused by pre-establishing mathematical expression. Compared with classical BP neural network model, this method can overcome the problem in local minimum value and low rate of convergence. The deficient irrigation experiment of rice in 2015 shows that RAGA-BP neural network model has high adaptability during the process of fitting for solution of water production function of rice; the accuracy and speed are high, which provides new effective method for calculation of water production function of rice.

Keywords: *Rice*; *water production function, RAGA-BP neural network model; Jensen model; BP neural network model*

1. Introduction

Heilongjiang Province is the major province for commodity grain output in China, and rice irrigation water accounts for above 90% of agricultural water. The rice irrigation area in Heilongjiang Province is located in cold region and black soil area. In recent years, the imbalance between supply and demand caused by water resource shortage is increasingly serious ^[1]. Therefore, the study on relationship between rice and water and establishment of water production function model of rice suitable to this area have great significance for the planning and systematic evaluation of water-saving irrigation and for the promotion and application of deficient irrigation system [2-6].

At present, Jensen model is mostly adopted for the water production function for rice, and this model mostly adopts least-squares regressive analysis to calculate the model parameters via massive calculation [7]. During the solution process, the problem that the fitting precision is not high may be caused due to improper structure selection. Furthermore, during the confirmation process, the parameters in the model may be negative, which is contradictory to the water demand regulations of crops [8]. BP (Back propagation) [9] neural network is suitable to solving nonlinear problem, calculation and forecasting still can be performed under the condition that the measured data is not so complete; however, there are the following defects: easily fall into local minimum, low rate of convergence, the fitting precision is not high.

RAGA-BP neural network model is a kind of new computational algorithm formed by

extending accelerating genetic algorithm and BP neural network model, and it has been widely applied in such fields as hydrogeololgy, food, medicine, and so on ^[10-11]. However, there is little research on water production function of crops at home and abroad. For this model, the water production function model for rice based on RAGA-BP neural network is established by making use of the measured evapotranspiration data in different stages of 2015, and it is compared with Jensen model, BP neural network model and the model based on genetic algorithm.

2. RAGA-BP Neural Network Model

Optimization of RAGA-BP neural network model ^[12-14] mainly involves two steps: BP neural network training fitting and genetic algorithm optimization. The specific operation steps are as follows:

Step 1 Confirmation of input layer node. According to the standards for division of crop growth stages in the *Irrigation Experiment Standards*, the evapotranspiration data in the 4 growth stages (tillering, jointing-booting, heading and flowering, milk-ripe stage) is adopted to establish BP model, and the relative evapotranspiration data in the 4 growth stages is taken as the input node of the model.

Step 3 Confirmation of hidden layer node number. There is no definite method for confirming the hidden layer node number and the theoretical calculation is complex, so generally, the following formula is adopted to confirm the range of neuron number in hidden layer, *i.e.*

$$l = \sqrt{n+m} + a \tag{1}$$

In formula (1), 1- hidden layer node number; n- input node number; m- output node number; a- the regulating constant between 1-10.

Through the calculation in this paper, the hidden layer node number is 3-12, and then training comparison is performed for the network of different neurons. It is found that when the hidden layer node number of the network is 10, the network has enough generalization ability and output accuracy, and the number of training steps of the network is small. Therefore, the hidden layer node number of the network is confirmed as 10.

Step 3 Confirmation of output layer node. The output layer node shall be confirmed according to the forecasted performance parameters; in this network, the relative yield is taken as the output node.

Step 4 Transfer function and algorithm. The transfer function of hidden layer is Tansig and Logsig, and the transfer function of output layer is Purelin. Levenberg-Marquardt is adopted as error algorithm. Compared with traditional BP algorithm, the gradient descent is faster, so from the aspect of convergence of the whole network, the error requirements may be met by very small iterations.

Step 5 Optimization of genetic algorithm. The system output is forecasted after BP neural network is trained by training data according to the initial weight value and threshold value of BP neural network obtained by individuals, and the sum E of the absolute value of error between predicted output and expected output is taken the fitness value F of individuals. The calculation formula:

$$F = K\left(\sum_{i=1}^{n} abs(y_i - o_i)\right)$$
(2)

here: n- network output node number; y_i -BP- expected output of the ith node of neural network; o_i - the predicted output of the ith node of neural network; k- coefficient.

Then, look for the corresponding input value when global optimum via selection, crossing and mutation operation.

2. Water Production Function Model of Rice Based on RAGA-BP Neural Network Model

During the 4 growth stages of rice, the potential evapotranspiration in different stages is $(ETm)_{j}$, j = 1, 2, ..., 4, mm; the potential yield of crop is Ym ,kg /hm². The actual evapotranspiration (E Ta)_{ij}, i = 1, 2, ..., N, j = 1, 2, ..., 4, mm and the actual yield (Ya) i, i = 1, 2, ..., N, kg /hm² of N groups of crops are obtained through deficient irrigation experiment. The actual evapotranspiration and the actual output of N groups shall be subject to standardizing processing according to the following formula.

$$x_{ij} = (ETa)_{ij} / (ETm)_j \quad i = 1, 2, ..., N, j = 1, 2, ..., 4$$
 (3)

$$y_i = (Ya)_i / Ym \quad i = 1, 2, ..., N$$
 (4)

here, x_{ij} , y_i - the processed value is taken as the training sample for input and output; ratio, dimensionless.

Making use of the obtained training sample, automatic optimization of model is performed via RAGA-BP, thus the ideal water production function model of crops f(X), $X = (x \ 1, x \ 2, ..., xt)$ can be found.

The sum of relative absolute value error is used to express the accuracy of fitting data of model, and it may be calculated by the following formula:

$$Err = \sum_{i=1}^{n} Err_{i} = \sum_{i=1}^{n} \left| \frac{f(x_{i} \bullet Y_{m} - y_{i} \bullet Y_{m})}{y_{i} \bullet Y_{m}} \right| = \sum_{i=1}^{n} \left| \frac{f(x_{i} - y_{i})}{y_{i}} \right|$$
(5)

here, Err- the sum of relative absolute value error; Erri-the relative absolute value error of the ith group of sample; Xi = (xi 1, xi2,..., xit) - the vector representation of the ith group of sample; f (Xi) – the actual output value of the ith group calculated by RAGA-BP neural network model; yi- the ideal output value of the ith group; Ym- the potential yield of crops; kg/hm². The smaller the relative error, the higher the fitting precision.

3. Application Examples

3.1. Materials and Method

The experiment is conducted at the rice irrigation experiment station of Heping irrigation area in Qing'an County, Heilongjiang Province in 2015. This area has semiarid and subhumid climate in the north temperate zone. The multi-year average precipitation is 702.3 mm and the multi-year average temperature is $1.6 \,^\circ\text{C}$, and it in the third accumulative temperature belt. The test area has black soil; $0 \sim 30 \,\text{cm}$ saturated volumetric water content is 55.9% (average), and the pH value is 6.5.

To eliminate the influence of natural precipitation on the experiment, lysimeter with automatic weighing function is adopted during the research; in addition, mobile canopy is provided, and irrigation water is used to control the soil moisture content in different growth stages. Treatment is performed based on different drought levels in different stages, and sufficient irrigation is adopted for control treatment. Since there is steeping field residual water in the period of seedling establishment and the time is short, so the rice will not suffer from drought. The water is drained in yellow ripening stage, which is favorable to rice mature. Normal water management is performed according to the high yield requirements for the two stages. The 4 levels- normal irrigation, light drought, medium drought and heavy drought can be respectively arranged for other 4 stages. According to the definitions in the local standards DB23 of Heilongjiang Province *Technical Code for Water-saving Irrigation for Rice in Cold Region*, light drought: the soil moisture content of

root layer is controlled at 90% \sim 100% of the saturated water content of soil; medium drought: 70% \sim 90%; heavy drought: 60% \sim 80%. To make the practice more approach the possible drought and perform all-round research for the water production function of rice, 2-stage and 3-stage continuous drought is arranged for the experiment. Each treatment is repeated for 2 times, and there are 24 lysimeters in total. The area of single lysimeter is 1m². The varieties, transplanting density and fertilization are subject to uniform management according to the high yield and high quality mode of local area. See Table 1 for the experimental result.

Treatme nt No.	Characte ristics	① Tillering stage	② Jointing-bootin g stage	(3) Heading and flowering stage	(4) Milk-ripe stage	Yield
		/mm	/mm	/mm	/mm	kg/hm ²
1	①Light drought	126.78	108.19	103.15	75.26	6447.8 4
2	①Heavy drought	120.51	98.90	95.09	71.90	5125.6 8
3	②Light drought	149.97	101.92	119.73	78.74	6844.3 2
4	②Light drought	147.95	87.25	105.17	72.80	5102.1 6
5	③Light drought	143.58	111.33	95.54	88.14	6182.4 0
6	③Heavy drought	145.26	103.60	80.53	77.73	5969.0 4
7	④Light drought	157.36	126.45	121.63	76.83	7106.4 0
8	④Heavy drought	151.54	120.96	113.90	72.80	6765.3 6
9	①,② Medium drought	123.87	93.30	106.62	80.98	5685.1 2
10	②,③ Medium drought	143.81	101.25	93.41	82.43	6095.0 4
11	(3,4) Medium drought	145.71	114.91	106.06	68.77	6866.1 6
12 (CK)	Sufficien t irrigation	150.79	113.83	126.97	91.03	7268.2 9

Table 1. Evapotranspiration and Yield by Different Experimental Treatments

3.2. Standardizing Processing of Experimental Data

Perform standardizing processing for the evapotranspiration data of different stages and the yield data under different treatment conditions according to formula (3) and (4), and matrix X and Y are respectively obtained.

	0.8408	0.9505	0.8124	0.8268		0.8871
	0.7992	0.8688	0.7489	0.7899		0.7052
	0.9945	0.8954	0.9430	0.8650		0.9417
	0.9812	0.7665	0.8283	0.7997		0.7020
	0.9522	0.9780	0.7524	0.9683		0.8506
X =	0.9634	0.9101	0.6342	0.8539	Y=	0.8212
	1.044	1.1109	0.9580	0.8440		0.9777
	1.005	1.0626	0.8971	0.7997		0.9308
	0.8215	0.8196	0.8398	0.8896		0.7821
	0.9537	0.8895	0.7357	0.9055		0.8386
	0.9663	1.0095	0.8353	0.7554		0.9447

3.3. Comparison for water Production Function Modeling of Rice Based on RAGA-BP Neural Network Model

Real coded accelerating genetic algorithm (RAGA) is adopted, since the optimizing function only has 4 input parameters, so the individual length is 4 and the individual fitness is the predicted value by BP neural network. The smaller the fitness value, the more optimal the individuals. In this paper, the population size in RAGA is 20, the crossover probability is 0.4, the mutation probability is 0.2, and the evolution times are 100. BP neural network takes the 11 groups of data in deficient irrigation treatment as the input signal of neural network; the network is trained; the maximum training times is 500; and training time is 0.1s, and the expected error is 10⁻⁵. See Figure 1 for the fitting result.

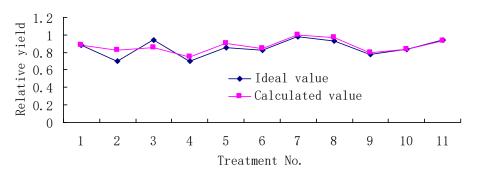


Figure 1. RAGA-BP Data Fitting Chart

Meanwhile, BP neural network model, genetic algorithm model and Jensen model are also established in this paper. See the following for details:

BP neural network model: the maximum training times: 500; training time: 0.1s;

expected error: 10^{-5} ; the weight matrix W, V of input and output layer after successful training are respectively: W=

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0.2185	1.1248	0.2572	0.4986	0.8668	0.7417	0.3943	0.5801	0.5893	0.6343	
0.7095	1.0019	0.4357	0.6560	0.1468	0.9532	1.0206	0.8619	0.4860	1.0704	
0.3906	0.7677	0.1329	1.0189	0.3791	0.8562	0.1890	0.2514	0.1227	0.9494	
-0.0112	0.9512	1.0737	-0.1668	0.8670	0.8867	-0.0235	-1.1294	0.2002	0.2852	
V=										

 $\begin{bmatrix} 0.4642 & -0.6798 & 0.2870 & 0.3840 & 0.3512 & -0.3105 & 0.6788 & 0.9915 & 0.4329 & 0.0585 \end{bmatrix}$ Genetic algorithm: population size: 20; crossover probability: 0.4; mutation probability: 0.2; evolution times: 100. The calculation result is:

$$f'(X) = \sin(x2) \arctan(x2 + \operatorname{arccot}(x3 + 0.0002))$$
(6)

Jensen model:
$$\frac{Y_a}{Y_m} = \prod_{i=1}^n \left[\frac{ET_a}{ET_m} \right]_i^n$$
 (7)

here, Ya- the actual yield of crops, kg /ha; Ym- the potential yield of crops, kg /ha; Etathe actual evapotranspiration of crops in the jth growth stage, mm; ETm- the potential evapotranspiration of crops in the jth growth stage, mm; λ i- the sensitivity coefficient (power exponent) of crops in the jth growth stage.

The calculation result by least square method is:

$$\frac{Y_a}{Y_m} = \left[\frac{ET_a}{ET_m}\right]_1^{0.2362} \bullet \left[\frac{ET_a}{ET_m}\right]_2^{0.2485} \bullet \left[\frac{ET_a}{ET_m}\right]_3^{0.7938} \bullet \left[\frac{ET_a}{ET_m}\right]_4^{0.1721}$$
(8)

See Table 2 for the calculation data of the models. The sum of relative absolute value error of the models is calculated by formula (5), and see Table 3 for the result.

Table 2. Comparison for Function Result of RAGA-BP Neural Network, BP Neural Network, Genetic Algorithm and Jensen Model

Treat ment No.	RAGA-BP neural network model	BP neural network model	Genetic algorithm model	Jense n model	Idea l value
1	0.8869	0.7897	0.8289	1.329	0.88
				l 1 222	71 0.70
2	0.8242	0.7841	0.7702	1.223 2	0.70 52
3	0.8577	0.7936	0.8015	1.330 4	0.94 17
4	0.7494	0.7859	0.7003	1.173 2	0.70 20
5	0.9013	0.7913	0.8423	1.373 8	0.85 06
6	0.8476	0.7878	0.7921	1.285 3	0.82 12

7	1.0003	0.8046	0.9348	1.569 2	0.97 77
8	0.9664	0.8010	0.9031	1.499 3	0.93 08
9	0.7926	0.7825	0.7407	1.192 8	0.78 22
10	0.8386	0.7877	0.7837	1.279 0	0.83 86
11	0.9281	0.7973	0.8673	1.424 2	0.94 47

Table 3. Comparison for Relative Error of RAGA-BP Neural Network, BP Neural Network, Genetic Algorithm and Jensen Model

RAGA-BP neural network model	BP neural network model	Genetic algorithm model	Jensen model
0.5096	1.1425	0.6285	6.2706

3.4. Result Analysis

(1) According to Table 3, the fitting precision of RAGA-BP neural network, genetic algorithm, BP neural network and Jensen model is from high to low, and the sum of the calculated relative absolute value error of the first 3 models is far lower than that of Jensen model.

(2) According to formula (6), the function obtained based on genetic algorithm only contains X_2 and X_3 , and the reason is that the two columns of data in the input sample has strong functional relationship with the output sample. Therefore, we can know that the key growth stages affecting rice yield are jointing-booting stage and heading and flowering stage.

(3) According to formula (7), the impact of sensitivity coefficient calculated by Jensen model on rice yield: heading and flowering stage> jointing-booting stage> tillering stage> milk-ripe stage.

4. Conclusion

The study is based on the actual experimental data of 2015; the latest research theory and achievements of real coded accelerating genetic algorithm (RAGA) and BP neural network are sufficiently absorbed and evolved. The advantages of the two are combined to establish the water production function model of rice suitable to this area, and this model can avoid the inconvenience in pre-establishing mathematical expression and overcome the problem in local minimum value and low rate of convergence. Detailed comparison is performed for RAGA-BP neural network, genetic algorithm, BP neural network and Jensen model by making use of the evapotranspiration data in different stages. The result shows that the water production function of rice based on RAGA-BP neural network has the highest fitting precision and powerful automatic search and optimization ability. Furthermore, it is convenient for use and has high adaptability and very good application value, which provides theoretical basis for establishing deficient irrigation system for rice and for the theoretical research for water conservation.

Acknowledgment

The authors thank the financial supported by National Science and technology support program of China (No: 2012BAD08B05) for this research project.

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