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A Back-Propagation Model to Evaluate Safety Risks on Chinese Agricultural Products

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Abstract: How to evaluate the safety risks of agricultural products is a crucial issue in current China. Based on agricultural products source, we first identify key elements to establish an evaluation framework with 5 first grade indicators and 17 secondary indicators. Subsequently we apply back-propagation model to set up a neural network risks evaluation model and train the established neural network with data collected from main Chinese food bases. Simulation shows the maximum error between trained neural network and the evaluation score of the experts is rather small and certify that back-propagation model can be applied to evaluate the safety risks of agriculture products.

Key words: Agricultural products, safety risks, neural network

INTRODUCTION

In current Chinese society, the food demand of consumers has converted from quantity-focused to quality-focused. Meanwhile, the food safety incidents are emerging in an endless stream, such as from illegally recycled cooking oil to contaminated vegetables and rice. Farmland is the beginning source to influence the quality of agricultural products. For the sake of agricultural products quality safety, the whole society necessitates supervision and control over the agriculture source (Shen, 2012). In fact, mass merely focus on control over terminals rather than source like producing area. It is a commonsense that superfluous inputs of fertilizer like phosphorous and nitrogen and all sorts of pesticide are the main reasons of the non-point source pollution. Deterioration of the rural ecological environment has seriously affected not only Chinese products competitiveness and continual development of agriculture but also the income of peasantry, even rural stability (Xin *et al.,* 2013).

Risks evaluation is the fundamental technical method of food safety management (Ahumada and Villalobos, 2009; Wang and Zhang, 2009). Risks evaluation of farm products quality has transferred to risks control other than merely terminal management which is the basic crux to the issue of food safety under circumstance of agriculture globalization and competitive improving. Risk management based on risks evaluation have been actively explored and practiced in western countries. For example, a cross-organ risks evaluation agency funded by American government was established in 1997. After that, the European Food Safety Authority (EFSA) has been set up a risk evaluation system in 2002 (Van der Vorst, 2006).

The focus of this article is no how to evaluate safety risk of Chinese agricultural products. Majority of literatures concentrate on the basic theory analysis such as the reason and strategy of farm products safety rather than systematical analysis based on quantify model, notwithstanding there are so many literatures on agricultural products risks as a hotspot issues. Among this, one barrier of agricultural products safety management would be scarce of scientific evaluation method. In this study, we establish a risks evaluation framework on Chinese agricultural products with a package of comprehensive assessment indicators. In order to evaluate the risks, we apply back-propagation neural network model which is a suitable for the multiple factors system.

EVALUATION INDEX FRAMEWORK FOR AGRICULTURAL PRODUCTS SAFETY

Identification of index system: This study aims to analyze the safety risks of Chinese farming products. Before assessment, it is an initial stage for us to set up a framework of evaluating indicators. On the basis of its own quality attributes of agricultural production source, we choose first grade assessment indicators, respectively, land utility, soil analysis, irrigation water detection,

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Table 1: Evaluation indicators

First grade indicators	Second grade indicators (E_i)
Land utility	E_1:Historical safeguard of tilled land
	E_2: Latent hazards governance
Soil analysis	E_3: Pesticides residues supervision
	E_4: Heavy metals control
	E_5: Adequacy of soil nutrient
	E_6: Soil structure applicability
Irrigation water detection	E_2: Water sufficiency
	E_8: Water quality suitability
	E_9: Microbial content
	E_{10}:Irrigating water pollution control
Environment governance	E_{11}:Surrounding environment of tilled land
	E_{12}:Ecological environmental conservation
	E_{13}:Resources preservation
Base management system	E_{14}:Manangement Information system
	E_{15}: Identification and traceability
	E_{16}: High-technology Hardware
	E_{17}: Compatibility with government system

environmental governance and base management system. Subsequently, we identify second grade indicators. As result, a evaluation index framework is shown as Table 1.

Description of index system: As can be seen, the basic indexes include 5 first grade indicators and 17 second grade indicators. Specifically, land utility index has two dimensions such as historical safeguard of tilled land and latent hazards governance. The former describes the security accident of particular tilled land in history recorders and the latter describe the possible hazards in the future such as measures which have been taken and options which have been scheduled to adopt.

Soil analysis can be demonstrated in four aspects, namely, pesticides residues supervision, heavy metals control, adequacy of soil nutrient and oil structure applicability. Among these factors, pesticides residues are one of the most critical problems which affect the quality of farming produce which are generally separated and determined by gas chromatography in fruits and vegetables in China.

Irrigation water detection consists of four items such as water sufficiency, water quality suitability, microbial content and irrigating water pollution control. Some provinces of China have given up agricultural self-sufficiency as depletion of water resources was unsustainable. The microbial content of water in bad quality water was examined in cases (Huo *et al.*, 2011).

It is crucial for society to maintain a correct knowledge on the relation between government leadership and mass participation and build an intact environmental management regime (Wang and Zhang, 2009). In this article, such factors are identified to describe the environmental governance as surrounding environment of tilled land, ecological environmental conservation and resources preservation.

Management systems in produce bases have significant influence on agri-food risks which need not only advanced management information system but also valid identification and traceability technologies with the application of high-tech hardware. Today, we have embarked upon the era of Internet of Things and era of big data and real-time in which human experiences are changed in revolutionary ways and also bring far-reaching impact to the agriculture. Furthermore, many bad managed base systems attribute to the failure of linking with governance organs of the state. Above factors are conclude as four indicators to reflect the base management system. It is crucial for food bases to coordinate with authorities in China which necessitates government organs to institute control and those bases to be familiar with state regulations and policies as well so as to decrease lemons market effects resulting from information asymmetry to certain extent.

ESTABLISHMENT OF BACK-PROPAGATION MODEL

Back-propagation model is an artificial neural network model. Neural network is of highly non-linear, associational memory, self-study, dynamic management and error tolerance. The learning process in back-propagation algorithm is basically divided into a forward and back propagation. Signals input from the input layer, transmit to the output layer with hidden units and generate output signals. When output expected would not be gotten at output end, the second step with back propagation of error signal will launch realistic output will get closer to the expected output such an adjustment (Balachandranand Radhakrishnan, 2005).

If the output of network realize the requirement error or action of training arrives the designated learning times, the program of learning would suspend, or the program would weights would continue to adjust the threshold of back propagation. With the steepest descent method, the learning rule of back-propagation network continuously adjust the weights and thresholds, thus minimize the sum of squared errors of that network (Chen, 2004; Robinson and Malhot, 2005).

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Network layers and neurons numbers: Through a back-propagation network with a hidden layer, any closed interval continuous function can be reached. Similarly, any n to m-dimension image chaotic system will be ended in a 3-layer back-propagation neural network (Shen, 2012). We select a three-layer BP neural network with a hidden layer. According to above evaluation index framework and indicators identified, we determine the input node of network model and choose 17 indicators as the input neuron of the network model. For the sake of calculation, we choose empirical formula as follows:

$$n_i = \sqrt{n+m} + \alpha \quad (1)$$

Among the equation, n_i, n, m and a, respectively stands for the number of hidden layer neuron,input layer neuron, output layer neuron and the constant from 1 to 10. In the following step, we determine the node number of hidden layer as 8 and number of output layer as 1. Here, we choose the function of Sigmoid excitation with the data range of output status [-1, +1] and rigidity adjusted by coefficient x. The function format is shown as follows:

$$f(x) = \frac{1}{1+e^{-x}} \quad (2)$$

EVALUATION OF BACK PROPAGATION MODEL

Transmission, network weights and threshold would be regulated by the error feedback, the learning speed determine the changing capacity of weighting value and threshold in each revolving training program. Here changing adaptive learning rate is chosen to automatically control the learning rate of network training in different stage. Generally, the learning rate range is between 0.01 and 0.8. For the sake of evaluating with back-propagation neural network, it is fundamental to collect suitable samples to train the network which will be done in the following section. Every neuron output value after initial weighting prone to zero, so each neuron weight value would be regulated while the change of Sigmoid function is at the maximum stage.

Collecting and processing of training sample data: We collect data from main Chinese agricultural production bases as samples to train the network. Chinese farming production base are mainly distributed in the Northeast of China, Yangtze river basin region, Huanghuai area, South and Northwest of China. Northeast of China has land of 1.0368 million km^2 which is the greatest produce production base. For an instance, Heilongjiang province, one of three provinces of Northeast, has steady grain production capacity of 50 billion kilograms per year since 2009 (Liu and Shen, 2009; Liu *et al*., 2011).

Table 2: Indicator scores of each sample

	Sample of bases							
Index	1	2	3	4	5	6	7	8
E_1	90	90	88	85	90	85	83	93
E_2	85	88	87	84	87	80	89	90
E_3	88	93	89	88	90	79	88	94
E_4	87	94	85	85	93	74	91	90
E_5	86	95	87	82	92	70	90	88
E_6	84	85	89	90	89	78	85	95
E_2	89	89	92	83	90	69	80	91
E_8	86	88	90	91	94	85	85	96
E_9	78	87	90	86	91	78	75	98
E_{10}	88	89	90	88	90	87	78	95
E_{11}	80	93	87	90	90	83	75	92
E_{12}	91	92	86	87	82	78	89	95
E_{13}	83	95	73	85	76	87	90	96
E_{14}	85	93	75	84	82	89	79	94
E_{15}	81	92	78	81	81	89	83	93
E_{16}	89	97	90	88	77	93	73	90
E_{17}	90	95	92	82	73	95	88	92

Table 3: Comprehensive score of each sample

	Sample of bases							
Score	1	2	3	4	5	6	7	8
	2.7	1.6	2.9	3.1	1.9	4.2	3.3	1.1

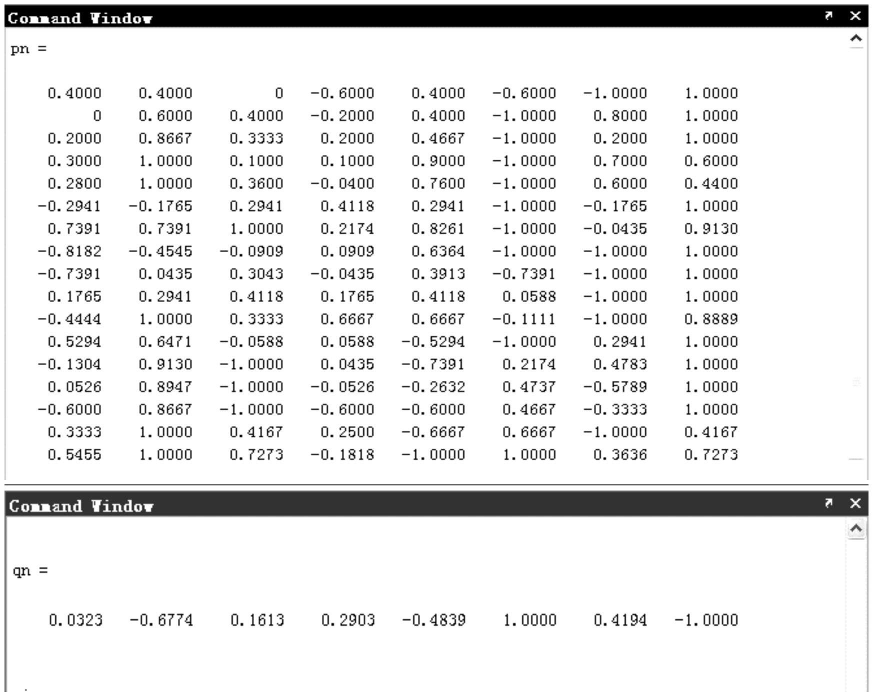
After collecting data, we invited relevant experts to assess specific bases. The state designed N = {100-90, 90-80, 80-70, 70-60, 60-0} which accordingly stands for {very good, good, ordinary, bad, very bad} as in Table 2 shown. The assessed scores of samples are cited in Table 3 which are confirmed by those experts based on designated state with expression as S. S = (0.5-1.5, 1.5-2.5, 2.5-3.5, 3.5-4.5, 4.5-5.5),which status accordingly stands for (very good, good, ordinary, bad, very bad).

Next, we standardize or normalize above data to limit the input and output data in the interval of [0, 1]or [-1, 1]. Such standardization of vectors can be realized through "premnmx" function with format:

$$[pn, minp, maxp, qn, minq, maxq] = premnmx(p, q) \quad (3)$$

$$[pn, minp, maxp] = premnmx(p) \quad (4)$$

Here, p and q means input and target output vector of network. Pn, minp and maxp presents quantifiable input vector, minimization of input vector and maximization of input vector. Qn, minq and maxq, respectively viewed as quantifiable target vector, minimization and maximization of target vector. Figure caption result of MATLAB is shown in Fig. 1.



Command Window

pn =

0.4000	0.4000	0	-0.6000	0.4000	-0.6000	-1.0000	1.0000
0	0.6000	0.4000	-0.2000	0.4000	-1.0000	0.8000	1.0000
0.2000	0.8667	0.3333	0.2000	0.4667	-1.0000	0.2000	1.0000
0.3000	1.0000	0.1000	0.1000	0.9000	-1.0000	0.7000	0.6000
0.2800	1.0000	0.3600	-0.0400	0.7600	-1.0000	0.6000	0.4400
-0.2941	-0.1765	0.2941	0.4118	0.2941	-1.0000	-0.1765	1.0000
0.7391	0.7391	1.0000	0.2174	0.8261	-1.0000	-0.0435	0.9130
-0.8182	-0.4545	-0.0909	0.0909	0.6364	-1.0000	-1.0000	1.0000
-0.7391	0.0435	0.3043	-0.0435	0.3913	-0.7391	-1.0000	1.0000
0.1765	0.2941	0.4118	0.1765	0.4118	0.0588	-1.0000	1.0000
-0.4444	1.0000	0.3333	0.6667	0.6667	-0.1111	-1.0000	0.8889
0.5294	0.6471	-0.0588	0.0588	-0.5294	-1.0000	0.2941	1.0000
-0.1304	0.9130	-1.0000	0.0435	-0.7391	0.2174	0.4783	1.0000
0.0526	0.8947	-1.0000	-0.0526	-0.2632	0.4737	-0.5789	1.0000
-0.6000	0.8667	-1.0000	-0.6000	-0.6000	0.4667	-0.3333	1.0000
0.3333	1.0000	0.4167	0.2500	-0.6667	0.6667	-1.0000	0.4167
0.5455	1.0000	0.7273	-0.1818	-1.0000	1.0000	0.3636	0.7273

Command Window

qn =

0.0323	-0.6774	0.1613	0.2903	-0.4839	1.0000	0.4194	-1.0000

Fig. 1: Example of a figure caption

Establishment of back-propagation model: We determine back-propagation neural network as a three-layer network structure (17-8-1) which consists of 17 input layer neurons, 8 hidden layer neurons and a output neuron. In this article, we apply delivery function of hidden layer and output layer individually as “tansig” and “purelin”.

Taking sample volume limitation into Consideration, we decide to choose improved training algorithm so as to avoid the disadvantage of traditional algorithm of back-propagation neural network. In such case, we apply the function of "traingdm" as training function with the momentum of the gradient descending method. The momentum tends to decrease the network sensitivity of errors.

In the graded descending method, the value of weighting is revised along the directions of negative gradient in K time, respectively without account of historical experience and previous gradient directions, concussion occur during the course of learning program and convergence turns slow The improved algorithm is shown as follows:

$$w_{ji}(k+1) = w_{ji}(k) + \eta\left[(1-\alpha)D(k) + \alpha D(k-1)\right] \tag{5}$$

where, D(K) stands for negative gradient in K time,D(k-1) stands for negative gradient in time of k-1.

When α = 0, weighting revision has some relationship with current negative gradient; while α = 1, weighting revision will rely on negative gradient of the last cycle. In this algorithm, as equivalent of damping item, the momentum decrease the volatility tendency during learning program,and have great possibility to improve the convergence. Through function of “net.trainParam”, we determine the training parameter of back-propagation neuron network. Here, two items will be determined, one is the maximum tolerable error (net.trainParam.goal) and the other is maximum learning times (net.trainParam.epochs). We set 5000 times as the maximum tolerable error and 10^{-5} as the maximum learning times. Specific codes is cited in the following equation:

$$\text{net.trainParam.epochs} = 5000 \tag{6}$$

$$\text{net.trainParam.goal} = 0.00001 \tag{7}$$

Training result and simulation: After calculating with MATLAB7.0, training result of back-propagation neuron network is shown in Fig. 2. The precise target demand realizes up to 10^{-5} after involving iterative 1910 times. Then we apply Sim function to simulate the network trained which demand format is shown as follows:

$$[Y, Pf, Af, E, perf] = sim(net, P, Pi, Ai,T) \tag{8}$$

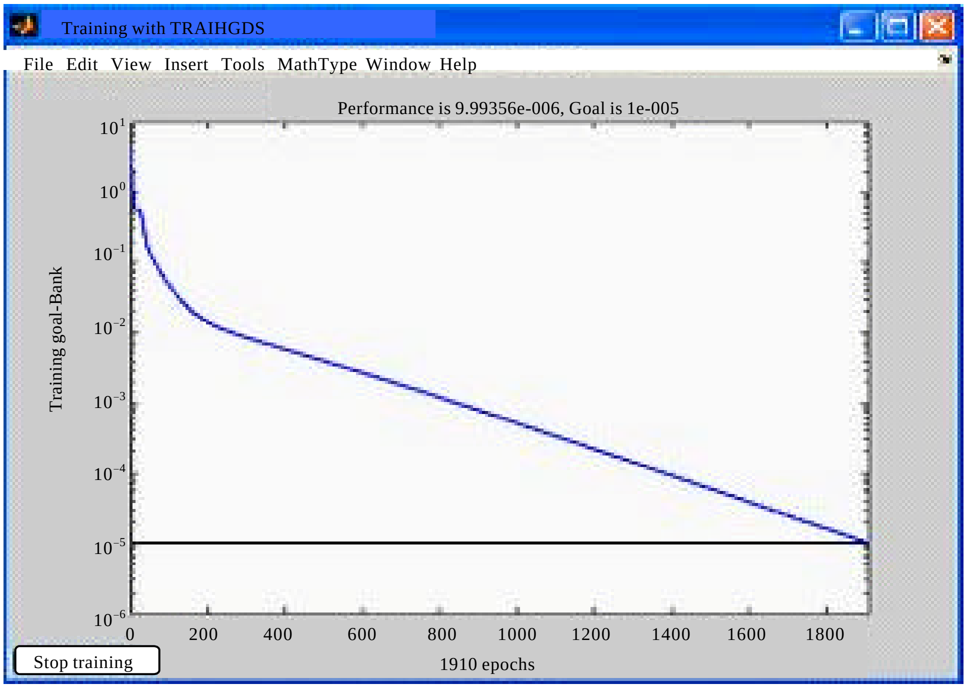


Fig. 2: Error curve of network training

Table 4: Error between output of BP network and the assessing score of the experts

Sample	Score of expert	Output	Error (%)
1	2.7	2.6970	0.10
2	1.6	1.6013	0.08
3	2.9	2.9046	0.15
4	3.1	3.0889	0.36
5	1.9	1.9043	0.22
6	4.2	4.2032	0.08
7	3.3	2.2326	0.19
8	1.1	1.0990	0.09

Here, Y, Pf, Af, E and perf stands for, namely, output of network, input delay status in training termination, the layer delay status in training termination, error between output and target vector and network performance. And net, P, Pi and Ai, stands for, namely, simulated network, input of network, initial status of input delay and the initial status of layer delay.

In order to apply better, we set Pf, E, Af, Pi, Ai, T, perf as network default value and choose the function of "postmnmx" to release the data. Demand format of standardized function "premnmx" is shown as follows:

$$[q1] = \text{postmnmx}(qln, minq, maxq) \qquad (9)$$

Here, q1 stands for data after reverse normalized;q1n, minq and maxq stands for, namely, output neuron network, minimum value and the maximum value of target vector. Though above function, the errors between the evaluation score of the experts and output of back-propagation network are shown as Table 4.

As can be seen, the maximum error between output of back-propagation network and the evaluation scores of the experts is merely at 0.36%,consequently, the training result is rather satisfactory.

CONCLUSION

With the relationship of the inherent connection of data known, back-propagation neural network sets up a sort of nonlinear mapping relationship between the inputs and outputs, so carries out forecast and judgment to new input. For the calculating time of back-propagation neural network model, it is not necessary to establish any precise mathematical model, nor relevant premise and hypothesis and merely necessitate direct and simple methods and high modeling accuracy. In this study, it can be presented in the simulation results of back-propagation neural network that with back-propagation neural network comprehensive evaluation results of agricultural products safety risks are correspondence with expert ratings.

As a consequence, this train of thought and method are proved to evaluate the safety risks of agricultural products with the neural network model. With regard to supervision and regulation of Chinese agriculture product, there are a variety of countermeasures to adopt based on Chinese actual circumstance. At the outset, it is essential to identify the latent hazard for bases produce and suitable alternatives are taken to improve the soil condition and limit pesticides residues. Moreover, it is fundamental to conserve the surrounding eco-environment of the produce bases, reinforce the full pollution supervision of irrigate water. Lastly, further improvements are required in identification and traceable system for agricultural products. Perfect safety risks management will help firms identify market changes that have quick benefit versus long term results but this owing to do instead of talking.

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