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Research Article

Research on Performance Evaluation Indicators and Method of Food Traceability System

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Abstract: Food traceability system is an effective way to guarantee food safety and its performance evaluation plays a key role food quality management. The paper takes pork traceability system performance evaluation for example and presents a new performance evaluation indicator system and method based on data mining technology. First based on analyzing attributes and functions of pork traceability system, a performance evaluation indicator system of pork traceability system with three grades is designed; Second, rough set and modified genetic algorithm are used to simplify the calculation structure, search the weights in BP algorithm calculation globally, optimize BP algorithm locally to avoid the network falling into the local extremes and then a new method for evaluating pork traceability system performance is presented. Finally the simulation results show that the presented performance evaluation indicators and method can improve evaluation efficiency and accuracy and can be used for evaluating pork traceability system performance practically.

Keywords: BP neural network, food quality management, performance evaluation indicator system, pork traceability system, rough set

INTRODUCTION

Food security problems directly impact on people's health and life safety and there is also low confidence from consumers for food safety and security. The food safety has caused globally extensive and serious concern. So, the current instance of the world in the entire food production process traceability system still need to be enhanced and building food production process traceability system is the best way to ensure food safety for food industry (Duc and Hilton, 2013). So how to find an effective method to evaluate the performance of the traceability system of food supply chain has become an important issue for the researchers related in the world also. The paper takes pork food for example to build a new evaluation indicator system and present a new evaluation based on BP neural network to evaluate the performance of pork traceability system (Feng and Ma, 2013).

Up to now there is limited literatures research on performance evaluation of food traceability system directly, so here take performance evaluation of food supply chain for example to summarize the present literatures. The paper provides a comprehensive view of the existing research of performance evaluation of food supply chain by 3 aspects as evaluation principles, evaluation contents and evaluation methods. Amandal (2012):

- At present, concerning evaluation principles, researchers in the fields related hold different points. Some claim that the evaluation principles to be followed for performance evaluation of food traceability system should satisfy the food management law, combine feasibility with scientificity, combine quantitative indicators with qualitative indicators and combine characteristic indicators with basic indicators. Other's view is objectivity principle, directionality principle, typicality principle, comparability principle, feasibility principle, quantification principle (Dresdner, 2014).
- Currently, concerning evaluation contents, the views of researchers in the fields related are various. Some think that the contents performance evaluation of food supply chain are food production, food transportation and food sales. And some focus on the management process evaluation of each node enterprise of food supply chain, including planning, reform, imparting knowledge, conditions and materials used in the various node enterprise of food supply chain (Disney and Towill, 2013).
- Concerning evaluation methods, Analytic hierarchy process (AHP) (Phien, 2012), Fuzzy Comprehensive Evaluation (FCE) (Souza, 2009), Data Envelopment Analysis (DEA) (Zhang and Yuan, 2015) and BP neural network algorithm (Amandal, 2012) are the most popular performance evaluation method of food traceability system, but all of above methods has its application defects

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which limits their practical application values. Here take BP neural network for example, it is a typical evaluation method based on data mining and it is wildly used for its powerful data mining ability and high evaluation accuracy. But BP neural network has the defects such as over-learning, local minimum which make the method easy to be trapped into local optimal.

In order to conquer the defects in training BP neural network, this study consults foreign documents, then advances a new method to improve BP training process through rough set and modified genetic algorithm. The comparison indicates that the new algorithm has many superiorities than ordinary BP algorithm. This superiorities include: simple algorithm process, fast convergence speed, get out local minimum easily, small oscillation and so on. In brief, this new algorithms can make the whole BP training process fast and stable.

MATERIALS AND METHODS

Evaluation indicator system analysis:
Attributes and functions analysis of pork traceability system: It can analyze attributes and functions of pork traceability system from the following aspects.

Analyzing safety factors in each supply chain node: As the standard of pork supply chain organization in the world is different, so the infrastructure of each production and distribution node is good and bad mixed together which plants many potential safety hazards for pork safety accidents. Concrete production and distribution nodes includes purchase link, transport link, processing link, packing link, storage link, sale link.

Analyzing the asymmetry of pork quality and safety information: The asymmetry of pork quality and safety information are regarded as the main reasons for pork safety accidents by most researchers. It includes asymmetries among different nodes of pork supply chain, asymmetries between governments and all the nodes in pork supply chain, asymmetries between governments and customers, asymmetries between management agents and clients.

Analyzing the tracing process of pork safety information: In order to eliminate food safety hazards, master food safety information, it is necessary to trace the total pork supply chain process bilaterally. One kind of tracing direction is from the pork production base to the end consumer which can be called positive direction trace; Another kind of tracing direction is from the end consumer to the pork production base which can be called reverse direction trace.

Table 1: Evaluation indicator system for pork traceability system performance

Target hierarchy	First -class indicator	Second -class indicator	Third-class indicator
Performance of pork traceability system	Financial investment and output	Financial investment	Traceability system construction investment
			Government subsidies
		Output of the investment	Sales growth rate
			Growth of market shares
			Brand awareness growth
	System construction and management	Information file	Information file of breeding enterprises
			Information file of slaughter enterprises
			Information file of logistics enterprises
			Information file of sale enterprises
		Technical safeguard	Pork information database construction
			Pork safety information tracking technology
			Safety logistics construction and security
		Pork traceability system construction	Pork accident punishment system and execution
			Unexpected event handling capability
			Pork safety information disclosure
			Coordination and cohesion between the nodes of the system
			The environmental protection of the system
	Customer service	Customer satisfaction	The satisfaction of government supervision department
			Pork customer satisfaction
		Customer service	Consumer complaints handling capacity
			Pork quality assurance ability
			Fast and accurate processing capacity of unsafe pork
	Learning and development	Regulation construction	Self evaluation and promotion system of pork traceability system performance
			Pork safety knowledge and comprehensive quality improvement system of employees
		Training system	The application and training of pork tracking quality
			Application and training of new technology for pork safety information processing

Table 2: Part evaluation results of different traceability systems of pork supply chain

	Financial investment and output	System construction and management	Customer service	Learning and development	Final evaluation
A	3.002	3.221	3.889	2.342	3.278
B	3.662	3.579	4.054	3.912	3.889
C	4.017	4.358	4.531	4.001	4.321

Analyzing the main contents of pork traceability system: Pork traceability system is a systematic engineering and contains many nodes of supply chain. Each nodes has its own strict management standard to document different information for Behavior subject and product information. That means that it has unique information document requirements for production stage, processing stage, logistics stage and sale stage.

Evaluation indicator system construction: It is found from the study on the unique production process of traceability system of pork supply chain and the paper uses the BSC (Balanced Score Card, BSC) to analyze the concrete requirements of the performance evaluation of traceability system of pork supply chain and builds a new performance evaluation indicator system from four dimensions of financial investment and output, system construction and management, customer service, learning and development. BSC is a popular tools to build system evaluation indicators and wildly used in many famous corporations in the world (Chen and Huang, 2010). The new performance evaluation indicator system is an extensive and scientific system and includes four hierarchies, four categories, nine second-class indicators, twenty-six third-class indicators, Table 1 for details.

Optimizing BP algorithm structure by rough set: BP neural network is the learning supervised by instructors and the learning rule is offered by a group of training set describing network behavior: $\{p_1, t_1\}$ $\{p_2, t_2\}$, …, p_Q, $t_Q\}$In the rough set, the training set is the decision set. p_i is the condition attribute of decision table, expressed by C; t_i is the decision attribute of decision table, expressed by D. Generally, there is a certain degree of dependence between condition attribute and decision attribute, defined by the degree of dependence, see Eq. (1) (Guo, 2013):

$$\gamma_C(D) = |pos_C(D)|/|U| = \left|\bigcup_{X \in U/D} C(X)\right|/|U| \tag{1}$$

In the Eq. (1), $pos_C(D)$ is the C positive domain of D. $\gamma_c(D)$ makes a measurement on proportion that the objects in the decision table can be correctly partitioned in decision class based on the knowledge of attribute C.

Due to the dependence and relevance between condition attribute and decision attribute, as for decision attribute, not all the condition attributes are necessary, thus bringing the problem of attribute reduction, i.e., on the premise of unchanged classification ability, expressing the decision table in the simplest way.

While determining the attribute reduction of decision table, often used is the concept of attribute significance, the definition of which is $sig(\alpha, B; D) = \gamma_{\{\alpha \cup B\}}(D) - \gamma_{\{B\}}(D)$, showing the significance of attribute α, on attribute B with respect to decision attribute D (Mentzer and Keebler, 2014).

Determining the attribute reduction of decision table: As the relative reduction of decision table includes core attribute and intersection is core, in the algorithm for determining relative reduction, we generally use definition first to determine the relative core of decision table.

As for $\forall R \in C$, if R meets the condition for satisfied $pos_{\{C-R\}}(D) = pos_c(D)$, R is called D unnecessary in C, otherwise, R is called D necessary in C. All the sets constituted by D necessary original relationship in C are called the core of C with respect to D, recorded as $CORE_D(C)$ (Guo, 2013).

Some of the relative core of decision table is the relative reduction, so after determining relative core, we shall first decide it to be relative reduction or not. Judgment is made based on the following 2 conditions generally.

If the non-empty subset P of condition attribute C meets the condition of (1) $pos_p(D) = pos_C(D)$; (2) $pos_R(D) \neq pos_C(D)$ of R exists for any $R \subseteq P$, P is called the reduction of C with respect to D, recorded as REDD(C).

Therefore, make $reduct = CORE_D(C)$, redundant attribute set $redundant = C\text{-}CORE_D(C)$. If $pos_{reduct}(D) = pos_C(D)$, it means the set $reduct$ (relative core at this time) is the relative reduction of decision table; otherwise, add every attribute in the redundant attribute set to $reduct$, so as to determine the attribute α_i reaching the largest value according to the definition of attribute significance, making $reduct = reduct \cup \{\alpha_i)$, $redundant = redundant \cup \{\alpha_i)$ updating to be tested reduction set $reduct$ and redundant attribute set $redundant$. Continue to cycle until $pos_{reduct}(D) = pos_C(D)$ satisfied; $reduct$ at this time is the relative reduction of decision table (Mentzer and Keebler, 2014).

Improving BP algorithm structure by rough set: Determining the relative reduction is expressing original decision table in the simplest way, but making no changes on the classification ability. Hence, first make a judgment on whether training set has relative reduction via rough set so as to reduce its dimensionality, then input BP neural network model to carry out the training on learning rules. Besides, neural network can filter the random noise brought in the process of training sampling to certain extent, while rough set is sensitive to the noise. Combining such two can not only improve the real-time performance of system but also strengthen the fault-tolerant capability of system.

Specific steps for rough set improving BP neural network are as follows:

Table 3: Evaluation performance of different algorithms

Algorithm	Method in the paper	Ordinary BP evaluation method	Ordinary fuzzy evaluation method
Accuracy rate	91.98%	80.299%	75.22%
Time consuming (s)	13	587	12

- Discretizing and normalizing original sample space to obtain original decision table
- Making use of the reduction algorithm of attribute significance to carry out reduction on the decision table to eliminate redundant condition attribute and obtain reduction decision table
- Deduction decision table inputting BP neural network training, successively updating weight and threshold, until meeting the given accuracy
- Testing the trained BP neural network with testing sample to obtain predictions, verifying the performance of improved BP network.

Improving genetic algorithm for optimizing network parameters: Making use of global rough search of genetic algorithm and local detailing and optimizing of BP algorithm to look for the optimal weight and threshold of network, so as to conquer the defect that using BP algorithm only is easy to fall into local extreme point. Encoding the weight and threshold of network into the individual of genetic algorithm; first using genetic algorithm to optimize individual, until the sum of absolute value of BP network prediction error reaching the given accuracy; at this time, individual, after decoding, is the approximate solution of the optimal solution of weight and threshold. Based on this, local optimization is carried out with BP algorithm to find the optimal weight and threshold of network.

Individual encoding: There are generally two kinds of individual encoding in genetic algorithm: binary encoding or real number encoding. As the former needs to discretize continuous space while optimizing, which may cause a certain encoding error, while the latter has no discretization error, with intuitive description of problems and high solution accuracy, this thesis adopts the latter.

BP network adopts 3-layer network, comprised of input layer, hidden layer and output layer, so the individual consists of weight w_1 and threshold b_1 from input layer to hidden layer and weight w_2 and threshold b_2 from hidden layer to output layer. w_1, b_1, w_2 and b_2 are matrix or vector, each element being encoded as real number.

Fitness function: Training sample predicts system output after inputting BP network, taking the sum of absolute value of error between actual output and expected output as individual fitness value, see Eq. (2):

$$F = k(\sum_{i=1}^{n} abs(y_i - o_i)) \tag{2}$$

In the Eq. (2),

n = Network output contacts number
y_i = The expected output of the ith node of BP network
o_i = The predicted output of the ith node
k = Coefficient

The small the absolute value of error is, the better the predictive ability of network is. However, in the genetic algorithm, reciprocal is generally adopted as fitness value. The larger the fitness value is, the better the predictive ability is.

Selecting operation: Calculate selective probability according to the fitness value of each individual in the population and select excellent individuals from parent population pursuant to the selection strategy of “survival of the fittest” to form new population. This thesis adopts roulette selection, first calculating the selection probability of each individual, then generating one [0, 1] random number in each round according to population size iteration. After that, calculate cumulative probability; when the cumulative probability is larger than the generated random number, the pointed individual at this time is selected, cycling like this until meeting iteration number. Eq. (3) is for selection probability calculation and Eq. (4) is for cumulative probability (Lummus and Cochan, 2013):

$$P_i = \frac{(k / F_i)}{\sum_{i}^{N} (k / F_i)} \tag{3}$$

$$cumul_i = cumul_{i-1} + P_i \tag{4}$$

In the Eq. (3), F_i is the fitness value of individual i; as it is better to have small fitness value, reciprocal shall be determined on fitness value before individual selection; k is coefficient; N is population individual number.

Crossover operation: Arbitrarily select two individuals from new population and interchange part of genes according to certain way to generate two new individuals.

The value of crossover probability p_c in crossover operation exerts a direct impact on the convergence and effectiveness of genetic algorithm. The large the p_c is, the faster the new individual is generated, but the large the possibility that genetic algorithm is degenerated into random research algorithm; the small the p_c is, the slower the search speed is, even stagnating. Hence, crossover probability with self-adaption is adopted, as shown in the Eq. (5):

$$P_c = \begin{cases} \dfrac{(P_{c1} - P_{c2})(f' - f_{avg})}{f_{\max} - f_{avg}}, & f' \geq f_{avg} \\ P_{c1} & f' \prec f_{avg} \end{cases} \tag{5}$$

In the Eq. (5), f_{avg} indicates the average fitness value of each generation of population, $f_{\max}$ indicates the largest fitness value of each generation of population, f' indicates the larger fitness value between 2 individuals to be crossed over. When f' is equal to or greater than f_{avg}, reduce the crossover probability; otherwise, increase the crossover probability.

As the individual adopt real number encoding, crossover operation adopts the method of single-point crossover of real numbers. When meeting the crossover probability, the crossover operation algorithm of k th chromosome a_k and the l th chromosome a_l in the position of j is shown in Eq. (6) and (7), in which b is a random number among [0, 1]:

$$a_{kj} = a_{kj}(1-b) + a_{lj}b \tag{6}$$

$$a_{lj} = a_{lj}(1-b) + a_{kj}b' \tag{7}$$

Mutation operation: Arbitrarily selecting one individual from new population and substituting some gene values in the encoding string with other genes, thus forming a new individual. Similar to crossover probability, if the mutation probability p_m is too large, the genetic algorithm will be degenerated into random search algorithm; if it is too small, the algorithm is easy to be converged in local extreme point untimely, not easy to generate new individual gene. Therefore, mutation probability with self-adaption is adopted, as shown in the Eq. (8) (Lummus and Cochan, 2013):

$$P_m = \begin{cases} \dfrac{(P_{m1}-P_{m2})(f'-f_{avg})}{f_{\max}-f_{avg}}, & f' \geq f_{avg} \\ P_{m1} & f' \prec f_{avg} \end{cases} \tag{8}$$

In the Eq. (8), the meanings of f_{avg}, $f_{\max}$ and f' is the same as those in Eq. (8). When meeting mutation probability, randomly select mutation position. Select the jth chromosome a_{ij} of the ith individual to carry out the mutation; mutation operation is as Eq. (9):

$$a_{ij} = \begin{cases} a_{ij} + (a_{ij} - a_{\max}) * f(g) & r \succ 0.5 \\ a_{ij} + (a_{\min} - a_{ij}) * f(g) & r \geq 0.5 \end{cases} \tag{9}$$

In the Eq. (9), $a_{\max}$ is the upper limit for the value range of chromosome a_{ij}, $a_{\min}$ is the lower limit of chromosome a_{ij}; $f(g) = r_2(1-g/G_{\max})^2$, r_2 is a random number; g is the current iteration frequency, $G_{\max}$ is total iteration frequency, r is the random number among [0, 1].

Improving genetic algorithm: Although genetic algorithm has a lot of advantages, there are also many problems, like easy to be converged in premature set. This thesis adopts the method of protecting elite individuals to improve the classic genetic algorithm, i.e., the individual with the best fitness in each round of iteration will be kept to the next generation of population without the operation of crossover or mutation operation. Besides, substituting the individuals with the worst fitness generated after crossover and mutation operation in the population with the optimal individual in current population, also able to improve classic genetic algorithm. After the genetic algorithm optimization is finished, optimal individuals are generated, i.e., roughly selecting optimal weight and threshold to be the initial structure parameter of BP network, then making use of the parameter of BP algorithm for locally optimizing network, so as to achieve more accurate mapping from input to output.

RESULTS AND DISCUSSION

With C language, the presented evaluation indicator and method are realized. 3 traceability systems of pork supply chain are taken as experimental data to built experimental database to evaluate pork traceability system performance. The 3 pork traceability systems of supply chain are named A, B and C respectively.

Table 2 and 3 show the specific evaluation results. Table 2 shows part of the evaluation results of the presented evaluation indicator and method in the study and Table 3 shows the evaluation results of ordinary multi-layer fuzzy comprehensive evaluation model (Souza, 2009), ordinary BP neural network algorithm (Amandal, 2012) and the method presented in the study. The experiment is conducted through PC. PC configurations are as follows: P4 2.5G CPU and 512 M memories.

Limited to paper space, the evaluation of intermediate results is omitted here, Table 3 only provides parts of evaluation results and final comprehensive evaluation results.

CONCLUSION

Comprehensive evaluation of traceability systems performance of food supply chain is an effective method for guaranteeing food quality and safety, lying in the core status of the entire evaluation system of food industry. Thus, there is a favorable application prospect for the analysis and competitiveness evaluation of traceability systems performance of food supply chain. And, on the basis of the principle of performance evaluation, the paper analyzes and builds comprehensive evaluation indicator system of traceability systems performance of food supply chain. And, through rough set and modified genetic algorithm, taking advantage of the high system evaluation accuracy of BP neural network algorithm, overcoming the actual defects of original BP algorithm in poor calculation convergence, a new BP neural network algorithm for food traceability system performance evaluation based on rough set and improved genetic algorithm, is presented The experimental results show that the algorithm and evaluation indicator system presented in this study can be used to evaluate food traceability systems performance of supply chain practically.

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