RESEARCH ON SUPPLY CHAIN PERFORMANCE EVALUATION OF FRESH AGRICULTURAL PRODUCTS
/
农鲜产品的供应链绩效评价研究

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Abstract: *Supply chain performance evaluation for fresh agricultural products is one of the key techniques and a research hotspot in supply chain management and in fields related. In order to overcome the deficiencies of traditional models, a new fuzzy neural network algorithm for supply chain performance evaluation of fresh agricultural products is presented based on the analysis of present literatures in the field. First the model structure of the presented algorithm is designed and simplified combining the advantages of BP neural network model and fuzzy comprehensive evaluation model; secondly the presented algorithm is improved through improving its calculation procedures and learning methods. Finally the model is performed with the data from certain supply chains of fresh agricultural products enterprises and the experimental results show that the algorithm can improve calculation efficiency and evaluation accuracy when used for supply chain performance evaluation of fresh agricultural products, practically.*

Keywords: *supply chain management, performance evaluation, fuzzy neural network algorithm, fresh agricultural products*

摘要*：农产品的供应链绩效评价是供应链管理中的一个关键技术，也是相关领域的研究热点之一。为了克服传统绩效评价模型的缺陷，在分析现有研究文献的基础上，本文提出了一个农产品供应链绩效评价的模糊神经网络。首先在结合BP 神经网络和模糊多级评判的优势，本文设计并简化了模糊神经网络的网络结构；其次通过改进模糊神经网络的运算步骤和学习方法，以达到改进本文模型的目的。最后利用某农产品企业的供应链数据，实现了本文模型，实验结果表明本文算法应用于农产品供应链管理绩效评价时，能够提升算法效率和评价精度。*

关键字*: 供应链管理, 绩效评价，模糊神经网，农产品*

INTRODUCTION

Because fresh agricultural products are perishable and difficult to store, during transportation and storage they are often damaged and unable to achieve their value function for all kinds of reasons, so that the enterprises participated in the fresh agricultural product supply chain pay attention to supply chain and its management model. They try to use the minimal cost to optimize the process of production to meet customers' demand. Supply chain performance evaluation (SCPE) is used to evaluate and assess the benefit and effect of supply chain implementation, which is one of the key components of supply chain management. Building a completed set of fresh agricultural product supply chain performance evaluation metrics is conducive to assess the competitiveness of fresh agricultural product supply chain member enterprises as well as the advantages and shortages of supply chain management. So the supply chain performance evaluation has become a research hotspot for researchers and enterprises related [1].

There are mainly following methods used for the overall evaluation of the performance of supply chain.① Multi-hierarchy comprehensive evaluation of fuzzy mathematics, its principle is to firstly evaluate various kinds of factors of the same thing, dividing into several big factors according to certain attribute; Then carry out initial hierarchical comprehensive evaluation on certain big factors, and carry out high hierarchical comprehensive evaluation on the result of initial hierarchical comprehensive evaluation based on that. The key of successful application lies in correctly specifying the factor set of fuzzy evaluation and reasonably form fuzzy evaluation matrix, obtaining evaluation result according to matrix calculation result. Make use of fuzzy

前言

由于生鲜农产品容易腐烂变质、贮存难度大，因此生鲜农产品在长途运输和存贮过程中经常会因各种原因而出现各种损坏，无法使农鲜产品实现保值和增值，因此农鲜产品相关企业为此需要承担相当的市场风险。为了实现农鲜产品的保值和增值，并降低市场风险，农鲜产品企业将采用了供应链及其管理模式，企业通过供应链管理实现用最少的成本实现产品从生产到销售的整个过程达到利益最优化。供应链绩效评价就是对企业供应链实施的结果和成效进行评估考核，这也是现代供应链管理的关键组成部分之一。农鲜产品企业构建一套合理的供应链绩效评价指标体系不仅有利于提升企业供应链管理绩效，也有利于评价企业竞争力，从而引导企业采取针对性措施，提升产品供应链绩效。因此供应链绩效管理和评价研究已经成为业内研究者企业的研究热点之一[1]。

目前用于供应链绩效综合评价的方法主要有以下种。① 模糊多层次评价法，该方法原理是首先根据评价对象的各个评价指标的具体特征进行单个评价，随后对不同层级的评价根据前面评价结果逐层进行不同层级的评价指标进行评价，根据模糊矩阵的计算结果获得最终的绩效评价结果。该方法的成功应用的关键在于正确确立一套模糊评价因子和建立模糊评价隶属矩阵。该方法能够获得评价对象的各个指标之间权值梯度的相互关系，方法简单易行，但是该方法需要为评价对象构建合理的评价矩阵，而由于不

comprehensive evaluation method can obtain the value grade of evaluated object or mutual precedence relationship; however, the method requires to establish appropriate evaluation matrix of evaluation object, which will obtain different evaluation matrixes due to the non-conformity of different experts, leading to the non-conformity of final evaluation results[2]. ② Data envelopment analysis (DEA), starting from the perspective of relative efficiency, evaluates each decision-making unit, and the indicators selected are only relied on input and output. As it doesn't rely on specific production function, it is effective for dealing with the evaluation with various kinds of input and output indicators, suitable for the analysis of benefit, scale economy and industry dynamics. But it is complicated in computational method, subject to certain limitations in application[3]. ③ Grey correlation analysis is a multi-factor statistical analysis method, which takes the sample data of each factor as basis to describe the strength, size and order of relationship among factors with Grey correlation; If the situation of change of two factors reflected by sample data is relatively consistent, they have relatively large correlation; otherwise, the correlation is relatively small. The merits of this method lie in that that it is intellectually clear, able to reduce the loss caused by information asymmetry to a great extent and less requires for data with less workload; however, its main demerits are that it requires for human determination of the optimal values of each indicator, it has strong subjectivity and it is difficult to determine the optimal values of some indicators[4].④ Analytic hierarchy process (AHP) effectively combines qualitative analysis with quantitative analysis, not only able to guarantee the systematics and rationality of model, but also able to let decision makers make full use of valuable experience and judgment, so as to provide powerful decision-making support for lots of regulatory decision making problems. The method has such strengths as clear structure and simple computation, but due to its strong subjective judgment, the method also has shortcomings like low evaluation accuracy[5]；⑤BP neural network method, the method is adopted in the processing of uncertain information. If the input mode is close to training sample, the evaluation system is able to provide correct reasoning conclusion. The method has such advantages as wide applicability and high evaluation accuracy, but it also has some disadvantages like easy to fall into local minimum in the computation, low rate of convergence, and etc [6].

Supply chain performance evaluation is a dynamic process and there are lots of factors influencing its quality, and the influences of these factors are different; therefore, it is difficult to express the evaluation results only with a mathematical formula, which actually is a complicated, non-linear comprehensive decision-making problem. Hence, there is irrationality to adopt the above five methods to carry out comprehensive evaluation of its quality. So the paper tries to integrate the BP neural network model and fuzzy comprehensive evaluation model and advances a new fuzzy BP neural network algorithm which can achieve the advantages and overcome the deficiencies of the two models.

MATERIAL AND METHOD

Establishment of evaluation indicator system

As the supply chain of fresh agricultural products needs to focus on quality safety and circulation efficiency, meanwhile, trying to reduce the loss in the logistics process, which is a special and complicated supply chain, the similarity of general supply chain and the specialty of

同专家评价的不一致，从而使得评价矩阵的合理构建难度较大，这也容易导致最终评价结果的不完整性和评价精度不高[2]；② 数据包络分析法(DEA)，数据包络分析法评价时的出发点是从相对有效性的角度，对各个评价对象的各个单元进行逐一评价，选取的评价指标依赖于投入和产出。该方法在处理多投入、多产出指标时的供应链绩效评价时比较有效，比较适用于企业的效益分析、规模经济分析、产业动态分析。同时该方法计算上较为复杂，使得他的应用价值受到很大的局限[3]。③ 灰色关联度分析法，该方法是一种多因素的统计分析方法，它依据各因素的样本数据，描述各因素间关系式时采用灰色关联度，如果样本数据的变化趋势与某两因素变化态势基本保持一致，则可以认为它们之间的关联度较大；反之则认为其关联度较小。灰关联评价法的评价思路明晰，可以大大减少由于信息不对称所导致的评价误差，该算法对样本数据的要求也不高，计算方法的工作量也不多；但是该方法需要对确定各项指标的最优值，而这个过程的主观性太强，甚至有些指标最优值根本就无法确定[4]。④ 层析分析法，该方法结合了定性分析和定量分析的各自优势，能确保算法运用中的合理性和系统性，也能能让批判者运用其有自己的评判经验，为大量规则决策的评判问题提供决策支持。层次分析法具有计算简单、模型结构结构清晰、易于理解等许多优点，同时该方法也由于是基于平均专家的主观判断的原因，导致该方法的评价精度不高[5]；⑤BP 神经网络法，该方法主要采用了梯度搜索技术，使得模型结构的期望输出值与实际输出值之间的误差最小，该模型具有强大的非线性信息处理能力，假如训练样本与输人模式比较接近，很容易就可以得到就正确的评价结果。该方法的优点是适用性广，有较高评价精度，但是该方法也具有在计算中收敛速度慢、算法效率低等缺点[6]。

供应链绩效管理评价是一个动态的过程，其中的涉及到的许多因素会影响评价的质量，因此仅仅用一个数学方法难以进行精确有效的评价，因为这些方法确实也存在复杂的、非线性的综合决策问题。本文试图整合模糊综合评价和 BP 神经网络评价的优势，并力图克服两方法的缺陷，从而提出一种的新的模糊神经网络模型，并使之能够应用于农鲜产品企业的供应链绩效评价。

材料与方法

评价指标系统构建

如前述，生鲜农产品的企业产品供应链需要高度注重产品的质量安全和供应链的流通效率，同时还应该尽量减少物流运转中的各种损耗，农鲜产品供应链是一个复杂且特殊的

cold chain of fresh agricultural products shall be combined to establish evaluation indicator system of performance. Integrating the general idea of performance evaluation of supply chain and performance evaluation of logistics system, combining existing research literature, this paper will, from such two aspects as evaluation of internal and external performance, establish the evaluation indicator system of the performance of supply chain of fresh agricultural products, which includes 4 hierarchies, 2 categories, 6 second-grade indicators, 16 third-grade indicators; see table 1 for details [7,8,9].

供应链，因此构建农鲜产品供应链绩效评价指标体系时既要考虑普通供应链的公共特点，更要考虑生鲜农产品供应链的个性化特性。结合农鲜产品供应链绩效评价和物流系统绩效评价的思想，参阅大量现有研究文献，本文将从内部绩效和外部绩效评价两个角度构建生鲜农产品供应链绩效评价指标体系， 该体系包括四层，其中 2 个一级指标，一个二级指标，16 个三级指标，具体见表 1 [7, 8, 9]。

Table 1 / *表 1*

Evaluation indicator system of supply chain performance / *供应链绩效评价指标系统*

Target Hierarchy / *目标层*	First-class Indicator / *一级指标*	Second-class Indicator / *二级指标*	Third-class Indicator/ *三级指标*
Performance of Supply Chain of Fresh Agricultural Products / *农鲜产品供应链绩效*	External Performance / *外部绩效*	Customer Service Level / *顾客服务水平*	Timeliness of Delivery / *运输及时性*
			Accuracy of Delivery / *运输准确性*
			Security / *安全性*
			Customer Dissatisfaction Rate / *顾客不满意率*
		Adaptability of Logistics Service / *物流服务可行性*	Applicability of Products / *产品适用性*
			Applicability of Time / *时间适用性*
			Applicability of Quantity / *质量适用性*
		Integration of Logistics Service / *物流服务集成性*	Integration Level of Service / *服务集成度*
			Intimacy of Cohesion / *凝聚力*
	Internal Performance / *内部绩效*	Enterprise Input / *企业投入*	Assets Input / 财产投入
			Personnel Expenditure /个人支出
			Logistics Cost /物流成本
		Internal Operation / *内部运作*	Informational Level /信息水平
			Resource Utilization /资源利用率
			Logistics Operation / 物流运作
		Enterprise Income / *企业收入*	Cost Benefit /成本收益
			Business Growth Rate/业务增长率
			Profit Growth Rate/利润增长率

Derivation of supply chain evaluation algorithm

- Network structure design of fuzzy neural network: The fuzzy neural network structure adopted by this paper is based on Takagi-Sugeno model, and the network consists of antecedent network and consequent network, in which the former is used to match the antecedent of fuzzy rule and the latter is used to realize the consequent of fuzzy rule. Network structure is as shown in picture 1.

供应链评价模型

-网络结构设计和模糊神经网络：基于 Takagi-Sugeno 算法结构，本文设计了一种新的模糊神经网络结构，该模型的网络结构主要由前件网络和后件网络构成，其中模糊规则的前件匹配工作由前件网络来完成，模糊规则年工作则由后件网络来完成，模糊神经网络的结构图如图 1 所示[9]。

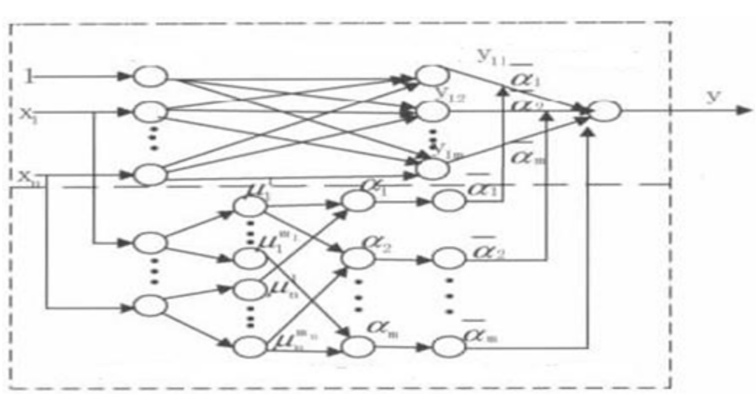

Fig. 1 - The structure of the improved fuzzy BP neural network algorithm / *改进模糊神经网络结构图*

(1) Antecedent Network: Antecedent network is comprised of 4 layers. The first one is the input layer, each node of which is directly connected to each component of input vector, playing a role of directly propagating input value $x=(x_1,x_2,...x_n)^T$ to the next layer. The number of nodes of the layer is $N_1=n$. The second layer is the fuzzification layer, and each node represents one linguistic variable value; this paper chooses 4 linguistic variables (excellent, good, medium and poor). The function of the layer is to compute the membership degree μ_i^j of each input component subordinating to each fuzzy set of linguistic value, which meets formula 1[10].

（1）前件网络

前件网络由4 层组成。第一层为输入层。它的每个节点直接与输入向量的各个分量连接，它起着直接将输入值 $x=(x_1,x_2,...x_n)^T$ 传送到下一层的作用。该层的节点数为 $N_1=n$。

第二层是模糊化层。每一个节点代表一个语言变量值，本文选择4个语言变量(优、良、中、差) 。该层的作用是计算各输入分量属于各语言值模糊集合的隶属度 μ_i^j，其满足式1[10]。

$$\mu_i^j=\mu_{Ai}^j(x_i), i=1,2,...n,\ j=1,2,...m_j, m_i=4 \tag{1}$$

In formula 1, n is the dimension of input, and the fuzzy partition of x_i is 4. The membership functions in this paper adopt Gaussian function, as shown in formula 2.

n 表示输入量的维数，x_i 的模糊分割数是4。高斯函数是本文采用的函数，形式如式2所示。

$$\mu_i^j=e^{\frac{-(x_i-c_{ij^2})}{\delta_{ij}^2}} \tag{2}$$

In formula (2), c_{ij^2} and δ_{ij}^2 indicate the center and width of membership function respectively. The total number of nodes of the layer is formula 3.

在公式(2)中，c_{ij^2} 表示隶属函数的中心，δ_{ij}^2 表示宽度，第二层的节点总数可以通过公式3计算得到。

$$N_2=4n \tag{3}$$

The third layer is the rule-based reasoning layer, each node of which represents a fuzzy rule, the role of which is to match the antecedent of fuzzy rule and compute the fitness of each rule, i.e. formula 4.

本文网络结构的第三层为规则推理层。规则推理层中的每个节点均对应于计算中的一条模糊规则，其作用主要是匹配模糊规则的前件，并据此计算得出每条规则的具体应用适用度，具体如公式4所示。

$$\alpha_j=\mu_1^{i1}\mu_2^{i2}...\mu_n^{in} \tag{4}$$

In formula (4), $i_1\in\{1,2,3,4\},...j_n\in\{1,2,3,4\}$, , $j=1,2,...m.m=4$, The total number of nodes of the layer $N_3=m$. As for the given input, only those linguistic variable values close to input point have relatively large membership degree, and the membership degree of those linguistic variable values far away from input point is either too small or 0. If the membership degree is too small (such as less than 0.05), it can be approximately valued as 0.

The fourth layer is the normalization layer, the number of nodes of which is the same as that of the third layer, i.e. $N_4=N_3=m$; what it realizes is the normalization computing, i.e. Formula 5.

在公式(4)中，$i_1\in\{1,2,3,4\},...j_n\in\{1,2,3,4\}$, $j=1,2,...m.m=4$。在这一层中的节点总和为 $N_3=m$。对于实际计算中给定的某个输入值，只有权值接近输入点的那些输入变量值，其隶属度才有较大权值，远离输入点的输入变量值的隶属度一般很小，甚至为0。当隶属度权值较小时(本文定义为小于0.05) 时，可将其值视为0。

本文算法结构中的第四层为归一化层。归一化层的节点总数与上层相同，也是 $N_4=N_3=m$，归一化层是实现归一化计算的层级，如公式5所示。

$$\overline{\alpha_j}=\frac{\alpha_j}{\sum_{i=1}^{m}\alpha_i}, \qquad j=1,2,...,m \tag{5}$$

(2) Consequent Network: The first layer of consequent network is the input layer, which propagates the input variable to the second layer. The input value of the 0th node in the input layer $x_0=1$, the function of which is to provide the constant term in the consequent of fuzzy rule. There are m nodes in the second layer, and each node represents one rule; the function of the layer is to compute the consequent of each rule, i.e. formula 6. The third layer is the output layer, the evaluation result value of which is formula 7.

（2）后件网络 输入层是后件网络的第一层，输入层将输入变量传输到第二层。第一层（输入层）中第0个节点的输入值为规定为 $x_0=1$，这样的规定可以为后继计算提供模糊规则运算后的常数项。在第二层总共有 m 个节点，他们分别代表 m 条不同的规则，第二层的作用主要是计算各条规则的后件值，可以通过公式6计算求得。本文模型的第三层为输出层，该层的评价值可以通过公式7计算求得。

$$y_{ij} = p_{j0}^1 + p_{j1}^1 x_1 + p_{j2}^1 x_2 + p_{j3}^1 x_3 + ... + + p_{jn}^1 x_n, \qquad j = 1,2,...m \tag{6}$$

$$y_1 = \sum_{j=1}^{m} y_{1j} \alpha_j \tag{7}$$

In formula 7 y_1 is the weighted sum of consequent of each rule; weighting coefficient is the fitness $\overline{\alpha_j}$ after normalization of each fuzzy rule, i.e. the output of antecedent network serves as the link weight of the third layer of consequent network. The simplified network structure is as shown in picture 2.

y_1 是各个规则后件的加权和，加权系数为各模糊规则经归一化后的适用度 $\overline{\alpha_j}$ ，即前件网络的输出用作后件网络第三层的连接权值。简化的网络结构如图2 所示。

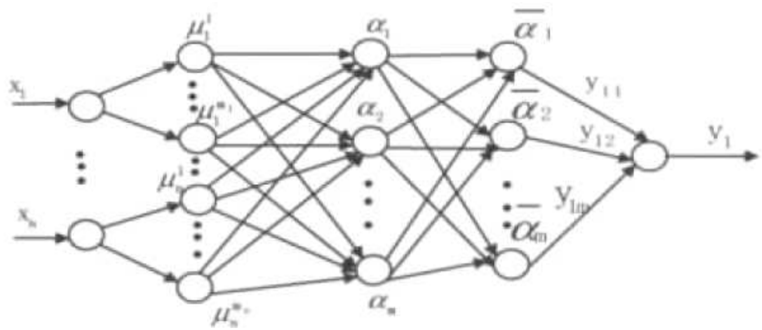

Fig. 2 - The simplified network structure of the improved algorithm/简化后的改进模型结构图

Improvement of learning methods

The fuzzy neural network provided in this paper is actually a kind of multilayer feed forward network, so error back propagation algorithm can be adopted to adjust parameters. It mainly adjusts the link weight p_{ji}^1 of the fifth layer, as well as the central value c_{ij} and width δ_{ij} of parameters of membership function of the second layer. Suppose that the input of the j th neuron node of the q th layer of fuzzy neural network in Picture 1 is $f^{(q)}$, the output is $x_j^{(q)} = g^{(q)}(f^{(q)})$. The node functions in the first layer to the fifth layer of fuzzy neural network are as shown in formula 8 to formula 12. In which, x shall be computed with corresponding functions, which is omitted here.

学习算法的改进

本文所提出的模糊神经网络在本质上是一种多层前馈型神经网络模型，故可以采用传统的误差反向传播算法来调整计算相关参数，连接权 p_{ji}^1（第五层的）、c_{ij}（第二层的隶属函数参数的中心值）和 δ_{ij}（宽度）进行调整计算。假定模糊神经网络结构中的第 q 层第 j 个神经元节点（如图 1 所示）的输入输出分别为 $f^{(q)}$、$x_j^{(q)} = g^{(q)}(f^{(q)})$。则本文模糊神经网络结构中的第一层到第五层的节点函数值分别可以用公式 8 至公式 12 表示。公式中 x 可以通过相应的函数计算求得，这里不再赘述。

$$f_i^{(1)} = f_i^{(0)} = x_i, x_i = g_i^{(1)} = f_i^{(1)}, i = 1,2,...,n \tag{8}$$

$$f_{ij}^{(2)} = \frac{-(x_i^{(1)} - c_{ij})^2}{\delta_{ij}^2} \tag{9}$$

$$f_j^{(3)} = x_{1i}^{(2)} x_{2i}^{(2)} ... x_{ni}^{(2)} = \mu_1^{i1} \mu_2^{i2} ... \mu_n^{in} \tag{10}$$

$$f_j^{(4)} = \frac{x_j^{(3)}}{\sum_{i=1}^{m} x_j^3} = \frac{\alpha_j}{\sum_{i=1}^{m} \alpha_j} \tag{11}$$

$$f_1^{(5)} = \sum_{j=1}^{m} y_{1j} x_j^{(4)} = \sum_{j=1}^{m} y_{1j} \overline{\alpha_j} \tag{12}$$

Suppose that error cost function is as shown in formula 13, in which t_1 and y_1 indicate desired output and actual output respectively.

假设误差表示函数如公式 13 所表示，式中 t_1 和 y_1 分别为期望输出值和实际输出值。

Adjust p_{ji}^{1}, c_{ij} and ∂_{ij} according to error back propagation algorithm, and solve and train the learning algorithm accordingly.

可以根据误差反向传播函数来调节计算 p_{ji}^{1}、c_{ij} 和 ∂_{ij}，最后据此对学习算法进行求解运算。

$$E = \frac{1}{2}(t_1 - y_1)^2 \tag{13}$$

Improvement of calculation procedures

Improved operation process of the presented algorithm can be listed as follows [10]. ①Reduce dimension of samples with factor analysis, establish sample set; ②Calculate the fitness value of each individual in the group, save the optimal fitness value; ③Turn to the 4th step if reaching the set evaluation generation or current optimal individual meeting conditions; otherwise, turn to the 2nd step; ④ Decode the optimal individual in the 3rd step into network parameter to serve as the initial parameter of fuzzy BP neural network algorithm; ⑤Modify current network parameter with fuzzy BP neural network algorithm;⑥Terminate if reaching the condition for terminating fuzzy BP neural network algorithm; otherwise, turn to the 5th step.

算法运算步骤的改进

改进算法的计算步骤如下所示。①通过因子分析并建立样本集合，从而减少样本的维度；②计算群组中的每个个体适应值，并存着优化此适应值；③如果运算符合结束条件的话，则转入第四步进行计算，否则转入第二步进行计算；④将第三步中的优化个体进行解码模糊网络参数，作为模糊网络算法的初始参数；⑤采用模糊网络算法修改当前网络参数；⑥如果达到运算终止条件则中止运算，否则转入第五步进行计算。

RESULTS

Data acquisition and pre-processing

Choose m typical supply chains of fresh agricultural products, make use of statistical data to compute the values of n indicators of each supply chain, and compute corresponding overall evaluation score of each supply chain with n indicator weights through determination and normalization processing of experts, so as to obtain m training mode pairs, training the model of this paper with such m training mode pairs. Subsequently, model in this paper can be applied to the performance evaluation of supply chain of fresh agricultural products. Every time when inputting 18 third-class evaluation indicators of supply chain to be evaluated, we can obtain the performance of supply chain of the fresh agricultural products.

The questionnaires of all the evaluation indicators were made and surveyed to the enterprises and consumers related to get the score of each indicator for different supply chains of fresh agricultural products. The original data acquired by the survey are pre-processed to the scope of the fuzzy matrix and the final scope of the score is [0, 5].

实验结果

数据采集与预处理

本文在实际评价中，选取了 m 条典型的生鲜农产品企业供应链作为样本，采用统计数据逐一计算出每条供应链的 n 个评价指标的得分情况，再经过相关业内专家评判后确定取值，归一化预处理的 n 项指标分值，从而计算得出各供应链的相应的综合绩效得分，据此得到 m 对训练模式组队，随后用此 m 个训练组队作为训练样本验证模型。最后将本文模型应用于生鲜农产品供应链的绩效综合评价。每当输入待评价供应链的 18 个三级评价指标时，就能够得到改生鲜农产品的供应链绩效。

制定了每个评价指标的问卷调查，并对相关农鲜产品供应链企业和客户进行了现场调查，以获得每个不同农鲜产品供应链的每个指标的得分情况。获得原始数据经归一化预处理后，使之取值范围符合模糊矩阵以及最终的取值范围[0, 5]之间。

Experimental results and analysis

Limited to paper space, the evaluation of intermediate results is omitted here, only providing secondary evaluation results and final comprehensive evaluation results of three typical chains, see table 2.

实验结果与分析

考虑到论文字数有限，评价的中间过程这里略去，仅仅列举出三条典型农鲜产品供应链的绩效评价的二级评价结果和最终的评价结果，具体见表 2 所示。

Table 2 / *表 2*

Secondary evaluation results of the paper / *二级指标的实证评价结果*

	Customer Service Level / *客户服务水平*	Adaptability of Logistics Service / *物流服务可行性*	Integration of Logistics Service / *物流服务集成性*	Enterprise Input / *企业投入*	Internal Operation / *内部运作*	Enterprise Income / *企业收入*
1	3.647	3.451	3.651	3.572	3.413	3.631
2	4.118	4.326	4.179	4.210	4.009	4.357
3	4.431	4.621	4.170	4.345	4.626	4.521

In order to illustrate the value of the presented algorithm and some other algorithms which are used for performance evaluation, the calculation indicators are realized with the same calculation platform in the paper. The indicators of the calculation platform can be listed as follows Intel i3 2120, 2GB DDR3, AMD Radeon HD 7450 and 3.3GHz CPU, and windows XP. The table 3 shows the evaluation accuracy and time consuming of the different algorithms. From the table we can see clearly that the algorithm in the paper has greater value than that of BP neural network [9] and fuzzy evaluation algorithms[5] in evaluation accuracy or time consuming. In practice, the paper takes some obvious indicators as sample to calculate evaluation accuracy in order to make our comparison more believable.

为了说明本文所提出算法与目前其他典型算法的优势，本文采用相同的计算平台实现了本文算法和常规模糊评价[9]和 BP 神经网络算法[5]。计算平台性能参数如下：Intel i3 2120, 2GB DDR3, AMD Radeon HD 7450 and 3.3GHz CPU, and windows XP。表 3 给出了本文算法、传统模糊评价方法和 BP 神经网络的评价精度和时间消耗对照表。通过此表可以清楚地看出本文算法应用于农鲜产品供应链绩效管理时在评价精度和时间消耗上具有明显优势。具有可在实际评估中，为了使得评价具有更好的可信度，本文采用了一些明显的参数作为评价准确度的参数。

Table 3 / *表 3*

Realization results of different algorithms/ *不同算法的实现结果*

	Algorithm in the paper / *本文算法*	Ordinary Fuzzy model / *普通模糊算法*	BP Neural Network / *普通BP 算法*
Evaluation Accuracy / *评价准确率*	95.66%	71.34%	85.64%
Time Consuming (S) / *时间消耗（秒）*	13	13	793

CONCLUSIONS

It is shown through empirical research that the evaluation combination model of the performance of supply chain of fresh agricultural products based on fuzzy neural network established in this paper is practicable, effective and feasible, and is able to effectively conquer some shortcomings of traditional evaluation models, as well as equipped with capabilities like self-learning, self-adaptation, strong fault tolerance and ability of expression, able to reduce some human subjective factors to the hilt, so as to improve the reliability of the performance evaluation of enterprises, making evaluation results more objective and accurate. For the next studies, it is planned to further improve the adjustment and optimization of reduction and membership functions of fuzzy rule to enhance the generalization ability of model.

结论

本文提出了一个基于模糊神经网络农产品供应链绩效管理和评价新模型，通过实证研究也表明本文模型在实践应用中是可行性和有效性，同时实验结果还说明了本文模型不仅能够克服传统神经网络绩效评价模型的一些困难，还具有诸如自学习、自适应、容错力强、人为干预少的优势，因此本文模型能够提高农鲜产品企业供应链绩效评价的可靠性，并能够提高绩效评价的客观性和准确性。下一步研究中拟将模糊规则的约简和隶属函数参数的调整与优化方面继续改进，以提高模型的泛化能力。

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