RESEARCH ON SUPPLY CHAIN DEMAND PREDICTION BASED ON BP NEURAL NETWORK ALGORITHM
/
基于神经网络的供应链需求预测研究

Ph.D. Wang G.
Jiangxi University of Finance and Economics / China
Tel: 0086-18170020218; E-mail: liyi7611@163.com

Abstract: *Demand prediction is a hot research field in markets management, especially for fresh agricultural products prediction based on supply chain management. Based on BP neural network, a new demand prediction algorithm for fresh agricultural products is presented in the paper. First, the structure and data indicators of BP neural network algorithm are redesigned and the training function is selected for the fresh agricultural products prediction algorithm. Second, the improvement of excitation function, (including trigonometric function and sigmoid function) and orthogonalizable design, are presented and analyzed to speed up the calculation and improve the prediction accuracy of ordinary BP algorithm. Finally, data from certain fresh agricultural product corporations are taken for example and the simulation results show that not only the problem of convergence speed has been solved, but also the prediction accuracy is ensured when the improved algorithm is used in demand prediction for fresh agricultural products .*

Keywords: *supply chain management, demand prediction, BP neural network algorithm, fresh agricultural products.*

摘要: *需求预测是市场管理（尤其是农鲜产品的供应链管理）的研究热点之一。本文在改进 BP 神经网络的基础上，提出了一个新的农鲜产品供应链需求预测模型。首先，本文为农鲜产品供应链需求预测模型设计了 BP 神经网络模型的网络结构、数据指标和训练函数；其次，通过改进 BP 神经网络的激励函数（包括 trigonometric 和 sigmoid 函数）和正交选择以优化提升原算法的运算效率、收敛速度和需求预测的精度；最后选用某农鲜产品供应链的数据为例进行了实验仿真预测，实验结果表明，本文算法不仅解决了 BP 神经网络在供应链需求预测时的收敛速度问题，也提高了预测精度。*

关键字: *供应链管理，需求预测，BP 神经网络，农鲜产品。*

INTRODUCTION

Supply chain management plays an important role in today's society. The study and application of supply chain of fresh agricultural products have also obtained remarkable achievement in recent years. Application study on "organizing supply of goods according to customers' orders" is growing vigorously, and the most basic job to achieve this is to establish prediction system of market demand on fresh agricultural products, which is the important factor driving the entire supply chain. Reasonable and effective prediction method can lower the inventory cost, provide basis for making production plan and improve the overall efficiency of supply chain. However, as the demand prediction of fresh agricultural products has not only common characteristics of general demand prediction, i.e. derivation, complexity, timeliness, spatiality, but also some unique ones, for example: ① prediction demand of fresh agricultural products is wide in range, great in scale, mainly reflected in the demand prediction of fresh agricultural products involving in lots of departments, including agricultural sector, industrial department, circulation department, consumers, and etc.; ② demand prediction of fresh agricultural products is high in complexity, mainly because fresh agricultural products has numerous kinds, which leads to various and variable specific applications; ③ fresh agricultural products, due to high perishability, random life cycle and continuous physical deterioration, are affected not only by human factors, but also by natural factors. It is due to the above specific features of prediction of fresh agricultural products as well as the bullwhip effect in supply chain management that the effects of traditional prediction methods are not that satisfactory. Therefore, it is urgent to explore the demand prediction

引言

在当今社会供应链管理具有越来越重要的作用，而且最近国内外学者在农鲜产品的供应链管理理论研究和实践应用方面都取得了显著成就。按客户订单组织货源更是供应链管理实践中的研究热点之一。按客户订单组织货源的研究前提就是要构建实际有效的农鲜产品供应链需求预测系统。供应链需求预测也是推动整个供应链合理运转的关键要素。准确合理的预测模型，能够帮助企业降低库存，为企业制定合理的生产计划提供依据，从而提高企业供应链管理综合效率。但是农鲜产品的供应链需求预测不仅具有空间性、派生性、时间性、复杂性等普通需求预测的共同特点，还具有农鲜产品的个性化的特征，如（1）农鲜产品供应链需求预测涉及的规模大、范围广，且需求预测所涉及的行业部门众多，包括农业部门、流通部门、工业部门、消费者等。（2）农鲜产品供应链需求预测实现难度大，因为农鲜产品品目众多，其在各行业的具体用途也同样复杂多变。（3）由于生鲜农产品具有易损性、易腐性和生命周期随机性等特点，这些特点不仅受到人为主观因素的影响，还受到众多自然因素的影响。由于农鲜产品供应链预测的以上复杂特点，又由于供应链管理中存在的牛鞭效应，一般预测模型的实际应用效果难以让人满意，因此针对

method of fresh agricultural products based on supply chain, so as to improve prediction accuracy, reduce storage and production cost, enhance the overall efficiency of supply chain of fresh agricultural products market [1,2].

As for demand prediction of agricultural products at home and abroad, this paper will mainly carry out the analysis from the following two aspects. ① traditional methods are moving average, exponential smoothing, linear regression, time series decomposition, time series forecasting, grey prediction and other methods[3.4,5], all of which adopt historical demand data to carry out prediction, not considering the change factors influencing specific demand. While in fact, factors influencing logistics demand are very complex, not only closely related to society, economic consumption and price, but also to natural resources and geographical conditions; relations among these factors are very complicated and all of them are non-linear relations, thus the prediction results of these models are not that ideal [3-5]; ② demand prediction method based on artificial intelligence; in recent years, with the continuous maturity of artificial intelligence technology, neural network with non-linear predictive ability is applied to logistics demand prediction, having broadened the space for logistics demand prediction, and obtained decent achievement. Neural network is a prediction method based on empirical risk minimization principle, the prediction performance of which is greatly related to the size of logistics sample set. If the quantity is too small, it is easy to be over-fitting; meanwhile, there are lots of neural network parameters and complex network structure, such defects exist as low rate of convergence and local optimization, causing not high prediction accuracy of small sample logistics [6-7].

Neural network has the capacities like non-linear, curve fitting, learning and anti-interference, which is a generally-used non-linear function approximation tool. Through the training of BP neural network algorithm, especially applicable to construct non-linear forecasting function and the accuracy can reach preconcerted requirements. The features of logistics demand of fresh agricultural products just adapt to the performance of neural network. Therefore, theoretically, if such defects of neural network as local optimization and low rate of convergence can be conquered, the method is a relatively superior analysis method of demand prediction of fresh agricultural products. So the trigonometric function , sigmoid function and orthogonalizable design of BP neural network algorithm is improved in the paper to speed up its calculation and convergence of original BP algorithm, and then presents a new demand prediction algorithm of supply chain for fresh agricultural products based on BP neural network algorithm.

农鲜产品供应链需求预测模型研究成为业内的研究热点之一[1,2]。

目前国内外农鲜产品供应链需求预测的主要方法可以分为传统预测方法和基于人工智能的预测方法。（1）传统预测方法：线性回归预测法、移动平均法、时间序列预测法、时间序列分解法、指数平滑法、灰色预测等方法等。传统预测方法主要是根据企业历史的需求量数据进行未来需求预测，这种方法很难考虑需求在实践中的变化性，又由于影响供应链需求的因素非常的复杂，并且个因素之间存在复杂的非线性关系，这使得传统的供应链预测精度差强人意[3-5]。（2）人工智能的供应链需求预测方法，随着人工智能技术近年来的不断发展，具有非线性模拟和预测能力的人工智能技术广泛应用于供应链需求预测中，这大大拓宽了供应链需求预测空间，研究也取得了较好的研究成果。人工智能技术方法（这里以神经网络技术为代表）基于历史预测经验风险最小化的原理，预测精度和性能与供应链样本数量和质量有较大关系。如果供应链样本数量选择过小，则可能会出现过拟合现象，又由于神经网络的拓扑结构比较复杂、模型参数众多，使得该模型存在局部最优和收敛速度慢的缺点，这使得这类算法对数量较少的样本供应链预测精度不高[6-7]。

考虑到神经网络具有强大的非线性曲线拟合能力、学习能力和抗干扰能力, 因此神经网络是一种强大的非线性函数模拟工具。因此BP神经网络非常适用于构造非线性预测函数, 而且曲线拟合的精度能达够工程实践的具体要求。因此在理论上, 如果能够克服神经网络的收敛速度慢和局部最优的模型缺点时，神经网络完全可以成为较好的农鲜产品供应链需求预测分析方法。本文就是利用神经网络的这些优点，并通过改进原模型的激励函数和正交选择方法，力图克服原始模型的缺点，从而提出一个符合实践预测精度需求和算法效率的农鲜产品供应链需求预测模型。

MATERIAL AND METHOD

Structure design for BP neural network

According to the characteristics of logistics demand of fresh agricultural products, while applying neural network to predict logistics demand of fresh agricultural products, it needs to establish three-layer (input layer, hidden layer, output layer) BP neural network algorithm prediction model based on logistics quantity prediction of agricultural products (sees Fig. 1) [8].

Input Layer: the input layer neurons take gross retail sales of fresh agricultural products, output value, yield, resident income and fresh agricultural products expenditure of enterprise as reference inputs, 5 in total.

材料与方法

BP 神经网络的结构设计

根据农鲜产品供应链需求预测的实际特点, 在应用BP神经网络预测农鲜产品供应链需求时, 需要重新构建基于农产品供应链流量预测的三层拓扑层结构，即输入层、隐含层、输出层的 BP神经网络预测模型，具体网络结构设计见图1 [8]。输入层: 该层神经元由农鲜产品的产值、零售总额、产量、企业的农鲜产品支出和居民收入为基准输入, 共有5个输入变量。

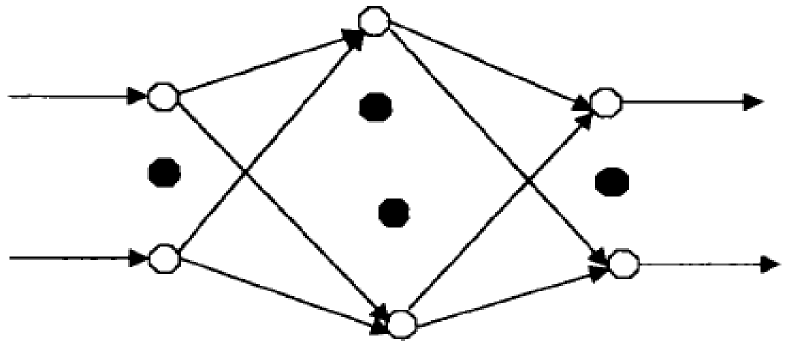

Fig. 1 - Basic structure of BP neural network / *BP 神经网络的基本结构*

Hidden Layer: the determination of hidden layer in this paper is to make use of the empirical equation of the three-layer neural network of trained linear basic function, in which s means the number of nodes of hidden layer; m,n indicate the number of input nodes and output nodes, the conversion relation among which is as shown in equation 1 [9].

隐含层: 本文利用线性基本函数的三层神经网络的经验方程来确定隐含层。在该层中 s 表示隐含层中节点的个数; m,n 则分别表示输入节点和输出节点的个数, 如式2表示他们之间的换算关系。

$$s = m(n+1)+1 \qquad (1)$$

Through the equation 1, it can be temporarily determined that the number of hidden layers is 16, increasing or decreasing several nodes of hidden layer in this interval to finally determine that the unit interval of hidden layer is 10~19, adjusting according to error analysis after adjustment and training. Output Layer: the output layer neurons are only to predict single variable, and the obtained node of output layer of neural network prediction model shall be 1. Hence, as for the prediction result of this paper, as prediction is only carried out on logistics demand of fresh agricultural products, there is only one output layer. Propagate the input vectors $(X_1^{(t)}, X_2^{(t)}, X_3^{(t)}, X_4^{(t)}, X_5^{(t)})$ forward to the hidden layer through transfer function of input layer tan- sigmoid. Upon the effect of transfer function tan- sigmoid through hidden layer, transfer the output vector of node of hidden layer to output node to obtain the results. BP neural network algorithm, in the process of learning, has the characteristics of forward propagation of working signal and back propagation of error signal. If there is error between actual output and expected output (i.e. set output vector) of network and the error is beyond permitted range, it turns to back propagation, returning the error signal layer by layer along with the original propagation route, and network weights shall be adjusted by error feedback. Make the actual output of network more approximate to expected output through continuous amendment of weights [10].

根据以上方程暂定16为隐含层的节点取, 实际计算中可以在此区间上适当增减此数字, 最终确定的隐含层单元数目将落在10~19取值区间, 该取值区间可以在模型运算中根据计算误差分析进行适当调整。

输出层: 在该层神经元仅仅预测单一变量, 该层得到的输出层节点理论取值应为1。因此输出层只有1层。

随后通过输入层的tan-sigmoid传递函数将输入向量 $(X_1^{(t)}, X_2^{(t)}, X_3^{(t)}, X_4^{(t)}, X_5^{(t)})$ 向前逐步传播至隐含层。再经由隐含层的log- sigmoid传递函数计算后，把输出向量（隐含层节点的）传递到输出节点上，就可以得到最终的计算结果。考虑到BP神经网络在训练过程中工作信号向正向传播、误差信号则向反向传播。因此假如模型的期望输出与实际输出之间存在较大误差， 则模型转入反向传播机制，从而能够将误差信号沿传播路线逐层返回，网络节点的权值通过误差反馈进行调整。模型通过权值的反复调节，最终使模型的实际输出与期望输出之间的误差符合要求。

Determination of data indicators of BP neural network algorithm

As it is very difficult to collect logistics demand data of fresh agricultural products in actual work, indirect indicator method is adopted in the model, i.e. adopting relevant economic indicators besides logistics demand of fresh agricultural products to establish economic indicator system of logistics demand of fresh agricultural products, carrying out induction and derivation through mathematical methods so as to determine logistics demand type of agricultural products.

As logistics demand of fresh agricultural products is a derivative demand, the size of logistics demand of fresh agricultural products is closely related to its self demand. In a macro perspective, it mainly includes internal and external

BP 模型中数据指标的确定

考虑到农鲜产品供应链需求的仿真数据收集的难度较大，本文采用间接指标法进行模型计算。就是借用与农鲜产品供应链需求之外的、但与之相关的一些经济学指标构建农鲜产品供应链需求预测的经济学指标体系，通过数学模型进行相应的归纳与推导, 从而确定农鲜产品的供应链需求预测模型。

由于农鲜产品供应链需求预测并不是模型本身所具备的能力, 因此农鲜产品供应链需求数量与其具体的真实需求有

factors: production capacity of agricultural products, external economic environment and regulating influence. Basically, the production capacity of fresh agricultural products is the key factor of logistics demand of agricultural products. The higher the output value and yield of fresh agricultural products are, the faster the logistics demand increases; if the output value and yield of fresh agricultural products reduce, the logistics demand of fresh agricultural products will be insufficient and reduce. Therefore, this paper adopts certain output value and yield of fresh agricultural products as the indicators for predicting logistics demand of fresh agricultural products. Secondly, another key factor influencing logistics demand of fresh agricultural products comes from external economic environment and national policy orientation. Gross retail sales of products consumption, per-capita income of rural residents and expenditures governments using for agriculture influence the demand function of logistics of agricultural products and the scale of logistics demand; better economic environment and more support from the nation on agriculture have, to a large extent, exerted an impact on the size of logistics demand scale of agricultural products. Therefore, these relevant economic indicators can be served as the influencing factors of demand logistics scale of fresh agricultural products in the model, i.e. 5 indicators of input layer neurons. Suppose that $X_1^{(t)}$, $X_2^{(t)}$, $X_3^{(t)}$, $X_4^{(t)}$, $X_5^{(t)}$ indicate relevant economic indicator systems in different period respectively, $Y^{(t)}$ indicates logistics demand scale of agricultural products determined under the influence of relevant economic indicators, it can be expressed as Equation 1 with an equation. In equation 2, $y(t)$ is the output vector of BP neural network algorithm; $f()$ is the decision function for connection weight and threshold of neural network [9].

着紧密的关联。这需要从宏观层面上考虑内外两部分因素，即外部经济环境和调控政策的影响和农产品自身的产能情况。从本质上说，农鲜产品的自身产能是农产品供应链需求的关键因素。农鲜产品产量和产值越高，它对供应链的需求增长也就增快； 反之将导致农鲜产品供应链需求不足和下降。对此本文选取某农鲜产品产量、产值作为预测农鲜产品供应链需求的经济指标。其次影响农鲜产品供应链需求的另一个要素是外部经济环境和国家政策调控。农鲜产品的消费零售总额、政府对农业的支出、农民的人均收入、农鲜产品供应链的需求规模等都在较大程度上会影响农产品供应链需求量和需求规模。因此在模型具体计算中可以以上述经济指标作为农鲜产品供应链需求预测的影响因素, 即作为模型输入层的5个输入值。

假设 $X_1^{(t)}$，$X_2^{(t)}$，$X_3^{(t)}$，$X_4^{(t)}$，$X_5^{(t)}$ 表示不同时期的相关经济指标, $Y^{(t)}$ 则代表输出，即农鲜产品供应链需求量，具体可以用方程2表示。在方程2中, $y(t)$ 表示网络模型的实际输出， $f()$ 表示模型的阈值和连接权的决定函数。

$$y() = f(X_1^{(t)}, X_2^{(t)}, X_3^{(t)}, X_4^{(t)}, X_5^{(t)}) \tag{2}$$

Training function selection for BP algorithm

There are various kinds of training functions of BP neural network algorithm; the training function used in prediction model of logistics demand of agricultural products based on neural network is BFGS Quasi-Newton BP algorithm function which is able to train neural network in any form, as long as its transfer function is derivable towards weights and input. In this regard, available transfer functions are tansig and logsig, meeting the premise for the training of train bfg [10].

Take the determined macroeconomic indicators as the input sample of logistics demand model of agricultural products, train function train bfg with input sample, make use of different input vectors to obtain corresponding output vectors, so as to establish prediction model. Through continuous test, after reaching relatively small error, the network can be used for logistics demand prediction of agricultural products, thus obtaining final prediction results.

BP神经网络训练函数的选取

有众多函数可以作为BP神经网络的训练函数，本文采用BFGS准牛顿BP算法函数为BP模型的训练函数，只要该网络的传递函数对于输入和节点权值可导，BFGS准牛顿BP算法函数就能够训练任意形式的网络，因此本文使用的传递函数分别为logsig和tansig函数，完全满足模型的训练前提。

以确定好的宏观经济指标为农产品供应链需求量模型的输入， 运用输入train bfg样本训练函数, 输入不同的输入向量就可以得到不同的输出向量，从而建立起需求预测模型。经过模型不断的调整，最终达到误差最小，就得到了农鲜产品供应链需求预测模型，经过该模型就可以得到合理的预测结果。

Excitation function improvement of BP algorithm

Theoretically, functions differentiable in any order and non-constant can be served as the excitation function of H. Generally, BP neural network adopts sigmoid function as excitation function; however, it is found in research that S type function often causes low rate of convergence of network, low learning efficiency, and network easy to fall into local minimum instead of global minimum, and other shortcomings. Thus, to improve excitation function becomes one of the concepts to improve BP neural network model [6].

-Improvement of trigonometric function: This paper proposes to adopt trigonometric function to substitute sigmoid function, as shown in equation 3.

改进 BP 神经网络的激励函数

在理论上讲，非常数的且任意阶可导的函数均可作为 BP 网络模型的激励函数，一般 BP 网络均选用 sigmoid 函数为激励函数。许多研究发现，sigmoid 函数常会导致 BP 模型局部最优、算法效率低、模型运算收敛速度慢等缺陷，因此通过改进 BP 模型的激励函数而提升 BP 模型算法性能成为主要的模型改进思路之一。

-采用三角函数的激励函数改进: 本文尝试采用三角函数取代 sigmoid 函数作为 BP 模型的激励函数，具体如式 3 所示。

$$f(x)=0.5\sin(\lambda x)+0.5 \tag{3}$$

In which, according to the experience, the value of λ is among [1.2, 1.8]; and the simulation result in this thesis shows that adopting the trigonometric function to be the excitation function of BP neural network achieves remarkable results on the global optimization, but not that obvious in the improvement of learning rate of network. Through further analysis and test, it is found that the reason why learning rate is not obviously enhanced is that there is no connection between two parameters in the above equation: 0.5 and λ; thus if change equation 3 into equation 4 [10].

在公式 3 中，根据经验一般 λ 的取值落在在 [1.2, 1.8] 取值区间。仿真结果也表明：以三角函数作为 BP 模型的激励函数，会使得模型在全局最优化上的改进效果显著，但是对模型算法效率提升效果不是很理想。经过深入仿真实验可以找到模型算法效率不高是由于公式 3 中参数 0.5 和 λ 不发生联系， 因此尝试将公式 3 改进为公式 4 [10]。

$$f(x)=(0.5/\lambda)\sin(\lambda x)+0.5/\lambda \tag{4}$$

In this way, while the period of function $f(x)$ is changed, the amplitude can be changed with the change of function period, thus changing the excitement degree of two connected neurons in layers, i.e. changing corresponding link weight values, in which the value of λ is still among [1.2, 1.8]; as a result, it can both guarantee global optimization of network and obviously enhance learning rate.

- Improvement of sigmoid function for BP algorithm: Traditional BP neural network adopts sigmoid function as shown in equation 5. As action function is fixed in shape, influencing the rate of convergence of network, the rate of convergence of network shall be accelerated through increasing its steepness, i.e. adding steepness factor (also called shape factor) λ. The improved excitation functions in this paper are as shown in equation 6, equation 7 and equation 8.

通过公式 4， $f(x)$ 的函数周期改变发生变化，同时函数的幅值也能随之发生相应的变化，使不同层间两个相连的神经元之间的兴奋程度发生关联，也就改变了相应节点的连接权值，参数 λ 的取值仍然落在[1.2, 1.8]区间，这样不仅可以保证 BP 模型的全局最优，同时模型的算法效率也明显提高。

-采用 sigmoid 函数的激励函数改进: 一般的 BP 模型采用的 sigmoid 函数如式 5 所示。由于该函数的作用形状一般保持不变，这大大限制了算法模型的收敛速度，通过加大 sigmoid 函数的陡峭度来可以加快 BP 模型的收敛速度，即在模型中加入形态因子 λ。改进后的激励函数可以用公式 6、公式 7 和公式 8 表示。

$$f(x)=\frac{1}{1+e^{-x}} \tag{5}$$

$$f(x)=\frac{1}{1+e^{-\lambda x}} \tag{6}$$

$$x=u_j \tag{7}$$

$$f(u_j)=\frac{1}{1+e^{-\lambda * u_j}}=\frac{1}{1+e^{-\lambda*(\sum_i w_{ij}x_i-\theta_j)}} \tag{8}$$

In which u_j is the status value of the j th neuron, s is shape factor, w_{ij} is the weight from pre-input x_{ij} to the j th neuron, θ_j is the threshold of the neuron; due to the introduction of shape factor λ, sigmoid function, as for input, is able to freely stretch out and draw back as well as translational transformation.

上述公式中，第 j 个神经元的取值用 u_j 表示，形态因子用 s 表示， x_{ij} 前级输入至第 j 个神经元的权重取值用参数 w_{ij} 表示， 该神经元的阈值用参数 θ_j 表示，由于引入了 λ 形态因子，使得 sigmoid 函数的伸缩和平移变换可以自由地进行。

- Improvement of Orthogonalizable Design: In order to further optimize BP neural network algorithm, this thesis adopts orthogonalizable design method to optimize relevant parameters of BP neural network. Variables intended to be chosen are nodes of hidden layers, accuracy requirements and transfer function. Each

-正交化设计优化 BP 神经网络: 为了能够进一步改进 BP 模型，本文尝试采用正交设计方法优化 BP 模型的相关参数。本文拟选择传递函数、精度要求、隐含层节点数等三个变量，每个变量均可以选择两个层级取值，采用梯度下

variable can choose two levels. Training function adopts gradient descent and LM method; the number of neurons of hidden layers can also be chosen between two levels, less than 7 or more than 7; accuracy required by training can be high accuracy or low accuracy.

This paper, while making use of orthogonalizable design to optimize BP neural network algorithm, adopts 7 nodes, algorithm accuracy as $\varepsilon \le 0.001$, transfer function as traingdx function. First, BP neural network learning input adopts n evaluation indicators, thus preliminarily determining n indicators used for establishing system model. Also adopt m in effective sample M as training samples ($M \succ m$), $M-m$ as test sample. The algorithm process is designed as below.[1] Randomly divide sample data into two groups; [2] Respectively establish two groups of C analysis programs; [3] Carry out simulation with original data; [4] Analyze simulated results; [5] Compare simulated results of the test with actual results, make a judgment on whether needs to rebuild model; if yes, turn to the 3rd step; if no, the simulation process finishes.

降法和 LM 法为模型训练函数，隐含层神经元的节点个数也可以有两个层级取值（大于 7 个或小于 7 个），训练的期望精度值也定义为两个，即高精度期望和低精度期望。

在正交化设计优化 BP 模型时本文采用$\varepsilon \le 0.001$的算法精度、7 个节点数、traingdx 传递函数。首先 BP 模型输入学习时使用 的评价指标数为n，并以此初步确定系统模型构建的 n个指标。具体计算时采用M个样本中的m个做为训练样本（$M \succ m$），检测样本为$M-m$个。优化后的算法流程设计如下。[1] 将样本数据随机分为两组；[2] 构建两组 Matlab 分析程序；[3] 对经过预处理的数据进行模拟；[4] 仔细分析仿真模拟结果；[5] 比较实验仿真结果与实际预测效果的差异，判断是否需要继续重建模型，如果需要的话转入第 3 步进行计算，否则算法运算结束。

RESULTS

Data acquisition and pre-processing

The data from a certain fresh agricultural product corporation were taken as experimental sample and the data include 12 years from 2003-2013 of the corporation. As BP neural network prediction model is the most sensitive to data among 0~1 while training, in order to improve the learning speed of BP neural network algorithm, we shall firstly carry out normalization processing on influencing factors of logistics demand; see equation 9 for details, in which x_i is original data, $x_i^{'}$ is normalized data, $x_{\max}$ and $x_{\min}$ indicate the maximum and minimum values of each variable.

实验结果

数据采集与预处理

经验表明BP神经网络预测模型，对在0~1 之间的数据训练时最为敏感，因此为提高模型的学习效率，本文首先对供应链个影响要素的采集数据进行归一化预处理，具体形式见公式9，公式9中x_i表示原始数据，$x_i^{'}$表示是归一化运算后的数据，$x_{\max}$和$x_{\min}$则表示各个变量的最大取值和最小取值。

$$x_i^{'} = \frac{x_i - x_{\min}}{x_{\max} - x_{\min}} \tag{9}$$

Experimental results and analysis

The paper realized the demand prediction for fresh agricultural products with improved BP neural network algorithm. Table 1 and table 2 are the realization results of the paper, in which Table 1 shows some experimental results realized by the improved model presented in the paper and table 2 shows the experimental results of prediction performance (including prediction accuracy and time consumption) of different algorithms, including traditional methods (taking exponential smoothing prediction for example)[7], original BP algorithm[9] and improved BP algorithm in the paper. As for the time consuming, calculation time needed by the model presented in the paper is 8 seconds and calculation time for the original BP neural and network is 278 seconds with the calculation platform as follows: hardware is Dell Poweredge R710, in which processor is E5506, memory 2G, hard disk 160G; software platform is Windows XP operating system, C programming language environment.

实验结果与分析

本文采用某农鲜产品供应链的数据实现了本文改进模型。表1和表2是本文的实现结果，其中表1为本文改进算法的实现结果，表2则为传统算法[7]（这里以指数平滑算法为例）、改进前的BP神经网络算法[9]、本文算法的的预测性能（包括预测精度和时间消耗）。至于时间消耗本文改进算法为8秒，普通BP神经网络则为278秒，采用的计算平台如下，硬件平台：Dell Poweredge R710，E5506，2G，160G；软件平台：Windows XP, C 语言。

Table 1 / *表 1*

The prediction results of the improved algorithm / *本文改进算法的预测结果*

Year / *年份*	Quarter/ *季节*	Actual demand / *实际需求*	Prediction demand / *预测需求*	Prediction error / *预测错误率*
2003	2	6034 unit / *单位*	6098unit / *单位*	1.1%
2004	3	6567 unit / *单位*	6771 unit / *单位*	3.1%
2005	4	6882 unit / *单位*	6975 unit / *单位*	1.4%
2006	1	7135 unit / *单位*	7265 unit / *单位*	1.8%/
2007	2	7689 unit / *单位*	7765 unit / *单位*	1.0%
2008	3	7999 unit / *单位*	8201 unit / *单位*	2.5%
2009	4	8699unit / *单位*	8787 unit / *单位*	1.0%
2010	1	8567unit / *单位*	8689 unit / *单位*	1.4%
2011	2	9335 unit / *单位*	9596unit / *单位*	2.8%
2012	3	9795 unit / *单位*	9921unit / *单位*	1.3%

Table 2 / *表 2*

The prediction performance of different algorithms / *各算法的预测性能*

	Exponential smoothing algorithm / *指数平滑算法*	Original BP algorithm / *原始BP算法*	Improved BP algorithm / *改进算法*
The overall prediction error / *总体预测错误率*	15.41%	4.79%	1.65%
The prediction error of the first quarter / *第一季度预测差错率*	14.22%	4.23%	1.45%
The prediction error of the second quarter / *第二季度预测差错率*	14.56%	4.91%	1.87%
The Prediction error of the third quarter / *第三季度预测差错率*	14.33%	4.78%	3.11%
The prediction error of the forth quarter / *第四季度预测差错率*	16.87%	6.08%	1.39%
Time consumption（S）/ *时间消耗（秒）*	7	278	8

From table 1 and table 2, we can see clearly that the improved BP neural network algorithm in the paper can realize the demand prediction for fresh agricultural products for corporations in practice and the improved BP neural network algorithm has more advantages in prediction accuracy and time consumption compared with exponential smoothing prediction and original BP algorithm.

通过表 1 和表 2，可以清楚的看到本文改进算法能够在实际应用中实现农鲜产品供应链需求预测，并且与传统预测方法和普通 BP 神经网络相比，本文算法在预测精度和时间消耗上具有较大的优势。

CONCLUSIONS

Prediction based on logistics demand of BP neural network algorithm provides a brand-new research approach. In allusion to the characteristics of logistics demand of fresh agricultural products, this thesis applies BP neural network algorithm to the demand prediction of fresh agricultural products, and the test results show that as BP neural network algorithm is the prediction method specially for multi-dimensional and non-linear data with better generalization ability, the accuracy of demand prediction of fresh agricultural products is higher than other models, having a broad application and theory prospect in logistics demand prediction.

结论

将BP神经网络应用于供应链需求预测，为供应链管理提供了广阔的应用前景。本文针对农鲜产品供应链需求的个性化特征，通过改进BP神经网络的激励函数，将其应用于农鲜产品供应链需求预测，实验表明由于BP模型本身所具备的非线性曲线拟合能力、多维数据处理能力和泛化能力，改进BP神经网络模型应用于农鲜产品供应链的需求时具有预测精度高、时间消耗少等优点，在理论和实践上具有广阔的前景。

REFERENCES

[1]. Feng Y., Ma J. H.(2010) – *Nonlinear method research on demand forefoundry for supply chain*, in Journal of Beijing Institute of Technology (Social Science Edition) , vol. 10, no.5;

[2]. Tommy K. S., Jim S. R.(2011) –*A new method for demand prediction of supply chain for agricultural products*, in Journal of Management Science, vol. 17, no.4;

[3]. Paulito S. T.(2012) –*Nonlinear prediction method research on supply chain demand*, in Computer Engineering, vol. 14, no.8;

[4]. Wu J. M., Li Y. Q., Wang L.(2011) – *Simulation research on forecast algorithm of logistic demand*, in Journal of Computer Simulation, vol. 28, no.9;

[5]. Cai J. F., Yang M.(2009) – *Optimal model of multi_agent supply chain demand forecasting based on genetic algorithm*, in Industrial Engineering Journal, vol. 19, no.5;

[6]. Reynolds K. X., Hearda M. N. (2011) –*Procurement of agricultural products using the CPFR approach,* În Suply Chain Management, vol. 19, no.11;

[7]. Ruben G. H., Suwan B. W. (2010) –*The study of a forecasting sales model for fresh food*, in Expert Systems with Applications , vol. 37, no.12;

[8]. Bergegue L. Z.(2008) –A *new neural network model for demand classification,* În Journal of Applied Intelligene, vol. 17, no.10;

[9]. Kinser B. D., Seop Z. M. (2011) – *Improvement on regulating definition of BP neural network algorithm*, in Journal of Computer Application and Engineering, vol. 31, no.8;

[10]. Bergh S. K. (2012) –*Using selectionton to improve BP model optimization*, in Computer Science, vol. 17, no.11.

参考文献

[1] Feng Y., Ma J. H. (2010) –*供应链需求预测的非线性方法研究*, 北京工业大学学报 (社科版) , 第10卷, 第5期;

[2]. Tommy K. S., Jim S. R.(2011) –*一种新的农产品供应链需求预测方法*, 管理科学学报, 第17卷, 第4期;

[3]. Paulito S. T.(2012) –*供应链需求的非线性方法研究*, 计算机工程, 第14卷, 第8期;

[4]. Wu J. M., Li Y. Q., Wang L.(2011) –*物流需求的仿真研究*, 计算机仿真学报, 第28卷, 第9期;

[5]. Cai J. F., Yang M.(2009) –*基于遗传算法的多因子供应链优化模型*, 工业工程学报, 第 19 卷, 第 5 期;

[6]. Reynolds K. X., Hearda M. N. (2011) –*采用CPFR方法的农产品采购研究*, 供应链管理, vol. 19, no.11;

[7]. Ruben G. H., Suwan B. W. (2010) –*新鲜食物的销量预测模型研究*, 专家系统及其应用 , 第27卷, 第12期;

[8]. Bergegue L. Z.(2008) –*一种新的需求分类神经网络模型,* 智能应用学报, 第17卷, 第10期;

[9]. Kinser B. D., Seop Z. M. (2011) –*BP神经网络调整定义的改进*, 计算机应用与工程学报, 第31卷, 第8期;

[10]. Bergh S. K. (2012) –基于选择法的改进BP模型,计算机科学, 第17卷, 第11期。