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Research Article

A New Algorithm for Demand Prediction of Fresh Agricultural Product Supply Chain

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Abstract: Demand prediction plays a key role in supply chain management of fresh agricultural products enterprises and its algorithm research is a hotspot for the researchers related. A new algorithm for demand prediction of supply chain management of fresh agricultural products is advanced based on BP neural network and immune genetic particle swarm optimization algorithm. First, the deficiencies of traditional BP demand prediction models are analyzed. Second, the BP neural network and immune genetic particle swarm optimization algorithm are integrated and some measures are taken to overcome the deficiencies of traditional BP demand prediction models and calculation flows of the presented algorithm are redesigned. Finally, the presented algorithm is realized with the data from certain fresh agricultural products supply chain and the experimental results verify that the new algorithm can improve effectiveness and validity of demand prediction for fresh agricultural products supply chain.

Keywords: BP neural network, demand prediction, fresh agricultural products, immune genetic particle swarm optimization algorithm, supply chain management

INTRODUCTION

Along with the changes of market environment, the focus of supply chain management begins to keep its eye to market demand management, pay much more attention to market demand. Accurate market demand prediction can decrease error degree of decisions, strengthen the supply chain service level and make more economic benefits for enterprises. Especially for fresh agricultural product enterprises, due to strict requirement for the storage period of products, in case of prediction error on inventories demand, enterprises will suffer heavy loss, so the research of demand prediction for fresh agricultural products based on supply chain management has become the hotspot for the researcher and corporations related (Rudulf, 2012).

Up to now, mathematical models adopted by demand prediction of supply chain management mainly include the following categories:

- BP neural network evaluation method makes use of its strong capability in processing nonlinear problems to carry out evaluation of online education performance; the method has advantages like self-learning, strong fault tolerance and adaptability; however, the algorithm is easy to be trapped into defects like local minimum, over-learning, strong operation specialization (Sridharan and Bolt, 2011; Zhu and Jiang, 2010).
- **Delphi method:** Its process mainly includes: first, according to the goal and demand of prediction, prepare opinion consultation table. Second, choose those experts, who engage in professional job related to prediction topic, are proficient in specialty and possess analysis ability, as consultation objects. Third, repeatedly consult experts' opinion. Finally, make prediction conclusion. The merit of this method is drawing on the wisdom of the masses, beneficial to a comprehensive and reliable prediction. But the demerit is the lack of objective standard due to main reference to subjective judgment, with low reliability (Whybark, 2010).
- **Time series method:** It is to make use of sale volume data of past period or other level-one data and adopt certain mathematical methods, with existing demand data, to predict future development change trend and demand. This method is high in prediction precision but has a sensitive demand on season (Williams and Hajam, 2012; Karl, 2009; Disney *et al*., 2006).

BP neural network algorithm has fairly well in accuracy when used in supply chain demand prediction but leaves behind the question of slow convergence speed of BPNN. The study takes Immune Genetic Particle Swarm Optimization algorithm (IGPSO) to modify and improve BP Neural Network (BPNN) model to overcome the question of slow convergence speed of original BPNN. In doing so a new algorithm for demand prediction of supply management of fresh agricultural products is advanced.

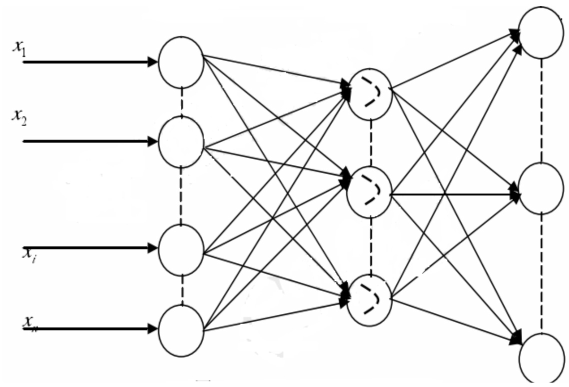

Fig. 1: Working principle of BP neural network

MATERIALS AND METHODS

Working principle of BP neural network algorithm: BP neural network is a single-direction propagation multi-layer forward network, which can be viewed as height non-linear mapping from input to output, the basic structure chart of which is as shown in Fig. 1 (Yang and Tian, 2011).

The input signal, from the nodes of input layer, successively transmits to the nodes of each hidden layer, then to the output nodes; the output of nodes of each layer only impacting the output of nodes of next layer and every node is a neuron structure. Suppose that the input node of BP neural network to be x_j, hidden node to be y_i, output node to be s_i, network weight value between input node and hidden node to be w_{ij}, network weight value between hidden node and output node to be u_{ij} and the desired output of output node to be z_i. Through adjusting the weight and threshold of each node, make the error between output of neuron network and target value reach the requirement of training accuracy, thus completing the training of network. Actually, there are lots of training methods for BP neural network other than gradient descent method; many scholars have forward several kinds of training methods, further optimizing training effects, rate of convergence and etc (Gao and Zhang, 2010).

Defect and reason analysis of BP neural network algorithm: The theory of BP neural network is solid in basis, rigorous in derivation, clear in physical concept and strong in generality. However, BP algorithm is the steepest descent method based on gradient, taking square error as objective function, so there inevitably have the following four great defects: training easy to fall into local minimum, learning process slow in rate of convergence, structure of network difficult to be confirmed (including the difficulty in determining the number of hidden layers and the nodes of each hidden layer), generalization ability of designed network unable to be guaranteed, which dramatically influence the further development and application of BP neural network The reasons of the existence of defects of BP neural network are analyzed as follows:

- Reason that training is easy to fall into local minimum is that from the perspective of structure, the nonlinear relation between input and output of BP neural network causes the error of network or energy function is a nonlinear space with many poles; while BP algorithm gets a headlong pursuit of the monotonic decrease of network error or energy function, i.e., algorithm only grants the ability to “downgrade” instead of “climbing” to the network. Just because of this, the network is always falling into local minimum and unable to break away, leading to failure to reach global minimum. So some people say that it is a “greedy” algorithm anxious for success.
- Reason that learning process is slow in rate of convergence is that there is fixed learning rate η and inertia factor α in BP neural network, which is the direct reason for the slow rate of convergence in learning process of BP neural network. BP algorithm, in essence, is the steepest descent method based on gradient, making use of the first derivative information of error towards weights and thresholds to guide the adjustment direction of weight in the next step, so as to realize the minimum final error. In order to guarantee the convergence of algorithm, learning rate η has to be less than certain previous one, which determines that it is impossible for BP neural network to be fast in rate of convergence.
- Reason that the structure of network is difficult to be confirmed is that while using BP neural network, the first problem is the confirmation of the best structure of network. To be specific, set certain application task, how to determine the layers of network and the number of nodes of each layer. At present, the theoretical basis is not sufficient to determine the number of hidden layers of BP neural network and the number of nodes of hidden layers, most of which are decided with experience. Besides, laws are different for different problems, so the structure of BP neural network is difficult to be determined.
- Reason that the generalization ability of designed network is unable to be guaranteed is that such factors exert certain impact which is both quantitative and qualitative on the generalization ability of neural network as the complexity of the structure of BP neural network, quantity and quality of training samples, initial weight of network, learning time, the complexity of objective function, priori knowledge of objective function and the influence is complex, leading to the difficulty in guarantee of the generalization ability of BP neural network.

Prediction algorithm design:

BP neural network algorithm improvement with IGPSO algorithm: This study tries to put forward combination training algorithm combing Immune

Genetic Particle Swarm Optimization algorithm (IGPSO) with BP algorithm to optimize BP neural network parameter and avoid the defects of network, i.e., IGPSOBPNN combination training algorithm. The basic concept is that first training BP neural network with IGPSO to find out a relatively optimal solution, then take the network parameter at this time as the initial parameter of BP algorithm to carry out the training, finally searching the optimal network parameter. Apply this combination training algorithm to nonlinear function approximation and stock price prediction with complex nonlinear dynamics features; the simulation experiment shows that the algorithm in this thesis avoids that the network falls into local minimum, having improved the generalization ability of network and provides a brand new idea for the confirmation of BP neural network parameter, making BP neural network obtain favorable performance from a new perspective.

IGPSOBPNN algorithm design: In consideration of the characteristics of IGPSO which is strong in global searching ability and poor in local searching ability and that of BP algorithm which is poor in global searching ability and strong in local searching ability, this thesis combines these two to form efficient combination training algorithm (IGPSOBPNN). The basic concept is that first training network with IGPSO to find out a relatively optimal solution, then take the network parameter as the initial parameter of network in BP algorithm to carry out the training, finally searching the optimal network parameter. Basic problems needing to be solved by combination training algorithm are encoding of particles, formation of fitness function, updating of particles speed and position, improvement on particle swarm optimization by using immunization information processing mechanism, combination of optimal particles and BP algorithm (Wang and Gu, 2012).

Encoding of particles: Learning process of BP neural network is to carry out optimization study on such two continuous parameters of network as weight and threshold. As the initial value is difficult to be confirmed, this thesis adopts IGPSO to determine the initial parameter values of network, guaranteeing the scientificity of initial parameter values. In the encoding process of particles, if binary encoding is adopted on parameters, the encoding string will be too long and shall be reverted to real numbers while decoding, thus influencing the learning accuracy of network and the running time of algorithm. Therefore, this thesis adopts real number encoding form, i.e., code string form, as shown in formula 1, in which $V = (v_1, v_2, \ldots, v_D)$, X represents the position of particles, V represents the speed of particles, D represents the total number of optimal network parameters; D can be obtained through formula 2:

$$X = (w_{n1}, \ldots, w_{n2}, \theta_1, \ldots, \theta_{n1}, w_{m1}, \ldots, w_{mn1}, \theta_1', \ldots, \theta_m') \quad (1)$$

$$D = n * n_1 + n_1 * m + n_1 + m \quad (2)$$

Formation of fitness function: PSO algorithm basically makes no use of external information in the evolution searching, only taking fitness function as reference, making use of the fitness value of each individual in the group to carry out searching, judging the excellence of individuals with fitness value. Therefore, it is critical to choose fitness function, directly influencing the rate of convergence of PSO algorithm and whether able to find optimal solution. Generally, fitness function is transformed from objective function. This study defines the network error as formula 3. Error function is also the objective function in this thesis. As the small the objective function value is, the larger the fitness value is and the larger the objective function value is, the smaller the fitness value is, fitness function shall take the reciprocal of objective function, i.e., fitness function as shown in formula 4:

$$E_A = \sum_{p=1}^{P} E^{(P)} = \frac{1}{2} \sum_{p=1}^{P} \sum_{k=0}^{m-1} (d_k^{(p)} - y_k^{(p)})^2 \quad (3)$$

$$F(E_A) = 1 / E_A \quad (4)$$

Updating of particles speed and position: PSO algorithm first initializes a group of random particles, then find out optimal solution through iterations. During each iteration, particles update themselves through tracking two "extremum", i.e., individual extremum P_i and global extremum P_g. Suppose that the initialized group size is N, the position of the i^{th} particle in the d th dimension is x_{id}, flying speed is v_{id}, the optimal position searched by it at present is p_{id}, the optimal position searched by the entire particle swarm at present is p_{gd}, then the algorithm formula for the updating of particles position and speed is formula 5:

$$\begin{cases} V_i^{k+1} = x(V_i^k + C1 * r1 * (P_i^k - X_i^k) \\ +C2 * r2 * (P_g^k - X_i^k)) \\ X_i^{k+1} = X_i^k + V_i^{k+1} \\ w = w_{\max} - \dfrac{w_{\max} - w_{\min}}{num_{\max}} * num \end{cases} \quad (5)$$

In which $w_{\max}$ and $w_{\min}$ represent the maximum and minimum values of w, respectively, $num_{\max}$ and num are largest iterations and current iteration, respectively, $v_{id} \epsilon [-v_{max}, v_{max}]$, x is constriction factor which can be obtained through formula 1. According to application experience, $x = 0.729$, $c1 = c2 = 2.05$, r_1 and

r_2 are random numbers among (0, 1), $v_{\max}$ is constant which is set by users; termination condition of iteration, according to specific problems, is generally the largest iterations or that the optimal position searched by particle swarm up till now meeting the presupposed minimum threshold.

Improving PSO by immunization information process mechanism: Immunological memory means that immune system often saves the antibody intruding antigen reaction part as memory cells. While the antigens of the same kind re-intrude, memory cells will be activated and generate large quantity of antibodies. In IGPSO, this concept is used for saving excellent particles, viewing relatively excellent particles generated during the process of every iteration as memory cells. While new particles are tested to not conform to the requirements, it is considered that it is very low in fitness and shall be substituted by memory cells. Immunological regulation mechanism means that it will be promoted while the affinity of antibodies and antigens is large or low in concentration; while it will be restrained while the affinity of antibodies and antigens is small or high in concentration; different antibodies keep certain concentration all along. Such features are used for selecting new particles in IGPSO:

- **Substitute inferior particles:** Test the newly-generated N particles; if the position of particles is infeasible solution, i.e., certain-dimensional component of X is not within the designated scope, substitute with memory particles.
- Randomly generate M new particles meeting requirements.
- Re-select N particles according to affinity and concentration of antibodies and antigens.

While training BP network, the higher the fitness of particles (antibodies) is, the stronger the affinity is; the lower the fitness is, the poorer the affinity is; hence, affinity can be expressed with the reciprocal of fitness function, as shown in formula 6, selection probability determined by affinity as shown in formula 7, concentration of particles can be calculated with fitness, as shown in formula 8, selection probability determined by concentration as shown in formula 9, probability for particles to be selected can be obtained through formula10, in which i = 1, 2, …, $M + N$, α is a weight coefficient among (0, 1); $M + N$ particles can be ordered according to P_i, the first N particles with large P_i values will be selected:

$$Q_i = 1/F_i \tag{6}$$

$$P_{i1} = Q_i / \sum_{u=1}^{M+N} Q_u \tag{7}$$

$$D_i = 1/\sum_{u=1}^{M+N} |F_i - F_u| \tag{8}$$

$$P_{i2} = D^{-1}{}_i / \sum_{u=1}^{M+N} D^{-1}{}_u \tag{9}$$

$$P_i = \alpha P_{i1} + (1-\alpha) P_{i2} \tag{10}$$

In immune system, vaccines are a kind of estimate on certain gene of optimal antibody, based on people's more or less priori knowledge on solving problems and extracting characteristic information. Vaccination is to alter certain components of antibodies according to vaccines. Immunization selection is used to check the performance of antibodies through vaccination. If the fitness is not as good as paternal generation after vaccination, the paternal generation shall be kept; if the fitness is better than paternal generation after vaccination, then choosing whether substitute its paternal generation through probability. In IGPSO, p_g generated in every iteration can be considered to be the most closed to the optimal solution, taking its certain component as vaccine to carry out vaccination and selection on particles. Methods are as follows:

- **Vaccination:** Randomly draw a particle from N new particles, then randomly draw a component in p_g and exchange with the drawn particle in corresponding position, finish one vaccination.
- **Immunization selection:** Check whether the vaccinated particle meets the constraint conditions, abandon if not; carry out fitness calculation if yes. If the fitness is less than that before vaccination, then abandon; otherwise, carry out probability calculation. While calculating probability, randomly generate a number through Rand () to compare with threshold p_g, selection the particle if it is larger, otherwise, abandon.
- **Generate new-generation particles:** After q times of looping execution (i.e., q times of vaccination) on the above vaccines and immunization selection, generate new-generation N particles and carry out next iteration.

Combination of particles and BP algorithm: After training through IGPSO, find out p_g particle, decoding each component in p_g into corresponding parameter values, then train with BP algorithm until the algorithm meeting termination conditions.

IGPSOBPNN algorithm training steps: IGPSOBPNN combination training algorithm steps are:

- Randomly initialize N particles according to parameter setting.

Table 1: The prediction results of the improved algorithm

Month	Actual demand	Model prediction demand	Relative error (%)
Jan.	12456 unit	12778 unit	2.6
Feb.	13673 unit	13879 unit	1.5
Mar.	14678 unit	14989 unit	2.1
Apr.	14765 unit	15021 unit	1.7
May	14953 unit	15334 unit	2.5
June	15231 unit	15665 unit	2.8
July	15441 unit	15579 unit	0.9
Aug.	15641 unit	15976 unit	2.1
Sep.	15678 unit	15945 unit	1.7
Oct.	15641 unit	15988 unit	2.2
Nov.	14321 unit	14666 unit	2.4
Dec.	13297 unit	13572 unit	2.0

Table 2: The prediction results of different algorithms

Algorithm	Algorithm in this study	Ordinary BP neural network algorithm	Ordinary genetic algorithm
Accuracy rate	97.89%	81.66%	70.33%
Time consuming (sec)	13	782	31

- Calculate the fitness of each particle in the group and save the particle with optimal fitness as memory particle.
- Generate new *N* particles according to formula 5.
- Test each particle in particle group, substitute with memory particles if not meeting conditions; otherwise, turn to the 5th step.
- Randomly generate M particles, select N particles in *M*+*N* particles according to affinity and concentration.
- Re-generate new *N* particles according to vaccination and immunization selection mechanism.
- Turn to the 8th step if reaching the set evolution generation or current optimal particle meeting conditions; otherwise, turn to the 2nd step.
- Decode the optimal particle in the 7th step into network parameter to serve as the initial parameter of BP network.
- Modify current network parameters with BP algorithm.
- Terminate if reaching the termination condition of BP algorithm; otherwise, turn to the 9th step.

RESULTS AND DISCUSSION

The proposed prediction model is realized taking the demand of certain month in 2012 of certain fresh agricultural product enterprise for example to carry out model application and demand prediction; specific prediction results see Table 1 and 2, in which Table 1 is the part of the prediction results of the improved algorithm in the study and Table 2 is the prediction result comparison among ordinary genetic method (Wang and Gu, 2012), general BP neural network (Gao and Zhang, 2010) and improved algorithm in the study in the practical application and the experiment is conducted through PC. PC configurations are as follows: And the calculation platform as follows: hardware is Dell Poweredge R710, in which processor is E5506, memory 2 G, hard disk 160 G; software platform is Windows XP operating system, C programming language environment.

CONCLUSION

The key of the successful supply chain management is to realize demand prediction to reduce safety stock without prejudicing product supply situation, specifically for fresh agricultural product corporations related. This study presents a new algorithm for demand prediction for supply chain management based on BP neural network and immune genetic particle swarm algorithm and when the algorithm is used in demand prediction for fresh agricultural product corporation, the experimental results verify the validity and feasibility of the model.

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