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A Novel GA-BP Based Bidding Prediction Algorithm for Contract Logistics of Road Freight Transportation

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Abstract. In this paper, we propose a novel bidding prediction algorithm based on the hybrid GA (Genetic Algorithm) and BP (Back Propagation) model for contract logistics of road freight transportation. Seven factors of GDP, fuel price, market requirement, cargo weight, transportation distance, carrier, and truck specification are concerned as the major factors. According to the nonlinear nature of transportation cost and carriers' psychological price, the BP neural network is applied to fit the nonlinear features. By training the dataset, GA is good at predicting the short-term bidding prices. In addition, genetic algorithm is integrated into the GA model to improve the long-term searching performance. The hybrid GA-BP algorithm is experimented to be of a good predictor. This study gives implication to 3PL providers that mining previous records with artificial intelligent algorithm is effective and feasible in road freight transportation bidding managements.

Introduction

Contract logistics is the major type of third-party logistics (3PL) for road freight transportation [1]. Manufactory enterprises outsource logistics services to 3PL suppliers [2]. 3PL providers bring benefits to the contractors by reducing operation costs of transportation and warehousing, cutting down logistics-related fixed assets, improving information accuracy and order fulfilment [3, 4]. In order to control the logistics costs and enhance the service quality, most manufactory enterprises beyond a certain scale take the form of open auction to procure logistics services [5, 6]. To the 3PL companies, optimizing the biding strategy is very important. The estimation and prediction of costs of road freight transportation is the most important thing of all [7].

However, 3PL has various carrier-mode options, their combinations impact on the bottom line cost of the end product [8]. On the side of supply chain management of contractors, 3PL provider selection criteria and performance evaluation also contain the transportation cost [9]. In order to establish long term effective supply chain collaboration with the clients, the 3PL provider needs to know how to make trade-off between 'hard' contractual aspects and 'soft' relationship aspects [10]. In addition, 3PL companies also provide third-party purchase service to increase revenue [11]. Therefore, it is difficult to estimate the transportation cost and bid in the auctions. In this study, we propose a hybrid BP neural network algorithm and Genetic Algorithm to predict bid prices.

Related Works

Road freight transportation pricing is affected by several factors. Fuel price is the first factor. Havenga [12] proposed a road transport cost model based on a gravity-orientated freight flow model and found that the increasingly negative outlook for the oil price will push up the freight price. Vehicle routing is another factor, as Figliozzi [13] studied that in a competitive environment, the estimation of incremental cost of new arrival requests can help carrier companies find optimal solution with look-ahead. Topal [14] found that previous knowledge on the less than truckload carrier's price schedule and retailers' ordering behavior can improve carriers pricing decision. In

addition, carbon emission causing air pollution toll [15], government subsidy [16], and zone pricing tactical decision [17] are also influence the road freight transportation pricing.

Auction bidding is the competitive pricing mechanism. Kuyzu [18] formulated a stochastic bid price optimization model aimed at maximizing the carrier's expected profit to study the bidding strategies for carriers participating in simultaneous independent single auctions. Triki [19] also developed a probabilistic optimization model, integrating the bid generation and pricing problems together with the routing of the carrier's fleet. Song [20] examined computationally tractable approximation methods for estimating bid values and constructing bids. Hou [21] founds that online bidding is affected by the number of bids in an auction, and thus indirectly influence the final deal prices. However, the models from these studies are not practical. In this study, we propose a practical non-linear model for bidding decision.

Major Factors Analysis

There are three categories of factors affecting the cost of road freight transportation. That is, macroeconomic factors, market factors, and operation-related factors.

Macroeconomic factors include national economic state and fuel price. The demands of road freight transportation are positively relates to the developing level of the country's economy. The growth of manufacture and consumption boost the requirement of road freight transportation and leverage the price. In general, Gross Domestic Product (GDP) is always used to reflect the national economic state. On the other side, the fluctuation of international crude oil price also influences the price of diesel, the dominant fuel type of freight trucks.

Market factors are mainly influenced by seasonal and periodic fluctuation and other impulsive promotions, such as Alibaba's "Double 11" Online Shopping Festivals and Jingdong June 18th Shopping Festivals.

Operation-related factors include cargo specifications, truck specifications, routes, and carriers. Cargo specifications, such as weight, volume, package, loading-unloading requirements, transportation requirements, and other specific constraints, are the primary dimensions of cost estimation. Truck specifications, such as length, carriage structure, determine the costs of fuel consumption, truck depreciation, and tolls. The route factors include origin-destination city, road condition, and distance. At last, carriers, actual outsourcing contractors themselves, affect the costs directly. The bigger is the scale of carrier; the lower is the cost.

In summary, we choose 7 influence factors: GDP, fuel price (FP), market requirement (MR), cargo weight (CW), transportation distance (TD), carrier (CR), and truck specification (TS).

The GA-BP Based Bidding Prediction Algorithm for Contract Logistics

However, the bidding of contract logistics is a complex problem. The determining factors interact each other. BP algorithm is the typical nonlinear regression approaches. BP algorithm has three advantages: self-learning, association storage, and optimized solving with high efficiency. In addition, we choose the three-layer structure with 7 input neurons, 15 hidden neurons, and 1 output neuron (Fig. 1). We choose the Levenberg-Marquardt (LM) [23] approach as the training algorithm.

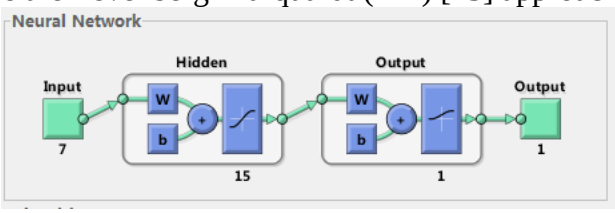

Figure 1. The 7-15-1 BP neural network

The flowchart of the BP training approach is as follows:

Step (1): Initialize the maximum training counts and error stop conditions.

Step (2): Input the training dataset $(\{x_i\}_q, \{y_i\}_q)$, $q = 1,2,...,Q$, where Q is the size of the dataset, $\{x_i\}$ is the input vector and $\{y_i\}$ is the actual price vector. Calculate the output of each neuron.

$$g_j^p = f\left(\sum_{i=0}^{N} w_{ji} x_i^p\right), \tag{1}$$

$$h_k^p = f\left(\sum_{j=0}^{M} w_{kj} g_j^p\right), \tag{2}$$

$$y_l^p = f\left(\sum_{k=0}^{L} w_{lk} h_k^p\right) \tag{3}$$

where N, M, and L are the quantities of neurons in the layer of input, hidden, and output, respectively. $\{g_j^p\}$, $\{h_k^p\}$, and $\{y_l^p\}$ are the output vectors of the layer of input, hidden, and output, respectively. $\{w_{ji}\}$, $\{w_{kj}\}$, and $\{w_{lk}\}$ are the weight matrix interlinking the layer of input, hidden, and output, respectively.

Step (3): Calculate the errors of each layers backwards. Go back to Step (2) and train all the data in the training dataset.

Step (4): Adjust the weights with the formulas as follows:

$$w_{lk}(n+1) = w_{lk}(n) + \theta \sum_{p=1}^{a} \delta_l^p h_k^p, \tag{4}$$

$$w_{kj}(n+1) = w_{kj}(n) + \theta \sum_{p=1}^{a} \delta_k^p g_j^p, \tag{5}$$

$$w_{ji}(n+1) = w_{ji}(n) + \theta \sum_{p=1}^{a} \delta_j^p x_j^p. \tag{6}$$

where Q is the learning rate.

Step (5): Iterate Step (2) to (5) till for each training vector the following inequality is satisfied:

$$\left|t_l^p - y_l^p\right| < \varepsilon \tag{7}$$

where $p = 1,2,...,a$, $l = 1,2,...,Q$, $\{t_1\}$ denotes the output vector of the output layer, and ε is a given error criteria. At last, put the test dataset into the trained BP network and obtain the predictors. However, BP algorithm also has four disadvantages: easily being trapped into local optimums, slowly converging, experience-based parameter setting, and initial weights influencing.

The hybrid GA-BP algorithm

Genetic Algorithm (GA) is a good candidate to avoid the BP algorithm's disadvantage. GA has a global searching strategy by a random walk. From the population, GA searches the solution space in parallel. By the method of inheritance, GA filters the individuals. GA is not limited with the differentiability and continuity of the function. Therefore, our GA-BP model combines the advantages of two algorithms. The flowchart of GA-BP model is presented in Figure 2.

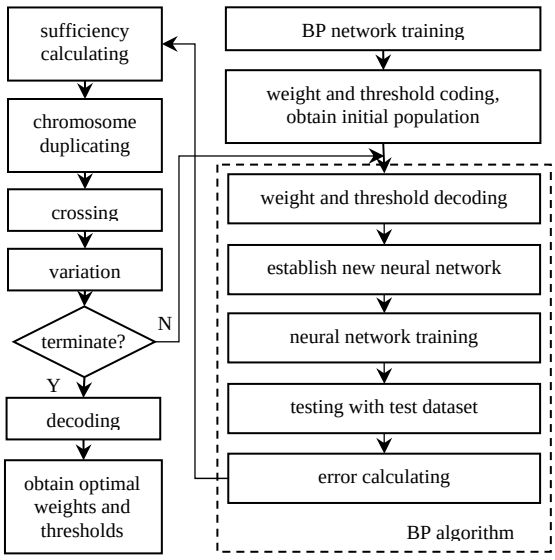

Figure 2. The flowchart of GA-BP algorithm

Experiments and Concluding Remarks

We compare GA-BP algorithm with two types of products: cable products and household appliances. We use the training dataset to train the BP neural network and use the test dataset to verify the correction of the output. After 50 generations, the GA-BP algorithm presents convergence in Figure 3.

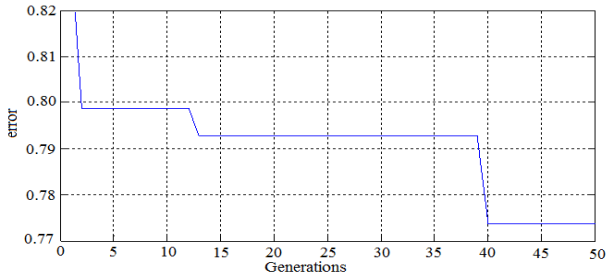

Figure 3. The error convergence of GA-BP algorithm

The comparison curves of prediction and actual bid of the test datasets for cable products and household appliances are shown in Figure 4.

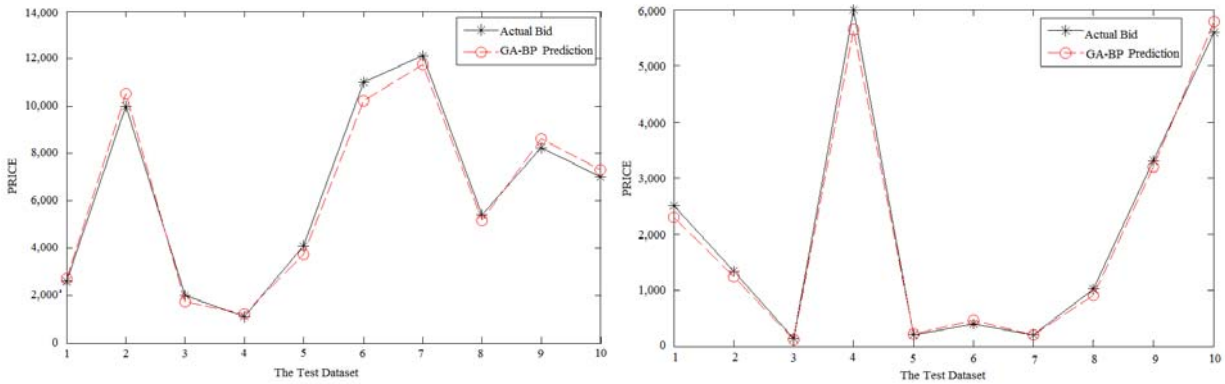

Figure 4. The prediction of GA-BP (a) for cable products (b) for household appliances

In order to show the performance of our GA-BP algorithm, we use household appliances as example to compare the iterating insensitivity. We settle the training goal as 0.01. The error curves of first 300 iterations in BP and GA-BP algorithms are plotted in Fig. 5. By comparing these two curves, we find that GA-BP algorithm converges faster than BP algorithm with the smaller error. Therefore, we can draw the conclusion that our GA-BP algorithm has a better performance in bid predicting.

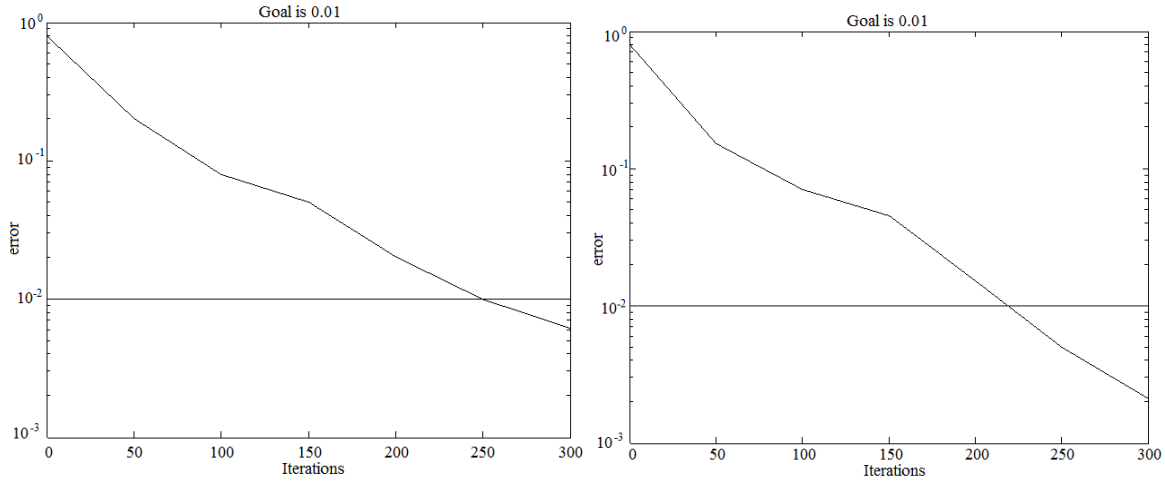

Figure 5. (a) BP training iterations (b) GA-BP training iterations

At last, the comparisons of performance for both cable products and household appliances are listed in Table 1. Therefore, we can draw the conclusion that our GA-BP algorithm has a better prediction for the transportation bidding.

It is important to predict the bid prices for the 3PL company. According to the nonlinear nature of transportation cost and carriers' psychological price, the GA-BP algorithm proves to have good performance in predicting short-term and long-term bidding prices. The proposed algorithm is effective and feasible in road freight transportation bidding managements.

Table 1. Comparison of the performances

	cable products			household appliances		
No.	BP	GA-BP	Actual Bid	BP	GA-BP	Actual Bid
1	2,415.9	2,689.3	2,600	2,727.8	2,302.8	2,500
2	11,911.1	10,511.1	10,000	1,514.7	1,241.7	1,333
3	1,726.3	1,750.6	2,000	147.2	121.2	133
4	870.5	1,196.3	1,100	5,339.2	5,639.2	6,000
5	3,689.0	3,698.4	4,100	179.1	216.8	200
6	12,511.3	10,210.3	11,000	462.8	453.8	400
7	10,866.2	11,746.2	12,130	185.3	203.3	200
8	4,473.2	5,160.6	5,410	736.4	896.4	1,011
9	9,382.2	8,598.2	8,245	3,707.1	3,190.1	3,300
10	6,368.2	7,295.5	7,000	5,014.4	5,791.4	5,600
average error	13.5%	6.3%	/	12.76%	7.15%	/

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