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Research Article

Construction of a Health Food Demand Prediction Model Using a Back Propagation Neural Network

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Abstract: For business operations, determining market demands is necessary for enterprises in establishing appropriate purchase, production and sales plans. However, many enterprises lack this ability, causing them to make risky purchasing decisions. This study combines a back propagation neural network and the Particle Swarm Optimization Algorithm (PSOBPN) to construct a demand prediction model. Using a grey relational analysis, we selected factors that have a high correlation to market demands. These factors were employed to train the prediction model and were used as input factors to predict market demands. The results obtained from the prediction model were compared with those of the experiential estimation model used by health food companies. The comparison showed that the accuracy of PSOBPN predictions was superior to that of the experiential estimation method. Therefore, the prediction model proposed in this study provides reliable and highly efficient analysis data for decision-makers in enterprises.

Keywords: Artificial neural network, demand prediction, particle swarm optimization algorithm

INTRODUCTION

Because of the intense competition among enterprises, every enterprise must develop methods for the efficient and accurate estimation of market demand, thus enabling them to make correct decisions regarding their business operations. Enterprises that can predict market demands earlier than other competing enterprises can succeed within a competitive environment because they perform advanced preparations such as stock purchases, personnel arrangements and the planning and modification of efficient operation strategies. Therefore, constructing a prediction model in which demands can be efficiently and accurately predicted is advantageous to enterprises because it can prevent revenue losses and cost accumulation caused by excessive stock and the loss of product orders resulting from insufficient stock, enabling enterprises to purchase the precise amount of stock needed to secure an advantage (regarding competitiveness and profits) over their competition. In addition, this ability plays a crucial role in the long-term and sustainable development of enterprises.

Previous studies have developed numerous demand prediction or estimation models based on the Delphi method, market research methods, panel discussion methods, exponential smoothing, the auto regression model and the moving average model (Huang *et al*., 2012; Mandischer, 2002; Song, 2012). Because of the various restrictions entailed in their application, these models are gradually being replaced by Artificial Intelligence (AI) prediction models. Among AI models, Artificial Neural Networks (ANNs) have been shown to be the most effective model for prediction functions (Wu *et al*., 2007).

ANNs possess the following characteristics: high-speed computing power, fast recall speed, high learning accuracy and fault tolerance. Therefore, ANNs are widely applied in various fields. When an ANN model is used for complex problems, a longer computational time is required and local optimum situations may be encountered (Farahmand *et al*., 2010; Lin, 2007; Kizil and Sacan, 2010).

Therefore, based on previous studies (Eberhart and Shi, 2001; Farahmand *et al*., 2010; Huang and Ho, 2012; Kizil and Sacan, 2010; Lin, 2007; Wu *et al*., 2007), we propose a demand prediction model that combines a back propagation neural network and a Particle Swarm Optimization Algorithm (PSOBPN). This study develops a demand prediction model that can conduct rapid calculations and avoid local optimums. The model was compared with the experiential estimation method used by a certain health food company in Taiwan. The results of this study can provide enterprises with a reference that has higher reliability and efficiency for practical business operations.

LITERATURE REVIEW

Predictions: Predictions are valued because of their importance regarding decision-making and project proposals. Calculations and estimations are used to elucidate possible events in business operations and can allow managers to implement low-risk decision-making (Stevenson, 2009). Traditional prediction methods can

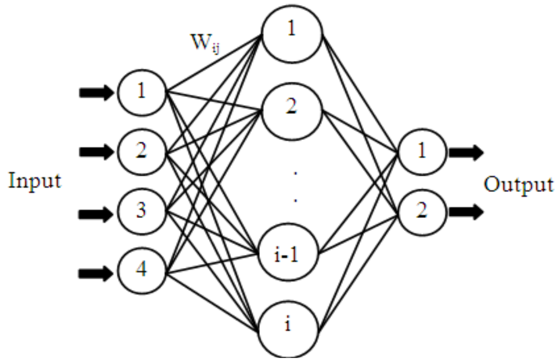

Fig. 1: Three-layer feed forward artificial neural network configuration

be divided into three types, including qualitative, time series analysis and projection and casual methods. However, these traditional methods entail various restrictions. In recent years, numerous AI methods have been developed to resolve prediction problems[11]. The term AI refers to computer systems that store human knowledge or provide human knowledge capabilities, including learning, reasoning, problem solving, knowledge storage and language processing. General AIs include expert systems, ANNs and fuzzy theory (Kennedy *et al*., 2001; Peng and Dong, 2011).

Artificial neural network: ANN is an information processing system developed by imitating the properties of biological neural networks. The primary characteristic of ANNs is their learning capabilities. In recent years, numerous models have been developed by applying ANN and because of its characteristics (i.e., high-speed computing, fast recall, high learning accuracy and fault tolerance), ANN has been widely applied in various fields, including optimization, identification and classification, prediction, evaluation, diagnostics and decision-making, association, approximation and induction and deduction (Law and Au, 1999). Figure 1 shows a three-layer neural network consisting of four neurons in the input layer, i neurons in the hidden layer, two neurons in the output layer and interconnecting weighting factors (W_{ij}) between the neuron layers (Huang and Ho, 2012). Training in an ANN model is a procedure in which ANN repeatedly processes a set of test data (input-output data pairs). The values of the weighting factors change according to the predetermined algorithm, enhancing the performance of the model. Back propagation is the most popular algorithm for training ANNs and is a supervised learning method in which an output error is fed backward through the network and alters the connection weights, minimizing errors between the network output and the targeted output (Huang and Ho, 2012).

Particle Swarm Optimization (PSO) algorithm: ANN models can process non-linear problems. However, using this model for calculations is time consuming and the data obtained from calculations may result in a local optimum situation. Therefore, this study used a PSO algorithm to solve the defects in the ANN model, enhancing its calculation efficiency and effectiveness. The PSO algorithm functions using a population (swarm) of particles, in which each particle searches independently. When a particle encounters an optimal value for a function, the optimal search is recorded in the particle's memory. That is, each particle contains its own optimal search memory. Based on this memory, particles can correct and adjust the subsequent search direction. This process is the particles' cognition-only model (Kennedy *et al*., 2001; Mamsor *et al*., 2012; Pilpayeh *et al*., 2010; Wang *et al*., 2012).

Table 1: The various input factors

Level	Input factors
Overall economic level	Gross national product
	Unemployment rate
	Consumer price index
	Taiwan stock market index
Past sales records	Sales of t-1 months
	Sales of t-2 months
	Sales of t-3 months
	Sales of t-4 months
	Sales of t-5 months
	Sales of t-6 months

RESEARCH METHODS

Market demands are affected by several factors, such as economic cycles, consumers' demands, national economic environments and industry developments (Huang and Ho, 2012; Lin, 2007; Li and Wang, 2012). This study collected data for the ten factors shown in Table 1. These data were used as the input variables for the model, which was used to predict the monthly product sales for a certain health food company in Taiwan. The data that were collected from January 2008 to December 2010 and from January 2011 to December 2011 were used for the model training and predictions, respectively. Applying too many input factors in the prediction model influences the model training speed. Therefore, a grey relational analysis (Chao, 2004; Deng, 1989) was used to select the crucial factors in this study.

The calculation procedure for the PSOBPN model is described as follows (Eberhart and Kennedy, 1995; Huang and Ho, 2012; Lin, 2007):

Step 1: Establish the PSOBPN network parameters, including input variable number, hidden layer number, output variable number, number of randomly generated particles, matrix sizes of the training samples and the number of times that the training is performed.

Step 2: Randomly generate the initial positions and velocities of the particles.

Step 3: Evaluate the fitness function of the particles and record the optimal memory of the individual particles and swarms.

Step 4: Update the positions and velocities of the particles.
Step 5: Repeat Steps 2 through 4 until termination conditions are satisfied.
Step 6: Calculate the output values for the hidden and output layer, then determine the objective function values.
Step 7: Repeat Steps 5 and 6 until the ANN model reaches the standard for concluding calculations.

EMPIRICAL ANALYSIS

This study combined a back propagation neural network and a particle swarm optimization algorithm to develop a health food demand prediction model. The proposed model was compared with an experiential estimation method employed by a health food company. We obtained the Mean Absolute Percentage Error (MAPE) as an indicator to evaluate the prediction errors that were produced by the various models:

$$MAPE = \frac{1}{n}\sum_{t=1}^{n}\frac{|p_t - r_t|}{r_t} \quad (1)$$

where, p_t represents the (t)th period prediction value, r_t represents the (t)th period actual value and n represents the number of periods.

The PSOBPN was developed using MATLAB software. The weight modification method employed the PSO algorithm, with the following specifications: initial range = [10, -10], maximum velocity of 10 and a hidden layer number of 1. The hidden layer processing element and learning rate parameters were selected using genetic algorithm methods (i.e., tournament selection and arithmetic crossover). The optimal selected parameters for the hidden layer processing element and learning rate were 27 and 0.53, respectively. The comparisons between the PSOBPN predicted values and actual values are shown in Table 2. The average of the MAPE was 12.13% (the mean predicted accuracy was 87.87%) and the maximum and minimum percentages for the MAPE were 38.08 and 6.50%, respectively.

A comparison of the PSOBPN prediction model and the experiential estimation method used by a health food company in Taiwan is shown in Table 3. A small MAPE indicates that the method accurately predicts the actual value and that the PSOBPN predicted value was close to the actual sales amount. This suggests that the prediction ability of the proposed model is superior to the experiential estimation method. The mean and maximum MAPE for the PSOBPN model were 12.13 and 38.08%, respectively. The mean and maximum MAPE for the experiential estimation method employed by a Taiwanese health food company were 28.69 and 73.58%, respectively.

Table 2: MAPE for the PSOBPN predicted values and actual values

Month	Actual value	Predicted value	MAPE (%)
JAN	2510	2687	7.05
FEB	1788	1516	15.21
MAR	906	1251	38.08
APR	1850	2016	8.97
MAY	1509	1658	9.87
JUN	2156	1959	9.14
JUL	1877	1999	6.50
AUG	1068	1234	15.54
SEP	741	688	7.15
OCT	1877	1689	10.02
NOV	1625	1765	8.62
DEC	2455	2687	9.45
Mean MAPE			12.13
MAPE standard deviation			8.66
Maximum MAPE			38.08
Minimum MAPE			6.50

Table 3: MAPE for the PSOBPN model and the experimental estimation method

	PSOBPN prediction model (%)	Experiential estimation method (%)
Mean MAPE	12.13	28.69
MAPE standard deviation	8.66	19.97
Maximum MAPE	38.08	73.58
Minimum MAPE	6.50	17.35

CONCLUSION

The ability to predict product or market demands is crucial for enterprises. The accuracy of predictions can directly affect enterprises' purchasing, production and sales plans, operational costs and reputations. If scientific prediction methods can be used to enhance the accuracy and reduce the time of predictions, decision-makers can effectively control and utilize their enterprises' overall resources, increasing enterprise competitiveness. This study combined a back propagation neural network and a PSO algorithm to develop a demand prediction model that was used to predict the monthly sales for health food. The results showed that the PSOBPN prediction model was able to predict the monthly sales with greater accuracy (i.e., the accuracy of the prediction model was 87.87%) than was an experiential estimation method (which is currently used by enterprises). Therefore, using a PSOBPN model to predict health food demand can assist enterprises in reducing losses caused by prediction errors.

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