Supply Chain Forecasting Model Using Computational Intelligence Techniques

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ABSTRACT

Nowadays, supply chain is more complex with the advance of technology. One of the important tasks in supply chain management is product demand forecasting as it provide initial figure for various plan to work on, for example, production, inventory, personnel. The complexity of supply chain makes the traditional techniques become less appropriate. This paper propose an application of Artificial neural network (ANN) and Support vector regression (SVR) to forecast product demand. A case study of an arm coil of a hard disk from a hard disk drive part manufacturing was used to demonstrate the proposed techniques.

Keywords: Supply Chain, Forecasting, Artificial neural network, Support vector regression.

INTRODUCTION

Supply Chain Management (SCM) has gained a great deal of attention in recent years. It emphasizes the integration of all operations along the chain from supplier, manufacturer, and distribution centre until the product or service reaches the final customer. Today's competitive global business environment has made the supply chain become larger and more complex. Usually, each of these entities is able to make a locally optimum decision. However, the performance of the entire supply chain depends on optimum decisions about the supply chain as a whole. A lack of fundamental knowledge about supply chain operation and behavior is a key problem faced by much of industry.

One of the important tasks in supply chain management is forecasting. The error results from inaccurate forecasting model got amplified as it passed along the supply chain. As the supply chain grows bigger and more complex, traditional forecasting techniques such as moving average and exponential smoothing are not always suitable to deal with the complexity and nonlinearity nature of the problem. As a result, there is a need for more reliable and accurate forecasting model.

Artificial neural network (ANN) is one of the artificial intelligence tools that have been used widely for modeling tasks due to their versatility, ability to learn from examples, and noise tolerance. However, a very limit amount of work has been published concerning the use of ANN for supply chain modeling. This is the research gap which will be exploited by this proposed research. Because of the above advantages, ANN has good potential to be used to model complex system such as supply chains. ANN has seldom been reported to be applied directly to supply chain management. However, it has been applied in a number of areas which constitute the core components of supply chains (Leung, 1995). Recently, support vector machine (SVM) has been reported in some literature (Zheng and Song, 2004, Cheng and Cheng, 2008, Guosheng and Guohong, 2008, Yang and Su, 2008). to be either similar or superior to ANN in various tasks. This is due to the fact that SVM overcomes the drawback of ANN such as over fitting problem.

This research focused on the development of an accurate supply chain demand forecasting model by comparing between computation intelligence techniques including ANN, SVM with traditional statistical techniques including Moving Average, Exponential Smoothing, and Auto-Regressive Integrated Moving Average (ARIMA). Two case studies of demand forecasting were demonstrated using actual data.

FORECASTING METHODS

a. Traditional techniques

The term 'Traditional forecasting techniques' in this paper refer to forecasting methods based on statistical and mathematical theory, for example Moving Average, Exponential Smoothing, and Auto-Regressive Integrated Moving Average (ARIMA).

ARIMA, also know as Box-Jenkins model is the most general model for time series forecasting. The general form of the ARIMA model is written as the follows:

$$\text{ARIMA } (p,\ d,\ q)\ (P,\ D,\ Q)_s \tag{1}$$

Where p is the number of autoregressive terms, d the differencing degree, q the number of parameters in moving average model, P the number of parameters in autoregressive seasonal model, D the seasonal differencing degree, Q the number of parameters in moving average seasonal model, and s the period of seasonality. ARIMA model can be written as

Demand forecasting becomes more difficult in current business environment due to the diversity of product, globalization and rapid changes in technology. This changing environment makes traditional techniques become less accurate.

b. Artificial neural network

Artificial neural network (ANN) is a computer programming that mimic human nervous system. It can be used to model relationship between given inputs and their related outputs from examples, this learning process is similar to human learning system. ANN is made up of simple processing element, neuron, connected together. Neurons can be located in the input layer, hidden layer or output layer. ANN is used to model or 'learn' relationship by tuning a set of parameters called 'weight' (the strength of the connection between neurons). This weight alteration process is called training. In the training process, a set of examples of input-output pairs is passed through the model and the weights adjust in order to minimize the error between the answer from the network and the desired outputs. The weight adjustment procedure is controlled by the learning algorithm. Once the error is minimal, the network is successfully trained. The trained network is able to predict output for unseen input.

Back Propagation (BP) algorithm is the most extensively adopted learning algorithm. BP is the algorithm used in the case study. The algorithm can be summarized as follows (Dayhoff, 1990),

1) Forward pass

Feed input through the network to attain output by calculate weighted sum (*Sj*) for every neuron.

$$S_j = \sum_i a_j w_{ij} \tag{2}$$

where a_i = the activation level of unit i, and w_{ij} = the weight from unit i to unit j (unit i is one layer before unit j)

Transfer function was then applied to the output, in this research, Sigmoid transfer function was used. The equation for the sigmoid function is as follows

$$f(x) = \frac{1}{1+e^{-x}} \tag{3}$$

The result becomes the output of unit j. The same procedure repeat for all neurons.

2) Backward pass

Calculate error δ and weight changes for all neuron as follows

for the output layer, $$\delta_j = (t_j - a_j) f'(S_j) \tag{4}$$

for the hidden layer, $$\delta_j = \left[\sum_k \delta_k w_{kj}\right] f'(S_j) \tag{5}$$

where t_j = the target value for unit j, a_j = the output value for unit j, $f'(x)$ = the derivative of the sigmoid function f, S_j = weighted sum of inputs to j

weight adjustment is calculated as $\Delta w_{ji} = \eta \delta_j a_i$ (6)

where η is the learning rate.

These processes of forward and backward pass repeat with new input vector until stopping criterions are met.

Some of the applications of ANN in forecasting are summarized in Table I. MLP (Multi-layer perceptron) learning with back propagation is the most widely used type of ANN reported in literatures. According to Leung (1995), advantage of using ANN in forecasting is that ANN is suitable to model system where rules for governing the system behavior are not very well understood.

Table 1. Literatures in demand forecasting.

Authors (year)	Applications	Methods used	Best methods
Leung (1995)	General forecasting concept of ANN in SCM	MLP	-
Tseng *et al* (2001)	The exchange rate	Fuzzy ARIMA	-
Chu and Zhang (2003)	Aggregate retail sales forecasting	ARIMA, Reg, MLP	MLP
Zhang (2003)	Wolf's sunspot data, the Canadian lynx data and the British pound/ US exchange rate	ARIMA+MLP	ARIMA+MLP
Pai and Lin (2005a)	Stock price forecasting in Taiwan	ARIMA, SVM, SVM+ARIMA	SVM+ARIMA
Pai and Lin (2005b)	Production value of the machinery industry in Taiwan	SARIMA, GRNN, SVM	SVM
Yujun *et al.* (2006)	Short term daily load forecasting at Hebei province of China	SVM+ARIMA	SVM +ARIMA
Co and Boonsara-wondse (2007)	Thailand's rice export forecasting	ARIMA, Exp Smt, MLP	MLP
Zou *et al* (2007)	Chinese food grain price forecasting	ARIMA, MLP, ARIMA+MLP	MLP
Arburto and Weber (2007)	Supermarket demand forecasting	Tradition techniques, ARIMA, MLP, MLP+SARIMAX	MLP+SARIMAX
Aslanargun *et al.* (2007)	Tourist arrival fore-casting to Turkey	ARIMA, MLP, RBFN	ARIMA+MLP
Carbonneau *et al.* (2008)	Foundries monthly sales data and simulated data from MATLAB	Naïve, MA, Trend, Reg, MLP, RNN, SVM	RNN, SVM

Note: ARIMA=autoregressive integrated moving average, Exp Smt = exponential smoothing, GRNN= general regression neural network, MA= moving average, MLP= multilayer perceptron, RBFN=radial basis function network, Reg= regression, RNN= recurrent neural network, SARIMAX = seasonal time series auto regression integrated moving average, SVM= support vector machine.

There have been reports comparing ANN with traditional forecasting techniques. For example, Chu and Zhang (2003) compare the accuracy of ARIMA, regression, and ANN to forecast aggregate retail sales. The results suggested that the nonlinear method was the preferred approach to model retail sales. The overall best model for retail sales forecasting was the Artificial neural network model with deseasonalized time series data. The results agreed well with Co and Boonsarawondse (2007), where Exponential Smoothing, ARIMA and ANN were used to forecast Thailand's rice export. The results suggested that Holt-Winters and the Box-Jenkins models showed satisfactory result with seen data, but did not perform well with unseen data, while ANN produced better predictive accuracies. Similar results were also reported in Zou *et al.* (2007), in which ARIMA, ANN, and combined method were compared in forecasting Chinese food grain price. The results suggested that ANN outperform other techniques.

There have also been reports combining ANN with traditional forecasting techniques. For example, reference Zhang (2003) integrate ARIMA with ANNs in order to take advantage from both linear and nonlinear modeling and found that this integrated techniques provide better forecasting accuracy. Similar result was reported Aslanargun *et al.* (2007). In this study hybrid forecasting model between ANN and ARIMA was developed to forecast the number of monthly tourist arrivals to Turkey. The results indicated that the hybrid model had a better performance.

c. Support vector machine

Support Vector Machine (SVM) is a type of function approximator that is based on the structured risk minimization principle. Recently, SVM has become more interested by researchers and has been increasingly applied in forecasting. For example, Pai and Lin (2005b) used SVM to forecast production values of machinery industry. They also used the seasonal time series autoregressive integrated moving average (SARIMA) model and general regression neural networks (GRNN). The results showed that SVM outperform other techniques. Similar result was reported by Carbonneau *et al.* (2008), where advanced machine learning techniques, including neural networks, recurrent neural networks, and support vector machines were used to forecast demand of simulated supply chain in comparison with more traditional techniques including na?ve forecasting, trend, moving average, and linear regression. The results suggested that, recurrent neural networks and support vector machines showed the better forecasting accuracy but the results were not statistically significantly better than that of the regression model.

Instead of comparing SVM against traditional forecasting technique, some researcher took different approach by combining the two together. For example, Yujun *et al.* (2006) suggested hybrid model of ARIMA and SVM. A case study of forecasting Hebei province daily load power data. The results showed that the hybrid model can effectively improve the forecasting accuracy.

RESULTS

a. Data collection and preparation

Actual demand of an arm coil of hard disk from an electronics part manufacturer was used to demonstrate the proposed method. Monthly demand data product was available from January 2004 to November 2007 (Fig.1).

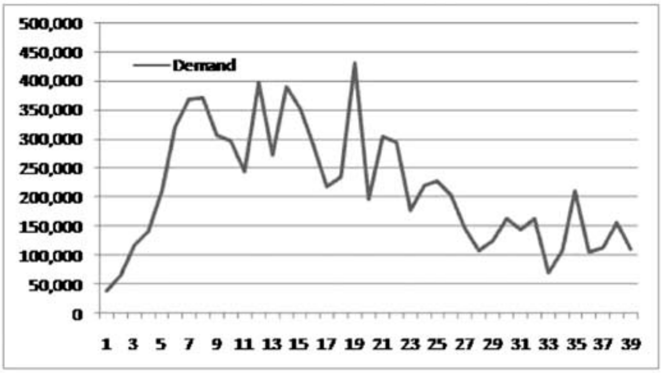

Figure 1. Actual demand plot.

b. Model building

i. Traditional forecasting methods

Traditional forecasting models were implemented using Minitab software. Inputs to the models were summarized in Table 2. and Table 3. Table 2 provides all input used and their description. Table 3 provides the summary of input used in all 8 models.

Table 2. Model's input description.

Input No.	Symbols	Description
1	D_t	Demand of the current period
2	D_{t-1}	Demand t-1 period from the current period t
3	D_{t-2}	Demand t-2 period from the current period t
4	D_{t-3}	Demand t-3 period from the current period t
5	D_{t-4}	Demand t-4 period from the current period t
6	D_{t-5}	Demand t-5 period from the current period t
7	D_{t-6}	Demand t-6 period from the current period t
8	D_{t-7}	Demand t-7 period from the current period t
9	D_{t-8}	Demand t-8 period from the current period t
10	D_{t-9}	Demand t-9 period from the current period t
11	Y	Year of the period to forecast
12	M	Month of the period to forecast (1 to 12)
13	P	Accumulated number of period from the start of forecast
14	S	Seasonal index of the period to forecast

Table 2. (Continue).

Input No.	Symbol	Description
15	3MV	3-month moving average
16	6MV	6-month moving average
17	9MV	9-month moving average
18	Next	Tendency (1 if $D_t>D_{t-1}$, 0 if $D_t=D_{t-1}$, -1 if $D_t<D_{t-1}$)
19	Direction	Accumulate value of 'Next'

Table 3. Inputs used for each model.

Models	Input no. used to construct the model
ANN	No. 1 to No. 19
SVM	No. 1 to No. 19
3MV	No. 1 to No. 3
5MV	No. 1 to No. 5
9MV	No. 1 to No. 9
Single Exponential	No. 1
Double Exponential	No. 1
ARIMA	No. 1

Three, five and nine moving ranges were used for moving average model. Parameters other traditional forecasting were optimized by Minitab. For single exponential, alpha of 0.56 was used and for double exponential, alpha of 0.88 and Gamma of 0.01 were used. Finally ARIMA (2,1,1) was used.

ii. CI forecasting techniques

For ANN model, 19 input nodes and one output node (demand of the next period) network was constructed. Search was carried out to identify number of hidden layer and number of hidden nodes in each layer that provide highest modeling accuracy. Up to two hidden layers, and up to 30 neurons in each layer were tested with step size of one neuron. Best architecture obtained was 10 nodes in the first hidden layer and 15 nodes in the second layer. Learning rate of 0.1, momentum of 0.75 were set.

For SVM model, parameter search was carried out at the following range, [50-500,000] for capacity (c), [0.000001-0.0001] for epsilon (ε), and [0.0001-10] for gamma (γ). Best architecture obtained was 993.69, 0.000001, and 0.053 for c, ε, and γ respectively.

c. Model comparison

Graph results of the last 9 periods was shown in Fig. 2 was a plots of actual demand and forecast value from all 8 models. ANN and SVR have shown better performance than the traditional models as the prediction plot were closer to the actual plot.

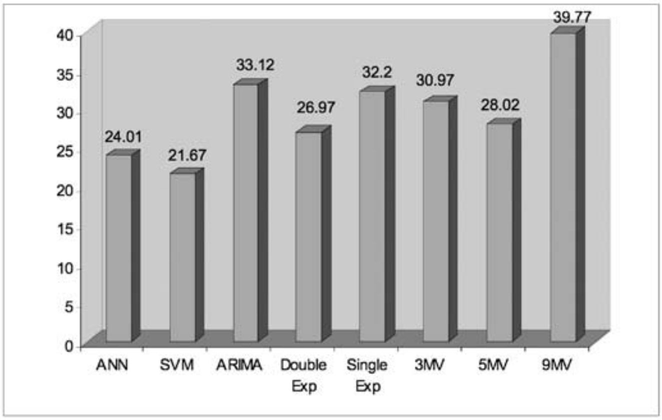

Figure 2. MAPE of all forecasting models.

In order to compare error of all models to find the most accurate one, MAPE (Mean absolute percentage error) of all models was calculated using equation (10) and the results are displayed in Fig. 3.

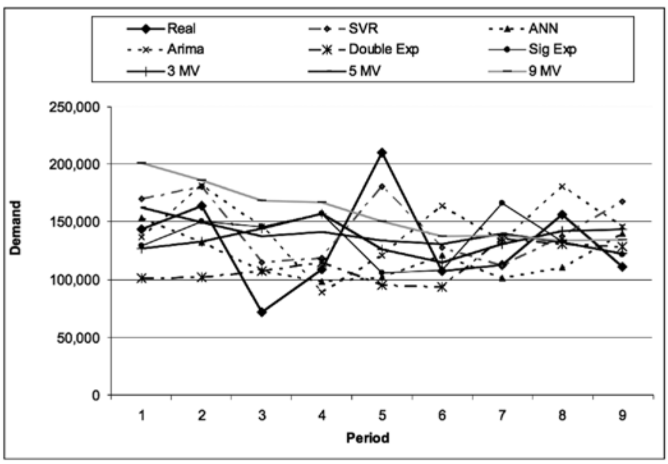

Figure 3. Actual vs Forecast demand plot.

$$MAPE = \frac{1}{N}\sum_{i-1}^{N}\frac{|Actual_t - Forecast_t|}{Actual_t}\times 100 \qquad (10)$$

Fig. 3 indicated that the best traditional forecasting method was the double exponential with MAPE of 26.97%. However, both proposed CI techniques outperform the traditional techniques as they have lower MAPE. SVM (MAPE = 21.67) performed slightly better than ANN (MAPE = 24.01). The results were agreed with the previous literatures (Pai and Lin, 2005b) and Carbonneau *et al.,* 2008).

DISCUSSION AND CONCLUSION

This paper examined the application of two computational intelligence techniques namely artificial neural network and support vector machine in product demand forecasting in comparison with traditional techniques. A case study of an arm coil part of hard disk drive was used to demonstrate the proposed method. The results suggested the proposed methods provide higher accuracy.

ANN provides better accuracy than the traditional methods because it is a non-linear mapping between input and output. Furthermore, ANN has no statistical assumption about the distribution of data, hence made it more versatile. However, ANN suffered from 'overtraining' problem and also another major drawback of ANN was it 'black-box' like ability. SVM has recently been compared with ANN as it solve 'overtraining' problem suffered by ANN. In this work SVM slightly outperform ANN in terms of forecasting accuracy.

The methods proposed can also be applied to other product. However, input used may have to change to be suitable to the nature of that product.

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