COMPARISONS OF DECISION METHODS FOR ORDER QUANTITY FORECASTING IN A MECHANIC COMPANY

F. Michael Chang, National Taitung College, Taiwan, fmc@ntc.edu.tw
Chien-Chung Chan, University of Akron, USA, chanc@uakron.edu
Evan Lin, Printech International Inc., Taiwan, hchs810268@yahoo.com.tw

ABSTRACT

For an enterprise, no orders no profits. The forecast of order quantity affects the decision of the balance of production capacity. In the field of Industrial Engineering and Management, some traditional time series forecasting technologies such as moving average and exponential smoothing methods are popular and have been used for order forecast. Recently, machine learning methods in the field of Artificial Intelligence (AI) have also been used for prediction, among them including Artificial Neural Network (ANN) and Fuzzy Neural Networks (FNN) approaches. In this study, real mechanic order quantity data are used to compare the forecasting efficiency of the above mentioned four methods. The results indicate that FNN method has better forecast accuracy than the others.

Keywords: moving average, exponential smoothing, ANN, FNN, forecast

INTRODUCTION

To an enterprise, orders are important. Many factories begin their production activities after they receive product orders. If orders come intensively in a short period of time, it causes the paucity of materials, parts, and human powers. In order to deliver the goods in time, laborers have to work overtime, which would incur extra cost in wedges. On the other hand, when production capacities are idle, employees have no work to do, and costs are wasted. Therefore, it is very important to forecast order quantity as accurately as possible.

This study mainly uses the data of the CHTA Herng Industry company as a case study in order to control the balance of the capacity requirements and the order quantity. CHTA Herng Industry company is a hardware company that manufactures heat sink, stator, bracket, isolated cover, outer case for machine, and mechanic faceplate manufactured using Computerized Numerical Control (CNC) punches and press brakes. Four kinds of packaging machines parts for a long term customer comprise of 70% of the company's income. Actually, this company is the largest company to provide packaging machines parts in Taiwan. However, the product demands are usually unsteady and cause the unnecessary wastes of costs. Therefore, applying forecasting technology to predict the order quantity for CHTA Herng Industry for cost saving is an important issue.

There are some time series forecasting technologies based on moving average [1-2] and exponential smoothing [3-4] methods. These methods consider only previous order quantities to predict further demands without considering other affecting factors. However, factors such as season, price, and economic trend may affect product demands. Although season, trend, and cycle factor can be calculated and adapted from the past data, forecasting errors are large when not enough data are available on hand. In this work, we try to use machine learning methods introduced in artificial intelligence researches to reduce forecasting errors caused by lack of available data, this study includes other affecting factors coupled with applying artificial intelligence methods in order to increase the forecast accuracy for the further order quantities.

More specifically, this study uses CHTA Herng Industry company's historical data processed by moving average, exponential smoothing, Artificial neural network (ANN), and Fuzzy Neural Networks (FNN) methods to help control the production capacity and make a comparison of these four methods.

In the following sections, we will first provide brief reviews of the four methods used in our study. Then, we describe the data used in our experiments. Next, we present the experimental results and discussion, followed by conclusions and references.

REVIEW

Moving average method

Moving average method averages the data values over a certain period of time of past and uses the average value to forecast the upcoming value. The benefit of this method is that the extreme datum with large difference from general data in the period of time will be offset and smoothed. Therefore, average data or forecast data values are renewed dynamically. When new datum arrives, the old forecast value is removed and the new predicted value is refreshed. The system always keeps the newest forecasting datum. The number of time units of the data affects the variation of the average values. If the length of time period is short, the variation among the average values is large. Otherwise, the variation is small but the prediction is

not smart.

Moving average method takes average over all the data in t period of time up until the current data. It could be calculated as:

$$MA_n = \frac{\sum_{t=1}^{n} A_t}{n}$$

where MA_n is the moving average forecast value, n is the number of period of time, and A_t is the tth value.

Exponential smoothing method

Exponential smoothing method is a kind of moving average methods but needs simple information only. It is easy to calculate and is easy to change data weights, also it needs only small storage space in a computer. When there are many items for forecasting, it is specially suitable for computerized implementations. Exponential smoothing method uses the value of an Alpha Factor to decide the degree of reaction for the previous forecast error. The range of Alpha Factor value is between 0 and 1, where a value in 0.2 to 0.5 is commonly used. It means that the current forecast value shall consider 20% to 50% of the previous forecast error. Exponential smoothing can be calculated as:

$$F_t = F_{t-1} + \alpha(A_{t-1} - F_{t-1})$$

where F_t is the forecast value of the tth period of time, F_{t-1} is the forecast value of the (t-1)[th] period of time, A_{t-1} is the actual value of the (t-1)[th] period of time, and α is Alpha Factor, $0 \le \alpha \le 1$.

Artificial neural network

Artificial neural network was introduced in the era of 1940's inspired by biological neuron networks of human brains, and it introduced a new paradigm parallel and distributed computing [5, 9-17]. It was popularized by a simple family of two-layer neural networks called Perceptron [10, 11, 12], which is capable of learning solutions from training data to linearly separable classification problems. One important and useful feature of Perceptron is the convergence property, which says that if a linearly separable problem is solvable, then the solution can be found by a Perceptron in a finite amount of time [16]. However, for non-linear problems as simple as the XOR problem, they cannot be solved by simple two-layer networks [10]. Multi-layer artificial neural networks with back-propagation learning procedure for solving non-linear problems was introduced by [13-15]. However, in general, the convergence to a solution cannot be guaranteed for multi-layer networks. Another popular ANN was introduced in the form of learning associations from training data [17].

One example of multi-layer neural network is the Fuzzy neural network that will be reviewed in the following section. While applying ANN, we need two sets of data, one is used as training data set, the other is used as checking data set. Training data are used to train ANN in order to increase the forecast accuracy, and checking data are used to check the prediction accuracy.

Fuzzy neural network

Fuzzy Neural Networks, also known as Neuro-fuzzy systems, are multi-layer neural networks integrated with fuzzy inference systems. ANFIS (Adaptive Network based Fuzzy Inference Systems) is a popular FNN tool proposed by Jang [6]. Given a set of input and output data, ANFIS can construct a fuzzy inference system with membership functions generated by adaptive back-propagation learning.

The basic model of ANFIS is the Sugeno fuzzy model [7, 8]. Let x and y be two input variables, let z be the output variable, and the fuzzy if-then rules are formatted as:

$$\text{If } x = P \text{ and } y = Q \text{ then } z = f(x, y)$$

Consider two first-order rules of Sugeno fuzzy model, the if-then rules can be:

$$\text{Rule } A\text{: If } x = P_1 \text{ and } y = Q_1\text{, then}$$
$$f_1 = m_1 x + n_1 y + c_1,$$
$$\text{Rule } B\text{: If } x = P_2 \text{ and } y = Q_2\text{, then}$$
$$f_2 = m_2 x + n_2 y + c_2$$

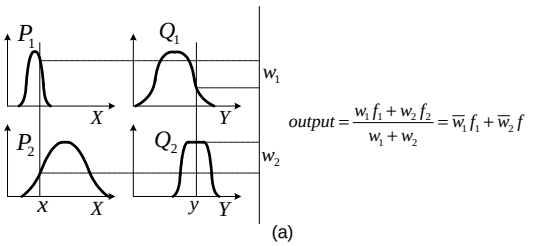
where P_i ,and Q_i are fuzzy sets, and m_i , n_i and c_i are constants for i = 1, 2. The Sugeno model is shown in Fig. 1(a), and the corresponding ANFIS structure with a five-layer artificial neural network is shown in Fig. 1(b).

The following is a brief description of the five layers in ANFIS. Let the output of the i-th node of layer l be $O_{l,i}$. In Layer 1 of ANFIS,

$$O_{1,i} = \mu_{M_i}(x)\text{, } i = 1, 2, \text{ or}$$

$$O_{1,i} = \mu_{N_{i-2}}(y),\ i = 3,4$$

where μ_{M_i} and $\mu_{N_{i-2}}$ are arbitrary fuzzy membership functions of any types such as triangular or generalized bell function.



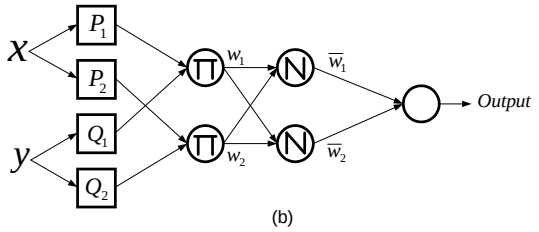


Fig. 1 (a) The Sugeno fuzzy mode; (b) The ANFIS structure.

For nodes in Layer 2, the outputs w_i are the products of the outputs of Layer 1, and they are used as the weights of Layer 3:

$$O_{2,i} = w_i = \mu_{M_i}(x)\mu_{N_i}(y),\ i = 1,2$$

In Layer 3, the output of every node is normalized as follows:

$$O_{3,i} = \overline{w}_i = \frac{w_i}{w_1 + w_2},\ i = 1, 2.$$

Next, Layer 4 is the defuzzification layer which adapts node values with the following equation:

$$O_{4,i} = \overline{w}_i f_i = \overline{w}_i (m_i x + n_i y + c_i),\ \text{for } i = 1, 2$$

where m_i, n_i, and c_i are parameters of the nodes.

Finally, the fifth layer is to compute the output from all the input signals using the equation:

$$O_{5,1} = \sum_i \overline{w}_i f_i = \frac{\sum_i w_i f_i}{\sum_i w_i},\ \text{for } i = 1, 2$$

Root mean squared error

In this study, the measurement of errors used to compare the four different forecasting methods is based on the Root Mean Squared Error (RMSE). The RMSE is used to estimate the prediction error, and it is defined as:

$$RMSE = \sqrt{\frac{\sum_{t-1}^{n}(A_t - F_t)^2}{n}}$$

where A_t is the actual value of the tth period to time, F_t is the forecast value of the tth period to time, and n is the total data number.

EXPERIMENTAL DATA SETS

Experiments conducted in this study to compare the forecast efficiency of both time series and machine learning methods are based on data collected from the CHTA Herng Industry company between 1996 to 2007. There are 980 records in total, including four products: TC-002, TC-043, TJ-002-203, and TC-2-20110 which are represented as P1, P2, P3, and P4, respectively.

For the Moving average and the Exponential smoothing methods, monthly order quantities are used. Table 1 shows 11 data points from the monthly order data set.

For the ANN and FNN methods, the information used for training the learning methods and for predicting order quantities is different from time series methods. Each item in the data set consists of input and output attributes. The input attributes include year, month, and price, and the order quantity is the output attribute. Some of this data set is shown in Table 2. Data from 1996 to 2006 are used as training data sets, and data of 2007 is used as checking data.

Table 1. Part of the data for time serial methods

No.	Quantity
1	1652
2	385
3	1756
4	1204
5	1400
6	1200
7	1350
8	1800
9	1000
10	1904
11	1414

RESULTS

Moving average method

The results of applying moving average method to the experimental data are shown in Table 3. The time series moving average method is applied with three different lengths of period of time N = 3, N = 5, and N = 7. The forecasting results are collected for the four different products P1, P2, P3, and P4. Their RMSE values are as shown in Table 3. For P1, P2, and P4, the RMSE in 7 period of time are better than the others. For P3, their RMSE are almost the same. Therefore, the results indicate that RMSE for 7 period of time is better than the others.

Table 2. Part of the data for machine learning.

Year	Month	Price	Quantity
2007	1	180	1652
2007	2	180	385
2007	3	180	1756
2007	4	180	1204
2007	5	180	1400
2007	6	190	1200
2007	7	190	1350
2007	8	190	1800
2007	9	190	1000
2007	10	190	1904
2007	11	190	1414
2007	12	190	900

Table 3. RMSE of moving average method

	N=3	N=5	N=7
P1	397	382	376
P2	237	237	232
P3	70	71	71
P4	108	98	97

Exponential smoothing method

Data used for the exponential smoothing method are the same as those used in the moving average method. The Alpha Factor α is set as 0.1, 0.3, 0.5, 0.7 and 0.9 to forecast the order quantities. The RMSE values are listed in Table 4. In the results, when α =0.1, the forecast errors are smallest in P1, P2, and P4. Although α =0.3 has the smallest error in P2, but the error is similar to α =0.1 and α =0.5. In summary, α =0.1 has the better forecast results in exponential smoothing method.

Table 4. RMSE of exponential smoothing method

	α				
	0.1	0.3	0.5	0.7	0.9
P1	358	377	405	440	484
P2	236	225	234	249	267
P3	71	72	75	80	88
P4	94	99	105	112	120

ANN(1)

We use two kinds of data to predict order quantities by the ANN approach. In this subsection, following the different period of time concept in moving average method, we use the previous certain period of time data to forecast newest value by ANN. For example, when N=3, three periods of time data $\{x_1, x_2, x_3\}$ are used as 3 input data to forecast x_4 the fourth value. When $\{x_2, x_3, x_4\}$ are used as 3 input data, x_5 is the value to be predicted. The RMSE results are shown in Table 5. It is clear that when N=3, RMSE is the smallest.

Table 5. RMSE of ANN(1)

	N=3	N=5	N=7
P1	479	533	564
P2	265	280	480
P3	103	98	182
P4	115	224	175

ANN(2)

Another way to apply ANN method for prediction is to use more attributes to represent data. In this section, data attributes year, month, and price are used as inputs and quantity is used as output. After training and checking, the RMSE for each product is presented in Table 6.

Table 6. RMSE of ANN(2)

P1	368
P2	221
P3	83
P4	111

In Fig. 2, RMSE of ANN(1) with N=3 is compared with the result of ANN(2). It is clear that ANN(2) is better than ANN(1).

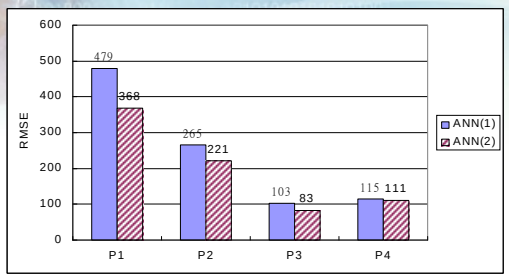


Fig. 2. The comparison of ANN(1) and ANN(2)

FNN

For the FNN method, the data set used for learning is the same as in ANN(2) with three input attributes and one output attribute. After learning and checking, the RMSE for the four products are shown in Table 7.

Table 7. RMSE of FNN learning

P1	346
P2	170
P3	69
P4	87

In Fig. 3, the RMSE of ANN(2) and FNN methods are compared. For all four products, it is clear that using FNN is better than using ANN(2).

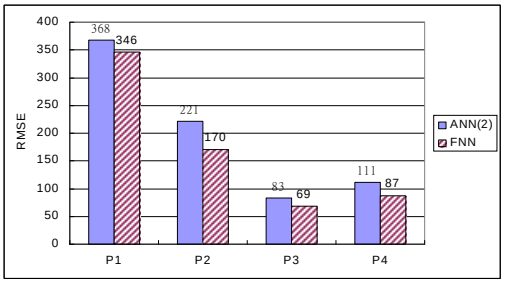


Fig. 3. The comparison of ANN(2) and FNN

Discussion

The prediction results from our experiments based on five different methods are summarized in Table 8. In the table, the best result for product P1 in moving average method with N=7 is 376, in exponential smoothing method is 479, in ANN(2) is 368, and in FNN is 346. Therefore, the best forecast method for P1 is FNN.

The bar charts shown in Fig. 4, 5, 6, and 7 provide another look of the comparison of prediction performance on the four products P1, P2, P3, and P4 by using the five different forecasting methods. The figures indicate that FNN is the best forecast method for all the products. Also, results of ANN and FNN are better than the others. It may be that data for ANN and FNN provide more information, three input attributes, to help the system increases prediction accuracy.

Table 8. Summary results

		P1	P2	P3	P4
Moving	N=3	397	237	70	108
average	N=5	382	237	71	98
method	N=7	376	232	71	97
Exponential	α=0.1	358	236	71	94
smoothing	α=0.3	377	225	72	99
method	α=0.5	405	234	75	105
	α=0.7	440	249	80	112
	α=0.9	484	267	88	120
ANN(1)	N=3	479	265	103	115
	N=5	533	280	98	224
	N=7	564	480	182	175
ANN(2)	{year,	368	221	83	111
FNN	month, price}	346	170	69	87

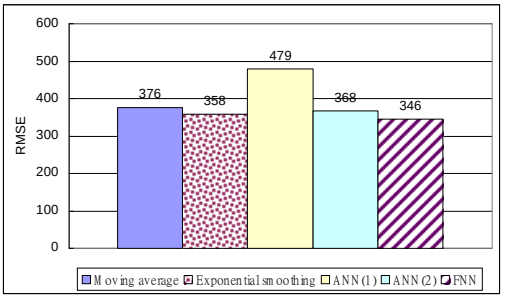


Fig. 4. Comparison of forecast methods for P1.

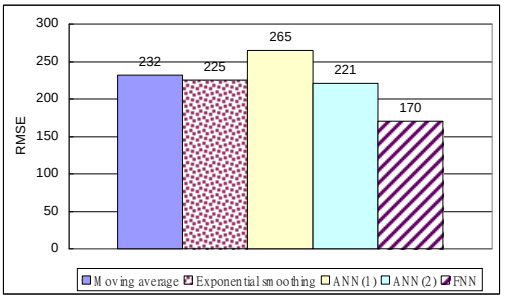


Fig. 5. Comparison of forecast methods for P2.

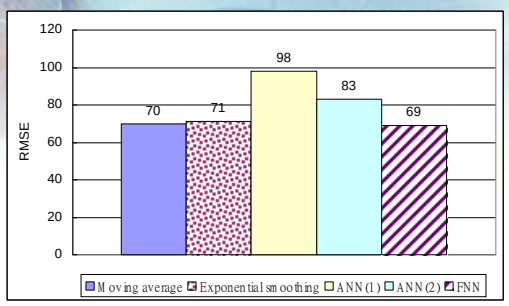


Fig. 6. Comparison of forecast methods for P3.

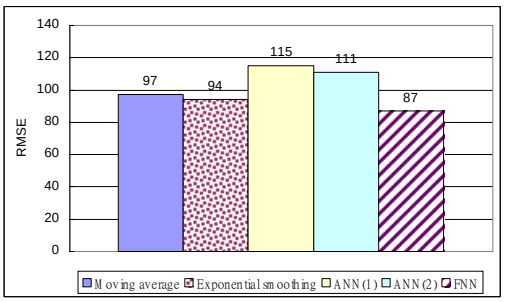


Fig. 7. Comparison of forecast methods for P4.

CONCLUSIONS

It is very important for a company to balance its production capacity and required orders. However, it is challenging to predict order quantities, since order demanding patterns are unsteady in general. It is clear that production capacity may become insufficient when the quantity of orders jumps up abruptly, and it may lead to extra overtime labor costs, delay of finishing products, or losing customers. On the other hand, when the quantity of orders suddenly decreases, production capacity is wasted. Labors and machines are idle but the company still has to pay salaries and machine costs.

In this study, we compared traditional time series forecasting methods with artificial intelligence machine learning methods by using historical data collected from a real company. The problem faced by the company is a common problem to most of the companies, namely, the quantity of orders is uncertain and with wide variations.

Our experiments was conducted by using the real data collected from four different kinds of products. The results indicate that FNN machine learning method has the best forecasting accuracy for all the products.

REFERENCES

[1] Zhang, N.F. (2006) 'The batched moving averages of measurement data and their applications in data treatment', *Measurement*, Vol. 39, No. 9, pp. 864-875.

[2] Moon, Y.S. & Kim, J. (2007) 'Efficient moving average transform-based subsequence matching algorithms in time-series databases', *Information Sciences*, Vol. 177, No. 23, pp. 5415-5431.

[3] Taylor, J.W. (2004) 'Volatility forecasting with smooth transition exponential smoothing', *International Journal of Forecasting*, Vol. 20, No. 2, pp. 273-286.

[4] Billah, B., King, M.L., Snyder, R.D., & Koehler, A.B. (2006) 'Exponential smoothing model selection for', *International Journal of Forecasting*, Vol. 22, No. 2, pp. 239-247.

[5] Agatonovic-Kustrin, S. & Beresford, R. (2000) 'Basic concepts of artificial neural network (ANN) modeling and its application in pharmaceutical research', *Journal of Pharmaceutical and Biomedical Analysis*, Vol. 22, No. 5, pp. 717 – 727.

[6] Jang, J.-S. R. (1993) 'ANFIS: Adaptive-Network-based Fuzzy Inference Systems', *IEEE Transactions on System, Man, and Cybernetics*, Vol. 23, No.3, pp.665-685.

[7] Sun, Z.L., Au, K.F. Au, & Choi, T.M. (2007) 'A Neuro-Fuzzy Inference System Through Integration of Fuzzy Logic and Extreme Learning Machines', *IEEE Transactions on Systems, Man, and Cybernetics, Part B: Cybernetics*, Vol. 37, No. 5, pp. 1321 - 1331.

[8] Huang, Y.P., Hsu, L.W., & Sandnes, F.E. (2007) 'An Intelligent Subtitle Detection Model for Locating Television Commercials', *IEEE Transactions on Systems, Man, and Cybernetics, Part B: Cybernetics*, Vol. 37, No. 2, pp. 485 - 492.

[9] McCulloch, W. & Pitts, W. (1943), 'A Logical Calculus of Ideas Immanent in Nervous Activity', 1943, *Bulletin of Mathematical Bio*physics 5:115-133.

[10] Minsky, M. L. & Papert, S. A. (1969). *Perceptrons*. Cambridge, MA: MIT Press.

[11] Rosenblatt, F. (1958), 'The Perceptron: A Probabilistic Model for Information Storage and Organization in the Brain,' Cornell Aeronautical Laboratory, *Psychological Review*, v65, No. 6, pp. 386–408.

[12] Rosenblatt, F. (1962). *Principles of neurodynamics*. Spartan, New York.

[13] Rumelhart, D. E., Hinton, G. E. & Williams, R. J. (1986), 'Learning representations by back-propagating errors,' *Nature* **323** (6088): 533–536.

[14] Rumelhart, D. E., McClelland, J. L., & the PDP Research Group (1986). *Parallel Distributed Processing: Explorations in the Microstructure of Cognition. Volume 1: Foundations*. MIT Press, Cambridge, MA.

[15] McClelland, J. L., Rumelhart, D. E., and the PDP Research Group (1986). *Parallel distributed processing: Explorations in the microstructure of cognition. Volume 2: Psychological and biological models*. MIT Press, Cambridge, MA.

[16] Novikoff, A. B. (1962), 'On convergence proofs on perceptrons,' *Symposium on the Mathematical*

Theory of Automata, 12, 615-622. Polytechnic Institute of Brooklyn.
[17] Kohonen, T. (1977). *Associative memory: A system theoretical approach*. Springer, New York.