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A neuro-fuzzy based forecasting approach for rush order control applications

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Abstract

This paper proposes an adaptive neuro-fuzzy inference system (ANFIS) and a KERNEL System to solve the problem of predicting rush orders for regulating the capacity reservation mechanism in advance. The adopted approaches generalize the association rules among rush orders, as well as to forecast product items, quantities and the occasion of the contingent rush orders via learning from the sales data of an actual electronic manufacturing firm. Especially, we compare results with the traditional regression analysis and obtain preferable forecasts. In sum the overall forecasting correctness is 83% by ANFIS which is superior to regression manner with 63%. Preliminary results on the application of the proposed methods are also reported. It is expected to offer managers to refer to arrange the reserved capacity and to construct a robust schedule in anticipation.

Keywords: Rush orders; Capacity planning; Adaptive neuro-fuzzy inference system; KERNEL System; Association rules

1. Introduction

With the fast advances in production and information technologies, the growing trends towards customer-driven globalization and the shortening of product life cycles, the need to quickly respond customer requirements became crucial in order to maintain market competitiveness. The increasingly intensity of domestic and global competition contagiously has forced enterprises to explore more efficient and effective ways to conduct their businesses. As a result manufacturers are experiencing a wide range of pressure which makes it necessary for them to continuously adapt their operations and consider the impacts on relative production activities. Apparently, this cannot be achieved without effectively forecasting demands to become able to solve intricate capacity reservation problems.

For satisfy customer needs, firms must do their utmost to reap profits and competition predominance. Nowadays numerous manufactories adopt make-to-order production for not only pursuing the product quality and shortening delivery due dates, but also enhancing the ability for dealing with the order abnormality. However, many make-to-order firms face total expected demands in excess of available capacity. This is especially true, in the short range, for capital intensive firms such as those in the flow process industries, firms making short life cycle products like those in high-technology electronic industries. In suchlike environments the managers are left with the complicated task of allocating the available capacity between competing classes of products and/or customers. Accordingly, many companies have started to address this problem (Sridharan, 1998). Towill (1996) illustrated that as often as not the decisions in an enterprise were guided by orders and inventories. Once market demands varied abnormally, it easily resulted in undependable distribution and an excess of inventories. Zhou (1999) indicated that major problems associated with the wafer fabrication factories comprises order receipt decisions as well as the proportion of rush orders for a small amount but a great diversity of production.

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According to the varying on both products and the market, industry has to handle the unexpected change, even cancellation of the order. Ehteshami, Petrakian, and Shabe (1992) disclosed that the rush order would diminish the service level of the general orders, rise up the inventory level or delay cost and increase the instability of production system. It may strike against the current production schedule planning when due date is changed or rush order is happened which has high priority and should be inserted into the current schedule to satisfy the requirement if the manufacturing system does not reserve capacity in advance. In some case, the production flow would be disarranged; industry may even lose the credit because the goods cannot be delivered on time.

Due to the crucial influences of rush orders, managers should deliberately consider corresponding methods to solve the rush orders. We illustrate the general reasons and corresponding solutions of rush orders in Fig. 1 as below. Most of the research in this topic, that focus on rush orders' acceptance evaluation, and rescheduling models. However, it still cause quite perturbation to manufacturing system. Suppose the manager decides to reserve some capacity or inventory in advance to solve the rush orders, resource may also be wasted and fund may become backlog. Lin (2002) interpreted the definition of rush orders which is the order that did not arrange on current schedule period but need to be mapped out related production activities with regard to the designated products. It however must be satisfied in precedence for some specific criteria, such as the order placed by major customers, possessing extra profits, any amount of the products or money in that order has achieved the threshold, should have great priority to be fabricated. Chen (1998) demonstrated that industry should take seriously on the rush orders which would cause the due date deferred, inventory level changed, capacity rearranged, and significant impacts on the customer relationship.

Only if the prediction techniques have employed are factories unnecessary to keep quantities of stocks to increase customers' satisfactory (Chou, 2002). These forecasting approaches evaluate future demands through analyzing previous sales records and build up appropriate production capacity. Wotruba and Simpson (1992) explained that the sales prediction is contributory to the long-term planning, the goals establishment, and operational decisions in short term. If production system can forecast the occasion of rush orders and its amounts precisely, it can really conduce to arrange the indispensable capacity reservation. Furthermore, a firm also can make use of the information quoted from forecasts to design a robust schedule that may moderate disturbances and damages with the lowest level even the rush orders happened.

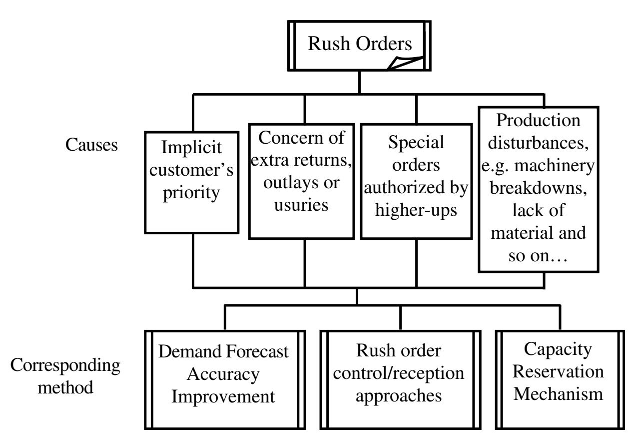

Fig. 1. Causes and the corresponding solutions for rush orders.

This paper lay stress on order forecasts in regard to the exploration of rush orders regulation. It is in accordance with former orders by using data analysis technique to anticipate several attributes of future rush orders like the possibility and timing of emergence, quantities, types, and so on. Managers at present constantly deal with the occurrence of rush orders merely by their experiences. Such means cannot take account of the capacity constraints and the planned orders. Moreover, the prerequisite is that related managers should possess adequate professional knowledge and plentiful experiences for coping with the perplexities originated from rush orders. The consequences are easily teeming with controversy, and are unsuitable for novices. Except subjective judgments by experts, more objective and conventional manner is to analyze historical data and further to carry off appropriate and accommodating information as the foundation of forecast activities.

Recent years have witnessed increasing developments in information technique and recognition on data significances. The tendency towards data collection and accumulation results in more maturity. However, as the database grows up it lapses into predicament for data analysis, and then is arduous to obtain valuable information effectively. Consequently, in this paper, two algorithms, ANFIS and KERNEL, are adopted respectively to simulate the adaptive mechanism of capacity reservation. It is expectant to lessen the impacts from rush orders on manufacturing systems.

Fuzzy theory and neural network are integrated into a neural-fuzzy system in which it is based upon two adopted models as the foundation. The proposed approach generalized the membership function and fuzzy rules from the attributes of historical orders. It enabled the fuzzy decision rule database of rush order forecasts to possess adaptability. We use the neural-fuzzy system due to advantages on data handling and down-to-earth problem resolution to sift given historical data. The data and rules generated from orders may induce the relationship regulations to further predict possible items and amounts of rush orders, as well as to provide the foundation of capacity reservation decisions and production schedule. In addition, traditional regression analysis was executed for comparing the performance with the proposed approach. Finally, we verify the efficiency and feasibility of the proposed approach by drawing on the authentic data from an electronic manufacturing company for an in-depth analysis. The sales data is employed to carry out data analysis, to generalize the association rules among rush orders, as well as to predict product items and quantities of the contingent rush orders in advance. We hope to offer managers to refer to arrange the reserved capacity and to construct a robust schedule.

The paper is organized as follows. In Section 2, we present the theoretical rationale of the proposed neuro-fuzzy system, ANFIS and KERNEL, respectively. The execution processes are demonstrated and the comparisons with regression analysis are given in Section 3 while Section 4 concludes the paper.

2. Rationale of the neuro-fuzzy system

There exist numerous statistical models already applied to forecasting fields. Nevertheless, they always possess two chief shortcomings. It is necessary to assume a potential tendency towards collected data first of all. Secondly it is highly probable that data analysis ability is influenced by hidden regularity of time series, and is incapable of applying in multidimensional nonlinear time series. In practice, sale issues usually possess complex features of nonlinear and non-continuity, as well as the significant interaction of input parameters (Thiesing & Vornberger, 1997; Von Altrock, 1997).

This study explored the connections existed between order parameters imported and rush orders via analyzing the historical data. The IF–THEN fuzzy rule base was therefore established to be directed against rush order forecasts. Such is for the sake of settling problems that fuzzy rules and the membership function are arduous to be found when data is immense. Even the inference system may possess the learning ability for accommodating environments as well as applying capably in practice. This paper adopts neural-fuzzy network as the method of forecasting model. Due to a broad range of applications with ANFIS, we employ it to act on forecasting order items. For predicting order quantities with the mode of multi-input and multi-output, another KERNEL System is carried out further analysis on the side.

2.1. Theoretical rationale of ANFIS

Nowadays, neuro-fuzzy systems have found a wide gamut of industrial and commercial applications that require analysis of uncertain and imprecise information (Chen & Linkens, 2001; Kruse, Nauck, Nürnberger, & Merz, 1997; Nauck, Nauck, & Kruse, 1996; Shi & Mizumoto, 2000; Studer & Masulli, 1997). Among the various neuro-fuzzy models only the hybrid integrated neuro-fuzzy model make use of the complementarity strength of artificial neural network and fuzzy inference systems. The neuro-fuzzy model used in this study is ANFIS, the hybrid technology of integrated neuro-fuzzy model and a part of Matlab's Fuzzy Logic Toolbox. ANFIS uses a hybrid learning algorithm that combines the back-propagation gradient descent and least square methods to create a fuzzy inference system whose membership functions are iteratively adjusted according to a given training set of input and output.

ANFIS has fixed number of layers to represent fuzzy inference system structure. ANFIS in comparison the other ones has high speed of training, the most effective learning algorithm and simplicity of the software (Jang, Sun, & Mizutani, 1997). Although ANFIS is one of the first integrated hybrid neuro-fuzzy models, surprisingly it is the best function approximator among the several neuro-fuzzy models and is faster in convergence when compared to the other neuro-fuzzy models (Akcayol, 2004). Furthermore, ANFIS provides better results when applied without any pretraining (Altug, Chow, & Trussell, 1999).

Most of the neuro-fuzzy systems are either based on Takagi–Sugeno or Mamdani type. The former based neuro-fuzzy models (Sugeno & Tanaka, 1991; Sugeno & Yasukawa, 1993) are widely used for model-based applications. However, the latter based neuro-fuzzy systems can be modeled using faster heuristics but with a low performance (Thiesing & Vornberger, 1997). Takagi–Sugeno type combines the advantages of being general approximators that can reach high accuracy and being easy to interpret, since they are represented in a quite natural way. The generality of Takagi–Sugeno type makes the data driven identification such systems very complex (Wang & Langari, 1996). Takagi–Sugeno type based neuro-fuzzy systems have high performance, but often requires complicated learning procedures and computational expensive. Because of having high performance, Takagi–Sugeno type fuzzy inference was used in this study and the typical fuzzy rule is

$$\text{If } x \text{ is } A_i \text{ and } y \text{ is } B_i,\ \text{THEN } z = f(x,y) = p_i x + q_i y + r_i,$$

where A and B are fuzzy sets in the antecedent and $z = f(x,y)$ is a crisp function in the consequent. Usually, function z is a first-order or a zero-order for Takagi–Sugeno fuzzy inference. The first-order Takagi–Sugeno type fuzzy inference was used in this application as shown in Fig. 2, and ANFIS structure is shown in Fig. 3.

ANFIS has fixed five layers and each layer represents a defined task for FIS. The significances of ANFIS structure are:

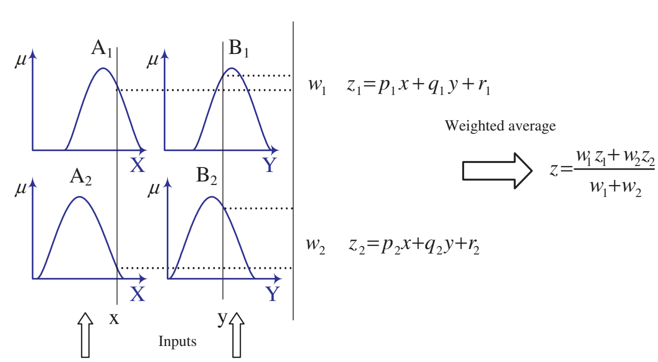

Fig. 2. The first-order Takagi–Sugeno type fuzzy inference.

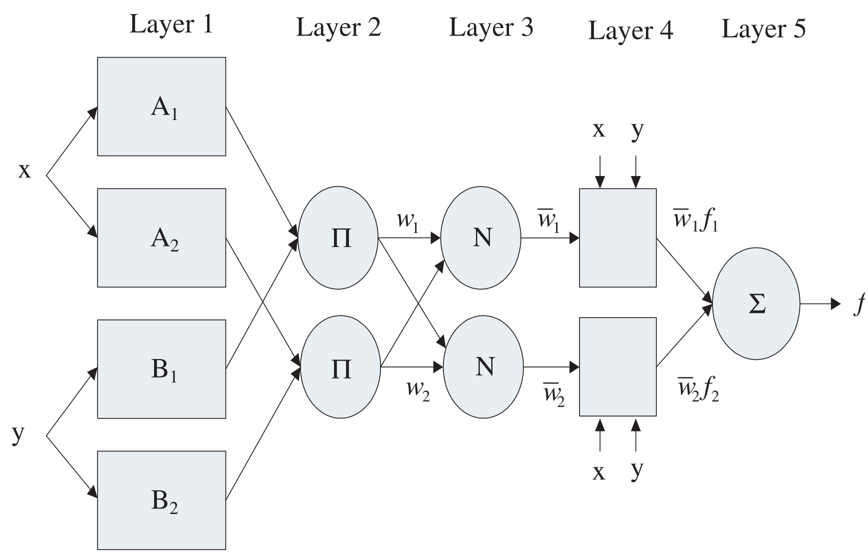

Fig. 3. ANFIS structure.

Layer 1: Each adaptive node in this layer generates the membership grades for the input vectors. Because of their smoothness and concise notation, bell membership function, well known in the fields of probability and statistics, are becoming increasingly popular methods. In this study bell membership functions were used. Bell membership functions are automatically generated by ANFIS of MATLAB. The node function is a generalized bell membership function and can be represented as below:

$$O_{1,i} = \mu_{A_i}(x) = \frac{1}{[1 + |x - c_i/a_i|^{2b_i}]}, \tag{1}$$

where $O_{1,i}$ denotes the output of the ith node in this layer, x is the input to the node i; A_i is the input vectors associated with the ith node and $\{a_i, b_i, c_i\}$ is the parameter set that changes the shapes of the membership function. Parameters in this layer are referred to as the premise parameters.

Layer 2: Each fixed node in this layer is symbolized by a notation of Π, and the output is the product of all input signals. The output of every node represents the activation level of a rule:

$$O_{2,i} = \omega_i = \mu_{A_i}(x)\mu_{B_i}(y), \quad i = 1, 2. \tag{2}$$

Layer 3: Fixed node i in this layer is symbolized by a notation of N, and computes the ratio of the ith rule's activation level to the total of all activation level. The output of this layer denominates as normalized firing strength:

$$O_{3,i} = \bar{\omega}_i = \frac{\omega_i}{\omega_1 + \omega_2}, \quad i = 1, 2. \tag{3}$$

Layer 4: Adaptive nodes i in this layer calculate the contribution of the ith rule towards the overall output, with the following node function:

$$O_{4,i} = \bar{\omega}_i f_i = \bar{\omega}_i (p_i + q_i + r_i), \quad i = 1, 2, \tag{4}$$

where $\bar{\omega}_i$ is the output of layer 3, and $\{p_i, q_i, r_i\}$ is the parameter set. Parameters in this layer are referred to as the consequent parameters.

Layer 5: The single fixed node in this layer is symbolized by a notation of Σ, and calculates the overall output as the summation of contribution from each rule:

$$O_{5,i} = \sum_i \bar{\omega}_i f_i = \sum_i \omega_i f_i \Big/ \sum_i \omega_i. \tag{5}$$

When the values of premise parameters are constants, the overall output can be denoted the linear combination of the consequent parameters and can be represented as below:

$$\begin{aligned} f &= \frac{w_1}{w_1 + w_2} f_1 + \frac{w_2}{w_1 + w_2} f_2 \\ &= \bar{w}_1(p_1 x + q_1 y + r) + \bar{w}_2(p_2 x + q_2 y + r_2) \\ &= (\bar{w}_1 x)p_1 + (\bar{w}_1 y)q_1 + (\bar{w}_1)r_1 + (\bar{w}_2 x)p_2 \\ &\quad + (\bar{w}_2 y)q_2 + (\bar{w}_2)r_2. \end{aligned} \tag{6}$$

Fundamentally, ANFIS takes a fuzzy inference system and modulates it with a back-propagation algorithm based on some collection of input–output data. This allows fuzzy inference system to learn. The network structure facilitates the commutation of the descendent gradient vector for parameters in a fuzzy inference system. Once the gradient vector is obtained, a number of optimization routines can be applied to reduce an error measure.

ANFIS is more complex than traditional fuzzy inference systems, and is not applicable for all fuzzy inference systems (Arafeh, Singh, & Putatunda, 1999). The specific limits are as follows:

1. a first-order or a zero-order form for the Sugeno fuzzy inference,
2. single output: make use of weighted average method to execute defuzziness,
3. distinct rules use identical different membership functions, i.e. the number of output membership functions should be equal to the number of rules,
4. each rule has the identical weight,
5. ANFIS permits really not perfect for the self-options of all fundamental fuzzy inferences. It is suggested to utilize default membership functions and defuzziness functions (Bersini & Bontempi, 1997).

As for the development of a fuzzy inference system, the more the properties and quantities of data, the possibility to searched out the helpful hiding knowledge due to concepts of data analysis. However, fuzzy rules raise exponentially with grid partition when quantities of data features increase, and result in a laborious analysis. This paper therefore adopts the subtractive clustering manner to establish a concise amount of rules of the fuzzy inference system.

ANFIS has been applied very successfully in a variety of research as yet; even so, not only order entries but also order quantities is expected to enter into the prediction analysis simultaneously. Consequently, we weighed in another neuro-fuzzy system, KERNEL System, for supplementing further forecasts beyond the proposed ANFIS. The intentional contribution towards decision makers is to provide multidirectional assistances in drawing up robust capacity reservation mechanism.

2.2. The KERNEL System

KERNEL (Knowledge Extraction and Refinement by NEural Learning) is a multistep neuro-fuzzy system which works on the basis of successive phases. It is capable to initialize and then to refine a fuzzy rule base to be applied in classification or regression tasks. The peculiarity of KERNEL consists in its ability to extract and refine knowledge starting directly from observational data (without any human expert intervention) making use of neural learning (Castellano, Fanelli, & Mencar, 2001). The KERNEL System is endowed with a core that consists of a particular neural network, the neuro-fuzzy network, embodying in its topology the structure of the fuzzy rule base.

The network scheme of the KERNEL System (Fig. 4) has four layers (Castellano, Castiello, & Fanelli, 2002). The grey part in the figure stands for the premise parameters of fuzzy rules, and is referred to as meta-nodes of the network. Each meta-node k connects two premise weight vectors, C_k and σ_k and a consequent weight vector b_k. The functions in accordance with each layer are:

L_1: Introductory data for providing input values.

L_2: The nodes are used for receiving input values $x_1, \ldots, x_n$, and ct as the fuzzy set of the membership

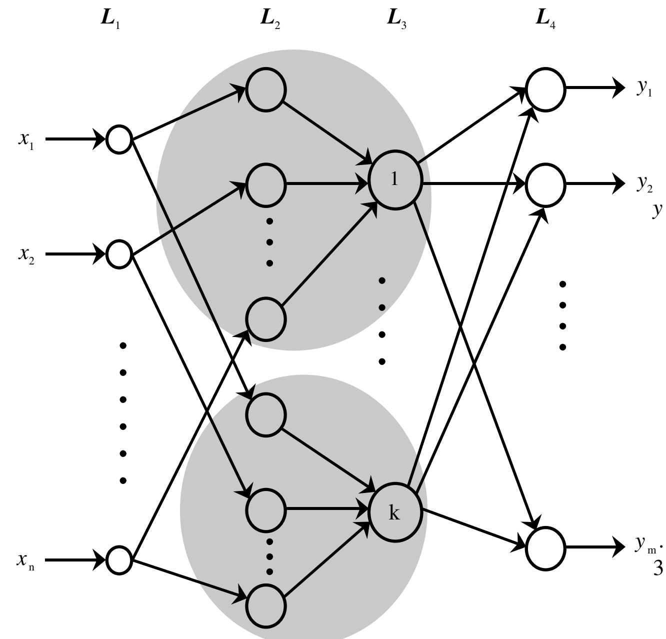

Fig. 4. The scheme of the KERNEL System.

function describing corresponding input values. The node set possesses k groups (corresponding k rules), and each group composes of n units for corresponding the premise of k fuzzy rules defined by the input fuzzy set. Every unit $\mu_{ik} \in \mathrm{L}_2$ receives the input value x_i and computes the membership value $\mu_{ir}(x_i)$. The output of $\mu_{ik} \in \mathrm{L}_2$ is calculated as below, and C_{ik} and σ_{ik} denote the center and width of gauss function:

$$O_{ik}^{(2)} = \exp\left[-\frac{(x_i - c_{ik})^2/\sigma_{ik}^2}{2\sigma_{ik}^2}\right], \quad i = 1, \ldots, n; \quad k = 1, \ldots, K. \tag{7}$$

L_3: It is made up of k units (k rules corresponding to the fuzzy model), and each node evaluates the suitability degree of premise terms of fuzzy rules, which is a fixed parameter. Each unit has n connections originated in L_2 to act on the premise of fuzzy rules. The output of $\mu_{ik} \in \mathrm{L}_2$ hinges on the arousing intensity and can be calculated by

$$O_k^{(3)} = \prod_{i=1}^{n} O_{ik}^{(2)}, \quad k = 1, \ldots, K. \tag{8}$$

L_4: The output value of $\hat{y}$ can be computed by the following formula:

$$\hat{y} = O^{(4)} = \frac{\sum_{k=1}^{K} b_k O_k^{(3)}}{\sum_{k=1}^{K} O_k^{(3)}}. \tag{9}$$

The core of KERNEL System forms on the foregoing scheme, and is divided into two learning phases. The initial phase is accomplished by means of a data clustering performed via an unsupervised learning step, and utilize competition learning algorithm to automatically provide the proper number of clusters matching with the number of rules in the fuzzy model. The second phase modifies the parameters of the initial fuzzy rule base so as to enhance its precision by applying a supervised learning of the neuro-fuzzy network. The structure and process of a KERNEL System present approximately identical in comparison with concepts of the ANFIS, but diversity of the function and algorithm. Initial FIS obtained from the first phase carries out neural training after determining data for the model, and learns to regulate parameters and weights of the network from data. The optimization of FIS can be achieved in the end.

3. Verifications and exemplificative results

The selected exemplification is a real electronic manufacturing company founded in 1997 in the Neihu District of Taipei, Taiwan. It is a fabulous IC components company with high-caliber professionals specialized in designing, manufacturing, and supplies leading edge, high performance memory products and memory-intensive logic products to numerous high growth and performance-demanding markets. The major product categories are computing (PCs, disk drives, printers, graphics, multimedia, etc.), communications (telecommunications, data communications, cellular phones, switches hubs network interface, modems, etc.) and consumers (VCD, DVD, Set Top Box, Digital Camera, Video games, etc.), respectively. It has been in operation for almost ten years, employs approximately 100 employees, as well as its annual sales are approximately $7 million.

The firm continues to serve these diverse market segments by utilizing and adapting its innovative design methodologies, advanced CMOS process technologies, and loyal manufacturing relationships to provide state-of-the-art, and cost-effective products that meet diverse application needs. However, over the past few months, the firm has detected some perplexity resulted from rush orders, and contemplated anxiously countermeasures for reducing the loss of commercial benefits. Its former actual orders were therefore cited for applying ANFIS and KERNEL to analyze rush orders. The firm carries out the scheduling activity on every Monday and Thursday. When original schedule is incapable to fulfill the designate due date, it necessitates to revise temporarily the established schedule by intervening order for a remedy namely the rush order. For example, an order was received on Tuesday, March 18, 2003 and was due on Thursday, March 20, 2003. Owing to exceeding in the regular scheduling time slot, it is obliged to alter the former schedule and to insert the order into the planned schedule for on time delivery.

3.1. Forecasting items of rush orders by ANFIS

There are altogether 122 order data (see Appendix) which comprise for the duration of January to July of 2003 and November to December of 2003. The overall business connections are ten involved six product items. The order data of January to July of 2003 (87 data in all) are chose with which to act as the training materials. In addition, the order data of November to December of 2003 (35 data in all) are selected as the testing materials for verification of the proposed approach. Input parameters are 9 in all:

- Factory code x_1: the value ranges from 1 to 10 to represent distinct customers;
- Code of order product item $x_2, x_3, \ldots, x_7$: the value stands for the order quantities of the specific item;
- Days to the due date designate x_8: the value means the days between the arrival date and due date of the order;
- Whether rush order x_9: if the value is 1 then rush order occurs, otherwise the value is 0.

The value of input parameter y is the product item code of next order for which the rush order occurs ($y = 1, 2, \ldots, 6$), or $y = 0$ for nothing. Arranging the training and testing data for the foregoing pattern we introduce ANFIS and employ Subtractive Clustering method to establish automatically initial fuzzy inference system and network frame from the collected data (Fig. 5).

Owing to a great variation impact on network parameters the hybrid learning algorithm is unsuitable for users to amend oneself the membership function. We hence adapt back-propagation learning algorithm to implement 150 times of learning period training. Regulating the membership function and rule base of FIS, then, carries off the optimized fuzzy rule base. Via the attributes of ordered firms, ordered items, due dates and whether rush order or not of the input order data users ascertain possible items of the next order that the rush order happened through the transformation of membership function. The verification results of 35 testing data are shown in Fig. 6.

After the neural network training, the original setup of output membership function generates fluctuations and leads into the outputs which are not integers from 1 to 6. However, the variation amplitude is not very significant, and can still diagnose the forecasts of rush order items. There are 7 rush orders occurred in the existing 35 testing data. The results obtained by ANFIS also predict 7 rush orders. The ANFIS approach forecasts precisely 4 times (the 2nd, 11th, 18th and 27th order) not only the occurrence times but also the product items.

3.2. Forecasting items of rush orders by KERNEL

KERNEL System is applied to analyze identical data used in ANFIS, and to observe the capability of multi-input single output model between ANFIS and KERNEL. Introducing the training data into the initial phase of KERNEL, the prearrangement of data normalized is implemented, and the distance is calculated by the Mahalanobis Distance, as well as the recession character of learning rate is supposed as linear. After input 15 clusters

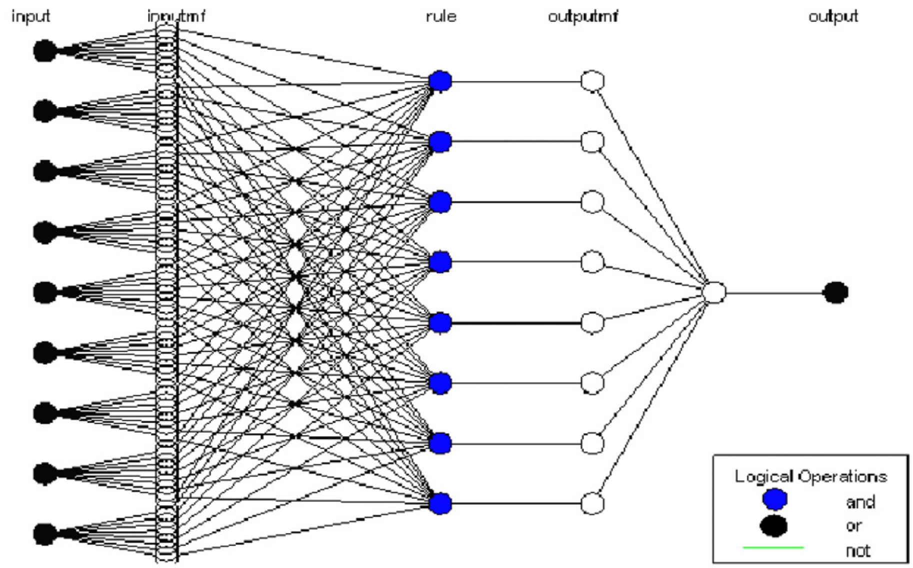

Fig. 5. The network frame of ANFIS.

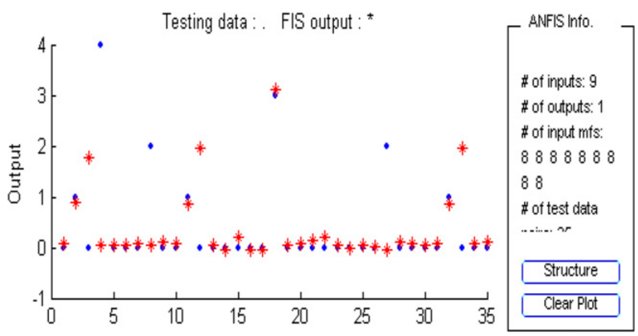

Fig. 6. The test results of ANFIS.

the process automatically executes clustering and generates the initial FIS.

Introducing the training data, testing data and the foregoing initial FIS into the second phase, the beginning learning rate is set for 0.05, increasing factor of varying learning rate is 1.1, and decreasing factor is 0.9, respectively. In addition, the training optimization manner is in the light of the regression and classification to carry out 30 learning periods individually. The fuzzy rule base obtained by the optimization process is verified through the testing data and the effects are as shown in Fig. 7. The outcomes resulted from KERNEL exist 6 rush orders in which only 3 orders (the 8th, 11th, and 32nd order) are forecasted precisely for their product items and occasions. It is worse than ANFIS and can be concluded that ANFIS has better capability for analyzing the multi-input single output model.

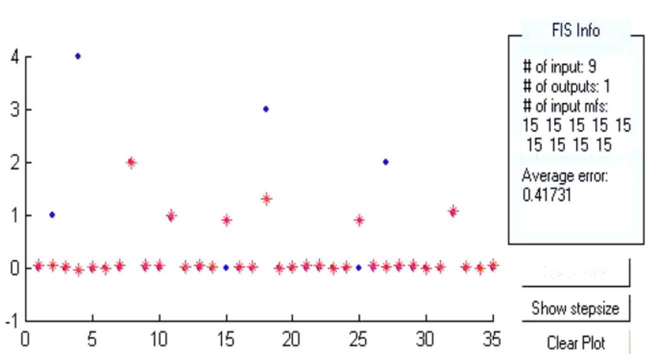

Fig. 7. The verification of KERNEL System.

3.3. Forecasting items and quantities of rush orders by KERNEL

Seeing that AFNIS is incapable of implementing multi-input and output analysis, the KERNEL System is used for predicting the product items and quantities of rush orders. We rearrange the foregoing order data in 2 output parameters. The value of y_1 represents the product item code from 1 to 6 if next data is rush order, otherwise the value is 0. The value of y_2 indicates the order quantities if next data is rush order, otherwise the value is 0. The way to setup input parameters is identical to the above-mentioned.

As a same process expressed previously, after input 15 clusters the process automatically executes clustering and generates the initial FIS. Entering the training data, testing data and the foregoing FIS into the second phase, the initial learning rate is set for 0.07, increasing factor of varying learning rate is 1.2, and decreasing factor is 0.8, respectively. The training optimization manner on the side proceeds according to the regression manner for executing 100 learning periods individually. The fuzzy rule base gained by the optimization process is verified through the attributes of input data, and determines simultaneously possible items and quantities of the next order that the rush order happened. Suchlike effect is incapable of executing by ANFIS. The summarized results are shown in Table 1.

Table 1
The results obtained from the KERNEL System

The number of data	Items forecast	Quantities forecast	Actual items	Actual quantities
2	0	0	1	100
4	2	533	4	1000
8	1	309	2	500
11	0	0	1	300
18	1	134	3	1000
27	2	194	2	350
29	1	153	0	0
32	1	189	1	170

The forecast outcomes present 4 precise rush orders and 2 exact ordered items in such 7 actual rush orders. However, there exists more error in order quantity forecasts except the 32nd data. This is due to more complexity involved in the multi-output model, and results in a very arduous analysis. The data used in this case have great order variation, especially obvious fluctuation in quantities of the rush orders. It is hard to look for the inherent regularities under insufficient analysis information.

3.4. Forecasting items of rush orders by regression analysis

In order to interpret the suitability of applying neuro-fuzzy system in our production problem, the popular manner, regression analysis, is carried out to forecast the product items of rush orders happened. The results are as compared with ANFIS. It is all the same to the determinant mode of the input and output parameters involved. The floating points of forecasts round off the integer, and the results are in contrast with actual orders (see Fig. 8).

Due to high randomness and inapparent tendency of rush orders, the effects of applying regression analysis are worse than the forecasts of using ANFIS. Only 2 rush orders can be predicted accurately, the 8th and 18th order. Table 2 reveals the effect comparison between ANFIS and regression analysis. The first column is total accuracy which denotes the judgement accuracy in deciding whether the next order is emergent or not. The second column, item accuracy, indicates the judgement accuracy in predicting the product items of the rush orders happened. The third column, correct quantities of item ordered, presents the judgement accuracy in predicting the order quantities of the rush orders happened. There exist 2 data involved in 7 actual rush orders, which quantities ordered are 1000 units and have remarkable impacts on the capacity regulation. ANFIS predicts correctly one of them, regression analysis however is incapable to forecast them. In sum, the overall forecasting correctness is 83% by ANFIS which is superior to regression manner (63%). As regards the forecasting accuracy of product items occurred in rush orders, the outcome of ANFIS, 57%, is apparently much better than regression (29%). Furthermore, the quantities associated with rush orders which can be forecasted precisely by ANFIS are greatly more than regression way.

Table 2
The effects of ANFIS in comparison with regression analysis

	Total accuracy	Item accuracy	Correct quantities of item ordered
ANFIS	83% (29/35)	57% (4/7)	1570
Regression	63% (22/35)	29% (2/7)	470

Fig. 9 represents the comparison of judgement accuracy of the next order that the rush order happened. Correct forecasting is 0, and wrong judgement is 1. The results derive from the multiplication of binary logic value and the weights which originate with the order quantity. Consequently, the more quantities of order are forecasted wrong, the more the peak rises high and erect. That means more loss occurs. Observing Fig. 9 we may perceive that there are a good many and high peaks for implementing regression analysis. It indicates that ANFIS is more excellent in the accuracy and significance of forecast than the regression analysis. From the result comparison it is evident that regression analysis owns a great forecasting error and leads

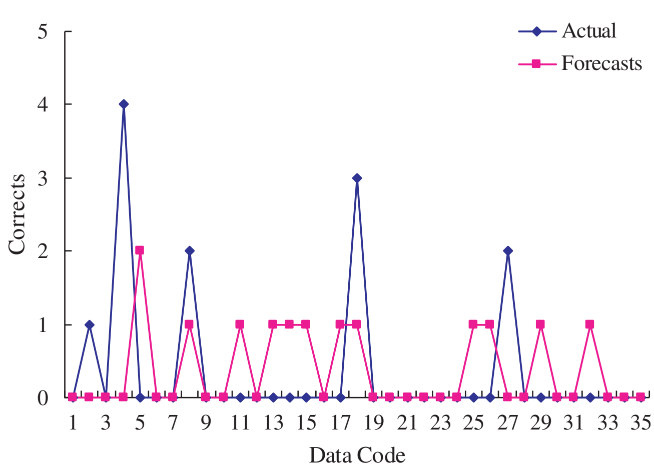

Fig. 8. Comparison of actual orders and results of regression analysis.

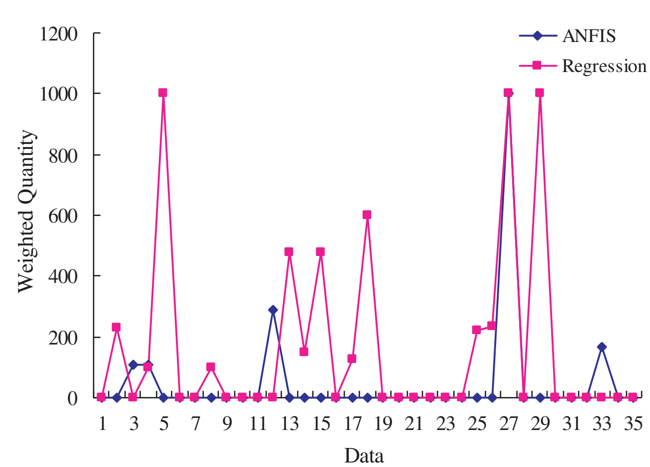

Fig. 9. The error of ANFIS in comparison with regression analysis.

to be unworthy of implementing rush orders forecast due to low accuracy. This demonstrates that forecasting rush orders holds high difficulty and the suitability of neuro-fuzzy system approach proposed in this paper is much better than the traditional regression analysis.

4. Conclusions

The globalization circumstances nowadays are under a severe strain. Of many changes to which enterprises must respond for the sake of conquering turbulent business environment, none is more vital than being customer focused and being able to adjust production schedule quickly to deal in production disturbances. Recognizing and carrying out every customer's increasingly diverse needs are consequently, the indispensable responsibility for the undertakings at present. The critical role for a production manager is to administer production quality, manage delivery due dates, and production disturbance to efficiently serve each customer uniquely.

In order to satisfy customer needs, firms must do their utmost to reap profits and competition predominance. It is most likely to result in order variation and fluctuation. The quality of rush order decisions causes even more perplexity and confusion of scheduling. Establishing efficacious and suitable mechanism of capacity reservation is therefore quite important for managerial topics. This paper concerned how forecasting model precisely collected applicable information from order background. An established neuro-fuzzy model was based on ANFIS and KERNEL Systems. The approach generalized membership function and fuzzy rules from historical orders. It enabled fuzzy rules database of forecast rush orders to possess adaptability. Finally, we employed the sales data of an actual electronic manufacturing firm to carry out data analysis, to generalize the association rules among rush orders, as well as to predict product items and quantities of the contingent rush orders in advance. In order to compare with the traditional and popular method, regression analysis was implemented in accordance with the above-mentioned data, and cannot obtain preferable result for the rush order forecasts. This demonstrates that forecasting rush orders holds high difficulty and the suitability of neuro-fuzzy system approach proposed in this paper is much better than the traditional regression analysis. According to the proposed approach, it is expected to offer managers to refer to arrange the reserved capacity and to construct a robust schedule.

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Appendix

The sales data of an actual electronic manufacturing firm

Firm code	1 w78e54	2 w78e52	3 w78	4 lc46a	5 btch 6001	6 Mdt 2005ep	Days for delivery	Rush?	Next rush item code	Quantity	Received date
2	0	0	100	0	0	0	9	0	0	0	2003/1/6
1	0	0	0	0	505	0	1	0	0	0	2003/1/6
6	0	0	0	500	0	0	10	0	0	0	2003/1/7
6	0	400	0	0	0	0	10	0	1	200	2003/1/7
4	200	0	0	0	0	0	1	1	0	0	2003/1/8
2	0	50	0	0	0	0	17	0	0	0	2003/1/9
2	50	0	0	0	0	0	18	0	0	0	2003/1/10
2	100	0	0	0	0	0	22	0	0	0	2003/1/10
8	0	0	300	0	0	0	5	0	0	0	2003/1/11
6	0	0	0	30	0	0	4	0	0	0	2003/1/16
1	0	0	0	0	910	0	4	0	0	0	2003/1/17
2	12	0	0	0	0	0	6	0	0	0	2003/1/17
7	300	0	0	0	0	0	5	0	0	0	2003/1/18
7	0	0	1500	0	0	0	3	0	0	0	2003/1/18
9	0	500	0	0	0	0	3	0	0	0	2003/1/20
2	0	100	0	0	0	0	21	0	0	0	2003/1/23
10	0	0	0	0	0	200	7	0	0	0	2003/2/5
1	0	0	0	0	505	0	4	0	5	905	2003/1/23
1	0	0	0	0	905	0	1	1	0	0	2003/1/28
6	0	1000	0	0	0	0	8	0	0	0	2003/2/12

(*continued on next page*)

Appendix (*continued*)

Firm code	1 w78e54	2 w78e52	3 w78	4 lc46a	5 btch 6001	6 Mdt 2005ep	Days for delivery	Rush?	Next rush item code	Quantity	Received date
2	210	0	0	0	0	0	15	0	0	0	2003/2/12
2	0	0	100	0	0	0	14	0	0	0	2003/2/12
6	0	0	0	200	0	0	7	0	0	0	2003/2/12
9	0	0	300	0	0	0	4	0	0	0	2003/2/13
10	0	0	0	0	0	525	5	0	0	0	2003/2/13
5	0	0	0	0	0	500	11	0	0	0	2003/2/18
5	0	0	0	500	0	0	3	0	0	0	2003/2/18
9	0	1000	0	0	0	0	7	0	0	0	2003/2/19
10	0	0	0	0	0	2000	21	0	1	170	2003/2/19
3	170	0	0	0	0	0	0	1	0	0	2003/7/9
2	0	120	0	0	0	0	24	0	0	0	2003/3/4
7	0	0	0	1500	0	0	5	0	0	0	2003/3/6
6	0	0	0	100	0	0	10	0	0	0	2003/3/6
3	180	0	0	0	0	0	2	0	0	0	2003/3/7
2	0	0	100	0	0	0	22	0	0	0	2003/3/9
9	0	300	0	0	0	0	4	0	0	0	2003/3/17
2	100	0	0	0	0	0	15	0	4	500	2003/3/17
5	0	0	0	500	0	0	2	1	0	0	2003/3/18
8	0	0	600	0	0	0	8	0	0	0	2003/3/19
9	0	500	0	0	0	0	15	0	0	0	2003/3/25
2	120	0	0	0	0	0	5	0	0	0	2003/3/27
6	0	0	0	50	0	0	5	0	0	0	2003/4/1
2	0	0	100	0	0	0	21	0	0	0	2003/4/2
8	0	400	0	0	0	0	3	0	0	0	2003/4/8
2	320	0	0	0	0	0	6	0	0	0	2003/4/9
6	0	150	0	0	0	0	7	0	0	0	2003/4/10
9	0	300	0	0	0	0	2	0	0	0	2003/4/10
5	0	0	0	2500	0	0	4	0	3	400	2003/4/11
7	0	0	400	0	0	0	2	1	0	0	2003/4/11
6	0	0	0	50	0	0	5	0	0	0	2003/4/11
2	0	120	0	0	0	0	13	0	0	0	2003/4/15
1	0	0	0	0	1000	0	5	0	0	0	2003/4/16
6	0	0	0	300	0	0	5	0	0	0	2003/4/16
8	0	0	200	0	0	0	5	0	0	0	2003/4/17
9	0	500	0	0	0	0	4	0	0	0	2003/4/23
1	0	0	0	0	1000	0	9	0	1	260	2003/4/24
4	260	0	0	0	0	0	1	1	0	0	2003/5/2
2	0	120	0	0	0	0	20	0	0	0	2003/5/9
10	0	0	0	0	0	1000	7	0	0	0	2003/5/13
7	0	0	800	0	0	0	6	0	0	0	2003/5/14
6	0	0	0	200	0	0	3	0	2	500	2003/4/29
9	0	500	0	0	0	0	0	1	0	0	2003/5/14
10	0	0	0	0	0	2000	10	0	1	250	2003/5/22
4	250	0	0	0	0	0	1	1	0	0	2003/5/27
9	200	0	0	0	0	0	6	0	0	0	2003/5/28
9	0	300	0	0	0	0	8	0	0	0	2003/5/28
2	30	0	0	0	0	0	5	0	0	0	2003/5/29
8	0	0	500	0	0	0	5	0	0	0	2003/5/29
8	0	150	0	0	0	0	4	0	0	0	2003/5/29
3	250	0	0	0	0	0	2	0	0	0	2003/6/9
2	100	0	0	0	0	0	29	0	0	0	2003/6/10

Appendix (*continued*)

Firm code	1 w78e54	2 w78e52	3 w78	4 lc46a	5 btch 6001	6 Mdt 2005ep	Days for delivery	Rush?	Next rush item code	Quantity	Received date
8	0	400	0	0	0	0	7	0	0	0	2003/6/10
5	0	0	0	500	0	0	3	0	0	0	2003/6/11
1	0	0	0	0	0	620	4	0	0	0	2003/6/11
7	0	0	1000	0	0	0	3	0	0	0	2003/6/11
9	0	1300	0	0	0	0	12	0	0	0	2003/6/12
6	0	0	0	200	0	0	6	0	3	300	2003/6/21
8	0	0	300	0	0	0	1	1	0	0	2003/6/13
5	0	0	0	2500	0	0	14	0	2	500	2003/6/19
8	0	500	0	0	0	0	0	1	0	0	2003/6/16
6	0	0	0	150	0	0	5	0	0	0	2003/7/14
10	0	0	0	0	0	1000	10	0	1	300	2003/7/1
4	300	0	0	0	0	0	1	1	0	0	2003/7/1
10	0	0	0	0	0	300	8	0	0	0	2003/7/8
1	0	400	0	0	0	0	4	0	0	0	2003/7/4
9	300	0	0	0	0	0	14	0	0	0	2003/6/12
5	0	0	0	0	0	500	10	0	0	0	2003/7/13
6	0	400	0	0	0	0	6	0	0	0	2003/10/12
2	0	240	0	0	0	0	18	0	1	100	2003/10/22
3	100	0	0	0	0	0	1	1	0	0	2003/10/18
8	0	0	100	0	0	0	7	0	4	1000	2003/10/21
5	0	0	0	1000	0	0	1	1	0	0	2003/10/21
7	0	0	1000	0	0	0	3	0	0	0	2003/10/22
10	0	0	0	0	0	200	5	0	0	0	2003/10/23
6	0	0	0	100	0	0	4	0	2	500	2003/10/22
9	0	500	0	0	0	0	1	1	0	0	2003/10/22
10	0	0	0	0	0	100	12	0	0	0	2003/10/22
2	0	120	0	0	0	0	16	0	1	300	2003/10/20
4	300	0	0	0	0	0	1	1	0	0	2003/10/22
5	0	0	0	0	0	500	5	0	0	0	2003/10/23
3	150	0	0	0	0	0	5	0	0	0	2003/10/23
5	0	0	0	500	0	0	12	0	0	0	2003/10/26
3	270	0	0	0	0	0	3	0	0	0	2003/10/27
2	120	0	0	0	0	0	4	0	0	0	2003/10/27
1	0	0	0	0	600	0	5	0	3	1000	2003/10/16
7	0	0	1000	0	0	0	0	1	0	0	2003/10/28
7	500	0	0	0	0	0	4	0	0	0	2003/10/28
9	0	500	0	0	0	0	3	0	0	0	2003/10/28
8	0	500	0	0	0	0	23	0	0	0	2003/10/29
7	0	0	700	0	0	0	6	0	0	0	2003/11/3
4	260	0	0	0	0	0	3	0	0	0	2003/11/4
2	220	0	0	0	0	0	14	0	0	0	2003/11/4
6	0	0	0	250	0	0	7	0	0	0	2003/11/8
10	0	0	0	0	0	1000	5	0	2	350	2003/11/9
9	0	350	0	0	0	0	1	1	0	0	2003/11/15
5	0	0	0	0	0	1000	8	0	0	0	2003/11/16
7	0	0	600	0	0	0	3	0	0	0	2003/11/19
9	200	0	0	0	0	0	4	0	0	0	2003/11/20
1	0	0	0	0	405	0	11	0	1	170	2003/11/20
3	170	0	0	0	0	0	1	1	0	0	2003/11/21
8	0	0	400	0	0	0	4	0	0	0	2003/11/22
8	0	400	0	0	0	0	5	0	0		2003/11/22

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