Demand forecasting for apparel manufacturers by using neuro-fuzzy techniques

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Received 5 October 2011
Revised 16 January 2012
4 April 2012
29 August 2012
Accepted 17 September 2012

Abstract

Purpose – According to literature research and conversations with apparel manufacturers' specialists, there is not any common analytic method for demand forecasting in apparel industry and to the authors' knowledge, there is not adequate number of study in literature to forecast the demand with adaptive network-based fuzzy inference system (ANFIS) for apparel manufacturers. The purpose of this paper is constructing an effective demand forecasting system for apparel manufacturers.

Design/methodology/approach – The ANFIS is used forecasting the demand for apparel manufacturers.

Findings – The results of the proposed study showed that an ANFIS-based demand forecasting system can help apparel manufacturers to forecast demand accurately, effectively and simply.

Originality/value – ANFIS is a new technique for demand forecasting, combines the learning capability of the neural networks and the generalization capability of the fuzzy logic. In this study, the demand is forecasted in terms of apparel manufacturers by using ANFIS. The input and output criteria are determined based on apparel manufacturers' requirements and via literature research and the forecasting horizon is about one month. The study includes the real-life application of the proposed system, and the proposed system is tested by using real demand values for apparel manufacturers.

Keywords Decision making, Forecasting

Paper type Research paper

1. Introduction

The term supply chain is used to describe the flow of goods from the very first process encountered in the production of a product right through to the final sale to the end consumer (Bruce *et al.*, 2004). There are many factors affect supply chain performance.

The authors would like to thank the anonymous referees for reading the paper and offering many helpful comments.

Journal of Modelling in Management
Vol. 9 No. 1, 2014
pp. 18-35

1746-5664
DOI 10.1108/JM2-10-2011-0045

One of the most important factor also affects the planning decisions of the other departments is the accuracy of forecast. Because most retailers do not know their demand with certainty, they have to make their inventory decisions based on demand forecasts. With inaccurate forecasts, the quantity of materials ordered does not match the demand. Inaccurate forecasts can, therefore, significantly influence the performance of the supply chain in terms of increased inventory costs, backorders or loss of sales, and customer goodwill throughout the supply chain. They can also cause low utilization of capacity and other problems in production (Zhao *et al.*, 2002). Even with much effort and funds spent to improve supply chain processes, they still lack reliability and efficiency if the demand forecast accuracy is poor (Sayed *et al.*, 2009).

Forecasting refers to computing the probability of the future value. The underlying assumption in most forecasting methods is that the past patterns or behavior will continue in the future (Frank *et al.*, 2003). The ability to respond to customer requirements on a timely basis has always been a fundamental element of the marketing concept. However, there has never been as much pressure as there is today to further accelerate the responsiveness of marketing systems (Christopher and Peck, 1997).

In the present world, all industries need to be adaptable to a changing business environment in the context of a competitive global market. To make decisions related to the conception and the driving of any logistic structures, industrial managers must rely on efficient and accurate forecasting systems (Sun *et al.*, 2008). A good forecasting system is essential for avoiding problems such as inventory shortages and excesses, missed due dates, plant shutdowns, lost sales, lost customers, expensive expediting, and missed strategic opportunities (Frank *et al.*, 2003). Improving forecasting models is considered a vital part in the overall supply chain process (Sayed *et al.*, 2009).

In this research, an adaptive network-based fuzzy inference system (ANFIS) is used to forecast the demand for the apparel industry. Inputs and outputs of the system, training data set, and system rules are determined by interviewing specialists in apparel firms and via literature research. The remainder of this paper is organised as follows. Section 2 presents a literature review of the apparel industry and demand forecasting in supply chain management. Section 3 explains the proposed approach and the demand forecasting model for an apparel manufacturer based on the ANFIS. The application examples and results are provided in Section 4. Finally, conclusions are presented in Section 5.

2. Literature review

2.1 Apparel industry

Apparel industry is a major sector for both the industrialised and the lesser developed economies, contributing both to wealth generation and employment (Bruce *et al.*, 2004). The year 2005 marked the end of a 30-year stretch of textile quotas. As the industry enters the global "free market" competition, many developing countries fear the uncertainty in the existing competition (Ballestero, 2004). To enhance the commercial competitive advantage in a constantly fluctuating environment, apparel companies must improve their supply chain management, which requires sales forecasting systems adapted to the uncertain environment of the apparel industry. The accuracy of the demand forecast significantly affects inventory levels, costs and customer satisfaction levels. To set up all of the logistic steps required for producing and selling a product, apparel managers must rely on efficient and accurate forecasting systems

(Thomassey *et al.*, 2002). The effectiveness of the supply chain optimisation depends on the forecast accuracy of the finished product sales (Graves *et al.*, 1998).

The fashion industry is characterised by aggressive competition levels, a large marketplace sourcing high-variety, high-margin, short product life cycles in a global context, high level of impulse purchasing and unpredictable demand (Bruce *et al.*, 2004; Mason *et al.*, 2007; Cao *et al.*, 2008). The short life cycle of products implies that available sales data are reduced (Thomassey *et al.*, 2002). Demand forecasting in apparel industry is very complex. Indeed, a wide range of textile item references exists, and their historic sale data are often short and particularly perturbed by numerous factors, which are neither strictly controlled nor identified (DeToni and Meneghetti, 2000). These factors can depend on the item (colours, prices, etc.), distributor (number of stores, merchandizing, etc.), customers (fashion, etc.) or external factors (weather, holidays, etc.). These factors have different impacts on sales and not always available.

In the apparel industry, the lead times from retailer order to delivery are quite long. As a result of these long lead times, the risks of having too little or too much inventory increases if the retailers have to place the orders long before the season. In addition to long lead times, product proliferation is increasing the risks a manufacturer faces. As the product proliferation increases, the variability of demand for each time also increases (Tan, 2001). The long supply pipeline makes the lead time of textile-apparel supply chain relatively long and uncertain in response to the volatile characteristics of fashion markets. So, the coordination in textile-apparel supply chain becomes even more important (Cao *et al.*, 2008). In order to reduce stocks and to limit stock out, apparel companies require specific and accurate demand forecasting systems (Thomassey *et al.*, 2005).

The last decade apparel industry has learnt that the supply chain can be made more efficient in order to decrease lead times and related demand forecast errors (Jacobs, 2006). A demand forecasting system is required to respond to the versatile fashion market and the needs of the distributors. Nowadays, due to the specific constraints of the apparel sales (numerous and new items, short life time), existing forecasting models are generally unsuitable or unusable (Thomassey and Fiordaliso, 2006).

An apparel demand forecasting system requires; to quickly react to a significant variation of trend and seasonality, to identify and to smooth purely random events, to perform forecasting on short historic sales data and to take into account the influences of explanatory variables such as: product features, marketing strategy, distribution area, distribution mode, competitive environment, space-time environment, consumer environment, economic situation (Thomassey *et al.*, 2002).

2.2 Forecasting in supply chain management

To have an available decision-making system is becoming a crucial issue for organisations in a constantly fluctuating environment where the economic uncertainty needs mathematical models. Forecasting the expected demand for a certain period of time with one or more products is one of the most relevant targets in an enterprise. Despite the need for accurate forecasting to enhance the commercial competitive advantage, there is no standard approach (Efendigil *et al.*, 2009).

In practice and in literature, various demand forecasting techniques have been studied and used. Most of these techniques are based on statistical methods such as moving average, time series analysis, exponential smoothing, Box-Jenkins method, and casual models. These methods assume that historical data are recorded in the past and that they are precisely known. Furthermore, the statistical forecast methods assume that a historical pattern of demand is a good indicator of future demand. They can be applied successfully when historical data are reliable and when environments being forecasted are relatively stable. However, these methods are perceived as being slow to react to changes in dynamic environments (Petrovic *et al.*, 2006).

Kuo *et al.* (2002) stated that statistical methods, such as regression modelling and ARIMA, have been the candidates for decision makers; however, these methods are only efficient for data that are seasonal or cyclical. If the data are influenced by a special case, such as a promotion, these methods are not feasible. Efendigil *et al.* (2009) also concluded that statistical methods are only efficient for data having seasonal or trend patterns, while artificial neural techniques are also efficient for data that are influenced by special cases, such as promotions or extreme crises. Huang (2009) presented that statistical methods frequently fail to accurately capture and manage the components of random variability in demand.

Garetti and Taisch (2009) determined some limitations using quantitative methods. First, a lack of expertise might cause a misspecification of the functional form linking the independent and dependent variables together, resulting in a poor regression. Second, a large amount of data is often required to guarantee an accurate prediction. Third, non-linear patterns are difficult to capture. Finally, outliers can bias the estimation of the model parameters. Some of these limitations can be overcome by the use of neural networks (NNs), which have been mathematically demonstrated to be universal approximators of functions.

A literature review reveals no effective and practicable forecasting method for forecasting demand for a range of products with demand having high random volatility (Huang, 2009). Escoda *et al.* (1997) stated that the uncertainty in economic environment makes the design of mathematic models with statistical methods very difficult. Thus, if the economic environment is uncertain, fuzzy logic may help to solve problems that are difficult to solve by the use of traditional methods.

Escoda *et al.* (1997) compared the NN, fuzzy NN and Winter's method for demand forecasting. They had 73 historical data points and used 59 of them in the training stage and 14 in the validation stage. They stated that the fuzzy NN system generates more accurate results than do the other two methods. Chen *et al.* (2000) focused on determining the impact of demand forecasting on the bullwhip effect. They have shown that if a retailer periodically updates the mean and variance of demand based on observed customer demand data, then the variance of the orders placed by the retailer will be greater than the variance of demand. They have also shown that providing each stage of the supply chain with complete access to customer demand information can significantly reduce the increase in variability. Frank *et al.* (2003) forecasted demand by using three different methods: exponential smoothing, Winter's method and NN using the same historical data. They stated that the forecasting accuracy of the NN method is higher than those of the other two methods. Thomassey *et al.* (2005) developed a specific demand forecasting tool for the textile market. Their method was based on two different models: the FIS for the median-term forecasting model and the neuro-fuzzy system for the short-term forecasting system. They stated that the use of the FIS results in more accurate forecasts than with the linear classical statistical models employed for the comparison. Sun *et al.* (2008) applied a novel NN technique called extreme learning machine (ELM) to investigate the relationship between sales amounts and some significant factors that affect demand in fashion retailing. In ELM, the input weights (linking the input layer to the hidden layer) and hidden biases are randomly chosen, and the output weights (linking the hidden layer to the output layer) are analytically determined by using the Moore-Penrose (MP) generalised inverse. Efendigil *et al.* (2009) presented a comparative forecasting methodology regarding uncertain customer demands in a multi-level supply chain structure using neural techniques. The objective of the paper is to propose a new forecasting mechanism that is modelled by artificial intelligence (AI) approaches, including the comparison of both artificial NNs and ANFIS techniques to manage the fuzzy demand with incomplete information. Their results indicated that the ANFIS performs more effectively than does the artificial NN structure in estimation of the more reliable forecasts for their case. Huang (2009) used Monte Carlo simulation to solve the demand forecasting problem in the marketplace with an expansive range of products with high random volatility of demand and correlations between demands of product. Sayed *et al.* (2009) introduced a decision support system for industrial companies using a hybrid forecast model based on combining statistical forecasting methods and an improved genetic algorithm to model demand factors with the demand series. They stated that the use of a combined intelligent model is necessary for providing accurate forecasting specially for complex environments that have different demand factors. Thomassey (2010) studied on sales forecasts in clothing industry in terms of distributors. The paper also includes the comparison of fuzzy logic, NNs and data mining methods.

Due to increasing competition, the demand forecasting issue has been studied by many researchers. There has been a great deal of work arguing that combining methods results in better performance than using individual methods. Combined methods, such as combinations of NN and fuzzy systems, increase the accuracy of forecasts (Hibon and Evgeniou, 2005). Escoda *et al.* (1997), Kuo (2001), Kuo and Xue (1998) and Kuo *et al.* (2002) used NNs and fuzzy systems in demand forecasting models; but still there is a lack of implementing neuro-fuzzy methods in demand forecasting (Efendigil *et al.*, 2009).

According to literature research and conversations with apparel manufacturers' specialists, there is not any common analytic method for demand forecasting in apparel industry and to our knowledge, there is not adequate number of study in literature to forecast the demand with ANFIS for apparel manufacturers. Thomassey *et al.* (2002, 2005) and Thomassey (2010) presented fuzzy systems for fashion sales forecasting; but they focused on fashion distributors or fashion retailers and their forecasting horizon is about one week (for short-term) or one season (for mean-term). In this study, the demand is forecasted in terms of apparel manufacturers. The input and output criteria are determined based on apparel manufacturers requirements and the forecasting horizon is about one month.

3. Proposed model

In this research, the ANFIS is used forecasting the demand for apparel manufacturers. Demand forecasting is a challenging problem due to the volatility of demand in the apparel industry. In addition, the replacement of products at each collection is very problematic for demand forecasting. The replacement of products in each season deletes the historical data; for this reason, quantitative methods are not easily usable in the apparel industry (Thomassey and Fiordaliso, 2006). AI methods can cope better with complexity, conflicts and uncertainty under different situations than traditional methods can because they are designed to function more like human judgment. Although AI methods have been applied to a wide range of manufacturing problems, their use in supply chain management is quite recent, and there are as yet few related applications. The objective of this research is to propose a new demand forecasting method using ANFIS for apparel industry.

NN is a powerful data modelling tool capable of capturing and representing complex input/output relationships. The motivation for the development of NN technology stemmed from the desire to develop an artificial system that could perform "intelligent" tasks similar to those performed by the human brain. The true power and advantage of NNs lies in their ability to represent both linear and non-linear relationships and in their ability to learn these relationships directly from the data being modelled. Traditional linear models are simply inadequate when it comes to modelling data that contains non-linear characteristics. NNs "learn" from examples, if trained carefully, and may exhibit some capability for generalisation beyond the training data, that is, to produce approximately correct results for new cases not used for training.

Fuzzy set theory has been studied extensively over the past 40 years. When considering uncertainty in models, some difficulties can arise to estimate parameters such as high cost in acquiring data information and lack of statistical observations. Because sufficient data are not always available for predicting uncertain parameters, the choice of the fuzzy set theory is more logical and convincing for expression of the uncertainty of expert knowledge (Mula *et al.*, 2008). Most of the interest in fuzzy set theory pertains to representing uncertainty in the human cognitive process (Zadeh, 1965). Fuzzy set theory is a method of incorporating additional information in the uncertainty model when no statistical information is available or when we are dealing with qualitative descriptions corresponding to expert declarations about the data or the impact of the alternatives (Matos, 2007). Combining fuzzy logic with other method can be seen in Li and Li (2009, 2010). Li and Li (2009) combined human judgment, analytic hierarchy process, simulation and fuzzy expert system for formulating marketing strategies and related internet strategies. Li and Li (2010) presented a multi-agent hybrid system by integrating multiple software agents, simulation, knowledge bases and fuzzy logic for international marketing decision making process.

The effect of variables on demand, such as "event day", is not always definite (Thomassey *et al.*, 2005). For this reason, the fuzzy-based model, which is useful when modelling expert knowledge and mapping the non-linear influences of the variables, is more suitable than, for example, neural tools (Kuo, 2001).

Fuzzy logic and NNs are complementary technologies. NNs extract information from systems to be learned or controlled, while fuzzy logic techniques most of the use verbal and linguistic information from experts (Lin and Lee, 1996).

Combinations of NNs and fuzzy systems have been recognised as a powerful alternative approach to develop fuzzy systems (Figueiredo and Gomide, 1999). Neuro-fuzzy models describe systems by means of fuzzy if-then rules represented in a network structure, to which learning algorithms known from the area of artificial NNs can be applied. Both NNs and fuzzy systems are motivated by imitating human reasoning processes. In fuzzy systems, relationships are represented explicitly in the form of if-then rules. In NNs, the relations are not explicitly given but are instead "coded" in the network and its parameters. In contrast to knowledge-based techniques, no explicit knowledge is needed for the application of NNs. Neuro-fuzzy systems combine the semantic transparency of rule-based fuzzy systems with the learning capability of NNs (Babuška and Verbruggen, 2003).

The integrated neuro-fuzzy system will possess the advantages of both NNs (e.g. learning abilities, optimization abilities, and connectionist structures) and fuzzy systems (e.g. humanlike if-then rules thinking and ease of incorporating expert knowledge). By this way, while, the low-level learning and computational power of NNs is put into fuzzy systems and also high level, humanlike if-then rule thinking and reasoning of fuzzy systems is put into NNs (Lin and Lee, 1996).

The adaptive neuro-fuzzy method works similarly to that of NNs. Neuro-adaptive learning techniques provide a method for the fuzzy modelling procedure to learn information about a dataset. The fuzzy logic method computes the membership function parameters that best allow the associated FIS to track the given input/output data.

The parameters associated with the membership functions change through the learning process. The computation of these parameters (or their adjustment) is facilitated by a gradient vector. This gradient vector provides a measure of how well the FIS is modelling the input/output data for a given set of parameters. When the gradient vector is obtained, any of several optimisation routines can be applied to adjust the parameters to reduce the error measure. This error measure is usually defined as the sum of the squared difference between actual and desired outputs. ANFIS uses either back propagation or a combination of least squares estimation and back propagation for membership function parameter estimation (Matlab, 2009).

An adaptive network, as its name implies, is a network structure consisting of nodes and directional links through which the nodes are connected. Moreover, some or all of the nodes are adaptive, which means that each output of these nodes depends on the parameters pertaining to this node, and the learning rule specifies how these parameters should be changed to minimise a prescribed error measure (Jang, 1993).

Suppose that the presented FIS has two inputs (x and y) and one output (z) and the rule base contain two fuzzy if-then rules of Takagi and Sugeno's type:

$$Rule_1 : If \;\; x \;\; is \;\; A_1 \;\; and \;\; y \;\; is \;\; B_1, \;\; then \;\; z = f_1(x,y)$$

$$Rule_2 : If \;\; x \;\; is \;\; A_2 \;\; and \;\; y \;\; is \;\; B_2, \;\; then \;\; z = f_2(x,y)$$

In this model the consequent part is a linear function of the input variables.

The architecture of the ANFIS is constituted by several layers (Figure 1). Layer 0 is the input layer and the neurons in this layer simply pass external crisp signals to Layer 1. The output of the each node in this layer is essentially membership grade for inputs. Generally membership function is chosen as bell shaped with a maximum value of 1 and a minimum value of 0, where a generalized bell function can be shown as:

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

or the Gaussian function:

$$\mu_{A_i}(x) = \exp\left\{ -\left(\frac{x - c_i}{a_i}\right)^2 \right\} \tag{2}$$

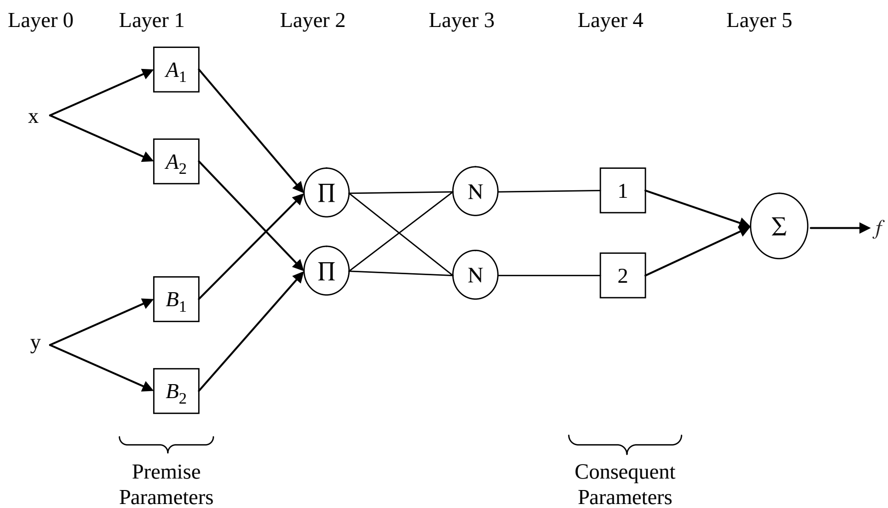

Figure 1.
ANFIS structure for two inputs and two rules

In this expression $\{a_i, b_i, c_i\}$ is the parameter set. As the values of these parameters change, bell-shaped functions also change accordingly, exhibiting various forms of membership functions on linguistic label A_i. These parameters are adverted as premise parameters. Each neuron in this layer corresponds to a single Sugeno-type fuzzy rule. A rule neuron in Layer 2 receives inputs from the respective fuzzification neurons and calculates the firing strength of the rule it represents and the output of Layer 2 can be shown as:

$$O_i^2 = w_i = \mu_{A_i}(x) \times \mu_{B_i}(y) \tag{3}$$

Each neuron in Layer 3 receives inputs from all neurons in the Layer 2, and calculates the normalised firing strength of a given rule. The normalised firing strength is the ratio of the firing strength of a given rule to the sum of firing strengths of all rules:

$$O_i^3 = \bar{w}_i = \frac{w_i}{w_1 + w_2} \tag{4}$$

The neurons in Layer 4 are adaptive and perform the consequent of the rules:

$$O_i^4 = \bar{w}_i f_i = \bar{w}_i(p_i x + q_i y + r_i) \tag{5}$$

In this expression $\bar{w}_i$ is the output of Layer 3, and $\{p_i, q_i, r_i\}$ is the parameter set. The parameters are to be determined and are referred to as the consequent parameters. Layer 5 represented by a single summation neuron. Single node of Layer 5 computes the overall output as a summation of all incoming signals:

$$O_i^5 = overall\ \ output = \sum \bar{w}_i f_i = \frac{\sum_i w_i f_i}{\sum_i w_i} \tag{6}$$

In the ANFIS architecture, it is observed that given the values of premise parameters, the overall output can be expressed as linear combinations of the consequent parameters. More precisely, the output of the model can be rewritten as (Jang, 1993):

$$f = \frac{w_1}{w_1 + w_2} f_1 + \frac{w_2}{w_1 + w_2} f_2$$

$$f = \bar{w} f_1 + \bar{w} f_2 \tag{7}$$

ANFIS is much more complex than the conventional FIS. Specifically, ANFIS model must have the following properties (Matlab, 2009):

- Be first or zeroth order Sugeno-type systems.
- Have a single output, obtained using weighted average defuzzification. All output membership functions must be the same type and either is linear or constant.
- Have no rule sharing. Different rules cannot share the same output membership function, namely the number of output membership functions must be equal to the number of rules.
- Have unity weight for each rule.

Using ANFIS technique in demand forecasting is a new approach. To incorporate both quantitative and qualitative forecasting criteria by using ANFIS technique is a suitable method for apparel manufacturers.

In apparel industry, due to the lack of historical data and the high impulse of purchase, demand forecasting is labelled as a "complex process" of a supply chain. Christopher and Peck (1997) stated that the most important reason that many apparel firms are unable to match the supply and demand is the inaccurate demand forecasts. Sayed *et al.* (2009) presented the reasons for the inaccurate forecasts. These reasons are: unsatisfactory forecasters, inappropriate forecasting methods, dynamic environment and short-term activity plans. ANFIS requires less data to be trained and has better generalisation performance compared with NNs (Jang, 1993).

After interviewing firm specialists, it was concluded that there is no common analytic method for demand forecasting in the apparel industry. Usually, demand is forecasted based on the experts' decisions. Furthermore, forecasted values are not reliable because of the unsatisfactory forecasters or methods.

In the literature, statistical methods are commonly used in demand forecasting; however, in the apparel industry, purchasing decisions can be easily effected by the political or financial volatility of the environment. This volatility also increases the complexity of the demand forecasting system. It is very difficult to capture this volatility by using statistical methods. Therefore, the ANFIS technique which combines the learning capability of the NN system with reasoning capability of the fuzzy logic system can be well suited approach for such a dynamic environment.

This study includes the case study of the proposed approach. The data used in case study were obtained from apparel manufacturers in Germany. The products' data used in this study from real company are not basic or fashion products. According to interviews with apparel manufacturers' experts, they specified that, the basic products (e.g. white t-shirt) have regular demand value for each season and the shelf-life of fashion products is four to six weeks and they do not have any place in the consecutive collections. The data presented in this study is pertained to semi-fashion products which have shelf-life more than one season. The demand forecast for the semi-fashion products is needed well before the start of the season when no historic demand data is available. Training and validation data set and rules were generated by making interviews with specialists in firms. When composing the data sets, general structure of the semi fashion products and the expertise over those products are considered for the apparel manufacturer. The apparel manufacturer has several products belong to several product groups (like trousers, t-shirt, sweat-shirt, etc.). These products have four main seasons: winter, spring, summer and autumn. The forecasting procedure starts well before (~6 months) the start of the production and each month the forecasted value is revised by the specialists. Matlab's Fuzzy Logic Toolbox was used for the construction of ANFIS system.

The first stage of ANFIS structure includes determining of input and output parameters. Determined criteria should affect the demand and should be attainable.

There are several criteria related to the demand forecasting process described in the literature. Kuo *et al.* (2002) used promotion methods, advertising media and competitor's action for their demand forecasting system. Thomassey *et al.* (2005) have three indicators for their system: price, holidays, and season. Thomassey and Fiordaliso (2006) forecasted demand for the textile market and their system includes three criteria: price, the starting date of the sales and lifespan of each item. Sun *et al.* (2008) used colour, size and price to forecast the demand for apparel manufacturer. Escoda *et al.* (1997) presented that significant variables for demand forecasting are mainly of subjective nature and then hardly quantifiable. When variables are of quantifiable nature, traditional tools methods are useful for the forecasting demand system. However, subjective nature variables are quite often difficult to analyse with these methods. Subjectivity of some relevant variables in demand makes its quantification, and therefore the possibility to introduce them in the model without any loss of relevancy in the forecasting, difficult. Fuzzy logic techniques can be very helpful because they allow introducing into the system in a calculable way any subjective variable by means of linguistic terms showing its subjectivity ranges. Fuzzy sets may represent uncertainty and inherent vagueness to linguistic variable definition.

In this research, the designed system performs forecasts with a monthly horizon. Five input criteria are determined by making interviews with firms' specialists of apparel industry in Germany and by inspection of the literature. The criteria are as follows:

(1) *Kind of customer*. Kind of customer is a "qualitative" variable. This variable shows the purchasing behaviour of the customer; for example, a targeted customer may be willing to pay more for a product. This factor has two sub-criteria: Class_A with higher purchasing power and Class_B with lower purchasing power.

(2) *Lifespan of product*. Lifespan of product is a "quantitative" variable. This variable represents the lifetime of a product and has two sub-criteria: short for more fashionable products (the lifespan of the fashion products is almost six weeks) and long for less fashionable or basic products (the lifespan of those products is longer than the fashion products).

(3) *Past experience*. Past experience is a "qualitative" variable and includes the information about the behaviour of the demand pattern in the past. If the product is "new" (there is no past experience), the experts use the demand pattern of similar products. Determining the value of past experience based on the

antecedent (maximum past three years) sales behaviour of the products for similar conditions. This criterion has three sub-criteria: low, medium and high.

(4) *Price level.* Price level is a "quantitative" variable and affects the demand pattern of the product. Price level has two sub-criteria: low and high.

(5) *Year sequence.* Year sequence is a "qualitative" variable and represents event day and/or normal day in the planning period. This criterion has two sub-criteria: events' day and normal day.

In this study, construction of the ANFIS structure includes the four steps. Step 1 includes the preparation of the numerical values of training and test data sets for input and output criteria. Numerical values (training and testing data sets) were determined by interviewing firm specialists in the apparel industry. The total data set includes 375 examples. The proposed methodology was trained with 337 examples corresponding the 90 per cent of the data set and was tested 38 samples corresponding the 10 per cent of the data set. The testing data set were selected in random from the total data set. The data set includes the different examples for different conditions. The examples consist of different product groups (the product group aggregates the demand value of the different sizes of the specific product (e.g. t-shirt with long sleeves or t-shirt with short sleeves) for a given demand).

Step 2 includes the construction of Sugeno-type FIS for ANFIS. In Matlab's ANFIS editor, the user can either initialise the FIS parameters to their own preferences or let ANFIS initialise the parameters. For this study, 48 rules were generated for FIS.

Sugeno-type FIS rules are different from Mamdani-type FIS; for example, in Sugeno type, FIS builds a rule such as "*If* INPUT is linguistic variable *Then* OUTPUT is a linear function of INPUT". Table I includes the examples of the rules.

Determining the type of membership functions is a very complex process in constructing FIS. In this study, different experiments are made for different membership functions (such as trapezoidal-shaped, generalised bell-shaped and Gaussian curve) types. A general structure of the ANFIS can be seen in Figure 2.

Step 3 includes the training stage of the system. ANFIS uses a hybrid learning algorithm to identify parameters of Sugeno-type FIS. It applies a combination of the least-squares method and the back-propagation gradient descent method for training FIS membership function parameters to resemble a given training data set. The ANFIS model structure can be seen in Figure 3.

ANFIS with five neurons for input and one neuron for output was trained for 100 epochs with 0.05 per cent error tolerance. ANFIS was run according to different types of membership functions and the output functions. In Sugeno type FIS output

Rule	Kind of customer (x_1)	Life span of product (x_2)	Past experience (x_3)	Price level (x_4)	Year sequence (x_5)	Forecasted demand
1	Class_A	Long	Medium	High	Normal day	$f_1(x_1, x_2, x_3, x_4, x_5)$
2	Class_B	Short	Low	Low	Normal day	$f_2(x_1, x_2, x_3, x_4, x_5)$
3	Class_A	Short	High	Low	Events' day	$f_3(x_1, x_2, x_3, x_4, x_5)$
4	Class_B	Long	Medium	High	Events' day	$f_4(x_1, x_2, x_3, x_4, x_5)$

Table I. Example rules for the Sugeno-type FIS function can be either constant or linear. In this study, experiments are made for both constant and linear output.

Step 4 includes the testing stage of the system. In this stage, the testing data set, which includes unseen data, was used to measure the generalisation capability of the system. Table II shows the mean percentage error for the testing data set for different membership functions and the output function type. According to Table II, a first-order Sugeno type output function with Gaussian-curve-shaped membership functions has satisfactory results for proposed ANFIS.

4. Application examples

Incorporating both quantitative and qualitative criteria by using the ANFIS system is a suitable new method for demand forecasting. In this research work, the ANFIS system is presented to forecast the demand in the apparel industry. The ANFIS system is designed by using the Fuzzy Logic Toolbox in Matlab.

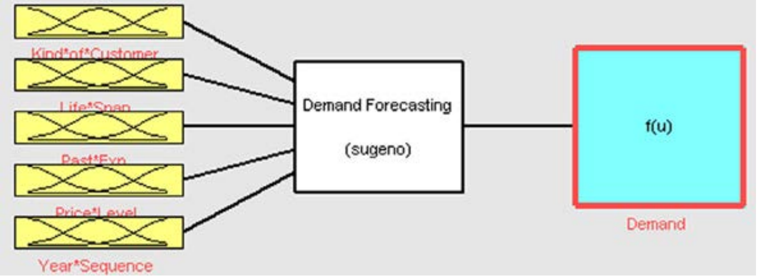

Figure 2. ANFIS for demand forecasting system

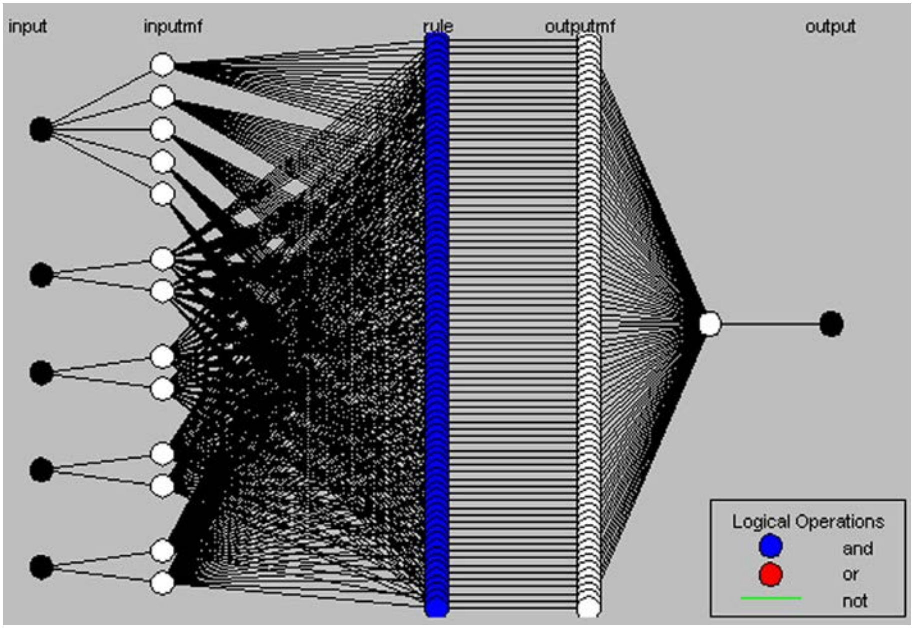

Figure 3. ANFIS model structure for proposed approach

The proposed approach in this study is applied using data of an apparel firm, and the results showed that the proposed system can be used effectively. Figure 4 represents the fitness graphic of the 24 month real demand value and FIS output for a specific product group and Figure 5 represents the different demand forecast for 38 different product groups. According to fitness graphics, it is significantly seen that ANFIS gives good answers.

Table III presents the details of application examples with the results of forecasted demand and real demand values for related input in the apparel industry.

5. Discussion and conclusions

Supply chain management in the apparel industry is characterised as a "complex" process because of the stochastic characteristics of the apparel demand and product proliferation. Therefore, supply chain members are at greater risk of having excess or insufficient inventory at the end of a selling season.

Table II.
Mean percentage error of the proposed ANFIS

	Output function type	
Membership function type	Constant	Linear
Trapezoidal shaped	0.035	0.026
Generalised bell shaped	0.020	0.019
Gaussian curve	0.021	0.015

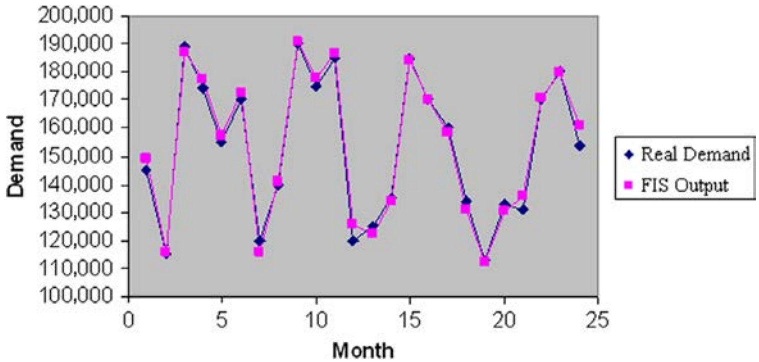

Figure 4.
The fitness of the real demand value and the FIS output for a product group

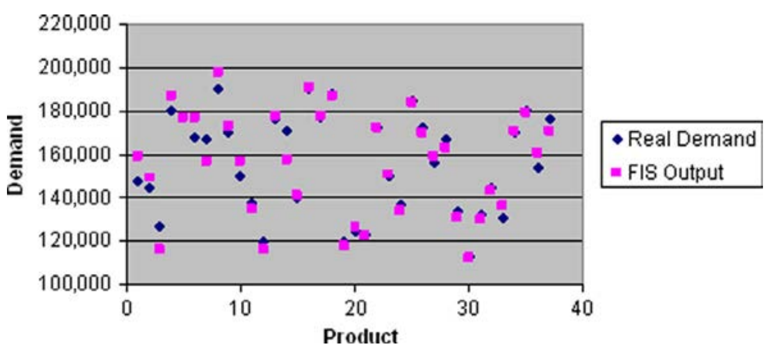

Figure 5.
The fitness of the real demand value and the FIS output for different products

Table III. The details of application examples and results for the demand forecasting system

Input					Output	
Kind of customer	Life span of product	Past experience	Price level	Year sequence	Real demand value ($\times 10^3$ unit)	Forecasted demand value ($\times 10^3$ unit)
Class_B	Short	Low	High	Event's day	148	159
Class_A	Long	High	High	Normal day	178	173
Class_A	Short	Medium	High	Event's day	137	134
Class_B	Short	Low	Low	Normal day	145	149
Class_A	Long	High	High	Event's day	154	161
Class_B	Short	Low	High	Normal day	127	116
Class_A	Short	High	High	Event's day	156	159
Class_B	Long	Medium	High	Normal day	171	158
Class_B	Short	Medium	Low	Normal day	177	177
Class_A	Short	High	Low	Event's day	172	172
Class_B	Short	Medium	High	Event's day	168	177
Class_A	Short	High	Low	Event's day	185	184
Class_B	Short	Medium	High	Normal day	167	157
Class_B	Short	High	Low	Normal day	190	198
Class_B	Short	High	High	Normal day	170	173
Class_B	Long	Low	Low	Event's day	150	157
Class_A	Short	Low	Low	Event's day	120	118
Class_A	Long	Medium	Low	Normal day	145	143
Class_B	Long	Low	High	Event's day	138	135
Class_A	Long	Low	High	Event's day	113	112
Class_B	Long	Low	High	Normal day	120	116
Class_A	Short	Low	High	Normal day	125	126
Class_B	Long	Medium	Low	Event's day	176	178
Class_A	Long	High	Low	Normal day	180	179
Class_B	Short	Medium	High	Event's day	180	187
Class_A	Long	Low	High	Normal day	134	131
Class_A	Short	High	Low	Normal day	172	170
Class_B	Long	Medium	High	Normal day	140	141
Class_A	Short	Medium	Low	Normal day	150	151
Class_A	Long	Low	High	Normal day	132	130
Class_A	Short	Low	High	Normal day	123	122
Class_B	Long	High	Low	Event's day	190	191
Class_A	Long	Medium	High	Event's day	131	136
Class_A	Short	High	High	Normal day	167	163
Class_B	Long	High	Low	Normal day	177	178
Class_A	Long	High	Low	Event's day	170	171
Class_B	Long	High	High	Event's day	188	187
Class_A	Long	High	High	Normal day	176	171

In recent years, apparel manufacturers have preferred global outsourcing. The complexity of the supply chain management increases with new global members in the chain.

The demand forecasting in the apparel industry is also known as a complex process due to the lack of historical sales data (even when it exists, data is typically unreliable) and high impulse purchasing. Furthermore, there is no commonly used analytical method for demand forecasting in the apparel industry. Demand is forecasted based on the experts' experiences. Owing to unsatisfactory forecasters and the lack of an analytical demand forecasting method, most forecasted values are unreliable. We have selected ANFIS for this study for the following reasons:

- Criteria used for demand forecasting are both qualitative and quantitative. Fuzzy-logic-based systems are well suited when working with qualitative criteria.
- Hybrid methods such as neuro-fuzzy techniques have more realistic results in the forecasting area. Individual fuzzy systems are not suggested for demand forecasting. ANFIS combines the reasoning capability of the fuzzy logic with learning capability of the NN system.
- According to literature research and conversations with apparel manufacturers' specialists, there is not any common analytic method for demand forecasting in apparel industry and to our knowledge, there is not adequate number of study in literature to forecast the demand with ANFIS for apparel manufacturers. Thomassey *et al.* (2002, 2005) and Thomassey (2010) presented fuzzy systems for fashion sales forecasting; but they focused on fashion distributors or fashion retailers and their forecasting horizon is about one week (for short-term) or one season (for mean-term).
- In the apparel industry, purchasing decisions can be easily affected by the political or financial volatility of the environment. This volatility also increases the complexity of the demand forecasting system. It is very difficult to capture this volatility by using statistical methods. For this reason, the ANFIS technique can be well suited approach for such a dynamic environment.
- The proposed ANFIS method can deal with the complexity of the decision making process and does not require the formulation of the decision making process.

In literature about demand forecasting in apparel industry, focused on fashion distributors or retailers and their forecasting horizon is about one week (for short-term) or one season (for mean-term). In this study, the demand is forecasted in terms of apparel manufacturers. The input and output criteria are determined based on apparel manufacturers requirements and the forecasting horizon is about one month.

In this research work, five input criteria and one output criterion were determined for ANFIS. Training and testing data sets and rules were generated by interviewing apparel firm specialists in Germany. The demand is forecasted based on the experts' experiences in the interviewed apparel manufacturer. The proposed system reduces the dependency of the experts experience and amount of time required for demand forecasting procedure.

In practice, the response of the demand forecasting system about the unpredictable events (like natural disasters or economic crisis) is a critical problem. According to our observation, the "past experience" criteria has a wide range of scope and the proposed ANFIS can cope well with the unpredictable events by the support of "past experience" criteria; but, the ANFIS demand forecasting model can fail, if the unpredictable events occur so rarely (like world wars, nuclear disasters or big natural disasters, etc.).

Despite the satisfactory test results of the ANFIS, there are some difficulties occurred in constructing the system. Determining the type and range of membership functions, developing the rule base and composing the training, validation data sets are very complex process and require high degree of care and accuracy in constructing the system.

The results of the proposed study showed that an ANFIS-based demand forecasting system can help apparel manufacturers to forecast demand more accurately, effectively and simply. Further research can be performed by adding new criteria, if required, according to different application areas.

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