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Abstract

Purpose – The purpose of this paper is to capture the dynamic variations in sales of a product based upon the dynamic estimation of the time series data and propose a model that imitates the price discounting and promotion strategy for a product category in a retail organization. A modest attempt has been made in the study to capture the relationship between the sales promotion, price discount and the batch procurement strategy of a particular product category to maximize sales volume and profitability.

Design/methodology/approach – Time series data relating to sales have been used to model the sales estimates using moving average and proportional and derivative control; thereafter a sales forecast is generated to estimate the sales of a particular product category. This provides valuable inputs for taking lot sizing decisions regarding procurement of the products that considerably impact the sales promotion and intelligent pricing decisions. A conceptual framework is developed for modeling the dynamic price discounting strategy in retail using fuzzy logic.

Findings – The model captures the lag effect of sales promotion and price discounting strategy; other strategies have been formulated based upon the sales forecast that was done for taking the lot sizing decisions regarding procurement of products in the selected category. This has helped minimize the inventory cost thereby keeping the profitability of the retail organization intact.

Research limitations/implications – There is no appropriate empirical data to verify the models. In light of the research approach (modeling based upon historical time series data of a particular product category) that was undertaken, there is a possibility that the research results may be valid for the product category that was selected. Therefore, the researchers are advised to test the proposed propositions further for other product categories.

Originality/value – The study provides valuable insight on how to use the real-time sales data for designing a dynamic automated model for product sales promotion and price discounting strategy using fuzzy logic for a retail organization.

Keywords Causality, Modelling, Automation, Intelligent agents, Fuzzy logic

Paper type Research paper

1. Introduction

The world is facing challenges of environmental sustainability of supply chain. Retail supply chain management plays a key role to reduce the carbon footprints of a supply network. Online retailing gives a wider perspective to lower the CO_2 emissions. Researchers are widely creating a space for online retailing where supply chain surplus could be maximized (Carrillo *et al.*, 2014; van Loon *et al.*, 2015). Organizations are looking for multiple channel options to gain maximum shares in demand. While considering the customers' behavior nowadays it is essential for the players of a supply chain to balance the network in terms of online and offline retailing options (Melis *et al.*, 2015; Zhou and Duan, 2015). The prevalence and nature of price promotions (i.e. deal

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types and discount depths) in the USA and the UK have taken a key sustainable issue for a retail organization. (Bogomolova *et al.*, 2015) have analyzed the important aspects of sales promotion and price discount strategies in UK and US. The analysis comprises of 23 categories across five retail chains. One of the key findings is that multiple-unit promotions – deal types that have been under-researched – account for approximately half of all price promotion activity. The analysis also identifies an increase in price promotion prevalence since the Global Financial Crisis, predominantly driven by national brand promotions. Keeping in view of these critical aspects of the retail organization, this research focusses on automation of sales promotion and price discounting strategies for a retail organization.

Increased consumer awareness in today's world forced the retail industries to think about competitiveness in terms of quality, availability, and price (Afshari and Benam, 2011; Das, 2014). Dynamic pricing is a major tool for both online and store retailers to not only increase the flexibility in prices but also remain competitive (Levy *et al.*, 2004). Dynamic pricing has become a major pricing strategy in several industries such as hospitality, travel, entertainment, energy, power and retail. Competitors pricing (Greenleaf, 1995), supply and demand (Gustafsson *et al.*, 2000), price sensitivity (Gijsbrechts, 1993) and other external factors are major variables that affect dynamic product promotion and price discounting strategies. Dynamic pricing, as it considers inventory levels, plays a vital role in eliminating inventory waste and consequently adds up to the profitability of the organization (Elmaghraby and Keskinocak, 2003; Hall *et al.*, 2010; Esary *et al.*, 2008; Fisher and Raman, 1996).

Historical sales data plays a pivotal role in forecasting the future sales and consequently develop a framework for pricing strategy (Cunningham and Kerber, 2000). Developing a sales forecast for a particular product category is a key concern for the retail organizations (Schroeder *et al.*, 2010). Seasonality and time series analysis play an important role in forecasting sales (Štěpnička *et al.*, 2013). There are a number of decision models and tools available to generate sales forecast such as neural network, fuzzy logic and econometrics tools (Guo *et al.*, 2013; Hanssens and Parsons, 1993; Kuo, 2001; Lal, 1990; Choi *et al.*, 2014; Du *et al.*, 2015; Tanaka, 2010), that may be used to generate sales forecast. The paper aims to develop a dynamic pricing and discounting model, hence in dynamic environment, it is appropriate to use dynamic moving average forecast using control theory presented in Kumar *et al.* (2013a).

Pricing research plays an important part in intelligent pricing systems (Rao, 1984; Gijsbrechts, 1993), helps to develop dynamic price discounting models. Price sensitivity toward a product, the market price of the product and sales forecast are major variables that decide pricing strategy and systems (Esary *et al.*, 2008). Batch ordering inventory policy and proper selection of reordering point also play a significant role in dynamic pricing and discounting (Elmaghraby and Keskinocak, 2003). Point of sales data and continuous inventory replenishment policy may be used to automate dynamic pricing (Freeny Jr, 2000). Reference pricing is important to increase the profitability in dynamic pricing and discounting system (Greenleaf, 1995), the effect of category management and brand by brand approaches to deciding prices is studied, for improving the revenue (Hall *et al.*, 2010; Mulhern and Leone, 1991). Rational expectations and theory of price movements affects the dynamic pricing system and discounting system (Muth, 1961).

The major drivers for retailer's price are competitor's price, sales volume or traffic, manufacturer's price and price elasticity of the product (Nijs *et al.*, 2007). Price intelligence plays a vital role to discover the dynamic price of a product (Yeh, 2008).

On the basis of stated consideration and variables, dynamic pricing and discounting systems are developed (Srinivasan and Shamos, 2001).

Sales promotion is the key to profit maximization for a retail organization. The need of dynamic sales promotion models and their significance in different sectors is highlighted by Blattberg and Neslin (1993) and Bemmaor and Mouchoux (1991). The short-term effect of in-store promotion and retail advertising on brand sales is studied (Berck *et al.*, 2008) to maximize the volume of sales (Blattberg and Neslin, 1993). New economic conditions have led to innovations in retail industries, such as more dynamic retail approaches based on flexible strategies. "The deal effect curve analysis and the time series linear model do not provide enough expressive capacity, and nonlinear promotional models more accurately follow the actual sales pattern obtained in response to the implemented sales promotions. The quarterly temporal analysis conducted enabled the authors to identify long-term changes in the dynamics of the model for several products, especially during the early stage of most recent economic crisis, consistent with the information provided by the reliability indices in terms of the feature space" (Soguero-Ruiz *et al.*, 2014; Tellis and Zufryden, 1995).

Inventory control and lot sizing strategies could play a significant role in discounting and pricing of a product (Subrahmanyan and Shoemaker, 1996; Woo *et al.*, 2005). Inventory management is essential for a firm to be cost competitive and acquire decent profit in the market, but how to achieve an outstanding inventory management has been a popular topic in both the academic field and in real practice for decades. As the production environment is getting increasingly complex, various kinds of mathematical models are being developed, such as linear programming, nonlinear programming, mixed integer programming (MIP), geometric programming, gradient-based nonlinear programming and dynamic programming, to name some. However, when the problem becomes extremely complex, heuristics tools may be necessary to solve the problem. To solve the lot sizing problems with multiple suppliers, multiple periods and quantity discounts a MIP model is first constructed. Thereafter an efficient genetic algorithm is proposed to tackle the problem when it becomes quite complicated, to minimize the total cost, the costs include ordering cost, holding cost, purchase cost and transportation cost, under the requirement that no inventory shortage occurs in the system, and to determine an appropriate inventory level for each planning period (Lee *et al.*, 2013; Dulaney and Waller, 2002).

A few researchers have focussed on how to use sales data to decide retail space, pricing strategy and lot sizing through integrated models. Lohse and Spiller (1999) studied how the user interface influences traffic and sales of a product. Freeny Jr (2000) has developed an "automated synchronous product pricing and advertising system" and shown how to integrate models (Cragun *et al.*, 1998). Variable margin pricing system was developed by Hartman and Lewandowski (1998) that lead to the development of dynamic pricing systems. A price management system was proposed for dynamic pricing (Esary *et al.*, 2008; Cragun *et al.*, 1998; Marshall, 1993). Dynamic modeling and information control may be used to integrate the models and in the supply chain management in retail organizations (Perkowski, 1999; Sarimveis *et al.*, 2008; Sivakumar and Weigand, 1997).

Fuzzy logic becomes a widely acceptable tool in decision making in a multi- dimensional fuzzy environment, it has been used to assert what would be in- admissibly vague in classical logic (Zadeh, 1974, 1975). Sales forecast system has been developed using fuzzy logic for better planning and control (Kuo, 2001; Kuo and Xue, 1998; Lin and Hong, 2008).

From the review of above literature, it is clear that though a lot of research has been done to design a model for sales promotion and dynamic pricing and discounting strategy for retail organizations, however there still exists a gap in literature as studies relating to integration of sales data with inventory lot sizing decisions that can help in automation of price discounting strategy formulation in a fuzzy dynamic environment are still not sufficient. It also appears that there are some missing links as important aspects like how to capture the price sensitivity of a product in a dynamic pricing environment and how to capture causality have also not been sufficiently explored.

In view of the above- stated gaps, a modest attempt has been made in the study to achieve the below-mentioned objectives that can help in filling up the gaps:

(1) to develop a framework for the proposed model that deals with dynamic sales promotion and fuzzy dynamic price discounting strategy (DPDS) in a retail organization; and

(2) to develop an integrated model for dynamic pricing and lot sizing of a product in a retail organization.

In light of the objectives of the study, the research aims to develop a model that integrates sales promotion strategy, price discounting strategy and lot sizing strategy, and from the literature review variables have been carved out that impact these strategies. Historical sales data, price sensitivity, price intelligence and inventory and lot sizing combine to form a pricing system and dynamic price discounting model (DPDM) which is discussed in coming sections. Section 2 contains a brief description of the proposed framework and presents the inventory control model that has been used for generating sales forecast and lot size. Section 3 contains the application of fuzzy logic in formulating different discounting strategies. Section 4 contains results and discussions.

2. Framework of proposed model

The conceptual framework of the proposed model is shown in Figure 1, which consists of five entities that are inputted to the dynamic pricing and discounting strategy formulation. The framework presented has five inputs and one output as dynamic discounts. The dynamic process to decide about discounts could be understood by following steps.

Step 1: generate sales forecast using historical sales data for calculation of rate of change of sales forecast.

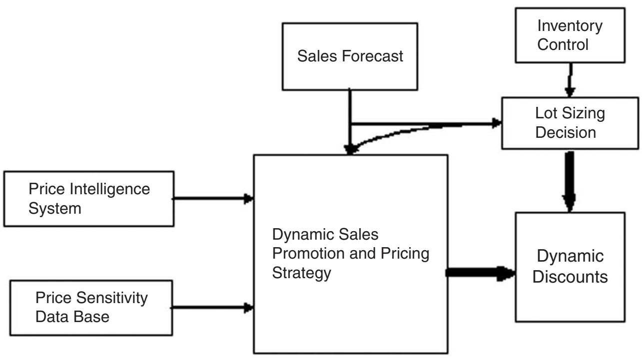

Figure 1. Framework of proposed model

Step 2: using appropriate inventory control mechanism, current inventory position could be calculated thereby using forecasted sales data lot size could be estimated.

Step 3: from price intelligence system current competitor price or market price could be generated.

Step 4: using lot size, market price and price elasticity of the product category sales promotion and pricing strategy could be formulated and, in turn, dynamic discounts may be decided using company competitive strategy.

Proposed framework is an integration of several models proposed (Cragun *et al.*, 1998; Esary *et al.*, 2008; Perkowski, 1999; Schroeder *et al.*, 2010). The unique feature of the proposed integrated model is a fuzzy rule-based decision making that had not been considered by previous models. The model has also considered how to use real-time analytics for formulating DPDM; online real-time analytics for price tracking is included in this model.

The entities are described one by one in Section 2.1-2.4.

2.1 Sales forecast

The increase in competition has forced the retailers to minimize the cost so as to increase their profit margins. Furthermore, the fluctuating consumer behavior has affected the demand of products. The above factors have made it imperative for retailers to resort to accurate sales forecast so as to maximize their profits and minimize the cost. Accurate sales forecasts can help the retailers to efficiently design products according to the needs of the customers, timely make them available in the market and improve the sales revenue and customer satisfaction. In this era of globalization and cut-throat competition, sales forecasting holds the key for the success of an organization.

Sales forecasting is a technique that helps in the prediction of future sales based on past historical data. In the 1950s, exponential smoothing and decomposition methods were used to forecast sales but with the discovery of computers in 1960s, advanced methods of sales forecasting like ARIMA models started getting used. Later on, econometric methods and Bayesian methods which were much more advanced and dynamic were used for sales forecasting. The intelligent or soft computing algorithms that combined fuzzy theory with neural networks and can perform the variety of applications in various fields of study are preferred over traditional methods.

Dynamic sales forecast lays the foundation for dynamic product promotion and price discounting strategy. A lot of research is undertaken to forecast sales which include neural network method, furrier method, vector auto regression method and other multi-criteria decision methods (Guo *et al.*, 2013; Tanaka, 2010). Moving average with proportional and derivative control method (Kumar *et al.*, 2013b) of dynamic forecasting which enables better inventory control has been used in this research.

Historical sales data (192 data points) of a single product category (mobiles and tablets) in a retail organization is considered for the research. A sales forecast is generated using the moving average method. After forecasting, proportional and derivative control (Kumar *et al.*, 2013a, b) is used to minimize the forecast error which decreases significantly using proportional and derivative control. The procedure for generating dynamic sales forecast is explained in Figure 2, and a sample Table I is provided for illustration.

The rate of change of sales forecast is taken as one of the three inputs (lot size, price sensitivity, rate of change of demand) for the formulation of the fuzzy dynamic price discounting strategies.

2.2 Inventory control and lot sizing decision

Control of inventory is one of the significant areas of operations management, to remain competitive and minimize expenses. It is imperative for retailers to have an efficient and responsive inventory control mechanism. Inventory control as a research agenda has got plenty of literature (Chen and Ho, 2013; Maity and Maiti, 2008; Roy *et al.*, 2009). Samal and Pratihar (2014) have proposed a mechanism to minimize the inventory cost in a fuzzy environment. Optimal inventory policy and discounting have attracted many researchers, for example, Bera *et al.* (2012), Monica Lam and Wong (1996), Roy *et al.* (2009) and Taleizadeh *et al.* (2015).

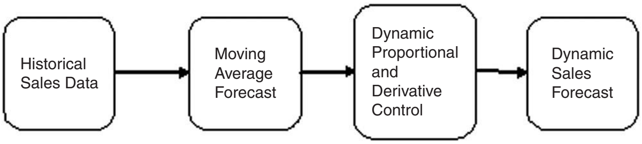

Figure 2. Procedure for generating dynamic sales forecast

Time	Number of actual units sold	Forecast using moving average	Forecast error (moving avg.)	Derivatives	Forecast with proportional and derivative control with $\alpha = 0.99$	Forecast error (proportional and derivative control)	Absolute forecast error (proportional and derivative control)	Absolute forecast error (moving avg.)
2010 Jan	1,608	1,865.0019	(257)	(468)	1,612.40	(4.68)	4.684695333	257.2859
2010 Feb	1,652	1,841.95077	(190)	44	1,651.62	0.44	0.443470667	189.8877
2010 Mar	2,071	1,629.88953	441	419	2,066.87	4.19	4.189964667	441.17
2010 Apr	1,658	1,861.5613	(204)	(413)	1,661.86	(4.13)	4.133302	203.8319667
2010 May	1,670	1,864.39443	(195)	12	1,669.52	0.12	0.119075333	194.7575667
2010 Jun	2,088	1,663.6831	424	419	2,083.98	4.19	4.185272	424.4809667
2010 Jul	1,680	1,878.90047	(199)	(408)	1,684.39	(4.08)	4.078476	198.584
2010 Aug	1,680	1,884.24027	(204)	0	1,680.38	0.00	0.000642667	203.8595333
2010 Sep	2,097	1,680.3486	416	416	2,092.36	4.16	4.161393333	416.1714667
2010 Oct	1,694	1,888.4504	(194)	(402)	1,698.50	(4.02)	4.020420667	193.9724
2010 Nov	1,707	1,895.49903	(189)	12	1,706.59	0.12	0.122371333	188.7839
2010 Dec	2,107	1,700.59657	407	401	2,103.47	4.01	4.0076	406.8785667
2011 Jan	1,737	1,907.09513	(170)	(370)	1,740.90	(3.70)	3.702818667	169.9018667
2011 Feb	1,734	1,922.3342	(188)	(3)	1,734.28	(0.03)	0.029388667	188.0798
2011 Mar	2,156	1,735.72383	421	422	2,152.19	4.22	4.22161	420.6915667
2011 Apr	1,757	1,945.3349	(188)	(399)	1,761.16	(3.99)	3.992494	188.1689
2011 May	1,730	1,956.7907	(227)	(27)	1,730.03	(0.27)	0.274081333	227.0328333
2011 Jun	2,168	1,743.46193	424	438	2,163.54	4.38	4.381645333	424.4604667
2011 Jul	1,750	1,948.84013	(199)	(418)	1,754.13	(4.18)	4.179698	198.8875333
2011 Aug	1,748	1,958.9375	(211)	(2)	1,748.36	(0.02)	0.016099333	210.5948333
2011 Sep	2,208	1,749.14763	459	460	2,203.44	4.60	4.596954667	458.8905
2011 Oct	1,783	1,978.1904	(196)	(425)	1,786.92	(4.25)	4.253714667	195.5237333
2011 Nov	1,780	1,995.3524	(216)	(3)	1,779.71	(0.03)	0.029895333	215.6752667
2011 Dec	2,238	1,781.1719	457	458	2,233.30	4.58	4.582056	456.7108333
2012 Jan	1,797	2,008.77993	(211)	(441)	1,801.76	(4.41)	4.405275333	211.4247333
2012 Feb	1,792	2,017.61897	(226)	(6)	1,791.66	(0.06)	0.057542667	226.0180333
2012 Mar	2,280	1,794.47807	485	488	2,274.68	4.88	4.879574	485.0802667
Forcasted value for Apr 2012					2,279.56			

Note: The values shown in parenthesis are negative

Table I. Sales forecast using PD control

Inventory control module of the proposed DPDS provides information to decide the economic lot size regarding procurement of product category which plays an important role in developing the proposed DPDM.

The basic dynamic inventory control model that provides a dynamic rate of change of demand forecast at a retail location (j) is shown in Figure 3.

A mathematical model for a single item has been developed for a retail location (j) to explain the above inventory control model.

The notations used in the model at retail location (j) for suppliers (i) and customers (k) are $S_j(t)$ inventory at retail location (j) at time t; $Q_{ij}(t)$ incoming order at retail location (j) at time t; $Q_{jk}(t)$ actual sales at retail location (j) at time t; $O_{ji}(t)$ lot-order size at retail location (j) at time t; $O_{kj}(t)$ is equal to $Q_{jk}(t-1)$ (actual sales at time $(t-1)$); $h_j(t)$ lot size decision factor at time t (transfer function for lot size decision); l is lead time for the product category.

The balance equations at retail location j are as below:

$$S_j(t) = S_j(t-1) + Q_{ij}(t-1) - Q_{jk}(t) \tag{1}$$

$$O_{ji}(t) = h_j(t) \times \left[O_{kj}(t) - S_j(t)\right] \tag{2}$$

$$Q_{jk}(t) = \begin{cases} 0 & O_j(t-1) \leqslant 0 \\ O_j(t-1) & 0 \leqslant O_j(t-1) \leqslant S_j(t-1) \\ S_j(t-1) & 0 \leqslant S_j(t-1) \leqslant O_j(t-1) \end{cases} \tag{3}$$

$$O_{ji}(t) = h_j(t) \times \left[O_{kj}(t) - S_j(t-1) - Q_{ij}(t-l) + Q_{jk}(t)\right] \tag{4}$$

$$\begin{aligned} O_{kj}(t) &= Sales\ forecast\ at\ time\ t(orders\ at\ time\ t) \\ &= Q_{jk}(t-1) + \alpha\left(Q_{jk}(t) - Q_{jk}(t-1)\right) \end{aligned} \tag{5}$$

The value of α depends upon the type of product and marketing strategy used, it varies between 0 and 1. Here the value of α is calculated by simulation which is equal to 0.99 because the forecast depends upon recent sales and the forecast error is less.

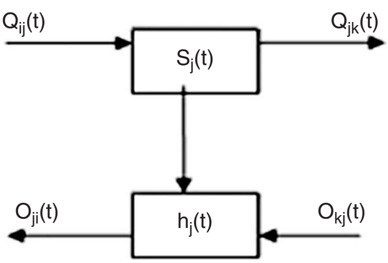

Figure 3.
Basic dynamic inventory control model

The lot sizes are decided by the proposed forecasting and inventory control mechanism which helps to formulate quantity discount schedule.

It has been assumed that prices and lot sizes are negotiable in most of the cases. Quantity discount schedule that is governed by lot sizes has been used for a long time in many countries. The proposed model utilizes the quantity discount schedule as input, which is presented in Table II for formulating DPDS. A detailed quantity discount function (QDF) for deciding lot sizes is discussed by Schotanus *et al.* (2009). The concept of QDF helps to formulate the membership function of the fuzzy variable lot size.

2.3 Price intelligence system

The world is now connected and huge data is available on the internet and various sources of media, it seems like the world moves at a faster pace. Organizations are trying to react with globally connected and changing environment; tools are being developed to process the big data for decision making. Online retailing is the future of the retail organization as predicted by many authors. Therefore, a state of the art infrastructure is required to handle the online real- time data thereby creating a price intelligence system to track the market price and competitor's price of the product. Market price and competitor's price is used to formulate the discounting strategy in this study.

Price intelligence block in proposed framework provides inputs regarding competitor's price of the product. Competitor's price is one of the major decision variables in formulating DPDS which can be extracted from price intelligence. Online retailers are using business analytics for finding competitor's price. A mechanism needs to be developed for the offline retailers also to help them keep track of the competitor's price. In this study, the competitor's price of the product category is taken from the database of the retailer.

Market price is assumed as the reference price for the product category. The market price of a product is a major variable for pricing strategy. Price intelligence system conceptually provides the current market price of a product category through real-time streaming data analytics. Real- time data analytics is a concept where one can use Online Analytic Process for knowing the current price and price trend of a product category.

2.4 Price sensitivity database

In order to develop DPDM, price sensitivity or elasticity of a product category is crucial. The price of a product category may be sensitive to so many variables; a price sensitivity database is required to develop to know the association between price and other variables like sales in this study.

Price sensitivity has been calculated using historical sales data using correlation. A price sensitivity model (PSM) helps in mathematically analyzing the effect of a

Lot size	Discount (%)
200-300	10
300-400	15
400-600	20
600 and above	20

Table II. Quantity discount schedule change in the price of a product on the buyer's demand for that product. It helps also to predict the price sensitivity of buyers for the product(s).

The model holds a lot of significance as the price sensitivity calculations that are done through this model are used in the dynamic pricing model to predict the changes in sales of the product at different prices while deciding the price of the product that maximizes the profit.

In other words, the PSM analyzes how the changes in the price have affected the sales of product(s) in the past and uses these results to predict the effect on future price adjustments.

In addition to the above, the proposed DPDM helps to determine separate price sensitivity functions of every product or category segment. For the purpose of forecasting it uses statistical methods like linear regression or nonlinear regression analysis using curve-fitting based on exponential, power, logarithmic, Gompertz, logistic or parabolic functions and also uses numerous averaging, smoothing and decomposition techniques to further increase the accuracy of the forecasts.

3. Dynamic fuzzy price discounting strategy-methodology proposed

Fuzzy sets are used to map the price discounting strategy with three fuzzy inputs: price sensitivity, rate of change in demand forecast and lot size. The output fuzzy set consists of dynamic price discounting linguistic variables like mega sales offer, bumper sales offer, big-bang sales offer and normal sales offer.

Input fuzzy set $\Longrightarrow$ Output fuzzy set

1. Price sensitivity: {0,1}
2. Rate of change in demand forecast: {-10,10}
3. Lot size: $\{Q_1, Q_4\}$

Dynamic product promotion and pricing strategy:
$$\begin{Bmatrix} Big{-}Bang{-}Sales{-}Offer \\ Mega{-}Sales{-}Offer \\ Bumper{-}Sales{-}Offer \\ Normal{-}Sales{-}Offer \end{Bmatrix}$$

The range of discount will be calculated based upon the competitor's price and purchasing cost of the product. The discounting range will be:

$$\text{Competitor's price} - (\text{purchasing cost} + \text{expected inventory holding cost}).$$

3.1 Fuzzification

Membership function. Three input fuzzy variables have been proposed for dynamic sales promotion and price discounting mechanism and they have been mapped to dynamic product promotion and pricing strategy as shown above. Mapping these variables for fuzzy decision making in a properly defined format is known as fuzzification and for this, an appropriate membership for each variable is selected based upon historical data. Membership functions for input and output variables have been defined below using historical data.

The linguistic output variables are defined as:

(1) big-bang-sales-offer $D \geqslant 40$;

(2) mega-sales-offer $30 \leqslant D < 40$;

(3) bumper-sales-offer $20 \leqslant D < 30$; and

(4) normal-sales-offer $10 \leqslant D < 20$.

"D" denotes percentage of discounts.

Hence, a universal set "S" is defined for discount values where "S" is a continuous function ranging from 0 to 50, "D" is a subset of "S." The membership function of output variable (discounting values) is shown in Figure 4.

Let $\underset{\sim}{A}$ denote the fuzzy set of price sensitivity; $\underset{\sim}{B}$ denote rate of change in demand forecast; and $\underset{\sim}{C}$ denote lot size.

Four linguistic membership functions have been defined by inferences.

Membership function for linguistic input variable ($\underset{\sim}{A}$):

(1) high price sensitivity;

(2) medium price sensitivity;

(3) low price sensitivity; and

(4) insensitive toward price change.

The membership function of price sensitivity is shown in Figure 5.

Membership function for linguistic input variable ($\underset{\sim}{B}$):

(1) high rate of change (greater than 5 percent);

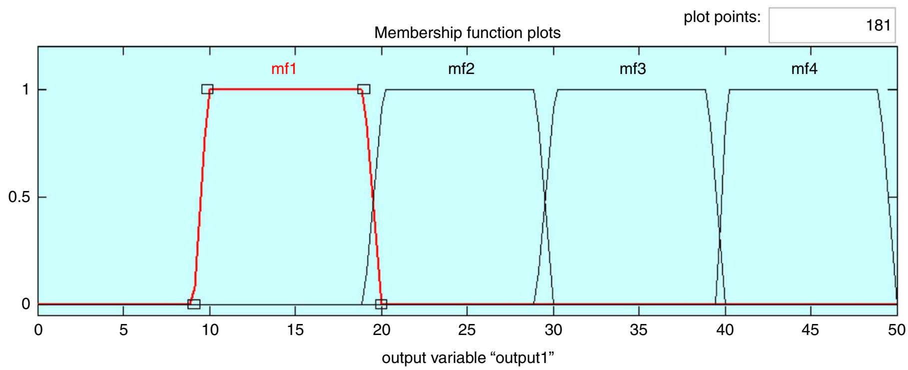

Figure 4. Membership function of discounting values

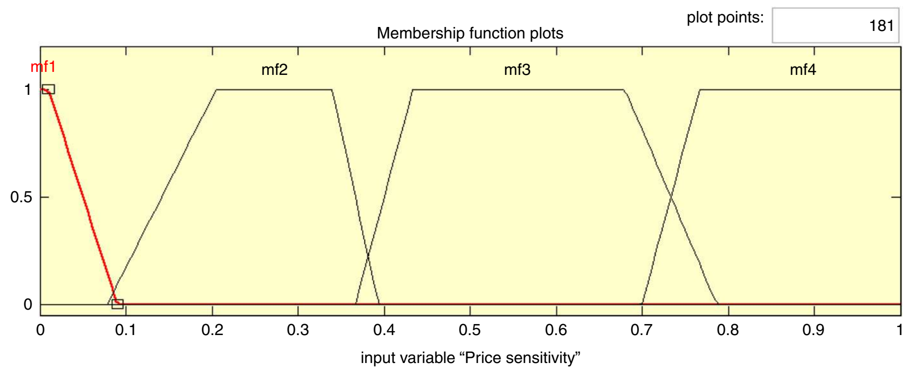

Figure 5. Membership function of price sensitivity

(2) medium rate of change (between 2 and 5 percent);

(3) low rate of change (between 0 and 2 percent); and

(4) negative rate (less than 0 percent).

The membership function of rate of change in demand is shown in Figure 6.

Membership function for linguistic input variable ($\underset{\sim}{C}$):

(1) high-discount lot size (greater than Q1 and less than Q4);

(2) medium-discount lot size (between Q2 and Q1); and

(3) low-discount lot size (between Q3 and Q2).

The membership function of lot size is shown in Figure 7.

Schedule of Q1, Q2 and Q3 is provided in Table II. Table II represents the value of discounts for a particular range of product lot size; this schedule may be different for different product categories and company's promotion strategy.

Table III presents different possible rule for fuzzy decision making, rules formation is a major part of providing intelligent input to the program for selecting a suitable output for a given rule in a fuzzy environment.

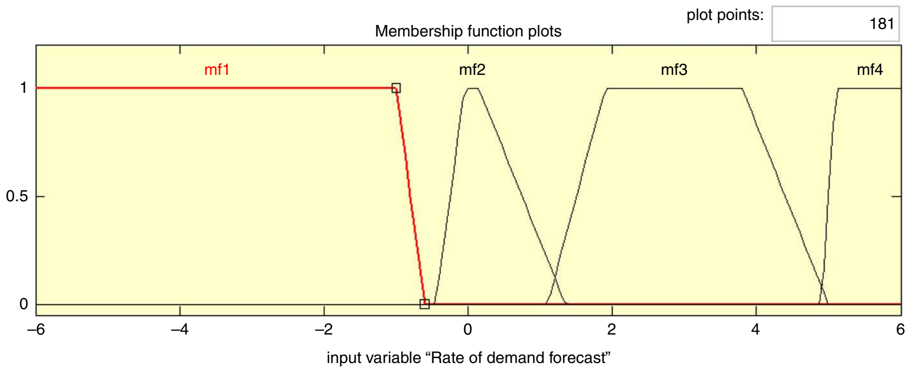

Figure 6.
Membership function of rate of change in demand

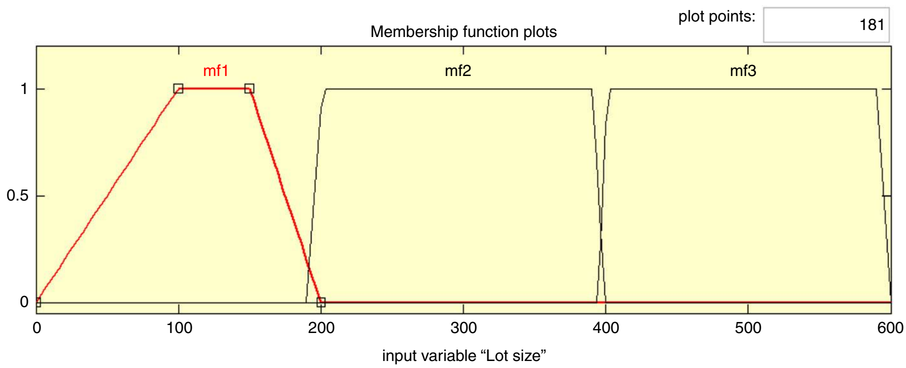

Figure 7.
Membership function of lot size

On the basis of membership functions and rules detailed in Table III, a fuzzy interface system has been formulated using MAT LAB as described in Tables IV-VI. Table IV has the input and output variables membership function and its linguistic name. Table IV has been transformed in Table V for a better understanding of input and output fuzzy variables. Table VI provides the output for the various combinations of inputs in a particular rule.

Antecedents	Consequent
If price sensitivity is high	Apply dynamic pricing and discounting
If price sensitivity is medium	Apply dynamic pricing and discounting
If price sensitivity is low	Dynamic pricing and discounting may not be used
If price change is insensitive	Do not use dynamic pricing and discounting
If change in demand forecast (D) is high	Reduce the discount and increase the price of the product
If change in demand forecast (D) is medium	Increase the discount and reduce the price
If change in demand forecast (D) is low	Increase the discount and reduce the price
If change in demand forecast (D) is negative	Discount is high and price is low
If lot size is high	Discount is high
If lot size is medium	Discount is moderate
If lot size is low	Discount is low

Table III. Antecedents and consequents fuzzy rules formation

Linguistic variables	Type of membership function (trapezoidal) and range	Input
(1) High price sensitivity	MF4 = 'mf4':'trapmf',[0.6999 0.7667 1.033 1.3]	Price sensitivity (A)
(2) Medium price sensitivity	MF3 = 'mf3':'trapmf',[0.3667 0.4333 0.6799 0.7867]	
(3) Low price sensitivity	MF2 = 'mf2':'trapmf',[0.07834 0.2051 0.3401 0.3933]	
(4) Insensitive toward price change	MF1 = 'mf1':'trapmf',[-0.3 -0.03333 0.01 0.09]	
(1) High rate of change (greater than 5%)	MF4 = 'mf4':'trapmf',[4.9 5.1 6.4 9.596]	Rate of demand forecast (B)
(2) Medium rate of change (between 1 and 5 %)	MF3 = 'mf3':'trapmf',[1.1 1.9 3.8 5]	
(3) Low rate of change (between 0-0.5 and 1.5%)	MF2 = 'mf2':'trapmf',[-0.45 -0.05 0.15 1.35]	
(4) Negative rate (less than −0.5%)	MF1 = 'mf1':'trapmf',[-9.6 -6.4 -1 -0.6]	
(1) High-discount lot size (greater than Q1)	MF3 = 'mf3':'trapmf',[395 401 590 600]	Lot size (C)
(2) Low-discount lot size (between Q3 and Q2)	MF2 = 'mf2':'trapmf',[190 201 390 400]	
(3) No discount lot size (less than Q3)	MF1 = 'mf1':'trapmf',[0 100 150 200]	
		Output
(1) Big-bang-sales offer $D \geqslant 40$	MF4 = 'mf4':'trapmf',[39.5 40.1 49 50]	Discount rate in percentage (D)
(2) Mega-sales offer $30 \leqslant D < 40$	MF3 = 'mf3':'trapmf',[29 30.1 39 40]	
(3) Bumper-sales offer $20 \leqslant D < 30$	MF2 = 'mf2':'trapmf',[19 20.1 29 30]	
(4) Normal sale offer $10 \leqslant D < 20$	MF1 = 'mf1':'trapmf',[9.1 9.9 19 20]	

Table IV. Linguistic variables and membership functions (MF)

Table V. Types and range of input and output membership functions (MF)

Type of input membership function (trapezoidal) and range	Input	Output	Type of output membership function (trapezoidal) and range
MF4 = 'mf4':'trapmf',[0.6999 0.7667 1.033 1.3]	Input 1	Output	MF1 = 'mf1':'trapmf',[9.1 9.9 19 20]
MF3 = 'mf3':'trapmf',[0.3667 0.4333 0.6799 0.7867]			MF2 = 'mf2':'trapmf',[19 20.1 29 30]
MF2 = 'mf2':'trapmf',[0.07834 0.2051 0.3401 0.3933]			MF3 = 'mf3':'trapmf',[29 30.1 39 40]
MF1 = 'mf1':'trapmf',[-0.3 -0.03333 0.01 0.09]			MF4 = 'mf4':'trapmf',[39.5 40.1 49 50]
MF4 = 'mf4':'trapmf',[4.9 5.1 6.4 9.596]	Input 2		
MF3 = 'mf3':'trapmf',[1.1 1.9 3.8 5]			
MF2 = 'mf2':'trapmf',[-0.45 -0.05 0.15 1.35]			
MF1 = 'mf1':'trapmf',[-9.6 -6.4 -1 -0.6]			
MF3 = 'mf3':'trapmf',[395 401 590 600]	Input 3		
MF2 = 'mf2':'trapmf',[190 201 390 400]			
MF1 = 'mf1':'trapmf',[0 100 150 200]			

Table VI. Fuzzy rules

	Rules				
		Input			Output
Serial no.	A	B	C	D	
1	1	1	1	1	(1):1
2	1	1	1	1	(1):1
3	1	2	1	1	(1):1
4	1	3	1	1	(1):1
5	1	4	1	1	(1):1
6	1	4	1	1	(1):1
7	1	4	1	1	(1):1
8	2	1	4	1	(1):1
9	3	1	4	1	(1):1
10	4	1	4	1	(1):1
11	2	2	2	1	(1):1
12	3	2	4	1	(1):1
13	4	2	4	1	(1):1
14	4	3	1	1	(1):1
15	4	4	1	1	(1):1
16	4	1	4	1	(1):1
17	3	1	3	1	(1):1

The MAT LAB FIS model is shown in Figure 8, and the fuzzy rules formulated for DPDM are shown in Figure 9.

4. Results and discussion

The proposed model captures the effect of rate of change of demand, lot size and price sensitivity on sales promotion and fuzzy dynamic pricing strategy to develop DPDM. How to calculate the rate of change of forecasted demand, lot size and price sensitivity have also been discussed in various sections. Fuzzy dynamic discounting strategies have been formulated based upon the sales forecast, price sensitivity and

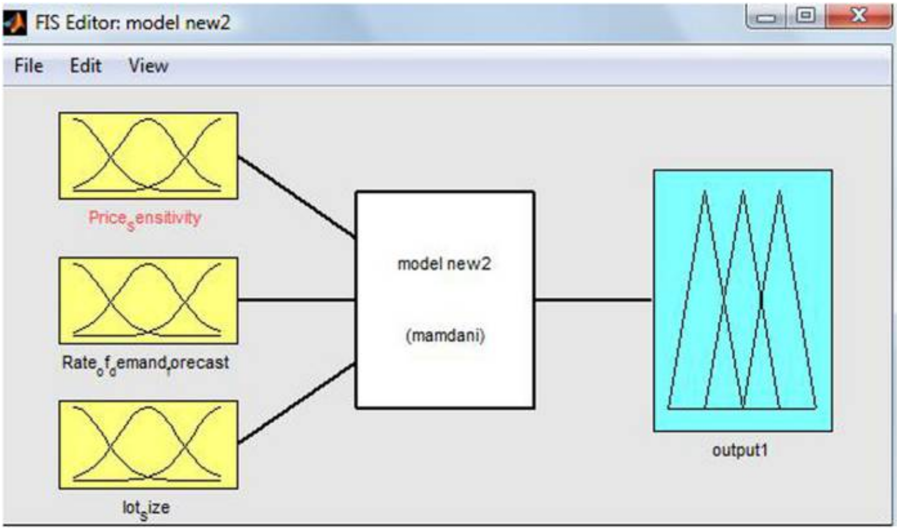

Figure 8.
FIS model prepared using MAT LAB

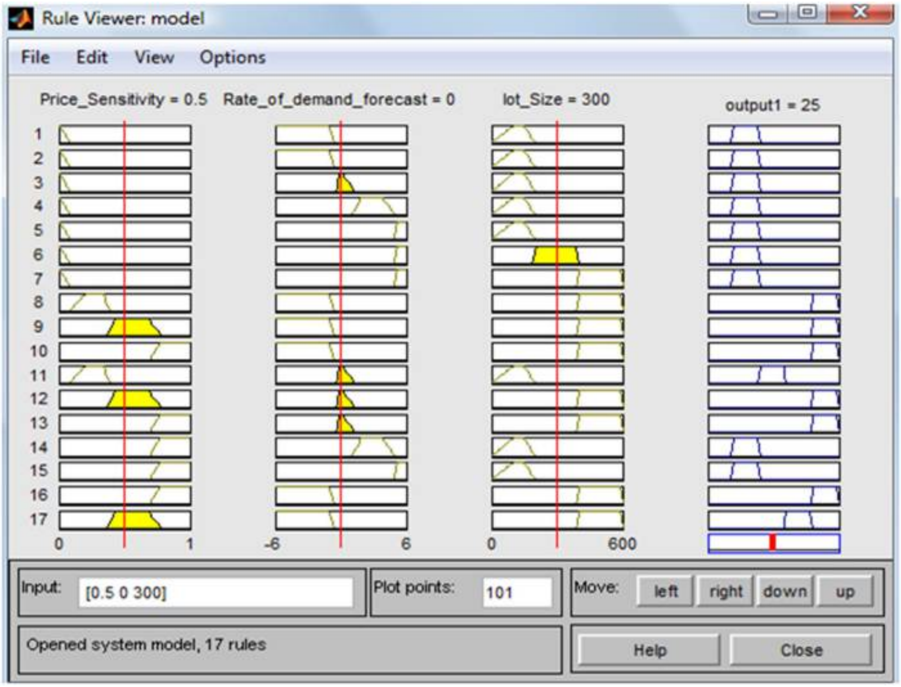

Figure 9.
Rules of fuzzy DPDM

lot size that was done for taking the price discounting decisions regarding procurement of the product category. This has helped minimize the inventory cost thereby keeping the profitability of the retail organization intact. The uncertainty in sales forecasts, competitor's price and procurement is mitigated in proposed model by using fuzzy logic. The proposed model may be useful for automation of price discounting strategy of a retail organization, which was mentioned in the second objective of the study.

In light of the research approach (modeling based upon historical time series data of a particular product category) that was undertaken on a particular product category at a retail location, there is a possibility that the research results may be valid only for the product category that was selected. Therefore, the researchers are advised to test the proposed propositions further for another category of products.

The study provides valuable insight as to how to use the real- time sales data for formulating dynamic product sales promotion and price discounting strategy using fuzzy logic in a retail organization. It has helped in designing the proposed model. The extension of research may include testing of proposed model over other product categories, relaxation in constraints and addition of other input variables. In addition, future research studies in this direction can also consider incorporating artificial-neuro-fuzzy-interface for further improving the performance of the proposed model.

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