ISSN (Print) : 2319-5940
ISSN (Online) : 2278-1021

International Journal of Advanced Research in Computer and Communication Engineering
Vol. 2, Issue 12, December 2013

Dynamic Web System Upgrading With Strategic Customers Analysis Using FP growth Algorithm

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Abstract: A stylized dynamic pricing model in which a monopolist price a product only at the beginning and change in price will be done with a set of constraints based on the product availability and customer strategic behavior analyzed by frequent pattern (FP) Algorithm. Using this algorithm the least accesses products are analyzed and the product price is adjusted to increase the sale. First, this paper prescribes a threshold policy for customer purchasing: the customer will buy the product if his valuation for this product is above a threshold, and will not otherwise. The threshold increases as TSP decreases, customer transaction cost increases, or customers become more risk averse. Second, we derive the optimal price of each period and identify the optimal policy for web system upgrading there exists a threshold for each period such that the online retailer should upgrade their web system to the state of art (i.e., achieve highest available TSP) if current TSP is below the threshold, and should not upgrade otherwise. The threshold (total discounted profit) increases as customer transaction cost decreases, customer valuations for the product become higher, or customers become more (less) risk averse. Third, the online retailer tends to price higher if it ignores customer strategic behavior. The cost of ignoring customer strategic behavior is substantial. The profit loss rate of ignoring customer strategic behavior increases as customer transaction cost increases, customer valuations for the product become lower, or customers become more risk averse.

Keywords*:* Online retailing, strategic customers, technology adoption, TCP.

I. INTRODUCTION

Data mining is a system of which is used for searching large amounts of data for. It is relatively a new concept which is directly related to computer science. Despite this, it can be used with a number of older computer techniques such as statistics and pattern reorganization. The aim of data mining is to extract the most wanted information from data that was not known previously. Data mining technique has a large number of applications in a wide variety of different fields. However, it is widely used by businesses or organizations that need to recognize certain patterns or trends. As information technology has been developed, more and more retailers have opened online channels for sales; thus, online sales have seen a dramatic increase in the past several years. Website issues often make consumers abandon transactions, leading to transaction failures. Moreover, website issues result in negative customer experiences. The customers may tell their friends about their bad experiences, or write them down on some related forums. Other online shoppers can have easy access to the comments, which leads to word-of-mouth effects that damage the reputations of online retailers. As the online retailer market grown up, the consumer is also undergoing changes. The trust of people on internet is growing and they are shopping more frequently. In addition e-commerce has started to have a vital effect on the traditional sale. Consumers have gradually stopped differentiating between online and offline reail, and the two now complement each other as said in [14].

By Consumer Mercantile Model in [8], consumer purchasing activity consists of three phases: pre-purchase interaction, purchase consummation and post-purchase interaction. Consumers obtain various types of information on online retailers in the phase of pre-purchase. It is documented that these kinds of information do affect consumers' attitudes toward a website (or an online retailer). The attitudes, in turn, lead to their intentions to use the website and the eventual acceptance of the website (or the online retailer) [9].One type of information that affects the customers 'final choice is the website's (the online retailer's) ability to complete transactions without any problem [10]. Therefore, website issues can lead to transaction failure and customer defection, causing huge losses to online retailers. This paper takes an initial step to answer this question. We propose adjusting selling prices and upgrading web systems to reduce online retailers' profit losses from website issues. The network operation and maintenance engineers of Baidu Inc. (China's largest search engine service provider) explain to the authors that website issues are mainly attributed to hardware and software problems of web systems. The hardware problems mainly include the lack of enough severs to support huge traffic on the website and the unstable network supported by Internet Service Providers. On the other hand, the software problems are mainly caused by redundant processing logic which results in denials of access, and unreasonable web design which brings inconvenience or failures to online customers.

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Therefore online retailers can upgrade the web systems by improving the hardware capacity (e.g. purchasing new severs) and optimizing the processing logic and the web design. Since these actions could be very costly, then how to price and when to upgrade web systems are crucial problems for online retailers. We propose an analytical model in which an online retailer sells a type of product to a group of strategic customers through Internet. Comparing to nonstrategic customers who ignore the effect of transaction failure, strategic customers anticipate the transaction failure probability and make purchasing decisions based on the utility of a successful purchasing and the disutility of an unsuccessful one. All the customers have unit demand in each period and heterogeneous valuations for the product. To be successful, a monopolist must upgrade their web system dynamically. To upgrade the system certain strategy must me followed. Using FP growth algorithm the customer strategic behavior is analyzed and the selling prices are adjusted as follows.

First, we characterize a threshold policy for strategic customer purchasing: There exists a unique threshold such that a customer will buy the product if his valuation is greater than the threshold; and will not buy the product otherwise. We further demonstrate that a customer will be more likely to conduct an online purchasing if the website is technically more reliable (lower probability of website issues), the transaction cost of the purchasing is lower, or the customer is less risk averse.

Second, this paper provides guidelines for the online retailer on how to price and when to upgrade the web system. We propose a multi-period model in which the online retailer has an opportunity to set price and upgrade its web system at the beginning of each period. The optimal price for each period is derived and a threshold policy is proposed for upgrading: there exists a threshold for each period such that the online retailer should upgrade the web system to the highest available TSP if the current TSP is below the threshold, and not upgrade otherwise. Sensitive analysis is conducted to investigate how the threshold and the optimal profit of the online retailer change with various model parameters.

Third, this paper discusses the online retailer's cost of ignoring customer strategic behavior. It is proved that the online retailer tends to price higher when ignoring customer strategic behavior. Numerical examples show that the profit loss is substantial (sometimes the profit loss rate can be up to 65%). To alleviate the negative effect of ignoring customer strategic behavior, the online retailer should (1) increase customer valuations for the product by better product design or more impressive advertising; (2) decrease the customer transaction cost by providing better navigation aids. Besides, if the customers are less risk averse, the negative effect of ignoring customer strategic behavior is smaller.

II. RELATED WORK

In this model [3], customers have heterogeneous valuations for the product and face reduce n the prices for two periods. Customers are assumed to have identical risk preferences and know the price path and fill rate in each period. Through its capacity choice, the respective firm can control the fill rate and also control the rationing risk faced by customers. Customers make decision strategically and weigh their payoff of immediate purchase against the expected payoff of delaying their purchases. It analyze that the capacity choice maximizes the firm's profits. First, it consider a monopoly market and characterize conditions in which rationing is optimal. It tells how the optimal amount of rationing is affected by the magnitude of price changes over time and the degree of risk aversion among customers. It also analyzes the case of aggregate demand uncertainty and show that demand uncertainty reduces a firm's optimal fill rates. Lastly, analyze an oligopoly version of the model and show that competition reduces the firms' ability to profit from rationing. Indeed, there exist a critical number of firms beyond which a rationing equilibrium cannot be supported.

Varying prices over time is a natural way for firms to increase revenue in response to uncertain and fluctuating market conditions. Apparel retailing is a canonical example. Demand for apparel is affected by factors such as weather, fashion trends and economic conditions, all of which are highly uncertain; hence, forecasting demand is inherently difficult. Moreover, lead times for design, production and distribution are normally longer than the selling season, so retailers must commit to their order quantities in advance of observing sales. As a result, they often end up with some popular products which sell out fast, while other unpopular products languish. In response, retailers dynamically change prices – maintaining full prices for their best-selling items while marking down slow sellers over time. While most retailers still make such pricing decisions manually, many are now deploying sophisticated modeling and optimization software to help support pricing decisions. Such systems have proved quite effective; Ann Taylor, a U.S. women's apparel retailer with over 580 stores nationwide, reported a year on-year increase in sales by 26% over the Christmas period of 2003 after it implemented markdown optimization software. Success stories like this have led to increased acceptance of model-based approaches to pricing among major retailers.

In traditional, literature studying overbooking problems focuses on risk-neutral decision makers. This paper[4] propose a multi-period overbooking model which incorporates risk-aversion and extends a well-known structural results (the 3-region policy) under the risk-neutral case to the risk-averse one on the basis of an exponential utility function. It is also shown that the optimal policy for the risk-neutral decision maker can be obtained by letting the risk-aversion parameter approach to zero under the risk-

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averse case. Therefore, the extant results under the risk-neutral case can be interpreted as a special case of ours. It is also investigate how the optimal policy changes with the decision maker's degree of risk-aversion and some cost parameters. Numerical results tells that the optimal bounds in the 3-region policy may increase or decrease with the decision maker's degree of risk-aversion.

According to [2] many storable-goods markets, firms are often alert that consumers may adjust purchasing timing in response to expected price dynamically. For example, in some periods when prices are low then ever, consumers stockpile for future consumption. This paper investigates the dynamic impact of consumer stockpiling on competing firms' strategic pricing decisions in differentiated markets. The necessity of equilibrium consumer storage for storable products is re-examined. It is shown that preference heterogeneity generates differential consumer stockpiling propensity, thereby intensifying future price competition. As a result, consumer storage may not necessarily arise as an equilibrium outcome.

Economic forces are also investigated that may mitigate the competition intensifying effect of consumer inventories and that, hence, may lead to equilibrium consumer storage. When offering price promotions, firms are often aware that consumers may adjust their purchase timing in response to dynamic price changes. Specifically, in periods when prices are low, consumers may accelerate their purchases of a product that is expected to be consumed in the future when prices go up. As a result, consumer stockpiling could create inter temporal demand shifts from the future to the current period. Therefore, to ascertain the strategic rationale underlying competing firms' inventory-inducing promotion efforts, it is important to investigate the dynamic effects of consumer storage. Consumer stockpiling could potentially generate incentives for competing firms to offer price promotions, in order to compete away potential future demand of the competitors.

To investigate this possibility we consider price competition through time in a two-period model among differentiated firms facing heterogeneous consumers. Consumers in each period desire to consume exactly one unit of any product and do not change preferences over time, but have the possibility of buying more than one unit in one period for storage and future consumption. Both firms and consumers are forward-looking, and consumers take into account their relative product preferences and expected arbitrage opportunities from price dynamics. Firms are fully aware of how consumer stockpiling behavior responds to price changes, and balance the immediate benefits from expanding temporary demand against the consequent dynamic effects of consumer storage on future price competition.

Other related literatures are the ones on competition with durable goods and on competition with the possibility of forward contracts. Under competition with durable goods, a firm, when selling, substitutes for possible renting in the next period. However, there the no arbitrage condition requires the durable sale price to be equal to the discounted value of the rental prices, while here the no arbitrage condition requires the current nondurable sale price to be equal to the discounted future price. Under competition with the possibility of forward contracts then arbitrage condition is that the forward price be the same as the expected future spot price, which is also different from the no arbitrage condition under the possibility considered here of consumer stockpiling.

In [11] the information system acts as intermediaries between the buyer and the sellers in market which creates an electronic marketplace that reduce the buyers cost to acquire information about seller prices and product offerings.

[5] Consist of a monopolist firm which sells a fixed capacity of products. The firm sets a price before demand is resolved. Speculators will enter the market purely with the intention of resale, which can be profitable if demand turns out to be high. Consumers may choose when to purchase, and they may also choose to purchase from the firm or from the speculators. Then characterize equilibrium prices and protects and analyze the long run capacity decisions of the firm. There are three major findings. First, the presence of speculators increases the firm's expected profits even though the resale market competes with the firm. Second, by facilitating resale, the firm can mimic dynamic pricing outcomes and enjoy the associated benefits while charging a fixed price. Third, speculative behavior may generate incentives for the seller to artificially restrict supply and thus may lead to lower capacity investments. It also explores several model extensions that highlight the robustness of the results.

Many items are available only in limited quantities. Since there is a lucrative arbitrage opportunity, speculative behavior naturally emerges. Unlike "true" consumers, speculators make purchases purely with the intention of reselling them at a profit. The objective of this paper is to introduce a tractable modeling framework that captures such speculative resale and to understand its implications for the firm.

[16] Characterizes a decision framework by which a firm manages general product replacements under stochastic technological changes. It characterizes a optimal threashold-based product replacement policy that maximizes the firm's expected total profit for a finite planning horizon.

[6] Consider a stylized dynamic pricing model in which a monopolist prices a product to a sequence of customers, who independently make purchasing decisions based on the price according to a logit choice model. The parameters of the logit model are unknown to the seller, whose objective is to determine a pricing policy that minimizes the regret, which is the expected difference between the seller's revenue and the revenue of a clairvoyant seller who knows the values of the parameters in advance. When there is a single unknown

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parameter, it show that the T-period regret is (log T), by establishing an (log T) lower bound on the regret under an arbitrary policy, and presenting a pricing policy based on maximum likelihood estimates that achieves a matching upper bound. For the case of two unknown parameters, it proves that the optimal regret. Using the logit model it focuses on two regimes of demand uncertainty. In the first regime, corresponding to the case of one unknown parameter, the seller faces uncertainty about the customer's price sensitivity, or the degree to which the expected demand changes with respect to a change in price. In the second regime, corresponding to the case of two unknown parameters, the seller faces uncertainty about both price sensitivity and his market share, or the proportion of the available market serviced by the seller. We measure the performance of a pricing strategy in each regime in terms of the regret: the difference between the expected revenue gained by the pricing strategy, and the revenue gained by an omniscient strategy that has full information about the demand curve in advance. While it is a simplified model of customer behavior, the logit model yields a number of insights into the above questions. When the seller is only uncertain about the customer price sensitivity, it demonstrates the effectiveness of an optimal “greedy" policy that simultaneously explores the demand curve and exploits at the best-guess optimal price.

In contrast, when both the price sensitivity and the market share parameters are unknown, it exhibits an optimal policy that separates exploration and exploitation. Relate this difference to an analytic property of the demand curves; intuitively, the demand curves are well-separated" in the one-parameter case, in the sense that for any two different parameter values, the demand curve for one value strictly dominates the demand curve for the other value. Thus, a seller can uniquely identify the unknown parameter from the expected demand at any price, making simultaneous exploration and exploitation possible, and leading to small regret. This phenomenon is absent in the case of two unknown parameters, in which the presence of “uninformative" prices leads to large worst-case regret for any pricing policy.

III. EXISTING MODEL

The existing system consist of a dynamic pricing model in which a monopolist prices a product to a Sequence of customers, who independently make purchasing decisions based on the price offered according to a log it choice model. Customer behaviour modelling have been gaining increasing attention in operation management community [15].The parameters of the log it model are unknown to the seller, whose objective is to determine a pricing policy that minimizes the regret, which is the expected difference between the seller's revenue and the revenue of a clairvoyant seller who knows the values of the parameters in advance. When there is a single unknown parameter, we show that the T-period regret is (log T), by establishing an (log T) lower bound on the regret under an arbitrary policy, and presenting a pricing policy based on maximum likelihood estimates that achieves a matching upper bound. According to [17] there is a impact of strategic customer behaviour on supply chain performance. In this paper the seller iitialy charges a regular price but may salvages the leftover inventory at a lower salvage price after random demand is realized.

In [1] Web system upgrading with transaction failure and strategic customers is related to four streams of studies:

1. Online retailing
2. Customer behavior
3. Technology adoption
4. Risk aversion.

In recent years, online retailing attracts a great deal of attention, and mean while tremendous studies emerge to consider issues related to this field. In general, the studies in this field can be divided into two categories. The first focuses on the design of channel structure and the influences of online retailing entry over traditional retailing forms. Examples of this category include mixed channel, price competition, channel substitution and so on.

The second is devoted to designs and attributes of the online retailing website. Among the researches in this category, some focus on characteristics of the website(e.g., perceived risk, trust, service quality, ease of use etc.), and others provide suggestions on how to design the website by exploring consumer characteristics, such as consumer shopping orientations(e.g., convenience oriented, price oriented, experiential oriented etc.), demographic variables(e.g., educational level, age, gender etc.),psychological variables(e.g., attitudes towards online shopping, intention to use Internet for information search, risk aversion etc.). Chang provide a comprehensive review of this literature.

This paper falls into the second category and contributes to this literature by considering transaction service failure due to website issues. A number of researches are devoted into transaction service failure of online retailing. These researches mainly focus on the causes and costs of transaction /service failure, and the value of service recovery. Comparing to all these empirical researches, this paper proposes a mathematical model to provide guidelines for online retailers on pricing excisions and technology upgrading policy. More importantly, it introduce the notion of strategic customers who anticipate the possibility of transaction failure and make purchasing decisions based on their beliefs on transaction success probability which is not considered in those researches on transaction/service failure.

Customer Behavior

In traditional operations management (OM) literature, customer demand is often assumed to be exogenous, i.e., demand functions are usually set as specified functions of price or other product attributes. However, in the real world, all customers do, at some point, actively evaluate alternatives and make choices, e.g., how much to pay, which product to buy, when to buy, etc. That is to say, the customer will engage in decision-making processes and are not simply governed by the demand profile specified at the outset. It is shown that these customers' decision processes (customer behavior) deserve attention and for many practical problems, neglecting these decision processes on the demand side may have significant repercussions.

A few studies discuss the firms' decision incorporating strategic customer behavior. Consider a monopolist firm selling a fixed capacity with speculators and strategic consumers. Consumers may strategically choose when to purchase, and they may also choose to purchase from the firm or from the speculators. It studies a dynamic pricing problem for a class of products with stable consumption patterns (e.g., household items, staple foods). Consumers may stock up the product at current prices for future consumption, but they incur inventory holding costs. Consider a model with strategic customers who anticipate the likelihood of stock outs and compare two inventory display formats: Display All (DA) and Display One (DO) for a retailer who anticipate the probability of online transaction failure and make purchasing decisions based on their beliefs over this probability.

Technology Adoption

The studies on technology adoption have a long history. Schumpeter introduces the concept of "creative destruction", which means the discovery and adoption of a new innovation effectively destroys the old technology by rendering it obsolete. Balcer and Lippman illustrate that the firm will adopt the current best practice if its technological lag exceeds a certain threshold or even purchase a technology that has been available although it was not profitable to do so in the past.

Chambers investigate learning effects of technology; Chambers and Kouvelis study the influence of competition over new technology adoption; Cho and McCardle consider the adoption of multiple dependent technologies. While most of existing literature directly sets profit (or profit rate)as a function of technology level/technology lag, this paper employs a consumer choice model to derive the profit function, which enables us to study how consumer characteristics(e.g., risk attitude of consumers)affect the firms' pricing and upgrading decisions. Liu and Ozer also utilize a consumer choice model to analyze aproduct family management problem. However, their consumer choice model is completely different.

Risk Aversion

In the field of OM, the studies incorporating risk aversion are rich Choi et al and Eeckhoudt et al [7] investigate the optimal decisions of risk averse newsvendors. Xiong et al [4] consider overbooking problems of risk averse decision makers. Gan et al. provide the definition of coordination of supply chains consisting of risk averse members. Gan et al. propose a new contract to coordinate a supply chain with a risk neutral supplier and a downside-risk-averse retailer. While these researches assume the firms (the decision makers of the firms) to be risk averse, our paper assume that the customers are risk averse. More importantly, the research questions of our paper are totally different from the above ones.

In general, the characterizations of risk averse consist of

1. Mean-variance framework
2. Concave utility functions according to expected utility theory
3. Other measurements like downside-risk, value-at-risk.

It employs the second one and assumes the customers have an identical utility function that is increasing and concave. The major drawbacks of the existing systems are website issues often make consumers abandon transaction, leading to transaction failiure. The transaction failiure will cause defection to the customers.

IV. PROPOSED METHOD

This paper takes an initial step to improve the web system by dynamic upgradation. The strategy used to upgrade the system is strategic customer behaviour. The customer strategy is studied using a data mining concept. The data mining is used to collect the most and least accessed data by the customers. To collect these details a data mining algorithm called FP GROWTH algorithm and THREASHOLD policy is used.

Method Description

In this section, we describe our proposed method in detail. The proposed system consists of three phases which describes about the web system establishment and system analysis using data mining technique. The analyzed data will helps to upgrade the web system dynamically without human interference. The analysis of customer behavior includes the analysis of frequent data accessed by the

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ISSN (Online) : 2278-1021

International Journal of Advanced Research in Computer and Communication Engineering
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customer. This data will be stored in the database which will be taken as a key factor while adjusting the selling price and upgrading the system uses the threshold policy.

A. Initial Phase

In this phase the web system will be established with all the basic requirements and the products along with their price and varieties. The established web system will be registered using service registration and will be displayed which can be accessed by any one among the people.

B. Customer purchase behaviour analysis Phase

Fig .1 in this phase describes about the customer purchasing behavior analysis. Customer visits the website and will search the product based on need and money availability. The monopoligist need to analyse the customer behavior where the customer searches the product depends upon the cost range using Data Mining concept. The customer will be ready to purchase the product only if his evaluation for the product (H) is higher than the original cost of the product (P) and he will buy the product if it is needed most irrespective of the cost. Otherwise the customer won't purchase. If the customer is ready to purchase the product, we need to collect the basic information like, Name, Phone Number, E-Mail, Address and Payment details. Then we need to send the date through message when the product will be delivered to them. Before customer leaves the website we need to collect the feedback even if he purchased or not. The customer behavior is studied at the place where they make their choice if product. The product which are visited will be incremented and a graph is formed using the FP Growth algorithm.

The steps involved in FP Growth algorithm are

Second, it derives the optimal price of each period and identifies the optimal policy for web system upgrading: there exists a threshold for each period such that the online retailer should upgrade their web system to the state of art (i.e., achieve highest available TSP) if current TSP is below the threshold, and should not upgrade otherwise. The threshold (total discounted profit) increases as customer transaction cost decreases, customer valuations for the product become higher, or customers become more (less) risk averse.

1. The algorithm counts the occurrence of items in the dataset, and stores them in the "header table".
2. At the second pass, the algorithm builds the FP tree structure by inserting instances.

Items in each instance have to be sorted by descending or ascending order of their frequency in the dataset with respect to the need, so that the tree can be processed quickly. Items in each instance that do not meet minimum coverage threshold are analyzed whose selling price will be adjusted. If many instances share most frequent items, FP tree provides high compression close to tree root.

C. Dynamic upgradation phase

Fig 2 describes the analysis for upgrading the Web system. First, check for customer feedback, if it is really reasonable retailer will upgrade the following changes in the system. Then retailer has to look for seasonal cost of product and do the necessary updates regarding the same. Obviously for the fixed rate product will get no changes as it should remain fixed. Finally retailer has to look forward for Predefined target sale which prevails in that period whether we have achieved or not. If it is achieved retailer will not be upgrading the option but the same has not been achieved retailer should do the upgradation as the process requires according to the threshold policy. The threshold policy include the following constraints,

First, it prescribes a threshold policy for customer purchasing: the customer will buy the product if his valuation for this product is above a threshold, and will not otherwise. The threshold increases as TSP decreases, customer transaction cost increases, or customers become more risk averse.

Third, it finds that the online retailer tends to price higher if it ignores customer strategic behavior. The cost of ignoring customer strategic behavior is substantial. The profit loss rate of ignoring customer strategic behavior increases as customer transaction cost increases, customer valuations for the product become lower, or customers become more risk averse.

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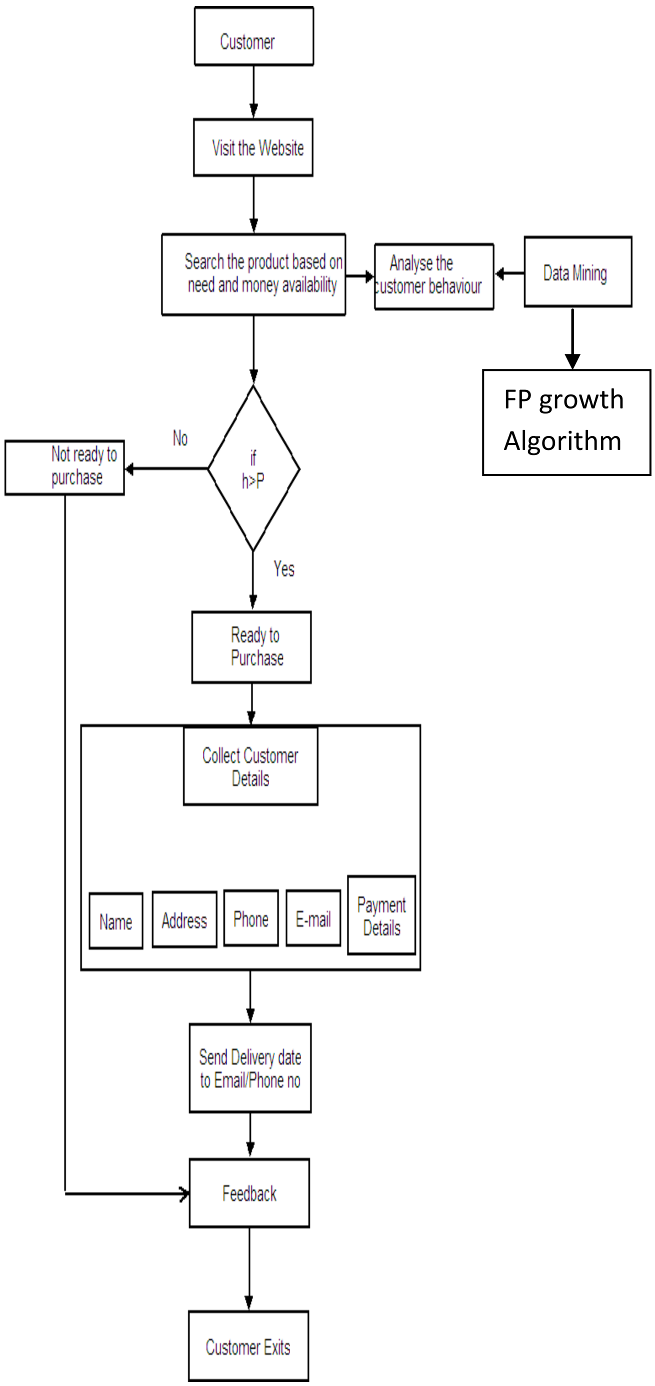

Fig. 1: Customer purchase behaviour analysis

D. Dynamic upgradation phase

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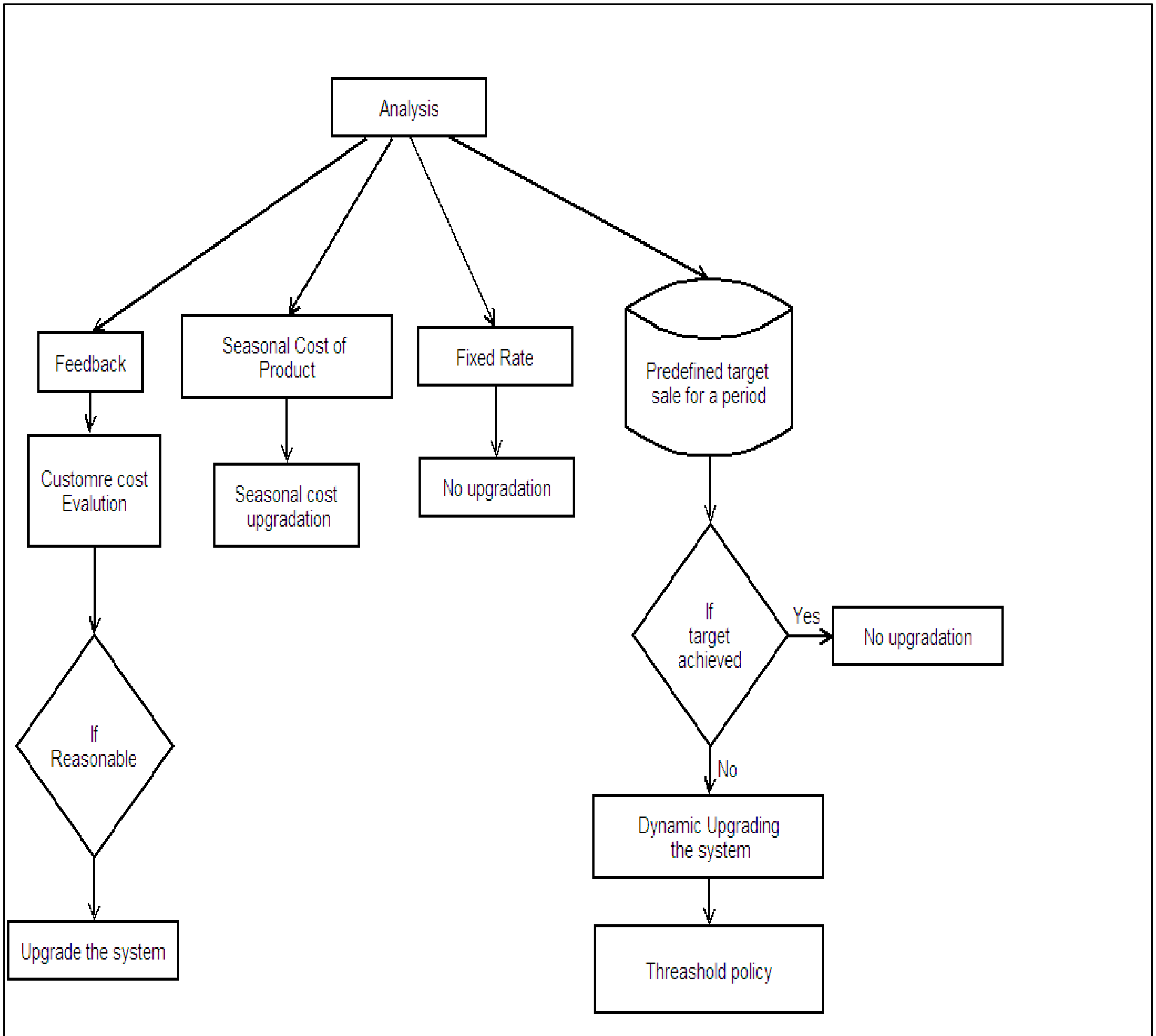

Fig. 2: Upgrading the system

V. CONCLUSION

Thus we illustrate that our method efficiently upgrade the web system dynamically without human interference and maintenance. The FP growth algorithm is more efficient than any other algorithm to collect information about frequent pattern among a huge data items. Thus it helps to adjust the selling price depending upon the customer behavior analyzed. The dynamic updating depends on the reasonable feedback along with the threshold policy. These factors will lead to be successful in online retailing which does not mind the transaction failure if the cost is reasonable. Thus using periodical automatic dynamic web system upgrading human efforts are reduced.

REFERENCES

[1] "Web System Upgrading with Transaction Failure and Strategic Customers" Xiaoxue Deng, Zhong Liu, Jinxing Xie, and Huachun Xiong, IEEE transactions on systems, man, and cybernetics: systems.

[2] "Consumer Stockpiling and Price Competition in Differentiated Markets" LIANG GUO ,Department of Marketing, Hong Kong, China, J. MIGUEL VILLAS-BOAS, Haas School of Business, University of California ,Berkeley, CA 94720-1900, June 200

ISSN (Print) : 2319-5940
ISSN (Online) : 2278-1021

International Journal of Advanced Research in Computer and Communication Engineering
Vol. 2, Issue 12, December 2013

[3] Liu,and G.van Ryzin, "Strategic capacity rationing to induce early purchases," Management Science, vol. 54, no. 6, pp.1115-1131, June 2008.
[4] H. Xiong, J. Xie, and X. Deng, "Risk-averse decision making in overbooking problem," Journal of the Operational Research Society, vol. 62, no. 9, pp. 1655-1665, September 2011.
[5] X. Su, "Optimal pricing with speculators and strategic consumers", Management Science, vol. 56, no. 1, pp. 25-40, January 2010.
[6] J.Broder, and P.Rusmevichientong, "Dynamic pricing under a logit choice model,"Cornell University Working Paper, March 2010.
[7] L.Eeckhoudt,C.Gollier,and H.Schlesinger, "The riskaverse(and prudent) newsboy," Management Science, vol.41, no. 5,pp. 786-794, May 1995.
[8] R. Kalakota, and A. B.Whinston,*Electronic Commerce: AManager's Guide*. Reading MA:Addison-Wesley, 1997.
[9] S.Devaraj, M.Fan, and R.Kohli, "Antecedents of B2C channel satisfaction and preference: validating e-commerce metrics," *Information Systems Research*, vol. 13, no. 3, pp. 316-333, September 2002.
[10] Tealeaf, "New Survey Reveals Online Transaction Issues Have Negative Effect on Customers and Businesses, "http://www.tealeaf.com/news/news-releases/2006/0925.php, September 2006.
[11] J. Y. Bakos, "Reducing buyer search costs: Implications for electronic market places," *Manage. Sci.*, vol. 43, no. 12, pp. 1676–1692, Dec. 1997.
[12] Data mining: http://www.exforsys.com/tutorials/data-mining.html
[13] Algorithm: http://en.wikipedia.org/wiki/Association_rule_mining.
[14] PricewaterhouseCoopers, Finding the Future Online, Nov. 2011. [Online].Available: http://www.pwc.ru/en_RU/ru/retail-consumer/assets/Finding-the_future-online-for-mailing-eng.pdf.
[15] Z. J. M. Shen and X. Su, "Customer behavior modeling in revenue management and auctions: A review and new research opportunities," *Prod. Oper. Manage.*, vol. 16, no. 6, pp. 713–728, Dec. 2007.
[16] H. Liu and O. Ozer, "Managing a product family under stochastic technological changes," *Int. J. Prod. Econ.*, vol. 122, no. 2, pp. 567–580,Dec. 2009.
[17] X. Su and F. Zhang, "Strategic customer behavior, commitment, and supply chain performance," *Manage. Sci.*, vol. 54, no. 10, pp. 1759–1773,Oct. 2008.