DYNAMIC PRICING IN SUPPLY CHAINS: BRINGING THE PERISHABLE APPROACH

TO DYNAMIC CAR MARKET

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ABSTRACT

In a business environment, using dynamic pricing is a standard practice, especially in the management of revenue. Given the availability of online information concerning inventory and pricing, customers are in a position to understand pricing strategies that sellers employ, and at the same time to be able to develop a possible response strategy. In this thesis, *Dynamic Pricing in the Supply Chain: Bringing the Perishable Approach to Dynamic Car Market* is investigated and evaluated.

This study incorporates strategic consumer response to dynamic prices, particularly for perishable goods, using a number of variables, such as income, demand and price. The main factors that influence stochastic behavior of prices in car market supply chains are the focus of the analysis. It also includes the appropriate parameters to include in a dynamic optimization-pricing supply chain problem and a discussion of how businesses can efficiently optimize the pricing problem in a stochastic market situation.

ACKNOWLEDGEMENTS

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CHAPTER 1: INTRODUCTION

1.1. Background Information

Optimal dynamic pricing is of great economic and theoretical interest in supply chains. Marketing practitioners may use optimal analysis to set prices that increase firm profitability in dynamic conditions. The internet has heralded a new epoch in international trade with the advent of e-commerce, giving businesses cheap, global access to a worldwide network of stakeholders in the business supply chains. This has been made possible by the ease of real time exchange of information and transfer of funds on the internet. One aspect in conducting online business that is still growing is the application of dynamic pricing models to businesses' trading activities.

The success story of dynamic pricing is fuelling the growth of new concepts and products in business, such as broad-based portals relying on e-commerce and virtual marketplace-focused exchanges. The growth of interactive platforms and adoption of e-commerce technology is giving rise to electronic market platforms in which goods and services are traded in real-time dynamic pricing similar to the trading in securities on the stock exchanges in developed economies. Dynamic pricing is also an ideal method of selling excess or slow-moving inventory and antique products. The way businesses source their raw materials and sell their products has been altered considerably because of this innovation in trading. Innovators in the business arena have shown that dynamic pricing is a critical aspect of e-commerce; creating significant bottom-line results through higher revenues, lower costs, and more efficient processes. Business experts argue that up to one-third of business-to-business e-commerce in the future will employ dynamic pricing strategies to increase profitability. The method of dynamic pricing is usually understood to mean trading in goods and services by continuously setting prices to match the changes in supply and customer demand. A case in point is the instructive, simple but highly effective type

of dynamic pricing in online auctions. Innovators in dynamic pricing techniques are using this type of pricing in several unique ways. There are those that are using online "English auctions" to sell excess inventory and some are using "Reverse auctions" as a method of bidding-out procurement contracts, like the "Request for Quotes" (RFQs) for rare and limited products.

Economists have always found it complex to balance supply and demand in a dynamic setting and the possible solution lies in dynamic pricing if done efficiently. The usual approach has been analyzing pricing problems in which a single product over a time interval which only requires simple rules (nesting) for setting values for prices quoted by clients. The case of dynamic pricing in supply chains in the market for cars means that the multiple stages with respective resources have to be considered which makes the situation tricky. The approach of dynamic pricing considered in this paper provides a better attempt at realistically working out a solution in a more tractable way.

The car business involves many people along the supply chain including manufacturers, distributors, transporters, and retailers. The large numbers of people involved ultimately affect prices of the cars and the resultant profit margins. The situation is further complicated by the fluctuation in demand arising from changes in international prices, exchange rates, national economic performance and competition from substitute brands. As a result, car sales may sometimes rise or drop depending on the demand levels in the market. This dynamism in demand conditions affects pricing and calls for efficient optimization to set prices. The attempts by airline managers (in the 1970s) to manage their revenues by manipulating prices continuously have attracted other industry players to actively set prices continuously. If dealers set high prices, they will enjoy the benefits of immediate high profits, but bear the risk of selling fewer units. On

the other hand if they set low prices, they will reap smaller profits, although in this case higher number of units will be sold.

The ideal situation requires that for one to engage in a strategy of continuously varying prices, one would need to evaluate features affecting variability of demand by consumers such as their buying behavior and the value chain trends affecting car availability. In traditional dynamic pricing models it is assumed that consumers behave myopically by making purchases immediately when they notice prices dropping in value compared to their valuations of the product and fail to put into consideration future conditions that could alter product availability or capacity to make purchases of the product. This is a simplistic assumption that is used to analyze dynamic pricing using heuristics and structural conditions amenable for designing strategies that affect pricing.

However, in the reality, many consumers think strategically and have been reported to strategize in a way that they benefit more but pay less. This is notable because some consumers will delay making purchases if they hope that prices are likely to drop in future. Some consumers tend to observe the market and if they note that supplies are limited, they strategically evaluate the volumes of the product in that market and the expected behavior of major buyers who could affect demand in that market. Therefore, a dynamic option-pricing model should include this possibility of strategic behavior among consumers and that between, car dealers and buyers in the market (Perakis & Sood, 2006)

There is increasing popularity of Internet use for e-commerce, which is affecting supply chain management. The movement towards dynamically changing prices of products is a new fad in the retail and manufacturing industries encouraged to flourish by the online based producer and consumer transactions that are one on one (Direct To Customer model). In

producer to consumer models, the producers or manufacturers may change prices based on trends in demand, stock levels, or manufacturing schedules. This approach facilitates the real time monitoring of changes in demand, which is convenient for setting varied prices over time and space. This type of business model is now on the rise online and uses auctions (both forward and reverse) that consumers use to bid on all types of goods, whether intermediate or final.

The strategic value in dynamic pricing as a pricing mechanism in the manufacturing and retail industries is that it totally alters supply chain efficiencies. Dynamic pricing reduces procurement costs; if used in competitive bidding dynamic pricing will reduce contract costs and ease the RFQ process (request for quote process), which even when relying on emailing and faxing, is a laborious and sluggish process that requires changes to reduce costs and time used significantly. The automation of the RFQ process and use of dynamic pricing techniques will help companies cut the cost of vendor contracts and reduce purchase cycle times. Such cost and time savings leave procurement teams with more time to concentrate on those aspects of their work that are highly valued like vendor evaluations and approval, taking care of bigger or more complex supplier processes and strategic activities.

This paper focuses on using a new approach in which we attempt to show how dynamic pricing can be used with car manufacturers, distributors and retailers in the supply chain make pricing decisions that take into consideration different time horizons so that they can maximize profitability. The car merchants have to consider periodically varying demand, production capability, and costs of holding stock and actual production expenses. The firm's revenue curves are assumed to be a concave since its objective is to maximize revenue; solving this problem efficiently requires using optimization techniques. The focus is optimization in dynamic pricing that accounts for supply chain-stock levels and fluctuating consumer demand while also

factoring in car manufacturing capacity in multiple periods. Thus, the model seeks to factor

multi-period situations into decisions on production and final car pricing.

1.2. Problem Statement

The desire by business owners to strategize efficiently on car pricing in dynamic markets

is challenging because conventional approaches do not provide solutions. The dynamism arises

from constant changes in consumer demand, fluctuations in inventory levels and consequently

price variability. The erstwhile approach has been to take a deterministic approach, which

assumes that consumers are biased, and their demands exhibit monotonicity. However, current

efforts are directed at finding optimization methods that can help businesses arrive at price levels

that maximize profits in stochastic markets. This paper explores dynamic optimization in seeking

pricing solutions.

1.3. Research Objectives

The influence of the internet as a host platform for companies carrying out e-commerce

and supply chain management has continued to increase. Many companies now use internet

platforms to change the dynamics of pricing the products while at the same time monitoring

inventory levels through the bar code system. Therefore, most companies need to understand

how best they can arrive at profit maximizing prices through dynamic pricing. The knowledge in

the mainstream has dwelt much more on deterministic markets without taking into account

stochastic markets. Lack of proficient methodology for dynamic optimization of pricing

prompted the formulation of this approach in this paper. Hence, the main objective is to

demonstrate the way dynamic optimization is employed in supply chain pricing of cars based on

the perishable approach. The approach takes into account variations in price, consumer demand,

changes in inventory, distribution channels and changes in production resources in a multi-period regime.

1.4. Research Questions

i.   How to develop and propose a new model depending on factors discussed in previously researched optimization models

ii.   Solve the previously researched models for the variables and assumptions

iii.   How to optimize the pricing problem for that particular scenario

CHAPTER 2: LITERATURE REVIEW

2.1. Dynamic Pricing in Manufacturing and E-Commerce

From the success story of growth in airline revenues in the 1970s because of the focus on a revenue management approach, many businesses have attempted to replicate the success but challenges arising from spurious models of consumer behavior have led to failure in improving profitability. The challenges have emanated from the problem of using deterministic approaches when in fact markets are stochastic. The contention has been that consumers are not prejudiced and that piecemeal analysis of markets fails to take into account supply-chain dynamics. From the producer to the consumer many parameters exhibit variability over space and time thus affecting the ability of static models to optimize prices efficiently. Hence, there is a shift towards the use of dynamic pricing techniques along with new business models. These dynamics suit the changes fostered by information and communication technologies such as e-commerce. Making direct sales over the Internet, is amenable to variability in pricing because the whole process is easily managed electronically.

Research on products offered on the internet versus those sold in physical markets revealed that web-based markets are very efficient considering the price levels offered and the cost of displaying different products online. This means it is easier to manipulate prices by changing catalogues online because it is less costly. Some of the pricing strategies marketers use online are auctions (forward and reverse) and discounts based on points earned by clients on their personal purchases. Modern companies use online linked bar code scanners in the distribution channel and selling points to collect accurate demand data for used in designing effective dynamic pricing strategies. (Gallo, 2002)

Companies like Boise Cascade have reported that for their 12,000 most popular products online their prices were also found to be the most inconstant and sometimes changed daily. Dell Computer has employed a system of dynamic pricing by segmenting customers, or changing price levels depending on stock levels or how the prices offered by competitors (Swann, 2002). The computer firm uses other strategies such as differentiate product pricing in spatially segmented markets, and price valuations for components from suppliers. In a successful case of dynamic optimization of prices research has shown that a firm that varied its product prices much more rapidly compared to its competitors made a huge profit of USD 25 million (McKinsey, 2002). Another company was also reported to have manipulated the price of concert tickets and the schedule of events to match supply and demand enabling it to rake in 45 percent more profits per event. Another case of relevance in the study of optimization of the pricing problem for car business is the optimization algorithms for dynamic pricing that have been employed in manufacturing in the case of Campbell Foods who strategically controlled prices based on inventory levels. (Waller, 2001)

The assumption in a deterministic approach is that the firm will not be faced with variability in clients' demand for its products and therefore designs a static pricing policy. The argument has been that the firm has the capacity to predict consumer behavior accurately and evaluate how its pricing policy performs. Nevertheless, the reality observed from human behavior is that most markets exhibit highly stochastic behavior and so dynamic pricing is more attractive if employed since the trend of sales is never wholly determined by the firms' pricing decisions. Findings by Levin et al. (2009) indicate that, production and trading processes in the market are influenced by other random events. They argued that consumers place different value on products in an unpredictable way and their propensity to consume as determined by their

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income levels and other unknown intervening factors remains uncertain until the time of purchase, especially when they make advance purchases. This has been reported in studies on customer hotel bookings, holiday packages, sports attendance and in the entertainment industry where valuations by clients will mainly be influenced by the weather conditions which are unpredictable and their seasonal or time preferences or availability after work. Unpredictability in consumers' valuations has also been manifested in a variety of services especially those that require advance booking or reservation of space and time such as medical checkup, restaurant tables, home cleaning, and home repairs, among others.

Consumer behavior studies have shown that sometimes when people form intentions to buy a product on a given day, hour or price point, it is not a guarantee that it must result into a purchase. Notable cases are those where although a consumer has observed that a certain price point is within her means she may fail to buy immediately due to procrastination, buying point congestion, or if the terms and conditions of purchasing the product are unfriendly such as the need for visa cards. The majority of consumers dither a lot when faced with a decision to buy unfamiliar items especially in the case of discretionary purchases – choosing at one point to buy but then in the next moment they decide that they should not purchase. Many customers also perform an information search before deciding what to buy and where to buy it. All these variations in behavior make it difficult to specify valuations and the relevant assumptions. This boils down to the problem of unpredictable demand, which causes difficulties in planning for and predicting product availability for both the sellers and buyers.

For car merchants, the supply chain participants need to develop a pricing policy that optimizes profits but with the hindsight that consumer demand will be determined by the company's existing manufacturing capacity and the time lag required to fulfill customer orders.

The company's challenge is in coming up with a credible price commitment if the consumers are not considered to be myopic in which case they are strategic. In such cases, a deterministic policy cannot be used and so there is need to develop a pricing policy that considers price variability when targeting a known number of consumers who think and make decisions strategically in a market that is expected to be inherently indeterminate or cannot be predicted by sellers. Some researchers have assumed that the firm selling cars is a monopolist who sets prices depending on conditions in the market in which she offers fixed number of cars for known period of time while the car buyers make choice decisions based on the consideration of variables that are strategic to them in the market.

The formulation of such a choice model is designed to consider demand uncertainty while defining the parameters for production capacity that go into the model. Unlike other stochastic models shown in conventional research papers, in this case the modeling neither limits the variations in prices to two time horizons, nor to a decreasing trend in prices. Recall that formulations of deterministic valuations (or random valuations base on seasonal periods such as the start of the sales season) assume that prices will remain fixed until the end of the season, the behavior of homogeneous buyers is thought to be such that they all make purchases simultaneously if and when ''conditions are right.'' This is at variance with observed behavior in real markets. The traders will most likely observe incremental price changes whether they are a case of rising prices or falling prices as the speed of sales and stock vary. We therefore consider a dynamic model that is formulated with consideration of variability in consumer behavior where as individuals they will tend to respond to price changes (up or down) and changes in differing variables in the market whereby they strategically manage the magnitude of their purchases or demands. The resultant effect of this variation in consumer demand is that actual completion of

sales may be distributed over space or time in an unpredictable pattern which reflects that buyers of products can be strategic.

Gallego and Van Ryzin (1994) formulate an approach in which they consider a dynamic pricing model in which the consumer purchase behavior or demand intensity varies they demonstrated that choices by consumers were exhibiting structural monotonicity in outcomes in an optimal Makeover process. Their paper proves the asymptotic behavior of prices that is optimal as proven in other conventional announced price heuristics commonly shown in deterministic problems. The outcomes in fixed price formulations bounds the additional expected revenue obtainable compared to a dynamic pricing strategy. Gallego et al. (1997) further show how to take the case of a single product in assessing the pricing problem and extrapolate it to a multiple product dynamic pricing problem. Bitran et al. (1997) analyze a discrete time framework in a dynamic pricing model that incorporates a case of periodic pricing for customer's re-valuations with monotonically decreasing price trend as a constraint. Zhao and Zheng (2000) in their report give a case of a continuous period dynamic pricing model in which there is non-homogeneous consumer demand behavior and provide a sufficient condition which ensures there are monotonically decreasing price trends.

Feng et al. (1995) were able to arrive at a limit level of time that was optimal in a Markovian pricing process where only a unit price variation from the starting announced price moving to a different announced price is prevailing. Feng and Gallego (2000) described an optimal situation in periodic cases of prices changes for a set list of possible price trends. Feng and Xiao (2000a,b) specified an optimal level of prices which has a closed form type with an expectation that the possible price(s) announced is/are discrete but are known, so the price variations in the markets may be either reversible or irreversible. Perakis and Sood (2006)

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analyzed a multiple time period scenario with competitive dynamic pricing in the case of a single perishable asset where the stock level is fixed and specified the demand uncertainty problem by estimating a robust optimization model.

Nguyen and Perakis (2005) further reviewed the single asset scenario in a case where multiple outcomes in a competitive pricing case is used and demonstrated that iterative learning helps in computing market equilibrium strategies. Mookherjee and Friesz (2005) studied a case of formulating combinations of price levels and resource level choice strategies when there is an overbooking revenue management problem in the networks and those in competitive environments. Other studies appear in the formulations of supermodular strategy strategies (SG) which allow sufficient states in order to ensure the existence and clarity of equilibrium outcomes similar to super modularity and "diagonal dominance" conditions respectively used. Another case such an approach by Bernstein and Federgruen (2005) is published in papers expounding on cooperative pricing and stock level choice decisions for retailers in value chains. Bernstein and Federgruen (2003) evaluate a two-tier distribution arrangement showing a case with one supplier and many retailers.

Gallego et al. (2005a) investigated Bertrand type oligopoly pricing strategy in which there is a general demand function with convexity in costs. This stochastic approach to consumer behavior negates the requirement for defined rationing controls in the car trade because practically, haphazard rationing of products to consumers is determined automatically as a spontaneous consequence of the movement of prices in that market. In their model they make obvious by an assumption that consumer choice behavior should be pre-determinable at the start of the sales period. The stochastic approach requires one to assume that buyers will always repeat their product valuations at each stage of their buying decision without recourse to past

valuations they may have made. Of course, another assumption is that consumers have no memory and do not make choices or decisions based on experience.

Su (2007) expounds on a deterministic formulation of demand analysis where the buyers are divided into four different classes depending on their price point level, waiting costs and by deriving circumstances that differ between situations in which the seller would choose to give price reductions or increments. Aviv et al. (2008) studied the optimal determination of prices for seasonal items and formulated a modeling approach in which the seasonal goods are demanded by strategic customers whose flow follows a Poisson process and are thought to have deterministically declining valuations over time. This approach employs a model that uses sub-game-perfect Nash equilibrium between traders and strategic consumers with conditional (inventory-dependant) discounting strategies and known price discount levels set by sellers. The research findings were that businesses could not effectively mitigate the damaging impact of negative behavior by consumers who think strategically during the times when they have low beginning inventory, and pre-fixed discounting mechanisms. These variable methods have sometimes been found to outperform condition dependent pricing strategies.

Xu et al. (2004) have demonstrated a continuous-time analysis price setting method wherein buyers' arrival pattern is a Poisson flow and is sensitive to price (a condition that is reported to vary over some time horizon). The findings were that consumers may decide to make a purchase at a time which models an open-loop pattern in a mapping of their decision or choice making process. They argued that optimally modeled prices follow a sub-martingale especially if price sensitivity is static or reducing in value, while in some other cases the optimal price will tend to follow a super-martingale if the consumers' sensitivity to price changes is rising. The work of Zhang et al. (2008) analyzed the impact of some strategic buyers in a dual-period

formulation that sets off with an initial case of the period being one, which looked at regular

prices. The prices were regarded as clearance price levels and the sellers had the option of

manipulating or lowering product volumes available in the second time horizon.

Cachon et al. (2007) analyzed valuations made by consumers in a case where they chose

an extra item or good during procurement, christened ''quick response,'' in a dual scenario in

which the final stage price is a reduced value. Their framework looks at triple classifications for

consumers; those consumers who are myopic, then those who are known to be bargain hunters

and lastly the strategic. They found that ''quick response'' offered more value for consumers

who are strategic in their choices. In their case Gallego et al. (2008) studied formulations of the

same classes of models with many trading seasons and 2-period pricing for each season. They

consider a case of consumers who improve on their expectations by assessing afresh their

probable chances for making purchases of the product at a discount by banking on the reciprocity

gained through past transactions with a given trader. The research findings in the case reveal the

prevalence of complex and very stochastic behavior in consumer–trader relationships.

This research is designed to demonstrate how car dealers can attempt to set prices with

the hindsight that although they investigated the market some parameters of the consumer

demand that arise along the value chain are unknown. Over time, the dealers can improve their

knowledge of the state of demand through sales observations. The dynamic optimal pricing

strategy should take into account the balance between high and low prices and the impact of

price dynamics on the understanding of the demand trend itself. The findings in past research

have dealt at length on the idea that consumers are myopic, an assumption that provides an

acceptable evaluation of consumer behavior when they are thought to be spontaneous while

choosing products (common in cases of low-price items). They have not taken time to search for

information on cheaper sellers or there is completely no information to enable them to behave strategically. However, for the case of expensive goods or durable items for which price information is announced, this assumption is less realistic. The proponents of the approach averred that failure to consider the effect of strategic customer behavior is likely to reduce expected profits or revenues for traders using dynamic pricing.

Dynamic pricing strategies are usually found to be useful in a common market type – referred to as a finite market. This is a market in which traders have a determinate time horizon, known seller stock capacity, and known buyer population size. In such market situations for example sports tickets, airline tickets and short-term goods, the main benefit in using dynamic pricing can be demonstrated when sellers can ensure that all their stock is sold. Also a common characteristic to the small markets is the importance of variations in buyers' demand for goods. If sellers become opportunistic by manipulating prices in response to variations in demand they could charge higher prices at different times. We can therefore foresee that in the future, continuous adjustment of prices by sellers pricing will become an attractive strategy for competitive trading, especially in markets with a defined time horizons. Faced with a choice to dispose of excess stock, traders in small markets may decide to dispose of the excess stock in an untargeted side market such as auctions.

A good case of such a market on the web was the Fair Market's Auto Markdown reported in research by Keskinocak et al.*(2005)*. Auto Markdown trades as a multiple-unit auction where goods are at the beginning offered at high starting prices and they are then progressively offered at lower prices, targeting a specified price boundary, or until all the firm's stock is exhausted. Although Auto Markdown's pricing strategy does not show any response to variation in demand in the marketplace, it demonstrates that dynamic pricing can be used to achieve a small trader's

goal of selling all her stock in a finite market. In a recent research paper (Kotler 2010) about vehicle industry business researchers have demonstrated through a dynamic pricing scenario where there are varying demand levels, the resultant gains in revenue are reflective of its advantages over a set-price strategy. It has been shown successfully that the model increases its efficiency depending on the strength of variance exhibited in reserve prices set by the consumers and the frequency with which the seller changes her prices. Simulating market situations through models helps researchers to visualize diverse and complex or unknown scenarios. Researchers at IBM have examined buyer and seller driven situations in ideal markets by doing simulations, using data from markets that deal in information goods. Their investigation of agent driven scenario markets shows the shortcomings of automated or computer programmed dynamic pricing, which include pricing wars. In the study, they evaluate four agent pricing stratagems: theoretic game formulations, derivative based following, dynamic but myopically optimal and Q-learning also called reinforcement learning. They conclude that if a pricing agent seeks to maximize profits made in the business over a longer period much more than in the short run purchase time horizon, a learning algorithm gives better results for scenarios in which markets have high levels of unpredictability.

When seeking information on prices, data from aggregate sales forecasts fails to account for detailed pricing by competitors. This is because at one end of the continuum businesses seek to combine setting price levels plus capacity allocation into a single system which considers pricing and quality characteristics of goods offered to customers at sales outlets. The paper reports how such a system behaved by expounding on the stochastic dynamic pricing of perishable assets in a competitive car market. It is believe that well specified and implemented dynamic pricing can "ration" capacity more profitably. This is due to; first, the argument that

dynamic pricing will allow the firm to factor into its optimization of the pricing problem the real time changes of prices by its competitors that yield accurate and reliable sales projection targets; and finally, variable pricing is not limited to a pre-determined offering of prices. When there is room for adjusting price and factoring into the analysis current competitors' prices, the method of dynamic pricing can be more effective compared to the conventional capacity allocation within a given static price. Price openness created by online platforms enables customers' to do price comparisons and requires a competitive choice model that does a good job of accounting for the range of options available.

Generally, studying the individual's strategic behavior must of necessity be accompanied with simplifying assumptions. Past studies on this problem have assumed that only cases of deterministic demand exist, including the more realistic stochastic models. The majority of the research papers in mainstream publications strictly confine the dynamics of price changes to markdowns.

CHAPTER 3: MARKET DEMAND

3.1. Car Demand in Market and Income

Over time the demand for the Honda Civic car has risen. According to kbb.com, car demand stands at 30% of all the civic models and slightly below 1 percent among all car models, this is a high number. One of the drivers for the high demand of the car among consumers is the revisions that the manufacturer made on the car after it debut. For example, in 2012, the media, according to kbb.com, made a lot of fuss on the 2012 civic models. This is because it had some lackluster interior materials and flabby handling characteristics, which brought high cabin noises. This criticism, however, did not have adverse effects on the sale numbers and the comparison results.

The demand came back in the 2013 Civic model, which brought greater refinements and high performance as expected from a segment leader. The model provides standard features in the expanded form and has sharper driving dynamics. Most of the customers prefer the car due to its affordability and reliability and a stellar resale value, which makes it one of the best values in the automotive industry (kbb.com). The civic model has more varieties that comprise an expansive lineup that include the Sedan and the Coupe body styles. The car raises demand with the higher driving impressions due to the chassis modifications and suspension. These features transform the Honda civic model into a better performer (kbb.com). It also has the ACE II body structure, which makes it lighter and more or less rigid than the predecessors do. The car delivers a good steering and pedal response that is not very available from other automakers. Other features that raise the car's demand include Bluetooth music streaming from a smartphone and i-mid display.

The vehicle has other details for the interior that include an unusual layout for the dashboard that conveys a more upscale ambiance with relevant nameplates. Customers prefer this car as it is very compact for the interior space, the storage and the outward visibility with the flawless ergonomics. The controls provide a cinch to operate with the soft-touch materials for the instrument panel. There are no more hard plastics and a bland look in the upper door trim, which also help in giving the previous cabin a low budget impression. The car's exterior had a design that failed to resonate with style minded buyers hence lowering demand. However, the design team revised the exterior design and created a new front and rear styling especially on the 2001 Sedan. The look is composed of a wide lower grille and an opening with a taller trunk lid (kbb.com). There is also a rear horizontal chrome trim, which is also similar to the Honda Accord 2013. These diffident cosmetic modifications escape a casual observer's eye making it hard to argue for a specific styling strategy, which maintained the Civic at the top of demand.

3.2. Mathematical Optimization Model

The Honda civic company, according to kbb.com maximizes its usage on the network capacity to increase profitability and reduce other costs while it maintains a high level of services. Using the mathematical optimization model, there is more focus on efficiency. This comes with predictive analysis and statistics, which provide the mathematical disciplines used in the business world. The approach applies mathematics and logical input in pursuing efficiency objectively. Furthermore, mathematical optimization does not get a lot of concern with providing probabilities and attempting to predict the future by only looking at past occurrences. Optimization uses facts on costs and yields for the available resources and the demand for the goals and constraints. There is also a better plan for scheduling the activities for mathematics and logic.

Based on the new simulated data from kbb.com, optimization on the pricing of the Honda civic vehicle takes several aspects. The first aspect is on the vehicle performance vis a vis the demand it creates. First, there are very tight vehicle emission regulations from the government, which intensify demand for fuel-efficient cars. Additionally, customers expect that they can get the same performance from the new vehicle, as they expected when the fuels were low. These are conflicting demands, which also present a challenge for optimization for the kbb.com and, by extension, the automotive manufacturer.

It is a challenge for the engineers to minimize carbon dioxide emissions while keeping the performance high. In the past, Honda Civic manufacturers tackled this problem by ensuring that they could optimize the power efficiency of the power train separately. For example, in the times of fuel crisis, large automaker developed some in-house computer simulation models that helped them achieve optimum performance in their systems. This good move brought in system-level-optimization. The optimization is still very common in the emerging markets, and optimizes individual car components.

The mathematical optimization model enables kbb.com achieve the ideal results as it has the resources for developing large simulations and models for the optimization program. In this case, kbb.com uses a system model that can incorporate the engine, axle ration, transmission, vehicle, and the driver. The engineers are, therefore, able to optimize the hardware variables, for example, axle ratios and parameters for calibration such as the shift schedules simultaneously. This avoids making rough estimates on the fuel economy that come from expensive alternatives in technology and have metrics upon which they base the vital decisions for selecting the hardware.

When optimizing the powertrain for the Honda Civic car with five speed, 2 liter engine with 4 cylinders and Dual Clutch Transmission (DCT), the goal is to use as little fuel as possible. This takes place over a Federal Team Procedure drive cycle. In addition, it will maintain a minimum threshold of 10 seconds for performance for about 0-100 Kilometers per hour (kph), in acceleration time. As provided in Table 1, these typical car characteristics, for the Honda Civic 2014 aid in price optimization.

When pricing the Honda Civic models, there is always the manufacturer's suggested price for retail, which for the 2014 model goes up to $ 19,000. For example, a fully loaded EX-l sedan including the navigation system comes in at about $25,000. There are competitors such as Toyota Corolla, Mazda and Ford Focus, which may start in the $17,000 range. However, the strength in the civic model is that none of them can match the comprehensive roster and standard features that the civic provides. The dealer, kbb.com, also provides loan arrangements at a rate of 1.99% for up to 60 or 72 months. The sales tax is normally placed at 8%. The online loan application for car purchase from kbb.com is available at www.roadloans.com.

Table 1. Vehicle characteristics.

Equipment	5-inch multi information display, Bluetooth integration, internet, rearview camera, USB port, blind spot monitor and forward collision warning system.
Wheels	Alloy Sixteen inch
Radio	Pandora Internet with 6 speaker premium audio facility
Entry	Button, keyless
Climate control	Automatic
Upholstery	Leather
Performance parameter	
Power	143 horse Power at 6500 rpm and 129 at 4,300 rpm
Transmission	5 speed Automatic
Engine	1.8 liter
Fuel economy	City/highway at 28/36 mpg (manual transmission) and 30/39 mpg (automatic) and 31/41 for the civic HF with a CVT automatic)
Vehicle class (mass)	Small to mid-size about 1,600kg
Drag coefficient Cd	0.4
Drive Cycles	FTP75 (fuel economy) 0-100 kph acceleration (performance)

3.2.1. Solving the deterministic model

Using the deterministic approach for pricing provides a natural way to study the stochastic problems. In this method, consider the availability of time horizon while optimizing the system. We also exploit the kbb.com data to get information on the system. The optimizations give the upper bound on the problems within the stochastic optimization within the given instance. Solving the deterministic problem efficiently allows for an optimization heuristic. With the demand forecast from kbb.com, there are expected results derived for application in line with the stochastic problem.

3.2.2. Tables and graphs for optimized price against demand

Putting the features aside, other factors that contribute to the pricing of the Honda Civic models at kbb.com are such as the current market conditions, the seasonal buying trend and the local demand of the vehicle. Some of the market conditions involve discounts from the dealer, which are likely in most of the models. This is especially when there is a "buyers' market," meaning the buyer gives most of the terms and he expects to find willingness for negotiation. The prices depend on such factors as the manufacturing price, which is also the fair purchase price and may have no options. Including taxes raises the prices accordingly and the additional DMV fees too. The current rebates or cash back, which are the supplemental customer incentives and may have restrictions due to the regional and fleet rules according to the dealership. A combination of these factors gives the target price. Furthermore, the customer may decide to provide a down payment on a basis of 20% and will get financing on the balance and provide installments for 60 months according to kbb.com pricing.

3.3. Problem Setting

In this mode, the initial inventory amount of investment provides the maximum quantity of cars that can be sold one at a time. The mathematical model provides assumptions made that demand appears at different times and seasons for zip code 77346. In this case, there are real and positive demands, which provide the price of the Honda civic at a particular time. Therefore, the following equation will determine the price of a car at the time or year of manufacture.

$P_t = p\ (x_t,\ t)$: Y = 59.952x + 13614 (Y = mX + c, where m = slope = tan -1 (59.95), c = 13614)

$$(3.1)$$

This equation shows that there is a linear relationship between the price of a car and the demand at the time. The relationship also indicates that its application must exist when there is fixed price and demand.

In this model, the initial inventory is denoted as s_o. In simple terms, initial inventory refers to the maximum quantity of products that can be sold within the time T. As contained in the previous section of the mathematical model, the assumption being made here is that demands appear at different times 1, 2,….., T, whereby x_t is the demand at the time t. In this case there are real and positive demands. In addition to that, the price of an item at a particular time t is denoted as p_t. The following equation represent price as a function of time and demand:

$$P_t = p\ (x_t,\ t). \hspace{3cm} (3.2)$$

As far as the above equation is concerned, it is assumed that a one to one relationship exists between price and demand at any particular time t where $t = \{1,2,….T\}$. In this relationship, $x_t = (p_t,\ t)$ and it only apply when there is fixed demand and price. Another assumption with regards to this model includes:

1. $x\ (p,t)$ can be differentiated continuously with respect to p

2. $x(p, t)$ is bounded at lower and upper levels, however, its value tends to zero as p's value approaches its maximal level.

Therefore, the problem can express in the following function:

Maximize

$$\sum_{t=1}^{T} pt.xt \tag{3.3}$$

Subject to:

$$\sum_{t=1}^{T} xt \leq s0 \tag{3.4}$$

$x_t \geq 0$ for t ϵ { 1, 2,.... T}

$x_t \leq x (p_t^{min}, t)$ for t ϵ {1, 2,....T}

In this equation p_t^{min} represents the minimal value of p_t

3.3.1. Solving the problem

An overall approach for solving this problem involves the use of Kuhn and Tucker model which is focused on Langrange multiplier. Given that $p_{t\ (price\ at\ time\ t)}$ is a function of $x_{t\ (demand\ at\ time}$ $_{t)}$, then it means that $p_t x_t$ is also the function of x_t. This is done while taking into consideration constraint problems. The following represent the Lagrangian:

L (x1,..., x $_t$, λ, μ $_1$,...,μ $_T$,l$_1$,...,l $_T$) = $\sum_{t=1}^{T} \sum p (x t, t) x t - \lambda (\sum_{t=1}^{T} xt - s0)+ \sum_{t=1}^{T} \mu t\ xt$

$$- \sum_{t=1}^{T} lt (x t - x(ptmin, t)) \tag{3.5}$$

The main objective is to solve T equations

$$\partial L/\partial x_t = 0 \text{ where } t = (1, 2,.....T) \tag{3.6}$$

With complementary slackness conditions of the 2T +1

$$\lambda (\sum_{t=1}^{T} x t - s0) = 0 \tag{3.7}$$

$\mu_t x_t = 0$ for $t = 1,2,...T)$

$$l_t (X_t - x (p_t^{min}, t) = 0 \text{ for } t = \{1,2,...T) \tag{3.8}$$

With respect to the above model, there are 3T +1 with the following unknowns:

$x_1, \ldots \ldots, x_t, \lambda, \mu_1, \ldots l_1, \ldots, l_T$

Finding solutions to the equations 3.6 to 3.8 is only admissible if $\lambda \geq 0$, $l_t \geq 0$ $\mu \geq 0$ and in case

the following equations hold: (3.8) - (3.7)

Similarly, because of the relationship between 3.7 and 3.8 $\lambda = 0$ or $\sum_{t=1}^{T} x = s_0$

$\mu_t = 0$ and $x_t = 0$ where $t = \{1, 2, \ldots T)$

$l_t = 0$ and $x\, t = x\, (p_t^{min}, t)$ for $t = \{1, 2, \ldots \ldots T)$

Assumptions for simulated data in Table 3:

1.) Starting inventory of Honda Civic Car for simulation has been assumed to be 133 cars.

2.) Ending inventory of Honda Civic Car for simulation has been assumed to be 578

3.) Market demand (D_t) in table has been randomly generated for minimum value of 2 cars and maximum value of 7 cars.

4.) Holding cost (h_t) generated for minimum value 0 and maximum of 2.

5.) Inventory cost (K_t) in table has been randomly generated for minimum value of $200 cars and maximum value of $500.

Graph for Optimized Car against Demand
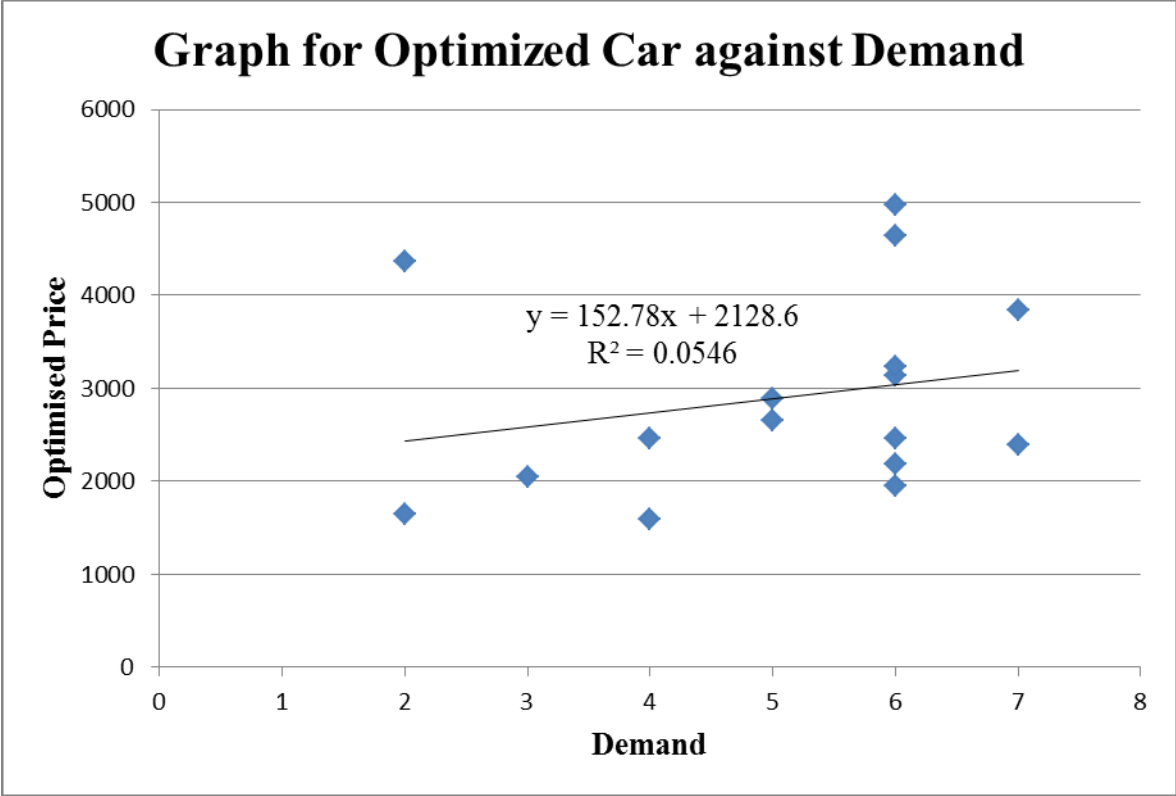
$$y = 152.78x + 2128.6$$
$$R^2 = 0.0546$$

Figure 1. Deterministic model: optimized car price vs. demand. Plotting Y (Y=Axis) against demand (X-Axis) will show how the optimized car prices behave according to Deterministic Car Price model.

Table 2. Deterministic model: simulation table.

Starting Inventory (Xt)	End Inventory (lt = It +Xt – Dt)	Market Demand (Dt)	Holding Cost (ht)	Inventory Cost (Kt)	Optimized Car Price [Pt= 1*(Rt (Dt) – htIt - ktXt]
8	5	3	0	410	3277
11	14	2	1	319	3493
10	21	3	0	350	3497
11	25	7	0	463	5086
7	25	7	0	316	2205
11	32	4	1	447	4881
10	39	3	1	467	4628
10	47	2	1	306	3011
8	48	7	0	382	3049
8	52	4	0	386	3084
8	54	6	0	275	2194
8	57	5	0	293	2339
8	59	6	0	364	2906
9	63	5	0	223	2002
11	69	5	0	215	2360
7	70	6	0	420	2934

From the graph, the line of best fit is given by: $Y = -207x + 3935.6$ while $R^2 = 0.1985$

3.4. Civic Si Coupe Model Illustration

According to kbb.com, Honda announced the pricing of its Civic Si Coupe (2014) and the Sedan models, in which both have a price bump of about $265 over the offerings going out of 2013. With the sales that took place in march 12 2014, the starting price, for example, of the Civic Si Coupe was at $23,480, which is inclusive of a $780 destination fee. Additionally, the base Civic Si Sedan cost the buyer $23,700 after it arrived in the dealership in March. A fully loaded Civic Si Coupe, which has summer tire fittings and a navigation system, goes for about $25,280. This is the price of a Civic Si Sedan with complete navigational systems without including the summer tires, which is always optional for the sedan. The EPA ratings indicate that the Civic Si Sedan and the coupe are the fastest outgoing models.

Additionally, the Si model, which has a 2.4-liter, 4-cylinder engine is among the latest models with an additional four horsepower. This gives a total output of 205 horsepower. It also has an improved torque by about 4 pounds per foot. The power increments occur due to the return of the once efficient exhaust system for the Civic Si models incorporated in the 2014 models. There is also a 6-speed gearbox, which is also the sole transmission for the sedan and the coupe models. The upgraded Honda has a better suspension with a design of 18-inch alloy rims. It also has full taillight lenses and auto controlled side mirrors. Several trim specific cues for styling include a rear diffuser, front grille and a spoiler. Inside the Honda Civic 2014 is a 7-inch touch screen, a push button instead of key for starting, a lane-watch system for blind spot display, which is a Honda innovation and a smart entry system.

3.5. The Optimization Process

Optimization contains sets of inputs for the car demands, the resources used, the cost, assumptions, the preferences, constraints and the goals. The equation to find the ultimate price for the customer must consider all these aspects. This will provide the optimized plan and schedule with information for the best possible solution. There are also binding constraints and underlying economics, which provide the operational efficiency. The structural components used in the pricing process include the available resources, which are the cars that the consumers will purchase. The second component is the demand to fill and the kind of services that the car will provide. In addition to this, there is the building of products, filling the customer orders, marketing offers made and the scheduled dates of activities. This may also require forecasting the best or worst case, such as the most likely car brand to sell over time.

3.5.1. Other optimization processes

The kbb.com optimizing process also adjusts for the mileage costs, depreciation rates especially on the older model cars, the cost of supply, the switchover costs, marginal costs and the cost of capital on equipment purchases. It is necessary to make some yield or throughput assumptions for example, when the cars are in a warehouse, it is necessary to consider the average driving time from one warehouse to the customer. Other considerations depend on the agreement on marketing offers for the company in exchange for discounts. As kbb.com is a global operating company, it may face global operating constraints such as different policies and operational taxes for different countries. There are also individual operating preferences and constraints, for example, there are customers who prefer not to take car deliveries past 11 AM and prioritization of orders for top accounts for shipment and fulfillment among others.

The goals set for the optimization model must minimize total or empty mileage, total costs or one cost, handling, total time cycle and the total risks or the particular risks. The goals are also to maximize the revenue, profitability, throughput, customer satisfaction and the employee preferences. For this plan to succeed, the solution supplements the optimized schedule and plan. Therefore, the complete profile solution includes the calculations that summarize the plan efficiency and the schedule in financial, operational and the hybrid terms.

3.6. Optimization Model Structure

The first part of the structure involves the input, which is the demand to meet, the available resources. The resources, in this case are the cars and the services that follow up to facilitate a smooth purchase. The third inputs are the costs, the yields and the recipes. The fourth input is customer dependent and include the operational constraints and the customer preferences. These inputs are always in line with the business goals for kbb.com. The mathematical model follows with the optimization engines. For example, the model will include minimized costs, the minimized yields, the best possible timing of activities and the specific car. Putting together these components into the optimization model, it executes using the multiple optimization engines. This results in the best possible plan and the set of schedules to achieve the set goals.

3.7. The Stochastic Models

This model contains the randomly selected pricing models. The model helps in determining the outcome probability as projected and it helps in predicting the conditional nature in different situations for marketing and selling a car. In the normal situation, the random price data is constrained by the nature of the existing historical data. In practice, the stochastic process has random variables with values that change randomly over time. Additionally, the time series

is the important realization point of any stochastic process. Using this approach, the sequence will exhibit the random variables.

The cars or products differ from one another with the non-existence of a solvable closed from solution. Kbb.com uses its increased computer capacity and simulation approach for pricing the cars. This becomes intuitive and reflects the most probable result, which the marketers can imagine and then tag the prices. To compute the prices for the cars with the discontinued payouts, there are certain theories to present. The most important part that kbb.com uses is to base the pricing strategy as a function. This degenerates to a mathematical expression of the possible payouts in the future. The pricing function varies to represent the car's construction. In this method, consider a car is considered as something represented by a stochastic process and the local dynamics are approximate using a time series equation.

3.7.1. A stochastic equation for the car's value

The pricing problem sets up a stochastic equation for Cars for Sale New and Used Car Classifieds from kbb.com. Therefore, we must create a stochastic differential equation for the car prices at time t, this will also take into consideration the cars' depreciation and the stochastic payment made. It is worth noting that the blue book value of cars depends on the mileage, which makes it a random variable. The market value of a car depreciates with time, which depends on the mileage and the condition. The optimized value or price of a car, considering depreciation is provided in an exponential law $P(t) = V_0 e^{-kt}$

where $P_0 =$ is the price of the new car and k is the rate of depreciation, assumed to be 6%. The price at the initial time or the first month is assumed to be 10,000 dollars. Remember that the value of the car is maximized at time t=0 and therefore equal to P_0.

3.7.2. Table and figure for the stochastic model

Assumptions for simulated data in Table 3:

1.) Recorded time changes are in terms of months and not weeks or days.

2.) Demand of car reduces with time. This time includes the period it stays un-sold.

3.) The mathematical constant k, which is equal to demand rate is 0.06 (or 6%).

The value depreciates with time exponentially at a rate that will depend on the brand of the car. The car could be old or new and will need repairs that can be modeled through a Poisson process, *Nt* at a constant rate r. Consider the cost of the repairs independent in respect to the number of occurrence Nt. The car needs servicing or repairs at times *t1, t2,t3……* , which have a gamma distribution. For example, if at time t1 the initial repair occurs, then the car value will decrease by the amount of the costs of repair R1.

$$P_{t1-} = P_o e^{-kt} , P_{t1+} = P_0 e^{-kt1} - R_1 \tag{3.9}$$

Table 3. Stochastic model: simulation table.

Time in months	Demand rate	E	k	Car Price [P(t)= V0e-kt]
1	99	2.71828	0.06	
2	93	2.71828	0.06	8869.205083
3	87	2.71828	0.06	8352.703125
4	81	2.71828	0.06	7866.279881
5	75	2.71828	0.06	7408.183702
6	69	2.71828	0.06	6976.76495
7	63	2.71828	0.06	6570.470054
8	57	2.71828	0.06	6187.835916
9	51	2.71828	0.06	5827.48464
10	45	2.71828	0.06	5488.118576
11	39	2.71828	0.06	5168.515639
12	33	2.71828	0.06	4867.524917
13	27	2.71828	0.06	4538.040416
14	21	2.71828	0.06	4218.092206
15	15	2.71828	0.06	3898.143995
16	9	2.71828	0.06	3578.195784

Stochastic Car Price Versus Demand
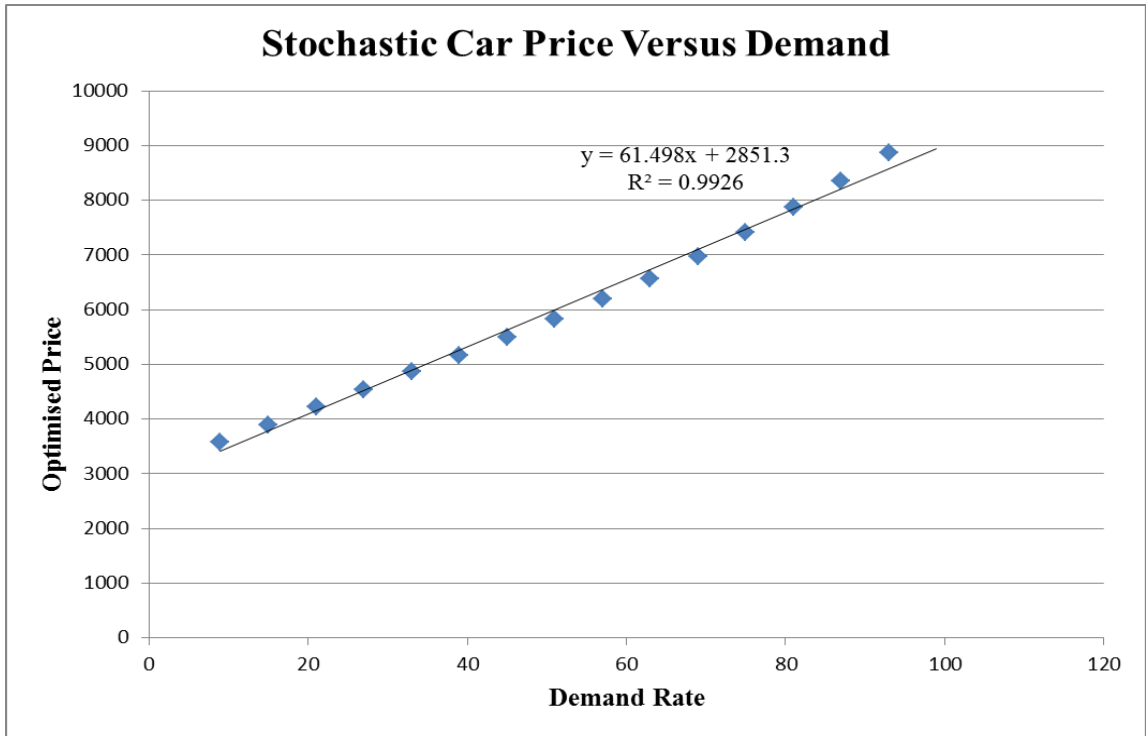
$y = 61.498x + 2851.3$
$R^2 = 0.9926$

Figure 2. Stochastic model: optimized car price vs. demand. Plotting Y (Y=Axis) against demand (X-Axis) will show how the stochastic optimized car prices behave according demand of a car.

As the cars for this project are new, repair values and time $R_t = 0$. Additionally, as the car takes more time (t) without getting sold, its demand decreases. This means that demand (D) is a function of time (t).

CHAPTER 4: METHODOLOGY

4.1. Methodology Approach

The research methodology adopted in the study uses an experimental approach to get data on the variables that determine the price of the car. The guiding principle in the methodology is that the choice for the customer price is anchored on another variable. The variables include personality, income, the environment, tastes and preferences, the location, gender of the buyer and many others. The pricing strategy for the car formulates on a discrete times. For example, the time of the year depends on the demand month at which the sellers offer the car in different prices.

4.2. Model Notations (Quantitative Notations)

1. The average Quantity of Cars demanded by the clients at time T is given by: Y.

2. The price of the Honda Civic model for this study is given by X1

3. The Individual income of the consumer is given by X2

4. The Predicted demand is given by P^d.

The regression equation for the simulated data provided from the line of best fit is $P_d = Y_t + (X_1/X_2)$ is the demand at a particular time t.

From the equation on the line of best fit, Y= 14.084x+ 5884.8, Y is the dependent variable and 14.084 is the mean. The standard deviation for demand (D_t) variable in this case is therefore 5888.5.

It is good to note that the regressions on weighs in exactly n to recapture the construction of Y_1. The constant is a higher number, meaning that there is need for adjustment, which will be necessary to make $P_d = (14.084X+ 5884.8) + (X_1/X_2)$

For simplicity, the study will only rely on the Honda Civic model and impute the findings as a reference to other models. Additionally, the findings in this study based on the choice of the Honda Civic model can be used refer to other car models. An individual has income as the main resource to determine whether he can purchase the car or not. The amount of money that the client has will determine the car supply he will get. Clients differ based on preference classes for different model/car price pairs and according to market information available from kbb.com. The objective here is to optimize prices and consequently the profit.

4.3. The Optimal Price Problem

The optimization of dynamic pricing is approachable as a regression of the quantity on price to establish the best price within a range of prices. Let P^d denote the optimized quantity of cars demanded. For example, for the Honda Civic Coupe 2013, retailing at the price of $ 18,133, the price is thus calculated at the entry level. For this car, it should be 2013 and the car will be carrying the manufacturers recommended retail prices of about 16,000 dollars.

4.4. Optimal Pricing Details

4.4.1. The average paid

The statistical accuracy is required to help understand what other buyers in the local area are paying for the car. The adjustments to the calculations exclude the make; the model and the trim normalize based on the details of the information from the anonymized transactions. This effect accounts for the recently sold vehicles and include the optional combinations for the specific vehicle configurations. The data that underlies the average paid calculations is filtered for the extreme outliers and are subject to the weighing averaging process, considering the transaction recency and the data lag timings. In addition, sometimes there are adjustments in accounting for the abrupt changes in the market, which may not satisfactorily reflect the recency

in the transaction prices. In cases where the car average paid shows, there is enough statistical reliability for the sample size. The payable price has three divisions.

4.4.2. The manufacturer suggested retail price (MSRP)

This is the '*sticker price*' that the manufacturer suggest. This is only a suggested price from the manufacturer; hence, the dealer, kbb.com, chooses to sell the car at a higher or lower price than the MSRP. Normally, many dealers will sell at a lower price.

4.4.3. The estimated price

This price represents an estimate of the savings available to the true car users from the car dealers or kbb.com in the area. This goes for the vehicle that is consistent with the configured preferences and includes the available customer incentives.

4.5. Further Divisions on the Pricing Detail Categories

a. Base: This is the base vehicle and shows the value of the vehicle before fitting of any optional equipment or adding the destination fees. It only includes the standard features.

b. Options: These show the total charge for the optional equipment and include the configuration for the virtual vehicle. Kbb.com's options provide varying charges that depend on whether it will have calculations based on the MSRP or the factory invoice. The options are not inclusive in the base vehicle price and, therefore, cannot be the standard features.

c. Regional fees: This is the fee charged by the manufacturer to the dealer for promotional and advertising fees while the vehicle is in the market for kbb. Kbb.com will also include the manufacturer preparation charges. They are the payments that the manufacturer charges the dealer to cover all the work done on

the car before delivering to the dealership. There are also the fuel remittances, which are charges of the fuel in the fuel tank before the buyer takes the car. Kbb.com includes the regional advertising fees in the factory invoice calculations.

d. Destination fees: They include all the amounts chargeable for delivery of the car from the factory to the dealership.

e. Custom incentives: They are the bonus or cash incentives that the manufacturer offers to entice the buyers into purchasing a particular car. The manufacturer passes on the customer incentive to the buyer while kbb.com factors this figure into the average paid price.

4.6. Optimizing the Model

Based on client assessments', the price choice and income collected, the values obtained are optimized to generate the best price and quantity expected by individual clients. The optimization part of the model gives a quantitative approach to measure demand of the Honda Civic model. The findings can be inputted to other car models.

4.7. Qualitative Model

The qualitative part of this study aims to expound on other factors that affect or influence consumer choice demands. Ultimately, the qualitative findings will build a credible support to the quantitative model (Optimization model) hence making it more plausible. The qualitative methodology will capture areas such as the social factors that affect clients' choice of car models. Other factors include the company design factors that significantly influence sales and the policy environment affecting the market operations. It is worth noting that to make recommendations to boost the market performance from consumer perspective.

CHAPTER 5: FINDINGS

5.1. Study Findings

Optimization, with regard to the customer behavior shows a standard method applicable in most of the cases. Table 1 shows that the decisions that consumers make are in line with the car price and the demand level on the Honda civic model. This may raise an observable optimization problem. The results show that consumers' desires are well set and defined in a numerical utility function. There is also the assumption that the choice of a consumer is the optimum and the decision based on utility level, which means that the high utility products retain a higher preference. The consumer behavior theory states that there are thee optimization components, which are, the choice objective, the functional objective and the constraints objective.

Both tables 1 and 2, show the estimates on the Honda Civic demand-effects, implying the price and demand relationship in the market. The variable for the prices are the quantity demanded, time of demand (season), income, and the projected demand over one year. Increasing the price of a Honda Civic results to a corresponding decline in the quantity demanded. Additionally, customers who have higher income levels have a position to buy the luxurious and higher priced cars. The higher income earner may not consider price as influencing the purchase of the car.

The quantities demanded have an optimized regression with no alteration from the Honda civic demand and customer numbers at any time. The demanded quantity is almost constant. The predicted demand over a period of a year provides meaningful residual demand values. Amount the lower income earners; there is a higher level of predictable demand. Kbb.com's trend analysis recorded, for example, a demand of 12.34 in one year, which was lower that the residual level.

The phenomena links with the monotone optimal pricing model, consumer behaviors and projection of demand; which express in two ways: One is where consumers are not keen on following the rational approach, but they evaluate the utility of the car based on what they see or perceive. Customers may also follow an approach that involves observing the projected utility value of the car. The regression on the demanded quantity, without the price aspects also indicate that demand projection is sensitive to the changes and the income levels. This is an important element to kbb.com, as it bases the company's predicted demand through segmentation of the income level and the average price of the utility items.

CHAPTER 6: CONCLUSION AND FUTURE RESEARCH

6.1. Conclusion

Based on the study results, it can be summarized that the theory of consumer behavior has played an important role by trying to explain the relationship between changes in product prices and consumer demand changes. On the other hand, the concept of utility is employed to represent usefulness and subjective satisfaction on the side of consumers. Using the consumer behavior theory, one is able to understand strategies employed by consumers in allocating their limited resources among different needs in order to attain a certain level of personal satisfaction. However, the main issue in this case is the system that can be employed in measuring and quantifying product utility. Due to such issues, a reformulation was done on consumer behavior theory, particularly, to help in a case where the utility function is important in explaining consumer product preference. Based on the recognized aspects, it was noted that utility matters is governed by a state where one option has a high utility compared to another option, however, the amount of utility variation is insignificant. As observed in various successful marketing strategies and formulation of public policy, it is important to have a thorough understanding of existing customers and potential consumers with respect to preference and behavior. Having such information is important, especially in product optimization and development, optimal pricing strategy, consumer reactions evaluation to changes in competitive products.

Referring to classical economic theory, consumers focus on utility maximization meaning that when having several choices to handle, the selection made will highly depend on the overall utility value. Neo classical utility maximization, on the other hand, is faced by some limitations. In the first place, the theory is applied through comparison of two products, which may not be necessarily competing. This study tried to explain consumer behavior foundation through a

review on decision theory and processes employed in decision-making. The main research goal was to examine main factors that influence the stochastic behavior of prices in car market supply-chains. It also investigated the parameters that would be appropriate to include in a dynamic optimization-pricing problem of a supply chain and finally, investigated on how businesses efficiently optimize the pricing problem in a stochastic market situation. The car model of choice in the study was Honda Civic. The number of variables, which were employed in the analysis, includes the prevailing market price of the product, the average income level of consumers in the market, the demand of products with respect to price and income levels and finally the projected demand in a one-year period. Results noted that price and income are very significant in projecting future demand of product in the market.

6.2. Future Research

Based on this paper, one of the promising future research directions is that analysis should develop a model explaining the impacts that such practices may have on the revenue of the firm. This should be done analytically by quantifying the tradeoffs between low pricing offered by some consumers and high sales volumes. Based on the analytical results posted in this report, they are based on a modeling technique addressing a single strategic consumer base, however, by having a modeling technique addressing multiple strategic consumers, stability will be realized in the utility gain and accessibility to products. Similarly, it is advantageous to the firm because it will increase the average revenue proportion to the company. Future reports should focus on multiple strategic consumers and game theoretical framework in order to study and understand the above related issues. Though the mentioned facts are beyond the coverage and scope of the report, they remain the most interesting direction to be addressed in future research.

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