# A STUDY ON OPTIMIZING PRICE USING BUSINESS RULE AS A PRIOR

SoheilaNassiri and MudiarasanKuppusamy

***Abstract:*** *This study tries to propose the new model to have more accurate price optimization for a specific business. Usually the optimal pricing solutions which come from the estimated sales models suggest prices that are unfairly inaccurate, which leads the manager to come up with some decision rules and constraints on the shelf price as a more appropriate solution. Using this information as a post hoc instead of prior information leads to inefficient pricing decisions. This study tries to use manager's constraints on the price solution as a prior information about the model. The study argues that the model and its prior (Business Rules about optimal prices) can be translated into informative prior distributions. These prior distributions appropriately weight the managerial knowledge against the data unlike the traditional approach. Moreover, this study considers situations in which the analyst may not know either the business rule or model with complete certainty of demand and illustrate the impact of this uncertainty on the optimal pricing solution using Bayes theorem by conducting Monte Carlo algorithm.*

***Keywords:****Price Optimization; Business rules; prior information; Monte Carlo algorithm; Bayes theorem;*

---

## I. INTRODUCTION

Pricing decision is a big challenge for companies. For any company who is involved with producing goods or rendering services, after coming up with the answer of what to produce they should answer the question how much a potential client is willing to pay for that specific product or services and this leads businesses' big concern for.Making decisions about the price is a decisive decision for all the companies owing to the fact that this will have an impact on corporate objectives, directly or indirectly. Minimizing the cost and maximizing the profit are two general factors for any business, regardless of the size of the business, level of complexity, being private or public and its objectives (Oladepo and Abimbola, 2015). Setting the price for a companies' product is one of the most vitally important decisions faced, because of the factors which should be considered such as demand, contestants, cost, political issues and etc. (Hilton, 2013).Horngren et al., (2010) argued principles are faced with setting business rules on pricing and profitability of products. The primary objective of any organization is to maximize profit and minimize cost. Therefore, there is need to set prices, which imply the importance of business rules decisions in all kinds of organizations. The principal approach to imply effective business rules is to manage income in ways which support the company's profitability goals. Many studies have been done to find out the factors and solutions for making more effective business rules for having better pricing decisions, to obtain overall objectives, which confirms the maximization of profit.

Therefore, business rules have become an important part of the practice of price optimization systems. These rules are meant to capture managerial knowledge and insights that impose important constraints on the pricing problem. Traditional approaches to price optimization take a two-step approach to setting prices. First, a sales response model is specified, and the parameters are estimated given an observed dataset. Secondly, this model is used for inference to

*University of Cyberjaya, Persiaran Bestari, Cyber 11, 63000 Cyberjaya, Selangor, Malaysia.drarasan@cyberjaya.edu.my.*
*University of Cyberjaya, Persiaran Bestari, Cyber 11, 63000 Cyberjaya, Selangor, Malaysia.*

make decisions about the optimal price. The general problem is that when retailers want to make optimal pricing decisions, it has different meanings in comparison with other contexts on marketing when the goal is making decisions about a promotion which can be based upon some expected responses from consumers. This problem implicitly refers to any knowledge that managers have as a part of the prior setup. Therefore, the aim is using data science techniques in order to make inferences from the data about these unknown parameters.The goal of this project is to emphasize on those business rules that reflect prior information so instead of putting them after the problem as a constraint on the optimization, to use this information when we are building our models as prior and develop the model to be more practical for the enterprises. Specifically, this research had the following objectives:

- To analyse the existing situation of product demand by visualizing the data with the help of Tableau (a visualization software).
- To find out which factors affecting the demand through visualizing the demographics using Tableau as a data mining tool.
- To establish a model for price optimization for profit enhancement through running different promotions in the branch with R studio using Monte Carlo algorithm.
- To design the Dashboard with the existing business rules as prior factors to show the efficiency of the proposed model and facilitate the work for the managers

**Price Optimization in Practice**

Pricing has a very vital role in one’s business. There is a need of market to price changes and there should be guidance or a model in order to clear the path of how the price should be changed. Price optimization is concerned with determining the prices which are needed to be on the shelves in the next period of time. Therefore, managers set a lot of strategic pricing constraints (Wildavsky, 2017). Retailers have had access to this kind of data from long ago and the first consideration to optimize the price was managing the inventory (Laudon,2016) during the last 20 years there is a huge growth and desire to use the data for optimization. It is not just among the retailers, but it carries the same weightage for manufacturers and marketers or any position which involves optimizing decisions. In this case price is just a useful vehicle to think (Davis Huckabay and Smith, 2010).Lots of changes have happened in the industry, so a huge growth of price optimization is in practice for both retailers and manufactures. As an example, IBM demanded Tec, DunnhumbyKSS Retailers, Oracle, Pros, SAP, Khi-metrics, VendavoVistoar Technologies and Zillanans are all examples of start-ups and big companies who offer price optimization solutions which in most cases is the result of their studies that are private (Patrick, 2017).

Fletchers annual report in 2012 states that price optimization technology in the future may have a straighter effect on enhancement of revenue and margins than any other kind of introduced CRM Technology. Moreover, the Yankee Group estimated that more than one million dollars is spent on these systems in 2007. Anecdotal reports suggested increases in gross margins in the range of 2to 8%, retailers typically have gross margins of about 25% and have annual revenue off 2.5 trillion. Besides it is suggesting benefits for retailers alone would be between $12.50 b and $50 b annually (Love and Gharavi and Merchant, 2008).Therefore, if the company is working in the margin of 1% and the company is capable to increase the gross margin by 2%, that is huge gain and it can be translated into a reality by understanding the important factors in determining the optimization.

## II. METHOD

This study is about designing a quantitative model. Some part of the data used in the modelis categorical and is used in data mining to evaluate the demographic parts to obtain self-report of relations among them for designing a better campaign. Moreover, the researcher has done some predictive analysis by using the data to forecast the future demands and profits.Proposed Modelling Process for multi-product pricing decision process is shown in Figure 1:

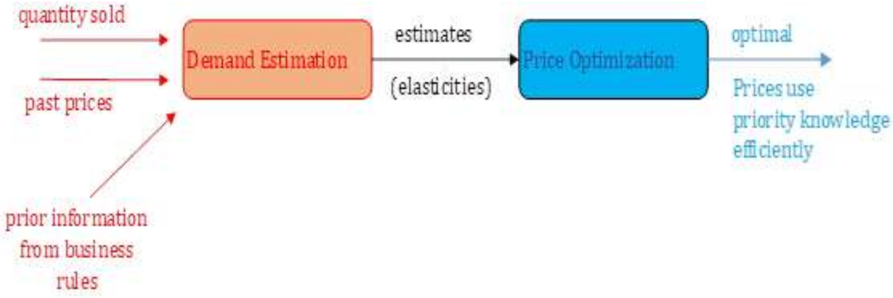



**Figure 1: The Proposed Model**

The population of this study is explained as a major group to whom a study is targeted for the purpose of popularized findings (Ary et al., 2013). The population of the current research is made up from the famous Iranian company which is part of the B2C market in the gold handcrafted industry called ZarsamHonar. Based on the report of ZarsamHonar which is attached in Appendix B the number of customers who are active buyers online and offline are 42000.In this study the process of data preparation and part of the data exploration has done by SAS studio.In this study R programming language is used to design the traditional and new approach model, compute the calculations, developand run the Monte Carlo algorithm in different stages of the study and generating the result in the form of graphs.

Sales data was collected from a company named ZarsamHonar in Iran. There is a registration form in branches as well as online stores. Customers need to fill this form if they want to be part of the loyalty program. Normally about 99% of the customers fill this form. Cashiers need to complete the customer's profile. All the purchases are recorded in the panel since without that cashiers are not able to generate factor for customers. Later admins can generate data from this panel.

## III. RESULTS

***Price versus demand curve***

Figure 2 is the illustration for one branch, and it shows one-year movement quantity and price combination. As it is clear most of the time the price is 149.

**Figure 2: Demand Variation**

Occasionally based on the promotion events it drops down to the other prices. One point which is needed to consider is that how the demand is varying during this one year and how it drops and jumps up during the promotion times. Therefore, it shows clearly people are price sensitive and since there are some variations obviously there is no linear relationship but by transforming this plot to log model then the graph will turn in to a better linear relationship.In order to check how the demand has a variation the average daily demand is summarized as follows:

**Table 2: Average Daily Demand**

| Quarter | Actual_Price | Promotion | Total_Sales | Duration | Daily_Sales |
|---|---|---|---|---|---|
| 1 | 134.1 | 1 | 68 | 7 | 9.7143 |
| 1 | 141.55 | 1 | 102 | 7 | 14.571 |
| 1 | 149 | 0 | 305 | 79 | 3.8608 |
| 2 | 134.1 | 1 | 50 | 7 | 7.1429 |
| 2 | 141.55 | 1 | 90 | 7 | 12.857 |
| 2 | 149 | 0 | 351 | 78 | 4.5 |
| 3 | 126.65 | 1 | 209 | 15 | 13.933 |
| 3 | 149 | 0 | 296 | 76 | 3.8947 |
| 4 | 119.2 | 1 | 208 | 10 | 20.8 |
| 4 | 149 | 0 | 285 | 80 | 3.5625 |

As the table shows the daily demand in the normal days without the promotion is approximately 4 units per a day but during the promotion days the demands even reach to 14 units per a day and it shows the increase in the rate of sales during the promotion. As it is clear at the certain price the quantity sold per a day is different.

***Elasticity***

The law of demand specifies that the relationship between the quantity demand and price is reverse. If the price of good changes, the demand of goods will change as well. The important point is that the amount of variation is not the same in all situations. The variation can be broad or just a nominal. The extent of variation in demand therefore is defined as elasticity of demand. If the phrase elasticity of demand is used without clarification, usually it is referred to price elasticity of demand. This is a broad explanation of the term. The elasticity of demand is a measure of the area of change in demand in response to the change. Economist discuss three important types of elasticity of demand namely price, income, and cross-validity of demand.

- **Different Types Elasticity for price**

Based on the responsiveness of demand to a change in price of a good three types of price elasticity of demand can be defined.

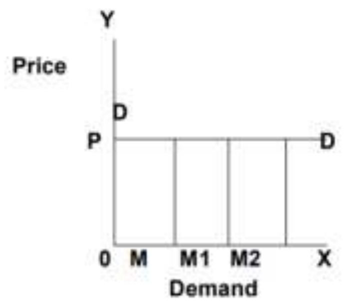



**Figure 3 - Perfectly Elastic Curve**

A: Perfectly Elastic Demand is the endless demand at a certain given price in which perfectly demand is elastic. In this case a small increase in the price will decrease the demand to zero and a small decrease in the price raises the demand to infinity. The scope of demand curves reveals the elasticity of demand. If the demand is perfectly elastic the curve should be a horizontal straight line as follows:

B: Perfectly Inelastic Demand: When the demand for the good has no response to price changes, no matter how much this price is changing still the demand for that special product remains the same. In other words, changing in prices fails to make any changes in demand. The demand curve can be drawn as follows:

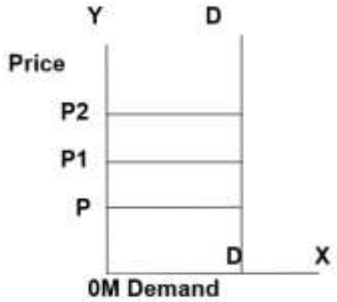



**Figure 4: Perfectly inelastic demand Curve**

C: Unitary Elastic Demand is defined as the portion of change in demand which is absolutely the same as the change in price. In this case the change in price should bring equal change in demand. The demand curve can be drawn as follows:

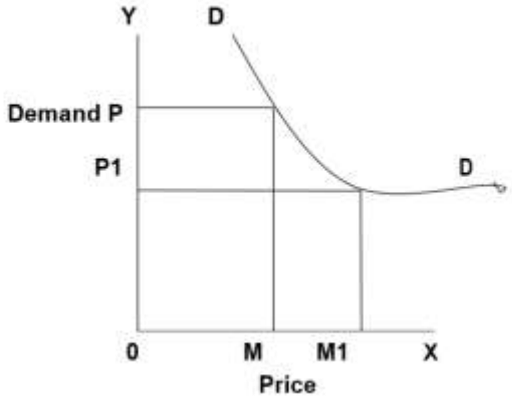



**Figure 5: Unitary Elastic Demand Curve**

**Optimal Product Pricing**

***Traditional model process***

Since the optimal price is equal to elasticity divided by elasticity plus one times the cost, still the lower bound of price is in the elastic area, it proves that all promotion prices are still in the elastic area.

Profits:

$$\Pi = (p-c)\, q$$

Optimal Pricing Rules:

$$P^{*} = \frac{\beta}{\beta+1}\, c$$

Where price elasticity measures demand responsiveness to price changes:

$$\beta = \frac{\%\,\Delta Q}{\Delta P} * \frac{P}{Q} = \frac{\textit{The percentage change in quantity demanded}}{\textit{The percentage change in price}}$$

The optimal price (conditioned upon parameter and the cost (c) :

$$P^{*} = f(\beta) = \frac{\beta}{\beta+1}\, c \quad c \le p^{*} \le \tau$$

Based on the data set the quantity is clear and multiply that times to the mark up price-cost then we can come up with the profit for that product. So implicitly profit is defined by the model as well. Since optimal price is a function of the β so in this the model elasticity is equal as β. In some cases, the elasticities are a function of betas and price of the parameters. In this study researcher got the cost-plus rule so the optimal is equal to beta divided by one plus beta.

If the optimal price is a function of the price elasticity (beta):

$$P^* = \frac{\beta}{\beta+1} c = f(\beta).c, \text{ where } f(\beta) = \frac{\beta}{\beta+1}$$

Then by transforming between optimal price space and price and the price elasticity space using inverse function, the elasticity can be calculated as follows:

$$\beta = f^{-1}\left(\frac{P*}{c}\right) = \frac{P*}{c-P*} \quad \text{where } f^{-1}(x) = \frac{x}{1-x}$$

So, in other words by using the change of variables formula and moving from a probabilistic statement about the optimal pricing space to make a statement about elasticity space or the parameter space so there is one to one relationship in this univariate problem. Using the R programming the calculation for each β has done and the following histogram shows the β for each quarter and based on the β s optimal prices by traditional method are calculated and summarized as follows:

**Table 2 - Summery of Traditional model**

| Quarter | Actual_Price | Promotion | Total_Sales | Duration | Daily_Sales | Price_Elasticity | Traditional_Price |
|---|---|---|---|---|---|---|---|
| 1 | 134.1 | 1 | 68 | 7 | 9.7143 | -5.4231 | 118.75 |
| 1 | 141.55 | 1 | 102 | 7 | 14.571 | -13.966 | 104.32 |
| 1 | 149 | 0 | 305 | 79 | 3.8608 | 0 | 0 |
| 2 | 134.1 | 1 | 50 | 7 | 7.1429 | -3.33 | 138.42 |
| 2 | 141.55 | 1 | 90 | 7 | 12.857 | -12.35 | 105.38 |
| 2 | 149 | 0 | 351 | 78 | 4.5 | 0 | 0 |
| 3 | 126.65 | 1 | 209 | 15 | 13.933 | -4.0827 | 128.27 |
| 3 | 149 | 0 | 296 | 76 | 3.8947 | 0 | 0 |
| 4 | 119.2 | 1 | 208 | 10 | 20.8 | -3.3149 | 138.69 |
| 4 | 149 | 0 | 285 | 80 | 3.5625 | 0 | 0 |

Table (2) summarized the information in the traditional model. As the table shows price elasticity (β) is calculated and generated from the data about daily sales for each campaign. Since the 149 is the price for non-promotion time the researcher excludes them and in the table the elasticity for this price shows as zero. Then based on this 6 s the optimal price for each campaign is calculated and summarized in the table as the traditional prices. As it is mentioned before these prices are far from the managers expectations and they add some business rules and further calculations. Table (2)summarized the managers and decision makers desires under the title of the actual price. By comparing these two columns it is crystal clear that the optimal price and the actual shelf price are far from each other. Therefore, in the traditional model after calculating optimal price, other calculations should be done based on the business rules of the company.As the table shows based on the traditional model the difference between actual prices and optimal prices are 15.35, 37.23, -4.32, 36.17, -1.62, -19.49 respectively. As it is clear this price and the final price which the business rules are executed are so different.

**Calculating the expected profit**

***Demand in Different quarters***

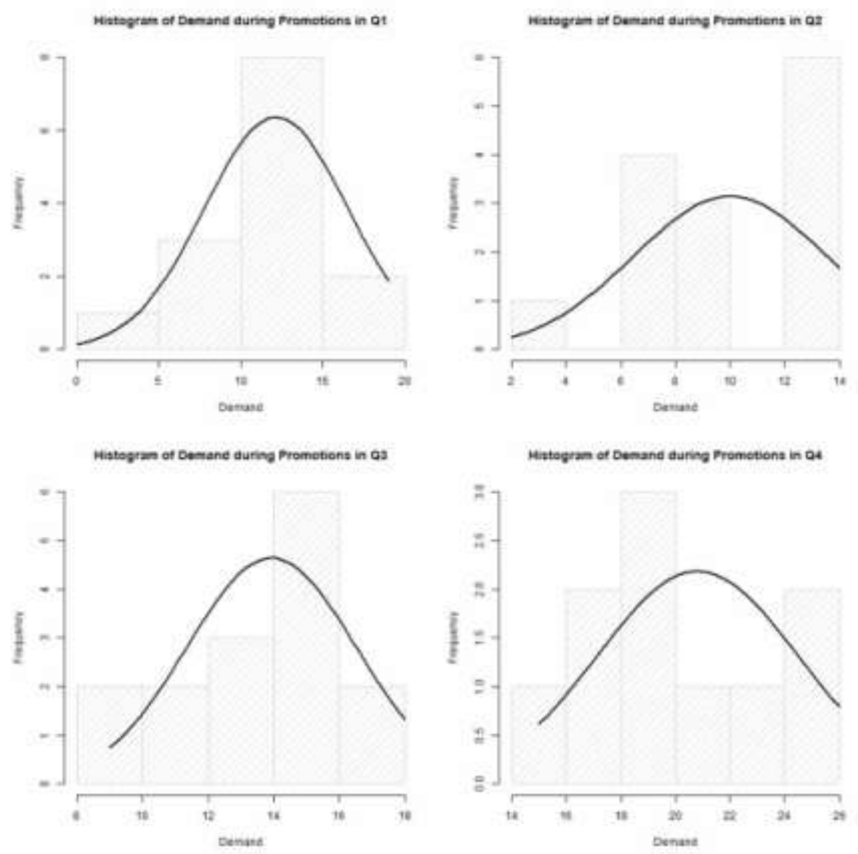



**Figure 6: Demand Distribution per a quarter**

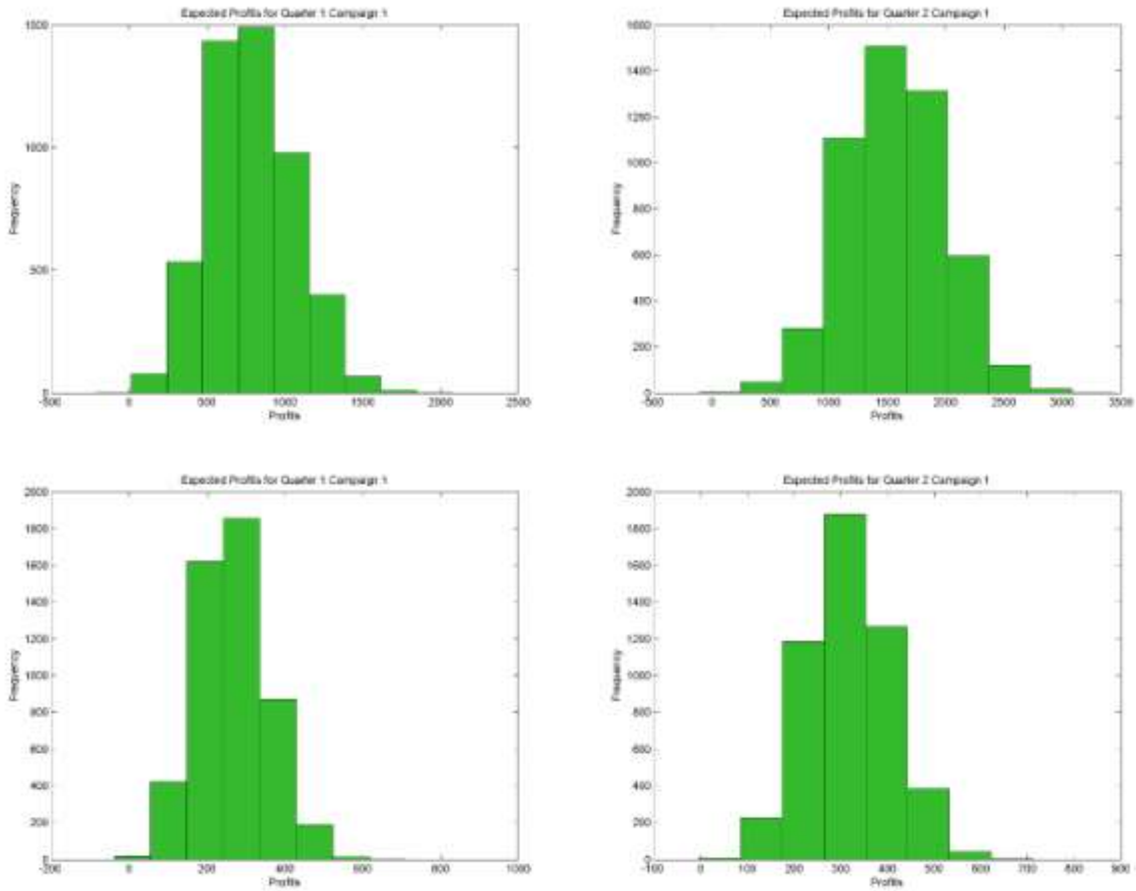
As the histograms of demand per quarter shows that it is also natural.The demand is not normally distributed in most quarters. In the first quarters the histogram shows the highest demand frequency range is peak in the range 10 to 15 while in the second quarter this frequency range is distributed between three different ranges. In quarter three the most frequent range is between 14 and 16 and in quarter four again the range of demand is distributed variably. For finding the best optimal price we ran the Monte Carlo algorithm to return a random sample from the range of sales to see how much the expected profit on certain optimal prices is quarterly. It means that the researcher is going to calculate quarterly expected profit on certain optimal prices because the demand is not the same, and it changes. Monte Carlo is independent of distribution and it is useful since there is no fixed distribution. The researcher creates the data frame including price, quarters and dates. Days are uniquely variable in the sense that the researcher is calculating the demand for those days with promotions so by calculating the profits by Monte Carlo the researcher will find out the expected profit for each quarter.

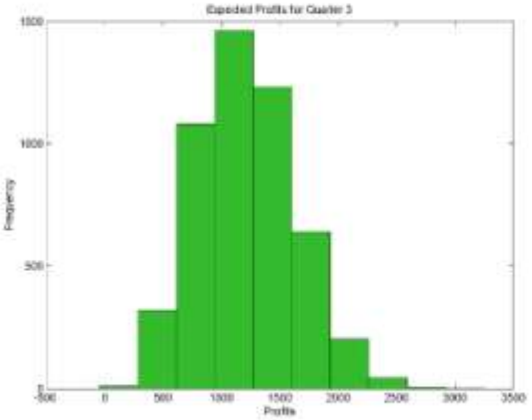
In a Monte Carlo simulation, a random quantity sold is chosen for each of the promotions, based on the range of sales. The expected profitsare calculated based on this random value. The outcome of this simulation is recorded, and the whole process is repeated. A Monte Carlo simulation computes the model thousands of times, each time using values selected randomly. In this study seven random sales for each quarter are chosen to calculate the optimal profit expected for running a week of the campaign.

**Table 3: Suggested price and Expected profit from Monte Carlo Algorithm**

| Quarter | Suggested_Price | Expected_Profit |
|---|---|---|
| 1 | 118.75 | 816.08 |
| 1 | 104.32 | 757.33 |
| 2 | 138.42 | 1485.3 |
| 2 | 105.38 | 757.04 |
| 3 | 128.27 | 1108.2 |
| 4 | 138.69 | 1640.2 |

The outcome of the Monte Carlo simulation for the expected profits is plotted as the histograms by each campaign. The bin with highest frequency corresponds to the expected profit for the particular quarter, particular campaign on the prices determined by the traditional model. The summary of this highest pick is summarized in table 3. As the table revealed the profit based on each campaign for each quarter based is equal to the 1,52.41for quarter one 2242.04 for quarter two,1108.02 for quarter 3 and 1640.02 for quarter 4.





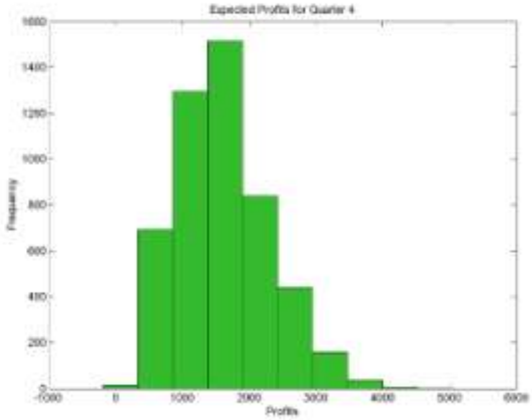




**Figure 7: Expected Profits histograms**

**New Approach process**

In order to use the business rules as a prior information in this step the business rules are defined based on the rules and information that the company provided for the researcher based on their pricing systems. These rules are defined for each quarter based on each campaign as follows:

The manager of the company believes to run six promotional sales for one year.Two promotions run in quarter 1. Same with the promotions run in quarter 2. One promotion should be run in quarter3 and one promotion in quarter 4. The target sales and the discount based on the dataset for each promotion is defined as follows:

- **Promotion 1:** 5% discount the target sales defined as 100
- **Promotion 2:**10% discount the target sales defined as 150
- **Promotion 3:**15% discount the target sales defined as 200
- **Promotion 4:**20% discount the target sales defined as 250

**Rule 1:**The maximum selling price for each campaign is equal to 149 which is equal to actual price and the lower bound is defined as the 10% lower sales in comparison with non-campaign days normal bound because managers believe since they sell luxury items, many customers carry the belief that this luxury item will not be provided with good quality and they are on promotion because of the same reason. Therefore, there is a possibility that the demand decreases. Based on the target sales and the promotions the average daily sales for campaign days and non-campaign days are calculated and summarized as follows (same as the traditional approach):

As people believe when the cost of luxury items goes down the quality is going down too. So, there is an assumption that in this promotion time people buy less because the quality of the product is not good. So, 10%less daily sales are also calculated for the promotion as fixed lower bound which is equal to 107.

**Rule 2:** This rule considers and gives weight to the manager preference price for each campaign which is equal to the shelf price (If we consider that we are going to find the optimal price for the campaign future we should consider this price as the price in the last promotion).

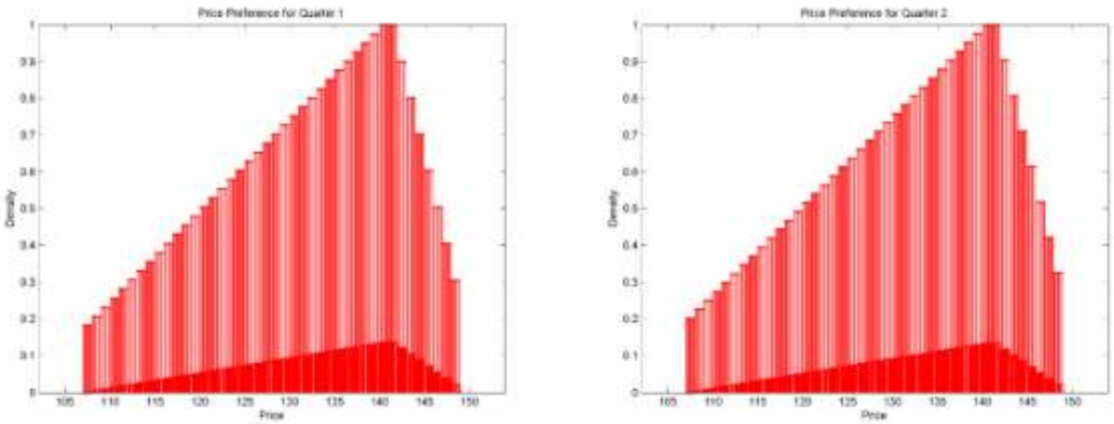
**Rule 3:**For the luxury items the preference is price ends to the even number as it is discussed in the literature review. So, the researcher set rules as the price finishes at 0 and 4 since regarding the literature review the probability of 0,4 is more than the other even numbers for purchasing.

**Table 4 - Average daily sales**

| Quarter | Actual_Price | Promotion | Total_Sales | Duration | Daily_Sales |
|---|---|---|---|---|---|
| 1 | 134.1 | 1 | 68 | 7 | 9.7143 |
| 1 | 141.55 | 1 | 102 | 7 | 14.571 |
| 1 | 149 | 0 | 305 | 79 | 3.8608 |
| 2 | 134.1 | 1 | 50 | 7 | 7.1429 |
| 2 | 141.55 | 1 | 90 | 7 | 12.857 |
| 2 | 149 | 0 | 351 | 78 | 4.5 |
| 3 | 126.65 | 1 | 209 | 15 | 13.933 |
| 3 | 149 | 0 | 296 | 76 | 3.8947 |
| 4 | 119.2 | 1 | 208 | 10 | 20.8 |
| 4 | 149 | 0 | 285 | 80 | 3.5625 |

**Applying Business Rules**

The range of possible optimal prices is generated using the price suggested by the 10% lower than actual sales as minimum, and the non-campaign price as maximum.




All possible price endings for 0, like 120.00, 120.10, 120.20, and price endings at 4, like 120.04, 120.14, 120.24, are generated. The target daily sales for each of these prices is obtained by interpolating the target daily sales computed in above table. The targets for the prices ending at 0 is made six times the target for prices ending at 4 (already discussed in literature review).

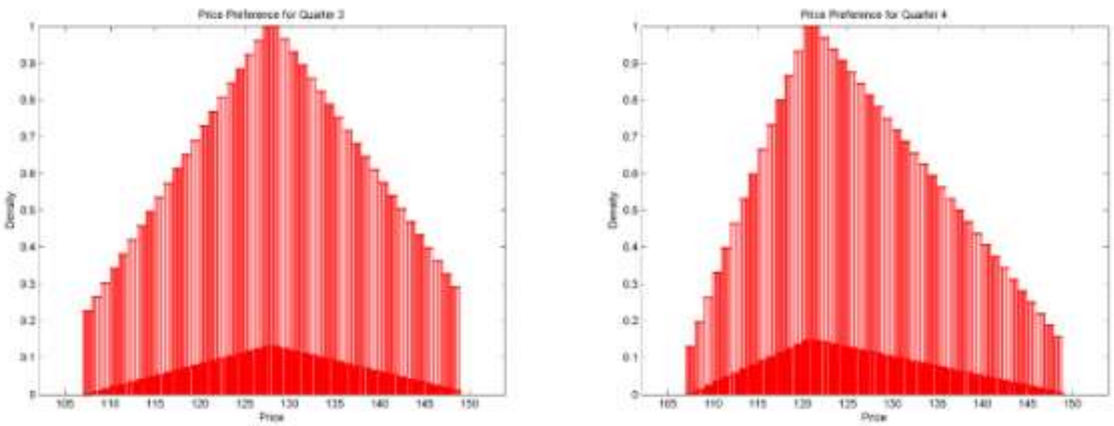



**Figure 8: Normal distribution of business rules for each quarter**

The resulting targets are normalized to range [0, 1] and used as a density function. This function is roughly triangular in nature and converts the three business rules mentioned above into mathematical forms. The conversion of the rules in this format makes it possible to apply them as prior in statistical modelling of optimal prices. The density graph for each quarter is summarized in the figure below:

The table below summarizethe business rules in the model. The first column represents the lower bound which is fixed at least 10% higher than the cost, the second column represents the managerial preference rules, the third column representsthe non-campaign price, the fourth column is a target sale less than 10%, the fifth column is target sales during the campaign and the last column shows the daily sales for non-campaign sales.

**Table 5: Summarized data for Business rules**

DV =

| | | | | | |
|---|---|---|---|---|---|
| 107.0000 | 140.0000 | 149.0000 | 3.7600 | 17.8500 | 4.1800 |
| 107.0000 | 140.0000 | 149.0000 | 4.1500 | 17.8500 | 4.6100 |
| 107.0000 | 127.0000 | 149.0000 | 3.4500 | 13.3300 | 3.8300 |
| 107.0000 | 120.0000 | 149.0000 | 3.7600 | 25.0000 | 3.6500 |

The price in the X axis of the histograms in figure 18 are possible P* in each quarter. For finding the best optimal price we run the Monte Carlo algorithm to return a random sample from the range of P*. The most frequent P* is generated and summarized as plot as follows:

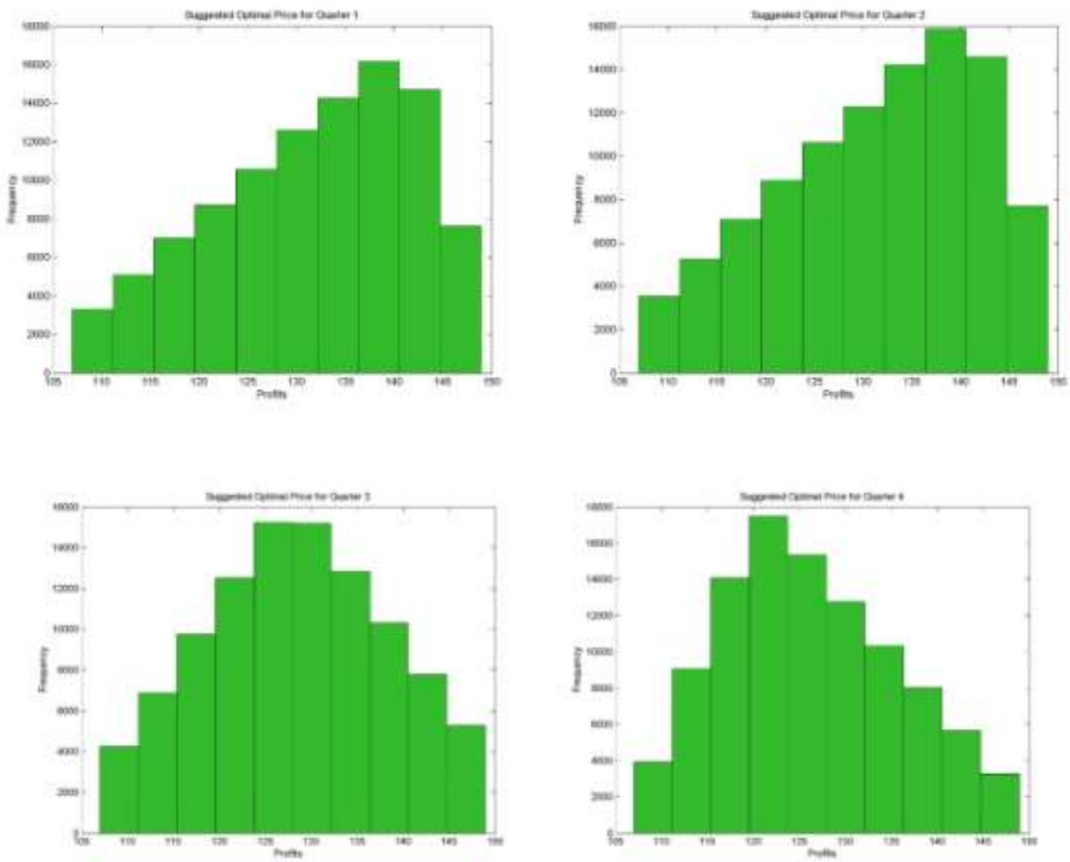


**Figure 9 - Monte Carlo suggested optimal price for each quarter**

Asthe above figure shows since the range of P * is generated from x-axis of normal distribution of business rules for each quarter,the outcome of the Monte Carlo simulation for suggested optimal prices is plotted as the histograms by each quarter. The bin with the highest frequency corresponds to the optimal price for the particular quarter which is based on the table 5 it is equal to 141.50, 141.70, 127.30, and 120.40, for each quarter respectively.

***New profit***

For calculating the profit another Monte Carlo is run. The expected profit is calculated based on this random value. The outcome of this simulation is recorded as follows:

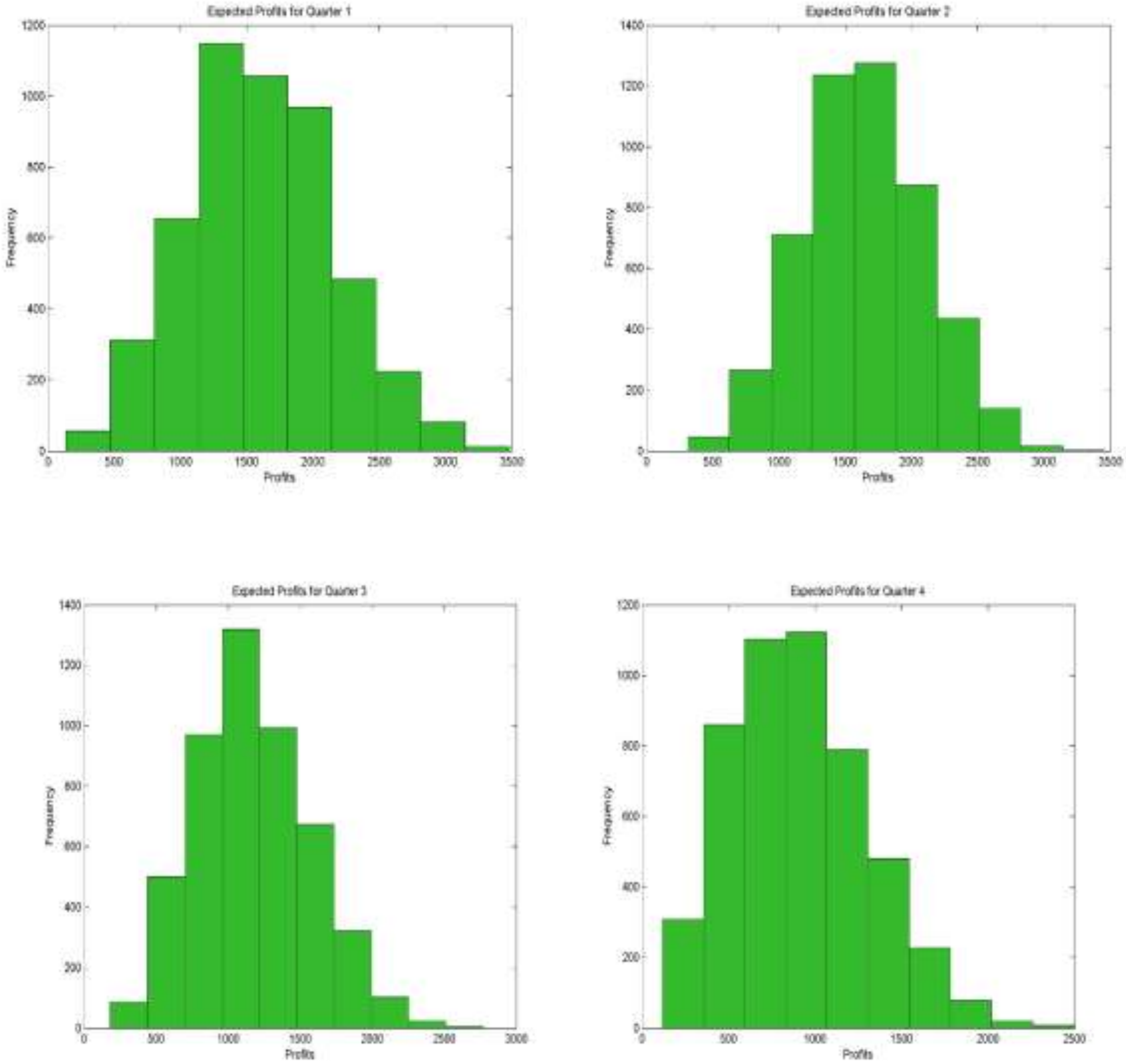



**Figure 10: Expected Profits histograms**

The outcome of the Monte Carlo simulation for expected profits is plotted as the histograms by each campaign. The bin with the highest frequency corresponds to the expected profit for the particular quarter, on the prices determined by the new proposed model. The summary of this highest pick is summarized in Table 6. As the table revealed the profit based on each quarter is equal to the 1611.2 for quarter one 1698.2 for quarter two,1012.1 for quarter 3 and 877.27 for quarter 4.

**Table 6: Suggested price and Expected profit from Monte Carlo Algorithm (new approach)**

| Quarter | Suggested_Price | Expected_Profit |
|---|---|---|
| 1 | 141.5 | 1611.2 |
| 2 | 141.7 | 1698.2 |
| 3 | 127.3 | 1012.1 |
| 4 | 120.4 | 877.27 |

## IV. COMPARISON OF THE RESULTS

The below table summarizes and compares the optimal price for the traditional and proposed model. As it is clear proposed model report closer accuracy than traditional approach towards the manager's belief and business rules.

**Table 7: Traditional optimal price via new approach optimal price**

| Quarter | Actual Price | Traditional | proposed model |
|---|---|---|---|
| Q1 | 141.55 | 104.32 | 141.50 |
| Q2 | 141.55 | 105.38 | 141.70 |
| Q3 | 126.65 | 128.27 | 127.30 |
| Q4 | 119.20 | 138.69 | 120.40 |

As the table 7 shows the difference between the new approach and actual price is so low in quarter one it is just 5 cents, in quarter two it is 15 cents and in quarter three is 35 cents and in quarter four it is one Toman and 20 cents.

## V. DISCUSSION AND CONCLUSION

The empirical worksin this research reveals that real customers are not targeted properly. Although the company reaches their annual target sales, but they were not successful in terms of targeting the real customers. By applying data mining and visualization managers are not only able to target real customers but also, they can plan their campaign in a more proper way since one of the most important features of price optimization is using data analytical techniques derived from management science.Besides, it is observed that the proposed model is more accurate and close to the managerial preferences. It means by applying this model managers and staff will spend less time regarding to the optimal price selection and calculation. At the same time, they can be assured the job is done with more accuracy and more systematic ways.

Finally, since business rules and managerial decisions matter a lot they can be used to impact the parameter estimates which influence the prices and profitability. Instead of taking business rules and using them as ad hoc, the new model developed in this study tries to put them up front as a prior information. Managers can budget their campaign well with less cost and more profits in advance by having more accurate models which are closer to the real rules and regulations of the market.Consequently, this will lead to the better profit optimization as well.

## REFERENCES


1. Davis, S.M., Huckabay, G.L. and Smith, J.S., REVIONICS Inc, 2010. Market-based price optimization system. U.S. Patent 7,853,473.
2. DegliEsposti, S., 2014. When big data meets dataveillance: The hidden side of analytics. Surveillance & Society, 12(2), p.209.

3. Hilton, R.W. and Platt, D.E., 2013. Managerial accounting: creating value in a dynamic business environment. McGraw-Hill Education.
4. Horngren, C.T., Foster, G., Datar, S.M., Rajan, M., Ittner, C. and Baldwin, A.A., 2010. Cost accounting: A managerial emphasis. Issues in Accounting Education, 25(4), pp.789-790.
5. Love, D.E.P., Gharavi, H. and Merchant, V., 2008. CRM technology and bulding material suppliers. In European and mediterranean conference on information systems.
6. McAfee, A., Brynjolfsson, E., Davenport, T.H., Patil, D.J. and Barton, D., 2012. Big data: the management revolution. Harvard business review, 90(10), pp.60-68.
7. Oladepo, O.I. and Abimbola, O.S., 2015. The influence of brand image and promotional mix on consumer buying decision-a study of beverage consumers in Lagos State, Nigeria. British journal of marketing studies, 3(4), pp.97-109.
8. Patrick Schneidau, 2017. TOP 8 MYTHS OF Price OPTiMizaTiOn. Pros Education United states.
9. Phillips, R.L., 2005. Pricing and revenue optimization. Stanford University Press.
10. Shiller, B.R., 2014. First-degree price discrimination using big data. Available at from Ben Shiller's hompage at http://benjaminshiller. com/images/First_Degree_PD_Using_ Big_Data_Apr_8, _2014. pdf.
11. Taylor, L.D. and Houthakker, H.S., 2009. Consumer demand in the United States: Prices, income, and consumption behavior. Springer Science & Business Media.
12. Wildavsky, A., 2017. Speaking truth to power: Art and craft of policy analysis. Routledge.