Towards Dynamic Pricing for Digital Billboard Advertising Network in Smart Cities

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Abstract. The emergence of technologies and the availability and accessibility of information through open data source has a big impact on companies' management strategies. Some companies make changes to be adaptable to the smart world. Dynamic pricing, reflective of available market information, as opposed to static pricing is a strategy towards the changing environment. This study shows a proof of concept on how a self-organizing dynamic pricing system may optimize a company's long-term revenue in this smart era. The system is designed for a digital billboard provider considering fluctuations in market demand and based on data extracted from available sources.

Keywords: Digital Billboard, Dynamic Pricing, Smart Cities, Revenue Management, Big Data

I.INTRODUCTION

Local digital billboard operators, currently have access only to the local advertising budgets and they cannot participate in the bidding for national advertising campaigns where the advertising agencies are looking for national coverage. These coverage are only offered by the "big three" players (CBS, Clear Channel, Lamar) in the market. A startup company is developing a business model for infrastructure development and management with the goal of creating an optimum working platform, which consolidates multiple LED outdoor billboards under one umbrella. Their goal is to build a model, which is similar to what Expedia provides to the hotel business. The new system should also be adaptive to the fluctuations in the market demand.

In the new era of dynamic and continuous change in technologies and information, organizations should continuously assess their process to ensure the quality of their performances. They require consistent evaluation of their routines and decision-making processes, as well as their underlying assumptions to keep pace with the Smarter business environment [8]. One organizational routine that greatly affects company's outcome is pricing strategies. Therefore, companies shift from static pricing to dynamic pricing in order to adapt to the current dynamic business environment.

The biggest challenge for the company in our case study is to design a dynamic system that assigns user requests to specific billboard spots and optimizes the network's revenue in a self-organizing manner. This system had to be able to maximize the revenue for billboard providers by optimizing the offered price for each advertisement slot. This optimization had to be in a way that increases the demand and fills as much of their capacity as possible. The system should also be adaptable to the changes in demand according to seasonal fluctuations. Hence, it should iteratively receive current demand, adjust price, influence demand, readjust price (if necessary) and fill as much capacity as possible.

The current business follows a static pricing strategy that is only dependent on the general location of the billboard (market) and is not reflective of other characteristics such as date, time, capacity, size of the billboard, impressions, etc. Moreover, one of the main determinants of revenue in companies -especially small to medium sized companies- is market demand. In the current digital billboard industry market demand is not considered as a factor that influences offered price.

This work is the preliminary step to investigate how this industry may benefit from available information. We proposed a dynamic pricing model that provides an adjusted price, which is reflective of the characteristics of the billboard and characteristics of the advertisement slot. This is along with the consideration of market demand according to the historical data. This model may be modified to include other factors that would affect either the demand or market price. These factors may include but are not limited to traffic information and whether information that would affect the slot's price as well as social media information, which could be reflective of consumers' characteristics affecting their demand trend. The main research question that we aim to address is:

RQ- How billboard companies may benefit from dynamic pricing according to fluctuations in customers' demand?

To address this question we built a model according to available data. This model is flexible and may benefit from any additional information. The model was tested through a simulation of randomly generated demands using real life data.

The structure of this paper is as follows: section 2 describes related works including dynamic pricing strategy and its applications. In section 3 the design of the model will be described, which includes the description of the data as well as model variables. In Section 4 discussion of the results is provided and section 5 describes the threats to the validity of our study. Section 6 wraps up the study by providing conclusion and future direction.

II.RELATED WORK

Revenue management is the application of disciplined analytics that optimizes product availability and price to maximize revenue growth. The primary aim of revenue management is selling the product to the right customer at the right time for the right price. In order to maximize revenue, dynamic price is suggested. Price is one of the main marketing factors that generates cash and determines a company's survival [10]. Dynamic pricing, also called real-time pricing, is an approach to setting the cost for a product or service that is flexible.

Businesses are able to stay competitive by changing prices based on algorithms that consider competitor pricing, supply and demand, and other external factors. Dynamic pricing is a common practice in several industries such as hospitality, travel, entertainment, retail and advertising. Each industry takes a slightly different approach to repricing based on its needs and the demand for the specific product.

In business practice, varying prices is often the most natural mechanism for revenue management. In most retail and industrial trades, firms use various forms of dynamic pricing, including personalized pricing, markdowns, display and trade promotions, coupons, discounts, clearance sales, and auctions and price negotiations, to respond to market fluctuations and uncertainty in demand. Firms and individuals have always resorted to price adjustments in an effort to sell their goods at a price that is as high as possible yet acceptable to customers. However, the last decade has witnessed an increased application of scientific methods and software systems for dynamic pricing, both in the estimation of demand functions and the optimization of pricing decisions (for details, see [13]).

In terms of applications, dynamic pricing practices are particularly useful for those industries having high start-up costs, perishable capacity, short selling horizons, and a demand that is price sensitive. The use of revenue management techniques in applications is pioneered by the airline industry in terms of capacity and seat control [14]. Later on it has spread out to other industries such as car rental agencies [15], retailers [16] and hotels [17].

A new pricing policy has been introduced in [18] for perishable products where the price is selected from a predetermined set of discrete prices. The question of how a retailer should dynamically adjust the price of a perishable product as the time at which the product will perish approaches. Moreover, the demand of the product is modeled by a random variable with a Poisson distribution.

III. THE DESIGN OF THE STUDY

In this study, we introduce a new dynamic pricing approach for digital billboard industry. With this approach a reference price is refined using control variables as multipliers. Our model is inspired by Bayoumi et al. [19]'s that used the same approach for revenue management in hotel industry. The final price is given as the product of the reference price and the multipliers. Each 'price multiplier' provides a varying discount/premium over some regional reference price.

These multipliers are optimized with the goal of maximizing the revenue of the whole network. The proposed model utilizes a Monte Carlo experiment to simulate the process. Monte Carlo experiment is a computational algorithm that relies on repeated random sampling to obtain numerical results [20].

To simplify the problem formulation, these multipliers are taken as linear or piecewise linear functions of the influencing variables, whose levels and slopes are determined according to the other variables. The piecewise linear functions are selected based on logically expected relations identified by the industry experts. In addition to these multiplier-specific constraints, we defined a global constraint for the overall price correction (the product of all multipliers). This product should not exceed a certain percentage, defined by industry expert, for example 40%. This means that the price of the proposed solution has to be within plus and minus 40 percent of the reference price of the network. The rationale for this constraint is to ensure that the proposed price does not deviate a lot from the reference price of the network.

We tested the proposed approach in a real life case study. We conducted this study as the proof of concept for our proposed dynamic pricing strategy in digital billboard industry. The result provides valuable insights for practitioners and decision makers in this industry.

IV.METHODOLOGY

As stated, the proposed approach was dynamic pricing for revenue management using 'price multipliers' that provide a varying discount/premium over some reference price, collected in our data gathering phase. Equation (1) shows overview of the dynamic pricing approach, in which RP is the reference price, M_i is the multipliers and DP is the dynamic price.

$$RP. \prod M_i = DP \tag{1}$$

The selected control variables are Impressions, Size of the Billboard, Appearance time of the slot (whether it is Day or night, Rush hours, weekend or weekdays), Seasonal impact (high season, low season or special events), Time from reservation until the appearance of the slot, remaining capacity of network, number of slots reserved at the same time by the same request (group size). Each of these influencing variables are set as price multipliers that were defined to adjust the price either through a discount or a premium.

To simplify the problem formulation, these multipliers were taken as linear or piecewise linear functions of the influencing variables. In addition to these multiplier-specific constraints, we defined a global constraint for the overall price correction (the product of all multipliers). The result should not exceed a certain percentage, which is set to be 40% according to industry expert's advice.

As an example for the change in different multipliers according to the change of control variable, Figure1 presents the time multiplier trend according to the change in time from reservation till the slot appearance.

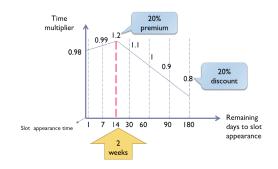


Figure 1. Time multiplier according to time from reservation until slot appearance

To test our proposed model we conducted a simulation that receives business experts' inputs at the calibration phase and automatically calculates an optimal price for each time slot on each billboard available in the network. This adjusted price is set in a way to generate maximum long run revenue. Demand should also be considered as one of the main indicators of price. Therefore, all variables used as multipliers are set depending on the current demand.

To compare the performance of our model we first calculated the current network's revenue with probabilistic demand through simulation and we calculated the long run average of the revenue for the current situation (static pricing method). To perform the simulation we used MATLAB software and we tested the system for 3000 iterations with different probabilistic demand. For the adjusted price we defined the range for price multipliers according to industry experts' advice. We selected these ranges according to the probabilistic demand in order to optimize the long run revenue.

DATA

The data was collected from one of the big three billboard advertising companies, Lamar website¹. The selected markets for data collection was between Nashville and Atlanta markets including: Nashville, Atlanta, Anniston, Athens, Calhoun,

¹ http://www.lamar.com/

Macon, McMinnville, and between Nashville and Atlanta markets.

The total number of billboards in the area was 85 and the information collected was the Panel number, Tab ID, Location, Latitude/Longitude, Media Style, Impressions, Price, Total number of advertising spots available on digitals, Available spots per day, and Total market population over 18 years old. We only focused on digital bulletin and digital poster billboards that was the main focus of our study.

An exploratory data analysis was conducted. The main finding of this analysis was that currently prices of each slot in each billboard is only dependent on the market location of the billboard and other factors do not have any impact on the price. For instance, there is no difference between the price of a small billboard and a large one as long as they are in the same market area. This observation supports our aim in designing a dynamic pricing strategy that is dependent on the factors that affects the value of each slot in each billboard. One of these factors is impression.

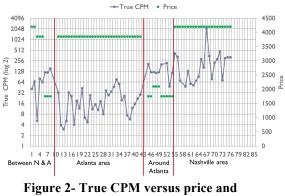
Cost per impression (CPM) is a term used in advertising and marketing related to traffic. It refers to the cost of marketing or advertising campaigns where advertisers pay each time an ad is seen. Specifically, it is the cost or expense incurred for marketing potential customers who view the advertisement(s). CPM defines the cost an advertiser pays for 1,000 impressions of an advertisement. Publishers use the CPM to measure the revenue per 1,000 impressions. Lower CPM is more desirable for the advertisers and higher CPM is more desirable for the publishers:

$$CPM = (cost / impressions) \times 1000$$
(2)

True
$$CPM = CPM \times$$
 the number of advertisers (3)

Figure 2 provides a graphical view of the relation of price versus true CPM in the dataset. As it can be seen in this graph, although Nashville market has the highest price but it also has the highest CPM the means they are less desirable.

However, this basic strategy used in other advertising domains is not implemented in digital billboard industries. In fact, our exploratory analysis shows that the impression, although available, is not taken into account for setting the price of the billboard. It is only available as side information for customers. Hence, one of the main multiplier considered is impression.



impressions

The size of the billboard is also another factor that might have an effect on the value of the advertisement and currently is not taken into account for the price setting. Other factors that should be considered in pricing of each slot, as validated by an industry expert, are listed and explained as control factors in the next section. This factors are mainly selected as they not only affects the value of the slot but also have an effect on the market demand.

V. RESULT AND DISCUSSION

The results show that long run daily revenue for the reference network with the same demand distribution after 3000 experiments will be approximately 20% less than that of the proposed model. This shows that price adjustment has a great impact on long run revenue of the network given the same distribution of demand. The comparison of the daily revenue range for the reference network and dynamic price is presented in Figure 3.

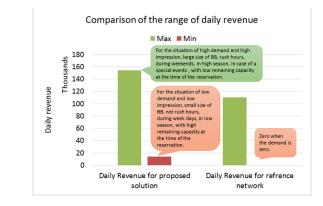


Figure 3- Comparison of the daily revenue range for the reference network and proposed solution

To better illustrate the difference between the use of static and dynamic pricing in the network, Figure 4 and 5 show the distribution of price for the reference network model and proposed network model respectively.

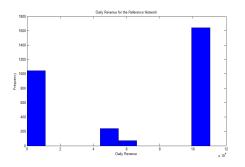


Figure 4- Distribution of daily revenue in 3000 experiments for the reference network

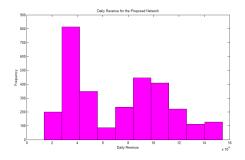


Figure 5- Distribution of daily revenue in 3000 experiments for the proposed solution

As illustrated, the reference network only offers limited range of pricing. This is not reflective of the characteristics of the billboard and it does not change according to the demand. Whereas, the distribution of pricing using dynamic pricing suggested by our proposed model provides a wide range of price options. These price options are adjusted according to market demand.

The result of the analysis shows significant increase in long run revenue and suggests that the model may be used and modified further to include other factors and therefore it increases the revenue of the network even further.

VI. THREATS TO VALIDITY

Threats to validity of this research include external, internal, construct, and statistical threats:

External validity: This study was performed on a publicly available datasets that might not be good

representatives of the whole population. Also, we considered the demand to follow a Poisson distribution. This may not be the case in real situations.

Internal validity: our analysis was an evaluation and comparison of long run revenue for a company. The measure we chose was the common calculation of revenue, which is the product of demand and price. Hence, this type of threat is minimal in this study.

Construct validity: The procedures in this study were well defined and thus this validity is fulfilled.

Statistical validity: we followed Monte Carlo experiment. It is a computational algorithm that relies on repeated random sampling to obtain numerical results. This method is mainly used in problem classes such as optimization. Also, it is able to generate numbers from any probability distribution. Moreover, it can be run many times to obtain the distribution of the unknown probabilistic entity. Therefore, it was appropriate to use it in our case [20].

VII. CONCLUSION AND FUTURE DIRECTION

The availability and accessibility of information have significant impact on companies' management strategies. The decision on how to benefit from available information may vary from industry to industry and company to company. Thus, managers and decision makers may take advantage of the huge available data to become successful in business competitions in this smart era.

Changes in the nature and amount of information available provide opportunities for innovative revenue management strategies. Pricing, as one of the main factors of marketing strategies, may significantly influence companies' annual revenue. Decision makers may select different pricing strategies to increase their marginal profit and manage their firm's annual revenue.

This study shows a proof of concept that shifting from static pricing to dynamic pricing strategy may significantly improve total annual revenue of digital billboard companies. The study was performed for a startup company in digital billboard industry with the new business plan to merge digital outdoor billboards and manage the whole network systematically. The new business plan provided valuable information that was not available in the traditional market. Our proposed solution for their revenue management system is to use this information as the input for their pricing strategy. The available information is mainly regarding the demand and the characteristics of the billboards as well as their advertisement slots.

The result of our analysis shows that by switching to dynamic pricing strategy instead of static pricing, company's annual revenue increases significantly. This new strategy not only increases their short-term profit but it may also be used as their competitive advantage. They would be offering competitive prices to their customers as they use real time information and they make price adjustment decisions in a real time manner. Since the price is adjusted due to the fluctuations in demand they would also have a higher chance to use their full capacity in order to increase their long term revenue.

In our future work, we would like to test our proposed pricing strategy with real historical demand data collected by the same billboard company. We also would like to add more information that may be gathered through traffic, whether and social media websites. These extra information may be easily added to our general model to adjust price even further.

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REFERENCES

- Beath, C., Becerra-Fernandez, I., Ross, J., Short, J.: Finding value in the information explosion. MIT Sloan Management Review, 53(4), 18. (2014)
- [2] Manyika, J., Chui, M., Brown, B., Bughin, J., Dobbs, R., Roxburgh, C., Byers, A. H.: Big data: The next frontier for innovation, competition, and productivity, (2011)
- [3] Schmidt, R., Möhring, M., Maier, S., Pietsch, J., Härting, R. C.: Big Data as Strategic Enabler-Insights from Central European Enterprises. In Business Information Systems, 50-60. Springer International Publishing. (2014)

- [4] The 5 V's of Big Data, http://www.ats.avnet.com/na/enus/news/Pages/The-5-Vs-of-Big-Data.aspx
- [5] Malhotra, Y. Knowledge Management and New Organization Forms: A Framework for Business Model Innovation Information Resources Management Journal, 13(1), 5-14. (2000)
- [6] Hirt, M., Willmott, P.: Strategic principles for competing in the digital age. McKinsey Quarterly, 1-13. (2014)
- [7] Lykova, A., Atras, A., Atras, A., Lykova, A.: Driving the markets in the 21st century: how to enhance proactive market. Management, 22, 464-482. 2013
- [8] Malhotra, Y.: Knowledge Management and New Organization Forms: A Framework for Business Model Innovation Information Resources Management Journal, 13(1), 5-14. (2000).
- [9] Brown, B., Chui, M., Manyika, J.: Are you ready for the era of 'big data'. McKinsey Quarterly, 4, 24-35. (2011).
- [10] Yaprak, Attila, Solberg, C. A.: "Developing a Framework for International Price Setting from a Contingency Perspective." In EMAC Annual Conference: Marketing in a Changing World. (2001).
- [11] Kung, D. S., Lin, F., Dyck, H.: Information Technology Strategy Incorporating Dynamic Pricing in the Business Model of the Future. In Ubiquitous Information Technologies and Applications, 897-903. Springer Netherlands. (2013)
- [12] Han, Y. H., Park, D. S., Jia, W., Yeo, S. S. Ubiquitous Information Technologies and Applications: CUTE 2012, 214. Springer. (2012)
- [13] Talluri, K.T., Van Ryzin, G.: The Theory and Practice of Revenue Management. Springer Verlag (2005)
- [14] Rothstein, M.: An Airline Overbooking Model. Transp. Sci. 5, 180–192 (1971)
- [15] Carol, W.J., Grimes, R.C.: Evolutionary Change in Product Management: Experiences in the Car Rental Industry. Interfaces. 25, 84--104 (1995)
- [16] Bitran, G., Mondschein, S.: Periodic Pricing of Seasonal Product in Retailing. Manage. Sci. 43, 42--443 (1997)
- [17] Bitran, G., Gilbert, S.M.: Managing Hotel Reservations with Uncertain Arrivals. Oper. Res. 44, 35--49 (1996)
- [18] Chatwin, R.E.: Optimal Dynamic Pricing of Perishable Products with Stochastic Demand and a Finite Set of Prices. Euro. Jour. of Oper. Res. 125, 149--174 (2000)
- [19] Bayoumi, A.E., Saleh, M., Atiya, A., Aziz, H.A.: Dynamic Pricing for Hotel Revenue Management Using Price Multipliers. Jour. of Revenue and Pricing Manage.12, 271--285 (2013)
- [20] Rubinstein, R.Y., Kroese, D.P: Simulation and the Monte Carlo Method.Willey.Second Edition. (2007)
- [21] Xiuli, H., Prasad, A., Sethi, S.P.:Cooperative Advertising and Pricing in a Dynamic Stochastic Supply Chain: feedback Stakelberg Strategies. Production and Operation Management. 18.1, 78-94 (2009)