Abstract—Tidal TV is an online video advertising, optimization, and yield management solutions provider. Their current business strategy includes purchasing online video advertising inventory from content providers and delivering ads to their clients, using demographic targeting to maximize value. The problem is to develop, test, and simulate the best bidding strategies for both second price and first price auctions and then to identify the tradeoffs of using the optimized strategies over current existing strategies. Tidal TV will then incorporate learning from this exercise to further develop strategies to bid for online video ads.

I. MOTIVATION

This paper presents a methodology for Tidal TV to provide optimized online video advertisements. The research described in this paper overviews current auction strategies and then reviews proposed algorithms that were developed, tested, and evaluated. We present general concepts to give the reader a broad understanding of the approaches proposed.

A. Online Video Advertisement Market Background

The online advertising market is expanding rapidly. Looking at Fig. 1, online ad revenue grew from $6 billion in 2002 to $22 billion in 2009 [1]. One of the fastest growing sectors within online advertising is online video (OLV), which grew 38% in 2009 [1]. As the marketplace is neither well established nor well regulated, fast growth forces participating companies to adapt quickly to rapidly shifting marketplace conditions.

Fig. 1. Online Video Revenue chart. Taken from IAB [1].

At the same time, online video advertisements still maintain a relatively small portion of Internet advertising revenues. According to Fig. 2, digital video accounts for approximately 4 percent of overall Internet advertising. Search ads, on the other hand, currently account for the largest amount of Internet advertising revenue with 47 percent of all Internet advertising revenue.

Fig. 2. Internet advertising breakdown from IAB [1].

B. Client Background

Tidal TV is a third party video advertisement intermediary that utilizes demographic information to target ads on behalf of their clients. Targeted advertisements viewed by a user are more valuable to the advertiser, since the user viewing the ad is more likely to purchase the product or service in the future. According to [2], approximately 80 percent of online...
video advertisers use demographic information to target their ads. Fig. 3 on the following page depicts the major stakeholders in the Internet Online Video advertisement market. The video advertisements slots, or impressions, are bought from publishers and sold to advertisers. In this context, publishers are websites that provide video content to viewers (e.g. Hulu). There are two ways these ads can be purchased by Tidal TV. The first is the traditional upfront purchases, in which Tidal TV negotiates a flat price rate with a publisher for a set number of video advertisement slots. The second is real-time bidding, in which the slots are bid on the instant a viewer begins watching a video. Along with Tidal TV, the competing bidders are other video ad networks. For this project, we worked solely with real-time bidding strategies.

Tidal TV must utilize real-time spot market video advertisement exchanges to fill approximately 10-20% of its inventory. Currently, existing video ad networks only have primitive bidding strategies in the spot market (i.e. 70% of revenue from showing the ad). An efficient bidding strategy will allow Tidal TV to minimize costs and dominate the online video exchanges.

These exchanges use either a second-price or first-price auction format, requiring different bidding strategies. It is important to note that the objects being auctioned are very similar, but each bidder has a different valuation of the impression and that there are an extremely large number of these auctions occurring. In fact, there are about 3 million auctions occurring everyday currently, and that number is expected to increase drastically over the next couple of months.

In most cases, the second-price auction is best described as a Vickrey Auction [3]. Second-price auctions allow for information about competitors to be gathered. Winners of second price auctions know not only their bid price but also the second highest bidder’s price (payout). Second-price bidding strategies are often more dynamic and robust given the extra payout information gathered.

First-price auctions are best described as a first-price sealed-bid auction [4]. First-price auctions are similar to English auctions where the highest bidder pays the bid price for the item with the exception that the bidder can only submit one bid. Therefore, there is a significant lack of information obtained by bidders in first-price auctions.

Online video advertisements are not the only Internet related advertisement where there are “multiple bidders with limited budgets... [where] advertisers attempt to optimize their utility by equalizing their return-on-investment” [5]. Online keyword advertising auctions are similar to those occurring in the online video advertisement market.

Due to financial and technical limitations, Tidal TV could not immediately implement, deploy, and test the bidding strategies in the online video ad exchanges. Consequently, we constructed a working simulation that followed the current market to allow us to deploy and test the bidding strategies developed.

II. ALGORITHMS RESEARCH

Understanding that there are different auction types, similar objects auctions off, different valuations by the bidders on the same object, and many auctions per day, we were able to analyze and compare similar auctions to develop innovative and dynamic strategies.

A. First Price Algorithms

Algorithms for first-place auctions are often more difficult to devise because first-price auctions bring about the “Winner’s curse”. The winner’s curse can be described as the winner bidding significantly more than the second highest bidder and, in turn, overpaying. Therefore, if we are able to predict the second highest bidder’s bid price, we will be able to determine exactly what to bid in order to win the first price auction without suffering the winner’s curse. This will lead to a reduced cost to Tidal TV while allowing the purchase of all the impressions needed.

Reference [6] illustrated an algorithm used in electricity auctions in California. The auctions are similar in format to the first-price auctions where market participants would bid on supply for an hour and day ahead of time. Essentially, the algorithm adds a margin to the cost of the product. For example, if a block of electricity cost $75, then the margin algorithm would add a certain margin depending on the amount of time remaining and the number of bidders currently participating. The algorithm appeared to be successful and provided valuable insight allowing for better developed algorithms.

Another algorithm considered came from [7]. This algorithm utilizes two theories presented in the paper to help mitigate challenges presented by the lack of information available in first price algorithms. The first is directional learning. Directional learning holds that in sequential first price auctions, a bidder should adjust the price up if the bid is unsuccessful, and should adjust the price down if the bid is unsuccessful. This is because an unsuccessful bid implies that the bidder did not bid a high enough value, while a successful bid means that the bidder paid too much. As a standalone theory, directional learning is not sufficient to produce a robust algorithm. However, directional learning can be combined with impulse balancing to produce an acceptable algorithm. Impulse balancing mitigates many of the issues with directional learning by adding a parameter to
the size of the jumps in each direction. This parameter is equal to the odds of the frequency needed to fulfill a sufficient number of impressions. The result of applying impulse balancing is that the net effect of the balanced jumps will keep the bid near the market price, with the correct proportion of bids won.

Finally, the last algorithm came from [8]. The algorithms in this paper identify a successful strategy in first price auctions where there many asymmetric bidders. Reference [8] proved that there was Bayesian equilibrium and that two bidders have the same equilibrium strategy if their valuations are the same.

B. Second Price Algorithms

Second-price auction strategies were much easier to develop dynamic algorithms. The main reason for this is that the winning bidder obtains more information. For example, the winning bidder obtains the second highest bid in the form of the price paid. There is an imbalance of information since the winner of the auction knows more information than competing bidders. Therefore, algorithms were much easier to develop for second-price strategies.

An algorithm first examined came from [9]. This paper examines multiple adaptive agent algorithms and determines that AA agents perform the best against other adaptive agent algorithms including ZI-C, ZIP, and GD. AA agents determine the percentage of bids won out of all bids and uses that percentage to then formulate an eagerness for its next bid [9]. ZIC traders are zero intelligence bidders which submit random bids constrained by budget constraints [10]. ZIP algorithms are simple agents that make stochastic bids [11]. Lastly, in GD algorithms, sellers believe that an offer will be accepted and buyers believe that their offer will be accepted. As a result, traders attempt to maximize their surplus. This leads to competitive equilibrium and market efficiency [12].

Optimal bidding strategies can also be found in numerous places. Reference [13] shows similar auction strategies to the online video advertisement market. The best strategies to evaluate were identified as sequential Vickrey auctions. Additional strategies were obtained from [14]. [14] outlines the optimal bidding strategies for simultaneous Vickrey auctions with perfect substitutes. As previously stated, the video ad slot auctions are sequential and are near substitutes of each other. Therefore, the strategies mentioned are ideal for the auctions of the online video advertisement market.

A final algorithm considered was developed by Zhang at MIT [15]. Zhang attempts to find “Edgeworth Cycles” in online advertising auctions. Fig. 4 shows the bidding history of bid prices over the first 100 observed bids. The figure shows that the bid prices tend to rise until they reach a certain point, in the figure around 0.6, and drop down again to 0.45. In the online video ad market, we could identify when the high points are reached, then capitalize on the low prices afterward. The curve itself appears to rise exponentially and then drop dramatically to the floor repeatedly in a cyclic fashion.

![Bidding History (First 100 Bids)](image)

Fig. 4. Edgeworth cycles identified in Internet advertising according to Zhang [15].

C. Simulation

We attempted to model and simulate the video advertisement auctions. From the literature, Bunn and Oliveira developed an agent-based simulation to simulate the electricity trading arrangements in England and Wales [16]. Agent based simulation was considered early, but later, we decided that other simulation models would work better. Other simulations considered were Monte Carlo and data driven simulations. Due to Tidal TV’s financial and implementation limitations aforementioned, these simulation types helped us evaluate algorithms without testing in the real world.

III. METHODOLOGY AND DESIGN

We researched existing strategies previously developed by others in financial markets, online advertisement, and other industries. Using the research, we refined and developed ideas to produce the best bidding strategies for the two auction types. Using data analysis, we analyzed the data from Tidal TV of the OLV advertisement auctions to determine if there were any underlying trends (e.g. time series, correlations, etc.). We then developed a simulation environment in C sharp, selected for its quickness and ease of deployment, to run and test the bidding strategies. Despite not being able to confirm with live testing, the simulation environment, according to Tidal TV, was intrinsically more robust and complex than the current environment.

After developing the simulation, we tested the developed strategies against those used by other bidders, including Tidal TV. Following the testing, we performed data analysis to determine which bidding strategies performed the best. Using a Pareto frontier, we determined the bidding strategies that dominated the other strategies for the two types of auctions. Additionally, we performed risk and decision analysis to determine the savings, profit maximization, and increased robustness of the strategies compared with those currently used by Tidal TV. An
important aspect is that, at the current time, Tidal TV and other bidders bid without efficient and dynamic strategies. Therefore, any dynamic strategy developed was better than current strategies.

A. Monte Carlo Simulation

The Monte Carlo version of the simulation used random processes to determine the rate of bid requests and their demographic makeup. Inter-arrival rates were modeled from a data set provided by Tidal TV. The demographic makeup was similarly analyzed. For the purposes of algorithm analysis, these demographic factors were not included. The Monte Carlo simulation then created a series of bid requests using the underlying distributions. Competing bidders drew values from normal distributions with different means and standard deviations.

Algorithms were initially evaluated using the Monte Carlo simulation. Each algorithm was assigned a campaign of identical size. The simulation was then run, with the algorithm competing against three black box bidders drawing from normal distributions. Each simulation run was for the same amount of time with the same black box bidders. Algorithms were evaluated on their ability to fulfill the target volume successfully, while paying the lowest possible price for the acquired impressions, and thus achieving the highest profit.

B. Data-Driven Simulation

The Data-Driven version of the simulation used actual bid-request data received from Tidal TV to determine the bid requests in the simulation. The bid request data was transferred into a database, which was incorporated into the simulation environment. Both bid request arrival times and demographic makeup were drawn directly from the database. The same bidders from the Monte Carlo simulation were used to perform testing of our developed strategies. Additionally, actual campaign data was used for the simulation to simulate the demand needed.

IV. RESULTS

A. Day to Day Patterns

With data from 1 million real time auctions, ranging over a week, we found pricing patterns in the day by day time frame. To find out how the time of day affected price, we focused specifically on a particular age group and gender. If the demographics were left unspecified, the age and gender influences on price would have biased the results from the time of day influences. Preliminary analysis showed that certain hours of the day had higher average prices and certain hours of the day had lower average prices. Fig. 5 shows the pricing patterns witnessed in the analysis. The green indicates a higher price relative to the overall day average and the red indicates a lower price relative to the overall average. The findings may be related to the Edgeworth cycles previously mentioned.

B. Simulation

We developed a C sharp simulation, shown in Fig. 6, which allowed for both Monte Carlo and Data Driven simulations to be tested. Further, first-price and second-price auctions can occur by selecting a radio button. Lastly, there is a price floor applicable. Overall, the simulation is one of the best ways to test the developed algorithms and strategies. Without the simulation, testing of the strategies would not have been feasible. In addition, it would have been difficult to validate the results.

Next, we developed and tested four distinct second price bidding strategies against black box bidders. For proprietary reasons, the authors cannot reveal the actual algorithms developed, only that they were developed using the research from above to develop the strategies. Figure 7 below shows that Joe’s algorithm performed the best for the second-price auction. The figure is a Pareto frontier, which is an effective tool to identify the trade-offs between profit and meeting the desired number of impressions. According to Fig 7, Joe’s algorithm dominates Tomu/Au’s algorithm. It is difficult to determine if Joe’s dominates Craig’s since Craig’s algorithm obtained more impressions, but at a slightly less profit.
With regards to the first price auctions, similar results were obtained. Pareto frontiers were used to evaluate the 2-3 different algorithms developed. The first-price and second-price algorithms developed will greatly aid Tidal TV in maximizing profits while still fulfilling the impressions needed.

V. CONCLUSION

Overall, the online video advertisement market is significantly increasing in terms of revenues. Over time, more advertisements will be shown via video, both on computers and mobile devices. Tidal TV is targeting an industry that is rapidly changing.

Using previous strategies developed for both first-price and second-price auctions, we developed 3 algorithms for first price auctions and 4 algorithms for second-price algorithms. The results were then evaluated using Pareto frontiers to determine which strategies dominated other strategies. The simulation developed was able to complete Monte Carlo and Data Driven simulations which provided us and Tidal TV adequate ways to evaluate the algorithms developed.

Future work would include further refinement of the strategies developed. In addition, refinement of the simulation could provide better results. Live testing in the real world would validate that our simulation is simulating accurately. Lastly, actual implementation in the real world would allow us and Tidal TV the ability to determine how much better their developed algorithms were than other ones currently in use.

ACKNOWLEDGMENT

The authors would like to cordially thank Tidal TV for all their aid in the research performed and for providing the data needed to complete the research. We could not have attempted nor completed the project without their aid.

REFERENCES


