

Optimal Budget Allocation for Digital Display Ads Inventory



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I. INTRODUCTION AND BACKGROUND

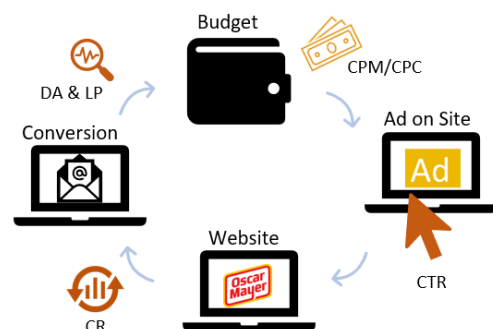
Oscar Mayer, a subsidiary of Kraft Heinz was founded by Oscar Ferdinand Mayer in 1883. This company has specialized in selling cold cut meats and sausages for over a century. Oscar Mayer was an independently held company until 1981 when it was sold to General Foods. In 1985, the company was sold to General Foods and merged with Kraft Foods shortly after. Oscar Mayer has been known for their successful advertising throughout the years. In 1936, this company created the first ever branded vehicle, known as the Wienermobile (Oscar Mayer, 2019). The Wienermobile displayed the Oscar Mayer brand name and logo throughout parades, store openings and even hospitals. However, with technological advances and consumers exposed to ads online and through social media, Oscar Mayer has recently focused on engaging more customers online. This is because digital marketing offers advertisers the ability to reach specific target audiences at scale, who are likely to deliver desired results through increased exposures. For this task, Oscar Mayer is reducing their average ad spend annually. This brand publishes various types of ads on digital media like display, video etc... and the major vendors they utilize include YouTube, Facebook, Twitter, Hulu, Pandora, and Safeway.

II. PROJECT DESCRIPTION

This project studies and illustrates how to optimally allocate digital marketing budgets to specific ad publishers for brand awareness campaigns to get higher conversions from three particular sites. The goal of the model is to provide an optimized budget distribution to the three publishers based on return on ad spend (ROAS) through data analysis and linear programming. By publishing sites, we mean the sites where the ad is displayed. For the purpose of this project, the sites include Facebook, Pandora and Twitter.

Agency campaign managers negotiate and buy advertising space (reserved on websites) predominantly through CPM (cost per mille impressions) or CPC (cost per click) rate types, which vary in terms of price and performance. Users are targeted based on demographic and behavioral attributes collected from cookies, and then they are served banner ads with custom creative and messaging determined by the advertiser and agency. Once someone who meets the targeting requirements is identified on Facebook, Twitter, or Pandora, they are served an impression with the intention of getting the user to click on the advertisement.

The diagram on the right explains the flow of digital advertising. A user is served a relevant display ad on a website. If said user clicks on the ad, they will be redirected off the current website into a specified landing page. Oftentimes for Oscar Mayer the user will be redirected to a brand specific microsite with the intention of getting them to subscribe to a mailing list. If the user completes the desired action, that activity is monitored up



to 30 days after being served the advertisement and then captured as a conversion. Since the majority of sales for Oscar Mayer occur offline, the conversion KPI (Key Performance Indicator) is typically tied to non sales engagement activities, in this case it is measured with email subscriptions.

III. PROJECT FOCUS

The project goal is to create a model that informs Oscar Mayer how to optimally allocate budget based on past three year performance with respect to impressions, clicks, conversions, cost and click-through rate (CTR). In other words, based on cost efficiency and click-through rates, where the advertising dollars should be distributed across three digital media sites. Data source, major assumptions, model, results and conclusion is explained in the remaining sections of this paper.

IV. DATA SOURCE

i. From Ad Agency

The data procured for the model is a mix of predominantly data from the ad agency and some assumed data based on industry related information, which was not made available to us due to data privacy concerns. The data obtained from the ad agency for Oscar Mayer uses a reputable ad server to collect their campaign performance data. The data collected tracks three years of performance from 2017 to 2019 of a particular ad campaign published on the sites Facebook, Pandora and Twitter. Every year's data file contains around 2,760 to 3,000 records, a small portion of which is illustrated in Figure 1. The data table includes information on actual cost to company, publishing site, impressions, clicks, and planned budget. This data, based on actual results, has no assumptions and was processed further to feed input values for the model.

Prisma Campaign Name	MDM PL Site	Date	Impressions1	Clicks1	MediaCost1	PlannedCost
KRAFT_OSCARMAYER_JAN_DEC_2018_DISPLAY	Twitter	11/9/2018	115,512	147	381	292
KRAFT_OSCARMAYER_JAN_DEC_2018_DISPLAY	Twitter	11/10/2018	114,801	141	378	292
KRAFT_OSCARMAYER_JAN_DEC_2018_DISPLAY	Twitter	11/11/2018	122,788	158	405	292
KRAFT_OSCARMAYER_JAN_DEC_2018_DISPLAY	Twitter	11/12/2018	127,100	186	419	292
KRAFT_OSCARMAYER_JAN_DEC_2018_DISPLAY	Twitter	11/13/2018	122,327	205	403	292
KRAFT_OSCARMAYER_JAN_DEC_2018_DISPLAY	Twitter	11/14/2018	120,034	207	396	292
KRAFT_OSCARMAYER_JAN_DEC_2018_DISPLAY	Twitter	11/15/2018	128,360	165	423	292
KRAFT_OSCARMAYER_JAN_DEC_2018_DISPLAY	Twitter	11/16/2018	107,175	165	326	292
KRAFT_OSCARMAYER_JAN_DEC_2017_DISPLAY	Pandora	3/31/2017	20,001	13	102	309
KRAFT_OSCARMAYER_JAN_DEC_2017_DISPLAY	Pandora	4/1/2017	10,467	9	53	309
KRAFT_OSCARMAYER_JAN_DEC_2017_DISPLAY	Pandora	4/2/2017	8,855	4	45	309
KRAFT_OSCARMAYER_JAN_DEC_2017_DISPLAY	Pandora	4/3/2017	29,705	13	152	309
KRAFT_OSCARMAYER_JAN_DEC_2017_DISPLAY	Pandora	4/4/2017	23,452	13	120	309

Figure 1. Year data record for Oscar Mayer Campaign (2017-2019)

We totaled (Figure 2) and averaged the data of the three years and created a pivot table in Excel of required information for the yearly ad campaigns published on each publishing site (assuming ad content and design was constant throughout). Thus, the resulting data, shown in Figure 3 are the relevant input values for the model design.

KRAFT_OSCARMAYER DATA							
2017-2019	Row Labels	Sum of Impressions	Sum of Clicks	Cost to Company	CPM	CPC	CTR
	JAN_DEC_2017_DISPLAY	233,161,475	5,788,474	\$1,038,220			
	Facebook	119,725,757	5,532,419	\$424,781	\$3.55	\$0.08	4.6209
	Pandora	52,494,148	182,760	\$304,500	\$5.80	\$1.67	0.3482
	Twitter	60,941,570	73,296	\$308,939	\$5.07	\$4.21	0.1203
	JAN_DEC_2018_DISPLAY	248,426,381	639,679	\$1,126,027			
	Facebook	3,890,851	167,756	\$15,475	\$3.98	\$0.09	4.3116
	Pandora	58,227,655	130,442	\$381,630	\$6.55	\$2.93	0.2240
	Twitter	186,307,875	341,481	\$728,923	\$3.91	\$2.13	0.1833
	JAN_DEC_2019_DISPLAY	176,815,021	2,557,616	\$1,001,792			
	Facebook	23,099,701	1,906,604	\$143,257	\$6.20	\$0.08	8.2538
	Pandora	60,465,291	166,239	\$513,001	\$8.48	\$3.09	0.2749
	Twitter	93,250,029	484,773	\$345,534	\$3.71	\$0.71	0.5199
	Grand Total	891,564,353	14,774,243	\$4,204,258			

Figure 2. Pivot table showing totals ad campaign and site-wise

Row Labels	Avg Impressions	Avg Clicks	Avg CTC	Avg CPM	Avg CPC	Conversion	Avg CTR	1.5 Avg CTC	0.5 Avg CTC
Facebook	48,905,437	2,535,593	\$194,504	\$4.58	\$0.081	9.21%	5.7288	\$291,756	\$97,252
Pandora	57,062,365	159,813	\$399,710	\$6.95	\$2.56	2.90%	0.2824	\$599,565	\$199,855
Twitter	113,499,825	299,850	\$461,132	\$4.23	\$2.35	1.20%	0.2745	\$691,698	\$230,566
Grand Total	219,467,626	2,995,256	\$1,055,346						

Figure 3. Averaged data derived from Figure 2 serving as model input

ii. Major Assumptions

Due to unavailability of conversion related data (number of conversions and conversion rate), these figures were assumed based on extensive internet research of industry-related generic range. The major assumption being made is that Facebook yields the highest conversion rate at over 9.2% (Irvine, 2020), which was based on industry averages. Furthermore, we assumed the conversion rate for Pandora and Twitter by taking the base case of Facebook's user base vs CR. When we dug deeper into this through internet research and consulting with various people from the advertising industry, it was gathered that generally speaking the conversion rate for email subscriptions is between 0.05 to 5%. Instead of assigning random numbers to the publishing sites, we went ahead with the former assumption for model computation and further did a sensitivity analysis to see how the dynamics change.

Another assumption made is about the overall budget. It was calculated by taking the average of the three years as input for the model, which further aids in comparing previous years performance with the proposed one.

V. DIGITAL DISPLAY ADVERTISING INVENTORY MODEL

For the task, we developed a Simplex Linear Programming model to find the best allocation of Digital Display Advertising Inventory. The approach, relevant formulae for the model and their implementation in MS Excel (Figure 4 & 5) are explained in this section.

V.i. Objective

Objective is to maximize the total conversions as a sum of the three sites. Our definition of conversions for this project is email signup.

V.ii. Model Approach

The approach to set up the LP model is essentially based on inventory mix to maximize conversions by optimizing CPM and conversion rate. The ad spend is based on cost per 1000 advertisement impressions, which the ad agency pays the vendor based on total impressions served. CTR provides an idea about the relation of impressions to clicks. However, it is not used in the model for calculation and is for information purposes only. Further, campaign engagement is measured through cost per click (CPC) which is calculated through the number of clicks achieved from total impressions. To find the conversions based on the number of clicks, the conversion rate is tracked through historical data and the same rate is applied to the model assuming no changes are made to the design or content of the campaign or site. For this project, we assumed conversion rates based on research and logic since the ad agency could not reveal them. From the model, we are looking to achieve an optimal balance between CPM and conversion rate under the individual and overall budget constraints.

The influence chart below (Figure 4) illustrates the flow of the model considering the data obtained.

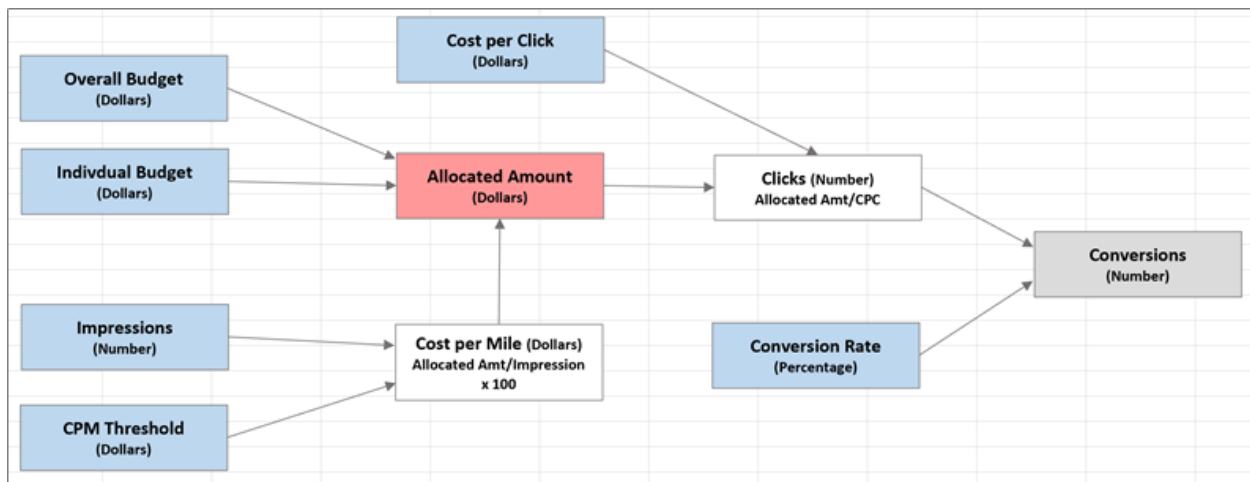


Figure 4. Digital Ad Inventory Influence Chart

V. iii.Input Data

Campaign Name	JAN_DEC_2020_DISPLAY			
Annual Budget	\$1,055,346			
Inputs	Average of 3 year data is taken for the inputs			
Each network	Facebook	Pandora	Twitter	Total
CPC	\$0.081	\$2.560	\$2.350	
Conversion Rate	0.0921	0.029	0.012	
Impressions	48,905,437	57,062,365	113,499,825	219,467,626
Calculated Quantities				
CPM	\$4.58	\$6.95	\$3.83	
Clicks	2,765,270	154,915	185,011	3,105,197
Decision Variables				
Allocated Amount	\$223,987	\$396,583	\$434,776	\$1,055,346
Constraints				
	≤	≤	≤	
MaxAllowableBudget	\$292,000	\$600,000	\$692,000	
	≥	≥	≥	
MinAllowableBudget	\$97,000	\$200,000	\$230,000	
	≤	≤	≤	
CPMThresh	\$4.58	\$6.95	\$4.23	
Objective to Maximize				
Conversions	254,681	4,493	2,220	261,394
				Maximize

Publishing Site -wise average data of last three years is taken for the following:

1. Annual Budget = \$1.05 Million- Overall average of the 3 years
2. $CPC = CTC / \# \text{ Clicks}$, Cost per click of each inventory type
3. $CTR = Clicks / Impressions \times 100$, Click through rate

Figure 5. LP model for Digital ad

inventory

4. $CR = \# \text{ Conversions} / \# \text{ Clicks} \times 100$, Conversion rate of each publishing site type- Assumed
5. Impressions, Number of impressions
6. MaxAllowableBudget = 1.5 times the average budget of each inventory type
7. MinAllowableBudget = Half of the average budget of each inventory type

For upper and lower limits to be spent on each site, a consistent multiplier of as low as half and as high as 1.5 the average spend is applied.

8. CPMThresh = Average CPM of each inventory type

V. iv.Decision Variables

The model's decision variables are the amount allocations to each pay per click site Facebook, Twitter and Pandora.

V. v. Constraints

1. $CPM = \text{Cost} / \# \text{ Impressions} \times 100$, Cost per 1000 impressions of each inventory type
2. $\text{Clicks} = \text{Budget per publishing site} / \text{CPC}$, Number of clicks expected from impressions
3. The sum of allocated amount on each site must not exceed the total budget fund
4. $\text{Conversions} = \text{Clicks} \times \text{Conversion Rate}$, Amount of conversions expected from clicks
5. Amount spent on any of the sites cannot take a negative value

V.vi. LP Model (Simplex)

1. Maximize total conversions

Subject to :

2. $\text{Total Amount} \leq \text{Annual Budget}$
3. $\text{Allocated Amount} \leq \text{MaxAllowableBudget}$
4. $\text{Allocated Amount} \geq \text{MinAllowableBudget}$
5. $CPM \leq \text{CPM Threshold}$

The objective function maximises the conversions where the first constraint requires the total budget to be within the overall budget set for the year. Further, the individual allocations should be within the minimum and maximum individual budget range based on the limit spent in the last three year. Additionally, the individual CPM threshold forces the optimal CPM to be less than or meet it.

With three variables and four constraints, the model is optimally solved very quickly with Solver. Other outputs are also generated to enable better understanding and assist the campaign manager. They are the total number of impressions and clicks expected through the optimal solution, the total expected CPM and individual publishing site conversions expected based on the conversion rate.

VI. RESULTS

The LP model yields the optimal solution of maximum conversions by utilizing the entire budget out of which the conversions achieved are with 20% allocated budget to Facebook, 38% to Pandora and 41% to Twitter.

A closer look reveals that the model results are not predictable in terms of numbers, but the logic behind the algorithm is understandable. Facebook inventory has significantly better performance compared to the other two sites, i.e. the conversion rate at 9.21%, with only a 19% higher CPM relative to Twitter and a lower CPM than Pandora. Solver tries to maximize the CPM in the order of conversion rates since our goal is maximizing conversions. Facebook with the highest conversion rate is allotted one-fourth of the budget achieving 2.7 million expected clicks. Subsequently, the second highest conversion rate of Pandora is taken into account in the algorithm to utilize the CPM cap even though it is quite expensive. And, since Twitter yields the least conversions and is the cheapest, the algorithm gives it the lowest preference and under utilizes the CPM. It is noted that even though Facebook is given just a fourth of the budget, the clicks and conversions it achieves are higher by a huge margin, which ultimately boils down to conversion rate. Therefore, looking at the comparison table in Figure 6 it is observed that the model results show a 3.67% increase in expected clicks and thereby an 8.12% increase in conversions assuming no change in the content of the ad campaign.

Comparison of optimized vs previous results					
Year		2017-2019	2020	2017-2019	
	Conversion Rate	AvgClicks	Expected Clicks	AvgConversions	Expected Conversions
Facebook	9.21%	2,535,593	2,765,270	233,528	254,681
Pandora	2.90%	159,813	154,915	4,635	4,493
Twitter	1.20%	299,850	185,011	3,598	2,220
Total		2,995,256	3,105,196	241,761	261,394
% Change			3.67%		8.12%

Figure 6. Percentage comparison of performance over the averaged data of last three years with the proposed model

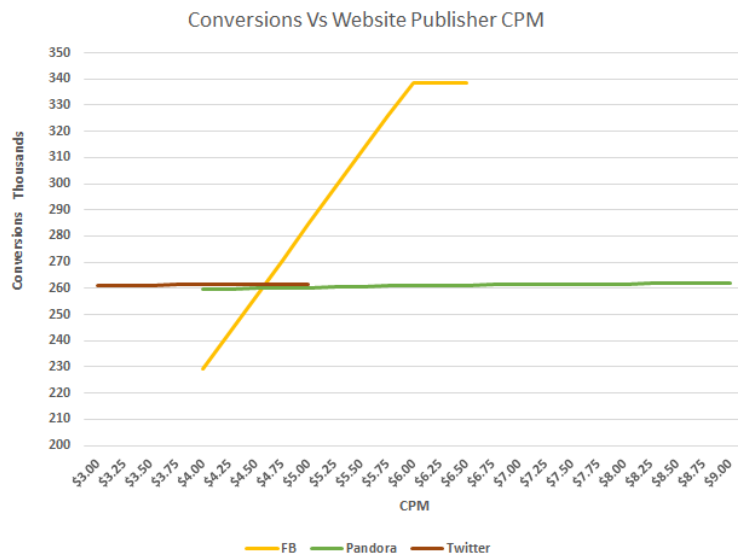
This means the optimal inventory mix could have saved the company quite a lot in total media spend to achieve the same conversions. Consequently, it is evident that notably better solutions are found through data and subsequent analysis with LP approach for optimal budget allocation on digital display inventory.

VII. SENSITIVITY ANALYSES

The sensitivity report details out two aspects - how changes in the coefficients of the objective function affect the solution (variable cells table) and also how changes in the constants on the right hand side of the constraints (constraints table) affect the size of the feasible region (the solution). For example, for the former part, if the coefficient of Twitter is raised or reduced within the allowable limit values, the optimal budget allocation remains unchanged. For the latter part, an illustration is that the shadow price for the CPM constraint on Facebook is \$55,357 indicating that if CPM is increased by \$1 (from \$4.58 to \$5.58), the corresponding budget allocated in the optimal solution will increase by \$55,357 as long as the right hand side stays within allowable limits.

The sensitivity analysis could be run by taking different approaches for conversion, for example conversion rate, budget and CPM. Since the conversion rates are between 0.5 to 5% as per industry standards, we brainstormed and ran a two way solver to study the same (refer Excel Model Sensitivity 2way FB Pandora, 1 way CR FB, Comparison sheets). However, we took a different approach because historically, observing the trends, we noticed CPMs changed constantly. The same is reflected in the sensitivity analysis indicating that CPM of Facebook and Pandora constraints are binding apart from total budget. The CPM for Twitter is not binding with \$0.4 slack that is not being used to produce the final solution. We took the same approach by running one-way Solver Tables (add-in for Excel) for sensitivity on CPMs individually exploring various ranges to study and compare how the conversions differ (keeping the other CPMs and budget parameters at their base case values). As one may observe in Figure 7(a & b) the graph shows marginal variation in Pandora and Twitter conversions with respect to the CPM range. For Pandora, the range is \$259,719 to \$262,122 and for Twitter the range is also very small and similar. However, for Facebook the range is \$229,287 to \$338,380. Therefore, maximum variation is seen in Facebook conversions which is expected due to the high conversion rate.

Figure 7a. Individual sensitivity analysis combined in a graph



Sensitivity Analysis Results			
1. 1 way table for conversions vs CPM range of every publishing site			
Max CPM	FB	Pandora	Twitter
\$3.00			260,913
\$3.25			261,058
\$3.50			261,202
\$3.75			261,347
\$4.00	229,287	259,719	261,394
\$4.25	243,126	259,880	261,394
\$4.50	256,965	260,042	261,394
\$4.75	270,805	260,203	261,394
\$5.00	284,644	260,365	261,394
\$5.25	298,484	260,527	
\$5.50	312,323	260,688	
\$5.75	326,162	260,850	
\$6.00	338,380	261,011	
\$6.25	338,380	261,146	
\$6.50	338,380	261,234	
\$6.75		261,323	
\$7.00		261,412	
\$7.25		261,501	
\$7.50		261,589	
\$7.75		261,678	
\$8.00		261,767	
\$8.25		261,856	
\$8.50		261,944	
\$8.75		262,033	
\$9.00		262,122	

Figure 7b. Sensitivity analysis (combined table) for impact of individual CPM thresholds on Conversions

VIII. CONCLUSION AND RECOMMENDATIONS

After developing this model, and analyzing the data results, we drew several conclusions. One of them was that it is good to diversify between publishing sites by distributing the allocated budget to reach a wider audience. That said, the rates for every publishing site (e.g. Facebook, Pandora, Twitter) are nonlinear and dynamic. The quality and content of an ad displayed, as well as the audience segment it is reaching, will dictate the CTR (click-through-rate). However, at one point, for every dollar invested, there will be a lesser and lesser return. Once this occurs, the more beneficial thing to do is to invest in different publishers given that every site's reach composition, audience type, search volume etc... differs extensively. Since every site has a different pool of users, investing in a mix of sites increases the ad exposure to a variety of audiences.

Because of this, one approach we took was to derive our inputs for the model. We came up with the CPM threshold and CTR by averaging the data across all three years. However, we believe that this may not be the best approach given the dynamic nature of digital advertising and its varying rates. For example, placement inventory will have varying CPM prices based on the quality of the site, user, time of day, quality of the location of the ad unit on the page, and several other factors as well. After observing the trends of the previous three years, we noticed that Facebook's CPM had consistently increased given its high CTR but simultaneously, Pandora's CPM increased every year even though its clicks were only a fraction compared to Facebook's clicks. We believe that this is because Pandora's audience segment is different from Facebook's

and there is a higher conversion occurring from Pandora's users despite having the lowest CTR. Comparably, we observed that Twitter's CPM was consistently reduced throughout the three years. However, in 2019, it generated nearly 3x more clicks than Pandora with only 1.5x the impressions. We also noticed in our model that the maximum budget allocated was to Twitter, achieving approximately 4% higher CTRs than the average of the last three years.

Given the input dynamics, our recommendation is that the model be converted to an iterative process with evolutionary/nonlinear modeling to find further optimized results. Given the variation of rates in the advertising market, this model is scalable and upgradable. That said, new rate values can be fed to the model and/or even expanded to add more website publishers.

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