A Decision Framework for Allocating Advertisement Budget to Online and Offline Channels

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***Abstract*— Companies use various advertising channels—such as online platforms, TV, newspapers, radio, and billboards—to promote their products and services. Selecting the right mix is challenging due to budget constraints and audience segmentation. Deciding the target or focus group is crucial, as it influences channel selection. Segmentation can be based on factors like age, income, gender, and education. This study aims to optimize advertising budget allocation by incorporating segmentation weights provided by companies. Using five optimization models—maximum exposure, minimum cost, minimax, maximin, and compromise programming—the research identifies the most efficient strategy. Results from the Nielsen case show that the compromise programming model best balances exposure and cost, making it the most effective approach for budget allocation.**

***Keywords*— Budget allocation, advertisement, segmentation, maximum exposure, compromise programming.**

I. Introduction

Advertising is a fundamental tool for companies to attract and inform potential customers about their products or services. Today, advertising utilizes every available medium to convey messages—ranging from traditional platforms such as television, print (newspapers, magazines, journals), and radio to modern options like the internet, social media, and even personalized approaches such as direct selling, mailers, sponsorships, posters, events, and endorsements [1].

With the increasing intensity of market competition and the rapid growth of information sources, the role of marketing and advertising has become more critical than ever. Companies face a multitude of advertising options, which makes it challenging to determine how to allocate their budgets most effectively. A well-structured advertising strategy not only ensures cost efficiency but also maximizes exposure to the right audience.

The allocation of advertising budgets has long been a topic of interest in marketing and operations research. As companies continue to face increasing competition, identifying optimal ways to reach target audiences through cost-effective advertising has become essential. Traditional literature on advertising emphasizes the role of various media platforms in promoting products and services, including television, newspapers, magazines, radio, and billboards, as well as digital media such as online ads and social media marketing [1].

Several studies have addressed the challenge of choosing the right mix of advertising channels. Early research often focused on cost-effectiveness and reach of traditional media channels [2]. With the proliferation of digital advertising, newer research has incorporated online platforms into the mix, highlighting their ability to reach segmented audiences with greater precision and lower costs [3].

Customer segmentation is a foundational concept in advertising strategy, and numerous studies have emphasized its importance in budget allocation. Segmentation is typically based on demographic variables such as age, gender, income, and education [4]. These factors influence media consumption habits and, consequently, the effectiveness of different advertising channels. For example, younger demographics may respond more favorably to online and social media ads, while older populations might be more influenced by television or print media [5].

Optimization techniques have increasingly been used to guide advertising budget decisions. Linear programming, goal programming, and multi-objective optimization models have been proposed to balance competing goals such as maximizing exposure and minimizing cost [6]. In particular, compromise programming has gained attention for its ability to handle trade-offs between multiple objectives, making it suitable for real-world decision-making where perfect optimization is rarely achievable [7].

Recent research has applied these models to various industries and market conditions. For instance, studies using compromise programming and maximin models have shown improved results in budget allocation by accounting for business-specific weights and constraints [8]. These models enable marketers to evaluate the impact of different allocation strategies and choose the most effective one based on empirical data. The budget allocation for advertisement has been analyzed and discussed in many aspects in other researches such as [9], [10], [11], [12], [13], and [14] that show the validity of the problem of the companies.

This study builds upon this body of literature by combining segmentation criteria with five distinct optimization models—maximum exposure, minimum cost, minimax, maximin, and compromise programming. By applying this framework to a real-world case (Nielsen), it adds to existing knowledge on how companies can optimize their advertising strategies in both online and offline contexts.

II. The Problem Formulation

Budget allocation is a particularly vital aspect of an advertising strategy, especially in competitive environments where success is determined by both visibility and efficiency [2]. Allocating advertising budgets effectively requires a dual focus: reaching the appropriate target audience and managing costs within acceptable limits. Consequently, determining the

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most effective advertising channels involves considering customer segmentation factors such as age, income, education, and gender, as well as the cost associated with each channel.

Despite the broad array of advertising channels—online platforms, TV, newspapers, radio, billboards, and more—selecting the optimal mix is a complex task. The challenge lies in balancing multiple objectives: reaching the ideal customer segments, maximizing exposure, and staying within budget.

This study presents a decision-making framework to optimize the allocation of advertising budgets between online and offline channels. By integrating segmentation weights provided by companies, the framework applies five optimization models to identify the most efficient strategies:

Maximum Exposure: Maximizing audience reach.

Minimum Cost: Achieving advertising goals with minimal financial expenditure.

Minimax: Minimizing the cost while maximazing possible exposure.

Maximin: Maximizing the minimum exposure while minimizing cost.

Compromise Programming: Striking a balance between exposure and cost based on assigned priorities.

Using a case study from Nielsen, the research demonstrates that compromise programming provides the best balance between cost and exposure, making it the most effective model for advertising budget allocation. This paper contributes to the literature by offering a novel optimization-based approach that combines practical business segmentation criteria with multi-objective decision-making strategie

By analyzing exposure levels and total costs, companies can select the most suitable strategy to maximize their advertising effectiveness. We know provide the notation that is used in this paper:

Notation:

i : Advertisement channels ($i\in I$)
j : Resources ($j\in J$)
B: total budget available
y: percentage of online budget for over all
Zon: total online budget
Zof: total offline budget
E: the number of exposures that must be satisfied
A_i: the number of exposures that i^{th} channel has or calculated according to segment weights.
R_j: the number of channels that allowed to use for j^{th} resources.
C_i: unit cost of i^{th} channel ($i\in I$)
U_j: Number of advertisements for channels that are allowed to use for j^{th} resources
AC_i : Cost of advertisement allocated channel i
R^0_j: the number of channels that are allowed to use for j^{th} resources. This number is smaller than R_j to avoid usage of all channels obtained from minimum cost solution.
W_e: weight of exposure determined by the decision maker
W_c: weight of cost determined by the decision maker
Max Z_e: maximum exposure that is determined by using maximum exposure integer model
Min Z_c: minimum cost that is determined by using minimum cost model
Kj : Number of channels in resource j
X_i: a binary variable that takes the value 1 if an advertisement is placed with i^{th} channel and 0 otherwise.

A. Maximum Exposure Integer Programming for Budget Allocation

In order to maximize the maximum exposure and appropriately allocate budget, an integer model is proposed in this section. The resources such as Tv, magazines, and newspapers and channels among these resources are varied.

This paper builds a linear programming model for deciding how to allocate advertising budget. There are many resources and channels so this model use integer programming model to decide which channel to invest. The constraints can limit the number of channels and or resources to be used. The maximum exposure integer programming model can be defined as follows:

$$Maximize_{X_i} = \sum_{i=1}^{\sum_{j=1}^{J} K_j}(A_i\, X_i) \qquad i\in I,\, j\in J \quad (1)$$

St.

$$\sum_{i=1}^{\sum_{j=1}^{J} K_j}(A_i\, X_i) \geq E \qquad i\in I,\, j\in J \quad (2)$$

$$\sum_{i=1}^{K_j} X_i \leq R_j \qquad i\in I,\, j\in J \quad (3)$$

$$X_i \in \{0,1\} \qquad i\in I,\, j\in J \quad (4)$$

The objective function given in Eq. (1) maximizes exposure while constraint (2) ensures that required exposure levels are reached. Constraint (3) ensures that allocated budget to each resource is not violated. Constraint (3) shows the binanry variable for the decision variable.

B. Minimum Cost Integer Programming Model

Not all companies prefer maximum exposure, they might prefer minimum cost. The cost for each channell is different and the allocated total budget is limited. It is also possible to allocate the advertisements as online and offline by determining a ratio y for online budget. Assuming that ratio y for online budget is determined, the total online and offline budget can be defined as follows:

$$Z_{on} = yB \quad (5)$$

$$Z_{of} = (1-y)B \quad (6)$$

In such case, the cost of advertisement to allowed channels can be calculated as:

$$AC_i = \frac{U_j}{R_j} C_i \qquad i\in I,\, j\in J \quad (7)$$

Then the model for this problem can be defined as:

$$Minimize_{X_i} = \sum_{i=1}^{\sum_{j=1}^{J} K_j} AC_i X_i \qquad i\in I, j\in J \qquad (8)$$

s.t.

$$\sum_{i=1}^{\sum_{j=1}^{J} K_j} (AC_i\, X_i) \leq B \qquad i\in I, j\in J \qquad (9)$$

$$\sum_{i=o^o}^{\sum_{j=1}^{J} K_j} AC_i X_i \leq Z_{on} \qquad i\in I, j\in J \qquad (10)$$

$$\sum_{i=1}^{\sum_{j=1}^{J} K_j} (AC_i\, X_i) - \sum_{io^o}^{\sum_{j=1}^{J} K_j} AC_i X_i \leq Z_{of} \qquad i\in I, j\in J \qquad (11)$$

$$\sum_{i=1}^{K_j} X_i \geq R_j \qquad i\in I, j\in J \qquad (12)$$

$$X_i \in \{0,1\} \qquad i\in I \qquad (13)$$

The objective function given in eq. (8) aims to minimize the total cost. On the other hand, the total budget should not be exceeded as given in eq. (9). The decision makers can determine the total online and offline budget allocation ratios. Eq. (10) and eq. (11) represent the limits for online and offline budget limits. As the model is the cost minimization model, the decision maker still can impose a minimum lover limit for number of channells that can be used as given in eq. (12). Constraint (13) shows that the decision variable is binary.

C. *Multiobjective models*

The aim for advertisement of products and services is to reach maximum exposure while having minimum cost. The companies might have priorities to reach to different groups such as young, old, more people or minimize cost. Such objectives can be modeled as a multiobjective problem. In this section, the problem is modeled as Minimax, Maximin, and compromise programming methodologies to allow decision makers to prioritize their preferences.

D. *Minimax model*

It is natural that one company might want to maximize exposure while minimizing the adertisement cost. This approach minimizes the total cost first, then based on the results, the best advertisement means to maximize the exposure that also satify the constraints will be selected. The problem can be defined as follows:

$$Maximize_{X_i} = \sum_{i=1}^{\sum_{j=1}^{J} K_j} A_i X_i \qquad i\in I, j\in J \qquad (14)$$

s.t.

$$\sum_{i=1}^{\sum_{j=1}^{J} K_j} (A_i\, X_i) \geq E \qquad i\in I, j\in J \qquad (15)$$

$$\sum_{i=1}^{\sum_{j=1}^{J} K_j} (AC_i\, X_i) \leq B \qquad i\in I, j\in J \qquad (16)$$

$$\sum_{i=o^o}^{\sum_{j=1}^{J} K_j} AC_i X_i \leq Z_{on} \qquad i\in I, j\in J \qquad (17)$$

$$\sum_{i=1}^{\sum_{j=1}^{J} K_j} (AC_i\, X_i) - \sum_{io^o}^{\sum_{j=1}^{J} K_j} AC_i X_i \leq Z_{of} \qquad i\in I, j\in J \qquad (18)$$

$$\sum_{i=1}^{K_j} X_i \leq R_j \qquad i\in I, j\in J \qquad (19)$$

$$X_i \in \{0,1\} \qquad i\in I \qquad (20)$$

The objective function given in eq. (14) aims to maximize the total exposure while eq. (15) impose a lower limit to number of exposures. The number of exposures can be increased depend on the decision maker’s preferences. The total budget should not be exceeded as given in eq. (16). The decision makers can determine the total online and offline budget allocation ratios. Eq. (17) and eq. (18) represent the limits for online and offline budget limits. The decision makers can impose constraint to advertisements that are given to different channels as given in eq. (19). Constraint (20) shows that the decision variable is binary.

E. *Maximin model*

If the exposure is more important than the cost, a maximin model can be used. This model maximizes exposure while minimizing the cost. The constraints should also not be violated. Then the model can be uptaded as below:

$$Minimize_{X_i} = \sum_{i=1}^{\sum_{j=1}^{J} K_j} AC_i X_i \qquad i\in I, j\in J \qquad (21)$$

s.t.

$$\sum_{i=1}^{\sum_{j=1}^{J} K_j} (A_i\, X_i) \geq E \qquad i\in I, j\in J \qquad (22)$$

$$\sum_{i=1}^{\sum_{j=1}^{J} K_j} (AC_i\, X_i) \leq B \qquad i\in I, j\in J \qquad (23)$$

$$\sum_{i=o^o}^{\sum_{j=1}^{J} K_j} AC_i X_i \leq Z_{on} \qquad i\in I, j\in J \qquad (24)$$

$$\sum_{i=1}^{\sum_{j=1}^{J} K_j} (AC_i\, X_i) - \sum_{io^o}^{\sum_{j=1}^{J} K_j} AC_i X_i \leq Z_{of} \qquad i\in I, j\in J \qquad (25)$$

$$\sum_{i=1}^{K_j} X_i \geq 1 \qquad i\in I, j\in J \qquad (26)$$

$$X_i \in \{0,1\} \qquad i\in I \qquad (27)$$

The objective function given in eq. (21) aims to minimize the total cost while eq. (22) imposes a lower limit to number of exposures. The number of exposures can be increased depend on the decision maker’s preferences. The total budget should not be exceeded as given in eq. (23). The decision makers can determine the total online and offline budget allocation ratios. Eq. (24) and eq. (25) represent the limits for online and offline budget limits. The decision makers can impose constraint to advertisements that are given to different channels as given in eq. (26). Constraint (27) shows that the decision variable is binary.

F. *Compromise programming model*

Another option for the companies is to assign weights to exposure and cost. Once the weights are given based on the importances, a compromise programming methodology can be used to determine the solution. Then, the model can be modified as below:

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$$maximize_{X_i} = W_e \frac{Z_e}{Max\, Z_e} - W_c \frac{Z_C}{Min\, Z_c} \tag{28}$$

s.t.

$$\sum_{i=1}^{\sum_{j=1}^{J} K_j} (A_i\, X_i) \geq E \qquad \text{i}\in\text{I, j}\in\text{J} \tag{29}$$

$$\sum_{i=1}^{\sum_{j=1}^{J} K_j} (AC_i\, X_i) \leq B \qquad \text{i}\in\text{I, j}\in\text{J} \tag{30}$$

$$\sum_{i=o^o}^{\sum_{j=1}^{J} K_j} AC_i X_i \leq Z_{on} \qquad \text{i}\in\text{I, j}\in\text{J} \tag{31}$$

$$\sum_{i=1}^{\sum_{j=1}^{J} K_j} (AC_i\, X_i) - \sum_{io^o}^{\sum_{j=1}^{J} K_j} AC_i X_i \leq Z_{of} \qquad \text{i}\in\text{I, j}\in\text{J} \tag{32}$$

$$\sum_{i=1}^{K_j} X_i \geq 1 \qquad \text{i}\in\text{I, j}\in\text{J} \tag{33}$$

$$X_i \in \{0,1\} \qquad \text{i}\in\text{I} \tag{34}$$

The objective function given in eq. (28) aims to maximixe exposure and minimize the cost based on the assigned weight. The methodology is a multiobjective model and the number of exposures can be increased depend on the decision maker’s preferences. Other objectives are the same with the previous constraints.

III. A Case study for Turkiye

The proposed methodologies namely maximum exposure, minimum cost, minimax, maximin and compromise programming provide useful information for the decision makers. The decision maker provides data, and the solution methodology provides the results so that the best decision can be obtained. The solution methodology can be summarized as a pseudo code given in Figure 1.

1. Start
2. Load age, gender, income, and education segment data
3. Load advertisement budget, target group, and desired exposure data
4. Load advertisement channels and sources
5. For each budget and exposure target
6. Solve Maximum Exposure Integer Programming for Budget Allocation
7. Solve Minimum Cost Integer Programming model
8. Solve Minimax, Maximin, and compromise programming models
9. Calculate Cost and exposure for each solution
10. Next
11. Return the solution of each model to decision maker
12. End

Figure 1. Pseudo code for the advertisement problem

This solution methodology is implemented in a spreadsheet and converted to a decision support system where the data is fed to the system, and the algorithm finds the best solution for each problem. Microsoft Excel Solver is used to solve the problems and to implement the decision support system. The screenshots for the decision support system are given in Appendix.

The proposed solution methodology is applied to Turkiye using the real data provided accrediated institutions. The resources for the advertisement are determined as TV, Newspaper, radio, cinema, outdoor, magazine, and online. All the data for ratings, views and audience from different groups are collected from Nielsen company. The data is real and tested using different resources.

The audience should be segmented for the best exposure level. Based on the preferences, the audience is segmented based on the age, gender, income level, and education. The detail for the segmentation is given in Table 1.

Table I. Segmentation for advertisement

Category	**Subcategories**
Age	Kids (5–14 years)
	Young (15–24 years)
	Middle (25–44 years)
	Adult (45–55+ years)
Gender	Female
	Male
Income	Low income
	Mid level
	High income
Education	High School
	University

The data for segment information and interests of different groups is provided at TIAK’s public website (Television Audience Measurement Company) [14]. A company can determine the targets for each category and subcategory can run the models for determine the best outcome.

The data also include important information about advertisements. The name of advertisement source, channel, advertisement types (Introducing ads, extra spot ads, normal spot ads, separator ads, social ads etc.), the total amount of advertisement in a month, total cost, advertisement time and/or space are some of the important information that are provided. The case study considers a company with a certain budget for advertisement and expectation channels. The information for the budget and minimum number of channels that are required are given in Table 2.

Table II. Company advertisement budget and information

Budget (TL)	150000000
Online Budget (TL)	30000000
Offline Budget (TL)	120000000
Tv Channels	8
News Channels	3
Radio channels	6
Cinema channels	1
Outdoor channels	1
Magazine channels	4
Online channels	18
Online percentage (%)	20
Offline percentage (%)	80
Exposure	5000000

Using the segmentation data, company aims to reach certain groups within audience from different age, income level, gender, and education. The targeted audience information is given in Table 3.

TABLE III. TARGET FOR THE AUDIENCE GROUPS

Category	Weight	Subcategory	Distribution
Age	0,4	Kids (5–14)	0,1
		Young (15–24)	0,4
		Middle (25–44)	0,3
		Adult (45–55+)	0,2
Income	0,3	Low income	0,3
		Mid level	0,5
		High income	0,2
Gender	0,2	Female	0,6
		Male	0,4
Education	0,1	University	0,65
		High School	0,35

Based on the estimation and analysis, the minimum required number of advertisements (ads) from each resource are also determined as given in Table 4.

The solution methodology is run using the provided information and the problem is solved using Max Exposure (Maximum Exposure Integer Programming for Budget Allocation), Min cost (Minimum Cost Integer Programming model), Minimax, Maximin, and Compromise programming. Table 5 shows the exposure, cost and cost per exposure for the best solution for each problem type.

TABLE IV. MINIMUM DESIRED NUMBER OF ADS FROM EACH RESOURCE

Channel Type	Number of Ads
TV Ads	20
News Ads	100
Radio Ads	1
Cinema Ads	500
Outdoor Ads	1
Magazine Ads	100
Online Ads	2,000,000

TABLE V. EXPOSURE AND COST FOR EACH BEST SOLUTION

Alternative	Exposure	Cost (TL)	Cost per Exposure (TL/exposure)
Max Exposure	1,851,457,014	4,192,366,516	2.26
Min Cost	50,438,051	23,828,705	0.47
Minimax	47,880,938	3,206,671	0.06
Maximin	58,594,172	35,404,285	0.60
Compromise	4,925,687,291	20,825,094	0.004

Results show that maximum exposure is reached in compromise programming while minimum cost is reached in Minimax. But one should keep in mind that these are the best solution for each objective function of each problem type where the objective in each problem is to reach a different cost and exposure composition. Hence all solutions have a meaning for the decision maker.

Table 6 shows the distrubition of exposures for the best solution provided in Table 5. While online always gets the highest share, the distribution within alternatives for each solution type differ. TV and outdoor are still popular advertisement channells while radio loose its popularity in many cases. The decision maker can select one solution based on the budget and time limitations.

TABLE VI MINIMUM DESIRED NUMBER OF ADS FROM EACH RESOURCE

Alternative	Max Exposure	Min Cost	Minimax	Maximin	Compromise
TV	5117650	581436	0	352611	1483286
News	1236162	10866	6185	379127	59861
Radio	6363	914	655	763	222330000
Cinema	1200000	1200000	1200000	1200000	3000000
Outdoor	16302828	1680063	1680063	16302828	40418427
Magazine	273462	37136	33231	37060	96
Online	1827320547	46927633	44960802	40321781	4658299717

IV. CONCLUSION

In an increasingly complex advertising landscape, effectively allocating a finite budget across multiple channels is a critical challenge for decision makers. This paper has presented a comprehensive decision-making framework that integrates customer segmentation and multi-objective optimization models to support budget allocation between online and offline advertising channels. By applying five optimization models—maximum exposure, minimum cost, minimax, maximin, and compromise programming—the study offers a robust methodology for evaluating different strategic approaches depending on a company's priorities.

The application of this framework to a real-world case using Nielsen data from Türkiye demonstrates the practical value of these models. Notably, the compromise programming model emerged as the most balanced and effective solution, achieving high exposure at a relatively low cost. This suggests that when both exposure and cost are important, a compromise approach offers a meaningful trade-off and superior performance.

The results highlight that no single model is universally optimal; rather, the best solution depends on the company’s objectives—whether maximizing reach, minimizing expense, or balancing the two. The segmentation-driven structure of the models ensures that advertising decisions are tailored to the preferences and behaviors of specific audience groups, improving targeting efficiency.

This study contributes to the academic and practical discourse on advertising optimization by proposing a flexible, data-driven toolset that can be adapted across industries and markets. Future research can build on this framework by incorporating dynamic market factors, real-time campaign performance feedback, or advanced machine learning techniques to further refine decision-making in advertising strategies.

The solution methodology is generic and can be applied by the companies to allocate their advertisement budget effectively and reach the target group. The spreadsheet-based decision support system is also another practical tool that allows decision makers to analyze the results and do sensitivity analysis.

V. Appendix

This section presents the screenshots of the decision support system.

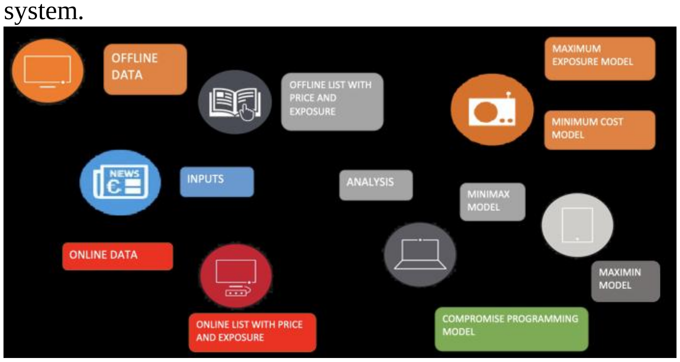

Fig.1. The main menu

Fig. 2. The data for the online advertisement

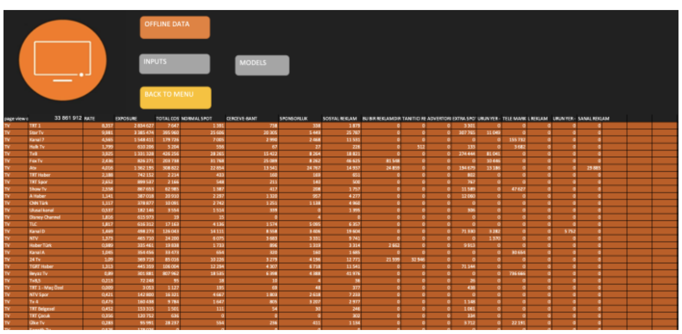

Fig. 3. The data for the offline advertisement

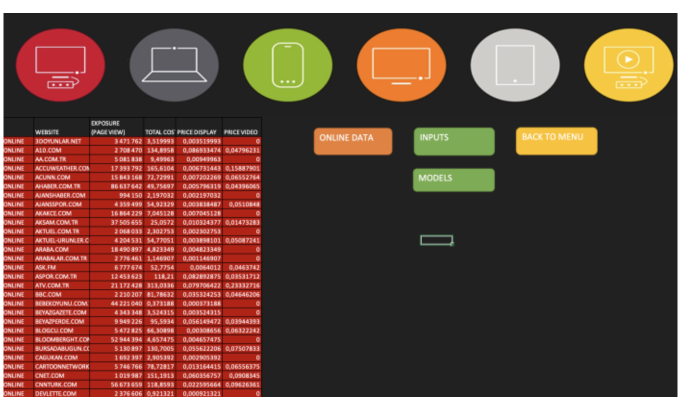

Fig. 4. The data for the online channels

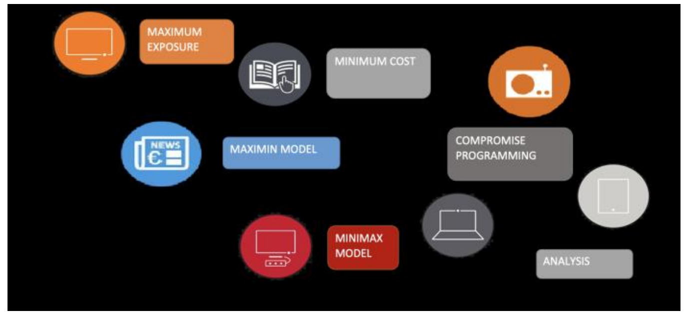

Fig. 5. The menu for the solution methodologies

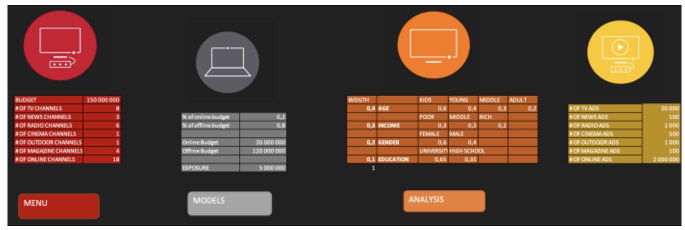

Fig. 6. Inputs for the exposure and cost preferences

Fig. 7. The results and analysis section

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