Optimizing Customer Assignments to Direct Marketing Activities: A Binary Linear Programming Formulation

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***Abstract*—Direct marketing has become a fundamental advertising method in many industries. In direct marketing, companies target specific customers with personalized product offers. By optimally assigning customers to direct marketing activities, the effectiveness of direct marketing campaigns can be greatly increased. In this paper, we study a real-world customer assignment problem of a leading telecommunications provider in Switzerland. The planning problem contains many business and customer-specific constraints that have not yet been covered in the literature. We propose a binary linear programming formulation that solves instances involving up to one million customers and over 100 direct marketing activities to optimality in short running time. The novel formulation delivers substantially better solutions in terms of expected profit than the current practice at the company.**

***Keywords*—Direct marketing, customer assignment, real-world problem, binary linear programming**

I. Introduction

Direct marketing is an advertising method that promotes products and services to specific customers with personalized offers. Contacting customers directly with a *call*, a *direct mail*, an *email*, or a *text message* has proven to be more effective in many industries than using mass-communication media such as posters, television, or radio (cf. Monard et al. [1]). By targeting the right customers, one can greatly enhance the impact of the available direct marketing budget. To identify the right customers, companies have started to develop so-called response models, which estimate the probability of a customer to react positively to a direct marketing activity (cf. e.g., Lessmann et al. [2]). In this way, response models deliver key information for companies to decide which customers to assign to which direct marketing activity.

The subject of this paper is a real-world planning situation that was reported to us by a leading Swiss telecommunications provider. The planning of direct marketing campaigns is carried out in two phases. In the first phase, direct marketing campaigns are broken down into direct marketing activities (DMAs) that are then scheduled over time. In the second phase, individual customers are assigned to DMAs. We concentrate in this paper on the second phase, which can be described as follows. A time horizon and a set of DMAs that take place on specific days during the time horizon are given. Each DMA is associated with a product, a channel (*call center*, *direct mail*, *email*, or *text message*), a cost of contact, and a group of potential customers with individual response probabilities and expected profits. The company defines various business constraints, such as budgets that must not be exceeded, as well as channel capacities and product-specific sales constraints that must be met. Furthermore, two types of customer-specific constraints are defined which ensure that a customer is not assigned too often. A feasible solution of customer assignments to DMAs is sought that maximizes the total expected profit.

The considered planning problem can be abstracted to an assignment problem with specific side constraints. Even though some of the side constraints have been discussed in the literature (cf. Öncan et al. [3]), there are no models in the literature that can be directly applied to the reported planning problem. Related planning problems were mainly addressed for applications in the financial sector (cf. Cohen [4], Delanote et al. [5]). Most of the proposed models focus on a single period (cf. Cohen [4], Nobibon et al. [6]). The few models that cover multi-period planning problems are applied to customer segments instead of individual customers and do not consider all relevant customer-specific constraints (cf. Delanote et al. [5]), or focus on the design of campaigns instead of the customer assignment (cf. Nair and Tarasewich [7]). Furthermore, we face large-scale instances involving hundreds of thousands of customers. Some instances contain even several million customers. For these instances, heuristics are required. In the literature only few heuristics have been applied to large-scale instances of related problems. Thoroughly evaluating the performance of these heuristics based on optimal solutions or lower bounds has been difficult because existing exact approaches are only applicable to small-sized instances.

We address this gap by contributing a novel binary linear programming formulation (BLP). In contrast to related multi-period formulations from the literature, our formulation does not employ time-indexed decision variables. We consider the timing information of activities by defining constraint-specific sets of DMAs. For example, if a budget constraint is imposed for January, we define a set that comprises only DMAs from January. This modeling technique not only enhances the readability of the formulation but also helps to cope with large-scale instances. Such instances typically have millions of customer-specific constraints. By using our modeling technique, we introduce a problem structure that can be exploited by preprocessing procedures of state-of-the-art solvers. We test the novel BLP formulation on four generated instances and one real-world instance. All instances can be solved optimally in short running time. A business case for the company is established by comparing optimal solutions of the BLP to

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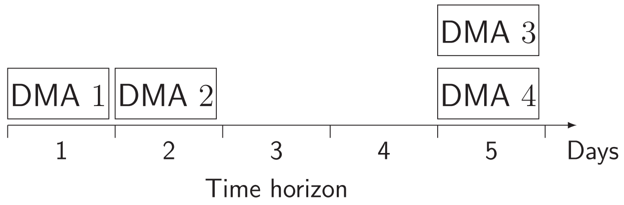

Fig. 1: Illustrative example: scheduling of DMAs

optimal solutions of a non-profit-based approach that simulates the telecommunications provider's current practice. Even though the non-profit-based approach tends to assign more customers to DMAs, the solutions of the BLP deliver on average more than 50% higher expected profits.

This paper is structured as follows. In Section II, we describe the planning problem in detail. In Section III, we review the related literature. In Section IV, we present the novel binary linear formulation. In Section V, we describe the experimental design and report the computational results. Finally, in Section VI, we provide an outlook with suggestions for future research directions.

II. Planning problem

The planning problem was reported to us by a leading Swiss telecommunications provider. In Section II-A, we formally describe the reported planning problem. In Section II-B, we illustrate it with an example.

A. Problem description

A time horizon and a set of DMAs are given. Each DMA occurs on a specific day during the time horizon and is characterized by a product, a channel (*call center*, *direct mail*, *email*, or *text message*), a cost of contact, and a group of potential customers. Note that the groups of potential customers of different DMAs can overlap. For each customer in a group, a response model estimates an individual response probability. Furthermore, a change in revenue is computed per customer and DMA based on the customer's current plan and the characteristics of the DMA. An expected profit per customer and DMA can be derived from the change in revenue, the response probability, and the cost of contact.

The company defines various constraint groups that must be satisfied, i.e., budget constraints, capacity constraints, sales constraints, revenue constraints, min-max-assignment constraints, and customer-specific constraints. Barring a few customer-specific constraints, all constraints can be defined either for the entire time horizon or for a period of time within the time horizon. Next, we describe each constraint group in detail.

Budget constraints are defined for individual channels or groups of channels and must not be exceeded, e.g., the number of *calls* multiplied by the cost per *call* must not exceed a budget of CHF 10,000 for a particular month. Capacity constraints are defined for individual channels as lower and upper bounds that must be satisfied, e.g., there must be at least 1,000 and at most 5,000 *calls* during

TABLE I: Illustrative example: input data

	DMA 1	DMA 2	DMA 3	DMA 4
Anne	5/0.20	15/0.10	5/0.15	12/0.22
Bob	-	-	$-5/0.05$	-
Chloe	12/0.12	-	18/0.14	-
Dean	9/0.25	-	-	10/0.11
Channel	Call center	Call center	Direct mail	Call center
Product	Mobile	TV	Mobile	TV

TABLE II: Illustrative example: optimal solution

	DMA 1	DMA 2	DMA 3	DMA 4
Anne	☑	☐	☑	☐
Bob	-	-	☐	-
Chloe	☑	-	☑	-
Dean	☑	-	-	☑

a particular week. Sales constraints are determined for individual products and also comprise lower and upper bounds. For example, the summed response probabilities, i.e., the expected sales, of all customers assigned to a *mobile*-DMA must exceed a lower bound of 100 for a particular week. Revenue constraints ensure a target value, i.e., a lower bound, on the average change in revenue for a product, e.g., the average change in revenue of contacted *TV* customers must be at least CHF 5 over a particular month. Min-max-assignment constraints include lower and upper bounds on the number of customers assigned to individual DMAs and groups of DMAs.

Customer-specific constraints comprise two types of constraints that ensure that customers are not assigned too often. The first type refers to so-called collision constraints which correspond to a channel- and product-specific time lag between two consecutive assignments of the same customer to two DMAs and are imposed for the entire time horizon. For example, a minimum time lag of three weeks must be guaranteed between two customer assignments to activities that are associated with the channel *text message* and the product *internet*. The second type refers to so-called min-max-contact constraints that set a lower and an upper bound on the number of contacts per customer either for the entire time horizon or a period of time within the time horizon. A feasible solution of customer assignments to DMAs is sought that maximizes the total expected profit.

The given planning problem is NP-hard as it can be reduced to a generalized assignment problem that is known to be NP-hard (cf. Garey and Johnson [8]).

B. Illustrative example

To illustrate the planning problem described above, we consider four customers and four DMAs that are scheduled as shown in Figure 1. The group of potential customers of each of the four DMAs can be seen in Table I. The values in rows 1–4 correspond to the individual expected profits and response probabilities, respectively. The dash (-) indicates that the customer does not belong to the group of potential customers of the respective DMA. Moreover, the channels and products associated with the DMAs are reported in the last two rows. The costs of contact for the channels *call center* and *direct mail* is CHF 10 and

TABLE III: Problem features covered in literature

Problem feature	Cohen [4]	Nobibon et al. [6]	Oliveira et al. [9]	Coelho et al. [10]	Nair and Tarasewich [7]	Delanote et al. [5]	Ma and Fildes [11]	BLP
	Single-period				Multi-period			
Decisions								
Customer assignment	✓	✓	✓	✓		(✓)		✓
Business constraints								
Budget constraints	✓	✓	✓	✓		✓		✓
Channel capacity constr.	✓					✓		✓
Sales constraints						✓		✓
Revenue constraints	(✓)	(✓)	(✓)	(✓)				✓
Min-max assignment constr.	✓	(✓)	(✓)	(✓)				✓
Customer-specific constr.								
Collision constraints					✓			✓
Min-max-contact constr.	(✓)	(✓)	(✓)	(✓)				✓
Objective								
Expected Profit	✓	✓	✓	✓		✓	✓	✓

CHF 4, respectively. The following customer-specific and business constraints are defined for the entire time horizon. A max-contact constraint guarantees that each customer can be assigned at most two times. A collision constraint prevents that the same customer is *called* twice within three days. Furthermore, a minimum sales constraint of 0.8 for the product *mobile* must be satisfied. There is a budget constraint of CHF 12 for the channel *direct mail* as well as a capacity constraint with lower and upper bounds of four and six, respectively, for the channel *call center*. No revenue constraints, min-max-assignment constraints, and min-contact constraints are imposed.

The optimal solution is given in Table II. The check marks indicate which customers are assigned to which DMAs. The objective function value of the optimal solution is $5 + 12 + 9 + 5 + 18 + 10 =$ CHF 59. Anne belongs to the group of potential customers of all four DMAs. Since the maximum number of contacts per customer is two, Anne can only be assigned to two of the four DMAs. Even though Anne has the highest expected profits for DMAs 2 and 4, she cannot be assigned to both because of the collision constraint. Furthermore, Anne must be assigned to DMAs 1 and 3 to satisfy the sales constraint. Bob has no assignment in the optimal solution because his assignment would yield a negative expected profit. Dean can be assigned to DMAs 1 and 4, since the four days between his assignments exceed the minimum three-day time lag of the collision constraint.

III. Related literature

To the best of our knowledge, none of the existing models can be directly applied to the planning problem described above. Related planning problems have been addressed in the literature, mostly for single-period problems. Table III shows the problem features covered by approaches from the literature. Row 2 indicates if the approaches perform a customer assignment. Rows 4–12 indicate which constraints the approaches address. The last row lists the approaches that optimize an expected profit. A check mark in parenthesis means that the problem feature is only partly covered. Below, we describe the most closely related approaches in more detail.

Cohen [4] studies a real-world product targeting problem at a bank. To tackle large-scale instances, they aggregate customers to segments. Nobibon et al. [6] simultaneously determine the products that are included in the campaign and assign customers to them. They test their approach with instances involving up to ten thousand customers. Based on the model of Nobibon et al. [6], Oliveira et al. [9] and Coelho et al. [10] devise heuristic approaches. Delanote et al. [5] develop a multi-period model that incorporates the planning of an entire year but only consider customer segments. Also Nair and Tarasewich [7] and Ma and Fildes [11] consider multi-period settings, but their developed models focus on promotion design instead of customer assignment. Note that all exact approaches from the literature that consider customer-specific constraints are only applied to instances involving up to ten thousand customers.

IV. Binary linear programming formulation

In this section, we present the BLP formulation. Unlike related multi-period formulations from the literature, our formulation does not employ time-indexed decision variables. We consider the timing information of activities by defining constraint-specific sets of DMAs. The BLP is based on binary variables x_{ij} that indicate if customer i is assigned to DMA j. The notation of the BLP is provided in Table IV.

The objective function (1) computes the total expected profit of a feasible solution and is maximized.

$$\sum_{j \in J} \sum_{i \in I_j} p_{ij} x_{ij} \tag{1}$$

Constraints (2) ensure that each budget b_l for an individual channel or a group of channels is not exceeded.

$$\sum_{j \in J_l^B} \sum_{i \in I_j} c_j x_{ij} \leq b_l \qquad (l \in B) \tag{2}$$

Constraints (3) make sure that each minimum channel capacity $\underline{k}_l$ is achieved.

$$\sum_{j \in J_l^{\underline{K}}} \sum_{i \in I_j} x_{ij} \geq \underline{k}_l \qquad (l \in \underline{K}) \tag{3}$$

Constraints (4) ensure that each maximum channel capacity $\overline{k}_l$ is not exceeded.

$$\sum_{j \in J_l^{\overline{K}}} \sum_{i \in I_j} x_{ij} \leq \overline{k}_l \qquad (l \in \overline{K}) \tag{4}$$

Constraints (5) guarantee that the number of expected sales for an individual product does not fall below the prescribed lower bound $\underline{s}_l$.

$$\sum_{j \in J_l^{\underline{S}}} \sum_{i \in I_j} q_{ij} x_{ij} \geq \underline{s}_l \qquad (l \in \underline{S}) \tag{5}$$

TABLE IV: Notation

Sets	
A	Indices of revenue constraints
B	Indices of budget constraints
I	Customers
J	DMAs
$\underline{K}$	Indices of minimum channel capacity constraints
$\overline{K}$	Indices of maximum channel capacity constraints
$\underline{M}$	Indices of min-contact constraints
$\overline{M}$	Indices of max-contact constraints
$\underline{N}$	Indices of min-assignment constraints
$\overline{N}$	Indices of max-assignment constraints
$\underline{S}$	Indices of minimum sales constraints
$\overline{S}$	Indices of maximum sales constraints
T	Pairs of DMAs for which a collision constraint applies
I_j	Group of potential customers of DMA j
J_i	DMAs for which customer i is a potential customer
J_l^A	DMAs associated with revenue constraint l
J_l^B	DMAs associated with budget constraint l
$J_l^{\underline{K}}$	DMAs associated with minimum channel capacity constraint l
$J_l^{\overline{K}}$	DMAs associated with maximum channel capacity constraint l
$J_l^{\underline{M}}$	DMAs associated with min-contact constraint l
$J_l^{\overline{M}}$	DMAs associated with max-contact constraint l
$J_l^{\underline{N}}$	DMAs associated with min-assignment constraint l
$J_l^{\overline{N}}$	DMAs associated with max-assignment constraint l
$J_l^{\underline{S}}$	DMA associated with minimum sales constraint l
$J_l^{\overline{S}}$	DMA associated with maximum sales constraint l
Parameters	
a_l	Target value for revenue constraint $l \in A$
b_l	Budget of budget constraint $l \in B$
c_j	Cost per contact of DMA j
$\underline{k}_l$	Minimum channel capacity of constraint $l \in \underline{K}$
$\overline{k}_l$	Maximum channel capacity of constraint $l \in \overline{K}$
$\underline{m}_l$	Minimum #contacts per customer in constraint $l \in \underline{M}$
$\overline{m}_l$	Maximum #contacts per customer in constraint $l \in \overline{M}$
$\underline{n}_l$	Minimum #assignments for DMAs in constraint $l \in \underline{N}$
$\overline{n}_l$	Maximum #assignments for DMAs in constraint $l \in \overline{N}$
p_{ij}	Expected profit of customer i when assigned to DMA j
q_{ij}	Response probability of customer i when assigned to DMA j
$\underline{s}_l$	Minimum expected sales of constraint $l \in \underline{S}$
$\overline{s}_l$	Maximum expected sales of constraint $l \in \overline{S}$
v_{ij}	Change in revenue when customer i positively responds to assignment to DMA j
Decision variables	
x_{ij}	$= 1$, if customer i is assigned to DMA j; $= 0$, otherwise

Constraints (6) make sure that the number of expected sales for an individual product does not exceed the prescribed upper bound $\overline{s}_l$.

$$\sum_{j \in J_l^{\overline{S}}} \sum_{i \in I_j} q_{ij} x_{ij} \leq \overline{s}_l \qquad (l \in \overline{S}) \tag{6}$$

Constraints (7) ensure that each expected average change in revenue $\frac{\sum_{j \in J_l^A} \sum_{i \in I_j} v_{ij} q_{ij} x_{ij}}{\sum_{j \in J_l^A} \sum_{i \in I_j} q_{ij} x_{ij}}$ is equal to or greater than the corresponding prescribed minimum average change in revenue a_l for an individual product.

$$\sum_{j \in J_l^A} \sum_{i \in I_j} v_{ij} q_{ij} x_{ij} \geq a_l \sum_{j \in J_l^A} \sum_{i \in I_j} q_{ij} x_{ij} \qquad (l \in A) \tag{7}$$

Constraints (8) guarantee that the number of assigned customers to an individual DMA or a group of DMAs does not fall below the prescribed lower bound $\underline{n}_l$.

$$\sum_{j \in J_l^{\underline{N}}} \sum_{i \in I_j} x_{ij} \geq \underline{n}_l \qquad (l \in \underline{N}) \tag{8}$$

Constraints (9) ensure that the number of assigned customers to an individual DMA or a group of DMAs does not exceed the prescribed upper bound $\overline{n}_l$.

$$\sum_{j \in J_l^{\overline{N}}} \sum_{i \in I_j} x_{ij} \leq \overline{n}_l \qquad (l \in \overline{N}) \tag{9}$$

Constraints (10) guarantee a channel- and product-specific minimum time lag in between two consecutive assignments of a customer i to DMAs j_1 and j_2 during the entire time horizon. For example, if two *call center*-DMAs are scheduled four days apart from each other and the minimum time lag between two *calls* is seven days, then the pair of the two DMAs belongs to set T.

$$x_{ij_1} + x_{ij_2} \leq 1 \qquad ((j_1, j_2) \in T, i \in I_{j_1} \cap I_{j_2}) \tag{10}$$

Note that these constraints introduce a problem structure that can be exploited by clique cuts of state-of-the-art solvers. Thus, the preprocessing procedures of the solvers are able to add effective cutting planes.

Constraints (11) guarantee that customer i is assigned at least $\underline{m}_l$ times to activities j from set $J_l^{\underline{M}}$.

$$\sum_{j \in J_l^{\underline{M}} \cap J_i} x_{ij} \geq \underline{m}_l \qquad (i \in I, l \in \underline{M}) \tag{11}$$

Constraints (12) ensure that customer i is assigned at most $\overline{m}_l$ times to activities j from set $J_l^{\overline{M}}$.

$$\sum_{j \in J_l^{\overline{M}} \cap J_i} x_{ij} \leq \overline{m}_l \qquad (i \in I, l \in \overline{M}) \tag{12}$$

In sum, the formulation reads as follows:

$$(\text{BLP}) \begin{cases} \text{Max.} & (1) \\ \text{s.t.} & (2) – (12) \\ & x_{ij} \in \{0,1\} \quad (j \in J, i \in I_j) \end{cases}$$

Subsequently, we refer to another variant of the formulation as non-profit based approach (NPBA):

$$(\text{NPBA}) \begin{cases} \text{Max.} & \sum_{j \in J} \sum_{i \in I_j} x_{ij} \\ \text{s.t.} & (2) – (12) \\ & x_{ij} \in \{0,1\} \quad (j \in J, i \in I_j) \end{cases}$$

With this variant, we can roughly imitate the current practice at the company.

V. Results

In this section, we first describe the test instances and the experimental design in Subsection V-A and then report the computational results in Subsection V-B.

A. Experimental design

We applied the BLP and the NPBA to four generated test instances A1–A4 and one real-world test instance B1. The instances differ with respect to the length of the time horizon, the number of DMAs, the number of customers (Table V), and the constraints. Test instances A1–A4 were generated based on real-world data. We implemented the BLP in Python 3.7 and used Gurobi 8.1 as solver. All

TABLE V: Problem instances

Instance	Source	Time horizon	#DMAs	#Customers
A1	Generated	3 months	50	5,000
A2	Generated	3 months	100	40,000
A3	Generated	3 months	120	80,000
A4	Generated	3 months	150	80,000
B1	Real-world	1 week	133	987,486

TABLE VI: Numerical results

	BLP			NPBA			
Ins.	OFV $[10^6]$	#Asgmt $[10^4]$	CPU [s]	OFV $[10^6]$	#Asgmt $[10^4]$	CPU [s]	Imp. [%]
A1	**2.1**	1.2	7.7	1.9	1.3	7.6	7.3
A2	**45.9**	20.3	151.0	33.6	23.7	109.9	36.6
A3	**86.0**	35.5	476.5	59.0	41.9	802.1	45.7
A4	**83.6**	34.6	2,070.1	57.8	40.7	1,206.8	44.7
B1	**11.0**	22.6	228.6	4.7	23.3	183.2	134.8

computations were performed on an HP workstation with one Xeon CPU with clock speed 2.20 GHz and 128 GB of RAM. No time limit was imposed.

B. Computational results

Table VI reports the numerical results. Columns 2–4 show the objective function value (OFV) in million CHF, the number of assignments made in the optimal solution (#Asgmt) in ten thousands, and the running time (CPU) in seconds of the BLP. Columns 5–7 list the same information for the NPBA. Column 8 quantifies the relative improvement in the OFV (Imp.) of solutions obtained with the BLP in comparison to solutions obtained with the NPBA. The best OFV for each instance is highlighted in bold face.

The BLP generates solutions that are up to 134.8% better than solutions generated by the NPBA within comparable running time (Table VI). This improvement is realized although the BLP tends to assign fewer customers to DMAs than the NPBA. The BLP chooses high-profit customers, while the NPBA assigns as many customers as possible. There are customers who have a negative expected profit for a DMA because the cost of contacting them is higher than the change in revenue expected from them. While those customers are still assigned with the NPBA, they are not with the BLP. These results demonstrate the substantial advantage of the BLP in comparison with the NPBA.

VI. Conclusions

We have reported a planning problem of a telecommunications provider who assigns customers to direct marketing activities (DMAs). This planning problem contains various business- and customer-specific constraints that have not yet been described in the literature. Therefore, we formulated a novel binary linear programming formulation (BLP) that is easy to read and whose structure can be exploited by state-of-the-art solvers. This property can be applied to related planning problems. Our computational results with test instances involving nearly one million customers and over 100 DMAs show the great advantage of the BLP to the companies' current practice in terms of expected profit. The expected profit could be improved by 54% on average.

In future research, we plan to use array-computing to identify and remove redundant customer-specific constraints before they are added to the model. This removal might substantially reduce the running time of our approach. Moreover, we plan to develop a matheuristic for instances that have a longer time horizon than the instances tested here.

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