Published paper
Fleming, P.J. and Pashkevich, M.A. (2007) *Editor View of Item: Optimal advertising campaign generation for multiple brands using MOGA,* IEEE Transactions on Systems Man and Cybernetics Part C, Volume 37 (6), 1190 - 1201.

Optimal Advertising Campaign Generation for Multiple Brands Using MOGA

Peter J. Fleming and Maksim A. Pashkevich

***Abstract*—The paper proposes a new modified multiobjective genetic algorithm (MOGA) for the problem of optimal television (TV) advertising campaign generation for multiple brands. This *NP*-hard combinatorial optimization problem with numerous constraints is one of the key issues for an advertising agency when producing the optimal TV mediaplan. The classical approach to the solution of this problem is the greedy heuristic, which relies on the strength of the preceding commercial breaks when selecting the next break to add to the campaign. While the greedy heuristic is capable of generating only a group of solutions that are closely related in the objective space, the proposed modified MOGA produces a Pareto-optimal set of chromosomes that: 1) outperform the greedy heuristic and 2) let the mediaplanner choose from a variety of uniformly distributed tradeoff solutions. To achieve these results, the special problem-specific solution encoding, genetic operators, and original local optimization routine were developed for the algorithm. These techniques allow the algorithm to manipulate with only feasible individuals, thus, significantly improving its performance that is complicated by the problem constraints. The efficiency of the developed optimization method is verified using the real data sets from the Canadian advertising industry.**

***Index Terms*—Advertising, evolutionary computation, genetic algorithm (GA), multiobjective optimization.**

I. Introduction

EVERY year, an enormous amount of money is spent on *advertising*. In 2003, the total cost of advertising in the U.S. was about 200 billion dollars, and about 50% of this money was spent on television (TV) commercials. Since advertising involves "big money," the mediaplanners are responsible for making the mediaplans as effective as possible, and increasing the efficiency of the mediaplanning results in huge profits for advertising agencies and television networks. For example, Bollapragada *et al.* [1] describe the case where their effective optimization of the sales processes for the U.S. National Broadcasting Company (NBC) resulted in an increase of revenues by over 15 million dollars annually.

TV mediaplanning involves two major participants that are television networks (stations) and advertising agencies, and can be briefly outlined as follows. After announcing program schedules, the TV networks finalize their rating forecasts, estimate market demand, and set the rate cards for the available advertising breaks. The rate cards contain 1-s price and expected rating of a spot in a particular TV show. Mediaplanning agencies buy advertising time for each of their clients from the networks, and then produce advertising campaigns (mediaplans) for the brands of clients.

Both networks and agencies face a number of time-consuming *mathematical problems* during this planning process. The *networks*, on one hand, have to develop optimal program schedule, accurately predict the ratings of the programs, and expected demand for the commercial breaks in the shows. Besides, they are faced with a problem of finding optimal advertising breaks distribution between the agencies subject to the agency requirement constraints and limited advertising inventory restrictions. A simplified flow chart of the TV network planning process is given in Fig. 1. In real life, advertising agencies can buy commercial breaks by parts and negotiate with the network on the percentage of the spots that will be aired in the first and last positions of the break. This creates an additional cumbersome problem of rescheduling commercials during the last week before they are broadcasted [2].

The *advertising agencies*, on the other hand, develop their own buying strategies and intend to bring their customers the most efficient mediaplans possible. They deal with a number of clients, with each client having a set of brands to be advertised subject to brand-specific restrictions. A simplified flow chart of the advertising agency planning process is presented in Fig. 2. The first important problem for the agency is efficient purchasing of advertising time. Besides, since major advertisers (such as Proctor and Gamble, for example) buy hundreds of commercial breaks and decide on the actual distribution of the breaks between the advertising brands later, the agency meets the problem of optimally assigning breaks in the pool purchased for a client to the client's brands, subject to the budget, minimum impact, and other constraints. This problem includes two subproblems, both of them being quite nontrivial. The first difficulty is to develop a model that would allow accurate forecasting of impact efficiency for the future advertising campaigns. The second issue (that is a subject of this paper) is generating optimal mediaplans (advertising schedules) for the client brands that maximize the impact on the TV viewers while satisfying all the required restrictions.

Forecasting the efficiency of future advertising campaigns is a statistical problem that usually involves longitudinal (panel) data analysis techniques. A number of papers were published on this topic, a good review of the approaches proposed can be found in [3]. Besides, Weber [4] published some encouraging results on application of neural networks to forecasting of viewing patterns based on German telemetric viewing data for

Manuscript received August 4, 2005; revised June 11, 2006. This work was supported by the International Association for the Promotion of Cooperation with Scientists from the New Independent States of the former Soviet Union (INTAS) under Grant YSF 03-55-869. This paper was recommended by Associate Editor R. Subbu.

P. J. Fleming is with the Department of Automatic Control and Systems Engineering, University of Sheffield, Sheffield S10 2TN U.K. (e-mail: p.fleming@shef.ac.uk).

M. A. Pashkevich is with the CISNET Modeling Team, R.M. Lucas Center for Magnetic Resonance Spectroscopy and Imaging, Department of Radiology, Stanford University, Stanford, CA 94305-5488 USA (e-mail: maksim.pashkevich@stanford.edu).

Digital Object Identifier 10.1109/TSMCC.2007.900651

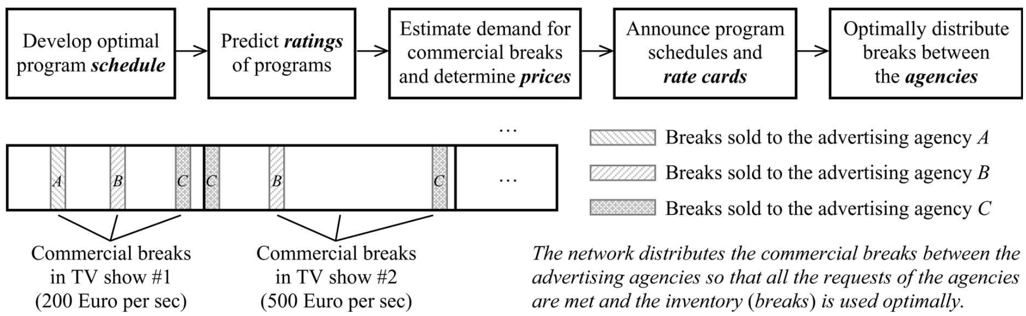


Fig. 1. Simplified flow chart of the mediaplanning process for a TV network.

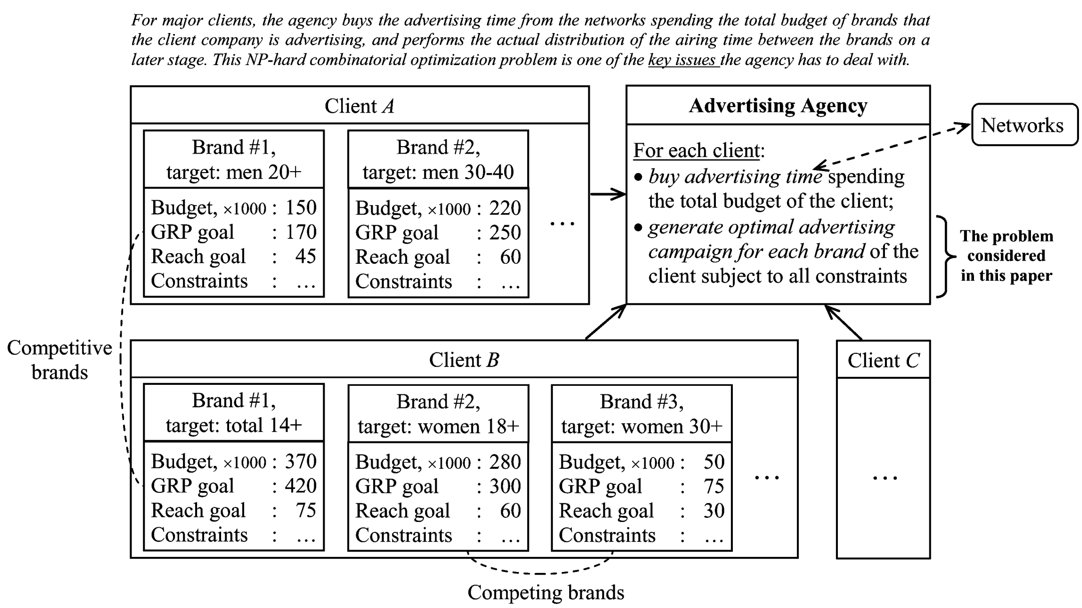


Fig. 2. Simplified flow chart of the mediaplanning process for an advertising agency.

specific target audiences. Recently, Pashkevich and Kharin [5] proposed a robust version of the beta-binomial model that was successfully applied for increasing forecasting accuracy in case when the past exposure data were available in binary form (a real data set from the German advertising market).

Optimization of advertising campaign efficiency is an *NP*-hard combinatorial multiobjective optimization problem that involves a number of complicated constraints. A classical approach to the solution of this problem is the greedy heuristic that relies on the strength of the preceding breaks when selecting the next break to add to the campaign. Literature review presented in the Section II indicates that very little research was done on this topic. Besides, the proposed optimization algorithms were developed either for generating campaigns for one advertising brand or were based on reducing the multiobjective optimization problem to a single objective by the weighted sum approach (a common way to select weights is based on the budgets of brands being advertised) [6]. This usually leads to discriminating the brands with smaller budgets, that is undesirable from the mediaplanners point of view. Hence, there is a need for a true *multiobjective optimization algorithm* that would provide the planner with a set of Pareto-optimal solutions and let him decide which one should be used as a final solution, based on his expertise and experience.

In this paper, we propose to use the *multiobjective genetic approach* [7] to generate a set of Pareto-optimal solutions for the problem of the advertising campaign efficiency optimization.

II. Related Works

A majority of literature on using the optimization techniques in mediaplanning deals with scheduling programs for *television networks* in order to optimize audience ratings. The common method is the "lead-in" strategy that relies on the strength of the preceding programs to boost the ratings of a newly introduced one. This approach was successfully applied in a number of papers (for details, see [8]–[11]). Several publications, such as [12] and [13] deal with an individual's television viewing choice. A comprehensive review of the viewing choice models can be found in [6] and [14]. Rust and Echambadi [15] developed a heuristic algorithm for scheduling a television network's program to maximize a network's share of audiences. Reddy *et al*. [16] developed an optimal prime time TV program scheduler based on the mixed-integer near-network flow model that was successfully tested using the 1990 data from a U.S. cable TV network. Several authors dealt with advertising scheduling strategies; a review of this approaches is presented in [17]. Recently, Bollapragada *et al*. [1] developed an optimization system for the sales processes of the NBC. They used integer and mixed-integer programming techniques to automatically develop the schedules of commercials that meet all the requirements [2], and to schedule the commercials evenly throughout the advertising campaign [18].

Although the mediaplanning issues for the *advertising agency* and the TV network have much in common, they essentially differ in mathematical formulation that opposes using common optimization tools, including those mentioned above. In contrast to the network mediaplanning, the problem of optimal campaign generation for the advertising agency received very little attention in scientific literature, although a number of papers were published on audience perception forecasting [4], [19], [20]. *Classical approach* to the optimal advertising campaign generation utilizes greedy heuristic that selects the most promising admissible break (for a particular brand campaign, step-by-step) [3]. The breaks are assigned to the brands one by one, and can be ordered in different ways (randomly, depending on a distance to goals, etc.). Within this approach, the multiobjective problem reduces to a single objective one by the weighted sum technique, and the weights are calculated as normalized brand budgets [21]. Being very simple to implement, this approach is not robust to the local dynamic restrictions, and usually uses some kind of rollbacks to overcome the violated constraints.

Recently, Pashkevich and Kharin [22] proposed a multistage technique based on the hybrid genetic algorithm (GA) for generating optimal advertising campaigns for multiple brands. Although this approach proved to be successful in real-world applications, it still relies on the weighted sum technique to improve the solution after all the goals are attained. To our knowledge, no results were published on the application of the multiobjective methodology to the problem of optimal advertising campaign generation for multiple brands.

It should be noted that other advertising problems, which involve newspaper advertising and web-page commercials, were also considered by the optimization research community. Merelo *et al*. [23] used the GA for optimal advertisement placement in different media. Naik *et al*. [24] utilized the GA for developing the optimal pulsing mediaplans. Van Buer *et al*. [25] considered solving the medium newspaper production/distribution problem by means of the GA. Collins and Harris [26] proposed to use the evolutionary approach to optimal generation of print and multimedia advertising campaigns. Ohkura *et al*. [27] employed an extended GA for the Japanese newspapers advertisement optimization. Carter and Ragsdale [28] addressed the problem of scheduling the preprinted newspaper advertising inserts using the GA. Dawande *et al*. [29] proposed special heuristics for optimal advertisement scheduling on a web page. A lot of this research was inspired by [30], which advocated using the GAs paradigm for solving time-consuming marketing problems.

As follows from the aforementioned literature review, the single-objective GAs were efficiently used to solve various mediaplanning optimization problems. Since the theory of multiobjective GAs (MOGAs) was efficiently evolving over the last decade, and had shown to be very valuable for practical applications, the authors propose to rely on the multiobjective evolutionary paradigm to solve the problem considered in this paper.

III. Problem Description

Before presenting a mathematical problem statement, let us give its informal problem description focusing on some practical details. When an advertising agency buys commercial breaks for major advertisers like Proctor & Gamble, Coca-Cola, etc., it sums the budgets of all the brands that the client wants to advertise, and purchases common advertising time from the TV networks. Then, the corresponding set of commercial slots bought, usually referred to as a *pool*, must be *distributed between the brands*, taking into a count a number of specific constraints and goals (as shown in Fig. 3).

The *major constraints* associated with the brand are the maximum budget allowed to spend, the minimum gross rating points (GRP), and the effective reach to be gained from broadcasting. There are also several *minor constraints*, which can be divided into two types. The first of them, the *search space constraints*, can be taken into account prior to the optimization by narrowing the brand search space. Some common examples are the genre of a TV show, its day part and weekday, and the commercial break length (since a brand commercial length must not exceed the break length). Besides, it is prohibited to expose competitive brand commercials in the same TV advertising break. The second type, the *solution space constraints*, highly depends on the mutual positions of the brand commercials in the entire adverting campaign plan. They can be also subdivided into local and global ones, depending on the relationship between the brands. Examples of the first subtype include minimum time interval between the successive brand exposures, and maximum number of the brand commercials in the same TV show. The second subtype arises when separate advertising campaigns (for single brands) are combined together. Relevant examples comprise maximum sum of the brand commercial lengths within the same TV break, and taboo on exposing competing brand commercials in the same TV advertising break (for instance, washing powders Ariel and Dash of Proctor and Gamble).

For each brand, the *efficiency* of an advertising campaign is measured by two performance indices: 1) GRP and 2) effective reach (Reach). These indices are computed for a particular segment of the viewing audience (*target group*) defined by the agency client. By definition [3], the GRP is the cumulative sum of audience percentages that watched the brand commercial, which was exposed several times. It is obvious that this index *may overestimate the commercial impact*, since it duplicates (triplicates, etc.) the percentage of regular viewers who were

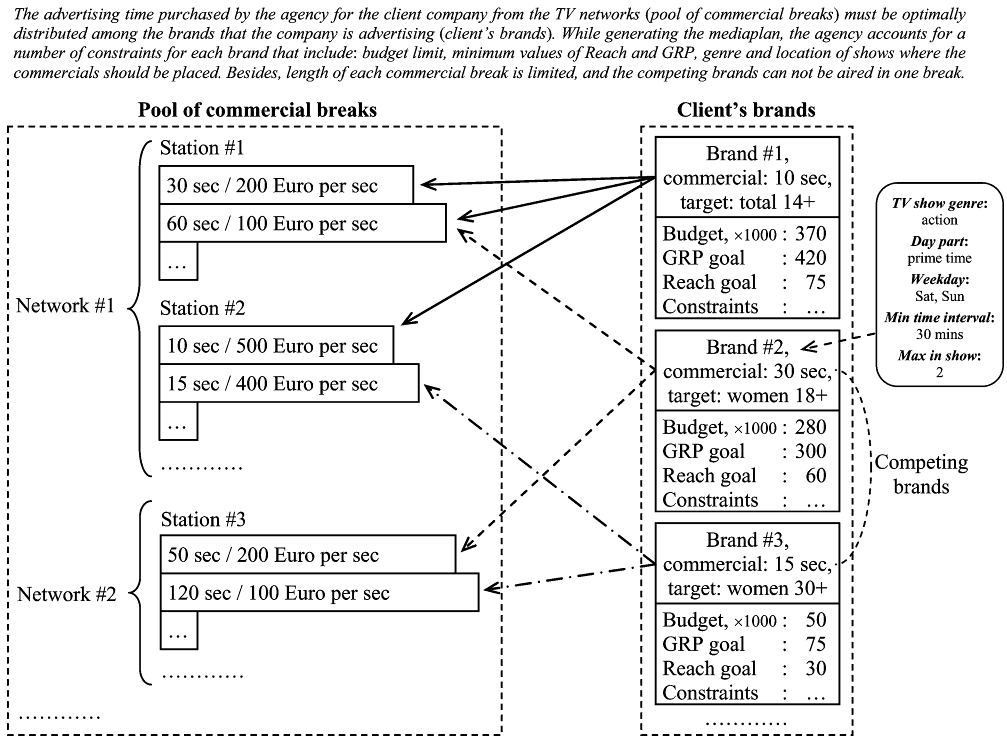


Fig. 3. Generating optimal advertising campaigns for multiple brands based on the purchased pool of the commercial breaks.

covered by all the exposures. In contrast, the Reach index measures the unduplicated audience, and is defined as the percentage of the viewers that watched the brand commercial at least once (twice, thrice, etc.). It should be noted that the Reach index saturates up to 100% as the campaign size increases, while the GRP index is additive and may exceed 100%. An example of the client requirements for a brand can be given as follows: 1) target group "Men 35+," i.e., males of age 35 years and older; 2) contact class "2+," i.e., only target group members who watched the commercial at least twice are included; 3) minimum Reach 65%; and 4) minimum GRP 240%.

The *primary goals* of the advertising campaigns optimization are achieving the best GRP and Reach for each separate brand, while satisfying the lower bounds on both of them, as defined by the client. Usually, mediaplanners optimize only one of these criteria (Reach or GRP), and use the second one as a lower bound constraint. Nevertheless, this leads to multiobjective setting with highly competing objectives for different brands and numerous constraints. It should be noted that when assessing the efficiency of the mediaplan, the mediaplanners often rely on additional criteria that can not be formalized and, therefore, embedded into the optimization algorithm in full scale. This may be caused by rapid changes on the advertising market or some short-term strategical issues that make the planers partially rely on their intuition. For this reason, we consider prudent to propose to the decision maker a set of Pareto-optimal solutions satisfying the formal goals and constraints, and let him make final decision relying on his expertise, experience, and intuition. This motivates application of the MOGAs, which are capable of undertaking such a problem.

IV. Problem Formulation

A. Basic Notation

We use the following notation to formally introduce the problem:

B the set of commercial breaks, $B=\{b_1, b_2, \ldots, b_m\}$;
m the number of commercial breaks;
i an index of a commercial break;
T_i the length of the commercial break b_i, in seconds;
P the set of brands being advertised, $P=\{p_1, p_2, \ldots, p_n\}$;
n the number of brands being advertised;
j an index of an advertising brand;
q_j the number of commercials for the brand p_j;
t_j the set of commercials for the brand $p_j, t_j = \{t_{j1}, t_{j2}, \ldots, t_{jq_j}\}$ sorted in ascending order;
t_{jv} the length of the commercial v for the brand p_j;
M_j the advertising budget of the brand p_j;
h_{jv} the budget share of the commercial v for the brand $p_j, \sum_{c=1}^{q_j} h_{jv} = 1$;
Δ_j the minimum time length between two consecutive commercials for the brand p_j;
k_j the maximum number of commercials in one show for the brand p_j;
G_j the GRP goal for the brand p_j;
R_j the Reach goal for the brand p_j;
c_{ij} the advertising price of one second in the break b_i for the brand p_j;
X the $m \times n$ matrix of the decision variables, $X = \{x_{ij}\}$;

x_{ij}	the commercial length if the brand p_j is advertised in the break b_i, and 0 otherwise;
X_j	the advertising campaign for the brand p_j, $X_j = \{x_{1j}, x_{2j}, \ldots, x_{nj}\}$;
D_j	the admissible breaks for the brand p_j after applying the search space constraints;
d_{ij}	1 if the brand p_j can be advertised in the break b_i, 0 otherwise, $D_j = (d_{1j}, d_{2j}, \ldots, d_{mj})$;
$R(X_j)$	the Reach of the campaign X_j for the brand p_j;
$G(X_j)$	the GRP of the campaign X_j for the brand p_j;
S	the set of commercial breaks grouped by TV shows, $S = \{s_1, s_2, \ldots, s_k\}, \Sigma_{c=1}^{q_j} h_{jv} = 1$;
k	the number of distinct TV shows;
l	an index of a TV show;
F	the $n \times n$ binary symmetric matrix of competing brands constraints, $F = \{f_{j_1 j_2}\}$;
$f_{j_1 j_2}$	1 if the brands j_1 and j_2 compete, and 0 otherwise;
$t(b_i)$	the absolute airing time of the break b_i.

B. Problem Statement

Using the notation above, we present the mathematical problem formulation as follows.

Optimize Reach for each brand

$$R(X_j) \rightarrow \max_{I(X_j) \in D_j}, \qquad j = 1, 2, \ldots, n \tag{1}$$

subject to the

- budget constraints

$$\sum_{i=1}^{m} I_{t_{jv}}(x_{ij}) x_{ij} c_{ij} \leq h_{jv} M_j, \qquad j = 1, \ldots, n, \quad v = 1, \ldots, q_j \tag{2}$$

- goal attainment constraints

$$R(X_j) \geq R_j, \quad G(X_j) \geq G_j, \qquad j = 1, 2, \ldots, n \tag{3}$$

- commercial-break length constraints

$$\sum_{j=1}^{n} x_{ij} \leq T_i, \qquad i = 1, 2, \ldots, m \tag{4}$$

- minimum time length between two consecutive commercials constraints

$$|t(b_{i_1}) - t(b_{i_2})| \cdot I(x_{i_1 j} x_{i_2 j}) \leq \Delta_j, \quad i_1, i_2 = 1, \ldots, m, \quad i_1 \neq i_2 \tag{5}$$

- maximum number of commercials in one TV show constraints

$$\sum_{b_i \in s_l} I(x_{ij}) \leq k_j, \qquad l = 1, 2, \ldots, k, \quad j = 1, 2, \ldots, n \tag{6}$$

- competing brands constraints

$$\sum_{i=1}^{m} \sum_{j_1=1}^{n} \sum_{j_2=1}^{n} x_{ij_1} x_{ij_2} f_{j_1 j_2} = 0 \tag{7}$$

where $I(x) = \{1$ if $x > 0$, and 0 otherwise$\}$, $I_y(x) = \{1$ if $x = y$, and 0 otherwise$\}$, and the functions are applied componentwise in case x and y are vectors.

The objective function (1) simultaneously maximizes the Reach index for all advertising brands $\{p_1, p_2, \ldots, p_n\}$ that compete over the pool of commercial breaks $\{b_1, b_2, \ldots, b_m\}$. Each brand p_j has q_j different commercials $\{t_{j1}, t_{j2}, \ldots, t_{jq_j}\}$ available for it, and each commercial t_{jv} has a budget share assigned (meaning that the subbudget of this commercial is $h_{jv} M_j$). Hence, the budget constraints (2) for every brand are formulated as a set of inequalities (one for each of the brand commercials). Please note that in the general case, the 1-s advertising price c_{ij} in the break b_i depends on the product p_j being advertised due to the specific agreements between the advertising agency and the TV network. The goal attainment constraints (3) ensure that in the generated set of Pareto-optimal solutions, every brand gains at least a minimum value of Reach and GRP indexes. The commercial break length constraints (4) guarantee that the total length of the commercials placed into a break does not exceed its length. Equation (5) describes the constraints for the minimum time length between two consecutive commercials for the same brand, while (6) limits the number of commercials of one brand placed in the same break. Competing brand constraints (7) make sure that only one of the competing brands can be placed in the same commercial break.

In addition to the aforementioned hard constraints, there are additional soft problem constraints that are not mandatory but are desired to be accomplished. The budget for each commercial length of every advertising brand should be spent as completely as possible. This requirement arises from the practical aspects of the problem, since the profit of the mediaplanning agency depends on the advertising budgets of their clients.

The formulated mathematical problem is an *NP*-hard multiobjective optimization problem of high dimension (usual values for n and m are 1500–125000 breaks and 30–75 brands for one month optimization depending on a county). Hence, applying the branch-and-bound or other exact technique does not seem prudent, and the problem is solved by means of metaheuristics. In this paper, we apply a specially designed version of the MOGA of Fonseca and Fleming [7] to solve the problem (1).

V. Multiobjective Evolutionary Approach

The evolutionary computation employs biology concepts of natural selection and population genetics to solve optimization problems that are hard or impossible to solve using traditional optimization techniques [31]. The major difference of the evolutionary algorithms (EAs) and other heuristical methods is that the EAs rely on a population of solutions, rather than on a single individual in the decision variable space. This research direction was started by the pioneer work of Rechenberg [32] who proposed the evolutionary strategies to solve complex optimization problems, and was followed by Fogel [33] with the evolutionary programming, and Holland [34] with the GAs. The theoretical results for the GA obtained by Goldberg [35], such as the Schema Theorem, made them very popular search techniques that resulted in numerous applications and enhancements of this optimization paradigm [36].

The GAs maintain a population of individuals that compete with each other for survival. After evaluation, individuals are given a probability of recombination that depends on their fitness. Offsprings are produced via crossover, where they inherit some features from the ancestors, and via mutation, where some innovative features can appear. At the next iteration, the offsprings compete with each other (and possibly also with their parents). Population improvement happens due to the repeated selection of the best parents, which are likely to produce better offsprings, and elimination of solutions that have low performance.

The MOGAs use the GA ideas to solve the multicriteria optimization problems. Historically, the population-based non-Pareto approaches were used to deal with this problem to start with. The first version of this technique was proposed by Schaffer [37], whose vector evaluated GA (VEGA) had modified selection procedure so that, at each generation, a number of subpopulations are generated according to each objective. Fourman [38] proposed to use the selection scheme based on the lexicographical ordering of the objectives according to the user priorities. Another version of the Fourman's algorithm consisted of randomly selecting the objective to be used for comparison of individuals in the tournament selection. Kursawe [39] proposed a multiobjective version of the evolutionary strategies, with each objective used to delete an appropriate fraction of the population during selection. Hajela and Lin [40] combined the GA with the weighted sum approach by explicitly including the weights into the chromosome, and using the fitness sharing to promote their diversity.

The Pareto-based MOGAs use the concept of Pareto optimality to rank the individuals in the population. The first version of the Pareto ranking was proposed by Goldberg [35], and was based on the consecutive computing of the dominating subpopulations, thus, assigning the ranks to the individuals according to the subpopulation index. Fonseca and Fleming [7] proposed an extension of this approach, where a solution's rank corresponds to the number of individuals in the current population by which it is dominated. Therefore, the nondominating individuals are all assigned the same rank, while the dominated ones are penalized according to the density of the population around them. The calculated ranks are then sorted and mapped into fitness, and the stochastic universal sampling (SUS) is used to perform the selection [41]. Besides, Horn and Nafpliotis [42] proposed a modification of the tournament selection based on the Pareto dominance. Cieniawski [43] and Ritzel *et al.* [44] used the tournament selection that relied on the Goldberg's Pareto-optimal ranking scheme.

The MOGA of Fonseca and Fleming [7] was the first Pareto-based evolutionary technique proposed for the multicriteria optimization problems. In addition to the aforementioned special ranking procedure, it relies on the niche-formation methods to distribute the solutions uniformly over the Pareto-optimal region, with the fitness sharing performed in the objective function space, and special method for the niche size calculation. Besides, the decision maker (DM) can incorporate the goal attainment information into the ranking procedure. The algorithm extensions proposed in [45] also allow the inclusion of the DM preferences for the objectives into the ranking. The MOGA was successfully used to solve a number of applied problems, e.g., design of a multivariable control system for a gas turbine engine [46], multiobjective optimization of ULTIC controller [47], design of a coal burning gasification plant [48], and other applications.

Other well-known versions of the evolutionary multiobjective algorithms include the niched Pareto GA (NPGA) of Horn and Nafpliotis [42], and the nondominated sorting GA (NSGA) of Srinivas and Deb [49]. In the late 1990s, a number of new methods for the considered problem were developed, which focused on improving the selection-for-survival aspect, including the techniques for population density estimation. The developed techniques include the strength Pareto evolutionary algorithm (SPEA) of Zitzler and Thiele [50], the Pareto envelope-based selection algorithm (PESA) of Corne *et al.* [51], and the elitist nondominated sorting GA (NSGA-II) of Deb *et al.* [52]. It should be noted that a more detailed review of the evolutionary approaches to multiobjective optimization problems can be found in [53]–[55].

This paper proposes an application-specific modification of the MOGA for the aforementioned mediaplanning optimization problem. The developed algorithm uses the original MOGA framework, but employs the specially developed encoding procedure and genetic operators, as well as the original local optimization routine. These modifications allow manipulating only with feasible solutions on each algorithm iteration. We verify the efficiency of the developed optimization technique using the real data sets from the Canadian advertising industry.

VI. Developed Modified MOGA

The major challenge in developing the efficient MOGA for the problem of optimal advertising campaign generation for multiple brands is effective constraints handling. We propose to use a modification of the MOGA of Fonseca and Fleming [7], which takes into account the problem specificity by using specially developed solution encoding scheme and related genetic operators. Another innovation deals with the local optimization routine, which employs an original approximation procedure for the problem objective functions.

To handle the constraints (2)–(7), we divide them into four groups, which are processed in the following ways.

1) The *search space constraints* $\{D_j\}$, i.e., the commercial break length constraints (4), and the competing brands constraints (7) are taken into account by the solution encoding.
2) The *solution space constraints*, i.e., the budget constraints (2), the minimum time length between two consecutive commercials constraints (5), and the maximum number of commercials in one TV show constraints are taken into consideration via the genetic operators.
3) The *goal attainment* constraints are handled via special ranking procedure that is used to calculate the solution fitness.

4) The *soft budget constraints* are accomplished by rejecting the solutions that have commercials with the budget surpluses of more than a user-defined threshold.

The authors believe that the "death penalty" approach used in 4) is suitable here, since the large budget surplus in a solution usually means ineffective handling of the commercial break length constraints, and thus, it is not expected to contribute to the tradeoff surface.

The following sections describe the proposed solution encoding, initial population generation, genetic operators, local optimization routine, as well as the fitness and population management used in the developed algorithm.

A. Encoding and Decoding

To encode the problem solution, let us introduce the following notation.

- G the chromosome (solution, individual) of the algorithm, $G = \{g_1, g_2, \ldots, g_m\}$;
- g_i the gene that corresponds to the commercial break $b_i, g_i \in \{0, 1, \ldots, r_i\}$;
- r_i the number of possible states for the gene g_i;
- W_i the set of possible states for the gene $g_i, |W_i| = r_i, W_i = \{w_i^z | z = 0, 1, \ldots, r_i\}$;
- z the break state index;
- w_i^z the state number z for the gene $g_i, w_i^z = \{v_{i1}^z, v_{i2}^z, \ldots, v_{in}^z\}$;
- v_{ij}^z $= 0$ if the state z of the gene g_i does not include the brand p_j, else index of a commercial.

The notation implies that the advertisements for the break b_i are coded in the gene g_i by a break-state index z, and there is a bijective mapping between this index and the actual commercials that are aired in the break. The set of possible states W_i for the gene g_i is defined as

$$w_i^z = \{v_{i1}^z, v_{i2}^z, \ldots, v_{in}^z\} \in W_i \Rightarrow \begin{cases} v_{ij}^z > 0 \Rightarrow d_{ij} = 1 \\ \sum_{j=1}^{n} I(v_{ij}^z) \cdot t_{jv_{ij}^z} \leq T_i; \\ v_{ij_1}^z > 0,\ v_{ij_2}^z > 0 \Rightarrow f_{j_1 j_2} = 0 \end{cases} \quad (8)$$

and the states are numbered from 0 to r_i for implementation convenience. For example, assuming the states lexicographical ordering and two brands with all the commercial lengths admissible for a break, the zero break state means that the break is empty, the states $z = 1, \ldots, q_1$ correspond to airing the commercials $t_{1v}, v = 1, \ldots, q_1$, in the break, while the states $z > q_1 + q_2$ stand for airing a mix of commercials for both brands in the break.

As mentioned earlier, the proposed encoding takes into account the search space constraints, the commercial break length constraints (4), and the competing brands constraints (7), thus, minimizing the restrictions to be handled during the algorithm run. Another advantage of the proposed encoding approach is the ability to quickly code and decode solutions, since the sets of the possible states $\{W_i\}$ have to be computed only once before the GA iterations start. Having a set of tables of this kind for each break enables fast coding and decoding of the solutions during the algorithm run.

B. Initial Population

To generate the initial population, we use the classical greedy heuristic. In the case when the heuristic is not able to generate a defined number of distinct solutions, we use multiple mutations of the obtained individuals to fill the gap. This approach has shown to be substantially more efficient when compared to various random initial population generation techniques, while still being able to develop an even distribution of the Pareto-optimal solutions along the tradeoff surface.

The idea of the greedy heuristic is to assign the values to the decision variable one by one, making the best available decision at every step [31]. In the case of the problem considered in this paper, at each greedy algorithm step, the current advertising brand picks an admissible commercial break that ensures the minimum cost per incremental Reach point, and adds it to the campaign. The order in which the brands are scheduled to select the breaks is defined by a random permutation at each algorithm round, and thus, the heuristic can produce different solutions in different runs.

It should be noted that other versions of the greedy heuristic for the considered optimization problem exist. For example, each brand can be allowed to spend a defined share of the budget (5%, for instance) on each algorithm round. For the case studies considered in this paper, the described version of the algorithm has showed to be the most efficient one. However, we implemented both versions, and performed the preliminary analysis of their efficiency before each computational study.

The mutation procedure that we have used to complete the initial "greedy" population is described in Section VI-C. We employ it only if the classical heuristic fails to generate a defined number of distinct individuals. This may lead to the undesired lack of population diversity during the first iterations of the algorithm; thus, adaptive tuning of crossover and mutation rates might be needed to overcome this difficulty.

C. Mutation

We perform the mutation of a solution $G = \{g_1, g_2, \ldots, g_m\}$ on componentwise basis, with all the genes having a small fixed probability to be modified. If the gene g_i is selected for the mutation, we randomly change its value to that of one of the equiprobable states $\{0, 1, 2, \ldots, r_i\}$. In the phenotype terms, it means that different brands and commercials that satisfy the break length, search space, and competitive brands constraints, are assigned to the break b_i instead of the old ones. After the genes modifications, there exists a possibility of the budget, minimum time interval, and maximum number of commercials constraints violation such that the obtained solution may be infeasible. To overcome this problem, we utilize the approach of "repairing" the infeasible individuals by the mutation operator. The repairing is performed by withdrawing some commercials from the breaks, while selecting the ones that lead to the minimum objective function decrease per unit cost. Besides, some brands can have their budgets under-spent after the genes

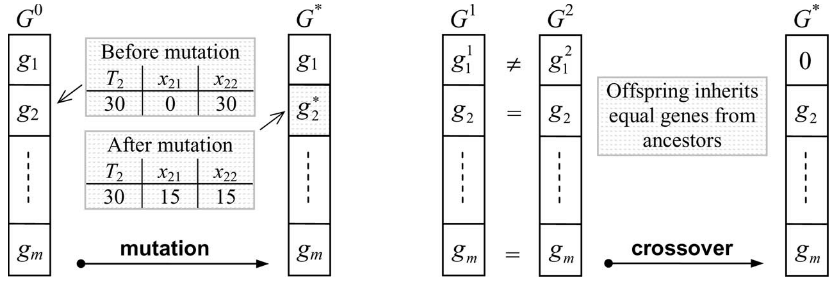


Fig. 4. Mutation and crossover operators (before "repairing").

modifications, and it is intuitively appealing that spending the rest of the budget will make the solution more feasible. Hence, we use a special version of the greedy heuristic to optimally distribute the budget surpluses [62].

D. Crossover

We perform the crossover of solutions $G^1 = \{g_1^1, g_2^1, \ldots, g_m^1\}$ and $G^2 = \{g_1^2, g_2^2, \ldots, g_m^2\}$ by: 1) copying the equal genes of the individuals G^1 and G^2 to the new chromosome and 2) optimally distributing the rest of the budget for the offspring solution by means of the greedy heuristic.

Fig. 4 illustrates the ideas of the proposed mutation and crossover operators before the resulted solutions are repaired with respect to violated constraints.

To optimally distribute the budget surpluses for the offspring chromosome, we apply a modification of the greedy heuristic. To handle the soft budget constraints of the problem, we give priority to longer commercials when purchasing the advertising time; thus, the algorithm starts from distributing the rest of the budget for the longest commercial, and proceeds step by step to the shortest.

To avoid lethal offsprings, we introduced mating restrictions to the crossover process. The similarity measure between two chromosomes was defined as

$$D(G^1, G^2) = m^{-1} \sum_{i=1}^{m} I_{g_i^1}(g_i^2) \tag{9}$$

and we allowed the individuals to mate only if their similarity measure was above a defined threshold. The empirically defined value of the threshold for both case studies was 0.9.

The developed genetic operators and the solution encoding technique allow having feasible solutions at each iteration of the developed MOGA (for hard problem constraints). The soft problem constraints are taken care of by the "death penalty" approach. In Section VI-E, we present a local optimization routine that is used to speed-up the performance of the algorithm.

E. Local Optimization Routine

To improve the performance of the algorithm, we hybridize it with a specially developed local optimization routine. The basic idea of the proposed technique is to generate a set of close promising feasible solutions for the individual, which can be then used to develop a part of the tradeoff surface in the neighbourhood of this individual. Thus, the developed local optimization procedure was subject to the following requirements.

1) The generation of the neighbourhood solutions process must not be time consuming.
2) Each solution in the generated set must be feasible.
3) From all the solutions close to the individual, the promising ones must be favored.
4) The technique must not be limited to the greedy heuristic philosophy.

The first requirement is to enable the algorithm to apply the local optimization search to all new individuals generated by the genetic operators (memetic approach). The last requirement is meant to overcome the limitation of the mutation and crossover operators that both rely on the greedy heuristic ideas.

We propose the following approach that takes into account all the aforementioned properties. First, we unload a defined small share of the budget (5% was used for the case studies) for each brand, using the same approach as for the mutation operator. Then, we calculate Reach per cost (RpC_{ijv}) for each brand p_j, the commercial t_{jv}, and the admissible break b_i (or we set it to zero if this combination is not admissible). This value is considered to measure the validity of adding the break b_i to the campaign of the brand p_j using the commercial t_{jv}. Then, we transfer Reach per cost to the "attractiveness" probability for every brand using

$$P_A(i,j,v) = f(i,j,v) / \sum\nolimits_{i_1=l}^{m} \sum\nolimits_{v_1=1}^{q_j} f(i_1,j,v_1)$$
$$f(i,j,v) = \left(RpC(i,j,v) / \min_{i_1,v_1} RpC(i_1,j,v_1) \right)^{\alpha} \tag{10}$$

where $\alpha \geq 1$ defines the importance that is assigned to the breaks with higher Reach per cost ($\alpha = 2$ was used for the case studies). Finally, at each procedure step, the brands randomly select breaks from the corresponding distributions (10); with brands order also being defined randomly on each step.

The developed local optimization technique contributes both to the improvement of the objective function values, and to the uniform distribution of the solutions in the Pareto-Optimal set. Fig. 5 illustrates the key ideas that make this additional genetic operator useful for the considered problem. We apply the local optimization to all new solutions that were generated by the crossover and mutation [Fig. 5(a)]. For each of these solutions, we produce a neighbourhood of promising individuals, which results in the new Pareto-optimal chromosomes being added to

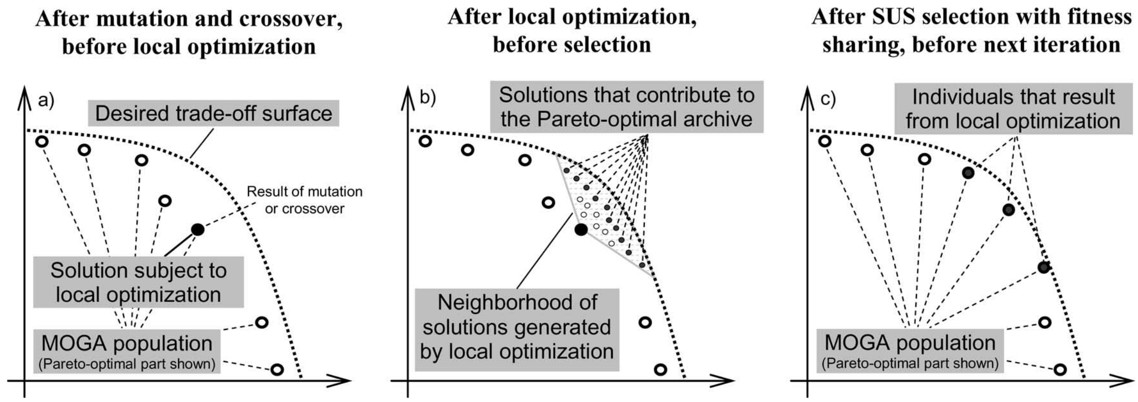


Fig. 5. Contribution of the local optimization operator to the developed modified MOGA.

the archive [Fig. 5(b)]. Besides, these Pareto-optimal individuals are uniformly distributed around the solution that was used for local optimization, thus, increasing the result of the classical genetic operators (since instead of getting a single point for each new solution, there is also a sub-Pareto-optimal surface piece for this individual). Finally, after applying the selection with the fitness sharing and SUS, the new generation contains the solutions that tend to distribute evenly along the developed tradeoff set [Fig. 5(c)].

F. Fitness and Population Management

Following the comparison results reported in [55], we use the combination of the adaptive fitness sharing [7] and the elitist selection [57] to manage the population. The simulation results have supported this approach, with the adaptive fitness sharing ensuring better individuals distribution along the tradeoff surface, and the elitist selection speeding up the algorithm convergence. Besides, we use the modified multiobjective ranking procedure, which allows including the goal attainment information when ranking the individuals. We present an overview of the employed techniques in the following.

In the multiobjective ranking of Fonseca and Fleming [7], an individual is assigned a rank based on the number of solutions in the population that dominate it. Consider a chromosome G^i of the generation t that is dominated by $p_i^{(t)}$ solutions in the current population. Then, the rank of the individual G^i is defined as

$$\text{rank}(G^i, t) = 1 + p_i^{(t)}.$$

Hence, all the nondominated individuals will be assigned rank 1, while the dominated ones will be penalized according to the population density of the corresponding region of the tradeoff surface. Besides, this ranking technique is extended to the case when each objective is assigned a goal and priority. For example, a dominated solution that satisfies all the goals may be considered more preferable to the nondominated solution that does not meet all the objectives. In this paper, we use the described ranking procedure to take into account the goal attainment constraints (3). Subsequently, the exponential rank-to-fitness mapping with the selective pressure e is used to calculate the fitness.

The fitness sharing in the MOGA is aimed at providing the uniform sampling of the solutions in the Pareto-optimal set [56]. During the GA iterations, the diversity of the population can be lost due to the effect of the random genetic drift [35], where the solutions tend to converge to a single point that represents the optimum solution. While being acceptable for the single-objective unimodal optimization problem, this phenomenon can lead to identifying only a small region of the tradeoff surface for the multicriteria setting. To overcome this difficulty, niche induction techniques were introduced to improve the diversity in the population [57]. According to this approach, the solutions tend to distribute themselves around the multiple optima and form regions that are referred to as niches. Fitness sharing is one of the niching techniques that lowers each individual's fitness by an amount that depends on the number of "similar" individuals according to some measure [58]. For the multiobjective optimization problems, the similarity measure is usually introduced in the objective function space, since the goal is to achieve an even distribution of the Pareto-optimal solutions along the tradeoff surface [45].

In the fitness sharing approach, the shared fitness of the individual l is defined as $f'_l = f_l/m_l$ where the niche count m_l measures the approximate number of individuals with whom the fitness f_l is shared

$$m_l = \sum_{t=1}^{N} sh(d_{lt}).$$

Here, N is the population size, d_{lt} is a distance between the individuals l and t, and *sh*(.) is the function that measures the individuals similarity

$$sh(d_{lt}) = \begin{cases} 1 - (d_{lt}/\sigma_s)^\alpha, & \text{if } d_{lt} < \sigma_s \\ 0, & \text{otherwise.} \end{cases}$$

The parameter α regulates the shape of the sharing function and is commonly set to one, with the resulting sharing function referred to as the triangular function [35].

The algorithm developed in this paper relies on the phenotypic sharing that measures the distance d_{lt} in the objective function space. The Euclidian measure is employed to compute d_{lt}, and the estimation of the niche size parameter σ_s is performed by

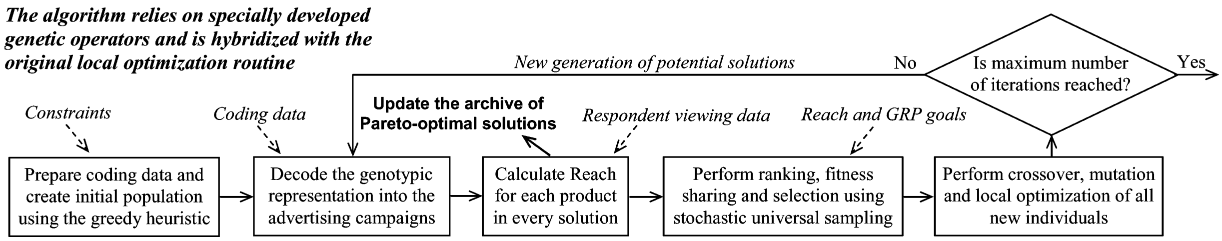


Fig. 6. Flow chart of the developed modified MOGA.

solving

$$N\sigma_s^{n-1} - \frac{\prod_{j=1}^{n}(M_j - m_j + \sigma_s) - \prod_{i=1}^{n}(M_j - m_j)}{\sigma_s} = 0$$

where M_j and m_j are the maximum and minimum of each objective, respectively.

Elitism can be summarized as preserving the high-performance solutions from one generation to the next. This approach has proved to be a powerful tool for improving the efficiency of the evolutionary algorithms [59], [60]. The conducted simulation study has shown that this fact also holds for the optimization problem considered in this paper; hence, we always kept one individual with the highest fitness in the population.

Fig. 6 summarizes the work-flow of the developed modified MOGA. Using the classification employed in [61], the proposed routine is based on the generic framework when the local search is applied to all new solutions generated by the multi-objective evolutionary algorithm. Implementation details of the procedures described in Section VI can be found in [62]. In Section VII, we present the application example that confirms the efficiency of the proposed technique.

VII. Computational Results

We tested the developed modified MOGA using real data from the Canadian advertising market. We used a mediaplan for September 2004, which was generated by an advertising agency for one of the major advertisers in Canada. To develop the advertising campaigns, the agency used the greedy heuristic described earlier. We demonstrate the efficiency of our algorithm by improving the advertising effectiveness for subsets of brands from the original campaign, thus, increasing the overall impact of the mediaplan. It is to be noted that exact methods for the solution of the problem considered in the paper are not available, and the problem sizes considered in the case studies are already too high for straightforward techniques like the branch-and-bound method.

In case study, we selected two low-budget noncompeting brands p_1 and p_2, and generated the pool of commercial breaks as all the advertising time that was assigned to these two brands by the agency in the original mediaplan. Then, we distributed this pool between the brands: 1) by means of the greedy heuristic and 2) by using the developed modified MOGA.

Finally, we compared the tradeoff surface generated by the developed modified MOGA to the "greedy" solution. We would like to note that in this case, the multiple runs of the greedy heuristic produced very similar individuals that resulted in low diversity during the first algorithm iterations.

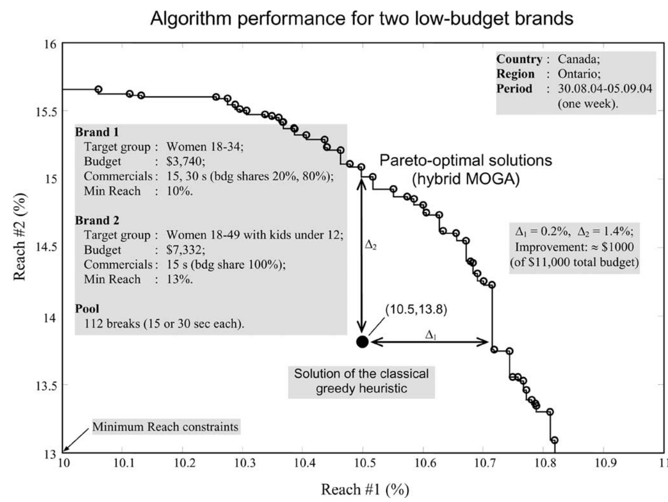


Fig. 7. Classical greedy heuristic versus the developed modified MOGA.

The selected brands p_1 and p_2 had the budgets of $3740 and $7332, respectively, and were aimed at the heavily intersecting target groups "Women 18–34" and "Women 18–49 with kids under 12." The first brand p_1 had commercials of length 15 and 30 s with the corresponding budget shares of 20% and 80%, respectively, while the second brand p_2 had commercials of length 15 s. The minimum Reach constraints were set at 10% and 13%, respectively, while the GRP goals for these brands were, respectively, defined as 15% and 40%. The pool consisted of 112 commercial breaks—about 73% of them being 15s long, and 27% being 30s long.

We present the results of the study in Fig. 7. As follows from the figure, the solution of the classical greedy heuristic is essentially improved and dominated by the Pareto-optimal solutions generated by the developed modified MOGA. An aggregated improvement of the MOGA versus the classical approach can be roughly estimated as $1000 versus about $11 000 total budget of the brand, that is a very significant increase. We calculated this figure based on the cost per gained Reach point of the greedy solution, so that it can be interpreted as to how much money the agency would have to spend to achieve the results of the developed technique while using the greedy heuristic to solve the problem. A more detailed analysis of the presented case study, as well as further application examples can be found in [62].

VIII. Conclusion

We proposed a multiobjective algorithm approach for the problem of optimal TV advertising campaign generation for multiple brands. The advertising agencies use the greedy heuristic to solve this *NP*-hard combinatorial optimization problem with numerous constraints. While this traditional approach is limited to the solutions that are closely related in the objective space, the developed modified MOGA produces a Pareto-optimal set of solutions that: 1) outperforms the greedy heuristic and 2) allows the decision-maker to choose from a variety of optimal tradeoff alternatives.

To achieve high performance, we developed the problem-specific solution encoding, genetic operators, and original local optimization routine for the algorithm. These techniques allow the algorithm manipulating with only feasible individuals, thus, significantly improving its convergence that is complicated by the problem constraints. The efficiency of the developed modified MOGA is verified using the case studies for the real data sets from the Canadian advertising market.

Future work will deal with improving the algorithm operators to let them take into account additional constraints that may arise in the considered problem. Besides, an additional study needs to be performed to allow choosing the best algorithm parameters in different application settings. Another challenge will be to include additional optimization objectives to the problem for each of the brands.

Acknowledgment

The authors are grateful to the Omega Software GmbH for the data used in the case studies.

References

[1] S. Bollapragada, H. Cheng, M. Phillips, M. Garbiras, M. Scholes, T. Gibbs, and M. Humphreville, “NBC’s optimization systems increase revenues and productivity,” *Interfaces*, vol. 32, no. 1, pp. 47–60, 2002.

[2] S. Bollapragada and M. Garbiras, “Scheduling commercials on broadcast television,” *Oper. Res.*, vol. 52, no. 3, pp. 337–345, 2004.

[3] J. Sissors, R. Baron, and E. Ephorn, *Advertising Media Planning*. New York: McGraw-Hill, 2002.

[4] R. Weber, “Methods to forecast television viewing patterns for target audiences,” in *Communication Research in Europe and Abroad—Challenges of the First Decade*, A. Schorr, B. Campbell, and M. Schenk, Eds. Berlin, Germany: Gruyter, 2002.

[5] M. Pashkevich and Yu. Kharin, “Robust estimation and forecasting for beta-mixed hierarchical models of grouped binary data,” *Statist. Oper. Res. Trans.*, vol. 28, no. 2, pp. 125–160, 2004.

[6] R. T. Rust, *Advertising Media Models: A Practical Guide*. Lexington, MA: Lexington, 1986.

[7] C. M. Fonseca and P. J. Fleming, “GAs for multiobjective optimization: Formulation, discussion and generalization,” in *Proc. 5th Int. Conf. Genetic Algorithms*, 1993, pp. 416–423.

[8] G. J. Goodhardt, A. S. C. Ehrenberg, and M. A. Collins, *The Television Audience: Patterns of Viewing*. England, U.K.: Saxon, 1975.

[9] R. S. Headen, J. E. Klompmaker, and R. T. Rust, “The duplication of viewing law and television media scheduling evaluation,” *J. Market. Res.*, vol. 16, pp. 333–340, 1979.

[10] M. D. Henry and H. J. Rinne, “Predicting program shares in new time slots,” *J. Advert. Res.*, vol. 24, no. 2, pp. 9–17, 1984.

[11] J. G. Webster, “Program audience duplication: a study of television inheritance effects,” *J. Broadcast. Electron. Media*, vol. 29, no. 2, pp. 121–133, 1985.

[12] D. Gensch and P. Shaman, “Models of competitive television ratings,” *J. Market. Res.*, vol. 27, pp. 307–315, 1980.

[13] R. T. Rust and M. Alpert, “An audience flow model of television viewing choice,” *Market. Sci.*, vol. 3, no. 2, pp. 113–124, 1984.

[14] P. J. Danaher and D. F. Mawhinney, “Optimizing television program schedules using choice modeling,” *J. Market. Res.*, vol. 38, pp. 298–312, 2001.

[15] R. T. Rust and N. V. Echambadi, “Scheduling network television programs: A heuristic audience flow approach to maximizing audience share,” *J. Advert.*, vol. 18, no. 2, pp. 11–18, 1989.

[16] S. Reddy, J. Aronson, and A. Stam, “SPOT: Scheduling programs optimally for television,” *Manag. Sci.*, vol. 44, no. 1, pp. 83–102, 1998.

[17] G. L. Lilien, P. Kotler, and K. S. Moorthy, *Marketing Models*. Englewood Cliffs, NJ: Prentice-Hall, 1995.

[18] S. Bollapragada, M. Bussieck, and S. Mallik, “Scheduling commercial videotapes in broadcast television,” *Oper. Res.*, vol. 52, no. 5, pp. 679–689, 2004.

[19] H. M. Cannon, J. D. Leckenby, and A. Abernethy, “Beyond effective frequency: Evaluating media schedules using frequency value planning,” *J. Advert. Res.*, vol. 42, no. 6, pp. 33–47, 2002.

[20] H.-G. Kim and J. D. Leckenby, “How media directors view traditional and interactive media planning,” in *Proc. Amer Acad. Advert.*, 2001, pp. 189–195.

[21] W. B. Goodrich and J. Z. Sissors, *Media Planning Workbook*. Lincolnwood, IL: NTC, 2001.

[22] M. A. Pashkevich and Yu. S. Kharin, “Statistical forecasting and optimization of television advertising efficiency,” in *Proc. 3rd Int. Conf. Modeling Simul.*, Troyes, France, Apr. 25–27, 2001, pp. 835–842.

[23] J. J. Merelo, A. Prieto, V. Rivas, and J. L. Valderrabano, “Designing advertising strategies using a ge-netic algorithm,” in *4th AISB Workshop on Evolutionary Computing*. Lecture Notes in Computer Science. Berlin, Germany: Springer, 1997.

[24] P. A. Naik, K. M. Mantrala, and A. G. Sawyer, “Planning media schedules in the presence of dynamic advertising quality,” *Market. Sci.*, vol. 17, no. 3, pp. 214–235, 1998.

[25] M. G. Van Buer, D. L. Woodruff, and R. T. Olson, “Solving the medium newspaper production/distribution problem,” *Euro. J. Oper. Res.*, vol. 115, no. 2, pp. 237–253, 1999.

[26] J. H. Collins and S. Harris, “Print and multimedia optimization: An evolutionary approach,” presented at the Worldwide Readership Res. Symp., England, U.K., Nov. 1999, Section 6.7.

[27] K. Ohkura, T. Igarashi, K. Ueda, S. Okauchi, and H. Matsunaga, “A genetic algorithm approach to large scale combinatorial optimization problems in the advertising industry,” in *Proc. 8th IEEE Int. Conf. Emerg. Technol. Factory Autom.*, 2001, vol. 2, pp. 351–357.

[28] A. E. Carter and C. T. Ragsdale, “Scheduling pre-printed newspaper advertising inserts using genetic algorithms,” *Omega, Int. J. Manag. Sci.*, vol. 30, pp. 415–421, 2002.

[29] M. Dawande, S. Kumar, and C. Sriskandarajah, “Performance bounds of algorithms for scheduling advertisements on a web page,” *J. Sched.*, vol. 6, no. 4, pp. 373–393, 2003.

[30] S. Hurley, L. Moutinho, and N. Stephens, “Solving marketing optimization problems using genetic algorithms,” *Euro. J. Market.*, vol. 29, no. 4, pp. 39–56, 1995.

[31] Z. Michalewicz and B. Fogel, *How to Solve It: Modern Heuristics*. London, U.K.: Springer, 2000.

[32] I. Rechenberg, *Evolutionβtrategie: Optimierung Technischer Systeme nach Prinzipien der Biologischen Evolution*. Stuttgart, Germany: Frommann-Holzboog, 1973.

[33] D. B. Fogel, *System Identification Through Simulated Evolution: A Machine Learning Approach to Modeling*. Needham, MA: Ginn, 1991.

[34] J. H. Holland, *Adaptation in Natural and Articial Systems*. Ann Arbor, MI: Univ. Michigan Press, 1975.

[35] D. E. Goldberg, *Genetic Algorithms in Search, Optimization and Machine Learning*. Reading, MA: Addison-Wesley, 1989.

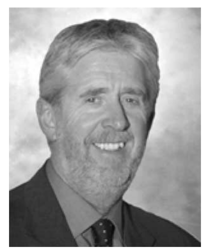
[36] K. F. Man, K. S. Tang, and S. Kwong, *Genetic Algorithms: Concepts and Designs*. New York: Springer, 1999.

[37] J. D. Schaffer, “Multiple objective optimization with vector evaluated genetic algorithms,” in *Proc. 1st Int. Conf. Genetic Algorithms*, Pittsburgh, PA, 1985, pp. 93–100.

[38] M. P. Fourman, “Compaction of symbolic layout using genetic algorithms,” in *Proc. 1st Int. Conf. Ge-netic Algorithms*, Pittsburgh, PA, 1985, pp. 141–153.

[39] F. Kursawe, “A variant of evolution strategies for vector optimization,” in *Parallel Problem Solving from Nature*. Lecture Notes in Computer Science, H.-P. Schwefel and R. Manner, Eds. Berlin, Germany: Springer-Verlag, 1991, vol. 496, pp. 193–197.

[40] P. Hajela and C.-Y. Lin, "Genetic search strategies in multicriterion optimal design," *Struct. Optim.*, vol. 4, pp. 99–107, 1992.
[41] J. E. Baker, "Reducing bias and inefficiency in the selection algorithm," *Proc. 2nd Int. Conf. Genetic Algorithms*, pp. 4–21, 1987.
[42] J. Horn and N. Nafpliotis, "Multiobjective optimization using the niched Pareto genetic algorithm," Univ. Illinois Urbana-Champaign. Urbana, IL, 1993, IlliGAL Rep. 93005.
[43] S. E. Cieniawski, "An investigation of the ability of genetic algorithms to generate the tradeoff curve of a multi-objective groundwater monitoring problem," Master's thesis, Univ. Illinois Urbana-Champaign, Urbana, IL, 1993.
[44] B. J. Ritzel, J. W. Eheart, and S. Ranjithan, "Using genetic algorithms to solve a multiple objective groundwater pollution containment problem," *Water Resources Res.*, vol. 30, no. 5, pp. 1589–1603, 1994.
[45] C. M. Fonseca and P. J. Fleming, "Multiobjective optimization and multiple constraint handling with evolutionary algorithms—Part I: A unified formulation," *IEEE Trans. Syst., Man Cybern. A: Syst. Humans*, vol. 28, no. 1, pp. 26–37, Jan. 1998.
[46] A. Chipperfield and P. Fleming, "Gas turbine engine controller design using multiobjective genetic algorithms," in *Proc. 1st IEE/IEEE Int. Conf. Genetic Algorithms in Eng. Syst.: Innovat. Appl*. Univ. Sheffield, Sheffield, U.K., pp. 214–219.
[47] K. C. Tan and Y. Li, "Multi-objective genetic algorithm based time and frequency domain design unification of linear control systems," Univ. Glasgow, Scotland, U.K., 1997. Tech. Rep. CSC-97007.
[48] I. A. Griffin, P. Schroder, A. J. Chipperfield, and P. J. Fleming, "Multiobjective optimization approach to the ALSTOM gasifier problem," *Proc. IMECHE–I, J. Syst. Control Eng.*, vol. 214, pp. 453–468, 2000.
[49] N. Srinivas and K. Deb, "Multiobjective optimization using nondominated sorting in genetic algorithms," *Evol. Comput.*, vol. 2, no. 3, pp. 221–248, 1994.
[50] E. Zitzler and L. Thiele, "Multiobjective optimization using evolutionary algorithms—A comparative study," in *Proc. Parallel Problem Solving Nature V Conf.*, pp. 292–301, 1998.
[51] D. W. Corne, J. D. Knowles, and M. J. Oates, "The Pareto envelope-based selection algorithm for multiobjective optimization," in *Proc. Parallel Problem Solving Nature VI Conf.,* 2000, pp. 839–848.
[52] K. Deb, A. Pratap, S. Agarwal, and T. Meyarivan, "A fast and elitist multiobjective genetic algorithm: NSGA-II," *IEEE Trans. Evol. Comput.*, vol. 6, no. 2, pp. 182–197, Apr. 2002.
[53] C. M. Fonseca and P. J. Fleming, "An overview of evolutionary algorithms in multiobjective optimization," *Evol. Comput.*, vol. 3, no. 1, pp. 1–16, 1995.
[54] C. A. Coello, "An updated survey of GA-based multiobjective optimization techniques," *ACM Comput. Surveys*, vol. 32, no. 2, pp. 109–143, 2000.
[55] R. C. Purshouse, "On the evolutionary optimisation of many objectives" Ph.D. thesis, Univ. Sheffield, Dept. Autom. Control Syst. Eng., 2004.
[56] D. E. Goldberg and J. Richardson, "Genetic algorithms with sharing for multimodal function optimiza-tion," in *Proc. 2nd Int. Conf. Genetic Algorithms*, 1987, pp. 41–49.
[57] D. E. Goldberg and L. Wang, "Adaptive niching via coevolutionary sharing," in *Genetic Algorithms and Evolution Strategies in Engineering and Computer Science*, D. Quagliarella, J. Periaux, C. Poloni, and G. Winter, Eds. Chichester, U.K.: Wiley, 1998, pp. 21–38.
[58] B. Sareni and L. Kraahenbuhl, "Fitness sharing and niching methods revisited," *IEEE Trans. Evol. Comput.*, vol. 2, no. 3, pp. 97–106, Sep. 1998.
[59] E. Zitzler, K. Deb, and L. Thiele, "Comparison of multiobjective evolutionary algorithms: Empirical results," *Evol. Comput.*, vol. 8, no. 2, pp. 173–195, 2000.
[60] K. Deb, *Multi-Objective Optimization Using Evolutionary Algorithms*. New York: Wiley, 2001.
[61] H. Ishibuchi and T. Yoshida, "Hybrid evolutionary multi-objective optimization algorithms," in *Soft Computing Systems: Design, Management and Applications, Frontiers in Artificial Intelligence and Applications*, vol. 87, A. Abraham, J. Ruiz-del-Solar, and M. Köppen, Eds. Amsterdam, The Netherlands: IOS, 2002, pp. 163–172.
[62] P. J. Fleming and M. A. Pashkevich, "Optimal advertising campaign generation for multiple brands using multi-objective genetic algorithm," Dept. Autom. Control Syst. Eng. Univ. Sheffield, Sheffield, U.K., 2004, preprint #876, 29 p.



Peter J. Fleming received the B.Sc. (Hons) degree in electrical engineering and the Ph.D. degree in engineering mathematics from Queen's University Belfast, Belfast, U.K., in 1969 and 1973, respectively.

He is the Chair of Industrial Systems and Control in the Department of Automatic Control and Systems Engineering and the Director of the Rolls-Royce University Technology Centre for Control and Systems Engineering at the University of Sheffield, Sheffield, U.K. He has previously held the positions of Professor of Computer Systems Engineering with the University of Wales, Bangor, U.K., Associate Professor with Syracuse University, Syracuse NY, and Research Scientist with NASA Langley, VA. He is currently the Pro-Vice-Chancellor for External Relations with the University of Sheffield. His research interests include multicriteria decision-making, optimization and scheduling, grid computing, software for control system design and implementation, and real-time control and instrumentation. He has authored over 350 research publications, including six books. He is the Editor-in-Chief of the *International Journal of Systems Science*.

Prof. Fleming is a Fellow of the Royal Academy of Engineering, the Institution of Electrical Engineers, and the Institute of Measurement and Control. He is the Vice-President of the International Federation of Automatic Control.

Maksim A. Pashkevich received the Ph.D. degree from the Belarusian State University, Minsk, Belarus, jointly with the University of Sheffield, Sheffield, U.K., and the Ecole Nationale Supérieure des Mines de Saint-Etienne, France, in 2005.

He is currently a Postdoctoral Research Fellow with the Richard M. Lucas Center for Magnetic Resonance Spectroscopy and Imaging, Department of Radiology, Stanford University, Stanford, CA. He was a Postdoctoral Researcher with the Ecole Nationale Supérieure des Mines de Saint-Etienne, France. His research interests include multicriteria optimization and scheduling, demand forecasting in inventory management, robust statistical inference and stochastic modeling, and biostatistics.