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A Multi-Objective Optimization Algorithm for Out-of-Home Advertising

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Abstract. This paper presents a Multi-Objective Optimization (MOO) approach for Out-of-Home (OOH) advertising campaign billboard selection. In particular, it exploits a large variety of features from different sources, such as Geographic Information Systems (GIS) and demographics data, for the construction of billboard profiles that take into account all factors that affect the attractiveness of each billboard both in general and for different types of customers. These profiles are utilized by a Multi-Objective Evolutionary Algorithm based on Decomposition (MOEA/D) hybridized with two problem specific techniques to provide a set of non-dominated solutions, each corresponding to a different allocation of billboards to a given campaign. The experimental results enable exploration of the trade-offs between multiple conflicting objectives (e.g., cost vs. coverage) as well as demonstrate that the two problem specific techniques have improved the conventional MOEA/D performance with respect to both convergence and diversity.

Keywords: Billboards advertising · Out-of-Home advertising · Multi-Objective Optimization · Evolutionary computation · GIS

1 Introduction

Out-of-Home (OOH) advertising [8] is one of the oldest, yet among the most popular, forms of advertising. This is testified by the fact that, amid the COVID-19 crisis, the global market for OOH advertising was estimated at $27Bn (2020) and is projected to grow to $33Bn by 2026 [7]. In OOH advertising, selecting the "right" billboards for a given customer campaign (with implications on corresponding impressions, conversions, footfall, and ROI) remains an open challenge [9]. The optimal selection of billboards needs to consider multiple, often conflicting, objectives and constraints, such as the campaign cost, the area covered by the selected billboards and the similarity between the billboard and customer profiles. Consequently, this needs to be tackled as a Multi-Objective Optimization Problem (MOOP), providing a set of near-optimal solutions, as opposed to other studies [5] that treat multiple objectives as a single weighted function.

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A MOOP [1] can be mathematically formulated as:

$$\text{minimize } F(X) = (f_1(X), ..., f_k(X)), \text{ subject to } X \in \Omega$$

where Ω is the decision space and $X \in \Omega$ is the decision vector. F(X) consists of k objective functions $f_i : \Omega \rightarrow R$, $i = 1, ..., k$, where R^k is the decision space. Objectives often conflict with each other and improving one objective may lead to the deterioration of another. Thus, no single solution exists that can optimize all objectives simultaneously. In such a case, the decision maker often requires the means for exploring the trade-offs between multiple alternative solutions, called the set of Pareto optimal (or non-dominated) solutions. The Pareto optimality concept is formally defined as follows:

Definition 1. A vector $u = (u_1, ..., u_k)$ is said to dominate another vector $v = (v_1, ..., v_k)$, denoted as $u \prec v$, iff $\forall i \in \{1, ..., k\}$, $u_i \leq v_i$ and $u \neq v$.

Definition 2. A feasible solution $X^* \in \Omega$ is called *Pareto optimal solution* iff $Y \in \Omega$ such that $F(Y) \prec F(X^*)$. The set of all Pareto optimal solutions is called the Pareto Set (PS) in the decision space, denoted as:

$$PS = \{X \in \Omega |\ \exists Y \in \Omega, F(Y) \prec F(X)\}$$

The image of the PS in the objective space is called Pareto Front (PF)

$$PF = \{F(X) | X \in PS\}$$

Multi-objective Evolutionary Algorithms (MOEAs) [2] can obtain an approximate PF in a single run by accommodating different forms of operators to iteratively generate a population of such solutions. A major goal of MOEAs when dealing with a MOOP is to produce a diverse set of non-dominated solutions that is as close as possible to the real PF.

In our previous work [6], we have introduced and demonstrated the Smart OOH Advertising web platform, focusing on its Graphical User Interface and main functionalities. In this paper, the main focus and contribution is on the Multi-Objective Optimization Problem for OOH Advertising (MOOP for OOHA) definition and formulation, as well as on the extended MOEA/D approach. Specifically, we have mathematically formulated the MOOP for OOH advertising billboard selection using a variety of data features constructed from data sources such as demographics and GIS data. Based on this formulation, the proposed approach mitigates much of the hurdles involved with OOH advertising through the use of advanced AI techniques. Specifically, the presented approach uses (i) *Feature Engineering* - cleaning, preparing and extracting knowledge from raw data; and (ii) *Multi-Objective Optimization* - obtaining a set of Pareto optimal solutions for exploring the trade-offs between multiple conflicting objectives in a single run, thus providing the decision maker (customer) with a set of near-optimal choices (based on their specific objectives/constraints).

The rest of this paper starts with an overview of the data used in this study and the feature engineering process performed in Sect. 2. Section 3 gives the mathematical formulation of the OOH advertising MOOP, while Sect. 4 describes the Multi-Objective Evolutionary Algorithm Based on Decomposition (MOEA/D) as well as two problem specific heuristics used in this work. Section 5 presents three experimental studies and discusses their results. Finally, Sect. 6 gives the conclusions and future directions of this work.

2 Data and Feature Engineering

In order to achieve more accurate profiling of both billboards and customers, it is required to identify, collect and analyze the most appropriate data related to OOH advertising. This data is not limited to billboard specs and locations, but also includes geo-spatial and demographics data. Geographical data was provided by *Geomatic Ltd*, a local cartography company in Cyprus, and was enriched with billboard locations from *Adboard Media Ltd*, one of the largest media firms in Cyprus.

2.1 GIS Data

The digital geographical database of *Geomatic Ltd*, i.e. Geomatic Maps^{TM}, covers the entire island of Cyprus and includes data on the National, Urban and Provincial Road Network of Cyprus (>23,785 Km), providing detailed navigation to 522 Municipalities and Communities. The incorporated GIS data are described in more detail below:

Road Network Data. The effectiveness of OOH advertising (via billboards) is greatly affected by the road network surrounding the billboards. The database used contains data about the national and local road network of Cyprus (accounting for a total of 98% island coverage). The road network's hierarchy, which categorizes roads according to their functions and capacities, as well as the traffic load, are a few of the characteristics that have a significant impact on OOH advertising. In particular, the following types of data are considered:

- Network hierarchy (freeways/highways, arterials, collectors, residential roads, and pedestrian roads)
- Street Names as defined by the Cyprus Post Office, the responsible authority for naming streets in Cyprus.
- House numbering.
- One-way or two-way roads.
- Distance of roads from billboard locations.

Points of Interest (POI) Data. Factors affecting how people are attracted to POIs include their preferences and needs, but also the "importance/role" of a given POI. The level of attraction reflects the number of people who are likely to view a billboard located close to certain POI. 15 main POI categories are identified (e.g., Accommodation, Culture, Education, Shopping), which are divided into 74 subcategories (e.g., Hotels 5 stars, Museums, Universities, Supermarkets). The POI data consists of the list of POIs with information regarding their type as well as their distance from billboards.

Public Transport Network Data. If the location of a billboard is traversed by the Public Transportation Network, it is more likely to be viewed by more people. Our presented approach combines data regarding the location of billboards and the relevant geographical data on the Public Transportation Network (within a radius of 60 m around the billboards). The corresponding features used in our study include: bus stops, bus routes, and bus lines, which corresponds to the number of times a given route is performed.

Building Footprints Data. The spatial characteristics of buildings such as their footprint, covered area, total volume, height and floor count.

Planning Zones Data. Zoning is a method of urban planning in which all tiers of government divide land into areas called zones. Each zone has a set of regulations for new development that differs from other zones. For planning purposes, Cyprus is divided into various planning zones. These mainly include residential, industrial, agricultural and tourist zones. The type of each planning zone surrounding a billboard is considered.

2.2 Demographics Dataset

The demographics data used are based on the Statistical Service of Cyprus (CYSTAT) 2011 decennial census survey. The data is provided at different granularities, namely at the postal code, quarter, municipality, and district levels. The demographic data includes 196 different statistical variables regarding the population, employment, education, and living conditions. In particular, the features used in our study are: total population by postal code, gender, age ranges, living quarters, employed persons by place of work and employed persons per NACE Rev.2 sectors (primary, secondary and tertiary).

2.3 Billboards Dataset

This data were provided by *Adboard Media Ltd* and includes data for 202 static billboards. The exact considered features include: billboard types, face count, frame dimensions, height from ground, illumination option, address, location, and monthly rental price. Additionally, further features regarding over than 1800

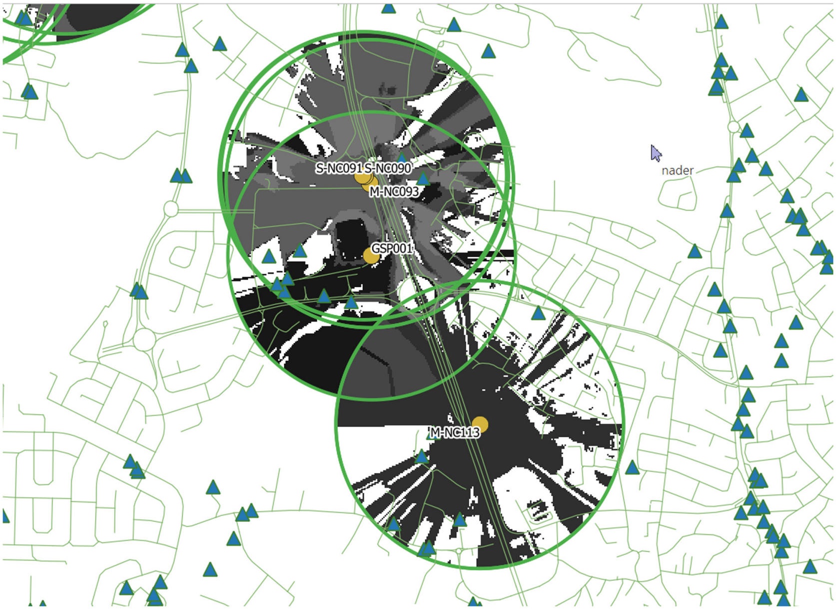

Fig. 1. Visibility analysis, Billboards & POI locations

customers are considered, including features such as the company name, type of industry and location, as well as data on campaigns, including historical records of customers, billboards per campaign and budget.

2.4 Feature Engineering

Feature engineering refers to the process of using domain knowledge to select and transform the most relevant features from raw data. This may lead to combining, deleting, aggregating and transforming features into new ones. The data concerning a particular billboard is defined based on the billboard's location and its corresponding viewing distance. A billboard's viewing distance depends on its size and image resolution. After consulting our media partner, a 500-m range has been adopted in this work.

The demographics-related data concerning a certain billboard are inherited from the billboards' postal code. However, since the billboard's viewing area may fall across multiple postal codes, the visible portions of all surrounding areas (i.e., within the 500-m radius) are considered and the corresponding demographics-related data are adjusted accordingly.

Additionally, important new features are generated through *Visibility Analysis*, which takes into consideration what is visible by an observer from a given location. Key terrain, observation posts, and other locations are used to assess capabilities (what is visible) and vulnerabilities (blocked view). The visibility analysis tools use elevation data and observer information to produce linear line of sight (LLOS) and radial line of sight (RLOS) information. The visibility analysis (illustrated in Fig. 1) has been conducted based on features such as: (i) the coordinates and height from ground of the billboards, (ii) the Digital Elevation Model, and (iii) the buildings surrounding the billboards within a 500-m range.

For simplicity, the billboard's orientation and viewing angle were not considered. The outcomes of this analysis include the visibility pixel count and the visibility percentage of an area covered by a certain road that can view a given billboard. This data was provided by *Geomatic Ltd* based on LiDAR data processed by the ArcGIS software.

3 Problem Formulation

Various objective functions for optimizing OOH advertising from the perspective of both advertising companies and customers have been identified:

Maximize Visibility/Attractiveness. The visibility is calculated for each billboard based on a weighted sum function. For a billboard $B_j \in \{B_0, ..., B_n\}$:

$$\max \mathit{visibility}(B_j) = \sum_{i=0}^{k} w_i B_j(a_i), \text{where} \sum_{i}^{k} w_i = 1,$$

$B_j(a_i)$ is the value of visibility variable i for B_j and w_i is its weight. The included visibility variables in the aforementioned weighted sum function are the following: visibility pixel count, visibility percentage per road type based on road type importance and speed, population, POI count, living quarters, employment count by place of work, road length, urbanization degree, building footprints volume and count, and bus lines for each billboard location within the predefined 500 m range.

Minimize Cost. Let c_j be the rental cost for the billboard B_j in solution X_i. The objective is to minimize the total cost (billboards rental costs for one month):

$$\min \sum_{B_j \in X_i} c_j.$$

A primary goal of advertising customers is to minimize spending and not exceed the planed advertising budget.

Maximize Similarity – Customer to Billboard Matching. Similarity refers to how well a billboard matches customer preferences based on the corresponding billboard and customer profiles. The traditional cosine measure [3] is used to determine the similarity between customers and billboards, which are both represented as vectors of attributes. These include the targeted age ranges, educational level, and related POIs, which are captured through appropriate online questionnaires incorporated into the platform.

$$similarity(x, y) = \frac{x.y}{\parallel x \parallel \cdot \parallel y \parallel},$$

where $\parallel x \parallel$ is the Euclidean norm of vector $x = (x_1, x_2, ..., x_p)$, defined as:

$$\parallel x \parallel = \sqrt{x_1^2 + x_2^2 + ... + x_p^2}.$$

In our case, x is the vector of customer profile data and y is the vector of billboard profile data.

Maximize Coverage. Coverage represents the distribution of billboards on the map. To maximize coverage, one needs to select billboards that have a higher visibility rate, while at the same time aiming for a wide geographically-dispersed configuration, which is represented by a spread function as in [4]. Given any two billboards B_i and B_j in $\{B_0, \ldots, B_n\}$, let $D(B_i, B_j)$ denote the length of the shortest path between them, i.e., the distance between B_i and B_j. Let $maxD$ denote the maximum such length of the shortest path between any pair of billboards in $\{B_0, \ldots, B_n\}$. The spread of the selected billboards in solution X is expressed as the normalized average distance between all possible pairs of billboards and is denoted by:

$$Spread(X) = \frac{\overline{D_x}}{maxD}, \text{ where } \overline{D_x} = \frac{\sum_{B_i \neq B_j \in X} D(B_i, B_j)}{n(n-1)}.$$

The Haversine distance method is applied in order to compute the shortest distance between any pair of billboards based on their geo-location.

Budget Constraint: Is a customer predefined budget for a specific marketing campaign, denoted as:

$$\sum_{B_j \in X_i} c_j <= C,$$

where C is the predefined budget and c_j is the cost billboard B_j in solution X_i.

4 Multi-Objective Evolutionary Algorithm Based on Decomposition (MOEA/D)

Initially, MOEA/D needs to decompose a MOOP into a set of sub-problems. Any decompositional technique can be used for this purpose [10]. In this paper, the Weighted Sum approach is used, as follows. The multi-objective problem is decomposed into m scalar optimization sub-problems considering two objectives from the problem set of objectives. The ith scalar optimization sub-problem can be defined as: $g^i(X, \lambda^i) = \lambda^i F_a(X) + (1 - \lambda^i) F_b(X)$, where λ^i is the weight

Algorithm 1. The MOEA/D general framework

Input:

- m: population size and number of subproblems;
- T: neighborhood size;
- uniform spread of weight vectors $(\lambda^1, 1-\lambda^1), ..., (\lambda^m, 1-\lambda^m)$
- gen_{max}: maximum number of generations;

Output: the external population, EP;
Step 0 – Setup: Set $EP := \phi; gen := IP_{gen} := \phi$;
Step 1 – Initialization: Generate an initial internal population $IP_0 = \{X^1, ..., X^m\}$
Step 2: For $i = 1, ..., m$ **do**
Step 2.1 – Genetic Operators: Generate a new solution Y using the genetic operators.
Step 2.2 – Repair heuristic: Apply a problem-specific repair heuristic on Y to produce Z.
Step 2.3 – Update Populations: Use Z to update IP_{gen}, EP and the T closest neighbour solutions of Z.
Step 3 – Stopping criterion: If stopping criterion is satisfied, i.e. $gen = gen_{max}$, **then** stop and output EP, **otherwise** $gen = gen + 1$, go to step 2.

coefficient of sub-problem $i = 1, ..., m$. For the remainder of this paper, we consider a uniform spread of the weights λ^i, which remain fixed for each i for the whole evolution and are determined as follows: $\lambda^i = 1 - (i/m)$, for $i = 2, ..., m$ and $\lambda^1 = 1$. Hence, the λ^i coefficient is mainly utilized for decomposing a MOOP into a set of scalar sub-problems by adding different weights to the objectives.

A general MOEA/D approach proceeds as in Algorithm 1:

- The internal population IP_{gen} of size m keeps the best solution found so far for each sub-problem. The initial solutions of IP_0 are generated either randomly as in [3] or deterministically using a problem-specific heuristic.
- Then at each iteration, a random selection operator chooses two parent solutions from the IP_{gen}, e.g., Pr_1, Pr_2. A one-point (1X) crossover operator produces an offspring solution O from Pr_1, Pr_2 and a random mutation operator modifies O to generate a new solution Y.
- Solution Z is finally produced by using a repair method on Y in case of any infeasibility (e.g., violation of the budget constraint).

4.1 Problem-Specific Heuristics

For further improving the convergence and diversity of the MOEA/D approach, two enhancements have been developed.

Population Initialization: in the case of a min-max objective functions in Sect. 3 (e.g., cost and coverage objectives), the initial population has been

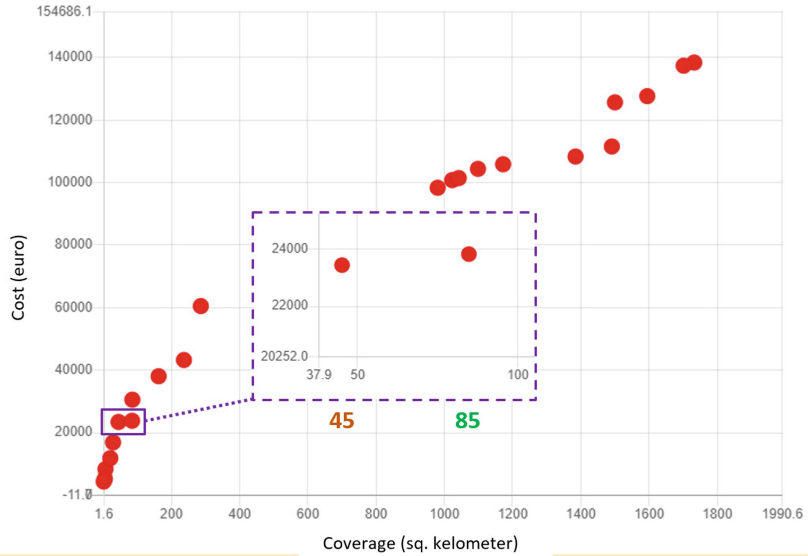

Fig. 2. Cost vs. Coverage

injected with the extreme solutions each satisfying one objective. The first extreme solution includes all billboards and therefore benefits the maximization objective function and the second extreme solution includes only one billboard and therefore benefits the minimization objective function. By including the two extreme solutions in the initial population it is expected to enhance the diversity and convergence of the MOEA.

Repair Heuristic: for handling the infeasible solutions there are several techniques that can be adopted. For example, one can be just dropping the infeasible solutions or repairing them. In this paper, a repair heuristic has also been implemented that removes one billboard iteratively until satisfying the budget constraint, as defined in Sect. 3.

5 Experimental Setup and Results

In this section, the algorithmic parameters used during the experimental studies are initially introduced followed by the experimental results.

5.1 Experimental Setup

For all experimental studies, the following algorithmic parameters are used: maximum number of generations $gen_{max} = 250$, population size $m = 100$, one-point (1X) crossover rate $r_c = 0.5$, random mutation rate $r_m = 0.2$ and neighborhood size $T = 2$. The contribution of the proposed problem-specific heuristics

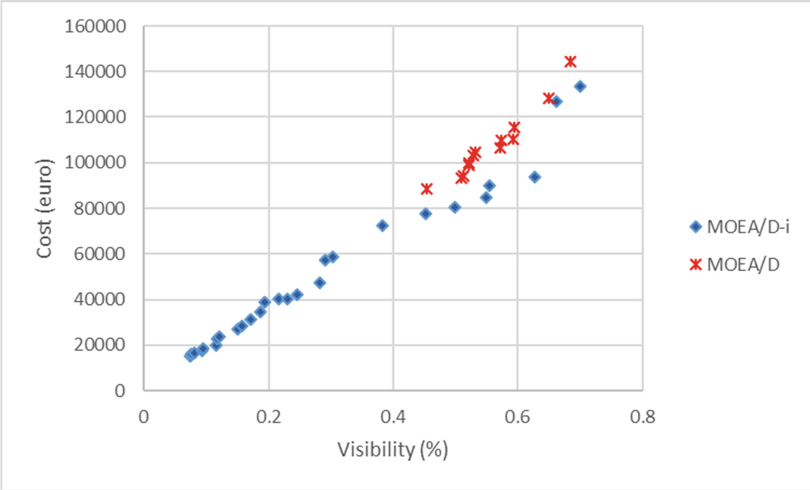

Fig. 3. MOEA/D vs MOEA/D-i

has been also demonstrated with individual experimental studies. That is the conventional MOEA/D has been compared with MOEA/D-i that includes the proposed population initialization as well as with MOEA/D-r that includes the proposed repair heuristic.

5.2 Experimental Study 1: MOO for OOH Advertising

In the first experimental study, the MOEA/D approach with both the population initialization and the repair heuristic is used for tackling the two conflicting objective functions namely maximizing coverage and minimizing cost (price). A thorough discussion follows for explaining the contradiction between the objective function as well as the benefit that a decision maker can have tackling OOH advertising in the context of MOO.

The Pareto front in Fig. 2 shows the trade-off between maximizing coverage and minimizing cost, where optimizing one deteriorates the other. Each feasible solution provides a certain level of coverage which could be desired in term of the solution cost depending on the customer budget. A decision maker can obtain further marketing insights by comparing Pareto front solutions. For example, Fig. 2 shows a comparison between two consecutive solutions. The first solution has a coverage of 45 km^2 while the next one has almost double the coverage (84 km^2) for an additional cost of 380 EUR. Therefore, a customer could opt to spend 1.5% more in order to gain twice as much coverage.

5.3 Experimental Study 2: MOEA/D Versus MOEA/D-i

In this subsection, we examine the contribution of the proposed population initialization technique by comparing the conventional MOEA/D with random

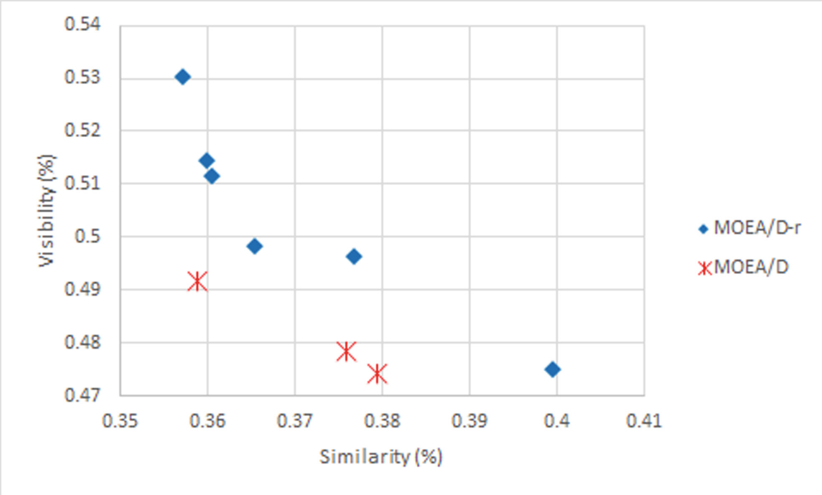

Fig. 4. MOEA/D vs MOEA/D-r

population initialization against the MOEA/D-i that injects the initial population with the extreme solutions as explained in Subsect. 4.1 in a min Cost - max Visibility MOOP. The results of Fig. 3 show that the proposed technique significantly improves the performance of the conventional MOEA/D by obtaining a higher quality and more diverse Pareto Front. In particular, MOEA/D-i offers the decision maker about three times more non-dominated solutions, which cover the objective space much better, while all of its solutions clearly dominate the solutions obtained by the conventional MOEA/D.

5.4 Experimental Study 3: MOEA/D Versus MOEA/D-r

In this subsection, we examine the contribution of the proposed repair heuristic by comparing the conventional MOEA/D that drops solutions in case of infeasibility against the MOEA/D-r that repairs infeasible solutions as explained in Subsect. 4.1 in a max Visibility - max Similarity MOOP. The results of Fig. 4 demonstrate the effectiveness of the repair heuristic compared to its counterpart. Similarly to the results of experimental study 2, the Pareto Front obtained by MOEA/D-r improves the performance of the conventional MOEA/D with respect to both convergence and diversity. Particularly, MOEA/D-r offers to the decision maker two times more non-dominated solutions, covering the objective space better and again all of its solutions clearly dominate the non-dominated solutions obtained by the conventional MOEA/D.

6 Conclusions

In this work, a Multi-Objective Optimization Problem (MOOP) for optimizing the selection of billboards for OOH advertising campaigns is initially defined and formulated. In the literature, previous studies treat the optimization of multiple objectives as a single weighted function and therefore provide a single solution, the proposed approach provides a set of near-optimal solutions (i.e., a Pareto Front) enabling the exploration of trade-offs between conflicting objectives. In order to tackle the proposed MOOP for OOH advertising a Multi-Objective Evolutionary Algorithm based on Decomposition (MOEA/D) is adopted and enhanced with two problem-specific heuristics. The experimental results show the benefits of tackling this problem in the context of Multi-objective Optimization, as well as the improvement of the conventional MOEA/D when combined with the problem specific heuristics in terms of both convergence and diversity.

Our future directions include the application of the proposed approach on data from other countries. This will allow further experimentation and evaluation of the approach with different parameters.

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