

Spatial Assignment Optimization of Vaccine Units in the Covid-19 Pandemics

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Abstract. In this work we present the application of evolutionary algorithms to the problem of spatial assignment optimization of vaccine units. In the framework of urban planning of health facilities, the problem consists into optimizing the overall cost of building and running vaccine units with respect to costs and benefit for the public by deciding their size and location. The complex non linear objective function, depends on populations distributions, transportation infrastructure costs, travel times and distances and vaccination units capacities. The problem domain is described by a model based on a layered approach, where the layers embed knowledge of different types at a scalable resolution. Although many purposely designed algorithms for spatial locations assignment of health facilities, have been proposed in the literature, in a pandemics situation, for vaccination units, faster optimization tools are needed not necessarily designed for a specific problem model, which can quickly change dynamically. We have investigated and compared the application of several evolutionary optimization algorithms from PSO to Differential Evolution. Results show that evolutionary algorithms allow an high degree of flexibility in objective function without compromising in optimisation performance.

Keywords: Spatial planning · Urban planning · Evolutionary algorithms · Particle swarm optimization · Differential evolution · Health management.

1 Introduction

Optimising the spatial allocation of health facilities is a very relevant problem in urban planning which is carefully considered by government organizations since

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it heavily affect quality of life and financial budget. During major pandemics, like the current COVID-19 emergency, optimal spatial allocation of vaccination units is influenced by the typical factors of healthcare models, but in addition it is also complicated by the fact that there is the lack of precise model of people's behaviour, and there is not a long time available, the decision of unit allocation is usually a matter of weeks or days instead of years, like in normal situations. Therefore, there is the need of tools which allow to quickly model and optimize at different level of scale, depending on the actual current context.

In [18] five classes of factors that hamper access to healthcare for patients are listed, i.e. availability, accessibility, affordability, acceptability and accommodation. The latter three deal with the social organization and wealth of a population, reflecting cultural factors and political decisions, while the former two are solely related to the territorial distribution of facilities and people. In particular, availability refers to the number of healthcare facilities which can be chosen by a patient, while accessibility analyzes the travel distance or time between a patient and service points; the two factors are often merged in one concept, *Spatial Accessibility*, applicable to dense urban contexts. The allocation of healthcare facilities can be modeled as a location-allocation problem [17], where the demand is sustained by potential patients and the offer consists of medical centers, e.g., Covid-19 hospitals or vaccine centers during a pandemic needing special measures [5]. Spatial accessibility measures have been presented in literature and applied to different components of the healthcare system, which in turn may present specific requirements, e.g. primary health structures [12], mental health facilities [16], qualified work personnel [4], and hospitals [11]; notable classes of measures include *Provider-to-population ratios*, *travel impedance measures* and *gravity models* [22]. Because of the differences in terrain conformation of different areas, combined with usually un-even urban development spanning through decades or centuries and different economic history, each area presents specific challenges and impediments for patients; several case-studies are reported in literature for specific locations and at different data resolutions, e.g. the Chinese towns of Kaifeng [25] and Wuhan [24], the Sichuan Chinese province [23] and the Chicago region [15]. Globally, the Covid-19 pandemic highlighted the structural weaknesses of different healthcare systems. To limit the diffusion of the virus, disease spread control strategies were enforced; at the same time, sectors of existing facilities were dedicated to covid-19 patients and separated from the rest of the resources, to protect the rest of the patients, or completely built from the ground to cope with the needs of a rapidly growing portion of infected population. When vaccines became available, accurately planning the distribution on the territory of vaccination centers was of paramount importance, considering the population distribution and the availability of infrastructures, i.e. transportation routes, and specialized equipment to store, distribute and inoculate the vaccine doses. For this purpose, the design of planning tools to devise resources distribution plans became a crucial task. Planning the distribution of healthcare facilities is a process which usually spans several years, requiring major public works and considerable financial investments, in a slowly developing scenario, e.g. the con-

struction of a new city district. A pandemic situation, instead, induces sudden changes which follow the contagion situation, which strongly influence both the logistics and the emotional response of the population [7], which can lead to management issues; therefore, tools need to provide users with the ability of performing rapid what-if analys is to plan ahead the response to various likely future scenarios.

In this work we present a novel layer-based model to efficiently distribute Covid-19 vaccination units in a territory. Our model can incorporate in specific layers several factors defining the total cost of building and running units, classes of stakeholder their behavior and consequently social costs. We analyze the performance of different evolutionary algorithms in optimizing a custom fitness function which takes into account the role of each considered layer. Evolutionary algorithms can be applied to numerical problems of various sorts, providing general optimization strategies which are independent from specific fitness functions. For this reason, they prove useful in the scope of this work, where an epidemic scenario is considered. In such a context, the requirements can rapidly change, in unpredictable manners; resources, often in limited amount, have to be diverted or re-located on the basis of unforeseeable developments in the spread of diseases, driven by factors including the movement of people and goods, or climate [20]. Evolutionary algorithms are more resilient to changes in the fitness function, which reflects updated needs in the pandemic context, whereas ad-hoc strategies are tailored to more static, predictable scenarios.

In Sect. 2 we introduce the architecture of our framework and provide details on the layer-based model, the problem parameters, the relevant costs, and the designed objective function In Sect. 3 we introduce the characteristics of the evolutionary optimizers and the Nevergrad framework which has been used in the experiments and integrated with the objective function. In Sect. 4 we describe the experimental settings, datasets used and the experimental results obtained. We finally draw conclusions and discuss future work.

2 Covid Facilities Distribution Model

The purpose of the model is to describe the territory characteristics in order to assess both cost for installation and running, i.e. management, of Covid-19 vaccination units, and evaluating the effectiveness of the service provided to the population in term of amount and quality of services supplied and reachability of the assigned locations, which influences both the logistics and the emotional affordance [10]. The territory features are modelled by $M = \{L^k\}$ a set of k overlapping bi-dimensional layers of the same size $m \times n$, $i \in m$, $j \in m$. Each layer k represents a dimension of the relevant information by a 2-dimensional grid containing values in its elements $L^k_{i,j}$. The approach is scalable, since it allows to approximate solutions for the allocation optimisation problem by compromising between the desired resolution of details and the available computational resources. The grid size determines the different scale levels, while it impacts the computational performances.

In computing the quality of a given solution, the different layers are traversed depending on specific algorithmic rules, which embed the semantic of the model and health facilities user behavior in terms of logistics and emotional response [9].

2.1 Population Distribution Layers

Population distribution layers gives an estimate of the population living in each square of a certain grid element. Each different layer of population L_t^{Pop} refers to a different population type t, which has different income, socio-cultural background and ultimately behavior. The unit used is the thousand of people. The approximation given the *Population distribution layer* provides, in each entry, the amount of population of a certain type living in each element of the territorial grid expressed in thousands of people units, i.e. $L_u^{Pop}pper[2,3] = 23$ $L_l^{Pop}ower[2,3] = 4$ indicate that 23 thousands upper class and 4 thousands lower class people lives in territory grid area (2,3). The general assumption is that users of the same type behave according to shortest path cost to services, verifying their own cost criteria, i.e. we assume that the populations assigned to an element is attracted by the Covid vaccination unit closest to its residence, i.e. the one needed a minimal cost to reach. The shortest path [8] between a given location and a Covid-vaccination unit is computed by taking into account of distance, travel time, transportation cost and quality, as expressed in the transportation infrastructure layer for a given population type.

2.2 Transportation Infrastructure Layers

Each layer L_t^{Trans} of the Transportation Infrastructure refer to a specific transportation network type t,i.e. road, highway, train, underground, taxi, etc. Each grid element (i, j) contains a value, $L_{train}^{Trans}(i, j) = d$ which represents the distance d needed to cross it and to reach its center from an adjacent element laying on the same infrastructure, here *train*, for example from position $(4, 2)$ of the transportation grid shown in Fig. 1 we can move to positions $(4, 1)$, $(3, 2)$, $(4, 3)$ and $(5, 2)$ respectively with a distance cost of 6, 1, 9 and 1. To compute the actual path cost this distance value needs to be weighted with population specific cost for that type of infrastructure, predicting the paths to be chosen by the population [6]. The path are represented directly in the grid by sequences of 2D grid elements. A special value Inf is used to codify an empty square, see positions $(2, 5)$ and $(3, 5)$ in Fig. 1, i.e. a square which is at infinite distance and cannot be reached from its neighbor cells. Moreover, in addition to distance from neighbors, every infrastructure cell contains a boolean value which denotes that an entry/exit to the cell is available from the road crossing it, for instance, an underground or a railway have no exits in every grid element they traverses. A path can be composed by sections belonging to different transportation layers provided that each starting/ending point of each section has a entry/exit for the transportation layer type to which it belong, for instance a path can be made

of a *bus* subpath connected to a *underground* path and then to a *walking* path section. In Fig. 1 the shortest path between cell $(4, 1)$ and cell $(3, 4)$ within a single transportation layer is highlighted .

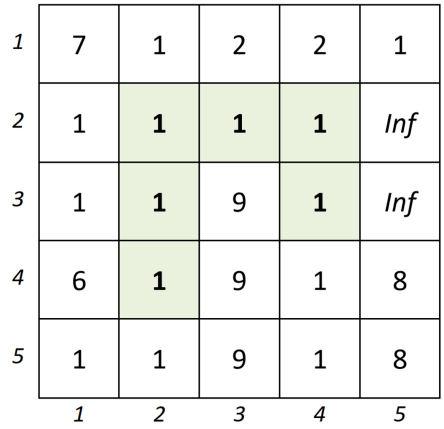


Fig. 1. Path in a transportation layer grid

In the configuration settings, for each population type a *per km* cost is set. The *per km* cost summarizes for each population different elements: the actual monetary cost of the travel and the quality of life value in using the specific transportation network, it basically acts as a weight inducing a preferential choice behaviour in people from different classes. For example for "lower class" population the cost tend to directly reflect cost of tickets, i.e. bus is preferable than taxi, instead for "higher class" people, quality considerations will prevail and for example, for this people taking buses may have a higher cost than using own car, finally certain minority group, e.g. "environmental sensitive" people, may consider bicycles the most preferable transportation mean despite of their income level. The shortest cost paths will then depend both on the shortest distance weighted by the population depending cost.

2.3 Covid Facilities Layer

The Covid Facilities Layer represents the actual candidate solution for our optimization problem. Given a number k of Covid vaccination units to allocate in a territory grid, each grid element represents how many Covid units are allocated there, the values assigned have to be integer and the constraint $\sum_i^m \sum_j^n L_{units}^{Covid}(i, j) = k$ must hold. The entries of this layer are the inputs of the overall objective function described in Sect. 2.5.

2.4 Problem Parameters Setting

A set of parameters characterise a problem instance model, in addition to the population, transportation and Covid-19 facilities layers. The basic parameter is the pair $m \times n = r$ deciding the *layers dimensions*, they directly affect the resolution, how precisely the model approximate the reality, and determine the computational resource requirements. Since most algorithms used in computing fitness have a complexity $O(r^3)$, although it is not exponential, territory high resolution can easily become a bottleneck, because population based evolutionary algorithms strongly depend on a large number of fitness evaluations [2,3].

The number u of *Covid vaccination units* to allocate in the grid.

The *capacity* u_{cap} of a Covid vaccination unit in term of how much population can be vaccinated in a time period (usually a year).

The cost u_{est} of building a Covid unit from scratch,i.e. establishing the infrastructure, power lines, air conditioning systems, medical tools etc.

The u_{save} percentage of the *saving* obtained from establishing a Covid unit where already exist one. Building a vaccination center with a double capacity does not have a doubled cost, the saving mostly decreased cost in infrastructures, parkings, power lines, bureaucracy and organization.

The cost u_{mng} for managing a vaccination center in a time period.

The *time horizon* $t_] - hor$ denotes the number of time periods over which optimization is held. A lower management cost u_{mng} with respect to u_{est} could favour different choice on a longer horizon.

Other important parameters are represented by the cost value assigned to each pair $(pop_{type}, trans_{type})$ in order to map preferences of different classes of people with respect to the use of different transportation infrastructures, and the population pop_{type}^{wait} waiting time cost, an percentage increment to be applied when a give vaccination unit attract more people of its capacity.

2.5 Overall Objective Function

Given a candidate solution, a spatial assignment of vaccination units to the Covid facilities layer, the *overall objective function* represents the costs to be optimized in a given time period. The general cost includes building the vaccination units, once, running them for a given time horizon, the cost of moving the population on a shortest path according to distances and their preferential behaviour, and finally adding the social cost due to bad quality services, i.e. time to wait in case of exceeding the units capacity. In order to formally define the overall objective function, we will use a function $[u_{pos}, s_{path_cost}] = fsp((i,j), pop_{type})$ which returns the position u_{pos} of the vaccination unit closest to position (i,j) and the cost s_{path_cost} of the shortest path from (i,j) to u_{pos} according to the transportation cost mapping, inducing the preferential behavior of population type pop_{type}.

$$
\begin{aligned}
&o(L_{units}) = \\
&(\textstyle\sum_{\forall u \in L_{units} \wedge L_{units}(u)=1(u_{est})}) \\
&+(\textstyle\sum_{\forall u \in L_{units} \wedge L_{units}(u)>1(u_{est})*u*u_{save})} \\
&+(\textstyle\sum_{\forall u \in L_{units}(u_{mng}*t_{hor}))} \\
&+(\textstyle\sum_{\forall t \in Pop_{type}} \sum_{i \in m, j \in n} (L_t^{Pop}[i,j]*fsp((i,j),pop_t)*t_{hor}))} \\
&+ \textstyle\sum_{\forall u \in L_{units}} \begin{cases} \sum_{\forall t \in Pop_{type}} (assigned(u,t) * pop_t^{wait} * t_{hor}), & \text{if (over_capacity(u))} \\ 0, & \text{otherwise} \end{cases}
\end{aligned}
$$

3 The Evolutionary Algorithms

The evolutionary algorithms, that we have considered, all share the characteristics of being population based. Despite of the different details of each algorithm, they all share the concepts of:

- *population* of candidate solutions,
- *fitness*, a function aimed at evaluating the performance of a single solution, i.e.the cost to be minimized;
- an *evolution mechanism*, which, is able to generate a new population of solution with an improved fitness.

The core difference between algorithms consists in how they create a new generation using fitness and current solution population. Variations range from applying mutation and crossover operators to solution representation, as in Differential Evolution [21], to applying the concept of inertial movement and attraction among individual solutions in the search space, as in PSO [14]. The mechanism is iterated thru generations, effectively exploring the solution search space, until a *termination condition*: typically when a given number of iterations or fitness threshold is reached.

3.1 The Nevergrad Environment

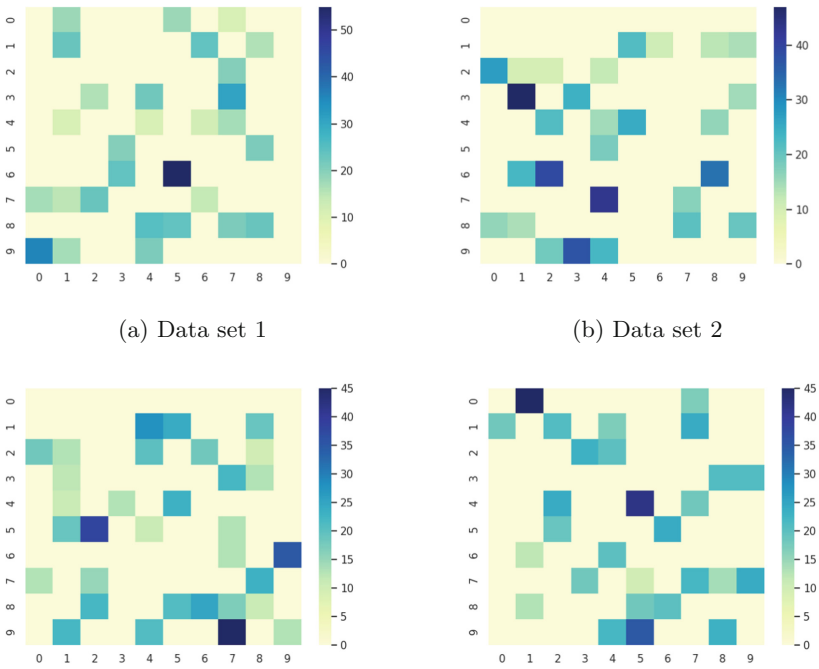
Nevergrad [19] is a Python library, developed by Facebook and released under the MIT license, which implements a set of popular gradient-free and evolutionary optimisers, to perform single-objective or multi-objective optimisation. The optimisers considered in this work are Particle Swarm Optimization (PSO) [14], Differential Evolution (DE) [21], Differential Evolution with Two Points Crossover (TwoPointsDE), ScrHammersleySearch, and Covariance Matrix Adaptation Evolution Strategy (CMA-ES) [13]. An additional pure RandomSearch optimiser is used as a baseline for comparison purposes only.

The structure of *Nevergrad* allows to easily integrate in the evolutionary algorithm loop an external fitness evaluator [1]. In our experiments the fitness evaluator consists in a implementation of the*overall objective function* taking as input the layers of the Covid facilities distribution model and the parameters and cost settings. Nevergrad solutions are returned as a vector of length u, containing the coordinates of Covid units locations.

4 Experiments

4.1 Data Set and Settings

The data sets consist of ten 10 × 10 grids with 600 randomly distributed inhabitants. People are distributed on the grids by randomly picking a location and placing from 10 to 25 inhabitants there; when the chosen budget of 600 is over, the remaining locations are filled with 0. The length of road segments for each location is set to 1 or 2km. Due to the randomness in the population distribution process, collisions are possible, i.e. some locations can have more than 25 inhabitants. In Fig. 2a, Fig. 2b, Fig. 2c and Fig. 2d four population distribution layers from different data sets are shown. In the figures, a darker shade means a higher density of population in the corresponding grid sector.



(a) Data set 1 (b) Data set 2

(c) Data set 3 (d) Data set 4

Fig. 2. Four population distribution layers

The Differential Evolution CR, F1 and F2 parameters are set, respectively, to 0.5, 0.8 and 0.8, and the adopted mutation strategy is current-to-best. The population consists of 30 randomly initialised individuals; such settings apply both to the DE and TwoPointsDE strategies. The PSO transformation function is set to

"arctan", and the population size to 40. The "omega", "phip" and "phig" parameters are set, respectively, to 0.5/(log(2)), 0.5+log(2) and 0.5+log(2). The CMA scale is set to 1.0, and the population size to 7. The considered fitness evaluation budgets for Nevergrad are: [500, 1000, 2000, 3500, 5000]; each algorithm has been run for ten times on the same data set/budget pair to level possible differences due to the random initialisation.

4.2 Results

In this section we present the results of our experiments.

In Table 1 the results of the experiments are reported for data set 1. The best average results and the second best average are respectively shown in **bold** and ***bold-italic*** case. Differential Evolution (DE) and Differential Evolution with Two-Points Crossover achieve similar performance for all the iteration budgets, with TwoPointsDE slightly prevailing in all cases except 500 iterations. Next come CMA and ScrHammersleySearch, and finally PSO. RandomSearch values, kept for reference, are more than two times those of the worst performing optimiser, i.e. PSO. These results highlight the capability of all the optimisers to effectively navigate the fitness function space to find local minima, although with sensibly different results.

Table 1. Experiments results on data set 1, average fitness value

Algorithm	500	1000	2000	3500	5000
CMA	18202	17177	17425	17387	17210
DE	**17612**	***17501***	***16685***	***16286***	***16494***
PSO	21854	21874	20800	22223	22239
RandomSearch	47796	47848	46741	46449	45778
ScrHammersleySearch	19415	18600	18515	17941	18039
TwoPointsDE	***17750***	**16877**	**16584**	**16198**	**16192**

Table 2 shows the minimum (best) fitness value achieved by each algorithm in any of the ten runs on data set 1. The results agree with those in Table 1 both Differential Evolution strategies achieve the overall best value of 16080 with a budget of 2000 iterations (or higher), with other strategies which

Table 2. Experiments results on data set 1, minimum fitness value

Algorithm	500	1000	2000	3500	5000
CMA	17530	16830	16890	16330	16830
DE	**16450**	***16990***	**16080**	**16080**	**16080**
PSO	19230	18890	17880	18730	19800
RandomSearch	43430	45510	42190	40640	40640
ScrHammersleySearch	18120	17380	17390	17150	16990
TwoPointsDE	***16750***	**16140**	**16080**	**16080**	**16080**

5 Conclusions

This work presents a model for the optimal spatial assignment of vaccination units in a territory affected by a Covid-19 pandemics. The model is based on layers embedding knowledge about population types distribution and transportation infrastructures types. Different behaviors of different population types can be modeled. The model is scalable with a trade-off between accuracy and computational resources, obtaining rapid modeling and optimization for response units allocation, as required by a pandemics situation.

The model has been implemented and experimented with different evolutionary optimization metaheuristics on randomly generated datasets. Results comparisons show generally good performances of the evolutionary approach with a clear prevalence of differential evolution algorithms.

The grid based layers approach is a very flexible representation which allows to augment the expressivity of the model, by introducing new kind of layers connected to the territory, i.e. green area, climate info, crime rate etc., this knowledge can be incorporated in people behaviour and quality of solution evaluation algorithm.

Future Works. The scalability characteristics of the grid based layers approach suggest to explore the use of grids with different resolutions in order to better articulate the precision/computational resources balance. An extension toward a more accuracy model is also represented by differentiating the cost of developing units with respect to their position in the territory, this is not relevant for health facilities which usually enjoy the strong exemptions for public interest, while it would reflects more accurately the real situation, where private developing cost strongly depends on town areas.

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