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# Emission-reducing deployment of shared office networks

Matthieu Mastio[a,b,c], Sebastian Hörl[d,c], Milos Balac[e], Vincent Loubière[a]

[a] *Odyssee Act One, Paris, France*
[b] *Institut de Recherche en Informatique de Toulouse, Université Paul Sabatier, Toulouse, France*
[c] *COSYS-GRETTIA, Université Gustave Eiffel, Champs-sur-Marne, France*
[d] *Institut de Recherche Technologique SystemX, Palaiseau, France*
[e] *Institute for Transport Planning and Systems, ETH Zürich, Switzerland*

**Abstract**

In this paper, we propose generic method based on publicly available data to design a master plan optimizing the number of coworking spaces to deploy in a given area, as well as their placements across the territory, with the goal of reducing the GHC emissions linked to car commuting. As a first step, we collect and preprocess population data to convert them into an exploitable form. Then we design a decision model that describes when a person would choose to work in a shared office, and which transport mode they would use. We finally perform an optimization to maximize the gains in terms of traveled distance using a linear solver and heuristic methods, and comparing their respective effectiveness. The results are encouraging, since they show that using an optimized network computed with our method, we could reduce the total car commuting distance by 23%, which represents a reduction in carbon emissions of hundreds of tons per day at the scale of the studied use case region around Toulouse.



*Keywords:* urban planning; shared office; coworking space; optimization; emissions

## 1. Introduction

Urban planning methods inherited from functionalist theory have led to an extreme concentration of economic activity in the urban and peri-urban parts of the territory [6]. In consequence, congested megalopolis have emerged, in which the geographical distribution of activities by function tends to produce a dissociation and distancing between workplaces and centers of life. According to [7], in France, the transport sector overall, which is the first item of GHG emissions due to its strong dependence on fossil fuels, accounted for 31% of national greenhouse gas emissions, of which around 15% are due to journeys from home to work (74% of them are traveled by car). Decentralization of the territorial system is thus crucial for a sustainable development and injection of new life in deserted rural areas. We aim to develop a systemic approach, in line with the strategic duty of territorial forces with regard to environmental footprint reduction, and in support to their decision making-process for resource allocation as part of national and regional investment plans for co-working spaces development as a 'non-mobility' and rural reviving solution.

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Shared offices (workspaces capable of accommodating teleworkers, entrepreneurs or remote employees of company offices) represent a major lever for action on transport demand, by reducing the traveled distance. In line with the national investment plan initiated by the French Prime minister in August 2021, and backed by numerous studies [10], these spaces could be seen as urban seeds that will initiate positive feedback loops, stimulating the organic growth of human scale resilient infrastructures. A number of studies [3, 4, 11, 18, 22] have focused on measuring the environmental impact of emerging work practices such as teleworking and working in coworking spaces. In [4, 22], the authors proposed a framework taking into account the direct and indirect costs and gains of implementing such spaces. According to these studies, the distance traveled can be reduced with wide implementation of shared offices, thus reducing GHG emissions, energy and road maintenance costs, and improving the quality of life of the commuters. However, their conclusions are nuanced, since the environmental cost generated, for example, by the construction of new buildings, and the energy consumed in each one of them can offset the gains linked to the reduction in distances traveled if the deployment of new offices was not carefully thought out.

The choice of office locations strongly influences their potential use, and strategically chosen locations are critical to maximize their combined impact. The present study aims to provide decision-making entities with a systemic and dynamic vision allowing to define an optimal combination of shared offices, and completes previously suggested static and empirical evaluation approaches, like for example [8]. We address the entire working population likely to relocate their offices to areas with sparser economic activity. To do so, we rely on computer simulation and optimization, which are powerful tools for precisely testing the territorial impacts of the proposed schemes before deploying them in an operational context.

## 2. Methodology

The distance traveled by car is directly correlated with the commuting emissions, and thus, the optimal combination of shared offices is the one maximizing car displacement reduction. To achieve it, we need to treat the set of shared offices not as independent entities, but as a collective networked system, and test its interaction and performance over the large territory. This will allow fine adjustment of public action, arbitrating between the creation of shared offices and an improvement of the public transport supply. The proposed method revolves around three main stages: extraction of the relevant population from the census data, computation of saved travel distance and optimization of the office placement.

### 2.1. Census data

To evaluate the efficiency of a coworking network, we need two things: an estimation of the population that could be interested to go to work in these places, and the distance traveled by this population to go to their usual place of work. In this work, we use the French population census data provided by INSEE, and more specifically the professional mobility data [15]. This data set contains a list of persons representing the population, with their socio demographic attributes. Amongst those, we extracted information like municipality of residency, municipality where the person is working, socio-professional category, transport mode used by the individual to go to work, and number of cars owned by the person's household. We filter the totality of the people eligible for teleworking. As no official statistics exists, we used for this purpose a rough estimation based on the French definition of socio-professional categories: among the working population, we selected only people appertaining to the categories that would exclude from the list the workers who need to be on site, like farmers, laborers, artisans or shopkeepers.

### 2.2. Travel distance computation

We propose a simple strategy in which the individuals choose the office they want to use as an alternative to their usual workplace based on their travel time. For this, we define two parameters that will dictate the behavior of the individuals. The first, that we call isochrone, is the maximum travel time for an employee to consider using a coworking space. This represents the fact that even if using a given alternative office would take less time than going to the usual office for an individual, it may not know about the existence of this office, or does not want to go to work there because it is too far from its home. The second is the minimum saved time: the employee will not work in a given coworking space if they do not save at least this travel time in comparison to their usual place of work. Indeed, if the benefit of changing workspace is not substantial, an employee would probably not be keen to change its habits. In the rest of this work, we set the minimum saved time to 10 minutes.

With these parameters defined, we consider that the employees will try to minimize their individual travel time, and that they will switch their office if a better option exists. We thus need to calculate the car travel time (and distances) between their home and their place of work, to compare them with any candidate office location. The car travel distances and travel times are calculated with a free flow transport network generated from OpenStreetMap data. As the granularity of work and residency location in the available data is the municipality, we will use their centroids to compute all the distances. We computed the public transportation travel time using GTFS data. So if using public transport to go to a coworking space would take less time than going to their usual place of work, an employee would potentially switch mode (and thus reduce their car travel distance to 0). Inversely, if an employee was using public transport before, but going to a coworking space by car would save them some time, they would also switch mode (if they own a car) and increase their car travel distance from zero to the new distance. We also take into account that some people were using their car even if a better public transport option was available to them. We consider here that these people would not switch mode.

Let $\mathcal{T}$ be the set of travelers, and $\mathcal{O}$ the set of the candidate offices location. These locations are the centroids of all (or a subset of) the municipalities in the territory. For each traveler $t \in \mathcal{T}$ and each candidate office $o \in \mathcal{O}$, we define $d_{t,o}$ the matrix containing the gain in distance for the traveler $t$ to go to work at the office $o$. The gain is set to zero if the employee would not choose this office (based on the choice model), and negative if it would switch to a less environment friendly transport mode.

### 2.3. Location optimization

The reduction of car travel distance achieved is strongly dependent on office space available to the travelers. The number of offices to be placed being limited, we need optimization algorithms which, starting from a finite initial set of candidate locations, evaluate combinations of shared office locations until the best combination is identified. This optimum here corresponds to the set of offices that maximizes the cumulative saved distance and, therefore, the GHG emissions saved collectively.

Let $n$ be the number of offices we want to select. Let $\mathcal{S}$ (subset of $\mathcal{O}$) the set of offices to be selected. Equation 1 gives the total distance $f(\mathcal{S})$ saved if all the employees that would benefit to switch to one of the offices $\mathcal{S}$ would do so.

$$f(\mathcal{S}) = \sum_{s \in \mathcal{S}} \max_{t \in \mathcal{T}} d_{t,s} \tag{1}$$

The set of chosen offices during the optimization process represents a system optimum: it is not based on a greedy approach, where the coworking spaces would be chosen based uniquely on their individual performances.

## 3. Optimization

The placement of a set of entities across a geographical space is a computationally intensive task that often depends on many factors. This is an extensively studied problem, for example to provide solutions for petrol wells or sensor networks placement. Although numerical simulation is very helpful to provide insight on these issues, this class of problems is NP-hard [16], which means that it is generally not suitable to find an optimal solution for large scale instances.

The solutions proposed in the literature rely either on finding an exact solution of a subset of the problem with Mixed Integer Linear Programming [17], or on approximating the optimum with the use of heuristic methods. In [2] the authors provide a comparison between different gradient descent techniques, like simultaneous perturbation stochastic approximation, finite difference gradient, and very fast simulated annealing. In [16], they propose network distance-based clustering algorithms based on simulated annealing and fuzzy clustering. In [12], they introduce an alternating optimization penalty method. The most frequently applied heuristics are evolutionary methods, and variations of genetic algorithms, like in [13], where the authors developed a hybrid genetic algorithm, or in [5] and [20], where they show the efficiency of different genetic methods for sensor placement.

In the following parts, we will adapt the proposed solutions to the office placement problem. We will first investigate the feasibility of using linear optimization, and then consider heuristic approaches.

### 3.1. Linear optimization

We define the matrix $x_{t,o} \in \{0, 1\}$ which describes if the commuter $t$ chooses the office $o$ to go to work and the vector $y \in \{0, 1\}$ describing whether the office $o$ is globally selected as one of at maximum $n \in \mathbb{N}$ required offices.

A mixed integer linear problem can then be formulated with the objective

$$\underset{x_{t,o}}{\text{maximize}} \sum_{t \in \mathcal{T}} \sum_{o \in O} d_{t,o} x_{t,o} \tag{2}$$

and the constraints

$$\sum_{o \in O} y_o = n \tag{3}$$

$$\sum_{o \in O} x_{t,o} \leq 1 \quad \forall t \in \mathcal{T} \tag{4}$$

$$x_{t,o} \leq y_o \quad \forall t \in \mathcal{T}, o \in O \tag{5}$$

Equation 2 is the objective function, where we want to maximize the distance saved by all active displacement relationships. Equation 3 ensures that the number of offices selected is equal to $n$. Equation 4 guarantees that an individual can not choose more than one alternative office, and Equation 5 ensures that an individual can choose to go to an office $t$ only if this office is part of the list of selected sites. This generic formulation allows additional constraints to be added in the future, for example on the capacity of each office. The objective function can also be changed, for example, by including a compromise between environmental savings and construction and operating costs.

As this method is computationally expensive, and is meant to be applied to large territories, counting thousands municipalities, and hundreds of thousands people that could potentially change their place of work, it is necessary to evaluate only a limited number of offices from a predefined selection of potential sites. We determined that a preselection of 50 municipalities gave good results, while allowing considerable reduction of the execution time. Due to the lack of space, the preselection algorithms we used will not be discussed in this paper, but they will be described in details in future publications.

### 3.2. Heuristics

Given the size of the search space, heuristic methods are an interesting alternative to exact methods like integer programming. They are strategies to quickly explore the space of solutions, but without guaranteeing to provide an optimal result. They are widely used to deal with complex problems, and they generally approximate very effectively the optimum in short time. These algorithms often start with an initial estimated solution, which is improved during an iterative process, with the aim of maximizing the objective function.

The computation time of the two methods we propose here is substantially shorter than the integer optimization. This allows us to execute them on the entirety of the possible locations, and not only on a preselected subset.

#### 3.2.1. Monte-Carlo

We use a Monte-Carlo municipalities selection algorithm as a performance baseline. The algorithm takes as parameters the saved distance matrix $d$, the number of municipalities to select $n$, and the number of unsuccessful iterations before stopping the execution. We start with an initial solution which is composed by the n municipalities that would allow to save the most distance if taken individually. This algorithm then randomly selects in a loop n distinct municipalities locations from all possible locations. The probability of each municipality to be picked is weighted with the square root of their individual performance, so a location that performs better individually is slightly more likely to be selected. We evaluate the performance of the solution with our evaluation function $f$, and we keep track of the current best solution. If no improvement has been made during a given number $i_{stop}$ of iterations, the algorithm returns the best found solution.

#### *3.2.2. Parallel evolutionary algorithm*

An evolutionary algorithm takes inspiration in the natural selection mechanisms, approaching the optimum with a structured stochastic approach. It emulates Darwinian evolution: each solution could be considered as a competing organism in a population, where the fittest individuals are allowed to reproduce and give part of their characteristics to the next generation. We adapted this concept to propose an algorithm that gives very efficient solutions to our offices location problem.

It requires the same parameters as the Monte-Carlo algorithm, and starts similarly by picking an initial solution and weighting the municipalities by their individual performances. We take this time the squared values of the performance, to favor the best performing ones during the random selection more strongly. We found experimentally that this was improving the quality of the solution, without impacting noticeably the computation time. It then performs the iterative process, to construct the next solution: half of the locations of the current solution is kept, selected randomly with a weight being the square of the number of times they would have been the best choice for a person in this solution. The other half is a random selection of the municipalities that were not part of the current locations, still weighted with their individual performances. Once again, it evaluates the new solution with $f$, and stops after $i_{stop}$ if no improvement has been made. In our parallel implementation, each individual of a population is managed by an allocated thread.

## 4. Experiments and Results

The methodology we propose in this study relies on openly accessible data, and thus can be applied to any territory in France (or in other countries that share similar data sets). For the purpose of illustration we will demonstrate here the value of our method on an area located around Toulouse (south west of France), containing the departments of Ariège, Tarn-et-Garonne, Tarn, Aude, Haute-Garonne and Gers. The population of this area is 2.7 million people, and 588,570 of them are commuting everyday using their personal vehicle to work in another municipality, cumulatively traveling 27.33 millions kilometers. We filtered amongst these commuters 439,842 people that could potentially work remotely, according to the INSEE socio-profesional categorization. Figure 1 shows the observed territory, and how the eligible population is distributed across it.

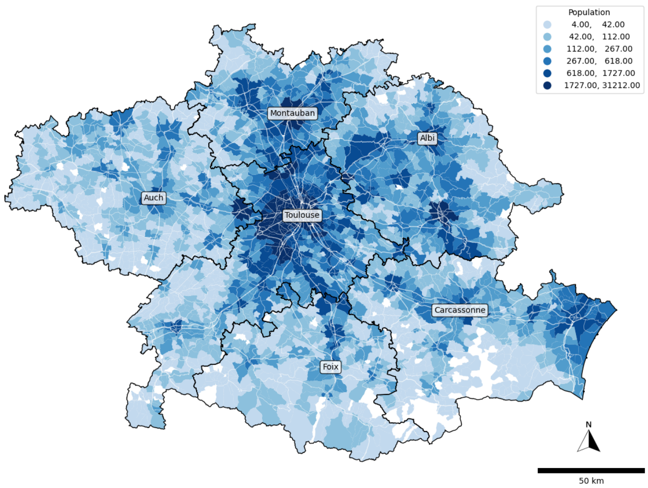


Fig. 1: Studied territory (departments of Ariège, Tarn-et-Garonne, Tarn, Aude, Haute-Garonne and Gers) and the distribution of the 439,842 commuters

| | **CBC** | **Monte-Carlo** | **Parallel Evolutionary** |
|---|---|---|---|
| **saved distance (Mio km)** | 4.094 | 3.344 | 4.502 |
| **execution time (s)** | 192.32 | 13.21 | 48.64 |

Table 1: Saved distance and execution time for the different method with isochrone=15 minutes and n=20

### *4.1. Evaluation*

We tested the different algorithms presented in section 3 on the studied territory. We excluded Toulouse (which is the biggest city and the center of the area) from the list of potential candidates, because it is so densely populated that it would systematically be selected as a shared office location, when our goal is rightly to decentralize the activity that is too concentrated in big urban area.

We performed all our tests on an Intel Xeon E5-2620 cpu with 12 cores at 2.40GHz, and 32GB of RAM. Our metric to compare the performance of the solutions proposed by the algorithms was the distance cumulatively saved if all the people that would save time going to work to one of the proposed coworking offices locations decided to switch their place of work.

The integer program was solved using CBC [9], an open source mixed integer linear programming solver written in C++, and Pyomo [14], which offers a Python interface to a variety of open source and commercial solvers. As we discussed in Section 3, it is needed to perform a municipality preselection phase in order to be able to solve the integer program in an acceptable time.

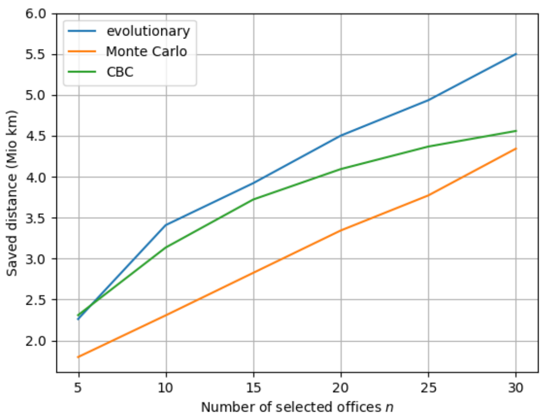


Fig. 2: Comparison of the saved distance (in million km) for each method in function of the number n of offices

To test our hypothesis that using suboptimal algorithms without location preselection could approach or even exceed the performances of the exhaustive integer program, we compared the cumulative saved distances and the execution times for different scenarios. Figure 2 shows the cumulative saved distances obtained with the Monte-Carlo algorithm, the parallel implementation of the evolutionary algorithm and the CBC solver for different $n$ values and with an isochrone of 15 minutes, while Table 1 indicates the computation times for the different methods for a given scenario ($n = 20$ and $iso = 15$ min). These computation times are not varying so much with different values, and can be generalized for other scenarios.

We see that while being about 4 times faster than the evolutionary algorithm and 15 times faster than the integer solver, the Monte-Carlo method is significantly less efficient than the other two. With an isochrones of 15 minutes, the evolutionary algorithm (which evaluates all possible municipalities) is always outperforming the saved distance returned by the integer method with a municipality preselection, while being almost 4 times faster, and so even more with a higher number of selected locations. This is due to the fact that with the integer method, we needs to preselect a subset of municipalities, while the evolutionary algorithm is fast enough to consider the integrality of possible choices.

### 4.2. Results analysis

Here, we will focus on a set of 20 spaces in the Toulouse region. We applied the evolutionary algorithm, as it is the best performing method for this particular scenario.

| Municipality | attractiveness | saved distance (km) | saved distance per person (km) |
|---|---|---|---|
| Launaguet | 10,713 | 699,197 | 65.26 |
| Vernet | 11,471 | 530,097 | 46.21 |
| Coufouleux | 7,744 | 457,654 | 59.09 |
| Fonsorbes | 12,360 | 433,665 | 35.09 |
| Labastide-Saint-Pierre | 6,300 | 418,882 | 66.48 |

Table 2: Top 5 performing municipalities for n=20 and iso=15

Table 2 gives details concerning the top 5 (in terms of saved distance) chosen municipalities: for each one of them, the table shows the index of attractiveness, the cumulative distance gain, as well as the saved distance per person. What we call attractiveness is the number of commuters who would benefit to work in this office (given this set of selected offices) instead of their usual place of work, and can thus be considered a good indicator of the potential demand for a particular area.

If the totality of these people decided to work in one of those coworking spaces, that would represent a cumulative gain of 6,242,446 km saved per day, and would represent a total commuted distance reduction of about 23%. We are aware that it is likely that only a smaller proportion of the filtered population will be able, or will want to relocate their office. However, the study gives in our opinion a good estimation of the strategic areas. And even a small part of the potentially interested population switching their offices would lead to significant reduction in carbon emission.

Indeed, according to data available on the French government website [21], French automobile fleet is composed 59% of diesel vehicle and 39% of petrol vehicle. The 2% remaining are electric cars and other alternative combustible that have negligible emissions in comparison. The consumption for the vehicle sold since 1995 is given by [1]: it is in average 5.3 L/100km for diesel vehicle and 6.2 L/100km for petrol ones. Finally, [19] tells us that 1L of diesel burnt will emit 3.17 kgCO2/L, while 1L of petrol will emit 2.79 kgCO2/L. These data allow us to get a rough estimation of 0.166kgCO2 per kilometer traveled by particular car in France. If we consider that only 20% of the population we picked for this study would agree to relocate their activity, deploying the proposed network of shared offices would still allow to save up to 200TCO2 per day.

## 5. Conclusion and Outlook

This paper presented a macroscopic framework to design a master plan for the optimal placement of a shared offices network, as well as an evaluation of the theoretical gain induced by its deployment on the territory. We believe that we demonstrated the feasibility of the method, that can easily be applied to any territoriy, and gives a precise idea of the areas where it would be the most beneficial to deploy coworking spaces. Our methodology also gives information on the marginal gain for each new space added, which is in our opinion very valuable, especially in the frame of national investment plans, as it allows local authorities to make an informed decision, and help them prioritize the subsidies and financial supports they will allocate against a tangible evaluation of GHG impact, by rationalizing the evaluation down to the emission benefit of the proposed network, we provide the necessary legitimacy for public forces to intervene in the heterogenous field of perspective and stakeholders, and a strong lever for territorial redeployment and redevelopment.

However, we are aware that our proposition is not sufficient to model all the parameters that should be taken into consideration in an operational context. The large scale analysis is a first brick of a systemic methodology, to be completed and looped in with a scale down to city level and block to enable a complete evaluation of the network and design of the territorial adaptation for greatest impact. The next step will be to perform a microscopic simulation to account for all the local particularities of the observed territory, like the road infrastructure (and its usage over time), the offices hosting capacities and the building vacancies. It will include a local analysis on the land use of the territory, a more precise discrete choice model capable of capturing trade-offs between different transport modes, that will allow us to take into account for example the annex journeys (nursery/school, shops) usually included in the journey between home and work, as well as the occupancy of the traffic network by hour to get a realistic estimation of the travel times.

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