A structured simulation-based methodology for carpooling viability assessment

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ABSTRACT

Growing urban traffic congestion requires the study of measures to reduce the number of automobiles traveling every day to the city centers. Carpooling is a system by which a person shares his private vehicle with one or more people that have similar origins and trips. In theory these systems could lead to great reductions in private vehicle trips but past experiences show different results and one of the reasons is the schedule differences between people. Because one does not know at the outset who is willing to participate on these systems or not, there is the possibility to use a simulation methodology based on census data from the commuter trips and the population characteristics in an urban area to generate random commuter trips. Those trips are then evaluated to find their grouping possibilities, through an optimization heuristic, having in consideration time and capacity constraints. Simulations were run on top of Lisbon Metropolitan Area (Portugal) and results show probabilities of finding a match consistently inferior to 50%, showing that Time-Space constraints may play an important role in determining the results that this mode has obtained in the last decades.
INTRODUCTION

The rising of auto usage deriving from suburban occupation and car ownership growth is making traffic congestion more frequent in urban areas. This results in air pollution, energy waste and consumption of time. Moreover the majority of the trips in individual transport are single occupant vehicle (SOV) trips (1). In Europe, numbers of 1997 from the International Energy Agency showed that automobile occupancy rates in commuter trips was between 1.1 and 1.2 people per vehicle(2).

One may conclude that most of the major cities were not able to insure effective mobility polices for controlling modal split and traffic congestion, thus needing recovery measures. Some measures have been tested in the last years in the perspective of Transport Demand Management (TDM) strategies whose main objective is to use the existing transportation infra-structure in a more efficient way (3).

Public Transportation (PT) is many times pointed as the best solution to mitigate traffic congestion because it has a higher ratio between space occupied and number of passengers transported. But improvements in PT to make it more appealing may be costly and studies show that only a relatively small proportion of the new trips attracted to improved PT have diverted from car trips (4). Underlying this weakness is the way people perceive the different transportation modes, many times based in subjective factors. One of the most important factors is “status”, cars are not regarded only as a means of transportation but also as a way of showing some degree of ascent in society (5). This attractiveness can be used as an advantage through an increase in vehicle occupancy, moving the same number of people in fewer cars.

Carpooling systems search that higher occupancy, particularly in commuter trips, associating neighbors who travel to work places next to each other, using their vehicles one at a time on a day-to-day or week-to-week basis. The advantages for the user can be fuel cost reduction, automobile maintenance reduction, parking availability and increased trip comfort.

From its viability point of view the most difficult pools to form are those constituted by people who are not part of the same household, “external” carpooling, and that is why they represent a smaller share of the total carpoolers in the USA where these programs started earlier (6). At the same time these are the most interesting from its potential result in congestion reduction, because the “external” carpool feels the responsibility for vehicle provision and driving which is difficult to break when there is less intimacy between people (7). A study about the relation between carpooling and household vehicle trips concluded that if most carpools created under commute trip reduction programs are household carpools, then regional reductions in vehicle trips may not result (8).

Some experiences have been conducted to incentive “external” carpooling, mainly in the USA and Europe, but they have been obtaining limited success mainly for schedule differences between participants and because of the difficulty in matching people who are strangers to each other. Studies show that only a small percentage of the people who make a positive change in commute mode to carpooling are likely to stay with the new mode until they are not traveling to that workplace (9). “Carpooling is inferior to driving alone because it requires an increase in travel time due to the need to pick-up and drop-off carpool members. Probably more importantly, carpoolers suffer from significant reduction in convenience due to the schedule rigidity which this mode usually entails” (7).

In this study we start from the fact that if there are no compatible trip characteristics, namely origin and destination coordinates and time schedules it is not possible to maintain a stable system of carpooling. The question that arises is to what extent is this factor important for carpooling viability.
The proposed method to find this is to generate simulated trip attributes based on survey data and analyzing their matching possibilities allowing determining an upper-limit for the probability of a random participant obtaining a partner for his everyday commuting trip. This will vary accordingly to urban distribution and density as well as trip characteristics from area to area.

The following section discusses the existing research in carpooling modeling. Then the new simulation-based method for modeling these systems is presented. The paper continues with the Running of the simulation for Lisbon Metropolitan Area (LMA) and is finalized with conclusions and future work.

REVIEW OF CARPOOLING MODELLING

Some studies have been conducted in the past to evaluate the viability of carpooling. In 1994 Van der Touw and Krishnamoorthy (10) started with the assumption that an 80% match rate would be the minimum to make a carpooling system viable, and then they divided the city of Melbourne (Australia) in zones and formulated lists of acceptable trips between them. This was represented as a matrix where indirect paths between zones/nodes were not considered.

The main conclusion of this work was that a 2.5% population participation rate would result in an 80% success rate. At a first glance this result appear to be very positive because the population participation rate necessary to achieve good results is not very high, but there were several factors which were not taken in consideration namely the lack of time and capacity constraints. This fact may have had an overestimating effect in the results of the experience. On the other hand by limiting indirect paths between zones/nodes in the construction of the pool groups, the method introduces a border limitation, by not allowing pool groups between people whose origins are situated in different zones.

In 1999 Tsao and Lin (11), used a matrix of 2 mile side squares to simulate the trip generation and attraction in the city of Los Angeles. The objective was to find an upper-limit for the ride matching probability based on spatial and temporal constraints. The authors assumed a development pattern in which the densities of workers and jobs were uniform over an infinitely large flat geographical area. Due to this assumption they were able to focus just on the trip generation/distribution from one particular zone to all the other zones and extract conclusions about the potential demand reductions with the implementation of carpooling.

Considering a minimum distance for carpooling to be interesting greater that 10 miles and using a gravitational method for the trip distribution they were able to search for compatible trips, which meant two trips beginning in the same square and finishing in another common square. Assuming a given distribution of departure time and dividing the peak hour into time intervals, they assumed that only people with a departure in the same interval could carpool together.

The conclusion was that carpooling was not viable for this city because it would be difficult to find a carpool partner due to the small number of trips from the same origin zone to the same destination zone.

This research introduced some constraints that do not correspond to reality and that can have a significant effect in underestimating the impact of these systems. This was actually assumed by Tsao and Lin in the report conclusions when they stated that the “more fundamental limitation of the model is that two people who live on opposite sides of a street separating two zones would not carpool. This in some cases may be unrealistic” (11). Also the assumed constant density in jobs and workers across an infinitive area does not take into account the greater density of jobs in areas such as the downtown or other centralities.

METHODOLOGY
The method introduced in this paper to estimate an upper-limit for the matching probability of carpooling systems, consists in generating random SOV commuter trips for a specific geographic area based in Census Data and evaluate the possibility of associating those people in carpools.

It requires three main tools:

- A GIS program to generate compatible origin and destination coordinates for the random trips;
- A Visual Basic Program application embedded in the GIS program to generate the remaining trip attributes, to connect the geographic and optimization tools and also to generate the outputs.
- An optimization software to analyze the possibility of carpooling between potential carpooling clients. This implies solving an NP-Complete combinatory problem from OR known as LCPP (Long Term Carpooling Problem) (12);

In the next sub-section the LCPP is revisited and updated with the changes compatible with the model to be tested, and then the heuristic method used to find the groups for a real-world instance is explained.

**The Long Term Carpooling Problem updated**

The LCPP can be defined as follows: A number n of users must reach their work destination, and latter on the day get back home. The problem objective is to partition the set of users into subsets, or pools, such that each pool member in turns will pick-up the remaining members in order to drive together to the workplace and back (12). In what concerns to the common destination constraint we introduce the possibility of different work places as long as their relative distances do not surpass a certain limit.

Hence the present approach considers that the server (driver) picks up his colleagues (clients), takes them to his workplace and then they have to walk from this point to their destinations. In the afternoon they return to this point were they are picked up by the server and taken to their homes. It was not considered that the server would drop-off people in their workplaces in the city center due to traffic congestion (Figure 1).

![Figure 1 – Pick-Up and drop-off scheme](image)

In order to solve this combinatory problem each user i enlisted in the carpooling program specifies:

- The maximum extra driving time Ti user i is willing to accept, when picking up colleagues, in addition to the time needed to drive directly from home to the workplace or back;
• The minimum time $e_i$ acceptable for leaving home;
• The maximum time $u_i$ acceptable for arriving at work;
• The minimum time $e'_i$ acceptable for leaving work;
• The maximum time $u'_i$ acceptable for getting back home;
• The capacity $Q_i$ of his car, this is the maximum number of people he is willing to take in the automobile;
• The maximum distance $\text{DistMAX}_i$ user $i$ is willing to walk from the server destination to his workplace;

The objective is to define user pools such that as few cars as possible are used and that the routes to be driven by the drivers are as short as possible, subject to time and capacity constraints. Note that pools are supposed to be stable over a period of time and will not change every day. This means that the number of people in a pool will be at most equal to the capacity of the smallest car among those owned by pool members, since each member will eventually pick-up all other ones, in a day-to-day or week-to-week basis.

This LCPP problem can be modeled by means of a direct graph $G = (V,A)$, where $V=\{1, \ldots, 2n\}$ is the set of nodes and $A$ the set of arcs.

The set $V$ is partitioned as $V = V^1 \cup V^2$, where $V^1$ is the subset of nodes associated with the houses of the carpool members and $V^2$ is the subset of nodes associated with their workplaces.

The set $A$ is a set of directed weighted arcs $(ij)$, where each arc $(ij)$ is associated with a non-negative cost $c_{ij}$, it may include travel time, toll payment, attitudinal factors, etc.

The LCPP as defined above is actually a multi-objective problem, requiring to (12):
• Maximize car usage, thereby minimize the number of cars traveling to/from work;
• Minimize the length of the path to be driven by each employee, when acting as a driver;

The problem structure suggests that it is possible to combine these two objectives in a single objective function, as follows.

Let $k$ be a pool of clients. Each of them, on different days, will use his car to pick-up the other pool members and go to work (and latter come back), thus he has to define an Hamiltonian path on the partial subgraph of $G$ identified by $k$, starting from the node associated to his house, passing through all the other nodes and ending at his workplace.

Let $Hpath(i,k)$ be such an Hamiltonian path, starting from $i \in k$, connecting all $j \in k\setminus\{i\}$ and ending at the workplace of the server.

$Hpath(i,k)$ is a feasible path iff $|k| \leq Q_j$, $\forall j \in k$, and all user constraints are met.

The minimum path, $\text{min}_{path}(i,k)$, for $i \in k$ is the shortest feasible Hamiltonian path for $i$.

In this formulation, it is assumed that the shortest paths are chosen. The cost of a pool $k$ is then defined to be:

$$
\text{cost}(k) = \sum_{i \in k} \text{min}_{path}(i,k)/|k| \quad \text{if} \quad |k| > 1
$$

$$
|c_{io} + p_i| \quad \text{otherwise}
$$

(1)

If a person is alone, this has an increased penalty, whose amount is associated with him and equal to penalty $p_i$.

The cost of a complete solution is the sum of the costs of all the pools in it, that is, $\text{cost}(\sigma) = \sum_{k \in \sigma} \text{cost}(k)$. This perspective optimizes both objective functions, provided that
the penalty $p_i$ of a client is sufficiently greater than 0, it is more convenient to pool clients together than to leave them alone.

The problem can be translated in a four indices formulation considering the variables:

- $x_{ij}^{hk}$: Binary variable equal to 1 iff arc $(ij)$ is in the shortest Hamiltonian path of a server $h$ of a pool $k$;
- $y_{ik}$: Binary variable equal to 1 iff client $i$ is in pool $k$;
- $\xi_i$: Binary variable equal to 1 iff client $i$ is not pooled with any other client;
- $S_i^h$: Non negative variable denoting the pick-up time of client $i$ by server $h$;
- $F_i^h$: Non negative variable denoting the arrival time of each client $i$ at his workplace when traveling with server $h$;
- $H_i^h$: Non negative variable denoting the departure time of each client from his workplace traveling with server $h$;
- $L_i^h$: Non negative variable denoting the arrival time of client $i$ at home, driven by server $h$;
- $t_{ij}$: Time travel between trip origins of clients $i,j$;
- $tOD_{ij}$: Time travel between trip origin of client $i$ and destination of client $j$;
- $t0_{ij}$: Time travel between trip destination of client $i$ and destination of client $j$ – this is a walking distance;
- $d0$: Destination distance between clients;
- $K$: Index set of all pools;
- $C$: Index set of all clients;

Objective function:

$$Z_{LCP} = \min \left( \sum_{k \in K} \sum_{i \in C} \sum_{(j)\in A} c_{ij} x_{ij}^{hk} y_{ik} + \sum_{k \in K} \sum_{i \in C} c_{i0} x_{ij}^{hk} y_{ik} \right) + \sum_{i \in C} \sum_{x_{ij}^{hk} \in N} p_i \xi_i$$ (2)

The cost is equal to the travel time when no other component is considered.

Constraints:

$$\sum_{j \in C \cap [0]} x_{ij}^{hk} = y_{ik}$$ (3)

Force a client $i$ to be declared to be in pool $k$, if there is a path originated in $h$ going from $i$ to $j$:

$$\sum_{i \in C \cap [0]} x_{ij}^{hk} = y_{jk}$$ (4)

Force a client $j$ to be declared to be in pool $k$, if there is a path originated in $h$ going from $j$ to $i$:

$$\sum_{j \in C} x_{ij}^{hk} = \sum_{j \in C} x_{ij}^{hk}$$ (5)

Continuity of the paths:

$$\sum_{k \in K} y_{ik} + \xi_i = 1$$ (6)
Force each client to be assigned to a pool or to be penalized;
\[
\sum_{(i,j) \in A} x_{ij}^{hk} \leq Q_h
\]
(7)

Car capacity limitation in each group;
\[
T_h \geq S_i^h - S_i^h + TOD_i^h - TOD_h^h
\]
(8)

Maximum extra travel time;
\[
\sum_{k \in K} \sum_{i \in C} Y_i^k \leq \sum_{j \in C} Y_j^k
\]
(9)

Disables the possibility of forming groups of only one element;
\[
F_j^h \geq F_h^j + t_{0_{jh}} + M \left( 1 - \sum_{k \in K} \sum_{j \in C} x_{ij}^{hk} \right)
\]
(10)

The time in which each client arrives at his job has to be greater than the time in which the server arrives at his job plus the time between both of them;
\[
S_j^h - S_i^h \leq t_{ij} + M \left( 1 - \sum_{k \in K} x_{ij}^{hk} \right)
\]
(11)

The difference between the time that client j is picked up by server h and the time client i is picked up has to be greater than the time to travel between i and j;
\[
F_h^j \geq S_j^h + t_{OD_{ih}} - M \left( 1 - \sum_{k \in K} x_{ij}^{hk} \right)
\]
(12)

The time in which the server reaches his destination has to be greater than the time to pick-up the last client in his path and the time between this point and the server workplace;
\[
F_j^h \leq u_j + M \left( 1 - \sum_{k \in K} \sum_{j \in C} x_{ij}^{hk} \right)
\]
(13)

The Time in which the clients reach their workplace has to be less than the maximum time acceptable for reaching their destination;
\[
S_h^h \geq S_i^h - t_{hi} + M \left( 1 - \sum_{k \in K} x_{hi}^{hk} \right)
\]
(14)

The time in which the server leaves home has to be less than the time to pick-up the first client less the time between both points;
\[
S_i^h \geq e_i
\]
(15)

The pick-up time has to be greater than the minimum time acceptable for leaving home;
\[
L_i^h \geq H_i^h + t_{OD_{ih}} - M \left( 1 - \sum_{k \in K} x_{ij}^{hk} \right)
\]
(16)

The time in which the server drops-off the first client has to be greater than the instant the server leaves work and the time to travel between this point and the client’s home;
\[
H_h^j \geq H_i^h + t_{0_{ih}} - M \left( 1 - \sum_{k \in K} \sum_{j \in C} x_{ij}^{hk} \right)
\]
(17)

The time in which the server leaves his work has to be greater than the time each client leaves his work and the time between this point and the server’s workplace;
\[
L_j^h - L_i^h \leq t_{ij} + M \left( 1 - \sum_{k \in K} x_{ij}^{hk} \right)
\]
(18)

The difference between the time that client j is dropped at home by server h and the time client i is dropped has to be greater than the time to travel between i and j;
The time in which the clients arrive home from work has to be less than the maximum acceptable:

\[ L^h_i \leq u'_i + M \left( 1 - \sum_{k \in K} \sum_{j : j \neq i} a_{kij} \right) \]  

The time in which the server arrives home has to be greater than the time in which he drops the last client and the time from that point to the server home:

\[ L^h_i \geq L^h_i + t^h_i - M \left( 1 - \sum_{k \in K} x_{kij} \right) \]  

The time in which each client leaves his workplace has to be greater than the minimum acceptable:

\[ H^h_i \geq e_i^h \]  

Where \( M \) is a big constant;

This formulation was set in the Optimization Program Xpress-MP (Dash Optimization Software), having as input a text file with the attributes of a list of potential carpooling clients (Figure 2).

![Figure 2 – Xpress-MP application to find optimal groups](image-url)

**Divide-and-Conquer Algorithm**

The LCPP is an NP-Complete Problem (13) thus there is the need to use a heuristic approach to find the groups out of a set of clients. The ANTS and the Bee-Colony algorithms are examples of metaheuristics that have been applied to this problem (12; 14). But the use of a single metaheuristic is less efficient and flexible when dealing with real-world and large scale instances such as this. A recently proposed practical combination is using clustering techniques with metaheuristics in a divide-and-conquer approach (15) producing satisfactory solutions to real-world instances to NP-Complete optimization problems in a short runtime (16). In 2003 Mulder and Wunsch (17) solved a 20,000 TSP size problem in 98 seconds. This suggests being a good method to find an acceptable solution in reduced time.

The algorithm that is used to cluster the initial set of users (divide stage) is the k-means clustering algorithm which in short allows classifying objects based on attributes into K number of groups. The grouping is done by minimizing the sum of squares of distances between data and the corresponding cluster centroid.

There are several formula distances between two objects, but the most used is the Euclidean distance which is the square root of the summation of differences between the values i and j for all the variables that characterize the objects (v = 1, 2, …, p).

\[ d_{ij} = \sqrt{\sum_{v=1}^{p} (X_{iv} - X_{jv})^2} \]  

(22)

If we consider as attributes the origin and destination coordinates, we are joining in clusters the people that have trips more close in space to each other. This is actually one of the most used methods for automated pattern spotting and knowledge discovery in spatially referenced data (18).

But geographic proximity does not guaranty for itself a good match between trips because schedules may vary significantly, thus this was also introduced in the formula distance by adding the acceptable schedules (equation 24).

\[ d(i, j) = \lambda_1 \times ((x_i - x_j)^2 + (y_i - y_j)^2 + (x_{di} - x_{dj})^2 + (y_{di} - y_{dj})^2)^{\frac{1}{2}} + \]
\[ \lambda_2 \times ((e_i - e_j)^2 + (u_i - u_j)^2 + (e'_{i'} - e'_{j'})^2 + (u'_{i'} - u'_{j'})^2)^{\frac{1}{2}} \]  

(23)

- xi, yi, xdi and ydi are the coordinates of the trip origins and destinations respectively;
- ei, ui, ei’ and ui’ are the minimums and maximums time schedules available for carpooling;
- \(\lambda_1\) and \(\lambda_2\) are weighting factors.

The process starts with all clients in a large size list of potential users of the carpooling system, then they enter the K-means clustering algorithm, where the members are divided in clusters such that every one of these is smaller than the maximum number of elements (Nmax) that we want the Optimization program to consider at a time, value that should be calibrated in function of the computing time.
When this process is complete, all the clusters are sent to the optimization program which searches for the possible group combinations in order to find the smallest number of groups with maximum people.

If the resulting groups are composed totally from people who have completed their car capacity they are saved as complete groups. As for the remaining groups and all the other people that were not able to find a match in the previous iteration, they are set together for another iteration. The process ends when the user-defined iterations are met or no new groups are formed.

THE SIMULATION APPLIED TO LISBON METROPOLITAN AREA

The present case-study respects to the commuting movements inside Lisbon Metropolitan Area (LMA) (Portugal) from the surrounding boroughs towards central Lisbon. This encompasses great traffic flows which have been rising in the last years. In Figure 3 the main interaction volumes in LMA from the Census 2001 are represented (Commuting people in both directions between each O/D pair).

Generating trip attributes

Having established a method to determine the minimum number of groups with maximum people that we are able to form out of a set of carpooling clients, we need to generate input data for the area that we are analyzing and this is where the simulation component is actually introduced. Data is generated accordingly to discrete probability distributions depending on census data and constrained to a specific geographic area.

The process starts with the origins and destinations coordinates of the commuter trips. These are generated randomly, taking out the areas where there is low population density (<
2 people/km²), so that trips are not placed in unpopulated places. There are differences between the several boroughs in terms of trip generation, so for every statistical unit we take the total SOV trips in commuting hours (from 6:00 to 10:00 a.m.) with origin in that area and destination in Lisbon accordingly to the Census 2001 survey. Then we generate randomly as many origin points as we want to consider for that borough using a GIS tool. The chosen number represents the scale of participation in the carpooling scheme, different participation rates will result in different probabilities of finding one or more partners for a commuter trip.

The trip destination points are generated in Lisbon parishes accordingly to an indicator of job density. We take the relative weight of office area in every borough and using Monte Carlo Simulation chose a parish for each of the trips.

After generating the trip coordinates we need to find survey compatible values for the remaining trip attributes. These attributes can be divided in stochastic parameters and user-defined parameters. The first are generated through Monte Carlo Simulation over discrete distributions obtained through the Census or other available surveys like Ti, Qi, and schedule variables ei, ui, ei', and ui'. The second ones are constant and defined for each simulation; that is the case of the Average Driving Speed, Walking Speed, DistMAX and pi.

The schedule variables are generated accordingly to Census 2001 where departure times are divided in four categories: 6-7 a.m., 7-8 a.m., 8-9 a.m., 9-10 a.m., resulting in a discrete distribution. Again by Monte Carlo Simulation, we are able to generate a time departure for each commuting trip.

The Trip times are also available in the Census but these are based in the interviews perception of travel time which can vary significantly (19). Hence there is the option to compute more accurate Trip Times using traffic assignment. To make it simple a grid is used to calculate trip times between all the cells for four departure intervals: [6,7] h, [7,8] h, [8,9] h and [9,10] h (Figure 4). This way travel times are a function of the congestion levels for different morning intervals.

![Figure 4 – Calculation method for Trip Times](image)

The other trip times (between the origins and between the destinations for the pick-up and drop-off) can be calculated using the Euclidean distances and an average speed for driving (origins) and walking (destinations). The arrival time at work can now be obtained by summing the Departure from Home and the modeled Trip Time.

Introducing a degree of flexibility around these schedules one obtains maximum and minimum times to depart and arrive at home and work. To obtain this schedule flexibility we
will need more data than the one we usually find in a National Census hence it would be more rigorous to proceed with a survey focused on the acceptability and preferences for carpooling.

From a carpooling survey we should also obtain the Car Capacity a person is willing to share with his partners and the Maximum Distance a person is willing to walk to/from gathering points.

After this data is generated, a list of simulated clients is sent to the optimization heuristic which will find the groups and outputs the following indicators:

- Number of groups formed;
- Number of groups of two participants;
- Number of groups of three participants;
- Number of unmatched participants;
- Percentage of unmatched participants;
- Number of unused vehicles;
- Percentage of unused vehicles;
- Time of calculation;
- Number of iterations.

**Defining input parameters**

Because there is no Carpooling specific survey available, the extra driving time a person is willing to spend was considered as a linear function of the total travel time, hence, people who drive more have a greater willingness to spend time to pick-up partners:

\[
T_{\text{Extra}} = \begin{cases} 
\text{TripTime} \times 0.5 & \text{if} \quad \text{TripTime} \times 0.5 < 0.7 \text{ hours} \\
0.7 \text{ hours} & \text{otherwise}
\end{cases}
\]  

(24)

The Car capacity is also considered constant and equal to 2 (maximum capacity) because better data is not available.

The user-defined constant parameters were considered to be:

- \(P_i = 999\), sufficiently big number for the heuristic;
- Walking Speed = 4 km/h;
- DistMAX = 600 m;
- Driving speed = 50 km/h.

One also has to define the heuristic parameters which have to be calibrated in order to produce the best results. These parameters are mainly the Cluster Distance Weights (\(\lambda_1\) and \(\lambda_2\)) and the Cluster Maximum Dimension (Nmax).

This was done running several simulations for LMA considering different scales of participation, varying the cluster distance weights first and then varying Nmax, taking as performance indicators the percentage of unmatched people that resulted from the simulation and the time it took to compute.

For the Cluster weights we concluded that both components, distance between coordinates and distance between schedules, are important for the results, however there is a great interval where there is no significant variation (95% confidence interval) (Figure 5).
Thus it was decided to use the weights that originate the less Average of % of Unmatched participants, $\lambda_1 = 0.8$ and $\lambda_2 = 0.2$.

In what concert to the Nmax, the average % Unmatched was compared to the Average time that took to compute the simulations (minutes) (Figure 6). Over Nmax= 10, there is no statistical significant difference between the results and moreover the average time begins to grow exponentially, thus it was decided to use Nmax = 10 to run the simulations.

Results

The final simulations were run for all Boroughs of LMA, considering 5% of the total SOV trips (7000 trips). The following graphical output shows the percentage of people who did not found a match for every parish of all the boroughs.
There are better results next to the main network and close to Lisbon. Although there are also some fairly good results in more far locations due mainly to a significant population density and to a greater willingness to spend time picking-up partners.

CONCLUSIONS AND FUTURE WORK

The simulation-based methodology for the spatial-time viability of carpooling that we presented is more advanced than the previous research by limiting the border effects inherent to the cellular models presented in the state-of-the-art to a minimum. Moreover, by applying real trip characteristics one gets a more faithful image of the urban mobility possibilities of carpooling. The results show a significant variation in the matching probability of areas in the same borough, due to different population densities, personal schedules and distance to Lisbon city center. The percentage of people who did not find a match is consistently greater than 50%, with almost half of the area of LMA reaching the 100% probability of not finding a partner. This indicates that Time-Capacity constraints may have an important role in determining the viability of these systems as a good tool to mitigate traffic congestion.

Nevertheless, some limitations of this methodology remain and these are to be worked out in future research. One aspect that needs extra attention is the flexibility of carpooling clubs to personal near term schedule changes, which is one of the main deterrents to carpooling viability. An indicator for this flexibility is necessary in order to find the alternative pool groups for a person that has a different destination or the same but at a different time, on a particular day.

The carpooling survey is the most important missing component of the work developed. The specific technique to extrapolate the values for the car capacity and the extra time that people are willing to accept is yet to be established. It is expected that different
social profiles of the inhabitants in each region will generate different types of behavior, constituting this way another differentiating aspect of the probability of finding a partner for carpooling.

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