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Decision making approaches optimizing the benefits of fully autonomous and connected collective cars

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Abstract—An Intelligent Transportation System (ITS) operating without prior reservations while offering high quality, door-to-door services at reduced fares is studied. The structure, comprised of fully autonomous cars, covers arbitrary urban areas and operates without prior reservations. Specifically developed control algorithms based on Optimization, Operations Research and Artificial Intelligence optimize the system management for any demand level and geometry. Due to V2V, V2I and V2C connectivity a fast and secure information update is achieved. Well-adapted itineraries considering customer preferences are dynamically defined. Idle vehicles are controlled and travel durations are reduced. Adequate use of the available vehicle capacity allows an important reduction of the costs for both cars and users. A comparative study with a self-service manually driven car scheme is also introduced. Qualitative and quantitative measurements appraise the system performance. The presented micro transit scheme in association with innovative technology (UV light sanitizing cars) could form a successful and affordable alternative for all involved entities commuters, traffic and environment under pandemic crisis where mass public transport operators increase traveller risks.

Index Terms—Demand responsive transportation, micro transit, autonomous connected cars, queueing network model, event-driven systems, discrete-event simulation, asynchronous behavior, Monte Carlo simulation, parameter optimisation, cloud computing, self-service vehicle schemes.

I. INTRODUCTION

According to various researches, congestion in urban areas is mostly due to private vehicles and less to freight movements. Surface transportation is a large source of greenhouse gas emissions significantly contributing to global climate change. Statistics indicate that one third of America’s carbon dioxide emissions comes from moving people while 80% of these emissions are due to traffic. Unsuccessful attempts have been made encouraging other transportation modes, inter-modality combining private and public transportation or imposing restrictions. As private car remains the first choice of most commuters a large market diversification exists on different types of vehicle fleets. Car-sharing programs form an alternative to private vehicle use. [1] studies the evolution and importance of car-sharing systems in North America. They can reduce from 4.6 to 20 cars per shared-use vehicle from the transportation network as [2], [3], [4], [5], [6] present. Despite the supportive beneficial public policy (carsharing parking zones, exemption from parking limits etc.) such systems do not necessarily diminish the passenger to vehicle ratio and can be followed by a poor spatial distribution (greater concentration on high-demand destinations) unless additional constraints are imposed

obliging users to return cars to specific stations. Moreover, potential clients have to schedule their own arrangements defining mutually acceptable meeting points. Non-recurrent demand variations, cancellations or any other modifications on the planned trip can be hardly handled. In [7] odd-even vehicle rationing encourages ride-sharing on restriction days. Demand Responsive Transport (DRT) forms an alternative for regions associated with reduced demand [8], [9], [10]. Audi, has already created its own car sharing program while Toyota is about to examine partnerships. In many existing DRT structures, [11], [12], [13], [14], various limitations are imposed such as fixed routes, advanced booking etc.

[15], [16] and [17] accentuate multiple advantages of fully autonomous and connected cars such as optimized traffic flows, enhanced safety, reduced energy consumption and gas emissions etc. Ongoing research is being carried out by the Massachusetts Institute of Technology’s AgeLab, developing “new ideas to improve the quality of life for older adults” involving transportation issues.

This work presents an optimized decentralized management of a flexible transportation scheme comprised of fully autonomous, connected cars following a different operation mode regarding the previously presented transportation structures. It is destined to all commuter types, provides independent mobility, direct trips and travel conditions similar to private cars while it is associated with reduced costs. The structure imposes a minimum number of constraints on both vehicles and clients. At any time, the system makes *appropriate* use of the available vehicle capacity while optimized itineraries are adjusted depending upon the vehicle state, traffic conditions and passenger preferences. System connectivity (V2V, V2I, V2C communications) provides updated reliable knowledge of actual traffic state and demand available after a secure and accurate cloud computing. Such a micro transit scheme involving high performance at affordable rates could form an efficient solution for daily trips under all contexts. Furthermore, during crisis periods (e.g. pandemics, lockdown, transit restrictions) as mass public transportation implies high risks and requires a lot of maintenance to keep operate innovations need to be reimagined and tested. In fact, keep running re-used smart cars could be a promising transportation form overcoming serious risks.

The remainder of the paper is organized as follows:

§II introduces the considered structure. The adopted mathe-

mathematical approach based on Discrete Event Theory is justified. §III refers to the system management. Controls related to the client acceptance or rejection to specific cars, dynamic construction of vehicle itineraries according to current vehicle state and client preferences etc. are presented. Management of idle vehicles is introduced. §IV suggests a methodology for appraising the system performance. §VI develops a comparative study among two transportation structures. The performance of the newly introduced scheme is compared with a vehicle fleet consisted of manually driven cars in a self-service mode (SSMV). Finally, §VII resumes the achievements of the suggested transportation scheme. Some future projects are discussed.

II. PLANING AND LEARNING

A. Operational system characteristics

A vehicle fleet consisting of fully autonomous and connected cars operating within an arbitrary road network is considered. In particular, each vehicle aims at a double achievement. Reaching passenger destinations within the best possible time and maximizing the utility of the available seat capacity all by respecting customer constraints. Vehicle itineraries potentially change whenever the vehicle state and/or traffic conditions vary. Meanwhile, trip durations are minimized. With shared telematics and many other techniques involving concepts of operations research&optimisation vehicles may broadcast sensor data which can be analyzed and then provided to the rest of the system. Hence, multiple decisions are taken upon accurate real time knowledge and reliable predictions (e.g. travel time estimation, client demand etc.). The embedded V2I sensors provide real time advisories about road conditions, traffic congestion, accidents, construction zones and parking availability. Through V2V technology updated information is propagated. A vehicle-to-cloud (V2C) connection allows the creation of a specific platform, utilized as an alternative for exchanging local validated information in a secure manner between the system entities.

The presented scheme also accounts for demand behavior. Whenever a client demand cannot be immediately satisfied then prospective passengers decide whether to quit or wait during a maximum waiting period depending upon their preferences. Each client tolerates a maximum number of trip detours which are taken into consideration when building car itineraries.

B. Discrete event approach (DES)

As the considered structure is comprised of interactions between various entities involving customers, vehicles and network it constitutes a complex, dynamic system evolving in asynchronous manner and where uncertainty is frequently manifested. It is neither natural nor efficient to use time as a synchronizing element driving the system dynamics. Moreover, phenomena presenting synchronisation, parallelism and concurrent features all associated with randomness frequently occur. In this framework a *state space* approach that focuses

on the qualitative and quantitative aspects of discrete event dynamic systems (DEDS) is adopted where state transitions are due to the occurrence of events. The issues of observability and stability by output feedback are considered. In this modeling it is assumed that

- at least some events are *controllable* and thus the system can be brought into *desirable* states
- only some occurring events are visible since in particular cases decisions should be made only under knowledge of observations.

Modeling, analysis, control, optimization and simulation will be employed to address the implied issues when optimizing the considered “collective cars” structure. Simulation is a highly recommended approach when dealing with DES. A made-to-measure decision tool is developed respecting the event-driven methodology.

The principal entity classes interfering to the system evolution involve events related to

- prospective clients e.g. demand, abandonment etc.
- vehicles, i.e: arrivals at nodes, service durations etc.
- client and vehicle interactions as well V2X exchanges examining customer requests, exits, traffic estimations etc.

III. CONTROLLING THE SYSTEM

Constructing vehicle itinerary

The aim of this control algorithm is to decide whether a new prospective client can join a particular vehicle in which case the new itinerary must be provided.

Let’s consider the following notations:

- t_0 : current (meeting) time;
- n_0 : present node;
- n_i^o : origin node of passenger i (already on board);
- n_i^d : destination node of passenger i ;
- c : index of candidate client;
- n_c^d : destination node of the candidate client (whose origin node is naturally n_0);
- $L = \{n_1, n_2, \dots, n_m\}$: *sorted* list of destination nodes of passengers according to the planned itinerary (prior to acceptance of the candidate);
- $\ell = L \cup \{n_c^d\}$: *unsorted* list of destinations in case the candidate would be accepted (one part of the decision consists in finding the best order with which to visit those nodes);
- J : index set of elements in ℓ ; namely, $J = \{1, \dots, M\}$ where M is the length of ℓ (indeed $M = m$ or $m + 1$, according to whether n_c was already present in L or not);
- I index set of vehicle passengers *and* candidate c ($I = I \cup \{c\}$);
- $d : I \rightarrow J$: mapping providing the destination nodes of clients, that is, $\forall i \in I, n_i^d = n_{d(i)} \in \ell$;
- $p(j)$: for $j \in J$ is the number of passengers whose destination is node j , that is, $p(j)$ is the size of $d^{-1}(j)$;
- $\delta(a, b)$: duration (in time units) of the direct trip from node a to node b through the graph by the shortest path

using average travel times (this matrix is pre-computed and part of the data);

- t_i^o : time at which passenger i entered the given vehicle (for $i = c$, $t_c^o = t_0$);
- t_j^p : forecasted arrival time at destination $n_j \in L$ prior to acceptance of the candidate;
- t_j^{lim} : deadline for arrival time at node $n_j \in L$;
- s : the diversion threshold tolerated by each client with respect to his direct travel. This is a parameter to be optimized.

Then

$$t_j^p = t_0 + \delta(n_0, n_1) + \sum_{\substack{n_k \in L \\ k=1, \dots, j-1}} \delta(n_k, n_{k+1}) \quad (1)$$

$$t^{\text{lim}}(j) = \begin{cases} \max(t_j^p, \\ \min_{i \in d^{-1}(j)} (t_i^o + s \times \delta(n_i^o, n_i^d))) \\ \text{if } n_j \in L, \\ t_0 + s \times \delta(n_0, n_c^d) \\ \text{if } n_j = n_c^d \text{ and if } n_c^d \notin L. \end{cases} \quad (2)$$

We can proceed to a mathematical formulation of the decision problem as a dynamic programming problem (as inspired from [18]). The purpose consists in finding an order for visiting the nodes in ℓ such that the deadline of each node is respected whilst a certain objective function (defined hereafter) is minimized. If no feasible solution is found, the candidate must be rejected (and the planned taxi itinerary is not modified). Otherwise, a new itinerary is defined by this order (including the possible additional stop n_c in ℓ).

The entire itinerary requires M moves between the $M + 1$ nodes in $\ell \cup \{n_0\}$; those stages are indexed by k from 0 to M .

Problem formulation

Define

- $x(k), k = 1, \dots, M$, a sorted sequence of x in ℓ ; in addition, set $x(0) = n_0$;
- $u(k), k = 0, \dots, M - 1$, choice of the next node to visit once $x(k)$ has been reached; thus $x(k + 1) = u(k)$;
- $\mathcal{E}(k)$ set of nodes already visited at stage k ; consider that $\mathcal{E}(0) = \emptyset$; of course $\mathcal{E}(k + 1) = \mathcal{E}(k) \cup \{u(k)\}$; in order that all nodes be visited after M moves, we require that $\forall k, u(k) \notin \mathcal{E}(k)$;
- $t(k)$ arrival time at $x(k)$; $t(0) = t_0$ and $t(k + 1) = t(k) + \delta(x(k), u(k))$.

We aim at solving the following problem:

$$\min_{u(\cdot)} \sum_{k=1}^M p(x(k)) t(k) \quad (3)$$

$$\text{s.t.} \quad (4)$$

$$x(k + 1) = u(k), \quad k = 0, \dots, M - 1, \quad x(0) = n_0, \quad (5)$$

$$\mathcal{E}(k + 1) = \mathcal{E}(k) \cup \{u(k)\}, \quad k = 0, \dots, M - 1, \quad (6)$$

$$\mathcal{E}(0) = \emptyset, \quad (7)$$

$$t(k + 1) = t(k) + \delta(x(k), u(k)), \quad k = 0, \dots, M - 1, \quad (8)$$

$$t(0) = t_0, \quad (9)$$

$$u(k) \notin \mathcal{E}(k), \quad k = 0, \dots, M - 1, \quad (10)$$

$$t(k) \leq t^{\text{lim}}(x(k)), \quad k = 1, \dots, M. \quad (11)$$

Inactive Vehicle Control

A station node should be chosen for an empty vehicle as well an associated maximal parking duration. If no client is found during this period, the vehicle makes a new request for updating the previously taken decision. The choice of the parking node is provided by a control algorithm based on a probability law involving:

- the distance (measured in secs) between the present vehicle position and the candidate station node
- the client arrival intensity as well the client queue length of the candidate node.

Broadly speaking, a car interconnection within an acceptably *reliable* vehicle neighborhood is considered. After a specific treatment issued information is processed by cloud computing. For *safety* and *security* reasons a car has the option to consider or ignore V2X available information. As a result, the involved decision algorithm selects *validated* real time available traffic information or statistical entries. The same principle is adopted in the client acceptance algorithm as previously discussed. Similarly for the knowledge of the current demand and client queue length of the candidate parking node as well of the potential number of vehicles heading to a particular node.

IV. POLICY AND PRACTICE-CASE STUDY

Hereafter, the reformulated employed data are briefly discussed. Due to confidentiality restrictions real data information cannot be easily presented. As a result, well-constructed *fictitious* but also *realistic* data entries are employed. Nevertheless, the intended suggested methodology remains always valid. Under different data different numerical values will be resulted.

A. Operating area-Demand

The utilized network is inspired by the Paris area including the suburbs. Figure 1 illustrates the considered region comprised of 288 nodes and 674 edges. Approximately 15,000 clients are generated per hour according to a centripetal type of demand geometry reflecting the early morning hours.

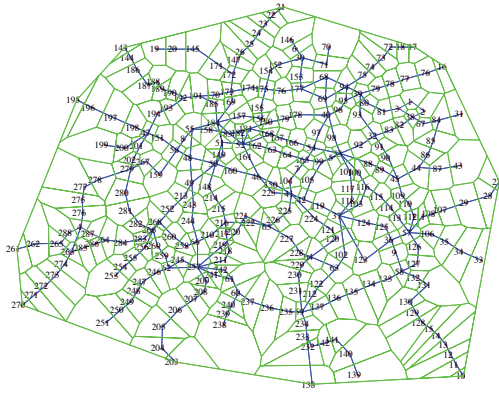


Fig. 1. Network: Paris area

B. Client and Vehicle Features

The maximal waiting time of each client at the origin node is 10 minutes. By the end of this period if no vehicle is found the client quits the system and a penalization is associated to the structure. The acceptable client detour threshold w.r.t. direct travel is taken equal to $s = 1.9$. Each autonomous car has 5 available passenger seats while 3,744 unmanned vehicles are totally employed. The maximal station time of each idle vehicle is 15 minutes. The considered demand intensity and the number of vehicles in service are in accord with the current context in Paris (manually driven cars).

V. PERFORMANCE APPRAISAL

The system stability is going to be examined under the employed policy.

A. Client Assessment

Under the considered demand intensity, approximatively 117,948 customers appeared in total everywhere on the network. Amongst these clients, 247 persons quit the system without being served. As the blue horizontal line in Figure 2 presents, the average client abandonment rate all over the network equals to 0.21%. Observation of Figures 1 & 2 shows that higher client abandonment is “mostly” associated with nodes located at the periphery of the network. This is an expected result as a *centripetal* geometry encourages client movements towards the city centre.

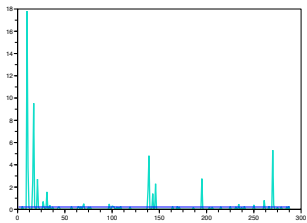


Fig. 2. Client Abandonment Rate per Network Node

Figure 3 illustrates the client waiting time (Y axis) per node (X axis) \pm the standard deviation. The corresponding mean value of the average waiting time over the entire network is 19 seconds with a standard deviation of 55. The average client queue length over the entire network is 0.29 clients.

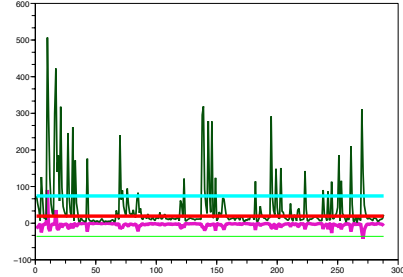


Fig. 3. Client Waiting Time per Node

B. Fully Autonomous Vehicle Performance

The average vehicle activity is represented in Figure 4. During the 90% of the time vehicles were travelling (orange chart) while they were stopped for 2% of the considered time (yellow chart) doing various operations at nodes e.g. examining new requests, entries/exits etc. Finally cars were stationed at nodes for approximately during the 8%. Hence, *real-time decisions* such as selection of parking nodes and duration, itinerary definition as well *off line decisions* related to system dimensioning and the desired *service quality* e.g. number of vehicles in service, car capacity etc. are responsible for the car performance. Furthermore, encountered *environmental* conditions influence the idle car state e.g. traffic flows, client preferences etc. Under a low client abandon rate (0.21%), one could say that the control decision determining station nodes for vehicles with empty itineraries and for the considered car fleet configuration is rather *satisfactory*.

Let’s now recall the considered system dimensioning. In the particular strategy, 3,700 *unmanned* vehicles were involved each of 5 available passenger seats. The mean vehicle occupancy is of 1.4 passengers while the total number of transported passengers per car is 31.37. Table I presents the average percentage of time spent by each vehicle transporting x passengers. Despite the fact that clients are accepting rather reasonable detour levels, (max accepted diversion threshold equal to 1.9), during the 65% of the service time, vehicles were travelling with one passenger on board. Obviously, the considered vehicle fleet presents high performance in terms of travel times (appropriate itineraries, increased performance of the autonomous cars) allowing small *client queue lengths* and thus *low client abandonment rates* at nodes. A system involving fewer vehicles would result to smaller idleness duration for the same demand intensity. Nevertheless, cars remain “busy” for the majority of their service duration.

TABLE I
AVERAGE VEHICLE OCCUPANCY

Number of Vehicle Passengers	Total Time Spent (%)
0 client	4%
1 client	65%
2 clients	21%
3 clients	6%
4 clients	2.5%
5 clients	1.5%

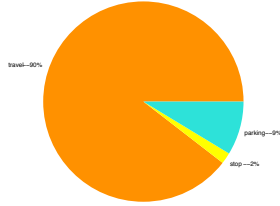


Fig. 4. Average Vehicle Activity

C. Detour measurement

The *total diversion ratio*, determined as the ratio of the client effective trip duration plus the client waiting time over the direct trip duration, is evaluated.

Figure 5 illustrates the total diversion ratio of which the average value equals to 1.25 with a standard deviation of 0.31. The max accepted diversion threshold by the client preferences was taken equal to 1.9. One observes that the client detour constraint was respected for the majority of passengers.

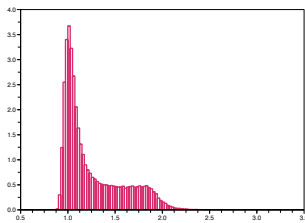


Fig. 5. Total Trajectory Detour

VI. SHARED AUTONOMOUS CONNECTED CARS VERSUS SELF-SERVICE MANUALLY DRIVEN VEHICLES

A system consisting of conventional manually driven cars is now introduced. In this scheme, cars are not shared amongst potential customers. Additionally, the system indicates the driver an optimized itinerary to follow. Users who also have to be drivers themselves appear at nodes wishing an immediate departure. If no car is available, clients decide whether to wait or to quit the structure. Aiming at a performance comparison the two structures have the same dimensioning (number of

vehicles in service and seat capacity) where identical client demand is utilized.

Among the 117,948 client arrivals everywhere in the network, 30.88%, that is 36,563 potential customers abandoned the SSMV system since during their waiting period no vehicle was available. The related value for the scheme of the fully autonomous and connected cars was 0.21% (247 clients). Histogram in Figure 6 represents the global client waiting time in SSMV scheme. The mean value is of 446 seconds with a standard deviation equal to 202.

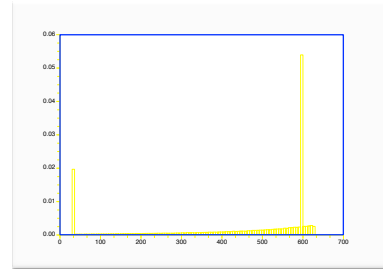


Fig. 6. Distribution of the Client Waiting Time-SSMV scheme

It would be of interest to examine the client waiting time per network node. Plot in Figure 7 illustrates this measurement. The network node id is represented on the X axis while the corresponding client waiting time is illustrated on the Y axis. The average client waiting time is of 406 seconds where the standard deviation is of 202. The related values for the autonomous vehicle scheme was 19 seconds for the client waiting time with a standard deviation equal to 55.

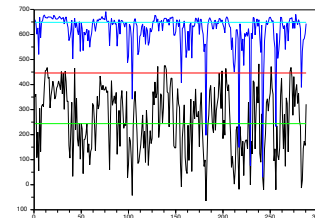


Fig. 7. Client Waiting Time per Node-SSMV system

The average client queue length at all network nodes for the self-service vehicle fleet equals to 6.57 clients while the related value for the autonomous cars was 0.29 customers.

Figure 8 depicts the client abandonment rate (Y axis) per network node (X axis).

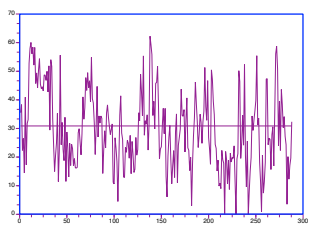


Fig. 8. Client Abandon Rate per Node-SSMV structure

Figure 9 represents the average vehicle activity for the structure of the manually driven self-service cars. Vehicles travel for the 91% while they are parked during the 6% of their service time. The average number of transported passengers per car during the total service duration equals to 21 while the related value for the fully autonomous cars was approximately 31 clients whereas during the 61% of time one passenger was associated per car. These are expected observations, as for the SSMV the client abandonment rate is significantly raised (30.88%). Then how the 6% of client abandon can be explained? The SSMV scheme is also related to a *poor vehicle distribution* as vehicles move only when a client uses them. Consequently no optimized parking locations are selected.

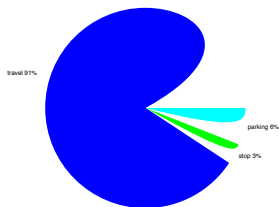


Fig. 9. Vehicle Activity-SSMV scheme

VII. DISCUSSION

An independent and flexible transportation system, comprised of autonomous cars offering high quality door-to-door services is presented. No seat reservation is required while the available car capacity is intelligently utilized decreasing costs for both customers and cars. Appropriate real time constructed itineraries respect client preferences while contribute to traffic improvement. Specific algorithms control idle vehicles. V2X connections allow real time knowledge of the traffic state and demand efficiently handling environmental variations. A major element differentiating this work is the decentralized management. Hence all decision algorithms are associated with low computational complexity. The asynchronous and stochastic system behavior encourages the adoption of DES theory. Metrics quantifying and qualifying the performance of the considered scheme are presented. Furthermore, a comparative

study is conducted appraising a self-service scheme composed of manually driven cars versus the introduced automated structure. A significant raise in the client abandonment rate is observed. Despite an insufficient number of cars regarding demand a non zero car idle time is observed justified by a related poor vehicle distribution. Future research aims at the development of advanced decision policies involving improved cloud computing and vehicle connectivity. Due to the optimized management and low costs the introduced micro transit scheme could form an efficient and affordable alternative for daily urban trips reducing risks of mass public transportation especially occurring under pandemic crisis. A re-organization of the car interior sanitized by innovative technology could contribute to a safe utilization by all commuters.

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