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A SIMULATION FRAMEWORK FOR REAL-TIME ASSESSMENT OF DYNAMIC RIDE SHARING DEMAND RESPONSIVE TRANSPORTATION MODELS

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ABSTRACT

Sustainable mobility is not merely a technological question. While automotive technology will be part of the solution, it will also be combined with a paradigm shift from car ownership to vehicle usage, which itself will be facilitated by the application of Information and Communication Technologies that make it possible for a user to have access to a mobility service from anywhere to anywhere at any time. Multiple Passenger Ridesharing and its variants appear to be one of the promising mobility concepts that are emerging. However, in implementing these systems while accounting specifically for time dependencies and time windows that reflect user needs, challenges are raised in terms of real-time fleet dispatching and dynamic route calculation. This paper analyzes and evaluates both aspects through microscopic simulation emulating real-time traffic information while also interacting with a Decision Support System. The paper presents and discusses the obtained results for a Barcelona model.

1 INTRODUCTION

Urban areas must take a holistic perspective when addressing the challenges and threats of sustainability, namely in providing services to companies and citizens. Cities are complex systems and any city must be thought of as a "System of Systems". Mobility is only one component in such a complex system, and it is a non-isolated component that strongly interacts with all the other components; therefore, its implications must be analyzed in the context of these interactions. In a recent analysis of the Future of Mobility and New Mobility Business Models, Frost and Sullivant (2015) identify the growing trend of "Ride Sharing" models as one of what they call "Transformational Shifts in Mobility". This trend can be seen as one of the consequences of the paradigmatic shift from "car ownership" to "vehicle usage", leading to a new concept of multi-modal mobility network that overcomes the limitations of conventional public transport systems by means of the pervasive penetration of Information and Communication Technologies (ICT). Technology enables a comfortable, seamless real-time point-to-point travel service.

According to the definition of the European Commission's Directorate-General for Energy and Transport, Demand Responsive Transport (DRT), Dial-a-Ride Transit or Flexible Transport Services "are emerging user-oriented forms of public transport characterized by flexible routing and scheduling of small/medium vehicles operating in shared-ride mode between pickup and drop-off locations according to passenger needs". DRT were initially thought to provide public transport services for areas with low passenger demand and where regular bus services would not be available. However, this concept is quickly evolving as a result of ICT deployment. Initiatives like KUTSUPLUS (Anon 2015), an on-demand minibus service run by Helsinki's public transit authority, let riders choose their own route by summoning a trip with a smartphone. They decide the start and end point of their trip and choose whether to share their journey or not. This is a new Demand Responsive Public Transport service designed to achieve maximum flexibility.

This concept of Demand Responsive Transport is rapidly evolving into services provided by private companies that operate point to point with full dynamics and flexibility while also offering the possibility of sharing trips. E-hailing is a process for ordering a transportation service in a private car (e.g., Uber services), special taxi services, etc. The system currently has a variety of implementations, but the essential variant of interest in this paper assumes that the customer books or hails the trip electronically and provides the pickup location (automatically identified by GPS), the drop-off location, and the desired time windows. What is more, multiple passengers can share the trip. Our research specifically addresses this variant, which is known as a "Multiple Passenger Ridesharing System" (MPRS).

A state-of-the art-survey on the variants of ridesharing systems, their alternatives and likely future evolution can be found in Furuhata et al.(2013). According to their classification, the variant studied in this paper corresponds to what is known as Detour Ridesharing with Multiple Passengers, in which multiple passengers, with relatively close but different origins and destinations share rides that can partial or totally overlap. Our research has analyzed the potential uses of special fleets of dedicated vehicles in an urban area. Assuming that, beyond the pickup and drop-off locations and time windows, the system also knows the current and desirable short-term forecasted traffic conditions timely determining the optimal routes for satisfying customers' time constraints. That is, we assume that the system is operating in a network in which an Advanced Traveler Information System (ATIS) provides the travel time estimates. This type of real-time ridesharing system has also been studied by Ma et al. (2015), but with simplifications concerning the availability of traffic information. The special case when the fleet of service vehicles is composed of autonomous vehicles has deserved special attention from the agent-based simulation approach. A general perspective on this can be found in Fagnant and Kockelman (2014), which analyzes the environmental impacts, while Martinez et al.(2015) propose a general agent-based simulation to assess the impacts and apply it to the city of Lisbon. This work was the basis of the report by the International Transport Forum (OECD – International Transport Forum 2015). One of the critical aspects highlighted in these last references concerns the operational efficiency of the system, which is determined by the fleet management dispatching system, among other factors. This concerns the decision process and its dependencies on fleet size and demand, an aspect that has been studied in Boesch et al. (2016) for a simplified dispatching strategy. Consequently, our work deals namely with the Decision Support System that supports the decision-making process that optimally assigns the vehicle for providing the requested service to a customer. It takes into account the new service requirements, the confirmed rights of the customers already receiving the service, and the current and estimated travel times in the urban network, which have been provided by a microscopic traffic simulation platform. The system, whose evaluation is the objective of this paper, is assumed to work under the following modelling hypothesis:

1. There is a fleet of n dedicated identical vehicles, each with a capacity of p passengers. The system continuously tracks the fleet vehicles and at t, each instant of time, it knows the current position, space availability, destinations and expected arrival times of customers being serviced. These vehicles can be in various states:
    a. Idle, meaning it is either traveling on the road network, or parked at a designated location waiting for a service request.
    b. In service but not at full capacity while providing service to various customers.
    c. In service but full and therefore unable to provide a new service.
2. At a given time t_i, a client (let us assume the i-th client) C_i calls for a service. The system

automatically identifies the client's location (e.g., by georeferencing), and the user indicates his/her destination D_i, the time window (e_i, earliest time, l_i, latest time) of his/her expected pick-up (how long he/she will accept waiting to be picked up), and the desired arrival time at his/her destination (that is, an expected arrival time a_i and a time slack ε_i).

3. When the system receives the new service request, it checks the status of the vehicle fleet to determine whether any of the vehicles that are currently in service or idle can feasibly provide the new service. If in service, it determines if a detour can be made to collect the new customer and satisfy his/her conditions without violating the requirements of the customers currently on board. In other words, the system checks the feasibility of the new service.
4. In the case that there is more than one vehicle available for that service, a Decision Support System determines which is the most profitable, both from the customer's point of view in terms of the quality of the system and from the system's point of view in terms of a cheaper service.
5. Then the system assigns the service to the selected vehicle along with the most efficient route for providing it, including potential detours and changes in the previous routes.
6. To achieve the greatest possible added value, the system is assumed to have access to an ATIS that provides current and short-term forecasted link travel times on all traffic network links.

To conduct the analysis and evaluation of the proposed MPRS by simulation, the simulator to be used must have certain capabilities:

1. It must be able to represent the road network geometry in full detail, i.e., import it as is from a GIS, including the explicit representations of traffic control strategies at signalized intersections.
2. It must be able to realistically emulate the time evolution of traffic flows on the road network by properly describing the dynamics of individual vehicles. Such a capability requires the modeling of driving behaviors in terms of leader-follower, lane changing, gap acceptance, etc. Stochastic parameters are included in the model in order to appropriately mimic human driving behavior.
3. It must deal with multiple vehicle classes with differentiated behaviors in order to account for the specific characteristic of the vehicles in the fleets being studied.
4. Vehicles in the simulation model travel from origins to destinations along time dependent routes, which are selected according to stochastic route choice models that are timely updated (e.g., as in the case of rerouting the fleet vehicles to provide new services).
5. The simulation platform must be able to interact with external applications, such as those implementing the functions of the Decision Support System.

In summary, these requirements mean that the appropriate simulator is a microscopic traffic simulator with the required extended functionalities. The proposed system has been tested through microscopic traffic simulation using a model of the Barcelona Business District. Specialized fleets are defined, and the design factors in the simulation experiments use: the demand of shared vehicles, the sizes p of the shared vehicles, the size n of the fleet providing the service, the conditions of customer time windows (e.g., tight or soft) and the degree of dynamism that is the percentage of total demand for the ride-sharing services that is not known before the start of the journey.

2 SYSTEM FRAMEWORK AND ARCHITECTURE

Figure 1 depicts the system architecture that implements a simulation framework to test the feasibility and performance of the MPRS, which combines a microscopic traffic simulation with a Decision Support Module that includes the Dynamic Router and Scheduler (DRS). The microscopic traffic simulator emulates with great detail and realism the traffic conditions on a road network, as well as the information provided by ICT (for instance, by GPS). It supplies all information needed during the process and performs the other global tasks required. The DRS lies at the core of the framework and consists of a set of algorithms providing an on-line solution to the real-time vehicle routing problem with time windows and time dependencies. The DRS is triggered every time an event is detected by the system, whether it be external or internal. The external events depend on the demand, while the internal events depend on the observed traffic flow dynamics which could be the cause of delays in the estimated arrival times to customer locations. Events randomly occurring during the fleet operations are generated by the microscopic traffic simulator according to stochastic patterns.

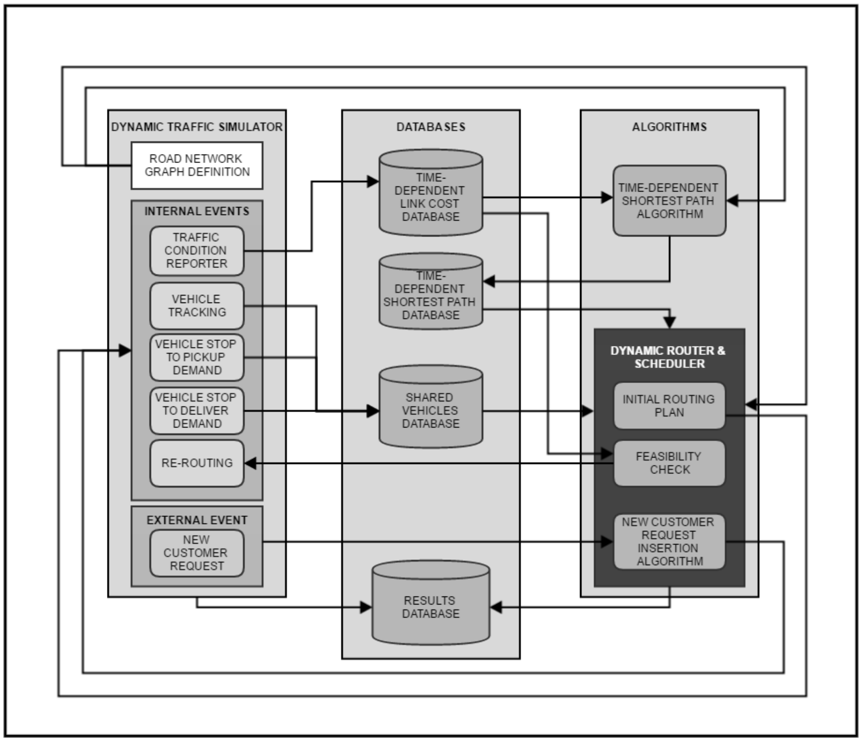

Figure 1: System Architecture.

2.1 Algorithms

The system uses different algorithms to provide an on-line solution to the real-time vehicle routing problem.

2.1.1 Dynamic Router and Scheduler

As the core of the computational framework, the DRS consists of a set of algorithmic tools that provide on-line solutions to the proposed real-time vehicle routing problems. The algorithm used can be exact algorithms, heuristics or hybrid approaches.

In the case being analyzed in this paper, we focus on the use of dynamic insertion heuristic solutions based on feasibility and profitability concepts. Feasibility is considered in the sense that vehicles serving those routes have enough time to travel to the new customer, taking into account the time window constraints of all customers already being served. The profit of a new insertion is the negative of the additional travel time incurred from inserting the new customer into a route. Its required inputs are:

- The time-dependent link costs, stored in the Time-Dependent Link Cost DB.
- The time-dependent shortest paths, stored in the Time-Dependent Shortest Path DB.

- The cooperative vehicle fleet state reported by the Dynamic Traffic Simulator and stored in the Shared Vehicles DB.
- The road network graph. This graph, stored in a file on the server, will be generated offline during the installation phase.

This module contains three modules in order to respond to three different problems:

- **Initial Routing Plan:** To find the initial routing plan. As a first step, the initial routing plan is computed considering the pre-booked demand that must be served at the beginning of the journey.
- **New Customer Request Insertion Algorithm:** For responding to new customer requests by assigning both a vehicle to pick this customer up and a route to reach the customer's destination. When a new customer request arrives, this module fires an execution and the vehicle routing problem is solved. When a solution is reached, this module generates a response to the simulator component divided into two parts. On the one hand, it informs the customer accepting its requests and gives him/her information about the vehicle assigned. On the other hand, the assigned vehicle receives a new route in order to pick up its new passenger.
- **Feasibility Check:** To check if the previously assigned routes are feasible after a traffic condition update by recalculating the routes when needed. Feasibility is considered in the sense that vehicles serving those routes have enough time to travel to their passengers' destinations. This module checks if all the currently assigned routes are still feasible with the new traffic conditions. If the current solution is not feasible, new routes will be calculated, and cooperative vehicles affected by the route changes will be informed of the new routes.

2.1.2 Time-Dependent Shortest Path Algorithm

The Time-Dependent Shortest Path (TDSP) algorithm is responsible for calculating all the routes and their travel times from any section to any section of the network and storing them in the TDSP DB. Its required inputs are: the link travel costs, which are provided by the Traffic Condition Reporter and stored in the Links Travel Cost DB; and the network graph, which is stored in a file on the server and generated offline during the installation phase.

The algorithm calculates the optimal vehicle paths among the pickup and delivery stops and the corresponding travel times. The shortest path problem considered in our research differs from the usual shortest path approaches in that we do not consider link travel times to be constant but instead time dependent; in other words, the link cost depends on the arrival time at the origin of the link, meaning that the considered shortest paths are dynamic or time-dependent (TDSP).

In this work, we have implemented a variation of the DOT (Decreasing Order of Time) TDSP algorithm proposed by Barceló et al. (2013). The authors present an implementation of the DOT TDSP by Chabini (1998) using the structures proposed by Ziliaskopoulos and Mahmassani (1993). The main features of this solution are the reduction in the time obtained from using the DOT concept and the reduction in in-memory space by using the Yale format for Sparse Matrices. A detailed description of the algorithm can be found in the reference Barceló et al. (2013).

2.2 Microscopic Traffic Simulator

The second component of the computational framework is a microscopic traffic simulator. In addition to the functionalities already described in the Introduction, it also: generates databases of time-dependent link travel times; randomly generates the different external and internal events previously mentioned; tracks fleet vehicle positions and states at every time step of the simulation; assigns dynamic routes to fleet vehicles; provides the DRS with the input data required by the algorithms.

In this work we chose Aimsun v7 (Transport Simulation Systems 2013) from among the currently existing microscopic traffic simulators. The reason for this choice is that its functional architecture and the

Micro API (APPI) auxiliary tool support the extended modeling utilities that are required for working with the user applications that implement the algorithms needed for the study.

The exchange of information between the external application and the microsimulator is made at every simulation step, which is the time interval at which the estate of the simulation model is updated. The development languages were C++ and Python since they are the allowed languages in Aimsun.

The key system components are: the Road Network Definition; the Internal Events (Traffic Condition Reporter, Vehicle Tracking, Vehicle Stop to Pickup Demand, Vehicle Stop to Deliver Demand and Re-Routing); and the External Event (New Customer Request).

2.3 Databases

The information generated by the simulator and the application modules is stored in a set of Databases:

- **Time-Dependent Link Cost Database:** To store the link travel cost provided by the Traffic Condition Reporter. TDSP Database: To store all the generated routes with their travel times from any section to any section of the network.
- **Shared Vehicles Database:** To maintain updated information of the vehicle fleet state. This stores the position (UTM coord.) and state (customer pickup, arrival at destination) of every fleet vehicle.
- **Results Database:** To store the results obtained in every performed simulation and the calculated Key Performance Indicators.

The flow chart shown in Figure 2 summarizes the described process. When a simulation starts, it communicates its corresponding settings to the server. These settings are stored in a Redis database, and the TDSP algorithm starts in a new thread. In parallel, the Vehicle Routing Problem (VRP) Algorithm is triggered, and the Pre-booked Demand begins to be loaded. The VRP waits for two synchronization points: the TDSP needs to be computed and the Pre-Booked Demand load must end. Then, the VRP creates the initial solution. From this point, the server continues to attend to the demand requests as they arrive until the end of the simulation.

3 REAL-TIME TRAFFIC INFORMATION SYSTEM

The described computational framework for testing the MPRS assumes that the fleet management approach and the core component of the DRS are embedded into a microscopic traffic simulation model according to a process whose logic is the following:

1. Selection of a time interval step to check the feasibility of the current routes.
2. At each time interval step, the simulator sends the current travel times of each network link to the link costs data base.
3. With this new information, the TDSP module re-computes the TDSP between all the nodes of the network at each departure time interval.
4. With these new TDSP costs, the TDSP data base is updated.
    i. The feasibility check method is launched using this new information stored in the TDSP DB.
    ii. It modifies the current solution in order to solve the feasibility problems.

The microscopic traffic simulation plays a twofold role by providing the information required by the logics of the fleet dispatcher’s decision and the real-time information required by the dynamic routing algorithms, including link travel times. In other words, in a real-life system, we would consider that the fleet manager has access to an ATIS supplying such information. In the computational implementation of the system, we have considered that the emulation of such an ATIS is also the function of the dynamic traffic simulator. Therefore, the fleet manager has access to such information, and the vehicle routing algorithms are able to “continuously” check the traffic conditions as well as the fleet’s expected timing. In this way, the algorithm is able to manage sudden changes in actual travel times.

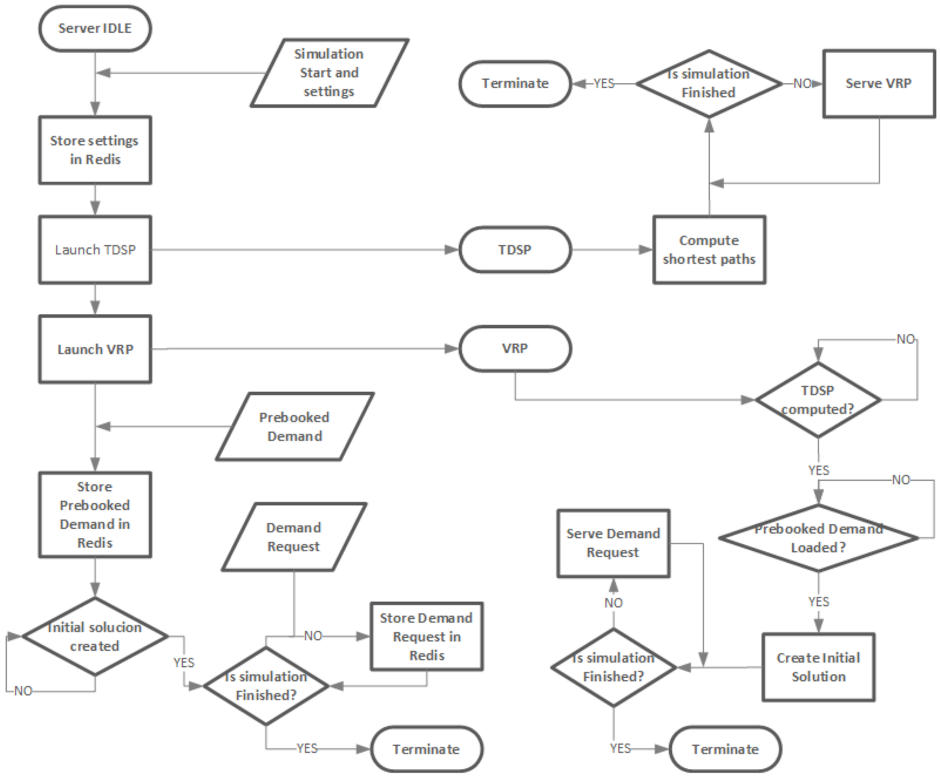

Figure 2: Flow diagram of the system process.

4 DESIGN OF EXPERIMENTS

4.1 Model Description

The selected microsimulation scenario was the Barcelona CBD known as the "Eixample" (see Figure 3), which comprises 7.46 km^2 and more than 250000 inhabitants. The Aimsun (Transport Simulation Systems 2013) model consists of 1720 links, 528 nodes, 120/130 generation and attraction centroids, and 877 non-zero OD pairs. The horizon study is 30 min, accounting for a total of 20700 vehicle trips.

Figure 3: L'Eixample in Barcelona (left), simulation test-site (central), and the Aimsun model (right) – with spatial distribution of demand requests for the new mode in the base scenario.

The microscopic traffic simulator model updates the model state every half a second, specifically the positions of all vehicle classes considered: passenger cars, buses and ride-sharing vehicles. Passenger car demand is modeled as 15-min time-sliced demand whose Origin-Destination pattern reproduces the actual working day morning period in the Eixample district. The model includes the detailed description of the 50 routes operating in the “Eixample” by accounting explicitly for frequencies and stops for boarding/alighting. Finally, in order to serve passenger requests, a fleet of multiple passenger ride-sharing units (MPRS units) are moved over the network according to the dynamic routing and scheduling. The fleet of shared units being dispatched considers time-dependent routing algorithms according to real-time emulated traffic conditions provided by the simulator.

4.2 Methodological Proposal

The goal was to evaluate the new transport mode in an urban area, particularly in regard to its impacts on urban traffic while taking into account a very detailed description of the mobility service’s characteristics. The implementation of mobility strategies in a specific real scenario was considered. The system was designed to be flexible in order to host a wide range of possible services by setting the values of parameters that determine the behavior of the system. For example:

- Fleet size, vehicle capacity of the market quota for the new mode as a percentage of the total passenger car demand in the study period
- Fully flexible routes, fixed routes or mixed routing
- Boarding/Alighting allowed either everywhere in the network, at pre-defined stops, at regular bus stops or at any chamfer in the Eixample geometry
- Depot existence: number and location
- Pre-booked demand service available or not
- Combined service for passenger and freight distribution
- Use of reserved bus lanes

Currently, all the indicated service and operational strategies are not implemented, although they will be in the future. The involved factors in the preliminary design of considered experiments are:

- **Global Traffic Demand Scenarios:** Testing was performed on the morning rush-hour scenario, allowing request generation in the first 30 min.
- **Demand Request Generation:** There are two options for generating requests: they are either a percentage of the passenger car demand (the OD pattern) defining the rates of the exponential distributions for the interarrival time of requests or homogeneously distributed over the area. The first option was chosen, and requests were generated over a circle with a ratio of 200 meters around the centroid with the minimum travel distance constrained to 0.5 km (to be set). Hence, the total numbers of trips for the new mode are set to *5%, 10% or 15% of the total passenger car demand* in the study period. Figure 3 shows an example of the distribution of 1000 requests over the site (origins in red and destinations in green).
- **Capacity of the Units** that operate in the new mode. The rank of seated capacities is set to 8, but it is a configurable parameter (between 6 and 10 passengers will be assessed in the future).
- **Fleet Dimension:** this was considered for 250, 500, 750 and 1000 vehicles. A no-depot solution was implemented, and fleet vehicles were parked in specifically allowed zones at the beginning/end of the passenger journeys. These emulated zones are the regular loading/unloading areas for freight distribution in the chamfers around the Eixample road network. When a new mode’s unit is not operating (i.e., it is empty and waiting for the arrival of a new request), it goes and parks in the allowed zones until a new requested demand has to be served. The fleet is allowed to use restricted bus lanes and to also pick up and deliver passengers at bus-stops.

- **Time Window Width:** The width of the time interval in which the demand requests must be served (pickup and delivery time windows). Considered levels are 10, 15 and 30 min. The basis of comparison assumes no restrictions.
- **Degree of Dynamism:** The percentage of the total demand that is not pre-booked in advance during the study period (% real time requests). Considered levels are 0%, 20%, 50%, 80% and 100%. The "Customer Request Emulator" is an API specifically developed for generating three types of new mode demand requests (on-time demand, pre-booked demand to be served when the simulation starts, and pre-booked demand to be served at a certain specific time during the simulation different to the starting time). The percentage of each of these proportions could be easily modified.

The base scenario for comparison purposes was defined as 10% of total passenger car demand, a fleet size of 500 vehicles, with a pre-booked demand of 50% and a time-window length of 15 min.

The Aimsun result tables account for the statistical performance measures for each interval of time-splitting the results into vehicle classes. Nevertheless, the new mode has a fleet of vehicles whose routes do not have an origin-destination but instead correspond to a dynamic vehicle routing problem that optimizes the overall requests by using the available fleet size, capacity, real-time traffic conditions and time-window limitations. Thus, an *ad hoc* module was designed and implemented in order to gather all the data from the new mode's operations – specifically, the data required to calculate the performance measures. The collected results are the position of each fleet vehicle and its number of passengers for each simulation replica, fleet unit and simulation step.

From the passenger's point of view, the defined performance indicators are: average travel time per passenger (in-vehicle plus waiting time); average in-vehicle time per passenger; average service speed (effective travel time divided into Manhattan distance for pickup and delivery); average waiting time; and rejected requests. The indicators from the operator's point of view are: average number of persons per vehicle-unit; average number of occupied vehicles; number of person-trips per hour; average commercial speed per vehicle-unit; and total vehicle-km. For each replication, statistical data was stored in the default Aimsun DB and the specific Redis DB that was designed to collect data for multiple ride-sharing services.

5 ANALYSIS OF SIMULATION RESULTS

The computational time strongly depends on the fleet size and the total number of requests, with the computing times having resulted in about 10 hours per replica on average. The base scenario was previously tested for variability in the selected performance indicators at 95% statistical confidence. For example, we found that a relative precision of less than 10% in the effective service speed performance indicator would need around 125 served requests per replica (requests are independently generated over time). Each of our replicas contained more than this amount of served requests for the study horizon.

A reasonable number of 5 replicas was considered in the design of experiments, since – according to the base scenario and selected performance indicators – the relative estimation error was less than 5% at 95% statistical confidence. For example, the average passenger service speed across replicas was 13.78 min and its variance was 0.0449 min^2, leading to a relative estimation error of less than 2% or an absolute error of around 0.25 km/h at a 95% confidence level. Figure 4 shows the effective service speed over replicas, but variability was checked in order to guarantee the quality of the obtained results. A non-parametric Kruskal-Wallis test was undertaken in the base scenario, and it confirmed that the null hypothesis of equal effective service speeds across replicas could not be rejected. Equal variability across replicas for the effective service speed was also accepted. From the point of view of MPRS units, and for one replica in the base scenario, results show an average commercial speed that depends on occupancy for the new mode (see Figure 5). The median occupancy is 2.0 passengers/vehicle when non-empty. When 1 to 4 passengers occupied the MPRS unit, commercial speed conforms to the mean with no differences (according to hypothesis testing results), while over 5 passengers increase the speed at a 95% confidence level.

A graphic representation of a fixed replica can be obtained by post-processing the ad hoc Redis database for fleet after collecting data during the simulation. Time window restrictions on the pickup and arrival times were found to be the most important factor in the experiment design. Regarding the average in-vehicle travel time per passenger, Figure 6 shows a tridimensional plot considering the most important factors in the design. Clearly, as the percentage of dynamism in the requests decreases, the average in-vehicle time decreases. Assuming a pre-booked demand from the previous day or from a horizon before the current simulation period, the time window factor defines the planes in Figure 6 and shows a significant effect that explains nearly 80% of the total variability of in-vehicle travel time. The coefficient of determination for the linear model of in-vehicle travel time on the percentage of dynamism, the time-window length and the percentage of the total travel demand for the period served by the new mode is almost 85%. Clearly, an infinite time-window (no restriction) contributes to increasing in-vehicle travel times for passengers. The fleet size is a non-significant variable for explaining the in-vehicle travel time for a passenger.

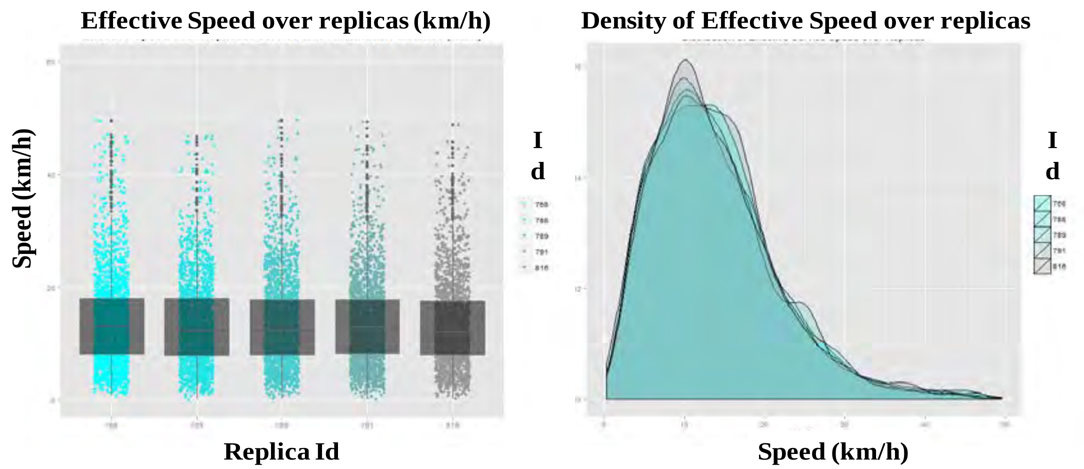

Figure 4: Effective passenger service speed (km/h) performance indicator in the base scenario: variability study across replicas.

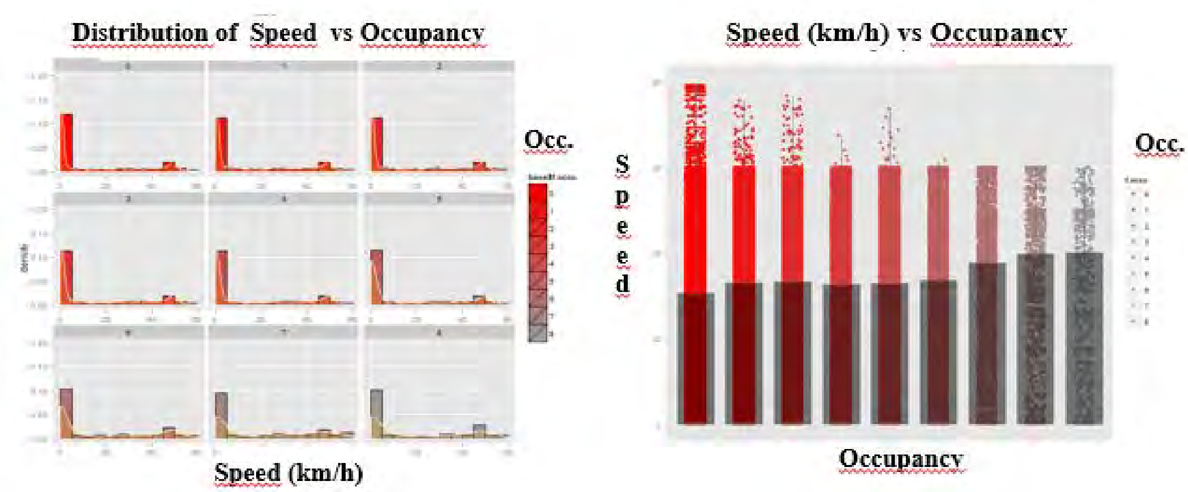

Figure 5: Commercial speed of MPRS units (km/h) while non-empty, according to passenger occupancy (histograms-left and boxplots-right). Base scenario.

Fleet size has an important effect on the percentage of served requests according to the statistical results analysis of the linear model for the percentage of the served request on fleet size, %MPRS demand, %Pre-booking and Time-Window length variables; fleet size accounts for 80% of total variability in the response, followed by %MPRS demand and time-window length. The percentage of pre-booked demand has proved to be non-significant.

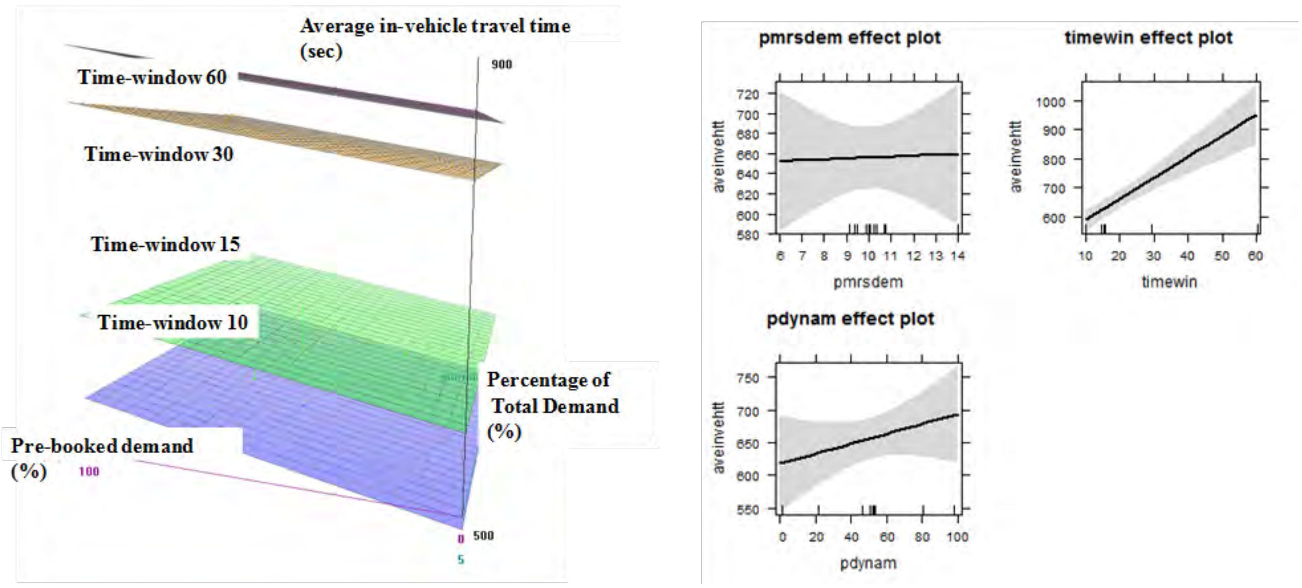

Figure 6: Average in-vehicle travel time (sec) depending on time-window restrictions, the percentage of dynamic and total demand for the new mode..

6 CONCLUSIONS AND FUTURE RESEARCH

The research carried out was based on an approach consisting of a general framework and simulation architecture for emulating and evaluating the general policies of new mobility services. It has demonstrated the potential feasibility and impacts of some of the proposed mobility concepts for on–demand, multiple passenger ride-sharing in urban areas.

In the near future, specific operational strategies that have not yet been implemented will be included in the proposed general framework and tested. It could easily be implemented by modifying the algorithms included in the Dynamic Router and Scheduler Module.

Additionally, the flexibility of the developed environment allows changing the value of the design parameters, such as the capacity of the units or the time window length.

Regarding our experiment results, they seem to indicate that the percentage of time consumed when picking up customers quickly increases as the demand for the new mode increases for a fixed fleet size. A non-linear relationship with the percentage of served requests is observed, and it should be analyzed in depth in future research.

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