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▶ To cite this version:

Philippe Mathieu, Antoine Nongaillard. Effective evaluation of autonomous taxi fleets. ICAART 2018 - 10th International Conference on Agents and Artificial Intelligence, Jan 2018, Funchal, Portugal. hal-02143005

HAL Id: hal-02143005
https://hal.inria.fr/hal-02143005

Submitted on 5 Nov 2020

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Effective evaluation of autonomous taxi fleets

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Keywords: Simulation, Multiagent systems, Complex systems, collective strategies, trafic management systems

Abstract: With the advent of autonomous vehicles, self-management of taxis fleet becomes an important issue for the automotive industry. Designing strategies for taxis turns out to be a difficult task due to a large number of parameters and metrics involved. Performance evaluation of these strategies is also a complex problem since effectiveness in some configurations may become inefficiency in others. After formalizing this problem we propose several strategies based on swarm-computing techniques. Finally, we show that metric unification is necessary and that only a multi-criterion approach illustrated by an economic analysis allows a comparison. We conclude with a description of the simulator implemented and some examples showing the measurements made with the proposed strategies.

1 INTRODUCTION

In recent years, research related to autonomous vehicles has been on the rise for car manufacturers as well as for academics. (Tlig et al., 2012; Cheikh and Hammadi, 2014; Dresner and Stone, 2008). Nowadays, fleets of autonomous vehicles can be created and used to solve collective tasks. One of them is the establishment of taxi fleets, able to negotiate and effectively manage customers in a geographical area.

The use of centralised optimisation techniques is only possible if all requests from clients in a time window are known, in order to optimise the assignment of taxis to clients according to their position. Unfortunately, in real life, it is not true. Without prior knowledge on client requests, the system must handle dynamic data, which is the main advantages of multi-agent system approaches.

On one side, clients perceive taxis movement in two steps: waiting to get into the taxi, which must be carried out efficiently according to its own criteria (speed, comfort. . .) and the transportation phase to its destination, which must also be carried out effectively (speed, price. . .). On the other side, three major steps structure the behaviour of a taxi. (i) The **positioning strategy**, when there is no client. A reasonable attitude requires taxis positioned in the vicinity of future applications if they are known. The number and position of the various customer requests vary over time. Depending on the time of the day, hot spots appear or disappear (arrivals of trains, exits from concerts. . .) creating varied dynamics of offers and requests. (ii) The **selection of a client** when there are several. Which taxi takes which customer? This choice requires negotiation either between taxis or with customers or even both. (iii) The **transport** of the selected client. This transport requires considering static information related to the road infrastructure (in particular speed limitations, positions of traffic lights) and dynamic information on this infrastructure (e.g., congestion of roads).

The fleet manager wishes of course to maximise its profits: on the one hand reducing costs (number of vehicles, inactive vehicles. . .), maximising the number of people taken on, on the other hand. Consequently, the number of taxis, their waiting position, and their coordination become the primary factor (the distribution of taxis should be based on the prediction of applications: sometimes all at the same place, but sometimes all equally distributed). It is necessary to design vehicle behaviours maximising the effectiveness of the whole fleet, from the point of view of customers, taxis or the manager. Our objective is to identify collective strategies for the management of taxi fleets and to know how to compare them.

This article is organised as follows. Section 2 presents the state-of-the-art related to managing vehicle fleets through optimisation and simulation approaches. Section 3 describes the benefits of using multiagent systems for this kind of problem and we describe different positioning strategies of empty taxis as well. Section 4 presents the assessment method and the comparison of the strategies we propose. Section 5 concludes and describes the prospects for future research.

2 LITERATURE REVIEW

Numerous works dealing with problems related to traffic/road simulation are referenced in the literature as (Bazzan and Klgl, 2014). These problems deal mostly with two aspects.

Traffic regulation is one aspect in which many works study multi-agent road simulation. Vehicle coordination for effective intersection management is carefully explored: using multiagent modelling of intersection and vehicles, the overall behaviour is self-adaptive in situations such as the appearance of priority vehicles (Dresner and Stone, 2008), or using a two-player game modelling to characterise specific situations (Mandiau et al., 2008), but also in a more general framework as in (Badeig et al., 2008).

Other works focus on the design of behaviour: either by proposing tools to support this design (Bonhomme et al., 2014), or by proposing behaviours dedicated to enhance the realism of simulations: for instance (Lacroix et al., 2009; Lacroix et al., 2013) propose generation methods in order to increase behaviour diversity as well as the simulation realism through a normative approach while (Bonte et al., 2006) introduces heterogeneity in simulation through two-wheel agents and specific behaviours in order to study their impact on the traffic. Finally, other works propose cooperative behaviours to improve the overall efficiency of a system by managing conflicts locally, guaranteeing a limited perception of agents as well as little communication (Tlig et al., 2012).

Studies on the simulation and evaluation of a transportation system as a whole are numerous (Manley et al., 2014; Yang, 1997; Bonhomme et al., 2016; Barceló et al., 2005). Such works often support the design and evaluation of road behaviour. Some works address issues related to the impact of road infrastructure modification while others deal with more specific problems such as urban-area parking (Bessghaier et al., 2012). Recently, other studies have focused on specific phenomena as for the vehicle-sharing (Cheikh and Hammadi, 2014): a hybrid method based on optimisation techniques and multi-agent systems allows the parallel assignment of vehicles on demand, on an environment, divided into distinct geographical areas within which an optimal assignment is scalable. (Billhardt et al., 2014) study the dynamic coordination of a transportation system but focus on the architecture required to achieve it and not on individual behaviour as we propose. They still require centralised entity to act as a fleet operator, which we claim unnecessary.

The problem we are interested in, the management of taxis fleet, has already been studied under different aspects. (Lioris et al., 2010) proposes a discrete-event simulator supporting the design of optimal behaviour through learning and systematic testing of many strategies (centralised and distributed). However, these behaviours cannot adapt themselves in front of different situations that may arise (peaks of applications, congestion…). Other studies focus on the benefits of cooperation between taxis in the assignment process (Maciejewski and Nagel, 2013). This approach relies on the existence of a dispatcher and on the amount of information shared, which might nevertheless be reduced to a minimum if the strategy developed becomes complex.

In contrast to approaches based on optimisation techniques as (Cheikh and Hammadi, 2014) or (Lioris et al., 2010), we propose an approach based on autonomous and adaptive agents, allowing distributed coordination based on agents with local perception and reasoning.

3 MULTIAGENT APPROACH

One can easily understand that in such a system, no client should wait too long, and no taxi should remain too inactive. Strategy evaluation contains an essential temporal dimension. This temporality can only be measured based on real travel time as well as considering distances and congestion. Therefore, the road infrastructure must be represented using an GIS (Geographic Information System) graph or an adjacency matrix encoding both distances and travel times.

Based on such a representation of the road infrastructure, it is possible to simulate congestion, to compute the shortest distance and travel time from one point to another, and to determine the number of customers that can be conveyed for a given period of time, as soon as their application is regular and infinite. However, as soon as positioning strategies are necessary, patterns of customer applications are irregular or, as soon as one seeks to evaluate heterogeneous fleets, the notion of behaviour becomes preponderant. It constitutes a complex system, with many retro-action loops. Moreover, under incomplete information, notions of perception and neighbourhood are required: an GIS map with vehicles moving on it become unavoidable.

3.1 A distributed solving required?

While it is quite clear that an GIS map and simulated vehicles moving on it are required, such a simulation can be implemented in two ways: centralised computation that optimises constraints and assigns taxis, or thanks to a behavioural model in which each taxi has its own decision model.

The perception halo restricts the volume of information which each taxi can access, and also allows a limited rationality. Three types of information can be distinguished *perception of infrastructure* (including roads, congestion...), *perception of customers* (interaction with customers within the halo), and *perception of other taxis* (exchange of information between close taxis).

A behavioural approach such as the one we propose allows the test of all these hypotheses based on the same model: perception radius, halos shape, nature of interactions as well as information exchanged. The ideal system in which all information would be public and immediately known to all is directly obtained by considering halos of infinite radius, accounting as a centralised system.

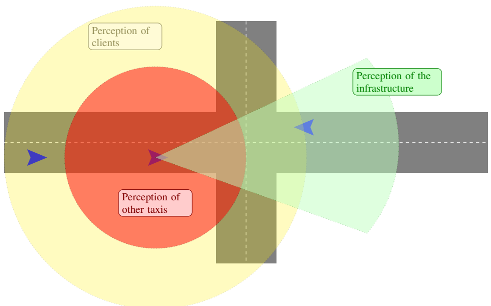


Figure 1: Different perception halos for a vehicle

Numerous events only have a local impact: a congestion to the south of Manhattan leads to very few consequences for vehicles travelling solely to the north. Broadcasting such information to all is useless.

Any modelling requires choosing the level of granularity desired. Each business expert decides what is relevant to his model, for his experiments. Of course, the finer the granularity, the more important the number of concepts to consider. It enriches the model and makes it more complex, impacting its implementation and its effectiveness. All models require a compromise. For instance, is it required to specify a behaviour to pedestrians or traffic lights? These alternatives are both possible by extending our model. However, we choose to only individualise taxis and customers. Other vehicles will simply be represented by a flow. Thus, each GIS road segment contains a speed limit and its level of congestion. Similarly, customers do not have their own behaviour, but simply a place of appearance and a destination.

The use of individual-centred approach guarantees the design of autonomous agents, and a self-adaptive system as well that is very suitable for this fundamentally dynamic problem. Taxis automatically adapt to customer requests, to other taxis, to traffic congestion...

3.2 Description of strategies

First of all, the way clients are considered must be detailled. In this study, clients are generated at specific places called *client generators*. Each generator creates clients according to a predefined probability distribution, each client is associated with a destination and a time-to-live. If no taxi picks a client up before the term of its time-to-life, the request is cancelled. Generators have been used to simplify modelling assumption, to represent hot spots where clients appear regularly and to facilitate stategy comparisons. Of course, if needed, it is possible to generate clients on any node of a given area.

The distributed management of a fleet of autonomous taxis is based on three distinct tasks mentioned above: customer selection, customer transport and positioning of the taxi when it is empty. The behaviour of a taxi should describe these three aspects for which it is possible to adopt specific strategies. In all these strategies, we consider that all agents (clients and taxis) are cooperative, meaning that they all aim at contributing to the maximization (or minimization) of the same objective function.

3.2.1 Client selection

The question of the customer selection will arise in two situations: when a taxi receives several requests for transport and when a customer applies. In the first case, the taxi must decide which customer takes priority, whereas in the other case the question becomes which taxi should move and transport him or her. Obviously, an efficient management of the taxi fleet minimises unnecessary travel and thus avoids multiple taxis to move towards the same customer.

The client selection can be managed via a *contract-net*-like protocol (Smith, 1980). Indeed, when a customer appears, he broadcasts a signal to all taxis in the fleet (e.g., using his or her smartphone application). Each taxi always answer to all requests by an arrival time. Taxis decide independently of each other to answer it or not. Indeed, each taxi has its own policy based on various elements such as already having a customer or not, depending on the distance with the client, or depending on the constraints emitted by this client.

After receiving responses from the taxis, the client then chooses the one that will transport him. Similarly, each customer may have a selection process based on its own criteria (more ecological, faster, shortest distance..., lowest price). By default, a client always chooses the taxi associated with the closest arrival time. We consider that taxis will not be selected by the client himself but by its smartphone application, which can consider the so-called social criteria related to the taxi fleet. The radius of the customer call may vary in order to reach either only close vehicles, or the whole fleet.

3.2.2 Taxi positioning

The major difficulty relies mainly on the positioning of the vehicles. Indeed, when the number of customers is low, taxis should wait for customers. An inactive taxi must question its positioning according to the evolution of its knowledge (either by exchange with others or by direct perception of its environment): Would it more likely have a client by being placed elsewhere? All taxis must not position themselves and wait at the same place: some forms of coordination is necessary for this purpose. The two first strategies described next do not require any information, their decision-making is based on their own information and the notion of fleet is nonexistent for each individual. At the opposite, the two last strategies are swarm-based since taxis share information and use them to make their decision that can be based either on self-interest or on social motives.

The different positioning strategies considered are:

- *random*: when a taxi is empty, it selects randomly one of the generators and goes there. If there is no client, the vehicle waits for one.
- *closest*: as soon as a taxi is empty, it selects the request generator the closest to its position and goes there. If there is no customer, the taxi join the queue.
- *probabilistic*: when a taxi is empty, it selects a generator according to the number of requests pending and goes there. The more pending requests a generator has, the more chances it has to be selected. If there is no request, the taxi lines up and waits. Such a strategy assumes that taxis know the number of customers waiting on all generators.
- *most-requested*: when a taxi is empty, it selects the generator associated with the largest number of pending requests, according to its knowledge. Without knowledge on waiting clients, it randomly selects one generator. When taxis intersect, they can exchange information on the status of applications in order to update their knowledge. This strategy, based on local exchanges of information, constitutes a swarm-based strategy.

This list of strategies does not aim at being exhaustive. Each of these strategies can be extended in different versions according to the amount of information that a taxi can recover. Indeed, the exchange of local information can have an impact on the effectiveness. The strategies described here are primarily intended to illustrate the range of possibilities.

4 COMPARING STRATEGIES

4.1 Preconception

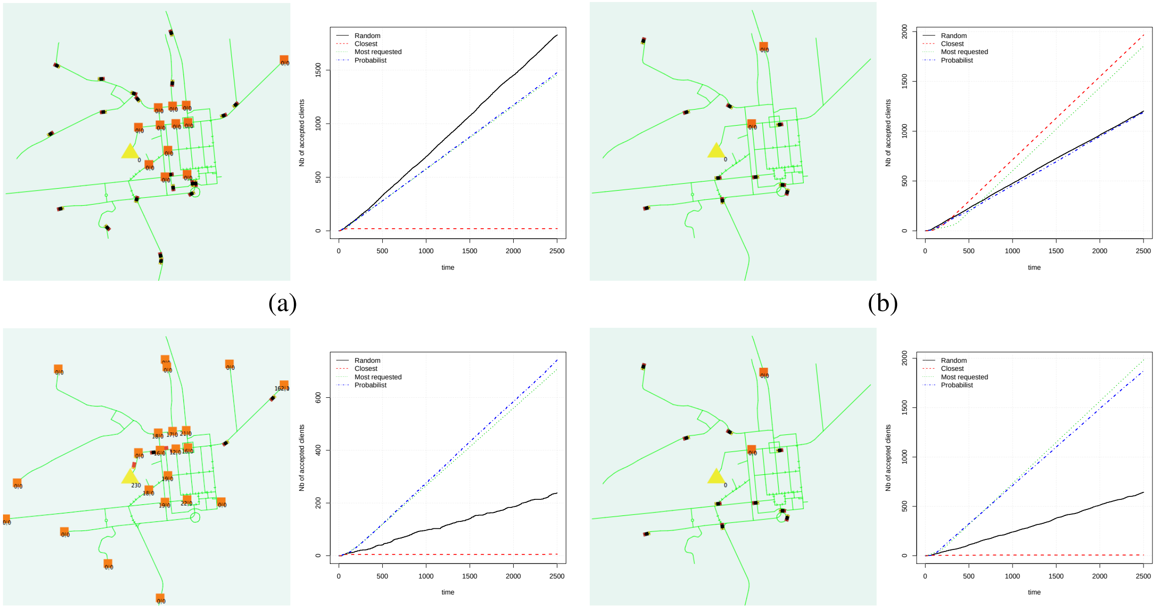
The comparison of behaviours in such a context raises a large number of difficulties that must be considered if relevant results are desired. We assume that the evaluation of such a system relies on the aggregation of a set $\mathcal{C}$ of n criteria $\mathcal{C} = \{c_i\}_{i=1}^{n}$. The objective function can be written in a very generic way:

$$\mathcal{F}(c_1, \ldots, c_n) = f(c_1, \ldots, c_n)$$

The comparison of different fleet management strategies must imperatively compare them under the same experimental conditions, these conditions being scripted in time. This is what we call an execution scenario and define as a tuple $S = (\mathcal{G}, \mathcal{E}, \mathcal{S}, \mathcal{D})$ where $\mathcal{G}$ is the GIS graph describing the road infrastructure, $\mathcal{E}$ describes the traffic conditions, $\mathcal{S} = \{s_i\}_{i=1}^{u}$ is the set of client generators (GIS position and appearance rate of clients at this point) and $\mathcal{D} = \{d_i\}_{i=1}^{v}$ is the set of destinations requested by customers.

All these parameters define a scenario, which must be the same to allow comparison of strategy effectiveness. These common experimental conditions are essential to assess the impact of simulation parameters and behaviour of taxis: such as the fleet size, the taxis perception/interaction radius, the positioning strategy, client selection rules...

The effectiveness of strategies is highly dependent on the scenario used. Indeed, a very effective strategy on one scenario may perform terribly on another. Figure 2 illustrates the manipulability of results. Each simulation was carried out on the same road infrastructure, on which a fleet of 10 taxis having complete



(a) (b) (c) (d)

Figure 2: On the same road infrastructure (Richelieu town), four scenarios makes a different strategy becomes the most effective.

information operates. The number of customers transported is used to measure the fleet efficiency. In each of the scenarios, client generators are represented by an orange square while the yellow triangle represents the destination requested by customers.

According to scenario (a), a large number of clients (2,400 clients) are waiting on the client generator the furthest from the destination, the nearest generator generates 1 client every 240 minutes and the other 10 generators have a higher generation rate (1,200 customers generated in 480 minutes per generator). Taxis that position themselves according to a *random* strategy will mostly take clients from very active generators (since they represent 10 generators out of 12): the fleet can thus take over a maximum of applicants. However, if taxis position themselves according to a *closest* strategy, they will stop at the nearest generator, which only generates few customers and the fleet can only achieve very limited results. According to a positioning *most-requested* strategy, taxis will always move to the farthest generator (on which a large number of clients are waiting), therefore limiting the number of taken clients. A *probability* strategy encourages taxis to take clients from the most distant generator and the 10 closer generators according to the number of clients, leading the fleet to achieve reserved results.

According to scenario (b), a customer-generator close to the destination is very active (2,400 customers generated in 240 minutes), while the further one is associated with a lower rate (480 clients in 480 minutes). Taxis following the positioning strategies *random* and *probabilistic* will serve both generators, reducing the total number of clients that can be accepted. Taxis acting according to a *closest* positioning strategy will only take clients from the closest generator, maximising the number of clients taken. A *most-requested* positioning strategy leads taxis to the nearest generator until more pending requests appear on the most distant one, sending taxis to the latter. Such a strategy does not maximise the number of clients taken.

According to scenario (c), close to the lone destination, 1 weak generator (1 client every 240 minutes) and 10 strong generators (136 customers in 480 minutes), while in remote areas rely on a very strong generator (1,496 customers in 480 minutes) and 11 weak generators (1 customer in 480 minutes). Following the positioning strategy of *closest*, taxis quickly exhaust the nearest client-generator and come to a halt, leading to a low total number of customers accepted. The *random* positioning strategy makes taxis spend time on remote generators containing only a few clients while the *most-requested* strategy makes taxis head to the generator where the largest number of requests are pending, which is also the furthest, ultimately reducing the total number of customers taken. Only the *probabilistic* strategy distributes taxis between close generators with numerous waiting clients.

According to scenario (d), a strong generator is close to the destination (1,680 customers in 240 minutes) while a weak generator is more distant (1,215 customers in 480 minutes). As before, the strategies *random* and *probabilist* distribute taxis on all generators, wasting time by taking clients from further generators while a lot of requests are pending closer. The *nearest* strategy quickly exhausts the closest generator and then immobilises the fleet. Only *most-requested* strategy distributes taxis on both client-generators, but will first exhaust the closer one, maximising the total number of clients transported.

These 4 scenarios allow us to show that it is possible to design a scenario specifically dedicated to making any strategy the most effective. Moreover, here we have chosen to look only at the total number of clients taken to assess the effectiveness of the taxi fleet, but it is possible to do the same with other metrics. Indeed, behavioural assessment is also very sensitive to another aspect: the metrics chosen for the evaluation. Indeed, even if the scenario (i.e., the experimental conditions) is the same, the evaluation of behaviours can lead to opposite conclusions according to the metrics chosen for the evaluation. In addition, some metrics which may seem wise at first, turn out to be perfectly disastrous. Indeed, let us assume that the efficiency of a taxi fleet is evaluated through the waiting time of customers that should be minimised: $\mathcal{F} = \min(t_a)$. It is then sufficient to match the number of taxis n_{taxi} to the number of applications r: the waiting time t_a tends to zero but taxis will be inactive most of the time.

$$n_{taxi} \rightarrow r \Rightarrow t_a \rightarrow 0 \quad \text{but } t_i \rightarrow \infty$$

On the other hand, if the effectiveness of a taxi fleet is evaluated through the inactivity time of taxis which should be minimised: $\mathcal{F} = min(t_i)$. It is then sufficient to reduce the number of taxis n_{taxi} to one whatever the request.

$$n_{taxi} \rightarrow 1 \Rightarrow t_i \rightarrow 1 \quad \text{but } t_a \rightarrow \infty$$

The lone taxi of the fleet would thus always be busy taking customers. However, the number of accepted clients would be very low and their waiting time extremely long.

An intuitive idea could then be to aggregate these different aspects within the same objective function. A solution could be to minimise the product of customers' waiting time and taxis' inactivity time: $\mathcal{F} = t_i \times t_a$. The use of a product can be interpreted as aiming at a compromise between taxis and customers which can sometimes have opposite interests. Unfortunately, such a function is no more relevant than the previous ones. Indeed, it is very easy to get a nil value by playing only on size of the taxi fleet: (i) if the fleet size tends towards infinity, the client waiting time t_a tends towards 0 as well as the whole objective function; (ii) on the other hand, if the fleet size tends towards 1, the taxis inactivity time tends towards 0 just like the objective function.

(i) $n_{taxi} \rightarrow \infty \Rightarrow t_a \rightarrow 0 \Rightarrow \mathcal{F} \rightarrow 0$

(ii) $n_{taxi} \rightarrow 1 \Rightarrow t_i \rightarrow 0 \Rightarrow \mathcal{F} \rightarrow 0$

Thus, finding an objective function aggregating the different aspects of the problem is a difficult task. It is always possible to design a scenario or manipulate a parameter in order to shape the value of the objective function without achieving a meaningful comparison. The different criteria aggregated by the objective function do not have links between them: each represents the problem according to a specific point of view. Moreover, these aspects have their own value scales: their comparison often has no meaning. Thus, in order to evaluate such a complex problem with multiple facets, it is necessary to create a common scale of values to allow comparison of strategies. The more the evaluation metric aggregates various aspects, the more difficult the manipulation.

4.2 An economical approach to compare strategies

A lot of aspects can be considered as common values scale for the evaluation: kilometres, time, energy... One a unifying solution: Money. The use of money as a unification of the other parameters is the conventional projection of $\mathbb{R}^n$ on to $\mathbb{R}$ with the attendant problems of coverage of all the contributory factors and how to weight their combination. The taxis are not individually economically autonomous, in the sense that they do not try to maximize their own utility, even though that may have a negative impact on their individual welfare. The aim for a manager is to maximise the efficiency of the whole fleet, without considering individuals.

The effectiveness of such a system must be assessed by considering the different aspects of taxi satisfaction as well as customer satisfaction.

$$\mathcal{F}(w_{client}, w_{taxi}) = f(w_{client}, w_{taxi})$$

Customer satisfaction is based on various criteria such as price, waiting time and travel time. Another possible approach could be to consider a customer satisfied as soon as he is accepted, whatever the time he waited or the price charged. Such an assumption clearly focuses on taxis. The objective of such a system is to maximise the number of customers taken. Such a study really makes sense if customers have limited *patience* and stop waiting for a taxi a certain time. They can then be considered as a perishable resource of the system.

The satisfaction of taxis must consider the positioning time (empty-ride) t_{empty}, the travel-time t_{ride}, the flat rate per customer p_f, the price per kilometre when riding a client p_k, the cost per kilometre c_k, the vehicle paying for itself ζ.

The empty-ride time occurs when a taxi moves without a client, which occurs whenever he has to reposition itself: the taxi always incurs the costs of using the vehicle. The more a taxi moves without a customer, the more it costs and the least profitable it is. The purchase/rental price of the vehicle is also considered, which must be calculated on the basis of the vehicle price and the time needed for the vehicle to pay for itself. Each customer accepted is charged and an additional cost per kilometre travelled. Thus, the profits of taxis depend directly on the number *nb* of customers it takes.

The satisfaction function that a taxi aims to maximise can be formulated as:

$$w_{taxi} = \left[(p_f + (p_k - c_k)t_{charge}\right] nb - c_k t_{vide} - \zeta$$

In order to assess the effectiveness of the system, it is necessary to aggregate the satisfaction of all taxis. The choice of this aggregation function also has a lot of serious consequences and must result from an informed choice: the most common choice is the sum $\sum$. However, the maximisation of a sum does not consider the standard deviation: some drivers could be very profitable while others would be dedicated to making shorter journeys for example. If the direct remuneration of drivers depends directly on the number of customers taken, aggregation by means of a sum is not fair. An alternative would be to use a product $\prod$, allowing a fairer distribution of the less profitable rides between different drivers. This small example shows the need for an informed choice for the selection of the aggregation functions involved in evaluating the effectiveness of our complex system.The economic approach avoids manipulation thanks to the design of dedicated scenarios. The *probabilist* strategy achieves great results in all scenarios whereas some of them have been designed to make another strategy the most effective.

Different strategies have been described in Section 3. The effectiveness of some strategies depends on the quality of information available. Indeed, the positioning strategies *random* or *closest* do not required more information than the place of the client generators. However, other strategies like *probabilistic* or *most-requested* perform better if the information available for each taxi is updated in time, to know the number of requests pending on each client generators. By interacting between each other, taxis can update their knowledge if a taxi with more recent information enters within its perception radius. The larger the perception radius, the more effective the fleet.When no information is exchanged between taxis, when a first generator is exhausted, taxis select randomly a new one since no information is available.The taxi fleet needs a lot more time to accept all waiting clients. If information can be exchanged, the speed of client acceptance will be much greater. A taxi with no information has just to interact with one which have newer information to make a new wiser positioning decision. The larger the interaction distance, the quicker all clients are accepted. Depending on the size of the halo, compared to the size of the road infrastructure considered, also according to the number of taxis, the benefit of exchanging information vary.

To run our experiments, the system described in this paper has been implemented in a powerful simulator. The system is able to simulate up to the whole of the island of Manhattan (shown in Figure 3) with a fleet of 3,000 taxis, which is globally the maximal instance size of all traffic simulators.

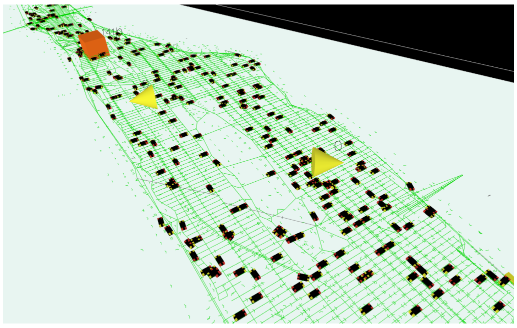


Figure 3: Simulation of Manhattan Island, with several clients sources and destinations and a fleet of 500 taxis supporting customers.

5 CONCLUSION AND FUTURE WORKS

We have presented in this paper the *DCarPool* model, based on a multiagent architecture for distributed management of autonomous taxi fleets. This centred-individual model considers the speed limitations and the congestion of each road, as well as customisable variations in applications and the definition of individual behaviour for each taxi. The system relies on a real map (GIS environment). We have shown that this type of problem constitutes a multi-criteria complex system difficult to evaluate, especially due to its dynamic nature. We have proposed here a list of criteria to combine as well as a unified economic evaluation function allowing an overall evaluation of this system. Thanks to the model we have proposed, it is now possible in a given situation to compare different strategies in order to obtain a multi-criteria optimum based in particular on the satisfaction of taxis (costs of daily use and depreciation) and the satisfaction of customers (fares and time spent waiting and traveling). This system and the numerous possible settings allow the flexible design of a multi-criteria objective function relevant to any desired optimisation. Next, the results obtained with the different decentralised strategies must be compared with the optimal assignment in order to determine the absolute effectiveness of the proposed approch.

As electric vehicles are becoming more and more popular, a new dimension similarly becomes essential. The notable difference between a petrol-powered vehicle and an electric vehicle is that the latter requires a downtime for its recharging. It is obviously not desirable for all taxis to recharge at the same time. A collective energy management policy is thus required, leading to a modification of individual strategies. A taxi must be able to recharge during empty periods or with an offset during a full period. This obviously impacts the fleet size: it becomes more and more important as the longer the recharging time.

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