Location-Based Dispatch to Reduce the Waiting Time for Taxi Services

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Abstract

One possible solution to increase the operational efficiency of taxi dispatch systems is to use location-based services (LBS) in order to choose the best vehicle available to attend a customer request. In this work, three different algorithms to implement and to improve taxi dispatch are evaluated. The third one, based on customer smallest waiting time and minimum computational cost criteria, is a novel contribution. Simulation experiments showed that the proposed LBS algorithm presents a small waiting time for customers and shorter distances to travel by taxi drivers, when compared to broadcasting methods and Euclidean Distance algorithms.

Keywords: Taxi dispatch problem, Location-based services, Urban taxi transportation, Real-time routing, Assignment problems, Vehicle routing problem.

1. Introduction

Taxi is an agile and comfortable transportation mode that is very popular in urban areas, mainly in big cities. Taxi transportation systems are affected by different factors, that change their availability. Among them, it is important to mention:

- Rush times (peaks of traffic);
- Rainy/snowy days, which motivate people who usually move by walking, subway or bus, to use taxis. This situations generate a scattered demand - in other words: there is not a concentration of users in specific locations;
- Cultural and social events, such as concerts, sport matches, parties and conferences, which generate strong demands at specific locations, usually concentrated in small periods of time;
- Beginning and end of holidays, when users choose to go to airports, bus and train stations to travel.

The operational efficiency of taxi services, generally, is unsatisfactory. The reasons for that are related to the lack of a proper methodology to serve existing requests and the poor organization of the system services: phone call schedules, random search methods to take customers (taxi drivers and passengers looking for each other) and the use of taxi ranks [1].

In search of effective improvement of taxi services, it is necessary to achieve a balance between taxi avail-

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ability, number of requests by region and knowledge of detailed information about preferences, traffic flow and route access. Joining these informations together, it is possible to build models which can better describe the behaviour of taxi environments. However, due to their own characteristics - such as number of available taxis, autonomous stochastic demands in different locations and absence of patterned behaviour of drivers - creating of those models to aid taxi operation is not feasible, even for average sized representations [1].

An alternative solution for this scenario is to use GPS-based trackers in taxi vehicles, to collect location information of available drivers, and centralized information systems to collect customers demands. Location-based services can increase the operational efficiency of such situation: knowledge of geographical location about taxis and customers allows for choosing the best vehicle for each request, improving global results of the systems [2], [7].

The use of global location technology for taxi dispatch was already studied by [2], [3], [7] and [8]. In these papers, the request of taxi services is realized through telephone calls, in which the customers inform their locations and the operator identifies the closest vehicle to serve each request. These papers indicate that some systems use straight line distances to choose the best available taxi driver, and others use the old-fashion broadcasting model, transferring to drivers the choice of a taxi to serve each customer request, based solely on the collective impression about their distances to each customer.

This work proposes to evaluate the advantages, in terms of global average customer waiting time, of using GPS-based algorithms to taxi dispatch over broadcasting methods. Specifically, a novel algorithm is proposed to implement GPS-based dispatch systems in a computationally efficient way. Discrete-event simulation techniques are used to analyse three different taxi dispatch methods and to calculate computational processing time of all algorithms, as a measure of the possibility to use them in real-time dispatch systems.

The paper is organized as follows: the next section contextualizes the problem to be approached, Section 3 discusses in more details the available models and techniques to implement taxi dispatch systems and Section 4 presents experimental tests realized with those techniques and obtained results. Section 5 evaluates the experiments in terms of the chosen criteria and Section 6 concludes the paper highlighting important points and future work.

2. Background

Nowadays, taxi services are everywhere: big cities, medium-sized cities and even small cities around the world have reasonable infrastructure to provide this service. Taxi systems try to meet service demands of native population and tourists that visit or work on these places.

At most of the cities around the world, it is possible to observe that taxi drivers waste a large portion of time - about 50% - at vacant times [1], [9] and [10]. Because of this high rate of wasting time, there is a large number of studies that intend to improve the efficiency of these services, without increasing the costs [1].

Some years ago, the use of geographical location information has been incorporated into modern taxi dispatch systems [3]. From the knowledge of the absolute position of a prospective customer, it is possible to estimate which services can be of interest for this possible consumer and to improve the offer and quality of products and services provided [4].

There are different techniques, used by taxi drivers and companies, to find customers: from random search methods to telephone based bookings, up to GPS-based methods, the market becomes more and more competitive as technologies improve. Talking specifically about taxi dispatch systems, the knowledge about passengers and taxis positions at given times allows for a big advantage over other methods: it is possible to choose the best vehicle in the fleet to meet every request, in a more efficient manner [7]. [2], [3], [7] and [8] describe actual systems that store absolute positions of taxis over time and, when a customer calls a dispatch center, define the best vehicle to attend each request, according to their relative distances.

3. Taxi Dispatch Techniques

3.1. The Broadcasting Technique

The broadcasting technique is one of the most used methods for choice of the taxi driver responsible to attend a customer after a call to the taxi service center [7], [8]. After each customer call, the operator informs the taxi drivers, by radio, the approximate location of the prospective passenger. One of the taxi drivers, which understands that is located near the customer, confirms that he/she is available and can serve the request. Then the operator assigns to him the call and informs back the customer about taxi information and expected time to serve.

To use this method does not guarantee that the nearest taxi driver will be chosen and so the resulting dispatch system does not meet the demands on a optimized way. It is possible to conclude that the choice of the driver is carried out in a way of random, since the driver who first answers the demand, under certain conditions, is the one that will attend the request.

To simulate this method, a computer algorithm was developed using concepts of discrete event modeling. In this algorithm, after each request, a subset of taxi drivers near the customer's position is randomly selected inside a certain proximity zone (at a certain radial distance from the given position) and one of them is picked up at random, representing the first one to answer the call.

3.2. GPS-based with Euclidean Distance Algorithm

An common algorithm, currently used by several commercial taxi dispatch systems, is being referred here as the GPS-based with Euclidean Distance algorithm (GPS-EDA or EDA). This technique elects the best taxi to attend a customer call as that one in available state which possess the minimum Euclidean Distance (shortest straight-line) from that customer. This calculation is realized on a event-driven basis, for each customer call, at the service central. Then, the chosen driver is informed that he/she is the closest from the customer and has been chosen, and the customer is informed about that taxi details and expected time to serve.

According to [8], in some situations, the Euclidean Distance-based algorithm may prove to be inefficient, since the nearest taxi may take longer to travel to the customer than a taxi slighly farther, but that can take a faster route to reach the customer position. One example of this can be seen in Figure 1. There, Taxi 1 is closer to the customer than Taxi 2, using Euclidean distance calculation. Nevertheless, Taxi 2 will travel a lower distance than Taxi 1 to reach the customer position and to attend the demand.

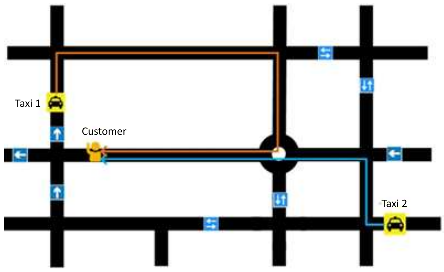

Fig. 1: Illustration of a common problem with GPS-EDA.

Despite the problems discussed above when using only the Euclidean Distance to define a best taxi to attend each customer, this solution has a considerably low computational cost, and can deliver good results in the average case.

To simulate this taxi dispatch model, a computer algorithm was developed with the same concepts as in the broadcasting technique, but using as the top criterion to choose the taxi driver with the lowest Euclidean Distance between those inside a certain proximity zone (at a certain radial distance from the customer given position) to attend the customer, at each call made to service central.

3.3. GPS-based with Lowest Estimated Time for Service Algorithm

With the purpose of improve the existing taxi dispatch systems, a novel technique is proposed in this work. The main criterion in the new algorithm is to define the best taxi available to serve a customer request by using the lowest attendance estimated time. From now on, this algorithm will be referred here as GPS-LET (or LET), following the initials of its denomination. To choose the best taxi using this technique, one have to estimate each travel time of each available taxi, based on the actual best route between these vehicles and the prospective customer. Of course, there is a high cost to evaluate all available taxis for each customer request, making this technique very slow, when compared to the other ones, due the complexity of routing algorithms. Moreover, this high cost will scale up with the size of the taxi fleet.

In order to decrease the response time, a pre-processing of linear Euclidean Distance between the available taxis and the customer position can provide a significant decrease in processing time, without affecting the quality of the algorithm. In this approach, it is assumed that for greater distances exists a proportionality between this distance and the corresponding time to attendance.

Using Euclidean Distance, the available taxis are categorized by their distance to the customer. Then, GPS-LET algorithm will be executed only for those taxis with positions inside a given range from the customer position. The first step is to rank the available taxis by ascending distance to the customer. If there are no taxis in an initial range defined at beginning, the algorithm proceeds as follows:

1. Defines a initial distance range to find taxis;
   (a) If at least one taxi was found in the new range, processes the vehicles found;
   (b) Otherwise, increases the range by *dx* and evaluates:
      i. If at least one taxi was found in the new range, processes the vehicles found;
      ii. Otherwise, concludes that there are no vehicles near and puts the customer in a queue.

It is possible to better understand this pre-processing (or filtering) algorithm looking at Figure 2. Available taxis are firstly searched in the darker region of concentric circles. If there is no taxi found, then they are searched in the next bigger region and, finally, if necessary, in the lighter region (identified by a lightgray circle). If no taxi is found, the algorithm puts the customer in a queue and waits for taxis' position and availability updates. Using

Fig. 2: Pre-processing method to filter taxis, by their distance to the customer.

the range concept above defined, it is possible to limit the maximum distance for a taxi to be evaluated for serving a customer request. This maximum limit prevents taxis lying really far from the customer to be processed by GPS-LET algorithm, so decreasing its processing time. Beyond the algorithm processing time issues, it is easy to understand that vehicles far from the customer will have to travel a big distance to reach him/her and possibly the resulting profit will not pay the costs of the driving. Furthermore, customers would have to wait for more time to be attended, which is also not a good thing.

If the technique, using the taxi filtering algorithm, finds a big number of taxis that fit for the service, the system will limit to a number of N near drivers, based on previous attendance rate, further reducing processing cost and contributing to drivers attendance balance. Among these N drivers, the system will estimate each travel time to the customer and define the best taxi to attend the request.

4. Tests and Results

For the experiments presented in this paper, all estimations of requested time for service were performed using Google Maps API, which gives the lowest actual car route connecting any two points in a covered urban area. To calculate the average time service, Google Maps API was also used in order to estimate the travel time between the chosen taxi and the corresponding customer. This estimate was defined as the time to start the service, for statistics purposes. The simulator does not evaluate, at the time of these tests, traffic information.

As pointed out earlier in the text, the type of simulation engine designed to test the algorithms described in the last section is classified as a Discrete Event Simulation. Using this approach, simulated tests were performed for all algorithms under same conditions, that is, starting from the same number and location of available taxis and trying to attend the same customer requests. Each method then defined its best taxi option, according to these own criteria, and departed the chosen taxi to attend each request. The time spent by the chosen taxi to attend each customer request was then computed for each of the techniques, allowing for fair comparison of the algorithms.

The results presented here are averaged values of twenty instances of execution of each algorithm, used at a subsequent analysis and discussion.

4.1. Taxi Distribution

To implement the distribution of service demands and available taxis in the area used as a representation of a given city, a event placement generator for taxis and customers was built. Here, the probability of an event occurring in a peripheral area of the city is smaller than the probability of an event occurring in the central region. This behaviour represents a situation where a small region of interest receives more taxi requests. In large cities, for most of the time, several places concentrate the major number of requests, unlike a single area. However, these usual behaviour is complex to be fully modelled, especially when related to stochastic demand for taxi services [1].

So the taxis, likewise the customer demands, were not uniformly distributed. Using the same placement algorithm, they occupy, preferably, the central region of the city under study. The peripheral area has less taxis available and less requests. The taxi displacement distribution, compared to the midpoint, can be seen in Figure 3. At that figure, it is possible to see that the regions near to the point defined as the center of the experiment (midpoint) concentrate the major number of requests and taxis. In the peripheral area, the number of available taxis also decreases.

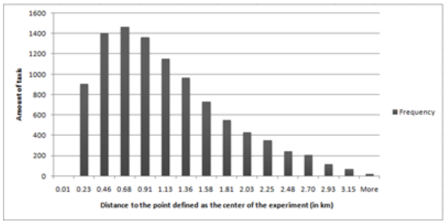

Fig. 3: Histogram showing the distribution of taxi drivers in relation to city midpoint.

It is important to say that the undertaken experiments do not take care of directions of taxis allocated at the streets. The position of each taxi is randomly generated, using the discussed criteria, and sent to Google Maps API. Google than takes the geographical location of the taxi and defines its current address and direction of movement.

4.2. Taxi Service Flow

To represent the dynamics of actual taxi dispatch systems, the built simulator changes the positions of taxis around the city after each actual attendance event. As the simulation was built based on discrete time events paradigm, these movements occur only after the time estimated to process a request plus an averaged random service time is reached.

The simulator maintains an approximate ratio between the number of occupied taxis and the total amount of vehicles. This number is kept constant during the tests, with no tendency to increase or decrease supply in relation to the number of customer requests.

The maintenance of the number of taxis in a stationary state guarantees that the waiting time keeps similar, if not equal. This analogy derives from the relationship proposed by [5], where the waiting time is directly related to the amount of spare time of taxi drivers.

Another characteristic of the built simulator is related to amendment of taxis' states. In a actual scenario, taxis start and release attendances all over the city and at random times. To represent this in a discrete way, the simulator, after processing a customer request, modifies the availability of a few taxi drivers at random, with some probability.

It is also important to state that time elasticity of customer demands were ignored by the simulator. In practice, there are variations of amounts of requests depending on days of weeks, rush hours, climate conditions, etc. However, during the simulation tests, conducted under homogeneous conditions, there are no changes on the supply of services and neither are in the generation of customer requests.

As a summary of the procedure used to perform the simulations, the following sequence of events can be identified and listed:

1. The system defines a number N of taxis and puts them randomly in the city;
2. Half the amount of taxis is set as occupied;
3. Taxi drivers move randomly around an area in discrete time without significantly changing their geographical position inside the city;
4. Some of the taxis change their status from "Occupied" to "Free" and vice versa, simulating the start/end of service in an actual scenario;
5. The system generates a customer request;
6. Each taxi dispatch system chooses the best taxi under defined criteria and the time until the service starts is measured for each algorithm;
7. If the number of requests planned for the test is not yet reached, the system goes back to Step 3. Otherwise, the system sums all the waiting and service times for each algorithm and shows the results.

4.3. Tests Conditions

The city of Belo Horizonte (Brazil) was chosen as the place where the tests were performed. Due to the existence of a large urbanized area in the center of the city, with a low number of large green areas and an extensive road network, the taxis and requests were distributed over the central area and vicinity (defined as the peripheral area).

Besides the actual geographic location where tests were run, adjustments were made to the model in order to simulate conditions near to the average in the city. The next list of adjustable parameters defines the scenario of the tests undertaken for Belo Horizonte.

- Average load factor: 50%;
- Maximum number of taxis evaluated in "circles" next to the customer: 7;
- "Circles" search radius: $0.7km$, $1.2km$ and $1.5km$;
- Probability of moving a taxi: 90%;

- Maximum probability of changing the taxi status ("Free" to "Occupied" ou vice versa): 10%.

In a first test, using the actual average conditions of Belo Horizonte, a scenario was created so that 300 taxis were spread over an area of approximately $34.84km^2$. The average rate of taxis per km^2 was 8.61, or a taxi allocated at every $0.12km^2$ on average.

In a second test, the number of taxis was decreased, in order to analyse the influence of the availability of services into customer waiting times. To accomplish that, a total of 200 taxis was allocated in the same area (average rate of 5.74 taxis per km^2).

4.4. Results

The results of 20 instances of the simulations, as described in this section, were subjected to analysis of variance (One-way ANOVA) followed by Tukey Test for multiple comparison averages. A confidence interval of 95% was adopted, and the alternative hypothesis of algorithms being considered as non equals was considered significant when $P < 0.05$. Statistical analysis was done by Graph Pad Prism software (version 5.01).

To reduce the name of the algorithms at the graphics shown in this section, according to the type of test, the naming standard described at Table 1 was adopted.

4.5. Test I: higher taxi availability

The graph on Figure 4 presents the results of Test I, highlighting the customers average waiting time to be served by a taxi for each of the three algorithms implemented.

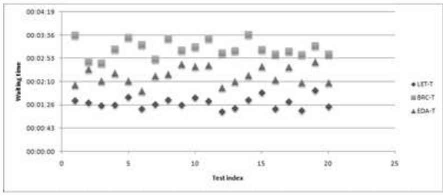

Fig. 4: Customer's average time to be served.

GPS-based algorithm with lowest estimated time for service (LET) presented lower values, when compared to the GPS-based algorithm with Euclidean Distance (EDA) and the Broadcasting method (BRC). Therefore it is possible to infer, according to tests carried out, that this algorithm provides lower average waiting time to customers. These results were obtained with a confidence level of 95% and show that there is statistical evidence that LET algorithm performed better than the other two algorithms.

The results corresponding to the average distance travelled by taxis to reach customers can be seen in Figure 5. It is possible to observe by the

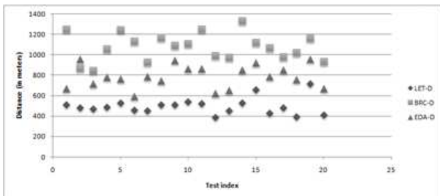

Fig. 5: Average distance travelled by taxis to serve a request.

figure that the average distance travelled by taxi drivers in the LET algorithm is smaller than the distance travelled by taxis chosen by EDA and BRC algorithms.

According to the results shown, and considering that the proposed tests do

Algorithm	Time	Distance	Processing
Broadcasting Method	BRC-T	BRC-D	BRC-P
GPS-based with Euclidean Distance Algorithm	EDA-T	EDA-D	EDA-P
GPS-based with Lowest Estimated Time Algorithm	LET-T	LET-D	LET-P

Table 1: Adopted naming standard for tested algorithms.

not consider traffic information, it is possible to correlate the average waiting time and the distance to travel, as shown in Figure 6. As already discussed, the average time to serve is related to the distance that the driver must travel to reach the customer: the farther from the driver, the longer the customer will wait until he/she is served.

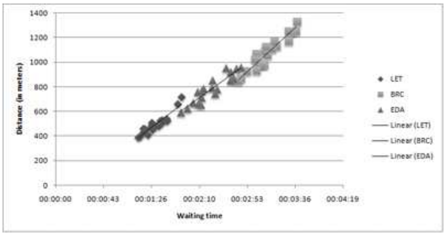

Fig. 6: Correlation between service time and distance from customer.

Finally, the run times for the algorithms execution were evaluated, indicating a way to measure the efficiency of each algorithm in the search for the best available taxi. Figure 7 shows the average time of computational processing for each of the three implemented algorithms.

The analysis of Figure 7 indicates that GPS-based algorithm with Euclidean Distance (EDA) and Broadcasting algorithm (BRC) demanded significantly lower processing time than GPS-based algorithm with lowest estimated time for service (LET).

Despite the values of processing time of LET algorithm, when compared to

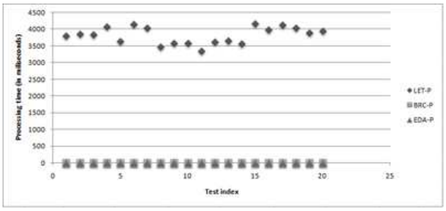

Fig. 7: Average processing time of algorithms.

the other algorithms, its absolute value is low, so that it can be used in real-time applications not compromising time to service customers, at least for the studied scenarios. This can be stated by comparing its average processing times ($3-4s$) to average customer waiting times to be served ($80-240s$). Due to the own LET algorithm characteristics, which limits the number of processed taxis by a distance range to the customer, it can be expected that the processing time will be stable even with a increase of taxis and customers in an actual scenario, thus indicating that the LET processing will not scale up with taxi fleet size and customer grows.

4.6. Test II: lower taxi availability

For the second test, the supply of taxis was significantly decreased. To simulate this, the number of available taxis in the same area of the city was reduced to an average of 1 vehicle for each $0.17km^2$. To evaluate the impact caused by the changes in the test, simulations were rescheduled. The results for each algorithm with the new conditions were stored and can be seen in Figure 8.

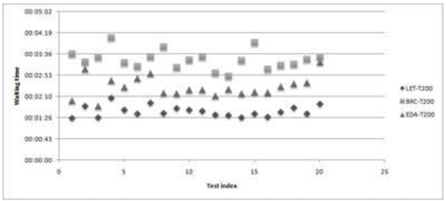

Fig. 8: Customer's average time to be served, by each algorithm.

Now in the second test, at the same way as the first one, it is possible to say, with 95% of confidence, that LET algorithm provided significantly lower waiting times than EDA and BRC algorithms. The results of the average distances to travel by taxi drivers in the second test can be seen in Figure 9.

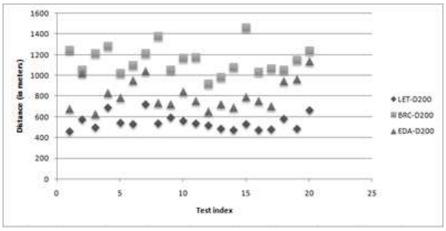

Fig. 9: Taxi average distance travelled to serve a request, by each algorithm.

As in the first test, the average distance travelled by taxi drivers chosen by LET is smaller than the distances travelled by taxis chosen by the other algorithms. These results come to confirm experimentally, by means of simulation, what was expected by the time the new algorithm was conceived: LET should be more efficient than EDA.

5. Discussion

The major criterion for the choice of the best algorithm, among those described in this work, is the contribution of each one to reduce the average customer waiting time for taxis services. A second criterion used to evaluate the techniques is the computational cost of each algorithm. They will be discussed in the following sections, from the viewpoint of the results obtained in the experiments.

5.1. Average Customer Waiting Time Criterion

Evaluating the average customer waiting time criterion, it is possible to see that GPS-based algorithms had a decrease of at least 25% when compared to BRC algorithm. After a careful analysis, yields that LET decreased 52.8% on average, when compared with BRC. The decrease of time by EDA was 26.1%. At least, the gain of LET algorithm over EDA algorithm was about 36.1%.

In the second test, simulation results indicate that the reduction on the availability of the services slightly decreased the gain of the GPS-based algorithms when compared to BRC. LET algorithm reduced waiting time by 51.3% and EDA algorithm achieved a reduction of 27.1%, when compared to BRC algorithm.

As indicated by Figure 6, there is a correlation between the distance to travel by taxi drivers and the customer waiting time for a taxi service. However, the relation between both values was kept uniform, once traffic conditions were not evaluated in the tests.

In a actual scenario, traffic information may cause important changes on the values found. A different route, that is usually slower, may be the fastest one in rush hour or in bad traffic conditions. On the other hand, traffic conditions may not affect the algorithm. To discuss the impact of traffic conditions on the algorithms, the following assumptions should be evaluated:

1. In a concentrated bad traffic situation, limited to a small area, the speed of a congested road will significantly decrease and the linear relationship between distance and time can change: a longer route may be faster than a route that uses congested roads;
2. In rush hour, there is a overall decrease of velocity in all routes. In this scenario, it is not possible to say that rerouting is always justified. So in rush times, it is possible to say that distance-time linear relationship keeps being valid.

5.2. Computational Cost Criterion

The response time of EDA and BRC are similar, with negligible differences. The response of LET algorithm is significantly slower than other algorithms, with average response of $3.8s$.

A software that takes a long time to respond a request may impact the final result of the algorithm, delaying the chosen taxi to start moving through the city and to attend this request. A given best vehicle, after a while, can start to attend another request or can not be the best choice any more, because it moved to another place. An example of how processing time can affect the resulting taxi dispatch is a vehicle moving at $30km/h$, waiting over 1 minute to algorithm response: this vehicle may go about $500m$ away from the point it was located before and evaluated by the algorithm.

The computational cost evaluation results of GPS-based algorithms, when compared to BRC method, must be taken with care, because BRC algorithm does not really exists - it represents only an interaction between taxis and service central operators. Given this warning, it is easy to calculate the impact of the slower processing time of GPS-based LET, based on the average time to be executed, gathered from simulation results. Considering a taxi driver moving at $30km/h$ around the city, the displacement which happens until the algorithm chooses the best taxi to attend a specific request is, at most, about $32m$. For the city of Belo Horizonte, where the simulations where undertaken, this value of displacement can be considered acceptable, not compromising significantly the overall effectiveness of the technique.

6. Conclusion

It is possible to conclude, from the experimental results and after the analysis discussed in the previous section, that GPS-based algorithms presented better results than broadcasting technique, taking into account the customer waiting time criterion. The results statistically indicate that GPS-based methods can improve the quality of services, as was expected by [3].

One of the purposes of this work was fully achieved, as the proposed LET algorithm effectively decreased customers average waiting times, when compared with EDA algorithm. Another achieved goal of this work was the indication of an existing correlation between the distance to travel by drivers to attend a request and the customer waiting time. This correlation effectively influences the method used to choose the best taxi to attend a customer.

The analysis of processing time of the algorithms indicates that all implemented algorithms have low response time. Due to their own characteristics, as well as the processing times found in the simulations, it can be stated that all three solutions have practical feasibility.

In a future work, it is possible to consider different environmental and traffic conditions in order to produce more accurate and realistic results. The use and evaluation of external factors to influence taxi dispatch policies, in a similar way to that was shown by [6], e.g. to predict bus arrival times for specific customer requests, can be included in the algorithms for more comprehensive modelling and simulation.

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