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Agent based modelling for simulating taxi services

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Abstract

Taxi services account for a significant part of the daily trips in most of cities around the world. Due to the fact that most of the taxi markets are regulated by a central authority there is the need for developing tools for understanding the behavior of these markets to policy regulations and supporting decision makers. This paper presents an agent based model for simulating taxi services in urban areas. Taxi models presented in the literature can be grouped into aggregated, equilibrium and simulation models, with the latter having been studied to a lesser extent. Agent simulation is a powerful tool for analyzing such complex problems, where stochastic nature of the variables and spatial distribution hinders the application of aggregated models. The agent-based model is presented together with the behavioral rules of the agents and applied to the city of Barcelona, obtaining the optimum number of vehicles and performance indicators of the provision of taxi services under the dispatching operation mode.

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Keywords: Agent-based modeling; Taxi modeling; Taxi services; Barcelona

1. Introduction

Taxi services are present in most of cities around the world, accounting for a small yet significant part of the daily trips. There are three basic organizational and operational modes: stand, hailing and dispatching. Taxi markets are usually composed by the three operation modes, but when the demand for taxi services is small the stand and dispatching modes are the most usual ones. The hailing model is usually found in cities with high densities of population and a Business District zone concentrating a high percentage of the daily trips. Most of the taxi markets are regulated by a central authority, which usually monitors the performance of the taxi services provision and

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defines the policies applied to the taxi sector[1]. There is the need for developing models for supporting decision makers and understanding the behavior of these markets to policy regulations or to deregulation. Most of the models developed for analyzing the taxi market are based on econometric measurements and do not account for the spatial distribution of both demand and supply for taxi services. Only few simulation models have been developed that are able to better understand the operational characteristics of the taxi market[2,3,4,5,6,7]. The agent-based model presented in this paper is based on discrete-event simulation, modeling the behavior of multiple agents operating in a real city road network and taking their own decisions for completing as many trips as possible. Matching between drivers and users is based on event-driven interactions. An earlier version of the model has been presented in Salanova et al[8]. The new version contains more mathematical details and the application to a real case study.

The paper is structured as follows: the proposed agent based model is described in chapters two, three and four while the obtained results are presented in chapter five. Conclusions are presented in the final chapter.

2. The proposed agent-based model

The two basic inputs that define system performance and costs are the supply and the demand. The supply is determined by the number of taxis running in the city network searching for a customer, while the demand is composed by the users looking for a ride. Then, the three basic actors of the model are the city, characterized by a street network and taxi stands, the taxi drivers and the customers. The model simulates the real taxi market, where taxis are looking for users and are modeled as agents, with their own rules, goals and behavior.

2.1. The road network

Let $G(N, A)$ be a directed graph, where N is the set of nodes and A the set of links. The set of nodes N contains intersections between two links as well as trip origins and destinations while the set of links A has the following characteristics: Length; Free flow travel time; Volume-delay parameters; Flow of vehicles; Capacity.

2.2. The demand for taxi trips

Users appear following a two-dimensional geographic distribution based on the demand density functions. The demand level from each origin to each destination is generated as presented in the following equation:

$$D_{ij} = D_0 \cdot f_i \cdot f_j \quad (1)$$

Where D_{ij} is the demand for trips with origin in zone i and destination in zone j, D_0 is the maximum potential demand and f_i, f_j are the probability density functions of trips of zone i and j respectively.

2.3. Link performance function

The speed of a taxi is considered to be equal to the speed of the rest of the traffic, which is calculated using the link performance function (Sheffi[9]) presented in the equation below:

$$t_i(x_i) = t_{0_i}(1 + \alpha_i({}^{x_i}/_{c_i})^{\beta_i}) \quad (2)$$

Where t_{0_i} is the free flow travel time for the link I, α_i and β_i are the i-link parameters (normally $\alpha = 0.15$ and $\beta = 4$ for all links), c_i the capacity of the link i and x_i the flow on link i.

2.4. Pricing structures

The trip cost is calculated by applying the same logic as that of real world. In addition to the flag-drop charge, two counters (one for the time (c_t^1) and one for the distance (c_t^2)) are used for charging the cost increments depending on the speed of the vehicle at each moment, which depends on the congestion of each link.

$$c_{t+1}^1 = c_t^1 + \|(x_i, y_i)_{t+1} - (x_i, y_i)_t\| \quad and \quad c_{t+1}^2 = c_t^2 + \Delta t \quad (3)$$

When one of the two counters reaches the roof value, the related charge is added to the cost of the trip (c_t) and the counters are set to zero.

$$c_{t+1} = c_t + \begin{matrix} c^1 \; if \; c^1_{t+1} > M_1 \\ c^2 \; if \; c^2_{t+1} > M_2 \end{matrix} \quad (4)$$

Where c^1 is the distance-based charge (euros per M_1meters), c^2 is the time-based charge (euros per M_2 seconds), M_1 is the distance at which the system charges c^1 and M_2 is the duration at which the system charges c^2.

3. Logic Module

The agents run in parallel (massively parallel) following the logic modules, which have been developed for each driver class (hailing, stand and dispatching). Figure 1 shows the modules of the agent-based model. More detailed explanation of the modules and graphical representations can be found in Salanova[10].

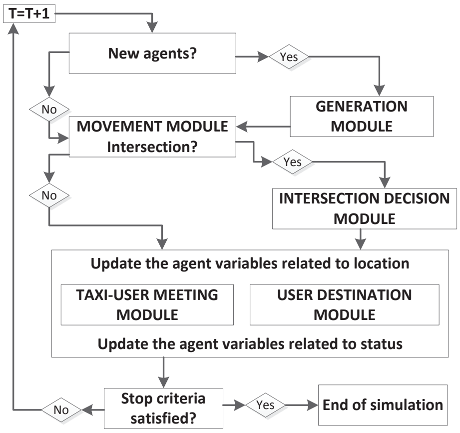

FIGURE 1 Agent-based model.

Generation module: The generation module creates the demand and the supply at each time interval based on the OD matrix and the temporal distribution of demand, which has been considered to be uniform. If neither taxis nor customers are created, the model progresses to the movement module.

Movement module: This module moves each taxi with a speed that depends on the congestion of the corresponding link. If the taxi arrives to an intersection, the intersection decision module decides the route that the taxi will follow. If the taxi continues in the same link, the position of the taxi is updated along the same link.

Intersection decision module: When a vacant or not assigned taxi reaches an intersection, it chooses where to go based on experience. When an occupied/assigned taxi or a taxi looking for a stand reaches an intersection, it follows the route between the origin and the destination of the customer, looking for the assigned customer or a taxi stand.

Taxi/user meeting module and user destination module: If an assigned taxi meets its assigned user, the taxi will pick up the user. When a taxi picks up a customer, the shortest route between the origin and the destination is calculated and recorded in the intersection decision module. If an occupied taxi reaches the destination point of its customer, the trip ends and the taxi will be free for the next time interval.

4. Analytical formulations

4.1. Taxi movement

The distance traveled within the time period is related to the duration of the time period and the congestion of the link and it is calculated as follows:

$$(x_i, y_i)_{t+1} = (x_i, y_i)_t + \frac{\Delta t}{t_j}\left[(x_E, y_E)_j - (x_S, y_S)_j\right] \quad (5)$$

Where $(x_i, y_i)_t$ are the coordinates of the vehicle i at the time interval t, $(x_S, y_S)_j$ and $(x_E, y_E)_j$ are the coordinates of the starting and ending nodes of the link j, t_j is the travel time of link j and Δt is the duration of the time interval.

4.2. Route decision

When the taxi arrives to an intersection, it chooses the next link (i), based on its actual route (if exists) or based on the experience of the driver as follows: all the alternatives (links with the origin in the intersection) are listed clockwise from A_1 to A_n, where $n + 1$ is the number of links having the intersection as their origin (u-turns are prohibited, all other turn movements are permitted). The probability of each link at an intersection depends on its attractiveness and is calculated as presented in eq. 6:

$$P(A_i) = \frac{w(A_i)}{\sum_{j=1}^{n} w(A_j)} \quad (6)$$

Where $w(A_i)$ is the attractiveness of link i calculated as the total number of trip origins in link i during the last Ns simulations, which provides learning procedure to the drivers that can simulate their experience. Results from the simulations demonstrate that $Ns = 10$ is sufficient for providing adequate network knowledge.

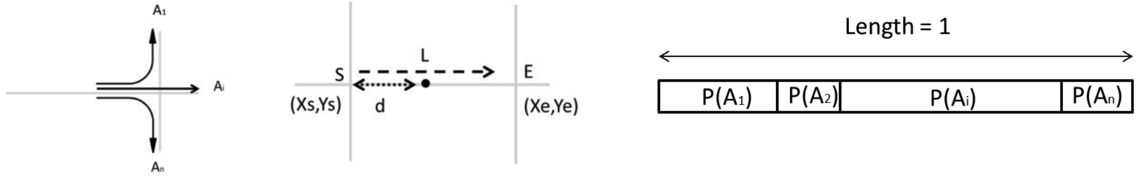

FIGURE 2. Intersection numeration (left), location of an agent (middle) and roulette for the intersection decision procedure (right).

Once the probabilities have been defined, when a taxi arrives at each ending node (intersection) a random number (Rn) is generated and the roulette rule applies for selecting the next link.

$$next\ link = A_i if \sum_{j=1}^{i-1} P(A_j) < Rn \leq \sum_{j=1}^{i-1} P(A_j) + P(A_i) \quad (7)$$

4.3. Assignment of a customer

This module is only applied to the dispatching market. When a user asks for a taxi, the nearest free taxi (taking into account the load factor of taxis) in dispatching mode is assigned to him/her (network distance is calculated using the Dijkstra algorithm (Dijkstra[11]) based on the travel time of each link). This is made by a proxy variable (x_{ij}).

$$x_{ij} = \begin{cases} 1\ if\ d_{ij} = min_k\{d_{ik}\} \\ 0\ otherwise \end{cases} \quad (8)$$

Where d_{ij} is the network distance between customer i and vehicle j

The taxi then follows the shortest path between its current location and the location of the customer using the Dijkstra algorithm (Dijkstra[11]) until the customer location is reached.

4.4. Pick-up and delivery of a customer

The customer pick-up and delivery interactions are detected by using a local coordinates system for all agents. Instead of using the geographic coordinates, the agents are located in the network by knowing the link and the distance from the origin of the link. The detection of a customer origin, destination or a taxi stand is executed then by comparing the link where each agent is located and the last two relative positions within the link. The relation between the geographical location and the one used in the agent-based model (link identity - L, distance from the origin - d) is the one presented in the equations below.

$$x = x_s + \frac{d}{\sqrt{(x_E - x_S)^2 + (y_E - y_S)^2}}(x_E - x_S)\ and\ y = y_s + \frac{d}{\sqrt{(x_E - x_S)^2 + (y_E - y_S)^2}}(y_E - y_S) \quad (9)$$

5. Case study: Barcelona

5.1. Data of the Barcelona Taxi Sector

The taxi sector has a high importance in the Metropolitan Area of Barcelona, being an important transport mode in an urban region of more than 3 million inhabitants and roughly 500 km^2 area.

The Barcelona road network consists of more than 1.600 kilometers of streets and more than 8,000 intersections. The supply side is composed by more than 20,000 links and 8,000 nodes, representing the most significant streets of the city. The lower road categories have not been taken into account, in order to reduce the processing time.

The demand side is composed by more than 270,000 recorded taxi trips during 4 years (2009-2012) provided by Center for Innovation in Transport (CENIT). The data of the taxi database have been filtered, in order to use the trips with origin and destination within the city's network, generating a total of 235,000 trips. A sample of 1,200 trips between 8 and 9 a. m. of all Tuesdays has been used for validating the model in terms of travel distance, time and cost.

5.2. Results of the agent-based model

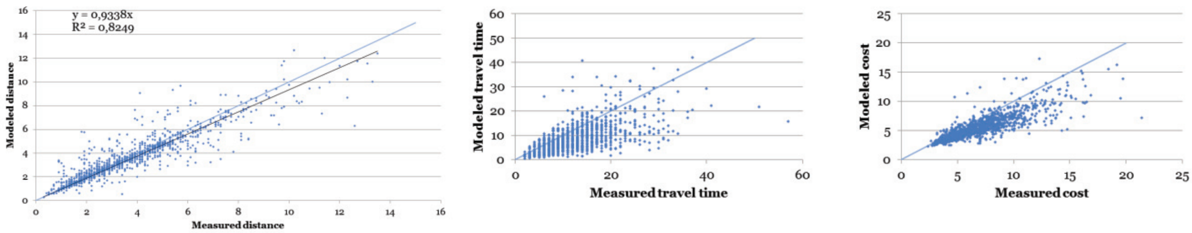

FIGURE 3 Regression results for distance, travel time and cost.

The relation between the measured and modeled travel distance shows the validity of the model. There are two issues that affect this relation, one is the detail of the network used in the model, where the lower street categories have been eliminated; the second issue is that the route chosen by the taxi driver cannot always be the shortest one. The relation between the measured and modeled travel times present more scattered results. The reason is that the model uses an average congestion factor for each link, but since this value is changing within a day and within days, it will not always be representative of the real congestion levels. In addition, the lack of the lowest category streets reduces the travel time, especially since delays at traffic lights are not considered.

The demand between 8 and 9 a. m. of all Mondays, Wednesdays, Tuesdays, Thursdays and Fridays (4.800 trips) has been used in the model and different taxi fleet sizes (between 20 and 60 taxis/hour and km^2) have been tested with the dispatching model, obtaining the waiting time and the system costs presented in Figure 4.

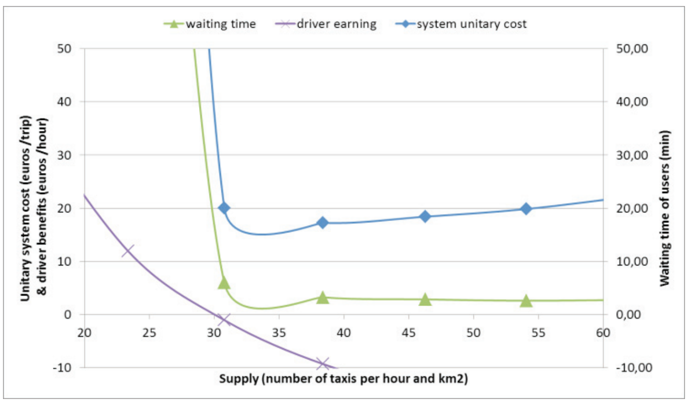

FIGURE 4 Waiting time, driver benefits and unitary costs for each fleet size obtained by the agent-based model.

It can be observed that the satisfactory number of taxis per hour and km^2 is higher than 28, since the waiting time for smaller fleets is very high due to the small number of free taxis. It can also be observed that the maximum number of taxis with positive benefits (including the drivers' salary) is 30 taxis/hour*km^2 (second best solution) since the presence of more taxis than this value will generate losses to the drivers (less salary than the expected). The optimum number of taxis taking into account the system costs (i. e. that minimize the unitary cost) is 33 – 34 taxis/hour*km^2, which can be considered as social optimum (first best solution).

6. Conclusions

An agent-based model for simulating taxi services in urban networks has been presented in detail. The model is capable of simulating the market for dispatching taxi services. One of the main limitations of the aggregated models is the assumption of uniform demand distribution over the service area, which can be overcome applying simulation models such as the one presented in this paper, which considers the spatial and temporal dimension of both the demand and the supply, providing more accurate and detailed results.

The proposed model has been applied to the city of Barcelona using real data from the network and the conducted taxi trips. The results obtained in terms of number of vehicles per hour and area have concluded that the system´s optimum number of taxis in Barcelona ranges from 33 to 34 vehicles per hour and km^2, while the maximum feasible number of taxis form the drivers point of view is slightly lower (30 vehicles per hour and km^2). With a subsidization of 4-5 euros per trip, the optimum number of vehicle-hours of the social optimum can be offered to the customers retaining drivers´ benefits, which means that the waiting time of the customers will be reduced to the one of the social optimum, while the drivers will not face losses.

Future research should focus on modeling the demand side, the taxi users as agents, providing them with decision rules when looking for a taxi service. The complexity of the methods for estimating the routes, the turning direction, the demand or the congestion level should be further increased with the use of dynamic simulation platforms. New technologies and taxi models should be tested using agent-based simulation models, which, in combination with the demand models, will provide useful insights on the impact of the new technologies in the taxi market.

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