Taxi Service Simulation: A Case Study in the City of Santa Maria with Regard to Demand and Drivers Income

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Abstract: Taxi is an already well-established service in many cities around the world. Nowadays, the service request is mainly made through mobile applications, where the user selects the desired options, including the payment method. An information system, aware of the location of taxis, associates the closest taxi to the customer request. In general, taxi allows the user to enjoy the mobility service without being directly charged by the vehicle maintenance. The vehicle owner, who can be a company or a self-employed person (frequently the taxi driver), is the one in charge with vehicle maintenance, fuel payment, etc. However, recently the taxi service has lost much of its appeal due to competing car sharing services. Thus, it is necessary to evaluate more carefully the implementation and maintenance of taxi service in cities with regard to the drivers income. This work contributes in this way. Here, the taxi service is considered, with a standardized vehicle fleet but using different vehicle types (electric, ethanol, gasoline and CNG). Given a demand and costs, a simulation is proposed to detail and evaluate the appropriate balance between drivers income and demand scheme to keep the service viable to the drivers. Simulation was performed in a real scenario, the city of Santa Maria in Southern Brazil. Input values in the simulation scenario (fuel price, demand, etc.) were chosen, based on literature, city hall documentation and Internet news, to make the simulation as realistic as possible. Simulation results shown that for feasible taxi service, the city town hall must define a maximum number of taxi licenses. The vehicle type has a large impact in the taxi driver's profit. Electric vehicles have a lower cost per km driven, but still have high cost of acquisition. Finally, if the daily traveled distance increases, the difference between electric vehicles and the others decreases, making it possible electric vehicles to become more advantageous.

1 INTRODUCTION

Public transportation is known to be of poor quality in many cities. And it is also known that there is a preference of passengers for individualized transportation due to practicality, reliability, comfort, and safety. In a recent survey (CNDL and SPC Brazil, 2017), 60.1% of respondents who own private vehicles stated that they would stop using it, if efficient public transportation alternatives existed. In fact, the success of proposals to improve urban mobility depends on mass acceptance by users (Alazzawi et al., 2018). The availability of tools and systems that bring together different city mobility options is a key point for tracking and understanding the city's mobility needs.

One way to mitigate public transportation problems is vehicle sharing services, and one of the well-established sharing services is the taxi. Nowadays, a taxi service request is typically made through a mobile application, where the costumer selects the desired options, trip origin and destination, including the payment method. In general, taxi allows the costumer to enjoy the mobility service without having to pay the necessary amounts for the maintenance of the car. An information system, aware of the location of taxis, allows the taxi closest to the customer to meet the request. The vehicle owner, who can be a company or a self-employed person (frequently the taxi driver), is the one in charge with vehicle maintenance, fuel payment, etc. However, recently the taxi service has lost much of its appeal due to competing car sharing services. Thus, it is necessary to evaluate more carefully the implementation and maintenance of taxi service in cities.

In this work, the taxi service is considered, with a standardized vehicle fleet. Given a fleet size and demand, a simulation is proposed to detail and evaluate the pricing scheme with regard to the taxi demand in a city. More specifically, we assess taxi drivers income given a city demand and with regard to different vehicle types (electric, ethanol, gasoline and CNG). Thus, questions we aim answer in this paper

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include: How many runs does the driver have to make per day/month to be worth it? Considering different energy sources to the vehicle engines, what is the source of energy most profitable?

To run the simulation, we use SUMO (Behrisch et al., 2011), a transportation network simulator with open implementation. Simulation of the service is performed in a real scenario, the city of Santa Maria in Southern Brazil. In the simulation, we assume that an information system manages the entire fleet service and associates customers with taxis, according to a given demand. Input values in the simulation scenario (fleet size, demand, etc.) were chosen based on literature, city hall documentation (Prefeitura de Santa Maria, 2014) and Internet news, to make the simulation as realistic as possible.

This paper is structured as following. Related works are described in section 2. Simulation details are described in section 3, and experiments in section 4. Conclusions are presented in section 5.

2 RELATED WORKS

In the literature, there are recent works that describe, from the point of view of computer science and simulation, the behavior and the impact of shared vehicles and taxis in transportation networks. The impact of shared vehicles in the city of Milan, Italy, was simulated with the aim of optimizing traffic by reducing the number of vehicles circulating in streets (Alazzawi et al., 2018). The simulation combined autonomous robot-taxis, with on-demand mobility services. Data used in the simulation include the number of vehicles circulation on the streets and mobile cellular network usage, to model the concentration of passengers in some areas. The simulation takes into account the following parameters: travel time, travel speed, waiting time for passengers to board the robot taxi, emission of pollutants and taxi configurations (with different amounts of seats). An algorithm matches robot-taxis and consumers. According to the authors, to eliminate congestion in Milan, it would be necessary to reduce by 30% the number of vehicles on the roads. To reduce demand at peak times, a dynamic pricing system, combined with other initiatives, could be used to motivate users to travel other time periods. According to the seats in each car, the more seats the robot-taxi has, the longer the costumers will have to wait and travel due to route deviations. Robot-taxis with around 20 seats are indicated for long distance travel. Robot-taxis with two seats allow better travel flexibility, but do not provide such a significant reduction in city traffic.

The combination of independent agent model simulators was also explored (Segui-Gasco et al., 2019). MATSim (Horni et al., 2016) generates transportation demand, associating costumers to mobility options according to their preferences and IMSim[1] provides an operational execution environment for transportation networks. By this combination, authors evaluated the impact of mobility scenarios from different perspectives: costumers, service-operators and city hall. The simulation was calibrated with data from London traffic control and MERGE Greenwich Consortium (2017-2018). Evaluated metrics were optimum vehicle fleet size, vehicle type (traditional taxis and rideshare vehicles), vehicle size (4 and 8 seating places), vehicle occupancy, as well as wait and detour times for each costumer. A main feature of the proposal was the evaluation of the trade-off between quality of service and demand. Thus, a service-operator may investigate how fleet size and energy (or even the travel duration) affect a pricing model.

Simulation was also carried out in order to compare business models for vehicle rental services (Perboli et al., 2017). The comparative analysis highlights aspects of different business models and solutions applied to improve service. Business models for vehicle rental services can be vehicle delivery-receipt or free-floating. In the delivery-receipt model, fleet does not need to be managed and relocated, but consumers need to travel to a particular pick-up and release location. In the free-floating model, vehicles can be released anywhere. The free-floating model tends to better satisfy consumers, since there is no need to travel to a particular pick-up location. However, it requires fleet management to guarantee the availability of vehicles in some locations, i.e., the company needs to take vehicles that are in points of less interest to places of higher demand. In this scope, different costumers profiles can be defined: commuters (those that travel from home to work), professional and casual. These profiles are randomly assigned to routes. In addition, different vehicle types can be used, such as electric and combustion vehicles. With regard to the fleet management, electric vehicles need more effort when compared to combustion vehicles, due to recharging time and the need to find a charging point.

Efficient route optimization was proposed as an opportunity to increase drivers revenues (Li et al., 2017). A vacant taxi represents wasting of both fuel and taxi driver time. Moreover, inefficient routing can create more traffic in the city and consequently more pollutant are emitted. Therefore, the Markov Decision Processes can be used to maximize drivers revenues by the application of an efficient routing ap-

[1] http://www.talon.world

Table 1: Summary of related works.

Authors	Vehicle type	City	Simulation platform
Alazzawi et al. 2018	Autonomous and Conventional	Milan	SUMO/TraCI
Segui-Gasco et al. 2019	Autonomous	London	MATSim/IMSim
Perboli et al. 2017	Conventional	Turin	none
Li et al. 2017	Conventional	New York	none
This work	Conventional	Santa Maria	SUMO/TraCI

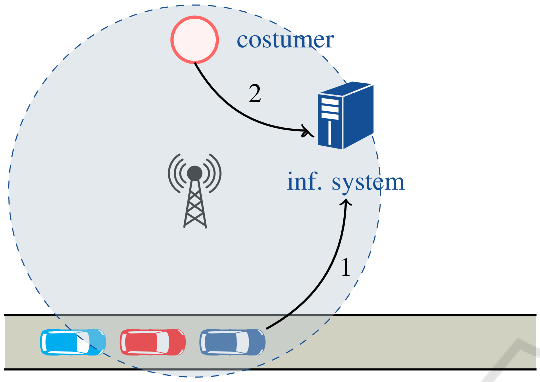

Figure 1: An information system manages taxi fleet and answers client requests.

proach. Data from the taxi service from New York City was used in the experiments. Simulation results shown that the proposed model can collaborate to improve drivers income since it reduces the time a costumer needs to find a vacant taxi.

Related works are summarized in Tab. 1. Unlike Alazzawi et al. and Segui-Gasco et al., which simulate the impact of using shared vehicles in cities, seeking to reduce the number of vehicles in circulation here, such as Perboli et al., we are focusing on the provider side. In particular, in this work we are focusing on the drivers income. Unlike Perboli et al. and Li et al., and as in Alazzawi et al. and Segui-Gasco et al., we use simulation to investigate how different parameters impact the expected results and drivers income.

3 PROPOSED SIMULATION

In this work, taxi service is considered in a simulation to detail and evaluate the drivers income in the end of journeys. Fig. 1 depicts the required Information System (IS) to support this service. Taxis publish their locations in the IS (1) and customers make requests (2). The IS allocates taxis according to the location of the customers.

The simulation scheme, implemented in SUMO traffic simulator (Behrisch et al., 2011), is depicted in Fig. 2 and consists of three main parts: scenario, input

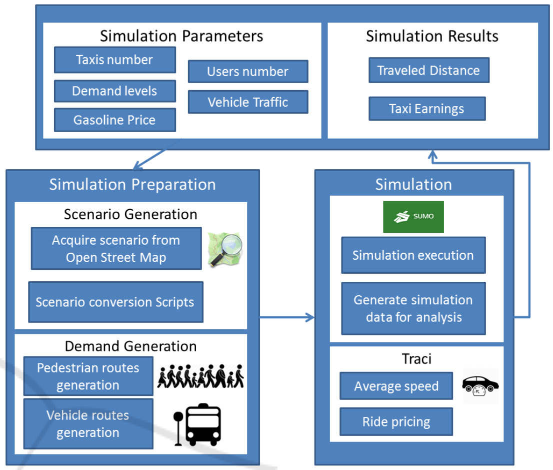

Figure 2: Simulation scheme.

parameters and results. The scenario presents the map of the geographic region to be simulated. The map has tow layers: a static layer and a dynamic layer. The static layer is previously obtained through a cut in the map of Open Street Map[2], exported in .osm format.

Using the SUMO Simulator script, the osm file is converted into a transportation network, a scenario formatted to be simulated by SUMO. The network is composed by edges (street corners) and connections between edges (street blocks). In the scenario conversion, the path to the .osm file is indicated and additional parameters, such as the generation of sidewalks along the roads can also be informed. After completing the stage of generating the map scenario, the output is a file in .net.xml format (i.e., the description of the transportation network). This map runs in a server in which other simulation parameters can be configured. For instance, the duration of the simulation.

The simulation parameters are sent to the simulation server via Traffic Control Interface (TraCI) (Wegener et al., 2008). On the server side, the parameters are used by the simulator generate the demand (i.e., the taxi runs) that associate costumers and taxis. Using the randoTrips.py script, provided by SUMO, random trips are automatically generated, both for costumers and vehicles. We have the possibility to define

[2] https://www.openstreetmap.org

parameters for this script such as:

- maximum distance that a costumers can walk,
- probability that a trip can start at the scene, and
- vehicle intensity flow and costumers/pedestrians flow and, in addition, to establish which vehicle a costumer can choose to complete her/his journey trip.

The randoTrips.py script generates a file in the .rou.xml format with valid routes to be used by SUMO. The next step is running the simulation. The SUMO simulations are presented by a .config file, which contains the name of the file with the scenario, .net.xml, of the additional items, .add.xml and of the routes, .rou.xml. When loading the simulation, SUMO searches for the information in the files provided. Also in the .config file, it is possible to define the output to be presented after the simulation.

With regard to our simulation, some output information can be obtained automatically by SUMO and include, for example, the vehicle average speed. However, some specific routines have been coded, since SUMO does not implement all the necessary routines required in the scope of this work.

In general, simulation results that we are mainly investigated in our scenario include:

- gross and net drivers incomes, with regard to the number of runs, and
- drivers incomes, with regard to the vehicle type (engine).

To summarize, the developed simulation receives the data from the simulation files, and presents the resulting values that we discuss in more details in the section 4.

Parameters in our simulation defined according to real-world available data to drivers/taxis include:

- price of the fuel, vehicle model, etc.,
- monthly rental amount and vehicle consumption related to the taxi model,
- formula to compute the payment for a taxi run, which is composed by a fixed amount and the amount per km traveled,
- working hours for drivers, and
- number of available taxis.

Reference values are shown in Tab. 2. These values directly influence the driver's revenue. Parameters that can be defined in the simulation, using city/traffic information, according to real-world observations include:

- intensity of the vehicles flow in the scenario to be defined by counting the number of vehicles in a given simulation interval,
- average travelled distance, defined according to the behavior of costumers in that region, and
- demand for runs, which can be calibrated using information provided by city hall.

At the end of the simulation, the travel cost can be computed and, therefore, the drivers income. The travel cost depends on the period of the day and the distance driven by the taxi driver.

4 EXPERIMENTS

In this section, we first present the scenario setup taking into account the city of Santa Maria, then we describe the demand generation process, i.e., the addition of costumers in the simulation interested in riding a taxi. In the following, we describe the simulation process, and finally, we focus on the simulation results of our experiments.

4.1 Scenario Setup

In Santa Maria downtown, there are 14 taxi stops which are part of our simulation map. We assume that half of these points have 2 taxis and the other half have 3 taxis, resulting in a total of 35 taxis in the simulation. Fig. 3 presents a screenshot of our simulation environment in SUMO, with a set of streets in the center of Santa Maria city.

In general, the city has a very irregular layout in its streets. Each red diamond in the green map represents a taxi station. Each blue square represents a pick up or an unboarding point, manually chosen for this simulation.

4.2 Demand Generation

The pedestrian (costumer) demand in our simulation is generated by *PersonFlows* routine from SUMO, in which people are inserted at different points on the map. This component periodically generates pedestrians in a defined location. Pedestrians follow a predefined route to reach their destination, being able to get around on foot or using a taxi vehicle. Other vehicles are not inserted in the simulation, but the effect on the traffic behaviour of the other vehicles (bus, trucks and private vehicles) is due to the configured speed limitation that the taxi can develop in the city.

The simulation in SUMO takes place so that the vehicles present in a routing list are inserted in the

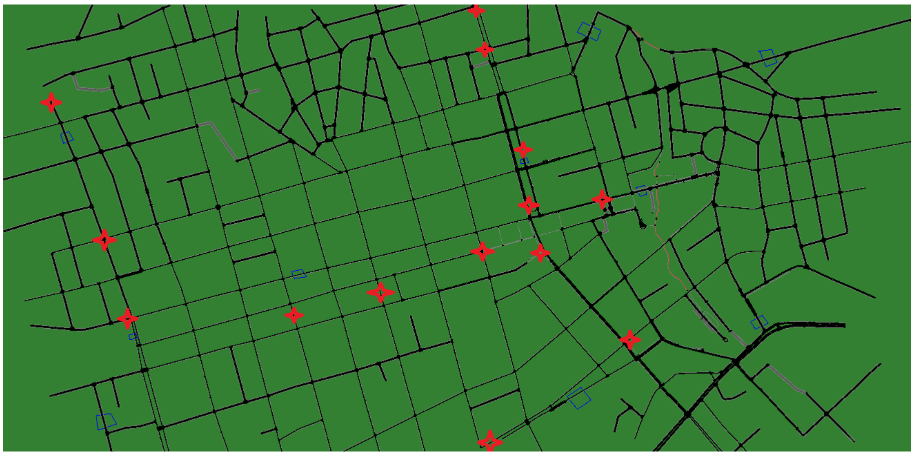

Figure 3: Screenshot of SUMO simulation environment.

simulation at the given time and after completing the route these vehicles are removed from the simulation. In order to make it possible for a taxi to perform multiple trips during the simulation, it is necessary to use an auxiliary script to generate new routes for this vehicle during the simulation. The script used for this purpose is the *Demand Keeper*. This script is part of the Net Populate[3] project, a set of scripts for generating and controlling demand in SUMO experiments. Finally, *Demand Keeper* call is used in conjunction with the TraCI interface, which allows to interact in real time with SUMO.

4.3 Simulation Parameters and Drivers Income

In the simulation, taxis are set to be in service from 8:00 a.m. to 4:00 p.m. Thus, we consider each taxi service operates with three driver shifts per day, and each taxi journey has the duration of 8 hours. Each step of the simulation represents one second of time, so the total number of steps in the simulation is 28,800 (i.e., 8 simulation hours). We run the simulation four times, each time with an average demand for taxi rides (i.e., 5, 10, 20 and 30 rides/day in average per taxi). These values for the number of runs were chosen for only 5 runs per day per driver to reflect a lockdown scenario due to the new coronavirus pandemic, for instance, and 30 runs would be a more optimistic scenario. The number of costumers in each simulation is modeled in order to create an average number of rides per taxi in each simulation run. For simulation purpose, we consider a standardized vehicle fleet.

Simulation parameters are summarized in Tab. 2. Each taxi run starts with an initial value called flag B_i, in which $i = \{0, 1, 2\}$, given the day of the week and time, and the cost per kilometer traveled. The values charged by the taxi drivers are stipulated by the city hall (Araujo, 2020). Driver expenses also include the fuel consumption per litre C, the maintenance cost per kilometer traveled M, insurance expenses I, and vehicle loan P.

Table 2: Simulation parameters.

Symb.	Parameter	Value
B_0	flag-down fare	5.64 BRL/km
B_1	flag-down fare 1	3.36 BRL/km
B_2	flag-down fare 2	4.03 BRL/km
G	fuel price	4.50 BRL/L
C	fuel consumption tax	10 km/L
M	vehicle maintenance	0.20 BRL/km
I	annual insurance	2,000.00 BRL
P	vehicle loan (monthly)	600.00 BRL

In addition to the parameters of Tab. 2, we add that taxis move at an average speed of 36 km/h. For the costumer-taxi association, we use the algorithm implemented by SUMO where the taxi closest to the costumer wins the run. In the simulation, we calculate the gross income average obtained by taxis drivers during the 8 hours of work, using Eq. 1 to compute the individual Gross Income (GI) for each taxi driver:

$$GI = R \cdot B_i + D_t \cdot B_i, \quad (1)$$

where R means taxi runs for the driver and D_t means the total of the traveled distance (km). We also compute the Net Income (NI) per taxi driver, using Eq. 2, which is obtained by subtracting the vehicle expenses from the gross amount, given by:

$$NI = GI - D_t \cdot \frac{G}{C} - \frac{P}{30} - \frac{I}{365}. \quad (2)$$

[3]https://github.com/maslab-ufrgs/net-populate

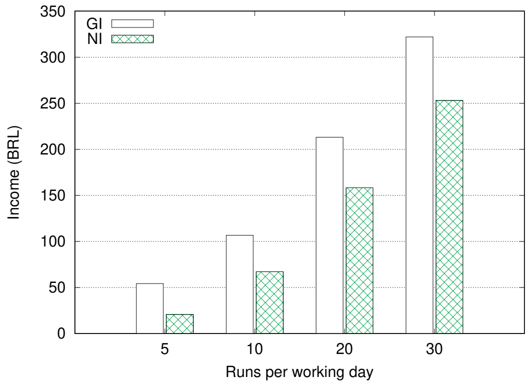

Figure 4: Values for GI and NI obtained in the experiment using the parameters described in the Table 2.

We do not consider the amount paid in maintenance of the vehicle in our equations, but this value should be considered in a future study. In fact, some values such as maintenance, insurance and financing can be shared by drivers who drive the same vehicle.

In the following, we highlight the simulation results of computing net and gross incoming and for taxi drivers. We evaluate two different aspects: simulation results with regard to drivers income and simulation results with regard to the vehicle energy source.

4.4 Simulation Results with Regard to Drivers Income

Here we assess the drivers income in different scenarios, from the pessimistic to the more optimistic. Tab. 3 shows the simulation results for the average travelled distance for costumers and drivers, given different amounts of taxi runs.

Table 3: Travelled distance with regard to costumers and total average distance, per driver.

Taxi runs (R)	Costumers dist. avg. (km)	Drivers total dist. avg. (km)
5	7.7	12.6
10	14.9	21.5
20	29.8	45.5
30	45.2	65.8

In our simulation, the average distance traveled in each trip is 1.5 km. In the most pessimistic scenario (5 runs), the driver drives only 12.6 km per day, and in the most optimistic scenario, the driver drives 65.8 km per day. Considering both scenarios (pessimistic and optimistic), Fig. 4 depicts the (average) gross and net values (GI and NI) obtained by the drivers per day depending on the number of runs performed.

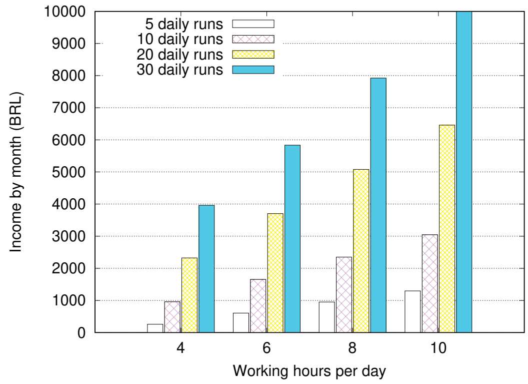

Figure 5: Monthly NI based on working hours.

In Fig. 5, income values are plotted by month, with regard to different number of working hours. We, in particular, extrapolate the depicted values to 10 working hours. It is clear that the more the driver works, the more she/he earns. However, if demand is not enough, the driver is unable to pay the service costs.

From the simulation results depicted in Figs. 4 and 5, we may conclude that it is impracticable to provide taxi service in scenarios where the demand for taxi runs is only 5 daily. Only 5 runs results in a monthly gain of 952.24 BRL, less than the minimum wage currently in force by Brazilian legislation, given the law number 14,013 (Brazil, 2020), which is 1045.00 BRL. In contrast, if the taxi driver works in periods with demands of 10 daily taxi runs, it is possible to guarantee to the taxi driver an income above the minimum wage working only 4 hours a day.

Given these results, it is important to highlight the importance of balancing the amount of taxi licenses allowed by the city hall and demand, in order to guarantee a sufficient number of vehicles to serve passengers while allowing the activity to remain profitable for taxi drivers. It is also important to observe that in pessimistic scenarios, such as lockdown scenarios, for instance, government contributions need to be considered for taxi service providers.

Another important observation is about the deviation pattern we computed to the drivers income. In our experiments, the deviation was quite high, as the routing algorithm always ends up choosing the same taxis that are closest to the passengers while other taxis barely manage to run. For scenarios with high demand, there is a greater turnover between taxis and traveler origin points and destination points. Therefore, a new algorithm to associate taxis and pedestrians needs to be proposed in future work.

4.5 Simulation Results with Regard to the Vehicle Energy Source

In addition to demand, another factor that impact the taxi drivers income is the vehicle energy source. Here, we consider three types of vehicles, according to the energy sources:

- flexible-fuel (flex) vehicles, which are capable of running with gasoline and ethanol,
- bi-fuel vehicles, which engines are capable of running on two fuels: a internal combustion engine (with gasoline or diesel), and the other alternate fuel such as natural gas (CNG), and
- electric vehicles, which are charged through the electric power network.

In order to keep the vehicle in good condition, the taxi driver changes her/his vehicle for a new one every 5 years. Assuming that the taxi driver has a flex vehicle that is completing 5 years of use and needs to change for a new one, she/he can choose from the three types of vehicles mentioned above.

To purchase a new vehicle, we consider that the driver current vehicle is worth 30,000.00 BRL, which is used as an input for financing. The financing rate is 1% monthly on average and the financing term is 60 months. We emphasize that in Brazil, new vehicles purchased by taxi drivers have tax incentives that resulting in a value up to 30% less than paid by an ordinary consumer. We also considering that, in case of CNG as energy source, typically, a conversion kit is installed in the taxi and allows an originally flex vehicle to be supplied with CNG. The cost of installing a CNG kit in a vehicle is 5,000.00 BRL on average.

To allow the evaluation of energy source, we consider other values described in Tabs. 4 and 5. Tab. 4 shows the different types of vehicles and the respective installment to be paid. For flex vehicles, the price of the Renault Logan was considered, presented by the manufacturer's website in October 2020, for sale with exemption for taxi drivers. The electric vehicle chosen to the simulation was the one with the lowest value found for sale currently in Brazil, JAC iEV20. The price we used was according to the manufacturer's website in October 2020, considering an exemption of 30% of the value for taxi drivers.

The choice of vehicle type in order to maximize driver profit must take into account acquisition cost and the cost per kilometre for travel. Tab. 5 presents vehicles comparison cost per travel kilometer. Values for electric vehicle consumption we consider here are based on the literature (Besselink et al., 2011). Fuel price here used is based on the price national survey carried out by the Brazilian National

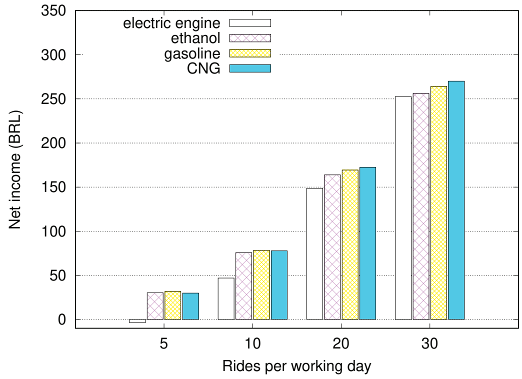

Figure 6: Drivers NI with regard to energy source.

Petroleum Agency[4], relative to October 2020. In general, flexible-fuel vehicles have higher maintenance costs when compared to electric vehicles (Alexander and Davis, 2013). In contrast, electric vehicles have a considerably high acquisition cost when compared to vehicles with internal combustion engines.

Fig. 6 depicts our simulation results to drivers NI based on energy source. Among the energy sources we analyzed, it is possible to state that CNG maximizes the NI of taxi drivers in the scenarios of 20 and 30 daily taxi runs and ties with gasoline in the scenario of 10 runs. For 5 daily runs, gasoline provides the highest profit, with CNG being affected in this scenario by the cost of installing the conversion kit, which reflects in a higher installment value. Although ethanol has a lower cost per liter than gasoline, its autonomy has resulted in a lower NI than gasoline in all scenarios.

Actually, the use of electric vehicles is not profit to taxi drivers when there are only 5 daily runs, but as the number of daily runs increases, the difference with regard to the profit in relation to other energies decreases. With 30 daily runs, the electric vehicle has a profit similar to a vehicle with ethanol. Although it has the lowest cost per km traveled among all the considered energies, the electric vehicle still has high acquisition cost that results in large fixed expenses, harming the taxi driver's NI.

5 CONCLUSIONS

This work proposed the evaluation of the taxi service from the point of the view of the taxi driver (income). The evaluation was conducted with simulation support, and considering an information system to deal with entire taxi fleet service and to associating customers with taxis. From a real scenario, a simulation

[4] http://preco.anp.gov.br

Table 4: Estimated vehicle acquisition cost.

Vehicle type	First installment (BRL)	Rate % a.m.	Term (months)	Final price (BRL)	Installment (BRL)
Electric	30,000.00	1	60	98,000.00	1,500.00
Flex	30,000.00	1	60	42,000.00	267.00
CNG	30,000.00	1	60	47,000.00	378.00

Table 5: Fuel comparison costs, given in kilometre per litre (Total) with regard to vehicle maintenance.

Vehicle type	Price	Mileage	Maint. (BRL/km)	Total (BRL/km)
Electric	0.50 (BRL/kWh)	0.2 (kWh/km)	0.10	0.20
Flex (ethanol)	4.00 (BRL/L)	7.0 (km/L)	0.20	0.77
Flex (gasoline)	4.50 (BRL/L)	10.0 (km/L)	0.20	0.65
CNG	3.72 (BRL/m^3)	12.3 (km/m^3)	0.20	0.50

from a service journey was performed.

Simulation results shown that for the taxi service to be feasible for drivers, the city town hall must define a maximum number of taxi licenses in order to ensure that the average daily travel per driver is not less than 10 runs. Smaller values mean that the monthly taxi gain does not reach the minimum wage established by the Brazilian government. The minimum number of taxis allowed in a region must consider the quality of the service, so as not to compromise the availability of the service to costumers.

Vehicle type has a large impact in the taxi driver's profit. Simulation results showed that although electric vehicles have a lower cost per km driven, the high cost of acquisition made the taxi driver's net profit result in lower values than other types of vehicle. Finally, we mention that as the daily traveled distance increases, the difference between electric vehicles and the others decreases, making the new technology to become more advantageous.

REFERENCES

Alazzawi, S., Hummel, M., Kordt, P., Sickenberger, T., Wieseotte, C., and Wohak, O. (2018). Simulating the impact of shared, autonomous vehicles on urban mobility - a case study of Milan. *SUMO 2018- Simulating Autonomous and Intermodal Transport Systems - EPiC Series in Engineering*, 2:94–110.

Alexander, M. and Davis, M. (2013). Total cost of ownership model for current plug-in electric vehicles. In *TECHNICAL REPORT 3002001728. Electric Power Research Institute (EPRI).*

Araujo, M. (2020). Prefeitura de Santa Maria concede, após três anos sem aumento, reajustes nas tarifas de táxis. https://www.santamaria.rs.gov.br/noticias/20395-prefeitura-de-santa-maria-concede-apos-tres-anos-sem-aumento-reajustes-nas-tarifas-de-taxis.

Behrisch, M., Bieker, L., Erdmann, J., and Krajzewicz, D. (2011). SUMO - simulation of urban mobility (an overview). In *Proc. 3rd Int. Conf. on Advances in System Simulation (SIMUL 2011)*, pages 63–68.

Besselink, I. J., Hereijgers, J., Van Oorschot, P., and Nijmeijer, H. (2011). Evaluation of 20000 km driven with a battery electric vehicle. *EEVC - European Electric Vehicle Congress, Bruxelles*, pages 1–10.

Brazil (2020). Lei nº 14.013, de 10 de junho de 2020.

CNDL and SPC Brazil (2017). *Hábitos e Prercepções sobre a Mobilidade Urbana no Dia a Dia dos Brasileiros*. SPC Brazil.

Horni, A., Nagel, K., and Axhausen, K. W. (2016). *The multi-agent transport simulation MATSim*. Ubiquity Press London.

Li, P., Bhulai, S., and van Essen, J. T. (2017). Optimization of the revenue of the New York city taxi service using markov decision processes. In *Proc. 6th Int. Conf. on Data Analytics*, pages 47–52, Barcelona (Spain).

Perboli, G., Ferrero, F., Musso, S., and Vesco, A. (2017). Business models and tariff simulation in car-sharing services. *Transportation Research Part A: Policy and Practice*, 115.

Prefeitura de Santa Maria (2014). Lei municipal nº 5.863, de 09 de maio de 2014.

Segui-Gasco, P., Ballis, H., Parisi, V., Kelsall, D. G., North, R. J., and Busquets, D. (2019). Simulating a rich ride-share mobility service using agent-based models. *Transportation 46*, pages 2041–2062.

Wegener, A., Piorkowski, M., Raya, M., Hellbrück, H., Fischer, S., and Hubaux, J.-P. (2008). TraCI: An interface for coupling road traffic and network simulators. *11th Communications and Networking Simulation Symposium (CNS)*, pages 155–163.