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ALLOCATION OF CHARGING STATIONS IN AN ELECTRIC VEHICLE NETWORK USING SIMULATION OPTIMIZATION

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ABSTRACT

Growing concerns with environmental issues have led to the consideration of alternatives to urban mobility. Among available options, electric vehicles have been considered in advantage in terms of sustainability as well as emission of pollutants. This work presents an optimized solution to allocate electric charging stations based on a simplified traffic model for urban mobility and vehicles' energy consumption. It is particularly interesting for prototypes and initial studies on deploying charging stations. A discrete event simulation is built in Arena and an optimization is implemented with OptQuest package. The simulation model considers stochastic information whose characterization is difficult to obtain for particular cases. The results show that there are several variables that can be correctly determined to avoid prohibitive costs in the deployment of charging stations.

1 INTRODUCTION

A new generation of urban vehicles powered by electric engines can now be seen in different cities around the world. According to Frade et al. (2011), electric vehicles (EV) are ecologically friendly as the emission of carbon dioxide is very low compared to the internal combustion motor vehicles. They also have the advantage of being more silent – reducing noise pollution in cities. Electric vehicles are one of the most promising alternatives in order to reduce carbon dioxide in the transportation system. Even a small proportion of EV's in transportation network could lead to a substantial reduction in emissions (Tikka et al. 2012).

However, the autonomy of these vehicles is still very limited by their battery capacity. Charging stations are required both at home and in public areas to meet the battery recharge demand of these vehicles. Chen, Khan and Kockelman (2013) mention the logistics of recharging outside home as the major issue for long-term success of the EV's.

Although recent in the literature of EV's, solutions to deal with refueling problems for all types of motor vehicle are fairly found. For example, Lin, Gertsch and Russell (2007) minimize the vehicle refueling cost using fuel stations in a fixed route. Lin (2008) suggests an algorithm for simultaneously finding the optimal path and refueling policy in a network.

These problems are generally classified as Flow Interception Facility Location Problems (FIFLPs) first studied by Hodgson (1981). According to Wen et al. (2013) it is assumed that the demand of a path in FIFLPs can be fully satisfied by one facility located anywhere on the path. Other applications were proposed, such as the location of police inspection stations (Hodgson, Rosing, and Zhang 1996) and road detecting sensors (Liu and Danczyk 2009). Kuby and Lim (2005) formulated a new model that maximizes the total refueled flow based on combinations of pre-planned station. Upchurch, Kuby and Lim (2009) extended this model considering the capacity of facilities in which a station can refuel only a limited number of vehicles. Hess et al. (2012) provides a model for electric vehicles and aim to find a solution for optimal placement of charging stations using a genetic programming.

This work proposes to optimize the location of charging stations considering a simplified model of urban traffic restricted to certain routes which is different from those presented before. A simulation optimization approach is taken where candidate solutions are generated by a proprietary metaheuristic based optimization package and evaluated by simulation. Uncertainty information is directly considered through stochastic variables as for urban traffic or indirectly by defining a penalty factor as for cross traffic between routes which affects the vehicles' energy consumption.

The paper is organized as follows. Section 2 describes the problem considered. The simulation model is presented in Section 3. The results for four different scenarios are shown in Section 4 and conclusions are presented in Section 5.

2 PROBLEM DESCRIPTION

According to the International Energy Agency (2013), there is a special area of R&D to develop fundamental activities for countries seeking improvements in the technological innovation market of energy. However, especially in third world countries the investments in transportation are not yet enough.

Figure 1 shows the investment made from 2008 to 2012 by the Electric Vehicles Initiative (EVI) (a multi-governmental forum dedicated to accelerating the introduction and adoption of electric vehicles worldwide) in urban transport of many countries.

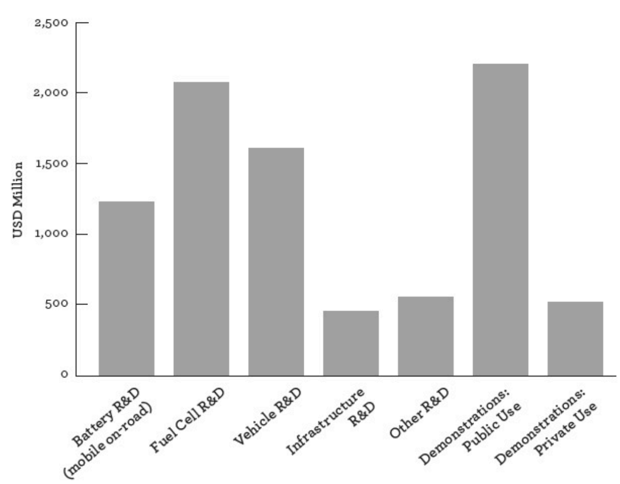

Figure 1: R&D in transportation from 2008 to 2012 by EVI (International Energy Agency 2013).

These numbers are underestimated as some data is not available for all countries. Nevertheless, it should be noticed that there is still a large effort to develop battery and fuel cells which correspond to the top cost in an EV. In contrast, there is a lack of financing in infrastructure. Morrow, Karner and Francfort (2008) show that investing in infrastructure rather than investing in higher capacity batteries can reduce the total cost of a transportation system based on EV. A challenge for improving this infrastructure is determining the right location of charging stations, as vehicles should be able to circulate and recharge their batteries in acceptable time not compromising their autonomy (Hess et al. 2012).

The problem considered in this paper can then be formulated as an optimization problem. Charging stations should be placed at particular locations along to a route or set of routes allowing vehicles to be charged before their batteries are empty while reducing the corresponding waiting time for recharge. This problem depends on several variables such as consumption of each vehicle for different paths and traffic experienced on urban roads.

The methodology used in this work is known as optimization simulation (Fu 2002), where a discrete event simulation provides fitness for candidate solutions in a metaheuristic optimization approach. In our work, the simulation is carried out by Arena (Kelton 2007; Sadowski and Bapat 1999) associated with the commercial software package OptQuest for optimization. OptQuest is an optimization package that utilizes evolutionary methods and scatter search (Kleijnen 2007) to find optimal or near-optimal solutions. This tool works in cycles of optimization, simulation and review of the proposed solution until no significant improvement is obtained. This solution is then considered the best solution (Fu 2002). These commercial packages has been chosen due to the extensive support material found in Internet and the cumulative experience obtained by the authors over the last years. The steps followed to obtain a suitable solution is depicted in Figure 2.

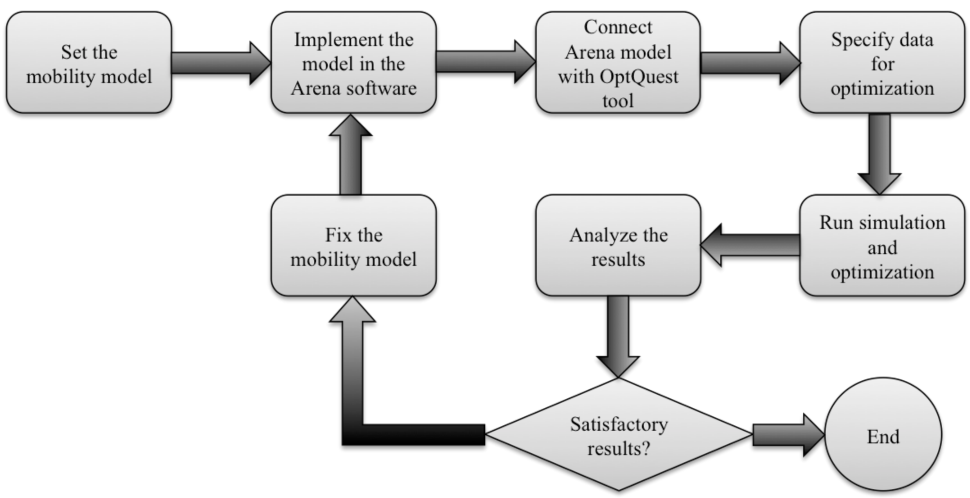

Figure 2: Simulation and optimization process.

The first step is to define a model for urban mobility, selecting a particular urban area. After implementing this model in Arena (step 2), the necessary data for optimization have to be specified, i.e., the objective to be optimized, control variables and constrains. The simulation is run followed by optimization. If results are satisfactory, the process ends. If not, other possibilities are tried by modifying parameters like maximum number of active stations or station capacity for charging more than one vehicle at the same time. The process returns to step 2 until satisfactory results are obtained.

3 SIMULATION MODEL

A simulation model is developed assuming a simplified representation of traffic in lanes. This example has been obtained from a urban area of Curitiba, Brazil. Three different paths are considered as shown in Figure 3. They represent favorite paths in the urban area, where is expected to have higher concentration of vehicles. Only a certain number of stations is selected for charging as their deployments are usually expensive.

The variables used in the simulation and optimization are presented in Table 1. They have chosen to represent energy consumption of vehicles during their run.

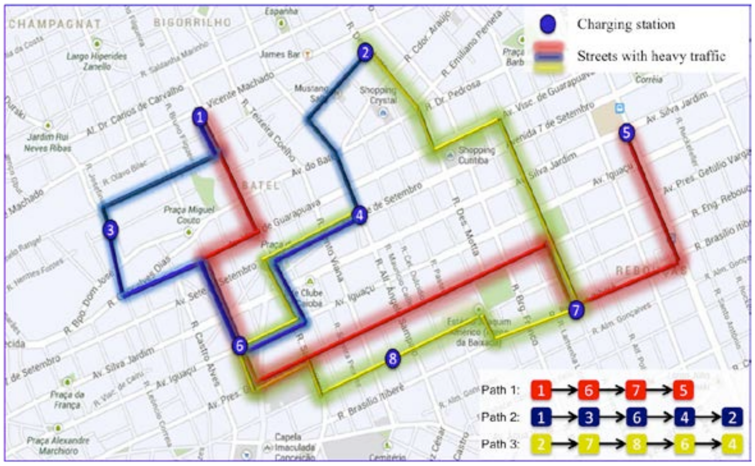

Figure 3: Map of the three paths considered in the urban area of Curitiba, Brazil

Table 1: Simulation variables

Variable	Description
Energy	Current power level of each vehicle.
NoEnergy	Number of vehicles that ran out of power during the simulation horizon.
ActiveStation	Binary decision variable indicating which charging station is active.
Distances	Matrix of distances between charging stations.
RechargeTime	Average waiting time in queue for recharge.
TrafficFactor	Parameter that represents traffic level on each section between stations.

The variable *Distances* takes values from Table 2 which shows distances in kilometers between two stations.

Table 2: Distances in kilometers between two stations

	St.1	St.2	St.3	St.4	St.5	St.6	St.7	St.8
St.1	0	0	2	0	0	4.5	0	0
St.2	0	0	0	3	0	0	5	0
St.3	2	0	0	0	0	3	0	0
St.4	0	3	0	0	0	3.5	0	0
St.5	0	0	0	0	0	0	4	0
St.6	4.5	0	3	3.5	0	0	5	2.5
St.7	0	5	0	0	4	5	0	2.5
St.8	0	0	0	0	0	2.5	2.5	0

The variable *TrafficFactor* is introduced to penalize sections between stations that are shared by two or more paths according to Table 3. This variable assumes values that represent sharing of sections between two stations. For example, TrafficFactor receives value 1 between stations 2 and 4 as this section is only used by path 2. However, TrafficFactor is 1.25 between stations 1 and 3 as 25% of this section is shared by paths 1 and 2. Similarly, TrafficFactor is 1.50 between stations 1 and 6 as 50% of this section is shared by paths 1 and 2. This variable capture delays caused by cross traffic due to vehicles from different paths. These delays are taken into account when computing vehicles' energy consumption.

Table 3: Variable TrafficFactor between stations

	St.1	St.2	St.3	St.4	St.5	St.6	St.7	St.8
St.1	0	0	1.25	0	0	1.50	0	0
St.2	0	0	0	1	0	0	1.20	0
St.3	1.25	0	0	0	0	1.40	0	0
St.4	0	1	0	0	0	4	0	0
St.5	0	0	0	0	0	0	1	0
St.6	1.50	0	1.40	2	0	0	1.40	1.45
St.7	0	1.20	0	0	1	1.40	0	1
St.8	0	0	0	0	0	1.45	1	0

Whenever a vehicle arrives at a charging station, the procedure shown in Figure 4 is taken.

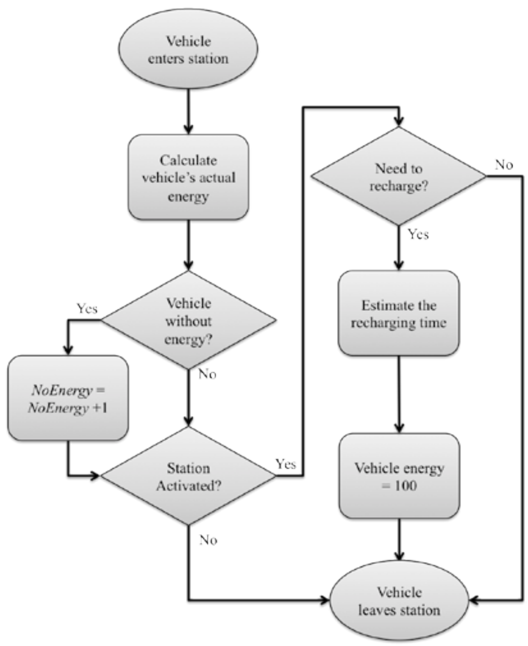

Figure 4: Flowchart for simulation of a vehicle at a charging station.

According to Figure 4, the current battery energy ranging from 0 to 100 units is computed from (1) upon arriving at the station. The energy spent is proportional to the distance run between current and last station taking into account a penalty factor (*TrafficFactor*) due to traffic experienced on this section. The variable *Dist2EnergyFactor* is a scalar that relates the distance traveled with the energy consumed.

$$Energy(i) = Energy(i) - [TrafficFactor(LS,CS) * Distances(LS,CS) * Dist2EnergyFactor] \quad (1)$$

where, $i = 1,2,\cdots N$ is the vehicle identification, *LS* is the last station visited and *CS* is the current station. In case a vehicle does not have enough energy to get from previous to current station, a counter variable is incremented according to (2). This variable is used as a constraint in the optimization process.

$$if\ Energy \leq 0, then\ NoEnergy = NoEnergy + 1 \quad (2)$$

The next step is to test if the station is active. If so, then the need for recharging is checked. The following condition is then evaluated in (3) where *NS* is the next station for vehicle *i*.

$$if\ Energy(i)\ \leq\ [TrafficFactor(CS, NS)\ *\ Distances(CS, NS) *\ Dist2EnergyFactor] \qquad (3)$$

If the vehicle needs to recharge, then it will enter the charging station. Recharge time is related to the current energy level of the battery. It is defined by a normal probability with average of *100 - Energy(i)* seconds and standard deviation of 10 seconds. This interval of 10 seconds represents external factors that may occur during charging such as waiting for the attendant or paying for service. It is assumed that all vehicles are fully recharged after leaving a station.

The optimization is performed by OptQuest with decision variables, constraints and cost function defined as:

- Decision variable: the binary variable *ActiveStation* for each station which can be set or unset according a particular station is active or not (1 or 0, respectively);
- Constrains:
  - No vehicle may run out of energy during the journey (i.e., *NoEnergy* = 0);
  - The maximum number of active stations is three (investment limited in infrastructure);
- Cost function: (minimize) the total waiting time in charging stations.

4 RESULTS AND ANALYSIS

This section presents the results obtained for four different scenarios. The first two scenarios have three and two active stations, respectively. The third scenario has two active stations with one station allowing to charge more than one vehicle simultaneously. The last scenario is the same of the third but the number of vehicles is increased to evaluate the performance of charging with two stations subject to higher incoming traffic.

Incoming traffic is modeled by a constant rate which changes hour by hour during the day as shown in Figure 5. This pattern of traffic is currently observed in many urban areas due to people going to and returning from work as well as opening and closing hours of commercial buildings. It should be noticed that time of traffic peak occurs between 17h and 19h with up to 1,000 vehicles per hour. This traffic represents all vehicles entering into the system with equal distribution among different paths.

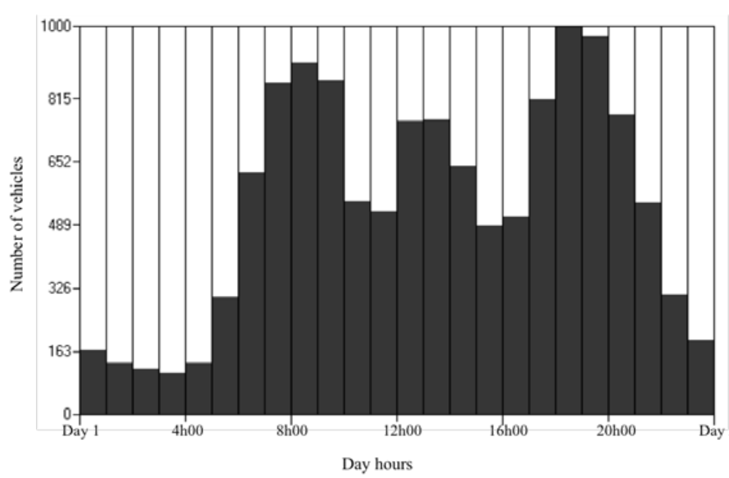

Figure 5: Incoming traffic during the day

It is also assumed that a vehicle starting its path has an initial energy characterized by a triangular probability function with parameters 80%, 95% and 100% for the minimum, most likely and maximum values, respectively, as we assume that most vehicles recharge batteries at night.

The first scenario considers only three active charging stations among eight available positions. Table 4 presents the results obtained. They are shown with 95% confidence level for total waiting time and queue lengths in each active station. Optimization is set to evaluate at most 50 simulations with 10 replications for each simulation. OptQuest has reached the best result for simulation 22 (see Figure 6) with active stations 6, 7 and 8.

Table 4: Results for the first scenario

Simulation with best result	22 of 50
Active stations	6, 7 and 8
Total waiting time	2.28 ± 0.10 minutes
Average queue length at station 6	7 ± 0.05 vehicles
Average queue length at station 7	2 ± 0.05 vehicles
Average queue length at station 8	0 ± 0.05 vehicles

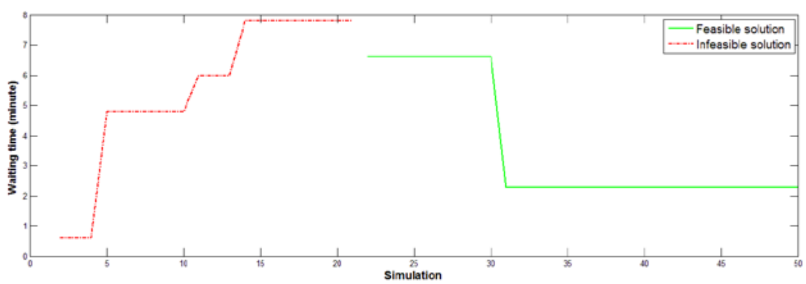

Figure 6: Cost function evolution through optimization for the first scenario.

The total waiting time and queue lengths are suitable for operation of the system. However, a queue length of zero vehicles at station 8 indicates that two stations could be used. This case is evaluated in the second scenario.

A second scenario is then considered by restricting the optimization to two active stations. The results are shown in Table 5. The best result has been obtained for simulation 13 as can be seen in Figure 7. The total waiting time has been increased a little bit but the average queue length at station 6 is more than twice the number of vehicles obtained before.

Table 5: Results for the second scenario

Simulation with best result	13 of 50
Active stations	6 and 7
Total waiting time	2.41 ± 0.11 minutes
Average queue length at station 6	15± 0.05 vehicles
Average queue length at station 7	2± 0.05 vehicles

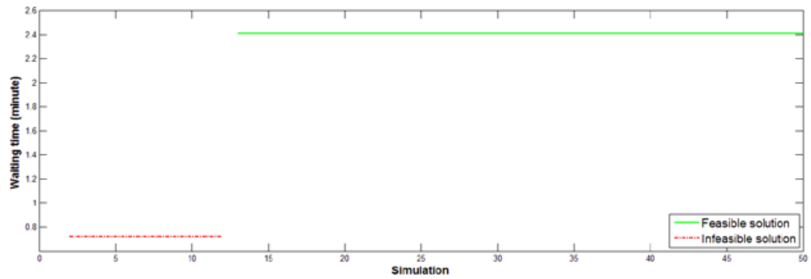

Figure 7: Cost function evolution through optimization for the second scenario.

Except for the queue length at station 6, two charging stations are still suitable in terms of waiting time representing important savings in the deployment of stations.

A third scenario is then considered with two active stations, but having station 6 with capacity to charge two vehicles at the same time. The results are shown in Table 6.

Table 6: Results for the third scenario

Simulation with best result	4 of 50
Active stations	6 and 7
Total waiting time	0.44 ± 0.02 seconds
Average queue length at station 6	1± 0.05 vehicles
Average queue length at station 7	2± 0.05 vehicles

According to Table 6, the best result is obtained for simulation 4 as can be seen in Figure 8. A significant reduction is observed both in the total waiting time as in the queue lengths by allowing station 6 to serve two vehicles at the same time. It should be noticed that an increasing in the number of power outlets of a station is less expensive than deploying another station.

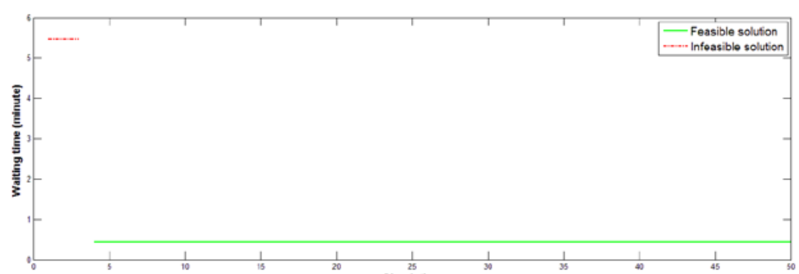

Figure 8: Cost function evolution through optimization for the third scenario

Finally, a fourth scenario is considered by increasing the incoming traffic with the same station configuration of the last scenario. The incoming traffic is taken from Figure 5 with increasing flat steps of 10%, 20% and so on up to twice number of vehicles for each hour of the initial distribution. The total waiting time is shown in Figure 9.

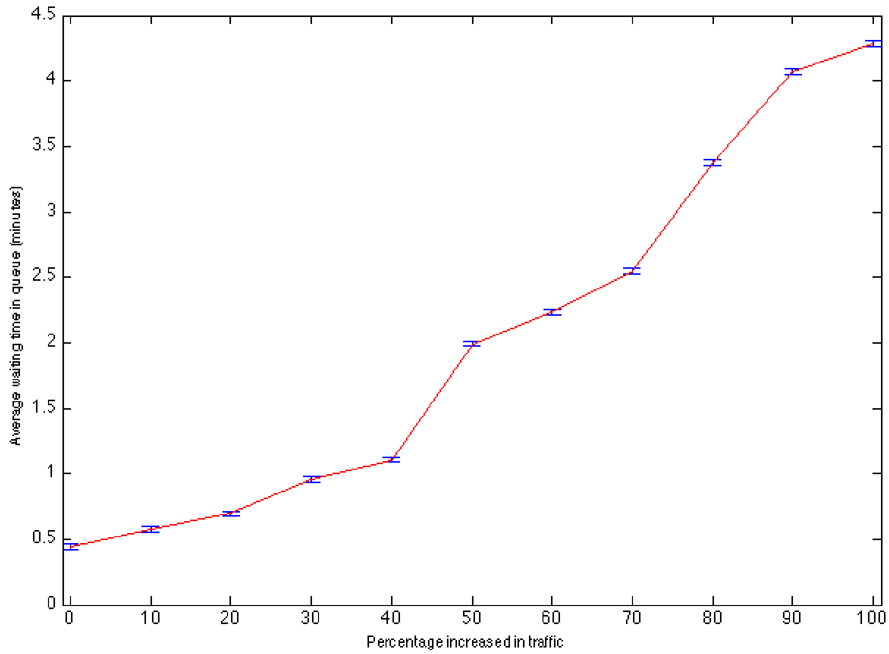

Figure 9: Total waiting time for increasing traffic.

The total waiting time in queues starts from 0.44 ± 0.02 minutes as in scenario three and reaches almost 5 minutes when twice number of vehicles is entering into the system. This waiting time is still considered fair for most users. This means that two charging stations located at positions 6 and 7 with station 6 being able to charge up to two vehicles simultaneously is suitable to provide the necessary charge within acceptable waiting time even for a significant traffic increase.

5 CONCLUSION

This paper has presented a simulation optimization approach to determine charging stations for electric vehicles in a small size urban area. A simplified model of urban mobility is taken by considering three different paths with shared sections in a particular urban area of Curitiba. The interaction of traffic generated for each path is indirectly represented by penalizing the energy consumed when a vehicle crosses sections shared by two or more paths. Moreover, part of vehicles' energy consumption is proportional to the distance run. Although this model of energy consumption is quite simple in a real-world, it can be adjusted for particular cases. Specially for prototypes and initial studies on deploying charging stations. The results have shown that a good compromise can be obtained between number of stations and capacity to charge more than one vehicle. Moreover, they have shown that a particular configuration can deal with traffic changes if a previous optimization goal has been satisfied in terms of energy demand and waiting time for recharging. This approach seems to be an efficient way of dealing with city infrastructure considering a possible growth of electric vehicles fleet. This structure can be easily adapted to other cities and regions with similar sets of data. In the future, better models for vehicles' energy consumption and battery charging times should be considered as well as an extension to public transportation systems using electric buses.

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