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ANALYZING THE CHARGING CAPACITY OF ELECTRIC VEHICLES FOR INTERURBAN TRAVEL USING SIMULATION

Adrian Ramirez-Nafarrate
Juan Carlos Grayeb Pereira
Hugo Briseño

Facultad de Ciencias Económicas y Empresariales
Universidad Panamericana
Álvaro del Portillo 49
Zapopan, Jalisco 45010, MÉXICO

Francisco Ruiz

Facultad de Ingeniería
Universidad Panamericana
Álvaro del Portillo 49
Zapopan, Jalisco 45010, MÉXICO

Ozgur M. Araz

College of Business
University of Nebraska-Lincoln
HLH 511 L
Lincoln, NE 68588, USA

ABSTRACT

The adoption of electric vehicles (EVs) has been increasing around the world in recent years. EVs present many advantages for sustainability. However, they have some drawbacks, including the high upfront cost, low range of some models and the availability of chargers. Hence, traveling long distances might be compromising for EVs. In this paper, we present a simulation-based study to analyze the charging capacity between two main cities in Mexico. Although the sales of EVs in Mexico are increasing, the number of this type of vehicles in the roads is relatively very low. In consequence, the charging infrastructure might not be sufficient to complete long trips given the large extension of the country. The modeling approach proposed in this paper helps identifying areas where new charging stations are needed to complete long trips. Furthermore, the results reveal a high correlation in the congestion of neighboring charging stations.

1 INTRODUCTION

Electric Vehicles (EVs) are being preferred by many people around the world because they represent an environmentally friendly transportation option. There are several configurations of EVs, but two of them stand out: the Battery Electric Vehicle (BEV) and the Plug-in Hybrid Electric Vehicle (PHEV) (Amsterdan Roundtable Foundation and McKinsey & Company. 2014). The propulsion of the BEV is based on an electric motor whose energy comes from a battery that needs to be charged from the grid. On the other hand, the motion of a PHEV is primarily based on an internal combustion engine (ICE) supported by a small electric motor. The electric motor requires a battery that can be charged from the grid and also from the ICE. The PHEVs can use the electric motor to move at low speed for a short distance. BEVs have zero greenhouse gas (GHG) emissions during usage, while PHEVs have low emissions compared with conventional ICE vehicles (International Energy Agency. 2020).

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The adoption of EVs has increased significantly in the last decade. According to the Global EV Outlook Report 2020, there were about 17000 BEVs and PHEVs around the world in 2010 and they increased to more than 7.2 million by 2019 (International Energy Agency. 2020). Most of the new registered EVs are in Europe, United States, and China. Although the worldwide market share of EVs is below 3%, there are countries with remarkably high sales (International Energy Agency. 2020). For instance, most of the new cars sold in 2020 in Norway were BEVs (54%) (Klesty 2021).

The low/null emissions of EVs is not their only advantage, they might also incur in lower maintenance cost than ICE vehicles. However, there are some barriers in the adoption of EVs, including the high upfront purchase price and the anxiety range caused by the relative low range of some BEV models, and scarce charging stations (Li et al. 2017; Berkeley et al. 2017). By 2019, there were 598000 public slow chargers and 264000 public fast chargers around the world (International Energy Agency. 2020).

In Mexico, the sales of EVs have increased in recent years as shown in Figure 1. According to Mexico's Bureau of Statistics, between 2016 and 2020, 7675 EVs were sold, from which 19% were BEV and 81% were PHEV (this statistic excludes Tesla models and Zacua models) (INEGI. 2021). Despite their increasing adoption, EVs in Mexico only represented 0.112% of new light vehicle sales during this period. Most new EVs have been sold in states with relatively high economic development, including Mexico City, Jalisco, and Nuevo Leon (Briseño et al. 2021).

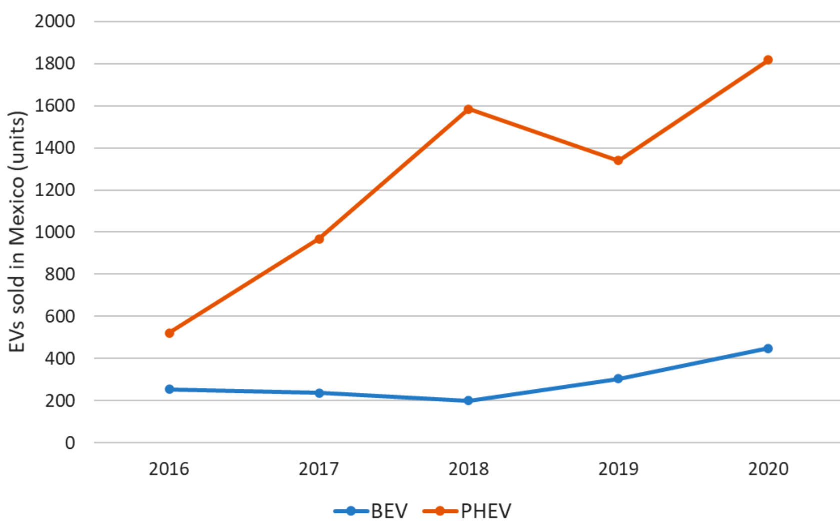

Figure 1: Sales of EVs in Mexico during 2016-2020.

On the other hand, according to PlugShare website, the charging infrastructure in Mexico consists of approximately 530 public charging locations, including 67 sites for fast charge (PlugShare. 2021). Considering that many of these sites have 2 or more chargers, it seems that the ratio chargers:EVs is larger than 1:10, which is the ratio suggested in Europe (European Parliament and of the Council. 2014). However, most of these chargers are located in urban areas. Moreover, considering the size of the country, in average, there is 1 charging location for every 3,756 km^2. In contrast, there were 250000 slow chargers and 38000 fast chargers in Europe by 2020 (International Energy Agency. 2021), which results in 106 chargers for every 3,756 km^2.

Therefore, motivated by the increasing adoption of EVs in Mexico and the lack of charging infrastructure to complete interurban travel, we present a simulation-based study to evaluate the capacity of the charging stations to travel between two major cities in Mexico (Guadalajara - Mexico City) based on BEV sales. In particular, we analyze the feasibility of BEVs to complete a trip between these cities using only fast chargers.

The location of chargers for EVs has been increasingly studied in recent years. For instance, Xi et al. (2013) proposed a simulation-optimization approach to determine the number of slow chargers to install at candidate locations. Their objective function consisted on maximizing the energy recharged in EVs in the proposed stations. They found that the best solutions are combinations of two types of chargers, instead of only one (they only considered slow chargers). Capar et al. (2013) proposed an efficient formulation to determine the location of new stations in order to maximize the covered EVs flow. Their results provide valuable insights regarding the impact of the cost of the land and the range of the vehicles in the number of stations to open.

Recent publications include Csiszár et al. (2020) who proposed an arc-based model using a weighted multi-criteria location optimization method considering ranking and selection. They found that traffic volume plays the biggest role on candidate sites evaluation. Pan et al. (2020) formulated a charging location model for EVs with and without home charger as first step. Then, as second stage a coverage location model was solved using a genetic algorithm. They found that missing trips are the ones that require longer distances and do not have home chargers.

Deb et al. (2021) proposed two algorithms: chicken swarm optimization and teaching-learning based optimization. Both algorithms were combined in order to minimize the cost of installation of chargers, operation cost, travel time cost, and penalty cost due to adaptation of the electric grid network. According to their results, both algorithms have a similar performance compared to other state of the art algorithms. Liu et al. (2021) presented a mixed-integer non-linear approach with a genetic algorithm in order to place and determine the charging station size using the existence serving areas in the German motorway. Their model provided high coverage solutions with low cost profile.

Kınay et al. (2021) used a flow-based model to present a full cover modeling using Benders decomposition. Their model achieved 100% coverage compared to maximal covering problems with large size-instances. Anjos et al. (2020) proposed a mixed-integer linear programming model supported by a rolling horizon-based heuristic. Their model contributes to solve large scale data set with dynamic charging demand.

These studies propose optimization frameworks to determine the location of chargers mostly based on deterministic models. In this paper, we propose a modeling approach using simulation to take into account randomness and dynamics of EVs' flows for interurban traveling.

The remaining sections are organized as follows. Section 2 describes the development of a base model to replicate the vehicle flow in the route under study and how we adapted this model to analyze the capacity of charging stations. Section 3 presents and discusses the results of our experiments. Finally, Section 4 presents the concluding remarks.

2 MODEL DEVELOPMENT

In this section, we describe the development of the discrete-event simulation model, the input data, the assumptions, and the experimentation setting.

The model was developed to evaluate the current charging infrastructure to travel between Guadalajara (state of Jalisco) and Mexico City (both ways) considering the characteristics of the BEVs sold in Mexico. The metro area of Mexico's valley, which includes Mexico City (CDMX herein) and other cities from Mexico State, is the largest metro area in the country with an estimated population of 21.8 million people, while the metro area of Guadalajara (GDL herein) is the third largest metro area with an estimated population of 5.2 million (INEGI. 2020). The distance between GDL and the limit of CDMX is approximately 515 km and it crosses four states: Jalisco, Michoacan, Estado de Mexico, and Mexico City.

Figure 2 shows the route under study between GDL and CDMX. The markers labeled from A to N represent the location of traffic flow measurement points taken into account. In addition, the current location fast chargers is shown. The location of the traffic flow measurement points are near intersections with other state highways. In order to analyze the capacity of current charging infrastructure and the service level received by BEVs owners, we developed a discrete-event simulation model using Simio software to replicate the traffic flow of light vehicles between GDL and CDMX (Simio LLC. 2021).

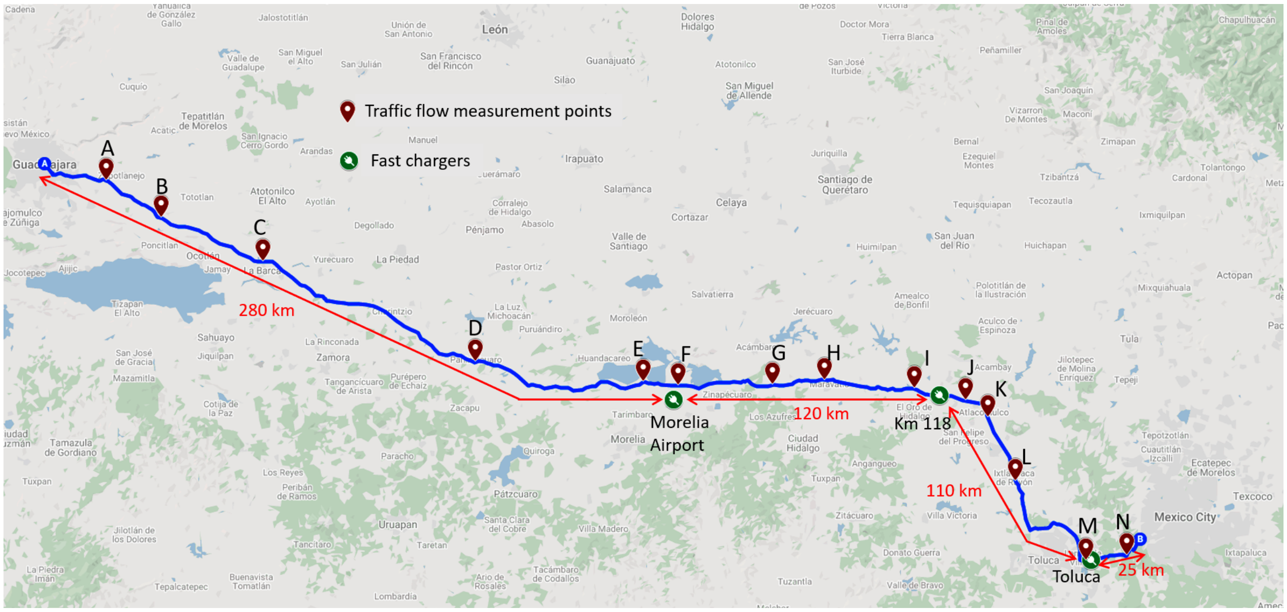

Figure 2: Route under study between GDL and CDMX.

2.1 Base Model

We first developed a base model to replicate the traffic flow observed in the measurement points. We used data from the daily average flow of light vehicles observed in 2019 by the transportation bureau in Mexico (SCT. 2020). The measurement points shown in Figure 2 correspond to the locations reported by SCT. (2020). We assume that the number of vehicles departing from GDL (eastbound) is given by the average traffic flow observed in point A and the number of vehicles departing from CDMX (westbound) is given by the average traffic flow observed in point N. At each subsequent measurement point, we compute d_i, which is the difference in traffic flow respect to the previous point, according to Equation (1), where f_i is the average daily flow of light vehicles observed at measurement point i. Therefore, if $d_i > 0$, we create new vehicles departing from point i. Otherwise, if $d_i < 0$, a vehicle ends its trip at point i with probability $r_i = |d_i|/f_{i-1}$ or it continues its trajectory with probability $1 - r_i$. Note that, for CDMX and GDL, $r_i = 1$ for eastbound and westbound trips, respectively.

$$d_i = f_i - f_{i-1}. \tag{1}$$

New vehicles are created based on an homogeneous Poisson process (unfortunately, there is no information available about the distribution of traffic in a day). Hence, at departing cities GDL and CDMX, the departures of new vehicles follow an exponential distribution with mean interdeparture time of $16(3600)/f_i$ seconds (for $i \in A,N$), while at intermediate points where $d_i > 0$, the mean interdeparture time is given by $16(3600)/d_i$ seconds. These expressions assume that light vehicles traveling between GDL and CDMX begin their trip between 6 am and 10 pm. Although there is no public data about how traffic flows varies depending on the hour of the day, we believe that it is reasonable to assume that most trips made by light vehicles, which excludes trailers and large trucks, are made during this time window. In addition, we assume that each vehicle travels at a random speed uniformly distributed between 90 and 120 km/h.

In order to verify the model and validate these assumptions, we ran 10 replications of this terminating simulation and we implemented common random numbers throughout all the experiments presented in this paper (Law 2015). Each replication ended when the last vehicle arrived to its destination. Table 1 shows the observed mean traffic flow of light vehicles and the average simulated flow with the half width of 95% confidence intervals on the mean.

Table 1: Mean observed flow of light vehicles per day and simulated results based on 10 replications (half width for a 95% confidence interval on the mean). Some measurement points were not included in the simulated direction. [1] confidence interval does not cover the observed mean.

	Eastbound (GDL-CDMX)			Westbound (CDMX-GDL)		
Measurement point	Observed flow (vehicles)	Avg. simulated flow (vehicles)	Half width	Observed flow (vehicles)	Avg. simulated flow (vehicles)	Half width
A	4467	4467.4	42.6	4497	4324.1	33.4[1]
B	3869	3891.7	42.3	-	-	-
C	4785	4805.7	40.7	4739	4751.5	28.8
D	2576	2590.5	39.5	2576	2571.2	37.9
E	3495	3509.8	43.4	-	-	-
F	2992	3026.7	32.3[1]	3399	3397.2	40.8
G	-	-	-	3552	3532.7	41.7
H	3365	3398.4	33.4	-	-	-
I	3566	3598.5	36.9	3484	3466.1	39.4
J	-	-	-	4118	4076.6	35.0[1]
K	16046	16070.7	73.2	-	-	-
L	19504	19504.2	69.7	18468	18448.6	93.9
M	52183	52138.3	123.3	73410	73534.3	217.6
N	56766	56753	114.3	54392	54464.4	181.5

The validation results show that 19 out of 22 confidence intervals accurately estimates the observed mean. The three measurement points whose observed flow are not included in the confidence intervals might be due to Error Type I. Nevertheless, the absolute deviation between observed and simulated mean is quite small at all measurement points (max deviation = 3.84%, avg deviation = 0.55%). According to this table, dense traffic is observed at points near CDMX because of the high interaction between CDMX and Toluca.

Table 2 shows the average number of vehicles created on each replication and the average travel time for each route (considering only the vehicles that traveled along the whole path). Even though the base model does not include stops to refuel, it would help to evaluate the delay if charging is needed. Based on the results of both tables, we believe that the model accurately resembles the traffic flow in the route under study.

Table 2: Average number of vehicles created and average travel time. [1] it only considers the vehicles that traveled the whole path.

	Eastbound (GDL-CDMX)		Westbound (CDMX-GDL)	
Statistic	Average	Half width	Average	Half width
Vehicles created	60027	114.9	75781.2	206.6
Travel time[1] (h)	4.94	0.009	4.94	0.008

2.2 Model for BEV Traveling

The following step consisted in adapting the base model to analyze the charging needs of BEV while traveling along the path under study. There are three important factors to define in the model: the range of the BEV, the location and capacity of fast chargers, and the magnitude of the traffic of BEVs. Next, we describe the assumptions made for each factor.

2.2.1 Range of BEV

In Mexico, 1446 BEVs were sold between 2016 and 2020 and they belong to ten different models (for unknown reasons, this data set excludes Zacua and Tesla models that are also sold in Mexico) (INEGI. 2021; García 2020). Table 3 shows the maker, model, range, and percentage of BEVs sold in this period. In the simulation model, we randomly assign a range to every new BEV created using the share as a probability.

Table 3: Characteristics of BEVs sold in Mexico between 2016 and 2020. Range obtained from the maker's website in Mexico. This table excludes Zacua and Tesla models because they are not in the INEGI data set and it also excludes Renault's Twizy and Kangoo because they cannot be charged at fast chargers

Maker	Model	Range (km)	BEV's share (%)
Nissan	Leaf	240	37.3
BMW	i3	260	35.0
GM	Bolt	416	9.2
Audi	e-tron	446	7.8
JAC	E Sei 1	360	3.5
JAC	E Sei 4	450	2.8
Jaguar	I-Pace	415	2.3
JAC	E Sei 2	350	2.1

After assigning the range to a new BEV in the simulation model (considered the maximum range), they are also assigned with a departing range which is uniformly distributed between 80% and 100% of its range. With this departing range, BEVs begin their trip. Current range of the vehicle is checked at the origin point and after charging in order to determine if the vehicle has sufficient range to reach the next charger or its destination. If a vehicle does not have enough range, then the BEV entity is destroyed and it is considered a failed trip. Otherwise, the BEV continues its trajectory until reaching the final destination. The flow of BEVs in the simulation model, from creation until destruction, is described in Figure 3.

2.2.2 Location and capacity of fast chargers

According to Plugshare, there are three locations of fast chargers near the route under study: Morelia Airport, Km 118 and Toluca (PlugShare. 2021). These stations are shown in Figure 2. The station in the Morelia Airport consists of 4 Tesla Superchargers. In order to reach this station, vehicles have to deviate from the highway for 10 km, which are also included in the simulation model. The station at Km 118 consists of 6 Tesla Superchargers. In Toluca, there are three stations with universal fast chargers: one with 2 chargers and two with 1 charger. In the simulation model, we assume that there is only one location with 4 fast chargers. The station included in the model is the one located next to the highway (it has 2 GE J-1772 fast chargers). The other stations with one charger each are relatively close to the one included in the model. When a vehicle needs charge at any of these stations and there is not an available charger, we assume that the vehicle joins a single queue based on a first come first served dispatching rule until a charger is free to be used by the vehicle.

In this paper we assume that any BEV can charge at a Tesla Supercharger. However, there are technical and market constraints that do not allow it. Nevertheless. without this assumption, the conclusion is that

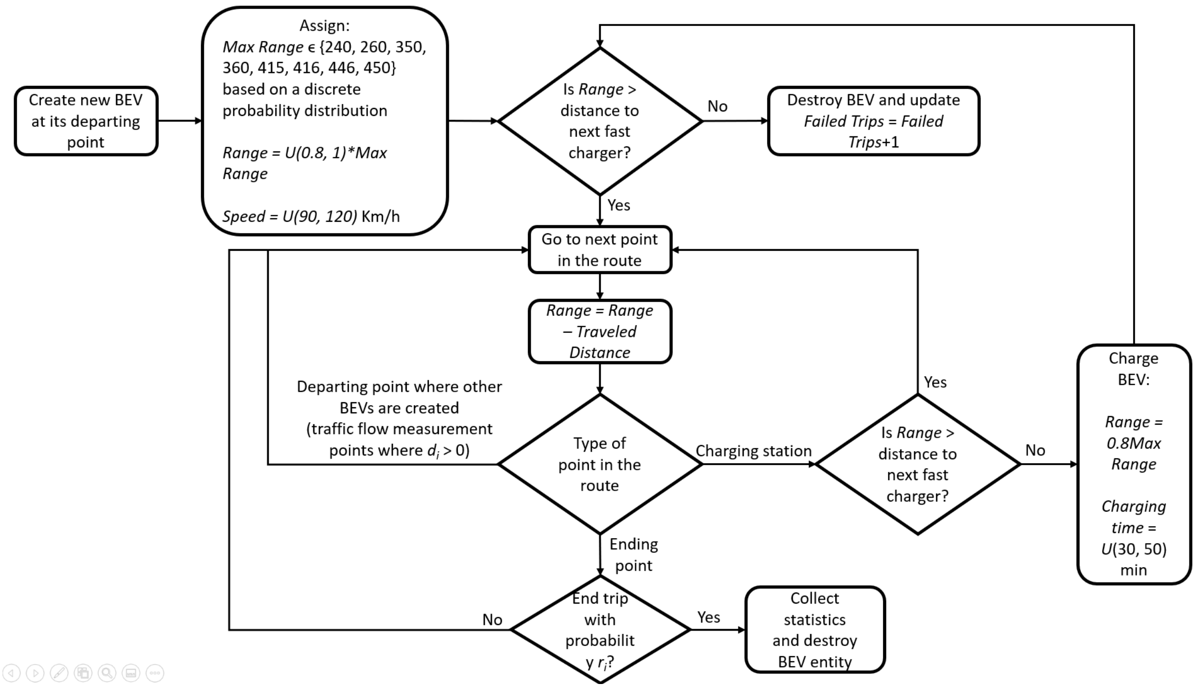

Figure 3: Flow of BEVs in the simulation model.

only Tesla vehicles can complete a trip between GDL and CDMX, while others would need to deviate significantly from the highway, spending more time in the road, and some others would not be able to complete it. Therefore, the results shown in this paper also highlight the importance of compatibility and resource sharing (e.g., chargers or locations) to enable BEVs to complete interurban trips.

Based on the maker's websites and other specialized sites, we assume that BEVs that charge at any station in the model only charge up to 80% of its range. This value is suggested in order to protect the battery of the vehicles and also considering that the speed of charge declines significantly after reaching this level (Lilly 2020). In addition, based on the charging time reported in specialized sites, we assume that the charging time to reach the above level is uniformly distributed between 30 and 50 minutes (Lilly 2020). These assumptions are also depicted in Figure 3.

2.2.3 Traffic flow of BEVs

The data presented in Table 1 obtained from SCT. (2020) do not provide any information about how many BEVs pass through the traffic flow measurement points. Therefore, in order to estimate the number of BEVs that could be on the road under study, we assume that only BEVs sold in any of the states that the route crosses are eligible to move along that highway. Although this assumption excludes other states that are relatively near the analyzed route, we believe that most vehicles that could be found in this segment are vehicles with license plates from any of the four states mentioned earlier: Jalisco, Michoacan, Estado de Mexico, and Mexico City. According to INEGI. (2021), 992 BEVs were sold in these states between 2016 and 2020. Thus, they represent about 69% of the total BEVs sold in the country during that period. In addition, they represent approximately 0.035% of the total light vehicles sales in these states, which is larger than the national average of 0.021%.

To determine the expected number of BEVs on the road and how they are created in the simulation model, we followed the next steps:

1. Based on the observed traffic flow (f_i and d_i defined in Section 2.1), we estimate that, in average, $v = 135717$ vehicles are on the road (60076 traveling east and 75641 traveling west). Note that these numbers are close to the values obtained in the simulation model shown in Table 2. This assumption discards vehicles that join and exit the road without being registered by the traffic measurement devices.
2. According to INEGI, there were 16349036 registered vehicles in the four states that the route under study crosses. Therefore, in average, 0.83% of the registered vehicles are on road on a given day.
3. Considering that 843 BEVs are enabled to be charged at fast chargers (85% of 992), then 7 BEVs are expected to be on the road (0.83% of 843). Approximately, 3 would be traveling east and 4 would be traveling west. Therefore, in the current scenario, 0.0052% of the vehicles on the road are BEVs (i.e., $7/v$).
4. We estimated the percentage of vehicles departing at each point using $q_i = d_i/v$ (considering only the points where $d_i > 0$).
5. Hence, the expected number of BEVs departing at each point is given by $7q_i$. Similarly to the base model, we assume that interdeparture time of BEVs is exponentially distributed with mean $16(3600)/7q_i$ seconds.

In addition to the scenario described above (i.e., current scenario), we designed a set of experiments varying the percentage of BEVs respect to all vehicles on the road. In the current scenario, this value is 0.0052%. We also tested 0.10%, 0.50%, 1.00%, 1.50%, 2.00%, and 2.50%. For these scenarios, we also assumed that BEVs are created using the exponential distribution for interdeparture time using a 16-hour time window.

Table 4 describes the experiments. Note that increasing the percentage of BEVs on the road assumes that more BEVs were sold in the period between 2016 and 2020. Hence, we also estimated the share of BEV that had to be sold in order to reach the tested flow levels while keeping constant the percentage of registered BEVs on the road (0.83%). In the next section, we analyze the results of these scenarios.

Table 4: Set of experiments to analyze the charging capacity of BEVs in the route between GDL and CDMX.

	Current scenario	Varying the percentage of BEVs on the road					
Percentage of BEVs on the road	0.0052%	0.10%	0.50%	1.00%	1.50%	2.00%	2.50%
Expected number of BEVs on the road	7	135.7	678.6	1357.2	2035.8	2714.3	3392.9
Share of BEVs	0.035%	0.7%	3.5%	6.9%	10.4%	13.8%	17.3%
BEV units that would have to be sold	992	19234	96171	192342	288512	384683	480854

The base simulation model adapted to study the flow of BEVs was executed for 100 replications for each scenario. The performance measures of interests are the following:

- Average number of failed trips. This is the number of vehicles that could not reach their destination because of insufficient range.
- Average number of charges. This is the average number of times that BEVs have to stop to recharge considering only those vehicles that travel the whole path.
- Average travel time. This is the average time that BEVs take to travel the whole path, including the recharging time.

- Average waiting time at charging stations. This is the average time that BEVs have to wait at the stations to begin recharging the battery.
- Average utilization level of chargers. This is the percentage of time that chargers are busy with a BEV.

3 RESULTS

Table 5 shows the results of the simulation model considering the existing charging capacity. As expected, as the flow of BEVs increases, the average number of failed trips also increases, but they only represent about 4.3% of all BEV trips in any scenario. These failed trips correspond to BEVs with low range (240 and 260 km) that are unable to complete a trip between GDL and the station at Morelia Airport (both directions). But, not all BEVs with these ranges are failed trips. Other vehicles with these ranges may complete their trip if their origin and destination are within range. The range of the other BEVs (greater than or equal to 350 km) explains why the average number of charges is 1 for any scenario. This table also suggests that, under the current scenario, the charging stations are not stressed. Furthermore, only if the demand increases above 2%, the station at Morelia Airport gets slightly congested, increasing the average waiting time and the average time to complete the whole trip.

Table 5: Results considering the existing charging capacity.

		Percentage of BEVs on the road						
Measure		Current	0.10%	0.50%	1.00%	1.50%	2.00%	2.50%
Failed trips (Avg. and %)	Both ways	0.3 (4.3%)	5.8 (4.3%)	29.5 (4.4%)	58.1 (4.3%)	87.1 (4.3%)	114.7 (4.2%)	144.7 (4.3%)
Avg. Number of charges	GDL-CDMX	1	1	1	1	1	1	1
	CDMX-GDL	1	1	1	1	1	1	1
Avg. Travel time (h)	GDL-CDMX	5.6	5.7	5.8	5.8	5.8	5.8	6.1
	CDMX-GDL	-	5.7	5.8	5.9	5.9	6.0	6.6
Avg. Waiting time (min)	Morelia Airport	0	0	0.06	0.76	3.68	12.64	46.41
	Km 118	0	0	0	0.01	0.10	0.26	0.76
	Toluca	0	0	0	0	0	0	0
Avg. Charger utilization (%)	Morelia Airport	0.0009	0.4	5.9	19.6	32.0	48.9	63.4
	Km 118	0.0008	0.2	3.0	9.9	16.5	25.3	32.1
	Toluca	0.00003	0.02	0.3	1.1	1.9	2.7	3.8

The results above suggest that the station at Morelia Airport is very important to complete the trips between GDL and CDMX. Furthermore, they also show that not all BEVs can make that trip. BEVs with low range are unable to complete it. Therefore, we used the same BEV flow scenarios to evaluate the performance if a new charging station is added between GDL and the station at Morelia Airport. We assume that the new station is located at La Barca, Jalisco (measurement point C in Figure 2). The distance between GDL and La Barca is approximately 100 km, and between La Barca and the station at Morelia Airport is 180km. We assume that 2 fast chargers would be installed in this new station. The results of the simulation model are shown in Table 6.

These results confirm that a new station between GDL and the station at Morelia Airport would allow all BEVs completing the trips. Consequently, the average number of charges increases because more low-range vehicles are on the road. Given that many vehicles need 2 or 3 recharging stops, the average travel time for the whole route increases significantly to almost 7 hours with the current expected flow of BEVs. We notice that for low flow levels of BEVs, including the current level, the charging stations are not stressed. However, if the flow increases 1% or more, the new station would be highly congested.

Table 6: Results considering an additional charging station at La Barca with 2 fast chargers.

Measure		Percentage of BEVs on the road: Current	0.10%	0.50%	1.00%	1.50%	2.00%	2.50%
Avg. Failed trips	Both ways	0	0	0	0	0	0	0
Avg. Number of charges	GDL-CDMX	2.6	2.5	2.5	2.5	2.5	2.4	2.4
	CDMX-GDL	2.9	2.6	2.6	2.6	2.6	2.6	2.6
Avg. Travel time (h)	GDL-CDMX	6.8	6.8	6.8	7.6	9.3	11.5	13.9
	CDMX-GDL	7.0	6.8	7.0	8.3	12.4	18.0	23.9
Avg. Waiting time (min)	La Barca (new)	0	0.1	6.7	70.7	256.8	482.8	690.9
	Morelia Airport	0	0	0.2	2.0	7.4	33.8	93.8
	Km 118	0	0	0	0	0.2	0.5	1.3
	Toluca	0	0	0	0	0	0	0
Avg. Charger utilization (%)	La Barca (new)	0.002	1.0	16.5	52.6	76.4	90.7	94.3
	Morelia Airport	0.001	0.6	8.0	25.4	37.6	44.3	46.4
	Km 118	0.001	0.3	4.3	13.8	20.7	24.5	25.6
	Toluca	0.00003	0.03	0.4	1.2	1.8	1.9	2.1

Furthermore, we note that a new charging facility increases the demand at the current stations. Analyzing both tables we observe that the average waiting time at existing stations, particularly at Morelia Airport, increases when the new station is added. In order to study the correlation in the waiting time at the new station and the station at Morelia Airport, we simulated other scenarios varying the number of chargers in these stations. The results are shown in Table 7.

Table 7: Average waiting time (min) varying the number of chargers in the new station at La Barca and at Morelia Airport (currently with 4 chargers).

Stations and number of chargers	Percentage of BEVs on the road: Current	0.10%	0.50%	1.00%	1.50%	2.00%	2.50%
La Barca (2 chargers)	0	0.1	6.7	70.7	256.8	482.8	690.9
Morelia Airport (4 chargers)	0	0	0.2	2.0	7.4	33.8	93.8
La Barca (4 chargers)	0	0	0.23	1.97	9.61	37.99	79.63
Morelia Airport (4 chargers)	0	0	0.23	2.25	12.80	62.16	146.30
La Barca (4 chargers)	0	0	0.25	1.84	11.34	56.88	135.79
Morelia Airport (6 chargers)	0	0	0.005	0.16	0.86	3.58	8.60
La Barca (6 chargers)	0	0	0.005	0.11	0.76	3.10	11.97
Morelia Airport (6 chargers)	0	0	0.005	0.14	0.99	4.43	15.39

This table confirms that the bottleneck station shifts between the new La Barca station and the station at Morelia Airport. When the capacity increases at one them, the average waiting time decreases at that station but increases at the other. Thus, adding capacity to one station allows BEVs to move faster to the next station, thereby increasing the demand at the next station more quickly than it can meet with available charging capacity. In addition, it seems that the bottleneck shift occurs only at stations whose distance is large enough to require BEVs to stop at both. We found that the performance at Km 118 and Toluca, that are closer to each other and to other stations, is not affected under the current assumptions.

The results presented in this section must be interpreted in the light of the assumptions. First, the initial range between 80% and 100% might underestimate the demand at Km 118 and Toluca chargers. In addition, the current demand could be slightly larger than the simulated because of the exclusion of Tesla models. Second, we assume that any BEV can charge at a Tesla Supercharger, but it not possible under current conditions. Nevertheless, without this assumption, the conclusion would be that only Tesla models can complete the trip between GDL and CDMX without deviating significantly from the highway. Hence, it is of the utmost importance to develop technology and incentives to allow resource sharing in charging infrastructure. Under the ideal scenario, BEVs of different makers could share chargers. However, a more realistic approach would consist on designing incentives to allow facility sharing to install different types of chargers. As presented by Hardman and Tal (2021), charging convenience is not only crucial to incentive the adoption of EVs, but it is also very important for owners to use and keep EVs.

4 CONCLUSIONS

Increasing adoption of BEVs requires a strategic plan to deploy charging stations for both, allowing owners to make long trips without getting range anxiety and incentivizing potential customers to acquire electric vehicles. Currently, the upfront cost of BEVs is significantly higher than ICE vehicles. Therefore, most sold models are BEVs with relatively low cost and consequently low range. In large size countries, like Mexico, covering a significant proportion of the area with chargers is challenging. Consequently, a significant percentage of BEVs would not be able to complete interurban travel within the country.

Hence, decision support systems could help design plans to effectively deploy chargers to satisfy the interurban travel needs of drivers. In this paper, we propose a simulation-based study to evaluate the existing capacity of charging stations for traveling between two main cities in Mexico. In addition, we illustrate how this model can help determining the location of new stations.

The results not only show the utility of new charger locations, but also they reveal that neighboring stations are highly correlated. New charging stations increase the demand of other stations because more BEVs are able to travel long distances. As a result, increasing the capacity in one station causes BEVs to move faster to the next station, increasing its demand and potentially causing long delays.

Therefore, it is important to consider not only the flow coverage of new stations (focus most of the existing literature), but also studying the bottleneck shift of neighboring stations. Our future research lines include combining location optimization with simulation to take into account these factors.

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AUTHOR BIOGRAPHIES

ADRIAN RAMIREZ-NAFARRATE is Professor in the School of Business at Universidad Panamericana in Zapopan, Mexico. He received his Ph.D. in Industrial Engineering from Arizona State University. His research interests include simulation and optimization of manufacturing and service systems. His email address is aramirezn@up.edu.mx.

JUAN C. GRAYEB PEREIRA is undergraduate student in the School of Business at Universidad Panamericana in Zapopan, Mexico. His major is International Business. His interests include technology and sustainability. His email address is 0155287@up.edu.mx.

FRANCISCO J. RUIZ BARAJAS is doctoral student in the School of Engineering at Universidad Panamericana in Zapopan, Mexico. He received a master degree in technology innovation from Universidad Panamericana. His interests include location models and statistical data analysis. His email address is 0185303@up.edu.mx.

HUGO BRISEÑO is Professor in the School of Business at Universidad Panamericana in Zapopan, Mexico. He received his Ph.D. in Economics Sciences at Universidad de Guadalajara, in Mexico. His research interests include econometric models in public services. He is member of the Mexican Institute of Finance Executives (IMEF). His email address is hbriseno@up.edu.mx.

OZGUR M. ARAZ is Associate Professor in the College of Business at the University of Nebraska-Lincoln. He received his Ph.D. in Industrial Engineering from Arizona State University and was a postdoctoral research fellow at the Center for Computational Biology and Bioinformatics of The University of Texas at Austin. His research interests include systems simulation and business analytics. His email address is oaraz2@unl.edu.