An evaluation of the actual electric vehicles charging infrastructure in Uruguay and possible designing approaches

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***Abstract*—This paper presents those methodological, theoretical and computational tools used to plan the performance of the Electric Route in Uruguay for recharging of electric vehicles. The study focuses on service times analysis of charge points over periods of intense vehicular traffic and for prospective scenarios of high penetration of electric vehicles. The first goal is to quantify performance limits for the current recharging infrastructure and vehicles capabilities under stressful contexts, but at the same time realistic, considering existing data of traffic flows and prospective studies for possible electric vehicles penetration scenarios. Queueing Theory is the underlying framework to tack this part of the analysis. The second part of the study uses Markov Chains, whilst assumes a near future with greater driving range of electric vehicles and seeks to estimate how many additional charge points are required to provide a satisfactory level of service. Main results show that the current infrastructure is capable of fulfill near future needs, but for some growth scenarios of the electric vehicles fleet, that infrastructure should be updated to sustain mid to long-term recharging needs.**

***Index Terms*—Electrical vehicles, charging infrastructure, stochastic system design, queueing theory**

I. Introduction

The increasing use of electric vehicles is currently being observed in the transport sector, representing a growing alternative to the use of fossil fuels. These changes are having repercussions on the automotive and the electricity market, the environment, as well as on the replacement of oil derivatives for the transport sector as it is known today. This replacement may have a tremendous impact on those countries, such as Uruguay, with no local oil production and with renewable surpluses from the electricity sector. According to [1], between 2014 and 2018, the number of electric vehicles in the global market has been increasing at an annual rate of 60%, reaching a total amount of 5.500.000 in 2018. In the same year, the total sales of electric vehicles reached 2.000.000, which represents 2.1% of the total car sales market. According to a survey published by the UK Department of Transport [2], the main barrier to the adoption of an electric vehicle by buyers is the availability of chargers on public roads (45%), followed by vehicle driving range (39%) and the initial investment (28%). Other causes raised by respondents in the study were lack of knowledge (13%), unproven technology (11%), among other reasons. As a result, having a public charging network for electric vehicles is of fundamental importance to break down certain barriers and to drive the growth of the electric automotive market. Countries such as China, USA, Norway or UK, spurring the penetration of electric vehicles in their markets [3], have deployed a wide charging infrastructure network. From these countries, Norway, which may be compared to Uruguay in terms of population density and human development index, has reached 11.45% (i.e. 312.376 vehicles) penetration of BEV (Battery Electric Vehicles) and PHEV (Plugged Hybrid Electric Vehicles) [4]. The amount of public recharge points in Norway deployed along the territory (which is approximately 1.8 times Uruguay size) is currently more than 12.000, which combine different types, AC or DC for slow, standard, rapid and ultra rapid charging. In the case of Uruguay, current penetration of electric vehicles is below 250, which represents less than 0.05% of the automotive park. From this amount 67% corresponds to the electric utility fleet of UTE (the National Electricity Company), 27% are taxis, and only 6% are private [5]. In order to promote the use of electric vehicles, UTE has launched the Electric Route, which currently has 64 points for charging, all in AC with different capacities (e.g. 7.4 kW, 22 kW and 43 kW) [6]. This measure was implemented as part of a larger public plan of electric mobility promotion, which also includes taxes reductions and subsidies. UTE has also created a task force on electric mobility which is working on various projects. In addition, an agreement between UTE and the School of Engineering from UDELAR (the University these authors belong to) was signed to assess different problems related to electric vehicles. This paper presents some of the results from that work, related to the charging infrastructure, in order to evaluate the performance of the Electric Route for different scenarios of electric vehicle penetration and also to assess possible design approaches. Although this work focuses upon a concrete and particularly simple application case, these techniques can be extended to more general instances. This study focuses on the Electric Route from Colonia to Chuy, using existing data of vehicles traffic. Two different approaches are used. The first assumes that the driving range is determined by the car, and it seeks to evaluate the useful life limits for the current charging infrastructure over prospective scenarios of electric vehicles penetration. The second approach lays upon the hypothesis of technological improvements, which move the driving range from cars to drivers. For this approach we look for a long-term solution for the charging infrastructure.

Main contributions of this work are: i) the decomposition of aggregated vehicular traffic statistics into specific traffic-flows, which capture design goals combined with capabilities of cars and drivers; ii) the application of stochastic modeling to craft long-term infrastructure planning based on quantitative analysis of the problem of fulfilling needs of those flows, for current traffic data as well as for prospective scenarios; and iii) the real-world application case this paper elaborates on.

The remaining of this article is organized as follows. Section II introduces the problem, describes the case study of the Electric Route in Uruguay and envisioned data for electric vehicles penetration scenarios, as well as the two reference models used to quantify the system performance. Section III presents actual statistical traffic information for peak traffic at this route at different points, which is broken down into vehicular flows according to each of the problem versions to tackle. When analytical solutions are not available for some problem instance, simulation algorithms are used instead. Finally, Section IV presents the conclusions and lines of future work.

II. Problem Definition and Cases of Study

A. The Electric Route of Uruguay

Electric Vehicle Supply Equipments (EVSEs) allow electric vehicles to be safely connected to the power grid. EVSEs comprise three main kind of components. The *power block* (through which the energy of the load circulates) contains those conductors and protections necessary to carry out the load safely. The *communications block* is responsible of determining what charging protocol/scheme is to be used between the EVSE and the electric vehicle. This communication is determined by the type of connector that the EVSE has. There are also chargers that have more than one connector as it may be seen in Figure 1 [7].

Fig. 1. Public charging with three different connectors [EVSE]

The *managment block*, which is the one where communications are established between the EVSE and external servers. This is the block responsible for authorizing and registering the charging session. There is a protocol called OCPP (Open Charge Point Protocol) which allows to standardize the communication between the EVSE and some servers, being able to implement functions such as accounting the energy consumed, billing and EVSE booking, among others.

After adopting some of the connector types, national authorities need a plan to install these EVSEs. The scheme of the electric load infrastructure in Uruguay was guided by firstly covering the route with the higher flow of vehicles; allowing then the movement of electric vehicles alongside the south coast of the country (departments of Colonia, San José, Montevideo, Canelones, Maldonado and Rocha), which coincides with the largest influx of tourists along the year. After this first step (2017-2018), other locations of the country were covered, adding up today to 64 AC charging points, half of them of 43 kW, and nearly the other half with 22 kW, plus a very few of 7.4 kW capacity [8]. This paper focuses on the first stage of the Electrical Route, i.e. the south area from Colonia del Sacramento to Chuy, which is highlighted in Figure 2. Most of these stations count only one EVSE.

Fig. 2. Public charging infrastructure in Uruguay [Electric Route highlighted]

B. Scenarios of penetration of electric vehicles

The relative share of electric and Hybrid Vehicles (HV) in the Uruguayan sales market has been growing in recent years, although not at a great pace, as presented in table I [5].

Year	2014	2015	2016	2017	2018
Total vehicles	53.429	49.438	45.633	54.522	43.807
Total HV	2	2	38	99	839
% participation HV	0,004%	0,004%	0,083%	0,182%	1,915%
Total EV	30	72	10	27	63
% participation EV	0,056%	0,146%	0,022%	0,050%	0,144%

TABLE I
Percentage of hybrid and electric vehicles in Uruguay.

Scenarios were taken from the 2018 National Energy Demand Prospective Report prepared every year by the National Energy Directorate (DNE) of the Ministry of Industry, Energy and Mining (MIEM) of Uruguay [9], where 4 scenarios were established growth in demand depending on the policies applied. The rate of electric vehicles (in the global automotive park) varies from less than 1% in the most pessimistic scenario to nearly 7% in the most optimistic one, for the period 2020-2035. Premisses these scenarios are based on are: 1) *Trend* is the scenario where no public policy is applied; 2) *Energy Efficiency Policy* is built on the basis of the Trend scenario, assuming that certain measures are applied, such as energy efficiency labeling, promotion of efficient technologies, improvement in the use of energy and renewable energies, among others; 3) *Unconditional NDC (National Determined*

Contribution): is carried out based on Energy Efficiency Policy scenario, but assuming that no external support is received for the achievement of goals. It is assumed, however, that those goals related to measures that are already being implemented are achieved; 4) *Conditional NDC* also derives from Energy Efficiency Policy, improving specific goals and modifying the moment in which the measures begin to have an impact and conditional on receiving funds for their application. In addition, specific hypotheses are incorporated for the penetration of electric vehicles in fleets of specific companies (captive fleets). EVs penetration scenarios used in this work are based upon optimistic projections, mainly in the Conditional NDC scenario, whose figures are presented in Table II.

Year	Total	Nº EV's	%
2020	814.145	770	0,09%
2025	997.574	33.524	3,36%
2030	1.160.591	62.489	5,38%
2035	1.292.104	87.378	6,76%

TABLE II
MARKET SHARE PROJECTION IN URUGUAY UNTIL 2035, CONDITIONAL NDC(NATIONAL DETERMINED CONTRIBUTION) SCENARIO.

HV commercialized in Uruguay are (generally) not plugged-hybrid vehicles, what explains why that kind of vehicles (HV) are not considered in this study in terms of its incidence in the charging infrastructure of the country.

C. A queuing system approach for a charging station

A first concern in this analysis aims upon quantifying useful life limits for the current charging infrastructure over prospective scenarios of electric vehicles penetration. Actual data shows that this infrastructure is up to ongoing requirements, and that it is updated according to the state-of-the-art technology. However, how much longer that infrastructure is going to fulfill demand needs is a main concern.

In this section, we are modeling the problem with the goal of assessing lifetime limits for the charging points, and not with the aim of rescaling that infrastructure. Electric vehicles technology is rapidly evolving, so long-term infrastructure charging planning cannot be bounded by current limitations.

Nowadays, recharging times of electric vehicles are too long when compared with refills in gasoline ones. Additionally, the maximum travel distance range of affordable electric vehicles is still quite under that of internal combustion powered cars. Since electric cars do not have the choice but the imperative to charge during a long trip, and servicing times are expected to be long, in this section, we have decided to model a power-station to serve cars charging as a classical queueing system.

A classical queueing system framework is that described by the Kendall-Lee notation, which characterizes a single-queue system by six parameters, three of whom are mandatory. These parameters are: i) the arrival process; ii) the service process; iii) the number of parallel servers; iv) the queue discipline; v) the capacity of the system; and vi) the size of the origin population. Classical examples of arrival and service processes are Poisson distribution (represented as M, by markovian) and Deterministic times (represented with D). Regarding the queue discipline, typical cases are FCFS (first come, first served) and LCFS (last come, first served). For instance, an $M/D/2/FIFO/10/\infty$ Kendall-Lee notation for some system means that: the arrival time between any two customers has exponential distribution; the service time of each customer at each of the two available servers is fixed; customers are attended in the order they arrive; and there is a limit of 10 customers in the whole system, accounting those in-line as well as those being attended. Whenever any or the last three parameters are omitted, they are assumed to be $FIFO/\infty/\infty$. For further information about the general framework of queueing theory, we recommend [10] and [11].

An $M/M/./././.$ system allows a fully analytical resolution, because it is assimilable to a Birth-Death Process, which in turn is a Continuous Time Markov Chain. Unfortunately, the queueing system that better matches current cars-to-station interaction is an $M/D/s$ since: inter-arrival times are independent and there is no reason to assume that a new arrival affects the time of the next one (memoryless property of exponential distribution); cars limited autonomy forces a car to arrive with minimal charge in its batteries (no matter how many cars are previously in the queue), so it has to stop and wait for a full-recharge, which is constant over a reference uniform fleet.

A first concern of any stochastic system is its stability, which corresponds to the long-term asymptotic behaviour. Long-term expected service times in an unstable system are unbounded. Let $1/\lambda$ be the mean interarrival time between any two cars, and $1/\mu$ be a representative full-charge time for a vehicle. A general result of queueing theory establishes that such a system is stable when $\lambda < s\mu$, in a station with s chargers. A stable system usually reaches its stationary distribution rapidly. Once in it, performance metrics are well defined; two of which are of primordial interest in this work. They are $\overline{n}$: the average number of vehicles at some station, and $\overline{t_s}$: the average end-to-end service time, which includes waiting-in-line and charging times. A result of Pollaczek y Khinchin [12] allows an analytical expression for the first of them when $s = 1$, which is:

$$\overline{n} = \frac{\lambda(2\mu - \lambda)}{2\mu(\mu - \lambda)},\ \lambda < \mu \tag{1}$$

Besides, under stability conditions, Little Equations [11] allow to compute $\overline{t_s}$ up from $\overline{n}$ by the following expression: $\overline{t_s} = \overline{n}/\overline{\lambda}$, being $\overline{\lambda}$ the expected arrival rate, which matches λ in this case. Recall that as seen in Section II-A, a number of $s = 1$ servers is characteristic along stations in the current Electric Route in Uruguay, so we will use previous formulations to compute service metrics under the existence of steady state conditions. When those conditions are not met, we utilize simulation as a mean to estimate metrics for conditions as onto the peak-traffic window.

D. No-waiting charging station model

There are two underlying premisses of the previous model that are expected to change with technology improvements. One of them is related to charging times, which involves updates in both batteries and chargers. However, in the context of our application case, the most important change is expected to come from extended ranges in travel distances. This is based on several facts: the country is relatively small and the Electric Route is even smaller; cars abandon home to go on vacations with a full-charge in their batteries, so most of them can reach coast resorts without charging at all, specially considering that the main source of tourists (Montevideo and its Metropolitan Area) is half the way along that route. Therefore, in this second model, we are assuming that the driving range is not determined by the car but by the driver itself.

We suppose then that after traveling for some known distance, the driver will voluntarily stop at a station to stretch its legs and/or to have some meal, and in the meanwhile, car batteries will be charged (swiftly). We assume that the stop-time is long enough to substantially recharge cars batteries. Since this is an option for the driver (not an imperative), we also assume that in the event of blocking (all chargers busy), the driver will continue the travel until getting to the following station on the road. Observe that in this scheme there is no queue, which simplifies the model. Conversely, since we are now planning the long-term solution, we must consider multiple per-station chargers.

Hence, the model for a station consists of: i) a fixed number of chargers s; ii) a Poisson arrival process of per-time rate λ; iii) some per-customer service time of known mean $1/\mu$, which being variable and uncertain we assume as independent and exponential aleatory variables with parameter μ. The goal is to find the minimum number of servers/EVSEs (N), such that the probability of customers intending to stop at the station that effectively do, to be over some threshold $(1 - T)$. The remaining of this article refers to this target-threshold as the *Effectiveness*, which is a global goal for the whole system. Because of the uncertainty of arrival and service processes, the system should be stochastically analyzed. Since both inter-arrival and service times are random variables, it can be modeled with a Continuous Time Markov Process; in fact, with a Birth-Death Process as in Figure 3.

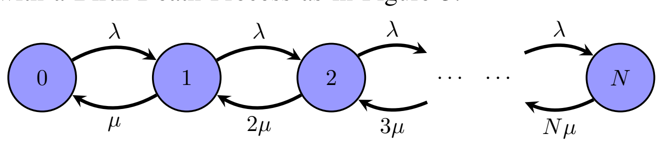

Fig. 3. Reference birth-death process for the no-waiting model.

Let $\pi_j(t)$ be the probability of finding the system with j chargers busy at time t. In steady state condition ($t \to \infty$), it must hold that $\pi_j(t) \to \pi_j$ and $\pi_j = \frac{\lambda}{j\mu}\pi_{j-1}$, for $1 \leq j \leq N$. Besides, since π values assign probabilities, they add up to 1. Therefore, those probabilities are:

$$\pi_j = \frac{\frac{1}{j!}(\frac{\lambda}{\mu})^j}{\sum_{k=0}^{N} \frac{1}{k!}(\frac{\lambda}{\mu})^k}, \; 0 \leq j \leq N \tag{2}$$

Thus, we aim at finding N for a threshold $0<T<1$ such that:

$$N = \min\{n : (\frac{1}{n!}\,(\lambda/\mu)^n) \leq T \cdot \sum_{k=0}^{n} \frac{1}{k!}\,(\lambda/\mu)^k\} \tag{3}$$

III. Resolution and Experimental Evaluation

A. Breaking down traffic into flows

Some parameters of the problem are independent of the placement of stations along the route. The service time for a car as in the Section II-C model is determined by current technological constraints. A vehicle with a 60kWh battery that can be charged at a 43kW power level, can get a full-charge in 2 hours whether that level is available, so its service rate is μ_{43}=0.5vh. A refill with a 22kW charger would take almost twice longer, then the rate is slightly over the half (i.e. μ_{22}=0.256vh). Complementarily, this model is used to estimate limits of current infrastructure, where most charging stations only have one recharge point ($s = 1$). Hence, λ is the only parameter left to determine to either compute Eq.-1 or to simulate the performance. Unlike μ, this parameter is highly variable and specific. It depends on the placement of each station, but also from seasonal conditions. Moreover, as we will see, λ also depends on the underlying model and its goals. The reference traffic used during this study is that registered along summer vacations, whose peaks are scattered among late December and January weekends. As a reference of how many vehicles circulate along the route at different points, we use registers of ticket sales at toll booths in this route, which are: Cufré, Barra de Santa Lucía, Arroyo Pando, Arroyo Solís and Garzón. Toll booths are marked with red circles in Figure 4, and the peek per-hour tickets sold is highlighted with purple fonts. These tickets are complemented with traffic data from other routes connecting with this one, and with statistics of touristic preferences, which conclude that destination for most tourists are placed after (at the right of) Arroyo Pando toll booth. Charging stations are marked with blue circles in that figure, so are estimations of the hourly number of cars passing by these points, which are marked with grey fonts. For example, Figure 4 indicates that the expected number of cars passing aside San Luis charging station during peak summer traffic is 1445 vehicles per hour.

In order to estimate the rate of vehicles *arriving* at each station, we disaggregate those bulks figures into what we called *traffic flows*. Traffic flows are groups of vehicles, whose levels of battery charge boost them, or directly force them to make a stop to recharge. Stopping is mandatory for the approach of Section II-C. Besides, since we used a reference battery capacity of 60kWh, with an estimated consumption 1kWh every 4.3km, we conclude that the average vehicles range is 260km. Complementing that with official scenarios for penetration of electric cars, we can determine how many per-hour vehicle are expected to arrive at each station.

Table III shows the set of parameter estimations for different time-horizons, used to craft instances data sets for the model as in Section II-C. These figures are based on the optimistic NDC-Conditional of Table II. The only stations with more than one EVSE are in Montevideo and Punta del Este, so we assume that $s = 1$ for all on-route stations. λ_{yy} indicates the hourly expected number of vehicles arriving to charge at that station during peaks in traffic for the summer of year 20yy.

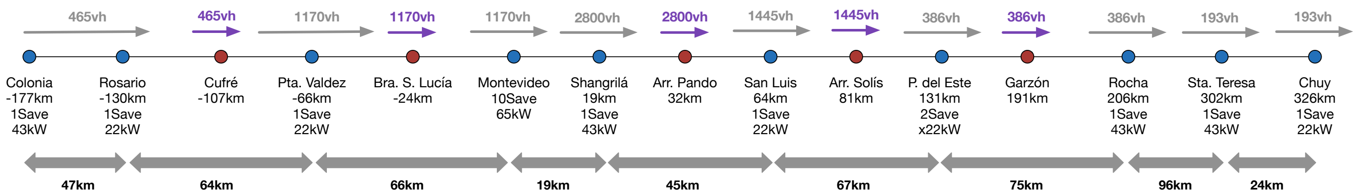

Fig. 4. Peak vehicular traffic along the Electric Route [red for toll booths / blue for charging stations; purple for per-hour tickets sold / grey for traffic].

So, Table III completes all the information necessary to either use Eq.-1 or to run simulations.

STATION	μ [vh]	λ_{20}[vh]	λ_{25}[vh]	λ_{30}[vh]
Colonia	0.500	0.13	6.13	11.43
Rosario	0.256	0.13	6.13	11.43
Punta de Valdez	0.256	0.20	9.30	17.33
San Luis	0.256	0.12	5.27	9.82
Rocha	0.500	0.16	7.20	13.42
Santa Teresa	0.500	0.03	1.44	2.68
Chuy	0.256	0.01	0.66	1.23

TABLE III
PARAMETERS FOR STATIONS IN ELECTRIC ROUTE (QUEUEING MODEL)

Regarding the model in Section II-D, there are several adjustments to make. First of all, we must determine s, which is a variable rather than a parameter in this case. Besides, the per-vehicle average service time in the second model is half an hour (i.e. μ=2vh), so it is considerably smaller than in the queueing model as well as uniform among stations. Main differences are in the computation of λ, for in this case, traffic-flows are dependent of our target quality standards. Consider a target success rate of 70% ($1 - T = 0.7$), which means that our goal is that at least 70% of the cars intending to charge at every station to succeed in their attempt. Conversely, we might think that up to 30% of potential customers of any station might end up charging their cars in the following, or in the next one if that second attempt also fails. So, the lower the target effectiveness, the higher the rate of new arrivals along subsequent stations on that route.

STATION	Effectiveness 70%		Effectiveness 90%	
	2%	**NDC-Co35**	**2%**	**NDC-Co35**
Colonia	4.64	15.69	4.64	15.69
Rosario	6.04	20.40	5.10	17.24
Punta de Valdez	8.89	30.03	7.53	25.46
Montevideo	9.70	32.80	7.77	26.26
Shangrilá	2.87	9.70	0.70	2.36
San Luis	0.44	1.48	0.08	0.27
Punta del Este	0.48	1.62	0.58	1.95
Rocha	1.06	3.57	1.59	5.39
Santa Teresa	0.46	1.55	0.48	1.62
Chuy	0.14	0.47	0.04	0.13

TABLE IV
PROJECTED ARRIVAL RATES FOR 2035 (70% AND 90% EFFECTIVENESS) UNDER SCENARIOS OF EVS PENETRATION (2% AND NDC-CO35)

Table IV shows the estimated arrival rates (λ) at each station along the peak hours of traffic projected for 2035, under different scenarios of electric cars penetration and for different thresholds of effectiveness. NDC-Co35 corresponds to the NDC-Conditional of Table II, also used in Table III, though now is for the year 2035. Columns labeled with 2% correspond to a least optimistic scenario considered by authorities. Target effectiveness are 70% (i.e. T=0.3, 30% of cars intending to charge at stations that do not because of congestion) and 90% (i.e. T=0.1). The driving range is now set to 300km. Recall that that range is proper of the driver preferences and it does not force a car to stop whether all EVSEs are busy.

B. Performance metrics for the queueing model

Table V shows the performance estimations for the two electric vehicle penetration scenarios nearest in time a couple of years ago (when this study was realized). All stations in the table have only one EVSE. The information contained in this table is as follows: i) the name of the station as in Figure 4; ii) the estimated time for a full-charge time (expressed in hours) according on the power of the corresponding EVSE; iii) the expected number of electric vehicles at each point, either waiting or charging; and iv) the expected service time for each vehicle, adding waiting and charging times.

STATION	CT[h]	NDC-Co20		NDC-Co25	
		$\overline{n}$	$\overline{t_s}$[h]	$\overline{n}$	$\overline{t_s}$[h]
Colonia	2.00	0.32	2.37	57.60	112.60
Rosario	3.91	0.81	6.05	60.10	229.20
Punta de Valdez	3.91	2.33	11.46	91.88	353.30
San Luis	3.91	0.63	5.50	51.69	196.34
Rocha	2.00	0.39	2.46	68.78	134.85
Santa Teresa	2.00	0.07	2.07	10.98	20.14
Chuy	3.91	0.06	4.02	5.64	18.77

TABLE V
PERFORMANCE RESULTS FOR THE QUEUEING MODEL (CONDITIONAL NDC-20 AND 25)

Observe that for the NDC-Co20 scenario, λ_{20} values in Table III are always lower than the corresponding μ, so queueing systems are all stable and Eq.-1 can be used to compute $\overline{n}$. The expected waiting time ($\overline{t_s}$) is derived from Little Equations. Verify that the relative difference between minimal charging times (column CT) and expected ones ($\overline{t_s}$) are small, except for Punta de Valdez and Rosario. These bottlenecks are caused by a combination of high arrival rates (λ's) with low service ones (μ's). Regarding the NDC-Co25 scenario, the situation is quite the opposite. Rates λ_{25} are always higher than μ ones, so systems are unstable. The figures in this case were obtained up from 10.000 simulations along a time window of 10 hours around the instant of peak traffic. All simulations were independent, starting from empty stations, with ramp-up (linearly increasing λ) and ramp-down (linearly decreasing) lapses of 2 hours each, and a sustained arrival rate period of 10 hours between ramps. The maximum number of cars waiting as well as the maximum end-to-end service time are registered at each simulation. Later on, the average of these figures is calculated. Resulting worst-case averages are presented over the rightmost of Table V (NDC-Co25). The expected service times at all stations is significantly higher than in the previous scenarios, and all of them are above the period for which those parameters are meaningful (10hs), and they must be taken as numerical evidence of the incapability to attend such demand.

C. Optimized update for the no-waiting version

Unlike the previous experimentation and model, which aimed at the estimation of useful life-limits of current infrastructure, this model seeks to estimate how many technologically updated EVSEs will be necessary in the mid-term, in order to satisfy VEs charging needs. Another difference is that we do not longer have stability issues, because in this case cars simply do not enter to stations if there is no free charging point. Conversely, some basic quality of service standards are to be set. In this case, it is the percentage of drivers intending to enter into some station that succeed in their goal. Table VI shows the minimum number of EVSEs at each station, necessary to attain the desired effectiveness when those stations are receiving potential customers at rates as in Table IV. These figures are the result of solving Eq.-3 for a Poisson arrival process with λ's of Table IV and independent aleatory exponential service times with mean of 30 minutes.

STATION	**Effectiveness 70%**		**Effectiveness 90%**	
	2%	**NDC-Co35**	**2%**	**NDC-Co35**
Colonia	3	7	5	11
Rosario	4	9	5	12
Punta de Valdez	5	13	7	16
Montevideo	5	14	7	16
Shangrilá	2	5	2	3
San Luis	1	2	1	2
Punta del Este	1	2	2	3
Rocha	2	3	3	5
Santa Teresa	1	2	2	3
Chuy	1	1	1	1

TABLE VI
PROJECTED NUMBER OF EVSES AT EACH STATION NECESSARY TO MEET 2035 SCENARIOS FOR DIFFERENT EFFECTIVENESS GOALS

Observe that the optimal number of EVSEs per station is always under ten for the 2% penetration scenario. For the NDC-Co35 scenario there are three stations that need more than ten EVSEs, they are: Colonia, Rosario and Punta de Valdez, the last being also the bottleneck for the previous model. which actually counts many charging stations.

IV. Conclusions and Future Work

This work shows the application of quantitative methods for the planning of the Electric Route in Uruguay. Two models were considered. The first with the aim of assessing life limits for the current charging infrastructure, while the second seeks to estimate how many additional EVSEs would be necessary along the one and a half decade to come.

Considering the existing traffic flow data and prospective studies for possible penetration scenarios (2020/2025/2035) of electric vehicles and also taking into account the capabilities of vehicles in stressful contexts, it is possible to conclude that the current charging infrastructure is suitable for the number of electric vehicles at the present, but it would not be enough in the near future for the studied scenarios. Taking into account an overall driving range of 300 km per-driver, an upgrade to the number of charging points at every station will be required in order to attain the desired effectiveness. However, estimations regarding the additional number of EVSEs are mostly under ten, which is reasonably attainable.

We also remark that although higher, the additional number of necessary EVSEs does not change significantly with the target effectiveness. Usually, the outcome to such kind of problems shows that the number of resources to attain much higher grades of service are unaffordable. Conversely, results of this study show that additional expenditures to move from 70% to 90% of effectiveness are relatively low, between 24% and 40% of extra EVSEs, depending on the scenario. An explanation to this particular behavior is that lower effectiveness increase rebounds of cars, which merely moves the dimensioning problem to following stations along the route.

This study took into account the existing charging infrastructure in the country, which only has AC chargers, and only considerar a reference model of EV. However, additional car/chargers combinations can be captured by breaking down traffic into additional traffic-flows, what makes possible to use this studio methodology under scenarios with greater complexity; for instance, when there is a combination of fast chargers (AC) with superchargers (DC), where charging times are substantially different. Superchargers are expected to begin in Uruguay in 2021. As the main line of future work, we identify the problem of applying such techniques to whole network of routes in the country, which incorporates not only topological issues but also inter-seasonal ones.

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