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Cloud Computing Based Speed Control Optimization of Electric Bus Fleet with Fast Charging Infrastructure

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ABSTRACT

For urban electric buses, it is important to develop a schedule for fast charging of batteries as a function of existing operating conditions. The paper presents a model for the optimization of charging process of electric bus batteries in the electric vehicle charging station system on their routes, with a determined structure. The place and time of battery charging are selected as a function of the existing bus operating conditions, assessment of the battery charge level and location in the transport urban infrastructure, using the Monte Carlo simulation approach. The aim of the article is to optimize the speed of electric buses with the use of cloud computing aimed at the collision-free use of a limited number of charging stations for electric vehicles on their routes and minimizing the total energy demand.

KEYWORDS: cloud system, charging process, electric buses

1. Nomenclature

1.1 Index

i – Index for stops.
t – Index for time.
k, n, m – Sub-indices to denote variation.

1.2 Parameters

d_i – Distance between stop i and i-1 in the bus route.
μ_{as} – Bus average speed on the route.
σ_{as} – Bus average speed standard deviation on the route.
μ_{st} – Average bus duration time at one stop.
σ_{st} – Standard deviation of the average bus duration time at a stop.
v_i – Speed between stop i and i-1 on the bus route.
td_i – Duration time at bus stop i.
wp – Net weight of a passenger.
λ_{up} – Average number of passengers boarding the bus.
λ_{down} – Average number of passengers leaving the bus.
Np_{up_i} – Number of passengers boarding at bus stop i.
Np_{down_i} – Number of passengers leaving at bus stop i.
wb_0 – Empty bus net weight.
ts_i – Time on the street between stop i and i-1 on the bus route.
tr_i – Time between stop i and i-1 including the duration time at bus stop i.
P_0 – Bus power consumption.
P_1 – Load power infrastructure.
N – Route duration time.

1.3 Variables

wb_i^t – Bus weight between stop i and i-1 at time instant t.
Pb_i^t – Power consumed by the bus between stop i and i-1 at time instant t.

x_i^t Binary variable denoting the state ($x = 1$ the bus receives load at stop i,

$x = 0$ the bus does not receive load at stop i) at time instant t.

2. Introduction

Global warming, decarbonization of the transport sector and energy efficiency policies to increase the use of public transport are objectives set by the EU [1]. Although these strategies are globalized and adopted by many countries, for example, China [2]. For these reasons, the number of publications about electric buses and their application in public transport has increased exponentially in recent years.

The massive introduction of electric bus fleets has barriers, but there are viable solutions associated with the two main problems of this type of technology, batteries types [1] and charging technologies [3].

In the paper [4], the authors propose to introduce electric buses to reduce levels of CO_2 concentration in cities and the problems associated with this type of technology. The paper ends proposing a decision-making model associated with a specific type of technology [5] that seeks to replace the conception of current electric buses and provide a real and viable solution. In addition, they express that the new technology [5] could replace the current electric trams because this new technology eliminates overhead lines, reducing considerably the maintenance costs.

In this paper we continue the work [4] and we explore other problems related with this type of system and its operation. We propose an objective function with two targets, and we consider the interactions between the routes. In addition, we focused the discussion of the paper on analyzing the problem associated with bus agglomeration at stops, proposing a possible solution for this problem (see Fig. 1).

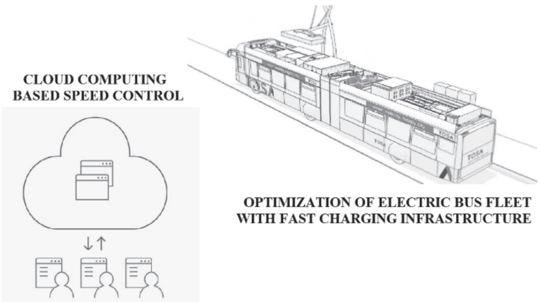

Fig. 1. Conceptual framework [own study]

To solve the bus agglomeration at stops problem, we propose to use a bus fleet speed control based on the cloud, taking as a reference the effectiveness of this type of control [6]. The solution is viable because the proposed model allows controlling the speed of buses. The results of the investigation show that when we control the speed of the buses, the charging moments of the electric buses change, evidencing the applicability of the model and its compatibility with this the conceptual framework.

3. Materials and methods

The optimization model objective (1) is to determine an infrastructure of charging stations that guarantee to minimize the energy $E^t\left(x_i^t\right)$ needed by the bus for the passengers transportation, as well as to minimize the chargers stations number $\sum_{i=1}^{N_E} x_i^t$ on the route. The input is described by a set of charging events x_i^t, which have a possible starting time ts_i and a duration td_i. The charger optimization assigns charging events to chargers and matches the bus stops. The rescheduling of the charging events to minimize the energy and the charger's number is a complex scheduling problem. Penalties for shifting when the bus is not able to reach its destination are included.

$$\min\left\{F\left(x_i^t\right)\right\}$$
$$F\left(x_i^t\right)=\left\{E^t\left(x_i^t\right),\sum_{i=1}^{N_E} x_i^t\right\} \tag{1}$$

The variables and parameters of public buses operation are known for the transportation companies experience operating these systems. However, they depend on the route characteristics. For this reason, this paper assumes probability distribution laws to simulate the variables and parameters of the proposed model, knowing that in a real study case, all the variables and parameters stated would be known, allowing to obtain the problem solution according to the route studied. The optimization model objectives are described below from the variables and parameters necessary for the process simulation.

The modeling begins with the initial conditions:

- Stops number in the route and the distance between each stop d_i.
- Average speed μ_{as} of the bus on the route.
- Standard deviation σ_{as} of the average bus speed on the route.
- Average duration μ_{st} of the bus at stop i.
- Standard deviation σ_{st} of the average bus duration at stop i.

The parameters above allow us to estimate the bus speed and the stop bus duration with probability distribution laws in each route section, assuming that they follow a Normal probability distribution, which we denote as $v_i \sim N\left(\mu_{as},\sigma_{as}\right)$ and $td_i \sim N\left(\mu_{st},\sigma_{st}\right)$ respectively.

On the other hand, it is necessary to know:

- The net weight wp of the passengers.
- The average number of passengers λ_{up} that board the bus at stop i.
- The average number of passengers λ_{down} leaving the bus at stop i.

The parameters above allow us to simulate the weight that the bus wb_i^t has at stop i at the instant of time t. Assuming that the number passengers boarding and leaving the bus at stop i follows a Poisson probability distribution, which we denote $Np_{up_i} \sim P\left(\lambda_{up}\right)$ and $Np_{down_i} \sim P\left(\lambda_{down}\right)$ respectively. Knowing these parameters can be estimated with the equation (2) the bus weight in each route section.

$$wb_i^t = wb_0 + \left(wp \times Np_{up_i}^t - wp \times Np_{down_i}^t\right) \tag{2}$$

The time it takes to travel the bus ts_i between the i and i-1 in the bus route is determined by the section distance d_i and the simulated speed v_i. Therefore, the equation (3) defines the travel time in the street. When the street time and the stop time is added, we obtain the time of each route section, as shown in equation (4).

$$ts_i = \frac{d_i}{v_i} \tag{3}$$

$$tr_i = ts_i + td_i \tag{4}$$

The bus weight during each route section i does not change. The weight for each section remains constant in time. Therefore, the variable $t = [ts_{i-1}, ts_i]$ varies in each route section.

If we are in the presence of an electric bus, and that we know the weight in each route section, it is possible to estimate the bus energy consumption for each condition, because they are directly proportional. Equation (5) shows the power consumed by the bus in each route section.

$$Pb_i^t = Pb_i^{t-1} - \left(\frac{wb_i^t}{wb_0} \times P_0 \times \Delta t \right) \tag{5}$$

Where P_0 is the bus power consumption and $\Delta t = t - (t - 1)$.

The power consumption value is constant but depends on weather conditions (consumption of air conditioning, consumption of lights, auxiliary devices, among others). This electricity consumption is during the route from stop i to stop i+1. Therefore, the variable $t = [ts_{i-1}, ts_i]$ varies in each route section.

The problem to solve in this investigation is to determine which is the best distribution of charging stations at intermediate points along the route. The charging points matches with bus stops i and the time required for charging is determined by the duration time td_i of the bus at the stop to pick up passengers. The investigation uses a binary variable x, defined in equation (6) to vary the points where the bus receives load.

$$x_i^t = \begin{cases} 1 & \text{the bus reseives load at the stop } i \text{ in the interval } [ts_i, td_i] \\ 0 & \text{the bus does not reseives load at the stop } i \text{ in the interval } [ts_i, td_i] \end{cases} \tag{6}$$

To introduce this condition, the equation (7) is formulated.

$$Pb_i^t = \begin{cases} Pb_i^{t-1} + (P_1 \times \Delta t) & x_i^t = 1 \\ Pb_i^{t-1} & x_i^t = 0 \end{cases} \tag{7}$$

Where P_1 is the load power infrastructure and Pb_i^t is power consumed by the bus between stop i and i-1 at time instant t.

In this case, the variable t in equation (7) is determined by the interval $[ts_i, td_i]$. Therefore, to determine the bus consumption along the entire route, equation (8), is proposed, as shown below.

$$Pb_i^t = \begin{cases} Pb_i^{t-1} - \left(\frac{wb_i^t}{wb_0} \times P_0 \times \Delta t \right) & \text{if} \quad [ts_{i-1}, ts_i] \\ Pb_i^{t-1} + (P_1 \times \Delta t) & \text{if} \quad x_i^t = 1 \quad [ts_i, td_i] \\ Pb_i^{t-1} & \text{if} \quad x_i^t = 0 \quad [ts_i, td_i] \end{cases} \tag{8}$$

From the equation (8) it is possible to determine the energy consumed by the bus in the whole route by means of equation (9). The power is determined by the intermediate load points in the route, therefore, an optimization model is proposed that minimizes the energy consumed by the bus in the whole route. The optimization model varies the variable x_i^t looking for the best combination of charging stations on the route.

$$\begin{gathered} \min \left\{ E^t\left(x_i^t\right) = \int_{ts_0}^{ts_N} Pb_i^t \, dt \right\} \\ E^t\left(x_i^t\right) = \frac{1}{2} \sum_{n=1}^{N} [t_{n+1} - t_n] \left[x_i^t \times Pb_i^t(t_n) + x_i^t \times Pb_i^t(t_{n+1}) \right] \end{gathered} \tag{9}$$

Where N is the time duration of the route and $[t_{n+1}, t_n]$ is the sampling time.

On the other hand, the number of charging stations on the route is proportional to the investment cost. For this reason, it is defined as the second objective, minimize the number of charging stations, defined in the equation (10). The second objective inclusion establishes the compromise between minimizing the number of charging stations against minimizing the energy used by the bus through a Pareto frontier:

$$\min \left\{ \sum_{i=1}^{N_E} x_i^t \right\} \tag{10}$$

Where N_E is the number of charging stations on the route, because the binary variable $x_i^t = 1$ when a charging station is required at stop i.

Once the two objectives have been defined, it is described how to determine the number of charging stations and their distribution in the route based on the proposed model results. The existence of random variables induces the need to use the Monte Carlo simulation method to estimate the number of charging stations expected on the route $E[x_i^t]$. Table 1 shows the results structure.

A model with probabilistic variables introduces fluctuations in the simulation results, but according to the large numbers theory if we repeat the process k times the result tends to the simulation process average behavior. Table 1 is the main result of this investigation, which shows the charging stations distribution necessary for the bus to reach the route destination. If the number of ones in each row (simulation) of Table 1 are added, the number of charging stations in each simulation is obtained, the column resulting average value shows us the number of charging stations $E[x_i^t]$ that the route needs for the bus to reach the final destination. The frequency distribution for each simulation, showing the stops where the charging stations should be located. This result is obtained by adding the number of ones in each column of Table 1.

Table 1. Distribution of charging stations [own study]

Number of simulations	Terminal stops				
	1	2	3	⋯	m
1	x_{11}	x_{12}	x_{13}	⋯	x_{1m}
2	x_{21}	x_{22}	x_{23}	⋯	x_{2m}
3	x_{31}	x_{32}	x_{33}	⋯	x_{3m}
⋮	⋮	⋮	⋮		⋮
k	x_{k1}	x_{k2}	x_{k3}	⋯	x_{km}

In this work, to estimate $E\left[x_i^t\right]$ the Monte Carlo simulation method is used. The convergence process is fluctuating in this method. However, the error level decreases when the number of samples increases, according to the law of large numbers. In this method it is not practical to run a simulation with many samples, because more calculation time is required. Therefore, it is necessary to balance, the required precision and the calculation time. In this work, a stop criterion is used. This criterion guarantees that the simulation continues, until the $E\left[x_i^t\right]$ has the precision specified for the simulation. The parameter used as stopping criterion in the method is the coefficient of variation.

If $E\left[x_i^t\right]$ is the number of charging stations estimated on the route, in the Monte Carlo simulation, the expected value and the variance of x_i^t are (11) and (12) respectively.

$$E\left[x_i^t\right] = \frac{1}{N}\sum_{k=1}^{N} x_{i\,k}^t \tag{11}$$

$$V\left[x_i^t\right] = \frac{1}{N-1}\sum_{k=1}^{N}\left(x_{i\,k}^t - E\left[x_i^t\right]\right)^2 \tag{12}$$

Where $x_{i\,k}^t$ is the observed value of x_i^t in the simulation *k*, and *N* is the total number of simulations.

It is important to note that (11) only estimates the expected value of x_i^t. However, the uncertainty around $E\left[x_i^t\right]$ is measured by the variance (13) and standard deviation (14) of the expected value.

$$V\left(E\left[x_i^t\right]\right) = \frac{V\left(x_i^t\right)}{N} \tag{13}$$

$$\sigma\left(E\left[x_i^t\right]\right) = \sqrt{V\left(E\left[x_i^t\right]\right)} = \sqrt{\frac{V\left(x_i^t\right)}{N}} \tag{14}$$

The level of simulation precision is expressed by the coefficient of variation β defined in (15). This coefficient is rewritten conveniently in (16), where $\sigma\left(x_i^t\right) = \sqrt{V\left(x_i^t\right)}$.

The simulation is controlled with the coefficient of variation β, selecting the error tolerance ε in the simulation (17). The error tolerance ε is the estimate maximum error. In the estimates it is typical to use 5% or 0,05.

$$\beta = \frac{\sigma\left(E\left[x_i^t\right]\right)}{E\left[x_i^t\right]} \tag{15}$$

$$\beta = \frac{1}{E\left[x_i^t\right]}\sqrt{\frac{V\left(x_i^t\right)}{N}} = \frac{\sigma\left(x_i^t\right)}{E\left[x_i^t\right]\sqrt{N}} \tag{16}$$

$$\frac{\sigma\left(x_i^t\right)}{E\left[x_i^t\right]\sqrt{N}} \le \varepsilon \tag{17}$$

The value of β decreases when the number of simulations *N* increases, as shown in (16). Therefore, the simulation process is stopped when β is less than ε.

The precision level of the Monte Carlo simulation method is related to the number of samples in the simulation and is independent of the system dimension. This condition is appropriate for handling systems with complex functions and large dimensions.

4. Results and discussions

The paper proposes several scenarios to verify the model applicability. The routes used have 22 stops and are shown in Fig. 2, one of urban environment with 11 km and one of regional environment with 23 km. Scenario 1 shows the proposed model solution with the 11 km route for various percentages of bus battery capacity, Scenario 2 shows the solution for the 23 km route with 100% battery capacity and, the Scenario 3 shows the model solution when there is interaction between the routes, and for the same scenario and operating conditions, we show how the results change when we control the speed of the buses.

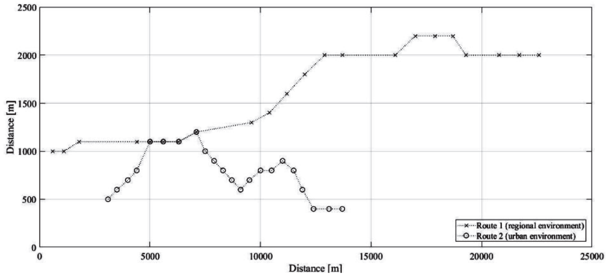

Fig. 2. Transport route distribution [own study]

4.1 Scenario 1

The research uses data from previous paper [7] and [8]. Fig. 2 shows the distance by stops in meters of a route with 22 stops and 11 km (urban environment) of distance. The bus average speed on the route is μ_{as} = 4,5 m/s and a standard deviation of $\sigma_{as} = 0{,}05\mu_{as}$ is assumed. The bus duration time at the stops is μ_{st} = 20 seconds and a standard deviation of $\sigma_{st} = 0{,}05\mu_{st}$ is assumed. The passengers net weight is wp = 75kg, the average number of passengers going up and down on the bus at each stop *i* is $\lambda_{up} = 9$ and $\lambda_{down} = 10$ respectively. It is assumed as an initial condition that 10 passengers ride the bus at the first stop. The empty bus weight is 8 000 kg.

The bus battery has a capacity of 90 kWh. The bus auxiliary consumption is 4,5 kW, the bus load in lights and equipment for passenger tickets is 3,5 kW, the consumption of air conditioning is 2 kW and the consumption of electric motors is 90 kW. The charging infrastructure offers a power of 500 kW in 20 seconds. Fig. 3 shows the bus power consumption in the simulated route sections, evidencing that in the sixth stops the bus receives load and the fifth stop does not receive load, and Fig. 4 shows the number of charging stations and their distribution on the route according to the percentages of battery capacity for Scenario 1.

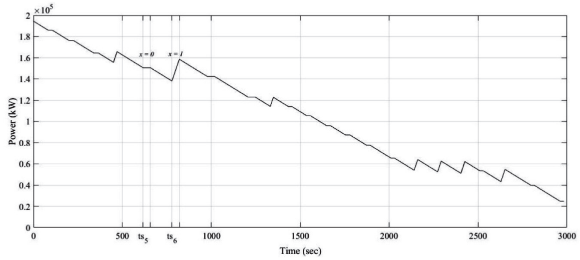

Fig. 3. Power behavior [own study]

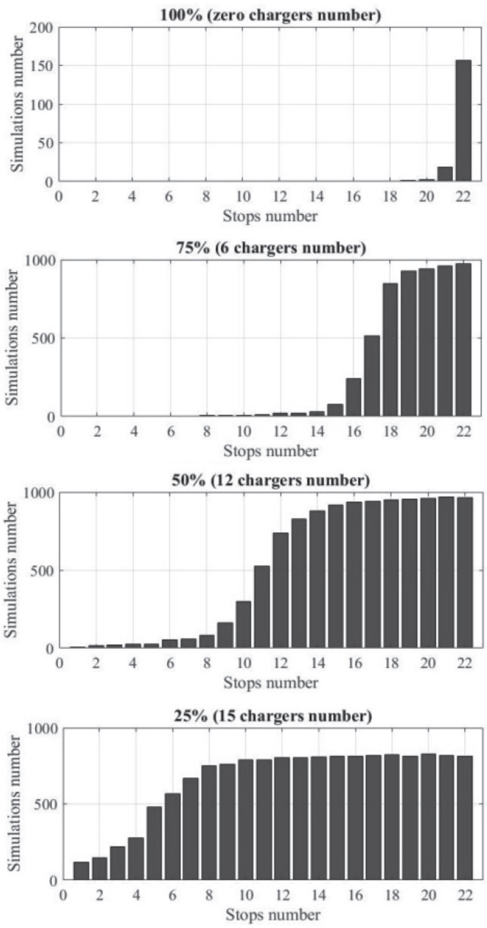

Fig. 4. Scenario 1 results [own study]

4.2 Scenario 2

In this scenario, a route with 22 stops and distance of 23 km is used (regional environment). Fig. 2 shows the distance by stops in meters. The bus average speed on the route is μ_{as} = 6,8 m/s and a standard deviation of $\sigma_{as} = 0{,}05\mu_{as}$ is assumed. The bus duration time at the stops is μ_{st} = 25 seconds and a standard deviation of $\sigma_{st} = 0{,}05\mu_{st}$ is assumed. The passengers net weight is *wp* = 75 kg, the average number of passengers going up and down on the bus at each stop *i* is λ_{up} = 11 and λ_{down} = 13 respectively. It is assumed as an initial condition that 5 passengers ride the bus at the first stop. The empty bus weight is 8 000 kg.

The bus battery has a capacity of 90 kWh. The bus auxiliary consumption is 4,5 kW, the bus load in lights and equipment for passenger tickets 3,5 kW, the consumption of air conditioning is 2 kW and the consumption of electric motors is 90 kW. The charging infrastructure offers a power of 500 kW in 20 seconds. Fig. 5 shows the number of charging stations and their distribution on the route for Scenario 2.

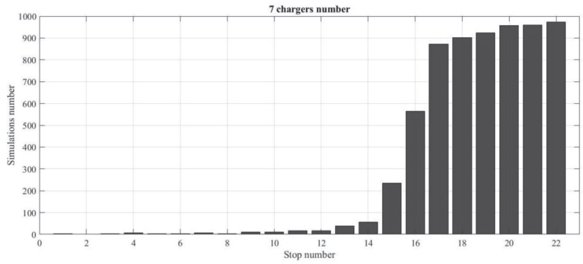

Fig. 5. Scenario 2 results [own study]

The probabilistic variables of the model introduce fluctuations in the simulation results, but according to the theory of large numbers if we repeat the process *k* times the result tends to the simulation process average behavior. The simulation process stability is analyzed. To analyze the convergence, the simulation results of 100, 500 and 1000 process samples and their corresponding errors are shown in the Table 2.

Table 2. Simulations results [own study]

Total samples	Mean	Standard deviation	Error
100	6,13043	5,99488	0,117724
500	6,73504	5,98865	0,047461
1000	7,14058	6,13602	0,032714

The results show that the process is stabilized when the number of simulations is increased and the error (see Equation 17) allows to determine when the number of samples is enough, in this case when the error is lower than 0,05 is considered acceptable the number of samples. Therefore, the number of charging stations is 7 stations.

4.3 Scenario 3

In this scenario, both routes shown in the Fig. 2 are analyzed. Table 3 shows the parameters of the routes analyzed. At stops where there is interaction between routes, 40 seconds are assumed for the passenger's line load.

The Scenario 3 shows how the model results are modified when there are interactions in the routes. The different routes are independent, and the result depends on their characteristics, but in the stops where there are interactions it is appropriate to install a charging station that provides service to the two routes, reducing the investment costs. The proposed model is consistent with the previous statement. In Scenario 3 it is evident how the interaction modifies the proposal of charging stations distribution (see Fig. 6).

The solution is achieved by superimposing the simulations at the stops where exist interaction.

The bus agglomeration at stops can be a problem for this system, because each bus needs a relatively short time to battery charging at the stop, and as we can see from the previous results, the interactions on the routes determine the moment at battery charging of the electrical buses. Based on the experience of previous papers [6] in the systems with interactions in the routes it is frequently to use the bus speed control based on the battery State of Charge. The model proposed in this paper considers the battery State of Charge of the buses and minimizes the bus charging points number on the route as evidenced in the previous results. Fig.s 7 and 8 show how when we control the speed of the buses the results are modified for the same scenario.

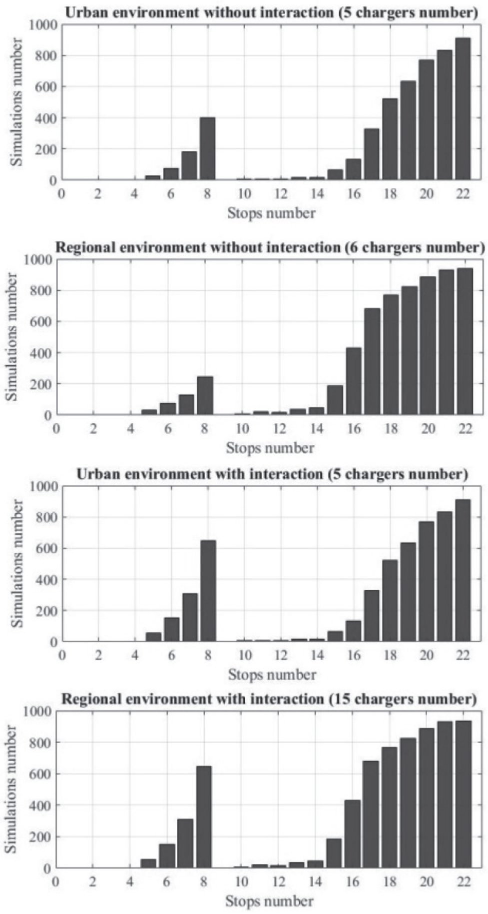

Fig. 6. Scenario 3 results [own study]

Table 3. Routes parameters [own study]

Parameter	Route 1	Route 2
Distance	23 km	11 km
Bus average speed (μ_{as})	6,8 m/s	4,5 m/s
Standard deviation (σ_{as})	$0{,}05\mu_{as}$	
Bus duration time at the stops (μ_{st})	25 seconds	20 seconds
Standard deviation (σ_{st})	$0{,}05\mu_{st}$	
Passengers net weight (*wp*)	75 kg	
Passengers average number (up)	11	9
Passengers average number (down)	13	10
Empty bus weight	8 000 kg	
Bus battery capacity	90 kWh	67,5 kWh
Bus auxiliary consumption	4,5 kW	
Bus load in lights and equipment	3,5 kW	
Consumption of air conditioning	2 kW	
Consumption of electric motors	90 kW	
Charging infrastructure	500 kW in 20 seconds	

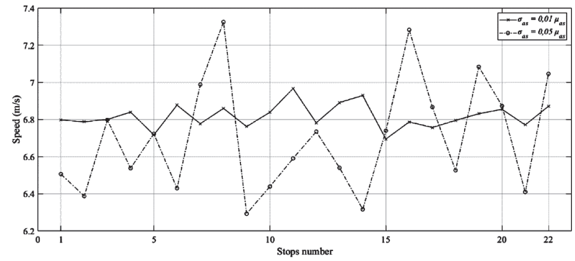

Fig. 7. Speed behavior of the electrical bus in the route [own study]

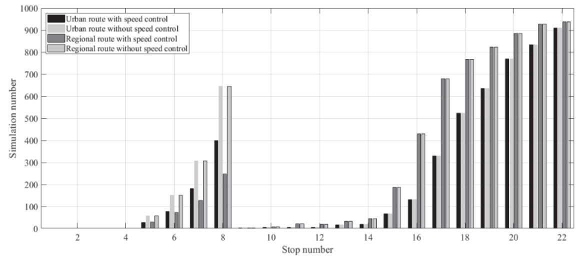

Fig. 8. Bus charging distribution [own study]

Fig. 8 shows how the bus battery charging moment change when speed control is performed, for example, the bus in urban environment needs 5 fast charges on the route. When the speed control is not carried out, the bus charging the battery at stops 8, 19, 20, 21 and 22; when speed control is performed, the bus charging the battery at stops 18, 19, 20, 21 and 22.

5. Conclusion

The investigation results show the distribution of the charging stations necessary for the bus to reach the route destination. The proposed optimization model allows estimating the best charging infrastructure distribution of a bus in a route. The paper shows how the interaction between the routes defines the final problem solution. The results of the investigation show that when we control the speed of the buses, the charging moments of the electric buses change, evidencing the applicability of the model and its compatibility with this the conceptual framework, therefore, with this model we can avoid the bus agglomeration at stops problem. The results support the decision-making process.

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