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A Two-step Optimization Process for Efficient Scheduling of Heterogeneous Fleets of Electric Buses with Synchronized Transfers

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Abstract

Public transport systems are undergoing a significant change in most cities thanks to the advances in technology. The focus is not only on sustainability but also on efficiency and the experience of the passenger. In this work, we propose a complete redesign of the public transportation that considers a heterogeneous fleet of electric buses that dynamically changes in terms of the needs of each bus line at different hours, as well as a new bus schedule that minimizes passenger waiting time at bus stops by synchronizing different bus lines. In order to get optimal solutions, two optimization steps are needed. Preliminary results suggest that it is possible to implement an electrical bus fleet with different passenger and battery capacities that addresses the passenger demand, including the transfers on extensive trips where the users reduce travel times due to the synchronized schedule.

Keywords: Sustainable transportation; bus synchronization; vehicle scheduling; battery electric buses; evolutionary algorithms.

1. Introduction

An efficient and sustainable public transportation system is the cornerstone of an adequate city development but also one of the main challenges of the 21st century. It has to be sustainable because of the greenhouse emissions, efficient so that operators consider it as a profitable business, and comfortable, making public transport an attractive alternative to users. Transit buses are among the most popular modes of public transport worldwide (UITP (2019)). Together with light and heavy rail transport, they account for 96% of all passengers in the USA (Dickens (2021)). Because of their relevant role in urban mobility, thinking about sustainable transport draws particular attention to systems operated

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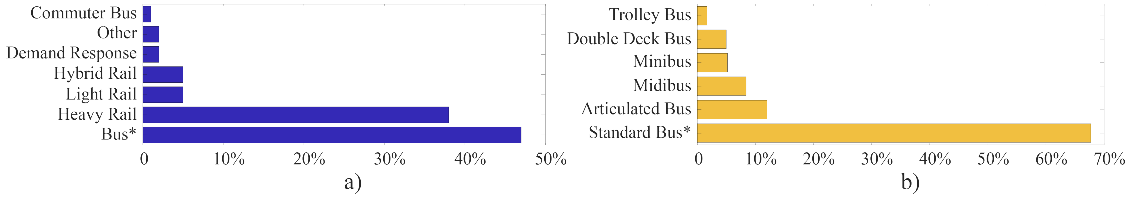

Fig. 1. (a) Ratio of trips by different modes of transport (Dickens (2021)). (b) Types of vehicles that constitute bus fleets worldwide (UITP (2019)).

by bus fleets, which are currently primarily diesel-powered. In addition, traditional buses have a significant presence in most fleets compared to other alternatives such as minibuses that can offer lower fuel consumption or occupy less space (see Fig. 1). Moreover, with the rise of electro-mobility, it is estimated that 16% of buses worldwide are electric, and it is expected that by 2050 all buses will be electric. However, this generalization of fully electric buses, planned globally, is happening at diverse rates depending on the country and city. China, the nation with the most extensive fleet of electric vehicles, and Europe are the dominant regions in reducing the traditional fossil-fuelled mobility, and they will continue leading in clean technologies up to 2025 (BNEF (2021)). The European program ZeEUS (2018) (Zero Emission Urban Bus System), led by UITP (International Association of Public Transport), estimates that by 2030 the most popular propulsion system used in public transport will be electric energy. This shift to electro-mobility raises important challenges, mainly motivated by the limited autonomy of electric buses with onboard batteries.

This scenario is appropriate to develop intelligent transportation systems that can adequately manage a heterogeneous fleet of electric buses for the mobility of a growing demand of passengers with high quality of service. This can significantly reduce noise pollution levels, greenhouse gas emissions (almost zero emissions at operation time), and road congestion by reducing the number of vehicles in transit. To motivate citizens to use public transport, offering a good experience and high comfort to passengers is a must. In this sense, passengers in public transport systems are expected to walk to and from services, transfer between vehicles, and wait for their arrival. Time spent walking is usually valued higher by passengers since it implies a much greater effort than time spent onboard a vehicle. The same applies to transfers and waiting time at stations or stops since passengers have fewer opportunities to use their time effectively. In this regard, surveys have shown that passengers perceive time spent transferring as between 1.4 and 2.5 times longer than the time spent within the vehicle (Wardman (2004)). Consequently, reducing the waiting time of passengers—especially when transferring—increases the perceived quality of service offered by the public transport system. For this purpose, timetable scheduling can maximize the number of synchronized transfers, thus minimizing the waiting time experienced by users during transfers.

Timetable design and vehicle scheduling are two crucial phases of public transport planning (Ceder (2016)). This work aims to tackle those stages using a heterogeneous fleet of electrical buses looking to maximize the onboard battery utilization, prioritizing recharging methods that preserve the state of health that could extend the battery life, while adjusting timetables to minimize waiting times in transfers. In addressing those stages, there is a need for an integrated modeling approach to support the bus manager company in carrying out frequency planning and vehicle scheduling for a bus fleet composed of electric buses (eBuses), with batteries onboard, of diverse types. The problem can be addressed in two steps, consisting in the optimization of the timetables and of the heterogeneous fleet use. The former, called the Bus Synchronization Problem (BSP), was addressed in our previous work (Massobrio et al. (2022)), and its results are used in this work to address the latter. The experimental results are computed using an instance based on real information provided by the Metropolitan Transportation System in Montevideo, Uruguay, and a set of eBuses composed of typical vehicle features available from several brands in the electro-mobility market.

The remainder of this work is organized as follows. Section 2 presents a brief literature review. Section 3 describes the model formulation, and Section 4 illustrates the development of the optimization algorithms, whose computational tests are described in Section 5. Section 6 presents the experimental results. Conclusions and future research suggestions are outlined in Section 7.

2. Related Work

With the rapidly growing population, the planning of public transport has become a new concern, specially in big cities. Researchers are tackling this problem from different perspectives, many of them using computational intelligence methods to compute approximate solutions because it is a NP-hard problem (Lenstra and Kan (1981)). Ceder (2016) proposed the timetabling problem as one critical phase in public transport planning, along with the vehicle scheduling problem (VSP). Those phases were addressed at the same time in most cases, performed in sequence, where one or more instance problems for the timetable development are solved, and the solution is taken as an input of the following approach that computes a solution for the VSP (Guihaire and Hao (2008), Carosi et al. (2019)).

The use of a heterogeneous fleet of vehicles can be very useful for the purpose of improving the utilization of the vehicles, avoiding overloads in peak hours or an unprofitable and energy inefficient operation (Potter (2003), Ceder (2011)). Early works on this matter only consider minimizing the operational cost (important for transport companies). However, works such as Ceder (2011), Ibarra-Rojas et al. (2014), or Peña et al. (2019) formulated multiobjective problems that combine the operational cost and the quality of service (desired from perspective of the user).

Recently, the reduction of greenhouse gas emissions in transportation attracted the interest of the administration and researcher due to its high contribution and direct detriment of the air quality (Yang and Liu (2020), Peña et al. (2022)). However, many cities rely on diesel-powered vehicles for some or all of their urban transport needs, but novel battery technologies make fully electric buses more competitive as a fleet replacement option. This incursion of electric vehicles introduces novel constraints to develop an appropriate schedule that considers the battery capacity in watts per hour, range in km, or the recharging methods (Yang and Liu (2020)), e.g., Yao et al. (2020), introduce an approach for the VSP using multiple types of electric buses to reduce the annual operating cost. In this work we propose an approach that consider two stages. The first one is to find a set of headways (i.e., the time between consecutive vehicles) of a specified set of routes that minimize the passengers waiting time at transfers (Nesmachnow et al. (2020); Massobrio et al. (2022)). For the second step, we develop in this work a cellular Genetic Algorithm (cGA) to solve the multiple type eBus scheduling problem using the results from the first step as an input.

3. Heterogeneous fleet energy consumption formulation

Given a set of timetabled trips $T = t_1, \ldots, t_q$ of a defined set of routes R, where T is constructed using the synchronization timetabling approach under a established scenario, and a set of n bus types ($n \in N$) where B_n is a set of eBuses of type n, such that $B = \cup_{n \in N} B_n$ is the total available fleet. The formulation for the energy consumption of the whole fleet is based on a objective function F_1 as follows:

$$Min : F_1 = \frac{1}{|N|} \sum_{n=1}^{|N|} SoC_n \quad , \tag{1}$$

where SoC_n is the average state of charge of the onboard batteries in the heterogeneous eBuses fleet at the end of the day in ampere-hour (Ah) that represents the % of battery utilization which is to be maximized.

The main idea is to reduce the total remaining energy so that the use of electrical energy from the batteries is maximized, and the number of eBuses required is reduced. eBuses could be recharged, but it is well known that fast charging methods may damage the battery life. Therefore, the problem considers recharging the vehicles using slow charging methods overnight, in order to extend the State of Health (SoH) (Lipu et al. (2018)). SoC_n is defined as:

$$SoC_n = \frac{1}{|B_n|} \sum_{m=1}^{|B_n|} SoC_m \quad , \tag{2}$$

$$SoC_m = SoC_m^{ini} - \frac{E_m + E_{aux}}{V_m} \quad , \tag{3}$$

$$0.2 \times SoC_m^{max} \leq SoC_m \leq 0.8 \times SoC_m^{max} \quad , \tag{4}$$

$$E_m = \frac{3600}{\eta_m^{bd}} \times \left(\sum_{p=1}^{|T_m|} PC_p - \sum_{c=1}^{|C_m|} PR_c \right) \quad , \tag{5}$$

where SoC_m is the state of charge of each bus m in B_n, and its initial charge is SoC_m^{ini}. SoC_m^{max} is the maximum capacity of the eBus batteries in Ah (different for each kind of bus), and with the purpose to preserve the SoH an important constrain is to maintain SoC_m level above 20% of SoC_m^{max} thus avoiding the zone where the discharge efficiency get worse. Additionally, batteries are not charged further than 80%, because otherwise battery stress levels would affect their useful life. E_m is the total energy-related to the m bus operation per day in watts hour (kWh). E_{aux} is the energy used for the auxiliary elements like air conditioner, lights, radio or open/close doors. V_m is the bus battery voltage in volts (v). PC_p is the total power consumption in watts (W) used to cover the trips T_m (set of trips assigned of a m bus). PR_c is the electrical generator power that considers recharging cycles during the operation or recapturing kinetic energy from braking (or transiting downhill) with a generator efficiency of 60%. The discharge efficiency of the eBus is η_m^{bd}.

$$PC_p = \frac{FT_p^m \times \bar{\upsilon}_p^m}{\eta_m^{total}} \quad , \tag{6}$$

$$\eta_m^{total} = \eta_m^{motor} \times \eta_m^{trans} \times \eta_m^{DC-DC} \quad , \tag{7}$$

$$FT_p^m = Fd_p^m + Fr_p^m + Fh_p^m + Fa_p^m \quad , \tag{8}$$

$$FT_p^m = \frac{\rho_{air} \times A_n \times C_{df} \times (\bar{\upsilon}_p^m)^2}{2} + g \times C_{rr} \times \cos\alpha \times mass_n + g \times \sin\alpha \times mass_n + a_p^m \times mass_n \quad , \tag{9}$$

where FT_p^m is the total traction force in Newtons (N). Fd_p^m is the aerodynamic drag force, Fr_p^m is the rolling friction force, Fh_p^m is the hill-climbing (slope) force, and Fa_p^m is the acceleration resistance force. Equation (7) refers to the total drive-train efficiency (η_m^{total}) including the motor, transmission, and DC-DC converter efficiencies.

Constant g is the gravity, $\bar{\upsilon}_p^m$ is the average speed (in $\frac{m}{s}$), a_p^m is the bus acceleration (in $\frac{m}{s^2}$), α is the angle of inclination in degrees, and C_{rr} is the coefficient of rolling resistance, it depends on air pressure in tires, the wear and tear of tires, and road roughness. ρ_{air} is the ambient air density; C_{df} is the drag coefficient; A_n is the frontal area in m^2 and $mass_n$ is the accumulated mass in kg of the vehicle of type n. The speed was defined considering the suggestion of ATUC (in Spanish: Asociación de Empresas Gestoras de los Transportes Urbanos Colectivos) in Spain. They claim that the average speed of a standard bus on Labor Day could be 12 km/h approximately (Cortés et al. (2011)). The stop-and-go routines of a bus or the urban transport characteristics like traffic do not allow buses reach velocities over 30 km/h, which may define the mass of the vehicles (curb weight). The passenger mass does not influence because the overweight is relevant to the energy consumption only for speeds higher than 30 km/h (Yu et al. (2016)). The slope of the route is computed using an elevation API for several control points on the road. These points define whether the eBus moves uphill or downhill (where energy is recovered with the regenerative brakes system).

4. Description of the Optimization Algorithms

This section describes the approach proposed to solve the considered problem. The first optimization step is done as in Nesmachnow et al. (2020), so we focus here on the description of the method developed for the second step.

4.1. Evolutionary algorithms

In order to find feasible solutions, we develop a heuristic approach using a combination of Evolutionary Algorithms (EA), a well-known search and optimization technique based on the Darwinian theory of evolution (Goldberg (1989)). Fundamentally, an EA is an iterative method with a panmictic or distributed population of eclectic individuals that represent potential solutions with a quality defined by the fitness function that determines their performance to solve the stated problem.

After the first optimization step, a cellular genetic algorithm (cGA) was applied for the bus scheduling stage, where the assignment of a heterogeneous eBus fleet that maximizes the batteries utilization after the operation time is computed. Individuals are encoded as arrays of integers, representing the bus types assigned to cover the timetabled trips, whose departure time is specified in the sequence.

The initial populations are randomly generated, taking into account the restrictions like minimal headways of each route. Throughout each repetition, the individuals are evaluated and given a fitness value representing their performance to solve the problem. New individuals are generated from each iteration to the next using biologically inspired operators such as mutation, recombination, and selection. We will describe the representation and processes employed in our approach in the following.

4.2. Fitness function

The scheduling problem is formulated as defined in Equation (1), which seeks to reduce the remaining energy in the onboard batteries of the vehicles composing the bus fleet. F_1 consists of the average of the available power at the end of the day. In order to preserve the SoH of batteries, they are recharged overnight, and using slow charge. In the same way, the operation range of the batteries is defined between 20% to 80% (see Equation 4) in order to prevent the stress levels and the zone of worse discharging efficiency of the batteries that reduce its SoH (Lipu et al. (2018)). Therefore, a good fitness value is an average SoC of the buses at the end of the operation time close to 20%. The fitness function computes the minimum number of each type eBuses to cover the chromosome's distribution, guaranteeing an adequate number of buses to cover the route. Each solution could have different heterogeneous fleet sizes.

4.3. Genetic operators

The individuals that compose the initial population are generated randomly. After the BSP solver ends (Nesmachnow et al. (2020)), the computed set of headways determines the chromosome size of the VSP algorithm and randomly assigns different types of vehicles to each departure. The cGA distributes those individuals in a toroidal grid to create a connected graph. The algorithm traverses the whole population, individual after individual, in the evolutionary process. Everyone in the grid has a neighborhood (we use C9, also known as Moore neighborhood) that overlaps the neighborhoods of adjacent individuals. The main idea of the cGA is that every individual can only interact with their respective neighbors in the reproductive cycle. In the selection process, the first parent is the central individual per neighborhood, and the second is chosen using binary tournament within the neighborhood.

The recombination or crossover methods are genetic operators that generate new buses assignment (offspring) by combining two other chromosomes (parents) with probability ρ_R. Based on our previous work (Peña et al. (2022)), the offspring is generated taking each variable value from one of the two parents with equal probability. The mutation operator is a method that produces slight changes with low probability. In our algorithm, a new value from the available set is chosen at random with a probability ρ_{rr}.

5. Experimentation

As previously described, the two stages problem considered requires first computing a timetable that minimizes the transfer waiting times, and second finding the best bus schedule such that the load demand is satisfied and the global required energy is minimum considering a heterogeneous fleet.

The Bus Synchronization Problem (BSP) Nesmachnow et al. (2020) consists in finding the headways of each bus line in a public transportation system, that maximize the number of synchronized bus transfers. A bus transfer is synchronized when the waiting time at the transfer bus stop does not exceed a given threshold for the tolerance to wait of passengers. Headway values are constrained within a range, defined considering both passengers' demand and the economic viability of the bus service. This problem formulation considers transfers between any pair of bus lines at any pair of bus stops, accounting also for the time spent walking between the transfer stops.

Realistic problem instances were built using data from the public transportation system in Montevideo, Uruguay. Different sources of data were combined to generate the problem instances, including open data and ticket sales data from smartcard transactions. Open data from the city transportation authorities include bus lines, bus stops, and timetables for the entire public transportation system. Transfers information corresponds to real data from ticket sales in 2015 using smartcards (Massobrio and Nesmachnow, 2020).

In the first step pf the optimization process, synchronization nodes were randomly chosen with uniform probability among the 171 most demanded transfers for the considered period. The demand of each synchronization node was assigned according to the real transfer demand in May 2015, as registered by smartcard transactions. As can be seen in Fig. 2 public transportation system is at peak usage in terms of ticket sales between 12:00 p.m. and 14:00 p.m., thus we used the EA described in Nesmachnow et al. (2020) to calculate the optimal headways of the lines, which maximize the number of synchronized trips for the peak hours.

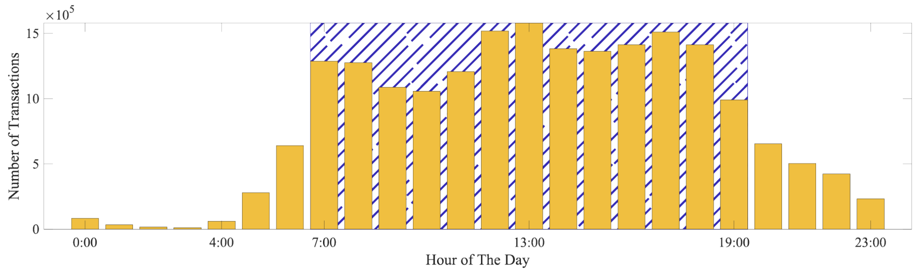

Fig. 2. Smartcard transactions per hour for May 2015.

In the second step, the cellular genetic algorithm described in Section 4 is applied. Three bus lines are considered, i.e., routes 116, 124, and 125, which connect the Old Town with Pocitos, Santa Catalina, and Cerro neighborhoods, respectively. Bus trips correspond to working days departing between 7:00 a.m. and 19:00 p.m., and the bus frequency used is the output of the first step of the optimization process.

The parameters described in Table 1, are considered for three realistic vehicles whose characteristics are based on commercial bus brochures that include the battery capacity, weight, frontal area, and comfort capacity (UITP (2019)). We considered regenerative braking when the vehicle moves downhill (see Equation 5) and overnight recharge methods in a time period between 12:00 a.m. to 7:00 a.m., considering five or six hours (depending on the SoC and the battery characteristics) to reach 80% of the onboard batteries.

Table 1. Parameters of the selected vehicle types.

Bus Type			**Vehicle Parameters**		
	Range	***Area***	***Weight***	***Battery Capacity***	***Passengers***
Microbus	208km	8.37m^2	13800kg	250kWh	20
Midibus	260km	8.66m^2	15600kg	380kWh	31
Standard	290km	9.26m^2	19300kg	440kWh	54

6. Results and Discussions

Fig. 3 presents the performance of the cGA evolution process after 6,000 fitness evaluations with a population of 100 individuals. As it can be seen, the performance of the algorithm is stable and converges, reaching fitness values of percentage of SoC on average less than 29%, guaranteeing feasible solutions for the proposed problem. The best solution obtained suggests a eBus distribution where the energy remaining at the onboard batteries is 26.88% on average after the operation. The gradual diffusion of the best individuals in the overlapped neighborhoods (where elitism is predominated to maintain an exploitation level) increases the population diversity.

The results observed in Fig. 3 show that the distribution of trips by each type of vehicle changes during the exploration, producing new individuals with genetic information that represents feasible solutions close to the optimal. Minibuses, on average, performed 10% more trips than midibuses or standard buses. Therefore, the electrical fleet proposed to cover those routes under the BSP constraints required a more significant number of small vehicles, around 25%, than the others. The vehicles distribution represents a challenge when considering passenger demand.

The proposed approach uses a greedy algorithm to assign the programmed trips to the minimum number of required vehicles to compose the heterogeneous fleet and evaluate each individual's fitness. This algorithm defines the eBus fleet size, i.e., the number of buses of different types. The importance of the vehicle assignment algorithm is observed in Fig. 4 where two different solutions with almost the same performance (less than 1% of remaining SoC of difference) are displayed. Those results represent a certain level of flexibility and adaptation possibilities of the solutions, attending to other constraints in different or dynamic scenarios, e.g., companies with a pre-existing electrical fleet that look to complement it instead of fully renewing.

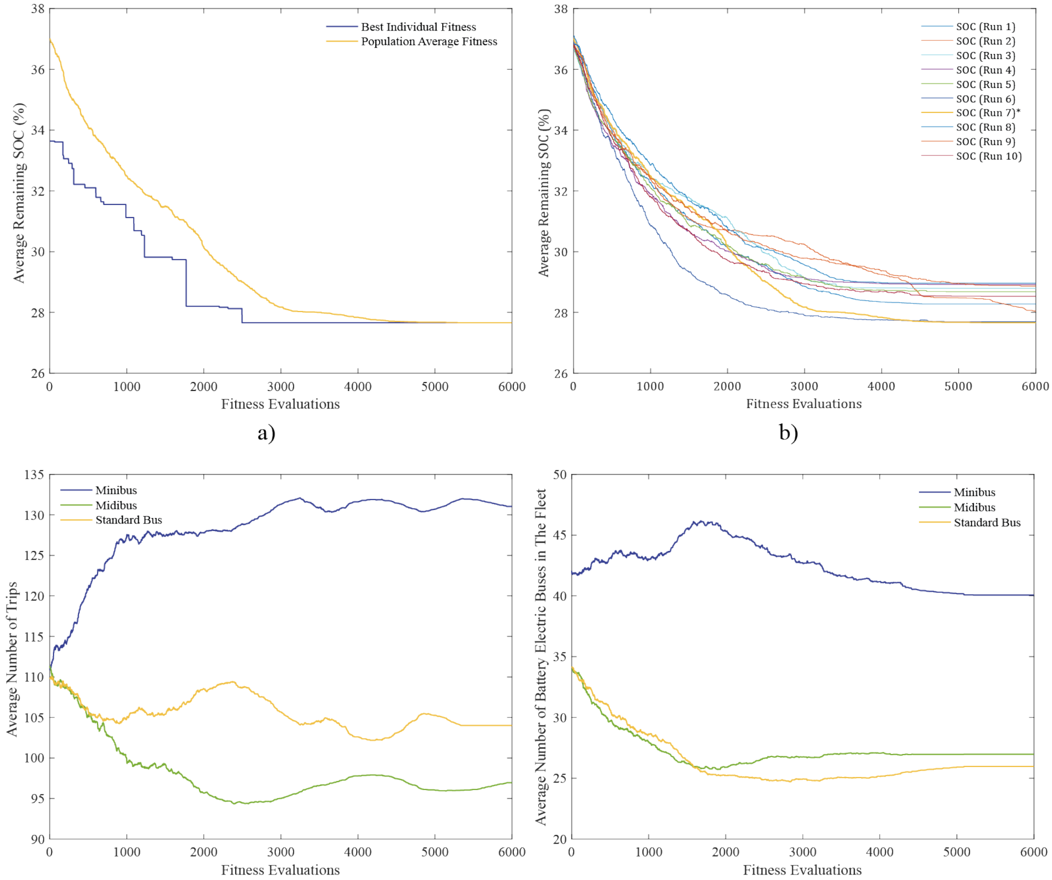

Fig. 3. (a) Comparison between the evolution process of the best individual and the whole population (average). (b) Performance of the fitness function from 10 independent runs of the cGA. (c) The behavior of the number of trips assigned to each type of vehicle. (d) Fleet composition during the evolution process in order to increase the efficiency in terms of the number of vehicles and their battery utilization.

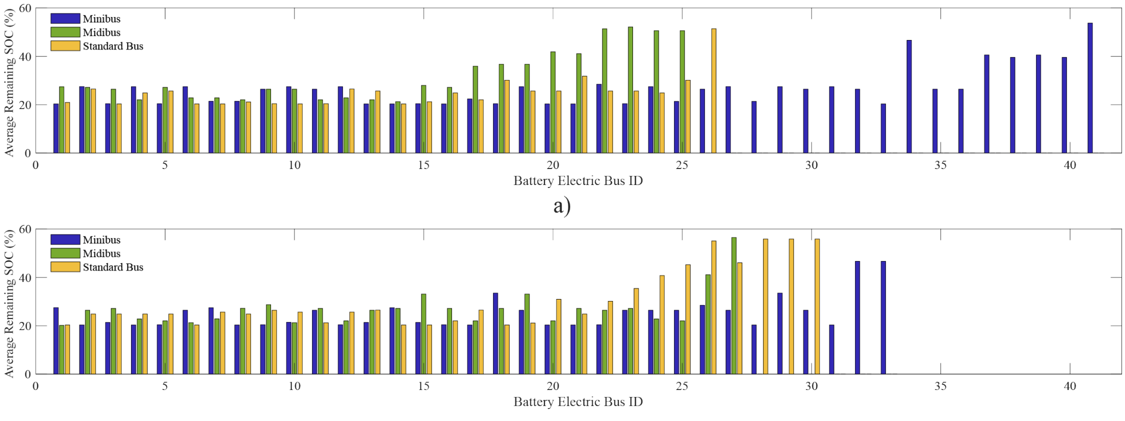

Fig. 4. Electrical energy distribution across the buses that constitute two different fleets. (a) A solution with good performance but with more presence of small vehicles with less passenger capacity which may reduce the quality of service. (b) The best-founded solution (1% best performance than solution a) uses a bus distribution with a stronger presence of minibusses but contains a more homogeneous distribution of the other bus types.

7. Conclusion and future works

We address in this work the holistic problem of the development of a sustainable, optimal and comfortable bus transportation system, simultaneously taking into account the bus lines timetables to reduce transfer waiting times and the schedule of a heterogeneous fleet of electric buses to minimize costs and maximize energy used. We consider the large public transport system of Montevideo, in Uruguay, for minimizing first the waiting time in main bus transfers at peak hour. Using this optimized headways, a second optimization process is performed in order to determine the most suitable type of buses that should comprise the heterogeneous bus fleet so that the use of their batteries is maximized. Results show that different configurations are possible with almost similar performance. As future work, we are planing to consider the passenger demand at every bus stop as well as redesign the bus assignment algorithm with a more advanced mechanism that could make better use of the unused available resources of buses nearby.

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