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Sustainable driving operations of urban plugin hybrid buses considering restricted emission mapping zones

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ABSTRACT

Road traffic is the major source of air and noise pollution. It is also one of the largest contributors to anthropogenic greenhouse gas emissions. Transport electrification can significantly reduce these negative externalities. However, electric buses do not often meet public transport requirements, due to their limited battery capacity. In contrast, plug-in hybrid electric buses offer a versatile alternative, providing zero-emission capabilities that depend on battery capacity, charging frequency, and the distribution of electric drive along a route. However, current electric drive assignment systems are oversimplified, thus not fully leveraging their potential. This work extends our previous research, which introduced a novel combinatorial optimization problem aimed at determining optimal electric drive assignment strategies for Plugin Electric Hybrid (PEH) buses. A large number of bus lines as well as zero-emission and restricted-emission zones are considered. The objectives are to maximize the buses' electric range and minimize the overall pollution while adhering to mandatory zero-emission and restricted-emission zones. In this study, we analyze seventy bus lines from Barcelona's urban public bus network (Spain), and tackled this large problem with two parallel implementations of the Cooperative Co-evolutionary Multi-objective Cellular Genetic Algorithm (CCMOCell). The strategies provided by both CCMOCell versions are validated against GreenK, a state of the art heuristic that only focuses on the electric range. Results demonstrate that the obtained solutions achieve up to 7.67% reduction in carbon dioxide (CO_2) emissions, compared to GreenK, at the cost of a slight decrease in terms of electric range, i.e. 2.28%. However, the strategy found by GreenK is unfeasible, because it exceeds the pollution threshold established for one restricted-emission zone by 635 CO_2 kilograms per day.

1. Introduction

Since the second half of the 20th century, rapid global urbanization has led to a surge in mobility demands (Allen, 2019). Resulting in a significant rise of greenhouse gas emissions, noise levels and air pollution. This increasingly influences the climate, as well as impacts public health and urban livability. These negative externalities can be significantly reduced via transportation electrification (Seredynski, 2023). The combination of battery electric vehicles and attractive public transport (PT) leads to a sustainable transportation system, allowing to address major transportation and environmental problems in cities. However, due to the current limitations in battery capacity, not all bus operations can be fully electrified (Fiori et al., 2021). To bridge this gap, alternative solutions such as plug-in electric hybrid (PEH) buses have been introduced. They have an electric motor (EM), a small battery that can be charged from the grid, and a combustion engine (ICE). PEH buses combine benefits of electrification with unconstrained driving range (Gallo et al., 2014). Due to the high daily mileage requirement of PT operations, PEH buses are designed to use opportunity charging at layovers. Overall, environmental and societal benefits of PEH buses depend on the distance covered in electric mode and carbon intensity of electricity generation. However, an important research question remains: how to optimally manage the use of the limited pure electric driving mode along bus routes, considering both societal and environmental factors?

A large number of European cities have already deployed PEH buses on a limited scale, along with green corridors or mandatory zero-emission zones (mZEZ). These are designated areas where city authorities prohibit noise and emissions, typically situated around highly polluted locations, as well as near hospitals, schools, parks, or pedestrian zones. The current strategies for assigning electric drive to PEH

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buses are relatively naive. They rely on a basic offline plan that utilizes a first-come, first-served method to determine electric drive locations. This oversimplified approach does not take advantage of the full potential of tailored electric drive management, which could increase the distance buses travel in electric mode while simultaneously reducing pollutants and noise levels, thereby resulting in direct economic and societal benefits (Seredynski, 2018). Developing an effective assignment strategy is complex because the relationship between the distance traveled in electric mode and harmful emissions is not straightforward. For instance, driving uphill with an ICE can lead to increased emissions. In contrast, using pure electric mode requires a significant amount of energy. Designating an uphill segment for electric drive can reduce emissions but may decrease the total distance traveled in electric mode. Moreover, any strategy selection must take into account the existence of mandatory green corridors.

Sustainable urban transport cannot exist without a competitive PT. To make PT an attractive alternative to private cars, it has to deliver high level of service, i.e. it has to be punctual, frequent and prioritized in traffic (Seredynski et al., 2020). This requires a significant increase in the number of buses operating throughout the city. However, the increase of operating buses can lead to areas where multiple bus lines converge, resulting in additional traffic, pollution, and noise, which can reduce livability. In consequence, this work does not only consider mZEZ but also restricted-emission zones (REZ) for the public transport buses. These are zones where driving in electric mode is not mandatory, but the overall pollution and noise levels are regulated to ensure a healthier urban environment. Some examples where REZs can be established are dense traffic areas, or zones where lower pollutants and noise levels are desirable (e.g., near hospitals, schools or parks). Currently, the driving assignment strategy for the real world deployed PEH buses is established beforehand, in an offline mode, and it changes automatically during their operation with no intervention of the bus driver. Therefore, the consideration of both mZEZ and REZ in the operation of public PEH buses can be easily implemented, enhancing the quality of air and livability of cities. However, these policies must be implemented by administrations to comply with city regulations.

This work is an extension of our previous paper (Aragón-Jurado et al., 2024), where a novel multi-objective combinatorial optimization problem is introduced to find optimal drive assignment strategies for PEH buses to reduce carbon dioxide (CO_2) emissions and enlarge their electric range. In comparison to Ruiz et al. (2023), where one bus line is optimized at a time, we considered six bus lines that are to be optimized simultaneously under the presence of both mZEZs and REZs. The latter are defined so that CO_2 emissions are restricted to half the amount of emissions released when all buses traverse them using their ICE. Therefore, electric drive assignment strategies will promote the use of the EM in these areas when possible, while targeting the CO_2 and electric range optimization in the whole route.

The main contribution of this work is the simultaneous optimization of drive assignment strategies for a large number of urban buses, under the presence of both mZEZs and REZs. In particular, we consider the 70 bus lines from Barcelona metropolitan area that are currently operating in the city. In order to address such a complex problem, we make use of a parallel Cooperative Co-evolutionary Multi-objective Genetic Algorithm, based on the well-known Multi-objective Cellular Genetic Algorithm (MOCell), which has demonstrated to achieve competitive results with super-linear speedups in a number of problems (Atashpendar et al., 2018; Dorronsoro et al., 2013). We consider two versions of the algorithm, namely the synchronous one used in our previous publication (Aragón-Jurado et al., 2024) and an asynchronous one, where decoupled communications between the islands are allowed in order to achieve faster convergence and better exploration of the search space. This algorithm was only applied before to small academic problems using a short number of parallel islands (up to 12) (Atashpendar et al., 2018). In contrast, the algorithm is applied in this work to a large-scale real-world problem with 3,534 variables using 70 islands.

The paper is structured as follows. Section 2 provides a review of the existing literature on sustainable urban bus transportation. Following that, Section 3 introduces the Sustainable Urban Transportation (SUTRA) problem. Sections 4 and 5 detail the proposed methodology for solving SUTRA and outline the experimental setting, respectively. Finally, Section 6 presents an analysis of the obtained results, while Section 7 concludes the work and suggests directions for future research.

2. Literature review

Electro-mobility significantly reduces emissions and noise associated with transportation. Nevertheless, transitioning an entire city's transportation fleet to electric vehicles demands substantial financial investments. In addition, it raises new challenges, as transportation systems need to be reconsidered due to the new requirements of these vehicles and their different behavior or performance. Beyond this issue, there are several inherent problems that make difficult and slow progress of electric vehicles in urban areas. The most significant studies targeting the different challenges in this sector are discussed in detail below, and those areas where knowledge gaps still exist are emphasized.

According to Mastoi et al. (2022), a critical factor is the strategic placement of charging stations, which affects many types of road transport, such as commercial vehicles (Carra et al., 2022), taxis (Li et al., 2022b), logistics (Li et al., 2022a), or electric buses (Lopez de Briñas Gorosabel et al., 2022), as well as PEH buses (Pternea et al., 2015; Rogge et al., 2015).

One of the main challenges that arise when working with operating vehicles is to accurately estimate their energy consumption (Vepsäläinen et al., 2018). In fact, the literature extensively discusses various factors that have influence in their consumption (Chen et al., 2021; Fiori et al., 2021), such as driving patterns (Tang et al., 2015; Zhang et al., 2019), passenger load (Yang and Liu, 2022) or weather conditions (Al-Wreikat et al., 2022; Liu et al., 2018), among others (Heißing and Ersoy, 2011; Zener and Zkan, 2020). A significant concept is Vehicle Specific Power (VSP), which measures the instantaneous energy required for the vehicle's movement and its correlation with emitted pollutants, fuel consumption, or electric energy use (Ruiz et al., 2023; Jiménez-Palacios, 1999; Yazdani Boroujeni and Frey, 2014). Therefore, it is a valuable parameter for modeling PEH buses. The energy consumption model presented in this work integrates concepts from the ICE consumption models by Sun and Zhu (2014), as well as those by Larminie and Lowry (2012) for EMs. Additionally, this model introduces a novel regenerative braking factor for a more realistic battery charging emulation. This consumption model builds upon the emissions model proposed by Jiménez-Palacios (1999).

The development of techniques that optimize the energy efficiency of PEH buses is a major issue too. The successful implementation of PEH bus systems in countries like Luxembourg, Poland, Germany, and Belgium is noteworthy. Despite these successes, challenges have emerged that required collaboration among researchers, policymakers, and operators. A significant research focus in this context is energy efficiency, particularly through energy management strategies (EMS), since it highly influences both its lifetime and the performance of the bus. Several studies aimed to enhance EMS for PEH bus motors using dynamic programming (Peng et al., 2017). Also, Naser et al. (Sina et al., 2022) employed a neural network to estimate the optimal state of charge (SOC) trajectory, while He et al. (2022) utilized a deep deterministic policy gradient algorithm. Techniques for optimizing battery lifetime, often relying on dynamic programming, have also been proposed. López-Ibarra et al. (2020) improved EMS by updating it, while Du et al. (2018) introduced a battery degradation model and an algorithm based on Pontryagin's minimum principle to find the optimal control strategy. Similarly, Wang et al. (2022) used this approach to determine the best real-time EMS. A notable research has integrated Genetic Algorithms (GAs) with dynamic programming to optimize velocity profiles and SOC sequences, providing real-time EMS based on predictive control (Zhang et al., 2020). Wu et al. (2019) used deep reinforcement learning to develop an EMS that considers driving cycles, traffic constraints, and passengers number. Despite these progress, Fan et al. (2020) argued that EMS might not adapt well to dynamic cycles, suggesting a combination of rule-based energy strategies, dynamic programming, equivalent fuel consumption algorithms, and vehicle drivability. The literature has also targeted fuel economy improvements by understanding driving behavior (Li et al., 2016). Hou et al. (2019) introduced a comprehensive approach that considers both driving behavior and terminal SOC along with fuel consumption. Finally, studies by Guo et al. (2019) and Li et al. (2016) have explored regenerative braking technologies.

It should be highlighted the importance of the mZEZs management strategies for PEH buses. These strategies aim to enhance bus performance by improving fuel efficiency and reducing pollutants emissions, while also maximizing environmental benefits for citizens and improving urban livability. One notable technology in this context is geofencing, which has been studied for managing zones for PEH vehicles, including both passenger cars (Storsæter and Arvidsson, 2018) and buses (Seredynski, 2018).

The adaptability of PEH buses transitioning from the EM to ICE presents an opportunity to improve bus operation performance, focusing on fuel efficiency and emissions reduction, ultimately maximizing environmental advantages for citizens and city livability. Current strategies for managing mZEZs rely on simplistic rules like "first come, first served" (Seredynski, 2019), constraining the dynamic management potential. Tailored strategies specific to particular routes can adjust mZEZs assignments in response to real-time variables such as weather, traffic conditions, battery charge status, and integration with intelligent transportation systems (ITS) (Seredynski, 2018). Prioritizing route segments with low energy consumption has shown to increase electric range by up to 20%, and cooperative ITS can further alleviate stop-and-go situations, further improving PEH bus up-time by up to 6% (Seredynski, 2019).

Exploring effective management of electric driving modes for PEH buses has led to two distinct approaches. In Ruiz et al. (2023), a multi-objective GA optimizes offline strategies to maximize electric range and minimize emissions while adhering to mZEZs regulations. Accurate consumption models and route topography are integral to this approach, producing a significant increase in electric range and emissions reduction compared to existing strategies. Deep learning is used in Aragón-Jurado et al. (2023a) to dynamically respond to traffic anomalies, learning optimal strategies from offline optimization and recalculating in real time. This approach achieves high prediction accuracy and outperforms existing results in emissions reduction and electric range.

Despite their efficacy in managing mZEZ for PEH buses, existing approaches consider routes in isolation. Consequently, high dense traffic areas may result in concentrated pollution and noise because buses from other routes adopt similar strategies, like using the ICE. In order to address this issue, a novel concept of restricted emissions areas was proposed in Aragón-Jurado et al. (2024), aimed at limiting pollution levels in specific zones. A Cooperative Co-evolutionary Multi-objective Genetic Algorithm (CCMOCell) was suggested for finding optimal strategies balancing pollution and electric range while complying with mZEZ and predefined REZ. The work considered 6 bus lines in the city center of Barcelona. This paper extends that work by optimizing the entire public transportation system in Barcelona metropolitan area. Additionally, an asynchronous version of CCMOCell is considered to look for better algorithmic performance in the resolution of the problem.

Table 1 provides an overview of the contributions and limitations of most relevant existing studies, identifying the aspects covered by previous research while emphasizing the unique advancements introduced in the proposed work.

3. Problem definition

The Sustainable Urban Transportation Problem (SUTRA) generalizes the multi-objective efficient PEH bus operation problem (MEPBO), initially defined in Ruiz et al. (2023), where electric drive management is optimized to reduce the environmental impact of PEH services. In this work, we adopt the problem definition proposed in Aragón-Jurado et al. (2023a), where the bus route is divided into segments with constant bus consumption, and the goal is to decide whether each segment should be traveled using the ICE or EM, to minimize tailpipe emissions while maximizing the total distance covered by the EM. Additionally, some segments are designated as green corridors (e.g., mZEZ), which must be entirely traveled using the EM. The original problem definition in Ruiz et al. (2023) allowed switching the propulsion system at any point within a segment; however, a binary choice (i.e., no changes are allowed within a segment) was found more appropriate, as it significantly reduces the size of the solutions space without negatively impacting the quality of solutions (Aragón-Jurado et al., 2023a).

MEPBO focuses on optimizing bus routes independently, while SUTRA optimizes multiple routes at the same time. Along with mZEZs, SUTRA introduces REZs, a new concept presented in this work. REZs are defined for heavily polluted or busy urban areas, where public transport tailpipe emissions are limited to reduce pollution and noise. These zones are often found in city centers, major transportation hubs, intersections, and areas with dense traffic. Also, REZs could be established in areas where low emissions and noise levels are a priority, as those near schools, hospitals, or parks.

SUTRA problem is not just solving multiple MEPBO problems simultaneously. The challenge lies in the interdependence of tailpipe emissions across different bus lines within the REZs, making the problem non-separable and demanding the simultaneous optimization of all lines. To solve SUTRA, the goal is to determine the optimal electric drive assignment strategy for all PEH buses involved, in order to maximize the overall electric driving range $f_d(\vec{x})$, while minimizing the tailpipe emissions generated by the ICE $f_e(\vec{x})$ across all bus lines. This is done while ensuring compliance with mZEZs and adhering to the prescribed maximum emission levels within REZs.

The problem is formulated as follows. Let $\mathbf{B} = \{\mathbf{S_1}, \mathbf{S_2}, \dots, \mathbf{S}_m\}$ represent the m bus lines to be optimized, and $\mathbf{L} = \{L_1, L_2, \dots, L_p\}$ denotes the p predefined REZs. Each route $\mathbf{S_i}$ is divided into n_i segments, $\mathbf{S_i} = s^i_1, s^i_2, \dots, s^i_{n_i}$, where each segment s^i_j is characterized by the tuple $\langle l^i_j, \alpha^i_j, gz^i_j, rz^i_j, bs^i_j \rangle$. In it, l^i_j represents the segment's length (in kilometers), α^i_j is its slope, gz^i_j is a binary variable indicating whether the segment is part of a mZEZ ($gz^i_j = 1$) or not ($gz^i_j = 0$), rz^i_j is an integer identifying the REZ the segment belongs to ($rz^i_j \in \mathbf{L}$, with $rz^i_j = 0$ if it belongs to none), and bs^i_j is another binary variable indicating if the segment begins at a bus stop ($bs^i_j = 1$) or not ($bs^i_j = 0$). Segments are defined where driving conditions change or at bus stops, ensuring constant bus energy consumption within a segment, as outlined in Ruiz et al. (2023). The energy consumption for each segment is then estimated using the bus consumption model from Ruiz et al. (2023), which considers factors like speed, mass, drag coefficient, route elevation profile, regenerative braking, and vehicle efficiency, among others.

The mathematical formulation used in this work to model the problem is formally defined by Eqs. (1a) to (1h). In this context, $\vec{x}$ denotes a solution, represented as a binary vector, where $x^i_j = 1$ means segment j of route i, s^i_j, is covered using the EM, 0 indicating that ICE is used.

In Eq. (1a), $g(x^i_j, s^i_j)$ represents the distance traveled using the EM in s^i_j. It corresponds to the length of the segment if it is decided to be traveled using the EM, 0 in other case. In the particular case where $x^i_j = 0$ and $bs^i_j = 1$ (i.e., the segment begins at a bus stop), the bus starts using its EM, switching to the ICE after $l_{st} = 25$ meters, the distance typically needed to reach 15 km/h under normal conditions. This assumption is based on the fact that the initial rolling phase is

Table 1
Comparison of most relevant existing studies and contributions of this work.

Literature	Real instances	Mathematical energy models	mZEZ management strategies	Bus fleet optimization	Heuristics	Multi-objective
Aragón-Jurado et al. (2024), Ruiz et al. (2023)	✓	✓	✓	×	✓	✓
Mastoi et al. (2022), Li et al. (2022a), Vepsäläinen et al. (2018), Chen et al. (2021)	×	✓	×	✓	×	×
Al-Wreikat et al. (2022), Liu et al. (2018), Heißing and Ersoy (2011), Yazdani Boroujeni and Frey (2014)	×	✓	×	×	✓	×
Jiménez-Palacios (1999), Sun and Zhu (2014), Larminie and Lowry (2012)	×	✓	×	×	×	×
Sina et al. (2022)	×	✓	×	✓	×	×
López-Ibarra et al. (2020), Fan et al. (2020), Zhang et al. (2020), Wang et al. (2022), Li et al. (2016), Hou et al. (2019), Guo et al. (2019)	×	✓	×	×	✓	✓
Aragón-Jurado et al. (2023a)	✓	✓	✓	×	✓	×
Our work	✓	✓	✓	✓	✓	✓

a highly polluting and energy-intensive stage of bus operation, which can be reduced by using the EM, as commonly practiced with hybrid vehicles.

Eq. (1b) targets the minimization of CO_2 emissions in all routes, where $p(x^i_j, s^i_j)$ denotes the CO_2 emissions in kilograms produced in s^i_j, as formulated in Eq. (1d), where e^i_j is the amount of CO_2 emissions produced if segment s^i_j is fully traversed with the ICE. Here, we need to consider that segments starting at a bus stop are not totally traversed using the ICE, as the first l_{st} meters are covered with the EM. Also, emissions produced in REZs are weighted twice when computing the fitness value of the solution, in order to penalize tailpipe emissions in REZs and guide the algorithm towards less pollutant solutions in these areas.

$$\mathbf{Max}\, f_d(\vec{x}) = \sum_{i=1}^{m} \sum_{j=1}^{n_i} g(x^i_j, s^i_j) \tag{1a}$$

$$\mathbf{Min}\, f_e(\vec{x}) = \sum_{i=1}^{m} \sum_{j=1}^{n_i} p(x^i_j, s^i_j) \tag{1b}$$

$$g(x^i_j, s^i_j) = \begin{cases} l^i_j & \text{if} \quad x^i_j = 1 \\ l_{st} & \text{if} \quad x^i_j = 0 \wedge stop(s^i_j) \\ 0 & \text{otherwise} \end{cases} \tag{1c}$$

$$p(x^i_j, s^i_j) = \begin{cases} e^i_j & \text{if} \quad x^i_j = 0 \wedge rz^i_j = 0 \wedge \text{ not } stop(s^i_j) \\ e^i_j \cdot \left(1 - \frac{l_{st}}{l^i_j}\right) & \text{if} \quad x^i_j = 0 \wedge rz^i_j = 0 \wedge stop(s^i_j) \\ 2 \cdot e^i_j & \text{if} \quad x^i_j = 0 \wedge rz^i_j \neq 0 \wedge \text{ not } stop(s^i_j) \\ 2 \cdot e^i_j \cdot \left(1 - \frac{l_{st}}{l^i_j}\right) & \text{if} \quad x^i_j = 0 \wedge rz^i_j \neq 0 \wedge stop(s^i_j) \\ 0 & \text{otherwise} \end{cases} \tag{1d}$$

Constraints:

$$\forall i, j | gz^i_j = 1, \text{ then } x^i_j = 1 \tag{1e}$$

$$\forall l \in \mathbf{L} \sum_{s^i_j \text{ s.t. } rz^i_j = l} e^i_j \cdot (1 - x^i_j) \leq \tau \cdot \sum_{s^i_j \text{ s.t. } rz^i_j = l} e^i_j \tag{1f}$$

$$SoE^i_j \geq 0.0 \;\; \forall i \in [1, m], j \in [1, n_i] \tag{1g}$$

$$SoE^i_j \leq SoE_{max} \;\; \forall i \in [1, m], j \in [1, n_i] \tag{1h}$$

A valid solution to SUTRA problem must satisfy four constraints. First, all segments s^i_j designated as mZEZ must be traveled exclusively using the EM (Eq. (1e)). Second, emissions within REZs must not exceed a predefined threshold for maximum allowable emissions (Eq. (1f)), which is set to $\tau = 0.5$ in this study. This threshold limits emissions to no more than half of what all buses would emit in REZs if they were all running on their ICE. Third, the State of Energy (SoE) of all buses must remain positive at all times, as defined by Eq. (1g). Finally, the fourth constraint states that the SoE must not exceed the maximum battery capacity, as stated in Eq. (1h).

4. The proposed methodology to solve the SUTRA problem

The following section provides a detailed description of the methodology followed in this work. To accurately estimate energy consumption, real topographic data is necessary. First, the methodology to get, process and aggregate essential information from real data of bus lines is presented. Subsequently, the multi-objective optimization algorithms used to solve the problem are introduced, as well as the greedy heuristic using for comparison purposes.

4.1. Route segmentation

To accurately estimate the bus energy consumption along the route, the consumption model proposed in Ruiz et al. (2023) is employed. This model requires various bus parameters and real route data, including bus stop locations and the route topography, such as latitude, longitude, and altitude, in order to provide realistic estimations of the energy consumption. The efficiencies parameters are set by default to the values in the literature, however, battery degradation can be simulated by changing these parameters. Additionally, in order to have real topological information, digital databases and Digital Elevation Models (DEMs) are employed. Specifically, a DEM with a 2 m mesh size (i.e. MDT02-ETRS89-HU31-0420/0421/0448-1/2/3/4 COB2) from the Spanish Geographic Institute is used to retrieve the altitude of each bus stop in the studied area.

Information of the bus stops locations is obtained from specific public transportation databases (TMB, 2025), however it does not include the precise geometry of the routes. In order to reconstruct the trajectories followed by buses between stops, and the required driving maneuvers, two different routing Application Programming Interfaces (APIs) are used. These APIs enable to determine the path followed by the bus, as well as data about travel time, distance, and intermediate locations (primarily intersections). Fig. 1 illustrates the segmentation methodology applied in this work. Two routing APIs,

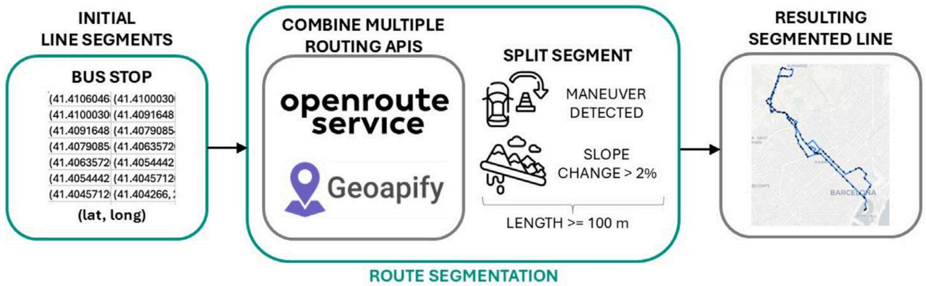


Fig. 1. Route segmentation methodology combining different routing APIs. The coordinates of two consecutive bus stops are given to the routing applications for obtaining the required maneuvers between these two points. If significant maneuvers or significant slope changes are identified, this piece of route is divided into two segments. The resulting segmented route is the one used during the optimization phase.

Geoapify (Geoapify, 2024) and Openrouteservice (Openrouteservice, 2024), are employed to accurately segment the initial route, collecting information on bus route geometries, conditions and features from both sources to avoid measurement inaccuracies. Initially, the route is split at every bus stop, indicating the beginning or end of a segment. It implies that the bus accelerates until the cruise speed is reached, and then breaks until it stops. This cruise speed is calculated from the available bus timetabling and double checked with the value obtained from the APIs. Then, segments can be further split based on the following criteria:

- *Intersections and turns*: Significant maneuvers are identified using the different routing APIs and define new segment boundaries.
- *Slope variations*: If the slope difference between two consecutive points exceeds 2%, a new segment is created to account for impact in the energy demand.

A minimum segment length of 100 meters is enforced to prevent excessive fragmentation. Independently of the driving mode use, i.e. ICE or EM, the cruise speed is satisfied in order to comply with the bus schedules. This segmentation approach ensures that within each segment the driving conditions are similar, allowing a more precise estimation of energy consumption. Additionally, the segments are overlaid on the DEM to obtain accurate elevation data. Since terrain variations influence bus performance, the elevation of the start and end points of each segment is retrieved from the DEM to refine energy consumption estimates.

4.2. Cooperative Coevolutionary Evolutionary Algorithms

Cooperative Coevolutionary Evolutionary Algorithms (CCEA) (Potter and De Jong, 1994) split the main population into subpopulations, each focused on the optimization of a component of the overall solution to an optimization problem (e.g., a subset of decision variables). These subpopulations evolve independently but must cooperate, because the fitness of an individual depends on the quality of the full solution it contributes to build. Typically, chromosomes are split across subpopulations, each optimizing a subset of variables. After every generation, solutions from every subpopulation are combined with the best solutions from the other subpopulations to form a complete solution, which is then evaluated using the fitness function.

When it comes to multi-objective optimization, there is not one single best solution, but a set of non-dominated ones. Therefore, islands in multi-objective CCEAs do not share a single best partial solution, but a set of them (randomly taken from its local Pareto front). The structure of a typical multi-objective CCEA is shown in Fig. 2. Each island focuses on a specific subset of problem variables and shares a set of local best solutions (i.e., some random ones from its local Pareto front) with all other islands for evaluation purposes.

In this work, a cooperative coevolutionary version of the Multi-objective Cellular Genetic Algorithm (CCMOCell) (Dorronsoro et al., 2013) is used. MOCell (Nebro et al., 2009) is a dominance-based optimization algorithm that employs a toroidal grid structure to arrange individuals in its population. An auxiliary population stores the best non-dominated solutions, determined by the crowding distance metric, and periodically integrates some of these into the current population to accelerate convergence speed. Each iteration involves evolving individuals through selection (within their neighborhood), recombination, mutation, and replacement. If a newly generated individual is not dominated by any current solution in the Pareto front, it is included. After each generation, a feedback mechanism injects solutions from the Pareto front back into the population. The algorithm continues evolving until the termination criteria are satisfied.

Algorithm 1 Pseudocode of Synchronous Parallel CCMOCell

1: $t \leftarrow 0$
2: $\parallel$ i ∈ [1,m] :: setup(P^0, i) // Initialize each subpopulation
3: sync() // Synchronization point
4: for i ∈ [1,m] do broadcast(P^0, i) // Share random local partial solutions within each subpopulation
5: $\parallel$ i ∈ [1,m] :: evaluate(P^0, i) // Evaluate solutions in each subpopulation
6: sync()
7: **while not** stoppingCondition() **do**
8: $\quad\parallel$ i ∈ [1,m] :: generation(P^t, i) // Perform one generation
9: $\quad$sync()
10: $\quad$for i ∈ [1,m] do broadcast(P^t, i) // Share best local partial solutions within each subpopulation
11: $\quad t \leftarrow t + 1$
12: **end while**
13: mergeParetoFronts() // Merge the Pareto fronts from each subpopulation into a single one

SUTRA is a multi-objective combinatorial optimization problem with a large number of variables, so a parallel cooperative coevolutionary algorithm as CCMOCell stands as a good approach to address it. We employ two parallel versions of the CCMOCell algorithm, namely synchronous (Dorronsoro et al., 2013) and asynchronous (Nielsen et al., 2012). The pseudocode for the synchronous version is presented in Algorithm 1. The algorithm begins by simultaneously initializing each subpopulation with randomly generated individuals (Line 2). Subsequently, a synchronization point is reached, where each subpopulation shares its randomly generated local partial solutions with the others (Lines 3 to 4). Then, each subpopulation evaluates its individuals in parallel (Line 5). Another synchronization point is reached in Line 6, marking the start of the evolutionary loop (Lines 7 to 12). Within the loop, each subpopulation executes one generation simultaneously (Line 8). Following this, another synchronization point is reached in Line 9, before the exchange of the best local partial solutions between subpopulations can be made (Line 10). This process continues iteratively until the stopping condition is met. Finally, the Pareto fronts obtained from each subpopulation are merged into a single unified front (Line 13).

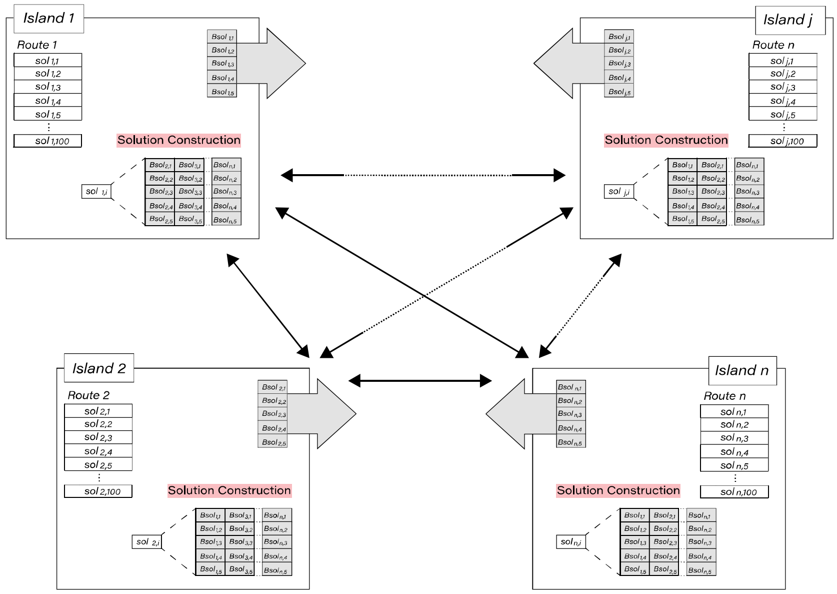


Fig. 2. Structure of a multi-objective CCEA. The model is composed of n islands. All islands share a fixed number of solutions from the Pareto front in order to enable the evaluation of the complete solution to the problem.

The asynchronous version of CCMOCell is similar to the synchronous one, but removing the synchronization point after every generation (the one in Line 9). Therefore, each subpopulation evolves its partial solutions independently, without waiting for the others to finish their current generation. This approach introduces a higher degree of diversity during the evolution of the algorithm, as solutions can be built using individuals belonging to different generations from the other subpopulations.

Each solution is represented as a binary vector with length the number of segments in the route, where each gene indicates whether the bus travels a segment of the route using the electric motor (1) or the combustion engine (0).

To guide the evolution of solutions within both versions of CCMOCell, the algorithm employs several genetic operators. For parent selection, a Binary Tournament operator is employed: two random individuals from the neighborhood are selected, and the fittest is chosen as the parent. Recombination is performed using two-point crossover, where the longest substring from the best parent is used to produce a single offspring. Mutation is applied by flipping the value of a gene. The algorithm utilizes a neighborhood structure to promote localized interactions among solutions while maintaining diversity. When the archive becomes full, Crowding Distance (Deb et al., 2002) is employed to discard less promising solutions. To manage the diversity of solutions across subpopulations, a migration policy is implemented. After each generation, a fixed number of random solutions from the local Pareto front of each subpopulation are migrated to a shared memory object. These solutions become accessible to other subpopulations, which can use them to build new candidate solutions for evaluation.

4.3. Greenk heuristic

GreenK (Ruiz et al., 2023) is a simple greedy heuristic from the state of the art designed to maximize the distance traveled using the EM by prioritizing the electric mode operation in those segments with the lowest slopes. This approach aligns with the actual strategy currently used by plug-in hybrid bus operators (Seredynski, 2019). However, GreenK does not focus on the emissions, nor consider the presence of REZs, meaning the provided solution may be infeasible for the specific problem addressed in this work. Despite this limitation, it serves as a useful reference for assessing the potential electric range of a solution, as it focuses solely on maximizing the kilometers covered in electric mode without accounting for tailpipe emissions nor emissions restrictions.

The GreenK algorithm follows a structured process to optimize the electric range of a bus. It first assigns all segments within mZEZs to be traversed in electric mode. Next, it orders the remaining route segments based on their slope, from downhill to uphill, and processes them sequentially, prioritizing electric mode usage as long as the SoE of the battery allows. This ensures that downhill segments, where energy regeneration occurs, are utilized first, followed by flat and then progressively steeper uphill segments until the battery is depleted. Additionally, the heuristic prevents overcharging by ensuring that energy recovered from downhill segments does not exceed the maximum capacity of the battery. The pseudocode for GreenK is provided in Algorithm 2, detailing its step-by-step execution.

5. Experimental setting

The performance of the proposed methods is evaluated considering 70 real-world bus lines in Barcelona (Spain). The Barcelona Metropolitan Transport (TMB) offers an online platform with detailed information of the public transport system of the city, including stations, bus stops or transport lines, among other aspects (TMB, 2025). This information includes the geographical coordinates of bus stops, expressed in terms of their longitude (X) and latitude (Y). In order to determine the altitude of each (X,Y) point, the DEM used by the Spanish National Geographical Institute is applied (de España, 2025). Finally, this dataset is further enriched and enlarged with information related to the geometries of the different bus routes obtained from the APIs. Thus, obtaining a real reconstruction of the bus transport network of Barcelona.

From the 101 lines composing the public bus network of Barcelona, all lines circulating in the city center have been included in this study, i.e. seventy lines. The remaining ones are less interesting because they give service to peripheral areas where pollution levels are generally lower and service less frequent.

Twenty-eight of the selected lines compose the Barcelona Orthogonal Bus Network, where the lines are identified by a letter and a number, depending on whether the line crosses the city horizontally (H lines), vertically (V lines) or diagonally (D lines). This set of bus lines creates a square mesh with a large number of junctions. Additionally, with the aim of building the studied scenario as close as possible to the

Algorithm 2 Pseudocode of GreenK heuristic

Input
S : Segments composing the route
SoE_{ini}: Initial state of energy of the battery
sol = [0,...,0]; SoE = SoE_{ini} // Variables initialization
for $s_i \in S$ / $s_i.z_i$ == 1 **do**   // Set all segments in mZEZ to 1
  sol[i] = 1
  SoE − = computeRequiredEnergy(s_i)
  if SoE > SoE_{max} **then**   // Battery capacity cannot be exceeded
    SoE = SoE_{max}
  end if
end for
OS = orderBySlope(S)   // Order all segments from low to high slope
for $s_i \in$ OS / $s_i.z_i$ == 0 **do**   // Add segments in order, when possible
  kWh = computeRequiredEnergy(s_i)   // kWh to traverse the segment
  if SoE − kWh ≥ SoE_{min} **then**
    sol[i] = 1
    SoE = SoE − kWh
    if SoE > SoE_{max} **then**   // Battery capacity cannot be exceeded
      SoE = SoE_{max}
    end if
  end if
end for
Return sol: Proposed strategy for battery management

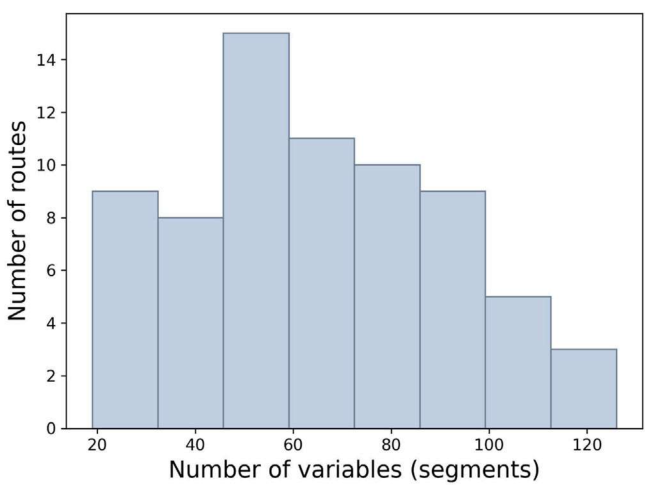


Fig. 3. Histogram of the number of variables (segments) that compose each of the bus routes after the segmentation process.

existing real bus network, forty-two other types of bus lines (numbered lines) have also been included. They cross the city center, and are partially overlapped with the previous lines, sharing the defined REZs with them.

As previously explained in Section 4.1, all bus routes are segmented to accurately estimate the energy consumption of the bus. The number of segments depends on the characteristics of each route. Fig. 3 illustrates the histogram representing the number of segments that compose each bus route after segmentation.

The energy consumption model considers regenerative braking, real topography data, and all the efficiency parameters are those considered in the literature for operations in normal conditions (Ruiz et al., 2023). The impact of the degradation of the battery on the performance of the bus can be analyzed by modifying these efficiency parameters. In order to be as realistic as possible, and because currently there are no en-route charging stations in the city of Barcelona, the optimization algorithm assumes initially full battery, i.e. it considers a charging station at the depot or at the beginning of the route (a complete charge only takes a few minutes for PEH buses). However, in previous works (Ruiz et al., 2024), different charging stations were considered along the routes, i.e. if their location is known, en-route recharging can be easily included in the optimization process.

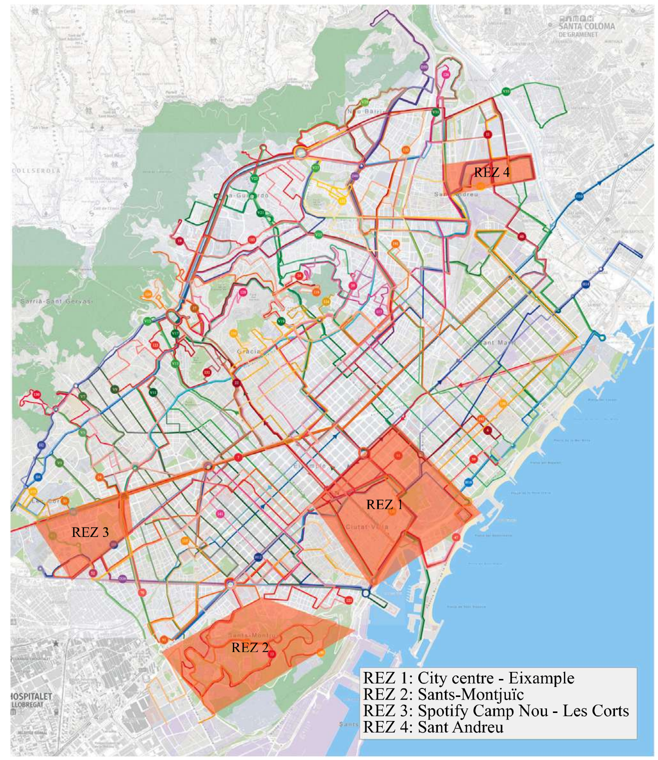


Fig. 4. Representation of the studied scenario, including the seventy bus lines of Barcelona, as well as the four predefined REZs (emphasized in red color).

It should be noted that green corridors, i.e. mZEZs, do not exist in Barcelona yet, so they are artificially established in this work for those bus route segments near hospitals, schools and parks, because of the societal benefits they imply. A total of thirty-one mZEZs have been identified following this criterion within the bus network.

Additionally, to further reduce pollution in dense traffic areas of the city, several REZs have been established. More precisely, REZs are located in areas where pollution and noise may adversely affect public health or quality of life, e.g. close to parks, residential areas, or in very dense traffic areas where the high levels of pollution reduce the livability due to very frequent services of many bus lines. So that, within these zones, the pollution generated must be kept below 50% of the total emissions produced when all buses are operating with their ICE. Specifically, four REZs have been defined in strategic areas of the city, as it is shown in Fig. 4.

The first REZ considered, REZ 1, is located in the heart of the city, with a large and frequent bus service. The second one, REZ 2, contains a large recreational area including parks, hills, etc. REZ 3 is a busy district in the city, e.g. sports areas, faculties, university residences, etc., being a very suitable location for improving air quality and reducing traffic noise and emissions, therefore enhancing people's welfare. Finally, REZ 4 is a popular area in the city, with shopping centers, sports areas, parks, hospital, etc. It should be noted that many bus lines are crossing each of the four REZs. Table 2 presents the main characteristics of the selected REZs, the bus lines affected by their restrictions, the location, size, as well as the main reason for their selection.

Table 2
Description of the main features of the four REZs studied.

REZs	Districts; REZ coordinates	Surface (km^2)	Lines crossing REZs	REZ description
REZ 1	City center; Eixample (41.387, 2.166) (41.399, 2.182) (41.374, 2.178) (41.386, 2.198)	4	23 lines: D20, D50, H12, H14, H16, V13, V15, V17, V19, V21, V27, 6, 7, 19, 22, 24, 39, 47, 52, 54, 59, 120, 136	City Center characterised by a high daily population density and dense traffic. It contains a large recreational area.
REZ 2	Sants-Montjuïc; (41.365, 2.136) (41.373, 2.155) (41.355, 2.146) (41.369, 2.174)	2.88	5 lines: V5, 13, 121, 125, 150	Predominantly green area comprising parks, gardens, etc. It also includes sports facilities as stadiums and tracks.
REZ 3	Spotify Camp Nou - Les Corts (41.384, 2.110), (41.389, 2.128), (41.376, 2.117), (41.382, 2.129)	1.34	14 lines: D20, H6, H8, V1, V3, V5, 6, 7, 33, 34, 52, 54, 59, 175	Busy district hosting educational institutions such as university faculties and student residences, soccer fields and other sports facilities.
REZ 4	Sant Andreu; (41.438, 2.190) (41.439, 2.208) (41.434, 2.191) (41.437, 2.209)	0.65	8 lines: H4, H8, V31, V33, 11, 60, 126, 133	Key hub of urban activity because of the presence of shopping centers, sports facilities, parks, and a hospital.

Table 3
Configuration parameters for the experimentation.

Parallel CCMOCell algorithms	
Number of subpopulations	70
Number of processes	70
Number of evaluations	100,000 per subpopulation
Population size	100 per subpopulation
Migration policy	5 random non-dominated solutions
Selection operator	Binary tournament
Crossover probability	1.0
Crossover operator	Two-point crossover
Mutation probability	1/chromosome length
Mutation operator	Bit flip
Neighborhood	C9
Archive	Crowding distance

The optimization algorithms are configured with a total of seventy subpopulations, one complete bus line being assigned to each. Despite the fact that the high differences on the number of segments composing the routes implies an uneven problem decomposition that negatively affects runtime performance, the decision was taken based on the fact that splitting routes between different islands hinders the search capabilities of the algorithm for this specific problem, worsening its capacity to find accurate solutions. The reason is that the combination of partial solutions with others from the different islands in the evaluation process (which are taken from randomly chosen local solutions, probably specialized in other objectives tradeoffs) introduce significant changes that likely produce low quality solutions, or even unfeasible ones due to battery limitations. Regarding the rest of parameters, we use similar values to those proposed for solving MEPBO (Ruiz et al., 2023), as detailed in Table 3. Each subpopulation consists of 100 individuals. The termination criterion is set to a maximum of $7,000,000$ fitness evaluations. The Binary Tournament operator is used for parent selection. Crossover is performed using a two-point crossover, and mutation is applied with a probability of 1 divided by the number of variables. The C9 neighborhood structure (Alba and Dorronsoro, 2008) is applied, which consists of the individual itself and its eight immediate neighbors (i.e, in its surrounding 3×3 grid). To manage solution diversity, Crowding Distance is used when the archive is full. Additionally, five random solutions from the local Pareto front of each subpopulation are migrated to a shared memory object after each generation.

Comparing the performance of multi-objective algorithms is not a simple task, as each run of the algorithm reports a set of non-dominated solutions, known as a Pareto front approximation. To simplify comparisons between algorithms, it is common in the literature to rely on performance metrics that measure the quality of the Pareto front from some perspective. However, no single metric can comprehensively capture all aspects of the quality of a Pareto front. Therefore, multiple metrics must be employed to evaluate specific features of the front. The two main aspects to consider are the accuracy and diversity of solutions in the front, as well as the number of solutions composing the Pareto front. Accuracy reflects how closely the approximated solutions align with the true optimal ones, while diversity indicates how evenly solutions are distributed across the front. A well-approximated Pareto front should have solutions that are both near-optimal and evenly spaced, avoiding large gaps or overly concentrated regions.

We employ three commonly used metrics in the literature to compare multi-objective algorithms. They are:

- *Hypervolume (HV)* (Zitzler and Thiele, 1999). This metric accounts for both accuracy and diversity of solutions. It calculates the volume in the objective space covered by each solution, relative to a reference point (typically an anti-global optimum). Higher HV values indicate better approximated Pareto fronts.
- *Additive Epsilon (EP)* (Zitzler et al., 2003). EP represents the smallest distance required to shift every solution in the approximated Pareto front so that it weakly dominates the true Pareto front (i.e., none of the solutions is worse than those in the true front in all objectives). Lower EP values are preferred.
- *Inverted Generational Distance (IGD)* (Veldhuizen and Lamont, 1998). IGD measures the distance between solutions in the approximated Pareto front and their closest counterparts on the true Pareto front. When the approximated front perfectly matches the optimal one, this metric takes value 0.

It is important to note that both EP and IGD rely on the true Pareto front for their calculations. Since the optimal Pareto front is unknown for the problem at hand, it is approximated by merging all non-dominated solutions found by the two algorithms across 30 independent runs into a pseudo-optimal Pareto front. This approximated front is then used in the aforementioned metrics as a stand-in for the true Pareto front. This approach is commonly adopted in the literature when evaluating the performance of multi-objective algorithms on

Table 4
Performance of the two algorithm versions (median and interquartile range values).

Quality indicator	Synchronous CCMOCell	Asynchronous CCMOCell	
HV	$\mathbf{5.11e+03_{9.70e+01}}$	$2.82e+03_{1.10e+03}$	✓
EP	$\mathbf{6.83e+00_{2.01e+00}}$	$5.30e+01_{2.36e+01}$	✓
IGD	$\mathbf{1.46e+01_{3.60e-01}}$	$4.81e+01_{2.24e+01}$	✓

real-world problems (Dorronsoro et al., 2014). Additionally, for the HV metric, the reference point is constructed by selecting the worst value for each objective across all Pareto fronts obtained from the independent runs.

To provide statistical confidence in the conclusions, the Wilcoxon signed-rank test is applied to compare the results of the two algorithms on each metric, using a 95% confidence level.

All algorithms are implemented in Python 3, utilizing the JMetalPy library (Benítez-Hidalgo et al., 2019). The parallel implementation of CCMOCell takes advantage of the multiprocessing library in Python 3. To facilitate the efficient information sharing among subpopulations while minimizing computational overhead, a ShareableList object is employed. Experiments were conducted on a Huawei TaiShan 2280 V2 server, which features two Kunpeng 920-4826 CPUs, each equipped with 48 cores running at 2.6 GHz. This server is optimized for massive parallelism, with a total of 96 ARM computing cores distributed across four NUMA nodes. The operating system used is Ubuntu 20.04.1 LTS. To mitigate potential biases from the non-deterministic behavior of the algorithms, each GA is run independently 30 times.

6. Results and discussions

The main results obtained with the two studied algorithms are presented in this Section. As it was mentioned along this paper, to the best of our knowledge, the problem considered has not been addressed before in the literature. The problem was first introduced in the work we are extending here (Aragón-Jurado et al., 2024), where a synchronous CCMOCell implementation using six islands is used to optimize a small problem instance considering six bus lines in Barcelona downtown. In contrast, this work solves the SUTRA problem using two parallel versions of CCMOCell, both synchronous and asynchronous, considering the 70 bus lines operating in Barcelona's metropolitan area.

First, Section 6.1 compares the performance of the different algorithms in terms of the quality of the solutions they obtain. Then, Section 6.2 performs a detailed analysis of the solutions, paying special attention to emissions produced and the electric range of the vehicles.

6.1. Comparison of the performance of the algorithms

Next, an analytical comparison of the overall performance of the two algorithms on the large SUTRA problem instance considered is provided. The comparison is based on the HV, EP, and IGD values of the Pareto front approximations, obtained from 30 independent runs. The results are summarized in Table 4, where the median and interquartile range values obtained by the two algorithms for the three considered metrics are shown (best values are highlighted in **bold font**). Symbol '✓' in the rightmost column indicates a statistically significant difference between the performance of the two algorithms, as determined by the Wilcoxon signed rank test with 95% confidence.

The obtained results demonstrate that the synchronous version of CCMOCell clearly outperforms the asynchronous one, with statistically significant differences in all the cases studied. The reason is that the uneven division of the problem into subproblems negatively impacts on the asynchronous version of the algorithm, given that each bus line is considered to be one subproblem (so there are 70 subpopulations), and routes can have between 20 and 120 segments, as shown in Fig. 3. This unequal distribution leads to certain subpopulations evolving much slower than others: some subpopulations can approximately perform 6 generations in the same time as the longest routes perform only one.

Regarding the runtime, on average across the 30 independent runs, the synchronous version takes $26,429.09$ seconds to produce results, while the asynchronous one requires $24,177.54$ seconds. This suggests that the asynchronous CCMOCell is generally faster than the synchronous version for this problem, achieving a speed up of 1.09. However, this runtime improvement comes at the cost of solution quality loss due to the unequal distribution of the problem.

6.2. Performance of the solutions obtained

This section presents an analysis on the quality of the pseudo-optimal solutions generated by the two multi-objective algorithms. As already mentioned, GreenK is used for comparison purposes. A simple greedy heuristic for creating driving assignment strategies only by prioritizing the selection of the lowest slopes to be traversed with the EM. This strategy is similar to what current plugin hybrid buses operators follow nowadays (Ruiz et al., 2023). It is important to note that GreenK is used as an upper bound reference in terms of the electric range, but it does not consider the existence of REZs, so its solution may be unfeasible for the problem considered in this work.

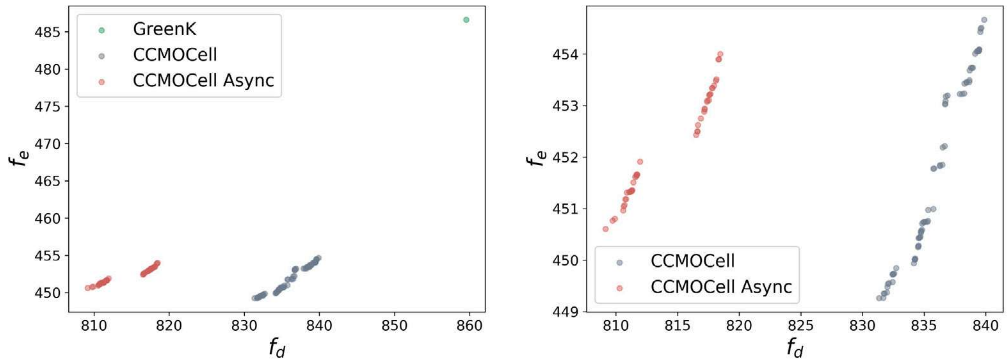
The best non-dominated solutions obtained by the two parallel versions of CCMOCell algorithm in the 30 independent runs are shown in Fig. 5(a), together with the solution obtained by GreenK (in green color). As it can be seen, solutions obtained by both CCMOCell versions outperform GreenK in terms of the level of tailpipe emissions. Indeed, the best solution found for the synchronous version is 7.67% better than GreenK in terms of f_e objective. However, it is 2.28% worse than GreenK in terms of the overall electric range of buses in the city. At this point, we would like to emphasize that GreenK solution does not comply with the REZs defined in the city, so this compared solution is an unfeasible solution for the studied problem, as it exceeds the CO_2 emissions in the third considered REZ by 3.03 kilograms. The mentioned differences can be significantly magnified to up to 635.09 kilograms of CO_2 considering that the 14 lines traversing REZ 3 make 3,144 trips a day.

In the comparison of the two CCMOCell versions, we found that solutions in the Pareto front obtained by the synchronous algorithm dominate all solutions found by the asynchronous one, as illustrated in Fig. 5(b). The synchronous version increases the kilometers driven using the EM by up to 8.52%, while simultaneously reducing pollutant emissions by up to 5.40%. Once again, the negative impact of the uneven split of the problem into complete bus lines to be optimized in the subpopulations is evident on the evolution of the asynchronous CCMOCell. However, its performance is not expected to improve when using other even partitions that allocate segments of the same route in different subpopulations, given the strong existing dependency among the driving assignments of the different segments within the routes.

The existing solutions in the Pareto front reported by the synchronous CCMOCell algorithm highlights the multi-objective nature of the problem, where deciding which trade-off solution to adopt is not trivial. The largest difference between solutions in the front in kilometers driven using the EM is 8.5289, while in the case of the pondered pollutant emissions it is 5.4067.

To analyze the actual CO_2 emissions values obtained from each of the best solutions found, we calculate the real, unweighted kilograms of CO_2 emitted by each solution on the Pareto front. Based on these new emission values, a new Pareto front is built, considering pollutant emissions and kilometers driven using the EM, retaining only the non-dominated solutions. This new Pareto front is presented in Fig. 6.

The unweighted emission differences among the best solutions are significantly lower in Fig. 6, with a maximum difference of 0.6835 kilograms of CO_2, highlighting the substantial impact that REZs have on solution quality. Furthermore, it is important to note that there are solutions with almost identical CO_2 emissions, differing by approximately



(a) With GreenK solution (b) Without GreenK solution

Fig. 5. Pareto front approximation of the solutions obtained by the synchronized and asynchronous versions of CCMOCell as well as the mono-objective heuristic GreenK.

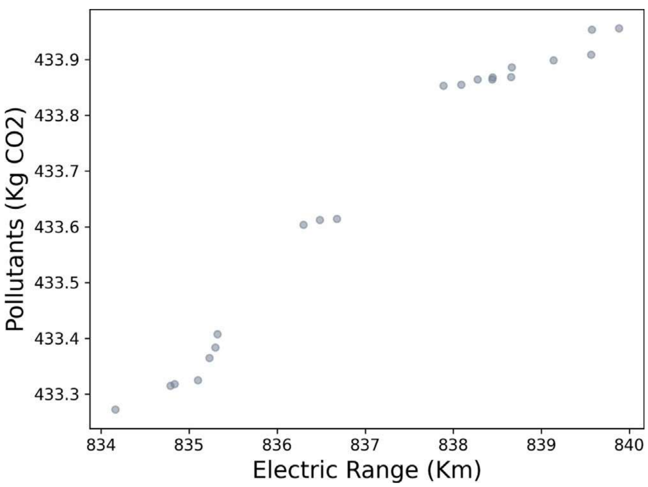


Fig. 6. Best solutions found by CCMOCell relative to the value of CO_2 emissions in kilograms.

0.0453 kilograms, which can differ by more than 1.2492 kilometers in electric driving distance. In comparison to GreenK, the solutions provided by CCMOCell can achieve up to 1.6618 less CO_2 kilograms emitted, meaning 295.80 kilograms of CO_2 a day, considering the 178 return trips every bus perform every day, in average. In terms of cost, the solutions found may save up to 109.87 liters of fuel per day.

To study the emissions produced by the considered bus network, the multivariable visualization tool proposed in Aragón-Jurado et al. (2023b) is used. Fig. 7(a) describes the emission map of the solution obtained using the GreenK heuristic, while Fig. 7(b) displays the solution found by CCMOCell with the lowest CO_2 emissions. In these Figures, every segment of every route is displayed with a color that varies according to the tailpipe emissions, ranging from dark green color representing the lowest value (i.e. driven in electric mode), to red color representing the most polluting segments. The considered REZs are shaded in red.

As it can be seen, the solution obtained by GreenK (Fig. 7(a)) has significantly a lower number of dark green segments compared to the CCMOCell solution, but many of them are close to this dark green color. While these segments do not emit large amounts of CO_2, they still contribute to battery savings, allowing a higher number of kilometers driven in electric mode compared to the CCMOCell solution. In the REZs, we can observe that GreenK has sections with higher emission values than the CCMOCell solution. This is particularly notable in REZ 2 and REZ 3. Indeed, in the latter, the emissions exceed the allowed levels.

It is important to note that in the northern part of Barcelona, there are sections where the solution proposed by GreenK emits a significant amount of emissions, with one section emitting nearly 3 kilograms of CO_2. This section corresponds to an uphill slope, and using the EM would lead to a substantial loss of battery energy (as proposed by CCMOCell). However, if the ICE is used, there is a considerable increase in CO_2 emissions (as proposed by GreenK). This situation highlights the complexity of the problem, requiring a trade-off between both objectives, while also considering the needs of urban residents and livability within cities.

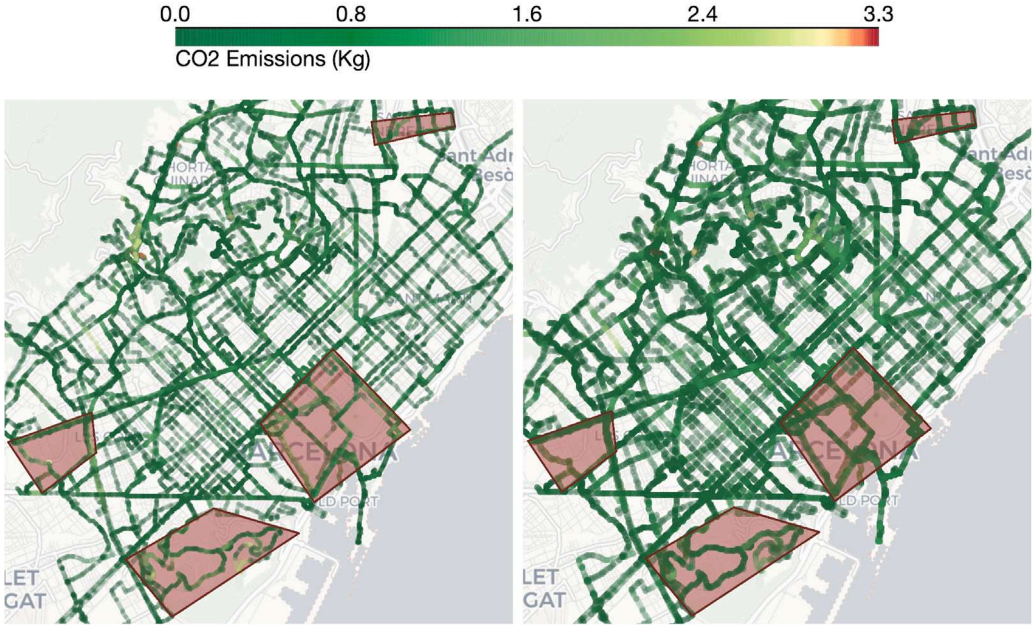
Finally, in order to show more granularity of this comparison, Fig. 8 shows the detailed solution profiles obtained by both algorithms, in terms of electric range and pollution, for each bus line in the considered network. The electric range of the seventy studied bus routes is displayed in stacked bars. The solution of CCMOCell is represented in green color and GreenK in red. Similarly, the total number of kg of CO_2 for each route is displayed in gray color for CCMOCell and in black for GreenK.

Fig. 8 shows that GreenK is better in only in 54.28% of the bus routes, in terms of the electric range. However, the difference is usually larger than when CCMOCell outperforms GreenK, leading to a larger total electric range of the network. On the contrary, it can be seen that CCMOCell is, in general, similar or better that GreenK in terms of CO_2 emissions. It should be noted that as previously mentioned, one of the limitations of GreenK is that the proposed solutions might not comply with the restricted emissions zones. Indeed, this is the case for the fourteen lines crossing REZ3 (shadowed in Fig. 8), where the total emissions generated by GreenK exceed the established level. There are several bus routes that perform better than GreenK both in terms of electric range and in terms of emissions, e.g. lines V3, 54, H8 or H2, among others.

The complexity of the problem can be also highlighted from Fig. 8. It can be seen that there are solutions with a longer electric range but also a higher level of pollutions, e.g. lines V27, 122, 126, 132, 185 among others. This highlights that using the EM for longer periods does not necessarily imply lower tailpipe emissions.

7. Conclusions and future works

This work extends our previous paper (Aragón-Jurado et al., 2024), where the novel Sustainable Urban Transportation problem (SUTRA problem) was introduced, along with a proposed Cooperative Coevolutionary Multi-objective Genetic Algorithm to solve a small instance. The main goal of this problem is to optimize electric drive assignment strategies for a fleet of PEH buses to maximize their overall electric range while simultaneously minimizing CO_2 emissions, taking into account both mZEZs and REZs (or reduced emissions zones, firstly introduced in this work to limit pollution in designated urban areas).



(a) GreenK solution.

(b) Lowest polluting solution obtained from the synchronous CCMOCell.

Fig. 7. Emission maps caused by the solution obtained by GreenK and the solution obtained by CCMOCell with the lowest total emissions value. REZs are shaded in red.

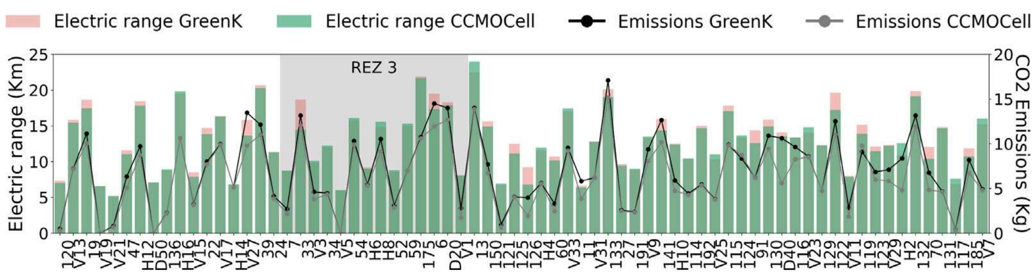


Fig. 8. Performance of each bus route in terms of the CO_2 emissions (in kg) and electric range (in km), considering the solution proposed by both GreenK (red and black colors) and CCMOCell (green and gray colors). The solution with the lowest total emissions value was selected for CCMOCell. The stacked bars represent the electric range provided by each method, while the lines indicate the corresponding CO_2 emissions. The gray shaded area represents the set of lines that cross REZ3, where GreenK solution is unfeasible.

In this study, we simultaneously optimized a total of 70 different bus routes, corresponding to all bus lines traversing Barcelona city center, compared to the original six bus lines from our preliminary previous work.

A state of the art multi-objective optimization algorithm for high dimensional problems, CCMOCell, was chosen to solve SUTRA problem. Two different versions of CCMOCell have been considered: a synchronous one, used in the previous work, and an asynchronous version, where decoupled communication between the islands is allowed. This aims to achieve faster convergence and better exploration of the search space. Notably, this algorithm has only been previously applied to small academic problems, utilizing a limited number of parallel subpopulations (up to 4). Furthermore, the results found by both algorithms are compared to GreenK, a heuristic from the literature that aims to identify optimal battery management strategies only focusing on the maximization of the electric range of the PEH bus.

Results indicate that the strategies proposed by both versions of CCMOCell save up to 109.87 liters of fuel per day with respect to the strategy proposed by GreenK. At the same time, the heuristic does not account for REZs, consequently offering invalid strategies that exceed the emissions threshold established for the third REZ by more than 3 kilograms of CO_2 (i.e., over 635 kilograms of CO_2 per day).

Regarding the performance of the two studied versions of CCMOCell, the synchronous version outperforms the asynchronous version with statistical significance for all the three quality indicators considered (namely, hypervolume, additive epsilon, and inverted generational distance), at the cost of being 9.31% slower. The asynchronous version was negatively impacted by the unequal distribution of the problem, where each parallel island corresponds to the solution variables associated with a specific bus line. This disparity, although considered necessary because of the strong dependencies among segments strategies in the same route, leads to some islands evolving significantly faster than others.

The proposed work provides the optimal driving assignments of seventy bus lines in an offline fashion, i.e. not accounting for dynamic changes. Therefore, as future work, we plan to extend our study by considering the design of an adaptive approach able to dynamically modify the driving assignment of PEH buses in response to changing traffic conditions or stochastic effects that can influence the energy consumption by means of machine learning techniques. In addition, we will work on other types of electrified buses, such as regular hybrids and new algorithms and parallel designs to ensure an equitable distribution of computational load among all processes in order to solve the problem more accurately and faster, as well as tackling larger instances. We also aim to extend these techniques beyond buses to other types of electrified vehicles, such as cars and trucks, for both public and private transport.

CRediT authorship contribution statement

Marina Díaz-Jiménez: Writing – original draft, Visualization, Validation, Software, Methodology, Investigation, Data curation. **José Miguel Aragón-Jurado:** Writing – original draft, Visualization, Validation, Software, Methodology, Investigation, Formal analysis, Data curation, Conceptualization. **Bernabé Dorronsoro:** Writing – review & editing, Supervision, Project administration, Methodology, Investigation, Funding acquisition, Formal analysis, Conceptualization. **Pablo Pavón-Domínguez:** Writing – review & editing, Visualization, Validation, Investigation, Formal analysis, Data curation. **Marcin Seredynski:** Writing – review & editing, Supervision, Investigation, Formal analysis, Conceptualization. **Patricia Ruiz:** Writing – review & editing, Visualization, Supervision, Project administration, Methodology, Investigation, Funding acquisition, Conceptualization.

Declaration of competing interest

The authors declare the following financial interests/personal relationships which may be considered as potential competing interests: Jose Miguel Aragon-Jurado reports financial support was provided by University of Cadiz Higher School of Engineering. Marina Diaz-Jimenez reports financial support was provided by University of Cadiz Higher School of Engineering. If there are other authors, they declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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Data availability

Data will be made available on request.

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