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Urban bus fleet-to-route assignment for pollutant emissions minimization

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ABSTRACT

This study proposes a methodology to optimize the assignment of an urban bus fleet to a set of fixed routes, taking into account the differences among routes and the differences among vehicle types and propulsion technologies in order to reduce pollutant emissions (CO_2, CO, THC, NO_x and PM). A Mixed Integer Linear Programming optimization model is stated and two scenarios are assessed: minimization of CO_2 and NO_x. The results show that it is feasible to obtain a fleet distribution in which emissions for any given pollutant are reduced without increase in emissions of other pollutants.

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1. Introduction

Over the last ten years, policy makers have given increasing attention to the efficient use of energy and the improvement of air quality. Vehicle traffic emits substances which pollute the atmosphere and contribute to global warming (Chapman, 2007; Gurjar et al., 2008). In the case of Madrid, the inventory of pollutant gases reveals that during 2012, road transportation caused 32.7% of greenhouse gas emissions, 53.7% of NO_x generation, 13% of the non-methane volatile organic compounds, 45.3% of CO and 67.3% of particulate matter (PM) with a diameter of less than 10 μm (MCC, 2014).

In order to ease pollution in urban centers, some measures frequently used by legislators consist in establishing low emission zones (Boogaard et al., 2012), promoting the utilization of public transportation systems (Buehler and Pucher, 2012), developing a non-motorized transport infrastructure (Kim and Dumitrescu, 2010), and stimulating vehicle fleet renovation and improving its maintenance conditions (Zachariadis et al., 2001). In particular, Madrid's Air Quality Plan 2011–2015 (MCC, 2012) proposes 70 measures to reduce pollution levels regarding different economic sectors, and more than 10 are related to urban bus transport, such as general use of bus lanes, introduction of new propulsion technologies in buses that moves in the low emissions zone, etc. However, these kinds of solutions requires significant economic investments (Creutzig and He, 2009), broad time intervals (EEA, 2011) and, quite frequently, after completion, the achievements are difficult to identify and evaluate (Lake and Ferreira, 2002), so the proposal of novel low-cost but efficient measures would be a challenge.

The research reported in this paper is more modest in scope and cost than the initiatives outlined above. It focusses on the assignment of vehicles to routes, seeking a close match between bus technologies and the characteristics of the routes that

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they serve, so as to minimize emissions of relevant pollutants. So far as we are aware, no research has been published on this assignment task, even where the focus is on non-environmental criteria. Research within the broader context of bus operations planning and environmental objectives is however of general interest and is reviewed in the next section.

2. Background

Vehicle fleet planning has been studied from diverse perspectives, differentiating, in this context, operational considerations and environmental impact, although both aspects may converge. For instance, emission levels and fuel consumption are closely related to the distance traveled; therefore an optimization intended to minimize aggregate travel distance may be expected to generally provide more favorable results from an environmental standpoint. McKinnon et al. (2010) analyze the environmental consequences of logistics, highlighting that vehicle routing and scheduling are factors which influence the economic and environmental performance of a distribution system, and have a potential to contribute to greenhouse gas and other pollutant emissions reduction. Furthermore, local conditions determine the precise form of the planning task in any given scheme, and this circumstance could condition the selection and assignment of the vehicles to their routes or services. A classical approach consists in designing routes to be traveled by the vehicles of a logistic company in order to accomplish the delivery of goods to a set of customer locations at a minimal cost. This problem is known as the Vehicle Routing Problem (Dantzig and Ramser, 1959). Its framework admits multiple alternatives (Kumar and Panneerselvam, 2012) and different methodologies for its resolution (Laporte, 1992).

On the other hand, significant efforts have also been dedicated to developing methodologies for optimal route and bus headway design with the intention of minimizing the system's total cost, while providing an adequate customer service level (Byrne and Vuchic, 1971; Mandl, 1980; Spasovic and Schonfeld, 1993; Chien et al., 2003). The complete planning process of a bus operation consists of five phases: (i) design of the route network, (ii) setting the journey frequencies, (iii) timetable planning, (iv) bus scheduling, and (v) driver arrangement (Ceder and Wilson, 1986). This problem has a high degree of complexity, but it is arguably incomplete in its coverage of bus operations planning, in that it does not include the assignment of vehicles to routes, which is the primary focus of the present paper. A variety of metaheuristic techniques have been applied to specialized tasks concerned with bus fleet planning, route planning and operational management; for example genetic algorithms (Pattnaik et al., 1998; Afandizadeh et al., 2013), simulated annealing (Han et al., 2005) and bee colony optimization (Nikolić and Teodorović, 2013) during its resolution. Specific versions for the layout of school routes appear in Bowerman et al. (1995) and Spasovic et al. (2001).

Another optimization problem category frequently posed in bus transportation planning consists in assigning each vehicle to the most adequate depot in order to minimize the distance traveled by the fleet (Sharma and Prakash, 1986; Djiba et al., 2012). In this analysis it is assumed that, every vehicle has been previously allocated to a particular route and the depot's capacity is also known. The main drawback of this approach is that the distance proportions associated with pull-out and pull-in trips to and from the depot are not very significant in comparison with the total range traveled during daily operation. Therefore, the fleet's performance throughout the most representative time period is not evaluated.

Alam et al. (2014) examine the impact of transit improvement strategies on bus emissions along a busy corridor in Montreal. Smart cards, limited-stop (express bus) service and reserved bus lane measures applied by the system's operator are assessed, estimating bus pollutant emissions at three levels: road segment, bus stop and per passenger. Its effects on emissions and idling time reductions are discussed. Alam and Hatzopoulou (2014) analyze the effects of transit signal priority, queue jumper lanes and the relocation of bus stops on bus emissions using simulation with two alternative fuels: diesel and compressed natural gas (CNG).

Concerning fleet renewal, Figliozzi et al. (2013) propose a methodology to select the optimal replacement strategy taking into account the investment in vehicle acquisition, operating costs and the savings derived from emission reductions.

André and Villanova (2004) evaluate urban bus operation and its impact on emissions, surveying the bus network in Paris using two methods to appraise and classify the routes: the first approach uses statistics related to route characteristics, travel time, commercial speed, annual statistical data and the irregularity of travel and information on the problems encountered; while the subsequent procedure considers other aspects related with the socioeconomic peculiarities of each route's setting. In André et al. (2005), the influence of the vehicle's operating conditions on the generation of pollutant emissions is assessed.

In summary, bus operations and management have been well-studied with respect to conventional optimization criteria (cost, ridership, accessibility, etc.), but with little attention so far to environmental performance. This paper is concerned specifically with the assignment of vehicles to routes, taking into account which types of vehicles are more appropriate with respect to the peculiarities of each route for reducing emissions. Considering that not all routes within a city have similar characteristics, our approach is focused on a detailed matching of relevant vehicle attributes to inferred attributes of routes, in a fine-grained analysis which can yield significant environmental benefits.

3. Methodology

The methodology is based on the information related to the kinematic performance of each vehicle type on every route. In order to perform a fine-grained analysis, the vehicle's operational driving cycle is segmented into microcycles and motionless intervals. Microcycles are defined as the time interval between two consecutive stops, so 2 microcycles are separated by a motionless interval. Furthermore, microcycles segmentation also includes phases corresponding to three states: (a) accelerating; (b) traveling at constant speed, and (c) decelerating.

Initially, a clustering process is implemented with the purpose of creating groups of routes with similar characteristics and thereafter, a representative driving cycle is constructed for each cluster. Mathematical models are then used to estimate emissions for a generalized allocation of the vehicle fleet to the set of routes. Finally, an optimization model is established in order to compute the ideal vehicle distribution which meets the current service requirements. A scheme of the complete methodology is illustrated in Fig. 1.

Routes and fleet data requirements are summarized in Appendix A. In addition, a model that processes the kinematic variables related to the vehicle's operation is utilized to compute emissions for every type of bus (INSIA-UPM, 2010). This model segments the vehicle's driving cycle into microcycles and motionless intervals.

The complete methodology consists of five main steps, although the optimization model presented in this article deals specifically with the final stage:

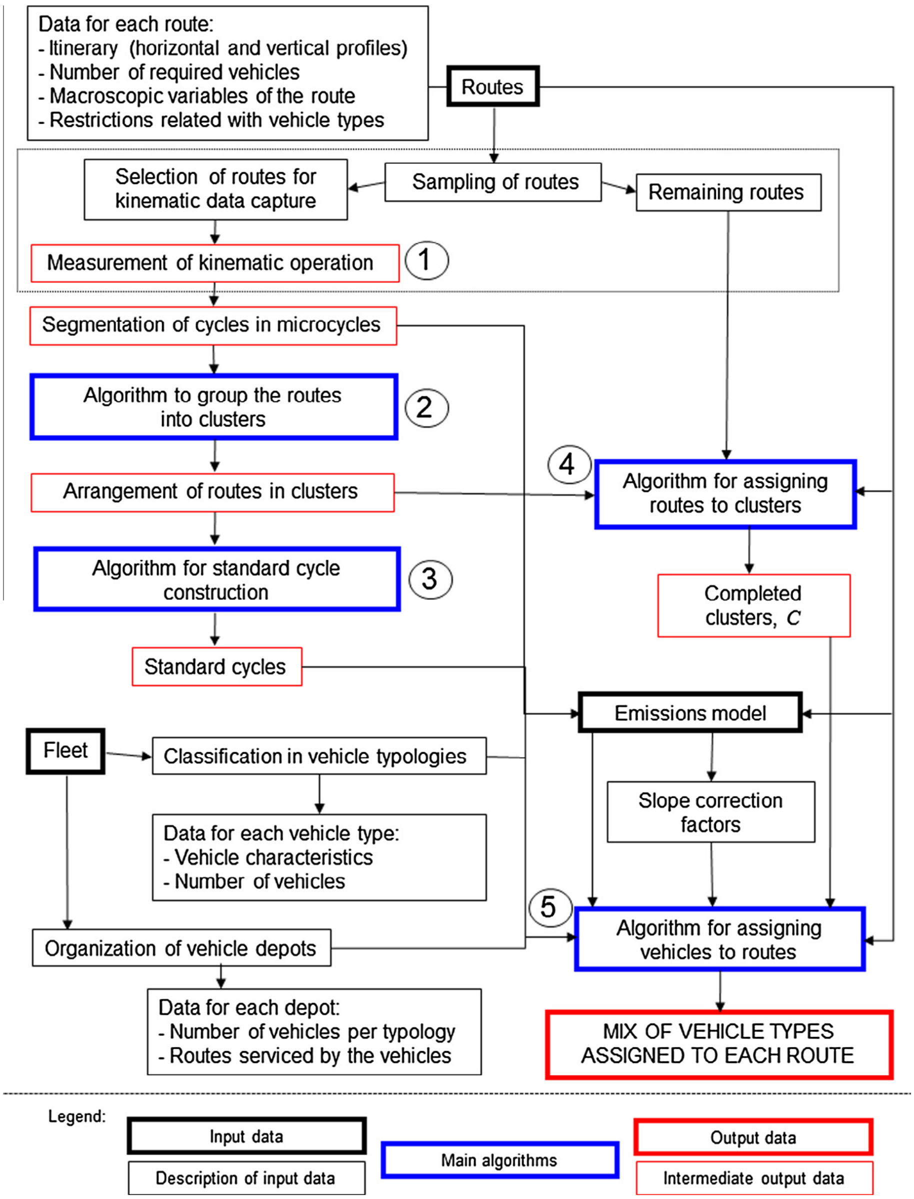

Fig. 1. Flowchart of the complete methodology.

1. Measurement of the vehicle's kinematic behavior on each route. During the initial stage, the kinematic and operational parameters of the vehicles traveling the routes are recorded by means of an onboard device (López et al., 2008). If it is unfeasible to monitor the complete fleet, an adequate sample of routes must be chosen. This selection is performed on the basis of a preliminary classification of the routes using macroscopic variables such as the average speed, usual occupancy rate and ratio of bus stops per unit length (INSIA-UPM, 2010).
2. Arrangement in clusters containing routes with similar kinematic characteristics. Once the information has been compiled, an algorithm is required in order to evaluate the similarity among routes. For this purpose, the vehicle's operational driving cycle is segmented into microcycles. Kinematic variables are identified (average speed, maximum speed, acceleration time and level, deceleration time and level, etc.) in order to characterize the actual vehicle operation on every route. Subsequently, statistical hypothesis testing is used to determine the existing degree of similarity between each pair of routes. This approach improves the segregation of the groups of routes based on kinematic variables that will be used afterwards during the pollutant estimation, as compared to other methods that generate the clusters based on macrocospic information, such as land use. Jiménez et al. (2013) describes the suggested algorithm for the grouping process, and the indicators that are utilized to evaluate the affinity level accomplished within each cluster. Route clustering is used because not all routes are sufficiently distinctive to justify the construction of individual kinematic cycles. Furthermore, specific cycles would imply measuring kinematic data on every route and this requisite could be non-viable. Consequently, step 4 is implemented to solve this limitation.
3. Construction of a driving cycle that represents the peculiarities of each cluster (Nesamani and Subramanian, 2011). Since the existence of significant differences among the kinematic parameters of the routes is confirmed, a polygonal driving cycle is constructed to represent each cluster of similar routes. The ratios between the different microcycle typologies are known. Therefore, this phase requires establishing a criterion to determine the approximate number of representative microcycles that are needed to compose the kinematic cycle and identify the frequency of the microcycle that will act as reference so as to establish which types of microcycles, and the number of these per type, are required in the construction of each cluster's representative cycle. This process is explained in detail in Jiménez et al. (2013). Even though the intra-day time frame may influence the cycle, its impact is limited as indicated by the experimental information (Gómez, 2005). Furthermore, variations of the vehicle load along the day have not been considered. Thus, each route's cycle is constructed without considering these differences. Similarly, the journey between the depot and the route's starting point is not taken into account, as it is assumed negligible when compared with the total distance covered by the vehicles in a complete daily operation.
4. Clustering of the routes for which no kinematic information has been gathered. This step is only necessary when the first phase requires route sampling, and conveys identifying a set of variables that allows a macrocospic classification of the routes by associating their features to the most appropriate cluster. These variables include comprehensive operational parameters such as the average speed or the occupancy rate, and supplementary information concerning the number of stops or their concurrence with those of other public transportation systems as well as city's spatial structure, the types of roads traveled by the vehicles and their transit in dedicated lanes are also evaluated. The allocation of these routes to the cluster structure achieved during phase 2 is performed using a neural network which is trained with the route classification obtained from the microscopic data, as explained in Jiménez et al. (2014). Macroscopic data quality and the quantity of available information significantly condition the network's learning and estimation capacity, although the results obtained are acceptable. It should be noted that the neural network is only used during the assignment of routes to the previously structured clusters, but kinematic driving cycles have been generated in the previous phase.
5. Statement and resolution of an optimization model to allocate the most appropriate vehicles to every route in order to minimize the total emissions caused by the fleet and comply with the constraints. The preliminary equations are inferred in INSIA-UPM (2010) and estimate, for every vehicle type and each driving cycle, the emissions produced during any microcycle or motionless interval. These equations are employed to formulate an optimization model in which the objective function comprises a linear combination of the diverse pollutant emissions, and includes a set of variables that represent the number of vehicles of each type that must be assigned to every route. The resolution provides the most suitable fleet arrangement for reducing pollutant emissions. The deduction of the optimization model is explained in more detail in the following section.

4. Optimization model

The objective of the optimization model is to distribute a fleet of V vehicles in R routes grouped in C clusters, so that certain emissions (CO_2, CO, THC, NO_x and PM) produced during the operation are minimized. The vehicles are classified in T types considering their propulsion technology and physical characteristics. This perspective requires an evaluation of the emissions caused by every type of vehicle, which derive from the specific kinematic conditions related to the route on which they travel. It is assumed that every vehicle within a type follows the same emissions expressions and that the kinematic behavior of the vehicles that travel along routes of the same cluster is similar. On the basis of this information, the objective function is assembled, and binding constraints are included to ensure a feasible solution. Table 1 shows the notation that is used in the optimization model.

Table 1
Notation.

Total number of vehicles	V
Vehicle types ($t = 1\ldots T$)	T
Total number of routes ($r = 1\ldots R$)	R
Number of routes clusters ($c = 1\ldots$C)	C
Distance traveled on each route	L_r
Driving cycle length	L_c
Vehicles of type t	V_t
Vehicles in route r	V_r
Number of microcycles of the characteristic driving cycle for routes of cluster c	m_c
Number of motionless intervals of the characteristic driving cycle for routes of cluster c	m'_c
Emissions	
General notation	
– Emissions represented by a lineal model	E_x ($x \in \{CO_2, NO_x, PM\}$)
– Emissions represented by a potential model	E_x ($y \in \{CO, THC\}$)
– General case	E_i ($i \in \{CO_2, CO, NO_x, THC, PM\}$)
Specific notation in calculations	
– Emissions of pollutant i when vehicle type t is traveling a microcycle q	E_{itq}^{mcycle}
– Emissions of pollutant i when vehicle type t is traveling a microcycle q considering flat vertical profile	$\hat{E}_{itq}^{mcycle}$
– Emissions of pollutant i of vehicle type t during a motionless interval q	E_{itq}^{s}
– Emissions of pollutant i of one vehicle of type t during a completion of the driving cycle that represents routes grouped in cluster c	$E_{itc}^{cluster}$
– Emissions of pollutant i of one vehicle of type t during a completion of the driving cycle that represents routes grouped in cluster c considering flat vertical profile	$\hat{E}_{itc}^{cluster}$
– Emissions of pollutant i per vehicle type t for all vehicles servicing route r	$E_{itr}^{t\text{-}route}$
– Emissions of pollutant i per vehicle type t for all vehicles servicing route r considering flat vertical profile	$\hat{E}_{itr}^{t\text{-}route}$
– Difference between emissions for route r, vehicle type t and pollutant i with and without adjustment for vertical profile $E_{itr}^{t\text{-}route} - \hat{E}_{itr}^{t\text{-}route}$	$\Delta E_{itr}^{t\text{-}route}$
– Emissions of pollutant i in route r	E_{ir}^{route}
– Emissions of pollutant i for the complete fleet that services the R routes	E_{i}^{total}
Emission model regression coefficients (see text for details)	A_{xt}, B_{xt}, C_{xt}, O_{yt}, P_{yt}, D_{it}
Characteristics of microcycle q	
– Duration time of microcycle q	d_q
– Duration time of motionless interval q	d'_q
– Average speed of microcycle q	$\bar{s}_q$
– Time during acceleration process of microcycle q	d_q^{acc}
– Mean slope of roads traversed during microcycle q	p_q
Route characteristics	
– Average speed of route r	$\bar{s}_r$
– Occupancy rate of route r	o_r
Optimization problem	
– Number of type t vehicles that should be allocated to route r	N_{tr}
– Appropriateness of designating a type t vehicle to route r	F_{tr} (0, 1)
– Variables that account for the slope's influence	$z_{r1}, z_{r2}, \ldots, z_{rM}$
– Regression coefficients that account for the slope's influence	β_{Oit}, β_{1it}, $\beta_{2it}, \ldots$, β_{Mit}
Emissions weighting coefficient for pollutant i	W_i, K_i

4.1. Emissions calculation

The fleet assignment takes into consideration the kinematic characteristics during its operation and the topography in each of the routes for which emissions are estimated, therefore models utilizing these types of variables are required. With this purpose, the model proposed by INSIA-UPM (2010) is used. It has been validated using experimental data gathered in vehicles operating under real conditions. According to this model, emission values for a vehicle, when traveling a microcycle q may be expressed as follows, choosing between linear or potential models considering each specific emission:

$$\text{Linear model}: E_{xtq}^{mcycle} = A_{x_t}\bar{s}_q d_q + B_{xt}\ d_q^{acc} p_q + C_{xt} \tag{1}$$

$$\text{Potential model}: E_{ytq}^{mcycle} = O_{yt} \cdot (E_{CO_2 q}^{mcycle})^{P_{yt}} \tag{2}$$

Concerning the motionless intervals, emissions are directly proportional to the duration of the stationary period, therefore:

$$E_{itq}^{s} = D_{it} d'_q \tag{3}$$

A, B, C, O, P and D being the coefficients characteristic for each vehicle type. Their values have been obtained by a regression process using real data from buses with onboard emissions measurement systems operating along real routes and they are taken from INSIA-UPM (2010). These coefficients depend also on the vehicle load. In our case, average load conditions have been considered but, in case different load conditions would be introduced in the mathematical formulation, specific coefficients values should be used for each condition but the main formulation would remain unaltered.

However, the driving cycles generated in stage 3 of the methodology do not foresee the existing slope of the route during the acceleration process (Jiménez et al., 2013) so, when applying Eqs. (1) and (2) to the clusters characteristic driving cycles, this geometric information cannot be taken into account and $p_q = 0$ is introduced. The emissions of one vehicle of type t during a completion of the driving cycle that represents those routes grouped in cluster c may be deduced from Eqs. (1–3), and expressed as:

$$\hat{E}_{itc}^{cluster} = \sum_{q=1}^{m_c} \hat{E}_{itq}^{mcycle} + \sum_{q=1}^{m'_c} E_{itq}^{s} \tag{4}$$

where m_c and m'_c are the number of microcycles and motionless intervals of the characteristic driving cycle for routes of cluster c.In addition, an initially unknown integer variable N_{tr} is created to signify the number of type t vehicles that should be allocated to route r. In order to ensure that the assigned vehicle types meet the route's operational requisites, a binary parameter S_{tr} is established to indicate the appropriateness of designating a type t vehicle to route r. Finally, because the previous results are restricted to the driving cycle of length L_c, they are extrapolated to the real distance traveled on each route L_r by each of its vehicles. In consequence, the emissions per vehicle type for all vehicles servicing route r belonging to cluster c can be expressed as indicated in Eq. (5):

$$\hat{E}_{itr}^{t\text{-}route} = \frac{L_r}{L_c} \cdot S_{tr} \cdot N_{tr} \cdot \hat{E}_{itc}^{cluster} \tag{5}$$

At this point, it is necessary to consider the slope influence on the vehicle's emission values once the model has been applied to the driving cycles with no slope information. For such purpose, an estimation of the influence of route r gradients on emissions during the acceleration phase must be introduced. For the estimation of the relationship between the difference between emissions for route r, vehicle type t and pollutant i with and without adjustment for vertical profile and the term that considers the emissions model's portion which is independent of the slope $\hat{E}_{itr}^{t\text{-}route}$ that has been previously calculated, it is presumed that it can be approximated by means of a linear function which depends on a set of macroscopic variables for route r, $\{z_{r1}, z_{r2}, \ldots, z_{rM}\}$, as follows:

$$\frac{\Delta E_{itr}^{t\text{-}route}}{\hat{E}_{itr}^{t\text{-}route}} \approx \beta_{0it} + \beta_{1it} z_{r1} + \beta_{2it} z_{r2} + \cdots + \beta_{Mit} z_{rM} \tag{6}$$

The z_{rk} selected variables are the average speed $\bar{s}_r$, the occupancy rate o_r, and the distance proportion traveled in accordance with some slope intervals. In the practical application, five intervals are established, although one is disregarded since its value depends on the rest ($M = 6$). These variables are selected after performing diverse tests to pursue the expression that correlates best. The adjustment of the regression coefficients β for each sort of emissions is performed using the experimental information gathered for each vehicle type during the development of the model described in INSIA-UPM (2010).Then, total emissions includes the term that considers the emissions model's portion independent of the slope $\hat{E}_{itr}^{t\text{-}route}$ and the term that takes into account the slope's influence, $\Delta E_{itr}^{t\text{-}route}$.

$$E_{itr}^{t\text{-}route} = \hat{E}_{itr}^{t\text{-}route} + \Delta E_{itr}^{t\text{-}route} = \hat{E}_{itr}^{t\text{-}route} \left(1 + \frac{\Delta E_{itr}^{t\text{-}route}}{\hat{E}_{itr}^{t\text{-}route}} \right) \tag{7}$$

Finally, the emissions of each pollutant in route r are:

$$E_{ir}^{route} = \sum_{t=1}^{T} E_{itr}^{t\text{-}route} \tag{8}$$

and the total emissions of each pollutant for the complete fleet that services the R routes during the period of time considered is:

$$E_{i}^{total} = \sum_{r=1}^{R} E_{ir}^{route} \tag{9}$$

4.2. Formulation of the optimization model

The optimization model is stated as a Mixed Integer Linear Programming (MILP) model, in which the objective function represents the weighted sum of each pollutant emission. A weighting coefficient W_i is introduced in order to quantify the relative importance given to each type of pollutant. The inclusion of these weights enables awarding greater or lesser significance to each substance. An adjustment parameter K_i is also incorporated to compensate the differences in the order of magnitude values of the diverse types of emissions within the objective function. Therefore, the resolution consists in calculating the value of the N_{tr} variables that minimize Eq. (10), which represents the weighted sum of the different emissions (CO_2, CO, THC, NO_x and PM):

$$\min Z = \sum_i W_i K_i E_i^{total} = \sum_i W_i K_i \sum_{r=1}^{R} \sum_{t=1}^{T} E_{itr}^{t\text{-}route} \tag{10}$$

The resolution requires compliance with the following constraints related to fleet size and composition:

- The total number of vehicles needed to service each route must equal the sum of the amount of units of each type assigned to that particular route.

$$V_r = \sum_{t=1}^{T} F_{tr} N_{tr} \tag{11}$$

- The total number of vehicles assigned per type cannot exceed the quantity of available units for such type.

$$V_t \geqslant \sum_{r=1}^{R} F_{tr} N_{tr} \quad \forall t \tag{12}$$

The problem may be posed from two possible perspectives concerning the distribution of the fleet, since the assignment process can either consent a vehicle's relocation to a different depot, or alternatively, only distribute the existing vehicles in each depot individually, thus preserving the fleet's composition in every depot. The two optimization models are quite similar since, in the event that all depot configurations remain invariable, each depot's arrangement is a submodel of the optimization case in which vehicles may be transferred to other depots.

5. Application to the urban bus fleet of Madrid: results and discussion

The methodology's application is based on the information supplied by the Madrid Municipal Bus Company (EMT) for the year 2009. In particular, the information contains data concerning the available fleet, the number of buses needed to service each route and the distance actually traveled by every vehicle type on each route. Additional relevant route information has been gathered from the Madrid City Council, the Statistics Institute of Madrid, and the representation of the bus routes in a GIS using the mapping information provided by the Spanish National Geographic Institute.

The fleet is composed of biodiesel vehicles, with articulated or rigid chassis, and vehicles using compressed natural gas (CNG), all of these being rigid. Diesel vehicles are also categorized in accordance with the European regulatory level for pollutant emissions (Euro II, III or IV) which they fulfill. CNG buses satisfy the European standards for Enhanced Environmentally-friendly Vehicles (EEV). The articulated buses are either Euro III or Euro IV. The fleet requires 1492 buses, from a total of 2069 available vehicles, which are classified in 6 categories considering the previous criteria (fuel, chassis and regulatory level), as shown in Table 2. The company has an excess of vehicles in order to assist special services and incidences. Likewise, information has been obtained from the system's operator regarding a total of 160 routes, excluding night routes and special services. The constraints of the model will distinguish those routes on which only certain types of vehicles may travel (articulated buses, in particular).

Due to practical constraints, only operational variables for a sample of 25 routes could be measured. Jiménez et al. (2013) explains the results of the clustering process based on microscopic variables. Quality indicators illustrate that a reasonable number of groups would be 8. Thereafter, a representative driving cycle was constructed for each cluster. However, during the cluster-assignment procedure of the remaining routes, the pre-established groups presented apparent difficulties because the available information was scarce, thus Jiménez et al. (2014) suggests a reduction in the number of clusters to 3. Consequently, following the method presented in Jiménez et al. (2013), new driving cycles were constructed and the assignment of these routes to the new clusters was achieved by means of a neural network that processed inputs comprising the known macrocospic variables for all routes, and previously trained using the classification obtained from the sample of 25 routes for which kinematic microscopic information was available.

The last step entailed the resolution of the optimization model. Two scenarios were evaluated: minimum emission of carbon dioxide and minimum emission of nitrogen oxides, due to their significance in atmospheric pollution assessment. In

Table 2
Vehicle fleet composition.

Biodiesel					CNG	Total
Euro II	Euro III		Euro IV		EEV	
Rigid	Rigid	Articulated	Rigid	Articulated	Rigid	
461	772	81	339	5	411	2069

addition, for both assumptions, the minimization of the corresponding pollutant was first performed without establishing any additional constraints affecting other types of emissions (case 1). However, provided that certain measures cause opposite effects on other pollutant emissions, the optimization model may also include supplementary constraints in order to avoid an emission level increase for other pollutants when compared to the amounts originated with the fleet's actual organization (case 2). In all circumstances, bus relocation to a different depot is allowed, considering that each depot provides vehicles to a fixed set of routes. Finally, it is supposed that each depot's vehicle composition remains invariable and identical to the operator's actual arrangement (case 3) because vehicles cannot be transferred from one depot to another, so they should continue attending altogether the same set of routes. The optimization models are solved using the General Algebraic Modeling System (GAMS) with the CPLEX solver, with its computation time on an average performance personal computer (with an Intel CORE i7-3770 3.4 GHz processor) being below 7 s.

5.1. Fleet assignment for a minimum emission of a certain pollutant

The application of the optimization model to minimize either carbon dioxide or nitrogen oxides results in the ideal fleet arrangement shown in Table 3 (case 1). Thus, Eq. (10) is applied using the adequate weight coefficients W in order to minimize the desired emissions. Similarly, Table 4 includes the comparison of the emission values per unit length in the arrangements attained for minimized carbon dioxide or nitrogen oxide emissions, and the values for the actual fleet organization employed by the EMT. The outcome is contrasted with the results obtained for the vehicle arrangement employed by the company.

The results reveal that, in order to minimize carbon dioxide emissions, it is preferable to assign vehicles with Euro II and Euro IV technologies, rather than vehicles consuming CNG. In this case, the articulated vehicles do not influence the result. The comparison indicates that minimizing CO_2 emissions could provide a 7.1% reduction in the aforementioned pollutant with regard to the fleet distribution performed by the system's operator. This condition is primarily due to the non-utilization of vehicles that use CNG. It is also important to emphasize that, in this assumption, THC and CO generation diminish significantly. Unfortunately, NO_x and PM emissions exceed the levels obtained in accordance with the allocation implemented by the EMT.

As expected, the results indicate that the most favorable technology for NO_x emission minimization corresponds to vehicles consuming CNG. The comparative shows that NO_x emissions could be reduced by 16% with regard to the operator's arrangement. Regrettably, the solution implies an increase in carbon oxides and hydrocarbon emissions when the complete EEV fleet is assigned.

5.2. Fleet assignment in order to avoid increases in the remaining emissions

Due to the opposite effects that the use of certain fuels has on CO_2 and NO_x emissions, additional constraints are included in the optimization model in order to avoid any emission increase that exceeds the values actually generated by the fleet. According to these premises, Tables 5 and 6 include the results for the optimization of CO_2 or NO_x emissions which prevents adverse effects on other pollutants (case 2). An emissions comparison between the assignments proposed for optimized carbon dioxide or nitrogen oxides emissions versus the values for the actual fleet organization employed by the EMT and the prior minimization without additional emission constraints are shown.

These results, when compared with the distribution implemented by the company, indicate that it would be feasible to reduce CO_2 emissions by 6.3%, while obtaining, in addition, a decrease of almost 2% in NO_x generation. Hydrocarbon emissions would diminish significantly to less than half and those of CO by 23%. Moreover, CO_2 emissions exceed the feasible minimum by only 0.9%, even though hydrocarbons exceed the minimum by 60.3% due to the presence of EEVs. The optimized CO_2 condition assigns all Euro II and Euro IV biodiesel vehicles. Without the constraints introduced to avoid an increase in nitrogen oxides and particles, and given the availability of Euro III vehicles, CNG-consuming vehicles would not be allocated, since 1658 diesel buses are available, and only 1492 are required. Nevertheless, achieving the additional constraints included in this case requires the use of EEV buses to prevent NO_x and particle emission limits being exceeded. Consequently, the solution recommends that the selected EEV fleet be assigned to cluster 3*, since in its representative cycle, the difference in the impact among CNG and biodiesel is lower. For clusters 1* and 2*, Euro II technology is chosen to operate on those routes where vehicles travel longer distances. The contrary reasoning is applicable to Euro III, as these vehicles are designated to routes with a lower distance-per-bus ratio, while Euro IV units are assigned to routes with intermediate values.

Table 3
Fleet assignment for minimum CO_2 or NO_x emissions.

	CO_2 minimization				NO_x minimization				
	Euro II	Euro III	Euro IV	EEV	Euro II	Euro III	Euro IV	EEV	Total
Cluster 1*	294	233	23	0	385	19	5	141	550
Cluster 2*	137	67	54	0	76	36	0	146	258
Cluster 3*	30	387	267	0	0	221	339	124	684
Total	461	687	344	0	461	276	344	411	1492
Available	461	853	344	411	461	853	344	411	2069

Table 4
Emissions comparison between the assignment proposed and the values for the actual fleet organization (case 1).

	CO_2 minimization		NO_x minimization	
	Consumption or emissions (kg/km)	Difference with actual organization (%)	Consumption or emissions (kg/km)	Difference with actual organization (%)
CO_2 emissions	0.7829	−7.1	0.8449	0.3
THC emissions	0.00017	−70.3	0.00082	41.1
NO_x emissions	0.0122	1.4	0.0101	−16.0
CO emissions	0.0052	−26.1	0.0072	3.4
PM emissions	0.000048	10.1	0.000027	−37.8

Table 5
Optimized fleet assignment for CO_2 or NO_x emission optimization, preventing an increase in any other pollutant.

	CO_2 optimization				NO_x optimization				
	Euro II	Euro III	Euro IV	EEV	Euro II	Euro III	Euro IV	EEV	Total
Cluster 1*	326	181	43	0	305	14	23	208	550
Cluster 2*	122	60	76	0	132	26	76	24	258
Cluster 3*	13	335	225	111	24	294	245	121	684
Total	461	576	344	111	461	334	344	353	1492
Available	461	853	344	411	461	853	344	411	2069

Table 6
Emissions comparison between the proposed assignment and the values according to the actual fleet organization (case 2).

	CO_2 optimization			NO_x optimization		
	Consumption or emissions (kg/km)	Difference with actual organization (%)	Difference with solution without additional restrictions (%)	Consumption or emissions (kg/km)	Difference with actual organization (%)	Difference with solution without additional restrictions (%)
CO_2 emissions	0.7897	−6.3	0.9	0.8190	−2.8	−3.1
THC emissions	0.00028	−52.4	60.3	0.00058	0.0	−29.2
NO_x emissions	0.0118	−1.9	−3.2	0.0106	−11.6	5.3
CO emissions	0.0054	−23.0	4.1	0.0063	−9.3	−12.3
PM emissions	0.000044	0.0	−9.2	0.000033	−24.6	21.2

In contrast, NO_x optimization including additional emission constraints implies that the complete EEV fleet should not be allocated. In consequence, the proposed distribution assigns the complete Euro II and Euro IV fleet (805 vehicles), as both technologies are the biodiesel types that produce lower NO_x, and only 353 CNG buses from the total 411 available units. The excess of carbon oxides and hydrocarbons that would be originated by the remaining 58 units is attenuated using Euro III vehicles, although this alternative increases NO_x and PM emissions. In this case, the technology with lower nitroxide emissions (EEV) is not uniquely assigned to those routes with a greater distance traveled per bus, since such disposition would simultaneously cause a significant increase in carbon oxides and hydrocarbons which impede meeting the constraints set for these pollutants. Accordingly, the Euro II fleet is selected for this kind of routes. Thus, 66.2% of this fleet is designated to cluster 1* since its representative cycle causes the highest emissions per unit length traveled. The preferred fleet for cluster 3* comprises vehicles of all technologies. The composition is influenced by the additional constraints, which induce a higher presence of biodiesel vehicles. Likewise, the results reveal that it is preferable to assign Euro III buses to cluster 3*, since its cycle produces fewer emissions. However, 26 Euro III units are allocated to cluster 2* in order to meet the articulated vehicle requisite for one of its routes. Concerning the CNG fleet, 58.9% of EEVs are designated to cluster 1*, provided that in its representative cycle, the difference in NO_x emissions with the biodiesel technologies is lower than in those of other clusters. In addition, 121 units (34.3% of the total) are assigned to the low distance traveled per vehicle routes contained in cluster 3*. This new arrangement would decrease NO_x emissions by 11.6%, with a supplementary reduction of 2.8% in carbon dioxide emissions. In addition, carbon monoxide would diminish 9.3% and particles by 24.6%. In comparison with the minimization scenario, nitrogen oxides emissions are 5.3% higher.

5.3. Influence of preserving the actual vehicle organization of the depots

In the previous cases, the arrangement process allowed vehicle relocation to other depots in order to modify the vehicle composition in each depot, bearing in mind that every depot services specific routes. However, it may occur that this flexibility is not possible, so fleet-to-route reorganization must be performed independently within each depot but not globally, thus avoiding vehicle exchanges among different depots (case 3). In this study, such supposition conveys a limitation, since the total EEV fleet during the time period studied was centralized in a single depot (with a total of five depots owned by the company), thus limiting the optimization algorithm's potential to enhance the fleet's organization. Table 7 includes the

Table 7
Emissions comparison between the assignments proposed and the values for the actual fleet organization and assignments of case 2.

	CO_2 optimization		NO_x optimization	
	Case 3 vs. EMT organization (%)	Case 3 vs. Case 2 (%)	Case 3 vs. EMT organization (%)	Case 3 vs. Case 2 (%)
CO_2 emissions	−2.9	3.6	−2.9	−0.1
THC emissions	−2.9	103.8	−3.0	−3.0
NO_x emissions	−10.5	−8.8	−10.5	1.2
CO emissions	−7.8	19.8	−8.1	1.4
PM emissions	−20.5	−20.5	−20.6	5.2

comparison of the results obtained for this case with those corresponding to the distribution implemented by the EMT, and the optimization of the fleet presented in the previous section which allows vehicle inter-depot relocation (case 2).

For both pollutants, the comparison of the results with those obtained according to the distribution used by the EMT is similar, since the EEV bus fleet may only be assigned to routes that are serviced from a particular depot, therefore both reorganizations seem analogous. Thus, for the CO_2 minimization without inter-depot arrangements, it is unfeasible to reduce EEV allocation sufficiently, since such vehicles must service routes which are assigned to that specific depot. Even so, a 2.9% CO_2 emission reduction could be achieved with regard to the operator's distribution. Nevertheless, the improvement is not as relevant as the result obtained with inter-depot reorganization, since CO_2 emissions increase by 3.6% in comparison with the optimal arrangement. Concerning NO_x, its emission could still diminish by 10.5% concerning the operator's organization, and slightly worsen the ideal solution obtained with inter-depot vehicle transfer by 1.2%.

6. Conclusions

This article presents a methodology which assigns a vehicle fleet to a set of fixed urban routes with the intention of reducing the environmental impact caused during its operation. The suggested process is simple to establish and economically viable, and does not cause a deterioration in service quality.

The methodology's justification resides in assuming that operational characteristics are specific to each route, and may not cause similar effects on all vehicle types, therefore a fleet reorganization is plausible, without new vehicle acquisition, for which the fleet's overall environmental impact may be minimized.

In the fleet assignment optimization process, two relevant environmental scenarios are considered, these being the minimization of carbon dioxide emissions, for its impact as greenhouse gas and nitrogen oxides for their influence on acid rain and tropospheric ozone generation in urban areas. Due to the opposite effects among bus types using biodiesel or CNG concerning their particular emissions behavior, additional constraints are included in order to ensure that the actual emission is not exceeded for any of the evaluated pollutants. The results indicate that, in both assumptions, it is feasible to obtain a fleet arrangement that significantly reduces the majority of the pollutant emissions without causing an increase in other pollutants. It should be noticed that the additional constraints on the emissions of each pollutant could be used to impose upper limits provided by environmental regulations. Furthermore, a sensitivity analysis for the respective weighting factors could provide a more general approach to the objective of reducing emissions than the one presented in the application case study.

The reliability of the results relies on the model's goodness-of-fit in emission calculations. However, both the methodology and the structure of the optimization equations are completely generic, thus admitting any number of vehicle categories. In addition, vehicle movements between the depots and the starting or ending points of the route are not considered, so emissions produced on those trips are not taken into account in the total emissions calculation and this circumstance could influence the final results if the new vehicle assignments involve inter-depot bus relocations. However, this contribution is expected to be negligible in terms of the fleet assignment.

Finally, the proposed methodology may be utilized to evaluate the environmental impact caused by any potential alteration in the fleet's composition, while the preferred vehicle-to-route assignment could also be calculated in advance.

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Appendix A. Routes and fleet input data

This Appendix lists all the data required for the methodological framework as set out in Section 3.

Routes:

- Itinerary: data related with each route's itinerary (horizontal and vertical profiles, slopes, types of road, etc.).
- Macroscopic variables of the routes: this type of variable specifies conditions associated with the infrastructure and the socioeconomic scope in the areas traveled by the vehicles (number and type of stops, concurrence with other transportation systems, distance proportion traveled in exclusive lanes, etc.).

– Constraints concerning vehicle type applicability: it is compulsory to identify and evaluate possible route-related conditions which may limit the use of certain types of vehicles (passenger capacity, turning radius, low emission zones, etc.).
– Number of vehicles per route: representing the number of vehicles needed to operate each route.
– Distance traveled by each vehicle type: this information is relevant so as to estimate emissions originated on every route in accordance with the fleet organization implemented by the system's operator.

Fleet:

– Composition of the fleet: denoting the number of available vehicles per type and technology.
– Initial vehicle allocation to the routes.
– Preliminary distribution of the vehicles in depots:
  • List of routes serviced from each depot in the current organization.
  • Number of vehicles per type and technology assigned to each depot.
  • Record of routes serviced by the vehicles according to the initial arrangement.

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