Intelligent Electric Drive Management for Plug-in Hybrid Buses

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Abstract. Plug-in hybrid (PH) buses offer range and operating flexibility of buses with conventional internal combustion engines with environmental. However, when they are frequently charged, they also enable societal benefits (emissions- and noise-related) associated with electric buses. Thanks to geofencing, pure electric drive of PH buses can be assigned to specific locations via a back-office system. As a result, PH buses not only can fulfil zero-emission (ZE) zones set by city authorities, but they can also minimize total energy use thanks to selection of locations favouring (from energy perspective) electric drive. Such a location-controlled behaviour allows executing targeted air quality improvement and noise reduction strategies as well reducing energy consumption. However, current ZE zone assignment strategies used by PH buses are static—they are based on the first-come-first serve rule and do not consider traffic conditions. In this article, we propose a novel recommendation system, based on artificial intelligence, that allows PH buses operating efficiently in a dynamic environment, making the best use of the available resources so that emission- and noise-pollution levels are minimized.

Keywords: Sustainable urban transport · Plug-in hybrid bus · Zero emission zone management · Genetic algorithms · Artificial neural networks.

1 Introduction

Air pollution and noise are the main problems in densely populated urban areas. Public transport (PT) is the only emission- energy- and space-efficient mobility solution for urban corridors with high mobility demand. While Euro 6 regulation has significantly lowered the emissions of pollutants from buses with internal combustion engines (ICE), there is still a question of noise and energy efficiency. The only technology that allows to reduce noise and in the same time offer high energy efficiency are battery-electric buses (BEB). However, BEB require charging infrastructure. With today's battery capacity, in most of the cases buses need to be charged during the operations. Such charging requirements might interfere with operators' primary concern, which is the revenue service (with on-time performance and reliability being the key performance indicators). The process towards full electrification of city buses has started but as it is not a simple one-by-one replacement of ICE; it will last for many years and will require some additional bridge solutions. The first one are full hybrid buses. They are cost-effective clean vehicle solution with zero-emissions capability that comes without complications and costs of charging infrastructure. In addition to significant reductions of fuel consumption and CO2 emissions, hybrid buses take advantage of using high power electric machine. This enables high energy recovery, and certain amount of pure electric drive (in particular around bus stops). Plug-in hybrid (PH) buses (also referred to as electric hybrids) are the second bridge solution. These buses have batteries of higher capacity (around 20 kWh) and rely on battery charging from the grid. Typically, they use high-power opportunity charging at the end points of routes. The electric distance driven by such buses depends on the charging setup (i.e. how often they charge) — typically is in the range of 50 to 70% of a route. In case if PH is not charged from the grid, it behaves like a hybrid. PH typically use zero emission zone management system, that allows to pre-set locations (via geofencing) where the bus would drive in electric mode. This enables implementing a targeted environmental strategy to the worst-affected areas rather than aiming at overall reduction in average levels of harmful pollutants and noise. This operating flexibility is their main novelty and the reason why they are being deployed in several European cities. One of the reasons is that this feature allows respecting zero-emission (ZE) corridors in cities. While locations of some ZE zones are defined by city authorities, there is still an open question how to distribute the electric drive on a given route in an optimal (energy-efficient) way. The decision about when to use the ICE or the electric motor is a complex task because the energy consumption of the PH bus depends on many external, internal and dynamic elements (speed, elevation, weather, driving style, etc.) highly influencing their electric range. This opens a wide variety of new challenges that have not been tackled yet.

In addition to the trend towards PT electrification, authorities are promoting other actions in the redesign of urban transportation to minimize both its environmental and its societal effects. One of the most common followed strategies consists in defining ZE corridors that aim at limiting noise from vehicles and reduce tailpipe emissions to zero. Examples of such areas are the city downtown, schools or hospital surrounding areas, or pedestrian streets. Such measures are already being put in place nowadays, and they will be soon essential in the future for livable cities. Therefore, any solution for sustainable public transportation must consider and respect these ZE corridors.

The main contribution of this work is the modeling and resolution of a novel optimization problem for the effective management of electric drive PH buses, looking for minimum energy consumption during their operation, and respecting ZE corridors. The problem, that we call Efficient PH Bus Operation (EPBO), is to decide whether the vehicle should use the electric or explosion motor at any time in order to cover the route with minimum energy use. We solve it following two different approaches: (i) a genetic algorithm (GA) that assumes full knowledge of the whole system to find a static optimal strategy, and a decentralized recommendation system, based on supervised machine learning, that makes use of local knowledge to dynamically take decisions.

The structure of this paper is as follows. Next section presents an overview of the main existing works in the field of sustainable urban transport. After that, Section 3 defines the problem tackled in this work, and Section 4 presents the tools we used to solve the problem. Results are summarized in Section 5, and our main conclusions are given in Section 6.

2 Sustainable urban transport

Bus electrification brings several new benefits to society. Particularly, it reduces energy consumption as well as emissions of noise, greenhouse gases and pollutants. Consequently it makes buses more comfortable [14]. As argued in Section 1, PH buses arise as a bridge solution to full electric buses. They are able to charge their batteries from an electric grid via "en-route opportunity charging". This allows to downsize battery and extend bus range to desirable values [6].

Charging infrastructure creates a strong link between infrastructure planning and bus operations [15], and some recent research focuses on developing a proper system design such as deploying strategic locations of e-charging stations [13]. Energy efficiency is also addressed via energy management strategies for the engine [12], and regenerative breaking technologies [11]. In addition, technology allows the use of batteries with more and more capacity in buses. Thanks to recent advances in all these fields, PH buses currently provide an autonomy of almost 10 km in electric mode, they can efficiently charge their batteries while on route, and the time to fully charge their batteries at charging stations is a matter of several minutes. Therefore, e-bus systems are currently moving from pilot projects [13] to small-scale deployments with very few charging stations. For example, the TOSA system in Geneva uses both terminal (3-4 minutes with low power) and at bus stops e-charging (15-second each 1-1.5 kilometres with high power) [3]. The potentials and needs of large-scale e-bus systems were investigated by the EU's flagship project on e-buses Zero Emission Urban Bus System (ZeEUS), and the challenges of the best choice for the electrification technology for each bus route and the optimum charging strategy were raised.

Zero emission zone (ZEZ) management is a new category of Intelligent Transportation Systems (ITS) telematics dedicated to optimize vehicle performance via off-board intelligence. Preliminary works are proposing to use geofencing for ZEZ management in the field of PH commercial vehicles [2]. In [17] the authors indicate potentials of dynamic ZEZ management for PE buses. However, to the best of our knowledge, the literature does not propose any methods that could overcome the limitations of today's static approaches. ZEZ management is an essential part of PH, which unlike in the past, are no longer just vehicles sold to operators but rather a turn-key solution that includes charging infrastructure, telematics and battery contracts. The current ZEZ management of PH buses simply assigns electric mode into predefined zones in an offline planning (based on the first-come first-served rule). Thus, it does not account for real-time factors influencing the range, as the load of the bus, the use of air conditioning, traffic, etc. Consequently, the assignment is very conservative and the full potential of dynamic ZEZ is not exploited [18]. However, we envision high potential benefits of applying dynamic strategies that adapt zone assignment according to weather, traffic conditions, initial battery state of charge or cooperation with cooperative ITS (C-ITS). Authors show in [16] that the use of C-ITS to mitigate stop-and-go progression can increase up to 6% the electric distance of PH buses.

3 The Efficient PH Bus Operation Problem

We model and address in this work the problem of Efficient PH Bus Operation, or EPBO. Let us assume that the bus route $\mathbf{T}$ is composed of n segments, $\mathbf{T} = \{t_1, t_2, \ldots, t_n\}$, where each segment t_i is defined by (i) its length (l_i), measured in kilometers, (ii) its slope (s_i), that can take values 0, 1, or -1, if it is flat, uphill, or downhill, respectively, and (iii) variable zone (z_i), that can take value 1 or 0 to indicate whether it is a ZE zone or not, respectively.

The EPBO problem is to maximize the following fitness function:

$$f(\mathbf{x}) = \sum_{i=0}^{n} x_i \cdot g(\mathbf{x}, t_i) \ ; \quad g(\mathbf{x}, t_i) = \begin{cases} 2 \cdot l_i & \text{if } z_i = 1 \wedge c_i = l_i \\ c_i & \text{if } z_i = 0 \\ -K \cdot (l_i - c_i) & \text{if } z_i = 1 \wedge c_i < l_i \end{cases} . \quad (1)$$

In the equation, $\mathbf{x}$ is the solution vector, assigning whether every route segment t_i should be covered with electric ($x_i = 1$) or explosion ($x_i = 0$) engine, and c_i is the distance covered in segment t_i by the bus in electric mode. Function $g(\mathbf{x}, t_i)$ assigns a quality value to segment t_i, according to a simulation that takes into account the strategy followed by the bus since the beginning of the route until the end of segment t_i. This is computed with the proposed PHSim simulator, presented in Section 4.1, that estimates the battery level of the bus after every segment, when following the strategy defined by solution $\mathbf{x}$. Function $g(\mathbf{x}, t_i)$ favors the green segments that were fully covered in electric mode (i.e., the segment is green, $z_i = 1$, and the distance covered using the electric engine, defined as c_i, is the same as the length of the segment), and penalizing those green segments that were not fully covered (i.e., when $c_i < l_i$). In the former case, the segment contributes to the fitness function with twice its length. In the latter case, the fitness function is penalized with the distance not covered in electric mode, namely $l_i - c_i$, multiplied by a large constant K. This constant must be high enough to ensure that the fitness value of any non valid solution, defined as the strategy in which at least one green segment is not fully covered using the electric engine, is worse than any valid one. In this work, we set K to 10,000. When the segment is not defined as a green one ($z_i = 0$) but the bus covers it in electric mode, either fully or partially, it contributes to the fitness function with the distance covered in electric mode.

4 Solving the problem

We present in this section how we tackled the resolution of EPBO problem using a GA and an artificial neural network (ANN). Before, we present in Section 4.1 the simulator used in this work to estimate the performance of the bus during its operation, when following a given strategy.

4.1 Simulator

We have built a simple simulator to emulate the energetic performance of the bus during its operation in a given route. It is called PHSim. The inputs to the simulator are (i) the route, as a set of segments, each with a number of features characterizing it (its length, inclination, or if it is in a ZEZ or not), and (ii) the battery management strategy, a vector with length the number of segments in the route. The value of each position in the vector can be 1, if the bus is covering it in electric mode, or 0, if it should use the explosion engine.

Regarding the output, the simulator estimates the distance covered in electric mode for every segment, as well as the battery level at the end of every segment. With these values it is direct to compute the required values to compute the fitness function defined in Section 3 to evaluate the quality of a given battery management strategy.

The pseudocode of the simulator is given in Algorithm 1, and it works as follows. It first takes the initial battery level, and initializes a number of variables, used to store the battery level after each segment and the number of kilometers covered in electric mode in each segment. Then, for every segment, it first checks if the strategy requires covering it in electric mode. If it is the case, it computes the electric consumption of covering the segment. If the battery level allows covering the whole segment, it is decreased by the estimated amount of energy to cover the segment. In other case, the battery level is set to zero and the distance covered of the segment is computed, according to the consumption.

In order to estimate the battery consumption of the bus, we assume three different consumption levels: 0.8 kWh/km, 1.2 kWh/km, or 1.6 kWh/km, depending on whether the segment is light downhill, flat, or light uphill [17]. In addition, this consumption is increased by 30% if air conditioning is activated [8].

4.2 Genetic Algorithms

Genetic Algorithms (or GAs) [7, 9] are iterative search processes for solving optimization problems. They work on a set of tentative solutions, called the population, that are evolved for a number of iterations, normally referred as generations.

Algorithm 1 Pseudocode of PHSim simulator

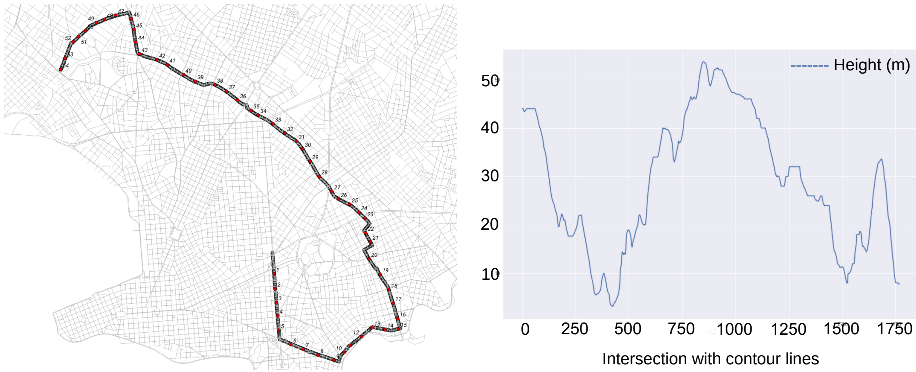
```
Input: B                                        ▷ Initial battery level
Input: RouteSegments     ▷ Information on the segments composing the route
Input: x                                        ▷ The strategy to follow
bl = zeros(|RouteSegments|+1)  ▷ Estimated battery level after every segment
c = zeros(|RouteSegments|)     ▷ Estimated distance covered in electric mode
if x[0] == 1 then        ▷ The first segment should be covered in electric mode
    ▷ Returns the consumption, b, and the distance covered, c[s], in electric mode
    (b, c[s]) = batteryConsumption(s, batteryLevel)
    bl[s] = B - b
end if
for s ∈ [1, |RouteSegments|) do                ▷ For the rest of the segments
    if x[s] == 1 then      ▷ This segment should be covered in electric mode
    ▷ Returns the consumption, b, and the distance covered, c[s], in electric mode
        (b, c[s]) = batteryConsumption(s, batteryLevel)
        bl[s] = bl[s-1] - b
    end if
end for
Return: (bl, c)
```

The evolution of the population is achieved by creating new solutions (or individuals) through the application of a set of operators on the population, and the survival of the fittest ones. These operators are typically (i) selection, to choose a number of parents from the population, (ii) recombination, that combines the information of the parents into one or more new individuals (i.e., the offspring), and (iii) mutation, that performs slight random changes in individuals to hopefully generate better ones. From one generation to the next one, the best fitting solutions survive. Which ones and how many of them survive is defined by the elitist criterion of the algorithm. Solutions are assigned a fitness value that allows comparing them in order to decide whether one is better than the other or not. This value is computed by the fitness function, which must be specifically designed for the problem to be solved.

In this paper, a solution represents the strategy of the bus to efficiently cover the hole route, so that the emission of pollutants is minimized, or, said in other words, the use of the battery of the bus is maximized. In order the strategy to be feasible, it must respect all ZEZs: the bus must use its electric engine in these areas. We use in this work the simulator presented in Section 4.1 to emulate the strategy. The output of the simulator is then used to compute the fitness value of the solution, as described in Section 3.

4.3 Artificial Neural Networks

ANNs [10] are very well known machine learning methods that can be used for classification or regression problems. In this work, we focus on classification problems. They have an architecture composed of layers of neurons, being the



(a) Route used in our simulations. (b) Height variations of the route.

Fig. 1: Graphical representation of route 181 in Montevideo, Uruguay.

first and last layer the input and output ones, respectively, and the rest are hidden layers. All neurons from one layer are connected to all neurons from the next layer. The number of hidden layers and the number of neurons composing them are hyperparameters of the system, that need to be adjusted experimentally. The input layer has as many neurons as the number of features in our model, while the number of neurons in the output layer is defined by the number of classes.

In ANNs, neurons can be excited according to the values received through its input connections, their associated weights, and an activation function. Each neuron computes the sum of the weighted signals received through each input connection. This sum is then passed to the activation function to decide whether the computed value will be propagated to the output of the neuron or not, according to its magnitude. Training an ANN implies finding the right weights for every connection between neurons.

5 Experimentation

We first describe the scenario used in our simulations. Then, we present the details and configurations of the algorithms used to solve the problem. Finally, we present and discuss the main results achieved in Section 5.5.

5.1 Scenario

The selected scenario is a real route of the urban transportation system in Montevideo, Uruguay. We took route number 181, one of the most important routes in the city, with a high number of passengers. The route, shown in Fig. 1, is among the longest routes in the city with 16.07 kilometers length, a feature that makes it challenging the efficient management of the battery.

We propose a first basic approach to the problem in this paper. We divide the route into 183 segments. Boundaries between segments are defined by bus stops, as well as by significant slope changes. Therefore, the consumption of the bus is constant within a given segment. Segments were created using a geographical information system, used to compute the elevation of the route at its intersections with the contour lines, as shown in Figure 1b.

The considered route does not have any ZEZ, so we generated them. We considered five different cases, when the percentage of green segments (i.e. segments belonging to a ZEZ) is 2, 5, 10, 15, and 20% of the 183 segments. This assignment was randomly done, and we created 20 different routes of every kind, making a total of 100 routes. For some of these routes we did not find any feasible solution, so we discarded them. Therefore, taking into account that each route is composed of 183 segments, and we discarded 4 routes, we have a total of around $17,500$ segments that will be used for training our ANN.

5.2 Configuration of the experiments

We used the *eaMuPlusLambda* GA implementation from the Distributed Evolutionary Algorithms in Python (DEAP) library [5]. It is a $(\mu + \lambda)$-GA, meaning that the new population for the next generation is created from among the μ individuals of the current population plus the newly generated λ solutions [1].

We did some preliminary experimentations to adjust all the parameters of the GA. The algorithm was configured with the well known two-points crossover and bit-flip mutation operators. Parents are selected from the population with a binary tournament method, and they are recombined with 50% probability. Randomly, 20% of the resulting solutions are mutated, and the probability to flip the value of each variable is set to 0.1. The population size was set to 100 individuals, as well as μ and λ. Regarding the maximum number of evaluations, we performed some convergence studies for the different problem versions studied and decided to use $1,000,000$ evaluations.

We used Keras Framework [4] for the experiments performed with the ANN. We generated a dataset with a large number of route segments, that will be the samples to train and test our models. Every segment (or sample) contains information about the battery level of the bus at the beginning of the segment, its length and inclination (for simplification, we discretized the inclination with only three values, meaning uphill, downhill or flat), a binary value indicating whether it belongs to a ZEZ (value 1) or not (value -1), and some additional information about the rest of the route that the bus still needs to cover, as the remaining kilometers of the route, and how many of them are ZEZs. The class of every segment is whether it should be covered in electric mode or not. This information is taken from the results of the GA, close to optimal solutions that will provide the ANN with enough information to perform accurate predictions.

We followed a well accepted methodology to train the model. We divided the whole dataset into two disjoint sets: testing (70% of the dataset) and validation (30%), and these two sets are randomly generated in every epoch (we use $3,000$ epochs in this work). All data was normalized by standardizing each input variable (i.e. zero mean and unit variance) in order to avoid any possible bias due to the magnitude differences in the values of the variables. In addition, both the

Table 1: Results from the GA for a sample instance with 20% green segments. Route length is 16.07 km, 3.11 km of them being ZEZs.

Battery level	Air conditioning	Electric Engine Regular zones	Electric Engine ZE zones	Diesel Engine Regular zones	Diesel Engine ZE zones
9 kWh	off	5.53 km	3.11 km	7.43 km	0.00 km
9 kWh	on	3.80 km	3.11 km	9.16 km	0.00 km
7 kWh	off	3.81 km	3.11 km	9.15 km	0.00 km
7 kWh	on	1.86 km	3.11 km	11.10 km	0.00 km

testing and validation datasets were created so that they have a balanced number of samples of each class. This was done just by discarding random samples of class 0 (supposing around 65% of the dataset).

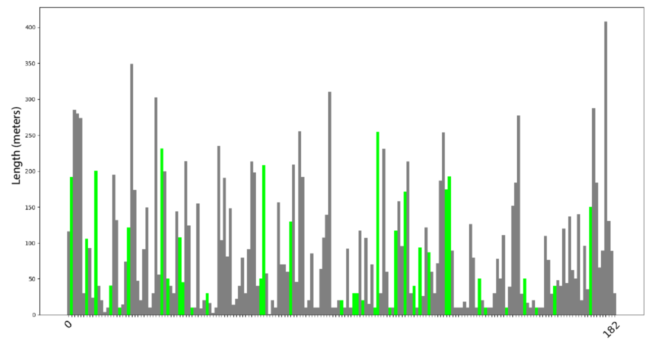
Once the ANN model is trained, it is used for validation in new, unseen, routes. The trained model is used to predict whether the corresponding route segment should be covered in electric or diesel mode, and this prediction is done from the first to the last segment, sequentially, updating the battery level of the bus after covering every segment, when necessary.

All experiments were performed on an Intel Core i5-8600K 3.6GHz processor with 16GB RAM memory, with Ubuntu 18.04 operating system.

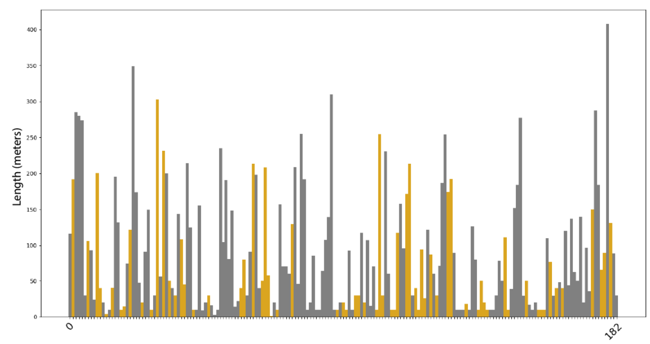
5.3 Solving the problem with the GA

Once the routes conforming our dataset are generated, we still need to classify every segment, so that the ANN can learn, based on local variables, whether the route segment should be covered in electric mode or not. For that, we solve every route with a basic GA, as presented in Section 4.2. Solving a route gives as many observations for our dataset as the number of segments it contains, namely 183.

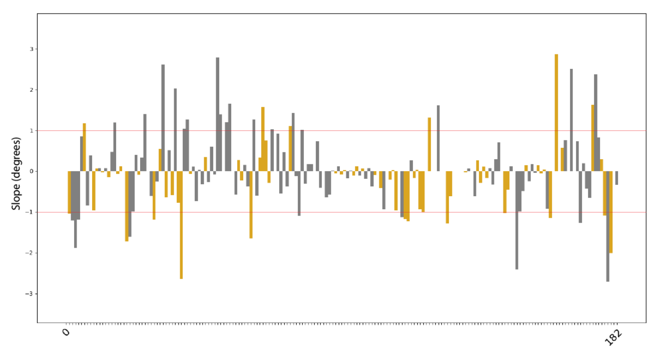
We show in Table 1 the results found by the GA for a selected instance where 20% of segments are ZEZs. This particular instance is composed by 3.11 km of ZEZs, and the rest of the route is 12.96 km long. It can be seen that the GA can always find feasible solutions. In the most favorable case, the bus can cover more than half the route lenght in electric mode. This percentage quickly decreases when the initially battery level is reduced and/or the A/C is on. We graphically show in Fig. 2a all the segments composing the route, emphasizing in green color those belonging to ZEZs. We present the results obtained for that route with two different initial battery capacity levels, and also when using air conditioning or not. Figures 2b and 2c present the result obtained by the GA for the considered instance showing the length and the slope of the segments, respectively, for the most restrictive instance studied: when the initial battery level is 7kWh and A/C is in use. As it can be seen, all green segments are covered by the solution. As it could be expected, from all uphill segments, the GA chose only those ones belonging to ZEZs to be covered in electric mode. It is also natural that most selected segments to be covered in electric mode are downhill and short ones.



(a) Segments length of the studied route. ZEZs are in green.



(b) GA solution (yellow means electric). Segments length.



(c) GA solution (yellow means electric). Segments slope.

Fig. 2: Route segments and result of the GA (7kWh battery and A/C on).

5.4 Hyperparameters selection and tuning for the ANN

We set the number of input and output neurons to 6 (the number of available variables) and 2 (the number of classes), respectively. We set the number of epochs to $3,000$, and the model is trained, iterating on the data in batches of 32

Table 2: Results of the experiments for ANN hyperparameters selection.

Architecture						Weights optimizer	
Hidden neurons	Hidden layers	Accuracy	Hidden neurons	Hidden layers	Accuracy	Optimizer	Accuracy
3	1	0.75	7	1	0.76	sgd	0.76
3	2	0.76	7	2	0.76	adam	0.77
3	3	0.75	7	3	0.76	adamax	**0.78**
3	4	0.76	7	4	**0.77**	adagrad	0.75
5	1	0.75	10	1	0.76	adadelta	0.76
5	2	0.76	10	2	0.76	rmsprop	0.77
5	3	0.76	10	3	**0.77**	nadam	0.76
5	4	0.76	10	4	0.76		

samples. The activation function used for the output layer is *softmax*, and the sigmoid function for the hidden layer neurons. We used the *categorical_crossentropy* loss function from Keras. We made some experiments to decide the architecture of the network, as well as the optimizer to use for computing the weights. The data used for training the ANN correspond to all route segments for 2, 5, 10, 15, and 20% ZEZs. The class every sample belongs to is obtained from the GA solution, when the initial battery level is set to 7 kWh and A/C is in use.

We can see in Table 2 the results of the accuracy of the model, when testing from 1 to 4 hidden layers each with a number of neurons of 3, 5, 7, and 10. The optimizer used in this study is the Stochastic gradient descent, the most basic one. We can see that the highest accuracy is obtained in the cases of 4 hidden layers with 7 neurons each, and 3 hidden layers with 10 neurons each. From these two configurations, we adopted the latter one, because it is faster to execute, given that it has one hidden layer less.

Once the architecture is defined, we evaluate the performance of seven different optimizers, available in Keras. For this study, we set the number of epochs to $10,000$, as an attempt to emphasize the differences between the optimizers. Table 2 shows that the most accurate one is *adamax*, so we chose it.

5.5 Validation of the ANN model

We present in Table 3 the average fitness value obtained by the GA and the ANN on the 20 different instances of each of the studied percentage of ZEZs in the route. We considered the case when the initial battery level is 7 kWh and A/C is in use. It can be seen that the solutions of the GA (assuming global knowledge) outperforms the results obtained by the ANN for the instances with shortest ZEZs (namely, 2 and 5% of the segments). However, the ANN outperforms the results reported by the GA in the rest of the instances. These instances are more challenging because they include longer ZEZs. At this point, we would like to emphasize that ANN makes use of local data to take decisions, and it learned how to decide the strategy from the solutions reported by the GA. Meaning that,

Table 3: Average fitness of solutions found by GA and ANN.

ZEZs	2%	5%	10%	15%	20%
GA	**6.100**	**6.918**	6.751	7.200	7.747
ANN	5.700	6.491	**6.787**	**7.410**	**7.944**

even when it learns the strategy from the GA, it is able to outperform it. This fact is possible because the ANN learns the recommended action (either to use electric or explosion motor) for every segment individually, according to local variables. This approach allows it detecting anomalies in the training process in those cases where the GA took a wrong decision, ignoring them.

6 Conclusions and future work

Plug-in hybrid buses are flexible solutions to significantly reduce noise and emissions in urban public transport. They provide 10 km electric drive autonomy, and can operate with either motor any time. We model in this paper the Efficient PH Bus Operation problem (EPBO) to find the best strategy for a PH bus to operate with minimum emissions, and respecting zero-emission zones.

We built a simple simulator to emulate the performance of PH buses when following a given route strategy, and used it to solve the problem with a GA. This approach finds pseudo-optimal static solutions, making use of global knowledge. Additionally, we propose an ANN to allow the bus taking on-line decisions on the strategy to follow in a dynamic environment, according to local variables. The ANN is trained with the strategies discovered by the GA.

The parameters of the GA and the ANN were tuned experimentally, and the performance of both methods was carefully analyzed. The ANN was able to learn the right decisions from the GA to build a good strategy, discarding the wrong ones. This is evidenced by the fact that the solutions found by ANN outperformed those of the GA, in general, despite the fact that ANN only uses local information to take decisions while the GA makes use of global information.

As future work, we plan to define a more realistic version of the problem, characterizing the consumption of the bus from real data. Additionally, we will investigate the use of unsupervised learning models to find accurate strategies.

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