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Evaluation of the Performance of HEV Technologies using a MILP Model to Minimize Pollutants Emissions

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Abstract—This paper presents a mixed integer linear programming (MILP) model to optimizing the maintenance costs during the operation of the hybrid electric vehicles (HEVs) aiming at reducing CO₂ emissions during operating along of the day. This target is obtained by an appropriate selection of navigation modes and the optimal scheduling of deliveries. The proposed model considers the average speed, battery state of charge (SOC), and the set of deliveries to be made by each type of HEV. A set of constraints that ensures the performance of the HEVs is considered while the uncertainties of the trip on each urban road are modeled using the traffic density values according to the levels of service (LOS). The proposed model is implemented in AMPL and solved using the solver CPLEX showed the effectiveness in the evaluation of each type of HEV technology.

Index Terms— Battery state of charge, navigation modes, scheduling of deliveries, performance of the HEVs.

NOMENCLATURE

A. Sets

Ω_i Set of intersections i .
 Ω_{ur} Set of urban roads ki .
 Ω_D Set of density values u .

B. Parameters

au Autonomy value (km).
 d_{ki} Length of urban road ki (km).
 D_{ki} Traffic density in each urban road ki (veh/km).
 D_u Value of the traffic density of element u (veh/km).
 D_j Saturation density (veh/km).
 D_0 Optimal density related to F_{max} (veh/km).
 E^{CO_2} CO₂ emissions (gCO₂/km).
 F_{max} Maximum traffic flow (veh/h).
 K^E Battery energy capacity (kWh).
 K^C Tank fuel capacity (L).
 M Big value used in the linearization process.
 $MR_{r,d}$ Matrix of possible routes.
 N^d Number of deliveries.
 N^p Total number of periods.
 NR Number of possible routes.
 $\bar{P}^{ch}, \underline{P}^{ch}$ Upper and lower battery charge limits (kW).
 r_i^s Location of the charging station (0/1: intersection i without/with charging station).
 SOC^0 Initial state of charge of the battery of HEV (kWh).
 $t_{d,i}^n$ Type of intersection i in delivery d (−1: starting; 0: intermediate; 1: arrival).
 t_{ki}^{ur} Type of urban road ki (1: main; 0: secondary).
 $\bar{v}_{ki}$ Maximum average speed in urban road ki (km/h).

v_f Free flow speed (km/h).
 v_0 Optimal speed related to F_{max} (km/h).
 δ^{km} Maintenance costs (\$/km).
 Δt Duration of each period (h).
 δ^C Fuel expense (km/L).
 ρ^C Levels of CO₂ emissions reduction.
 τ^{max} Maximum limit of total operating time (h).
 δ^{PE} Percentage of energy that defines the state of charge of the HEV at the arrival intersection (warehouse).
 δ^D Energy spent during the navigation of HEV (kWh/km).
 $\bar{\tau}^{ch}, \underline{\tau}^{ch}$ Upper and lower limits of the charging time (h).
 η^{cE}, η^{dE} Charging and discharging efficiencies.

C. Variables

$\omega_{d,ki}$ Binary variable that indicates the navigation of the HEV in urban road ki for delivery d .
 $n_{d,ki}$ Integer variable indicating the number of periods during navigation of the HEV in urban road ki for delivery d .
 $v_{d,ki}$ Average speed value in the navigation of the HEV in urban road ki for delivery d (km/h).
 $d_{d,ki}^{SM}$ Length of urban road ki for delivery d traversed in charge-sustaining mode (km).
 $d_{d,ki}^{DM}$ Length of urban road ki for delivery d traversed in charge-depleting mode (km).
 $\Delta \tau$ Extra hours related to HEV (h).
 $SOC_{d,i}$ State of charge of the battery of the HEV at intersection i for delivery d (kWh).
 $SOC_{d,i}^a$ State of charge of the battery of HEV at the moment of arrival at intersection i for delivery d (kWh).
 $\varepsilon_{d,i}$ Total energy for charging of the HEV at intersection i for delivery d (kWh).
 $P_{d,i}^{ch}$ Charging rate of the HEV at intersection i for delivery d (kW).
 $\tau_{d,i}^{ch}$ Charging time of the HEV at intersection i for delivery d (h).
 $y_{d,i}$ Binary variable that indicates the charging status of the HEV at intersection i for delivery d .
 $\alpha_{d,ki,t}$ Binary variable used in the discretization of $n_{d,ki}$.
 $\Delta \alpha_{d,ki,t}$ Continuous variable that represents the product of $v_{d,ki}$ and $\alpha_{d,ki,t}$ in the linearization process.

I. INTRODUCTION

HYBRID electric vehicles (HEVs) technologies the most sustainable option for the transport sector due to the

reduction of pollutant emissions that implies its use in this sector. This transport technology has two navigation modes, such as charge-sustaining and charge-depleting modes that determining the energy state of the battery [1]. The delivery and emergency services are some of the diverse applications of the HEVs within the industrial sector. In the operation of the HEVs, information related to the variation of the traffic density for a given period in each type of service should be considered. Also, the development of an operational strategy which considers the navigation modes, efficient battery recharge, and optimal scheduling of deliveries is essential [2]. Therefore, a computational tool for the evaluation of the performance of HEVs technologies is developed considering, speed limits during the trip, and energy requirements of the HEV batteries for each CO₂ emission reduction level. In literature, works related to the optimal performance of the HEVs that consider, specifically, the navigation modes in each urban road during operation (deliveries to the specified points) taking into account scenarios with emission reduction are scarce. In [1], an approach which minimizes the cost of fuel consumption based on the selection of appropriate driving modes was proposed. In this approach, the trip information integrated into path planning, and charging stations was used to analyze the Chevrolet Volt performance. In [2], a MILP model to minimize the cost of extra hours and maintenance which considered a set of prespecified deliveries on a city map was proposed. The path planning problem for the HEVs considering two aspects of energy usage and battery were proposed in [3, 4]. Also, a mathematical model was developed in [5], aiming at evaluating the performance of HEVs concerning the internal combustion engine vehicle (ICE) regarding fuel economy along a given route. In other works, the charging of the HEVs at specific points located along the main path was considered. These works have taken into account traffic flow information for the operation of HEVs in urban areas. Charging strategies were developed in [6]-[8], aiming at minimizing the total charging costs of EVs, and determining the optimal scheduling considering trip historical data. In [9, 10], two algorithms for optimal control and fuel economy optimization during operating of the HEVs were developed. These algorithms guaranteed the optimal energy distribution for the powertrain system. In [11] a time-varying scaling method to generate fixed-route driving data was implemented. A pseudospectral algorithm to solve the problem of optimizing HEV power management was developed in [12]. An efficient control for the optimal distribution of power between batteries and engines for a driving cycle considering real traffic data, changing traffic conditions for the HEV operations was presented in [13]. Algorithms for optimization of the charging rate profile and energy consumption in the powertrain of the HEV were proposed in [14, 15]. A DP algorithm was implemented in [16] aiming the optimal shift scheduling and energy management mode of HEVs during a driving cycle. Traditional optimization methods are not robust enough to face dynamic changes, and usually, a complete restart must be provided to obtain a feasible solution (e.g., DP). In contrast, evolutionary algorithms are used in such changing circumstances. However, none of them can guarantee finding the optimal global solution [17].

This paper proposes an MILP model which evaluates the optimal performance of HEVs during their operation on the city map by minimizing the maintenance costs. The navigation modes (charge-sustaining and charge-depleting), efficient battery recharging, and optimal scheduling for deliveries constitute the operating strategy which ensures the optimal performance of each HEV. Constraints related to the set of possible routes for deliveries, battery capacity, speed variation, charging and discharging rates, as well as the levels of CO₂ emission reductions, are considered. Moreover, charging points (with variable charging rates) located on urban roads and the intersections near these roads, are also taken into account. In order to ensure the optimal performance of the HEVs, an iterative process is used to evaluate all possible strategies in the operation of the HEVs. Uncertainties in the HEVs navigation, which are the result of traffic density variation, are modeled using probability values related with the levels of service (LOS). A city map containing roads and intersections is modeled as a graph with 71 nodes (intersections) and 131 edges (main and secondary roads). The evaluation of the proposed model, shows promising results in the application of this type of hybrid transportation technology. The proposed model is implemented in the AMPL and the solver CPLEX is used to find the optimal solution. Therefore, the main contributions of this paper are threefold:

- Proposing an MILP model for the evaluation of the performance of HEVs considering CO₂ emission reduction levels that presents an efficient computational behavior with conventional MILP solvers.
- The optimization model is flexible and guarantees the appropriate navigation modes of different HEV types so that they can be charged at charging points on the city map.
- This model contributes to fuel economy and sustainable HEV performance.

The remainder of this paper is structured as follows. In section II, the hypotheses and uncertainties in the navigation are presented. The mathematical formulation of the MINLP model and the linearization process are discussed in section III. Section IV presents the case studies and results. Section V contains concluding remarks.

II. MATHEMATICAL MODELING

In this section, the main hypotheses related to the charging infrastructure, delivery points, and uncertainties during the HEVs operation are considered in detail. In order to handle the problem appropriately, the following hypothesis are considered. Charging points are predefined on the city map. The vehicle, after doing the predefined deliveries, return to the same starting point, namely warehouse. A set of deliveries to be made consecutively is considered for each HEV. All the HEVs begin with their full state of charge (SOC). The location of the charging and delivery points is modeled as in [2].

The urban roads ki are differentiated by t_{ki}^{ur} , which determines a main or a secondary urban road on the city map [17]. Fig. 1 shows the number of charging points (in gray squares) located ($r_i^s = 1$) along the main road (gray line). On secondary roads (dashed lines), charging points are located at

intersections i ($r_i^s = 1$) near the main road. The warehouse and delivery points are represented by circles and triangles in blue, respectively. Furthermore, each delivery d located at intersection i is characterized by $t_{d,i}^n$, with values of -1 or 1 . Thus, the same intersection i may present $t_{d,i}^n = 1$ (arrival intersection), and $t_{d+1,i}^n = -1$ (departure intersection) values to deliveries d , and $d+1$, respectively. The location (intersection i) of the delivery and charging points as well as the warehouse are detailed in [26].

Fig. 1. Charging and delivery points on the city map.

In the proposed model, the uncertainties are represented by the traffic density variation along of each route. This variation in the number of vehicles per kilometer traveled determines the speed of navigation of the HEVs on each urban road ki [2], [27]. A density-speed curve and its main parameters, are defined by the equations (1)-(3) [21].

$$\bar{v}_{ki} = v_o \ln \left(\frac{D_J}{D_{ki}} \right) \quad (1)$$

$$F_{max} = \frac{v_o D_J}{e} \quad (2)$$

$$D_o = \frac{D_J}{e} \quad (3)$$

In order to determine the variation of average speed value in each urban road ki , the Monte Carlo simulation algorithm is used. This algorithm calculates the $\bar{v}_{ki}$ values, considering, the values LOS. Thus, as a result of this iterative process the value $\bar{v}_{ki}$ is obtained and used as the input data in constraint (10) of the MILP model.

III. THE PROPOSED MODEL

The proposed model is formulated initially as an MINLP problem, (4)–(29). In (4), the total costs related to maintenance costs for each HEV is minimized. The constraints of this problem are as follows.

$$\text{Min: } \delta^{km} \sum_{d=1}^{N^d} \sum_{\forall ki \in \Omega_{ur}} d_{ki} \omega_{d,ki} \quad (4)$$

$$\begin{aligned} \text{s.t.} \\ \sum_{\forall ki \in \Omega_{ur}} \omega_{d,ki} - \sum_{\forall ij \in \Omega_{ur}} \omega_{d,ij} = \mu; \\ \forall d \in 1..N^d, \forall i \in \Omega_i / t_{d,i}^n = \mu \end{aligned} \quad (5)$$

$$d_{ki} \omega_{d,ki} = v_{d,ki} n_{d,ki} \Delta t; \forall d \in 1..N^d, \forall ki \in \Omega_{ur} \quad (6)$$

$$0 \leq v_{d,ki} \leq \bar{v}_{ki}; \forall d \in 1..N^d, \forall ki \in \Omega_{ur} \quad (7)$$

$$d_{ki} \omega_{d,ki} = d_{d,ki}^{DM} + d_{d,ki}^{SM}; \forall d \in 1..N^d, \forall ki \in \Omega_{ur} \quad (8)$$

$$0 \leq E^{CO_2} \left((1 - \rho^c) \omega_{d,ki} d_{ki} - d_{d,ki}^{SM} \right); \quad \forall d \in 1..N^d, \forall ki \in \Omega_{ur} \quad (9)$$

$$SOC_{d,i} = SOC^0; \quad \forall d \in 1..N^d, \forall i \in \Omega_i / d = 1 \wedge t_{d,i}^n = -1 \quad (10)$$

$$SOC_{d,i} = SOC_{d,i}^a + \varepsilon_{d,i}; \quad \forall d \in 1..N^d, \forall i \in \Omega_i / t_{d,i}^n \geq 0 \quad (11)$$

$$SOC_{d,i} = SOC_{d-1,i}; \quad \forall d \in 1..N^d, \forall i \in \Omega_i / d > 1 \wedge t_{d,i}^n = -1 \wedge t_{d-1,i}^n = 1 \quad (12)$$

$$SOC_{d,i} = \delta^{PE} K^E; \quad \forall d \in 1..N^d, \forall i \in \Omega_i / d = N^d \wedge t_{d,i}^n = 1 \quad (13)$$

$$0 \leq SOC_{d,i} \leq K^E; \forall d \in 1..N^d, \forall i \in \Omega_i \quad (14)$$

$$SOC_{d,i}^a = \sum_{\forall ki \in \Omega_{ur}} \omega_{d,ki} (SOC_{d,k} - \eta^{dE} \delta^D d_{d,ki}^{DM}); \quad (15)$$

$$\forall d \in 1..N^d, \forall i \in \Omega_i \quad (16)$$

$$0 \leq SOC_{d,i}^a; \forall d \in 1..N^d, \forall i \in \Omega_i \quad (17)$$

$$\varepsilon_{d,i} = 0; \forall d \in 1..N^d, \quad \forall i \in \Omega_i / (d = 1 \wedge t_{d,i}^n = -1) \vee (t_{d,i}^n \geq 0 \wedge r_i^s = 0) \quad (17)$$

$$\varepsilon_{d,i} = \eta^{cE} y_{d,i} P_{d,i}^{ch} \tau_{d,i}^{ch}; \quad \forall d \in 1..N^d, \forall i \in \Omega_i / t_{d,i}^n \geq 0 \wedge r_i^s = 1 \quad (18)$$

$$\underline{P}_{d,i}^{ch} \leq P_{d,i}^{ch} \leq \bar{P}_{d,i}^{ch}; \forall d \in 1..N^d, \forall i \in \Omega_i \quad (19)$$

$$\underline{\tau}_{d,i}^{ch} \leq \tau_{d,i}^{ch} \leq \bar{\tau}_{d,i}^{ch}; \forall d \in 1..N^d, \forall i \in \Omega_i \quad (20)$$

$$\omega_{d,ki}, \text{ binary}; \forall d \in 1..N^d, \forall ki \in \Omega_{ur} \quad (21)$$

$$y_{d,i}, \text{ binary}; \forall d \in 1..N^d, \forall i \in \Omega_i \quad (22)$$

$$n_{d,ki}, \text{ integer}; \forall d \in 1..N^d, \forall ki \in \Omega_{ur} \quad (23)$$

Constraint (5), guarantee the determination of the shortest route for each HEV technology for delivery d . For μ equal to -1 , is obtained the shortest urban road d_{ij} to be traversed, starting from intersection i ($t_{d,i}^n = -1$) for all possible intersections j . The value $\mu = 0$, is related with the navigation of HEV on urban roads formed with intermediate intersections i ($t_{d,i}^n = 0$), where the navigation from intersection k to i and from intersection i to j constitutes a minimum route, d_{ki} , and d_{ij} . In this case, an intermediate intersection represents the arrival intersection for the HEV coming from possible intersections k and, at the same time, it represents the departure intersection for the HEV going to the possible intersections j . In $\mu = 1$, urban road ki is selected such that the length that must be traversed, starting from the possible intermediate ($t_{d,k}^n = 0$) intersections k to the arrival intersection i ($t_{d,i}^n = 1$), is the shortest, d_{ki} . Constraints (6), (7), and (8) are related to the number of periods and speed values in each urban road ki during the navigation of the HEV. In (6), the inverse relationship of $v_{d,ki}$ and $n_{d,ki} \Delta t$ for each d_{ki} related to the urban road ki and delivery d is shown. Constraint (7) ensures the speed limits. Note that, $\bar{v}_{ki}$ is obtained by the proposed algorithm. In order to determine the values of $d_{d,ki}^{DM}$ and $d_{d,ki}^{SM}$ in each urban road ki and delivery d , constraints (8), (9), and (10), are considered. In (8), the summation of the lengths of urban road ki for delivery d that is traversed in charge-depleting ($d_{d,ki}^{DM}$) and in charge-sustaining ($d_{d,ki}^{SM}$) modes must be equal to the length of the urban road to be traversed (d_{ki}) for delivery d and each urban road ki . The

relationship between the kilometers traveled in the charge-sustaining ($d_{d,ki}^{SM}$) mode and the total number of kilometers, d_{ki} , for each urban road ki are established in (9). Thus, an increase in the ρ^C values represents that CO₂ emissions in the charge-sustaining mode must be less than $1-\rho^C$ times the total CO₂ emissions during the HEV operation. The battery's state of charge, $SOC_{d,i}$ of the HEVs is determined by (10)-(14). In (10), the initial state of charge, SOC^0 , at intersection i for the first delivery d , ($t_{d,i}^n = -1$) is considered. $SOC_{d,i}$ for delivery d at intersection i ($t_{d,i}^n \geq 0$) is calculated in (11). In this calculation, the available energy, $SOC_{d,i}^a$, and the energy to be recharged by the HEV at the charging points located at ($r_i^S = 1$) intersection i , $\varepsilon_{d,i}$, is considered. The state of charge, $SOC_{d-1,i}$, for the battery of the HEV in delivery $d-1$ at intersection i ($t_{d-1,i}^n = 1$) is equal to its SOC in delivery d at intersection i ($t_{d,i}^n = -1$), (12). In (13), the final state of charge, $SOC_{d,i}$ for the last delivery d at intersection i ($t_{d,i}^n = 1$), is established. In (12), the limits of the state of charge of the battery are guaranteed. In (15), the available energy in the battery, $SOC_{d,i}^a$, is calculated as the difference between $SOC_{d,k}$ at intersection k and $\eta^{dE} \delta^D d_{d,ki}^{DM}$, which is the energy used during travel in the charge-depleting mode on ($\omega_{d,ki} = 1$) urban road ki . The non-negativity of $SOC_{d,i}^a$ is guaranteed in (16) at intersection i . Constraint (17), guarantees that no charge is necessary for the starting intersection i ($t_{d,i}^n = -1$), for the first delivery d , and for subsequent deliveries d with intersections i ($t_{d,i}^n \geq 0$) without charging points ($r_i^S = 0$), respectively. The recharge energy, $\varepsilon_{d,i}$, is calculated in (18) where the charging depends on variables $y_{d,i}$, $P_{d,i}^{ch}$, and $\tau_{d,i}^{ch}$ at each intersection i in the presence of charging point ($r_i^S = 1$). Constraints (19) and (20) guarantee that $P_{d,i}^{ch}$ and $\tau_{d,i}^{ch}$, lie between their lower and upper limits, respectively. Constraints (21), (22), and (23) stand for the main binary and integer decision variables, $\omega_{d,ki}$, $y_{d,i}$ and $n_{d,ki}$, respectively.

The Big-M method is used to linearize non-linear constraints (6), (15), and (18), [20]. It is worth mentoring that the big M value should be defined properly to prevent any computational difficulties or miscomputation [28]. To linearize constraint (6), $n_{d,ki}$ is discretized with N^P binary variables $\alpha_{d,ki,t}$ in (24.2) and replaced in (24.1).

$$d_{ki} \omega_{d,ki} = \Delta t \sum_{t=1}^{N^P} \Delta \alpha_{d,ki,t}; \forall d \in 1..N^d, \forall ki \in \Omega_{ur} \quad (24.1)$$

$$n_{d,ki} = \sum_{t=1}^{N^P} \alpha_{d,ki,t}; \forall d \in 1..N^d, \forall ki \in \Omega_{ur} \quad (24.2)$$

$$0 \leq -\Delta \alpha_{d,ki,t} + v_{d,ki}; \quad \forall d \in 1..N^d, \forall ki \in \Omega_{ur}, \forall t \in 1 \dots N^P \quad (24.3)$$

$$-\Delta \alpha_{d,ki,t} + v_{d,ki} \leq M(1 - \alpha_{d,ki,t}); \quad \forall d \in 1..N^d, \forall ki \in \Omega_{ur}, \forall t \in 1 \dots N^P \quad (24.4)$$

$$0 \leq \Delta \alpha_{d,ki,t}, \quad \forall d \in 1..N^d, \forall ki \in \Omega_{ur}, \forall t \in 1 \dots N^P \quad (24.5)$$

$$\Delta \alpha_{d,ki,t} \leq M \alpha_{d,ki,t}; \quad \forall d \in 1..N^d, \forall ki \in \Omega_{ur}, \forall t \in 1 \dots N^P \quad (24.6)$$

Also, the linearization technique in [2] is used in (24.3) - (24.6). Constraint (15) and (18) are linearized in the same way.

IV. CASE STUDY AND RESULTS

To evaluate the proposed MILP model, the system presented in Fig. 1 is used. The main features of the HEVs can be found in [26], obtained from [18]. The value of δ^D for each HEV is 0.8 (the difference between 0.9 and 0.1) of K^E divided by au . The initial state of charge of the HEVs' batteries, is equal to K^E , and each HEV arrives at the warehouse with a value of δ^{PE} of $0.9K^E$. In addition, all HEVs start with $K^C = 40$ L and a fuel price of \$3.65 per L [19], is also considered. To implement and solve the proposed model, a modeling language for mathematical programming AMPL [23] and the commercial solver CPLEX [24] is used on a 2.67-GHz computer with 3 GB of RAM. For each charging point shown in Table V the values $\underline{P}^{ch}$ and $\overline{P}^{ch}$, as well as $\underline{\tau}^{ch}$ and $\overline{\tau}^{ch}$, are considered to be 22 kW and 50 kW, and 0.3 h and 0.5 h, respectively [2], [16].

Fig. 2. Flowchart for the iterative process

The values of η^{rE} and η^{dE} are set to 0.98 and 1.00, respectively [1], [14]. For each HEV, four emission reduction levels, ρ^C , are used; the values of ρ^C for these levels are 10%, 20%, 30%, and 40%, respectively. The coefficient related to maintenance costs, δ^{km} , presented in (4), is assumed to 1. In the operation of the HEV, time τ^{max} is 8 hours (habitual working hours) [25]. In addition, Δt is 0.1 h, and the total number of periods, N^P , for each urban road ki to be traversed for delivery d is 10. All the possible strategies that aim the attendance to the delivery points, N^d , are available in [26]. Note that for all possible strategies the HEVs depart and arrive at the intersection 35 which represents the warehouse. Thus, matrix

$MR_{r,d}$ for each possible strategy r and delivery d is obtained and used as the input data on the flowchart shown below. Fig. 2 shows the flowchart of the iterative process to evaluate the MILP model for each possible route r in each delivery d . In the evaluation of the MILP model, the features of the HEVs, the emission reduction percentages, and the results obtained by the simulating algorithm, are necessary. To start the iterative process, the values of N^d , NR , and $MR_{r,d}$, and $t_{d,i}^n$ are initialized to zero. Applying the iterative process, the optimal performance of the HEVs under emission reduction conditions is obtained. Thus, an iterative process is carried out for all possible routes r . Then, the other iterative process related to the deliveries d is taken into account. For each delivery d , one iterative process for all intersections i is also performed. These intersections i are compared under the conditions $i = MR_{r,d}$, and $i = MR_{r,d+1}$. Depending on the value of intersection i , the conditions can be true or false, and values of -1 and 1 are assigned to $t_{d,i}^n$. Thereafter, each intersection i is compared under the condition $i = |\Omega_i|$. If the condition is *Not*, then a new iteration for i is done, otherwise, each d is compared under a new condition $d = N^d + 1$, if this condition is *Not*, then an iteration to the next d is performed. Otherwise, the MILP model is evaluated considering the input data mentioned above. Finally, r is compared under the condition $r = NR$ thus; if the condition is *Not*, a new iteration for r is performed, otherwise, the process terminates.

TABLE I. SHORTEST ROUTE TO BEST STRATEGY FOR EACH HEV

Route 1 for best strategy	
Deliv. 1	35 → 33 → 32 → 31 → 53 → 55 → 65 → 66
Deliv. 2	66 → 56 → 52 → 51 → 50 → 49
Deliv. 3	49 → 48 → 38 → 36 → 22 → 21 → 20 → 19 → 18
Deliv. 4	18 → 1 → 2 → 3 → 4 → 5 → 6 → 7
Return	7 → 8 → 9 → 10 → 27 → 35

Table I shows the urban roads ki to be traversed for each delivery d , and return to the warehouse. Note that the direction of traffic, as well as the chosen route, have a strong influence on the determination of the shortest route of the HEVs.

Fig. 3. Routes for the best and worst strategy.

Fig. 4. Average speed, times and number of charging for HEVs.

Figs. 3 (a)-(b) show the routes of the best (red) and worst (blue) operating strategies. Note that in Fig. 3 (a) the best strategy is represented by route 1 (278 km), and deliveries at intersections 66, 49, 18, 7, with a return to 35. The worst

strategy is represented by route 15 (366 km) as shown in Fig. 3 (b). The shortest routes in Figs. 3 (a)-(b) are obtained for each level of CO₂ emission reduction.

Figs. 4 (a)-(d) show the average speed, total operating and charging times, as well as the total number of charges during the operation of the HEVs. In Fig. 4 (a) red bars and black-dashed lines represent $v_{d,ki}$ and $\bar{v}_{ki}$, respectively. In most cases the speed limit values, $\bar{v}_{ki}$, are not reached. In Figs. 4 (b)-(d) the red, green, blue, and gray bars represent the variables values related to the performances of HEVs 1, 2, 3, and 4, respectively. These bars are categorized into four groups, where each group represents a ρ^C level. Fig. 4 (b) shows the total operating time of the HEVs for each value of ρ^C . Solid and dashed lines represent the maximum limit of the total operating time (8h 0m 0s) and total navigation time (9h 48m 0s), respectively. Thus, the total navigation time is unique for all HEVs due to the results shown in Figs. 3 (a) and 4 (a). All the HEVs require extra hours. Moreover, the lowest total operating time, 10h 6m 0s, is achieved by HEVs 1 and 4 with emission reduction levels of 10%, and HEVs 2 and 3 with 30%. Fig. 4 (c) shows the influence of the total charging time on the operating time of the HEVs. The highest charging times are 36m 0s (HEVs 2 and 3), and 54m 0s (HEV 1) for ρ^C values of 10% and 20%, respectively. For levels of 30% and 40%, the highest charging time is 1h 12m 0s (HEV 4). This demonstrates that emission reduction implies that HEVs mostly use the charge-depleting mode. Fig. 4 (d) shows the number of recharges done by the HEVs for each emission reduction level. HEV 4 presents the highest number of recharges (11 total recharges) due to its lower capacity battery.

TABLE II. CHARGING RATE AND CHARGING POINT VISITED BY HEVs TO CO₂ EMISSION REDUCTION LEVELS

HEVs	Charging points	Charging rate (kW)	ρ^C
1; 2; 3; 4	7; 9 → 27; 9 → 27; 27	22; 22 → 22; 22 → 22; 26	10%
1; 2;	21 → 2 → 27; 9 → 27;	30 → 32 → 32; 22 → 22;	20%
3; 4	7 → 27; 50 → 27	22 → 22; 22 → 22	
1; 2; 3;	21 → 27; 9; 27;	22 → 22; 50; 50;	30%
4	50 → 21 → 7 → 27	26 → 26 → 22 → 26	
1;	50 → 2 → 27;	32 → 32 → 32;	40%
2; 3;	7 → 27; 9 → 27;	22 → 22; 23 → 22;	
4	51 → 21 → 4 → 27	26 → 26 → 26 → 24	

The sequence of charging points shown in Table II indicates the order of the points visited during the navigation of the HEVs. As can be seen, HEV 1 presents the highest charging rate at charging points 50 (delivery 2), 2 (delivery 4), and 27 (return) that results in a reduction of 40% of emissions, while HEVs 2 and 3, with a 30% emission reduction show the highest charging rates (about 50 kW) at charging points 9 and 27 (both during the return to the warehouse).

Fig. 5. Navigation modes and fuel consumption for each HEV.

In Figs. 5 (a)-(f), the charge-depleting and charge-sustaining modes, as well as the fuel consumption by each HEV, are shown. In Figs. 5 (a)-(b), the black bars represent the total length (approximately 278 km) of the routes related to the best strategy shown in Fig 3 (a) and detailed in Table I. Also, in Figs. 5 (c)-(f) the dashed lines with black squares represent habitual fuel consumption values (charge-sustaining mode navigation). Thus, the bars in each group (delivery or return) show the values of optimal fuel consumption for each ρ^C . Fig. 5 (a) shows the inverse behavior of the ρ^C levels and $d_{d,ki}^{SM}$ for all HEVs. In most emission reduction levels, namely 10%, 20%, and 30%, the highest value of kilometers traveled is obtained by HEV 1 or 4 with lower capacities, K^E . The values of the bars in Fig. 5 (b) are related with the bars in Fig. 5 (a) using (8) in the MILP model, so that these bars represent the total number of kilometers traveled in depleting mode. Fig. 5 (c) shows the fuel consumption profiles (habitual and optimal) for HEV 1. For each ρ^C , the optimal profile values (red bars) decrease for deliveries 1 (0.68L for 10%, 0.60L for 20%, 0.53L for 30%, and 0.42L for 40%) and 2 (0.76L for 10%, 0.67L for 20%, 0.59L for 30%, and 0.50L for 40%). The same occurs for a 20% emission reduction, for deliveries 3, 4, and for the return to the warehouse, the optimal profiles present differentiated values of 0.58L, 0.12L, and 0.09L, respectively. The fuel consumption profile related to HEV 2 is shown in Fig. 5 (d). The highest values of the optimal profiles for each delivery and return are 1.65L, 1.63L, 2.07L, 1.10L, and 1.11L for the emission reduction levels of 10% in delivery 1, 20% in delivery 2, 30% in delivery 3, 10% in delivery 4, and 20% in the return to the warehouse, respectively. For HEVs 3 and 4, the profiles of fuel consumption shown in Figs. 5 (e) and (f), respectively, present a decreasing behavior for ρ^C levels ranging from 10% to 40% related to deliveries 1, 2, and 3. Also, the lower values of fuel consumption profile related to delivery 4 and the return to the warehouse for HEV 3 are 0.60L and 0.08L for emission reductions of 30% and 10%, respectively, and for HEV 4, they are 0.31L and 0.28L with a 30% emission reduction for both values of fuel consumption. All the HEVs show a significant reduction in their optimal consumption profiles with respect to their habitual consumption profiles. In addition, the lowest values of the fuel consumption profiles (habitual and optimal) occur during the last delivery and return to the warehouse for each HEV in all the profiles.

TABLE III. HABITUAL AND OPTIMAL FUEL CONSUMPTION FOR EACH LEVEL OF EMISSION REDUCTION

HEV	Habitual fuel Consumption (L)	Optimal fuel consumption (L)			
		10%	20%	30%	40%
1	3.89	3.42	2.06	2.72	2.03
2	9.45	6.86	6.86	6.57	5.66
3	6.96	4.86	4.84	4.59	4.18
4	5.84	5.14	4.62	3.38	3.32

Table III shows the habitual and optimal values of the total fuel consumption of each HEV considering emission reduction. Note that for an operating period of 1 day each HEV has habitual fuel consumption of 3.89 L, 9.45 L, 6.96 L, and 5.84 L which represent expenses of \$14.2, \$34.5, \$25.4, and \$21.3, respectively. For a sustainable scenario that considers levels of 10%, 20%, 30%, and 40% emission reduction, each HEV shows a significant economic reduction in fuel consumption costs.

Thus, for the scenario with the highest emission reductions, all HEVs achieve fuel reductions near 50% and result in economic savings of \$6.8, \$13.8, \$ 10.15 and \$9.2 for each HEV during operation, respectively.

V. CONCLUSIONS

In this paper, a MILP model to Evaluation of the performance of the HEVs technologies was proposed. The performance is related to the operating strategy which is composed of a selection of navigation modes, and optimal scheduling of deliveries. This model considers a set of operational and environmental constraints related to the scheduling of deliveries, average speed variation, battery capacity, charging and discharging rates, number of kilometers traveled in charge-sustaining, and CO₂ emission reduction levels, as well as, the probability values associated with LOS are also used to represent the uncertainties during operation of the HEVs. A city map with 71 intersections and 131 urban roads, main and secondary, was used. In the results, each level of CO₂ emission reduction, and the optimal performance for each HEV, were obtained with minimum operational cost. This proposed model results a useful tool for the analysis and evaluation of several HEVs technologies, allowing the optimal performance of the HEVs for be used to specific operations into the service sector among other activities ensuring the fuel economy and lower CO₂ emission.

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