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Total Cost of Ownership Optimization of a plug-in Hybrid Electric Truck Operating on a Regional Haul Cycle

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Abstract: This paper introduces a novel methodology for minimizing the total cost of ownership (TCO) of plug-in Hybrid Electric Vehicles (pHEVs) in the context of heavy duty application. This approach enables the best powertrain components sizing to be determined coupled with the optimal energy management. A detailed financial cost model of the truck is developed to take into consideration the differences in spending from a conventional Diesel vehicle. The introduction of eight design variables enables to explore both internal combustion engine, electrical motor and battery alternative designs. Then, a coupled optimization problem is formulated as a bi-level form with powertrain optimal energy management based on a combinatorial problem formulation solved by Simplex algorithm and Branch & Bound in the inner loop and exhaustive evaluation of the powertrain designs in the outer loop. The results obtained from this new optimization framework show a 2% potential financial savings for a pHEV operating by the end of the decade on a regional haul application while decreasing CO₂ emissions by more than 38% compared to a conventional Diesel truck.

Keywords: total cost of ownership, optimization based design, plug-in hybrid electric vehicles, component sizing, optimal energy management

1. INTRODUCTION

New European CO₂ emission standards for heavy-duty vehicles sets at least 30% average reduction from new lorries in 2030 compared to a 2019-2020 reference period. In addition zero-emission zones are planned to be introduced in large European cities such as Paris in 2024 to restrict or ban Diesel internal combustion engine (ICE) usage with the aim of improving air quality.

In the meantime, minimizing the vehicles total cost of ownership (TCO) is constantly sought in the transportation industry in order to improve the profitability of operations. Plug-in Hybrid Electric Vehicles (pHEVs) can certainly improve fuel economy benefits compared to a conventional Diesel truck (Stockar, 2010), but the electrical charging costs from the grid combined with the additional components of the electric propulsion including the motor drive systems, the battery pack and the on-board charger are increasing the TCO of the vehicle. In order to minimize the TCO of the pHEVs, the objective therefore consists in optimizing the powertrain design as well as its energy management strategy. (Silvas, 2015).

However, these studies combining design and energy management optimization often consider simplified total cost of ownership formulation. (Pourabdollah et al., 2013; Silvas et al., 2014). Nevertheless, other financial costs not included in these papers can also differ between the two types of vehicles such as the insurance, the maintenance, the funding cost or the resale value which must also be

taken into account to better reflect the real expenses of owning such a vehicle and to be able to draw a fair comparison with a purely Diesel truck.

In Huin et al. (2021a), we developed an optimization based methodology for the design of hybrid dedicated internal combustion engines. The introduction of five design variables were used to perform parametric transformations of the engine static efficiency and maximum torque characteristics. This methodology was however limited to the study of alternative engine designs. In order to optimize even more the pHEVs powertrain, Pourabdollah et al. (2013) and Silvas et al. (2014) proposed one additional design variable for scaling linearly in torque the electric machine (EM) static efficiency and maximal torque and one for optimizing the number of battery cells. However, this last sizing variable only allows to explore batteries of the same family with identical ratio of maximum power output to capacity performances (C-rate). In this paper, we introduce a third design variable which, combined with the second one, offers the opportunity of scaling independently the battery number of cells and its C-rate.

Fathy et al. (2001) studied the different strategies that can be used to solve design and control optimization problems. Among the four possible approaches, only the bi-level (or nested) and the simultaneous strategies can guarantee optimality. However, this second strategy requires to heavily re-formulate the problem as in Pourabdollah et al. (2013) where the entire problem is formulated as a

convex optimization problem. This leads to a lower fidelity of component modeling and simplified energy management without discrete variables such as the transmission selected gear for example. Since this strategy strongly affects the vehicle model fidelity, a bi-level approach is chosen in the present work.

Review and comparison of different optimal energy management strategies were performed. (Silvas et al., 2014). Dynamic programming developed by Richard Bellman is often implemented and used because it offers a global optimum and deterministic solution to this mixed and non-convex problem. However, this technique requires a lot of storage memory for large scale problems and the computation time increases exponentially with the number of state variables. (Bellman, 1957). In addition it can be difficult to integrate some of the constraints without introducing penalty coefficients (Murgovski et al., 2010) that require calibration leading to a lack of robustness.

Chauvin et al. (2015) proposed a re-formulation of the original problem under several combinations of mixed-integer linear problems which can be solved using Branch & Bound algorithm. Commercial solvers such as Cplex or Gurobi have good computational performances for this type of problem ensuring acceptable resolution time. With the same ability to find a global optimum as dynamic programming, this approach enables to easily integrate additional constraints in the problem formulation without requiring calibration. Hence, we select this method as it provides a fair evaluation of the potential achievable TCO for each powertrain design. However, the proposed approach have still some limitations regarding the computation time for large problems. With the introduction of all the different design variables previously mentioned, the development of an improved optimization framework has been conducted and is also one of the contributions of this paper. Some integers constraints of the problem have been relaxed in order to solve linear sub-problems faster and heuristically sort the design to converge faster towards the best solution.

This paper is organized as follows: Section 2 presents the TCO calculation. Then, Section 3 introduces the problem formulation and Section 4 presents the new optimization framework. Section 5 describes the results achieved by the methodology and the last section summarizes conclusions.

2. TCO CALCULATION

In this paper the optimization problem is defined as follows: from a predefined regional haul mission and a parallel hybrid topology, we want to find the best powertrain component sizes and the optimal energy management strategy to minimize the total cost of ownership (TCO) also called the objective function of our problem. It consists of operational costs which are function of the mileage of the vehicle: fuel and electricity costs but also fixed costs which includes truck purchase, maintenance, insurance, funding and resale costs.

2.1 Operational costs

Operational costs include both fuel and electrical grid charging costs which form the energy consumption of

the pHEV truck. For the conventional vehicle, only fuel cost is obviously considered. These financial charges are calculated for the predefined vehicle duty cycle discretized in N steps and then we assume to repeat this mission M times over a total period of ownership. It can be expressed as:

$$J_o = \sum_{k=1}^N M(c_1 \dot{m}_{fuel}(k) + c_2 i_c(k)) \Delta t(k) \quad (1)$$

with c_1 and c_2 constants to convert fuel and electricity consumption to financial costs, \dot{m}_{fuel} the engine fuel mass flow, i_c the battery cell current and Δt the sampling time between two discretized steps. It should be noted that the Diesel and electric energy consumption of the truck is highly dependant of the sizing selected as well as the energy management strategy defined.

2.2 Fixed costs

Fixed costs regroup the other vehicle expenses which are assumed to be independent of the transportation missions. First of all, the initial purchase of the vehicle consists of the truck frame, cabin and combustion driveline for the reference truck and is denoted as J_v^{ref} . In addition the pHEV truck powertrain is also equipped with a motor drive system, a battery pack and an on-board charger. Its combustion driveline and these components sizing are to be found during the optimization. While the electric machine cost is chosen linear with respect to its maximum power, the battery price model is of the following form:

$$J_{bat} = a_1 P_{bat} + a_2 E_{bat} \quad (2)$$

with a_1 and a_2 constant values to calculate with reference battery costs, P_{bat} and E_{bat} the maximal power and capacity of the battery considered. The total purchase cost of the pHEV is designated as J_v^{pHEV} . A loan with a rate of $r\%$ must also be included in the TCO to finance the initial purchase. This additional cost can be expressed as:

$$J_{fi} = J_o r T \quad (3)$$

where T corresponds to the total period of ownership in years. Insurance cost for the reference vehicle is described by J_i^{ref} and a linear relationship is assumed to estimate the pHEV insurance cost:

$$J_i^{pHEV} = \frac{J_i^{ref} J_v^{pHEV}}{J_v^{ref}} \quad (4)$$

Vehicle resale percentage at the end of ownership with respect to the purchase cost are denoted by r_s and assumed to be zero for the battery pack. Finally, maintenance costs are assumed to be equivalent between the two vehicles since the additional electric propulsion requires barely no servicing during its lifetime. They are integrated into J_e which regroup all other equivalent costs such as the driver salary, the toll and taxes or the trailer. The fixed costs can then be summed up as:

$$\begin{cases} J_f^{ref} = J_v^{ref}(1 + rT - r_s) + J_i^{ref} + J_e \\ J_f^{pHEV} = J_v^{pHEV}(1 + rT - r_s) + J_{bat} r_s + J_i^{pHEV} + J_e \end{cases} \quad (5)$$

with J_{bat} the battery cost of the pHEV truck. In the end the total cost of ownership or the objective function of our problem consists in minimizing:

$$J = J_o + J_f^{pHEV} \quad (6)$$

3. PROBLEM FORMULATION

In order to find the sizing that minimizes the total cost of ownership of the truck, an accurate evaluation of the vehicle fuel consumption for each powertrain design must be performed. Indeed, there is a strong coupling between the sizing and the energy management strategy. (Fathy et al., 2001). It thus requires a simultaneous resolution of the complete problem. The assumptions made and the chosen reformulation of this optimization problem to ease the resolution are described in the next section and are similar to Huin et al. (2021a).

3.1 Vehicle powertrain description modeling

The considered topology is a parallel plug-in hybrid electric truck as depicted in Fig. 1. The powertrain is mainly composed of the internal combustion engine connected to the transmission system by a clutch and the electric propulsion which consists in the energy storage system (battery), an on-board charger, the power electronics and the electrical motor. The latter is connected to the counter shaft of the gearbox by an additional reduction gear in order to operate in higher efficiency areas while driving. Using a backward modeling approach, we can deduce the

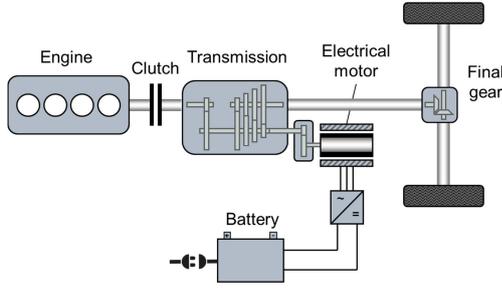


Fig. 1. Parallel plug-in hybrid topology considered

required traction force F_t to propel the vehicle at the desired velocity and to overcome external forces:

$$\begin{aligned} F_t(k) &= (m_v + I_v(k))a(k) + F_r(k) + F_g(k) + F_a(k) \\ &= (m_v + I_v(k))a(k) + m_v g c_{rr} \cos \alpha(k) \\ &\quad + m_v g \sin \alpha(k) + \frac{1}{2} \rho_a A_f c_d v^2(k), \end{aligned} \quad (7)$$

with m_v the vehicle mass which is dependent of the powertrain sizing, I_v the powertrain rotating parts inertia which changes with engaged gear, a the vehicle acceleration, F_r the rolling resistance, F_g the gravitational force, F_a the aerodynamic drag force, g the gravitational constant, c_{rr} the rolling resistance coefficient, α the road angle with horizontal, ρ_a the air density, A_f the frontal area, c_d the aerodynamic coefficient and v the vehicle speed. From the traction force and the vehicle speed we can respectively calculate the torque demand at the output shaft T_d of the transmission and its rotational speed ω_d that the engine and the electrical motor must meet in order to follow the input trajectory:

$$\begin{cases} \omega_d(k) = \frac{v(k)R_{fg}}{R_w}, \\ T_d(k) = \frac{F_t(k)R_w + S_f(v(k)R_{fg})^{e_f} + D}{R_{fg}\eta_{fg}^{sgn(F_t(k))}} \end{cases} \quad (8)$$

with R_{fg} the final gear ratio, R_w the wheel radius, S_f and e_f speed dependent losses coefficients, D dry force coefficient and η_{fg} the final gear efficiency. sgn refers to the mathematical sign function. The 12-speed automated manual gearbox is represented by gear-dependent ratios γ_i for $i \in [1, \dots, 12]$. With the choice of the following command variables : the engine torque T_{ice} , the gear selected γ , the engine state st_{ice} and the clutch state st_{clu} , we can then deduce the relation of the power split between the two actuators and write the expression of the electrical motor (EM) torque T_{em} :

$$\begin{aligned} T_{em}(k) &= \frac{T_d(k)}{R_{em}(\gamma(k))\eta_{em}(\gamma(k))^{sgn(T_{em}(k))}} + S_g\omega_d^{e_g}(k) \\ &\quad - T_{ice}(k)R_{ice}(\gamma(k))\eta_{ice}(\gamma(k))^{sgn(T_{ice}(k))}, \end{aligned} \quad (9)$$

with R_{em} and R_{ice} the ratios of the EM and the ICE to the output shaft of the gearbox, η_{em} and η_{ice} the efficiencies through the gearbox, S_g and e_g speed dependent losses coefficients. The Diesel engine and the electrical machine are characterized by their static efficiency maps and maximum torque curves. Engine rotation speed is function of the engine state (on or off), clutch state (engaged or disengaged) and the gear selected:

$$\omega_{ice}(k) = \begin{cases} 0 & \text{if } st_{ice}(k) = 0 \\ \omega_{idle} & \text{if } (st_{ice}(k), st_{clu}(k)) = (1, 0) \\ \omega_d(k)R_{ice}(k) & \text{otherwise,} \end{cases} \quad (10)$$

where ω_{idle} is the engine idle speed. The electrical machine rotation speed is dependent of the gear selection:

$$\omega_{em}(k) = \omega_d(k)R_{em}(\gamma(k)) \quad (11)$$

The following relation establishes the power demand on the battery P_{bat} :

$$\begin{aligned} P_{bat}(k) &= \omega_{em}(k)T_{em}(k) + P_{aux}(k) \\ &\quad + P_{em}^{losses}(\omega_{em}(k), T_{em}(k), s_{em}), \end{aligned} \quad (12)$$

with P_{em}^{losses} the electric machine and power electronics losses map, P_{aux} the auxiliary power demand of the vehicle and s_{em} the EM sizing variable detailed further. The battery is modeled using an equivalent circuit including an ideal open-circuit voltage source V_{oc} in series with an internal resistance r_c as in Guzzella and Sciarretta (2007) expressing the cell current i_c as:

$$i_c(k) = s_{bat}^P \frac{V_{oc} - \sqrt{V_{oc}^2 - \frac{4r_c P_{bat}(k)}{s_{bat}^P n_c}}}{2r_c}, \quad (13)$$

where n_c represents the number of cells in the battery pack and s_{bat}^P is a battery sizing variable described in the next section. Finally the state of charge SoC of the battery can be expressed as:

$$\frac{dSoC}{dt} = \frac{s_{bat}^C i_c(k)}{s_{bat}^P Q_c} \quad (14)$$

with Q_c the cell capacity and s_{bat}^C a second battery design variable.

3.2 Sizing and command variables

As previously mentioned, the sizing optimization of the powertrain components of the pHEV truck is one of the levers that enables the total cost of ownership to be minimized. In a previous paper we develop an optimization

based methodology for hybrid electric vehicle dedicated internal combustion engine design. (Huin et al., 2021a). With the introduction of five sizing variables, we can explore alternative engine designs through parametric transformations of engine static efficiency map and maximum torque curve. These variables are then optimized in the framework presented in the next section to find the most suitable engine design for our problem.

In addition to this work, we introduce in this paper three extra sizing variables for the electrical machine and the battery designs. The first one denoted s_{em} consists in scaling linearly with respect to the torque a reference electric machine efficiency map and its maximum torque curve (both in propulsive and regenerative operating modes) as in Pourabdollah et al. (2013) and Silvas et al. (2014). A similar approach is used for the battery with s_{bat}^P which scales the number of cells connected in parallel in the battery pack at a given voltage. This variable enables to explore different power outputs and capacity of the battery.

Finally, the last design variable s_{bat}^C enables to investigate different battery C-rates which correspond to the maximum power the battery can discharge relatively to its maximum capacity. In other words, it measures the ratio between the battery maximum discharging power and capacity. From a reference battery characteristics, s_{bat}^C can be scaled to explore new battery capacity with a fixed maximum power output:

$$\begin{cases} P_{bat}^{new} = s_{bat}^P P_{bat}^{ref} \\ E_{bat}^{new} = \frac{s_{bat}^P}{s_{bat}^C} E_{bat}^{ref} \end{cases} \quad (15)$$

where P_{bat}^{new} and P_{bat}^{ref} are respectively the scaled and reference battery maximum power output, E_{bat}^{new} and E_{bat}^{ref} the scaled and reference battery capacity. The vector of design variables \mathbf{p} is therefore set as:

$$\mathbf{p} = \{\delta\omega, \delta T, \delta d\omega, \delta dT, s_{eng}, s_{em}, s_{bat}^P, s_{bat}^C\}, \quad (16)$$

with $\delta\omega$, δT , $\delta d\omega$, δdT and s_{eng} the five engine design variables whereas the vector of command variables $\mathbf{u}(k)$ is expressed as:

$$\mathbf{u}(\mathbf{k}) = \{T_{ice}(k), \gamma(k), st_{eng}(k), st_{clu}(k)\}. \quad (17)$$

3.3 Constraints and performance requirements

As in Huin et al. (2021a), not only static operating constraints of the powertrain components such as maximum and minimum speed and torque for the engine or the electrical machine, limits on the current and the state of charge of the battery are applied to our problem but also additional constraints on the engine. Due to the air management system and in particular the presence of a turbocharger, the response dynamics of the engine is not neglected and therefore the torque produced by the ICE is constrained as:

$$\frac{T_{ice}(k+1) - T_{ice}(k)}{\Delta t(k)} - \overline{\Delta T_{ice}} \leq 0 \quad (18)$$

with $\overline{\Delta T_{ice}}$ the engine maximum positive change in torque over time. Moreover, a constraint on the number of engine state changes is added to the optimization problem to prevent early degradation of ICE internal components

coming from excessive occurrences of ignition and shut-down phases. This is expressed as:

$$\frac{1}{2} \sum_{k=1}^N |st_{ice}(k+1) - st_{ice}(k)| - \overline{N_{st_{ice}}} \leq 0 \quad (19)$$

where $\overline{N_{st_{ice}}}$ corresponds to the maximum number of engine state changes possible during the cycle.

Vehicle performance requirements both in full electric and hybrid modes are also taken into account in this study. Gradeability, acceleration and range in zero-tailpipe emission requirements are used to determine minimal battery power and capacity as well as engine and electrical power through backward approach and the vehicle model presented in the previous section. These requirements then act as a constraint on the values of the design variables and help reducing the search space while ensuring that the powertrain found will meet the expected performances.

4. OPTIMIZATION FRAMEWORK

As presented in the previous section, the optimization problem has a strong coupling between the sizing and the command variables and requires a simultaneous resolution of the complete problem. In addition energy management is written using mixed-integer and non convex mathematical expressions making the problem difficult to solve. A chosen reformulation of the problem based on a bi-level strategy and derived from operational research is selected in this study. (Gaoua et al., 2013; Chauvin et al., 2015). After discretizing sizing and continuous com-

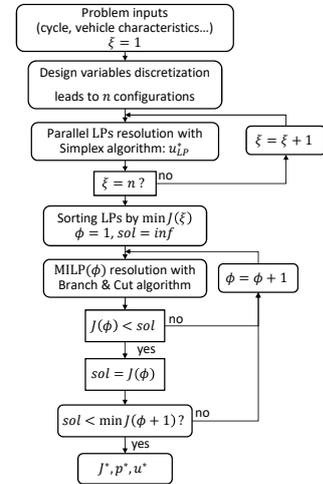


Fig. 2. Optimization framework developed

mand variables, n combinatorial mixed integer linear sub-problems (MILP) are formulated. In order to accelerate the resolution time, integer constraints of these problems are relaxed in a first step to enable a fast linear problem (LP) resolution. The algorithm finds the command inputs \mathbf{u}_{LP}^* that globally minimizes the objective function for each sizing combination and for the given drive cycle. This optimal solution is found using a Simplex algorithm from a commercial solver such as (Gurobi, 2021). It should be noted that the parallelization of this task enables to speed up even more the solving process. Then the solutions of the different LPs are sorted with respect to their objective

function values in ascending order. The MILPs are then solved starting by the lowest potential TCO obtained from the LP resolution using a Branch & Cut algorithm and the best value sol from \mathbf{u}^* is stored. Once a mixed-integer solution has a lower objective value than the next LP, the algorithm is stopped and the best solution found so far corresponds to the optimal one denoted $J^*(\mathbf{p}^*, \mathbf{u}^*)$. The optimization approach is depicted in Fig.2.

The optimization process has been improved compared to the work of Chauvin et al. (2015) in order to enable the resolution of larger problems in acceptable computation time. This approach has been selected and developed because it has better computational performances than dynamic programming for optimization problems with multiple command variables and enables to more easily take into account additional constraints.

5. SIMULATION AND RESULTS

The mission profile used in this study is the regional delivery cycle (see Fig. 3) developed by the European Commission to measure the CO2 emissions and fuel consumption of heavy-duty vehicles in Vehicle Energy Consumption Calculation Tool (VECTO).

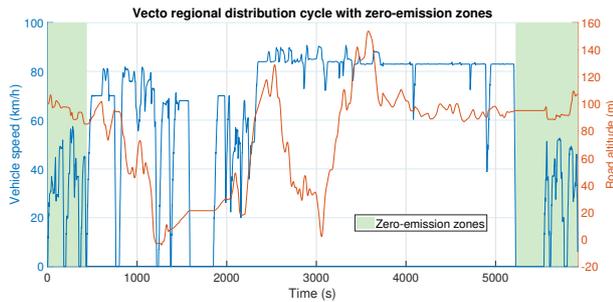


Fig. 3. Regional delivery cycle: vehicle speed (in blue), road altitude (in red) and zero-emission zones (in green)

In order to take into account possible future regulations in cities, we have included zero-emission zones at the beginning and at the end of the cycle where the vehicle operates at relatively low speeds. This additional constraint compels the truck to operate in fully electric mode. Since the vehicle has plug-in capability the cycle is assumed to be performed four times in a row, i.e. 400km, every day without charging events in order to simulate real depleting scenario. Moreover this repetition of operating conditions enables a faster resolution of the problem while providing a representative duty cycle. In addition a variable time discretization of the cycle based on torque demand and vehicle speed temporal variations is performed. It enables to reduce even more the computational time and maintain the fidelity level of the new discrete cycle. This pre-processing of the duty cycle is necessary to obtain a good trade-off between the resolution time and the results quality and is similar as the one developed in Huin et al. (2021a).

Table 1 presents a non-exhaustive list of the parameters values used for this numerical application. The cost assumptions used in this study are based on Volvo internal projections for the end of the decade.

Table 1. Cost and vehicle parameters.

| Parameter | Value | Unit |
|---------------------------------|--------|---------|
| Possession time | 5 | Years |
| Price of Diesel | 1.30 | EUR/L |
| Price of electricity | 0.16 | EUR/kWh |
| Reference vehicle mass | 28 146 | kg |
| Reference engine maximum power | 370 | kW |
| Reference EM peak power | 350 | kW |
| Reference battery pack capacity | 65 | kWh |
| Minimal ZEZ range requirements | 50 | km |

In order to evaluate the total cost of ownership of the reference Diesel vehicle, we perform a first optimization of the powertrain energy management. In this case the optimization is limited to the selection of the transmission gear at each time step. From this fuel consumption result, the TCO of this vehicle can then be easily calculated. Then the coupled optimization of the 8 design variables and energy management is performed leading to a search space of more than 32000 different pHEV configurations since between 3 and 5 values are considered for each design variable. This exhaustive design research ensures that the best solution will be found among these different combinations. At the end of the process, the couple $(\mathbf{p}^*, \mathbf{u}_{opt}^*)$ minimizing the pHEV's TCO is identified. The problem with a size of 8 design variables, 444 command variables for each of the 2000 steps of the cycle is solved using Matlab 2017b in 6.5 hours on a personal computer with 16-GB random access memory and a 2.90 GHz processor. The TCO results are detailed in Fig.4.

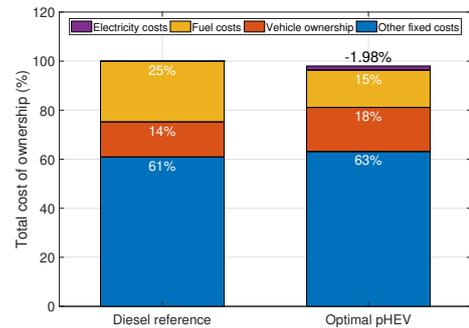


Fig. 4. Comparison of Total Cost of Ownership for operating Diesel reference vehicle and optimal pHEV on Regional Haul application.

As anticipated the pHEV has higher vehicle ownership and fixed costs compared to the reference Diesel truck of about 6% because of the additional electric propulsion that increases both the insurance, the truck purchase and its financing. However, the operational costs which consists in the fuel and electricity consumption are much lower for the electrified vehicle. From a contribution of 25% of the energy consumption in the Diesel vehicle, the optimized pHEV decreases these expenses to less than 17% by globally increasing the powertrain efficiency from 37% to 62 % thanks to the electric propulsion and reducing the fuel consumption with the battery charging from the grid. As a result, the hybridation of this vehicle can lead to a potential gain on total cost of ownership of almost 2% by the end of the decade on this regional haul cycle for a five years ownership while decreasing tank to wheel CO2 emissions by over 38%.

The best sizing obtained by the optimization process is depicted in Fig. 5. The first observation we can make

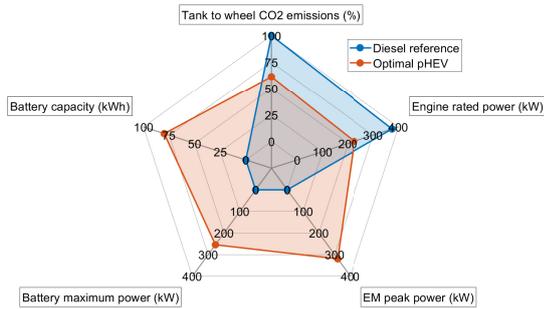


Fig. 5. Comparison of tank to wheel CO2 emissions and powertrain sizing between the reference Diesel vehicle and the optimal pHEV.

is that the internal combustion engine is downsized by almost 40%. Indeed, the additional source of power from the electrical motor can be used when the power demand is high making the reference engine inappropriate in this new powertrain. More detailed results on the new engine design are presented in Huin et al. (2021a). The obtained EM sizing is mainly due to the full electric operating points in the zero-emission zones in addition to the regenerative abilities to maximize energy recovery during braking phases. Conclusions are similar for the battery maximal power as this component operates in tandem with the electric machine. However, the optimal battery capacity is a compromise between weight, cost and fuel saving as it fulfills extensively the minimal range in full electric requirements by over 20%.

These results clearly highlight the potential financial savings of a plug-in hybrid electric truck operating by the end of the decade on a regional haul application while significantly decreasing CO2 emissions and energy consumption as well as having the ability to run in full electric mode. The methodology developed provides a robust optimization framework for minimizing total cost of ownership of hybrid electric trucks.

6. CONCLUSION

In this paper, a detailed total cost of ownership minimization based-methodology has been developed for sizing the powertrain of a plug-in hybrid electric truck. The good computational performances of this approach enable to address a large problem with multiple design variables with an acceptable resolution time. The right sizing of the internal combustion engine, the electrical motor and the battery of the vehicle could provide a potential TCO reduction of almost 2% for the pHEV compared to a reference Diesel vehicle by the end of the decade on a regional haul mission with a five years possession time. In addition, the electrified vehicle offers a CO2 emissions reduction of over 38% while bringing the possibility of a full electric mode for urban operations.

Further work will involve the development of a sensitivity analysis methodology to measure the robustness of the solution resulting from the optimization but also to understand the impacts of input parameters variations on

the results such as the drive cycle, the powertrain design or the vehicle characteristics (Huin et al., 2021b).

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