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An Optimization and Analysis Framework for TCO Minimization of Plug-in Hybrid Heavy-duty Electric Vehicles

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Abstract: This paper develops an optimization framework to minimize the Total Cost of Ownership (TCO) for Plug-in Hybrid Electric Vehicles (PHEVs). In this paper, TCO is the summation of operational and main vehicle powertrain components cost. The developed optimization framework is formulated via combining convex optimization and Dynamic Programming technique. This framework is aimed at minimizing TCO by optimizing not only the sizing of the main powertrain components but also the powertrain topology. Using the developed optimization framework, this paper elaborates relevant design factors for a considered bus application namely: i) the value of equipping a HEV with plug-in functionality; ii) the effect of battery aging and replacement cost; iii) the sensitivity to fuel and electricity cost. Simulation results show that the TCO can be reduced by having plug-in functionality in the HEVs. However, this may not hold if the electricity price (in Euros/kWh) is higher than certain times of the fuel price (in Euros/kWh), e.g. 2.25 for the simulated cases in this paper. Simulation results also suggest that it is more profitable to equip the vehicle with a big enough battery to avoid replacing it during the vehicle economical life.

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

1. INTRODUCTION

Hybrid electric vehicles (HEVs) are able to reduce fuel consumption by: (i) exploiting additional control freedom to optimize the ICE operating point, (ii) recuperating brake energy, and (iii) downsizing the ICE Pourabdollah et al. (2016). Compared to HEVs, Plug-in Hybrid Vehicles (PHEVs) are able to charge the vehicle battery directly from the electrical grid to reduce fuel consumption further. However, the improved fuel reduction benefits are achieved at cost of electric grid charging and possibly additional component cost. This may increase Total Cost of Ownership (TCO) compared to a conventional vehicle in the same class. Therefore, for a strong marked position of PHEVs it is important that the TCO of those vehicles are minimized. This objective requires an optimal designed PHEV powertrain, considering: topology, component sizing, and Energy Management Strategy (EMS) Silvas (2015).

A promising method to find the optimal component sizing and EMS simultaneously is Convex optimization, due to its higher computational efficiency, compared to optimal control methods such as Dynamic programming (DP) and Equivalent Consumption Minimization Strategy (ECMS); who cannot handle component sizing directly, and require an outer-loop for component sizing optimization. On the other hand, a disadvantage of Convex optimization is its incapability to optimize discrete optimization variables such as gear shifting and ICE on/off switching because those decision variables are not convex Tobias Nüesch et al. (2014).

The authors in Murgovski et al. (2012), have overcome this disadvantage by solving the discrete optimization variables prior to convex optimization by applying heuristic rules in an outer loop; for a Series and Parallel PHEV with variable battery sizing. The study showed that the adopted approach achieves a solution close to the brute force nested Dynamic Programming approach, applied on the original nonlinear, non-convex, mixed-integer vehicle model. Pourabdollah et al. extended the work of Murgovski by adding ICE and EM sizing to the convex optimization problem in Pourabdollah et al. (2016, 2014). Additionally, in Pourabdollah et al. (2014) an optimization method is introduced that iteratively combines Dynamic Programming and Convex Optimization for optimizing a parallel topology with gear shifting and engine on/off switching as discrete optimization variables. This method can find the optimal sizing parameters with good accuracy after few iterations when component sizes are chosen appropriately e.g., the engine size and battery size may not severely be over-sized initially.

To the best of our knowledge, TCO minimization of Series-Parallel HEVs by Convex optimization is still an open research topic. This paper studies TCO minimization for a Series-Parallel topology with different battery replacement strategies, and compares the results to a Conventional,
The main contribution of this paper are: (i) TCO analysis \( \text{with respect to a conventional powertrain; for a Series, Parallel and Series-Parallel topology, as depicted in Fig. 2, Fig. 3, and Fig. 4, respectively. A description for all time dependent control inputs in Figures 1-4 is shown in Table 1. The control inputs are divided in two types (i) Continuous inputs; and (ii) Discrete inputs. Discrete input } \mu_{ICE} \in \{0, 1\} \text{ with 0 indicating that the engine is off, and } \mu_m \in \{0, 1\} \text{ with 0 indicating series mode. The control inputs together form the Energy Management Strategy (EMS) that aims to minimize the operational cost. The component sizes to be optimized are the ICE, Battery, and both EMs. These components are scaled with scaling factor } S_i \text{ with } i \in \{ICE, Bat, EM1, EM2\}. \) The resulting TCO minimization problem is discussed in 2.1.

### 2.1 TCO Minimization Problem

The minimization problem is defined as follows: given predefined vehicle transportation mission and a set of topologies, find the: optimal topology, main component sizes and optimal EMS to minimize TCO, while satisfying predefined system performance e.g. acceleration and gradeability requirements. This is expresses mathematically as in Silvas (2015) by

\[
[x_p, x_c] = \arg \min_{x_p, x_c} J_o(x_p, x_c(k), \Lambda(k)) + J_e(x_p) \tag{1}
\]

where the cost function consists of operational cost \( J_o \) and component cost \( J_e \). Operational cost consist of fuel and electricity cost and component cost are the weighted cost of the topology main components. In (1) design vector \( x_p \) contains all design variables of the plant which are the topology with associated component sizing, while control
vector $x_c$ contains all control variables discussed in Table 1. Both vectors are optimized for vehicle mission $\Lambda$ and will be discussed in 2.2. The minimization problem is subjected to system dynamics consisting of the battery State of Charge (SoC) and State of Health (SoH). Both states have a predefined initial value and a specified final value at the end of the vehicle mission.

**Operational cost**  
The operational cost consists of fuel and electrical grid charging cost calculated over a discretized vehicle mission with length $N$ and sampling interval $\Delta h$. The operational cost is denoted as

$$J_o = w_f \sum_{k=1}^{N} P_f(k) \Delta h + w_g \sum_{k=1}^{N} P_g(k) \Delta h$$  

(2)

where $P_f[W]$ and $P_g[W]$ are the fuel power and electrical grid power, respectively. Parameter $w_f$ is a weight factor for converting fuel energy to fuel cost in €/100km calculated as $w_f = \frac{\phi_f \cdot \text{LHV}}{\text{d}}$. In this $\phi_f$, $\rho_f$, $\text{LHV}$, and $d$ are fuel cost [€/l], fuel density [kg/l], Lower Heating Value [J/kg], and vehicle mission distance [km], respectively. The baseline diesel cost are set to 1.30 €/l. Weight factor $w_g$ that converts electric energy to electricity cost in €/100km, is expressed by $w_g = \frac{\phi_e \cdot 100}{(3.60 \cdot \text{e}^{-6} \cdot \text{d})}$ with electricity cost $\phi_e$ in €/kWh set to a baseline value of 0.2 €/kWh.

**Component cost**  
Component cost is a function of the selected topology in combination with the sizing of the main components, being selected as the Transmission, ICE, EM component cost is a function of the scaling law given by

$$J_c = \begin{cases} \frac{w_c \cdot (\Psi_{ICE} + (1 + n_r)\Psi_{Bat} + + \Psi_{EM1} + \Psi_{EM2})}{(\Psi_{Bat} + + \Psi_{EM1} + \Psi_{EM2})} & \text{for } S \text{ Top} \\ \frac{w_c \cdot (\Psi_{ICE} + (1 + n_r)\Psi_{Bat} + + \Psi_{EM1} + \Psi_{EM2})}{(\Psi_{Bat} + + \Psi_{EM1} + \Psi_{EM2})} & \text{for } P \text{ Top} \\ \frac{w_c \cdot (\Psi_{ICE} + \Psi_{EM1} + \Psi_{EM2})}{(\Psi_{Bat} + + \Psi_{EM1} + \Psi_{EM2})} & \text{for } C \text{ Top} \\ \end{cases}$$

(3)

with weight factor $w_c = \frac{1}{\delta_{ICE} \cdot \text{d}} \cdot 100$ converting component cost from € into €/100km by taking into account the average yearly vehicle mileage $\delta_{y}$ [km/year] and the total vehicle lifetime $L_i$ [years]. The component cost of the baseline main components are expressed by $\Psi$ as shown in Table 2, while the sizable main components are expressed by $\Psi$. For component scaling cost a linear relation has been assumed. Herewith, the scalable component cost are calculated by

$$\Psi_i = S_i \cdot \psi_i, \quad i \in \{ICE, Bat, EM1, EM2\}.$$  

(4)

The baseline ICE cost $\psi_{ICE}$ is obtained by linear scaling of the provided ICE cost in Silvas (2015). The specific EM cost $\psi_{EM}$ including inverter cost is obtained from Kailasam (2014), and the battery cost are provided by an OEM.

<table>
<thead>
<tr>
<th>Component</th>
<th>Power/capacity</th>
<th>Specific Cost</th>
<th>Cost ($\psi_i$)</th>
</tr>
</thead>
<tbody>
<tr>
<td>ICE</td>
<td>210 kW</td>
<td>25.7 €/kW</td>
<td>€5397</td>
</tr>
<tr>
<td>EM1</td>
<td>90 kW</td>
<td>46.6 €/kW</td>
<td>€4194</td>
</tr>
<tr>
<td>EM2</td>
<td>90 kW</td>
<td>46.6 €/kW</td>
<td>€4194</td>
</tr>
<tr>
<td>Bat</td>
<td>12 kWh</td>
<td>200 €/kWh</td>
<td>€2400</td>
</tr>
<tr>
<td>$Tr$</td>
<td>-</td>
<td>-</td>
<td>€3500</td>
</tr>
</tbody>
</table>

**2.2 Vehicle mission profile**  
Topology selection and component size optimization for PHEVs requires knowledge about the lifetime driving of the vehicle Pourabdollah et al. (2016). This includes the velocity- and slope profile of the trip, as well as, the distance driven between plug-in possibilities, the charging time, and maximum available charging power. Therefore, powertrain design requires a vehicle mission that is representative for real world driving. The design of such a mission is not within the scope of this study. This study uses a simple measured bus route that includes a 30km long zero-emission zone where the ICE is not allowed to be switched on. Figure 5 (a), shows the 217 minute measured vehicle mission profile. This vehicle mission consists of two 30 min stops at bus stations where it is possible to charge the battery directly from the electrical grid. After the second stop the bus enters the zero-emission zone where the vehicle is propelled pure electrically.

**Remark 1**. This paper assumes that the bus will drive the measured vehicle mission over its entire vehicle economical life for TCO minimization.

**Remark 2**. For analyzing TCO sensitivity to fuel and electricity cost the SORT cycle based vehicle mission shown in Figure 5 (b) has been used. Similar as in the measurement based vehicle mission the mission contains two charging opportunities and a zero emission zone. For the sensitivity analysis a shorter vehicle mission has been used to reduce the computational burden. This is reasonable since there is observed that both vehicle missions showed similar trends in component sizing and TCO for the results presented in 5. When using a laptop with Intel Core i7 processor, 2.8GHz and 16GB RAM, it takes about 90 and 730 seconds for the SORT and measured cycle, respectively.

Both vehicle missions are captured by their time dependent vehicle mission matrix of the form

$$\Lambda(k) = [v(k) \ a(k) \ \theta(k) \ \zeta(k) \ \Theta(k)]^T, \quad k \in [1, N]$$  

(5)

where $v$, $a$ and $\theta$ defines the velocity, acceleration, and slope profile, respectively. While $\zeta$ is a zero emission zone flag for which a high value indicates that the vehicle is driving in a zero emission zone and $\Theta$ is a flag for which a high value indicates that the vehicle has a grid charging opportunity. The measurement based vehicle mission does not contain any extreme conditions where the vehicle is loaded to its maximum payload. To make sure that the vehicle is able to operate under these heavy conditions some performance requirements for acceleration and gradeability are defined.
The torque demand at the wheels is calculated by

\[ T_w(k) = R_w \left( m_v \left( g f_r \cos(\theta(k)) + g \sin(\theta(k)) + a(k) \right) + J_w a(k) + \frac{1}{2} a v^2(k) \right) \]

for which an overview of symbols is given in Table 3. Vehicle mass \( m_v \) is expressed by

\[ m_v = \begin{cases} m_g + m_p + m_T + M_{Bat} + M_{ICE} + M_{EM1} + M_{EM2} & \text{if } S \text{ and } S-P \\ m_g + m_p + m_T + M_{Bat} + M_{ICE} + M_{EM1} & \text{if } P \end{cases} \]

where \( m_g, m_p, \) and \( m_T \) are the baseline masses of the glider, payload, and transmission respectively. While masses indicated with a capital \( M \) are provided by OEMs.

### 4. SYSTEM MODEL

#### 4.1 Vehicle road load

The torque demand at the wheels is calculated by

\[ P_{f,ICE} = S_{ICE} \cdot \mu_{ICE} \cdot \alpha_0 + \alpha_1 \cdot T_{ICE}(k) + \alpha_2 \cdot \frac{T_{ICE}(k)^2}{S_{ICE}} \]
Angular velocity dependent coefficients $\alpha_0$, $\alpha_1$, and $\alpha_2$ are determined by fitting the fuel power with the measured engine fuel map.

The torque limit of the scaled ICE model $\bar{T}_{ICE}$ is included by assuming a linear relation between $S_{ICE}$ and the maximum admissible baseline ICE torque $T_{ICE,b}$.

**Electric Machine** The electrical power $P_{EM}$ including power electronic losses is modeled as a function of the electric machine torque $T_{EM}$, angular velocity $\omega_{EM}$, and scaling factor $S_{EM}$. Moreover, an angular velocity dependent second-order polynomial function is used to approximate the electric machine efficiency map. The inclusion of $S_{EM}$ in the model is based on similar assumptions as in the ICE model. Herewith, EM electrical power flow $P_{EM}$ with sizing factor $S_{EM}$, is estimated by

$$P_{EM}(k) = S_{EM} \beta_0 + \beta_1 T_{EM}(k) + \beta_2 \frac{T_{EM}(k)^2}{S_{EM}}$$  \hspace{1cm} (10)

with angular velocity dependent coefficients $\beta_0$, $\beta_1$, and $\beta_2$. EM torque limits $\bar{T}_{EM}$ and $\underline{T}_{EM}$ are included by linear scaling of the maximum and minimum admissible torque of the baseline EM.

**Engine Generator Unit** The Engine Generator Unit (EGU) converts fuel energy to electrical energy by propelling an EM by an ICE. The control input of the model is selected to be $T_{EGU}$ and the scaling factors are $S_{EM}$ and $S_{ICE}$. The highest possible efficiency is obtained when the EGU is operated at the economy line. However, for simplicity since the EGU needs to be convex in $T_{EGU}$, $S_{EM}$ and $S_{ICE}$ the angular velocity is fixed on a velocity near the sweet spot of the baseline EGU. This approach is justified since in the optimal solution it is expected that the EGU is operated in its highest efficiency range where both the e-line based model and the fixed angular velocity based model are nearly equal as depicted in Figure 7. By using $T_{EGU}$ as the control variable it is possible to use the ICE and EM model as afore-mentioned. Herewith, EGU fuel power $P_{f,EGU}$ and electrical power $P_{e,EGU}$ are expressed by

$$P_{f,EGU} = S_{ICE} \alpha_0 + \alpha_1 T_{EGU}(k) + \alpha_2 \frac{T_{EGU}(k)^2}{S_{ICE}}$$ \hspace{1cm} (11)

$$P_{e,EGU} = S_{EM} \beta_0 - \beta_1 T_{EGU}(k) + \beta_2 \frac{T_{EGU}(k)^2}{S_{EM}}$$ \hspace{1cm} (12)

The EGU torque is limited either by the ICE or the EM depending on the machine with the smallest admissible torque. Both machines use a linear scaling factor for the torque limit.

**Battery energy model** The battery pack consists of lithium-iron-phosphate cells (ANR26650m1A). Each cell is modeled by a resistive equivalent circuit model. By assuming equally distributed power over each individual battery cell Pourabdollah et al. (2016); Murgovski et al. (2012); Hu et al. (2015); Johannesson et al. (2013), the power at the battery pack terminal $P_b[W]$ as a function of the number of battery cells $S_{Bat}$, is

$$P_t(k) = P_0 - R \cdot \frac{P_b^2(k)}{(S_{Bat} \cdot V_n^2)}$$ \hspace{1cm} (13)

In which $P_b[W]$ is the internal battery power. From expression (13), and utilization of conversion of energy; the stored electrical energy in the battery is

$$E_b(k+1) = E_b(k) - P_b(k) \Delta h(k)$$ \hspace{1cm} (14)

where by definition the battery is discharged if a positive internal battery power $P_b$ is applied, and vice-versa for charging the battery. With $E_b(k+1) \in [E_{b,(k)}, E_{b}(k)]$, and $E_b(0) = E_b(N)$.

**Battery wear model** Battery wear is expressed by its capacity degradation as a function of charge/discharge rate $C_r$, lumped cell temperature, and tolerated Ah throughput $I_{Ah,t}$ Wang et al. (2011). From this, assuming battery end of life at 20% capacity degradation, the allowable number of discharge cycles $N_c$ are calculated, by

$$N_c(C_r) = \frac{I_{Ah,t}(C_r) \cdot 3600}{Q_{b,c}}$$ \hspace{1cm} (15)

The State of Health (SoH), as a function of $N_c$ and energy throughput is expressed by Ebbesen et al. (2012)

$$SoH(t) = 1 - \frac{1}{(2 \cdot N_c(C_r) \cdot Q_{b,c} \cdot V_{OC})} \int_0^t |P_{b,c}(\tau)|d\tau$$ \hspace{1cm} (16)

where $P_{b,c}$ is the internal cell power. By definition the $SoH \in [0,1]$ with $SoH = 0$ indicating battery end of life.

The resulting derivative of (16) has been approximated by a quadratic piecewise function for concavity

$$\hat{SoH} = \begin{cases} 
    h_{0,1} P_{b,c}^2 + h_{1,1} & \text{if } |P_{b,c}| \leq 43 \\
    h_{0,2} P_{b,c}^2 + h_{1,2} & \text{if } 43 < |P_{b,c}| < 55 \\
    h_{0,3} P_{b,c}^2 + h_{1,3} & \text{if } 55 < |P_{b,c}| \leq 61 \\
    h_{0,4} P_{b,c}^2 + h_{1,4} & \text{if } 61 < |P_{b,c}| 
\end{cases}$$ \hspace{1cm} (17)

Figure 8 (b) shows the Original SoH model derivative and its convex approximation. Furthermore, Figure 8 (a) indicates that the battery in the lowest internal power range can withstand less cycles than in the medium range. This is a result of not decoupling battery cycle-life and calendar-life (in (15)). Due to the assumption that each cell is accountable for a similar internal power throughput, the scalable battery wear model at pack level is obtained as

$$SoH_b(t) = h_{0,j} \cdot \frac{P_b(t)^2}{S_{Bat}} + S_{Bat} \cdot h_{1,j}, \text{ } j \in \{1,2,3,4\}$$ \hspace{1cm} (18)

Fig. 7. Baseline EGU efficiency according to e-line operation and fixed angular velocity in sweet-spot
This section analyzes two design choices: (i) effect of plug-in functionality, and (ii) effect of battery replacement strategy.

Effect of Plug-in functionality & Topology This section investigates how plug-in charging effects TCO for the hybrid topologies discussed in section 2, and compares them to the conventional topology. Figure 9 shows how TCO, Component cost, and Operational Cost are effected by plug-in charging for the hybrid topologies optimized for the Measurement based vehicle mission with diesel cost of 1.30 €/l and electricity cost of 0.2 €/kWh. For this analysis the maximum grid charging power is limited to 120kW. As shown, although component cost increases when using plug-in charging, operational cost decreases for all topologies. As can be seen, reduction of TCO are achieved by enabling plug-in charging since operational cost reduction is larger than component cost increasement.

The conventional topology is significantly outperformed by all hybrid topologies even when no Plug-in functionality is present. This is mainly driven by the assumption that all brake energy is available for regenerative braking as shown in Figure 10. This figure shows TCO reduction for the Parallel Topology in comparison to the conventional topology with different regenerative brake energy potentials. The brake energy potential indicates the percentage of the total brake energy that is available for regenerative braking. As shown, there is better TCO reduction performance when the regenerative brake energy potential is higher. In case no regenerative braking is applied there is only 11.35% TCO reduction in comparison to a reduction of 52.9% when all energy is available for regenerative braking.

Effect of battery replacement strategy This section presents the influence of battery replacement strategy on the TCO (Figure 11). As seen, all topologies show a similar trend. For each topology the TCO of the ‘ideal’ case are the lowest since operational cost and component cost are not
compromised by battery wear limitation. However, TCO increases significantly when for the 'ideal' case the battery wear is post calculated as in the 'No pres' case, where the battery needs to be replaced ones, as shown in Figure 12. This confirms the need for battery wear model inclusion as indicated in literature. When battery wear is preserved for the different replacement strategies there is seen that it is most beneficial to not replace the battery at all, but rather select a higher capacity battery that requires less energy throughput per cell to preserve the battery life. The additional advantage of this strategy is that battery power losses are reduced for equal terminal battery power since the power is divided over more cells.

6. SENSITIVITY TO ENERGY COST ANALYSIS

The Electricity price and Diesel price has an impact on vehicle design choices such as plug-in charging functionality and therefore on component sizing as well. This section analysis the TCO sensitivity, and sizing sensitivity to energy cost for the Parallel topology for demonstration purpose. Figure 13 shows the sensitivity of vehicle design cost $\phi_e$ for the SORT cycle based vehicle mission. As shown, TCO increases with increasing energy price but saturates from a certain electricity price for each Diesel pricing scenario. This saturation is a result of a breakpoint in electricity cost from which it is no longer beneficial to apply plug-in charging. As can be seen, this brake point moves towards a higher electricity price when the diesel price increases. For analyzing the breakpoint the energy cost ratio $\epsilon$ \text{[\$/kWh]} is defined as $\epsilon = \frac{\phi_e}{\phi_f}$ in (5.6)\text{[kWh]} . Figure 13 shows that for each diesel price plug-in charging is no longer beneficial when the Energy Cost ratio exceeds approximately 2.25, i.e. as long as Diesel Energy is 2.25 times as cheap as electricity it is not beneficial in terms of TCO to apply plug-in charging. Additionally, the vehicle acts as a full electric vehicle when the Energy Cost Ratio is lower than approximately 1.5. Moreover, when Energy Cost ratio $\epsilon \in [1.5 \ldots 2.25]$ operational cost consists Diesel cost and Electricity cost. A similar trend is expected for the Measurement based vehicle mission , although the value of the energy cost ratio is uncertain.

Fig. 10. Sensitivity of TCO, Component Cost, and Operational Cost to brake energy potential in relation to the Conventional Topology. The 0% potential indicates that all brake energy is dissipated in the friction brake, while for the 100% potential all energy is available for regenerative braking.

Fig. 11. Effect of the selected battery replacement Strategy on TCO, Absolute Component Cost, and Battery Capacity for the selected hybrid topologies. For which 'Ideal' represents an ideal scenario where the battery does not wear, and 'No pres' indicates that SoH preservation is not taken into account. While '0 rep', '1 rep', and '2 rep' are scenarios where the SoH is preserved according to 0, 1, and 2 battery replacements, respectively.

Fig. 12. SoH trajectory for different battery replacement strategies for the Series-Parallel Topology. The graph on the left shows the SoH trajectory for the first ever vehicle mission of the vehicle, while the graph on the right indicates the SoH trajectory over the entire vehicle life. SoH 1 indicates that the battery is unused while SoH 0 indicates that the battery needs to be replaced.
Fig. 13. TCO and component sizing sensitivity to different energy pricing scenarios

equipped with a relative large EM when plug-in charging is not beneficial, because regenerative braking efficiency has a part in EM sizing.

7. CONCLUSIONS & RECOMMENDATIONS

In this study, an optimization framework combining Convex Optimization and Dynamic Programming is developed to minimize TCO for heavy duty plug-in hybrid electric vehicles. The framework optimizes component sizing, energy management strategy including battery wear, in order to minimize the sum of component- and operational cost for a Series, Parallel, and Series-Parallel topology. Two design decisions for TCO minimization were analyzed for a Heavy Duty Transit Bus application: (i) the value of equipping a HEV with a plug-in functionality, and (ii) the effect of the battery replacement strategy.

Adding a plug-in functionality appeared to be beneficial for all topologies in the case study. Although the initial powertrain investment went up, the additional investment is earned back over the course of the vehicle life time. Energy cost sensitivity analysis were performed for the plug-in Parallel topology, there is concluded that plug-in charging is no longer beneficial when the electricity prise becomes approximately 2.25 times the diesel price for the Parallel topology and SORT cycle based vehicle mission.

Battery replacement for TCO reduction is not beneficial for the studied scenario. It is more profitable to equip the vehicle with a sufficiently large battery for SoH preservation. For future work, sensitivity analysis are recommended to study the effect of the battery wear model on the optimal battery replacement strategy. It is relevant to refine the cost model of powertrain components to take into account start-up costs as well as cost reduction / inflation.

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