Methods

This study applies a multi-objective E-LCO to identify traction-battery architectures that minimize environmental impacts over the vehicle life cycle. The approach consists of three main stages:

(1) defining the use scenario and technical requirements for a long-haul 40 t BE-HDV;

(2) implementing a detailed, hierarchical battery model based on a real TB to define input parameters (battery-equivalent replacements and cell-to-pack mass share) for the *carculator_truck* tool to calculate impacts across all EF 3.1 midpoint categories and normalize them;

(3) applying a multi-objective evolutionary algorithm (i.e., NSGA-II capable of handling discrete multi-objective problems) to optimize design parameters such as module configuration and component replaceability according to the normalized impact categories.

Section 2.1 describes the underlying LCA structure and vehicle specification in more detail, before proceeding with the actual optimization logic in Section 2.2.

Overview of LCA calculations

Case Background: Use Scenario and Derived Technical Requirements

The present study investigates battery system design options for a 40-tonne BE-HDV intended for long-haul freight transport in Austria, with a projected market entry in 2030. Key technical parameters are derived from component and performance specifications of a real TB[1] used for reference. The two parameters of *volumetric packing efficiency* and *penalty for replaceable mounting* are additionally used to calibrate the model to the reference TB. Both of these

[1] Three industry contacts with several years of experience provided the data necessary to develop the battery model presented in this investigation, as well as the scenario-specific parameters. Due to confidentiality issues, neither the industry contacts nor more information on the battery model or parameters can be shared.

parameters are validated by 3 experts from the BE-HDV industry. They also provided masses for all battery components not part of the TB specifications and vehicle-level technical and operational details. The BE-HDV is assumed to operate with an average payload of 15 tonnes and is designed for a real-world driving range of 600 km per charge. The vehicle lifetime is set at 1,000,000 km to reflect long-haul fleet expectations.

Several critical battery parameters are defined early in the development process by technical or logistical constraints and are treated as fixed in the present study. The system voltage of 710 V is determined by high-power charging requirements. A total battery energy capacity of 690 kWh is specified to meet range and payload trade-offs. The number of battery packs (six) is set based on space and mass constraints within the vehicle chassis, while the use of prismatic LFP cells is defined by supplier availability and internal business relationships.

The traction battery follows the hierarchical structure common to heavy-duty applications (Cerdas, 2022): Individual cells are electrically connected in series and parallel to meet target voltage and capacity requirements and are combined (together with local sensing and control components) into modules. These modules constitute semi-independent subsystems whose internal layout and accessibility determine the degree of integration or modularity. Multiple modules are then assembled, again with additional control, sensing, and protection components, into battery packs that include mechanical housing, thermal management, and high-voltage interfaces. Finally, several packs are connected within the battery system to form the full-vehicle energy supply.

While the parameters from engineering requirements are considered exogenous, the design of the internal battery architecture, particularly the module configuration and the component replaceability at both module and pack levels, remains open and subject to optimization. The implementation of these design variants, and their representation within the modeling framework, is described in Sections 2.2 and 2.3.

Goal, scope and system model

The primary goal of this study is to minimize the environmental impacts of the reference BE-HDV TB from 2022 by quantifying how alternative traction-battery architectures, ranging from highly integrated to strongly modular, affect the environmental life cycle impacts of the corresponding long-haul BE-HDV. The scope includes a granular model of the battery structure embedded within the full vehicle life cycle. The functional unit is defined as one tonne-kilometer (tkm) driven. The full set of scenario parameters (also including specific component volumes, masses, and failure rates) is provided in the associated data repository.

A cradle-to-grave system boundary based on the open-source *carculator_truck* tool (v.0.5.0) (Sacchi et al., 2025) is adopted - encompassing raw material extraction, battery and vehicle manufacturing, vehicle operation (including charging electricity and battery replacements), maintenance, and EoL treatment - and extended with user-defined battery architecture parameters. Background inventories are sourced automatically by *carculator_truck* from ecoinvent v3.10.

The environmental performance of each battery configuration is assessed across the 14 EF 3.1 midpoint impact categories for which safe operating spaces were derived by (Sala et al., 2020). The impacts are normalized with respect to down-scaled SOSs (allocated via grandfathering to sector allowances and via equality principles to Austria, look into associated data repository for more information) to perform a multi-objective optimization. For clarity of presentation, the results section illustrates the optimization behavior mainly using the TEI, calculated applying the EF 3.1 specific weighting factors. Sporadically, also GWP and resource scarcity (RS) impacts are provided as specific impact examples.

Details of the optimization model

In this study, a multi-objective E-LCO model is developed around the LCA tool *carculator_truck*. Figure 1 provides a first overview on the entire optimization structure. The full implementation is available via the public GitHub repository (see data availability statement).

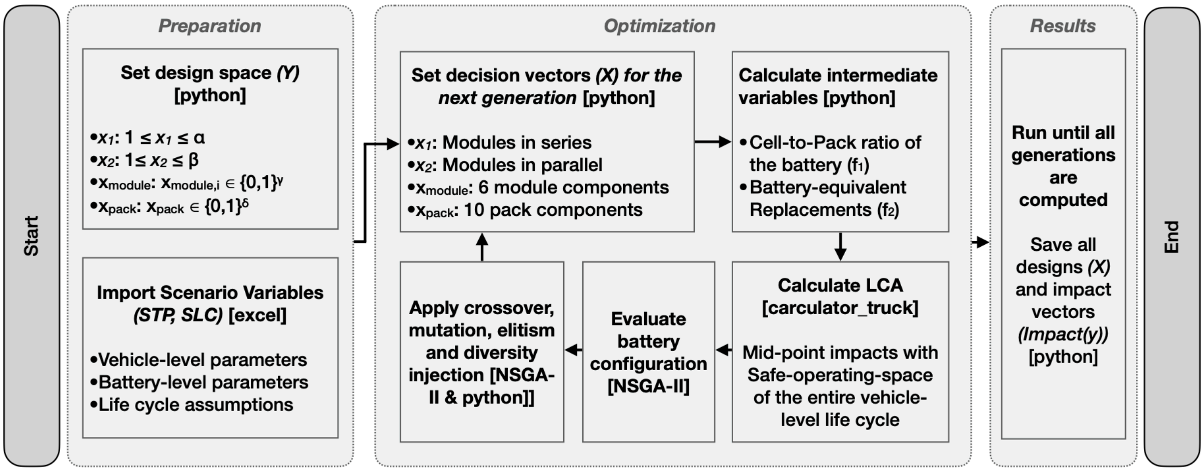

Figure 1: Modelling and optimization flowchart.

The traction battery is modeled hierarchically in three levels (cell → module → pack) to capture both physical scaling and design interdependencies. The optimizer operates on a two-layer abstraction:

- Module components (lower level, indexed with *i*): structural and electrical sub-elements within each module, including cells, voltage and temperature sensors, printed circuit boards (PCBs), battery management system (BMS), and signal connector.
- Pack components (upper level, indexed with *j*): elements enclosing modules (cooling, casing, electronics, etc.), with modules themselves considered as one of them, as well as the components of voltage and current sensors, PCBs, BMSs, signal and power connectors, busbar, relays, and fuses.

The optimization structure

The optimization problem is defined as a simultaneous minimization of normalized environmental impacts across $k \in \{1, 2, \ldots, 14\}$ EF 3.1 midpoint categories:

$$\min_{y \text{ in } Y} Impact_{norm}(y) = \min_{y \text{ in } Y} \begin{pmatrix} Impact_1(y)/Normalization_1 \\ Impact_2(y)/Normalization_2 \\ \vdots \\ Impact_{14}(y)/Normalization_{14} \end{pmatrix} \tag{1}$$

Where y represents a specific point (i.e. battery configuration X) in the design space Y, leading to the life cycle impact $Impact_k(y)$ in category k. Normalized with the correspondant $Normalization_k$ and $Weighting_k$ factors, they form the entirety of the environmental impacts $Impact_{norm}(y)$. Each impact value is derived from *carculator_truck* as:

$$Impact_k(y) = LCA_k(f_1(X, STB), f_2(X, STB), SLC) \tag{2}$$

which depends on the two intermediate metrics of

i. $f_1(X, STB)$: the effective cell-to-pack mass ratio;

ii. $f_2(X, STB)$: the expected number of battery-equivalent replacements over the vehicle lifetime;

and the scenario parameters concerning the overall life cycle *SLC*. While the *SLC* are directly passed to *carculator_truck*, both functions (f_1 and f_2) are calculated based on the decision vector X and the TB-specific scenario parameters *STB*.

A parameterized two-tier model (pack → module) is employed in both intermediate metrics to capture mass and reliability calculation. A representative snapshot of both, *SLC* and *STB* scenario parameter, is provided above in *Table 1* and the full set in the associated data repository.

The decision vector X comprises four groups totaling 18 design variables:

$$X = \{x_1, x_2, x_{module,i}, x_{pack,j}\} \tag{3}$$

where

(1) x_1: number of modules in series

(2) x_2: number of modules in parallel

(3) $x_{module,i} \in \{0, 1\}$: a binary variable for each of the six ($\gamma = 6$) module components indexed with i, describing their replaceability

(4) $x_{pack,j} \in \{0, 1\}$: a binary variable for each of the ten ($\delta = 10$) pack components indexed with j, describing their replaceability

For notational compactness, a helper index l is introduced to refer to any component l = *{module components i, pack components j}*, relating to all battery components, both on the module- and pack-level.

The discrete design space Y is thus defined as:

$$Y = \{X \mid x_1 \in \{1, \dots, \alpha\}, x_2 \in \{1, \dots, \beta\}, x_{component,l} \in \{0, 1\}\} \quad (4)$$

With

$$x_{component,l} = \{x_{module,i}, x_{pack,j}\} \quad (5)$$

The search across the design space Y uses the NSGA-II genetic algorithm, chosen for its capability to handle discrete, nonlinear, and multi-objective problems. The population size is set to $N = 50$ individuals and $G = 150$ generations. Mutation probabilities M are defined separately for integer and binary variables, so that $\forall x \in \{x_1, x_2\}$ it is set to 0.35 and $\forall x \in \{x_{module,i}, x_{pack,j}\}$ it is set to 0.1. Elitism (best individual carried forward) and diversity injection (perturbed variants of x_1, x_2 of the best individual) are also introduced to enhance exploration of the design space Y and avoid premature convergence on local minima.

The gravimetric energy density ($f_1(X, STB)$) – target for integrated designs

To quantify the influence of design choices on the gravimetric energy density of the traction battery, a hierarchical, mass-based physical model was developed and calibrated against the reference reference pack. The objective function $f_1(X, STB)$ expresses the cell-to-pack mass share, defined as the ratio between the total mass of all cells m_{cells} and the overall pack mass m_{pack}:

$$f_1(X, STB) = \frac{m_{cells}}{m_{pack}} = \frac{m_{cell,STB} * n_{cell}(STB)}{\sum_j m_{pack\ comp,STB,j}(X,STB) * n_{pack\ comp,STB,j}(X,STB)}, \quad 0.5 < f_1 < 0.9 \quad (6)$$

The ratio f_1 serves as a proxy for structural integration and gravimetric efficiency. Since no system-level components are modeled, f_1 also equals the cell-to-system mass share. It is limited by the three industry experts to a feasible range between 0.5 and 0.9.

Starting at the cell-level, the total cell mass m_{cells} is obtained from the mass of a single cell $m_{cell,STB}$ and the total number of cells n_{cell}

$$m_{cells} = m_{cell,STB} * n_{cell}\,(STB) \tag{7}$$

The latter is determined as the product of number of cells in series $n_{cell\ series}$ and in parallel $n_{cell\ parallel}$, both required to achieve the TB-related scenario parameters of nominal target voltage $V_{nom,STB}$, power $P_{nom,STB}$, and energy $E_{nom,STB}$.

As multiple cells are grouped within modules, $n_{cell\ series}$ and $n_{cell\ parallel}$ directly affect the design space for the design variables x_1 and x_2, so that the maximum number of modules in series is set to $\alpha = n_{cell\ series}$ and the number of modules in parallel is set to $\beta = n_{cell\ parallel}$.

At the module level, the total module mass m_{module} is computed as the sum of all module components $i \in \{1, 2, \ldots, \gamma\}$:

$$m_{module} = \sum_{i=1}^{\gamma-1}\left[m_{module\ comp,STB,i} * n_{module\ comp,i}(X,STB) * \left(1 + p_{module\ comp,STB,i} * x_{module,i}\right)\right] + m_{module\ casing}(X,STB) \tag{8}$$

Here, $n_{module\ comp,i}$ and $m_{module\ comp,STB,i}$ denote the quantity and mass of each module-level component i, respectively. However, the number of each module component per module depends on the design variables x_1 and x_2, as the quantity of sensing and control module components (i.e., $n_{module\ comp,STB,i}$ with $i \in \{2, 3, 4, 5\}$) is set dynamically based on the ultimate number of cells (i.e., $i = 1$) per module. Thus, less overall modules ($x_1 * x_2$) result in more cells per module (and consequently more module components as well) and vice versa:

$$n_{module\ comp,i} = \frac{n_{cell}(STB)}{(x_1 * x_2)} * n_{module\ comp,STB,i} \tag{9}$$

The module casing mass $m_{module\ casing}$ (i.e., $i = 6$) depends on the module casing design $d_{module\ casing,TBS}$ (specifying wall width and avg. material density) and on the internal surface area A_{module} of the internal module structure. The latter is approximated through cubic-root scaling based on the effective volumetric packing efficiency $\eta_{vol\ packing,STB}$ and the component inventory $n_{module\ comp,i}$:

$$m_{module\_casing} = A_{module}\left(\eta_{vol\ packing,STB}, n_{module\ comp,i}\right) * d_{module\ casing,STB} \quad (10)$$

The penalty factor $p_{module\ comp,STB,i}$ represents the additional structural mass required when a module component is mounted in a replaceable fashion ($x_{module,i} = 1$). Both, the penalty factor $p_{module\ comp,STB,i}$ and for the volumetric packing efficiency $\eta_{vol\ packing,STB}$, lie within ranges validated by the three industry experts. Nonetheless, applying a single penalty factor $p_{module\ comp,STB,i}$ and a uniform volumetric efficiency $\eta_{vol\ packing,STB}$ across all battery components introduces some approximation error, since in reality both parameters vary by component type and ultimate battery design. This limitation reflects the eco-design paradox (only limited design information is available in early development phases) and is mitigated in this investigation by calibrating the battery model with the reference TB to match its volume and mass.

At the pack level, the total pack mass m_{pack} is determined by aggregating all pack-level components $j \in \{1, ..., \delta\}$, including modules themselves (i.e., $j = 1$; $n_{pack\ comp,1} = x_1 * x_2$), the pack casing (i.e., $j = 9$) mass $m_{pack\ comp,9}$, and cooling system (i.e., $j = 10$) mass $m_{pack\ comp,10}$:

$$m_{pack} = \sum_{j=1}^{\delta-2}\left[m_{pack\ comp,STB,j} * n_{pack\ comp,j}(X, STB) * \left(1 + p_{pack\ comp,STB,j} * x_{pack,j}\right)\right] + m_{pack\ comp,9}(X, STB) + m_{pack\ comp,10} \quad (11)$$

The pack-level replaceable components again incur the penalty factor $p_{pack\ comp,STB,j}$ to account for additional structural mass associated with access, fasteners, and insulation. The number of each pack component $n_{pack\ comp,i}$ and the casing mass $m_{pack\ casing}$ are modelled analogously to $n_{module\ comp,i}$ and m_{module_casing} (see Eq. 9-10).

The $f_1(X, S_{TB})$ function thus quantifies how the chosen hierarchical architecture (through modularity, volumetric efficiency, and replaceable mounting) affects the cell-to-pack share and thus the system-level efficiency of the traction battery.

The value retention of the battery ($f_2(X, S_{TB})$) – target for modular designs

To evaluate the effect of modular design on battery value retention, a mass-based reliability model was developed to simulate expected replacements of traction-battery components. The objective function $f_2(X, S_{TB})$, expresses the lifetime-equivalent number of battery replacements, normalized by total pack mass:

$$f_2(X, S_{TB}) = \frac{m_{repl,tot}}{m_{pack}} = \frac{\sum_{l \in TB} m_{comp,l} * n_{repl,l}(X, S_{TB})}{m_{pack}} \tag{12}$$

where $m_{repl,tot}$ is the total expected mass of replaced components over the vehicle lifetime, and m_{pack} is the pack mass. Each component l is characterized by its mass $m_{comp,l}$, belonging either to the module-level (i) or the pack-level (j) grouping:

$$m_{comp,l} = \{m_{module,i}, m_{pack,j}\} \tag{13}$$

The expected total mass replaced $m_{repl,tot}$ is thus calculated as the sumproduct of the number of component replacements $n_{comp\ repl,l}$ times the component's mass $m_{comp,l}$ over all battery components l.

The number of component replacements $n_{comp\ repl,l}$ then depends on their reliabilities ($\lambda_{comp,l}$, derived from (Shu et al., 2020)), replaceability ($x_{module,i}$ and $x_{pack,j}$), and position within the battery hierarchy (module or pack level). The number of failure events expected over the vehicle lifetime is derived from the mean time between failures ($MTBF = 1/\lambda_{comp,l}$), which is the inverse of failure-in-time values (i.e., FPMH with failure per million hours as representative of $\lambda_{comp,l}$):

$$n_{comp\ fail,l} = t_{HDV} * \lambda_{comp,l} \tag{14}$$

with the powered hours t_{HDV} of the vehicle calculated as the total milage per cycle-average velocity, both of which are provided by *carculator_truck*.

Subsequently, the number of component replacements $n_{comp\ fail,l}$ together with a replacement logic link to the expected actual number of component replacements $n_{comp\ repl,l}$, and ultimately battery equivalent mass replacements $m_{repl,tot}$: Each component l is linked to a binary replaceability variable $x_l \in \{0, 1\}$, where $x_l = 1$ denotes replaceable and $x_l = 0$ denotes integrated (and thus irreplaceable) mounting. The number of component replacements $n_{comp\ repl,l}$ is then determined by:

$$n_{comp\ repl,l} = \begin{cases} n_{comp\ fail,l}, & x_l = 1 \\ n_{comp\ fail,l} * r_{cascade\ comp,l}\,(X, S_{TB}), & x_l = 0 \end{cases} \tag{15}$$

Where the cascade-replacement factor $r_{cascade\ comp,l}(X, S_{TB})$ captures hierarchical failure propagation: If a component failure propagates to a module or pack replacement, $r_{cascade\ comp,l}(X, S_{TB})$ corrects the number of replacements for affect components $n_{comp\ repl,l}$. This leads to the following rules encoded in $r_{cascade,l}(X, S_{TB})$:

i. If a replaceable component fails and is more failure-prone than any non-replaceable component, only that component is replaced.

ii. If a non-replaceable component fails and is more failure-prone than any other non-replaceable component on the same level (module or pack), the entire corresponding module or pack is replaced, respectively.

iii. If a (replaceable or non-replaceable) component fails but is less failure-prone than any other non-replaceable component on the same level (module or pack), it is assumed that it has already been replaced by that other component's failure intervention.

iv. If the module is not replaceable, the failure intervention of a non-replaceable module component leads to a full pack replacement.

This hierarchical structure covers both module-level $x_{module,i}$ and pack-level $x_{pack,j}$ design variables and assumes an intelligent BMS capable of detecting early failures and preventing cascading effects, ensuring independent replacements. The model thus captures how reliability ($1/n_{comp\ fail,l}$), replaceability (x_l), modularity (x_1 and x_2), and mass ($m_{comp,l}$) jointly determine the expected replacement burden. A full overview of the applied variables and parameters is provided in the associated data repository.

The resulting f_2 value is then passed as an input to the *carculator_truck* model (along with f_1 (see Section 3.2.2) and life cycle scenario parameters S_{LC}), which translate into corresponding life cycle environmental impacts.