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The JRC DIONE model version II

Assessing the Costs of Road Vehicle CO_2 Emission Reduction

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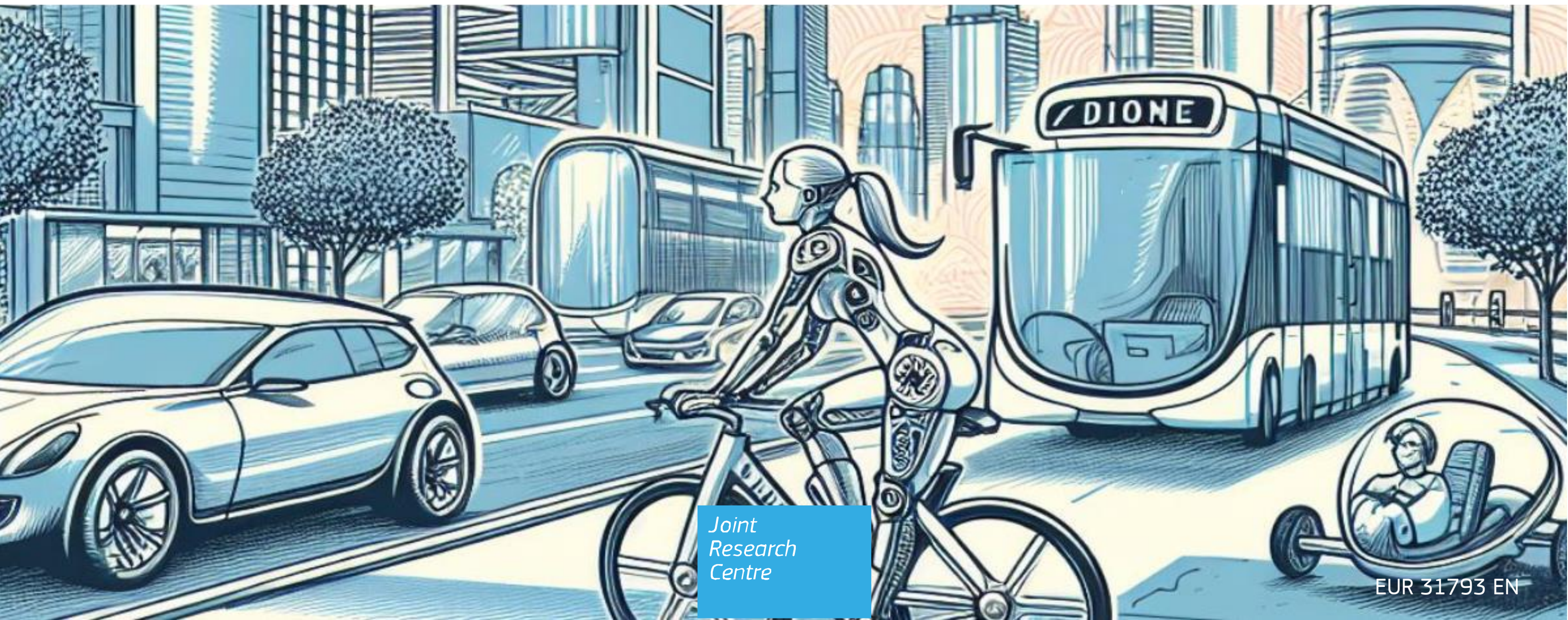
2024



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Contents

Abstract

The DIONE cost model is used to assess the costs and benefits of European Union road vehicle CO_2 standards, from the perspective of vehicle users, vehicle producers, and the society. The model has been developed and employed at the European Commission's Joint Research Centre (JRC) since 2014, and has recently undergone major extensions in its scope as well as updates in its computational implementation.

The present report documents the second, fully revamped version of this model.

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The development of the models described in this report is based on datasets provided to the Commission under framework contract CLIMA.A4/FRA/2019/0011, in particular, Service Request No. 2020/03 (for light-duty vehicles). The authors thank Ricardo Energy & Environment and the Graz University of Technology for the provision of data within this framework and for the review of preliminary versions of the cost curves.

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Responsibility for any errors remains with the authors.

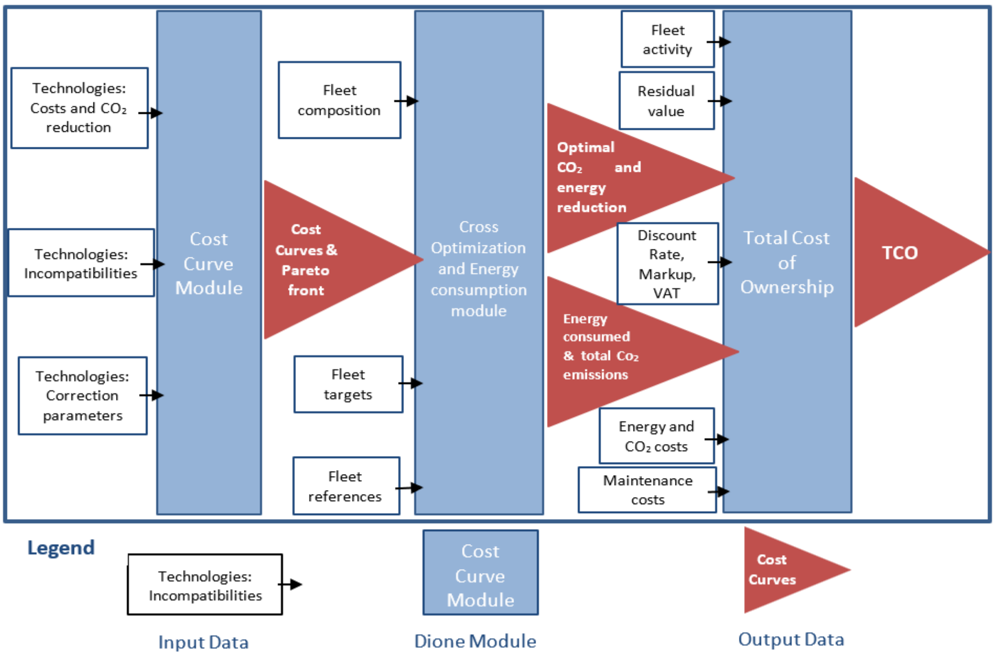
Executive summary

The European Union (EU) is committed to reducing its greenhouse gas emissions and energy consumption. In 2021, the European Union introduced its Climate Law (EU, 2021), which requires achieving climate neutrality by 2050 and sets an intermediate target of reducing net greenhouse gas emissions by 55% by 2030, compared to 1990 levels. Transport presently causes a quarter of EU greenhouse gas emissions and it is the only major economic sector that has exhibited a growing greenhouse gas emissions trend since 1990 (European Environment Agency, 2022). CO_2 standards are one of the key measures to reduce emissions from road vehicles. At the same time, they may have substantial impacts on the costs and affordability of transport options, and on the competitiveness of the EU automotive industry. A rigorous assessment of such impacts is warranted and, to support such assessments, the European Commission's Joint Research Centre (JRC) has been developing its DIONE cost model since 2014. The present report documents the second, fully revamped version of this model.

The assessment of the costs of potential vehicle CO_2 emissions standards is carried out through three computational modules: The cost curves module, the cross optimization and energy consumption module, and the total cost of ownership module. The interaction between the modules, as well as the inputs needed and the outputs produced, are shown in Figure 1. The DIONE modules are represented by blue boxes:

- DIONE cost curve module: it develops cost curves, which describe the cost of reaching different levels of CO_2 emission reduction and energy consumption reduction for each vehicle type and powertrain.
- DIONE cross optimization and energy consumption module: it identifies cost-optimal strategies to reach given emission standards, building on the cost curves. For the optimal solution, it computes the energy consumed and the CO_2 emitted by the new vehicle fleet.
- DIONE total cost of ownership (TCO) module: it calculates the fuel costs, the maintenance costs, and the total costs of ownership from different perspectives (e.g., first user, second user, society) for the optimal solution. Changes in total costs of ownership caused by CO_2 standards are determined by comparing these results for different scenarios.

Figure 1. Flowchart of the DIONE model.



Source: JRC, 2024

When running DIONE, in the first step, the cost curve module produces vehicle CO_2 reduction and energy consumption reduction cost curves for each vehicle group, powertrain, year of analysis, and cost type considered. These curves are provided to the cross optimisation module, which outputs the optimal CO_2 reduction and energy consumption reduction and the total energy consumed, per given fleet, scenario, cost type, and registration year. At this point, it is possible to check whether the CO_2 emission reduction targets can be met with the given input technologies. The third module, the total cost of ownership module, uses the optimal CO_2 reduction and energy consumed to compute the fuel and energy savings of vehicles. It combines them with manufacturing and maintenance costs to calculate the TCO for each scenario.

The white boxes in Figure 1 indicate input data needed to run the modules, whereas the red triangles signify outputs from one module, which can also be used as input to the next step when running the modules sequentially.

The DIONE Cost model has been developed to assess the costs of road vehicle CO_2 emissions standards. At the JRC, it has been used to assess policy scenarios for cars and vans, as well as, for trucks, buses, and trailers. In fact, due to the generalized structure of the new model version II, which is documented in this report, DIONE can handle any input dataset of a similar structure, regardless of the application.

1 Introduction

Throughout the past decades, passenger and goods road transport volumes have increased strongly both in the European Union and globally. Since 1990, EU transport has been emitting increasing quantities of greenhouse gases, in contrast to all other major economic sectors, which have exhibited decreasing trends. Presently, the transport sector accounts for a quarter of the European Union's greenhouse gas emissions (European Environment Agency, 2022), the majority of which (77% in 2020) comes from road transport.

In 2021, the European Union introduced its Climate Law (EU, 2021), which requires to achieve climate neutrality by 2050. This same law also sets an intermediate binding target for 2030, which stipulates a domestic reduction of net greenhouse gas emissions (emissions after deduction of carbon sinks) by at least 55% compared to 1990 levels. CO_2 emission standards for light-duty vehicles (LDV) and heavy-duty vehicles (HDV) are key policy initiatives for reducing road transport CO_2 emissions (EC, 2020a).

As regards new passenger cars and vans, stricter standards for up to the year 2030 were introduced in Regulation (EU) 2019/631, and were strengthened to account for the climate objectives enshrined in the European Climate Law with Regulation (EU) 2023/851 (EU 2023), adopted in April 2023. The regulation sets a 55% CO_2 emission reduction target (49.5 g CO_2/km) for new cars and a 50% reduction target (90.6 g CO_2/km) for new vans from 2030 onwards, compared to 2021 levels. As of 2035, a 100% reduction of tailpipe CO_2 emissions for both new cars and vans is in place.

Heavy-duty vehicles, i.e., trucks, buses, and coaches make up for about a quarter of CO_2 emissions from road transport. The first-ever EU-wide CO_2 emission standards for heavy-duty vehicles were adopted in 2019 ((EU) 2019/1242). Fleet reduction targets were set for CO_2 emissions of the most relevant groups of new heavy-duty trucks for the years 2025 (15%) and 2030 (30%), compared to the reference period 2019/2020. In 2023, the European Commission made a proposal (European Commission, 2023) to strengthen the standards, to extend them towards 2040, and to cover further heavy-duty vehicle groups. This proposal is presently under discussion by the European Parliament and the Council.

Greenhouse gas emission standards for vehicles can have substantial socio-economic impacts, among others on the affordability of transport options for citizens, on the competitiveness of the automotive industry, and on transport operators. In this context, the JRC DIONE cost model allows a systematic comparison of different options, and their assessment from the point of view of vehicle producers, vehicle users, and society. The model consists of different modules that can be run sequentially or separately. The modules serve to determine vehicle CO_2 emission reduction costs curves, to find an optimal allocation of emission reduction efforts over a given vehicle fleet, and to calculate the total cost of ownership changes triggered by CO_2 standards from different perspectives. DIONE can thus be used to compare the impacts of different policy options for road vehicle emission reduction.

The DIONE model has been developed by the Joint Research Centre (JRC) of the European Commission since 2014. The first version of DIONE was implemented to evaluate the impacts of CO_2 emission standards for cars and vans, as documented in Krause et al. (2017). Subsequently, the model was extended to cover the most active and emission-intense groups of trucks, see Krause and Donati (2018). In the following years, the model was further enhanced and generalized, leading to DIONE version II. A main new element regards the model's capacity to produce three-dimensional cost curves, which represent the cost of liquid and gaseous fuel consumption reduction (or, by proportionality, CO_2 emission reduction) on one branch, and the cost of total energy consumption reduction as a second branch. Moreover, heavy-duty vehicle analysis was extended to a wider range of vehicle groups and powertrains, as well as trailers. As regards model architecture, substantial progress has been made in generalizing the model towards a unique computational framework applicable to all vehicle types and scenarios. The new version does not differentiate between light-duty or heavy-duty data and scenarios any longer, but reads input files following a unified structure and gives back complete output files, regardless of the use case.

This report provides technical documentation of the latest version of DIONE developed by the JRC in 2022/2023, the DIONE model version II. The second section following this introduction provides a mathematical description of the modules. The third section presents a use case of DIONE for light-duty vehicles and exemplary results obtained, specifying the type of data used as an input and their sources. The fourth section presents major model extensions for heavy-duty vehicles. The report terminates with a short conclusion.

DIONE model overview and mathematical description

The present model DIONE version II builds on two previous model versions, which have been extensively documented in two reports: Krause et al. (2017) presented the first DIONE model version for light-duty vehicles, and Krause and Donati (2018) discussed the model enhancements made and results obtained for heavy-duty vehicles. These models have now been integrated into a generalized framework and further extended in functionality. The 2023 DIONE model version II is presented in this section.

Compared to the previous version, the current model has been enhanced in three main regards:

- Model extensions

Energy consumption reduction cost curves: While the calculation and minimization of CO_2 emission reduction cost is the central purpose of the DIONE model, vehicle energy consumption will gradually come into focus, to ensure the energy efficiency of carbon neutral transport. Previous DIONE cost curves represented CO_2 emission reduction for any emitting vehicle and energy consumption reduction for zero-emission vehicles such as battery electric vehicles. In the new model version, three-dimensional cost curves have been introduced, with one branch representing liquid and gaseous fuel consumption reduction (or, by proportionality, CO_2 emission reduction for any vehicle running exclusively on a fuel with carbon content), and a total energy consumption branch, which can represent the change in total energy efficiency for vehicles running partially or entirely on electricity. Details are presented in section 2.1. For both the cross optimization and the total cost of ownership module, the energy consumption is included in the calculations and results.

Model extensions to additional powertrains and segments: In particular, for heavy-duty vehicles, a wealth of powertrains and segments exist that were not covered by the previous DIONE model. The new model version has been extended to cover additional groups of trucks, as well as buses, coaches, and trailers, and to include a range of electrified and zero-emission powertrains. See section 3 for details.

- Model generalization

The previous version of DIONE was subdivided into two branches, one to assess scenarios for light-duty vehicles and a second one for heavy-duty vehicles. An effort has been made to generalize the computational structure of the model and to create a unique input/output file containing all data and parameters specific to a model run. Model code and input data or settings are now strictly separated, i.e., none of the settings, input data, calculation, or transformation parameters are hardcoded in the model. DIONE version II has been successfully run on input files for light- as well as heavy-duty vehicles and can be run on any dataset that is structured appropriately.

- Model accessibility and user friendliness

The three computational modules were integrated into a user-friendly, efficient, and accessible tool. All modules for which suitable input data is provided are automatically launched in sequence. The input/output files guarantee transparency and traceability of any run carried out. The model can be accessed via a server-based interface or in a stand-alone version, and the operation does not require advanced computational skills. A stepwise opening of the model to external users is intended.

DIONE is made of three modules: cost curves, cross optimization, and total cost of ownership (see Figure 1). These are described in the following sections. The modules are generally run one after the other, using the outputs of the previous as inputs of the following. However, because each module has its specific purpose, it is possible to run them stand-alone, on condition that the user provides the necessary input data.

1.1 Cost curves module

Many technologies that reduce energy consumption and CO_2 emissions exist and can be deployed throughout the next decades. Some vehicle components or features can be improved with regard to energy consumption (e.g., the engine, tires, or aerodynamics). Alternative powertrains can reduce vehicle tailpipe CO_2 emissions through reduced energy consumption or the shift towards low- or zero-carbon fuels. Different technologies can be combined into bundles to achieve higher emission reductions and lower energy consumption. Since each of these technologies has an implementation cost, it is possible to associate each bundle with a corresponding overall cost. The DIONE Cost Curve module aims to develop a continuous function describing the costs associated with reaching a given energy reduction. This reduction is described relative to the consumption of a reference vehicle with conventional powertrain of the same segment or group in a given year. Two energy reduction modes are available; therefore, the cost function can be plotted against two axes:

1. "Conventional" energy reduction cost curve: It corresponds to the reduction of liquid and/or gaseous fuel consumed to propel the vehicle, with respect to the reference vehicle. Regarding CO_2 emissions we have to distinguish three cases:

    - For pure internal combustion engines (ICE) and full or mild hybrids using CO_2-emitting fuels (such as combustion engine powertrains using diesel, gasoline, or natural gas as fuels), CO_2 emissions are proportional to fuel consumption. Thus, the conventional energy consumption reduction corresponds to the relative CO_2 emission reduction.

    - For plug-in hybrid electric vehicles (PHEV) or range-extended electric vehicles (REEV) using CO_2-emitting fuels, the reduction includes fuel saving due to usage of the energy stored in the battery. Therefore, also in this case, "conventional" fuel reduction relative to the reference vehicle is proportional to relative tailpipe CO_2 emission reduction.

    - Fuel cell electric vehicles (FCEV) or hydrogen internal combustion engine vehicles (H2 ICE) do not emit any tailpipe CO_2. Therefore, there is no CO_2 emission reduction from applying efficiency technologies.

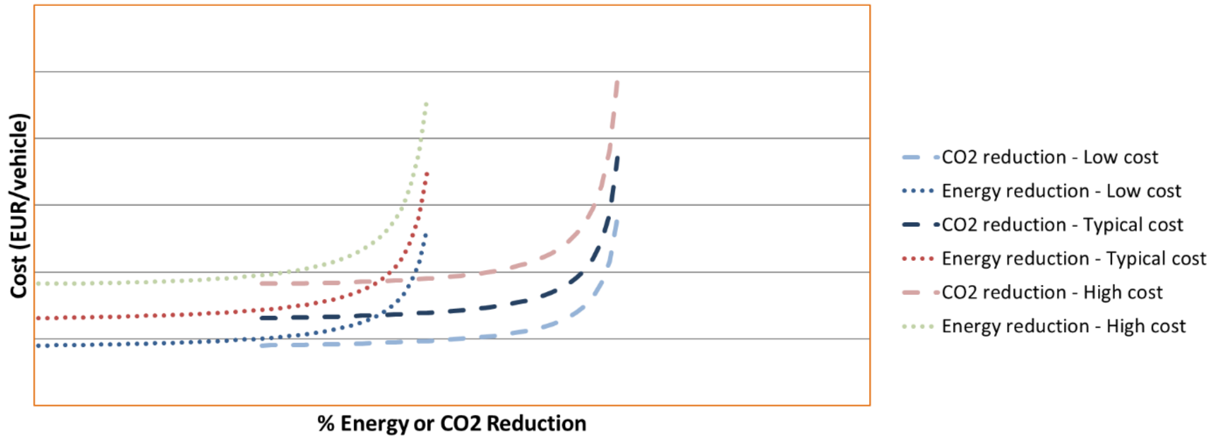
2. "Total energy" reduction cost curve: It corresponds to the overall reduction of the total energy consumed by the vehicle. In this case, we can distinguish three cases:

    - For pure ICE or FCEV or H2 ICE, this corresponds to conventional energy reduction. Thus, the "total energy" reduction cost curve overlaps with the "conventional" energy reduction cost curve.

    - For PHEV or REEV, both the change in consumption of electric energy (which is not included in "conventional") and the reduction of conventional fuels, relative to the reference vehicle, are taken into account. Therefore, total energy reduction is lower than conventional energy reduction. An example is shown in Figure 2.

- For battery electric vehicles (BEV), which consume only electricity, only the "total energy" reduction curve is defined. It shows the energy consumption reduction relative to the energy consumed by the reference vehicle.

Figure 2. Schematic example of three-dimensional cost curves for PHEV. "Conventional" reduction (labelled CO2 reduction in the legend) is higher than "total energy" (labelled energy reduction).



Source: JRC, 2024

Due to the linearity of "conventional" fuel consumption reduction and CO_2 emission reduction for vehicles using liquid and gaseous carbon-based fuels, the conventional reduction curve can be used to determine CO_2 emission reductions for those vehicles, and in these cases, the axis label %conventional reduction can be replaced by %CO_2 reduction. Therefore, in the following, "CO_2 reduction cost curve" is used as a synonym for "conventional energy reduction cost curve". For zero-emission vehicles (FCEV, H2 ICE, BEV), the "CO_2 reduction cost curve" does not exist, as they always achieve a 100% tailpipe CO_2 reduction.

The 2017/2018 DIONE model version was producing only cost curves for the conventional reduction mode. Technology costs depending on the total energy consumption reduction is a novelty of DIONE version II.

The cost curve module carries out several steps to derive the cost curves, described in the following paragraphs.

Identifying optimal technology packages

The first step aims to identify cost optimal technology packages to reduce CO_2 emissions as well as energy consumption. Given the set of available reduction technologies, the challenge consists in finding, among all feasible packages (i.e., combinations of compatible technologies or subsets of them) the set of optimal configurations with minimal total costs and maximum total reduction.

Given a set of technologies $T = \{t_1, \dots, t_N\}$, each characterized by its cost c_i, its energy reduction in conventional mode $r_{conv,i}$, its energy reduction in energy mode $r_{ener,i}$, and by a list of incompatible technologies $\{t_{ij}\}$, we aim at finding a set of all feasible subsets of T (in terms of compatibility between technologies), called packages P_k, which is optimal according to the following equations:

$$\begin{cases} \min C(P_k) = \sum_{t_i \in P_k} c_i \\ \max R_{conv \mid ener}(P_k) = 1 - \prod_{t_i \in P_k} \left(1 - r_{conv \mid ener,i}\right) \end{cases} \tag{1}$$

$C(P_k)$, $R_{conv|ener}(P_k)$, are respectively the total cost and the reduction of conventional energy for CO_2 emitting vehicles or the reduction of total energy for no CO_2-emitting vehicles, due to the implementation of the technology package P_k.

The resulting technology packages solving these equations are called Pareto optimal technology packages, and the set of these solutions is called raw Pareto front. They constitute the combination of technologies that can be added to a baseline vehicle to achieve a reduction at the lowest possible costs. The user can decide to exclude some technologies from the set of available technologies, which will then not be considered in T.

Not all technologies can be combined among themselves, which means a simple combinatorial approach cannot be applied. For example, in the case of engine downsizing technologies, there would never be a package containing more than one of them. These incompatibilities and the large number of possible technology combinations make the problem computationally difficult.

The previous versions of DIONE used an Ant Colony Optimization algorithm to identify optimal packages, as documented in Krause et al. (2017). The new DIONE version II uses a Non-dominated Sorting Genetic Algorithm with a default termination criterion, which has proved to be computationally much faster. Testing results for the new approach can be found in Annex 1.

Parameter transformation

The second step of the cost curves module is the parameter transformation. Once the set of Pareto optimal technology packages (the set of raw Pareto points) has been found, some adjustments are made to each point before fitting the cost curve:

- Baseline adjustment: Accounting for technologies that are already deployed in the reference year.
- Scaling for batteries: Handling battery cost for advanced electrified vehicles (xEV), i.e., BEV, FCEV, REEV, PHEV and battery catenary electric vehicles (BCEV), or H2 storage cost savings for vehicles with a hydrogen tank.
- Scaling for overlapping technologies: Avoiding that potentials covered by different technologies are double counted.
- Re-baseline xEV: Setting xEV energy and CO_2 savings relative to reference year conventional vehicles.

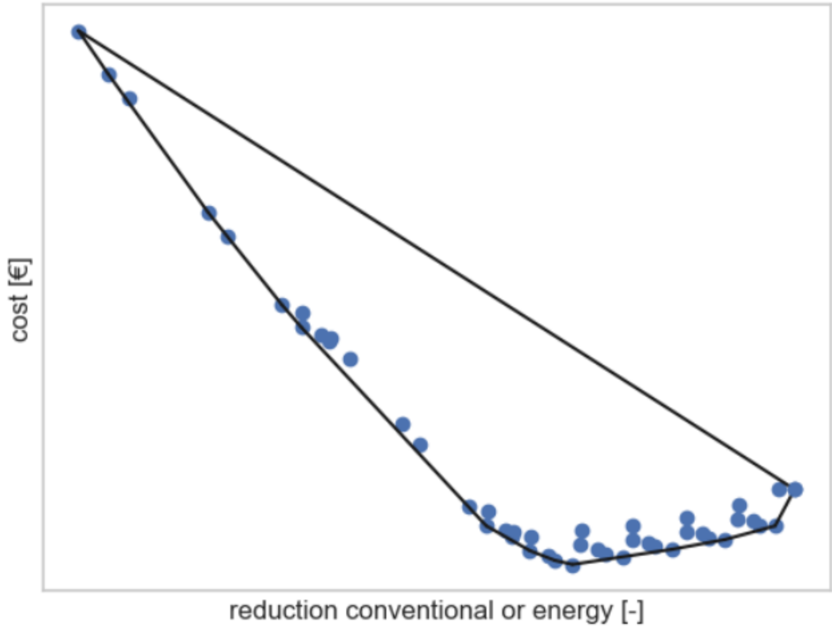
The outcome of the transformation is called the transformed Pareto cloud. These transformation steps have undergone no substantial changes from the previous model version and are documented in Ricardo Energy & Environment (2016).

Optimal Pareto front and cost curves

Once the optimal technology packages that can be applied to a vehicle have been computed, along with their energy consumption reductions and technology costs, the final steps of this module are to identify the optimal technology combinations at the level of a fleet of new vehicles with the same powertrain and segment or class, and to fit the cost curves to the points representing the optimal technology packages.

The transformed Pareto cloud found in the previous steps indicates the best technology combinations at the vehicle level, i.e., distinct technology packages that can be applied to an individual vehicle. With regard to a vehicle fleet containing a number of (at least two) vehicles of the same powertrain and segment, individual packages implemented in different vehicles can be combined to achieve intermediate reductions that relate to a combination of packages. This results in a continuous reduction cost curve. A reasonable solution for establishing the cost curve at the fleet level is to employ linear combinations of two technology packages. For example, if we have 100 vehicles with technology package A and another 100 vehicles with package B, the fleet energy consumption reduction is equal to the average reduction achieved by the two bundles, and the cost is halfway between the two packages' costs. The optimal Pareto front is defined as the segments of the lower part of the convex hull of the transformed Pareto cloud, which forms a piecewise linear continuous function.

Figure 3. Convex hull (in black) of the optimal technology packages (blue dots). The lower segments of the convex hull correspond to the optimal Pareto front.



Source: JRC, 2024

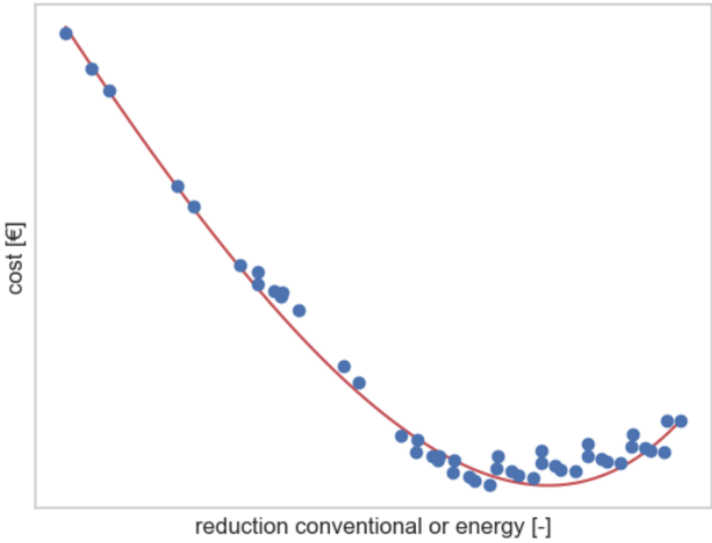
The optimal Pareto front gives the least-cost, continuous, technically feasible solutions for reducing vehicle fleet energy consumption. Each reduction can be traced back to an exact combination of technology packages implemented on a given vehicle. However, as the optimal Pareto front is piecewise linear, it is not as versatile as a parametric function. Therefore, a continuous analytical function of the cost curves was fitted, based on 1000 equally distributed points of the optimal Pareto front. This type of cost curves is called the **fitted cost curves**. Several functional forms of fitting functions were tested, with the requirement of having a non-negative second derivative. The functional form showing the required behaviour is the following:

$$\begin{cases} C(x) = Ax^2 + Bx + C + \dfrac{c}{x - x_0} \\ C(z) = Az^2 + Bz + C + \dfrac{c}{z - z_0} \end{cases} \tag{2}$$

where A, B, C, c, x_0, and z_0 are the unknown parameters to be fitted, C(x) and C(z) represent the technology cost, and x and z are the relative conventional and total energy consumption reduction. The final outputs of the cost curves module are the parameters of the curves depending on the vehicle powertrain, segment, registration year, and cost type.

The optimal Pareto approach has been introduced in the 2022/23 DIONE version II release. In the previous version of DIONE, cost curves were fitted directly to the raw Pareto cloud. The new approach is advantageous in that the optimal Pareto front provides more stable results than the raw Pareto cloud because the previous fitting results depended on the Pareto cloud density distribution. Moreover, this new approach describes the reductions at the level of a fleet of vehicles of the respective powertrain and segment/class.

Figure 4. Optimal technology packages (blue dots) and fitted cost curve (in red).



Source: JRC, 2024

1.2 Cross optimization module

The DIONE cross optimization module uses the optimal Pareto fronts previously defined for vehicles of a given powertrain and segment or class to identify the cost-optimal distribution of reduction efforts over all powertrains (pt), and segments (sg), to reach a given overall vehicle fleet-wide emission reduction target across all powertrains and segments that corresponds to a scenario *s* for a specific registration year (ry).

The problem consists in finding the optimal total energy reduction $z_{sg,pt,ry,s}$ for all segments (sg) and powertrains (pt) for each registration year (ry) and scenario (s) respecting the overall CO_2 reduction target at minimum overall fleet cost. Analytically, the cross-optimization problem is formulated as follows:

$$\begin{cases} \min C_{ry,s} = \sum_{sg,pt} p_{sg,pt,ry,s} \cdot cost_{sg,pt,ry}\left(z_{sg,pt,ry,s}\right) \\ CO_{2\,ry,s} \leq CO_{2\,\mathrm{trg},ry,s} \\ CO_{2\,ry,s} = \sum_{sg,pt} p_{sg,pt,ry,s} \cdot CO_{2\,\mathrm{ref}\,sg,pt,ry,s} \cdot \left[1 - z2x_{sg,pt,ry}\left(z_{sg,pt,ry,s}\right)\right] \end{cases} \tag{3}$$

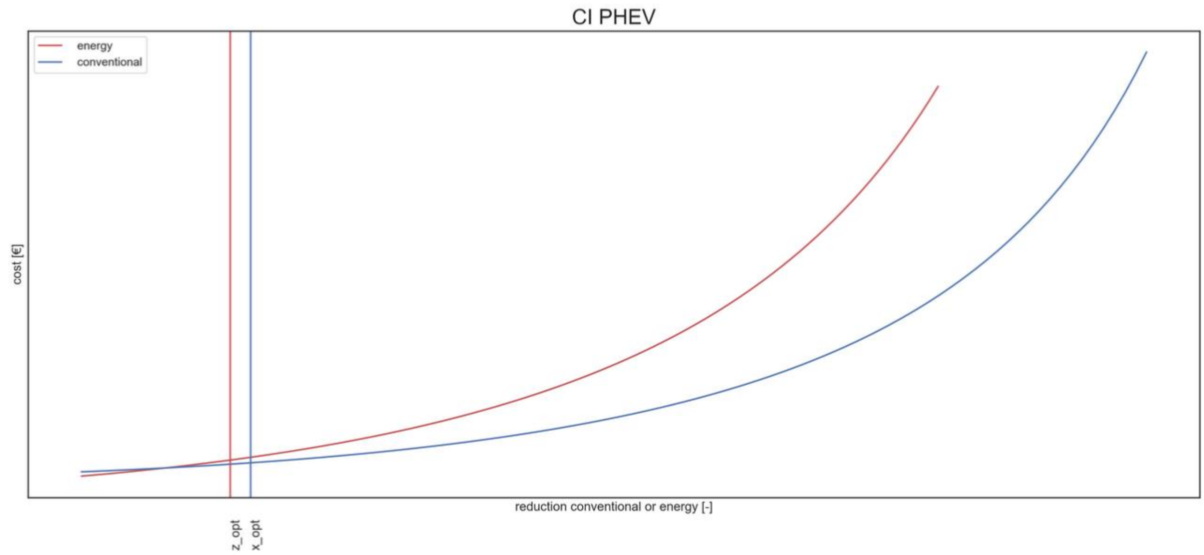
where $C_{ry,s}$, $CO_{2\,\mathrm{ry},s}$ and $CO_{2\,\mathrm{trg,ry},s}$ are respectively the optimization cost, the total CO_2 emission, and the CO_2 emission target for each registration year (ry) and scenario (s); while $p_{sg,pt,ry,s}$ and $CO_{2\,\mathrm{ref}\,sg,pt,\mathrm{ry},s}$ are respectively the fleet shares and the reference CO_2 emission for each segment, powertrain, registration year, and scenario. Note that the reference CO_2 emission for non-emitting vehicles is zero. $z2x_{sg,pt,ry}$ is a function that converts the total energy reduction to the conventional energy reduction according to the optimal Pareto front (see Figure 5). While $cost_{sg,pt,ry}$ is the cost function and it is defined according to the optimization approach:

- Manufacturing cost: uses the optimal Pareto front as a minimization cost function. This is the approach used in the previous DIONE version (see Krause et al. (2017)).
- Total Cost of Ownership (TCO): uses as minimization cost function the TCO – i.e., the sum over the manufacturing cost, energy cost, and maintenance cost as explained in later section 1.3. This cross-optimization option was first introduced in the previous heavy-duty vehicle variant of the DIONE model and is documented in Krause and Donati (2018).

The module uses a Particle Swarm Optimization algorithm to find the optimal points. Further details on this algorithm and the testing carried out are included in Annex 1.

Module outcomes: For both optimization approaches, the first outputs of the cross optimization are the optimal total and conventional (using $z2x_{sg,pt,ry}$ functions) energy reductions, and the related CO_2 emission reductions per vehicle, along with their respective costs. Figure 5 below shows exemplary cost curves for a vehicle with a PHEV powertrain, along with an example of conventional reduction (x_opt, in blue) and total energy consumption reduction (z_opt, in red) achieved by employing the same technology bundle. As can be seen, for the same bundle, conventional reduction is higher than total energy reduction.

Figure 5. Schematic PHEV conventional (blue) and total energy reduction (red) cost curves, along with an exemplary reduction found for a given optimal technology bundle.



Source: JRC, 2024

The module then computes the energy consumed per vehicle with the selected technologies. The conventional ($EC_{sg,pt,s}$) and electric ($EE_{sg,pt,s}$) energy consumptions are calculated according to the following equations:

$$\begin{cases} EC_{sg,pt,ry,s} = EC_{\text{ref } sg,pt,ry,s} \cdot \begin{cases} \dfrac{1 - x_{sg,pt,ry,s}}{cs_{sg,pt,ry,s}} & cs_{sg,pt,ry,s} > 0 \\ 0 & cs_{sg,pt,ry,s} = 0 \end{cases} \\ EE_{sg,pt,ry,s} = EE_{\text{ref } sg,pt,ry,s} \cdot \begin{cases} \dfrac{x_{sg,pt,s} - z_{sg,pt,ry,s}}{1 - cs_{sg,pt,ry,s}} & cs_{sg,pt,ry,s} < 1 \\ 0 & cs_{sg,pt,ry,s} = 1 \end{cases} \end{cases} \tag{4}$$

Where $EC_{refsg,pt,s}$ and $EE_{refsg,pt,s}$ are the reference vehicle's conventional and energy consumption (both are the same as long as the chosen references remain conventional vehicles).

Moreover, $cs_{sg,pt,ry,s}$ is the percentage of kilometers driven using conventional energy. Conventional energy ($EC_{sg,pt,s}$) is the energy contained in liquid and gaseous fuels the vehicle consumes, assuming it is driven using only this kind of fuel. Electric energy $EE_{sg,pt,s}$, in analogy, is the electric energy consumed by the vehicle if it uses only electricity. For PHEV and REEV, there are non-zero results for both categories, and they are combined into total energy consumption by calculating the sum of these two consumption types weighted by their shares.

The technology cost and the vehicle energy consumption computed by the cross optimization module can be used as inputs to determine the average total cost of ownership across the fleet, which will be done in the third DIONE module.

1.3 Total cost of ownership module

The DIONE TCO module is designed to summarize the different cost types over different timeframes, thus assessing the economic impacts of CO_2 emission reduction from the perspective of vehicle users and society. The TCO (i.e., $TotalCost$) is calculated as follows:

$$TotalCost = TechCost + OMCost + EnCost \tag{5}$$

Where $TechCost$ is the manufacturing cost, $OMCost$ is the operation and maintenance cost, and $EnCost$ is the fuel and energy cost. These components are described below.

Manufacturing costs

Manufacturing costs ($TechCost$) are based on the outputs of the cross optimization module, i.e. they are the technology costs corresponding to the optimal total energy reduction ($z_{sg,pt,ry,s}$). Depending on the perspective (p), e.g., vehicle user or society, the manufacturing cost can be increased by a manufacturer profit margin factor (M_p) and value added taxes (VAT_p). The manufacturing costs are distributed over the vehicle's lifetime using a residual value factor ($Res_{ry,a}$) that depends on the vehicle's registration year (ry) and its age (a), to consider vehicle technology depreciation, and discounted using a discount rate (DR_p) to reflect time preferences according to the perspective of the user or society. The following formula is used to calculate the annual manufacturing costs:

$$TechCost_{sg,pt,ry,s,a,p} = cost_{sg,pt,ry}\left(z_{sg,pt,ry,s}\right) \cdot \left(1 - Res_{ry,a}\right) \cdot \left(1 + M_p\right) \cdot \frac{1 + VAT_{ry,a,p}}{\left(1 + DR_p\right)^a} \tag{6}$$

Total fuel and energy costs

The annual fuel and energy cost ($EnCost_{sg,pt,s,a}$) is calculated as the sum of the product of the amount of fuel and energy of a given type of vehicle consumes with the mileage and the costs for the respective fuel type. Indices for vehicle age (a) and projection year (py) are used to trace energy costs over the vehicle's lifetime. Fuel and energy prices can vary with the projection year to reflect assumed fuel price trajectories, and as vehicle activity varies with its age. Vehicle age results as the difference between the projection year and the registration year of a vehicle. Analytically, the total fuel and energy cost per vehicle type in a given year is calculated as follows:

$$EnCost_{sg,pt,ry,s,a} = \frac{EC_{sg,pt,ry,a} \cdot MC_{sg,pt,s,a} \cdot CC_{pt,s,ry,a} + EE_{pt,s,ry,a} \cdot ME_{sg,pt,s,a} \cdot CE_{pt,s,ry,a}}{\left(1 + DR_p\right)^a} \tag{7}$$

where $MC_{sg,pt,s,a}$ and $ME_{sg,pt,s,a}$ are the kilometres driven using liquid or gaseous fuels and electric energy, respectively; $CC_{pt,s,ry,a}$ is the specific fuel cost in a projection year; and $EE_{pt,s,ry,a}$ is the specific energy cost. Depending on the perspective, the fuel and energy costs can include value added and excise taxes (for end users) and are discounted over time.

Operation and maintenance cost

Operation and maintenance costs ($OMCost_{sg,pt,s,ry,a}$) are considered as an annual cost, varying by vehicle powertrain and segment or group. They can include value added tax (VAT), and are discounted (with discount rates DR depending on the perspective):

$$OMCost_{sg,pt,s,ry,a} = OM\_Base\_Cost_{sg,pt,s,ry,a} \cdot \frac{1 + OM\_VAT_{ry,a,p}}{\left(1 + DR_p\right)^a} \tag{8}$$

where $OM\_Base\_Cost_{sg,pt,s,ry,a}$ is the base maintenance cost without VAT, and $OM\_VAT_{ry,a,p}$ is the respective VAT rate.

Further component costs over vehicle lifetime, e.g., possible battery replacement in the lifetime of a battery electric truck, can be included on top of other maintenance costs.

Perspectives and scenarios

One of the purposes of the DIONE model is to allow the comparison of TCO results for different scenarios, e.g., to assess the impact of different CO_2 standard levels on user groups or society. Therefore, the model allows to set different perspectives, and to compare scenarios.

The perspectives, such as first, second, or third end user, or societal perspective, are associated with different timeframes for vehicle use, set for the TCO calculations. As a default, e.g., for cars and vans, it is assumed that the first user keeps the vehicle over its first five life years, the second user from vehicle life year six to ten, and the third for life years eleven to fifteen, whereas in the social perspective, the TCO is calculated over vehicle lifetime. Moreover, some parameters such as taxation settings and discount rates vary by perspective (e.g., taxation is considered as a transfer in the societal perspective, and hence is not taken into account as a cost in the TCO calculation).

Scenarios are used to evaluate either different policy options or changes in exogenous conditions, e.g., setting fleet CO_2 standards of varying stringencies, making different assumptions on the development of fuel or energy prices, changing fleet composition trajectories or activities. Typically, a reference or baseline scenario is defined that represents business as usual, and one or more policy scenarios are developed, for which the results are evaluated versus the reference scenario. For each scenario, all perspectives can be evaluated.

Cumulative costs and scenario comparisons

The cumulative costs representing the total costs per cost type, scenario and perspective are calculated as follows, using the results obtained from (6), (7) and (8):

$$\begin{aligned} TechCost_{s,ry} &= \sum_{sg,pt,a} TechCost_{sg,pt,s,ry,a} \\ EnCost_{s,ry} &= \sum_{sg,pt,a} EnCost_{sg,pt,s,ry,a} \\ OMCost_{s,ry} &= \sum_{sg,pt,a} OMCost_{sg,pt,s,ry,a} \end{aligned} \tag{9}$$

For the age, the sum is calculated over the time indexes depending on the perspective. To obtain fleet results for each scenario, the sum over all combinations of vehicle segment or group and powertrain in the fleet is calculated.

Finally, the **scenarios** are used to evaluate different policy options or exogenous trends versus a reference scenario. For example, by setting different CO_2 emission reduction targets in the cross optimization module, different TCO outcomes can be derived for business as usual (reference) and policy alternatives. The DIONE model user can assess the economic impacts of these different policy options, from the perspective of vehicle users or the society, by calculating the costs differences between a given policy scenario s and a reference scenario ref.

$$\begin{aligned} \Delta TechCost_{s,ry} &= TechCost_{s,ry} - TechCost_{\mathrm{ref}\ ry} \\ \Delta EnCost_{s,ry} &= EnCost_{s,ry} - EnCost_{\mathrm{ref}\ ry} \\ \Delta OMCost_{s,ry} &= OMCost_{s,ry} - OMCost_{\mathrm{ref}\ ry} \end{aligned} \tag{10}$$

According to equation (5), the sum of the results of the three equations in (10) corresponds to the total cost induced by policies and trends reflected in scenario s. The comparison of the TCO results for several scenarios allows assessing different policy options. An example is presented in the following section.

2 Use Case I: Light-duty vehicles

To illustrate the theoretical model description with a practical use case, this section presents exemplary assumptions and results obtained running the current DIONE version II for light-duty vehicles.

The DIONE cost model was first created and applied in 2017 to assess the economic impact of CO_2 emission reduction policies for cars and vans. The results were documented in Krause et al, 2017. Since those first runs, vehicle technology performance and availability have evolved, technology costs have changed, in particular battery costs, and the prospects for the market uptake of zero-emission vehicles have developed. The model has therefore recently been run using an updated dataset. Moreover, the DIONE model itself was further developed and enhanced, as documented in Section 1 of this report. Therefore, recent results differ from those previously published as described below.

2.1. Cost curves module

Cost curves input data

To run the cost curves module, the following input data must be provided to the model:

- Technology costs, in Euro
- Conventional (gaseous and liquid) fuel consumption reduction and total energy consumption reduction corresponding to each technology, in %
- Incompatibilities between technologies
- Parameters for the transformation, unitless or in Euro.

In this described use case, the data was sourced from analysis made by Ricardo Energy & Environment for the European Commission (Ricardo Energy & Environment et al., forthcoming), where a description of the approach to data collection and processing is given as well.

The DIONE runs have been carried out for the six registration years 2025, 2030, 2035, 2040, 2045 and 2050, and seven light-duty vehicle segments: small, lower medium, upper medium, large cars, and, small, medium, and large vans. Eight powertrains were considered: gasoline and diesel combustion engines, potentially hybridized (SI ICE+HEV and CI ICE+HEV), gasoline and diesel plug-in hybrids (SI PHEV, CI PHEV), gasoline and diesel range-extended electrified vehicles (SI REEV, CI REEV), battery electric vehicles (BEV), and fuel cell electric vehicles (FCEV).

Cost curves were constructed for three cost scenarios: typical, low, and high costs. These last two scenarios have been introduced to account for uncertainties related to the overall rate of cost reduction and technology deployment. For further details see Ricardo Energy & Environment (2016), where this approach was developed and documented in detail.

Cost curve results

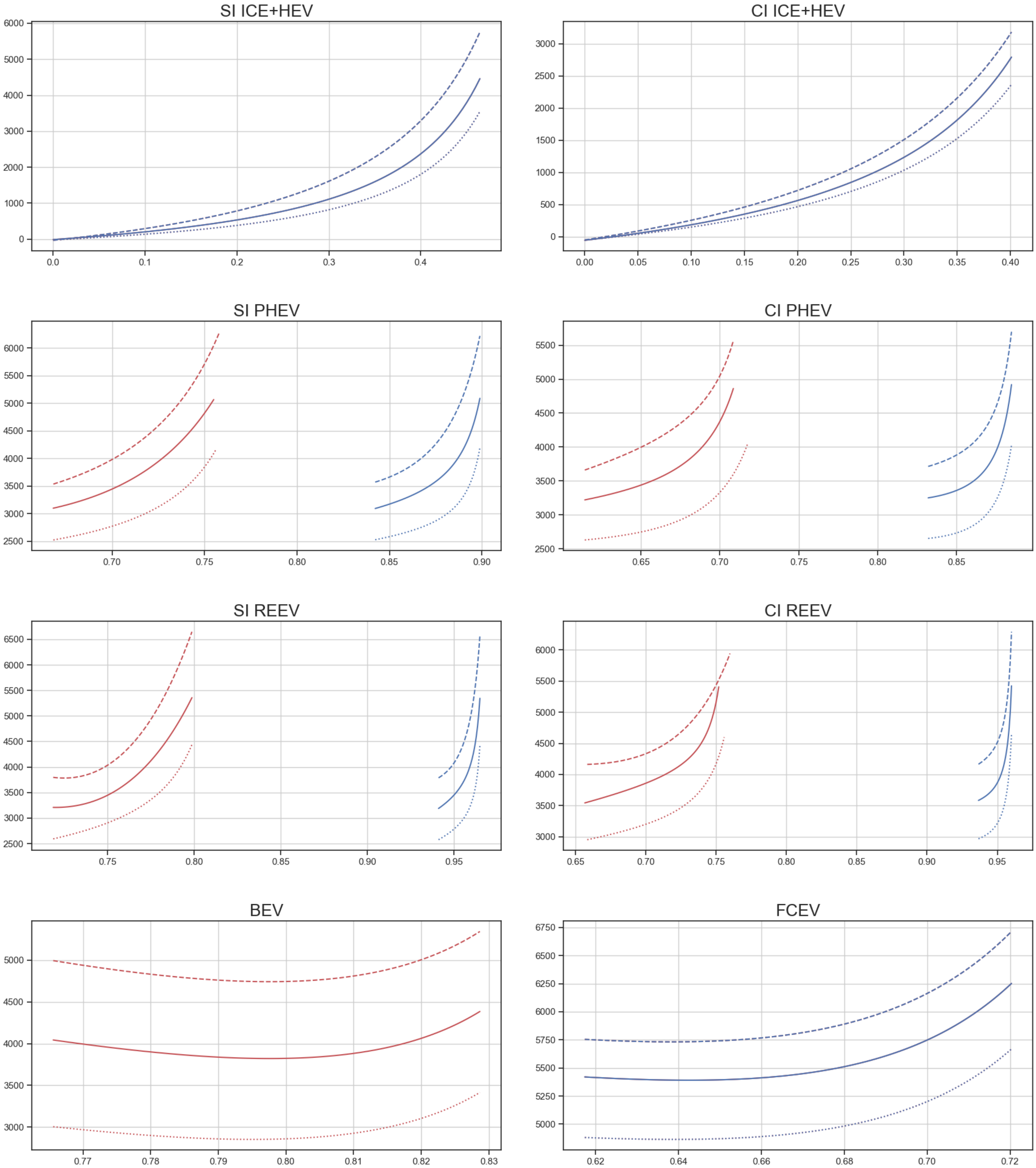
A total of 336 cost curves have been computed for LDVs. All curves show the costs of reducing CO_2 emissions as measured under the Worldwide harmonized Light vehicles Test Procedure (WLTP) drive cycle, relative to a 2013 baseline vehicle of the same segment. Reference powertrains are conventional gasoline spark ignition vehicles for all powertrains using spark ignition motors, as well as for battery and fuel cell electric vehicles (SI ICE+HEV, SI REEV, SI REEV, BEV, and FCEV), and conventional diesel compression ignition vehicles for all vehicles equipped with a compression ignition engine (CI ICE+HEV, CI REEV, and CI REEV). This applies for energy, as well as for CO_2 reference, but reference CO_2 emissions are zero for all non-emitting vehicles.

A selection of the cost curves is shown in Figure 6 for lower medium cars registered in the year 2030 and for all powertrain types. In the graphs, the y-axis displays the technology costs (EUR) for reaching a given energy consumption reduction in a 2030 new car of a given powertrain type, relative to the reference vehicle of the same segment (i.e., lower medium car). The curves are plotted in the order: low (dotted), typical (solid lines), and high cost (dashed). Since the curves have been computed for two reduction modes, conventional and total energy reduction, the x-axis shows both the total energy consumption reduction for the energy curves (red curves) and the liquid and gaseous fuel consumption reduction (blue curves) for the "conventional" mode. In the case of powertrains using only carbon-based fuels, the fuel consumption reduction is proportional to the CO_2 emission reduction. Therefore, their conventional curves can be interpreted as CO_2 emission reduction cost curves. For instance, in the case of a conventional diesel combustion engine vehicle, a 10% reduction in diesel consumption (conventional mode) is equivalent to a 10% reduction in CO_2 emissions.

Given these two types of cost curves, one describing the costs of reducing liquid/gaseous fuel consumption ("conventional curves", shown in blue), and one determining the costs of reducing total energy consumption ("energy curves", shown in red), several curve patterns exist, depending on the powertrain and fuel type:

- Gasoline and diesel internal combustion engine vehicles, optionally with hybridization (SI ICE+HEV and CI ICE+HEV), and fuel cell electric vehicles have overlapping red and blue cost curves. Since all three vehicle types use just one energy carrier to propel the vehicles, the relative fuel consumption reduction is the same as the total energy consumption reduction.
- Battery electric vehicles (BEV) exhibit just the total energy reduction curve (red), because only electricity is used to propel the vehicle, but no liquid or gaseous fuel.
- The remaining powertrains, i.e., plug-in hybrid electric vehicles (PHEV) and range-extended electric vehicles (REEV) present higher reductions in conventional mode than in energy mode. These vehicles can operate in charge-sustaining mode, using liquid fuels for propulsion where CO_2 emissions occur, or in charge-depleting mode, where emissions can be lower or zero. This causes a non-linear relationship between energy consumption reduction and CO_2 emission reduction. For example, a technology bundle enabling an 85% total energy consumption reduction (liquid fuel plus electricity, in red), can lead to an even higher consumption reduction in conventional fuel only (liquid and gaseous fuels, blue curve), as electricity is used in addition. For PHEV and REEV, as for the SI and CI ICE, the blue curve can also be interpreted as a CO_2 emission reduction cost curve, as proportionality between liquid (carbon-based) fuel consumption and CO_2 emission holds also here. A part of the very high CO_2 emission reduction versus the baseline vehicles stems from the fact that electricity substitutes a part of the energy needed for propulsion and has zero tailpipe emissions.

Figure 6. Cost curves for lower medium segment cars, 2030, all powertrains. The y-axis shows the costs (EUR) for achieving the conventional or total energy consumption reduction given by the x-axis (unitless), relative to the baseline vehicle of the same segment. Red curves: total energy consumption reduction cost curves, blue curves: liquid/gaseous fuel consumption ("conventional") reduction cost curves. High (dashed), typical (solid) and low (dotted) curves are shown for each powertrain.



Source: JRC, 2024

As regards the reduction performances of the various powertrains, in general, xEVs reach higher emission reductions than gasoline and diesel hybrid internal combustion engine vehicles. Gasoline and diesel hybrid reduction curves start at zero emission reduction, while the conventional energy (or CO_2 emission) reduction cost curves of xEV powertrains have been rebased to include the benefits of moving from a reference ICE powertrain to that of an xEV vehicle. The costs associated with the reductions vary according to the powertrain type. Also, the shape of the curves depends on the powertrain:

- BEV and FCEV powertrains present U-shaped cost curves, with an inflection point that indicates the position of the minimum cost. The minimum cost point indicates the point up to which the additional costs of technologies to reduce energy consumption are overcompensated by reductions in the battery capacity or hydrogen tank size needed to keep the vehicle range constant.
- For all other powertrains, the minimum cost is the starting point, with the curve gradually increasing until it reaches the maximum cost point. The maximum cost corresponds to the maximum reduction.

Comparison with previous DIONE LDV cost curves

The cost curves presented above differ from the previous DIONE light-duty vehicle cost curves, presented in Krause et al. (2017) for several aspects:

Firstly, the most important quantitative changes stem from the fact that the input dataset containing the technologies and their associated reductions and costs was updated. In particular, the costs and performances of xEVs and hybrid technologies were re-evaluated since those technologies have progressed strongly in recent years. Two more technologies were added (predictive system control and advanced electric boosting), and the period covered by the data was extended to 2050. A discussion of the updates made and presentation of the new dataset is included in Ricardo Energy & Environment et al. (forthcoming). The changes in the dataset have caused a considerable modification in the final curves.

Secondly, the DIONE version II cost curves module has introduced algorithm changes that have led to some minor changes compared to the previous cost curves. In more detail:

- To find the optimal technology packages, the 2023 model version uses a genetic algorithm with a default termination criterion instead of the previous Ant colony optimization approach. To evaluate the performance of the new algorithm, the optimal technology packages found by the new version of DIONE have been compared with those found by the previous approach. In more than 99.99% of the cases, the new Pareto fronts overlap with the previous ones. For the few remaining cases (less than 0.01%), the differences are negligible.
- To fit the cost curves, the new approach has introduced the concept of the optimal Pareto front. This new approach is not directly comparable with the previous implementation. However, it is possible to compare the results of the two methods: The comparison demonstrates that both the previous and the current code implement the same parameter transformation algorithm.
- The use of different machines (laptop, computer) and computational environments can induce minor changes in the results. Distinct computational power, architecture, and versions of Python libraries can cause variations that are, however, negligible.

More detailed comparisons between the code of DIONE versions I and II, as well as performance indicators of the new approach, can be found in Annex 1.

2.2. Cross optimization and TCO modules

Cross optimization input data

The Cross Optimization module uses the optimal Pareto front computed by the Cost Curve module to identify the cost-optimal technologies to reach given emission targets. For running this module, the following data should be additionally provided by the DIONE user:

- The fleet composition, i.e., the number of vehicles registered each year per vehicle segment/group and powertrain.
- The CO_2 emission reduction targets, in gCO_2 per vehicle kilometre, calculated from % reduction levels versus a given base year (2021 in the present application) and the respective base year new fleet emissions. By setting different targets, for reference scenarios and policy scenarios, the impacts of different options for vehicle CO_2 standards can be compared.
- The CO_2 emissions, in g/vkm, WLTP basis, and energy consumed in MJ/km by the reference vehicles.
- The share of the kilometres driven in conventional (combustion engine) mode for PHEV and on conventional fuels for REEV. The fuel emission factors, in gCO_2/MJ, corresponding to the fuels used by the respective baseline powertrains.

For the exemplary runs illustrated in this section, fleet composition and targets used reflect the settings for the target level options low, medium, and high in the EC impact assessment for strengthening the EU LDV CO_2 emissions standards under the European Green Deal (European Commission, 2021a). The target levels are shown in Table 1.

Table 1. Scenarios for new car / van CO_2 target levels (% change versus 2021).

	2025	2030	2035	2040
Baseline	15.0% / 15%	37.5% / 31%	37.5% / 31%	37.5% / 31%
Low	15.0% / 15%	40% / 35%	60% / 55%	80% / 80%
Medium	15.0% / 15%	50% / 40%	70% / 70%	100% /100%
High	15.0% / 15%	60% / 50%	100% / 100%	100% / 100%

Source: JRC, 2024

Baseline vehicle energy consumption and CO_2 emissions were based on data from the EEA's monitoring database[1]. The shares of kilometres driven in combustion engine mode or on conventional fuels for PHEV and REEV were based on Ricardo Energy & Environment et al. (forthcoming). Once the optimal total energy consumption and conventional reduction have been computed using these input values, the results are employed to calculate the total costs of ownership.

TCO input data

The total cost of ownership is calculated as the sum of three terms: the additional manufacturing, the fuel/energy, and the maintenance/operation cost. The optimal technology costs identified after running the cross optimization module are used to calculate the final additional manufacturing costs, while the corresponding conventional and total energy consumption reduction is used to compute the fuel and energy costs.

The following additional data is necessary to run the TCO module:

[1] http://co2cars.apps.eea.europa.eu/

- The technology cost depreciation, to calculate residual values
- The vehicles' activity, i.e., the distance covered per vehicle in each life year
- The fuel and energy price trajectories over time
- The annual operation and maintenance costs per vehicle
- The settings for perspective parameters: Vehicle use periods for different vehicle perspectives, value added tax (VAT), discount rates (DR) and mark-up factor applied to convert technology costs into prices (including dealer margins, logistics, and marketing costs).

Table 2. Input parameters specifying the cost calculation perspectives.

	Perspectives	**Values**
Discount Rate (DR)	Social	4 %
	End user	Car: 11% Van: 9.5%
Markup factor	End user	Cars: 1.4 Vans: 1.11
Value Added Tax (VAT)	End user	20%
Vehicle life years covered by the perspective	Social	1-15
	End user 1	1-5
	End user 2	6-10
	End user 3	11-15

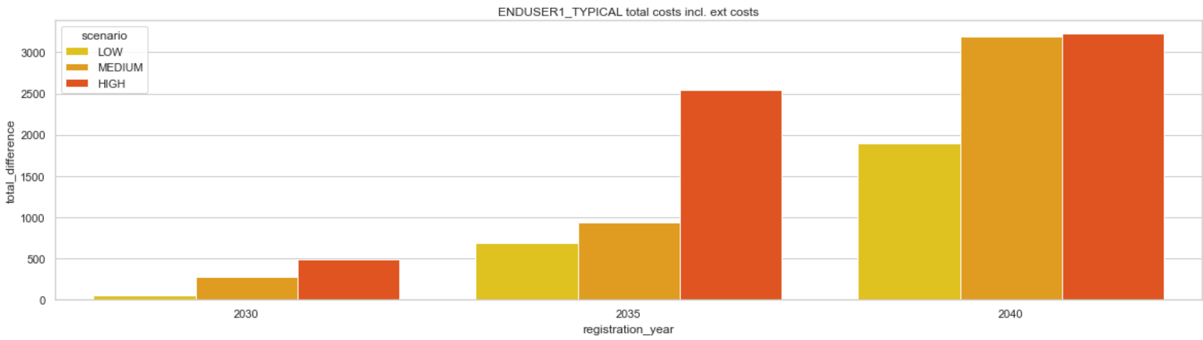
Source: JRC, 2024

In the case of this exemplary run, the vehicle's residual values were kept as in the previous model version, and are based on CE Delft and TNO (2017). Similarly, vehicle activities were kept as previously. Fuel and energy price trajectories were aligned with the Mix scenario developed on behalf of the European Commission for the impact assessment for stepping up Europe's 2030 climate ambition (European Commission, 2020b). This scenario takes into account the policies of the EU's Fit for 55 package which have impacts on the energy system, such as the strengthening of the EU emission trading system and the emissions trading for buildings and road transport, as well as the increased ambition on renewable energy and energy efficiency policies. The operation and maintenance costs were updated based on Ricardo Energy & Environment et al. (forthcoming). Finally, the parameters specifying the settings which vary between the different perspectives for the calculation of total costs of ownership can be found in Table 2. These include the discount rate, reflecting the rate of time preference which is higher for endusers than in the social perspective, the markup factor which includes dealer margins, logistics and marketing costs (set to one for the social perspective), the settings for value added tax, which represents a cost only in the end user perspectives, and the vehicle life years covered in the respective perspectives.

TCO results

The total cost of ownership results of this module, run with the above presented inputs, are presented below, for the three target levels low, medium, and high, and for the years from 2030 to 2040. Outcomes are presented below for the typical cost estimate, and from the perspective of a first vehicles user who owns and runs a vehicle during its first and fifth life year. Results show average savings over the vehicles fleet, compared to the baseline where no strengthening of CO_2 standards occurs after 2030 (see Table 2 for CO_2 standards settings).

Figure 7. Average savings in total TCO versus baseline, for passenger cars, from the first end user perspective, for low, medium and high CO_2 standards, at typical technology costs.

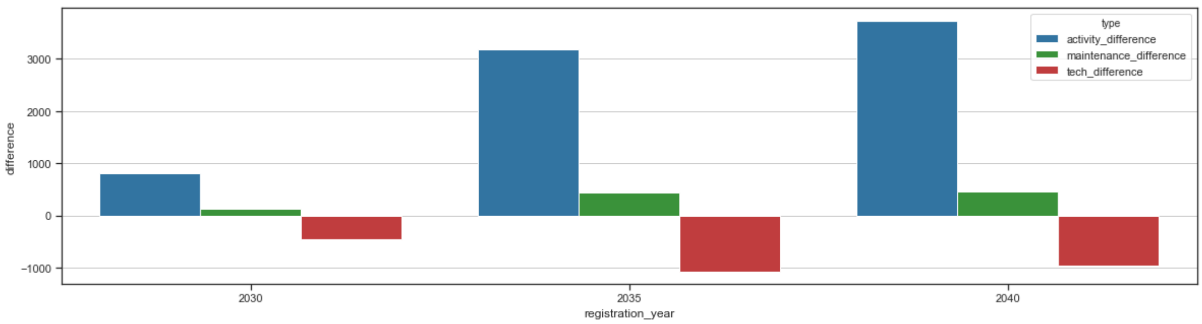


Source: JRC, 2024

As can be seen, from the perspective of the first vehicle end user, setting more stringent standards than in place in the baseline is beneficial, as it results in savings over the vehicle use phase. The higher the target, the higher the total savings over the usage period, compared to a baseline where no strengthening of standards occurs after 2030. This effect can be seen both when comparing different standard levels, and when tracing the increasingly strict standards over time. The net savings are explained mainly by the fact that the savings in the fuel and energy costs exceed the higher upfront capital costs of more efficient and zero- and low-emission vehicles. The different cost types are shown in Figure 8. As can be seen, savings in fuel and energy costs occur over the vehicle use period when stricter standards apply, shown by the blue bars, from the first vehicle user perspective. Additional, but lower savings are caused by somewhat lower average car maintenance costs in case of stricter standards, shown as green bars. These savings are higher than the additional technology costs for the average car in the scenario, shown as the red bars. Thus, the positive total cost of ownership balance previously seen in Figure 7 is explained by the compensation of additional technology costs by the energy and manufacturing cost savings.

For different perspectives, i.e., second and third end users, and from the social perspective, the same trends hold, with increasing total savings for stronger standards and over time.

Figure 8. Average savings in user costs per car versus baseline, by cost type, from the first end user perspective, for a high CO_2 standard scenario at typical technology costs.



Source: JRC, 2024

3 Use case II: Model extensions for heavy-duty vehicles

The heavy-duty vehicle market is characterized by a large variety of vehicles with specific applications and use patterns. The development of reduction cost curves for truck, bus, and coach emissions and energy consumption is the first step in the analysis of emission reduction pathways for heavy-duty vehicles.

DIONE version I was used to assess the economic impacts of the CO_2 standards for the most prominent and widely used classes of heavy-duty trucks in the past, see Krause and Donati (2018). A large-scale extension to further truck classes, buses, and coaches, additional - mostly electrified - powertrains, trailers, and years beyond 2030 has been carried out in parallel to the development of DIONE model version II. The extension covers all modules described in Section 1. As novel elements regard in particular the cost curve module, a brief description of the main additions in terms of cost curves is given in this section.

3.1 Extension of cost curves to a variety of heavy-duty vehicle groups and powertrains

The DIONE model I version was used to assess the costs of new truck CO_2 emission standards for the four vehicle groups regulated in the present EU heavy-duty vehicle CO_2 standards (EU) 2019/1242 (EU 2019), i.e., groups 4, 5, 9, and 10. It covered two powertrains (diesel and liquid natural gas combustion engines), and the two years 2025 and 2030 (see Krause and Donati, 2018).

Table 3. Heavy-duty vehicle groups and powertrains previously and newly covered by the DIONE model.

		Combustion Engine Only						Advanced Electrified Powertrains				
Vehicle type (1)(2)	Vehicle (3) Group	CI ICE DSL	CI HEV DSL	CI ICE LNG	SI ICE CNG	SI ICE LNG	SI ICE H2	CI PHEV DSL	BEV	FCEV	FC-REEV	BCEV
Trucks between 5 and 7.5t	0 ML	X	X		X		X	X	X	X	X	
Heavy trucks below 16t	1	X	X		X		X	X	X	X	X	
	2	X	X		X		X	X	X	X	X	
	3	X	X		X		X	X	X	X	X	
Heavy trucks above 16t	4	**X**	X	**X**	X		X	X	X	X	X	X
	5	**X**	X	**X**		X	X	X	X	X		X
	9	**X**	X	**X**		X	X	X	X	X	X	X
	10	**X**	X	**X**		X	X	X	X	X		X
	11	X	X	X	X		X	X	X	X	X	X
	12	X	X	X		X	X	X	X	X		X
	16	X	X	X	X		X	X	X	X	X	
Busses	P31	X	X		X		X	X	X	X	X	
	P33	X	X		X		X	X	X	X	X	
	P35	X	X		X		X	X	X	X	X	
Coaches	P32	X	X	X		X	X	X	X	X	X	
	P34	X	X	X		X	X	X	X	X	X	

(1) Bold **X**: Powertrains and vehicle groups included in the DIONE model version I of 2019. Blue shading: Additional powertrains or vehicle groups in DIONE model version II, 2023.

(2) Powertrains: CI – compression ignition, SI – spark ignition, ICE – internal combustion engine, HEV – Hybrid Electric Vehicle, PHEV – Plug-in Hybrid electric vehicle, BEV – battery electric vehicle, FCEV – Fuel cell electric vehicle, FC-

REEV – Fuel cell range-extended electric vehicle, BCEV – Battery catenary electric vehicle. Fuels: DSL – Diesel, CNG – compressed natural gas, LNG – Liquefied natural gas, H2 – Hydrogen.

(3) See regulation (EU) 2017/2400 for the technical characteristics of the heavy-duty vehicle groups.

Source: JRC, 2024

While transiting into DIONE model version II, the model was extended to cover many additional segments and powertrains, to reflect the European green deal's broader scope and higher climate ambition. As regards vehicle categories covered, on top of the previously regulated truck groups, the model was extended to medium trucks (groups 1, 2 and 3), as well as additional heavy trucks of groups 11, 12, and 16[2]. Moreover, buses and coaches as well as trailers were newly introduced.

A major extension of the powertrain/fuel combinations was also undertaken. On the one hand, this regards additional combustion engine options fuelled by gaseous fuels, extending the range of fuels covered to diesel, compressed natural gas, liquefied natural gas, and hydrogen. On the other hand, cost curves for electrified powertrains have been developed, including hybrids, plug-in hybrids, battery electric vehicles, fuel cell electric vehicles, fuel cell range extenders, and battery catenary electric vehicles. The input data needed to develop the new heavy-duty vehicle cost curves, in particular the costs and CO_2 reduction potentials of diverse technologies, were taken from analysis carried out by Ricardo Energy & Environment for the European Commission. An overview of the powertrain/fuel combinations now present is shown in Table 3. Cost curves were developed for different cost scenarios and in five-year steps from 2020 to 2050. The latter constitutes an additional extension of the model's scope, as previous cost curves covered only the years up to 2030.

3.2 Development of three-dimensional curves for bi-fuelled powertrains

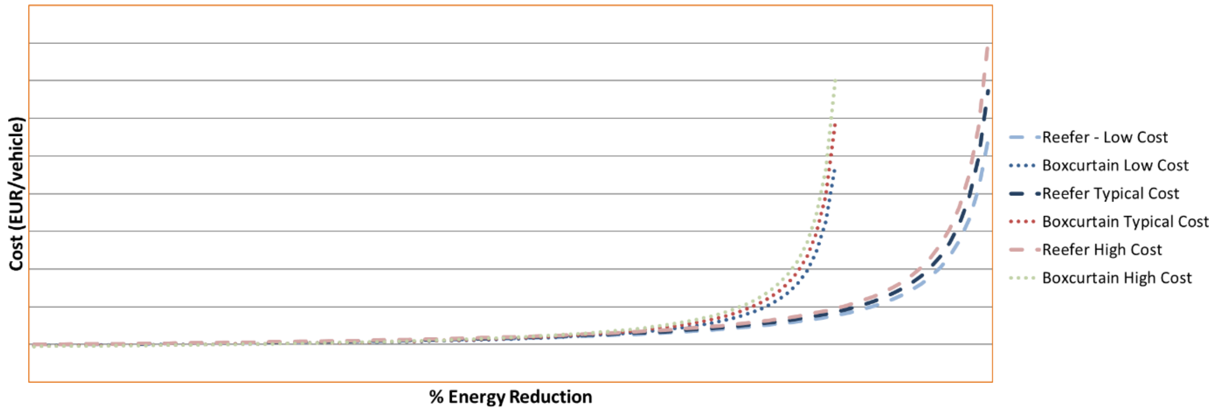
The major extension of scope for heavy-duty vehicles, and in particular the inclusion of vehicle types that use more than one fuel type, triggered the need for a rigorous approach to both CO_2 emission and energy consumption calculation where the two do not coincide. The reduction in CO_2 emissions is relevant for meeting emission standards, whereas the corresponding reduction in energy is crucial for calculating fuel costs, as a part of total costs of ownership of the vehicles. Therefore, the approach of three-dimensional cost curves was developed and first implemented for heavy-duty vehicles, see model enhancement described in section 1.1.

3.3 Development of trailer cost curves

Heavy-duty truck categories of tractor type, such as group 5 or 10, can be operated with various semi-trailers. In addition, the certification procedure (EU) 2017/2400 mandates the use of full trailers under specific operating conditions for many categories of full trucks or tractors. Although trailers do not consume energy by themselves, their energy efficiency has an impact on the total towing vehicle energy consumption, which must be determined according to the provisions of Regulation (EU) 2022/1362 as of January 2024.

[2] Truck groups are defined in Regulation (EU) 2017/2400

Figure 9. Schematic example of cost curves for semi-trailers of box curtain and reefer body types.



Source: JRC, 2024

To better understand the available options to reduce energy consumption in freight transport, trailer cost curves have been developed for the first time. As trailers can be combined with different towing vehicles and thus can reduce the consumption of different fuels, the trailer curves are defined to describe the costs of implied energy consumption reduction. Cost curves have been developed for drawbar trailers towed by trucks of groups 4, 9, and 11 and for semi-trailers added to groups 5, 10, and 12 trucks. Moreover, for each of these trailers, two body options, a box curtain body and a refrigerated trailer (reefer), have been considered, and different cost scenarios are evaluated. A schematic example of trailer cost curves is shown in Figure 9. It can be seen that reefer trailers can improve their energy consumption more strongly than box curtain body trailers. This is due to additional improvements that regard the cooling system.

4 Conclusions

The JRC's DIONE cost model is used to calculate end user and social costs of road vehicles and to compare how different policies may impact them. The model has been developed by the JRC since 2014. This report provides technical and mathematical documentation of the second, fully updated DIONE model version II, and presents an overview of the main extensions made, both for light- and heavy-duty vehicles. More resources, as well as access to the cost curve module, are available at the DIONE website, https://dione.jrc.ec.europa.eu.

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List of abbreviations and definitions

DR	Discount Rate
EU	European Union
HDV	Heavy-Duty Vehicles
LDV	Light-Duty Vehicles
JRC	Joint Research Centre
LPG	Liquefied Petroleum Gas
TCO	Total Cost of Ownership
VAT	Value Added Tax
WLTP	Worldwide harmonized Light vehicles Test Procedure
xEV	Advanced Electrified Vehicle, including BCEV, BEV, FCEV, REEV, PHEV

Powertrains and Fuels:

BCEV	Battery Catenary Electric Vehicle
BEV	Battery Electric Vehicle
CI	Compression Ignition
CNG	Compressed Natural Gas
FCEV	Fuel Cell Electric Vehicle
FC REEV	Fuel Cell Range-Extended Electric Vehicle
HEV	Hybrid Electric Vehicle
ICE	Internal Combustion Engine
ICE-H2	Internal Combustion Engine, run with hydrogen as fuel
LNG	Liquefied Natural Gas
PHEV	Plug-in Hybrid Electric Vehicle
SI	Spark Ignition

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Annexes: DIONE model Refactoring – major changes and testing

The present report presents the refactored DIONE model version II. Intense testing has been carried out to ensure the reliability and efficiency of the new software. The major computational changes and the results of tests comparing the performance of the new software to the previous version are summarized in the following appendices, in a dedicated section for each of the modules.

Annex 1. DIONE cost curve model

Pareto front

The first version of the DIONE cost curve model, in use at JRC between 2016 and 2020, applied an optimization approach (named `ACO` optimization), combining Ant Colony Optimization and Local Search, documented in Donati et al. (2020), to identify optimal technology packages for reducing CO_2 emissions from road vehicles.

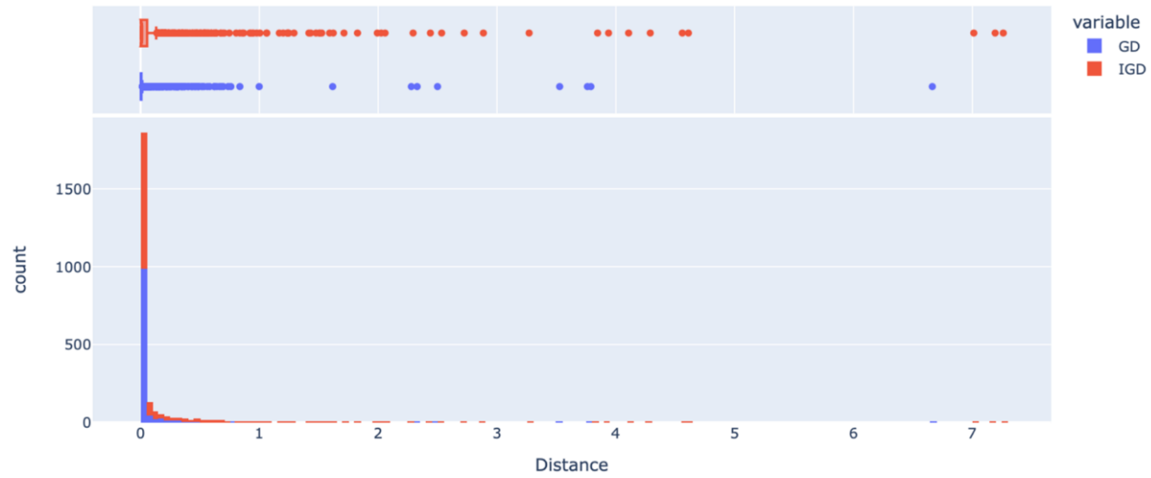
The `ACO` approach was computationally demanding, and it has required a big machine with overall 128 CPUs and 1.9Tb of RAM (i.e., 14Gb per process). The algorithm set every optimization to run for 10 minutes to find the Pareto front.

Hence, we have decided to replace the previous approach with a hybrid system that uses brute force optimization when there are less than 16 technologies; otherwise, it uses a genetic algorithm (i.e., `NSGA2` implemented by the library pymoo) with a default termination criteria. This approach and its implementation have a considerable speed improvement since now every optimization requires about 20 seconds. Moreover, it reduces the resources needed per process to a maximum 1Gb of RAM. On average, it requires 200Mb.

The new approach results were compared with the previous ones using the generational distance (GD) and the inverted generational distance (IGD) as performance indicators. The GD and IGD measure the mean Euclidean distance from each `NSGA2` Pareto point to the nearest `ACO` Pareto point and vice-versa. Hence, when GD=IGD=0, the two Pareto fronts are identical. For our analysis, we can assume that when the GD is lower than 1€, the curves are graphically overlapping.

The following chart shows the histogram of generational and inverted generational differences between ACO results (old code) and new code. From the upper part of the chart, we can observe that 75% percentiles are equal to 0.0007 and 0.06, respectively, for GD and IGD. The findings show that just a few cases (i.e., eight over 1176) are not "overlapping" (i.e., GD > 1). In these cases, we have performed a specific test, which replaces the termination criteria with a time-dependent one that forces the `NSGA2` algorithm to run for 10 minutes.

Figure A.10: Histogram (lower part) and percentiles 75% and 95% (upper part) of GD and IGD between ACO results (old code) and new code



Source: JRC, 2024

The findings showed that the Pareto fronts calculated using the previous and new code with 10 minutes termination criteria are identical. The new code with its termination criteria has a higher deviation from the old code when the Pareto front has some discontinuities. This deviation is negligible when using the optimal Pareto front concept.

In conclusion, the new approach with basic termination criteria is accepted because it is 30 times faster with respect to the old one, and it finds Pareto fronts that mainly overlap with the ones calculated using the old approach. A few cases (i.e., eight over 1176) are not "overlapping", but the differences are acceptable.

Fitting curves

Based on the optimal packages found by the previous step, the DIONE model can construct the vehicle's CO_2 emission reduction cost function by fitting a model that represents them.

The new approach has introduced the concept of the optimal Pareto front. A reasonable solution to reduce technology cost is a linear combination of two technology packages for cost curves used at the fleet level. For example, if we have 100 vehicles with package A and 100 with package B, the result at fleet level is equal to the average point of CO_2 emission reduction and implementation cost between the two packages. Hence, the optimal Pareto front (the optimal packages' distribution) is defined in a discrete form by a series of segments. The `convex hull` algorithm implemented by the `scipy` library is used for finding the optimal points that define the linear front from the raw Pareto cloud.

This new approach is not directly comparable with the previous implementation. The last was using the raw Pareto cloud and some custom-made rules for fitting a continuous analytical function. The rules consist of finding and fixing two curve points to control the curve calibration.

The old approach makes the fitting unstable because it depends on the Pareto cloud density distribution. Cost curves representing the cost of reducing emissions at fleet level are the standard case, but a representation of the costs to reduce emissions of a single vehicle is also needed to calculate payback periods from the perspective of a single user. Therefore, the new approach implements a method for fitting the cost curve in a continuous analytical form. It consists in fitting the curve using 1000 equally distributed points of the optimal Pareto front. The curve has a stable fitting that is not influenced by the Pareto cloud. The fitting algorithm used for fitting the parameters of the curves is the Levenberg-Marquardt method, also known as the damped least-squares (DLS) method. It is used to solve non-linear least squares problems.

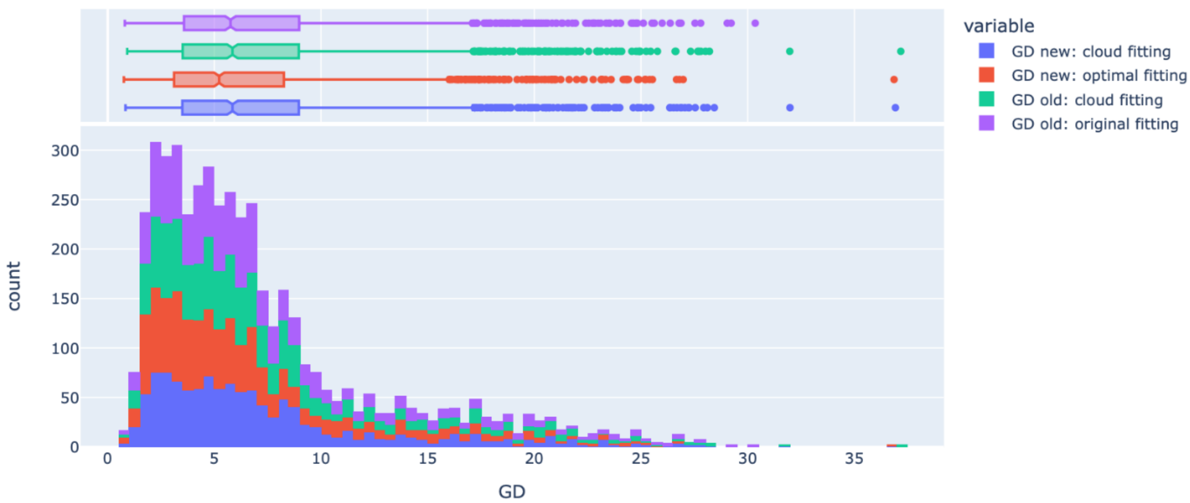
We improved the original implementation of the fitting algorithm and simplified it to have comparable results for testing the parameter transformation results (i.e., baseline adjustment, scaling for batteries, scaling for overlapping technologies, and re-baseline xEV).

The results of the two approaches are compared using the GD from the optimal Pareto front and the coefficient of determination R2 between the old and new code using 1000 equally distributed points. The following table and histograms show the results for:

- **GD new: cloud fitting**: GD from the optimal Pareto front to the new code in python implementing the cloud fitting,
- **GD old: cloud fitting**: GD from the optimal Pareto front to the old code in R implementing the cloud fitting,
- **GD old: original fitting**: GD from the optimal Pareto front to the solution given by the corrected old code in R,
- **GD new: optimal fitting**: GD from the optimal Pareto front to the new code in python fitting the optimal cost curve,
- **R2 new vs. old: cloud fitting**: R2 between the old code in R and the new code in python both implementing the cloud fitting,
- **R2 old original vs. new optimal fitting**: R2 between the old code in R and the new code in python.

Figure A.11 shows the histograms (lower part) and the 75% and 95% percentiles upper part of GD described above. The new approach of optimal cost curve fitting has, on average, the best GD because the Pareto cloud does not influence it. Moreover, all methods are not graphically overlapping because the mean GD is always greater than 1.

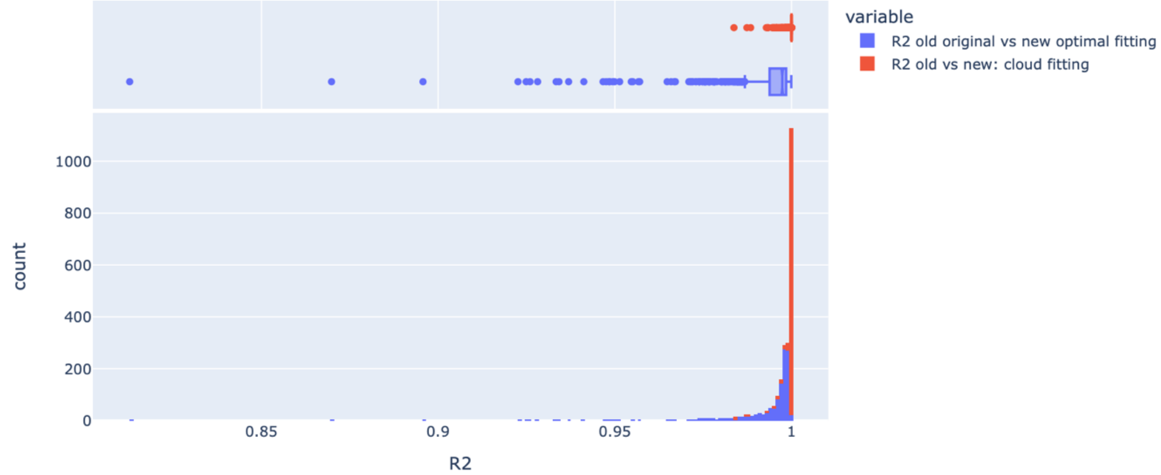
Figure A.11: Histogram (lower part) and percentiles 75% and 95% (upper part) of GD distribution fitting methods vs optimal Pareto front



Source: JRC, 2024

Figure A.12 shows the histograms (lower part) and the 75% and 95% percentiles (upper part) of R2 described before. The coefficient of determination R2 comparing the old code versus the new one. It is evident that the old code in R and the new code in python both implementing the cloud fitting are overlapping (i.e., R2 > 0.95). The worst R2 coefficient is 0.98. Therefore, we demonstrated that the old and new code implement the same parameter transformation algorithm. Some cases (i.e., using cloud fitted approach) are not overlapping because the raw Pareto clouds are not the same - due to the difference of `ACO` and `NSGA2` results.

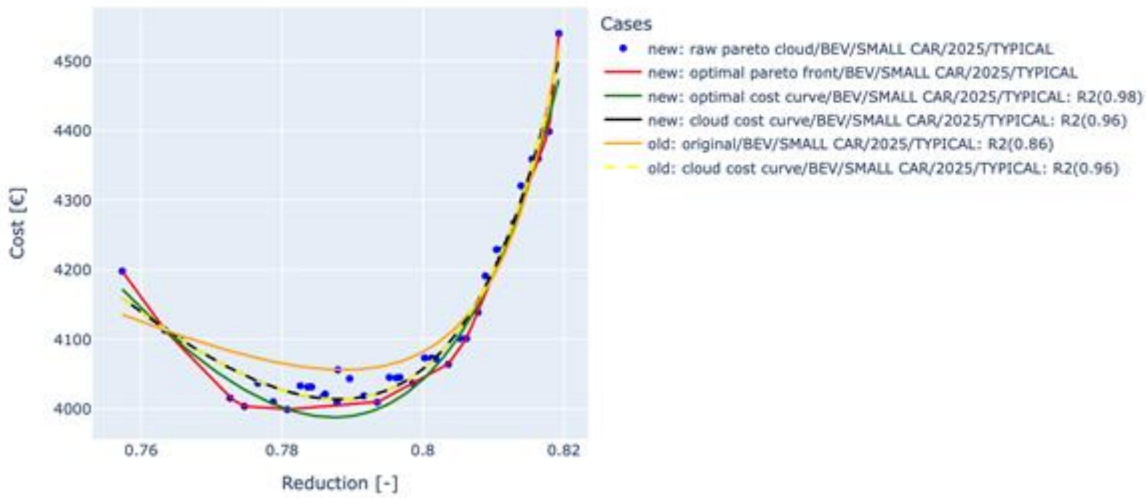
Figure A.12: Histogram (lower part) and percentiles 75% and 95% (upper part) of R2 distribution old code vs new code



Source: JRC, 2024

Moreover, we can observe a higher deviation from the old code using the original fitting approach and the new code using the optimal fitting. The following chart shows one of the worst cases - i.e. when R2 < 0.95. The graph also reports the R2 coefficients from the optimal Pareto front and the relative fitted curve.

Figure A.13: Example of a case with large divergence between old cost curve (orange) and new approaches, for small BEV cars, 2025.



Source: JRC, 2024

In conclusion, we have verified that the new python code produces the same results as the old R code for the parameter transformation (i.e., baseline adjustment, scaling for batteries, scaling for overlapping technologies, and re-baseline xEV). The DIONE vII Cross-Optimization Module does not use the fitted curves, because all fitting methods produce a GD > 1. Therefore, it is better to use the optimal Pareto front at the fleet level while the cloud fitting approach can better suit the vehicle level, and fitted curves remain an output of the DIONE cost curve module.

Annex 2. Cross-Optimization Module

The DIONE Cross-Optimization Module (named `Xopt`) is developed to determine the cost-minimizing distribution of CO_2 and energy consumption reduction over all powertrains and segments, given a CO_2 reduction target and fleet composition scenario as well as the cost curves. The old code uses the `Nelder-Mead` algorithm to find the optimal points, while the new code uses the `Particle Swarm Optimization` (i.e., PSO). The later has been chosen because it improves the cost solution results. Moreover, to improve the speed performance, the new code reduces the cost curve solution space removing all points that have CO_2 reduction lower than the CO_2 reduction at minimum cost.

The `Xopt` testing consists in comparing:

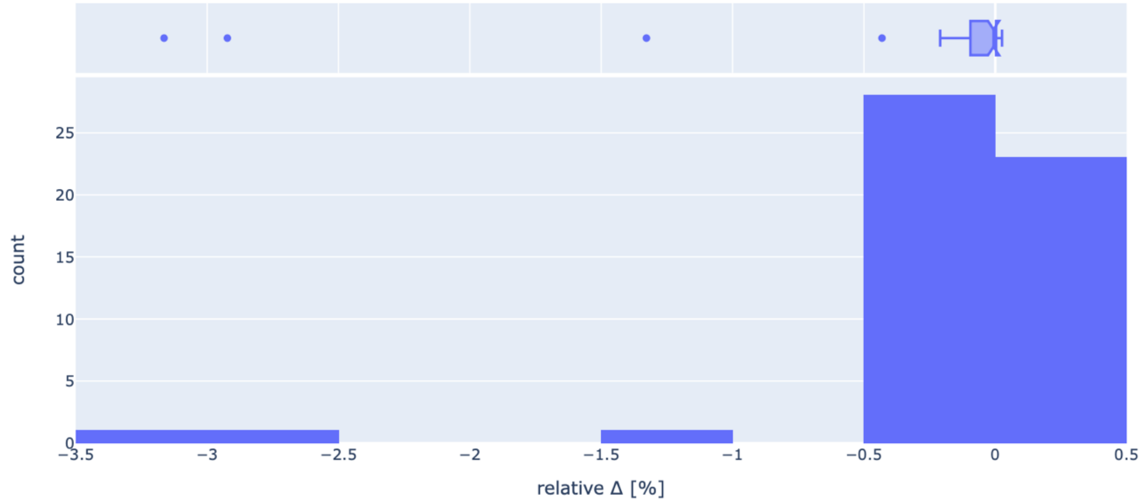
- [test A]: the new Xopt code vs. the old one using the same inputs - i.e., the cloud fitted curves from old corrected code;
- [test B]: the new Xopt code using the cost curves from a scenario run with the old code vs. the old results from that specific run;
- [test C]: the new Xopt code using the optimal Pareto vs. the new Xopt code using the optimal cost curve;
- [test D]: the new Xopt code using the optimal cost curve vs. the new Xopt code using the cloud fitted cost curve.

The findings are shown and commented in the following sections. In conclusion, the new code can always find the same or a better overall cost solution than the old code. The old code, in some cases, did not find the optimal solution at a cost minimum for BEV and FCEV, but we fixed the delivered results with a post-processing stage. The optimal Pareto is the most accurate solution, and it is comparable with the old code with a maximum deviation of 8%. The cost curve types, defined above for each test, do not influence the Xopt results.

Test A

The old code, in some cases, did not find the optimal solution at a cost minimum for BEV and FCEV. These powertrains are not influencing the distribution of efforts among other powertrains because they have 100% CO_2 emission reduction, regardless of the energy consumption reduction achieved. Therefore, we have decided to set to zero their implementation cost for testing purposes. The following histogram (lower part) and the 75% and 95% percentiles upper part shows the overall cost deviations between the old vs. new code using the old cloud-fitted cost curves and excluding BEV and FCEV powertrains. Negative values of the overall cost deviation are when the new code finds a cheaper solution respect to the old code. Therefore, the new code can always find the same/similar (the differences are due to the machine error) or even better overall cost solutions than the old code.

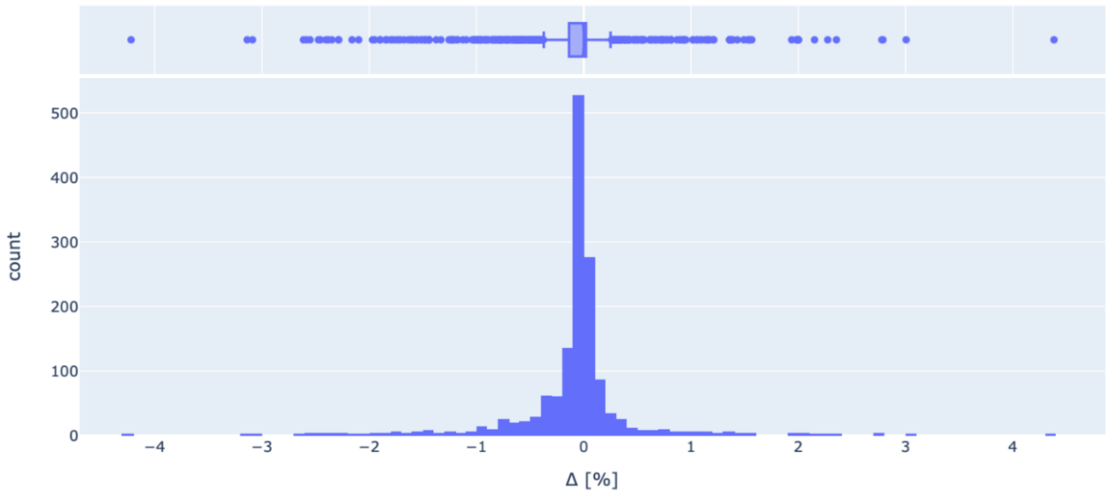
Figure A.14: Overall cost difference (old vs new code) using the old cloud fitted cost curves and excluding BEV and FCEV powertrains



Source: JRC, 2024

Figure A.15 shows CO_2 reduction difference for each powertrain between the old vs. new code using the old cloud fitted cost curves and excluding BEV and FCEV powertrains. The CO_2 reduction difference for each powertrain is contained mainly (95% of the cases) within 0.3%.

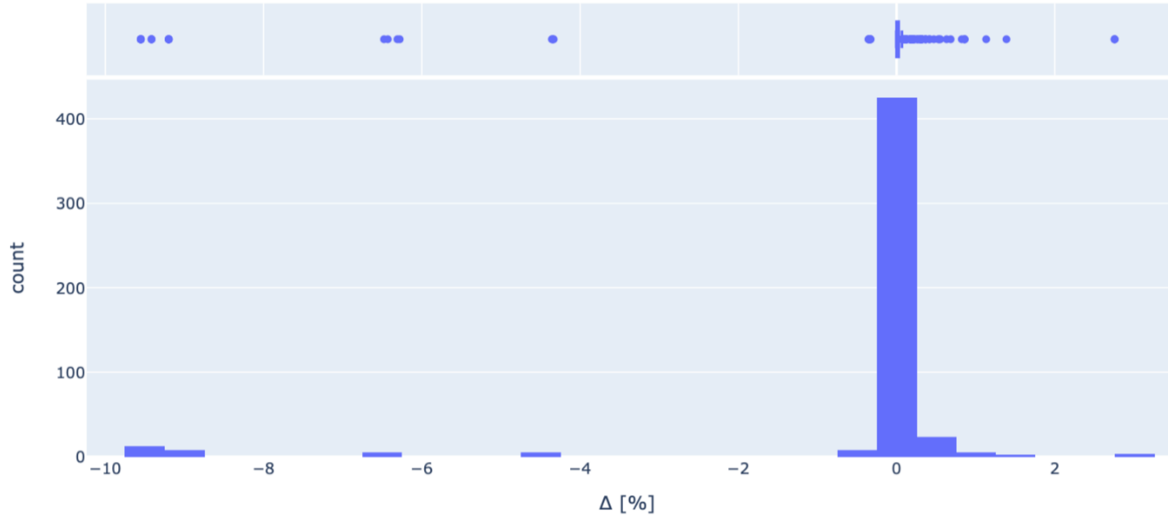
Figure A.15: CO_2 reduction difference (new - old) using the old cloud fitted cost curves and excluding BEV and FCEV powertrains



Source: JRC, 2024

Figure A.16 shows energy reduction differences for BEV and FCEV powertrains between the old vs. new code using the old cloud fitted cost curves. For them, there is a considerable deviation because the old code did not find the optimal solution.

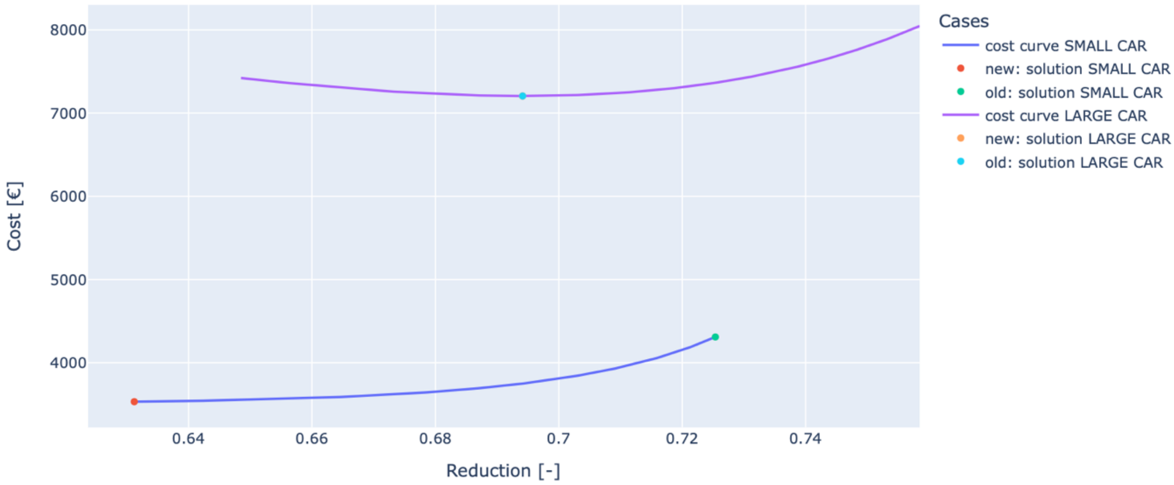
Figure A.16: Energy reduction difference (new - old) using the old cloud fitted cost curves and only BEV and FCEV powertrains



Source: JRC, 2024

Figure A.17 shows two cases, one where the old code succeeded (i.e., for small cars FCEV the new and old solutions are overlapping) and one where it failed (i.e. for large cars FCEV, the new approach finds the minimum value while the old code has selected the maximum).

Figure A.17: Comparison of solutions from old vs new code, for FCEV cars in 2035, for a given (same) scenario setting

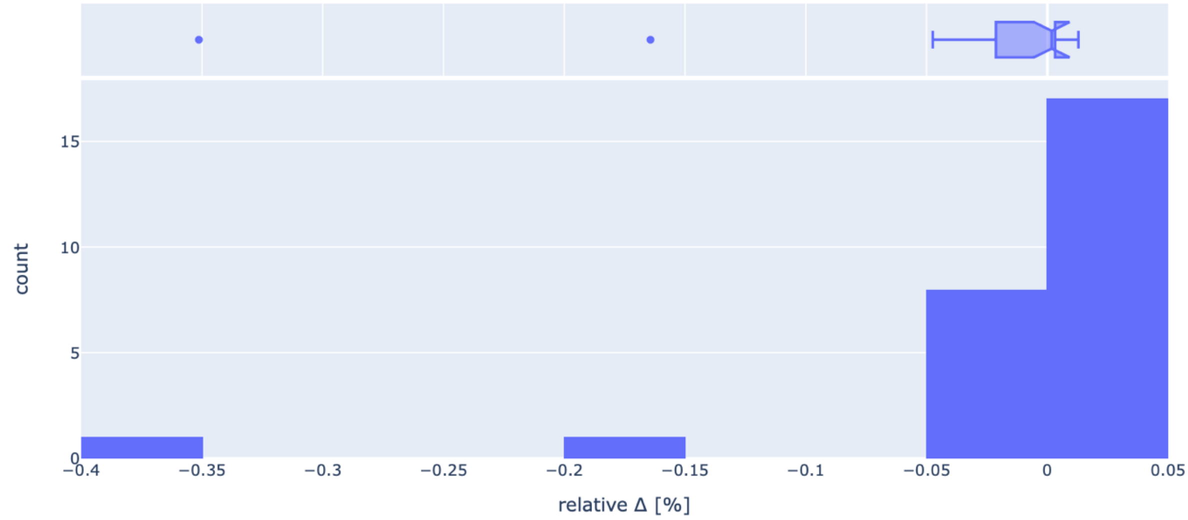


Source: JRC, 2024

Test B

This test compares a run of the new code using previous cost curves and scenario inputs with results obtained running the previous code, all scenario settings equal. Before comparison, the BEV and FCEV powertrains solutions for the old code results were corrected in a post-processing stage. The histogram in Figure A.8 shows that the new code can always find the same/similar (the differences are due to the machine error) or even a better overall cost solution than the old code.

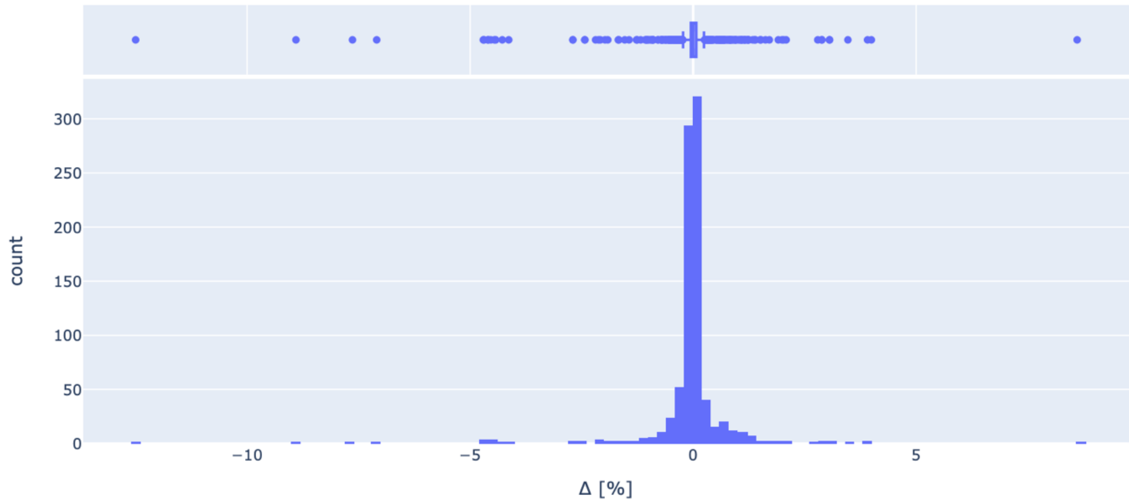
Figure A.18: Overall cost difference (old vs new) using the same previously fitted cost curves. Negative values indicate that a better solution has been found by the new code.



Source: JRC, 2024

Figure A.19 shows the CO_2 reduction difference for each powertrain between the old vs. new code, using again the old cold curves in both runs. The CO_2 reduction differences for each powertrain is contained mainly (95% of the cases) within 0.24%.

Figure A.19: CO_2 reduction difference (new vs old), using previously fitted cost curves

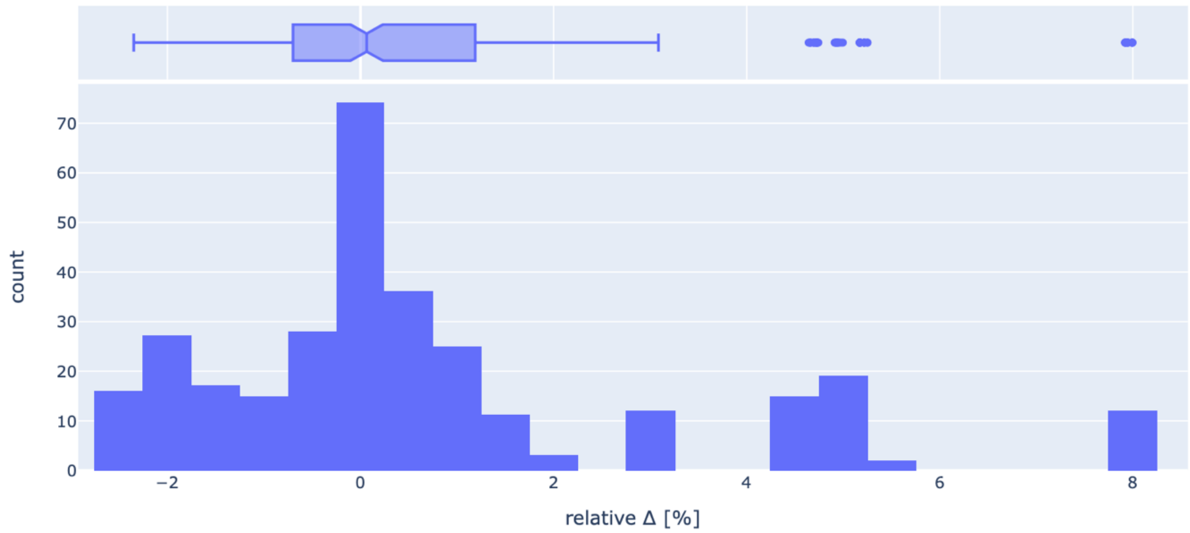


Source: JRC, 2024

Test C

This test compares the new code using the optimal Pareto vs. the new code using the optimal cost curve. As expected, the histogram in Figure A.10 shows an overall cost solution difference that is more wide-spread then the previously shown comparisons between old and new code. The maximum deviation is below 8%.

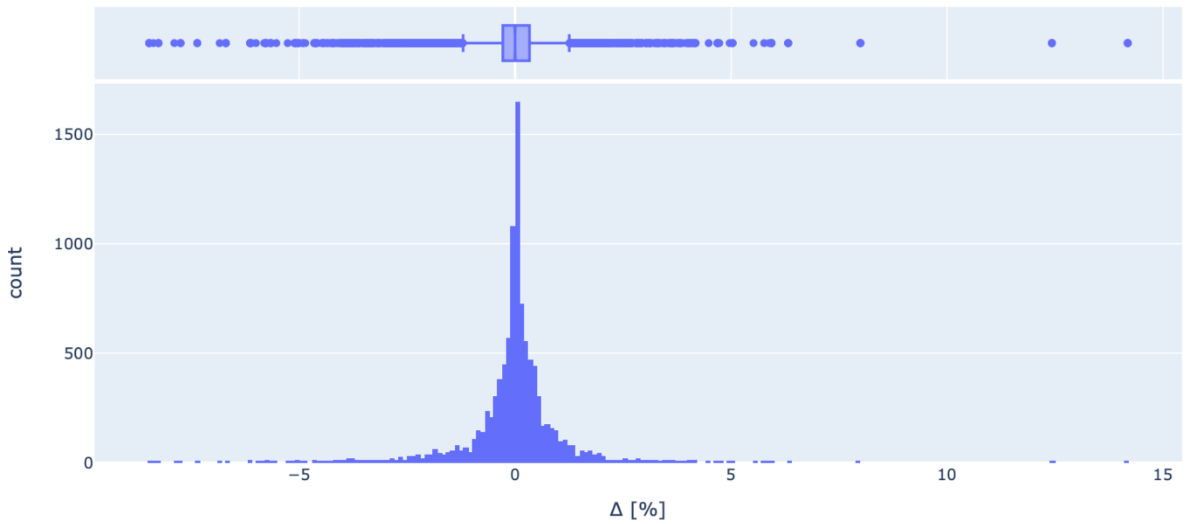
Figure A.20: Overall cost difference (Pareto vs opt-curve) using the new code



Source: JRC, 2024

The following histogram shows CO_2 reduction differences for each powertrain between the new code using the optimal Pareto vs. the new code using the optimal cost curve. The CO_2 reduction difference for each powertrain is contained mainly (95% of the cases) within 1.26%.

Figure A.21: CO_2 reduction difference (Pareto vs opt-curve) using the new code

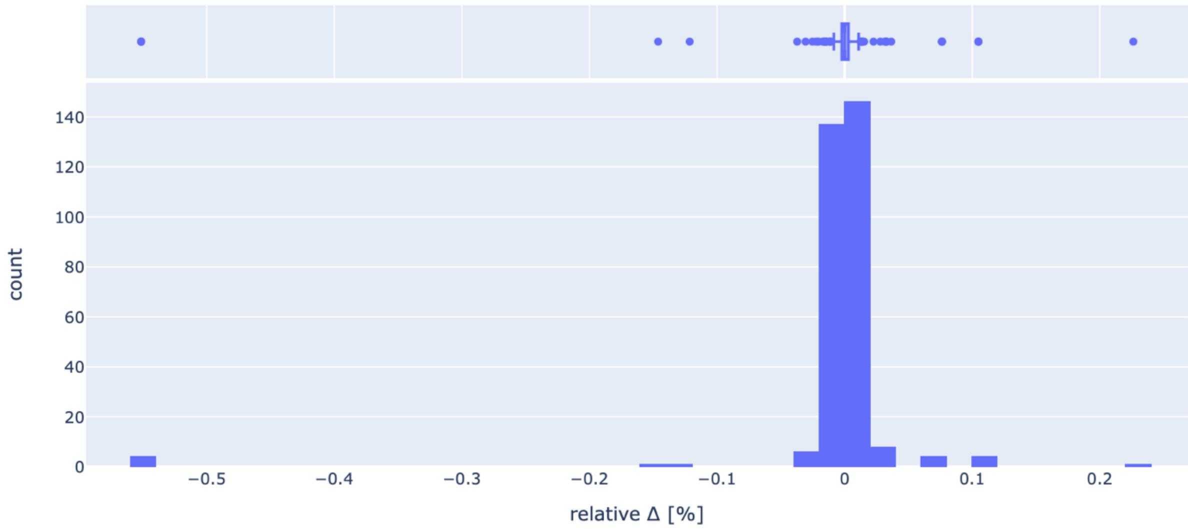


Source: JRC, 2024

Test D

This test compares the new code using the optimal cost curve vs. the new code using the cloud-fitted cost curve. The following histogram shows the overall cost solution differences between the two approaches. The maximum deviation is 0.5%, and it is negligible. Therefore, the cost curve type does not influence the Xopt results significantly.

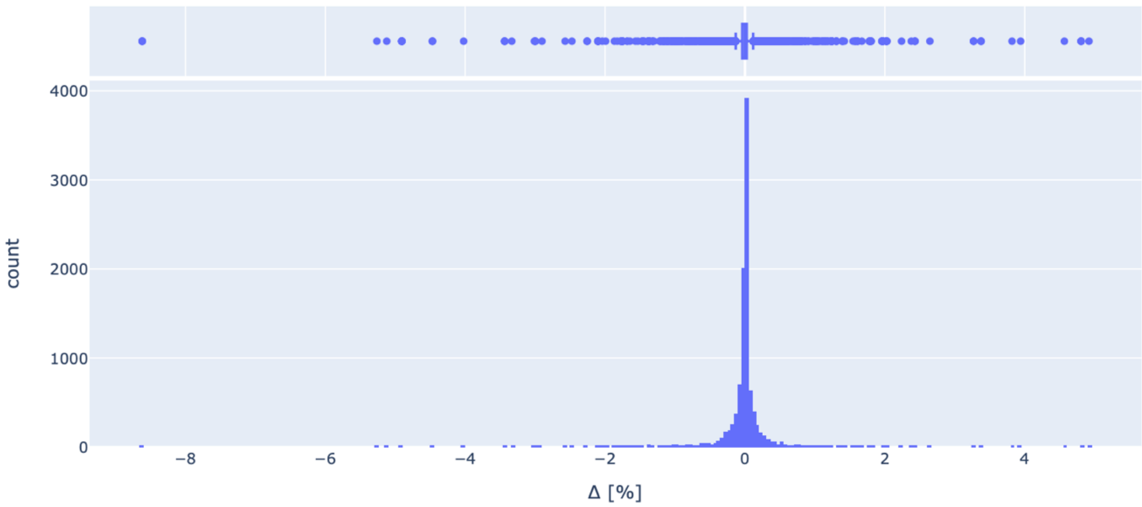
Figure A.22: Overall cost difference (optimal cost curve vs. cloud-fitted curve) using the new code



Source: JRC, 2024

The following histogram shows CO_2 reduction differences for each powertrain between the new code using the optimal cost curve vs. the new code using the cloud-fitted cost curve. The CO_2 reduction difference for each powertrain is contained mainly (95% of the cases) within 0.13%. As before, it confirms that the cost curve type does not significantly influence the Xopt results.

Figure A.23: CO_2 reduction difference (optimal cost curve vs. cloud-fitted curve) using the new code



Source: JRC, 2024

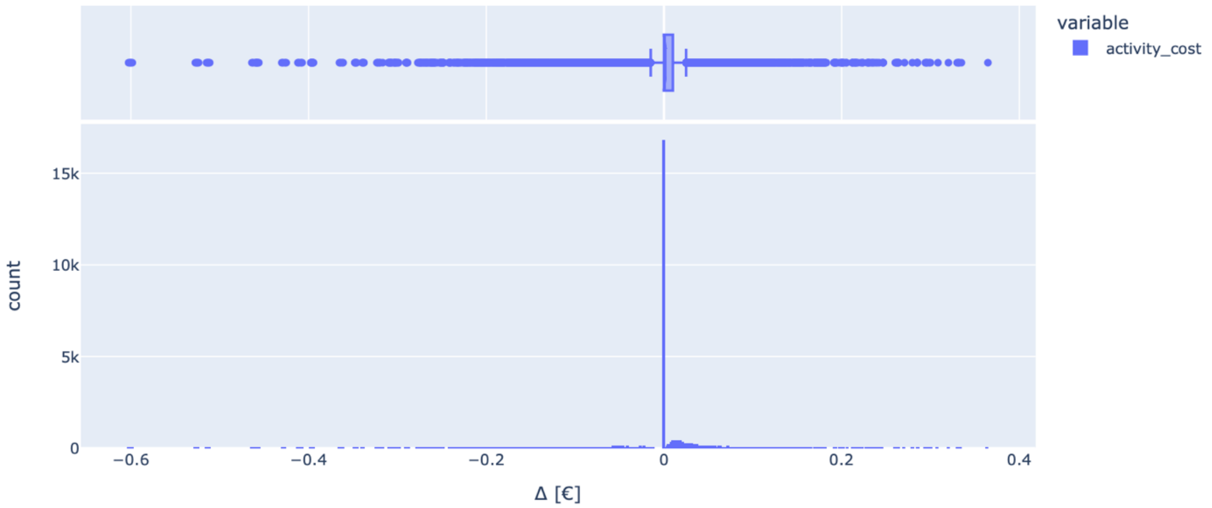
Annex 3. DIONE total cost of ownership (TCO) module

The DIONE total cost of ownership (TCO) module is designed to summarize the different cost types over different time frames, thus assessing the economic impacts of policy options from the perspective of vehicle end-users and society.

The new code and the old one differ in the way fuel conversion factors are assigned. These factors describe the evolution of carbon intensity of the fuels sold at gas stations over time. Hence, they are unrelated to the registration year of the vehicle, but they are a function of the projection year. Therefore, we have corrected the approach of the old code using fuel conversion factors per projection year instead of per registration year.

The TCO testing compares the new code vs. the old results for a scenario with identical settings. Figure A.24 shows the differences in the energy consumption costs of all vehicles between the new code versus the old code. The minor deviations are due to the updated fuel conversion factors.

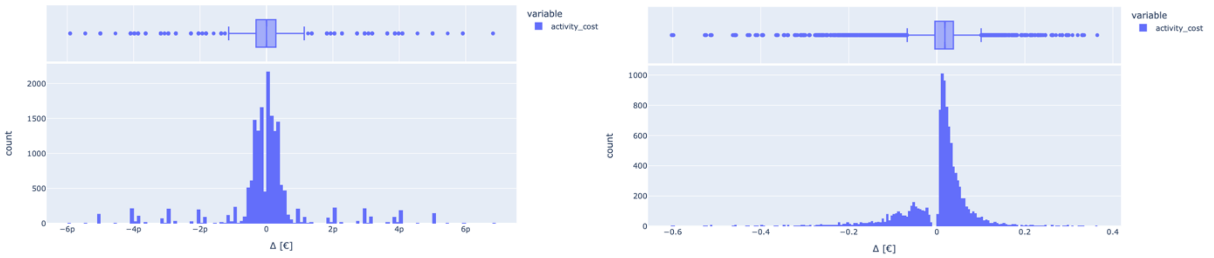
Figure A.24: Difference in fuel and energy costs (old vs new code)



Source: JRC, 2024

From the histograms in Figure A.25, we can observe that relevant deviations occur only for diesel-fuelled internal combustion engine vehicles, whereas deviations are tiny for all other powertrains (note that the unit of x-axis of the left handside of Figure A.25 pico (10^{-12})). This is due to the fact that fuel conversion factors are constant for gasoline, hydrogen and electricity, but vary for diesel.

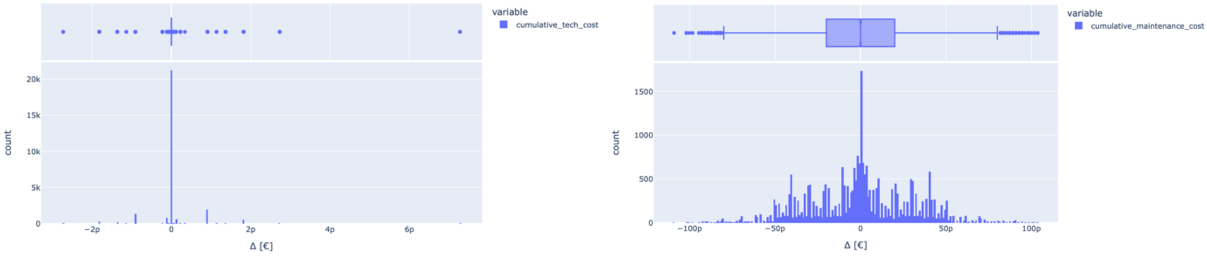
Figure A.25: Differences in fuel and energy costs (old vs new code), for a) all powertrains except diesel-fuelled ICE vehicles and b) only diesel-fuelled ICE vehicles



Source: JRC, 2024

The following two histograms show the difference in all vehicles' cumulative technology and maintenance costs between the new code and the old code. The results are almost identical (machine error only).

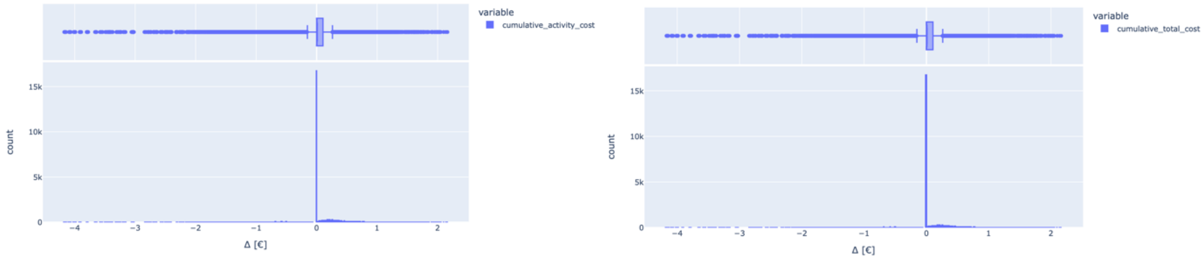
Figure A.26: Differences in a) cumulative technology and b) cumulative maintenance costs (old vs new code)



Source: JRC, 2024

The following two histograms show the differences in the cumulative energy consumption and in the overall total costs of ownership of all vehicles between the new code and the old code. As expected, there are minor deviations which are due to the update of fuel conversion factors.

Figure A.27: Differences in a) cumulative_fuel and energy costs and b) cumulative_total_cost of ownership (old vs. new code)



Source: JRC, 2024

Conclusion from software testing

In conclusion, the new code produces very similar results for all cases, except for intended corrections in code performance, and those influenced by the fuel conversion factors. The difference is acceptable because it is due to the correction of the logic in the TCO model that now uses fuel conversion factors per projection year instead of registration year of the vehicle.

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