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Project Portfolio Planning Under CO_2 Fleet Emission Restrictions in the Automotive Industry

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Abstract

Due to more stringent CO_2 fleet emission standards, project portfolio planning (PPP), a strategic approach to choose between projects sharing limited resources to achieve certain business objectives, must now account for emission limitations and the associated penalty costs. To address this, we employ a mixed-integer programming (MIP) model, as proposed by Thies et al. (2022), to optimize the net present value (NPV). This optimization encompasses various factors such as sales revenue, production costs, development activities, production capacity costs, and emission penalty payments. Following the implementation, sensitivity analyses for new model development cost and penalty cost are performed. Notably, the analysis reveals that the development cost of battery electric vehicles significantly influences the resulting NPV. Intriguingly, even with a 10% increase in penalty costs, car manufacturers should continue to prioritize exceeding the emission threshold.

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Abbreviations

BEV	Battery Electric Vehicle.
FCEV	Fuel-Cell Electric Vehicle.
GDP	Gross Domestic Product.
ICEV	Internal Combustion Engine Vehicle.
KPI	Key Performance Indicator.
MIP	Mixed-Integer Programming.
MOCO	Multiple-Objective Combinatorial Optimization.
NPV	Net Present Value.
PHEV	Plug-in Hybrid Electric Vehicle.
PPP	Project Portfolio Planning.
SOP	Start Of Production.
ZEV	Zero-Emission Vehicle.

1 Introduction

Project Portfolio Planning (PPP) is a strategic approach that involves managing an entire portfolio of products or services to achieve overall business objectives. Since the elements in the portfolio share limited resources, firms must decide which projects to prioritize, considering their objectives while respecting resource constraints and other limitations (Archer and Ghasemzadeh (1999); Mohagheghi et al. (2019)). PPP is particularly crucial in industries with lengthy research and development timelines, project-specific investments, and significant interdependence among projects, such as the automotive sector (Raasch et al. (2007)).
Successful PPP enables automakers to stay competitive, innovate, and adapt to the dynamic market demands. It facilitates initiatives to research, develop, and implement cutting-edge technologies such as electric vehicles, autonomous driving, connectivity, and advanced safety features. It associates not only the development of new vehicle models but also improvements to existing ones and the efficient management of the entire product lifecycle from conception to end-of-life. More importantly, PPP involves projects focused on ensuring compliance with regulations, which may involve redesigning vehicles, updating manufacturing processes, or adopting new materials. However, due to increasing environmental awareness and regulations set by governments, CO_2 fleet emissions are getting more attention in the PPP. The EU regulation set the first fleet-wide CO_2 emission standard in 2015: 130 gCO_2/km (Commission (2019)). Later in the amended Regulation (EU) No 333/2014, the EU fleet-wide CO_2 emission target for cars is set to 95 gCO_2/km. It is expected that these targets will get stricter throughout the years. From 2035, the EU fleet-wide CO_2 emission target for both cars and vans is 100% reduction, meaning 0 gCO_2/km (Erbach (2019)). Hence, it is crucial to assess how the project portfolio would be affected by variations in the annual acceptable threshold for CO_2 emissions and corresponding penalty costs.
To avoid penalty payment resulting from the violation of these regulations, car manufacturers need to make decisions on the project portfolio considering not only financial Key Performance Indicator (KPI), strategic KPIs (e.g. market shares) but also environmental KPIs (e.g. fleet emissions) before market introduction. Various methods exist to address this challenge (Palencia et al. (2012)). One common approach involves adopting alternative fuel and vehicle technologies (Pasaoglu et al. (2012)), such as Plug-in Hybrid Electric Vehicle (PHEV), Battery Electric Vehicle (BEV) and Fuel-Cell Electric Vehicle (FCEV). Of these, BEV and FCEV are deemed Zero-Emission Vehicle (ZEV) but have higher costs for powertrains compared to Internal Combustion Engine Vehicle (ICEV) (Grube et al. (2021)). Hence,

PPP can serve as an effective tool in deciding which powertrain to produce to maximize benefits. Various powertrain technologies in vehicle projects entail distinct development costs, influenced by the unique challenges associated with each engine type during the development phase (Verma et al. (2021)). Therefore, the project cost for each engine type should account for these challenges.
This research paper aims to implement a Mixed-Integer Programming (MIP) model proposed by Thies et al. (2022) for PPP in automotive projects and assess the impact of regulated CO_2 emission thresholds, penalty costs, and varying powertrain expenses. The paper is organized as follows: Chapter 2 provides an overview of current research. Following that, Chapter 3 presents the model developed for PPP. Furthermore, Chapter 4 outlines the instances used and presents two experimental studies along with managerial insights. Finally, Chapter 5 concludes the paper with a summary.

2 Literature Review

Companies generally have the goal of building an attractive product portfolio for the different customer profiles as long as the costs incurred are low or other performance objectives are achieved. This problem is also referred to as PPP (A. Sadeghi and Zandieh (2011)). The most common performance objectives of PPP include maximizing the financial value of the portfolio (e.g. NPV, return on investment), ensuring strategic alignment, meaning how well the chosen projects align with the company's strategy (Santiago and Soares (2018)), and maintaining portfolio balance which considers long-term versus short-term goals or high-risk versus low-risk investments (Cooper et al. (1999), Jugend and da Silva (2014)).
Initially, projects' financial criteria were mainly assessed in PPP. Cooper et al. (1999) mentioned that the objective of maximizing the financial value has become less popular. Since it only provides short-term benefits for the firms, the emphasis changed to other strategic criteria, for instance, risk of investment, strategic alliance, and sustainable development (Khalili-Damghani and Soheil (2013)). Elbok and Berrado (2017) provided some examples of strategic goals and their evaluation criteria. Khalili-Damghani et al. (2013), Mohagheghi et al. (2015) and Mohagheghi et al. (2016) put sustainability in the center of PPP when evaluating the environmental impacts of the available projects. While there might be a trade-off between sustainability cost and profit, the NPV of projects is maximized under sustainability consideration (Kudratova et al. (2018)).
In the automotive industry, the mass customization of products requires the division of the product portfolio into several product families to simplify its management (Fogliatto et al. (2012)). Given that, automobile CO_2 emissions are mostly based on their size and powertrain technology, in Thies et al. (2022) the product families were divided based on the vehicle size, powertrain technology, and power range to conduct a PPP with a focus on complying with emissions restrictions. Similarly, Bersch et al. (2021) consider engine types (e.g. combustion engine) and car models (e.g. Sedan) to form the product families and create a plan to introduce new products in the market. On the other hand, El bok and Berrado (2022) suggest a data-driven project categorization process designed for PPP where a clustering analysis is used to eliminate the inconsistencies, ambiguities and multiple interpretations related to the taken-for-granted categories.
To conduct PPP for the automakers, several methodologies are proposed in the related research area. For instance, Thies et al. (2022), Bersch et al. (2021) and Lee et al. (2019) propose to address PPP with MIP model in automotive industry. Alfieri et al. (2020) formulate PPP problem into multiple-objective multi-dimensional

knapsack which belongs to the class of Multiple-Objective Combinatorial Optimization (MOCO) and they solve the problem through a heuristic algorithm. Moreover, Archer et al. (1996) present a review of different approaches including non-mathematical methods, such as project portfolio matrix. This research paper aims to apply the MIP model proposed by Thies et al. (2022) with sensitivity analysis for two parameters: vehicle project development cost and emission exceedance penalty cost.

3 Methodology: Mixed- Integer Programming Model

For generating the optimized portfolio, given the industry and manufacturer restrictions, a MIP model presented by Thies et al. (2022) is used to execute portfolio planning for a car manufacturer.

In the model, the planning horizon is the set of periods that can be influenced by the decision-maker. Before the planning horizon starts, the project portfolio and installed production resources are fixed in some periods, which influence the decisions during the planning period, especially the first year.

The model's input parameters can be sorted into four main groups: the vehicle projects , the production resources, the EU CO_2 emissions legislation, and the manufacturer's limitations. The **vehicle projects** are defined by the vehicle size, powertrain technology, power class, and the project-specific Start Of Production (SOP). For each project, there are also some project-specific parameters defined: CO_2 fleet emissions, production cost, and sales revenue. For all the projects, it is also considered a finite market life cycle and a fixed development cost - the last being allocated to the years before the SOP.

For each project, there is a specific **production resource** type that is required. The resources are shared between the vehicle projects with the same vehicle size, powertrain technology, and development year. For each resource, fixed and variable yearly costs for ramp-up decisions and fixed production yearly costs are defined. In the first period for the ramp-up of any resource, the capacity utilization is limited to a certain percentage level, depicting the ramp-up process. At any given time, the resources can be expanded or ramped down.

EU **emission legislation** is defined as a threshold of the entire manufactured fleet's CO_2 emission for each period and a penalty payment for the threshold exceedance. In the model, it is possible to determine if the threshold will be restrictive for the planning horizon or not, using an exceedance rate parameter (ε).

Furthermore, some parameters for the **manufacturer's setting** are defined, including a target interest rate for the year cost payments and revenues, a maximum emission threshold exceedance tolerated (ε), a minimum production target per year, and a maximum number of projects starting in one period. These parameters' values are defined by the manufacturer to depict its business strategy and limitations.

For each period in the planning horizon, there are 3 types of **decisions** to be made: the realization of vehicle projects y_v - a binary variable that is 1 if project v is realized -, the production quantities for the realized projects q_{vt} - where v is the project and t the period, and the decisions to ramp up or down the capacities of the production resources - k_{ct}^{Bin} is a binary variable that is 1 if the capacity of resource c is ramped up in period t and k_{ct}^{Rampup}, $k_{ct}^{Rampdown}$, and k_{ct} are the ramp-up, ramp-down, and capacity quantity of resource c in period t respectively.

To choose the best portfolio, the model's **objective function** maximizes the NPV of the cash flows from mainly six sectors during the whole period: sales revenues, production costs, development costs, fleet emission exceedance penalty costs, resource capacity ramp-up costs and the remaining value of the production resources, after depreciation, at the end of the planning horizon as illustrated in A. 1.

The model is restricted by **constraints** determined by the manufacturer. All the constraints are listed in the Appendix 1.5. Several important constraints are mentioned in the following. In the expression A. 10, the maximum annual number of projects' realization is limited by development budget. In the expression A. 17, the production quantities are limited by the assumed demand for the different market segments. In the expression A. 18, the CO_2 fleet emission tolerated threshold shall not be exceeded. In the expression A. 22, the minimum production quantity target must be met to ensure employment and market shares and prevent factory closures (Fleischmann et al. (2006)).

The full optimization model implemented is provided in the Appendix 1 of this article.

4 Computational Study

4.1 Instance

The data used for the parameters in the model implementation is the same as in Thies et al. (2022), which represents an European passenger car manufacturer's setting, created with publicly available data and assumptions. Tables 4.1, 4.2, and 4.3 present some input values of the baseline model.

Parameter	Input
Vehicle Size	Small, Medium or Large
Powertrain Technology	BEV, FCEV, ICEV or PHEV
Power Class	Low or High
Fixed Development Cost	€420 million
Period Length for Development Cost Distribution	3 years
Maximum Market Life Cycle	7 years

Table 4.1: Input values for Vehicle Projects in the baseline scenario

Parameter	Input
Fixed Ramp-up Cost	€20 million
Variable Ramp-up Cost per Capacity Unit Increased	€2,750
Fixed Installed Capacity Cost per Unit per Period	€50
Fixed Development Cost	€420 million
Percentage Available to Utilization in the Ramp-up Year	75%
Period Length for Ramp-up Costs Distribution	5 years
Resource Depreciation Period	5 years

Table 4.2: Input values for Production Resources in the baseline scenario

Parameter	Input
Yearly Minimum Production Target	1 million vehicles
Maximum Realized Projects per Year	6 projects
Target Interest Rate	5% per year
Tolerated Emission Excedeence	100%
Emission Exceedance Penalty Cost	€95 per gram and vehicle sold

Table 4.3: Input values for Manufacturer Settings and Emission Regulation in the baseline scenario

4.2 Main Assumptions

The assumptions encompass information on vehicle projects, production resources, CO_2 fleet emission legislation, and the manufacturer's specific setting.

4.2.1 Vehicle Projects

For each project, variable production cost and CO_2 emission rate based on powertrain technology, vehicle size, and power class are defined. On top of that, the variable production costs of ICEVs and PHEVs are assumed to be increasing over time, and their CO_2 emission rates are decreasing over time because the internal combustion engine technology is regarded to be improved consistently. Owing to these technological improvements, additional investments are considered, leading to increasing variable production costs. Another trend being considered is for the BEVs and FCEVs, their variable production costs are decreasing over time because of the assumption of the further advancements in both battery and fuel cell technology (Berckmans et al. (2017), Lutsey and Nicholas (2019)). On the other hand, the sales price for each project is assumed to be dependent only on the vehicle size and the power class.

4.2.2 Demand

The projects' demand is presumed as mutually exclusive market segments. The market segments are defined by three vehicle characteristics: size (small, medium, and large) with time-invariant market shares, power class (low and high) with equally distributed demand, and powertrain technology (ICEV, PHEV, BEV, and FCEV). Six market scenarios are introduced in Thies et al. (2022)'s work. However, only one scenario is implemented in the model which assumes a fast increase in demand for ZEV, reaching 63% of the market share in the year 2035. Also, in this scenario, the market share of ZEV is considered a preference for BEV with a ratio of 75% while 25% for FCEV. In addition, the market interest for PHEVs grows at the same rate of demand decrease for ICEVs.

4.2.3 Production Resources

For the automotive industry, the resource capacity is usually measured in units produced (Thies et al. (2022)). The resources are shared between projects with the same vehicle size, powertrain technology, and year of development; however, all resources are considered to have the same fixed and variable costs for simplification. For the calculation of cash flows' NPV, the total ramp-up cost is considered to be distributed over the years before the first ramp-up year, and the resource value is linearly depreciated over the following years.

4.2.4 Emission Legislation

The CO_2 fleet emission regulation parameters are based on the EU legislation published in 2019 for the baseline scenario. The emission thresholds are assumed to decrease through the years as stated in the Regulation EU 2019/631 (Commission (2019)). In this EU Regulation, the penalty payment is also set constant per gCO_2 exceedance and vehicle sold per year.

4.2.5 Manufacturer's setting

The assumptions for the manufacturer setting are the same as considered in Thies et al. (2022). The planning horizon is from 2026 to 2035. The previously determined vehicle projects and installed capacity since 2020 are demonstrated in the Table A4 and A5.

4.3 Computational Information

The results presented in the following sections were generated by implementing the MIP model in Gurobi 11.0, and the program has approximately 19,000 integer variables (thereof roughly 3,500 binary), about 200 continuous variables, and approximately 15,000 constraints for the instances analyzed. With a standard PC (AMD Ryzen 7 2700U, 2.2 GHz, 8 GB RAM, 64-Bit Windows 10), the model needs less than 0.5 minutes to be solved to optimality, which is fast enough given the strategic character of the PPP task.

4.4 Sensitivity Analysis of Development Cost

One of the assumptions of the baseline model proposed by Thies et al. (2022) mentioned in section 4.2.1 is that vehicles of every powertrain technology have the same development cost, €420 million, but this doesn't align with practical evidence. Research indicates that BEV and FCEV generally incur higher development costs due to advancements in battery and fuel cell technologies (König et al. (2021); Wolfram and Lutsey (2016)). Hence, it would be intriguing to explore the sensitivity of development cost stemmed from different powertrain technologies.

4.4.1 2^k Factorial Design

The goal of the sensitivity analysis is to find out which factor among all four powertrain technology development costs has the largest effect on resulting NPV. An approach proposed by Law et al. (2007), so-called 2^k factorial design is to get an initial estimate how each factor affects the response and how each factor interacts with each other. However, using this approach requires a parameter study beforehand to decide on "+" and "-" level of each factor. Also, to avoid too much computational effort, a preliminary test to find out key factors for "+" and "-" scenarios can be helpful. To conduct the preliminary parameter study, the method of altering only the value of one factor -40%, -20%, +20% and +40% at a time, that is, ceteris paribus, is implemented.
After running the model with and without changes of development cost of each powertrain vehicle, the result is illustrated in the Figure 4.1. Evident response of NPV occurs when development cost changes from €420 million to €336 million (-20%) or to €503 million (+20%). This shows the objective value is responsive enough. For the purpose of simplification, "+" level is decided to be +10% and "-" level is -10% for the 2^k factorial experiment. Furthermore, Figure 4.1 also implies that changing BEV development cost or ICEV development cost alone has greater impact on NPV whereas changing PHEV development cost yields little response. As a result, the factor: PHEV development cost will not be considered in the 2^k factorial experiment. The experiment design is shown in the Table 4.4 with "+" representing increasing development cost of designated powertrain vehicle 10% and "-" representing decreasing development cost 10%.

Combination	$\Delta C_{RD,ICEV}$	$\Delta C_{RD,BEV}$	$\Delta C_{RD,FCEV}$	ΔNPV(million €)
1	-	-	-	809.86
2	+	-	-	184.54
3	-	+	-	103.59
4	-	-	+	575.72
5	+	+	-	-521.73
6	+	-	+	-49.6
7	-	+	+	-130.55
8	+	+	+	-755.87

Table 4.4: 2^k factorial design and NPV response

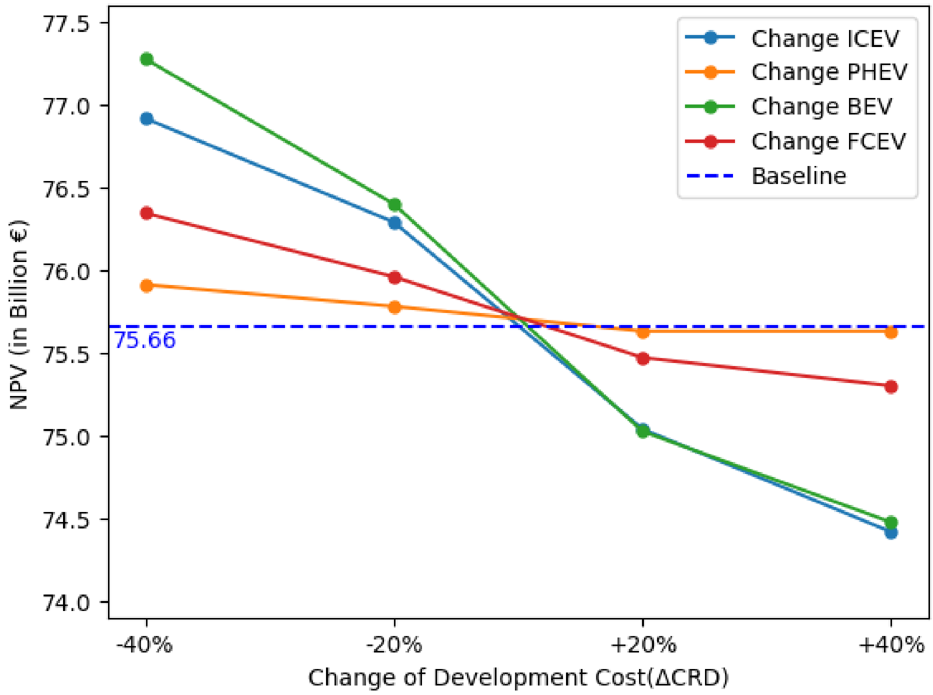

Figure 4.1: Result of Parameter Study

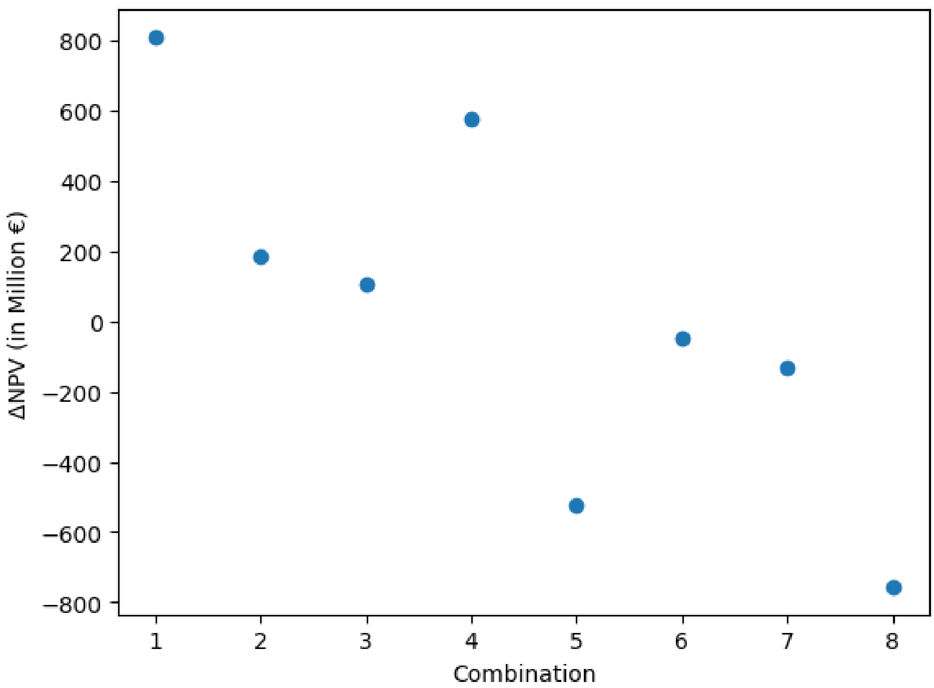

Figure 4.2: Result of 2^k factorial experiment

4.4.2 Main Effect and Interaction Effect

The graphical result of 2^k factorial experiment is illustrated in the Figure 4.2 and the corresponding values are shown in the Table 4.4. The first interpretation of the result is, for example, regarding to the Combination 1, that if the development costs of ICEV, BEV and FCEV decrease €42 million respectively, NPV will increase €809,86 million in total. To further analyze the result, the formulas of quantifying main effect and interaction effect are introduced in the Equation 4.1 and 4.2 where $\mathbb{S} = \{1, 2, ..., 8\}$ is the set of all eight combinations, $\mathbb{F} = \{\Delta C_{RD,ICEV}, \Delta C_{RD,BEV}, \Delta C_{RD,FCEV}\}$ is the set of all the factors and ΔNPV_i is the NPV difference to the baseline NPV for Combination $i \in \mathbb{S}$ (Law et al. (2007)).

$$E_j = \frac{\sum_{i \in \mathbb{S}} f_{ij} * \Delta NPV_i}{2^{k-1}} \qquad \forall j \in \mathbb{F} \tag{4.1}$$

$$E_{jh} = \frac{\sum_{i \in \mathbb{S}} f_{ij} * f_{ih} * \Delta NPV_i}{2^{k-1}} \qquad \forall j, h \in \mathbb{F}, j \neq h \tag{4.2}$$

where

$$f_{ij} = \begin{cases} 1 & \text{if factor } j \text{ is at the "+" level in the Combination } i \\ -1 & \text{if factor } j \text{ is at the "-" level in the Combination } i \end{cases} \qquad \forall j \in \mathbb{F}, \quad \forall i \in \mathbb{S} \tag{4.3}$$

Calculation outcomes of quantified main effect and interaction effect of the three factors $\Delta C_{RD,ICEV}$, $\Delta C_{RD,BEV}$, $\Delta C_{RD,FCEV}$ are presented in the Table 4.5 and Table 4.6. Values in the Table 4.5 can be interpreted as the change of NPV if the factor j changes from -10% to +10%, while the values in the Table 4.6 represent how much does one factor change if another changes from -10% to +10%.

j	E_j
$\Delta C_{RD,ICEV}$	-625.32
$\Delta C_{RD,BEV}$	-706.27
$\Delta C_{RD,FCEV}$	-234.14

Table 4.5: Main Effect

j, h	E_{jh}
$\Delta C_{RD,ICEV}$, $\Delta C_{RD,BEV}$	0
$\Delta C_{RD,BEV}$, $\Delta C_{RD,FCEV}$	0
$\Delta C_{RD,FCEV}$, $\Delta C_{RD,ICEV}$	0

Table 4.6: Interaction Effect

4.4.3 Managerial Insights

Based on the outcomes in the Table 4.5 and the Figure 4.1, the sensitivity of BEV development cost to NPV is highest, followed by ICEV development cost. In contrast, PHEV development cost has a relatively minor effect on NPV. Consequently, if a car manufacturer aims to reduce development costs, prioritizing BEV development would be the most effective strategy, with PHEV development considered as a last resort. For instance, reducing BEV development costs from €420 million to €336 million could lead to a substantial increase in NPV, amounting to €737.96 million, as illustrated in Figure 4.1. On the other hand, reducing the same amount of development costs for PHEV could only result in NPV increase of €119.49 million. Furthermore, the Table 4.6 reveals that there is no significant interaction between ICEV, BEV, and FCEV development cost changes. This is reasonable because alterations in the development cost of one type of powertrain do not appear to impact the development costs of other types.

4.5 Sensitivity Analysis of Emission Penalty Cost

One assumption of the baseline model proposed by Thies et al. (2022) mentioned in section 4.2.4 is that the penalty cost for the exceedance of the CO_2 fleet emission threshold stays constant at €95 per gram exceeded and vehicle sold through the entire planning horizon. However, the substantial accountability of the greenhouse gas emissions and the fossil-fueled transportation system to the climate change have been assessed, especially in the EU and in the USA (Urain et al. (2022), Kinney (2018), Wendeker et al. (2022)). Thus, it is reasonable to imagine that the penalty cost could be increased in later versions of the EU Regulation (Commission (2019)) to increase the pressure for the European fleet decarbonization. On the contrary, the automotive industry is a major component of the total industrial value added to the European GDP, becoming vital for the European economy (Demiraj et al. (2022)). Considering this importance for the continent, the automotive industry could pressure the authorities to decrease the penalty cost to not hinder the thriving business in this economy section. In addition, Regulation (EU) 2019/631 (Commission (2019)) has been updated 8 times since its publication in April 2019, proving the possibility of constant changes in the regulations for current topics. In the baseline model the thresholds mentioned in section 4.2.4, which were calculated by Thies et al. (2022) is utilized. The penalty cost sensitivity experiment is conducted with the newly updated thresholds from Decision 2023/1623 (Commission (2023)) to understand the impact of the new regulation standards and to compare the results with the two sets of threshold values, which are available in the Table A6.

4.5.1 Design

With the two sets of threshold values - the ones from the 2019 Regulation and the ones from the 2023 Regulation, sensitivity experiments are implemented as shown in Table 4.7. First, Scenario 1 was run, in which the parameter ε was equal to zero. It is possible to evaluate the model outcomes where it is ensured compliance with the CO_2 fleet emission thresholds. Consequently, the emission penalty cost is altered by -10%, -5%, +5%, and + 10% in each scenario to analyze the impacts in the model result. The main objective of this experiment is to assess the configuration of the production portfolio in terms of the percentage of each powertrain technology used in production per period.

Scenario	Penalty Cost Variation	Penalty Cost (€ per g CO_2/km)	ε
Baseline	0%	95,00	100%
Scenario 1	–	–	0%
Scenario 2	-10%	85,50	100%
Scenario 3	-5%	90,25	100%
Scenario 4	+5%	99,75	100%
Scenario 5	+10%	104,50	100%

Table 4.7: Experiment Design for Emission Penalty Cost Sensitivity Analysis

4.5.2 Result

4.5.2.1 Thresholds from 2019

The NPVs obtained for all 6 scenarios with the CO_2 fleet emission thresholds from 2019 can be seen in Figure 4.3. It is more profitable to exceed the emission thresholds and; therefore, pay the penalty costs for it than to comply entirely with them. Respecting the thresholds would be as profitable as exceeding them if the penalty cost would be €266 or higher.

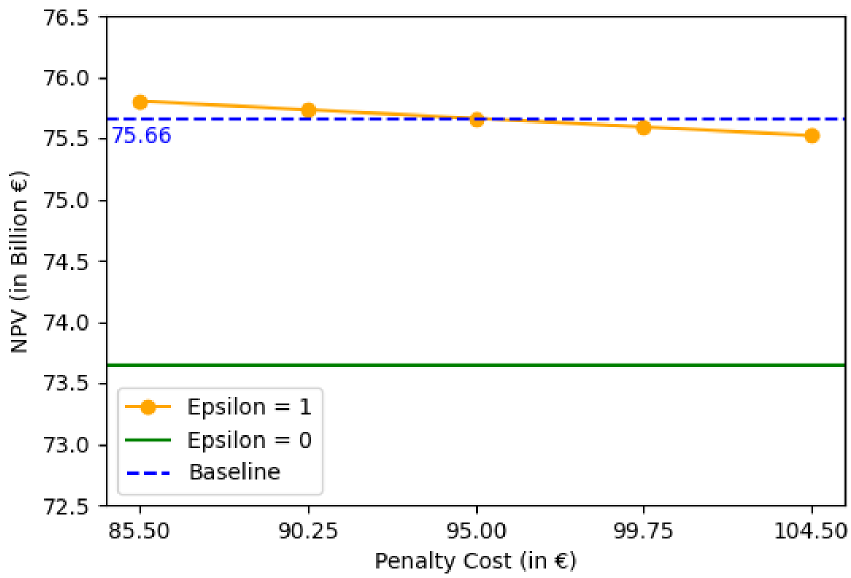

Figure 4.3: NPV under different scenarios using the thresholds from 2019

When comparing the scenarios where it is allowed to exceed the thresholds between each other, it is possible to verify that there are no differences in the configuration of the production portfolio regarding the powertrain technology used. Furthermore, when enforcing total compliance with the thresholds, the difference in the powertrain chosen is small, due to only having penalty costs occured in periods 2026 and 2027. The only expressive difference in the production portfolio between scenarios where ε equals 1 or 0 is the first year of the planning horizon: the share of ICEVs needed decreases from 83,4% to 79,8% as seen in Figure 4.4.

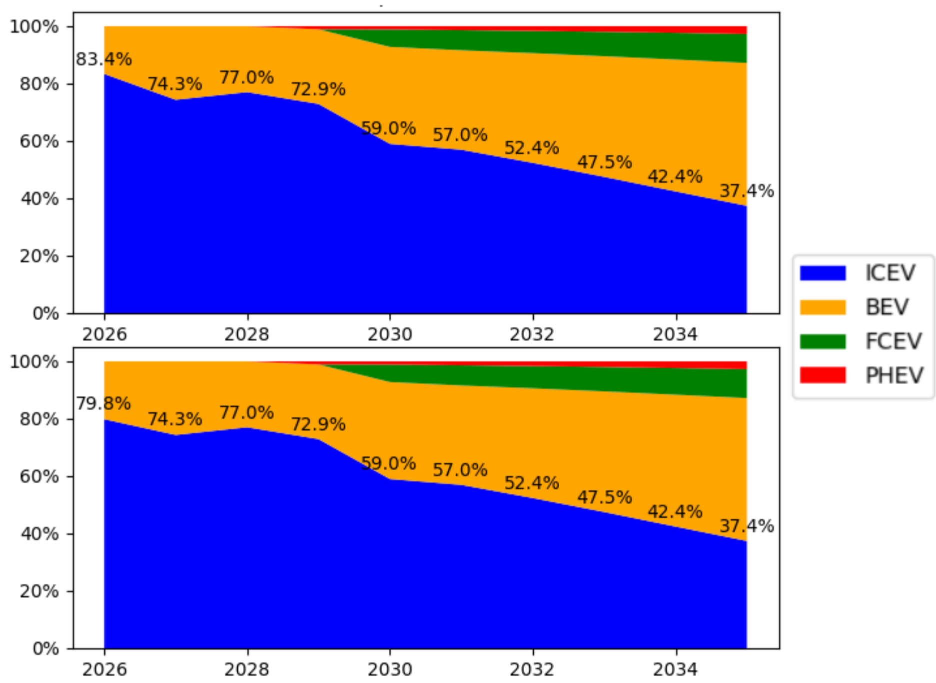

Figure 4.4: Production portfolio in terms of powertrain technology using the thresholds from 2019 when ε = 1 (above) and ε = 0 (below)

4.5.2.2 Thresholds from 2023

After running all six scenarios with the CO_2 fleet emission thresholds from 2023, NPV under each scenario is illustrated in the Figure 4.5). Similar to the result presented in Section 4.5.2.1, it is more profitable to exceed the emission thresholds; therefore, pay the penalty costs for it than to comply entirely with the regulation. Respecting the thresholds defined in 2023 would be as profitable as exceeding them if the penalty cost would be €137 or higher.

Similar to the outcome presented in Section 4.5.2.1, there are no differences in the configuration of the production portfolio regarding the powertrain technology used when comparing the scenarios where it is allowed to exceed the thresholds between each other. In addition, when enforcing total compliance with the thresholds, the difference in the powertrain chosen is small, due to only having penalty costs in periods 2026, 2029, and 2030. The evident differences in the production portfolio between scenarios where ε equals 1 or 0 are the share of ICEVs needed to decrease from 57,5% to 49,4% in the period 2030, when this difference was partially covered with BEVs and partially covered with FCEVs, and from 53,2% to 52,9% in the period 2031, when it was overridden by BEVs only, as seen in Figure 4.6.

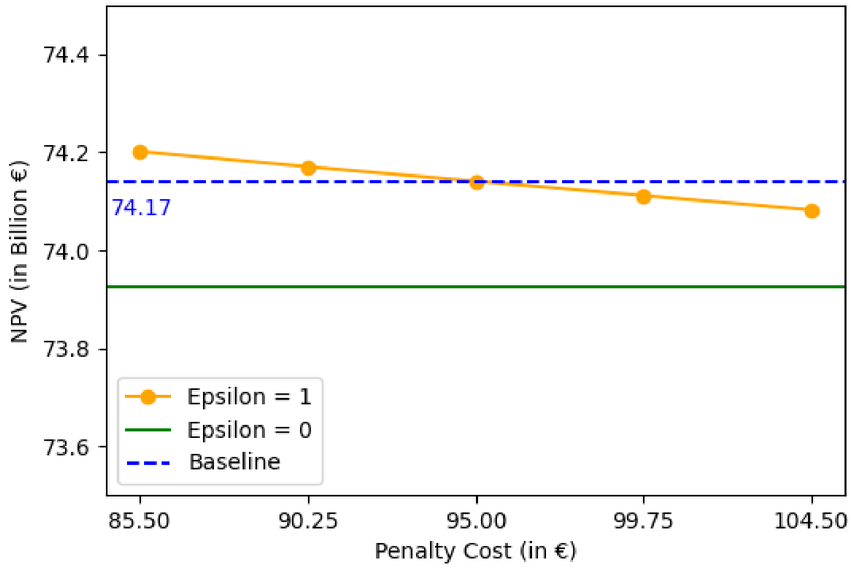

Figure 4.5: NPV under different scenarios using the thresholds from 2023

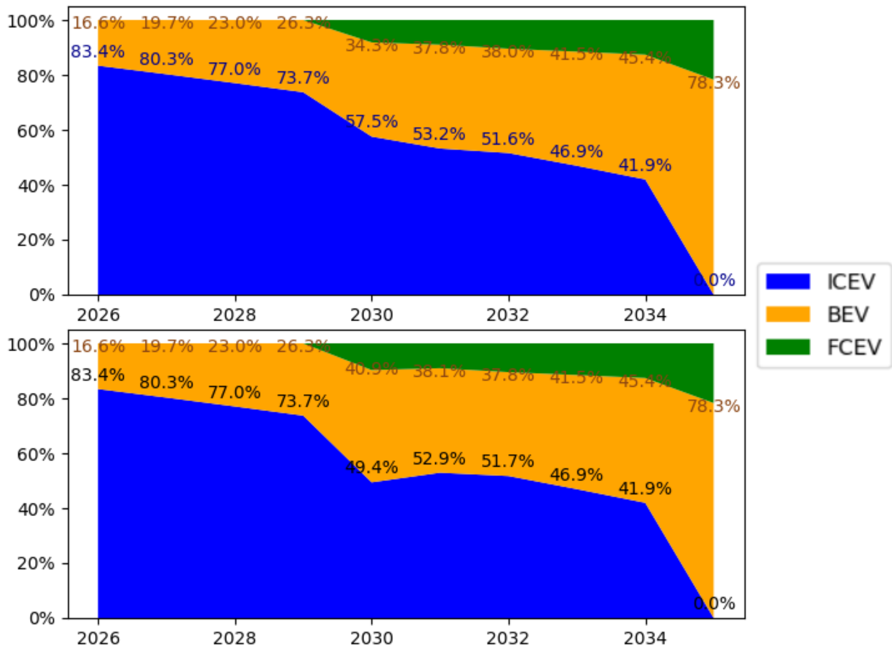

Figure 4.6: Production portfolio in terms of powertrain technology using the thresholds from 2023 when $\varepsilon = 1$ (above) and $\varepsilon = 0$ (below)

4.5.2.3 Comparison and Analysis

After completing the two experiments, it is possible to compare both results and analyze the impact of the change in the regulation. With the NPV plots (Figure 4.3 and Figure 4.5), one can identify that with the threshold from 2023, there is a lower incentive to exceed the thresholds, because the difference between the NPVs from the scenario that it is possible to exceed and from the scenario that is it not is lower.

Also, comparing the NPV from the baseline scenario, the threshold from 2019 led to a more profitable outcome due to a higher percentage of ICEVs on average, which are the powertrain technology of the most profitable vehicles available in the model. With the new regulation, the year with the highest absolute variation in the threshold value is the last one in the planning horizon, the period 2035. With a threshold of zero in this period, the portfolio with the set of thresholds from 2023 ended with an entire portfolio with ZEV, even in the scenario where $\varepsilon = 1$. This happened because of the possibility of investing in resources for the ZEVs through the planning horizon gradually.

Comparing the baseline scenarios for the two sets of thresholds, it is possible to identify that in both cases only in a few periods there was penalty cost payments, but in each scenario the periods that this happened were different. In the 2019 thresholds scenario, the emissions threshold exceedance only happened in 2026 and 2027, mainly due to the chosen projects and already installed resource capacities before the planning horizon started, which was entirely composed of ICEVs. On the other hand, in the 2023 thresholds scenario, the periods with penalty costs were 2026, 2029, and 2030. The first one with the same cause as in the previous scenario and the others are because of the decrease in the threshold between 2029 and 2030 of approximately 47%.

4.5.3 Managerial Insights

Given the decreasing thresholds through the periods, it is clear that the near future of mobility is ZEVs, at least in Europe. Also, the companies that prepare themselves for it sooner with early investment in resources to produce these vehicles and with early development of vehicle models with this technology will achieve higher financial results. This is observed in the scenario with the threshold set of 2023 and $\varepsilon = 1$ when there is 100% of ZEVs in 2035, because there has been enough time to prepare the manufacturing resources for this new era of the automotive industry with investments in BEVs and FCEVs.

Taken that exceeding at least one emission threshold was more financially beneficial with both sets of thresholds, the only reason to comply 100% with the regulation thresholds with this problem setting would be the manufacturer strategy. If having a positive environmental impact was a goal for the manufacturer, then it would be worthwhile to undertake the small portfolio changes mentioned in the previous sections. Moreover, if having a diversified portfolio is also desired by the manufacturer, it could be convenient to add a new constraint to the model that ensures the election of at least one vehicle from each powertrain technology, since with the 2023 thresholds the optimal portfolio does not contain any PHEVs.

After conducting this experiment, the importance of international regulations is clear since a lack of obligation to decrease the fleet emissions, would not incentivize the manufacturers to produce ZEVs, or at least less polluting vehicles. This is true, especially because of the high profitability of ICEVs and already installed production resources. Also, it is valuable to always be attentive to what is being discussed in the political sphere as the regulations can change. As soon as the manufacturer prepares its portfolio and resources for the newest limitations, the negative financial of the change impact may be smaller.

5 Conclusion

This article implements the PPP MIP model from Thies et al. (2022), which is a NPV maximization problem that considers the cash flows from sales, production, development, and fleet emissions regulation. Also, this paper presents two experimental analyses, one focusing on the vehicle development cost and the other on the fleet emission penalty cost.

The sensitivity analysis regarding powertrain-specific development costs reveals that BEVs exhibit the highest sensitivity to NPV, followed byICEVs, FCEVs, and PHEVs. The second sensitivity analysis regarding the emission penalty cost uncovered the high profitability of ICEVs. Even when the penalty cost increased by 10%, the production of ICEVs is still preferred in some periods. The second experiment also highlighted the importance of regulations that force companies to consider sustainable options in their portfolio. Without these regulations, industries may lack financial incentives to change how they do business.

There are many simplifications in this study. Demand is considered to have a time-invariant part, regarding vehicle sizes and power class, and a time-variant part, regarding the power train technology. However, demand forecasting is more complex than this, and requires a more in-depth analysis to be a better representation of the reality. Also, there is no minimum percentage of the demand that is supposed to be fulfilled in this implementation. Nevertheless, many manufacturers have the goal to remain an important player in particular market segments, especially the significant market share holders. Another simplification is the possibility of ramping up the resource capacities at any time without considering a limited budget or facility restrictions.

Future research articles could take into account these complexities. Forecasting vehicle demand already considering the most recent years of activities, between 2020 and 2023, would be a more realistic input data set for the model. Also, one could add constraints to ensure a minimal demand percentage for each market segment or to guarantee a diverse portfolio as mentioned in Section 4.5.3. Last but not least, regarding to the production resources capacities, it is possible to add a constraint that limits the ramp-up size for each period to account for the limited available financial resources and finite shop floor.

Bibliography

A. Sadeghi, A. Alem-Tabriz, M. Zandieh. 2011. Product portfolio planning: a metaheuristic-based simulated annealing algorithm. *International Journal of Production Research* **49**(8) 2327–2350. doi:10.1080/00207540903329338. URL `https://doi.org/10.1080/00207540903329338`.

Alfieri, Arianna, Claudio Castiglione, Erica Pastore. 2020. A multi-objective tabu search algorithm for product portfolio selection: A case study in the automotive industry. *Computers & Industrial Engineering* **142** 106382.

Archer, Norman P, Fereidoun Ghasemzadeh, et al. 1996. Project portfolio selection techniques: a review and a suggested integrated approach .

Archer, N.P, F Ghasemzadeh. 1999. An integrated framework for project portfolio selection. *International Journal of Project Management* **17**(4) 207–216. doi:https://doi.org/10.1016/S0263-7863(98)00032-5. URL `https://www.sciencedirect.com/science/article/pii/S0263786398000325`.

Berckmans, Gert, Maarten Messagie, Jelle Smekens, Noshin Omar, Lieselot Vanhaverbeke, Joeri Van Mierlo. 2017. Cost projection of state of the art lithium-ion batteries for electric vehicles up to 2030. *Energies* **10**(9). doi:10.3390/en10091314. URL `https://www.mdpi.com/1996-1073/10/9/1314`.

Bersch, Christopher V., Renzo Akkerman, Rainer Kolisch. 2021. Strategic planning of new product introductions: Integrated planning of products and modules in the automotive industry. *Omega* **105** 102515. doi:https://doi.org/10.1016/j.omega.2021.102515. URL `https://www.sciencedirect.com/science/article/pii/S0305048321001249`.

Commission, European. 2019. Regulation (eu) 2019/1242 of the european parliament and of the council of 20 june 2019 setting co2 emission performance standards for new heavy-duty vehicles and amending regulations (ec) no 595/2009 and (eu) 2018/956 of the european parliament and of the council and council directive 96/53/ec. *Off. J. Eur. Union* **50** 202–240.

Commission, European. 2023. Commission implementing decision (eu) 2023/1623 of 3 august 2023 specifying the values relating to the performance of manufacturers and pools of manufacturers of new passenger cars and new light commercial vehicles for the calendar year 2021 and the values to be used for the calculation of the specific emission targets from 2025 onwards, pursuant to regulation (eu)

2019/631 of the european parliament and of the council and correcting implementing decision (eu) 2022/2087. *O*ff. J. Eur. Union 5–35.

Cooper, Robert G, Scott J Edgett, Elko J Kleinschmidt. 1999. New product portfolio management: practices and performance. *J*ournal of Product Innovation Management: An International Publication of The Product Development & Management Association **1**6(4) 333–351.

Demiraj, Rezart, Suzan Dsouza, Mohammad Abiad. 2022. Working capital management impact on profitability: Pre-pandemic and pandemic evidence from the european automotive industry **1**0(12). doi:10.3390/risks10120236. URL `https://www.scopus.com/inward/record.uri?eid=2-s2.0-85144475161&doi=10.3390%2frisks10120236&partnerID=40&md5=2c507e149d07261e4d30bcea400a0921`.

El bok, Ghizlane, Abdelaziz Berrado. 2022. A data-driven project categorization process for portfolio selection. *J*ournal of Modelling in Management **1**7(2) 764–787.

Elbok, Ghislaine, Abdelaziz Berrado. 2017. Towards an effective project portfolio selection process. *I*nternational Conference on Industrial Engineering and Operations Management Rabat, Morocco.

Erbach, Gregor. 2019. standards for new cars and vans .

Fleischmann, Bernhard, Sonja Ferber, Peter Henrich. 2006. Strategic planning of bmw's global production network. *I*nterfaces **3**6(3) 194–208. URL `http://www.jstor.org/stable/20141389`.

Fogliatto, Flavio S., Giovani J.C. da Silveira, Denis Borenstein. 2012. The mass customization decade: An updated review of the literature. *I*nternational Journal of Production Economics **1**38(1) 14–25. doi:https://doi.org/10.1016/j.ijpe.2012.03.002. URL `https://www.sciencedirect.com/science/article/pii/S0925527312000989`.

Grube, Thomas, Stefan Kraus, Julian Reul, Detlef Stolten. 2021. Passenger car cost development through 2050. *T*ransportation Research Part D: Transport and Environment **1**01 103110.

Jugend, Daniel, Sérgio Luis da Silva. 2014. Product-portfolio management: A framework based on methods, organization, and strategy. *C*oncurrent Engineering **2**2(1) 17–28. doi:10.1177/1063293X13508660. URL `https://doi.org/10.1177/1063293X13508660`.

Khalili-Damghani, Kaveh, Soheil Sadi-Nezhad, Farhad Hosseinzadeh Lotfi, Madjid Tavana. 2013. A hybrid fuzzy rule-based multi-criteria framework for sustainable project portfolio selection. *I*nformation Sciences **2**20 442–462. doi:https://doi.org/10.1016/j.ins.2012.07.024. URL `https://www.sciencedirect.com/science/article/pii/S0020025512004963`. Online Fuzzy Machine Learning and Data Mining.

Khalili-Damghani, Kaveh, Sadi-Nezhad Soheil. 2013. Strategic framework for sustainable project portfolio selection and evaluation. *I*nt. J. of Sustainable Strategic Management **4** 66 – 82. doi:10.1504/IJSSM.2013.056391.

Kinney, Patrick L. 2018. Interactions of climate change, air pollution, and human health **5**(1) 179 – 186. doi:10.1007/s40572-018-0188-x. URL `https://www.scopus.com/inward/record.uri?eid=2-s2.0-85051692268&doi=10.1007%2fs40572-018-0188-x&partnerID=40&md5=b9644966420c99f81007c9811137871c`.

König, Adrian, Lorenzo Nicoletti, Daniel Schröder, Sebastian Wolff, Adam Waclaw, Markus Lienkamp. 2021. An overview of parameter and cost for battery electric vehicles. *W*orld Electric Vehicle Journal **1**2(1) 21.

Kudratova, Shamsiya, Xiaoxia Huang, Xiaoguang Zhou. 2018. Sustainable project selection: Optimal project selection considering sustainability under reinvestment strategy. *J*ournal of Cleaner Production **2**03 469–481.

Law, Averill M, W David Kelton, W David Kelton. 2007. *S*imulation modeling and analysis, vol. 3. Mcgraw-hill New York.

Lee, Seunghoon, Young Hoon Lee, Yongho Choi. 2019. Project portfolio selection considering total cost of ownership in the automobile industry. *S*ustainability **1**1(17) 4586.

Lutsey, Nicholas, Michael Nicholas. 2019. Update on electric vehicle costs in the united states through 2030 doi:10.13140/RG.2.2.25390.56646.

Mohagheghi, Vahid, Sana Mousavi, Behnam Vahdani. 2015. A new optimization model for project portfolio selection under interval-valued fuzzy environment. *A*rabian Journal for Science and Engineering **4**0. doi:10.1007/s13369-015-1779-6.

Mohagheghi, Vahid, Sana Mousavi, Behnam Vahdani. 2016. A new multi-objective optimization approach for sustainable project portfolio selection: A real-world application under interval-valued fuzzy environment **1**3 41–68.

Mohagheghi, Vahid, Meysam Mousavi Einehvarzani, Jurgita Antucheviciene, Moe Mojtahedi. 2019. Project portfolio selection problems: a review of models, uncertainty approaches, solution techniques, and case studies. *T*echnological and Economic Development of Economy **2**5 1380–1412. doi:10.3846/tede.2019.11410.

Palencia, Juan C González, Takaaki Furubayashi, Toshihiko Nakata. 2012. Energy use and co2 emissions reduction potential in passenger car fleet using zero emission vehicles and lightweight materials. *E*nergy **4**8(1) 548–565.

Pasaoglu, Guzay, Michel Honselaar, Christian Thiel. 2012. Potential vehicle fleet co2 reductions and cost implications for various vehicle technology deployment scenarios in europe. *E*nergy Policy **4**0 404–421.

Raasch, Christina, Arne S Schneider, Gunther Friedl. 2007. Strategic portfolio planning in industries with long r&d cycles and interrelated product offerings: a practical approach to optimisation. *International Journal of Technology Intelligence and Planning* **3**(3) 271–291.

Santiago, Leonardo P, Verônica Mariana Oliveira Soares. 2018. Strategic alignment of an r&d portfolio by crafting the set of buckets. *IEEE Transactions on Engineering Management* **67**(2) 309–321.

Thies, Christian, Christoph Hüls, Karsten Kieckhäfer, Jörg Wansart, Thomas S Spengler. 2022. Project portfolio planning under co2 fleet emission restrictions in the automotive industry. *Journal of Industrial Ecology* **26**(3) 937–951. doi:https://doi.org/10.1111/jiec.13228. URL `https://onlinelibrary.wiley.com/doi/abs/10.1111/jiec.13228`.

Urain, Idoia, José Alberto Eguren, Daniel Justel. 2022. Development and validation of a tool for the integration of the circular economy in industrial companies: Case study of 30 companies. *Journal of Cleaner Production* **370**. doi:10.1016/j.jclepro.2022.133318. URL `https://www.scopus.com/inward/record.uri?eid=2-s2.0-85135990187&doi=10.1016%2fj.jclepro.2022.133318&partnerID=40&md5=8a632af80e463f8506ca035320ceb264`.

Verma, Shrey, Shubham Mishra, Ambar Gaur, Subhankar Chowdhury, Subhashree Mohapatra, Gaurav Dwivedi, Puneet Verma. 2021. A comprehensive review on energy storage in hybrid electric vehicle. *Journal of Traffic and Transportation Engineering (English Edition)* **8**(5) 621–637. doi:https://doi.org/10.1016/j.jtte.2021.09.001. URL `https://www.sciencedirect.com/science/article/pii/S2095756421000842`.

Wendeker, Mirosław, Michał Jan Gęca, Łukasz Grabowski, Konrad Pietrykowski, Nanthagopal Kasianantham. 2022. Measurements and analysis of a solar-assisted city bus with a diesel engine. *Applied Energy* **309** 118439. doi:https://doi.org/10.1016/j.apenergy.2021.118439. URL `https://www.sciencedirect.com/science/article/pii/S0306261921016640`.

Wolfram, Paul, Nicholas Lutsey. 2016. Electric vehicles: Literature review of technology costs and carbon emissions. ICCT Washington, DC, USA.

Appendix

1 Appendix I - MIP Optimization Model

In this section, the full mathematical formulation of the MIP model introduced in the Section **??** is presented (Thies et al. (2022)). It comprises the model's sets and indices in Table 1.1, the decision variables in Table 1.2, the parameters in Table 1.3, the objective function 1.4 and the constraints 1.5.

1.1 Sets and Indices

Set	Index	Description
V	v	Vehicle projects
$W \subseteq V$		Vehicle projects with SOP before planning horizon
T	t, τ	Periods
$U \subseteq T$		Periods within the planning horizon
M	m	Market segments
C	c	Production resources

Table A1: Sets and indices

1.2 Decision Variables

Variable	Range	Description
y_v	{0, 1}	Vehicle project realization: 1 if vehicle project v is realized, and 0 if not
q_{vt}	$\mathbb{Z}^+$	Production quantity of vehicle project v in period t
k_{ct}	$\mathbb{Z}^+$	Capacity of resource c in period t
k_{ct}^{Bin}	{0, 1}	Binary ramp-up: 1 if capacity for resource c is ramped up in period t, and 0 if not
k_{ct}^{Rampup}	$\mathbb{Z}^+$	Ramp-up of resource c at the beginning of period t
$k_{ct}^{Rampdown}$	$\mathbb{Z}^+$	Ramp-down of resource c at the beginning of period t
$z_t^{Penalty}$	$\mathbb{R}^+$	Penalty payment for the exceedance of the CO_2 fleet emission threshold in period t
z_c^{Back}	$\mathbb{R}^+$	Cash inflow for resource c with residual value at the end of the planning horizon

Table A2: Decision Variables

1.3 Parameters

Vehicle projects	
Parameter	Description
SOP_v	SOP of vehicle project v
$c_v^{ProdVar}$	Variable production cost for vehicle project v
$p_v^{ProdVar}$	Sales revenues for each produced unit of vehicle project v
E_v	CO_2 fleet emission of vehicle from vehicle project v
n_v	Market segment corresponding to vehicle project v
r_v	Resource type corresponding to vehicle project v
τ^{LC}	Maximum duration of the market life cycle
c^{RD}	Development cost of a new vehicle project/model
$Vect_{vt}^{RD}$	Percentage of total development cost (c^{RD}) in period t for vehicle project v
y_v^{Preset}	Preset for the realization of vehicle project v

Production resources	
Parameter	Description
$c^{RampupFixed}$	Fixed ramp-up cost for each resource
$c^{RampupVar}$	Variable ramp-up cost for each unit of resource
τ_c^{Rampup}	First ramp-up year for resource c
$Vect_{t\tau}^{PC}$	Percentage of total ramp-up cost in period t for capacities installed in period τ
δt^{Rampup}	Installation duration for ramp-up resource
$c^{ProdFixed}$	Fixed annual costs for existing resources
k_c^{Preset}	Capacity of resource c at the beginning of the planning horizon
V_c^{res}	Residual value of resource c at the end of the planning horizon T

Demand	
Parameter	Description
d_{mt}	Demand of market segment m in period t

Emissions legislation	
Parameter	Description
E_t^{Law}	CO_2 fleet emission threshold in period t

c^{CO_2}	Penalty payment per gCO_2/km threshold exceedance and per vehicle sold
Manufacturer's setting	
Parameter	Description
i	Target interest rate
dr_t	Discount rate in period t with $dr_t = (1+i)^{-(t-min(T))}$
ϵ	Maximum CO_2 emission threshold exceedance
q_t^{min}	Minimum production quantity in period t
φ^{max}	Maxmimum utilization of production capacity in ramp-up year
SOP^{max}	Maximum project realization/number of SOPs per period
Other parameters	
Parameter	Description
N	Large number ($\geq 1,000,000$)
T^{max}	Last period of the planning horizon U

Table A3: Parameters

1.4 Objective Function

$$\begin{aligned} Max \quad NPV = & \sum_{t \in U} ((CF_t^{SalesProd} - CF_t^{ProdFixed} - CF_t^{Penalty}) * dr_t) \\ & - \sum_{t \in T} ((CF_t^{RD} + CF_t^{Capacity}) * dr_t) \\ & + CF^{CapaBack} * dr_{T^{max}} \end{aligned} \tag{A. 1}$$

where

$$CF_t^{SalesProd} = \sum_{v \in V} ((p_v^{ProdVar} - c_v^{ProdVar}) * q_{vt}) \tag{A. 2}$$

$$CF_t^{ProdFixed} = \sum_{c \in C} (c^{ProdFixed} * k_{ct}) \tag{A. 3}$$

$$CF_t^{Penalty} = z_t^{Penalty} \tag{A. 4}$$

$$CF_t^{RD} = \sum_{v \in V} (c^{RD} * Vect_{t\tau}^{RD} * y_v) \tag{A. 5}$$

$$\begin{aligned} CF_t^{Capacity} = \sum_{c \in C} \sum_{\tau \in U} ((c^{RampupFixed} * Vect_{t\tau}^{PC} * k_{c\tau}^{RampupBin}) \\ + (c^{RampupVar} * Vect_{t\tau}^{PC} * k_{c\tau}^{Rampup})) \end{aligned} \tag{A. 6}$$

$$CF^{CapaBack} = \sum_{c \in C} z_c^{Back}. \tag{A. 7}$$

1.5 Constraints

Vehicle projects

$$y_v = y_v^{Preset} \qquad \forall v \in W \tag{A. 8}$$

$$q_{vt} \leq N * y_v \qquad \forall v \in V, \forall t \in U \tag{A. 9}$$

$$\sum_{v \in V : SOP_v = t} y_v \leq SOP^{max} \qquad \forall t \in U \tag{A. 10}$$

$$q_{vt} = 0 \qquad \forall v \in V, \forall t \in T : t < SOP_v \vee t \geq SOP_v + \tau^{LC} \tag{A. 11}$$

Production resources

$$\sum_{v \in V : r_v = c} q_{vt} \leq k_{ct} \qquad \forall c \in C, \forall t \in U \tag{A. 12}$$

$$\sum_{v \in V : r_v = c} q_{vt} \leq \varphi^{max} * k_{ct} \qquad \forall c \in C, \quad \forall t \in T : t = \tau_c^{Rampup} \tag{A. 13}$$

$$k_{ct} = k_c^{Preset} + \sum_{\tau \in U : \tau \leq t} (k_{c\tau}^{Rampup} - k_{c\tau}^{Rampdown}) \qquad \forall c \in C, \forall t \in T \tag{A. 14}$$

$$k_{ct}^{Rampup} \leq N * k_{ct}^{Bin} \qquad \forall c \in C, \forall t \in T \tag{A. 15}$$

$$z_c^{Back} \leq V_c^{res} * \sum_{t \in T} \sum_{\substack{\tau \in U: \\ \tau > T^{Rampup}}} \Big((c^{RampupFixed} * Vect_{t\tau}^{PC} * k_{c\tau}^{Bin}) + (c^{RampupVar} * Vect_{t\tau}^{PC} * k_{c\tau}^{Rampup}) \Big) \qquad \forall c \in C \quad \text{(A. 16)}$$

where $T^{Rampup} = T^{max} - \delta t^{Rampup}$

Vehicle demand

$$\sum_{v \in V: n_v = m} q_{vt} \leq d_{mt} \qquad \forall m \in M, \forall t \in U \quad \text{(A. 17)}$$

Emission legislation

$$\sum_{v \in V} (E_v * q_{vt}) \leq E_t^{Law} * (1 + \epsilon) * \sum_{v \in V} q_{vt} \qquad \forall t \in U \quad \text{(A. 18)}$$

$$z_t^{Penalty} \geq c^{CO_2} * \Big(\sum_{v \in V} (E_v * q_{vt}) - E_t^{Law} * \sum_{v \in V} q_{vt} \Big) \qquad \forall t \in U \quad \text{(A. 19)}$$

$$z_t^{Penalty} \geq 0 \qquad \forall t \in U \quad \text{(A. 20)}$$

$$E_t = \frac{\sum_{v \in V} E_v * q_{vt}}{\sum_{v \in V} q_{vt}} \qquad \forall t \in U \quad \text{(A. 21)}$$

Production volume

$$\sum_{v \in V} q_{vt} \geq q_t^{min} \qquad \forall t \in U \quad \text{(A. 22)}$$

2 Appendix II - Parameters Values

In this section, there are the values that were imputed in the model to obtain the results described in the article. Tables A4 and A5 contain the decisions already made before the planning horizon starts, and Table A6 presents the 2 sets of the fleet emission thresholds defined in 2019 and 2023 by the EU Commission.

Vehicle Size	Powertrain Technology	Power Class	SOP
small	ICEV	low	2020
small	ICEV	high	2020
medium	ICEV	low	2020
medium	ICEV	high	2020
large	ICEV	low	2020
large	ICEV	high	2020
large	ICEV	low	2021
large	ICEV	high	2021
small	ICEV	low	2024
small	ICEV	high	2024

Table A4: Vehicle projects decided before the start of the planning horizon

Vehicle Size	Powertrain Technology	Year	Capacity in 2025
small	ICEV	2020	260,000
medium	ICEV	2020	200,000
large	ICEV	2020	300,000
large	ICEV	2021	360,000
small	ICEV	2024	260,000

Table A5: Production resources already installed before the start of the planning horizon and their capacity in vehicles/year in 2025

Period	Thresholds (2019)	Thresholds (2023)
2026	80.00	93.90
2027	80.00	93.90
2028	80.00	93.90
2029	80.00	93.90
2030	60.00	49.50
2031	60.00	46.50
2032	60.00	49.50
2033	60.00	49.50
2034	60.00	49.50
2035	45.00	0.00

Table A6: CO_2 fleet emission thresholds defined in 2019 and in 2023 in Regulation (EU) 2019/631 (Commission (2019)) and in Decision 2023/1623 (Commission (2023))

Ehrenwörtliche Erklärung

Wir erklären hiermit ehrenwörtlich, dass wir die vorliegende Arbeit selbständig angefertigt haben. Die aus fremden Quellen direkt und indirekt übernommenen Gedanken sind als solche kenntlich gemacht.

Wir wissen, dass die Arbeit in digitalisierter Form daraufhin überprüft werden kann, ob unerlaubte Hilfsmittel verwendet wurden und ob es sich - insgesamt oder in Teilen - um ein Plagiat handelt. Zum Vergleich unserer Arbeit mit existierenden Quellen darf sie in eine Datenbank eingestellt werden und nach der Überprüfung zum Vergleich mit künftig eingehenden Arbeiten dort verbleiben. Weitere Vervielfältigungs- und Verwertungsrechte werden dadurch nicht eingeräumt. Die Arbeit wurde weder einer anderen Prüfungsbehörde vorgelegt noch veröffentlicht.

Ort, Datum

München, 09.02.2024

Unterschrift

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