

A multi-criteria decision-making approach for assembling optimal powertrain technology portfolios in low GHG emission environments

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Editor Managing Review: Lynette Cheah

Abstract

Environmental regulations force car manufacturers to renew the powertrain technology portfolio offered to the customer to comply with greenhouse gas (GHG) emission targets. In turn, automotive companies face the task of identifying the “right” powertrain technology portfolio consisting of, for example, internal combustion engines and electric vehicles, because the selection of a particular powertrain technology portfolio affects different company targets simultaneously. What makes this decision even more challenging is that future market shares of the different technologies are uncertain. Our research presents a new decision-support approach for assembling optimal powertrain technology portfolios while making decision-makers aware of the trade-offs between the achievable profit, the achievable market share, the market share risk, and the GHG emissions generated by the selected vehicle fleet. The proposed approach combines “a posteriori” decision-making with multi-objective optimization. In an application case, we feed the outlooks of selected market studies into the proposed decision-support system. The result is a visualization and analysis of the current real-world decision-making problem faced by many automotive companies. Our findings indicate that for the proposed GHG restriction at work in 2030 in the European Union, no optimal powertrain technology portfolio with less than 35% of vehicles equipped with an electric motor exists.

KEYWORDS

automotive sector, decision-support system, industrial ecology, portfolio optimization, powertrain technologies, technology selection

1 | INTRODUCTION

Among scientists, politicians, and throughout the population, there is a high awareness of the urgent need to respond to the threat of climate change by limiting the global temperature rise (Cook et al., 2016). A central element of climate change mitigation strategies is the reduction of greenhouse gas (GHG). Since a considerable share of the overall GHG emissions is caused by fossil fuels' combustion (IPCC, 2007; UNFCCC, 2018; USEPA, 2018), the automotive sector has material leverage to contribute to climate change mitigation.

The Paris Agreement of 2015 legally binds member countries to limit the global warming to a maximum of 2°C above the average temperature of the pre-industrial times (EC, 2020b). To comply with this goal, governmental and non-governmental organizations have adjusted political strategies

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and launched several initiatives. For instance, the European Union (EU) has set the objective to be climate neutral by 2050 (EC, 2020a). An EU strategy's key focus is the road transport sector, accounting for around 20% of the overall GHG emissions in the EU (EC, 2018). As an interim goal, the EU has specified an emission target for passenger cars of on average 95 g CO₂ per km for 2021 (EC, 2020c) and a further GHG reduction of the emission values from 2021 by 37.5% by 2030 (EP, 2019), resulting in an estimated emission target of around 60 g CO₂ per km in 2030.¹ Such regulations significantly impact the automotive market as they indirectly prescribe the powertrain technologies to be promoted. The recent plans of car manufacturers to become carbon neutral by 2040 (e.g., General Motors) or 2050 (e.g., Volkswagen) may serve as illustrative examples (GM, 2021; VW, 2019).

The different regulatory initiatives to reduce GHG emissions of the product fleet of automotive companies (e.g., EP, 2019) have fostered the need for new decision-support tools. Such tools, if they are correctly applied and consider all available data, improve a strategic management decision concerning the direction of the future powertrain technology portfolio. Different powertrain technologies (such as fossil fuel-based mobility, electric mobility) comprise various characteristics, such as distinct levels of GHG emissions or market shares, and thus require a decision-support system that considers respective trade-offs. Multi-criteria decision-making literature has dealt with comparable decision situations (Gutjahr, 2011), and some research proposes models to optimize technology portfolios (e.g., Dickinson et al., 2001). Our research suggests overcoming methodological and data-concerned restrictions in the powertrain technology portfolio selection problem using a new multi-criteria approach for strategic decision-making.

From a methodological point of view, the powertrain technology selection is a multi-criteria decision-making problem in strategic management (e.g., Montibeller & Franco, 2010). Many approaches to solve the powertrain technology selection problem have been conceptualized to select one single technology only, without determining the shares of an optimal technology portfolio and without considering uncertain market demand conditions. Despite the importance of the estimation quality of market shares of different powertrain technologies (Gómez Vilchez & Jochem, 2019; Jochem et al., 2018), there is currently no approach available to transform market share uncertainties into measurable risk and to provide the automotive companies with clear visual decision-support when deciding which technology to choose. The proposed methodology is a multi-objective decision-making model allowing decision-makers to determine an optimal choice for the multi-criteria technology portfolio configuration problem. Hence, the most critical portfolio characteristics act as objectives. They will either be maximized (e.g., the market share) or minimized (e.g., the GHG emissions). In this way, objectives need to be balanced. This is crucial since the one objective's achievement typically hinders attaining the other objectives' maximum/minimum values. Contributions in related business fields, such as supply chain management (e.g., Hosseininasab & Ahmadi, 2015; Kellner et al., 2019) and marketing (e.g., Cardozo & Smith, 1983, 1985; Devinney et al., 1985), show that the multi-criteria optimization framework proposed by Harry Markowitz (1952, 1959) for investment portfolio theory supports portfolio assembling decisions effectively after carefully considering relevant assumptions (Devinney et al., 1985)—especially if risk needs to be considered. Our research combines the technology portfolio configuration problem with theoretical concepts of portfolio optimization to construct technology portfolios reducing the long-term risk of market share estimation failure.

This research's contribution is threefold: (1) We present a multi-objective optimization model for the powertrain technology portfolio problem. The proposed model transfers the portfolio theory fathered by Markowitz (1952, 1959) to the technology selection case. Thus, our approach is in line with prior studies that show that this theory might effectively be applied in areas other than finance (cf., Cardozo & Smith, 1985; Kellner & Utz, 2019; Kundisch et al., 2008). (2) We feed the outlooks of selected market studies into this optimization model and visualize the efficient set² of technology portfolios. The result is a visualization of the current real-world decision-making problem many companies face in the automotive sector. The opportunity to draw an efficient set is advantageous for decision-makers. The graph of an efficient set illustrates the available optimal technology portfolios and allows analyzing trade-offs between the different objectives before deciding. (3) We show how selecting a specific powertrain technology portfolio may be facilitated by utilizing an interactive web application.

Section 2 reviews prior research and positions our article in the literature dealing with the powertrain technology portfolio selection problem. Section 3 presents the new multi-criteria decision-support system. Section 4 covers a real-world application case. Section 5 discusses the modeling assumptions and the results of the application case. Finally, Section 6 concludes the paper.

2 | LITERATURE REVIEW

Decisions about the target market, product mix, and technology selection significantly influence a company's economic success (Mansfield & Wagner, 1975). Thus, product planning comprises a set of strategic decisions to pursue the right markets and products (Krishnan & Ulrich, 2001). In this article, we focus on product portfolio selection (see Ali et al., 1993).

¹ All GHG emission values reported in this paper and used in our analyses are tank-to-wheel emissions. Tank-to-wheel describes the use of fuel in the vehicle and emissions during driving, while the term well-to-tank describes the sub-range of fuel supply—from the production of the energy source to fuel supply (VW, 2020). However, our model is not restricted to the tank-to-wheel setting. The input data could also comprise well-to-tank or well-to-wheel (i.e., well-to-tank plus tank-to-wheel) emission volumes.

² In Markowitz's theory, a portfolio is called "efficient" if it has, for a given level of risk, the highest possible expected return (Markowitz, 1952, 1956, 1959). The efficient frontier graphically represents the risk-expected return trade-off of efficient portfolios, and the set of all efficient portfolios is called the "efficient set."

Concerning the planning problem (decision situation), the methodology proposed in this paper is instrumental in the strategic production planning phase during which the management makes decisions about the “great goals” to be achieved. In this phase, the management decides, following the overall company strategy and within the time frame of about 10 years, what products, projects, and technologies are to be promoted and to what extent. It is then the task of the tactical production planners to adopt these goals and detail them by, for example, indicating in what year what quantities of which technology are to be produced. This classical hierarchical concept of production and manufacturing planning, which many manufacturing companies apply, is described in detail, for instance, by Vollmann et al. (1997), who present the different scopes and time horizons in operations planning. In this context, also the concept of cycle planning needs to be mentioned. In the automotive industry, a cycle plan reflects a company’s plan for the life cycle of all of its different vehicle models along a multi-year time axis; that is, a cycle plan is the manifestation of all of an automotive company’s program plans, including the configuration of the product portfolio at a given moment in time. Typically, a cycle plan spans 10–15 years and is reviewed and renewed annually, with another year added at the end of the planning horizon. Important inputs for the update of the cycle plan are the customers’ voice (consumer research, market studies) and broad demographic, political, economic, and social factors. These inputs are considered in the annual product strategy and development process, where the corporate strategic plan, the technology plan, and the business plan are reviewed and updated. The outcome of these planning activities feeds into the updated cycle plan. CAR (2007) presents a detailed description of this process. We argue that the proposed methodology is a useful approach to support the annual cycle plan update activities, where the cycle plan is reviewed and updated according to the latest results from ongoing market research studies, and emission regulations, amongst others.

Our proposed model supports the decision-maker in aligning the powertrain technology portfolio with market shares, profit, and the automotive sector’s regulatory environment in 2030. Such models’ application is critical since successful firms often fail to recognize technology and market shifts as product planning is biased toward existing markets (Christensen & Bower, 1996). Particularly in the automotive sector, decisions on future product portfolios are crucial since new products’ markets can change rapidly. Currently, the introduction of alternative (hybrid or battery) powertrains require automotive manufacturers to integrate powertrain decisions into strategic product portfolio management (Kieckhäfer et al., 2012). Strategic decisions in this respect are crucial since the regulatory environment forces automotive manufacturers to reduce the CO₂ emissions of the product fleet (see, for instance, CO₂ regulation in the EU (EC, 2010) and the Corporate Average Fuel Economy (CAFE) regulation in the United States (NHTSA, 2011)). Following Kieckhäfer et al. (2009) and Walther et al. (2010), the automotive manufacturer has three options to comply with future CO₂ regulations: (1) improve the efficiency of conventional (gasoline and diesel) powertrain technology, (2) offer higher shares of small vehicles with low fuel consumption, or (3) integrate vehicles with an alternative (e.g., electric) powertrain technology into their vehicle portfolios. Raasch et al. (2007) highlighted that the automotive sector virtually cannot make short-term modifications to the product portfolio. Otherwise, a large amount of sunk cost for the investments made will be incurred.

Due to the high importance of finding the “right” technology portfolio, it is not surprising that approaches supporting the powertrain portfolio choice problem have been suggested (Gómez Vilchez & Jochem, 2019; Jochem et al., 2018). For instance, several quantitative studies (Byrd & Moore, 1978; David, 2001; Hirshfeld, 1984; Little, 2004) present models aiming to improve portfolio strategies with mathematical optimization. Moreover, Umpfenbach et al. (2018) classify the decision situation as an assortment planning problem. They developed a methodology to solve this problem in low-emission vehicle regulation in the automotive sector. The authors highlight the trade-offs between the increasing environmental targets of the regulation and economic quantities the automotive manufacturer has to consider to be profitable. Ma et al. (2020) present a multi-criteria framework to solve these trade-offs in a project portfolio selection application with the fuzzy logic model in a Technique for Order of Preference by Similarity to Ideal Solution (TOPSIS) approach to achieve the most sustainable solution. However, to the best of our knowledge, no previous approach provides automotive companies with visual decision-support regarding which technology to choose and allows them to visualize and analyze the total amount of trade-offs associated with the powertrain portfolio selection, and that translates market share uncertainties into measurable risk.

According to Raasch et al. (2007), the two main requirements for an appropriate model to determine the product portfolio in the automotive sector are (1) an economic, complete, and comparative usage of available data sources and (2) the presentation of all relevant outcomes of alternative product portfolios. Regarding forecasting data, expected market shares and sales volumes of different powertrain technologies directly influence financial performance indicators (see Edwards et al., 2007; Kieckhäfer et al., 2009). Regarding outcomes, interactive decision-making tools should display possible solutions that are well prepared for management to use in executive meetings. The decision-support approach proposed in this article considers these aspects.

3 | METHODOLOGY

At the heart of the proposed decision-support system is a multi-objective powertrain technology portfolio model with four objectives: (1) to maximize the average profit cost ratio that may be realized with the selected powertrain portfolio, (2) to maximize the share of those technologies that have the highest expected future market shares, (3) to minimize the market share risk (MSR), that is, the uncertainty that the selected technology portfolio realizes the expected market share, and (4) to minimize the overall GHG emissions caused by the vehicle fleet.

Indices

i, j 1 ... N Technologies

Decision variables

$x_i \in [0, 1]$ Proportion of technology i in a technology portfolio of an automotive company

Parameters

$profit_i \in R^+$ Profit cost ratio of technology i (in percent)

$m_{sp_i} \in [0, 1]$ Expected market share of technology i (in percent)

$cov_{ij} \in R$ Covariance of the market share in technologies i and j

$ghg_i \in R^+$ GHG emissions generated by technology i (in g CO₂ per km)

Objectives

$$\text{Profit cost ratio (Profit) } \max \sum_i profit_i * x_i \quad (1)$$

$$\text{Market share potential (MSP) } \max \sum_i m_{sp_i} * x_i \quad (2)$$

$$\text{Market share risk (MSR) } \min \sum_{ij} cov_{ij} * x_i * x_j \quad (3)$$

$$\text{GHG emissions (GHG) } \min \sum_i ghg_i * x_i \quad (4)$$

Constraints

$$\text{Full investment } \sum_i x_i = 1 \quad (5)$$

$$\text{Overall GHG emissions } \sum_i ghg_i * x_i \leq 60 \quad (6)$$

Objective function (1) maximizes the average per-unit profit cost ratio (in the following “profit”) of the technology portfolio. The idea behind this is to invest as much as possible in the technologies most efficient in a profit–cost consideration and thus provides the greatest relative profit.

Objective function (2) maximizes the market share potential (MSP) of the technology portfolio. The MSP is indicated by the expected market shares of the unique technologies that are part of a specific portfolio weighted with the corresponding portfolio shares. The idea is to invest as much as possible in the technologies predicted to have the highest future market shares. The goal of maximizing the MSP may be interpreted as maximizing the targeted market size or maximizing the market coverage. Note that the absolute value of the MSP is hard to interpret. The MSP is rather a relative figure that indicates which one of several portfolios has the largest expected sales market. A higher number indicates a larger expected sales market. At this point, it should also be noted that, in general, firms can shape the markets by their supply, as stated in the study of Umpfenbach et al. (2018) for the automotive market. However, the restriction on our approach to consider fixed MSPs is not a methodological limitation but rather an input data constraint. Being aware of possible market-shaping activities by supplying a specific product portfolio could be easily depicted in adjusting the input data.

Objective function (3) minimizes the MSR. The MSR reflects the uncertainty about the future market shares of single technologies. Several predictions have been made on the future spread of the various technologies (see Section 4). However, the individual market studies’ outlooks are not uniform but differ to a more or less significant degree. Thus, we measure the risk about the future market shares of the single technologies with the predicted market shares’ covariance across the available market studies. These covariances provide at least two insights. First, the covariance of the market share of one technology (variance) indicates the risk that the estimate will err. The higher the variance, the more the various estimates differ, and the higher the risk of a deviation of the actual market share from the expected one. Second, the covariance between the market shares of two distinct technologies indicates the correlation, that is, it implies whether the increase of one technology’s market share is accompanied by an increase or a decrease in the market share of the other technology. Note that for decision situations with at least three different technologies, an increase in one technology does not cause a decrease in both of the other technologies. This second insight helps generate portfolios that have low exposure to changes in the market shares since a portfolio is composed so that different technologies compensate each other concerning the predicted market shares. Equation (3) minimizes the MSR of a technology portfolio by minimizing the expected market shares’ covariance between

the single technologies. Since the covariance measures the interaction between the market shares of the different technologies, the purpose of objective function (3) is to minimize the MSR by (a) choosing those technologies that have a low variance in the predicted market shares across the single market studies or (b) by assembling technology portfolios with negatively correlated market shares. Or, put differently, the desirable situation is achieved when (a) the predicted market shares for a specific technology are similar across the single market studies; or (b) when the different technologies compensate each other concerning the expected market shares, that is, when one technology is predicted to lose in market shares, the other(s) will win—and vice versa.

Objective function (4) minimizes the fleet average GHG emissions per vehicle. Equation (5) ensures that the sum of the portfolio weights of the single technologies adds up to 100%. The portfolio weights represent the percentage shares of the single technologies in the considered automotive company's technology portfolio. These weights indicate the share of the number of vehicles that are equipped with a specific powertrain technology. A portfolio weight of 30% for internal combustion engine, for instance, means that 30% of all vehicles produced by the considered automotive company are equipped with the internal combustion engine technology. Equation (6) guarantees that the average per-vehicle GHG emissions of the fleet do not exceed the limiting value of 60 g CO₂ per km, consistent with the upcoming regulations in 2030 (cf., Section 1).

Generally, the classification of multi-objective optimization techniques depends on the point in time when the decision-maker states preferences among different objectives: this classification comprises “a priori” techniques, “a posteriori” techniques, interactive techniques, techniques without an articulation of preferences, and combinations of them (Eskelinen et al., 2010; Hirschberger et al., 2013; Hwang & Masud, 1979; Marler & Arora, 2004; Mavrotas, 2009). “A priori” means that the decision-maker has to determine her preferences for the individual objectives before the optimization and obtains one solution optimal for this specific set of preferences. In contrast, “a posteriori” techniques do not require any articulation of preferences before the optimization. In the “a posteriori” case, all efficient solutions are first computed and visualized graphically. A particular portfolio can then be selected following the company's product strategy (Miettinen, 1998, 2014). We suggest an “a posteriori” approach to tackle the multi-objective technology portfolio problem. Such an approach refrains from stating ex ante preferences by the decision-maker. Moreover, it identifies the trade-offs between the objectives and studies how these objectives may be balanced (Kellner et al., 2019). To solve this portfolio selection problem, we suggest applying the ϵ -constraint method (Chankong & Haimes, 1983; Haimes et al., 1971). Details of the implementation of the ϵ -constraint method in our context are presented in Appendix A in the Supporting Information.

4 | APPLICATION

This section shows the outcome of feeding the outlooks of some well-accepted market studies concerning the future market shares of different powertrain technologies into the proposed decision-support system. Thus, we visualize and analyze the current real-world decision-making problem faced by many companies in the automotive sector. Also, we show how an interactive web dashboard facilitates identifying the most preferred technology portfolio.

4.1 | Input data

Table 1 provides an overview of nine studies with market share forecasts for the year 2030 related to passenger vehicle technologies and published within an 18-month time frame between 1 October, 2018 and 31 March, 2020. These nine studies have been identified in a two-stage process. The first stage consisted of analyzing meta-research that descriptively compares individual studies on global market shares of electric vehicles (cf., Bakken et al., 2017; GCC, 2019). We included the individual studies or their updates if these studies had been publicly available within the defined time frame and if passenger market share data had been provided. The second stage consisted of a Google search and was performed to include studies not mentioned in the meta-analyses of Stage 1. We only included pdf files in our search to reiterate our analysis to studies by institutions rather than private personnel websites. Additionally, we filtered the results by only allowing primary studies in the English language and illustrating global market shares.

Table 1 illustrates the differences between the various studies. Besides differences in the provided data quantity type (individual, cumulative), we see deviations in the portrayed technologies' detail. Overall, the studies cover technologies related to internal combustion engines (ICE), battery electric vehicles (BEV), plugin-hybrid electric vehicles (PHEV), full-hybrid electric vehicles (FHEV), mild-hybrid electric vehicles (MHEV), and fuel-cell electric vehicles (FCEV).

Apart from the specific technologies, the studies show substantially different assumptions in the expected future market shares. For instance, an automotive company choosing the study of BCG (2020) as the main source would expect a market share of 48% for ICE technology, a market share of 18% for BEV, and 33% for hybrid solutions in 2030. Other market studies (e.g., BNEF, 2019; Deloitte, 2019) attribute substantially higher shares to ICE and expect hybrid solutions to be less important than in the BCG (2020) study. A material difference between the expected and the actual market shares results in allocating resources in the development and production of products that do not meet the customer's needs. Considering the uncertainty in market share estimates does not guarantee a precise forecast; however, it indicates how likely a certain forecast is.

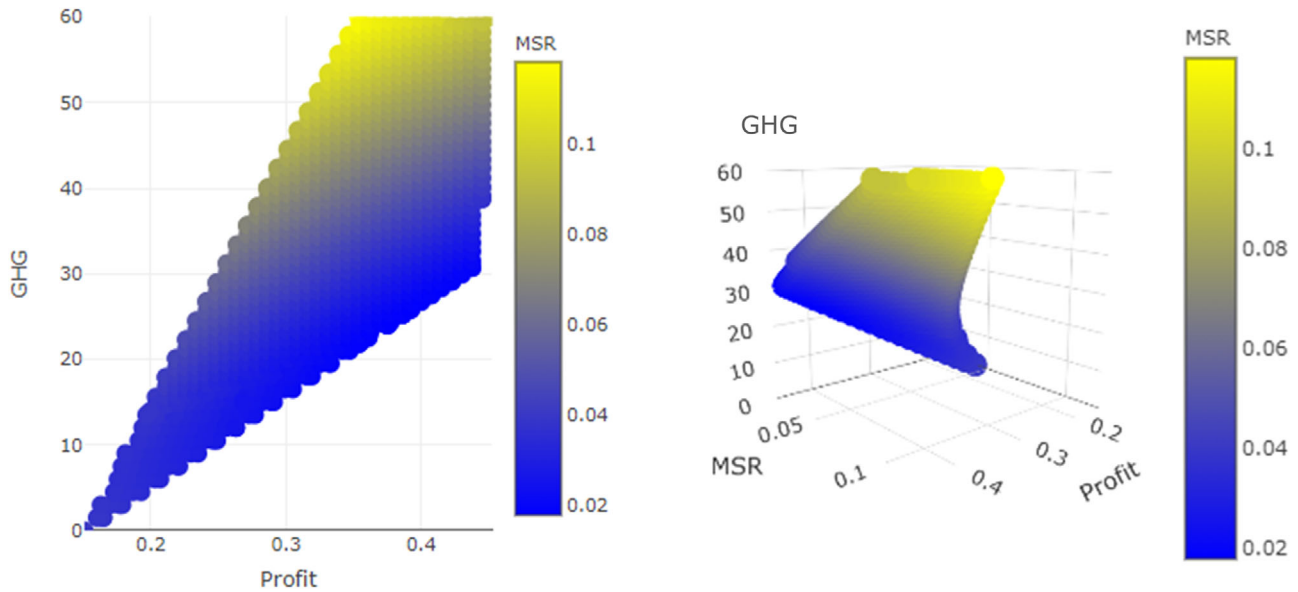


FIGURE 1 Efficient set (two- and three-dimensional projections). Efficient set illustrated as a projection of the greenhouse gas emissions (GHG), average profits (Profit), and market share risk (MSR). The color indicates the market share risk (MSR, yellow = high risk, blue = low risk). The MSP values of the single portfolios vary in the range between $v_{MSP}^{Nad} = 0.050$ and $v_{MSP}^{Opt} = 0.452$

In our study, we rely on the mostly discussed technologies, that is, ICE, PHEV, and BEV. PHEV combine an internal combustion powertrain with an electric powertrain (Bradley & Frank, 2009; Plötz et al., 2018). BEV are entirely based on an electric powertrain. We filtered our data basis for studies that include these technologies. As a result, we use the market studies by Bloomberg (BNEF, 2019), Boston Consulting Group (BCG, 2020), JP Morgan (JPM, 2018), and Deloitte (Deloitte, 2019). For the market shares of the single technologies in 2030, we take the values as estimated by the four market studies. Using these values for each of the three technologies allows us to calculate the mean market shares, that is, the market shares that we would expect if we consider all four market studies and the market share covariance matrix (Table 2). The estimates for the GHG emission rates and the profits of the three technologies are also stated in Table 2. Appendix B in the Supporting Information describes in detail how these figures are calculated.

4.2 | Determining and visualizing the efficient set

For applying the ε -constraint method, we first calculate the optimal and nadir values for the objectives Profit, MSP, and GHG. The concept of nadir values is explained in Appendix A in the Supporting Information (Solution procedure). The result is as follows: $v_{Profit}^{Opt} = 0.453$, $v_{Profit}^{Nad} = 0.151$, $v_{MSP}^{Opt} = 0.452$, $v_{MSP}^{Nad} = 0.050$, $v_{GHG}^{Opt} = 0$, and $v_{GHG}^{Nad} = 60$. Next, the ranges of the optimal and nadir values are sub-divided into $m = 40$ equidistant intervals. This means that, in total, $68,921 (= 41 \times 41 \times 41)$ optimization runs are started. The number of feasible unique solutions with respect to the applied rounding accuracy (Profit: 5 decimals; MSP and MSR: 4 decimals; GHG: 1 decimal; portfolio shares: 3 decimals) is 976. These solutions constitute the efficient set.

Figure 1 shows a two- and a three-dimensional projection of the efficient set, reflecting the technology portfolio problem. The surface-like geometry comprises the 976 unique optimal technology portfolios. Figure 1 shows the single portfolios' characteristics in terms of the average Profits, the MSR, and GHG emissions. For MSP, this objective is not visualized in Figure 1 as it is hard to integrate the fourth dimension into the graph. However, as will be shown in Section 4.5, it is possible to set minimum values and intervals for the fourth dimension, and as will be shown, setting minimum values for the MSP will remove those portfolios that do not meet the minimum MSP requirements from the efficient set. That is, the result is the same graph as shown in Figure 1, only the surface is smaller. The figure on the left side reports the portfolio characteristics in terms of the average profits on the x-axis, the y-axis shows the GHG emissions of the single portfolios. The color scale indicates the portfolios' performances for the MSR. The MSR is indicated with the standard deviation of the market shares of the technology portfolios. Concerning the level of the MSP, no upper or lower bound values are set in Figure 1, that is, the values of the single portfolios vary in the range between $v_{MSP}^{Nad} = 0.050$ and $v_{MSP}^{Opt} = 0.452$. All portfolios in combination, that is, the entire efficient set, show the trade-off between achieving the different goals as each portfolio is optimal for a specific combination of preferences. This means that it is impossible to improve in a particular objective without worsening in another objective when moving from one point of the efficient set/from one portfolio to another (cf., Eskelinen & Miettinen, 2012; Kellner et al., 2019). The figure on the right side shows the same set of efficient portfolios in three dimensions.

TABLE 2 Technology characteristics in 2030: Profits, market shares, GHG emissions, and market share covariance matrix

Market study / Parameter	Market studies: Details	Parameter (technical name)	ICE	BEV	PHEV
BCG (2020)	Estimated market shares in 2030		48%	18%	6%
BNEF (2019)	Estimated market shares in 2030		70%	23%	6%
JPM (2018)	Estimated market shares in 2030		41%	18%	2%
Deloitte (2019)	Estimated market shares in 2030		81%	13%	6%
Mean market share 2030		msp_i	0.60	0.18	0.05
Profit: (sales price—manufacturing costs)/manufacturing costs		$profit_i$	0.46	0.15	0.44
Greenhouse gas emissions (g CO ₂ per km, tank-to-wheel)		g'_{hg_i}	92.8	0.0	31.2
Covariance ICE		cov_{1i}	3.49E-02	-1.83E-03	2.53E-03
Covariance BEV		cov_{2i}	-1.83E-03	1.67E-03	1.08E-19
Covariance PHEV		cov_{3i}	2.53E-03	1.08E-19	4.00E-04

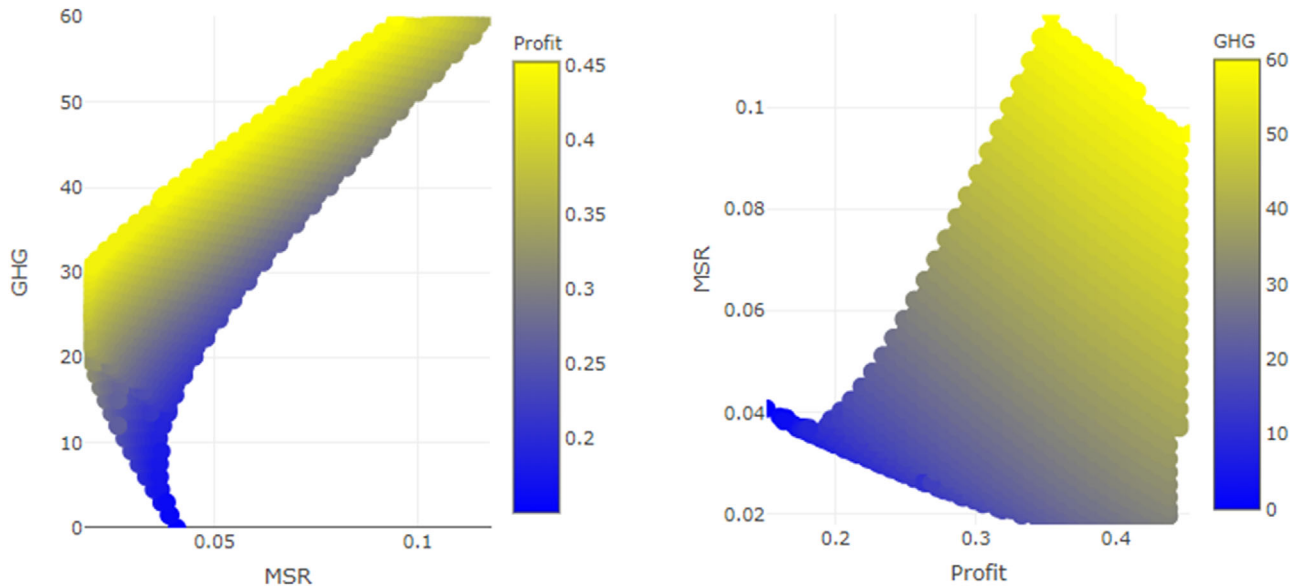


FIGURE 2 Efficient set (two-dimensional projections, changed axes). Efficient set illustrated as different projections: in the left picture the GHG emissions on the y-axis and the market share risk on the x-axis, the color indicates the average profits; in the right picture the MSR on the y-axis and the Profit on the x-axis, the color indicates the GHG. The MSP values vary in the range between $v_{MSP}^{Nad} = 0.050$ and $v_{MSP}^{Opt} = 0.452$

Figure 2 shows two additional two-dimensional projections of the efficient set. Note that the four plots in Figures 1 and 2 show the same object—only the axes are changing.

Each point of the efficient set represents one option for an efficient combination of objectives matching one specific technology portfolio; that is, each point/portfolio of the efficient set is optimal for a particular set of preferences between the objectives Profit, MSP, MSR, and GHG emissions. Decision-makers draw a final decision about the desired portfolio by selecting a specific point/portfolio from the full set that fits best with their preferences. The advantage of this approach is that decision-makers get, for any predefined minimum value of the MSP (set to 0 in Figures 1 and 2, i.e., there is no limitation), the full picture of all optimal options. They have an overview of all trade-offs that are associated with the technology portfolio problem before deciding. This position allows for a better understanding of the decision-making problem and a better-informed decision-making process. Figure 1, for instance, shows that many high-profit portfolios come with an unusually high MSR. Moreover, Figure 1 indicates that some portfolios allow for very low GHG emissions; however, these portfolios do not reach the same high profits as other portfolios do. Further, Figures 1 and 2 show that there are notably high numbers of optimal portfolios in the area of Profit around 0.35 and in the area of GHG around 30 g CO₂ per km.

4.3 | Analyzing the decision-making problem: Summary statistics

An advantage of the “a posteriori” decision-making approach is that it allows the analysis of the efficient set and provides deeper insights into the decision-making problem. For the sake of convenience, we indicate the MSP and the MSR of the single portfolios with the “raw” and normalized values, that is, the highest MSP/MSR value across all vehicle portfolios is set to 1, and the lowest MSP/MSR value is set to 0. All other MSP/MSR values are adapted accordingly. Thus, the portfolio with the highest MSP/MSR is conceptualized as the “100%-MSP”/“100%-MSR” portfolio, and the portfolio with the lowest MSP/MSR is seen as the “0%-MSP”/“0%-MSR” portfolio.

Unreported results show that, for the data used in this study (presented in Table 2), the MSP’s raw values of the optimal technology portfolios range between 0.052 and 0.452, with a notable concentration around 0.2. The portfolio that achieves the highest MSP consists of 64.7% ICE and 35.3% BEV. For the MSR, the standard deviation of the market share of the portfolio with the highest risk is almost seven times greater than the standard deviation of the portfolio with the lowest risk (0.118 vs. 0.018). The portfolio with the highest standard deviation consists of 64.7% ICE and 35.3% BEV. The portfolio with the lowest standard deviation comprises 20.4% BEV and 79.6% PHEV. For the objective GHG, the average per-vehicle CO₂ emissions cover the whole range from 0 to 60 g CO₂ per km. A notable concentration can be seen: many optimal portfolios exhibit GHG emission around 30 g CO₂ per km. The minimum GHG portfolio consists of BEV only (0 g CO₂ per km). For the objective Profit, a great share of the optimal powertrain portfolios comes with an average profit of around 0.35. The portfolio with the lowest profit (0.151) consists of BEV only, while the portfolio with the highest profit (0.453) comprises 46.7% ICE and 53.3% PHEV. Table 3 presents statistics for the portfolio shares of the three technologies.

TABLE 3 Summary statistics for the portfolio shares of the investigated technologies across the efficient set

Aspect	Aspect (Details)	ICE (%)	BEV (%)	PHEV (%)
Portfolio share	Minimum	0.0	0.0	0.0
	Median	21.4	37.7	34.9
	Mean	23.6	39.2	37.2
	Maximum	64.7	100.0	98.3
Frequency of being included in an optimal portfolio		95.9	99.7	97.3
Frequency of having a portfolio share	>5%	84.5	94.3	89.9
	>10%	72.8	88.5	81.9
	>20%	52.0	75.5	68.8
	>30%	35.2	61.8	56.0
	>50%	7.9	32.5	31.9

A closer look at the single optimal technology portfolios reveals that 93.0% of all portfolios consist of all three technologies, 6.9% include two technologies, and one unique portfolio consists of one technology (BEV). As shown in Table 3, the technology "BEV" receives particular attention as this technology is included in 99.7% of all optimal technology portfolios, with an average portfolio share of 39.2%. This means that independent of a decision-maker's preferences for the four objectives, BEV will be combined in almost every case with at least one other technology. As can further be seen in Table 3, in 32.5% of all portfolios, BEV has a portfolio share of at least 50%. Table 3 further shows that PHEV receives slightly less attention than BEV; however, the figures are quite similar. Both BEV and PHEV receive significantly more attention than ICE in terms of the mean and the maximum contribution to the single portfolios as well as in the number of cases where the considered technology contributes at least 5%, 10%, 20%, 30%, and 50% to an optimal portfolio. Table 3 also shows that the maximum portfolio share of ICE is around 64.7%. This implies that, according to the data used, regardless of a decision-maker's preference for the single objectives, the share of vehicles equipped with an electric motor should be at least 35% in 2030.

4.4 | Trade-off analyses

To gain deeper insights into the technology portfolio problem, we carry out sensitivity analyses. The goal is to understand the effect on the efficient set when a company sets specific requirements regarding the objectives Profit, MSP, MSR, and GHG.

Table 4A shows the effect on the maximum MSP, the minimum MSR, and the minimum GHG achievable when a company sets specific minimum requirements concerning the profit cost ratio of each vehicle sold (Table 4A, left-most column). The table shows that, according to the data used, when a company's profit requirements are not higher than 35%, it can still choose the 100%-MSP or the 0%-MSR portfolio. The cost of setting higher profit expectations in terms of a lower MSP and a higher MSR increase rapidly when these expectations exceed a minimum level of 40%. For the trade-off between profit and GHG emissions, there is a continuous increase in average per-vehicle CO₂ emissions when a company sets higher requirements regarding the profit. The right-most column of Table 4A shows that the shares of ICE and PHEV rise with rising profit requirements and the BEV shares decrease.

Table 4B shows the effect on the maximum Profit, the minimum MSR, and the minimum GHG emissions achievable when a company sets specific requirements concerning the MSP that has to be realized (Table 4B, left-most column). The table shows a continuous trade-off between the MSP and the MSR. Further, Panel B shows that when a company's MSP requirements are not higher than 60%, the company can still choose the maximum Profit portfolio. Moreover, when a company's MSP requirements are not higher than 30%, it can still choose the 0-GHG portfolio. If a company wants to achieve an MSP of 100%, the GHG emissions incurred will be 60 g CO₂ per km. Like Panel A, ICE rises permanently, and BEV is reduced when there are higher MSP requirements. Further, higher MSP requirements reduce the share of PHEV in the optimal technology portfolios considerably.

Table 4C summarizes the effect of decreasing the maximum MSR taken on the maximum Profit, the maximum MSP, and the minimum GHG emissions achievable. The table shows that, according to the data used, there is a continuous trade-off between the MSR and the maximum market share achievable. Interestingly, raising the requirements concerning the MSR taken barely affects both the maximum Profit and the minimum GHG achievable. Even if the MSR is reduced to 30%, a profit of 44.5% and 0 g CO₂ per km are possible. As the right-most column shows, especially PHEV benefits from higher MSR requirements while ICE and BEV become less important.

Finally, Table 4D shows the effect on the maximum Profit, the maximum MSP, and the minimum MSR achievable when a company sets tighter GHG requirements, starting from 60 g down to 0 g CO₂ per km. As can be seen, there is a substantial trade-off between the three objectives of

TABLE 4 Trade-Off analyses. This table shows the effect on the other objectives when setting higher requirements regarding (A) the average profit, (B) the market share potential, (C) the market share risk, and (D) the effect when setting higher requirements regarding the GHG emissions

A: Effects of setting higher requirements regarding the average per-vehicle profit					
Profit		Max. MSP (normal / raw)	Min. MSR (normal / raw)	Min. GHG (g CO ₂ per km)	Avg. portfolio shares: ICE BEV PHEV
At least	10%	100.0% / 0.452	0.0% / 0.018	0.0	23.6% 39.2% 37.2%
	15%	100.0% / 0.452	0.0% / 0.018	0.0	23.6% 39.2% 37.2%
	20%	100.0% / 0.452	0.0% / 0.018	6.0	24.2% 37.7% 38.1%
	25%	100.0% / 0.452	0.0% / 0.018	12.0	25.5% 33.0% 41.5%
	30%	100.0% / 0.452	0.0% / 0.018	16.5	27.1% 26.7% 46.2%
	35%	100.0% / 0.452	0.0% / 0.018	21.8	27.0% 17.8% 55.1%
	40%	82.4% / 0.381	0.1% / 0.018	26.7	25.5% 9.3% 65.2%
	45%	63.8% / 0.307	76.8% / 0.095	60.0	46.7% 0.0% 53.3%
B: Effects of setting higher requirements regarding the market share potential					
MSP (normalized)		Max. Profit	Min. MSR (normal / raw)	Min. GHG (g CO ₂ per km)	Avg. portfolio shares: ICE BEV PHEV
At least	0%	45.3%	0.0% / 0.018	0.0	23.6% 39.2% 37.2%
	10%	45.3%	1.0% / 0.019	0.0	24.9% 40.7% 34.3%
	20%	45.3%	6.4% / 0.024	0.0	27.2% 42.1% 30.7%
	30%	45.3%	11.8% / 0.030	0.0	31.1% 42.1% 26.8%
	40%	45.3%	17.7% / 0.036	9.0	36.1% 40.1% 23.9%
	50%	45.3%	24.5% / 0.043	17.9	41.0% 38.2% 20.8%
	60%	45.3%	36.6% / 0.055	26.7	45.9% 36.8% 17.3%
	70%	42.3%	52.0% / 0.070	35.6	50.8% 36.7% 12.5%
	80%	40.0%	68.8% / 0.087	44.5	55.6% 36.6% 7.8%
	90%	37.0%	86.5% / 0.104	53.3	60.5% 36.7% 2.8%
	100%	35.4%	100.00% / 0.118	60.0	64.7% 35.3% 0.0%
C: Effects of setting higher requirements regarding the market share risk					
MSR (normalized)		Max. Profit	Max. MSP (normal / raw)	Min. GHG (g CO ₂ per km)	Avg. portfolio shares: ICE BEV PHEV
At max.	100%	45.3%	100.0% / 0.452	0.0	23.6% 39.2% 37.2%
	90%	45.3%	92.5% / 0.422	0.0	23.0% 39.3% 37.7%
	80%	45.3%	87.4% / 0.401	0.0	21.5% 39.8% 38.7%
	70%	44.5%	82.4% / 0.381	0.0	19.6% 40.8% 39.6%
	60%	44.5%	74.9% / 0.351	0.0	17.4% 41.8% 40.7%
	50%	44.5%	69.8% / 0.331	0.0	15.1% 43.1% 41.8%
	40%	44.5%	62.3% / 0.301	0.0	12.7% 44.2% 43.1%
	30%	44.5%	57.3% / 0.281	0.0	10.1% 45.4% 44.4%
	20%	44.5%	44.7% / 0.231	3.0	7.2% 45.1% 47.7%
	10%	43.8%	27.1% / 0.160	10.5	3.5% 33.2% 63.3%
0%	39.3%	5.8% / 0.075	25.2	0.0% 18.8% 81.2%	
D: Effects of setting higher requirements regarding the GHG emissions					
GHG (g CO ₂ per km)		Max. Profit	Max. MSP (normal / raw)	Min. MSR (normal / raw)	Avg. portfolio shares: ICE BEV PHEV
At max.	60	45.3%	100.0% / 0.452	0.0% / 0.018	23.6% 39.2% 37.2%
	50	44.5%	87.4% / 0.401	0.0% / 0.018	19.1% 42.3% 38.6%
	40	44.5%	77.4% / 0.361	0.0% / 0.018	14.3% 46.9% 38.8%
	30	43.0%	64.8% / 0.311	0.0% / 0.018	10.0% 55.1% 34.9%
	20	33.3%	52.2% / 0.261	1.8% / 0.020	7.3% 68.8% 23.9%
	10	23.5%	42.2% / 0.221	11.6% / 0.030	2.8% 86.2% 10.9%
	0	15.1%	32.0% / 0.180	22.8% / 0.041	0.0% 100.0% 0.0%

low GHG emissions, high profit cost ratio, and high MSP; lowering the maximum GHG emissions caused by a technology portfolio reduces both the maximum Profit and the maximum MSP possible. Interestingly, the effect of lowering the GHG requirements does not affect the MSR, that is, decision-makers can still choose a low-risk portfolio even if the GHG requirements are high. As expected, the shares of ICE and PHEV are reduced when there are higher GHG requirements, while the BEV share increases.

It should be noted that the results of the trade-off analysis (e.g., the effect on the average portfolio shares when setting the MSR to a lower level) depend on the data fed into the optimization model. The same holds for the results presented in Sections 4.2 and 4.3. If a company applies more appropriate data for its specific environment (e.g., concerning the profit figures), the proposed optimization model generates customized analyses and decision-support.

4.5 | Interactive decision-support for identifying the most preferred technology portfolio

To facilitate selecting a specific point from the efficient set, we developed an interactive web application. This provides different views of the efficient set. Further, it allows to set filters to eliminate the most disliked options in a step-wise process (Figure 3).

By utilizing this dashboard, identifying the most preferred solution can be carried out in a step-by-step process. In each step, the least favorite portfolios are excluded from the efficient set. We can demonstrate this process using an illustrative example case. For this demonstration, we contacted a senior executive manager working in the business development department of a leading German automotive manufacturing company. We asked the manager to use the dashboard for the selection of the desired portfolio.

As up to a profit of 25% the maximum MSP, the minimum MSR, and very low GHG emissions can be achieved (cf., Table 4), the executive manager first moved the profit lower bound filter to the right side, thereby deselecting all technology portfolios with profits below 25% (Figure 4: Step 1).

Having noticed that the number of the very high-GHG portfolios is relatively small (as can be seen from the histograms in Figures 3 and 4), the executive manager decided to move the upper bound filter for the GHG emissions slightly to the left, thereby excluding the very high-emission portfolios. The manager justified her decision with a proactive environmental product strategy, an expected further tightening of environmental regulations, and with a low effect on the number of the remaining portfolios as only a minor share of the portfolios is excluded when reducing the maximum GHG to 50 g CO₂ per km (Figure 4: Step 2).

Next, the manager concentrated on the objectives MSP and MSR to emphasize the predictions concerning the future market conditions. By moving the lower bound MSP slicer to the right (0.5), she implicitly placed more importance on those technologies that are predicted to have a high future market share and she eliminated all portfolios with relatively low predicted sales figures. To limit the MSR to a medium level, the manager moved the upper bound MSR slicer to the left (0.6). The result is shown in Figure 4: Steps 3 and 4.

The manager then gradually moved the filters representing the lower bound for the profit and the lower bound for the MSP to the right until two portfolios remained (Figure 4: Steps 5 and 6). From the two remaining portfolios, the executive manager selected the portfolio with the highest average per-vehicle profit cost ratio, that is, average profit = 36.2%, MSP = 64.8% (raw: 0.31), MSR = 59.3% (raw: 0.08), GHG = 46.5 g CO₂ per km. The corresponding portfolio shares of the three technologies are: ICE = 40.2%, BEV = 30.6%, PHEV = 29.2%. Note that this optimal portfolio refers to the specific preferences of the interviewed executive manager.

5 | DISCUSSION

The numerical example of Section 4 illustrated that a great advantage of the proposed methodology is that managers instantly gain a complete overview of all optimal options and trade-offs associated with the technology portfolio problem. Further, they can carry out different analyses that provide a more in-depth understanding of the decision-making problem. We strongly believe that a good solution can only be found if the decision-maker is aware of all available solutions and can then select the most favored one—for instance, using an interactive dashboard. After demonstrating the proposed approach's applicability, we want to discuss some aspects concerning the modeling assumptions and the case study results in more detail.

5.1 | Modeling assumptions

For the planning problem (decision situation), we argue that the proposed methodology is instrumental in the strategic production planning phase during which the management makes decisions, following the overall company strategy (including marketing, finance, etc.), about the “great goals” to be achieved. In this phase, the management decides what products and technologies are to be promoted and to what extent within a time frame of about 10 years. In this context, the term “management” refers to the board, the CEO, or any committee deciding about the company's product portfolio. It should be noted that any of these persons may use the interactive web application; however, it is more likely that people involved in the

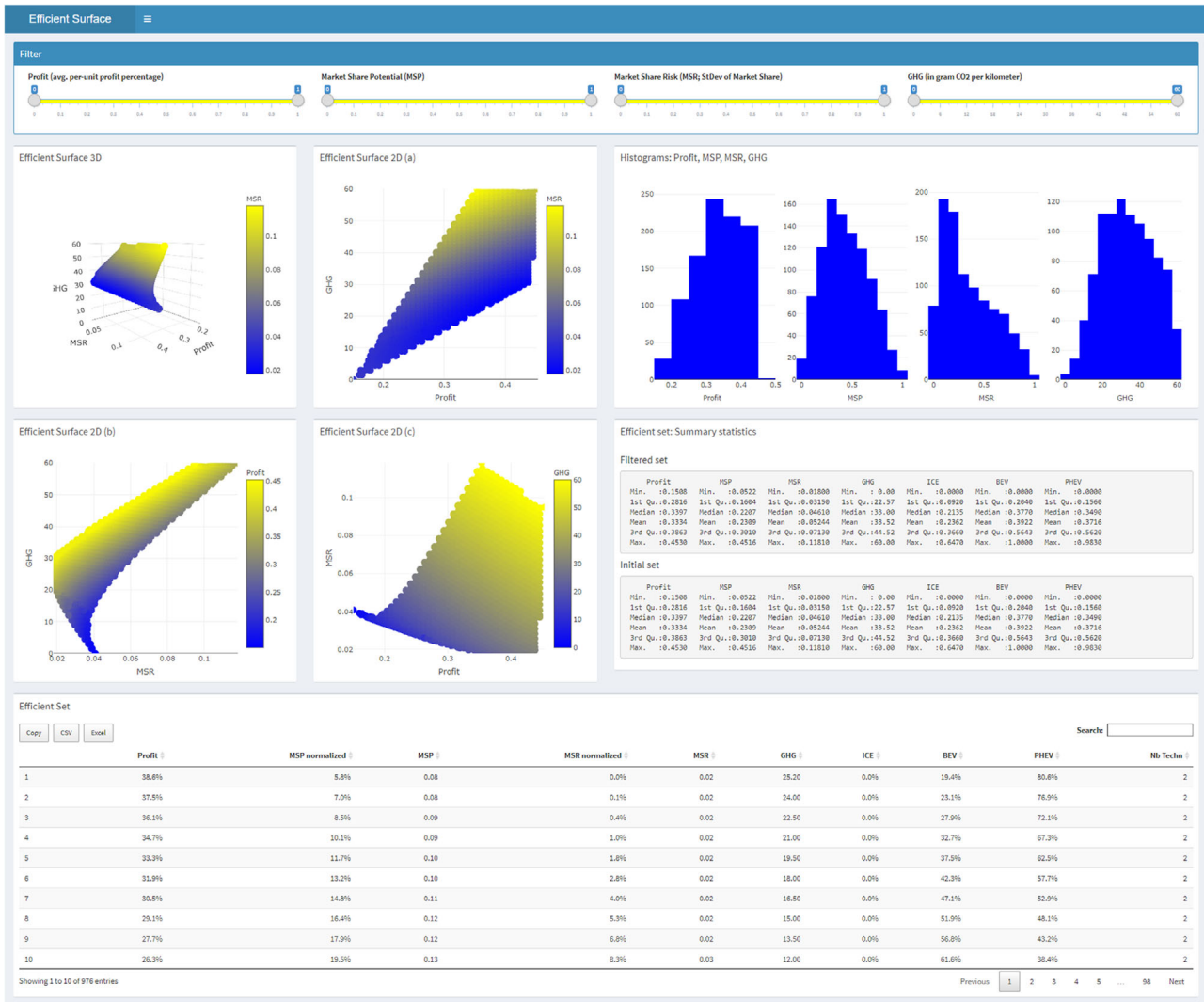
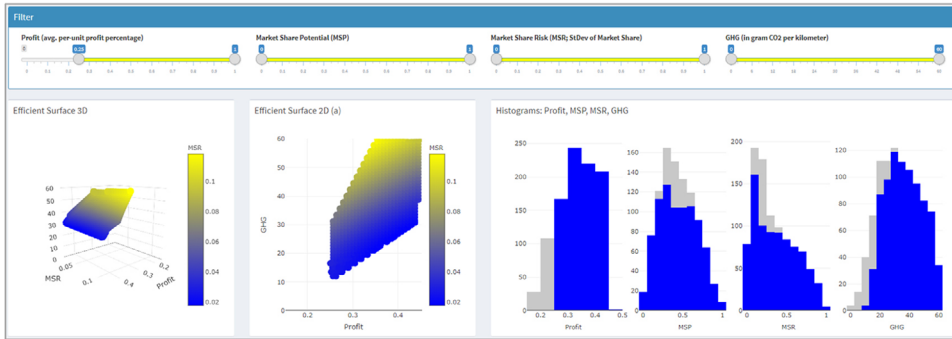


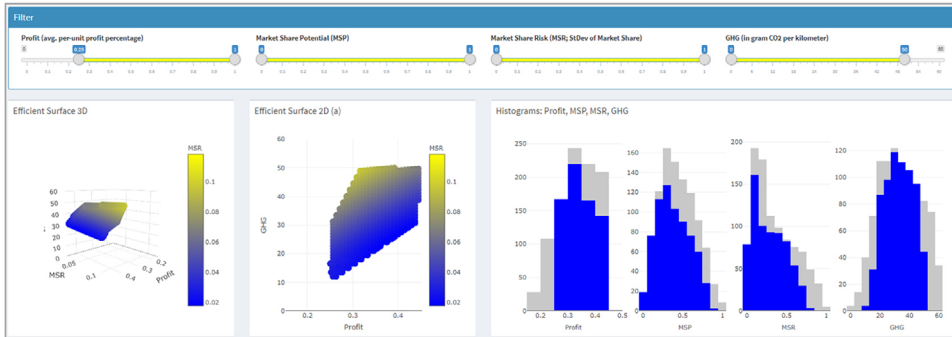
FIGURE 3 Interactive dashboard to support the technology portfolio selection process. The dashboard’s first row contains four filter slicers that allow the preferred ranges for the Profit, MSP, MSR, and GHG to be set. The second row shows a three- and a two-dimensional projection of the efficient set. Also, there are histograms for the four objective values over the efficient set. The third row shows additional views of the efficient set and some summary statistics and the fourth row lists all optimal technology portfolios, including the raw and the normalized MSP and MSR values, the profits, the GHG emissions, the portfolio shares of the single technologies, and the number of technologies included in the single portfolios. All elements below the filter row are interactive, meaning that the plots, statistics, and values in the table are modified as a function of the ranges set by the filter slicers

decision-making process, such as business development managers, will use this application to prepare and support the decision-making process. It is then the task of the tactical production planning to adopt and to detail this plan by deciding, for instance, in what periods the different products are going to be promoted, or by making decisions about the specific quantities of the specific car models in the single markets (cf., Vollmann et al., 1997). For the two objectives MSP and MSR, it should be noted that in the strategic production planning phase, it is not necessary to exactly know the future demand because production is scalable to a certain extent. However, it is good to know whether expected market shares are predicted more or less unanimously by different market studies. One can then place more or less importance on the aspects “high expected future market share” and “low market share risk” in the decision-making process. Moreover, suppose companies generated market studies other than the publicly available ones used in this setting (e.g., from an internal market research department). In that case, they can feed these studies into the procedure. Also, market studies (forecasts) that directly consider market uncertainties, for example, in terms of different scenarios or by providing estimates on standard deviations, can be processed by the model after minor modifications. These modifications comprise removing objective function (3). For each scenario or standard deviation level, one would run the optimization procedure and record the results. The general approach remains unchanged, that is, one would replace the different MSR levels with different scenarios or standard deviation levels to analyze the trade-offs between Profit, MSP, and GHG. Finally, we want to point out that the methodology can also be applied in the strategic production planning process to adapt the product

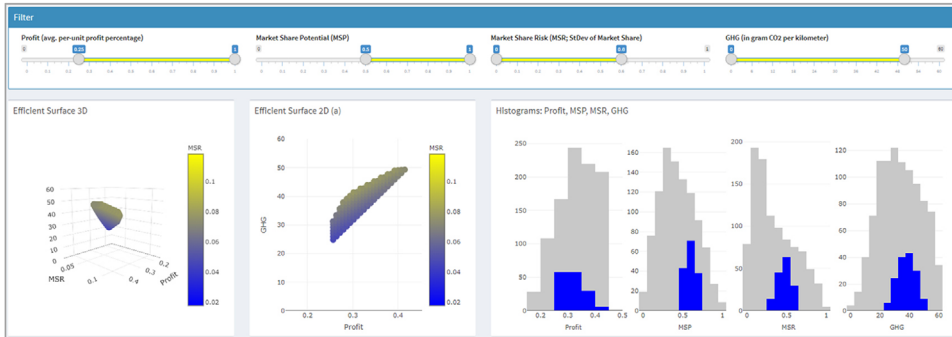
Step 1. We deselect all portfolios with low levels of profit percentages with the left-most slicer filter at the top of the dashboard. The two left plots show how the efficient set changes. The histograms indicate how the ranges of the objectives are affected. The gray shadows show the initial ranges without filters, while the blue ranges are the ones that are still achievable after increasing the minimum profit percentage level of the portfolios.



Step 2. We remove the high-GHG portfolios.



Step 3 and 4. We remove the low-MSP and the high-risk portfolios.



Steps 5 and 6. We further reduce the minimum profit and the minimum MSP set. Note: in the 2-dimensional projection, we modify the ranges of the x- and the y-axis to zoom into the remaining portfolios.



FIGURE 4 Interactive vehicle portfolio selection

portfolio to a changed demand, that is, decisions may be revised and changed according to a changed (demand) environment. In these cases, that is, in a cycle planning context / dynamic environment (see Section 2), the methodology may help in the decision-making process/while updating the cycle plan.

For the representation of risk in the optimization model, we follow the Markowitz portfolio theory and represent this aspect with the covariances between the available market studies' estimates for the different technologies. At this point, it should be noted that the different market forecasts are not random samples, but that the single authors will probably cross-check their estimates. Yet, the decision-maker faces more or less varying market forecasts. From her point of view, it is irrelevant if she faces conditional or unconditional correlations.

In the application case, the objective Profit is integrated into the optimization model through the profit cost ratio, that is, $(\text{vehicle sales price} - \text{manufacturing costs}) / \text{manufacturing costs}$. That means that the costs used for the profit calculation are the sum costs of components and assembly, excluding the (fix) costs for design, development, and other corporate overhead costs. This represents high volume production costs. Note that using manufacturing costs for the profit calculation might underestimate the costs for vehicles with low sales. In many company cases, there are still significant ongoing design and redesign costs required to maintain the appeal of product offerings. Therefore, objective function (1) can easily be extended by adding another component, namely, the fix cost of investing in a certain powertrain technology (e.g., product design costs). In this way, the optimization model can be adapted to a certain company case.

For possible extensions of the proposed approach, we generally argue that the ϵ -constraint method allows the user to add additional complexity to the model. For instance, constraints could be added to ensure that if a company opts to integrate a particular technology into its vehicle fleet, this technology should be represented by at least 10% of the overall portfolio share. Or it would be possible to limit the maximum portfolio share of a certain technology to 80%. Moreover, it is possible to determine powertrain technology portfolios for different geographical markets or to calculate technology shares for different vehicle segments (cars, SUVs, etc.). The modeling of new/changed environmental regulations, possibly even specific to different geographic markets, could be carried out by modifying the GHG boundary constraint (change the right-hand side of the equation, use changed emission rates for the single technologies, or introduce an index capturing the relevant geographical market).

Moreover, our model is appropriate to be applied in other regulatory environments than in the EU setting, for instance, the US and Chinese context. The US CAFE regulation specifies the GHG emission standards in the US for passenger cars and light trucks. The emission standards determined in April 2020 cover the years 2021 through 2026. For instance, the average fleet-wide CO₂ emissions for passenger cars are limited to 171 g CO₂ per mile in 2025. This number turns into a threshold of about 106 g CO₂ per km. If the fleet-wide emissions do not achieve the required CAFE levels, the firm can either apply for CAFE credits or pay a penalty dependent on the deviation from the CAFE level and for every vehicle produced for the US market. Also, China introduced several regulations to reduce CO₂ emissions for on-road vehicles. The policy entitled "Measures for Passenger Cars CAFC and NEV Credit Regulation," which is also called the Dual Credit policy, was implemented in 2019 to foster the development and commercialization of new energy vehicles, including BEV, PHEV, and fuel cell vehicles (He et al., 2020). According to this standard, the average consumption of an average vehicle fleet should be reduced to 4.5l/100 km in 2025. To compare this quantity to the EU and the US standards, we use the conversion that 1l/100 km refers to 23.8 g CO₂/km. Thus, an average Chinese vehicle fleet is allowed to emit about 110 g CO₂ per km. Thus, to apply our model in these two countries, the decision-maker would substitute the threshold value 60 g CO₂ per km (in the EU) to 106 g CO₂ per km (in the United States) or 110 g CO₂ per km (in China). Consistent with findings for these regions (e.g., He et al., 2020), the proportion of ICE in the portfolio increases with higher allowed CO₂ emissions.

5.2 | Application case

The results of the application case depend on the input data (Table 2). For the MSP and MSR, we used four broadly accepted market studies. For the GHG emission rates, we integrated some of the latest estimates on how emission rates will develop into our study (Islam et al., 2020). At this point, we want to reiterate that there are, however, more sophisticated methods for forecasting the future emissions of the single powertrain technologies. For the profits of vehicles equipped with the different powertrain technologies, we admit that the assumed values are based on some simplifying assumptions, which allows us to estimate profits crudely (e.g., identical selling prices). Yet, we are using values that have been reported by accepted sources (Islam et al., 2020; McKinsey, 2017, 2019). We also want to stress that there are other studies that predict different values for both future vehicle selling prices and manufacturing costs (e.g., Lutsey & Nicholas, 2019). Finally, we recommend that automotive companies feed their profit values into the proposed optimization model to obtain customized recommendations.

We want to highlight two particular aspects concerning the obtained results: (1) According to Table 3, no vehicle portfolio with an ICE portfolio share greater than 65% exists in 2030. This contradicts the predictions of BNEF (2019) and Deloitte (2019) (cf., Table 2). However, the plausibility of the results reported in Table 3 may easily be verified, at least for the European market: given the fact that in Europe, the average new ICE vehicle will emit 92.8 g CO₂ per km in 2030 and the GHG limit will be 60 g CO₂ per km and given the fact that the vehicle portfolio is only composed of ICE and the "no-emitting" BEV, then the ICE share cannot exceed $(60 \text{ g CO}_2 \text{ per km} / 92.8 \text{ g CO}_2 \text{ per km}) = 65\%$. In contrast to studies showing that large shares of the ICE technology in powertrain technology portfolios are a solution to comply with regulatory CO₂ emission targets in the United States or China (e.g., He et al., 2020), our results for a European setting attribute less importance to ICE to satisfy the regulatory requirements.

This relationship is because the thresholds in China and the United States are still substantially higher than in the EU context. (2) We also want to stress that our results attribute significantly more importance to PHEV than foreseen by the single market forecasts. These results are mainly attributable to the good combination of high profits and low GHG emissions of this technology, and generally the inclusion of the profits in our model (i.e., we make suggestions for optimal production plans by considering future market shares and profit). Note that the profits have been derived from the values reported by Islam et al. (2020) and McKinsey (2017, 2019). If we would assume other profits for the PHEV, then the importance of PHEV might be reduced. Finally, we want to reiterate that the objective of the numerical example is mainly to demonstrate the applicability of the proposed approach, and OEMs/automotive companies are advised to feed their own profit figures into the optimization model to receive customized decision-support.

6 | CONCLUSION

This article's novelty is the presentation of a new decision-support system for the multi-criteria technology portfolio problem. The proposed approach supports decision-makers, such as business development executives, in understanding the trade-offs between the achievable profit, the market share, the MSR, and the GHG emissions generated by the selected vehicle fleet.

A special feature of the presented approach is that it is not based on one single market study, but it allows compiling the findings of several studies quantitatively. The real-world application reveals, among other insights, the trade-offs between a lower MSR taken and the maximum market share achievable. Furthermore, we analyze the effects of opting for a certain level of profits and GHG emissions (complied with the 2030 GHG target in the European Union) and show that no optimal powertrain technology portfolio exists in 2030 with less than 35% of vehicles equipped with an electric motor. Our approach is not limited to the European setting but can also be applied to other regulatory environments, such as the United States and China.

ACKNOWLEDGMENTS

The authors thank Editor-in-Chief Reid Lifset, Associate Editor Lynette Cheah, and three anonymous reviewers. The authors are also grateful to the seminar participants at the International Conference on Decision Aid Sciences and Applications for valuable feedback. Preliminary versions of the research methodology of the paper were presented in Kellner and Utz (2019).

CONFLICT OF INTEREST

The authors declare no conflict of interest.

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SUPPORTING INFORMATION

Additional supporting information may be found online in the Supporting Information section at the end of the article.

How to cite this article: Kellner F, Lienland B, Utz S. A multi-criteria decision-making approach for assembling optimal powertrain technology portfolios in low GHG emission environments. *J Ind Ecol*. 2021;1–18. <https://doi.org/10.1111/jiec.13148>