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Optimal engine technology mix in a low carbon economy

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Abstract— Environmental regulations force automotive companies to modify the powertrain technology portfolio offered to the customer to comply with greenhouse gas (GHG) emission targets. Automotive companies, in turn, are faced with the decision of finding the right powertrain technology portfolio because the selection of a particular technology portfolio affects different company targets at the same time. What makes this decision even more interesting is the fact that future market shares of the different technologies are uncertain. With its numerous objectives, this challenge requires multi-criteria decision-making techniques to identify the optimal powertrain technology portfolio. The objective of this research is to present a new decision support approach for assembling optimal powertrain technology portfolios while making decision-makers aware of the trade-offs between 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, multi-objective optimization, and the Markowitz portfolio theory. In an application case, the outlooks of selected market studies are fed 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. Interesting findings of this research include that for the assumed GHG restrictions in place in 2030, there exists no optimal powertrain technology portfolio that is not composed of at least 20% of electric vehicles.

Keywords—Decision support system; Automotive industry; Powertrain technologies; Portfolio optimization

I. INTRODUCTION

Regulatory initiatives to reduce the greenhouse gas (GHG) emissions of the product fleet of automotive companies 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 about 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. So far, automotive companies mainly rely on single scenario-based market studies for their strategic technology portfolio allocation and ignore sophisticated model-based solutions. However, multi-criteria decision-making literature has dealt with comparable decision situations, and some research proposes models to optimize technology portfolios. This paper suggests overcoming methodological and data-concerned restrictions by using a new multi-criteria approach for strategic decision-making.

The contribution of this research is threefold: 1) It introduces a new multi-objective optimization model for the powertrain technology portfolio problem. The proposed model transfers the portfolio theory developed by Markowitz

to the technology selection case. Thus, the proposed approach is in line with prior studies that showed that the Markowitz portfolio theory [1-3] might effectively be applied to other areas than the finance sector [4-6]. 2) This research summarizes the outlooks of some well-accepted market studies concerning the future market shares of different powertrain technologies. The fact that the predictions of the single market studies are not uniform reflects the significant uncertainty regarding the future spread of the various technologies. 3) The outlooks of selected market studies are fed into this optimization model to visualize the set of Pareto-optimal technology portfolios. The result is a visualization of the current real-world decision-making problem faced by many companies in the automotive sector. The possibility of drawing the efficient set is advantageous for decision-makers as they get a picture of the available optimal technology portfolios and can analyze the trade-offs between the different objectives before deciding.

II. LITERATURE REVIEW

Due to the importance of identifying the right technology portfolio, several approaches have been suggested to support the powertrain portfolio selection problem [7]. There are, for instance, numerous quantitative studies [8-11] that present models to improve portfolio strategies based on mathematical optimization. Moreover, Umpfenbach et al. [12] classify the decision situation as an assortment planning problem. They show an approach to solve this problem in low-emission vehicle regulation in the automotive industry. 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. [13] present a multi-criteria approach to solve these trade-offs in a project portfolio selection application with the fuzzy logic model in a TOPSIS approach to achieve the most sustainable solution. However, no approach has been presented before that provides visual decision support for automotive companies on which technology to choose, that allows visualizing and analyzing the complete set of trade-offs that are associated with the powertrain portfolio selection problem, and that translates market share uncertainties into measurable risk.

III. METHODS

A. Multi-objective powertrain technology portfolio model

At the heart of the presented decision support system is an optimization model with three objectives: 1) to maximize the share of those technologies that have the highest expected future market shares, 2) to minimize the market share risk, i.e., the uncertainty of the selected technology portfolio realizing the expected market share, and 3) to minimize the overall GHG emissions caused by the vehicle fleet.

The first objective function maximizes the market share potential (MSP) of the technology portfolio as a whole. The idea is to invest as much as possible in those technologies that are predicted to have the highest future market shares.

The second objective function minimizes the market share risk (MSR). The MSR reflects the uncertainty about the future market shares of the single technologies. Following the Markowitz portfolio theory, the risk about the future market shares of the single technologies is measured with the variance of the predicted market shares across the available market studies. The covariance measures the ‘interaction’ between the market shares of the different technologies, i.e., the fact that when a specific technology is predicted to lose in market share, the other one is likely to suffer as well. Thus, the idea 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 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, i.e., when one technology is predicted to lose in market shares, the other(s) will win—and vice versa.

The third objective function minimizes the overall GHG emissions that are caused by the selected vehicle fleet.

Finally, there are some constraints that need to be considered: The first constraint ensures that the sum of the investments in the single technologies adds up to 100%. The second constraint guarantees that the average per unit GHG emissions of a specific technology that is part of the technology portfolio do not exceed the limiting value of 60g CO₂ per kilometer, consistent with the upcoming regulations in 2030.

B. Solution procedure: determining the efficient set

The techniques for solving multi-objective optimization problems can be classified according to the moment in time when the decision-maker expresses a preference for the different objectives: there are methods with ‘a priori’ articulation of preferences, methods with ‘a posteriori’ articulation of preferences, interactive methods, methods with no articulation of preferences, and variations of all of these. ‘A priori’ means that the decision-makers have to indicate their preferences between the objectives before the optimization and obtain one single optimal solution. ‘A posteriori’ methods, in contrast, do not require any articulation of preferences before the optimization. In the ‘a posteriori’ case, all optimal (Pareto-efficient) solutions are first computed and visualized graphically. Then, a particular portfolio can be selected following the company’s product strategy. This research suggests analyzing and solving the multi-objective technology portfolio problem using an ‘a posteriori’ approach because this allows the decision-maker to forgo an ex-ante articulation of preferences, identify the trade-offs between the criteria, and study how the different aspects of the technology portfolio problem can be balanced [14-16].

In Markowitz’s theory, a portfolio is called ‘efficient’ if it has the best possible expected level of return for a given level of risk, which is represented by the variance of the portfolio’s return [1-3]. Equations (1) and (2) are the ‘traditional’ objective functions in the Markowitz portfolio theory.

$$\text{Equation (1) } \max \sum_i \text{return}_i * x_i$$

$$\text{Equation (2) } \min \sum_{ij} \text{cov}_{ij} * x_i * x_j$$

with return_i = return on asset i , cov_{ij} = covariance of the returns on assets i and j , and x_i = weighting of asset i (i.e., the proportion of asset i in the portfolio). The risk-expected return trade-off of efficient portfolios is graphically represented by the efficient frontier, and the set of all efficient portfolios is called the ‘efficient set.’

While the proposed optimization problem is based on the concepts of the Markowitz portfolio theory, it is a non-standard portfolio selection model because it is a combination of the classical risk-expected return trade-off—which could be associated with the expected future market share and the MSR—and an additional third objective. Equations (3)-(5) show the optimization functions of the proposed multi-objective model.

$$\text{Equation (3) } \max \sum_i \text{msp}_i * x_i$$

$$\text{Equation (4) } \min \sum_{ij} \text{cov}_{ij} * x_i * x_j$$

$$\text{Equation (5) } \min \sum_i \text{ghg}_i * x_i$$

with msp_i = expected market share of technology i (in percent), cov_{ij} = covariance of the market share in technologies i and j , ghg_i = GHG emissions generated by technology i , and x_i = proportion of technology i in the technology portfolio.

For solving this non-standard portfolio selection problem, it is suggested to apply the ϵ -constraint method. The idea is to optimize one of the objectives while using the other objective functions as constraints with varying binding values. An advantage of this approach is that it allows carrying out any numbers of optimization runs with diverse binding values and, thus, determining any numbers of efficient portfolios. Another advantage of this approach is that it is flexible concerning the optimization model itself; i.e., it is easily possible to extend the optimization model by introducing additional constraints.

IV. APPLICATION, RESULTS, AND DISCUSSION

A demonstrative application is used to show 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. In doing so, the current real-world decision-making problem faced by many companies in the automotive sector is visualized and analyzed. This allows for deeper insights into the decision-making problem and a more informed decision-making process. Furthermore, this application shows how the identification of the most preferred technology portfolio may be facilitated by utilizing an interactive web dashboard.

A. Input data

The application case focuses on three of the most discussed powertrain technologies: internal combustion engines (ICE), electric vehicles (EV), and plugin-hybrid electric vehicles (PHEV). In addition, the market studies by Bloomberg, Boston Consulting Group, JP Morgan, and Deloitte are used. These studies allow a comparison of the forecasted global passenger car sales in the year 2030 for the selected technologies. Table I summarizes the information about the three technologies.

TABLE I. INPUT DATA

	Powertrain Technologies		
	ICE	EV	PHEV
BCG [17]: Estimated market shares in 2030 (normalized values)	67%	25%	8%
BNEF [18]: Estimated market shares in 2030 (normalized values)	71%	23%	6%
JPM [19]: Estimated market shares in 2030 (normalized values)	67%	30%	3%
Deloitte [20]: Estimated market shares in 2030 (normalized values)	81%	13%	6%
Mean market share (from normalized values)	0.71	0.23	0.06
Greenhouse gas emissions (gram CO ₂ per km)	167	0	50
Covariance ICE	4.42E-03	-4.43E-03	1.02E-05
Covariance EV	-4.43E-03	4.87E-03	-4.38E-04
Covariance PHEV	1.02E-05	-4.38E-04	4.28E-04

B. Determining and visualizing the efficient set

To determine the efficient set, the procedure presented in Section II.B is executed. All optimizations are carried out with IBM ILog Cplex 12.10. For the visualization of the efficient set and the portfolio selection process, an interactive web application has been built based on R Shiny.

Figure 1 shows a 2-dimensional projection of the efficient set, reflecting the technology portfolio problem. The surface-like geometry is made up of 4,556 unique points.

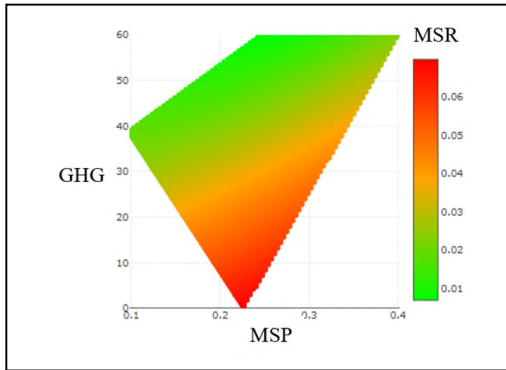


Fig. 1. Efficient set (2-dimensional projection).

Figure 1 shows the characteristics of the single portfolios in terms of the MSP, the MSR, and GHG emissions. The figure reports the portfolio characteristics in terms of the MSP on the x-axis, the y-axis shows the GHG emissions of the single portfolios, and the color scale indicates the portfolios' performances concerning the MSR. The MSR is indicated with the standard deviation of the market shares of the technology portfolios. All portfolios in combination, i.e., the entire efficient set, shows the trade-off between the achievement of the three goals as each portfolio is optimal for a specific combination of objectives. This means that it is not possible 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.

C. Analyzing the decision-making problem

An advantage of the 'a posteriori' decision-making approach is that it allows the analysis of the efficient set and, thus, provides deeper insights into the decision-making problem.

Unreported results show that the values for the MSP of the optimal technology portfolios are between 0.0981 and 0.4019, with a notable concentration between 0.2 and 0.3. The portfolio that achieves the highest MSP consists of 35.93% ICE and 64.07% EV. The portfolio with the lowest market share is made up of 23.20% EV and 76.80% PHEV. Concerning the MSR, the standard deviation of the market share of the portfolio with the highest risk is almost ten times greater than the standard deviation of the portfolio with the lowest risk (0.0698 vs. 0.0069). The portfolio with the highest standard deviation consists of EV only, i.e., the product strategy relies on one single technology. The portfolio with the lowest standard deviation is made up of 21.09% ICE, 29.35% EV, and 49.57% PHEV. Concerning the objective 'GHG,' the CO₂ emissions of the portfolios cover the whole range from 0g to 60g CO₂ per kilometer. Similar to the market share, a notable concentration can be seen: there are many optimal portfolios with GHG emission between 35g and 40g CO₂ per kilometer. The portfolio with the lowest GHG emissions is made up of EV only (0g CO₂ per km). On the other side, 32 portfolios come with 60g CO₂ per kilometer.

A closer look at the single optimal technology portfolios reveals that 98.5% of all portfolios consist of all three technologies, 1.5% is made up of two technologies, and one unique portfolio consists of one technology only. The technology 'EV' receives particular attention as this technology is included in every optimal portfolio with an average portfolio share of 57%. This means that independent of a decision maker's preferences for the three objectives, EV will be combined with at least one other technology. Furthermore, the minimum portfolio share of EV is 22.56%, i.e., EV contributes to at least 20% of every(!) optimal technology portfolio and in 63.1% of all cases, EV contributes more than 50% to an optimal technology portfolio. PHEV receives 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.

D. 4.5. Interactive decision support for identifying the most preferred technology portfolio

The 'a posteriori' approach has the advantage that decision-makers can instantly access the full picture of all optimal options and trade-offs that are associated with the technology portfolio problem. In addition, they can carry out different analyses that provide a more in-depth understanding of the decision-making problem.

To facilitate the selection of a specific point from the efficient set, an interactive web application has been developed. This application provides different views of the efficient set and allows filters to be set to exclude the disliked options.

Utilizing this dashboard, the identification of the most preferred solution can be carried out in a step-wise process. In each step, the least favorite portfolios are eliminated from the efficient set.

V. CONCLUSION

The novelty of this research is the presentation of a 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 market share, the market share risk, and the GHG emissions generated by the selected vehicle fleet. A specificity of the presented approach is that it is not based on one single market study but that it allows compiling the findings of several studies quantitatively. The real-world application reveals, amongst other things, the trade-offs between a lower market share risk taken and the maximum market share achievable. Furthermore, the effect of opting for a certain level of GHG emissions on the minimum market share risk is analyzed. The results show that no optimal powertrain technology portfolio exists that is not composed of at least 20% of electric vehicles.

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