Scenario-based determination of product feature uncertainties for robust product architectures

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Abstract Modular product architectures are used by many firms today to achieve a high degree of product differentiation whilst reducing cost through economies of scale. At the same time, the firms are increasing architecture lifetimes to 10 years or more, which brings up new challenges for the development process. Uncertainties regarding future product features need to be anticipated when designing the architecture to minimize modification efforts. Nevertheless, existing approaches for designing modular product architectures are mainly based on static requirements and thereby neglect the dynamics of the market that influence future product features. This paper aims at presenting a method utilizing scenario-planning and simulations in the product range planning process to determine future product features and their uncertainties as a basis for the product architecture design. Possible feature specifications are derived from product environment scenarios and linked to the factors influencing the scenarios, to calculate their expected values and deviations.

Keywords Product range planning · Scenario planning · Simulation · Platform development · Product architecture design

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1 Introduction

In recent years many industries face an increase in the variety of products due to historically grown product programs as well as an increasing micro-segmentation of markets. In addition, individual customer demands and the desire for customized products lead to a change in the way markets work. The situation is exacerbated by the emerging markets of Asia, South America and Eastern Europe, which require a further differentiation of products and hereby increase the external diversity even more [1–5].

To master this challenge of increasing variety and participating in the price competition of globalized markets, many companies try using new product architecture approaches (e.g. platforms). The latter generates a high level of external diversity via customized variants with less internal diversity by combining few architectural elements such as modules. Using those product architectures, allows producing almost individually configurable products without having to renounce scale effects across the model range [6–8].

Thus, an increasing number of variants and product generations are based on a product architecture that, in order to really take advantage of scale effects, has longer life cycles. This, however, has one major disadvantage, as it leads to an increased uncertainty in the customer requirements that have to be met. Furthermore it results in rising costs of changes to the product architecture [9–12]. This implicates the need for better predictability of future product features and their specifications. Companies have to anticipate dynamics in early stages of product development and variant definition, to limit future changes to certain parts of the architecture. Thus they have to be included into products and product architectures [10, 12, 13].

Therefore, prospective approaches for structuring products have to be adjusted to meet those challenges. Currently this process is largely static and inadequately involves future requirements. This results in readapting or discarding the product architecture. Using scenario-planning and simulations of key factors influencing the product environment in the product range planning process is a possibility to enable a forecast-based product architecture design [13]. Possible feature specifications are derived from the developed future scenarios and linked to the factors influencing the scenarios, to calculate the expected value and deviation regarding their realization.

2 Prior research related to the dynamic oriented product range planning and architecture design

The inclusion of dynamics into the product range planning and architecture design process has been receiving increased attention. In the following, important representatives of approaches for dynamic-oriented product range planning and product architecture design are discussed.

2.1 Approaches on dynamic-oriented product range planning

Rathnow [14] introduces a cost-benefit-approach for the appropriate handling of product variety. The determination of the overall optimum diversity consists of ascertaining the maximum profit of the product program and the cost-oriented control of the product variety. He uses activity-based costing to determine the unit costs of each variant. The benefit of each variant is quantified through a tool based on a conjoint analysis. The cost-oriented control shows how to minimize cost consequences of the product variety. The overall optimum takes into consideration the above mentioned partial solutions as well as interdependencies and uncertainty of planning data. Beyond a certain extent of variety negative effects on the company occur. Due to a lack of determining the extent of variety in detail, insufficient decision supporting statements for variant management can be derived [15].

Another combined approach within the context of product variety is presented by Lösch [15]. This approach is based on the cost-benefit assessment of product variants, the observation of the business and of changes in the competitive environment. The corporate entities affected by this diversity need to be coordinated. The measurement of the product benefit is based on the conjoint analysis. The costs of each product variant are estimated at an early stage. Lösch [15] offers no combined approach but partial solutions for the cost-benefit assessment of product variety. Further research is needed to combine the different tools.

The approach of Hülle [16] deals with the design of a realistic cost-benefit-oriented variant valuation model. The basis for this approach is the Analytic Network Process (ANP) by Saaty [17]. For complex decision making, network structures with dependencies and feedback are used. Result of the approach of Hülle is an overall ranking of cost and benefit aspects based on which the company can deduce the strategic importance and the contribution of each variant to achieve its goals. However, dynamic customer requirements are not considered in this approach.

2.2 Approaches on dynamic oriented product architecture design

Design for Variety (DFV) by Martin [12] is a method that supports the development of product platforms. It focuses on making the platform insensitive to influences from outside as well as to reduce platform internal interactions and dependencies. Therefore two indices are defined. The Generational Variety is a measure for the future redesign efforts required by individual components related to changing product features. The Coupling Index measures the coupling of the components in the product structure. Based on these indices, a set of rules to optimize the components for a robust product platform are defined. However, this is done without describing the essential influencing parameters on the product architectures and possible prediction methods for the changes of the product features.

The aim of the robust modular product family design methodology by Jiang and Allada [18] is to determine the optimal control factors for the quality of a product architecture and to evaluate the lifecycle time of the product architecture that enables the highest possible robustness. The design of the product architecture is also part of the methodology, however, it is not its focus. To achieve the objectives stated above, a ten-step model is used. Jiang and Allada take the customer requirements and the related uncertainties as a precondition, their determination is not a part of the methodology.

Suh [10] focuses his work on a methodology for the identification of potential flexibility within a product architecture. For this purpose, he first determines the target market segments, and based on that the desired product variants, and the uncertainties influencing these variants. As a second component he describes a model of the relationships between the customer requirements and the components implementing them. This model and the uncertainties are used to identify critical elements in the product structure. These must be flexible in order to match the uncertainties of the requirements they implement. Suh's model is based on the assumption that the values of the significant uncertainties are given, which in fact implies another process step before the design phase to determine these uncertainties.

Considering the relevant literature, it becomes clear that existing approaches on the dynamic oriented product range planning and product architecture design take uncertainties related to the realized product features into account, but do not show how these uncertainties can be determined.

3 Scenario-based approach for the determination of product feature uncertainties

To allow firms to react in a timely manner, future uncertainties need to be identified early and be considered in the product architecture. Future uncertainties arise due to alternative developments of influence factors. A future situation that may occur with some probability dependent on certain influence factors can be described by a scenario. Scenario-planning can be used to create a set of different future situations. By taking the interaction of influence factors into account, this approach allows to consider more than just one possible development of influence factors [19]. Being able to analyze the whole set of possible future circumstances allows the firm to choose those alternatives today, that allow it to be more flexible and react more timely in the future [20]. With different future scenarios, implications for the new product development can be derived. In the following, the product features are determined based on scenarios which in turn are evaluated with respect to their probability of realization. The methodology is illustrated by a case study.

3.1 The scenario-planning approach

Decision makers may not only lack information on alternatives but also on the impact of choosing a particular alternative [21]. Scenario-planning is a powerful method for filling this information gap by constructing alternative scenarios and comparing their consequences [22]. The original approach for scenario-planning developed by [23] consists of fife steps. The first step, scenario-preparation, includes the scope for design as well as the type of scenario necessary for determining product feature uncertainties. Within the second step, the scenario-field-analysis, key factors are identified and subsequently selected. The third step, scenario-prognostic, consists of forecasting the key factors with their probabilities for realization. The fourth step, scenario-development, consists of developing a set of scenarios. In step five, scenario-transfer, the scenarios are utilized for the strategic management process. As the goal of the approach presented here is the scenario-based determination of product feature uncertainties, rather than the scenario-based strategic management, step fife is replaced by three new steps. These three steps have been especially designed to acquire the information that is needed to assess the uncertainties of product features based on the key influence factors from the scenario analysis. The approach presented here hence consists of the four preparatory steps (I–IV) from the original approach (see Fig. 1) and three new evaluation steps (see Fig. 6).

In this paper, the methodology is applied to the practical example of electric vehicles. For this, we slightly modified the methodology as described in [24] as follows. For step two, [24] recommends a combination of discursive and intuitive techniques for the identification of influence factors. The identification method for influence factors is assessed on the basis of a scoring model, which takes into account the identification, the interdependencies as well as requirements for small and medium-sized enterprises (SME). In order to identify key factors, following [24] an influence matrix, a relevance matrix and a system grid are applied. In step three, instead of a literature research and expert consultation, the independent variables are forecasted via a SARIMA[1] model and a bootstrap simulation[2] of the regression model. In step four, the scenario-development, scenarios with respect to consistency are developed by a consistency matrix or a cross-impact analysis [24]. The scenario-development done with regressions based on the resulting data of the bootstrap simulation and a cluster analysis of these regressions.

This procedure has been applied to electric vehicles because rapidly rising oil and gas prices have led to increasing concerns about future forms of mobility. The changing forms of mobility have led to a debate about the launch of electric vehicles. However, numerous technological problems concerning the vehicle itself and its production need to be resolved before starting a mass production of such vehicles. Therefore a concept for a new type of electric vehicle is developed within the project "StreetScooter"[3] in close cooperation with the industry. The case at hand analyzes the power train with respect to StreetScooter and is subsequently referred to as "StreetScooter power train". The power train of an electric vehicle consists only of the battery, the electric motor and the associated control devices. Compared to the power train of a conventional vehicle, depending on the rotation speed, there does not have to be e.g. a complex transmission [26].

[1] Seasonal Autoregressive Integrated Moving Average (SARIMA) is a model for forecasting time series data including seasonal components.

[2] A bootstrap simulation draws random samples with replacement from the original data.

[3] In the StreetScooter project an electric car family is designed explicitly for short-haul traffic by a consortium of 80 medium-sized companies and numerous research facilities. The development follows a purpose design approach, aiming at a module-based product architecture, which allows economies of scale and thus an affordable concept even in small quantities for several variants.

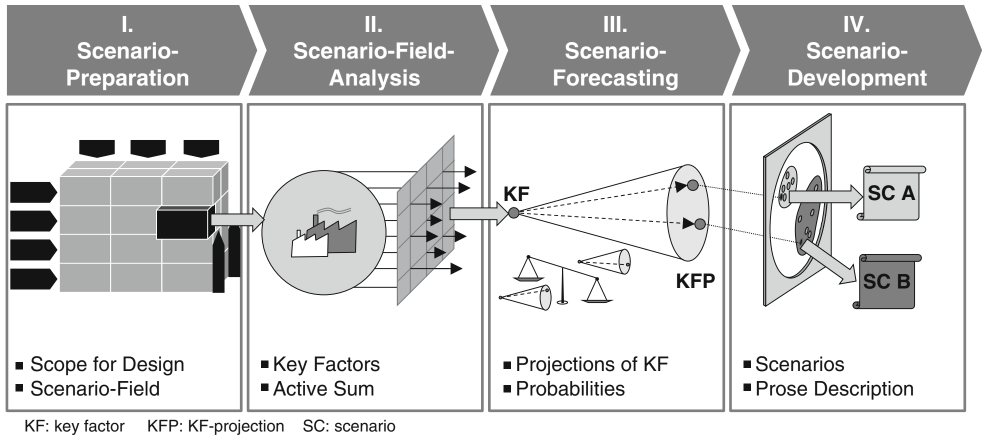


Fig. 1 Main steps and results of scenario-planning [25]

3.1.1 Step 1: Scenario-preparation

The purpose-design approach[4] is applied to achieve a highly efficient combination of scale and scope effects. The combination of scale and scope through a clear description of basic characteristics is possible [27]. The internal integrated modules of the basic vehicle can be prepared by highly automated mass production processes and thus reduce costs through economies of scale. Feature upgrades are interpreted as a supplement to and not a substitute for basic functions to avoid cannibalization effects. A cost reduction in terms of economies of scope is realized by an efficient network of cooperation and open-interface approach.

Case study StreetScooter In the course of the scenario-preparation the areas of influence concerning "StreetScooter power train" are identified. The StreetScooter as a means of transportation is based on a holistic innovative approach that requires the consideration of a wide number of areas of influence. The selected area for the scenario is electrified road traffic. With respect to the intended starting date for large-volume production in 2019, 2020 is chosen as target date. As sales are primarily going to be concentrated in Germany and to reduce the complexity of the areas of influence a restriction on the geographic area of Germany is implemented.

3.1.2 Step 2: Scenario-field-analysis

The scenario-field-analysis consists of two steps: the identification of influence factors and the selection of key factors.

The first step is based on a systematic approach for the identification of influence factors. The approach consists of the preliminary identification of influence factors, implemented by the bottom-up as well as the top-down approach. These are executed within the framework of brainwriting,[5] i.e. both at the management as well as the project-level influence factors are collected in written form. Simultaneously the Delphi method[6] is conducted and the derived influence factors are consolidated. During a workshop the integrated method subsequently employs Porter's 5 Forces in order to complete the list of influence factors from brainwriting and Delphi. Missing factors, which were identified with respect to Porter's 5 Forces analysis, are added to the list. Finally a Fishbone-Diagram[7] is drawn to complete the list. These steps provide an exhaustive list of influence factors.

Subsequently an influence analysis consisting of an influence matrix (Fig. 2) and a relevance matrix (Fig. 3) is conducted. Results of the two matrices allow a selection of key factors out of the list of influence factors.

Case study StreetScooter Experts, particularly engineers, valuated the influence factors concerning their influence and relevance. The identified key factors have strong influence on "StreetScooter power train" and high relevance for the scenario area "electrified road traffic".

A system grid (Fig. 4) gives a supplementary overview of selected key factors. The system grid aggregates results from the influence and the relevance matrix.

In addition to the factors complying with relevance and influence certain factors are chosen despite they are only satisfying one of the conditions. An example would be the limits to CO_2-emission which is characterized by a limited integration in the overall system. However, there is

[4] Fundamental new development without the constraints of existing designs [27].

[5] "Silent, written generation of ideas by a group of people [28]".

[6] Delphi method is a structured, multi-stage model for the anonymous survey of experts [29].

[7] Intent of the Fishbone-Diagram is to generate a comprehensive list of possible causes associated with one problem or effect [30].

Fig. 2 Influence matrix

Influence matrix

Standard of valuation:
0 = no influence
1 = weak influence
2 = average influence
3 = strong influence

Key factors	No.	1 GDP Germany	2 Electricity price	3 Limits to CO_2-emission	4 Population development	5 Innovation focus of OEM	6 Investment behavior of suppliers	7 Degree of optimization for conventional vehicles	active-sum	ranking
GDP Germany	1		1	1	3	3	2	1	11	2
Electricity price	2	1		3	0	3	2	1	10	3
Limits to CO_2-emission	3	0	0		0	3	3	3	9	5
Population development	4	3	1	2		3	3	1	13	1
Innovation focus of OEM	5	1	0	3	0		3	3	10	3
Investment behavior of suppliers	6	1	0	2	0	3		3	9	5
Degree of optimization for conventional vehicles	7	0	0	3	0	3	3		9	5
	passive-sum	6	2	14	3	18	16	12		
	ranking	5	7	3	6	1	2	4		

Fig. 3 Relevance matrix

Relevance matrix

0 = row less important than column
1 = row more important than column

Key factors	No.	1 GDP Germany	2 Electricity price	3 Limits to CO_2-emission	4 Population development	5 Innovation focus of OEM	6 Investment behavior of suppliers	7 Degree of optimization for conventional vehicles	relevance	ranking
GDP Germany	1		0	0	1	0	0	0	1	6
Electricity price	2	1		1	1	1	1	1	6	1
Limits to CO_2-emission	3	1	0		1	0	0	1	3	4
Population development	4	0	0	0		0	0	0	0	7
Innovation focus of OEM	5	1	0	1	1		0	1	4	3
Investment behavior of suppliers	6	1	0	1	1	1		1	5	2
Degree of optimization for conventional vehicles	7	1	0	0	1	0	0		2	5

indication that this factor will significantly gain importance in the European market within the next decade. This prompted the decision to include the factor in the list of 21 key factors. The list includes the Gross Domestic Product (GDP), electricity price, gas price, climate change, governmental actions to implement e-mobility, limits to CO_2-emission, surcharges, mega cities, overall concept of mobility, supply strategies of Original Equipment Manufacturers (OEM), competitive ability of the BRIC-countries, general innovation dynamics, shifts in the model mix,

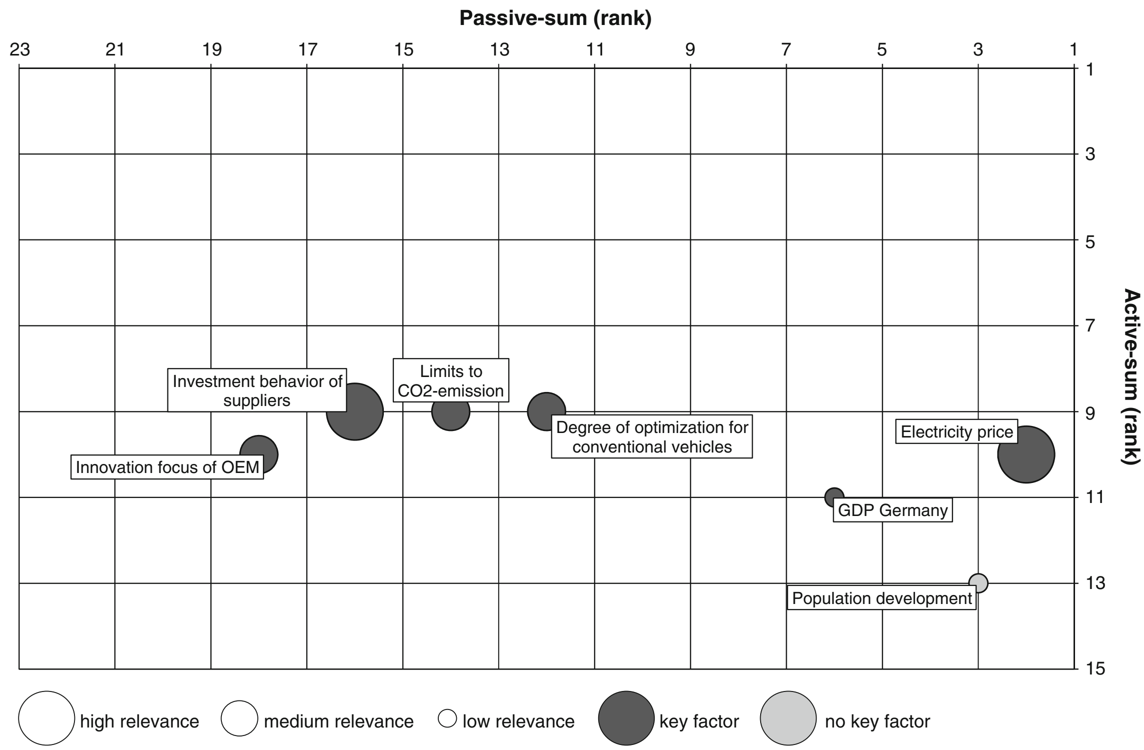


Fig. 4 System grid

innovation focus of OEM, investment behavior of suppliers, sales mix of power train in 2020, degree of optimization for conventional vehicles, Total Cost of Ownership (TCO) of conventional vehicles, dispersion of loading stations, battery costs and energy density of batteries.

3.1.3 Step 3: Scenario-prognostic

The formulation of the projections is the basis for assessing the probability of the realization of product features (see Sect. 3.2.2). Reasonable and realistic projections with probabilities form the best basis for anticipating potential influence on product features.

Case study StreetScooter In order to forecast the key factors identified in the scenario-field-analysis a bootstrap simulation within a regression model is applied. The bootstrap simulation is used, as the basis for the simulation is a short data row. This kind of simulation weakens the strong dependencies on account of the small database. From the set of 21 key factors, a sampling with replacement on seven key factors that are quantifiable is applied exemplarily. A deterministic relation between the dependent variable "market share of conventional vehicles"[8] and its independent variables "fuel price index"[9], "carbon dioxide emission"[10], "model mix"[11], "R&D expenditures"[12], "motor vehicle tax"[13], "vehicle optimization"[14] and "guiding principles for mobility"[15] is set up. "1-market share of conventional vehicles" is used as an approximation for the future development of electric vehicles. The following regression model is used:

$$ms = cons + \widehat{a}_0 * fuel + \widehat{a}_1 * ems + \widehat{a}_2 * mix + \widehat{a}_3 * rd \\ + \widehat{a}_4 * tax + \widehat{a}_5 * opt + \widehat{a}_6 * mob + \mathring{a} \qquad (1)$$

Ms market share of conventional vehicles (%), *fuel* fuel price index/100, *ems* emission standard/1,000, *mix* model mix of vehicles (%), *rd* R&D expenditures of the automotive industry (M €), *tax* motor vehicle tax index/100, *opt* optimization of the vehicle (g/km), *mob* principles for mobility (%).The bootstrap simulation is applied 1,000 times from the original historical sample. The historical

[8] Initial admission and registration of a brand new conventional vehicle with a license plate in Germany.

[9] Consumer price index for fuels in Germany.

[10] Permitted emissions of carbon dioxide for gas engine in Germany.

[11] Percentage of initial admitted and registered small and lower middle class cars in Germany.

[12] R&D expenditures in automobile industry in Germany.

[13] Motor vehicle tax index in Germany.

[14] Average carbon dioxide emissions per kilometer of new cars registered in Germany.

[15] Motorized individual transport/public transportation in Germany.

Table 1 Clustered allocation of regression equations

Cluster	Number
1	260
2	56
3	15
4	105
5	368
6	196

sample contains quarterly data from the 4th quarter of 2002 to the 1st quarter of 2013. The data row is limited due to the availability of data for new conventional car registered. Hence, additional data is generated with a bootstrap simulation and forecasted by a SARIMA model. The leap in technology and society is still considered by the retrieval on the basis data over 10 years. A time lag of one quarter concerning the influence of independent variables on the dependent variable is assumed. This is due to the fact that the decision of buying a car takes about 2 months [31]. As a result, 1,000 simulated values are generated on which regressions are based.[16] The deterministic relation between the dependent variable and the independent variables are clustered through a k-means algorithm with an Euclidean similarity measure [33] with six groups. Data clustering is one way to analyze a big set of vectors. As a result, the different regression models are clustered (Table 1).

The most regression equations are clustered within the fifth cluster. This cluster is used later on to obtain the market share for conventional vehicles. The forecast values for the dependent variables are obtained through a SARIMA model. A percentile calculation deals with outliers. Extreme deviations from the mean are included to ensure an acceptable level of precision. Values for the different percentiles obtained are shown in Table 2.

According to the percentile table a fuel price index/100 smaller than 1.350 has a probability of 50 %. In forecasting there is a certain residual risk that cannot be completely excluded i.e. the highest possible percentile rank would be 99.9 %.

The forecast values for the two different scenarios are obtained through the comparison of the historical values (Table 3) and the forecast values of the percentiles (Table 2).

3.1.4 Step 4: Scenario-development

Case study StreetScooter In general, the selection of the scenarios within the scenario-planning is carried out with the consistency and the subsequent cluster analysis. In this case a different approach is used by selecting the characteristics of each scenario through the values obtained by the SARIMA-forecasts (see Table 2). Hence, the quantification of different projections of the scenarios is possible.

[16] For similar approach see Fama and French [32].

Table 2 Percentile ranks of forecast values for independent variables

Percentile ranks	Fuel	Ems	Mix	Rd	Tax	Opt	Mob
20	1.001	0.09	0.349	19,475	0.88	89.34	0.807
30	1.133	0.44	0.401	20,659	0.93	95.31	0.816
40	1.245	0.73	0.445	21,670	0.98	100.42	0.823
50	1.350	1.01	0.486	22,616	1.02	105.19	0.830
60	1.455	1.29	0.528	23,562	1.06	109.97	0.837
70	1.567	1.58	0.572	24,574	1.11	115.07	0.844
80	1.699	1.93	0.623	25,758	1.16	121.05	0.853
90	1.881	2.41	0.695	27,400	1.24	129.33	0.865
95	2.031	2.81	0.755	28,756	1.30	136.18	0.875

Table 3 Historical values of the 1st quarter of 2013

Ms	Fuel	Ems	Mix	Rd	Tax	Opt	Mob
0.873	1.318	1.0	0.481	22,438	1.019	139.9	0.828

For 2012, only the internal expenditures for rd were available, the external were calculated with the help of the mean portion of the overall expenditures over 4 years (2007–2010) and were added. Rd data of 2012q4 are assigned on account of the temporal movement by a quarter (see p. 10) to "market share of conventional vehicles" data of 2013q1

A positive (scenario A) and a negative (scenario B) scenario for the 4th quarter of 2020 result (Table 4):

An optimistic scenario for developers of electric vehicles is scenario A. In contrast, scenario B describes a negative development of the acceptance of electric vehicles. A raise of the fuel price index favors a positive implementation of non-conventional vehicles and vice versa. On the basis of a historical value of 1.318, the values below and above are taken with its probabilities. The permitted emission standard of 2013 is 1.0. Hence, a permitted emission standard lower than 1.0, enhances the diffusion of non-conventional vehicles. In scenario A, the shift in the model mix continues and has a favorable effect on the sales prospects of electric vehicles. In scenario B, the demand for smaller vehicles is saturated in the long run. This is disadvantageous for the sale of electric vehicles. The level of research and development is crucial for the further development of non-conventionally powered vehicles. Compared to a level of R&D expenditures of € 22,438 million in the first quarter of 2013 the dynamics of innovation remains at the current level or decreases for scenario B. In scenario A, the pace of innovation continues to gain intensity and thus favors the development of non-

Table 4 Positive and negative extreme scenario

Indicator	Scenario A		Scenario B	
	Value<	Probability	Value<	Probability
Fuel	1.455	0.6	1.245	0.4
Ems	0.73	0.4	1.29	0.6
Mix	0.528	0.6	0.445	0.4
Rd	23,562	0.6	21,670	0.4
Tax	1.06	0.6	0.98	0.4
Opt	136.18	0.95*	136.18	0.95*
Mob	0.837	0.6	0.823	0.4

* A probability of 95 % is presumed as a 100 % certainty

conventional vehicles. Since electric vehicles are tax exempt for ten (registration until 2015)/five (registration until 2020) years, a raise in motor vehicle tax is favorable for the sale of electric vehicles and vice versa. The combined CO_2-value is expected to be fewer than 136.18 for the fourth quarter of 2020 with a probability of 95 %. Therefore, this value is assumed for both scenarios. In scenario A, the possession and use of an own vehicle increasingly dominate the principles for mobility. In scenario B, the vehicle is increasingly losing its leadership position. It is assumed that if the leadership position is lost, innovations are not recognized sufficiently.

The positive extreme scenario results in a market share of conventional vehicles between 65.9 and 87.4 % i.e. a market share of non-conventional vehicles between 34.1 and 12.6 %. The median of the market share of conventional vehicles of the negative extreme scenario is 89.0 % i.e. a market share of non-conventional vehicles of 11.0 % (see Fig. 5; Table 5).

The regression analysis and the results obtained through clustering validate the combination of the different forecasts for the independent variables.

3.2 Future-robust analysis of product features

The second part of the methodology comprises the scenario-based analysis of product features, which is divided into three sub-steps. In step five product features are identified based on the previously developed scenarios. The next step is, to link these features and their possible specifications with the key factor projections from step four, to evaluate their probability of realization. The results provide the partial expected values of the product feature specifications. These are evaluated across the different scenarios in the seventh step. The results in form of product features categorized regarding their uncertainty are the basis for the further product architecture design, which is not the focus of this paper. Figure 6 summarizes the steps that are described more detailed below.

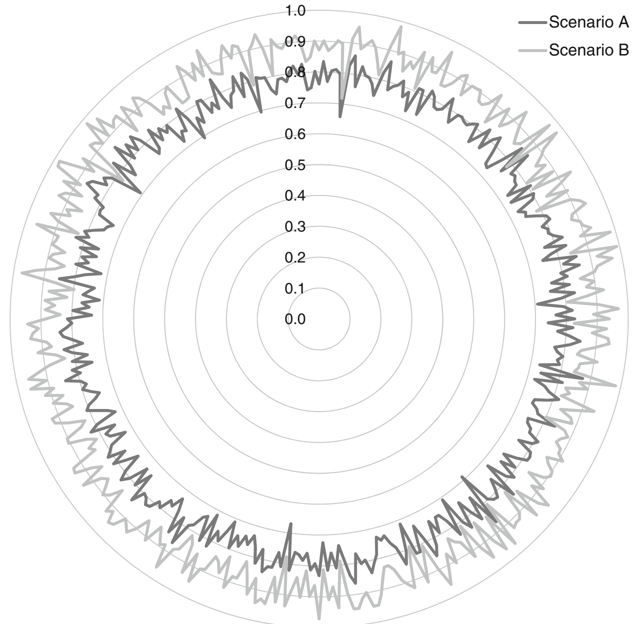


Fig. 5 Market share of conventional vehicles of the 4th quarter of 2020 of cluster 5

Table 5 Description of the two scenarios of cluster 5 by market share of conventional vehicles

Ms	Scenario A	Scenario B
Minimum	0.659	0.718
Maximum	0.874	0.991
Median	0.790	0.890

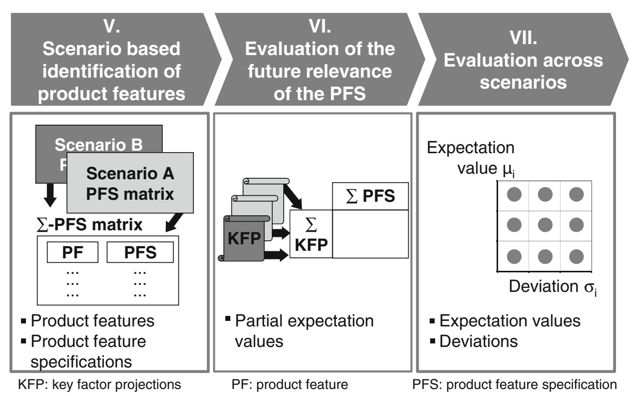


Fig. 6 Main steps and results of the future-robust analysis of product features

3.2.1 *Step 5: Scenario-based identification of product features*

The fifth step corresponds to an early stage of the product innovation process, with the need for a detailed analysis of

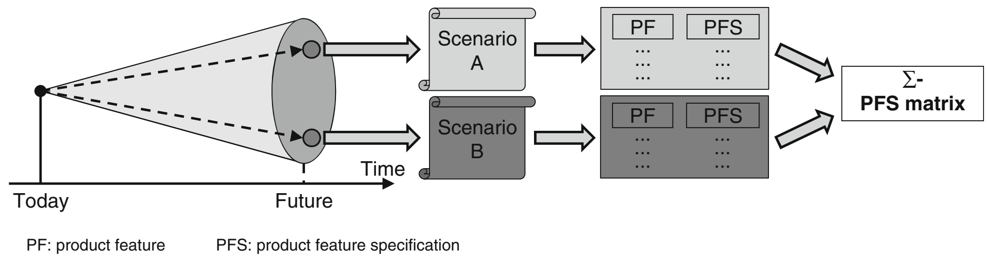


Fig. 7 Scenario-based identification of product features

the requirements for the product. These arise from the previously developed scenarios and are then transformed into product features. Is the product or its fundamental nature familiar to the company, they are likely already aware of a list of feature specifications, which have been used with success for comparable product families [34]. Critical and therefore more interesting at this point, is the identification of future features due to shifting customer needs which will be introduced after the start of the first products based on the architecture [2]. These requirements and features can only be identified on the basis of the scenarios describing the potential future product environments.

External product requirements are based on customer needs, but also environmental factors (e.g. laws) and the structure and quality of competition (e.g. technical standards by big competitors). These parts of the product environment are systematically searched for possible requirements.

As well as in Quality-Function-Deployment (QFD) and in the target cost management, identifying matching product features based on the previously identified requirements does not follow any fixed structured process scheme [35]. The goal is to find an optimal matching between the external and internal requirements and the offered product program. Once features have been identified the next step is to plan the specifications of each feature.

The identified product features and their specifications are entered into a scenario-specific feature-specifications matrix and then merged into a maximum feature-specifications matrix (Fig. 7). This creates a temporary product program that contains all possible product feature specifications. Due to the high number of variants it can hardly be implemented yet, as it would require a product architecture providing maximum flexibility in all its elements and would therefore be very expensive. To shrink this wide variation of product feature specifications the following steps of the method assess the uncertainties of the individual specifications.

Case study StreetScooter Regarding the StreetScooter case study the scenarios developed in step four were used to identify scenario-based product features and set up a product program for the power train of the StreetScooter. Due to the limited experience with electric vehicles, the scenarios are a good starting point to identify relevant product features and their characteristics.

To enable an affordable basic variant for the future potential of a mass market for electric vehicles with more cost sensitive customers, a low power version of the power train (e.g. 30 kW) must be provided. Critical product features for the performance are for example the drive inverter and the main battery. To meet the requirements of an appropriate cruising range the share of costs of the battery will be comparatively high in all scenarios. According to this, there should be interfaces for additional battery packs to give customers the opportunity of an individual battery configuration based on their cruising range needs and budget. Regarding the offered electric motor designs, future technical improvements and cost reduction potentials for the synchronous and reluctance machine were explicitly considered. Therefore, it is possible that these will represent an actual alternative to the now established standard asynchronous machines in 7 years, so these were also included in the maximum product range (see Table 6).

3.2.2 *Step 6: Assessment of the probability for the product feature specification*

In step six the key factor projections from step four are used to assess the realization probability for the product feature specifications. The individual projections are entered into the feature projection matrix (see Fig. 8), if they were relevant for at least one of the scenarios. Due to an expected realization probability of 100 %, all specifications that are already present in all scenarios are filtered out to limit the effort for this process.

The next step is to check the influence of the respective projection on the realization probability for the different specifications. For this purpose, a mono-directional relationship from the key factor projection on the specifications of the product features is assumed. The influence is expressed by the partial expected value T, which is based on a five-level rating scale (see Fig. 8).

The feature projection matrix ensures that all relevant factors for the evaluation of the probability of realization

Table 6 Power train product feature specification matrix for the RWTH StreetScooter Project

No.	Feature	Specification 1	Specification 2	Specification 3
1	Electric motor	Asynchronous machine	Reluctance machine	Synchronous machine
2	Drive power	30 kW	50 kW	
3	Drive inverter	Inverter 30 kW	Inverter 50 kW	
4	Gearbox	Planetary gear	Spur gear stage	
5	Main battery	Main battery 30 kW	Main battery 50 kW	
6	Additional battery packs	No additional packs	One additional pack	Two additional packs
7	Cooling	Water-cooling	Air-cooling	

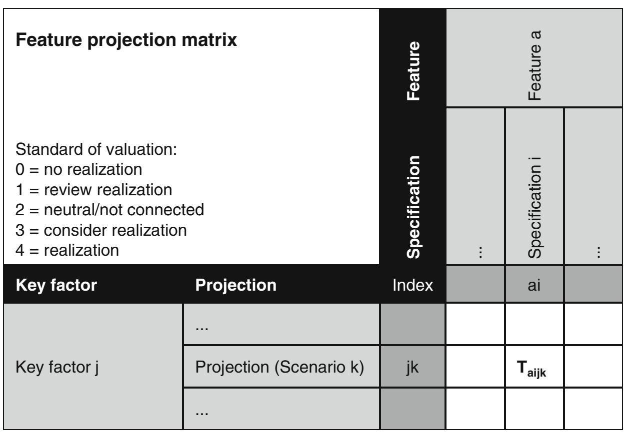


Fig. 8 Feature projection matrix

are taken into account. Due to the assessment it is used as an appropriate tool to quantify the qualitative results of the scenario technique. The partial expected values allow the evaluation of these results.

The complexity of this evaluation is highly depended on the respective key factors. Thus at the beginning of every evaluation, the first step is to analyze the focused factor. More global factors can be distinguished from closely product related factors. For closely product related factors, the evaluation is less complex as they have a direct influence on the product features. Examples for these kinds of factors are technical performance indicators or technology maturity levels. More global factors like for example the climate change have an impact on the system level. Thus they can be identified by analyzing the influence matrix. Due to their indirect way of influencing specifications, the evaluation is more complex and needs a revision of their connection to the scenario field.

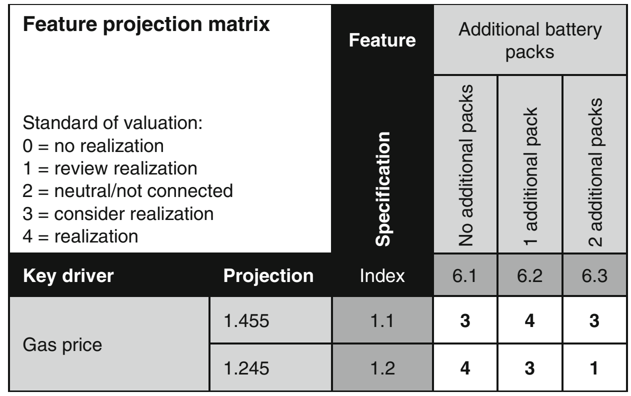


Fig. 9 Valuation example "gas price index" with "additional battery packs "

Case study StreetScooter To determine the partial expected values of the product feature specifications from the StreetScooter power train, the specifications shown in Table 6 were compared with the key factor projections from Table 4 by a team of experts from the StreetScooter project. The reliability of the acquired data is strongly dependent to the expertise of this team, thus the members have to be chosen carefully. The partial expected values in the resulting feature projection matrix were estimated by the project members. In the following, the procedure is illustrated by the example of the key factor "fuel price index" and the product feature "additional battery packs".

At a high fuel price e.g. there is a high probability of implementing all possible specifications, as customers will use electric cars for long and short cruising ranges, because of the higher costs per driven kilometer for conventional combustion engines. At a low fuel price, electric vehicles will primarily be used for short ranges e.g. in towns, where combustion engines will be especially ineffective. For those short ranges the main battery alone or supported by one additional pack will be sufficient (see Fig. 9 for the detailed evaluation).

3.2.3 *Step 7: Cross-scenario evaluation*

In this step the partial expected values (see Figs. 8, 9) are combined to get a cross-scenario evaluation of the uncertainty of the product feature specifications. Therefore the cross-scenario expected values and the affiliated deviation per specification are needed.

The expected value μ_{ai} of the specification i of the product feature a is calculated in two steps. First, the projection-specific partial expected values T according to formula (2) are aggregated into a key factor specific expected value. The calculated value indicates the probability of realization of a product feature specification, taking into account all projections of a key factor, which have been included in at least one scenario.[17]

$$\overline{T_{aij}} = \sum_{k=1}^{n} P_{jk} T_{aijk} \tag{2}$$

$\overline{T_{aij}}$ partial expected value for the specification i of the product feature a under the influence of the projections of key factor j, p_{jk} scaled probability of the projection k of the key factor j, T_{aijk} partial expected value for the specification i of the product feature a under the influence of the projection k of the key factor j, n number of scenarios.

In the second step the key factor specific expected values $\overline{T_{aij}}$ are weighted based on the activity of the underlying key factor and added up for the respective specification. This is to ensure that particularly active key factors have greater influence on the realized scenarios. The expected value μ_{ai} of the specification is calculated according to formula (3) by scaling the sum to the unit interval.

$$\mu_{ai} = \frac{\sum_{j=1}^{n} \|(S_{Aj})\| * \overline{T_{aij}}}{\max\left\{\cup_{a=1}^{z} \cup_{i=1}^{c} \left(\sum_{j=1}^{n} \|(S_{Aj})\| * \overline{T_{aij}}\right)\right\}}; \mu_{ai} \in [0, 1] \tag{3}$$

μ_{ai} expected value for the specification i of the product feature a, S_{Aj} active sum of the key factor j, $\overline{T_{aij}}$ partial expected value for the specification i of the product feature a under the influence of the projections of key factor j, n number of key factors, z, number of product features; c, number of specifications of the product feature.

Using the feature projection matrix the standard deviation of the expected value can be determined as well. The standard deviation is also very important as it allows the identification of critical specifications with high uncertainty. The standard deviation σ_{ai} is calculated analogous to the calculation of the expected value μ_{ai} in two steps. First, the standard deviation of the projection-specific partial expected values is used to calculate the standard deviation of the key factor specific expected value according to formula (4).

$$T^{*}_{aij} = \sqrt{\sum_{k=1}^{n} \left[p_{jk} * \left(\overline{T_{aij}} - T_{aijk}\right)^2\right]} \tag{4}$$

T^{*}_{aij} standard deviation of the partial expected values for specification i of the product feature a and key factor j, p_{jk} scaled probability of the projection k of the key factor j, $\overline{T_{aij}}$ partial expected value for the specification i of the product feature a under the influence of the projections of key factor j, T_{aijk} partial expected value for the specification i of the product feature a under the influence of the projection k of the key factor j, n number of scenarios.

The calculated key factor specific standard deviations are then weighted according to the level of activity of each key factor and added up. This sum term is also scaled to the unit interval. The standard deviation σ_{ai} is calculated according to formula (5).

$$\sigma_{ai} = \frac{\sum_{j=1}^{n} \|(S_{Aj})\| * T^{*}_{aij}}{\max\left\{\cup_{a=1}^{z} \cup_{i=1}^{c} \left(\sum_{j=1}^{n} \|(S_{Aj})\| * T^{*}_{aij}\right)\right\}}; \sigma_{ai} \in [0, 1] \tag{5}$$

σ_{ai} standard deviation of the expected value μ_{ai} for specification i of the product feature a, S_{Aj} active sum of the key factor j, T^{*}_{aij} standard deviation of the partial expected values for specification i of the product feature a and key factor j, n number of key factors, z number of product features; c number of specifications of the product feature.

The expected value and the standard deviation of the feature specifications represent two significant values for the design of a product architecture that takes into account all uncertainties. The expected value is the central result of all previous steps and expresses the probability for the realization of each product feature specification. It gives information about the future relevance of the respective specification and thus an indication of whether the specification should be considered when designing the product architecture or not.

The standard deviation, however, expresses the expected variation of the expected value with respect to the dynamics of the product environment. Thus, possible uncertainties of the product feature specification can be estimated and included into the design.

By plotting these two values in a portfolio (see Fig. 10) different categories of feature specifications can be formed. The unit intervals are divided into three categories: "low", "medium" and "high". Thus there are nine different categories.

Specifications with a high probability and low uncertainty are characterized by a high expected value with a low standard deviation. Thus, these product feature specifications are very likely to be realized and safe to be implemented when designing the product architecture. Features with a higher uncertainty however, require more flexibility regarding the implementation. A modular concept for the components realizing this feature would be one possible choice, to provide this flexibility.

Case study StreetScooter After entering the partial expected values for all combinations, the power train feature specification matrix for the RWTH StreetScooter Project was created in the cross-scenario evaluation (see Fig. 11). The evaluation has shown that only two product

[17] Formula 1 is equivalent to the equation for the expected value of discrete random functions, utilized for the present application.

Fig. 10 Feature specification

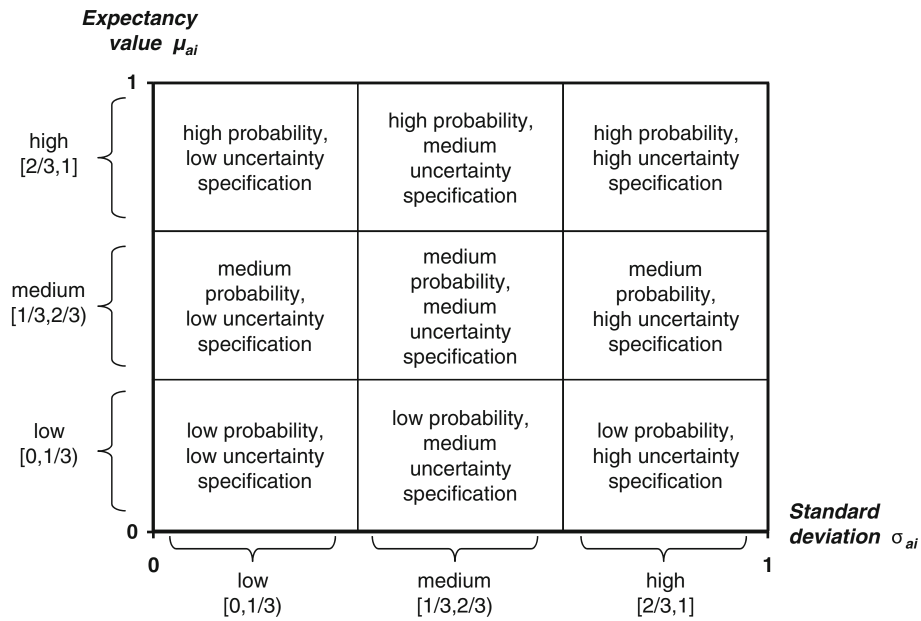
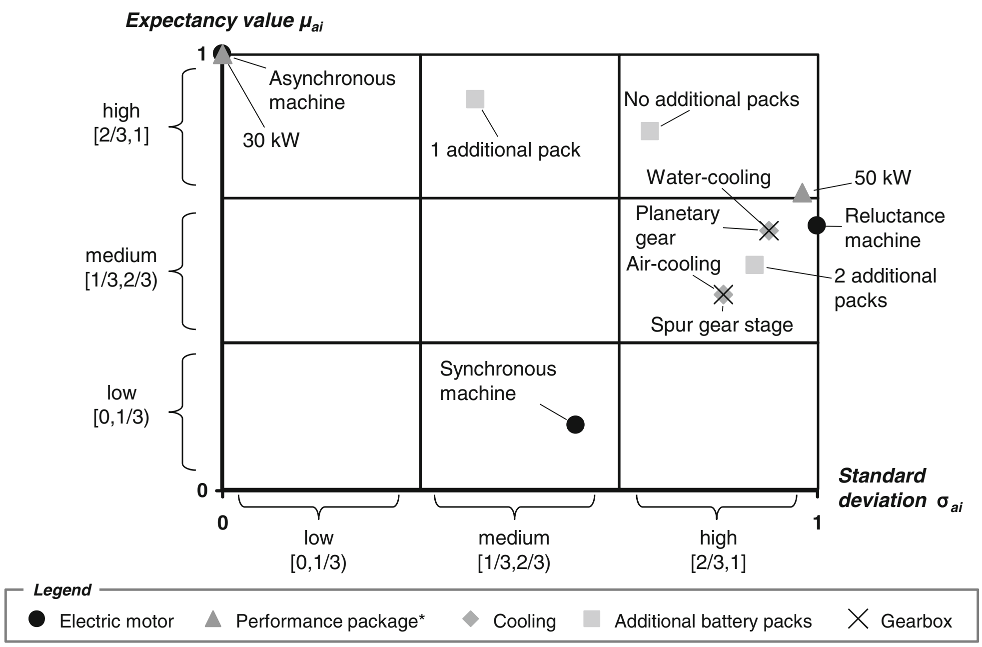


Fig. 11 Power train feature specification matrix for the RWTH StreetScooter Project



* The performance package contains the features drive inverter, main battery and drive power

feature specifications have a high probability with low uncertainty and are therefore safe to implement. However, the major part of the product feature characteristics fits into the categories with a medium expected value and/or high standard deviation. Due to the imponderables in the future product environment their realization is rather uncertain and has to be considered carefully taking into account the benefits and costs implementing them. Looking at the example of the feature "additional battery packs", the specifications one and no additional battery packs have a high expectancy value and a medium to high standard deviation, whilst the specification two additional battery packs has a medium expectancy value and a high standard deviation and therefore the highest uncertainty. To make a decision on the offered specifications, effects of the feature within the product architecture as is have to be evaluated. In this case, using the existing architecture, the additional battery packs would have required big changes to other components. As the demand for additional battery packs has a high probability, the architecture was changed that way, that one and two additional battery packs could be realized. The additional costs for this concept were expected to be lower than the possible changing costs and achievable scale effects.

4 Conclusion and further research

A seven-step methodology to evaluate the uncertainty of product feature specifications based on the scenario-planning has been introduced. For this purpose, a modified version of the scenario-planning by Gausemeier has been utilized, to identify key factors with great influence on the environment of the product range considered. In the next steps, alternative projections of these key factors are created and evaluated concerning their probabilities, applying a bootstrap simulation within a regression model. Based on the resulting future scenarios scenario-specific product features and specifications are defined, which are linked in a second step with the key factors in order to derive their expected values and deviations. The methodology has been applied to the case study of the StreetScooter power train.

On this basis, further research will be done, using the gathered information for a scenario robust design of product architectures. Therefore, the categories from the feature specification matrix will be used, to identify critical architecture elements which need to be designed with special attention. For different feature categories, different design strategies will be developed, to match the variety and uncertainty of the product features with the product architecture.

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References

1. Schuh G, Bender D (2012) Grundlagen des Innovationsmanagements. In: Schuh G (ed) Innovationsmanagement. Springer, Berlin, pp 1–16
2. Schuh G (2005) Produktkomplexität managen: Strategien—Methoden—Tools, 2nd edn. Carl Hanser, München [u.a]
3. Brecher C, Karmann WO (2012) Introduction. In: Brecher C (ed) Integrative production technology for high-wage countries. Springer, Berlin, pp 1–15
4. Lindemann U, Maurer M, Braun T (2009) Structural complexity management: an approach for the field of product design. Springer, Berlin
5. Firchau NL (2003) Variantenoptimierende Produktgestaltung. Dissertation, Technische Universität Braunschweig
6. Schuh G, Arnoscht J, Vogels T (2013) Controlling der Varianzsensitivität in Baukastensystemen. Controlling: Zeitschrift für erfolgsorientierte Unternehmenssteuerung 13(2):82–89
7. Schuh G, Lenders M, Arnoscht J, Rudolf S (2010) Effizienter innovieren mit Produktbaukästen. WZL, Aachen
8. Simpson TW, Siddique Z, Jiao J (eds) (2006) Product platform and product family design: methods and applications. Springer, New York
9. Schuh G, Schiffer M, Arnoscht J (2012) Scenario based development of robust product architectures. In: Kocaoglu DF, Anderson TR, Daim TU (eds) Proceedings of PICMET '12: Technology Management for Emerging Technologies, pp 2542–2549
10. Suh ES, de Weck OL (2007) Flexible product platforms: framework and case study. Res Eng Design 18(2):67–89
11. Suh ES (2005) Flexible product platforms. Dissertation, Massachusetts Institute of Technology
12. Martin MV, Ishii K (2002) Design for variety: developing standardized and modularized product platform architectures. Res Eng Design 11(13):213–235
13. Schuh G, Lenders M, Bender D (2009) Szenariorobuste Produktarchitekturen. In: Gausemeier J (ed) Vorausschau und Technologieplanung. HNI, Paderborn, pp 99–119
14. Rathnow PJ (1993) Integriertes Variantenmanagement: Bestimmung, Realisierung und Sicherung der optimalen Produktvielfalt. Innovative Unternehmensführung, vol 20. Vandenhoeck & Ruprecht, Göttingen
15. Lösch J (2001) Controlling der Variantenvielfalt: Eine koordinationsorientierte Konzeption zur Steuerung von Produktvarianten. Berichte aus der Betriebswirtschaft, Shaker
16. Hülle J (2012) Strategische Steuerung der Variantenvielfalt. Der Analytic Network Process (ANP) zur kosten-nutzenoptimalen Produktvariantenbewertung, 1st edn. Controlling und Performance-Management, vol. 7. Cuvillier, Göttingen
17. Saaty TL, Vargas LG (2006) Decision making with the analytic network process: Economic, political, social and technological applications with benefits, opportunities, costs and risks. International series in operations research and management science, vol 95. Springer, New York
18. Jiang L, Allada V (2005) Robust modular product family design using a modified Taguchi method. J Eng Des 16(5):443–458
19. Gausemeier J (ed) (2009) Vorausschau und Technologieplanung: HNI-Verlagsschriftenreihe, vol 265. HNI, Paderborn
20. Wade W, Wagner N (2012) Scenario planning: a field guide to the future. Wiley, Hoboken
21. Bazerman MH (1986) Judgment in managerial decision making: Wiley series in management. Wiley, New York
22. Schoemaker PJ (1995) Scenario Planning: a tool for strategic thinking. Sloan Manag Rev 36:25–40
23. Gausemeier J, Fink A, Schlake O (1998) Scenario management: an approach to develop future potentials. Technol Forecast Soc Chang 59(2):111–130
24. Gausemeier J, Plass C, Wenzelmann C (2009) Zukunftsorientierte Unternehmensgestaltung: Strategien, Geschäftsprozesse und IT-Systeme für die Produktion von morgen. Hanser, München
25. Gausemeier J, Fink A, Schlake O (1995) Szenario-Management: Planen und Führen mit Szenarien. Hanser, München
26. Naunin D (2007) Hybrid-, Batterie- und Brennstoffzellen-Elektrofahrzeuge: Technik, Strukturen und Entwicklungen; mit 8 Tab, 4th edn. Kontakt & Studium, vol 255. Expert, Renningen
27. Wallentowitz H, Freialdenhoven A, Olschewski I (2010) Strategien zur Elektrifizierung des Antriebstranges: Technologien, Märkte und Implikationen. Strategien zur Elektrifizierung des Antriebstranges
28. VanGundy AB (1984) Brain writing for new product ideas: an alternative to brainstorming. J Consum Mark 1(2):67–74
29. Fischer RG (1978) The delphi method: a description, review, and criticism. J Acad Librariansh 4(2):64–70
30. Maze-Emery E (2008) Knowing the cause is half the battle. Symptoms can be signposts on the route to curing problems. Tooling & Production November/Dezember:28–29
31. Capgemini U.S. LLC (2013) My car, my way. Cars Online 12/13
32. Fama EF, French KR (2010) Luck versus skill in the cross-section of mutual fund returns. J Finan 65(5):1915–1947
33. Jain AK, Murty MN, Flynn PJ (1999) Data clustering: a review. ACM Computing Surveys 31(3):264–323
34. Korreck A (2002) Methodik zur markt- und kostenorientierten Variantenplanung. Shaker, Aachen
35. Call G (1997) Entstehung und Markteinführung von Produktneuheiten. Schriftenreihe Unternehmensführung und Marketing, vol 33. Gabler, Wiesbaden