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Developing Key Performance Indicators for Variant Management of Complex Product Families

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Abstract

In this paper, we present a method for the development of key performance indicators for variant management purposes. It provides decision makers, product portfolio managers and -architects with a generally applicable way to gather information on how well a product portfolio and architecture perform in terms of balancing external and internal variety. The method employs tools from the field of product development and combines them with a data analytics perspective for general applicability. Each phase of the product life cycle is examined for its variant management goals, e.g. reduction of supply chain complexity in logistics or reduction of change request cycle time in engineering change management. The goals are analyzed for mutual influence in a cross-impact matrix and thereby classified into influencing factors, indicators, or critical factors. Indicators and critical factors are promising candidates for key performance indicators, and they are made measurable by linking them to available data in the company. Therefore, the existing database is analyzed for data objects, e.g. product components, and their relevant attributes, e.g. manufacturing costs. Each indicator is linked to suitable data. Based on the evaluated attainability and aggregability of data, the most suitable indicators and the correct level of aggregation are selected, e.g. business unit-, product-, component- or part level. In total, the indicators reflect all relevant aspects of variant management in the company and their implementation is prescribed by our method. We apply the method in a case study at MAN Truck & Bus AG, a German commercial vehicle manufacturer. Highly diverse market demands and accordingly complex product portfolios characterize the commercial vehicle industry. Using systematically developed performance indicators in variant management is crucial for manufacturers. The case study results are critically discussed with product architects as well as engineering management at MAN to show applicability and quality of the presented method.

Keywords: Variant Management, Performance Indicators, Data Analytics, Complexity Management

1 Introduction

With an increasingly individualized market situation, companies are forced to offer highly diversified product ranges. As a common solution, product family design provides a logical portfolio organization in form of generic product families, containing product variants with a set of common features and yet specific properties to meet distinct sets of costumer needs within the same product outline (Jiao et al., 2007). A high variety of end-products (i.e. external variety) is created while trying to maintain a limited set of technical elements by using shared components (i.e. internal variety). In industrial applications however, high function density generates a characteristic complexity within the product architecture. Function density hereby refers not only to a rising number of components in shrinking space, but also to intensified functional interaction between components (ElMaraghy & ElMaraghy, 2014). The ability to follow a clear modular product architecture (Blees et al., 2010; Erens & Verhulst, 1997) is aggravated, since functional and technical dependencies prohibit certain component combinations. As a result, variety becomes multilayered, occurring on all product structure levels from the product down to an individual part within a component.
The practice of a corresponding variant management is a challenge that has been discussed alongside product family design. Its goal is to ensure optimized variety during the entire product life-cycle. A majority of available methods tend to display product variety by so-called variant trees, further allowing optimization in tree structures (Schuh & Schwenk, 2001). Nevertheless, companies continuously lack the ability to enable transparency over complex interdependencies within the different, company-wide aspects of variety to the end of creating a holistic view on variant management (Braun & Deubzer, 2007). Multi-disciplinary involvement in development processes additionally projects variety-induced complexity into the organizational domain, e.g. by interlinking process steps of different business segments (Maurer & Lindemann, 2007). As consequence, each involved party perceives their own interpretation of variety including specific critical factors. For example, management and marketing focus mainly on external variety in portfolio positioning while costs and flexibility of internal variety are highly important for engineering. The interaction of these specific factors with variety-induced characteristics of the product family architecture has to be covered in a continuous variant management at all points of the product family life cycle (Schuh et al., 2014).
Long time maintenance of a developed product family architecture after its initial implementation is the foremost challenge. Simple quantification of complexity development in the form of costs is no sufficient approach to this challenge (Bahns et al., 2015). It is essential to reflect the multidisciplinary aspects of variety including functional, economical and organizational factors in an interrelated manner. In this paper, we present a systematic and tool-based approach to this task. We employ methods from research on performance measurement and from the field of matrix-based complexity management to provide a model of interrelations between all aspects of variety that are relevant in a specific company. Based on this model, new key performance indicators can be developed or existing indicators can be challenged regarding their significance in variety-related performance measurement. For adjustable applicability, we provide an analytic procedure for the development of individual key performance indicators based on the applier's environment and data structure.

2 State of the Art

2.1 Existing approaches to performance measurement in product family design

Mainly serving performance measurement purposes from a financial perspective, several aspects of complexity controlling have been applied to product family design. However, most existing methods are only suitable for momentary assessment (Weiser et al., 2016). The approaches by Junge (2005) and Schuh et al. (2014) apply common performance measurement tools such as key performance indicators (KPIs) and the balanced scorecard for product families. By general definition, performance measurement is known as the process of identification and quantification of measurable indicators that can be continuously tracked to assess progress made in achieving predetermined goals (Springer Gabler Verlag, 2018). Performance must be measured from multiple perspectives by means of specific KPIs, which add up to a balanced scorecard. Following those common methods, Junge (2005) developed his approach, which assesses the performance of an existing modular product family and furthermore allows forecasting of further development. Following the procedure of setting up a classic balanced scorecard, Junge first defines necessary perspectives, each representing general aims concerning the modular structure. Next, particular objectives for all respective perspectives are determined and arranged in a hierarchical order. The third step targets cause-and-effect relationships between the particular objectives to create an integrated network of strategies. KPIs for each perspective are determined and fitted to the particular objectives in a next step, followed by the final instantiation of the so-called modular balanced scorecard. Adapting Junge's approach, Schuh et al. (2014) introduce a constitutive performance measurement framework for variant management activities in machinery and plant engineering companies. They develop KPIs for a balanced scorecard consisting of five dimensions: product program, program architecture, finance, production and supply chain. Within these dimensions, three to four KPIs are developed, each controlling the primarily identified set of objectives, e.g. reduction of development time, stored material etc. The KPIs are defined in a way that company-internal data can be evaluated automatically for the balanced scorecard. Schuh et al. point out that the key figures can vary slightly among different company backgrounds, nevertheless the automatic collection required data should be feasible in general applications. Both approaches target a continuous complexity control and provide KPIs based on exemplary industrial applications. However, direct applications can be hindered by differences in product structure or data structures and -availability within a company.

2.2 MDM-based approaches to variant management

The Multiple Domain Matrix methodology uses combinations of Design Structure Matrices (DSM) and Domain Mapping Matrices (DMM) with the purpose of interrelated views from different domains on the modeled system (Maurer, 2007). While the DSM method abstractly depicts a system by showing its elements and corresponding relations in a square matrix, a DMM further enables correlation of different domains by utilizing a non-square matrix. An MDM ultimately combines the two techniques to a product development methodology that uses matrix operations for analyses of complex systems in order to identify potential for reduction of variety (Maurer, 2007).

The powerful methodology has been applied to variant management by expressing complex product structures and product architectures on an MDM basis. Tilstra et al. (2012) model a highly complex product structure by combining an infinite number of sub-system DSMs in an adapted MDM approach. The so-called High-Definition-DSM intends to simplify the process of developing a DSM for complex hierarchical system structures and to further allow application of known DSM analysis techniques regarding variety.

Braun and Deubzer (2007) use MDMs to represent product variants as clusters of feature combinations. noting that if a range of variants can be transferred to matrix notation, common analysis tools offered by MDM methodology can be applied for the benefit of variant management. This application allows a visualization of links between features and variants to decipher correlations between the sales/marketing and the technology perspective. The approach is refined by Deubzer et al. (2008) for applications in the automotive industry by adding equipment- and product line domains to the existing functional- and component domains for additional accuracy of a holistic view on variant management. By comparing different variants, the method provides a packing- and module determination based on graph analysis.

2.3 Variant Management at MAN Truck & Bus AG

MAN Truck & Bus AG as a commercial vehicle manufacturer faces the challenge of a highly diverse product family, which is contrasted by relatively low sales figures typical of the commercial vehicle industry (Stocker et al., 2016). The task of an effective variant management is met by a two-layered modular product structure. At product level, i.e. the complete vehicle, a first layer of the modular structure realizes cross-product synergies in main components while a second layer at component level enables modularity and part commonality within variants of components (Kreimeyer et al., 2014). Embedded into product architecture planning, the so-called component variant planning process translates market-driven functional requirements of individual components into product characteristics. While product characteristics can be configured by the costumer and represent external variety, the combination of technical restrictions and functional requirements yield the necessary number of variants for each component, i.e. internal variety (Schumacher et al., 2015). A package planning process then assures consistency of the resulting product architecture. While the modular kit at product level is subject to standardized planning processes, the modular kits at component level underlie less standardized processes. Each responsible department attempts to maximize component reuse (Kreimeyer, 2012). To further meet the requirement of a systematic variant management, current development targets comprehensive transparency over existing internal variety. In a data-driven approach, scenarios of variety introduction and -expiration are evaluated with respect to market relevance, variety-induced cost effects, and effects on the product structure's modularity.

2.4 Intermediate conclusion & research gap

Summarizing the state of the art, it can be stated that research in performance measurement provides either general frameworks such as balanced scorecards. Or it provides ready-made KPI solutions suitable for specific management challenges, but they are difficult to transfer to other industry fields due to differences in product family characteristics. Furthermore, aggregated KPIs of that kind are difficult to link to available data in a specific company, requiring complex adaptation processes. The field of complexity management offers a broad set of methods and tools for systematic analysis of product structures and -families. However, metrics for complexity assessment cater to product designers who are in the process of altering or creating a product architecture rather than they meet the requirements of continuous performance measurement of architectures in complex product families. The methods do, however, allow to model highly complex correlations of multiple domains. We therefore suggest a novel approach combining performance measurement purposes with multiple-domain-matrix-methods in application to the variant management context. The approach shall consider all perspectives on variety-related issues in a typical manufacturing company. For maximum applicability it is furthermore required to incorporate available product- and process information in the company, so the performance indicators developed with the method are easy to implement. Ultimately, the definition of the right aggregation level for each performance indicator shall be supported, altogether delivering a toolbox to engineering managers and variant management experts who need to implement a transparent performance measurement system.

3 Development of key performance indicators for variant management purposes

The presented method is structured into four steps (Figure 1). The first three steps aim to create an MDM-based model of company-wide goals regarding variant management, which are put into relation with the data that represents product family variety from product-, process- and organizational perspectives. Based on the created system, correlations between the three modeled domains are analyzed in the fourth step to provide tool-based support for the aggregation of variant management KPIs.

1 Data acquisition	2 Prioritization	3 Interrelated system	4 KPI aggregation
by expert interviews: a. Variant management goals b. Relevant key figures c. Data objects	of variant management goals: a. Analysis of correlations between the identified goals b. Correlations are represented in a cross-impact matrix c. Prioritization by a derived Active-Passive-portfolio	of goals, key figures and data objects in a multi-layered MDM: a. Representation of composed key figures in the Key-figure-DSM (K-DSM) b. Representation of data objects in the Data-object-DSM (D-DSM) c. Mapping of key figures to data objects in the Key-figure-Data-object-DMM (KD-DMM) d. Reducing the cross impact matrix to the binary Goal-DSM (G-DSM) e. Mapping of goals and key figures in the Goal-Key-figure-DMM (GK-DMM)	by graph-based analysis of the interrelated system: a. Identification of significant key figure - goal relations b. Selection of key figures composing the KPI c. System integration of the new aggregated KPI d. KPI environment analysis

Figure 1: Process steps of the presented method

3.1 Acquisition of relevant data

In this first step, the elements of the three MDM-domains are defined. The relevant variant management goals are identified in interviews with experts of all variety-affected parties within the company. The goals are formulated regarding four main topics of effective variant management, namely market fit of the product portfolio, profitability of the developed product family architecture, modular structural quality, and general transparency over variety. Adapting Schuh et al.'s system of objectives (Schuh et al., 2014), the particular goals of each involved party should refer to one or more of the main topics. Ideally, an effective variant management covers all four topics. There may be specificities regarding the focus of variant management, and therefore the number of particular goals or the emphasis on single topics might differ from company to company. However, the comparison of the results observed by Schuh et al. and those observed at MAN does show overall compliance in the main topics and goals of variant management regarding complex product families of different branches.

Analysis of leviable company data with respect to the identified goals yields sets of key figures and data objects in all involved business areas. A key figure is defined as the general term for a variety-influenced figure. This figure can either be a directly ascertainable value or the composed result of a calculation between two or more subleveled key figures. Data objects denote entities in the company's data base that represent objects originating from either the development and production processes or the organizational structure. Key figures thus can be seen as attributes of data objects, e.g. a specific value of the key figure *sales volume* is attributed to *vehicle series* as data object.

3.2 Prioritization of correlating variant management goals

The variant management goals attained in the first step are inserted into a cross-impact matrix to create an Active-Passive-Portfolio (AP-Portfolio) (Hess & Müllner, 2007). Possible impact of each goal on every other goal is denoted with a factor of 0 (no impact) or 1 (impact). While this binary indication leads to first results, we recommend weighting the impact on a scale from 1 (indirect impact) to 3 (direct and strong impact), based on the directness and the severity of impact. The additional weighting results in a more differentiated AP-Portfolio. This process should be performed individually by the interviewed experts, respectively focusing on their particular goals. The results are compared and incorporated in a following workshop with all participants to also detect less obvious relations. Active and passive sums of each goal allow for classification as influencing factors, critical factors or indicators. Goals with high active- and low passive sums represent influencing factors. Critical factors possess both high active and high passive sums. Indicators are strongly influenced by other goals with small self-inflicted impact, showing in low active- and high passive sums. This classification serves as guidance for prioritizing correlating goals. Indicators often refer to corporate strategic topics without much given possibility to achieve them by direct measures whilst critical and influencing factors provide leverage for measures of variant management. For tracking and performance measurement purposes, critical factors and indicators serve as the main subjects to further KPI definition.

3.3 Modeling interrelations of variant management goals, key figures and data objects

The goal of this next step is to make the variant management goals measurable based on available information. This is achieved by linking the prioritized variant management goals to existing key figures and data objects available in the company. These three domains are combined into a multilayered MDM (see Figure 2). This MDM, represented in a matrix- or graph type visualization, serves as foundation for the KPI-definition-step. But first, we define the MDM and its contents in the following.

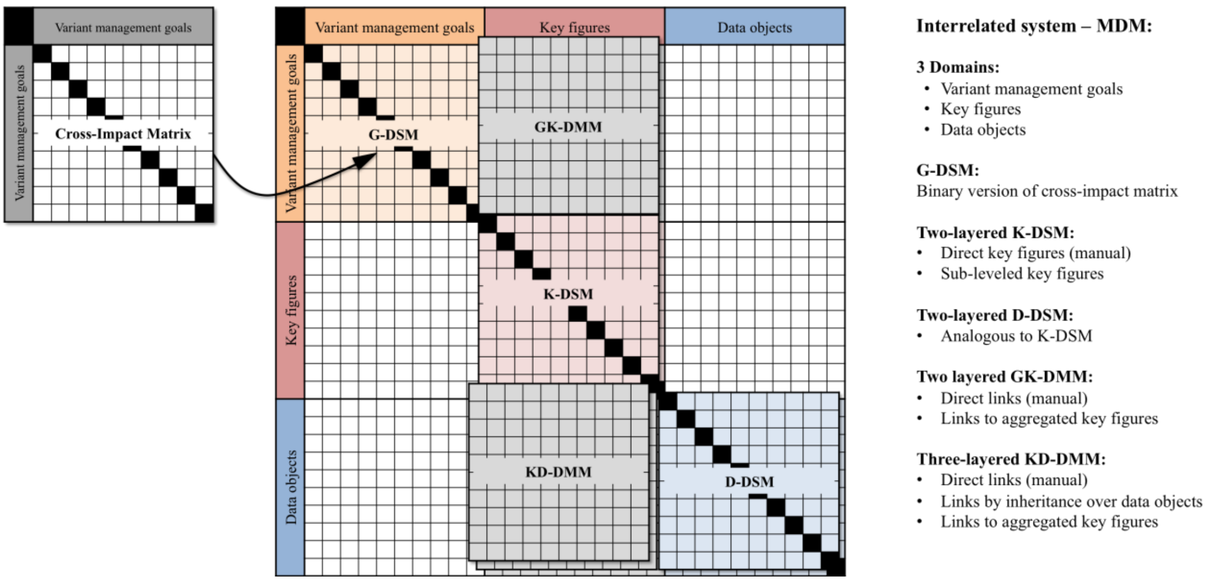


Figure 2: Interrelated-system-MDM

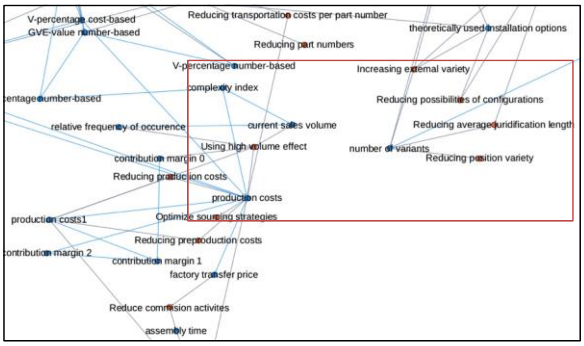
In step 1, both direct and aggregated key figures were collected. Aggregated key figures are calculated from other key figures and therefore should not be linked directly to data objects. Furthermore, direct key figures should only be linked to the lowest structural data object level to avoid redundant linking. The interrelations of key figures and aggregated key figures are modeled in the directed binary key-figure-DSM (K-DSM). All interrelations at sub-aggregation-levels are generated by DSM calculation, resulting in a two-layered K-DSM (Kreimeyer & Lindemann, 2011). An equivalent two-layered data-object-DSM (D-DSM) represents structural composition of data objects. And a multilayered DMM linking key figures to data objects (KD-DMM) completes the MDM, which serves as representation of the developed key figure system. The first KD-DMM layer is filled manually with links between direct key figures and data objects, following the previously defined premises. Multiplication with the D-DSM then yields a second layer, where upwards-inherited key figures represent mean values or value ranges for the composed data object. The result of this calculation must be revised because not every aggregation is reasonable. In an iterative multiplication process, the same can be done with the K-DSM where an aggregated key figure is only added if all composing key figure are already assigned to the data object.
The final step towards linking variant management goals to available data is prepared by manually filling in direct links between goals and key figures in a binary DMM (GK-DMM). After reducing the weighted cross-impact matrix to a binary goal-DSM (G-DSM), it can be multiplied with the K-DSM. This adds a second layer to the GK-DMM with indirect links, and thus completes the interrelated-system-MDM. In our initial case study at MAN, the input for the GK-DMM was partly based on expert opinions and partly based on prior empirical studies of company data. Certain correlations displayed variety effects in available data, e.g. between number of component variants and number of assembly errors. Other correlations could not be proven, also due to insufficient data quality. This lead to more thorough discussions with the experts to ascertain a valid MDM-model.

3.4 Developing key performance indicators based on the interrelated system

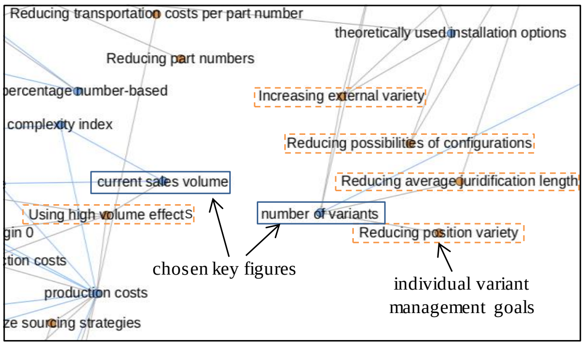
Using both matrix- and graph-based representations of the interrelated system creates versatile transparency over complex correlations. This helps with identifying appropriate KPIs and fields of key figures for different perspectives of aggregation.
Aggregation perspectives and -levels are company specific since organizational structures and -processes as well as product architectures can vary significantly. Analysis of these aspects with respect to variety yields several aggregation levels that can be discussed for KPI-definition. Extensive analysis at MAN has led to five perspectives, namely Market/Branches, Product Structure, Model years/Development Projects, Organization and specific Variant Management Projects. Each of these perspectives yields several aggregation levels, which cannot necessarily make the same use of all KPIs. Therefore, a set of perspective-specific KPIs should be developed referring to the data objects that matter for the perspective.
The development of key performance indicators depends on existing knowledge of variety effects on the company‘s processes and structures. We present two ways of developing KPIs with the interrelated-system-MDM, depending on the extent of existing knowledge of variety effects. One option is the top-down approach beginning with pre-defined KPIs, e.g. taken from existing research or from other performance measurement applications the company. Inserting these KPI candidates into the developed interrelated systems provides verification and reconsideration possibilities. The KPI candidates are analyzed for their significance regarding variant management goals and for their consistency in the company’s aggregation perspective context. An additional result is a gain in transparency over cause-effect-relations of the KPI candidates, which helps with their redefinition. The other option is the bottom-up approach,

which is applicable in the case of insufficient knowledge about variety effects. System analysis of the interrelated-system-MDM using common matrix- or graph-based analysis methods yields potential aggregation points.

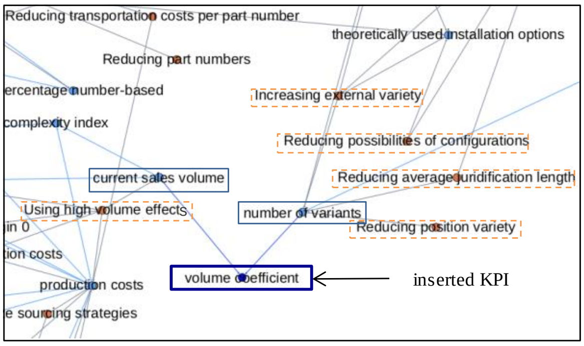
In our initial case study, both approaches are applied to a KPI that was developed with experts at MAN: the so-called sales-volume coefficient (SVC). The MDM in our case study comprised 28 variant management goals from seven variety-affected parties. The key figure domain comprised 10 potential KPIs and 44 key figures total, of which 23 key figures were aggregated from 21 direct key figures. These key figures were mapped to 14 data objects and later aggregated to KPIs serving five aggregation perspectives. Targeting general comparability on component variety in terms of market fit and profitability, the SVC indicates, which quantity of orderable variants constitute 80 % of the component's current sales volume. For example, if there are ten component variants, and the accumulated sales volume of two variants exceeds 80 % of the total sales volume, the SVC has a value of 0.20 or 20 %. The narrative is "It takes 20 % of our offered variants to reach 80 % of our sales volume". Using key figure aggregation logic in the interrelated system of MAN, the aggregated KPI *SVC* thus conjoins the direct key figure *current sales volume* of the data object *component variant* and the direct key figure *quantity of variants* of the data object *component* (Step 4b in Figure 3). Scenario 1 exemplifies the top-down approach. The SVC is inserted into the system as part of the key figure domain (Figure 3, Step 4c). Following that, possible transfer options to other aggregation levels are highlighted, in this case to higher product structure levels such as fully composed vehicles (Figure 3, Step 4d). Furthermore, 5 out of 28 form a composed set of variant management goals, such as the reduction of internal variety, whose effects could now be simultaneously tracked with the inserted KPI (Figure 3, Step 4d). Scenario 2 follows the bottom-up approach. Herein, we add a preparing analysis step (Figure 3, Step 4a) for identification of potential aggregation points using visual examination of the system graph.



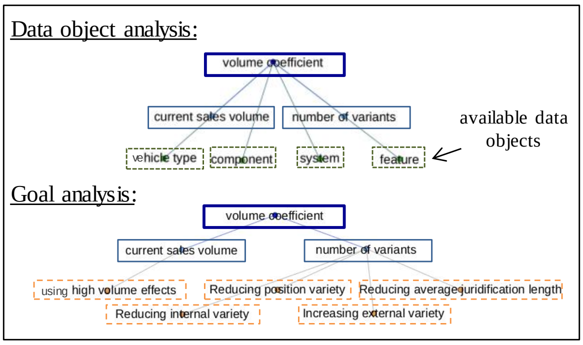
Step 4a: Identification of significant key figure and variant management goal correlations



Step 4b: Selection of composing key figures



Step 4c: Integration of the aggregated KPI



Step 4d: KPI environment analysis

Figure 3: KPI-development process using graph-based representation of the interrelated system

Suitable aggregation points are characterized by key figures with high individual but small mutual goal correlation. They can be identified as key figure with strict 1:n relations to goals, meaning that the goals have no relations to other key figures. Aggregating several of such key figures would create a KPI that balances the otherwise individual goals. In our case study, most goals were covered by more than one KPI. We could minimize this redundancy by comparing the KPIs regarding their goal coverage. Out of similar KPIs, we selected only one to remain in the KPI-framework. In total, we could reduce the framework by 50 % from 16 to 8 KPIs with the same overall goal coverage. Current research in cooperation with MAN works towards a framework with at least one aggregated top-level KPI for each main topic, which are supported by key figure fields in all aggregation perspectives. The presented method is applied in iterations following both the top-down and the bottom-up approaches. Management feedback at the end of each iteration leads to redefinition of KPIs or to their reallocation to other aggregation levels per each perspective. The presented method is applied by the variant management experts who design the KPIs for engineering management.

4 Conclusion & Outlook

We presented a method for developing KPIs in the special context of variant management. Performance measurement is required in this context because the effects of high product- and process variety have a high impact to the whole company. In addition, the highly complex nature of this context makes KPI-development an exceedingly challenging task. To cope with this challenge, we followed a systematic approach of modelling the interrelations of variant management goals and existing data in the company. This assures that resulting performance indicators provide relevant information and at the same time are applicable to any company environment. Our method employs a multi-layered MDM with three domains, namely variant management goals, data objects, and key figures as attainable attributes of the data objects. Manual input is required in three DSMs and two DMMs, only in one layer respectively. Matrix calculations produce the remaining interrelations, which only require manual revision in some cases. Based on the resulting MDM, KPI-definition and evaluation is possible in two approaches, depending on predominant knowledge of variety effects in the company. The top-down approach evaluates pre-defined KPIs and showcases their significance regarding variant management goals as well as their consistency concerning available data. The MDM thereby allows for systematic definition of the right KPIs for a given performance measurement purpose. The method was applied in an initial case study at MAN, a German commercial vehicle manufacturer. Both the product- and process complexity as well as the variety-related challenges are high in the commercial vehicle industry. The method therefore could be tested in a demanding setting. Identifying and analyzing the variant management goals, steps 1 and 2, accounted for most of the effort that was necessary for successful implementation of the method. Two stages of interviews with variant management stakeholders from across the company were required for input and discussion. Steps 3 and 4, namely modelling the key-figures- and data-object-matrices needed less coordination with experts and could be performed within the engineering variant management team in comparably short time. All in all, it should be possible to apply the method at any company within a few weeks. At MAN, the method provided strong support for the complex task of evaluating predefined KPIs. However, it should be advanced regarding the following aspects. The cross-impact analysis of variant management goals currently relies on subjective ratings when weighting the impact between goals. Objective and ideally quantitative criteria are necessary, e.g. for the degree of directness and severity. The identification of variant management goals could also be supported by a list of generic goals gathered from empirical studies on variant management across different industry branches. This would make the method's initial steps easier and less time consuming for first-time applications at any company. The correlations between key figures should also be supported by empirical studies of company data as far as possible. This would reduce subjective judgement and increase the validity of the model and thus the defined KPIs. A valuable extension to the MDM-model could be the domain of data origin, which contains the company's different data bases. Thereby, data availability could be evaluated and used as a feasibility- and prioritization criterion for KPIs. The most elaborate application of the MDM-model could be decision support in variant management. Before and after variety handling measures are taken, key figures could be analyzed for their cause-effect-relations, which would help in decision making and in performance tracking.

Contributions

Michael Schmidt conducted research work on the general topic of variant management in engineering management in the commercial vehicle industry and initiated as well as wrote this paper. Johanna Schwöbel developed large parts of the methodology presented in this paper, conducted the modelling and calculations for the case study, and wrote according passages of the paper. Markus Lienkamp contributed to the conception of the research project and revised the paper critically for important intellectual content.

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