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Data-driven modelling of the functional level in model-based systems engineering – Optimization of module scopes in modular development

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Abstract

The modelling of the functional level of technical systems can be supported by the analysis of machine usage data. By creating an understanding of the actual use of provided functions of offered machine configurations, the definition of module scopes in modular development can be optimized. Characteristics of specific machine usage can be assigned to physical elements using model-based systems engineering. Analyses on a purely functional system level can thus be placed in context with each other via the connection to physical elements. Consequently, critical elements in the system design can be systematically uncovered.

Keywords: Data-driven decision making; Product architecture; Modular systems; Reference system

1. Introduction

The development of product systems is becoming more and more complex as the requirements and the solutions implemented for them are growing increasingly complicated and unmanageable. The reasons for this are partly megatrends such as individualization and technological progress, which companies must cope with [1,2].

This often results in many solutions that influence and shape the architecture of a product system. The targeted planning, selection, and development of such solutions in the product architecture help to make the complexity that has arisen manageable or to be able to avoid foreseeable complexity at an early stage [3].

Data-driven analyses make it possible to get to the core of this multitude of information and to draw valid conclusions based on it [4,5]. To ensure this, a data-driven analysis of the reasons for the resulting diversity can be used. In the design of the architecture of machine tools, for example, this can be the utilization of data and programming aspects of the work sequences. However, the question arising here is how this information is transferred to the design of the architecture. A persistent linkage of field gathered data must be transferred to the implementation of the design. This paper pursues the approach of modeling the functional level and their corresponding requirements as well as their product properties by analyzing machine usage data. The systematic integration of knowledge gained from the analysis of machine usage data enables the data-driven optimization of the product structure. An example exemplifies the instance from the development of machine tools.

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2. Literature review

2.1. Product architecture

In developing mechatronic product systems, engineering is a crucial part of designing the underlying product architecture [2,6]. The product architecture is the key to successfully designing and covering external properties (product properties) and customer requirements. In this paper, product properties are also described as product functionalities, representing the customer's objective [7].

The proven design of modular product families can be used to implement continuously increasing volatile requirements and the resulting product properties in a complexity-reduced manner [8]. Various established methods consider both technical-functional and product-strategic modularization. An example of technical-functional modularization is the Design-Structure-Matrix [9]. For product-strategic modularization, Modular Function Deployment [10] and Life-Phase modularization [11] can be consulted. Furthermore, there are holistic approaches, such as the Product Family Master Plan [12] and the Integrated PKT-Approach [7], which consider both technical-functional and product-strategic modularization.

The Integrated PKT Approach offers a validated approach for handling variant-induced complexity, which is considered further in this paper. By including a methodology for Design for Variety [13], variety can already be considered analytically in advance. This offers further advantages for this paper, as the mapping of the product architecture over the levels of Design for Variety enables the linkage of the data-driven analysis with the modeling at the functional level up to the mapping of already existing modular product structures. Regarding systems engineering, this also establishes the immediate link with the RFLP-Approach [14].

2.2. System architecture

Projects are becoming increasingly complex, therefore various disciplines must cooperate in order to manage the existing complexity. Focusing on this kind of project, the literature links to systems engineering.

System Engineering is an interdisciplinary approach for successfully analyzing and managing complexity and risk. The approach includes several tools, techniques, standards, and concepts. In this context, System Engineering starts in the early phase of the system engineering by collecting requirements from Stakeholders.

Followed by the system architecture design; afterward, the verification & validation of the system is in focus. Interestingly, the method does not stop here while helping to manage the complexity of the live cycle [15]. Model-based systems engineering is a valid approach for building a stable and effective architecture. Modeling a system encourages a common understanding and enables the analysis of the technical system [16]. Due to the consistent RFLP-Chain and because of the interconnection there is a huge potential for analysis through the model.

2.3. Data-driven requirements management

Requirements can be classified as functional or as non-functional requirements. Functional requirements describe the functional scope of a new product or development generation. Non-functional requirements consist of quality requirements and general conditions. Requirements management is used for transparent documentation in the development process. It enables systematic reuse and iterative and interdisciplinary further development of all requirements [17].

As a result of digitalization, a large amount of data is generated in mechatronic system development [18]. However, simply gathering and storing data without utilizing it with a clear purpose is impractical. Instead, data must be processed and analyzed to gain knowledge that benefits the organization [19]. The gaining of information from raw data is described in Figure 1, according to Anderson [20].

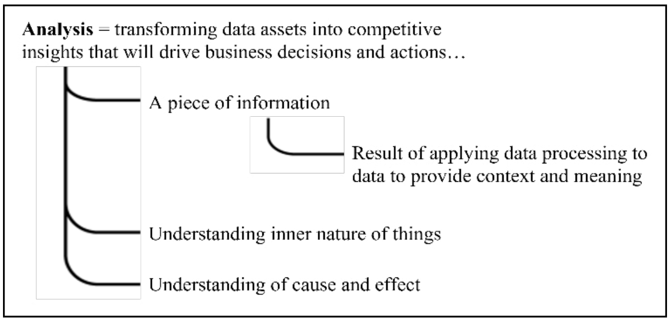

Fig. 1. Transforming data to gain information by using a data analysis.

The value added by analyzing data in the mechatronic system development hereby depends on data accessibility, quality, heterogeneity, analysis, and the synthesis of findings and gained knowledge [21]. In data-driven requirements management, the analysis and interpretation of data are used to define and validate requirements. Thereby, data mining techniques are applied to generate knowledge about how customers use products on the market to derive targeted, customer-oriented requirements for the development processes of new products. This effective use of data can accelerate development processes and achieve competitive advantages [22].

3. Research methodology

Although extensive literature is available on the individual research areas, it has not yet been considered how analyses of machine data can be implemented in the methods of Model-Based Systems Engineering to systematically optimize modular designs. In this paper, the research goal is to describe functional modeling using the analyses of machine data to optimize system modules via the interconnection of functional and physical elements in models. For this purpose, the following research questions are answered:

RQ1: How can the analysis of machine data support functional and requirement modeling?

RQ2: How does functional modeling using machine data analysis affect the maintenance and optimization of modular structures?

RQ3: How can modular structures be optimized through the consistent application of MBSE and machine data analysis?

The approach is structured by the Design Research Methodology (DRM) of Blessing and Chakrabarti [23]. In descriptive study I, research question 1 is answered by analyzing machine data of a gripping unit for the automated removal of punched sheet metal parts to help model the functional level in correspondence to its requirements. The analysis of machine data supports a deeper understanding of the parts produced in the expression of descriptive dimensions of elements in the functional modeling of system modules. In the prescriptive study, research question 2 is answered, where Chapter 5 establishes the relationship between elements in physical modeling and with corresponding analyzed functions. Using the additional knowledge generated by the data-driven validation of the functions, respectively the requirements and properties, the model is further developed. In descriptive study II, Chapter 6 answers research question 3 by optimizing modular structures by applying MBSE and analyzing machine data. An optimized system model is created based on the knowledge generated from the analysis of the actual machine usage on the customer's shop floor.

4. Analysis of machine data for functional modelling

The potentials for supporting functional modeling are shown below using the example of the gripper unit of an automation solution in sheet metal production which is shown in Figure 2. On the one hand, the automation solution enables the operator-free loading of a machine tool with a raw sheet, and on the other hand, the automated unloading of finished sheet metal parts and the remaining grid of the sheet. The motion unit moves on a traverse to position the gripper unit according to the raw sheet metal machine or unloading position. The gripper unit enabled the suction of raw sheet metal and finished sheet metal parts via various vacuum suction cups to remove both filigree light parts and large-area heavy parts.

Fig. 2. Automation solution for loading and unloading manufactured sheet metal parts with a gripping unit

Based on elements in the reference system of the existing automation solution a model can be derived. The initial model gives a first hint at the functional relationships in the system. The functional structure is strongly related to the requirements underlying these functions. Changes in the requirements for a technical system to be developed or in the functional mapping, for example, of the system module of the gripping unit, must be transferred to the model and validated.

By analyzing machine usage data, the dimensions for the use of technical systems can be analyzed in terms of their characteristics according to the implemented user profiles. The analysis of different functions provides information about the congruence between the intended and actual use by customers. By describing individual functions, corresponding requirements, and properties can be validated, refined, and subsequently modeled in connection with individual functions. The result is a holistic picture of the actual requirements profile of customers for the technical system and the suitability of defined function scopes in the reference system for realizing these.

The manufactured sheet metal parts are subsequently analyzed according to their dimensions in X and Y directions, part weight, and sheet metal thickness. The presented analyses herewith are based on randomized data due to company regulations and do not resemble the real distribution of described dimensions while still allowing to prove the theoretical applicability of the presented instance. Figure 3 shows exemplary distributions for sheet metal parts that are removed automatically and those that are not removed automatically.

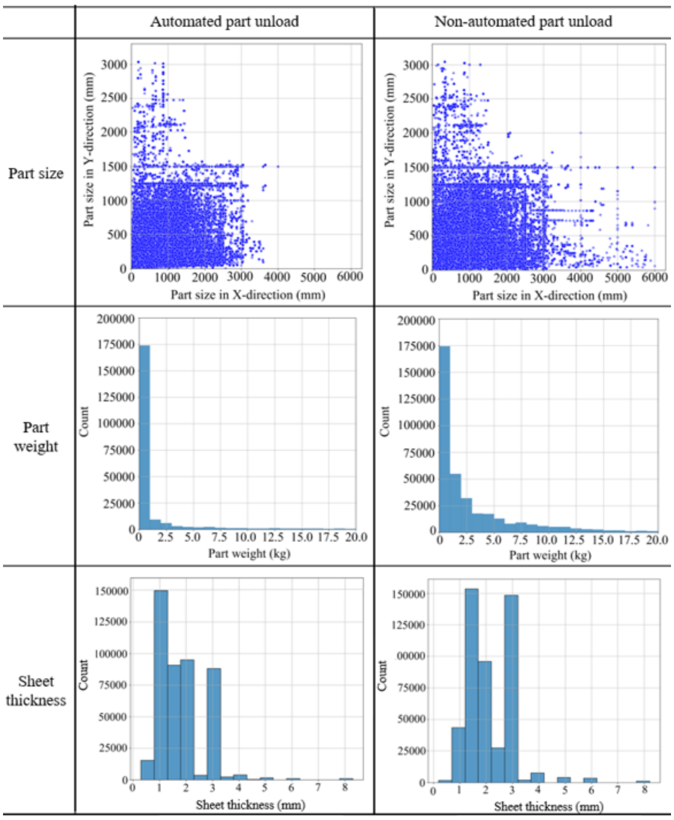

Fig. 3. Analysis of machine data of unloaded parts

Functional modeling of the gripping unit can be supported using the analyses provided here. Through a deeper understanding of the parts produced by sheet metal manufacturers, requirements for a gripping unit can be described, and functions can be precisely assigned. Figure 4 shows the derived relationships of specified requirements and properties to the corresponding functions.

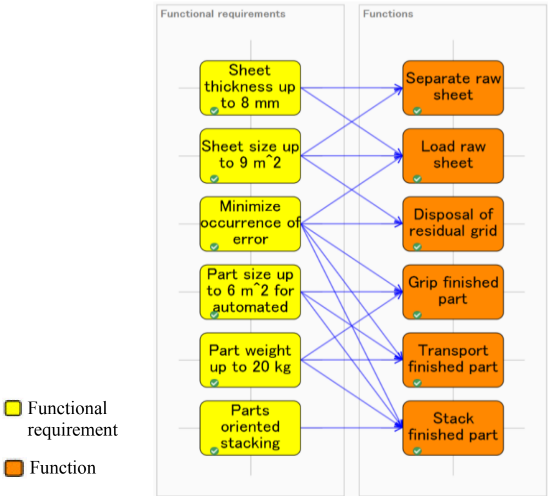

Fig. 4. Modelled requirements and functions of the gripping unit

The modeling of the requirements and corresponding functions can be described and specified based on the data analysis. For automated removal, for example, it should be noted that parts up to 6m², with up to 20 kg and a maximum sheet thickness of 8mm, are removed. However, the design of technical systems based on the maximum usage characteristics is only useful to a limited extent. Most automatically removed parts weigh less than 1 kg, and only a few non-automatically removed parts are significantly above a value of 5 kg. Consequently, designing the gripper unit for a removal weight below 5kg allows the automated removal of most sheet metal parts. However, a larger dimensioning offers the potential to address other customer groups. Subsequently, cluster analyses for specific customer groups with usage profiles for parts over 5 kg could be considered in more detail by means of data analyses. As a result of such analysis, variants can be derived, and modules defined and optimized. Consequently, the data-driven validation of requirements offers excellent potential for requirements modeling and functional modeling.

Table 1. Error codes with a relative occurance greater 5%.

Error Codes	Count	Relative share of all error messages of the Gripping unit [%]
Error Code 1	7972	22.44
Error Code 2	6366	17.92
Error Code 3	5259	14.78
Error Code 4	4335	12.20
Error Code 5	2461	6.93

Error data describe how process-safe functions are executed on mechatronic systems. Frequently occurring errors in the application become transparent through the analysis of error codes. Table 1 shows that around 74% of all error codes can be traced back to just five overarching error types. For example, safe removal is influenced by whether parts are tilted, parts are jammed, or surfaces are contaminated. Furthermore, functional modeling can be further developed with defect data. As a result, the model must be supplemented with the requirement "Minimize the occurrence of error messages." It is related to a large part of the functions. Consequently, the networking of different data sources is useful for the support of functional modeling. The implementation of functions can be further developed by analyzing machine data. Modeling the findings from data analyses thus enables the further systematic development of functions and requirements.

5. Impact of analyzed data in modular product structure

In the initial analysis, it was found that the machine data used for the analysis has excellent potential to sharpen the focus for development on the derivation of requirements and product properties. The new requirements and properties concretize the previous specifications, primarily based on subjective empirical values. The functional modeling based on this, which maps the requirements and properties to the functions, results in a first step for defining a modified product architecture.

To relate the effects of the modified requirements and properties to the modular product structure, it is necessary to link the modeled requirements and functions to the components at the product structure level. As shown in Figure 5, these references can already be taken from the automation reference systems and extended to include the new findings. Modeling the dependencies between properties, functions, and components results in a transparent implementation representation, as already presented in chapter 2. The data-driven validation of the requirements thus enables targeted design options at the level of the modular product structure.

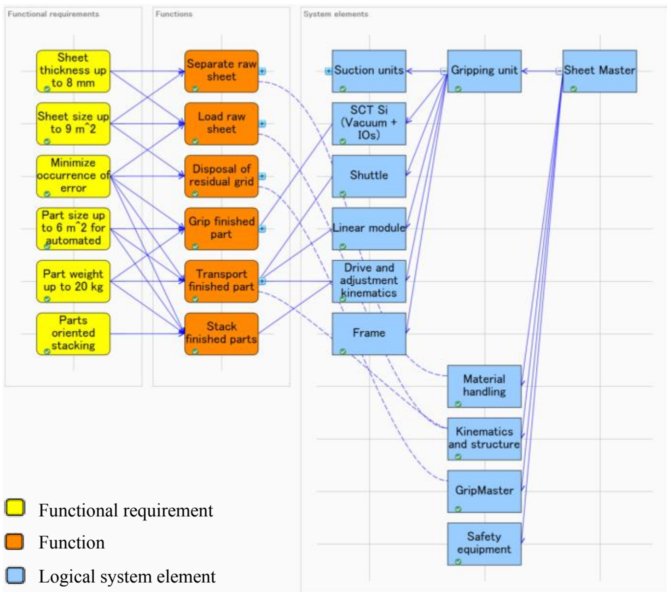

Fig. 5. Initial System Model

In the example shown, various modulation potentials of the product can be derived from the data analysis, which can directly or indirectly influence the modular structure.

For example, the analyzed data show that most automatically removed parts weigh less than 2 kg (see Figure 2, top center). Conversely, it can be concluded from the analysis that parts weighting more than 5 kg are almost exclusively removed manually. However, the original requirement to remove parts weighing up to 20 kg was demonstrably not implemented by the customer. Consequently, an alternative concept was derived, which provides for the targeted use of variance to automatically remove parts weighing less than 5 kg and parts weighing more than 5 kg. This concept directly impacts the modular structure of the gripper unit since two different gripper units are not to be developed. Given this requirement, the impact of the requirements in this concept could only be limited to the submodule of the Suction Unit. By explicitly creating variants of the Suction Unit, part weights of up to 5 kg and over 5 kg are possible.

Furthermore, it can be concluded from the analysis that part removal over 5 kg is made more difficult by tilted or tilted parts. To implement the concept presented for the two Suction Units, it is also necessary to meet the new requirement and product characteristic of "safe part removal". As can be seen in Figure 6, the new concept creates a link between the safe part removal and the Suction Unit (>5 kg).

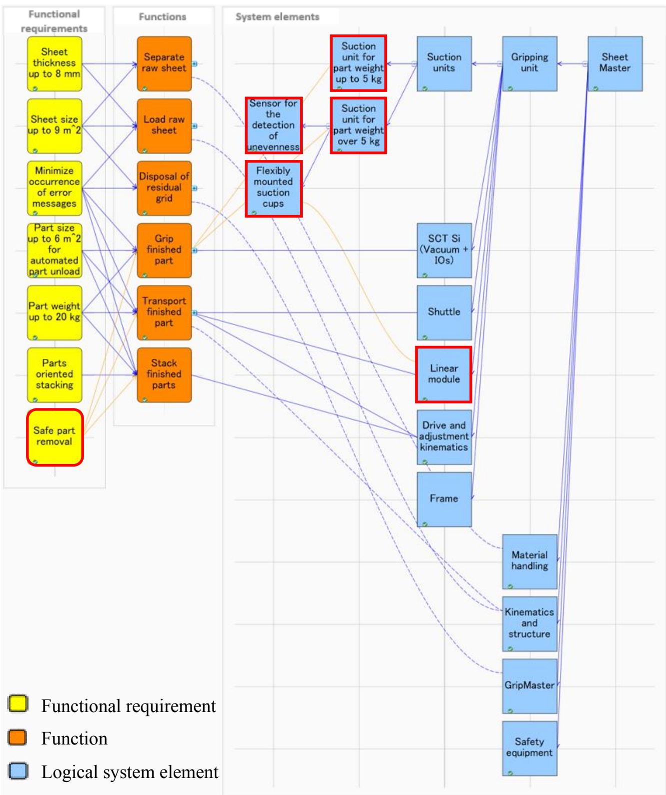

Fig. 6. Adapted System Model

Due to the transparency in the modeling, concept ideas can be derived again, which considers the impact on the existing modular structure. In joint workshops, different concepts were elaborated, whereby the concept of an additional sensor for unevenness or flexibly mounted suction cups showed the most significant potential. Through modeling, the effects of both concepts on the structure can be directly considered. On the one hand, the additional sensor offers the possibility of being easily retrofitted, as it can be seen as a separate assembly and would, therefore, only affect the previous structure in terms of interfaces. On the other hand, the concept of flexibly mounted grippers offers the possibility of getting by without additional electronics but affects the variance and design in the "Linear Module" submodule due to another principle. Both concepts require additional investigation effort regarding the feasibility, but the data-driven analysis has only led to the impetus for the concepts, and the modeling has generated and ensured the transparency for the optimizations in the modular product structure.

6. Benefit of data-driven optimization in modular structure

After analyzing machine data and the proven impact on the modular product structure, the next step is to examine how we can use the consequent machine data analysis and MBSE for optimizing modular product structures. Due to the strong connection between requirements, functions, the logical layer, and the product structure, machine data recognition can affect the product structure. Therefore, one needs to consider the obtained machine and derivate requirements. An optimized modular product structure should be a non-functional requirement for the architecture of a modular building kit. To improve the common understanding, it is necessary to build a system model shown in Figure 5.

The system model created here contributes to the alignment of the requirements of the reference system to the requirements derived from the actual machine usage on the customer's shop floor through the analysis of machine data. In addition, it makes an essential contribution to transparency in the representation of the product structure via the consistent mapping of requirements via functions. The continuity and clarity gained have meant that the adaptation and modification of the product could be addressed much better than possible using the previous approach in the test environment. Participating developers and product managers confirmed this assessment in participant observation. Such product decisions have been based primarily on random samples and experience. The approach demonstrated here enables a more targeted validation of the previous requirements and product properties and a more resource-friendly modification of the modular product structure through a transparent linking of external to internal structures through modeling.

7. Discussion and Outlook

By applying analyses of machine data, untransparent interrelationships can be described in their characteristics based on the actual customer use of the mechatronic systems. Considering the ever-increasing complexity of development projects, companies are forced to adapt new methods and ways of working. This work illustrates the potential of machine data analysis to support the data-driven design of requirements and features, as well as the allocation of functions and the design of the technology-oriented level of the product architecture. Creating a better understanding of the customer's use of earlier product generations of the mechatronic systems to be developed forms the basis for an efficient product development process.

The example shows how simple analyses of machine data can already provide great added value for defining the system of interest. With the increase in possibilities for data analyses through more extensive databases and easier access to these through methodical supporting measures for developers, requirements, for example, can be increasingly validated in a data-driven manner. The better the requirements and properties of the system of interest are designed and defined, the better the structures or architecture underneath can be derived. The use of machine data for analysis purposes thus contributes to functional modeling and thus to the optimization of module scopes through a better understanding of the actual use of functions in corresponding use cases.

Limitations of the present work result from the consideration of an exemplary system module and the restrictions regarding the data analyzed under chapter 4. In the following work, the potentials of data-driven module optimization and the support of functional modeling using machine data analysis will be further investigated with case studies. For example, interrelationships across system modules can be made transparent. This holds potential for the definition of module interfaces. In further research, it is possible to build on the given allocations here. Due to the data-driven analysis, feedback on the given requirements and properties of the systems and products can be derived. In addition, the allocations between physical structures, functions, and properties or requirements can be analyzed more holistically due to the possibilities of big data analytics. It could be increasingly efficient to model the whole system architecture by analyzing data, including structures of physical components and logical behaviors. This carries great potential to generate short release cycles for the development of modular architectures by providing a systematic for the data-driven validation of system elements.

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