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Data Enabled Failure Management Process (DEFMP) across the Product Value Chain

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Abstract

The continuously increasing amount of production data and the advancing development of digitization solutions promote advanced data analytics as a promising approach for failure management. Beyond the consideration of single units, examining the end-to-end value chain, including development, production, and usage, offers potential for failure in management-related investigations. Nonetheless, challenges regarding data integration from different entities along the value creation process, data volume and formats handling, effective analytics, and decision support arise. The CRISP-DM approach has become a widely established reference as a conceptual framework for data-driven solutions. However, the linkage between existing failure management procedures and the subsequent development of data-driven solutions needs to be specified. Accordingly, this paper presents a cross-value chain Data Enabled Failure Management Process (DEFMP). The central element is a process model to implement a cross-value chain data-enabled failure management, considering established quality management and data analytics approaches. Based on available failure, product, and process knowledge along the value chain, a path towards developing a comprehensive decision support system is shown. DEFMP combines a reactive failure process with a data-driven approach to incorporate data analytics for proactive improvements. Using DEFMP, the failure management process of a commercial vehicle manufacturer is adapted. With this, partial automation of failure management is made possible. In addition, the potential for improvements is identified and prioritized.

Keywords

Data Analytics; Data Management; Decision Support; Data Enabled Failure Management Process; Production; Value Chain

1. Introduction

Failure management deals with the systematic detection, analysis and correction of failures while pursuing proactive measures to obtain quality knowledge and prevent failures before occurrence [1, 2]. Currently, data utilization across the entire value chain is limited and complex structures and interrelations within the value chain cannot be uncovered [3, 4]. Applied to use cases of the commercial vehicle industry, which is characterized by complex production and distribution networks, the potentials of data-enabled failure management across the value chain are explored. A prerequisite for fully exploiting the potential of failure management is the horizontal integration of value-creation networks [5]. Integrating data sources and collaborative data use along the value chain enables the uncovering of far-reaching interrelations between involved partners and divisions [6].

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Deploying data-based methods, particularly their embedding into existing failure management procedures, is still a significant challenge for companies. This can be explained by the need for a precise analysis strategy or a deficit of methodological knowledge [7]. Several reference models already intend to standardize the data analytics approach. Particularly worth highlighting is the Cross-industry Standard Process for Data Mining (CRISP-DM), which has become quite established for industrial applications [8]. Even though this process already guides data analysis projects, transferability to challenges of failure management is not trivial since specific requirements of the discipline are not considered. Furthermore, integrating data-based solutions into existing improvement procedures is not further specified. Expanding the focus beyond the company's boundaries further enhances the complexity of data-driven approaches. In addition to increasing data preparation and processing requirements, systematic mechanisms for integrating various data sources are necessary. It becomes apparent that the procedure requires further development to create a suitable framework for use cases of cross-value chain failure management.

Accordingly, this paper aims to outline and specify a methodology concept for cross-value chain failure analysis in the use case of the commercial vehicle industry. The standard procedure of the CRISP-DM is extended according to the specific requirements of the target area. Furthermore, a direct connection to existing failure management procedures is shown. Challenges and potentials of cross-site data exploitation enable comprehensive decision support for reactive and proactive handling of failures. The paper is structured as follows: Chapter 2 shows relevant reference models of adjacent fields. Subsequently, the requirements and objectives of cross-value chain failure management are discussed (chapter 3). Chapter 4 describes the structure of the DEFMP in detail. The evaluation of the methodology is carried out in chapter 5. Finally, the reflection on the results and the following work are presented in chapter 6.

2. Foundations

2.1 Failure Management Processes for Production Environments

To improve the company's overall performance, the efficient identification and elimination of failures is a primary objective [9]. A holistic failure management approach is essential to elaborate adequate measures for achieving quality goals, for example, preventing failures before their occurrence. [10]. The tasks of failure management include the recording, evaluation, and elimination of failures as well as failure prevention in following products through a corresponding analysis of the failure causes. The central aspect is the purposeful provision and processing of relevant information. This is crucial for building a knowledge base of previously solved failures [11]. In the literature, various reference processes are dedicated to failure identification, processing, and avoidance.

The earliest relevant approach that deals comprehensively with failure elimination in production is the phase model, according to HOFMANN. Starting with failure detection, the model shows five phases for failure elimination [12]. The SAFE model offers a comprehensive concept for the design of failure management in manufacturing environments. The process model consists of eight steps that derive preventive and reactive measures for failure avoidance or elimination. The importance of systematic archiving of failure knowledge is emphasized. In addition to prioritizing failure cases, selecting suitable measures is facilitated to continuously improve the decision process in the event of failures [13]. The Complaint and Failure Management Model (CFM) describes a data-oriented reference process. The CFM is a sub-process of the Aachen Quality Management Model, which represents the company's interaction of quality-creating processes, management, and support services. In this regulatory framework, CFM can map process-based and data-supported quality control loops and report failure knowledge to companies in a targeted manner. The CFM thus forms a regulatory framework but remains at a high level of abstraction despite the precise design of the individual elements [14]. Therefore, recent research is expanding the CFM model by considering data quality aspects. Focusing on manual assembly, mechanisms for standardizing the failure type and object description are discussed. A consistent description of the failure information improves the data quality and simplifies the failure analysis [15].

The approaches considered present a distinct development in the failure management process. In many cases, generic reference processes are derived and described, which must be run through for a successful failure correction. The contents of the individual process steps show some similarities. It can be determined that the topic of data organization receives special attention in most approaches. For example, ORENDI and CFM provide the first possible solutions without going into more detail about possible data analytics methodologies. In particular, the interaction across the product value chain is not considered.

2.2 Data Analytics Methodologies

Standard processes to enable data-driven decisions are already well established. Common process models are CRISP-DM (Cross Industry Standard Process for Data Mining), KDD (Knowledge Discovery in Databases), and SEMMA (Sample, Explore, Modify, Model, Assess) [15]. Many of the individual sub-steps are comparable or identical between the three approaches. Especially the CRISP-DM methodology has established itself as a standard methodology as it provides a structured approach for data mining projects. The phases of business understanding, data understanding, data preparation, modelling, evaluation and deployment are distinguished [16]. The steps are carried out sequentially. However, different iterations between the steps are recommended. In recent years, different adaptions have been suggested to address case-specific requirements [17]. Especially with a strong focus on machine learning applications, multiple extensions of CRISP-DM regarding data preparation and modelling have been developed [18].

Regarding quality management, approaches to harmonize existing quality management standards with data analytics methods already exist. SCHÄFER ET AL. combine quality management methods of the DMAIC cycle with corresponding steps of the CRISP-DM. The result forms the integrated QM-CRISP-DM cycle [19]. HUBER ET AL. pursue a similar approach and consider specific engineering requirements [20]. In particular, the increased complexity in engineering assessment and implementation plays a leading role. The resulting data mining methodology for engineering (DMME) adds the phase of technical understanding before data understanding. The addition of the process step allows for evaluating the technical problem and implementing necessary technical adjustments to extract relevant data. Additionally, they add a phase for technical implementation prior to the implementation phase, as the solution deployment likely requires technology changes.

2.3 Reflection

CFM and CRISP-DM are widely accepted approaches. However, these are unsuitable for implementing a cross-value chain failure management approach due to the absence of essential process steps and, in particular, a need for more linkage between the two areas of failure management and data analytics. The reference models in failure management provide different frameworks for standardized (reactive and prospective) failure investigation and strategies for continuous improvement. Knowledge transfer as structured documentation is already discussed, and, in some cases, analysis methods are implied. However, the approaches merely address internal improvement processes. Furthermore, appropriate data analytics methodologies and practical strategies for their deployment are not provided.

Data analytics approaches enable a structured deployment of data-based solutions. Nevertheless, the CRISP-DM and related extensions show deficits for immediate application in commercial vehicle production networks. Even if quality orientation becomes more important in data analytics, the specific failure management requirements still need to be addressed, for example, by defining a link between existing failure management initiatives and the deployment of advanced analytics. Additional challenges arise from broadening the investigation focus to additional data from various stakeholders. This challenge requires introducing an extra step of data integration to enable the use of quality knowledge and process and product data from different phases along the value chain. This reveals a need for a structured methodology that meets the challenges of cross-value chain data exploration and seamlessly connects to existing failure management procedures – building on existing quality knowledge.

3. Objective and requirements for a cross-value chain failure management

According to chapter 2.3, there is a need for further development of existing data analytics and failure management approaches. Through additional design workshops at companies in the commercial vehicle industry, relevant gaps and potentials for failure management were identified. The main aspects being addressed in this regard are the following:

Failure identification and handling need to incorporate both internal failures during production and external failures and associated data beyond a company's boundaries. This requires the development of rule-based failure identification methods and advanced analytics to identify trends and provide forecasts. Mechanisms are required that allow efficient handling of failure events and foster knowledge management for continuous improvement.

Data integration and valorization are essential components of cross-value chain failure management. Collecting and interconnecting process data from relevant product lifecycle phases (deployment, production, usage, recycling) is needed to generate meaningful data-driven insights and optimizations. Technical challenges, e.g., providing sufficiently detailed data, are to consider. Existing expert knowledge on processes, failure patterns, process and product characteristics must also be made available because many characteristics are not, or only insufficiently, contained in measured data points. Furthermore, information security is of central importance. Requirements towards confidentiality (restrict access appropriately), integrity (data validity), and availability (service functionality) are to apply.

Data-enabled services provide d*ecision support* to stakeholders across the value chain. These need to complement existing failure management mechanisms and allow advanced insight generation. The failure management-related deployment objectives, process optimizations, availability optimizations, and performance optimizations are considered [21]. Process optimizations aim to identify failure sources, implement predictive quality control in the manufacturing process, and evaluate associated failure costs, risks, and proactive measures. Availability and performance optimization provides extensive condition information and maintenance and usage recommendations for customers. The benefits provided to manufacturers are advanced failure knowledge regarding costs, time in service, and quality decline, including failure forecasting. To address different stakeholders from development, production, quality management, and usage, different areas of improvement are considered:

- **Process optimization**
  Field level: Employees receive advanced information on the production order, including failure risks for the product and measures for failure avoidance and resolution.
  Control and operation level: For daily and intraday reviews, advanced failure information is aggregated in terms of cost, time, and patterns. This serves an early identification of trends and anomalies, derivation of actions at an early stage and the support of failure control working and planning groups.
- **Availability & performance optimization**
  Customer level: Product users receive information on current system states (e.g., for health monitoring) and optimized recommendations for maintenance (regarding minimal costs and downtime) to prevent malfunctions and failures.
  Operation level: In addition to the advanced failure information mentioned above, indications of possible failure causes are relevant for the availability extension. The availability of spare parts or maintenance initiatives can be initiated on time.

4. Data-Enabled Failure Management Process (DEFMP)

Fig. 1 shows the approach of the Data-Enabled Failure Management Process (DEFMP). Two interconnected sub-control loops are distinguished. The inner loop describes the failure management process for the reactive and proactive handling of failure cases and the corresponding accumulation of quality knowledge. The outer control loop presents the procedure for developing extended analysis methods. Both sub-control loops rely on continuous monitoring and diagnosis. Established procedures and software applications are necessary to acquire relevant data along the entire product life cycle. The inner and outer control loop and the principle of their interaction are explained below.

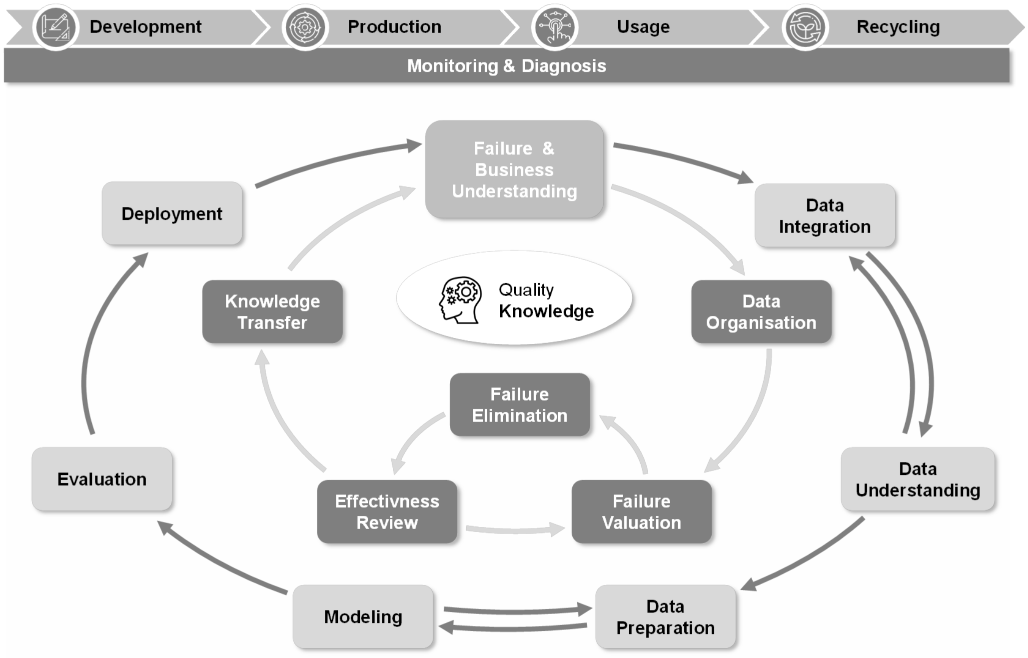

Fig. 1: Data Enabled Failure Management Process across the Product Value Chain

4.1 Inner control loop - Building Quality Knowledge

The failure management process presented in the inner control loop of the DEFMP is based on the previously presented CFM model (see chapter 2.1). Compared to the reference model, the failure management process is built as a loop. This considers the continuous learning process, and necessary feedback loops during the resolution process are represented. Starting with the phase of *Failure and Business Understanding* serves to investigate the problem prior to the failure handling itself. In addition, an initial assessment of significant influencing factors and relevant information is included. For manual assembly, the employee in charge carries out the initial assessment of the problem and the initiation of further action. This phase can also include comprehensive project management, which defines responsibilities and allocates resources and capacities in case of more complex issues. An important part is the failure identification along all considered processes. For this purpose, several quality sensors must be available, which, on the one hand, support the continuous process monitoring and diagnosis and, on the other hand, identify occurring or occurred failures as early as possible. *Quality Knowledge* forms the centrepiece of failure handling. It reflects the expertise in dealing with quality-oriented issues. The existing quality knowledge is used to process failures. In addition, the knowledge base is supplemented or updated according to the results gained during the loop. Findings on cause-effect correlations and effective and ineffective measures are incorporated following failure processing. Therefore, several data sources must be considered. Proper information management for structured and comprehensive *Data Organization* benefits this context. Targeted documentation and provision of relevant information for the considered case is thus a critical business resource. A well-structured and systematically implemented failure database provides fast access to existing failure knowledge. Identified failures are described or coded according to predefined rules and supplemented with further information. By comparing the data with explicit failure descriptions or codes, documented knowledge can be accessed easily. Particularly when recurring failures or similarities occur, problems that have already been solved provide essential assistance in identifying root causes and deriving suitable measures.

The *Failure Valuation* is carried out with the help of already documented failure information. This step can be described as pre-analysis and evaluates the failure's severity and relevance. It is beneficial in the case of many failure events to be processed. Based on the relevance, prioritization can be performed. By comparing detected characteristics with the existing quality knowledge, it is possible to derive indications for problem-solving. Based on the existing quality knowledge, measures declared successful are selected to resolve the failure rapidly. If there is no documentation of measures, a solution-finding process is needed; for example, within the project team defined at the beginning. The actual failure handling takes place within the *Failure Elimination and Prevention*. Following the elaboration, measures are initiated. A distinction can be made between immediate and long-term measures. The former address failure symptoms and are intended to prevent further failure consequences. In addition, long-term measures address the root cause for preventing failure repetition. Initiated countermeasures must be checked with an *Effectiveness Review*. If a measure has not led to the expected success, the failure case must be re-evaluated, and further initiatives must be developed. If the measure is successful, the information is made usable for future failure processes. For this purpose, a *Knowledge Transfer* is included, which incorporates the findings of the failure management process into the quality knowledge. According to the step of data organization, a systemic, structured recording is beneficial as a supplement to the failure description.

Established failure management is a prerequisite for initiating extended, data-based analysis tools. The process step *Failure and Business Understanding* interconnect both control loops. The expertise gained during historical failure processing and the resulting quality knowledge is incorporated into developing data-based decision support. Insights from data analyses and permanently applicable solutions supplement established failure management routines, see chapter 4.2 and 4.3.

4.2 Outer control loop – Evolution through Data Integration

The outer loop of the DEFMP likewise begins with *Failure and Business Understanding*. The digitization potential of a failure management use case is evaluated during the failure process's initiation by the project team in charge. The resources and capabilities required, the objectives pursued, and the associated analysis strategy must be defined. After this initial assessment, the outer control loop can be triggered by the group of process and data experts. The next phase is *Data Integration*, which is not part of the CRISP-DM approach. However, it plays an essential role in cross-value chain failure management, as data from different sources must be included in the decision-making process. Accordingly, a stand-alone process phase is introduced in DEFMP to address this challenge. In industrial practice, products are usually assigned by identification numbers to enable mapping to captured data (entity matching). It is usually sufficient to create an assignment logic for simple problems in an industrial context. For more complex matching problems, sophisticated automatic or rule-based approaches must be developed [22]. Another crucial aspect is the selection of a suitable digital infrastructure. Established databases and platforms rely on data integration in a single, trusted source. Recent research approaches investigate data ecosystems based on decentralized data sources combined with a management system to provide semantics and access controls (cf. [23]). Both architectures are subject to precise data security requirements to restrict access to authorized individuals, protect data from tampering, and ensure accessibility.

Already during the integration phase, data quality is of high importance [24]. Therefore, steps of *Data Preparation* and *Data Integration* are iterated when beneficial. An example is the preliminary data reduction to reduce the storage requirements throughout data integration. Following the additional data integration phase, the established phases of CRISP-DM are likewise relevant in failure management. Regarding *Data Preparation* and *Modeling*, typical challenges of failure management are the classification of process success (good / not good), regression models to predict points of failure and anomaly detection, classification models to predict failure causes and suitable measures or clustering to identify unknown failures. For *Evaluation*, using model accuracy as a performance metric is often insufficient. Many cases in the failure management context contain a relatively small ratio of failures, consisting of imbalanced datasets. Recall, MCC and F1 score are relevant metrics in such cases.

Deployment in DEFMP needs to be suited to provide decision support regarding specific actions after failure recognition and to uncover areas for improvement. For this purpose, suitable options for displaying anomalies and incidents and key figures for assessing criticality must be established as part of the deployment. The realization of such a decision support system requires close communication with experts from different departments. For this purpose, communication mechanisms that enable an immediate valuation of the generated recommendations for action must be included. On this basis, a knowledge management system is implemented that enriches the quality knowledge and cleans it of erroneous correlations. The step-by-step data optimization increases the performance of the models.

4.3 Interaction of the control loops – The Data-enabled Failure Management

DEFMP comprises the two control loops to combine knowledge and data-driven approaches to failure management. Focusing on efficient actions for problem solving, the inner loop requires rapid technical understanding of the failure and expertise-driven actions. The outer circle utilizes existing quality knowledge and supplements it with expanded data from relevant value chain stages. Using data analysis methods, failure management-related decision-making processes are systemized. Despite the different approaches, the two control loops are highly codependent and can enable one another. The inner loop of DEFMP benefits from data-enabled failure information. A quantified failure analysis facilitates the prioritization of failures and the definition of fast and decisive actions. This is particularly important if security concerns or high-quality costs are associated with a specific failure. Quantified transparency regarding the number of potentially affected products can aid in the initial assessment.

As product complexity increases, cause-and-effect relationships of failures are difficult to distinguish. Especially machine learning models need to be equipped to uncover if two events are correlated or caused by one another. Therefore, expert and domain knowledge are necessary to use machine learning in failure management effectively. Likewise, the outer loop in DEFMP is enabled. Hence, the inclusion of quality knowledge and domain expertise is required to develop effective data-enabled decision support systems.

5. Evaluation

DEFMP is implemented and tested on use cases in the logistics and commercial vehicle industry for cross-value chain assessment. One use case deals with expertise- and data-based failure warning systems based on existing failure handling processes. The goal is to identify relevant failure accumulations that occur in the utilization phase of trailers at an early stage. Currently, the identification of relevant failure accumulations is primarily based on the experience and subjective assessment of employees in quality management. The preparation of quality data is carried out manually and on request. Each analysis requires a particular dataset and time-consuming pre-processing. In addition, resulting reports are static, therefore preventing further investigations on-the-fly. Anomalies are communicated in weekly steering committees for failure management. In these panels, results of root-cause analyses for specific failure patterns are discussed, and appropriate measures for their elimination are defined. Furthermore, already implemented measures are evaluated, and a knowledge database is used to document the collected findings. In conclusion, current activities in failure management are limited to the inner loop displayed in Fig. 1 and, therefore, heavily rely on quality knowledge stored in employees' minds.

DEFMP now offers an approach to extend the existing failure management process with data-driven analytics to accelerate the identification of relevant failure accumulations. As an intermediate result, a web-based dashboard was developed, providing data insights to employees in quality management. After uploading a data sample, initial analytical processes are automatically performed, and their results are presented to the user, thus allowing for quick insights on key metrics. Furthermore, dynamic filter options were implemented to enable on-the-fly analysis as a basis for steering committee discussions and explorative data analytics. Besides, rule-based valuation of failure criticality and standardized data processing algorithms provide increased objectiveness.

A key challenge is integrating data from multiple sources along the value chain. Here, the iterative nature of DEFMP allows for the gradual implementation of these sources one by one. This helps break down the complexity of data integration into smaller, more manageable tasks while enabling learning from experience. The focus is on ensuring a uniform structure of failure data and its enrichment with further information required for developing AI models. In this case, the primary data source is customer complaints with a corresponding service contract. Using an existing tool, failures are documented by service workshops. Standardized selection masks are used to describe the location and type of failure. All information is mapped to a specific vehicle via the vehicle identification number. This way, further information from different data sources can easily be added. As of now, it is already possible to observe failure frequencies and costs.

Following the guideline provided by DEFMP, future efforts will focus on implementing advanced machine learning algorithms for automated anomaly detection and trend evaluation. In addition, appropriate alert mechanisms must be defined, allowing for effective communication that provides a user-oriented indication of failure accumulations. For such instances, the inner loop focusing on expert-driven actions and developing new solutions for problems remains indispensable. With inner and outer control loop operating alongside the existing failure management process is enhanced by a data-driven decision support system enabling increased quality and speed of failure assessment.

6. Conclusion

The DEFMP represents a framework that enables the initiation of data-based analyses for cross-value chain failure management. A logical linkage with existing procedures, including the quality knowledge of a company, was explicitly highlighted. The inner circle of the process model contains the activities to quantify and resolve a failure through immediate actions. Likewise, data-enabled methods in the outer loop are incorporated to expand the quality knowledge and provide decisions to solve quality issues. Integrating data from different value chain stages require additional measures to ensure data security, especially with increasing parties involved. For this reason, data-oriented reference models were expanded to include data integration as a fundamental activity. Applied in the commercial vehicle industry, the cross-value chain data integration approach for failure management enables the quantified linkage of failures with production data.

In future activities, data integration approaches, including aspects of data security, must be explored further to handle different use cases. Subsequent studies will focus on deriving a standardized procedure for evaluating existing systems and data structures. The goal is to gain insight into existing interdependencies, data types, and data quality. Based on an ideal reference process, existing structures and data streams will be identified, and gaps in information availability will be revealed. This approach prepares the further development of decision support by identifying stakeholders within the processes requiring systemic support. In addition, the focus is on developing standardized data architecture models for the operational implementation of data integration. Furthermore, methods of the modelling phase are to be applied that make the data volume processable for comprehensive decision support.

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Biography

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Felix Bartels (*1996) studied industrial engineering at Leibniz University Hannover. Since 2021, he works as project manager at Krone Business Center GmbH & Co. KG focusing on the implementation of AI-solutions for failure management, predictive quality and predictive maintenance in the commercial vehicle sector.

Sebastian Beckschulte (*1990) studied industrial engineering at the University of Duisburg-Essen. Since 2019, he has been working on his doctorate as a research assistant at the Laboratory for Machine Tools and Production Engineering of RWTH Aachen University, focusing on quality intelligence and failure management.

Goy Hinrich Korn (*1964) studied computer science at the TU Braunschweig and earned his doctorate as Dr. Ing. in 1995 (TU Braunschweig). Since 2004, he works as CIO for the Krone Group (Spelle) and since 2020 also as CDO. Since 2019 he is Management Director of the Krone Business Center GmbH & Co. KG.

Robert H. Schmitt (*1961) has been professor of Chair of Metrology and Quality Management and Member of the Board of Directors at Laboratory for Machine Tools and Production Engineering WZL of RWTH Aachen since 2004. He is also Member of the Board of Directors at Fraunhofer Institute of Production Technology (IPT).