

Intelligent Data and Potential Analysis in the Mechatronic Product Development

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Abstract

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This thesis explores the imperative of intelligent data and potential analysis in the realm of mechatronic product development. The persistent challenges of synchronization and efficiency underscore the need for advanced methodologies. Leveraging the substantial advancements in Artificial Intelligence (AI), particularly in generative AI, presents unprecedented opportunities. However, significant challenges, especially regarding robustness and trustworthiness, remain unaddressed.

In response to this critical need, a comprehensive methodology is introduced, examining the entire development process through the illustrative V-Model and striving to establish a robust AI landscape. The methodology explores acquiring suitable and efficient knowledge, along with methodical implementation, addressing diverse requirements for accuracy at various stages of development.

As the landscape of mechatronic product development evolves, integrating intelligent data and harnessing the power of AI not only addresses current challenges but also positions organizations for greater innovation and competitiveness in the dynamic market landscape.

Keywords: Intelligent Data, Potential Analysis, Mechatronic Product Development, Artificial Intelligence, Decision Support Framework, Knowledge Management, Human Experts, Trustworthy AI

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To Henry, Lea, Martina and Thomas

List of Papers

This thesis is based on the following papers, which are referred to in the text by their Roman numerals.

- I. **Nüßgen, A.**, Degen, R., Irmer, M., Boström, C., Ruschitzka, M., “Leveraging Robust Artificial Intelligence for Mechatronic Product Development—A Literature Review,” *International Journal of Intelligence Science*, Vol. 14, No. 1, January 2024.
- II. **Nüßgen, A.**, Degen, R., Irmer, M., Boström, C., Ruschitzka, M., “Intelligent analysis of components with regard to significant features for subsequent classification,” *SAE Technical Paper*, June 2023.
- III. **Nüßgen, A.**, Richter, F., Lerch, A., Degen, R., Irmer, M., Boström, C., Ruschitzka, M., “Intelligent Component Manufacturability Testing in Virtual Product Development,” *Proc. Artificial Intelligence und Machine Learning in der CAE-basierten Simulation*, October 2023, Munich, Germany.
- IV. **Nüßgen, A.**, Richter, F., Krach, N., Irmer, M., Degen, R., Boström, C., Ruschitzka, M., “Robustness and Sensitivity of Artificial Neural Networks for Mechatronic Product Development,” *Proc. Automotive meets Electronics*, June 2023, Dortmund, Germany.
- V. Degen, R., Tauber, A., Irmer, M., **Nüßgen, A.**, Klein, F., Schyr, C., Leijon, M., Ruschitzka, M., “Integration of Vulnerable Road Users Behavior into a Virtual Test Environment for Highly Automated Mobility Systems,” *Proc. Kolloquium Future Mobility*, June 2022, Ostfildern, Germany.
- VI. Degen, R., Tauber, A., **Nüßgen, A.**, Irmer, M., Klein, F., Schyr, C., Leijon, M., Ruschitzka, M., “Methodical Approach to Integrate Human Movement Diversity in Real-Time into a Virtual Test Field for Highly Automated Vehicle Systems,” *Journal of Transportation Technologies*, Vol. 12, No. 3, pp. 296-309, July 2022.

- VII. Degen, R., **Nüßgen, A.**, Irmer, M., Klein, F., Schyr, C., Leijon, M., Ruschitzka, M., “Data Flow Management Requirements for Virtual Testing of Highly Automated Vehicles,” *Proc. AVL German Simulation Conference*, September 2022, Regensburg, Germany.
- VIII. Degen, R., de Fries, M., **Nüßgen, A.**, Irmer, M., Leijon, M., Ruschitzka, M., “Stereoscopic Camera-Sensor Model for the Development of Highly Automated Driving Functions within a Virtual Test Environment,” *Journal of Transportation Technologies*, Vol. 13, No. 1, pp. 87-114, January 2023.
- IX. Irmer, M., Degen, R., **Nüßgen, A.**, Thomas, K., Henrichfreise, H., Ruschitzka, M., “Development and Analysis of a Detail Model for Steer-by-Wire Systems,” *IEEE Access*, Vol.11, pp. 7229-7236, January 2023.
- X. Irmer, M., Rosenthal, R., **Nüßgen, A.**, Degen, R., Thomas, K., Ruschitzka, M., “Design of a Model-Based Optimal Multivariable Control for the Individual Wheel Slip of a Two-Track Vehicle,” *SAE Technical Paper*, 2023-01-1219, June 2023.
- XI. Irmer, M., Ott, H., Degen, R., **Nüßgen, A.**, Thomas, K., Ruschitzka, M., “Methodical Data Collection for Light Electric Vehicles to validate Simulation Models and fit AI-based Driver Assistance Systems,” *Proc. Kolloquium Future Mobility*, June 2022, Ostfildern, Germany.

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Introduction

The modern (virtual) product development for mechatronic products has developed steadily in recent years. Complexity has increased throughout, development cycles have become shorter, and demands have become greater. At the same time, however, the knowledge base has also grown continuously: on the one hand, through "real" data and information and, on the other, through virtual or synthetic sources of knowledge - Artificial Intelligence (AI).

For the sustainable operation of AI systems, a data-driven mindset must be anchored throughout the company.

Beate Hofer, CIO, Volkswagen AG

As a result, there are major shifts, propelled by the impressive advancements in AI technologies, as evidenced by [1] and [2]. This technological progress has emerged as a potent force in development, offering augmentation and support throughout the entire lifecycle of mechatronic product development. AI's capacity to analyze extensive datasets, identify patterns, and learn from examples positions it as a formidable catalyst with the potential to revolutionize the industry, as elucidated in [3].

Many large companies are already taking advantage of this circumstance, although in many cases, they may not accurately assess the holistic situation or have thoroughly considered all the challenges. For example, in early January 2024, it was announced that the management, strategy consulting and auditing firm Deloitte is rolling out its internal AI co-pilot to a significant portion of its workforce. As a result, this AI system is intended to assist with daily tasks such as composing emails and creating presentations. However, the company simultaneously cautions its employees to exercise carefulness, as the AI has the potential to generate false statements about real individuals, places, or facts. To counteract this, Deloitte is implementing corresponding training measures. Given that untruths in fields such as medicine, defense, and politics, which are among Deloitte's clients, could have devastating consequences, developing an awareness of the limitations of AI and simultaneously assessing the reliability of the models becomes a logical imperative. [4]

Intelligence-driven Opportunities

Mechatronic product development is a multifaceted endeavor encompassing various disciplines, including mechanical engineering, electrical engineering, control theory, and software engineering. This means that many different domains and thus also human experts as well as domain-specific tools, working methods and even languages must harmonize with each other. [5], [6]

VDI 2206 underscores these observations. In 2021, the document underwent a generous revision with the expanded title “Development of mechatronic and cyber-physical systems”. According to the Association of German Engineers, this is due to the fact that mechatronic systems now “also have data interfaces to other components and devices. In this way, they are themselves cyber-physical systems and become part of a higher-level network. The complexity, interdisciplinarity and heterogeneity of such systems is thus constantly increasing.” [7]

Subsequently, it is worth taking a look at the corresponding and current V-model that emerges from VDI 2206. This can be found in Figure 1.

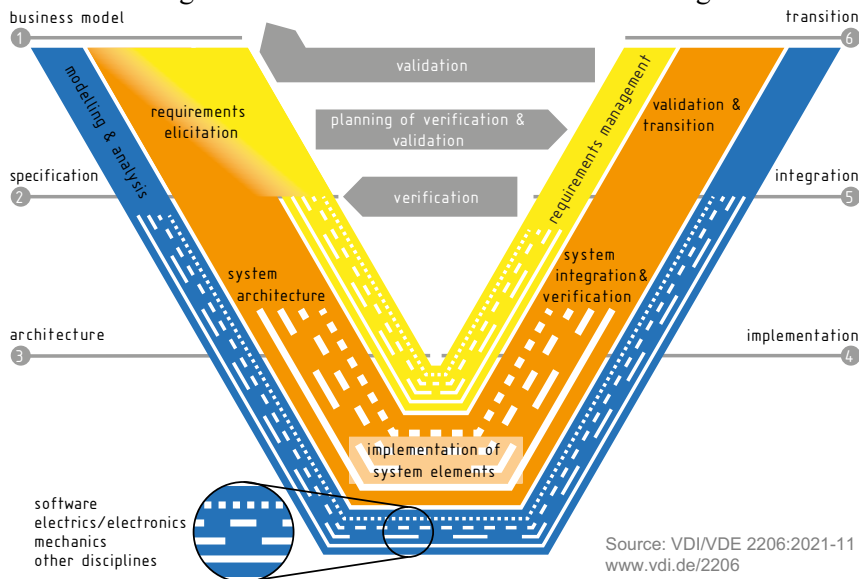


Figure 1: The latest version of the V-model according to VDI/VDE 2206 of November 2021

New in this version is, that the depicted framework illustrates the comprehensive approach to system analysis, modeling, and development, wherein three interrelated strands encapsulate distinct yet interconnected aspects.

The inner strand is devoted to the crucial aspect of requirements engineering, underscoring the perpetual management and refinement of requirements throughout the development lifecycle. The middle strand encompasses the core activities involved in system development. Finally, the outer strand

pertains to the modeling and analysis of the system along with its potential subsystems, which operate in parallel to the central development tasks. This systematic representation facilitates a rigorous and holistic scientific examination of the entire development process.

To visually illustrate the interplay between these disciplines, the three strands are depicted as interconnected subareas using various line styles, such as dotted, dashed, or solid lines. This graphical portrayal accentuates that the implementation of system elements relies on profound interconnections between the involved disciplines. The intricate networking between these facets ensures a cohesive and comprehensive approach to system development, bolstering its scientific rigor.

The challenges of effective interdisciplinary collaboration

To operationalize interdisciplinary collaboration effectively, it is imperative for domains to collaboratively advance in unison. However, the practical manifestation of this collaborative spirit often deviates from the ideal. This discrepancy can be attributed to several factors:

Synchronization Imperatives - Instances frequently arise where individual domains necessitate information or knowledge from other domains at specific junctures. However, these domains may not have reached the requisite stage, rendering them unable to provide any information, not even a rudimentary estimate. This intricacy engenders the subsequent phenomenon.

Divergent Work Paces and Sequences - Given that each domain pursues distinct goals, and these objectives may not align resource-wise with those of other domains, the tempo and sequential arrangement of steps can markedly differ. This incongruity poses significant challenges concerning the aforementioned synchronization, making it arduous or delayed.

Impaired Communication through disparate Languages - Owing to the diverse nature of domains, which demand expertise from distinct professionals, variations in knowledge bases and communication styles emerge, resembling a scenario of heterogeneous languages. Consequently, communication may lack precision, leading to the inadvertent loss of crucial details.

Addressing these challenges necessitates a strategic and adept incorporation of AI which holds promise as a robust solution to these multifaceted issues. By deploying these technologies, such as Intelligent Knowledge Management, AI-based Data Analysis Tools and Interface Automation, domains will bridge the gaps in synchronization, expedite workflows, and facilitate more seamless communication. This targeted and judicious utilization of AI not only addresses the outlined challenges but also opens avenues for enhanced efficiency and innovation in interdisciplinary collaboration.

With regard to the initial identified use cases for the methodology, which will be implemented later in the actual project, the examination of the mentioned possibilities to address challenges and simultaneously increase efficiency and innovation levels takes place. A practical application for this will involve supporting the development department of a large and well-known research institutions, aiming to achieve a better interface between design and manufacturing in the future. This specifically means fewer deviations in terms of planning and eventual completion. To achieve this, a corresponding body of knowledge is intended to be created through the use of AI and made available in early stages, allowing for more targeted and realistic planning of new projects.

Aim and Outline of the Thesis

The Overall Research Question of this thesis is:

How can the mechatronic system design be supported and synchronized in the context of Co-Simulation by using predictive information and rules generated by a robustness-checked AI which is fed through the knowledge base?

This derives into four detailed Research Questions:

- R1 How can the **relevant areas of knowledge and non-knowledge** in mechatronic development processes be identified, evaluated and delimited from each other in order to reach the **acceptable level of ignorance competence** through targeted knowledge mining?
- R2 How can the critical **analysis parameters for success** and the **ideally suitable segments of the development process** for the use of robust and context-sensitive AI be identified?
- R3 How does the **process for the linking** of diverse mechatronic domains within a co-simulation framework succeed **through translation, interpretation and prediction approaches** using AI?
- R4 How can previous development sub-processes for cross-domain tasks evolve with respect to the **new mutual synchronization capabilities** made possible by the robust AI and how do these new requirements **influence the current methodology**?

Following the formulation of the four specific research inquiries, the subsequent step involves identifying and delineating the requisite research methodology. This process entails selecting appropriate methods and approaches to systematically investigate and address the research questions effectively.

Research Design

At the beginning of a thesis, the question usually arises as to which research method should be used to achieve the goals. This method aims to both acquire insights and verify them, thereby aiding in solving scientific challenges. The choice of method significantly influences the process. Therefore, it is important to systematically plan and purposefully design the research approach to generate a coherent argumentation chain and promising results. [8], [9]

The research methodology adopted in this study adheres to the constructive principles of Design Science proposed by [10], while also incorporating the extended methods introduced by [11]. According to these methodologies, Design Science encompasses two primary activities: creation and assessment. "Creation" involves constructing an artifact tailored for a particular purpose, while "assessment" entails evaluating the effectiveness of said artifact.

A conceptual framework for information system research has been developed based on these approaches, as depicted in Figure 2.

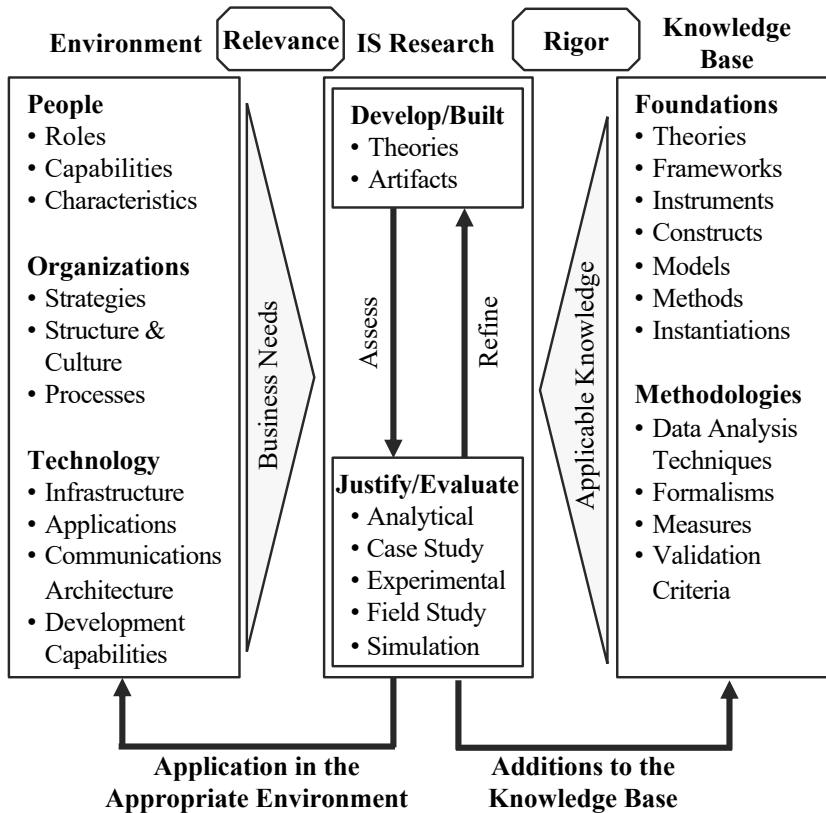


Figure 2: Conceptual framework for information systems research according to [12], layout-matched

The criteria for ensuring quality, as formulated by [13] and pursued in this work, include: relevance, rigor, objectivity, reliability, authenticity, transferability, and action orientation.

After selecting the methodology, the question arises of which research approach the scientific work belongs to and consequently, how it should be structured. The approach of this work is inductive in nature and can be classified in the field of applied research. The aim of this genre is to develop and shape a new theory, or in the case of this work, a new methodology or solution, based on research. Works in this field typically address significant practical challenges. In relation to the project presented here, this therefore concerns the integration of efficient and robust AI into mechatronic product development, including the resulting effects and the outlook for the future and the corresponding prospects.

The criteria for a contribution to the state of the art include the following points according to [12] and therefore especially the Guideline 4:

- new process, product or design object
→ **synchronize newly linked cross-domain tasks smarter through robust AI**
- important unsolved problem class to be solved
→ **existing asynchrony of domains and different language**
- proposes generalizable solution
→ **positively influence the current methodology over time**
- investigates the solution empirically
→ **proof of concept through appropriate data and examples**

Four steps are derived from these circumstances, shown in Figure 3.

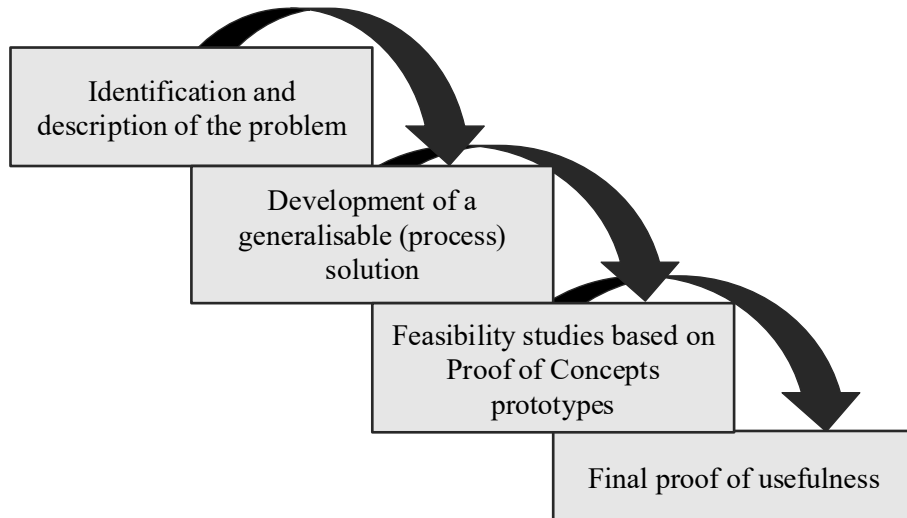


Figure 3: The four identified steps for this work in the context of Applied Research based on [10], [12], [14]

Having successfully accomplished the identification and description of the problem at hand, the next phase of the investigation involves a comprehensive examination of the current state of the art within both the research landscape and industrial practices. This analysis aims to provide a contextual backdrop for the subsequent development of the methodical approach, which is designed to facilitate a broad and generalized integration of AI within the developmental process.

The Methodical Approach is a pivotal component of the research, serving as a strategic framework for the application of AI across diverse facets of the development process. This involves a systematic and carefully designed approach to harnessing AI's capabilities, thereby enhancing efficiency and effectiveness.

Following the formulation of the Methodical Approach, the research will delve into the exploration of individual aspects related to potential application areas. This detailed investigation seeks to unravel the intricacies of applying AI, providing insights into its nuances, challenges, and potential synergies with existing practices. The focus here is not only on theoretical considerations but also on practical assessments to confirm the real-world effectiveness of AI applications.

As the research progresses, the conclusive proof of the utility of the proposed method will be a critical juncture. Positive results from the explorations will serve as the empirical foundation to substantiate the benefits of integrating AI within the development process. This final step aims to provide a compelling case for the adoption of the method, underscoring its value and significance in addressing the identified problem. [14] [10]

State of Science and Technology

In the context of the research landscape, significant activities are evident. However, when it comes to mechatronic product development, the situation is different. While looking at current and past publication titles there are occasional attempts to leverage AI profitably, but these efforts typically focus on individual aspects, neglecting a holistic examination of the entire development process. Examples for this would be [15], [16], [17].

To thoroughly investigate and substantiate this observation, a compilation of pertinent categories with the target of a detailed analysis has been undertaken. These categories are crucial for the meaningful utilization of intelligent methods for the product development. They include:

- **Consideration of the Holistic Cycle** - Evaluate the extent to which AI is already integrated into the overall mechatronic product development process. This involves assessing the incorporation of AI at various stages, from conceptualization to prototyping, testing, and deployment.
- **Domain Linking** - Investigate how AI facilitates the integration and linking of diverse domains involved in mechatronic product development, such as mechanics, electronics, controls, and software. Assess the impact on decision-making, interoperability, and the identification of design conflicts or trade-offs.
- **Replacement for Human Expert Knowledge** - Analyse the role of AI in complementing or potentially replacing human expert knowledge in mechatronic product development. Evaluate how AI models, trained on big data and domain-specific knowledge, contribute to consistent and reliable decision-making.
- **Differentiation from non-relevant Knowledge** - Assess the capability of AI databases to differentiate between relevant and non-relevant knowledge. Explore how advanced search algorithms, Natural Language Processing (NLP), and semantic analysis contribute to prioritizing pertinent information and reducing information overload.
- **Consideration of Knowledge Gaps** - Investigate how AI databases assist in identifying and bridging knowledge gaps within mechatronic product development. Explore the use of knowledge graphs and machine learning algorithms to infer missing

information, and validate the integrated data to ensure accuracy and reliability.

- **Robustness of Prediction Quality** - Evaluate approaches to quantify and predict uncertainties inherent in AI, especially within Artificial Neural Networks (ANNs). Examine methods to calculate additional output values reflecting the network's confidence in predictions, providing users with insights into potential deviations.
- **Consideration of Optimization Proposals with AI** - Explore the opportunities provided by AI databases for suggesting optimization proposals in mechatronic product development. Assess how AI analyses data to identify areas for improvement, propose design modifications, and enhance performance based on historical data, simulations, and benchmarks.
- **Application to one or more Proofs of Concept** - Examine the application of AI concepts and methods to one or more proofs of concept.

In order to be able to provide an assessment of the respective research activities, a corresponding scale is introduced. The evaluation will employ a five-level scheme represented by circles, each indicating the degree of consideration for a specific characteristic:

1. **No consideration** (circle not filled): The literature lacks attention to the introduced characteristic, with no meaningful references or discussions.
2. **Rudimentary consideration** (circle 1/4 filled): The literature provides a basic acknowledgment of the characteristic, with minor references or brief discussions lacking substantial depth or analysis.
3. **Balanced consideration** (circle 1/2 filled): The literature exhibits a moderate and well-rounded consideration, with reasonable attention, various aspects discussed, and a relatively comprehensive analysis.
4. **High focus** (circle 3/4 filled): The literature demonstrates a substantial focus on the characteristic, dedicating a significant portion of content to in-depth exploration, offering valuable insights and extensive discussions.
5. **Holistic consideration** (circle fully filled): At the highest level, the literature exemplifies a comprehensive and all-encompassing consideration of the characteristic. Thorough analysis covers every aspect, showcasing a profound understanding and valuable contributions to the field.

Figure 4 illustrates the outcomes of the conducted investigation regarding the theoretical deficit.

Theory Deficit



	Consideration of the Holistic Cycle	Domain Linking	Replacement for Human Expert Knowledge	Differentiation from Non-relevant Knowledge	Consideration of Knowledge Gaps	Robustness of Prediction Quality	Consideration of Optimization Proposals with AI	Application to one or more proofs of concept
[15] An Artificial Intelligence approach for the multicriteria optimization in mechatronic products design								
[18] Application and research of artificial intelligence in mechatronic engineering								
[19] Application of Intelligent Systems in Multi-modal Information Analytics (...)								
[20] Application Research of Mechatronics System Based on Computer Artificial Intelligence Technology								
[21] Concept for an integrated product and process development of electric drives using a knowledge-based system								
[22] Difficulties of mechanical engineering students in developing integrated knowledge for the cross-discipline of mechatronics: a conceptual investigation								
[23] Early reliability estimation in automotive industry								
[24] Exploration of the Application of Artificial Intelligence Technology in Mechatronics Technology Based on								
[25] Grundlagen für einen mechatronischen Effektkatalog								
[26] Industrial Artificial Intelligence in Industry 4.0 - Systematic Review, Challenges and Outlook								
[27] Integration of Artificial Intelligence Techniques in Mechatronic Systems for Smart Manufacturing								
[28] Introducing the Electronic Knowledge Framework into the Traditional Automotive Suppliers' Industry: From Mechanical Engineering to Mechatronics								
[29] Knowledge capitalization in mechatronic collaborative design								
[30] Knowledge sharing for mechatronic systems design and optimization								
[31] Knowledge-based engineering for multidisciplinary systems: Integrated design based on interface model								
[32] Konzept für eine simulationsgetriebene-wissensbasierte Produktentwicklung im Umfeld mechatronischer Produkte								
[16] Mechatronic Design and Optimization Using Knowledge Based Engineering Applied to an Inherently Unstable and Unmanned Aerial Vehicle								
[33] Mechatronics - A unifying interdisciplinary and intelligent engineering science paradigm								
[17] Overview of the Relationship between Mechatronic Engineering and Artificial Intelligence								
[34] Requirements Management When Introducing New Mechatronic Sub-systems - Managing the Knowledge Gaps								
[35] Special Issue on Application of Artificial Intelligence in Mechatronics								
[36] Systemorientierte Visualisierung disziplinübergreifender Entwicklungsabhängigkeiten mechatronischer Automobilsysteme								
[37] The science and education of mechatronics engineering								
[38] Towards an Integrated Conceptual Design Evaluation of Mechatronic Systems: The SysDICE Approach								
[39] Transdisciplinary Approach of the Mechatronics in the Knowledge Based Society								
[40] Verknüpfungsmodell zuverlässigkeitsrelevanter Informationen in der Produktentwicklung mechatronischer Systeme								
[41] Wissensmanagement: Zwischen Wissen und Nichtwissen								
[42] Zuverlässigkeitsbewertung mechatronischer Systeme in frühen Entwicklungsphasen								

Figure 4: The literature analysis in detail, developed in Paper I

The visual result is emphasizing the anticipated observation that while individual aspects are occasionally explored in great detail, a comprehensive perspective on the overall context is still lacking.

Consequently, there is an absence of a recommended course of action that stakeholders can follow to effectively harness the potential of AI. This deficit in a holistic approach impedes the identification of a strategic pathway to fully exploit the opportunities presented by the intelligent methods. Additional investigations and aspects can be found in Paper I.

In practice, the situation is analogous, with substantial expectations concerning current and future potentials. This is corroborated by trend reports from leading global consulting companies. For instance, **McKinsey & Company**, in their document titled *The economic potential of generative AI*, published in June 2023, explore various future impacts of the ongoing mega-trend of generative AI. They shed light on diverse scenarios, including the transformation of software engineering and R&D resulting from the effective use of AI, as seen in Figure 5. [43] The prevailing expectation is unequivocally oriented towards holistically supporting the development processes in both areas – commencing from initiation and planning, extending to system design, and culminating in maintenance and diagnosis.

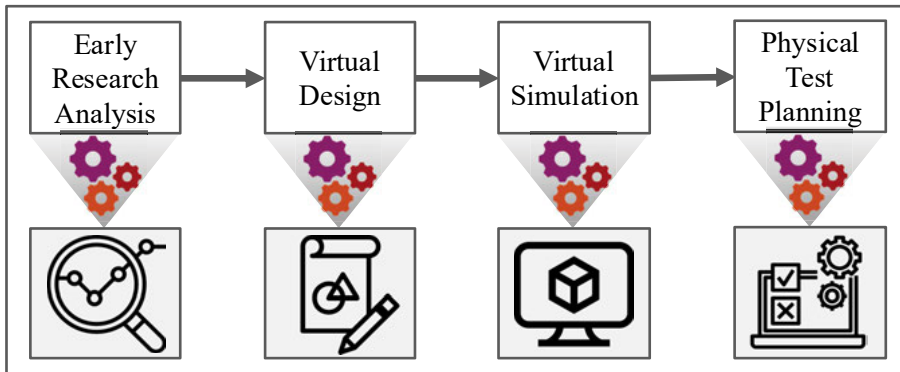


Figure 5: The possible transformation fields of product R&D through AI according to the report of McKinsey & Company [43]

As emphasized Research and Development stands on the brink of transformation, with the integration of cutting-edge technologies promising to revolutionize traditional processes.

Early-stage analysis is undergoing a profound shift as researchers leverage generative AI to augment market reporting, ideation, and the initial drafting of products or solutions. This application empowers them to delve deeper into market insights and swiftly generate innovative concepts.

The virtual design phase sees a significant evolution as generative AI enables researchers to swiftly generate drafts and designs based on prompts, thereby facilitating rapid iteration with a plethora of design options. This

acceleration not only expedites the design process but also enhances creativity and exploration.

Virtual simulations, a crucial aspect of product development, are also benefiting from advancements in generative AI. By integrating new deep learning techniques, researchers are streamlining and optimizing virtual simulations, leading to faster and more precise outcomes.

Furthermore, in the realm of physical testing, generative AI is revolutionizing test planning. Researchers are now able to optimize test cases, resulting in more efficient testing processes and reduced time requirements for physical build and testing. This optimization not only saves time and resources but also enhances the overall efficacy of the testing phase.

Similarly, **Gartner**, a trend research company, annually publishes so-called *Hype Cycles* for a general technology radar and specific disciplines. The *Hype Cycle for Artificial Intelligence, 2023*, as well as the others, comprises phases such as

1. Innovation Trigger,
2. Peak of Inflated Expectations,
3. Trough of Disillusionment,
4. Slope of Enlightenment
5. and Plateau of Productivity.

As shown in Figure 6 the time axis is represented on the abscissa, while the degree of expectation is depicted on the ordinate.

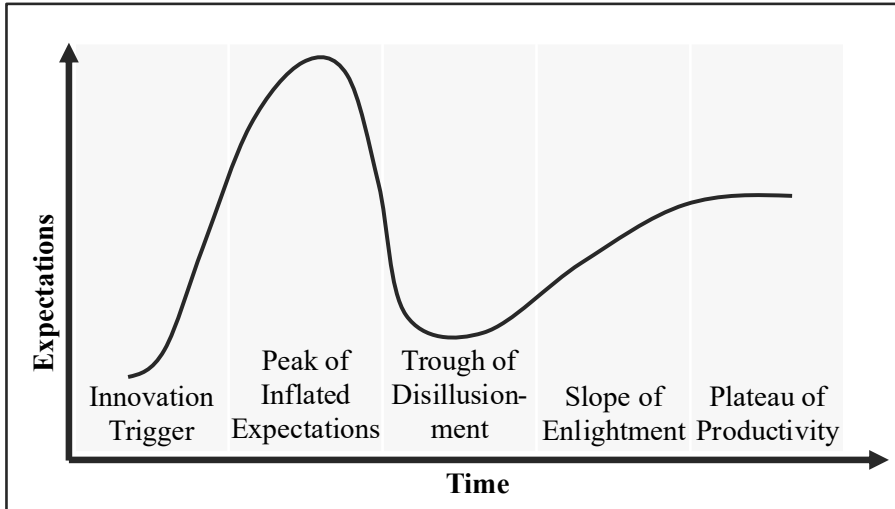


Figure 6: The scheme of the 2023 Gartner Hype Cycle™ for Artificial Intelligence (AI) [44], layout-matched

It is important to emphasize that the temporal categorization is symbol-based. For instance, Artificial General Intelligence is currently transitioning between Phase 1 and 2 but is anticipated to reach the plateau in more than ten years – a significant temporal duration in the realm of technologies.

Turning attention to technologies relevant to mechatronic product development, terms like AI Engineering and AI Simulation quickly emerge. According to Gartner's assessment, these technologies are currently in the first phase and are expected to reach the plateau in five to ten years. Knowledge Graphs, experiencing a resurgence in research due to AI trends, currently find themselves in the Trough of Disillusionment and are projected to reach the desired plateau of productive utilization in two to five years.

In summary, it is evident that individual phenomena related to AI potentials exist and are adequately explored. However, a comprehensive understanding and utilization of these effects are still pending. Such a holistic perspective will serve as a guide for stakeholders, aiding in the initial integration of possibilities and the exploration of new avenues.

Conception of the Methodology

Following the presentation of the initial project outline and the underlying situations in theory and practice with associated deficits, the development of a methodology for successful potential analysis of robust AI along the development process is now underway. As a first step, the development of the necessary rough concept is based. For this purpose, the development of a corresponding request image is initially carried out, visualizing the utilization potentials of the approach in detail once again. Subsequently, a detailed analysis of the phases and handover points of the V-model takes place, aiming to identify suitable support options for AI applications and the associated requirements as well as the prospects for success. Following this, requirements for the methodology to be developed are elaborated to ensure alignment with the identified deficits and target criteria. Building on this, the actual rough concept is constructed with the associated methodological steps.

Utilization Potential of AI along Product Development

In the realm of product development, the integration of AI holds immense potential for enhancing efficiency, innovation, and competitiveness. However, harnessing this potential requires careful consideration of various requirements, particularly in terms of accuracy and reliability. Therefore, the goal is to present a request image that visualizes the evolving demands placed on AI throughout the product development process.

As products evolve from conceptualization to market launch, the requests placed on AI systems undergo a corresponding evolution. At each stage of development, specific requirements regarding accuracy and reliability become increasingly critical. Understanding this evolution is essential for effectively harnessing AI's potential in product development.

The request image serves as a visual representation of the evolving requirements for AI accuracy and reliability throughout the product development process. It provides a clear and concise overview of how the demands placed on AI systems change as products progress from conceptualization to deployment.

The horizontal axis of the request image delineates the various stages of product development, from conceptualization and design to production and

deployment. Each stage represents a distinct phase in the product lifecycle, characterized by specific activities, milestones, and objectives. By organizing the stages of development along the horizontal axis, the target image provides a chronological framework for understanding how the demands placed on AI systems evolve over time.

The vertical axis of the request image quantifies the level of requirements for AI accuracy and reliability at each stage of the product development. This axis serves as a metric for assessing the criticality of accuracy and reliability in AI applications. At the bottom of the vertical axis, the level of requirements is minimal, indicating that accuracy and reliability are of lesser importance. As the axis ascends, the level of requirements increases, reflecting the growing importance of accuracy and reliability in AI systems.

By examining the request image, stakeholders can gain valuable insights into the evolving demands placed on AI systems throughout the product development process. Trends and patterns in the image can highlight areas where AI capabilities need to be strengthened or where additional resources should be allocated to ensure the success of the product.

The resulting request image is shown in Figure 7. The individual phases are explained in more detail in the following.

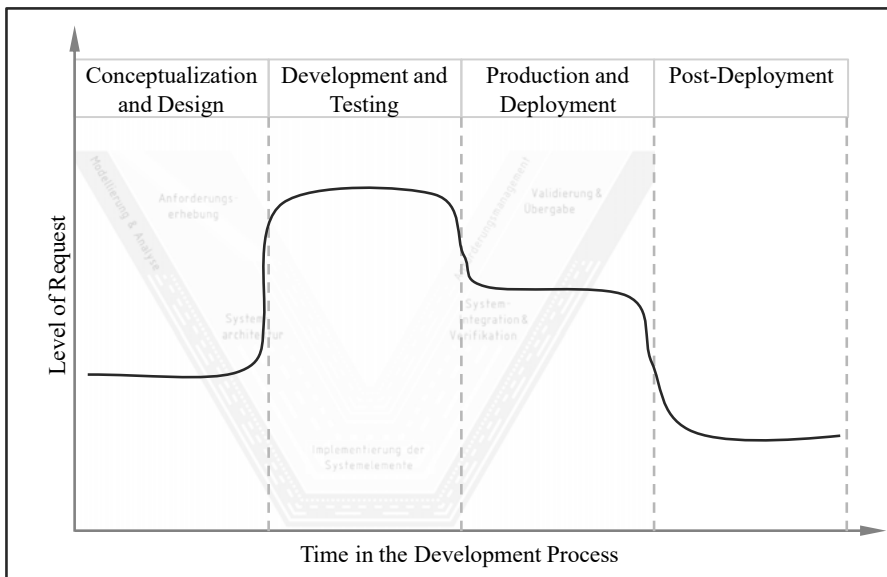


Figure 7: Request Image for Utilization Potential of AI along Product Development

During the **conceptualization and design phase**, AI is primarily utilized for ideation, prototyping, and feasibility analysis. At this stage, the emphasis is on creativity, exploration, and experimentation. While accuracy and reliability are important, they are not always paramount. The request image reflects a

relatively low level of requirements for AI accuracy and reliability during this phase, as the focus is on generating diverse ideas and concepts.

As the product moves into the **development and testing phase**, the demands placed on AI systems reach their peak. Here, AI is used for tasks such as simulation, optimization, and validation. Accuracy and reliability become critical considerations, particularly as AI algorithms are deployed to predict performance, simulate behavior, and identify potential defects. The request image illustrates a significant increase in the requirements for AI accuracy and reliability during this phase, reflecting the need for robust and trustworthy AI solutions.

In the final stages of **production and deployment**, AI is used for tasks such as quality control, predictive maintenance, and customer support. At this stage, the reliability of AI systems is paramount, as they directly impact product performance, safety, and customer satisfaction. The request image depicts a peak in the requirements for AI accuracy and reliability during this phase, reflecting the critical role of AI in ensuring the success and longevity of the product in the market.

Even after the product is launched, in the so called **post-deployment phase**, the demands placed on AI systems continue to evolve. As data accumulates and user feedback is collected, AI algorithms must adapt and improve over time. The request image represents this ongoing process of refinement, with the requirements for AI accuracy and reliability fluctuating as new challenges emerge and new opportunities arise.

The Linking Points of AI in the V-Model

As delineated earlier, the V-Model serves as a pivotal framework in software development and testing, offering a systematic approach to ensure the quality and dependability of software systems. Its distinctive "V" shape visually captures the interconnectedness of development and testing stages, with each development phase mirrored by a corresponding testing phase on the opposite side of the V. This model's applicability extends notably to mechatronic product development, providing a structured means to develop and validate all constituent components and their intricate interconnections. [7]

The overarching aim is to bolster and enhance the effectiveness of all phases within this development process, as well as analogous or comparable processes, by introducing meaningful value additions. Therefore, the subsequent phase involves the formulation of a dedicated process concept tailored for the context-sensitive and robust utilization of AI in V-Model-related product development.

This tailored process concept seeks to leverage the capabilities of AI in a manner that aligns seamlessly with the specificities of the V-Model, as seen in Figure 8.

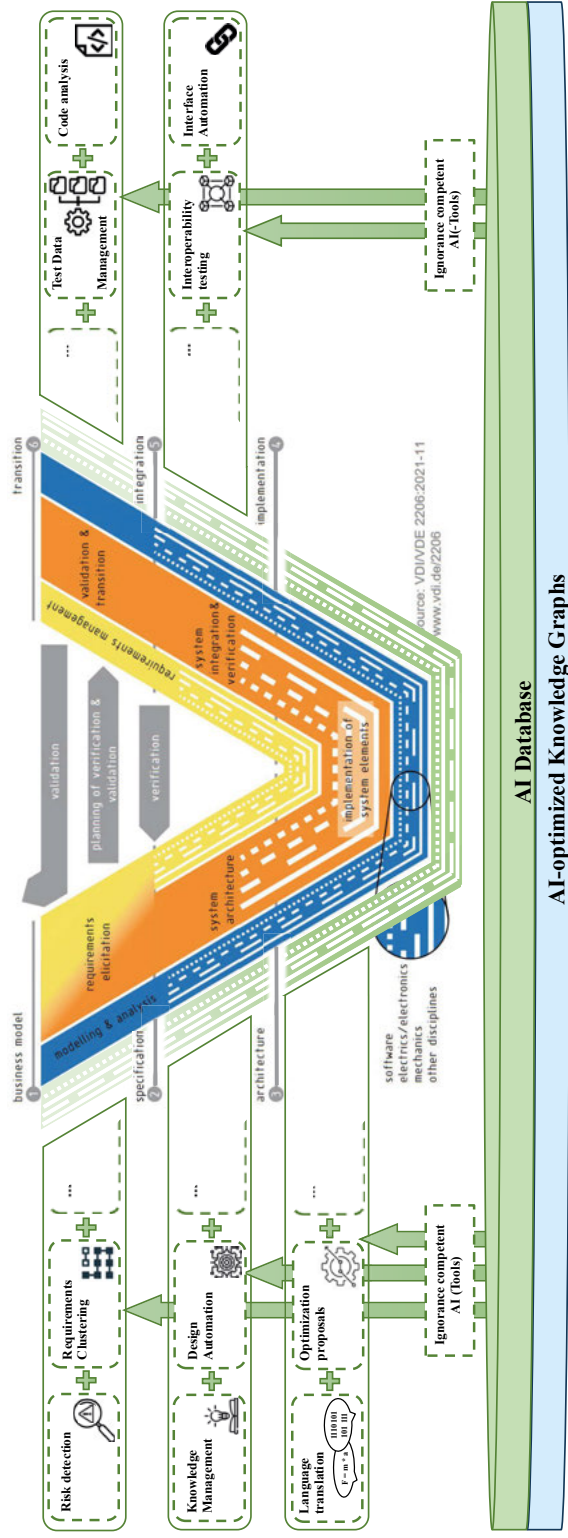


Figure 8: The process concept for holistic utilization of the potential of AI in the product development cycle

The concept addresses the nuances of integrating AI across diverse stages, ensuring not only contextual relevance but also resilience in the face of uncertainties and variations inherent in the product development lifecycle. By doing so, the proposed concept aims to advance the state-of-the-art in mechatronic product development, offering a roadmap for the effective incorporation of AI within the structured framework of the V-Model.

Initiating with an established business model (**Checkpoint 1**), the cycle transitions into the specification phase, where requirements for the mechatronic system are meticulously gathered and analyzed, spanning mechanical, electronic, and software aspects. These requirements form the foundation for the entire development process. AI's utility in this phase extends to automated requirement capture, NLP, and early risk detection, among other capabilities. [45], [46], [47], [48]

Checkpoint 2 marks the conclusion of the specification phase, leading to the commencement of the System Architecture phase. This stage involves integrating mechanical, electronic, and software components, ensuring alignment with requirements using the V-Model. The phase culminates in the establishment of architecture (**Checkpoint 3**). AI's support in this stage encompasses design automation, simulation models, error detection, collaboration, and knowledge management. [49], [50], [51], [52]

The implementation of system elements, the visually lengthiest phase, follows, encompassing the development of subsystems like mechanical structures, electronic components, and software modules. AI plays a pivotal role in translation, interpretation, and prediction approaches throughout this phase. The successful completion leads to **Checkpoint 4**, Implementation. [18], [53], [54]

System integration and verification come next, emphasizing seamless collaboration among mechanical, electronic, and software subsystems. The V-Model ensures proper functioning, concluding at **Checkpoint 5**. AI's support in this phase extends to interface automation and real-time monitoring, as highlighted in sources such as [55], [56], [57].

The final phase involves validation and transition, ensuring each component and subsystem meets requirements and functions correctly within the integrated mechatronic system. **Checkpoint 6** marks the completion, with AI contributing to intelligent test selection, test data management, and the generation or anonymization of synthetic data. [7], [58], [59]

Requirements for the Methodology

For a successful deployment of AI into the product development it essential to define the right requirements and generate the correct specific metrics. The task is therefore to examine how these processes can be designed to develop robust AI solutions that meet the requirements of product engineering. [60]

Requirement collection is the foundational stage in the process of seamlessly integrating AI into product development. It entails a detailed examination of the company's overarching goals and objectives, alongside a comprehensive understanding of the demands and preferences of end-users. To achieve this, various methodologies such as interviews, surveys, workshops, and focus groups are often employed, facilitating a holistic grasp of the intricate nuances and specificities of the desired AI-powered solution. Additionally, stakeholder consultations and market research play pivotal roles in ensuring that the collected requirements are not only comprehensive but also align closely with market trends and emerging technological advancements. This phase serves as the bedrock upon which subsequent stages of AI implementation, such as design and development, are built, thereby laying a solid foundation for the creation of innovative and user-centric AI-driven products and services. [61], [62], [63]

Key questions to be addressed include:

- What problems are to be solved through the use of AI?
- What are the requirements of end-users for AI-powered products?
- What data is required for the development of the AI solution?
- What technical and regulatory requirements need to be met?

After eliciting requirements, the subsequent crucial step entails the development of specific metrics meticulously crafted to gauge the efficacy and success of the AI solution. These metrics serve as quantifiable benchmarks, allowing for a structured evaluation of the AI system's performance and impact. They must be designed to reflect the intricacies of the company's objectives and align seamlessly with its overarching goals and requirements.

Each metric should be clearly defined with precise parameters delineating its scope and measurement methodology. Moreover, these metrics ought to be dynamic, capable of adapting to evolving business needs and technological advancements. By closely aligning these metrics with the company's strategic vision and operational objectives, stakeholders can effectively monitor progress, identify areas for improvement, and make informed decisions to optimize the AI solution's functionality and impact. [64], [65], [66]

Possible metrics may include:

- **Precision and Dependability of AI Models:** This evaluates the accuracy and reliability of the AI solution in making predictions or decisions, as well as its consistency over time.
- **Effectiveness and Scalability:** This assesses the efficiency and ability of the AI solution to operate swiftly and utilize resources optimally, while also examining its capability to scale seamlessly with increasing data volume or complexity.
- **End-User Satisfaction:** This measures the level of satisfaction among end-users with the AI-powered product solution, determining whether it effectively meets their needs and expectations.

- **Regulatory Compliance and Security:** These metrics scrutinize whether the AI solution adheres to regulatory standards and if it provides robust security measures against potential threats.

Gathering requirements and crafting precise metrics are pivotal stages in the creation of resilient AI solutions for product development. By conducting meticulous requirement analyses and establishing unambiguous metrics, companies can guarantee that their AI solutions effectively meet their intended objectives, delivering tangible value to both their products and customers.

Application to the Proof of Concept

In the course of the already hinted proof of concepts, a corresponding development of case-specific requirements and metrics will take place further in the course of the research project. In the case of the described example regarding the optimized interaction between design or development and production, the previous questions can be asked and the possible answers forecasted accordingly:

What problems are to be solved through the use of AI?

The (improved) and intelligent provision of expert knowledge to efficiently access insights from the past and utilize them purposeful in the present and future.

What are the requirements of end-users for AI-powered products?

One of the biggest demands is the easy utilization of insights through as natural as possible posing of requirements. A model here is certainly the currently public large language models like ChatGPT & Co., where users can ask natural queries and immediately receive as accurate information and assistance as possible. If only an uncertain response is possible for the corresponding query, this must be appropriately marked, as the reliability of the information plays a role in product development. However, the level of detail depends on many circumstances - see chapter Utilization Potential of AI along Product Development for more details.

What data is required for the development of the AI solution?

On the one hand, sufficient knowledge from past projects must be usable. The major hurdle here is often the insufficient processing of information to date and the unstructured storage of it. In addition, it will generally be necessary to gather supplementary knowledge, as the data for training the AI must be diverse enough to ensure comprehensive knowledge and ensure usability.

What technical and regulatory requirements need to be met?

In addition to the requirements already described such as robustness, there are always data protection and security requirements for the AI as well as its data foundations and forecasts. However, these are company-specific or governmental and must be declared and subsequently implemented accordingly. Only in this way can the tool also be used in the real world.

General Concept and Classification

Below, the high-level concept for the robust and holistic AI support of mechatronic product development is presented. The methodology, depicted and explained in the following Figure 9, consists of three sub-models that converge in the actual support of the V-model using intelligent methods.

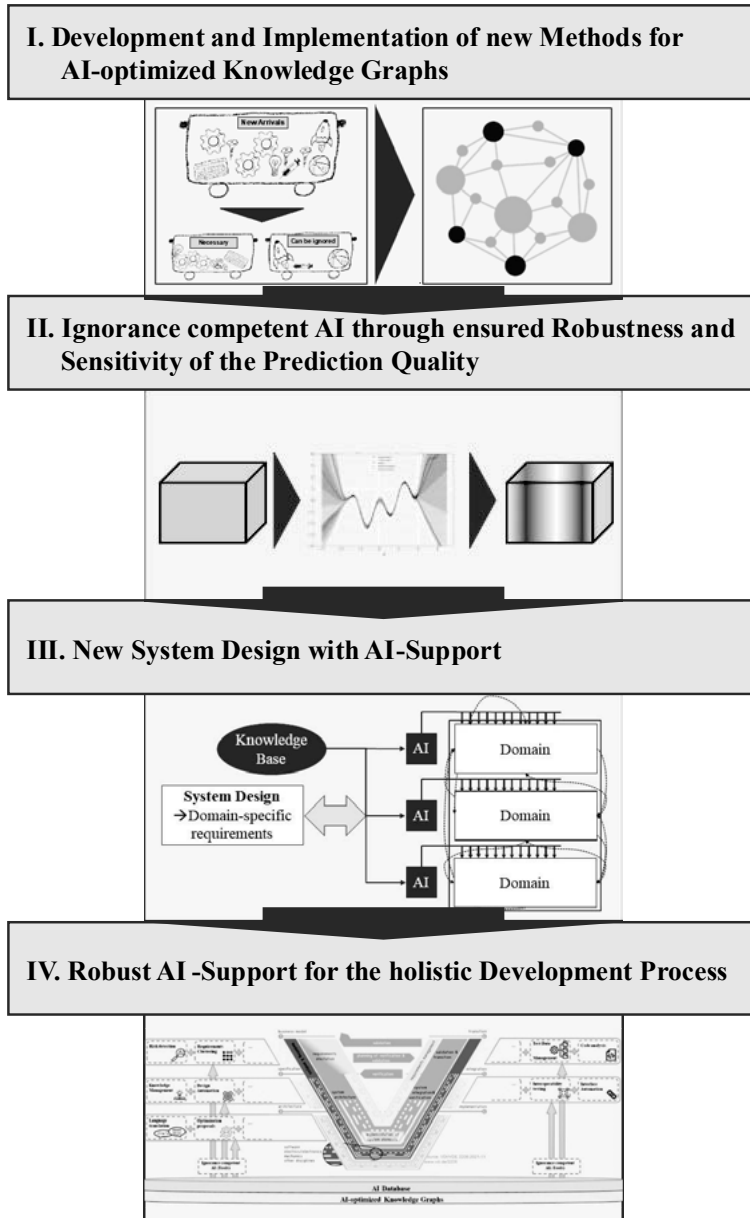


Figure 9: General concept for the robust and holistic AI support

In the initial phase, the focus is on the creation and enhancement of AI-optimized knowledge graphs. This involves the identification and integration of diverse data sources, ensuring comprehensive coverage of relevant information. The development process includes employing advanced machine learning algorithms to extract, classify, and link data points, resulting in a dynamic and evolving knowledge graph. The goal is to build a robust foundation that serves as the backbone for subsequent AI-driven processes.

To ensure the effectiveness and reliability of the AI system, the second step emphasizes the implementation of robustness and sensitivity measures. This involves thorough testing under diverse conditions and scenarios to identify potential biases, weaknesses, and vulnerabilities in the AI model. Addressing these issues ensures that the AI system is competent enough to handle uncertainties and ignorance in real-world situations, enhancing its reliability and usability.

With the AI-optimized knowledge graphs and a robust AI model in place, the next step involves integrating AI support into the overall system design. This includes identifying key decision points, processes, and interactions within the development lifecycle where AI can provide valuable insights, predictions, or automation. The goal is to create a symbiotic relationship between human expertise and AI capabilities, enhancing overall efficiency and decision-making.

The final step encompasses the seamless integration of AI throughout the holistic development process. This involves continuous monitoring, learning, and adaptation of the AI system to evolving requirements and challenges. The AI support is designed to complement human expertise, offering insights, predictions, and automation that contribute to a more efficient, informed, and adaptive development process. Regular updates and refinements to the knowledge graph and AI model ensure that the system remains at the forefront of technological advancements.

In summary, the proposed methodology follows a systematic approach, starting with the development of AI-optimized knowledge graphs and ensuring the robustness and sensitivity of the AI model. It then integrates AI support into the overall system design, culminating in a robust AI-supported development process that enhances decision-making and efficiency across the board.

Detailing the Methodology

Building upon the developed rough concept, the subsequent step involves the four-step detailing of the method for the holistic potential analysis and utilization of AI possibilities in the development of mechatronic systems.

The initial phase involves creating and improving the knowledge base for AI-optimized Knowledge Graphs by identifying and integrating diverse data sources, utilizing advanced machine learning algorithms to extract, classify, and link data points, with the aim of establishing a dynamic foundation supporting subsequent AI-driven processes. The second step emphasizes implementing robustness and sensitivity measures through thorough testing under diverse conditions to enhance the AI system's reliability and usability.

The third step involves integrating AI support into the system design, identifying key decision points and processes where AI can provide insights or automation, aiming for symbiosis between human expertise and AI capabilities to enhance efficiency and decision-making. Within this work, this point will be exclusively addressed as a future outlook. It examines the actual approach to the operational implementation of the developed methodology. In the final step, integration into the development cycle will occur, along with an examination of the resulting outcomes and phenomena. Thus, using the use cases introduced in the introduction, the methodology will undergo verification or validation.

AI and Knowledge

In the initial phase, the focus is on creating and refining AI-optimized methods for knowledge mining. This entails identifying and integrating diverse data sources to ensure comprehensive coverage. Using advanced machine learning algorithms, the extraction, classification and linking of the data points takes place, resulting in a dynamic knowledge graph. The objective is to establish a robust foundation, serving as the backbone for subsequent AI-driven processes. From this arises the first research question, visualized in Figure 10.

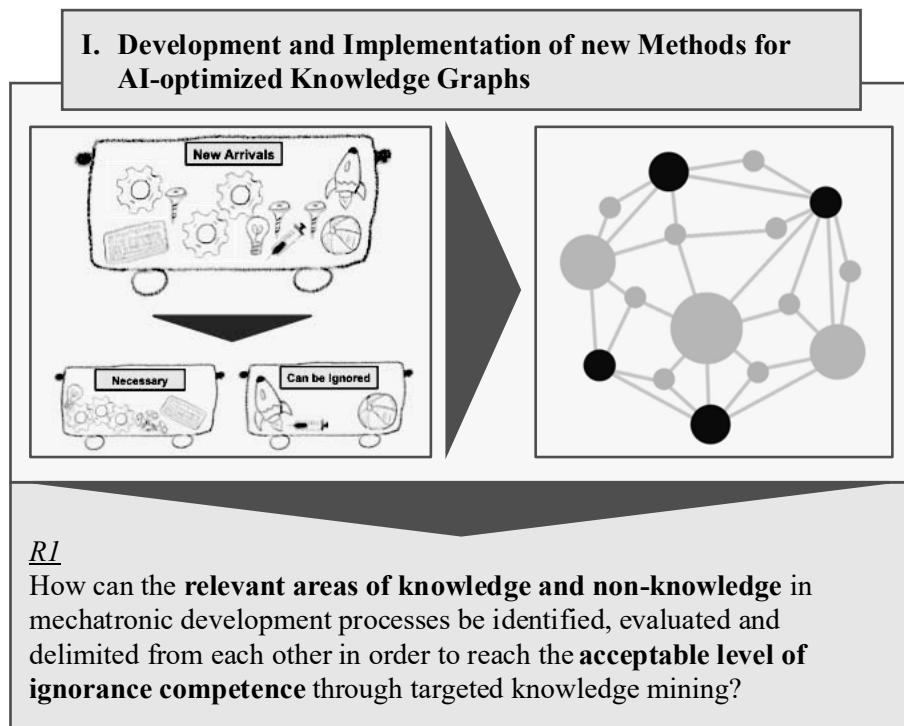


Figure 10: Development and Implementation of new Methods for AI-optimized Knowledge Graphs

AI plays a crucial role in mechatronic product development, particularly as a robust database. Leveraging AI methodologies like machine learning and knowledge representation, it efficiently manages extensive volumes of information, ensuring organized storage and retrieval. This AI-driven database serves as a valuable asset, granting engineers rapid and comprehensive access to a wealth of knowledge, including past designs, simulations, test results, and best practices. The centralized repository not only expedites the design process but also fosters collaboration among interdisciplinary teams by offering a shared platform for exchanging information. [67]

The basis for this is, in any case, an appropriate database. In this context, the quantity of the necessary information is not even the actual problem but the identification of the selection relevant for the purpose – keyword Knowledge Explosion. This phenomenon refers to the rapid proliferation of information and data, particularly in the fields of science and technology. This surge in knowledge is driven by technological advancements, especially the internet and powerful computers, combined with increased global interconnectedness and collaboration. These factors have greatly facilitated the accessibility, storage, and sharing of information. [68]

The Knowledge Explosion has brought numerous advantages, including widespread access to extensive information, the capacity to exchange ideas,

and collaborative efforts in research and development. However, it has also presented challenges, such as grappling with information overload and the necessity for advanced techniques and tools to navigate and derive meaning from the data. Therefore, the objective is to adeptly navigate and harness the abundance of available information, but individual experts often hold essential knowledge within companies, limiting its availability. This may result in unnecessary redundancies and hinder further development. [69], [70]

To overcome this challenge and effectively utilize existing knowledge, processes of identifying, evaluating, and organizing information are crucial. Techniques like data mining, statistical analysis, and machine learning analyze data from various sources to extract meaningful insights. The goal is to convert data into actionable knowledge for informed decision-making, applicable across fields like engineering, finance, and sustainability. The knowledge analysis process involves data cleaning, visualization, and interpretation - an iterative approach that may lead to new questions. [71], [72], [73], [74]

But what happens in cases where this knowledge cannot be fully captured, and thus there is no uniform information base for the use of intelligent methods? At this point, AI can provide significant added value. AI databases can identify such gaps and assist in addressing them. As a result, a more comprehensive understanding of the system is achieved, enabling better prediction. [75]

Knowledge Graphs and Data Imputation

To appropriately assess the situation and evaluate the knowledge base, Knowledge Graphs can be employed as a technique. While the methodology is not new – initial publications date back at least to the 70s – they have experienced a kind of renaissance following the AI boom. [76], [77]

At its core, a Knowledge Graph is a graph-based data structure that captures entities, their attributes, and the relationships between them. Unlike traditional databases that store information in tables, Knowledge Graphs embrace a graph-oriented approach, where nodes represent entities and edges denote the relationships between them. This interconnected structure enables the representation of complex, real-world knowledge in a highly expressive and flexible manner. [78]

The concept of semantic enrichment lies at the heart of Knowledge Graphs, where raw data undergoes augmentation with semantic annotations to imbue it with significance. They achieve this by harnessing ontologies, taxonomies, and schemes, enabling them to encode not just the data, but also the underlying semantics. This semantic layer facilitates robust inferencing and reasoning capabilities, empowering AI systems to extract deeper insights and make more informed decisions. [79]

The construction of a Knowledge Graph comprises multiple stages, commencing with data acquisition and preprocessing. Raw data sourced from a variety of outlets, including structured databases, unstructured text, and online content, is initially ingested and then standardized. This transformation process often includes entity recognition, relationship extraction, and disambiguation techniques aimed at guaranteeing data quality and coherence. After preprocessing, the data is translated into a graph-based representation, where entities are mapped to nodes and relationships to edges. This mapping process entails establishing ontologies, schemes, and vocabularies that dictate the structure and semantics of the Knowledge Graph. Utilizing graph-based algorithms, patterns can be uncovered, related entities clustered, and missing relationships inferred, thereby enhancing the graph with supplementary knowledge. The four steps for the so called extraction pipeline can be found in Figure 11. [80], [81], [82]

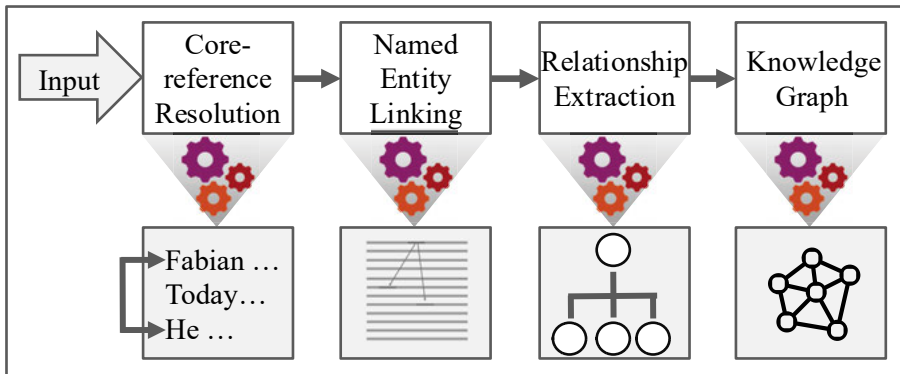


Figure 11: The four process steps for creating Knowledge Graphs

In NLP, knowledge graphs facilitate entity linking, semantic parsing, and question answering by providing a structured representation of knowledge that can be leveraged to interpret and generate natural language text. Moreover, in machine learning, Knowledge Graphs serve as a source of structured data for training and inference, enabling models to exploit rich relational information and generalize more effectively. This integration into the intelligent systems has profound implications for the field, unlocking new possibilities for knowledge representation, reasoning, and decision-making. By encapsulating domain knowledge in a graph-based format, AI systems gain a deeper understanding of the underlying semantics, enabling them to perform more sophisticated tasks with greater accuracy and efficiency. Furthermore, Knowledge Graphs facilitate interoperability and integration across disparate AI systems and data sources, fostering collaboration and knowledge sharing in complex AI ecosystems - as a parallel representation of the real situation, as already explained in the Introduction. [83], [84]

But despite their promise, Knowledge Graphs are not without challenges. Scaling knowledge graphs to handle large-scale, dynamic datasets poses scalability and performance issues. Additionally, ensuring the quality, completeness, and consistency of knowledge graphs remains a persistent challenge, requiring ongoing efforts in data curation, validation, and maintenance - similar to the situation of AI use in product development with resilient deployment. [85]

Subsequently, it is possible to fill in incomplete knowledge areas using Machine Learning methods. These methods are capable of inferring missing information, detecting implicit relationships, predicting new connections, and filling gaps based on existing data. This process is referred to as data imputation. Further details can be found in, among other sources, Paper IV. [86]

Following that, there is an opportunity to validate the data incorporated into the knowledge Graph, ensuring its accuracy and reliability. More details on this can be found in the Chapter AI and Ignorance Competence and again Paper IV. It is essential to establish quality assurance processes for consistently reviewing and updating the data. [67], [87], [88], [89]

Below are two approaches for applying intelligent methods for both knowledge generation and early analysis through simulated expert knowledge, supporting the creation of corresponding Knowledge Graphs as well as the next steps in using the actual intelligent methods.

Intelligent Analysis of Components

The presented method, visualized in Figure 12, serves the intelligent analysis of components with the goal of consolidating them into a feature table.

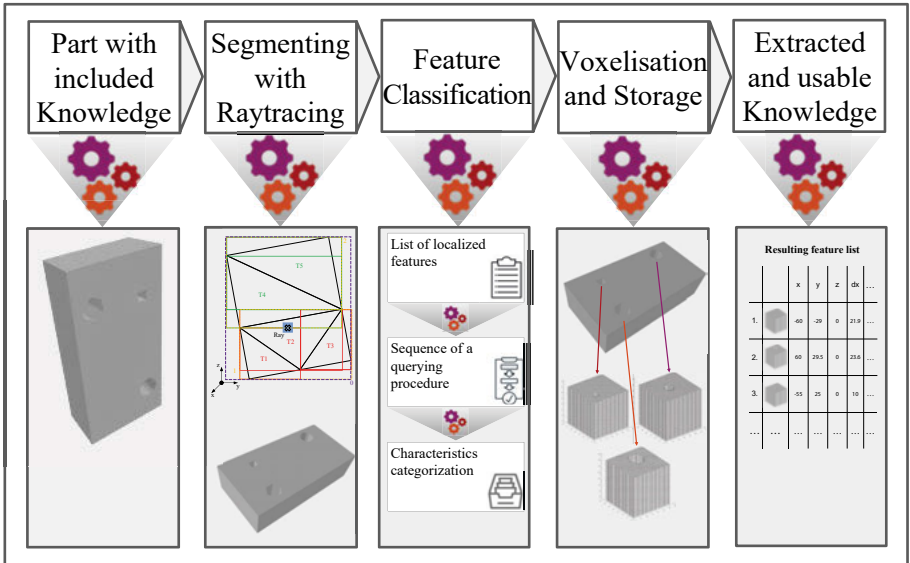


Figure 12: The process steps for the intelligent analysis of components and features leading to the extracted knowledge, developed in Paper II

Initially, an approach is devised to swiftly localize features while also determining their origin and dimensions using raytracing techniques. This approach offers the advantage of enabling precise segmentation of features and their immediate surroundings. Regions devoid of features are disregarded, streamlining subsequent analysis.

The selected approach provides resolution advantages for the subsequent voxelization, which serves as a crucial preparatory step for supplementary analysis utilizing techniques like ANNs for automated recognition of trained phenomena. By avoiding a uniform resolution in favor of individual segments with sufficiently high resolution, the examination of features attains necessary detail. Opting for a uniform resolution would render such detailed examination impractical due to increased computational demands.

Following segmentation, the next phase involves classifying the segmented areas based on known feature classes. A method is developed to assign features to defined classes using rule-based catalogs and associated examination procedures. Incorporating precise dimensional data and contextual placement within the component facilitates cataloging and further processing.

An example of a special feature could be an existing hole drilled in the component. If a ray starts outside the component and exits on the opposite end, it must intersect the hole at least two times. If the number of intersections is greater, it could indicate another feature or multiple instances of the same feature type being examined. Further querying procedures are then required to investigate these possibilities and provide a conclusive determination. Figure 13 illustrates the querying procedure for the selected example of boreholes.

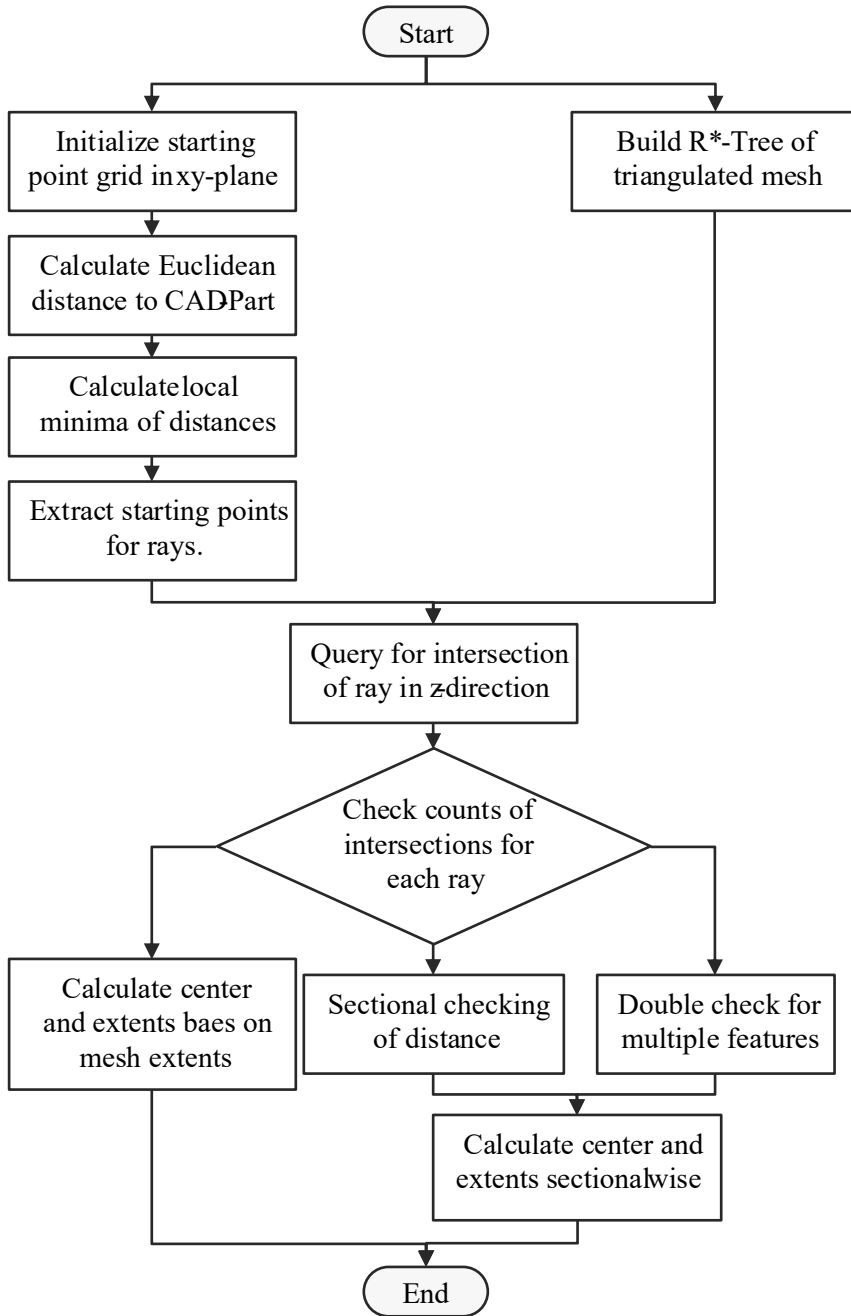


Figure 13: Sequence procedure for the detection of boreholes, developed in Paper II

Finally, the component segments are converted into a format conducive to mathematical analysis and subsequent processing, utilizing the ongoing voxelization approach. Leveraging the segmentation accomplished earlier, an

appropriate resolution is chosen to maintain computational efficiency without sacrificing detail. Thus, this approach not only facilitates the extraction of knowledge but also adheres to sustainable practices throughout the development process. An exemplary result can be found in Figure 14. In this case, all 38 features in the xy-plane were automatically detected.

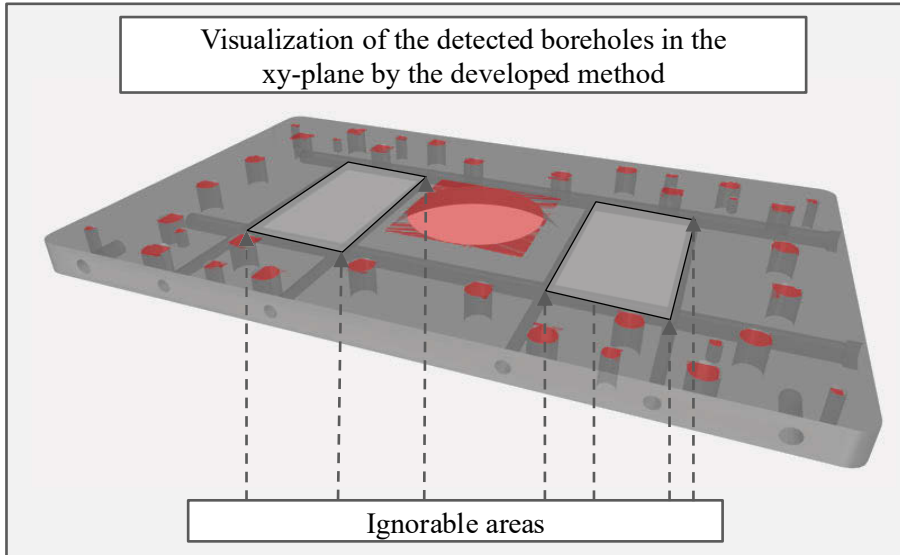


Figure 14: Visualization of the detected features by the developed method in the xy-plane, developed in Paper II

In conclusion, the detailed process established serves as a valuable tool to effectively manage existing masses of information. Existing projects are thoroughly examined and labeled, while new components are appropriately addressed. This process also establishes essential precautions for future AI utilization. Completed projects become valuable content rather than cluttering storage space. This method was developed in collaboration with a manufacturing company for exactly this purpose. Their projects served as a corresponding proof of concept. More details on the used techniques as well as the process steps can be found in Paper II.

With regard to the development process, the developed methodology is particularly beneficial for creating the knowledge base – as evident in Figure 15.

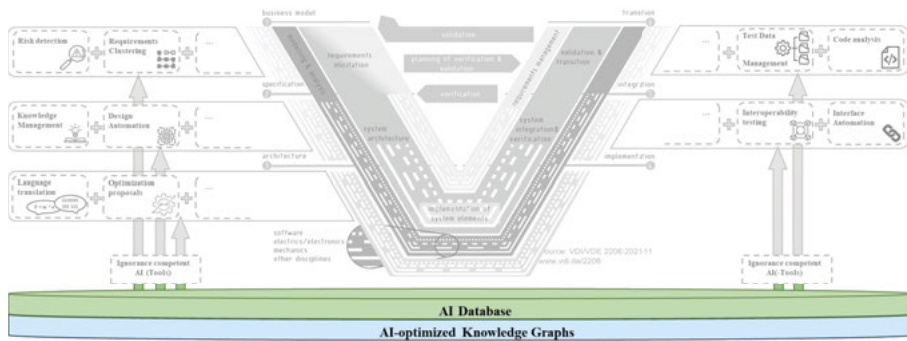


Figure 15: The placement of the Intelligent Analysis of Components method within the development process

Intelligent Component Manufacturability Testing

AI can make certain statements, focusing on the feasibility and success potential of projects or components. By utilizing knowledge resources and suitable algorithms, AI assesses the likelihood of achieving desired outcomes and identifies potential obstacles or challenges during the development process. This enables companies to make informed decisions regarding resource allocation, time management, and overall project feasibility.

In this context, an AI-based approach, visualized in Figure 16, combined with preprocessing to address the knowledge explosion, was developed in Paper III. This involves selectively ignoring irrelevant information within a CAD model to effectively support and secure production-oriented design in virtual product development. The specific case discussed is the feasibility of holes in components for milling processing. 37 different wells were successfully analyzed in Figure 16. The outcomes match those of commercial tools, yet the efficient and assured management of irrelevant data provides a time advantage, facilitating targeted analysis concerning producibility.

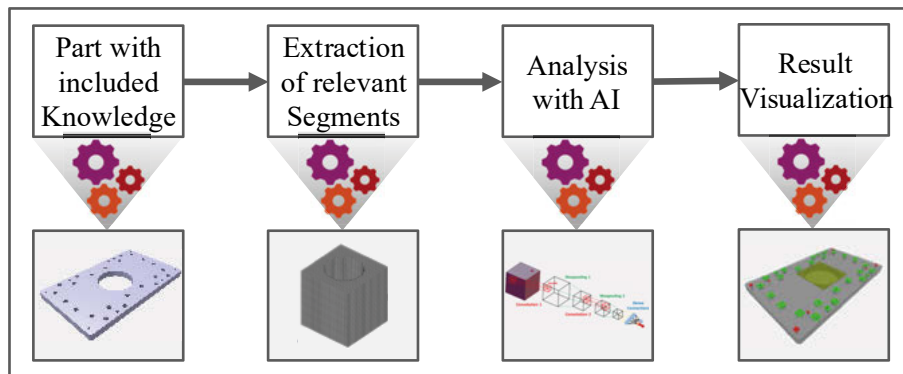


Figure 16: Exemplary visualization of the AI-supported method for the detection of manufacturability, developed in Paper III

The workflow in Figure 16 illustrates the intelligent assessment of manufacturing feasibility in virtual product development. In the preprocessing step, relevant areas are initially extracted from the examined product. Subsequently, these voxelized regions enter the 3D-Convolutional Neural Network (CNN), enabling the analysis of individual construction elements. The final step involves visualizing the results. Any identified manufacturing deficiencies can be rectified using a CAD program.

The process follows an iterative development approach. Employing a bottom-up strategy, it begins with task formulation (feasibility analysis of drillings) and then generates the required dataset. The approach is clearly influenced by CRISP-ML(Q) and QUA3CK methodologies. CRISP-ML(Q) is a machine learning methodology adapted from CRISP-DM, focusing on iterative data analysis and model development. QUA3CK integrates quality management into agile product development, emphasizing continuous improvement and customer satisfaction. Unlike traditional linear processes, both methodologies are iterative and prioritize adaptability and quality, aligning with modern agile practices. [90], [91], [92]

For a comprehensive understanding of the developed 3D-CNN and the intricacies of the completed training processes, refer to Paper III. This document provides a detailed exploration of the architecture, configurations, and outcomes of the 3D-CNN, shedding light on the methodologies employed in its development and training.

In summary, it can be concluded that while the basic feasibility check can also be performed with conventional tools, the developed methodology significantly increases speed due to the quick decision-making capability of AI methods. Furthermore, the AI enables feasibility checks that do not follow conventional logic and only allow for an assessment as a whole. Here, the AI recognizes corresponding patterns and implements them in the future. Particularly when combined with the methods from Paper II, AI can ignore irrelevant areas and thus analyze only the relevant areas quickly.

This method was developed in collaboration with a manufacturing company whose projects served as corresponding proof of concepts and aimed to improve interaction with customers in the early phases of development.

With regard to the development process, the developed methodology is particularly beneficial for the phase between Checkpoints 1 and 2 – as evident in Figure 17.

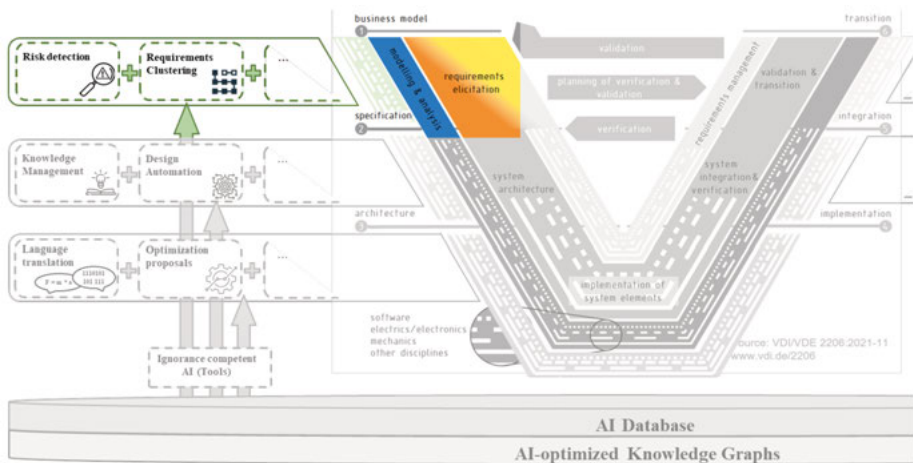


Figure 17: The placement of the Intelligent Component Manufacturability Testing method within the development process

Addressing the 1st research question

The first research question, developed in the Introduction, concerns

R1 How can the **relevant areas of knowledge and non-knowledge** in mechatronic development processes be identified, evaluated and delimited from each other in order to reach the **acceptable level of ignorance competence** through targeted knowledge mining?



and was methodically addressed.

In the course of the previous chapter, existing methods for the knowledge base in the form of knowledge graphs were presented and the specially developed methods for the targeted differentiation between relevant and ignorable information as well as for fast and intelligence-supported manufacturability checks were introduced. Consequently, the first research question can be regarded as successfully answered, as the methods function reliably and existing information becomes usable knowledge in this way.

AI and Ignorance Competence

As the second step in the presented general concept, ensuring the effectiveness and reliability of the AI system is emphasized through the implementation of robustness and sensitivity measures. Addressing the potential issues enhances the AI system's competency in handling uncertainties and ignorance in real-world situations, boosting its reliability and usability. This condition is

referred to in the following as ignorance competence. The term refers to the recognition and acknowledgment of one's lack of knowledge or understanding in a particular subject or field. Rather than being a state of complete ignorance, it entails being aware of the boundaries of one's expertise and being open to learning and seeking further knowledge. In essence, ignorance competence involves understanding what one doesn't know and being willing to engage in the process of acquiring new knowledge and skills to bridge those gaps. This mindset promotes humility, curiosity, and continuous growth, as individuals who possess ignorance competence are more likely to seek out opportunities for learning and development, leading to personal and professional advancement. From this arises the second research question, visualized in Figure 18.

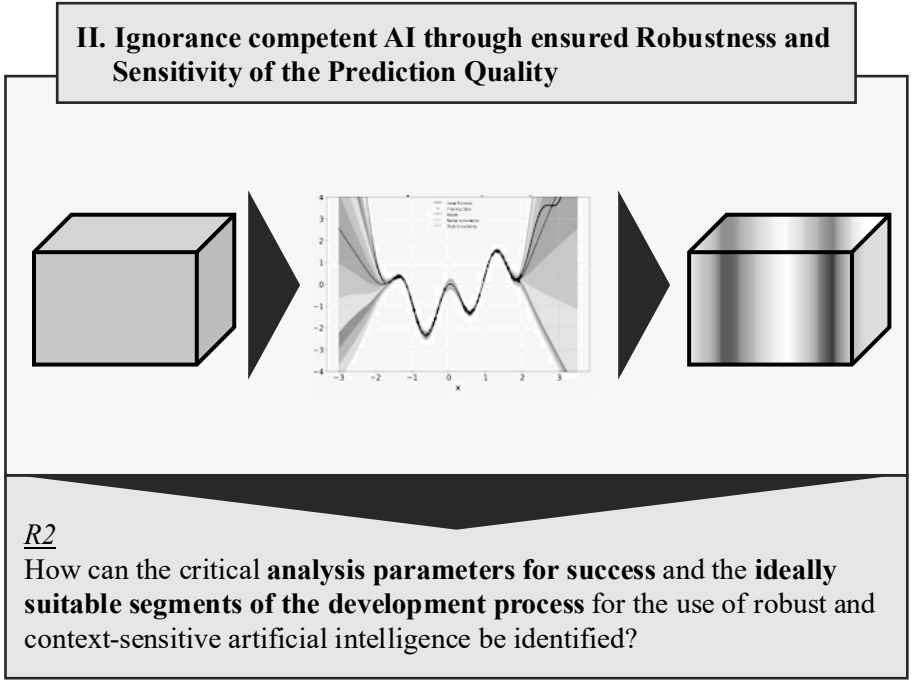


Figure 18: Ignorance competent AI through ensured Robustness and Sensitivity of the Prediction Quality

In the context of the V-Model or comparable development processes, it becomes evident that the robustness of the forecasting model plays a fundamental role. From a temporal perspective, it may be sufficient in early development phases to obtain a rough estimate. For example, to acquire an initial metric for further work or to obtain a general forecast of the temperature ranges in which the application operates, thereby considering materials that can be taken into account. In subsequent stages, it might become imperative for the predictions to demonstrate either a heightened level of precision or a minimal margin of error, particularly in contexts like autonomous driving or other

safety-sensitive domains. To ensure the suitability of the model for each phase and, for economic reasons, to train the model to a sufficient extent for its intended use, the consideration of robustness and sensitivity is indispensable, as [93] and [94] also examine in their work.

Within the method, the concept of Ignorance Competence emerges as a compelling area of inquiry. As one navigates through the intricate seas of information, the aim is to uncover the delicate equilibrium between the robustness and sensitivity inherent in intelligent systems. These systems not only possess the prowess to sift through overwhelming data volumes but also exhibit a remarkable sensitivity to contextual nuances. [95]

The robustness of AI systems becomes evident as they grapple with the challenges posed by vast and diverse datasets. Therefore AI systems have to fortify themselves against noise, uncertainties, and adversarial inputs, ensuring resilience in the face of complex information landscapes, as [96] also clarifies. Understanding the robust nature of AI is integral to appreciating its adaptability and reliability in diverse decision-making scenarios, which also plays a major role in the medical sector, for example, as [97] shows.

Conversely, the sensitivity of AI systems is another aspect that contributes to their nuanced decision-making processes. These intelligent systems have the capability to selectively ignore irrelevant information, honing in on the salient features that are critical for informed decision-making. The exploration of sensitivity in AI involves understanding how these systems discern patterns, recognize context, and navigate the delicate balance between information retention and intentional ignorance.

With this intersection between AI and Ignorance Competence, it is crucial to dissect the dual nature of these systems - robust in their ability to handle complexity and sensitive in their capacity to discern and prioritize information. Through this exploration, the aim is to illuminate the evolving landscape of AI, shedding light on the dynamic interplay between robustness and sensitivity as essential attributes in shaping the future of intelligent decision-making processes.

Understanding Uncertainty and Sensitivity

Utilizing ANNs for predictions necessitates a thorough assessment of their reliability and addressing potential undesired consequences related to AI. Quantifying uncertainties within ANNs is crucial for computing an additional output value reflecting prediction certainty, thereby informing users about potential deviations. [98], [99]

Before delving into uncertainty analysis in ANNs, it's essential to grasp the underlying sources. Aiding in comprehension, these uncertainties can be categorized into data and model uncertainties. [100]

1. **Data Uncertainty:** Data uncertainty stems from inherent inaccuracies due to noise or imperfect structuring, such as sensor-recorded data. Collecting more data doesn't fully mitigate this uncertainty, which can manifest as homoscedastic (constant variance) or heteroscedastic (variance dependent on input data). [101]
2. **Model Uncertainty:** Conversely, model uncertainty arises from insufficient training data, impacting the model's accuracy, especially in regions with limited reference data. This limitation hinders the model's generalization capability, affecting its representation of patterns and relationships in the data. [102]

An ensured **robustness** is crucial for ensuring reliable predictions within the dynamic landscape of ANNs. Robustness assessment involves gauging both training success and prediction quality. ANNs learn from data during training to capture patterns, while the prediction phase tests their adaptability to novel inputs. Deviations from expected values indicate low robustness, whereas accurate predictions for unknown data signify high robustness. Extending this evaluation to Out-of-Distribution (OOD) data enhances understanding of the network's robustness. [103], [104]

Modern development processes prioritize robustness, especially in early stages with limited data. This necessitates the incorporation of model uncertainty considerations. Model uncertainty, influenced by training data and accentuated in regions with scarce reference data, is integral to comprehensively assessing robustness. The analysis strategically focuses on areas involving new and unknown input data, offering a holistic perspective by integrating considerations of model uncertainty. [105]

Sensitivity analysis is crucial for understanding how ANNs respond to variations in parameters. The influences of network parameters, such as neuron count and learning rate, are evaluated for their impact on training outcomes. Assessing sensitivity becomes vital when predictions are required for previously measured inputs, as high sensitivity can lead to diverse effects and potential additional costs in real development processes. [106], [107]

Within sensitivity analysis, data uncertainty serves as an imperative measurement. It allows the evaluation and classification of predictions' sensitivity by determining uncertainty arising from disturbances in training and input data. This nuanced approach ensures a thorough understanding of how the network responds to variations in parameters and input variables, providing valuable insights for robust and reliable AI applications.

The following section presents a method developed in Paper IV, which uses appropriate techniques to pave the way for ignorance-competent AI and thus the appropriate application for each development phase.

Ignorance Competence through ensured Robustness and Sensitivity

In the realm of uncertainty analysis for network predictions, diverse techniques with unique strengths and drawbacks exist. Evaluating the performance characteristics of these procedures is crucial to discern their suitability for specific applications. Within Paper IV, a method was therefore developed to counter this situation with a suitable process, the aim of which is to enable proficient handling with AI. This can be seen in Figure 19. The details for the techniques can be read for example in [108], [109], [110] as well as in Paper IV.

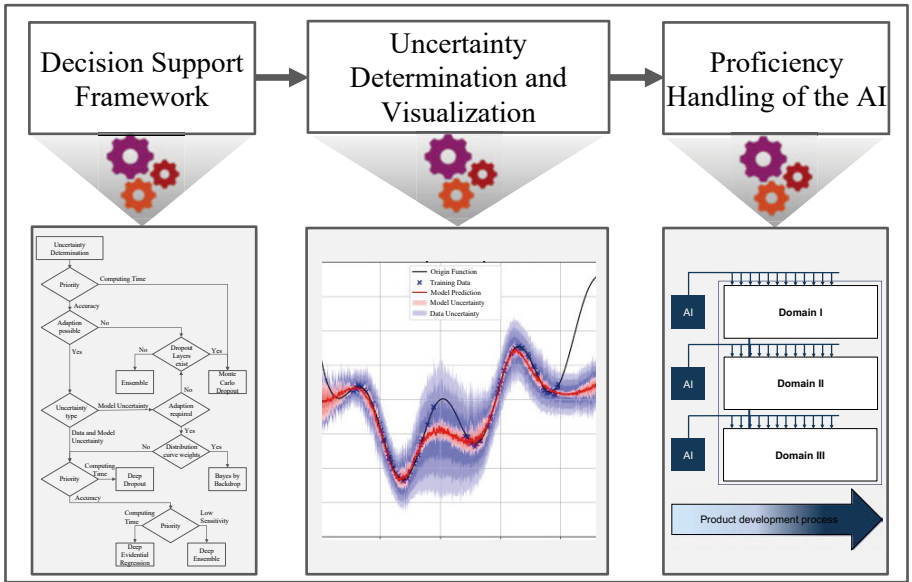


Figure 19: The method for the use of Robustness- and Sensitivity-checked AI, developed in Paper IV

Employing a decision tree approach, visualized in Figure 20, facilitates this assessment, guiding users to choose a routine aligning with their specific needs and situational requirements.

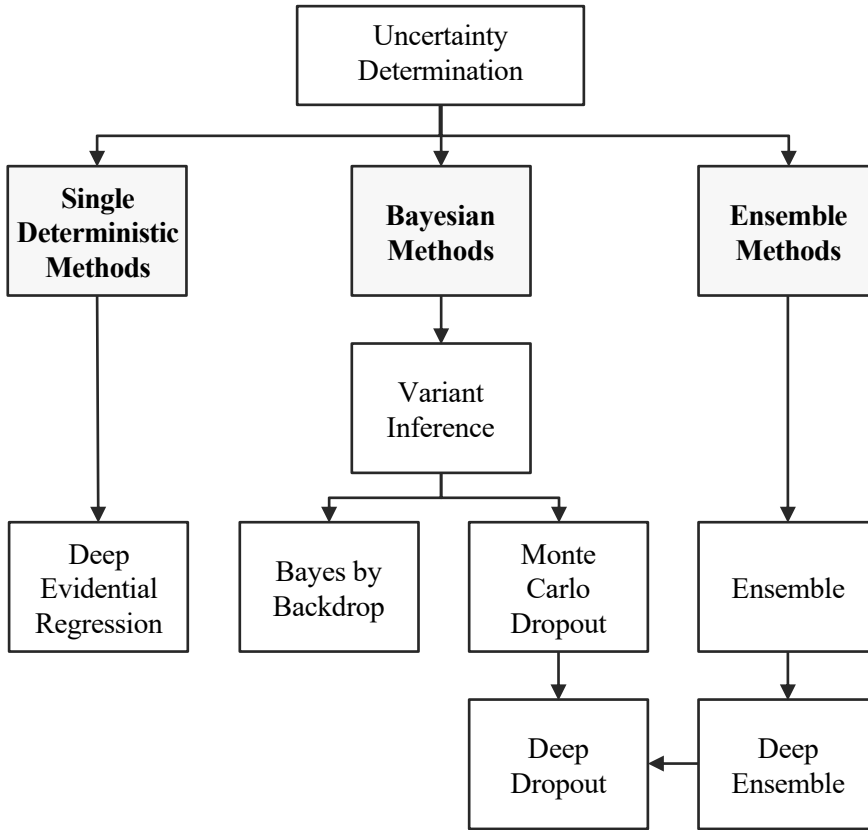


Figure 20: Overview of the techniques for determining uncertainty, developed in Paper IV

In order to gauge the suitability of these techniques for particular applications, it becomes imperative to thoroughly evaluate and analyze their performance characteristics. This comprehensive assessment is essential for making informed decisions about the most fitting approach based on the specific requirements and intricacies of the given application.

In the subsequent analysis, the goal is to subject the previously mentioned methods to testing, comparing their outcomes while considering their distinct underlying approaches. The evaluation focuses on assessing two crucial types of uncertainty: data uncertainty and model uncertainty.

For the performance test, a function that incorporates both a cosine and an exponential component is chosen. Additionally, a gap within the training data is introduced to scrutinize the behavior within the interpolation range.

In Figure 21, the left side visually represents the predictions of the methods post-training. The original function is depicted in black, and the training data is represented by the x-symbols. The network prediction is shown in red, accompanied by the variance displayed in pink. This diagram includes divisions into various variance ranges, based on the probabilities of the Gaussian normal

distribution. Notably, some of the presented methods possess the capability to distinguish between uncertainties and provide them based on their respective types, as illustrated on the right side. Here, the model uncertainty is represented in red, while the data uncertainty is displayed in blue.

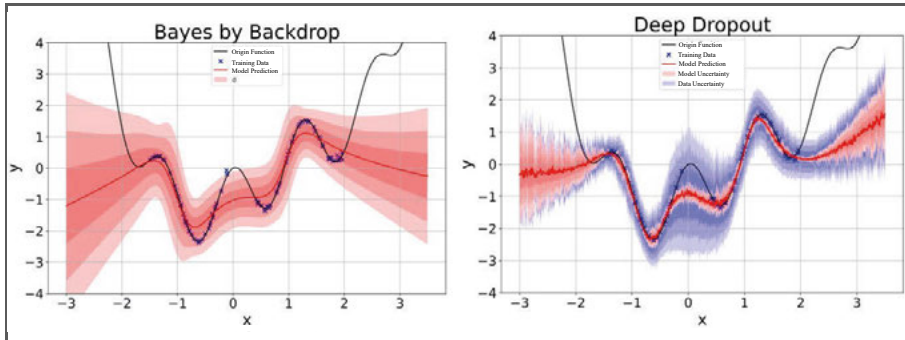


Figure 21: Exemplary results of the uncertainty determination, on the right with distinction between model (red) and data uncertainty (blue)

Following the analysis of the process results, the subsequent step involves the creation of a performance spectrum for each method. The outcomes are then assessed and visually represented in the form of a structured tree, serving as a decision-making aid. When employing uncertainty analysis for predicting ANNs, users can choose the most suitable method based on the available data and framework conditions. The decision tree offers users a navigational tool through different branches, allowing them to determine the most appropriate procedure tailored to their specific circumstances.

Given that each method comes with its own set of advantages and disadvantages, there is no universally preferred solution. Specific use cases create conditions where one method may excel, while another may yield different outcomes. Ultimately, the selection of the method hinges on the user and the application at hand.

The resulting decision tree from Paper IV is depicted in Figure 22. It allows the identification of the most suitable procedure, enabling users to interpret procedures and AI results effectively. This approach shifts away from perceiving them as black boxes, fostering proficiency in handling them. Consequently, AI-based prediction models can serve as effective communicators between domains in modern product development, fostering trust. More details can be found in Paper IV.

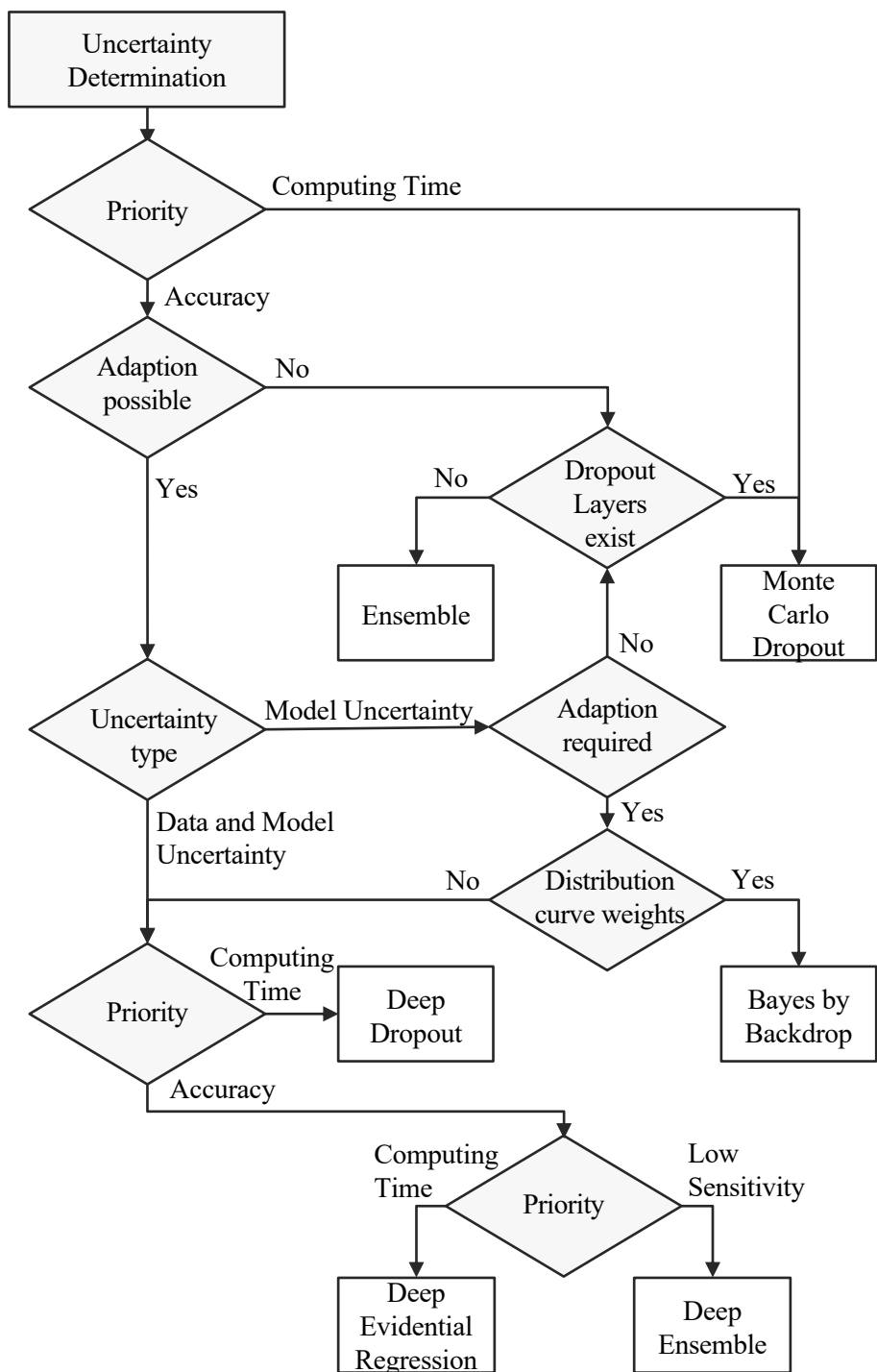


Figure 22: The resulting decision tree for practical applications

With regard to the development process, the developed methodology is particularly beneficial for the phase between Checkpoints 2 and 4 – as evident in Figure 23.

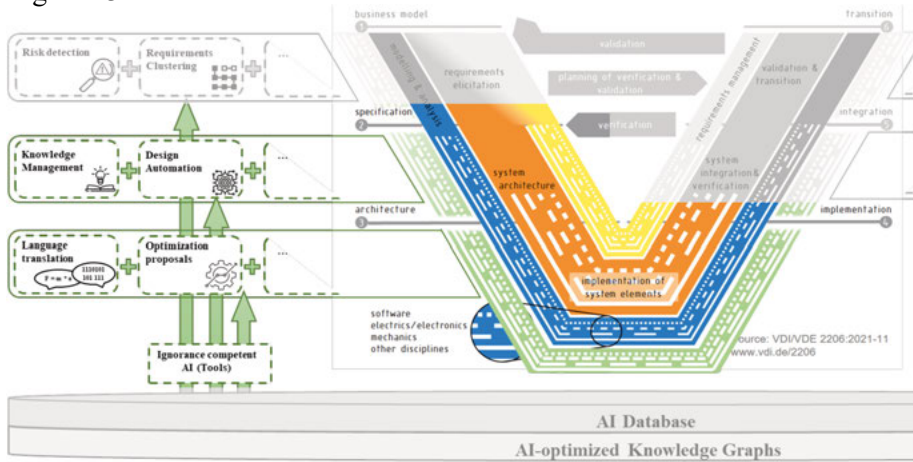


Figure 23: The placement of the Ignorance Competence through ensured Robustness and Sensitivity method within the development process

Here, the robustness of AI predictions, optimization suggestions, and translations must be known as precisely as possible. It is crucial to determine whether it is merely an early estimation or a reliable and safety-critical statement.

Addressing the 2nd research question

The second research question, developed in the Introduction, concerns

R2 How can the critical **analysis parameters for success** and the **ideally suitable segments of the development process** for the use of robust and context-sensitive artificial intelligence be identified?



and was methodically addressed.

Relevant requirement questions and corresponding metrics were proposed that could lead to the investigation with the aim of answering the stated question. The specially developed methods for the best possible use of robustness tests for AI were also presented in order to ensure application potential and requirements, as shown in Figure 7. The findings also show that AI can provide support in all phases, the conditions are just different. As a result, and on the basis of the progress made, it is possible to use AI safely and in line with requirements in mechatronic product development. At the same time, this means that the research question has been addressed and answered accordingly. In the next phase of the project, specific metrics & co. will be developed on the basis of the proof of concepts indicated, which can be used for subsequent validation.

Outlook: New System Design

Given the imperative to harmonize multifaceted requirements and disciplines throughout the process of mechatronic product development, the necessity for seamless integration across various domains becomes progressively apparent. Co-simulation frameworks offer a promising avenue for achieving this integration by allowing different components of a mechatronic system to interact in a simulated environment. [111], [112], [113]

However, ensuring effective communication and coordination among these disparate domains remains a significant challenge. The goal therefore is to explore the role of AI in facilitating the linking of diverse mechatronic domains within a co-simulation framework, as the process concept in Figure 24 demonstrates. Specifically, the focus is on three key aspects: translation, interpretation, and prediction.

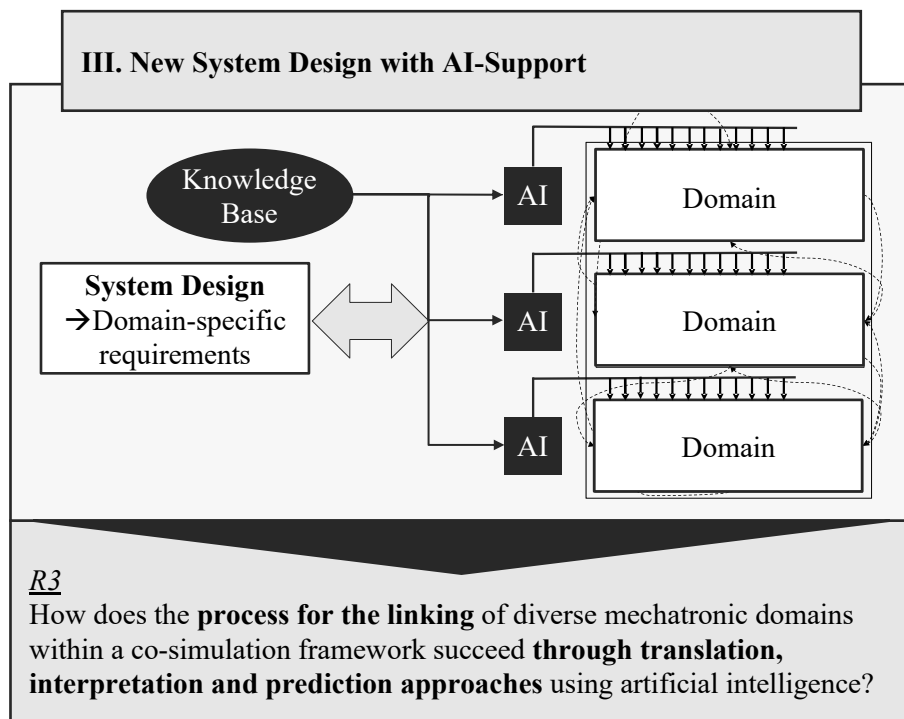


Figure 24: New System Design with AI-Support

Bridging the Gap Between Domains by Translation

One of the fundamental challenges in co-simulation is the disparity in representation and semantics across different domains. For example, mechanical and electrical systems often employ different modeling techniques and notations, making it difficult to establish meaningful connections between them.

AI techniques, particularly NLP and machine learning, can play a crucial role in bridging this gap. [114], [115], [116]

NLP algorithms play a pivotal role in the integration process by scrutinizing textual descriptions, specifications, and documentation linked with each domain. They extract pertinent details and transform them into a standardized format, streamlining the mapping of variables, parameters, and interfaces across various components. This harmonization facilitates smooth communication within the co-simulation framework. Furthermore, machine learning algorithms enhance this process by discerning patterns and relationships from historical data, progressively refining the accuracy and efficiency of the translation process. [117], [118], [119]

Interpretation: Extracting Meaning from Interactions

Once the various domains are linked within the co-simulation framework, the next challenge is to interpret the interactions and exchanges that occur between them and the associated players. This involves understanding the cause-and-effect relationships, identifying anomalies or deviations from expected behavior, and making real-time decisions to ensure the stability and performance of the overall system.

Incorporating AI techniques such as pattern recognition, anomaly detection, and decision-making algorithms significantly enhances the integration process. These algorithms analyze the data streams generated by each domain during simulation, enabling them to discern patterns of interaction and identify any unusual or unexpected behaviors.

Subsequently, appropriate corrective actions can be taken. For example, a decision tree algorithm trained on historical data can analyze the current state and inputs of a mechatronic system to predict potential future paths. By identifying critical decision points and their likely outcomes, the system can proactively adjust its parameters or configurations, thereby mitigating the risk of undesirable outcomes before they occur. [120], [121]

Prediction: Anticipating Future States

In addition to interpreting the present interactions within the co-simulation framework, AI can also be used to predict future states and behaviors of the integrated mechatronic system. This proactive approach enables preemptive decision-making and optimization, leading to improved performance, reliability, and efficiency.

Machine learning techniques such as regression, time series analysis, and reinforcement learning can be employed to forecast the evolution of system variables and parameters over time. By learning from historical data and incorporating real-time feedback from the simulation environment, these algorithms can generate accurate predictions of future states, enabling advanced

control strategies and optimization algorithms to be applied. [122], [123], [124]

AI-Enabled Co-Simulation of Design and Production

Let's think of the scenario from the Introduction again: integrating the design and production domains within a co-simulation framework is essential for optimizing processes in industries like manufacturing, design, and infrastructure development.

In this case, the design domain involves activities such as site layout planning, material procurement, scheduling, and resource allocation. On the other hand, the production domain encompasses manufacturing processes, supply chain management, inventory control, and quality assurance.

By integrating these two domains using a co-simulation framework, it is possible to optimize the entire lifecycle of a design project, from planning and design to execution and delivery. However, the complexity of coordinating activities across these domains poses a significant challenge.

AI techniques can play a crucial role in addressing this challenge by enabling seamless communication and coordination between the design and production domains.

NLP algorithms offer a prime example of this capability. They sift through textual descriptions, specifications, and documentation linked to design plans and production schedules. In doing so, these algorithms extract pertinent details and convert them into a standardized format. This process streamlines the mapping of tasks, resources, and dependencies between the design and production domains, fostering seamless integration.

Following NLP's preparatory work, machine learning algorithms step in to interpret interactions and exchanges between the design and production processes. Leveraging historical data and real-time feedback from sensors and monitoring systems, these algorithms scrutinize patterns of behavior, pinpoint bottlenecks, and inefficiencies. Subsequently, they generate data-driven recommendations for optimizing processes, thus enhancing overall efficiency.

Furthermore, predictive analytics can anticipate future states and outcomes, enabling proactive decision-making and risk management. For example, machine learning models can forecast the availability of materials and resources, predict development delays or production bottlenecks, and optimize scheduling and resource allocation to mitigate potential risks.

Summary and Conclusion

In conclusion, the imperative for intelligent data and potential analysis in mechatronic product development is well-founded, given the persistent challenges related to synchronization and efficiency. The substantial advancements in AI, particularly in generative AI, present unprecedented opportunities. While some pioneering companies have already embraced proprietary AI solutions, it is evident that significant challenges, particularly in terms of robustness and trustworthiness, remain unaddressed.

Responding to these pressing needs, two fundamental research questions have been successfully addressed and answered.

Firstly, the comprehensive methodology introduced examines the entire development process through the illustrative V-Model and strives to establish a robust AI landscape. This approach effectively identifies, evaluates, and delimits the relevant areas of knowledge and non-knowledge in mechatronic development processes, reaching an acceptable level of ignorance competence through targeted knowledge mining.

Secondly, first critical analysis parameters for success and the ideally suitable segments of the development process for the use of robust and context-sensitive AI have been identified. By addressing diverse requirements for accuracy and other factors at various stages of development, the created method ensures the integration of AI is both effective and efficient.

Notably, a decision support framework has been crafted, empowering users to interpret procedures and model results. This approach moves away from perceiving AI as black boxes, fostering a sense of proficiency in effectively managing them.

While navigating through the evolving landscape of mechatronic product development, integrating intelligent data and harnessing the power of AI not only addresses current challenges but also positions organizations for greater innovation and competitiveness in the dynamic market landscape.

The comprehensive examination of the theoretical and methodological aspects concludes this chapter. The transition to the application examples, illuminating the practical implementation of the findings, is now warranted.

Future Work

Looking ahead, the next phase of the project demands a meticulous examination of the real-world practical situation. This involves delving into the intricacies of mechatronic product development, understanding the nuances of challenges faced by industry practitioners, and identifying specific pain points that intelligent data and potential analysis can address.

The exploration will extend to applications and methods pertaining to the lower and right sides of the V-Model. This involves a detailed consideration of implementation strategies, testing procedures, and validation methodologies. Understanding how AI can seamlessly integrate into the execution phase and the subsequent testing and validation processes is essential. This phase aims to bridge the gap between theoretical concepts and practical applicability, ensuring that the proposed methodology aligns seamlessly with the realities of mechatronic product development.

Additionally, the project will advance to the stage of proving the concept(s), as already mentioned for the interaction between design and production as an example. This involves the practical demonstration of the proposed methodology in a controlled environment, verifying its effectiveness in addressing challenges and optimizing the product development process. The proof of concept(s) will serve as a crucial validation step, providing tangible evidence of the viability and potential impact of intelligent data and potential analysis in mechatronic product development.

Through these successive steps, the project aims to refine and validate the proposed methodology, ensuring its practical relevance and effectiveness in real-world scenarios. The outcomes of this phase will contribute not only to the academic understanding of the subject but also to the practical implementation and adoption of intelligent data and potential analysis in the dynamic field of mechatronic product development.

Summary of Papers

This chapter summarizes the content of the papers on which this thesis is based upon and describes the author's contribution to each paper.

Paper I

Leveraging Robust Artificial Intelligence for Mechatronic Product Development—A Literature Review

This paper explores the existing literature regarding the application of AI as a comprehensive database, decision support system, and modeling tool in mechatronic product development. It analyzes the benefits of AI in enabling domain linking, replacing human expert knowledge, improving prediction quality, and enhancing intelligent control systems. For this purpose, a consideration of the V-cycle takes place, a standard in mechatronic product development. Along this, an initial assessment of the AI potential is shown and important categories of AI support are formed. This is followed by an examination of the literature with regard to these aspects. As a result, the integration of AI in mechatronic product development opens new possibilities and transforms the way innovative mechatronic systems are conceived, designed, and deployed. However, the approaches are only taking place selectively, and a holistic view of the development processes and the potential for robust and context-sensitive AI along them is still needed.

The author was the main person responsible for selecting, analyzing and subsequently evaluating the literature. Moreover, the author wrote the paper.

Published in *International Journal of Intelligence Science* in January 2024.

Paper II

Intelligent analysis of components with regard to significant features for subsequent classification

This paper develops an intelligent method to analyze existing data appropriately and, at the same time, prepare it ideally for further applications, such as forecast models based on AI. To achieve this, several steps need to be taken. Firstly, a suitable segmentation of the component is performed. The aim is to detect areas in a component where features and form elements are found. Other regions are ignored after the inspection by segmentation and voxelization. Subsequently, the voxelization of the component takes place, which

results in the three-dimensional component or Computer- Aided-Design file being mathematically readable. This is done by rasterizing the component based on a previously selected resolution and other upcoming steps. Finally, the segmented and relevant areas are analyzed accordingly.

The author developed the concept and method regarding the Intelligent analysis of components. Moreover, the author wrote the paper.

Published in SAE Technical Paper, presented orally by the author in July 2023, Stuttgart, Germany.

Paper III

Intelligent Component Manufacturability Testing in Virtual Product Development

The paper implements a series of steps to address the increasing knowledge acquisition in the automotive industry. It emphasizes a targeted approach to information processing and evaluation, with AI playing a key role. AI is used to assess existing knowledge, assign attributes, and assist in the economic evaluation of new components or projects. The integration of intelligent methods enables companies to make informed decisions regarding resource allocation, time management, and project feasibility. Additionally, AI-based approaches are combined with preprocessing to handle the knowledge explosion and enable efficient analysis of product manufacturability.

The author developed the concept and method regarding the Intelligent Component Manufacturability Testing. Moreover, the author wrote the paper.

Published in Proceeding of Artificial Intelligence und Machine Learning in der CAE-basierten Simulation, presented orally by Fabian Richter in October 2023, Munich, Germany.

Paper IV

Robustness and Sensitivity of Artificial Neural Networks for Mechatronic Product Development

This paper aims to evaluate the performance characteristics of different uncertainty analysis methods and assess their applicability in agile automotive development processes. By considering the specific requirements and constraints of each method, a decision tree is proposed to recommend suitable and situation-appropriate methods for performing uncertainty analyses in network prediction. The goal is to enhance data exchange between departments, mitigate disruptions, and ensure informed decision-making throughout the development process.

The author developed the concept and method regarding the final decision tree for the efficient use of Robustness and Sensitivity. Moreover, the author wrote the paper.

Published in Proceedings of Automotive meets Electronics and presented orally by the author in June 2023, Dortmund, Germany.

Paper V

Integration of Vulnerable Road Users Behavior into a Virtual Test Environment for Highly Automated Mobility Systems

This paper describes an approach to integrate real human traffic behavior into the approval and testing process of highly automated vehicle systems. It provides a safe and valid way to test critical traffic scenarios between vehicles and pedestrians. Basically, two different methodologies for the metrological detection of human movements are analyzed and experimentally examined for their suitability for this use case. Besides the general functionality, plausibility and real-time capability are further investigation criteria. The paper concludes with the integration of the proposed solution into a test bed for highly automated vehicle systems using a representative traffic scenario.

The author was involved in discussions, supported implementation and assisted in writing the paper.

Published in Proceedings of Kolloquium Future Mobility in June 2022, Ostfildern, Germany.

Paper VI

Methodical Approach to Integrate Human Movement Diversity in Real-Time into a Virtual Test Field for Highly Automated Vehicle Systems

This paper measures, processes and integrates real human movement behavior into a virtual test environment for highly automated vehicle functionalities. The overall system consists of a georeferenced virtual city model and a vehicle dynamics model, including probabilistic sensor descriptions. By using motion capture hardware, real humanoid behavior is applied to a virtual human avatar in the test environment. Through retargeting methods, the virtual avatar diversity is increased. To verify the biomechanical behavior of the virtual avatars, a qualitative study is performed, which is based on a representative movement sequence.

The author was involved in discussions, supported implementation and assisted in writing the paper.

Published in Journal of Transportation Technologies in July 2022.

Paper VII

Data Flow Management Requirements for Virtual Testing of Highly Automated Vehicles

This paper presents a virtual co-simulation approach for highly automated vehicle systems and uses it to demonstrate the data management requirements for a co-simulation platform such as AVL Model.CONNECT™. The basis for this is a real urban driving cycle for modern hybrid vehicles to investigate emissions, consumption and range as well as the effects of highly automated driving functions on these parameters.

The author was involved in discussions, supported conducting the study and assisted in writing the paper.

Published in Proceedings of AVL German Simulation Conference and presented orally by René Degen in September 2022, Regensburg, Germany.

Paper VIII

Stereoscopic Camera-Sensor Model for the Development of Highly Automated Driving Functions within a Virtual Test Environment

This paper documents the development of a sensor model for depth estimation of virtual three-dimensional scenarios. For this purpose, the geometric and algorithmic principles of stereoscopic camera systems are recreated in a virtual form. The model is implemented as a subroutine in the Epic Games Unreal Engine. Its architecture consists of several independent procedures which enable a local depth estimation and a reconstruction of an entire three-dimensional scenery. In addition, a separate program for calibrating the model is presented.

The author was involved in discussions, assisted in writing the paper and supported implementation as well as evaluation.

Published in Journal of Transportation Technologies in January 2023.

Paper IX

Development and Analysis of a Detail Model for Steer-by-Wire Systems

This paper presents an innovative nonlinear detailed model of a Steer-by-Wire system. The detailed model represents all characteristics of a real Steer-by-Wire system. In the context of a dominance analysis of the detailed model, all dominant characteristics of a Steer-by-Wire system, including parameter dependencies, are identified. Through model reduction, a reduced model of the Steer-by-Wire system is then developed, which can be used for a subsequent robust control design. Furthermore, this paper compares the Steer-by-Wire system with a conventional electromechanical power steering and shows similarities as well as differences.

The author was involved in discussions, assisted in writing the paper and supported implementation as well as evaluation.

Published in IEEE Access Journal in January 2023.

Paper X

Design of a Model-Based Optimal Multivariable Control for the Individual Wheel Slip of a Two-Track Vehicle

This paper presents a model-based optimal multivariable control for the wheel slip, which allows specifying the wheel slip and thus the tire force individually for each wheel. The plant model consists of a multibody two-track model of a vehicle, a tire model, an air resistance model and a motor model. In addition, the contact forces of the individual wheels are calculated dynamically. The resulting nonlinear model is linearized and used for the design of a linear optimal static state-space controller with reference and disturbance feedforward. The contact point velocities at the wheels are defined as the controlled variables, since they are proportional to the wheel slip and thus to the driving forces within the operating range of the controller. Furthermore, the rates of change of the contact point velocities are also chosen as controlled variables to set the damping of the closed-loop system. The four drive torques of the wheels represent the control variables. Therefore, a true multivariable control is developed. In the first step of the analysis, the linearized closed-loop system is investigated regarding stability, robustness and its dynamic behavior. The control system shows a high bandwidth, well-damped dynamic behavior and a large phase margin. In the second step of the analysis, various simulations of realistic experiments, such as an accelerated cornering maneuver or the Fishhook road test, are performed with the nonlinear closed-loop system. The results of these experiments confirm the high robustness and good dynamic behavior of the control system in most cases. Moreover, the results demonstrate how the control considers the dynamic contact forces of the wheels to achieve the requested wheel slip at any time. Lastly, dominant transfer paths are identified based on the gain matrix of the state-space controller, showing which input and state variables have a significant influence on the control variables.

The author was involved in discussions, assisted in writing the paper and supported implementation as well as evaluation.

Published in SAE Technical Paper, presented orally by Robert Rosenthal in July 2023, Stuttgart, Germany.

Paper XI

Methodical Data Collection for Light Electric Vehicles to Validate Simulation Models and Fit AI-based Driver Assistance Systems

This paper presents an approach to collect vehicle dynamic parameters for the validation of simulation models. For this purpose, a measurement system is developed to capture and monitor driving dynamic information of the device under test in real time. This data is used to fit pre-developed simulation models and DAS. To investigate the vehicle dynamic behavior in critical driving situations, an extensive test study is conducted. Therefore, different ordinary driving situations in urban traffic scenarios are analyzed. Finally, the collected measured data is compared with the simulation results of a multi-body model for a multi-lane cargo vehicle.

The author developed the simulation model, the measurement setup and the verification study. Additionally, he supervised the realization of the study. Moreover, the author wrote most parts of the paper.

Published in Proceedings of Kolloquium Future Mobility in June 2022, Ostfildern, Germany.

Svensk Sammanfattning

Denna avhandling utforskar nödvändigheten av intelligent data- och potentialanalys inom mekatronisk produktutveckling. De ständiga utmaningarna med synkronisering och effektivitet understryker behovet av avancerade metoder. Att utnyttja de betydande framstegen inom AI, särskilt inom generativ AI, ger oöverträffade möjligheter. Det finns dock fortfarande betydande utmaningar, särskilt när det gäller robusthet och tillförlitlighet.

Som svar på detta kritiska behov introduceras en omfattande metodik som undersöker hela utvecklingsprocessen genom den illustrativa V-modellen och strävar efter att skapa ett robust AI-landskap. Metoden utforskar hur man skaffar sig lämplig och effektiv kunskap, tillsammans med metodisk implementering, för att hantera olika krav på noggrannhet i olika utvecklingsstadier. Ett ramverk för beslutsstöd ger användarna möjlighet att tolka procedurer och modellresultat, så att AI inte längre uppfattas som svarta lådor utan kan hanteras på ett effektivt sätt.

I takt med att landskapet för mekatronisk produktutveckling utvecklas kan man genom att integrera intelligenta data och utnyttja kraften i AI inte bara hantera aktuella utmaningar utan också positionera organisationer för ökad innovation och konkurrenskraft i det dynamiska marknadslandskapet.

Acknowledgement

The research findings presented in this thesis were obtained during my time at the CAD CAM Center Cologne. I extend my heartfelt gratitude to my supervisor, Margot Ruschitzka, for providing me with the opportunity to pursue my PhD studies. Her strategic ideas and guidance aspects have been invaluable throughout this journey. I am also grateful to Cecilia Boström, my co-supervisor, for her unwavering support and insightful contributions. Her introduction to the unique aspects of doctoral studies at the Division of Electricity, Uppsala University, has been immensely beneficial.

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