Human-AI Teaming in a Digital Twin Model for Virtual Product Development

Atefeh Gooran Orimi,*
Sascha Saralajew,
Jiatai Feng,
Zhuoqun Dai,
Rayen Hamlaoui,
Timo Stauss and
Roland Lachmayer

Digital Twin Models (DTMs) are key to Industry 4.0, improving manufacturing and product development through AI. They enable real-time monitoring, predictive maintenance, and optimization across the product lifecycle. However, none human-comprehensible AI algorithms, especially deep neural networks, present challenges. In this regard, this study explores human-AI collaboration to create an AI-driven DTM for virtual product development. We propose a DTM that combines AI and expert knowledge to enable informed decision-making for product design optimization. For this, the architecture and functionality of the developed model will be first outlined, and further, the application of the model will be demonstrated in analyzing LiDAR systems.

Introduction

The concept of Digital Twin Models (DTMs) has significantly developed in recent years, especially with the advances in the Internet of Things (IoT) and the rise of Industry 4.0. The model mirrors the attributes, states, and behaviors of the investigated physical entities in the virtual space [1–3]. Intuitively, DTMs allow for efficient storage and analysis of product-related data throughout the entire Product Lifecycle (PLC), from the early design conceptualization stage to further use and recycling. Among these, the product development stage is crucial in the product and the DT lifecycles. In fact, during the conceptualization and development phases, what is known as the 'digital prototype' or 'digital model' (e.g., [1, 4, 5]) of a product is created, which sets the foundation of the considered DTM.

During the development phase of PLC and the early stage of building the investigated DT (A) data from previous generations is utilized to identify product faults and integrate market preferences, shaping the new generation of the product. This involves analyzing vast volumes of data aggregated from earlier DTs, encompassing horizontal and vertical data related to the product in previous generations [6–8]. (B) The data obtained during the new generation of the product is used to evaluate the system's configuration for further product development. This data may include simulated data or real data collected from product prototypes. In this regard, well-established models assess the behaviors of the system based on the design expectations and objectives and identify the different positive and negative behaviors, specifically the Unpredicted Undesirables (UUs) [9], to make an informed decision. In fact, through iterative simulations and analysis, the number of errors should be decreased to optimize and refine the virtual product and its prototype.

Nonetheless, despite the pivotal role of the product development phase, most existing studies on DTs have focused pre-

* **Corresponding Author**
Dr. Atefeh Gooran Orimi; Leibniz University Hannover, Institute of Product Development (IPeG); An der Universität 1, 30823 Garbsen; Phone: +49 (0) 511 762 4338, E-Mail: gooran-orimi@ipeg.uni-hannover.de

Co-authors
Dr. rer. nat. Dr.-Ing. Sascha Saralajew; NEC Laboratories Europe GmbH, Heidelberg
Jiatai Feng, M.Sc.; IPeG at Leibniz University Hannover
Zhuoqun Dai, M.Sc.; IPeG at Leibniz University Hannover
Rayen Hamlaoui, M.Sc.; IPeG at Leibniz University Hannover
Timo Strauss, M.Sc.; IPeG at Leibniz University Hannover
Prof. Dr.-Ing. Roland Lachmayer; IPeG at Leibniz University Hannover

Note
This article is peer reviewed by the members of the ZWF Special Issue Advisory Board.

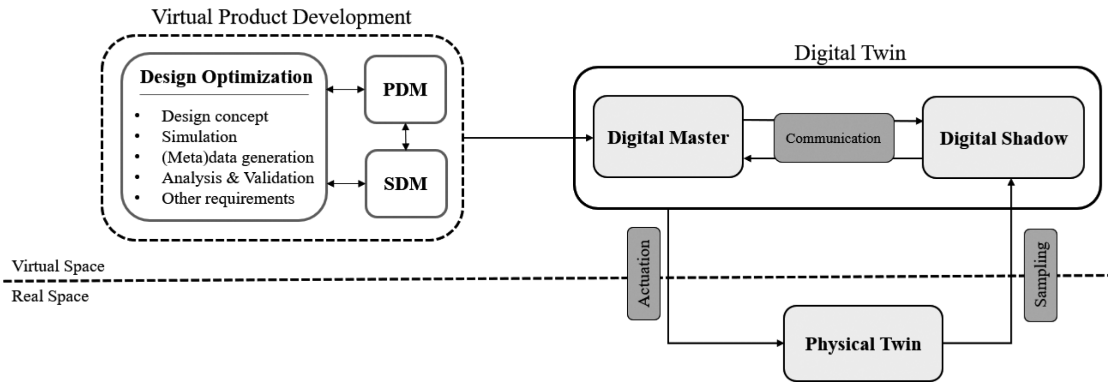

Figure 1. The investigated DTM

dominantly on the manufacturing process and the post-production phase of the products [10, 11]. Consequently, the role of product development within this context of DTM and, importantly, how current Artificial Intelligence (AI) methods can be exploited in the process remain underexplored. Thus, in contrast to previous studies that have mainly focused on the capabilities of DTMs at the actual production stage, we here investigate the product As-Designed.

To this end, the current work focuses on the initiation and modeling phases of the DT lifecycle corresponding to the product development phase of the PLC (see, e. g., [12] for a comparison). The aim is to enhance virtual product development as the basis for building an AI-based DTM by using an AI and human experts teaming (referred to as human-AI teaming). Such a human-in-the-loop procedure can utilize the power of both aspects and enhance the design and other conceptual stages of product development. This can effectively minimize the expensive costs of trial and error with physical product developments by detecting potential sources of defects and validating the design parameters for product quality assurance.

The paper is organized as follows: Section 2 discusses the general specification of the DTMs and how AI models have been explored in related work. Later, Section 3 discusses the investigated AI-driven DTM. Moreover, Section 4 is devoted to the investigated use case, where we demonstrate the applicability of the proposed approach using an ongoing project on Light Detection and Ranging (LiDAR) systems. For this, we assess the performance of LiDAR, focusing on its angular resolution, and explore how a human-AI teaming can consider design precision and optimize the system's performance (for the specific tasks of object detection). Finally, Section 5 concludes the paper with a short discussion on future work.

Related Work

Our work at the Institute of Product Development and Equipment Construction (IPeG) at Leibniz University Hannover focuses on product development. It investigates how AI models can assist engineers during this process. Previous work includes the concept of design for additive manufacturing [13–15] and in conjunction with technical inheritance [8, 16], as well as DTM for distributed systems [17]. In the following, we discuss the state-of-the-art DTMs, DT throughout the PLC, and AI's role in DTMs.

Digital Twin Models

The concept of the DTMs was first introduced by Grieves [1–3] within the context of product lifecycle management in engineering. In general, a standard DTM consists of three key components: (A) the real space, which consists of the actual or intended physical entity, also known as the Physical Twin (PT); (B) the virtual space that hosts the corresponding digital counterparts, referred to as Digital Twins (DTs), (C) the digital thread, which bridges the physical and virtual spaces by establishing a communication between and within the two spaces [1, 4, 5, 18].

A distinguishing characteristic of DTMs is their ability to establish bidirectional communication between and within physical and virtual spaces [1, 19]. In a DTM, data flows from the physical environment to the virtual space, enabling continuous processing and extraction of critical insights. The obtained information is then transferred back to the real space to optimize real-world operations. This ongoing exchange of data and information forms a digital thread throughout the PLC, which supports seamless decision-making and operational enhancements (see, e. g., [19–21] for a complete discussion).

Recent work by *Stark, Anderl et al.* [4], conducted under the Wissenschaftlichen Gesellschaft für Produktentwicklung (WiGeP) association in Germany, categorizes DTs (the corresponding part of the virtual space) into two distinct parts of Digital Master (DM) and Digital Shadow (DS), where each part relates to different attributes of the framework (see Figure 1 which will be discussed further below). The DM encompasses meta-data, design parameters, and simulation data and models for product development, primarily generated during the early stages. On the other hand, the DS includes the data and all the related processing and is continuously updated with data collected from the physical object throughout the operation or maintenance phase of the lifecycle [22, 23]. The studies emphasize that a DT will be completed after the actual production of the product, where the corresponding DSs are established.

Furthermore, the communication between DM and DS is likewise established using different tools, such as Simulation Data Management Digital Twin (SDM-DT) [24–25], and Virtual Part Inspection (VPI) [26], discussed in previous related studies. Data collection enables DS to provide up-to-date information that enhances simulation models, monitoring, and predictive analysis.

In another study, *Eigner et al.* [19] discussed the concepts of digital models and digital twins in DTMs (also see [20, 27]). The digital model counts as the basis for implementing DTs, which will be defined during the early "Concept and Design" phase of the PLC and further updated and enriched throughout the PLC. The digital twins are later defined as the instances from the digital model that occur in the production phase.

DT Throughout the Product Lifecycle

A DT's lifecycle is tied to its physical counterpart's product lifecycle [2, 25], and the connection has been discussed in previous works based on a specific definition of the DT. In this regard, *Grieves and Vickers* [28] in 2017 classified DTs into two types: Digital Twin Prototype (DTP) and Digital Twin Instance (DTI). The former corresponds to the creation and sharing of detailed system designs, enabling simulations and assessments (sometimes even without the need for costly physical prototypes), while the latter represents a physical product virtually and remains linked to it throughout its lifecycle. The two types of DT are further discussed in connection to the four PLC phases of "Creation", "Production", "Operation", and "Disposal".

Based on this definition and in the Creation phase, the physical product does not yet exist. It takes shape in virtual space as a DTP by analyzing and defining system requirements, characteristics, and parameters. Iterative simulations are performed to predict desirable and undesirable behaviors while minimizing unforeseen adverse outcomes. The Production phase involves implementing the physical system and its synchronization with the virtual system, creating a bidirectional data flow that links the physical and virtual components. During the Operation phase, real-time data exchange supports predictive maintenance and performance optimization by correlating state changes with potential failures. Finally, the Disposal phase leverages data from previous system generations to prevent recurring issues and optimize future systems while addressing environmental concerns. This systematic approach enables the DT to evolve as a complex system and highlights its significance in Industry 4.0.

The concept of "digital twin lifecycle" was further discussed by *Schützer et al.* [29] in 2019. The work aimed to create a DT that integrates both the product and its development process, follows a lifecycle approach from design to manufacturing and usage. Based on their definition, the DT is first conceived within the Creation phase and will be completed and implemented at the end of the Production phase as the virtual and physical systems are functional and linked. The work also enhanced the DT by integrating AI, turning it into a "Smart Digital Twin" to improve its capabilities further.

In another line of research in 2019, *Stark and Damerau* [30] investigated and analyzed various aspects of developing and operating DTs and provided a new definition of DT lifecycle based on the concept of DM and DS. Correspondingly, they considered four phases for the DT lifecycle of "Initiation", "Modeling", "Enrichment and Utilization", and "Reuse". "Initiation" encompasses tasks such as market research and defining the requirements for the operational needs and potential opportunities. During this phase, DM is established by integrating input parameters, requirements, and architectures. Moreover, "Modeling" corresponds to the design phase of the PLC. In this phase, DM will be completed by models and simulations of the product in the virtual space. "Enrichment and Utilization" further aligns with production planning, production, and the Operation phase of the PLC, where DT evolves by utilizing data collected from the DS. This phase overlaps with the "Modeling" phase, taking the modeling and fundamental information from that phase and ensuring that the DT is actively utilized to enhance the product's performance and user experience. Finally, the "Reuse" phase corresponds to the end-of-life stage of the PLC. In this phase, knowledge and outputs from the existing DT are leveraged to create and improve the next generation of the product.

In [5], *Eigner et al.* considered the three phases of "prototype-twin-phase", "production-twin- phase", and "service-twin-phase-as-maintained" for a DT lifecycle corresponding to "Design", "Production", and "Maintenance" phases of PLC.They explained that the product will be developed first as a "digital model" during the "as-designed" and "prototype-twin-phase" in both product and DT lifecycles, respectively.

Later, in 2023, Grieves [1] completed his definition in [28] by defining a new type of DT named Digital Twin Aggregated (DTA), corresponding to the disposal phase in PLC. DTAs are longitudinal and latitudinal representations of product behavior from individual DTIs to predict future behaviors such as product failures. The definition further closes the loop between product design and real-world product behavior to prevent recurring flaws in future product generations. Additionally, Anderl et al. [7] provided a similar concept by discussing the vertical and horizontal product data obtained throughout the PLC. Earlier, *Lachmayer and Mozgova [*8] presented the idea of Technical Inheritance by leveraging life cycle data from previous product generations to shape new product development. This approach incorporates systematic data collection, monitoring, and analysis to facilitate continuous improvement and prevent design flaws across generations.

In our contribution here, the main focus is on product development using the DT concept. Based on the discussion above, product development and creating the digital twin prototype shape the DTs' foundation. Compared to the other phases of the PLC and the DT lifecycle, the initial development and design processes and the DM have received comparatively little attention from researchers and engineers. This is important when we realize virtual prototyping significantly reduces physical prototyping costs and time. In this regard, there is still a gap in how advanced AI and ML algorithms can be exploited to optimize the virtual product design of a desired product within the DTM.

AI in Engineering and Manufacturing

Recent advancements in data science and AI have significantly broadened the capabilities of DTs. In this regard, integrating AI into DTs has become essential to enhance their accuracy, predictive power, and decision-making functionality [18, 31, 32]. Standard AI models utilize potent algorithms to solve complex prediction tasks, which have been of great interest in promoting innovative and AI-based product development processes [33, 34].

They enable more dynamic and effective DTs throughout the entire PLC.

In general, vast volumes of usually heterogeneous data are generated by the manufacturing processes. In general, such AI systems investigate the key questions of "What happened?", "Why did it happen?", "What will happen in the future?", "What action should be taken?" throughout the PLC [35]. To address these questions, data analytics approaches, including descriptive, diagnostic, predictive, and prescriptive analytics, are respectively explored in the literature [22, 36].

While managing and analyzing such volumes of data offers the opportunity to extract valuable information and knowledge, it also significantly increases the complexity of the corresponding data analysis methods. Recent advancements in AI and ML, particularly in deep learning algorithms [37, 38], generative models [39], Large Language Models (LLMs), and foundation models [40, 41, 42], have facilitated this process by improving methods for handling such data, allowing for the extraction of more accurate and meaningful information.

Nevertheless, many of the previously established AI systems operate as black-boxes, meaning their decision processes are opaque and difficult for users or developers to interpret. Such a black-box nature poses challenges, especially:

- if developers want to improve the AI system to fix identified errors and
- if they‘re going to understand the decision process of the AI system to enhance their mental model or to enable an efficient decision.

To address these challenges, researchers are developing post-processing methods to make black-box AI systems more interpretable, known as eXplainable AI (XAI) systems [43]. However, these post-hoc explanation methods can only approximate the actual reasoning process of the AI model, meaning that the explanations provided may not always be entirely accurate. Opposed to black-box models are white-box AI systems (e.g., prototype-based learning systems [44]), methods that are inherently interpretable and understandable to humans.

While the AI community continues to discuss and define contexts in which black-box or white-box models are most appropriate [45], XAI provides opportunities that should be considered to unlock the full potential of AI systems. The choice also depends on the specifics of the considered use case. It is increasingly shaped by regulations like the EU AI Act, which requires transparency for specific AI systems based on risk categories. While AI systems used in production and engineering (where the AI is not directly part of the product) generally fall outside the EU AI Act's scope, XAI offers new possibilities.

The Investigated AI-Driven DTM

As discussed, our primary focus is to enhance product design and development within the context of DTMs. We build upon the model proposed by *Stark, Anderl et al.* [4] and assume a model encompassing DM and different DS(s) in the virtual space. Importantly, we exploit AI algorithms to enable optimal product design and shorter development cycles to expand the creative work of the engineer. To ensure such a process, an efficient human-AI teaming is investigated. AI and advanced ML algorithms provide solutions or recommendations, and later, the engineer realizes and executes validation and design decisions. The engineer can extend and build on the proposed decisions by the model. If such a teaming is efficient, humans and AI will complement each other as, for instance, the AI can quickly process huge databases on a scale, and humans can understand common sense. The teaming is, therefore, based on a mutual understanding, which further promotes XAI.

The structure of the investigated DTM is illustrated in Figure 1. To explain the details of the model, we begin with the product development phase in the virtual space. In this phase, the DT is conceptualized, even before the physical product exists or when it is based on a previous generation model. Thus, the new generation of the product evolves from an initial concept to an optimized design before actual manufacturing begins. This phase is characterized by gathering information and requirements for virtual product development, as assigned to the DM (see, e.g., [26]). Once the virtual product design is finalized, it is transferred to the real space for manufacturing, represented as a PT in Figure 1. The DT entirely takes shape at the end of this phase, when the physical product is manufactured, and data from the physical product is fed back into the virtual space.

Throughout the DTM, particularly during the operational phase of the product, vast amounts of data are generated from various sources based on the product's performance in the market. This data is continuously sampled from the real space and transferred to the virtual space. The data is processed in DS(s), and as the physical and virtual systems are twinned, changes such as part replacements or state transitions can occur in both systems. Information is often transferred back to the physical space through actuators (e.g., [9]). Ultimately, the collected data, aggregated throughout the entire PLC, is utilized in the Disposal phase, e.g., failure prediction using AI and ML models.

In virtual product development, three main components are involved: Design optimization, Product Data Management (PDM), and Simulation Data Management (SDM). The former focuses on the requirements of each iteration step to achieve the optimal product design, while the latter two components are responsible for managing simulated data. In this framework, advancements in ML algorithms can facilitate the process by reducing iteration cycles, enhancing the creativity of design engineers, and improving accuracy. For example, generative models can be utilized to create new CAD models [46], thus opening new possibilities for design innovation and creativity.

Besides, simulation techniques are commonly used to predict the expected behaviors of the PT. By simulating system behavior, design engineers can access valuable data sets that are further leveraged by analytical AI-based approaches for evaluating the model (e.g., by exploiting optimization methods). Such approaches focus on discovering new insights, patterns, relationships, or dependencies in data to support data-driven decision-making.

Figure 2 details the structure of the optimization cycle for virtual product development. In this procedure, the engineers will realize the first concept and definition of the product and later use them for

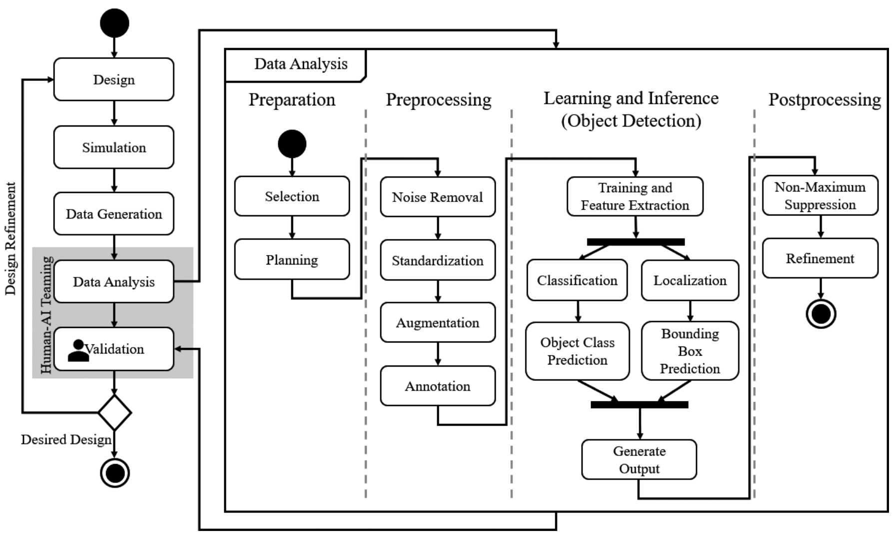

Figure 2: The diagram demonstrates the virtual product development process from design and simulation to validation and design optimization.

simulation. If a previous generation of the product exists, then all the relevant data (from the aggregated DTs of the previous generations) will be exploited to establish the new model. In the next step, simulation techniques and tools (such as CAD, CARLA, etc.) will be utilized to generate data corresponding to the product's current stage. The data will be further processed and used by the investigated human-AI teaming.

Here, we exploit deep learning algorithms to leverage their hierarchical learning representation capabilities and extract the desired features from the data. The choice of the corresponding ML algorithm depends on the details of the product, the acquired data, and the task we are investigating. It could be in the form of deep probabilistic models such as Variational Autoencoders (VAEs) [47] or conventional deep neural networks such as Convolutional Neural Networks (CNNs) [48]. For our use case in this study, a novel version of the CNNs is employed, which will be discussed further in the next section. The analysis part outlined in Figure 2 demonstrates the steps the investigated human-AI teaming takes to transform raw data into valuable knowledge. We exemplified the steps based on the considered use case and the methods that were applied for object detection.

After training, the corresponding results will be assessed and evaluated given benchmark metric values, and potential suggestions for design optimization will be obtained. Such analysis will be conducted by the human-AI teaming, where the design engineer can decide on further post-processing methods and modification of the design parameters for the desired product. Given the new parameters, a product redesign will be conducted, which is usually an enhanced version of the previous step. The loop will continue till the desired design is achieved. In the next section, we showcase this procedure using our use case of LiDAR systems.

The above procedure demonstrates the use of AI in product design. Applying such teaming can lead to an XAI, which provides several uncovered opportunities in production and engineering. For instance, an AI system is used to enhance the design process by analyzing a database of existing products. In this scenario, the final product will still be developed by an engineer, but as discussed, the process will be enhanced by AI.

Another example where XAI can be beneficial is the analysis of prediction errors of AI systems when applied, e. g., to monitor a manufacturing system. XAI can uncover spurious correlations picked up during the training of the AI system [49]. This means that an AI system might never have learned what a damaged product looks like but picked up features that co-occur, such as different reflection patterns of light sources on the product's surface. A change in the illumination conditions could lead to significant errors in this case, which is usually not intended; XAI could help identify such issues efficiently.

The Investigated Use Case

The following use case details the underlying concept of building a DTM for LiDAR systems, emphasizing how human-AI teaming can be integrated into the process. LiDAR is an advanced sensing technology that employs modulated lasers to measure the distance by calculating the laser's Time of Flight (TOF). This enables the creation of detailed 3D point cloud maps of the surroundings. Currently, the resolution requirements for LiDAR systems remain unstandardized. On the one hand, low point cloud density may lack the necessary detail to capture key object characteristics, potentially leading to detection failures. On the other hand, increasing point cloud density requires higher resolution detectors or sampling frequencies, which raises system costs and can introduce unnecessary redundancy.

For this use case, we are interested in assessing how a specific point cloud density, defined by a particular angular resolution and generated by the LiDAR sensor, affects object detection performance. This enables us to modify this parameter and find an optimal configuration that leads to systems with higher object detection accuracies. Intuitively, we aim to build the corresponding DTM of the new generation of LiDAR systems by initiating virtual product development and enhancing the product's design. This corresponds to the 'Initiation' and 'Modeling' phases of the DT lifecycle [12], i. e., the creation of the corresponding DM of the model. To this end, the main point that will be discussed in the following is how the proposed human-AI teaming will be applied.As the first step, data from the product's (in this case, LiDAR systems) previous generation should be collected and assessed. As mentioned, this denotes the horizontal and vertical data acquired by the aggregated DTs of the earlier generations. The corresponding DMs of the

Figure 3. A considered environment in CARLA, used for collecting point cloud data (left); The object detection using the trained PV-RCNN model. The figures correspond to the angular resolution 0.1 °x 0.1 ° (right)

previous generations facilitate the product‘s modeling, and DSs allow for detecting possible points of enhancement, unpredicted undesirable behaviors, and optimizing the product's next-generation design. Nonetheless, real data obtained from DSs often lacks insights into entirely new product designs, underscoring the importance of simulated data. While real-world data provides a valuable foundation for market research, defect diagnosis, and predictive analysis, its utilization is constrained by the high costs associated with physical prototyping during the product development phase.

We used CARLA [50], an open-source simulator that provides a controlled environment for research on autonomous driving. CARLA efficiently simulates the system and field environments based on different degrees of complexity. It further allows for data annotation by generating ground-truth bounding boxes.

The LiDAR configuration used in CARLA features a vertical Field of View (FOV) ranging from -30 ° to 10 °, along with a horizontal FOV of 360 °. It has a detection range of up to 150 meters and operates at a rotation frequency of 10 Hz. Furthermore, the number of channels and points per second can be adjusted to modify the angular resolution. The generated LiDAR data ranges from an angular resolution of 0.1 °x0.1 ° to 1.0 °x1.0 °. Each data set at the specified angular resolution has a 3-minute recording in a small-town scene, totaling 3000 frames of LiDAR point clouds, with 1600 frames used as the training set, 400 as the validation set, and 1000 as the test set [1].

The scene includes 30 vehicles (excluding the ego-vehicle), their speeds dynamically adjusted according to the area‘s speed limits, 13 bicycles moving at a constant speed of 4 m/s, and 40 pedestrians at 1 m/s. Given the data, we trained the considered algorithm (PV-RCNN discussed further below) with training times varying depending on the complexity of point cloud data, from 31 hours at 0.1 °x0.1 ° to 9 hours at 1.0 °x1.0 °. The experiments are conducted on a system equipped with one NVIDIA RTX 3060 GPU, 12 GB. Figure 3 illustrates a generated frame used for training, together with the corresponding point clouds.

PV-RCNN for LiDAR Systems

Developing an initial concept for an optimized product requires robust methods for data analysis and evaluation. This plays a pivotal role in assessing system's performance, identifying potential defects, and ultimately optimizing product design. We here employed Deep Neural Networks (DNNs) to learn and predict the performance of the considered LiDAR system with a specific angular resolution. This allows us to evaluate the potential functionality of the model by testing and analyzing device performance (for the task of object detection). Nevertheless, the model exploits a black-box approach that further requires expert knowledge (throughout the entire process) for informed decision-making, forming the discussed human-AI teaming.

We employed the PointVoxel-RCNN (PV-RCNN) model, introduced by Shi et al. in [41], demonstrating state-of-the-art performance in 3D object detection for point cloud data. This model combines grid-based and point-based methods to leverage each approach's advantages, addressing the inherent challenges in detecting objects within point cloud data. Grid-based methods are generally more computationally efficient but suffer from inevitable information loss. In contrast, while computationally more expensive, point-based methods can achieve superior spatial resolution and a larger receptive field through point set abstraction [42]. By integrating these two methods, PV-RCNN effectively balances computational efficiency and localization accuracy, resulting in improved performance for 3D object detection tasks.

The results are evaluated in terms of mean Average Precision (mAP) with 40 recall positions on test data and are further summarized in Table 1. In addition, Figures 4 and 5 provide the results across different angular resolutions and for the three distinct objects. We first match the predicted bounding boxes to their corresponding ground truth to calculate the corresponding values using a metric such as Intersection over Union (IoU). Predictions with an IoU above a predefined threshold are classified as true positives, while the remaining predictions are false positives. Precision and recall are then computed, where precision represents the proportion of correctly predicted bounding boxes among all predictions, and recall measures the proportion of ground truth instances successfully detected. To compute the Average Precision (AP) for a given class, precision values are averaged at 40 evenly spaced recall points. The mAP is then derived by averaging the AP values across all object classes, providing an overall performance metric for the detection model (i. e., the PV-RCNN model). Moreover, Fig-

AP@R40	Car	Pedestrian	Cyclist	mAP
BBox	88.36	84.69	87.56	86.87
BEV	82.97	74.09	77.76	78.27
3D	83.23	79.07	81.33	81.21
AOS	79.10	70.07	76.46	75.21

Table 1. The corresponding mean average precision values with 40 recall positions obtained using the PV-RCNN model. Here ‘BBox’ denotes Bounding Box, ‘BEV’ denotes Bird’s Eye View, and ‘AOS’ denotes Average Orientation Similarity. The results correspond to the angular resolution 0.1 ° x 0.1 °. We used a threshold of 0.7 for cars and 0.5 for both pedestrians and cyclists

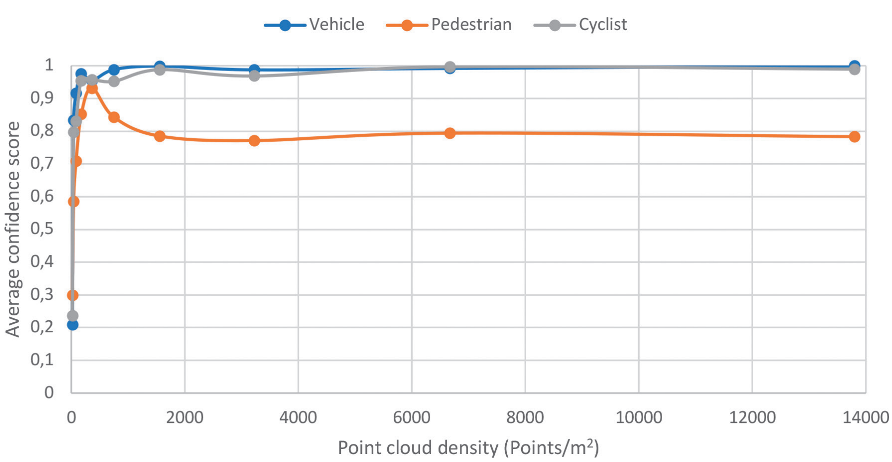

Figure 4. Illustration of the average confidence scores for detecting three different objects using PV-RCNN trained on data with an angular resolution of 0.1 ° x 0.1 °

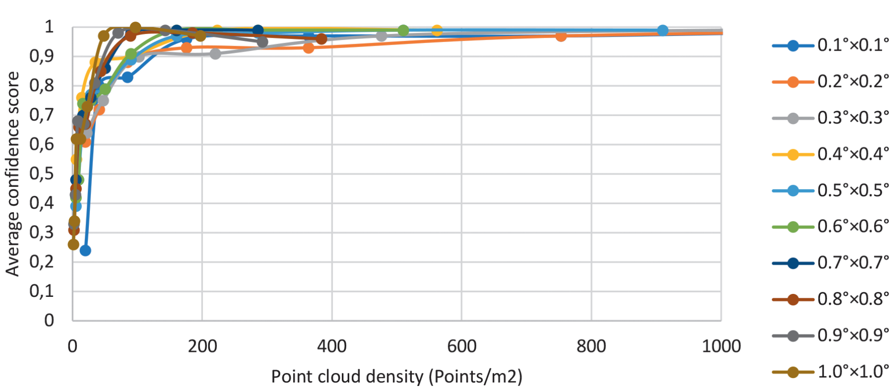

Figure 5. Illustration of the average confidence scores for detecting cyclists using PV-RCNN trained on data at various angular resolutions.

ures 4 and 5 present the average confidence scores as an additional metric for analyzing the considered use case. These values were computed by segmenting the point cloud data into different density intervals. The confidence scores assigned by the PV-RCNN model to the predicted bounding boxes within each interval were then averaged. As observed, an increase in point cloud density generally leads to higher confidence scores, which highlights the impact of density thresholds on enhancing detection capabilities.

Conclusion and Future Work

Integrating DTMs with advances in AI and ML transforms product development and manufacturing by enabling the processing and analysis of vast, heterogeneous data from diverse sources. AI-driven DTMs provide sophisticated diagnostic and decision-making support in this context, enhancing product quality and production efficiency. These technologies make it possible to address core manufacturing challenges, such as maintaining high product quality and boosting customer satisfaction.

In this paper, we investigated virtual product development as the basis for building an AI-driven DTM, utilizing human-AI teaming to leverage the distinct strengths of both the AI model and the design engineer. This approach allows for optimized design processes and more informed decision-making. We further demonstrated the framework’s capabilities by thoroughly examining LiDAR systems.

Future work includes expanding the framework’s application to various use cases, further developing its versatility and utility. Additionally, exploring other deep learning algorithms, especially generative models capable of extracting structural information, holds promise for improving model performance in product design tasks. These enhancements could be particularly impactful for tasks in image analysis, such as those involved in CAD designs.

Literature

1. Grieves, M. W.: Digital Twins: Past, Present, and Future. In: Crespi, N.; Drobot, A. T.; Minerva, R. (eds.): The Digital Twin. Springer, Cham 2023, pp. 97–121 DOI:10.1007/978-3-031-21343-4_4
2. Grieves, M.: Intelligent Digital Twins and the Development and Management of Complex Systems. digitaltwin 2 (2022) 8 DOI:10.12688/digitaltwin.17574.1
3. Grieves, M.; Vickers, J.: Digital Twin: Mitigating Unpredictable, Undesirable Emergent Behavior in Complex Systems. In: Kahlen, F.-J.; Flumerfelt, S.; Alves, A. (eds.): Transdisciplinary Perspectives on Complex Systems: New Findings and Approaches. Springer, Cham 2017, pp. 85–113 DOI:10.1007/978-3-319-38756-7_4
4. Stark, R.; Anderl, R.; Thoben, K.-D.; Wartzack, S.: WiGeP-Positionspapier: „Digitaler Zwilling“. Zeitschrift für wirtschaftlichen Fabrikbetrieb ZWF 115 (2020) 1, pp. 47–50 DOI:10.3139/104.112311
5. Eigner, M.; Detzner, A.; Schmidt, P. H.; Tharma, R.: Holistic Definition of the Digital Twin. International Journal of Product Lifecycle Management 13 (2021) 4,

pp. 343–357
DOI:10.1504/IJPLM.2021.119527
6. Barricelli, B. R.; Casiraghi, E.; Fogli, D.: A Survey on Digital Twin: Definitions, Characteristics, Applications, and Design Implications. IEEE Access (2019) DOI:10.1109/ACCESS.2019.2953499
7. Anderl, R.; Haag, S.; Schützer, K.; Zancul, E.: Digital Twin Technology – an Approach for Industry 4.0 Vertical and Horizontal Lifecycle Integration. it – Information Technology 60 (2018) 3, pp. 125–132 DOI:10.1515/itit-2017-0038
8. Lachmayer, R.; Mozgova, I.: Technical Inheritance as an Approach to Data-Driven Product Development. In: Krause, D.; Heyden, E. (eds.): Design Methodology for Future Products: Data Driven, Agile and Flexible. Springer, Cham 2022, pp. 47–64 DOI:10.1007/978-3-030-78368-6_3
9. Schützer, K.; Andrade Bertazzi, J. de; Sallati, C. et al.: Contribution to the Development of a Digital Twin Based on Product Lifecycle to Support the Manufacturing Process. Procedia CIRP 84 (2919), pp. 82–87 DOI:10.1016/j.procir.2019.03.212
10. Tao, F.; Zhang, H.; Liu, A.; Nee, A. Y. C.: Digital Twin in Industry: State-of-the-Art. IEEE Transactions on Industrial Informatics 15 (2019) 4, pp. 2405–2415 DOI:10.1109/TII.2018.2873186
11. Liu, M.; Fang, S.; Dong, H.; Xu, C.: Review of Digital Twin about Concepts, Technologies, and Industrial Applications. Journal of Manufacturing Systems 58 (2021), pp. 346–361 DOI:10.1016/j.jmsy.2020.06.017
12. Stark, R.; Damerau, T.: Digital Twin. In: CIRP Encyclopedia of Production Engineering. Springer, Berlin, Heidelberg 2019 DOI:10.1007/978-3-642-35950- 7_16870-1
13. Lachmayer, R.; Ehlers, T.; Lippert, R. B.: Design for Additive Manufacturing. Springer, Berlin, Heidelberg 2024 DOI:10.1007/978-3-662-68463-4
14. Lachmayer, R.; Ehlers, T.; Lippert, R. B.: Is Additive Manufacturing Worth It? In: Lachmayer, R.; Ehlers, T.; Lippert, R. B. (eds.): Design for Additive Manufacturing. Spirnger, Berlin, Heidelberg 2024, pp. 215–232 DOI:10.1007/978-3-662-68463- 4_10
15. Lachmayer, R.; Gembarski, P. C.; Gottwald, P.; Lippert, R. B.: The Potential of Product Customization Using Technologies of Additive Manufacturing. In: Bellemare, J.; Carrier, S.; Nielsen, K.; Piller, F. T. (eds.): Managing Complexity. Springer, Cham 2017, pp. 71–81 DOI:10.1007/978-3-319-29058-4_6
16. Lachmayer, R.; Mozgova, I.; Reimche, W. et al.: Technical Inheritance: A Concept to Adapt the Evolution of Nature to Product Engineering. Procedia Technology 15 (2014), pp. 178–187 DOI:10.1016/j.protcy.2014.09.070
17. Dierend, H.; Altun, O.; Mozgova, I.; Lachmayer, R.: Management of Research Field Data Within the Concept of Digital Twin. In: Valle, M.; Lehmhus, D.; Gianoglio, C. et al. (eds.): Advances in System-Integrated Intelligence. Springer, Cham 2023, pp. 205–214 DOI:10.1007/978-3-031-16281-7_20
18. Rathore, M. M.; Shah, S. A.; Shukla, D. et al.: The Role of AI, Machine Learning, and Big Data in Digital Twinning: A Systematic Literature Review, Challenges, and Opportunities. IEEE Access 9 (2021) DOI:10.1109/ACCESS.2021.3060863
19. Eigner, M.; Detzner, A.; Schmidt, P.; Tharma, R.: Holistic Definition of the Digital Twin. International Journal of Product Lifecycle Management 13 (2021) 4 DOI:10.1504/IJPLM.2021.119527
20. Eigner, M.: System Lifecycle Management: Engineering Digitalization (Engineering 4.0). Springer, Berlin, Heidelberg 2021 DOI:10.1007/978-3-662-62183-7
21. Fett, M.; Macko, S.; Wilking, F. et al.: Retrofitting Digital Twins of Existing Systems. In: 2024 IEEE International Symposium on Systems Engineering (ISSE), Oct. 2024, pp. 1–8 DOI:10.1109/ISSE63315.2024.10741101
22. Röhm, B.; Anderl, R.: Concept of a System Architecture for a Simulation Data Management in the Digital Twin. In: ASME 2021, 30th Conference on Information Storage and Processing Systems, American Society of Mechanical Engineers Digital Collection, (2021) DOI:10.1115/ISPS2021-65300
23. Stark, R.; Kind, S.; Neumeyer, S.: Innovations in Digital Modelling for Next Generation Manufacturing System Design. CIRP Annals 66 (2017) 1, pp. 169–172 DOI:10.1016/j.cirp.2017.04.045
24. Roehm, B.; Anderl, R.; Schleich, B.: Development of an Information Model for Simulation Data Management in the Digital Twin. Procedia CIRP 119 (2023), pp. 681–686 DOI:10.1016/j.procir.2023.03.120
25. Röhm, B.; Anderl, R.: Simulation Data Management in the Digital Twin (SDM- DT) – Evolution of Simulation Data Management along the Product Life Cycle. Procedia CIRP 105 (2022), pp. 847–850 DOI:10.1016/j.procir.2022.02.140
26. Krückemeier, S.; Anderl, R.: Concept for Digital Twin Based Virtual Part Inspection for Additive Manufacturing. Procedia CIRP 107 (2022), pp. 458–462 DOI:10.1016/j.procir.2022.05.008
27. Kasper, N.; Pfenning, M.; Eigner, M.: The Digital Thread for System Lifecycle Management with a Native Graph Database in a Polyglot Architecture. Proceedings of the Design Society 4 (2024), pp. 2079–2088 DOI:10.1017/pds.2024.210
28. Grieves, M.; Vickers, J.: Digital Twin: Mitigating Unpredictable, Undesirable Emergent Behavior in Complex Systems. In: Kahlen, F.-J.; Flumerfelt, S.; Alves, A. (eds.) Transdisciplinary Perspectives on Complex Systems. Springer, Cham 2017, pp. 85–113 DOI:10.1007/978-3-319-38756-7_4
29. Schützer, K.; Bertazzi, J. de A.; Sallati, C. et al.: Contribution to the Development of a Digital Twin Based on Product Lifecycle to Support the Manufacturing Process. Procedia CIRP 84 (2019), pp. 82–87 DOI:10.1016/j.procir.2019.03.212
30. Stark, R.; Damerau, T.: Digital Twin. IN: CIRP Encyclopedia of Production Engineering. Springer, Berlin, Heidelberg 2019 DOI:10.1007/978-3-642-35950-7_16870-1
31. Bariah, L.; Debbah, M.: The Interplay of AI and Digital Twin: Bridging the Gap between Data-Driven and Model-Driven Approaches. IEEE Wireless Communications 31 (2024) 3, pp. 219–225 DOI:10.1109/MWC.133.2200447
32. Emmert-Streib, F.: What Is the Role of AI for Digital Twins? AI 4 (2023) 3, pp. 721–728 DOI:10.3390/ai4030038
33. Mitschke, F.; Metternich, J.: Prozessüberwachung durch bildverarbeitende KI. Zeitschrift für wirtschaftlichen Fabrikbetrieb ZWF 119 (2024) 10, pp. 768–771 DOI:10.1515/zwf-2024-1132
34. Redlich, T.; Mariscal-Melgar, J. C.; Moritz, M.; Ingrassia, D.: AI Meets Distributed Manufacturing: Wie KI die Verbreitung digitaler Fertigung fördert. Zeitschrift für wirtschaftlichen Fabrikbetrieb ZWF 119 (2024) 10, pp. 772–779 DOI:10.1515/zwf-2024-1144
35. Sarker, I. H.: Data Science and Analytics: an Overview from Data-Driven Smart Computing, Decision-Making and Applications Perspective. SN Computer Science 2 (2021) 5 DOI:10.1007/s42979-021-00765-8
36. Sarker, I. H.: AI-Based Modeling: Techniques, Applications and Research Issues towards Automation, Intelligent and Smart Systems. SN Computer Science3 (2022) 2 DOI:10.1007/s42979-022-01043-x
37. Goodfellow, I.; Bengio, Y.; Codevilla, A. et al.: Deep Learning: Adaptive Computation and Machine Learning. MIT Press 2017
38. LeCun, Y.; Bengio, Y.; Hinton, G.: Deep Learning. Nature 521 (2015) 7553, pp. 436–444 DOI:10.1038/nature14539
39. Goodfellow, Pouget-Abadie, J; Mirza, M. et al.: Generative Adversarial Nets. Advances in Neural Information Processing Systems 3 (2014) 11 DOI:10.1145/3422622
40. Bommasani, R.; Hudson, D. R.; Adeli. E. et al.: On the Opportunities and Risks of Foundation Models. 2021 DOI:10.48550/arXiv.2108.07258

41. Devlin, J.; Chang, M.-W.; Lee, K.; Toutanova, K.: BERT: Pre-training of Deep Bidirectional Transformers for Language Understanding. 2018 DOI:10.48550/arXiv.1810.04805
42. OpenAI et al. (eds.): GPT-4 Technical Report. Mar. 04, 2024 DOI:10.48550/arXiv.2303.08774
43. Mohseni, S.; Zarei, N.; Ragan, E. D.: A Multidisciplinary Survey and Framework for Design and Evaluation of Explainable AI Systems. The ACM Transactions on Interactive Intelligent Systems 11 (2021) 3–4, pp. 1–45 DOI:10.1145/3387166
44. Biehl, M.; Hammer, B.; Villmann, T.: Prototype-based Models in Machine Learning. WIREs Cognitive Science 7 (2016) 2, pp. 92–111 DOI:10.1002/wcs.1378
45. Rudin, C.: Stop Explaining Black Box Machine Learning Models for High Stakes Decisions and Use Interpretable Models Instead. Nature Machine Intelligence 1 (2019) 5, pp. 206–215 DOI:10.1038/s42256-019-0048-x
46. Koch, S.; Matveev, A.; Jiang, Z. et al.: ABC: a Big CAD Model Dataset for Geometric Deep Learning. In: Proceedings of the IEEE/CVF Conference on Computer Vision and Pattern Recognition, 2019 DOI:10.1109/CVPR.2019.00983
47. Kingma, D. P.; Welling, M.: Auto-Encoding Variational Bayes. 2022 DOI:10.48550/arXiv.1312.6114
48. LeCun, Y.; Bengio, Y.: Convolutional Networks for Images, Speech, and Time-Series. In: Arbib, M. A. (ed.): The Handbook of Brain Theory and Neural Networks. MIT Press, Cambridge, MA 1998, pp. 255–258
49. Ribeiro, M. T.; Singh, S.; Guestrin, C.: Why Should I Trust You? Explaining the Predictions of Any Classifier. In: Proceedings of the 22nd ACM SIGKDD International Conference on Knowledge Discovery and Data Mining. Association for Computing Machinery (2016), pp. 1135–1144 DOI:10.1145/2939672.2939778
50. Dosovitskiy, A.; Ros, G.; Codevilla, F. et al.: CARLA: An Open Urban Driving Simulator. Proceedings of the 1st Annual Conference on Robot Learning, PMLR 78 (2017) 1, pp. 1–16 DOI:10.48550/arXiv.1711.03938

Authors

Dr. Atefeh Gooran Orimi received her Ph.D. in Applied Mathematics from Ferdowsi University of Mashhad, Iran. She joined IPeG in 2023 as a postdoctoral researcher, specializing in data management, analytics, and AI.

Dr. rer. nat. Dr.-Ing. Sascha Saralajew studied Mechanical Engineering and Mathematics at UAS Mittweida. He completed his doctorate in both fields at Leibniz University Hannover and University Bielefeld, respectively. He is currently a senior research scientist at NEC Laboratories Europe GmbH in the human-centric AI group.

Jiatai Feng, M. Sc., studied Optical Technologies and completed his M.Sc. degree at IPeG in 2025.

Zhuoqun Dai is a dedicated research assistant at IPeG, where he has been contributing since 2020. Specializing in optical design and LiDAR technology, his work focuses on advancing cutting-edge solutions for precision measurement and sensing applications.

Rayen Hamlaoui, M. Sc., has been a research associate at IPeG since 2023. He studied Mechatronics at Leibniz University Hannover.

Timo Stauss, M. Sc., studied Mechanical and Biomedical Engineering at Leibniz University Hannover. Since 2023, he is working at IPeG as a research assistant.

Prof. Dr.-Ing. Roland Lachmayer is the Founding Director and the Head of IPeG. He is the senator of Leibniz University Hannover, a speaker of the graduate school “Tailored Light,” a member of the scientific directorate of the Laser Zentrum Hannover, the Managing Director of the WiGeP, and has been a speaker of the EFRE-funded research network GROTESK, since 2018. Since 2019, he has led the task group Additive Manufacturing of the cluster of excellence PhoenixD.

Abstract

Mensch-KI-Zusammenarbeit in einem Digitalen Zwillingsmodell für die virtuelle Produktentwicklung.. Digitale Zwillingsmodelle (DTM; von Digital Twin Model) sind ein wichtiger Bestandteil von Industrie 4.0 und verbessern die Fertigung und Produktentwicklung durch KI. Sie ermöglichen Echtzeitüberwachung, vorausschauende Wartung und Optimierung über den gesamten Produktlebenszyklus. Für den Menschen unverständliche KI-Algorithmen, insbesondere tiefe neuronale Netze, stellen jedoch eine Herausforderung dar. In dieser Studie wird daher die Zusammenarbeit zwischen Mensch und KI untersucht, um einen KI-gestützten DTM für die virtuelle Produktentwicklung zu entwickeln. Wir schlagen einen DTM vor, der KI und Expertenwissen kombiniert, um fundierte Entscheidungen für die Optimierung des Produktdesigns zu ermöglichen. Zu diesem Zweck werden zunächst die Architektur und die Funktionalität des entwickelten Modells skizziert. Anschließend wird die Anwendung des Modells bei der Analyse von LiDAR-Systemen demonstriert.

Acknowlegements

The authors would like to thank the Federal Government and the Heads of Government of the German States, as well as the Joint Science Conference (GWK), for their funding and support within the framework of the NFDI4Ing consortium. Funded by the German Research Foundation (DFG) – project number 442146713. This article has also been written in the context of the Leibniz Young Investigator Grants Programme by the Leibniz University Hannover and is funded by the Ministry of Science and Culture of Lower Saxony (MWK) Grant Nr. 11-76251-114/2022.

Schlüsselwörter

Künstliche Intelligenz, Digitales Zwillingsmodell, Mensch-KI-Zusammenarbeit, Produktentwicklung, Produktdesign

Keywords

Artificial Intelligence, Digital Twin Model, Human-AI Teaming, Product Development, Product Design

Bibliography

DOI:10.1515/zwf-2024-0141
ZWF 120 (2025) Special Issue; page 76 – 84

ISSN 0947-0085 · e-ISSN 2511-0896