Hybrid Learning-based Digital Twin for Manufacturing Process: Modeling Framework and Implementation

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Abstract

Digital twin (DT) and artificial intelligence (AI) technologies are powerful enablers for Industry 4.0 toward sustainable resilient manufacturing. Digital twins of machine tools and machining processes combine advanced digital techniques and production domain knowledge, facilitate the enhancement of agility, traceability, and resilience of production systems, and help machine tool builders achieve a paradigm shift from one-time products provision to on-going service delivery. However, the adaptability and accuracy of digital twins at the shopfloor level are restricted by heterogeneous data sources, modeling precision as well as uncertainties from dynamical industrial environments. This article proposes a novel modeling framework to address these inadequacies by in-depth integrating AI techniques and machine tool expertise using aggregated data along the product development process. A data processing procedure is constructed to contextualize metadata sources from the design, planning, manufacturing, and quality stages and link them into a digital thread. On this consistent data basis, a modeling pipeline is presented to incorporate production and machine tool prior knowledge into AI development pipeline, while considering the multi-fidelity nature of data sources in dynamic industrial circumstances. In terms of implementation, we first introduce our existing work for building digital twins of machine tool and manufacturing process. Within this infrastructure, we developed a hybrid learning-based digital twin for manufacturing process following proposed modeling framework and tested it in an external industrial project exemplarily for real-time workpiece quality monitoring. The result indicates that the proposed hybrid learning-based digital twin enables learning uncertainties of the interaction of machine tools and machining processes in real industrial environments, thus allows estimating and enhancing the modeling reliability, depending on the data quality and accessibility. Prospectively, it also contributes to the reparametrization of model parameters and to the adaptive process control.

Keywords:
Digital Twin; Digital Shadow; Artificial Intelligence; Machine Tool; Smart Manufacturing;

1. Introduction

Machine tools and metal-cutting techniques are the backbones of modern manufacturing and national industries. The primary concern of production is to produce qualitative products in an available and productive fashion. Balancing these partially contradictory objectives drives the emerging Industry 4.0, in which machine tools and production procedures are envisioned to be more interoperable, adaptive, and intelligent [1, 2, 3] in order to optimize quality, productivity, and availability in traditional production systems [4]. Compounded with the increasing global climate and lessons learned from crisis periods, this financial aspect is being replaced to include sustainable consideration of environmental, social, and governance aspects, i.e., ESG factors [5]. Against this backdrop, new challenges are raised for machine tools and production systems in order to confront this profound transformation toward sustainable resilient manufacturing. This requires the in-depth integration of advanced digital techniques [6] and AI techniques to provide machine tools and production systems with the forward process and machine intelligence, and provide a fully-transparent production fingerprint and process understanding that supports human decision-making on the sustainable factors while maintaining the profitability of manufacturing enterprises.

Digital twin (DT) and AI are powerful enablers for such a profound shift [5]. A digital twin is a virtual representation of an asset in the physical world with sufficient accuracy and in (near) real-time [7, 8]. In the production context, DT virtually maps machine tools and manufacturing processes from aggregated data sources. Along with the progress in edge computing [9], fog computing [10], cyber-physical production systems [11] and machine tools [12], AI-driven DT technique plays as new driven-force to create value-added and service from machine data in the era of Industry 4.0 [5, 2]. Fig. 1 illustrates one use case of using the DT to process-parallel predict workpiece

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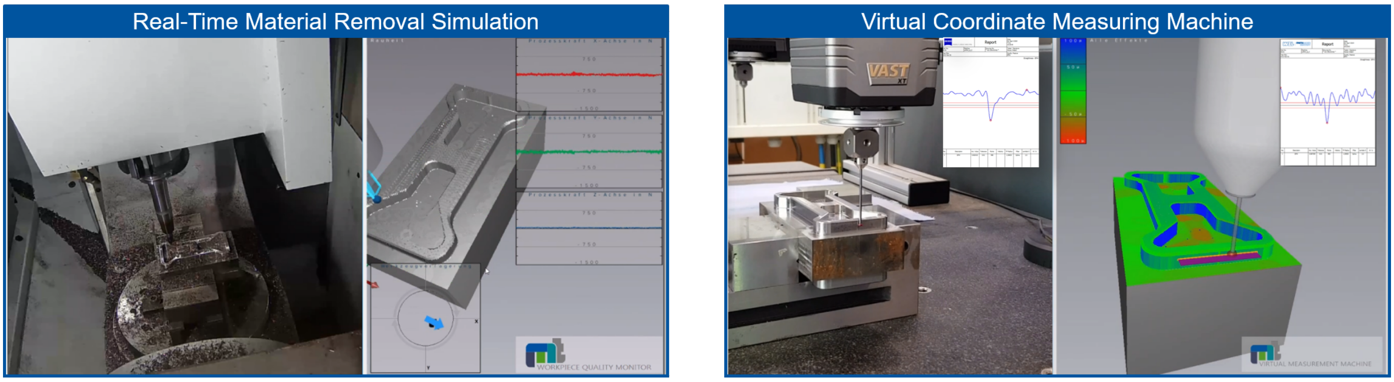

Figure 1: Process-parallel prediction of workpiece quality via a digital process twin at the EMO Hannover 2019. Deployed machine: Chiron FZ 12. ©WZL-RWTH Aachen, MT Analytics GmbH.

quality, where machining process with geometrically defined cutting edges [13]) is simulated at *micro/meso* scale (within the range of a few to a few hundred microns [14]) on the GPU (graphics processing unit) via a real-time material removal simulation MRS) and advanced sensory solution and virtually measured directly in the digital environment. In this way, production data is combined with machine tool and manufacturing process expertise into simulation models that are continuously optimizing production planning and quality control cycle. Therefore, in the ongoing structural transformation, the DT provides practitioners with an on-demand and real-time capable analysis foundation for enhancing the transparency and resilience of production systems towards next-generation smart manufacturing.

Despite various case studies [15, 16, 17] and proposed frameworks for intelligent manufacturing systems and production lines ([18, 19, 20, 21]), there are still several deficiencies that hinder the practical implementation of DT and AI at the manufacturing shopfloor. As the digital replica of the real manufacturing process, the foundation of the DT is the infrastructure and data, the core is the modeling and algorithm, and the application is the software and service. Therefore, from the *modeling* aspect, challenges are concluded in the above three aspects that are intertwined across these three levels (*C1*, *C2*, *C3*):

1. Heterogeneous data sources regarding the different availability, quality, and fidelity in the production context (foundation level, C1). In general, labor experiments can deliver more reliable labeling data under constrained conditions, their amounts and manufacturing conditions are relatively limited. Take the cutting force for example, additional sensor systems like rotating measuring platforms and other advanced sensory solutions exist mainly in demonstration machines and laboratory environments, while in industrial environments, the current-based force model is widely adopted instead of installing external sensors or expensive advanced sensory systems. Since the data has direct influences on the model findings, processing procedures are required to contextualize and link such various data types, while considering the multi-fidelity nature of industrial data that differs in amounts, formats, features, and coverage of manufacturing scenarios arising from separate environments [5, 22, 23].

2. Modeling precision and efficiency owing to the coarse model approximation, e.g., simplified assumptions of boundary conditions or rough modeling resolution (core level, C2). To date, certain machining phenomenons still remain open research topics, especially the dynamics and damping issues of machine tools [24], resulting the epistemic uncertainty of DT modeling. Moreover, the DT for manufacturing process is normally a model chain consisting of several single models. The output of the individual model is usually a latent variable that is difficult or not possible to validate. The uncertainty is thus carried over to the next modeling stage and the final results, making the root cause analysis of model (re)-parameterization difficult, especially when the final result does not reflect the ground truth, e.g., the workpiece quality or remaining useful life (RUL). This entails a systematic investigation of the DT modeling approaches with uncertainties that include both process variables and machining process.

3. Extending model boundaries to adapt to the changing industrial environments (application level, C3). Conventional parametrization or numerical methods are either not flexible or computationally efficient to dynamic boundary conditions, which significantly restrict their implementation and servitization in the industry. In addition, various conventional models, e.g., cutting force models [24], are constrained to certain manufacturing scenarios or machine tools and have to be iteratively tuned to the optimized stage. Once the goal is reached, the process parameters are utilized in mass production. However, due to uncertainties in industrial environments (workpiece stock allowance fluctuation, machine component and tool wear, etc.), a question arises whether the process is robust enough over time and continuously changing environment. The key is the in-depth integration of prior knowledge and machine learning / AI techniques [25], namely hybrid learning-based models, to learn stochastic effects from the real world, thus improving the explainability and reliability.

We thus propose a hybrid learning-based modeling strategy to tackle these three challenges. The main concern is how to leverage data with a multitude of availability, quality, and fidelity to optimize DT modeling in different real manufacturing

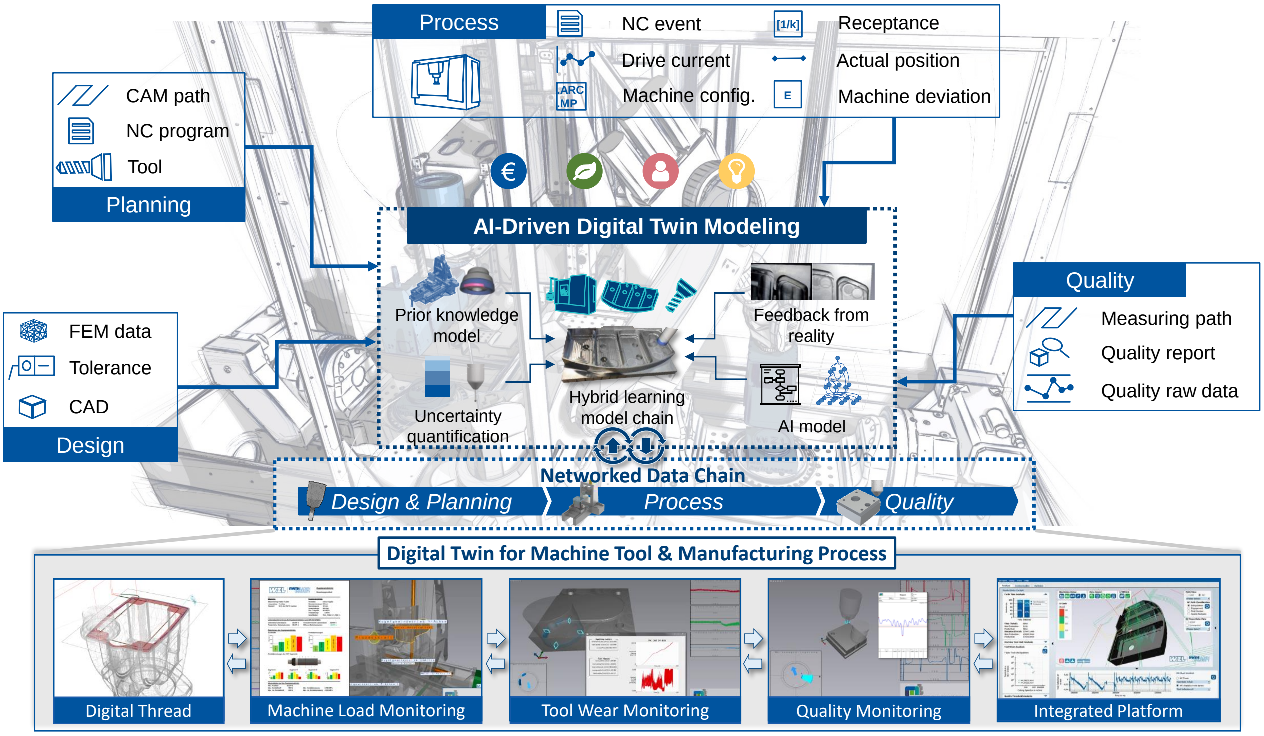

Figure 2: The motivation and objective of AI-driven digital process twins, modified from [5]. ©WZL-RWTH Aachen.

cases with different constraints, so that to provide practitioners with a reliable and real-time analytical foundation for decision-making regarding the traditional quality, availability, productivity, and the sustainability issues in the next-generation manufacturing, as shown in Fig. 2. Concretely, the following contributions of this work are concluded.

- A modeling framework consisting of a modeling pipeline and a data processing procedure for integrating production domain knowledge and AI technologies, while considering multi-fidelity data sources in industrial environments.
- An implementation architecture for hybrid learning model chains as the model foundation for building the DT for manufacturing process.
- Implementation of the proposed framework and methods in the real manufacturing environment.

The remainder of this article is organized as follows. Section 2 reviews the related work. Section 3 describes the general modeling approach for the machining process and the proposed modeling framework through prior knowledge-embedded machine learning techniques. Section 4 first presents our implementation workflow of the DT machine tool and manufacturing process, and then introduces a hybrid learning model chain as the core unit for the workpiece quality. Section 5 introduces the implementation of the proposed approach in an external industrial use case. Section 6 summarizes the work and future research.

2. Related Work

The modeling foundation for DTs in machine tools and machining technologies can be traced back by the virtual machine tool techniques summarized by Altintas and Brecher [24], where kinematic and dynamic analysis methods of machine tools and the integrated simulation of machines and processes were elaborated. Further basic components include spindles [26], feed drives [27], metal cutting simulations [28]. These research foundations provide the capability to predict production results under controlled conditions. However, A-priori modeling techniques encounter the dilemma of high parameterization complexity, computational efficiency, and error-proneness in disparate industrial setups.

Along with the development of Industry 4.0 and the increasing computational power at the production field level, recent research concentrated on combining live production data with high-performance process models and advanced sensor and soft sensing techniques. Within the infrastructure of cyber-physical machine tools [29], stochastic implications from real-world manufacturing environments can be coupled with high-performance simulation models in a process-parallel manner, enabling a rapid response to the physical production process. Brecher et al. [30] demonstrated a material removal simulation powered by the GPU in combination with a spindle-integrated sensor (SIS) to simulate and estimate the virtual workpiece quality in real-time. Similarly, Denkena et al. [31] proposed a MRS-based approach with a cutting force-sensitive sensory component of a machine tool for process monitoring. Altintas and Aslan [32] proposed a method that uses a virtual machining system and a drive current-based cutting force model to monitor the tool condition as well as the process stability. Schmucker et al. [33] introduced an approach for online parametrization of the cutting force model based on a pre-simulated material removal model and synchronized with dynamic time warping and Bayesian optimization. Although knowledge-based DT modeling endeavors to incorporate perturbations from physical processes, their modeled insights are highly dependent on laborious parameterization efforts as well as the discretization model resolution, which is limited by workpiece and cutting tool characteristics, as well as the hardware performance in practical use.

Networked production landscape and machine tools also contribute to the development and exploitation of AI techniques by providing novel approaches for building process variables and quality indicators as inherent parts in DT for manufacturing processes. Denkena et al. [34] applied a long short-term memory (LSTM) NN taking drive current signals as inputs to reconstruct the process cutting forces. On this basis, the tool deflection was compensated, thus optimizing the resulting workpiece shape deviation. Brecher et al. [4] developed an artificial neural network (ANN)-based cutting force model that combined machine internal data and the tool engagement map derived from an MRS. However, the deployment of data-driven techniques in industry is substantially restricted by the available datasets and the robustness, generalizability, and explainability of training models. The concept of informed ML techniques was proposed to facilitate this dilemma [25], where prior knowledge in the represented form of algebraic equations or logic rules is integrated in the ML pipeline. Rahimi et al. [35] presented a hybrid learning approach for chatter detection, where an NN was combined with a Kalman filter to online identify the unstable vibrations. A study of using ontology and knowledge graphs to scale the usability of ML in quality prediction was presented by Zhou et al. [36]. Guo et al. [37] introduced a framework for the automatic construction of machining processes knowledge base, thus enhancing the process design. Friederich et al. [19] presented a framework utilizing ML and process mining techniques to automatically generate simulation models of manufacturing systems and continuously optimize and validate them. Various research efforts on physics-informed machine learning have been also conducted to investigate the feasibility of using AI to address complex numerical problems, such as partial differential equations, by embedding physics principles into NN loss functions [38, 39, 40]. Huang et al. [5] proposed a roadmap for incorporating AI techniques in multiscale/fidelity DTs with multiscale/fidelity data sources. Alexopoulos el al. [41] presented a framework for developing DT-driven supervised ML applications using synthetic datasets in manufacturing.

The digital thread is another key enabler for modeling the DTs of manufacturing processes, since it links disparate systems across the product lifecycle and enables the connection, unification, and orchestration of heterogeneous data throughout the entire manufacturing process [42]. Hedberg et al. [43] define the digital thread as the ensemble of data that enables the combination of model-based enterprise, manufacturing, and inspection and allows a seamless real-time collaborative project development across the product lifecycle. Considering the data security issues, Helu et al. [44] proposed a four-tiered reference architecture for a digital thread that aims to integrate heterogeneous manufacturing and product lifecycle data. The proposed architecture allows effective management and contextualization of manufacturing data and hence enables knowledge generation and decision-making support. Aiming to establish an industrial Internet platform, Wang et al. [45] proposed a digital thread that consists of a digital resource chain and an integrated information chain to link all resource units and metadata. In their case study, a dedicated digital thread throughout the compressor assembly process was developed to improve production efficiency. Data interoperability is a critical issue in developing the digital thread. It is commonly recognized that the development of the digital thread should take advantage of existing international standards for manufacturing [46]. Kwon et al. [47] proposed a standards-based digital thread to fuse as-designed data and as-inspected data based on ontology with knowledge graphs. Various international standards such as STEP AP242, G-code, MTConnect, and QIF were utilised to translate lifecycle data and build an integrated knowledge base. Hedberg et al. [48] introduced a graph-based approach to develop a digital thread that links and traces data throughout the product lifecycle, in which MTConnect and QIF were used to integrate the machine data and quality data.

To briefly summarize, to our best knowledge, there exists presently no industrially validated framework to build an AI-driven and hybrid learning-based digital twin for machining processes that systematically accommodates the model chain and heterogeneous data sources in the production context.

3. Modeling Framework

This section first introduces the general framework hypothesis (Sec. 3.1) for hybrid learning-based DT modeling for machining process and then describes our proposed framework (Sec. 3.2) based thereon.

3.1. General Approach of DT Modeling for Machining Process

The machining process with geometrically defined cutting edges is described via the cutter-workpiece engagement along the trajectory in the interaction of machine and process. Conventionally, the coupled simulation of drive control and process model with the machine model uses time-consuming machine structure dynamics and process model, normally in the form of FEM (finite element method) and MBS (multibody simulation), as well as the measured characteristics results for calibrating the numerical models regarding machine, tool, and workpiece [24, 49]. Therefore, the corresponding DT modeling requires certain simplifications to meet domain-specific real-time requirements while retaining task-specific model granularities. To this end, a general modeling strategy is first described.

Model foundation. The machining process is regarded as a function $\varphi : (T, C, W) \to W$ that maps the process-machine interacted trajectory T of the cutters C to the workpiece W, where W is dynamically updated. The trajectory T is handled as the superposition of the indirectly observed tool center point (TCP) in the workpiece coordinate system (WCS) from the NC controller (T_{NC}) and model estimated TCP deviation (ΔT), namely: $T = \Sigma(T_{NC}, \Delta T)$. The formerly observed trajectory T_{NC} is identified by the 5-axis transformation $\phi : (T_{NC}^{MCS}, \varkappa) \rightarrow T_{NC}^{WCS}$ that converts the observed NC position signals T_{NC}^{MCS} from the machine coordinate system (MCS) to the WCS according to the individual machine kinematics configuration $\varkappa$. The latter machine-process coeffected TCP deviation ΔT is majorly contributed by the cutting force-induced deviation ΔT_F formulated by the function $\tau : (F, K, T_{NC}) \rightarrow \Delta T_F$ that takes cutting force F, TCP stiffness K and position T_{NC} as inputs, which are in turn identified by the corresponding models and metrology. So far, the DT modeling can be processed via the GPU-enabled MRS that calculates the cutter-workpiece engagement (φ) at *micro/meso* scale in real-time on the live trajectory T revised by process variable models. Conducting the virtual quality measurement of the feature k is a function $\pi : (W, V^k) \rightarrow \hat{q}^k$ that samples virtual points $\hat{q}^k$ from the digital workpiece W according to the feature-specific virtual measuring path V^k. The difference between the $\hat{q}^k$ and the real measured result $\mathring{q}^k$ is considered as the model uncertainty Δq^k.

Model evaluation. From the above, the final DT result W can only be validated by comparing the quality features ($\hat{q}^k$, $\mathring{q}^k$), and the DT outcomes (W, $\hat{q}^k$) are largely determined by the precision of process variables and the discretized process model. The uncertainties arise from individual modules, i.e., force F, stiffness K, and process model φ due to the simplified modeling as well as the stochastic effects in the manufacturing environment. These uncertainties (noted as ΔF, ΔK, $\Delta\varphi$), or the so-called *residuals*, are expected to be included in the individual AI models, which take additional observation parameters from internal machine signals and the external sensor system. This enables us to quantify the uncertainty of each module, and also the final model uncertainty Δq, usually in the form of tolerance bands, by extending the individual model in the model chain into an uncertainty model using AI methods to encompass these *residuals*.

Model optimization. Apart from the force-induced displacement T_F, the trajectory deviation ΔT may contain further errors regarding the machine, tool, and workpiece. Some of them can be experimentally identified, e.g., the machine geometric-kinematic error and tool runout (noted as ΔT_{Exp}). Others such as thermoelastic error and workpiece deformation are very process-dependent and difficultly measurable (noted as ΔT_{Res}). In specific machining tasks, they are not negligible and their implications for the final result should be estimated as needed, i.e., when the virtual quality does not meet the required manufacturing tolerance. The model can be adjusted with two approaches. 1) Extending the model chain with hybrid learning-based models (similar to ΔT_F) or with experimental models (similar to ΔT_{Exp}) to cover these process-specific effects. 2) Implicitly inclusion of these remaining effects by learning the *residual* of the quality feedback. The strategy selection depends on the practical requirements of model precision (acquired as tolerance) and available/accessible data constricted by production companies.

To summarize, the hybrid learning-based DT modeling for the machining process is formulated as:

$$W = \varphi(\Sigma(T_{NC}, \Delta T_F, \Delta T_{Exp}, \Delta T_{Res}), C, W) \quad (1)$$

The feature-specific virtual quality control is formulated as:

$$q^k = \pi(\varphi(\Sigma(T_{NC}, \Delta T_F, \Delta T_{Exp}, \Delta T_{Res})^k, C^k, W), V^k) \quad (2)$$

In the implementation, π is the virtual measuring machine (VMM) model according to quality standards [50], φ is the MRS model [28], C and W are discretized 3D models, normally in the form of tri-dexel or LDNI for the GPU parallel computing [51]. V is the quality measuring path for the coordinate measuring machine (CMM). ΔT_{NC} is the transformed online NC signals or offline NC traces. ΔT_F is the result of hybrid learning models considering additional production signals to include the cutting force and stiffness uncertainty identified from spindles [26] and feed drives [27]. ΔT_{Exp} is experimentally identified errors [52, 53], usually conducted once over a long period (before the production ramp-up or during the maintenance). ΔT_{Res} is the theoretically overlooked deviation and can be implicitly covered in the case of the complete quality measuring data. k stands for feature-related (data or models). From the perspective of real performance, ΔT_F contributes to the major trajectory deviation and the final model uncertainty. ΔT_{Exp} and ΔT_{Res} could be excluded from the DT modeling in various manufacturing scenarios, but are sensitive to certain machining cases. The treatment of these process-specific terms depends on manufacturing requirements and available production resources. Via certain simplifying and reconstructing co-simulations of virtual machine tools and machining process [24, 49], we define the general modeling strategy for hybrid learning-based DT modeling for machining process that flexibly adapts to dissimilar production scenarios as well as the production data landscape. In the next section, we present our proposed framework to handle these modeling pipelines and heterogeneous data sources involved.

3.2. Framework

Fig. 3 illustrates the general hybrid learning-based DT modeling framework with the consideration of multi-fidelity data sources based on the above modeling strategy. The framework consists of three aspects: networked digital process chain (Fig. 3a, Sec. 3.2.1), prior knowledge-based DT modeling (Fig. 3b, Sec. 3.2.2), and prior knowledge-embedded ML modeling (Fig. 3c, Sec. 3.2.3). These three modules address the challenges of *C1*, *C2*, and *C3*, respectively, as summarized at the beginning.

In essence, the concept builds on traditional domain knowledge-based approaches (Fig. 3b) to extend a modeling framework with the data-driven and ML techniques (Fig. 3c) that encompass implications of extra parameters from dynamic environments [54]. Consequently, each individual model in the model chain is extended into an uncertainty model with a data-driven component to account for certain effects overlooked in the knowledge-based model. To optimize AI-driven DT development and deployment, the DT modeling pipeline of an entire

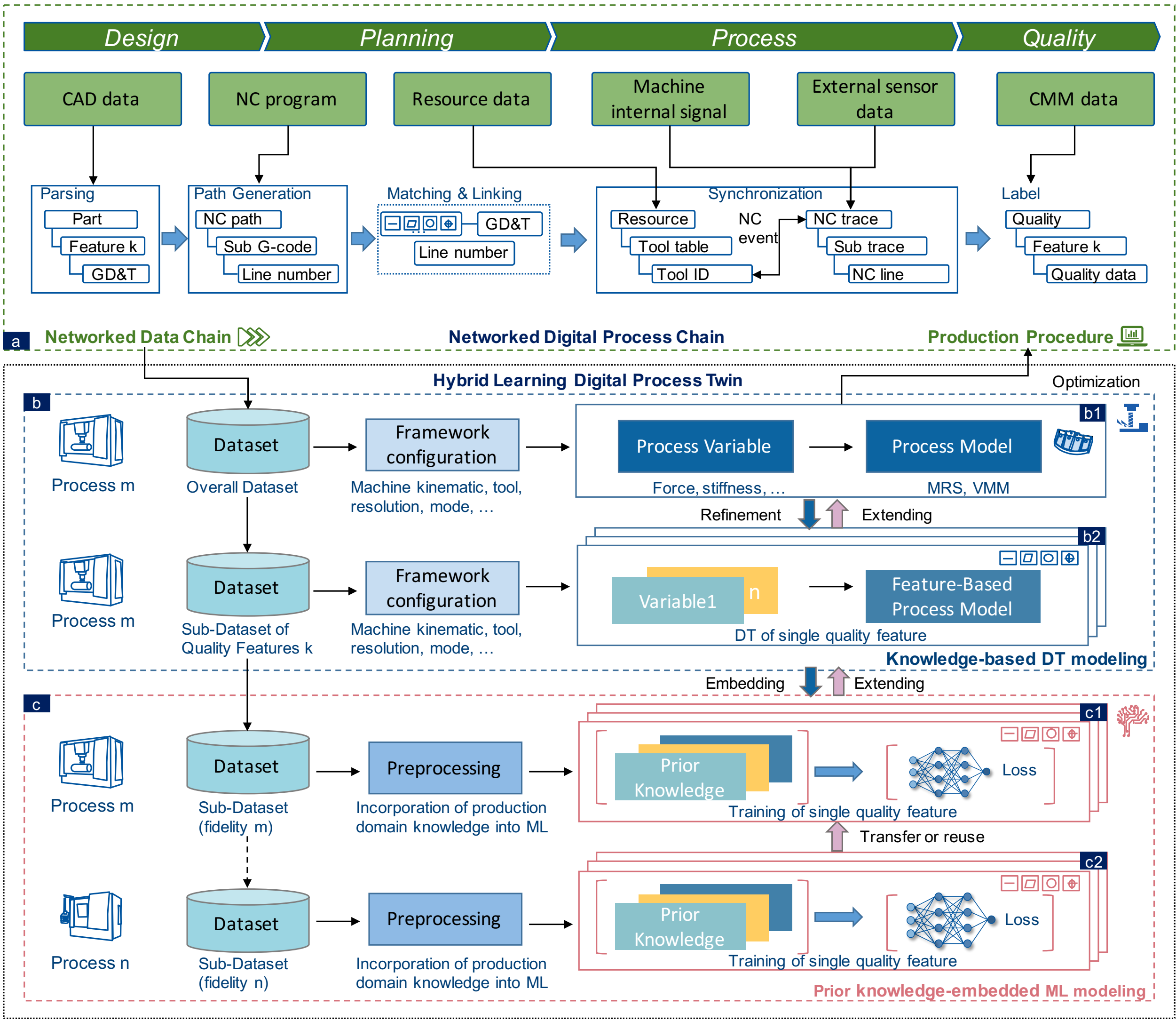

Figure 3: The modeling framework of hybrid learning-based DT for manufacturing process on the basis of the networked digital process chain. a: the data processing procedure for achieving a networked data chain; b: domain knowledge-based DT modeling of the overall part; b2: domain knowledge-based DT modeling of the quality feature on demand; c1: generalized ML modeling for single quality feature; c2: ML modeling for the single quality feature on data with improved quality and fidelity.

manufacturing process (Fig. 3b1), typically for one or multiple workpieces (Eq. 1), is divided into series quality feature-based sub-processes (Eq. 2) that can be directly accessed on-demand (Fig. 3b2). As a result, AI-driven models are developed efficiently by incorporating production domain prior knowledge in a mini-batch fashion (Fig. 3c1), ensuring robust ML training. Additionally, pre-trained ML models built from *high-fidelity* datasets (e.g., laboratory data) or existing processes can be transferred to an existing or new real industrial manufacturing process with *lower or medium fidelity* data (Fig. 3c2). The data foundation is contextualized data throughout the process lifecycle (Fig. 3a). Now we describe each module in detail.

3.2.1. Networked Digital Process Chain

This module aims to achieve a networked data chain across the production procedure (*design*, *planning*, *process*, *quality*) that allows flexible handling of data as needed for DT modeling in different cases. Available data for developing DT machining processes derives from sensors in real-world environments, e.g., machine internal signals, as well as metadata silos and simulation results from engineering software. In modern model-based systems engineering (MBSE), a digital part is semantically decomposed by machining features in conjunction with 3D geometric dimensioning and tolerancing (GD&T). Similarly, a CAM/NC program is parsed into a tree structure containing NC line numbers. This makes it possible to link and match quality features and NC line blocks after conversion in a consistent coordinate system. The result is a feature-aware detector for tracking feature-related segments of NC traces that are acquired from the NC controller and synchronized with external sensor data if available (fusion normally based on reference signals or data fusion algorithms like Kalman filter). Meanwhile, cutting tools and zero-point exchange information are updated in NC events. After connecting with quality data, the entire data chain is turned into a quality feature-based digital thread (networked data chain). In other words, the unstructured data formats that arise from disparate production stages are contextualized into a set of tree structures that are interlinked according to the quality features, as illustrated in Fig. 3a. This networked data chain facilitates straightforward feature-specific knowledge-based DT modeling and the required data transformation operations in the ML pipeline. When developing a specific hybrid training-based model, feature-related datasets can further be extracted from the digital thread as semi-structured data (CSV, JSON, XML, etc.), thus enabling on-demand data provision from the metadata sources.

3.2.2. Hybrid Learning Approach: Domain Knowledge-based DT Modeling

DT integrates the simulation of machine tools and metal-cutting processes. Therefore, the modeling involves the process variable modeling based on the machine tool and components, such as process force, and stiffness, as well as the process modeling based thereon, e.g., the MRS. This module derives from the conventional knowledge-based approach (b1). In the engineering implementation, a trade-off between the model precision and computational efficiency of DT must be taken, since the maximum discretization resolution that can be performed is constrained by hardware performance. Moreover, a DT is normally designed as a *model chain* that comprises multiple models, e.g., force model, stiffness model, and material removal model (Eq. 1). Therefore, the primary concern in practice is the parameterization effort and the resulting uncertainties under rapidly changing conditions. Thus, building on the feature-based data chain (Sec. 3.2.1), we design a feature-based modeling pipeline (b2), which shares the same modeling modules yet allows us to speed up the iterative parameterization or process planning [55] while focusing on parts with imprecise parameters. In addition, this decentralized model pipeline design ensures a targeted consideration of the quality feature as frequently only certain elements (holes, edges, surfaces, etc.) in the workpiece suffer from quality issues. Regarding the software and model development and deployment, a configuration toolset is also beneficial in order to flexibly adapt the model and service mode (online, offline) according to manufacturing scenarios with variable data accessibility.

Common presentations of prior knowledge in machining modeling include the following types: 1) Simulation results, e.g., FE models regarding machines' stiffness. They contain high model complexity and, in practice, may require model order reduction techniques to achieve computational efficiency. 2) Experiment results, e.g., machine geometric-kinematic error and thermo-elastic deformation. They are tailored to the single machine and conducted only once over a protracted time period, depending on machining and model precision requirements. 3) Analytical models, e.g., the Kienzle model for cutting force, the LuGre model for friction. They are fast calculation models yet are normally parametrized according to specific cases. 4) Hybrid models. They encapsulate several models to get better performance and to meet more general situations. Prior knowledge type 1 often requires type 2 for defining the boundary condition. Due to the system complexity, they are performed once over a given timespan and the parametrized models are stored as lookup tables. Prior knowledge type 2 can combine type 3 into experimental-analytical models as efficient substitutes for FE models (type 1), e.g., for receptance coupling. Prior knowledge types 3 and 4 may contain expert knowledge and are handled with logical or condition rules.

3.2.3. Hybrid Learning Approach: Prior Knowledge-Embedded ML Modeling

Following the quality feature-specific digital thread (a) and DT process modeling (b), the prior knowledge is embedded into AI approaches, e.g., neural network loss functions. It forces the ML training process to obey prior constraints, thereby enabling the uncertainty quantification of existing models and extending the model boundary [39] (c1). Modeled outcomes from data-driven approaches rely on the model granularity and complexity of neural networks and ML models, as well as on industrial datasets, which vary in availability, quality, and fidelity. Transferring or reusing ML models previously trained on data with better accessibility and quality will enhance the real industrial situation (c2). For instance, the current- or position-based force model is extended into a hybrid learning model with the help of force sensors and subsequently transferred into mass production. Moreover, domain knowledge exists commonly implicitly in a variety of domain-specific programs and software. For complicated DT modeling like MRS, certain refinement is instrumental to ensure that the production domain knowledge is available for inclusion in ML models and pipelines, e.g., through the construction of rapid analytical computations or high-fidelity surrogate models.

According to the roadmap for AI-driven DTs [5], the data-driven techniques involved in the DT modeling can be broadly divided into four categories: 1) Supervised learning, e.g., NN, LSTM, and CNN, requires labeled data and can be used to build soft sensors as substitutes for expensive sensory solutions. 2) Unsupervised learning, e.g., clustering, requires no labeled data and is suitable for tool wear and anomaly detection. 3) Reinforcement learning, e.g., Q-learning, is frequently designed for process design and optimization. 4) Intelligent computational method, e.g., adaptive filter, is efficient, optimal, and can be used for online parameterization or combined with other ML algorithms. Among them, supervised learning is still the most robust and broadly used approach. Apart from using ML/NN to build surrogate models (forward problems), parameter identification in the machining system (inverse problems), e.g., the cutting force or friction model, is another crucial means for building the hybrid learning model. For learning residuals of the entire DT from the quality feedback, the refined prior knowledge type 1 to 4 (lookup tables, analytical models, logical rules, etc.) can be processed vectorially, and thus embedded as penalty or regularization terms in the loss function of the model chain. The associated feature-based training pipeline (c1 and c2) corresponds to Eq. 2, enables the selective treatment of faulty quality features, and optimizes the DT if necessary, thereby providing an analytical foundation for the optimization of the production procedure.

4. Implementation

This section first introduces the current implementation infrastructure of the DT machine tool and DT manufacturing process at the WZL (Sec. 4.1), since the DT is a system more than modeling. This infrastructure has been already set up for providing the necessary software and hardware modules for deploying DT in different machining scenarios including turning, milling, and drilling. Within this general infrastructure, we present hybrid learning modeling as the core unit for building an AI-powered DT for quality monitoring (Sec. 4.2). The implementation infrastructure (Sec. 4.1) and hybrid learning digital twin for machining process (Sec. 4.2) conform to the framework hypothesis (Sec. 3.1) and proposed modeling framework (Sec. 3.2), respectively.

4.1. Implementation of DT Machine Tool and Machining Process at the WZL

Fig. 4 presents the current implementation infrastructure of DT machine tool and machining process that have been deployed in the machine park at the Laboratory for Machine Tools and Production Engineering WZL of RWTH Aachen University. Within the future vision of the German Cluster of Excellence "Internet of Production", infrastructure is to be established that will provide a comprehensive analysis and collaboration foundation for users in all production domains [56]. To this end, WZL has set up a DT shop floor.

Data. We systematically gather and fuse data from different data silos to build a comprehensive digital shadow of the manufacturing systems. This contains design and simulation data, planning data, manufacturing process data, and QM data. Results from design (digital part, tolerancing), planning (technology parameters in NC programs), process, and quality (measuring paths) are coupled into a semantic modeling workflow [9] according to the digital process chain (Fig. 4a1) proposed in Sec. 3.2.1, with the simulation result being interpolated depending on the TCP position [4]. Live production data (Fig. 4a2) covers high-frequent machine-internal signals, i.e. motor currents, encoder feedback signals, PLC signals, and additional sensor data such as spindle-integrated force sensor (SIS). Machine internal production data is recorded with a trace server connected to the machine CNC with a standard sampling rate of 500 Hz (up to 1000 Hz, dependent on the cycle time of the position control loop) via manufacturer-specific interfaces [57]. Additional equipped sensors sampling software, e.g., SIS, is deployed on a Beckhoff IPC. A data synchronization module is used to adapt the internal and external data into a uniform data stream based on the reference signals of the spindle [30] and to transmit them to DT models via the MQTT communication protocol. Other includes preprocessing software for the parameterization work of analytical models.

Model. DT describe the kinematics and dynamic characteristics of production machines on the shop floor and their interactions with the manufacturing process at a meso/micro scale in domain-specific real-time. At the machine and component level (Figure 4b1), relevant signals and indicators for condition monitoring and predictive maintenance, such as spindle current and feed drive forces, are estimated and logged. At the manufacturing process level (Fig. 4b2), the manufacturing process modeling (Sec. 3.1) is coupled with digital and domain knowledge models, including a machine dynamic model, a workpiece model, and models for cutting tools. In the graphically described model chain (machine kinematic $\rightarrow$ cutting force $\rightarrow$ stiffness $\rightarrow$ MRS) illustrated in Fig.4b1&b2, the actual TCP during production is translated as a superposition of raw sampled axis positions from controllers with deviations regarding machine, tool, and workpiece, the latter are derived from simulations models and production data. In this way, a scalable hybrid model chain is established, and meantime incorporates the models across the whole digital process chain. We used an XML-based semantic description to set up required model configurations and interactions on-demand.

Service. Based on the feature-based digital thread (Fig. 4d1), the DT modeling at the machine and process level enables the condition monitoring of machine components (Fig. 4d2) and cutting tools (Fig. 4d3) as well as the quality monitoring of workpiece (Fig. 4d4) at the production line. Cutting models on the spindle and friction models are used for condition monitoring and predictive maintenance. The spindle force/cutting model is one of the most critical factors for estimating the process. However, external force sensors are either not robust to the harsh metal cutting environments, or they could change the dynamic behavior of machines, leading to unstable process and quality issues. Many force models are proposed in previous research, including classic motor current-based, novel ANN, and advanced sensory-based. Specifically, we developed a force model based on contactless eddy current sensors, that are integrated into the spindle-integrated sensor, in order to reliably estimate cutting forces on the tooltip while maintaining the dynamic behavior of machines tools [30]. The force model is then coupled with a high-performance cutting process simulation [4] or a high-fidelity edge computing-powered analytical model [9] that is used for tool wear monitoring and workpiece quality monitoring. The real-time generated DT workpiece, together with the machine and tool condition, can be further incorporated into an integrated platform (Fig. 4d5) [58] that provides practitioners with additional process information and understanding, thus facilitating them to make decisions based on the achieved machine and process transparency.

4.2. Hybrid Learning Digital Twin Modeling for Manufacturing Processes

While the general infrastructure constitutes the foundation for conducting the overall DT for machine tools and manufacturing processes, this subsection details the hybrid learning DT modeling for virtual quality evaluation according to the proposed modeling framework (Sec. 3.2). Concretely, it contains a production data processing toolset and an implementation architecture for the hybrid learning model chain along with its conceptual realization.

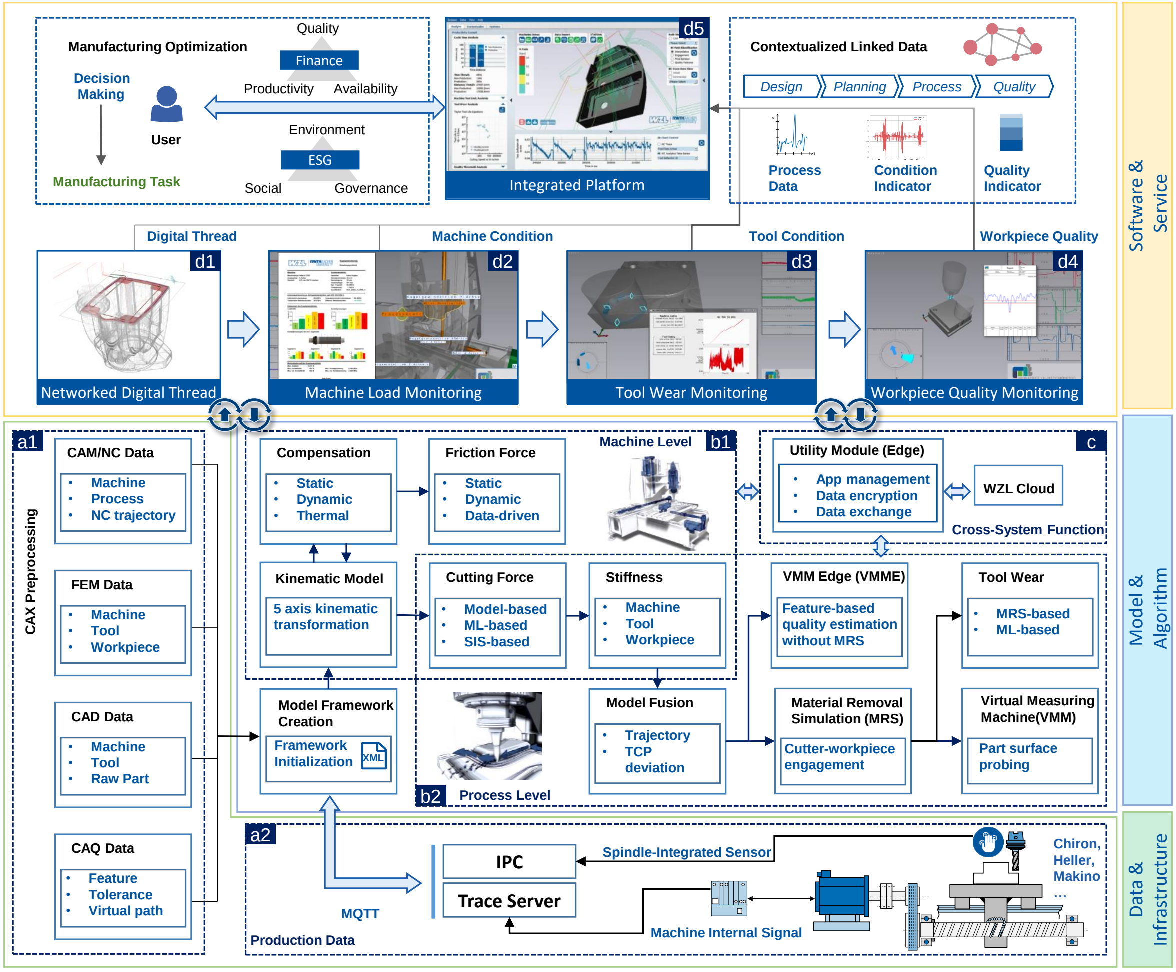

Figure 4: Implementation of digital twin machine tool and machining process at the WZL. ©WZL-RWTH Aachen. Images d2-d4 ©MT Analytics GmbH.

4.2.1. *Networked Digital Process Chain*

To achieve a consistent data foundation, we have developed several data preprocessing toolsets to semantically represent and interlink metadata sources across the digital process chain based on the MBSE. They enable to flexibly process data formats in dissimilar industrial cases.

One main part is the STEP parser for contextualizing the current AP 242 protocol. This part utilizes product and manufacturing information (PMI) as the bridge for the automatic detection and linking of the quality feature and the belong the metadata sources. PMI provides graphical and schematic representations of 3D geometric dimensioning and tolerancing (GD&T), as well as associated quality features and geometries, which are are comprised in the up-to-date STEP AP 242. The geometric features are extracted into a parametric model that is then used to construct a bounding box leading to the automatic generate a feature-specific digital thread. Additionally, we developed a controller-independent NC parser to contextualize the NC programs, e.g., from Siemens and Fanuc. First, we define the standard ISO regex pattern for the fundamental functions. Then, controller-specific instructions are extended in each separate module. Afterward, we leverage ANTLR [59] to generate parsers regarding NC controllers. NC instructions from mainstream controllers are converted into internally defined motion instructions in the form of a tree structure, where each knot has the position, instruction, and NC line number information. Specifically, the machine kinematic and tool table information is optionally integrated to ensure the simulation of NC traces. Likewise, NC traces and virtual quality paths can be connected if they are available prior to the manufacturing, e.g., from the production ramp-up phase.

Moreover, coordinate systems are usually changed in different stages of production. This information can be extracted from CLSF files or other formats depending on the individual software. The consistent coordinate system contributes to automatically detecting and linking contextualized metadata silos through the collision detection of bounding boxes derived from parametric quality features. The bounding box is defined as “bounding volume” in this work, as its type is able to be parametrized in other forms, e.g., cylinder, the size of which is determined by the tool radius. The result from the *design* and *planning* stage is thus a feature-based detector and descriptor that can either be used online to track the live NC traces of targeted regions *(process)* according to NC line numbers or of-

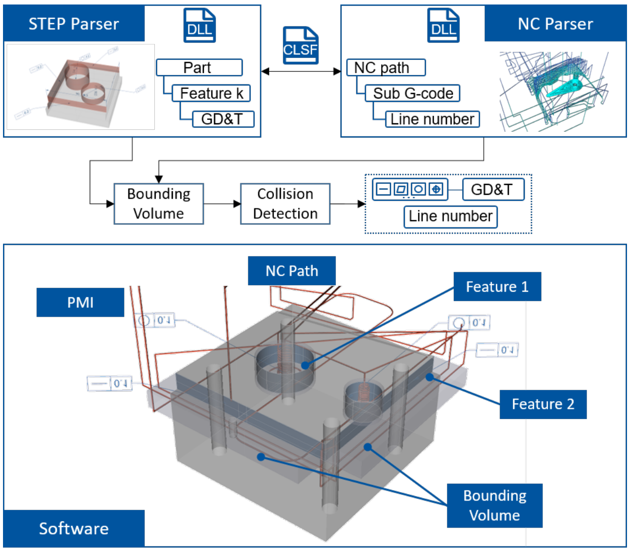

Figure 5: Contextualized STEP file, NC paths, and the bounding volumes.

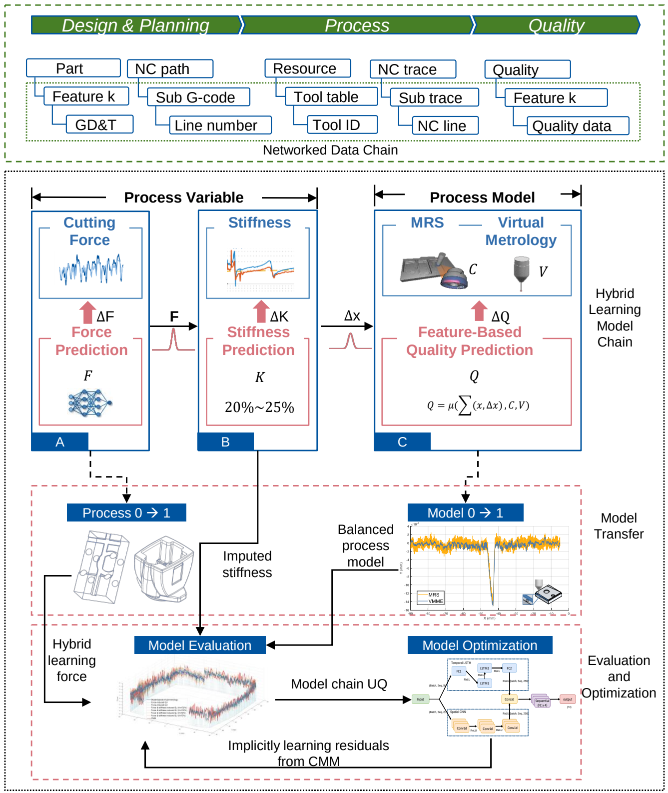

Figure 6: Implementation architecture for the hybrid learning digital twin modeling.

fline to generate a consistent feature-related dataset containing the *process* or/and *quality* data for training the hybrid learning DT. In this way, heterogeneous data sources are networked into a digital thread, leading to atomized tracking and operation. Fig. 5 shows the match and linking results. An illustration of the linked digital thread including NC traces (*process*) and virtual quality paths (*quality*) will be shown in the next section in the case of a real industrial project.

4.2.2. Hybrid Learning Model Chain for Manufacturing Process

Fig. 6 represents the hybrid modeling implementation architecture leveraged in a DT for process-parallel virtual quality evaluation. In the current modeling foundation, each TCP is treated as a superposition of NC traces sampled from the machine NC controller and modeled evaluated deviations. The TCP deviation Δx induced by the process force is determined from the cutting force F (Fig. 6A) and stiffness K (Fig. 6B) that vary from machines, tools, and workpieces:

$$\begin{pmatrix} \Delta x_x \\ \Delta x_y \\ \Delta x_z \end{pmatrix} \cdot (K_x, K_y, K_z) = \begin{pmatrix} F_x \\ F_y \\ F_z \end{pmatrix} \tag{3}$$

The overlaying TCPs are as input feed in a GPU-powered machining removal simulation followed by a virtual measuring machine (Fig. 6C). In real-world operations, uncertainties in each process variable modeling stage are propagated to the outcome and could inhibit the real acceptance of using DT in industrial cases. Hence, we propose a *hybrid learning model chain* concept for building an AI-enabled DT according to the proposed modeling framework, in which individual submodule (A, B, and C) is extended into an uncertainty model predicted by AI methods (in red).

We have first established the overall implementation foundation so that it is scalable to disparate manufacturing cases, and continuously refined the submodule according to accessible datasets. Specifically, we implemented AI modeling of cutting forces from one machining process equipped with force sensors and applied it to the normal industrial cases (UQ for Fig. 6A) while taking into account uncertainties arising from other submodules. In engineering practice, the stiffness of machine axes is determined with a reference tool. The position-dependent TCP stiffness is interpolated via the lookup table, whereby the three-dimensional machine axis value in the described workspace is coupled with the tool-specific static stiffness. The corresponding stiffness values are determined via FE, experimental-analytical or metrological models, depending on data availability, since the FE of machines can also be confidential products in industrial projects. However, when considering that the workpiece and other unidentified damping values also influence the deflection at the TCP, whose stiffness could range by up to 25% depending on measuring uncertainty as well as transient effects during machining, it is difficult to precisely describe the stiffness behavior with a constant value (UQ for Fig. 6B). Moreover, we developed a *high-fidelity* feature-based analytical model to eliminate the discretization error induced by the process model as needed (Fig. 6C). The estimated uncertainty was treated as tolerance bands for the final estimated outcome. In this way, the implication of uncertainty in each individual submodule is identified and can be extended prospectively. Finally, we investigate the potential to reduce the uncertainty of the entire model chain by learning the residual between the virtual and real quality data.

Cutting Force Modeling. The cutting force is one of the most essential indicators for a machining process. The cutting force is normally acquired during production with effort. The installation of external sensors brings additional costs and potentially changes the machine structure. Hence, a force model based on machine internal data has been developed for identifying the axis load according to the machine behavior. This includes the friction $f_{fric}(x, v)$, inertia force $f_{acc}(a)$, position dependent error of the feed drive axes $f_{sp}(x)$, and a position dependent coefficient k_{enc} [60].

$$F_{phy} = k_{enc}(x)(\delta x - f_{fric}(x, \dot{x}) - f_{acc}(\ddot{x}) - f_{sp}(x)) \quad (4)$$

All these model parameters (k_{enc}, f_{fric}, f_{acc}, f_{sp}) are obtained by reference movements on the machine and are subjected to a certain degree of uncertainty. Moreover, the transmission behavior between the sampled signals and TCP has an influence on the prediction accuracy. To incorporate these disturbances from real processes, this physical part is extended into an uncertainty model that takes additional inputs from machine internal signals. The loss function J_F of the corresponding NN is formulated as [61]:

$$J_F = arg\,min\,MSE(F_{NN}(X) + \lambda(F_{phy}) - F_{sensor}) \quad (5)$$

where X are additional observation parameters including axis currents and spindle currents. In addition, the NN can parameterize the model parameters online by extending the output to 4 additional parameters, and correspondingly more test datasets under different processing scenarios are required. Regarding the NN design, our experimental results have indicated that NNs with the capability of learning time series features, such as the LSTM, gate recurrent unit (GRU), and temporal convolutional neural network (TCN), have demonstrated superior performance than the conventional fully connected network (FCN). However, a shallow FCN can as well provide reliable cutting force estimation when incorporating the MRS [4]. Hence, for the prior knowledge-embedded machine learning, the construction of the NN depends on the data set on the one hand and the form and quality of prior knowledge on the other hand.

Process Modeling. Current approach leverages the MRS to generate a DT workpiece and predict the surface quality Q by virtual metrology. The result needs to be meticulously evaluated due to the discretization-induced error in the MRS that uses the discrete model, the so-called tri-dexel model. To better distinguish the implication of the force model and the varying stiffness, we implemented an edge computing-powered, generalized analytical model *VMME* (Virtual Measuring Machine at the Edge) for arbitrary features μ to estimate the virtual quality Q^k [9] as the nominal result of the discrete approach (MRS):

$$Q^k = \mu(\sum(x^k, \Delta x^k), C^k, V^k)) \quad (6)$$

where μ is a quality feature-specific function that estimates intersected points based on the TCP trajectory x, the pose of the cutter model C, and virtual measuring paths V. The convention k stands for the quality feature enabled by the feature-based digital thread (Sec. 4.2.1). The pseudocode is described in Algorithm 1. The convention $\hat{x}^k$ denotes the traces with the final contour relevance.

Algorithm 1 *VMME* [9]

Input: x^k, Δx^k, C^k, V^k
Output: $\hat{Q}^k$, $\hat{x}^k$, $\Delta\hat{x}^k$

procedure GETVMMFINGERPRINT
  for each point V_i^k in V^k **do**
    $Init(\hat{Q}_i^k, \hat{x}_i^k, \Delta\hat{x}_i^k)$
    for each point x_i^k in x^k **do**
      if $Distance(V_i^k, x_i^k) \leqq Radius(C^k)$ **then**
        $R_{e,i} \leftarrow Engagement(V_i^k, x_i^k, \Delta x_i^k)$
        $\tilde{Q}_i^k \leftarrow RayTracing(V_i^k, x_i^k, \Delta x_i^k, R_{e,i})$
        $\hat{Q}_i^k \leftarrow Update(\hat{Q}_i^k, \tilde{Q}_i^k)$
        $(\hat{x}_i^k, \Delta\hat{x}_i^k) \leftarrow Update(x_i^k, \Delta x_i^k)$
      end if
    end for
    $\hat{Q}^k \leftarrow Append(\hat{Q}_i^k)$
    $(\hat{x}^k, \Delta\hat{x}^k) \leftarrow Append(\hat{x}_i^k, \Delta\hat{x}_i^k)$
  end for
end procedure

The model retains the same inputs and parameter modeling as the MRS, but is no longer associated with the resolution of the digital workpiece. Consequently, the analytical results do not exhibit the peak effect from dexel-based models, as shown in Fig. 7. While the analytical model *VMME* shows superior performance as MRS in normal quality features, it suffers the drawback of increasing parametrization efforts when confronting with high-complex contours, e.g., free-form in the five-axis machining, whereas quality monitoring of these contours remains as an open research issue. One way to enhance the model is to perform adaptive spatial partitioning according to the feature property (knowledge-based). Another approach is to construct a hybrid learning process model that learns the uncertainty from its own rough approximation by continuously comparing the gap between the discrete and analytical model results (AI-based).

Evaluation and Optimization. Based on the previous outcomes, the quality uncertainty (QU) ΔQ^k can be estimated from the unconfident TCP deviation Δx derived from the uncertainty part of the process variables F and K:

$$Q^k \pm \Delta Q^k = \mu(\sum(x^k, \Delta x^k), C^k, V^k) \quad (7)$$

$$With\ \Delta x = (F \pm \Delta F)/(K \pm \Delta K) \quad (8)$$

When the measuring data is in an adequate extent, i.e., a complete CMM data instead of a mean value from statistical process control (SPC), the hybrid learning model chain empowers the ability of DT to learn the residual from real inspection data that in order to implicitly compensate the transient effects in a flexible way.

Generally, each visually sampled point on the digital part can be seen as the function of the high-dimension inputs of

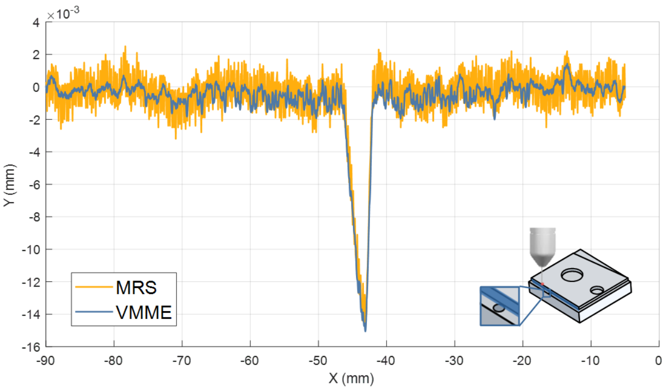

Figure 7: Comparison of estimated workpiece quality using the MRS and VMME.

the corresponding real production data containing machine internal signals. The NN learns thus residual from real inspection data in order to implicitly compensate for the transient effects in a flexible way. Note that is this process is normally not straightforward, as the measuring paths and NC traces are not 1:1 mapped. Owing to the knowledge-based process modeling, this relationship can be established, facilitating a hybrid learning approach. In data-driven modeling, temporal and spatial features are to be learned by leveraging corresponding functional modules such as LSTM and CNN. The concrete module selection and design are still tailored to the manufacturing scenario. By incorporating the process model into the ML, a generalized loss function J_Q is formulated as:

$$J_Q = arg\,min\,MSE(Q^k_{NN} + Q^k_{phy} - Q^k_{sensor}) \tag{9}$$

where Q_{sensor} is the CMM data, Q_{phy} is the domain knowledge-based modeled outcome from DT, Q_{NN} is the data-driven part that learns the uncertainty. This approach provides an implicit way to flexibly cover the systematic model uncertainty. However, acquiring and saving the full quality path is relatively rare in industry. Therefore, disparate approaches are used according to the data availability in practice.

5. Use Case

This section presents an external industrial use case of the proposed approach for machining the surface of a pumping casting. To meet the target quality tolerance (0.03 mm flatness), a roughing tool was initially taken to quickly remove the raw material of the casting. A finishing cutter was subsequently utilized to achieve the final surface shape. Due to the vagaries of the proceeding casting operation, such as disparate stock allowances, subsurface porosity, trimming and washings, the machining status of the process may not be invariant for all parts. To this end, we have developed a DT for manufacturing process to simulate the machining process and the associated uncertainty in a process-parallel manner. We estimate the virtual quality and its upper and lower tolerance bands to check whether they are within the required tolerance range.

5.1. Networked Digital Thread

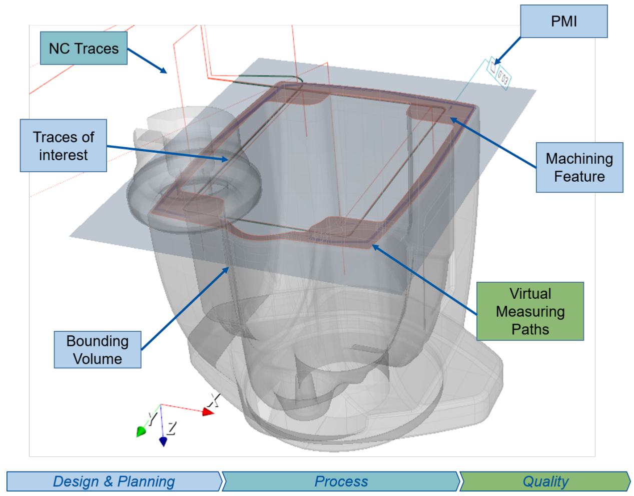

Figure 8: The feature-based digital thread of contextualized metadata sources across the manufacturing procedure: design, planning, NC process, and quality inspection.

In the first step, we processed and interlinked heterogeneous metadata sources across manufacturing procedures: *design*, *planning*, *NC processes*, and *quality inspection*. Using the proposed data processing procedure (Sec. 3.2.1) and toolset (Sec. 4.2.1), the PMI in conjunction with the referenced quality geometry (red region in Fig. 8 was extracted from the STEP data format in the actual AP 242 edition and converted into a parametric model (*design*). Virtual measurement paths (*quality*) and NC traces (*process*) containing NC line numbers (*planning*) were also processed with the zero point transformation (e.g., from CLSF files) and the 5-axis kinematic transformation, in order to exist in a consistent coordinate system. Then, the bounding volume was generated based on the parametric model and the involved tool radius, where the tool ID in use is available in the NC events associated with NC traces. After the collision detection for the graphically represented data, all potential traces that can affect the machining feature, including the approach and retraction of cutting tools, are included and can be processed into a consistent dataset in CSV format. Fig. 9 illustrates the linked data of a flatness feature enabled by the digital thread.

5.2. Hybrid Learning Model Chain

The prototypical model chain has been developed according to the hybrid learning DT architecture (Sec. 4.2.2). In normal industrial commissioning and manufacturing, production machines (DMC-80H-Linear) are not equipped with external force sensors. Hence, a position deviation-based force model was leveraged to estimate this expensively measurable process variable. The force model-entailed uncertainty is compensated with a data-driven part that was pre-trained on another dataset in the laboratory environment using the force measuring platform. The uncertainty in this stage ΔF is then combined with the imputed process variable stiffness ΔK and counterbalanced process model μ, culminating the UQ of the overall model chain

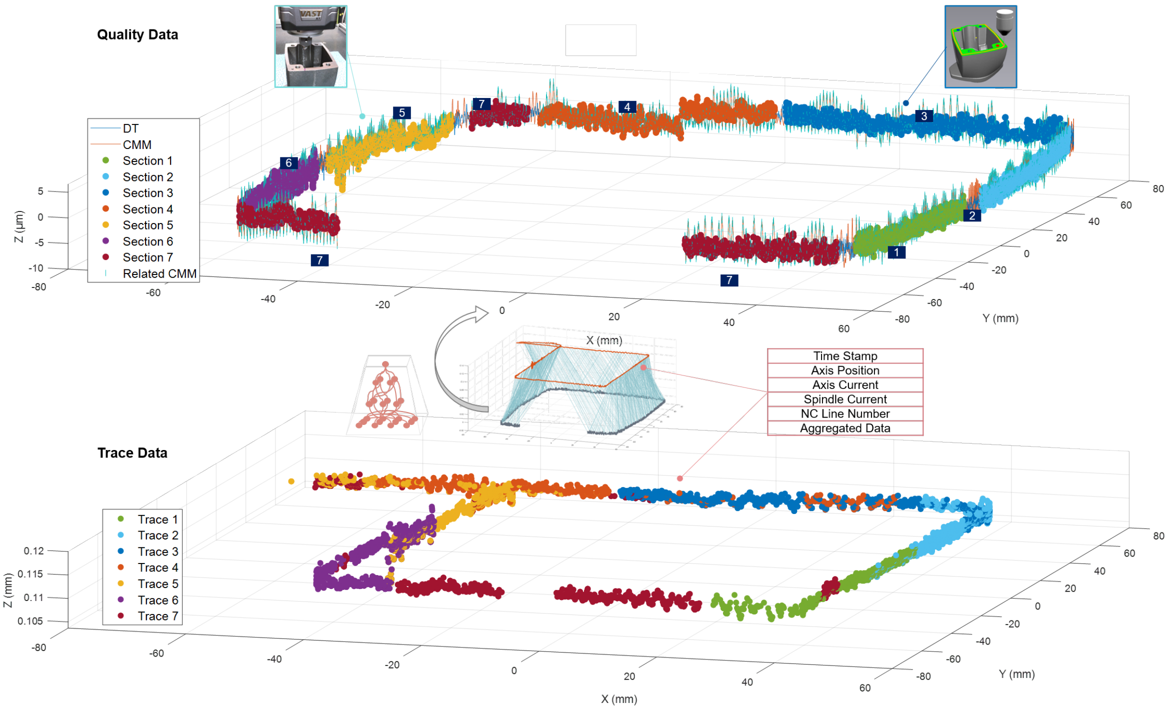

Figure 9: Linked data as the foundation for developing a hybrid learning model chain.

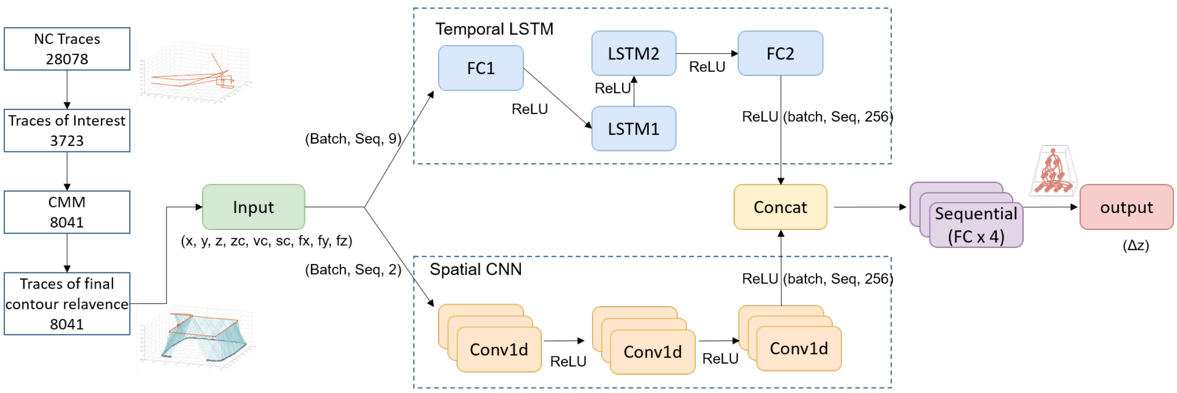

Figure 10: Structure of the VMMNet.

ΔQ. Finally, we investigated the potential to reduce the quality uncertainty (UQ) of the hybrid learning model chain by comparing the real inspection data of a manufactured part taken from the company.

5.2.1. *Hybrid Learning Force Model*

We first identified the parameters of the force model on the machine tool DMC-80H-Linear in use and treated the parametrization results in the form of look-up tables, which is a typical approach for parameterizing complex systems in engineering practice. As mentioned previously, the force model entails some uncertainty and for this part, the main force component is in the z-axis direction as it affects directly the surface. To estimate the uncertain component F_z, we constructed an LSTM block with a sequence length of 32 followed by a trivial fully connected neural network (FCN) with two hidden layers and 300 hidden neurons on each layer and took z-axis current and spindle current (in the machine coordinate system) as additional inputs. Afterward, we incorporated the physical part into the loss function of the NN and trained this physics-embedded NN on the dataset of a training part, where a force measuring platform was utilized to accurately obtain the cutting force. Note that the machine in manufacturing companies is not equipped with force sensors and has a fully disparate workpiece (Fig. 11). The cutting force modeling uncertainty ΔF is therefore defined as the bias between the predicted force from the hybrid learning model and the existing force model. In this implementation, the force uncertainty is equal to the F_{NN}, however, when extending the output to additional four parameters (for the purpose of online parametrization), this result could change as the physical part is also adapted online.

The outcome of the hybrid force model is combined with the

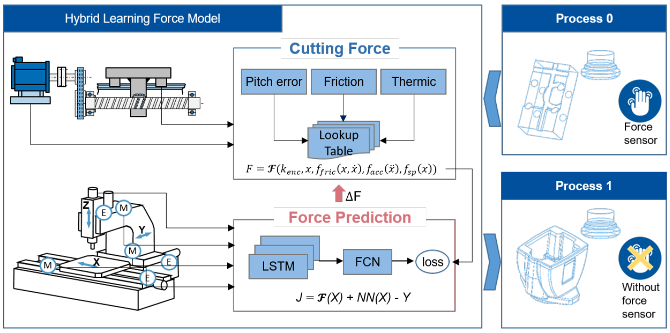

Figure 11: Transfer of the pre-trained force model into the hybrid model chain.

stiffness and feature-based process model to predict the final quality uncertainty. In this way, we obtain the final modeling findings and their tolerance intervals as a basis for decision-making. We now discuss the potential of the model chain for learning residuals of DT and finally compare the modeling results under these two data availabilities (without/without complete quality paths).

$$\Delta F = F_{NN} \tag{10}$$

5.2.2. Evaluation and Optimization

When the available quality data is a fully sampled path instead of the single mean and variance value, the DT can learn the system residual by comparing the virtual and real inspection data, implicitly compensating for neglected effects of the model chain. This reduces the overall uncertainty of the DT and extends the reliable predictable quality features to include the higher order varieties such as waviness and roughness while remaining the model resolution and computational efficiency.

Data Preparation. As the first step, the existing dataset needs to be further processed in order to map the dissimilar-sized machine trace data and quality data exactly 1:1. We achieve this by leveraging the outputs from the process modeling μ, where the virtual quality path with related NC traces are used as inputs and interlinked to the real inspection results. Domain knowledge-based modeling serves in this context as a smart data container for carrying refined production data. Consequently, the refined dataset enables full traceability at an atomic scale, and each sampled quality data is linked to production data and real production resources including corresponding NC line numbers and cutting tools. Fig. 9 illustrates the linked data that describes the relationship between the quality path and NC traces with the final contour relevance. It should be noted that an NC tracepoint may involve multiple spatial quality points because the quality path has more sample points compared to the NC trace. Hence, NC traces of the whole workpiece (28078 sample points) were first extracted into the traces of interest (3733 sample points) from the previous feature-based processing procedure (Sec. 5.1), and then 1:1 remapped according to the CMM data (8041 sample points).

DT Modeling. After the data preparation, we designed an LSTM + CNN + FCN network (*VMMNet*) to learn the transient effects and implicit relationships that were overlooked in the model chain, as illustrated in Fig. 10. The trial network encompasses a temporal LSTM module and a spatial CNN module to learn the sequence- and position-dependent features, which are then concatenated into an FCN with 4 hidden layers with the objective to reduce the Δz of the quality data. The temporal module takes 9 inputs including TCP positions (x,y,z), cutting force (fx, fy, fz), axis current and one order difference (zc, vc), and spindle current (sc). The spatial module takes 2 inputs including the TCP position x and y, representing the working area. These features are constructed to cover the position-dependent stiffness, dynamic force and associated effects, which are seen as a high-dimension mapping to the resulting difference Δz. Regarding model training, we divided 90% of the whole quality path into 7 sections (illustrated in different colors in Fig.9) and chose one section (Section 7 with 1063 points) together with the rest 10% part as test data (1985 points totally). In this manner, we implemented the 80/20 splitting strategy as CNN requires normally massive data amounts and sophisticated transient effects are intertwined in both temporal and spatial terms. Moreover, regarding the knowledge-based modeling, we have implemented the classical Altintas motor current-based force model combining with our process model *VMME* (Sec. 4.2.2) as the reference.

Comparison. Table 1 shows the RMSE of the trial results. Both domain knowledge-based DT modeling approaches have already provided satisfactory results, with our existing model performing slightly superior to the classical model. In comparison, hybrid learning-based DT modeling allows the evaluation of the existing model uncertainties and further optimization of existing residuals with feedback from the quality results. The 3D results are illustrated in Fig. 12, where CMM (green), *VMME* (blue), and *VMMNet* (red) have shown the reasonable consistency. This indicates the potential of enhancing the overall DT modeling boundary while maintaining the model explainability and robustness. We now compare the hybrid learning-based results in two cases, namely with and without the feedback of real inspection data, illustrated in Fig. 13. The upper and lower forward estimated quality uncertainty (yellow) are between $\pm$ 7 µm. This falls within the industry's desired tolerance range ($\pm$ 15 µm), indicating that practitioners can trust the virtual quality estimated by the DT. Similar tool marks also demonstrated the consistency between simulated and real outcomes. The modeling result with the CMM feedback has shown superior performance in some detailed regions. These are not necessarily relevant to the demonstrated feature (flatness), however, are vital for the prediction of higher-order features such as waviness and roughness.

Interpretation. Fig. 14 illustrates the coherence of observation parameters (motor current, NC trace) and model-identified process variables (cutting force and trace deviation) of the targeted quality feature. The time series observation parameters acquired from the edge device (Sinumerik Edge) are linked to the position-dependent quality measuring path, illustrated in Fig. 9. The model-identified process variables interpret the uncertainty of each module (force, stiffness, in medium and light blue, respectively) as well as the uncertainty of the entire model chain

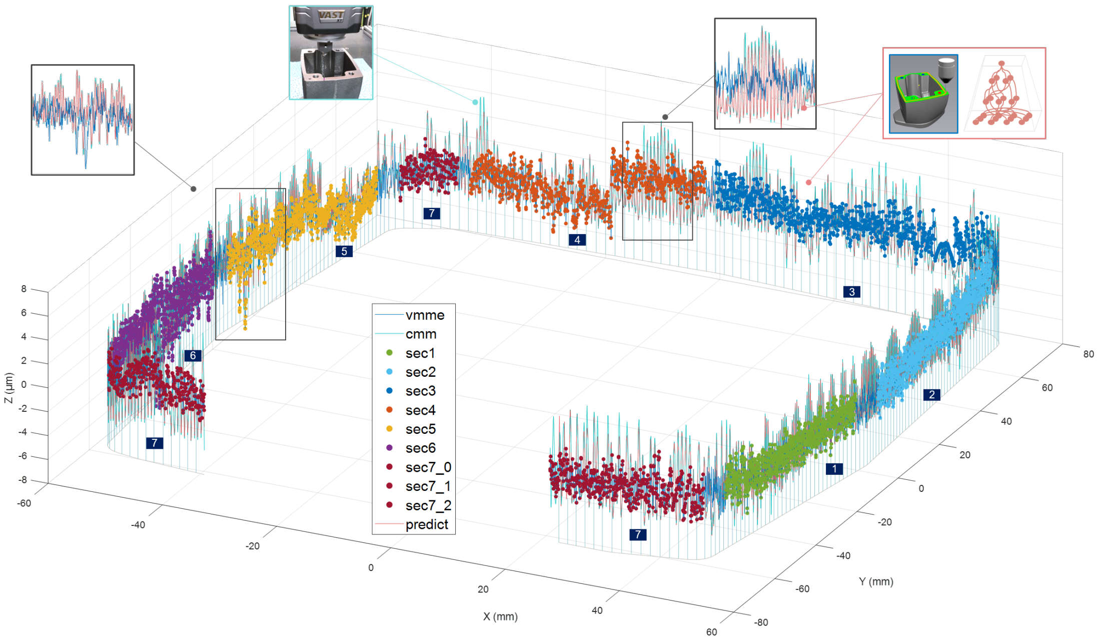

Figure 12: DT results with UQ. Measured and modeled flatness of the selected surface.

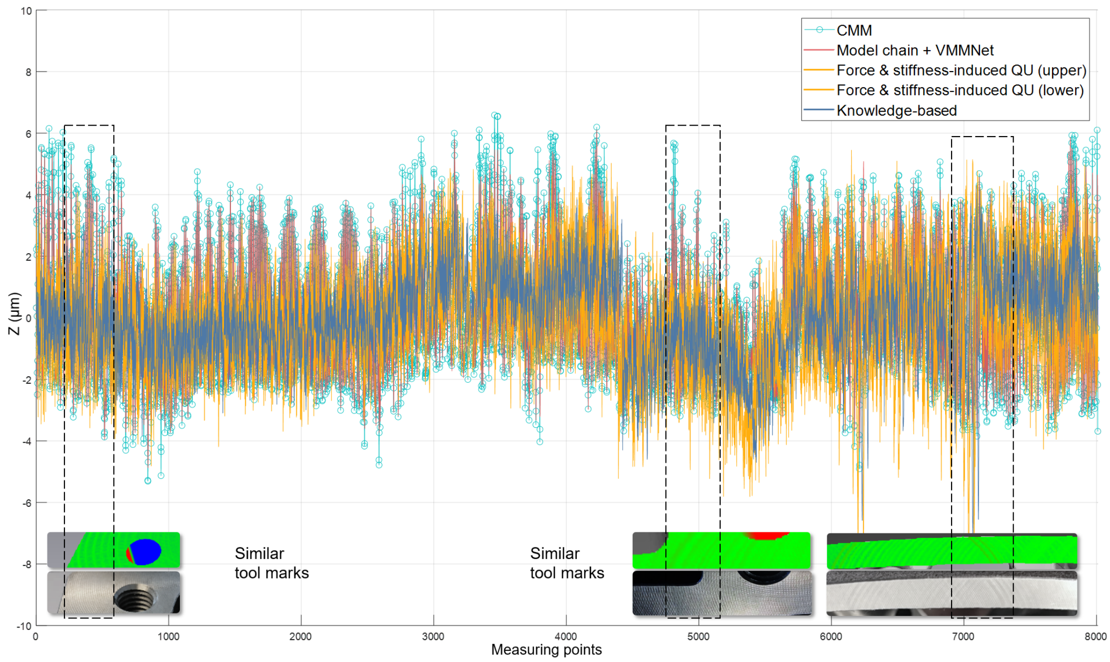

Figure 13: Comparing with results from separate DT models.

RMSE (µm)	**Section 1**	**Section 2**	**Section 3**	**Section 4**	**Section 5**	**Section 6**	**Test Section**
Domain Knowledge-Based (classical model)	2.1151	2.1083	2.3679	2.4571	2.4452	3.0246	2.5491
Domain Knowledge-Based (our model)	1.8458	1.8156	1.8317	1.8961	1.9667	2.4675	2.2576
Hybrid Learning-Based	0.0769	0.0794	0.0812	0.0775	0.0733	0.0819	0.2515

Table 1: RMSE of DT modeling results.

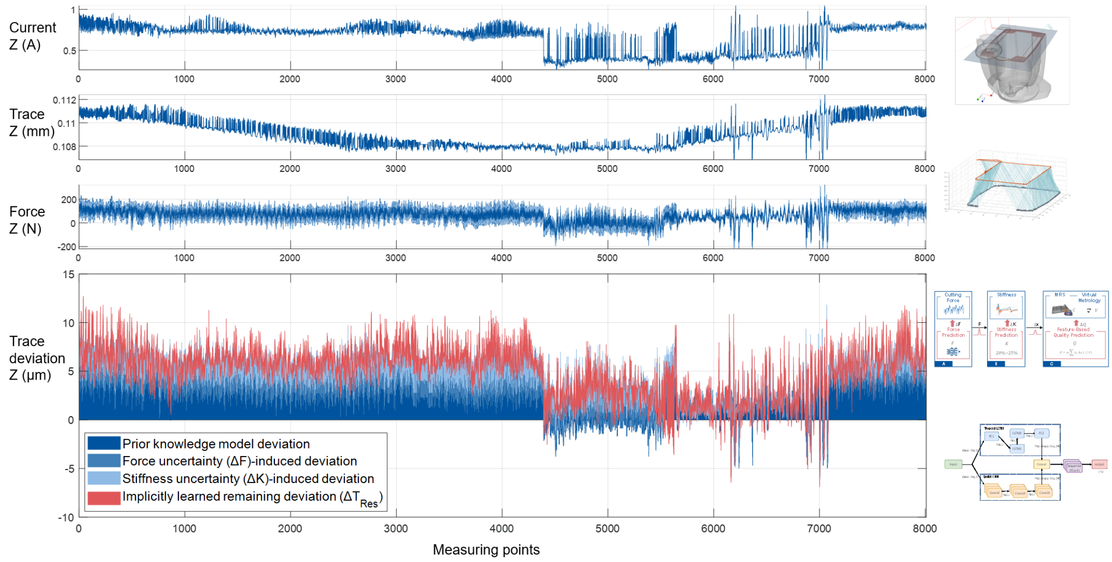

Figure 14: Deviation distribution along the measuring path.

due to the overlooked modeling modules (residuals, in red) in Fig. 13. The process variables associated with the observation parameters reflect the influence of the individual modules of the DT modeling on the final model results. In industrial practice, the accuracy of DT modeling can be further optimized at micro/meso scale by extending the model chain or implicitly covering the residuals that are overlooked during DT development; correspondingly, the cost of DT modeling normally increases. With this constraint, hybrid learning-based DT modeling enables achieving a balance in the development and deployment of DT models on demand with optimal efforts while meeting industrial quality requirements depending on the final modeling uncertainty.

5.3. Discussion

Results of the case study prove that the proposed hybrid learning-based DT is capable of learning uncertainties of the interaction of machine tools and machining processes in real industrial environments, thus enabling estimation and enhancement of the modeling reliability, depending on the data quality and accessibility. Nevertheless, there are several further improvements that can be investigated to transfer this work to broader industrial applications.

- Force model. A position-based force model was incorporated into the AI model. Extending the output for online parametrization can facilitate adaptive process control. In addition, an extended inclusion of MRS is envisioned to further enhance the model precision.

- Stiffness model. The stiffness uncertainty was imputed on measured value with expert knowledge. In engineering practice, developing hybrid learning stiffness models regarding the machine, workpiece, and cutting tool is beneficial to the more adaptive and imprecise implementation.

- Process model. A feature-specific process model was leveraged to simulate the process uncertainty. Adaptive spatial partitioning or a similar hybrid learning process model can further improve the UQ in complex free-form simulation in a process-parallel manner.

- Model chain. The trial *VMMNet* is to be tested with more real manufacturing cases, and extended and modified with other NN modules in terms of generality and causality inference.

6. Conclusion and Outlook

This paper proposes a modeling framework for hybrid learning-based DT for manufacturing process with the corresponding trial implementation. We have constructed a data processing procedure to contextualize metadata sources across the process chain, and a modeling pipeline for the integration of production domain knowledge and AI techniques. In addition, we have designed an implementation architecture for building hybrid learning-based DT that takes into account the multi-fidelity nature of industrial data. This research work indicates that hybrid learning-based DTs can learn uncertainties from real-world manufacturing environments and estimate / enhance the model reliability according to the disparate data availability and fidelity. In future research, we envision the further investigation of the proposed hybrid learning-based DT modeling approach and enhancement of the individual modules (cutting force model, stiffness model, process model, etc.) as well as the entire model chain based on more industrial cases covering disparate manufacturing scenarios. In addition, we plan to develop approaches for automatic reparametrization of the models within this model chain, enabling the DT to self-adaptive process control in dynamic environments.

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References

[1] J. Chen, P. Hu, H. Zhou, J. Yang, J. Xie, Y. Jiang, Z. Gao, C. Zhang, Toward intelligent machine tool, Engineering 5 (4) (2019) 679–690.

[2] X. Xu, Machine tool 4.0 for the new era of manufacturing, The International Journal of Advanced Manufacturing Technology 92 (5) (2017) 1893–1900.

[3] H. ElMaraghy, L. Monostori, G. Schuh, W. ElMaraghy, Evolution and future of manufacturing systems, CIRP Annals 70 (2) (2021) 635–658.

[4] C. Brecher, A. Epple, M. Fey, M. Königs, S. Neus, F. Wellmann, Lernende produktionssysteme, in: Proceedings of the Internet of Production für agile Unternehmen: AWK Aachener Werkzeugmaschinen-Kolloquium, Vol. 18, 2017.

[5] Z. Huang, Y. Shen, J. Li, M. Fey, C. Brecher, A survey on ai-driven digital twins in industry 4.0: Smart manufacturing and advanced robotics, Sensors 21 (19) (2021) 6340.

[6] C. Liu, P. Zheng, X. Xu, Digitalisation and servitisation of machine tools in the era of industry 4.0: a review, International Journal of Production Research (2021) 1–33.

[7] M. Grieves, J. Vickers, Digital twin: Mitigating unpredictable, undesirable emergent behavior in complex systems, in: Transdisciplinary perspectives on complex systems, Springer, 2017, pp. 85–113.

[8] T. Bauernhansl, J. Krüger, G. Reinhart, G. Schuh, Wgp-standpunkt industrie 4.0.

[9] Z. Huang, M. Wiesch, M. Fey, C. Brecher, Edge computing-based virtual measuring machine for process-parallel prediction of workpiece quality in metal cutting, Procedia CIRP 107 (2022) 363–368.

[10] D. Wu, S. Liu, L. Zhang, J. Terpenny, R. X. Gao, T. Kurfess, J. A. Guzzo, A fog computing-based framework for process monitoring and prognosis in cyber-manufacturing, Journal of Manufacturing Systems 43 (2017) 25–34.

[11] S. Jeschke, C. Brecher, T. Meisen, D. Özdemir, T. Eschert, Industrial internet of things and cyber manufacturing systems, in: Industrial internet of things, Springer, 2017, pp. 3–19.

[12] C. Liu, H. Vengayil, Y. Lu, X. Xu, A cyber-physical machine tools platform using opc ua and mtconnect, Journal of Manufacturing Systems 51 (2019) 61–74.

[13] DIN 8580:2022-12, Fertigungsverfahren - Begriffe, Einteilung, Deutsches Institut für Normung, 2022.

[14] K. Dohda, J. Ni, N. De Rooij, Micro/meso-scale manufacturing.

[15] W. Luo, T. Hu, Y. Ye, C. Zhang, Y. Wei, A hybrid predictive maintenance approach for cnc machine tool driven by digital twin, Robotics and Computer-Integrated Manufacturing 65 (2020) 101974.

[16] X. Yang, Y. Ran, G. Zhang, H. Wang, Z. Mu, S. Zhi, A digital twin-driven hybrid approach for the prediction of performance degradation in transmission unit of cnc machine tool, Robotics and Computer-Integrated Manufacturing 73 (2022) 102230.

[17] H. Yu, D. Yu, C. Wang, Y. Hu, Y. Li, Edge intelligence-driven digital twin of cnc system: Architecture and deployment, Robotics and Computer-Integrated Manufacturing 79 (2023) 102418.

[18] F. Mo, H. U. Rehman, F. M. Monetti, J. C. Chaplin, D. Sanderson, A. Popov, A. Maffei, S. Ratchev, A framework for manufacturing system reconfiguration and optimisation utilising digital twins and modular artificial intelligence, Robotics and Computer-Integrated Manufacturing 82 (2023) 102524.

[19] J. Friederich, D. P. Francis, S. Lazarova-Molnar, N. Mohamed, A framework for data-driven digital twins for smart manufacturing, Computers in Industry 136 (2022) 103586.

[20] Q. Wu, Y. Mao, J. Chen, C. Wang, Application research of digital twin-driven ship intelligent manufacturing system: Pipe machining production line, Journal of Marine Science and Engineering 9 (3) (2021) 338.

[21] Y. Fan, J. Yang, J. Chen, P. Hu, X. Wang, J. Xu, B. Zhou, A digital-twin visualized architecture for flexible manufacturing system, Journal of Manufacturing Systems 60 (2021) 176–201.

[22] B. Zhou, Machine learning methods for product quality monitoring in electric resistance welding.

[23] B. Zhou, Z. Zheng, D. Zhou, G. Cheng, E. Jiménez-Ruiz, T.-K. Tran, D. Stepanova, M. H. Gad-Elrab, N. Nikolov, A. Soylu, et al., The data value quest: a holistic semantic approach at bosch, in: The Semantic Web: ESWC 2022 Satellite Events: Hersonissos, Crete, Greece, May 29–June 2, 2022, Proceedings, Springer, 2022, pp. 287–290.

[24] Y. Altintas, C. Brecher, M. Weck, S. Witt, Virtual machine tool, CIRP annals 54 (2) (2005) 115–138.

[25] L. von Rueden, S. Mayer, K. Beckh, B. Georgiev, S. Giesselbach, R. Heese, B. Kirsch, M. Walczak, J. Pfrommer, A. Pick, R. Ramamurthy, J. Garcke, C. Bauckhage, J. Schuecker, Informed machine learning - a taxonomy and survey of integrating prior knowledge into learning systems, IEEE Transactions on Knowledge and Data Engineering (2021) 1–1.

[26] E. Abele, Y. Altintas, C. Brecher, Machine tool spindle units, CIRP annals 59 (2) (2010) 781–802.

[27] Y. Altintas, A. Verl, C. Brecher, L. Uriarte, G. Pritschow, Machine tool feed drives, CIRP annals 60 (2) (2011) 779–796.

[28] Y. Altintas, P. Kersting, D. Biermann, E. Budak, B. Denkena, I. Lazoglu, Virtual process systems for part machining operations, CIRP Annals 63 (2) (2014) 585–605.

[29] C. Liu, H. Vengayil, R. Y. Zhong, X. Xu, A systematic development method for cyber-physical machine tools, Journal of manufacturing systems 48 (2018) 13–24.

[30] C. Brecher, H.-M. Eckel, T. Motschke, M. Fey, A. Epple, Estimation of the virtual workpiece quality by the use of a spindle-integrated process force measurement, CIRP Annals 68 (1) (2019) 381–384.

[31] B. Denkena, B. Bergmann, M. Witt, Feeling machine for process monitoring of components with stock allowance, Machines 9 (3) (2021) 53.

[32] Y. Altintas, D. Aslan, Integration of virtual and on-line machining process control and monitoring, CIRP Annals 66 (1) (2017) 349–352.

[33] B. Schmucker, F. Trautwein, R. Hartl, A. Lechler, M. Zaeh, A. Verl, Online parameterization of a milling force model using an intelligent system architecture and bayesian optimization, Procedia CIRP 107 (2022) 1041–1046.

[34] B. Denkena, B. Bergmann, D. Stoppel, Tool deflection compensation by drive signal-based force reconstruction and process control, Procedia CIRP 104 (2021) 571–575.

[35] M. H. Rahimi, H. N. Huynh, Y. Altintas, On-line chatter detection in milling with hybrid machine learning and physics-based model, CIRP Journal of Manufacturing Science and Technology 35 (2021) 25–40.

[36] B. Zhou, T. Pychynski, M. Reischl, E. Kharlamov, R. Mikut, Machine learning with domain knowledge for predictive quality monitoring in resistance spot welding, Journal of Intelligent Manufacturing 33 (4) (2022) 1139–1163.

[37] L. Guo, F. Yan, T. Li, T. Yang, Y. Lu, An automatic method for constructing machining process knowledge base from knowledge graph, Robotics and Computer-Integrated Manufacturing 73 (2022) 102222.

[38] M. Raissi, P. Perdikaris, G. E. Karniadakis, Physics-informed neural networks: A deep learning framework for solving forward and inverse problems involving nonlinear partial differential equations, Journal of Computational physics 378 (2019) 686–707.

[39] G. E. Karniadakis, I. G. Kevrekidis, L. Lu, P. Perdikaris, S. Wang, L. Yang, Physics-informed machine learning, Nature Reviews Physics 3 (6) (2021) 422–440.

[40] Q. Zhu, Z. Liu, J. Yan, Machine learning for metal additive manufacturing: predicting temperature and melt pool fluid dynamics using physics-informed neural networks, Computational Mechanics 67 (2) (2021) 619–635.

[41] K. Alexopoulos, N. Nikolakis, G. Chryssolouris, Digital twin-driven supervised machine learning for the development of artificial intelligence applications in manufacturing, International Journal of Computer Integrated Manufacturing 33 (5) (2020) 429–439.

[42] M. Helu, A. Joseph, T. Hedberg Jr, A standards-based approach for linking as-planned to as-fabricated product data, CIRP Annals 67 (1) (2018) 487–490.

[43] T. Hedberg, J. Lubell, L. Fischer, L. Maggiano, A. Barnard Feeney, Testing the digital thread in support of model-based manufacturing and inspection, Journal of computing and information science in engineering 16 (2).

[44] M. Helu, T. Hedberg Jr, A. B. Feeney, Reference architecture to integrate heterogeneous manufacturing systems for the digital thread, CIRP journal of manufacturing science and technology 19 (2017) 191–195.
[45] J. Wang, C. Xu, J. Zhang, J. Bao, R. Zhong, A collaborative architecture of the industrial internet platform for manufacturing systems, Robotics and Computer-Integrated Manufacturing 61 (2020) 101854.
[46] Y. Lu, X. Xu, L. Wang, Smart manufacturing process and system automation–a critical review of the standards and envisioned scenarios, Journal of Manufacturing Systems 56 (2020) 312–325.
[47] S. Kwon, L. V. Monnier, R. Barbau, W. Z. Bernstein, Enriching standards-based digital thread by fusing as-designed and as-inspected data using knowledge graphs, Advanced Engineering Informatics 46 (2020) 101102.
[48] T. D. Hedberg Jr, M. Bajaj, J. A. Camelio, Using graphs to link data across the product lifecycle for enabling smart manufacturing digital threads, Journal of computing and information science in engineering 20 (1) (2020) 011011.
[49] S. T. Witt, Integrierte simulation von maschine, Werkstück und spanendem Fertigungsprozess, Shaker, 2007.
[50] DIN EN ISO 1101:2017-09, Geometrische Produktspezifikation (GPS) - Geometrische Tolerierung - Tolerierung von Form, Richtung, Ort und Lauf (ISO 1101:2017); Deutsche Fassung EN ISO 1101:2017, Deutsches Institut für Normung, 2017.
[51] C. C. Wang, Y.-S. Leung, Y. Chen, Solid modeling of polyhedral objects by layered depth-normal images on the gpu, Computer-Aided Design 42 (6) (2010) 535–544.
[52] H. Schwenke, W. Knapp, H. Haitjema, A. Weckenmann, R. Schmitt, F. Delbressine, Geometric error measurement and compensation of machines—an update, CIRP annals 57 (2) (2008) 660–675.
[53] J. Mayr, J. Jedrzejewski, E. Uhlmann, M. A. Donmez, W. Knapp, F. Härtig, K. Wendt, T. Moriwaki, P. Shore, R. Schmitt, et al., Thermal issues in machine tools, CIRP annals 61 (2) (2012) 771–791.
[54] Z. Huang, T. Xi, M. Fey, C. Brecher, Ai-driven digital process twin via networked digital process chain, in: 2022 IEEE Intl Conf on Dependable, Autonomic and Secure Computing, Intl Conf on Pervasive Intelligence and Computing, Intl Conf on Cloud and Big Data Computing, Intl Conf on Cyber Science and Technology Congress (DASC/PiCom/CBDCom/CyberSciTech), 2022, pp. 1–6.
[55] L. Wang, W. Wang, D. Liu, Dynamic feature based adaptive process planning for energy-efficient nc machining, CIRP annals 66 (1) (2017) 441–444.
[56] P. Brauner, M. Dalibor, M. Jarke, I. Kunze, I. Koren, G. Lakemeyer, M. Liebenberg, J. Michael, J. Pennekamp, C. Quix, et al., A computer science perspective on digital transformation in production, ACM Transactions on Internet of Things 3 (2) (2022) 1–32.
[57] M. Vitr, CAM-NC-Kopplung für einen durchgängigen, bidirektionalen Informationsfluß zwischen Planung und Fertigung, Apprimus-Verlag, 2012.
[58] F. Wellmann, Datengetriebene, kontextadaptive Produktivitätssteigerung von NC-Zerspanprozessen, Apprimus Wissenschaftsverlag, 2019.
[59] T. Parr, The definitive antlr 4 reference, The Definitive ANTLR 4 Reference (2013) 1–326.
[60] M. Fey, A. Epple, S. Kehne, C. Brecher, Verfahren zur bestimmung der achslast auf linear- und rundachsen (DE20161013890 G01L1/04;G01B21/02, 2016).
[61] Z. Huang, T. Xi, M. Fey, C. Brecher, Prior knowledge-embedded machine learning-driven cutting force monitoring in machinery industry, in: 2022 International Conference on Electrical, Computer and Energy Technologies (ICECET), IEEE, 2022, pp. 1–6.