ML Framework for Positioning Optimization in Robotic AM Using Digital Twin-Based Digital Assets

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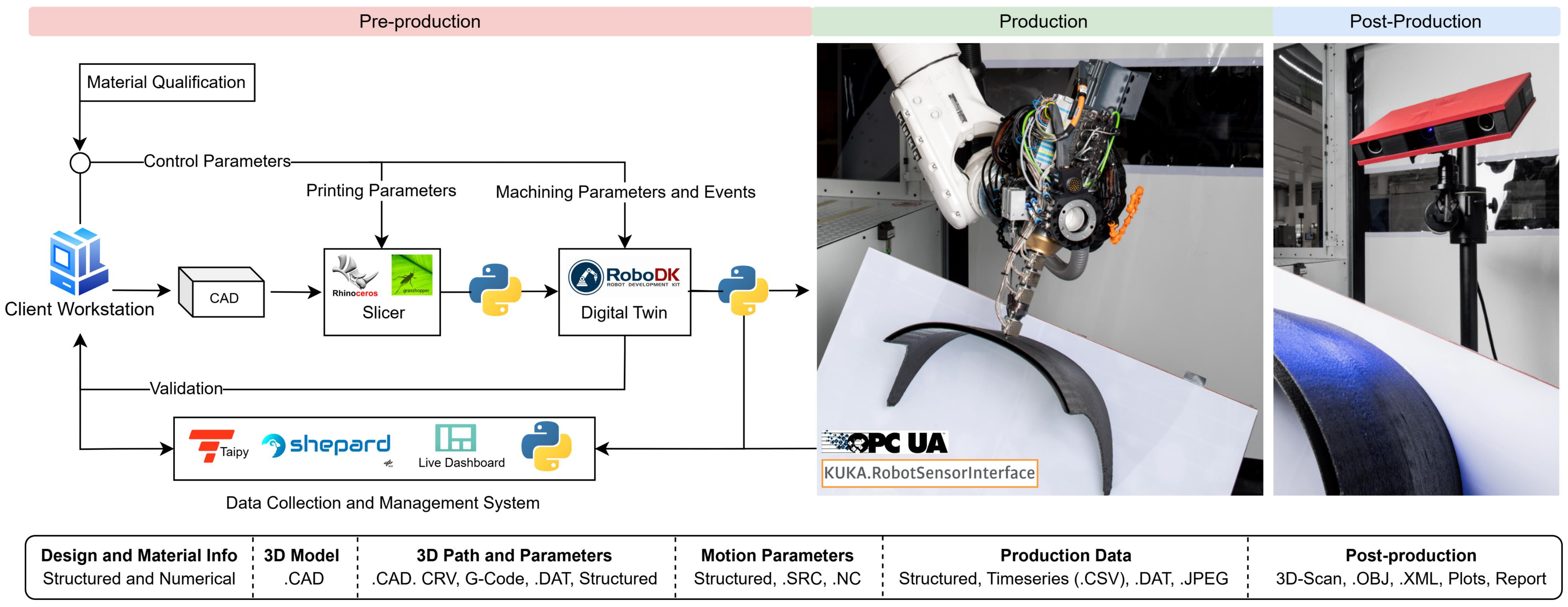


Fig. 1: Digital process chain and heterogeneous data in robotic SEAM [1]. The digital twin plays a central role prior to deployment, enabling the development of digital assets that bridge planned trajectories and actual production behavior.

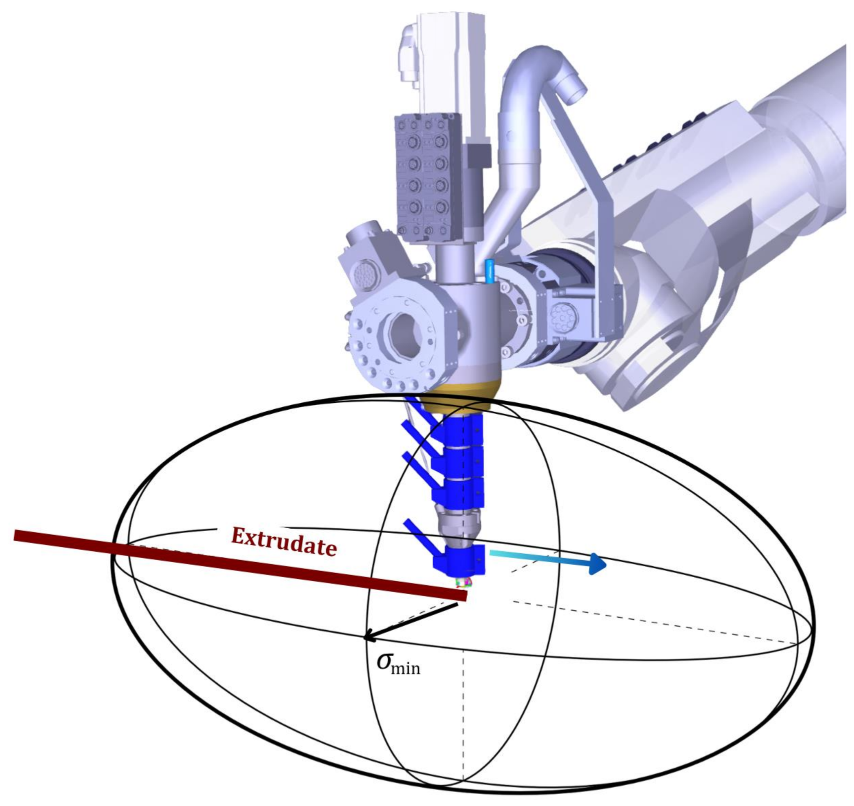


Fig 4. Manipulability Based Kinematic Assement of Extrusionpath [2]

Robotic Additive Manufacturing

When integrated, robotic systems provide enhanced spatial freedom due to their higher degrees of freedom (DOF), allowing adaptive orientation of the extrusion end-effector for additive manufacturing (AM). One such robotic AM system is Space A at DLR FK lab. The Space A process chain with heterogenous data is shown in Fig 1.

Digital Twin

The digital twin (DT) of the Space A (Fig 2) is developed in RoboDK to simulate motion and generate executable robot programs. However, simulation alone does not capture implicit relationships between trajectory design and positioning behavior. To address this, a machine learning–based digital asset can be developed within RoboDK Python API which enables seamless integration with external libraries. This requires a structured feature representation, a direction to which is introduced within this poster.

Feature Generation Using the Digital Twin

Trajectory simulation is performed within the digital twin environment. When trajectories contain sparsely distributed points, commonly arising from polyline-based slicing, long linear segments are subdivided into smaller segments. This enables:

- Improved resolution of robot motion simulation
- Extraction of feasible joint configurations
- Accurate estimation of joint transitions and velocities

Using segment-level information, multiple in-process features are derived, including joint utilization metric, angular velocities per layer etc. This segmented data improves the alignment between planned and measured temporal data. While Cartesian mapping is straightforward, joint-space mapping can be further granularized via quintic polynomial interpolation to ensure smooth transitions and accurate time-series alignment (Fig 3).

Furthermore, via the DT kinematic conditioning highlighting configurations along a contour can be studied. For this Yoshikawa Index [3] is integrated (Fig 4).

Moreover the complete feature set incl:

- Geometric Features: Capture contour complexity, geometric characteristics, and workspace coordinate frames
- Process-Specific Features: Include metrics such as energy deviation ratios
- Kinematic Features: Represent robot conditioning (e.g., manipulability, condition number)
- Frequency-Domain Features: Include joint spectral characteristics
- Horizon Features: Capture look-ahead behavior, torque stability, and temporal dependencies

Initial machine learning results indicate that kinematic, horizon, and frequency-domain features contribute most significantly to trajectory fidelity. These findings will be discussed in detail in an upcoming publication.

Fig 2. Space A Digital Twin

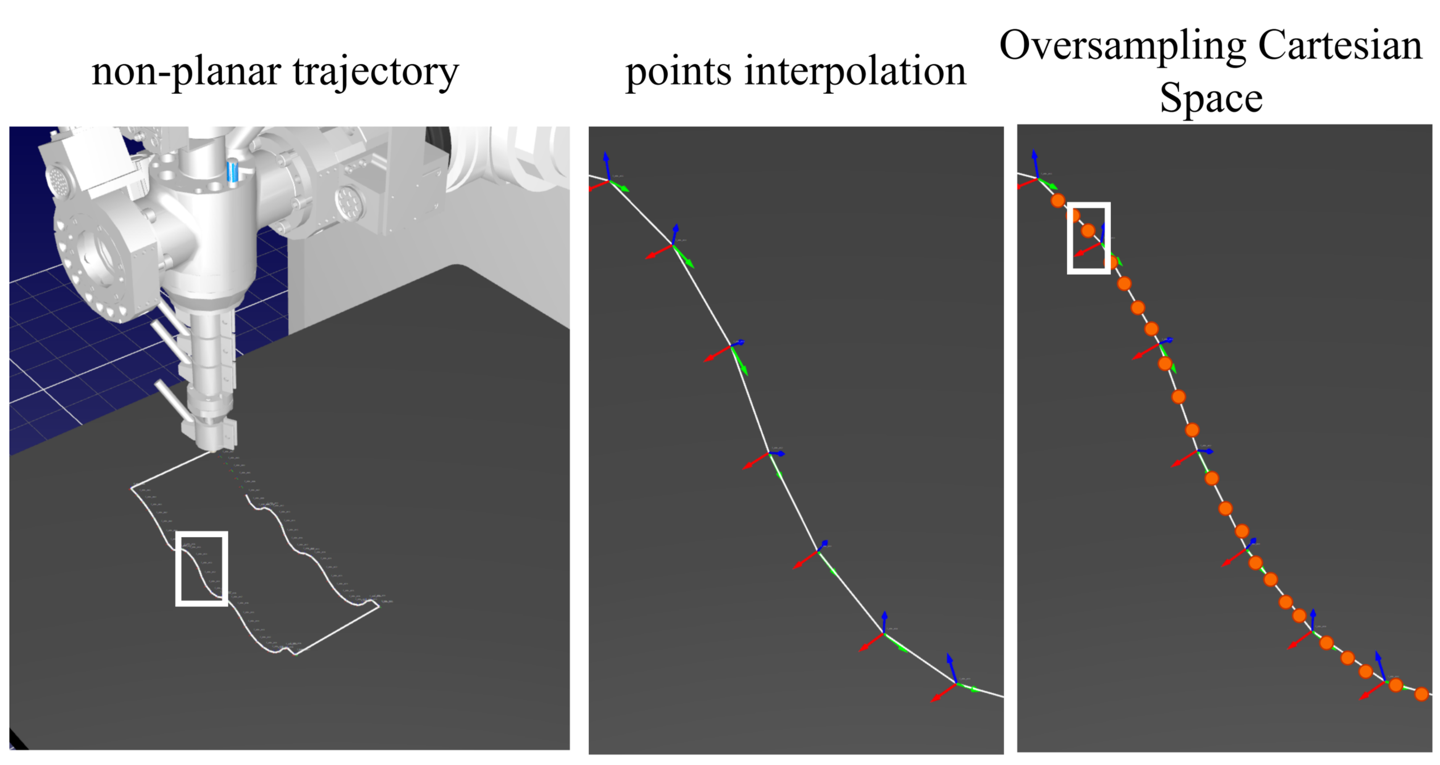
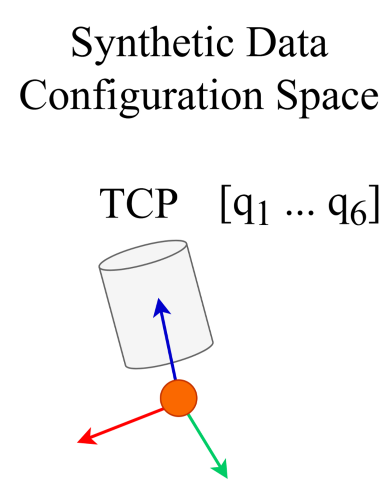


Fig 3. A Digital Asset within Digital Twin, Oversampling the Cartesian space of a non-planar trajectory with quintic polynomial sampling



Outlook:
How can planned and production data with knowledge be unified into a digital asset that fully represents the part?

Reference:
[1] Kamble, Pradnil, Nicolas Unger, Mathieu Vinot, and Roland Glück. "Project MEMAS: A Framework for FAIR Data Storage in Composite Engineering." (2025). Available: https://elib.dlr.de/215508/
[2] (In Publication) Kamble, Pradnil, Choudhary, Pranav. "Towards Kinematic Assessment of Robotic AM Toolpaths, Evaluating A Contour Manipulability-Based Pre-Production Metric." (2026)
[3] T. Yoshikawa. Manipulability and redundancy control of robotic mechanisms. In Proceedings. 1985 IEEE International Conference on Robotics and Automation

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