IAC–21–D1,1,2,x64264

AI-In-Orbit-Factory – AI approaches for adaptive robotic in-orbit manufacturing of modular satellites

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Abstract

Ongoing advances in modular satellite architectures, coupled with improvements in adaptive manufacturing processes are paving the way for innovations in manufacturing in space and, beyond that, even on-orbit servicing. Current challenges for in-orbit manufacturing of satellites include, in particular, highly reliable, precise and adaptive manufacturing and inspection processes, teleoperation methods to resolve unexpected problems from Earth, and means for a digital representation of all relevant activities and conditions to maintain full control.

Each challenge is addressed in the project AI-In-Orbit-Factory with various of AI methods.

For the necessary digital representation of the in-orbit factory and all ongoing processes a knowledge-based approach and digital-twin methodology is used, which enables adaptive, flexible and understandable manufacturing processes. Especially the complex information flow between different manufacturing machines, digital process twins that orchestrate the production process and digital twins of satellites in production can be described. Furthermore, conflicts and possible error sources can be identified through inference.

Utilizing the aforementioned knowledge base and standardized modular components the composition of a mission specific satellite is automatically planned based on the desired mission requirements. With the help of a robotic manipulator each module is optically inspected for production errors using a high-resolution camera and reference images, before they are integrated into the satellite structure. Once integrated, the submodules undergo optimized testing and anomaly detection routines with learned nominal subsystem behaviour models as input. Additionally, each manipulation step is supervised using force-feedback and vision-based anomaly detectors.

For cases where automated assembly fails, a bilateral teleoperation system with force feedback is developed. In order to increase precision during teleoperated assembly and reduce mental and physical load, the human operator is assisted by adaptive virtual fixtures (haptic constraints). Adaptive fixtures are learned from both demonstration and simulation and parametrized depending on the manipulation phase, providing coarse to fine-grained support throughout approaching, positioning and haptic manipulation phases. An arbitration component detects the current manipulation phase to select the appropriate supporting fixture and ensure smooth transitions.

This paper outlines the AI methods and our approach to reliable and adaptive in-orbit manufacturing and presents first results.

Keywords: digital twin, AIT, teleoperation, AI, robotic manufacturing

Acronyms / Abbreviations

AI artificial intelligence. 3

AIT automated integration and testing. 3, 4, 6, 10

DPT Digtal Process Twin. 7, 8

FEM finite element method. 7

FMI functional mock-up interface. 7

HW hardware. 4

MES manufacturing execution systems. 7, 8

OI optical inspection. 4, 5

SW software. 4, 11

1. Introduction

1.1 *Motivated by New Developments in Space*

Since the preceding Space Factory 4.0 project [23], the number of satellite launches has increased rapidly. OneWeb aims to launch 900 satellites in the next few years while SpaceX plans to launch 12,000 satellites for its Starlink network service which will multiply today's total of 2,800 satellites [29].

Although not as lightweight as the CubeSats we are focusing on in the AI-In-Orbit-Factory, satellites in such mega-constellations are significantly less heavy than traditional satellites. These satellites, however, must be designed to be launched on rockets, withstand the vibrations and high forces of launch, and use foldable solar panels due to space constraints. The in-orbit assembly of satellites overcomes these difficulties. Furthermore, individualised satellites can be deployed in a very short timeframe which would be impossible with individual rocket launches [23].

Producing such high numbers of satellites at reasonable cost requires scalable manufacturing processes with increased automation and digitization. In the Space Factory 4.0, methods from Industry 4.0 were therefore employed to enable mass production while still allowing customization. A digital twin was used to track individual satellites and their configuration.

However, since most satellites are highly customized, artificial intelligence methods could help to account for specialized configurations and realize greater autonomy and robustness of the automated integration and testing as well as the teleoperation process.

1.2 *Related Projects*

Especially for long-running missions, manufacturing replacement parts in orbit is of high interest. NASA is therefore researching in-space manufacturing technologies e.g. via using 3d printers on the ISS [16], [21]. It has been shown that for various satellite components as well as for spare parts, manufacturing in space is the more cost-effective solution compared to servicing missions with replacement parts manufactured on Earth [19].

The recent research project MOSAR* aims to design modular, reconfigurable satellites where parts can be exchanged for maintenance, allowing for a longer service life time. In the PULSAR† project, technologies for assembling large structures in space are studied. Exemplary, a large mirror is assembled which allows to build much larger telescopes than those which can currently be launched given the size constraints in spacecrafts. Such large mirrors allow to look even further in the space.

The PERIOD‡ project aims to pave the way for such concepts to be deployed to space. It includes satellite assembly, reconfiguration and verification.

All of these projects, however, focus on large structures. A notable exception is the approach of the group around Uzo-Okoro [36], [37], which aims to create a prototype factory for CubeSat assembly. This factory, which consists of a small box, is planned to be later deployed to ISS.

1.3 *AI-In-Orbit-Factory*

Building on the Space Factory 4.0 project, which focused on a flexible, holistic approach for CubeSat assembly guided by Industry 4.0 principles [22], we are now employing artificial intelligence to develop an even more flexible approach. The German Federal Government has also identified this technology as key to future economic development in its AI strategy [20]. Despite the promising methods that can be realised with AI, it is not yet employed in space applications. We believe that AI is a key enabler for future space applications and therefore place it at the centre of the AI-In-Orbit-Factory project's research.

Specifically, we shift the main focus from the individually configured CubeSat towards the fabrication process. This allows the newly developed digital process twin to enhance production by not only supervising the assembly of one satellite but also continuously adapting with knowledge generated from the assembly of multiple satellites, thus increasing flexibility and adaptability. Artificial intelligence methods are also a key enabler for autonomous planning, fault detection and mitigation, which allow for

*https://www.h2020-mosar.eu/
†https://www.h2020-pulsar.eu/
‡https://period-h2020.eu

adaptive manufacturing of CubeSats. As direct human intervention is not possible because sending astronauts to the factory would be too costly, we are designing an intuitive teleoperation interface. This interface allows the human operator on Earth to control the assembly process while being optimally assisted by intelligent virtual fixtures. The novel methods developed for the AI-In-Orbit-Factory are

- integration process planning and optimization
- automated component inspection, integration and testing using learned models
- Digital Process Twin for monitoring and orchestrating entire processes
- the teleoperated robotic assembly assisted by intelligent virtual fixtures.

which we will present in the remainder of the paper.

2. Overview

Overarching goal of the joint research project "AI-In-Orbit-Factory" is the development of a cyber-physical production system to showcase in-orbit manufacturing, automated integration and testing (AIT) of small satellite systems, using artificial intelligence (AI)-based methods to improve adaptivity, efficiency and reliability of the production process. Central components and steps of this AIT process can be seen in fig. 1.

Starting from a mission / payload definition, a central planning system first derives a component integration plan for the individual subcomponents of the satellite to be assembled. This assembly is done using a robotic arm. During integration, every component undergoes different inspection steps, using AI-based supervision methods to ensure correct assembly, check for damage and ensure proper functionality. System tests can be run on the fully assembled satellite before launch, as well as a maintenance plan generated for later in-orbit-servicing. The assembly is performed adaptively and autonomously; should human intervention be required, a teleoperation link can be established from an Earth-based ground station to directly control the robot arm. To account for the difficult control requirements during this intervention, having large communication delays as well as high precision and reliability demands, teleoperation of the manipulator uses AI-based shared control approaches to optimally support the human operator during this demanding telemanipulation process. All the components of this cyber-physical production system are in parallel modelled as a digital process twin, providing real-time data sharing and communication between all system components as well as allowing for autonomous interaction between system parts. Furthermore, AI-based methods enable automated learning from production data to improve individual steps of the assembly process.

All individual components of the AI-In-Orbit-Factory production system are presented in more detail in the following, with special focus on how AI-based methods are employed to improve robustness, reliability and quality of the production process.

3. AIT - Smart Manufacturing

Smart manufacturing of small satellites has been a major focus in the project consortium before with a focus realizing scalability for large scale production [41] using process permeating digitalization [39], robotic automation [17][18] and modularity with the UNISEC satellite bus. The ai and support components complimenting and optimizing these AIT process principles are introduced in the following paragraphs.

3.1 *Component integration plan generation*

The first step in the AIT process is to generate an optimal integration plan, consisting of the integration order of the (sub-) systems to be integrated so that the individual hardware requirements and test requirements of each system are fulfilled at integration time. An example for a hardware requirement would be the electronic power system (EPS) on which almost all other subsystems depend on for their operation. An example for a test requirement would be the necessity of an already tested and integrated on-board-computer if house-keeping tasks of a subsystem need to be tested as part of the automatic subsystem test routines. All these dependencies are stored in the digital twins of all subsystems/components that are to be integrated and are designed at the system engineering and test-engineering phase in advance. The planning of the integration plan can therefore be reduced to a classical constraint-satisfaction-problem where integration order is realized with binary "before" and "after" constraints. To solve such problem combinatorial planning approaches [2], [5], [8] can be used. We use the classic branch-and-bound algorithm which is granted to find a solution to the constraint-satisfaction-problem if it exists. The algorithm is also fast considering the nature of our problem with a small size of decision variables. Details for the current state-of-art of branch-and-bound can be found in [12] and an overview of the planning process is visualized in fig. 2.

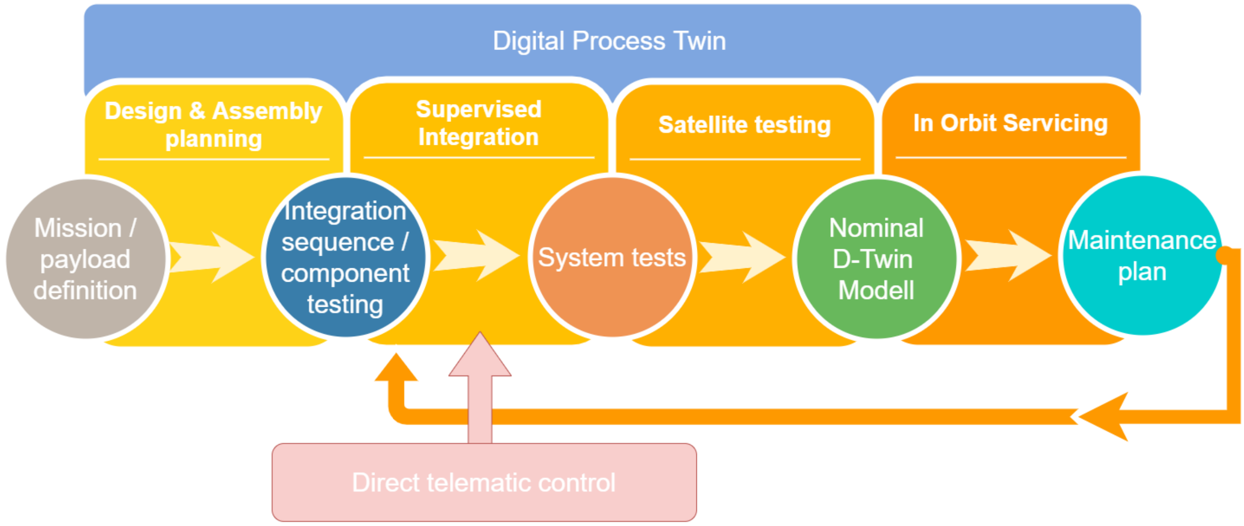

Fig. 1: The automated integration and testing (AIT) process in the "AI-In-Orbit-Factory" project

3.2 *Information Compositor*

In the proposed robotic AIT process, the main means of information exchange between AIT components is realized through their respective digital twins. However as the software (SW) as well as the hardware (HW) architecture of AIT components in the setup is very diverse (robotic manipulators, embedded satellite-components, process-workstations, ...) the need arose for a central information hub that coordinates the exchange of information. This so called Compositor component needs to deal with very different interfaces, SW/HW capabilities and information structure. The information exchange between different AIT components is visualized in fig. 3 where different information providers of the digital twin are connected to the Compositor which provides two way information exchange through a single hierarchical information map, called DPM, and encapsulates the requested or provided information content in a JSON data structure.

Therefore the Compositor was designed as a modular Python software block, allowing new information sources and sinks to be easily added through backend and frontend plugins. The backends provide access to an Inventree database storing the non-realtime digital twin state of a real component, a S3 storage storing big binary data (e.g. component 3D models for simulation) and the Compass-Realtime system providing live data from the satellite components in the test-bed. Each backend registers its provided information content in a tree like map called domain protocol map, that links requested information to the corresponding backend component. Frontends allow access to the backend information through different means, e.g. a WEB REST API. The compositor now takes care of coordinating information requests as well as provided data from the frontends to the backends corresponding to the respective entry in the DPM. Employing wildcards in the DPM identifier when addressing the requested information allows for multi-source queries. An exemplary data exchange and the modular architecture is visualized in fig. 4 where the requested 3d model data is collected through the S3-backend and provided via the WEB REST-API frontend. In fig. 5, a multi-source query is shown that returns live and stored test-data from multiple information providers utilizing different backend modules.

3.3 *Optical Inspection*

After the type and order of the components to be assembled have been established during the integration plan generation, before actual assembly, an optical inspection (OI) is performed on all of the assembly parts first. The purpose of this inspection step is multifold: first, the component needs to be identified and alignment checked, to verify that a correct component has been picked up and that is has been grasped correctly and with the right orientation. Then, a fault check of the part itself is performed, to ensure the right subcomponents have been correctly mounted on it, and furthermore to inspect the component for production anomalies, defects or pollution. If any of the latter are detected, these spots represent points of interest that require further inspection and AI-based analysis to determine whether the anomalies are critical and can be fixed, or the component needs to be replaced. Optical inspection thus serves as another verification and testing step to increase robustness, reliability and adaptivity of the remote

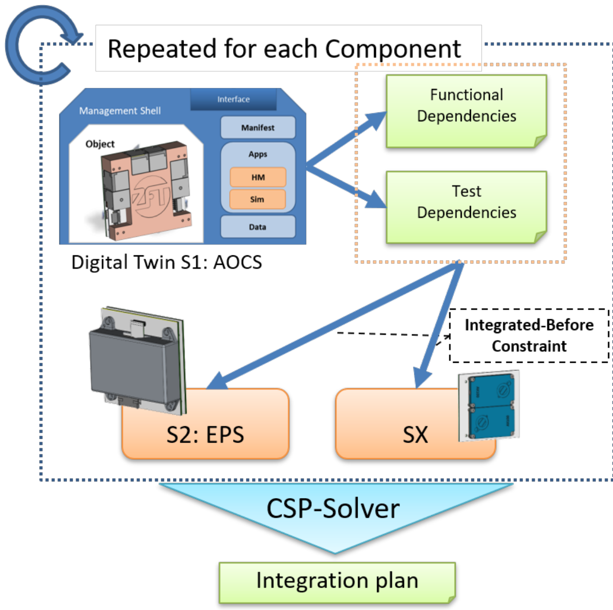

Fig. 2: Integration plan generation solving a Constraint-Satisfaction-Problem on the collective subsystem HW and Test-dependencies stored in the individual digital twins. In this example the Attitude Determination Control System (ADCS) has a functional requirement on the Electric-Power-System (EPS) and a test dependency on another system (SX).

assembly process.

The OI process is divided into two separate stages: stage 1 uses a camera with polarized filters to generate clear, reflection-free high resolution images of the whole component to be assembled. The camera can either be mounted on a robotic arm and positioned over the inspection part by the robot, or vice versa fixed on an assembly with the robot positioning the parts in front of them. Taken overview images are then used as input for a databank-based comparison with reference images of those components, to identify and verify their type, grasping location as well as mounted subcomponents. If during this step anomalies are detected, macro- and microscope-cameras are used to take even more detailed images of these points of interest. These extremely detailed high resolution images are then used as input for stage 2 of the OI-process, where AI methods are employed to classify type and severity of potential defects on the board (see below). If no such anomalies are detected during stage 1, assembly of this component can proceed as determined by the component integration plan.

If however deviations from the norm are detected, stage 2 of the OI process then uses detailed microscope-level views of those areas on the components to decide type and severity of those anomalies. Potential defects that can be detected include wrong or misplaced components, production defects like solder bridges / balls, dry joints or tombstones as well as pollution like dust particles or solder residue. For detection and classification, several different AI methods are deployed, among others Region Based Convolutional Neural Networks [11] as well as Support Vector Machines [3]. These methods use training data [31] to learn to reliably recognize the mentioned types of defects. Besides the initial training, data from the actual production process can then be used to further enhance the performance of the stage 2 classification. Result and severity of the defect classification during this stage is fed back into the assembly planning process to decide on how to react to those detections (continue, repair, replace).

3.4 *Robotic Solarcell Assembly*

As a practical use case, the developed OI solution was employed during the assembly of solar cells onto a solar panel carrier board, utilizing a smart manufacturing system [40]. The components to be assembled were placed onto mechanical fixtures, while an ABB Yumi robot then grasped the solar cells using a suction system and placed them on top of the glue covered surface of the carrier panel. An overview of the system setup can be seen in fig. 6 left. A mounting accuracy of 0.1mm needs to be achieved, which first requires verifying correct placement of the components on the fixture. For that purpose, a microscope camera was mounted on the gripper of the robot and then moved to several inspection positions on the edges of each solar cell: images recorded there were used to automatically check whether components had been placed sufficiently accurate, or needed to be corrected before assembly (pre-check). Furthermore, after placement the solar cell positions were inspected to determine correct alignment within the carrier frame, to ensure the desired production quality (post-check). Besides those assembly checks, further images could be taken of the solar cells' surfaces to check for pollution or defects. This developed solution was employed during assembly of several solar panel boards for space-qualified satellites, and thus serves as an example for how OI can be used to achieve and ensure high robustness, reliability and quality during the production process.

3.5 *Autonomous Subsystem Tests*

Besides the optical inspection, satellite subcomponents in the AI-In-Orbit-Factory project also undergo further autonomous functionality tests, first to assess nominal electrical properties of the components, and then to assert correct functionality using software unit tests. For both test-

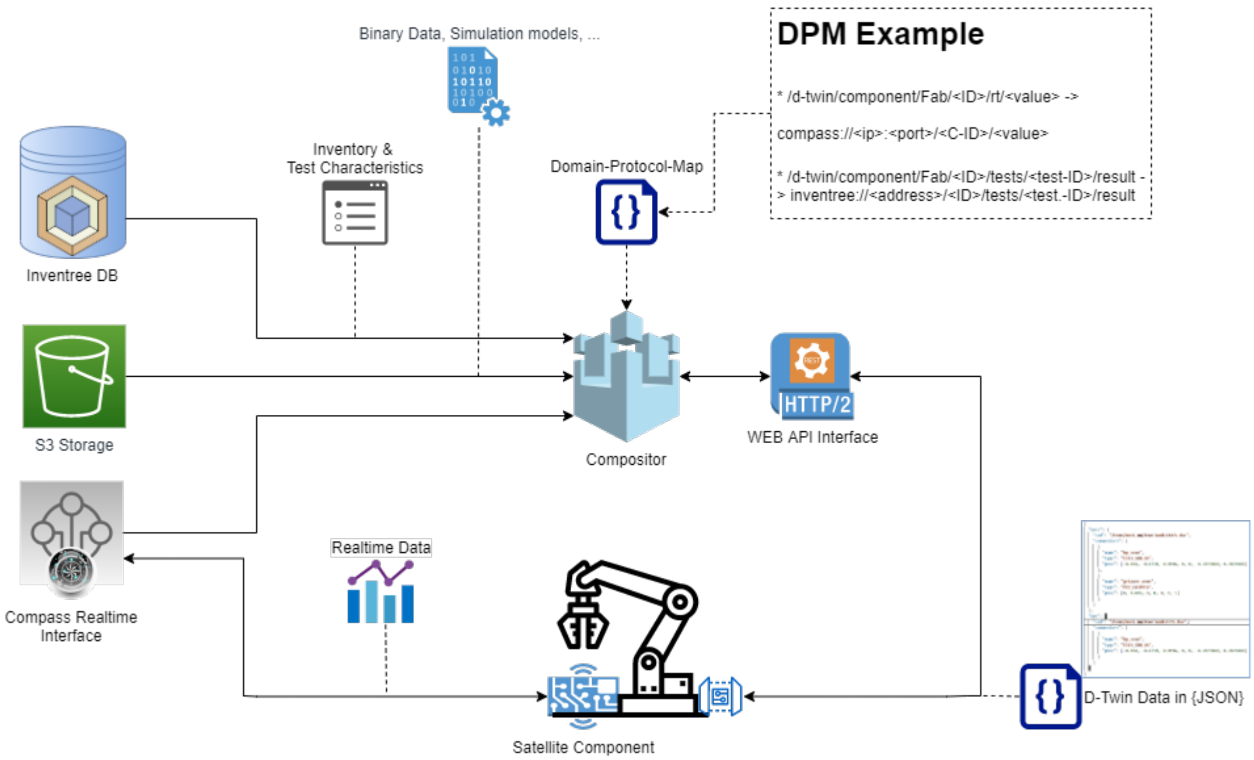

Fig. 3: Information flow between components in the AIT process showing the Compositor as central digital twin information hub. The modular architecture allows inclusion of very diverse component SW/HW architectures.

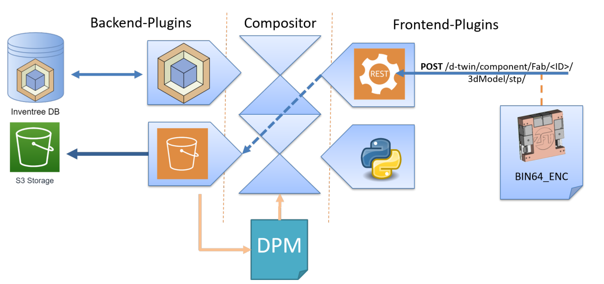

Fig. 4: Information query of digital twin data through the Compositor information hub. The requested 3d model data is collected through the S3-backend and provided via the WEB REST-API frontend.

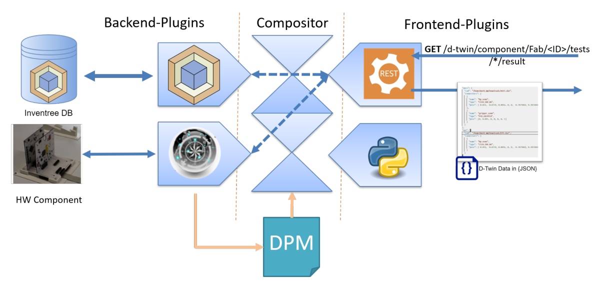

Fig. 5: Information query of stored and live test data through the digital twin and collected from multiple sources at the same time. The compositor utilizes multiple backends and encapsulates the results in a JSON structure.

ing procedures, the assembled satellite subsystem board is first inserted into a testing backplane board providing the appropriate UNISEC bus standard interfaces. After successful insertion, this board can then provide power to the subsystem, allowing to measure and monitor voltage, current and power consumption of individual subcomponents on the board. These measured values can either be used to directly check for production defects (by comparison with data-based nominal values), but can also serve as training data for AI-based learning methods to learn nominal values of new types of subsystems during system operation.

Besides supplying power to the subsystem, the testing development board also provides communication interfaces to allow debug communication, microcontroller programming and in-system-debugging of those satellite subsystems. This first enables testing whether successful communication with the subsystem board is possible

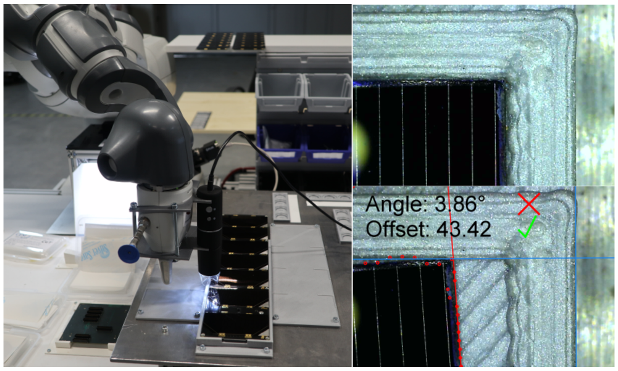

Fig. 6: Solar cell assembly setup with microscope OI camera mounted to the robot (left); inspection result image with correct placement (top right) and identified misaligned component (bottom right).

at all, but then also further opens the option to run software unit tests on the component. These software tests allow to autonomously check whether a component works as intended by providing a series of inputs to it, receiving (or measuring) the outputs and reactions of the subcomponent to them and comparing those with the specified desired reactions. These tests thus finally also enable automated verification of correct functionality of the subsystem. Besides optical and electrical inspection, this enables a further layer to ensure proper production of the satellite subcomponent, to increase reliability and robustness of the automated assembly procedure.

4. **DPT**

4.1 *Digital Process Twin*

The Digtal Process Twin (DPT) is a continuation of the development regarding the Digital Twin. While the Digital Twin focuses on the individual Asset, the DPT aims to enhance entire processes. Therefore, we provide a definition regarding the DPT: The digital process twin orchestrates the production of a product instance by allocating the relevant product components, instantiating the digital product twin as start of the physical production process and providing information to the digital twins of production machines. The structure of the digital process twin is based on the digital twin concept with adaptions for process control and functions for a holistic, multi-agent production optimization. As the DPT aims to organise the production process it takes a comparable role within the larger industry to the manufacturing execution systems (MES). But while MES systems follow a hierarchical design philosophy in order to maintain the conventional automation pyramid, the DPT diverts from this. It is more based on the decentralised approach of the Digital Twin and targets a service-oriented automation, with more flexible production routes. However the DPT is distinct from the Digital Twin by not having a distinct bidirectional connection to one specific counterpart. While this connection is an integral part for the Digital Twin [35], the DPT has no distinct physical equivalent but is tied to a succession of action which are not determined at the creation of the DPT.

4.2 *Architecture*

The architecture of the Digital Process Twin serves to organise an autonomous production. It is derived from the structure of a digital twin. A schematic overview of the digital process twin is given in fig. 7. It can be divided in four main layers [14]. The digital process twin interface provides an access point for operator interaction to monitor the production process and provide options for intervention. The data section contains first and foremost the manifest and the ID. It is used to authenticate and identify the process twin and provide information of available models and services. For data aggregated over the lifetime the operational data storage provides space in form of a database. It is a continuation of the concept of the digital shadow [35]. This data can be used in the lower sections of the Digital Process Twin to provide services for the costumer, like evaluation, monitoring and optimization of the production process. While the digital process twin focuses on performance data, the Digital Process Twin diverges from this approach, to enable a broader spectrum of applications [33]. The technical data storage contains models and simulations of the physical product and the underlying functional models. It provides access to the models via the functional mock-up interface (FMI). The used database needs to be much more versatile compared to the one used for operational data. The service layer contains all models and services used for performing tasks for the product, the costumer and other digital twins. Models within this layer provide a support role and are used by services to create estimations and predictions of possible outcomes. These models provide the product representation, among others through CAD models, simulation models such as Simulink models or finite element method (FEM) models. In addition, control models for product operation and additional services such as AI-enabled functionalities and product presentation services may be implemented. The Digital Process Twin can provide next to these applications also the ability to sequence and orchestrate an entire production, due to the larger scope compared to a digital twin. These contain data aggregation of the production process for a long-term archive, process analysis or the detection of errors within the production. The last section is

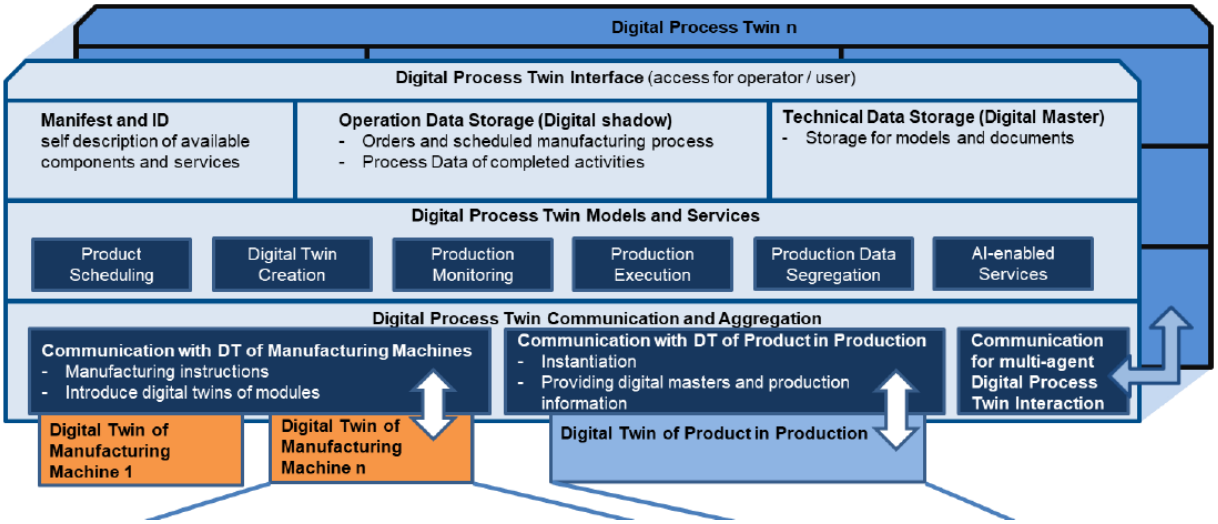

Fig. 7: The Digital Process Twin

the communication layer. This includes both the bidirectional interaction with physical counterpart as well as the interaction with other digital twins. While a digital twin is connected to one physical product the Digital Process Twin has no single asset. Therefore it only perceives the actual occurrences in the factory through information allocated from digital twins with a direct physical twin as well as other systems [28]. This indirect information gathering is the main difference between the two concepts for twins.

4.3 *Process Planning*

While the concept of the Digital Process Twin (DPT) is an adoption of the Digital Twin for the automation of production systems it is not directly redundant to current MES. While the DPT will take same responsibilities away from MES it will not be a replacement. While MES systems are limited to production facilities and company borders the DPT is not constrained by such. In contrast it can be regarded as a third party within the own production facilities, which will need to buy the services from the company. Which means that a product might be assembled in parts by a competitor if the costs for services are lower compared to in house alternatives. In order to plan the process the DPT will need information regarding the available services and the own product structure. Therefore, the DPT will reach out to all currently available production resources and get information regarding the services they provide. While in a larger industrial environment it will be a given to use standardized ways of communicating such information, in a more confined space like a space factory there will be more specialised solutions like the compositor. For an industrial adoption the DPT will integrate the OPC UA stack to access the companion specifications of production facilities [32]. Once these information are available the DPT has multiple ways to determine the steps to follow. In this instance it will use it will first create a production graph. This graph will be a directed graph with non-negative weights, due to all production steps having an inherent cost associated with them. Based on this production graph a shortest path search will be able to determine the most cost effective sequence for production. Once the production is underway the production graph can be used in order to react to changes in the price structure or availability of services.

4.4 *Error Recognition*

One of the main advantages of the Digital Process Twin is the broad range of information it can accumulate. With the operational data pool applications for error recognition within the production process can be created. While there are several systems for error recognition within a Smart Factory the underlying concept for the implementation for the Digital Process Twin is based on a state machine. [25] With the use of the simulation models of the production process the Digital Process Twin is able to create a large but finite state machine categorising the possible states a production process can reach, if no unexpected event occurs. [4] If therefore the values provided be the physical devices suggest a state, that is not part of the state machine an alarm is given and the Digital Process Twin can request a human intervention, for example a teleoperation.

5. Teleoperation Process

Automated methods can be used for most parts of the CubeSat assembly. Having an interface for humans to control assembly operations is however still desirable when certain tasks cannot be automated or if the automated assembly fails as we have found in the preceding Space Factory 4.0 project [23].

To provide such an interface, we implement a haptic telemanipulation system where the user commands actions using a haptic input device on Earth which are then executed on the remote robot in the in-orbit factory. The forces felt by the remote robot are relayed back to the input device which increases the system transparency for the human operator and allows the execution of dexterous tasks. Modern passivity-based control ensures stability of the teleoperation system even with the time delays commonly observed when communicating from a satellite factory in space to an operator on Earth while providing accurate force feedback [27], [34]. Such haptic teleoperation systems have been applied to solve a broad range of remote manipulation tasks in the space domain as in [10], [30] for space to ground teleoperation and [9] for on-orbit servicing.

However, execution of tasks which require high precision for both position tracking and force application (as in the case of CubeSat assembly shown in fig. 8) demands high physical and cognitive effort from the operator. This gets more critical in long-distance teleoperation systems which include large latencies in the communication links. To support the operator with the task execution, a shared control system is implemented combining vision-based autonomy and teleoperation. Virtual fixtures [1] are generated using the target pose supplied by the digital twin, which supports the operator move the robot end-effector to the insertion point on the backplane. Closer to the insertion point, vision-based fixtures [15] increase the precision. The operator receives haptic guidance from the forces produced by the virtual fixtures and also the real interaction forces during the final insertion. Such shared control approaches have been demonstrated to significantly aid task execution [13], [24]. Bowyer et al. [7] provides an overview of different geometric virtual fixtures and related definitions. Model-Augmented Telemanipulation [38] combines teleoperation and such virtual fixtures.

Using information from our newly developed vision system and from the digital process twin we can implement virtual fixtures which are both accurate and able to flexibly adapt to the assembly process. An arbitration component adaptively allocates authority to the different types of fixtures and thus ensures the best possible support for the operator [26]. Currently, both fixtures and arbitration are handcoded but this framework allows us to explore artificial intelligence methods both parametrising those methods from data and also adapting to different environmental conditions.

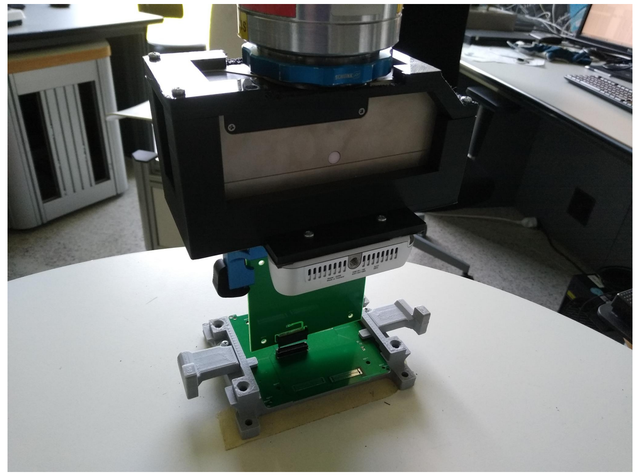

Fig. 8: Teleoperated insertion of subsystems into the backplane. A successful mating requires a position tolerance of ± 0.7 mm as well as an angular tolerance of less than $2°$ around the long axis and less than $4°$ around the short axis.[§]

5.1 *Task Description and Integration with the Digital Process Twin*

Assembling a CubeSat requires the execution of many different assembly operations. One of the most delicate tasks requiring high precision is connecting subsystem PCBs to the backplane which is shown in fig. 8. This task involves gripping the PCB from a holder, moving it to the assembly location and plugging it into the backplane. We use the system setup, especially the gripper from the SF4.0 project [23] and mount an in-hand camera on the gripper which allows to increase precision during the assembly operation.

Extending the Space Factory 4.0 teleoperation where only one subsystem was connected to the backplane, we implement an approach which allows to perform the full assembly which includes connecting multiple subsystems to the backplane. To ensure that each subsystem is put into the correct connector we tightly integrate the teleoperation process with the digital process twin. Once teleoperation is requested, the digital process twin supplies information of the location of the PCB to be grasped in the holder as

[§] https://www.erni.com/fileadmin/import/products/assets/DC0006021.PDF

Fig. 9: The bimanual robotic system HUG in teleoperation mode. The right arm is used as haptic input device while the left arm performs remote manipulation.

well as the plugging location. After the PCB has been connected successfully, this information is fed back and the digital twin of the CubeSat can be updated accordingly. Depending on the schedule of the manufacturing process, automated assembly can be continued in the next step or a new teleoperation operation can be requested.

5.2 *System Setup and Implementation*

We use the bimanual robotic system HUG [6] shown in fig. 9 for implementing the teleoperation. One of the robotic arms is equipped with a gripper and camera used for the visual servoing fixture. The other arm is currently used as haptic input device.

The robot controller is implemented in Simulink and requires hard real time to supply the robot with new commands at a rate of 1kHz. For good haptic feedback, the force generation of the virtual fixtures is also implemented in Simulink. Elements from a library of virtual fixtures consisting of geometric primitives like cylinders, spheres, cones or trajectories are combined with virtual springs and dampers to compute the forces. The fixtures are parametrised externally from supporting Python and C++ components with soft real time constraints. The middleware “links and nodes” is used to enable communication of the different components.

Currently, three different fixtures are used. A trajectory fixture (1) guides the user towards first the PCB picking location and then the insertion location. Using vision information, a visual servoing based fixture (2) is being developed which allows accurate positioning of the two connectors to be mated. Once in physical contact, a haptic manipulation fixture (3) locks all but the z axis to ensure a smooth plugging of the connector. An arbitration component switches between trajectory, visual servoing and haptic manipulation fixtures.

Learning approaches are being investigated to both learn the shape of these fixtures from data and to improve the arbitration component.

5.3 *Simulation-Driven Development and transfer to the Robot*

To manage the increased complexity of the new system, we developed a simulation environment capable of simulating the whole system, including robot dynamics and the camera sensor. This allows us to develop and test the novel virtual fixtures much quicker as we know the ground truth of e.g. the connector pose precisely. Furthermore, testing without risking to damage the real robot is possible.

The dynamics of the robot are simulated inside the same Simulink model used for controlling the robot. This ensures similar behaviour of the control and fixtures in both the simulation as well as on the real system and allows to get realistic joint torque values. Camera data is simulated using the Unreal engine. For user input, we currently use a 6dof Space Mouse.

Preliminary results in the simulation shows that our multi-phase telemanipulation approach has clear advantages when the target connector pose is not precisely known. This is very useful in real-world scenarios as otherwise, extensive and time-consuming calibration would be required. Transferring the approach to the real robot yields promising results as well, only the vision system needed updates as the lightning inside the lab is different from the simulation.

6. **Conclusion and Outlook**

The aim of the joint project “AI-In-Orbit-Factory” and therefore of this paper is to explore the possibilities of using artificial intelligence methods in the manufacturing, integration and testing of small satellite systems. We divided our effort into three distinct fields. On the process level, we were able to show that a multistage optical inspection can be deployed in solar cell assemblies to increase the robustness and quality. In another implementation example, we were able to create an autonomous testing board, in order to enable automated testing the functionality of subsystems of a satellite. Further, on we presented a more generalist approach how to monitor and control the entire process. Our teleoperation process with multi-phase virtual fixtures finally allows a human operator to be involved in the task.

In this paper, we introduced the Digital Process Twin, which serves as an overarching system across all phases of the AIT process. Used as a platform for services it can be used in order to deploy decision-making services based on state-machine like systems. It is additionally used to monitor the procedure and serves as a bridge from a self-organizing to a remotely operated system.

We are currently looking into a number of topics for further research, including extending the NN-based PCB fault classification models to more fault categories, building an automated subsystem electrical-test setup that uses learned statistical models of the nominal system characteristics and using the digital twin model of the internal subsystems SW state to identify SW anomalies in real-time. As the digital Process Twin aims to analyse its current state in order to initiate the necessary steps to reach its goal, the biggest challenge is to implement a system, that reliably identifies new states and creates the connections to existing ones. This work is underway on the basis of simulation models using CAD models of a process. For the teleoperation system, the most important future challenge is to integrate learned fixtures, e.g. using Gaussian Mixture Models and learned image features as well as a learned arbitration into the system to robustify, generalise and flexibilise the approach. One important challenge is furthermore time delay which is inevitable when communicating from earth to an in-orbit factory. Our controllers are stable under time delay but the virtual fixtures need to be tested and tuned for these conditions. An increased automation where the user is in control of the level of autonomy could help here.

The advances presented in this paper are another step towards our vision of an orbiting factory based on artificial intelligence methods. We currently work on a demonstration showing the feasibility of our approach with tight integration of all presented methods.

Author Contributions

TD wrote section 4 and 6. MM wrote the abstract, section 1 and 5. FK wrote the abstract, section 2 and 3. FL contributed to section 2 and 3. TH contributed to the abstract, section 1 and 5. RB contributed to section 5. MW wrote the abstract and contributed to section 4. RA contributed to section 4. KS contributed to section 2 and 3. AAS contributed to section 5.

Acknowledgement

The results presented here were achieved within the framework of the AI-In-Orbit-Factory project funded by the Federal Ministry for Economic Affairs and Energy (BMWi).

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