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White Paper

Ready for Take-off – Artificial Intelligence in Space Production

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European space travel in a period of change

Ever since the early days of space exploration, the importance of the international space industry has been growing - both in the public and private sectors. Particularly in the past two decades, various events have revived the development and use of technological innovations as well as research interest in the space industry. One example is the emergence of space programmes by commercial companies such as Blue Origin and SpaceX, as well as the successful launch and operation of the James Webb Space Telescope [1]. It is estimated that the value of the space economy has increased by 260 bn USD (91 percent) globally in the last decade and conservative forecasts suggest that the market will be worth 800 bn USD by the year 2028 [2].

The space industry is also regaining relevance in Germany: Between 2005 and 2017, the German space industry was able to increase its sector turnover from 1.4 bn EUR to 3 bn EUR. In September 2023, the Federal Ministry for Economic Affairs and Climate Action (BMWK) published an updated space strategy that emphasised the importance of the German space industry as a whole as well as the targeted promotion of space and its key technologies [4]. The overall goal is to achieve independent access to space.

To this end, the continuous expansion of satellite networks plays an important role in the European space strategy: satellites contribute significantly to modern infrastructure and their areas of application are diverse. These include the provision of GPS information, the collection of climate data and the processing of credit card transactions [5].

Accordingly, the strongest economic growth in the space market in recent years could be observed in the communications sector: the increased demand for broadband satellites has contributed to growth from around 24 bn USD in 2021 to 28 bn USD in 2023. Satellite production for commercial use could also record large growth from 2021 to 2022. The number of satellites sent into orbit increased by around 35 percent in these years. [2]

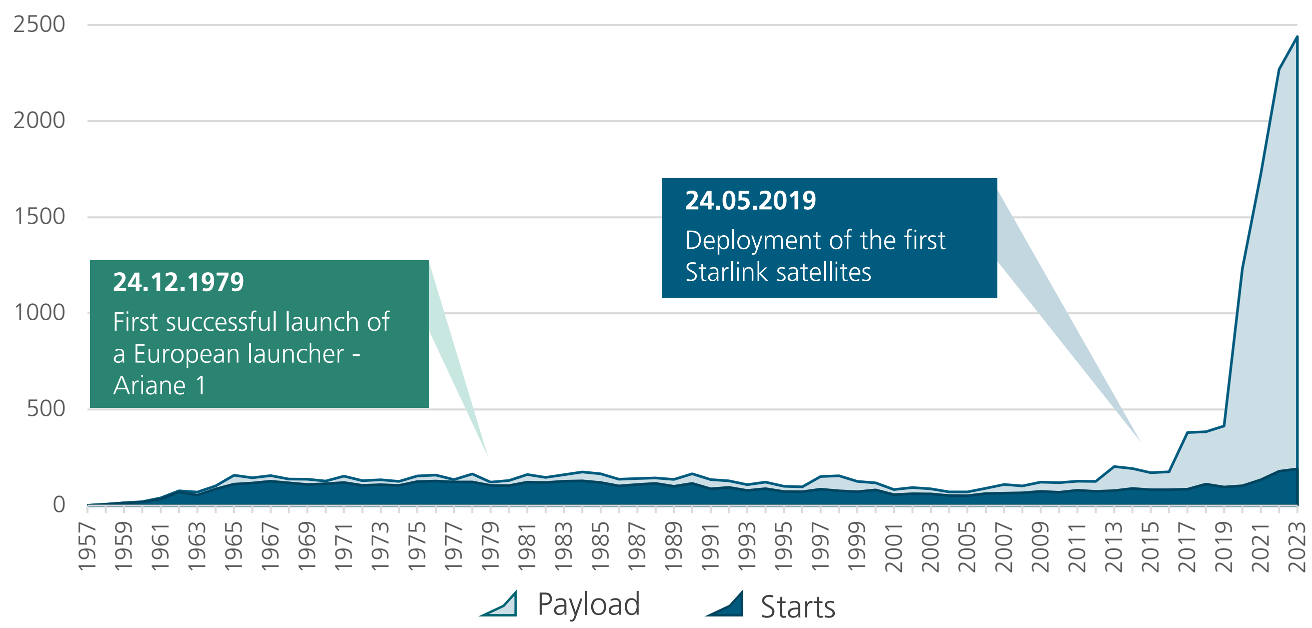

Figure 1: Rocket launches and payloads sent from 1957 to 2023 [6]

This increase in efficiency in both the production and deployment of satellites and the technologies required is leading to new applications, capabilities and users for satellite-based data [5]. Particularly in low earth orbit, new technologies for launch and propulsion technology have significantly reduced costs in recent years [7]. In conjunction with improved technologies for series production, the number of satellites sent into low earth orbit in the recent past has increased significantly [5, 7, 8]. The development of so-called micro-launchers, which transport miniaturised satellites into orbit at low cost, is also accelerating the growth of the communications sector in space travel [4].

This shift from a few satellites in geostationary orbit to a large number in low earth orbit opens up immense potential for innovation and growth and creates the need for new technologies and production processes for efficient mass production. This will enable the growing demand for communication satellites and the required capacities of launch vehicles to be met effectively.

The potential of artificial intelligence in the production of space components

Artificial intelligence (AI) equips machines in production processes with capabilities that are comparable to intelligent human behaviour. Various problem-solving methods for machines are summarised under the relatively generic term AI. The best-known, and most widely researched and applied method is machine learning (ML). The essence of machine learning is to independently process input training data and derive patterns and regularities within that data to analyse new, unknown data with the learned information [9]. There are various methodological approaches to this type of learning: deep learning is particularly well suited to processing large amounts of data for complex applications [10]. Deep learning uses deep artificial neural networks to recognise patterns from the input data. The underlying principle of this learning concept is to gradually minimise the error between the expected and generated result until a desired accuracy is achieved and the model is capable of analysing unseen data with minimal error [11]. Machine learning systems are therefore a type of artificial intelligence that allows learning from data and improving itself for use in a specific task.

To better understand the potential of AI applications for the aerospace industry, it is worth taking a broader look at the manufacturing industry in Germany: according to a study commissioned study commissioned by the Federal Ministry for Economic Affairs and Climate Action (formerly the Federal Ministry for Economic Affairs and Energy (BMWi)), between 40 and 69 percent of companies in Germany are planning to implement AI applications by the end of 2023, depending on the sector. y then, the use of AI is expected to generate a cumulative additional gross value added of 31.8 billion euros. This would correspond to around a third of the expected total growth of the manufacturing industry in Germany [12, 13].

In manufacturing companies, a large amount of data is generated across various production processes. Due to the amount of data available and the increased complexity of the processes, it is often no longer possible to evaluate all occurring data using conventional analysis and optimisation methods. Within the framework of digitalised production, however, the data provides an unforeseeable potential for data-driven technologies such as machine learning. [13]

Companies can make use of machine-learning systems to optimise production processes, automate quality controls, or detect and rectify system errors at an early stage, for example [14]. As soon as the system requirements for such applications are met, AI technologies can significantly improve productivity figures in companies [13].

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Nevertheless, AI is currently only used to a limited extent in German companies. On the one hand, this is due to a lack of knowledge about possible use cases and the potential of the technology. On the other hand, many companies still lack the necessary data quality, the corresponding data volumes and a suitable system infrastructure [13].

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The use of artificial intelligence in space production offers a wide range of interesting uses throughout the entire product development lifecycle [15]. For instance, currently an AI application that aims at automatically creating component design drafts, is being developed in cooperation with the US space agency NASA. The resulting mission hardware is more stress resistant and weighs less than comparable man-made designs. Using additive manufacturing processes, prototypes are to be produced directly from the designed components [16].

There are also numerous areas of application in other segments of the space industry, such as the development and construction of space telescopes or the development of weather satellites, for which the use of AI technologies could be immensely beneficial in comparison to traditional development process [17].

Especially in the final phase of the development process, there is significant potential in the acceleration of processes through the integration of AI technologies, as the complex sequential testing after assembly and final installation can take place during these processes.

In various industry and research projects, the Fraunhofer IPT has identified six use cases with great potential across different stages of the value chain in the space industry: (see Fig. 2)

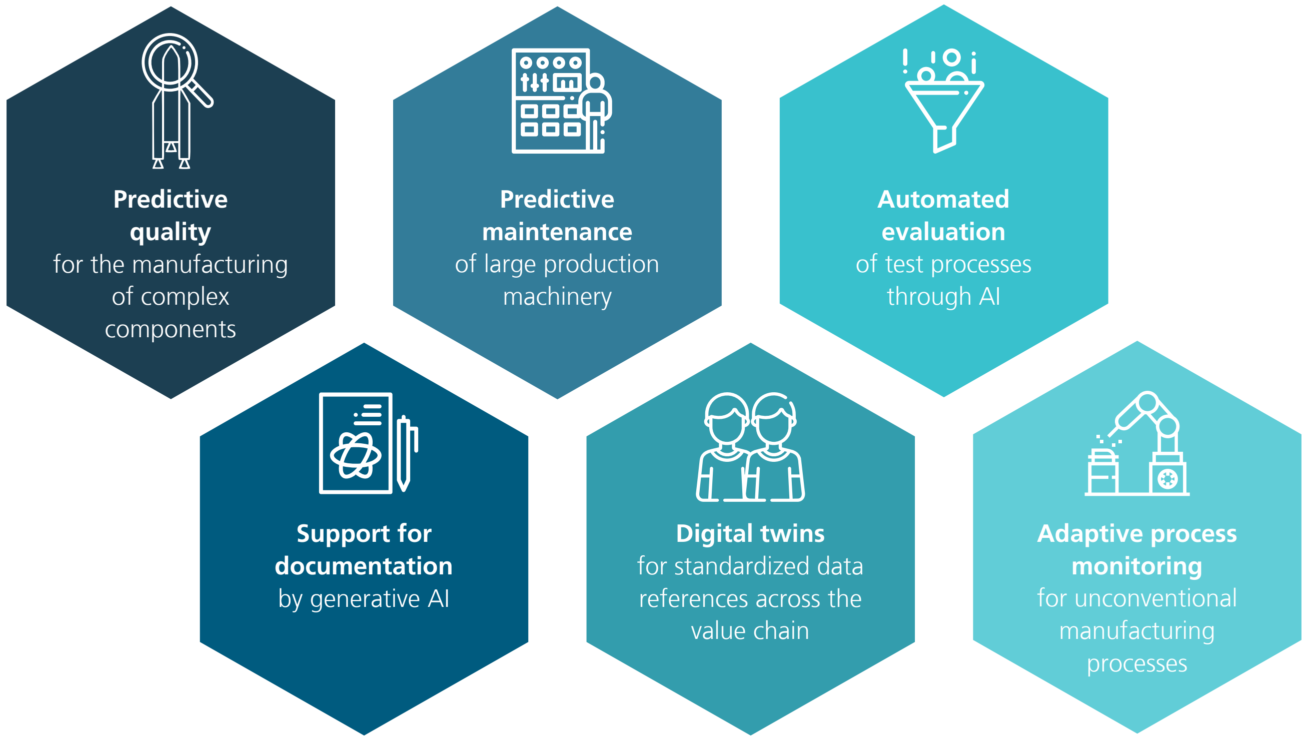

Figure 2: Selected use cases of AI in space production

Predictive quality
In collaboration with partners from the European aerospace industry, the Fraunhofer IPT investigated the extent to which predictive quality using AI can increase efficiency in aerospace production. The high degree of vertical integration of a single component means each individual work step is of crucial importance. The production of complex components is to be monitored closely so that any errors in the manufacturing process can be recognised and rectified at an early stage. If it is not possible to rectify the error, the production process can be terminated at the earliest possible stage so that further productivity losses can be avoided. This can contribute to a significant reduction in process time, particularly in the case of complex components with geometric structures that are difficult to manufacture, for example milling engine components or joining and surface processing large-volume structural components.

Predictive maintenance
Predictive maintenance entails the continuous monitoring of process parameters to predict the wear conditions of critical components and equipment. In this way, targeted maintenance can prevent long downtimes in production operations and accelerate the ramp-up of production processes and volumes.

Evaluation of operational tests
Space production places high demands on the quality and safety of the manufactured components. To fulfil these requirements, extensive test processes are needed, during which a large amount of data is generated. The automated evaluation of test procedures is therefore another area of application for AI in space production. The Fraunhofer IPT has therefore investigated the potential for increasing efficiency, for example by automating the deployment tests of different components in extreme environmental conditions.

Documentation
AI support can also help to reduce the manual effort involved in documentation activities. This is because every process step in aerospace production requires a considerable amount of documentation. The use of generative language models (large language models, LLM) can significantly reduce this effort.

Digital twins
The creation of so-called "digital twins" is another area of application for artificial intelligence in aerospace production: in European aerospace, components are produced in segmented value and supply chains. This process requires complex incoming goods inspections to ensure product quality and referencing. The use of digital product twins, which contain product and test data for all integrated components, can greatly reduce this process effort.

Adaptive process monitoring
Finally, the application of AI-supported adaptive process monitoring in space production should be mentioned. Unconventional manufacturing processes with sometimes considerable process times are used in aerospace production, for example additive manufacturing processes, joining processes with lasers or electron beams and friction welding processes. These processes require highly stable process monitoring with tight tolerances for the process parameters. With the aim of minimising the effort involved in such monitoring, it was investigated whether AI-supported control can be used to make the monitoring process adaptive.

Implementation example: Production of the Ariane 6 launcher

The reliable transport of new navigation and weather satellites into space is one of the most important goals of the German space strategy. The newly developed European Ariane 6 launcher will take off from the European spaceport in French Guiana for the first time in 2024. During the production of the components for the Ariane 6, which has already been launched at full speed, the Fraunhofer Institute for Production Technology IPT worked together with the ArianeGroup to develop a concept for continuously improving the manufacturing processes for the launcher's upper stage by analysing production data and unsing artificial intelligence.
(Picture: Arianespace / Master Image Programmes)

Challenges in the implementation of artificial intelligence in space production

Despite the wide-ranging potential of artificial intelligence, various challenges stand in the way of the widespread use of AI in the production of space components. These must be considered and solved for the further development of systems that have already been implemented [18].

In the aerospace industry, products are usually only manufactured in small batch sizes and with highly specialised processes [19]. Components are usually newly designed and realised using state-of-the-art manufacturing processes. The proportion of manual work steps is high. This affects, and in some cases limits, the availability and usability of relevant product and process data.

However, the available data basis plays a key role in the successful implementation of AI solutions. The accuracy, timeliness and clarity of the available data must be checked and evaluated in advance in projects for the development and implementation of AI applications. In some cases, data quality can be significantly improved by minimally optimising the measurements [20].

AI applications have the greatest added value if they can be used throughout several points in the production chain or at different locations with similar processes. This allows a larger amount of data to be generated across the various production steps and merged into a digital twin. However, most companies only use isolated AI applications, as the expertise to integrate such systems is often not yet available [12].

Furthermore, companies often lack comprehensive knowledge of the various capabilities of AI and thus lack an overview of relevant use cases for their specific challenges. The use of AI must be methodically planned at the strategic level of the company so that the scope of the project is understood, and sufficient resources can be made available for AI projects. In addition, possible scepticism among employees about implementing AI can only be overcome via the management levels [21]. Initial successful "bottom-up" initiatives facilitate the introduction of further AI projects in the company and increase the spread of an open data culture.

The successful implementation of AI applications requires interdisciplinary collaboration between development, production, IT and other departments, which are currently often organised in isolation due to traditionally established corporate structures. Success is significantly influenced by the commitment of the respective stakeholders, as AI projects can fail, even due to divergent prioritisation and a lack of support [21]. Due to the challenges described above, it is necessary to methodically support AI projects at an early stage with a systematic approach [22].

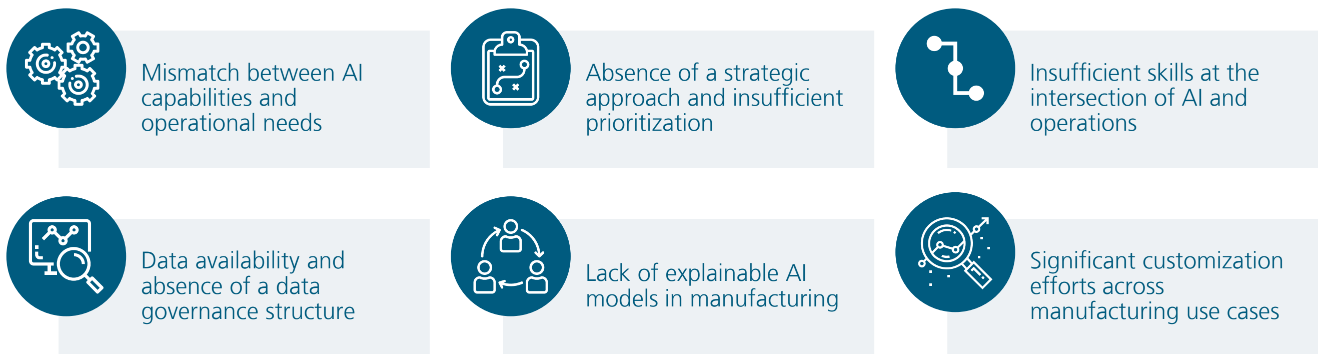

Figure 4: Rocket launches and payloads sent from 1957 to 2023 [6]

Methodological guidelines for realising AI potential in space production

One approach to making the use of machine learning systems in space production more efficient and reliable and thus more in line with the current state of the art is to create a structured approach to the implementation of AI projects - from planning to piloting.

To this end, the relevant use cases should first be systematically identified and analysed in terms of their benefits and applicability. This is followed by the practical implementation of such systems. Initially, this takes place in pilot applications which, if successful, are rolled out further and expanded in scope.

For this, the company's status-quo with respect to the application concepts for AI must be analysed. The main concern here should be on the analysis of the individual data basis of the respective use cases. The analysis of data availability and quality serves to examine which applications can reliably be implemented in the aerospace industry. Due to the low production volumes in the aerospace industry, the amount of data generated is also limited. It is therefore particularly important that the available data is of high quality.

The thus identified use cases must then be meticulously defined and analysed to enable a reliable evaluation. Particularly the specific requirements of varying process steps with respect to machine learning systems must be considered. These use cases are subsequently evaluated and prioritised as part of this critical assessment.

The objective of this comprehensive evaluation process is to identify the most suitable use cases for the respective company and to undertake them in pilot projects. Concurrent with the development of these test projects, all necessary skills should be developed. In terms of strategic long-term orientation, the knowledge required for the independent implementation of future AI projects should also be accumulated within the company.

Finally, a performance review should be carried out to identify further optimisation potentials and to be able to better evaluate future AI projects in terms of their cost-to-benefit ratio. Thus, further optimisation potential can be identified and adapted to facilitate the implementation of further applications.

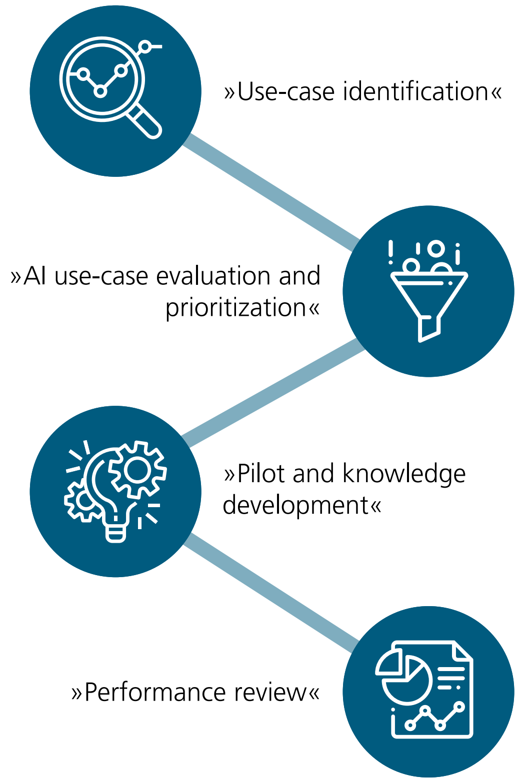

Figure 5: Overview of the 4 steps of the systematic approach to projects

Summary

The application of artificial intelligence has the potential to increase efficiencies in industrial production in diverse application scenarios. As part of various research projects with European aerospace companies, the Fraunhofer IPT identified use cases that are suitable for the application of AI. Six fields of application proved to be particularly promising for the use of AI in production:

1. Predictive quality applications in the production and processing of complex components
2. Predictive maintenance applications for operating resources of critical machines and systems
3. Automated evaluation of test processes
4. Support for documentation activities through generative language models
5. Creation of digital twins to ensure data references across the value chain
6. Adaptive process monitoring for unconventional, highly specialized manufacturing processes

However, the implementation of AI applications in the aerospace industry poses specific challenges. In particular, the low availability of data due to generally low production volumes makes the development and training of applications more difficult. Additionally, complex development and qualification processes contribute to the fact that the implementation of AI use cases is often delayed.

The present implementation procedure divides the process of integrating AI use cases into four phases: Useful AI use cases are to be identified, evaluated, prioritised, and then piloted. The objective of this process is to ensure that the use cases that are implemented up to deployment are those that are both technically feasible and offer the greatest possible benefit.

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