FT2025
SWEDISH AEROSPACE AT THE CROSSROADS
The 12th Swedish Aerospace Technology Congress
FT2025 in Stockholm
October 14-15, 2025

How Artificial Intelligence (AI) is Transforming the Aviation Industry

Peter Funk[1], Rickard Sohlberg[1], Nils Sundelius[1], Ella Olsson[2], and Peter Bovet-Emanuel[3]

[1]*Mälardalen University, School of Innovation, Design and Engineering, Sweden, peter.funk@mdu.se, nils.sundelius@mdu.se, rickard.sohlberg@mdu.se*

[2]*Saab Aeronautics, Solna, Sweden, ella.olsson@saabgroup.com*

[3]*Swedish Defence University, Department of War Studies, Joint Warfare Division, Stockholm, Sweden, peter.bovet-emanuel@fhs.se*

Abstract

AI is increasingly used in the aviation industry such as traffic management, predictive maintenance, flight operations and safety systems. The fast progress in AI increases the potential for improvements at all levels. Wise integration into aviation will enable improved performance, enable a faster pace of transition to environmental-friendly solutions and thus reduce the environmental impact, operational costs and safety.

We are conducting research in AI systems and developing "proof of concept" in a wide area of applications such as predictive maintenance, autonomous flight systems solutions, hybrid human-AI systems, flight path planning, decision support, mental state monitoring (tiredness, stress, distraction, etc.). At the same time, it is a risk to become overconfident in AI systems and it is critical to develop safe and secure hybrid AI systems; there are many examples of naive deployment of AI where lack of understanding of the application domain together with lack of understanding of the different AI methods, techniques, and algorithms have led to serious implications and even fatalities. Many AI systems we see today are by nature not fully trustable, since they relay heavily on statistical learning and lack reasoning capabilities and deeper understanding. We need to take this into account already when designing an AI system. Securing proper safeguards and validation already in the initial design phase is essential; otherwise, the system may become a dead end, unreliable, unscalable, or unsafe for deployment.

In conclusion, artificial intelligence is rapidly transforming the aviation industry in all areas, including safety, efficiency, and sustainability. We will over the next 5–10 years see more autonomous aircraft and drones occupying our airspace, see an increase in safety, performance and reduced environmental impact as a consequence of increased deployment of AI. At the same time, we need to be in control, and understand when, where and how to use AI as well as to know how much we can trust AI and how much responsibility we can delegate to AI.

Keywords: Artificial Intelligence (AI) in Aviation, Predictive Maintenance, Levels of Autonomy, AI-Supported Mission and Operations Planning, Hybrid Human-AI Systems

1 Introduction

Artificial Intelligence (AI) is a research field exploring and developing methods, techniques, and algorithms enabling computer systems to perform tasks typically requiring human intelligence and today they even outperform humans in certain tasks such as recognizing patterns, learning from experience, making decisions in complex situations normally requiring a human. Exploring intelligence and building intelligent systems is one of the main objectives of this cross-disciplinary research field in parallel with gaining a deeper understanding of intelligence. AI is already transforming society and industries such as healthcare, finance, and logistics, and its impact on aviation is only in its infancy. The requirements in the aviation industry are unique in many aspects with extremely high requirements in safety and efficiency. AI offers already today many new advantages in the aviation industry, that are operated, maintained, and managed, but the potential is huge and we have only seen the beginning. In this paper we explore areas and cases on how AI is used or can be used in aviation in the near future, including some discussions of its benefits, limitations and risks. We hope this paper will support a broader understanding of AI's role today and in the future of aviation.

Figure 1: Example of areas in aviation and the aviation industry where we see a high or very high potential for AI systems for the coming years. Much is already ongoing today, but the challenge is what is coming in a near future. In maintenance we see the highest activity, operations, design and navigation are areas in acceleration. Environment is an important area relevant in all areas of aviation.

2 Examples of AI applications in aviation

As mentioned, AI today is a major disrupter and plays a key role in society and industry. In avionics there is currently much focus on autonomous flights, but the imminent big disruptor is caused by integration of AI in all aspects of avionics, assisting pilot, design, maintenance, safety, fuel consumption to mention some. In this chapter we are summarizing some of the ongoing trends and give some examples of both existing and ideas for future use of AI in aviation.

2.1 AI enhanced pilot awareness

AI plays an increasingly important role in enhancing system intelligence in aircraft. There is a huge potential in decision support systems where AI collects, analyses and understands huge amounts of data and assist pilots. In critical situations AI enhanced systems extends the pilots awareness enabling the pilot to make more informed decisions in close collaboration with AI enhanced systems.

2.2 Intelligent predictive maintenance

AI driven predictive maintenance systems can not only predict and inform pilot of potential failures, but also assess consequences and how to resolve them and advice pilots of actions and prepare preventive maintenance at next stop. This has the potential to lower operational costs and increase safety. There are numerous cases in aircraft accidents where the forensic accident investigation team detected sound in the Cockpit Voice Recorder (CVR) indicating engine problems before any alarm sounded. If these subtle sound fingerprints detectable by AI systems would be distributed among all aircraft with same engine, the AI system could immediately alert the pilot of the similarity and brief the pilot of consequences and actions to take to avoid an accident.

2.3 Hybrid AI systems

By enabling communication between the different AI-based avionic systems a higher level of situational awareness can be achieved where an overall situational assessment can focus on the most critical aspects of the situation in collaboration with the pilot.

2.4 Integrating pilot and AI

The ongoing research effort to establish direct communication between humans and computers (using neuro-adaptive systems, e.g. with Brain Computer Interfaces, BCI) will enable exciting scenarios where the pilot both feels the aircraft as an extension of their body and can communicate directly with the aircraft. Research in this area has focused on sending commands to the computer system, but communication directly to a pilot is a more imminent and interesting idea. To feel it in your foot when one tyre of your aircraft is overheating at landing may be a more realistic imminent scenario and a first step towards more integrated "mind controlling" of an aircraft. Research so far struggles with direct mind control of external devices due to operators often experience mind-wandering and constantly sustain a strong focus is difficult. "Mind control" also relies on extensive machine learning techniques and requires extensive, individual calibration and large amounts of training data for each user [1].

2.5 Optimal aircraft design

In design of aircraft, 3D printers of both synthetic materials and metals (AM, additive manufacturing adding layer by layer, instead of milling or cutting, producing minimal waste and enabling production of complex geometries) is a disruptive technology in design of aircraft and enables new design of aircraft and in its combination with machine learning and generative AI systems it enables designs of customized, lightweight structures with advanced materials. Parts designed using generative AI can be both stronger and lighter [2]. Already 2019 Airbus designed a partitioning wall using generative AI with the same strength but 45% lighter than the traditionally design partitioning wall. A saving according to Airbus of nearly half a million metric tons of CO_2 emission per year.

2.6 Fuel/energy consumption

Weather services and sensors are giving increased information on what is happening both in proximity of the airplane as well as on other altitudes. All this information is increasingly used to adapt flight path and altitude to reduce fuel consumption and environmental impact. Already today AI models are in some cases surpassing traditional numeric weather models running on supercomputers [3] and research on using AI for 4D flightpath optimization with fixed landing times is ongoing [4].

2.7 AI-supported scheduling in aviation

In civilian aviation, managing aircraft operations involves a wide range of complex, interdependent activities—such as fueling, routine service, repair, inspection, baggage handling, and coordination teams and crews with different competences and skill levels. These tasks require extensive planning and dynamically re-scheduling in order to avoid delayed flight schedules, handle unforeseen maintenance issues, adapt to weather conditions, and personnel availability. For example in [5] an AI-supported enterprise modeling framework is proposed originally developed for a dynamic tactical decision-making context. It relies on enterprise modeling to capture workflows, roles, constraints, and information flows across the aviation ground operations ecosystem.

By introducing semantic modeling (ontology), digital twins, and AI-based reasoning into this system, various ground tasks can be matched in real time to available personal with appropriately skilled teams. By integrating the system with data from aircraft health monitoring, schedules, and logistics systems, enables automated re-prioritization and resource reallocation to optimize planning and scheduling according to desired priorities (in aviation maximizing aircraft flight time and minimizing delays). From an environmental perspective this is also an advantage since redundancy in aircraft, spare parts and staff can be optimized. Overall the main benefits we see of increased intelligence in scheduling and planning are:

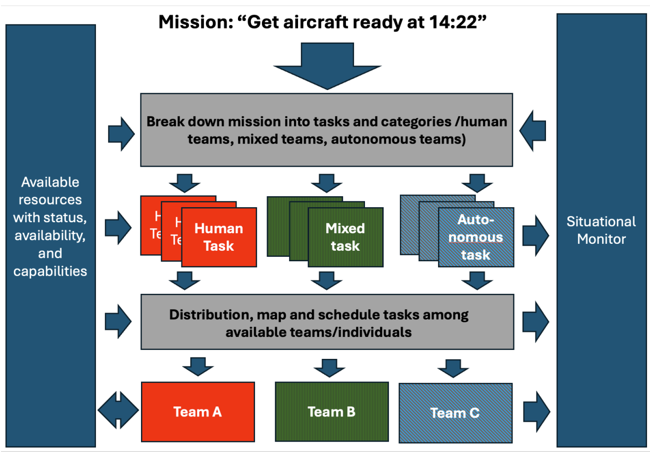

Figure 2: Example of a mission in aviation and how it is broken down into tasks mapped to available resources.

An AI enhanced planning and scheduling framework has a huge potential in improving operations efficiency in civil aviation, by combining enterprise modeling principles with AI functionality and shared ontology-based semantics offering transparent, knowledge-based infrastructure that supports automation and decision making. This has the potential to improved aircraft availability by scheduling tasks to ensure aircraft return to service faster and with higher reliability. It also enabled increased transparency and coordination trough the potential of sharing a semantic model and real-time data between ground crews, aircraft systems, and operations control to support better coordination and accountability. This closely relates to the Command and Control loop (C2), a model for organizing, coordinating and scheduling resources to achieve a specific goal [6]. The C2 loop has four stages: sensing, decision-making, execution, and feedback to carry out the mission. The resources in a mission may be humans, mixed teams and autonomous teams. With an shared ontology and shared resources it enables optimization, coordination and collaboration between different prioritized missions.

2.8 AI-driven mission planning for aviation intense Search And Rescue (SAR) operations

The proposed CAMP framework [7] offers potential for civilian aviation missions in complex SAR missions like wildfire, natural disasters like earthquake etc. In such operations different aircraft including Unmanned Aerial Vehicles (UAVs) have to be assigned different tasks to complete the mission as efficiently as possible. E.g. in a forest fire context ariel vehicles need to drop water, monitor fire spread, transport ground crew, airlift persons in need and direct trams in real time. The proposed framework will enables high-level missions to be dynamically translated into tasks and tasks will be distributed among available resources, teams and agents.

Dynamic planning and adjustments is a complex task where AI-driven assistance based on context analysis, mission monitoring and situation assessment will enable:

- **Faster Response** – achieved through real-time data fusion and AI-supported decision-making.
- **Better Coordination** – facilitates seamless collaboration between air and ground entities.
- **Optimized Resource Use** – by better matching team capabilities and platform functionalities to mission requirements.
- **Continuous Monitoring** – enables live re-planning and adaptation as conditions evolve.

3 Explainability in AI

In many applications of AI, a central challenge is how to handle explainability - the ability to make the output transparent and understandable to human users. AI techniques such as Artificial Neural Nets (ANN) and Large Language Models (LLMs) are often “black boxes” with the ability to produce high quality output without or with limited capability to explain how the output was achieved.

AI systems based on ANN and LLMs struggle with the ability to consistently produce trustworthy output. When building AI systems, this aspect needs to be addressed. Also, the lack of explainability is a risk, since human competence may deteriorate and lead to overconfidence on the system, if an AI system produces correct and good results in 99 cases and then produces a bad solution the hundred case, a human user may not question the solution critically enough. THIS may cause serious consequences in applications like avionics.

Interpretability refers to the property of a system enabling humans to understand and follow how it functions. This understanding enables users to assess the system's performance and reliability. In safety-critical domains, such as avionics, many AI applications require interpretability to increase trust and increase safety in situations where the system performance may be weaker.

4 Levels of control and autonomy

When using AI, levels of control and autonomy is important to consider. Different application may need different levels of autonomy and control. Below we have given an example of a generalized table of autonomy levels. The table is inspired by, and is a simplified version of Sheridan and Verplank's 10 levels of automation [8] reduced to 6 more generic and general levels of autonomy mapping the more specific SAE J3016 standard for driving autonomy [9].

Level	Name	Description
0	No automation	Human does everything.
1	Suggestion / Support	System provides options/recommendations; human decides.
2	Guidance	System guides with few ranked alternatives; human decides.
3	Shared execution	Executes action if human approves or if no veto within a short time.
4	Supervised autonomy	Executes actions automatically, informs human; human can intervene if needed.
5	Full autonomy	System decides and acts independently, human in the loop is optional.

Table 1: Generalized levels of automation for decision & action.

An approach taken in the military domain is the classification of human control levels. They define 3 levels of human control, human in the loop, human on the loop, human out of the loop as shown in table 2. In many situations here there is no time for having a human in the loop due to short response time requirements. This rises comcontrolplex ethical issues as AI systems today rarely are 100 percent reliable. In the WARA-PS project (The Wallenberg AI, Autonomous Systems and Software Program, WASP) the different aspects of autonomy and control are explored [10].

Concept of control	Explanation
Human-in-the-loop	A human actively participates in the decision-making process. AI suggests actions, and the human approves or modifies them before execution.
Human-on-the-loop	A human supervises the system while it operates autonomously. The AI makes most decisions, but the human can intervene if necessary.
Human-out-of-the-loop	The system operates fully autonomously without human intervention. Humans are not involved in real-time decisions.

Table 2: Levels of human involvement in AI systems.

5 Developing AI systems

The failure rate of AI projects in industry is estimated to be over 80 percent [11]. On the other hand if an AI project succeeds the benefits and values may outweigh the risks and the risks of failure can be minimized. If companies fail with some initial AI projects it is important to learn from the events and continue their effort to use AI, this may be a matter of survival. The potential for AI systems in aviation industry is very high, hence it is important to minimize the risks. There are many risks with developing AI systems and the right preconditions need to be in place (list inspired by [12] and own experience):

1. **Clear objectives and metrics** – well-defined problem and feasibility assessment.
2. **High-quality, relevant data** – sufficient, accurate, labeled data.
3. **Skilled and experienced personnel** – AI/ML specialists, domain experts, engineers, and legal/ethics advisors.
4. **Organizational support** – executive backing, governance, change management, and **a culture of experimentation**.
5. **Risk management and monitoring** – performance evaluation, safety checks, and fallback plans.

Our experience is that the better the preconditions are met, then bigger the chance to succeed with an AI project. If not, secure all five before you start and don't under estimate the importance and effort needed to reach this level. In aviation industry these preconditions are even more critical since for good reasons it is a conservative domain since safety and long life span. Our success rate in in academic applied research project are based on make sure that all five factors are in place before committing to lead or participate in a project. An example of a research project where we implemented an advanced research mock-up that has been evaluated in industry is [13].

The better the preconditions are met, the higher the likelihood to succeed with an AI project. Ensure these preconditions are covered before starting, and do not underestimate the effort required to do so. In a necessarily strongly regulated and conservative sector where safety, reliability, and long asset lifespans are paramount, such as in the aviation industry, these preconditions are even more important.

In traditional software development projects, implemented solutions behave as specified, enabling verification of the functionality. AI and machine learning systems are on a complexity level making it difficult or impossible to verify completely as they have the ability to learn and are to complex to verify fully. Thus making the outcomes unpredictable which has to be addressed and properly handled in any safety critical domain. Conventional software engineering methodologies are therefore insufficient for AI projects. The resolution to this challenge is to take a more rigorous approach: formulation of hypotheses, systematic experimentation and validation of results (Hypothesis-Driven Development or Continuous Experimentation). The approach often used in research is visualized in Figure 3.

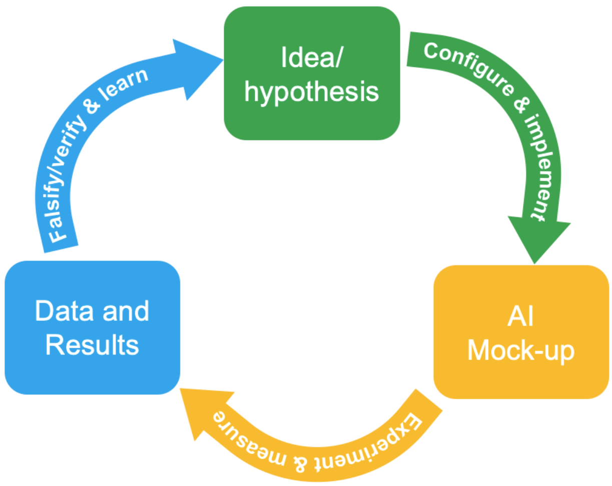

Figure 3: Development of AI systems often need an iterative approach. Deciding too early what AI algorithms and system constellations should look like can lead to dead ends later on in the process.

In hypothesis formulation you develop a hypothesis about how the AI system will solve the problem. The experimentation phase is not about producing code, it is about testing hypotheses, validating the outcome and learning with the purpose of either confirming, refuting, or refining the hypothesis. Insights from failures or partial success feed back into the next iteration. Both Hypothesis-Driven Development or Continuous Experimentation focus on a continuous cycle of experimentation mirroring scientific method and continuously working towards a sufficiently good solution. Traditional methodologies such as Waterfall and agile methods like SCRUM/Kanban work from the assumption that some clear requirements are formulated and that the solutions is known in advance, and that implementation will be a straight forward process. These methodologies are often mentioned as one of the reason for the high failure frequency of AI projects.

Iterative development is a concept often used in AI projects and our experience from more than 25 years of applied AI research projects in industrial and medical applications is that this is a key factor for success.

Also not starting with a "moonshot" project, putting all resources into a single high-risk initiative may be risky considering the high failure rate in AI projects in industry. A better approach is to begin with more manageable projects and gradually build experience, capabilities, and confidence also in an iterative way.

6 Conclusion

Artificial Intelligence (AI) is transforming the aviation industry—from flight operations and maintenance to mission planning and airspace management. In this paper we have explored some examples and areas of AI in aviation available today, under development or researched offering future opportunities and benefits of integrating AI. We have given examples on AI-driven predictive maintenance, intelligent pilot assistance, aircraft design, and context-aware mission planning and how AI can improve efficiency, sustainability and safety.

One promising development is the use of AI in complex mission planning in emergency situations, so called Search and Rescue (SAR) operations and in aircraft ground handling. AI systems that have context awareness and are able to interpret mission purpose, dynamically allocate tasks, and provide continuous situation monitoring can greatly enhance capabilities of human commanders, enabling more informed, faster and efficient decision-making.

The challenge is to bear in mind such AI systems are fallible, and over reliance without strong domain knowledge and safeguards can lead to severe consequences. Thus the first step is to apply AI in the context of hybrid human-AI systems with transparency, validation mechanisms, and human-in-the-loop control—especially in safety-critical contexts like aviation.

7 Acknowledgment

This research was funded by Vinnova, Sweden's Innovation Agency.

References

[1] Aureli Soria-Frisch. A critical review on the usage of ensembles for bci. *Towards Practical Brain-Computer Interfaces: Bridging the Gap from Research to Real-World Applications*, pages 41–65, 2012.

[2] Diego Carou. Generative design and its applications. In *Introduction to Generative Design for Aerospace Applications*, pages 45–69. Springer, 2025.

[3] Remi Lam, Alvaro Sanchez-Gonzalez, Matthew Willson, Peter Wirnsberger, Meire Fortunato, Ferran Alet, Suman Ravuri, Timo Ewalds, Zach Eaton-Rosen, Weihua Hu, et al. Learning skillful medium-range global weather forecasting. *Science*, 382(6677):1416–1421, 2023.

[4] Zhiyuan Shi, Min Xu, and Quan Pan. 4-d flight trajectory prediction with constrained lstm network. *IEEE transactions on intelligent transportation systems*, 22(11):7242–7255, 2020.

[5] Ella Olsson, Olov Candell, Peter Funk, and Rickard Sohlberg. Enterprise modeling for dynamic matching of tactical needs and aircraft maintenance capabilities. In *International Congress and Workshop on Industrial AI*, pages 370–383. Springer, 2021.

[6] Björn Johansson, Jesper Tordenlid, Jonas Lundberg, and Jens Alfredson. One system to connect them all-a core system for realizing integrated command and control research. In *Proceedings of the International ISCRAM Conference*, 2024.

[7] Ella Olsson, Peter Bovet-Emanuel, Peter Funk, Nils Sundelius, and Rickard Sohlberg. Context-aware mission planning and decentralized execution for heterogeneous teammates in dynamic environments. In *Proceedings of the 12th Swedish Aerospace Technology Congress (FT2025)*, Stockholm, Sweden, 2025. Accepted for publication; 4 pages, proceedings forthcoming.

[8] David B Kaber. Issues in human–automation interaction modeling: Presumptive aspects of frameworks of types and levels of automation. *Journal of Cognitive Engineering and Decision Making*, 12(1):7–24, 2018.

[9] J3016_201609: Taxonomy and definitions for terms related to on-road motor vehicle automated driving systems, 2016. Accessed: 2025-09-30.

[10] Olov Andersson, Patrick Doherty, Mårten Lager, Jens-Olof Lindh, Linnea Persson, Elin Anna Topp, Jesper Tordenlid, and Bo Wahlberg. Wara-ps: a research arena for public safety demonstrations and autonomous collaborative rescue robotics experimentation. *Autonomous Intelligent Systems*, 1, 12 2021.

[11] James Ryseff, Brandon F De Bruhl, and Sydne J Newberry. The root causes of failure for artificial intelligence projects and how they can succeed. *I: RAND Corporation. URL: https://www. rand. org/pubs/research_reports/RRA2680-1.*, 2024.

[12] Md Mahfuzul Islam Shamim. Artificial intelligence in project management: enhancing efficiency and decision-making. *International Journal of Management Information Systems and Data Science*, 1(1):1–6, 2024.

[13] Ricky Stanley D'Cruze, Marcus Bengtsson, Peter Funk, and Rickard Sohlberg. A Generative AI Framework for Smart Maintenance: Utilizing RAG Systems and LLMs to Assist Manufacturing Operations. In R. Kour, R. Karim, U. Kumar, D. Galar, and V. Jägare, editors, *International Congress and Workshop on Industrial AI and eMaintenance (IAI2025)*, Lecture Notes in Mechanical Engineering. Springer Cham, 2025.