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AIR TRAFFIC MANAGEMENT SYSTEM

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A Vision of AVENIR

On an early morning in 2040, American airliner N42TT had just crossed the Atlantic Ocean and was now approaching its destination, Paris Charles de Gaulle Airport.

200 nautical miles from the French coastline, AVENIR, the Artificial-Intelligence-Assisted Air Traffic Management system, detected the aircraft through radar. After verifying its identity, an individualized landing sequence was initialized automatically.

In the cockpit of N42TT, Captain Kirk and First Officer Spoke heard a clear, machine-generated voice: “N42TT, this is your personal approach assistance program. You are about to enter French airspace. Please set the radio communication language on the ACARS.”

First Officer Spoke entered “ENG” on the ACARS Control Display Unit. A few seconds later, a standard, calm English voice broadcasted again: “N42TT, CRNA, flight level 350, expect entry into French airspace at 1532Z, expect landing on runway 26R, descend to flight level 240, report upon reaching.”

Captain Kirk repeated, “CRNA, N42TT, descending to flight level 240, runway 26R, N42TT.”

“Readback correct.”

Everything returned to silence. Looking at the dense data points on the TCAS radar, Captain Kirk, with decades of flying experience, couldn't help but recall the busy times in the past when everyone’s nerves were highly strung and pilots competed for tower instructions on the same frequency. Now, AVENIR allows each pilot to receive only the relative information they need. Interference and misunderstandings have been greatly reduced. Flying has never been such an enjoyable experience.

N42TT descended smoothly as Captain Kirk scrupulously followed the instructions from the personal landing assistance program. The globally deployed AVENIR network, like a surgical knife, dynamically carved out the most optimized flight route for each aircraft.

The airplane entered the final approach phase without any delay. It smoothly approached the runway, pierced lightly through the fog, and gradually descended until the wheels touched down gently with a low rumble.

As N42TT landed, the sun slowly appeared from the horizon. Ahead, the future awaited.

The story above envisions the interaction between pilots and the Artificial-Intelligence-Assisted Air Traffic Management (AI-ATM) system AVENIR in 2040. The system utilizes state-of-the-art technologies and innovative work procedures to refine airport and airspace operational safety and efficiency, reduce staff workload, and promote environmental sustainability.

Background and Related Work

The foundational elements of ATM systems were established in the mid-20th century, a period marked by the rapid expansion of commercial aviation. The essential components of ATM systems are Air Traffic Control (ATC), Airspace Management, and Flow Control (See Fig.1). ATC is responsible for the safe and orderly movement of aircraft throughout all phases of flight. Airspace Management optimizes the allocation and usage of airspace resources for various traffic types. Flow Control regulates the volume of air traffic to ensure efficient operations without congestion.

Challenges Faced by the Air Industry

Today, the air traffic volume is further increasing. Projections indicate that passenger and cargo traffic will more than double in the next 20 years, with an annual growth rate of approximately 3.6% in developed markets like the USA and Europe. This growth is expected to be even more pronounced in developing regions, such as Asia Pacific and the Middle East [1].

A study, which reviewed 20,174 incident reports from 2000 to 2022, identified human factors, including lapses in attention and memory, as primary causes of ATC-related incidents [2]. Research suggests that the human brain can effectively track only 3-4 items at a time [3], while an individual air traffic controller may need to manage up to 20 aircraft during peak times simultaneously [4]. This cognitive overload is expected to worsen by 2040 as air traffic volume continues to grow.

Unlike ATC, airspace management and flow control may not directly cause severe incidents. However, inefficiencies within these subsystems indirectly affect flight safety, often leading to increased operational costs and higher carbon emissions for airlines and airports. For instance, airspace congestion frequently necessitates holding patterns, where aircraft fly racetrack-shaped loops at non-optimal speeds and altitudes, consuming up to 25% more fuel than during optimal flight operations [5]. The additional time spent in holding patterns also contributes to subsequent flight delays, leading to passenger dissatisfaction and potential airline revenue loss.

Challenges of Current Intelligent ATM Systems

Countries and enterprises have been exploring the modernization of ATM systems over the past two decades. For example, SESAR aims to define, develop, and deploy what is needed to increase ATM performance and build Europe's intelligent air transport system [6]. NASA's eXploration (ATM-X) Project focuses on integrating emerging air vehicles, such as VTOL (vertical take-off and landing) and UAV (unmanned aerial vehicles), into the air traffic ecosystem [7]. Additionally, Aimee, an Artificial Intelligence (AI) platform used at airports like London Heathrow, employs neural networks to detect and manage aircraft and airfield objects, showcasing AI's practical applications in modern ATM systems [8].

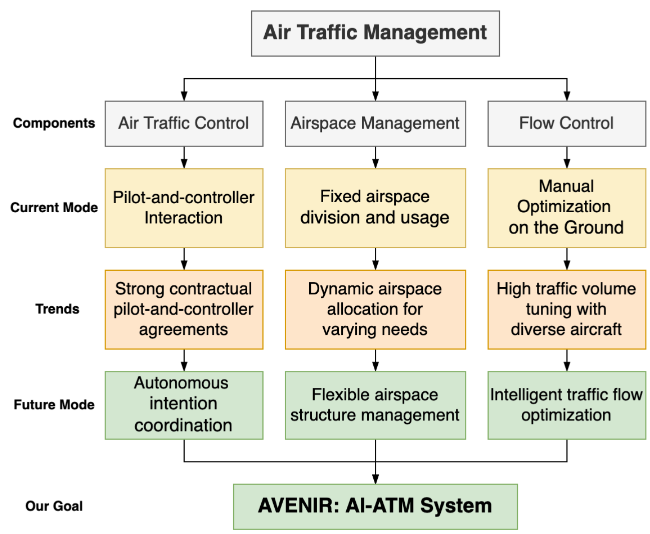


Fig. 1: ATM Function Structure and Trends

Hindrances to ATM modernization include various limitations. Firstly, the inherent complexity of ATM systems, composed of vast heterogeneous data types from multiple ends, complicates the integration of new technologies. Secondly, the available optimization algorithms and mechanisms for intelligent ATM systems always come with drawbacks and tradeoffs. Moreover, rigorous testing and validation of new technologies to ensure safety and reliability is a time-consuming and resource-intensive process. Last but not least, modernization requires substantial funding and aligning interests among various stakeholders. In other words, in most cases, adopting new technology will prompt investment and change only if it demonstrates substantial advantages and urgencies.

Since 2017, AI has experienced another significant technological breakthrough [9]. It paves the way for the development of new-generation AI-ATM systems that can potentially address the aforementioned challenges in the aviation industry.

Project Overview - What Is AVENIR?

AVENIR is an artificial-intelligence-assisted air traffic management system characterized by its **A**daptive, **V**isionary, **E**co-friendly, **N**etworked, **I**ntelligent, and **R**esilient features. The system utilizes the Decision Transformer neural network with a creative workflow to continuously generate and optimize ATM decisions. The system architecture and workflow of AVENIR are shown in Fig.2.

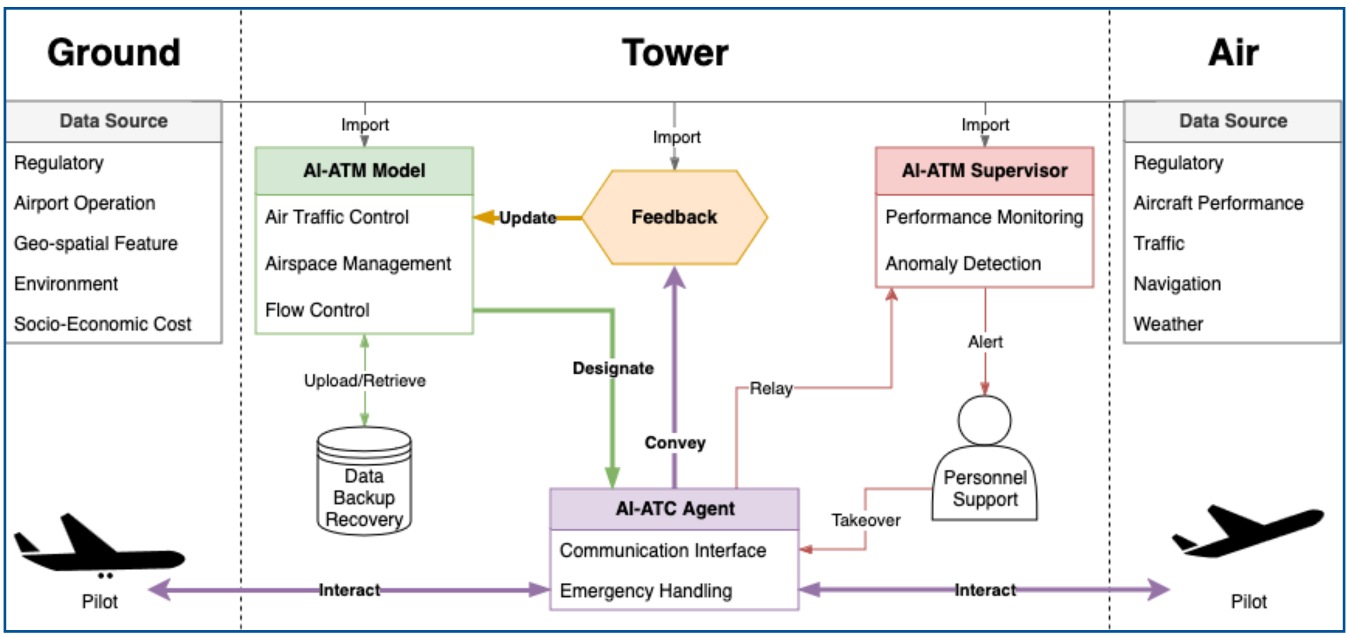


Fig. 2 System Architecture and Workflow of AVENIR

AI-ATM Model and Feedback Mechanism

The AI-ATM model functions as the central brain of the system, employing a pre-trained Decision Transformer neural network model. In practice, it gathers data from ground and air sources, such as flight paths and wind directions, to dynamically generate and optimize decisions and plans for ATC, airspace management, and flow control.

All instructions issued by the AI-ATM model are conveyed to the Feedback Mechanism, where they are assessed against more broadly defined criteria and benchmarks, identifying any discrepancies and areas for improvement. This analysis feeds back into the AI-ATM module, allowing for ongoing refinement of its algorithms and decision-making processes.

AI-ATC Agents

AI-ATC agents, incorporated with a fine-tuned Natural Language (NLP) Model, serve as a communication bridge between pilots and the AI-ATM model. A dedicated AI-ATC agent with selectable natural language options instructs each aircraft within the airspace dynamically. Upon receiving distress or warning signals, the Emergency Handling function within the AI-ATC

Agent module promptly notifies the human ATC personnel to collaborate and determine the best solutions.

AI-ATM Supervisor

Decisions made by the AI-ATM model are first passed on to the AI-ATC agents. Then, the AI-ATM supervisor monitors and evaluates all the decisions based on established regulations and rules before they are transmitted to the pilots. Once abnormal decisions have been detected, human controllers will take over the AI-ATM system without delay.

Safety Mechanism

Regardless of how rapidly technology advances, safety is always the first priority. In addition to the emergency handling and anomaly detection functions, we have also designed a real-time backup mechanism. If the supervisor module detects a biased decision that deviates from the standard and preset guidelines, the data backup and recovery module swiftly reverts the system to a previous stable version. Concurrently, human intervention is immediately applied as the AI-ATM system undergoes diagnosis and re-evaluation.

System Architecture - How AVENIR Works?

While many people today believe that Artificial Intelligence (AI) can solve nearly any problem, it is crucial to understand its capabilities and limitations. This section will provide detailed technical insights into AVENIR.

AI-ATM Model and Feedback Mechanism

Air traffic data are inherently sequential, including time series information such as flight paths, airspeed, altitude, and other changing metrics. Identifying temporal dependencies and patterns within data in real-time and updating predictions and decisions accordingly is crucial for optimizing air traffic management.

We utilized the Transformer model, a neural network architecture introduced in 2017, which preserves the sequential data processing capabilities of traditional RNNs (Recurrent Neural Network) and their variants, such as LSTMs (Long-Short-Term Memory), that were commonly used in earlier ATM implementations.

Unlike RNNs, which process data sequentially and face challenges with vanishing gradients in long sequences, the Transformer model leverages a Self-Attention mechanism that allows parallel data processing. This approach allows the model to weigh the importance of different inputs simultaneously, enhancing learning efficiency and providing a deeper understanding of complex relationships within the data.

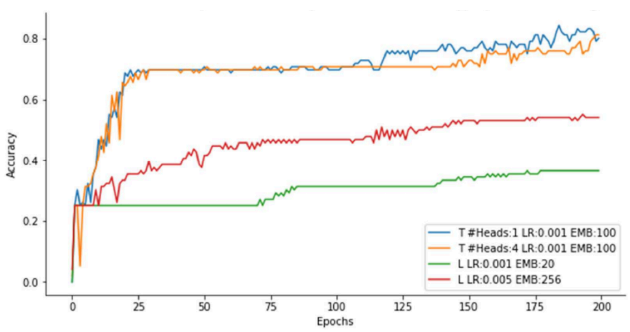


Fig. 3: Transformer-based vs. LSTM-based models performance comparison [10]

Fig. 3 compares the Transformer-based (blue and orange curves) model performance with LSTM-based (green and red curves). The accuracies of transformer-based models are significantly better than LSTM-based models.

We introduce the reinforcement Learning (RL) process to boost the Transformer's effectiveness further. RL is a technique where the model learns to make decisions by interacting with an environment, receiving feedback in the form of rewards or penalties, and adjusting its actions to maximize cumulative rewards. The model's actions are based on the environment's current state, representing all relevant information needed to make an informed decision.

Such an integrated architecture embedded in AVENIR is called a Decision Transformer [11]. The core innovation of the Decision Transformer lies in using the Transformer's attention mechanism to model the sequence of past states, actions, and rewards. This allows the system to learn the dependencies and relationships across these sequences, thereby predicting future actions more effectively.

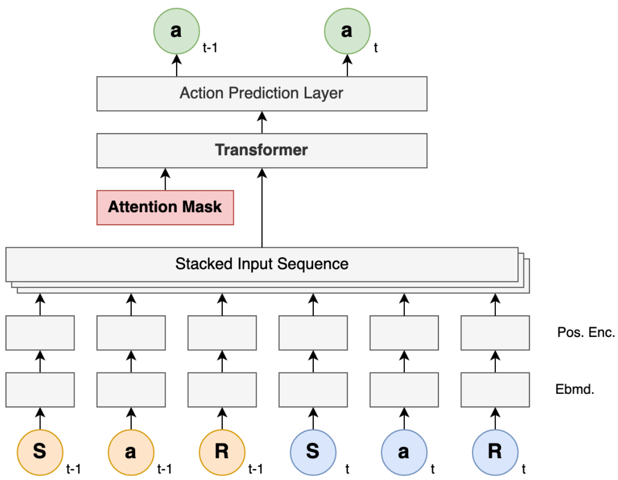


Fig. 4a Decision Transformer Flow Diagram

Fig. 4a depicts the Decision Transformer architecture and illustrates the data flow and processing at each time step during the training of the AI-ATM model. "Action (a)" refers to decisions like route adjustments and delay advisories, while "State (S)" represents ground and air data such as flight positions and weather conditions. The "Expected Reward (R)" is a function designed to optimize safety and efficiency, taking into account metrics like aircraft spacing and fuel consumption.

At each timestep, the model integrates the previous timestep's AI-ATM decisions, simulation airport environment data, and reward function value with the current timestep's decisions, environmental data, and corresponding reward value. These inputs are converted into modality-specific embeddings and enhanced with positional encodings. The transformer model then processes these embeddings, using autoregressive modeling and Self-Attention mechanisms, to predict the optimal decision the AI-ATM model should make for the current timestep. The predicted optimal decision, along with the current environment data and reward value, are then fed into the next timestep as the previous timestep's action. As time progresses, the AI-ATM gradually optimizes its decisions in air traffic management, which may even surpass human expert experience.

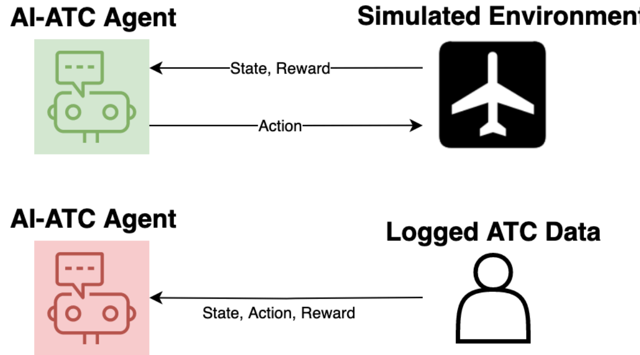


Fig. 4b Online (top) and Offline (bottom) Reinforcement Learning

Fig. 4b outlines two training methodologies for the Decision Transformer model. The top diagram illustrates online RL, where the AI-ATM model makes decisions (action) based on the air and ground data (state) in the current timestep and receives feedback (reward) in the form of rewards or penalties based on its decisions. The feedback helps the agent understand which actions lead to positive outcomes. Over time, the AI-ATM model adjusts its strategy to maximize cumulative rewards, refining its decision-making policy through repeated trials and updating its learning parameters.

The bottom diagram depicts offline RL, which trains the AI-ATM model using a pre-collected dataset of human ATC decisions and associated data without direct environment interaction. The latter is useful when direct simulation is impractical or costly. However, offline RL faces the challenge of the counterfactual query problem, where the model encounters situations not covered in the dataset, limiting its ability to learn practical actions.

The offline RL helps the AI establish a baseline understanding of decision-making processes and refine reward functions. Following this, the system transitions to online RL within a simulation environment, where the model interacts with a simulated air traffic setting that replicates real-world conditions. Consequently, the AI-ATM model integrates data from various air and ground sources to efficiently generate optimal decisions for managing traffic and airspace.

AI-ATC Agents

The primary role of AI-ATC agents is to facilitate smooth communication between pilots and the AI-ATM model. AI-ATC agents translate the AI-ATM's instructions from machine language to human language and convey pilots' responses back to the AI-ATM model in machine language. We will use existing NLP models as a foundation and fine-tune them with labeled data from actual tower-pilot communication recordings. This method will enhance AI-ATC agents' recognition accuracy and contextual understanding while assisting pilots. The fine-tuning process will involve training the models on a variety of communication scenarios, including jargon, different accents, speech patterns, and dialects, to ensure robustness and adaptability in various operational environments.

AI-ATM Supervisor

Our AI-ATM module is designed to offer innovative and adaptive solutions for managing ambiguous and complex air traffic scenarios. Complementing this flexible capability is the AI-ATM Supervisor module, which provides a rule-based, deterministic layer of oversight. The supervisor module ensures that all proposed actions by the AI-ATM adhere to established safety protocols and regulatory standards, preventing any actions that could compromise safety or violate regulations.

As air traffic regulations and safety standards evolve, it is essential to continually update the supervisor module's rule set. This ongoing maintenance requires an efficient process to incorporate regulatory changes and keep the rule set relevant and comprehensive.

Infrastructure Requirements

During the model training phase, we propose to apply for high-performance computing resources such as CSCS: Swiss National Supercomputing Centre, which is highly specialized and renowned for its capabilities in parallel computing.

To develop a suitable simulation environment for online RL, we can deploy AVENIR in existing simulators currently used in human ATC training, such as ATCoach [12] (FAA recommended) or ESCAPE [13] (EUROCONTROL recommended). While these simulators provide a solid foundation, modifications may be necessary to tailor the training scenarios to our specific requirements, ensuring that the AI-ATM system can handle a wide range of real-world situations.

During the technical validation process stage, cloud-based solutions can be utilized for data storage and real-time computing. However, as the system transits to larger-scale deployment, we highly recommend establishing dedicated computing centers at major airports. This setup will reduce latency and enhance cybersecurity measures, providing a more secure and responsive system for real-time data processing.

For voice communication interaction between AI-ATC agents and pilots, our system will primarily use existing VHF (Very High Frequency) radio and ACARS (Aircraft Communications Addressing and Reporting System). The reliability of machine-generated broadcasts via VHF has been well-established through systems like ATIS (Automatic Terminal Information Service), which has been effectively used for decades. We plan to extend the existing VHF and ACARS frameworks to incorporate AVENIR's advanced functionalities, ensuring seamless communication and data exchange between AI-ATC agents and pilots.

Technical Challenges

Over the years, Transformer-based architecture has become the gold standard in numerous fields of Computer Science, including NLP and Computer Vision. However, their application in the aviation industry requires further exploration and validation. The rest of the section will outline the potential challenges and limitations of implementing these advanced machine-learning techniques in our ATM system.

One of the key challenges in developing an AI model for an ATM system, perhaps a universal challenge for machine learning, is identifying the most relevant data inputs. It is essential to evaluate the accessibility of each data category and balance the model's performance with the available computational resources. This requires careful consideration of various data sources, such as regulatory, operational, environmental, and socio-economic information, ensuring the model can process various data within computational constraints. Additionally, the lack of comprehensive historical data for specific scenarios, such as rare but significant emergencies, poses a challenge. This scarcity can limit the model's ability to learn and predict outcomes accurately in real-world applications.

Designing an impactful reward function for balancing the different objectives, such as safety, efficiency, cost reduction, passenger satisfaction, and environmental impact, is also challenging. These objectives can sometimes be at odds with one another; for instance, optimizing for the fastest routes may conflict with fuel efficiency or noise abatement procedures. Moreover, accurately quantifying these objectives into a numerical reward that the system can optimize is difficult. Safety metrics, for example, are critical but difficult to represent adequately due to the rarity of incidents and the necessity for robust safety standards.

Ensuring the system's resilience across diverse scenarios presents another challenge, requiring extensive testing in simulated environments that closely replicate real-world complexities. This process involves not only assessing the system's performance during standard operations but also subjecting it to stress testing under extreme conditions to verify its reliability. In addition, the validation process must address the potential for unintended biases in the system's decision-making, which can result from skewed training data or incomplete representation of certain air traffic situations. Thorough benchmarking and validation are essential, requiring rigorous testing and a comprehensive approach to confirm that the AI-ATM system complies with all operational and safety standards before deployment.

Market Advantage - Why AVENIR?

Market Demand

The demand for AI-assisted ATM systems is closely linked to the number of airports in a country. In 2024, the United States, with its established aviation network, has more than 5,082 airports [14]. This extensive network highlights the maturity and scale of the U.S. aviation market, offering a vast landscape for implementing advanced ATM systems.

In comparison, developing nations like China present significant market potential for our AI-assisted ATM system. As of 2022, China has 254 [15] certified civil airports. While this number may not be as large as that of other major aviation markets, the Chinese government is actively planning to increase the number significantly. This expansion is part of a broader strategy to enhance transportation capabilities and support a rapidly growing aviation market. The Chinese government's proactive stance towards adopting new technologies, as evidenced by the recent deployment of AI-Taxi services in various cities, further underscores the nation's openness to integrating advanced Artificial Intelligence solutions.

Beyond China, other regions, such as India and the Middle East, are also making strides in incorporating the latest AI technologies into their urban development projects. These countries are actively expanding their airport networks, upgrading infrastructure to accommodate increasing air traffic, and leveraging AI technologies. This global trend towards modernization and technological advancement creates a favorable environment for the deployment of our AI-ATM system.

Fig. 5 Globally Networked Flight Coordinations

Strengths of AVENIR

Technically, our system offers superior handling of complex, dynamic air traffic data by leveraging the latest advancements in neural networks, particularly Transformer models. These models excel at processing large datasets and identifying intricate patterns, making them highly effective in optimizing air traffic flow, predicting potential disruptions, and providing real-time decision support.

From a user experience perspective, our system offers several enhancements designed to improve the pilot's experience. One of the key features is the implementation of multi-language support for tower-pilot communications, which helps eliminate language barriers and prevent misunderstandings, especially on international flights. The system also focuses on broadcasting only relevant information to targeted pilots, enabling them to concentrate on their primary tasks without the need to filter unnecessary data. This feature is particularly advantageous for Visual Flight Rules (VFR) pilots, who are more often involved in ATC-related accidents than IFR pilots [16]. Lastly, our system is designed to integrate uniformly with existing protocols, minimizing the need for additional training. Certified pilots can continue operating within a familiar framework, ensuring a smooth transition to the new system without requiring extensive retraining.

Phased Rollout Plan

Another key differentiator of our project is the extremely low initial investment required before demonstrating its capabilities. This is achieved through a phased rollout strategy that begins with offline RL using logged ATC data and then online RL in simulation environments. This cost-effective approach allows stakeholders to assess the system's effectiveness in a controlled setting before committing to the full-scale deployment.

During the actual testing phase, the system is initially operated in a "Shadow Mode," which runs parallel to existing systems without directly impacting ATM operations. This iterative testing approach is crucial for continuously verifying and ensuring the system's safety and reliability, ultimately laying the groundwork for investment success prior to full-scale deployment. Fig. 6 shows the phased rollout plan.

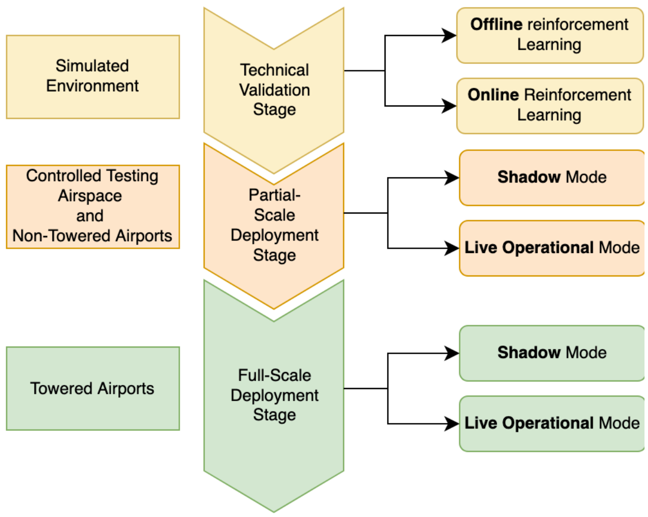


Fig. 6 Phased Rollout Plan

Economic Benefits

As we progress through the deployment stages, we establish clear, incremental, and quantitative goals for the system's performance. During the initial stage, our conservative estimates suggest that the system will achieve a 10% optimization in airport space and airspace allocation, alongside a 5% reduction in fuel consumption during flights. Additionally, based on the calculation of the SESAR program [17], we anticipate a 50% decrease in labor costs driven by the system's efficiency improvements.

As AVENIR transitions to full-scale deployment by 2040, with a linked AI-ATM network among domestic airports, these benchmarks are expected to improve significantly. Our target is to ultimately enhance airport management and airspace allocation efficiency by 20% and to achieve a remarkable reduction in labor costs by 80%. These ambitious goals reflect our commitment to maximizing operational efficiency and delivering substantial cost savings.

Beyond operational enhancements, our system addresses one of the aviation industry's long-standing challenges - language barriers. By eliminating these barriers, we open up a wider pool of qualified pilots for airline companies, regardless of their native language.

Broader Impact and Societal Challenges

Data Security

Quantum computing poses a significant threat to cryptographic algorithms essential for data security [18]. The implications are severe in the context of an intelligent ATM system, which involves the continuous exchange and processing of vast amounts of sensitive data. AI-ATM systems require access to vast amounts of sensitive data, including flight paths, passenger information, and real-time operational data. Ensuring this data is protected against breaches and unauthorized access is crucial. Therefore, it is imperative to adopt proactive measures to secure the data utilized by the AI-ATM system. The aviation industry must prioritize these measures to ensure ATMs' continued safety and security in the quantum computing era.

Manual Proficiency and Backup Plans

As AI systems increasingly take over the roles of human controllers, there is a growing concern about the human crew's ability to manage emergencies manually. The interconnectivity of future technologies means that a failure in one part can significantly impact the entire system, as evidenced by incidents where computer system outages led to global flight cancellations. Power grid, computer system, or data collection malfunctions can all potentially lead to AI-ATM system failure. There is a need to redesign the staffing allocation for airport control towers to ensure enough personnel to maintain hardware and software functionality and handle air traffic control and coordination during emergencies. Neighboring airports can also establish closer cooperation to respond more effectively to similar system failures and emergencies.

Smart City Infrastructure

As cities continue to develop, emerging technologies such as air VTOL taxis and delivery UAVs add a new layer of complexity to urban airspace management [19]. This evolution makes integrating ATM with urban planning and public transportation systems increasingly critical. VTOLs and UAVs operate under different navigation and separation standards. The communication and coordination mechanisms for VTOLs and UAVs also differ from the traditional pilot-tower interactions in general aviation. Moreover, the infrastructure required for these aircraft, such as vertiports, differs from conventional airport environments, demanding unique design and operational protocols. These factors highlight the need for a versatile AI-assisted ATM system with robust scalability to adapt to future technological advancements in urban air mobility.

Fig. 7 Future Urban Airspace Illustration [20]

Legal and Ethical Considerations

Integrating AI into ATM systems raises significant legal and ethical challenges, particularly around liability when an AI agent makes a mistake. Current legal frameworks primarily hold human operators accountable, but introducing AI requires reevaluating these rules. For instance, if an AI system follows established protocols and a failure occurs, it raises questions about whether the fault lies with the AI developers, the operators, or the regulatory bodies that set the standards. Conversely, if the AI agent deviates from the rules, it must be determined whether the circumstances justified this deviation or if it indicates a flaw in the AI's programming or decision-making processes. This legal ambiguity urges modifying existing laws to define responsibility in cases involving AI agents clearly.

Conclusion

Given the challenges currently confronting the aviation industry and the rapid advancements in machine learning technologies, the integration of artificial intelligence with air traffic management is poised to reshape the future of aviation.

I. The AI-ATM system AVENIR has the potential to significantly enhance operational safety and efficiency in both airports and airspace, reduce staff workload, and promote environmental sustainability by 2040.

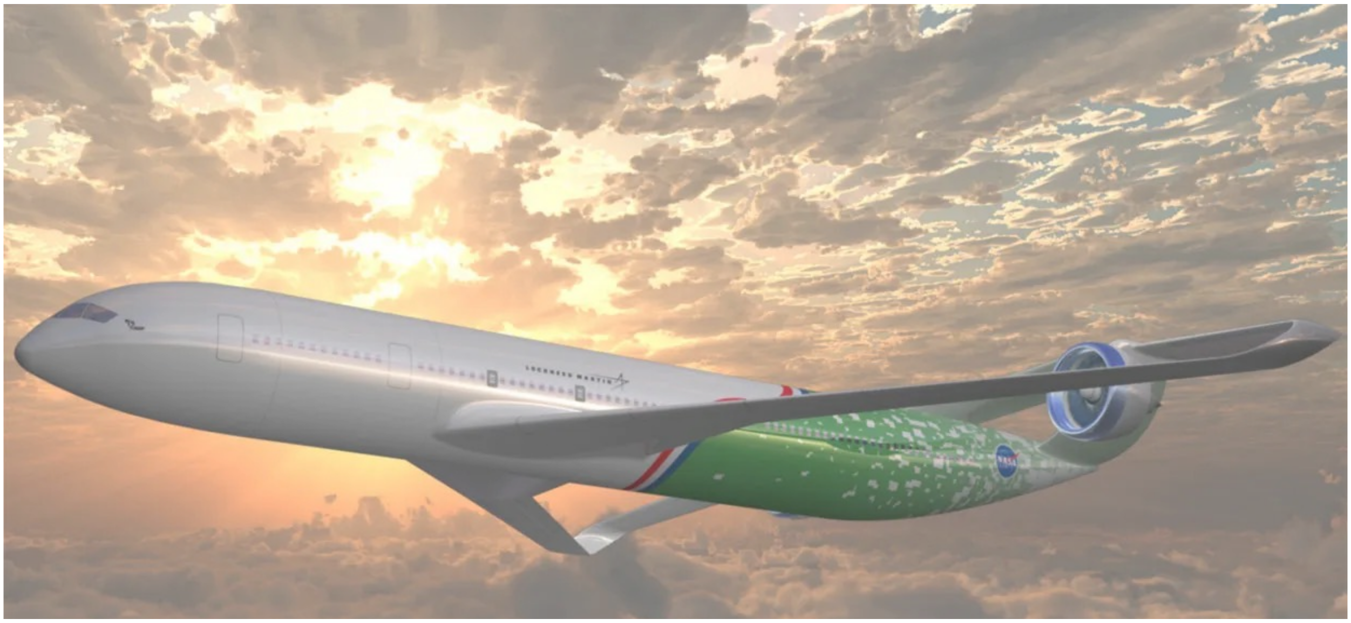
II. The natural language processing (NLP) model embedded within AVENIR offers personalized natural language instructions for flights, effectively minimizing interference and overcoming language barriers faced by pilots. Additionally, it will broaden the range of options and opportunities available to pilots and airlines globally.

III. The primary challenge in the practical application of AI-ATM system technology lies in ensuring safety. AVENIR addresses this by incorporating multiple safety mechanisms, thereby safeguarding data security and enabling intelligent decision-making.

IV. While the development and deployment of AI technology within the aviation industry represent a promising future, it is inherently a long-term investment. It is crucial that the deployment process be rapid yet phased, with strategic planning to mitigate risks effectively.

V. As we move towards increasingly complex application scenarios, AI-ATM systems like AVENIR will encounter challenges in terms of safety and technology as well as social and ethical domains. Addressing these challenges will require concerted efforts and collaboration from all stakeholders to realize the envisioned future of aviation.

As Jules Verne wrote in *Twenty Thousand Leagues Under the Sea:* "On ne peut connaître qu'en allant voir” — one can only know by going to see. This sentiment underscores our inspiration and determination to make AVENIR come true; the future awaits.



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