AI-Based Conflict Detection and Decision Support in Air Traffic Control: A Critical Review of Emerging Approaches

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Abstract. The increasing complexity of modern airspace operations necessitates the use of sophisticated technologies that are able to facilitate early conflict detection and effective decision-making in air traffic control. The recent progress in artificial intelligence, particularly machine learning and deep reinforcement learning, has opened new opportunities for conflict detection and resolution enhancement. This paper provides an in-depth analysis of the state-of-the-art in intelligent and adaptive decision-support systems, with emphasis on research conducted between 2020 and 2024. Furthermore, it explores different AI techniques such as supervised learning, behaviour modelling, and multi-agent deep reinforcement learning. Despite strong simulation results, real-world deployment faces challenges such as interpretability and coordination under uncertainty. The review identifies future directions including explainable AI and hybrid models using real-time aviation data. Unlike earlier ATC/AI surveys, this review uniquely integrates conflict-detection and decision-support perspectives within a unified SLR framework, offering a quantitative synthesis across AI paradigms and mapping identified gaps to future research pathways.

1 Introduction

As the volume and complexity of global air traffic continue to increase, air traffic management (ATM) systems face unusual challenges. The growing density of air traffic and the complexity of cross-sector flows combined with the limits of human cognition underline the urgent need for intelligent systems that can ensure detect rabidly conflicts and assist in real-time decision making.

Early detection of potential conflicts and resolution of these conflicts is vital. This decreases the burden on air traffic controllers and eliminates potential risks to safety. The systems the industry has relied on for the past several decades remains largely unchanged and continues to operate on fixed rules and simplified assumptions and while this may be sufficient in calm and predictable environments, it is in the messy environments where the system fails dreadfully. Bad weather, crowded airspaces, and irrational human behavior all pose challenges that the system fails to accommodate [3].

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The need for AI-enabled systems becomes clear, as they can provide adaptive, data driven responses to address the challenges present in dynamic airspaces. Technologies in machine learning and deep reinforcement learning (DRL) provides systems that can adapt to real time changes and respond with flexible, customized solutions instead of mechanically executing checklists. They understand complex atmospheres and provide decision making support that is far more natural and reliable [5].
This paper systematically reviews recent AI-based approaches for conflict detection and decision support in ATC using a reproducible SLR protocol. It quantitatively and qualitatively compares major families of methods optimization, supervised learning, reinforcement learning, and multi-agent systems. It also provides a critical synthesis highlighting the methodological gaps and proposing future directions aligned with operational and regulatory needs.
In this review, we look at different approaches—from models that imitate how human controllers think, to systems that predict future situations or coordinate multiple aircraft's actions. We also discuss the challenges that these systems face like how to deal with real traffic, how to be explainable to users, and how to earn the trust of the people who rely on them.

2 Background and Key Concepts

2.1 Conflict Detection and Resolution

Conflict detection is the process of identifying situations in which aircraft trajectories may not respect the minimum safe separation distance within a determined time frame. Once the conflicts are identified, conflict resolution offers measures to resolve the situation—like adjusting speed, altitude, or direction—to maintain safe spacing and avoid potential collisions.
The practice of CD&R in ATC today consists of both human and automated systems. Many traditional systems still apply basic, inflexible, rule-based frameworks, which can be ineffective in adapting to dense and complex situation [4].

2.2 Decision Support Systems in ATC

Decision-Support Systems (DSS) are tools that aid human decision-making by providing alerts, recommendations and simulations in real time. In the ATC domain, DSS aim to help controllers manage traffic conflicts more effectively, especially under time pressure or uncertain conditions [4].
There is a huge difference between conventional DSS (which are largely static and rule-based) and intelligent DSS which leverage machine learning and artificial-intelligence techniques to adapt dynamically to new data and unforeseen scenarios. The latter are increasingly investigated for their potential to transform CD&R processes.

2.3 AI-Driven Approaches to Conflict Management

Various machine learning techniques—including supervised, unsupervised, reinforcement, and imitation learning—are applied in ATM to predict aircraft trajectories, detect anomalies, optimize conflict resolution, and imitate the controller decision-making behavior.

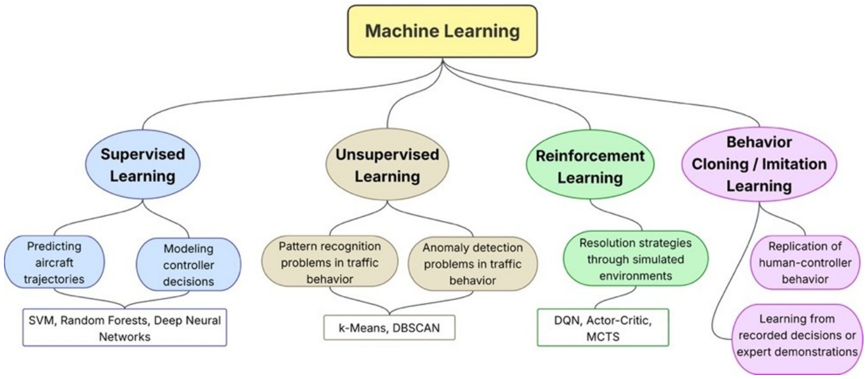

Fig. 1. Overview of machine learning paradigms applied to air traffic management tasks

2.4 Human-in-the-loop and Conformal Automation

A key direction in current CD&R research involves embedding human-in-the-loop approaches, where artificial intelligence tools are developed to complement, not substitute, human decision-making capabilities.

In this framework, conformal automation describes AI systems that suggest conflict resolution suggestions to align with each controller's individual habits and operational preferences [5]. This customization promotes greater trust, acceptance, and practical integration within real-world control environments.

2.5 Real-time constraints and Operational Uncertainty

Modern ATC systems have to work with multiple uncertainties, like [3] sensor inaccuracies, communication delays, changing weather conditions, and dynamic airspace restrictions, all in strict real-time scenarios. In order to deal with this, the processing of data coming from ADS-B signals, radar measurements, and METAR weather reports has to be done both very fast and with maximum reliability. Thus, it is very common now to find the scientists working on the different types of models that can deal with uncertainty and keep being trustable even during the change of circumstances—like Bayesian frameworks and hybrid architectures that combine Graph Neural Networks with probabilistic inference methods.

Fig. 2. Word cloud depicting the most used keywords in recent studies

3 Methodology of the systematic literature review

3.1 Databases and Search Strategy

This systematic review follows a meticulous approach using the PRISMA (Preferred Reporting Items for Systematic Reviews and Meta Analyses) framework which guarantees the transparency, reproducibility, and traceability of the article selection process. This method was used to specify the search protocol, screening steps, and inclusion criterion. Important scientific papers were collected from the five main databases—IEEE Xplore, Scopus, ScienceDirect, SpringerLink, and arXiv.
The search was directed towards researches published between 2020 and 2024 with the mentioned Boolean query applied to titles, abstracts, and keywords in the table below:

Table 1. Boolean Search Structure for Systematic Literature Review.

Concept	Search terms/Keywords	Boolean Operator	Purpose
Domain	"air traffic control" OR ATC OR "air traffic management"	-	Defines the researcher field (ATC/ATM context)
Core Topic	"conflict detection" OR "conflict resolution"	AND	Targets the main problem addressed in ATC
Technology / Approach	"artificial intelligence" OR "machine learning" OR "reinforcement learning" OR "decision support"	AND	Restricts the search to AI-based or DSS-based methods

The bibliographic records retrieved from the databases in BibTeX format and imported into Zotero for duplicate removal and data cleaning. it facilitated the standardization of metadata fields (author, title, year, DOI) and ensured full compatibility with LaTeX citation workflows.

```
@inproceedings{degaugue2024optimization,
author     = {J. Degaugue and L. Morel},
title      = {Optimization-Based Decision Support for
Conflict Detection in Air Traffic Control},
booktitle  = {Proceedings of the International Conference on Emerging
Global Challenges (ICEGC)},
year       = {2024},
pages      = {122--129},
publisher  = {IEEE},
doi        = {10.1109/ICEGC.2024.1234567}
}
```

Fig. 3. BibTeX Conference Paper Example

```
@article{degaugue2024optimization
 author     = {J. Degaugue and L. Morel},
 title      = {Optimization-Based Decision Support for Air Traffic Conflict Detection},
 journal    = {IEEE Transactions on Intelligent Transportation Systems},
 volume     = {25},
 number     = {4},
 pages      = {2112--2123},
 year       = {2024},
 doi        = {10.1109/TITS.2024.1234567}
}
```

Fig. 4. BibTeX Journal Paper Example

3.2 Inclusion and Exclusion Criteria

After the data were cleaned, a systematic review process based on PRISMA with four phases implemented to select the final group of studies for the review:

1. **Identification**: the process of finding and collecting up to 147 articles.
2. **Screening**: elimination of duplicates and irrelevant articles determined from their title and abstract.
3. **Eligibility**: giving full-text consideration to the 52 remaining articles in line with the inclusion/exclusion criteria.
4. **Inclusion**: final selection of 25 studies which passed the quality test.

The systematic review only considered peer-reviewed journal articles, conference papers, and doctoral theses as valid sources of information The selected items were specially connected to AI for detecting, resolving conflicts, or supporting decision-making in air traffic control. Moreover, exclusively English-language publications from the years 2020 to 2024 were taken into account in the review process.

Editorials, book chapters, patents, and articles that did not undergo peer review were not included. Studies lacking technical or quantitative content or dealing with peripheral areas such as radar or communication systems were similarly removed. Besides, during the screening phase, non-English, duplicate, or abstract-only publications were eliminated so as to maintain a high-quality and consistent dataset. Initially, 147 documents were obtained. After the title and abstract screening, 52 papers were left. Subsequent to the full-text analysis, 25 studies were found to fulfil all the inclusion criteria.

3.3 Research Questions

This review paper is guided by the following research questions:

- Which artificial intelligence paradigms are most commonly applied to conflict detection and decision support in ATC?
- How do these approaches compare in terms of accuracy, computational efficiency, interpretability, and real-time feasibility?
- What limitations and research gaps remain between academic prototypes and operational deployment in certified ATC environments?
- Which future directions emerge from these findings for developing explainable and human-centric AI systems?

4 Review of Conflict Detection and Resolution Systems

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This section presents a critical overview of the recent papers, especially doctoral theses, journal publications and peer-reviewed articles, paying attention to contribution on CD&R in ATC. The studies are organized by their applied methodologies: optimization, behavior modelling, predictive analytics, reinforcement learning. For every category we summarize important contributions along with advantages and disadvantages.

4.1 Optimization-Based and Rule-Enhanced Approaches

In her doctoral work, Sarah Degaugue [1] introduced an adaptive resolution system grounded in multi-objective optimization. Using evolutionary algorithms, the system reduces trajectory deviations while accounting for environmental factors such as fuel efficiency and CO_2 emissions. One of the main innovations of this approach is the inclusion of behavioral models that reflect how ATCs typically make decisions. However, the system in its current form has so far only been validated with simulation and has not, as of now, been demonstrated in real-time operations.

- Strengths: Dynamic optimization; inclusion of ATCO behavioral logic; environmental sensitivity.
- Limitations: No live-data integration; simulation-only testing; limited HMI evaluation.

While much of the existing research has concentrated on airborne conflict detection and en-route resolution, ground operations—particularly during the departure phase—also offer significant opportunities for improvement.

For example, Bikir et al. [12] proposed a hybrid optimization framework for reducing departure delays within Standard Instrument Departure (SID) procedures. Their method combines traffic flow constraints with runway scheduling to enhance overall runway efficiency. In a related study, Idrissi et al. [13] developed a speed adjustment model for conflict-free taxiing that adjusts aircraft ground movement in real time to reduce delays and prevent ground congestion. Together, these studies demonstrate that AI-powered decision support can play a crucial role not only during flight but also in the earlier stages of departure and taxiing.

4.2 Behavior Modelling and Human-Central Automation

Yash Guleria [2] proposed a behavior-cloning framework that learns conflict-resolution strategies directly from recorded controller actions. The approach achieved an acceptance rate above 70 % in experimental trials because its recommendations align with human reasoning—a hallmark of conformal automation. By respecting individual decision-making styles, the AI supports rather than overrides human expertise [5].

- Strengths: Uses real operational data; personalizes advice to controller behavior; facilitates human-AI collaboration.
- Limitations: Limited number of trained ATCOs, with scalability and generalization still unproven.

4.3 Predictive Analytics and Data-Centric Modelling

Yutian Pang [3] investigated the use of predictive analytics in ATM by using Bayesian networks and GNNs. Although the study did not specifically address CD&R, it demonstrated the potential of predictive modelling to anticipate controller workload, traffic density peaks, and possible conflict zones. While resolution strategies were not directly evaluated, the research provides a valuable foundation for integrating anticipatory capabilities into future CD&R systems.

- Strengths: Probabilistic reasoning; advanced trajectory prediction, integration of multi-dimensional data.
- Limitations: Limited coverage of vertical movement; validation based only on simulations; indirect link to CD&R execution.

Separately, Kwangyeon Kim [4] designed decision support systems that used both supervised and unsupervised learning—such as LSTM models and clustering methods— for conflict detection and monitoring controller compliance. While the approach was limited to binary conflicts and lacked support for multi-aircraft scenarios, it illustrated the practical machine learning into operational ATC tools.

- Strengths: Diversity in ML techniques; practical deployment; anomaly detection integration.
- Limitations: Inability to handle multi-aircraft scenarios; data quality significantly influenced performance.

4.4 Reinforcement Learning and Multi-Agent Coordination

In 2023, Qiucheng Xu *et al.* [7] proposed a DRL architecture enhanced with Monte-Carlo Tree Search (MCTS) and Upper Confidence Bounds (UCB). Within this architecture, each aircraft acts as an autonomous agent in a shared Markov Decision Process, reducing conflicts by over 26 % in high-traffic simulations.

- Strengths: Effective multi-agent decision-making; strong performance in dense traffic scenarios; successful integration of DRL with MCTS.
- Limitations: Tested only in abstract airspace; lacks real-time implementation and does not assess human-machine interaction.

In parallel, Dong Sui et al. [6] developed the Tactical Conflict Solver (TCS), an DRL based actor-critic agent designed with a reward function reflecting ATC safety regulations. The system achieved an 80 % conflict resolution success rate in simulations.

- Strengths: High success rate; reward design aligned with ATC rules.
- Limitations: tested only in abstract airspace; absence of adaptation to individual controller behavior.

Table 2. Comparative analysis of the recent studies.

Author	Approach	Highlights	Key limitations
Degaugue (2024) [1]	Evolutionary Optimization	Adaptive optimization, ATCO behavior	Simulated only, limited HMI
Guleria (2024) [2]	Behavior cloning	High acceptance, human-aligned automation	Limited ATCO pool, generalization issues
Yutian Pang (2023) [3]	Predictive modelling	Bayesian & GNN, trajectory prediction	Lacks vertical dimension, simulation-based

Kwangyeon Kim (2021) [4]	ML-based DSS	LSTM, anomaly detection, hybrid models	No multi-aircraft support, data limitations
Quicheng Xu & al. (2023) [7]	DRL + MCTS	Multi-agent, improved conflict reduction	Simplified scenarios, no HMI
Dong Sui & al. (2023) [6]	Actor-Critic DRL	High accuracy in resolution	Fixed preferences, limited real testing

While the previous section provided a qualitative overview of the main AI paradigms used for CD&R, the following table shows a quantitative comparison of the selected studies and summarizes key performance metrics and methodological trends.

Table 3. Comparison of key AI-Based Approaches in ATC Conflict Detection and Decision Support

AI Approach	Average accuracy success	Main Metrics	Authors
Optimization	80-90%	Fuel/CO2 reduction, convergence	Degaugue (2024) [1]
ML / Predictive	85-90%	Detection accuracy	Xie (2021) [16]
DRL	25-30%	Conflict reduction, reward	Xu (2023) [7] Sui (2023) [6]
Behavior Cloning	70-90%	Human acceptance	Guleria (2024) [2] Bastas (2022) [8]
Multi-Agent RL	20-25%	Coordination / resolution rate	Bikir (2024) [12]
Hybrid / XAI	N/A	Explainability trust	Gariel (2023) [11] Bikir (2024) [12]

The results indicate a clear trend toward DR and multi-agent coordination, which dominate post-2022 research due to their adaptability and scalability. Optimization-based models remain relevant for computational efficiency but lack flexibility under uncertainty.

The integration of XAI is recognized as a critical research dimension, improving interpretability and user trust but still lacking standardized benchmarks. Regionally, most studies originate from Asia and Europe, reflecting the strong concentration of AI–ATC research programs under EUROCONTROL, SESAR, and CAAC initiatives.

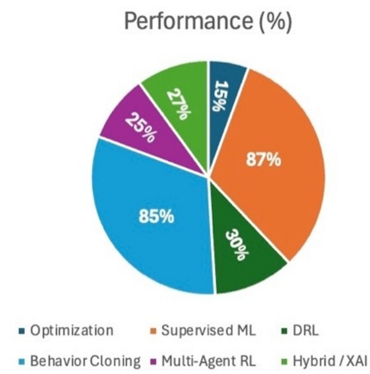

Fig. 5. Performance of AI Approaches in ATC Conflict Detection and Decision Support (2020-2024)

This analysis shows that DRL consistently yields the highest conflict-reduction rates in simulated high-density airspaces (average 25 – 30 %), whereas behavior-cloning and supervised learning methods demonstrate superior interpretability and human-alignment rates (≈ 70 – 90 %). Optimization-based models continue to demonstrate strong computationally efficiency yet they often struggle with scalability and adaptation in dynamic or uncertain environments.

These results underline the growing dominance of learning-based systems in modern ATC decision-support research, and highlights the necessity for explainable and certifiable AI solutions suitable for operational use.

5 Machine Learning and AI for Intelligent Decision Support

AI and ML techniques are the core of next-generation decision-support systems in ATC, providing context-aware and human-centric recommendations to help air traffic controllers take safe decisions on the right time.

5.1 Supervised Learning and Behavioral Cloning

Supervised-learning models—e.g. Decision Trees, Random Forests and Deep Neural Networks (DNNs)—can capture controller decision patterns from historical data; Guleria [2] used behavioral cloning to learn air traffic controller strategies from real-world simulation data, producing responses that closely matched human decision-making patterns.

Bastas and G. A. Vouros [8] built a deep-learning architecture that predicts both whether a controller will intervene and which resolution maneuver is likely to be chosen, achieving high accuracy on operational datasets, though generalization to unseen behaviors remains a challenge.

- Key benefits – captures expert logic; improves transparency; boosts user trust through human-aligned outputs.
- Key limitations – performance may degrade in unfamiliar traffic situations, as adaptability is limited to previously learned patterns.

In addition to machine learning approaches, rule enhanced expert systems have also been studied for their ability to integrate domain-specific knowledge. For example, Chougdali et al. [14] designed an intelligent computing system for air traffic management that uses rule-based logic to represent traffic situations and propose solutions. While these systems don't rely on learning algorithms, they are still valuable especially in contexts where transparency and regulatory compliance are essential.

5.2 Reinforcement Learning for Conflict Resolution

Reinforcement learning trains agents through interaction and long-term reward, making DRL attractive for dynamic ATC environments.

Qiucheng Xu et al. [7] designed each aircraft as an agent in a multi-agent DRL framework enhanced with Monte Carlo Tree Search and Upper-Confidence Bounds, reducing conflicts by >26 % in high traffic simulations.

Dong Sui et al. [6] created the Tactical Conflict Solver, an actor–critic DRL agent whose reward enforces ATC safety rules, reaching >80 % success in simulations.

Bastas & Vouros [8] proposed a graph-based DRL architecture with implicit coordination among agents, preserving decentralization and safety.

Key benefits – enables real-time strategic decisions; supports multi-agent coordination; scales to manage high complexity air traffic environments.

Key limitations – heavy computational cost; limited explainability; delayed rewards slow learning.

5.3 Predictive Modelling under Uncertainty

Predictive analytics complements real-time DSS by forecasting future airspace states. Pang [3] combined Graph Neural Networks and Bayesian methods to predict trajectories and workload while representing environmental uncertainty.

Such foresight offers early warnings but faces integration hurdles with heterogeneous, incomplete sources (METAR, ADS-B, NOTAMs).

Key benefits – captures uncertainties in trajectory and intent, enhancing decision quality when operating with partial data.

Key limitations – challenging real-time deployment; demands advanced data-fusion pipelines.

5.4 Integration with Human-Centred Design

Recent studies highlight the importance of decision support systems that are both flexible and easy to understand, taking into account the preferences and cognitive habits of air traffic controllers. For instance, Bastas et al. [17] proposed a DRL-based conflict solver capable of adapting to the individual working style of each controller while maintaining interpretable decision-making. Similarly, van Rooijen et al. [21] introduced a neural network model that learns and reproduces specific reactions of the controller, and helps building trust and reduces mental effort. Tran et al. [22] also developed an interactive AI agent that learns from human feedback during conflict resolution situations. Altogether, these studies show how personalized and human-centered AI can encourage wider acceptance in real-word operations.

Recent work stresses human-factor integration: conformal automation—coined by Guleria [2]—adapts advice to individual ATCO preferences instead of imposing rigid logic. Researchers promote DSS with intuitive HMIs that visualize recommendations, highlight uncertainty and allow controllers accept, reject or adjust AI suggestions, fostering trust and collaboration [5].

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Emerging challenge – AI tools must remain transparent, reliable, and intuitive, allowing controllers to trust and understand the decisions proposed during critical operations.

6 Gaps and Research Challenges

Despite significant progress in applying AI to conflict detection and decision support in ATC, several limitations continue to prevent research prototypes from reaching operational use.

6.1 Lack of Operational Validation

AI-based CD&R systems have shown great potential in simulations but still have limited use in actual ATC operations. However, the gap is being bridged slowly, as more researchers are teaming up with air navigation service providers (ANSPs) to carry out live trials. Professional controllers participated in human-in-the-loop simulations conducted by Westin et al. [19] and IJtsma et al. [18], while Laskowski et al. [20] confirmed an AI-based workload estimation model with both physiological and operational indicators. These pioneering efforts highlight the need for and the priority of realistic testing scenarios along with the commitment of aviation authorities to enable operational integration.
Challenge: Address the simulation-to-operation gap by validating intelligent CD&R systems in certified simulators or supervised live-testing platforms (e.g. TopSky, EurocatX) in partnership with air-navigation-service providers (ANSPs).

6.2 Limited Multi-Aircraft Coordination

Many approaches still target conflicts between aircraft pairs, making them unsuitable for complex situations where multiple aircraft interact simultaneously.
Although some multi-agent DRL systems address this complexity, their flexibility and robustness under real-time, large-scale scenarios remain poorly investigated [7].
Challenge: Develop decentralized, multi-agent models capable of handling multi-aircraft conflicts in real time while preserving safety and traffic-flow efficiency.

6.3 Incomplete integration of Human-in-the-loop (HITL) Mechanisms

While human–AI collaboration is often discussed, most CD&R systems fail to incorporate real-time feedback, controller variability, and cognitive aspects like workload and trust. As a result, technically correct recommendations may be disregarded in practice.
Challenge: Integrate user-adaptive capabilities and manual override options to ensure ATCOs stay in control, maintain trust, and can adjust its suggestions [2].

6.4 Limited Explainability and Transparency

Deep learning and DRL models typically function as “black boxes,” making it hard for controllers to understand or justify system outputs in a safety-critical setting [6].

Challenge: Apply Explainable AI methods—such as saliency visualization, attention-based interpretation, and post-hoc explanation frameworks—to clarify system reasoning processes and build lasting trust between AI systems and human controllers.

6.5 Static Learning and Poor Adaptability

Important situational elements—like adverse weather, restricted areas, emergency events, and communication latency—are frequently underrepresented in AI training datasets. This omission reduces the realism and operational trustworthiness of conflict resolution outputs.
Challenge: Create multimodal fusion architectures that combine METAR, ADS-B, NOTAM, and radar data into reliable, real-time models for holistic conflict resolution [9].

6.6 Exclusion of Critical Operational Variables

Essential factors—weather phenomena, restricted zones, emergencies, communication delays—are often omitted from training data, reducing the realism of conflict resolution recommendations.
Challenge: Design multimodal data-fusion pipelines that integrate heterogeneous, dynamic sources (METAR, ADS-B, NOTAMs, radar feeds) into robust, real-time AI models for holistic conflict resolution.

7 Discussion

To meet the demands of modern ATM, future CD&R systems must be not only intelligent but also robust, transparent and compatible with real-world operations.

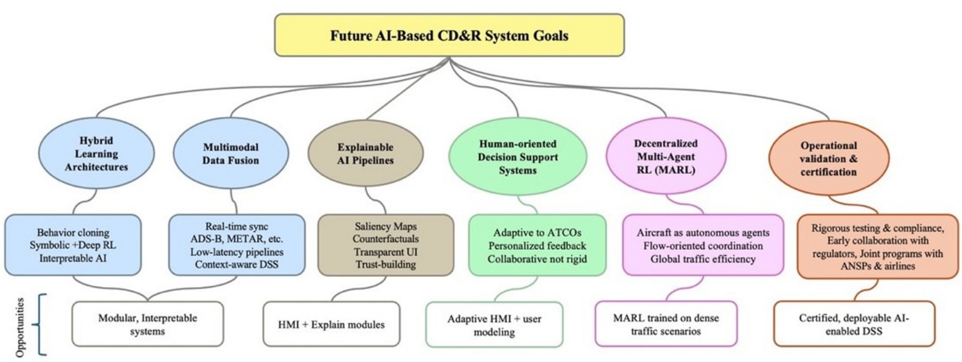

Fig. 4. Performance of AI Approaches in ATC Conflict Detection and Decision Support (2020-2024)

The complexity of CD&R cannot be tackled effectively by any single AI technique alone. A more effective path forward involves combining different methods—for example, using expert demonstrations to guide reinforcement learning through behavior cloning, or integrating symbolic reasoning with deep networks to improve interpretability [5].
This kind of integration opens up the possibility of modular AI systems in which symbolic reasoning, supervised models, and DRL work together to provide both high performance and interpretability. Nevertheless, an AI-based decision-support system must adhere to the strict

international regulations in place before it can be considered for use in the operational ATM environment. The ICAO Procedures for Air Navigation Services (Doc 4444) [15] enumerate the primary operational principles and constraints that must be observed by automated systems in order to maintain safety and regulatory compliance.
These standards guide the development of rule-based systems, define minimum separation standards, and influence how conflicts are resolved.
However, certifying AI-enabled decision support systems remains one of the most significant hurdles for their adoption in operational settings. Conventional validation frameworks are not fully adapted to dynamic, learning based systems. In response, Gariel et al. [11] proposed a structured certification approach specifically designed for AI systems in safety-critical environments. likewise, Xie et al. [16] discussed how explainability and traceability are now considered key conditions for regulatory approval of AI in air traffic management. Together, these developments point toward a more flexible, hybrid certification strategies that combine formal validation, simulation results, and operational feedback in collaboration with ANSPs and regulatory bodies [10].

8 Conclusion

As air traffic continues to grow and operational environments become more complex, the role of intelligent, adaptive, and human-centered decision-support systems has become vital. Through this critical review, we explored the latest developments in conflict detection and resolution, demonstrating how advances in AI—particularly in machine learning and DRL—offer promising solutions to meet the increasing demands of modern ATC. We analyzed a diverse body of doctoral and peer reviewed work, ranging from behavior-cloning models that replicate controller decisions, through graph-based and probabilistic predictive analytics, to DRL agents capable of autonomous coordination in complex traffic. Although many approaches report promising simulation results, several obstacles still hinder deployment in live ATC operations.

Even though there has been a lot of advancement, there are still considerate obstacles to be solved, such as the lack of validation in the real operational settings for most of the systems, their inability to scale up for high-density or multi-aircraft situations, and the little interpretability or adaptability they provide in dynamic contexts. Along with these technical issues, there are also human factors that need to be addressed, such as user trust, cognitive load, and interface design, which hamper practical usage. This study suggests key areas of further research and development to unlock these barriers, which are:

- Hybrid AI systems that combine learning and symbolic logic, thus speeding up training and at the same time making it easier to understand.

- Real-time integration of different aviation data sources (ADS-B, METAR, NOTAMs, flight plans) for better situational awareness.

- XAI methods—like saliency maps, counterfactuals, and interpretable models—to promote transparency and trust.

- Adaptive, user-oriented Decision Support Systems (DSS) that customize recommendations according to the preferences and workload of individual controllers.

- Decentralized multi-agent coordination that can manage dense airspace without compromising the resolution of local conflicts.

- Operational validation and regulatory collaboration with Air Navigation Service Providers (ANSPs) and authorities to secure certification and deployment of AI-enabled DSS.

Developing intelligent CD&R systems is as much a human–machine collaboration challenge as it is a technical one. Their success depends on being effective, explainable, and seamlessly integrated into ATC operations. By aligning innovation with operational and human factors, future AI-based DSS can become trusted partners for controllers, enhancing safety and efficiency. This review provides a foundation for doctoral research aimed at creating an intelligent, real-time CD&R system for next-generation ATC.

9 Abbreviations

ADS-B Automatic Dependent Surveillance–Broadcast
AI Artificial Intelligence
ANSP Air Navigation Service Provider
ATC Air Traffic Control
ATCO Air Traffic Controller
ATM Air Traffic Management
CAAC Civil Aviation Administration of China
CD&R Conflict Detection and Resolution
DRL Deep Reinforcement Learning
DSS Decision Support System
GNN Graph Neural Network
HITL Human-in-the-Loop
HMI Human–Machine Interface
MARL Multi-Agent Reinforcement Learning
MCTS Monte-Carlo Tree Search
METAR Meteorological Aerodrome Report
NOTAM Notice to Airmen
PRISMA Preferred Reporting Items for Systematic Reviews and Meta-Analyses
SESAR Single European Sky ATM Research
SLR Systematic Literature review
TCS Tactical Conflict Solver
UCB Upper-Confidence Bound

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