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Sustainable and Smart: The Role of AI and Automation in Greening Aviation Logistics

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Abstract- Background- The aviation industry facilitates global mobility and trade and at the same time, it only accounts for 2-3 percent of the world's carbon emissions. With the growing industry demand, aviation companies find themselves in a tight spot—striking a balance between operational efficiency and true sustainability. Objective- This review aims to address emissions and operational performance enhancement in aviation logistics with the help of Artificial Intelligence (AI) and automation technologies. Methods-This paper integrates the application of machine learning, computer vision, natural language processing, robotics, and industrial process automation in aviation industry with the help of case studies from India and the rest of the world alongside industry white papers and academic literature. It takes a systematic literature review of academic studies, white papers from the industry and documented implementations to assess the emerging role and impact of AI-driven technologies in aviation. Result- The findings indicate that AI applications can leverage predictive analytics, optimize resource utilization, enable autonomous operations, and usher in a new passenger experience. Qualitative evidence suggests significant improvements in operational efficiency, system resilience, and service consistency on the part of leading industry players. Conclusion- Collectively, these implementations help the aviation industry carbon reduction targets, including the IATA net zero 2050 emission target. Nonetheless, the more flexible AI systems face integration difficulty, high capital investment, and employee preparedness. The review determined that AI and automation could expedite the shift towards climate-friendly, intelligent aviation logistics, provided strong policies, quality data, and collaboration among all stakeholders is employed.

Keywords— Artificial Intelligence (AI), Automation, Sustainable Aviation, Green Aviation, Aviation Logistics, Smart Logistics, Supply Chain Management, Carbon Emissions Reduction, Energy Efficiency, Predictive Analytics, Machine Learning

I. INTRODUCTION

Aviation industry across the world is undergoing a massive transformation due to demands for rising efficiency, climate change and sustainability. The complex yet energy intensive nature of aviation logistics which involves air cargo operations, airport and ground handling, warehousing, maintenance logistics and supply-chain management plays a crucial role. Though the aviation sector accounts for a relatively lower share of global emissions when compared to other transport sectors, it has been experiencing a steady rise in its emissions levels. Furthermore, because of its highly visible nature, the industry has come under increasing pressure for its decarbonization. According to the International Energy Agency, the aviation industry accounts for about 2–3% of global energy-related CO_2 emissions, with other indirect impacts associated with logistics and support operations (IEA, 2023).

In other words, aviation logistics can improve sustainability outcomes. The planning and handling of cargo, routing, scheduling and maintenance create the impact on fuel use, emissions and resources. Wider environmentalists have known that logistics and freight transport are key contributors of global GHG emissions. This led to significant academic and industrial interest into 'green logistics,' that is improving the environmental performance of the sector without compromising service quality or economic efficiency (McKinnon et al., 2015). The ability to address all the challenges with the help of AI and automation are increasingly seen as effective enablers for data-driven decision-making and smart system integration.

II. REVIEW OF RECENT LITERATURE

Recent works on green logistics and intelligent transport systems show three closely interrelated streams relevant to aviation logistics. The first problem focuses on the sustainability-oriented logistics framework. It focuses on system-level efficiency and emission and waste management. An artificial work illustrating that decisions regarding logistics design and operation can facilitate reduced environmental impacts while ensuring price competitiveness (McKinnon, 2015). The second research stream is centred on the application of AI-based optimization and machine learning techniques to logistics and transport systems. Research indicates the optimization of processes and the enhancement of productivity along with improved forecast capability, real time decision making and better process control thus enhancing effciency and minimizing wastes in the business environment which is in line with the overarching goals of sustainability and competitiveness. (Md. Prince1 Am. J. IR 4. Beyond 3(1) 28-36, 2024). In aviation logistics characterized by higher uncertainties, safety restrictions and cost sensitivity, accurate forecasting and adaptive planning become more valuable, underscoring relevance of these approaches. The third stream tackles the use of digital twins, real-time data, IoT-enabled sensing and automation in achieving intelligent and resilient logistics systems. There has been growing attention to using digital twins for improving situational awareness, foresight, and resilience at the system level in complex logistics (Le 2024). It has also been reported that asset utilization, turnaround times, and environmentally efficient operations are improved through automation and autonomy across logistics networks. Aviation logistics could improve decision-making accuracy, lower inefficiencies, and help achieve sustainability goals through AI and automation, the literature suggests. Nevertheless, current research focuses more on technology and specific functions.

Academic interest is expanding, but there are gaps: "the research on automating logistic processes in aviation is primarily done in isolation in the various fields of operation like routing, warehousing, maintenance or ground handling, and does not sufficiently integrate over the entire logistics chain." Further, while numerous studies cite efficiency improvements, far fewer utilize standardized or transparent methodologies to quantify environmental impacts, notably emissions reductions, for the totality of aviation logistics. In addition, the connection between AI-powered operational improvements and wider climate mitigation objectives is weak. Data governance, legacy systems integration, cybersecurity, regulatory uncertainty, and capital investment are often recognized but not usually combined within an analytical framework. Recent reviews offer insights on the types of AI and automation interventions designed for systemic and methodological environmental benefits (Le & Fan, 2024).

With a view to fill the prevailing gaps this study will attempt to provide an integrated assessment of the contribution of AI and automation in greening aviation logistics. This will be achieved through identification and classification of applications in air cargo operations, airport and ground handling, and supporting supply-chain functions. In addition, it puts together recent academic literature to assess how these technologies contribute to operational efficiency, resilience of systems and sustainability of the environment and the key implementation challenges associated with data integration, governance, interoperability, and scale. Lastly, future research avenues supporting a coherent measurement of the environment impact as well as the end-to-end adoption of AI and automation in the aviation logistics has been highlighted by the study.

III. METHODOLOGY

1. Research Design

This study uses a combination of structured literature review and qualitative document based case analysis. The reason for adopting a structured review approach was mainly to achieve transparency, reproducibility and methodological rigour. In particular, it enables us to analyse scattered research in an organized way. In this way, we respond to the fragmentation of literature on the one hand regarding logistics in aviation and AI on the other hand, and the very limited availability of literature.

2. Literature Search Strategy

Databases

Peer reviewed academic literature was retrieved from the following databases to ensure comprehensive coverage of aviation, logistics, and AI research: Scopus, Web of Science (Core Collection), ScienceDirect (Elsevier), IEEE Xplore, SpringerLink, ACM Digital Library

Google Scholar was used only for backward and forward citation tracking to identify additional relevant studies not indexed in the above databases.

Timeframe

The literature search was restricted to articles published from January 2014 to December 2025. This timeframe captures the transition from early rule based automation to advanced AI techniques such as machine learning, computer vision, reinforcement learning, and digital twins, which are central to contemporary aviation logistics transformation.

Keywords and Search Strings

Search strings is grouped around four core concepts:

- Aviation context
- Logistics and operations
- AI and automation technologies
- Sustainability outcomes

Example search string:
("aviation" OR "airline" OR "airport" OR "air cargo" OR "ground handling" OR "turnaround")

AND ("logistics" OR "baggage" OR "cargo terminal" OR "warehouse" OR "airside" OR "supply chain")

AND ("artificial intelligence" OR "machine learning" OR "computer vision" OR "reinforcement learning" OR "automation" OR "digital twin" OR "robotic process automation")

AND ("sustainability" OR "carbon emissions" OR "fuel efficiency" OR "energy consumption")

To capture regional perspectives, especially for India, additional filters such as "India," "Indian aviation," "IndiGo," "Air India," "AAI" were applied.

Inclusion and Exclusion Criteria

Inclusion Criteria

Studies were included if they:

- Were peer reviewed journal articles or conference papers
- Examined AI and/or automation in aviation logistics or closely related operations (e.g., ground handling, cargo, maintenance logistics, turnaround processes)
- Reported operational outcomes (e.g., efficiency, delays, resource utilization) and/or environmental outcomes (e.g., fuel use, CO_2 emissions, energy consumption)
- Provided sufficient methodological detail to assess validity

Exclusion Criteria

Studies were excluded if they:

- Focused on aviation technologies without logistics relevance
- Were opinion pieces, editorials, or lacked empirical or analytical grounding
- Mentioned AI or automation only conceptually, without application or evaluation
- Were outside the defined timeframe or unavailable in full text

Thematic Analysis

All included studies were coded and analyzed thematically across five aviation logistics domains:

- Flight and network operations
- Ground and airside logistics (apron, turnaround, GSE)
- Maintenance and safety logistics
- Passenger and baggage handling
- Air cargo and terminal/warehouse logistics

AI and automation techniques were categorized (e.g., machine learning, computer vision, NLP, RPA, autonomous systems) and mapped to operational functions and reported outcomes.

Sustainability Metrics

Sustainability was evaluated using both direct and proxy indicators, including:

- CO_2/CO_2e emissions
- Fuel consumption
- Energy usage
- Waste reduction
- Operational efficiency improvements (used as proxies where direct emission data were unavailable)

When sustainability outcomes were inferred rather than directly measured, this was explicitly noted.

Thematic

The section uses evidence from peer-reviewed research papers and validated operational case documentation to assess the effect of AI and Automation on sustainability outcomes in the aviation logistics function. Following this, rather than providing examples one by one, this section provides an evaluation against five cross-cutting themes. The operational mechanism of each theme is discussed with their documented evidence quantified to measure environmental impact.

To ensure clarity and replicability of the approach, this study specifies the subject AI model(s) used within the reviewed papers and case studies. The models chosen are those which are most commonly used and tested for aviation logistics, airport operation, and air cargo system along with their relevance for efficiency improvement and emissions reduction.

AI-Enabled Optimization of Flight Operations

According to the reviewed literature, flying planning and trajectory optimisation is the most mature AI application related to aviation sustainability. Machine learning techniques such as gradient-boosted trees and neural networks have widely been employed in multi-criteria decision-support systems to combine weather and airspace constraints, aircraft performance and historical fuel-burn data.

According to peer-reviewed studies, AI-assisted routing together with altitude optimization (given operational constraints) results in a fuel-burn reduction of 1-4% per flight. Although insignificant at the level of individual flights, when aggregated across large fleets, they accumulate considerably. Studies reveal that the benefits of fuel efficiency enhancements are reliant on context. In particular, routes with different structures, traffic densities and weather volatility will yield different benefits.

Strategies to avoid contrails extend this capability further than CO_2. AI models which combine atmospheric humidity and temperature data are able to identify a small number of flights (normally <10%) that contribute to a large share of non-CO_2 warming effects. Experimental trials show that the climate impacts of contrails can be reduced substantially with fuel penalties of less than 1%. This goes against earlier assumptions that mitigating the impact of contrails necessarily leads to an increase in emissions. Still, the application has a limited geographical application and the airspace limitations.

Critical assessment

Although AI improves flight-level efficiency, many studies have shown that rebound effects can take place. That is, the efficiency gains are offset in part by network growth, or increased flight frequency. In addition, models that are trained on historical traffic patterns may inherit structural biases that perform poorly under out-of-sample conditions (e.g., intense weather/geopolitical airspace closures).

Predictive Analytics for Disruption Management and Operational Stability

The application of predictive analytics to delay propagation, maintenance forecasting, and crew scheduling appears to provide strong evidence of indirect emissions reduction through enhanced operational stability. The forecast of disruption through machine learning-based models helps to reduce the unplanned arrivals, which are highly correlated with excessive fuel burn through holding, speed-up recovery, and repositioning of aircraft.

According to empirical studies, when networks utilize predictive disruption tools, the delay reductions of around 10–20% lead to fuel savings at the system level. However, these delay reductions are rarely attributed to individual flights. The automation of reporting and maintenance diagnostics based on NLP mainly improves turnaround consistency.

Critical Assessment

Often, inference rather than direct measurement represents a methodological weakness in the literature regarding the sustainability contribution of predictive analytics. Using historical operational data, on the other hand, could result in a brittle model for low-frequency, high-impact disruptions.

AI and Automation in Ground Handling and Turnaround Operations

Ground operations are a vital source of emissions that has not historically been measured. Field studies that are peer-reviewed and validated indicate that it is possible to consistently reduce turnaround time (3–6%) and ground delays (5–10%). This can be done using computer-vision systems, reinforcement-learning-based schedulers and IoT-enabled automation.

A decrease in Turn Around Time will lead to lesser auxiliary power unit (APU) usage and fuel burn during taxi-out resulting in localized emissions reductions at congested hubs. Integrated systems (apron monitoring + resource allocation) are better than stand-alone tools, confirming literature of logistics systems that coordination at the system of system level yields more sustainable returns than automation at stand-alone level.

Critical Assessment

Although these systems bring operational benefits, they also expose organizations to elevated cybersecurity and data-governance hazards – more so if dashboards are shared by multiple parties. The hidden energy cost of camera networks, sensors and data processing infrastructure is seldom included in sustainability assessment thus is a blind spot for lifecycle accounting.

AI in Air Cargo and Logistics Networks

In cargo logistics, AI-driven demand forecasting, load optimization, and warehouse automation contribute to sustainability primarily through network-level efficiency. According to logistics papers published in peer-reviewed journals, network scale fuel-efficiency improvements with better load factors and lower empty segments can yield 5-15%.
Automation of cargo terminals enhances energy efficiency per unit handled by shortening processing times and improving space utilization. Nonetheless sustainability outcomes rely heavily on the integration between airside and landside logistics, which is uneven across regions.

Comparative Perspective: India vs. Global Aviation Logistics

Compared to the European and North American global mature aviation hubs, structural and comparatively lesser material AI implementation is getting envisaged in India. Many Indian airports are building their digital backbone from scratch while international hubs are progressively retrofitting AI capability into legacy systems. This allows for a faster application of AI-based coordination tools.

The main objective of the India implementations is to ensure operational reliability and capacity management. It is often seen as a co-benefit to achieve sustainability or other objectives. In contrast to global carriers, whose AI sustainability initiatives are often explicitly linked to net-zero pledges.

Theme	Typical AI Models	Reported Impact Range	Limitations
Flight optimization	XGBoost, ANN, RL	1–4% fuel reduction	Rebound effects, data bias
Disruption analytics	ML, NLP	10–20% delay reduction	Indirect emissions inference
Turnaround optimization	CNN, RL	3–6% TAT reduction	Cybersecurity, data energy use
GSE automation	RL, fleet optimization	Near-zero tailpipe emissions	Battery lifecycle impacts
Cargo logistics	ML, optimization	5–15% network efficiency	Integration gaps

Synthesis

According to the key points, AI and automation can achieve measurable efficiency and emissions gains, although there may be system level variations.

Moreover, the latest research calls out overly optimistic narratives by revealing usually overlooked trade-offs, such as lifecycle emissions, governance, and rebound effects.

Case Studies and Real-World Applications

Flair Airlines – AI-Driven Operational Efficiency and Sustainability

Overview

Flair Airways is incorporating AI solutions for operations in flight planning, performance modelling and Cost Index management. This will enhance operational efficiency and reduce environmental impact. It employs artificial intelligence to conduct a detailed performance forecast as well as monitoring of compliance which helps in reducing fuel use, emissions, and maintaining on-time performance.

Significance

This manufacturing company uses AI-based technology to automate its warehouse processes and streamline its supply chain management while controlling costs. Making use of predictive analytics into everyday airline operations has an application for greener logistics.

American Airlines – AI-Assisted Gate Assignment and Taxi Time Optimization

Overview

American Airlines is using AI gate assignment system at the Dallas, Fort Worth International Airport (DFW) and other major hubs to real-time optimization of gate assignments and provide better responses to passenger connections, runway availability and taxi times.

Impact

According to the data, when a taxiing is scheduled perfectly, it reduces the average taxi time. Hence, it reduces fuel burn and emissions from ground movement. The improvement of on-time performance further shows the environmental and efficiency co-benefit of AI.

Significance

Through this example, its illustrated how data-driven integration into ground operations can lead to quantifiable sustainability benefits, such as reduced idle engine time and fuel use.

AI-Enabled Contrail Avoidance Initiatives

Overview

With the help of AI atmospheric models, airlines and researchers have done research and test flights to know which altitudes and routes create the less persistent contrails.

Impact

Through operational experimentation, contrail formation is reduced substantially at a modest penalty in fuel-use. In this way, AI can help the industry combat climate impacts beyond CO_2 emissions. Non-CO_2 radiative forcing is one such area that requires attention.

Significance

To avoid contrail means to help expand the impact of the sustainability of AI beyond just fuel burn metrics, but operational implementation is limited to it.

Cargo Logistics Automation and Digitalization (IATA Vision)

Overview

The vision of the IATA initiative for the future of air cargo facilities 2025 indicates that automation, digitalisation, and smart infrastructure are strategic enablers for greener cargo logistics. This paper presents a data integration and forecast 74161e3a2f robotics system implemented at a major logistics hub. It describes actual implementations of robotics, AI-based tracking and data integration systems to achieve streamlined cargo movement between hubs so as to enhance throughput and avoid delays in handling and extra energy use.

Significance

This industry roadmap illustrates a multi-stakeholder coordinated vision for sustainable cargo logistics. It shows how sustainability spirits can be achieved at the ecosystem level through the application of AI/automation strategies – not as separate solutions.

AI-Powered Predictive Maintenance and Resilience Tools

Overview

Airlines and aviation service providers are utilizing machine learning-powered predictive maintenance systems that would help to anticipate equipment failure and scheduled maintenance. Unplanned interruptions are reduced, unnecessary flights or repositionings are avoided and component life is extended.

Significance

Predictive maintenance is excellent for the environment. It reduces waste and prevents unintentional fuel burn from delays or failures. It also lowers its life-cycle cost. team members is powered by machine learning. Such application is reported frequently in industrial use cases of AI in aviation operations and logistics.

AI in Smart Airport Operations

Examples

- Chandigarh International Airport (India): Introduction of Smart Visual Docking Guidance Systems (S-VDGS) using sensors and AI to automate aircraft parking and reduce ground operation times, thereby lowering fuel consumption and emissions during taxiing and parking.
- Noida International Airport (India): Greenfield design integrating AI for biometric flow management, baggage handling, and predictive analytics for dynamic system control, alongside sustainability-oriented infrastructure (e.g., solar power, energy-efficient design)

Significance

The cases clearly show how they bring in AI/automation at airports to ensure efficient throughput while also helping environmental goals. And they are doing this for an emerging hub while it is being built in a sustainable manner (vs retrofit challenges in legacy hubs).

Future Prospects of AI and Automation in Greening Aviation Logistics

In the future, AI and automation's role in aviation logistics may go beyond isolated efficiency benefits to system-level sustainability transformation, enabled by enhanced data integration, electrification and regulatory fit. The current deployments aim for operational efficiency. But with emerging trends, we will see greater synchronization and augmentation for aviation decarbonization.

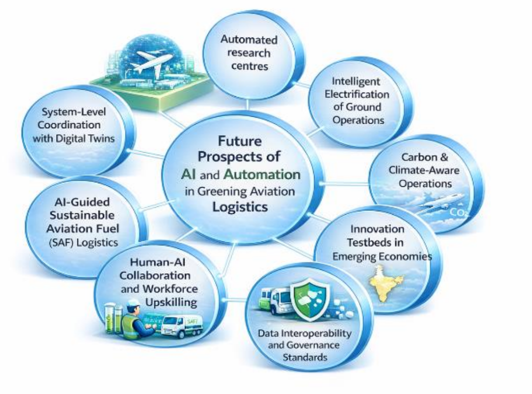

Fig 1 Future prospects of AI and Automation in Greening Aviation Logistics

As shown in the above figure, the future prospects of AI and Automation in Greening Aviation Logistics is incredible and is explained in a detailed way below.

Transition from Local Optimization to System-Level Sustainability

In the future, AI may help improve logistics end-to-end, not only performance of single processes but possibly their orchestration. Airports and air cargo networks as digital twins- airside, terminal, warehouse and landside logistics integrated, simulation-based decision making with carbon, energy and congestion constraints made explicit. Models at the level of systems can prevent rebounds from occurring, whereby a gain of efficiency in a subsystem emits elsewhere.

AI-Enabled Electrification of Ground Operations

One of the more tangible near-term opportunities is the integration of AI and electrified ground support equipment (eGSE). Airports will replace diesel-powered vehicles with electric fleets. AI will help in scheduling, optimizing charging, and fleet coordination to prevent operational bottlenecks and grid overload. Predictive optimization models and reinforcement learning may play a critical role in the airport scale energy demand, turnaround efficiency and emissions reduction balance.

Carbon-Aware and Climate-Aware Operational Decision Making

The AI systems of the future will soon include carbon-aware optimization, which evaluates operational decisions not only on costs and time but also on emissions intensity. This includes:

- The taxiing, gating, and boarding of an aircraft will be dynamically allocated depending on real-time congestion and fuel burn.
- Flight planning that takes contrails into account and integrates non-CO_2 climate impacts into routing decision
- Scheduling in an emission-weighted manner and selecting less impactful alternatives in case of disruptions

With the increased integration of climate data, atmospheric modeling and operational datasets, such approaches will become feasible.

IV. Integration of AI with Sustainable Aviation Fuel (SAF) Logistics

In addition to its impact on flight operations, AI is likely to increase its role in SAF supply chain logistics from feedstock sourcing to production optimization, blending logistics and airport fuelling. Artificial Intelligence can enhance forecasting, streamline inventory management, and improve distribution efficiency. This thus can lead to a reduction in lifecycle emissions through improvements in SAF adoption scalability. In turn, this will help to remove a key bottleneck in aviation decarbonization.

V. INTEROPERABLE DATA ECOSYSTEMS AND GOVERNANCE FRAMEWORKS

A key future development is creating interoperable data standards that will enable seamless operation of AI systems across airlines, airports, ground handlers and regulators. Efforts targetting a common data model and digital interoperability will enhance measurement and benchmarking of sustainability. In the future, when we deploy systems, we must prioritise data governance, cyber security and explainability. AI-driven outcomes on sustainability must be traceable, verifiable and in accordance with ruling safety critical aviation system.

Human–AI Collaboration and Workforce Transformation

Future AI in aviation logistics will not replace human expertise but will likely evolve towards decision-support and augmentation. Planners, dispatchers, and ground supervisors can make faster and more informed sustainability-aware decisions with the aid of advanced analytics and generative AI interfaces. The emerging aviation markets will necessitate specific upskilling of the workforce and organizational change.

Emerging Economies as Testbeds for Smart and Green Logistics

Countries like India that has a fast developing aviation infrastructure offers a great opportunity in new airports/logistics hubs to leverage A.I. and automation by design Greenfield developments can embed digital platforms, automations and sustainability metrics at the outset, unlike legacy systems in mature markets. Emerging economies could serve as innovation testing ground for empirical evaluation and standardized measurement frameworks of scalable, low-carbon aviation logistics models.

VI. CONCLUSION

In this research, we take a look at how artificial intelligence and automation may improve aviation logistics by linking operational intelligence to sustainability outcomes across flight operation, ground handling, turnaround management, and air cargo. Findings suggest that the most mature applications predictive analytics, resource scheduling, computer vision–based turnaround monitoring, and decision-support tools (for routing, gate management) can help reduce delays, idle time and fuel burn and therefore support emissions reduction targets. While design research on automated ship containers is being gathered, after the first assessment stage, there is still a long way to go. Further research will be necessary as the sub systems are still approaching isolation. Hence, it is not yet fully proven whether implementation will be workable as being reported. We will have to wait and see. Challenges posed by interoperability of data; cyber risks and question of model-bias; readiness of the workforce and tool integration in safety-critical and highly-regulated environments inhibit scaling. In India, national digital initiatives and greenfield airport developments can embed smart, low-carbon logistics "by design". But there need to be a stronger peer-reviewed evidence base and standardized emissions measurement to establish comparable impacts. The implementation of carbon capture and storage (CCS) technologies should be strictly monitored to prevent damages from negligence.

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