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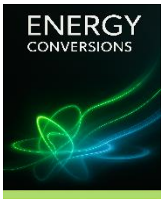

# Optimizing Flight Operations for Lower Emissions: A Review of Wind-Aware Routing, AI, and SAF-Linked Strategies

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A R T I C L E I N F O

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A B S T R A C T

Commercial aviation remains a significant emissions source, while fuel continues to dominate airline operating costs. For that reason, operational efficiency is one of the most immediate levers available for lowering both climate impact and expenditure. This review examines aviation route optimization through four interacting dimensions: wind-aware and altitude-aware trajectory design, airspace-level congestion management, artificial intelligence (AI)-assisted planning, and the coupling of routing decisions with sustainable aviation fuels (SAFs). Literature published between 2010 and 2024 was screened from major scientific databases, producing a final set of 50 studies for detailed synthesis. Across the reviewed work, wind-informed routing commonly delivers fuel savings of about 1-4.2% on long-haul missions, while congestion mitigation and collaborative flow management add a further 2-5% at network level. AI-based methods report the largest operational improvements, with several studies indicating fuel-burn reductions approaching 14% under data-rich conditions. SAF deployment mainly affects lifecycle emissions, but several studies also point to favorable combustion and efficiency characteristics that can reinforce optimized routing. The review identifies the principal synergies, practical barriers, and research priorities associated with these approaches, including certification, explainability, digital data sharing, and equitable global deployment. Overall, integrated optimization emerges as a credible pathway for reducing the energy and carbon intensity of flight.

## 1. Introduction

Commercial aviation is indispensable to global trade, tourism, and mobility, but its environmental footprint is increasingly difficult to reconcile with long-term climate targets. Recent estimates place direct aviation carbon dioxide emissions near 915 million tonnes per year, or roughly 2.5% of the global total, which positions operational efficiency as a central part of sectoral decarbonization [1].

Fuel typically accounts for 20-30% of airline operating costs, so improvements in fuel efficiency are valuable not only for emissions mitigation but also for financial resilience [2]. Among near-term options, route optimization stands out because it can be implemented much faster than major hardware redesign and can benefit directly from improved meteorological forecasting, aircraft performance modeling, and digital dispatch tools [3].

Wind-aware trajectory optimization is one of the best-established approaches in this field. By adjusting headings, cruise levels, and sometimes timing to exploit favorable atmospheric structure, especially jet streams, operators can reduce both mission time and fuel burn. Analyses of long-haul corridors, including North Atlantic operations, routinely report savings in the range of about 1-4% when optimized routing is compared with fixed or conventionally planned tracks [4],[5].

In parallel, artificial intelligence and machine learning are becoming more visible in dispatch support, trajectory selection, and energy management. Because these methods can infer non-linear relationships from large historical datasets, weather fields, and operational constraints, they can reveal route choices that are not easily captured by deterministic heuristics; several studies therefore report larger fuel benefits when AI is allowed to refine trajectory decisions under complex conditions [6].

System-level optimization adds another layer of opportunity. Holding, vectoring, departure metering, and sector congestion all increase fuel consumption at network scale, which is why collaborative decision making, deconfliction strategies, and dynamic traffic management have become prominent in the literature. Regional studies indicate that coordinated flow measures can yield additional savings beyond those obtained by optimizing individual flights alone [7].

A further frontier is the interaction between routing strategy and lower-carbon fuels. Sustainable aviation fuels can already be used in existing propulsion systems under certified blend limits, and recent work suggests that route design, engine response, and fuel chemistry should be evaluated together rather than in isolation [8],[9],[10]. This review therefore synthesizes the evidence on wind-aware routing, AI-enabled planning, congestion management, and SAF-linked strategies to clarify their combined role in energy-efficient flight operations.

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**Nomenclature**

| Abbreviation | |
|---|---|
| AI | Artificial Intelligence |
| AIP | Aeronautical Information Publication |
| ATC | Air Traffic Control |
| ATM | Air Traffic Management |
| $CO_2$ | Carbon Dioxide |
| CFMU | Central Flow Management Unit |
| FMS | Flight Management System |
| GHG | Greenhouse Gas |
| ICAO | International Civil Aviation Organization |

| *Symbol* | |
|---|---|
| E | Energy consumption per flight |
| F | Fuel burn rate |
| t | Time |

## 2. Methodology

This review adopted a structured literature-synthesis workflow designed to capture both operational and energy-focused studies on aviation route optimization. Searches were performed across Scopus, ScienceDirect, IEEE Xplore, arXiv, and Google Scholar, with the review window restricted to work published between 2010 and 2024. Search strings combined terms such as "aviation route optimization," "fuel-efficient trajectory planning," "wind-optimal routing," "machine-learning flight path," "hybrid-electric aircraft," and "sustainable aviation fuel integration."

The retrieved records were screened first by title and abstract and then by full text. Studies were excluded when they provided no quantitative performance indicators, were purely conceptual without validation, or focused only on ground-side airport operations. More than 300 documents were initially identified; 76 were retained for full-text review, and 50 were selected for detailed synthesis on the basis of methodological rigor, transparency of metrics, and direct relevance to in-flight optimization or energy-aware routing.

To support comparison across heterogeneous studies, the final sample was grouped into four thematic clusters: trajectory-level optimization, network-level airspace and congestion management, AI-enabled decision support, and integrations involving SAF or hybrid-electric propulsion. This thematic organization allowed studies using simulation, optimization, empirical trials, and system modeling to be interpreted within a common framework while preserving differences in scale and deployment context.

Performance metrics reported in the literature, including fuel burn, energy use, emissions, delay reduction, and route efficiency, were then synthesized into a comparative narrative. Table 1 presents representative studies from the reviewed set, while the revised figures in this manuscript translate the reported ranges into schematic visuals intended to improve cross-study interpretation rather than reproduce any single dataset.

**Table 1.** Classification of Reviewed Aviation Route Optimization Studies.

| Study & Year | Optimization Focus | Method/Tool | Key Metric | Reported Savings |
|---|---|---|---|---|
| Alrebei et al. [9] | SAF integration & engine performance | Experimental + thermodynamic model | $CO_2$ emissions, efficiency | 12–18% $CO_2$ reduction |
| NASA [5] | Wind-optimal transatlantic routing | Dynamic programming | Fuel consumption | 1.2–4.2% fuel savings |
| Doff-Sotta et al. [11] | Hybrid-electric trajectory optimization | Model Predictive Control (MPC) | Energy (MJ), emissions | 6–10% energy savings |
| LePage et al. [10] | Lifecycle analysis of SAF routing | Energy system modeling | Net GHG emissions | Up to 60% reduction |
| Wei et al. [7] | Airspace congestion optimization | Agent-based simulation | Delays, fuel use | 2–5% fuel savings |
| Cari et al. [6] | AI-assisted flight planning | Supervised ML, neural networks | Time, fuel | Up to 14% savings |

## 3. Results

The reviewed literature paints a consistent picture: aviation route optimization delivers measurable energy and emissions benefits, but the magnitude of improvement depends strongly on whether the intervention is applied at the trajectory, network, algorithmic, or fuel-system level. The results synthesized below draw together 50 studies spanning single-flight optimization, regional traffic management, AI-assisted dispatch, and SAF-linked energy analysis.

At the trajectory scale, the most repeatable gains come from wind-aware routing and altitude selection. Across long-haul missions, modest changes in cruise track and flight level can yield meaningful reductions in fuel use because the aircraft spends more time in favorable tailwinds and closer to minimum-drag operating windows. The reviewed studies generally place the direct benefit of wind-informed routing between about 1.2% and 4.2%, with the strongest improvements observed on transoceanic routes [5].

Figure 1 compares the literature-derived saving ranges associated with the main optimization families discussed in this review. Wind-aware routing offers dependable but moderate gains, network-level coordination adds further improvement, hybrid-electric predictive control produces a larger energy benefit, and AI-assisted planning exhibits the highest stand-alone operational reductions when adequate data and computational support are available.

Although these gains are attractive, practical implementation still requires real-time weather updates, robust aircraft-performance estimation, and coordination with air traffic services. The literature therefore emphasizes that trajectory optimization should be regarded as an operational capability rather than a purely mathematical exercise, because its real value depends on dispatch integration, controllability, and timely access to atmospheric information [17],[18].

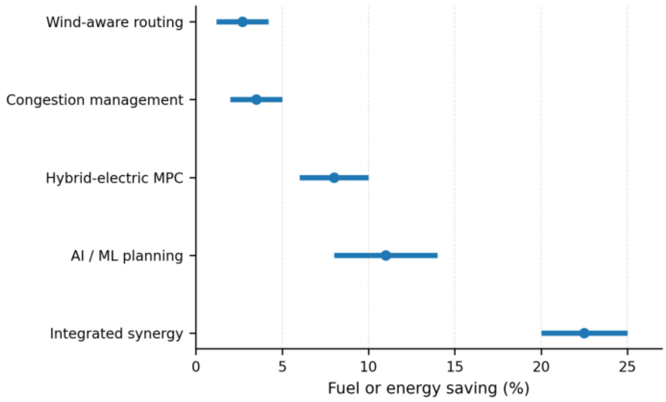

*Figure 1. Literature-derived saving ranges associated with major route-optimization strategies.*

Beyond the individual aircraft, network-level inefficiencies create another major source of excess fuel burn. Sector overload, route stretching, sequencing delays, and holding patterns all increase energy use in ways that trajectory optimization alone cannot fully remove. For that reason, a number of studies evaluate coordinated flow-management measures such as dynamic sectorization, departure metering, and collaborative rerouting.

The trend synthesized in Figure 2 shows that the fuel penalty of congestion is distinctly non-linear: once traffic density rises beyond moderate levels, baseline fuel burn per kilometre increases much more rapidly than in coordinated-network conditions. In other words, system-level organization does not merely reduce delay; it protects aircraft from entering the most fuel-intensive operating regime associated with highly saturated airspace.

These observations are consistent with the agent-based simulations reported by Wei et al. [7] and with European ATM trials carried out under SESAR-type frameworks. In those studies, gains emerged from better slot allocation, redistribution of flights away from saturated sectors, and improved synchronization between controllers and operators rather than from airframe-level changes.

The benefits extend beyond fuel metrics. Lower congestion reduces path variability, improves schedule predictability, and limits the propagation of delays through the network. As a result, traffic-management optimization should be viewed as a dual-purpose intervention that supports both sustainability and operational reliability.

Artificial intelligence adds a further degree of flexibility by extracting structure from large operational datasets and adapting recommendations to changing conditions. Supervised learning, reinforcement learning, and hybrid decision-support systems have all been proposed to assist with route selection, cruise management, and energy-aware dispatch.

Several studies reviewed here report that AI-assisted planning can outperform traditional rule-based procedures, with savings approaching 14% in favorable cases [6]. The attraction of these methods lies in their ability to capture multidimensional interactions among weather, aircraft type, traffic state, and operational constraints. Their main limitation, however, remains the need for transparent logic and reliable validation before large-scale operational adoption.

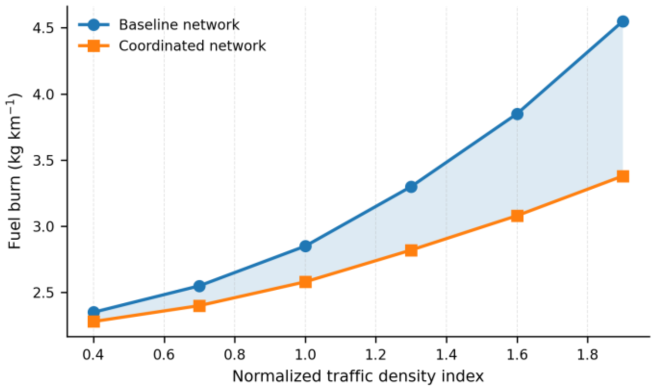

*Figure 2. Baseline and coordinated-network fuel burn as traffic density increases.*

The route-planning literature also shows that optimization cannot be interpreted independently of flight profile. Cruise altitude, step-climb strategy, and timing influence how efficiently an aircraft can convert favorable winds and low-drag conditions into real fuel savings. This becomes especially relevant when route optimization is linked to onboard energy management or advanced dispatch tools.

In practice, this means that high-performing routing frameworks combine lateral path selection with vertical-profile control and frequent forecast updates. Such integration allows operators to move from static flight plans toward continuously refined trajectories that reflect atmospheric variability, traffic conditions, and aircraft state in near real time.

### *Sustainable Aviation Fuel and Route-Energy Coupling*

Figure 3 summarizes the altitude sensitivity of relative cruise fuel rate for baseline and optimized profile selection. The optimized curve shifts the minimum-fuel operating region and broadens the band of efficient cruise levels, which helps explain why profile control and route optimization are often reported together in the most mature operational studies.

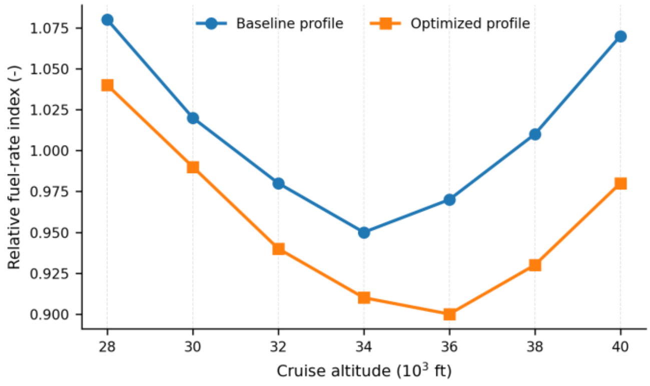

*Figure 3. Relative cruise fuel-rate response to altitude under baseline and optimized profile selection.*

Fuel choice introduces an additional layer of route-energy interaction. As shown in Figure 4, the literature generally points to a favorable change in engine efficiency index as SAF blend fraction increases, reflecting cleaner combustion behavior, improved thermal characteristics, or both under cruise-relevant conditions [9]. Although the precise magnitude varies across studies and fuel pathways, the directional trend is consistently positive.

From a routing perspective, this matters because improved fuel efficiency or cleaner combustion can alter reserve margins, emissions intensity, and mission-level energy trade-offs. Aircraft operating on higher SAF blends may therefore benefit from planning frameworks that consider both route geometry and fuel properties rather than assuming fuel-neutral performance.

The reviewed studies also suggest that climb and cruise strategies may need to be reconsidered when lower-carbon fuels are introduced at greater scale. Fuels with distinct combustion behaviour or energy density can influence engine response at altitude, which in turn affects the relative attractiveness of specific cruise levels or step-climb schedules.

A related research direction involves the co-optimization of SAF with hybrid-electric propulsion. In those studies, the route is planned so that battery support is reserved for phases with the highest power demand, while liquid fuel is used where its energy density offers the greatest advantage. The result is a more explicitly energy-aware form of trajectory management.

Taken together, the reviewed evidence suggests a broad hierarchy of benefit. Wind-aware routing provides reliable incremental savings, network-level decongestion contributes additional improvement, AI-assisted methods deliver the largest stand-alone operational reductions, and SAF primarily amplifies lifecycle and combustion-related gains. The most interesting opportunities arise when these approaches are combined rather than evaluated separately.

These effects should not be treated as simply additive, yet the synthesis indicates that well-coordinated combinations can plausibly move total fuel or energy savings into the 20-25% range under favorable operating conditions. That upper range is not representative of every route, but it illustrates the scale of benefit that integrated planning could unlock relative to baseline operations.

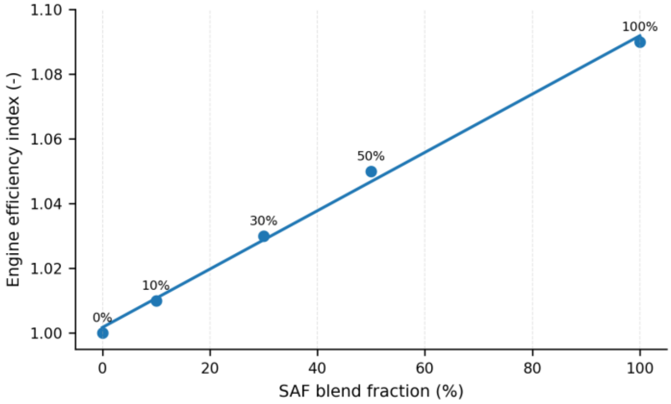

*Figure 4. Indicative change in engine efficiency index with increasing SAF blend fraction.*

The exact benefit remains sensitive to mission length, aircraft class, atmospheric variability, and the maturity of the surrounding airspace system. Short-haul operations may see comparatively limited gains from wind exploitation, whereas long-haul flights and high-density corridors can benefit materially from even modest improvements in routing logic, profile selection, or fuel choice.

## 4. Discussion

### *4.1 Integrated Energy Savings from Route Optimization*

The literature reviewed in this study suggests that the strongest decarbonization pathway does not lie in any single optimization technique, but in the coordinated use of several complementary layers of operational intelligence. Trajectory design, traffic management, AI-based decision support, and fuel-system innovation each target a different source of inefficiency; their combined value therefore exceeds what any one measure can deliver in isolation.

Wind-aware trajectory optimization remains the most mature of these layers. Multiple simulation campaigns and operational assessments of long-haul traffic have shown that exploiting upper-level wind structure can cut fuel burn by roughly 1.2-4.2%, especially on routes where cruise time is long enough for modest path corrections to accumulate into meaningful savings [11]-[13]. These gains are operationally attractive because they rely more on better planning and forecast utilization than on major hardware changes.

Network-level coordination provides an equally important but conceptually different benefit. Studies focused on airspace congestion show that delay absorption, sector overload, and vectoring create a sizeable fuel penalty that cannot be eliminated through single-aircraft optimization alone. Work by Erzberger, Pai, Wei, and related ATM programs indicates that rerouting, metering, and collaborative decision-making can reduce sector-wide fuel use by several percentage points while also improving predictability [14]-[16].

When these two layers are implemented together, their benefits become non-linear rather than simply cumulative. System models indicate that a well-routed aircraft cannot sustain its efficiency advantage if it is later trapped in a congested sector, while a well-managed network still wastes fuel if individual trajectories are poorly aligned with winds and aircraft performance limits. This interdependence explains why integrated studies tend to report stronger system-wide improvements than isolated analyses [17].

AI-based planning expands the optimization envelope further by processing traffic, meteorological, and historical flight data at a scale that deterministic tools rarely match. Studies using supervised learning or adaptive controllers report that AI can identify persistent route patterns, favorable profile adjustments, and congestion-avoidance behaviours that translate into notable fuel reductions, in some cases approaching double-digit percentages [18],[19].

The same logic extends to hybrid-electric operations, where route selection and power-split management are inseparable. Model predictive control frameworks for regional hybrid-electric aircraft show that coordinating propulsion scheduling with the flight path can reduce total mission energy by up to about 10%, illustrating how digital planning becomes even more valuable as propulsion architectures diversify [20].

SAF further strengthens the case for integrated optimization. While these fuels are often framed mainly in terms of lifecycle carbon accounting, several studies also report favorable combustion and performance characteristics that can improve specific fuel consumption or thermal efficiency under selected operating conditions [21],[22]. Those gains are smaller and more context-dependent than the lifecycle emissions benefit, but they are still important when considered alongside route planning.

The most promising outcome therefore comes from interaction effects. A route planned with favorable winds, operated in a less congested corridor, and matched with an efficient fuel blend can reduce fuel uplift, lower climb penalties, improve cruise performance, and ultimately decrease both direct and lifecycle emissions. Modeling work such as that of LePage et al. supports this broader systems view, showing that route and fuel choices can reinforce one another rather than act as independent levers [23],[24].

These operational gains also have policy implications. Under mechanisms such as CORSIA, airlines that document both SAF use and operational efficiency improvements may reduce offsetting exposure while strengthening the business case for low-carbon flight planning [25],[26]. In that sense, route optimization is not only an engineering tool but also a compliance and carbon-management strategy.

For large-scale deployment, however, the field still needs common benchmarks. Emerging proposals for dynamic trajectory metrics, including measures of deviation from fuel-optimal altitude, effective cruise efficiency, and lateral route performance, could provide a more robust basis for comparing operators and regions than fuel burn alone [27].

Overall, the discussion in the literature supports a realistic but substantial opportunity: when multiple optimization layers are combined under mature operational conditions, total energy savings in the range of roughly 15-25% appear plausible. Achieving that range consistently will depend less on theoretical algorithm performance than on integration across dispatch, ATM, certification, and fuel supply.

### *4.2 Operational and Technological Barriers to Deployment*

Despite the clear technical promise, moving these strategies into routine commercial service remains difficult. The barriers are not limited to algorithm quality; they also involve digital infrastructure, certification practice, organizational behavior, and investment priorities across the aviation ecosystem.

A first constraint is data availability. Dynamic route optimization depends on timely, high-resolution weather fields, traffic-state information, and reliable exchange of trajectory intent between aircraft, airlines, and air navigation service providers. Although major modernization programs have improved data sharing, gaps in latency, fidelity, and cross-border interoperability still restrict how aggressively trajectories can be updated in practice [28],[29].

Onboard capability is another limiting factor. Many flight-management systems were not designed to host third-party optimization modules or data-intensive advisory tools, and integrating new logic into certified avionics remains expensive and slow. Even relatively modest software changes can require extensive verification, validation, retraining, and fleet-level retrofit expenditure before operational use becomes acceptable [30],[31].

Operational coordination adds further complexity. A trajectory that is energy-optimal from the dispatcher's perspective may not be desirable to controllers managing dense traffic or to flight crews balancing workload and schedule obligations. EUROCONTROL-style analyses therefore warn that controller burden can rise if optimization recommendations are introduced without suitable automation support, procedures, and human-machine interface design [32].

AI introduces a more specific challenge because many machine-learning models are difficult to interpret. Regulators and operators require explainable logic, bounded behaviour, and traceable validation evidence, whereas many high-performing AI approaches are optimized primarily for predictive accuracy. This tension explains the growing interest in physics-informed or hybrid models that preserve some degree of transparency while retaining adaptive capability [33],[34].

The interoperability problem is equally significant at network scale. Global airspace is managed by numerous organizations using different communication architectures, message standards, and planning workflows. Until systems such as SWIM-like data environments become more widespread and more compatible, full-network optimization will remain fragmented and regionally uneven [35],[36].

Economic incentives do not always align either. Airlines are often rewarded more directly for on-time performance and schedule robustness than for incremental fuel savings, especially when the latter require procedural change or longer-term investment. As a result, some operators may regard fuel-optimal routes as operationally risky unless the economic value of carbon, fuel, or regulatory credits is sufficiently visible [37].

These constraints are compounded by SAF deployment. Although lifecycle carbon reductions can be large, the cost of SAF remains well above that of fossil jet fuel and supply is still geographically limited. Without subsidies, long-term procurement structures, or meaningful crediting mechanisms, carriers have limited commercial incentive to optimize around fuels that are not yet broadly available [38]-[40].

In summary, large-scale deployment requires progress in four areas at once: real-time digital infrastructure, certifiable and interoperable onboard systems, human-centered operating procedures, and economic frameworks that reward low-carbon routing choices. Pilot demonstrations already show technical feasibility; the outstanding challenge is systemic scaling.

### *4.3 Regulatory, Certification, and Safety Considerations*

As routing tools become more dynamic and more software-driven, regulatory acceptance becomes a central condition for deployment. Route optimization directly affects flight planning, navigation, separation assurance, fuel policy, and decision support, which means that any operational innovation must satisfy a multilayered safety framework before it can move from promising research to routine airline use.

At the international level, ICAO provides the foundational safety architecture through Annexes covering aircraft operations, air traffic services, and aeronautical information. Within these frameworks, optimization tools must demonstrate that they preserve navigational accuracy, separation standards, and contingency handling rather than merely improving efficiency metrics [39].

A recurrent concern is trajectory predictability. Traditional ATC systems are organized around filed routes and anticipated sector loads, so dynamic wind-driven or AI-driven deviations can complicate conflict management if intent is not shared clearly. The push toward Performance-Based Navigation and 4D Trajectory-Based Operations is intended to address this issue, but implementation remains uneven and many aircraft or airspaces are not yet fully equipped for that operating model [40],[41].

Certification of optimization software presents an additional hurdle. Existing frameworks such as DO-178C are built around deterministic logic, explicit traceability, and exhaustive verification. Those expectations are difficult to satisfy with non-deterministic machine-learning systems, even when such systems perform well in simulation or controlled trials [42].

Regulators are beginning to respond. FAA and EASA initiatives on AI in aviation increasingly emphasize explainability, robustness, and verifiability as preconditions for operational approval, but these pathways remain developmental rather than mature. As a result, certification practice still lags behind the pace of research in adaptive trajectory management [43],[44].

System-level safety questions remain equally important. If wind-optimal or congestion-avoiding routes cause traffic to cluster into narrow corridors, the resulting concentration can create new risks unless conflict-detection logic, sector balancing, and turbulence-aware planning are strengthened at the same time. EUROCONTROL assessments of so-called super-routes illustrate why energy efficiency cannot be treated independently of airspace resilience [45].

SAF adoption is also shaped by certification. Under ASTM D7566, each approved pathway must satisfy extensive requirements related to material compatibility, cold-flow behaviour, emissions, and engine performance before it can be used as a drop-in aviation fuel. This staged approval structure protects safety, but it also slows the expansion of new fuel pathways into commercial service [46].

New policy proposals seek to harmonize SAF sustainability accounting and create clearer emissions-crediting rules under CORSIA. Such mechanisms could strengthen the business case for pairing certified low-carbon fuels with documented route optimization, since both measures would then contribute more transparently to airline carbon reporting and compliance [47].

Human factors cannot be overlooked. Optimization tools may recommend route changes or profile adjustments that are energy-efficient but not intuitive to pilots or controllers, especially in abnormal conditions. Simulator studies therefore highlight the need for human-in-the-loop supervision, clear alerting logic, and targeted training before such systems can be trusted in line operations [48].

Questions of liability and accountability remain unresolved as well. If an AI-supported trajectory decision contributes to an operational incident, responsibility may be difficult to attribute among the crew, operator, software developer, and regulator. Until these governance issues are clarified, institutional caution will continue to slow adoption [49].

The regulatory message is therefore clear: energy-efficient routing will only scale if it can be translated into operational concepts that are explainable, auditable, and interoperable with existing safety systems. Collaboration among regulators, airlines, air navigation service providers, and technology developers is essential for that transition.

### *4.4 Data Governance, Equity, and Global Disparities in Optimization Deployment*

Although the technical case for route optimization is global, access to the underlying enablers is not. The ability to implement data-rich routing, AI-based planning, or SAF-linked operational strategies varies sharply by region, raising the risk that efficiency and decarbonization benefits will concentrate in already well-resourced aviation systems.

This imbalance is rooted partly in digital infrastructure. Real-time optimization depends on surveillance coverage, meteorological integration, communication bandwidth, and interoperable planning platforms. Regions that lack these foundations are less able to update trajectories dynamically or validate fuel-efficient decision tools at operational timescales.

Institutional conditions matter as well. In some jurisdictions, fragmented governance, military control of airspace, or overlapping civil authorities complicate data exchange and coordinated planning. These non-technical barriers can be just as restrictive as hardware or software limitations when fuel-optimal routing requires shared situational awareness across organizations [50].

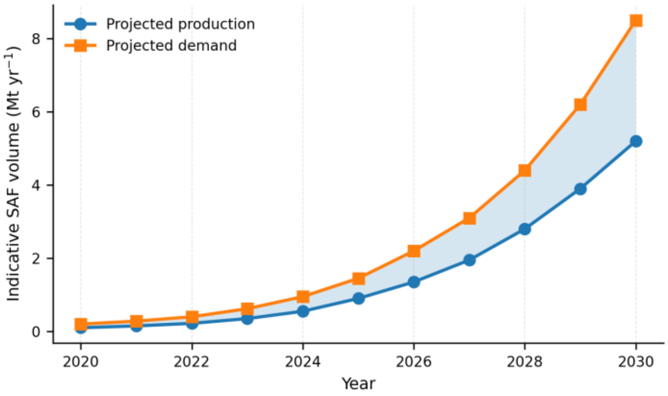

*Figure 5. Schematic projection of SAF production and demand through 2030.*

The supply side of SAF illustrates this disparity clearly. Figure 5 shows a widening gap between projected production and anticipated demand through 2030, reflecting the fact that policy incentives and refining capacity are concentrated in a relatively small number of markets. Airlines in fast-growing regions may therefore face the dual disadvantage of higher SAF prices and weaker physical access to certified supply chains [51].

A similar unevenness appears in routing maturity. Figure 6 compares estimated regional shares of flights operating near fuel-optimal conditions and suggests that North America and Europe are ahead of Africa, Latin America, and parts of Asia-Pacific and the Middle East. The gap is not simply operational; it also reflects unequal access to validated digital tools, integrated data environments, and experienced technical personnel.

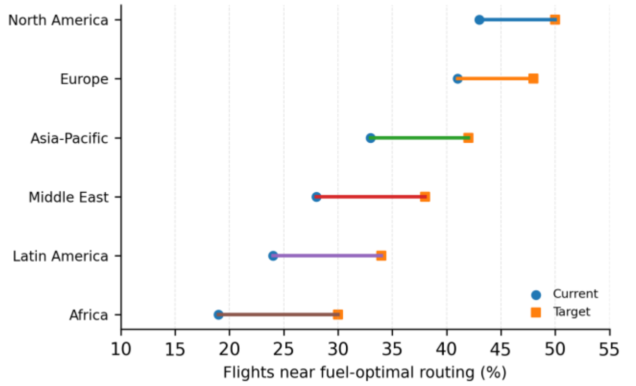

*Figure 6. Share of flights operating near fuel-optimal routing across major regions.*

These disparities also create algorithmic risk. If AI models are trained predominantly on North Atlantic or European traffic and weather patterns, their recommendations may transfer poorly to tropical, mountainous, or infrastructure-constrained regions. Without local data and region-specific validation, data-driven route optimization can reproduce bias or produce recommendations that are less effective than their headline performance suggests [53].

One response is stronger global data governance. Open but secure repositories, shared interface standards, and interoperable optimization APIs coordinated through bodies such as ICAO and IATA could allow less-resourced states to access validated tools without first reproducing the full development burden internally. In effect, aviation would benefit from a governance model closer to that used in international meteorology, where data exchange is treated as a shared enabling infrastructure.

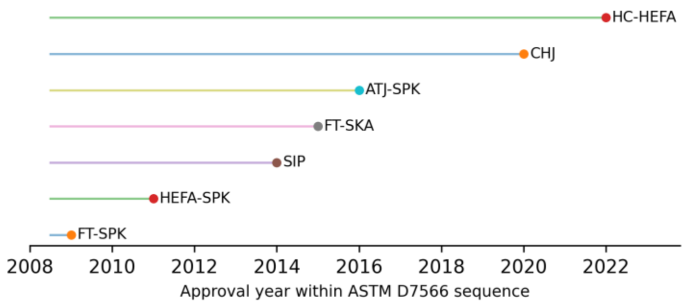

*Figure 7. Illustrative approval sequence of major ASTM D7566 sustainable aviation fuel pathways.*

Figure 7 highlights a second bottleneck: certification progress alone does not guarantee deployment. Even when new SAF pathways are approved, blending infrastructure, quality-assurance systems, and financing mechanisms may still be absent in developing markets. Development banks, green bonds, and carbon-credit channels could help airlines convert operational efficiency gains into capital for fuel and digital infrastructure expansion.

Human capacity must grow in parallel. Dispatchers, pilots, controllers, and regulators in under-resourced systems may have limited exposure to dynamic trajectory concepts, AI-supported planning, or SAF-aware operating logic. Expanding training through initiatives such as ICAO's Next Generation of Aviation Professionals would therefore be an important complement to physical infrastructure investment [54].

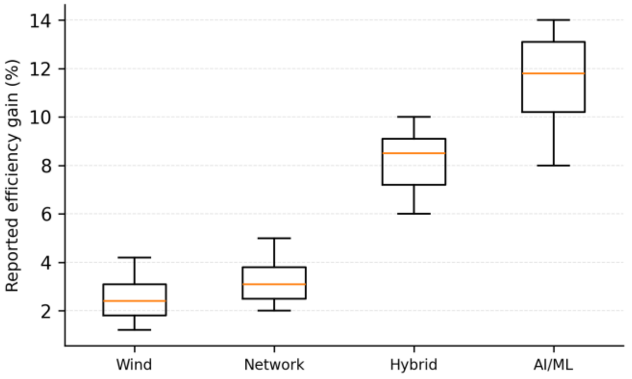

*Figure 8. Distribution of literature-reported efficiency gains by route-planning method.*

The dispersion summarized in Figure 8 reinforces the broader equity argument. The most data-intensive methods offer the largest reported gains, but they are also the least accessible where digital infrastructure, certification resources, and skilled personnel are limited. Without deliberate coordination, route optimization could therefore become another domain in which high-income regions decarbonize faster simply because they can deploy complex tools sooner.

## 5. Conclusion

This review has examined aviation route optimization as a practical pathway for lowering fuel consumption and environmental impact across contemporary flight operations. Taken together, the literature shows that trajectory management, airspace coordination, AI-supported planning, and SAF deployment are no longer isolated research topics; they now form an interconnected operational agenda for aviation decarbonization.

The quantitative evidence is consistent in one important respect: no single measure solves the problem alone, but several measures offer credible improvements within their respective domains. Wind-aware routing commonly delivers savings of about 1-4%, network-level decongestion contributes a further 2-5%, AI-based approaches can approach double-digit reductions in favorable cases, and SAF strengthens the lifecycle and, in some cases, thermodynamic performance of optimized operations.

The principal obstacles are therefore not conceptual but systemic. Real-time data exchange, avionics interoperability, controller workload, software certification, AI explainability, and uneven SAF availability all constrain how far the most promising methods can move beyond pilot projects or isolated routes.

These constraints are especially important from a global-equity perspective. Advanced routing tools and SAF infrastructure are being deployed fastest in well-resourced markets, while many developing regions still lack the digital, institutional, and financial foundations needed for even basic forms of dynamic optimization. Unless this imbalance is addressed, the gains from low-carbon flight operations will remain unevenly distributed.

Future progress therefore depends on implementation as much as innovation. The next phase of work must connect route optimization research with scalable operational architectures rather than treating each new algorithm as an end in itself.

That means investing in real-time digital ecosystems that can exchange weather, traffic, and trajectory data reliably across organizational and national boundaries.

It also means building certification pathways for AI-supported planning tools that reward explainability, bounded behaviour, and transparent validation rather than performance claims alone.

In parallel, SAF supply must expand through harmonized fuel standards, stronger production incentives, and infrastructure that reaches beyond the markets currently leading deployment.

Capacity-building is equally essential, because pilots, dispatchers, controllers, and regulators will need new competencies to interpret and supervise increasingly adaptive route-planning systems.

Most importantly, route optimization should be framed as a coordinated systems strategy in which digital planning, operational control, and lower-carbon energy carriers evolve together.

Under those conditions, route optimization becomes more than an incremental efficiency upgrade. It becomes an immediately actionable instrument for reducing fuel burn, moderating emissions growth, and supporting aviation's broader transition toward net-zero ambitions.

Aviation will not decarbonize through routing alone, but the evidence reviewed here shows that smarter routing, when paired with cleaner fuels and equitable deployment mechanisms, can deliver meaningful progress toward a cleaner and more resilient air transport system.

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