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Automated Air Cargo Operations Market Research and Forecast

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Crown Consulting

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LMÍ Automated Air Cargo Operations

Market Research and Forecast

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Automated Air Cargo Operations: Market Research and Forecast April 2021

Executive Summary

Air cargo companies and aircraft manufacturers are making significant investments to enable the movement of cargo via various levels of automated aircraft, such as aircraft with simplified operations requiring a pilot, remotely monitored or piloted aircraft, and fully autonomous aircraft. These investments will enable greater utilization of aircraft while unlocking new air markets traditionally served by ground transportation only. Many cargo companies and aerospace experts envision an operating environment where a single pilot can remotely pilot numerous aircraft for significant increases in aircraft utilization. The future operating environment is also expected to include air cargo companies flying smaller aircraft from airports and distribution centers outside of major U.S. cities directly to city centers, avoiding congested roads and increasing the velocity of cargo shipments, particularly those that are high-value, time-sensitive, and securitysensitive (e.g., pharmaceuticals). These are just a few benefits and use cases cargo companies and aerospace experts see with the advancement of automated aircraft.

To better understand industry's direction, NASA asked the LMI team to research the forecasted market, timeline, risks, and opportunities for integrating unmanned air cargo vehicles into the National Airspace System (NAS) for the development and prioritization of the NASA Air Traffic Management Exploration's research portfolio. To begin the market assessment, we gathered data via numerous interviews with key stakeholders and subject matter experts and literature reviews. We then incorporated the data into a custom-developed systems dynamics model and visualization dashboard. The systems dynamics model classifies the size of the market (e.g., overall fleet size of automated aircraft) for four distinct use cases over the next 20 years. The model projects the year in which various types of automated aircraft will enter the commercial cargo market based on our team's collective research on when the aircraft will become viable due to manufacturing and certification timelines and the lifespan of current, traditional aircraft in service, to name a few factors. While this report defines our team's estimated timeline of entry and growth, the model is dynamic-it enables NASA users to change variables based on future-year events. If the necessary technology does not mature in accordance with our assumptions, then NASA can change the entry of service point to a future year to evaluate the changes in market size in the out years. This flexibility will be key to deciding when and how NASA should invest in various areas.

Our assessment of the four use cases led to the following conclusions:

 Industry prioritization of automation for the heavy/long range and heavy/medium range use case is unlikely due to the wide variety and relatively low numbers of each type of legacy aircraft operating across each use case; in addition, pilot costs account for a small share of total operating costs. Asset utilization would not increase significantly based on automation, further limiting upside.

- The regional use case is the most promising for advancement of automation technology due to the opportunity to replace the current ageing fleet, higher pilot costs as a share of total operating costs, potential pilot labor challenges and cost creep moving forward, and benefits through increased productivity and asset utilization.
- The light use case is the hardest to predict because it is not based on an existing aviation market, but may offer the greatest upside due to new business models and continued increases in consumer demand for faster, more frequent deliveries of high-value, time-sensitive, and security-sensitive cargo, for business to business and business to consumer. Achieving the requisite airframe manufacturing volume to meet market demand will drive possible realization of this use case in the 20-year report timeline.

Other key findings and recommendations include the following:

- Most industry investment is directed at implementing the regional and light use cases. Industry seeks to rapidly achieve remote supervision of 1:N (i.e., 1-to-many) to enable greater utilization and decrease the overall cost of air transportation, making it more cost-competitive with ground transportation. NASA Aeronautics Research Mission Directorate (ARMD) should address automation challenges in the regional and light market segments, specifically, the certification of automation solutions for Cessna Caravan–type regional aircraft. NASA ARMD could work with the Federal Aviation Administration (FAA) to define the impediments to certification and then partner with industry to address the impediments that industry is least equipped to address or the most business sensitive technologies, such as advances necessary to achieve 1:N remotely supervised operations.
- The resounding issue impeding near-term automation progress is integration, meaning integration of the entire operation in the NAS under existing standards. A standard aviation flight operation involves many stakeholders who all must interconnect to support the intended mission seamlessly. Integration of new automation capabilities will fundamentally change stakeholder responsibilities and break current operating models. NASA ARMD should emphasize supporting a common vision for incorporating increased automation in aviation and create the appropriate documentation for industry-wide alignment on the future of autonomy.
- The regulatory pivot to performance-based requirements necessitates means of compliance (MoCs) to satisfy the standards. Moreover, MoCs are not developed by the regulator but by industry and research organizations to satisfy the standards. While NASA is ramping up efforts to support technology transitions and concept development with the FAA, the shift toward performance-based requirements necessitates creating multiple MoCs to satisfy those requirements. NASA ARMD should strengthen FAA partnerships to support integration into the NAS and the development of MoCs to satisfy performance-based requirements. NASA ARMD is positioned well to develop the MoCs to enable industry players to pursue one, if not many, paths to achieving compliance with regulations to accelerate growth by breaking down regulatory hurdles, clearing the way forward,

and potentially supporting early partnerships with NASA ARMD to develop solutions together.

- Near-term research challenges involve uncovering unknown unknowns, humanmachine teaming, scalable data collection and simulation, and software and hardware breakthroughs. With increased automation, breakthroughs in technology for digital integration and human-machine teaming will be critical to lay the foundation of automated capabilities. As technologies are at a low technology readiness level, methods to collect vast amounts of data (through experimentation or simulation) will be pivotal to establishing the safety case for the technology. Simulation capabilities will validate the standalone technology as well as integrations with existing or new elements of the NAS. Human-machine teaming will then enable improvements in pilot, operator, and controller workloads while maintaining consistent or improved levels of safety as the current state. Data collection and tools to analyze big data sets will enable training of intelligent machine learning and artificial intelligence models to make better decisions.
- NASA ARMD should thoroughly assess the existing and future research portfolio to understand the effect of advancing automation and uncover gaps with technology requirements. In addition to outlining the path forward to achieving increased automation, a deep understanding of the hardware and software required to enable use case specific automation will be a powerful tool for researchers and private organizations for targeted research. The understanding of technologies enabling automation will support enhancements to the portfolio to align research efforts with what is required from NASA. Other benefits of this analysis include highlighting the benefits of automation and key impediments to progress and parsing which problems must be solved by NASA rather than industry.

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Appendix B Automation Technology

Appendix C Abbreviations

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The following individuals, listed by company, contributed to the development of this report and the accompanying systems dynamics model and dashboard.

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- Dr. Demitri Mavris
- Dr. Cedric Justin

The air cargo industry, like the aviation industry in general, is poised to undergo radical transformation over the next two decades. Entire nascent market segments will mature over this time. This report researches the forecasted market, risks, and opportunities associated with the integration of unmanned cargo vehicles into the National Airspace System (NAS) to inform the development and prioritization of the NASA Air Traffic Management Exploration research portfolio. The report and accompanying dashboard were a true team effort. Table 1-1 lists each team member and their contribution to the final product.

Team member	Contribution
LMĨ	As the prime contractor, provided overall project leadership, facilitated survey dissemination and analysis, organized stakeholder interviews, captured stakeholder input, contributed supply chain management and logistics expertise, and facilitated model development working sessions.
CROWN AIR MOBILITY. ADVANCED.	Provided expertise on the aerospace industry and government regulators, leveraged connections across industry and government to obtain interviews with relevant stakeholders, and provided expertise for model development.
Georgia Aerospace Systems Tech Design Laboratory	Developed the systems dynamics model, input equations, built the dashboard, found relevant data, and synthesized expert input into the final product.
GRA, Incorporated	Provided expertise on commercial air operations, developed the economic model that feeds the systems dynamics model, and validated model outputs to ensure they aligned with the applicable data.

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The report is organized into the following chapters:

- Chapter 2, Method
- Chapter 3, Use Case Analysis
- Chapter 4, Assumptions
- Chapter 5, Findings and Recommendations.

In addition, there is a bibliography and three appendices. Appendix A is a user guide for the systems dynamics model dashboard. Appendix B offers additional background on automation technology. Appendix C defines the abbreviations in this report.

Study Approach

To capture the opportunities, challenges, and risks associated with the integration of unmanned cargo vehicles in the NAS accurately, the study assessed four primary interrelated drivers of the air cargo landscape: technology maturity, regulatory readiness of airspace integration and certification, economics, and market viability. Figure 2-1 shows an overview of our approach.



Figure 2-1. Study Approach Overview

Note: ConOps = concept of operations; R&D = research and development.

- 1. *Task Plan.* We began by developing a task plan, which was approved by NASA following the study's kickoff meeting. The task plan detailed our technical approach, description of roles and responsibilities, an integrated schedule, and a comprehensive list of deliverables to ensure our objectives aligned with NASA's desired outcomes.
- 2. Stakeholder Engagement. As shown in Figure 2-2, we engaged with stakeholders representing industry associations, traditional and non-traditional original equipment manufacturers (OEMs), regulators (e.g., the Federal Aviation Administration [FAA]), airports, and major cargo operators.





Our initial outreach to stakeholders was through a web-based survey, which we coordinated through two industry associations and provided to operators across the heavy/long range (HLR), heavy/medium range (HMR), and regional use cases. The survey addressed operational and market dynamics, economic growth forecasts, regulatory issues, technology constraints, and NASA investment priorities. Though the response rate was too low to be useful, it did help us develop effective interview questions while offering a useful additional perspective, especially from companies we did not interview. In addition to the survey, our team conducted over 30 interviews with stakeholders across the categories. Those discussions served as a baseline for the definition of the use cases. We are not sharing the names of the companies we interviewed because the information shared with us was non-attribution due to the business-sensitive topics of conversation.

- 3. Use Cases Definitions. In addition to the interviews, we reviewed literature extensively to inform the definitions of the use cases. In addition, while developing the model, we adjusted the use case parameters based on the real-world data we used as an input.
- 4. *Systems Dynamics Model Development.* The model development process was iterative. We established a baseline, tested its reasonability based on our assumptions, gathered additional data, and then repeated the process. Along the way, we continuously added usability features.
- 5. *Impact Analysis.* We analyzed impacts throughout the model development process to ensure that the model aligned to our assumptions, literature review background, and interview inputs.
- 6. *Economic Analysis.* Economic analysis was essential in ensuring that our model aligned to real-world data. For example, we validated that the fleet sizes for each use case mapped to actual fleet numbers. We also used economic data to validate and adjust our base use case definitions.
- 7. NASA R&D Analysis. We reached out to various NASA offices engaged in efforts that align to the automation of air cargo. Those interviews enabled us to develop a baseline understanding of current and planned NASA R&D priorities to inform our recommendations.
- 8. *Study Results.* We combined our model, interview feedback, and NASA input into the final briefing and this report.

Use Case Overview

The four use cases served as the foundation of the systems dynamics model and economic forecasting. The use case development method was, therefore, critical to capture the market segmentation and mission parameters defining each use case as input to the model. The four use cases were HLR, HMR, Regional, and Light which served as the starting point for use case development. Our use case development method was built on the three primary pillars of aircraft database development, a literature survey, and subject matter expert (SME) interviews to capture technology, regulatory, and economic perspectives from a diverse set of trusted sources. The aircraft database contains 59 former, current, or future concept cargo variant aircraft with documented performance specifications.

The database primarily served as a mechanism to assess the use case aircraft characteristics against reality but also was valuable in categorizing representative aircraft for the use cases and adjusting mission parameters based on ongoing model analysis. The literature survey included scientific research and papers on the air cargo market, aircraft automation, automation in other modes such as trucking, emerging markets, and existing market capabilities. SME interviews were pivotal to use case development because well-established and upcoming frontrunners in air cargo supplied valuable insight based on their experiences trying to trailblaze the path forward.

The use cases went through many iterations as the use case development process was exercised and work progressed on modeling and economic forecasting. The flexibility of the use case mission parameters enables agile responses in modeling. Table 2-1 illustrates the final set of use cases with mission parameters and includes a 10-year and 20-year perspective on use case automation at that snapshot in time.

Characteristic	Baseline values	
	HLR	
Mission range	> 3,000 nautical miles	
Payload	> 40 tons	
Speed	400–500 knots	
10-year outlook	 Current state (majority of aircraft) Automated taxi, takeoff, and landing (TTL) (minority) Simplified vehicle operations (minority) 	
20-year outlook	 Current state (minority) Automated taxi, takeoff, and landing (majority) Simplified vehicle operations (majority) 	
	HMR	
Mission range	500–3,000 nautical miles	
Payload	> 10 tons	
Speed	350–500 knots	
10-year outlook	 Current state (majority of aircraft) Automated TTL (minority) Simplified vehicle operations (minority) 	

Table 2-1. Use	Case Summary
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Characteristic	Baseline values	
20-year outlook	Current state (minority)	
	Automated TTL (majority)	
	 Simplified vehicle operations (majority) 	
	Regional	
Mission range	75–1,000 nautical miles	
Payload	1–10 tons	
Speed	150–300 knots	
10-year outlook	Current state (majority of aircraft)	
	Remotely piloted (minority-retrofit [majority], purpose-built [minority]	
20-year outlook	Automated cruise (minority)	
	Remotely piloted (minority)	
	 Remotely supervised (1:1) (minority–quick transition to 1:N) 	
	 Remotely supervised (1:N) (majority) 	
Light		
Mission range	< 250 nautical miles	
Payload	0.025–1 ton	
Speed	< 200 knots	
10-year outlook	Simplified vehicle operations (pilot onboard supervising)–larger	
	Remotely piloted-smaller and larger	
20-year outlook	Remotely piloted (minority)	
	Remotely supervised (1:1) (minority)	
	Remotely supervised (1:N) (majority)	

Table 2-1. Use Case Summary

Complementary to the use cases are levels of automation, as seen in the automation 10-year and 20-year outlooks in Table 2-1. The intent of the levels of automation are to capture the automation capabilities of a representative set of aircraft operating in the NAS. There is significant complexity involved in automation and classifying aircraft according to a level of automation; however, for simplification purposes, levels of automation are used for understanding and modeling purposes.

Automation and autonomy have been used interchangeably in industry to refer to a system capable of performing a task without human intervention or assisting a human operator. However, these words have different meanings and implications. For the context of this study, it is important to define each. Automation is a technological system used to perform a task that could otherwise be performed by a biological agent, most often humans.¹ Autonomy, on the other hand, is a state or quality of self-governance or direction.² This distinction is important as a self-governing system is a form of automation, but automated systems do not require autonomy. More specifically, an autonomous system can be defined as a technological system that has a level of perception, information processing, or decision-making that is significantly more

¹ Stouffer, V. L., Goodrich, K. H., "State of the Art of Autonomous Platforms and Human-Machine Systems," American Institute of Aeronautics and Astronautics (AIAA) Aviation Conference, June 22–26, 2015.

² Source: <u>https://www.merriam-webster.com/dictionary/autonomy</u>.

sophisticated than typical reactive control systems. The system can redirect itself based on its perceptions and processing without needing the explicit consent or direction of a human operator. Autonomous systems are intelligent and adaptive in reacting to various situations, making decisions based on assigned mission parameters. Understanding this difference offers context for defining how automated or autonomous aircraft systems are and the implications of using each. Figure 2-3 depicts the levels of automation.





The automation levels start with current state jet operations where a majority of the en route portion of the flight is automated; however, TTL are yet to be automated. While not included in modeling, the next level of automation is automated TTL: an aircraft can operate gate-to-gate with human pilots onboard managing the automation. SVO is the next evolution with automation capabilities enabling the simplified control and management of the aircraft using a reduced crew, given the automation supplies sufficient safety and backup to the reduced onboard crew. Remotely piloted takes things a step further by completely offboarding the pilots from the aircraft and managing the flight from a remote operational control center. For remote piloting, it is assumed one pilot will manage one aircraft (1:1) at a time and will be actively engaged in the flight operation. Remote supervision is the next level of automation, fundamentally pivoting the role of the remote pilot to supervise the flight, meaning constant attention is not required to safely operate the aircraft and the aircraft can respond to unknown scenarios without human intervention. The last progression of automation is remote supervision with one pilot managing multiple aircraft, referred to as 1:N for this report, where the complexity is significantly increased to safely manage fleet operations. The levels of automation are not exhaustive nor a linear evolution for all use cases—use cases may adopt certain levels of automation at different starting points and follow different paths toward increased automation.

Model Method

The use cases defined in the systems dynamics model forecast air traffic volumes, costs, benefits, technological maturity, market forces, economic impacts, required investments, and critical drivers. These use cases represent potential markets of interest. Unmanned aircraft systems (UASs) maturity levels (UMLs) from the NASA Urban Air Mobility (UAM) Vision Concept of Operations were used as the starting point to establish market readiness and technology.³ Despite our best efforts, even the best models are only as good as the underlying data and assumptions which feed them. As a result, the projections inherent in our model reflect the data and assumptions of this moment in time and could be inaccurate. Users can adjust the model to account for changes in the underlying dynamics, such as gross domestic product (GDP) and entry into service years by use case.

³ <u>https://ntrs.nasa.gov/api/citations/20205011091/downloads/UAM%20Vision%20Concept%20of%20Operations%20UML-4%20v1.0.pdf</u>.

The model dashboard offers robust output graphs for each use case forecasted out 20 years. For HLR, HMR, and regional use cases, its core consists of an existing fleet turnover model, in which older and more expensive to operate aircraft are replaced with newer and more efficient and cheaper to operate and maintain aircraft, which is calibrated to mimic the natural historical fleet turnover. The aircraft with automation are then introduced when selected with changes to the affected cost components, such as pilot labor cost, as well as cost of ownership. The basis of this assumption is from an assessment of the airline cost structure using Form 41 data (summarized in Figure 2-4).



Figure 2-4. Average Aircraft Operating Expenses, 2015–2019

Unique Considerations for Developing Each Use Case

We calculate a 10-year period of positive net present value (NPV) on the purchase of an aircraft. Therefore, after 10 years, the projected earnings generated by new and more profitable aircraft would exceed anticipated costs (e.g., generate a positive return on investment [ROI]). Conventionally piloted aircraft versus automation cashflows in labor, rents and ownership, and fuel were used for calculation.

For regional and light use cases, the conversion of truck cargo to air cargo includes the top five congested urban areas in the base case, with the option to include up to the top 10 congested urban areas. Congested areas, metro areas where the most time is lost due to traffic, offer opportunities for automated aircraft to augment or replace cargo moved by truck to increase the speed and frequency of cargo deliveries and avoid costs (e.g., traffic, tolls, and taxes). Since the truck cargo market is high in tonnage compared with the air cargo market, only cargo categories already being transported by air were considered in the model.

The light use case modeled vehicle R&D and production, given that the market space for light aircraft currently does not exist. The R&D timeline and cost components were considered for a flight model that met a specific entry to service year that coincides with a regulatory approval year. Like the automotive industry, the light use case model would then proceed with a production ramp mimicking a constant rate of production. In the model dashboard, the production estimate can be modified via a user-selectable conversion target. This use case assumes a 30-year overall production run to meet the conversion target.

This chapter reviews each use case in-depth. Our analysis focuses on the business case, definitions and timelines, baseline model outputs, and summary findings.

Heavy/Long Range

Business Case

Table 3-1 summarizes the fleet characteristics and observations for the HLR use case. The business case for accelerated automated aircraft in the HLR category is challenging due to several factors:

- The history of HLR-dedicated freighter aircraft is influenced by the conversion of mid-life passenger aircraft to freighters (passenger to freighter [P2F] conversions), while factory-built freighters are typically limited-production derivatives of twin-aisle passenger aircraft programs, such as the Boeing 747, 777, and 767 and Airbus 330-200 families. We expect this to continue over the timelines in this study due to high unit production costs of limited quantity runs. Given the low cycle missions for these aircraft, we predict longevity of service with relatively small fleets of 100 units or less per type in aggregate for U.S. carriers and foreign carrier fleets operating on U.S. international routes. For example, 747-8 and current production 777 and 767 aircraft would be operating 10 or even 20 years from now, likely supplemented by mid-life conversions of more digital aircraft, such as Boeing 787 and Airbus A350 types and a possible Boeing 777-X freighter version. As a reference point, freighter aircraft service life is around 30 years, or 10 years longer than equivalent passenger aircraft service life
- Given the variety of designs and avionics of representative aircraft (including 1970s-era 767s), developing and building multiple, limited series of automation retrofit black boxes would be a high-cost proposition, with most production runs limited to approximately 100 retrofit aircraft each.
- Potential HLR savings from reduced onboard flight crew complements represent a smaller percentage of total costs than other categories, with lesser gains in crew and aircraft utilization, given 10 hours plus flight segments and scheduling constraints driven by time zones and connection complexes' time channels. Eventual high-demand and higher flight crew wages tend to affect this category less than shorter-haul flying because the routes are more desirable for crews and more lucrative for operators.

Timeline	Fleet characteristics	Observations
10-year with automation	 Current state (majority of aircraft) 	 Most operations will use current or newly introduced wide- body aircraft.
	Automated TTL (minority)SVO (minority)	 Due to fractional benefit of removing pilots from the cockpit, smaller automation steps for automating all phases of flight and supporting single pilot operation begin development. Neither automated TTL or SVO comprise a large portion of the fleet size yet.
20-year with automation	 Current state (minority) Automated TTL (majority) SVO (majority) 	 A small, yet considerable, number of current generation aircraft are in service (passenger conversions). Automated gate-to-gate operations are more common across capable aircraft and SVO grows in share of fleet size with next generation aircraft. No business case for remotely piloting.

Table 3-1. Summary HLR Fleet Characteristics and Observations

Our baseline assumption is that, in the 10-year time horizon, only a small percentage of this fleet will be automated with SVO technology. In the 20-year time horizon, a more significant percentage of the fleet will employ SVO technology. The next section supplies model outputs based on our baseline assumptions.

Definitions and Timelines

Aircraft in this category primarily move containerized, palletized, and break bulk (i.e., not easily containerized) shipments on transcontinental and intercontinental routes. Aircraft fitting the specified mission parameters include Boeing 747, 777, 767 and Airbus 330 variants as well as MD-11s. Many of these types are expected to be operating 10 and 20 years from now, except for the MD-11s, in addition to mid-life passenger aircraft converted to freighters, such as the 787 and A350 families, and potentially a new build 777-X freighter. Disruptive concept configurations include Natilus' blended-wing body aircraft, aiming to increase payload volume while maintaining payload weight capabilities. Table 3-2 summarizes the baseline mission parameters and representative aircraft for the HLR use case.

Characteristic	Baseline value	Catalog of aircraft	
Mission range	> 3,000 nautical miles	Airbus A330	Boeing 777
Payload	> 40 tons	Boeing 747	Douglas MD-11
Speed	400–500 knots	Boeing 767	Natilus Domestic
		Natilus International	

Table 3-2. HLR Mission Parameters and Representative Aircraft

These aircraft predominantly fly long-haul intercontinental routes (the majority greater than 10 hours in duration) in the Pacific theater. The duration of flight requires additional flight crew (often three, and occasionally four pilots), to satisfy pilot rest requirements, including night-time flying. Operations over water are ideal for testing increased automation capabilities given the elimination of risk to people on the ground.⁴ However, operations over water are not safer than those over the land, with an equivalent risk to the flight crew and payload onboard the aircraft if the automation technology failed. Furthermore, intercontinental operations must consider the regulations of each jurisdiction traveled through. Some intercontinental aircraft also cycle through shorter, mid-range flight legs. A starting point is nonetheless required for increased automation in large aircraft—this use case generates revenue while building a safety record for operations over populous areas.

Table 3-3 depicts speculative regulatory approval years and entry into service years. These estimates for each use case are based on our understanding of the technology, the driving business case, the regulatory environment, and insight gained from SMEs. The three scenarios depicted are also reflected in the model: low, base, and high case. Low case represents a bearish perspective on timeliness for technology and regulatory developments to satisfy the business-driven demand. The base case represents our best estimate of timelines and is the nominal scenario for modeling. The high case represents an optimistic perspective of rapid regulatory standards implementation and sufficient technology innovation and demonstration. The low and high case deviate from the base case by +/-3 years for all automation capabilities. Only SVO, remotely piloted, and remotely supervised were considered in this analysis to mimic systems dynamics model capabilities.

Automation capability	Low case	Base case	High case
Potential regulatory approval year (SVO)	2031	2028	2025
Entry into service year (SVO)	2032	2029	2026
Potential regulatory approval year (remotely piloted)	2036	2033	2030
Entry into service year (remotely piloted)	—	—	—
Potential regulatory approval year (remotely supervised)	2041	2038	2035
Entry into service year (remotely supervised)	—	—	—

Table 3-3. HLR Regulatory and Entry into Service Timelines

Entry into service is included in the table to indicate the slight delay from regulatory approval to the aircraft entering the market; we used an assumption of 1 year. For instances without entry into service timelines, we suggest that automation capability will not be applicable to that specific use case. Numerous reasons contribute to regulatory approval but no entry into service, such as profitability of the business model, fleet characteristics, or general business drivers which influence adoption of the automation (for example, cost).

The HLR base case assumes an initial improvement in automation capabilities starting with SVO entry into service in 2029, implying that the flight crew size will decrease by one crew member. Large cargo operators' appetite for advanced automation in larger aircraft was significantly less than that of other use cases. In addition, industry feedback indicated only marginal expected improvements compared to today's operating aircraft.

⁴ Though not necessarily operations over the Pacific Ocean due to a lack of proximate emergency fields or airports.

Cargo operations over water are still an attractive use case as a testing arena for improving automation capabilities for operations over densely populated areas and cost savings occur with reductions in the onboard flight crew. Assuming that the business case is the driving factor for this use case, regulations can adapt to larger aircraft based on findings and innovation with smaller aircraft (regional and light use cases) to supply the regulatory basis for SVO operations. Technology capabilities exist today, as proven by concepts from Garmin (Autoland) and Aurora Flight Sciences (Optionally Piloted Aircraft).

Due to the perceived investment required to enable remotely piloted and remotely supervised flight, we do not see a business case that substantiates the effort required to significantly develop those automation capabilities for this use case in the next 20 years. This conclusion is largely driven from our stakeholder interviews with regulators and cargo operators who felt strongly that this capability would not mature in the near- to mid-term.

Baseline Model Outputs

Figures 3-1 through 3-4 represent outputs from the systems dynamics model using our base case assumptions. Figure 3-1 shows the HLR fleet size. The blue represents aircraft without automation and the orange represents SVO aircraft. Our baseline assumptions indicate a 27 percent larger fleet size made of 33 percent SVO aircraft in 20 years.



Figure 3-1. HLR Fleet Size by Type

Figure 3-2 shows the market share of automated aircraft. Starting from a base of 0 percent market share in year 9, the model predicts SVO aircraft accounting for 33 percent of the overall HLR market by year 20.



Figure 3-2. HLR SVO Aircraft Market Share

Figure 3-3 shows total revenue ton miles (RTM) by aircraft type. By year 20, the model predicts SVO aircraft accounting for 33 percent of the total RTMs for this market segment, which represents 9.6 billion RTMs.



Figure 3-3. HLR RTM Composition

Figure 3-4 shows the market share in RTMs of each aircraft type. By year 20, SVO aircraft account for 33 percent of the market by RTMs, which aligns to the model prediction for the SVO share of total fleet size.

Figure 3-4. HLR RTM Shares



The above baseline outputs are a subset of the outputs in the systems dynamics model dashboard and can be adjusted by changing the model inputs. The dashboard user guide, in Appendix A, supplies detailed dashboard operating instructions.

Summary Findings

Table 3-4 summarizes our findings for this use case. Overall, we see some operational benefit to automation technology for this use case but, because of the specific market dynamics, the benefits are limited.

Finding type	Observations
Benefits	 SVO certification result in a reduction of the number of pilots needed The average number of pilots reduces from three to two Reduced requirements on the number of qualified pilots considering a potential pilot shortage Pilot cost as a percentage of operational costs is reduced
Challenges	 Cost of automation (longevity of legacy aircraft such as 747s) Limited production runs for black box solutions Limited prospective gains in operational efficiency

Table 3-4. HLR Summary Findings

Heavy/Medium Range

Business Case

Table 3-5 summarizes the fleet characteristics and observations for the HMR use case. With the exception of Boeing 767 freighters (new build and P2F conversions), some Airbus A300s/310s, and updated Douglas DC-10s (designated as MD-10s) operating in this space, a large portion of the fleet is narrow-body aircraft, such as Boeing 757s and 737s, Airbus 321s, and some regional jets (e.g., Bombardier CRJ200s), with the most digitally capable aircraft being the 321s. The typical freighter in this use case is a mid-life aircraft P2F conversion, many with legacy systems, which may be challenging to automate via a singular solution. A further challenge to automation retrofits is the

relatively low value of these airframes compared to the likely cost of low production run black box solutions. On the other hand, the cost savings of reducing onboard flight crew complements are greater as a percentage of total costs compared with the HLR range use case. Ten years from now, P2F conversions will consist of mid-life passenger aircraft with greater digital characteristics, centered around aircraft such as the Airbus 321NEO, Boeing 737 MAX, and potentially the Embraer E-2 families. These more homogenous fleets may enable lower-cost automation retrofitting, though the lower airframe values will present an economic challenge compared with the investment cost of automation, even though the latter affords some increases in crew productivity and aircraft utilization at the margin.

Timeline	Fleet characteristics	Observations
10-year with automation	 Current state (majority of aircraft) Automated TTL (minority) SVO (minority) 	 Most operations use current or newly introduced narrow- body aircraft. Due to the fractional benefit of removing pilots from the cockpit, smaller automation steps for automating all phases of flight and supporting single pilot operation begin development. Neither automated TTL or SVO comprise a large portion of the fleet size yet.
20-year with automation	 Current state (minority) Automated TTL (majority) SVO (majority) 	 A small, yet considerable, number of current generation aircraft are in service (passenger conversions). Automated gate-to-gate operations are more common across capable aircraft and SVO grows in share of fleet size with next generation aircraft. No business case for remotely piloting.

 Table 3-5. Summary HMR Fleet Characteristics and Observations

Our baseline assumption is that, in the 10-year time horizon, only a small percentage of this fleet will be automated with SVO technology. In the 20-year time horizon, a more significant percentage of the fleet will employ SVO technology. The next section supplies model outputs based on our baseline assumptions.

Definitions and Timelines

HMR aircraft represent U.S. domestic narrow-body cargo transportation. As with the HLR market, the economics will change with reductions in direct operating costs. Aircraft need to be purpose-built for SVO or increased automation or be retrofit with black box automation hardware, requiring a new form of FAA certification. Pre-COVID-19, a portion of cargo transportation occurred through passenger aircraft in the belly of the aircraft. Given the additional risk of operating an automated aircraft over populated land areas, it is likely that automation will be introduced through purpose-built freighters or P2F retrofit conversions before passenger aircraft applications. Some examples include Boeing 737 and 757 variants, Airbus A300 and A321 variants, and select Bombardier aircraft. Some HLR aircraft (as previously discussed) also operate in medium-haul domestic sectors. The catalog of aircraft considered here focuses on cargo aircraft but not passenger aircraft that carry cargo in the belly. Shipments in this use case include a mixture of containerized, palletized, and break-bulk cargo, the former dominant. Table 3-6 summarizes the mission parameters and representative aircraft for the HMR use case.

Characteristic	Baseline value	Catalog of aircraft	
Mission range	500–3,000 nautical miles	Airbus A300	Boeing 737
Payload	> 10 tons	Airbus A321	Boeing 757
Speed	350–500 knots	Antonov An-124	Douglas DC-9
		Dougl	as MD-83

Table 3-6. HN	IR Mission Pa	rameters and	Representative	Aircraft
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Table 3-7 is the same set of assumptions from Table 3-3, meaning HMR aircraft regulatory approval and entry into service are expected to be the same as HLR aircraft. If the regulatory framework enables operations for HLR aircraft, that same set of standards and procedures applies to HMR aircraft. Although we assume the same values for regulation and entry into service, fleet adoption and operating economics are not the same between use cases.

Table 3-7. HMR Regulatory and Entry into Service Timelines

Automation capability	Low case	Base case	High case
Potential regulatory approval year (SVO)	2031	2028	2025
Entry into service year (SVO)	2032	2029	2026
Potential regulatory approval year (remotely piloted)	2036	2033	2030
Entry into service year (remotely piloted)	—	—	—
Potential regulatory approval year (remotely supervised)	2041	2038	2035
Entry into service year (remotely supervised)	—	—	—

There is significant complexity in predicting the future of cargo transportation for narrowbody aircraft, largely due to the cost drivers of flying cargo on passenger aircraft (typically at lower rates) versus freight forwarders' cargo on pure freighter aircraft, as well as the age of the operating fleet (majority P2F conversions). Automation will look different for this use case with an increased emphasis on retrofit of P2F conversions operating on low-risk domestic routes over land.

Baseline Model Outputs

Figures 3-5 through 3-8 represent outputs from the systems dynamics model using our base case assumptions. Figure 3-5 shows the HMR fleet size. The blue represents aircraft without automation and the orange shows SVO aircraft. Our baseline assumptions indicate a 10 percent larger fleet size comprised of just under 16 percent SVO aircraft in 20 years.





Figure 3-6 shows the market share of automated aircraft. Starting from a base of 0 percent market share in year 9, the model predicts SVO aircraft accounting for just under 16 percent of the overall HLR market by year 20.



Figure 3-6. HMR Automated Aircraft Market Share

Figure 3-7 shows total RTM by aircraft type. By year 20, the model predicts SVO aircraft accounting for just under 16 percent of the total RTMs for this market segment, which represents 2.7 billion RTMs.





Figure 3-8 shows the market share in RTMs of each aircraft type. By year 20, SVO aircraft account for just under 16 percent of the market by RTMs, which aligns to the model prediction for the SVO share of total fleet size.



Figure 3-8. HMR RTM Shares

Summary Findings

Table 3-8 summarizes our findings for this use case. Like HLR, we see some operational benefit to automation technology for this use case but, because of the specific dynamics of the HMR market, the benefits are limited.

Finding type	Observations
Benefits	SVO certification result in a reduction of the number of pilots needed
	- The average number of pilots reduces from 2 to 1
	Reduced pilot requirements considering a potential pilot shortage
	Leverage the reduced pilot cost as a percentage of operational costs
Challenges	Cost of automation (longevity of legacy aircraft such as 767s)
	- Limited production runs for black box solutions
	 Modest aircraft values versus passenger to freighter cost (approximately \$5 million)
	 Limited prospective gains in operational efficiency

Table 3-8. HMR Summary Findings

Regional

Business Case

Table 3-9 summarizes the fleet characteristics and observations for the regional use case. The regional use case benefits from automation to a larger extent than the HLR and HMR use cases because the average stage lengths are relatively short and some aircraft turn times at outstations are relatively long (for connections at the onward destination), which can create significant crew inefficiencies as the crew needs to remain with the aircraft at the out station. Many airframes (particularly the Cessna Caravan family) are nearing their end of life, or will in less than 10 years, driving the introduction of new aircraft, that could have new automation features built-in or could facilitate

automation retrofits. In the large regional aircraft space (covered by the ATR-72 turboprop), several OEMs are considering next generation aircraft with entry into service targets within 10 years. Furthermore, the regional segment is most susceptible to greater pilot cost creep than average due to the lower pay and lower work environment attractiveness and high turnover, which has led to crew shortages. In addition, this space is more likely to benefit from innovative propulsion developments, such as electrification, hybrid, or hydrogen propulsion.

Shorter stage lengths (75–1,000 nautical miles) result in significant potential for diverting cargo traveling via ground modes as reduced costs and greater efficiencies and scheduling flexibility narrow the cost gap versus trucking or intermodal (e.g., trucks to and from ferries) competition.

Timeline	Fleet characteristics	Observations
10-year with automation	Current state (majority of aircraft)Remotely piloted (minority)	 The fleet will age out around 2030—most of the fleet will match the current state due to operational and capital costs for legacy aircraft.
		 Innovation will occur for remotely piloted aircraft, with early innovation through automation deployed on trusted airframes and the introduction of fully capable remotely piloted, purpose-built aircraft.
		 Remotely piloted increases network flexibility. Technology and regulatory barriers will be addressed with a steady move to introduce remotely piloted technology to the fleet.
20-year with automation	Automated cruise (minority) Remotely piloted (minority)	 Innovation will propagate throughout regional aircraft quickly.
	 Remotely supervised (1:1) (minority, quick transition to 1:N) Remotely supervised (1:N) (majority) 	 A small number of legacy aircraft will be operational (due to low cost); however, remotely piloted will step quickly through remotely supervised (1:1) and remotely supervised (1:N).
	(majority)	 Built up trust in automation will enable the transition to the most favorable business case of remotely supervised 1:N.

Table 3-9. Summary Regional Fleet Characteristics and Observations

Our baseline assumption is that, in the 10-year time horizon, a small percentage of this fleet will be remotely piloted. In the 20-year time horizon, we predict the majority of the fleet will be remotely supervised (1:N), with the other automation technologies (automated cruise, remotely piloted, and remotely supervised [1:1]) making up the rest of the fleet. The next section supplies model outputs based on our baseline assumptions.

Definitions and Timelines

Regional aircraft serve a wide variety of use cases, covering traditional cargo movement and emergent use cases due to aircraft innovation. Holistically, hub-to-spoke and spoketo-outlier movements are the primary business models serving communities often difficult or expensive to otherwise serve via ground transportation. Aircraft will be a blended mix of retrofit and purpose-built conventional aircraft and disruptive short takeoff and landing (STOL) or vertical takeoff and landing (VTOL) configurations. Conventional aircraft categorized under this use case consist of ATR, Cessna, Beech, and other aircraft. Disruptive OEMs, including Natilus and Sabrewing, have designed concepts to operate under the specified mission parameters. Table 3-10 summarizes the mission parameters and representative aircraft for the regional use case.

Characteristic	Baseline value	Catalog of aircraft	
Mission range	75–1,000 nautical miles	ATR 42	Cessna SkyCourrier
		ATR 72	Fairchild Metro II
Payload	1–10 tons	Beech 1900	Fairchild Metro III Heavy
		Beech 99	Fokker 50
Speed	150–300 knots	Bombardier Q300 (Dash 8)	Saab 340B
		Cessna Caravan	Natilus Regional
		Cessna Grand Caravan EX	Sabrewing Rhaegal-B
		Cessna Turbo St	ationair HD Cargo

 Table 3-10. Regional Mission Parameters and Representative Aircraft

Regional missions are short intercity or interstate routes of about 1 to 3 hours in duration. This market is highly competitive with regional air cargo; in addition, there is the potential to compete with existing shipments via truck where cost savings in time or reductions in late fees or penalties support the business case to shift to air. Alternative use cases considered include transporting cargo in otherwise hard to access areas, such as islands, mountains, or areas where ground infrastructure is poor. SMEs gave the regional use case the highest priority, with strong interest from regulators, operators, and innovators.

As shown in Table 3-11, we set an aggressive baseline timeline for regulatory approval and entry into service for the regional use case based on strong stakeholder interest in advancing automation in this market segment. SVO enables operators to realize cost savings while using the technology as a stepping-stone to achieve higher degrees of automation. Most regional aircraft require only one pilot to fly the mission, drastically reducing the benefits of SVO because a pilot would still be required. Given industry interest, regulatory support, and innovator progress in remote pilot capabilities, we assume remotely piloted operations will receive regulatory approval in 2026 for the base case. The years building up to 2026 will include experimental or special certifications in addition to geographically limited approvals for remotely piloted operations. Our baseline projection is that regulatory standards and procedures will exist to operate remotely piloted at scale by 2026. From present to regulatory approval, hardware and software providers will iterate rapidly on technology to support scaled deployment of a fleet of remotely piloted aircraft.

Automation capability	Low case	Base case	High case
Potential regulatory approval year (SVO)	2025	2023	2021
Entry into service year (SVO)	—	_	_
Potential regulatory approval year (remotely piloted)	2029	2026	2023
Entry into service year (remotely piloted)	2030	2027	2024

Table 3-11. Regional Regulatory and Entry into Service Timelines

Automation capability	Low case	Base case	High case
Potential regulatory approval year (remotely supervised)	2031	2028	2025
Entry into service year (remotely supervised)	2032	2029	2026

Table 3-11. Regional Regulatory and Entry into Service Timelines

Industry sees one of the driving influences as removing the barrier of pilot colocation with the aircraft. A pilot remotely piloting can fly a mission, then quickly turn around to fly an aircraft at an entirely different location. These network benefits offer substantial gains in operational efficiency, leading to cost savings. Some regional aircraft operate over low-density areas, ideal for gaining public and regulatory confidence in automation technology. Under our baseline assumptions, remote supervision, starting with operations of one pilot to one aircraft, will gain regulatory approval quickly in 2028, just 2 years after approval of remotely piloted. Data will be collected and utilized to improve aircraft performance while building the safety case for remote supervision. The desired end state for operators is remote supervision of one pilot to many aircraft, or 1:N, which will accelerate timelines for innovation to sufficiently prove safety of the automation capability.

Baseline Model Outputs

Figures 3-9 through 3-12 represent four fleet mix scenario outputs from the systems dynamics model. Figure 3-9 shows the regional use case fleet size under our baseline assumptions. Dark blue indicates current state aircraft (non-automated). Orange represents remotely piloted; gray remotely supervised (1:1); and light blue remotely supervised (1:N). Our baseline assumptions indicate a 15 percent larger fleet size comprised of 75 percent remotely supervised (1:N) aircraft in 20 years.



Figure 3-9. Regional Base Case

■ Remotely supervised (1:1) ■ Remotely supervised (1:N)

Figure 3-10 shows the regional use case fleet size under the assumption that automation will enable operators to realize a 50 percent gain in utilization (i.e. operational time). The legend colors match the previous graph. Under this scenario, the model predicts a nearly 14 percent smaller fleet with nearly 70 percent remotely supervised (1:N) aircraft in 20 years.



Figure 3-10. Regional +50 Percent Utilization

Figure 3-11 shows the regional use case fleet size under the assumption that automation will enable operators to realize a 100 percent gain in utilization. The legend colors match previous graphs. Under this scenario, the model predicts a 29 percent smaller fleet with 64 percent remotely supervised (1:N) aircraft in 20 years.



Figure 3-11. Regional +100 Percent Utilization

Figure 3-12 shows the regional use case fleet size under our base case assumptions with a 10 percent shift of the relevant truck cargo market to air.⁵ The legend colors match the previous graphs. Under this scenario, the model predicts a 27 percent larger fleet with 77 percent remotely supervised (1:N) aircraft in 20 years.

⁵ As described in more detail in the light use case analysis, we defined the relevant truck market that might be susceptible to air competition to be a tiny fraction of overall truck cargo movements.



Figure 3-12. Regional Base Case (+10 Percent Truck Market Shift)

Summary Findings

Table 3-12 summarizes our findings for this use case. Overall, this is the most promising use case when the benefits are weighed against the challenges. Operators seeking to meet increased demand for same- and next-day air delivery and a legacy fleet approaching end of life will accelerate automation of the regional market.

Finding type	Observations
Benefits	 Accelerates the increase in same- and next-day air shipments to and from all markets (including small feeder markets)
	 Significantly increases velocity and utilization over legacy airframes
	 Enables replacement of a large fleet of aircraft approaching end of life
	Certification results in a reduction of the number of pilots and supervisors needed
	 The average number of pilots reduces from 1.5 to 0.5 to 0.2 (depending on the level of automation)
	 Addresses pilot turnover challenges in the regional segment
	Greatest reduction in pilot cost as a percentage of operational costs
Challenges	 Cost of automation versus longevity of legacy aircraft (i.e., Cessna Caravans) Achieving the ROI required to fund investment in automation

Table 3-12. Regional Summary Findings

Light

Business Case

Table 3-13 summarizes the fleet characteristics and observations for the light use case. The light business case depends on automation for viability because the distances are so short. As a result, pilot costs as a percentage of total operating costs are the highest of all the use cases. One OEM stakeholder is working with the FAA on a less stringent pilot certification standard via simplified operating controls to lower pilot costs in the period between vehicle development and remote piloting regulatory approval. If pilot offboarding can be achieved, the business case becomes more straightforward.

Most shipments in this segment will continue to move via ground but a subset of shipments will shift to air. That subset will likely consist of time-sensitive, high-value, and security-sensitive cargo (categories which may overlap). A frequent example is moving cargo via air to avoid congestion delays in crowded metro areas. In some instances, such as the Holland Tunnel in New York City, trucks are permitted only during certain times of the day and incur high taxes and tolls due to increased truck congestion. Air would thus offer operators a means of bypassing such restrictions. On the high-value/ security-sensitive side, we heard about the need for shipment security, especially for pharmaceutical shipments, which can be subject to theft during ground transport. Increasing the security of such shipments would enable distributors to centralize more of the commodity and fly directly to hospitals and pharmacies to reduce the risk of theft via ground. While the business case will be proven in congested metro areas, we see wider business applicability for these aircraft in the long term. Some examples include rural, mountainous, island, and emergency response scenarios.

Timeline	Fleet characteristics	Observations
10-year with automation	 SVO (minority) Remotely piloted (majority) 	 This use case is enabled through automation (no base case without automation).
		 Earliest stages of operations will occur with a pilot monitoring onboard for larger aircraft and with remotely piloted for smaller aircraft.
		 While public trust is built, and systems are proven reliable, larger aircraft will transition to remotely piloted.
20-year with	Remotely piloted (minority)	Automation capabilities will grow rapidly.
automation	 Remotely supervised (1:1) (minority) 	 Remotely piloted will comprise a small number of the fleet with most of the operation remotely supervised 1:N.
	 Remotely supervised (1:N) (majority) 	 Remotely supervised 1:1 will be a stepping-stone, advancing quickly from 1:1 to 1:N. Minimal physical adjustments to aircraft systems are expected, with the technology built-in from the onset for remotely supervised 1:1 aircraft.

 Table 3-13. Summary Light Fleet Characteristics and Observations

Our baseline assumption is that, in the 10-year time horizon, a small percentage of this fleet will operate via SVO, with the rest operating remotely piloted. In the 20-year time horizon, the majority of the fleet will be remotely supervised (1:N), with other automation technologies (remotely piloted and remotely supervised [1:1]) making up the rest of the fleet. The next section supplies model outputs based on our baseline assumptions.

Definitions and Timelines

Light aircraft represent a changing paradigm on how cargo is transported in that the market for this use case does not currently exist. Aircraft will vary from conventional takeoff and landing, STOL, and VTOL with multiple configurations, including conventional single and twin rotors, tiltrotors, and multi-rotors. Table 3-14 summarizes the mission parameters and representative aircraft for the light use case.

Characteristic	Baseline value	Catalog	g of aircraft
Mission range	< 250 nautical miles	Airbus CityAirbus	Airflow Aero STOL
		Ehang 216 (logistics)	Elroy Air
Payload	0.025–1 ton	Volocopter Volocity	Joby S4
		Volocopter VoloDrone	Kitty Hawk HVSD
Speed	< 200 knots	Bell Apt 70	Lilium Jet (5-seat)
		Bell Nexus (4EX)	Pipistrel Nuuva V300
		Bell Nexus (6HX)	Vertical Aerospace VA-1X

Variability in configuration may create difficulties in certifying automation capabilities since many other aspects of the aircraft design must go through the certification process. For the regional use case, most of the technology development and demonstrations are being completed on trusted airframes, such as the Cessna Caravan, enabling regulators to focus on certifying automation. Conversely, light aircraft must receive appropriate type and airworthiness certifications for novel designs with or without automation before operational capability. There are two pathways to this scenario, the piloted and pilotless aircraft paths. The piloted path involves initial aircraft certification with SVO, gradually building to remote piloting and remote supervision. The pilotless path is more direct with initial aircraft certification including the automation capabilities for remote piloting or remote supervision. While there is not an agreed-on approach, the piloted aircraft path is more popular with leading disruptive OEMs.

Light aircraft will fly some similar missions to the regional use case—intercity and interstate—but will also fly intracity missions moving cargo locally. One use case cited often by SMEs was connecting an airport to the city center to avoid ground traffic delays and late delivery penalties. Another example is warehouse-to-warehouse movement of goods as an alternative to truck movement. The main competitor for the light use case is truck-based shipments. The light use case enables a new market of cargo air transportation and pulls demand from ground operations to support the business scenarios.

Like regional, light aircraft have strong interest from industry stakeholders who seek faster innovation than conventional aviation. Table 3-15 summarizes our estimates for regulatory and entry into service timelines for the light use case.

Automation capability	Low case	Base case	High case
Potential regulatory approval year (SVO)	2026	2023	2021
Entry into service year (SVO)	2027	2024	2022
Potential regulatory approval year (remotely piloted)	2029	2026	2023
Entry into service year (remotely piloted)	2030	2027	2024
Potential regulatory approval year (remotely supervised)	2031	2028	2025
Entry into service year (remotely supervised)	2032	2029	2026

Table 3-15. Light Regulatory and Entry into Service Timelines

Regulators are working hard to keep up with innovation while ensuring the safety of infrastructure, aircraft, operators, and bystanders. The rapid pace of innovation paired with strong demand offers early opportunities for light aircraft to demonstrate automation capabilities with SVO in 2023. Regulators (specifically discussing aircraft that qualify in this use case) believe a light aircraft with SVO capabilities will be type-certified by the end of 2021. We assume that by 2023 the remaining regulatory hurdles will be overcome, and the OEM and operator will achieve the remaining certifications required for scalable operations. SVO is suboptimal for the business case; therefore, OEMs and operators are expected to transition quickly to advanced automation capabilities, such as remotely piloted. SVO is a needed step in achieving remotely piloted operations if following the piloted aircraft path, which most OEMs are leaning toward.

Our baseline projection is that the piloted and pilotless aircraft paths converge at certification of remotely piloted automation by 2026. This follows the same timeline mentioned for regional aircraft in large part because the automation technology required for remotely piloted will align across the light and regional use cases. Regional aircraft benefit from their status as trusted airframes, which makes them an ideal testbed for core automation technologies. Light aircraft have the advantage of completing a large amount of testing while going through the certification process where automation technology can be utilized and built-in to the aircraft. Both use cases developing in parallel will be essential to reaching the projected timeline for remotely piloted missions. Also, like regional, we project that light aircraft will see remotely supervised certification by 2028 after 2 years of data acquisition, technology development, and confidence built in automation technology. The 2028 timeline does not suggest that one pilot managing multiple aircraft will take place during the initial entry into service; however, that progression will occur in the next 20 years. Remote supervision 1:1 must first be sufficiently proven, and technology sufficiently developed, for the complex operations of managing multiple aircraft per pilot.

Baseline Model Outputs

Figures 3-13 through 3-15 represent outputs from the systems dynamics model using our base case assumptions. Figure 3-13 shows the light fleet size across three scenarios representing 5, 10, and 20 percent shift shares from the relevant truck cargo market. We defined the relevant truck market that might be susceptible to light aircraft competition to be a tiny fraction of overall truck cargo movements. To be included in the analysis, we looked only at truck shipments in the 250-mile range and the one-ton shipment size limit specified for this use case. Second, we considered only those commodity types already shown to be conducive to air shipments (such as high-valued or perishable goods). Third, we included only those shipments to or from the top five largest and most congested metro areas. Taken together, these restrictions result in a relevant market that comprises well under 0.5 percent of the total domestic truck cargo market.

The dark blue bar represents a 5 percent shift of the relevant truck market to air. The orange bar represents a 10 percent shift of the same truck market, while the light blue bar depicts a 20 percent shift of the same market. The 5 percent shift outputs a fleet size of 2,650 aircraft in 20 years. The 10 percent shift outputs a fleet size of 5,299 aircraft in 20 years. The 20 percent shift outputs a fleet of 10,599 aircraft in 20 years. These fleet numbers include piloted and autonomous aircraft.



Figure 3-13. Light Use Case with 5/10/20 Percent Shift from Truck to Air—Combined

■ 5% shift ■ 10% shift ■ 20% shift

Figure 3-14 shows only piloted aircraft with the same 5 percent, 10 percent, and 20 percent truck market shifts. Piloted aircraft peak in year 9 at 419 (5 percent shift), 838 (10 percent shift), and 1,676 (20 percent shift), before disappearing as those aircraft are converted to automated. For this use case, the model does not distinguish between remotely piloted and remotely supervised (1:1 or 1:N).





■ 5% shift ■ 10% shift ■ 20% shift

Figure 3-15 shows only automated aircraft with the same 5 percent, 10 percent, and 20 percent truck market shifts (i.e., this is the delta between Figure 3-13 and 3-14). Automated aircraft total 2,650 (5 percent), 5,300 (10 percent), and 10,599 (20 percent) respectively in 20 years (i.e., 100 percent of the fleet for this use case).



Figure 3-15. Light Use Case with 5/10/20 Percent Shift from Truck to Air—Automated

■ 5% shift ■ 10% shift ■ 20% shift

Summary Findings

Table 3-16 summarizes our findings for this use case. Overall, this use case is extremely promising, but the challenges are greater because of where and how these aircraft will operate. Congested metro areas tend to have daytime congested airspace and potentially night restrictions, adding operational complexity. In addition, the business case depends on these aircraft operating at a much higher utilization than larger aircraft. That operational tempo increases the likelihood of a mishap, which could delay certification if it causes the public to lose confidence in the technology. Despite those challenges, many OEMs are focused on developing aircraft for this segment because of its cost effectiveness.

Finding type	Observations
Benefits	 Accelerates the increase in same- and next-day air shipments Avoids ground delays and taxes/tolls in congested metro areas Unlocks rural and multi-modal uses (island and mountainous terrain) Increases security and delivery reliability of security and time-sensitive commodities Provides redundancy in emergency response situations
Challenges	 Achieving the ROI required to fund investment in automation

 Table 3-16. Summary Light Findings

Technology Assumptions

Several assumptions drove our technology assessment as a model input and output. Those assumptions with rationale are listed below.

1. *Assumption.* No widely accepted industry framework exists for aviation automation capabilities comparable to the SAE levels of automation for automobiles.

Reasoning. Despite literature on automation and autonomy framework concepts, no single framework has gained sufficient momentum to influence the population of stakeholders engaged in aviation-related industries, or beyond to the public. The SAE levels of automation have been widely accepted and are one of the tools used to describe overall automobile automation capabilities.⁶ Aviation frameworks have been complex and bogged down in the intricacies of aviation-related lexicon, making those concepts difficult to digest for a large audience but, nonetheless, useful pieces of work for researchers of the industry.

A successful framework may accelerate increased automation in aviation by giving the industry a common frame-of-reference and roadmap to innovate with clearly defined generational improvements in automation, like the automotive industry. Therefore, this work generates a framework for categorizing technology into described levels of automation to serve as an input and output to modeling.

Representative examples of aviation automation frameworks have been published:

- "TR1-EB—Autonomy Design and Operations in Aviation: Terminology and Requirements Framework"
- "TR2-EB—Developmental Pillars of Increased Autonomy for Aircraft Systems"
- "Taxonomy and Definitions for Terms Related to Driving Automation Systems for On-Road Motor Vehicles"
- "A Framework for Autonomy Levels for Unmanned Systems."
- 2. *Assumption.* The automation technology list is not exhaustive—it notes major technical challenges from the literature review.

Reasoning. Due to the scope of work, the technology analysis contributing to the generated framework was limited to the most critical concepts found during the literature review, SME interviews, and internal team expertise. The list of automation technologies is, therefore, a non-exhaustive list, highlighting critical technology gaps. A more robust in-depth analysis is required to generate a full

⁶ SAE, "Taxonomy and Definitions for Terms Related to Driving Automation Systems for On-Road Motor Vehicles," June 15, 2018.

360-degree perspective on automation technology for each aircraft system and subsystems.

3. *Assumption.* Not every technological challenge is for NASA to solve but must be resolved by stakeholders before full market introduction is possible.

Reasoning. The technological issues are not for targeted stakeholders (industry or government) to overcome but represent a generalized list, which the collective body of researchers and industry stakeholders must resolve to enable automation at scale. The business use cases discussed require scale to create sizeable economic effects, and scale is only possible through proven safety and reliability of automation technologies to overcome regulatory and societal barriers. The onus is on researchers and industry to develop solutions and mechanisms to satisfy safety requirements while pushing the boundaries of automation in aviation. Further research is required on which technologies must be addressed by NASA Aeronautics Research Mission Directorate (ARMD), industry, or collaborative efforts.

With these assumptions, our work formulated a framework for automation technology that first finds the type of technology and then classifies the technology based on its level of automation. There are three pillars of automation technology: core autonomy technology, enabling technology (vehicle), and enabling technology (integration). Core autonomy technology contributes to achieving a truly autonomous system that can perceive the surrounding environment and make decisions in unknown scenarios. The technology contributing to core autonomy is fundamental to the pillars of autonomy itself, such as trustworthiness, and is applicable to a wide spectrum of applications in end-toend operations across stakeholders.

Enabling technology for the vehicle and integration are the next two pillars, intentionally divided as unique focus areas. Aviation differs from the automotive industry, or other similar industries, by the level of integration requirements for routine operations. Multiple stakeholders must be involved in the operation beyond the vehicle itself, such as air traffic control, airports (or heliports and vertiports), and fleet operators. This level of integration adds significant complexity in achieving increasingly automated operations because each stakeholder of the end-to-end operation must be compatible with other stakeholders.

It is important to note that this framework is intentionally at a high-level, and lower-level or use case–specific technologies may not be included as part of the framework (ex. infrastructure technologies for the light use case).

Table 4-1 depicts a simplified list of autonomous capability technologies across three categories: core autonomy technology, enabling technology (vehicle), and enabling technology (integration). The colors in Table 4-1 align to the column headers in Table 4-2 to show which technologies are required for each use case. See Appendix B for a complete matrix of the research and sources that contributed to the table. The list of technologies was primarily derived from an extensive literature review of automation and autonomy in aviation (and similar industries) and notes extracted from SME interviews.

Core autonomy technology	Enabling technology (vehicle)	Enabling technology (integration)
Trustworthy and transparent human-machine teaming	Global Navigation Satellite System (GNSS) independent and highly accurate positioning, navigation, and timing	Cybersecure digital data exchange
Intelligent contingency and emergency flight management architecture	Intelligent anomaly identification and risk assessment	Flight standards integration
Nondeterministic verification and validation methods	Resilient, reliable, and low-latency communications	Cooperative surveillance and information sharing
Open-source autonomy software architecture	Integrated system health monitoring	Urban non-cooperative surveillance
Collaborative machine negotiation, prioritization, and decision-making	Digital twin "shadow-mode" data collection and labeling	Secure cloud networks
Multi-monitor run-time assurance	Localized microweather detection and prediction	Data exchange standardization
Complex software certification or licensing using over-the-air updates	Lost link procedures	Collaborative unmanned air traffic management framework
Data and reasoning fabric implementation	Low size, weight, and power (SWaP) sensors	Scalable, low-cost, live, virtual, and constructive air traffic management (ATM) simulation test bed

Table 4-1. Automation Framework: Three Pillar Technology Matrix

The automation technology was then transformed into three representative levels of automation: SVO, remotely piloted (1:1), and remotely supervised (1:N). These levels were chosen because they align with the aircraft modeled in the systems dynamics model. While the technology mapping to levels of automation was subjective in nature, we have performed several validation exercises to ensure proper alignment for the levels of automation with NASA ARMD and industry stakeholders. Table 4-2 serves as an input for the model user to validate model results and associated regulatory timelines, which is discussed in greater detail later in the report and is organized from left to right in order of maturity of technology.

Table 4-2. Automation Framework: Levels of Automation

SVO	Remotely piloted (1:1)	Remotely supervised (1:N)
Trustworthy and transparent human-machine teaming	Cybersecure digital data exchange	Nondeterministic verification and validation methods
Intelligent contingency and emergency flight management architecture	Flight standards integration	Open-source autonomy software architecture
GNSS independent and highly accurate positioning, navigation, and timing	Cooperative surveillance and information sharing	Collaborative machine negotiation, prioritization, and decision-making
Intelligent anomaly identification and risk assessment	Urban non-cooperative surveillance	Multi-monitor run-time assurance
Resilient, reliable, and low-latency communications	Secure cloud networks	Complex software certification or licensing using over-the-air updates

SVO	Remotely piloted (1:1)	Remotely supervised (1:N)
Integrated system health monitoring	Data exchange standardization	Data and reasoning fabric implementation
Digital twin "shadow-mode" data collection and labeling	Lost link procedures	Collaborative unmanned air traffic management framework
Localized microweather detection and prediction	Low SWaP sensors	Scalable, low-cost live, virtual, and constructive ATM simulation test bed

Table 4-2. Automation Framework: Levels of Automation

As a validation activity, we spoke with several senior researchers across the Transformative Aeronautics Concepts Program, the Airspace Operations and Safety Program, and the Integrated Aviation Systems Program to uncover current and future research efforts related to automation and autonomy. Those conversations confirmed the notional alignment of NASA ARMD research efforts with our technology findings. We discussed project and subproject research around automation for aviation, uncovering key focus areas for the program portfolio. Current and planned research is well-aligned with the technology framework that we developed in support of our market study and our broader findings (discussed in Chapter 3).

After comparing the NASA conversations to our literature review and industry SME interviews, we concluded the NASA ARMD portfolio aligns well with the appropriate technologies required to drive automation forward for aviation. Further research is required to complete a thorough investigation of each program portfolio combined with a use case–specific deep dive into automation technologies across the various systems and subsystems involved in the end-to-end operational process.

Economic Assumptions

A first step for assessing how automated technologies may affect air cargo services is to assess the size of the air cargo market, which is relevant for estimating the overall combined market that is applicable to the HLR, HMR, and regional use cases. The estimates from the economic model described below are used to reflect the air cargo market baseline *without* automation; these estimates are then used as inputs to the main systems dynamics model to consider automation technologies that affect pilot efficiencies, increased aircraft utilization rates, and other factors.

We used the Department of Transportation's (DOT's) monthly T-100 data for freighter aircraft services reported by U.S. and foreign carriers operating domestically or internationally.⁷ Using this data, we have developed a high-level analysis for estimating how changes in observed ton-miles correlate with changes in air freight prices and other factors.⁸ To begin this assessment, we must account for both the demand and supply for freighter air freight services. Recognizing that the demand for air freight services is a derived (or intermediate) demand for many different types of products, we expect that

⁷ https://www.bts.gov/topics/airlines-and-airports/data-bank-28dm-t-100-domestic-market-data-us-air-carriers-traffic-and.

⁸ Ton-miles are a unit of measurement used to summarize freight movements and defined as one ton of freight carried one mile.

such demand moves closely with changes in the overall economy. Thus, we specify a general relationship for the demand curve as follows:

 $Ton-mile\ demand = f(air\ freight\ price,\ general\ economy).$

On the supply side, one expects that air freight services will depend on price as well as the cost of providing services. This supply curve relationship is given by the following:

 $Ton-mile \ supply = f(air \ freight \ price, air \ freight \ operating \ costs).$

Air freight price and ton-miles are endogenous variables calculated simultaneously through the equilibrium relationship between supply and demand. By employing a suitable statistical method that accounts for this simultaneity, we can use the estimated functions to predict the equilibrium price and quantity at any time.

We measure changes in the general economy via a time series of annualized real (inflation-adjusted) U.S. GDP; changes in GDP shift the demand curve but are assumed not to affect the supply curve. On the supply side, we measure changes in real (inflation-adjusted) operating costs using freight operations financial data reported to DOT (see below); changes in operating costs shift the supply curve but are assumed not to affect the demand curve.

The estimated model utilizes quarterly activity for the 17-year period from the first quarter of 2003 to the fourth quarter of 2019 (68 total time-series observations) with the following data items:

- Ton-miles: Ton-miles from T-100 for freighter jet operations
- Air freight price: Producer price index for scheduled freight air transportation services (adjusted for inflation using the GDP implicit price deflator index)
- GDP: Real (inflation-adjusted) annualized U.S. GDP (2012\$)
- Operating costs: Average aircraft operating expenses per hour from DOT Form 41 Schedule P-5.2 (large certificated carriers), cargo configuration jet aircraft (adjusted for inflation using the GDP implicit price deflator index).

We have also included quarterly dummy variables in the demand and supply equations to account for any seasonal effects. In addition, to account for the abrupt effects of the 2008–2009 global recession, a dummy variable was added to each equation to represent the first three quarters of 2009.

Finally, the model specification also utilized operating costs lagged by one quarter relative to the other data—this offered the best fit to the data, and is consistent with the notion that carriers take time to adjust their service offerings in response to changes in operating costs.

Estimation and Results from the Economic Model

To operationalize the demand and supply relationships, we first transformed all variables (except the dummy variables) into natural logs and then assumed a linear specification for each equation. The log transformation enables us to interpret the estimated model coefficients as elasticities. We then performed an appropriate regression analysis to

estimate the model coefficients. The estimates from the analysis were quite good and showed that all coefficients had the expected signs and reasonable magnitudes:

- Estimated price elasticity of demand = -0.43, implying that a 1 percent increase in air freight price leads to a 0.43 percent decrease in demand; this is not surprising since the types of goods that move by air freight are typically highvalued or time-sensitive with limited alternatives.
- Estimated GDP elasticity = 0.86, implying that a 1 percent increase in GDP leads to a 0.86 percent increase in air freight demand.
- Estimated price elasticity of supply = 1.36, implying that a 1 percent increase in air freight price leads to a 1.36 percent increase in supply; in other words, suppliers are quite responsive to changes in price.
- Estimated operating cost elasticity = -0.90, implying that a 1 percent increase in operating cost leads to a 0.90 percent decrease in supply.
- The seasonal dummies (which are measured relative to the fourth quarter) were all negative, consistent with the observation that the fourth quarter tends to be the seasonal peak in the air freight market.
- The recession dummy had negative effects on demand and supply.

We can use these coefficient estimates to compute the predicted equilibrium price and ton-miles for any values of GDP and operating cost. We transform from quarterly to annual results, which is more useful for future projections of price and ton-mile totals.⁹

For an idea of how the GDP and operating cost variables affect the supply and demand equilibrium over time, Figure 4-1 shows the resulting baseline 2019 supply and demand curves as well as the projected curves for 2035, assuming a 2 percent annual increase in GDP combined with a 1 percent annual decline in operating costs.



Figure 4-1. Supply–Demand Baseline

⁹ We also slightly adjusted the constant terms in the equations for supply and demand so that the 2019 model predictions exactly match the observed 2019 annual data—the observed 2019 data then is used as the baseline starting point for future projections.

The equilibrium price and ton-mile estimates in each year occur where the supply and demand curves intersect. As seen in Figure 4-1, with these assumptions (and no other changes), the baseline results suggest that the overall air cargo market will increase from about 39,000 million in 2019 to about 49,000 million ton-miles by 2035. The annual ton-mile projections are then allocated to the HLR, HMR, and regional use cases in the systems dynamics model based on observed shares of the overall market.

In addition, the confidence intervals around the model coefficients are used to construct conservative and aggressive estimates that the user can select in the dashboard. Conservative estimates result in higher prices and smaller quantities relative to the baseline estimates, while aggressive estimates result in lower prices and higher quantities relative to the baseline.

Findings

Overall, industry feedback suggested three areas governing automation (in order of increasing challenge): business models, technology, and regulatory. Our findings are divided into two categories: business case for each use case and technology and certification issues.

Business Case

Industry and regulators have indicated strong interest in accelerating the regional and light use cases, with the regional use case being easier to define. These use cases generate the most interest and investment from industry (both OEMs and operators). By contrast, there was not much interest expressed in the HLR and HMR use cases during our outreach due to the age and variety of aircraft and the relatively small share that pilot costs contribute to overall operating costs in those segments, as well as limited operational benefits.

The regional use case creates an opportunity to tie automation to fleet turnover. This point came up repeatedly in our interviews. Operators have a 10-year window to fund the development and certification of automation technology that they can deploy in the regional segment. If automation technology can be certified in that window, operators can deploy capital to expand the automated fleet rapidly by replacing nonautomated legacy aircraft with new aircraft featuring automation capabilities. Our model indicates 75 percent fleet replacement in 10 years.

Industry players seek to achieve remote supervision of 1:N rapidly to close the gap in the business model. This is based on the assumption that the technology suite needed for remotely piloted aircraft is largely similar for 1:1 and 1:N remote supervision. Because the operating cost profile of aircraft is so high relative to ground transportation, operators will seek to move as quickly as possible to 1:N to win the market share needed to recognize the required ROI.

Potential market size for the light use case could be as big as 2.7 billion RTM; manufacturing capacity is the driving factor for how much of the market can be captured. The model output is 2.7 billion RTM for our base case in the light segment. That represents a shift of 5 percent of the relevant truck market in the top five metro areas. The market size could be much larger if one increases the metro area coverage or shifts additional percentages of the truck market. However, even a 5 percent shift requires OEMs to produce 2,650 aircraft in 20 years. In almost all scenarios, OEMs will need to ramp up production like the automotive industry to keep pace with demand.

Technology and Certification

Automation and autonomy are commonly referenced in research and technology development efforts, often with confusion on what each term means. Aviation

does not have a central roadmap detailing the end state for automation and the intermediate steps to lead to that point. By analogy, automotive companies have rallied around the SAE levels of autonomy to measure progress toward reaching fully autonomous (level 5) automobiles. Regardless of the application, this easy-to-grasp framework can be understood by all. While aviation operates much differently than automotive (as detailed in the literature), a roadmap or framework detailing what progress looks like for increased automation in aviation could be beneficial for advancing the state of the art.

The resounding issue impeding near-term automation progress is integration, meaning integration of the entire operation in the NAS under existing standards. A standard aviation flight operation involves many stakeholders who all must interconnect to support the intended mission seamlessly. Integration of new automation capabilities will fundamentally change stakeholder responsibilities and break current operating models.

The regulatory pivot to performance-based requirements necessitates means of compliance (MoCs) to satisfy the standards. Moreover, MoCs are not developed by the regulator but by industry and research organizations to satisfy the standards. NASA can play a key role in developing MoCs for increased automation for the use cases to enable a clear path forward. The business case becomes more attractive when the investment cost and time required to achieve automation is clear.

The capability to build complex aviation software systems using intelligent algorithms (machine learning and artificial intelligence) requires extensive testing and a proven validation method. Nondeterministic systems specifically do not have a clear path to regulatory certification. Each industry stakeholder is developing proprietary intelligent software systems, meaning scalability will be difficult beyond the organization that certified the software. However, if an open-architecture or proven method validates intelligent systems, industry could build solutions with the end state in mind. Elevated levels of automation, if not autonomy, will require this type of innovation.

Near-term research challenges involve uncovering unknown unknowns, humanmachine teaming, scalable data collection and simulation, and software and hardware breakthroughs. With increased automation, breakthroughs in technology for digital integration and human-machine teaming will be critical to lay the foundation of automated capabilities. As technologies are at a low technology readiness level (TRL), methods to collect vast amounts of data (through experimentation or simulation) will be pivotal to establishing the safety case for the technology. Simulation capabilities will validate the standalone technology as well as integrations with existing or new elements of the NAS. Human-machine teaming will then enable improvements in pilot, operator, and controller workloads while maintaining consistent or improved levels of safety as the current state. Data collection and tools to analyze big data sets will enable the training of intelligent machine learning and artificial intelligence models to make better decisions.

Recommendations

Our recommendations mirror our findings. We cover business case and technology and certification recommendations below.

Business Case

NASA ARMD should address automation challenges in the regional and light market segments, specifically, the certification of automation solutions for Cessna Caravan-type regional aircraft. NASA ARMD could work with the FAA to define the impediments to certification and then partner with industry to address the impediments that industry is least equipped to address or the most business sensitive technologies, such as advances necessary to achieve 1:N remotely supervised operations.

Technology and Certification

NASA ARMD should emphasize supporting a common vision for incorporating increased automation in aviation and develop the appropriate documentation for industry-wide alignment on the future of autonomy. One of aviation's most complex problems is integration, with multiple interconnected stakeholders working together to support flight operations. Due to the highly integrated process, stakeholders must agree on the benefits of increasing automation, definitions of key concepts, and a roadmap for how to get from the current state to automation. This knowledge offers the opportunity to clear any misnomers and misconceptions about automation while promoting a simplistic understanding of what progress looks like for innovation in aviation.

NASA ARMD should partner with NASA mission directorates, government agencies, and non-aviation private industry stakeholders. Autonomy is not unique to aviation. Many disciplines are pursuing advances in core autonomy technology that could apply to increasing automation in aviation. While concepts may not be a 1:1 transition, partnerships that break the model of the status quo may offer fresh thoughts and innovation to traditional aviation concepts. Partnerships of this magnitude could spur economic effects by generating interest from non-aviation stakeholders to contribute to the aviation industry.

NASA ARMD should strengthen FAA partnerships to support integration into the NAS and the development of MoCs to satisfy performance-based requirements. While NASA is ramping up efforts to support technology transitions and concept development with the FAA, the shift toward performance-based requirements necessitates developing multiple MoCs to satisfy those requirements. NASA ARMD is positioned well to develop the MoCs to enable industry players to pursue one, if not many, paths to achieving compliance with regulations, enabling industry to accelerate growth by breaking down regulatory hurdles, clearing the pathway forward, and potentially supporting early partnerships with NASA ARMD to develop solutions together.

NASA ARMD should thoroughly assess the existing and future research portfolio to understand the effect of advancing automation and uncover gaps with technology requirements. In addition to outlining the path forward to achieving increased automation, a deep understanding of the hardware and software required to enable use case specific automation will be a powerful tool for researchers and private organizations for targeted research. The understanding of technologies enabling automation will support enhancements to the portfolio to align research efforts with what is required from NASA. Other benefits of this analysis included highlighting the benefits of automation and key impediments to progress and parsing which problems must be solved by NASA rather than industry.

- 1. AIAA Intelligent Systems Technical Committee, "Roadmap for Intelligent Systems in Aerospace," June 6, 2016.
- 2. Airbus Acubed, "More Autonomous Flight Progress in 2021," February 2, 2021.
- 3. ASTM Standard, "TR1-EB–Autonomy Design and Operations in Aviation: Terminology and Requirements Framework," 2020.
- 4. ASTM Standard, "TR2-EB–Developmental Pillars of Increased Autonomy for Aircraft Systems," 2019.
- Chancey et al., "Enabling Advanced Air Mobility Operations through Appropriate Trust in Human-Autonomy Teaming: Foundational Research Approaches and Applications," AIAA SciTech Forum, January 19–21, 2021.
- 6. Das et al., "Deep Learning-Based Negotiation Strategy Selection for Cooperative Conflict Resolution in Urban Air Mobility," AIAA SciTech Forum, January 19–21, 2021.
- Ellis et al., "A Concept of Operations and Design Considerations for an In-time Aviation Safety Management System (IASMS) for Advanced Air Mobility (AAM)," AIAA SciTech Forum, June 19–21, 2021.
- FAA Air Traffic Organization Policy 5-2-9, "Unmanned Aircraft Systems Lost Link," October 11, 2016.
- 9. FAA, "Collaborative Air Traffic Management," January 29, 2021.
- 10. FAA, "Unmanned Aircraft System Traffic Management (UTM)," June 3, 2020.
- 11. Goodrich, K. H., "Automated Flight and Contingency Management, NASA Advanced Air Mobility Project," August 3, 2020.
- 12. Greenfield, I., "Concept of Operations for Urban Air Mobility Command and Control Communications," April 1, 2019.
- 13. Gregory et al., "Intelligent Contingency Management for Urban Air Mobility," AIAA SciTech Forum, January 19–21, 2021.
- 14. Huang, H., Pavek, K., Novak, B., Albus, J., Messina, E., "A Framework for Autonomy Levels for Unmanned Systems," June 2005.
- 15. Idris et al., "A Framework for Assessment of Autonomy Challenges in Air Traffic Management," AIAA Aviation Forum, May 20, 2020.
- 16. Mathur et al., "Paths to Autonomous Vehicle Operations for Urban Air Mobility," AIAA Aviation Forum, June 17–21, 2019.
- Memarzadeh et al., "Multi-Class Anomaly Detection in Flight Data Using Semi-Supervised Explainable Deep Learning Model," AIAA SciTech Forum, June 19–21, 2021.
- 18. MITRE, "Verification and Validation," Systems Engineering Guide, May 2014.
- 19. Mohen et al., "A Cybersecurity Framework for Aerospace Services," AIAA SciTech 2021, June 19–21, 2021.

- 20. Mueller et al., "Enabling Airspace Integration for High-Density On-Demand Mobility Operations," AIAA Aviation Forum, June 5, 2017.
- 21. NASA TechPort, "NASA Platform for Autonomous Systems (NPAS)," <u>https://techport.nasa.gov/view/94884</u>.
- 22. National Weather Service, "Glossary," June 25, 2009.
- 23. Price et al., "Urban Air Mobility Operational Concept (OpsCon) Passenger-Carrying Operations," May 1, 2020.
- 24. Robinson et al., "Development of a High-Fidelity Simulation Environment for Shadow-Mode Assessments of Air Traffic Concepts," Modeling and Simulation in Air Traffic Management Conference, November 14–15, 2017.
- 25. SAE, "Taxonomy and Definitions for Terms Related to Driving Automation Systems for On-Road Motor Vehicles," June 15, 2018.
- 26. Schierman et al., "Runtime Assurance for Autonomous Aerospace Systems," September 21, 2020.
- 27. Skoog et al., "Leveraging ASTM Industry Standard F3269-17 for Providing Safe Operations of a Highly Autonomous Aircraft," October 18, 2019.
- 28. Stouffer et al., "Reliable, Secure, and Scalable Communications, Navigation, and Surveillance (CNS) Options for Urban Air Mobility," August 12, 2020.
- 29. Unmanned Aircraft Systems Integration in the NAS Project Closeout Technical Interchange Meeting, September 30, 2020.
- 30. Van Dalsem et al., "A Data & Reasoning Fabric to Enable Advanced Air Mobility," AIAA SciTech Forum, January 19–21, 2021.

The following appendix describes the steps for accessing and using the systems dynamics model dashboard.

Extracting the Dashboard

To fully access the dashboard, save the compressed automated aircargo .ZIP file to your desktop. Once the .ZIP file has been saved, right click and choose "Extract All." A prompt screen will ask for a file path for the dashboard. Once you choose a file path, the file will decompress. Select the "Dashboard V_20" file. Your default browser will open a live version of the dashboard with baseline outputs and variables imported.

Dashboard Functionality

When values in the model are changed, specifically in the Use Case parameters, the Model Output updates immediately. Value changes show up in the Model Parameters as a dark blue icon. To restore to baseline inputs, select "Reset to Default Input Setting" in the bottom left corner of the dashboard. The dark blue icon will turn white, indicating a successful reset. However, to save model inputs, select "Save Input Setting." An Excel file containing the new parameters will be generated and saved to a corresponding download folder. Selecting "Import Saved Input Setting" will recover and import saved files containing dashboard changes.

The Model Output reflects changes made to the Use Case parameters. Selecting "Export to .CSV" captures these changes as variable outputs and saves them to an Excel file.

To switch use case scenarios, under "Use Cases," select "HLR," "HMR," "Regional," or "Light." Everything except for the baseline box will adjust depending on the use case. Tool tips supply abbreviations, variable names, and descriptions.

Figure A-1 shows the model output Baseline w/o Automation, which supplies a background scenario for air cargo and aviation. The main inputs are GDP Growth Rate set at 2 percent, outlining how fast the economy is growing and by default air cargo as well. Operation Cost Per Hour Change measures operation costs for air cargo operators per hour and per year. High and low baseline cases have been incorporated and can be adjusted as needed.

Low Case	Base Case	High Case
Model Paramete	rs	
Market		
GDF	Growth Rate: 2.	00%
Cost		
Operation C	Cost per Hour Cha	inge: 0.00%

Figure A-1. Baseline without Automation Section

Using the HLR as an example, Figure A-2 demonstrates the Regulatory Timeline or approval years for regulatory milestones. Hovering over the regulatory milestones updates the Autonomy Technology box with detailed descriptions and callouts for what will be in the core technology for the vehicle and its integration.

Figure A-2. The SVO Hover Over Showing Changes in the Autonomy Technology Box



The Regulatory Timeline displays an Entry into Service Year for an Aggressive, Base, and Conservative case. The dropdown menu under the Base case lets the user to pick any year in a 20-year forecast as the year after approval. The light blue box is used as a delta in years between the regulatory approval year and the actual entry into service year for the automated vehicle with the selected capabilities.

In Figure A-3, the Automation Scenario Assumptions section summarizes the technology most applicable to the use case in 10 years with autonomy and 20 years with autonomy.

Baseline	No progress on autonomy		
10-year with Autonomy	Simplified Vehicle Operations (SVO)*		
20-year with Autonomy	Simplified Vehicle Operations (SVO)*		

Figure A-3. Automation Scenario Assumptions Section

Use Case Scenarios

Use Case 1: HLR

Figure A-4 captures a snapshot of the HLR use case model parameters. Each use case has specific assumptions, displayed as text boxes where the user can enter text. The Use Case box tool hover overs supply a detailed definition of each parameter.

	Use	Cases		
HLR	HMR	Region	al	Light
	Charles and			-
Model Para	meters			
Cost				
Co	st of Automation: 3	000,000 \$	-	
Г			0	-
Aircraft Fina	"Cost of the requ provide the select automation"	ired equip: ted level o	ment to f	
Operation				
Operation Avergae I	Pilots per Flight (SV	O Aircraft): ft): 2190 hrs	2.00 ⊃ ()	
Operation Avergae I Final Util	Pilots per Flight (SV	O Aircraft): ft): 2190 hrs	2.00 ⊃ ○ /year ⊃ ○	
Operation Avergae I Final Util	Pilots per Flight (SV	O Aircraft): ft): 2190 hrs	2.00 ⊃ ○ ⁄year ⊃ ○	
Operation Avergae I Final Util Market e-Cc	Pilots per Flight (SV	O Aircraft): ft): 2190 hrs ange: 0.0 %	2.00 > () /year > ()	
Operation Avergae I Final Util Market e-Cc	Pilots per Flight (SV	O Aircraft): ft): 2190 hrs ange: 0.0 %	2.00 ⊃ ○ /year ⊃ ○	
Operation Avergae I Final Util Market e-Cc Model Assu Cost	Pilots per Flight (SV	O Aircraft): ft): 2190 hrs ange: 0.0 %	2.00 ⊃ ○ /year ⊃ ○	
Operation Avergae 1 Final Util Market e-Cc Model Asst Cost Elasticity o	Pilots per Flight (SV	O Aircraft): ft): 2190 hrs ange: 0.0 %	2.00 (year 0 0 0.25	
Operation Avergae 1 Final Util Market e-Cc Model Assu Cost Elasticity o Decision Tri	Pilots per Flight (SV ization (SVO Aircra ommerce Growth Ch umptions f Maintenance Cost ime Horizon	O Aircraft): ft): 2190 hrs ange: 0.0 %	2.00 (year) 0 0 0.25 10.00	years

Figure A-4. HLR Use Case

Several cost assumptions are associated with each model. Each use case has an existing fleet with an associated build year and survival age associated with it. As the model projects into the future, this existing fleet ages and slowly becomes more expensive to operate. The model knows the operating cost for the aircraft based on the age of the fleet. For any time-step, after the entry to service year has been set, the model will calculate an NPV for the existing fleet versus buying new aircraft with automation capabilities.

Notable variables: In the default HLR use case, HLR is defined as 60 percent of the entire air cargo market (under the Use Case Market Share assumption). The market percentage is projected into the future and allocated to a fleet of aircraft that has those capabilities. These aircraft are outlined under the Aircraft assumption. If the user is interested in the average payload capabilities for the HLR market, this can be projected using the Initial Payload (SVO Aircraft) and Final Payload (Baseline Aircraft) parameters.

Using historical data, an average number of pilots was added to the HLR Operation assumption. By default, this assumption is set to 3.00 since there must be more than two pilots (including crew) for long intercontinental flights under HLR. However, in the sliderbar, the Average Pilots per Flight (SVO Aircraft) can be adjusted to 2.00 pilots since it accounts for unnecessary spare crew for this aircraft. These two parameters work independently of each other.

The Elasticity of Maintenance Cost Parameter

This parameter represents the percent change in maintenance cost relative to the percent change in annual operating hours as specified in the base Boeing maintenance cost model. This reduces the change in maintenance cost relative to the change in annual operating hours.

Use Case 2: Heavy/Medium Range

The model assumptions between default case HLR and HMR do not change significantly. The model parameters that change are the Final Payload (SVO Aircraft), Final Utilization (SVO Aircraft), and Average Pilot per Flight (SVO Aircraft). In the default HMR use case, HMR is defined as 36 percent of the entire air cargo market.

Notable variables: Under model parameters for the default HMR case, there is an E-commerce Growth Change parameter that accounts for adjusting for the air cargo market independently of the baseline GDP growth. This enables the user to adjust the air cargo market for other factors, such as changes in E-commerce, not directly linked to GDP.

Use Case 3: Regional

Figure A-5 highlights key differences in regional use case parameters from HLR. Notably, the regional use case incorporates multiple generations of vehicles under its model parameters. A percentage of these vehicles quickly convert once the next tier of automation is available.

	U	se Cases	
HLR	HMR	Regional	Light
	and I	HALLING A	-
Model Parame	ters		
Cost			
Cost	of Automation: 1,	,000,000 \$	
Aircraft			
Final Payl	oad (Remotely Pi	iloted): 5.0 tons	
Final Payload	(Remotely Super	vised 1:1): 5.0 tons	
Final Payload	(Remotely Super	vised 1:N): 5.0 tons	
Operation			
Average Pilot	s per Flight (Rem	notely Piloted): 1.0	
erage Pilots pe	r Flight (Remotel	ly Supervised 1:1): 0.5	5
rage Pilots pe	r Flight (Remotel	y Supervised 1:N): 0.:	2
Market			
"Top 5"	or "Top 10" Truc	k Market: 0.0	

Figure A-5. Regional Use Case

Notable variables: Under the Cost parameter, the default Cost of Automation of \$1,000,000 represents the amount to automate a non-automated aircraft.

This use case includes a "Top 5" or "Top 10" Truck Market slider-bar, which adds the possibility of converting a percentage of the truck market to regional automated aircrafts. The percentage is limited to 1–10 percent shift.

Use Case 4: Light

The parameters for the light use case were based primarily on a shift from ground at 10 percent for the final year. This is reflected in the Market Shift parameter. This market is distinct from the regional use case because of the difference in size of the payloads and distance for the portion of the truck market addressed.

Appendix B Automation Technology

Technology	Supporting definitions	Rationale	Source
	Core Autonomy Technology		
Trustworthy and transparent human-machine teaming	Human-machine team: A distinguishable set of two or more agents who interact dynamically, interdependently, and adaptively toward a common and valued goal, objective, or mission. Performance describes a user's understanding of what the automation does, corresponding to current and historical operation of the automation. Process describes a user's understanding of how the automation operates, corresponding to the appropriateness of the automation's algorithms in achieving operator goals. Purpose describes a user's understanding of why the automation was developed and corresponds to how well the designer's intent has been communicated to the operator.	As trust is a foundational element of human-machine teaming, which in itself is foundational for increasingly automated systems, human trust in machines can be built through understanding of the automation or the transparency of performance, process, and purpose. "A lack of support for clear task allocation and effective human-machine communication and coordination, as well as poorly designed human-machine interfaces are known to result in breakdowns in joint system performance, even under nominal conditions with no component failures." (Mathur et al.)	Chancey et al., "Enabling Advanced Air Mobility Operations through Appropriate Trust in Human-Autonomy Teaming: Foundational Research Approaches and Applications," AIAA SciTech Forum, January 19–21, 2021. Mathur et al., "Paths to Autonomous Vehicle Operations for Urban Air Mobility," AIAA Aviation Forum, June 17–21, 2019.
Intelligent contingency and emergency flight management architecture	Using adaptive learning techniques to influence mission execution based-on aircraft capability, relative to the predefined mission, in response to known and unknown in-flight contingency and emergency scenarios. Contingency management : Anticipation, detection, recognition, and mitigation of unexpected or off-nominal situation	"Allow the vehicle to safely achieve its mission by flying from pt. A to pt. B under all vehicle-allowable weather conditions, in a high-density airspace complex urban environment, while reacting appropriately to off-nominal situations and contingencies without direct human control." (Gregory et al.)	Gregory et al., "Intelligent Contingency Management for Urban Air Mobility," AIAA SciTech Forum, January 19– 21, 2021. Goodrich, K. H., "Automated Flight and Contingency Management, NASA AAM Project," August 3, 2020.

Technology	Supporting definitions	Rationale	Source
	elements affecting flight safety, efficiency, etc. Flight management: Planning, monitoring, and execution of flight operations for an individual aircraft within an operational environment and broader airspace system.		
Nondeterministic verification and validation methods	Nondeterministic: Having characteristics or behavior that cannot be predetermined from starting conditions or input from the operating environment. Verification is the process for determining whether a product fulfills the requirements or specifications established for it. Validation is the assessment of a planned or delivered system to meet the sponsor's operational need in the most realistic environment achievable.	Autonomous systems are nondeterministic because they are self- governing systems capable of independent decision-making. For certification, human trustworthiness, and safety purposes, verification and validation methods must be established for scaling autonomy. "Improve autonomy design and implementation procedures to better capture what-ifs (contingency) cases. Establish clear validation and verification processes to minimize or eliminate chances of failure." (Mathur et al.)	AIAA Intelligent Systems Technical Committee, "Roadmap for Intelligent Systems in Aerospace," June 6, 2016. MITRE, "Verification and Validation," <i>Systems Engineering</i> <i>Guide</i> . Mathur et al., "Paths to Autonomous Vehicle Operations for Urban Air Mobility," AIAA Aviation Forum, June 17–21, 2019.
Open-source autonomy software architecture	Open-source software architecture to "enable reusable implementation of distributed hierarchical autonomous operations foundational capabilities."	Scalable autonomy is unachievable if developed in isolation—industry could benefit from a common starting point which is publicly available and deemed trustworthy or certifiable.	NASA TechPort, "NPAS."
Collaborative machine negotiation, prioritization, and decision- making	Agents work together to find a solution that satisfies the needs and concerns of each, involving holistic and creative decision- making for the individual agents to suggest different ideas that jointly benefit them.	Because not all information can be shared, for competitive reasons, machine-machine or human-machine negotiation decision-making strategies will enable onboard tactical and strategic separation in high-density airspace.	Das et al., "Deep Learning-Based Negotiation Strategy Selection for Cooperative Conflict Resolution in Urban Air Mobility," AIAA SciTech Forum, January 19–21, 2021.
Multi-monitor run-time assurance	The process of monitoring, using several distinctly separate monitors, a system containing untrusted software	"The software separation of each monitor allows each individual monitor to be mapped to a specific pilot responsibility, better ensuring that all intended safety responsibilities are being appropriately covered." (Skoog et al.)	Skoog et al., "Leveraging ASTM Industry Standard F3269-17 for Providing Safe Operations of a

Technology	Supporting definitions	Rationale	Source
	during run-time or live operation of the plant to evaluate whether the untrusted software is operating correctly.	Run-time assurance is a method to bound autonomy and autonomous decision-making in set boundaries. Developing a multimonitor run-time assurance software will enable verification and validation of nondeterministic systems for fail-safe autonomous systems.	Highly Autonomous Aircraft," October 18, 2019. Schierman et al., "Runtime Assurance for Autonomous Aerospace Systems," September 21, 2020.
Complex software certification or licensing using over-the-air updates	Over-the-air software updates: Software updates through a secure data link (over the air) and not through swapping out hardware boxes.	"Plan for vehicle software upgrades through a secure data link ('over the air') and not through swapping out hardware boxes, thus ensuring no disruption to air vehicle availability for software upgrades. Implement over-the-air or loadable software capabilities—avoid taking a vehicle out of service for prolonged periods for the purpose of making software upgrades." "The FAA of today is ill-equipped to respond quickly to increasingly complex code for certification. This points to the need for industry consensus bodies on modular design and software design, code, and implementation maturity for the programmers that write and maintain these codes. These bodies' deliberations should develop a maturity model and requirements for the requisite software capabilities. The FAA can then lean on these bodies for standards and guidelines for software validation, and to help facilitate the certification process."	Stouffer et al., "Reliable, Secure, and Scalable CNS Options for UAM," August 12, 2020.
Data and reasoning fabric implementation	A set of secured software infrastructure, tools, protocols, governance, and policies to implement, administer, manage, and operate data- sharing and reasoning services across the entire span of air mobility and other smart edge nodes.	To enable highly automated and efficient data sharing across machine agents, the data and reasoning fabric facilitates ease of information sharing across diverse sensors and data sources, which are standardized and consistent. "Optimize data acquisition and management across the variety of heterogeneous data sources and types. Data updates can be from UAM/UAS platforms as well as public assets." (Mathur et al.)	Van Dalsem et al., "A Data & Reasoning Fabric to Enable AAM," AIAA SciTech Forum, January 19– 21, 2021. Mathur et al., "Paths to Autonomous Vehicle Operations for UAM," AIAA Aviation Forum, June 17–21, 2019.
Enabling Technology (Vehicle)			
GNSS independent and highly accurate positioning, navigation, and timing	Navigation that can operate without a continuous GNSS signal and is highly accurate without the need for large or expensive ground-based equipment in urban environments.	High-density operations, especially those in urban environments or those aircraft relying on onboard sensors for localization, require high levels of position accuracy to safely navigate from point-to- point. Not only that, but GPS jamming and spoofing is becoming a more prevalent problem, as well as operating in GPS-denied environments.	Stouffer et al., "Reliable, Secure, and Scalable CNS Options for UAM," August 12, 2020.

Technology	Supporting definitions	Rationale	Source
Intelligent anomaly identification and risk assessment	Finding anomalies that would otherwise be non- identifiable using standard prescriptive techniques and calculating the risk for unknown events.	"The standard practice for anomaly detection in the aviation domain is exceedance detection, which is unable to identify unknown risks and vulnerabilities. Supervised learning can overcome this challenge but is afflicted with requiring a high number of processed and labeled data points to reach optimum performance. However, in many real- world applications, such as aviation, labeled data is either not available or scarce. As a result, aviation anomaly– detection literature has mainly focused on unsupervised reasoning to identify anomalies in high-dimensional time series of flight data. Unfortunately, unsupervised learning, by nature, suffers from a high number of false alarms and low accuracy in complex settings. This limits its applicability."	Memarzadeh et al., "Multi-Class Anomaly Detection in Flight Data Using Semi- Supervised Explainable Deep Learning Model," AIAA SciTech Forum, January 19– 21, 2021.
Resilient, reliable, and low- latency communications	Resilient: Able to withstand or recover quickly from difficult conditions. Reliable: Consistently good in quality or performance; able to be trusted. Latency: The delay before a transfer of data begins following an instruction for its transfer.	"The UAM system must also include provisions for consistent, reliable throughput and low latency communications." "Key factors regarding the collection of data from each information source include availability of data originating from the vehicle and its systems as well as data from performance models, latency of data, and accuracy of data collected from different sources. The data lags, different resolutions of data, and other variations in key parameter can limit data correlation and fusion. Moreover, the update rates can be synchronous and asynchronous between information classes."	Greenfield, I., "ConOps for UAM Command and Control Communications," April 1, 2019.
Integrated system health monitoring	Vehicle health monitoring systems continuously assess performance of onboard operational systems, e.g., battery power and motor performance.	Highly automated systems require intelligent system health monitoring capabilities to quickly detect and identify potential system malfunctions or degradation in sufficient time to respond appropriately and communicate intent across NAS stakeholders.	Ellis et al., "A ConOps and Design Considerations for an IASMS for AAM," AIAA SciTech Forum, January 19– 21, 2021.
Digital twin "shadow-mode" data collection and labeling	Agnostic-platform onboard data collection with virtually simulated autonomy running in the background of piloted aircraft operations.	The jump to autonomy is not expected to take place overnight, nor will passenger- carrying concepts make the jump to offboard the pilot without simplified vehicle operations or pilot supervision. Digital twin offers an intermediate solution to train autonomous systems on a variety of platforms for large-scale data analysis and model tuning.	Airbus Acubed, "More Autonomous Flight Progress in 2021," February 2, 2021.
Localized microweather detection and prediction	Microclimate : The climate of a small area, such as a cave, house, city, or valley, that may be different from that in	"Weather: As noted in the National Transportation Safety Board (NTSB) aviation accident database, adverse weather conditions (e.g., wind, visibility/ceiling, turbulence, up/downdraft,	Mathur et al., "Paths to Autonomous Vehicle Operations for UAM," AIAA Aviation Forum,

Technology	Supporting definitions	Rationale	Source
	the general region. Weather detection capabilities in a concentrated geographic region, most typically urban, that consider microweather phenomena, such as wind gusts, wake turbulence, etc.	wind shear, thermal lift, icing, lighting, etc.) accounted for approximately 20 percent of total aircraft accidents from 2003 through 2007. Therefore, it is critical to analyze possible scenarios involving adverse weather conditions in urban areas for UAM operations." (Mathur et al.) "Additionally, UAM aircraft operating in urban areas may encounter the threat of localized turbulence due to concentrations of large structures in the landing and takeoff environment. UAM aircraft will have to maintain a safe flight path in the face of this turbulence. Furthermore, as noted in a recent NASA sponsored study, turbulence can be unpleasant and frightening for passengers. The detection and prediction of microweather near urban structures is likely to require significant research, testing, and demonstration to enable full implementation of the UAM concept." (Price et al.)	June 17–21, 2019. Price et al., "UAM OpsCon Passenger- Carrying Operations," May 1, 2020. National Weather Service, "Glossary," June 25, 2009.
Lost link procedures	Preprogrammed or predetermined mitigations to ensure the continued safe operation of the Unmanned Aircraft (UA) in the event of a lost link (loss of the command and control link between the control station and aircraft).	"Lost link procedures are currently not scalable to full-scale file-and-fly commercial UAS operations. Currently, lost link procedures are defined in the Certificate of Authorization (COA) and are specific to the UAS and its operating environment. There is a need to develop procedures and/or automation to support robust and scalable lost link procedures." (UAS Integration)	"UAS Integration in the NAS Project Closeout Technical Interchange Meeting," September 30, 2020. "Federal Aviation Administration Air Traffic Organization Policy 5-2-9 UAS Lost Link," October 11, 2016.
Low SWaP sensors	Low SWaP sensors include vehicle health monitoring, detect and avoid (DAA), CNS technology, and electromagnetic interference (EMI), either adapted from larger legacy platforms or purpose-built for autonomy applications on UAS and UAM platforms.	This includes DAA (in low visibility), electromagnetic interference, and CNS. "UAM's unique operating environment, coupled with the high degree of autonomy, will require low weight and power engineering solutions to electromagnetic interference, communication of traffic information, and interoperability with the existing NAS." (Stouffer et al.) "UAS simply cannot perform all functions required for airspace integration because of size, weight, and power (SWaP) limitations." (Mueller et al.)	Stouffer et al., "Reliable, Secure, and Scalable CNS Options for UAM," August 12, 2020. Mueller et al., "Enabling Airspace Integration for High- Density On-Demand Mobility Operations," AIAA Aviation Forum, June 5, 2017.

Technology	Supporting definitions	Rationale	Source	
	Enabling Technology (Integration)			
Cybersecure digital data exchange	Digital, machine-based system that is ground- based but the integration between all the airborne and ground-based agents is performed via machines exchanging cybersecure digital information and negotiating decisions.	"Although an enhancement to communications efficiency, controller- pilot data link communication (CPDLC) is not sufficient as a means of compliance to voice communication equipment requirements of 14 CFR parts 91, 121, and 135, and is not required by these rules. CPDLC functions are not yet consistently supported across the domestic U.S. To allow for SVO and increasingly autonomous operations, greater use of digital data communications in the FAA infrastructure should be accelerated as part of NAS evolution." (Stouffer et al.) "In terms of cybersecurity perspectives, various cyberattacks such as SCADA (Supervisory Control and Data Acquisition) threats, GPS/light detection and ranging (LiDAR) spoofing, EMI, Vehicular Ad Hoc Networks (VANETs) compromises or Flying Ad Hoc Networks (FANETs) compromises, along with acoustics/sonic cyberattacks can create critical problems in operational safety. In fact, scenarios such as C2 [command and control] interruption in swarm flight, loss of datalinks, mass blackout, etc., must be considered for the worst operational events in cybersecurity attacks. UAM operations must be designed with fully safe emergency procedures in such complicated cybersecurity attacks." (Mathur et al.) "As the ATM automation level increases along the automation scale from decision support to the ability to perform functions under human supervision or independently from the human, the coordination needs to be transformed from human-based integration to digital- based integration. This digital connection enables automation systems to be integrated without the mediation of human flight operators or service providers. It also allows these systems to coordinate information and solutions and to support a higher level of function allocation to the machine from the	Stouffer et al., "Reliable, Secure, and Scalable CNS Options for UAM," August 12, 2020. Mathur et al., "Paths to Autonomous Vehicle Operations for Urban Air Mobility," AIAA Aviation Forum, June 17–21, 2019. Idris et al., "A Framework for Assessment of Autonomy Challenges in Air Traffic Management," AIAA Aviation Forum, May 20, 2020.	
Flight standards integration	Integration of increasingly diverse operations into the NAS through existing, modified, or new flight rules that do not segregate air traffic.	"A high-density on-demand mobility (ODM) system cannot have access to key takeoff and landing areas (TOLAs) shut down on most afternoons and evenings, so a third airspace integration barrier critical to enabling high-density ODM operations is the ability to preserve	Mueller et al., "Enabling Airspace Integration for High- Density ODM Operations," AIAA Aviation Forum, June 5, 2017.	

Technology	Supporting definitions	Rationale	Source
		visual flight rule (VFR)–like operations and separation even under conditions of instrument meteorological condition. This barrier is a particularly high one because such operations require not only remaining well clear of other traffic, which was the sole required function for DAA systems, but also maneuvering, sequencing, and spacing relative to other aircraft, conducting precision approaches and departures, following navigation routes, and avoiding obstructions. These capabilities exist today for the most sophisticated commercial aircraft when receiving IFR [Instrument Flight Rules] air traffic control (ATC) services, capabilities that must be replicated for ODM aircraft independently of ATC to surmount this barrier."	
Cooperative surveillance and information sharing	Exchange of airborne, ground-based, and satellite data detailing individual aircraft location and intent between cooperative aircraft operating in the NAS. Cooperative : Involving mutual assistance in working toward a common goal. Surveillance : Finding the exact location of aircraft and a clear vision of surrounding conditions, including weather patterns and aircraft. Surveillance systems detect aircraft and send detailed information to the air traffic control system, enabling air traffic controllers to safely guide the aircraft. Information sharing Describes the exchange of data between various organizations, people, and technologies.	 "projected UML-4 traffic density cannot be supported under standard separation, even a modified version of standard separation that merely reduces the distances between vehicles. UML-6 density will be much more dense and dynamic than UML-4. Operating under UML-6 will be so complex and computationally intensive that a new system must be initiated before UML-4, to allow time for the evolution of increased system performance needed to accommodate UML-6. NASA should devote research to the separation rules, networking protocols, redundancy requirements, and hazard assessments for cooperative surveillance-based tactical vehicle separation for high density UAM." "Cooperative surveillance and autonomous UAM-to-UAM separation is needed to accommodate thousands of flights in urban airspace. Onboard systems will need to communicate vehicle-to-vehicle to coordinate intent for safe passage." 	Stouffer et al., "Reliable, Secure, and Scalable CNS Options for UAM," August 12, 2020.
Urban non- cooperative surveillance	Surveillance of rogue aircraft in urban environments that are not participating in cooperative surveillance information sharing.	"When density or public sentiment reaches the point that non-cooperative surveillance becomes socially necessary, a well functioning system will take years to mature and implement."	Stouffer et al., "Reliable, Secure, and Scalable CNS Options for UAM," August 12, 2020.

Technology	Supporting definitions	Rationale	Source
Secure cloud networks	Cloud networking : An IT infrastructure in which some or all of an organization's network capabilities and resources are hosted in a public or private cloud platform, managed in- house or by a service provider, and available on demand.	The cloud enables distributed access to stored information across diverse stakeholders. Low-latency, distributed- edge connected cloud networks must be secure to facilitate the transmission and reception of data from the cloud network to prevent malicious cyberattacks targeted toward the NAS. "When it comes to outsourcing services to cloud service providers, there are challenges when it comes to security, or data suitability. In short, we lose the control of the data since the vendor now has control of the managed database service. To make sure data is secure, data should be encrypted before it is stored in the database. Secure sockets layer (SSL)/transport layer security (TLS) connections to the database ensure some level of security when in flight. For data at rest, AES-2565 is the standard for most Government and commercial organizations."	Mohen et al., "A Cybersecurity Framework for Aerospace Services," AIAA SciTech 2021, June 19–21, 2021.
Data exchange standardization	The standardization of data formats and exchange protocols for seamless data information sharing across stakeholders operating in the NAS (most commonly applied to the federated ATM concepts).	"There is a need for the establishment of standards for data exchange architecture and CNS services provided by the many separate UAS service supplier (USS) providers. A competitive avionics marketplace would thrive if CNS avionics serve both on UAS and UAM."	Stouffer et al., "Reliable, Secure, and Scalable CNS Options for UAM," August 12, 2020.
Collaborative unmanned ATM framework	Collaborative Air Traffic Management coordinates flight and flow decision-making by flight planners and FAA traffic managers to improve overall efficiency of the NAS, provide greater flexibility to flight planners, and make the best use of available airspace and airport capacity. UTM is a traffic management ecosystem for uncontrolled operations that is separate from, but complementary to, the FAA's ATM system.	"airspace integration barrier for the medium to long term is how to structure airspace used by ODM aircraft and define ATC's role in support of the ODM concept. ATC will require a certain degree of control over ODM activities, ignoring those aircraft under nominal circumstances but retaining sufficient visibility into the performance of that system so that it can intervene when necessary to ensure the safety of the overall airspace." (Mueller et al.) "The critical question arising from a decision to start conducting ODM operations under VFR is how difficult will it be to add capabilities to the ODM aircraft or supporting UTM-like system to enable airspace access equivalent to that of IFR aircraft (and without its capacity limitations)." (Mueller et al.) "Instead, remote command centers will allow humans to oversee the largely automated aircraft and intervene only when contingency procedures warrant. Procedural approaches to higher	Mueller et al., "Enabling Airspace Integration for High- Density On-Demand Mobility Operations," AIAA Aviation Forum, June 5, 2017. Verma et al., "Lessons Learned: Using UTM Paradigm for UAM," Digital Avionics Systems Conference, October 16, 2020. FAA, "Collaborative Air Traffic Management," January 29, 2021. FAA, "UTM," June 3, 2020.

Technology	Supporting definitions	Rationale	Source
		airspace densities will largely disappear except to provide continued service for traditional airspace users. This reliance on a matured, human-rated UTM-like system should greatly lower the marginal cost of additional ODM aircraft and operations and enable the high-density reference mission described in Section IIA." (Mueller et al.) "This study showed that overall, the UTM architecture can be successfully applied for UAM operations and that the implementation of services can have a considerable impact on the efficiency of the system. Future work will focus on improving the implementation of the advanced services and also investigating sharing routes between multiple operators." (Verma et al.)	
Scalable, low- cost live, virtual, and constructive ATM simulation test bed	A constructive simulation generally has no interactive human involvement in simulated conditions. Instead, scenarios unfold using rule-based decisions that control the interactions between simulated actors. Virtual simulations involve human participants operating simulated systems (e.g., a pilot flying a flight simulator). A live test environment involves human participants operating real systems.	Increasingly diverse airspace operations will require low-cost, scalable simulation capabilities to test innovative ATM concepts. Without the proper simulation capabilities, verification and validation of proposed concepts will be incrementally more expensive and may take longer to advance TRL capabilities. "This paper described the current state and vision for the shadow-mode assessment using realistic technologies SMART-NAS Test Bed (SNTB), an air traffic simulation platform that will enable real-time simulations that are currently impractical or impossible. SNTB has the ability to scale, connect, share, leverage other simulations. The combination of these features can permit additional benefits including, reproducible research, distributing the expertise related to the setup and execution of a simulation, and increasing the TRL development pace."	Robinson et al., "Development of a High-Fidelity Simulation Environment for Shadow-Mode Assessments of Air Traffic Concepts," Modeling and Simulation in Air Traffic Management Conference, November 14–15, 2017.

Appendix C Abbreviations

AAM	advanced air mobility
AIAA	American Institute of Aeronautics and Astronautics
ARMD	Aeronautics Research Mission Directorate
ATC	air traffic control
ATM	air traffic management
C2	command and control
CFR	Code of Federal Regulations
CNS	communications, navigation, and surveillance
ConOps	concept of operations
COA	Certificate of Authorization
CPDLC	controller-pilot data link communications
DAA	detect and avoid
DOT	Department of Transportation
EMI	electromagnetic interference
FAA	Federal Aviation Administration
FANET	Flying Ad Hoc Network
GDP	gross domestic product
GNSS	Global Navigation Satellite System
HLR	heavy/long range
HMR	heavy/medium range
IASMS	In-time Aviation Safety Management System
IFR	Instrument Flight Rules
IT	information technology
Lidar	light detection and ranging
MoC	mean of compliance
NAS	National Airspace System
NPAS	NASA Platform for Autonomous Systems
NPV	net present value
NTSB	National Transportation Safety Board

ODM	on-demand mobility
OEM	original equipment manufacturer
OpsCon	operational concept
P2F	passenger to freighter
R&D	research and development
ROI	return on investment
RTM	revenue ton miles
SCADA	Supervisory Control and Data Acquisition
SME	subject matter expert
SNTB	SMART-NAS Test Bed
SSL	secure sockets layer
STOL	short takeoff and landing
SVO	simplified vehicle operations
SWaP	size, weight, and power
TLS	transport layer security
TOLA	takeoff and landing area
TRL	technology readiness level
TTL	taxi, takeoff, and landing
UA	Unmanned Aircraft
UAM	Urban Air Mobility
UAS	unmanned aircraft system
UML	UAS maturity level
USS	UAS service supplier
UTM	UAS Traffic Management
VANET	Vehicular Ad Hoc Network
VFR	visual flight rule
VTOL	vertical takeoff and landing

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