Autonomous Drone Assisted Aircraft Inspections

by

Andrew Mighty

M.S., Cybersecurity, New York University, 2021
B.S., Mathematics, United States Naval Academy, 2014

Submitted to the MIT Sloan School of Management and Department of Electrical Engineering and Computer Science in partial fulfillment of the requirements for the degrees of

Master of Business Administration

and

Master of Science in Electrical Engineering and Computer Science

in conjunction with the Leaders for Global Operations program

at the

MASSACHUSETTS INSTITUTE OF TECHNOLOGY

June 2023

Authored by: Andrew Mighty
MIT Sloan School of Management and Department of Electrical Engineering and Computer Science
May 12, 2023

Certified by: Arnold Barnett
George Eastman Professor of Management Science
Professor of Statistics
Thesis Supervisor

Certified by: Luca Daniel
Professor of Electrical Engineering and Computer Science
Thesis Supervisor

Accepted by: Maura Herson
Assistant Dean, MBA Program, MIT Sloan School of Management

Accepted by: Leslie A. Kolodziejski
Professor of Electrical Engineering and Computer Science
Chair, Department Committee on Graduate Students

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Abstract

The safety of the passengers, crew, and mechanics is of the utmost importance for any aircraft manufacturer or operator. Visual inspections of the exterior of aircraft are critical to their safe operation, as defects such as corrosion, dents, lightning strikes, or missing parts can compromise the structural integrity of the whole aircraft. Currently, aircraft visual inspections are conducted by human mechanics in a process that is not only time consuming, but also puts the mechanics and the aircraft at risk, as mechanics must use lifts and cranes to inspect top portions of the aircraft, while at times even walking along the wings and spine. Throughout this process, paper records are maintained to document inspection findings, often without standard processes and dedicated equipment for capturing the current state of aircraft damage through imagery.

In an attempt to improve the safety, record management, and time required of this process, we developed an approach to the inspection process using autonomous small unmanned aerial systems (SUAS) to capture the required inspection imagery. This approach also implements the use of a computer vision model to process the inspection imagery, aiding the mechanic in the review of imagery and identification of inspection findings. During this process, we analyzed the effects of computer vision and machine bias on the human inspectors and inspection accuracy, recommending processes to mitigate these effects and maintain inspection accuracy equivalent to the current human-only process.

Thesis Supervisor: Arnold Barnett
Title: Professor of Management Science

Thesis Supervisor: Luca Daniel
Title: Professor of Electrical Engineering and Computer Science

Acknowledgements

I would first like to thank Boeing and the Applied Innovation team for hosting me during this internship, and for welcoming me into their family. I owe particular gratitude to Ayal Somech and Hayden Shea as my supervisors, Charles Coccia as my sponsor, and the larger LGO community wihin Boeing for their help and support.

I would also like to thank Arnold Barnett and Luca Daniel for advising me throughout this project and in the thesis writing process. Their guidance help me navigate the difficultly of connecting technical approaches with business applications. Broader thanks goes to those who have helped me throughout my time in the LGO program.

Most importantly, I would like to thank my parents Janet and Hugh, my brothers Matthew and Hugh Edward, and my companion Izzy. Without their continued support, none of this would have been possible.

Contents

List of Figures

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List of Tables

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Acronyms

AAI Assisted Autonomous Aircraft Inspection. 6, 16, 17, 19, 33, 35–38, 41–45, 50, 57, 61

AMM Aircraft Maintenance Manual. 27, 30, 37, 38

COTS Commercial Off the Shelf. 15

DoD Department of Defense. 14, 35, 36

EASA European Union Aviation Safety Agency. 41

EO electro-optical. 15, 35, 58, 59

FAA Federal Aviation Administration. 30, 41

GPS Global Positioning System. 15, 35

GVI General Visual Inspection(s). 5, 16, 30, 31, 35, 37, 38, 44, 47

IR infrared. 15, 35

LiDAR Light Detection and Ranging. 15, 35, 38

MRO Maintenance, Repair, and Operations. 41, 61

MSG-3 Maintenance Steering Group-3. 31

NDAA National Defense Authorization Act. 6, 35, 36

NDI Nondestructive Inspection(s). 13, 14, 19, 58

OEM Original Equipment Manufacturers. 30, 35, 41, 61

RVI Remote Visual Inspection(s). 14–16, 19, 31

simCLR Simple Framework for Contrastive Learning of Visual Representations. 48
sUAS Small Unpiloted Aerial System(s). 5, 13–17, 19, 21, 23–25, 33, 37, 38, 41–46, 49–52, 54, 57–59, 61

UAS Unpiloted Aerial System(s). 5, 14, 15

Chapter 1

Introduction

This chapter provides context to the reader regarding automation in the aviation industry and Nondestructive Inspection(s) (NDI) technology platforms to include Small Unpiloted Aerial System(s) (sUAS). Additionally, this chapter details the project approach and outlines the organization of this thesis.

1.1 Nondestructive Inspection Techniques

Nondestructive Inspection(s) (NDI) are defined as inspection methods to detect discrepancies, abnormalities, or defects in characteristics without adversely affecting the specimen.[8] The ability for organizations to conduct Nondestructive Inspection(s) of their assets is critical to maintaining operational excellence. The conduct of inspections without the requirement of disassembling or changing the structural integrity of the asset allows organizations to preserve operational efficiency through the reduction of time and costs associated with inspection processes. Two of the most common NDI techniques are thermography and visual.

Thermography is the NDI method of measuring the thermal radiation of the surface of an object.[8] When the structural integrity of a surface has been altered, there are differences in the thermal signature across the surface. This method of inspection is useful for detecting anomalies such as dents, cracks, corrosion, and other structural damages, especially of sizes which may be too small to be reliably recognized during visual inspection processes.

During visual inspections, personnel use their eyes, or are aided by a visual medium such as cameras to identify potential discrepancies and defects. Within this category of NDI techniques is Remote Visual Inspection(s) (RVI). Remote Visual Inspection(s) (RVI) implement the use of remote systems in order for personnel to acquire imagery of the inspection object without the requirement to be physically present in the space. RVI platforms include fixed cameras within the inspection location, wire guided camera systems, ground based rovers, submersible vehicles, and most commonly Small Unpiloted Aerial System(s) (sUAS).

There are multiple benefits to the use of RVI platforms to include decreased risk to personnel, conservation of time and resources, information sharing, and record management. RVI systems are able to reach areas that traditionally are difficult for human personnel to access or require additional equipment due to the increased risk. The use of RVI platforms to access these areas not only decreases the risks to personnel, but also decreases the time required to conduct the inspection as it negates the requirement for the setup and use of additional heavy equipment. Beyond the collection of information for the inspection process, RVI increase the efficiency of the data process and data management phases of an inspection, allowing for digital imagery to be disseminated to the appropriate subject matter experts rather than requiring their physical presence in the inspection facility, and through standardization of inspection discrepancy documentation and reporting.

1.2 Unpiloted Aerial System(s) (UAS) Technology

Unpiloted Aerial System(s) (UAS) are most commonly known for their uses within the military, for tasks such as intelligence surveillance and reconnaissance, logistics, and direct strike. As technology continues to advance, UAS have been designed and produced in multiple sizes, ranging from as small as the palm of a hand to platforms that weigh over 32,000 pounds. The Department of Defense (DoD) has classifies the different UAS Groups according to 1-1

UAS Classification Groups			
UA Category	**Maximum Gross Takeoff Weight (lbs)**	**Normal Operating Altitude (feet)**	**Speed (KIAS)**
Group 1	0-20	<1200 AGL	100 knots
Group 2	21-55	<3500 AGL	<250 knots
Group 3	<1320	<18,000 MSL	<250 knots
Group 4	>1320	<18,000 MSL	Any Airspeed
Group 5	>1320	>18,000 MSL	Any Airspeed

Figure 1-1: DoD UAS Category Classification Table [8]

Further analyzing the components that comprise UAS platforms, the term payload is used to described any additional capacity and weight carried by the drone that is not the weight of the drone itself. Common payloads include weapons systems, sensors such as lasers, cameras - typically electro-optical (EO) and infrared (IR), and autonomous navigation systems. The most prevalent autonomous navigation systems currently in use include Global Positioning System (GPS), camera guided, and Light Detection and Ranging (LiDAR).

Outside of the military use cases, another grouping of Small Unpiloted Aerial System(s) (sUAS) systems known as Commercial Off the Shelf (COTS) systems has emerged. COTS systems are commercial manufactured and sold systems by private companies and made available to public buyers. The availability of COTS systems provide other industries the opportunity to experiment with and implement drone systems into their operational processes COTS companies such as DJI, Parrot, and Skydio offer systems of various sizes and capable of carrying multiple different payload configurations, allowing individual users and organizations to customize systems to meet industry specific needs at a relatively low cost, with most systems ranging from $200 - $5,000. The prevalence and adaptability of Commercial Off the Shelf (COTS) systems is a driving factor into the increased exploration of Remote Visual Inspection(s) (RVI) techniques to include Small Unpiloted Aerial System(s) (sUAS) aided inspection processes.

1.3 Project Approach

The objective of this project is the exploration of an alternative means of conducting exterior aircraft General Visual Inspection(s) (GVI) through the use of autonomous sUAS for the collection of inspection imagery and machine learning damage detection models for the processing of imagery and identification of inspection findings. Areas of improvement between current processes and technology aided processes are identified along with technological, organizational, and regulatory requirements for the development of an Assisted Autonomous Aircraft Inspection (AAI) program. Significant consideration in this work focus on the human factors implications of introducing additional technological advancements into aircraft inspection processes with emphasis placed on the effects of machine bias on inspection personnel. We discuss the implications of the implementation of technology systems into aircraft inspection processes and provide recommendations for their use while maintaining the quality and accuracy required to complete a successful inspection.

1.4 Thesis Organization

This thesis is organized into seven chapters which further expand on Remote Visual Inspection(s) (RVI) processes in multiple industries, exploration of alternate aircraft inspection processes utilizing sUAS, the implementation of machine learning models for damage detection software, the impacts the use of technology has on human factors, and culminates with a discussion of the overall effectiveness of the project's goals and results.

Chapter 2 comprises the literature review, detailing previous work related to this thesis to help provide the audience the required contextual information. Areas covered in this chapter include other industries currently implementing drone based inspection processes, work previously completed on drone based inspections in the airline industry, and the human factors introduced through the introduction of a technical medium in inspection processes.

Chapter 3 discusses the different types of aircraft inspections and their requirements before concluding with an overview of the current inspection and maintenance processes implemented by inspection personnel and aircraft mechanics.

Chapter 4 focuses on the actions required to develop and test an AAI platform from the technological considerations for designing and selecting a sUAS platform and flight testing to regulatory considerations. This chapter concludes by detailing the Assisted Autonomous Aircraft Inspection (AAI) workflow.

Chapter 5 covers the unique considerations and focus areas that the Assisted Autonomous Aircraft Inspection (AAI) process seeks to improve, specifically in the areas of quality and accuracy, safety, time and resource availability, and record keeping and data exploitation.

Chapter 6 considers the human factors considerations created by the introduction of technology platforms into the aircraft inspection process. We focus on the implementation of machine learning models as an assistive tool for the identification of inspection discrepancies and the effects of machine bias on inspection personnel.

Chapter 7 discusses the findings of this effort in summary as well as additional work to be explored to improve the processes and functions discussed. This chapter concludes with a broader sentiment and perspective on the use of sUAS platforms and machine learning to modernize and improve aircraft inspection processes as a component of the "Smart Hangar" concept.

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Chapter 2

Literature Review

This chapter provides context to the reader regarding previous work towards the use of sUAS as a platform to conduct NDI across multiple industries to include the aviation industry. As previously described, this paper seeks to outline the requirements and process flow for Assisted Autonomous Aircraft Inspection (AAI) implementation, as well as the potential effects of machine bias on inspection personnel. As such, this chapter also provides the relevant context to work relating to the study of human factors .

2.1 Industries Employing Remote Visual Inspections

Remote Visual Inspection(s) (RVI) technologies have the potential to revolutionize multiple industries. Ground rovers and sUAS, commonly referred to as drones, are capable of performing a wide array of inspection related tasks that humans are not always well suited for, such as structures of extreme heights, small tunnels and piping, or underwater structures. The use of RVI technologies for tasks such as these reduces the risk to human personnel while capturing digital inspection records that help increase analytical assessment and regulatory compliance. In recent years, multiple industries have adopted the use of RVI systems to conduct non-destructive inspections. The current list of industries employing these techniques includes inspection and monitoring of power infrastructure, inspection and monitoring of renewable energy equipment,

Figure 2-1: Aerial Inspection Use Cases [8]

monitoring of buildings and urban planning to include roadway inspections, monitoring of archeological and cultural heritage sites, inspection of agriculture, inspection of bridges, inspection of construction sights, inspection of mining facilities, and inspection of telecommunications towers and wiring. [8][6] [4] [5] [12][11][10][9][2][3] Two of the industries with the greatest advancements in the implementation of aerial systems in inspection processes are bridges and energy systems.

2.2 Bridge and Structure Inspection Literature

Bridges, roadways, and building structures are all critical pieces of infrastructure that require regularly inspection in order to ensure their safe operation. Similar to aircraft inspections, these pieces of infrastructure are routinely inspected in order to determine their continued safe operational use, comparing inspection reports to their original condition or previous structure reports. Due to their size, length, and abundance, these inspections require significant amounts of labor hours and can incur significant costs. These two factors led industry professionals to implement the use of sUAS platforms into inspection processes to reduce costs and improve inspection results through technological improvements.[2]

In addition to the use of sUAS systems for the collection of imagery for the conduct of bridge inspections, the bridge development and inspection industry has further advanced the technology for the use of developing 3D models of structure through photogrammetry or the use of spatial point clouds developed from data obtained using laser payloads.[2][10]

One methodology used for the sUAS inspection of bridges designates three specific phases: data collection and model training, 3D construction, and damage identification and analysis.[3] During the first phase, data collection and model training, is further refined into sub-components of conduct test flights of drone systems, collection of imagery at regular intervals, data labeling of imagery containing cracks and damages, and identification of findings with bounding boxes before using this data to train the damage detection model. In the second phase of this methodology, a 3D model of the structure is created through a process called photogrammetry, creating of a 3D model from 2D imagery using spatial data and image stitching. The 3D model serves as a record of the inspection process and current state of the structural integrity, giving inspection personnel a singular model which contains all of the findings of the inspection. During the damage identification phase, a data set is created compiling the imagery containing bridge damage findings. This dataset is further used to train the machine learning model for future inspections of structures.[3]

Additional methodologies developed propose a five stage approach inspection process broken down into bridge information review, site risk assessment, drone pre-flight setup, drone-enabled bridge inspection, and damage identification.[11]

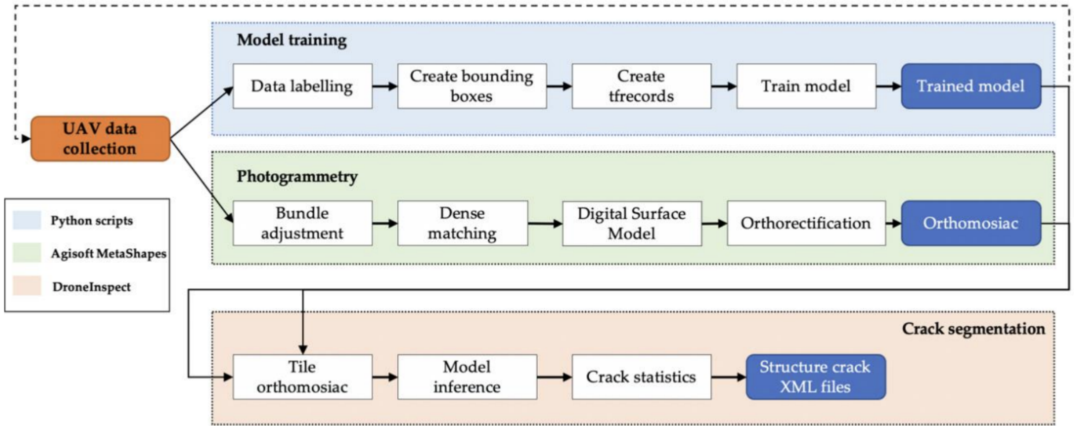

Figure 2-2: sUAS Bridge Inspection Methodology[3]

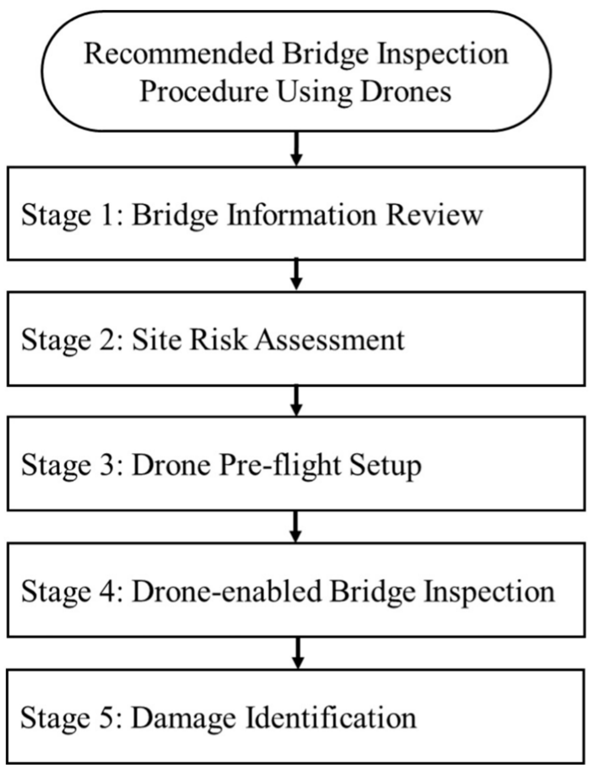

Figure 2-3: Bridge Inspection Process Flow [11]

2.3 Energy Sector Inspection Literature

In recent years, the emergence of clean and alternative energy sources have redefined the energy sector due to rising concerns around climate change and government initiatives to combat the negative environmental effects associated with traditional energy sources. Two of the biggest technologies implemented as alternative energy sources are wind turbines and solar farms. The vast areas of land covered by solar farms and the extreme height of wind turbines paired with their austere locations require industry personnel to redesign the way in which equipment inspections are conducted in order to decrease the risk to personnel and reduce the costs associated with maintaining equipment, leading to the emergence of sUAS platforms as a primary inspection medium. Previous work conducted on the use of sUAS platforms for the inspection of wind turbines is critical to understanding the implications of implementing similar processes for the inspection of aircraft. The structural components of wind turbines and the environments in which they are deployed causes damages and inspection findings similar to those discovered during aircraft inspections to include, cracks, denting, erosion, peeling, and pit corrosion.[5]

2.4 Aviation Inspection Literature

Previous literature and work on the use of Small Unpiloted Aerial System(s) (sUAS) platforms for inspections in the aviation industry predominantly focuses on use cases for civil aviation and small aircraft, due to their availability to researchers, as well as the smaller sizes of these aircraft which require simpler sUAS platforms and fewer resources. One such work examines the use of sUAS platforms for the conduct of preflight inspections. Work analyzing pre-flight inspection processes put significant emphasis on safety and quality procedures required to conduct a successful sUAS data collection phase. These factors include defining the inspection environment - determine outdoor or indoor location will have an effect on environmental considerations as well as potential collision obstacles, sUAS flight path planning - emphasizing the

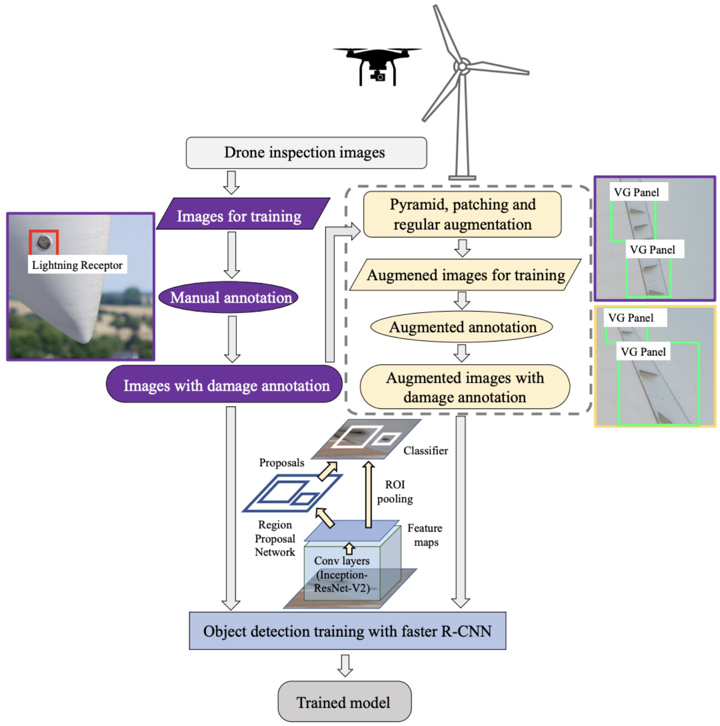

Figure 2-4: Wind Turbine Inspection Process Flow[12]

importance of determining sUAS trajectory and image capture intervals to ensure complete coverage of the aircraft, and safety precautions - including the development of sUAS restricted flight parameters to prevent collision with the aircraft.[4]

Along with providing frameworks for sUAS based inspections, other works study the limitations of implementing sUAS technology based inspection approaches. Many of the limitations discussed are based around the sUAS platform specifications. Since these platforms are designed to be small and lightweight, there are limitations to the size of the payload they are capable of carrying, and therefore the light compact cameras used have resolution limitations. Payload limitations also negative impact the flight operations of the platform, as the smaller battery systems used for power have shorter flight durations. The small and light weight nature of these platforms also make them susceptible to environmental factors which limits the locations and conditions in which they can be employed.[6] Other categories of limitations include those associated with regulatory compliance, as there are strict procedures required for the use of sUAS platforms, specifically within and around airports which have

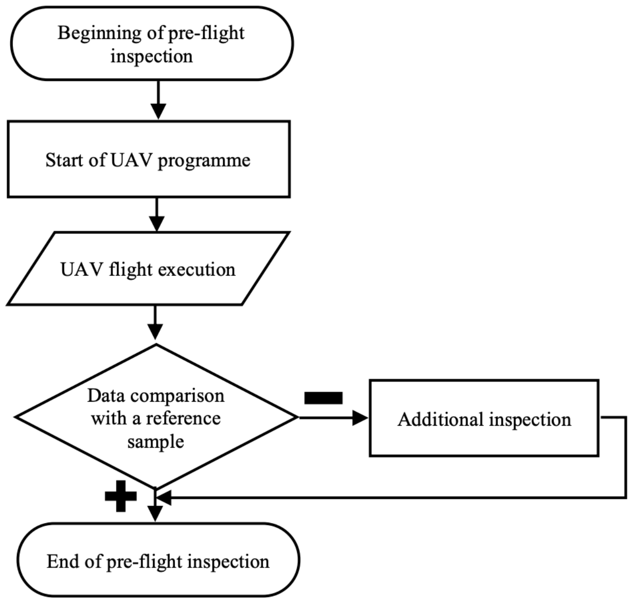

Figure 2-5: Pre-flight Inspection Process Flow[4]

historically been no-fly zones. Despite these limitations, multiple advantages still exists which make sUAS assisted aircraft inspections an appealing solution, such as the requirement for only one ground based inspector, low costs, real time data acquisition and evaluation, and digital data storage.[6]

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Chapter 3

Aircraft Inspections

This chapter discusses the different types of aircraft inspections and their requirements before concluding with an overview of the current inspection and maintenance processes implemented by inspection personnel and aircraft mechanics.

3.1 Current Inspection and Maintenance Processes

Current aircraft inspection and maintenance process can be broken down in five distinct phases: preinspection, inspection, services and repairs, functional checks, and validation and return to service.

Preinspection. During the preinspection phase, inspection personnel and mechanics designate the required level of inspection required based on flight hours and aircraft operation history. The appropriate aircraft inspection task cards are selected, and the required paperwork is completed. This phase also includes the designation of required facilities, equipment, and personnel to complete the inspection process.

Inspection. During the inspection phase, inspection personnel utilize inspection task cards to guide them through the inspection process, determining the areas of the aircraft to be covered, the required level of detail, and approved tools to be used during the process as outlined in the Aircraft Maintenance Manual. Depending the inspection type, this process can range from visual inspection of exterior components and surfaces with the human eye aided by minor magnification equipment to processes that require

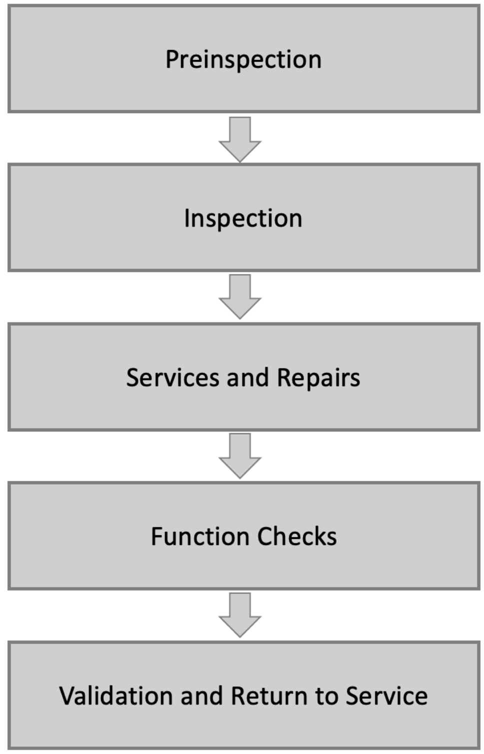

Figure 3-1: Current Inspection Process Flow

the removal of components of the aircraft for more detailed inspections. All inspection results, to include findings and discrepancies are recorded on the designated forms and submitted as part of the final inspection report. Specific defects and discrepancies may require the consultation of structural experts to determine the extent of the damage and requirement for further service and repair. The final inspection report outlines the following services and repairs required to certify the aircraft for further operations.

Services and Repairs. The services and repairs portion of the process is focused on the resolution of any discrepancies and findings from the inspection phase which are required to certify the aircraft for continued operations. The extent of repairs required determines the duration of this phase and the specialized personnel required.

Functional Checks. The repair or replacement of parts during the Services and Repairs phases requires further inspection and testing to validate the appropriate corrective actions have been taken before certifying the aircraft for further flight. Functional checks are the process are ensuring the appropriate function of the aircraft following these corrective service actions.

Validation and Return to Service. Following the completion of functional checks and the certification of appropriate maintenance procedures, the results of the inspection and repairs are certified by the appropriate authoritative body, clearing the aircraft for return to service and continued flight operations.

3.2 Types of Aircraft Inspections

Aircraft Inspections are designated into two main categories: scheduled and unscheduled inspections. Scheduled inspections are those which are mandated by a regulatory body at predefined intervals based on flight hours and/or calendar months to certify that the aircraft's current condition is equal to its original or approved modification condition with regards to structural integrity and aerodynamic function.[1] The determination of these regularly scheduled inspection intervals depends on the size of the aircraft and its intended use. The level of detail included in inspections is also determined by the number of flight hours that have been flown since an inspection of equivalent quality was performed. Another type of scheduled inspection is the preflight inspection, often involving the flight and/or ground crew walking around the exterior of the aircraft and inspection of flight controls and systems to certify airworthiness.

Unscheduled inspections occur when an event happens which creates a cause for concern of a potential malfunction of the aircraft or a specific part, or following a malfunction occurrence. Causes for these types of inspections can be related to issues created by damage caused by adverse weather experienced during a recent flight, or an issue discovered during a regularly scheduled inspection for a specific part produced by a manufacturer or supplier .

Table 3.1: Aircraft Scheduled Inspections

Letter Check	**Frequency** (dependent on type of aircraft)
A-Check	300-600 flight hours
C-Check	3,600 - 6,000 flight hours (or 15-18 months - whichever occurs first)
D-Check	25,000 flight hours (or 5-6 years - whichever occurs first)

3.3 Aircraft General Visual Inspection(s) (GVI) and Detailed Inspection

In order to ensure the continued health and safe operation of an aircraft, the Federal Aviation Administration (FAA) mandates the implementation of aircraft maintenance programs which include various levels of scheduled and unscheduled visual inspections. The timing and thoroughness of these inspections are to be determined by the operational frequency of the aircraft, and the findings from previous inspections. Following this guidance, Original Equipment Manufacturers (OEM), such as Boeing, develop specific Aircraft Maintenance Manual (AMM) and other relevant maintenance documents for their aircraft detailing the maintenance procedures required, the frequency of inspection occurrences, and qualified tools to be used in the conduct of the inspections. Scheduled inspections are commonly referred to by "letter checks" ranging from A-Check, least invasive to the aircraft and the fewest amount of required maintenance hours, to D-Check, the most invasive and highest maintenance hours required. Common ranges for the flight hours and aircraft service times associated with letter check inspections are included in 3.1.

One of the procedures associated with all aircraft scheduled maintenance occurrences is a visual inspection of the exterior of the aircraft. The FAA Advisory Circular 43-204 states the purpose of visual inspections as:

- Provide an overall assessment of the condition of a structure, component, or system.
- Provide early detection of defects before they reach critical size.

- Detect errors in the manufacturing process.
- Obtain more information about the condition of a component showing evidence of a defect.[1]

During visual inspections, inspection personnel identify and record airframe defects. Typical airframe defects found to include cracks, corrosion, disbanding, component wear, accidental damage, and environmental damage. One utilized form of visual inspection to identify such defects is the General Visual Inspection(s) (GVI). The general visual inspection is defined in documentation published by Maintenance Steering Group-3 (MSG-3) as a visual examination of an interior or exterior area, installation or assembly to detect obvious damage, failure or irregularity, made from within touching distance and under normally available lighting condition such as daylight, hangar lighting, flashlight or drop-light.[7] General Visual Inspection(s) have historically been conducted by human inspectors with RVI aids due to the requirement for the GVI to be conducted from within touching distance of the aircraft. Advancements in technology over recent years however have led to experimentation with the use of RVI platforms due to their perceived decrease in risk to inspection personnel, ease of use and decreased inspection time, ability to reach difficult inspection locations, and increased digital inspection record management.

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Chapter 4

Developing an Assisted Autonomous Aircraft Inspection Program

This chapter outlines the technical and regulatory requirements for developing an Assisted Autonomous Aircraft Inspection (AAI) program. Specifically, technical requirements cover the design considerations and testing of Small Unpiloted Aerial System(s) (sUAS) platforms before discussing regulatory considerations, and concluding with a proposed process flow for the conduct of sUAS aided inspections.

4.1 Small Unpiloted Aerial System(s) Platform Selection

The major platform specifications for consideration in the selection of a sUAS for the employment in the AAI process include: size and weight, flight time, payloads, navigation technology, country of origin.

4.1.1 System Size and Weight

The size and weight of the drone system has significant operational implications. Drones of larger sizes are capable of carrying larger payloads and sustaining longer flight durations. These benefits come at a cost however, as they have larger storage requirements, may require alternative fuel sources to battery power, and have the potential to require longer preflight and more complicated maintenance procedures. Systems of larger sizes also increase the requirement for additional equipment and personnel for the transportation, setup, and operation of the platform. Additional equipment and personnel requirements would negatively impact multiple implementation, as the introduction of more machinery, equipment, and personnel presents additional opportunities of injury to inspection personnel and aircraft, increasing safety concerns. This would also negatively impact time and resource availability, as inspection processes continue to be dependent on the availability of additional heavy machinery. The size and weight of the drone system also affects the operational environment in which the drone can be flown. Platforms of larger sizes are more resistant to the effects of weather such as wind on their operations, but are also limited in their ability to operate within indoor spaces such as aircraft hangars due to maneuverability and safety standoff distance requirements.

The desired system for an assisted autonomous aircraft inspection program needs to be large enough to carry multiple payloads to include at a minimum, a camera to capture imagery, an onboard computer for processing, and sensors for autonomous navigation. It is also desirable to have a system that is small enough that it can be easily moved between hangar facilities and aircraft without the requirement of additional equipment or personnel, and the potential to be stored on the aircraft with minimal space requirement. While hangar operations are the intended initial operating environment for drone inspections due to the ability to close off the facilities, putting a physical barrier between the drones and flight line operations, alleviating one of the major safety considerations of interruption to airfield operations, it is not unimaginable that these systems will be desired for outdoor use by airlines and operators in order to conduct preflight and post flight inspections directly at the gate. Considering these future evolutions of drone based aircraft inspections in an outdoor environment, the platform needs to be large enough to withstand moderate weather effects while flying repeatable flight paths and capturing high quality imagery. The planned conduct of outdoor operations also makes the use of tethered platforms an undesirable power source. Drone systems used for aircraft inspections are desired to be capable of operating off of battery power, with a flight time long enough to complete a full inspection. If such a flight time is infeasible when considering additional size and weight requirements listed above, the platform needs to be capable of battery replacement operations without the requirement to power off the system and conduct preflight procedures after each battery change.

4.1.2 Payload Configuration

The payloads included on the drone platform determine the quality and accuracy with which it is capable of conducting the data capturing phase of the inspection process. There are multiple navigation payloads available to be utilized in the autonomous navigation of drone systems to include cameras, LiDAR, and GPS. Each of these has varying levels of accuracy and environmental limitations for operations. Along with navigation payloads, drones can be equipped with multiple other sensors to aid in the capturing of data and imagery for the inspection process. The most common sensors that are attached to drones for image capturing are electro-optical (EO)l and infrared (IR) cameras, capable of capturing photos in different lighting as well as capturing full motion video. Less frequently used, but potentially relevant for the aircraft inspection use case due to the lighting condition requirements for a GVI, is an artificial lighting source payload to allow for the conduct of inspections in low light environments.

The desired payload attachments for an AAI drone system include a LiDAR navigation suite to allow for operations in GPS denied environments such as aircraft hangars, and an EO camera capable of capturing still and full motion video.

4.1.3 National Defense Authorization Act (NDAA) Compliance

As part of their business structure, some Original Equipment Manufacturers (OEM) serve as providers of aircraft to both multiple international commercial airlines, as well as the United States Department of Defense (DoD). Aircraft provided to the

United States Department of Defense for use by the military often contain classified technology that is highly sought after by other non-US nations. The sensitivity of the information captured throughout the inspection process means that any system used to capture, process, and store the data must meet specific guidelines. The National Defense Authorization Act (NDAA) details the requirements for systems that can be purchased by and use on United States DoD equipment and installations. One of the biggest requirements that affects drone manufactures is the requirement that no parts of the systems can be produced by adversarial countries.

The desired system for approval and use in the AAI program meets all NDAA compliance stipulations, allowing it to be used for both commercial and military aircraft inspections without the requirement to design separate systems.

4.2 Flight Testing

4.2.1 Safe Flight Operations Guidelines

The most critical aspect of flight testing is establishing safe flight operations guidelines. Part of these guidelines is the development of the flight path planning process. The flight path takes into consideration a safe standoff distance between the drone, the aircraft being inspected, and other objects within the aircraft hangar in order to avoid collisions. The safe operations guidelines testing phase allows the team members to further refine the drone system requirements. Most importantly is identifying the payload camera performance requirements. The standoff distance required determines the minimum camera performance requirements, as only cameras of specific pixel capabilities will be able to capture the required image resolution for inspections.

Another aspect of developing safe flight operations guidelines includes human considerations. The first being the proximity of humans to the drone and aircraft during the flight inspection process, and the second being determining the number of personnel required to the safe conduct of the inspection process.

4.2.2 Development of Roles and Responsibilities

At a minimum, it is recommended that there are three designated personnel roles for the conduct of the Assisted Autonomous Aircraft Inspection (AAI):

- Pilot - The pilot's sole responsibility during the inspection process is the safe operation of the drone. Although the system is designed to autonomously fly a flight path, the pilot is a trained operator who maintains visual contact with the drone and is prepared to take over manual flight in case of an emergency.
- Safety Operator - The safety operator is responsible for observing the drone and the surrounding environment for any possible signs of collision. Upon observation of such events, the safety office is responsible for notifying the pilot in order to take corrective action.
- Ground Station Operator - The ground station operator observes the images being captured by the drone from the user interface on the ground station. Ideally, the ground station operator has the ability to make minor modifications to the camera angle and focus prior to image capture in order to ensure the quality of inspection imagery and negate the requirement for a re-inspection flight.

Each of these roles requires unique training and certifications in order to ensure the safe and successful execution of the Assisted Autonomous Aircraft Inspection.

4.3 Regulatory Compliance and Policy

Following the completion of sUAS assisted inspection test flights to prove feasibility and determine the equivalency of inspection data to current methods, the following stage is updating policy documents in accordance with regulatory compliance. The Aircraft Maintenance Manual (AMM) details the tasks and procedures for the conduct of maintenance for a specific aircraft. In order for the drone inspection process to become accepted practice, the AMM needs to be updated, detailing the tasks for GVI procedures, utilizing the drone as a tool for the inspection process. In conjunction with the updates made to the AMM, alternative tasks cards are also required for the GVI tasks, detailing the appropriate use of the drone as a tool in the inspection process. An Engineering Substantiation Document is also required, detailing the analysis of the collected data during the testing phase, and analyzing the equivalency of the performance sUAS assisted visual inspection data compared to the manual visual inspection data.

4.3.1 Assisted Autonomous Aircraft Inspection (AAI) Workflow

The assisted autonomous aircraft inspection workflow is detailed in 4-1. The inspection workflow can be broken into three phases: Pre-flight, flight, and post-flight.

Pre-flight- During the preflight phase of the inspection, the inspection environment is inspected for any potential collision hazards, and to ensure appropriate inspection conditions, including lighting. Following the safety check, the ground control station for the drone system is established, and the pilot begins to perform system checks. The successful completion of all system checks ends the preflight phase of the inspection workflow.

Flight - The flight phase begins with a system calibration flight, in order to ensure proper function of the LiDAR navigation system. Following the calibration flight, the system is ground and positioned for the beginning of its inspection flight. At this point, the desired task card and associated pre-planned flight path are selected, and the drone is ready to begin its autonomous flight. During the autonomous flight, the drone captures inspection imagery at the desired waypoints in accordance with the task card. The images are subsequently transmitted to the ground control station for storage, as well as to a designated cloud environment for processing. Following the completion of the pre-planned flight path, the system is grounded, successfully ending the flight phase.

Post-flight - The post-flight phase is highlighted by the processing and analysis

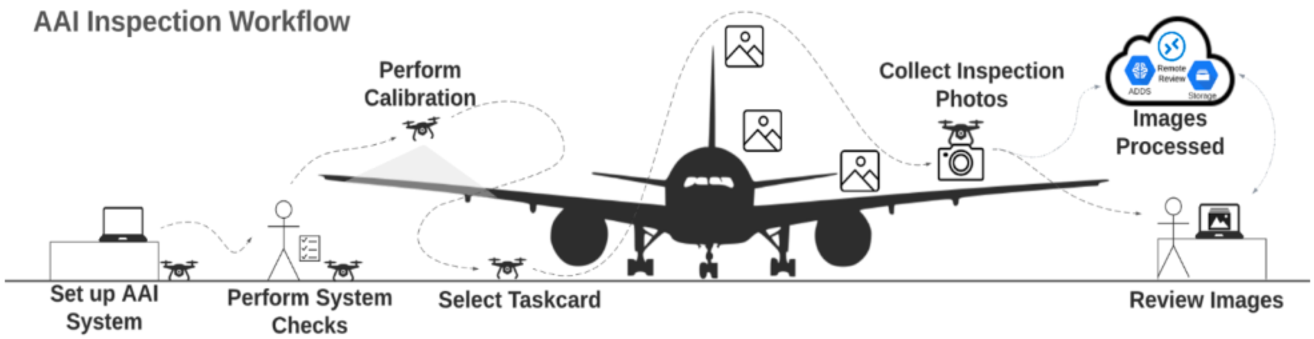

Figure 4-1: AAI Process Flow Diagram

of the data capture during the flight phase. This includes both processing of data by machine learning damage detection models in order to aid inspectors in the identification of defects in the inspection imagery, as well as inspection personnel visually inspecting each photograph. Other activities that may occur during this phase are the transmission of images to personnel specializing in the defect identified, as well as transmission of inspection results to data science specialists in order to identify inspection trends across an airline's fleet of aircraft. The post-flight inspection phase is complete once personnel have visually inspected each photograph and submitted their final inspection report.

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Chapter 5

Considerations and Results

This chapter outlines the key considerations and metrics associated with the aircraft inspection process that the implementation of an Assisted Autonomous Aircraft Inspection (AAI) program seeks to improve. To be a viable solution for adoption and use by Original Equipment Manufacturers (OEM), Maintenance, Repair, and Operations (MRO), and commercial airline providers, the AAI process needs to meet or exceed current inspection processes in the areas of quality and accuracy, safety, time and resource availability, and record keeping and data exploitation.

5.1 Quality and Accuracy

Aircraft inspection processes are highly regulated by organizations such as the Federal Aviation Administration (FAA) and European Union Aviation Safety Agency (EASA), and the use of sUAS in aircraft inspections will require approval from these organizations. Therefore, it is imperative to prove that the Assisted Autonomous Aircraft Inspection process produces equal, if not better, results for quality and accuracy than current inspection processes.

In order to test the equivalency of the Assisted Autonomous Aircraft Inspection (AAI) process, we arranged to have two separate aircraft inspected by separate inspection personnel, using the current manual inspection process, and the drone assisted inspection process, with inspection personnel reviewing the digital images

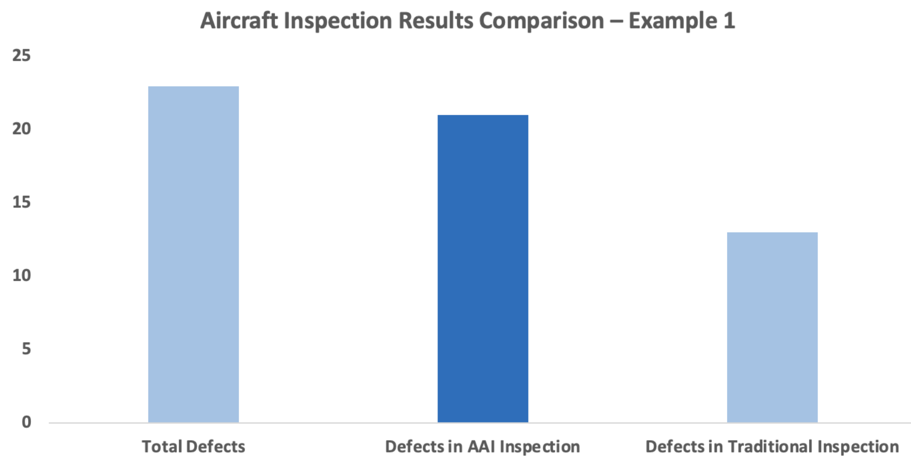

Figure 5-1: Current Inspection Process and AAI Results Comparison - 1

collected by the sUAS. The total number of defects associated with each aircraft was determine by comparing the inspection results gathered during the traditional inspection process and the AAI process, creating an aggregate list of unique defects identified. The results for the two separate aircraft inspections are included in 5-1 and 5-2. In 5-1, the inspector utilizing the sUAS platform outperforms the traditional inspection process, identifying 21 of the 23 total defects on the aircraft, while the traditional inspection process only documents 13 of the 23 total defects. In 5-2 however, the inspector utilizing the AAI process was only identifies 10 of the 19 total defects, while the the traditional inspection process reveals 16 of the total 19 defects.

Although there is a discrepancy between the two sets of inspection results, the results in 5-1 show that the Assisted Autonomous Aircraft Inspection process is capable of exceeding the results provided by current inspection processes. Reviewing inspection imagery in a digital format allows inspection personnel to use computer based tools, such as magnification and image lighting and contrast, to analyze areas of potential defects with a high degree of accuracy. The discrepancy between the two sets of inspection results can be attributed to two major categories, aircraft preparation and inspection personnel training. Comments collected from inspection personnel on the documentation associated with 5-2 highlight the lack of cleanliness of the aircraft exterior as an influencing factor in their final inspection results. While aircraft

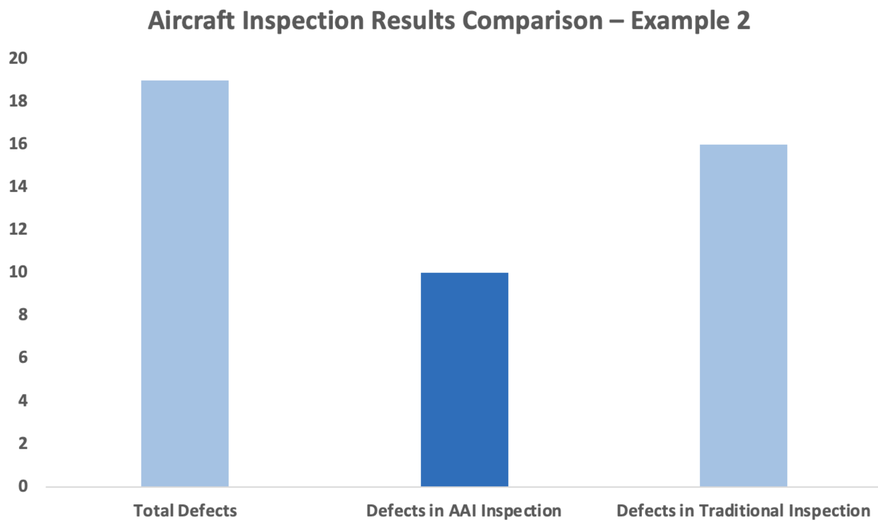

Figure 5-2: Current Inspection Process and AAI Results Comparison - 2

cleanliness is less problematic under traditional inspection process, where individuals are able to touch the aircraft to determine whether an area of interest is a defect such as a scratch rather than simply dirt or residue, inspectors utilizing the AAI process do not have the same luxury when reviewing imagery. Excess dirt and debris on the aircraft while the drone captures imagery creates additional noise that inspection personnel must sift through when reviewing imagery, making it difficult to discern inspection defects. Ensuring strict adherence to pre-inspection cleaning protocols is critical during the AAI process, as it reduces the noise within the imagery and therefore decreases the cognitive load on the inspection personnel.

Along with the lack of aircraft exterior preparation, the lower AAI process results associated with 5-2 can also be attributed to inspection personnel training and lack of process familiarity. During this data collection phase, inspection personnel received minimal training on the use of the AAI process prior to conducting the inspection, as no formal training program currently exists for these new processes. Inspection personnel also have varying degrees of familiarity with drone platforms and computer based technologies. The establishment of a formal training program and additional experience with the sUAS platform and user interface will likely increase overall inspection results associated with the AAI process.

5.2 Time and Resource Availability

Traditional GVI are a time consuming process that can require an aircraft to remain inside of a hangar for multiple days, as personnel wait on the proper lift equipment that may be in use for other maintenance operations, or as inspectors wait on specialists to examine and record specific defects discovered during the inspection. A key metric of consideration for the success of the implementation of Assisted Autonomous Aircraft Inspection will be the effects on resource availability. The use of sUAS in aircraft inspections seeks to increase the availability of hangar and other inspection resources, through decreasing the time required to conduct inspections. Assisted Autonomous Aircraft Inspection have the potential to decrease the time to conduct aircraft inspections through eliminating the reliance on heavy machinery, the use of drone capture imagery as the inspection medium, and allowing for the digital sharing of imagery with damage specialists.

During the inspection associated with 5-2, we also arranged to collected data related to inspection time required to complete inspections under current processes and inspections utilizing the AAI process. To determine inspection time requirements under the current inspection process, we use the standard time and personnel required listed on the inspection task cards. Eight task cards in total were used to conduct the inspection. Six of the task cards require three people for the inspection execution, and list the inspection time required as 1.23 hours, totaling 3.69 labor hours each for the completion of these six task cards. The two remaining task cards require one person for the inspection execution, and list the inspection time required as 0.9 hours, totaling 0.9 labor hours each for the completion of these two task cards. In total, the eight task cards require 23.94 labor hours for the completion of all inspection requirements. To determine the total time required to complete the inspection utilizing the AAI process, we calculate the time required for image capture by the sUAS and the time required for image review by inspection personnel. The completion of the image capture for the eight task cards required 2.73 flight hours. During the 2.73 flight hours, the sUAS platform, captured 335 total images. The image capture process requires two personnel, one pilot and one safety operator, totaling 5.46 labor hours. The image review process for all 335 images required 2.15 hours, and was conducted by a single inspector, totaling 2.15 labor hours. In total, the eight task cards require 7.61 labor hours for completion of all inspection requirements utilizing the AAI process. In an inspection flight tests consisting of eight task cards, totaling nearly 24 total labor hours utilizing current inspection process, the sUAS inspection process led to a completed inspection in a time of 7.61 labor hours, leading to a 68% reduction in inspection time requirements.

5.3 Safety

There are multiple perceived benefits to the use of sUAS systems to conduct aircraft inspections for both inspectors and the aircraft themselves. The use of drones alleviates the requirement for inspection personnel to use lifts and other heavy machinery to inspect the topside of aircrafts and other difficult to reach areas. This diminishes the risk of injuries from falls and operating heavy machinery, as well as the potential for accidents with heavy machinery making contact with the aircrafts themselves, causing damage to the airframe.

Although there are clear safety benefits to the successful implementation of an Assisted Autonomous Aircraft Inspection process, there are also additional safety concerns that the implementation of sUAS causes. Similar to the current process, there are risks to inspection pesonnel and aircraft caused by the potential for sUAS making contact with inspectors and mechanics in the vicinity of the aircraft, and the sUAS making contact with the aircraft, causing damage to the airframe. Unique to the use of sUAS technology in the inspection process are safety concerns associated with the drone systems interfering with flight line operations due to platforms being intercepted and controlled by bad actors, or autonomy technology failing allowing the sUAS to deviate from the flight plan. Similar to inspection quality and accuracy considerations, the use of sUAS in the inspection process should not increase the risk of harm to the inspections and the aircraft, to include implementing proper safeguards and mitigation procedures to ensure there is no potential impact to flight line operations.

5.4 Record Keeping and Data Exploitation

Multiple organizations still utilize paper records for aircraft inspections and lack standardized procedures for the documenting of inspection results and defect findings through imagery. The lack of a uniform dataset puts organizations at risk of not being compliant with inspection record keeping requirements and makes it difficult to further use the valuable data gathered during inspections to further refine and improve maintenance procedures and aircraft performance. sUAS imagery captured during the inspection process has the potential to improve upon multiple aspects from data collection, to data storage, and finally data exploitation. The use of preplanned and preapproved flight paths that ensure complete coverage of the aircraft during the inspection process creates standardized data collection procedures. The standardized collection and storage on a digital platform will increase recording keep procedures, allowing for greater organization and maintenance of historical records. Standardized digital records will ultimately allow organizations to use collected data in multiple new ways, such as identifying historical maintenance trends associated with specific aircraft or flight routes, allowing for preemptive maintenance to increase the availability of aircraft.

Chapter 6

Damage Detection with Machine Learning

6.1 Human Factors

The use of drone platforms, digital imagery inspections, and machine learning models, introduces multiple human factors considerations that do not currently exist in the manual visual inspection process.

The most notable change for inspectors is the change in the primary medium of inspection from the physical aircraft to digital imagery of the aircraft. Although the use of drones and digital imagery in the aircraft inspection process has proven to decrease the time required to conduct a GVI, it also significantly increases the time required for inspectors behind a computer screen. In the manual visual inspection method, the inspector's eyes are afforded a break from constantly scanning the aircraft for defects, as they move from section to section, and as lift equipment is repositioned. In the assisted autonomous inspection process, inspectors are expected to analyze anywhere from 500 images to 1500 images. This has the potential to cause increased fatigue on the inspector in the attempt to identify defects that may be as small as a few centimeters in size. Without a well designed user interface, containing a reference map displaying the progress of the inspection, and the location on the aircraft of the images, there is a risk for a decrease in inspection quality.

The conduct of inspections through a digital medium has the potential to negatively affect the performance of inspectors, as they are not able to use their other senses, such as touch, in order to feel and validate what their eyes are seeing. During these uncertain circumstances, the aircraft is always available to inspectors in order to confirm suspected defects before submitting the final report. Although the immediate use of touch in the inspection process is removed during the digital image review, these inspections are increased by certain digital aids, such as the ability to magnify imagery, quickly disseminate imagery to other inspectors for review, and the use of machine learning models to assist in the identification of defects.

6.2 Computer Vision Model Implementation and Process

There are two common methods for the use of computer vision models in assisted inspection processes. The first is the use as a preprocessing function, prior to human imagery review in an attempt to identify discrepancies within the imagery based on a robust library of training data. The second method is implementing models such that they compare the imagery of the most recent inspection to that of a baseline or the previous inspection, identifying any changes between the two sets of images. Due to difficulties associated with being able to inspect the same aircraft on multiple occasions because of maintenance schedules, and expressed interests from stakeholders, we tested a developed computer vision as a preprocessing feature, to identify discrepancies in inspection imagery based on a training set of collected aircraft inspection findings.

The model used to test the possibilities of machine bias on human inspectors was based on the open source Simple Framework for Contrastive Learning of Visual Representations (simCLR) model and trained on two thousand inspection images. The model output applies a grid overlay to the imagery with associated percentages indicating the model's confidence that there is a defect located within the section of the image. To simplify the overlay and reduce clutter, confidence scores under 50% are

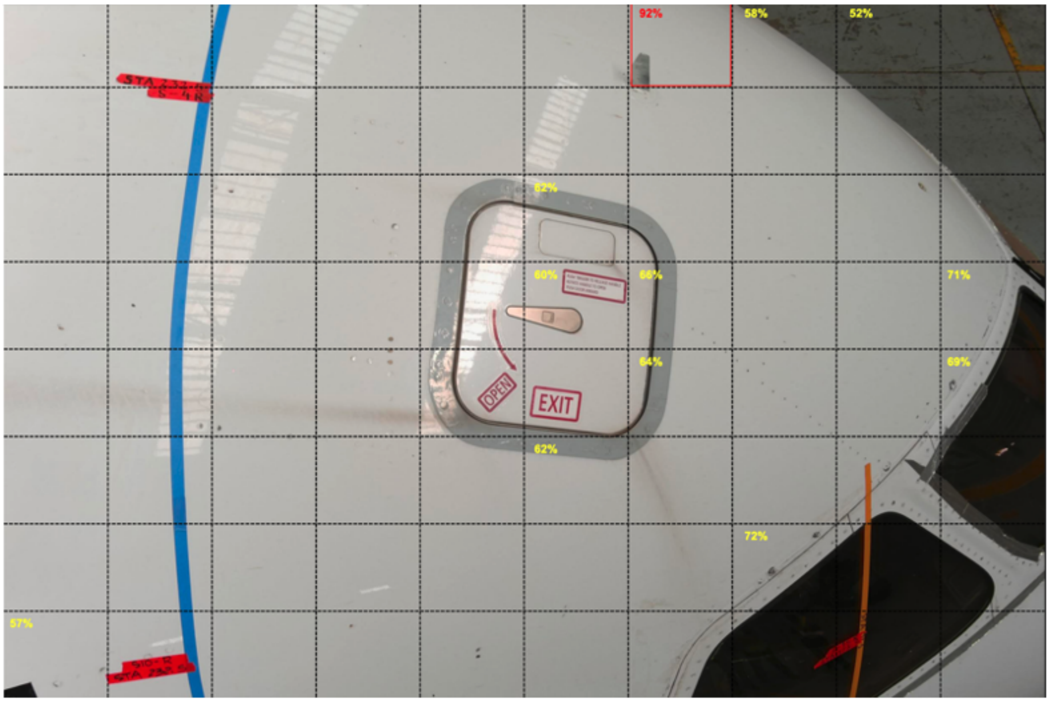

Figure 6-1: Damage Detection Model Output

omitted, 51%-75% are annotated in yellow to identify areas of moderate confidence, and 76%-99% are annotated in red to identify areas of high confidence of an inspection finding. The grid system was chosen during this test to provide inspectors with a systematic method for reviewing images and counter the human inclination to focus on a single point or few specific identified points within the image.

6.3 Machine Bias

The most critical human factors considerations are those related to the use of machine learning models in the inspection process, and the potential effects of machine bias on the inspectors. In order to assess the effects of machine bias on inspectors, four independent experienced professionals conducted an aircraft inspection using the different methodologies mentioned throughout this paper. One individual carried out the inspection using the traditional processes of maneuvering about the aircraft, inspecting the exterior frame at no more than an arms distance. A second individual conducted the inspection through imagery collected by the sUAS, but independent of the machine learning model. The final two individuals conducted their inspection of the sUAS collected imagery following the processing and annotation by the machine learning model. This method allows for the comparison of inspection results between the three different strategies and assess the effects the use of a sUAS platform and machine learning model have on the inspectors' performances.

6.4 Inspection Results

To test the effectiveness of implementing a damage detection model as part of the inspection process and the potential effects of machine bias on the inspection personnel, we used the same data set depicted in 5-1 above. During the human only inspection process, the inspector identified 13 of 23 inspection discrepancies, compared to 21 of the 23 inspection discrepancies identified in the sUAS only inspection. The introduction of the damage detection model significantly increased the number of discrepancies, as the model identified 50 high confidence discrepancy grid squares associated with 28 individual findings, as multiple findings such as paint erosion or rivet rash spanned multiple grid squares. The increase in findings produced by the damage detection model is caused by the introduction of false positive results, with the damage detection model incorrectly identifying dirty areas and areas associated with changes in aircraft paint coloring as defects.

Two separate individuals conducted the inspection process reviewing the imagery after it had been processed and annotated by the damage detection model to determine the effectiveness of the Assisted Autonomous Aircraft Inspection process with the inclusion of this tool. These results were compared to the traditional inspection and AAI without machine learning results depicted in 5-1. We calculated correlation percentages between the inspection personnel and the damage detection model to determine potential influence the model has on the decision making of inspection personnel. Specifically, we calculate the false positive and false negative identification rate to evaluate whether inspection personnel are inherently biased to accept the results of the damage detection model, or whether they are able to correctly discern

Table 6.1: Machine Bias Inspection 1 Results

False Positive Identification Rate	38%
False Negative Identification Rate	29%
Correlation with Damage Detection Software	**54%**

Table 6.2: Machine Bias Inspection 2 Results

False Positive Identification Rate	13%
False Negative Identification Rate	43%
Correlation with Damage Detection Software	**76%**

potential errors made by the machine learning model. Review of the damage detection processed imagery by Inspector 1, shown in 6.1, produced a correlation of 54% between the inspector's findings and those of the damage detection model. Inspector 2's results, shown in 6.2 produced an even higher correlation of 76%. The higher correlations observed in the sUAS and Damage Detection Software aided process are further supported by Inspector 1 correctly identifying 3 of 8 false positives and 2 of 7 false negatives, while Inspector 2 reported 1 of 8 false positives and 3 of 7 false negatives. The low false positive and false negative identification rates by both inspectors suggest an inherent bias to trust the damage detection model outputs as accurate in instances of uncertainty.

6.5 Machine Bias Conclusions

The use of the sUAS in the inspection process increased the overall quality of the inspection, identifying a higher number of findings than in the human only process. These additional findings were located on the vertical stabilizer and upper surface of the fuselage. These locations are more challenging for human inspectors to reach, as they require the use of lifts or cranes due to height. Even with the use of lift equipment, human inspectors are often limited in how close they can get to these areas due to mechanical equipment restrictions and precautions placed to ensure the safety of the inspector and the aircraft. The use of the sUAS to gather imagery at these locations allows the inspector to perform a more detailed inspection through the use of visual aids such as image magnification, leading to a higher number of discrepancies identified.

Specifically, the sUAS aided inspection process produced high fidelity in the identification of discrepancies related to rivet rash and sealant issues, but was less effective in identifying findings related to fasteners and covers being missing, or improperly configured. Inspectors reported difficulty identifying these issues due to angles at which imagery were taken, and lack of a reference system for proper orientation.

The introduction of the damage detection software to the process produced less conclusive inspection results. With correlation as high as 76% between the inspector's reported findings and the results of the damage detection software increased the number of false positives in the final report, as well as contributed to missed discrepancies that were not identified by the computer vision model. Inspectors were inherently biased to trust the results of the damage detection model over their intuition in areas of uncertainty, only identifying 25% of false positives and 33% of false negatives produced by the model. There are multiple factors associated with the introduction of technology into the process that led to these results.

The first major factor is familiarity with machine learning models and training. This was the first time inspectors were introduced to the process of performing an inspection that utilized damage detection software to preprocess inspection images. Inspectors reported and commented their uncertainty around the models findings in certain areas of the image, but assumed that since the area had been identified that there was likely a discrepancy that correlated to positive results identified in other areas of the image (most often paint erosion or rivet rash). Individuals were unfamiliar with the concept of false positive and false negative results. Without robust training and experience with these models and their limitations, inspectors were more inclined to confirm the findings of the model.

Another contributing factor is the training and accuracy of the model itself. The damage detection model used was primarily trained on imagery of aircraft with a single tone exterior. The use of the model on an aircraft with a livery consisting of multiple colors creating an increase of false positive results along color change lines, primarily classified as moderate confidence findings. Along with difficulties highlighted by the livery of the inspected aircraft are the increased requirements for the preparation of aircraft for inspection through a thorough cleaning process. Dirt and debris on the aircraft also contribute to false positives output by the model. Small areas of dirt and debris are easily overcome in the human unaided process, as the inspector is able to touch the aircraft to determine whether it is superficial or structural damage, but inspectors using digital aids do not have the same luxury. These areas increased the noise in the output, making it more difficult for inspection personnel to identify all discrepancies.

Similar to the noise created by uncertain results produced by the model are the effects that the chosen user interface had on the inspectors' decision making. The use of a grid pattern overlay and output confidence scores added to the cognitive load on personnel, as these added additional information to the imagery and in certain cases obscured the minute damage that they were attempting to identify.

When inspectors are reviewing hundreds or potentially even thousands of images throughout the inspection process depending on the size of the aircraft and associated task cards, these results are amplified by the fatigue associated with performing the repetitive event of reviewing images through a digital medium. These fatigue results are of lesser concern during the unaided human inspection process, as personnel are able to move about the aircraft, creating natural breaks and decreased eye strain.

In this instance, the use of the damage detection model to preprocess inspection imagery prior to review by inspection personnel further removed the human from the inspection process, introducing multiple human factors considerations that decrease the efficiency of the inspection process. The introduction of false positives into inspection results has the potential to further delay and increase the time of inspection processes, as this will require additional documentation and potential for re-inspection depending on the classification of the finding. More importantly, discrepancies missed due to false negatives produced by the damage detection model that are not corrected by human inspectors due to human factors and machine bias effects have the potential to be life threatening mistakes.

6.6 Machine Bias Mitigation Recommendations

In order to reduce the effects of machine bias on inspection personnel, the damage detection model should be repurposed from a preprocessing feature to a validation function. Doing so would move the damage detection model later in the process, after personnel have reviewed and marked the inspection imagery with their findings. In the proposed process, inspection would use sUAS platforms to capture inspection imagery. The inspector would then inspect the raw imagery prior to being shown the damage detection model output. Once the inspector has completed inspecting an individual image and annotated their findings, they would then be shown the model output overlay. The inspector can use the model output to confirm their findings and potentially identify areas of missed findings. Following the review of the image with the model output overlay, the inspector certifies their findings and continues with the inspection, conducting this same process for each image.

In this proposed process flow, many of the human factors considerations discussed above are removed from the process, the biggest being the effects of machine bias, and the inspector's inherent nature to trust the machine output. By inspecting the raw images without model annotations allows the inspector to draw their own conclusions using their skill and expertise from years of experience. Having drawn their own conclusions, inspection personnel are less likely to be influenced by model outputs and accept them as truth when they are overlaid on the image. Personnel will be more likely to critique the damage detection model results and only add or modify their findings if they are certain in the data being presented to them. This new process also reduces the cognitive load on the inspector as they review imagery for inspection purposes by reducing the amount of clutter and information presented in the user interface. Without gridlines and confidence scores, inspection personnel have a clear

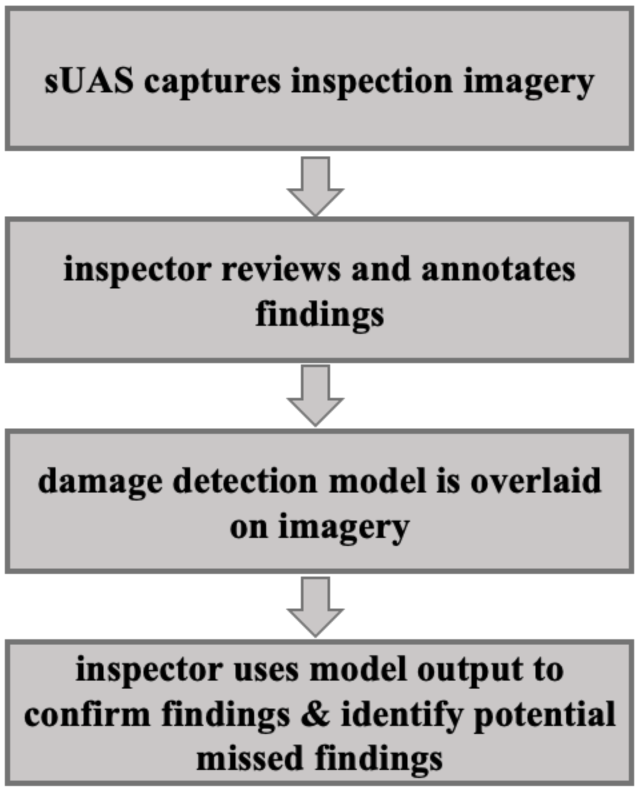

Figure 6-2: Damage Detection Validation Process Flow

view of the imagery, decreasing the possibility of critical defects being covered by model output annotations. This process flow maintains the integrity of the inspection while still allowing for the potential for increased inspection accuracy, as the damage detection model acts as an aid, verifying the results of trained personnel.

Chapter 7

Summary, Future Work and Recommendations

7.1 Summary

The sUAS Assisted Autonomous Aircraft Inspection process has multiple benefits and improvements over the current unaided human inspection process. The AAI process reduces the risk to inspection personnel and the aircraft by removing the requirement for the use of lift and heavy machinery equipment. The process also decreases the time required to conduct inspections, increasing the availability of equipment required to conduct repairs and hangar space for aircraft. Using a digital medium to collect, review, and store inspection results improves record keeping practices by reducing the reliance on paper inspection reports and standardizing documentation procedures. Most importantly, it has proven capable of increase the quality and accuracy of inspection results, as inspection personnel using the AAI process during this work identify and document more inspection discrepancies than through traditional processes.

Although there are multiple benefits to the implementation of this technology aided inspection process, it does not come without risks and additional complications. Inspection of aircraft imagery through a digital medium and the implementation of machine learning damage detection software introduces human factors considerations that do not exist in the current unaided human inspection process. The most notable of these human factors considerations is the effects of machine bias on the inspection personnel. The inspection results of personnel reviewing damage detection preprocessed imagery are influenced by the results of the machine learning model, as they are more likely to concur with false positive findings introduced by the model and fail to identify false negative results. This creates errors in inspection reporting and significant safety concerns for the future flight of aircraft. One solution to improve the implementation of damage detection software is to reorder the data processing section of the inspection, using damage detection software as a validation feature rather than a preprocessing function.

7.2 Future Work

The future work section of this paper focuses on potential improvements to two sections of the sUAS assisted aircraft inspection process, data capture and data processing. Data capture improvements seek to decrease the time required to conduct the aircraft inspection while also increasing the robustness of the data available to inspectors during the inspection process. Data processing future work consists of improvements to damage detection software models and decreasing human factor effects that are presented through the implementation of technology and digital mediums into the aircraft inspection process.

7.2.1 Data Capture

Current platform designs only implement and use electro-optical (EO) cameras for capturing inspection imagery. Multiple other sensors currently exist for conducting Nondestructive Inspection(s) (NDI) that are used in a hand held form. Some of these sensors include thermography, infrared cameras, and ultrasonic arrays. These sensors provide additional information that cannot be extracted from two-dimensional imagery, such as the depth of dents and cracks. Future work in the field explores ways to increase payloads available on sUAS platforms, giving inspection personnel a more robust tool, capable of delivering all of the information required to identify inspection findings and determine their severity. The addition of multiple payloads to a platform will inevitably increase the weight of the sUAS, which will negatively impact flight time or require a sUAS platform of increased size.

An additional solution to be explored to increase the number of payloads available for sUAS assisted inspections and decrease the time required to conduct inspections is the use of multiple sUAS platforms, commonly referred to as swarm technology. Using multiple platforms under the current methods of capturing imagery using EO cameras has the potential to decrease the team required to complete inspection flights, by having individual sUAS simultaneously collect imagery from different areas of the aircraft. Multiple platforms can also be used to carry different payloads, allowing for inspection personnel to implement a technique used in the military intelligence community known as "tipping and cueing." In this process, inspection findings identified using an EO imagery camera drone that require additional inspection and measuring techniques such as dents, would be designated by inspection personnel and damage detection software. This would automatically "tip" the "queued" secondary platform carrying a required additional sensor to the designated waypoint to collect the additional information required to complete the inspection process. The use of multiple sUAS platforms simultaneously increases the requirement of safety protocols to ensure there are no in-air collisions of sUAS platforms with each other and the airframe being inspected, as well as for the prevention of "run-away" sUAS outside of the designated inspection zone.

7.2.2 Data Processing

Future work in the data processing phase of the sUAS assisted inspection process is centered around improving the fidelity of damage detection models and reducing the effects of human factors on inspection personnel. One of the challenges with a central damage detection model capable of functioning across multiple commercial customer aircrafts is creating a large enough dataset that includes aircraft with multiple liveries, decreasing the false positive rate caused by multiple paint and color configurations. Due to the infrequency of inspections and the variability in damages certain aircraft may incur due to different flight regions and weather conditions, building a robust dataset is a challenging endeavor. One potential method to be explored is the use of synthetic imagery in the training set, overlaying common damages on multiple different airframes.

The current method of damage detection software implemented in this paper utilizes the computer vision model as a preprocessing feature, comparing captured imagery against a common dataset in order to identify inspection findings in the images. An additional method discussed was the comparison of collection imagery against a reference scan or previous inspection data of the same aircraft. This methodology decreases the requirement of a robust training set covering multiple airframes as stated above, but presents additional challenges in the repeatability of the autonomous inspection with minimal variance in the angle and distance from aircraft at which imagery is captured.

Along with exploring efforts to improve the implementation of damage detection software to improve performance and reduce machine bias on personnel, future work in the data processing phase includes improvements to the user interface to decrease cognitive load. In order to ensure complete coverage of the aircraft required to meet inspection requirements, images of adjacent sections contain overlap. This process significantly increases the number of imagery inspection personnel have to inspect during the review phase, numbering as large as thousands of images depending on the airframe size and inspection task cards used. This creates a significant amount of fatigue on inspection personnel. Image stitching is a potential method to be explored to decrease the number of images reviewed for final inspection. Along with decreasing imagery quantities, image stitching also has the potential benefits of improving imagery quantity by removing overlapping areas that contain reflections or shadows. Further potential benefits include providing a more holistic view of the aircraft, providing additional reference information that is currently missing from reviewing individual images.

7.3 Broader Interest in Assisted Autonomous Aircraft Inspection (AAI)

With the continued development and improvement of technology systems, Original Equipment Manufacturers (OEM) and Maintenance, Repair, and Operations (MRO) providers seek to exploit these developments in order to continuously improve efficiency. Through the implementation of these technological advancements the concept of "Smart Hangars" has emerged in the airline industry. The "Smart Hangar" concept is comprised of four major components: digitzation of the environment, analytical tools, automation and robotization of the environment, and intelligent production.[4] Digitization of the environment requires organizations to develop paperless processes and systems through the use of smart devices, increasing the availability of data. By making data available in digital formats, organizations are able to increase their ability to utilize this data through multiple analytical tools, continuously making process improvements and extracting insights that were not previously available. To further increase efficiency, automation principles and technologies are introduced to the environment, providing greater adherence to repeatability and higher quality. Intelligent production uses technologies such as 3D printing and additive manufacturing to decrease the reliance on supply chains while increasing the sustainability of the system.

The implementation of an Assisted Autonomous Aircraft Inspection (AAI) program is a critical component to the realization of "Smart Hangars." Through the use of autonomous sUAS platforms to collect inspection imagery, inspection personnel seek to develop a repeatable process that decreases the reliance on paper reporting through the digitization of inspection results. The AAI process allows OEM and MRO providers to extract greater analytical insights from the inspection process. The data gathered during this process can be used to help not only redefine inspection procedures, but influence the design of future aircraft, as historical damage insights identify potential weak points in aircraft design or materials used.

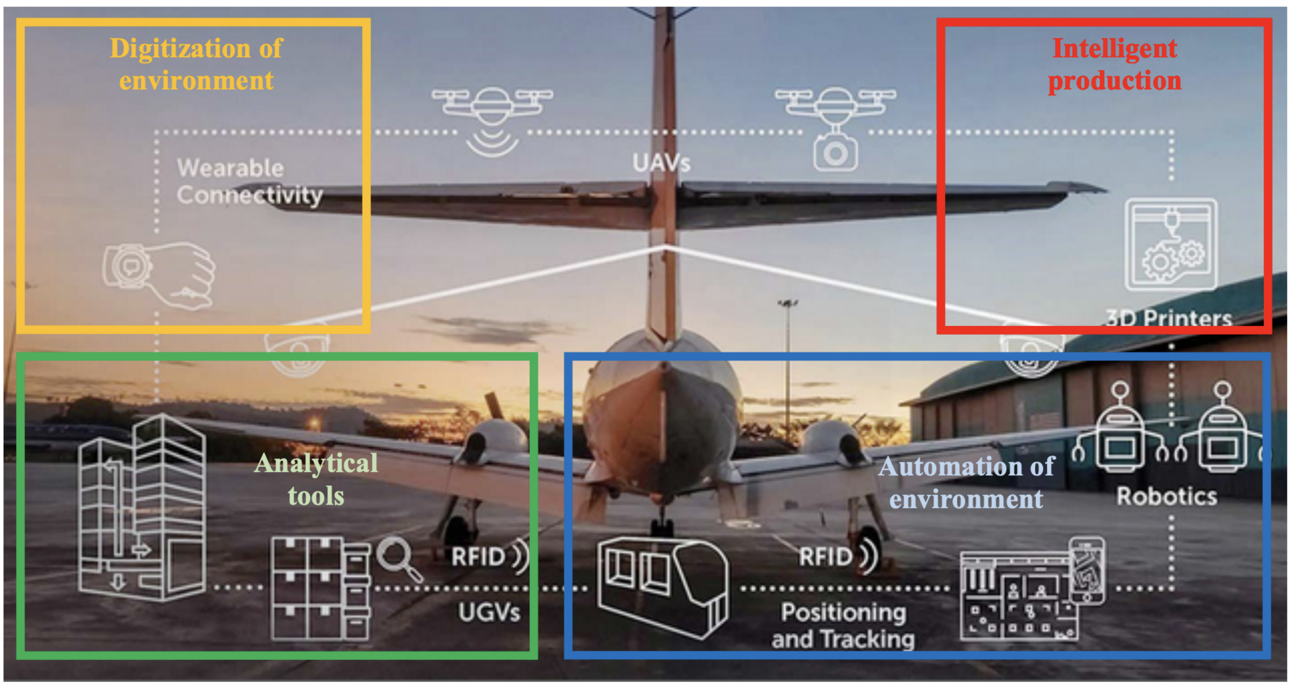

Figure 7-1: Smart Hangar Concept[4]

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