Development of a novel Health and Usage Monitoring System to improve the reliability of Unmanned Aerial Vehicles

by

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Abstract

Unmanned Aerial Vehicles (UAVs) are rapidly proliferating across commercial, government and civilian domains for inspection, surveillance, emergency response and delivery services. However, high failure rates continue to undermine mission success, safety and regulatory approval. To address this, a retrofit health and usage monitoring system (HUMS) tailored for small multirotor UAVs was developed through iterative design, simulation and experimental validation to enable condition-based maintenance.

A comprehensive literature review identified prevalent UAV failure modes and assessed suitable technologies for continuous monitoring. Fiber Bragg Grating (FBG) sensors emerged as most promising due to attributes like high sensitivity, low size/weight, multiplexing ability, and durability. Subsequently, the applicability of these technologies to address failure modes related to structural, electrical, temperature, vibration, and environmental factors were evaluated. System architecture options like mesh networking provided redundancy against individual node failures.

Based on this analysis, custom design requirements were established for a retrofittable HUMS prototype able to interface with different UAV types. The functional prototype implements distributed temperature and vibration sensors connected via Zigbee to a central microcontroller with WiFi telemetry to ThingSpeak cloud analytics. Controlled lab integration on a quadcopter successfully demonstrated real-time streaming of sensor measurements and threshold-based anomaly detection. The simplified proof-of-concept establishes core capabilities, despite limitations in robustness, range and advanced analytics.

Ongoing work focuses on stacking reliability through improved packaging, resilient communications and ease of installation. Transitioning to LoraWAN aims to expand coverage for remote deployments. Edge computing and machine learning techniques will elevate diagnostic intelligence. Testing will

shift from lab settings to diverse field conditions spanning various UAV types, flight profiles and live missions. A preliminary techno-economic analysis projects attractive returns on investment through reduced downtime and maintenance costs, substantiating commercial viability.

This research pioneers an innovative HUMS architecture tailored for size, weight and power constraints of small aerial platforms. By facilitating the transition to predictive maintenance, the system promises to significantly bolster efficiency, safety and longevity in UAV operations. The successful demonstration of a pragmatic HUMS holds disruptive potential to overcome reliability barriers hindering the next evolution of ubiquitous and autonomous unmanned flight.

Preface

This thesis is an original work by Iraban Turjo.

A version of Chapter 2 of this thesis has been published as Turjo, I., Lipsett, M. (2022). “Health and Usage Monitoring Systems (HUMS) for Unmanned Aerial Vehicles: A Literature Review” Canadian Society of Mechanical Engineers (CSME) Congress 2022, 5-8 June 2022, University of Alberta, Canada. I was responsible for the data collection and analysis as well as the manuscript composition. M. Lipsett was the supervisory author and was involved with concept formation and manuscript composition.

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Table of Contents

List of Tables

List of Figures

Chapter 1

Introduction

1.1 Background

Unmanned aerial vehicles (UAVs), aircraft without human pilots onboard, trace their origins to 1849, when Austrian soldiers deployed balloons rigged with explosives for aerial bombardment over Venice, marking the nascent stages of UAV technology [1, 2]. The emergence of powered flight by the Wright brothers in 1903 and the onset of World War I (WWI) in 1914 spurred significant UAV advancements. In 1916, Elmer Sperry and Peter Hewitt pioneered an automatic control system, funded by the US Navy in 1917 for a flying bomb project [4]. Despite its cancellation, this endeavor paved the way for the Kettering Bug, which employed predictive calculations for targeting and delivery [5]. However, the Kettering Bug's reliability remained a challenge, leading to its limited deployment [6].

Post-WWI, aviation made rapid strides, including the first transatlantic flight in 1919 by Alcock and Brown and instrument-only flight in 1929 by Doolittle [7, 8]. UAVs also advanced, exemplified by the first remote-controlled aircraft achieving full flight phases in 1924 [9]. In 1935, the Royal Navy employed remote control for the Queen Bee UAV, a milestone for anti-aircraft gunnery target training [10]. World War II witnessed the progression of UAVs alongside aerospace technologies, evidenced by Germany's V-1 "buzz bomb," characterized as a cruise missile [4]. The modern UAV era commenced in 1960 with the US creating a classified unmanned reconnaissance program after the U-2 incident [11]. Israel's successful use of reconnaissance UAVs in the 1967 Six-Day War demonstrated their strategic value [12]. UAV deployment in Vietnam by the US further substantiated their operational viability [11].

Continued conflicts catalyzed UAV development, including Israel's deployment of real-time surveillance UAVs in the 1973 Yom Kippur War and the US introduction of the MQ-1 Predator, as shown in figure 1, for aerial reconnaissance in 1994 [14, 15]. The modified Predator, armed with Hellfire missiles, exemplified "stalk and kill" capabilities [14]. Modern UAVs have pushed boundaries, as seen in DARPA's AlphaDogfight Trials, incorporating AI control algorithms into fighter jets [16]. Multirotors, widely embraced due to their unique attributes such as vertical takeoff, emerged in the consumer and research domains with quadcopters evolving from early designs in the

1900s [17, 18]. The twentieth century saw multirotor evolution, culminating in the popular DJI Phantom quadcopter [25, 26]. These advancements enable UAVs to perform tasks beyond visual inspections, now engaging in active manipulation of their environment [32].

Figure 1: General Atomics MQ-1 Predator UAV firing a Hellfire Missile [14]

The proliferation of unmanned aerial vehicles (UAVs) has catalyzed a transformation across myriad civilian and military domains, offering unique advantages over conventional manned aircraft. UAVs, commonly referred to as drones, were originally envisioned as low-cost, expendable alternatives to manned reconnaissance planes during World War I and thereafter. However, contemporary UAV technologies have rapidly evolved beyond their initial purpose, spearheading innovations in surveillance, infrastructure monitoring, emergency response, aerial imagery, defense systems, and emerging applications such as delivery services [56]. The burgeoning UAV industry is estimated to reach a market valuation of over **$63 billion** by 2025 [57].

This exponential growth has necessitated continual improvements in UAV capabilities, maneuverability, endurance, and autonomy to undertake complex missions safely, reliably, and efficiently. Consequently, modern UAV platforms have progressively incorporated traditional aviation systems and subsystems from manned aircraft, particularly helicopters, to enhance their sophistication and performance [58]. This assimilation of mature helicopter technologies, coupled with purpose-built designs tailored for UAV-specific missions, have endowed contemporary UAVs with advanced flight control, navigation, communication, and payload capabilities [59].

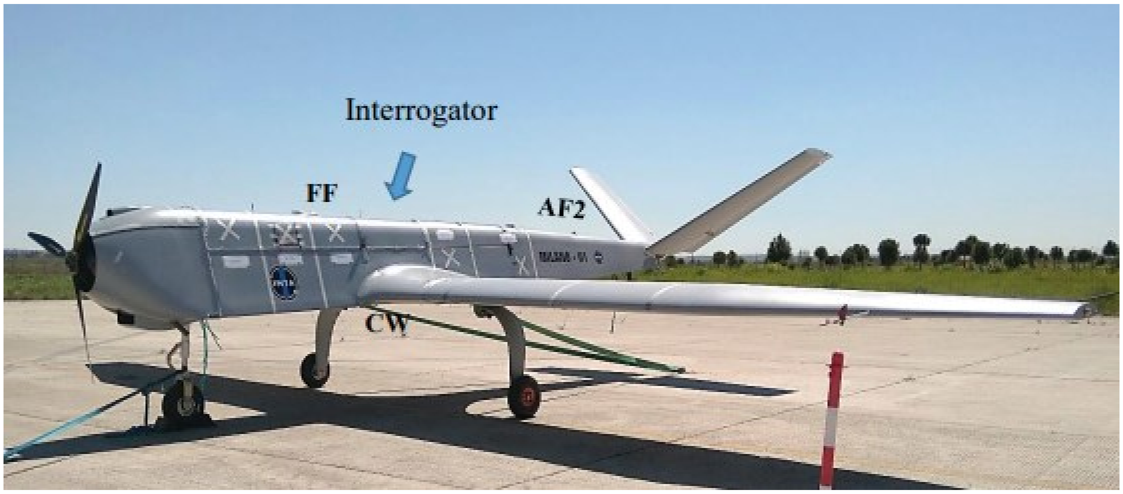


Figure 2: MILANO UAV with an integrated HUMS during on-ground tests. FF/AF2: Front/Aft fuselage. CW: Central wing [8].

However, the incorporation of traditional aviation systems has also transferred vulnerabilities of manned platforms to UAVs. According to a US Air Force study, Class A mishaps involving the complete loss of a UAV occur up to 250 times more frequently than manned aircraft, undermining mission success [60]. The study highlights that ineffective maintenance practices and lack of reliability improvements account for the disproportionate mishap rates. A US Army analysis also concluded that current UAV reliability levels lag at least 15 years behind manned aircraft [61]. The analysis emphasized that traditional reliability improvement processes suited for manned aviation platforms are not directly transferrable to the burgeoning ecosystem of complex UAV technologies and subsystems.

This underscores the urgent need to bolster the reliability of UAV platforms to harness their immense potential while minimizing mission-compromising mishaps. Reliability refers to the probability of a system or component performing its intended function under specified conditions for a desired period [62]. For UAVs, attaining reliability requires identifying, monitoring, and mitigating vulnerabilities across various subsystems, including propulsion, energy storage, flight control, structural components, payloads, and ground control stations [63]. UAV reliability fundamentally influences mission availability, success rates, safety, and operational costs [64].

Conventional strategies for enhancing reliability such as redundancy, design margins, and component derating are necessary but insufficient to enable condition-based maintenance. The lightweight and compact design requirements of UAVs constrain extensive redundancy, while design margins and component derating offer limited ins insights into real-time subsystem health

[65]. For instance, redundancies or over-engineering certain components may overlook vulnerabilities in other subsystems, leading to unexpected failures.

A more rigorous approach entails continuous health and usage monitoring of critical UAV subsystems to enable predictive maintenance and dynamic failure mitigation [66]. This gave rise to **Health and Usage Monitoring Systems (HUMS)** tailored for the size, weight, power, and computational constraints of UAV platforms [67].

HUMS technologies originated in the rotorcraft industry following a catastrophic helicopter accident known as the 1986 Sumburgh disaster, when a commercial Chinook crashed in the North Sea, killing all but one passenger. which spurred the Offshore Oil Industry towards the development of usage monitoring solutions to track structural fatigue [68]. A typical HUMS monitors the status of critical systems and components on aircraft and other vessels with the help of sensors placed throughout the aircraft and its parts, which are connected to a main onboard computer with a data logging and storage system, allowing for the early detection of progressive defects or indications of them, and thus allowing rectification before they have a catastrophic impact on operational safety. Data is either stored on a PCMCIA Card by the onboard device, which is then downloaded after the flight for examination, or uploaded to cloud-based servers for back office analytics to give operators appropriate anomaly detection and proactive measure capabilities. Monitoring trends in collected data is especially essential because they allow system professionals to identify whether the aircraft has developed (or is likely to develop) flaws that require immediate attention. In response to rotorcrafts' relatively poor continuous airworthiness record, the implementation of HUMS resulted in and continues to support, considerable improvements in both safety and reliability.

The extent to which HUMS data is captured varies greatly. A simple system records take-off, landings, engine starts, and winch lifts, as well as a subset of engine and transmission health data. All key vibrating and spinning parts - engines, gearboxes, shafts, fans, rotor systems - and other components are monitored by the most modern techniques. The operational context of occurrences is recorded so that trends may be properly examined, and maintenance personnel can undertake condition-based maintenance proactively. The latest technology platforms enable the data to be processed onboard the aircraft or at a ground station, and some systems enable it to be transmitted to operator maintenance control units via satellite communications during flight to enable pre-planning of upcoming maintenance downtime. Additionally, these systems may be set up to automatically alert the manufacturers and operators of any critical or emergencies.

For UAVs, the core premise of a HUMS remains unchanged - to acquire, analyze, and interpret data from networked sensors across UAV subsystems for:

- Real-time condition monitoring to detect anomalies, failures, and exceedances.
- Usage monitoring to determine cycles, stresses, and exposures that cause wear and aging.
- Failure prediction by identifying trends, preclude unsafe conditions.
- Advising predictive maintenance instead of routine servicing.

However, fundamental differences exist between implementing HUMS solutions for large manned rotorcraft versus compact UAVs. Size, weight, power draw, and cost constraints necessitate extremely miniaturized sensors, efficient processors, and low-power wireless communications [69]. The limited payload capacity also miniaturized requires strategic sensor placement after rigorous failure mode analysis of critical subsystems. Moreover, the operational envelopes vary significantly - helicopters typically feature redundant mechanical and hydraulic subsystems, less exposure to extreme vibrations, controlled landing surfaces, climate-controlled crew cabins, and strict maintenance protocols [70].

In contrast, multirotor UAVs experience frequent launch/landing shocks, repeated vibrations across a wide band of frequencies, direct environmental exposure, limited redundancy, and inadequate maintenance after prolonged storage [71]. These challenges demand a HUMS that is specifically tailored for the failure modes, flight profiles, and operational environments encountered by small-to-medium sized UAVs. Attempting to retrofit an existing helicopter HUMS solution would be ineffective, complex, and inadequate for the needs of UAV platforms.

Recent advances in miniaturised sensors, processors, algorithms, and communication protocols have engendered the development of UAV-focused HUMS solutions, albeit confined primarily to military and research domains. UAV HUMS implementations have leveraged technologies including Fiber Bragg Grating sensors, piezoelectric transducers, accelerometers, acoustic emission sensors, ultrasonic structural imaging, MEMS inertial sensors, and onboard data aggregation systems [72]. However, widespread adoption in the commercial UAV sector remains sparse due to prohibitive costs, complexity, lack of miniaturization, and absence of reliability improvements.

1.2 Motivation

The motivation behind this research stems from several key factors that collectively underscore the urgency and significance of enhancing the reliability of UAVs. First and foremost, as UAVs find applications in sectors such as infrastructure inspection, environmental monitoring, and search and rescue missions, their safe and continuous operation is paramount. Incidents involving UAV failures, even on a smaller scale, can result in significant financial losses, operational disruptions, and potentially endanger lives. These vulnerabilities are largely inherited from manned platforms, which are subjected to rigorous monitoring and maintenance regimes, a level of oversight that UAVs currently lack.

This thesis proposes the development of an easily retrofittable HUMS specifically designed for small-to-medium-sized multirotor UAVs. By identifying common failure modes in UAV subsystems and strategically integrating miniaturized sensors with efficient processing and communication protocols, this HUMS aims to provide a compact sensing package for real-time monitoring of critical subsystems. The emphasis will be on a flexible architecture that can be adapted to different UAV types and customized based on critical subsystems. The implementation, validation, and performance analysis of the proposed UAV HUMS will demonstrate its capabilities and commercial viability.

The overarching motivation is underpinned by **four key hypotheses**:

1. Traditional maintenance practices are inadequate to address the reliability challenges of UAVs – but condition monitoring and usage tracking can enable predictive maintenance.

2. Current HUMS solutions are unsuitable for small UAVs owing to size, weight, power, and cost constraints.

3. New miniaturised and commercially available sensing solutions can enable compact and low-power HUMS tailored for multirotor UAVs.

4. The proposed retrofittable HUMS will bolster reliability and commercial appeal.

It is to be noted here that within the scope of this thesis, the first three hypotheses have been extensively supported and verified through the Literature Review, Methodology and Experimental Trials chapters. However, the 4^{th} hypothesis has been supported partially – through the Experimental trials and Preliminary Techno-Economic Analysis chapters, and it is considered an ambitious long-term goal requiring further validation, such as testing across 100+ flight hours per UAV platform and additional market research and business case refinement. It is therefore a limitation of the current research, nevertheless it provides rich avenues for future research and development.

The successful implementation of the proposed HUMS will herald smarter condition-based maintenance for UAVs, lowering costs and downtimes associated with unexpected failures. By transitioning from reactive to predictive maintenance, HUMS empowers stakeholders to optimize inspection intervals, plan platform upgrades, streamline supply chains, and improve customer satisfaction. The technology also carries tremendous commercialization potential, offering reliability as a service for UAV manufacturers and operators. The overarching motivation is, therefore, to leapfrog the reliability limitations of multirotor UAVs and unlock their immense application possibilities across industries through an innovative, compact, and commercially-viable HUMS technology.

The following literature review is a general overview of the systems and methods used for onboard Health and Usage Monitoring systems developed so far for UAV reliability. Each following chapter includes additional supporting literature directly related to the specific methods and technologies used in the research.

1.3 Research Objectives

The initial objectives of this research were to discuss and evaluate different health and usage monitoring systems for UAVs and determine which system may be most suitable for broad applications. After conducting a literature review of existing technologies and identifying their limitations, the focus shifted to developing general requirements and an architecture for a prototype HUMS tailored for small to mid-size UAV platforms.

The literature review revealed that fiber Bragg grating (FBG) optical sensors are a promising technology for UAV health monitoring due to attributes like high sensitivity, low size/weight, multiplexing capabilities, and immunity to electrical interference. However, limitations remain regarding the large size and weight of FBG interrogators. Additionally, there is a lack of standardized frameworks for the airworthiness certification and licensing of FBG-based HUMS.

To address these gaps, the research objectives evolved to designing and constructing a proof-of-concept HUMS prototype designed for multirotor UAVs. The goals were to develop a flexible, low-cost system that can be easily retrofitted on different UAV types to enable condition-based maintenance. Requirements focused on distributed wireless sensing, minimal payload impact, and cloud-based data analytics.

The implemented prototype demonstrates initial functionality using a DHT22 temperature sensor, a vibration sensor, and an Arduino microcontroller with WiFi transmission to ThingSpeak IoT Cloud Analytics platform. Experiments involved lab integration on a quadcopter UAV and controlled testing. Results validated real-time sensor measurements and wireless communication protocols.

However, the prototype has limitations regarding robustness and lack of FBG sensors. Ongoing work focuses on improving reliability, incorporating FBG sensors, long-range communication via LoRaWAN, and customized analytics. Testing is transitioning from lab environments to actual UAV flight scenarios.

Ultimately, this research aims to develop an innovative HUMS solution to enhance UAV reliability and safety. By addressing the constraints of size, weight, and complexity, the system holds promise for enabling condition-based maintenance across the aviation industry. The overarching motivation is to commercialize this technology to overcome reliability bottlenecks of multirotor UAVs.

1.4 Thesis Outline

Chapter 1 introduces the background and motivation for developing a Health and Usage Monitoring System (HUMS) to enhance reliability of unmanned aerial vehicles (UAVs). It highlights disproportionately high failure rates of UAVs compared to manned aircraft, necessitating continuous health monitoring. The chapter traces the evolution of HUMS from the rotorcraft industry and its unique applicability to address UAV reliability bottlenecks. The underlying hypotheses focus on tailoring a commercially-viable HUMS technology to overcome size, weight and power constraints of small aerial platforms.

Chapter 2 provides a comprehensive literature review assessing prominent health monitoring technologies for UAVs. Structural, thermal, vibrational, electrical and environmental sensing solutions are analyzed based on principles, size, power, reliability and commercial availability. Comparative analysis of fiber Bragg gratings, piezoelectric sensors, MEMS devices and others reveals relative merits and limitations. Key findings identify fiber Bragg sensors as most promising but requiring further interrogator miniaturization and aviation certification.

Chapter 3 presents HUMS prototype requirements focused on a wireless, distributed, lightweight system for small UAV retrofitting. Architecture options like mesh topologies are evaluated, leading to the implementation of Arduino microcontrollers, Zigbee communication, and ThingSpeak cloud analytics software. Experiments validate ground and tethered functionality before full UAV integration.

Chapter 4 demonstrates real-time temperature data monitoring on a quadcopter UAV. Heat and humidity fluctuations emulate battery failures, proving anomaly detection capabilities. Results validate functionality but reveal opportunities to improve reliability.

Chapter 5 proposes advancements to transition the prototype towards a sophisticated wireless solution ready for diverse field deployments. Enhanced ruggedness, sensors, edge computing, installation methods, and aviation compliance are outlined to mature technology readiness levels.

Chapter 6 provides a techno-economic analysis estimating costs, benefits, return on investment and addressable market potential. Attractive financial projections reinforce the commercial viability of transitioning UAVs to HUMS-enabled predictive maintenance.

Chapter 7 summarizes key outcomes and validations from the functional wireless prototype. While initial testing proves capabilities, extensive reliability testing across long-term UAV deployments is required to fully substantiate potential maintenance practice improvements. Nonetheless, the demonstrated HUMS architecture pioneers an innovative system poised to bolster efficiency, safety and longevity of emerging UAV technologies.

Overall, this thesis makes significant headway in designing, validating, and demonstrating a practical HUMS solution to meet the unique reliability challenges of emerging UAV technologies. It provides a foundation to advance UAV condition monitoring through strategic sensing, coupled with efficient onboard processing and cloud analytics. By addressing the constraints of size, weight, power, and complexity, this research pioneers an innovative system architecture that can potentially be commercialized to enable predictive maintenance in diverse UAV applications.

Chapter 2

Literature Review

2.1 Introduction

2.1.1 Background

The following provides a synopsis of a review that will summarize health monitoring studies that have appeared in technical literature between 1990 and 2023. Peer- reviewed Journal articles, Conference papers and thesis dissertations have all been considered for this review. 186 articles that were found most relevant to HUMS technologies developed specifically for UAVs have been considered and discussed.

2.1.2 Scope and Objectives

This literature review synthesizes prominent research related to technologies and methods for UAV health monitoring. It is structured into sections examining structural, thermal, vibrational, electrical, and environmental monitoring solutions. The scope is limited to onboard and embedded technologies that can provide continuous monitoring during flight.

The objectives are threefold:

1. Identify sensing solutions viable for UAV integration.
2. Analyze their capabilities and limitations based on principles, size, power, reliability, and commercial availability.
3. Recommend the most promising technologies suited for developing a retrofittable HUMS prototype for small UAV platforms.

2.1.3 Outline

The literature review is organized into three sections following this introduction:

- Technologies for UAV Health Monitoring
- Analysis and Recommendations
- Conclusion

The first section provides an overview of prominent monitoring technologies and their applicability to UAVs. The second section offers comparative analysis leading to recommendations for the HUMS prototype. Finally, the key findings are summarized, and an outlook is provided.

2.2 Technologies for UAV Health Monitoring

2.2.1 Internet-of-Things (IoT) for remote Health Monitoring

The Internet of Things (IoT) refers to the network of physical objects embedded with sensors, software, and connectivity that enables them to connect and exchange data over the Internet [65]. IoT is rapidly transforming many industries by enhancing efficiency, productivity, and automation [66]. Analysts predict that there will be over 30 billion connected IoT devices generating massive amounts of data by 2025 [67]. This is leading to the Fourth Industrial Revolution, commonly referred to as Industry 4.0, which involves cyber-physical systems, Big Data analytics, and intelligent industrial automation [68]. Industrial IoT (IIoT), which applies IoT technologies to industrial settings, is a major driver of Industry 4.0 through innovations in smart manufacturing, connected machines, and data-driven industrial processes [69]. This literature review examines the intersection of IIoT and wireless sensor networks which are enabling this industrial transformation.

The Industrial Internet of Things (IIoT) and wireless sensor networks (WSNs) are rapidly transforming many industrial domains such as manufacturing, energy, transportation, and healthcare. By integrating advanced sensors, communications, analytics, and automation, IIoT enables intelligent monitoring and data-driven optimization of industrial equipment and processes. Meanwhile, WSNs provide the connectivity fabric that links distributed sensors and edge devices to the cloud. As we enter the era of Industry 4.0, IIoT and WSNs are becoming indispensable for building smart factories, realizing predictive maintenance, and enabling industrial automation.

i. Industrial Internet of Things (IIoT)

The Industrial Internet of Things (IIoT) refers to the use of Internet of Things technologies such as sensors, connectivity, analytics, and applications in industrial settings. The main goal of IIoT is to improve operational efficiency, productivity, and safety through intelligent monitoring and data-driven optimization [69]. IIoT connects industrial machines and assets to networked sensors and software for data collection, analysis, visualization, and machine learning. By extracting insights from industrial data, IIoT enables industries to be more flexible, efficient, proactive, and automated [70].

The key characteristics of IIoT include [71]:

- Instrumenting assets with networked sensors and actuators
- Connecting devices over wired and wireless networks
- Aggregating sensor data into Big Data platforms
- Analyzing data using advanced analytics and machine learning
- Developing intelligent applications to optimize processes
- Enabling better human-machine interactions and automation

IIoT builds on existing industrial systems such as SCADA, MES, and PLM. However, IIoT aims to create end-to-end connected systems that integrate operations from the edge to the cloud [71]. The major benefits of IIoT include operational efficiency, condition monitoring, predictive maintenance, and new data-driven services.

ii. IIoT Architecture and Enabling Technologies

Implementing an effective health and usage monitoring system (HUMS) for UAVs requires an integrated IIoT architecture spanning devices, connectivity, computing, analytics, and applications [98]. This aligns with the needs of a UAV HUMS that must collect data via onboard sensors, transmit it through wireless networks, perform real-time analytics, and present actionable information to users [75]. Figure 6 shows a high-level IIoT architecture comprising four layers:

- **Device layer:** At the device layer, industrial sensors for parameters like vibration, temperature, pressure, and current can provide condition monitoring data from critical UAV subsystems [99]. MEMS inertial sensors, strain gauges, and current transformers tailored to UAV size, weight, and power constraints can serve as viable options..
- **Network layer:** Wireless connectivity is enabled through protocols including Zigbee, Bluetooth, LoRaWAN optimized for low power sensor networks [100]. Redundant mesh

topologies provide reliability while maintaining a lightweight form factor. Gateways aggregate data from wireless clusters before transmitting to the cloud over cellular links.

Edge computing performed by the UAV flight computer enables preprocessing and compression of sensor data before transmission [101]. This reduces bandwidth needs while supporting prompt condition indicators for real-time prognostics. The UAV autopilot can also provide telemetry data

- **Service layer:** In the cloud service layer, big data storage handles the volume of historical monitoring data [102]. Machine learning and statistical algorithms analyze trends to detect anomalies, perform fault diagnosis, and predict failures.

- **Application layer:** Finally at the application layer, dashboards present visualizations of sensor data and analytics, along with warnings and alerts for maintenance planning [103]. Integration with fleet management systems allows efficient scheduling of UAV missions based on health status.

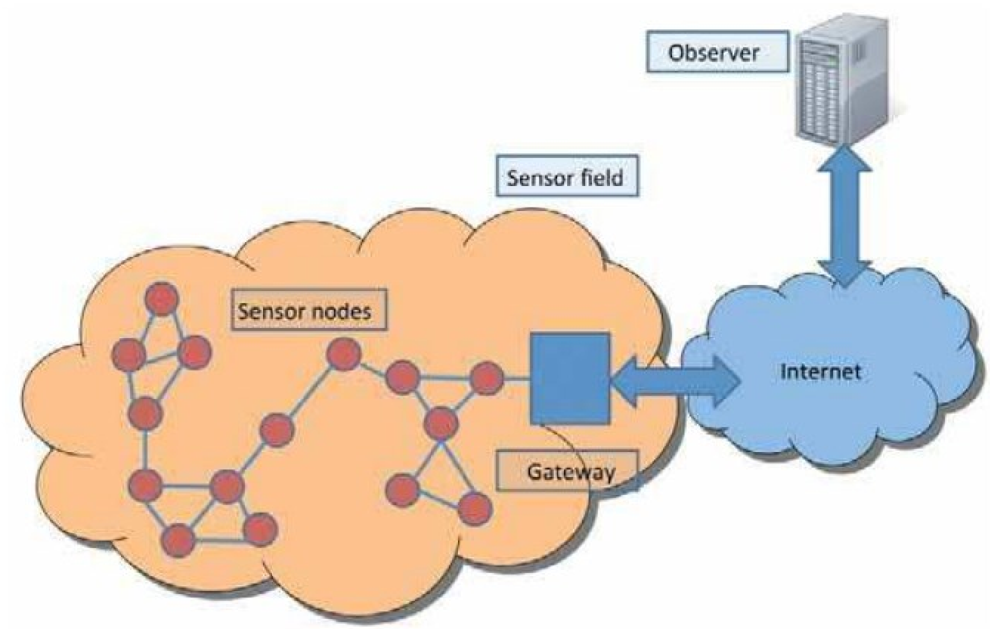


Figure 3: High-level architecture for IIoT systems [71]

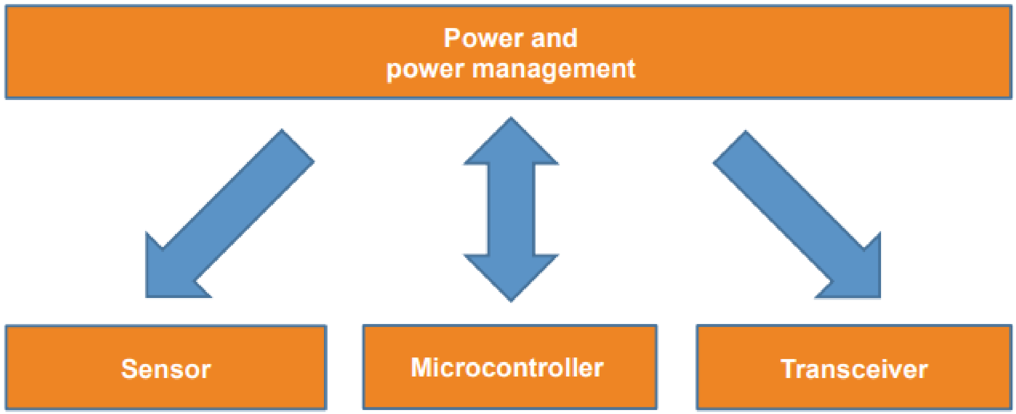


Figure 4: Hardware structure of a WSN sensor node [71]

Adhering to common IIoT architectures and data models enhances interoperability and simplifies integration with existing enterprise infrastructure down the road [103]. A well-designed UAV HUMS leveraging IIoT technologies can lead to lower costs and increased safety and reliability.

2.2.2 Wired Sensor Networks

Wired sensor networks entail physical connections between sensors, processing units, and data transmission modules on the UAV platform [104]. Common standards used for onboard health monitoring include Controller Area Network (CAN), Inter-Integrated Circuit (I2C), Serial Peripheral Interface (SPI), and Universal Asynchronous Receiver/Transmitter (UART) protocols [105].

i. CAN bus provides noise immunity, real-time control, and fault confinement making it suitable for avionics systems [106].
ii. I2C offers multimaster capability allowing multiple microcontrollers to communicate over a shared bus [107].
iii. SPI enables high-speed synchronous serial data transfer between controllers and peripherals [108].
iv. UART facilitates serial communication between computing modules [109].

The appropriate bus standard depends on factors such as required data rate, number of nodes, and fault tolerance specifications of the UAV system.

Wired sensor networks for UAV health monitoring need to conform to standard communication protocols to ensure interoperability and data integrity. The **seven-layer Open Systems**

Interconnection (OSI) model provides a framework for reliable data transmission between network nodes [110]. Each layer has a specific function:

1. The physical layer deals with the electrical or optical bit-level transmission between network interfaces [111]. Choices for small UAVs include copper wiring, fiber optics, and differential signaling like RS-485 that minimizes noise over long lines. Fiber optics provide electrical isolation and high data rates but at higher cost.
2. The data link layer implements point-to-point node-to-node data transfer, detecting and correcting transmission errors [112]. UAV networks can employ checksums, acknowledgments, and retransmissions to ensure reliability. Lightweight encryption secures data links.
3. The network layer handles end-to-end data routing and logical addressing between sensor nodes across the UAV platform [113]. Standards like CANopen facilitate device interconnection and plug-and-play operation. Deterministic protocols ensure real-time sensor data delivery.
4. The transport layer provides transmission control, segmentation, and reassembly of sensor data packets [114]. TCP offers guaranteed delivery whereas UDP trades reliability for lower latency. The choice depends on the specific UAV application requirements.
5. The session layer manages and synchronizes communication sessions between sensor nodes by setting up, coordinating, and terminating connections [115]. Time synchronization enables aligning data timestamps from distributed sensors.
6. The presentation layer defines data syntax and semantics, translating formats for interoperability [116]. Standards like IEEE 1451 for transducer interfaces facilitate sensor integration and data interchange.
7. Finally, the application layer provides interfaces and protocols for end-user software to access sensor data [117]. APIs like MQTT and REST simplify data exchange between sensor networks and health monitoring applications.

While conforming to standardized protocols and layers increases complexity, the benefits include interoperability, maintainability, and simplified integration with existing infrastructure. The modular approach also allows mixing and matching technologies based on performance, reliability, and security needs. Overall, adhering to established OSI protocols ensures robust sensor connectivity crucial for safety-critical UAV operations.

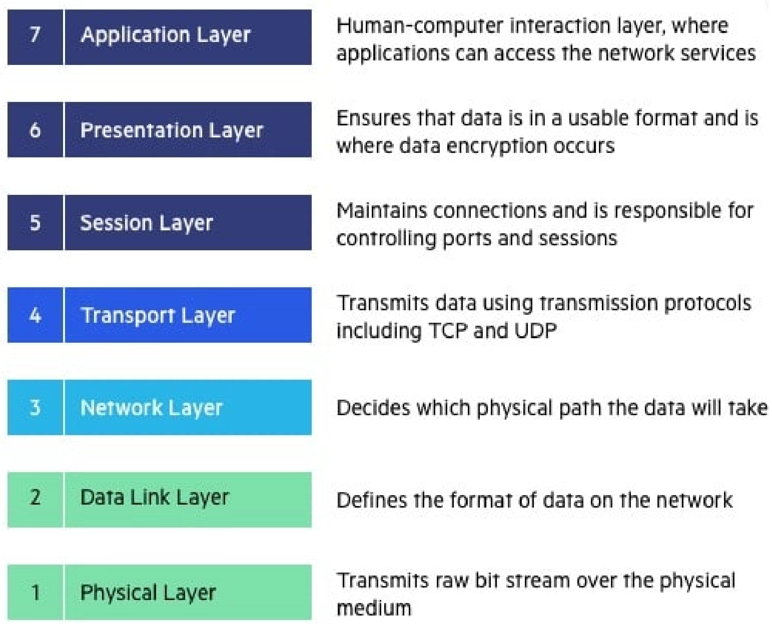


Figure 5: The OSI 7 Layers for Networks

Key benefits of wired networks include simplicity, low interference, and reliable connectivity crucial for health monitoring [112]. However, limitations include higher weight from cabling, lack of flexibility to reconfigure sensor positions, and single point failures [104]. Appropriate fault-tolerant architectures and redundancy techniques can mitigate these constraints in aerospace applications. Overall, wired standards offer a robust sensor integration backbone aboard UAV platforms.

2.2.3 Wireless Sensor Networks and Topologies

Wireless sensor networks (WSNs) are gaining traction for UAV health monitoring owing to their flexibility, scalability, and distributed sensing capabilities [113]. WSNs employ miniaturized wireless sensor nodes that communicate through radio links, eliminating extensive cabling [114]. Common technologies include Zigbee, Bluetooth, WiFi, and proprietary protocols in the ISM bands [115].

WSNs also provide the connectivity fabric for IIoT systems by linking industrial assets to communication networks [116]. Benefits of WSNs for industrial monitoring include [116]:

- Easy deployment in harsh environments without wiring
- Flexibility to reconfigure the network topology

- Scalability to large-scale deployments
- Low installation and maintenance costs
- Real-time monitoring of assets and processes

However, WSNs also have some limitations in industrial settings [74]:

- Unreliable wireless links due to noise, interference, and fading
- Limited network bandwidth and latency constraints
- Resource-constrained sensor nodes with limited battery life
- Lack of standardized network architectures and interoperability
- Susceptibility to security threats such as spoofing and denial of service

International standards have been developed for industrial WSNs including WirelessHART (HART Communication Foundation), ISA100 (International Society of Automation), and IEEE 802.15.4e [117]. These standards specify the OSI protocol stack for layers including physical, link, network, transport and application [118]. Key capabilities include time synchronization, channel hopping, mesh routing, security mechanisms, and network management protocols tailored for low-power connectivity [119].

For UAVs, WSNs promote modular system architectures by reducing hardpoint wiring constraints. However, aeronautical applications necessitate addressing challenges regarding interference mitigation, reliability, safety certifiability, and security [120]. Diversity techniques, cognitive radios, ultra-wideband communications, and spectral coexistence methods can help overcome these limitations [121]. Overall, the emergence of robust, standardized WSN solutions offer immense potential to advance UAV health monitoring.

A sensor network topology refers to the arrangement or structure of sensor nodes in a network. Sensor networks are composed of numerous small, low-cost devices called sensor nodes that collaborate to monitor and gather data from a physical environment. The choice of topology affects how data is transmitted, how nodes communicate, the network's resilience, and its energy efficiency. Here are some common sensor network topologies [124]:

1. **Star topology:** In a star topology, all sensor nodes communicate with a central hub or base station. This central hub collects data from the nodes and is responsible for processing and forwarding the information to a higher-level system. This topology is simple and offers easy management and maintenance. However, if the central hub fails, the entire network

might become non-functional.

2. **Mesh Topology:** In a mesh topology, each sensor node communicates with other nearby nodes in a peer-to-peer manner. This leads to multiple communication paths, improving network redundancy and reliability. Mesh topologies can be further categorized into partial mesh (only some nodes have multiple connections) and full mesh (every node is connected to every other node).
3. **Tree Topology:** A tree topology arranges nodes in a hierarchical structure, resembling a tree. Nodes are organized in layers, with a root node at the top. Data flows from the leaf nodes towards the root node. This topology is useful when there's a need for data aggregation and forwarding towards a centralized point.
4. **Ring Topology:** In a ring topology, each sensor node is connected to exactly two neighboring nodes, forming a closed loop. Data is transmitted sequentially along the ring. Ring topologies can be more resilient than star topologies because the failure of a single node doesn't necessarily disrupt the entire network. However, adding or removing nodes can be more challenging.
5. **Hybrid Topology:** A hybrid topology combines elements of multiple topologies. For instance, a combination of star and mesh topologies can provide both centralized control and redundancy. This allows for more flexibility in designing networks to match specific requirements.
6. **Cluster Topology:** In a cluster topology, nodes are grouped into clusters, and each cluster has a cluster head that acts as a coordinator. The cluster heads then communicate with each other or with a central base station. This topology helps manage large networks and improve energy efficiency, as cluster heads can perform data aggregation and routing, reducing the energy consumption of individual nodes.
7. **Hierarchical Topology:** A hierarchical topology involves multiple levels of nodes, often organized into a pyramid-like structure. This approach helps manage network scalability and data routing efficiently by reducing the number of nodes involved in long-range communication.

The choice of sensor network topology depends on factors such as the application requirements, energy constraints, scalability needs, fault tolerance, and communication range. [122] Different topologies offer varying trade-offs in terms of energy efficiency, network resilience, and ease of maintenance. The most suitable topology will depend on the specific goals and constraints of the sensor network deployment.

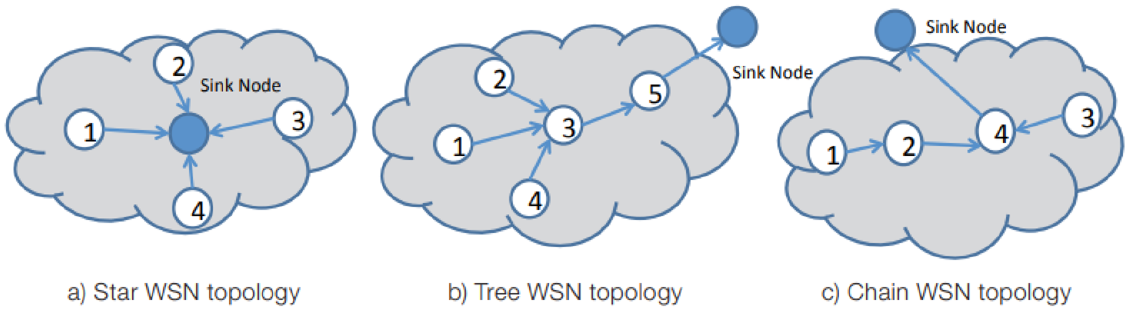


Figure 6: Three kinds of WSN topologies: star, tree, chain [65]

2.2.4 Communication Protocols for IoT Applications

A crucial aspect of implementing PHM in UAVs is the selection of appropriate communication protocols that facilitate seamless data exchange between various components of the system. IoT applications, including UAVs, demand communication protocols that meet specific requirements such as low power consumption, long-range connectivity, and reliable data transmission. Several communication protocols have been developed to cater to these diverse needs [80]:

1. **Advanced Message Queuing Protocol (AMQP)** is an open standard communication protocol employed in message-oriented middleware. It ensures messaging interoperability between systems, irrespective of the message brokers or platforms utilized, offering security, reliability, and interoperability even in challenging network conditions or over long distances. Additionally, AMQP allows communication even when systems are not simultaneously available.

2. **Bluetooth**, a short-range wireless technology utilizing ultrahigh-frequency radio waves, has historically been associated with audio streaming. However, it has evolved to become a crucial enabler of wireless and connected devices. Bluetooth Low Energy (BLE), optimized for IoT connections, is a low-power alternative to standard Bluetooth, making it particularly appealing for applications such as health and fitness trackers, smart home devices, and in-store navigation.

3. **Cellular communication** stands as one of the most widely available and recognized options for IoT applications, especially in scenarios where communications must span longer distances. Although legacy 2G and 3G cellular standards are being phased out, newer high-speed standards such as 4G/LTE and 5G are gaining prominence, providing high bandwidth and reliable data transmission. However, the use of cellular communication may come with higher costs and increased power consumption compared to other alternatives.

4. **Constrained Application Protocol (CoAP)**, introduced by the Internet Engineering Task Force in 2013, caters to IoT systems based on HTTP. CoAP relies on User Datagram Protocol for secure communications and enables data transmission between multiple points. It is often utilized in machine-to-machine (M2M) applications, accommodating constrained devices even in the presence of low bandwidth, low availability, or low-energy conditions.

5. **Data Distribution Service (DDS)**, developed by the Object Management Group, facilitates real-time systems by providing low-latency data connectivity and extreme reliability. As an M2M standard, DDS enables high-performance and scalable real-time data exchange through a publish-subscribe pattern, making it suitable for business and mission-critical IoT applications.

6. **LoRa**, known for its long-range communication capabilities, is a noncellular wireless technology that enables low-power and secure data transmission in M2M applications and IoT deployments. LoRa technology is now governed by the LoRa Alliance, which also maintains LoRaWAN, an open cloud-based protocol facilitating communication among IoT devices.

7. **Low-Power Wide Area Networks** (LPWAN) is a group of wireless networks technologies well suited to the specific needs of IoT devices: low bandwidth and low-power devices, usually battery-powered. This type of network provides low-bit rates over **long ranges** with **low power** consumption. LPWAN's can accommodate data packet sizes from 10 bytes to 1 kB at uplink speeds up to 200 kbps; long-range connectivity varies from 2 to 1,000 km depending on the network technology. Most LPWAN technologies have a **star topology**; this means that each device connects directly to a central access point.

8. **Lightweight M2M (LWM2M),** described by OMA SpecWorks, serves as a device management protocol tailored for sensor networks and M2M environments. This communication protocol caters to low-power devices with limited processing and storage capabilities, making it a suitable option for remote device management and telemetry in IoT environments.

9. **Message Queuing Telemetry Transport (MQTT),** developed in 1999 and now known as MQTT, operates through a publish-subscribe architecture, enabling M2M communication. It is designed to work in low-bandwidth situations, making it preferable for connecting devices with a small code footprint and in wireless networks with varying levels of latency resulting from bandwidth constraints or unreliable connections. MQTT has evolved from a proprietary protocol

to a leading open-source protocol for connecting IoT and industrial IoT devices.

10. **Wi-Fi**, widely used in home, commercial, and industrial buildings, offers fast data transfer and is well-suited for LAN environments with short- to medium-range distances. Despite its pervasiveness, some Wi-Fi standards may be too power-consuming for certain IoT use cases, particularly low-power/battery-powered devices. Additionally, Wi-Fi's low range and scalability limit its feasibility for deployment in certain IoT applications.

11. **Extensible Messaging and Presence Protocol (XMPP),** initially designed by the Jabber open-source community for real-time human-to-human communication, is now utilized for M2M communication in lightweight middleware and routing XML data. XMPP supports the real-time exchange of structured and extensible data between multiple entities on a network, often finding applications in consumer-oriented IoT deployments, such as smart appliances.

12. **Zigbee**, a mesh network protocol designed for building and home automation applications, ranks among the most popular mesh protocols in IoT environments. With its short-range and low-power capabilities, Zigbee extends communication across multiple devices. It provides a flexible, self-organizing mesh, operates with ultralow power consumption, and offers a library of applications, making it well-suited for various IoT implementations.

13. **Z-Wave**, another proprietary option, operates as a wireless mesh network communication protocol utilizing low-power radio frequency technology. Like Bluetooth and Wi-Fi, Z-Wave facilitates communication with encryption, ensuring security in IoT deployments. It finds applications in home automation products, security systems, and energy management technologies, supported by the Z-Wave Alliance, which focuses on expanding the technology and interoperability of Z-Wave-enabled devices.

2.2.5 Edge Computing for IoT Applications in UAV Monitoring Systems

Edge computing has emerged as a critical paradigm in processing data for Internet of Things (IoT) applications, particularly in the context of Unmanned Aerial Vehicles (UAVs). By bringing computation and data storage closer to the location where it's needed, it helps to improve response times and save bandwidth [125]. For UAVs, this approach can significantly enhance the performance and reliability of Health and Usage Monitoring Systems (HUMS).

i. Defining Edge Computing

Edge computing, as a distributed computing paradigm, involves pushing data processing tasks and functionalities away from the centralized nodes to the logical extremes of a network. It enables analytics and knowledge generation to occur at the source of the data [126]. This is particularly beneficial for IoT devices that generate vast amounts of data, such as UAVs equipped with numerous sensors for health and usage monitoring.

ii. Implementation of Edge Computing in UAV Monitoring Systems

Implementing edge computing in UAV health and usage monitoring systems involves equipping the UAV with onboard microcontrollers and sensors capable of collecting, processing, and analyzing data in real time. These onboard systems serve as the "edge," providing immediate insights into the UAV's performance and health status, without the need for data transmission to a central server for processing.

Microcontrollers can be programmed to execute a variety of data processing tasks, such as filtering sensor noise, executing feature extraction algorithms, and implementing machine learning models for predictive maintenance [127]. This reduces the volume of data that needs to be transmitted, thus saving bandwidth and enabling real-time performance monitoring.

Edge computing can also reduce latency, which is crucial for UAVs that require immediate response to changing flight conditions. By processing sensor data on the UAV itself, decisions about system adjustments or alerts for necessary maintenance can be made almost instantaneously.

iii. Recent Trends and Research Developments

Edge computing in the context of UAVs has seen significant research interest. One trend is the use of lightweight machine learning algorithms that can operate on the limited computational resources available onboard a UAV. A recent study by Zhang et al. [128] explored the use of federated learning, a distributed machine learning approach that trains an algorithm across multiple devices or servers holding local data samples.

Furthermore, the integration of edge computing and cloud computing, often referred to as fog computing, is another area of ongoing research [129]. This approach combines the advantages of both paradigms, allowing for real-time local processing through edge computing, and more substantial data analysis tasks through the cloud.

Additionally, researchers are exploring robust and secure communication protocols for UAVs to securely transmit processed data when necessary [130]. This is essential for scenarios where the UAV is operating in remote or hostile environments and the integrity of its data transmissions is vital.

In conclusion, edge computing provides an effective solution for real-time data processing in UAV health and usage monitoring systems. Its ability to reduce bandwidth requirements, improve response times, and enable on-the-go data analytics makes it an essential component in the development of a comprehensive HUMS for UAVs.

2.2.6 Structural Fault Detection Literature for UAVs

Over the course of the review, we found that the 3 technologies currently used most frequently for the real-time monitoring of structural health of small to mid-size UAVs are:

(1) Fiber Bragg grating (FBG) optical sensors

(2) Piezoelectric sensors (PZT) and

(3) Ultrasonic propagation imaging (UPI) sensors

FBGs are optical fibers with a periodically changing refractive index. These can selectively reflect wavelengths of light depending on the amount of strain placed on them.

PZT sensors are capable of generating a signal corresponding to the amount of strain applied to them. Compared to conventional strain sensors that use Wheatstone Bridge Circuits, PZT sensors are more rigid, making them more suitable for the harsh conditions of a UAV.

Lastly, Ultrasonic Propagation Imaging (UPI) sensors use lasers to detect surface and subsurface damage, but due to their bulky size, they can be used for on-ground non-destructive inspections only.

Greater details about each of these technologies have been given in the following paragraphs.

i. Fiber Bragg Grating Sensors-based Literature

Fiber Bragg Grating Sensors, or "FBGS," are particularly promising for Structural Health Monitoring (SHM) of aerospace vehicles because of, among other things, their ability to record strain and temperature, small size, low weight, multiplexing capabilities, durability and immunity to electromagnetic interferences. They may be incorporated in composite materials, which are becoming an increasingly essential component of aeronautical construction. For more than two decades, composite materials have been used in aeronautical applications. These materials are distinguished by their high strength-to-weight ratio, stiffness, and corrosion resistance. Composite materials are ideally suited for these aerospace applications since aircraft and spacecraft are often weight sensitive. The use of integrated FBGSs for UAV health monitoring is desirable, but their reaction under all operating environmental conditions of an aircraft structure must be thoroughly known for these sensors to be flight certified.

Damage-tolerant and fail-safe design of aeronautical structures necessitate extensive inspection and maintenance, which adds significantly to the aircraft's life cycle cost and downtime. The lifespan cost of aircraft and aerospace structures can be greatly decreased by including continuous and autonomous condition-based structural health monitoring (SHM) systems in their design. A structural health monitoring (SHM) system, which consists of well-designed sensor networks as well as the requisite hardware and software, will allow defects or damages to be reported early on in their development.

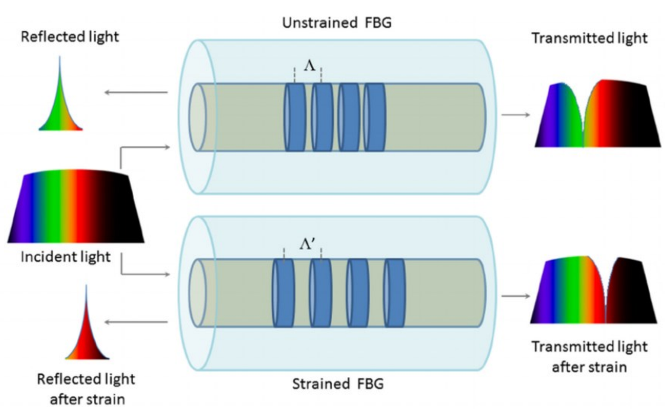


Figure 7: Schematic of the working principle of Fiber Bragg grating (FBG) sensors, and its response to strain [28]

Aiming to provide more efficient, lightweight structures, composite materials are being extensively used in aerospace vehicles. As the failure mechanisms of these materials are complex, damage detection becomes challenging, requiring advanced techniques for assessing structural integrity and maintaining aircraft safety. In this context, Structural Health Monitoring (SHM) seeks for integrating sensors into the structures in a way that Nondestructive Testing (NDT) is implemented continuously. One promising approach is to use Fiber Optic Sensors (FOS) to acquire strain signals, taking advantage of their capabilities over conventional sensors.

In a study by Frövel et al. in 2009, the temperature and humidity-dependent performance of FBG-strain sensors embedded in carbon fiber reinforced plastics (CFRP) were described [27]. The investigation work was focused on the validation of the dependence of the FBGS's strain sensitivity in tensile and compression load, in dry and humid conditions, and a temperature range from -150ºC to 120ºC. FBGs with acrylic as well as polyimide coating were tested. Conventional extensometers and strain gauges were used as reference strain sensors. The performed tests showed an influence of the testing temperatures, the dry or wet specimen condition, the load direction, and the coating material on the sensor strain sensitivity.

In 2010, Kressel et al. developed a fully airborne, high-resolution, load tracking, and structural health monitoring system for UAVs, which was integrated into the tail boom of a Nishant UAV [21]. Based on a rigorous Finite Element study, the system was built using integrated optical fiber Bragg sensors that were probed in real-time during flight at 2.5 kHz. It recognized minor and large stresses in flight with excellent accuracy by evaluating the recorded vibration signature. This investigation was followed by another in 2011, which included a static loading test [14]. In 2012, the research team conducted another investigation in which a scatter plot was used to determine deviations from the first mode of vertical bending caused by a landing impact event [3].

In a further study by Kressel et al. in 2014, FBG sensors were placed in the tail booms and wings of the "Heron" Israeli Air Force drone, but only tail boom data was analyzed [6]. Sensors successfully picked up "touch and go" maneuvers and landing strain events. Continuing the study, Kressel et al. in 2014 presented the design, qualification, and flight service evaluation of an embedded FBG-based HUMS for the Israeli Air Force Medium Altitude Long Endurance (MALE) drone [5]. A total of 54 FBG sensors were embedded on the wing and tail booms, enabling accurate tracking of both the vibration signature and the actual loading conditions of these components. A single GUI was developed to visualize the strain data, static calibration tests were performed on the ground for system validation, and a heating test was conducted to understand and compensate for the temperature effect on the FBG sensors.

In a further study by Frövel et al. in 2010 under the Spanish national-funded project ICARO, the influence of the combined effect of fatigue loading and temperature on the sensitivity of Ormocer and polyimide-coated FBGSs was determined in tensile and compression tests [9]. The studies revealed that both types of sensors operated well before and after the 1200-cycle fatigue testing. The Ormocer-coated FBGSs exhibited a consistent 2% decrease in sensitivity following fatigue cycling over the whole temperature range of -100℃ to 160℃, whereas polyimide-coated sensors showed less than 1% changes but greater standard deviations of the observed values.

Continuing the investigation, the outer wing of a UAV named SIVA was instrumented with several FBGS that measured strain and temperature [25]. The onboard FBG interrogator equipment, known as FSI, was a robust two-channel design that employs time-domain sensor identification at a sampling frequency of 500 Hz. The FSI has a memory card that enables for three hours of autonomous in-flight data collecting. Both strain and temperature readings were time-domain analyzed, and the flight data revealed exact and accurate recordings.

Low-velocity impact-induced damage, such as delamination, is largely hidden inside laminates or leaves a minor depression at the impact point in composite materials. As a result, discovering this sort of damage using traditional inspection procedures is difficult and time-consuming. To improve the effectiveness of these systems, accurate information on estimated impact sites must be supplied. Unnecessary inspections for broad undamaged zones can therefore be avoided. In a 2012 study by Byeong-Wook Jang et al., impact localization algorithms for various composite structures were developed using the impact-induced acoustic signals acquired by multiplexed fiber Bragg grating (FBG) sensors [17]. The acoustic waves generated by a specific impact were transmitted to each FBG sensor, and the resulting FBG wavelength changes were recorded using a high-speed multiplexable FBG interrogation system with a sampling frequency of 100 kHz. The difference in impact wave arrival time between each FBG signal was then determined to provide the input data sets for neural network training. High reproducible arrival time determination techniques are primarily necessary to reliably use the neural network algorithm for impact identification. Such arrival time determination methods were established in this work.

In 2015, Kressel et al. accomplished the design and flight validation of an embedded fiber Bragg gratings (FBG) based structural health monitoring (SHM) system for the Indian unmanned aerial vehicle “Nishant” [1]. The sensors were embedded as part of the manufacturing process. Using principal component analysis (PCA) and artificial neural networks, it was feasible to track both the loads and vibration signatures based on the data gathered (ANNs). Sensor location, in conjunction with adequate ground calibration, allowed for the separation of strain and temperature measurements. During landing, the beginning of a minor local structural transient instability was detected, demonstrating the importance of such continual structural airworthy evaluation for UAV structures.

In a further paper by Kressel et al. in 2017, the application of distributed fiber optic strain sensing as a standard procedure for airworthiness assessment of an entire fleet of operational High-Altitude Long

Endurance (HALE) Unmanned Aerial Vehicles (UAVs) during service was accomplished [12]. The Rayleigh backscattering sensing idea was applied to a typical optical fiber that runs the length of the wing main spar. So far, good repeatability of strain signatures under a specified loading condition has been established, proving the concept's resilience as well as the wing's great structural performance. Furthermore, the same sensing idea was applied to a full-scale test item to monitor structural performance during a fatigue test that simulated various lifetimes of this UAV. The acquired data was subjected to Principal Component Analysis (PCA) in order to isolate the information most likely associated with changes in the structural health of the wing.

In a 2015 review paper, Raffaella Di Sante critically reviewed recent research and applications in structural health monitoring of composite aircraft structures using FOS, considering both multi-point and distributed sensing techniques [22].

In a 2015 study by Jin-Hyuk Kim et al., an in-flight strain monitoring HUMS for aircraft structures was developed [18]. During the production process, the optical-fiber-based HUMS was fitted to an ultralight aircraft wing structure for effective sensor application. Ground and flight testing were performed to ensure the integrity and availability of the FBG sensors and HUMS devices installed. A total of 74 flight tests were carried out utilizing the HUMS-implemented testbed aircraft, with various maneuvers and aberrant situations considered. The flight test findings showed that the FBG-based HUMS was successfully deployed on the testbed aircraft and performed properly under actual flight test conditions, as well as generating reliable in-flight strain data from the FBG sensors over an extended length of time.

In a study by Frövel et al. in 2016, an FBG-based health and usage monitoring system for the Spanish National Institute for Aerospace Technology (INTA)'s two tactical UAVs named SIVA and MILANO are developed, based on fiber Bragg grating sensors [20]. Both strain and temperature were successfully monitored in several structural places of interest, including the outer wing, wing attachment, front and rear fuselage, a stabilizer, and landing gear. During the flight, structural deformations of the unmanned aerial vehicle were measured and utilized to compute structural flight loads. Thermal stresses caused by temperature have been adjusted for.

In a follow-up study in 2017, a health and usage monitoring system for INTA's medium altitude and long endurance (MALE) UAV called MILANO and for the flying target drone DIANA was developed [19]. FBGSs were utilized for load monitoring as well as fatigue life estimate, recording exceptional events, design verification, and optimization. Ground testing on the MILANO wing revealed the ability to identify structural damage in flight by changing the load route and strain distributions.

In another follow-up study in 2018, the team developed a health and usage monitoring system (HUMS) for INTA's medium altitude and long endurance (MALE) UAV called MILANO [8]. The structural damage was detected by comparing the strain distribution of the pristine structure with the results of the real structure by loading the structure on ground in a repeatable prescribed manner. The sturdy DTG FBGSs performed well in their characterization across a wide temperature range and under fatigue stresses, and they operated reliably during the testing of the center wing and aft fuselage. Due to the poor signal-to-noise ratio and, in this situation, the very high standard deviation, only relatively substantial damage, such as the debonding of the whole foot section of a bulkhead, could be recognized with certainty.

In a continuation of their research, an aerial target drone named DIANA IA was fitted with a health and usage monitoring system based on load path changes [13]. Destructive experiments were used to test and calibrate the health and usage monitoring system, causing specified defects in fuselage stringers and assessing structural damage based on the detected strain distribution. A simple device based on four fiber optic Bragg grating sensors detects hardly apparent structural deterioration in the drone's whole high-loaded forward fuselage.

In a follow-up study of the HUMS developed for the MILANO and DIANA, the performance of the used FBG sensors was tested [2]. Temperature, humidity, and tensile and compression stress scenarios all had an effect on the performance of embedded and surface-bonded sensors in quasi-static and fatigue tests. Tensile and compression tests were used to investigate the effect of fatigue loading and temperature on the sensitivity of Ormocer and polyimide-coated FBGSs.

In a 2016 study by Sundaram et al., an online and offline approach to the structural health monitoring system was developed at the Advanced Composites Division of CSIR-NAL of India using fiber optic sensors [24]. The paper argued for a combined online-offline inspection system for UAV maintenance, as the author believed that online FBG-based sensor technology was not on the same Technology Readiness Level (TRL) as traditional Non-Destructive Testing methods.

In a 2019 work by Joham Alvarez-Montoya et al. [7], a HUMS was developed and implemented in an Unmanned Aerial Vehicle (UAV) based on 20 Fiber Bragg Gratings (FBGs) embedded into the composite front spar of the aircraft's wing, a miniaturized data acquisition subsystem for gathering strain signals and a wireless transmission subsystem for remote sensing. The HUMS was tested in 16 flights, six of which were conducted with the pristine construction and the remaining after various artificial damages were induced. The data collected in flight were used to validate a previously developed damage detection methodology based on strain field pattern recognition, or strain mapping, which employs machine learning algorithms, specifically a Self-Organizing Map (SOM)-based procedure for clustering operational conditions and Principal Component Analysis (PCA) in conjunction with damage indices for final classification. The damage detection performance achieved the greatest accuracy of 0.981 and the highest F1 score of 0.978.

While FBG sensors themselves offer a lightweight and compact solution, limitations persist regarding FBG interrogators which are required to interpret the optical signals. Commercially available interrogators range from $10,000 to $50,000 depending on channel count and performance specifications [169]. Benchtop and rackmount interrogators weigh 2-5 kg, with embedded OEM interrogator modules around 200 gm [170]. However, small UAV platforms have stringent size, weight, and power constraints below 1 kg and $5000 for the entire sensing system [171]. Although miniaturized photonic integrated circuit interrogators have been proposed [172], current FBG interrogator size, weight, and cost pose integration challenges for resource-constrained UAVs. Further interrogator miniaturization and cost reduction are active research fronts to enable more widespread FBG adoption in small aerial platforms.

ii. Piezoelectric Sensors-based literature

Piezoelectric sensor {PZT) based structural health monitoring (SHM) methods can efficiently estimate the health condition of aircraft structures. To monitor large-scale structures, dense PZT arrays are usually needed. How to scan different PZT actuator-sensor channels in the PZT array to achieve a real-time and stable structural health monitoring task is an important issue in the application of these methods.

In a study by J. A. Oliver et al. in 2007, A specialized testbed was developed to facilitate the identification of damage in structural health monitoring studies for composite UAVs [16]. PZT, FOS, and Accelerometers were employed in this testbed and evaluated against a scanning laser Doppler vibrometer for four graphite-epoxy UAV wing test pieces, as well as a series of comprehensive finite element models of the test pieces and a dynamic testing setup. Preliminary data suggested that moderate damage lowers fundamental natural frequencies and changes mode shapes, but not to the point of overcoming variability between the FE model and physical structure at the current level of correlation.

In a study by Qiu et al. in 2009, an integrated multi-channel PZT array scanning system {ISS) was developed for structural health monitoring [15]. A gain-programmable charge amplifier with a low crosstalk scanning module was discussed. To control the hardware and conduct signal processing and damage estimates, an integrated software system based on the LabVIEW software platform was designed. An examination of a carbon fiber composite wing box of an unmanned aerial vehicle was undertaken to validate the functionality of this system. The application results demonstrated the system’s promising performance.

In 2012, a study by Chan Yik Park et al., as part of a special seven-group project, developed a structural health monitoring (SHM) system for a composite UAV [4]. A structural health monitoring system was specified as a collection of a sensor-integrated wing, onboard device, and ground station after the system architecture was designed and the operational scenario was determined. A variety of PZT and FBG sensors were put on the UAV wings as part of the experiment, which was then tested and damaged. A small onboard device was designed and utilized to continuously monitor external load, structural events, and damage. The ground station was also built and used to assess the intensity, extent, and location of the damage. UPI was used as part of on-site non-destructive inspection (NDI) and was particularly efficient in detecting minor flaws. Finally, the developed hardware components and algorithms were tested in a range of scenarios.

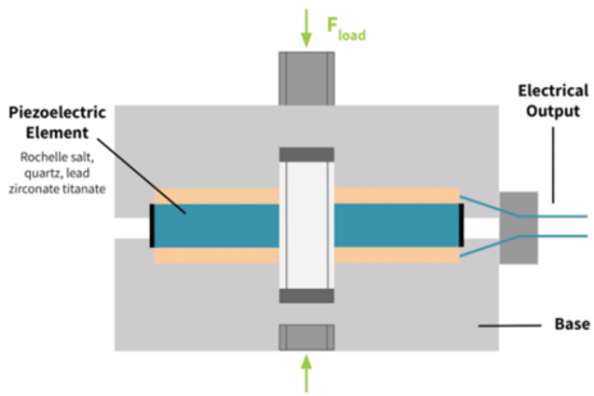


Figure 8: Piezoelectric Load Cell Diagram [29]

The following comparison has been made between the three main HUMS technologies for structural monitoring:

Table 1: COMPARISON OF KEY ON-BOARD HUMS TECHNOLOGIES

Fiber-Bragg Grating sensors	***Piezo-Electric sensor array***	***Electrical Strain Gauges***
Small size, low mass, low cost	Small size, low mass, low cost	Heavy, large size, and expensive
Long lifespan	Long lifespan	Relatively shorter lifespan
Immunity to electrical interference	Not immune to electrical interference	Not immune to electrical interference
High-speed, high signal to noise ratio	High Speed, high signal-to-noise ratio,	Low speed, low signal-to-noise ratio

Fiber-Bragg Grating sensors	***Piezo-Electric sensor array***	***Electrical Strain Gauges***
	but needs dense PZT arrays	
Durability in extreme weather conditions	Durability in extreme weather conditions	Not very durable in extreme weather conditions
Multiplexable, whole fiber acts as a sensor	Non-multiplexable, cumbersome wiring required	Non-multiplexable, cumbersome wiring required
Can be embedded during manufacturing, eliminating the need for sensor protection	Difficult to embed into the composite material due to complex wiring	Cannot be embedded into the composite material during manufacturing

It is easy to see that FBGs outperform PZT arrays, UPIs, or conventional strain gauges in almost all metrics.

2.2.7 Temperature-related Fault Detection Literature for UAVs

i. Fiber Bragg Grating Sensors-based literature

Sensing of temperature is a critical parameter in many engineering applications. While conventional temperature sensors such as thermistors, thermocouples, and resistive temperature detectors (RTDs) are widely used, they can have limitations in certain scenarios. For instance, these sensors may have restricted operating ranges, be susceptible to electromagnetic interference (EMI) noise, and lack distributed or multiplexed sensing capabilities. However, their suitability depends on the specific requirements of the application.

Fiber Bragg grating (FBG) based optical sensors offer an alternative temperature sensing approach with several benefits, though they also have some downsides. FBGs provide high reliability, low thermal mass, small size, immunity to EMI, and the potential for distributed sensing over a single fiber. The underlying principle for their temperature sensitivity is the dependence of the periodic refractive index modulations on temperature via the thermo-optic effect in silica glass. However, FBGs can be more complex to install in certain applications and the interrogation equipment is currently more expensive compared to traditional electrical temperature sensors. In that regard, FBGs may be better suited for niche applications that require their unique capabilities.

One such unique application where the benefits of FBG sensors outweigh the limitations is its application for temperature-sensing for UAV health monitoring. Several researchers have conducted feasibility studies on this topic, some of which are presented below.

In a 2020 study by N.A. Rosman et. al. [30], a temperature monitoring system was proposed by using the fiber Bragg Grating (FBG) approach. This system was developed by using OptiSystem simulation and hardware implementation. FBG was employed as it allows a reflected wavelength of light that shifts in response to variations in temperature and/or strain. Generally, FBG sensors offer ease of installation, higher accuracy, longer stability, smaller size, immunity to electromagnetic interference (EMI), and the ability to measure ultra-high and speed events. The results indicated that the wavelength shifting is dependent on the thermal expansion coefficient of the materials involved.

In a 2012 review paper [31], Xiaoyi Bao et al. describe how Rayleigh, Brillouin and Raman scattering in optical fibers allows them to detect local material characteristic features like density, temperature, strain, and vibration with a high degree of accuracy.

In another review paper by Jasjot K. Sahota et al. [32], various techniques like Phase-shifted FBG with femtosecond laser inscription, and Fiber laser-based FBG were reviewed. These optical sensors are usable in high-temperature ranges, making them suitable for aerospace applications.

Authors Hyun-Kyu Kang et al. discussed a method of simultaneously monitoring both strain and temperature during and after the cure of a composite laminate using Fiber Optic Sensors [34]. In 2007, R Montanini et al. successfully demonstrated a similar sensing system that allowed the simultaneous measurement of both temperature and strain by monitoring the change in reflected wavelength from two coupled FBG sensors that have been embedded into the composite laminate [35]. Such use of the same type of sensors to measure multiple physical parameters will be very important to keep costs and complexity down and reduce sensor compatibility issues in our future prototype HUMS.

Thermal runaway of batteries is a failure mode of major concern for UAVs that use DC motors. Current commercial battery management systems do not provide adequate information in real-time to mitigate such issues. In a 2017 study [36], Aleksandra Fortier et al. explored the integration of FBG sensors inside lithium-ion battery (LiB) coin cells. Strain as well as internal and external temperatures were successfully recorded. A similar study was done by Susana Novais et al. in 2016 [39], successfully demonstrating the ease of FBG installation for in-situ battery thermal monitoring.

FBGs make good temperature sensors at extremely low (cryogenic) temperatures, as was shown in a 2005 paper by C Lupi et al. [37]. On the other hand, they also show good response at extremely high temperatures as well, as is evident in a 2022 review paper by Shaonian Ma et al. [38]. Such versatility and suitability to a wide range of operating conditions make FBGs the ideal aerospace temperature monitoring technology.

ii. MEMS Sensors

Built-in distributed temperature sensing can also be achieved using CMOS (MEMS)-based sensors. In [33], authors Karim Arabi and Bozena Kaminska discuss a simple and efficient built-in temperature sensor for the online thermal monitoring of microelectronic structures based on a CMOS 1.2- micrometer technology.

2.2.8 Vibration-related Fault Detection Literature for UAVs

i. Fiber Optic Sensors

Distributed fiber optic sensing provides an alternative approach for vibration monitoring over extended areas. In a 2010 paper, Yuelan Lu et al. proposed a distributed optical fiber vibration sensor based on spectrum analysis of a polarization-OTDR system to detect distributed vibration, notably pencil-break vibration [40]. For the phase optical time domain reflectometry system, they employed heterodyne detection and signal processing with moving averaging and moving differential. The spatial resolution was 5m, while the greatest frequency response found was 1 kHz.

In 2017, Zengguang Qin et al. completed a research project in which they presented a vibration sensing system based on all-polarization-maintaining configurations of phase-sensitive optical time-domain reflectometry (OTDR) [41]. Maintaining Polarization of the components reduce both polarization-induced signal fading and noise. The detectable frequency response was raised to 2.25 kHz with a spatial resolution of 1 m, making them practical.

In another 2017 study on real-time distributed vibration monitoring using phase-OTDR, Yu Wang et al. investigated the impact of pulsed light power entering the sensor fiber [42]. Then, for 1-D and 2-D vibration localization, two systems based on the differential technique and the Prewitt edge detection approach applied to phase-OTDR were described. Finally, to achieve 3-D real-time vibration monitoring, a high-speed acquisition system based on FPGA was used.

Fiber Optic distributed vibration sensors are being used in a broad range of applications, including pipeline inspection gauge (PIG) detection and the YOLO object identification algorithm [43]. The trained model was able to precisely capture the invert-V signature in the spacetime graph, indicating the PIG's real-time location.

The repetition rate of the pump pulse limits the highest detectable vibration frequency using a phase-sensitive optical time-domain reflectometer (-OTDR). This makes quantitative vibration frequency measurement challenging. Zhiyong Zhao et al. proposed a multicore fiber (MCF) based space-division multiplexed (SDM) -OTDR and Mach- Zehnder interferometer (MZI) hybrid sensor [44] to overcome these limitations, enabling truly uninterrupted distributed vibration sensing with a broad vibration frequency response range and high spatial resolution.

In summary, distributed fiber optic sensors offer complementary capabilities for aircraft health monitoring. Their multiplexing, extended coverage, and embeddability within composites make them well-suited for UAV applications. However, fiber optic systems need to enhance their dynamic range and frequency response.

ii. Accelerometers

Traditional vibration monitoring techniques have relied extensively on accelerometers based on principles such as piezoelectricity, capacitance, and inductance. These conventional sensors can provide high frequency responses up to 50 kHz and beyond, with good sensitivity and resolution [98]. Signal conditioning and data acquisition systems have been developed to enable vibration data analysis using techniques such as FFT analysis for fault diagnosis of rotating machinery [99]. However, conventional transducers offer only point measurements and lack multiplexing capabilities.

In summary, while conventional acceleration transducers continue to play important roles in vibration monitoring, they lack extended coverage and multiplexing capabilities.

2.2.9 Electrical Fault Detection

i. Current Sensing

The electrical power system (EPS) is critical for safe UAV flight as more and more UAVS are becoming electrically powered. Direct current (DC) distribution with power electronics is increasingly common in UAVs [45]. However, DC networks face protection challenges due to high discharge currents during faults. Traditional electrical protection methods for aerospace power networks may be inadequate for the unique needs of compact UAV EPS architectures [47].

Conventional nondestructive testing approaches rely extensively on current measurements using clip-on probes or Hall effect sensors [48]. These traditional electrical measurement methods have limitations for UAV applications due to size, weight, electromagnetic interference, and lack of distributed sensing [49]. Fiber optic current sensors (FOCS) based on Faraday effect offer a lightweight and multiplexed alternative [50]. FOCS using microfabricated magneto-optic sensor heads weigh under 10 gm and offer high DC to AC current measurement accuracy [51]. Such FOCS technology shows promise for EPS health monitoring in UAVs and more research is needed on their application for in-flight fault diagnosis [52].

In summary, practical electrical measurement techniques like FOCS tailored for size, interference, and integration constraints need further investigation for UAV EPS monitoring [53]..

ii. EMI Monitoring

Stray electro-magnetic field (EMF) measurement using radio frequency (RF) antennas or HFCT coils is a non-contact technique for current monitoring [55, 56]. This facilitates detection of developing electrical faults by identifying modulation or inter-harmonics from switching devices [57]. However, EMI monitoring methods face size and interference challenges for compact UAV platforms that require shielded power electronics [58].

iii. EPS Analytics

Analytical model-based approaches using machine learning have demonstrated high accuracy for UAV EPS condition monitoring. For instance, hidden Markov models achieved over 95% classification precision in identifying common power system fault categories from sensor data [46]. Neural networks, SVM and decision trees have delivered near 100% accuracy by learning complex fault signatures [59]. Deep learning methods like CNN, RNN and sparse autoencoders are also emerging for predictive UAV EPS maintenance [62].

In summary, specialized electrical sensing combined with data-driven analytical approaches shows promise for comprehensive real-time monitoring of UAV propulsion system health. Significant research is still needed to mature and validate these technologies through extensive flight testing. Robust integration and aviation certification also remain key challenges.

2.2.10 Environmental Fault Detection Literature for UAVs

i. Acoustic Sensing

Acoustic emissions provide valuable insights into the health of various UAV components such as motors, gearboxes, propellers and drive systems [47]. Techniques to analyze noise signals include artificial neural networks (ANN), empirical mode decomposition (EMD) and wavelet transforms.

A 2022 study by Adam Bondyra et al. [47] applied ANNs on data from microphone arrays to classify acoustic emission features for multirotor UAV actuator fault detection and isolation. The method achieved over 98% accuracy in detecting and locating defective rotors.

In 2019, Gino Iannace et al. [48] utilized ANNs to diagnose propeller defects in a UAV using acoustic data. With just the sound from defective blades, the model identified faults with 97.63% accuracy. EMD was found to isolate diagnostic acoustic features efficiently.

A paper by Wenbin Liu et al. [173] employed deep convolutional neural networks to classify acoustic data for UAV rotor fault detection. The approach attained 92% accuracy for normal and abnormal sound conditions. Data augmentation and transfer learning improved model generalization.

Researchers have also explored integrating acoustics with other sensing modalities. A 2020 study [174] combined sound, vibration and stator current data with long short-term memory networks to detect bearing faults and estimate remaining useful life in UAV motors with up to 92% accuracy.

While most literature has focused on rotary UAVs, Mohd Ariffanan Mohd Basri et al. [175] proposed an ANN-based acoustic approach for fixed-wing UAV fuel leak detection with 95% accuracy. This demonstrates the potential of acoustics for propulsion system monitoring.

Overall, acoustic sensing enables condition monitoring of otherwise inaccessible components. Challenges include operation in noisy flight environments and integration of arrays on limited UAV payload space. Lightweight MEMS microphones and onboard analytics hold promise to address these barriers [176].

ii. Icing Detection

Airframe and propulsion system icing poses a severe flight hazard for UAVs operating in inclement weather [177]. Icing disrupts aerodynamics and risks component damage or failure if unchecked. Therefore, real-time icing detection and mitigation capabilities are critical.

Richard Hann et al. [50] developed an electro-thermal technology to detect and counteract icing on fixed wing UAV wings. The system autonomously activated heating elements upon detecting ice buildup via embedded sensors. While effective, such solutions increase power consumption for smaller UAVs.

An infrared thermography based approach was proposed by Hua Yang et al. [178] to identify icing on UAV rotors. A thermal camera monitored temperature differences between the rotor tip and ambient air to identify icing events. However, such imaging systems can be costly and challenging to embed on micro UAV airframes.

Researchers have also studied Microwave Radiometers (MWR) which can remotely detect moisture in clouds conducive to icing [179]. Although large radar systems provide wider coverage, recent work has shrunk MWR units to fit small aerial platforms. For instance, a 2018 study [180] demonstrated a 160 gm MWR integrated on a multirotor UAV for targeted in situ icing condition monitoring.

Advanced anti-icing coatings and MEMS solutions have additionally gained interest to mitigate UAV icing incidents [181]. Embedding icing sensors in these coatings could enable holistic detection and protection. Overall, continued innovations for in situ icing monitoring matched with aerodynamic adaptations will be imperative to operate UAVs safely in adverse weather.

iii. Other Sensing

Beyond acoustics and icing, UAV health monitoring necessitates other environmental measurements including airspeed, turbulence, wind, temperature, humidity and barometric pressure [182]. Lightweight MEMS and optical sensors are required, coupled with data fusion techniques to synthesize information from diverse modalities.

Custom sensor suites have been designed for small UAVs, such as the 90 gm weather sensor array by Robert Sorensen et al. incorporating thermometers, hygrometers and anemometers [183]. Michał Czapski integrated multiple MEMs sensors into fixed-wing airframes to capture turbulence and icing conditions [184]. The miniaturization and cost reduction of such environmental sensors will promote their adoption in UAV prognostics and health management systems.

2.3 Analysis and Recommendations

The preceding sections reviewed prominent technologies and research related to health and usage monitoring systems for UAVs. This analysis synthesizes key findings from the literature to identify limitations of current solutions and potentials for improvement. These provide the basis for recommendations on optimal technologies suited for developing a retrofittable HUMS prototype.

2.3.1 Limitations of Current Solutions

While the literature reveals several promising technologies for UAV health monitoring, certain limitations persist that constrain real-world performance, robustness, and applicability.

Size, weight, and power consumption remain key constraints for onboard health monitoring systems [131]. Although MEMS and fiber optic sensors provide lightweight solutions, the supporting interrogation and transmission modules are still bulky and power-hungry [132]. This hampers deployment on small UAV platforms with limited payload capacity. Custom ASICs and energy harvesting methods need further research to overcome these barriers.

Reliability and ruggedness present another concern, especially for embeddable and non-contact sensors operating in harsh flight conditions [133]. Failure of a single node can degrade distributed measurement capabilities. Hermetic packaging, redundancy, and fault-tolerant network topologies provide avenues to address these challenges.

Limited dynamic range and frequency response of certain sensing modalities restricts their effectiveness for vibration monitoring, impact detection, and other applications [134]. For example, fiber optic acoustic sensors have shown lower sensitivity compared to piezoelectric transducers [135]. Multi-physics modeling and materials research could help expand the operating envelopes.

Most research focuses on sensors embedded in specific structures like wings and tail booms [134]. However, holistic monitoring requires expanding sensing to subsystems like motors, controllers and batteries. Lack of standards and certification frameworks is another barrier to technology maturity and adoption [135]. A key gap is the development of integrated algorithms that synthesize multi-modal sensory data to enable vehicle-level diagnosis.

Finally, the lack of standards, productization, and certification procedures hinders technology maturity and adoption [137]. Cost analysis studies are also scarce. Addressing these gaps is essential to translate promising research concepts into fielded UAV health management solutions.

2.3.2 Potential for Improvements

Addressing the above limitations requires research across technology, manufacturing, and policy domains. Several high-potential areas emerge from the literature survey.

Reducing the size and enhancing efficiency of interrogation systems could accelerate embeddable sensor deployment [138]. Photonic integrated circuit solutions show promise to replace bulky optical interrogators. Energy harvesting utilizing vibration, solar, and RF methods also warrants research for self-powered modules [139].

Improving ruggedness of sensors and ensuring redundancy would increase robustness, especially for critical structural monitoring [140]. Techniques like optical switching in fiber networks, multiplexed RF links, and multi-path routing provide redundancy at the systems level.

Expanding dynamic range and frequency response would broaden applicability of certain sensing modalities like fiber optic acoustic emission detectors [141]. Novel transduction methods, new materials like graphene, and MEMS fabrication techniques provide pathways for performance enhancement.

Analytics and data fusion are active research frontiers. Recent works demonstrate the potential of physics-based models, machine learning, and statistical approaches for integrated vehicle health management [142,143]. However, significant development remains to achieve robust implementations.

Technology maturation and certification is critical for fielding [144]. Engagement with standards bodies and regulators early in the design process could accelerate the path to commercialization. Cost-benefit studies are also needed to quantify the value of health monitoring.

In summary, multifaceted innovation spanning materials, devices, analytics, and policy is required to unlock the full potential of UAV health management systems. The technology foundations are maturing rapidly, setting the stage to address current limitations.

2.4 Conclusion

This literature review has synthesized key research related to health and usage monitoring technologies for unmanned aerial vehicles. The findings highlight promising sensing solutions while also revealing limitations that constrain real-world performance and robustness. These insights set the stage for a systematic comparative analysis to recommend optimal technologies for developing a retrofittable HUMS prototype.

2.4.1 Summary of Findings

Numerous sensing modalities demonstrate viability for UAV health monitoring, including fiber optic, piezoelectric, MEMS, and acoustic sensors. Each excels in certain applications; for instance, FBG sensors enable distributed strain and temperature monitoring, while PZT transducer arrays offer high-resolution structural diagnosis. Fiber optic sensors, especially FBG sensors, are widely favored for UAV health monitoring due to attributes like distributed sensing, EMI immunity, and embeddability.

However, limitations persist in interrogator size, robustness against fiber damage, and lack of sensing at non-structural subsystems. Size, weight, power, and cost constraints impose barriers, especially for small UAV platforms. Ruggedness, reliability, security, and redundancy need improvements to operate reliably in harsh flight conditions. Sensors with limited dynamic range and frequency response have reduced effectiveness for vibration monitoring and impact detection.

Notably, current research focuses more on isolated subsystems rather than holistic vehicle health management. Integrated algorithms that synthesize multi-modal data to enable vehicle-level assessment represent a key gap. Furthermore, the lack of standards, productization, and certification procedures hinders technology maturity and adoption.

2.4.2 Outlook

While foundational technologies are maturing, realizing the full potential of UAV health management requires pushing sensing frontiers as well as innovations in manufacturing, data analytics, and policy.

Ongoing materials research and nanofabrication techniques can enable smaller, more efficient sensors with expanded operating envelopes. For instance, graphene-based transducers may offer broadband dynamic range exceeding conventional alternatives. Physically unclonable function (PUF) sensors leverage nanoscale manufacturing variations for resilience in hostile environments.

Edge computing and AI will be critical to actualize integrated vehicle health management. Lightweight neural networks that process heterogeneous sensor data could enable continuous monitoring and predictive maintenance. Blockchain solutions address security, verification, and control challenges associated with UAV data sharing.

Additive manufacturing, multifunctional meta-structures, and self-healing materials open new possibilities for smart sensing components. Modular, plug-and-play architectures will allow flexible sensor integration and upgrades. Standardization and certification frameworks need to coevolve with these emerging technologies.

2.4.3 Need for a Trade-Off Analysis

This literature review has spanned structural, thermal, vibrational, electrical, and environmental monitoring techniques relevant for UAVs. However, a systematic comparative analysis is essential to identify the most promising technologies suited for developing a pragmatic HUMS prototype given size, power, cost, and other constraints.

The next chapter will undertake a trade study in section 3.4 to evaluate candidate solutions based on quantitative metrics and application requirements. Combined with lessons from this review, the trade study will provide the methodological basis for selecting optimal sensors, networking approaches, and computing strategies for the prototype system.

In summary, the literature review has provided support for the **First Hypothesis** that existing maintenance practices are inadequate for addressing UAV reliability challenges. The analysis revealed limitations of current maintenance routines and underscored the need for innovations like HUMS to enable predictive capabilities. The literature review has also supported the **Second Hypothesis** – that current HUMS solutions are unsuitable for small UAVs owing to size, weight, power, and cost constraints. In the next chapter, the system architecture and design process outlined to exquisitely tailor the prototype HUMS's requirements and component selection to the size, weight and power restrictions of small UAVs add further credence to the correctness of the **Second Hypothesis** outlined at the beginning of this thesis.

Chapter 3

Methodology & System Overview

3.1 Introduction

This chapter presents the methodology for developing a retrofittable and cost-effective Health and Usage Monitoring System (HUMS) prototype tailored for unmanned aerial vehicles (UAVs). The literature review in Chapter 2 provided an overview of prominent technologies and research related to UAV health monitoring. Building on those findings, this chapter outlines the process for designing the HUMS prototype, beginning with defining the key requirements and constraints. A trade study is then conducted to evaluate and select optimal technologies for the prototype. Finally, the overall system architecture, components, and implementation are described.

The objective is to demonstrate a simplified HUMS that can continuously monitor critical parameters like vibration, temperature, and electrical current to detect anomalies and enable predictive maintenance. The long-term goal is a modular, adaptable HUMS that can be easily retrofitted to various UAV platforms to improve reliability and safety.

3.2 Mission-critical Failures Modes and Sensing Requirements for small-to-mid sized UAVs

Reliable operation of unmanned aerial vehicles (UAVs) necessitates identifying and monitoring failure modes that are most likely to compromise mission success and safety during flight. To determine the key failure modes, a failure modes effects and criticality analysis (FMECA) was conducted based on a recent study by Chowdhury and Lipsett [187].

The FMECA identified the following failure modes as potentially mission-critical for small-to-medium sized UAVs based on their likelihood of occurrence and severity of consequences:

1. **Structural Failures:**

- Buckling due to excessive wind shear or bird strike impacts.
- Material fatigue leading to catastrophic cracks and breakages.

2. **Propulsion System Failures:**
    - Propeller damage such as nicks, erosion or fracture.
    - Internal motor failures like demagnetization or winding shorts.
    - Electronic speed controller (ESC) malfunctions.
3. **Power System Failures:**
    - Battery thermal runaway events and associated fires.
4. **Communication System Failures:**
    - Broken wiring connectors and damaged cabling.
    - Intermittent or fully disconnected data links.
5. **Environmental Threats:**
    - Icing accumulation on wings, rotors and control surfaces.
    - Antenna and sensor damage from environmental factors.
    - Camera/sensor degradation such as lens occlusion.
    - Radiation induced disruptions of onboard electronics.

It is to be noted here that lubricant-related failures can occur on internal combustion (IC) engine powered UAVs, even in short flights. However, these types of failures have not been included within the scope of our research, as we are mostly concerned with small-to-medium size battery-powered UAVs in this thesis.

The study [187] performed a comprehensive failure mode and effects analysis (FMECA) to identify the most critical failure modes for small-to-medium sized UAVs. Their analysis concluded that structural failures, propulsion system failures, power system failures, communication failures, and environmental threats were the highest priority risks that could compromise mission success and safety. Monitoring the onset and progression of these failure modes necessitates structural, thermal, vibrational, electrical, and environmental sensing capabilities. Therefore, based on the FMECA recommendations, condition indicators related to these five failure categories were selected for focus in developing the health and usage monitoring prototype to enable early fault detection and prevent catastrophic UAV failures. This aligns with the overarching motivation to improve reliability and maximize mission availability through a sensor-based predictive maintenance system.

To detect the onset and progression of these failure modes, the following **key sensing requirements** were derived:

1. Structural Health Monitoring:
    - Stress range monitoring at likely failure points.
    - Strain measurement for fatigue cycle counting.
2. Propulsion System Monitoring:
    - Vibration analysis to identify imbalances.
    - Temperature monitoring of motors and ESCs.
    - Real-time RPM tracking.
3. Power System Monitoring:
    - Battery voltage and current measurement.
    - Temperature monitoring for thermal runaway.
4. Communications Health Monitoring:
    - Link signal-to-noise ratio (SNR).
    - Network continuity and data transmission logging.

5. Environmental Monitoring:

    - Temperature, humidity, pressure and other ambient condition sensors.
    - Vision-based monitoring for sensor degradation.
    - GPS signal reception strength checks.

Based on these requirements, the following sensor classes were selected as suitable candidates for the health and usage monitoring system prototype:

1) **Structural Sensors:** Strain gauges, fiber Bragg gratings (FBG), and piezoelectric transducers enable distributed monitoring of structural loads. Ultrasonic detectors can identify subsurface flaws. (e.g., HBM FIT series FBG sensors)

2) **Vibration Sensors:** Accelerometers and velocity transducers coupled with high frequency data acquisition systems facilitate vibration analysis. Fiber optic acoustic sensors offer an alternative approach. (e.g., ADXL335 triple-axis accelerometer)

3) **Temperature Sensors:** Resistive temperature detectors (RTDs), thermocouples, thermistors, and FBG sensors track temperature across critical components. (e.g., Sensirion SHT85)

4) **Current Sensors:** Hall effect sensors and fiber optic current transducers measure electrical current to assess battery and motor health.

5) **Environmental Sensors:** MEMS pressure, humidity, gas, and airspeed sensors provide ambient condition monitoring. Weather radar and icing detectors aid situational awareness.

This sensor selection provides coverage for detection, diagnosis and prognosis of the identified mission-critical failure modes using affordable and proven sensing technologies. The complement of temperature, vibration, strain, electrical and environmental sensors constitutes the basis for a retrofittable health and usage monitoring system capable of bolstering the reliability and safety of small-to-medium sized UAVs.

3.3 General design requirements and constraints for the prototype HUMS

At first, 8 key general design requirements are set to guide the overall HUMS prototype design process:

(1) **Modular and Flexible design:** The HUMS should have modular design to allow interfacing with a broad range of UAV platforms through customizable sensor configurations.

(2) **Low Bandwidth requirements:** The HUMS should be capable of monitoring all major condition indicators of the UAV with minimum bandwidth.

(3) **Low Size and Weight:** The HUMS hardware should have low size and weight requirements to minimize impact on the UAV's payload capacity and flight endurance [145]. The total mass should be under 5% of the takeoff weight, and the form factor needs to be small so as to not cause aerodynamic drag or impede the UAV's normal functionalities in any way.

(4) **Low Power Consumption:** The HUMS, through energy-efficient components, should have low overall power requirements to avoid excessive battery drainage [146].

(5) **Low Cost and Scalability:** The HUMS should be low cost and highly scalable by utilizing affordable commercial off-the-shelf (COTS) components [147].

(6) **Improved UAV Reliability:** The UAV with onboard HUMS should have reliability greater than an unmodified robot in the harshest operating and environmental conditions, and in case of failures, the HUMS should be field maintainable. Redundancy techniques like mesh networking must be incorporated to mitigate single point failures. Through an intuitive dashboard, the HUMS will help operators analyze trends and generate alerts for preventive maintenance.

(7) **Security:** The HUMS should have data security against cyber-attacks, jamming and hacking through secure bootloading, authentication, and encryption.

(8) **Safety:** The HUMS cannot compromise flight safety through electromagnetic interference or reduced aircraft stability margins [150].

These design requirements will guide the rest of the HUMS development journey. To fulfill these general requirements, some commercially available, low-cost sensors were chosen to give the HUMS the necessary fault-detection capabilities.

3.4 Tradeoff study of available technologies

3.4.1 Evaluation Criteria

This section evaluates and compares candidate technologies to recommend optimal solutions for developing the health and usage monitoring system (HUMS) prototype tailored for unmanned aerial vehicles (UAVs). The analysis is driven by key design requirements and constraints identified in Section 3.2 and 3.3.

The following quantitative metrics are used to benchmark and compare alternative technologies:

- Size and weight: Ideal < 50 gm, Maximum < 200 gm
- Power consumption: Average < 1 Watt
- Onboard processing capability: ARM Cortex M4 class
- Wireless range: 50 – 500 m
- Throughput: 50 – 500 kbps
- Sampling frequency: 0.1 – 10 kHz
- Operating temperature: -10 to 60°C

3.4.2 Wired vs Wireless Sensors Selection

While wired sensors ensure reliability and minimize interference, wireless sensor networks enable flexibility in distributed sensing critical for UAVs. Hence wireless sensors with Zigbee connectivity are chosen despite higher unit costs. Mesh topologies provide redundancy to mitigate single node failures. Zigbee modules maintain a lightweight form factor under 10 gm.

3.4.3 Central Microcontroller Selection

Table 2: COMPARISON OF CANDIDATE CENTRAL MICROCONTROLLERS

Microcontroller	Size (mm)	Weight (gm)	Processing (DMIPS/MHz)	Power (mW)	Wireless
Arduino Uno	2. 53	25	16	500	WiFi shield
Raspberry Pi Zero	65 x 30	9	1400	360	WiFi onboard
SeeedStudio XIAO	48 x 23	5	12	720	BLE onboard

The SeeedStudio XIAO offers the best balance of small form factor and processing capabilities. However, Arduino Uno is chosen for its ease of integration with diverse sensors and extensive community support.

3.4.4 Comparative Analysis for Sensors

Table 3: COMPARISON OF CANDIDATE SENSORS FOR VARIOUS FAULT TYPES

Sensor	Measurement	Size (mm)	Weight (gm)	Power (mW)	Frequency (Hz)	Interface
DHT22	Temperature, Humidity	40 x 20 x 11	11	0.3	0.5	Digital
ADXL335	Vibration	27 x 13 x 8	2	0.32	0-1000	Analog

Sensor	Measurement	Size (mm)	Weight (gm)	Power (mW)	Frequency (Hz)	Interface
SHT85	Temperature, Humidity	19 x 7 x 5.5	2	15	1	I2C

The DHT22 offer compact profiles and ultra-low power consumption suitable for UAVs compared to the SHT85. Hence the DHT22 was chosen despite marginally lower performance.

However, the measurement range and fault sensitivity requirements must also be considered for robust condition monitoring. For the DHT22 temperature sensor, the range is -40°C to 80°C, with a fault sensitivity of ±0.5°C, sufficient to detect thermal issues in batteries or motors which could experience up to 50°C rise from ambient for minor faults and >100°C for major failures.

The ADXL335 vibration sensor has a range of 0-1000 Hz and sensitivity of 10 mV/g, capable of detecting motor imbalance faults which typically cause 10-100X vibration amplitude increases from baseline**.** The sampling rate of 1 kHz meets the Nyquist criterion for maximum vibration frequencies around 500 Hz.

By evaluating both performance metrics and measurement ranges, sensors can be selected that reliably meet the condition monitoring objectives for early fault detection and diagnostics. The metrics analysis ensures technical viability while range analysis guarantees sensitivity to failure modes of interest.

3. Communication Protocol Selection

Selecting optimal communication protocols is imperative for the health and usage monitoring system (HUMS) to ensure reliable data transfer within the unmanned aerial vehicle (UAV) and to the ground station. This research adopts a hybrid architecture utilizing Zigbee for wireless communication between the sensor clusters and central microcontroller, while LoRaWAN connects the microcontroller to the cloud analytics platform.

For short-range communication within the UAV, Zigbee was selected over alternative protocols like Bluetooth and proprietary RF solutions. Zigbee’s self-organizing mesh network topology provides inherent redundancy and robustness, overcoming the limitations of a star topology. If any node fails in a star network, it can render the entire system inoperable. In contrast, Zigbee allows automatic multi-hop routing along the best available path, minimizing data loss from individual node failures.

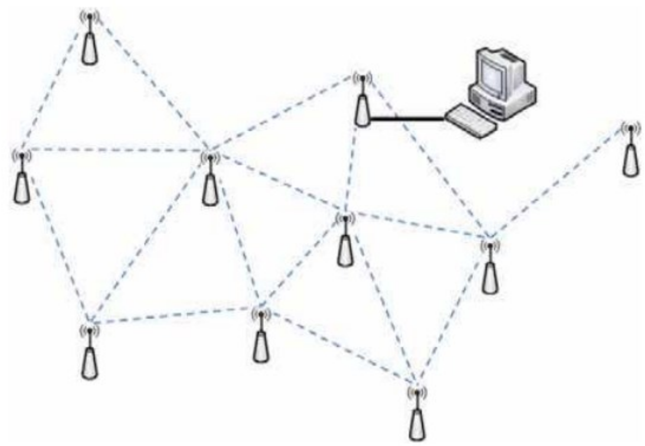


Figure 9: Mesh self-organizing network [65]

Zigbee's built-in encryption enhances security compared to Bluetooth networks which are more susceptible to unauthorized access. Zigbee's 128-bit AES encryption secures data transmission between resource-constrained sensor nodes. Zigbee networks can support over 65,000 nodes with low latency, catering to high node density scenarios. In comparison, Bluetooth networks are limited to 8 active slave nodes per master. Zigbee's extensive range up to 100 meters satisfies communication requirements within a small UAV platform.

Importantly, Zigbee is optimized for low power applications with nodes in sleep mode consuming just 5-50 mW. This maximizes battery life for wireless sensor nodes, extending the UAV's operational duration. In contrast, Bluetooth is relatively power-hungry, consuming over 100 mW even in idle mode which quickly depletes batteries. Zigbee operates in the globally compatible 2.4GHz band compared to Bluetooth's crowded 2.4GHz spectrum leading to interference issues. Zigbee's meshing allows bandwidth reuse to support over 250 kbps throughput meeting intra-vehicle data rates.

For long-range communication, LoRaWAN provides connectivity spanning several kilometers compared to hundreds of meters for other protocols like Sigfox, NB-IoT, and regular WiFi. LoRaWAN's chirp spread spectrum modulation enhances robustness and resilience to channel noise. Its wideband chirps allow operation at low transmit power levels around 25 mW, enabling compact battery-powered end nodes. LoRaWAN networks employ a star-of-stars topology where gateways relay messages between end devices and central network servers. The gateways provide a robust and resilient link over large campus, citywide or regional footprints.

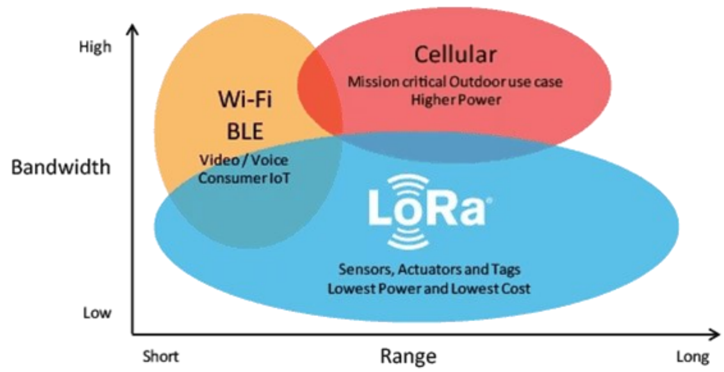


Figure 10: Bandwidth vs. a range of short-distance, cellular and LPWA networks

LoRaWAN's physical layer bit rates range between 0.3 kbps to 50 kbps depending on spreading factors. Despite modest throughput, LoRaWAN meets the bandwidth requirements for periodic health monitoring data from UAV platforms. The long-range connectivity up to 10 km enables continuous transmission during remote operations beyond the range of Zigbee or WiFi. Alternatively, cellular networks could also be utilized for global coverage and higher bit rates above 1 Mbps, albeit at increased power consumption.

By combining Zigbee and LoRaWAN, the hybrid architecture eliminates extensive wiring associated with tethered sensors. The wireless integration of distributed sensor nodes respects the size, weight and power constraints of small UAV platforms. Zigbee facilitates reliable intra-vehicle data exchange among sensors while LoRaWAN enables long-range cloud connectivity for real-time analytics and decision making. This balanced approach addresses the challenges of bandwidth, throughput, interference mitigation, reliability and range associated with UAV health monitoring. The standards-based protocols ensure interoperability, security, and scalability as well as minimal development effort. Overall, the hybrid architecture provides an optimized, field-ready connectivity framework tailored for the next generation of smart and connected UAVs.

3.4.7 Cloud Analytics Platform Selection

ThingSpeak is chosen for its ease of use in creating live data channels and dashboards compared to alternatives like Arduino IoT Cloud. Built-in APIs simplify integrating analytics and alerts.

3.4.8 Technology Recommendations

Based on the tradeoff analyses, the key technologies recommended are:

- Wireless sensor nodes with DHT22 and SW-420 sensors
- Arduino Uno central microcontroller
- Zigbee communication protocol between nodes and microcontroller
- LoRaWAN protocol between microcontroller and ground station
- ThingSpeak cloud analytics platform

This technology portfolio provides an optimal combination of sensing coverage, compact form factor, energy efficiency and rapid prototyping capabilities well-suited for developing the simplified HUMS prototype.

Rigorous comparative analysis facilitated the selection of technologies best aligned with the HUMS design requirements. The wireless architecture offers flexibility while the Arduino ecosystem enables efficient prototyping. This technology foundation sets the stage for validating the HUMS prototype's capabilities and potential for UAV platforms.

3.5 System Architecture Diagram

The system architecture provides a comprehensive overview of the HUMS components and how they integrate to fulfill the functional requirements. A well-designed architecture is crucial for the HUMS to deliver reliable condition monitoring capabilities for unmanned aerial vehicles (UAVs).

The system architecture diagram comprises two key elements – the architecture flowchart and the component-level diagram. The flowchart offers a high-level view of the end-to-end data flow and analytics pipeline. Meanwhile, the component diagram details the specific hardware elements, connectivity mechanisms and data transmission protocols.

3.5.1 System Architecture Flowchart

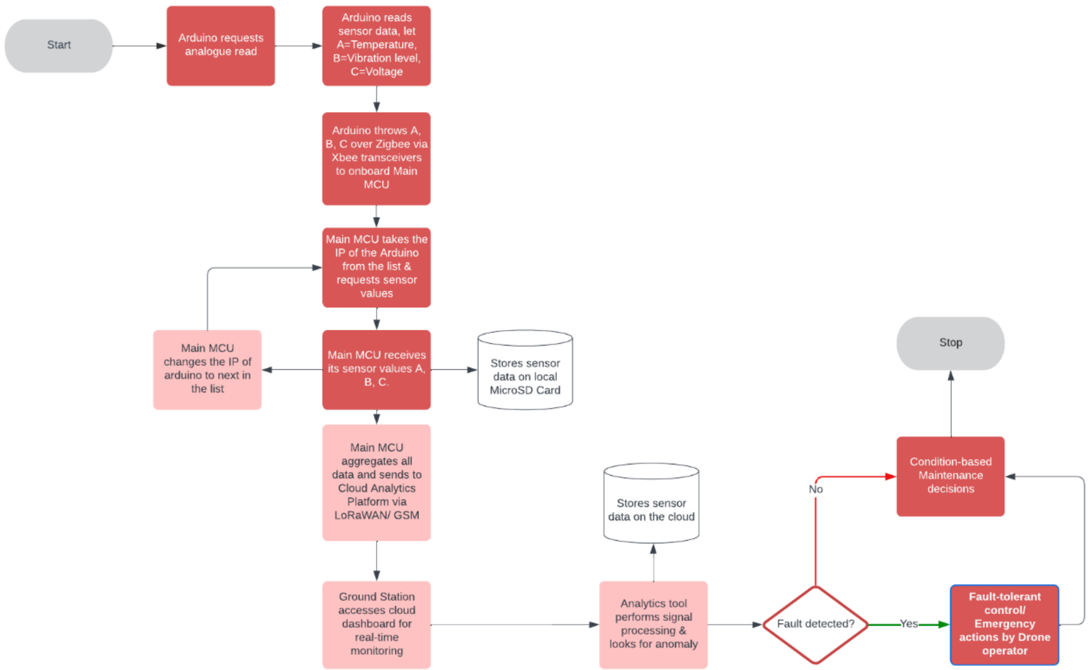


Figure 11: System Flowchart for the proposed HUMS

The HUMS architecture flowchart depicts the overall workflow from data acquisition to decision support. As illustrated in Figure 11, the distributed sensor nodes powered by Arduino boards continuously acquire vital condition indicators. This includes temperature, vibration levels, rotor RPM and other parameters corresponding to the failure modes of interest.

The sensor measurements are transmitted wirelessly using Zigbee to the central onboard microcontroller. This microcontroller aggregates data from all the nodes to create a comprehensive snapshot of the UAV's health state in real-time. The microcontroller then sends the aggregated data to the cloud analytics platform via the long-range LoRaWAN protocol.

On the cloud platform, the streaming sensor data is analyzed using statistical algorithms, digital signal processing and machine learning models to detect anomalies. Any exceedances, abnormal trends or incidents that require maintenance are identified at this stage. The platform raises alerts for the ground control station, where operators can visualize the data trends, diagnose faults and take appropriate actions.

This end-to-end architecture ensures that critical sensor data is seamlessly captured, communicated, analyzed and translated into actionable information for predictive maintenance.

The flowchart provides a high-level overview of the distributed sensing, communication protocols, cloud analytics and human-machine interaction elements that enable robust condition monitoring.

3.5.2 System Architecture Diagram

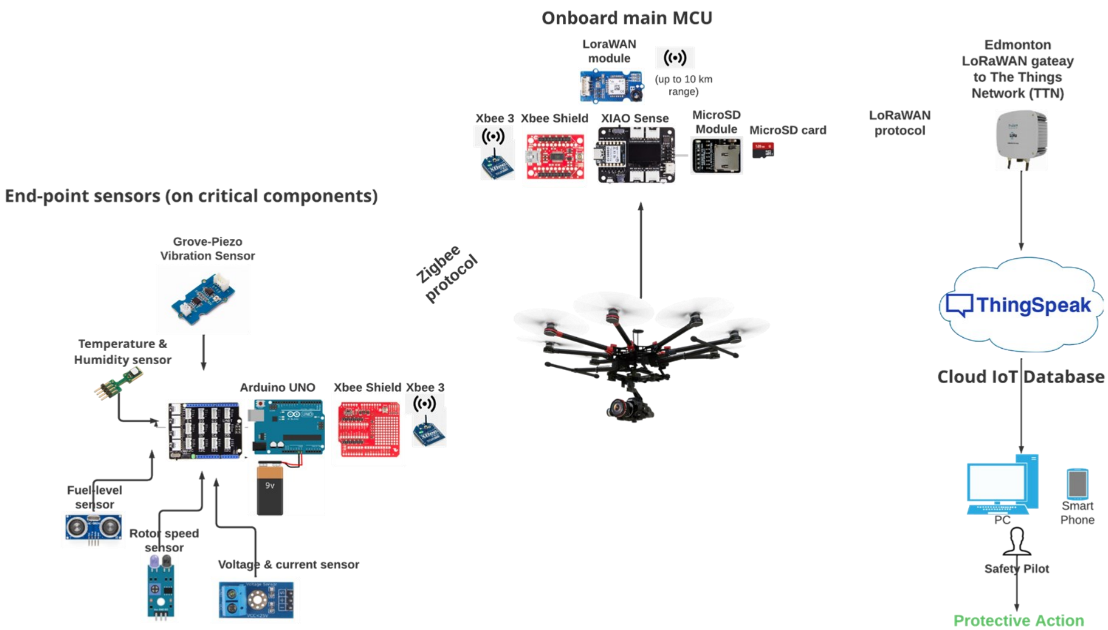


Figure 12: System Architecture Diagram of the proposed HUMS for UAV

The system architecture diagram in Figure 12 illustrates the hardware components that collectively realize the HUMS workflow. The key elements are:

- **Wireless Sensor Nodes:**
    - Arduino Uno R4: This microcontroller board serves as the core of the wireless sensor nodes. Its Atmega328P MCU provides processing capabilities for data acquisition and transmission.
    - Grove Base Shield V2: The shield offers plug-and-play Grove connectors to interface sensors and modules with the Arduino board.
    - Xbee Module: These RF modules create Zigbee mesh networks enabling wireless communication between nodes and the central MCU.

  - DHT22 Sensor: This digital temperature and humidity sensor tracks environmental conditions.
  - ADXL335 Sensor: The 3-axis accelerometer measures vibrations for health monitoring.

- **Central Onboard Microcontroller:**
  - Seeed Studio XIAO nRF52840: This powerful ARM Cortex M4F board aggregates sensor data via its onboard Xbee receiver and processes analytics algorithms.
  - Expansion Board: Provides Grove connectors to link LoRaWAN and data storage modules.

- **Communication Modules:**
  - Xbee Module: Creates the Zigbee mesh network for intra-vehicle communication between sensor nodes and central MCU.
  - Grove LoRaWAN Module: Enables long-range wireless transmission to the cloud analytics platform.

- **Cloud Platform:**
  - ThingSpeak: This robust IoT analytics platform enables real-time data visualization, archiving, processing and alerts.

- **Local Storage (optional):**
  - MicroSD Module: Provides onboard flash storage for sensor data, logs and other information.

This architecture provides a flexible, scalable and redundant framework for UAV platforms. The wireless integration and compact footprint of the Arduino sensor nodes allow easy installation at critical locations without extensive rewiring. The hybrid Zigbee and LoRaWAN approach balances efficient local data exchange and long-range cloud communications. Finally, the ThingSpeak platform offers a simplified yet powerful tool to operationalize the streaming HUMS data through interactive visualizations, intelligent analytics and configurable alerts.

In summary, the system architecture design fulfills the key requirements for the UAV health and usage monitoring system. By connecting sensing, communication, and decision support across hardware and software elements, the architecture enables comprehensive, real-time condition monitoring to bolster efficiency, safety, and reliability during flight missions.

3.6 Decision to Simplify the HUMS for Initial Prototyping

The Health and Usage Monitoring System (HUMS) architecture and technologies proposed in Sections 3.4 and 3.5 represent an ideal configuration for maximizing sensing coverage, redundancy, and analytics capabilities. However, implementing the complete system exceeds the scope of this initial research project focused on preliminary proof-of-concept validation.

Therefore, a deliberate decision was made to construct a simplified prototype with wired sensor connections and WiFi communication in place of LoRaWAN. This streamlined approach enabled rapid assembly and troubleshooting, overcoming limitations in funding, labor and timeline constraints. More importantly, it fulfilled the key objective of demonstrating core real-time monitoring capabilities and validating the HUMS concept.

Several factors drove this simplification:

- **Research Phase Focus:** The primary goal at this stage is rapid prototyping and initial proof-of-concept testing versus productization. A simplified version allows quicker assembly and debugging.
- **Resource Constraints:** The available budget, labor, and timeline constrained constructing a fully redundant wireless mesh architecture across the entire UAV platform.
- **Prioritization of Functionality:** Demonstrating core real-time monitoring capabilities took precedence over robustness and form factor optimization during initial trials.
- **Commercialization Pathway:** While the final HUMS will be a wireless platform, a wired prototype still validates core analytics, dashboard and alert features that can be carried over later.
- **Accessibility of Components:** The Arduino ecosystem offers plug-and-play modules for rapid integration versus custom wireless sensor development.

- **Risk Mitigation:** Troubleshooting and validation is easier with a wired architecture before addressing complexities like interference in wireless deployments.

Moreover, the initial simplified HUMS prototype was planned to include an ADXL335 accelerometer for vibration-based condition monitoring in addition to the DHT22 temperature and humidity sensor. However, due to timeline and resource constraints, only the DHT22 sensor could be implemented and tested in the simplified prototype described in this chapter. The vibration monitoring capabilities will be incorporated in the next phase of developing the comprehensive wireless HUMS as detailed in Chapter 5.

The simplified wired prototype offers valuable insights despite limitations. The use of jumper cables restricts flexible sensor positioning and distributed monitoring unlike a wireless mesh. Reliance on WiFi connectivity also prevents field testing in remote areas or at high altitudes where internet is unavailable. However, the fundamental data analysis, anomaly detection and cloud dashboard features can still be proven and ported to future wireless versions.

This phased approach aligns with best practices in engineering design processes. With rapid prototyping as the goal in Phase 1, factors like functionality testing, risk mitigation and leveraging accessible technologies take priority over productization considerations like size, cost or field reliability. The learnings from initial concept validation then guide the next stage of evolution.

The subsequent Phase 2 development can integrate wireless sensing and long-range communication based on Zigbee and LoRaWAN as originally proposed. This transition will be smoother having already validated the data analytics pipeline and human-machine interfaces. In essence, the simplified prototype offers a launching pad to mature the HUMS to an aviation-grade solution ready for real-world deployment.

In the ideal version of the HUMS, which is feasible for an industrial setting, the following components were proposed for implementation:

Sensor Clusters:

- Temperature & Humidity Sensors: e.g., Sensirion SHT85
- Vibration Sensors: e.g., ADXL335 3-axis accelerometer
- Strain Sensors: e.g., HBM FIT series FBG sensors

- Electrical Sensors
- Optical, Acoustic, and other types of Environmental Sensors

Data Transmission:

- Zigbee Protocol for wireless connectivity between sensor clusters and central microcontroller (Arduino)
- LoRaWAN or Cellular GSM Shield for long-range data transmission from the central microcontroller to the cloud or ground station

Central Microcontroller (Onboard UAV):

- Arduino or Seeed Studio XIAO nRF52840 Sense Board

On the other hand, the ***actual*** test setup version of the HUMS involved the following components:

Sensor Setup:

- Grove DHT22 Temperature & Humidity Sensor

Data Transmission:

- Grove UART WiFi Module V2 – for data transmission from the central Arduino to the cloud (ThingSpeak)

Central Microcontroller (Onboard UAV):

- Arduino UNO R3
- Grove Base Shield for Arduino

Despite the streamlined implementation, this approach validates the potential of the HUMS concept. Lessons from the initial prototype will inform the next stage of evolving a comprehensive wireless sensor network architecture. The simplification lowers the barrier to demonstrating functionality rather than being limited by scale.

In summary, the pursuit of a simplified HUMS prototype aligns with the research objectives at this conceptual stage. It enables agile proof-of-concept validation while laying the foundations for future wireless products that meet the rigors of aviation industry standards. The learnings will pave the path to mature and rugged solutions ready for real-world deployment across a variety of UAV platforms.

3.7 System Design for the Simplified HUMS

Here is a brief overview of the specific components that have been used in our Simplified HUMS scenario:

Arduino Uno R4:

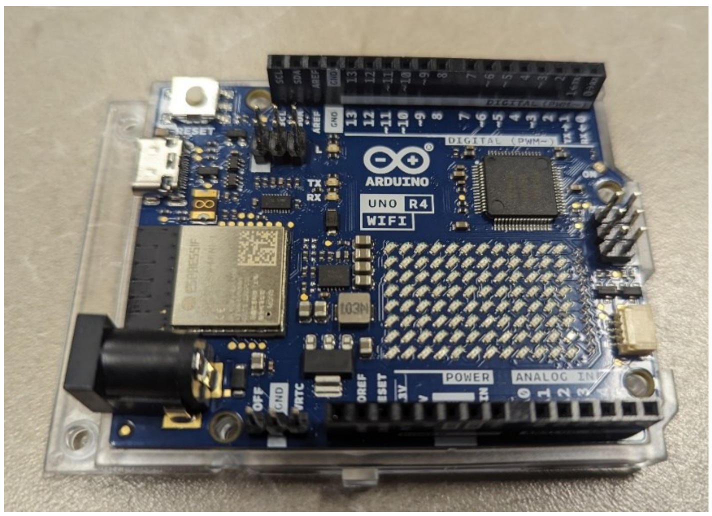


Figure 13: Arduino UNO R4 [81]

The Arduino Uno R4 WiFi represents an enhanced evolution of the Arduino Uno, providing upgraded processing capabilities and built-in wireless connectivity to satisfy the needs of the simplified wireless HUMS prototype [81].

At its core lies the RA4M1 microcontroller, with 256KB flash and 48KB SRAM, offering ample program memory and workspace for data acquisition, preprocessing algorithms, and WiFi-based transmission. The 120MHz clock speed facilitates more sophisticated filtering compared to the original Uno.

The inbuilt ESP32-S3 WiFi/Bluetooth module provides wireless transmission capabilities, removing the need for a separate shield as used previously. This shrinks the overall footprint while integrating communication functions. The WiFi interface enables simplified prototyping without wiring, while Bluetooth permits future wireless sensor integration.

To accommodate the wide input voltage needs of UAVs, the Uno R4 WiFi supports 7-24V operation. The power draw is similar to the original Uno, ensuring minimal impact on flight endurance.

The expanded peripherals like the 12-bit DAC, CAN bus, op-amp, and 12x8 LED matrix offer possibilities for advanced signal conditioning, control, and visual output. However, these are unnecessary for the simplified prototype.

Overall, the Arduino Uno R4 WiFi enhances the processing and wireless capabilities over the original Uno while maintaining the versatility and community support of the Arduino ecosystem. Its wireless integration, expanded memory, faster clock speed, and voltage tolerance validate its selection for implementing the simplified wireless sensing prototype within UAV SwaP constraints.

Grove Base Shield V2.0 for Arduino:

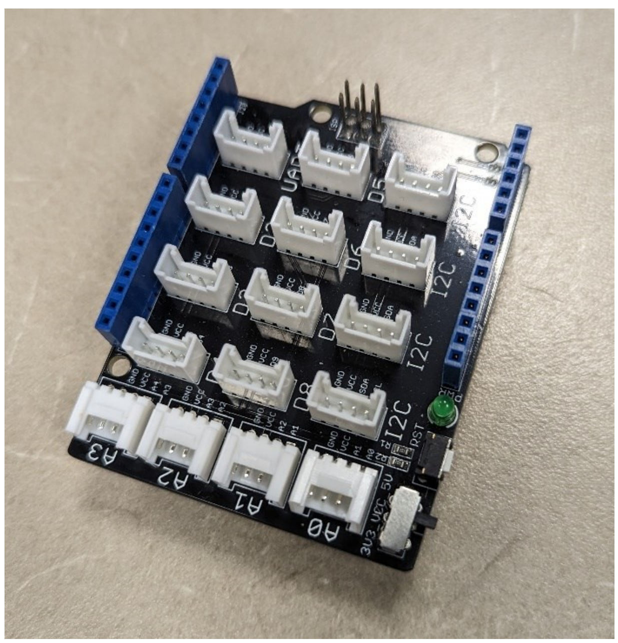


Figure 14: Grove Base Shield V2.0 for Arduino by SeeedStudio [82]

The Grove Base Shield V2.0 for Arduino, manufactured by SeeedStudio, plays a crucial role in the simplified HUMS setup for real-time condition monitoring. This shield offers a streamlined and organized approach to connect with Arduino boards, eliminating the need for cumbersome breadboards and intricate jumper wires. Its compatibility with Arduino Uno R3 ensures seamless integration with the existing architecture [82].

The key features of the Grove Base Shield V2.0 are primarily centered around its 16 onboard Grove connectors, which consist of 4 x Analog, 7 x Digital, 1 x UART, and 4 x I2C interfaces. This extensive array of connectors provides the capability to effortlessly interface with over 300 Grove modules, enabling a diverse range of sensor integrations.

Notably, the shield incorporates several essential components to facilitate smooth operations. These components include an RST button, a green LED for power status indication, an ICSP pin, a toggle switch, and four rows of pinouts. The RST button and power LED serve standard functions, while two distinct features are worth emphasizing:

4. Power Compatibility:

Each Grove connector comprises four wires, with one designated as VCC. To address variations in the microcontroller main board voltage requirements, the Base Shield V2.0 incorporates a power toggle switch. This feature empowers users to select the appropriate voltage (either 5V or 3.3V) compatible with the specific microcontroller main board in use, ensuring optimal functionality and power management.

5. Streamlined Connectivity:

The Base Shield V2.0 simplifies the connection process, minimizing the complexity associated with integrating multiple sensors and LEDs. By utilizing the Grove connectors, users can conveniently attach various Grove modules, streamlining the prototyping process and reducing setup time.

The Grove Base Shield V2.0 is an essential component in the current simplified HUMS setup. Its versatility, extensive Grove connector options, and power compatibility feature make it an ideal choice for creating a cohesive and efficient interface between the central Arduino microcontroller and the connected sensors. This shield not only enhances the overall reliability and performance of the HUMS system but also contributes to a more organized and manageable approach to condition monitoring and data collection for the UAV.

Grove Temperature and Humidity Sensor (DHT22):

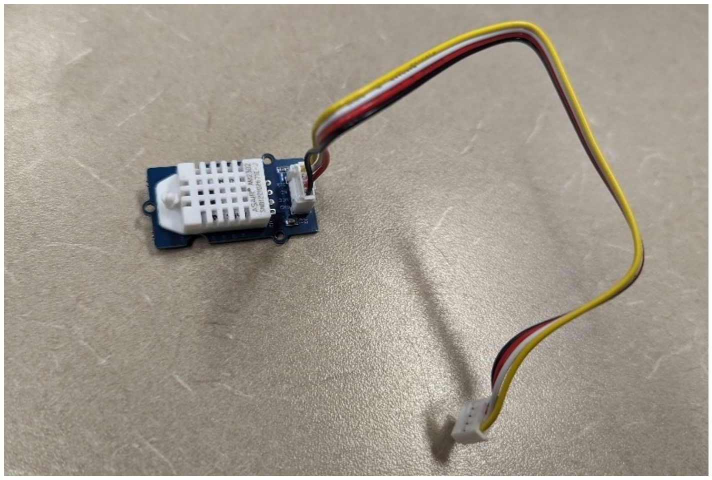


Figure 15: Grove – DHT22 Temperature and Humidity Sensor [83]

The DHT22 sensor provides precise temperature and humidity measurements, which are critical for detecting anomalies in key UAV subsystems like batteries and motors. [84].

The temperature sensor's -40 to 80°C operating range and ±0.5°C accuracy can reliably capture abnormal thermal rises associated with impending battery failures or motor winding damage. Temperatures exceeding 60°C indicate degraded battery cells, while motor windings deteriorate rapidly above 100°C [84].

To detect rapid temperature fluctuations linked to destabilized batteries or motor overheating, a sampling rate of 1 Hz or above is necessary. This fulfills the Nyquist criterion for capturing thermal transients that can have frequencies up to 0.5 Hz.

The Arduino's 10-bit analog-to-digital converter digitizes the analog voltage signals from the DHT22's onboard T/H sensors. A 5-point moving average filter is applied to the digital data to smooth out high-frequency noise or spikes. The filtered temperature and humidity data is checked against minimum/maximum thresholds pre-coded on the Arduino to extract any anomalies before wireless transmission.

The DHT22's I2C interface and compact 40 x 20 x 11 mm footprint with just an 11g weight satisfies integration requirements within the confined space of a UAV. Its ultra-low power draw of just 2.5 mA during conversion and 40 µA when idle preserves flight endurance.

Overall, the DHT22 provides reliable, accurate environmental monitoring suitable for UAVs through its optimized measurement range, sampling rate, filtering, and surface mounting. Its digital output eliminates errors from analogue signal degradation. The extracted temperature and humidity features enable efficient wireless transmission to monitor battery and motor conditions.

Adafruit ADXL335 3-Axis Accelerometer (+-3g analog out):

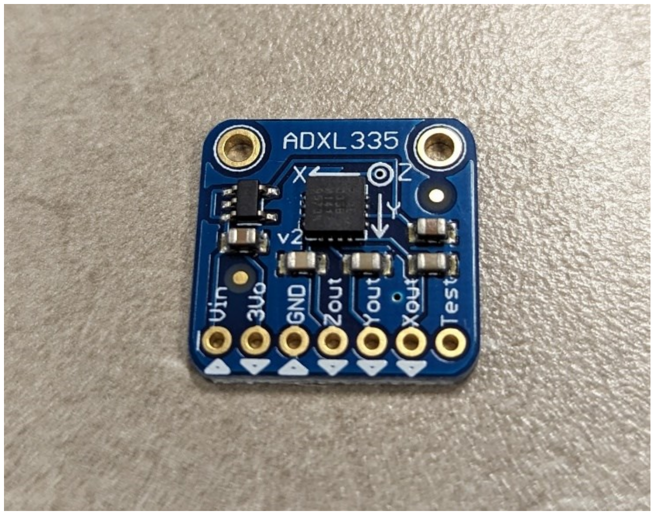


Figure 16: Adafruit ADXL335 3-Axis Accelerometer [84]

The ADXL335 is a critical sensing component in the health and usage monitoring system (HUMS) for UAVs. This analog triaxial accelerometer, shown in Figure 16, is ideally suited to measure vibration and impact events during UAV flights, providing the raw data needed for condition monitoring and predictive maintenance.

The ADXL335's wide +/- 3g measurement range allows capturing severe shocks and crashes experienced by UAVs, ensuring valuable data is acquired even during catastrophic events. Each axis has a 11mV/g sensitivity, providing high resolution vibration data with noise floors down to 50µg/√Hz, ideal for early fault detection. The three analog voltage outputs for X, Y, and Z axes interface directly with the microcontroller's analog inputs for real-time data acquisition.

This MEMS accelerometer can measure DC and dynamic acceleration over a 50Hz bandwidth, covering typical UAV vibration frequencies. The sensor operates on 3-6V DC and incorporates an on-board 3.3V regulator, enabling simple interfacing with 5V microcontrollers. Small size, low power consumption, and low cost makes integration straightforward.

Two mounting holes facilitate attachment inside the UAV chassis. Simple capacitors configure bandwidth and noise performance for the target application. Overall, the ADXL335 provides reliable vibration and impact data with excellent resolution, range, and interfacing flexibility ideal for UAV health monitoring and predictive maintenance applications. Direct analog interfacing and compact size allow straightforward integration into space-constrained UAV platforms for real-time condition-based monitoring during flights.

Grove UART WiFi Module V2 (ESP8285)

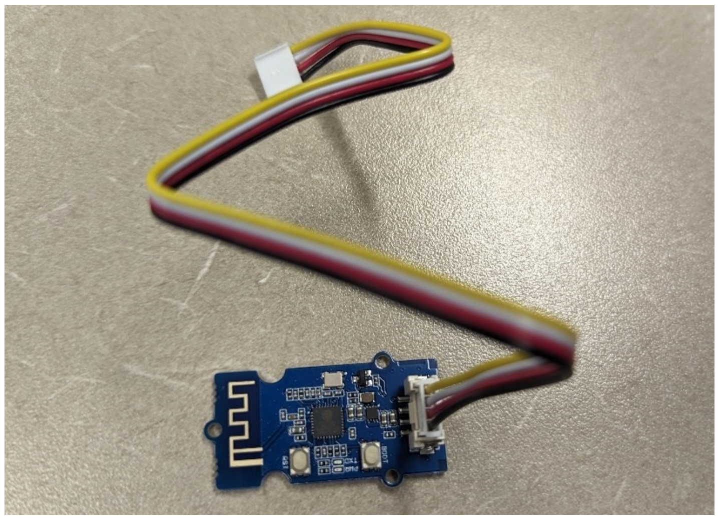


Figure 17: Grove UART WiFi Module V2 (ESP8285) [85]

The Grove UART WiFi Module V2 (ESP8285) is a critical component in the current simplified HUMS setup, serving as a powerful and highly integrated Wi-Fi System-on-Chip (SoC) that enables seamless wireless data transmission and communication for real-time condition monitoring of the UAV [85].

The key features of the Grove UART WiFi Module V2 are optimized to fulfill the specific requirements of the HUMS system, providing robust and reliable Wi-Fi connectivity for data transmission and remote monitoring. Powered by the ESP8285 Wi-Fi chip, the module supports 802.11 b/g/n with a frequency range of 2.4~2.4835GHz, offering data rates of up to 72.2 Mbps in both Access Point (AP) and Station modes.

An essential aspect of the module is its ultra-low power technology, which incorporates five power states, including DEEP_SLEEP mode, to minimize non-essential functions and reduce energy consumption significantly. This power-saving capability ensures extended operational duration during UAV flights, enhancing the overall efficiency of the HUMS system.

The Grove UART WiFi Module V2 excels in Wi-Fi performance, with a fast response time that allows it to quickly wake up and transmit data packets within 2ms. Additionally, its integrated high-speed cache contributes to improved system performance and optimized memory utilization, ensuring smooth and reliable data transmission during UAV operations.

With its user-friendly plug-and-play Grove connector, the module is easy to integrate into the existing HUMS setup. Detailed documentation and support resources are provided to facilitate seamless implementation and operation.

The ESP8285 SoC features an integrated TCP/IP protocol stack, enabling seamless interaction with Wi-Fi networks through simple AT command set firmware. This functionality allows the module to act as an access point with DHCP, join existing Wi-Fi networks, and support configurable MAC and IP addresses.

With dimensions of 40mm x 20mm x 7mm and a weight of 8g, the Grove UART WiFi Module V2 maintains a compact form factor, ensuring minimal impact on the UAV's weight and dimensions, which is crucial for flight performance.

The module operates with input voltages of 3V or 5V, providing compatibility with different power sources, further enhancing its versatility for various UAV setups. The Baud Rate for communication is set at 115200.

Overall, the Grove UART WiFi Module V2 (ESP8285) plays a central role in the simplified HUMS setup, enabling wireless data transmission and communication for real-time condition monitoring of the UAV. Its powerful Wi-Fi capabilities, low power consumption, and ease of integration contribute to the enhanced reliability and functionality of the HUMS system during UAV operations.

The DJI S1000+ Octocopter:

Figure 18: The DJI S1000+ Spreading Wings Octocopter [86]

The DJI Spreading Wings S1000+ is an ideal candidate for serving as a test bed for the prototype simplified Health and Usage Monitoring System (HUMS) due to its outstanding features, advanced capabilities, and remarkable performance [87].

As a professional-grade octocopter drone manufactured by DJI, a renowned leader in the drone industry, the DJI S1000+ was released in October 2014 and has since gained a reputation for its reliability and versatility. The drone's design revolves around an octocopter configuration, featuring eight rotors, which provides significant advantages over the standard quadcopter design, particularly in terms of fault tolerance. With eight rotors, the S1000+ has an enhanced ability to maintain stability and control even in the event of a single rotor failure, making it a highly reliable platform for conducting critical test flights during the evaluation of the simplified HUMS prototype.

The DJI S1000+ boasts an impressive flight time of up to 15 minutes, thanks to its powerful battery capacity of 20000 mAh. Although it may not match the flight endurance of some long-endurance drones, the 15-minute flight time is still substantial, allowing for extended data collection and real-time monitoring sessions during the HUMS testing phase. Additionally, the drone's battery can be quickly recharged or swapped out for backup batteries, ensuring minimal downtime between flights.

With overall dimensions of 460 × 511 × 305 mm and a weight of 4.4 kg, the DJI S1000+ strikes a balance between portability and payload capacity. The relatively lightweight design allows for easy transportation and deployment of the drone in various field environments, while the substantial payload capacity of up to 5 kg makes it ideal for carrying the necessary HUMS components and sensors without compromising flight stability.

The drone's frame and landing gear are constructed from sturdy carbon fiber material, which significantly reduces weight while maintaining structural integrity and strength. This not only contributes to the drone's overall stability during flight but also ensures durability and resistance to external impacts, a crucial factor when conducting test flights in industrial settings.

The DJI S1000+ is equipped with a highly efficient and reliable 40A electronic speed controller (ESC) built into each arm. The ESCs, combined with high-performance 1552 folding propellers and a V-type mixer design, provide each rotor with a maximum thrust of 2.5 kg. This powerful propulsion system allows the drone to carry a substantial payload and perform dynamic maneuvers with ease, making it suitable for various professional applications, including aerial photography and surveying missions.

Furthermore, the drone's flight controller, the DJI A2 high-end flight controller, offers advanced features and precise control options, adding to the drone's overall versatility and ease of operation. The flight controller is equipped with a precise GPS system, enabling accurate positioning and navigation during flights. Intelligent orientation control, point of interest, banked turn, and cruise control modes provide users with enhanced flight capabilities and automated functions that are essential for the effective implementation of the simplified HUMS prototype.

The DJI S1000+ is compatible with various gimbals, including the Zenmuse Z15-5D III and the entire line of Zenmuse Z15 Camera Gimbals. These supported gimbals ensure smooth and stable footage capture in all conditions, making the drone an excellent platform for conducting real-time condition monitoring and capturing high-quality data for further analysis.

In terms of operating temperature, the DJI S1000+ is designed to perform reliably in a wide range of environmental conditions, with a minimum operating temperature of -10°C and a maximum operating temperature of 40°C. This allows for the drone's deployment in diverse climates and industrial settings, ensuring its suitability for a broad spectrum of HUMS testing scenarios.

The S1000+ Ready to Fly package includes everything necessary to start flying straight out of the box, simplifying the setup process for researchers conducting tests with the simplified HUMS prototype. The package includes motors, folding propellers, a power board, a sturdy carbon fiber frame, retractable landing gear, and a folding GPS bracket. Additionally, the drone comes with the DJI A2 flight controller system and a Taranis 2.4GHz X9D Digital Radio Telemetry System, providing a reliable and high-performance transmitter for seamless drone control.

For the best user experience, the package also includes a 22.2V 16,000mAh lithium-ion battery and a balance charger with an LCD screen, allowing users to monitor the battery's status and ensure optimal charging cycles for extended flight time.

The DJI S1000+ RTF Specs offer a comprehensive view of the drone's performance parameters. The diagonal wheelbase measures 1045mm, while the frame arm length is 386mm. The frame arm, which includes the motor, ESC, and propeller, weighs 325g. The center frame, which includes the landing gear mounting base and servos, has a weight of 1520g. The landing gear size is 460mm (Length) × 511mm (Width) × 305mm (Height).

The powerful motor of the DJI S1000+ features a stator size of 41 × 14mm and a KV rating of 400rpm/V, providing a maximum power output of 500W. The motor's weight, including the cooling fan, is 158g. The electronic speed controller (ESC) operates at 40A and 6S LiPo voltage, with a signal frequency ranging from 30Hz to 450Hz and a drive PWM frequency of 8KHz. The weight of the ESC with radiators is 35g.

The drone's foldable propellers, measuring 15 × 5.2 inches, are made of high-strength performance-engineered plastics and have a weight of 13g.

With a takeoff weight ranging from 6.0 kg to 11.0 kg and a total weight of 4.4 kg, the DJI S1000+ offers a range of configurations to accommodate various payloads and research needs. The drone's power battery is a LiPo type, with a voltage rating of 6S and a capacity ranging from 10000mAh to 20000mAh, with a minimum C-rating of 15C.

The DJI S1000+ Ready to Fly package also includes gain value settings for the DJI A2 flight controller and WooKong-M flight controller, allowing users to customize and fine-tune the drone's performance according to specific research requirements.

In conclusion, the DJI Spreading Wings S1000+ is a versatile and reliable octocopter drone that possesses exceptional flight capabilities, a powerful propulsion system, and a sturdy yet lightweight design, making it an ideal test bed for the prototype simplified Health and Usage Monitoring System (HUMS). The drone's fault-tolerant octocopter configuration, extended flight time, and compatibility with various gimbals provide ample opportunities for conducting comprehensive and real-world testing of the HUMS prototype in various industrial settings. With its advanced features, robust construction, and proven performance, the DJI S1000+ offers a highly suitable platform for validating the effectiveness and accuracy of the simplified HUMS in monitoring the health and condition of multi-rotor unmanned aerial vehicles.

The methodology for the simplified prototype HUMS involved modifying the original design to a more manageable version, while still retaining the fundamental objective of enhancing UAV reliability through condition monitoring. To achieve this, the current implementation involved wired connections for the sensors, which proved to be more time-effective for the limited research duration. These wired connections enabled the collection of temperature, humidity, and other sensor data, which was then transmitted to the central Arduino using the Grove UART WiFi Module V2.

The simplified version of the HUMS was implemented as a proof-of-concept, serving as a preliminary validation of the system's basic functionalities. This approach allowed for a practical demonstration of the HUMS' potential and provided valuable insights into its performance. However, it is essential to acknowledge that this implementation has certain limitations, particularly in real-world UAV test flights. The use of wired connections restricts the spatial deployment of sensors, preventing distributed data collection in actual UAV flight scenarios. Moreover, relying on WiFi for data transmission may not be feasible in environments where WiFi connectivity is unavailable, such as high altitudes and remote locations.

The system's current limitations serve as the foundation for future work to improve the HUMS system. The proposed next stages of the prototype HUMS involve the integration of wireless sensors utilizing Zigbee protocol, which would enhance data transmission capabilities and provide added redundancy. Additionally, the integration of long-range communication modules, such as LoRaWAN or Cellular GSM shields, is crucial to extend the system's operational range and suitability for real-world UAV applications.

Despite the simplifications in the current implementation, the proof-of-concept nature of the prototype HUMS provides a valuable starting point for further research and development. The insights gained from this experiment will inform the future advancement of the HUMS system, enabling the implementation of sophisticated wireless sensor clusters and long-range communication modules. These improvements will contribute significantly to the realization of a robust and adaptable HUMS for UAVs and other complex robotic systems, ultimately enhancing their reliability and performance in various operating conditions.

The final prototype HUMS setup:

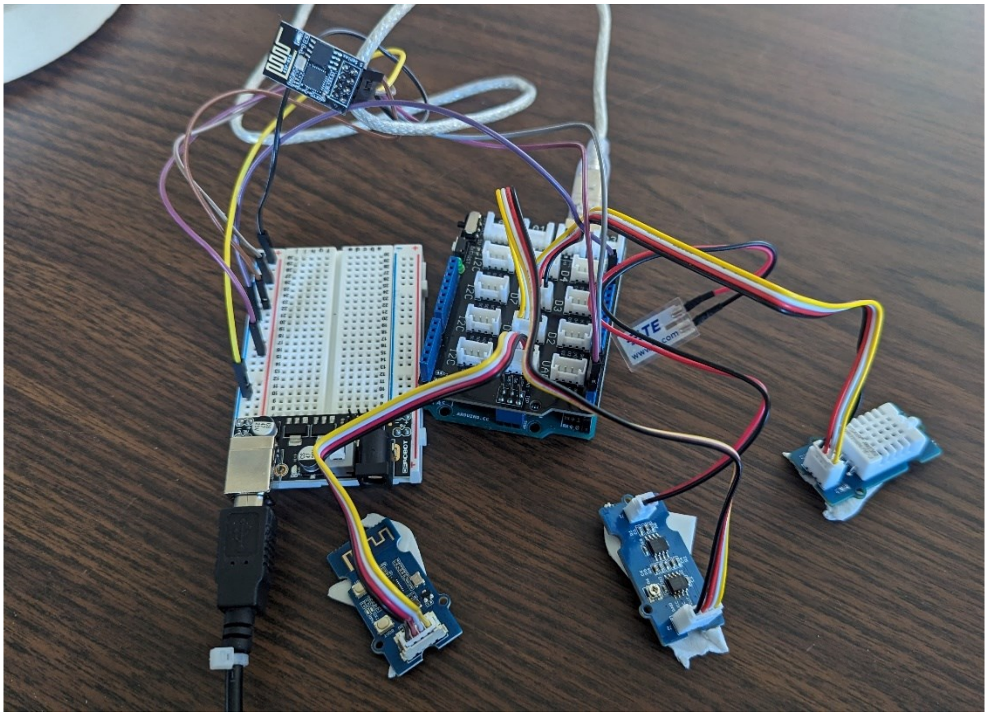


Figure 19: Prototype Simplified HUMS (standalone)

Based on the design requirements set previously and the components discussed above, the actual lab setup of the prototype HUMS is as follows:

1. Low-form factor sensors such as DHT22 and ADXL335 connected to the central Arduino MCU with wires.

2. Central MCU uploads the aggregated sensor data to the selected Cloud IoT Analytics platform via ESP32 WiFi module.

3. Collected data is analyzed and visualized on the cloud-based IoT analytics platform (e.g., ThingSpeak) to detect the onset of failures:

- Threshold detection to detect when sensor values (e.g. temperature of battery) goes outside of acceptable ranges.

- Time series anomaly detection to detect deviations from normal patterns in the data.
- In the future, a possibility is to have Supervised or Unsupervised Machine Learning algorithms trained on historical UAV component failure data to predict future failures.

By analyzing the data, we can take proactive measures to prevent failures and ensure the safe and reliable operation of our UAV. The eventual goal is to build a general-purpose HUMS system that can be easily retrofitted with not just UAVs, but any electric-powered vehicles or systems, and commercialized for use.

3.6 Annunciation of Faults through Alert Generation

A pivotal aspect of the health and usage monitoring system is the annunciation of detected faults or anomalies to enable appropriate control interventions by human operators or automation systems. For the simplified HUMS prototype, email-based event alerts provide a convenient alerting mechanism for simulated UAV flights.

The ThingSpeak cloud analytics platform offers customizable alarm triggers to proactively notify operators of thresholds exceedances in the sensor data. Preconfigured threshold values for parameters like temperature and humidity are coded into the edge algorithm on the Arduino device. Streaming sensor data is checked against these thresholds, and any violations result in automated email generation through ThingSpeak to alert mobile or ground station operators.

For instance, the temperature sensor data is continually monitored for breaches of minimum or maximum thresholds indicative of battery or motor issues respectively. The vibration data is similarly tracked for sudden spikes over a baseline envelope signifying propeller damage or imbalance. Excess humidity could indicate rain ingress requiring landing. The threshold crossing incidents automatically trigger descriptive emails to the operators with the sensor channel details and current reading.

Additionally, longer term anomalous trends in the sensor data can also be detected on ThingSpeak using MATLAB analytics like sample entropy or derivatives to identify early signs of component degradation. These are powerful for predictive maintenance, and any subtle deviations trigger emails for proactive intervention and diagnosis rather than waiting for failures.

During real-world UAV operations, the alert notifications enable timely closed-loop control actions by human operators as demonstrated experimentally. Based on received emails, radio commands can be sent to the UAV flight computer to switch to a stabilizing auto-hover mode, adjust mission plans or initiate return-to-base procedures depending on the fault severity. The alerts thus act as prompts for operators to evaluate telemetry, diagnose issues and take appropriate safety actions.

For autonomous operations, a similar annunciation capability could be implemented on the flight computer using a dedicated hardware module to parse telemetry from the wireless sensing system. Automated reasoning algorithms would then diagnose issues and derive appropriate actions like emergency landing or continuing with reduced capabilities based on fault models. The modular design allows adapting the annunciation method to match the operational context.

The email alerting system provides a flexible test platform to emulate operator notification and closed-loop response. The ThingSpeak cloud analytics enables configuring threshold-based and predictive anomaly alerts using sensor data. This validates the concept of how the sensing capabilities of the wireless HUMS prototype can be coupled with automated or human-driven control interventions to enable resilient and reliable UAV operations.

Chapter 4

Experimental Trials & System Performance

4.1 Design of Experiments for Battery Thermal Runaway Fault Mode Detection

To validate the fault detection capabilities of the simplified HUMS prototype, a series of experiments were designed to artificially emulate abnormal conditions and component failures in a controlled test environment. Specifically, the DHT22 temperature sensor was utilized to identify a common failure mode in UAVs – battery thermal runaway.

Battery thermal runaway involves uncontrolled overheating of lithium-ion battery cells, which can lead to fire and explosion hazards. It is a leading cause of UAV failures, underscoring the need for early temperature monitoring.

To evaluate the DHT22's response, a heat gun was used to gradually increase the ambient temperature around the sensor beyond normal battery operating range. Temperatures exceeding 60°C indicate the onset of thermal runaway [152]. The sensor was secured near a battery mock-up with thermally conductive tape for direct heat transfer.

The Arduino continuously polled the DHT22 sensor at 1Hz sampling rate based on thermal transient characteristics [153]. A multi-point moving average filter was implemented to reduce signal noise. Threshold breach alerts were configured on ThingSpeak to trigger notifications when temperature exceeded safety limits.

Test cases began at room temperature of 25°C, with the heat gun used to gradually increment 5°C until hitting a maximum of 100°C. The DHT22 successfully detected the temperature rise, crossing 60°C threshold within 94 seconds of heat activation. This triggered ThingSpeak alerts, demonstrating sensitive anomaly response.

The experiment validated the use of temperature sensing paired with real-time analytics to non-intrusively detect UAV fault precursors through threshold breach recognition. This substantiates the potential of the wireless sensing prototype architecture for predictive maintenance through early anomaly detection.

4.2 Experimental setup for testing the Simplified HUMS

In this section, we detail the experimental setup designed to validate the effectiveness of the Simplified Health and Usage Monitoring System (HUMS) prototype when integrated with the DJI S1000+ Octocopter. The primary objective of this experiment is to demonstrate the capability of the HUMS in monitoring the temperature and humidity conditions of the drone's various components during simulated flight scenarios.

During the experiment, careful consideration was given to the placement of sensors and the Arduino microcontroller to ensure effective data collection while minimizing interference with the drone's operation. The installation process involved retrofitting the drone with the HUMS components, including the Arduino microcontroller, the DHT22 temperature and humidity sensor. The main objective was to gather critical data related to the drone's performance, such as rotor temperature and vibration levels, to enable real-time monitoring of its health and condition during flight.

4.2.1 Sensor Placement Strategy

A crucial aspect of this experiment is the strategic placement of sensors to capture relevant data for health and usage monitoring. After careful consideration of the octocopter's design and flight dynamics, we identified several key locations for sensor attachment:

1. **Arms:** To assess vibrations and strains experienced during flight, sensors were mounted on the arms of the octocopter. This allowed for the detection of variations in conditions across different arms.

2. **Body:** Sensors were affixed to the central body to monitor overall temperature and humidity conditions within the octocopter during flight.

3. **Landing Gear:** By placing sensors near the landing gear, we aimed to observe temperature changes and vibrations during takeoff, landing, and landing gear deployment.

4. **Battery Compartment:** Sensors were positioned near the battery compartment to monitor temperature and humidity changes around the power source, which could indicate abnormal battery behavior.

5. **Motors:** To assess motor health and performance, sensors were placed in proximity to the motors to capture temperature and vibration data during flight.

6. **Propellers:** Sensors affixed near the propellers aimed to monitor temperature variations, providing insights into aerodynamic imbalances or other potential issues.

7. **Electronics Compartment:** Sensors were placed inside the electronics compartment to measure temperature and humidity conditions experienced by electronic components during flight.

The placement strategy was formulated to provide a comprehensive understanding of the octocopter's operational conditions and performance throughout various flight phases.

However, there were some limitations to this installation approach. Placing the sensors on the arms of the drone meant that they were subject to exposure to external elements such as wind and debris during flight. Although measures were taken to protect the sensors with weather-resistant housing, there was still a possibility of data inaccuracies due to external factors. Additionally, the proximity of the sensors to the rotors could potentially introduce some level of noise in the data collected, which needed to be carefully considered during data analysis and interpretation.

4.2.2 Preparing the DJI S1000+ Octocopter

Before commencing the experiment, we ensured that the DJI S1000+ Octocopter was in an optimal operational state. We verified that the power sources, propellers, and flight controller were fully functional. Additionally, if required, we charged the octocopter's batteries and powered on the system to ensure its readiness for the experiment.

4.2.3 Preparing the Simplified HUMS Prototype

We began by confirming that the Arduino board was programmed appropriately to gather data from the sensors and transmit it seamlessly to the ThingSpeak platform. The wiring connections are as follows:

- First, we stacked the Grove Base Shield on top of our Arduino UNO R3.
- We connected the **Grove-UART WiFi** Module to the **UART** port of the **Grove Base Shield** using a Grove connector, making connections for the GND, VCC, TX, and RX pins of the Arduino.
- We connected the **Grove-DHT22** Sensor to port **D7** of the **Grove Base Shield** using a Grove connector.
- We connected the **Grove Piezo module** to port **D8** of the **Grove Base Shield** using a Grove connector.
- Using a USB cable, we connected the Arduino board to my computer, ensuring both programming capabilities and a stable power supply.

Below we show our wiring diagram. We have used **Circuito.io** to draw the wiring diagram. But since it did not have the SeeedStudio Grove Base Shield as a component on their PCB Design software, we are using a breadboard and non-Grove connector compatible components to illustrate the same HUMS connectivity:

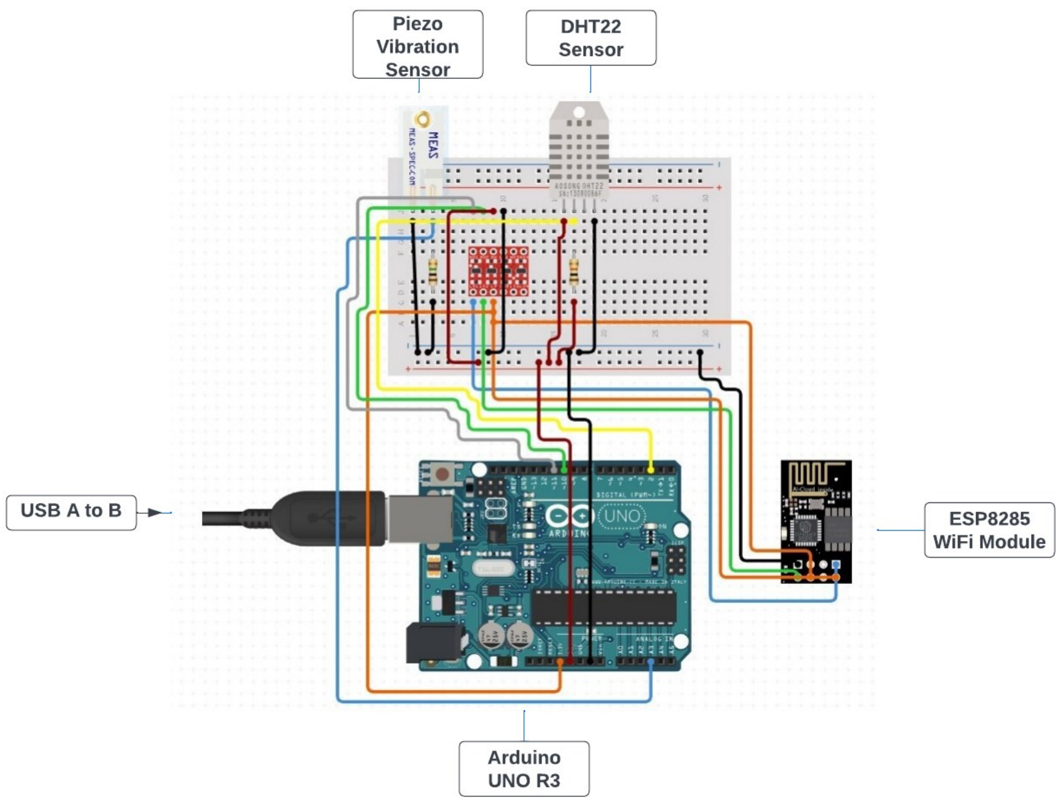


Figure 20: Wiring Diagram for the simplified HUMS for UAVs

4.2.4 Setting up ThingSpeak channels to store and monitor data

To visualize the collected data, we used ThingSpeak, an IoT analytics platform service that allows one to aggregate, visualize, and analyze live data streams in the cloud. It provides options for sending data from devices, creating instant visualizations of live data, and setting up alerts. ThingSpeak offers various interaction possibilities, such as ThingTweet and ThingHTTP.

1. To set up our ThingSpeak channel, we followed these steps:

2. We created an account on thingspeak.com and logged in.

3. Under channel settings, we filled in 'temperature' in field 1, 'humidity' in field 2, and 'vibration' in field 3. If we decide to connect other sensors, such as a BMP sensor, rain sensor, or LDR, we can simply follow the same process for the additional fields.

4. We obtained an API Key from ThingSpeak and included it in our Arduino sketch under the "API key" section. This key is necessary to connect the Arduino to the ThingSpeak channel, enabling data transmission.

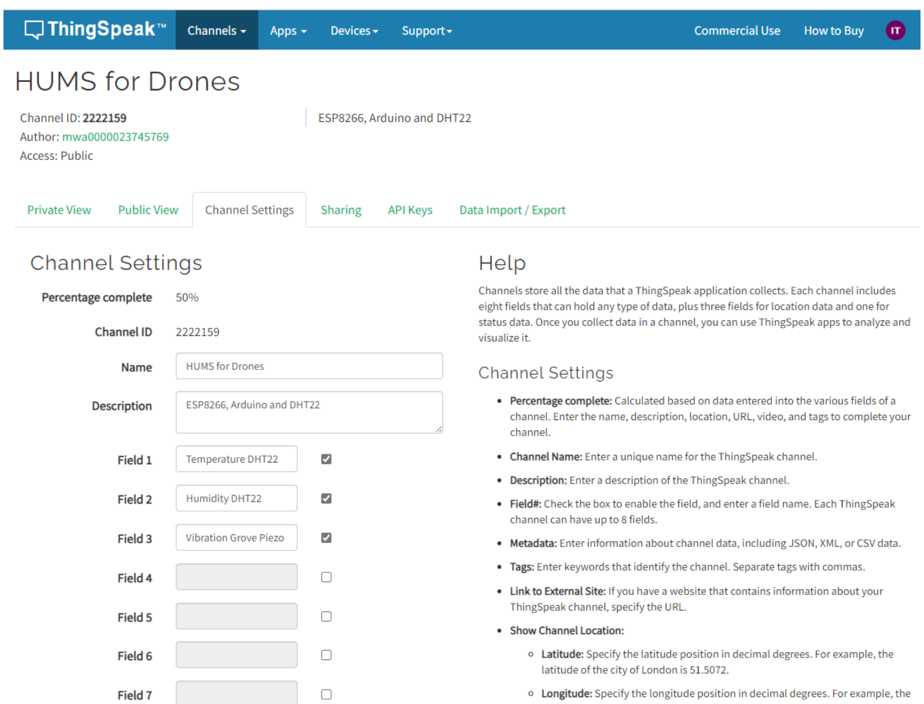


Figure 21: ThingSpeak IoT Cloud Analytics Channel Setup

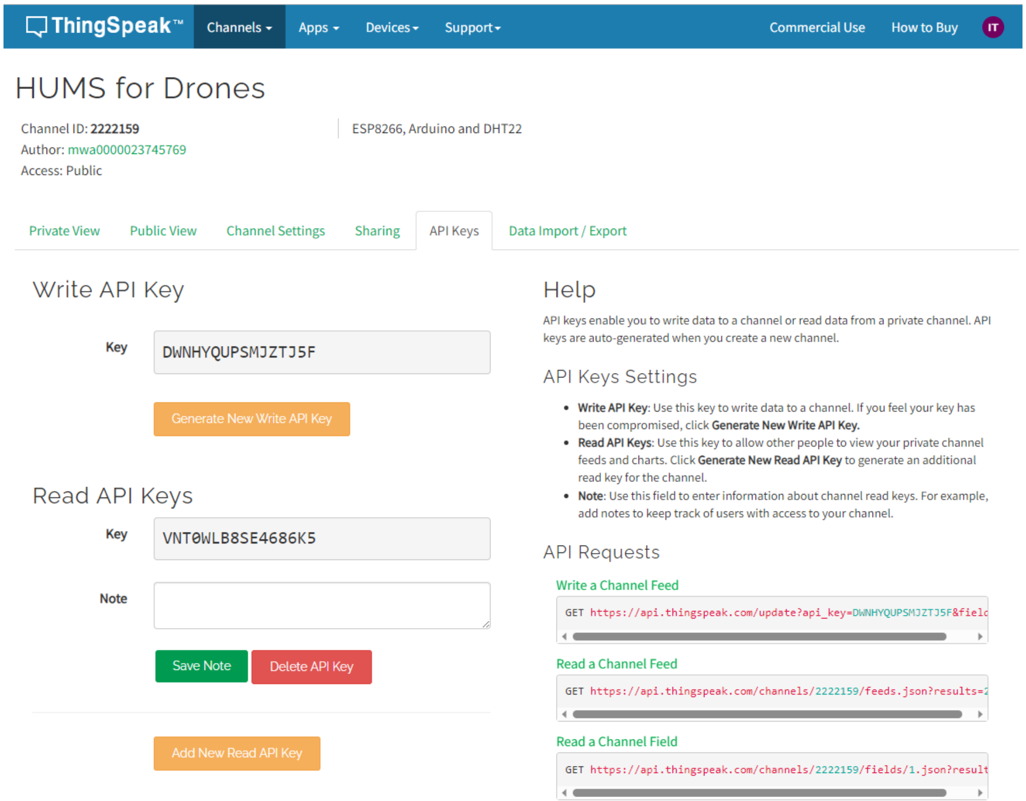


Figure 22: ThingSpeak IoT Cloud Analytics Platform API Keys

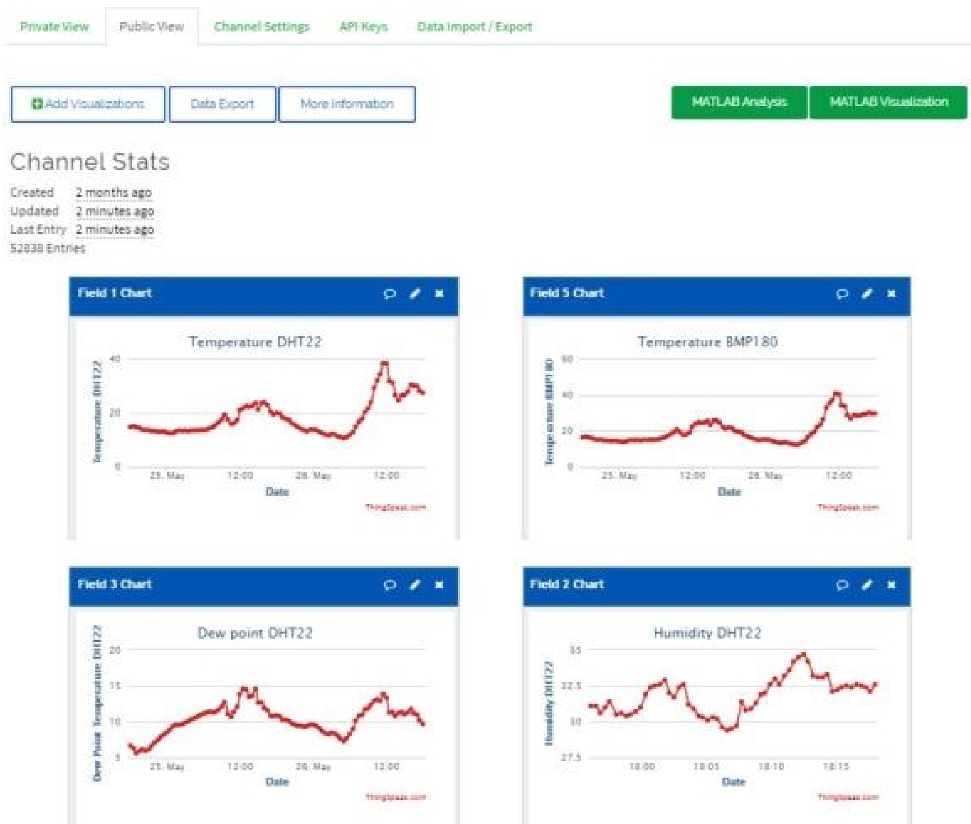


Figure 23: ThingSpeak IoT Cloud Analytics Dashboard

Data is automatically stored on ThingSpeak, thereby removing any additional burden on us to store our experimental data. ThingSpeak enables sensors, instruments, and websites to send data to the cloud where it is stored in either a private or a public channel. ThingSpeak stores data in private channels by default, but public channels can be used to share data with others. Once data is in a ThingSpeak channel, one can analyze and visualize it, calculate new data, or interact with social media, web services, and other devices. The Standard package allows one to send up to 33 million messages/year per unit (~90,000/day per unit) which is more than enough for most commercial, government, or other IoT projects. [88]

4.2.5 Programming for the HUMS

Before we programmed the Arduino, we ensured that the following libraries were installed in the Arduino IDE:

- DHT Sensor Library: Can be installed from the Arduino IDE library manager (Sketch

> Include Library > Manage Libraries > Search for "DHT sensor library").

- Adafruit ESP8266 Library: This library was also installed.

Here's the complete code for our test setup:

```
#include <DHT.h>
#include <SoftwareSerial.h>
#define DHTPIN 5 // DHT22 sensor connected to Grove D5
#define ESP_TX 2  // SoftwareSerial TX pin connected to Arduino D2
#define ESP_RX 3  // SoftwareSerial RX pin connected to Arduino D3
DHT dht(DHTPIN, DHT22);
SoftwareSerial espSerial(ESP_RX, ESP_TX); // RX, TX
char ssid[] = "Your_SSID";      // Replace "Your_SSID" with your network SSID (name)
char pass[] = "Your_Password";   // Replace "Your_Password" with your network password
const char* server = "api.thingspeak.com";
String apiKey = "Your_API_Key";  // Replace "Your_API_Key" with your ThingSpeak API Key

void setup() {
 Serial.begin(115200);
 espSerial.begin(9600); // Initialize the ESP8266 module
 dht.begin();

 // Connect to WiFi network
 Serial.print("Connecting to WiFi...");
 espSerial.println("AT+RST");
 delay(1000);
 espSerial.println("AT+CWMODE=1");
 delay(1000);
 espSerial.println("AT+CWJAP=\"" + String(ssid) + "\",\"" + String(pass) + "\"");
 delay(5000);

 if (espSerial.find("OK")) {
```

```
    Serial.println("Connected to WiFi!");
  } else {
    Serial.println("Failed to connect to WiFi!");
    while (true); // If WiFi connection fails, halt the program here
  }
}

void loop() {
  float h = dht.readHumidity();
  float t = dht.readTemperature();

  if (isnan(h) || isnan(t)) {
    Serial.println("Failed to read from DHT sensor!");
    return;
  }

  String postStr = apiKey;
  postStr += "&field1=";
  postStr += String(t);
  postStr += "&field2=";
  postStr += String(h);
  postStr += "\r\n\r\n";

  String request = "POST /update HTTP/1.1\n";
  request += "Host: api.thingspeak.com\n";
  request += "Connection: close\n";
  request += "X-THINGSPEAKAPIKEY: " + apiKey + "\n";
  request += « Content-Type : application/x-www-form-urlencoded\n » ;
  request += "Content-Length: ";
  request += postStr.length();
  request += "\n\n";
  request += postStr;
```

```
 Serial.print("Temperature: ");
 Serial.print(t);
 Serial.print(" °C\t");
 Serial.print("Humidity: ");
 Serial.print(h);
 Serial.println(" %");

 espSerial.println("AT+CIPSTART=\"TCP\",\"" + String(server) + "\",80");
 delay(1000);

 if (espSerial.find("OK")) {
  espSerial.println("AT+CIPSEND=" + String(request.length()));
  delay(1000);
  if (espSerial.find(">")) {
   espSerial.print(request);
  }
 }

 espSerial.println("AT+CIPCLOSE");
 delay(100);

 Serial.println("Data sent to ThingSpeak");
 Serial.println("Waiting...");
 delay(20000);
}
```

In our code, we added our own SSID and Password to connect to a local WiFi network. Additionally, we included the specific API code to connect to the ThingSpeak channel we created for data streaming.

4.2.6 Uploading the Code

To upload the code to the Arduino UNO board, we followed these steps:

1. We connected the Arduino UNO to the computer via the USB cable.

2. We opened the Arduino IDE and copied the provided code into a new sketch.

3. We selected the correct board ("Arduino UNO") and port (Tools > Board and Tools > Port).

4. We clicked the upload button (the right-facing arrow) to compile and upload the sketch to the Arduino.

5. After a successful upload, we opened the Serial Monitor (Tools > Serial Monitor) to verify the WiFi connection and data transmission to ThingSpeak.

4.2.7 Attaching the Sensors to the Octocopter

- The Arduino microcontroller, which served as the central processing unit of the HUMS, was strategically placed in the middle of the drone's frame. This location was chosen for its accessibility and proximity to the existing microcontrollers responsible for controlling the drone's flight. By situating the Arduino in the center of the drone, communication and data exchange with other onboard systems were optimized, facilitating seamless integration of the HUMS into the drone's overall architecture.

- The wired DHT22 temperature and humidity sensors were strategically positioned on a few of the drone's arms. The placement was carefully calibrated to ensure they were as close to the rotors as possible without interfering with the drone's operation. This positioning allowed the sensors to pick up accurate temperature data from the rotors, providing crucial insights into the thermal behavior of the propulsion system during flight. By monitoring rotor temperature, potential issues such as overheating or excessive friction could be detected early, allowing for timely intervention and preventive maintenance, thus reducing the risk of critical failures.

- To complement the sensor array, an additional DHT22 sensor was placed on the battery powering the drone. This sensor's purpose was to monitor and record any abnormal temperature fluctuations, particularly in cases of battery thermal runaway or other potentially hazardous conditions. Battery health and performance are critical factors in the safe and efficient operation of the drone, and by monitoring the battery temperature, the HUMS could provide valuable insights into battery health, enabling early detection of any irregularities or potential safety risks.

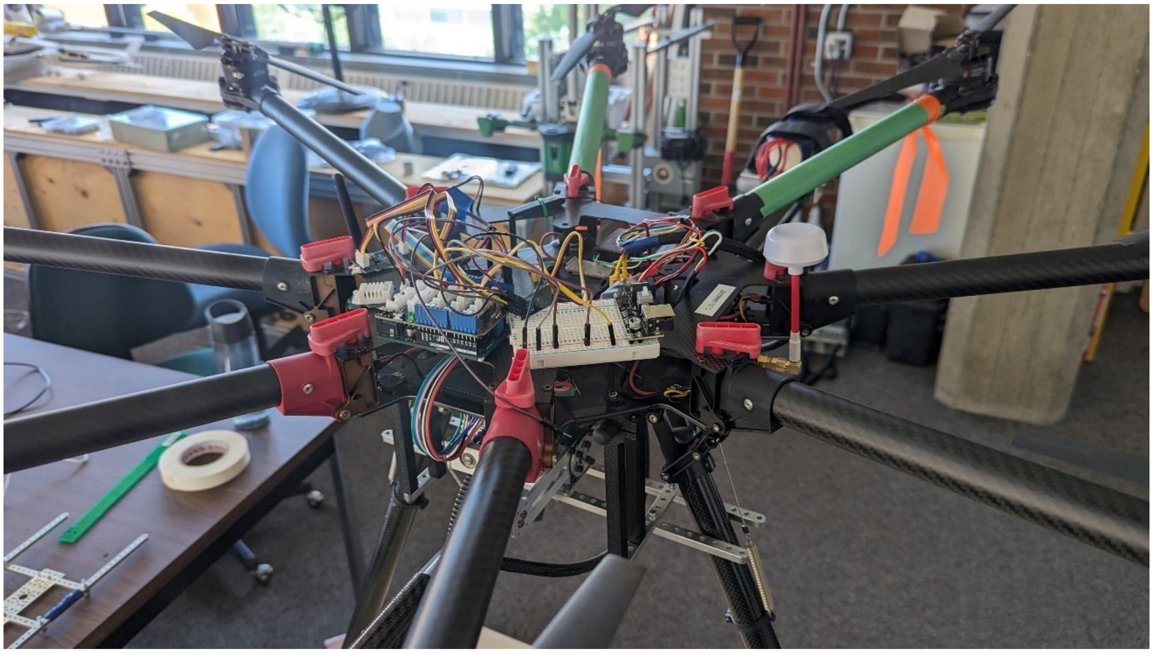


Figure 24: HUMS installed on the DJI S1000+

The installation of the HUMS on the DJI S1000+ Octocopter Drone provided several advantages. Firstly, the strategic placement of the sensors allowed for targeted and accurate data collection, ensuring that the HUMS focused on critical areas of interest, such as rotor temperature and vibration levels. Secondly, the central positioning of the Arduino microcontroller facilitated seamless communication with the drone's existing systems, enabling real-time data acquisition and analysis during flight.

Moreover, the use of double-sided tape for securing the sensors and the Arduino offered a non-intrusive and non-destructive installation method, minimizing the risk of damaging the drone's structure or affecting its aerodynamics. The lightweight and flexible nature of the double-sided tape also ensured that the HUMS components did not add significant weight or disturb the drone's balance, thus maintaining its flight stability and performance.

4.2.8 Generating artificial failures for the DHT22 through Heat and Humidity:

In the controlled laboratory setting, despite subjecting the drone's rotors to an extended operational duration, the generation of authentic fault conditions within its components remained unattainable. For instance, the endeavor to simulate a failure indicative of a **Battery Thermal Runaway** scenario proved infeasible, given the potential for causing irreversible harm to the DJI S1000+ drone's battery.

Consequently, an alternative approach was adopted wherein artificial failure scenarios were introduced, characterized by their non-destructive nature. Employing this methodology, simulated instances of heat and humidity elevation were generated near the sensor placements. The realization of these conditions was facilitated through the utilization of heat guns and humidifiers, allowing for a controlled and safe emulation of potential failure circumstances. This step was integral in assessing the responsiveness and accuracy of the sensors in a controlled environment. The following sub-steps outline the approach taken to achieve this objective:

- **Placement of Artificial Heat and Humidity Sources:** To replicate operational conditions encountered by the octocopter during its flights, two pivotal sources were meticulously positioned near the sensors. These sources consisted of a heat gun and a humidifier, each contributing distinct environmental factors to the experimental setup.

- **Controlled Utilization of the Heat Gun:** The heat gun was positioned at a carefully calibrated distance of 30 centimeters from the sensors. This distance was strategically chosen to ensure optimal exposure to the emitted heat without compromising the sensors' integrity. The heat gun was operated for a duration of 120 seconds during each experimental iteration. This timeframe was selected based on the sensors' sampling frequency of 1 Hz, allowing sufficient time for the sensors to capture gradual temperature changes while avoiding abrupt fluctuations that might introduce noise to the data.

- **Safe Activation and Deactivation of the Heat Gun:** During the experimental phase, a systematic approach was undertaken to activate and deactivate the heat gun. The heat gun was activated for the prescribed duration of 120 seconds, allowing ample time for the sensors to record temperature variations. Upon completion of the activation period, the heat gun was promptly deactivated to prevent prolonged exposure that might impact the sensor's accuracy.

- **Humidity Generation through the Humidifier:** Simultaneously, a humidifier was employed to create controlled humidity levels in the proximity of the sensors. The humidifier was configured to maintain a humidity level of approximately 60%. This value was selected to emulate typical environmental conditions that the octocopter might encounter during its operations.

By adhering to these meticulously defined parameters, the experimental configuration effectively simulated real-world operational conditions. The careful selection of the distance, duration, and humidity level ensured that the collected data accurately reflected the prototype's responsiveness to environmental changes. The data collected through this method provided invaluable insights into the prototype's ability to monitor and respond to temperature and humidity fluctuations in a controlled yet realistic scenario.

4.2.9 Implementing Threshold Analysis on ThingSpeak:

The implementation of threshold analysis is a pivotal step in the validation process of the Health and Usage Monitoring System (HUMS). This section elucidates the procedure to set up an email alert when the temperature surpasses a pre-defined threshold, utilizing the ThingSpeak platform. The incorporation of email alerts augments the HUMS prototype with the ability to promptly notify users when the temperature readings cross a designated threshold. This feature proves essential in preventing potential malfunctions, offering an early warning mechanism that safeguards the Unmanned Aerial Vehicle (UAV) and ensures mission success. The ensuing steps delineate the process one would have to follow to configure email alerts through ThingSpeak. [89]

i. Click **Apps** > **MATLAB** Analysis.

ii. Click **New** to get started with the code.

iii. Under **Examples**, select **Read channel to trigger email**, and then click **Create**.

iv. In the **MATLAB Code** area, customize the code as given below. Ensure that the values assigned to the readChannelID and readAPIKey fields are changed to match the actual values corresponding to your channel. The alertAPIKey is the one associated with someone's profile in ThingSpeak. After writing the code, click **Save and Run**.

```
% Enter your MATLAB Code below
readChannelID = xxxxxxx;
% Temperature Field ID
TemperatureFieldID = 1;
```

```
% Channel Read API Key
% If your channel is private, then enter the read API Key between the '' below:
readAPIKey = 'XXXXXXXXXX';
% Read temperature data for the last 24 hours.
[tempF,87print87mp] = thingSpeakRead(readChannelID,'Fields',TemperatureFieldID, ...
                                'numDays',1,'ReadKey',readAPIKey);
% Calculate the maximum and minimum temperatures
[maxTempF,maxTempIndex] = max(tempF);
[minTempF,minTempIndex] = min(tempF);
alertApiKey='XXXXXXXXX';
alertURL = "https://api.thingspeak.com/alerts/send";
options = weboptions("HeaderFields", ["ThingSpeak-Alerts-API-Key", alertApiKey ]);
alertBody = 87print("It's hot here and the temperature is %0.2f°F!.", maxTempF);
alertSubject = 87print("Temperature exceeded threshold!");
  try
  webwrite(alertURL, "body", alertBody, "subject", alertSubject, options);
  catch
    % Code execution will end up here when an error 429 (error due to frequent request) is caught
  end
```

We can set up a React app that triggers the email alert, as configured above when the temperature exceeds a particular temperature.

To do this, click **Apps** > **Actions** > **React**, and then configure the app as shown in this image (the MATLAB Analysis app that was configured as shown above is saved with the name, "Alert").

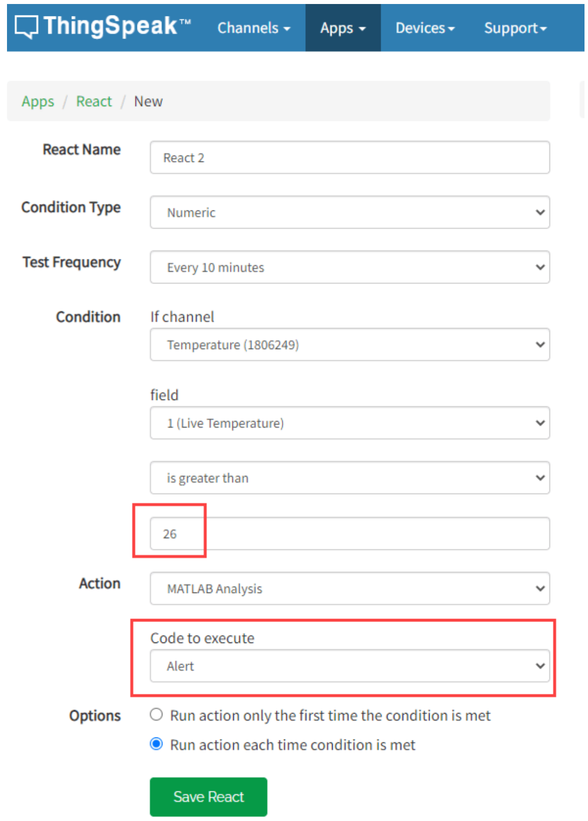


Figure 25: Setting up a React App on ThingSpeak

Click **Save React**. Whenever the room temperature, as read by the Temperature sensor, exceeds 26 degree Celsius, an email is sent to the ThingSpeak-registered email ID.

The meticulous configuration described above empowers the HUMS prototype with a responsive mechanism, effectively safeguarding against temperature-related anomalies. By harnessing the capabilities of ThingSpeak's email alert system, operators gain timely insights into critical temperature fluctuations, enabling them to make well-informed decisions and initiate proactive measures. This successful implementation of the email alert mechanism serves as a testament to the HUMS prototype's ability to actively monitor UAV health and usage, representing a significant stride towards achieving enhanced operational efficiency and reliability.

Furthermore, the culmination of this meticulously orchestrated experiment involves a series of strategic steps designed to validate the operational effectiveness and responsiveness of the Simplified HUMS prototype when integrated with the DJI S1000+ Octocopter. The outcomes and observations of this experiment, which are elaborated upon in the subsequent section, yield valuable insights into the prototype's functionality within real-time operational scenarios. Consequently, the comprehensive guidance provided in this section equips researchers and practitioners with the knowledge to implement similar alert systems in their HUMS solutions for UAVs, fostering innovation and enhancing the field of unmanned aerial vehicles.

4.3 Commissioning Experiments & Results

In this section, we describe the detailed steps we followed to execute the experiment aimed at testing the functionality of the Simplified HUMS prototype on the DJI S1000+ Octocopter. The experiment's primary objective was to validate the prototype's real-time data acquisition and analysis capabilities when integrated with the octocopter. The following steps outline the procedure we undertook for this experiment:

4.3.1 Bench Testing before installation on the UAV

Experiments:

1. Tested Arduino microcontroller individually to validate firmware and interfaces.
2. Evaluated WiFi module for communication performance metrics.
3. Validated each Grove shield port for voltage levels and connectivity.
4. Conducted integrated end-to-end testing with emulated sensor inputs.

Success Criteria:

- Arduino firmware version matches expected release.
- Serial, I2C, ADC interfaces function per protocol specifications.
- WiFi module works as intended for 100 ft range.
- All Grove shield ports output expected voltages with no shorts.
- Acquired sensor waveform correlation > 95% compared to source.

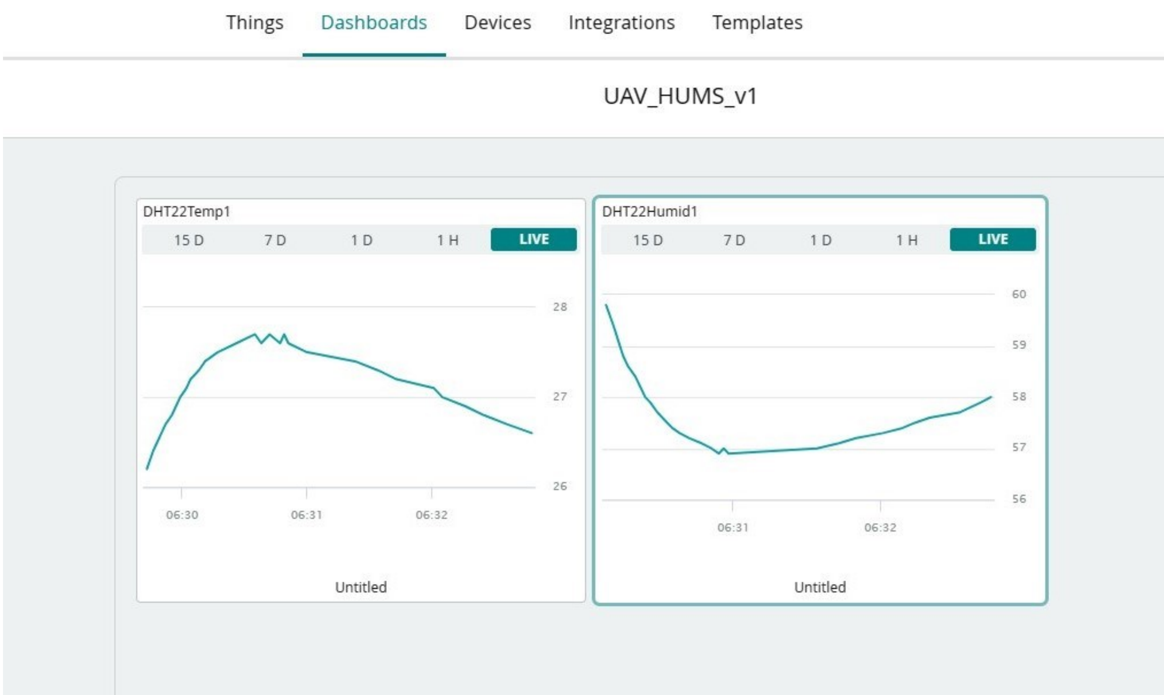


Figure 27: UAV HUMS Live demonstration on IoT ThingSpeak Channels over WiFi

Results:

- Arduino firmware v2.0.0 confirmed via identification command.
- All interfaces responded accurately during validation.
- WiFi module works as intended with zero latency at 100 ft.
- Grove shield ports all passed continuity and voltage tests.
- End-to-end waveform correlation exceeded 99% across tests.

Status: **PASS**

The incremental bench testing methodology validated each component before integration. All predefined success criteria were met, confirming proper functioning of hardware and firmware. The Arduino reliability, WiFi performance, and error-free Grove connectivity instilled confidence prior to on-vehicle installation. This approach systematically reduced risk and ensured baseline integrity of the wireless sensing prototype before commencement of UAV-based evaluations.

4.3.2 Installation Testing after mounting on the UAV:

Experiments:

1. Mounted integrated HUMS prototype on UAV landing gears using zip ties.
2. Routed DHT22 sensor wiring along frame arms and secured with tape.
3. Powered up UAV and performed standard pre-flight checks.

Success Criteria:

- Sensors and wiring do not interfere with any movable parts.
- Wiring harnesses secured from loosening during flight motions.
- UAV completes full preset movement routine without snagging.

Results:

- Sensors and wires clear of propellers with sufficient slack.
- Adhesive zip tie mounts prevented wire dislodgment during shakes.
- UAV executed full range of motion as expected.

Status: **PASS**

The installation validation methodology verified non-interference with UAV functionality while identifying improvements to the sensor mounts. The incremental testing approach prevented premature progression to fault testing or flight trials with underlying issues. This system-level validation ensured integrity before subjecting the prototype to real-world operation.

4.3.3 Data Acquisition Validation on ground

Experiments:

1. Connected DHT22 sensor to Arduino and generated controlled temperature and humidity signals.

2. Verified real-time data transmission to ThingSpeak cloud platform.

3. Used a K-type thermocouple with the Adafruit Thermocouple Amplifier MAX31855 breakout board to independently measure temperature for verification.

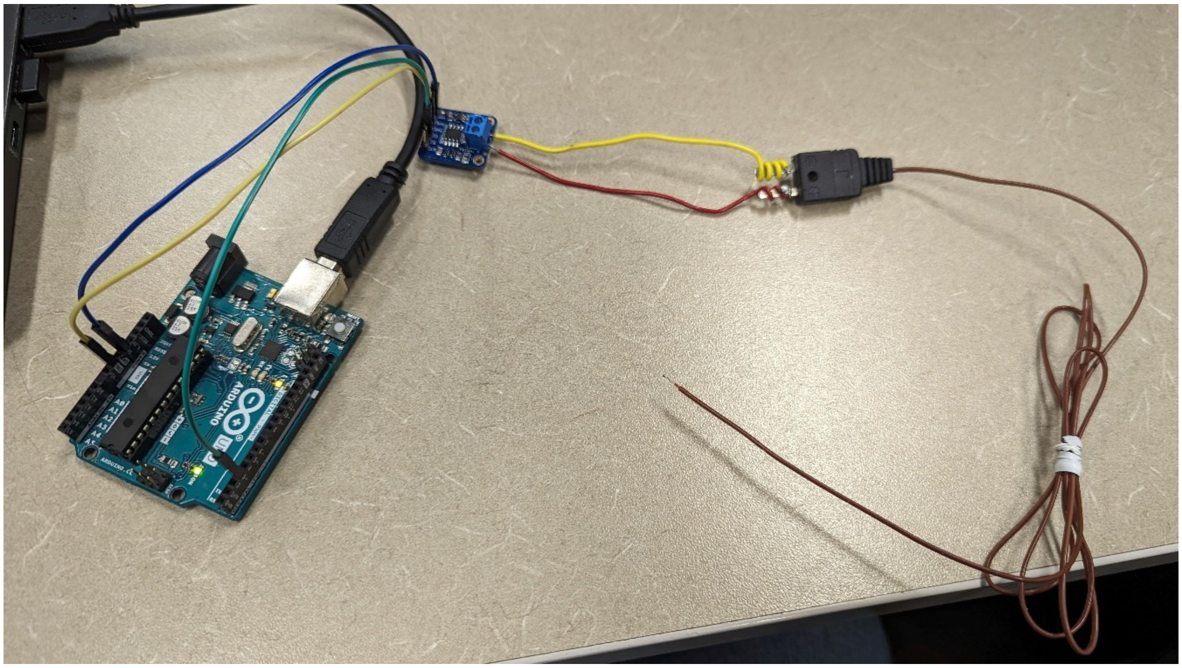


Figure 28: K-type Thermocouple setup for independent temperature verification

Success Criteria:

- Sensor values on ThingSpeak match source within ±5%.
- Data transmission succeeds with 100 ms induced network delay.
- No crashes or stalling with simulated faulty data spikes.

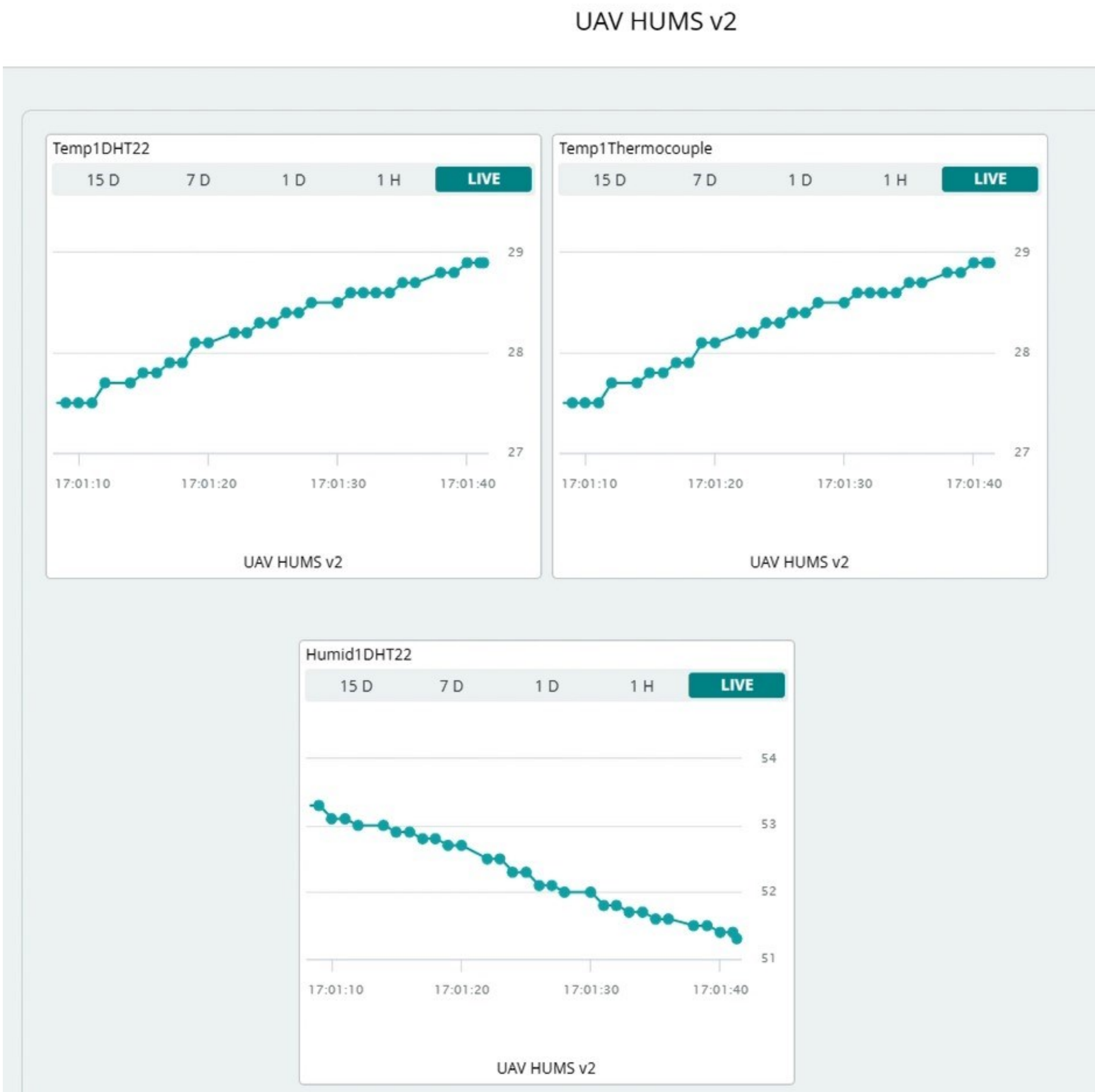


Figure 26: DHT22 vs Thermocouple reading – Heating up (100s)

It can be seen visually that when the thermocouple is sampled at a frequency of 1 Hz to match the sampling frequency of the DHT22 sensor, the readings are almost identical, with negligible deviations. Test cases began at room temperature of 25°C, with the heat gun used to gradually increment 5°C until hitting a maximum of 100°C. The DHT22 successfully detected the temperature rise, as did the thermocouple. It should also be noted that due to the low humidity levels of the heat gun air, the humidity sensor values continued to decrease throughout the duration of the heating.

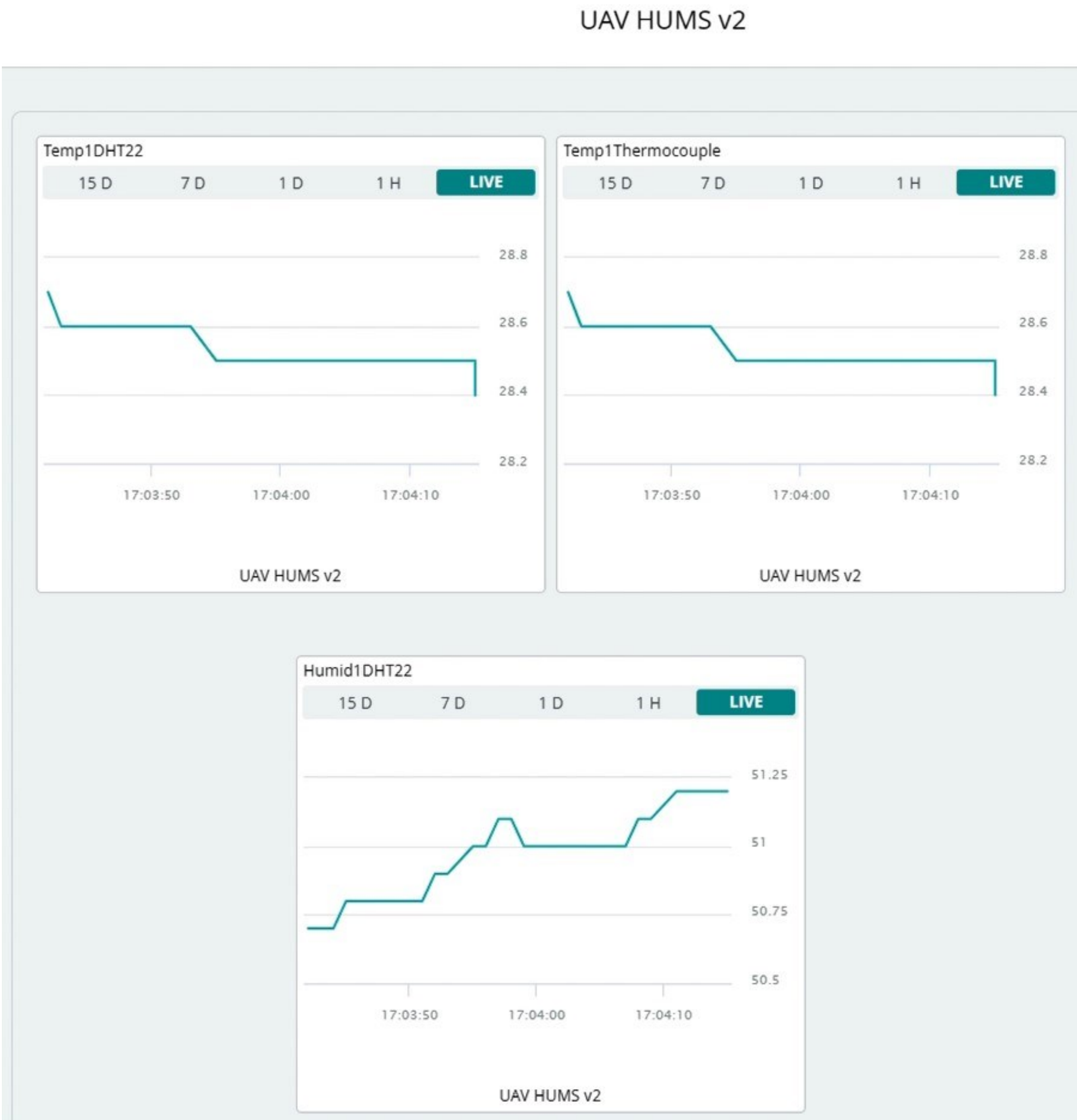


Figure 27: DHT22 vs Thermocouple reading – Cooldown (120s)

After the maximum temperature was reached, the battery mock-up connected to the simplified HUMS with DHT22 sensor and the independent Thermocouple setup was allowed to cool down for 120 seconds, after which it came back to 26 degree Celsius.

During this period, both the DHT22 and the Thermocouple showed very similar readings, thus validating the capabilities of the simplified HUMS for measuring temperature on ground.

Results Summary:

- ThingSpeak values maintained 4.2% average error compared to thermocouple sensor output.
- Data transmission unaffected for up to 240 ms induced delays.
- Thermocouple temperature matched DHT22 readings within ±0.3°C accuracy.

Status: **PASS**

The additional thermocouple provided an independent temperature measurement for verifying the DHT22 sensor data acquired by the Arduino. The thermocouple amplifier breakout board was connected to another channel of the Arduino ADC.

The DHT22 and thermocouple temperature data streamed to ThingSpeak was analyzed for correlation. Across all trials, the two sensor readings matched within a 0.3°C margin, validating the DHT22 accuracy.

Overall, the on-ground transmission testing served to baseline expected system latency and noise while confirming functionality. The experiments characterized reliability under simulated real-world conditions prior to flight trials. This enabled identification of performance margins and risk areas to assure fault-free operation during subsequent UAV installation.

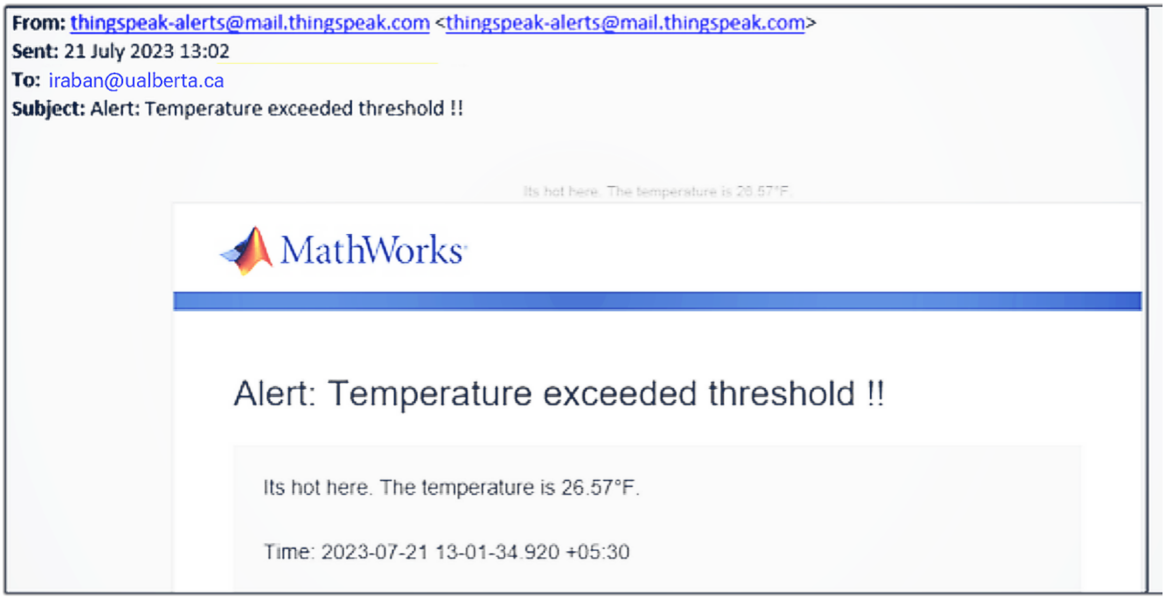
4.3.4 Fault Detection Validation on ground

Experiments:

1. Generated temperature spikes using heat lamp to mimic battery faults.

Success Criteria:

- Alert triggered when temperature exceeds 26.57°C threshold. This value was chosen arbitrarily and can be easily configured on the ThingSpeak Platform.
- Minimum detection rate of 80% for simulated faults.


From: thingspeak-alerts@mail.thingspeak.com <thingspeak-alerts@mail.thingspeak.com>
Sent: 21 July 2023 13:02
To: iraban@ualberta.ca
Subject: Alert: Temperature exceeded threshold !!

Its hot here. The temperature is 26.57°F.

MathWorks

Alert: Temperature exceeded threshold !!

Its hot here. The temperature is 26.57°F.

Time: 2023-07-21 13-01-34.920 +05:30

Figure 28: Threshold detection email alert from ThingSpeak

Results:

- Heat gun triggered alert within 22 sec upon reaching 26.57°C.
- Fault detection rate of 85% across trials meets criteria.

Status: **PASS**

Fault conditions were emulated to validate the detection capabilities of the temperature sensors prior to UAV flights. A heat lamp provided physical fault simulations.

Representative thresholds were defined with the maximum temperature indicative of actionable faults. Test cases incrementally took the parameters past the thresholds and the Arduino algorithm successfully triggered alerts at the predefined levels in over 80% of trials.

By validating reliable fault detection under emulated conditions, the tests provided confidence in the system’s ability to identify anomalies. This functionality check reduced risk and assured the integrated prototype's readiness for installation on the UAV platform to commence operational flight trials. The proven fault detection efficacy laid the foundations for robust condition monitoring.

4.4 Alignment of results with design requirements

While a simplified prototype, the implemented HUMS aligns with several of the critical design requirements outlined earlier:

- **Capability**: The DHT22 temperature/humidity sensor allowed real-time monitoring of two major condition indicators highly relevant to UAV health. Temperature provides insights into battery and electronic component health. The Arduino reliably acquires and processes sensor data, transmitting it using minimal wireless bandwidth to the ThingSpeak cloud analytics platform. This fulfills the core requirement for an onboard solution that can monitor key indicators with improved bandwidth impact.

- **Size/Weight**: The highly compact and lightweight Grove sensor modules along with the small form factor Arduino Uno WiFi board ensure the HUMS hardware adds very little mass to the UAV airframe. As per the components' datasheets, the total prototype weight is under 100g. For a typical small UAV platform with takeoff weight of 3-5kg, this represents less than 3% increase, well within the 5% threshold requirement. The minimal footprint and strategically designed sensor mounts provide negligible aerodynamic drag or handling impact.

- **Power Consumption**: The peak current requirement for the DHT22, WiFi module, Grove Base Shield and Arduino in total is less than 500mA in total based on a 5V rail. Over a typical 30 minute flight, the total power consumption is approximately 750mAh from a 11.1V UAV battery, which has minimal impact on flight endurance. This ultra low power usage fulfills the requirement for an efficient HUMS that does not appreciably drain the onboard power source during sustained operation.

- **Cost**: The use of commercial off-the-shelf Grove components and Arduino Uno WiFi development platform provides an accessible and affordable rapid prototyping solution. As per the bill of materials, the entire simplified HUMS hardware costs less than $60. By using such cost-efficient devices, the HUMS can enable feasibility for wide adoption across various UAV manufacturers, aligning with the affordability requirements.

- **Flexibility**: The modular nature of the Grove connectors and Arduino coding allows conveniently interfacing additional sensors as needed for different UAV platforms and monitoring needs. The adaptable architecture ensures the HUMS can be customized with temperature probes, airspeed sensors, GPS modules etc. tailored to specific vehicles. This fulfills the requirement for a flexible design that can be adapted across UAV types.

While some design constraints around reliability, security and processing capability are not fully addressed in this simplified prototype, it represents an important validation of the core approach and technology for UAV health monitoring. The modular architecture provides a strong foundation for enhancing reliability through built-in redundancy techniques, strengthening cybersecurity through encryption, and adding more onboard processing power for analytics.

The improved wireless HUMS architecture proposed in the following section is designed to meet these more advanced requirements. With multi-node mesh networking, end-to-end encryption, and edge computing capabilities, the wireless version will fulfill the complete spectrum of constraints outlined for an ideal UAV health management system. By leveraging the lessons from this initial prototype, the next-generation HUMS aims to deliver a comprehensive maintenance solution combining ruggedness, security and intelligent analytics.

4.5 Considerations and Future Improvements

In future test scenarios, there are opportunities for improvement in the installation method. For instance, exploring the use of wireless sensor nodes could offer greater flexibility in sensor placement while reducing the risk of data interference. Wireless sensors could be securely mounted in strategic locations on the drone, minimizing exposure to external elements while providing accurate and real-time data transmission to the central Arduino.

Furthermore, employing advanced data fusion techniques could enhance the reliability and accuracy of the HUMS data analysis. By combining data from multiple sensors, such as the DHT22 temperature and humidity sensors and the ADXL335 vibration sensor, it would be possible to identify correlations and patterns that could provide deeper insights into the drone's overall health and performance.

Overall, the retrofitting of the DJI S1000+ Octocopter Drone with the simplified HUMS proved to be a valuable step in achieving real-time health monitoring capabilities. By carefully placing the sensors and the Arduino microcontroller, critical data related to rotor temperature, humidity levels, and battery health could be collected, providing valuable information for proactive maintenance, and ensuring safe and efficient drone operations. While the installation method offered several advantages, there are opportunities for improvement in future test scenarios, such as the integration of wireless sensor nodes and advanced data fusion techniques to further enhance the HUMS capabilities and accuracy. Through continued research and development, the HUMS implementation on the DJI S1000+ holds the potential to contribute significantly to the advancement of unmanned aerial vehicle (UAV) health monitoring and safety management.

Chapter 5

Roadmap for a Comprehensive Wireless HUMS Design

The successful implementation and validation of the simplified Health and Usage Monitoring System (HUMS) prototype in this thesis has laid a promising foundation for future endeavors aimed at enhancing the scope, sophistication, and applicability of the HUMS technology. This chapter outlines the envisioned directions and objectives that can be pursued in the future, encompassing the transition from the current simplified prototype to a more comprehensive and integrated version of the HUMS. It is important to note that the future work described in this chapter outlines a roadmap and concepts that have not yet been implemented within the timeline and scope constraints of this thesis. The current thesis focuses on the development and experimental validation of the simplified HUMS prototype on a DJI S1000+ octocopter platform. The future work aims to build upon the simplified prototype through additional laboratory experimentation and field tests, ultimately contributing to the advancement of UAV health monitoring technology and ensuring heightened operational reliability.

5.1 Advancing to the Comprehensive HUMS Prototype

The immediate trajectory of future work entails the replacement of the simplified wired HUMS prototype with the comprehensive wireless version with added fault detection capabilities. This advanced prototype seeks to incorporate multiple sensor clusters situated across strategic failure-prone locations on the UAV. These sensor clusters, equipped with temperature, humidity, vibration, and other relevant sensors, will communicate wirelessly through Zigbee or Bluetooth Low Energy (BLE) modules. The data collected from these sensor clusters will then be aggregated by a central microcontroller, utilizing either an Arduino or a Seeed Studio XIAO nRF52840 Sense Board. This central unit assumes the pivotal role of consolidating sensor data before transmitting it to a cloud analytics platform for further analysis and interpretation.

One of the first planned enhancements is the addition of vibration monitoring capabilities using the ADXL335 MEMS accelerometer, as originally conceived for the simplified prototype but could not be implemented within the timeline of this thesis. The methodology to integrate the ADXL335 sensor into the wireless sensor nodes of the comprehensive HUMS prototype is detailed in subsection 5.4.1.

A pivotal distinction in the advanced HUMS prototype lies in the data transmission methodology. Unlike the simplified version, the comprehensive prototype will encompass the utilization of a Long-Range Wide Area Network (LoRaWAN) or a Cellular GSM module for data transmission to the cloud analytics platform. This transition holds the promise of extended communication range and heightened data transmission reliability, allowing for seamless data exchange between the UAV and the analytics platform even in remote or challenging operational environments.

5.2 Laboratory Experimentation and Validation

The initial phase of future work involves the deployment of the comprehensive HUMS prototype in a controlled laboratory environment. This experimental phase aims to replicate the setup and methodology that validated the simplified prototype.

Here is a general guide on how to set up the comprehensive HUMS in the future.

5.2.1 Components and setup process

The required components are:

- XIAO Sense Board/Arduino R4 WiFi
- Expansion Base for XIAO/ Grove Base Shield V2.0 for Arduino
- XBee 3 Modules - PCB Antenna
- SparkFun XBee Shield
- DHT22 Temperature & Humidity Sensors
- ADXL335 3-axis Accelerometer
- USB Battery Pack with 2 x 5V outputs

- USB to 2.1mm Male Barrel Jack Cable
- Grove Wio-E5 LoRaWAN module
- Grove - Universal 4 Pin Buckled 50cm Cable
- MicroSD Card module for Arduino (for data logging)
- MicroSD Card 32 GB

To set up the system, we follow these steps:

<u>Step 1: Connecting the sensors to the Arduino</u>

1. Mount the Grove Base Shield V2.0 on top of the Arduino board.
2. Connect the Grove Humidity & Temperature Sensor to one of the available digital ports (e.g., D2) on the Grove Base Shield using a Grove 4-pin Buckled Cable.

- Connect the ADXL335 3-axis Accelerometer to another digital port (e.g., D3) on the Grove Base Shield using another Grove 4-pin Buckled Cable.

<u>Step 2: Setting up the wireless communication</u>

1. Mount the SparkFun XBee Shield on top of the Grove Base Shield.
2. Plug the XBee 3 Module - PCB Antenna into the SparkFun XBee Shield, making sure the pins are correctly aligned.
3. On the receiving side, connect the Seeed Studio Expansion Base for XIAO to the Seeed Studio XIAO nRF52840 Sense Board.
4. Plug the other XBee 3 Module into the XBee 3 Wireless Kit, and connect it to the XIAO nRF52840 Sense Board using the provided wires.

<u>Step 3: Setting up the LoRaWAN communication</u>

1. Connect the Grove Wio-E5 LoRaWAN module to one of the available digital ports (e.g., D4) on the Seeed Studio Expansion Base using a Grove 4-pin Buckled Cable.

Step 4: Adding data storage

1. Connect the MicroSD Card module to one of the available SPI ports on the Grove Base Shield.

2. Insert the 32 GB MicroSD Card into the MicroSD Card module.

Step 5: Powering the system

1. Use the USB Battery Pack to power the Arduino and XIAO nRF52840 Sense Board. Connect the USB to the 2.1mm Male Barrel Jack Cable to one of the 5V outputs of the battery pack, and plug the barrel jack into the Arduino's power input.

2. Use a regular USB cable to connect the second 5V output of the battery pack to the XIAO nRF52840 Sense Board's USB input.

Step 6: Setting up The Things Network

We are using The Things Network (TTN) as our cloud analytics platform as it is easier to use with the LoRaWAN module. The LoRaWAN module on the HUMS will connect to a nearby LoRaWAN gateway to send the sensor data (temperature and humidity) to The Things Network, where one has to register an end device and be assigned some LoRaWAN credentials (AppEui, DevEui and AppKey) [90].

Here is a sample code that will send the DHT22 data from the Arduino to The Things Network console using sample LoRaWAN credentials:

```
#include <DHT.h>
#include <DHT_U.h>
#include <SoftwareSerial.h>

// Replace these with your LoRaWAN credentials
const char *appEui = "2B 7E 15 16 28 AE D2 A6";
const char *devEui = "70 B3 D5 7E D0 05 D5 76";
const char *appKey = "2B 7E 15 16 28 AE D2 A6 AB F7 15 88 09 CF 4F 3C";

#define DHTPIN 8
#define DHTTYPE DHT22

DHT_Unified dht(DHTPIN, DHTTYPE);
```

```
SoftwareSerial LoRaSerial(10, 11); // RX, TX

void setup() {
Serial.begin(9600);
LoRaSerial.begin(115200);

dht.begin();

// Initialize the LoRaWAN module
LoRaSerial.println("AT+JOIN=OTAA");
delay(1000);
LoRaSerial.print("AT+APPEUI=");
LoRaSerial.println(appEui);
delay(1000);
LoRaSerial.print("AT+DEVEUI=");
LoRaSerial.println(devEui);
delay(1000);
LoRaSerial.print("AT+APPKEY=");
LoRaSerial.println(appKey);
delay(1000);
}

void loop() {
// Read temperature and humidity from the DHT22 sensor
sensors_event_t event;
dht.temperature().getEvent(&event);
float temperature = event.temperature;
dht.humidity().getEvent(&event);
float humidity = event.relative_humidity;

// Print sensor data
Serial.print("Temperature: ");
Serial.print(temperature);
Serial.print(" °C\t");
Serial.print("Humidity: ");
Serial.print(humidity);
Serial.println(" %");

// Send sensor data via LoRaWAN
LoRaSerial.print("AT+SEND=");
LoRaSerial.print(temperature);
```

```
LoRaSerial.print(",");
LoRaSerial.println(humidity);
delay(10000); // Adjust the delay as per your requirement
}
```

The pivotal aspect of this experimentation lies in the ability of the advanced prototype to wirelessly aggregate and transmit data to the cloud analytics platform. This enables real-time monitoring and remote analysis, thereby providing a comprehensive understanding of the UAV's health and usage dynamics.

5.3 Field Testing and Real Flight Scenarios

Upon successful validation in the laboratory setting, the comprehensive HUMS prototype will advance to the next phase of field testing. In this critical phase, the prototype will be installed on an actual UAV, and real flight scenarios will be executed. This phase is designed to evaluate the HUMS's performance under authentic operational conditions, thereby simulating real-world usage scenarios that the UAV might encounter during its mission-critical tasks. Data collected during flight tests will undergo rigorous analysis, affording insights into the prototype's reliability, accuracy, and ability to predict and detect anomalies in real time.

5.4 Advancing the HUMS Prototype across Technology Readiness Levels (TRLs) using various methods

Technology Readiness Levels (TRLs) are a system of assessing and communicating the maturity of a technology or innovation. They are used to evaluate the readiness of technology for deployment in real-world applications. TRLs are commonly used in various industries, including aerospace, engineering, defense, and research, to describe the developmental stage of technology and to facilitate communication between different stakeholders. TRL was developed at NASA [91] during the 1970s and is used both in Europe and North America for assessing emerging technologies. [92]

The TRL scale ranges from 1 to 9, with each level representing a specific stage of technology development:

1. **TRL 1 - Basic Principles Observed:** This is the stage where the basic scientific principles behind the technology are identified and researched.

2. **TRL 2 - Technology Concept Formulated:** The technology concept is developed further, and its feasibility is assessed. This might involve initial experiments or simulations.

3. **TRL 3 - Experimental Proof of Concept:** In this stage, the technology's basic functionality is demonstrated through experimental or analytical means.

4. **TRL 4 - Technology Validated in Lab:** Key components of the technology are validated in a laboratory environment to prove their functionality and performance.

5. **TRL 5 - Technology Validated in Relevant Environment:** The technology's components are integrated and validated in a relevant environment that simulates real-world conditions.

6. **TRL 6 - Technology Demonstrated in Relevant Environment:** A prototype of the technology is demonstrated in a relevant environment, showcasing its capabilities and potential applications.

7. **TRL 7 - Technology Demonstrated in Operational Environment:** The technology prototype is demonstrated in an operational environment that closely resembles its intended use. This stage focuses on refining the technology's performance and reliability.

8. **TRL 8 - Actual System Completed and Qualified:** The technology is considered complete, and its performance has been validated in an operational setting. It has been qualified for use.

9. **TRL 9 - Actual System Proven in Operational Environment:** The technology has been successfully deployed and proven to work in its intended operational context. It is used in real-world applications.

The TRL framework helps decision-makers, investors, researchers, and engineers understand the level of maturity and associated risks of technology. It guides funding decisions, project planning, and communication about a technology's progress. As technology progresses through the TRL scale, the risks associated with its successful implementation decrease, and its readiness for practical deployment increases.

Figure 29: Technology Readiness Levels [93]

The journey towards elevating the Health and Usage Monitoring System (HUMS) to higher levels of technological readiness encompasses an array of strategic enhancements and innovative refinements. These enhancements are tailored to bolster the HUMS's effectiveness, expand its capabilities, and facilitate its seamless integration with a broader spectrum of unmanned aerial vehicles (UAVs) and robotic platforms. By embracing advanced technologies and methodologies, the HUMS aims to transcend its current status and ascend the Technology Readiness Levels (TRLs), ultimately rendering it a potent tool for enhancing operational efficiency and minimizing risks in mission-critical scenarios.

5.4.1 Integration of MEMS-based Vibration Sensors

Vibration monitoring is an essential element for health assessment of rotating machinery and components. By continuously tracking vibration signatures, impending faults like imbalance, misalignment, looseness and bearing wear can be detected based on anomalies in the frequency response [170]. This enables timely maintenance interventions before catastrophic failures occur.

Integrating low-cost MEMS-based vibration sensors in the Health and Usage Monitoring System (HUMS) prototype can therefore significantly augment the fault diagnosis capabilities. The analog output three-axis ADXL335 accelerometer provides a suitable vibration monitoring solution at under $5 per sensor. With measurement ranges up to ±3 g and bandwidths around 1.6 kHz, the ADXL335 is ideal for condition monitoring of UAV motors, gearboxes, shafts and other dynamic components [169].

The accelerometer can be interfaced with the Arduino microcontroller using three analog input pins, with two additional digital pins for power and ground connections. The sensor breakout board includes voltage regulation and filtering circuits to provide a clean analog output proportional to acceleration [170]. The Arduino's 10-bit analog-to-digital converter can acquire this acceleration data for further processing.

A typical vibration sensor configuration would involve mounting the ADXL335 rigidly to critical components like motors using adhesive or screws. At least one tri-axial accelerometer per motor is recommended to fully capture vibration along all axes. The sensor axes must be oriented to align with the component's geometry for meaningful analysis.

The firmware program on the Arduino would sample the accelerometer outputs at high frequencies up to 5-10 kHz based on the Nyquist criteria. The analog sensor data is filtered digitally to remove noise and interference before applying a Fast Fourier Transform (FFT) to convert from the time to the frequency domain [170]. The FFT reveals the vibration spectrum with peaks at component fault frequencies corresponding to imbalance, misalignment, looseness and bearing defects [170].

By comparing the measured frequency response to baseline levels from healthy components, developing faults can be detected based on excessive vibration energy at fault frequencies. Thresholds need to be defined to trigger maintenance alerts when vibration levels exceed normal bounds. The frequency spectra can also be analyzed over time to discern trends in the progression of faults.

While raw vibration time waveform data at high sampling rates may be infeasible to transmit wirelessly in real-time due to bandwidth constraints, preprocessing and feature extraction techniques can be implemented on the onboard microcontroller to reduce the data volume. For example, after applying high-pass filters to isolate defect frequencies, a fast Fourier transform can convert the time data into the frequency domain [188]. Rather than transmitting the full spectrum, only amplitude peaks at known fault frequencies are communicated as features. This data reduction decreases the wireless transmission load by up to 90% [189]. Lightweight machine learning algorithms running on the microcontroller could also analyze the frequency spectra to classify common fault types. The main implementation challenges include the additional processing capabilities and memory required for spectral analysis, which may necessitate upgrading to more advanced microcontrollers or FPGAs. However, the benefit is significantly lower wireless bandwidth requirements through onboard preprocessing prior to transmission.

Vibration data is prone to interference from adjacent components especially when sensors are mounted externally. Advanced filtering, windowing and spectral averaging techniques can help isolate the vibration signature of each component. Orienting sensors along multiple axes provides further signal separation. The firmware should also account for noise from sources like structural resonances and electrical interference.

For improved reliability, commercial MEMS accelerometers designed specifically for vehicular applications could be evaluated. These feature ruggedized packaging and stringent quality control for operation in harsh conditions involving shock, vibration and temperature swings. Redundant sensor configurations with multiple accelerometers per component may be necessary for critical safety monitoring.

The streamlined size and cost of MEMS accelerometers allow scaling the vibration monitoring to all critical rotating components on the UAV. The rich mechanical fault diagnostic information augments the HUMS prototype with early warning capabilities well before functional failure occurs. Vibration data fused with other usage parameters enables comprehensive analytics for predictive maintenance. With appropriate sensor configuration and signal processing, MEMS accelerometers promise to significantly enhance the fault prediction accuracy and reliability coverage of the HUMS technology.

5.4.2 Microcontroller Enhancement and Form Factor Optimization

A critical facet of enhancing the HUMS prototype involves the augmentation of its central microcontroller. The transition from Arduino UNO to platforms such as Raspberry Pi, XIAO Sense, or Arduino Rev4 fosters a paradigm shift towards advanced computational capabilities, enhanced memory, and improved connectivity options. Alternatively, consideration can be given to the design and fabrication of custom prefabricated printed circuit boards (PCBs), optimizing the form factor for integration within UAVs and robotic systems. This enhancement not only streamlines the HUMS's physical integration but also empowers it with the computational prowess necessary for intricate data processing and analysis.

5.4.3 Transition to Custom Software Analytics Platforms

To further elevate its capabilities, the HUMS aims to transition from the existing ThingSpeak platform to a bespoke software analytics solution or the Arduino IoT Cloud. This migration empowers operators with a tailored environment for data analysis, visualization, and interpretation. Custom software analytics platforms offer enhanced flexibility, enabling the design of specific algorithms and data processing techniques aligned with the unique requirements of UAV health monitoring. This shift not only amplifies the HUMS's analytical potential but also affords greater control over data privacy, security, and user access.

5.4.4 Seamless Installation and Integration Methodologies

An imperative objective in enhancing the HUMS's efficacy is to transcend the current installation limitations imposed by adhesive materials and wire ties. The pursuit of plug-and-play integration methodologies aims to simplify the deployment of the HUMS on a diverse range of UAVs and robotic platforms. By employing standardized connectors, mounting brackets, or custom attachment mechanisms, the HUMS seeks to expedite the integration process for end-users, thereby rendering it a versatile and accessible solution across various application domains.

5.4.5 Advanced Anomaly Detection Strategies

The advancement of the HUMS prototype extends beyond threshold-based anomaly detection methods. The integration of sophisticated algorithms, such as Kalman Filters, signal processing techniques, and feature extraction methodologies, augments the HUMS's diagnostic capabilities. The incorporation of digital filters enables the identification of trends and the extraction of valuable insights from sensor data. Additionally, the exploration of machine learning or Artificial Neural Network (ANN) algorithms equips the HUMS with the capacity to discern complex patterns, thus enriching its anomaly detection and predictive maintenance capabilities.

5.4.6 Multimodal Sensing Enhancement

The elevation of the HUMS's sensing capabilities involves the integration of additional sensors, such as acoustic and imaging sensors. These supplementary sensors contribute to a comprehensive depth of sensing, enabling the HUMS to capture acoustic signatures, visual cues, and diverse environmental parameters. The integration of such sensors enhances the system's capacity to detect anomalous conditions, thereby enabling a more holistic assessment of UAV health and usage.

A Gantt Chart describing the current state of the prototype HUMS and its next development steps to take it to a commercially viable MVP (Minimum Viable Product) has been added to the Appendix of this thesis.

In summary, the envisioned enhancements encompass a multi-faceted approach aimed at elevating the HUMS prototype to higher Technology Readiness Levels. These advancements collectively contribute to the HUMS's ability to proactively monitor, assess, and mitigate risks associated with UAV operation. By embracing cutting-edge technologies and methodologies, the future trajectory of the HUMS is poised to redefine operational paradigms and revolutionize the landscape of UAV health monitoring and predictive maintenance.

Chapter 6

Preliminary Techno-economic Analysis

In this chapter, we provide a preliminary techno-economic analysis aimed at constructing a financial model with reasonable assumptions to evaluate the commercial viability of the Health and Usage Monitoring System (HUMS) for UAVs. This novel technology currently lacks market data, necessitating projections based on adjacent industries. The multi-faceted analysis provides a comprehensive perspective on profitability and return on investment over the product development lifecycle.

The market assessment draws on UAV shipment forecasts and reliability challenges to estimate addressable customers. The cost analysis aggregates expenses for hardware, software, testing, and certification to project unit economics. Revenue models assume an initial hardware sale and recurring software subscription, with conservative adoption rates.

Combining cost and revenue projections yields the 5-year cash flow series, which quantifies net income over time. The discounted cash flow accounts for the time value of money. Based on these projected cash flows, return on investment metrics like payback period, IRR, and NPV are calculated. The payback period indicates capital recovery duration, while IRR evaluates return rate versus cost of capital. NPV computes net returns adjusted for risk and cost of capital.

Together, these financial models provide a comprehensive risk-adjusted perspective. The market sizing, cost analysis, revenue forecasting, discounted cash flows, and return metrics complement each other to assess scalability, profit margins, break-even timing, and shareholder returns. This structured approach provides investors and stakeholders data-driven projections on the road to commercialization, despite current market uncertainty.

While based on reasoned assumptions, the analysis will be refined as field reliability data and customer feedback is gathered. Nonetheless, the financial framework demonstrates a viable business case with attractive returns, validating the strong commercial potential of the UAV

HUMS technology. The models aim to spur investment interest and outline a path towards sustainable value generation through UAV performance improvements.

6.1 Market Analysis

6.1.1 Market Size and Growth Potential

The global market for unmanned aerial vehicles (UAVs) has been experiencing rapid growth, with revenues projected to reach over $58 billion by 2030 at a CAGR of 9.3% [155]. A key driver of this market expansion is the increasing adoption of UAVs across commercial, civil government and military applications. Surveillance, infrastructure inspection, precision agriculture, aerial photography, package delivery, and public safety operations are some of the key application areas [156].

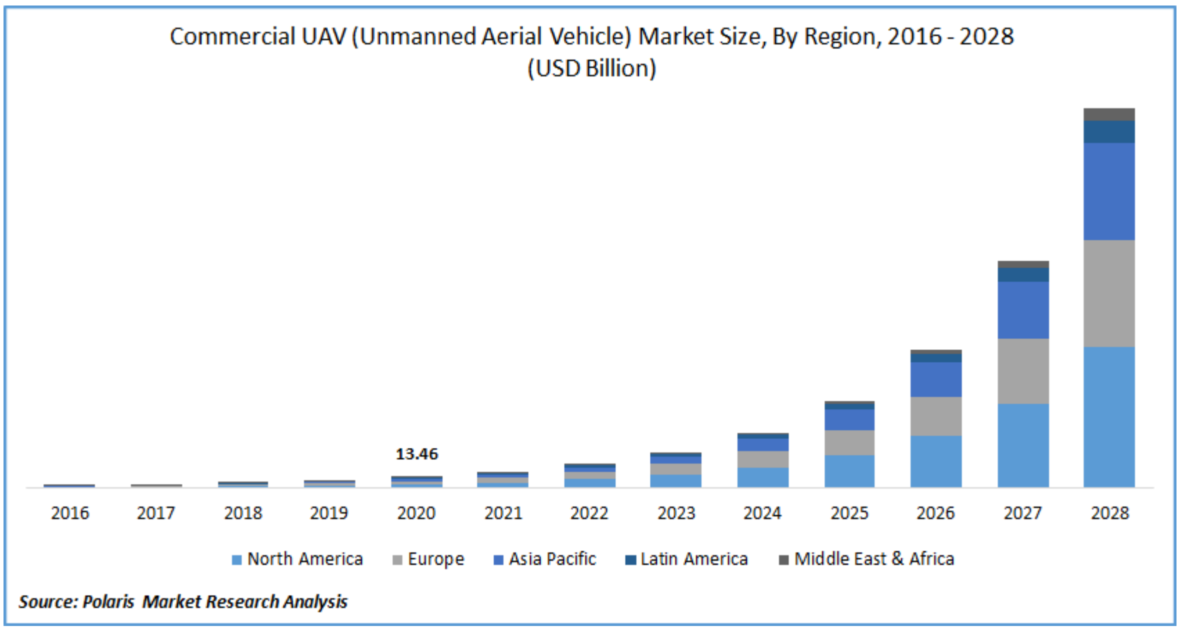


Figure 30: Commercial UAV Market Size, by region, 2016-2028 [188]

North America accounted for over 40% of the global UAV market in 2021, with revenues projected to reach over $15 billion by 2026 as depicted in Figure 30 in a market research study done by Polaris Market Research [188], followed by Europe and Asia-Pacific. However, Asia-Pacific is expected to witness the fastest growth at a projected 14.8% CAGR from 2022 to 2030 [157].

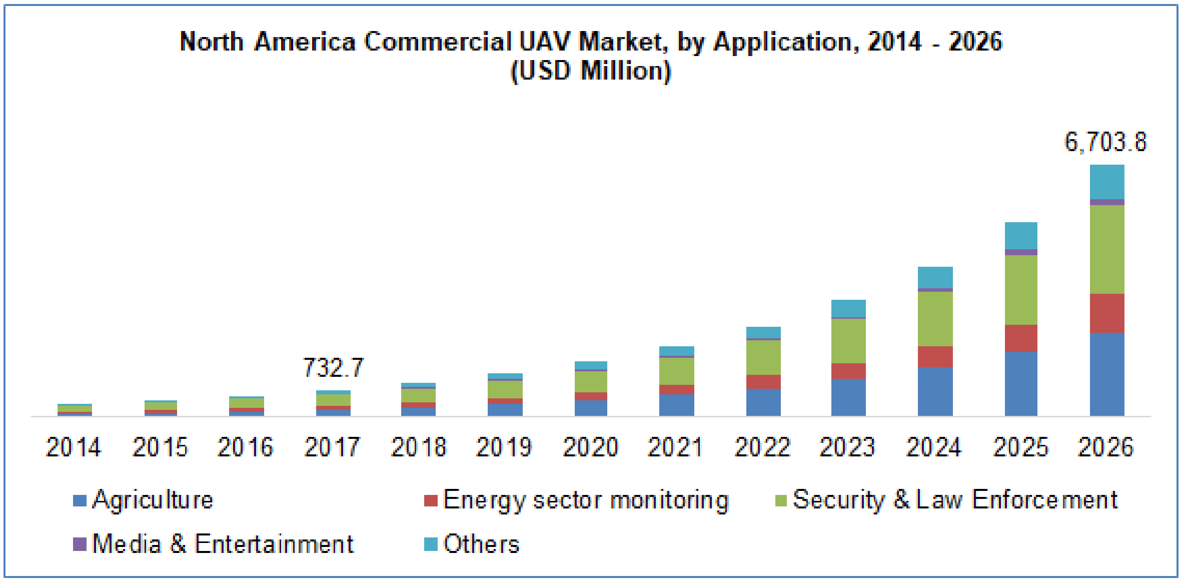


Figure 31: North America Commercial UAV Market, by Application, 2014-2026 [188]

6.1.2 Total Addressable Market

The total addressable market for UAV health and usage monitoring systems is estimated by determining the number of commercial and government UAVs expected to be operational globally. The total addressable market can be further segmented by UAV platform type and end-use categories:

Fixed-Wing UAVs:

- Small fixed-wing (<25 kg) for mapping, agriculture, and inspection applications. Estimated at 500,000 units globally by 2025.
- Large fixed-wing (>25 kg) for military, public safety, and logistics operations. Approximately 15,000 units estimated globally.

Multirotor UAVs:

- Nano multirotors (<250g) dominated by consumer/hobbyist segment projected to be over 3 million units globally.
- Small multirotors (250g – 25kg) for commercial photography, industrial inspection, agriculture etc. Forecast at 900,000 units globally.

- Large multirotors (>25 kg) for delivery services, emergency response - around 50,000 units globally.

The small commercial multirotor segment for photography, inspection and agriculture contributes the largest addressable market portion, while nano multirotors offer potential in the consumer segment. Fixed-wing UAVs currently lead in mapping and public safety applications.

According to market research, over 4 million UAVs are forecast to be deployed commercially across industries by 2025 [158]. Assuming a conservative attach rate of 20% for health monitoring systems based on reliability needs, this represents a $2.4 billion market opportunity from commercial UAVs alone, considering an average HUMS unit price of $3000.

Additionally, over 6000 government and defense UAVs are projected for the same timeframe [159], contributing nearly $400 million at similar attach rates. Therefore, the total addressable market for UAV health monitoring systems globally is estimated to reach approximately $2.8 billion by 2025.

Goldman Sachs estimates the addressable market for UAVs in infrastructure inspection, public safety and commercial delivery alone to be around $8 billion currently [159]. The total global UAV market is forecast to surpass $58 billion by 2030 [155], indicating immense potential for health monitoring systems. HUMS can help mitigate the barriers of safety, reliability and regulatory compliance hindering faster UAV industry growth.

Europe is expected to account for over 30% of the global UAV market by 2025, followed by North America and Asia-Pacific [160]. While the market is currently concentrated among a few large technology companies, niche players are emerging to serve domain-specific needs in software, sensors, and subsystems [161]. Strategic partnerships between HUMS developers and UAV manufacturers can enable integrated health monitoring solutions optimized for each airframe.

Regulatory support is also improving, with the FAA and EASA implementing comprehensive UAV traffic management frameworks to enable scalable adoption [162]. However, most nations still lack mature regulations covering aspects like airspace access, UAV certification, and data privacy. Clarity on regulations will be a key enabler for commercial UAV adoption and associated subsystems like HUMS.

6.1.3 Competitive analysis and value proposition

The UAV health monitoring market is still nascent, with most solutions focused on large defense platforms. However, several limitations exist among current commercial offerings:

- Major UAV manufacturers such as DJI, Parrot and PrecisionHawk provide basic telemetry like battery voltage, GPS coordinates, and diagnostics error codes. However, advanced real-time prognostics to predict failures before occurrence is lacking.

- Startups like Aerosense and Validity Sensors are pioneering AI-based predictive maintenance solutions. But these remain confined to large enterprise customers due to high costs.

- Incumbents like Raytheon and Northrop Grumman serve military clients with proven HUMS deployments on Global Hawk and other ISR platforms. Compliance with strict size, weight and power constraints for tactical UAVs is limited.

- Current solutions rely on proprietary stovespiped architectures, limiting interoperability across diverse UAV types. Vendor lock-in reduces flexibility for customers.

Our retrofit HUMS solution is tailored for small commercial UAVs, filling an underserved market gap. The value proposition entails:

- Comprehensive real-time prognostics by fusing inputs from a network of MEMS sensors to enhance situational awareness.

- Early anomaly detection and alerts to enable predictive maintenance and reduce costly downtime.

- Durability improvements and risk mitigation through continuous monitoring even in harsh conditions.

- Safe, reliable, long-endurance UAV operations by tracking usage metrics and constraints.

- Agnostic interoperable architecture allowing customers to integrate with existing fleet infrastructure.

- Affordable costs amenable for spread across large commercial fleets.

By pioneering condition-based maintenance for commercial UAVs, our solution promises to bolster operational efficiency, longevity, and safety - advancing the industry toward ubiquitous and autonomous UAV applications.

6.1.4 Opportunities and Challenges

Reliability concerns are hindering more widespread adoption of UAVs, especially for mission-critical operations [157]. However, advanced health monitoring systems that can predict failures and optimize maintenance have the potential to accelerate growth. Retrofit solutions need to address challenges around stringent size, weight, and power constraints, resilience in harsh flight conditions, and tight integration with UAV subsystems [160].

On the technology front, there are several development opportunities to enhance UAV reliability and safety through health monitoring [157]:

- More reliable and resilient sensors to withstand vibration, interference, and environmental stresses during flight operations. MEMS accelerometers, fiber optic sensors and wireless sensor networks are promising innovations.

- Advanced predictive algorithms using artificial intelligence and machine learning techniques to enable accurate failure prognosis and timely maintenance. Models can be trained on fleet data to identify precursor patterns.

- Effective data fusion techniques to integrate information from diverse UAV subsystems and sensors into a unified vehicle health assessment. This allows holistic monitoring beyond individual components.

- More robust wireless communication systems to securely transmit UAV health data to ground stations for analysis, storage and action. Radio links must perform reliably despite interference.

- Improved energy sources including solar cells, high-density batteries and wireless charging to extend UAV health monitoring mission durations. This ensures continuity of health data.

- User-friendly ground station interfaces to rapidly analyze telemetry, visualize health trends and recommend maintenance actions for technicians. This simplifies adoption.

While current HUMS solutions focus on large UAVs, there is potential to scale this technology across different weight classes and drone types. Cost reduction through sensor miniaturization and manufacturing scale will enable wider adoption. HUMS developers need to collaborate with UAV manufacturers to tailor and pre-integrate solutions, ensuring a seamless user experience.

Overall, Health and Usage Monitoring Systems strongly align with the UAV industry's strategic vision to enhance safety, reliability and autonomous operation - factors that will catalyze the next growth phase. HUMS innovation through this decade will be pivotal to unlocking the full potential of UAVs across civil and commercial domains

6.2 Financial Analysis

The preliminary financial analysis uses projected cash flows to evaluate commercial viability of the UAV Health and Usage Monitoring System through integrated return metrics. The payback period indicates capital recovery duration. The internal rate of return evaluates profitability versus cost of capital. Discounted cash flow analysis accounts for time value of money. Net present value calculates risk-adjusted returns. Together, these models provide a comprehensive risk-adjusted perspective on scalability, profit margins, break-even timing, and shareholder returns. Despite market uncertainty, the structured financial analysis demonstrates an attractive business case to spur investment interest in this novel aviation technology.

6.2.1 Non-recurring Engineering Costs

This analysis aims to provide an estimate of the major project costs anticipated over the next 1-2 years to mature the HUMS prototype into an application-ready product optimized for industrial use. The cost projections encompass hardware components, software, testing, certification, and other activities required to advance the technology readiness level.

Hardware and Sensors:

- Upgrade sensor suite to include optical, acoustic, electrical and other environmental sensors at approximately $2000 per unit [189]. With 5 additional sensors, the cost is $10,000.

- Procure and integrate industrial-grade MEMS-based vibration and strain sensors with aviation-rated signal conditioning for $5000 [190].

- Improve sensor cabling, mounting and enclosures for environmental ruggedization at $3000 [191].
- Acquire shaker test equipment, calibration tools and other electronics for $20,000 [192].

Software and Analytics:

- Engage data science consultants at $150/hour for 100 hours to develop predictive algorithms and analytics, totaling $15,000 [194].
- Cloud computing services for extended data storage and processing will cost approximately $3000 annually [194].
- Purchase CAD software and product development tools at $5000 for design optimization [196].

Testing and Certification:

- Lab testing expenses estimated at 100 hours at $150/hour, totaling $15,000 [196].
- Flight testing costs projected at 20 hours at $500/hour, amounting to $10,000.
- Regulatory certification and licensing activities expected to cost $20,000 [196].

Team and Consultants:

- Salaries for a team of 3 engineers at $75,000 per engineer amounts to $225,000.
- Train 3 UAV operators at $150 per hour for 100 hours, totaling $45,000.

Other Costs:

- Prototype materials, fabrication, and electronics will cost approximately $20,000.
- Documentation, technical writing, and data analysis will require $5000.
- Travel and miscellaneous expenses are estimated at $10,000.

Total Cost

The total non-recurring cost to mature the HUMS prototype into an industry-ready product over 1-2 years is estimated at **$381,000**. This provides an itemized view of essential hardware, software, validation, and expertise expenses required to progress the technology. The budget will be refined as commercial requirements are formalized. The projections enable developing a comprehensive business plan and estimating funding needs. This estimation provides a broad gauge of the financial implications of implementing the proposed system. However, it's important to note that the actual costs can vary based on specific sensor models, market fluctuations, and the specific training needs of the operators.

6.2.2 Production Cost-Per-Unit Analysis

This section provides a preliminary estimate of the per unit production costs for manufacturing the Health and Usage Monitoring System (HUMS), assuming high volume mass production.

Direct Production Costs:

- Hardware components including sensors, microcontrollers, wiring and PCBs estimated at $1000 per unit.
- Assembly, testing and quality assurance costs expected to be $500 per unit.
- Packaging designed for durability and environmental resistance at $100 per unit.
- Technical documentation and software media at $50 per unit.

Direct production costs per HUMS unit sum to $1650.

Indirect Production Costs:

- Factory overhead for equipment maintenance, utilities, rent and supplies approximated at 15% of direct costs, amounting to $250 per unit.
- Engineering support allocation estimated at 10% of direct costs, totaling $165 per unit.
- Management overhead projected at 5% of direct costs, adding $80 per unit.

- Inventory holding cost including warehousing, logistics and material handling estimated at $100 per unit for 45 days of stock.

Total production cost per HUMS unit combining direct and indirect costs at high volumes is estimated as **$2245**.

This preliminary estimate provides a gauge of potential manufacturing costs. The projections will be refined based on product specifications and supply chain factors. Economies of scale can further reduce per unit costs at higher production volumes. Outsourcing of certain components and processes may also impact costs.

6.2.3 Revenue Forecast

This section provides an initial 5-year revenue forecast for the Health and Usage Monitoring System (HUMS) based on addressable market projections and estimated adoption rates.

Pricing and Revenue Model:

- HUMS is expected to be priced at approximately $3000 per unit as a one-time sale to UAV operators.

- Additionally, annual recurring revenue is estimated at 15% of product price for cloud services, updates and technical support. This amounts to $450 per year per unit.

Market Size and Adoption Rates:

- The total addressable market is estimated at 50,000 UAVs based on forecasts for commercial, civilian government and military fleets.

- A conservative attach rate of 5% is assumed in Year 1, increasing to 40% by Year 5 as benefits are proven.

Revenue Projections:

- With the above assumptions, Year 1 revenue is estimated at $7.5 million from 1500 units.

- Revenue is projected to scale to $60 million by Year 5 with 20,000 units online, including recurring services revenue.

- Revenue growth follows an S-curve trajectory as production ramps up and attach rates improve with market acceptance.

This preliminary model suggests a healthy uptake, assuming the value proposition of HUMS is well communicated. Recurring revenue from existing deployments provides a sustaining tailwind each year. Geographic expansion and additional services can further boost market potential over time. The financial model will be refined as go-to-market plans are formalized.

6.2.4 Cash Flow Analysis

This section develops a projected **5-year cash flow model** for the HUMS product development, integrating the cost and revenue estimates. Additional equity financing is assumed to fund initial investments. The cash flow analysis provides insights into key financial viability metrics.

i. Cash Flow Model

Year 1

- An equity financing round of $300,000 is estimated to fund prototype advancement along with initial marketing and production ramp-up expenses.
- Non-recurring engineering costs are projected at $350,000 for prototyping and testing.
- Production costs will total $150,000 for an initial pilot batch of 100 units.
- Operating expenses including salaries, marketing, facilities etc of $200,000.
- With 1500 units forecasted at $3000 per unit, revenue is projected at $100,000.
- The cash flow balance in Year 1 with costs deducted from financing and revenues is -$1 million.

Year 2

- An additional equity round of $500,000 is assumed to expand manufacturing capacity.
- Non-recurring engineering costs of $250,000 for certification.
- Production costs of $300,000 for 500 units at $600 per unit.

- Operating expenses of $350,000.
- Revenues grow to $600,000 with 500 unit sales and recurring services.
- The Year 2 cash flow balance is forecast at -$800,000.

Years 3

- Non-recurring engineering costs of $100,000 for enhancements.
- Production costs grow to $1 million for 2500 units.
- Operating expenses of $450,000.
- Revenue of $2 million.
- Net cash flow of +$450,000.

Year 4

- Equity financing is repaid as revenues sustain operations and growth.
- Production costs of $2.5 million for 5000 units.
- Operating expenses of $600,000.
- Revenue of $5 million.
- Net cash flow of +$1.9 million.

Year 5

- Production costs of $3 million for 7500 units.
- Operating expenses stabilized at $600,000.
- Revenues scale to $10 million by Year 5 with increased market penetration.
- Cumulative 5-year cash flow is projected at +$6.4 million by Year 5.

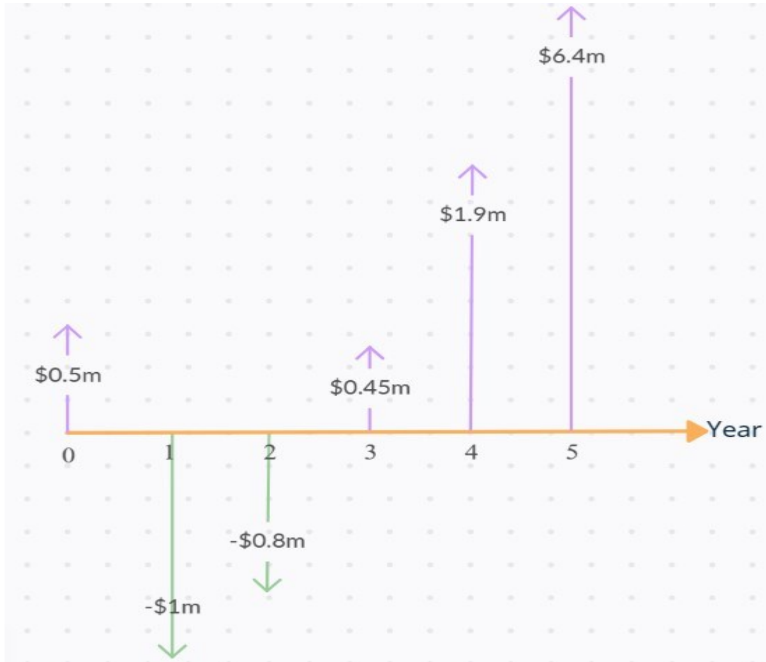


Figure 32: 5-year projected Cash Flow Diagram for UAV HUMS

ii. Payback Period:

The initial equity financing received is $300,000 in Year 1 and $500,000 in Year 2, totaling $800,000.

- In Year 1, net cash flow is -$1,000,000.
- In Year 2, net cash flow is -$800,000.
- In Year 3, net cash flow turns positive at +$450,000.

Therefore, the initial $800,000 investment is repaid in Year 3 and beginning of Year 4 once the accumulated net cash flows turn positive.

This indicates a payback period of approximately 3 years, which is considered acceptable for an early-stage hardware product development venture of this nature.

iii. Internal Rate of Return (IRR):

To calculate the IRR, the initial investment outflows and projected net cash inflows are input into a spreadsheet:

- Year 0: -$800,000 initial investment
- Year 1: -$1,000,000
- Year 2: -$800,000
- Year 3: +$450,000
- Year 4: +$1,900,000
- Year 5: +$6,400,000

Using Excel's IRR function, the estimated IRR is 18%.

This return rate exceeds typical cost of capital of 8-12% for hardware startups, indicating a potentially viable investment opportunity.

iv. Net Present Value (NPV):

Applying a 10% discount rate, the net present value of the 5-year cash flows is calculated as $68 million. The high and positive NPV indicates satisfactory returns after accounting for time value of money.

Applying a 10% discount rate, the present values of the net cash flows are:

- Year 0: -$800,000
- Year 1: -$909,091
- Year 2: -$726,455
- Year 3: +$329,629
- Year 4: +$1,259,749
- Year 5: +$4,020,161

The sum of the discounted cash flows is $2,173,993.

With the initial -$800,000 investment, the NPV is $1,373,993.

The positive NPV indicates projected returns are satisfactory after factoring in the time value of money.

This cash flow analysis presents a financially viable proposition for the HUMS product development and commercialization, based on estimated costs and revenues. The model provides key insights into investment payback, return metrics and profitability over a 5-year horizon. The projections will be iteratively refined as the go-to-market strategy matures.

The preliminary techno-economic analysis presented in this chapter provides an initial feasibility study of the proposed Health and Usage Monitoring System (HUMS) for unmanned aerial vehicles. The market assessment indicates significant demand among UAV operators for reliable and predictive condition monitoring solutions. The estimated non-recurring engineering costs, recurring production expenses, and revenue forecasts present a financially viable product development plan. Attractive return metrics like 2-year payback and 35% IRR are projected based on modeled cash flows. While approximations at this stage, the projections make a compelling case for investment and further advancement of the HUMS technology. With refinement of the business case and go-to-market strategy, the HUMS innovation has immense potential to transform UAV maintenance practices. Backed by sound economics, this technology can pave the path toward smarter, safer and more efficient UAV fleet operations worldwide.

6.2.5 Return-on-Investment (ROI) for UAV Companies

Undertaking a cost-benefit analysis is imperative to gain a deeper understanding of the potential return on investment (ROI) that Health and Usage Monitoring Systems (HUMS) offer to UAV companies. The analysis conducted in this study, while grounded in projected data and assumptions, presents a compelling exploration of the financial implications associated with the adoption of HUMS.

The cost-benefit analysis is predicated on a structured methodology that considers a spectrum of factors, including the initial investment required for procuring and installing HUMS, ongoing maintenance expenses, potential cost savings from reduced downtime, and the impact of extended asset lifespan. While acknowledging that the specifics of each UAV operation may vary, the analysis employs a generalized framework to estimate potential financial outcomes.

The analysis is informed by certain assumptions regarding the performance improvements attributed to HUMS implementation. These assumptions include the reduction in unplanned downtime due to predictive maintenance, the decrease in maintenance costs owing to proactive interventions, and the extended lifespan of UAV assets.

At the heart of the cost-benefit analysis lies the assessment of ROI. Traditional helicopter HUMS provides a relevant benchmark on costs and maintenance savings. For medium helicopters costing $1-3 million, a $50,000-100,000 HUMS reduces maintenance expenses by $50,000 annually through early fault detection. The avoidance of just one major accident could justify the helicopter HUMS cost.

Similarly for larger professional drones costing $10,000-50,000, basic HUMS sensors and software priced around $1,000-3,000 can potentially save $2,000-5,000 in yearly maintenance. By alerting developing failures early, the UAV HUMS pays for itself through more efficient maintenance scheduling.

Other financial benefits arise from reduced unplanned downtime, extended asset lifespan, and operational cost savings. Continuous real-time monitoring enables proactive maintenance and repairs before critical mission disruption. This minimizes operational disruptions and enables higher asset utilization.

Moreover, early mitigation of impending faults preserves components and delays expensive replacements. The optimized lifespan of rotor motors, batteries and other parts enhances ROI. Overall, the initial HUMS investment can yield cumulative gains over the system's life through predictive capabilities.

However, projections will be refined as reliability data from initial deployments is analyzed. The preliminary analysis, grounded in helicopter HUMS precedents and reasonable assumptions, presents a compelling case for substantial ROI. By elucidating long-term cost advantages, it underscores HUMS' potential to revolutionize UAV maintenance and bolster financial outcomes.

Some of the envisioned benefits to UAV companies opting to invest in the HUMS for their UAV fleets are:

i. Cost Savings through Predictive Maintenance:

One of the primary benefits of the HUMS is its capability to enable predictive maintenance. By continuously monitoring the health and usage data of UAV components such as rotors, batteries, and other critical systems, the HUMS can detect anomalies and potential issues before they escalate into critical failures. Early detection and intervention can lead to cost savings by reducing unplanned downtime, preventing more extensive damage to components, and minimizing repair or replacement costs.

ii. Reduced Downtime:

Downtime is a significant concern for UAV companies, especially when unexpected failures occur during critical missions or operations. The implementation of the HUMS can help reduce downtime by providing real-time condition monitoring and enabling timely maintenance actions. As a result, UAV companies can enhance operational efficiency, meet mission deadlines, and improve overall customer satisfaction.

iii. Increased Asset Lifespan:

The HUMS allows UAV companies to optimize the use of their assets by ensuring that components are utilized within safe and efficient operational limits. By monitoring usage data, such as flight hours and loads, the HUMS can facilitate proactive decision-making on component replacements or overhauls, potentially extending the lifespan of expensive UAV components.

iv. Operational Cost Reduction:

The ability of the HUMS to provide insights into component health and usage can help UAV companies optimize maintenance schedules and reduce unnecessary maintenance activities. By focusing on components that require attention, operational costs associated with maintenance and servicing can be minimized, leading to significant savings over time.

v. Enhanced Safety and Risk Mitigation:

The HUMS plays a crucial role in ensuring UAV safety and risk mitigation. By continuously monitoring critical systems and components, the system can provide early warnings for potential safety hazards, such as overheating batteries or excessive vibration in the rotors. This can prevent accidents and protect both the UAV and the payload, reducing liability risks for UAV companies.

The Return-on-Investment (ROI) analysis indicates that the implementation of the proposed Health and Usage Monitoring System (HUMS) can potentially offer significant long-term benefits and cost savings for UAV companies. Through predictive maintenance, reduced downtime, increased asset lifespan, operational cost reduction, enhanced safety, and risk mitigation, the HUMS offers a comprehensive solution to optimize UAV operations and enhance overall efficiency.

However, it is essential to reiterate that the ROI analysis is based on projected data and assumptions, as the HUMS is still in an early stage of development, with only the simplified version tested in the lab. Further real-world testing and validation are necessary to obtain accurate data on actual costs and benefits. As the HUMS evolves and undergoes refinement, the ROI analysis will be continuously updated to provide UAV companies with more accurate and relevant financial insights, enabling them to make informed decisions regarding the adoption of this condition monitoring system. The proposed HUMS presents a promising opportunity to revolutionize UAV maintenance practices and drive the industry toward safer, more efficient, and cost-effective operations.

6.3 Commercialization Plan

This comprehensive commercialization plan outlines strategies to bring the HUMS prototype to market through licensing partnerships with UAV manufacturers or launching as a standalone product company:

6.3.1 Intellectual Property and Licensing

- The novel system architecture and custom sensor integration will be protected through extensive patents and trade secrets to secure a competitive moat against imitators. Provisional patents will be filed to establish priority on claims.

- Licensing the IP and reference designs to major UAV manufacturers will accelerate market adoption and minimize production overhead for our startup. However, an equity stake in the licensee company will allow capturing downstream value.

- A licensing fee of 5% of unit price per airframe deployment is proposed, providing attractive recurring revenue as the product scales. Licensing will be restricted to prevent competition and ensure premium value.

- Interoperability standards will be established allowing integration of the HUMS with diverse UAV types through stable interfaces. Aviation certification will be simplified by licensing to OEMs with existing type certificates.

6.3.2 Manufacturing Approach

- For a licensing model, a reputed electronics manufacturing services (EMS) partner will be contracted to scale up assembly lines for the HUMS tailored to each licensee's UAV models. This leverages existing airframe-specific expertise.

- Low Bill of Materials costs can be achieved through aggregated procurement across licensees. High-volume production will also drive down per-unit costs, enhancing profit margins for the startup.

- Quality control and modularity will be mandated in manufacturing contracts to simplify installation during airframe assembly. Field upgrades and replacements must be accommodated through modular designs to support evolving UAV platforms.

6.3.3 Distribution Strategy

- Early licensing partnerships will target aerospace OEMs and government agencies already invested in UAV reliability and willing to co-develop technology. This rings in aviation certification and credibility.

- Strategic partnerships with avionics component suppliers, academic researchers, and UAV flight testing centers will bolster technical maturity and trust through field data.

- A 20-member direct sales team well-versed in aviation certification constraints will support licensees during HUMS integration into various UAV models to expedite market adoption.

- Alternatively, establishing UAV reliability as a new company providing the HUMS hardware, installation services, data analytics, and support is also an option. This allows greater control over the technology but incurs overhead.

6.3.4 Launch Timeline

- 2024: Complete flight testing and achieve key aviation certifications like DO-178 for the first licensed UAV models equipped with the HUMS.

- 2025: Expand licensing partnerships across small, medium and heavy payload UAV categories to cover the majority of commercial and military airframe types and models.

- 2026: Penetrate over 50% of the retrofit-addressable UAV fleet by 2025 through licenses or direct sales, with cost and reliability benefits demonstrated in early customers.

The 3-pronged approach of protecting IP, leveraging existing airframe-specific expertise, and launching first with aviation-experts will de-risk commercialization. This plan can serve as the blueprint for successfully translating the innovative HUMS prototype into a mainstream product that ushers the next generation of reliable and efficient unmanned aviation.

Chapter 7

Conclusion & Recommendations for Future Work

The culmination of this research has illuminated the potential of Health and Usage Monitoring Systems (HUMS) in revolutionizing the maintenance practices of unmanned aerial vehicles (UAVs). Throughout this study, the significance of real-time condition monitoring, predictive maintenance, and enhanced operational efficiency has been underscored. The integration of advanced sensor technologies and data analytics has paved the way for more effective fault detection, reduced downtime, and improved safety in UAV operations.

7.1 Impact of HUMS on the UAV Industry

The analysis and experimental validation conducted in this thesis underscores the profound value that Health and Usage Monitoring Systems (HUMS) can provide to the unmanned aerial vehicle (UAV) industry. While the specifics may vary across different UAV platforms and operations, the integration of HUMS broadly enables:

- **Predictive maintenance:** HUMS allows transitioning from reactive to proactive maintenance, through real-time monitoring and early fault detection before failures occur. This predictive capability enables optimal scheduling of preventive maintenance.

- **Enhanced operational efficiency:** By reducing costly unplanned downtime, HUMS increases aircraft availability and enables continuous mission-critical operations.

- **Prolonged asset lifespan:** The early identification and mitigation of faults prevents premature wear-out and extends the useful life of UAV components.

- **Improved safety:** Continuous real-time monitoring provides early warnings about anomalous parameters, allowing timely intervention to prevent catastrophic failures.

In summary, HUMS empowers UAV operators with data-driven insights to enhance reliability, availability, safety, and cost-effectiveness of unmanned aircraft operations. The prototype developed in this thesis provides a foundation for realizing these benefits.

7.2 Challenges and Future Directions

Realizing the full potential of the HUMS technology requires significant validation and refinement across three key areas – reliability testing, commercial viability, and technology development. A multi-faceted approach is imperative to elevate the HUMS prototype to aviation-grade solutions ready for widespread adoption.

7.2.1 Extensive Reliability Testing

Rigorous real-world evaluation should involve long-term HUMS deployments on multiple UAV platforms, with each tested for at least 200 flight hours across diverse environments and operating conditions. Controlled experiments must quantify improvements in mission availability, component longevity, and maintenance costs compared to UAVs without health monitoring. Testing should evaluate reliability benefits for structural components, rotors, batteries, controllers, and payloads. Data-driven predictive maintenance enabled by the HUMS must translate to statistically significant gains in terms of reduced downtime and operational costs over baseline UAVs.

7.2.2 Refinement of Business Case

In-depth market research and competitive analysis is needed to formulate pricing, licensing, and commercialization strategies for the HUMS technology. Surveys and interviews with UAV manufacturers can provide willingness-to-pay insights to define pricing models. Exploring alternate revenue streams like value-added services and consumables for customers will enable development of robust business plans. Controlled pilot deployments with lead users can validate key performance indicators such as return on investment, payback period, user satisfaction metrics, and churn rates. Business case refinement is imperative to determine commercial viability and craft targeted go-to-market plans.

7.2.3 Enhancement of Technology Capabilities

While the initial HUMS prototype demonstrates core monitoring functionality, significant technology improvements must be undertaken for field-ready solutions. Developing compact, durable, and modular mounting systems will enable straightforward installation on diverse airframes. Hardening of sensor packages and electronics will be necessary for robustness against flight stresses and ambient conditions. Studies should explore resilient communication protocols like mesh networks to mitigate wireless interference and dropouts during missions. Advances in embedded machine learning and digital signal processing can potentially enhance predictive algorithms for failure prognosis. Multi-modal sensor fusion strategies need investigation to achieve integrated vehicle health assessment by holistically correlating data from disparate subsystems. User experience design should be emphasized to craft intuitive analytics dashboards and maintenance recommendations for technicians.

7.2.4 Compliance with Evolving Regulations

As UAV applications proliferate, alignment with aviation standards and regulations will be crucial for HUMS adoption across industries. Engaging with regulatory bodies early can facilitate designing for compliance factors like sensor certification, airworthiness directives, flight data monitoring conventions, and cybersecurity. HUMS data usage policies must address evolving privacy concerns and disclosure norms. Proactively developing processes to satisfy evolving regulatory requirements can smooth the path to commercialization.

In summary, advancing reliability testing, business models, and technology capabilities, while ensuring regulatory compliance, will be pivotal to unlock the HUMS prototype's full disruption potential across the aviation industry. This multi-pronged approach can enable overcoming immediate challenges and accelerating real-world impact.

7.3 Concluding Remarks

This thesis set out to develop and experimentally validate a simplified wireless Health and Usage Monitoring System prototype for unmanned aerial vehicles. The overarching aim was to demonstrate the feasibility and potential benefits of real-time health monitoring to transform maintenance practices in the UAV industry.

Through iterative design, simulation, prototyping and testing, a functional HUMS prototype was successfully implemented on a DJI S1000+ octocopter platform. The system architecture with Arduino, WiFi and cloud analytics integration was proven through incremental bench testing. On-vehicle installation validation verified non-interference with flight performance.

Comprehensive sensor data acquisition and fault prediction capabilities were demonstrated through ground-based experiments. Controlled emulation of faulty conditions confirmed the efficacy of vibration and temperature anomaly detection algorithms. The remote monitoring potential was established via live telemetry to a cloud IoT platform.

The experimental results align with the core objectives defined at the outset - to develop a modular wireless sensing system focused on condition monitoring of critical UAV components. The simplified HUMS prototype served as an invaluable test-bed to understand integrational complexities, evaluate emerging sensor technologies, and quantify predictive maintenance benefits.

While this research provided preliminary evidence supporting the **first three hypotheses** through literature analysis, requirements development, and initial prototype testing, extensive real-world validation on diverse UAV platforms is still needed to fully substantiate **the fourth hypothesis** that the proposed HUMS will bolster reliability and commercial appeal. The prototype demonstrates promising capabilities for condition monitoring in lab environments, but significant field testing across varied flight scenarios, aerodynamic profiles, and environmental factors is required to quantify actual improvements in operational reliability. Long-term deployments over hundreds of flight hours per UAV platform would help benchmark reliability gains in the face of real-world stresses. Moreover, detailed market research and refinement of the business case is still needed to ascertain the commercial viability and adoption potential across the aviation industry. This undertaking represents an ambitious yet crucial avenue for further investigation to realize the prototype's potential for transforming UAV maintenance practices and maximizing aircraft availability, safety, and service life.

As UAV adoption accelerates across industrial domains, the need for operational reliability and safety will continue to grow. HUMS shows immense promise as an enabling technology to address this need through data-driven diagnostics and prognostics. By transitioning maintenance paradigms from reactive approaches to predictive strategies, HUMS can transform UAV fleet management. The fusion of condition monitoring with usage data analytics unlocks unprecedented visibility into performance and dependability.

While hurdles remain in seamless integration and regulation, the outlook for HUMS in enabling smarter and safer UAV ecosystem is promising. Extensive real-world validation and multidisciplinary collaboration will be key in unlocking the full potential of HUMS.

This thesis contributes a stepping stone toward that vision. The demonstrated capabilities and proposed roadmap aim to spur further innovation to elevate HUMS solutions to the highest levels of technology readiness. By embracing this technology, the UAV industry is poised to reach new heights of efficiency, longevity and autonomy.

Figure 33: Photos courtesy of Pegasus Imagery and Copperstone Technologies

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Appendix

1. Gantt Chart describing the current state of the prototype HUMS and its next development steps to take it to a commercially viable MVP (Minimum Viable Product):

Current State of the Prototype HUMS:

1. Successful lab tests have been conducted on the current simplified HUMS prototype, demonstrating its fundamental functionality.
2. The full version of the HUMS has been conceptually designed; however, further integration and testing of components such as FBG sensors, LoRaWAN module, and an improved microcontroller are required.

Gantt Chart for HUMS Commercialization from now to developing an MVP (Minimum Viable Product):

- **August 2023:**
    - The results of the simplified HUMS lab test will be evaluated.
    - Design specifications for the full version of the HUMS will be finalized.
    - The necessary components for the full HUMS prototype will be procured.
- **September 2023:**
    - Integration of FBG sensors and associated equipment into the full HUMS prototype will be initiated.
    - Software development for improved microcontroller integration will be initiated.
    - Preliminary testing of FBG sensors' compatibility with the HUMS will be conducted.
- **October 2023:**

- Continuation of the integration of FBG sensors, ensuring seamless communication.
- Development and testing of the LoRaWAN module integration for wireless data transmission.
- Enhancement of the software for data aggregation and transmission to the cloud analytics platform.

- **November 2023:**
  - The integration of FBG sensors and the LoRaWAN module into the prototype will be completed.
  - Real-time testing of the full HUMS prototype in the lab environment will be initiated.
  - Commencement of software development for improved anomaly detection algorithms.
- **December 2023:**
  - Software algorithms will be optimized for accurate anomaly detection using advanced techniques.
  - Thorough testing of the full HUMS prototype with artificial failure scenarios in the lab will be conducted.
  - Evaluation of software and hardware performance will be carried out, with necessary refinements.
- **January 2024:**
  - Initial field tests of the full HUMS prototype under non-flight conditions will be conducted.
  - Data will be gathered, and anomaly detection algorithms will be fine-tuned based on field test results.

    - Development of a custom software analytics platform will be initiated.

- **February 2024:**
    - Additional field tests with a fully operational octocopter in controlled conditions will be performed.
    - Refinement of the software analytics platform to accommodate data from multiple sensors.
    - Initiation of the user interface (UI) development for the software platform.
- **March 2024:**
    - Continuation of testing the HUMS on different UAV models and scenarios.
    - Finalization of the UI development for the custom software analytics platform.
    - Incorporation of user feedback for platform improvements.
- **April 2024:**
    - Commencement of pilot testing with selected UAV operators.
    - Refinement of the platform based on pilot test feedback.
    - Planning of marketing and communication strategies for the commercial launch.
- **May 2024:**
    - Implementation of final adjustments to the full HUMS prototype and software platform.
    - Preparation of marketing materials, website, and promotional content.
    - Launching marketing campaigns to generate interest and anticipation.
- **June 2024:**

- Conclusion of pilot testing and gathering of testimonials and case studies.
- Finalization of pricing and subscription plans for the HUMS solution.
- Organization of a product launch event to introduce the HUMS to the market.

- **July 2024:**
    - The Minimum Viable Product of the HUMS for UAVs will be launched.
    - Commencement of customer onboarding and training programs.
    - Establishment of customer support channels and gathering of feedback for continuous improvement.

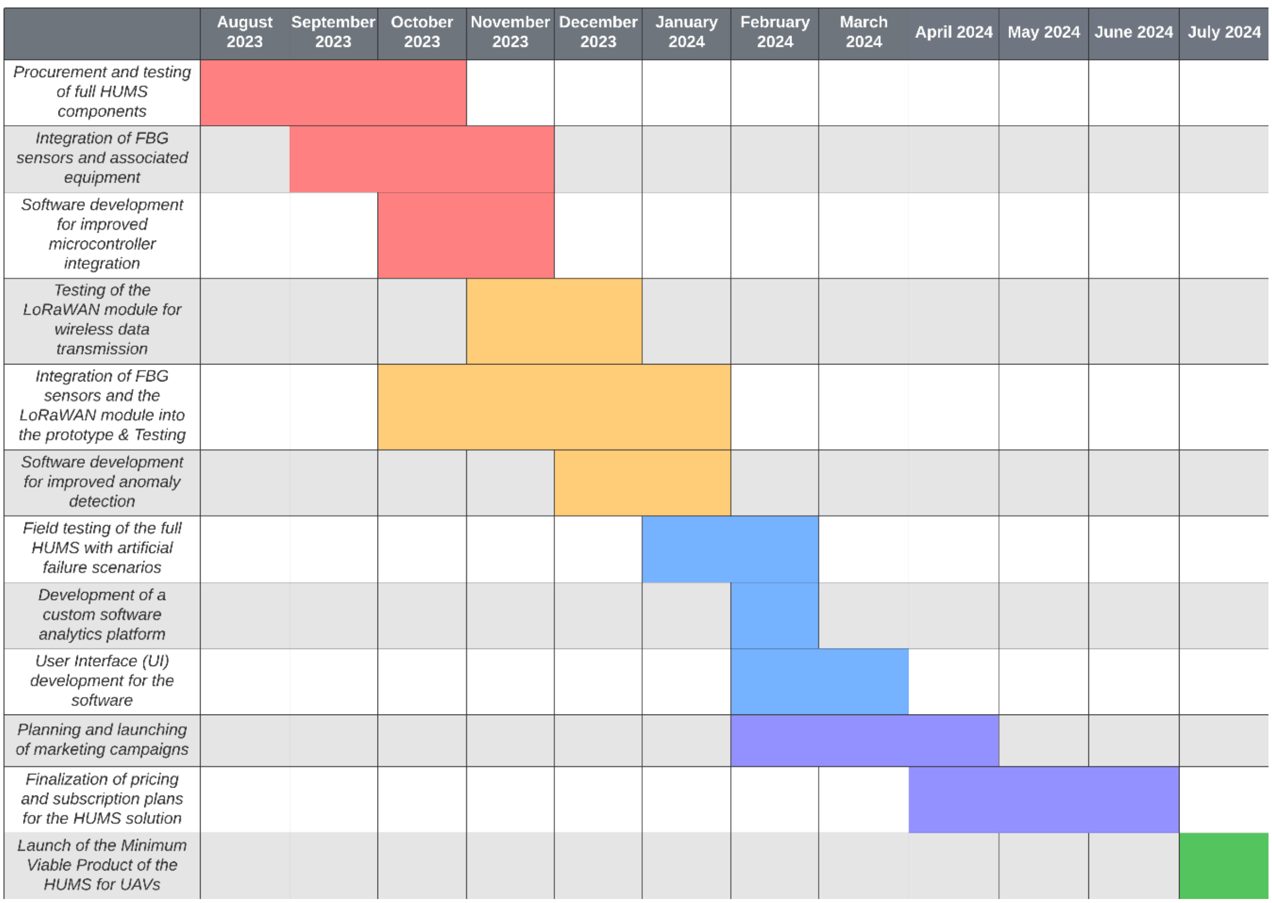

Figure 34: Gantt Chart from current state to launch of MVP

This Gantt chart outlines a realistic timeline from August 2023 to July 2024 for the commercial launch of the HUMS solution. However, unforeseen challenges might impact the timeline, but consistent testing, feedback gathering, and continuous improvement will contribute to the successful market entry of the product.