AMELIA: An Application of the Internet of Things for Aviation Safety

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***Abstract*—This paper presents *AMELIA: Aircraft Monitoring and Electronically Linked Instantaneous Analytics* as an application of the Internet of Things (IoT) for aviation safety—a safety-critical use-case—from an edge computing perspective. AMELIA is a multi-layered edge computing system that automatically detects aircraft emergencies, and only transmits relevant data and information to enable quicker and more efficient response to emergencies. We describe a prototype of AMELIA to illustrate, explore, and motivate the potentials of the IoT for aviation safety, and lay a foundation for the design of diverse high-impact edge computing systems on the IoT.**

***Index Terms*—Internet of Things, aviation safety, edge computing, automatic control, IoT prototype.**

I. Introduction

The Internet of Things (IoT) refers to a pervasive presence of connected devices that can interact with each other, and gather, interpret, and use data, in order to reduce reliance on human intervention. The IoT's goal is to provide new, diverse, and more efficient services, spanning a wide variety of domains, that promise to transform life, business, and the global economy [14]. In several IoT use-cases, edge devices gather data and transmit the data to high performance head nodes, where data visualization is performed [8]. However, the IoT's growth, involving billions of connected devices, also poses significant challenges. Due to the resulting exponential increase in acquired/transmitted data, overheads with respect to bandwidth bottlenecks, latency, energy consumption, and security issues are also bound to increase [5]. In real-time, safety-critical IoT use-cases, such as aviation and medical diagnostics, devices must adhere to stringent constraints in order to prevent potentially fatal events.

Edge computing addresses some of the attendant challenges of the IoT by equipping edge devices with sufficient computational resources to reduce, process, interpret, and use data. One of the clear advantages of edge computing is that it reduces the amount of transmitted data, and in effect, reduces the latency and energy overheads that arise from data transmission [4], [11]. Beyond these benefits, we also show, in this work, that edge computing also offers additional benefits, including, cost, security, and privacy.

In this paper, we demonstrate some of the potential benefits of edge computing using a high-impact IoT use-case: aviation safety [20]. Aviation is important because most aviation applications are safety-critical systems—failure can result in loss of life, significant property damage, or extensive damage to the environment. In addition, aviation is pervasive in everyday life, business, and the economy. On average, about 100,000 daily flights originate from approximately 9000 airports around the world [2]. While air travel is still considered one of the safest forms of travel, there are still small but present dangers in air travel. The disappearance of Malaysia MH370 on March 8, 2014 is a stark reminder of these dangers that necessitate innovative multi-disciplinary technologies for ensuring aviation safety.

Aviation safety involves aircraft monitoring, wherein flight data is continuously collected and stored using devices such as the Flight-Data Acquisition Unit (FDAU) and Flight Data Recorder (FDR) [10]. In addition, communication protocols such as the Automatic Dependent Surveillance-Broadcast (ADS-B) continuously transmit flight data to ground centers for real-time analysis and monitoring [13]. However, the overheads of collecting and transmitting massive amounts of data pose critical challenges for aviation safety due to the concomitant overheads of data transmission.

To address these challenges, we present *AMELIA: Aircraft Monitoring and Electronically Linked Instantaneous Analytics*. AMELIA illustrates a practical solution proffered by IoT edge computing to address some of the challenges with state-of-the-art aircraft monitoring. AMELIA is a multi-layered edge computing system that ensures that each flight data parameter received during a flight remains within a preset range of values. Any deviation from these preset values immediately generates an alert sequence that includes automated correction and simultaneous alerts to the required personnel (e.g., pilots and ground control), with the relevant data, for quick response. Thus, apart from enabling quick aircraft location or retrieval in case of a crash, AMELIA can also prevent crashes by providing ground controllers with all the relevant parameters, thereby giving pilots access to experts outside of the cockpit.

We have developed AMELIA as a motivation for exploring other high-impact IoT applications (e.g., real-time medical diagnostics). Our design goal for AMELIA is a simple, low-overhead, and highly efficient framework that generates real-time actionable information from the massive amounts of collected data, in order to reduce the overheads associated with the IoT. We have created a prototype of AMELIA, using commercial off-the-shelf hardware, and describe the prototype in this paper. Using our prototype, and experiments performed in actual flight tests on a glider aircraft, we demonstrate that

IoT edge computing offers significant potential for innovative and highly efficient systems to provide real-world solutions.

II. Background on Aviation Safety and Challenges with the State of the Art

The flight recorder, otherwise known as *black box*, is probably one of the most important technologies for aviation safety through aircraft monitoring. A flight-data acquisition unit (FDAU)—installed in most modern aircraft—receives various discrete, analog, and digital parameters from several sensors and avionic systems. The massive amounts of data collected by the FDAU are then recorded on the *flight data recorder (FDR)*, which is housed in the black box. The black box also includes the *cockpit voice recorder*, which records voice data in the cockpit. In the event of an accident, investigators can analyze the data on the black boxes, which are designed to survive accidents, in order to determine the causes of the accident.

In addition to FDRs, modern aircraft also use *automatic dependent surveillance-broadcast (ADS-B)*, which broadcasts information about an aircraft's location, airspeed, and other data, to air traffic ground control. Pilots can also receive weather and traffic position information delivered directly to the cockpit through the ADS-B system. Unfortunately, recent events like the disappearance of Malaysia MH370 have shown that these safety mechanisms, while extremely useful, are still severely lacking. The current paradigm of ADS-B and the black boxes faces three key challenges:

1) Cost: Data transmission, especially in aviation, comes with astronomical costs. Even though FDRs record rich flight data that can help prevent aircraft disasters in real time, it has been estimated that it would cost billions of dollars to implement flight data streaming across the airline industry [3]. In addition, the data transmitters required to achieve this real-time transmission could cost up to $100,000 a piece [1].
2) Security and privacy: Internet hackers can track airplanes in unnerving detail with equipment that cost less than $1000. With the ADS-B system employed in aircraft, especially with a two-way communication interface, hackers can easily interfere with vital communications or potentially cause security breaches.
3) Massive data loads: FDRs record such large amounts of data that they require complex automated analysis and data mining techniques and algorithms to extract useful information [10]. These could impose significant overheads, especially in hard real-time scenarios where the data interpretation and visualization must adhere to stringent latency constraints.

We propose AMELIA, as an example of IoT edge computing, to address these challenges in aircraft monitoring. Our goal in designing AMELIA was a simple, low-overhead, and efficient aircraft monitoring system, with the intelligence to detect emergencies in real time, and take appropriate actions to mitigate the emergencies. In addition, we aimed to design a system with low bandwidth requirements in order to not overwhelmed limited satellite communication resources. AMELIA represents a step towards such a system. We show, using a prototype, how AMELIA can mitigate challenges presented by the state-of-the-art in aircraft monitoring.

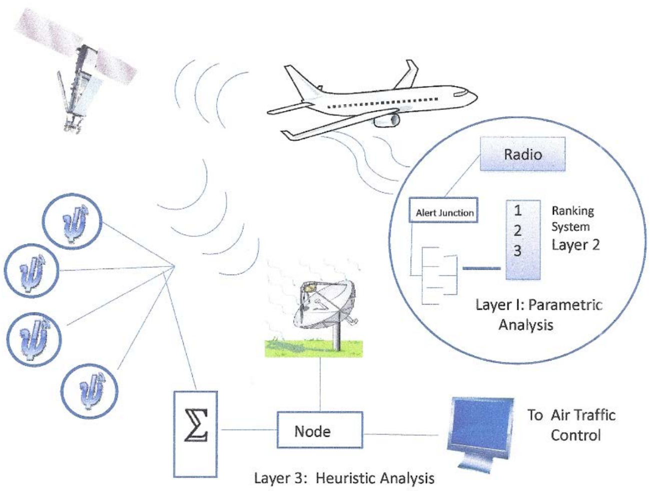


Fig. 1: A high level illustration of AMELIA.

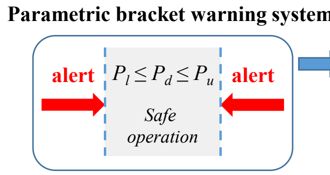
III. AMELIA Framework

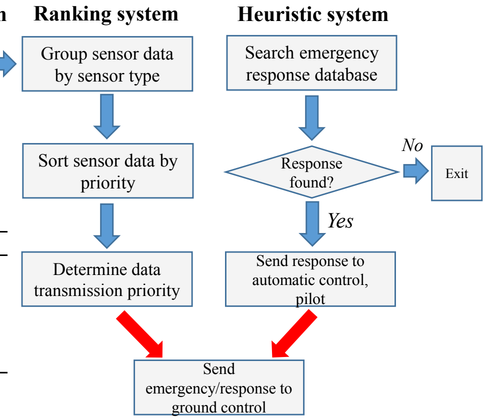
AMELIA acts as a delay-tolerant one-way node. Unlike passive devices, such as the flight data and cockpit voice recorders, that only store voice and aircraft data, AMELIA implements an active flight data recorder that can intelligently transmit data when necessary. Furthermore, AMELIA addresses the cost of communication via satellite. Since satellite mediated connection is the only true form of global communication, satellites are the operational choice for AMELIA's external communication. However, in contrast to an Emergency Location Beacon or other transponders/beacons that blindly transmit location signals, AMELIA automatically uplinks to the satellite system only when an emergency is detected, in order to minimize the communication overhead.

A. Functionality of AMELIA

Figure 1 depicts a high level illustration of AMELIA's functionality. We assume that AMELIA collects data from the on-board flight data acquisition unit (FDAU). The FDAU is currently installed on most state of the art aircraft, and it features multiple input ports and interfaces that allow easy integration of external hardware (such as flight data recorders). Thus, AMELIA can easily be installed and integrated into the state-of-the-art, with low overhead. In addition, it can be used to complement and augment other aircraft monitoring systems like the flight data recorder.

When AMELIA receives data from the FDAU, AMELIA performs data processing in three layers: *parametric analysis, ranking,* and *heuristic analysis*. Figure 2 depicts the algorithms in the parametric bracket warning, ranking, and heuristic systems that perform the required analysis for the different layers. The inset table illustrates sample parameters (using the Boeing 777 aircraft [18] as a reference) and outputs from the different





Sample parameters, group, priority, and transmission priority

Sensor	P_l	P_d	P_u	Grp	Priority	Transmit
Pitch	-50º	65º	50º	1	2	2
Roll	-270º	15º	270º	1	3	3
Climb rate	-35,00ft/min	3,800ft/min	3,500ft/min	1	1	1
Altitude	3,000ft	39,000ft	43,100ft	1	4	4
Cabin pressure	n/a	6,500ft	8,000ft	2	4	5

Fig. 2: AMELIA framework comprising of the parametric bracket, ranking, and heuristic systems. (Inset table: sample flight parameters, using a Boeing 777 aircraft as reference, and outputs from the AMELIA framework.)

layers of the framework. Instead of transmitting a continuous stream of data, as is the case in the state-of-the-art [10], the *parametric bracket warning system* performs continuous parametric analysis on the data to detect when any of the data oversteps the preset parameter brackets. The system consists of predefined lower bound and upper bound safe parameter values, P_l and P_u, respectively. If a detected value, P_d lies outside of the range of safe values ($P_d < P_l$ or $P_d > P_u$), an emergency is detected, and an alert sequence is generated. For example, the load factor (or g-factor)—the ratio of an aircraft's lift to its weight—of the average passenger aircraft should typically not exceed 2gs. The parametric bracket warning system detects if the airframe has exceeded the load factor during parametric analysis.

After an outlying parameter is detected, the parametric bracket warning system generates an alert sequence. One key characteristic of our parametric bracket system added as a security feature (Section III-B) is that the alert sequence can only be generated from within the airframe, since the system is not connected to any wireless/external inputs. After the alert sequence is generated, the ranking system groups the data points by sensor type, which could indicate the urgency of an emergency. For example, sensors that indicate malfunctioning equipment, such as wing flaps, landing gear, or steering may be in one group; sensors that indicate environmental conditions, such as temperature, altitude change, or obstacles may be in another group; and sensors that indicate travel and orientation, such as pitch, tilt, speed, or load factor, may be in a third group. The ranking system then ranks the data points within each group in order of priority—the priority is a function of the amount of deviation from the safe operation parameter bracket—and the response latency requirements for the detected emergencies. For example, data regarding a high load factor will be ranked as higher priority than data regarding a malfunctioning landing gear due to the urgency of the load factor event.

Finally, the ranking system simultaneously transmits the data to the on-board heuristic system, and through the satellite link to the appropriate ground control centers. The heuristic system is preprogrammed with algorithms of potential solutions to known emergencies, in order to enable real-time decisions and actions for mitigating the effects of the emergencies. The system performs heuristic analysis, which searches the solution space (i.e., all the potential solutions that relate to the detected emergencies) to determine the best solutions to the ensuing emergencies. Some of these solutions may be performed by the aircraft's automated system, while others may require the pilot's intervention. The heuristic system transmits the potential solutions to the appropriate aircraft automatic control, to the pilot, and to ground control, for continuous evaluation of any automated actions.

B. One-way Node and Security

Security and privacy of active flight data recorders are some of the most critical factors that impede the adoption of systems like AMELIA [13]. These concerns are motivated by the possibility that proprietary aircraft technical information can be leaked. In addition, pilots are concerned that every instance of a flight will be reviewed with unjustified scrutiny. AMELIA addresses these security and privacy concerns as follows:

1) Similar to current flight data recorder technology, data is stored directly on-board within the AMELIA system.
2) AMELIA only transmits data when the aircraft's parameters indicate an emergency. AMELIA can only be triggered by an error within the airframe; thus, the unit acts as a one-way node with no external radio communication inputs. While AMELIA does not address the susceptibility of the transmission medium to attacks, it is a step in the right direction towards more secure and private aircraft monitoring systems.

C. AMELIA Prototype Implementation Details

To build the AMELIA prototype, we used commercial-off-the-shelf hardware. To represent the FDAU during testing, we used the Adafruit 10-DOF inertia measurement unit (IMU) breakout, which combines three sensors to provide 11 dimensions of data: 3 dimensions of accelerometer data, 3 dimensions of gyroscopic data, 3 dimensions of magnetic

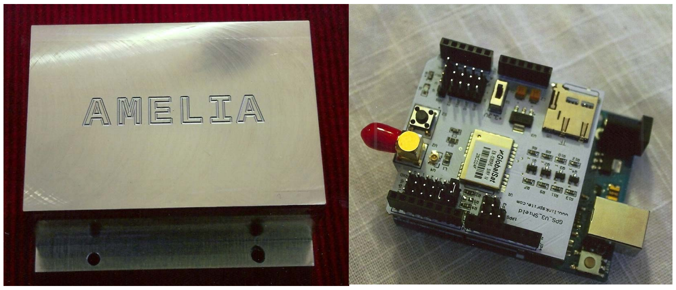


Fig. 3: AMELIA hardware: shell casing (left) and internal view (right).

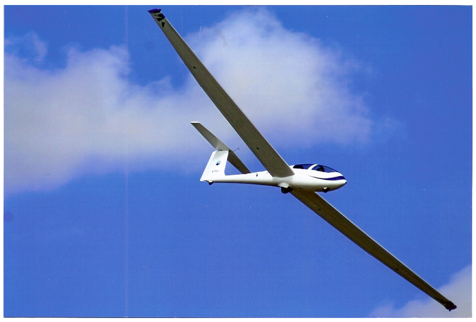


Fig. 4: Grob G103 glider in flight during our testing of AMELIA.

(compass)—direction of the strongest magnetic signal, barometric pressure/altitude, and temperature [16].

When AMELIA receives data from the IMU, through an RS-232 serial connector, the data is processed using an Arduino Uno microcontroller unit [7], which implements the parametric bracket warning and ranking systems; we intend to implement the heuristic system in future work. Data received from the IMU is stored in a non-volatile memory to maintain the data in the event of a power loss. We used a 4GB SD card, connected through a SeeedStudio SD card shield. To add GPS data and transmission capabilities for our test system, we used the Link Sprite GPS V3 and the TinyTrak4 GPS Position Encoder. The encoder supports Automatic Packet Reporting System (APRS) messaging, and allowed us to transmit APRS messages from the AMELIA prototype on the aircraft during flight tests. Finally, we used the VX-6R YAESU dual-band receiver for communications between the glider pilot and the ground station during testing.

Figure 3 depicts AMELIA's shell casing (left picture), which was created using a Computerized Numerical Control (CNC) machine and aircraft-grade aluminum; the picture on the right depicts the internal view of AMELIA.

IV. Evaluation

A. Flight Tests

We tested the AMELIA prototype on a Grob G103 glider aircraft as depicted in Figure 4, which shows the aircraft during one of our test flights. We performed two flight tests (Flights A and B), and used the aircraft pitch as the emergency parameter. We programmed AMELIA to collect data at 1.5 second intervals, and the parametric bracket system was programmed with pitch ranges to represent the *safe zone*, *caution zone*, and *danger zone* as depicted in Figure 5. We implemented the first two layers of AMELIA's functionality: the parameter analysis and ranking layers, and leave the heuristic layer for future work. The heuristic layer adds significant complexity to the system—it requires massive amounts of emergency parameters, potential solutions, and a design space exploration technique (e.g., using neural networks) to quickly determine the best solution in real time. In addition, the heuristic layer also requires more complex test scenarios. However, the parameter analysis and ranking layers provide a solid foundation for implementing the heuristic layer.

Our test metric was the automatic transmission of prioritized data, based on detected aircraft emergencies. During the two test flights, our glider pilot mimicked possible emergency scenarios using aerial acrobatic maneuvers on the aircraft. Figure 5 depicts the data obtained during both flight tests—Flights A and B. The peaks in the graph depict points at which AMELIA detected emergencies, based on the aircraft pitch, and transmitted data to a ground station with the outlying parameters.

During Flight A, AMELIA dynamically transmitted 13 GPS data points and 2,500 packets containing altitude, heading and roll sensing (AHRS) via the Automatic Packet Reporting System (APRS). We used the APRS as a substitute for a satellite relay; the APRS acted as a rudimentary cloud for storing the data online. The system of interlocking satellite coverage allowed the data to be successfully transferred via a 144 to 430 MHz FM transceiver to a location 85 miles away, with a latency of 1.5 seconds. Information was also transmitted to the Internet.

Data limitations inherent within the APRS limited the number of GPS NMEA that could be transmitted. Even though we set the TinyTrak 4 modem to a much higher frequency of 15s between transmissions, we observed a rate of 60s between transmissions.

For Flight B, we replaced the inertia measurement unit (IMU) with the Link Sprite GPS to test AMELIA's capabilities with different data collection units. During this flight, AMELIA transmitted 11 GPS NMEA data points and 2,500 packets containing altitude.

B. Cost Overhead Analysis

Cost is one of the most important factors that impede the adoption of devices like AMELIA. Figure 6 estimates AMELIA's cost compared to the state-of-the-art, with respect to certification cost (cost of ensuring that the device is safe and effective), operating cost (in-flight hourly cost), and capital cost (cost of building the device). The costs were estimated for an average size commercial aircraft, based on publicly available information. Note that AMELIA's costs were determined based on our prototype; these costs will likely increase in a commercial use-case. However, we expect that the cost in a commercial scenario will only be a small fraction of the cost of state-of-the-art systems (e.g., black box and ADS-B). Also,

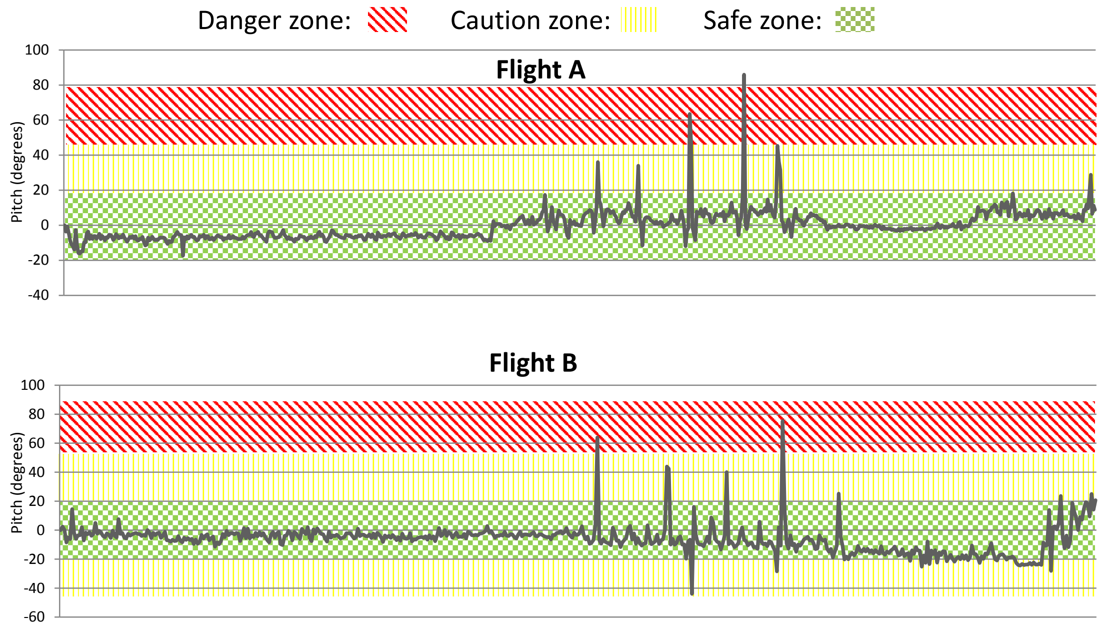
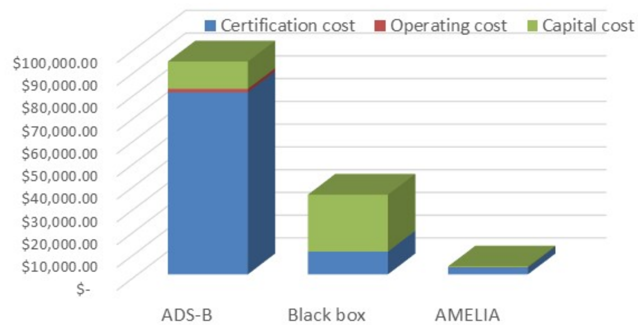


Fig. 5: Data points for our flight tests (Flight A and B) showing the data peaks, when emergencies are automatically detected, and reduced data and/or actionable information is transmitted.



	ADS-B	Black box	AMELIA
Certification cost	$80,000	$10,000	$3,000
Operating cost	$1,500	$0	$100
Capital cost	$12,000	$25,000	$350

Fig. 6: Cost analysis of AMELIA compared to the state of the art. The estimated costs are for an average size commercial aircraft.

AMELIA is not intended to replace the state-of-the-art, but to complement and update the existing systems. Thus, the design goal, with respect to cost, is to minimize the overhead.

Compared to the ADS-B's and the black box's certification costs of about $80,0000 and $10,000, respectively, AMELIA's certification would cost about $3,000. Compared to the ADS-B's operating cost of about $1500, AMELIA cost only $150. The black box, since it is a passive recording device, does not accrue any operating cost. Finally, compared to the ADS-B's and black box's capital costs of about $12,000 and $25,000, respectively, AMELIA costs only about $350. These costs show that AMELIA will constitute a low-cost addition to current systems.

V. Related Work

Aviation safety will be one of the most important applications of the Internet of Things (IoT) [6], [20]. Some prior work has been done with respect to using concepts related to the Internet of Things to provide solutions for challenges in aviation safety. Most previous proposals, however, involve continuous transmission of data using the Automatic Dependent Surveillance-Broadcast (ADS-B) [13] system. This solution imposes significant overheads, including bandwidth bottlenecks, operating cost, latency overheads. Other related research on aircraft monitoring have focused on designing more efficient flight data recorders [10], [15], [17] and techniques for efficiently extracting useful information from the massive amounts of data gathered by FDRs [12], [19], [21]. Some of these techniques (e.g., the cluster analysis technique proposed in [12] for anomaly detection in flight data) can be used in synergy with AMELIA.

The most related work to ours is the *glass-box* proposed by Kavi et al. [9], [10]. The glass-box provides real-time monitoring of airplanes using recent information, artificial intelligence, learning and network technologies. The system involves continuous communication between ground-based and on-board intelligent software agents to collect and analyze flight data, in order to detect potentially unsafe conditions in real-time and provide early warning to the pilot. The proposed work, while a vital step in the right direction, suffered from some of the aforementioned challenges of the state of the art (Section II).

To the best of our knowledge, ours is the first proposal that uses IoT edge computing to address some of the challenges of aircraft monitoring. In addition, we have developed a prototype, tested in an actual flight scenario, to illustrate the benefits of such a system, in order to motivate future applications.

VI. Future Research Directions

The work presented herein motivates several opportunities for future research. Some of the overheads associated with the Internet of Things can be significantly reduced in several high-impact applications by incorporating an AMELIA-like framework in those applications. While the design and prototyping of AMELIA was directly motivated by challenges in aviation safety/aircraft monitoring, we envisage that the proposed framework can apply to several high-impact applications.

For example, one key application of interest is medical diagnosis. We envision that portable medical devices (e.g., emerging wifi pacemakers, portable ultrasounds) can be augmented with an AMELIA-like system to increase accessibility to real-time diagnostic expertise, especially in remote locations. Rather than having diagnostic personnel travel to remote locations, the medical devices can be equipped with the computational resources and intelligence to diagnose emergencies remotely, and in real time, such that only actionable information is transmitted to medical personnel. Real-time automotive monitoring is another such application that can benefit from the framework proposed herein.

Finally, much future work exists for extending and further evaluating the different components of the AMELIA system. We intend to augment AMELIA with more complex parameter analysis techniques. For example, we could use a combination of pre-defined parameter thresholds and real-time analysis of historical flight data to detect flight anomalies. In addition, we also intend to implement the heuristic layer to allow for real-time exploration of potential solutions to detected emergencies.

VII. Conclusion

The Internet of Things (IoT) promises to spawn new and more efficient services to solve real-world problems. However, the IoT also introduces new challenges with respect to bandwidth bottlenecks, cost, latency, especially in safety critical real-time systems. Edge computing addresses some of these challenges by performing computations at the edge nodes in order to reduce the overheads associated with data transmission.

In this paper, we proposed *Aircraft Monitoring and Electronically Linked Instantaneous Analytics (AMELIA)* as an IoT edge computing framework in a high-impact safety critical use-case, aviation safety. Unlike the state-of-the-art aircraft monitoring systems that passively collect and/or transmit data, resulting in significant overheads, AMELIA is a multilayered system that analyzes collected data in order to reduce transmitted data and only transmit actionable information for faster response in emergencies. We described our prototype of AMELIA to demonstrate the potentials of the Internet of Things, from an edge computing perspective, for addressing some of the challenges associated with aircraft monitoring in aviation safety. AMELIA provides a foundation that can be extended to other high-impact edge computing use-cases, such as real-time medical diagnostics.

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