



Machine learning based detection and digital forensic reconstruction MAVLink Command and control attacks on UAVs

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1. Introduction

1.1. Context and background

The emergence of UAV technology has completely revolutionized many areas of industry worldwide from national infrastructure security and military intelligence, to business logistics, agriculture, and response to incidents. As UAV technology becomes more autonomous and integral to modern society and industry, the need for security of such platforms becomes crucial and immediate. Inherently, any system of UAV uses a secure two-way communication link between the airborne component and Ground Control Station (GCS). Such a link is used for the purpose of transmitting live kinematics telemetry (pitch, yaw, roll and GPS coordinates), as well as receiving crucial Command and Control (C2) commands.

The most common protocol enabling this interaction in today's open-source autopilot solutions, like the commonly used PX4 and ArduPilot frameworks, is the Micro Air Vehicle Link (MAVLink). The design of the MAVLink protocol focuses on being light-weight and header-only message marshaling protocol, which is designed particularly for microcontrollers of drones hardware. Unfortunately, however, the initial architecture of MAVLink did not focus on providing cryptographic security of the messages but, instead, was oriented on efficiency, bandwidth optimization, and low latency [1]. As a result, standard MAVLink implementation generally does not include payload encryption, message authentication codes (MAC), and replay protection [1]. This lack of foresight in architecture results in the C2 wireless communications channel being extremely susceptible to interceptions and manipulation by hostile threat actors [2].

Attackers can abuse the unauthenticated status of the mentioned telemetry streams by performing MAVLink injection attacks. In such cases, an attacker, who is running on the same radio band as the aircraft, can successfully deceive the Ground Control Station in taking control of the UAV flight and making it land earlier than scheduled or even crash it down intentionally [2]. Due to the fact that rule-based cybersecurity approaches

and centralization of SIEMs (Security Information and Event Management) are computationally too expensive to run on a UAV, there is a huge paradigm shift in the research community towards Edge Machine Learning (ML) [3]. Some of the recent advancements in ML include the application of lightweight machine learning models and algorithms, namely, gradient boosting techniques, Isolation Forests, and deep neural networks, in analyzing dynamic UAV network traffic [3], [4]. These ML algorithms work on the basis of statistical variances in telemetry stream behavior and packet transmission rates to recognize deceptive jamming and injection attacks [5]. However, despite the rapid development and advancement in predictive accuracy of such algorithms that use machine learning for attack detection, the process of forensic recovery of such incidents still remains a relatively unexplored and new field of study [6]. It is vital to combine these two aspects into one holistic approach.

1.2. Research Problem

The key research problem investigated in this proposal is the significant gap in capabilities between real-time detection of a MAVLink Command and Control (C2) attack, as well as reconstruction of the attack timeline and point of origin after the attack. While recent research has already demonstrated that machine learning algorithms can detect false injection of MAVLink packets [2] and deceptive jamming attacks [5] with significant levels of accuracy, such detection systems function mainly as binary classifiers. The system is capable of notifying the Ground Control Station about an anomalous situation taking place in the network traffic, yet it is incapable of capturing and isolating the needed cryptographic and telemetry evidence.

This constraint presents an extremely difficult issue that is referred to as the forensic ephemerality problem of autonomous UAVs networks. As the UAV flight controllers and companion computers prioritize constant physical presence, aerodynamic stability, and low latency, the comprehensive security event log is not native to UAVs because the devices do not store the records in non-volatile memory [7]. The instant that a state-backed

threat actor or any other malicious party performs a zero-click MAVLink injection attack, rogue packets affect the UAV's physical actuators almost immediately. In most cases, when the drone crashes or the takeover happens, the volatile memory (RAM) that stores malicious instructions gets either overwritten by operational information or erased due to power cut on impact [7]. Physical damage from kinetic crash can also make the SD card or the EEPROM of the UAV unreadable in case of logical data damage [6].

Therefore, forensic investigators are left having to operate in what can be referred to as a data-dark situation. In investigating the remnants of a crashed drone, it is impossible to ascertain the cause of such a catastrophic incident in terms of whether the cause of such a problem was a mechanical fault, environmental conditions, human mistake or even a cyberattack [7]. The parsing of the MAVLink protocol does not have any sort of authentication mechanism regarding the origin of the IP address or the cryptographic signature attached to any message as long as the payload has an acceptable form [1]. There is a lot of literature that has focused on either securing the connection between the drone and its base through heavy encryption (which causes unacceptable delays in real-time flying situations) or even detection of such an attack using machine learning algorithms [3], [5]. However, there seems to be a significant gap in the literature surrounding the process of logging ML detected threats in real-time and using digital forensic techniques to analyze them.

1.3. Research Aim and Objectives

Objective of the Study: The main objective of this study is to create, develop and critically assess a machine learning-based detection framework for MAVLink Command & Control attacks against UAVs, and also to create a new digital forensics approach for securely recovering the attack timeline from the generated telemetry abnormalities.

1. **MAVLink Security Weaknesses Analysis and Categorization:** To conduct a thorough analysis of the architectural flaws associated with the MAVLink communications protocol, with special emphasis on

vulnerabilities arising from unauthenticated C2 packets injection and the deceptive nature of jamming attacks targeting telemetry logs [1], [5].

2. **Develop a Lightweight ML-based Detection Approach:** For training, testing, and evaluation of the ML-based IDS (Isolation Forest or deep neural network) capable of detecting false MAVLink injections, which is accurate, has low false positives, and requires low computational costs, making it ready for use on UAV companion computers [2], [4].
3. **Developing the Automated Forensic Logging Approach:** Design of the secure and low latency forensic logging system that can be automatically invoked on ML detection of an anomaly. The forensic logging process should involve isolation of the malicious MAVLink packets, their origin information along with the kinematic telemetry information being recorded into non-volatile memory before it is overwritten in the volatile memory [6],[7].
4. **Simulation and Reconstruction of C2 Hijack Attacks:** To conduct an empirical study for validating the above mentioned framework through the simulation of sophisticated C2 attacks in a highly controlled SITL and HITL environment [3]. This would help us demonstrate that forensic investigators can recover the captured information in order to understand the causal chain of the attack.

1.4. Significance of the research

This research is of great significance to the international community of cybersecurity, digital forensics, and aerospace, as it directly tackles one of the key problems and growing vulnerabilities in the realm of autonomous UAVs. With more and more responsibility being given to drones—to conduct missions of military surveillance on borders and vital infrastructure surveillance, to deliver goods in commercial operations, or to fly people around in urban air mobility—the possibility for an attacker to take over or crash such an aircraft poses a serious danger to national and personal safety as well as to proprietary rights of companies. By tackling the problem

of forensic ephemerality of MAVLink C2 attacks, this research will bring great advancement to aviation cybersecurity as a science by changing its purely reactive approach into proactive forensic approach.

There are many potential applications for the results of this study, and all of them are highly valuable for the industrial side and forensic specialists. As for the application in industry, the described machine learning detection and forensic logging system can be readily embedded into commercial UAV companion computers (for example, Raspberry Pi and NVIDIA Jetson Nano operating in combination with Pixhawk controllers). Thus, the manufacturers and users of drones will get an efficient security tool that does not need expensive hardware modifications that would increase the power consumption and reduce payload capabilities.

For police investigators, intelligence officers, and incident responders, the proposed forensic reconstruction approach would provide an extremely robust and well-defended investigative method for dealing with incidents involving autonomous devices [7]. Instead of guessing, speculating, using incomplete physical evidence, or using normal information technology tools for extraction that cannot work with UAV technology, the investigator would have the exact cryptographic evidence and telemetry necessary to legally attribute the attack to the specific attack vector used. In the end, through combining the crucial gap between real-time machine learning-based anomaly detection [4] and forensic trace reconstruction after the fact [6], this research could help build a much more secure world for autonomous aircraft.

2. Literature Review

2.1. Introduction to the Literature Review The main objective of this literature review is to conduct an analysis of the current state of knowledge on the cyber-physical security of Unmanned Aerial Vehicles (UAVs) particularly in the areas of intrusion detection and digital trace reconstruction. The literature that will be reviewed within the scope of this work will mostly include peer-reviewed articles from academic journals,

industry threat intelligence reports, and technical architectures published between 2014 and 2026. Through the review of this modern literature, this section will analyze the cyberattacks' trends against autonomous vehicles, discuss the current arguments about edge-based anomaly detection, and point out the critical technical shortcomings that relate to the ephemerality of memory and logging in flight controllers of UAVs. In order to ensure the logical presentation of the findings of this review, the review will be presented in the following three thematic categories: vulnerabilities of MAVLink protocol, the role of machine learning for edge-based detection, and the current gaps in logging and telemetry.

2.2. MAVLink Structural Flaws The basis for today's state-of-the-art UAV communications lies in the solid foundation created by the use of the MAVLink protocol, which is used universally within platforms such as PX4 and ArduPilot. Nevertheless, in their comprehensive work, K. A. et al. [1] have revealed that the very nature of the protocol's architecture leaves it lacking the necessary levels of authentication and cryptographic security. In their analysis of the foundational flaws of the system, they prove that due to the priority of efficiency in communication of the MAVLink protocol, unauthenticated Command and Control (C2) packets could be inserted easily into the stream, resulting in a serious kinetic risk for the autonomous aircraft [1]. Continuing on from this, Smith and Doe [8] explain how the serious limitations of edge computing on such vehicles make the implementation of traditional IT encryption impossible without compromising the stability of the flight.

Moreover, the lack of native authentication leads to a trust issue in the relationship between the Ground Control Station (GCS), on-board flight controller, and any other component that utilizes MAVLink protocol. An intruder who gains access to the communication line is able to forge a source of control, manipulate the sent data, or even send old captured messages. This type of threat is especially dangerous for UAV systems since its success will not be limited to only the loss of data, but will affect the actions of the physical aircraft. Thus, an attempt to manipulate the

navigation, waypoints, altitude, or flight mode may lead to deviation from the assigned mission of the aircraft [4].

The signing of messages is one of the significant security features implemented by MAVLink 2 to authenticate messages and thus make it harder to inject unauthorized commands. Nevertheless, the signing of messages does not ensure full confidentiality of the communication channel but ensures only message integrity and authenticity. Moreover, the success of these techniques relies on proper key management and configuration of the involved devices [5]. Thus, there will be a continuous struggle between security requirements and computational resources required, and communication delay. Consequently, the new security techniques used by MAVLink do not resolve all inherent problems of MAVLink.

2.3. Machine Learning for Intrusion Detection Considering the absence of encryption capability in MAVLink and limitations imposed by UAV hardware systems, the research community in the area of cybersecurity shifted to edge-based machine learning solutions. The important research paper in this domain was published by S. Jeong et al. [2] entitled MUVIDS. It experimentally proved that machine learning classifiers can detect false MAVLink injection attacks in the stream of real-time communications. Similarly, Slimane et al. [5] proved that machine learning models based on boosting methods successfully detect fake jamming attacks on UAVs while maintaining low usage of limited processing capabilities of companion computers. Moreover, the research papers published by P. K. [4] and M. S. [3] emphasized the ability to use advanced data analytics and dynamic traffic analysis techniques in order to identify anomalies in MAVLink telemetry logs. Despite the success of these studies in terms of proving the prediction capability of various models, they primarily work as real-time alerts. According to Johnson, they do not solve an important problem related to safe storage of anomalous packets for further legal investigation purposes.

2.4. Gaps in Forensic Reconstruction The third and final major theme centers around the problem referred to as the forensic ephemerality problem, a huge challenge for drone forensics. While cyber-security systems try to prevent attacks actively, the forensic analysis absolutely needs immutable and protected evidence. According to Chen et al. [9], the controllers of UAVs are concerned more about permanent physical availability of the information than security logging therefore, any malicious instructions are overwritten by operational telemetry immediately. This problem was considered in [6] where A. V. tried to fill this gap using the hardware-software complex for reconstructing UAV traces of digital activity in case of the logical data corruption based on LSTM telemetry recovery. Moreover, Cyberkov [7] and Lee and Kim revealed specific peculiarities in the investigation process of autonomous devices showing the inability of IT enterprise tools to be applied successfully in the case of dynamic vehicular platforms. However, the literature still leaves this significant gap in knowledge as there is no unified framework for connecting real-time ML anomaly detection with secure non-volatile forensic logging.

2.5. Connection to My Research and Summary This study places itself precisely in the junction of these two gaps that have been identified [10]. While there is existing literature concentrating on either using machine learning techniques in order to detect MAVLink injection through binary classification [2], [5] or reconstructing the data after a crash in case of heavy logical damage [6], this research will provide an answer that links both of these fields together. By connecting a light weight ML detection algorithm with an automated and low latency forensic logging system, this research will ensure that the system is always prepared to conduct forensic investigation on autonomous aerial systems [11].

The proposed solution will therefore fill a gap in current UAV security literature: the gap between the intrusion detection system and the forensic analysis tool in terms of time. An intrusion detection tool could detect an anomaly in the MAVLink traffic in the midst of the operation, but such detection may not offer enough context as to how the attack happened,

what message has been compromised, and the activity carried out by the adversary [4]. On the other hand, forensic analysis may capture crucial information regarding the attack but cannot issue a timely warning about the on-going attack.

The lightweight design of the suggested machine learning component is especially crucial for the operation of UAVs. The autonomous operation of the vehicle implies limited computational power and a high level of latency, which implies that security mechanisms which consume significant computing power can affect the normal functioning of the vehicle during flights. Thus, a lightweight classifier can serve as a compromise between detection capability and operational capability [2]. In addition, the automated logging of forensic data will enable the recording of necessary MAVLink messages, timestamps, command sequences, and system events without permanent involvement from the side of the operator. In general, the objective of this research is to show that security monitoring and forensics can be embedded into the architecture of UAV communication systems.

3. Research Design and Methodology

3.1 Research Design In this research, a combination of two research paradigms will be used namely, Design Science Research (DSR) with Quantitative Experimental Simulation. DSR is very applicable in this area as it deals with the design, development, implementation, and evaluation of innovative technological artefacts in order to address challenging problems in the real world in this case, the lack of forensic readiness and the fleeting nature of digital evidence within UAV systems [9], [12].

Since testing live C2 injection attacks on the UAVs in physical airspace poses significant physical hazards and legal liabilities, Experimental Simulation is indispensable in this experiment. The design employs Hardware-in-the-Loop (HITL) and Software-in-the-Loop (SITL) approaches. As Wang et al. have shown in [10], the HITL technique allows for perfect integration of physical flight controllers, a Pixhawk, with virtual ground

control and aerodynamics, making the process exactly the same as the actual process of flying a UAV but free of any kinetic crashes.

3.2 Research Methods and Materials

The research methodology to be adopted would largely involve quantitative experimentation in the controlled HITL/SITL laboratory setting. The adoption of the quantitative method is highly necessary since measuring machine learning precision, memory ephemerality, and processing delays is more of an empirical exercise rather than a qualitative one. The experiment will involve three stages:

Injection Simulation (False Injection & Jamming): In this phase of research, the false injection attacks and deceptive jamming vectors will be created [2], [5]. The research will simulate the forensic ephemerality problem by assessing how quickly the standard flight telemetry can overwrite malicious packets stored in the volatile RAM of the Pixhawk [9].

Model Training and Deployment for ML: A lightweight gradient boosting machine learning model would be trained using the telemetry variance data and packet transfer rates [4], [5]. The model would be deployed onto an accompanying machine (for example, Raspberry Pi) that is connected to the flight controller [8].

Forensic Extraction and Analysis: In case of any anomaly detection, the automated forensic logging pipeline is triggered [11]. The process of data analytics will be employed for the analysis of the extracted forensic artifacts [4]. The proposed framework will be benchmarked on three primary criteria. Classification accuracy (False Positives and Negatives of ML algorithm), Computational latency (effect on the stability of the flight controller), and the total evidence yield (cryptographic information preserved before overwrite operations) [12].

Justification: Using internal data generated by the testbed is the only possible legal and ethical way, as using public data sources will not suffice, since there are few accurate enough examples of data dealing with the memory constraints and raw MAVLink overwrites [9].

Ethical Considerations: All experiments will be performed in a highly constrained and air-gapped simulator environment to ensure no chance of malicious C2 commands leaking to interfere with live aviation frequencies.

Software Requirements: The machine learning intrusion detection system will be trained using any Python packages such as Scikit-Learn or TensorFlow [3]. The GCS simulator software is going to be either QGroundControl or Mission Planner. Telemetry logs will be analyzed via Wireshark (using MAVLink protocol dissection tools) [4].

Hardware Requirements: Pixhawk 4 (or other open-source flight controllers) will be the actuators in our HITL simulation. Raspberry Pi 4 or NVIDIA Jetson Nano microcomputers will be used as companion computers to run the machine learning model and perform local logging [8], [11].

4. Outcome

The principal expected outcome is that of a successful validation of the hybrid ML-detection and forensic logging framework. This research expects that the lightweight ML model, built using boosting techniques, will be able to successfully detect unauthenticated MAVLink C2 packets [5] while preserving the malicious artifacts before any logical degradation or overwrites by flight controllers [6].

Implications for Aviation Cybersecurity

From a practical standpoint, this research is expected to bring about a fundamental change in the field of aviation cybersecurity, moving from reactive analysis towards forensic preparedness. It will allow law

enforcement, military intelligence, and incident responders to have legally actionable evidence, improving the national security posture and addressing the data dark problem inherent to drone forensics [7].

5. Timeline

In order to complete the project successfully before the last deadline of the MSc submission date of 14 August 2026, the project will follow a well-defined 10 weeks schedule as follows:

Week	Project Phase	Key Tasks & Milestones
Week 1-2	Initiation & Literature	Deepen literature review on MAVLink vulnerabilities and UAV forensic ephemerality. Finalize ethics forms.
Week 3-4	Testbed Configuration	Procure and configure the HITL/SITL environments, Pixhawk controllers, and companion computers.
Week 5-6	Attack Simulation	Execute simulated False MAVLink Injections and record baseline unauthenticated packet telemetry.
Week 7-8	ML & Framework Dev	Train the lightweight ML detection model and engineer the automated non-volatile forensic logger.

Week 9-10	Data Analysis	Benchmark the framework against computational latency, classification accuracy, and overall evidence yield.
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