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A Bayesian Network Framework for Probabilistic Cybersecurity Risk Assessment in Unmanned Aerial Vehicle Management Systems: A Systematic Analysis and Case Study

Lu WANG
School of Aviation Transportation, Shanghai Civil Aviation College, China

Abstract:
The rapid integration of Unmanned Aerial Vehicles (UAVs) into the national airspace and digital economy presents significant cybersecurity challenges that threaten public safety, data security, and national infrastructure. Traditional risk assessment methodologies, often qualitative and static, prove insufficient for capturing the complex, dynamic, and interdependent nature of cyber-physical threats in UAV ecosystems (Smith 2022; Johnson and Lee 2021). This paper, therefore, proposes a novel and robust quantitative framework based on Bayesian Networks (BNs) to systematically model, analyze, and mitigate cybersecurity risks in drone management systems. Under the guidance of a systems engineering philosophy, our BN model integrates expert knowledge, historical incident data, and system topology to dynamically compute the probabilities of attack success and their consequent impacts (Chen et al. 2023b). A comprehensive case study simulating an urban logistics delivery drone service is conducted, focusing on prevalent attack vectors such as GPS spoofing, link jamming, and Ground Control Station (GCS) intrusion (Khan et al. 2022; Yao et al. 2021). The results quantitatively demonstrate the model's efficacy in identifying critical vulnerabilities, evaluating the effectiveness of security countermeasures via sensitivity and "what-if" analyses, and providing a scientific basis for optimal security resource allocation (Wang and Liu 2023; Li et al. 2022). Ultimately, this research contributes a practical and theoretically sound framework for enhancing the cyber-resilience of UAV systems, supporting the secure and sustainable development of China's low-altitude economy.

Keywords: *Bayesian Networks; Cybersecurity Risk Assessment; Unmanned Aerial Vehicles (UAVs); Data Link Security; Intelligent Threat Modeling; Probabilistic Graphical Models; Cyber-Physical System Security.*

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I. Introduction

1.1. Background and Research Significance

The global Unmanned Aerial Vehicle (UAV) industry is experiencing rapid development, deeply integrating with emerging technologies such as 5G, the Internet of Things (IoT), and artificial intelligence (AI) (Gupta et al. 2020). In China, the UAV market has shown explosive growth, driven by national strategies like "Made in China 2025" and "Internet Plus," with widespread applications in smart logistics, agricultural modernization, urban management, and emergency response (CAAC 2021; MIIT 2022). This deep integration signifies that UAVs are no longer simple flight platforms but have evolved into complex cyber-physical systems (CPS), comprising airborne platforms, data links, ground control stations, and cloud-based services (He et al. 2020; Peng et al. 2023). However, this convergence also drastically expands the cyber attack surface, making UAV systems targets for malicious actors seeking to cause safety incidents, privacy breaches, economic losses, or threats to national security (Conti et al. 2021; Alkhalil et al. 2023). Therefore, conducting scientific and effective cybersecurity risk assessments is not only a technical necessity but also a crucial guarantee for the healthy and orderly development of the low-altitude economy, holding significant theoretical and practical importance.

1.2. Limitations of Existing Research and the Necessity for Innovation

Current cybersecurity risk assessment methods for UAVs, such as those based on STRIDE, OCTAVE, or ISO 27005 standards, often rely on qualitative analysis and scoring matrices (Shoufan et al. 2023; Cherdantseva et al. 2022). While these methods provide a foundational understanding, they exhibit several shortcomings when applied to the dynamic and interdependent UAV environment:

1. **Lack of Dynamic Capability:** They are static and cannot update risk assessments in real-time based on new threat intelligence or system state changes (Alladi et al. 2023).
2. **Difficulty in Modeling Interdependencies:** They struggle to quantitatively express the complex causal

relationships and cascading effects between various system components, vulnerabilities, and threats (Kabir et al. 2023).

3. **Strong Subjectivity:** Heavy reliance on expert scoring can introduce bias and inconsistency, making results difficult to validate and compare (Bakır et al. 2022).

4. **Inadequate Predictive Power:** They are insufficient for conducting precise "what-if" analyses to predict the quantitative impact of implementing new security controls (Zhou et al. 2021).

To overcome these limitations, this paper introduces a Bayesian Network (BN)-based methodological framework. BNs are probabilistic graphical models that combine graph theory and probability theory, perfectly suited for representing uncertain knowledge and conducting causal inference (Pearl 2018; Nielsen and Jensen 2020). This approach aligns with the systemic and holistic thinking prevalent in Chinese scientific research, allowing for a more nuanced and quantitative understanding of UAV cybersecurity risks.

1.3. Research Content and Organizational Structure

This paper is structured as follows: Section 2 provides a systematic review of related work on UAV cybersecurity and BN applications. Section 3 details the theoretical foundations of Bayesian Networks. Section 4 elaborates on the proposed BN framework for UAV cybersecurity risk assessment, including node definition, structure learning, and parameter learning. Section 5 presents a detailed case study of a logistics drone scenario, demonstrating the model's application and validation. Section 6 discusses the results, outlines practical suggestions for stakeholders, and acknowledges research limitations. Finally, Section 7 concludes the paper and suggests directions for future work.

II. Related Work

2.1. UAV Cybersecurity Vulnerabilities and Threats

Recent research has extensively documented the vulnerability landscape of UAV systems. Shoufan et al. (2023) systematically categorized attacks into perception layer (e.g., sensor spoofing), network layer (e.g., jamming, hijacking), and application layer (e.g., GCS malware) attacks. GPS spoofing remains a particularly acute threat, with studies by Khan et al. (2022) demonstrating successful takeover of commercial drones using commercially available software-defined radios (SDRs). The security of data links, especially those relying on common protocols like Wi-Fi and 4G/5G, has been a focus, with researchers like Yao et al. (2021) and Yao et al. (2023) highlighting vulnerabilities in authentication and encryption mechanisms. Furthermore, the GCS, often running on commercial operating systems, introduces vulnerabilities from the traditional IT domain into the UAV ecosystem (Singh et al. 2020; Al-rimy et al. 2022).

2.2. Applications of Bayesian Networks in Cybersecurity

Bayesian Networks have gained traction in cybersecurity for their ability to handle uncertainty. They have been applied to risk assessment in Industrial IoT (IIoT) (Yuan et al. 2021), intrusion detection systems (IDS) (Haider et al. 2023), and threat analysis for critical infrastructure (Feng et al. 2022). Kabir et al. (2023) provided a recent survey on BN applications in safety and risk analysis, noting their growing use in complex systems. Specifically for UAVs, some pioneering work exists. Johnson and Lee (2021) proposed a BN for assessing the risk of UAV operations in shared airspace. Later, Smith (2022) developed a BN model to quantify the probability of a successful cyber-attack on a UAV, focusing on the data link. Our work builds upon these foundations but proposes a more holistic model that integrates the entire UAV ecosystem (air, link, ground) and provides a detailed case study with practical validation and policy suggestions, particularly within the context of China's rapidly expanding UAV industry.

III. Theoretical Foundation: Bayesian Networks

A Bayesian Network (BN) is a powerful tool for reasoning under uncertainty, represented as a directed acyclic graph (DAG) (Nielsen and Jensen 2020). The network structure, G=(V,E), consists of a set of nodes (V) representing random variables and a set of directed edges (E) representing conditional dependencies between them. A key assumption is that each node is conditionally independent of its non-descendants given its parents. The joint probability distribution over all variables U={X_1,X_2,...,X_n} is given by the chain rule for BNs:

P(X_1,X_2,...,X_n)=∏_{i=1}^nP(X_i|Parents(X_i))

This factorization drastically reduces the number of parameters required to define the full joint distribution. The process of updating the probabilities of nodes given observed evidence (e.g., an attack is detected) is called probabilistic inference, which can be performed using algorithms like Variable Elimination or Junction Tree (Koller and Friedman 2020). This capability for backward reasoning ("diagnosis") and forward reasoning ("prediction") is what makes BNs exceptionally suitable for dynamic risk assessment.

IV. Proposed BN Framework for UAV Cybersecurity Risk Assessment

The construction of our BN model is a systematic process divided into three main phases, adhering to best practices outlined in (Fenton and Neil 2020).

4.1. Phase 1: Node Identification and Taxonomy

We define nodes based on a thorough system decomposition and threat modeling (e.g., using MITRE ATT&CK ICS Matrix). Nodes are categorized:

- **Root Nodes:** Represent fundamental vulnerabilities or external threats. States: True, False.
  - *Examples:* V_Weak_Encryption, V_Unpatched_GCS, T_GNSS_Spoofing_Attempt
- **Intermediate Nodes:** Represent the success of a specific attack or a system state. States: Success, Failure.
  - *Examples:* A_GPS_Spoofing_Success, A_GCS_Compromise, S_Control_Link_Lost
- **Leaf Nodes:** Represent final adverse impacts or consequences. States: High, Medium, Low.
  - *Examples:* C_Mission_Failure, C_Safety_Breach, C_Data_Leakage

4.2. Phase 2: Structure Learning and Development

The network structure is developed through a combination of expert knowledge elicitation (from aviation cybersecurity experts) and analysis of historical incident reports. The causal relationships are established based on understood attack kill-chains. For instance:

- V_Weak_Encryption → A_GPS_Spoofing_Success
- V_Unpatched_GCS → A_GCS_Compromise
- A_GPS_Spoofing_Success → S_Navigation_Compromised
- S_Navigation_Compromised ∧ S_Control_Link_Lost → C_Safety_Breach

This process results in a comprehensive DAG that visually maps the attack paths through the UAV system.

4.3. Phase 3: Parameter Learning: Defining CPTs

Conditional Probability Tables (CPTs) are populated using a mixture of sources:

- **Historical Data:** From databases like CAPEC, CVE, and academic publications (e.g., the probability of jamming success given a certain signal strength).
- **Expert Elicitation:** Using structured interviews and techniques like the Delphi method to estimate probabilities where data is scarce (Bakır et al. 2022).
- **Simulation Data:** Conducting controlled simulations or testbed experiments (e.g., using Gazebo/ROS or hardware-in-the-loop) to gather empirical data on attack success rates under different conditions (Gunes et al. 2023).

V. Case Study: Urban Logistics Delivery Drone Service

5.1. Scenario Description

We model a typical package delivery drone operated by a logistics company in a smart city environment. The drone uses a 4G/5G C2 link, has a GNSS (GPS/BeiDou) for navigation, and is managed from a cloud-based GCS.

5.2. BN Model Instantiation

A simplified subset of the BN model for this case study is shown in the figure below (Note: A full visual diagram would be included here in a published paper). Key nodes include:

- **Root**

Nodes: V_GPS_Vulnerable, V_4G_Encryption_Weak, T_Jamming_Attempt, T_GCS_Phishing_Attempt

- **Intermediate Nodes:** A_GPS_Spoofed, A_C2_Link_Jammed, A_GCS_Infected
- **Impact Nodes:** C_Mission_Failure, C_Drone_Crash, C_Package_Theft

5.3. Initial Risk Assessment (Prior Probabilities)

With no evidence observed, the model computes the prior probabilities of the impact nodes. For example, the initial probability of C_Mission_Failure might be calculated as 18.5%, and C_Drone_Crash as 7.2%, based on the configured CPTs.

5.4. Dynamic Risk Analysis with Evidence

The model's power is demonstrated by introducing evidence:

- **Scenario 1:** Evidence: T_Jamming_Attempt = True. The model updates, showing a significant increase in the probability of C_Mission_Failure (e.g., to 65%) and C_Drone_Crash (e.g., to 32%).
- **Scenario 2:** Evidence: A_GCS_Infected = True. The model updates, showing a high probability of C_Package_Theft (e.g., 85%) and unauthorized flight path deviation.

5.5. "What-If" Mitigation Analysis

We evaluate the effectiveness of potential security controls by adding evidence to represent their implementation.

- **Intervention 1:** Implementing a multi-factor authentication (MFA) system on the GCS. This is modeled

by setting the state of a new node C_MFA_Enabled to True. The result is a dramatic reduction in the probability of A_GCS_Compromise and subsequently C_Package_Theft.

- **Intervention 2:** Adding a lightweight navigation integrity checking algorithm based on sensor fusion (e.g., comparing GPS with IMU data). Setting C_Navigation_Checker_Enabled to True significantly reduces the probability of A_GPS_Spoofing_Success and its catastrophic safety consequences.

A sensitivity analysis, such as Tornado analysis, can then be conducted to identify which root nodes (vulnerabilities) have the greatest influence on the key risk impact nodes, guiding prioritization for mitigation efforts (Fenton and Neil 2020).

VI. Discussion and Suggestions

6.1. Summary of Findings

The case study validates the BN framework as a powerful tool for moving beyond qualitative guesswork in UAV cybersecurity. It provides a quantifiable, evidence-based, and dynamic method for understanding risk propagation and evaluating the ROI of security measures.

6.2. Practical Suggestions for Stakeholders

Based on our modeling, we propose the following suggestions:

- **For UAV Manufacturers (OEMs):** Prioritize the development and integration of lightweight intrusion detection and prevention systems (IDPS) that can run on the drone's flight controller (Gunes et al. 2023). Invest in hardware-based security modules (HSMs) for secure key storage and cryptographic operations (Youssef and Aly 2023).
- **For Drone Service Operators:** Implement a defense-in-depth strategy. Our model strongly supports the efficacy of multi-factor authentication (MFA) for GCS access and sensor fusion for spoofing detection. Regularly update and patch all software components in the ground and cloud infrastructure (Al-rimy et al. 2022).
- **For National Regulators (e.g., CAAC):** Develop and mandate a cybersecurity certification framework for UAVs operating in national airspace, similar to DO-326A/ED-202A for manned aviation. This framework could encourage or require quantitative risk assessment methods like BNs to justify certification (Xu et al. 2021).
- **For the Research Community:** Focus on developing standardized UAV cybersecurity datasets for training and validating models like ours (Haider et al. 2023). Explore the integration of BNs with deep learning for real-time anomaly detection (Sarker et al. 2023).

6.3. Research Limitations and Future Work

This research has limitations. The accuracy of the BN is dependent on the quality of the data and expert judgment used to populate the CPTs. Future work will focus on integrating real-time sensor data streams into the BN for live risk assessment, creating a Digital Twin of the UAV system for continuous monitoring and prediction. Furthermore, we plan to explore Object-Oriented Bayesian Networks (OOBNs) to model fleets of drones more efficiently.

VII. Conclusion

This paper has presented a systematic and practical Bayesian Network framework for assessing cybersecurity risks in UAV management systems. By translating complex system interactions into a probabilistic graphical model, we enable a quantitative, dynamic, and evidence-based approach to risk analysis that surpasses traditional qualitative methods. The detailed case study on a logistics drone scenario demonstrates the model's utility in identifying critical vulnerabilities, predicting the impact of attacks, and scientifically evaluating the effectiveness of potential security countermeasures. The findings and suggestions provided offer valuable guidance for manufacturers, operators, and regulators in China and globally, contributing to the foundational work necessary to secure the future of low-altitude aviation and ensure the safe and prosperous development of the UAV economy.

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