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Drone Surveillance System Availability and Reliability: A Comprehensive Analytical and Numerical Modeling Approach

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Abstract This paper proposes an approach to evaluate the availability and reliability of drone surveillance systems using complementary modeling techniques. Resilient system architecture with drone and battery redundancy is analyzed using two modeling strategies: (i) an analytical model based on Continuous-Time Markov Chains (CTMC), which yields closed-form availability equations, and (ii) a numerical model employing Stochastic Petri Nets (SPN) to handle more complex redundancy scenarios. Both models consider key factors such as battery charging/discharging times, drone failure and repair rates, and replacement operations. Sensitivity analyses highlight battery-related parameters as critical to system performance. Case studies show that optimizing component parameters can yield up to 97% availability, while redundancy alone can provide 91%. Combined strategies can achieve up to 99.89% availability. For long missions (30 hours), reliability analysis indicates that 15–20 redundant batteries and charging times below 36 minutes are needed to maintain over 80% reliability. For shorter missions, discharge times over 144 minutes are beneficial. This integrated modeling approach provides a robust framework for dependability assessment, guiding the design of resilient and cost-effective drone surveillance systems for mission-critical applications.

Keywords: Unmanned Aerial Vehicles, Drone Surveillance Systems, Continuous-Time Markov Chains, Stochastic Petri Nets, System Reliability, Availability Analysis

1 Introduction

Aerial computing is a paradigm that integrates computing and networking capabilities into the aerial environment, utilizing platforms such as Unmanned Aerial Vehicles (UAVs) and High Altitude Platforms (HAPs). This approach leverages aerial systems' mobility, flexibility, and broad coverage to provide computation, communication, and storage services, particularly in areas where traditional ground-based infrastructure may be inadequate or impractical. Advancements in wireless communication, miniaturized sensors, and edge computing technologies have facilitated the development of various applications, including environmental monitoring, disaster response, and real-time data processing in smart cities.

The growing adoption of UAV technologies across various sectors has revealed important challenges, particularly the energy limitations in small drones, which affect operational duration. This limitation directly impacts mission effectiveness and raises concerns regarding reliability in continuous surveillance applications. These challenges have prompted advancements in systems engineering and energy management strategies. For drone surveillance systems, assessing metrics such as reliability and availability is essential for system development, as failures may lead to security vulnerabilities, data loss, and compromised monitoring capabilities. As a result, research efforts have increasingly focused on optimizing power management strategies, enhancing battery technologies, and refining operational methodologies to improve overall system performance in critical monitoring applications.

In surveillance contexts, system uptime is critical for maintaining continuous monitoring capabilities and ensuring public safety in smart cities. Evaluating key performance indicators such as Mean Time Between Failures (MTBF) and Mean Time to Repair (MTTR) provides insights into system robustness. Additionally, considering external factors, including weather variables and network reliability, enhances the understanding of operational constraints. Implementing redundancy mechanisms and systematic maintenance protocols can improve system resilience, addressing the challenge of maintaining consistent surveillance coverage in dynamic environments.

The scientific community has increased efforts to enhance UAV systems' robustness and operational efficiency in response to existing challenges. Recent research has examined various innovative approaches. For instance, Kotikalpudi *et al.* [2020] investigated algorithmic redundancy to address reliability issues in small drones, providing an alternative to traditional hardware redundancy. Brito *et al.* [2021] employed advanced modeling techniques, including Stochastic Petri Nets and Reliability Block Diagrams, to assess availability in UAV networks, yielding insights into system performance across different scenarios. Additionally, Kharchenko *et al.* [2022] developed a framework to classify UAVs as Reliable Service Systems, focusing on their performance and availability, thereby contributing to a comprehensive understanding of these systems.

While these studies provide valuable insights, they often do not address the detailed interactions between UAV components and their operational dependencies. Machida and Andrade Machida and Andrade [2021]; Watanabe and Machida [2022] analyzed availability, performance, and power consumption in drone systems using fog and edge computing paradigms. They employed three different computing modes and a stochastic Petri net model to calculate system availability. However, this study focused primarily on network link and computational process failures and did not consider factors such as average time to failure and repair of the drone, loading and unloading times, or general availability assessment models that include systems with redundancy mechanisms.

This work addresses the need to enhance availability and reliability in UAV surveillance systems as their deployment expands in smart city applications. Existing research has broadly focused on system-level challenges; this approach specifically examines operational dynamics and analyzes how key parameters—such as battery management, component redundancy, and system configuration—impact performance metrics. The study employs complementary modeling techniques, combining Continuous-Time Markov Chains (CTMC) for analytical insights with Stochastic Petri Nets (SPN) for numerical evaluation of redundancy scenarios. A sensitivity analysis is conducted to identify components that significantly influence system behavior, providing direction for targeted improvements. The resulting modeling framework offers guidance for developing resilient UAV systems optimized for sustained operation in challenging environments and extended missions. The methodology aims to maximize system uptime in mission-critical surveillance applications by integrating strategic redundancy mechanisms with optimized maintenance policies.

This work provides three key contributions to UAV surveillance system dependability analysis:

- **Analytical CTMC Framework:** We propose a Continuous-Time Markov Chain model that provides closed-form availability expressions (Equation 7) for UAV surveillance systems, incorporating battery charge/discharge rates, hardware failure/repair rates, and drone swap operations. This enables direct mathematical analysis and supports rapid sensitivity assessments.
- **Numerical SPN Extension:** We develop complementary Stochastic Petri Net models to evaluate complex redundancy mechanisms, addressing state space explosion limitations of analytical methods while representing systems with multiple interdependent components and redundancy strategies.
- **Performance Assessment:** We conduct sensitivity analysis identifying critical system components, plus three case studies evaluating: (i) component optimization strategies, (ii) redundancy implementation, and (iii) integrated approaches achieving up to 99.89% availability for long-duration missions.

Note: This paper extends our previous work presented at the Latin American Dependable Computing Conference (LADC) [Lins *et al*., 2024]. The current version includes significant enhancements: (i) incorporation of a CTMC model for analytical availability analysis, (ii) expanded methodology section with detailed coverage of both analytical and numerical approaches, (iii) comprehensive background section covering UAV surveillance systems, and (iv) more extensive case studies with sensitivity analysis and reliability evaluation over extended mission durations.

This paper is organized as follows. Section 2 reviews recent related work; Section 3 provides an overview of the concepts of evaluation, reliability, availability, Petri nets, and sensitivity analysis relevant to this study; Section 4 outlines the methodology employed in this research. Detailed analytical and numerical models for availability and reliability are presented in Section 5. Section 6 examines three case studies that assess the impact of component time improvements, redundancy in drones and batteries, and their combination on system availability and reliability. The paper concludes in Section 7, summarizing the results and discussing potential directions for future research.

2 Related work

Recently, modeling systems and services that use drones has gained prominence. These studies range from drone swarm coordination to the development of optimized flight routes. A growing body of research focuses on evaluating the reliability and availability of these systems, including the use of redundancies to improve such metrics.

Aerial computing has emerged as an innovative paradigm that combines aerial radio access networks and edge computing to overcome limitations in traditional systems. A comprehensive computing architecture was proposed by Pham et al. Pham *et al*. [2022], encompassing low-altitude, high-altitude, and satellite platforms, and integrating enabling technologies such as AI, big data, and energy refilling. Their work highlighted potential applications in smart cities, factories, and grids, while addressing challenges like energy efficiency, resource management, and security. Building on this concept, a hierarchical aerial computing framework using UAVs and HAPs was introduced in Jia *et al*. [2023], providing Mobile Edge Computing (MEC) services for IoT devices and optimizing data offloading using matching game theory and heuristic algorithms.

In the context of surveillance, a systematic review by the authors in Gohari *et al*. [2022] examined drone applications in smart cities, including transportation, environmental monitoring, infrastructure inspection, object detection, disaster response, and data collection. The study emphasized the potential of rotary-wing drones equipped with cameras to deliver efficient, sustainable solutions through integration with technologies such as IoT, AI, and machine learning, while also noting that the field is still in early stages.

To address reliability concerns in small UAVs, Kotikalpudi et al. Kotikalpudi *et al*. [2020] explored limitations arising from the impracticality of hardware redundancy due to size, weight, and power constraints. Drawing parallels with systems like the Boeing 777's triple-redundant control, they proposed a "redundant algorithmic approach" that uses multiple fault detection and isolation (FDI) algorithms running in parallel. While this provides valuable insights for algorithmic redundancy, it does not address the modeling of physical redundancies such as additional batteries or drones.

An alternative focus on UAV reliability was presented by Petritoli et al. Petritoli *et al*. [2017, 2018], who emphasized optimizing maintenance activities by tracking reliability metrics assigned to each subsystem. Their method supports the optimization of maintenance intervals and associated costs. Nonetheless, their approach does not incorporate redundancy mechanisms or availability modeling that could further enhance system dependability.

Several researchers have also explored mathematical modeling techniques to analyze UAV reliability. Zaitseva et al. Zaitseva *et al*. [2020] and the work in Rusnak *et al*. [2019] represented UAV fleets using logical structure-functions interpreted via reliability block diagrams. While their models addressed availability, reliability, and critical states, they lacked the capability to model essential operational features such as battery discharge, spare UAV and battery availability, and switchover time from a failed drone to a replacement.

For evaluating trade-offs between availability, performance, and energy, Machida and colleagues Machida and Andrade [2021]; Watanabe and Machida [2022] examined three computing strategies in image-processing drones: onboard processing, fog offloading, and collaborative load balancing. Their work employed stochastic Petri nets to model system availability but did not consider drone hardware failure/recovery rates, loading and unloading durations, or redundancy-aware availability modeling.

Maccarthy MacCarthy [2019] developed an analytical stochastic model for K-out-of-N UAV systems based on Markov chains. The model incorporates parameters such as total fleet size, number of active drones, average repair time (charging duration), and average failure time (flight duration). While insightful, this work employs simplified assumptions and does not capture complex component interdependencies.

Brito et al. Brito *et al*. [2021] addressed availability and reliability in distributed UAV systems using Stochastic Petri Nets and Reliability Block Diagrams. Their sensitivity analysis identified critical availability-affecting components, especially cloud servers. Although they provided a robust global system analysis emphasizing redundancy to ensure continuity, detailed modeling of drone-specific operations was limited.

Energy-related constraints in UAV systems have also received attention. A cross-layer optimization approach was explored in Lin *et al*. [2019] to balance system throughput and energy efficiency in UAV-IoT networks. The study optimized parameters like speed, altitude, and MAC frame size. Similarly, Li et al. Li *et al*. [2020] proposed an energy-conscious strategy involving drone replacement based on battery level monitoring. Though promising, these studies do not assess how such strategies affect service availability or reliability in detail.

In disaster response scenarios, Mishra et al. Mishra *et al*. [2020] developed a deep learning-enhanced drone surveillance system for search and rescue missions. Their dataset supported human action detection (e.g., waving). A stochastic surveillance model for energy-aware UAV operation was proposed in Hosseinalipour *et al*. [2021], using random walks and inspection policies to minimize long-term energy use while ensuring drones return for recharging.

A broader reliability perspective was offered in Xing and Johnson [2023], which reviewed modeling and analysis techniques for UAV reliability in mission-critical contexts. The review discussed k-out-of-n models, failure mode and effects analysis, and phased-mission models, and also considered communication reliability and mission-abort scenarios.

More recent efforts focus on formal modeling of UAV operations. Moghadasi et al. Moghadasi *et al*. [2023] modeled wildfire-monitoring drone swarms using PRISM for formal verification. Their model incorporated leader-follower roles and continuous rotation of drones toward incident zones. López et al. Lopez and Akundi [2023] used Model-Based Systems Engineering and SysML tools to construct detailed UAV surveillance scenarios, particularly for monitoring armored vehicles.

In communication-focused applications, Falcão et al. Falcão *et al*. [2023] proposed a continuous-time Markov chain model with a virtual resource scaling scheme for ultra-reliable low-latency communications using UAVs. Their model balances onboard computational resource use against UAV physical limitations.

In summary, the reviewed literature reveals diverse approaches to modeling the reliability, availability, and performance of UAV systems. This work advances the field by modeling component-level interactions using complementary analytical and numerical techniques—namely, Continuous-Time Markov Chains and Stochastic Petri Nets. These models support the evaluation of UAV system behavior under varying operational and redundancy configurations.

The approach specifically assesses the impact of physical redundancies—such as spare drones and batteries—on service recovery. It incorporates detailed factors like battery charge/discharge durations, mean time between failures, mean time to repair, and drone handover timing. The geographic distance between the command base and surveillance zones is also modeled. Sensitivity analysis identifies the most influential components, offering guidance for targeted improvements in system design to enhance availability and reliability.

3 Background

This section outlines fundamental concepts essential for evaluating drone surveillance systems. It introduces key dependability metrics, stochastic modeling techniques, and analytical frameworks that establish the foundation of the methodology used in the evaluation process.

3.1 Modeling for Dependability Evaluation

Dependability refers to a system's ability to deliver its intended service consistently, even when some components are subject to failures. It is closely related to reliability, which measures the probability that a system will function without failure over a specified time interval t Avizienis *et al*. [2004]. Specifically, for a system that starts operation at time 0, reliability at time t quantifies the probability of uninterrupted operation during the interval $(0, t)$ Trivedi [2008]; Maciel [2023]. Equation 1 defines reliability in mathematical terms:

$$R(t) = e^{-\int_0^t \lambda(t')dt'}, \tag{1}$$

where $\lambda(t')$ is the instantaneous failure rate. When $\lambda(t') = \lambda$ is constant, the Time to Failure (TTF) follows an exponential distribution, and the reliability simplifies to $R(t) = e^{-\lambda t}$.

Another key metric is steady-state availability, which characterizes a system's ability to continue functioning despite failures and subsequent repairs Trivedi [2008]. It can be computed using the expected uptime and downtime as in Equation 2, or using the Mean Time to Failure (MTTF) and Mean Time To Repair (MTTR), as in Equation 3:

$$A = \frac{E[Uptime]}{E[Uptime] + E[Downtime]}, \tag{2}$$

$$A = \frac{MTTF}{MTTF + MTTR}. \tag{3}$$

The MTTF can be derived as the integral of reliability over time:

$$MTTF = \int_0^\infty R(t)dt. \tag{4}$$

When TTF and TTR follow exponential distributions with rates λ and μ respectively, availability becomes:

$$A = \frac{\mu}{\mu + \lambda}. \tag{5}$$

These fundamental relationships (Equations 1-3) provide the theoretical foundation for the specific UAV system models developed in Section 5, where reliability and availability expressions are derived for drone surveillance applications.

Modeling techniques are essential for analyzing systems that are either complex or not yet implemented. State-based formalisms such as Continuous-Time Markov Chains (CTMCs) and Stochastic Petri Nets (SPNs) have been widely adopted for dependability evaluation Pereira *et al*. [2021]; Maciel *et al*. [2022].

CTMCs offer a rigorous mathematical structure to model systems where future states depend only on the current state (the Markov property). They are especially useful for systems with exponentially distributed transition times due to the memoryless property of the exponential distribution. In UAV surveillance applications, CTMCs can model drone operational states, failure states, battery depletion, and repair or recharge events. These models allow closed-form analytical expressions for performance metrics such as availability Maciel *et al*. [2018].

The state space of a CTMC encompasses all possible configurations of the system, with transitions governed by rates that represent failure, repair, charging, or replacement events. Analytical solutions derived from CTMCs provide insights into system behavior, enabling design optimization and trade-off evaluations Maciel *et al*. [2022].

SPNs extend basic Petri Nets by associating firing times with transitions, typically modeled using exponential distributions. This study focuses on exponential firing times to enable CTMC-based solutions from the underlying model structure. Nevertheless, SPNs also support non-exponential distributions, enhancing modeling flexibility for systems exhibiting complex or state-dependent timing behavior Araujo *et al*. [2013].

For large systems with high-dimensional state spaces that would render CTMC modeling impractical, SPNs offer a compact, intuitive, and modular representation. They support numerical solution techniques that preserve model fidelity while allowing performance evaluation even in complex redundancy configurations.

3.2 Sensitivity Analysis Methods

Sensitivity analysis is used to determine how variations in input parameters influence system performance, particularly availability. Several techniques exist, including differential sensitivity analysis, the One-at-a-Time (OAT) method, relative deviation methods, partial rank correlation coefficients, and sensitivity indices Hamby [1995]. This work adopts the Sensitivity Index (SI), which measures the percentage change in an output metric due to variations in an input parameter.

Equation 6 defines the sensitivity index for a given parameter y, based on its maximum and minimum output values obtained by varying it within a range Clemente *et al*. [2022]:

$$S_y = \frac{max_y - min_y}{max_y}. \tag{6}$$

During the computation of S_y, other input parameters remain fixed, enabling a clearer assessment of y's influence. This approach is useful for identifying which parameters most strongly impact system performance, guiding targeted optimization efforts.

For the CTMC-based analytical model, sensitivity analysis can be performed through direct differentiation of the closed-form availability expression concerning specific input parameters. This enables precise characterization of how parameter changes affect availability and supports mathematical optimization.

For the SPN-based numerical model, sensitivity analysis involves varying one parameter at a time, solving the model under each scenario, and observing the resulting changes in availability or reliability. This is particularly useful when closed-form solutions are infeasible due to state space explosion or complex system interactions.

Computational Considerations: While SPNs effectively handle complex redundancy scenarios, their computational requirements merit discussion. The current models, with moderate redundancy levels (up to 20 spare batteries and 7 spare drones), maintain tractable state spaces suitable for numerical solution. However, larger-scale deployments with extensive UAV fleets could face computational limitations requiring optimization strategies such as model decomposition, approximate solution techniques, or hierarchical modeling approaches. The Mercury tool employed for SPN evaluation demonstrates good scalability for the presented scenarios, but performance monitoring remains important for more complex configurations. Future extensions to large-scale multi-drone systems may benefit from hybrid modeling approaches combining analytical tractability with numerical flexibility.

3.3 UAV Surveillance Systems

Evaluating the availability of UAV-based systems requires models tailored to distinct system configurations and redundancy mechanisms. CTMCs are well-suited for systems with a single operational drone or minimal redundancy, offering tractable analytical frameworks.

In contrast, SPNs are better suited for systems with extensive redundancy and complex dependencies. They can manage large state spaces without causing state-space explosions, providing a robust basis for evaluating systems with multiple spare drones and batteries.

This paper adopts a complementary modeling approach, applying CTMCs to derive analytical availability expressions and using SPNs for detailed, numerically solvable models in complex configurations. Both models address key operational aspects such as drone failures, hardware repairs, battery discharge and recharge cycles, and drone replacement dynamics.

By capturing these processes in a formal and structured way, the modeling framework enables a comprehensive understanding of UAV system behavior and supports the design of more dependable drone surveillance systems operating in dynamic, mission-critical environments.

4 Methodology

This section outlines the methodology employed to evaluate the availability and reliability of drone surveillance systems. A systematic approach is adopted, integrating analytical and numerical modeling techniques to assess system performance across diverse operational scenarios.

Figure 1 illustrates the proposed methodology. The process begins with a comprehensive understanding of the target system, including defining a baseline architecture and identifying key dependability metrics. These inputs guide the development of analytical (CTMC) and numerical (SPN) models, each capturing distinct aspects of system behavior.

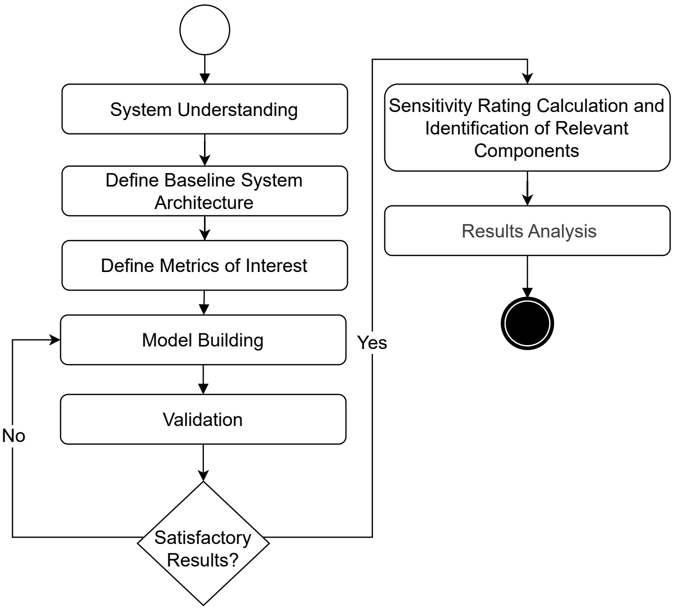


Figure 1. Comprehensive methodology for drone surveillance system analysis

Model validation ensures alignment with real-world behavior. Sensitivity analysis identifies critical components and parameters that influence performance. Findings from these analyses lead to results and recommendations, highlighting potential improvements and the effects of redundancy. The methodology concludes with presenting interpretable outcomes intended for stakeholders, including technical experts and decision-makers.

4.1 System Understanding and Baseline Architecture

The initial phase involves a thorough examination of the target drone surveillance system. This step includes collecting detailed information from manufacturers, literature, domain experts, and observational studies. Relevant aspects such as hardware specifications, operational parameters, failure modes, and maintenance procedures are analyzed to develop a grounded understanding of system behavior.

Based on this examination, a baseline system architecture is defined to represent the minimum configuration required for effective operation. For drone surveillance systems, this typically includes a command base with an operator, communication infrastructure, and at least one operational drone with its power supply. The analysis also identifies operational scenarios and failure modes to be incorporated into the models.

4.2 Define Metrics of Interest

Two principal dependability metrics are used to assess the performance of drone surveillance systems. The first is steady-state availability, which expresses the long-term probability that the system is operational at any randomly chosen point in time. This metric reflects the system's capability to maintain continuous surveillance.

The second metric is reliability over mission time, representing the probability that the system remains fully operational throughout the entire mission duration without experiencing any interruptions. This is especially relevant for time-critical surveillance operations.

From these primary metrics, additional measures can be derived, including expected downtime, mean time between failures (MTBF), and the number of availability "nines" (e.g., 99.9% corresponds to "three nines").

4.3 Model Building

The proposed methodology adopts a dual modeling strategy using Continuous-Time Markov Chains (CTMCs) and Stochastic Petri Nets (SPNs). This combination enables both analytical and numerical analysis of different system configurations.
The CTMC model describes the UAV flight system and its associated components, capturing transitions between operational, failure, and recovery or repair states. It incorporates essential parameters such as battery charging and discharging rates, drone failure and repair rates, and swapping rates between active and backup drones.

This analytical approach allows for the derivation of closed-form expressions for steady-state availability. These expressions support symbolic differentiation and provide insights into how system parameters affect performance. The CTMC model is particularly effective for systems with limited redundancy and well-defined behavior.
For systems with high levels of redundancy or complex interactions that make CTMC modeling impractical, SPNs are used. These models can be evaluated numerically using Mercury [Maciel *et al.*, 2017].

The SPN model preserves the fundamental behaviors represented in the CTMC model but allows for more flexible modeling of redundancy, operational policies, and multiple spare components. Its structure is compact and suitable for managing large state spaces without incurring state explosion.

Erlang distributions are incorporated into the SPN to enhance reliability modeling and to represent quasi-deterministic processes. For instance, they enable modeling the declaration of failure after a fixed duration of inactivity, better approximating real-world behavior than purely exponential models.

4.4 Validation

Model Validation Approach and Limitations: Before conducting detailed analyses, the models undergo validation to confirm that they accurately represent system behavior. This includes checking internal consistency between CTMC and SPN representations, analyzing model behavior under extreme parameter values, and consulting domain experts to validate assumptions. However, it is important to acknowledge that the current validation is primarily theoretical and based on expert knowledge rather than empirical data from actual UAV operations.

This limitation reflects a common challenge in dependability modeling where access to comprehensive failure data from real-world UAV deployments is often restricted due to operational security, proprietary concerns, or the relative novelty of large-scale drone surveillance systems. The inherent uncertainties in drone behavior, component reliability under varying conditions, and mission-specific factors necessitate future empirical validation studies. When discrepancies are found, models are refined through iterative improvements. While this validation approach ensures internal model consistency and expert-validated assumptions, empirical validation with real UAV operational data remains a critical future requirement to enhance confidence in the quantitative results and their practical applicability.

4.5 Sensitivity Analysis

A central component of the methodology is sensitivity analysis, which determines how variations in specific parameters affect availability and reliability. The objective is to identify the most influential parameters to guide optimization efforts.

This analysis is based on the Sensitivity Index (SI), defined in Equation 6, which quantifies the percentage impact of a parameter change on system performance. Each parameter is varied individually, while others remain fixed, and the resulting impact on availability or reliability is measured.

Scope and Limitations of Sensitivity Analysis: The current sensitivity analysis focuses primarily on battery-related parameters and drone operational characteristics, as these emerged as the most influential factors in the baseline configuration. However, a comprehensive dependability assessment would benefit from broader analysis encompassing additional critical subsystems such as communication link reliability, mechanical component degradation, software fault rates, and sensor failures. While battery management dominates system performance in the current architecture, other factors become increasingly important in more complex operational environments. Future extensions should incorporate environmental sensitivity (e.g., temperature effects on battery performance), communication reliability parameters, and mechanical wear factors to provide a more holistic view of system dependability across diverse operational conditions.

For the CTMC model, sensitivity analysis is performed analytically by differentiating the availability expression with respect to each parameter. For the SPN model, numerical methods are used to evaluate performance under varied parameter settings. The results are organized into a sensitivity ranking, highlighting the components with the greatest impact.

4.6 Analysis of Results

The final phase applies insights from sensitivity analysis to conduct case studies focused on performance enhancement strategies. Three main strategies are considered.

The first strategy involves optimizing component time parameters—such as battery discharge, recharge durations, and drone swap times—to reduce unavailability. The second strategy introduces redundancy mechanisms by adding spare drones and batteries, increasing fault tolerance. The third strategy combines both approaches to achieve high performance while balancing implementation costs.

Each case study evaluates performance across various parameter values or redundancy configurations. Results are visualized to facilitate comparison and interpretation, with emphasis on identifying cost-benefit trade-offs and practical design implications.

The final step translates technical findings into intuitive visualizations and actionable recommendations. These include the impact of parameter variations on availability and reliability, comparative performance of different strategies, identification of optimal configurations, and economic considerations. This ensures that stakeholders at all levels—from system designers to decision-makers—can interpret and apply the results effectively to real-world implementations.

5 Architecture and Proposed Models

This section introduces the base architecture of a drone surveillance system and presents models using Stochastic Petri Nets (SPNs) and Continuous-Time Markov Chains (CTMCs) to evaluate availability and reliability metrics. These complementary models incorporate redundancy mechanisms to optimize and improve system performance.

5.1 System Architecture

Figure 2 presents the base architecture of a small drone surveillance system. The system comprises an operator base and a communication tower, enabling communication between the operator and the drones during surveillance missions. Traditional surveillance systems that rely on a single drone suffer from single points of failure, potentially impacting site security and critical services like intrusion detection or fire alerting. The proposed architecture includes redundant drones and energy sources (batteries) to address this vulnerability.

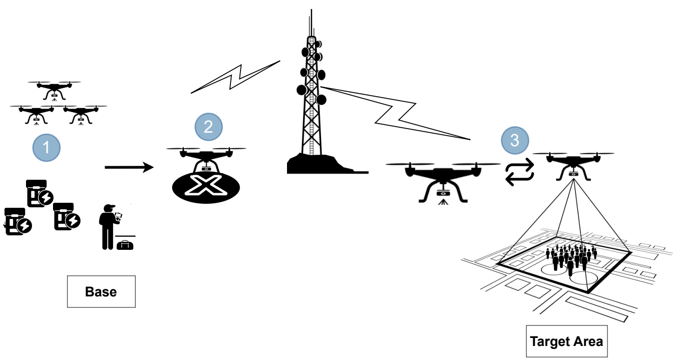


Figure 2. Baseline Surveillance Architecture

Marking M1 in the figure shows the arrangement of drones and spare batteries. At M2, a drone and battery are consumed and deployed to replace a faulty or discharged unit. M3 captures the delay until the swap operation is completed.

Model Scope and Limitations: The architecture assumes only one drone operates at a time and does not explicitly model communication failures or adverse weather conditions. While these simplifying assumptions facilitate tractable analytical modeling and provide valuable baseline insights, they represent important limitations for real-world deployments. Environmental factors such as wind, precipitation, and temperature variations can significantly impact battery performance, flight stability, and operational duration. Similarly, communication link failures between drones and base stations can affect coordination and mission execution.

Modeling Assumptions and Their Implications: The proposed models adopt several fundamental assumptions that affect their applicability: (i) **Component Independence** - failures of different components (drones, batteries, communication systems) are assumed statistically independent, which may not hold in practice where environmental stresses affect multiple components simultaneously; (ii) **Exponential Distributions** - transition times follow exponential distributions, providing the memoryless property essential for Markovian analysis but potentially simplifying real component aging and wear-out behaviors; (iii) **Constant Failure Rates** - the models assume time-invariant failure rates, not accounting for component degradation or maintenance effects that could change failure patterns over operational lifetime. These assumptions enable analytical tractability but may require validation against empirical data for specific deployment contexts.

Coverage Implications: While this single-drone architecture provides a foundation for dependability analysis, it introduces coverage limitations that merit discussion. During drone failures, battery discharge events, or swap operations, the monitored area experiences temporary coverage gaps. The proposed redundancy strategies aim to minimize these gaps by reducing replacement times and increasing system availability. However, the trade-off between battery redundancy and drone redundancy presents interesting coverage implications: while multiple spare batteries extend operational duration, multiple spare drones could achieve faster area restoration after failures. Modern UAV surveillance systems increasingly employ multi-drone configurations for enhanced coverage, load balancing, and cooperative redundancy. The current model focuses on service continuity rather than spatial coverage, but the framework's flexibility allows for future extensions to address multi-drone scenarios where coverage area and coordination become critical factors. Such extensions would require modeling inter-drone coordination, coverage overlap strategies, dynamic area allocation policies, and communication protocols, which represent natural directions for expanding this dependability framework toward more realistic operational scenarios.

5.2 Availability Model

A CTMC model is developed to provide analytical insights into the UAV flight system's availability. It represents the interactions between flying and backup drones and their power sources.

Figure 3 illustrates the CTMC model. **Table 1** describes the parameters, and **Table 2** provides detailed descriptions of each system state.

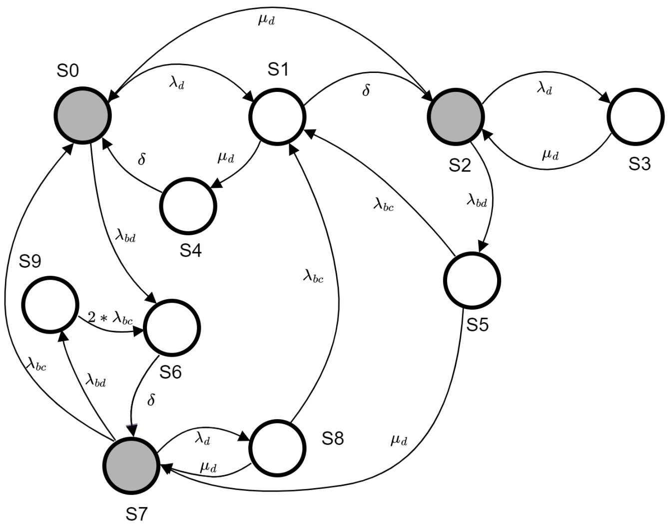


Figure 3. CTMC model of UAV flight system

Table 1. Parameter Description for the CTMC Model

Parameter	Description
λ_{bd}	Battery discharge rate (1/h)
λ_{bc}	Battery charge rate (1/h)
μ_{d}	Drone repair rate (1/h)
λ_{d}	Drone failure rate (1/h)
δ	Drone swap rate (1/h)

Table 2. CTMC State Descriptions

State	Description
S0	Drone operational with charged battery (primary operational state)
S1	Battery discharged, drone stopped, replacement drone being prepared
S2	Replacement drone deployed and operational (secondary operational state)
S3	Primary drone failed, battery operational, replacement being prepared
S4	Primary drone failed, battery depleted, system down
S5	Replacement drone operational, primary drone under repair
S6	Both primary drone failed and replacement drone's battery depleted
S7	System restored to operational state after repairs (tertiary operational state)

Dark-colored states (S0, S2, S7) indicate operational conditions. Other states represent failure scenarios. The steady-state availability, derived by solving the balance equations of the CTMC model, is given by Equation 7:

$$A_{\text{UAV}} = \frac{\delta\lambda_{\text{bc}}\mu_d(\alpha_2\delta\phi_2 + \beta_2\mu_d\phi_1)}{\alpha_2\delta^2\theta_2 + \lambda_{\text{bc}}\mu_d(\alpha_3\delta\lambda_{\text{bc}}\lambda_{\text{bd}}\lambda_{\text{d}} + \theta_1\mu_d) + \beta_2\mu_d^3\phi_3} \tag{7}$$

where auxiliary parameters are:

$$\begin{aligned}
\beta &= \lambda_{\text{bd}} + \lambda_{\text{d}} \\
\beta_2 &= \lambda_{\text{bd}} + \mu_{\text{d}} \\
\beta_3 &= \lambda_{\text{d}} + \mu_{\text{d}} \\
\beta_4 &= \lambda_{\text{bc}} + \lambda_{\text{bd}} \\
\beta_5 &= \lambda_{\text{bc}} + \mu_{\text{d}} \\
\alpha_1 &= \beta + \lambda_{\text{bc}} \\
\alpha_2 &= \beta + \beta_5 \\
\alpha_3 &= \beta_3 + \beta_4 \\
\alpha_4 &= \beta_3\lambda_{\text{bc}} + \lambda_{\text{bd}}\mu_{\text{d}} \\
\phi_1 &= \alpha_1\lambda_{\text{bc}} + \beta_4\mu_{\text{d}} \\
\phi_2 &= \beta_3\lambda_{\text{bc}} + \lambda_{\text{bd}}\mu_{\text{d}} \\
\phi_3 &= \beta\lambda_{\text{bc}}^2 + \lambda_{\text{bd}}(\lambda_{\text{bd}}(\delta + \lambda_{\text{bc}}) + 2\delta\lambda_{\text{bc}}) \\
\phi_4 &= \beta_3^2 + \beta_3(\lambda_{\text{bc}} + 3\lambda_{\text{bd}}) + \lambda_{\text{bd}}(2\lambda_{\text{bc}} + 3\lambda_{\text{bd}}) \\
\phi_5 &= \lambda_{\text{d}}^2 + \lambda_{\text{d}}\mu_{\text{d}} + \mu_{\text{d}}^2 \\
\theta_1 &= \alpha_1\beta\beta_2\lambda_{\text{bc}} + 2\beta\beta_2\delta\lambda_{\text{bd}} + \delta\lambda_{\text{bc}}\phi_4 \\
\theta_2 &= \alpha_4\lambda_{\text{bd}}\mu_{\text{d}} + \lambda_{\text{bc}}^2\phi_5
\end{aligned}$$

This analytical expression (Equation 7) supports rapid evaluation of system behavior under varied conditions, enabling parametric sensitivity analysis and direct computation of availability values for the case studies presented in Section 6. The closed-form nature of this solution facilitates mathematical optimization and provides insights into the relative importance of different system parameters.

5.3 Availability Redundant Model

To handle complexity from redundant components, a numerical SPN model is used (**Figure 4**), constructed with Mercury [Maciel *et al.*, 2017; Fernandes *et al.*, 2012; Lins *et al.*, 2024]. It computes metrics such as downtime, uptime, and steady-state availability.

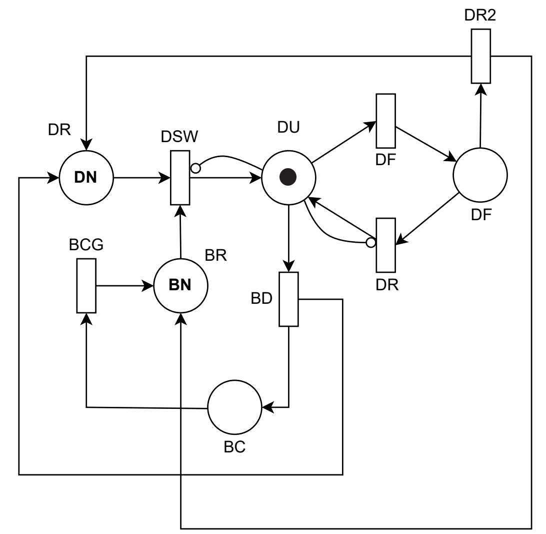


Figure 4. SPN Availability Model

The SPN availability model extends the CTMC representation to handle redundancy scenarios. Key places include: **DU**

(drone operational - system providing service); **DF** (drone failure state); **BC** (battery charge state); **DR** (drone repair facility - also stores spare drones with initial marking indicating available redundant units, denoted as DN in case studies); **BR** (battery recharge facility - also stores spare batteries with initial marking indicating redundant battery units, denoted as BN in case studies); and **SF** (system failure state). The model allows multiple tokens in **DR** and **BR** to represent redundant components. Transitions model operational events including failure (DF), repair (DR, DR2), battery discharge (BD), charging (BCG), drone swapping (DSW), and system failure detection (TE0). Guard conditions ensure proper sequencing, such as #SF = 0 preventing operations during system failure states. See **Table 3** for detailed transition definitions.
The SPN availability expression is:

$$A_{\mathrm{UAV}} = P\{\#DU > 0\} \tag{8}$$

which computes the probability of having a token in **DU**, derived via reachability graph and solved numerically.

5.4 Reliability Model

Reliability is modeled using an SPN with an Erlang-based absorbing structure (**Figure 5**). The model captures system transitions and applies a polyexponential Erlang distribution to represent service downtime that, if unresolved, leads to failure.

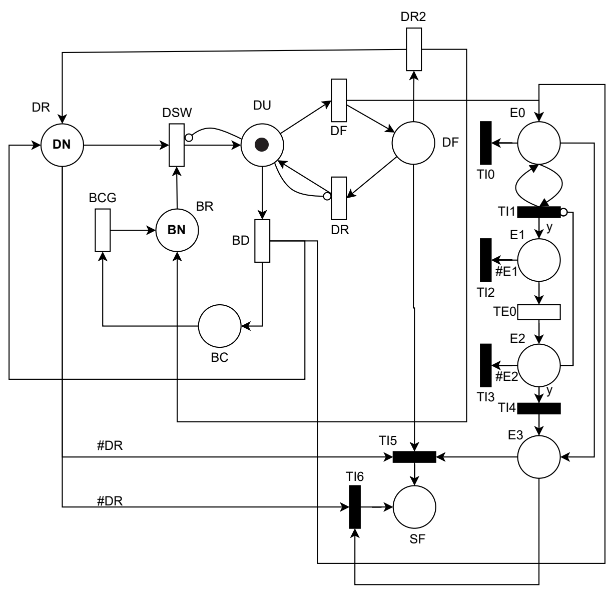


Figure 5. SPN Reliability Model

The SPN reliability model (**Figure 5**) incorporates the availability model structure with an additional Erlang-based absorbing subnet to capture time-dependent reliability. The core model preserves the same place and transition structure as the availability model, representing drone operations, failures, repairs, and redundancy. The key innovation is the Erlang subnet comprising places **E0** through **E9** that models the transition to irreversible system failure.

The subnet uses $Erl(\gamma = y, \lambda = 1/\beta)$, where $\beta = \mathrm{TTSF}/y$, with $y = 10$ phases approximating determinism. When the system experiences downtime (no token in **DU**), a token enters **E0** and propagates sequentially through the Erlang phases. If service is restored before reaching **SF**, fail-interrupt transitions **TI0–TI6** with guard conditions (#DU > 0) remove tokens from the Erlang subnet, representing successful recovery. If the token reaches **SF**, the system has experienced an irreversible reliability failure. This structure enables calculation of reliability over mission time by measuring the probability that no token reaches **SF** within the specified duration.

5.5 Integrated Modeling Approach

The CTMC and SPN models provide complementary perspectives on UAV system dependability, with formal connections that ensure consistency while addressing different analytical needs. The CTMC model serves as the foundational analytical framework, capturing essential system behaviors through states S0-S7 and providing closed-form availability expressions (Equation 7). The SPN models extend this foundation to handle complex redundancy scenarios and time-dependent reliability analysis.

Model Correspondence: The fundamental connection between models lies in their shared representation of core system behaviors. CTMC states S0, S2, and S7 (operational conditions) correspond to tokens in SPN place **DU**, while failure states map to the absence of tokens in **DU** and presence in failure-related places (**DF**, **BC**). Transition rates in the CTMC model directly correspond to SPN transition parameters: $\lambda_{bd} = 1/\mathrm{MTTBD}$, $\lambda_{bc} = 1/\mathrm{MTTBC}$, $\lambda_d = 1/\mathrm{MTTFD}$, $\mu_d = 1/\mathrm{MTTRD}$, and $\delta = 1/\mathrm{MTTSD}$.

Model Validation through Consistency: For baseline configurations (single drone, single battery), both models yield equivalent availability results, confirming structural consistency. The SPN availability expression $A_{UAV} = P\{\#DU > 0\}$ (Equation 8) reduces to the CTMC analytical result when redundancy parameters are set to zero. This formal equivalence validates the modeling approach and provides confidence in the extended SPN results for redundancy scenarios where analytical solutions become impractical.

These complementary approaches ensure accuracy and scalability across different system configurations, enhancing theoretical understanding and practical deployment of resilient drone surveillance systems.

6 Case Studies

This section presents a set of case studies designed to evaluate the availability and reliability of UAV surveillance systems under different configurations and operating conditions. The analysis includes sensitivity analysis of key parameters, redundancy evaluation, and integration of both strategies. Two modeling approaches are adopted: Continuous-Time Markov Chains (CTMC) and Stochastic Petri Nets (SPN). Results are based on numerical analysis, focusing on battery-related parameters and redundancy mechanisms.

Table 3. Parameters Associated with Transitions

Transition	Parameter	Priority	Guard	Description
DF	MTTFD	1		Time to drone failure (exp.)
DR	MTTRD	1		Time to drone repair (exp.)
DR2	MTTRD	1	#DU > 0	Redundant repair (exp.)
BD	MTTBD	1		Battery discharge (exp.)
BCG	MTTBC	1	#SF = 0	Battery charge (exp.)
DSW	MTTDS	1	#SF = 0	Drone swap (exp.)
TE0	TTSF	1		Time to system failure (Erlang)
TI0–TI6	*	1–2	Conditional	Immediate transitions

6.1 Input Parameters

Case studies are conducted to analyze the impact of variations in the redundant values of battery and drone components and improvements in their operational parameters. A percentage differencing technique is employed for this analysis. The sensitivity analysis involves systematically varying one parameter at a time while keeping others fixed [Hamby, 1994; Araujo *et al*., 2013]. Additionally, a sensitivity rating is created to illustrate the impact of each parameter on the system's efficiency. This ranking is intended to identify which parameter significantly influences the system's availability when it reaches a steady state, as shown in **Table 4**.

Table 4. Sensitivity Ranking

Parameter	Ranking	Sensitivity index
$MTTBD/\lambda_{bd}$	1^{st}	5.69×10^{-1}
$MTTBC/\lambda_{bc}$	2^{nd}	5.40×10^{-1}
$MTTSD/\delta$	3^{rd}	6.60×10^{-3}
$MTTFD/\lambda_{d}$	4^{th}	5.30×10^{-5}
$MTTRD/\mu_{d}$	5^{th}	3.51×10^{-5}

Critical Parameter Analysis: Table 4 reveals that battery discharge times (**MTTBD**/λ_{bd}) and charging times (**MTTBC**/λ_{bc}) have the greatest impact on system availability, with sensitivity indices of 0.569 and 0.540 respectively. The third most important factor is drone replacement times (**MTTSD**/δ) with a sensitivity index of 0.0066. Notably, drone failure and repair parameters show minimal sensitivity (< 0.0001), indicating that battery management dominates system performance. To improve availability, systems engineers and designers should prioritize: (1) reducing **MTTBC** through higher efficiency battery chargers, (2) extending **MTTBD** with greater capacity batteries, and (3) minimizing **MTTSD** with more agile drone deployment systems.

Table 5. Parameter Values for the CTMC Model

Parameter	Value (rate)
λ_{bd}	2.00×10^{0}
λ_{bc}	5.00×10^{-1}
μ_{d}	5.00×10^{-1}
λ_{d}	2.00×10^{-4}
δ	6.00×10^{0}

Table 6. Parameter Values for the SPN Model

Parameter	Values (Hours)
$TTSF$	5.00×10^{-2}
y	1.00×10^{1}
$MTTBC$	2.00×10^{0}
$MTTBD$	5.00×10^{-1}
$MTTFD$	5.03×10^{3}
$MTTRD$	2.00×10^{0}
$MTTSD$	1.60×10^{-2}

For the CTMC analysis, input parameter values are provided in rate format as amounts per hour. Specifically, λ_{bd} denotes the rate of 2 battery discharges per hour, λ_{bc} indicates 0.5 charges per hour, μ_d refers to 0.5 repairs per hour, λ_d represents 0.0002 failures per hour, and δ signifies 6 UAV changes per hour.

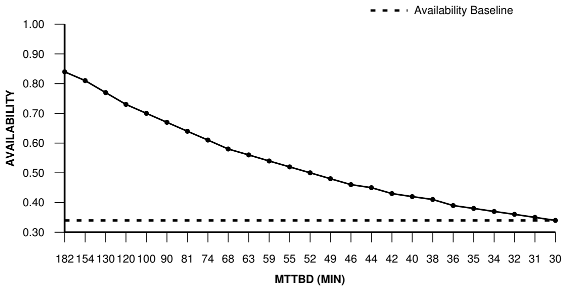
6.2 UAV Base Analysis

This case study utilizes the analytical Continuous-Time Markov Chain (CTMC) model and the Stochastic Petri Net (SPN) model to evaluate the potential impacts on system availability due to improvements in the times of certain components used as parameters in the models. The baseline parameter values for the CTMC model are presented in rate format in **Table 5**. In contrast, in time format, the SPN model parameter values are detailed in **Table 6**.

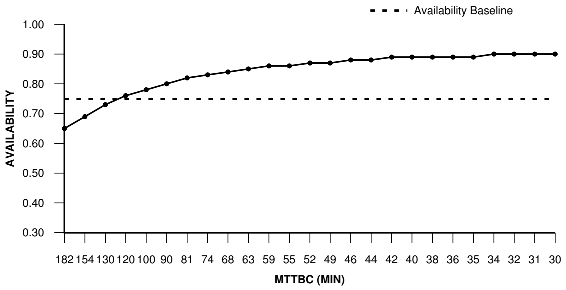
The analysis began by varying the value of λ_{bd}, followed by λ_{bc}, and finally δ, while keeping λ_{bd} and λ_{bc} fixed at enhanced values. The values of λ_d and μ_d (repair and failure rates of the UAV) were not evaluated in this study, as their impact on system availability is considered minimal relative to other factors.

Figure 6 presents the time improvement graphs derived from the CTMC analysis. **Figure 6a** displays the graph illustrating MTT time improvements of λ_{bd}, showing the effect of changes in flight or unloading time on system availability. The baseline system of the UAV flight demonstrates an availability of 34% with λ_{bd} set at 30 minutes of flight or unloading time. With an increase in this time to 180 minutes, the availability improves to 84%.

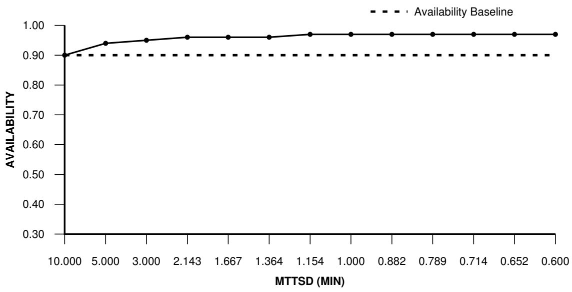
Similarly, **Figure 6b** presents the battery charging time improvement graph, demonstrating the impact of changes in charging time on the system availability. An improvement of 90% is achieved for 30 minutes of charging, considering a discharge time of 180 minutes.



(a) Battery Runtime Optimization: Effect of Battery Discharge Time (MTTBD) on System Availability



(b) Charging Efficiency Analysis: Relationship Between Battery Charging Time (MTTBC) and System Availability



(c) Operational Efficiency: Influence of Drone Swap Time (MTTSD) on Overall System Availability

Figure 6. Impact of Time Parameters on UAV System Availability

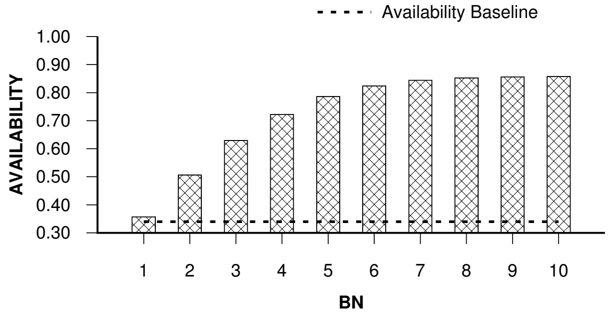
In **Figure 6c**, an availability of 97% was achieved with a UAV changeover time of less than 1.30 minutes, while the unload and load times were set at 180 and 30 minutes, respectively.

The SPN model analysis yielded results that align with those from the CTMC model, indicating a significant impact of battery discharge time, charging time, and drone swap time on system availability. The consistency between the two models supports the validity of the analysis and enhances the reliability of the recommendations for system improvement.

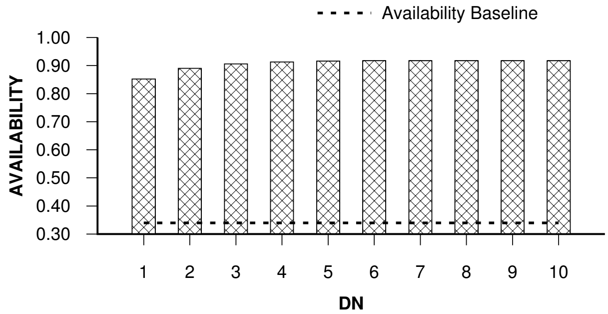
6.3 Redundant UAV Scenarios

In this analysis, the objective is to evaluate the impact of redundancy mechanisms on system availability, specifically the use of N unmanned aerial vehicles (UAVs) and battery redundancy. However, modeling systems with these redundancy mechanisms using continuous-time Markov chain (CTMC) models or analytical equations presents challenges related to state explosion. This complexity hinders comprehension of the CTMC and complicates manual calculations of the analytical equations.

To address this challenge, a stochastic Petri net (SPN) model is employed to model systems with redundancy mechanisms,



(a) Availability by the number of batteries with basic operating mode MTT parameters



(b) Availability by number of UAVs with basic operating mode MTT parameters

Figure 7. Effect of redundancy mechanisms on system availability

such as the UAV flight system availability model. SPNs are numerical models that can be evaluated through software simulation. For this study, the Mercury tool [Maciel *et al.*, 2017] is utilized to assess the model. The input parameters of the SPNs are provided in terms of mean time-to-failure (MTTF) values, as outlined in **Table 6**.

The plot in **Figure 7a** illustrates the progression of overall system availability achieved through redundancy applied specifically to the battery component (BN). Utilizing eight backup batteries results in an availability of 85%. Keeping the number of spare batteries constant at 8, the analysis then varies the number of spare drones (DN), yielding an availability of 90% with four backup drones, as shown in **Figure 7b**.

These results demonstrate that while redundancy mechanisms can significantly improve system availability, there is a limit to the improvements achievable through redundancy alone. Even with substantial spare batteries and drones, achieving availabilities higher than 90% seems challenging, suggesting additional strategies to enhance system performance further.

This third analysis combines the results of the previous two studies by evaluating redundancy variations of spare UAV components, incorporating improved load, unload, and switchover time parameters. This combination aims to achieve higher availability than the previous studies. The enhanced time values utilized as input are outlined in **Table 7**. However, integrating this data resulted in availability values approaching 100%, complicating the differentiation between larger redundancy numbers. Consequently, the availability approach using the formula in Eq. 9 was adopted to quantify the number of nines achieved.

$$\#9s = -\log_{10}(1 - A) \tag{9}$$

Table 7. Improved Parameter Values for the SPN Model

Parameter	Value (hours)
MTTFD	5.00×10^{3}
MTTRD	2.00×10^{0}
MTTBD	2.00×10^{0}
MTTBC	5.00×10^{-1}
MTTDS	1.67×10^{-2}
NB	1.00×10^{0}
ND	1.00×10^{0}

An analysis of the initial baseline configuration, incorporating separate timing and redundancy improvements, indicated a limitation in system availability, achieving a maximum availability of 97%. However, when redundancies were combined with the previously enhanced parameters at their maximum availability, the overall availability reached 99.58% with one spare UAV and 99.32% with two spare batteries, as shown in **Figure 8**. Additionally, employing seven redundant UAVs achieved an availability of 99.89%. The availability stabilized at 99.58% with four spare batteries. Reducing the number of UAVs and spare batteries compared to the previous study may lead to considerable cost savings in the overall budget of a system with these specifications.

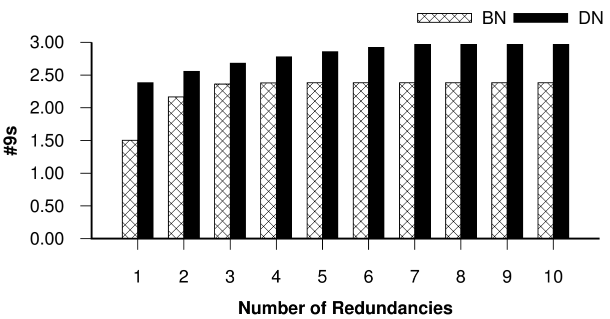


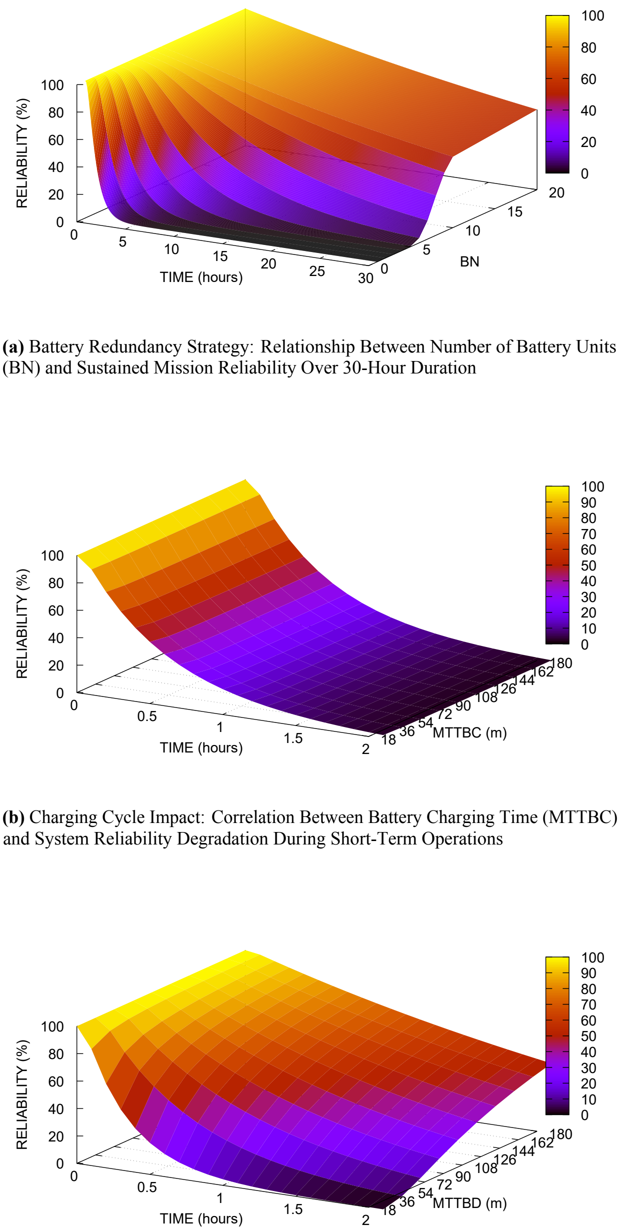
Figure 8. Number of nines of availability values per number of BN and DN redundancies with improved MTT parameters

6.4 UAV Reliability Analysis

In addition to availability analysis, an investigation into system reliability over extended mission durations was conducted. This analysis is pertinent for surveillance missions that require continuous operation for prolonged periods without failure.

An evaluation was conducted using the SPN reliability model to assess the influence of three critical factors on system reliability over time: the number of redundant batteries (BN), the Mean Time To Battery Charge (MTTBC), and the Mean Time To Battery Discharge (MTTBD). The findings of this analysis are illustrated in **Figure 9**.

Figure 9a illustrates the impact of the number of redundant batteries on system reliability over a 30-hour mission. The results indicate that with 15-20 redundant batteries, the system maintains reliability above 80% throughout most of the mission duration. In contrast, with 0-5 batteries, reliability drops rapidly to below 20% within the first few hours. These findings demonstrate battery redundancy's critical importance for long-duration surveillance missions.



(a) Battery Redundancy Strategy: Relationship Between Number of Battery Units (BN) and Sustained Mission Reliability Over 30-Hour Duration

(b) Charging Cycle Impact: Correlation Between Battery Charging Time (MTTBC) and System Reliability Degradation During Short-Term Operations

(c) Discharge Performance Mapping: Effect of Battery Discharge Time (MTTBD) on Operational Reliability Throughout Mission Timeline

Figure 9. UAV System Reliability: Time-Dependent Analysis for Mission Planning

Figure 9b illustrates the relationship between battery charging time and system reliability during a 2-hour mission. An inverse relationship between MTTBC and reliability is observed. With an MTTBC of 18 minutes, system reliability begins at 100%, declines to approximately 40% within 30 minutes, and reaches zero by the end of the 2 hours. The curves for different MTTBC values remain closely aligned, indicating that once charging time exceeds a threshold of around 18 minutes, additional increases in charging time result in diminishing returns for short-duration missions.

Figure 9c demonstrates the effect of battery discharge time on system reliability during a 2-hour mission. There is a direct relationship between MTTBD and reliability. With an MTTBD of 180 minutes, the system maintains reliability above 60% throughout the entire 2-hour period. In contrast, with a 36-minute MTTBD, reliability decreases dramatically, falling below 20% after just 1 hour of operation. These results highlight the importance of high-capacity batteries or power consumption optimization to maintain system reliability during surveillance operations.

6.5 Discussion of Results

The evaluation methodology aims to assess UAV systems' availability and reliability through the combined application of Continuous-Time Markov Chains (CTMC) and Stochastic Petri Nets (SPN). The sensitivity analysis indicated that battery-related parameters, specifically discharge and charge times, are critical factors influencing system performance, with the drone swap rate also playing a significant role. While this battery-centric focus reflects the dominant failure modes in the baseline system architecture, future comprehensive dependability assessments should consider broader subsystem interactions including communication reliability, mechanical degradation, and environmental factors.

The three case studies collectively demonstrate that different improvement strategies offer varying degrees of enhancement to system availability:

1. **Component time optimization** can achieve up to 97% availability through improvements in battery discharge time, charging time, and drone swap time.
2. **Redundancy mechanisms** can reach approximately 90% availability with eight backup batteries and four backup drones.
3. **Combined approach** can achieve availability values approaching three nines (99.9%) by integrating optimized component times with strategic redundancy.

The reliability analysis further emphasizes the importance of battery management and redundancy for maintaining system performance during extended missions. For long-duration operations (30 hours), maintaining 15-20 redundant batteries ensures reliability above 80%, while optimizing battery charging time to less than 36 minutes and using batteries with discharge times above 144 minutes substantially improves system reliability during shorter missions.

Economic Feasibility and Cost Implications: While the technical results demonstrate substantial availability improvements through redundancy strategies, the economic feasibility of implementing such configurations requires careful consideration. For instance, achieving 99.89% availability with seven redundant UAVs and 20 spare batteries represents a significant capital investment compared to baseline configurations. The cost-effectiveness of redundancy strategies depends on several factors including mission criticality, downtime costs, component pricing, and operational budgets. High-availability configurations may be justified for critical surveillance applications (e.g., disaster response, security monitoring) where service interruptions have severe consequences, but may be economically impractical for routine monitoring tasks.

A preliminary cost-benefit analysis suggests that component optimization strategies (achieving 97% availability) offer superior cost-effectiveness compared to extensive redundancy for many applications. The diminishing returns observed with additional battery redundancy beyond four units indicates optimal resource allocation points that balance performance with investment. Future work should incorporate economic models that consider component costs, maintenance expenses, mission value, and downtime penalties to provide stakeholders with quantitative cost-benefit guidance for different availability targets and operational contexts.

These findings provide valuable guidelines for designing more robust and reliable drone surveillance systems. They enable engineers to make informed decisions about component selection, system configuration, and resource allocation to achieve desired performance levels while effectively managing costs.

7 Conclusions and Future Work

This study presents an integrated approach for evaluating the availability and reliability of UAV surveillance systems, combining analytical modeling via Continuous-Time Markov Chains (CTMC) with numerical simulation using Stochastic Petri Nets (SPN). The methodology includes detailed sensitivity analyses to identify critical parameters and evaluate the effectiveness of performance improvement strategies.

The CTMC model enabled closed-form analysis of system availability, revealing that battery discharge rate (λ_{bd}) and charging rate (λ_{bc}) are the most influential parameters, followed by the drone swap rate (δ). The SPN model complemented the analytical approach by supporting evaluation of redundancy strategies and providing both steady-state availability and time-dependent reliability metrics.

Three case studies were conducted to explore enhancement strategies. First, component time optimization improved availability up to 97.08% without requiring redundancy. Second, redundancy analysis showed availability gains of approximately 91% using eight spare batteries and four UAVs, although this configuration was insufficient to reach very high availability levels. Third, a combined strategy achieved up to 99.89% availability with seven redundant UAVs and 99.58% with four spare batteries, demonstrating diminishing returns for battery redundancy.

The reliability analysis demonstrated that for 30-hour missions, maintaining reliability above 80% requires 15–20 redundant batteries. For shorter missions, optimizing charging times below 36 minutes and using batteries with discharge times above 144 minutes significantly improves reliability.

These results provide design guidance for UAV systems, helping engineers prioritize improvements that maximize performance while managing cost.

Study Limitations and Future Research Priorities: While this work provides valuable theoretical insights into UAV system dependability, several limitations should be acknowledged. The models primarily focus on battery-related parameters and single-drone operations, with validation based on theoretical consistency rather than empirical data from real deployments. Environmental factors, communication failures, and multi-drone coordination scenarios represent important extensions beyond the current scope.

Future work will expand the model scope and explore new strategies. Priority areas include: (i) empirical validation with real UAV operational data to enhance model credibility; (ii) modeling multi-drone missions with coordinated task execution to address coverage implications discussed in Section 5.1; (iii) incorporating environmental conditions and communication reliability for realistic operational modeling; (iv) developing comprehensive economic models for cost-benefit analysis of redundancy strategies; (v) expanding sensitivity analysis to include mechanical, software, and communication subsystems; (vi) evaluating computational optimization techniques for large-scale UAV fleet modeling; and (vii) assessing alternative energy sources and emerging battery technologies. These extensions will enhance the framework's practical applicability and support more comprehensive dependability assessment for diverse UAV surveillance applications.

These directions aim to improve the dependability, efficiency, and sustainability of UAV surveillance systems in real-world scenarios, supporting applications in public safety, emergency response, environmental monitoring, and infrastructure inspection.

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Authors' Contributions

LL contributed to the conception of this study, performed the experiments, and is the main contributor and writer of this manuscript. EN contributed to the model development and validation. JD contributed to the methodology design and sensitivity analysis. JA contributed to the reliability modeling and case study analysis. PM supervised the research, contributed to the theoretical framework, and provided critical revisions. All authors read and approved the final manuscript.

Competing interests

The authors declare that they have no competing interests.

Availability of data and materials

The datasets generated and/or analysed during the current study are available from the corresponding author on reasonable request. The Mercury modeling tool used in this study is publicly available at `https://www.modcs.org`.

References

Araujo, J., Alves, V., Oliveira, D., Dias, P., Silva, B., and Maciel, P. (2013). An investigative approach to software aging in android applications. In *2013 IEEE International Conference on Systems, Man, and Cybernetics*, pages 1229–1234. DOI: 10.1109/SMC.2013.213.

Avizienis, A., Laprie, J.-C., Randell, B., and Landwehr, C. (2004). Basic concepts and taxonomy of dependable and secure computing. *IEEE transactions on dependable and secure computing*, 1(1):11–33. DOI: 10.1109/tdsc.2004.2.

Brito, C., Silva, L., Callou, G., Nguyen, T. A., Min, D., Lee, J.-W., and Silva, F. A. (2021). Offloading data through unmanned aerial vehicles: a dependability evaluation. *Electronics*, 10(16):1916. DOI: 10.3390/electronics10161916.

Clemente, D., Pereira, P., Dantas, J., and Maciel, P. (2022). Availability evaluation of system service hosted in private cloud computing through hierarchical modeling process. *The Journal of Supercomputing*, 78(7):9985–10024. DOI: 10.1007/s11227-021-04217-1.

Falcão, M., Souza, C., Balieiro, A., and Dias, K. (2023). Dynamic resource allocation for urllc in uav-enabled multi-access edge computing. In *2023 Joint European Conference on Networks and Communications & 6G Summit (EuCNC/6G Summit)*, pages 293–298, Göteborg, Sweden. IEEE, IEEE. DOI: 10.1109/eucnc/6gsummit58263.2023.10188346.

Fernandes, S., Tavares, E., Santos, M., Lira, V., and Maciel, P. (2012). Dependability assessment of virtualized networks. In *2012 IEEE international conference on communications (ICC)*, pages 2711–2716, Ontario, Canada. IEEE, IEEE. DOI: 10.1109/icc.2012.6363992.

Gohari, A., Ahmad, A. B., Rahim, R. B. A., Supa'at, A. S. M., Abd Razak, S., and Gismalla, M. S. M. (2022). Involvement of surveillance drones in smart cities: A systematic review. *IEEE Access*, 10:56611–56628. DOI: 10.1109/ACCESS.2022.3177904.

Hamby, D. (1995). A comparison of sensitivity analysis techniques. *Health physics*, 68(2):195–204. DOI: 10.1097/00004032-199502000-00005.

Hamby, D. M. (1994). A review of techniques for parameter sensitivity analysis of environmental models. *Environmental monitoring and assessment*, 32:135–154. DOI: 10.1007/bf00547132.

Hosseinalipour, S., Rahmati, A., Eun, D. Y., and Dai, H. (2021). Energy-aware stochastic uav-assisted surveillance. *IEEE Transactions on Wireless Communications*, 20(5):2820–2837. DOI: 10.1109/TWC.2020.3044490.

Jia, Z., Wu, Q., Dong, C., Yuen, C., and Han, Z. (2023). Hierarchical aerial computing for internet of things via cooperation of haps and uavs. *IEEE Internet of Things Journal*, 10(7):5676–5688. DOI: 10.1109/JIOT.2022.3151639.

Kharchenko, V., Kliushnikov, I., Rucinski, A., Fesenko, H., and Illiashenko, O. (2022). Uav fleet as a dependable service for smart cities: Model-based assessment and application. *Smart Cities*, 5(3):1151–1178. DOI: 10.3390/smartcities5030058.

Kotikalpudi, A., Danowsky, B. P., and Seiler, P. J. (2020). Reliability analysis for small unmanned air vehicle with algorithmic redundancy. In *AIAA Scitech 2020 Forum*, page 0739, Orlando, Florida. IEEE. DOI: 10.2514/6.2020-0739.

Li, Y., Hassairi, S., Satloff, T., Burns, E., Majgaard, C.-P., and Liang, C. (2020). Energy efficient strategy for uninterrupted mission execution via automatic drone replacement. In *2020 IEEE International Systems Conference (SysCon)*, pages 1–7, Montreal, Quebec. IEEE, IEEE. DOI: 10.1109/syscon47679.2020.9275880.

Lin, X., Su, G., Chen, B., Wang, H., and Dai, M. (2019). Striking a balance between system throughput and energy efficiency for uav-iot systems. *IEEE Internet of Things Journal*, 6(6):10519–10533. DOI: 10.1109/JIOT.2019.2939823.

Lins, L., Nascimento, E., Dantas, J., Araujo, J., and Maciel, P. (2024). Stochastic modeling for assessing the reliability and availability of drone-based surveillance systems. In *2024 IEEE International Systems Conference (SysCon)*, pages 1–8, Montreal, Quebec. IEEE, IEEE. DOI: 10.1109/syscon61195.2024.10553470.

Lopez, V. and Akundi, A. (2023). Modeling a uav surveillance scenario-an applied mbse approach. In *2023 IEEE International Systems Conference (SysCon)*, pages 1–8, Montreal, Quebec. IEEE, IEEE. DOI: 10.1109/SysCon53073.2023.10131074.

MacCarthy, J. (2019). The drone system ii: Availability performance analysis and modeling. In *INCOSE International Symposium*, volume 29, pages 910–921. Wiley Online Library. DOI: 10.1002/j.2334-5837.2019.00643.x.

Machida, F. and Andrade, E. (2021). Availability modeling for drone image processing systems with adaptive offloading. volume 2021-December, pages 93–103. IEEE Computer Society. DOI: 10.1109/PRDC53464.2021.00021.

Maciel, P., Dantas, J., Melo, C., *et al*. (2022). A survey on reliability and availability modeling of edge, fog, and cloud computing. *Journal of Reliable Intelligent Environments*, 8:227–245. DOI: 10.1007/s40860-021-00154-1.

Maciel, P., Matos, R., Silva, B., Figueiredo, J., Oliveira, D., Fé, I., Maciel, R., and Dantas, J. (2017). Mercury: Performance and dependability evaluation of systems with exponential, expolynomial, and general distributions. In *2017 IEEE 22nd Pacific Rim international symposium on dependable computing (PRDC)*, pages 50–57, Christchurch, New Zealand. IEEE, IEEE. DOI: 10.1109/prdc.2017.16.

Maciel, P. R. M. (2023). *Performance, reliability, and availability evaluation of computational systems, Volume II: Reliability, availability modeling, measuring, and data analysis*, volume 2. CRC Press, Recife, Pernambuco. Book.

Maciel, R., Araujo, J., Dantas, J., Melo, C., Guedes, E., and Maciel, P. (2018). Impact of a ddos attack on computer systems: An approach based on an attack tree model. In *2018 Annual IEEE International Systems Conference (SysCon)*, pages 1–8. DOI: 10.1109/SYSCON.2018.8369611.

Mishra, B., Garg, D., Narang, P., and Mishra, V. (2020). Drone-surveillance for search and rescue in natural disaster. *Computer Communications*, 156:1–10. DOI: 10.1016/j.comcom.2020.03.012.

Moghadasi, N., Kulkarni, A., Crayton, D., Grissom, R., Lambert, J. H., and Feng, L. (2023). Formal methods in unmanned aerial vehicle swarm control for wildfire detection and monitoring. In *2023 IEEE International Systems Conference (SysCon)*, pages 1–8, JW Marriot Parq Vancouver. IEEE, IEEE. DOI: 10.1109/syscon53073.2023.10131075.

Pereira, P., Araujo, J., Melo, C., *et al*. (2021). Analytical models for availability evaluation of edge and fog computing nodes. *The Journal of Supercomputing*, 77:9905–9933. DOI: 10.1007/s11227-021-03672-0.

Petritoli, E., Leccese, F., and Ciani, L. (2017). Reliability assessment of uav systems. In *4th IEEE International Workshop on Metrology for AeroSpace, MetroAeroSpace 2017 - Proceedings*, pages 266–270. Institute of Electrical and Electronics Engineers Inc.. DOI: 10.1109/MetroAeroSpace.2017.7999577.

Petritoli, E., Leccese, F., and Ciani, L. (2018). Reliability and maintenance analysis of unmanned aerial vehicles. *Sensors (Switzerland)*, 18. DOI: 10.3390/s18093171.

Pham, Q.-V., Ruby, R., Fang, F., Nguyen, D. C., Yang, Z., Le, M., Ding, Z., and Hwang, W.-J. (2022). Aerial Computing: A New Computing Paradigm, Applications, and Challenges. *IEEE Internet of Things Journal*, 9(11):8339–8363. DOI: 10.1109/JIOT.2022.3160691.

Rusnak, P., Kvassay, M., Zaitseva, E., Kharchenko, V., and Fesenko, H. (2019). Reliability assessment of heterogeneous drone fleet with sliding redundancy. In *2019 10th International Conference on Dependable Systems, Services and Technologies (DESSERT)*, pages 19–24. DOI: 10.1109/DESSERT.2019.8770031.

Trivedi, K. S. (2008). *Probability & statistics with reliability, queuing and computer science applications*. John Wiley & Sons, Berlin, Germany. Available at: `https://onlinelibrary.wiley.com/doi/book/10.1002/9781119285441`.

Watanabe, K. and Machida, F. (2022). Availability analysis of a drone system with proactive offloading for software life-extension. In *2022 IEEE International Conference on Omni-layer Intelligent Systems (COINS)*, pages 1–6. IEEE. DOI: 10.1109/coins54846.2022.9854966.

Xing, L. and Johnson, B. W. (2023). Reliability theory and practice for unmanned aerial vehicles. *IEEE Internet of Things Journal*, 10(4):3548–3566. DOI: 10.1109/JIOT.2022.3218491.

Zaitseva, E., Levashenko, V., Kvassay, M., and Kharchenko, V. (2020). Reliability evaluation of heterogeneous drone fleet by structure function based method. pages 4883–4889. Research Publishing, Singapore. DOI: 10.3850/978-981-14-8593-$0_5 145 - cd$.