

Reliability, availability and maintenance man-hours analysis of uncrewed aerial vehicle systems

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Abstract

The reliability of uncrewed aerial vehicle (UAV) systems is essential for mission success in safety-critical scenarios such as military surveillance, rescue operations, and disaster assessment. System availability depends not only on subsystem reliability but also on maintenance work to keep UAV systems functioning. This study evaluates UAV reliability characteristics, focusing on availability, reliability, and maintenance man-hours (MMH) under scenarios. Unlike existing UAV reliability studies that primarily focus on overall system reliability and availability, the proposed framework provides comprehensive subsystem-level analysis by identifying critical subsystems, evaluating their impact on system performance, and integrating MMH with preventive replacement planning. A generalized stochastic Petri nets (GSPN) modeling framework is applied to examine failure and repair behavior and assess system availability and reliability. The GSPN determines maintenance personnel and identifies maintenance priorities for subsystems. The MMH is determined using an age replacement strategy to identify optimal replacement timing based on component degradation. The results show that the proposed GSPN-based framework improves system availability from 0.9388 to 0.9905 and enhances system reliability from 0.6157 to 0.9605. In addition, MMH is evaluated under preventive replacement policies corresponding to 60%–90% of characteristic life, enabling replacement intervals for efficient maintenance planning. The framework supports UAV fleet operators, maintenance planners, and defense organizations through comprehensive reliability and availability analysis of the overall UAV system and its critical subsystems. By estimating maintenance manpower, identifying critical subsystems, and determining preventive replacement schedules, the framework supports efficient maintenance planning, improves operational readiness, and minimizes unnecessary maintenance effort and costs.

Keywords

availability, GSPN, maintenance, MMH, reliability, UAV

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Introduction

Uncrewed aerial vehicles (UAV) systems, commonly referred to as drone systems, are widely used across diverse fields such as military operations, surveillance, agriculture, disaster response, environmental monitoring, and commercial inspection.^{1–3} Their ability to operate the vehicle in challenging environments without a human or pilot offers flexibility, efficiency, and, most importantly, cost effectiveness.⁴ Over the past few decades, advances in sensor technology and artificial intelligence have enabled the application of UAVs to become more helpful in developing and significantly expanding their capabilities, providing more accurate information for precise navigation, real-time data, and performing tasks in diverse applications. In various applications where tasks need to be executed, UAVs vary depending on the situation. In different situations and applications, different types of UAVs are used.⁵

UAVs are categorized based on their size, endurance, range, and operational capabilities for executing tasks

across various sectors. Micro or nano UAVs are lightweight UAVs designed for surveillance and reconnaissance missions, such as indoor building inspections and urban reconnaissance. Medium-altitude long-endurance (MALE) UAVs,⁶ on the other hand, are engineered to prioritize endurance, featuring sophisticated sensors and communication systems. Their versatility allows them to execute a wide range of tasks such as surveillance, reconnaissance, and border patrol, making them a fascinating subject of study. These UAVs can cover extensive

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areas without the necessity for frequent refueling or maintenance. High-Altitude Long-Endurance (HALE) UAVs are designed for prolonged endurance, capable of remaining airborne for extended periods, similar to those used for satellite operations.⁷ These vehicles execute tasks such as weather monitoring, environmental surveillance, and communications relay. Figure 1 shows the various applications of UAVs across different areas.

Considering the importance of UAV systems, it is important to prioritize their maintenance. Our research study focuses on the MALE UAV system.

In the context of proper UAV operation and successful mission execution, reliability and maintainability play a significant role. The reliability of a system refers to the chance that it operates without failure for a specified duration, while the maintainability of the system pertains to its capacity for immediate and efficient repair or restoration to normal operating conditions following a failure, utilizing minimal resources, efforts, and time.

High reliability is essential for UAV systems,⁸ since they frequently operate in complex, dynamic, and safety-sensitive environments where any failure of the system or its components can result in mission loss, equipment damage, or even significant safety risks. A reliable UAV ensures constant performance over time, diminishes the likelihood of unexpected breakdowns, and is essential for critical missions. As UAV applications have developed in autonomous technology, the investigation of long-duration mission reliability has become increasingly crucial for assessing component failure, mission success probability, and overall system robustness under unforeseen operating circumstances.

The maintainability of the UAV system, including the analysis of maintenance man-hours, is crucial for its sustained long-term operation, as the UAV system comprises various interconnected subsystems, and any failure of a subsystem can result in complete system failure. The system's high maintainability necessitated fewer maintenance man-hours, implying faults could be detected, diagnosed, and corrected more quickly and effectively. This improves fleet availability, decreases maintenance costs, and shortens downtime. Analysis of maintenance man-hours (MMH) also helps with scheduling preventive maintenance tasks, allocating repair crews, and planning for replacement components. In order to ensure the system's long-term performance and lower costs, it is imperative that it be repaired efficiently and that

the total number of man-hours required to do so be analyzed.

The main aim of this research is to examine the reliability, availability, and maintainability in terms of MMH of the UAV system. The analysis of system reliability and availability used a generalized stochastic Petri nets (GSPN) modeling approach, a sophisticated framework that is effective in capturing both structural complexity and the dynamic behavior of real-world systems. The GSPNs are particularly useful for reliability and maintainability analysis because they offer strong representations of systems that are characterized by randomness in failure occurrence, repair process, and limited resources. The utilization of GSPNs ultimately guarantees a more realistic and analytically rigorous reliability assessment compared to standard static models, thereby enhancing maintenance planning, resource allocation, and long-term performance optimization.

To analyze the maintainability of the UAV system, the concept of MMH has been employed. The age replacement policy is used to analyze the system's MMH. This approach replaces subsystems or components proactively when they reach a certain age, regardless of whether a failure has occurred. The total MMH, inspection time, preventative replacement time, and corrective repair time are computed by integrating age-based replacement intervals into models to determine the total maintenance effort needed to maintain system performance.

The following highlights the main objective of the present study:

Analyze the behavior of each subsystem of the UAV systems.

Determine the reliability as well as availability of the UAV systems.

Identify the critical subsystem of the UAV system that necessitates higher maintenance.

Estimates required MMH for each UAV subsystem.

The overall structure of this research is organized into nine well-defined sections, as follows. The literature review section presents a summary of the relevant literature related to this study. The architecture of the UAV, along with its subsystem description, is described in Designing Process of UAV systems section. The modeling of UAV using GSPNs is discussed in the Generalized Stochastic Petri Nets Modeling of UAV Systems section. Analysis of UAV Systems Reliability Characteristic section presents the reliability characteristics of the system. Section 6 describes the concept of formulating MMH for the UAV system. The mathematical model for calculating the system's man-hours is presented in Formulation of the Mathematical Model section. The Numerical Illustrations section describes the numerical outcomes of total man-hour requirements and presents a detailed analysis of the findings. Finally, the Conclusion and Future work section concludes the study by summarizing the main contributions and suggesting possibilities for future research.

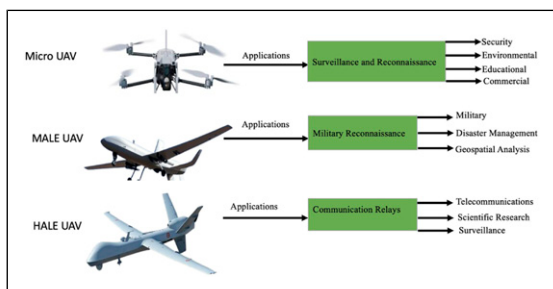


Figure 1. Classifications of UAVs with their applications.

Literature review

The application of UAV systems is rapidly developing in critical missions such as military, surveillance, and disaster management; therefore, maintaining their operational performance is essential. Any system failure in these applications increases downtime and maintenance needs while also decreasing operational efficiency. Thus, reliability, availability, maintenance man-hours estimation, and maintainability have become critical performance metrics of sustainable UAV systems. In response to this demand, various studies have been conducted to determine the maintenance plan and assess the system's reliability using a range of modeling and optimization methodologies, all with the common goal of enhancing system operation and reducing downtime.

Early studies on UAV systems reliability, including traditional methods such as fault tree analysis (FTA), reliability block diagrams (RBD), and the Markov approach, demonstrate the foundational efforts that many researchers and engineers have built upon.⁹ extended the RBD to dynamic RBD, showcasing ongoing efforts to improve UAV reliability analysis and inspiring confidence in the field's development. To incorporate the basic dynamic relationship between the failure repair transition, the Markov chain model emerged as an intermediate approach.¹⁰ Quamar et al.¹¹ developed a Markov decision process for UAV fault-tolerant mission management, facilitating navigation, failure management, and optimization of energy-constrained decisions to ensure reliable mission execution. Shih et al.¹² investigated how placing one or multiple propellers on a UAV wing affects its airflow and overall flight performance using experiments and simulations.

Wang et al.¹³ developed a novel hybrid air–electric driven fuel system for more electric aircraft engines to reduce fuel/oil overheating and improve overall system reliability. Raee et al.¹⁴ examined the reliability of UAV systems applying Markov analysis methods. Ambroziak et al.¹⁵ proposed a two-stage control method to improve how autonomous UAVs fly in a leader–follower formation, making it easier for the follower to match the leader's position and motion even when they start far apart. Cai et al.¹⁶ proposed the use of Bayesian Networks to evaluate reliability in real time. It analyzes the reliability of the system, detects failure causes, and shows how faults affect the system and which components are most critical. Although traditional reliability methods such as FTA, RBD, Markov models, and Bayesian Networks have been widely applied to evaluate UAV system reliability, most of these approaches are primarily intended for reliability assessment and have limited capability to simultaneously model dynamic failure and repair interactions, subsystem dependencies, component aging, and maintenance decision making. These limitations indicate the need for a more comprehensive framework that integrates reliability evaluation with maintenance planning for UAV systems.

To address these limitations, stochastic modeling techniques, particularly Petri nets, have drawn significant

attention. Goncalves et al.¹⁷ employed Petri nets modeling to assess the safety of the UAV system, identify significant failure situations, and facilitate airworthiness certification in accordance with STANAG 4671 regulations. Wang et al.¹⁸ produced a hybrid Petri nets framework to describe and analyze the individual behavior and continuous dynamics of a diverse UAV swarm during an attack mission. Yucheng¹⁹ presented a methodology for reliability analysis based on dynamic fault tree analysis and stochastic Petri nets to represent failure and uncertainty in complex balanced systems, utilizing an extended Monte Carlo approach, which was first tested on a six-rotor UAV. Jyotish et al.²⁰ employed the timed Petri nets to evaluate efficiency as well as accuracy of the safety-sensitive system. Brito et al.²¹ developed a stochastic Petri net model and RBD for a UAV-based system designed to offload IoT data to the cloud, aiming to evaluate the system's dependability and availability. Nan et al.²² proposed a hybrid path planning approach for multiple UAVs by combining Ant Colony Optimization with Particle Swarm Optimization and Simulated Annealing to handle obstacle avoidance in complex terrains.

Apart from the field of UAVs, Petri nets have been effectively utilized for modeling the dependability, availability, and performance of various complex engineering systems. Sachdeva et al.²³ employed the GSPN model in the paper industry to evaluate the dependability and availability of the pulping system. Bertolini et al.²⁴ designed the industrial system using Petri nets modeling to assess system dependability and identify essential components of the system. Zhang et al.²⁵ developed a modular Petri net-based approach to describe and evaluate the dependability of IoT-enabled smart manufacturing platforms. Renganathan et al.²⁶ used a multi-tank system to evaluate an observing strategy for finding defects and system performance optimization using hybrid Petri net models. Garg²⁷ proposed a new methodology integrating Petri nets and imprecise Lambda–Tau to evaluate system reliability based on uncertainty. The results indicate that it provides a more realistic and superior comprehension compared to traditional methods.

Overall, the above studies demonstrate that Petri net-based methodologies are effective for modeling the reliability, safety, availability, and performance of complex engineering systems by accurately representing dynamic failure and repair processes. However, most existing studies primarily focus on system-level analysis and do not provide a comprehensive framework that simultaneously evaluates the reliability and availability of both the overall UAV system and its critical subsystems. In addition, maintenance manpower estimation, maintenance man-hours analysis, repair priority determination, and preventive replacement planning have received limited attention. These limitations highlight the need for an integrated reliability and maintenance framework for UAV systems.

Maintenance is a crucial indicator in the aerospace industry,²⁸ significantly enhancing the operating efficiency of UAV systems and reducing their failures. The

maintenance of any system plays a critical and significant part in industrial operations, manufacturing processes, and technological infrastructure.²⁹ AliFarsi³⁰ constructed a maintenance framework for small UAV systems by identifying crucial parts through malfunctioning modes and impact evaluation. A fuzzy decision-making with multiple criteria methodology was subsequently employed to enhance inspection and maintenance schedules. To improve the maintenance schedules of UAV systems, Petritoli et al.³¹ used statistical confidence intervals that accurately predict the system's breakdown time.

Goncalves et al.³² initiated the fundamental UAV maintenance program, utilizing the steering maintenance group logic technique, as the study employed morphological analysis to assess the system's failure likelihood in the absence of real data. Zhao et al.³³ developed a *Q*-learning-based maintenance optimization model for parallel production systems, accounting for limited and skill-diverse engineers to maximize long-term system profitability. Regattieri et al.³⁴ implemented a RAM-based methodology that amalgamates failure/repair modeling, optimization, simulation, and inventory management to develop maintenance strategies for A320 airplane components, thereby ensuring improved availability while reducing maintenance costs.

Understanding the human issues associated with UAVs is crucial for enabling their operation within the national airspace system.³⁵ The MMH is a crucial human factor that significantly influences the reliability, operational expenses, and safety of UAV systems. The MMH is the fundamental measurement of performance used to assess the maintainability or maintenance strategy of any technical or manufacturing system.³⁶ Identifying the MMH is crucial for enhancing maintenance methods, reducing labor costs, and maximizing system performance. Wei and Youshi³⁷ proposed a strategy for evaluating airplane MMH by developing a task-sequence-based action library, establishing a matrix model for calculating task complexity and man-hours, and designing a data management tool for accurate maintainability assessment.

Hur et al.³⁸ constructed a man-hours estimation model for shipbuilding employing process analysis, multivariate regression analysis, and classified tree regression. The classification regression tree methodology proved to produce the most accurate and realistic forecasts for shipyard operations. Liu and Jiang³⁹ assessed the MMH of a ship's interim products employing three different models: artificial neural networks, simple linear regression, and multiple linear regression techniques. They determined that the artificial neural network model yielded a more precise and dependable estimation of man-hours than the regression models. Proverbs et al.⁴⁰ proposed a methodology for estimating man-hours at the beginning of the project using contractors' productivity rates to derive a labor estimate factor, allowing swift assessments of labor needs and costs in different areas.

Overall, the above studies demonstrate that a variety of methodologies have been successfully applied to optimize maintenance strategies and estimate MMH across

aerospace, manufacturing, shipbuilding, and other engineering systems. However, only limited studies have investigated maintenance man-hours specifically for UAV systems. Moreover, existing studies generally address maintenance planning, reliability analysis, and MMH estimation as separate problems, without integrating subsystem-level reliability and availability analysis, maintenance manpower estimation, repair prioritization, and preventive replacement planning into a unified framework. Therefore, there remains a need for a comprehensive framework that simultaneously evaluates system reliability and availability, identifies critical UAV subsystems, estimates maintenance manpower and maintenance man-hours, and supports effective maintenance decision-making.

Motivation and contribution

Based on the above literature review, it is evident that significant progress has been made in the reliability and maintenance analysis of UAV systems through the application of various methodologies, including fault tree analysis, reliability block diagrams, Markov models, Bayesian networks, Petri nets, and maintenance optimization techniques. However, most existing studies focus on individual aspects of UAV systems, such as reliability analysis, availability assessment, maintenance optimization, or maintenance man-hour estimation, rather than providing a unified framework that integrates these aspects. Furthermore, traditional reliability approaches have limited capability to model concurrent events, shared resources, and complex subsystem interactions. Although Petri net-based models overcome many of these limitations and have been successfully applied to UAV systems, most existing models assume constant failure rates, thereby neglecting component aging effects and the practical requirements of age-based preventive replacement planning. In addition, limited attention has been given to simultaneously evaluating the reliability and availability of both the overall UAV system and its individual subsystems, identifying the critical subsystems that have the greatest impact on system performance, estimating maintenance manpower and maintenance man-hours, prioritizing repair activities, and determining optimal preventive replacement schedules. Addressing these challenges is essential for improving maintenance planning, enhancing system availability and operational readiness, and reducing unnecessary maintenance effort and associated maintenance costs in UAV operations. Therefore, this study develops an integrated reliability and maintenance framework to address these research gaps.

To overcome these limitations, the present study evaluates the reliability and availability of UAV systems using the GSPN, which captures the dynamic interactions among multiple UAV subsystems. The system's failure behavior is time-dependent and adheres to the Weibull distribution. In the event of a system breakdown, repair facilities are immediately available, and the maintenance

Table 1. An overview of relevant research on UAV systems maintainability and reliability analysis.

Author(s)	System studied	Methodology	Focus	Key limitations
Dui et al. ⁴¹	UAV swarm systems	Polygonal linear consecutive- <i>k</i> -out-of- <i>n</i>	Mission reliability under UAV failure	Maintainability and repair priority is not included
Ahmed and Jenihhin ⁴²	UAV computing platform system	Survey on hardware reliability issue	Analyze the fault and failure models and proposed the cross-layer reliability model	No quantitative modeling of subsystem-level reliability; limited to survey and theoretical analysis
Zaitseva et al. ⁴³	Drone fleets	Evaluation of reliability	Study of reliability measures and their significance factors	Swarm structure was the main focus; system maintainability was not examined
Xu et al. ⁴⁴	UAV flight control station system	Reliability verification in real time	Evaluation of UAV flight control reliability under real-time constraints	Limited to control systems; absence of general system maintainability
Liu et al. ⁴⁵	Fixed-wing UAV systems	Stochastic modeling framework	Presents a quantitative evaluation of reliability that covers dynamic failure-repair interactions in UAV systems	Does not include the system mission reliability and MMH of system
Lizhi et al. ⁴⁶	UAV swarm systems	Multi-layer complex network modeling	Mission reliability of system	Does not discuss the repair procedures and MMH of system
This research	UAV systems	Petri nets modeling + Age replacement maintenance	Reliability, availability, maintenance, and MMH of a UAV subsystems	The study relies on realistically simulated data rather than real-world operational datasets

priority for each subsystem is determined. Furthermore, this study calculates the MMH for each UAV subsystem, taking into account the age replacement strategy, which includes both preventive and failed replacements.

Table 1 provides a summary of the main contributions of our research and how it addresses the gap in previous research studies.

Designing process of UAV systems

This study defines the design procedure of the proposed UAV systems by defining its key subsystems and their configurations to ensure reliable operations. The proposed UAV system is developed for the primary purpose of intelligence, surveillance, and reconnaissance of critical places. It is designed to meet the operational requirements of the armed forces, providing a cost-effective alternative to critical platforms, including advanced technologies for autonomous and long-endurance operations. The proposed UAV system operates under different environmental circumstances and is fitted with an advanced onboard system to support both autonomous and remotely piloted operations.

The RBD of the UAV system shown in Figure 2 illustrates the major subsystems and their interconnections, providing a clear representation of the overall system architecture. The mission-critical subsystems are connected in a series configuration; therefore, failure of any subsystem leads to failure of the overall UAV system. To improve system reliability, selected subsystems are equipped with redundant units. Consequently, failure of an individual unit within a redundant subsystem does not immediately cause subsystem failure but places the

subsystem in a degraded operating state until the standby unit also fails or the subsystem becomes unavailable.

Airframe Structure:- This encompasses the structural backbone of the entire system, including wings, T-tail configurations, and a fuselage. The UAV features a lightweight composite airframe to improve durability and aerodynamic efficiency. The airframe incorporates a T-type vertical stabilizer and a high-mounted horizontal tailplane, enhancing the UAV's aerodynamic performance. Any structural malfunction can lead to catastrophic system failure.

Main Display (MD) Subsystem:- This subsystem, a key component of the ground control station, is linked to the UAV via the communication link. It is responsible for monitoring and displaying a comprehensive range of real-time information, including battery charge level, fuel cell status, flight altitude, speed, GPS location, and hybrid engine data, among other data. This subsystem is a powerful tool that provides real-time information crucial to mission objectives, including camera feeds, sensor outputs, and target tracking. It is used to assess the communication status, payload conditions, alerts, and warning-related issues. The combination of maps and live video significantly enhances situational awareness, empowering operators with a comprehensive understanding of UAV environments and activities.

Data Communication (DC) Subsystem:- The data communications subsystem ensures reliable, secure, and continuous information exchange between the

UAVs and the ground control station, as well as inter-UAV coordination in multi-aircraft missions. For communication, the UAV utilizes a line-of-sight data link with a range of 250 km, augmented by satellite communications enabling beyond-line-of-sight operations. This subsystem delivers important flight data, sensor data from the payload, health-monitoring data, and mission-control directives with very little delay and a lot of backup. Advanced encoding, error correction, and frequency hopping make links more reliable and less likely to be affected by interference or hostile jamming.

Power Supply (PS) Subsystem:- This subsystem supplies power to all avionics, communication equipment, sensors, and navigation instruments on board. It features a power management unit, a crucial component that includes a voltage regulator and a protection circuit to prevent overload, short-circuiting, or voltage fluctuations. The voltage regulator is crucial for maintaining a stable power supply. The subsystem effectively manages the flow of electricity between batteries and engine-driven generators, ensuring that the system remains operational even if one of the generators fails. This subsystem's design aims to enable the entire UAV system to operate for more than 24 hours, allowing it to maintain continuous surveillance and gather information at all times.

Power Generator (PG) Subsystem:- This subsystem is the main source of electricity for the whole UAV system. It generates electricity with its dual-turbo diesel turboprop engine, which converts mechanical energy into electrical energy. The generator, typically an alternator or DC generator, can provide sufficient electricity for avionics and payload systems, depending on the design requirements. The generator subsystem also works with automatic control systems to keep the voltage and frequency stable, making sure that sensitive electronic equipment on board can work with it. Additionally, it is supported by a battery system that can take over during start-up, peak load demands, or emergency conditions.

Air Conditioner (AC) Subsystem:- It plays a more significant role in environmental control scenarios, aiming to provide safe operating conditions for on-board avionics, sensors, and electronic payloads. As UAVs operate on extended missions at altitudes up to 32,000 feet, variations in temperature and pressure occur. Consequently, electrical subsystems such as radar payloads, electro-optical sensors, and avionics computers may overheat during continuous operations, potentially leading to the combustion of these components during missions. This subsystem regulates temperature, humidity, and ventilation within avionics and payload compartments in all environments to address these circumstances. It generally employs vapor compression or air cycle cooling

technologies, circulating cooled air to sustain thermal equilibrium. Along with cooling, the subsystem ensures that extra moisture is removed and that condensation does not occur, which could damage delicate electronic components.

Guidance and Control (GC) Subsystem:- This subsystem operates as the central processing unit of the UAV system. It consists of the computer and sensors that facilitate the aircraft's autonomous operation using an autopilot system. This subsystem is the foundation of its autonomous flight capability, guaranteeing that the vehicle can execute long-endurance surveillance missions with safety, accuracy, and reliability. This is the most important part of the UAV system since it makes sure that the flight is stable and the mission is successful. It has an autopilot system, a flight control computer, gyroscopes, accelerometers, GPS, and actuators that regulate the aerodynamic surface. The primary components of this subsystem are a navigation sensor, algorithms for guidance, and control mechanisms. By combining GPS with inertial navigation, the navigation sensor provides precise and real-time information on the UAV's location, velocity, height, and orientation. The necessary trajectory is generated by the guiding algorithm using their data; this trajectory may include navigating around a target surveillance area using keypoints and modifying the path to avoid hazards. The actuators in the control system then process these commands and convert them into real-time corrective actions by adjusting the engine power, the rudder, the ailerons and the elevator functions.

Generalized stochastic Petri nets modeling of UAV systems

Petri nets provide an effective mathematical framework for analyzing the dynamic behavior of complex systems. It is used to describe, analyze, and simulate systems where events occur randomly, concurrently, or depend on certain circumstances. It was initially presented by Carl Adam Petri in 1962 in his doctoral dissertation.⁴⁷ The Petri nets model consists of four primary components: directed arcs, places, transitions and tokens.

In the graphical depiction of Petri nets, places are indicated by circles and transitions by rectangular bars;

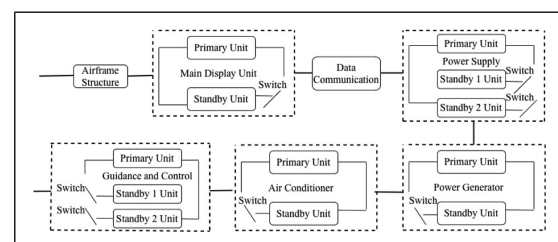


Figure 2. Reliability block diagram of proposed UAV system.

there exists a finite number of places and transitions. In the Petri nets model, tokens are denoted by small dots, whereas directed arcs are indicated by input and output arrows. Places and transitions are interconnected by directed arcs, where the arc from places to transitions serves as the input arc, while the arc from transitions to places functions as the output arc. The initial Petri nets illustrate the system's structure and logical behavior; however, they fail to capture the uncertainty that arises in real-world operations. To address these limitations, Petri nets have been expanded to stochastic Petri nets, which incorporate probabilistic timing into system transitions.

The stochastic Petri nets⁴⁸ incorporate probabilistic time transition information, facilitating the modeling of systems where events occur with uncertainty. The transitions are triggered by exponential and other probability distributions of the system, incorporating their failure and repair rate variables. Due to their stochastic nature, stochastic Petri nets are useful for risk assessment, performance evaluation, and system reliability analysis. Despite incorporating stochastic timing into the Petri net model, stochastic Petri nets are still unable to depict priority-based behavior and immediate actions effectively. To address these challenges, the generalized stochastic Petri nets (GSPN) framework offers an enhanced and more expressive modeling structure.

The GSPN, Ajmone et al.⁴⁹ extended the modeling capabilities of stochastic Petri nets by incorporating immediate time transitions and inhibitor arcs, thus providing a more comprehensive and flexible way to represent complicated system behavior. In GSPNs, places represent the system's state, transitions denote the events or actions that can change those states, and tokens are assigned to the places. The dynamic behavior of the system is defined by the movement of the token, which depends on the firing of transitions. When transitions are activated, the token moves from one state to another, indicating the system's movement from one state to another. There are two types of transition firing: time transition-based firing and immediate transition-based firing.

In the context of time-transition based firing, the failure transitions are modeled using the Weibull distribution, whereas the repair transitions follow the exponential distribution. The Weibull distribution is adopted because it can effectively represent the time-dependent failure behaviour of UAV subsystems. In contrast, the repair process is modeled using the exponential distribution by assuming that, once maintenance begins, the repair activity proceeds with a constant repair rate until completion. This assumption is adopted because the proposed GSPN model represents repair through timed transitions with a single repair-rate parameter for each subsystem, providing a practical and consistent representation of the maintenance process within the proposed framework. In all cases, a firing delay is associated with the timed transitions before they are enabled.

On the other hand, there is no delay between states in immediate transition-based firing, where the transition firing happens instantly. In these types of transition, they

activate immediately while satisfying their guard function requirements. In the immediate transition, they are fulfilling their guard functions. The GSPN model of the UAV systems, whereby each subsystem is initially in operational condition, is shown in Figure 3.

The notations for the various states of places and the transitions of each subsystem of a UAV within the Petri nets model are given in Table 2.

In the proposed GSPN model of the UAV systems, the initial state of the system is operational, and each place contains a certain number of tokens, representing the number of units in each subsystem. For example, " P_{1up} " which represents the up state of the main display subsystem, is initially in a fully operational state and contains two tokens, indicating that this subsystem has two units, one is primary and the other is in standby configuration. Similarly, " P_{6up} ", which represents the up state of the guidance and control subsystem, is initially in a fully operational state and contains three tokens, indicating that this subsystem has three units, of which one is primary, and the other two units are in a standby configuration.

The entire UAV system is initially fully operational; afterwards, the failure transition occurs with a Weibull-distributed firing time, resulting in the system entering a down state. An immediate transition is then triggered with their repair facility " $P_{repairman}$ ", which leads to the system entering a repairable state. Following this transition, a repair rate is activated, and the system ultimately returns to complete operational condition. For example, the place " P_{1up} " represents the initial operating (up) state of the main display subsystem. After transition T_1 fires, with a mean time to failure (MTTF), a token moves from " P_{1up} " to " P_{1down} ", indicating that the subsystem has failed and the system enters the down state. Immediately thereafter, transition t_2 is activated along with its guard function and repair availability ($P_{repairman}$), resulting in the system entering a repairable state, " P_{1rep} ". Following this, transition T_3 is triggered with its exponentially distributed repair rate, leading the system to revert to a working state " P_{1up} ".

The immediate transitions are activated with their guard functions. The programming for the guard function of immediate transition is given in Table 3.

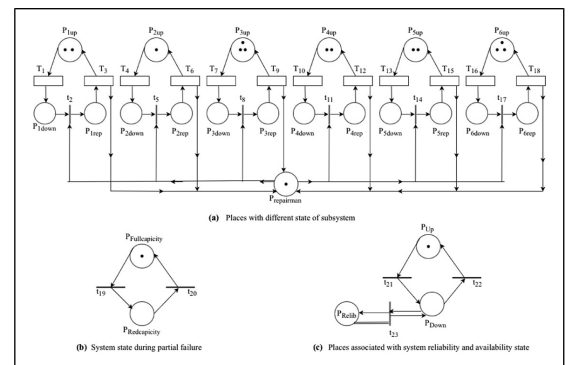


Table 2. Notations of Places and Transitions in the GSPN model of UAV system.

Subsystem	Places (states)			Transition types		
	Up	Down	Repair	Timed (Distribution)		Immediate
				Weibull	Exponential	
Main display	P_{1up}	P_{1down}	P_{1rep}	T_1	T_3	t_2
Data communication	P_{2up}	P_{2down}	P_{2rep}	T_4	T_6	t_5
Power supply	P_{3up}	P_{3down}	P_{3rep}	T_7	T_9	t_8
Power generator	P_{4up}	P_{4down}	P_{4rep}	T_{10}	T_{12}	t_{11}
Air conditioner	P_{5up}	P_{5down}	P_{5rep}	T_{13}	T_{15}	t_{14}
Guidance and control	P_{6up}	P_{6down}	P_{6rep}	T_{16}	T_{18}	t_{17}
UAV system	P_{Up}	P_{Down}	Sys_{redcap}	—	—	$t_{19}, t_{20}, t_{21}, t_{22}$
Reliability	P_{Relib}	—	—	—	—	t_{23}

Among the immediate transitions, t_{19} and t_{21} define the operational status of the UAV system based on the availability of redundant units. Initially, the UAV operates in the full-capacity state, where all primary and standby units are available. Transition t_{19} is enabled when one or more standby-supported subsystems experience the failure of a unit. In this situation, the remaining standby unit continue supporting system operation, allowing the UAV to remain functional despite the loss of redundancy. Consequently, the system transitions from the full-capacity state to the reduced-capacity state. Transition t_{21} is activated when all standby units of a redundant subsystem have failed or when a subsystem with a single unit fails. Under these conditions, the UAV can no longer sustain normal operation, and the system transitions from the working state to the down state.

Analysis of UAV systems reliability characteristics

The reliability characteristics of UAV systems are evaluated through a Monte Carlo simulation of the Petri net model using GSPN. The initial simulation is used to examine characteristics in a steady state, specifically for assessing system availability during operational conditions. The modeling and simulation were conducted using a licensed software package named Petri module GRIF-2023, which incorporates numerous parameters and their suitable predefined values. The simulation was performed for 1000 iterations at a 95% confidence level. Independent replications in simulation are utilized to evaluate the system's reliability.

The system availability represents the probability that the system is in an operational state. In Figure 3(b) and Figure 3(c), Places " P_{Up} " and " $P_{fullcapacity}$ " denote the states in which the system is operational, indicated as system availability. Figure 3(b) in this initial system operates at full capacity; thereafter, it transitions to reduced capacity. The transformation of tokens from full capacity to reduced capacity occurs based on the behavior of the subsystem. If any subsystem has more than one component, such as the primary display subsystem with

two units, one operational and the other in standby, the initial system operates at full capacity before transitioning to reduced capacity. In this case, the subsystem has multiple units, and places " $P_{fullcapacity}$ " represents system availability.

Figure 3(c) shows that when any subsystem fails, the entire system enters a non-operational state. Based on the subsystem's behavior, the token transitions from the operational state to the failed state. A subsystem containing a single unit, such as a data communication subsystem, will incur total system failure upon the failure of that unit. In this context, " P_{Up} " denotes system availability.

The behavior of failure and repair of each subsystem affects the operational process of the whole system. A sensitivity analysis has been performed to evaluate the effect of failure and repair durations of each subsystem on the total system availability by varying the MTTF and repair rate parameters of those subsystems. The potential combinations of the MTTF and repair rate parameters for the UAV subsystem are shown in Table 4, obtained from,⁵⁰ and their sensitivity analysis results are illustrated in Figures 4–9.

Figure 4 shows that variations in the failure and repair rate parameters of the primary display unit subsystem significantly affected system availability. The MTTF of the primary display subsystem decreased from 1650 h to 650 h, with an initial constant failure rate of 0.01, resulting in a decline in system availability from 0.9483 to 0.9528. As the repair facility of this subsystem rises from 0.04 to 0.2, system availability increases from 0.9483 to 0.9897. The failure and repair of this subsystem have resulted in an overall impact on system availability of 6.39%.

The failure and repair rate parameters of the data communication subsystem greatly impact system availability. When the MTTF of this subsystem decreases from 1200 h to 400 h, the system's availability declines from 0.9388 to 0.7660. Conversely, when the repair rate of this subsystem increases from 0.01 to 0.1, the system's availability rises from 0.9388 to 0.9909 as shown in Figure 5. This subsystem affected overall system availability by 22.49%.

Table 3. Guard functions for immediate transitions.

Transition	Guard functions for transitions
t_2	$(P_{1down} > 0) \wedge (P_{repairman} > 0)$
t_5	$(P_{2down} > 0) \wedge (P_{repairman} > 0)$
t_8	$(P_{3down} > 0) \wedge (P_{repairman} > 0)$
t_{11}	$(P_{4down} > 0) \wedge (P_{repairman} > 0)$
t_{14}	$(P_{5down} > 0) \wedge (P_{repairman} > 0)$
t_{17}	$(P_{6down} > 0) \wedge (P_{repairman} > 0)$
t_{19}	$(P_{1down} > 0 \vee P_{1rep} > 0) \vee (P_{3down} > 0 \vee P_{3rep} > 0) \vee (P_{4down} > 0 \vee P_{4rep} > 0) \vee (P_{5down} > 0 \vee P_{5rep} > 0) \vee (P_{6down} > 0 \vee P_{6rep} > 0)$
t_{20}	$(P_{1up} > 1) \wedge (P_{2up} > 0) \wedge (P_{3up} > 2) \wedge (P_{4up} > 1) \wedge (P_{5up} > 1) \wedge (P_{6up} > 2)$
t_{21}	$(P_{1down} > 0 \wedge P_{1rep} > 0) \vee (P_{1down} > 1 \vee P_{1rep} > 1) \vee (P_{2down} > 0 \vee P_{2rep} > 0) \vee (P_{3down} > 0 \wedge P_{3rep} > 0) \vee (P_{3down} > 1 \wedge P_{3rep} > 1) \vee (P_{3down} > 2 \vee P_{3rep} > 2) \vee (P_{4down} > 0 \wedge P_{4rep} > 0) \vee (P_{4down} > 1 \vee P_{4rep} > 1) \vee (P_{5down} > 0 \wedge P_{5rep} > 0) \vee (P_{5down} > 1 \vee P_{5rep} > 1) \vee (P_{6down} > 0 \wedge P_{6rep} > 0) \vee (P_{6down} > 1 \wedge P_{6rep} > 1) \vee (P_{6down} > 2 \vee P_{6rep} > 2)$
t_{22}	$(P_{1up} > 0) \wedge (P_{2up} > 0) \wedge (P_{3up} > 0) \wedge (P_{4up} > 0) \wedge (P_{5up} > 0) \wedge (P_{6up} > 0)$

The power supply subsystem shows minimal influence on system availability during repairs; however, its failure has a comparatively greater impact on system availability than the repair process itself, as shown in Figure 6. The repair rate of this subsystem increased from 0.003 to 0.2, resulting in system availability increasing from 0.9840 to 0.9864. Conversely, when the MTTF of this subsystem decreased from 5000 h to 3030 h , system availability decreased by 0.93%. The overall effect of system availability caused by this system is 1.17%, showing an extremely small impact.

Figure 7 illustrates the effect on system availability due to fluctuations in the MTTF and the repair processes of the power production subsystem. The reduction of the MTTF from 3700 h to 3300 h results in a reduction in system availability from 0.9545 to 0.9494, or 0.51%. Whenever the repair facility of this subsystem improves by 0.01 to 0.7, the system availability increases from 0.9545 to 0.9840. The overall effect of this subsystem on system availability is 3.46% due to its failure and subsequent repair.

The variation of the MTTF and repair rate of the air conditioning subsystem exerts a minimal impact on service availability, shown in Figure 8. As the repair facility of the subsystem increases from 0.025 to 0.25, the system's availability rises from 0.9781 to 0.9832; however, the MTTF of this subsystem fluctuates between 6200 h and 5800 h , resulting in a decrease in system availability from 0.9781 to 0.9758. The subsystem exerts a 0.74% influence on the overall availability of the entire UAV system.

Figure 9 shows the effect on system availability resulting from fluctuations in the MTTF and repair rates of the guidance and control subsystem. Analysis of our results shows that a decrease in the MTTF of this subsystem from 700 h to 300 h leads to a reduction of the system's availability from 0.9705 to 0.9629. The repair capability of this subsystem improves from 0.1 to 0.9, leading to an increase in system availability from 0.9705 to 0.9854. The overall system availability is affected by 2.25% due to the failure and repair process of this subsystem.

The overall effect of UAV systems availability, impacted by the MTTF and repair rate parameters of its subsystems, is illustrated in Figure 10.

The maintenance order priority for each subsystem has been determined by analyzing the failure and repair characteristics of each subsystem and their impact on overall system availability.

The number of repair personnel provides a crucial maintenance resource that significantly impacts system availability. The Petri net model of the UAV system, shown in Figure 3(a), depicts the location " $P_{repairman}$ ", indicating the availability of repair personnel who are immediately available for system repairs following a failure. The effect of the number of technicians on system availability is shown in Figure 11.

As the number of repair personnel increases, system availability correspondingly increases; nevertheless, over a particular number of technicians, system availability stabilizes at a steady level. As the number of technicians increases from 1 to 2, the system's availability improves from 0.9842 to 0.9961; however, when the number of

Table 4. MTTF and repair Data for the UAV subsystem.

Subsystem	MTTF h (hours)	Repair rate h^{-1} (hours)
Main display unit	1500	0.08
Data communication	800	0.06
Power supply	4000	0.07
Power generator	3500	0.09
Air conditioner	6000	0.065
Guidance and control	500	0.5

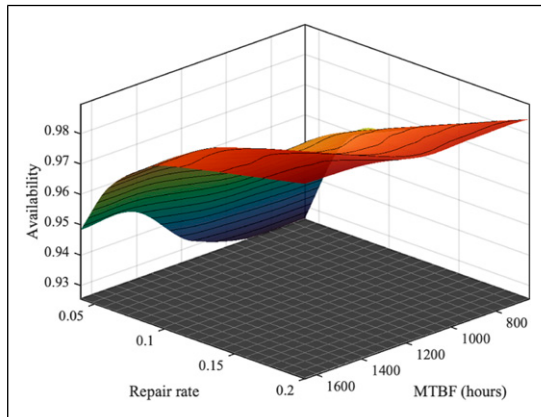


Figure 4. Effect on system availability due to the main display subsystem.

repair staff is beyond 2, the system's availability stabilizes at 0.9961. This analysis indicates that two repair technicians are sufficient for addressing the UAV subsystem in the event of a subsystem breakdown.

The reliability of UAV systems refers to the probability that the system will function properly under its intended operating conditions. In the GSPN model of the UAV Figure 3(c), the place " P_{Relib} " represents the reliability status of the system. In these places, two types of arcs are connected from the transition: input arcs and inhibitor arcs. In the presence of an inhibitor arc, firing occurs only when no token is available in the places P_{Relib} . This places obtains a token at the initial system failure, facilitating the assessment of the system's reliability. The reliability of the UAV systems depends on time, as seen in Table 5.

Initially, the entire UAV system is operational, resulting in a reliability is 1; nevertheless, as time passes, the system's reliability decreases. As time increases from 100 to 200, reliability decreases significantly from 0.9605 to 0.8822. After 200 hours, reliability undergoes a slight decrease; as time passes from 300 to 1000 hours, reliability decreases from 0.7915 to 0.6157.

Following an evaluation of the baseline system reliability, a further analysis was conducted to assess the variation in reliability across various parameter values, as

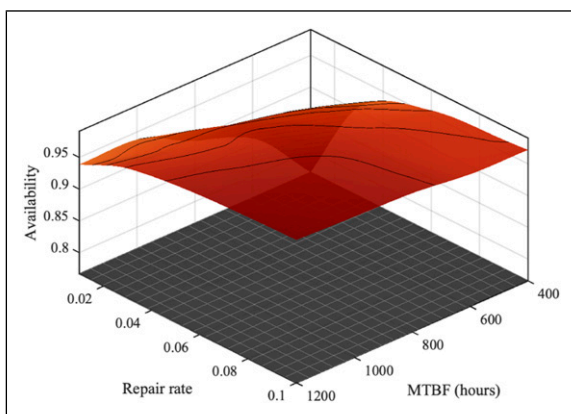


Figure 5. Effect on system availability due to data communications subsystem.

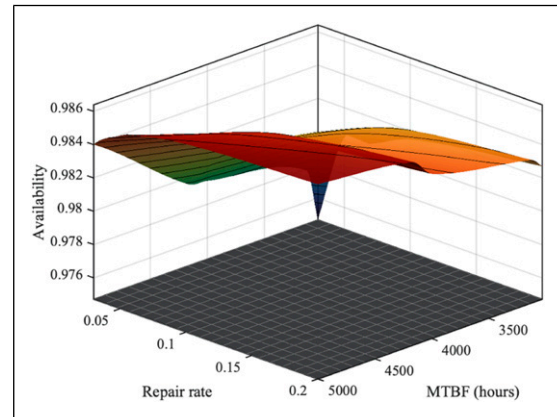


Figure 6. Effect on system availability due to power supply subsystem.

depicted in Figure 12. To achieve this objective, key model parameters, including MTTF and repair rate, were systematically varied. The evaluation of these parameters helps in understanding the system's sensitivity to each factor and enhances the understanding of the components that significantly affect overall reliability.

Theory of maintenance man-hours analysis

The MMH of a UAV system refers to the total amount of labor time required to complete corrective and preventive maintenance tasks on the system. In other words, it is the man-hours of a system that denote the total hours worked by labor on maintenance operations during an allocated time frame of the system. This includes planning, testing, breakdown, failure analysis, modification, component replacement or reassembly, and any calibration or testing required to restore the item to a serviceable condition. It is the key performance indicator employed to assess the maintainability or maintenance plan of any technical or manufacturing system.

Our primary objective is to maintain the UAV systems in a manner that enhances their reliability while

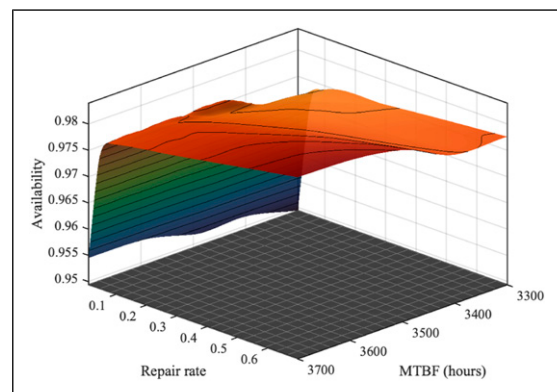


Figure 7. Effect on system availability due to power generation subsystem.

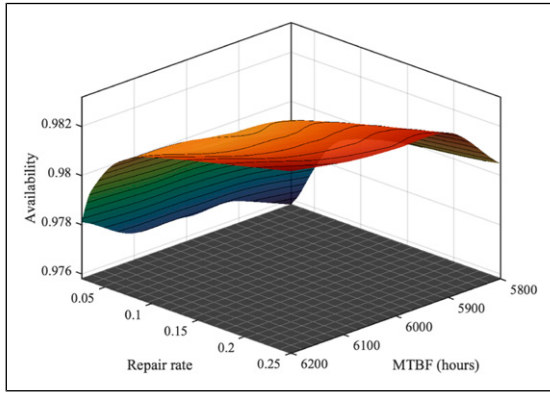


Figure 8. Effect on system availability due to air conditioner subsystem.

maximizing profit and minimizing costs. Therefore, MMH is essential, since higher MMH leads to substantial increases in operational expenses and diminished system availability, resulting in losses from both financial and operational perspectives. Analyzing MMH provides insights into improving the maintenance plan, determining necessary labor requirements, and reducing extra labor costs.

This study uses the following assumptions and notations to predict the MMH of the UAV systems.

The maintenance policy is based on the age replacement strategy, wherein components are replaced upon reaching a predetermined operational age.

The repair facility is limited; only one subsystem can be repaired at a given moment, while others remain in a waiting state of repair.

If a component fails before its scheduled maintenance interval, it is immediately replaced, without delaying the preventative replacement schedule.

θ : indicates the planned preventive replacement age of a component.

ψ : denotes the maintenance time calculation cycle.

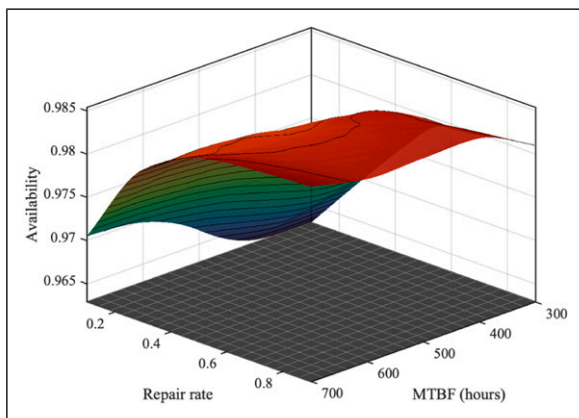


Figure 9. Effect on system availability due to guidance and control subsystem.

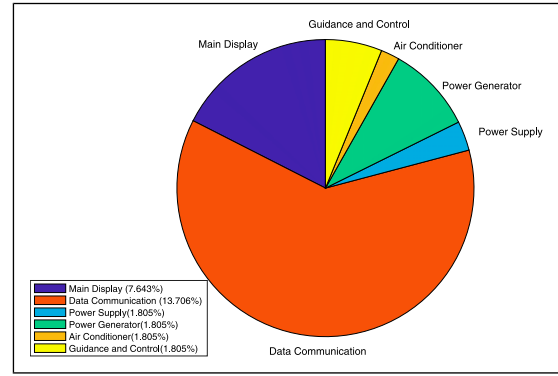


Figure 10. Impact of individual subsystems on overall system availability.

$M(\psi)$, $M(\theta)$: indicates the MMH due to failure replacement and preventative replacement, respectively.

δ_f , δ_p : represent the average failure replacement time and average preventive replacement time, respectively.

$R(\theta)$: denote the reliability of components at age θ .

$M(\psi, \theta)$: represents the total MMH associated with cycle ψ at a replacement age of θ .

α, β : represent the scale and shape parameters of the Weibull distribution, respectively.

t : denotes the time to failure of the components.

$f(x)$: denotes the probability density function of component failure times.

This study evaluates the total MMH of the UAV systems in accordance with its age replacement policy.

Analysis of MMH with the age replacement strategy

The age replacement strategy for UAV systems is a maintenance strategy in which the system is replaced at a predetermined age or interval, regardless of its operational

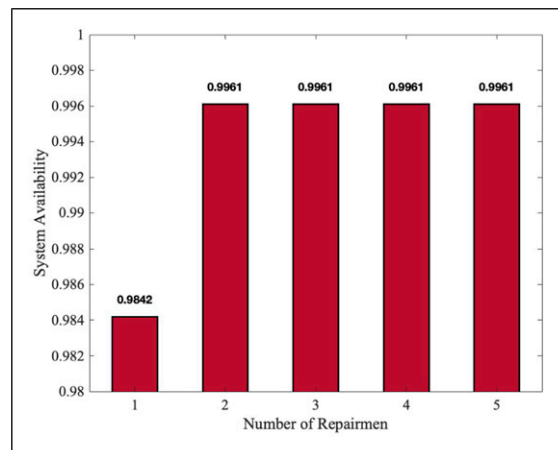


Figure 11. Effect of system availability based on the number of repair personnel.

Table 5. System reliability with Time.

Time (hours)	Reliability
100	0.9605
200	0.8822
300	0.7915
400	0.7436
500	0.7149
600	0.6916
700	0.6821
800	0.669
900	0.6450
1000	0.6157

status.⁵¹ If the system fails before this predetermined age, it will be replaced earlier than scheduled.

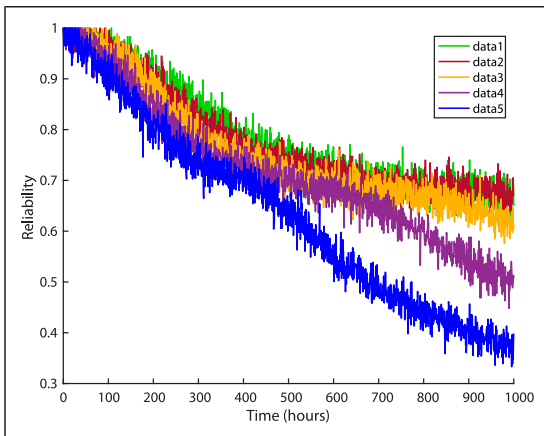
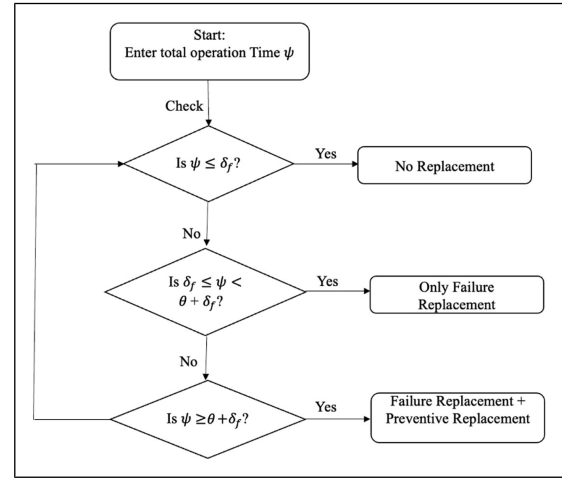
To examine the MMH of the UAV systems, we will first define the maintenance strategy of our proposed system. The proposed UAV systems incorporate two types of maintenance strategies as follows:

- (1) **Preventive replacement:** This is a scheduled maintenance strategy in which components of UAV systems are replaced preventively after reaching a predetermined age θ , irrespective of their operational status. In this procedure, we determine the expected lifespan of the components designated for replacement. The MMH in this case refers to the replacement age and operational lifespan of the component before it reaches the designated replacement threshold.

The MMH in this case, which is denoted by $M(\theta)$, is the defined by the total period of preventative replacement δ_p and the reliability $R(\theta)$ of the system before reaching a specified age θ , as shown as follows:

$$M(\theta) = \delta_p R(\theta), \quad \forall \theta > 0. \quad (1)$$

- (2) **Failure replacement:** In this case, failure occurred before the planned preventive replacement

**Figure 12.** Reliability degradation curves of the UAV system with five different subsystem parameter configurations.**Figure 13.** Flowchart for determining a replacement type based on equipment operating time ψ .

or occurred randomly; hence, the components were replaced immediately following the failure. Let $E[N_f\psi]$ be the expected number of failures in period ψ and δ_f denote the failure time replacement, representing the overall duration required for the replacement of the component due to its failure.

The MMH in this case, which is denoted by $M(\psi)$, is the duration of failure to repair and the probability of failure occurring, as specified by:

$$M(\psi) = \delta_f E[N_f\psi], \quad \forall \psi > 0. \quad (2)$$

Formulation of the mathematical model

To calculate the total maintenance work hours of UAV systems and their components, a mathematical model is developed by examining the behavior of each component of the UAV system. This analysis predicts the total operational lifetime of each component and the preventive cycle duration for age-based replacement of each component. Using the MTTF data of each component, we evaluated our findings for the total MMH of the system across three distinct cases, as shown by flowcharts in Figure 13, which provides a summary of the instances important for this research study.

- (1) **Case 1:** $0 \leq \psi \leq \delta_f$

The components of the UAV systems failed randomly before our observation period. The entire observation time is less than or equal to the failure replacement time. The replacement of component failure extends beyond our observation period or the time barriers ψ , as shown in Figure 14. In this instance, no replacement is necessary. In this case, there are no assigned working hours for maintenance, so the total MMH of the system, which is denoted by $M(\psi, \theta)$, is given as:

$$M(\psi, \theta) = 0, \quad \forall \psi > 0, \theta > 0. \quad (3)$$

(2) **Case 2:** $\delta_f < \psi \leq \theta + \delta_f$

The total observation duration exceeds the failure replacement time δ_f , as the failure occurs at time t before the interval $\psi - \delta_f$. The time period does not exceed the allowed preventative maintenance age θ , as shown in Figure 15.

The total MMH in this case includes the period essential to identify the fault and the time required to replace the faulty spare components, as shown in the following equation:

$$M(\psi, \theta) = \int_0^{\psi - \delta_f} (\delta_f + M(\psi - t - \delta_f, \theta)) f(t) dt \quad (4)$$

$$\forall \psi > 0, \theta > 0,$$

where failure happens at time $t \in [0, \psi - \delta_f]$, and $f(t)$ denotes the probability density function of failure time.

(3) **Case 3:** $\psi > \theta + \delta_f$

In this instance, the components reach their preventive replacement cycle θ during observation time ψ . Failure replacement is also taken into consideration in this situation, since there may be a chance that the system will fail before time $\psi - \delta_f$ as $t \in [0, \psi - \delta_f]$. Thus, as Figure 16 illustrates, the total MMH in this instance is the time spent on failure and replacement as well as preventive and replacement.

The total MMH or working hours resulting from the replacement failure are given by

$$M(\psi, \theta) = \delta_f + M(\psi - t - \delta_f, \theta) \quad \forall \psi > 0, \theta > 0. \quad (5)$$

The working hours that resulted from the replacement of the preventive measure are given by

$$M(\psi, \theta) = \delta_p + M(\psi - t - \delta_p, \theta). \quad (6)$$

The probabilities of failure within the defined unit interval $[0, \theta]$ relate to the unreliability at period θ , while the probability of reliable operation within that interval

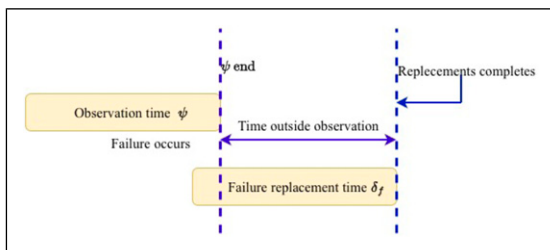


Figure 14. System behavior when the observation time is less than or equal to the failure replacement time.

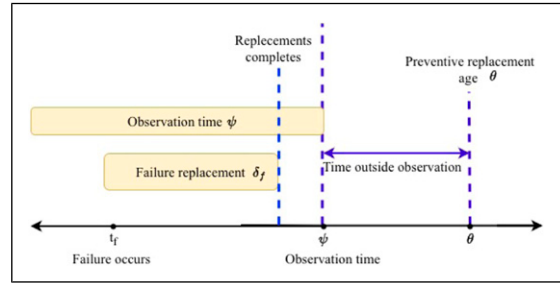


Figure 15. System behaviour when the observation time is less than or equal to the preventive replacement time.

equates to its reliability at period θ . The total MMH in this instance is expressed as, for $t \in [0, \theta]$

$$M(\psi, \theta) = (\delta_p + M(\psi - t - \delta_p, \theta)) R(\theta) + \int_0^\theta (\delta_f + M(\psi - t - \delta_f, \theta)) f(t) dt. \quad (7)$$

Numerical illustrations

In the proposed UAV systems, the MMH of each subsystem is determined under the age replacement policy, where components are replaced upon reaching a pre-determined age or in the event of random failure. The MTTF values for each subsystem are hypothetical yet realistic, derived from.⁵⁰ For illustrative purposes, these values fluctuate within a defined range to facilitate a more effective analysis of the variation results. Table 6 presents the MTTF values for each subsystem of the UAV system, along with the Weibull scale (α) and shape (β) parameters, which are derived from the MTTF data.

In maintenance planning, the age replacement policy is a proactive strategy that is determined based on the characteristic life of the Weibull distribution parameters. The Weibull distribution scale parameter indicates the time at which approximately 63.2% of the population is likely to fail. To minimize the risk of unforeseen failures and optimize maintenance costs, age replacement is scheduled prior to the majority of failures, often at 60% to 90% of the scale parameter value. This proactive approach allows us to be prepared and in control, ensuring that age replacement is implemented before any breakdown occurs.

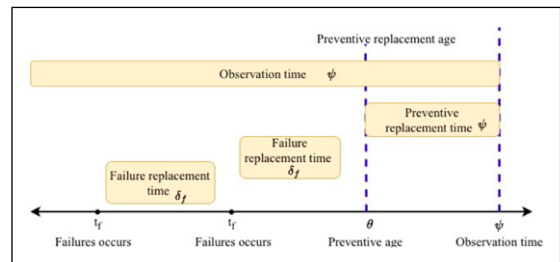


Figure 16. System behaviour when total replacement time is less than or equal to the observation time.

Table 6. Calculation of the Weibull parameter values of UAV subsystems (1–5 years).

Subsystem	Different values of MTTF (h)					Scale α (h)	Shape β
Main display	1650	1575	1500	1425	1350	2220.71	1.1206
Power supply	5000	4050	4000	3050	3000	7193.74	1.3224
Power generator	3700	3600	3500	3400	3300	4201.32	1.0690
Air conditioner	6200	6100	6000	5900	5800	6561.27	1.0403
Guidance and control	550	525	500	475	450	833.15	1.1206

In this study, the preventive replacement thresholds of 60%, 70%, 80%, and 90% of the Weibull characteristic life (α) are selected to represent early, moderate, and late preventive maintenance decisions before the expected failure age. These thresholds are used to systematically evaluate how different replacement schedules influence the MMH of each subsystem and to provide a practical comparison of maintenance planning strategies. The objective of this study is to compare the maintenance performance under different preventive replacement schedules rather than determine an optimal replacement threshold. The optimization of the replacement interval based on minimum MMH or maintenance cost is an important extension of this work and will be considered in future research.

For illustration purposes, we schedule the replacement age of each component of the UAV system at different ages of its corresponding α value and identify their effect on the MMH of each subsystem. Figure 17 presents a graphical representation of the scheduled choice age replacement time for each subsystem based on various values of α .

Afterwards, the scheduled age replacement of each component requires consideration of two types of maintenance events: failure replacement and preventive replacement. Failure replacement occurs when the subsystem fails prior to the scheduled replacement age, whereas preventive replacement is executed according to the planned replacement schedule. Failure and preventive replacement are essential to improve system performance and calculate the total MMH of each subsystem. Accurate accounting for these types of maintenance key indicators in optimizing maintenance planning ensures the continuous running of the overall systems.

The values of failure replacement (δ_f) and preventive replacement (δ_p) for each subsystem of the UAV systems are determined based on the system's design complexity and operational processes. Due to the unavailability of real data for each subsystem replacement, this research utilizes hypothetical yet realistic data. These data were meticulously selected based on the behavior of each subsystem and its corresponding maintenance schedules, ensuring their accuracy and reliability. Table 7 provides the required failure replacement and preventive replacement time periods for each subsystem within the UAV systems.

The total MMH for each subsystem of the UAV systems is computed based on the system's failure characteristics, maintenance approach, and age replacement policy. To evaluate the MMH of each subsystem, their

MTTF data are realistically acquired from the research.⁵⁰ For illustrative purposes, we have estimated the total MMH of each subsystem based on all conceivable appropriate cases of the age replacement strategy. Table 8 presents the period of service technicians for each subsystem within the age replacement framework.

After estimating the total MMH for each subsystem, the results highlight significant differences in maintenance effort dependent upon the selected age replacement schedule, emphasizing the importance of our research. The main display unit subsystem MMH shows a value of 7 hours when age replacement is scheduled at 60–80% of α . However, a slightly reduced MMH of 6 hours is observed when the component replacement age is set at 90% of the α value, indicating the potential benefits of adjusting the replacement schedule.

It is analyzed that the power supply subsystem requires a total number of 4 hours of MMH for the replacement of defective components, the preventative replacement of all components in every possible situation, and the execution of an age replacement strategy. The analysis of the age replacement policy for the power generator subsystem reveals that, in the event of replacement at 60% of its characteristic life, the maintenance staff will require 40 hours to complete the task. In the case where the subsystem adopts an age replacement policy of 70% of its characteristic life, the maintenance staff will need 39 hours. If the subsystem adopts an age replacement policy of 80% of its characteristic life, then 38 hours of MMH are identified. Moreover, in scenarios where this subsystem's age replacement policy is decided upon at

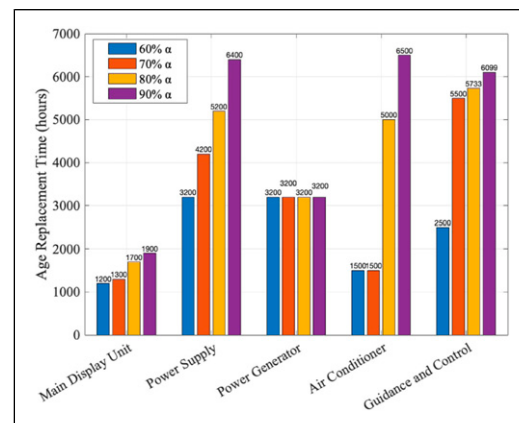
**Figure 17.** Scheduled age replacement of each subsystem for different α values.

Table 7. Period of failure replacement and preventive replacement of each subsystem in the UAV systems.

Subsystem	δ_p (hours)	δ_f (hours)
Main display unit	3	8
Power supply	5	18
Power generator	24	96
Air conditioner	8	36
Guidance and control	10	60

90% of its characteristic life, a total of 37 hours of MMH are required.

Upon considering the most appropriate age replacement policy for the air conditioner subsystem, it has been determined that a total of 10 hours of MMH are needed when the age replacement is set at 60% of its characteristic life. Meanwhile, 9 hours of MMH are required when the age replacement has been selected between 70% and 90% of its characteristic life.

When the guidance and control subsystem's age replacement policy is configured with the most appropriate choices, the total MMH variation of this subsystem is identified under a distinct age replacement policy. When the age replacement of this subsystem is set at 60% of the characteristic life, the total MMH is determined to be 109 hours. However, when the age replacement value is set at 70% of the characteristic life, the total MMH is identified as 107 hours, indicating a reduction in maintenance hours. As the age replacement value of this subsystem reaches 80% of its characteristic life value, the total MMH for this subsystem is determined to be 105 hours, further reducing the maintenance hours required. Meanwhile, if the age replacement value is set at 90% of its characteristic life value, the total MMH is identified as 104 hours for maintaining this subsystem, reinforcing the trend of reduced maintenance hours with higher replacement levels.

The results show that different preventive replacement thresholds influence the maintenance effort required for each subsystem. The proposed analysis enables maintenance planners to compare alternative preventive replacement schedules according to operational requirements and available maintenance resources. Although the 60%-90% thresholds provide a practical comparison of maintenance performance, determining the

Table 8. Calculation of the Maintenance man-hours of each subsystem.

Subsystem	MMH	MMH	MMH	MMH
	60% α	70% α	80% α	90% α
Main display unit	7	7	7	6
Power supply	4	4	4	4
Power generator	40	39	38	37
Air conditioner	10	9	9	9
Guidance and control	109	107	105	104

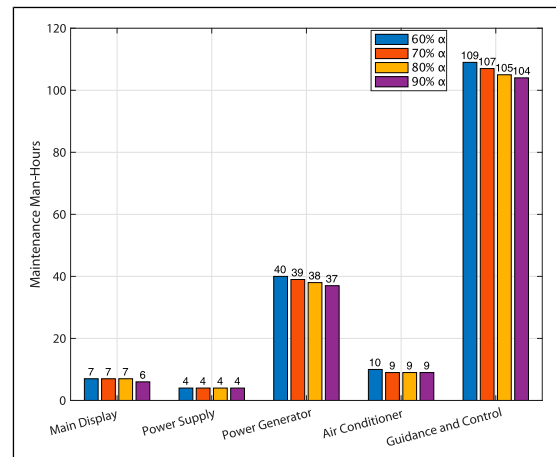
optimal replacement threshold by minimizing the total MMH or maintenance cost is beyond the scope of the present study and will be considered in future work.

The analysis of the age replacement behavior of each subsystem provides insightful results that may offer significant recommendations for practical implementations. Varying the age replacement technique produces significant or slight differences in the overall MMH of each subsystem, depending upon the specific subsystem. Figure 18 shows a graphic representation of the total MMH value fluctuations for each subsystem, showing the practical significance of our findings in real-world maintenance strategies.

Discussion on input data uncertainty

The numerical results presented in this study are based on hypothetical yet realistic maintenance and reliability parameters due to the limited public availability of operational UAV maintenance data. Such information, including subsystem failure characteristics, repair rates, and maintenance records, is generally not publicly available because UAV operational data are confidential. Therefore, the hypothetical data are used to demonstrate the proposed GSPN framework and to illustrate how it can be applied for the reliability and maintenance analysis of UAV systems.

To examine the impact of uncertainty in the input data, the failure and repair parameters of each subsystem were varied over a realistic range, and the corresponding changes in the overall system availability were evaluated. The results demonstrate that the proposed GSPN model consistently captures the influence of these parameter variations. For the Main Display subsystem, the overall system availability changes from 0.9258 to 0.9897 as different combinations of failure and repair parameters are considered. The Data Communication subsystem shows the largest variation in system availability, ranging from 0.7660 to 0.9909. This indicates that uncertainty in the failure and repair parameters of this subsystem has the

**Figure 18.** Maintenance Man-hours of each subsystem with different values of age replacement.

greatest impact on the overall availability of the UAV system. For the Power Supply subsystem, the availability varies between 0.9747 and 0.9864, while for the Power Generator subsystem it ranges from 0.9494 to 0.9840. Similarly, the Air Conditioner subsystem produces availability values between 0.9758 and 0.9832, and the Guidance and Control subsystem varies from 0.9629 to 0.9854. These results show that changes in the subsystem failure and repair parameters lead to corresponding changes in the overall system availability, as expected. However, the system availability changes consistently with variations in the failure and repair parameters of each subsystem. This indicates that the proposed GSPN model is capable of evaluating the effect of uncertainties in the input data on the overall system availability. The graphical representation of the system availability under different subsystem failure and repair parameter combinations is presented in Figures 4–9.

The effect of uncertainty in the input failure data was also evaluated by analyzing the system reliability under different combinations of subsystem failure parameters. The corresponding reliability curves are presented in Figure 12. For one representative dataset, the system reliability decreases from 0.9605 at 100 hours to 0.6157 at 1000 hours. The remaining datasets show a similar decreasing trend, although the rate of degradation varies with the selected failure parameters. At 1000 hours, the reliability ranges from approximately 0.37 to 0.68 for the different datasets. These results indicate that uncertainty in the input failure data directly affects the predicted system reliability, while the proposed GSPN model consistently captures this behaviour under different operating conditions.

The influence of uncertainty in the maintenance planning parameters was also examined by evaluating the MMH under different age replacement thresholds corresponding to 60%, 70%, 80%, and 90% of the Weibull characteristic life. The results show that changing the replacement threshold directly affects the maintenance effort required for each subsystem. For example, the MMH of the Power Generator subsystem decreases from 40 hours at 60% of the Weibull characteristic life to 37 hours at 90%, while the Guidance and Control subsystem decreases from 109 hours to 104 hours over the same range. A similar behaviour is observed for the remaining subsystems. These results indicate that the proposed maintenance framework effectively captures the influence of different maintenance planning decisions on the required maintenance effort.

Overall, the above results show that changes in the failure, repair, and maintenance parameters directly affect the predicted availability, reliability, and MMH of the UAV system. This confirms that the proposed GSPN framework is capable of capturing the effect of uncertainty in the input data. Although hypothetical but realistic data are used in this study, the proposed methodology can be applied to real UAV operational data when such information becomes available. Future work will focus on incorporating input uncertainty through approaches such

as interval analysis, fuzzy reliability modelling, or possibility theory.

Conclusions and future work

The reliability and MMH of UAV systems are crucial factors for their extended operation. This study examined the reliability, availability, and MMH of the UAV systems. The GSPN has been used for stochastic modeling to examine the availability and reliability of systems. The simulation results from the GSPN indicate that, due to variations in MTTF and the repair rate of the power supply subsystem, the maximum system availability is 99.05%. Our observations indicate that the data communication subsystem of the UAV system is more critical, as it affects system availability by 13.70%. In contrast, the air conditioner subsystem is less critical, impacting system availability by 1.80%. The maintenance order priority of the UAV subsystems has been determined as the basis for the availability outcome. The data communication subsystem necessitates higher maintenance, while the air conditioner requires lower maintenance compared to others. The GSPN modeling approach determines the required number of repairmen in UAV systems. Analysis indicates that two repairmen are sufficient to repair the system. The system initially shows high reliability; however, as its lifespan increases, its reliability consistently diminishes. After 1000 hours of operation, the system's reliability diminishes by exactly 61.57%.

Furthermore, the required total number of MMH for each UAV subsystem has been determined. The required man-hours for system maintenance have been determined using the age replacement strategy. The results show that maintaining the guidance and control subsystem requires significantly more man-hours, averaging 104 to 109 hours. Preventive replacement takes 10 hours, while failure replacement requires 60 hours, both of which exceed the time needed for comparison with other subsystems. The results from this study are beneficial for the UAV design team in determining optimal maintenance planning to enhance the operational hours and reliability of UAV systems.

Future studies can improve this research by incorporating real operational data to refine failure and repair distributions, thereby validating the Petri net model more accurately. Expanding the modeling framework to include semi-Markov or non-exponential distributions will enhance the representation of component behavior.

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