



Reliability and maintainability analysis of unmanned aerial vehicle under varied environmental conditions

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ABSTRACT

This paper presents a unified framework for modeling the reliability and maintainability of Unmanned Aerial Vehicle (UAVs) systems composed of multiple subsystems, such as the mission control unit (MCU), flight control unit (FCU), actuators, sensors, communication modules, and the ground control unit (GCU). A cost dimension is explicitly introduced alongside reliability analysis, extending the traditional non-linear wear-out degradation model to account for environmental, operational, and cost-related constraints. An optimization problem is formulated to minimize total subsystem degradation under these considerations. To validate the approach, a simulation framework is used to compare theoretical predictions with real-time degradation using Python and MATLAB. The results demonstrate that the proposed cost-augmented reliability model more accurately reflects UAV performance and resource utilization, offering a practical foundation for adaptive maintenance and operational planning.

1. Introduction

Unmanned Aerial Vehicles (UAVs) have emerged as critical assets in a wide range of civilian and military applications, including surveillance, package delivery, precision agriculture, disaster management, and search-and-rescue missions. Their versatility and operational flexibility make them indispensable in modern technological ecosystems. However, the increasing deployment of UAVs in dynamic and often harsh environments raises important concerns regarding their long-term reliability and maintainability. UAVs are composed of multiple interdependent subsystems — such as the mission control unit (MCU), flight control unit (FCU), actuators, sensors, communication modules, and ground control unit (GCU) — each of which is subject to degradation over time. The performance of the overall UAV system, therefore, depends on both the individual reliability of these subsystems and the strategies adopted for their timely maintenance.

Reliability engineering provides the theoretical and methodological foundation for assessing the probability of failure-free operation of UAVs over time. Traditional reliability models frequently employ exponential, Weibull, lognormal, or Gamma distributions to characterize subsystem lifetimes under static operating conditions. However, UAVs typically operate in environments characterized by stochastic variations

in factors such as wind speed, temperature, and mission intensity, all of which can accelerate degradation processes and alter failure behavior. This motivates the need for environment-dependent reliability models that more accurately reflect real-world operating conditions. Complementing reliability analysis, maintainability focuses on the ease and timeliness with which UAVs can be restored to service following partial degradation or failure. Together, reliability and maintainability are vital for ensuring sustained mission readiness, minimizing downtime, and optimizing lifecycle costs.

Recent research has emphasized the importance of incorporating environmental variability and cost constraints into reliability and maintenance frameworks. While conventional models offer valuable insights, they often neglect the fact that subsystem degradation is not only time-dependent but also strongly environment-driven. Furthermore, maintenance planning for UAVs must account for both preventive and corrective actions under limited resources and budget constraints. As a result, optimization-based approaches that integrate reliability, maintainability, and cost considerations have gained prominence, enabling operators to make informed decisions that balance system performance with economic feasibility.

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2. Literature review

The reliability and maintainability of complex engineering systems have been extensively studied using stochastic modeling frameworks. In particular, aggregated stochastic and Markov-based processes have been widely applied to reliability analysis of multi-component systems [1–6]. These approaches provide tractable analytical tools for modeling system evolution under random failures and repairs. Extending this line of work, Csenki [7–9] made foundational contributions to semi-Markov reliability theory by introducing availability measures such as interval availability and joint availability for finite-state systems. These studies form the theoretical basis for modeling systems with non-exponential sojourn times and state-dependent transitions.

Reliability and maintainability have also been central themes in classical engineering system analysis. Jardine and Tsang [10] provided a comprehensive framework for maintenance engineering, formalizing concepts related to failure modeling, replacement policies, and maintenance optimization. Complementing this systems-oriented perspective, Meeker and Escobar [11] introduced rigorous statistical methodologies for reliability data analysis, including parametric lifetime modeling, parameter estimation, and goodness-of-fit assessment. These statistical foundations remain widely used in aerospace, communication, and safety-critical systems and motivate the probabilistic modeling choices adopted in this study.

A significant body of literature focuses on degradation-based reliability modeling, which captures gradual performance deterioration rather than sudden failures. Gorjian et al. [12] presented a comprehensive review of degradation models and demonstrated their effectiveness in representing aging and wear mechanisms. Closely related is the field of maintenance optimization. Ben-Daya et al. [13] outlined general strategies for cost-effective maintenance planning, while Ding and Tian [14] developed opportunistic maintenance policies under imperfect repair assumptions. Although some of these studies were originally motivated by renewable energy systems, their underlying principles are directly applicable to UAV operations, where environmental stress, stochastic degradation, and cost constraints play a critical role. Building on these insights, the present work develops a degradation- and cost-aware optimization framework tailored to UAV subsystems.

Another important research direction concerns environment-dependent reliability estimation. Hu and Yang [15] demonstrated that environmental indicators can significantly alter lifetime distribution parameters and proposed maximum likelihood-based estimation methods under varying operating conditions. In the context of UAV systems, Petritoli et al. [16] proposed a logistic framework for optimizing maintenance scheduling, while Dui et al. [17] investigated the interplay among importance measures, maintenance strategies, and system resilience. Chen et al. [18] analyzed k -out-of- n phased-mission systems with phase-dependent requirements, and Zalisky et al. [19] conducted a comparative reliability study of UAV systems under technical deterioration, both with and without redundancy. These studies highlight the necessity of system-level reliability modeling under realistic operational conditions.

Simulation-based approaches have also been widely adopted for UAV reliability assessment, particularly when analytical solutions become intractable. Hua et al. [20] proposed a Monte Carlo-based method for evaluating UAV reliability modeled as a k -out-of- n pairs system. Yin et al. [21] extended this idea to multi-UAV disaster rescue missions, modeling system behavior as a dynamic k -out-of- n structure with shared UAV resources. Wang et al. [22] incorporated multiple functional dependence (FDEP) groups into phased-mission system analysis using Markov chains, while Xing et al. [23] developed efficient exact methods for evaluating k -out-of- n phased-mission systems with phase-varying requirements and failure distributions. More recently, Hou et al. [24] explored joint optimization of communication, computing, and caching, introducing the concept of *expected latency* as a combined performance and reliability metric.

Several studies address UAV-specific operational and maintenance considerations. Jiang et al. [25] employed techniques such as the Fuzzy Weighted Geometric Mean (FWGM), Benchmark Adjustment Search Algorithm (BASA), and Minimum Cut Sets (MCSS) for UAV reliability evaluation. Gonçalves et al. [26] proposed a methodology for establishing an initial UAV maintenance program using the MSG-3 logic method while accounting for safety through failure probability analysis. Manickam et al. [27] investigated multisource localization using multiple UAVs equipped with sensors, and Suresh et al. [28] proposed autonomous guidance strategies for single and multiple UAVs operating under emergency mission scenarios. While these works focus on specific UAV functionalities, they collectively underscore the importance of reliable subsystem coordination and maintenance planning in UAV operations.

Recent studies have emphasized the growing importance of rigorous reliability assessment and system-level analysis for UAV platforms and swarms. Xing and Johnson [29] provided a comprehensive synthesis of reliability theory and practical reliability engineering techniques for UAV systems, highlighting failure mechanisms, degradation behavior, and maintenance-oriented reliability metrics applicable to modern unmanned platforms. Extending the reliability perspective from individual UAVs to coordinated fleets, Zaitseva et al. [30] presented a detailed review of reliability assessment methods for drone swarms, identifying key challenges related to swarm topology, redundancy, and inter-UAV dependency, and proposing an importance-based structural evaluation framework to quantify the impact of individual UAV failures on overall swarm reliability. Simulation-driven analysis of swarm behavior has also gained prominence; Marek et al. [31] investigated the efficiency and adaptive characteristics of drone swarms within simulation environments, demonstrating how coordination strategies and environmental dynamics influence collective performance and robustness. Furthermore, Checker et al. [32] conducted a systematic review of multi-objective UAV swarm mission planning systems from a regulatory perspective, underscoring the necessity of incorporating reliability, safety, and compliance constraints alongside traditional performance objectives.

Despite the breadth of existing studies, limited attention has been paid to unified frameworks that jointly integrate reliability, degradation-based maintainability, environmental effects, and cost considerations at the subsystem and system levels for UAVs. The present work aims to bridge this gap by developing a comprehensive analytical and simulation-based framework that explicitly accounts for these interacting factors.

2.1. Contribution

UAVs are increasingly deployed in diverse applications such as surveillance, package delivery, agriculture, and search-and-rescue missions. However, their reliability is often compromised by environmental stresses, subsystem interdependencies, and frequent maintenance requirements. This paper advances UAV reliability research by integrating theoretical reliability and maintainability models with simulation-based validation, explicitly incorporating a time-dependent cost component that increases with physical degradation.

The contributions of this paper are twofold:

- An analytical framework is proposed to evaluate the reliability of a multi-subsystem UAV system.
- A maintainability model with simulation-based validation is developed, explicitly incorporating a time-dependent cost component that grows with subsystem degradation.

An optimization problem is formulated to minimize overall UAV degradation subject to environmental (wind speed and temperature) and cost constraints. The proposed framework demonstrates how theoretical predictions can be systematically validated against real-time

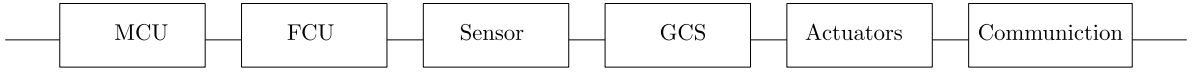


Fig. 1. Main subsystems of a UAV system.

simulation results, offering a practical pathway toward adaptive reliability and maintenance planning in UAV operations.

The remainder of this paper is organized as follows. Section 3 describes the reliability model of the UAV system. Section 4 defines the exponential wear-out model with environmental effects. Section 5 presents the proposed optimization framework for UAV maintainability analysis. Section 6 provides a detailed numerical illustration of the reliability and maintainability models. Finally, Section 7 concludes the paper.

3. Reliability model

In this study, the term *UAV system* refers to a single, self-contained unmanned aerial vehicle comprising multiple interacting subsystems, including mission control, flight control, sensing, actuation, communication, and ground control interfaces, etc. The reliability and maintainability analyses are performed at the subsystem level and subsequently aggregated to characterize the overall performance of an individual UAV. Cooperative multi-UAV systems, fleets, or swarm-based architectures are not considered in this work and are identified as potential extensions for future research. In this work, it is assumed that the UAV consists of multiple interdependent subsystems, listed as follows:

- **MCU Subsystem**
- **FCU Subsystem**
- **Sensor Subsystem**
- **GCU Subsystem**
- **Actuators Subsystem**
- **Communication Subsystem**

Fig. 1 shows the reliability block diagram (RBD) of the main subsystems of a UAV system.

The six subsystems considered in this study — MCU, FCU, sensors, actuators, communication module, and GCU — are selected to represent the primary functional layers governing UAV mission execution, control, perception, and coordination. While other components such as propulsion units and onboard energy storage (batteries) are also critical to UAV operation, their effects are implicitly reflected within the actuator and flight-control subsystems and through the degradation-driven and environment-dependent modeling framework.

In particular, propulsion-related degradation influences actuator performance and control effectiveness, while battery aging and energy depletion impact mission duration and operational stress, which are indirectly captured through time-dependent degradation, environmental loading, and cost accumulation. The proposed framework is modular, and additional subsystems such as propulsion and energy storage can be explicitly incorporated by extending the reliability block diagram and defining corresponding degradation and cost models. A detailed subsystem-level treatment of propulsion and battery dynamics is beyond the scope of the present study but it will be an important direction for future research.

The subsystem reliability is defined using a RBD as shown in Fig. 1. Each subsystems of the UAV system are arranged in series configuration. For comparison, different lifetime distributions are considered for each subsystem.

Exponential distribution: Let each subsystem (i) have a lifetime that follows an exponential distribution with failure rate parameter λ_i . The reliability of the i th subsystem is

$$R_i(t) = e^{-\lambda_i t}. \quad (1)$$

The reliability of the entire UAV system at time t is

$$R(t) = \prod_{i=1}^6 R_i(t) = \prod_{i=1}^6 e^{-\lambda_i t} = e^{-\sum_{i=1}^6 \lambda_i t}. \quad (2)$$

Weibull distribution: Assume that the lifetime of subsystem (i) follows a Weibull distribution with shape parameter $k_i > 0$ and scale parameter $\eta_i > 0$. The reliability of the i th subsystem is

$$R_i(t) = e^{-\left(\frac{t}{\eta_i}\right)^{k_i}}. \quad (3)$$

Accordingly, the system reliability is given by

$$R(t) = \prod_{i=1}^6 R_i(t) = \prod_{i=1}^6 e^{-\left(\frac{t}{\eta_i}\right)^{k_i}} = e^{-\sum_{i=1}^6 \left(\frac{t}{\eta_i}\right)^{k_i}}. \quad (4)$$

Gamma distribution: Let the lifetime of subsystem (i) follow a Gamma distribution with shape parameter $\alpha_i > 0$ and scale parameter $\beta_i > 0$. The reliability function is

$$R_i(t) = 1 - \frac{1}{\Gamma(\alpha_i)} \gamma(\alpha_i, \beta_i t), \quad (5)$$

where $\Gamma(\cdot)$ denotes the Gamma function and $\gamma(\cdot, \cdot)$ is the lower incomplete Gamma function. The overall UAV system reliability is then

$$R(t) = \prod_{i=1}^6 R_i(t) = \prod_{i=1}^6 \left[1 - \frac{1}{\Gamma(\alpha_i)} \gamma(\alpha_i, \beta_i t) \right]. \quad (6)$$

Lognormal distribution: Assume that the lifetime of subsystem (i) follows a lognormal distribution with parameters μ_i and $\sigma_i > 0$. The reliability of the i th subsystem is

$$R_i(t) = 1 - \Phi\left(\frac{\ln t - \mu_i}{\sigma_i}\right), \quad (7)$$

where $\Phi(\cdot)$ denotes the standard normal cumulative distribution function. The corresponding system reliability is

$$R(t) = \prod_{i=1}^6 R_i(t) = \prod_{i=1}^6 \left[1 - \Phi\left(\frac{\ln t - \mu_i}{\sigma_i}\right) \right]. \quad (8)$$

In the initial stage of reliability modeling, the exponential distribution is employed as a baseline to introduce the RBD formulation and to derive closed-form expressions for system-level reliability under simplifying assumptions. The exponential model assumes a constant failure rate and is commonly used in preliminary reliability analysis due to its analytical tractability and interpretability. However, this assumption is restrictive for UAV subsystems, which are subject to aging, wear-out, and environment-induced degradation effects.

To capture these realistic failure mechanisms, the analysis is subsequently extended to the Weibull and Gamma distributions, which provide greater modeling flexibility through their shape parameters. In particular, the Weibull distribution generalizes the exponential distribution as a special case when the shape parameter equals unity and allows for increasing failure rates when the shape parameter exceeds one. Such behavior is consistent with the progressive degradation observed in UAV components operating under variable environmental and operational stresses. The selection of the Weibull distribution is further supported by statistical considerations. For identical mean times between failures, the Weibull model exhibits superior flexibility in representing aging behavior compared to exponential, Gamma, and lognormal alternatives, as illustrated in the comparative reliability analysis. All reliability functions and system-level reliability expressions are therefore based on Weibull-distributed subsystem lifetimes.

The reliability block diagram adopted in this study assumes a purely series configuration, implying that the failure of any critical subsystem results in system-level failure. This modeling choice represents a conservative, worst-case reliability scenario and is appropriate for mission-critical UAV operations where subsystems such as flight control, communication, and power management constitute single points of failure. In addition, the series configuration allows for transparent analytical development and facilitates the integration of degradation-based maintainability, environmental effects, and cost considerations.

It is acknowledged that practical UAV platforms may incorporate redundancy in selected subsystems, such as sensors, communication links, or navigation modules, to enhance fault tolerance. Within the proposed framework, such redundancy can be incorporated by replacing the corresponding series blocks with parallel or k -out-of- n reliability structures. While redundancy is expected to improve system reliability, it may also introduce additional maintenance complexity, cost, and interdependency effects, which must be jointly evaluated. A detailed quantitative analysis of redundant UAV architectures is beyond the scope of the present work and is identified as an important direction for future research.

3.1. Varied environmental conditions

Consider the case where the UAV flight time T follows a cumulative distribution function (CDF) $F(t; \alpha_1, \alpha_2)$, where α_1 represents an unknown environment-dependent parameter and α_2 is treated as fixed. Typical models include exponential, normal, lognormal, and Weibull distributions. Under complete sampling, the environmental indicator is assumed to directly influence equipment reliability. Consistent estimators of reliability and their predictions are obtained under different population distribution assumptions, and simulation results are used to assess the validity of the proposed method.

3.2. Preliminaries

The system reliability is expressed as

$$R(t; \alpha_1, \alpha_2) = P(T > t),$$

where T denotes the system lifetime with CDF

$$F(t; \alpha_1, \alpha_2) = P(T \leq t).$$

Let $T_1, T_2, \dots, T_n$ be independent and identically distributed (i.i.d.) observations. As the environment e varies, system reliability changes accordingly. Define T_e as the system lifetime under environment e , with the associated reliability function

$$R_e(t; \alpha_1, \alpha_2) = P(T_e > t).$$

Suppose $T_{e_1}, T_{e_2}, \dots, T_{e_n}$ are sampled from the distribution of T_e , where $e_1 < e_2 < \dots < e_k$. The estimator of $R_e(t; \alpha_1, \alpha_2)$ is constructed over the interval $[0, t]$. For values of $e \notin \{e_1, \dots, e_k\}$, the reliability cannot be directly estimated.

Among the distributions widely used in practice (exponential, normal, lognormal, and Weibull), a single parameter is generally assumed to capture the effect of the environmental indicator. In this study, α_1 is assumed to depend on e according to the parametric form

$$\alpha_1(e) = a_0 + a_1 e + a_2 e^2 + \dots + a_p e^p. \quad (9)$$

The corresponding reliability function is then given by

$$R_e(t; \alpha_1(e), \alpha_2) = 1 - F(t; \alpha_1(e), \alpha_2) = \int_t^{+\infty} f(x; \alpha_1(e), \alpha_2) dx, \quad (10)$$

where $f(\cdot)$ denotes the probability density function. If $\alpha_1(e)$ is monotone in e , then $R_e(t; \alpha_1(e), \alpha_2)$ is also monotone in e , resulting in an increasing or decreasing reliability model.

3.3. Reliability estimation

Throughout this manuscript, parameters without a hat (e.g., μ , σ^2 , α_1) denote true but unknown population quantities, while the corresponding hatted symbols (e.g., $\hat{\mu}$, $\hat{\sigma}^2$, $\hat{\alpha}_1$) denote their estimators obtained from observed data. This convention is adopted consistently for all distributional parameters, reliability measures, and degradation-related quantities.

It is observed that, if X and Y are random variables with $R_X(t) \leq R_Y(t)$ for $\forall t \geq 0$, then variable X is randomly smaller than Y . In this study, the Weibull and normal distributions are discussed. Let $T_{e(i)j}$ ($j = 1, 2, \dots, n_i$) be a random complete sample along with distribution population $W(\beta_i, \eta_i)$ (take $\eta_i = \eta(e_{(i)})$). Computing maximum likelihood estimators (MLE) $\hat{\beta}_i$ of β_i and $\hat{\eta}_i$ of η_i by

$$\frac{1}{\hat{\beta}_i} + \frac{1}{n_i} \sum_{j=1}^{n_i} \ln T_{e(i)j} - \frac{1}{n_i} \sum_{j=1}^{n_i} T_{e(i)j}^{\hat{\beta}_i} \ln T_{e(i)j} = 0, \quad (11)$$

$$\hat{\eta}_i = \left(\frac{1}{n_i} \sum_{j=1}^{n_i} T_{e(i)j}^{\hat{\beta}_i} \right)^{1/\hat{\beta}_i}. \quad (12)$$

The MLE $\hat{\beta}_i$ and $\hat{\eta}_i$ are the strong consistency estimators of β_i and η_i , respectively. Compute the MLE of $\mu_i = \mu(e_i)$ and σ^2 by using

$$\hat{\mu}_i = \frac{1}{n_i} \sum_{j=1}^{n_i} T_{e(i)j}; \quad \hat{\sigma}_i^2 = \frac{1}{n_i} \sum_{j=1}^{n_i} (T_{e(i)j} - \hat{\mu}_i)^2. \quad (13)$$

Let $T_e \sim F(t; \alpha_1(e), \alpha_2)$, namely, $\mu(\alpha_1(e), \alpha_2) \approx ET_e$ and $\sigma^2(\alpha_1(e), \alpha_2) \approx VarT_e$. The maximum likelihood estimators $\hat{\alpha}_1(e_i)$ and $\hat{\alpha}_{2i}$ are given under indicator e_i and complete sample size n_i . The parameters' MLE is strongly consistent, and the laws of the iterated logarithm provide,

$$\hat{\mu}(\hat{\alpha}_1(e_i), \hat{\alpha}_{2i}) - \mu(\alpha_1(e_i), \alpha_2) = O(\sqrt{\ln \ln n_i}) \text{ a.s.} \quad (14)$$

From the Central Limit Theorem, it is obtained that

$$\varepsilon_i = \sqrt{n_i} \frac{(\hat{\mu}(\hat{\alpha}_1(e_i), \hat{\alpha}_{2i}) - \mu(\alpha_1(e_i), \alpha_2))}{\sigma(\alpha_1(e_i), \alpha_2)} \sim N(0, 1). \quad (15)$$

Hence

$$\hat{\mu}(\hat{\alpha}_1(e_i), \hat{\alpha}_{2i}) = \mu(\alpha_1(e_i), \alpha_2) + \varepsilon_i \cdot \sigma(\alpha_1(e_i), \alpha_2) / \sqrt{n_i}. \quad (16)$$

For Weibull distribution, it is given that,

$$\hat{\eta}_i = b_0 + b_1 e_i + b_2 e_i^2 + \dots + b_p e_i^p + \frac{\sigma^2(\eta(e_i), \beta) \varepsilon_i}{\sqrt{n_i} \cdot \Gamma(1 + 1/\hat{\beta}_i)}, \quad (17)$$

where $b_r = \frac{a_r}{\Gamma(1 + 1/\hat{\beta}_i)}$ and $\sigma^2(\cdot)$ denotes the variance of the estimator, which arises from the asymptotic variance under the Central Limit Theorem.

But for normal distribution

$$\hat{\mu}_i = a_0 + a_1 e_i + a_2 e_i^2 + \dots + a_p e_i^p + \frac{\sigma \varepsilon_i}{\sqrt{n_i}}. \quad (18)$$

Let μ and $\hat{\mu}$ denote mean, a and $\hat{a}$ denote coefficients, ε and $\hat{\varepsilon}$ denote random errors, and E denotes environment indicator matrix.

$$\hat{\mu}(\hat{\alpha}_1(e_i), \hat{\alpha}_{2i}) = a_0 + a_1 e_i + a_2 e_i^2 + \dots + a_p e_i^p + \sigma(\alpha_1(e_i), \alpha_2) \cdot \varepsilon_i / \sqrt{n_i}, \quad (19)$$

where $i = 1, 2, \dots, k$, $\hat{\mu}_i = \hat{\mu}(\hat{\alpha}_1(e_i), \hat{\alpha}_{2i})$, and $\mu_i = \mu(\alpha_1(e_i), \alpha_2)$.

Let the matrices be

$$\hat{\mu} = \begin{pmatrix} \hat{\mu}_1 \\ \hat{\mu}_2 \\ \vdots \\ \hat{\mu}_k \end{pmatrix}, \quad \mu = \begin{pmatrix} \mu_1 \\ \mu_2 \\ \vdots \\ \mu_k \end{pmatrix}, \quad \hat{a} = \begin{pmatrix} \hat{a}_0 \\ \hat{a}_1 \\ \vdots \\ \hat{a}_p \end{pmatrix}, \quad a = \begin{pmatrix} a_0 \\ a_1 \\ \vdots \\ a_p \end{pmatrix}$$

$$E = \begin{pmatrix} 1 & e_1 & e_1^2 & \dots & e_1^p \\ 1 & e_2 & e_2^2 & \dots & e_2^p \\ \vdots & \vdots & \vdots & \ddots & \vdots \\ 1 & e_k & e_k^2 & \dots & e_k^p \end{pmatrix},$$

and

$$\hat{\varepsilon} = (\sigma(\alpha_1(e_1), \alpha_2)\varepsilon_1/\sqrt{n_1}, \dots, \sigma(\alpha_1(e_k), \alpha_2)\varepsilon_k/\sqrt{n_k})^T.$$

Hence,

$$\hat{\mu} = \mu + \hat{\varepsilon} = E\mathbf{a} + \hat{\varepsilon}.$$

When $k \geq p + 1$, the $p + 1$ columns of E denote a subset, and E is an inverse matrix. Therefore, it is obtained that

$$\mu = E\mathbf{a}, \quad \mathbf{a} = (E^T E)^{-1} E^T \hat{\mu}. \quad (20)$$

By using the least squares estimates theory, it is obtained that

$$\hat{\mathbf{a}} = (E^T E)^{-1} E^T \hat{\mu}. \quad (21)$$

The problem of varied environment reliability is discussed as follows. For $a < e_{(1)} < e_{(k)} < b$, the estimator is given by

$$\hat{\alpha}_1(e) = \hat{a}_0 + \hat{a}_1 e + \hat{a}_2 e^2 + \dots + \hat{a}_p e^p, \quad e \in [a, b]. \quad (22)$$

Define $\hat{\sigma}^2(\alpha_1(e), \alpha_2)$. Then $\hat{R}_e(t; \alpha_1(e), \alpha_2)$ is given by

$$\hat{R}_e(t; \hat{\alpha}_1(e), \hat{\alpha}_2) = 1 - F(t; \hat{\alpha}_1(e), \hat{\alpha}_2) = \int_t^{+\infty} f(x; \hat{\alpha}_1(e), \hat{\alpha}_2) dx.$$

4. Nonlinear wear-out degradation model with environmental effects

An *adjusted nonlinear wear-out model* is employed to characterize how each subsystem i degrades over time t under environmental influences and random uncertainties. This formulation allows flexible representation of linear and accelerated aging behavior through an adjustable exponent parameter. The degradation is expressed as [33]

$$\tilde{D}_i(t) = \phi_{i,1} + \theta_i t^{\phi_{i,2}}, \quad (23)$$

where

- Here, $\tilde{D}_i(t)$ denotes the original (unnormalized) degradation function of subsystem i at time t ,
- $\phi_{i,1}$ represents the initial degradation (e.g., due to manufacturing imperfections or prior usage),
- $\theta_i t^{\phi_{i,2}}$ is the intrinsic wear-out term, where θ_i scales the rate of degradation and $\phi_{i,2}$ determines whether the wear-out is linear, sublinear, or superlinear.

The exponent parameter $\phi_{i,2}$ governs the rate of degradation over time and allows the model to capture different aging behaviors. Specifically, when $\phi_{i,2} = 1$, the degradation evolves linearly with time. When $0 < \phi_{i,2} < 1$, the model represents sublinear (decelerating) degradation, where the rate of wear decreases over time. In contrast, when $\phi_{i,2} > 1$, the model captures superlinear (accelerating) degradation, reflecting progressive wear-out effects commonly observed in UAV subsystems under varying operational and environmental conditions.

Subsystem i is considered to experience a *soft failure* if $\tilde{D}_i(t)$ exceeds a predefined threshold $H_i^{(\text{soft})}$, where functionality is retained, but performance is degraded. If $\tilde{D}_i(t)$ crosses a higher threshold $H_i^{(\text{hard})}$, the subsystem undergoes complete failure. The hard failure threshold $H_i^{(\text{hard})}$ represents a catastrophic degradation level beyond which subsystem operation is no longer recoverable through maintenance actions. When the degradation level exceeds this threshold, the subsystem is assumed to undergo permanent failure and immediate mission termination. Consequently, states satisfying $D_i(t) \geq H_i^{(\text{hard})}$ are excluded from the maintainability analysis.

4.1. Normalized degradation function in $[0, 1]$

To avoid unbounded growth, degradation is normalized within the interval $[0, 1]$ by introducing a finite *maximum life* T_i for each subsystem. The degradation function is redefined as [11]

$$D_i(t) = \min \left\{ 1, \left(\frac{t}{T_i} \right)^{\phi_{i,2}} \right\}, \quad (24)$$

where $\phi_{i,2} > 1$ implies that degradation accelerates as t approaches T_i , eventually reaching 1. During normalization, the initial degradation parameter ϕ_1 is eliminated by shifting the degradation reference such that all subsystems start from a common baseline with zero normalized degradation at $t = 0$. This transformation enables meaningful comparison of degradation trajectories across subsystems with different initial health conditions. In addition, the scaling parameter θ_i is normalized to unity to express degradation evolution in relative units rather than absolute magnitude. This normalization preserves the temporal progression pattern while reducing parameter redundancy and simplifying subsequent analytical and optimization formulations. As a result, the normalized degradation expression no longer explicitly contains ϕ_1 and θ_i , without loss of generality in the degradation trend representation.

Interpretation:

- For $t < T_i$, the degradation satisfies $(t/T_i)^{\phi_{i,2}} < 1$, so $D_i(t)$ remains below 1. In particular, $D_i(t) \approx 0$ when $t \ll T_i$.
- As $t \rightarrow T_i$, $(t/T_i)^{\phi_{i,2}} \rightarrow 1$, indicating that the subsystem is fully worn out.
- For $t > T_i$, Eq. (24) clamps $D_i(t)$ at 1, preventing degradation from exceeding the hard-failure threshold.

Thus, $D_i(t)$ remains bounded in $[0, 1]$ for all t , where $D_i(t) = 1$ naturally corresponds to hard failure.

4.2. Two-parameter model (T , exponent)

The customized degradation function can be expressed with only two parameters:

$$p = [T, \text{exponent}],$$

so that

$$\hat{D}(t; p) = \min \left\{ 1, \left(\frac{t}{p(1)} \right)^{p(2)} \right\},$$

where

- $p(1) = T$ is the maximum lifetime, i.e., the time at which degradation reaches 1, and
- $p(2)$ is the exponent governing the rate at which degradation accelerates as $t \rightarrow T$.

This form guarantees that $\hat{D}(0) = 0$, increases monotonically with t , and saturates at 1.

4.3. Preventive maintenance intervals and random deviation

In practice, degradation does not follow the deterministic curve exactly; it fluctuates around the mean due to real-world uncertainties such as:

- manufacturing variability across components,
- heterogeneity in flight usage or maneuvering profiles, and
- unpredictable environmental shocks (e.g., gusts, thermal surges).

Thus, at any time t , the observed degradation can be modeled as

$$D_i^{(\text{actual})}(t) = D_i(t) + \varepsilon,$$

where ε is a random deviation term with $\mathbb{E}[\varepsilon] = 0$.

4.4. Soft failure probability

Define $H_i^{(\text{soft})}$ as the *soft-failure threshold*, beyond which subsystem i continues to operate but with reduced performance. The probability that subsystem i has entered soft failure by time t is

$$P_i^{(\text{soft})}(t) = \mathbb{P}(D_i^{(\text{actual})}(t) \geq H_i^{(\text{soft})}).$$

If the random deviation is normally distributed, $\varepsilon \sim \mathcal{N}(0, \sigma_i^2)$, then [11]:

$$\begin{aligned} P_i^{(\text{soft})}(t) &= \mathbb{P}(D_i(t) + \varepsilon \geq H_i^{(\text{soft})}) \\ &= \mathbb{P}(\varepsilon \geq H_i^{(\text{soft})} - D_i(t)) \\ &= 1 - \Phi\left(\frac{H_i^{(\text{soft})} - D_i(t)}{\sigma_i}\right), \end{aligned} \quad (25)$$

where $\Phi(\cdot)$ denotes the standard normal cumulative distribution function.

It is assumed that the soft failure threshold satisfies $H_i^{(\text{soft})} < H_i^{(\text{hard})}$, such that soft failures correspond to recoverable degradation states occurring prior to catastrophic subsystem failure. The hard failure constraint $D_i(t) \leq H_i^{(\text{hard})}$ is implicitly enforced in the model through the bounded degradation formulation $D_i(t) \in [0, 1]$ and the definition of hard failure as a terminal state beyond which the subsystem is no longer considered in the maintainability analysis. Therefore, states satisfying $D_i(t) \geq H_i^{(\text{hard})}$ are excluded from further evaluation, and the simulation framework terminates the subsystem operation once this threshold is reached. As a result, this omission does not affect the reported results.

4.5. Wind and temperature integration into the degradation model

In the preceding sections, each subsystem was modeled using a baseline time-dependent degradation function, typically bounded within $[0, 1]$. This formulation is extended by explicitly incorporating environmental effects such as wind speed and ambient temperature.

1. Wind Speed Process: Wind speed, denoted by $W(t)$, is assumed to remain constant over random intervals (typically 2–8 h), after which it jumps to a new random level. For example, during a given day the wind may remain at 6 m/s, then drop to 3 m/s, and later spike to 10 m/s. This jump process captures realistic gusty wind conditions.

2. Temperature Daily Cycle: Ambient temperature is modeled as a deterministic periodic function with a 24-hour cycle. Specifically, let $\min(\Theta) = 3^\circ\text{C}$ (around 3 am), $\max(\Theta) = 30^\circ\text{C}$ (around 3 pm).

A simple representation is a sinusoidal function:

$$\Theta_{\text{base}}(\tau) = \frac{\min + \max}{2} + \frac{\max - \min}{2} \sin\left(\frac{\pi(\tau - 3)}{24}\right),$$

where $\tau = t \bmod 24$ is the hour of the day. Mapping $t \in [0, t_{\max}]$ through τ yields $\Theta(t) \in [3^\circ\text{C}, 30^\circ\text{C}]$ with daily peaks and troughs.

3. Combined Degradation Function: Let $D_i^{(\text{base})}(t) \in [0, 1]$ denotes the baseline time-only degradation, for instance,

$$D_i^{(\text{base})}(t) = \min\left\{1, \left(\frac{t}{T_i}\right)^{\phi_{i,2}}\right\}.$$

The environmental contribution is modeled as

$$\Delta_i(t) = \alpha_i^{(W)} f_W(W(t)) + \alpha_i^{(T)} f_T(\Theta(t)),$$

where $f_W(\cdot)$ and $f_T(\cdot)$ are normalized mappings, such as

$$f_W(w) = \frac{w}{12}, \quad f_T(\theta) = \frac{\theta - 3}{30 - 3},$$

ensuring $f_W, f_T \in [0, 1]$. The coefficients $\alpha_i^{(W)}$ and $\alpha_i^{(T)}$ represent the sensitivity of subsystem i to wind and temperature, respectively. For instance, GCU are weakly affected by wind ($\alpha_{\text{GCU}}^{(W)} \approx 0$), while actuators exhibit stronger wind sensitivity.

The final degradation model is therefore:

$$D_i(t) = \min\{1, D_i^{(\text{base})}(t) + \Delta_i(t)\}. \quad (26)$$

This ensures degradation remains bounded in $[0, 1]$, with the environmental effects accelerating or decelerating wear relative to the baseline.

4.6. Subsystem cost components

Let $C_k(t)$ denote the raw cost of subsystem k at time t , and w_k a corresponding weighting factor such that $\sum_{k=1}^6 w_k = 1$. The weights reflect the relative cost significance of the subsystems. The total cost at time t is given by

$$C_{\text{total}}(t) = \sum_{k=1}^6 w_k C_k(t). \quad (27)$$

Normalization: If the absolute subsystem costs are unknown, each $C_k(t)$ may be normalized to the interval $[0, 1]$, after which w_k governs its relative impact.

Cost Growth with Time: It is assumed that maintenance costs increase with operating time. For subsystem k , the growth is modeled as [13]:

$$C_k(t) = C_{k,0} + \gamma_k t, \quad (28)$$

where $C_{k,0}$ is a baseline offset and $\gamma_k > 0$ is the cost growth rate. Substituting Eq. (28) into Eq. (27), the total cost expands to

$$C_{\text{total}}(t) = \sum_{k=1}^6 w_k (C_{k,0} + \gamma_k t). \quad (29)$$

Thus, the aggregated cost increases monotonically with time, reflecting both baseline offsets and subsystem-specific growth rates.

5. Theoretical maintainability analysis

Maintainability quantifies the probability that a UAV, experiencing wear or partial failure in one or more of its subsystems, can be restored to an operational state within a minimal amount of time. Within this framework, the following aspects are emphasized:

- **Soft Failure Probability:** The likelihood that a subsystem exceeds its soft-failure threshold $H_i^{(\text{soft})}$ before a specified time t .
- **Restorability and Repair Times:** The ability of preventive maintenance actions to restore subsystem performance below $H_i^{(\text{soft})}$ once a soft failure is detected.
- **System-Level Maintainability:** The aggregation of individual subsystem maintainability measures to ensure sustained UAV operation.

5.1. Soft failure probability

From Eq. (25), the maintainability of each subsystem can be computed at time t as follows. The *theoretical maintainability* of subsystem i at time t is defined as [10]

$$M_i(t) = 1 - P_i^{(\text{soft fail})}(t) = \Phi\left(\frac{H_i^{(\text{soft})} - D_i(t)}{\sigma_i}\right). \quad (30)$$

5.2. System-level maintainability

To extend the analysis from individual subsystems to the UAV as a whole, it is necessary to evaluate whether the vehicle remains mission-capable under partial degradation.

If the soft failure of any single subsystem leads to immediate mission termination, the system maintainability is governed by the weakest subsystem. To more realistically represent subsystem interdependencies, compounded maintenance delays, and repair inefficiencies, this relationship is generalized as the following inequality:

$$M_{\text{system}}(t) \leq \min_{i \in \{1,2,3,4,5,6\}} \{M_i(t)\}. \quad (31)$$

This inequality implies that the system maintainability is bounded above by the minimum maintainability among all subsystems. Accordingly, the system-level maintainability is modeled as

$$M_{\text{system}}(t) = \beta(t) \min_{i \in \{1,2,3,4,5,6\}} \{M_i(t)\}, \quad 0 < \beta(t) \leq 1, \quad (32)$$

where $\beta(t)$ is a system degradation sensitivity factor that accounts for:

1. interdependence losses between subsystems,
2. compounded maintenance delays, and
3. system-level repair inefficiencies.

To reflect the fact that subsystem interdependencies and repair inefficiencies tend to worsen as degradation accumulates, the factor $\beta(t)$ is assumed to decrease with time and is defined as

$$\beta(t) = e^{-\kappa t/T_{\max}}, \quad (33)$$

where $\kappa > 0$ is a small positive constant controlling the rate at which system maintainability decays relative to the minimum subsystem maintainability, and $T_{\max}$ denotes the maximum operational time horizon.

Hence, the resulting system-level maintainability is given by

$$M_{\text{system}}(t) = e^{-\kappa t/T_{\max}} \cdot \min_{i \in \{1,2,3,4,5,6\}} \{M_i(t)\}. \quad (34)$$

This formulation ensures that $M_{\text{system}}(t)$ always remains less than or equal to the minimum maintainability among the individual subsystems.

It is noted that the present formulation assumes independent degradation evolution among individual subsystems in order to preserve analytical tractability and computational efficiency. Nevertheless, system-level interaction effects are partially incorporated through the degradation sensitivity factor $\beta(t)$, which captures compounded maintenance delays, interdependence losses, and reduced recovery efficiency arising from subsystem coupling. In practical UAV platforms, functional dependencies may exist, such as flight control unit (FCU) degradation affecting sensor data availability or communication reliability. Explicit modeling of such cascading failure mechanisms can be achieved by extending the proposed framework using dependency-aware reliability block diagrams, functional dependency models, or dynamic Bayesian network representations. Incorporating such interaction-aware models is identified as an important direction for future research.

5.3. Optimization problem formulation

An optimization problem is defined that jointly accounts for subsystem degradation and cost. The objective is to *minimize the total degradation along with a weighted cost term* [13]:

$$\min D_{\text{total}}(t) + \lambda C_{\text{total}}(t), \quad (35)$$

where

$$D_{\text{total}}(t) = \frac{1}{6} \sum_{i=1}^6 D_i(t), \quad C_{\text{total}}(t) = \sum_{k=1}^6 w_k C_k(t),$$

and $\lambda > 0$ is a trade-off parameter balancing physical degradation against cost. The weighting factors w_k are introduced to capture the relative economic contribution of each subsystem to the overall UAV maintenance and degradation cost. These weights reflect differences in replacement cost, repair complexity, and operational criticality among subsystems. In this study, the values of w_k are assigned based on relative subsystem cost proportions reported in UAV maintenance literature and typical component pricing trends. When precise cost data are not available, normalized weights are employed to preserve the relative cost hierarchy across subsystems while maintaining numerical stability in the optimization framework.

Constraints: The optimization is subject to the following conditions:

1. Failure Threshold Constraints:

$$D_i(t) \leq H_i^{(\text{hard})}, \quad \forall i \in \{1, 2, 3, 4, 5, 6\},$$

ensuring no subsystem exceeds its hard failure threshold.

2. Maintenance Cost Constraint:

$$C_m \leq C_{\text{budget}},$$

where C_m is the cumulative maintenance cost and C_{budget} is the maximum available budget.

3. Wind Speed Constraint:

$$V_w(t) \leq V_{\max},$$

where $V_{\max}$ is the maximum allowable wind speed for safe UAV operation.

4. Temperature Constraint:

$$T_{\min} \leq T(t) \leq T_{\max},$$

ensuring that operation remains within the permissible temperature range.

6. Numerical illustration

In this section, the results obtained from the reliability and maintainability analysis of UAV subsystems are presented.

6.1. Simulation framework and MATLAB–Python integration

The simulation framework developed in this study integrates Python and MATLAB to combine stochastic simulation capabilities with analytical reliability evaluation. The integration is designed to ensure both computational flexibility and reproducibility. The overall simulation is executed in discrete time steps (e.g., hourly updates). At each time step, subsystem degradation is updated based on stochastic wear increments and environmental conditions. Python is primarily used for:

- Controlling the simulation flow and time progression,
- Generating environmental inputs such as wind speed $W(t)$ and temperature $\Theta(t)$,
- Implementing stochastic degradation updates using Gaussian random variables,
- Logging simulation data and performing visualization.

The degradation update for each subsystem i is computed as:

$$D_i(t+1) = D_i(t) + \Delta D_i(t),$$

where

$$\Delta D_i(t) = \mathcal{N}(\mu_i, \sigma_i^2) + \alpha_i^{(W)} W(t) + \alpha_i^{(T)} \Theta(t).$$

Here, $\mathcal{N}(\mu_i, \sigma_i^2)$ represents the stochastic wear increment, while $\alpha_i^{(W)}$ and $\alpha_i^{(T)}$ denote sensitivity coefficients to wind and temperature, respectively.

MATLAB is used for:

- Analytical computation of reliability functions,
- Evaluation of maintainability measures,
- Validation of theoretical models against simulated degradation data.

The interaction between Python and MATLAB is implemented using the MATLAB Engine API for Python. This enables:

- Direct execution of MATLAB functions from Python,
- In-memory transfer of degradation and environmental data,
- Efficient coupling between simulation and analytical evaluation.

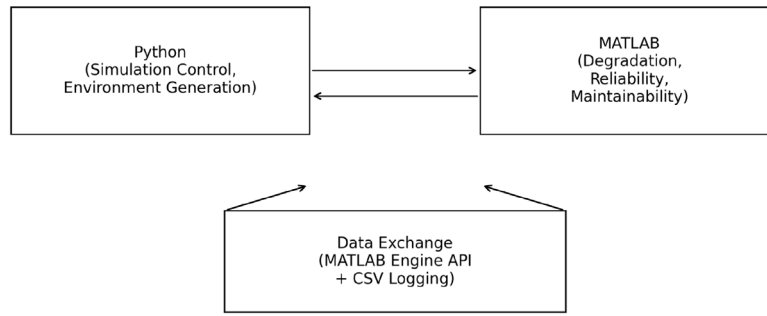


Fig. 2. Schematic representation of the simulation architecture.

At each time step, Python passes updated degradation states and environmental inputs to MATLAB, which computes the corresponding reliability and maintainability metrics and returns the results. Data exchange is primarily performed in memory via the MATLAB Engine API. In addition, CSV-based logging is used as a secondary mechanism to:

- Store time-series degradation data,
- Enable reproducibility,
- Facilitate post-processing and validation.

The overall workflow can be summarized as follows:

1. Initialize subsystem degradation levels,
2. Generate environmental inputs $W(t)$ and $\Theta(t)$,
3. Update degradation using stochastic and environmental components,
4. Transfer data to MATLAB for analytical evaluation,
5. Compute reliability and maintainability metrics,
6. Log and visualize results.

A schematic representation of the simulation architecture is shown in Fig. 2. The coefficients used in Section 4.5 to model the effects of wind speed and temperature vary across subsystems. These coefficients can be adjusted depending on the specific simulation scenario and modeling assumptions. The values adopted in this study are selected based on the expected physical influence of wind and temperature on individual subsystems. For instance, the GCU is assumed to be weakly affected by wind ($\alpha_{GCU}^{(W)} \approx 0$), whereas actuators exhibit relatively higher sensitivity to wind effects.

6.2. Reliability analysis

The reliability of UAV subsystems can be modeled using different lifetime distributions, depending on the underlying failure mechanisms. In this work, four widely used distributions for component failure modeling are considered:

1. **Exponential Distribution:** The CDF with rate parameter $\lambda > 0$ is

$$F(t) = 1 - e^{-\lambda t}, \quad t > 0.$$

2. **Gamma Distribution:** The CDF is given by

$$F(t) = \frac{1}{\Gamma(\alpha)} \gamma(\alpha, \beta t), \quad t > 0,$$

where $\Gamma(\alpha)$ is the Gamma function, and $\gamma(\alpha, \beta t)$ is the lower incomplete Gamma function,

$$\gamma(\alpha, \beta t) = \int_0^{\beta t} x^{\alpha-1} e^{-x} dx.$$

Table 1

Parameter values for various distributions [34].

MTBF (h) = 15 000			
Distribution	Parameter 1	Parameter 2	Failure rate
Exponential	–	$\lambda = 0.00006667$	0.00006667
Gamma	$\alpha = 2.0$	$\beta = 7500$	0.00007619
Weibull	$k = 1.5$	$n = 15\,615.98$	0.00007003
Lognormal	$\mu = 9.485$	$\sigma = 0.5$	0.00000167

3. **Lognormal Distribution:** The CDF is given by

$$F(t) = \frac{1}{2} + \frac{1}{2} \operatorname{erf}\left(\frac{\ln t - \mu}{\sigma\sqrt{2}}\right), \quad t > 0,$$

where erf denotes the error function,

$$\operatorname{erf}(z) = \frac{2}{\sqrt{\pi}} \int_0^z e^{-u^2} du.$$

4. **Weibull Distribution:** The CDF is given by

$$F(t) = 1 - e^{-(t/\eta)^k}, \quad k > 0,$$

where k is the shape parameter and η is the scale parameter.

For a UAV system comprising six subsystems connected in series, the overall system reliability is expressed as

$$R(t) = R_1(t) R_2(t) \dots R_6(t),$$

where $R_i(t) = 1 - F_i(t)$ denotes the reliability of the i th subsystem. Once the reliability of each individual subsystem is evaluated using its corresponding lifetime distribution, the series configuration yields the overall UAV system reliability.

To illustrate and compare the behavior of these lifetime distributions, an example is considered in which each subsystem has a mean time between failures (MTBF) of 15,000 h. Using this common MTBF value, the corresponding parameters for the exponential, Gamma, Weibull, and lognormal models are derived, and their respective reliability functions are evaluated and plotted. Table 1 summarizes the parameter values for the different distributions, while Table 2 provides the parameters specifically for the Weibull distribution. Fig. 3 illustrates the overall UAV system reliability under different failure distributions, and Fig. 4 depicts the system reliability for varying MTBF values of the MCU.

6.3. Maintainability analysis

This section presents the outcomes of our UAV maintainability simulation, including cost and environmental effects. Final parameter values are gathered, root mean square errors are computed to illustrate the modeled vs. observed degradation curves. Some parameter values will be:

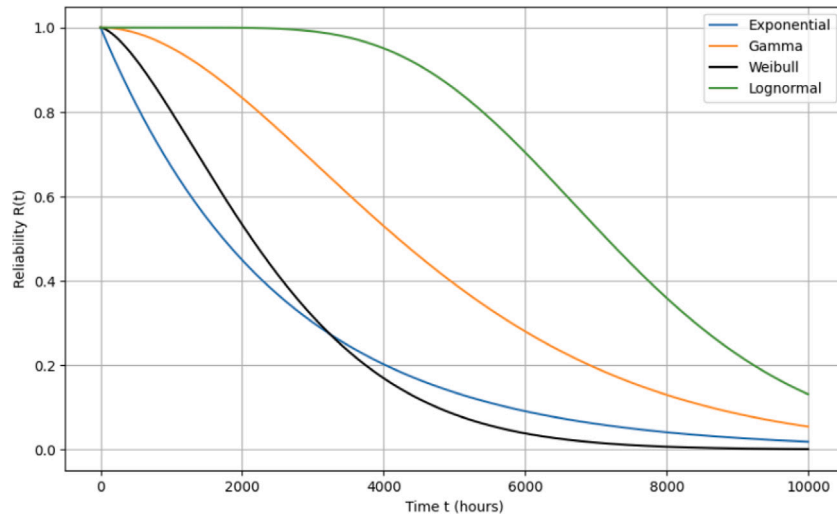


Fig. 3. Reliability versus time of a UAV system considering different failure distributions.

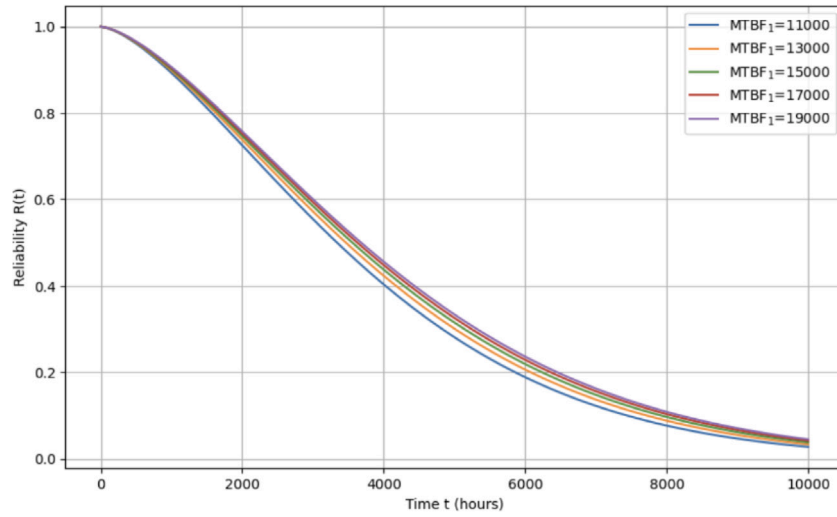


Fig. 4. Reliability of the UAV system considering various MTBF of the mission control unit for Weibull distributed failure time.

Table 2

Parameter values for Weibull distributions for each subsystem [34].

Subsystem	MTBF ($\times 1000$ h)	n
MCU	11, 13, 17, 19	11 615.98, 13 615.98, 17 615.98, 19 615.98
FCU	15	15 615.98
Actuators	15	15 615.98
Sensors	15	15 615.98
Comms	15	15 615.98
GCU	15	15 615.98

- $0 \leq t \leq 15,000$ (the entire time horizon),
- (maximum lifetime) $T_i \in [14,800, 15,100]$, i.e., randomly assigned but unique for each subsystem,
- $\phi_{i,2} > 1$, as t gets close to T_i , degrade accelerates to 1.

6.3.1. Subsystem cost components

- $C_k(t)$: Raw cost of subsystem k at time t .
- w_k : Weighting factor for subsystem k such that $\sum_{k=1}^6 w_k = 1$. Take $w_{GCU} = 0.688$, $w_{Comms} = 0.2649$, $w_{Sensor} = 0.0052$, $w_{actuator} = 0.0158$, $w_{FCU} = 0.0211$, $w_{MCU} = 0.037$.

6.3.2. Wind and temperature

- **Wind Speed**, $W(t)$, ranging from 0 m/s to 12 m/s, changing in bundles or chunks of hours (representing gusty periods).
- **Temperature**, $\Theta(t)$, imitating a daily cycle i.e., near 3 °C in the early morning (e.g., 3 am) to about 30 °C in the mid-afternoon (3 pm). Over 15,000 h, effectively have ≈ 625 day/night cycles.

6.3.3. Data logging and post-processing

If the UAV runs for N hours, the following is recorded:

- **Time (Flight Hours)** (t_j): The simulated clock or flight duration.
- **Subsystem Degradation** ($D_i^{(obs)}(t_j)$): Degradation levels at each time step.
- **Environmental Conditions** ($V_w(t_j)$, $T(t_j)$): Wind speed V_w and temperature T at each step.
- **Cost** ($C_k^{(obs)}(t_j)$): Maintenance cost related to each subsystem.

Figs. 5–9 show the wind and temperature values, degradation for each subsystem and combined maintainability. The figures show the individual system degradation with respect to the time. The analytical and simulated results shows alignment which validated the obtained results. Fig. 8 represents the maintainability of individual subsystem and the results shows that the maintainability decreases with respect to

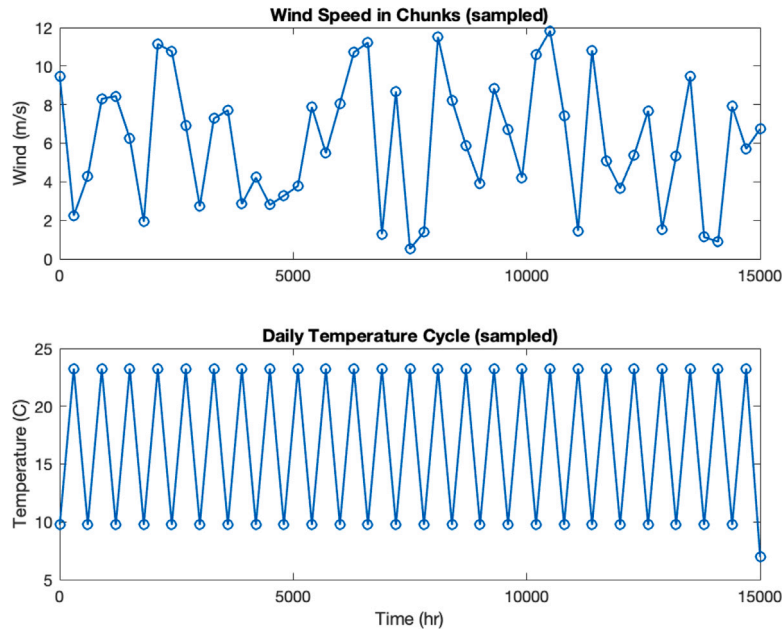


Fig. 5. Behavior of wind gust and temperature cycles with respect to time.

the time. Fig. 9 shows the maintainability of the complete UAV system which decreases with respect to the time.

6.3.4. Parameter fitting

In the previous sections, it is described how wind speed $W(t)$ and temperature $\Theta(t)$ are incorporated into the subsystem degradation via environment offsets $\Delta_i(t)$. Here, it is focused on:

1. **Parameter Fitting:** How the values for time-based degrade, wind/temperature sensitivities, etc. are estimated or assigned. if data is observed.
2. **Parameter Table:** Possible values for each subsystem, including superlinear exponents, random life T_i , and environment coupling.

6.3.5. Parameter fitting with environment

From the defined model in Eq. (26):

$$D_i(t) = \min\{1, D_i^{(\text{base})}(t) + \Delta_i(t)\},$$

Since parameters are unknown:

- T_i and $\phi_{i,2}$ (related to the base time-to-failure),
- $\alpha_i^{(W)}$ (wind sensitivity),
- $\alpha_i^{(T)}$ (temperature sensitivity).

If *observed degrade data* exist at discrete times t_j (e.g. from flight logs over 15,000 h), we form residuals:

$$r_{i,j}(p_i) = D_i^{(\text{obs})}(t_j) - D_i(t_j; p_i),$$

and minimize the sum of squared residuals:

$$\text{SSR}_i(p_i) = \sum_{j=1}^N [r_{i,j}(p_i)]^2, \quad p_i = [T_i, \phi_{i,2}, \alpha_i^{(W)}, \alpha_i^{(T)}].$$

A standard *nonlinear least-squares* method (e.g. Levenberg–Marquardt, Nelder–Mead [35]) then yields

$$\hat{p}_i = \arg \min_{p_i} \text{SSR}_i(p_i).$$

It can be done this *subsystem by subsystem* for all i if there are shared parameters (like the day/night temperature profile).

Table 3

Parameter values for six subsystems with wind and temperature.

Subsystem	T_i	$\phi_{i,2}$	$\alpha_i^{(W)}$	$\alpha_i^{(T)}$	RMSE
MCU	14 924	1.30	0.01	0.02	3.63×10^{-14}
FCU	14 805	1.50	0.03	0.01	5.05×10^{-14}
Act	14 827	1.40	0.05	0.02	1.87×10^{-14}
Sens	14 830	1.25	0.02	0.03	1.92×10^{-14}
Comm	15 091	1.20	0.01	0.04	2.38×10^{-14}
GCU	14 844	1.60	0.000	0.03	2.95×10^{-14}

Table 4

Observation from parameter values.

Subsystem	Notes
MCU	Minimal wind effect, mild temp effect
FCU	Moderately wind-limited
Act	Actuators strongly wind-affected
Sensors	Some temp sensitivity, moderate wind
Comm	High temp effect for RF amps
GCU	No wind effect, moderate temp effect

6.3.6. Parameter table

Table 3 shows a set of parameter values for six subsystems, consistent with an environment-based degrade approach.

Table 4 depicts the observation from parameter values.

Here:

- T_i is the base time (in hours) at which $(\frac{t}{T_i})^{\phi_{i,2}}$ hits 1 if the environment is zero.
- $\alpha_i^{(W)}$ captures wind coupling, $\alpha_i^{(T)}$ captures temperature coupling. A value of 0.05 (actuator) is quite high for wind, meaning a strong degrade jump in storms or gusts.

Observation from Figs. 10–12:

- For different values of $\phi_{i,2}$, the different behavior of degradation and maintainability is observed.
- As $\phi_{i,2} < 1$, $(\frac{t}{T_i})^{\phi_{i,2}}$ approaches 1 more quickly, resulting in faster degradation and reduced maintainability.
- As $\phi_{i,2} > 1$ increases, the degradation slows down because of $(\frac{t}{T_i}) < 1$.

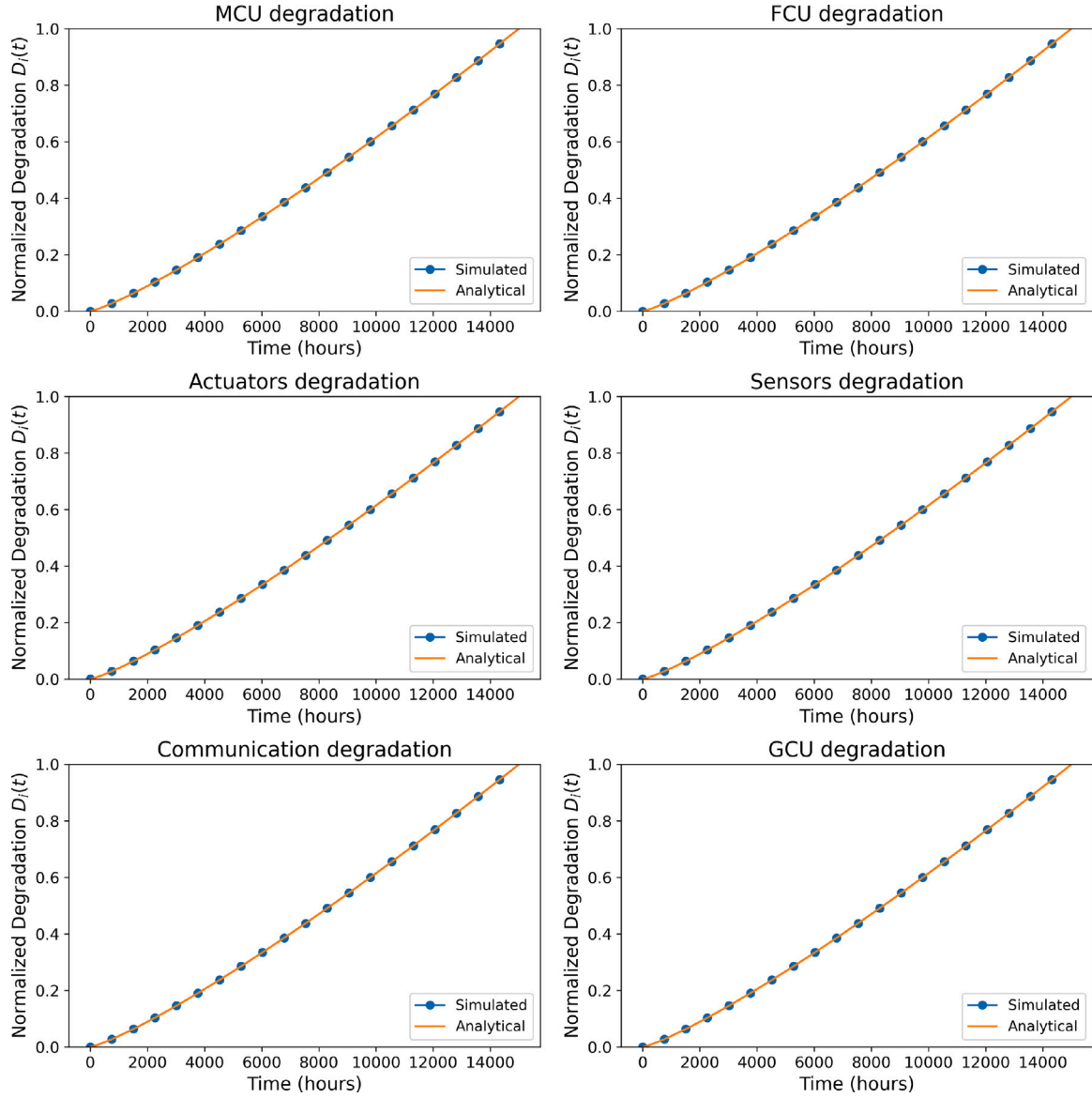


Fig. 6. Individual subsystem degradation versus time for simulated and analytical cases.

It can be observed from Figs. 9–11 that most flight-related subsystems exhibit pronounced fluctuations in their degradation trajectories, whereas the GCU shows a comparatively smoother trend. This behavior is primarily attributed to the lower sensitivity of the GCU to environmental stressors such as wind speed and temperature, as reflected in its corresponding environmental influence coefficients. While subsystems such as actuators, sensors, and flight control units are directly exposed to aerodynamic loads and mission-induced thermal variations, the GCU typically operates in a protected and relatively stable environment. As a result, its degradation evolution is governed mainly by gradual aging processes rather than short-term environmental fluctuations, leading to smoother degradation profiles.

6.3.7. Solving the optimization problem

An overall objective function is observed:

$$\min_{t \in \{1, \dots, H_{\max}\}} \frac{1}{6} \left(\sum_{i=1}^6 D_i^{(\text{model})}(t) \right) + \lambda C_{\text{total}}(t),$$

where $D_i^{(\text{model})}(t)$ is the modeled degradation for subsystem i at hour t , and $Cost(t)$ is some cumulative or instantaneous cost function. For simplicity, we take $\lambda = 1$. The constraints are imposed such as:

- $D_i^{(\text{model})}(t) \leq 1$ (hard fail if degrade hits 1).
- Probability constraints $P(D_i(t) \geq H_i^{(\text{hard})}) \leq P_{\max}$ if we incorporate a risk threshold.
- Possibly $W(t) \leq 12$ m/s for wind, or $0^\circ \leq \theta(t) \leq 30^\circ$ C , etc.
- User can keep another constraint $C_m \leq C_{\text{budget}}$ as per requirements. But for this case, this constraint is not taken into consideration.

Discrete vs. Continuous Approaches: Because t can range up to 15,000 h, one of two strategies can be adopted:

1. **Discrete Search:** Evaluate the objective at each $t = 1, \dots, 15,000$, check constraints, and pick the t that yields the minimum $\frac{1}{6} \left(\sum_{i=1}^6 D_i(t) \right) + \lambda C_{\text{total}}(t)$.
2. **Continuous or Interval-based:** If $D_i(t)$ is piecewise or monotonic, one might do a derivative-based approach. But since degradation is clamped at 1 and add environment effects, a smooth derivative is not obtained everywhere. So a simpler *discrete* check is often chosen in a real UAV scenario where flight hours are integral or near-integral anyway.

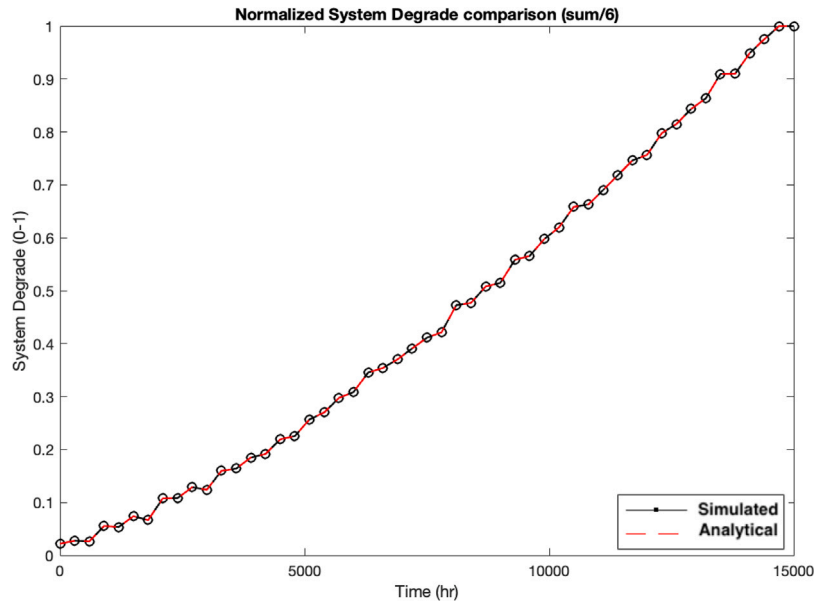


Fig. 7. Total system degradation versus time for simulated and analytical cases.

Table 5

Degrade and cost values.

Time (h)	$\frac{1}{6} \left(\sum_{i=1}^6 D_i^{(model)}(t) \right)$	$C_{total}(t)$	Objective
1	0.02204	0.0565	0.07854
2	0.02506	0.1131	0.13816
3	0.02686	0.1697	0.19656
4	0.03010	0.2263	0.25640
5	0.03220	0.2829	0.31510
6	0.03440	0.3395	0.37390
7	0.03670	0.3961	0.43280
8	0.03910	0.4527	0.49180
9	0.04160	0.5093	0.55090
10	0.04420	0.5659	0.61010
11	0.04690	0.6225	0.66940
12	0.04970	0.6791	0.72880
13	0.05260	0.7357	0.78830
14	0.05560	0.7923	0.84790
15	0.05870	0.8489	0.90760
16	0.06190	0.9040	0.96590
17	0.06520	0.9605	1.02570
18	0.06860	1.0170	1.08560
19	0.07210	1.0735	1.14560
20	0.07570	1.1300	1.20570
21	0.07940	1.1865	1.26590
22	0.08320	1.2430	1.32620
23	0.08710	1.2995	1.38660
24	0.09110	1.3560	1.44710
25	0.09520	1.4125	1.50770
26	0.09940	1.4690	1.56840
27	0.10370	1.5255	1.62920
28	0.10810	1.5820	1.69010
29	0.11260	1.6385	1.75110
30	0.11720	1.6950	1.81220
...	...	...	...
14112	0.93546	798.48	799.41546

Computation in a Discrete Setting: Here, $t \in \{1, \dots, 15000\}$, and $\lambda = 1$, plus a table of degrade sums and cost. The values after simulation are listed in Table 5.

Reading the final column, the minimum is seen at $t = 14112$ with an objective of 799.41546 less than all other times. Because $D_i > 0.95$ (hard failure) for the sensor subsystem at $t = 14113$ which violates the constraint, and then it might be disallowed, i.e., no longer feasible.

The discrete search strategy adopted in this study is well-suited for the current UAV system configuration, which involves a limited

number of decision variables and bounded parameter ranges. This approach ensures reliable convergence to near-optimal solutions while maintaining computational simplicity. However, for larger-scale UAV architectures or systems with higher-dimensional optimization spaces, alternative optimization techniques such as metaheuristic algorithms (including genetic algorithms, particle swarm optimization, and simulated annealing) or gradient-based methods may provide improved scalability and computational efficiency. Incorporating such advanced optimization strategies constitutes an important direction for future extensions of the proposed framework.

7. Conclusions and future work

In the present study, two types of analytical models have been proposed: a reliability model and a maintainability model. To evaluate the reliability of the UAV system, the RBD methodology has been employed, while for the maintainability analysis, an optimization problem has been formulated and subsequently solved.

The analysis reveals that the Weibull distribution effectively captures the progressive degradation of UAV components, leading to a more realistic estimation of system reliability. Therefore, the Weibull distribution has been considered for further reliability analysis. The impact of varying the MTBF of any subsystem has also been examined by varying the MTBF of the MCU from 11,000 to 19,000 h, for different values of the scale parameter (η) and a fixed shape parameter ($k = 1.5$) in the Weibull distribution.

This paper also presents a maintainability model and simulation framework for a UAV comprising six key subsystems: MCU, FCU, Actuators, Sensors, Communication, and GCU. By formulating an optimization problem aimed at minimizing overall degradation while adhering to environmental and operational constraints, a cost-effective and robust maintenance scheduling strategy is derived. By incorporating cost into the non-linear wear-out degradation model, the framework captures the resource and budget constraints that operators face when maintaining UAV operations under varying environmental conditions.

The simulation results align well with the theoretical predictions, indicating that the non-linear wear-out degradation model (26) captures real-world subsystem degradation trends accurately. This approach allows UAV operators to forecast soft failure points, schedule preventive maintenance, and reduce the risk of expensive corrective actions. Building on the above-discussed model, several promising directions remain open for exploration:

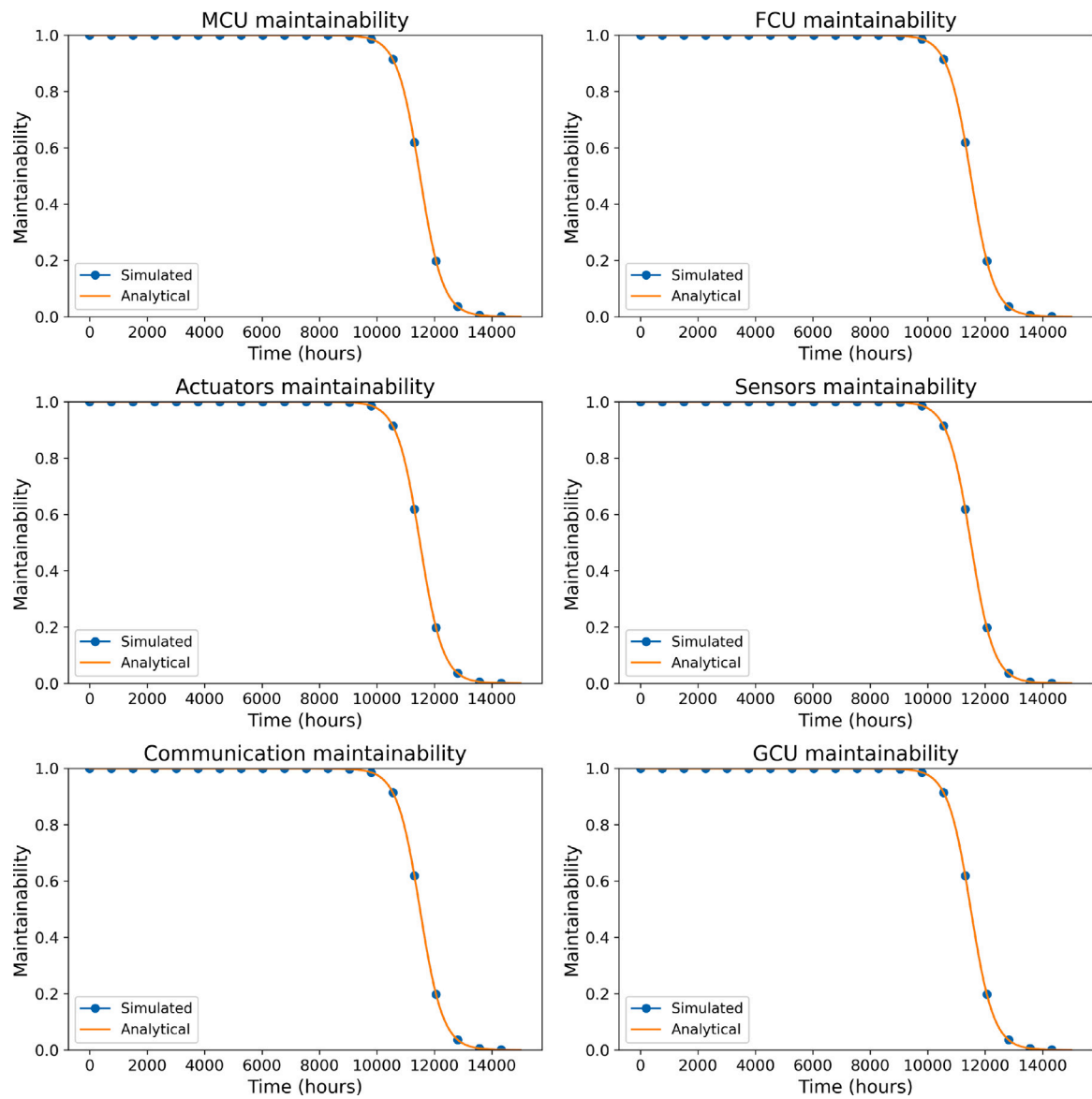
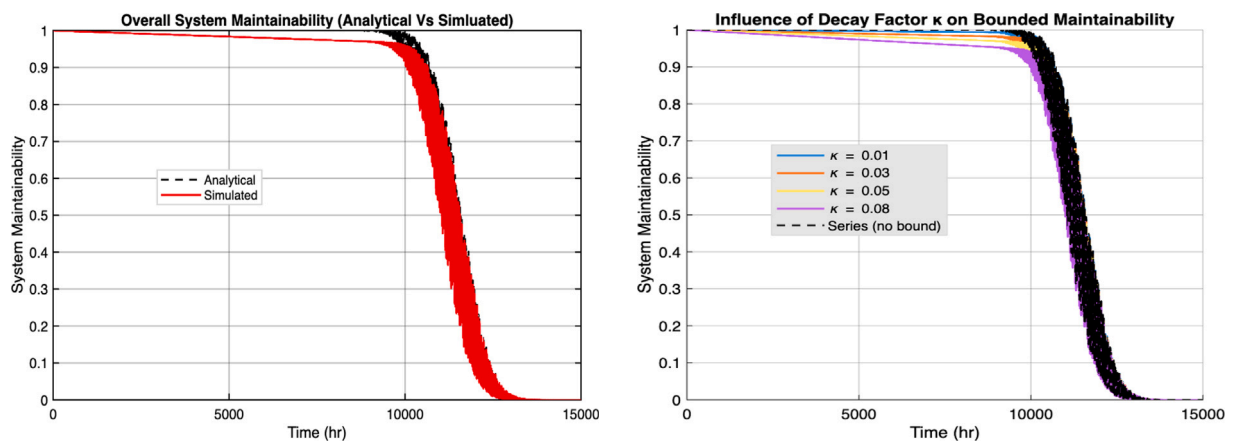


Fig. 8. Individual subsystem maintainability versus time for simulated and analytical cases.



(a) Comparison of overall system maintainability for analytical and simulated cases.

(b) Effect of κ on bounded maintainability.

Fig. 9. Overall system maintainability and effect of κ on bounded maintainability.

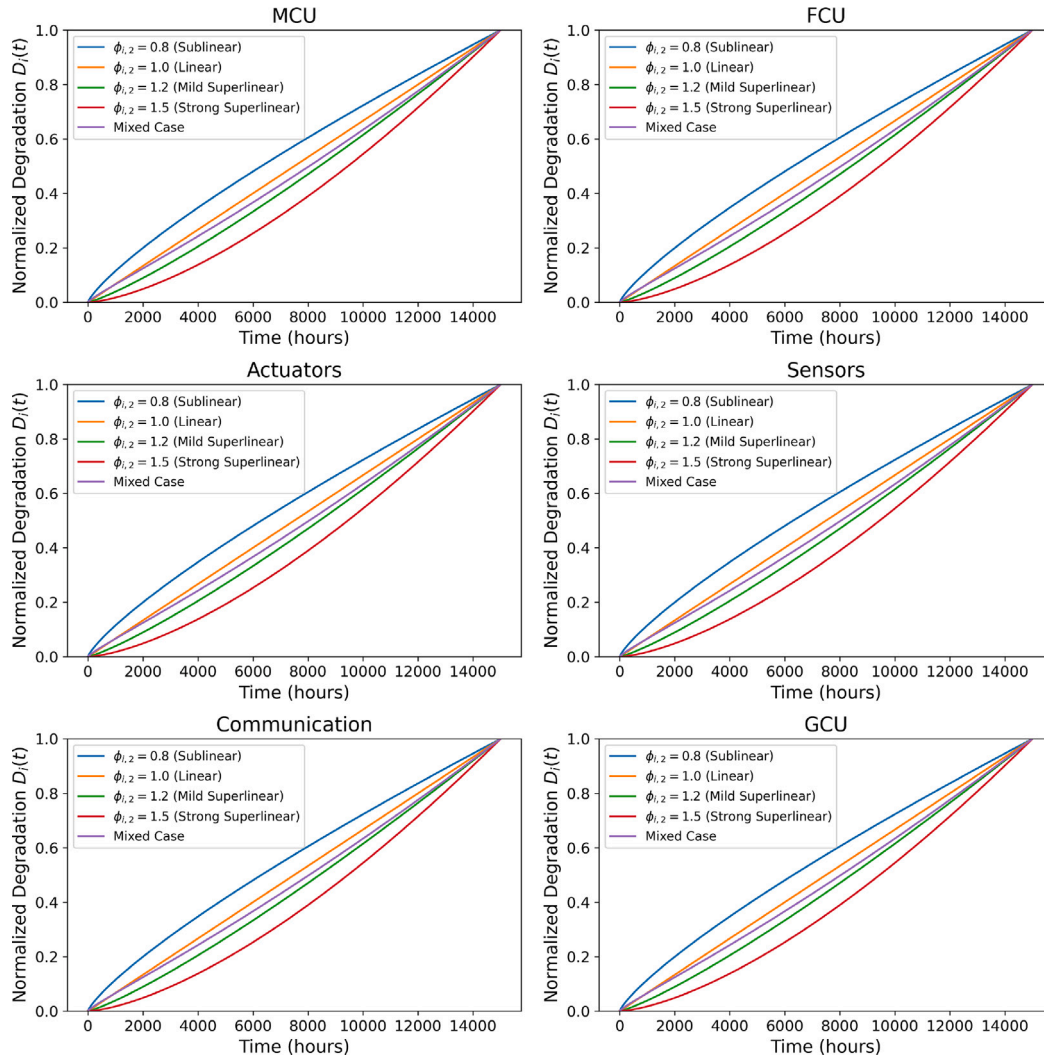


Fig. 10. Subsystem degradation for different values of ϕ_2 .

- The qualitative impact of redundancy on system reliability and maintainability, and identify redundancy modeling can be a natural extension of the present work.
- **Additional Environmental Factors:** Instead of just wind and temperature, environmental function depends on other variables like humidity, smog etc. It may contain *Quadratic* terms (e.g., $[V_w(t)]^2$), Cross-term $\delta [V_w(t) \cdot H(t)]$, capturing the idea that wind $\times$ high humidity might produce extra stress (e.g., rotor icing/corrosion), Logarithmic factor $\beta_2 T(t) \log(T(t))$ indicating temperature-driven stress that grows faster than linearly but not purely polynomially.
- **Nonlinear or Threshold-Driven Cost Relationships:** For each subsystem k , maintenance cost starts from a baseline $C_{k,0}$ and rises with the degradation level at a rate $\gamma_k^{(1)}$ until the soft-failure threshold δ_{soft} is met. Crossing δ_{soft} produces an immediate cost jump Δ_k , after which the cost continues to grow — often more steeply — with a (possibly different) rate $\gamma_k^{(2)}$. This represents the sudden and heavier maintenance burden that appears once partial failure occurs.
- **Discrete Usage Models:** Rather than applying one global degradation curve, the framework can show that the degradation rate D_i depends on operational or environmental inputs such as time, wind, temperature, and — crucially — *usage mode*. Usage mode is treated as a discrete switch between flight regimes (e.g., hover, cruise, dash), so the component follows distinct trajectories D_i^{hover} , D_i^{cruise} , or D_i^{dash} . This captures the fact that wear progresses differently under different mission profiles.

CRediT authorship contribution statement

Ankit Kumar: Writing – review & editing, Writing – original draft, Methodology, Investigation, Formal analysis, Conceptualization. **Raina Raj:** Writing – review & editing, Investigation. **Dharmaraja Selvamuthu:** Writing – review & editing, Supervision, Methodology, Investigation, Formal analysis, Conceptualization. **Sufal Chandra Swar:** Writing – review & editing, Supervision, Methodology, Investigation.

Declaration of competing interest

The authors declare the following financial interests/personal relationships which may be considered as potential competing interests: Dharmaraja Selvamuthu reports administrative support was provided by Indian Institute of Technology Delhi. Dharmaraja selvamuthu reports a relationship with Indian Institute of Technology Delhi that includes: employment. If there are other authors, they declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Data availability

No data was used for the research described in the article.

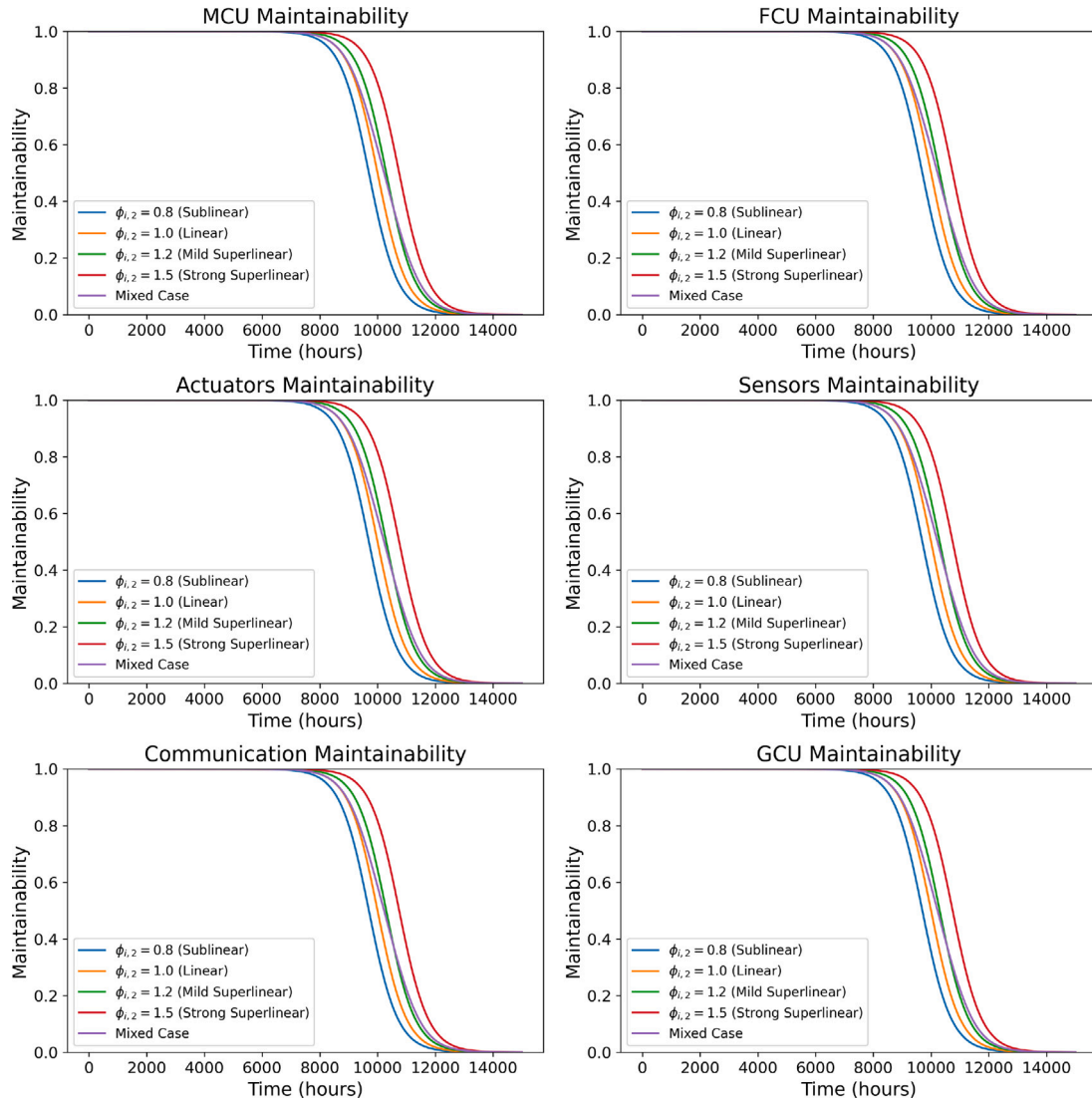


Fig. 11. Subsystem maintainability for different values of ϕ_2 .

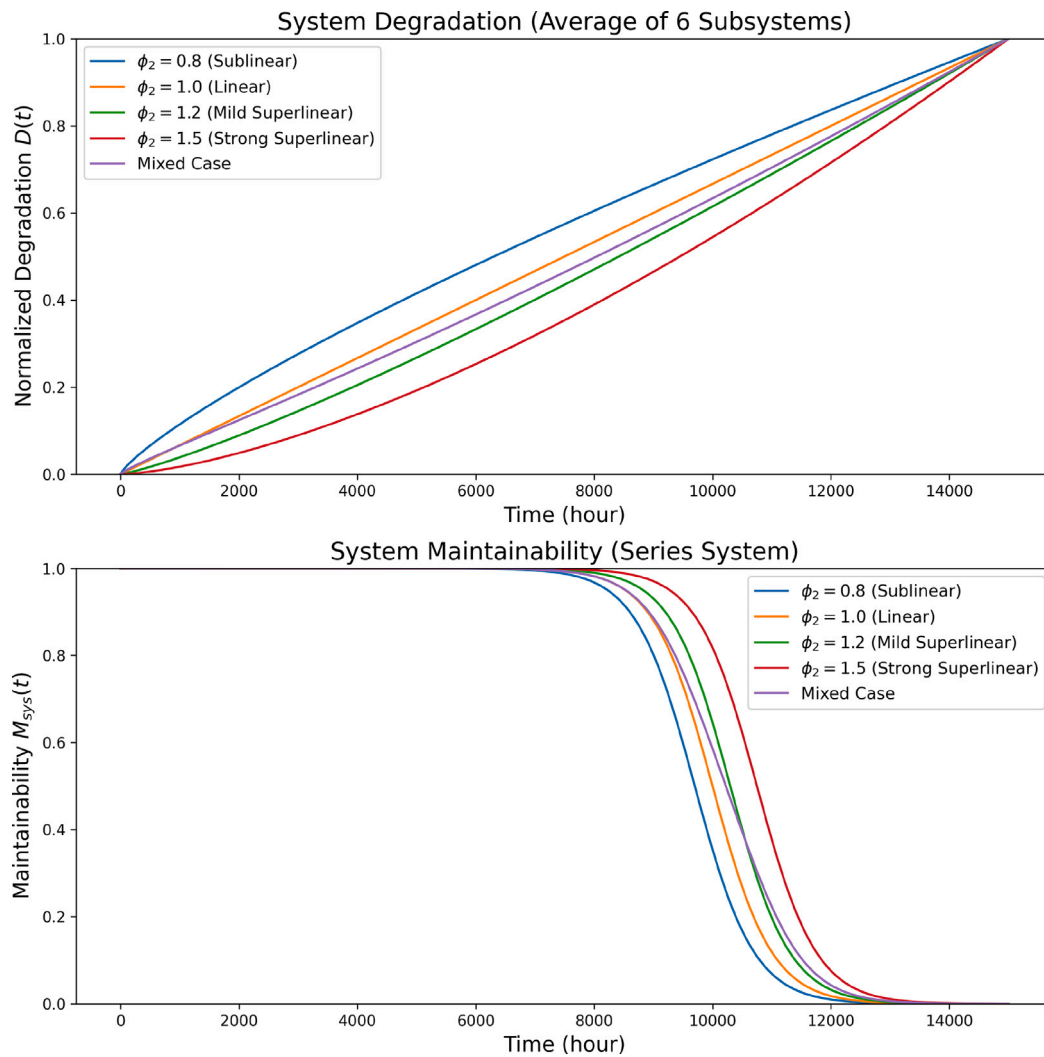


Fig. 12. System degradation and maintainability for different values of ϕ_2 .

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