

Modeling and Simulation of UAV Maintainability

Using an Optimization Approach with Environmental Constraints

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Abstract—This paper presents a comprehensive approach to modeling the maintainability of an Unmanned Aerial Vehicle (UAV) composed of multiple subsystems: Mission Control Unit (MCU), Flight Control Unit, Actuators, Sensors, Communication and Ground Control Station (GCS) and introduces cost as a new dimension. We extend the exponential wear-out model for each subsystem by incorporating environmental, operational, and now cost-related constraints, and formulate an optimization problem that helps minimize total degradation over time under these considerations. Finally, we provide a simulation framework to compare theoretical predictions against real-time degradation in a ROS2-based environment, illustrating that the augmented cost-based approach captures real-world performance and resource usage in a more realistic way.

I. INTRODUCTION

Unmanned Aerial Vehicles (UAVs) have become indispensable for a broad range of applications, including surveillance, package delivery, agricultural monitoring, and search-and-rescue missions. Despite their increasing popularity, UAVs can exhibit reliability challenges due to environmental stresses, subsystem complexities, and frequent maintenance requirements.

In this paper, we consolidate theoretical maintainability models with a simulation-based validation approach, *now including a time-dependent cost component that increases alongside the UAV's physical degradation*. The UAV considered has multiple subsystems:

- **MCU Subsystem**
- **Flight Control Subsystem**
- **Sensor Subsystem**: Navigation sensors (e.g. IMU, GPS) and communications.
- **GCS**: Maintains power distribution.
- **Actuators Subsystem**
- **Communication Subsystem**: Maintains communication

We formulate an optimization problem that aims to minimize total UAV degradation under key constraints (wind speed, temperature, cost), showing how theoretical maintainability predictions compare to a real-time simulated approach.

II. EXPONENTIAL WEAR-OUT MODEL WITH ENVIRONMENTAL EFFECTS

We utilize an *adjusted exponential wear-out model* [?] to capture how each subsystem i degrades with time t , environmental variables, and random uncertainties. Let

$$D_i(t) = \phi_{i,1} + \theta_i t^{\phi_{i,2}}, \quad (1)$$

where:

- $D_i(t)$: Degradation function of subsystem i at time t .
- $\phi_{i,1}$: Initial degradation (due to manufacturing or prior usage).
- $\theta_i t^{\phi_{i,2}}$: Intrinsic wear-out term; θ_i scales wear rate; $\phi_{i,2}$ adjusts whether wear is linear, sublinear, or superlinear.

If $D_i(t)$ exceeds a soft failure threshold $H_i^{(\text{soft})}$, subsystem i continues to function but with degraded performance. If $D_i(t)$ exceeds a hard failure threshold $H_i^{(\text{hard})}$, subsystem i fails outright.

A. Customising Degradation Function in $[0, 1]$

Rather than an unbounded or linearly growing function, we let each subsystem i have a *maximum life* T_i (in hours). Then, define a time-varying degrade:

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

where

- As t gets close to T_i , degrade *accelerates* to 1.

Interpretation.

- When $t < T_i$, $(t/T_i)^{\phi_{i,2}} < 1$, so degrade is below 1, e.g. $D_i(t) \approx 0$ if t is much smaller than T_i .
- As $t \rightarrow T_i$, $(t/T_i)^{\phi_{i,2}} \rightarrow 1$, meaning the subsystem is fully worn out.
- For $t > T_i$, we clamp $D_i(t)$ to 1, i.e. Equation (2) ensures degrade does not exceed 1.

Hence, degrade remains in $[0, 1]$ for all time. This is especially helpful if we interpret 1 as “hard failure.”

B. Two-Parameter Model: $(T, \text{exponent})$

Now, the customised degrade function has only **two unknowns**:

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

and the model is

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

- $p(1) = T$ is the time at which degrade hits 1.
- $p(2)$ is the exponent controlling how quickly degrade approaches 1 as t approaches T .

This form automatically yields $D_i(0) = 0$, grows with t , and saturates at 1.

C. Preventive Maintenance Intervals and Probability of Soft Failure

Real-World Uncertainty : Actual degradation in practice fluctuates around a mean due to:

- Manufacturing variability among components.
- Differences in flight usage or maneuvers.
- Unpredictable environmental spikes (e.g., gusts, temperature surges).

Hence, at any time t , $D_i(t)_{\text{actual}}$ can deviate from the mean $D_i(t)$, typically modeled by a random variable ε with zero mean, giving:

$$D_i(t)_{\text{actual}} = D_i(t) + \varepsilon.$$

D. Interpreting Soft Failure

Soft Failure Threshold : Define $H_i^{(\text{soft})}$ as the degradation level beyond which subsystem i becomes partially degraded (still functional but with reduced performance). We want:

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

If ε is assumed normally distributed ($\varepsilon \sim \mathcal{N}(0, \sigma_i^2)$) [?], then:

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

where Φ is the standard normal CDF.

III. INTRODUCING WIND AND TEMPERATURE INTO THE DEGRADATION MODEL

In the previous sections, we modeled each subsystem with a baseline time-based degrade, often clamped between 0 and 1. Now we extend this by:

1. Wind Speed Model. We let $W(t)$ remain constant for a small random interval (e.g. 2–8 hours), then jump to a new random level. Hence for *bundles of hours*, the wind is e.g. 6 m/s, then it drops to 3 m/s, then spikes to 10 m/s, etc. This mimics real conditions of gusty days.

2. Temperature Daily Cycle. We define a function $\Theta(t)$ that repeats every 24 hours. Let:

$$\min(\Theta) = 3^\circ\text{C} \quad (\text{around 3 am}), \quad \max(\Theta) = 30^\circ\text{C} \quad (\text{around 3 pm}).$$

A simple approach is a sine wave:

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

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

3. Combined Degradation Function. Let $D_i^{(\text{base})}(t) \in [0, 1]$ be the *time-only* degrade (like $\min\{1, (t/T_i)^{\text{ex}}\}$). Then define environment factors:

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

where $f_W(\cdot)$ and $f_T(\cdot)$ might *normalize* wind or temperature (e.g. $f_W(w) = w/12$ so that $f_W \in [0..1]$, $f_T(\theta) = \frac{\theta-3}{30-3} \in$

$[0..1]$). Each $\alpha_i^{(W)}$ or $\alpha_i^{(T)}$ scales how strongly subsystem i is impacted. E.g. GCU has $\alpha_{\text{GCU}}^{(W)} \approx 0$ and $\alpha_{\text{GCU}}^{(T)}$ small, while actuators have $\alpha_{\text{act}}^{(W)}$ bigger, etc.

Thus final degrade:

$$D_i(t) = \min\{1, D_i^{(\text{base})}(t) + \Delta_i(t)\}, \quad (3)$$

where :

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

clamping at 1 to ensure degrade never exceeds 1.

IV. SUBSYSTEM COST COMPONENTS

We take $C_k(t)$ (raw cost of subsystem k at time t) and w_k (weighting factor for subsystem k) such that $\sum_{k=1}^6 w_k = 1$. These weightings reflect the relative importance or cost impact of each subsystem.

Hence, the *total cost* at time t becomes:

$$C_{\text{total}}(t) = \sum_{k=1}^6 w_k C_k(t). \quad (4)$$

Normalization Assumption: If we do not know each absolute cost, we can assume each $C_k(t)$ is scaled to a $[0, 1]$ range or any dimensionless scale, then apply w_k to reflect its share. As time increases (and degradation rises), each $C_k(t)$ grows accordingly.

Cost Growth with Time and Degradation: We assume that *as times increases, the maintainability cost also increases*. This might be modeled by a function:

$$C_k(t) = C_{k,0} + \gamma_k t, \quad (5)$$

where:

- $C_{k,0}$ is a baseline cost offset,
- $\gamma_k > 0$ is a coefficient linking *time* to *cost growth*.

Thus, substituting (5) into (4) yields:

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

If t grows with time, so does $C_{\text{total}}(t)$.

V. THEORETICAL MAINTAINABILITY COMPUTATION

Maintainability quantifies the probability or ease that a UAV, experiencing subsystem wear or partial failure, can be restored to an operational condition in minimal time. In our framework, we focus on:

- **Soft Failure Probability:** The likelihood a subsystem crosses the soft failure threshold $H_i^{(\text{soft})}$ before a specified time t .
- **Restorability and Repair Times:** If soft failure is detected, does preventive maintenance quickly restore it below $H_i^{(\text{soft})}$?
- **Overall System Maintainability:** Combining the individual subsystem maintainability to ensure continuous UAV operation.

A. Soft Failure Probability

Recall from normal based scatter assumption:

$$P_i^{(\text{soft fail})}(t) = 1 - \Phi\left(\frac{H_i^{(\text{soft})} - D_i(t)}{\sigma_i}\right), \quad (7)$$

where Φ is the standard normal CDF, σ_i is the uncertainty in the i th subsystem's wear. The *theoretical maintainability* of subsystem i through time t against soft failure is thus:

$$M_i(t) = 1 - P_i^{(\text{soft fail})}(t) = \Phi\left(\frac{H_i^{(\text{soft})} - D_i(t)}{\sigma_i}\right). \quad (8)$$

B. System-Level Maintainability

To extend maintainability from individual subsystems to the entire UAV, we evaluate whether the UAV can stay airborne (or mission-capable) under partial subsystem degradation. If a single subsystem's soft failure immediately grounds the UAV, system maintainability $M_{\text{system}}(t)$ is the minimum of all $M_i(t)$; if some redundancy is present, we may adopt a more complex relationship.

$$M_{\text{system}}(t) = \begin{cases} \min_{i \in \{1,2,3,4,5,6\}} \{M_i(t)\}, & \text{if subsystems in series} \\ \text{function of } M_i(t), & \text{if parallel.} \end{cases} \quad (9)$$

VI. OPTIMIZATION PROBLEM FORMULATION

We define an optimization problem that aims to *minimize total degradation plus some function of cost*:

$$\begin{aligned} \min \quad & \underbrace{\frac{1}{6} \left(\sum_{i=1}^6 D_i(t) \right)}_{\text{total degradation}} + \underbrace{\lambda \left(\sum_{k=1}^6 w_k C_k(t) \right)}_{\text{normalized cost}} \\ \min \quad & D_{\text{total}}(t) + \lambda C_{\text{total}}(t), \end{aligned} \quad (10)$$

and $\lambda > 0$ is a weight balancing *physical degrade* vs. *cost*.

A. Constraints

1) Failure Threshold Constraints:

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

(None of the subsystems may exceed their hard failure threshold.)

2) Maintenance Cost Constraint:

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

The total preventive/corrective maintenance cost cannot exceed the budget.

3) Failure Probability Constraint:

$$F(D_i(t)) \leq P_{\text{max}}, \quad i = 1, 2, 3, 4, 5, 6.$$

Probability of catastrophic failure for each subsystem must remain below a certain threshold.

4) Wind Speed Constraint:

$$V_w \leq V_{\text{max}},$$

where V_{max} is a maximum allowable wind speed for safe flight.

5) Temperature Constraint:

$$T_{\text{min}} \leq T \leq T_{\text{max}}.$$

The UAV must operate within a permissible temperature range.

VII. SIMULATION RESULTS

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

- $0 \leq t \leq 15,000$ (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.

A. Subsystem Cost Components

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

B. Wind & 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*: near 3°C in the early morning (e.g. 3 am) to about 30°C in the mid-afternoon (3 pm). Over 15,000 hours, we effectively have ≈ 625 day/night cycles.

C. Data Logging and Post-Processing

If the UAV is run for N hours, we record the following:

- **Time (Flight Hours)** (t_j): The simulated clock or flight duration.
- **Subsystem Degradation** ($D_i^{(\text{obs})}(t_j)$): 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**: ($C_k^{(\text{obs})}(t_j)$)

Figures 1–5 show the wind & temperature values, degradation for each subsystem and combined maintainability.

VIII. PARAMETER FITTING

In the previous sections, we described how we incorporate wind speed $W(t)$ and temperature $\Theta(t)$ into the subsystem degradation via environment offsets $\Delta_i(t)$. Here, we focus on:

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

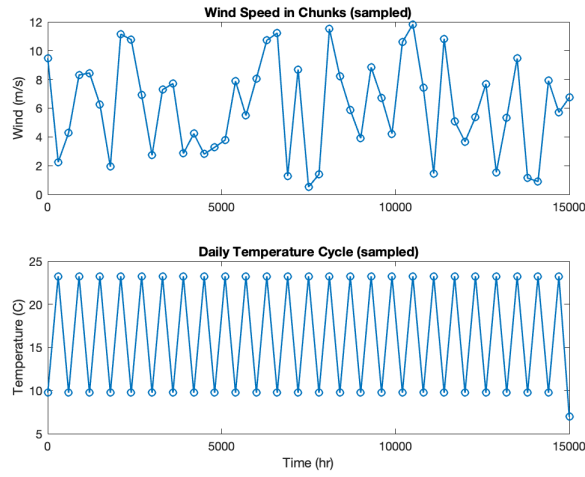


Fig. 1. Wind Gust & Temperature Cycles

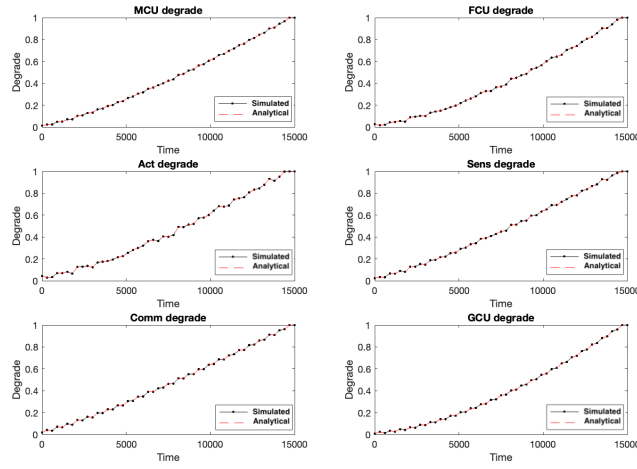


Fig. 2. Individual Subsystem Degradation

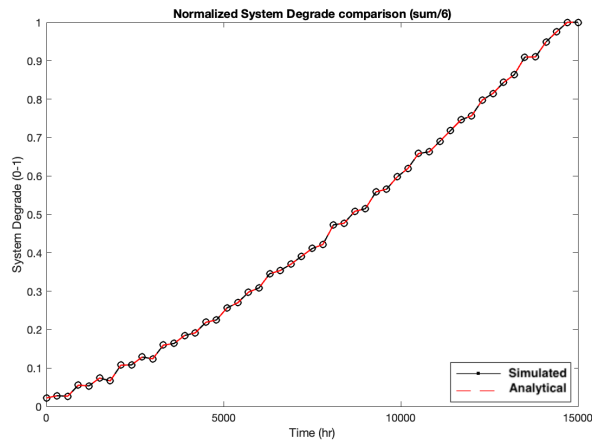


Fig. 3. Total System Degradation

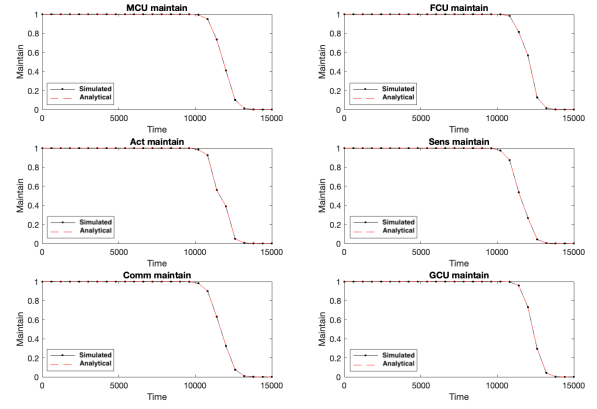


Fig. 4. Individual Subsystem Maintainability

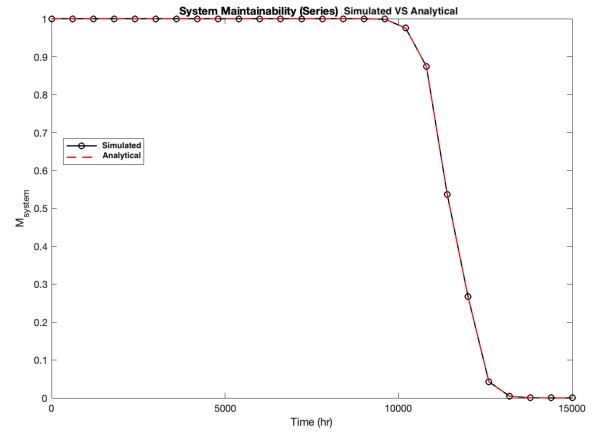


Fig. 5. Total System Maintainability

A. Parameter Fitting with Environment

From the defined model in Equation (3):

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

we have unknown parameters:

- 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 hours), we form residuals:

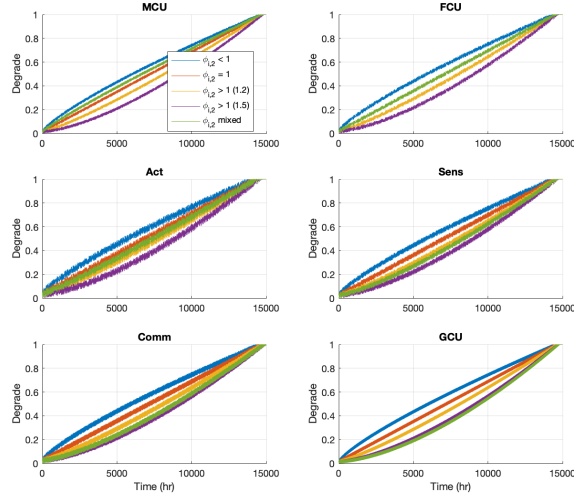
$$r_{i,j}(\mathbf{p}_i) = D_i^{(\text{obs})}(t_j) - D_i(t_j; \mathbf{p}_i),$$

and minimize the sum of squared residuals:

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

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

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


 Fig. 6. Subsystem Degradation for different values of ϕ_2

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

B. Parameter Table

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

TABLE I
PARAMETER VALUES FOR 6 SUBSYSTEMS WITH WIND & TEMPERATURE

Subsystem	T_i	$\phi_{i,2}$	$\alpha_i^{(W)}$	$\alpha_i^{(T)}$	RMSE
MCU	14924	1.30	0.01	0.02	3.63×10^{-14}
FCU	14805	1.50	0.03	0.01	5.05×10^{-14}
Act	14827	1.40	0.05	0.02	1.87×10^{-14}
Sens	14830	1.25	0.02	0.03	1.92×10^{-14}
Comm	15091	1.20	0.01	0.04	2.38×10^{-14}
GCU	14844	1.60	0.000	0.03	2.95×10^{-14}

TABLE II
OBSERVATION FROM PARAMTER VALUES

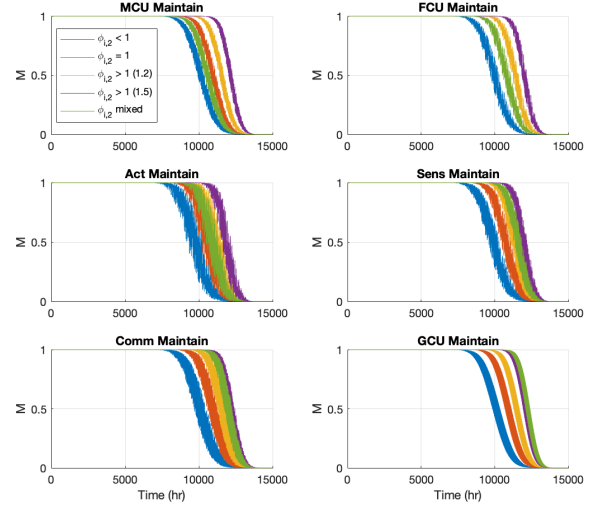
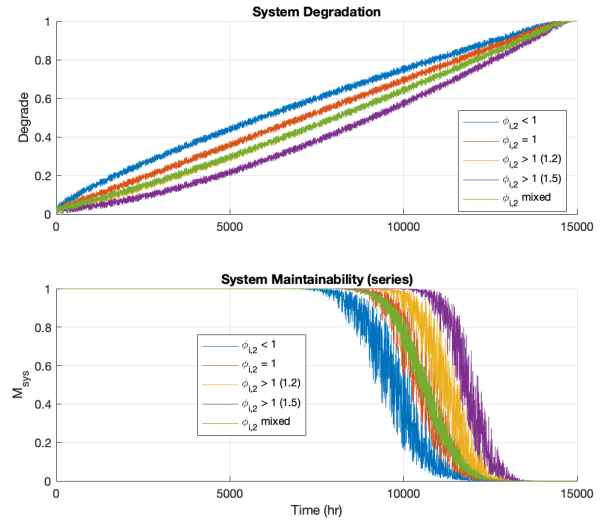
Subsystem	Notes
MCU	Minimal wind effect, mild temp effect
FCU	Moderately wind-limited
Act.	Actuators strongly wind-affected
Sensors	Some temp sensitivity, moderate wind
Comm.	High temp effect for RF amps
GCU	No wind effect, moderate temp effect

Here:

- T_i is the base time (in hours) at which $(\frac{t}{T_i})^{\phi_{i,2}}$ hits 1 if 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 Fig.6 to Fig.8:

- For different values of $\phi_{i,2}$, we see different behaviour of degradation & maintainability


 Fig. 7. Subsystem Maintainability for different values of ϕ_2

 Fig. 8. System Degradation & Maintainability for different values of ϕ_2

- As $\phi_{i,2} < 1$, $(\frac{t}{T_i})^{\phi_{i,2}}$ tends to go faster to 1. Hence, faster degradation & less maintainability
- As we increase $\phi_{i,2} > 1$, the degradation slows down because of $(\frac{t}{T_i}) < 1$

IX. SOLVING THE OPTIMIZATION PROBLEM

We now have an overall objective function:

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

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 tak $\lambda = 1$. We also impose constraints 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 $0 \leq \Theta(t) \leq 30^\circ\text{C}$, etc.
- User can keep another constraint $C_m \leq C_{\text{budget}}$ as per requirements. But for this case we don't take this constraint into consideration.

Discrete vs. Continuous Approaches: Because t can range up to 15,000 hours, we might do one of two strategies:

- 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 we clamp degrade at 1 and add environment effects, we typically do not get a smooth derivative everywhere. So a simpler *discrete* check is often chosen in a real UAV scenario where flight hours are integral or near-integral anyway.

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

TABLE III
DEGRADE AND COST VALUES

Time	$\frac{1}{6} \left(\sum_{i=1}^6 D_i^{(\text{model})}(t) \right)$	$C_{\text{total}}(t)$	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
...	...	...	...
14112	0.93546	798.48	799.41546

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

X. CONCLUSION & FUTURE WORK

This paper demonstrates a maintainability model and simulation framework for a UAV with 6 key subsystems: MCU, FCU, Actuators, Sensor, Communication and GCS. By formulating an optimization problem that aims to minimize overall degradation while respecting environmental and operational constraints, we arrive at a cost-effective, robust strategy for scheduling maintenance. By adding cost to the exponential wear-out model, we capture the *resource/budget dimension* that operators face when keeping UAVs operational under environmental constraints.

The simulation results align well with the theoretical predictions, indicating that the exponential wear-out model (3) 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:

- **Additional Environmental Factors :** Instead of just wind and temperature, we can denote environment function dependent 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 polynomial.
- **Nonlinear or Threshold-Driven Cost Relationships:** For each subsystem k , maintenance cost starts from a baseline $C_{k,0}$ and rises with degrade 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 apply one global degrade curve, the framework can show that the degrade rate D_i depend 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.

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