Prognosis of Mission-Aware Remaining Useful Life for ROV Thrusters Using a Physics-Consistent Simulation Framework

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ABSTRACT

Remotely operated vehicles (ROVs) are now widely used to perform underwater missions that vary in duration, maneuvering intensity, and propulsive load. However, these differences, although they typically have a significant impact on how propulsion components degrade over time, are not considered by predictive models. As a result, the remaining useful life (RUL) of the thrusters is typically estimated assuming that future operating conditions will be like past ones, an assumption that is often unrealistic in mission-driven underwater operations.

In our work, mission-aware prediction of the remaining useful life of ROV thrusters is investigated, focusing on how planned mission characteristics shape the degradation progression and RUL estimation. We use a physics-consistent simulation environment representative of the BlueROV2, with applicability to related platforms such as the BlueBoat surface vehicle, in order to study this interaction in a controlled and repeatable manner where mission profiles are defined through a set of descriptors that capture thrust demand, load variability, duty cycle, and maneuvering aggressiveness, allowing for systematic comparison of different operational scenarios. Degradation is introduced by gradually modifying the electromechanical performance parameters of the thrusters, producing distinct degradation trajectories under the same initial conditions.

Health indicators derived from simulated measurements, such as motor current, rotational speed, temperature, and thrust, are used to monitor the progression of degradation, and predictive estimates are obtained by propagating the estimated health state forward across the candidate mission profiles rather than assuming a single RUL independent of the future mission. The results show that missions with similar time durations, but different propulsion command characteristics can lead to substantially different RUL predictions, even when the initial health state is the same. The simulation framework, in addition to observing these differences, allows us to have a systematic investigation of the sensitivity of the prognosis results to the parameters of each mission. By varying the mission descriptors separately, we can determine which aspects of a mission, such as sustained high thrust versus intermittent peak loads, dominate the degradation behavior and leading to uncertainty in the RUL predictions. This type of analysis is difficult to perform only with field data, and it is quite important for understanding the limits of prognosis in operational environments. Also, these results suggest that the RUL should be considered as dependent on how a system is expected to be used, rather than as a single fixed value. Since different mission characteristics have been shown to affect degradation in different ways, considering the planned mission leads to predictive estimates that are easier to interpret and more directly linked to operational choices. In practice, the framework allows for the comparison of different mission options based on their expected impact on the thruster life and highlights missions that are likely to accelerate degradation while offering the ability to prioritize maintenance actions based on expected operational requirements.

Finally, our study through simulations offers a simple and repeatable way to investigate this behavior in underwater robotic systems, without requiring extensive real-world failure data, and can serve as a basis for future work on mission-aware PHM methods.

1. INTRODUCTION AND RELATED WORK

Remotely operated vehicles (ROVs) are widely used in underwater operations such as inspection, monitoring, and subsea intervention. These missions often differ significantly in duration, maneuvering intensity, and propulsion demand.

As a result, the propulsion subsystem of an ROV (particularly the thrusters) operates under highly variable loading conditions that may significantly influence degradation

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behavior over time. Monitoring the health condition of propulsion components and predicting their remaining useful life (RUL) are therefore important challenges in the context of prognostics and health management (PHM).

Research in PHM has focused extensively on methods for estimating the remaining useful life of engineering systems in order to support condition-based maintenance and reliability-aware operation.

Early work in PHM focused mainly on the foundations of machinery prognostics by linking degradation monitoring with predictive maintenance strategies and by demonstrating how condition indicators derived from sensor data can be used to infer system health and anticipate failures (Vachtsevanos et al., 2006; Jardine et al., 2006; Peng et al., 2010). These studies introduced the core concepts that later shaped modern prognostic methodologies, including degradation tracking, health indicators, and threshold-based end-of-life estimation.

Later studies extended these ideas by developing systematic frameworks for RUL prediction using statistical and signal-processing techniques. Methods based on degradation trend analysis, stochastic processes, and state-space modeling have been widely investigated for rotating machinery and industrial equipment (Heng et al., 2009; Si et al., 2011; Lei et al., 2018; Tsarouhas et al., 2015). In these approaches, the temporal evolution of degradation indicators is modeled and extrapolated to estimate the time at which predefined failure thresholds are expected to be reached.

In recent years, the increasing availability of operational data has led to the widespread adoption of data-driven prognostic methods. Machine learning and deep learning techniques have been applied successfully to RUL estimation problems in a variety of engineering domains. Architectures such as recurrent neural networks, convolutional neural networks, and attention-based models have demonstrated strong predictive capabilities when sufficient training data are available (Wu et al., 2024; Pan et al., 2025). Despite their effectiveness, purely data-driven approaches often assume that the operating conditions during prediction are similar to those observed in the training dataset. When systems operate under substantially different conditions, the predictive performance of these models may degrade.

Model-based and physics-informed prognostic approaches attempt to overcome this limitation by explicitly incorporating knowledge of system dynamics and degradation mechanisms. These approaches include stochastic degradation models, physics-of-failure formulations, and state-space representations that propagate the health state of a component forward in time under assumed loading conditions (Si et al., 2011; Lei et al., 2018). By embedding physical knowledge into the prediction process, such models can extrapolate degradation behavior beyond previously observed data. However, they often rely on simplified assumptions regarding future usage profiles, which may limit their applicability in systems characterized by highly variable operational requirements.

More recently, hybrid approaches combining physical models and data-driven methods have been proposed. In particular, the concept of the digital twin has emerged as a promising paradigm for predictive maintenance and system prognosis. Digital twins integrate simulation models with operational data in order to create a virtual representation of a physical asset that evolves alongside the real system. Such models enable the exploration of hypothetical operational scenarios and the evaluation of system behavior under different conditions without requiring direct experimentation on the physical system (You et al., 2022; Chen et al., 2023; Aivaliotis et al., 2023).

Within the maritime and underwater robotics domain, PHM research has traditionally focused on structural integrity monitoring, corrosion processes, and the reliability of marine power systems. Recent survey studies emphasize the growing relevance of PHM techniques for maritime equipment while also highlighting the challenges associated with harsh environmental conditions, limited failure observations, and strongly variable mission profiles (Liang et al., 2024; Zhang et al., 2022). In marine vehicles, propulsion subsystems are among the most critical components, as they directly influence maneuverability, energy consumption, and overall mission success.

Existing research related to marine thrusters has mainly addressed fault detection and diagnosis rather than long-term degradation prediction. Data-driven diagnostic methods based on vibration analysis, electrical current signatures, and multi-sensor fusion have demonstrated promising results for detecting and classifying faults in marine propulsion systems (Tsai et al., 2021; Cho et al., 2024). Reviews of fault diagnosis techniques for unmanned underwater vehicles also highlight the complexity of propulsion-related faults and the strong influence of operational variability on system behavior (Liu et al., 2022). Nevertheless, most of these studies primarily focus on identifying abnormal conditions once they occur rather than predicting long-term degradation trajectories or remaining useful life.

A growing body of literature has also recognized that degradation behavior is closely linked to how a system is used. Usage-aware prognostic models and prognostics-aware control strategies have been proposed in order to incorporate operational loading conditions into lifetime prediction (Thuillier et al., 2024; Tsarouhas et al., 2016). These studies point out that RUL should not be interpreted solely as an intrinsic property of a component but rather as a quantity that depends on the future operating conditions experienced by the system. Despite this observation, most existing prognostic formulations still rely on simplified usage assumptions or incorporate operational variability only implicitly.

For ROVs, mission characteristics may vary substantially in terms of thrust demand, duty cycle, maneuvering intensity, and load variability and operational constraints (Heshmati-Alamdari et al., 2024, 2023). These differences can have a strong influence on the degradation behavior of propulsion components and consequently on the estimation of their remaining useful life. However, current PHM approaches rarely incorporate explicit mission descriptions when estimating RUL for underwater propulsion systems.

Based on these observations, the present work investigates mission-aware RUL prediction for ROV thrusters using a physics-consistent simulation framework representative of a BlueROV2 platform with applicability to related systems such as the robotic surface vessel BlueBoat. Rather than focusing on the development of a new prognostic algorithm, the objective is to examine how different mission profiles influence degradation trajectories and RUL estimates when starting from the same initial health state. By explicitly propagating degradation dynamics under alternative mission scenarios, the proposed framework provides insight into how operational decisions may affect the lifetime of propulsion components in underwater robotic systems.

The main contribution of the proposed work is the systematic investigation of mission-conditioned degradation dynamics and their impact on remaining useful life estimation in marine propulsion systems. More specifically, the proposed framework provides a controlled environment for analyzing how mission characteristics influence degradation progression and mission-conditioned lifetime prediction.

2. PROBLEM FORMULATION

2.1. Classical Remaining Useful Life Definition and Degradation Dynamics

In prognostics and health management, the remaining useful life (RUL) of a component is defined as the time interval between the current time t_0 and the end-of-life (EOL) time t_{EOL}, at which one or more predefined degradation thresholds are reached. Formally,

$$RUL(t_0) = t_{EOL} - t_0 \tag{1}$$

In most typical formulations, the EOL time is estimated by extrapolating degradation trends observed under past operating conditions. Implicitly, this assumes that the future operating profile will remain statistically similar to the past. Under this assumption, the predicted RUL is treated as an intrinsic property of the component at time t_0, largely independent of how the system will be used in the future.

While this assumption may be acceptable for systems operating under relatively stationary or repetitive load profiles, it becomes questionable for mission-driven systems such as ROVs, where future operating conditions are dictated by mission objectives and can vary substantially from one mission to another.

To describe degradation progression, we introduce a scalar degradation state $D(t) \in [0,1]$ representing the cumulative wear of the thruster. The limits $D = 0$ corresponds to a nominal healthy condition and $D = 1$ represents a theoretical maximum degradation level, while the operational end-of-life is defined through threshold crossings of the health indicators. In practice, the component may reach its operational end-of-life before $D(t) = 1$, depending on the selected health indicator thresholds. The degradation state evolves over time according to

$$\dot{D}(t) = f(D(t), u(t), x(t)), \tag{2}$$

where $u(t)$ represents the commanded thruster input (mission command) and $x(t)$ denotes measurable or latent system states such as thrust output, electrical current, or temperature. The degradation function $f(\cdot)$ captures the dependence of wear progression on operational loading and is assumed to satisfy

$$\dot{D}(t) \geq 0 \tag{3}$$

ensuring monotonic degradation growth. At the current time t_0, the degradation state $D(t_0)$ is assumed to be known or estimated from available measurements and health indicators.

2.2. Mission Representation

In mission-driven systems such as remotely operated vehicles, the future evolution of degradation depends strongly on the operational profile to be executed. A mission can therefore be represented as a time-varying command sequence applied to the thruster over a finite horizon:

$$\mathcal{M} = \{u(t) \mid t \in [t_0, t_0 + T_{\mathcal{M}}]\}, \tag{4}$$

where $T_{\mathcal{M}}$ denotes the mission duration. Two missions with identical duration may differ significantly in their operational characteristics, including average thrust demand, duty cycle, command variability, and maneuvering aggressiveness. These factors directly influence the electrical and thermal loading experienced by the propulsion system and therefore affect the rate at which degradation accumulates.

In our approach, missions are explicitly specified and treated as known future inputs. This allows the degradation dynamics to be propagated forward under alternative mission scenarios starting from the same initial health state.

2.3. Mission-Aware RUL

Given the current degradation state $D(t_0)$ and a candidate future mission profile $\mathcal{M}$, the degradation dynamics can be propagated forward in time as

$$D(t) = D(t_0) + \int_{t_0}^{t} f\big(D(\tau), u(\tau), x(\tau)\big) d\tau \tag{5}$$

In practice, this integral is evaluated numerically within the simulation environment. The end-of-life time associated with mission $\mathcal{M}$ is defined as the earliest time at which one or more health indicators exceed predefined thresholds:

$$t_{\mathrm{EOL}}(\mathcal{M}) = \inf\{t \geq t_0 \mid h_i(D(t), x(t)) \geq \delta_i\}, \quad (6)$$

where $h_i(\cdot)$ denotes a health indicator function and δ_i represents the corresponding failure threshold. The mission-conditioned remaining useful life is therefore defined as

$$\mathrm{RUL}(t_0 \mid \mathcal{M}) = t_{\mathrm{EOL}}(\mathcal{M}) - t_0 \quad (7)$$

This formulation highlights that RUL should not be interpreted as a single intrinsic property of a component, but rather as a quantity conditioned on the assumed future mission profile. Two missions starting from the same initial health state may therefore lead to substantially different degradation trajectories and end-of-life times, even if their duration is identical. From an operational perspective, this formulation enables direct comparison of candidate missions in terms of their expected impact on component lifetime. The prognostic problem therefore shifts from estimating the general lifetime of a component to assessing whether it can safely complete a specific mission.

The following section describes how this formulation is implemented in the MATLAB/Simulink simulation framework that models thruster performance, degradation evolution, and thermal effects for a representative ROV propulsion system.

3. SIMULATION FRAMEWORK

3.1. Simulation Architecture

To investigate the mission-aware remaining useful life formulation introduced in the previous section, a physics-consistent simulation framework was developed in MATLAB/Simulink. The framework represents the propulsion subsystem of the BlueROV2 underwater robotic vehicle and focuses on the behavior of a representative single thruster unit. Rather than modeling the full vehicle dynamics, the developed simulation emphasizes the interaction between commanded thrust, electrical loading, degradation progression, and thermal stress, which are the dominant factors affecting thruster health. The architecture of the simulation environment is illustrated in Fig. 1.

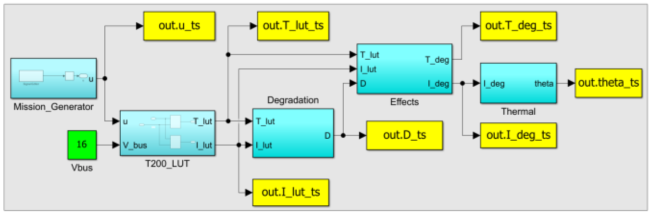

Figure 1. Overview of the MATLAB/Simulink simulation framework used for mission-aware RUL prediction.

The main signals and variables used in the simulation framework are introduced below and summarized in Fig. 1. The simulation architecture consists of four main components:

- a performance-mapped thruster model,
- a degradation state model,
- degradation-induced performance effects, and
- a lumped thermal model.

Mission commands are introduced as time-varying input signals and propagate through the thruster and degradation models. The resulting signals such as thrust, electrical current, temperature, and degradation state are recorded and used to compute the health indicators described in Section 4. This modular structure allows controlled investigation of how different mission profiles influence the evolution of degradation and the resulting remaining useful life.

3.2. Thruster and Degradation Model

The thruster is modeled using a static performance map that relates the normalized command input $u(t) \in [-1,1]$ and supply voltage to thrust output and electrical current consumption. This representation is consistent with the manufacturer-provided performance curves of the T200 thruster and avoids the need for detailed electromagnetic or hydrodynamic modeling (Blue Robotics, 2026).

The nominal thrust and current outputs are therefore expressed as

$$T_{\mathrm{lut}}(t) = \mathcal{L}_T(u(t), V_{\mathrm{bus}}), \quad (8)$$

$$I_{\mathrm{lut}}(t) = \mathcal{L}_I(u(t), V_{\mathrm{bus}}), \quad (9)$$

where $\mathcal{L}_T(\cdot)$ and $\mathcal{L}_I(\cdot)$ denote lookup table mappings derived from thrust performance data, and V_{bus} represents the supply voltage.

In this study, the supply voltage is assumed constant at 16 V, consistent with typical BlueROV2 operation. Thruster behavior is modeled using a lookup table derived from manufacturer thrust–current data, a common approach in marine robotics that avoids detailed electromagnetic or hydrodynamic modeling.

Thruster degradation is represented by the scalar state $D(t) \in [0,1]$, introduced in Section 2. The degradation rate is modeled as a function of mechanical loading and electrical stress:

$$\dot{D}(t) = c_T \mid T_{\mathrm{lut}}(t) \mid + c_I\, I_{\mathrm{lut}}^2(t) \quad (10)$$

where c_T and c_I are tuning parameters that scale the contribution of mechanical loading and electrical stress to degradation accumulation. The parameters c_T and c_I are selected to ensure that degradation progression occurs within the simulation horizon and correspond to an accelerated degradation scenario. They are not calibrated to a specific physical system but are used to illustrate the relative influence of mission characteristics. The absolute thrust term captures load-dependent mechanical wear, while the quadratic current term reflects Joule heating and associated electrical stress mechanisms. The degradation rate is defined in terms of the nominal (lookup-based) quantities rather than the degraded outputs in order to represent the applied loading conditions independently of the current degradation state.

This modeling choice avoids feedback effects where degradation would artificially reduce the estimated stress driving further degradation.

As degradation progresses, the effective performance of the thruster deteriorates. This behavior is modeled by scaling the nominal thrust and current outputs according to the degradation state:

$$T_{\mathrm{deg}}(t) = (1 - \alpha_T D(t))\, T_{\mathrm{lut}}(t), \tag{11}$$

$$I_{\mathrm{deg}}(t) = (1 + \alpha_I D(t))\, I_{\mathrm{lut}}(t) \tag{12}$$

where α_T and α_I represent degradation sensitivity coefficients. This formulation captures the expected degradation behavior where for the same command input, a degraded thruster provides less thrust and consumes more electrical current.

3.3. Thermal Dynamics and Simulation Outputs

Thermal effects are included through a first-order lumped temperature model driven by electrical losses. The motor temperature $\theta(t)$ evolves according to

$$C_{\mathrm{th}}\dot{\theta}(t) = h(\theta_{\mathrm{amb}} - \theta(t)) + \eta\, I_{\mathrm{deg}}^2(t) \tag{13}$$

where C_{th} denotes the thermal capacitance, h is the heat transfer coefficient, θ_{amb} is the ambient temperature, and η represents the conversion of electrical losses into heat. The quadratic current term reflects Joule heating generated by the motor during operation.

This simplified model captures the dominant temperature dynamics relevant to thruster health and allows the investigation of thermal stress under different mission profiles. The simulation produces time histories of the following variables:

- degraded thrust $T_{\mathrm{deg}}(t)$,
- degraded current $I_{\mathrm{deg}}(t)$,
- motor temperature $\theta(t)$, and
- degradation state $D(t)$.

These signals form the basis for constructing the health indicators used in the prognostic analysis presented in Section 4. The purpose of the simulation framework is not to create a high-fidelity digital twin of a specific thruster unit, but rather to provide a controlled environment for studying how different mission profiles influence degradation evolution and mission-conditioned RUL estimates.

Despite its simplified structure, the framework preserves the key couplings between mission commands, electrical loading, thermal stress, and degradation progression that are required for mission-aware prognostic analysis. This makes the framework suitable for studying the qualitative influence of mission characteristics on degradation behavior and prognostic estimates.

4. HEALTH INDICATORS AND PROGNOSTIC METHOD

4.1. Health Indicator Definition

Health indicators (HIs) are scalar quantities derived from measurable or estimated system signals that reflect the health condition of a component. In our proposed simulation framework, health indicators are constructed from variables that are directly affected by degradation and mission-dependent loading.

Three complementary indicators are considered in order to capture electrical, thermal, and mechanical aspects of thruster performance. These indicators are derived from the degraded current $I_{deg}(t)$, degraded thrust $T_{deg}(t)$, and motor temperature $\theta(t)$ obtained from the simulation framework described in Section 3. To enable comparison across different mission profiles, each indicator is normalized with respect to a nominal reference value corresponding to healthy operating conditions.

The current-based health indicator is defined as

$$HI_{\mathrm{cur}}(t) = \frac{I_{\mathrm{deg}}(t)}{I_{\mathrm{nom}}} \tag{14}$$

where I_{nom} represents the nominal current level under healthy operation.

Similarly, the thrust-based health indicator is defined as

$$HI_T(t) = \frac{T_{\mathrm{deg}}(t)}{T_{\mathrm{nom}}} \tag{15}$$

where T_{nom} denotes the nominal thrust generated by the thruster when no degradation is present.

Last, the temperature-based health indicator is defined as

$$HI_\theta(t) = \frac{\theta(t)}{\theta_{\mathrm{nom}}} \tag{16}$$

where θ_{nom} corresponds to the nominal motor temperature, typically close to ambient conditions at the beginning of the mission. It should be noted that the defined health indicators are not intended to isolate degradation independently of the input signal. Instead, they reflect the combined effect of degradation and mission-dependent loading. This is consistent with the objective of the present study, which is to analyze how mission characteristics influence degradation progression and the resulting prognostic estimates. In this context, variations in the health indicators are interpreted as mission-conditioned health responses rather than purely degradation-driven signals.

The nominal reference values I_{nom}, T_{nom}, and θ_{nom} are obtained from initial healthy operating period of the simulation, during which the degradation state remains close to zero. In this study, a reference window of $T_{\mathrm{ref}} = 300\mathrm{s}$ is used to estimate these values. This normalization ensures that the indicators remain dimensionless and comparable across missions starting from the same initial health state.

4.2. End-of-Life Criterion

The end-of-life condition is defined through threshold-based criteria applied to the health indicators. A thruster is considered to have reached its operational limit when one or more of the indicators exceeds a predefined degradation threshold. Specifically, EOL is detected when any of the following conditions is satisfied:

$$\begin{aligned} HI_{\mathrm{cur}}(t) &\geq \delta_{\mathrm{cur}} \\ HI_{\theta}(t) &\geq \delta_{\theta}, \\ HI_{T}(t) &\leq \delta_{T}, \end{aligned} \tag{17}$$

where δ_{cur}, δ_{θ}, and δ_{T} are the corresponding threshold values. In our simulation study, the following thresholds are used:

$$\delta_{\mathrm{cur}} = 1.30, \delta_{\theta} = 1.25, \delta_{T} = 0.80.$$

The current and temperature indicators increase as degradation progresses, reflecting increased electrical loading and thermal stress. In contrast, the thrust indicator decreases due to the gradual loss of propulsion efficiency. Consequently, the EOL condition for thrust is defined when the indicator falls below its threshold. These thresholds are selected to represent typical PHM practice and are intended to illustrate the mission-dependent behavior of the prognostic framework rather than to represent calibrated failure limits for a specific thruster unit.

4.3. Mission-Conditioned RUL Estimation

Given the current degradation state at time $t_0$and a candidate mission profile $\mathcal{M}$, the simulation framework propagates the degradation dynamics and corresponding health indicators forward in time. The mission-conditioned end-of-life time is defined as the earliest time at which any of the health indicators crosses its threshold:

$$t_{\mathrm{EOL}}(\mathcal{M}) = \inf\{t \geq t_0 \mid HI_{\mathrm{cur}}(t) \geq \delta_{\mathrm{cur}} \ \vee \ HI_{\theta}(t) \geq \delta_{\theta} \ \vee \ HI_{T}(t) \leq \delta_{T}\} \tag{18}$$

The corresponding mission-aware remaining useful life is then computed as

$$\mathrm{RUL}(t_0 \mid \mathcal{M}) = t_{\mathrm{EOL}}(\mathcal{M}) - t_0 \tag{19}$$

This formulation ensures that the predicted RUL explicitly depends on the assumed future mission. As a result, different missions can yield substantially different lifetime estimates even when starting from the same initial health condition. This formulation corresponds directly to the mission-conditioned RUL definition introduced in Section 2, where the end-of-life time is determined by the first threshold crossing of the health indicator functions.

To evaluate the effect of mission characteristics on component lifetime, the above prognostic procedure is repeated for multiple mission profiles. This allows us to directly compare how alternative operational scenarios affect the progress of degradation and the remaining useful life.

5. MISSION DESIGN AND SIMULATION PROTOCOL

5.1. Mission Profile Definition

For the evaluation of the proposed mission-aware RUL formulation, representative mission profiles are considered. Each mission is modeled as a time-varying thruster command sequence corresponding to different operational conditions of a remotely operated vehicle.

Mission commands are expressed as normalized control inputs $u(t) \in [-1, 1]$ consistent with the thruster model introduced in Section 3. These inputs determine the instantaneous thrust demand and therefore directly influence electrical loading, thermal stress, and degradation progression. To isolate the influence of operational characteristics on degradation, all missions are constructed with identical total duration but different command patterns. The missions therefore differ in their average thrust level, command variability, duty cycle, and maneuvering aggressiveness, allowing systematic comparison of how different operational conditions affect degradation evolution and remaining useful life. Mission profiles are implemented as piecewise-constant command signals using the Signal Editor in MATLAB/Simulink. The command signal represents the normalized thruster input and is bounded within the interval $[-1,1]$. In the present study, only positive thrust commands are considered, corresponding to forward propulsion.

5.2. Description of Mission Scenarios

Three mission scenarios are considered in order to represent different operational severities and propulsion loading patterns.

Mission A (Low severity – smooth operation): represents a mild operational scenario characterized by low to moderate thrust demand and smooth variations in the command signal. The command profile changes gradually and exhibits limited variability, resulting in a relatively low average load on the thruster. This mission serves as a baseline case representing mild operational stress and slow degradation progression.

Mission B (Moderate severity – high variability): maintains a moderately higher average thrust demand than Mission A but introduces frequent variations in the command signal. These variations cause repeated transitions between different load levels, increasing electrical and thermal stress even though the mean thrust demand remains comparable to Mission A. This mission is designed to highlight the influence of load variability on degradation progression.

Mission C (High severity – aggressive operation): represents a demanding operational scenario characterized by sustained high thrust demand combined with abrupt command variations. The command signal remains near the upper operating range for a significant portion of the mission while occasionally dropping to lower values. This results in a high duty cycle and increases electrical and thermal stress, leading to accelerated degradation. The corresponding command signals for the three mission scenarios are illustrated in Fig. 2.

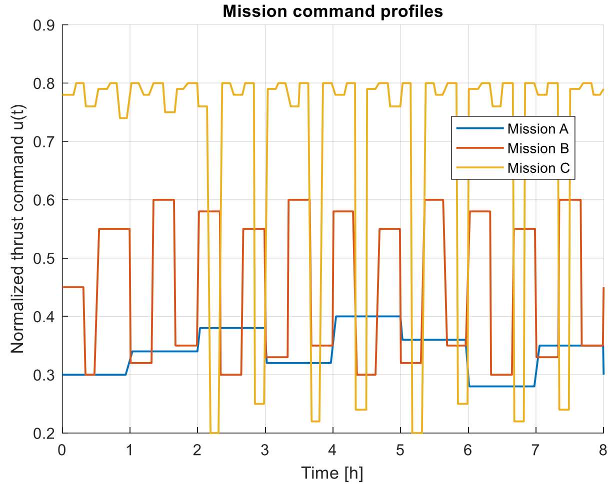

Figure 2. Command profiles for Missions A, B and C.

These missions are intentionally constructed to have equal duration while differing in their operational characteristics, enabling direct comparison of mission-induced degradation effects.

5.3. Simulation Setup and Parameters

All simulations are conducted using the MATLAB/Simulink framework described in Section 3. The supply voltage is fixed at 16 V, consistent with typical BlueROV2 operating conditions, and the ambient temperature is assumed constant. The simulation time horizon is set to 8 hours for all missions, which is sufficient to observe end-of-life conditions for the degradation parameters considered in this study and each simulation starts from the same initial health condition, with the degradation state initialized at $D(t_0) = 0$ corresponding to the initial time t_0. This ensures that all mission scenarios begin from an identical baseline.

The simulations are performed in a deterministic setting without stochastic disturbances or measurement noise. This configuration allows direct comparison of degradation trajectories and RUL estimates across the different mission profiles.

5.4. Evaluation Objective

The objective of the simulation protocol is not to produce calibrated lifetime estimates for a specific thruster unit but rather to demonstrate how different mission profiles influence degradation trajectories and mission-conditioned RUL predictions when starting from the same initial health state. By keeping the model structure and parameters identical across missions, any differences observed in degradation evolution or predicted RUL can be attributed directly to the characteristics of the mission profiles. This approach enables systematic investigation of how operational factors such as sustained thrust demand, duty cycle, and load variability influence degradation progression and remaining useful life.

6. RESULTS AND DISCUSSION

6.1. Health Indicator and Degradation Evolution

Figure 3 presents the evolution of the three health indicators $HI_{\text{cur}}(t)$, $HI_{\theta}(t)$, and $HI_T(t)$ for the three mission scenarios defined in Section 5. Given that all simulations start from the same initial health state, with the degradation state initialized at $D(0) = 0$, differences in the health indicator trajectories therefore arise only from differences in mission command profiles.

For **Mission A**, all health indicators evolve gradually and remain close to their nominal values for a large portion of the mission. The current and temperature indicators increase slowly, while the thrust indicator decreases only marginally. This behavior reflects mild degradation under smooth and relatively low propulsion demand.

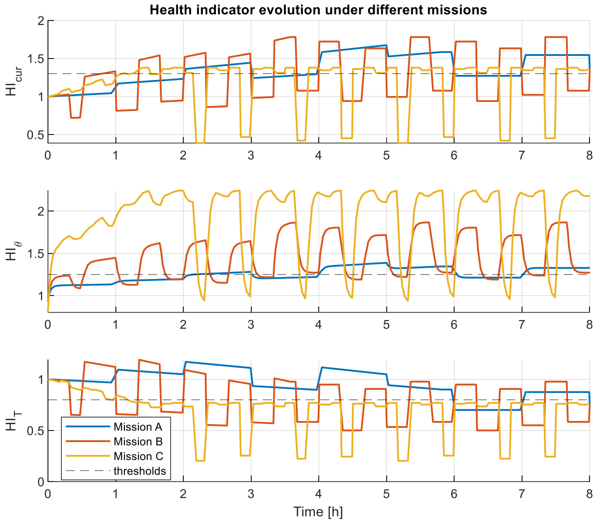

Figure 3. Evolution of current-based, temperature-based, and thrust-based health indicators for Missions A, B, and C.

In **Mission B**, the introduction of frequent command variations leads to noticeably faster growth in the electrical and thermal indicators. Although the average thrust demand remains comparable to Mission A, the repeated transitions between different load levels introduce additional electrical and thermal stress. This effect is particularly visible in the temperature indicator, which exhibits more pronounced excursions due to repeated current peaks.

In **Mission C**, the most aggressive mission scenario, the indicators evolve much more rapidly. Sustained high thrust levels combined with abrupt command changes result in rapid increases in both current and temperature indicators and a marked reduction in the thrust indicator. As a result, the health thresholds are reached significantly earlier than in the other missions.

The cumulative degradation state D(t) for the three missions is shown in Fig. 4, illustrating how mission characteristics directly influence degradation progression.

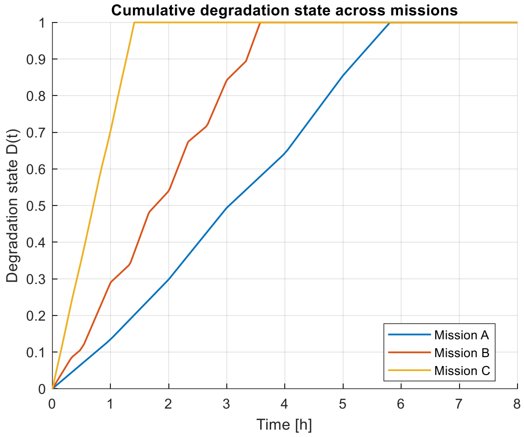

Figure 4. Evolution of the cumulative degradation state $D(t)$ for Missions A, B, and C.

6.2. Mission-Conditioned RUL Estimates

Mission-conditioned RUL estimates obtained using the threshold-based criteria defined in Section 4, are summarized in Table 1. The results show substantial differences in predicted RUL despite identical mission duration and identical initial health conditions.

Table 1. Mission-conditioned RUL estimates (simulation-based).

Mission	**Profile summary**	**Predicted RUL (hours)**
A	Low severity, smooth command (≈0.25–0.45, mean ≈0.35)	4.4147
B	Moderate mean load with high variability (0.30–0.60, mean ≈0.45)	0.3624
C	High duty, aggressive command with dips (0.20–0.80, mean ≈0.75)	0.1958

Mission A yields the longest predicted RUL of 4.41 hours, reflecting the relatively mild operating conditions associated with smooth and low-severity propulsion commands. The degradation trajectory remains gradual, and none of the indicators approaches the thresholds during the early portion of the mission. Mission B results in a significantly shorter RUL of 0.36 hours, indicating that frequent transitions between thrust levels increase electrical and thermal stress. Even when the average propulsion demand remains moderate, rapid fluctuations in load contribute to accelerated degradation accumulation. Finally, Mission C produces the shortest predicted RUL of 0.20 hours. In this case, sustained high thrust levels combined with aggressive maneuvering lead to the fastest degradation progression. The degradation state reaches the predefined threshold considerably earlier than in the other scenarios.

These results are illustrated in Fig. 5, which provides a quantitative comparison of the RUL estimates for the three mission scenarios and highlights how different operational profiles translate into distinct degradation trajectories.

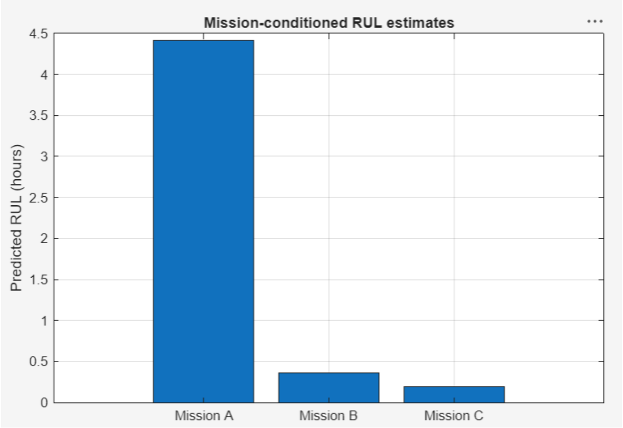

Figure 5. Mission-conditioned RUL estimates obtained for the three mission scenarios.

It should be noted that the absolute RUL values reported here depend on the selected degradation parameters and are intended primarily to illustrate the relative influence of mission characteristics on degradation progression.

The simulated degradation progression corresponds to an accelerated degradation scenario designed to highlight mission-dependent effects within a practical simulation horizon.

6.3. Discussion and Operational Implications

The comparative results highlight two primary mission-related mechanisms influencing degradation progression.

Sustained high thrust demand and duty cycle appear to be the dominant drivers of accelerated degradation. This effect is clearly illustrated by Mission C, where prolonged operation near the upper thrust range rapidly increases electrical loading and thermal stress, leading to significantly shorter predicted lifetimes. Load variability also plays an important role. Mission B demonstrates that frequent transitions between thrust levels increase electrical and thermal stress even when the average propulsion demand remains moderate.

This result highlights an important limitation of traditional mission-agnostic RUL formulations. Missions with similar average thrust levels may produce substantially different degradation trajectories when variability and duty cycle are taken into account. Mission B provides an indicative case where the average thrust level remains comparable to Mission A, while increased variability leads to faster degradation progression.

From an operational perspective, the results suggest that mission-aware RUL estimates can support more informed decision-making in underwater robotic systems. By conditioning lifetime predictions on planned mission profiles, operators can compare alternative missions in terms of their expected impact on component health and select mission plans that balance operational objectives with long-term system reliability.

Although the absolute lifetime values reported here depend on the selected degradation parameters, the relative differences between missions remain consistent. Overall, the results indicate that mission characteristics strongly influence degradation progression and the resulting remaining useful life estimates.

7. LIMITATIONS

Although the proposed framework provides useful insights into mission-aware degradation and RUL estimation, several limitations should be acknowledged.

This simplified formulation was selected intentionally in order to isolate the influence of mission profiles on degradation progression. Degradation dynamics are represented through a phenomenological formulation that relates thrust demand and electrical current to degradation progression. While this formulation captures the dominant stress mechanisms affecting small electric thrusters, it does not explicitly model detailed wear processes such as bearing degradation, propeller damage, or long-term motor efficiency loss. The model should therefore be interpreted as a representative abstraction of degradation behavior rather than a calibrated physical failure model.

A second limitation concerns the deterministic nature of the simulation environment. The framework assumes ideal operating conditions and does not incorporate stochastic disturbances, sensor noise, or environmental variability. In real underwater operations, factors such as hydrodynamic loading, water currents, voltage fluctuations, and measurement uncertainty may influence both system behavior and health indicator estimation. Incorporating stochastic effects would therefore provide a more realistic representation of operational conditions.

The analysis also focuses on a single thruster subsystem and does not explicitly consider the interaction with full vehicle dynamics or the closed-loop control system. In practice, propulsion operates within a multi-thruster configuration where control allocation, vehicle maneuvering dynamics, and mission-level constraints influence the distribution of load among thrusters.

The present study does not incorporate uncertainty in the degradation model or measurement process. Future work will consider stochastic modeling and uncertainty propagation in mission-aware RUL estimation. The framework assumes that degradation model parameters are known. In practice, these parameters would need to be estimated from data, which constitutes an important direction for future work.

Despite these limitations, the proposed framework illustrates the central concept of mission-conditioned remaining useful life estimation. The results show how different mission profiles can produce substantially different degradation trajectories even when starting from identical initial health conditions. Future work will therefore focus on extending the framework toward higher-fidelity models, incorporating uncertainty, and validating the approach using experimental data or field measurements.

8. CONCLUSIONS AND FUTURE WORK

This paper presented a mission-aware prognostic framework for estimating the remaining useful life of a thruster subsystem in an underwater robotic platform. The proposed approach combines a physics-inspired degradation model, health indicator monitoring, and mission-conditioned simulation to investigate how operational profiles influence degradation progression and lifetime predictions.

Three representative mission scenarios with identical duration but different propulsion characteristics were analyzed using a MATLAB/Simulink simulation framework. The results indicate that mission characteristics such as sustained thrust demand, duty cycle, and load variability can significantly influence degradation evolution and predicted remaining useful life. Aggressive mission profiles produced substantially faster degradation and markedly shorter RUL estimates compared with smoother operating conditions.

These findings clearly highlight the importance of incorporating mission information into prognostic analysis. In this sense, the present study highlights the importance of mission-aware prognostics as a complementary perspective to traditional mission-agnostic RUL estimation approaches. This perspective highlights the importance of integrating mission information into prognostic analysis for mission-driven robotic systems.

Treating RUL as a mission-conditioned quantity enables more realistic lifetime predictions and can support improved mission planning and maintenance decision-making for underwater robotic systems. Our future work will focus on extending the framework toward higher fidelity system models, incorporating uncertainty and environmental disturbances, and validating the approach using experimental or field data in order to further investigate mission-aware prognostics and their role in supporting reliability-aware mission planning for underwater robotic systems.

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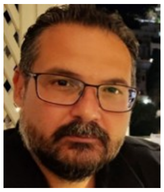

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