RUL-Aware RRT*: Degradation-Balanced Motion Planning for Robotic Manipulators

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Abstract

Industrial robotic manipulators operating over long durations may suffer from uneven joint degradation, causing the weakest actuator to fail prematurely and limiting the lifetime of the entire system. Although Prognostics and Health Management (PHM) techniques can estimate component health and remaining useful life (RUL), such information is rarely incorporated into online motion planning. To address this gap, this paper proposes an RUL-aware RRT* method that integrates joint RUL information into the trajectory generation process through a health-aware cost formulation and an adaptive joint weighting mechanism. A deterministic cumulative joint-usage surrogate is used to represent planning-level degradation in simulation. The method is evaluated in a Local Degradation Scenario, where one joint starts from a severely weakened condition and acts as the dominant lifetime bottleneck. Results show that the proposed method reduces the motion assigned to the weak joint, delays the first system failure, and maintains more balanced degradation than the baseline RRT*. These findings demonstrate that integrating prognostic information into motion planning provides a practical pathway toward health-aware robotic decision-making.

1. Introduction

Industrial robotic manipulators rely on multiple joint actuators operating cooperatively to execute complex tasks (Rüßmann et al., 2015). During long-term operation, however, uneven workload distribution often causes certain joints to degrade faster than others (Raviola et al., 2021). Since system reliability is ultimately constrained by its weakest component, the premature degradation of a single actuator can trigger unexpected shutdowns and significant production losses. While Prognostics and Health Management (PHM) and digital twin technologies have advanced continuous condition monitoring and remaining useful life (RUL) prediction (Lei et al., 2025), these tools are primarily utilized for predictive maintenance scheduling. They are rarely incorporated into online operational decision-making, meaning that component health information seldom influences how a robot physically executes its tasks (Kumar, Khalid, & Kim, 2023).

Concurrently, sampling-based motion planning algorithms like Rapidly-exploring Random Trees (RRT*) provide a flexible framework for trajectory generation, utilizing cost functions to optimize paths (Kingston, Moll, & Kavraki, 2018). Although existing planners have successfully integrated constraints for factors such as energy consumption and operational safety (Alam, Nishi, Liu, & Fujiwara, 2023), the integration of component-level health information—specifically uneven joint degradation—into the planning process remains largely unexplored. Related ideas have been studied in health-aware control, RUL control, and prognostics-aware control, where control actions or operating policies are modified to balance performance and equipment degradation (Thuillier, Jha, Le Martelot, & Theilliol, 2024; Matias & Jaschke, 2025; Felix, Martinez, & Berenguer, 2025). The proposed method is also related to control allocation for redundant or multi-actuator systems, in which actuator usage can be redistributed according to constraints, faults, or health indicators (Johansen & Fossen, 2013; Khelassi, Jiang, Theilliol, Weber, & Zhang, 2011; Tedesco, Akram, & Casavola, 2022; Brown et al., 2009). In contrast to these control-level approaches, this work acts at the motion-planning layer: it embeds joint-health information into the sampling-based path cost before low-level control execution, so that the generated trajectory itself is biased away from joints with limited RUL.

Motivated by this gap, this study proposes an RUL-aware motion planning method that integrates joint health directly into the trajectory generation process. We extend the classical RRT* algorithm by introducing a health-aware cost function combined with an adaptive joint weighting strategy. This mechanism dynamically adjusts the planning cost based on the current RUL distribution, penalizing excessive motion on joints with limited remaining lifetime. Consequently, the planner actively redistributes motion usage, mitigates degradation imbalance, and delays the emergence of system lifetime bottlenecks.

The main contributions of this work are summarized as follows:

- A health-aware motion planning framework that integrates RUL information directly into the RRT* algorithm for robotic manipulators.
- An adaptive joint weighting mechanism that dynamically adjusts joint usage according to the evolving health conditions of individual actuators.
- A local degradation case study demonstrating that the proposed method delays the first system failure and improves degradation balance under run-to-failure operation.

2. Problem Formulation

2.1. Motion Planning Problem

Consider a robotic manipulator with J joints operating in a configuration space $\mathcal{X} \subset \mathbb{R}^J$. Each robot configuration is represented by the joint-angle vector

$$q = [q_1, q_2, \ldots, q_J]^\top, \tag{1}$$

where q_j denotes the angle of the j-th joint. The objective of motion planning is to generate a collision-free trajectory in the free configuration space $\mathcal{X}_{\text{free}} \subset \mathcal{X}$ that connects a given start configuration $q_{\text{init}} \in \mathcal{X}_{\text{free}}$ to a goal region $\mathcal{X}_{\text{goal}} \subset \mathcal{X}_{\text{free}}$.

Sampling-based planners such as RRT* incrementally construct a graph $G = (V, E)$ in the configuration space by randomly sampling feasible states and connecting them through local collision-free motions. In the standard formulation, the cost of a path segment between two configurations q_i and q_{i+1} is defined by the Euclidean distance in the joint space,

$$c(q_i, q_{i+1}) = \|q_i - q_{i+1}\|_2, \tag{2}$$

which measures the geometric displacement of the manipulator in the configuration space. The planner then seeks a trajectory that minimizes the accumulated path cost while satisfying collision constraints.

Although this formulation ensures geometric efficiency, it implicitly assumes that all joints have identical importance and health conditions. Consequently, the planner may repeatedly generate trajectories that heavily utilize certain joints, which can accelerate their degradation during long-term operation.

2.2. Degradation-aware Planning Objective

In practical industrial robots, each joint actuator gradually degrades as mechanical usage accumulates. The degradation phenomena considered in this study correspond to usage-induced wear and fatigue in joint actuators and transmission components, such as motors, bearings, and harmonic drives. Since this paper focuses on the planning mechanism rather than on component-level physics, the simulation uses cumulative joint angular displacement as a first-order usage surrogate for lifetime consumption. This choice is consistent with the assumption that, under comparable payload and speed conditions, larger accumulated joint motion generally implies higher accumulated mechanical duty in actuator/transmission components. It also avoids introducing torque, temperature, or vibration measurements that are not available in the simulated setup and would require a separate component-level prognostic model. Let $\mathrm{RUL}_j(t)$ denote the remaining useful life of joint j after executing t tasks. The evolution of $\mathrm{RUL}_j(t)$ depends on the cumulative motion usage of the joint, which is typically reflected by the accumulated angular displacement.

When the remaining useful life of any joint reaches a failure threshold, the robot can no longer continue operation. Therefore, the system-level failure condition can be expressed as

$$\min_j \mathrm{RUL}_j(t) \leq R_{\text{fail}}. \tag{3}$$

Under this condition, the lifetime of the entire robotic system is determined by its weakest joint, which becomes the dominant reliability bottleneck.

The objective of degradation-aware motion planning is therefore not only to generate geometrically feasible trajectories, but also to distribute motion usage more evenly across joints so as to delay the occurrence of such bottlenecks. In this work, joint remaining useful life information is incorporated into the motion planning process, allowing the planner to adapt trajectory generation according to the health condition of each actuator. This formulation establishes the basis for the RUL-aware motion planning framework presented in the next section. Accordingly, the RUL value used by the planner should be interpreted as a planning-level health state derived from a degradation surrogate, not as a direct measurement of a physical crack length or wear depth. The planning decision variable remains the generated trajectory, while the RUL state biases the trajectory cost.

3. RUL-aware Motion Planning

This section presents the proposed RUL-aware motion planning framework, which extends the standard RRT* algorithm by incorporating joint health information into the planning process. The overall architecture of the proposed approach is shown in Fig. 1. Instead of treating motion planning as a purely geometric optimization problem, the planner is embedded into a closed-loop framework that continuously connects motion planning, execution, and health monitoring.

As shown in Fig. 1, after each task execution, the joint motion usage is collected and used to update the estimated remaining useful life (RUL) of each actuator. The updated RUL values are then mapped to adaptive joint weights, which are incorporated into the cost evaluation of the RRT* planner. Through this iterative process, the planner continuously adjusts motion allocation among joints according to their current health conditions, thereby reducing degradation concentration and delaying the formation of system lifetime bottlenecks.

3.1. RUL-aware cost

In the standard RRT* framework, the local cost between two configurations depends solely on the geometric distance in the joint space, where all joints are implicitly treated as equally important in motion generation. Although this formulation ensures geometric efficiency, it neglects the fact that different joints may operate under different health conditions. As a result, a geometrically shortest path may repeatedly use joints that are already degraded, leading to faster wear and earlier system failure.

To address this limitation and enable health-aware decision-making during path generation, the proposed method augments the geometric cost with a health-related penalty term. The cost between two configurations q_i and q_{i+1} is defined as

$$\mathrm{Cost}(q_i, q_{i+1}) = \alpha \sum_{j=1}^{J} |\Delta q_j| + \lambda \sum_{j=1}^{J} \frac{\gamma_j |\Delta q_j|}{\max(\mathrm{RUL}_j, R_{\mathrm{floor}})}, \tag{4}$$

where $\Delta q_j = q_{i+1,j} - q_{i,j}$ denotes the displacement of joint j, and α and λ are coefficients that balance geometric optimality and health awareness. The first term corresponds to the conventional geometric distance in the joint space and preserves path efficiency when the robot is in a healthy condition. The second term introduces a health-related penalty that increases the cost for joints with shorter remaining lifetime. Here, γ_j is the adaptive weight associated with joint j, RUL_j denotes its remaining useful life, and $R_{\mathrm{floor}} > 0$ is a numerical floor used only to avoid division by zero in the cost evaluation. It is distinct from the physical RUL lower bound and from the failure threshold introduced in Section 4.

Through this formulation, the planner no longer selects paths solely according to geometric length. Instead, it also considers the current health state of each joint, giving preference to motions that distribute workload more evenly across the manipulator. In this way, the RUL-aware cost encourages the use of healthier joints, reduces the stress on degraded ones, and achieves a controllable balance between path efficiency and long-term reliability.

3.2. Adaptive weighting

To dynamically reflect the current health condition of the robot, the joint weighting coefficients are derived from the distribution of the joint RUL values. The objective is to assign larger penalties to weaker joints while keeping the overall cost strength consistent.

First, an imbalance index B is introduced to quantify the dispersion of the joint RUL distribution:

$$B = \frac{\mathrm{std}(\mathrm{RUL})}{\mathrm{mean}(\mathrm{RUL}) + \varepsilon}, \tag{5}$$

where $\mathrm{std}(\cdot)$ and $\mathrm{mean}(\cdot)$ denote the standard deviation and mean of all joint RUL values, respectively, and ε is a small constant for numerical stability. A larger value of B indicates a stronger health imbalance among joints.

The imbalance index is then mapped to a sharpness parameter η, defined as

$$\eta = 1 + B, \tag{6}$$

which controls how strongly the weighting mechanism emphasizes weak joints. When the RUL values are sim-

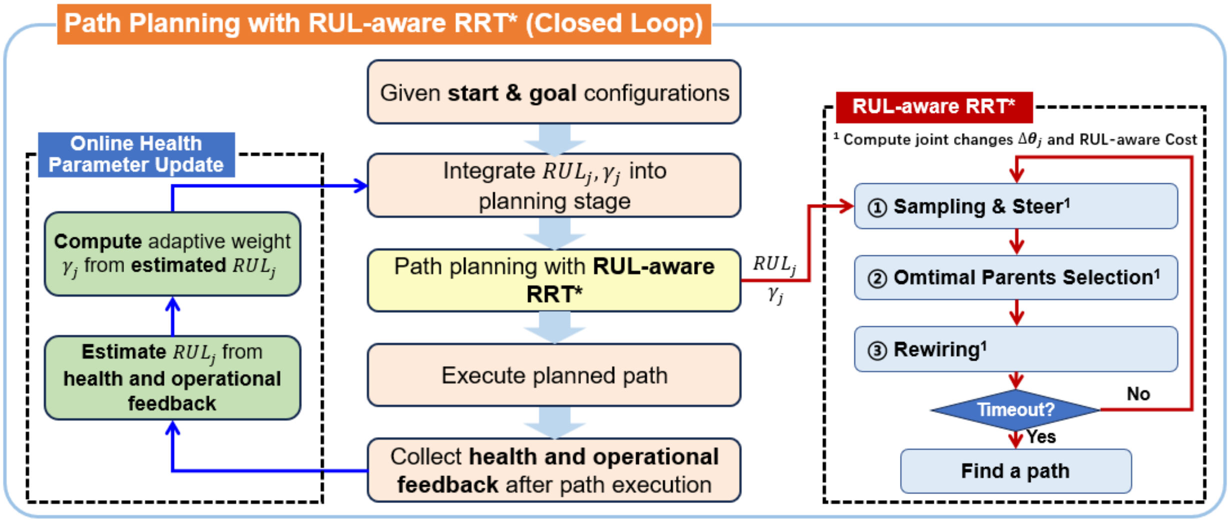

Figure 1. RUL-aware path planning with RRT* (closed-loop framework)

ilar, B is close to zero and the weighting difference between joints remains small. As the health imbalance increases, $\eta > 1$ produces a more concentrated weighting distribution that penalizes joints with lower RUL more aggressively.

Given this parameter, the raw weight of each joint is defined as

$$w_j = \frac{1}{\left(\max(\mathrm{RUL}_j, R_{\mathrm{floor}})\right)^{\eta}}, \tag{7}$$

where $R_{\mathrm{floor}} > 0$ is the same numerical floor used in Eq. (4) to avoid numerical instability when the remaining useful life becomes very small. This definition ensures that joints with smaller RUL receive larger raw weights, with the contrast amplified as η increases. This notation distinguishes the adaptive weighting sharpness η from the degradation-shape parameter p used later in Eq. (9).

To keep the overall cost magnitude consistent, the raw weights are then normalized as

$$\gamma_j = \frac{J\, w_j}{\sum_{i=1}^{J} w_i}, \tag{8}$$

so that the relative distribution of weights changes according to the health condition, while the average weight remains equal to one. In this way, the influence of joint degradation on the planning cost is adjusted without altering the overall scale of the objective function.

When all joints have similar RUL values, the resulting weights γ_j are nearly uniform, and the planner behaves similarly to a standard geometric planner. When one or more joints have much lower RUL, their corresponding γ_j increase, making motions involving those joints more costly. As a result, the planner tends to use healthier joints more often and reduce the workload assigned to weaker ones. This adaptive weighting mechanism enables dynamic redistribution of joint-level motion usage during long-term operation, thereby helping maintain more balanced degradation and improving system reliability.

4. Experimental Setup

The proposed RUL-aware motion planning framework is implemented and evaluated in a simulation environment to ensure controllability and repeatability. All implementations are carried out in the ROS Melodic framework using the MoveIt motion planning package integrated with the Open Motion Planning Library (OMPL). A simulated 6-DOF UR5 robotic manipulator is used as the evaluation platform, providing sufficient kinematic complexity to evaluate joint-level health-aware motion planning. The proposed planner is embedded in OMPL as a customized RRT* variant that incorporates the RUL-aware cost formulation and adaptive joint weighting mechanism introduced in Section 3. All planning and execution processes are visualized in RViz, which provides collision checking, trajectory interpolation, and real-time visualization of the robot motion.

Since the experiments are conducted entirely in simulation, no physical sensor measurements such as torque, temperature, or vibration are collected. Instead, the health state of each joint is represented by its angular displacement, which reflects the cumulative mechanical usage during repeated task execution. After each pick-

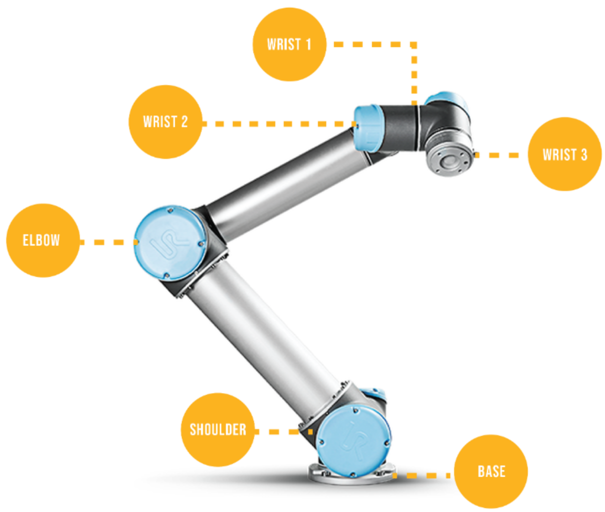

Figure 2. Simulated 6-DOF UR5 manipulator used for the motion-planning evaluation

and-place task, the incremental joint angle changes are recorded and used as feedback to update the estimated remaining useful life (RUL) of each joint. This design enables controlled evaluation of the planner's adaptive behavior without introducing uncertainty from sensor noise, while still establishing a direct link between motion usage and lifetime consumption. It should therefore be understood as a planning-level simulation model rather than a complete physical degradation model of a real robot joint. The degradation update is therefore deterministic for a given executed trajectory. Randomness is not injected directly into the degradation model; it enters the study through the randomly generated start-goal tasks and through the stochastic sampling process of RRT*. The reported means and standard deviations are computed over repeated runs under these random planning conditions. Propagating probabilistic RUL uncertainty, for example with particle filtering or Bayesian prognostics, is an important extension but is outside the scope of this first planning-focused study.

Both the baseline RRT* and the proposed RUL-aware RRT* use identical sampling strategies, step sizes, and connection radii to ensure a fair comparison. The weighting coefficients in the cost formulation are set to $\alpha = 1$ and $\lambda = 1$, providing a balanced trade-off between geometric optimality and health awareness. Each experiment is performed in a closed-loop manner: the planner first generates a path, the simulated robot then executes the motion, and the updated RUL and weighting parameters are subsequently fed back into the next planning cycle. This iterative process mimics long-term operation under progressive degradation while maintaining full control of experimental conditions.

In this study, the joint RUL is updated using a degradation-based model that depends explicitly on cumulative joint usage θ_j. The remaining useful life of joint j at task t is defined as

$$RUL_j^{(t)} = R_{\min} + (R_0 - R_{\min}) \left[1 - \frac{\theta_j^{(t)}}{\theta_{\max}}\right]_+^p, \tag{9}$$

where $[z]_+ = \max(z, 0)$, $R_0 = 1000$ denotes the initial remaining life of a healthy joint, $R_{\min} = 0$ is the physical lower bound of the simulated RUL state, and $\theta_{\max} = 1000$ is the maximum cumulative angular usage corresponding to complete lifetime consumption. The positive-part operator keeps the usage-to-RUL mapping well-defined when non-integer degradation-shape parameters are used. After each task, the accumulated joint usage is updated as

$$\theta_j^{(t+1)} = \theta_j^{(t)} + \Delta\theta_j^{(t)}, \tag{10}$$

where $\Delta\theta_j^{(t)}$ is the actual angular displacement of joint j during task t. Substituting $\theta_j^{(t+1)}$ into Eq. (9) yields the updated $RUL_j^{(t+1)}$. This formulation directly relates mechanical usage to lifetime degradation and allows the planner to adapt motion allocation according to the current health condition of each joint.

The exponent p controls the curvature of the degradation trajectory. In this study, it is used to examine the robustness of the proposed method under different degradation sensitivities within the local degradation case. Three representative settings, $p = 0.8$, $p = 1.0$, and $p = 1.5$, are considered in the experiments. In all cases, system failure is defined as the first instant at which one joint reaches the failure threshold $RUL_j \leq R_{\text{fail}} = 0$. Here, R_{fail} defines the system-level stopping condition, whereas R_{floor} in Eqs. (4) and (7) is only a numerical safeguard for cost computation. Thus, p is not a planner-tuning parameter but a simulation parameter describing the shape of the usage-to-RUL curve. Values below, equal to, and above one represent concave, linear, and convex degradation profiles, respectively.

5. Case Study: Local Degradation

To highlight the practical value of health-aware motion planning, this study focuses on a Local Degradation Scenario in which one joint starts from a severely weakened condition while the others remain healthy. The initial RUL configuration is set as

$$[RUL_1^{(0)}, RUL_2^{(0)}, RUL_3^{(0)}, RUL_4^{(0)}, RUL_5^{(0)}, RUL_6^{(0)}] = [100, 1000, 1000, 1000, 1000, 1000]. \quad (11)$$

This configuration represents an extreme but practically meaningful condition in which one actuator has already experienced substantial degradation and becomes the dominant lifetime bottleneck of the system. Under this setting, the central question is whether the planner can identify the weak joint and reduce its motion usage during task execution, thereby delaying its failure and extending the operational lifetime of the manipulator.

All experiments are performed on the same UR5 manipulator introduced in Section 4. Each task corresponds to a pick-and-place motion, where the start and goal configurations are randomly generated within the reachable workspace of the robot. For each planning cycle, the robot executes the generated trajectory, the joint-level angular usage is accumulated, and the corresponding RUL values are updated according to Eq. (9). The experiment continues until the first joint reaches the failure threshold, which corresponds to system-level failure.

The Local Degradation Scenario is selected in this study because it most directly reflects the decision-making value of health-aware motion planning under an explicit lifetime bottleneck. Unlike a fully healthy system, where all joints begin from a symmetric condition, the local degradation setting introduces a critical weak component from the outset. This allows the effectiveness of the proposed method to be evaluated in terms of three tightly coupled aspects: slowing down the degradation of the weakest joint, delaying the first system failure, and maintaining a more balanced degradation pattern during run-to-failure operation.

To evaluate these effects, the comparison between the baseline RRT* and the proposed RUL-aware RRT* is conducted under three degradation shape parameters, $p = 0.8$, $p = 1.0$, and $p = 1.5$. The results are analyzed in Section 6 from three perspectives: the evolution of joint degradation, the number of completed tasks before the first failure, and the degradation balance measured by the coefficient of variation of joint RUL.

6. Results

This section presents the results of the Local Degradation Scenario and compares the baseline RRT* with the proposed RUL-aware RRT*. The analysis focuses on three aspects: the evolution of joint degradation, the number of completed tasks before the first system failure, and the degradation balance during run-to-failure operation.

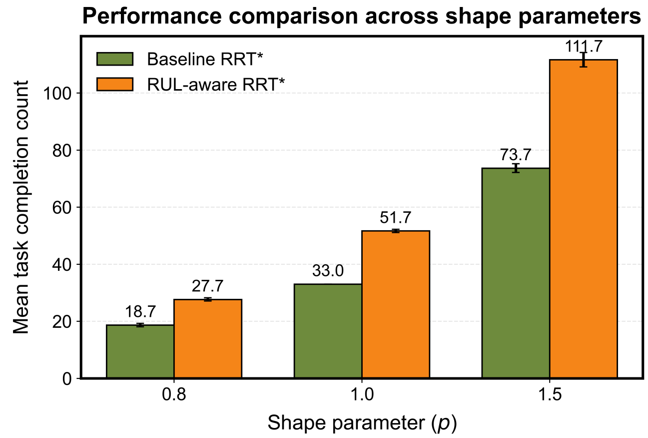

Figure 3. Comparison of the number of completed tasks for the Baseline RRT* and RUL-aware RRT* planners under the Local Degradation Scenario (LDS). Each group of bars corresponds to a different shape parameter ($p = 0.8$, 1, and 1.5). The two bars in each group represent the mean task completion counts of the Baseline and RUL-aware planners, respectively, with black error bars showing the standard deviation across repeated runs. Numeric values above the bars indicate the mean values.

6.1. Degradation evolution

Under the Local Degradation Scenario, the system starts with one severely weakened joint whose initial remaining useful life is much lower than that of the other joints. As a result, the system lifetime is dominated by this bottleneck component. In the baseline RRT*, the weak joint continues to receive considerable motion throughout the execution process, causing its RUL to decline rapidly and pushing the system to failure at an early stage. By contrast, in the proposed RUL-aware RRT*, the weight associated with the weak joint increases as its health condition worsens, which progressively reduces its participation in the planned trajectories. Consequently, the degradation rate of the weak joint is effectively slowed down.

This difference in trajectory-level motion allocation leads to substantially different degradation evolution patterns. Under the baseline planner, degradation remains concentrated on the weakest joint, whereas under the RUL-aware planner, motion usage is redistributed toward the healthier joints, thereby delaying the exhaustion of the bottleneck component. This result indicates that the proposed method can adapt trajectory generation according to the evolving joint health state and thus provide active protection for the most vulnerable actuator.

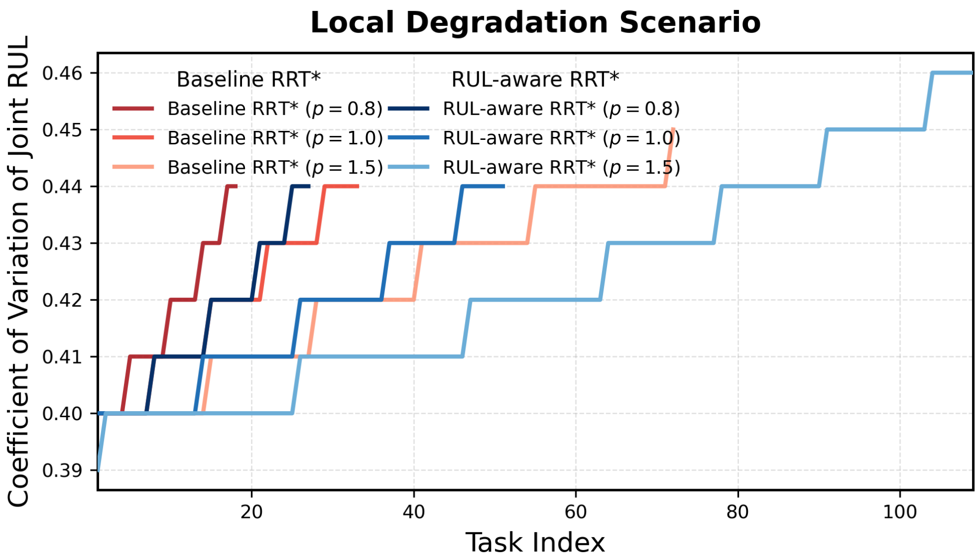

Figure 4. Evolution of the coefficient of variation of joint RUL in the Local Degradation Scenario. Each curve corresponds to a degradation-shape parameter ($p = 0.8$, 1.0, or 1.5), comparing the Baseline RRT* and the proposed RUL-aware RRT*.

6.2. First failure task

The most direct indicator of system-level benefit in the Local Degradation Scenario is the number of tasks completed before the first joint failure. As shown in Fig. 3, the proposed RUL-aware RRT* consistently outperforms the baseline RRT* across all three degradation shape parameters $p = 0.8$, 1.0, and 1.5.

For $p = 0.8$, the baseline planner completes only about 18.7 tasks before failure, whereas the RUL-aware planner achieves approximately 27.7 tasks, corresponding to a relative lifetime gain of about 48.1%. For $p = 1.0$, the completed task number increases from approximately 33.0 under the baseline to 51.7 under the RUL-aware planner, yielding a lifetime gain of about 56.7%. For $p = 1.5$, the baseline completes 73.7 tasks, while the proposed method reaches 111.7 tasks, corresponding to a gain of about 51.6%. These results demonstrate that the proposed method consistently increases the first failure task index k_{fail} regardless of the degradation curve shape.

The improvement arises because the RUL-aware planner continuously penalizes the usage of the weak joint as its health degrades. Instead of allowing the bottleneck component to be overused, the planner redistributes part of the workload to healthier joints, thereby extending the system's operational lifetime under run-to-failure conditions.

6.3. Degradation balance

In addition to delaying the first failure, the proposed method also improves degradation balance during system operation. Figure 4 compares the evolution of the coefficient of variation of joint RUL, CV_{RUL}, under the baseline and the RUL-aware planners.

Under the baseline planner, CV_{RUL} rises rapidly during the early stage and eventually reaches approximately 0.44 to 0.46 near failure, indicating that degradation remains highly concentrated on the weakest joint. In contrast, under the proposed RUL-aware planner, the imbalance level is consistently lower, with CV_{RUL} remaining around 0.40 to 0.42. This difference shows that the proposed method not only delays failure but also suppresses the amplification of degradation imbalance throughout the execution horizon.

This result is particularly important from a PHM perspective. A larger k_{fail} indicates that the system can perform more tasks before the first failure occurs, while a smaller CV_{RUL} indicates that the degradation distribution is more balanced during operation. Taken together, the results in Figs. 3 and 4 demonstrate that the proposed RUL-aware RRT* not only extends operational lifetime but also maintains a healthier and more balanced degradation pattern under local degradation conditions.

These benefits should be interpreted together with the operational performance requirements of industrial pick-and-place tasks. In the present study, the same planning parameters are used for both planners and the comparison focuses on lifetime extension rather than cycle-time optimization. In a production cell with a strict task-duration bound, the health-aware term would need to be balanced with timing or path-efficiency constraints through the coefficients α and λ, or by adding an explicit time constraint. Accordingly, the current results should not be interpreted as proving cycle-time preservation under strict industrial takt-time constraints; rather, they demonstrate the lifetime-extension potential of the proposed health-aware planning mechanism. Therefore, the proposed planner should be viewed as exposing a tunable trade-off: larger health penalties can protect the weakest joint more strongly, while smaller penalties preserve behavior closer to the baseline geometric planner.

7. Conclusion

This paper presented a RUL-aware motion planning method that integrates joint remaining useful life (RUL) into the RRT* algorithm. By combining a health-related cost formulation with an adaptive joint weighting mechanism, the planner accounts for both geometric feasibility and component health during trajectory generation. Evaluated under a Local Degradation Scenario where a single weakened joint acted as the system's lifetime bottleneck, the proposed approach effectively redirected motion away from the vulnerable joint. Consequently, the RUL-aware planner significantly extended the total number of tasks completed before system failure and maintained a more balanced distribution of joint-level degradation compared to the baseline RRT*.

These findings demonstrate the system-level benefits of incorporating prognostic information directly into motion planning. By allowing health data to influence online trajectory generation rather than merely dictating maintenance schedules, this framework highlights the potential of PHM in proactive robotic decision-making. The present results are obtained with a deterministic usage-based degradation surrogate, which is suitable for isolating the planning effect but does not capture all uncertainty sources of real robot joints or strict industrial cycle-time constraints. Future work will address real-robot experiments, probabilistic RUL estimation, cycle-time constraints, and richer degradation models.

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