# Health Aware Control Design for Extending Remaining Useful Life of Electro-Hydrostatic Actuator Based Steering

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## Abstract

Electro-hydrostatic actuators (EHAs) are used in aerospace, industrial, and off-road applications due to their efficiency and self-contained operation. However, degradation of critical components, such as the pump, can lead to reduced performance and unexpected failures.
Conventional control strategies often neglect real-time degradation effects, limiting their ability to optimize both actuator performance and remaining useful life (RUL). This study addresses this gap by developing a health-aware control (HAC) framework that integrates degradation modeling with predictive control for EHAs.
The proposed HAC system incorporates a nonlinear Wiener degradation model to estimate internal leakage progression in the pump. The degradation state is estimated online using an extended Kalman filter (EKF) and integrated into a model predictive control (MPC) framework to dynamically adjust control actions based on degradation predictions. The effectiveness of the approach is evaluated through simulations, comparing it to a baseline PID-controller. The choice of MPC and EKF over traditional PID control is justified by their ability to handle nonlinearities, provide predictive capabilities, and offer robust state estimation.
Simulation results show that the HAC system extends the RUL of the gear pump by 3.22 %, compared to the PID controller. The system successfully mitigates degradation effects, while maintaining an average position tracking error of 1.39 mm.
Although the RUL improvement is modest under accelerated degradation conditions, the proposed approach shows strong potential for real-world applications where degradation occurs over extended periods.
Future work will focus on experimental validation using physical test rigs and refining the degradation model to enhance prediction accuracy and control adaptability.

**Keywords:** electro-hydrostatic actuator, health aware control, hydraulic pump, model predictive control, remaining useful life

## 1 Introduction

Safety-critical systems in off-road mobile machinery such as steering mechanisms, braking systems, and actuators, play a critical role in ensuring both operator and machine safety during operations in challenging environments. Such systems are subjected to harsh conditions, increasing the likelihood of functional degradation and unexpected failures. Their failure can result in serious consequences, making reliability and timely maintenance essential. These safety implications highlight the need for proactive approaches that ensure sustained functionality even under continuous and demanding operating conditions. By maintaining safe operational states, these systems help prevent accidents, protect assets, and uphold regulatory compliance, particularly in mission-critical applications such as autonomous or remote-operated machines.

In recent years, the focus on sustainability and reliability in engineering has underscored the importance of extending the operational lifespan of key components. This is particularly relevant for off-road machinery, where operational downtime and maintenance costs have significant economic and environmental implications. Functional degradation in such systems often leads to unexpected failures, posing challenges to both performance and safety. Proactive measures such as health monitoring and prognostics are becoming essential tools in mitigating these risks, ensuring that safety-critical systems perform optimally throughout their life-cycle. A core concern for safety-critical systems is the accurate assessment and management of their Remaining Useful Life (RUL), which determines how long a component can operate before performance drops below acceptable thresholds. Degradation is often influenced by how the system is operated, with certain operating

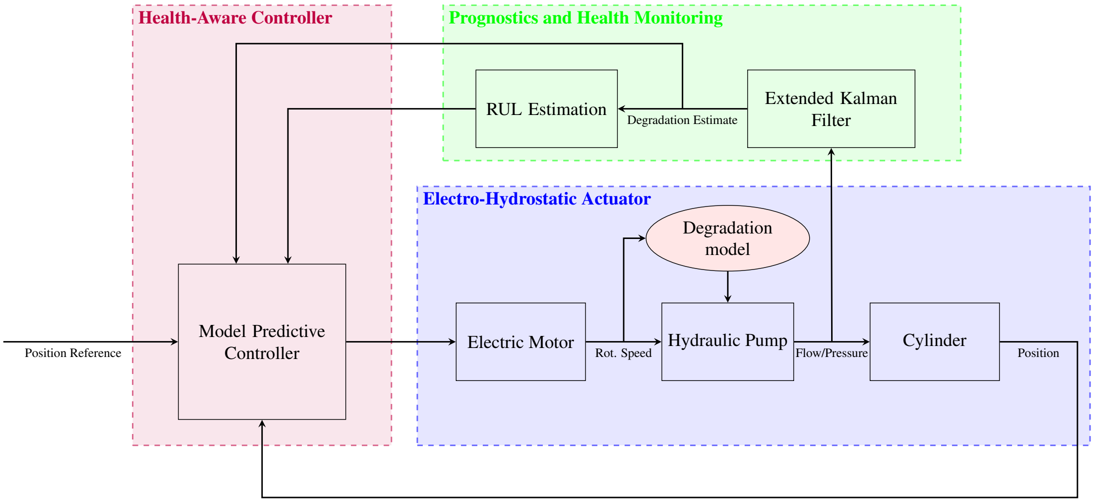



*Figure 1: HAC framework for EHA.*

points likely to accelerate degradation. Hence, manipulating operating points to manage degradation and reduce the risk of unplanned stoppages is desirable. Therefore health-aware strategies offer the potential to balance performance and reliability, minimizing resource use while maintaining system functionality.

The health-aware control (HAC) paradigm was introduced by Escobet et al. [1,2] as an approach that integrates system health monitoring with control and prognosis to enhance system reliability. In this paradigm, a prognosis module continuously estimates the health status and aging of system components, allowing the controller to modify its objectives accordingly. Unlike fault-tolerant control, HAC proactively adjusts the control strategy even before faults occur, aiming to optimize performance while extending the lifespan of components. Furthermore, while fault-tolerant control can assure acceptable performance when the actuator's health is poor, it may inadvertently accelerate degradation, highlighting the need for integrated health-aware strategies.

Model predictive control (MPC) has emerged as an effective framework for integrating prognosis and control to manage actuator degradation. The robustness and performance of MPC is shown to be better than a traditional control method in an electro-hydraulic system [3]. Unlike traditional PID-controllers, MPC can handle nonlinearities and constraints, making it more suitable for complex systems. For instance, Pereira et al. [4] developed a MPC framework that utilizes prognosis information to distribute control effort among redundant actuators, thereby avoiding breakdowns due to degradation. Similarly, a recent study by Dadash and Björsell [5] utilized MPC with novel methodology to calculate the state-action costs. This approach didn't use preconceived models of machine degradation. Zhang et al. [6] addressed the challenge of balancing reliability and performance in systems with degrading actuators, providing a foundational approach to degradation-aware control and demonstrating significant improvements in maintaining system functionality over extended periods.

To support HAC, accurate degradation modeling is crucial. The study by Letot and Dehombreux [7] provided insights into the use of degradation models for reliability estimation and residual lifetime predictions, showcasing their applicability in designing maintenance schedules that maximize system uptime. Recent advancements by Ma et al. [8] highlight the potential of physics-informed machine learning models to capture complex degradation phenomena in electro-hydrostatic actuators, achieving enhanced prediction accuracy compared to traditional models. Additionally, Zagorowska et al. [9] conducted a comprehensive survey on degradation models, emphasizing their applicability in control design and identifying gaps in existing methodologies. Their findings highlighted the influence of operating conditions on degradation, proposing strategies to mitigate accelerated wear. The combination of HAC and robust degradation modeling methodologies enhances the reliability and sustainability of safety-critical systems, facilitating predictive maintenance and minimizing the risk of unexpected failures.

Electro-hydrostatic actuators (EHAs) are used in modern hydraulic systems due to their efficiency, high power density, and ability to operate without centralized hydraulic circuits [10]. EHAs integrate electrical, mechanical, and hydraulic components, typically consisting of an electric motor, a hydraulic pump, and a hydraulic actuator. Unlike conventional hydraulic systems that rely on centralized pumps and fluid distribution networks, EHAs function as self-contained units, directly converting electrical energy into hydraulic power to drive actuators. This architecture enhances reliability, reduces maintenance needs, and eliminates hydraulic piping, making EHAs particularly attractive for aerospace, off-road machinery, and industrial automation applications [8, 10].

However, EHAs are subject to degradation and faults, particularly due to internal leakage and wear in the hydraulic pump. Previous research has explored real-time health monitoring [11,12] and fault-tolerant control methods [13] to sustain functionality under failure conditions, but these strategies do not actively mitigate degradation. Instead, they focus on ensuring operability, sometimes at the cost of accelerated wear. This limitation underscores the need for HAC strategies, which integrate degradation estimation and predictive control to extend the RUL while maintaining system performance.

The HAC paradigm enhances system reliability by integrating health monitoring, advanced control strategies such as MPC, and advanced degradation modeling to proactively manage actuator degradation. By dynamically adjusting control actions based on real-time health assessments, HAC optimizes performance while extending component lifespan. Robust degradation models further improve predictive maintenance and failure prevention. These works collectively underscore the growing recognition of the importance of integrating health monitoring and control to enhance system longevity and reliability.

While HAC has been explored in various actuator systems, its application to EHAs remains limited. As a result, control designs often fail to optimize both performance and RUL in real-world conditions. Additionally, there is a lack of frameworks that integrate HAC with accurate degradation modeling to achieve these optimizations in EHA systems.

The primary aim of this research is to develop a health-aware control system for previously proposed EHA-based steering mechanism [14], focusing on extending the RUL of a gear pump. This work addresses the need for integrating degradation modeling, real-time prognostics, and control strategies to prolong the lifespan of the EHA. By doing so, the study seeks to advance current methodologies and provide practical solutions for improving the sustainability and reliability of off-road machinery.

This study develops a HAC framework for EHA with a focus on the degradation of the gear pump. This framework is visualized in fig. 1. The proposed approach integrates real-time degradation modeling into the control strategy, allowing adaptive adjustments to optimize both actuator performance and RUL. By accounting for the progressive wear of the gear pump, the framework ensures reliable operation under varying conditions, enhancing the longevity and efficiency of the EHA system.

The remainder of this paper is organized as follows. Section 2 presents the EHA and pump degradation modeling. Section 3 discusses the implementation of degradation estimation and HAC using a MPC. Section 4 presents simulation results and performance analysis. Finally, Section 5 concludes the paper and discusses future directions.

# 2 System description and modelling

EHAs offer efficiency and reliability but are susceptible to degradation, particularly in the gear pump, which is the primary focus of this study. Increased internal leakage due to wear reduces performance and safety. First this section presents the EHA system model, capturing its electrical, mechanical, and hydraulic interactions. Then a degradation model for the pump is presented to support health-aware control strategies.

## 2.1 Electro-Hydrostatic Actuator System Model

The EHA system comprises an electric motor, a fixed displacement hydraulic pump, and a double-acting hydraulic cylinder. A hydraulic diagram of EHA is depicted in fig. 2. The system's dynamics are modeled to capture the interaction between electrical, mechanical, and hydraulic domains. The following EHA model is adapted from literature [8, 10, 13].

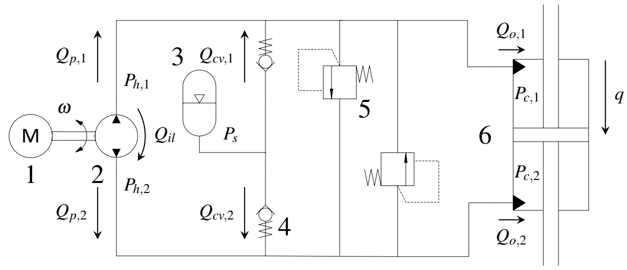



*Figure 2: EHA hydraulic diagram. 1. Motor, 2. Pump, 3. Accumulator, 4. Check valve, 5. Pressure relief valve, 6. Linear actuator.*

Given that the primary focus of this study is the hydraulic pump, the motor is approximated as a first-order system

$$\dot{\omega} = -\frac{1}{\tau_m}\omega + \frac{1}{\tau_m}\omega_{ref}, \tag{1}$$

where $\omega$ is the rotational speed of the motor, $\omega_{ref}$ reference rotational speed, and $\tau_m$ time constant. This simplification is justified by the high bandwidth of the torque control loop, which makes the transient dynamics of the motor negligible compared to the slower rotational speed and hydraulic system dynamics.

The main subject for investigation is the hydraulic pump. The inlet and outlet flows of the gear pump can be expressed as [8]

$$Q_{p,1} = D_p\omega - C_{il}\left(P_{h,1} - P_{h,2}\right) - C_{el}P_{h,1}, \tag{2}$$
$$Q_{p,2} = -D_p\omega + C_{il}\left(P_{h,1} - P_{h,2}\right) - C_{el}P_{h,2}, \tag{3}$$

where $D_p$ is the pump displacement, $P_{h,1}$, $P_{h,2}$ hose pressures, $C_{il}$ internal leakage coefficient, and $C_{el}$ external leakage coefficient. All internal leakage paths are lumped into single laminar leakage term to minimize the number of parameters that need to be estimated. The external leakage coefficient is assumed to be known.

The hoses connecting the pump to the cylinder chambers are modeled using flow continuity equations

$$Q_{p,1} + Q_{cv,1} = \frac{V_{h,1}}{\beta}\dot{P}_{h,1} + Q_{o,1}, \tag{4}$$

$$Q_{p,2} + Q_{cv,2} = \frac{V_{h,1}}{\beta}\dot{P}_{h,2} + Q_{o,2}, \tag{5}$$

where $V_{h,1}$ and $V_{h,2}$ are hose volumes, $\beta$ bulk modulus, $Q_{cv,1}$ and $Q_{cv,2}$ flows through the check valves, and $Q_{o,1}$ and $Q_{o,2}$ flows through the orifices.

To prevent cavitation, check valves have been integrated to the model with accumulator as a common pressure source $P_s$. It also serves as a source of oil for the system, replacing possible oil losses of the system. The accumulator dynamics are assumed insignificant and thus neglected from the mathematical model of the EHA [15]. The flow through the check valves can be expressed as

$$Q_{cv} = C_q A_{cv} \sqrt{\frac{2}{\rho} \max\{0,\ P_s - P_h\}} \tag{6}$$

where $C_q$ is discharge coefficient, $A_{cv}$ check valve area, and $\rho$ oil density.

The hoses are connected to the cylinder chambers via orifices. The orifice equations can be expressed as

$$Q_o = C_q A_o \sqrt{\frac{2}{\rho} |P_h - P_c|} \operatorname{sign}(P_h - P_c), \tag{7}$$

where $A_o$ is the orifice area and $P_c$ is the corresponding chamber pressure. The chamber volumes are

$$V_{c,1} = A_{c,1} q + V_{d,1}, \tag{8}$$

$$V_{c,2} = A_{c,2} (q_{max} - q) + V_{d,2}, \tag{9}$$

where $A_{c,1}$ and $A_{c,2}$ are effective areas of the piston, $V_{d,1}$ and $V_{d,2}$ dead volume of the chambers, and $q$ the displacement of the piston.

The flow continuity equations for the cylinder chambers are

$$Q_{o,1} = \frac{V_{c,1}}{\beta} \dot{P}_{c,1} + A_{c,1} \dot{q}, \tag{10}$$

$$Q_{o,2} = \frac{V_{c,2}}{\beta} \dot{P}_{c,2} - A_{c,2} \dot{q}, \tag{11}$$

where $\beta$ is the bulk modulus. The force created by the actuator is

$$F_c = A_{c,1} P_{c,1} - A_{c,2} P_{c,2} - B\dot{q}, \tag{12}$$

where $B$ is the viscous friction coefficient. Other friction forces are assumed small and thus neglected.

Finally, the force balance equation

$$F_c - F_l = M\ddot{q}, \tag{13}$$

where $F_l$ is the load force and $M$ is the equivalent load mass. The numerical values of the EHA model are presented in table 1.

The derived model is nonlinear and too complex to be used to design a controller and is thus used as the simulation model of EHA. A linear model derived in [15, 16] gives a good approximation of piston head dynamics from rotational speed of the pump. The transfer function relating the pump angular velocity to the linear displacement of the load is given by

$$\frac{q(s)}{\omega(s)} \approx \frac{\frac{2D_p \beta A}{M V_0}}{s^3 + \left(\frac{B}{M} + \frac{C_L \beta}{V_0}\right) s^2 + \left(\frac{2\beta A^2}{M V_0} + \frac{C_L B \beta}{M V_0}\right) s}, \tag{14}$$

where the total leakage coefficient of the system, consisting of pump internal leakage, pump external leakage, and actuator leakage, is given by $C_L = 2C_{il} + C_{el}$ and $V_0$ being the mean oil volume in the system.

*Table 1: EHA simulation parameter values.*

| Parameter | Symbol | Value |
|---|---|---|
| Motor time constant | $\tau_m$ | 0.1 s |
| Pump displacement | $D_p$ | $2.3125 \cdot 10^{-6}$ m³/rad |
| External leakage coefficient | $C_{el}$ | $1 \cdot 10^{-13}$ (m³/s)/Pa |
| Hose volume | $V_h$ | $4.5239 \cdot 10^{-5}$ m³ |
| Accumulator pressure | $P_s$ | $2 \cdot 10^{6}$ Pa |
| Check valve area | $A_{cv}$ | $1.9635 \cdot 10^{-7}$ m² |
| Orifice area | $A_o$ | $2.9225 \cdot 10^{-5}$ m² |
| Discharge coefficient | $C_q$ | 0.7 |
| Maximum stroke | $q_{max}$ | 0.5 m |
| Chamber dead volume | $V_d$ | $150 \cdot 10^{-6}$ m³ |
| Viscous friction coefficient | $B$ | 1500 N/(m/s) |
| Bulk modulus | $\beta$ | $900 \cdot 10^{6}$ Pa |
| Oil density | $\rho$ | 850 kg/m³ |
| Effective inertial load | $M$ | 650 kg |

### 2.2 Degradation Modeling for Gear Pumps

Gear pumps are critical components in hydraulic systems, where degradation typically manifests as increased internal leakage due to wear and tear. Since precise details of the degradation process are often unavailable, heuristic degradation models can be constructed to represent this behavior [9]. To effectively manage degradation, these models must account for the applied control effort and other influencing factors [17, 18]. For pumps, cumulative degradation models have been commonly used [4, 18, 19], demonstrating that high flow rates accelerate wear and degradation.

In this paper, the degradation of the pump is assumed to depend on rotational speed, with internal leakage increasing as the primary manifestation. This degradation is captured by an increase in the internal leakage coefficient, $C_{il}$, which serves as a key indicator of the pump's health.

Wiener-process-based models have been widely adopted in control applications due to their ability to handle stochastic variations [20, 21]. A nonlinear Wiener-process model, representing the progression of degradation, is formulated as follows:

$$\psi(t) = \varphi_0 + \int_0^t \mu(\tau, u(\tau), \Theta)\, d\tau + \sigma B(t), \tag{15}$$

where $\varphi_0$ is the initial degradation measure, $\sigma > 0$ is the diffusion coefficient, $B(t) \sim \mathcal{N}(0,t)$ standard Brownian motion and $\Theta$ parameter vector. The nonlinear part $\int_0^t \mu(\tau, u(\tau), \Theta)\, d\tau$ describes the deterministic degradation path of the actuator coupled with the control action $u(t)$. The form of $\mu(\tau, u(\tau), \Theta)$ is strongly context-dependent and should be carefully determined. Accelerated life test rigs can be utilized to identify the degradation path of the actuator.

This formulation can also be expressed as an ordinary differential equation (ODE)

$$\dot{\psi}(t) = \mu(t, u(t), \Theta) + \sigma w(t), \tag{16}$$

where $w(t)$ is white noise. This ODE can can be used as the degradation model in the controller design. It is also noted that the degradation speed $\dot{\psi}(t)$ can also depend on the current degradation or degradation at time $t$. Thus (16) is augmented and presented as

$$\dot{\psi}(t) = \mu(t, \psi(t), u(t), \Theta) + \sigma w(t). \tag{17}$$

To identify the degradation model for gear pumps, data from an accelerated life test rig was utilized [22]. By contaminating the hydraulic oil with particles, controlled wear was induced on a 16 cc/rev gear pump. The particle count used in the test was 23/22/19 in ISO4406:2021 standard [23]. The pump was driven with rotational speed of 1000 rpm for the whole duration of the test. The measured internal leakage data is shown in fig. 3, and the fitted deterministic degradation model is expressed as

$$\dot{\psi} = \Theta\,|\omega|\,\psi, \tag{18}$$

where $\Theta$ is the fitted parameter. The inclusion of degradation in equation (18) is motivated by higher internal leakage flow wearing the pump down even further.

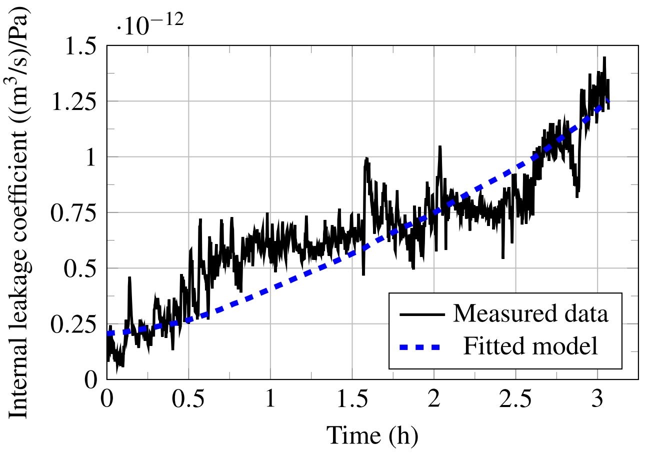



*Figure 3: Measured internal leakage coefficient and fitted degradation model in accelerated test conditions.*

The stochastic component of (15) is also considered by looking at the residuals of the fitted model in fig. 3. The residuals are shown in fig. 4. The effect of sensor noise to the residuals is assumed to be insignificant. The Wiener process satisfies

$$\mathrm{Var}\left[r(t)\right] = \sigma^2 t, \tag{19}$$

from which the diffusion coefficient can be estimated with

$$\hat{\sigma} \approx \sqrt{\frac{1}{n}\sum_{i=1}^{n}\frac{r^2(t_i)}{t_i}}. \tag{20}$$

From the residuals the diffusion coefficient $\sigma$ is estimated to be approximately $2.819 \cdot 10^{-15}$.

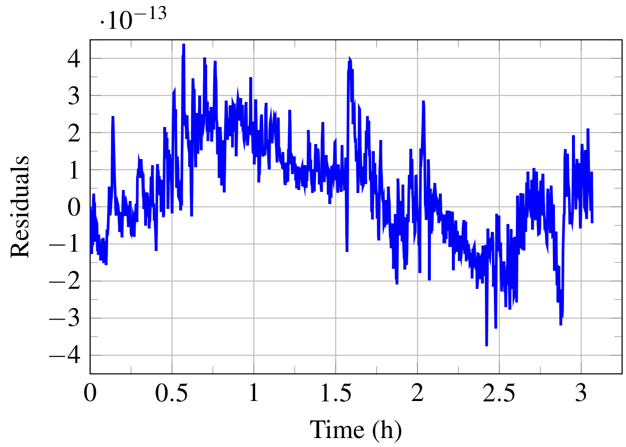



*Figure 4: Residuals of degradation model fit.*

Finally, the degradation model for the gear pump can be expressed as

$$\dot{\psi} = \Theta\,|\omega|\,\psi + \sigma w(t). \tag{21}$$

The internal leakage coefficient can be estimated using extended Kalman filter online.

To determine the RUL of the actuator, the future degradation trajectory is solved from equation (18) by separating variables and integrating both sides. It is assumed that $\omega$ stays constant and that the impact of noise is insignificant. Thus the degradation trajectory is

$$\psi(t) = \psi_0 e^{\Theta|\omega|t}, \tag{22}$$

where $\psi_0$ is the current degradation. By setting this equal to the failure threshold $S$ and solving for time, the RUL is

$$RUL(t) = \frac{\ln S - \ln \psi_0}{\Theta\,|\omega|}. \tag{23}$$

From (23) it is evident that the RUL will tend to infinity when pumps rotation speed approaches zero. This effect can be mitigated by adding a small constant to the denominator of (23). As $\omega$ was assumed constant, the RUL estimate needs to be updated every time $\omega$ changes. An estimate of average $\omega$ can also be used based on previous usage of the pump. This can be calculated using windowed average for example.

## 3 Health aware control of EHA

This section presents the implementation of HAC using a MPC strategy to dynamically adjust the control signal and balance system performance with degradation mitigation. While PID-controllers are simple and effective for linear and time-invariant systems, they lack the predictive capabilities and constraint handling required for a health-aware system operating under varying conditions. MPC, on the other hand, offers the ability to anticipate future behavior, explicitly incorporate system constraints, and optimize control actions over a prediction horizon. This predictive and constraint-aware nature makes MPC especially suitable for systems like EHA where maintaining both performance and component longevity is essential. Furthermore, MPC provides superior robustness against disturbances and model inaccuracies, and it can efficiently handle system nonlinearities, which are inherent in EHA systems. By using MPC, it is possible to systematically trade off between immediate performance needs and the long-term health of critical components, thus maximizing the RUL. In addition to the control strategy, this section also introduces the Extended Kalman Filter (EKF) for degradation estimation.

The EKF is chosen for its capability to estimate unmeasurable degradation states accurately in the presence of system nonlinearities and measurement noise. Unlike simpler estimators, the EKF linearizes the system dynamics around the current estimate, allowing it to maintain a high level of estimation accuracy. This real-time degradation information is crucial for the HAC system to adaptively manage the operation of actuator, ensuring reliable and safe performance. Therefore, the combined use of MPC and EKF provides a comprehensive framework for health-aware control, enabling robust, predictive, and adaptive management of system performance and degradation. By dynamically adjusting control actions based on the estimated degradation state, the system can mitigate wear while ensuring adequate actuator response. This approach reduces the risk of unexpected failures, improves overall system safety and sustainability, and aligns with the growing industry emphasis on reliability and proactive maintenance.

### 3.1 Extended Kalman Filter for Degradation Estimation

This subsection presents the implementation of an Extended Kalman Filter (EKF) to estimate the degradation state of a gear pump. The degradation is not directly measurable, requiring an estimation approach based on available system measurements. The EKF is chosen for its robustness in providing accurate state estimates in the presence of noise and uncertainties, which is crucial for adaptive control. The EKF algorithm is derived for the degradation model given in (21) and utilizes a linearization method at each time step.

The degradation model is formulated as a nonlinear state-space system:

$$\dot{\psi} = f\left(\psi, \boldsymbol{u}_{kf}\right) + w, \tag{24}$$

$$y_{kf} = h\left(\psi, \boldsymbol{u}_{kf}\right) + v, \tag{25}$$

where $y_{kf} = Q_{p,1}$ represents the measurable output. The function $h(\cdot,\cdot)$ corresponds to equation (2), and the input vector is defined as $\boldsymbol{u}_{kf} = \left[\omega, P_{h,1}, P_{h,2}\right]^{\mathsf{T}}$. The process noise $w \sim \mathcal{N}(0, \Sigma_w)$ and measurement noise $v \sim \mathcal{N}(0, \Sigma_v)$ are assumed to follow zero-mean Gaussian distributions. Thus, the estimation process relies on the measurements of $Q_{p,1}$, $\omega$, $P_{h,1}$, and $P_{h,2}$.

The EKF algorithm consists of two main steps: prediction and update. In the prediction step, the state and covariance are propagated forward in time using the system model. This *a priori* information is denoted by superscript minus ($^{-}$). In the update step *a posteriori* information is denoted by superscript plus ($^{+}$). Since the system is nonlinear, the model is linearized at each step using a first-order Taylor series expansion. The Jacobians of the system dynamics and measurement function are computed as:

$$f_{\psi}\left(\psi, \boldsymbol{u}_{kf}\right) = \frac{\partial}{\partial \psi} f\left(\psi, \boldsymbol{u}_{kf}\right) = \Theta\left|\omega\right|, \tag{26}$$

$$h_{\psi}\left(\psi, \boldsymbol{u}_{kf}\right) = \frac{\partial}{\partial \psi} h\left(\psi, \boldsymbol{u}_{kf}\right) = P_{h,2} - P_{h,1}. \tag{27}$$

The prediction step updates the state estimate and covariance as:

$$F_{\psi} = f_{\psi}(\hat{\psi}^{+}[k-1], \boldsymbol{u}_{kf}[k-1])T_s, \tag{28a}$$

$$\hat{\psi}^{-}[k] = \hat{\psi}^{+}[k-1] + f\left(\hat{\psi}^{+}[k-1], \boldsymbol{u}_{kf}[k-1]\right) T_s, \tag{28b}$$

$$\Sigma_{\hat{\psi}}^{-}[k] = F_{\psi}\Sigma_{\hat{\psi}}^{+}[k-1]F_{\psi}^{\mathsf{T}} + \Sigma_w. \tag{28c}$$

where $T_S$ is the sampling time of the filter.

In the update step, the measurement residual and Kalman gain are computed as:

$$H_{\psi} = h_{\psi}(\hat{\psi}^{-}[k], \boldsymbol{u}_{kf}[k]), \tag{29a}$$

$$\hat{y}_{kf}^{-}[k] = h\left(\hat{\psi}^{-}[k], \boldsymbol{u}_{kf}[k]\right), \tag{29b}$$

$$K = \Sigma_{\hat{\psi}}^{-}[k]H_{\psi}^{\mathsf{T}}\left(H_{\psi}\Sigma_{\hat{\psi}}^{-}[k]H_{\psi}^{\mathsf{T}} + \Sigma_v\right)^{-1}. \tag{29c}$$

The estimated degradation state is then updated using:

$$\hat{\psi}^{+}[k] = \hat{\psi}^{-}[k] + K\left(y_{kf}[k] - \hat{y}_{kf}^{-}[k]\right). \tag{30}$$

The covariance matrix update follows the Joseph form, which ensures numerical stability and preserves symmetry:

$$\Sigma_{\hat{\psi}}^{+}[k] = \left(I - KH_{\psi}\right)\Sigma_{\hat{\psi}}^{-}[k]\left(I - KH_{\psi}\right)^{\mathsf{T}} + K\Sigma_v K^{\mathsf{T}}. \tag{31}$$

The use of the Joseph form prevents loss of positive definiteness in the covariance matrix due to numerical errors. This formulation is crucial when dealing with small numerical updates in long-term estimation tasks.

By applying the EKF, the degradation state $\psi$ is continuously estimated based on the available system measurements. This enables real-time tracking of the pump's internal condition. The proposed estimation method ensures robustness against measurement noise and modeling uncertainties, improving the reliability of the health-aware control system.

### 3.2 Model Predictive Control for EHA Piston Head Position and Degradation Control

Model Predictive Control (MPC) is employed to achieve two primary objectives: regulating the piston head position and managing the degradation of the gear pump. The MPC framework optimizes the control inputs while considering constraints and performance criteria [4, 6].

The internal model is derived by augmenting the linear models (1) and (14) with the degradation model (21). The prediction model is

$$\dot{\boldsymbol{x}} = \begin{bmatrix} -a_3\ddot{q} - a_2\dot{q} + b_1\omega \\ \ddot{q} \\ \dot{q} \\ -\frac{1}{\tau_m}\omega + \frac{1}{\tau_m}\omega_r \\ \Theta\psi|\omega| \end{bmatrix} \tag{32}$$

$$\boldsymbol{y} = C\boldsymbol{x}, \tag{33}$$

where $\boldsymbol{x} = \begin{bmatrix} \ddot{q} & \dot{q} & q & \omega & \psi \end{bmatrix}^{\mathsf{T}}$ and

$$a_2 = \frac{\beta A_1^2}{MV_0} + \frac{C_L B_u \beta}{MV_0},\ a_3 = \frac{B_u}{M} + \frac{C_L \beta}{V_0},\ b_1 = \frac{2D_p \beta A_1}{MV_0}. \tag{34}$$

The controlled values are $\boldsymbol{y} = \begin{bmatrix} q & \psi \end{bmatrix}^{\mathsf{T}}$. The augmented model, also called degradation-incorporated state space (DISS) [6], is continuous and nonlinear. To be used in MPC-framework, the prediction model is discretized using the implicit trapezoidal rule.

MPC tries to find the optimal control sequence $\boldsymbol{u}_k$ by minimizing the cost function

$$J = \sum_{j=1}^{n_y} \sum_{i=1}^{N_p} \left\{ \frac{w_j}{s_j} \left( r_j[k+i|k] - y_j[k+i|k] \right) \right\}^2, \tag{35}$$

where $k$ is the current control interval, $N_p$ prediction horizon, $n_y$ number of controlled variables, $y_j[k+i|k]$ predicted value of the $j$th controlled variable at the $i$th prediction horizon step, $r_j[k+i|k]$ its reference trajectory, $s_j$ scale factor, and $w_j$ tuning weight.

The position reference values are kept constant for the duration of prediction horizon, if the reference trajectory is unknown. The degradation reference trajectory can be estimated from historical degradation data from same type of actuators which have successfully completed the mission. If acceptable historical data is available, it can be used as the reference trajectory. Additionally, a model based on (22)

$$r_\psi(t) = ae^{bt} + c, \tag{36}$$

where $a$, $b$, and $c$ are fitted parameters, can be fitted to the data and used as a reference trajectory.

The weights in (35) are usually treated as tuning parameters and chosen by hand. But for controlling the degradation, a more sophisticated approach must be used. Firstly the weight for degradation should not be higher than the weight for piston head position. Secondly, increasing the weight for degradation will reduce the reference following performance of piston head position. Thus the weight for degradation is chosen with

$$\begin{cases} w_\psi(t) &= \delta w_q \\ w_\psi(t) &= 0,\quad w_\psi(t) < 0 \\ w_\psi(t) &= w_{\psi,max},\ w_\psi(t) > w_{\psi,max} \end{cases}, \tag{37}$$

where

$$\delta = \frac{T_{req} - RUL}{T_{req}}. \tag{38}$$

The scaling parameter $\delta$ needs to be ensured to stay between zero and one. This approach increases the degradation weight if the RUL of the pump is not enough to complete the required mission.

# 4 Results and Discussion

The proposed HAC system was evaluated using a nonlinear simulation model of the EHA, where degradation was introduced as an increasing internal leakage coefficient in the gear pump. The system was tested under varying operating conditions to analyze its tracking performance, degradation progression, and RUL extension. The HAC system was compared against a baseline PID-controller. The comparison highlights the advantages of MPC and EKF in handling nonlinearities, providing predictive control, and offering robust state estimation, which contribute to the observed improvements in RUL.

The PID-controller was tuned with pole placement method. The linear model (14) includes an integrator, and thus the velocity form of PID-controller was used. The discrete time PID-controller algorithm is [24, 25]

$$\begin{aligned} \Delta u[k] &= u[k] - u[k-1] \\ &= K_p\left(e[k] - e[k-1]\right) + K_i T_s e[k] \\ &\quad - \frac{K_d}{T_s}\left(y[k] - 2y[k-1] + y[k-2]\right) \end{aligned} \tag{39}$$

where $e[k] = r[k] - y[k]$. Note that the derivative uses only the controlled variable $y$. The parameters of the PID-controller are presented in table 2.

The HAC-system was constructed according to section 3.2. The weight value for position error in (35) was chosen as 10. For degradation error, the weight was chosen according to equations (37) and (38), where the maximum was set to 5. This ensured that the position error is always kept small and degradation is a secondary objective. Static parameters of the MPC are listed in table 3.

*Table 2: PID-controller parameters.*

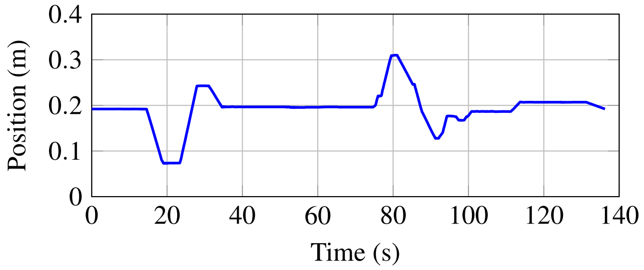
| Parameter | Symbol | Value |
|---|---|---|
| P-gain | $K_p$ | 103.9 rad/(s m) |
| I-gain | $K_i$ | 33 710 rad/(s$^2$ m) |
| I-time | $t_i$ | 0.003 081 s |
| D-gain | $K_d$ | 15.27 rad/m |
| D-time | $t_d$ | 0.1470 s |
| Sampling time | $T_s$ | 0.05 s |

*Table 3: HAC parameters.*

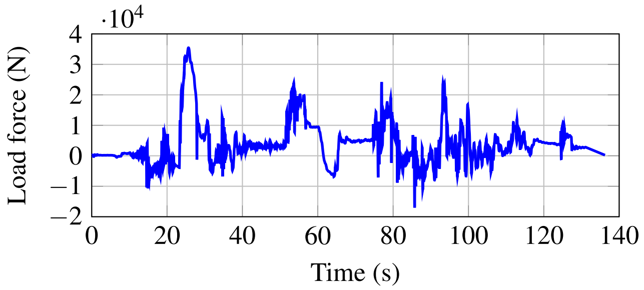
| Parameter | Symbol | Value |
|---|---|---|
| Prediction horizon | $N_p$ | 100 |
| Control horizon | $N_c$ | 40 |
| Position error weight | $w_q$ | 10 |
| Manipulated variable rate weight | $w_{\Delta u_k}$ | 1 |
| Sampling time | $T_s$ | 0.05 s |

The reference position and load force for the EHA are from Mevea virtual environment simulations [14] and are shown in fig. 5. The reference trajectories are cycled through 10 times.

The degradation speed of the pump is greatly accelerated to test the proposed HAC system. This leads to the pump breaking down after 1000 s.




*(a) Reference position values.*




*(b) Piston load force values.*

*Figure 5: Position and load reference trajectories for simulation.*

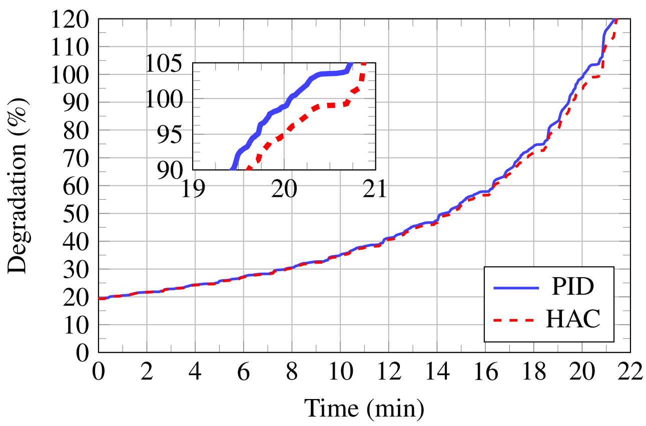



*Figure 6: Simulated degradation trajectories of PID-control and HAC in accelerated degradation conditions.*

Figure 6 shows how the degradation evolved with the two controllers. As the pump degradation was greatly accelerated, no major differences accumulated between the control methods. The EHA under PID-contol lasted 1203.894 s before the pump reached the breakdown degradation. The HAC system in turn lasted 1242.660 s, which was an increase of 3.22 %.

While the observed RUL extension of 3.22 % may appear modest, it holds significant practical implications. For example, in off-road mobile machinery that operates 8 hours daily, a 3.22 % RUL increase may translate into several additional operating cycles before failure. This can delay costly unscheduled maintenance, increase uptime, and improve plan-

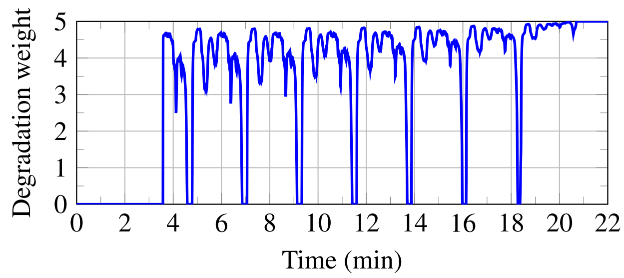



*Figure 7: Degradation error weight values.*

ning for component replacement. In critical systems, even minor improvements in RUL can help avoid cascading failures that might compromise safety. Over an extended operational lifespan, incremental improvements accumulate, enhancing overall system reliability and efficiency. Additionally, extended RUL contributes to operational safety by mitigating the risk of sudden component failure, which can prevent hazardous scenarios.

The HAC adjusted the weight of the degradation based on the RUL estimate. The RUL estimate was smoothed with moving average filter applied to the rotational speed of the pump, with window length of 20 s. Degradation weight is plotted in fig. 7. Initially, with minimal degradation, the HAC prioritized position control exclusively. As degradation increased, the HAC system adjusted pump usage to extend the RUL. When the load on the pump drops, so that the RUL estimate exceeds the requested useful life of 10 cycles, the weight also drops to zero. This strategic trade-off between degradation mitigation and position accuracy highlights a crucial consideration in real-world scenarios, where preserving equipment lifespan may necessitate temporary reduction in control precision. In systems where small deviations in actuator position remain within acceptable performance bounds, this trade-off is justified by the benefit of delayed component wear. However, for applications with tighter precision requirements, further tuning might be needed.

The control error of PID-control and HAC was compared with

$$\text{difference} = |\text{HAC error}| - |\text{PID error}|\,. \tag{40}$$

As seen from fig. 8, the difference in control errors for the position were mostly under 0.5 cm. The difference was closest to zero when the degradation weight from fig. 7 was zero. As the pump degraded, HAC system started to use the pump less to extend the RUL causing the control error to rise. This is can also be seen from fig. 8 during the last 5 min of the simulation.

The results demonstrate that the proposed HAC system effectively mitigates degradation effects and extends the RUL of the gear pump. Under accelerated degradation conditions, the observed RUL extension was comparable to that reported by Zhang et al. [6], who achieved an 8.3 s increase. However, while both studies show improvements in component lifespan, Zhang et al. focused on a different application area, whereas this study specifically addresses EHAs and the degradation of the gear pump.

The degradation model successfully captured the increasing

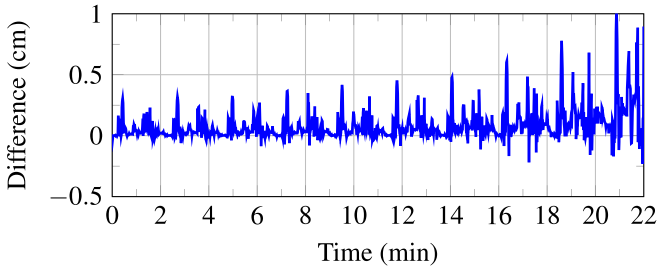



*Figure 8: Difference in control errors of HAC and PID.*

trend of internal leakage, validating its suitability for estimating wear progression in the gear pump. However, the test data used to calibrate the model was limited in scope and did not represent the full operational range. The simulation relied on accelerated degradation conditions, which may not fully replicate the usage patterns and variability encountered in real-world operations. This introduces uncertainty in how well the simulated results generalize to practical scenarios. Furthermore, the use of a nonlinear Wiener process with static parameters assumes a fixed degradation rate throughout the simulation. This may not accurately reflect the dynamic and often nonlinear nature of wear progression under varying loads, temperatures, or hydraulic fluid conditions. Wang et al. [21] emphasize the value of adaptive Wiener processes that update model parameters in real time to better capture evolving failure modes.

While the increase of 3.22 % may seem modest, it has significant practical implications. In real-world applications, even a small extension in RUL can lead to substantial improvements in operational safety and cost efficiency. For instance, extending the RUL by 3.22 % can reduce the frequency of maintenance interventions, thereby lowering maintenance costs and minimizing downtime. Over the lifespan of the equipment, small incremental improvements in RUL can accumulate, resulting in substantial long-term benefits. This is particularly important in industries where equipment availability is critical. Additionally, improved RUL can enhance operational safety by reducing the likelihood of unexpected failures, which can lead to hazardous situations.

## 5 Conclusions

This paper presented a HAC approach for an EHA system, aiming to extend the RUL of a gear pump. The proposed method integrates degradation modeling, real-time prognostics, and MPC to balance system performance and component longevity.

The degradation model captures internal leakage progression using a nonlinear Wiener process, estimated online with an EKF. The estimated degradation state is incorporated into the control design, allowing dynamic adjustment of control actions based on RUL predictions. The effectiveness of the HAC approach was evaluated through simulations, compared against a baseline PID-controller.

The results show that the HAC system successfully mitigates degradation effects, increasing RUL by 3.22 % under accelerated conditions. While the improvement is modest due to the accelerated scenario, the approach shows strong potential for real-world applications with gradual degradation. Additionally, the HAC maintains acceptable position control accuracy while reducing degradation impact.

The method relies on certain assumptions, such as constant rotational speed during RUL estimation and simplified electric motor dynamics, which may affect reliability. Deploying the system in real-world applications may also introduce challenges, including computational demands for real-time optimization and the need for robust controller tuning under varying conditions.

Future work will focus on experimental validation using physical test rigs, further refinement of the degradation model, and assessment of scalability and robustness across different system architectures. In addition, investigating the scalability and robustness of the control framework for diverse system architectures would enhance its industrial applicability.

Overall, the HAC strategy offers a promising pathway to extend the life of safety-critical actuators while preserving performance. With further development, it could become an essential component of advanced control systems that enable real-time decision-making and predictive maintenance, supporting sustainability and reliability goals in off-road applications.

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