

Load-dependent wiener degradation modeling and life prediction of wire-driven minimally invasive surgical instruments

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Abstract

This paper investigates the fatigue degradation and life prediction of a wire-driven parallel mechanism for minimally invasive surgical instruments under different external loads. Fatigue tests are conducted under 0 N, 0.5 N, and 1 N loads, and the trajectory radius loss of the end-effector is selected as the degradation indicator. The results show that the degradation rate increases with load, and ANOVA confirms that the load effect is statistically significant. A load-dependent Wiener degradation model is then established to describe the stochastic process. Compared with the conventional Wiener model, the proposed model shows better fitting performance. Based on a soft failure threshold and the first-passage-time distribution of the Wiener process, reliability, lifetime distribution, and mean remaining life are analytically predicted. The results indicate that higher loads significantly shorten the service life of the mechanism. The proposed method provides a basis for reliability evaluation and maintenance decision-making of wire-driven minimally invasive surgical instruments.

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Highlights

- Fatigue tests use radius loss to quantify motion accuracy degradation.
- Load-dependent Wiener model captures load effects on rate and fluctuations.
- RUL prediction estimates life of wire-driven minimally invasive surgical instruments.

1. Introduction

With the continuous development of minimally invasive surgery, surgical instruments are increasingly required to achieve compact structural design, flexible motion transmission, and reliable operation in confined anatomical environments [1–3]. Compared with conventional mechanisms of rigid transmission, wire-driven mechanisms provide notable advantages in terms of lightweight construction, low inertia, remote actuation, and reduced distal-end size. These features separate the actuators from the surgical end-effector, thereby improving the structural compactness and maneuverability of

the instrument. As a representative configuration, wire-driven parallel mechanisms combine the advantages of parallel kinematic structures and flexible cable transmission, making them suitable for applications that demand high motion accuracy, limited workspace occupation, and enhanced operational flexibility.

Early studies on wire-driven surgical instruments focused on friction modeling, hysteresis compensation, position control, and distal-end force prediction, indicating that friction, hysteresis, sheath bending, and transmission errors significantly affect motion accuracy [4–8]. These studies provide a basis for modeling and control compensation of wire-driven surgical instruments. However, they mainly address short-term control accuracy and transmission error compensation, while fatigue degradation, stochastic degradation behavior, and life evolution under long-term cyclic operation remain insufficiently investigated.

In fact, performance degradation modeling is an important part of reliability analysis and life prediction [9,10]. In

mechanical systems, degradation is affected by loading, friction, wear, material fatigue, and environmental disturbances, often showing strong randomness and individual differences [11–13]. The Wiener process can describe both degradation trends and random fluctuations, which has been widely used in accelerated degradation testing, soft failure analysis, and remaining useful life (RUL) prediction [14,15]. In 1997, Whitmore and Schenkelberg [16] first applied the Wiener diffusion process to accelerated degradation data modeling. Wang [17] further introduced stochastic effects to describe individual degradation differences. Si et al. [18,19] reviewed data-driven remaining life prediction methods and proposed a Wiener-process-based method using recursive filtering. Wang et al. [20] considered measurement errors in Wiener degradation modeling. Li et al. [21] proposed an accelerated degradation model with random effects and first-order autoregressive errors. Liu et al. [22] combined failure mechanisms with stochastic processes to model the degradation of rotating lip seals. Zhang et al. [23] considered strength degradation in fatigue reliability analysis of brake pads. These studies show that stochastic degradation models can effectively describe the uncertainty of mechanical performance degradation over time.

Remaining useful life prediction has further developed from single degradation indices to nonlinear degradation modeling, multi-stage degradation modeling, multi-feature fusion, and dynamic threshold modeling. For example, Kang et al. [24] developed a nonlinear degradation model for remaining useful life prediction of cylinder liners. Song et al. [25] investigated maintenance optimization for degraded components based on a two-stage Wiener process. Gu et al. [26] developed a two-phase degradation model based on the inverse Gaussian process to characterize degradation paths with changes in degradation rates and further derived the corresponding reliability and RUL distributions. Li et al. [27] considered the influence of maintenance actions and dynamic thresholds in remaining useful life prediction. These studies provide useful references for degradation modeling, reliability assessment, and maintenance decision-making of mechanical systems. However, for wire-driven minimally invasive surgical instruments, performance degradation is influenced not only by long-term cyclic motion, but also by external loads, wire transmission characteristics, friction and wear, and strict end-

effector motion accuracy requirements. Therefore, although existing degradation models for mechanical components provide an important basis for stochastic degradation analysis, they need to be further adapted to capture the load effect and trajectory-accuracy degradation characteristics of wire-driven mechanisms.

To address this gap, this paper investigates the fatigue degradation and life prediction of a wire-driven parallel mechanism for minimally invasive surgical instruments under different external loads. The main contributions of this paper are summarized as follows:

- (1) A fatigue degradation testing method is developed for wire-driven parallel mechanisms under different external loads, and trajectory radius loss is used to quantify the degradation of end-effector motion accuracy.
- (2) The effects of external loads on both degradation rate and random degradation fluctuation are analyzed, and a load-dependent Wiener degradation model is established for stochastic degradation modeling.
- (3) A soft-failure reliability analysis and remaining useful life prediction method is developed based on the identified load-dependent Wiener model and the first-passage-time distribution, enabling analytical evaluation of reliability, lifetime distribution, mean remaining life, and prediction intervals under different load conditions.

2. Fatigue degradation tests and degradation indicator

2.1. Experimental subject

For the wire-driven parallel mechanism studied, the end-effector achieves spatial attitude adjustment and periodic oscillation through the coordinated actuation of multiple drive wires. The transmission wire rope used for actuation was made of carbon alloy steel, with a 7×7 construction and a nominal diameter of 0.5 mm. Compared with mechanisms of rigid transmission, wire-driven structures are more compact, compliant, and suitable for remote actuation. Therefore, they are well suited for minimally invasive surgical instruments that require small structural size and high motion flexibility.

During long-term cyclic operation, friction between the drive wires and guiding components, together with repeated tensile and bending stresses, may cause wire wear, slackening, and clearance accumulation [28–30]. As shown in Figure 1, the

mechanism initially oscillates stably along the prescribed trajectory, and the trajectory radius of the end-effector is close to the nominal value. As the number of cycles increases, wire wear changes the preload and transmission stiffness, while the accumulated clearance reduces the motion accuracy of the end-effector. From a macroscopic perspective, this degradation process is reflected by the gradual contraction of the end-effector trajectory, namely that the trajectory radius decreases with increasing cycle number. Therefore, the trajectory radius loss is selected as the degradation indicator to characterize the comprehensive performance degradation caused by wire wear, slackening, and clearance accumulation.

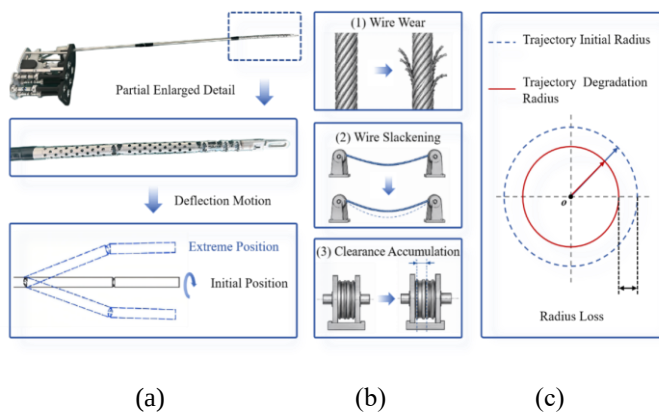


Figure 1. Structure and degradation mechanism of the wire-driven parallel mechanism: (a) mechanism structure; (b) degradation mechanism; (c) trajectory radius loss.

2.2. Test rig and protocol

A fatigue degradation test rig was designed to acquire degradation data of the wire-driven parallel mechanism under different external load conditions, as illustrated in Figure 2. The experimental platform mainly consists of the wire-driven parallel mechanism, a drive mechanism, a loading system, a magnetic field generator, and a magnetic navigation sensor. The drive mechanism actuates the mechanism to perform periodic motion along a predefined trajectory, while the loading system is used to simulate external resistance during operation. In addition, the magnetic field generator and the magnetic navigation sensor work cooperatively to acquire and record the motion trajectory of the end-effector at different stages of cyclic operation, thereby providing experimental data for subsequent degradation analysis and life prediction [31]. The magnetic field generator and magnetic navigation sensor used in the experiments were an Aurora Planar Field Generator 20-20 and

an Aurora 6DOF Tool 6D.P25.12-1 (NDI), respectively.

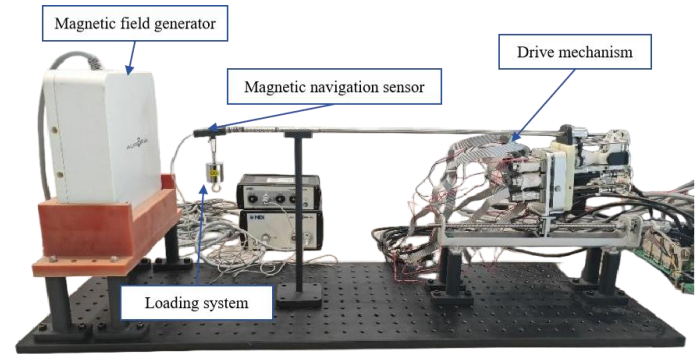


Figure 2. Fatigue degradation test rig.

During the test, the end-effector of the mechanism performs periodic oscillations along a set circular trajectory, starting from the limit position. Each oscillation cycle lasted 8 s, corresponding to a frequency of 0.125 Hz. To analyze the impact of external loads on the mechanism's degradation process, we set three load levels—0 N, 0.5 N, and 1 N—based on typical force scenarios encountered by minimally invasive surgical instruments during clinical procedures and the test rig's controllable loading range [32,33]. For the 0.5 N and 1 N conditions, the external loads were applied by suspending corresponding weights from the loading point, such that the force acted vertically downward under gravity. Five test samples were set for each load condition, yielding a total of 15 sets of fatigue degradation test data. During the test, the end-effector's motion trajectory was recorded at 200-cycle intervals, and the data collection continued until 2,000 cycles were reached. The same endpoint was established before the fatigue tests for all specimens and load conditions to provide a consistent observation window. The acquired trajectory points were then processed to extract the trajectory radius and degradation amount.

For the i -th specimen, let t_k denote the cycle count at the k -th sampling time, where i is the specimen index and k is the sampling index. The sampling interval is defined as $\Delta = t_k - t_{k-1} = 200$ cycles, with t_0 representing the initial state. Such equidistant sampling helps obtain a discrete degradation sequence of the mechanism throughout the entire fatigue test, providing a data foundation for subsequently establishing a stochastic degradation model based on the Wiener process.

2.3. Trajectory radius

Under ideal conditions, a wire-driven parallel mechanism

should move along a predetermined circular trajectory, and the trajectory radius of the end-effector directly reflects the mechanism's motion accuracy. As the fatigue degradation progresses, the end-effector trajectory contracts due to factors such as wire wear, slacking, and transmission clearance accumulation. To quantitatively describe this change, we perform circular fitting on the end-effector trajectory points obtained from each data collection, using the radius of the fitted circle as a characteristic measure of the mechanism's motion state at that moment.

Let the trajectory points collected at sampling time t_k for the i -th sample be:

$$(x_{ij}(t_k), y_{ij}(t_k)), \quad j=1,2,\dots,N \quad (1)$$

where $x_{ij}(t_k)$ and $y_{ij}(t_k)$ are the x - and y -coordinates of the j -th trajectory point collected from the i -th specimen at sampling time t_k , j is the trajectory-point index, and N is the total number of trajectory points used for circle fitting.

The center and radius of the trajectory circle at t_k are determined through least-squares circular fitting [34]. The fitted circle can be expressed as:

$$(x_{ij}(t_k) - a_i(t_k))^2 + (y_{ij}(t_k) - b_i(t_k))^2 = R_i^2(t_k) \quad (2)$$

where $a_i(t_k)$ and $b_i(t_k)$ denote the x - and y -coordinates of the fitted circle center, respectively, and $R_i(t_k)$ denotes the fitted trajectory radius of the i -th specimen at sampling time t_k .

Expanding the above equation yields:

$$x_{ij}^2(t_k) + y_{ij}^2(t_k) + Ax_{ij}(t_k) + By_{ij}(t_k) + C = 0 \quad (3)$$

Where $A = -2a_i(t_k)$, $B = -2b_i(t_k)$, $C = a_i^2(t_k) + b_i^2(t_k) - R_i^2(t_k)$.

The trajectory circles are fitted using the least squares method, and the objective function is defined as:

$$Q(A, B, C) = \sum_{j=1}^N [x_{ij}^2(t_k) + y_{ij}^2(t_k) + Ax_{ij}(t_k) + By_{ij}(t_k) + C]^2 \quad (4)$$

where $Q(A, B, C)$ is the sum of squared algebraic residuals used in the least-squares circle fitting. By taking the partial derivatives of A , B , and C and setting them to zero, the corresponding parameters can be determined. Furthermore, the coordinates of the center of the fitted circle and its radius are given by:

$$a_{ik} = -\frac{A}{2}, b_{ik} = -\frac{B}{2}, R_i(t_k) = \sqrt{\frac{A^2 + B^2}{4} - C} \quad (5)$$

By fitting circles to the trajectory data from different cycle intervals, the trajectory radius sequences for each test sample

can be obtained: $R_i(t_0), R_i(t_1), \dots, R_i(t_k)$, where $R_i(t_0)$ represents the trajectory radius at the initial state, and the subsequent $R_i(t_k)$ values reflect changes in the mechanism's motion capability during the fatigue cycle.

2.4. Degradation indicator

Since the fatigue degradation of wire-driven parallel mechanisms primarily manifests as a gradual decrease in the end-effector trajectory radius, here we adopt trajectory radius loss as the degradation indicator [35]. Trajectory radius loss directly characterizes the deterioration of the end-effector motion performance. Compared with local indicators such as wire tension variation or joint displacement error, it provides a mechanism-level measure of the ability to maintain the prescribed motion trajectory. For the i -th sample, the cumulative degradation at sampling time t_k is defined as:

$$X_i(t_k) = R_i(t_0) - R_i(t_k) \quad (6)$$

where $X_i(t_k)$ represents the cumulative loss in trajectory radius from the initial state to t_k : a larger value of $X_i(t_k)$ indicates a more pronounced contraction of the end-effector's motion trajectory and a higher degree of performance degradation.

To describe the degradation changes within adjacent sampling intervals, the degradation increment is further defined as:

$$\Delta X_i(t_k) = X_i(t_k) - X_i(t_{k-1}) \quad (7)$$

where $\Delta X_i(t_k)$ represents the increment in trajectory radius loss for the i -th sample within the interval $[t_{k-1}, t_k]$, which will serve as the observation of the discrete-time random degradation increment during the subsequent degradation modeling.

In the Wiener degradation model, the cumulative degradation amount $X_i(t_k)$ corresponds to the observation of the random process $X(t)$, while the degradation increment $\Delta X_i(t_k)$ corresponds to the random increment of the Wiener process between adjacent time intervals. Therefore, by fitting the trajectory radius and constructing the degradation amount, the precision degradation in mechanical motion can be transformed into the modeling of a continuous stochastic degradation process.

3. Degradation

3.1. Cumulative degradation

Figure 3 shows the mean cumulative trajectory radius loss under different load conditions. Under all three loads, the cumulative degradation increases with the number of cycles, indicating progressive performance degradation during cyclic operation [36]. For the same cycle count, higher loads lead to greater trajectory radius loss, suggesting that external loads accelerate the degradation of motion accuracy.

3.2. Degradation increment

To further quantify the load effect, the mean degradation increment of each specimen over 200-cycle intervals was calculated, as shown in Table 1. Specimen-level mean degradation increment.

Load / N	Specimen 1 / mm	Specimen 2 / mm	Specimen 3 / mm	Specimen 4 / mm	Specimen 5 / mm	Mean / mm	Standard deviation / mm
0	0.01220	0.00970	0.02318	0.01483	0.01108	0.01420	0.00536
0.5	0.01450	0.02673	0.02441	0.02104	0.01386	0.02011	0.00578
1	0.02670	0.03445	0.02777	0.02182	0.03270	0.02869	0.00503

Figure 4 presents the mean degradation increment among specimens for different load conditions. The bars in the figure represent the mean of the degradation increments of the five specimens under each load condition, while the vertical error bars indicate the corresponding standard deviation of the samples.

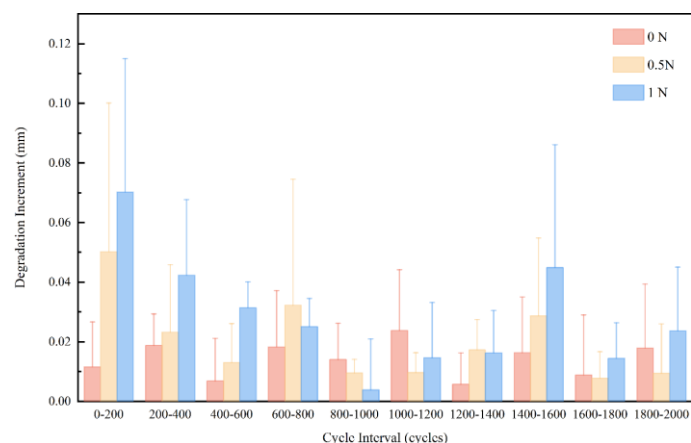


Figure 4. Mean degradation increment under different load conditions.

3.3. Significance of load effect

Based on the mean degradation increments of each specimen, a one-way analysis of variance (ANOVA) was conducted to test whether the differences in degradation rates under different load conditions were statistically significant. In this analysis, load level was treated as the factor, and the mean degradation

calculated, as shown in Table 1.

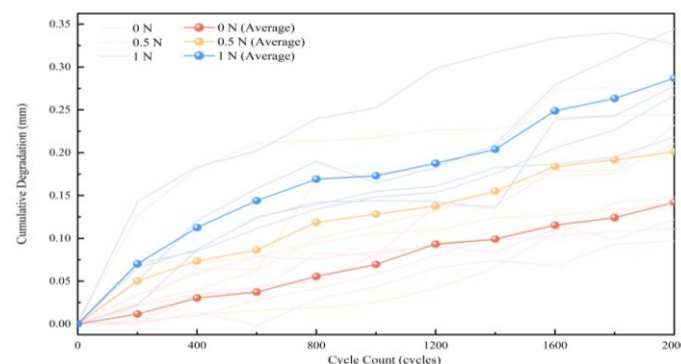


Figure 3. Cumulative trajectory radius loss curves under different load conditions.

increment of each specimen was treated as the response variable.

Let μ_0 , $\mu_{0.5}$, and μ_1 denote the population means of the specimen-level mean degradation increments under 0 N, 0.5 N, and 1 N load conditions, respectively. The significance level is set as $\alpha = 0.05$. The null hypothesis H_0 and the alternative hypothesis H_1 are defined as follows:

$$H_0: \mu_0 = \mu_{0.5} = \mu_1$$

vs.

H_1 : The means under the three load conditions are not all equal.

The null hypothesis H_0 states that there is no significant difference in the mean degradation increments under the three loading conditions; the alternative hypothesis H_1 states that the mean degradation increment under at least one loading condition differs from those under the other conditions. The one-way ANOVA results are presented in Table 2. Since the p -value is 0.0039, which is below the significance level of 0.05, the effect of external loads on the degradation rate is statistically significant.

Table 2. One-way ANOVA results for specimen-level mean degradation increment.

Source of variation	Sum of squares	Degrees of freedom	Mean square	F-value	p -value
Load	0.00053084	2	0.00026542	9.1002	0.0039
Error	0.00035000	12	0.00002917	—	—
Total	0.00088084	14	—	—	—

4. Degradation model

4.1. Wiener degradation

The Wiener process is commonly used for modeling continuous performance degradation, which features a simple model structure and clear physical interpretations of the parameters [37]. In this model, the drift term describes the average trend of degradation growth over time, while the diffusion term describes the random fluctuations during the degradation process. For the wire-driven parallel mechanism studied, the cumulative trajectory radius loss exhibits an overall increasing trend. However, within local sampling intervals, it may experience minor fluctuations due to factors such as measurement errors, circular fitting variations, and changes in friction conditions. Therefore, the Wiener process is well-suited for explaining the degradation of this mechanism. For the cumulative degradation process under a load level of L , a Wiener degradation model is established:

$$X_L(t) = \mu(L)t + \sigma(L)B(t) \quad (8)$$

where $X_L(t)$ is the cumulative trajectory radius loss at cycle number t , $\mu(L)$ is the load-dependent drift coefficient, representing the average degradation rate per unit cycle, $\sigma(L)$ is the load-dependent diffusion coefficient, and $B(t)$ denotes standard Brownian motion.

Based on the independent increments of the Wiener process, the degradation increment within adjacent sampling intervals satisfies:

$$\Delta X_L \sim N(\mu(L)\Delta, \sigma^2(L)\Delta) \quad (9)$$

where $\Delta X_L = X_L(t_k) - X_L(t_{k-1})$, $\Delta = t_k - t_{k-1}$, and $N(m, v)$ denotes a normal distribution with mean m and variance v . To describe the effect of load on the average degradation rate, the drift coefficient is expressed as a linear function of the load:

$$\mu(L) = \theta_0 + \theta_1 L \quad (10)$$

where θ_0 denotes the baseline drift coefficient per cycle under 0 N conditions, and θ_1 represents the effect of the load on the degradation rate per cycle.

To remain positive, the diffusion variance is expressed in exponential form:

$$\sigma^2(L) = \exp(\phi_0 + \phi_1 L) \quad (11)$$

where ϕ_0 and ϕ_1 are the parameters used to describe the load-dependent diffusion variance. The exponential form is adopted to ensure that $\sigma^2(L)$ remains positive.

Therefore, the load-dependent Wiener increment model is

$$\Delta X_L \sim N(\Delta(\theta_0 + \theta_1 L), \Delta \exp(\phi_0 + \phi_1 L)) \quad (12)$$

This model captures the effects of load on both average degradation rate and degree of degradation variability. Physically, a higher external load may accelerate wire wear, preload loss, and clearance accumulation, thereby increasing the average degradation rate, while variations in friction, contact conditions, and wear evolution lead to load-dependent random fluctuations.

4.2. Maximum likelihood parameter estimation

For a given load level L , the conditional probability density of the degradation increment is:

$$f(\Delta x | L; \theta_0, \theta_1, \phi_0, \phi_1) = \frac{1}{\sqrt{2\pi\Delta \exp(\phi_0 + \phi_1 L)}} \exp\left\{-\frac{[\Delta x - (\theta_0 + \theta_1 L)\Delta]^2}{2\Delta \exp(\phi_0 + \phi_1 L)}\right\} \quad (13)$$

where Δx is an observed value of the degradation increment ΔX_L , and L is the corresponding load level.

Let the degradation increment data under all load conditions be collectively denoted as:

$$D = \{(\Delta x_{ik}, L_i)\} \quad (14)$$

where Δx_{ik} denotes the observed degradation increment of the i -th specimen during the k -th sampling interval, and L_i denotes the load level applied to the i -th specimen.

Then its log-likelihood function is:

$$l(\theta_0, \theta_1, \phi_0, \phi_1) = -\frac{1}{2} \sum_{(\Delta x, L) \in D} \left[\ln(2\pi\Delta \exp(\phi_0 + \phi_1 L)) + \frac{[\Delta x - (\theta_0 + \theta_1 L)\Delta]^2}{\Delta \exp(\phi_0 + \phi_1 L)} \right] \quad (15)$$

The model parameters are obtained by maximizing the above log-likelihood function:

$$(\hat{\theta}_0, \hat{\theta}_1, \hat{\phi}_0, \hat{\phi}_1) = \arg \max_{\theta_0, \theta_1, \phi_0, \phi_1} l(\theta_0, \theta_1, \phi_0, \phi_1) \quad (16)$$

By substituting all the degradation increment data in this paper and their corresponding load levels into the above likelihood function, we can obtain the parameter estimates of the load-dependent Wiener model, as shown in Table 3.

Table 3. Parameter estimates of the load-dependent Wiener model.

Parameter	Estimate	Parameter	Estimate
θ_0	6.98×10^{-5}	ϕ_0	-13.43
θ_1	6.99×10^{-5}	ϕ_1	1.16

Therefore, the final load-dependent Wiener degradation increment model is established as:

$$\Delta X_L \sim N[(6.98 \times 10^{-5} + 6.99 \times 10^{-5} L)\Delta, \exp(-13.43 + 1.16 L)\Delta] \quad (17)$$

4.3. Model comparison

To verify the fitting performance of the load-dependent Wiener degradation model, we compare the model established in

Section 4.2 with a traditional Wiener degradation model that does not include load factors, denoted as M1 and M0, respectively. The Wiener degradation model M₀ does not account for the influence of load levels L on the degradation process, and assumes that the decay increments under all load conditions have the same drift coefficient and diffusion variance, i.e.

$$M_0: \Delta X \sim N(\mu_0 \Delta, \exp(\delta_0) \Delta) \quad (18)$$

where μ_0 is the uniform drift coefficient, and $\exp(\delta_0)$ is the

Table 4. Comparison between the conventional Wiener model and the load-dependent Wiener model.

Model	Drift coefficient	Diffusion variance	Number of parameters	Log-likelihood	AIC	BIC
M ₀	μ_0	$\exp(\delta_0)$	2	341.99	-679.98	-673.96
M ₁	$\theta_0 + \theta_1 L$	$\exp(\phi_0 + \phi_1 L)$	4	353.60	-699.19	-687.15

5. Life prediction

5.1. Failure threshold and life definition

In the fatigue degradation tests introduced in Section 2.2, the maximum motion radius of the mechanism was set as 25 mm, which is also a critical dimensional parameter to evaluate the mechanism's maximum motion capability during design and manufacturing. Considering the requirements for motion precision in clinical surgery, the safety margin at the mechanism's limit position, and the allowable range of motion radius deviation in production design, this study adopts 5% of the maximum trajectory radius as the soft failure criterion, defining the soft failure threshold as $x_f = 1.25$ mm.

This threshold represents a functional performance limit of the present mechanism rather than structural fracture or complete mechanical failure. When the trajectory radius loss reaches this threshold, the degradation is considered to have exceeded the allowable performance range defined for the prototype. It should be emphasized that the 5% threshold is an engineering criterion adopted for the mechanism investigated in this study and should not be interpreted as a universal clinical failure threshold. The lifetime under load level L is defined as the number of cycles at which the degradation process first reaches the failure threshold, i.e.

$$T(L) = \inf\{t: X_L(t) \geq x_f\} \quad (19)$$

where $T(L)$ is the random life at load level L.

5.2. Life prediction method

According to the lifetime definition given above, the failure

uniform diffusion variance.

Log-likelihood, AIC, and BIC were selected as evaluation metrics for the fitting performance and model complexity of the two models [38,29]. The comparison results of the two models, calculated based on experimental data, are shown in Table 4. Compared with the conventional Wiener model, the proposed load-dependent model achieves a higher log-likelihood and lower AIC and BIC, indicating improved fitting performance without excessive model complexity.

time of the mechanism corresponds to the moment when the degradation process first reaches the soft failure threshold. Therefore, the lifetime distribution, reliability function, and lifetime characteristics can be analytically obtained based on the first-passage-time distribution of the Wiener process [40].

Let X_0 denote the degradation amount at the start of prediction. For life prediction from the initial state, $X_0=0$; for remaining useful life prediction, X_0 can be taken as the current degradation amount. Thus, the remaining degradation margin before reaching the soft failure threshold can be expressed as:

$$\omega = x_f - X_0, \quad \omega > 0 \quad (20)$$

where ω is the remaining degradation margin before soft failure, and X_0 is the degradation level at the start of prediction.

According to the first-passage-time distribution of the Wiener process, when the drift coefficient satisfies $\mu(L) > 0$ and the diffusion coefficient satisfies $\sigma(L) > 0$, the cumulative distribution of lifetime can be expressed as:

$$F_T(t|L) = \Phi\left(\frac{\mu(L)t - \omega}{\sigma(L)\sqrt{t}}\right) + \exp\left(\frac{2\mu(L)\omega}{\sigma^2(L)}\right) \Phi\left(-\frac{\mu(L)t + \omega}{\sigma(L)\sqrt{t}}\right), \quad t > 0 \quad (21)$$

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

Accordingly, the reliability function of the mechanism under load level L is given by:

$$R(t|L) = 1 - F_T(t|L) \quad (22)$$

That is,

$$R(t|L) = 1 - \left[\Phi\left(\frac{\mu(L)t - \omega}{\sigma(L)\sqrt{t}}\right) + \exp\left(\frac{2\mu(L)\omega}{\sigma^2(L)}\right) \Phi\left(-\frac{\mu(L)t + \omega}{\sigma(L)\sqrt{t}}\right) \right] \quad (23)$$

The corresponding probability density of lifetime is:

$$f_T(t|L) = \frac{\omega}{\sigma(L)\sqrt{2\pi t^3}} \exp\left[-\frac{(\omega - \mu(L)t)^2}{2\sigma^2(L)t}\right], \quad t > 0 \quad (24)$$

Based on the lifetime distribution, the mean time to failure (MTTF) under load level L can be further obtained as:

$$MTTF(L) = \frac{\omega}{\mu(L)} \quad (25)$$

The standard deviation of lifetime is:

$$STD(L) = \sqrt{\frac{\omega\sigma^2(L)}{\mu^3(L)}} \quad (26)$$

5.3. Life prediction results

Based on the analytical life prediction established in Section 5.2, the drift coefficient $\mu(L)$, diffusion coefficient $\sigma(L)$, and remaining degradation margin ω identified under different load levels are substituted into the first-passage-time distribution expressions to obtain the lifetime distribution and reliability of the mechanism under each loading condition. The life prediction results under different load levels are shown in Figure 5, involving the reliability curves, lifetime cumulative distribution curves, and lifetime probability density curves.

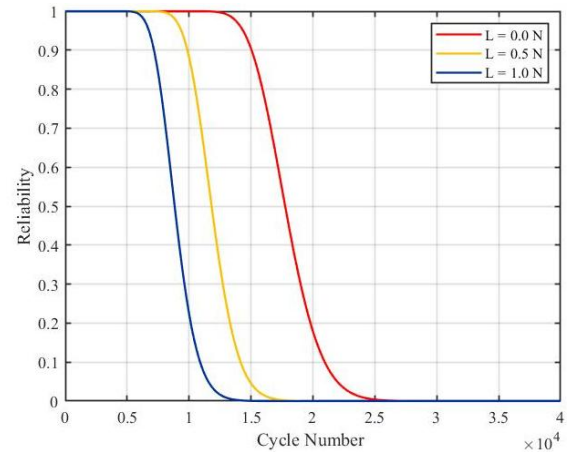
The results show a clear load-dependent lifetime trend. Under all load conditions, the reliability decreases with increasing cycle count, as more degradation paths reach the soft failure threshold. Compared with the low-load condition, higher loads lead to an earlier decrease in reliability, indicating that external loads accelerate performance degradation and shorten the service life of the mechanism. This trend is also reflected in the lifetime cumulative distribution curves. As the load increases, both cumulative distribution and probability density curves shift toward shorter lifetimes, meaning that soft failure is more likely to occur within fewer cycles under higher load conditions.

Table 5. Life prediction results under different load levels.

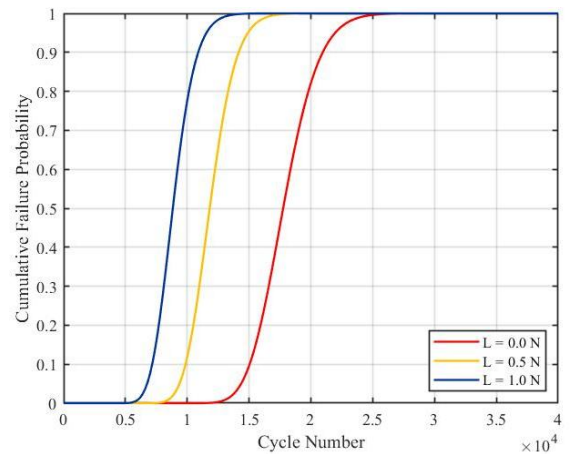
Load / N	MTTF / cycles	Standard deviation / cycles
0	17905	2321
0.5	11934	1689
1	8949	1468

The lifetime characteristic indices analytically obtained from the first-passage-time distribution are listed in Table 5. The predicted MTTF decreases from 17905 cycles at 0 N to 11934 cycles at 0.5 N and 8949 cycles at 1 N. This further confirms that external loads significantly reduce the expected lifetime of the wire-driven parallel mechanism by increasing the

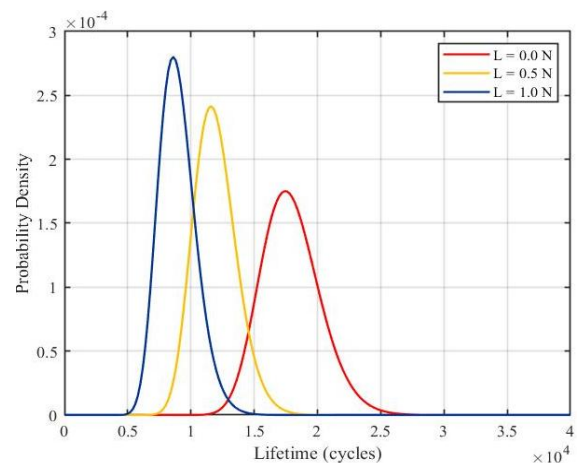
degradation rate and accelerating the degradation process to reach the soft failure threshold earlier.



(a)



(b)



(c)

Figure 5. Life prediction results under different load levels: (a) reliability curves, (b) lifetime cumulative distribution curves, (c) lifetime probability density curves.

5.4. Remaining life prediction

Let the current monitoring time be t_c , and let the corresponding

cumulative trajectory radius loss be x_c . As x_c approaches the soft failure threshold x_f , the remaining degradation margin of the mechanism gradually decreases. Therefore, the remaining useful life should be evaluated according to both the current degradation state and the load-dependent degradation parameters.

For the mechanism operating under load level L , the remaining degradation margin at t_c is defined as:

$$\omega_c = x_f - x_c \quad (27)$$

The RUL under the current degradation state can be expressed as:

$$T_R = \inf\{\tau > 0: X(t_c + \tau) - X(t_c) \geq \omega_c\} \quad (28)$$

where T_R is the remaining useful life, and τ denotes the future time elapsed after the current monitoring time t_c .

For the load-dependent Wiener degradation model, this first-passage time follows the same analytical distribution form as that used for lifetime prediction, with the degradation margin $x_f - x_0$ replaced by $x_f - x_c$. The corresponding mean remaining life is given by:

$$\text{MRL}(t_c, x_c, L) = \frac{\omega_c}{\mu(L)} \quad (29)$$

In addition, the lower and upper bounds of the RUL prediction interval can be determined from the quantiles of the analytical first-passage-time distribution.

To demonstrate the dynamic remaining life prediction capability of the proposed model, the load condition of 0.5 N is selected as a representative case, because it lies between the two boundary load conditions and thus provides a representative loaded condition for illustrating the evolution of RUL without being specific to either the no-load or the highest-load case. The degradation states used in the RUL illustration are obtained from the mean degradation trajectory predicted by the fitted load-dependent Wiener model under 0.5 N, rather than from an individual experimental trajectory or the average of the experimental trajectories. Several monitoring points along a typical degradation trajectory are used as the current degradation states, and the corresponding RUL distributions are calculated analytically. The MRL curve, prediction intervals, and RUL probability density evolution are shown in Figures 6 and 7. The results show that the predicted MRL decreases continuously as the monitoring cycle increases, which is consistent with the reduction of the remaining degradation

margin. Figure 7 further indicates that the RUL probability density gradually shifts toward the short-life region as the monitoring cycle increases. Meanwhile, the prediction interval reflects the uncertainty of remaining life estimation at different degradation stages.

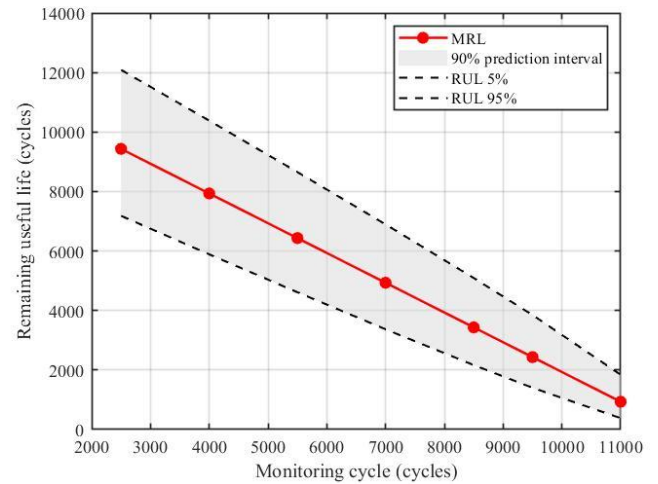


Figure 6. MRL prediction curve under $L = 0.5 N$.

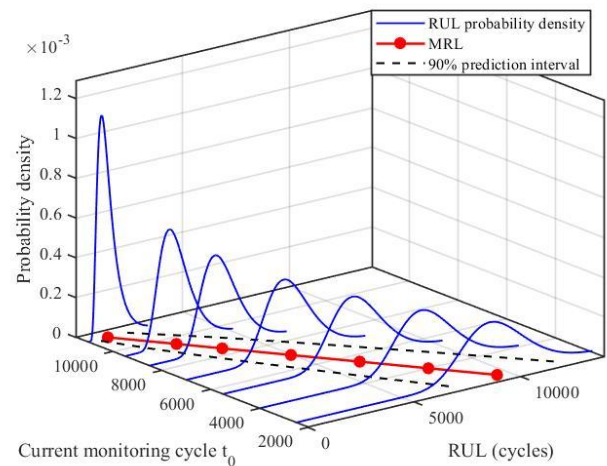


Figure 7. Three-dimensional evolution of the RUL probability density under $L = 0.5 N$.

In summary, the MRL prediction method based on the load-dependent Wiener model and the first-passage-time distribution can dynamically update the remaining useful life of the mechanism according to its current degradation state. This method directly obtains the RUL distribution, MRL, and prediction interval from the remaining degradation margin and model parameters, and can effectively reflect the variation trend and uncertainty of the remaining useful life at different degradation stages. Therefore, it can provide a reference for maintenance planning, replacement decisions, and safe-use

evaluation of wire-driven minimally invasive surgical instruments [41].

6. Conclusion

This paper investigated the fatigue degradation and life prediction of a wire-driven parallel mechanism for minimally invasive surgical instruments under different external loads. The trajectory radius loss of the end-effector was selected as the degradation indicator, and fatigue tests were conducted under 0 N, 0.5 N, and 1 N loads.

According to the experimental results, the trajectory radius loss increases with the number of motion cycles, indicating continuous degradation of the mechanism. Meanwhile, the degradation rate increases as the external load becomes larger. The mean degradation increment increases from 0.01420 mm under 0 N to 0.02011 mm under 0.5 N and 0.02869 mm under 1 N. The ANOVA result shows that the effect of load is statistically significant, with a p-value of 0.0039.

A load-dependent Wiener degradation model was established to describe the stochastic degradation process. By introducing the load effect into the drift and diffusion terms, the proposed model can reflect both the average degradation trend and the random fluctuation under different loads. Compared with the conventional Wiener model, the load-dependent model shows better fitting performance.

Based on the soft failure threshold and the first-passage-time distribution of the Wiener process, the reliability and lifetime distribution of the mechanism were analytically predicted. The predicted mean time to failure decreases from 17905 cycles under 0 N to 11934 cycles under 0.5 N and 8949 cycles under 1 N. This indicates that higher external loads accelerate degradation and significantly reduce the service life of the

mechanism. It should be noted that these lifetime results are model-based extrapolations beyond the 2,000-cycle experimental observation range, and further long-duration fatigue tests are required to validate the long-term prediction accuracy.

The analytical MRL/RUL prediction based on the first-passage-time distribution further shows that the remaining life decreases as the monitoring cycle and degradation level increase. Using the current degradation state to calculate the remaining degradation margin, we can obtain the remaining lifetime distribution, mean remaining life, and prediction interval. Therefore, the proposed method can provide a useful basis for reliability evaluation, maintenance planning, and safe operation of wire-driven minimally invasive surgical instruments.

Future work will focus on improving the experimental validation and extending the modeling framework. More fatigue degradation tests under additional load levels, longer operation cycles, variable loads, and different motion trajectories should be conducted to further verify the robustness and generalization ability of the proposed model. In addition, multiple degradation features, such as cable tension variation, friction, and positioning error, can be incorporated to establish a multi-source degradation model. Online monitoring and real-time parameter updating will also be investigated to improve the accuracy of remaining life prediction in practical applications. Beyond the present single-mechanism framework, future studies will further extend the proposed approach to multistate and multi-unit systems by considering performance interactions among different units, thereby improving its applicability to the reliability assessment of more complex system-level configurations [42].

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