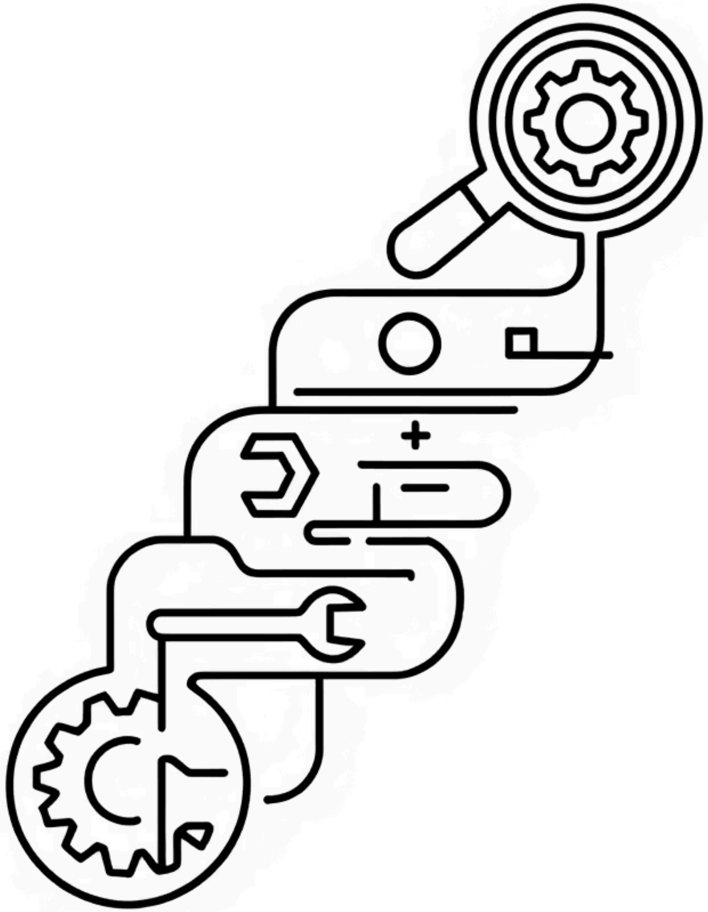
8.2.1 Modeling DysfunctionalBehavior:

Introduction and Fundamental Concepts

This comprehensive presentation explores the theoretical foundations and practical applications of maintenance engineering, with a focus on modeling dysfunctional behavior in industrial systems. We will examine various degradation processes with their mathematical models that enable engineers to predict and prevent equipment failures.

Introduction and Fundamental Concepts



Maintenance Strategies Taxonomy

Corrective Maintenance

Performed **after a failure** has occurred with the objective of restoring the system to an operational state. This reactive approach is typically used for non-critical components where the cost of failure is less than preventive measures.

Example: Replacing a broken bearing in a non-critical conveyor system.

Preventive Maintenance

Scheduled interventions at **regular intervals**, regardless of the equipment's condition. This time-based approach aims to prevent failures before they happen by replacing parts before their expected end of life.

Example: Oil changes every 10,000 km in vehicle engines.

Predictive Maintenance

Based on **condition monitoring** and failure prediction models. This approach uses sensors and data analytics to detect early signs of deterioration, allowing for intervention only when necessary.

Example: Vibration monitoring of turbines to detect impending bearing failure.

Prescriptive Maintenance

Goes beyond prediction to provide **decision support** regarding what, when, and how to perform maintenance. Utilizes **optimization algorithms** and **artificial intelligence** to recommend the most cost-effective action.

Example: AI system recommending specific maintenance actions based on equipment condition, spare parts inventory, and production schedule.

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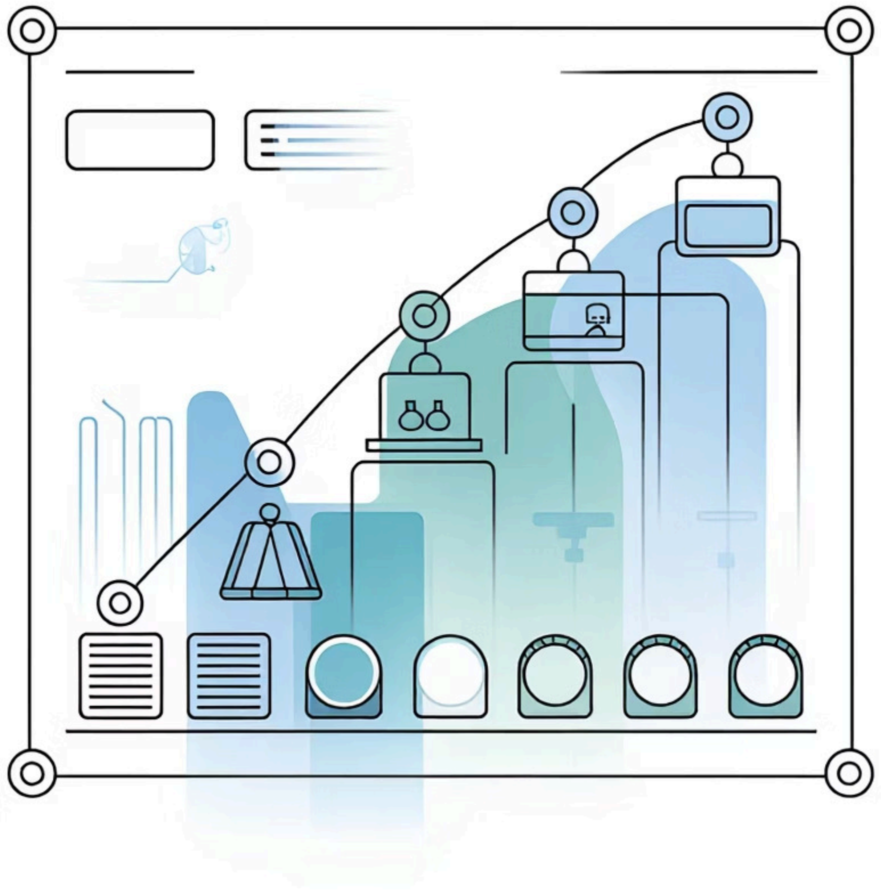
Concepts of Degradation and Failure

This section explores how engineering systems deteriorate over time and the relationship between degradation processes and failure events.



Understanding Degradation Processes and Failure Mechanisms

Fundamental Concepts

A **degradation process** represents the progressive loss of performance or reliability in a component or system over time. This deterioration continues until it reaches a **critical threshold**, at which point a **failure** occurs.

Let $X(t)$ denote the degradation level of a component at time t:

- Initial state: $X(0) = 0$ (new condition)
- Failure condition: $X(t) \geq D_{crit}$ where D_{crit} is the critical degradation threshold

The degradation process can follow different patterns:

- **Linear degradation:** Constant rate of deterioration over time
- **Non-linear degradation:** Accelerating or decelerating deterioration
- **Stochastic degradation:** Random variations in the deterioration process

Understanding these patterns is crucial for developing accurate predictive models and implementing effective maintenance strategies.

Degradation Parameters

Degradation Rate

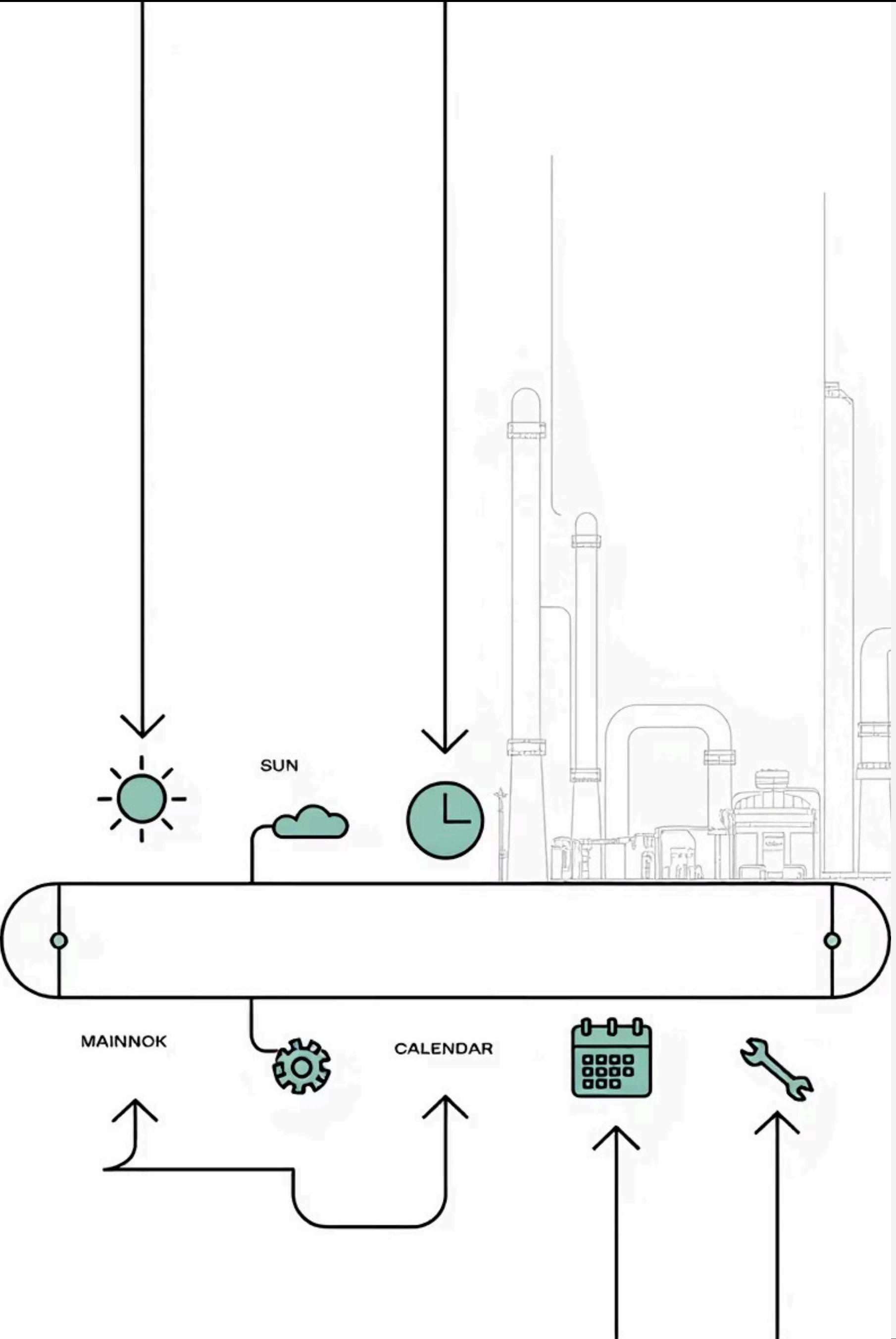
The speed at which a component deteriorates, often influenced by operational conditions and component quality.

Failure Threshold

The critical level of degradation beyond which the component is considered failed, often determined by functional requirements.

Warning Threshold

The level of degradation that triggers maintenance planning, typically set below the failure threshold to provide intervention time.



Influencing Factors of Dysfunctional Processes

This section examines the key variables that affect how and when equipment degrades, and how these factors can be incorporated into predictive models.

Complex Factors Affecting Equipment Degradation

Operational Conditions

The environment and usage patterns significantly impact degradation rates:

- **Stress and load:** Higher mechanical loads accelerate wear and fatigue
- **Temperature:** Elevated temperatures can increase chemical reaction rates, accelerating corrosion and material breakdown
- **Humidity:** Moisture presence accelerates corrosion and electrical insulation breakdown
- **Vibration:** Excess vibration leads to faster mechanical wear and fatigue failure
- **Cycling:** Thermal or mechanical cycling induces fatigue and material property changes

Example: A bearing operating at 20°C above its designed temperature range may experience a 50% reduction in service life due to accelerated lubricant degradation and material softening.

Component Interactions

Systems rarely fail in isolation - dependencies between components create complex degradation patterns:

- **Cascading effects:** Failure of one component increases stress on others
- **Resource sharing:** Multiple components sharing a common resource (e.g., lubrication)
- **Environmental influence:** One component's operation creating adverse conditions for others

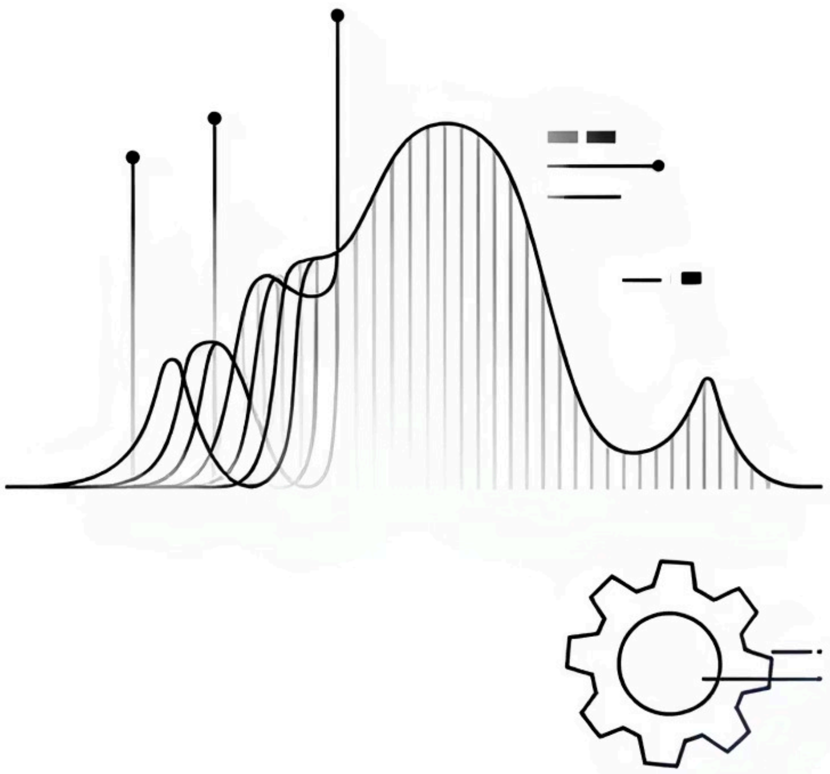
Example: Oil quality degradation in a gearbox accelerates bearing wear through increased particulate contamination, creating a feedback loop of degradation.

Economic Constraints

Financial considerations often dictate maintenance decisions and thereby affect degradation patterns:

- **Intervention costs:** Direct expenses for parts, labor, and equipment
- **Downtime penalties:** Revenue loss during maintenance periods
- **Spare parts logistics:** Availability and lead times for replacement components
- **Risk assessment:** Cost-benefit analysis of maintenance vs. potential failure

Example: A production facility may delay non-critical maintenance during peak demand periods, accepting increased degradation to avoid costly downtime.



Overview of Model Categories

This section presents the mathematical frameworks used to model equipment reliability, degradation, and failure prediction.

Life Duration Models: Statistical Approaches to Failure Prediction

Life duration models focus on the random variable T, representing the time to failure of a component or system. These models characterize the statistical distribution of failure times and provide important metrics for reliability analysis:

- **Survival Function S(t)**

  The probability that the system survives beyond time t:

  $$S(t) = P(T > t)$$

  This function starts at 1 (100% survival at t=0) and decreases monotonically toward 0 as t increases.

- **Probability Density Function (PDF) f(t)**

  The rate of change of the cumulative failure probability:

  $$f(t) = \frac{d}{dt}\big(1 - S(t)\big)$$

  This function represents the relative likelihood of failure at a specific time t.

- **Hazard Rate (Failure Rate) h(t)**

  The instantaneous rate of failure for a component that has survived until time t:

  $$h(t) = \frac{f(t)}{S(t)}$$

  This function is particularly useful for characterizing the failure behavior at different life stages.

Applications in Maintenance

Life duration models provide critical insights for maintenance planning:

- **Reliability prediction:** Estimating the probability of failure-free operation for a specified period
- **Spare parts planning:** Determining optimal inventory levels based on expected failure rates
- **Maintenance scheduling:** Setting preventive maintenance intervals based on component reliability characteristics
- **Risk assessment:** Quantifying the probability of system failures and their potential impacts

Note: Life duration models are particularly useful when degradation cannot be directly measured or when historical failure data is abundant. They provide a statistical view of failure behavior without requiring detailed knowledge of the underlying physical degradation mechanisms.

Life Duration Models: Common Distributions in Reliability Engineering

Exponential Distribution

Features a constant hazard rate (λ), making it suitable for modeling random failures during the useful life period:

$$f(t) = \lambda e^{-\lambda t}, \quad S(t) = e^{-\lambda t}, \quad h(t) = \lambda$$

The mean time to failure (MTTF) is 1/λ. This distribution lacks memory, meaning the probability of failure in the next interval is independent of how long the component has been operating.

Weibull Distribution

A flexible distribution that can model increasing, decreasing, or constant failure rates depending on the shape parameter β:

$$f(t) = \frac{\beta}{\eta}\left(\frac{t}{\eta}\right)^{\beta-1} e^{-(t/\eta)^{\beta}}$$

$$S(t) = e^{-(t/\eta)^{\beta}}, \quad h(t) = \frac{\beta}{\eta}\left(\frac{t}{\eta}\right)^{\beta-1}$$

Where η is the scale parameter (characteristic life) and β is the shape parameter:

- $\beta < 1$: Decreasing failure rate (early-life failures, infant mortality)
- $\beta = 1$: Constant failure rate (reduces to exponential distribution)
- $\beta > 1$: Increasing failure rate (wear-out failures)

Degradation Models

Unlike life duration models that focus on the random time to failure, degradation models directly track the physical degradation state $X(t)$ of a component over time. Failure occurs when the degradation reaches or exceeds a predefined critical threshold D_{crit}. These models offer a more mechanistic view of failure, linking it directly to observable physical changes.

Gamma Process

The Gamma Process models degradation as a non-decreasing, stochastic process, suitable for wear and cumulative damage where increments are non-negative. It assumes a continuous accumulation of degradation over time with inherent variability.

$$X(t) \sim \text{Gamma}(\alpha t, \nu)$$

Where α is the shape parameter controlling the degradation rate and ν is the scale parameter.

Expected degradation at time t is given by:

$$\mathbb{E}[X(t)] = \frac{\alpha t}{\nu}$$

Wiener Process (Brownian Motion with drift)

The Wiener Process represents degradation as a continuous random walk, ideal for modeling processes with gradual wear and random fluctuations (e.g., fatigue, corrosion). It allows for both increasing and decreasing degradation, though overall drift is typically positive.

$$X(t) = \mu t + \sigma W(t)$$

Where μ is the drift (average degradation rate), σ is the volatility (random shock intensity), and $W(t)$ is standard Brownian motion.

The time to failure is obtained when the degradation path $X(t)$ crosses the critical threshold:

$$X(t) \geq D_{\text{crit}}$$