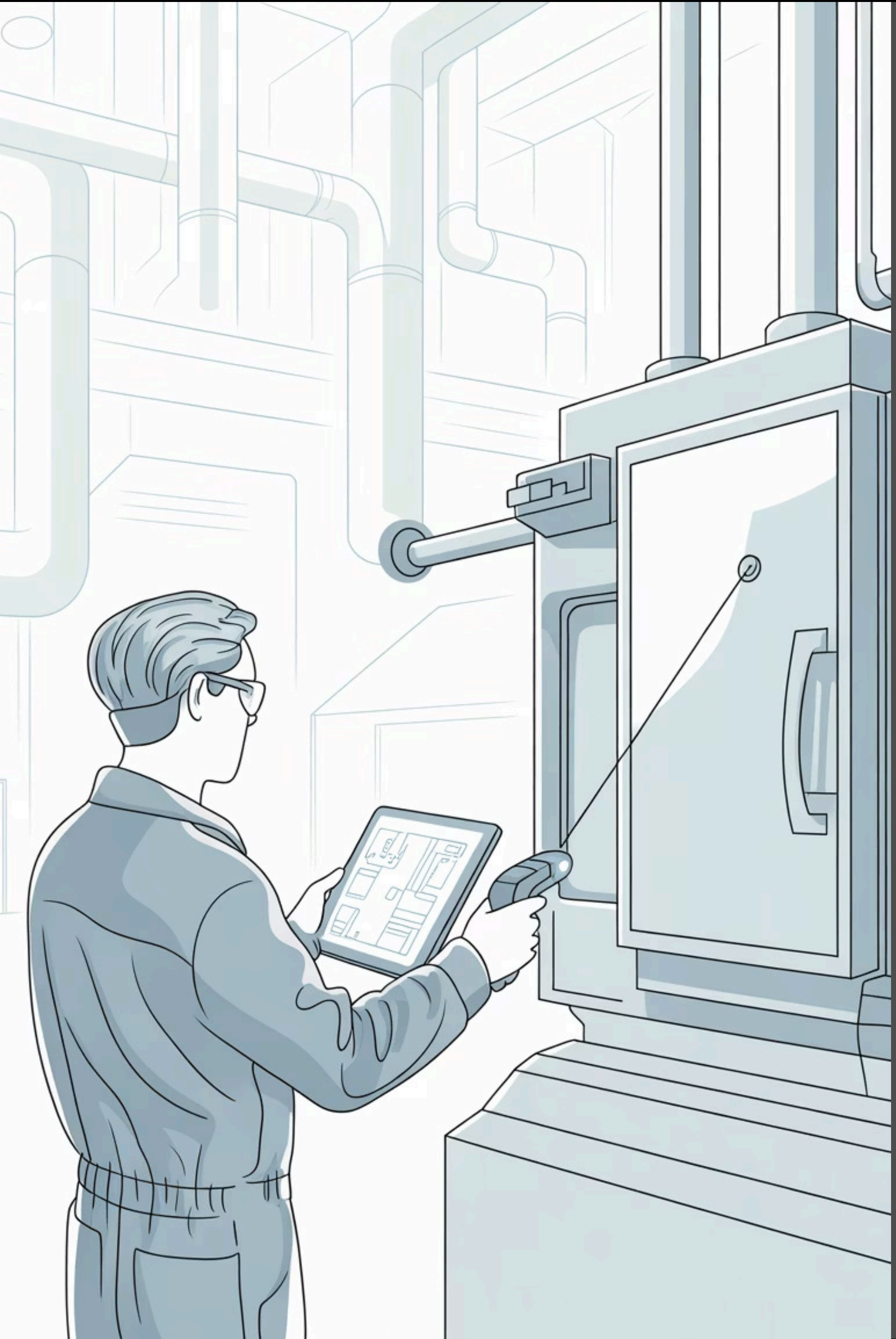
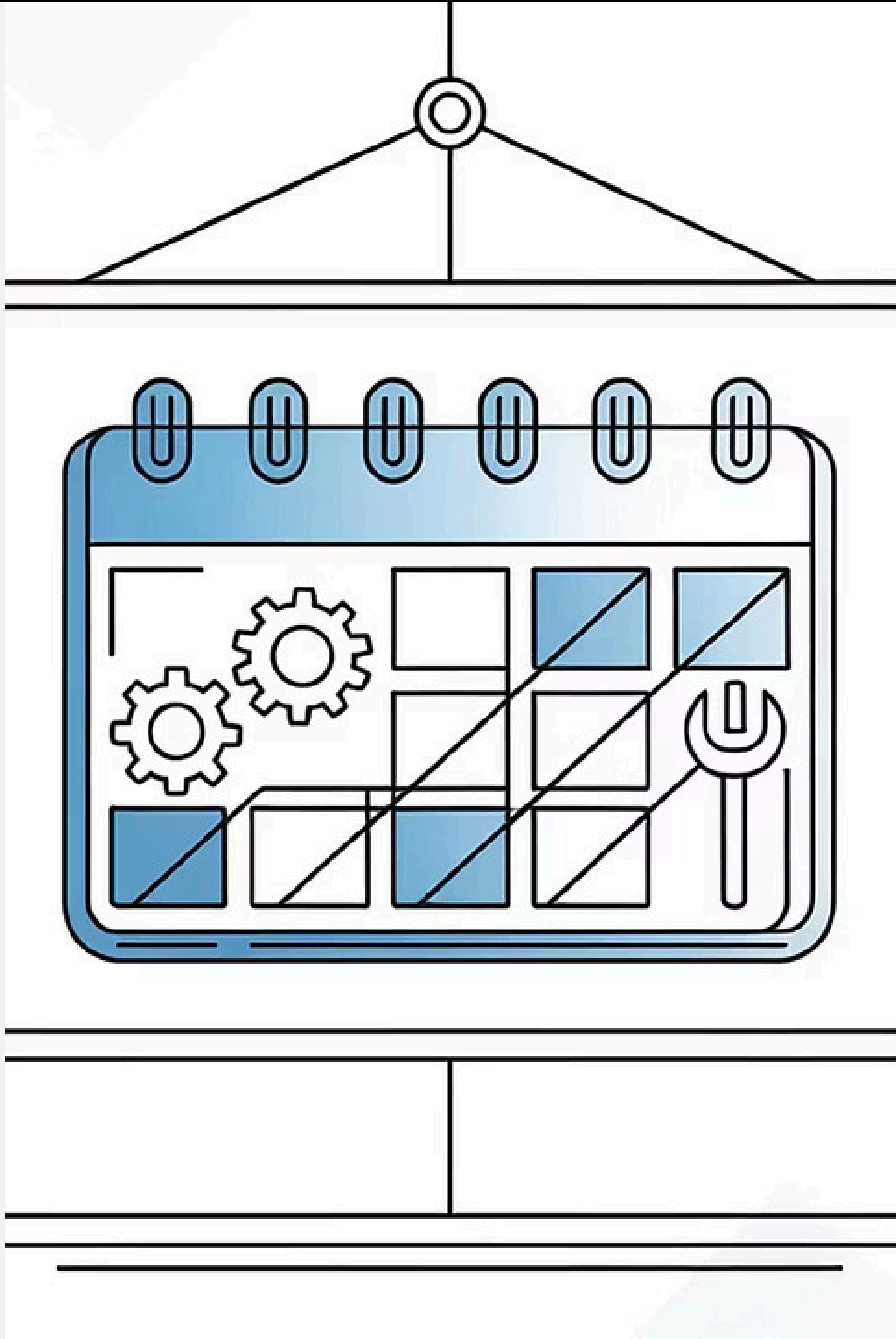


8.3.2 Maintenance StrategyModeling:

Component-Level Maintenance Models

This presentation explores the fundamental strategies for maintaining individual components within engineering systems.

Systematic Maintenance



Systematic Maintenance: Principles and Applications

Definition & Key Characteristics

- Preventive actions performed at predetermined fixed time intervals or usage cycles
- Based exclusively on component age or cumulative usage metrics
- Performed regardless of the actual component degradation state
- Relies on statistical reliability data and engineering specifications

Advantages

- Straightforward planning and resource allocation
- Simplified inventory management for spare parts
- Reduced complexity in maintenance scheduling
- Effective in stable, predictable operational environments

Limitations

- Interventions often occur too early, wasting useful component life
- Increased maintenance costs due to premature component replacement
- Risk of unexpected failures if intervals are set too conservatively
- Ignores actual condition variations between individual components

Systematic maintenance schedules components for replacement at fixed intervals, regardless of their actual condition, creating a predictable but potentially inefficient maintenance regime.

Mathematical Model for Systematic Maintenance

Cost Optimization Framework

The expected cost per unit time with a preventive maintenance interval (τ) can be modeled as:

$$C(\tau) = \frac{C_p}{\tau} + \frac{C_f \cdot F(\tau)}{\tau}$$

Where:

- Cp: Cost of preventive maintenance
- Cf: Cost of corrective maintenance (typically Cf > Cp)
- F(τ): Probability of failure before time τ (cumulative distribution function)
- τ: Preventive maintenance interval

The optimization problem becomes finding the optimal interval τ* that minimizes the expected cost:

$$\tau^* = \arg\min_{\tau} C(\tau)$$

Weibull Distribution Application

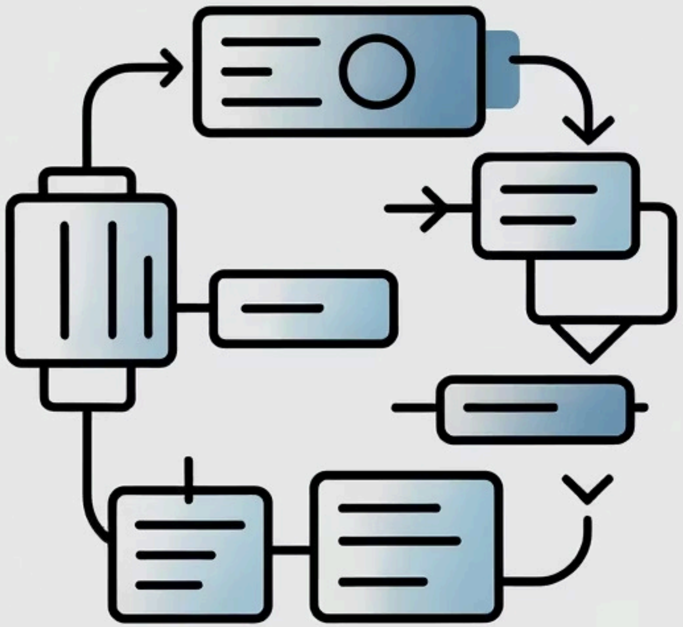
For components with Weibull failure distribution:

$$F(t) = 1 - e^{-(\frac{t}{\eta})^\beta}$$

Where:

- η: Scale parameter (characteristic life)
- β: Shape parameter (failure behavior)
- β < 1: Decreasing failure rate
- β = 1: Constant failure rate
- β > 1: Increasing failure rate

Systematic maintenance is most effective when β > 1, indicating wear-out failures rather than random failures.



Condition-Based Maintenance

Condition-Based Maintenance: Core Principles

Definition & Methodology

- Maintenance actions triggered by observed degradation rather than fixed schedules
- Relies on inspection data or continuous monitoring of condition indicators
- Common indicators include temperature, vibration, acoustic emissions, oil analysis, and electrical parameters
- Maintenance performed when indicators exceed predetermined thresholds

Advantages

- Better alignment with actual component health condition
- Reduces unnecessary interventions on healthy components
- Extends useful component life compared to systematic maintenance
- Catches developing failures before they become critical

Limitations

- Requires investment in inspection processes or monitoring equipment
- Effectiveness depends on data accuracy and measurement reliability
- May miss rapidly developing failure modes between inspections
- Threshold determination often involves complex engineering judgment

Condition-based maintenance relies on the accurate measurement of degradation indicators, allowing maintenance to be performed based on actual component health rather than arbitrary time intervals.

Mathematical Models for Condition-Based Maintenance

1

Hazard-Based Decision Rule

The hazard rate represents the instantaneous failure rate at time t, given survival up to that point:

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

Where:

- f(t): Probability density function of failure time
- S(t): Survival function (probability of surviving beyond time t)

The maintenance decision rule becomes:

$$h(t) > h_{\text{crit}} \quad \Rightarrow \quad \text{Perform Maintenance}$$

This approach optimizes maintenance timing based on the instantaneous risk of failure.

2

Markov Decision Process Model

For systems with discrete degradation states, the transition between states can be modeled as a Markov process:

$$P_{ij} = P(X_{t+1} = j | X_t = i)$$

The optimal policy π* maximizes the expected long-term reward:

$$V^\pi(s) = \mathbb{E}^\pi \left[\sum_{t=0}^{\infty} \gamma^t R(s_t, a_t) | s_0 = s \right]$$

Where:

- Vπ(s): Value function under policy π starting from state s
- γ: Discount factor (0 < γ < 1)
- R(st, at): Reward (negative cost) for taking action at in state st

3

Bayesian Updating with Imperfect Information

When monitoring provides imperfect information, Bayesian updating can incorporate measurement uncertainty:

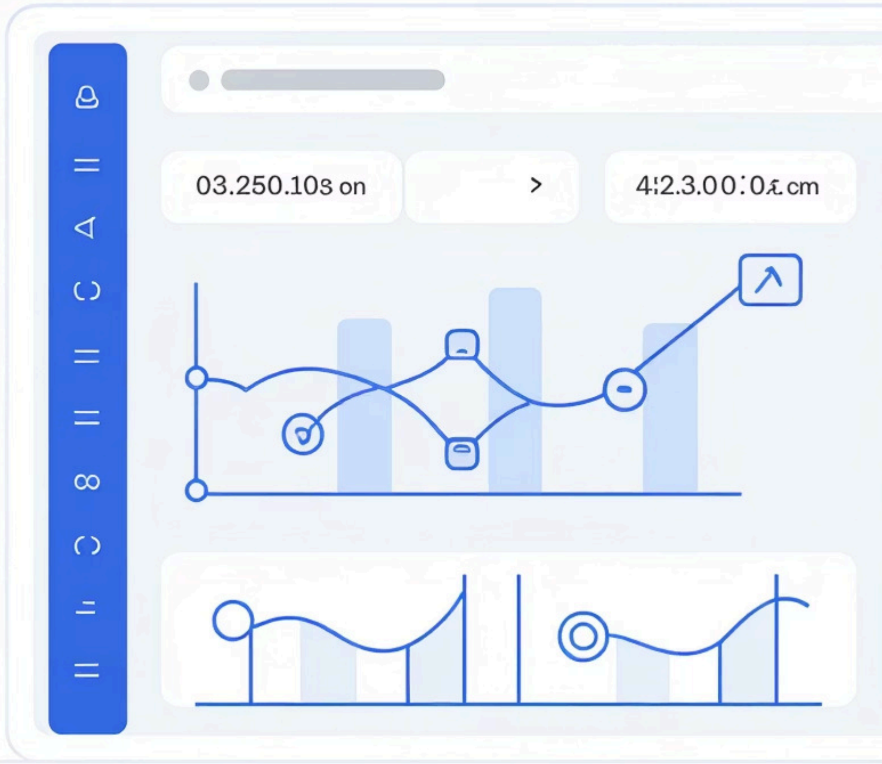
$$P(S|M) = \frac{P(M|S)P(S)}{P(M)}$$

Where:

- P(S|M): Posterior probability of state S given measurement M
- P(M|S): Likelihood of measurement M given true state S
- P(S): Prior probability of state S
- P(M): Marginal probability of measurement M

This approach allows for optimal decision-making even with noisy or incomplete condition data.

Predictive Maintenance



Predictive Maintenance: Advanced Prognostics

Definition & Key Elements

- Uses continuous monitoring and advanced algorithms to predict future component condition
- Focuses on estimating Remaining Useful Life (RUL) rather than current condition
- Integrates physics-based models with data-driven approaches
- Enables proactive scheduling of maintenance before failure occurs

Advantages

- Maximizes component utilization while minimizing failure risk
- Allows optimal maintenance scheduling to minimize operational disruption
- Enables just-in-time procurement of spare parts
- Supports long-term maintenance planning and resource optimization

Limitations

- Requires sophisticated sensors and data acquisition systems
- Demands advanced analytics capabilities and domain expertise
- Model development typically requires substantial historical failure data
- Higher initial implementation cost compared to other approaches

Predictive maintenance uses advanced analytics to forecast future component degradation, allowing maintenance to be scheduled at the optimal time before failure occurs but after maximum useful life has been extracted.

Mathematical Models for Predictive Maintenance

1

Degradation Process Modeling

Let X(t) represent the degradation level at time t. Failure occurs when:

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

Where Dcrit is the critical degradation threshold.

The Remaining Useful Life (RUL) is defined as:

$$\text{RUL}(t) = \mathbb{E}[T - t | X(t)]$$

Where T is the random failure time. This expectation can be calculated using stochastic process models that capture the degradation dynamics.

2

Gamma Process Example

The gamma process is frequently used to model monotonic degradation:

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

Where:

- α: Shape parameter (degradation rate)
- ν: Scale parameter

Expected degradation at time t:

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

For a critical threshold Dcrit, the expected failure time T is:

$$\mathbb{E}[T] = \frac{\nu D_{\text{crit}}}{\alpha}$$

3

Machine Learning Approaches

Data-driven RUL prediction can be formulated as a regression problem:

$$\text{RUL} = f(\mathbf{X}) + \epsilon$$

Where:

- f(·): Machine learning model (e.g., neural network, random forest)
- X: Feature vector from condition monitoring data
- ε: Model error

Common performance metrics include Mean Absolute Error (MAE) and Root Mean Square Error (RMSE) of RUL predictions.