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신뢰성 분석 및 몬테카를로 시뮬레이션을 활용한 승강장 스크린도어 유지보수 최적화

Optimizing Platform Screen Door Maintenance Using Reliability Analysis and Monte Carlo Simulation

Morris Alain Anthony*, Panju Shin**, Kiyoung Sung***, Hyun Kim†

* Master's Student, Transportation & ICT Convergence Research Center, Korea National University of Transportation (KNUT), 50 Daehak-ro, Chungju,Chungcheongbuk-do, Korea. alainmorrisdev@gmail.com **Doctor, Transportation & ICT Convergence Research Center, Korea National University of Transportation (KNUT), 50 Daehak-ro, Chungju,Chungcheongbuk-do, Korea. kankanni@ut.ac.kr ***PhD Student, Transportation & ICT Convergence Research Center, Korea National University of Transportation (KNUT), 50 Daehak-ro, Chungju,Chungcheongbuk-do, Korea. harok92@ut.ac.kr †Research Professor, Transportation & ICT Convergence Research Center, Korea National University of Transportation (KNUT), 50 Daehak-ro, Chungju,Chungcheongbuk-do, Korea. hyunkim@ut.ac.kr

1. Introduction

Platform Screen Doors (PSDs) are critical to safety and operational efficiency in urban rail systems. While fixed-interval maintenance is common, it is often inefficient and fails to reflect actual wear patterns. This study addresses the need for optimized PSD maintenance by applying reliability analysis and Monte Carlo simulation to real-world data from Seoul's subway system, aiming to minimize costs, reduce failures, and improve safety.

2. Methodology

2.1 Data Collection

We analyzed 10,078 PSD failure records from 279 stations (2019-2024), including metadata such as component type, manufacturer, installation date, and environmental context (above/below ground).

2.2 Reliability Analysis Framework

• **Metrics Calculated**: MTBF, failure rate (λ), B10 life, and reliability function R(t)
• **Distribution Modeling**: Weibull shape parameters (β) ranged from 1.63 to 2.30, indicating dominant wear-out failure behavior. Weibull parameters were estimated using maximum likelihood estimation (MLE), providing stable fits across components.
• **Environmental/Manufacturer Factors**: High failure rates were observed in summer. Manufacturer-specific MTBF ranged from 1,576 to 3,164 days.
• **Age-Ridership Interaction**: Components over 10 years old in high-ridership stations were significantly more failure-prone. Parameter estimation and reliability computations were conducted using Python's scipi.stats and lifelines libraries, ensuring robust statistical inference and repeatable analysis.

2.3 Maintenance Strategy Simulation

We evaluated four maintenance strategies:

1. **Reactive** – Repair after failure
2. **Preventive** – Scheduled replacement
3. **Condition-Based** – Age-based thresholds

4. **Predictive** – Reliability-threshold-based replacement

Simulations were run 50 times over a 10-year horizon using Weibull-based lifecycle modeling.

For each component, simulated lifecycles were generated using conditional Weibull sampling. Component states were updated daily across the 10-year period, and replacements were triggered based on each strategy's logic—reactive , preventive, condition-based, or predictive. Randomization was introduced using NumPy's uniform distribution to reflect stochastic degradation patterns.

2.3.1 Cost Framework

Costs included labor, part replacement, downtime, safety incidents, and reputational damage. Maintenance capacity was capped at 10 actions/day and $50,000/month.Maintenance cost estimates included both fixed and variable components. Planned maintenance assumed lower labor intensity (2 hours) and standard part costs, while reactive interventions incurred a 1.5x parts procurement multiplier and double the labor time (4 hours). A 2% safety incident probability per failure was applied, with $10,000 penalties per incident.

3. Results

3.1 Failure Patterns

Electrical stops and motors accounted for ~60% of failures.

Seasonal peaks occurred in July–August (21% of failures).

High-ridership stations saw more frequent failures in older components.

3.2 Strategy Comparison

Metric	Reactive	Preventive	Condition-Based	Predictive
Total Cost (USD)	$8.57M	$10.02M	$7.92M	$8.98M
Failures	2,699	2,062	1,540	1,084
Safety Incidents	49	44	32	24

3.3 Sensitivity and Optimization

- Optimal **condition-based** threshold (balanced): 1,095 days
- Optimal **predictive** reliability threshold: 0.70
- Component-specific tuning improved performance, with wear-prone elements like motors benefiting from aggressive strategies.

4. Discussion

Our study supports a shift from one-size-fits-all maintenance to an **integrated, adaptive strategy** incorporating:

- Component-specific schedules
- Manufacturer reliability profiles
- Seasonal and station-specific adaptations
- Cost-safety-reliability trade-off tuning

Predictive maintenance yields up to 29.6% fewer failures and 25% fewer safety incidents compared to condition-based strategies, at a modest cost increase.

5. Conclusion

We present a data-driven, simulation-backed framework for PSD maintenance optimization. Transit agencies can achieve substantial cost savings and safety improvements by transitioning to condition-based or predictive maintenance strategies. Our framework allows for scalable implementation and can be extended to other critical infrastructure components.