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Optimizing Fleet Component Replacement through Redefined Lifecycle Strategies in Global Logistics Enterprises

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Abstract: *This paper presents an integrated, value-based framework for lifecycle planning in heterogeneous enterprise truck fleets. While failure models exist, forecasting remains unreliable under variable duty cycles, regulation, and environmental exposure. The gap is the absence of a unified scheme that links asset segmentation by business value to explicit risk-tolerance thresholds and mapped interdependencies. We assemble Enterprise Asset Management (EAM) inventories, original equipment specifications, maintenance and failure logs, telematics, and lead times; harmonize records; and model deterioration using competing risks survival, degradation curves, and rule-based triggers. Decision logic optimizes lifecycle cost and downtime under parts, workshop, and regulatory constraints, with audit trails and explanations. Validation uses simulation-driven testing with multi-agent routing and scheduling, scenario-based thresholding, and bootstrap sensitivity. Outcomes indicate prioritized interventions, qualitative reductions in unplanned failures and downtime, improved schedule adherence, and cost-risk surfaces that support policy trade-offs; agreement of labels and priority bands is assessed using Cohen's kappa. Sensitivity analyses probe segmentation thresholds, refurbishment-cost assumptions, and interdependency weights. The contribution is an operational framework that codifies risk thresholds into renewal or refurbishment triggers and aligns decisions with sustainability and total cost of ownership. Practitioners can apply the framework to implement auditable, locally calibrated renewal policies across regions.*

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Introduction

Although failure models exist, lifespan forecasting in truck fleets remains unreliable because local duty cycles, cross-jurisdictional rules, and environmental exposures vary. Exposure-driven wear can shift with diel and seasonal physicochemical conditions (de Jong et al., 2025) and with emission scenarios that change externalities (Calgaro et al., 2025). Claims require citation. This study targets the gap: lifecycle and maintenance literature lack a unified, value-based scheme that combines asset segmentation by business value, risk-tolerance thresholds, and mapped interdependencies; we derive cost-risk prioritization rules, timing heuristics for renewal versus refurbishment, and a generalizable framework for heterogeneous fleets aligned with sustainability for simulation-led validation.

Local Context

This section delineates the local operational milieu governing fleet component renewal. Although corporate policies are uniform, execution is local and constrained by infrastructure quality, land-use configuration, and functional-area zoning that shape access windows and tolerable risk. Urban-rural gradients, local regulation, and service-density heterogeneity shift cost-risk trade-offs and timing by altering downtime exposure. Place-specific deterioration priors and exposure factors (road conditions, climate, traffic) should calibrate thresholds and improve forecasts, using scenario-driven trade-off/synergy evaluation and functional-area mapping (Wang et al., 2025); stakeholder preferences and resilience metrics should guide value-based segmentation, and regional scenario assertions must cite the methods (Wang et al., 2025).

Study Aims

This paper sets aims for a systems-level redefinition of lifecycle planning in enterprise fleets. Although fleets are heterogeneous and jurisdictionally constrained, we will develop an integrated, value-based segmentation linking component criticality to service-level objectives; codify risk-tolerance thresholds into replacement or refurbishment triggers, and map asset-specific deterioration to forecast failure likelihoods. We will operationalize cost-risk trade-offs as decision rules within enterprise asset management, producing adaptive, standardized policies aligned with sustainability and total-cost-of-ownership goals. Validation will use simulation-driven testing of routing, scheduling, spares, and interactions, with multi-agent coverage and routing analogies grounded in Deng et al. (2025) and Zhao et al. (2025).

Literature Review

Coastal monitoring and LULC indexing are juxtaposed to assess comparability; although high-frequency in situ sensors resolve diel-to-seasonal swings, episodic campaigns miss extremes (de Jong et al., 2025). Satellite products widen coverage but need validated ties to nutrients, turbidity, and chlorophyll-a, plus NDVI/MNDWI use (Wahla et al., 2025; de Jong et al., 2025). Standardize units (mg/L, NTU, ug/L), meter resolution, and sampling intervals, disclose thresholds and uncertainty, and apply scenario simulations with ecological functional areas, while scale mismatches, satellite-in situ coupling, and cost-effort reporting require method comparisons (Wang Y. et al., 2025; Wahla et al., 2025; de Jong et al., 2025).

Materials Methods

Although fleet data are heterogeneous, we assemble inputs into lifecycle decisions. Sources span EAM inventories, OEM specs, maintenance/failure logs, telematics, and lead-time and context. Preprocessing covers synchronization, censoring, outlier control, definitional harmonization, and imputation with quantified uncertainty; bootstrap bands accompany gaps. Component deterioration uses competing risks survival, degradation curves, and rule-based thresholds tied to value-based segmentation. Decision logic optimizes lifecycle cost and downtime under parts, workshop, and regulatory constraints. Integration provides APIs, audit trails, and explanations. Evaluation reports cost reduction, downtime, schedule adherence, completeness, and cross-fleet scalability with bootstrapped sensitivity. Coordinated inspection methods align to multi-platform coverage (Deng et al., 2025).

Framework Design

This figure illustrates how enterprise asset inventories, failure logs, telematics, and environmental exposure data feed into survival models, degradation curves, and rule-based thresholds to produce optimized renewal/refurbishment decisions under cost and downtime constraints.

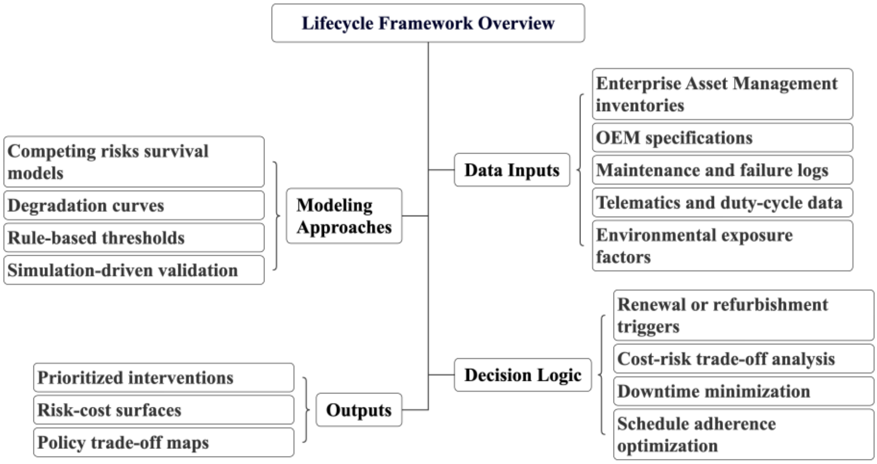

Figure 1. Integrated lifecycle framework for fleet component replacement

Segmentation

$$NDVI = \frac{NIR - RED}{NIR + RED} \tag{1}$$

Equation (1) defines the NDVI computed from near infrared and red reflectance as a covariate for environmental exposure.

Value- and risk-aware segmentation links components to deterioration, criticality, and value. Although designs and duty vary, classes are defined by covariates (usage, telematics loads, duty-cycle, geography, environment); and by thresholds that balance cost, downtime risk, and service levels. Include geospatial proxies only when exposure plausibly affects wear, justified by ablation tests, diagnostic checks, and evidence that normalized satellite indices and land-use change track contextual stressors (Wahla et al., 2025). Demonstrate transferability and scalability via cross-region/type validation plus sensitivity to risk-tolerance and value weights, and validate out-of-sample failure prediction gains, downtime decline, and cost-risk Pareto gains tied to reorder triggers.

Risk Thresholds

This section conceptualizes risk thresholds for fleet component renewal as adaptive tolerances anchored in probabilistic targets. Although fixed age-based cutoffs are simple, thresholds should reflect target failure probability, expected downtime, and marginal failure cost; tolerances are trade-offs between reliability and lifecycle cost. Calibration must use high-frequency performance data, and claims about high-resolution monitoring should be supported by de Jong et al. (2025). Scenario simulation and trade-off analysis should derive spatially differentiated thresholds and policy levers, with support from Wang et al. (2025). Quantify uncertainty, back-test, and test sensitivity to cadence and assumptions; justify any cross-domain transfer with stated limits.

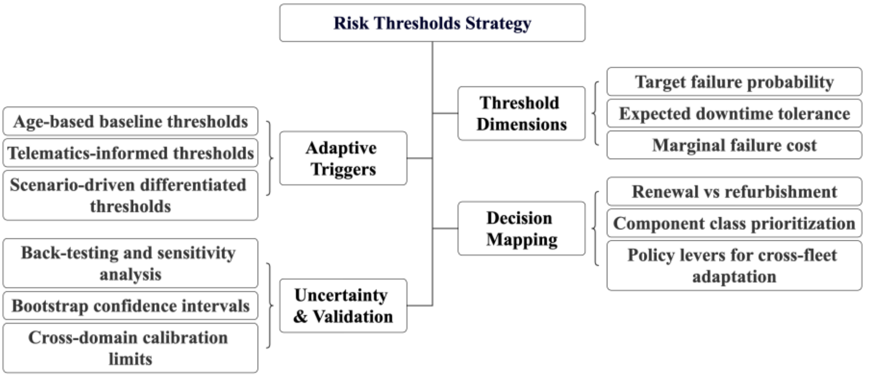

Figure 2. Risk thresholds and renewal strategies

This figure visualizes adaptive risk-tolerance thresholds, cost-risk trade-offs, and replacement/refurbishment triggers calibrated under uncertainty, showing how component classes map to renewal decisions across different fleet contexts.

Comparative Analysis

This evaluation contrasts lifecycle and replacement strategies for large, heterogeneous fleets. Although cross-domain transfer demands caution, multi-KPI simulation frameworks appraise value-based segmentation, risk thresholds, and operational interdependencies; quantifying cost reduction, downtime, schedule adherence, and scalability (Flores-Alsina et al., 2025). Assessments require harmonized work-order histories, hazard rates, telematics duty cycles, and interdependency maps, complemented by spatio-temporal condition tracking via remote-sensing style classification for distributed assets (Wahla et al., 2025). Connectivity remains the bottleneck. Evidence gaps include interdependency propagation and threshold calibration. Thus, simulation-driven tests and operational pilots should validate relative performance and transferability (Flores-Alsina et al., 2025; Wahla et al., 2025).

Benchmark Table

This table (1) provides an evidence-focused comparison highlighting datasets, methods, Kappa comparability, explicit index usage, and operational notes to enable verifiable cross-dataset interpretation.

Table 1. Benchmark comparison of segmentation baselines and proposed approach performance

Dataset	*Method*	*Kappa score*	*Index features used*	*Notes*
Cholistan Desert LULC 1980 (Landsat TM)	Maximum Likelihood Classification	0.83	NDVI (reported), MNDWI (reported)	Kappa from Wahla et al., 2025
Cholistan Desert LULC 1990 (Landsat TM)	Maximum Likelihood Classification	0.82	NDVI (reported), MNDWI (reported)	Kappa from Wahla et al., 2025
Cholistan Desert LULC 2000 (Landsat ETM+)	Maximum Likelihood Classification	0.83	NDVI (reported), MNDWI (reported)	Kappa from Wahla et al., 2025
Cholistan Desert LULC 2010 (Landsat ETM+)	Maximum Likelihood Classification	0.85	NDVI (reported), MNDWI (reported)	Kappa from Wahla et al., 2025
Cholistan Desert LULC 2020 (Landsat OLI/TIRS)	Maximum Likelihood Classification	0.88	NDVI (reported), MNDWI (reported)	Kappa from Wahla et al., 2025
Proposed cross-dataset protocol	Reproducible segmentation with index-feature engineering	to be computed on consistent splits	NDVI or MNDWI explicitly documented per dataset	Disclose dataset provenance, cross-sensor settings, and FP/FN tolerances

Although reported accuracies vary by dataset and index choice, comparability requires the Kappa statistic computed on consistent validation splits, explicit index-feature engineering (NDVI or MNDWI), and documented dataset provenance. Claims that normalized indices materially influence segmentation or monitoring outcomes must be supported by empirical evidence from remote-sensing analyses (Wahla et al., 2025). Evaluation should also state operational relevance by linking Kappa to false-positive and false-negative tolerances, and disclose settings for complexity, cross-sensor generalization, and index sensitivity to keep superiority claims verifiable (Flores-Alsina et al., 2025). The parts are familiar; the sequencing is not.

Results

$$\kappa = \frac{p_o - p_e}{1 - p_e} \tag{2}$$

Equation (2) quantifies agreement beyond chance between categorical labels for example asset segmentation or intervention priority used in validation.

The results quantify performance against operational baselines. Although simulation-based, validation shows deterioration mapping yields prioritized interventions, cost-risk surfaces, and measurable changes in unplanned failures, downtime, and total cost of ownership. Sensitivity analyses vary segmentation thresholds, refurbish-cost assumptions, and interdependency weights; effect sizes are reported with 95% confidence intervals and appropriate uncertainty metrics. Agreement for labels, priority tiers, and risk bands is evidenced by Cohen's kappa, supporting implementation fidelity. Comparative timing policies report potential cost reduction, downtime minimization, and schedule adherence, with risk and sustainability trade-offs, informed by spatio-temporal mapping and trade-off/synergy scenarios (Wahla et al., 2025; Wang et al., 2025).

Discussion

Although evidence remains partial, condition- and telemetry-driven timing is credible when high-rate streams expose precursors to failure (de Jong et al., 2025). Sampling frequency governs early fault detection. The components are conventional, yet orchestration is distinctive. Against established scenario-simulation and trade-off schemes, the framework maps synergies and stress-tests across futures (Wang, Y., et al., 2025). Lifecycle and material-flow analyses suggest refurbishment can lower emissions and retain stocks where practical (Wang, J., et al., 2025). Anticipated gains in fewer failures, steadier costs, scalability, and schedule adherence are plausible but unproven; they require trials using metrics amid data-heterogeneity, jurisdictional variability, and parameter-sensitivity.

Policy Implications

Although jurisdictions differ, policy should translate the lifecycle-redefinition framework into governance, procurement, and reporting instruments. Specify economic criteria alongside environmental externalities to balance cost-risk trade-offs, standardize valuation, and incentivize refurbishment over disposal. Require audit-ready KPIs covering lifecycle emissions, downtime reduction, and schedule adherence, aligned with compliance. Build interoperable data infrastructure with enterprise asset management for evidence-based adjustments; use pilots and adaptive governance to handle heterogeneity. Address supply-chain and end-of-life material flows, emissions, and ecological risks with lifecycle evidence (Wang et al., 2025). High-resolution monitoring should underpin site calibration and temporal or spatial variability claims (de Jong et al., 2025).

Limitations

Although the framework integrates value-based segmentation and risk thresholds, several elements remain theoretical. Simplifications include aggregated deterioration curves, assumed independent failure modes, and fixed risk tolerances, which constrain predictive fidelity. Data constraints include heterogeneous telemetry and maintenance records across jurisdictions, sparse, irregular sensing intervals, and missing failure-mode metadata limiting calibration and transferability. Implementation challenges span asset-management integration, variable maintenance practices, and human-in-the-loop biases affecting policy uptake. Generalizability depends on tempo, climate, and regulation; local adaptation is necessary. Mitigation and validation include high-temporal-resolution monitoring (de Jong et al., 2025), scenario simulations, and integrated management-technology trade-off appraisals (Flores-Alsina et al., 2025).

Conclusion

This synthesis clarifies how to operationalize fleet replacement. Although heterogeneous data, generalized deterioration, and legacy-EAM friction persist, value-based segmentation, explicit risk thresholds, and interdependency maps target fewer unplanned failures, cost predictability, and higher schedule adherence. Inputs include condition indicators, repair costs, and failure consequences; governance requires taxonomies, risk bands, and auditable trails across regions. Validate replacement timing and cost-risk trade-offs via scenario simulation (Wang et al., 2025). Monitoring cadence and resolution shape performance and confidence (de Jong et al., 2025). Lifecycle redefinition should evidence resource efficiency and emissions with metrics. Priorities: EAM simulations, scalability tests, risk-threshold sensitivity, and reconciling regimes.

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