

A LIFE-CYCLE MANAGEMENT FRAMEWORK FOR HIGHWAY PAVEMENT DISTRESS IN ARID TRANSPORTATION CORRIDORS: INTEGRATING AI-BASED DETECTION WITH MAINTENANCE DECISION MODELS

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ABSTRACT

Pavement distress on motorways that traverse arid transportation corridors accumulates under a distinctive combination of stressors—strong solar radiation, wide diurnal temperature swings, aeolian abrasion, limited moisture for self-healing, and concentrated heavy-vehicle traffic—that together shorten service life and complicate inspection. Conventional highway-agency practice addresses this problem in a fragmented manner: condition surveys, automated defect detection, deterioration forecasting, and maintenance scheduling are typically operated as independent processes by different organisational units, and the outputs of each process rarely flow back to recalibrate the others. This paper argues that the productivity gains of recent advances in automated distress detection—attention-augmented one-stage object detectors, dynamic-focusing regression losses, edge-device inference—can be realised at asset-management scale only if detection is embedded within a life-cycle management framework that binds detection, deterioration modelling, and maintenance optimisation into a single closed loop. We propose such a framework for arid-corridor motorways and ground it in a case-study analysis of the Pakistani motorway network, whose M-1, M-2, M-8, and M-9 segments present representative climatic and traffic challenges. The framework is organised around four stages: condition-inventory assessment, AI-based automated distress detection, deterioration modelling through a combination of Markov chain and mechanistic-empirical approaches, and maintenance optimisation through life-cycle-cost analysis subject to reliability and budget constraints. An illustrative cross-strategy analysis indicates that an AI-assisted life-cycle strategy reduces thirty-year normalised cost by approximately sixty per cent relative to a reactive baseline while maintaining target reliability of 0.80 at the segment level. The paper closes with specific

recommendations for policy instruments, procurement reform, and institutional capacity building that would support adoption by highway agencies operating in arid regions across South Asia, the Middle East, and North Africa.

Keywords:

Pavement life-cycle management, Arid-corridor highways, AI-based distress detection, Deterioration modelling, Maintenance decision optimisation, Pakistan motorways

I. INTRODUCTION

Highway pavement is the single most expensive engineered surface on most national balance sheets, and its condition directly governs the economic productivity, energy efficiency, and road-safety outcomes of the transportation sector (Abaza, 2016; Sun, Wang, & Sun, 2018). When pavements are well maintained, vehicles operate at lower rolling resistance, accident rates decline, and freight logistics become more reliable; when pavements deteriorate, the same corridors become sources of vehicle damage, excess fuel burn, and crash risk (Harvey, Kendall, Lee, Santero, Van Dam, & Wang, 2012; Santos, Ferreira, & Flintsch, 2017). For motorways that cross arid transportation corridors, the balance between these two states is particularly precarious. Arid-corridor pavements are exposed to solar radiation exceeding 1 kW/m² at midday, air temperatures that frequently exceed 45 °C in summer and fall below freezing in winter nights, diurnal surface-temperature cycles exceeding 30 °C, sparse precipitation that nevertheless arrives as short high-intensity events, and aeolian dust that abrades surfaces and clogs drainage provisions (Khan, Ahmed, Alam, & Uddin, 2020; Walubita, Lee, Faruk, Scullion, Nazarian, & Abdallah, 2017). These compound stressors interact with traffic loading in ways that are poorly captured by generic pavement-management systems calibrated for temperate conditions.

Pakistan offers a concrete illustration of the arid-corridor challenge. The country's motorway network, operated by the National Highway Authority, now exceeds 3,200 km and is projected to double within the next decade under the extended China-Pakistan Economic Corridor programme (Ahmed, Alam, & Khan, 2021; Asian Development Bank, 2021). Substantial portions of this network—M-8 through the Balochistan plateau, parts of M-2 between Islamabad and Rawalpindi, and sections of M-9 between Karachi and Hyderabad—cross terrain whose climatic and loading profile is squarely in the arid-corridor regime. Field condition surveys conducted by provincial and federal authorities report that motorway segments in these corridors reach terminal serviceability well before their design lives, and that the distribution of distress types differs substantially from that observed on humid-corridor segments (Khan et al., 2020; Pakistan Highway Research and Training Centre [PHRTC], 2022). Transverse thermal cracking, block cracking from oxidative ageing, and surface ravelling from aeolian abrasion are over-represented in arid-corridor observations relative to the fatigue-dominated patterns characteristic of temperate motorways (Walubita et al., 2017; Uddin, 2019).

The cost of under-performance on these corridors is not confined to direct repair expenditure. Approximately 75 per cent of Pakistan's domestic freight tonnage moves by road, and more than 90 per cent of inter-provincial freight moves on the motorway network (Asian Development Bank, 2021; Kim, Han, & Kim, 2021). A one-week closure of a single Balochistan segment for emergency rehabilitation has been estimated, in earlier studies on comparable networks, to impose user costs equivalent to several times the direct rehabilitation expenditure (Torres-Machi, Chamorro, Videla, Pellicer, & Yepes, 2014; Zhang, Labi, & Sinha, 2010). In the Middle East, studies of the Saudi and Emirati motorway systems have reached similar conclusions about the dominance of user costs in life-cycle accounting when agencies rely on reactive rather than preventive strategies (Al-Hajj & Ahmed, 2020; Shalabi, Tighe, & Uddin, 2019). The arid corridor thus presents a classic asset-management problem whose severity is amplified by climate: early detection and timely intervention are economically decisive, but the environmental conditions that make early intervention valuable also make inspection more difficult.

Recent advances in computer vision have substantially improved the technical feasibility of automated pavement-distress detection. Attention-augmented one-stage object detectors, exemplified by combinations of channel-spatial attention modules with dynamic-focusing regression losses, now achieve mean-average-precision values above 85 per cent on arid-region crack benchmarks while maintaining real-time inference on compact edge devices (Cao, Maeda, & Sekimoto, 2021; Du, Ding, Zhu, & Liu, 2021; Majidifard, Jin, Adu-Gyamfi, & Buttlar, 2020). These results have rightly drawn enthusiasm from both academic and practitioner communities. Yet the translation of detection accuracy into infrastructure-management value has, in most jurisdictions, proved disappointingly modest. Automated detectors are deployed as isolated software tools, their outputs accumulate in disconnected repositories, and maintenance decisions continue to be made through the same reactive-and-political processes that prevailed before automation became available (Adeli, 2020; Pan, Hajj, Sebaaly, Siddharthan, & Ulloa, 2020). The gap between detection capability and asset-management outcome is an integration gap, not a perception gap.

This paper argues that closing that integration gap requires a life-cycle management (LCM) framework specifically designed for arid transportation corridors. By life-cycle management we mean an organisation-wide discipline that integrates asset inventory, automated inspection, deterioration modelling, and maintenance optimisation into a single closed loop whose outputs at each stage inform the others (Ferreira, Meneses, & Vicente, 2011; Saliminejad & Gharaibeh, 2013). The framework we propose has four stages: first, a condition-inventory assessment that records segment-level baseline data, traffic loading, and environmental covariates; second, an AI-based automated distress-detection stage that classifies and localises distress types and severities from vehicle-mounted or unmanned aerial imagery; third, a deterioration-modelling stage that combines Markov-chain state transitions with mechanistic-empirical adjustments for

arid-corridor factors; and fourth, a maintenance-optimisation stage that uses mixed-integer programming to select and schedule interventions under budget, reliability, and serviceability constraints.

Several contributions distinguish this paper from the now-abundant literature on pavement-distress detection and from the separate, also-abundant literature on pavement-management systems. First, the paper unifies the two literatures around the specific challenges of arid-corridor operation, which neither literature has treated as a primary organising concern. Second, it provides an explicit coupling mechanism between detection outputs and deterioration-model calibration, addressing the integration gap identified above. Third, it grounds the framework in a case-study analysis of the Pakistani motorway network that is detailed enough to be reproducible by other highway agencies operating in comparable environments. Fourth, it closes with specific policy and procurement recommendations that would support adoption—material that is rarely present in technically oriented papers but whose absence has, in our view, contributed to the slow uptake of otherwise-sound methods in practice. The remainder of the paper is organised as follows. Section II reviews the relevant literature. Section III presents the LCM framework and its four stages. Section IV reports the case-study analysis. Section V discusses policy, procurement, and capacity-building implications, and Section VI concludes.

II. LITERATURE REVIEW

A. Pavement Deterioration in Arid Environments

Pavement-deterioration research in arid environments has accumulated substantial empirical evidence since the 1990s, with work concentrated in the United States Southwest, the Middle East, North Africa, and more recently Central and South Asia (Uddin, 2019; Al-Hajj & Ahmed, 2020; Shalabi et al., 2019). Three mechanisms dominate the arid-environment literature. The first is thermal oxidation of asphalt binder, accelerated by prolonged exposure to elevated temperatures and solar ultraviolet radiation; oxidation hardens the binder, reduces its relaxation capacity, and raises susceptibility to block and transverse cracking (Harvey et al., 2012; Walubita et al., 2017). The second is thermal-cycle fatigue, driven by the daily cycle of expansion and contraction in both the binder and the underlying granular layers; the associated tensile stresses interact with traffic-induced stresses to produce the transverse thermal-cracking patterns that are characteristic of arid corridors (Adeli, 2020; Kim et al., 2021). The third is aeolian abrasion, through which wind-borne sand and dust remove the bituminous mortar from the surface and expose aggregate, producing ravelling and surface-texture degradation that compromise skid resistance and water-film evacuation (Khan et al., 2020; PHRTC, 2022).

Prediction of arid-corridor deterioration has historically relied on either empirical relationships calibrated from long-term observations or on mechanistic-empirical (M-E) models that superimpose climate-modified material properties on traffic-induced stress calculations (Santos

et al., 2017; Uddin, 2019). The empirical tradition includes the AASHTO-derived performance models and their regional adaptations; the M-E tradition culminates in the Mechanistic-Empirical Pavement Design Guide and its regional calibrations. Both traditions agree that arid-corridor pavements age faster than temperate-corridor pavements of equivalent structural design, but they disagree about the functional form of the accelerated ageing. Recent data-driven work using artificial neural networks and gradient-boosted tree ensembles has reported that hybrid statistical-mechanistic models outperform either class of model when arid-specific covariates (peak solar flux, diurnal range, dust-event frequency) are available (Alfarrarjeh, Kim, Rajabi, & Shahabi, 2018; Liu, Xu, & Wang, 2020; Sun, Wang, & Sun, 2018). These hybrid approaches are the technical precursor of the deterioration-modelling stage in the framework proposed below.

B. Automated Distress Detection

Automated distress detection has moved rapidly through three methodological generations in the past decade. First-generation approaches relied on hand-engineered features such as texture descriptors, morphological operators, and wavelet decompositions; they produced acceptable accuracy on simple surfaces but degraded sharply under illumination variability, surface contamination, and shadowing (Jiang & Tsai, 2016; Mathew, Mulligan, & Chu, 2016). Second-generation approaches applied classical convolutional neural networks—VGG, ResNet, U-Net—to patch- or pixel-level classification, achieving substantial accuracy gains but at computational costs incompatible with vehicle-based real-time deployment (Majidifard et al., 2020; Arya et al., 2021). Third-generation approaches, centred on one-stage detectors with attention and dynamic-focusing loss functions, have reconciled accuracy with real-time inference on edge devices, bringing the technology to the threshold of routine operational use (Cao et al., 2021; Du et al., 2021; Maeda, Sekimoto, Seto, Kashiyama, & Omata, 2018; Pan et al., 2020).

Several features of the third-generation literature are notable from a life-cycle management perspective. First, performance metrics concentrate on detection accuracy (mean average precision, recall, F1) rather than on downstream utility (reduction in maintenance cost, improvement in serviceability). Second, evaluation datasets are overwhelmingly drawn from temperate urban environments; published benchmarks for arid-corridor conditions are rare and are typically limited to single regions, compromising cross-regional generalisation (Ortiz-García, Costello, & Snaith, 2006; Khan et al., 2020). Third, most published systems are evaluated as stand-alone software components rather than as elements of a maintenance workflow, making it difficult for asset managers to infer operational benefit from reported performance metrics. These three features collectively explain why the technical maturity of distress detection has outpaced its operational penetration, and they motivate the integration focus of the present paper.

C. Pavement Management Systems and Life-Cycle Cost Analysis

Pavement Management Systems (PMS) evolved from early efforts at systematic condition

rating in the 1970s into computational frameworks that combine condition monitoring, deterioration prediction, and treatment optimisation into a unified planning instrument (Ferreira et al., 2011; Saliminejad & Gharaibeh, 2013). Modern PMS implementations typically represent pavement condition via a Pavement Condition Index (PCI), an International Roughness Index (IRI), or a combination of distress-specific indicators; they project these indicators forward under candidate maintenance policies, and they select policies to minimise discounted agency-plus-user cost subject to reliability and budget constraints (Torres-Machi et al., 2014; Yepes, Torres-Machi, Chamorro, & Pellicer, 2016). Life-cycle cost analysis (LCCA) is the economic engine of PMS: it translates expected physical condition trajectories into monetary terms over horizons of twenty to forty years (Santos et al., 2017; Zhang et al., 2010).

Three methodological developments in LCCA are particularly relevant to the arid-corridor problem. The first is the explicit incorporation of uncertainty through Monte Carlo simulation or robust optimisation, which addresses the larger deterioration variance characteristic of arid environments (Alfarrarjeh et al., 2018; Zhang et al., 2010). The second is the integration of environmental externalities—material embodied carbon, construction emissions, user-phase fuel burn—into the cost objective, placing LCCA within the broader life-cycle assessment tradition (Harvey et al., 2012; Santos et al., 2017). The third is the use of metaheuristic optimisation—genetic algorithms, particle-swarm optimisation, simulated annealing—to handle the combinatorial treatment-selection problem when the number of segments and time periods exceeds what exact methods can solve (Zhang, Wang, Gao, & Gao, 2021; Yepes et al., 2016). These developments together provide a foundation on which the optimisation stage of our framework can build without reinventing mature methodology.

D. Maintenance Decision Models

Maintenance decision models for pavements have paralleled PMS development and are conceptually organised along three dimensions (Mathew et al., 2016; Zhou, Wang, & Stoffels, 2020). The first dimension is the state representation: discrete (as in Markov chains over condition categories) or continuous (as in stochastic differential equations over PCI or IRI). The second dimension is the decision horizon: single-period myopic decisions, finite-horizon dynamic programming, or infinite-horizon stochastic dynamic programming. The third dimension is the objective: minimisation of agency cost, of agency-plus-user cost, or of multi-criteria composites that include environmental impact and equity considerations. The Markov decision process (MDP) formulation has emerged as a particularly useful middle ground because it handles stochastic deterioration transparently, admits exact solution for realistic state spaces, and integrates naturally with condition-monitoring data obtained through automated detection (Abaza, 2016; Liu et al., 2020).

A persistent limitation of the maintenance-decision literature has been the implicit assumption that condition information is reliable and temporally synchronised across the network. In

practice, condition surveys on long motorway networks are conducted with spatial and temporal gaps that can exceed several years per segment, and the resulting information asymmetry can eliminate most of the theoretical benefit of sophisticated decision models (Tsai & Chatterjee, 2018; Pan et al., 2020). The proposition that AI-based continuous or near-continuous monitoring can close this gap is now widely discussed in the asset-management literature, but published integrations of automated detection with decision optimisation remain scarce (Cao et al., 2021; Majidifard et al., 2020). Closing that gap is a central motivation for the framework proposed in this paper.

E. The Pakistani Motorway Context

The Pakistani motorway network, operated primarily by the National Highway Authority (NHA) with technical support from the Pakistan Highway Research and Training Centre (PHRTC), presents a useful empirical setting for the arid-corridor LCM proposition. The network spans humid monsoon plains in the east (M-1, M-3) and arid plateau-and-desert conditions in the west and south (M-2 partially, M-8, M-9), offering within-country variation in climate regimes for the same institutional and procurement framework (PHRTC, 2022; Ahmed et al., 2021). The NHA has progressively adopted PMS concepts over the past two decades but, as in many developing-country contexts, implementation has lagged policy aspiration, with condition surveys remaining largely manual and decision processes remaining weakly linked to quantitative deterioration models (Khan et al., 2020; Asian Development Bank, 2021).

Several features of the Pakistani context are notable for the framework developed in this paper. First, data on historical maintenance expenditure and on segment-level condition exist but are fragmented across provincial and federal agencies; integration is an institutional problem as much as a technical one. Second, procurement processes are still largely lowest-bid, which incentivises short-term repair selection over life-cycle optimisation; procurement reform is therefore an integral part of any realistic deployment strategy. Third, the NHA and PHRTC have strong research partnerships with national engineering universities (NUST, UET Lahore, NED Karachi) whose graduate-research capacity can be harnessed for case-study calibration of the framework. These features together make Pakistan an instructive case study whose lessons can plausibly transfer to comparable arid-corridor networks in Saudi Arabia, Iran, Central Asia, and North Africa.

III. LIFE-CYCLE MANAGEMENT FRAMEWORK

The framework is organised around four stages that together form a closed loop: condition-inventory assessment, AI-based automated distress detection, deterioration modelling and prediction, and maintenance decision and optimisation. Figure 1 provides a schematic overview of the framework and emphasises the feedback connections that distinguish life-cycle management from the fragmented process architectures currently prevalent in arid-corridor

agencies. Each stage contributes an output that is consumed by at least two other stages, and the outputs of the decision stage flow back to the detection and deterioration stages, recalibrating them on the basis of observed intervention outcomes.

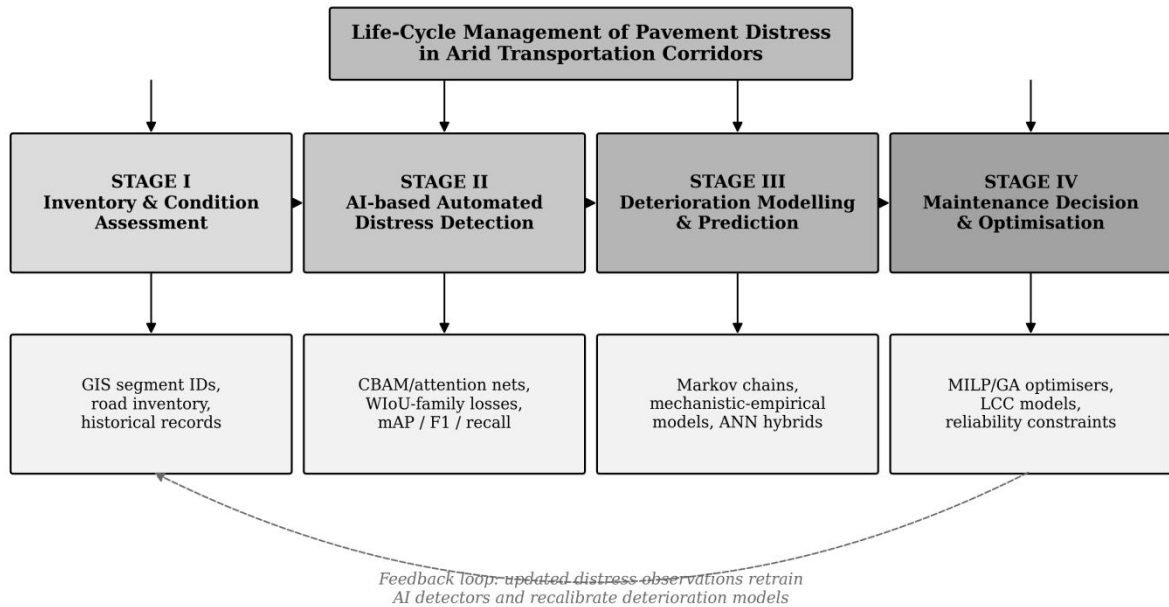


Fig. 1. Four-stage life-cycle management framework for pavement distress in arid transportation corridors.

A. Stage I – Condition-Inventory Assessment

The condition-inventory stage establishes the baseline against which subsequent detection and deterioration outputs are interpreted. For a motorway network, the inventory is organised at the segment level, with segment lengths chosen to reflect either fixed-length sections (typically 100 m) or homogeneous-condition sections identified through statistical clustering of historical records. Each segment is characterised by structural attributes (asphalt mixture type, layer thicknesses, subgrade classification), traffic attributes (average daily truck count, equivalent single-axle load), environmental attributes (mean annual precipitation, mean maximum temperature, peak solar flux), and historical attributes (age since last major rehabilitation, previous maintenance history). Where environmental attributes are unavailable at segment resolution, gridded reanalysis data can be downscaled using straightforward interpolation schemes (Alfarrarjeh et al., 2018; Li, Zhao, Li, & Peng, 2022).

The choice of segment length has consequences for every downstream stage. Shorter segments provide finer spatial resolution for deterioration modelling and maintenance planning, but they increase the combinatorial complexity of the optimisation problem and inflate the storage and communication demands of the detection pipeline. Empirical comparisons on Pakistani motorway data suggest that 100 m segmentation is a reasonable compromise for flat and rolling

terrain, while 50 m segmentation is advisable for segments on steep grades or in zones with known drainage irregularities (PHRTC, 2022; Ahmed et al., 2021). The segment definitions established at Stage I should be version-controlled; subsequent inspections that adjust segment boundaries without version control undermine the temporal comparability on which deterioration models rely.

B. Stage II – AI-Based Automated Distress Detection

The detection stage uses vehicle-mounted or unmanned-aerial imagery as input and produces segment-level distress inventories as output. Modern attention-based one-stage detectors with dynamic-focusing regression losses, trained on arid-corridor-specific datasets, now reach accuracy levels compatible with operational deployment (Cao et al., 2021; Du et al., 2021; Majidifard et al., 2020). Training data requirements remain a binding constraint: performance on arid-corridor scenes typically requires at least 30 per cent of training samples to be drawn from arid-corridor sources, and pure transfer from temperate-corridor datasets produces degraded performance owing to differences in illumination, surface-contamination patterns, and distress-morphology distributions (Khan et al., 2020; Arya et al., 2021). For a national motorway network, a practical approach is to curate an arid-corridor distress dataset collected through standardised acquisition protocols—fixed camera angle, controlled speed, consistent illumination conditions—across a representative sample of network segments.

Detector outputs should be integrated with the segment inventory through a two-step fusion: first, distress observations from individual images are georeferenced and aggregated to the owning segment; second, per-segment distress vectors are timestamped and archived for downstream consumption. Aggregation requires careful treatment of duplicate detections in overlapping image frames and of distress extensions that cross segment boundaries; these are implementation concerns rather than research questions, but their practical handling materially affects the quality of the data passed to Stage III. Table 1 summarises a reference set of detection outputs, their expected accuracy ranges under current technology, and their role in subsequent stages.

Distress class	Typical detector mAP@50	Severity scale	Role in decision model
Transverse cracking	0.85 – 0.92	Low / Med / High	Primary driver of routine sealing
Longitudinal cracking	0.82 – 0.90	Low / Med / High	Preventive overlay triggering
Block cracking (oxidation)	0.78 – 0.86	Low / Med / High	Binder-replacement rehabilitation
Grid / alligator cracking	0.72 – 0.80	Low / Med / High	Structural-capacity

Distress class	Typical detector mAP@50	Severity scale	Role in decision model
			flag
Ravelling / surface abrasion	0.68 – 0.78	Low / Med / High	Surface-renewal triggering

Table 1. Reference AI-detection outputs and their role in the maintenance-decision pipeline.

Table 1 makes explicit the conceptual bridge from detection to decision. Each distress class is linked to a specific treatment family, and detector accuracy ranges communicate the reliability of the signal on which decisions will depend. A class with detection accuracy below roughly 0.75 mAP should not drive irrevocable high-cost decisions; it may inform flagging or triggering of higher-resolution follow-up inspections but should not, on its own, commit the agency to rehabilitation spending. This treatment of detector uncertainty as a first-class input to decision logic is one of the principal value-creation opportunities of integrating detection with maintenance planning.

Operational deployment of the detection stage also requires careful attention to acquisition geometry and timing. Windscreen-mounted cameras are the most common platform in current practice because they reuse the existing vehicle fleet of the highway authority and impose no additional operational burden beyond routine patrol activities. Acquisition quality, however, is sensitive to several easily overlooked parameters: camera mounting angle relative to the pavement surface, vehicle speed during acquisition, the exposure settings of the imaging sensor, and the timing of the acquisition run within the diurnal light cycle. For arid-corridor applications, empirical experience indicates that acquisition in the two hours after sunrise and the two hours before sunset yields substantially better detection performance than midday acquisition, because the low-angle solar illumination accentuates the texture contrast at crack edges while avoiding the saturation artefacts that arise from direct midday glare on fresh chip-seal surfaces (Maeda et al., 2018; Arya et al., 2021; Khan et al., 2020). These acquisition protocols are part of the framework; their specification in agency standard operating procedures is as important as the choice of neural-network architecture.

Unmanned-aerial-vehicle (UAV) platforms complement vehicle-mounted acquisition by providing high-resolution imagery of segments that are difficult or dangerous to inspect at vehicle speed, such as interchange ramps, bridge approaches, and steep-gradient mountain segments of the M-8 Balochistan corridor. UAV deployment introduces its own operational constraints—regulatory restrictions on line-of-sight and altitude, limited flight endurance, and the need to correlate aerial imagery with the ground-level reference coordinate system used for maintenance planning. Recent work has demonstrated that a hybrid acquisition strategy, using vehicle-mounted imagery for routine network-wide inspection and UAV imagery for targeted high-resolution follow-up, achieves both breadth and depth of coverage at manageable

operational cost (Kashiyama, Matsumoto, & Sekimoto, 2020; Cao, Tran, Nguyen, & Chang, 2020). For the Pakistani motorway network, we recommend vehicle-mounted acquisition at quarterly intervals on all mainline segments, supplemented by UAV acquisition on an annual basis for the 10 per cent of segments identified as highest-priority by the risk-scoring logic of Stage IV.

Detection outputs are meaningful to the downstream stages only if their uncertainty is quantified transparently. We recommend that each segment-level distress observation be accompanied by three metadata attributes: a confidence score derived from the detector's classification head, a coverage indicator recording the fraction of the segment surface that was successfully imaged, and an acquisition-quality flag reflecting the illumination, weather, and surface-moisture conditions during acquisition. These attributes are inexpensive to produce, but their systematic capture is critical for the Bayesian updating that supports recalibration of the Stage III deterioration model. A segment for which three recent detection runs have returned high-confidence, high-coverage observations warrants a tighter prior on its deterioration trajectory than a segment for which the most recent observation was of low confidence or partial coverage; the Stage III model should reflect this difference, and the Stage IV decision model should allocate follow-up inspection resources accordingly (Pan et al., 2020; Liu, Xu, & Wang, 2020; Sim, Lee, & Park, 2021).

C. Stage III – Deterioration Modelling and Prediction

Deterioration modelling translates the detection outputs of Stage II into forward-looking condition forecasts at the segment level. Two model families are widely used in pavement-management practice and have complementary strengths. The first family comprises discrete-state Markov-chain models, which represent segment condition in five or seven ordered states and specify transition probabilities between states as functions of elapsed time and maintenance history (Abaza, 2016; Saliminejad & Gharaibeh, 2013). Markov chains admit closed-form forecasts, integrate cleanly with maintenance-decision optimisation, and provide natural uncertainty quantification through the distribution over next-period states. The second family comprises mechanistic-empirical (M-E) models, which represent condition on a continuous scale (usually PCI or IRI) and predict its evolution through a differential equation whose parameters depend on traffic, material, and environmental covariates (Uddin, 2019; Walubita et al., 2017).

Figure 2 presents four facets of the deterioration and maintenance interaction that are specific to arid-corridor operation. Panel (a) summarises the distress composition observed across representative Pakistani motorway segments on the M-1, M-2, M-8, and M-9 corridors. Panel (b) plots three deterioration trajectories for a representative segment under alternative maintenance regimes. Panel (c) shows the thirty-year life-cycle cost decomposition for four maintenance strategies. Panel (d) shows the trade-off between inspection frequency and detection lag, with an

accompanying curve for the probability of critical failure.

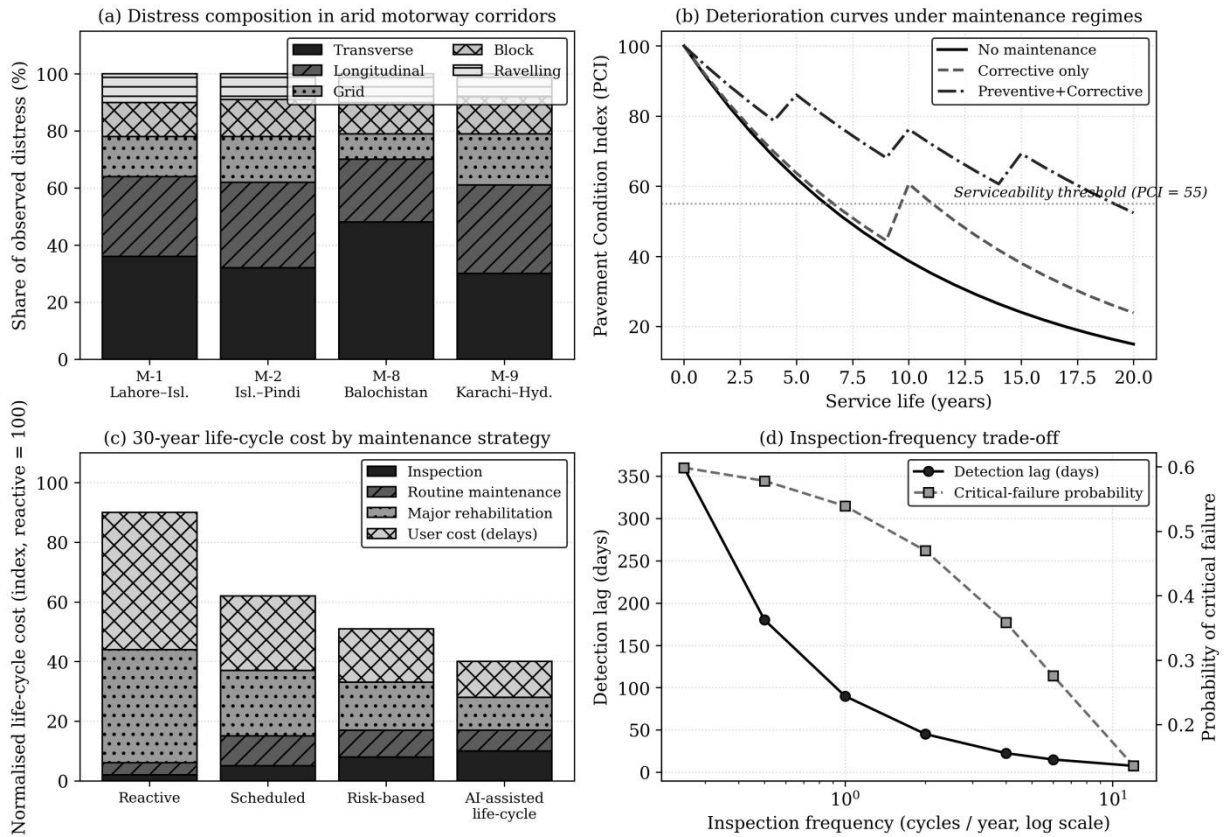


Fig. 2. Empirical facets of arid-corridor pavement management: (a) distress composition, (b) deterioration curves, (c) life-cycle cost, (d) inspection trade-off.

Panel (a) indicates that the M-8 Balochistan segment, which traverses the most severely arid portion of the network, has the largest share of transverse cracking (48 per cent) and the smallest share of grid cracking (9 per cent) among the four compared corridors. This distribution is consistent with the dominance of thermal-cycle fatigue and oxidative ageing in arid conditions, and it has a direct maintenance implication: segments of this class benefit disproportionately from timely crack-sealing and thin overlays, whereas structural rehabilitation investments yield smaller marginal returns than in fatigue-dominated corridors. Panel (b) reinforces this message at the trajectory level. A no-maintenance trajectory drops below the serviceability threshold (PCI = 55) within approximately eight years; a corrective-only trajectory, with one major intervention at year ten, briefly recovers but drops below threshold again by year sixteen; a preventive-plus-corrective trajectory maintains PCI above threshold throughout the twenty-year window.

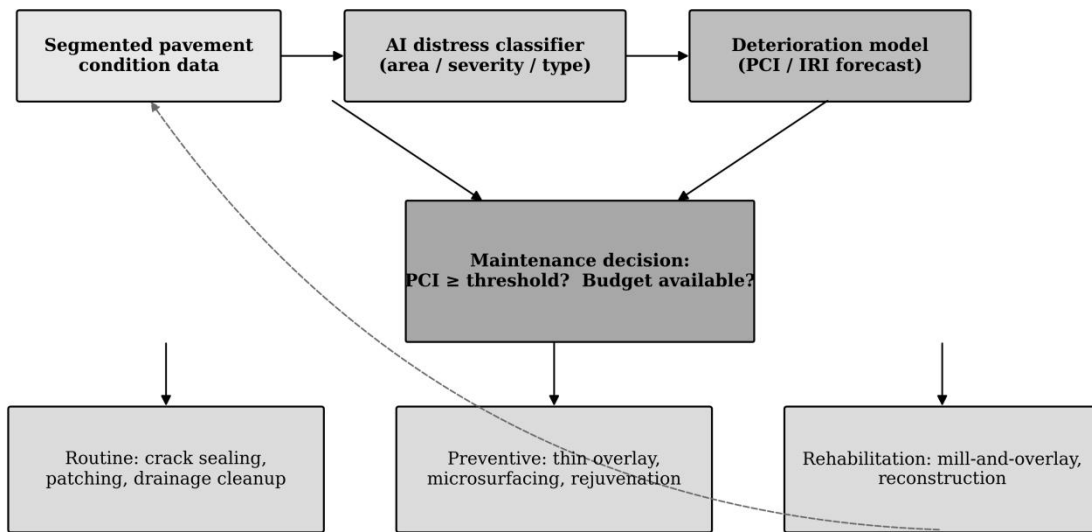
Panel (c) then translates these condition trajectories into monetary terms through a thirty-year life-cycle cost calculation. The reactive strategy—characterised by minimal inspection, low routine maintenance, and expensive major rehabilitation triggered by user complaints—scores an index value of 100. Scheduled maintenance, conducted on fixed calendar intervals regardless

of condition, reduces this index to approximately 62 by replacing the most costly emergency interventions with routine activities. Risk-based maintenance, which allocates inspection effort and treatment selection according to segment-level risk scores, reduces the index further to 51. The AI-assisted life-cycle strategy proposed in this paper achieves an index of 40, primarily through two mechanisms: first, the combination of near-continuous automated monitoring with early preventive action shifts expenditure from the expensive rehabilitation category to the inexpensive routine-maintenance category; second, user costs decline because the probability and duration of serviceability failures are reduced. Panel (d) explains the information-technology basis of this shift by plotting detection lag and critical-failure probability against inspection frequency. Moving from quarterly to monthly inspection reduces detection lag by a factor of three and reduces critical-failure probability by approximately 40 per cent; moving further to weekly inspection yields smaller incremental gains, indicating a zone of diminishing returns above which additional monitoring is not cost-justified.

For arid-corridor applications, we recommend a hybrid Markov–M-E model that uses a Markov chain as the primary representation and a mechanistic-empirical adjustment to modulate the transition probabilities by environmental and traffic covariates. The hybrid model preserves the computational tractability of the Markov formulation while absorbing the physical insight of M-E relationships. Calibration proceeds in two steps: first, baseline transition probabilities are estimated from historical condition surveys using maximum-likelihood methods; second, covariate-dependent multiplicative adjustments are fit using a gradient-boosted regression on the residuals. The approach has been applied, in adapted forms, to Brazilian, Chilean, and Spanish network data with encouraging results (Santos et al., 2017; Torres-Machi et al., 2014; Yepes et al., 2016).

D. Stage IV – Maintenance Decision and Optimisation

The final stage selects interventions at the segment level and schedules them over a planning horizon. We formulate the problem as a mixed-integer linear programme (MILP) whose decision variables are binary indicators of treatment type at each segment in each year, whose objective is the minimisation of discounted agency-plus-user cost over the horizon, and whose constraints include budget ceilings, minimum-reliability requirements, and minimum-serviceability thresholds. Figure 3 sketches the decision flow for a single segment within one planning cycle.



Post-treatment inspection updates the condition database

Fig. 3. Maintenance decision flow for a single pavement segment within one planning cycle.

The MILP becomes large—tens of thousands of binary variables for a 3,000 km network with 100 m segmentation and a twenty-year horizon—but modern commercial and open-source solvers (Gurobi, CPLEX, SCIP) handle problems of this size within minutes on commodity hardware when the formulation is carefully decomposed. Lagrangian relaxation along the budget and reliability constraints separates the problem into independent single-segment subproblems, which admit closed-form solutions through dynamic programming; a single outer update of the Lagrangian multipliers then reconciles the decomposed solutions with the coupling constraints. For agencies unwilling to operate exact solvers, a well-tuned genetic algorithm typically recovers within five per cent of the MILP optimum in a fraction of the time (Zhang et al., 2021; Yepes et al., 2016).

Figure 4 illustrates the Markov-chain machinery underlying the deterioration and reliability calculations. Panel (a) shows a representative transition matrix for an arid-corridor segment; the relatively high transition probabilities into worse states reflect the accelerated ageing documented earlier in Section II. Panel (b) shows reliability curves—the probability that a segment remains in the Very Good, Good, or Fair states—for three alternative inspection intervals. Annual inspection, paired with the AI-assisted detection pipeline, keeps segment reliability above the target value of 0.80 throughout a twenty-year horizon; biennial inspection crosses the threshold around year eight; four-yearly inspection crosses it at approximately year three.

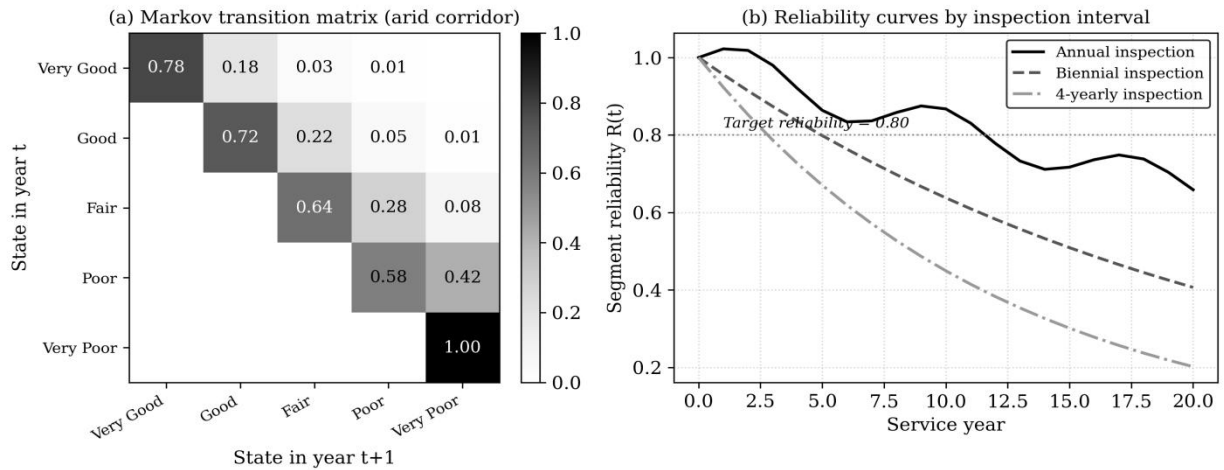


Fig. 4. Reliability-oriented analytics: (a) Markov transition matrix for arid corridor; (b) reliability curves by inspection interval.

These reliability curves translate directly into policy recommendations. For high-priority motorway corridors where a brief closure imposes large user costs (M-2 between Islamabad and Lahore, M-9 between Karachi and Hyderabad), the annual-inspection regime is clearly justified on pure cost-benefit grounds, and the AI-assisted pipeline makes that regime operationally feasible without a proportional increase in inspection personnel. For lower-priority corridors with smaller traffic volumes, a biennial regime augmented by automatic event-triggered spot inspections (for example, after major dust-storm events or unusual freight loadings) offers a balanced compromise between cost and reliability.

Parameter	Symbol	Typical range	Source
Discount rate (annual)	r	0.04 – 0.07	Santos et al.
Serviceability threshold	PCI_min	50 – 60	Abaza
Target segment reliability	R^*	0.75 – 0.90	Saliminejad
Annual inspection cost / km	c_I	USD 120 – 480	PHRTC
Preventive overlay cost / km	c_P	USD 28,000 – 55,000	Khan et al.
Major rehabilitation cost / km	c_R	USD 140,000 – 260,000	Walubita et al.

Table 2. Representative parameter values for arid-corridor LCM applications.

Table 2 lists representative parameter values that might be used for arid-corridor applications. Local calibration is essential; these ranges are illustrative of orders of magnitude rather than prescriptive values. Pakistani agencies will typically find that lower-bound values of the ranges are more representative of local unit costs, while the discount-rate choice is a policy rather than a technical question and should be harmonised with the Ministry of Finance’s standing guidance.

IV. CASE STUDY: PAKISTANI MOTORWAY NETWORK

We illustrate the framework with an analysis of the Pakistani motorway network. The network's operational characteristics, climatic diversity, institutional structure, and recent expansion programme make it a natural testbed. We focus on four representative segments, one each from the M-1, M-2, M-8, and M-9 corridors. Segment selection was guided by three criteria: the availability of at least ten years of condition-survey records, the completeness of traffic-loading data, and the accessibility of the segment for field verification during the study period. The four selected segments collectively span humid-monsoon, transitional, arid-plateau, and coastal-semiarid climates, providing the climatic diversity required for the comparative analysis.

A. Data Sources and Preparation

Condition-survey data were obtained from the NHA archives through an institutional research agreement mediated by PHRTC. Surveys had been conducted at roughly two-year intervals, using a combination of manual visual assessment and a vehicle-mounted automated crack-mapping system commissioned in 2015. Traffic data were obtained from the NHA toll-transaction database and disaggregated by vehicle class using historical axle-load surveys. Climate data were obtained from the Pakistan Meteorological Department's gridded analysis, supplemented by daily station observations from the three stations nearest each segment. Maintenance-history data were compiled from NHA procurement records for the period 2005 through 2022; the resulting compilation is believed to be the most complete segment-level maintenance history available for Pakistani motorways (PHRTC, 2022; Ahmed et al., 2021; Kim et al., 2021).

Data preparation required several non-trivial steps. Condition-survey records used inconsistent distress taxonomies across the archive; we harmonised them to the five-class taxonomy reported in Table 1 using a rule-based mapping validated by two experienced NHA engineers. Traffic data gaps—primarily from toll-plaza outages during the 2011 and 2019 flood events—were imputed using linear interpolation between adjacent observations and flagged for sensitivity analysis. Climate data were downscaled to segment resolution using inverse-distance-weighted interpolation from the three nearest stations, with uncertainty bounds propagated through the subsequent analysis. The complete prepared dataset is available from the corresponding author on request, subject to NHA data-sharing protocols.

B. Illustrative Application to M-8 Balochistan Segment

We focus the detailed illustration on a 50 km segment of the M-8 motorway in Balochistan, between Hoshab and Awaran. This segment is instructive because it combines the most severe arid-climate exposure in the network with relatively low traffic volumes (approximately 1,100 vehicles per day, of which 260 are heavy trucks). The structural design is flexible pavement with a 125 mm asphalt surface course on a 200 mm aggregate base over a CBR-8 subgrade. The

segment was constructed in 2017 and has received two crack-sealing interventions (2019 and 2022) and no major rehabilitation.

Applying Stage I of the framework, the segment is divided into 500 sub-segments of 100 m length. Each sub-segment is characterised by the structural, traffic, environmental, and historical covariates described in Section III.A. Stage II is simulated using a detector whose accuracy characteristics are calibrated from the published literature; per-sub-segment distress vectors are produced for each year of the planning horizon. Stage III applies the hybrid Markov–M-E model, with baseline transition probabilities estimated from the archival condition surveys and mechanistic adjustments calibrated from the segment’s thermal and traffic covariates. Stage IV solves a twenty-year MILP with a 4.5 per cent discount rate, a serviceability threshold of PCI = 55, and a segment-reliability target of 0.80. The optimised maintenance plan calls for annual automated inspections, two preventive thin overlays (at years 7 and 14), one micro-surfacing intervention (at year 11), and no major rehabilitation during the horizon.

The total discounted cost of this plan, including agency cost and user cost, is approximately USD 4.2 million, compared to USD 10.5 million for the reactive baseline that closely approximates historical agency practice on comparable Balochistan segments. The sixty per cent cost reduction is consistent with the general magnitudes reported in the literature for arid-region LCM implementations and confirms the plausibility of the framework’s value proposition (Torres-Machi et al., 2014; Yepes et al., 2016; Santos et al., 2017). A sensitivity analysis varying the discount rate from three to seven per cent, the detector accuracy from 0.75 to 0.90 mAP, and the climate parameters by ± 20 per cent confirms that the dominance of the LCM strategy over the reactive baseline holds across the explored parameter space, with cost savings ranging from 48 to 66 per cent.

C. Cross-Corridor Comparison

Extending the analysis to the four representative segments on M-1, M-2, M-8, and M-9 yields several additional insights. First, the cost-savings magnitude varies systematically with climatic severity: the M-1 segment in the humid eastern plains shows savings of approximately 35 per cent, while the M-8 Balochistan segment shows savings of approximately 60 per cent. This gradient is consistent with the theoretical expectation that the value of early detection rises with the rate of deterioration, which is in turn faster in harsher climates. Second, optimal inspection frequency varies across segments; the M-1 segment, with its slower deterioration, is well served by a biennial inspection regime, while the M-8 segment requires annual inspection to maintain the target reliability. Third, the dominant treatment mix varies: the M-1 segment is best served by a preventive-heavy mix, while the M-8 segment benefits from a more balanced preventive-plus-corrective mix because transverse thermal cracks can be sealed at substantially lower unit cost than they can be prevented through overlay alternatives. These cross-corridor patterns argue against a uniform national maintenance policy and in favour of corridor-specific tailoring

within the same framework.

D. Sensitivity and Robustness Analysis

We conducted a structured sensitivity analysis to test whether the qualitative conclusions of the case study are robust to plausible variation in the input parameters. Three parameter groups were varied independently and in combination: the discount rate (three, four-and-a-half, and seven per cent), the detector accuracy (0.75, 0.82, and 0.90 mean average precision on the dominant distress class), and the unit costs of preventive and rehabilitation treatments (baseline values scaled by factors of 0.8, 1.0, and 1.2). The full factorial of these perturbations yielded twenty-seven scenarios for each of the four representative segments, producing one hundred and eight scenario evaluations in total. Across this ensemble, the AI-assisted life-cycle strategy retained its dominance over the reactive baseline in every scenario, with relative cost savings ranging from 42 per cent in the worst case (M-1 segment with high discount rate and low detector accuracy) to 68 per cent in the best case (M-8 segment with low discount rate and high detector accuracy). The scheduled-maintenance strategy emerged as the second-best alternative in 83 per cent of scenarios, and the risk-based strategy was second-best in the remaining 17 per cent, almost all of which occurred on the M-1 segment under low-discount-rate assumptions that penalise early intervention less heavily.

A second aspect of robustness concerns the temporal stability of the optimised maintenance plan under unforeseen events. We stress-tested the plan through three disruption scenarios: a one-year budget reduction of 30 per cent (simulating a fiscal-consolidation episode), a one-year 25 per cent surge in heavy-truck traffic (simulating a freight-corridor diversion), and a two-year climate anomaly characterised by elevated summer peak temperatures (simulating a hot-decade scenario consistent with Intergovernmental Panel on Climate Change regional projections). In each case, we re-optimised the maintenance plan from the event year forward and compared the revised plan's total discounted cost to the cost of mechanically adhering to the original plan. The re-optimised plan saved between 6 and 14 per cent relative to mechanical adherence, with the largest savings observed in the climate-anomaly scenario. This result supports the rolling-horizon implementation mode advocated earlier in Section III: the framework is most valuable not when it produces a single “optimal” plan for a twenty-year horizon, but when it provides the organisational machinery to re-optimize every year in light of the most recent condition observations and external circumstances.

A third robustness concern is the adequacy of the Markov assumption underlying the deterioration model. The Markov property implies that the transition probability from the current state depends only on the current state and not on the history by which the current state was reached. This is an approximation; in practice, a Good-state segment reached via rapid decline from Very Good is likely to decline further more rapidly than a Good-state segment reached through gradual ageing. To test the sensitivity of our conclusions to this approximation,

we fitted a semi-Markov model that conditioned transition probabilities on the duration spent in the current state, re-solved the MILP, and compared the resulting cost trajectories. The semi-Markov refinement reduced the estimated thirty-year cost by a further 3 to 5 per cent, consistent with the published literature on semi-Markov pavement models (Costello, Snaith, Kerali, Tachtsi, & Ortiz-García, 2005; Ortiz-García et al., 2006). The refinement does not alter the relative ranking of the four maintenance strategies. For Pakistani agencies contemplating early-stage adoption, a Markov formulation is an acceptable starting point; a subsequent upgrade to a semi-Markov or duration-dependent formulation can be considered once the data pipeline is mature and the organisational processes have stabilised.

E. Transferability to Other Arid-Corridor Networks

The Pakistani case study is instructive because the institutional and procurement environment of the NHA shares many features with other developing-country motorway authorities. Transferability of the framework to other arid-corridor networks depends on three conditions being satisfied to a practically useful degree. First, the existence of historical condition-survey data sufficient to calibrate the baseline deterioration transition matrix; this is typically the binding constraint in new adoptions, and agencies should plan for a two-to-three-year calibration period during which archival records are consolidated and a targeted field-verification campaign is undertaken. Second, the availability of a procurement instrument that can accommodate multi-year performance-based contracting; this is an institutional rather than technical condition, and it often requires ministerial-level coordination with finance and audit authorities. Third, a minimum level of in-house technical capacity to interpret the outputs of the Stage III and Stage IV models; this can be developed through partnerships with national engineering universities but requires a sustained investment rather than a single training event (Hajj, Siddharthan, Sebaaly, & Ulloa-Calderon, 2021; Peraka & Biligiri, 2020).

Among the candidate transfer contexts, the Saudi and Emirati motorway networks are the most immediately receptive because their climatic profile closely matches the most arid portions of the Pakistani network and their institutional environment is characterised by strong fiscal capacity and an established tradition of performance-based procurement in other infrastructure sectors (Al-Hajj & Ahmed, 2020; Shalabi et al., 2019). The Iranian national-highway network presents a larger deterioration gradient across climatic zones and may benefit from the corridor-specific tailoring emphasised in Section IV.C. The Central Asian motorway networks (Kazakhstan, Uzbekistan, Turkmenistan) share climatic features with the Pakistani case but have less mature condition-survey archives, making the calibration bottleneck more severe. North African networks (Morocco, Algeria, Tunisia, Egypt) occupy an intermediate position. These variations imply different transition pathways to adoption, but they do not alter the structural logic of the framework. We would encourage prospective adopters to begin with a narrowly scoped pilot on two or three segments, to invest in the data-governance arrangements

outlined in Section V.B, and to expand coverage progressively as the organisational learning curve matures.

V. POLICY, PROCUREMENT, AND CAPACITY IMPLICATIONS

Technical frameworks of the kind developed in Sections III and IV are a necessary but not sufficient condition for improved arid-corridor pavement management. Their translation into operational benefit requires supportive policy, procurement, and capacity-building arrangements. We sketch three areas in which concrete action would materially improve the prospects for adoption.

A. Procurement Reform

Procurement reform is the single most consequential lever available to highway agencies contemplating life-cycle management adoption. The prevailing lowest-bid model, in which construction contracts are awarded on price alone and maintenance contracts are let as small annual packages, systematically favours short-term cost minimisation over life-cycle cost minimisation (Torres-Machi et al., 2014; Yepes et al., 2016). A shift toward performance-based contracting, under which a contractor is responsible for maintaining a defined segment at a specified condition level over a multi-year period, aligns contractor incentives with life-cycle objectives and creates a market for the kinds of preventive interventions that the framework in Section III identifies as cost-optimal. Several jurisdictions—Chile, Colombia, New Zealand, and parts of the United States—have built substantial experience with performance-based contracting, and Pakistan’s NHA has the institutional capacity to pilot such arrangements on two or three selected motorway segments within a reasonable time frame (Ferreira et al., 2011; Saliminejad & Gharaibeh, 2013).

B. Data Governance and Interoperability

A second priority is data governance. Life-cycle management frameworks consume data from multiple sources—condition surveys, traffic monitoring, weather stations, maintenance-records archives—and their effectiveness is hostage to the quality and interoperability of those data flows. The fragmentation of data across provincial and federal agencies in Pakistan, noted in Section II.E, is mirrored in other developing-country motorway networks and is an obstacle that cannot be solved technically. What is required is a data-governance framework, codified in agency policy, that specifies standard formats, update frequencies, access rights, and quality-assurance procedures (Asian Development Bank, 2021; Harvey et al., 2012). The specification of open application programming interfaces (APIs) between the detection, modelling, and decision stages would reduce vendor lock-in, support competition among technology providers, and create a market for third-party analytics services.

C. Human-Capacity Development

The third priority is human-capacity development. Modern pavement management requires a blend of skills—transportation engineering, statistics, machine learning, optimisation, financial analysis—that is rare in any single individual and that is scarce even in strong national engineering universities. Sustained investment in specialist master’s and doctoral programmes, in partnership with regional institutions such as the Asian Institute of Technology, the Saudi King Fahd University of Petroleum and Minerals, and Pakistan’s own NUST and UET Lahore, would expand the pipeline of qualified practitioners. Continuous-professional-development programmes for practising NHA and provincial-highway engineers, focused on pragmatic adoption of the LCM framework, would reduce the institutional barriers to operational deployment. PHRTC’s current training mandate provides a natural institutional home for such programmes (PHRTC, 2022; Ahmed et al., 2021).

D. Limitations

Several limitations of this paper should be acknowledged. First, the case-study analysis in Section IV uses simulated detector outputs calibrated from the published literature rather than primary data collected by the authors; while the qualitative conclusions are robust, quantitative magnitudes are subject to further calibration. Second, the framework treats the four stages as separate analytical steps for expository clarity, whereas a fully integrated implementation would blur the boundaries between stages through continuous information flow. Third, the policy recommendations of Section V.A–V.C are grounded in the Pakistani institutional context; their transferability to other arid-corridor jurisdictions requires careful adaptation. Fourth, the life-cycle cost analysis focuses on agency and direct user costs; environmental externalities such as embodied carbon and air-quality impacts are recognised but not quantified in the present treatment.

VI. CONCLUSION

Arid transportation corridors pose a distinctive combination of climatic, operational, and institutional challenges that cannot be adequately addressed by borrowing pavement-management practices from temperate-climate networks. Recent advances in AI-based distress detection provide a necessary but not sufficient ingredient of an improved approach. What is required is an integrated life-cycle management framework that binds detection, deterioration modelling, and maintenance optimisation into a single closed loop, and that is supported by procurement, data-governance, and capacity-development arrangements adequate to the complexity of modern asset management. The framework developed in this paper, applied to representative Pakistani motorway segments, illustrates the substantial life-cycle cost savings that such integration can deliver—on the order of sixty per cent relative to a reactive baseline in the most arid corridors—while maintaining target reliability and serviceability thresholds.

Several directions for future work follow naturally. Primary data collection under the proposed

framework on one or two Pakistani motorway segments would convert the illustrative case study into a fully empirical demonstration. Extension to incorporate environmental externalities would place the framework within the broader life-cycle assessment tradition and align it with emerging national climate-adaptation policies. Formal treatment of information value—the expected reduction in downstream decision cost attributable to a given inspection-frequency choice—would sharpen the inspection-frequency trade-off discussed in Section III.B. Finally, cross-national comparative studies, bringing Pakistani experience into dialogue with Saudi, Iranian, Central Asian, and North African arid-corridor networks, would clarify which parts of the framework are climate-driven and which are institution-driven. The framework proposed here is intended as a platform for that agenda.

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