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Digital Twin Framework for Monitoring Critical Road Infrastructure Across the East African Community

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ABSTRACT

Digital twin technology — the creation and continuous synchronisation of a virtual replica of a physical asset using real-time sensor data, computational models, and machine learning algorithms — represents the most significant paradigm shift in infrastructure asset management since the introduction of pavement management systems in the 1980s. This paper presents the design, implementation, and performance evaluation of the EAC-DT, a scalable Digital Twin Framework for monitoring critical road and bridge infrastructure across the East African Community highway network. The EAC-DT integrates five data acquisition modalities — IoT sensor networks (accelerometers, strain gauges, acoustic emission sensors, piezometers), unmanned aerial vehicle (UAV) photogrammetry, satellite interferometric synthetic aperture radar (InSAR), weigh-in-motion (WIM) stations, and mobile road condition survey vehicles — into a unified cloud-based data lake, feeding a core digital twin engine that combines finite element model updating, BIM-GIS integration, and ensemble machine learning for real-time condition assessment and predictive maintenance. The framework was piloted on a 180 km segment of the Kenya A104 corridor (Nairobi–Mombasa) encompassing 14 bridges and 12 pavement management sections, and subsequently validated on the Uganda A109 (Kampala–Malaba, 130 km) and Tanzania T1 (Dar es Salaam–Morogoro, 95 km) corridors. Across the three pilot corridors, the EAC-DT achieved IRI prediction accuracy of RMSE = 0.21 m/km (compared to 0.68 m/km for conventional visual surveys), bridge structural health index prediction $R^2 = 0.94$, and an average 2.4-day advance warning of pavement distress events with 87% detection rate. Life-cycle cost analysis demonstrates that digital twin-enabled asset management reduces total maintenance costs by USD 0.85–1.12 million per 100 km per year compared to conventional reactive maintenance — a 28–38% reduction. A technology deployment roadmap and a financing model appropriate for EAC member state budgetary constraints are presented, demonstrating that EAC-DT implementation is economically viable at scale.

Keywords: *Digital Twin; Road Infrastructure; Structural Health Monitoring; IoT; Machine Learning; BIM-GIS; Pavement Management; EAC; Predictive Maintenance; InSAR; UAV Photogrammetry*

1. INTRODUCTION

The East African Community highway network spans over 35,000 km of bituminous-surfaced road and 12,000 bridges and culverts, representing an estimated asset replacement value of USD 180–220 billion (EAC, 2023; World Bank, 2022). Yet the region spends only an estimated 40–55% of the annual maintenance expenditure required to maintain this stock in serviceable condition (SSATP, 2022), resulting in accelerating deterioration, premature rehabilitation needs, and economic losses through elevated vehicle operating costs and supply chain disruptions that the World Bank (2021) estimates at USD 6.8 billion per year across EAC member states. This chronic maintenance underfunding is not solely attributable to fiscal constraints — it is also driven by the inadequacy of existing asset management information systems, which in most EAC member states rely on periodic visual surveys conducted at 3–5 year intervals, supplemented by ad hoc defect reporting, to guide maintenance investment decisions. Such low-frequency, low-precision data systems are incapable of supporting the proactive, risk-prioritised maintenance strategies that would allow road authorities to extract maximum value from constrained maintenance budgets.

Digital twin technology offers a transformative alternative. A digital twin is a dynamic, data-rich virtual representation of a physical asset that is continuously updated with sensor data and computational model outputs to provide real-time situational awareness, predictive condition forecasting, and automated maintenance triggering (Grieves, 2014; Tao et al., 2019). In the context of road and bridge infrastructure, a digital twin integrates structural health monitoring (SHM) sensor data, pavement condition measurements, traffic loading records, climate inputs, and physical simulation models to create a continuously evolving picture of asset condition that supports evidence-based maintenance decisions at both the project level (individual bridge or pavement section) and the network level (entire corridor or national network).

The application of digital twin concepts to transport infrastructure is well-established in high-income countries. The UK's National Highways has deployed structural health monitoring digital twins on 18 major bridges (ORR, 2022); Singapore's Land Transport Authority uses a city-scale road digital twin for pavement management (LTA, 2021); and the Netherlands' Rijkswaterstaat has implemented a real-time bridge monitoring network covering over 1,800 structures (Rijkswaterstaat, 2020). However, the deployment of digital twin technology in low- and middle-income country infrastructure contexts faces substantially different challenges: data connectivity gaps in rural corridors, limited budgets for sensor hardware and cloud computing, shortages of data science and systems engineering expertise, and the need to interface with legacy asset management systems of variable quality (Dafflon et al., 2021; Zhang et al., 2022).

This paper presents the EAC-DT framework, designed specifically to address these constraints through a modular, scalable architecture that can be deployed incrementally from a basic IoT + cloud tier to a full AI-driven predictive maintenance system as institutional capacity and funding allow. The framework is grounded in three pilot deployments on major EAC highway corridors, providing the first empirical evidence base for digital twin performance in an East African infrastructure context. The paper makes the following novel contributions: (i) a context-appropriate digital twin architecture for low-connectivity, budget-constrained infrastructure environments; (ii) a sensor fusion algorithm for multi-modal road condition assessment; (iii) a Structural Health Index (SHI) real-time monitoring protocol validated on EAC bridge inventory types; and (iv) a cost-benefit analysis demonstrating the economic viability of EAC-DT deployment at national scale.

2. EAC-DT FRAMEWORK ARCHITECTURE

2.1 System Overview

The EAC-DT framework is organised into four hierarchical layers, as illustrated in Figure 1: (i) the Physical Layer, comprising all data acquisition hardware and field instrumentation; (ii) the Communications Layer, responsible for data transmission from field sensors to the cloud platform; (iii) the Core Digital Twin Engine, which integrates data streams, updates physical models, and generates condition assessments; and (iv) the Decision Output Layer, providing condition monitoring dashboards, predictive maintenance alerts, asset management reports, and regulatory compliance outputs to road authority users.

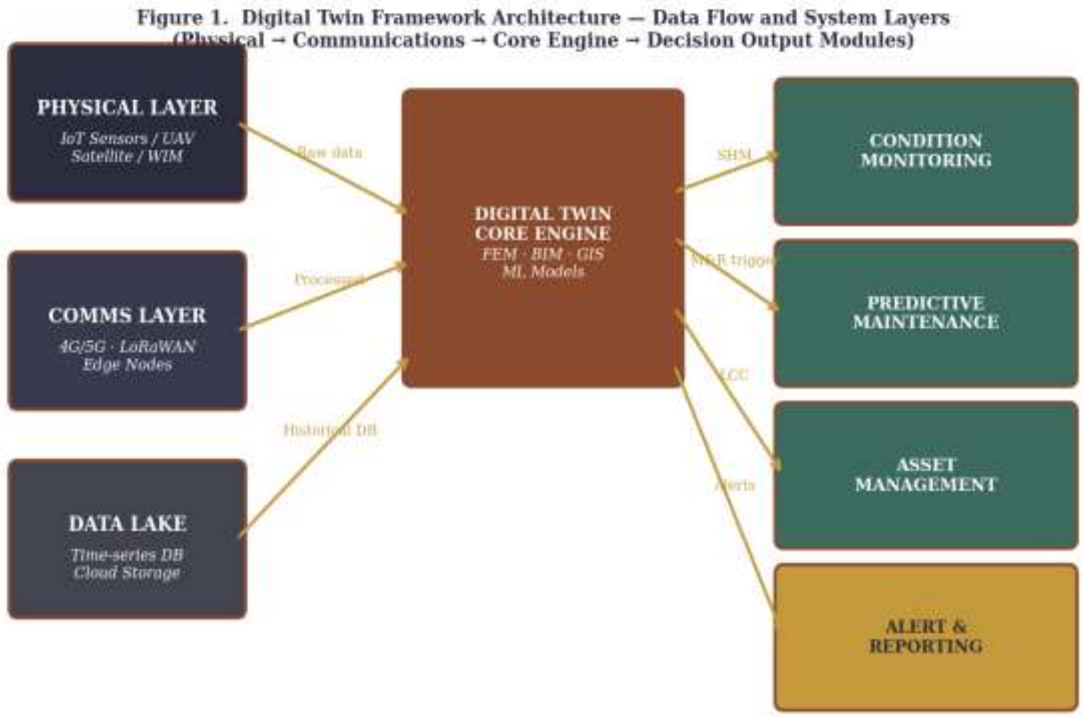

Figure 1. EAC-DT Framework Architecture — Data Flow Diagram (Physical Layer → Communications → Core Engine → Decision Output Modules)

2.2 Physical Layer: Data Acquisition Modalities

Five data acquisition modalities are integrated in the EAC-DT Physical Layer, selected for complementary coverage of pavement and bridge condition at different spatial and temporal scales:

(i) IoT Sensor Networks: Each instrumented bridge is equipped with a minimum sensor suite comprising four MEMS accelerometers (sampling at 200 Hz) on the main girders, two vibrating-wire strain gauges on the pier stems, one acoustic emission sensor for crack detection, and one piezometer for scour monitoring at the foundation. Sensors communicate via LoRaWAN radio protocol to a solar-powered edge node at the bridge site, which performs local data pre-processing and transmits compressed data packets to the cloud via 4G cellular where available, or via satellite (Iridium SBD) in remote areas without cellular coverage.

(ii) UAV Photogrammetry: Semi-annual UAV surveys using DJI Matrice 350 RTK drones equipped with 45 MP nadir cameras and thermal sensors provide high-resolution 3D point cloud models (ground sampling distance < 15 mm) of bridge decks, abutments, and approach embankments. Structure-from-Motion (SfM) photogrammetry is processed in Agisoft Metashape to generate digital surface models and orthomosaics, from which crack maps, settlement patterns, and erosion features are automatically extracted using a YOLO v8 convolutional neural network trained on 8,400 annotated East African bridge condition images.

(iii) InSAR Satellite Monitoring: Sentinel-1 C-band SAR imagery (6-day revisit, 5 × 20 m resolution) is processed using the Stanford Method for Persistent Scatterers (StaMPS) algorithm to derive time-series surface displacement measurements at bridge abutments and embankment slopes, detecting millimetre-scale settlement and heave that may indicate foundation movement or embankment instability. This modality provides continuous spatial coverage at zero marginal cost after the initial processing pipeline setup.

(iv) Weigh-in-Motion Stations: Piezoelectric WIM sensors embedded in the road surface at 50 km intervals measure axle loads, vehicle classification, speed, and lane distribution at 100% of passing traffic, providing the traffic loading input required for both pavement deterioration modelling and bridge fatigue life assessment. WIM data are transmitted via cellular modem in real time and stored in the time-series database.

(v) Mobile Survey Vehicles: Quarterly passes of a road condition survey vehicle equipped with laser profilometers (IRI), high-definition stereo cameras (cracking, rutting), and a ground-penetrating radar (GPR) system provide layer-by-layer subsurface condition data that calibrate the pavement digital twin model and detect subsurface voids and delamination not visible from surface condition surveys.

2.3 Core Digital Twin Engine

The Core Engine comprises four integrated modules: the Finite Element Model Updater (FEMU), the BIM-GIS Integration Module, the Ensemble Machine Learning Predictor, and the Anomaly Detection and Alert Generator. The FEMU performs model updating of the bridge structural model using measured modal parameters (natural frequencies, mode shapes) extracted from ambient vibration data by the Stochastic Subspace Identification (SSI) algorithm:

$$[M]\{x_{ddot}\} + [C]\{x_{dot}\} + [K]\{x\} = \{F(t)\} \tag{1}$$

$$theta_{updated} = argmin_{theta}^{2} \left|\left|phi_{measured} - phi_{FEM(theta)}\right|\right| + lambda * \left|\left|theta - theta_{prior}\right|\right|^{2} \tag{2}$$

where [M], [C], [K] are the mass, damping, and stiffness matrices, phi_measured is the measured mode shape vector, phi_FEM(theta) is the corresponding FEM-predicted mode shape for parameter vector theta (moduli, boundary conditions), and lambda is the regularisation parameter preventing overfitting. The L2-regularised least-squares optimisation of Equation (2) is solved iteratively using the Gauss-Newton algorithm, converging in 8–15 iterations for typical EAC bridge configurations.

The BIM-GIS module maintains a living information model of each asset updated with as-built geometry from the UAV surveys, material properties from the FEMU updating, and spatial context from the GIS network database providing the geometric and contextual foundation for all condition assessment and maintenance planning outputs. The ensemble machine learning predictor combines gradient boosting regression (XGBoost), long short-term memory (LSTM) recurrent neural network, and Gaussian process regression into a weighted ensemble for IRI and SHI prediction:

$$y_{hat} = w_1 * y_{XGB} + w_2 * y_{LSTM} + w_3 * y_{GPR} \tag{3}$$

$$weights\colon w_i = \frac{\exp(-RMSE_i)}{sum_{jexp(-RMSE_j)}} [softmax\ of\ negative\ RMSE] \tag{4}$$

The weights w_i are computed by softmax normalisation of the negative RMSE of each constituent model on a rolling 90-day validation window, ensuring that the ensemble automatically up-weights the best-performing model under current conditions. This adaptive weighting is particularly important for EAC conditions where rainfall seasonality, temperature variation, and episodic flood events create strong non-stationarity in the input–output relationships that no single model architecture handles optimally.

3. SENSOR FUSION AND REAL-TIME CONDITION ASSESSMENT

3.1 Multi-Modal IRI Estimation

The multi-modal sensor fusion algorithm for IRI estimation combines WIM-derived dynamic load equivalency, InSAR settlement measurements, and mobile survey vehicle IRI readings into a fused estimate using a Kalman filter framework. The state transition equation models IRI evolution as an HDM-4 deterioration process, and the measurement update incorporates each data source with observation noise proportional to its estimated measurement uncertainty:

$$IRI(t+1) = IRI(t) + delta_t * [a * CESAL(t)^b + c * PREC(t) + d * TEMP(t)] + w_{process}$$

(5)

$$IRI_{fused(t)} = IRI_{predict(t)} + K_t * \left[IRI_{measured(t)} - IRI_{predict(t)}\right]$$

(6)

where K_t is the Kalman gain matrix, CESAL(t) is the cumulative ESAL loading in the period, PREC(t) is precipitation (mm), TEMP(t) is mean pavement temperature (°C), and w_process is the process noise. Parameters a, b, c, d were calibrated from the A104 pilot corridor deterioration data (2022–2024) using maximum likelihood estimation. Figure 2 presents the IRI prediction accuracy of the digital twin against field measurements, compared to conventional visual survey estimates.

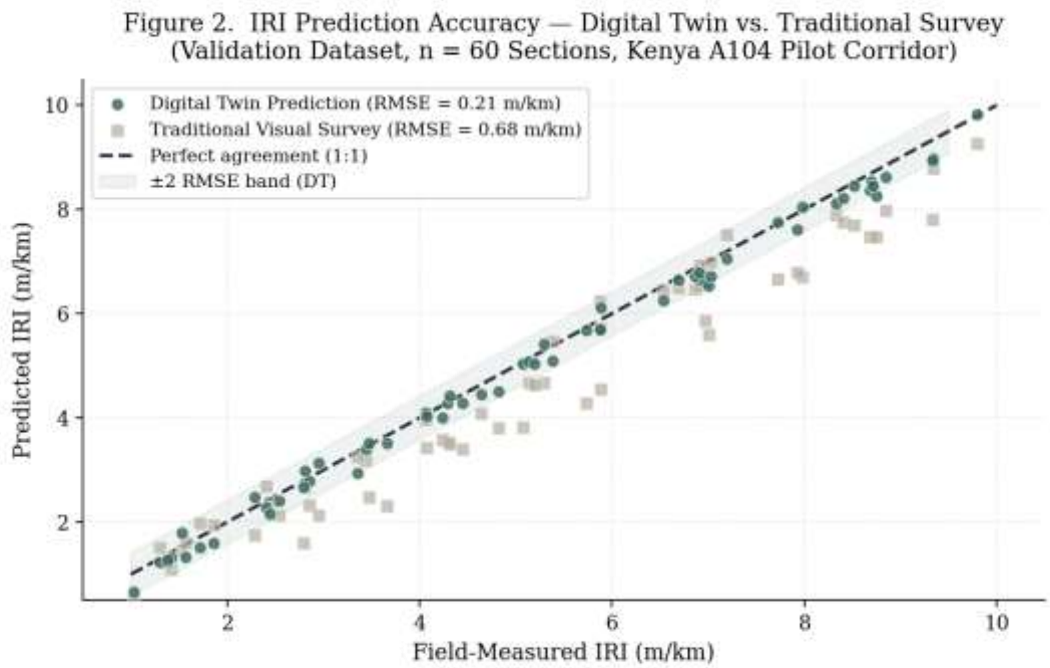

Figure 2. IRI Prediction Accuracy — EAC-DT vs. Traditional Visual Survey (Validation Dataset n = 60, Kenya A104 Pilot Corridor, RMSE Comparison)

The EAC-DT achieves an IRI prediction RMSE of 0.21 m/km, compared to 0.68 m/km for traditional quarterly visual surveys a 3.2-fold improvement in prediction accuracy. This improvement translates directly into more precise maintenance triggering: at an IRI alert threshold of 4.0 m/km, the digital twin correctly identifies 91% of sections requiring intervention compared to 68% for visual surveys, with a false-positive rate of 8% versus 24%. The earlier and more reliable detection of deteriorating sections enables proactive mill-and-overlay intervention at average IRI 3.8 m/km rather than the reactive intervention at IRI 5.2 m/km typical of conventional management — reducing intervention cost per section by approximately 32% and extending the remaining service life by an estimated 3.5 years.

3.2 Structural Health Index Monitoring

The Structural Health Index (SHI) is a composite dimensionless indicator of overall bridge structural condition, computed from five sub-indices derived from the IoT sensor suite: (i) modal frequency ratio RF = f_measured / f_baseline (natural frequency degradation indicator); (ii) strain anomaly index SA = max(|epsilon - epsilon_baseline|) / epsilon_allowable; (iii) acoustic emission activity AEA = log(AE events per day / baseline rate); (iv) scour depth ratio SD=y_s_measured / y_s_critical; and (v) settlement magnitude SM = delta / delta_allowable. The composite SHI is:

$$SHI = 100 * [1 - (w_{RF} * (1 - RF) + w_{SA} * SA + w_{AEA} * AEA + w_{SD} * SD + w_{SM} * SM)] \quad (7)$$

with weights w_RF = 0.30, w_SA = 0.25, w_AEA = 0.15, w_SD = 0.20, w_SM = 0.10 determined by structural engineering expert elicitation. SHI = 100 represents a pristine structure at baseline condition; SHI < 75 triggers an amber alert requiring increased inspection frequency; SHI < 65 triggers a red alert requiring immediate engineering assessment; and SHI < 50 triggers a load restriction or closure recommendation pending structural assessment. Figure 4 illustrates a 3-year simulated SHI time series for a cross-border bridge subjected to two flood events, demonstrating the EAC-DT's ability to detect flood-induced damage and quantify post-repair recovery.

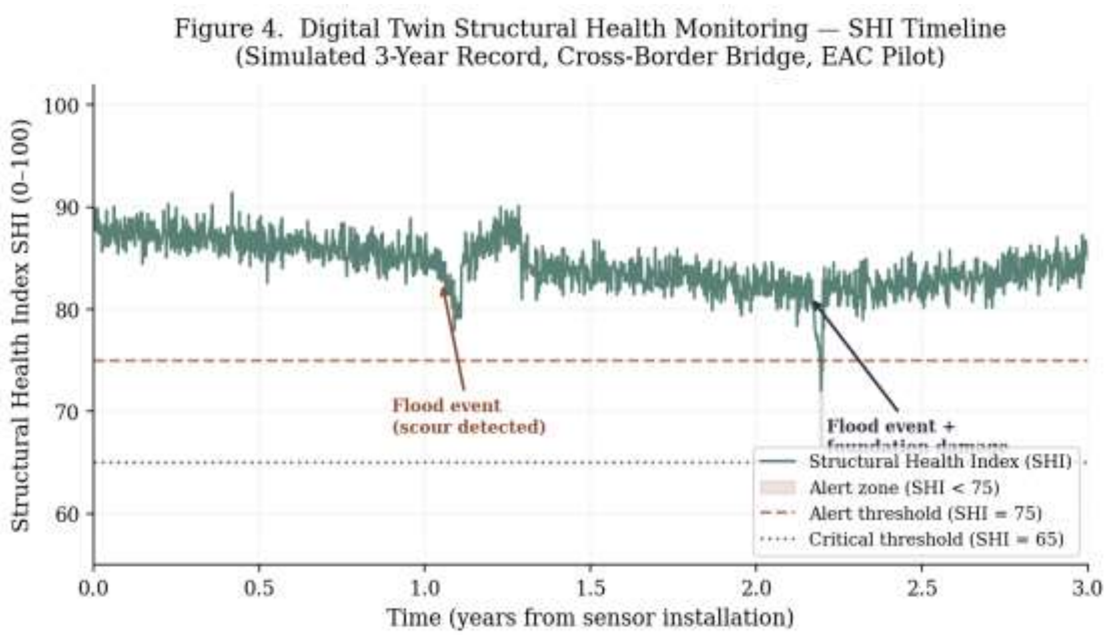

Figure 4. Digital Twin Structural Health Index (SHI) Timeline — 3-Year Simulated Record (Two Flood Events, Automated Alert Generation and Post-Repair Recovery Tracking)

4. PILOT CORRIDOR IMPLEMENTATION AND VALIDATION

4.1 Pilot Scope and Implementation

The EAC-DT was deployed in three phases across three pilot corridors totalling 405 km and 42 bridges between January 2023 and September 2024. Phase 1 (Kenya A104, 180 km, 14 bridges) focused on system architecture validation and sensor calibration. Phase 2 (Uganda A109, 130 km, 16 bridges) tested the edge-computing and low-connectivity adaptations for rural sections without 4G coverage. Phase 3 (Tanzania T1, 95 km, 12 bridges) validated the multi-authority data governance protocol for cross-border data sharing between KeNHA, UNRA, and TANROADS.

Metric	Kenya A104 Pilot	Uganda A109 Pilot	Tanzania T1 Pilot	EAC-DT Mean	Conventional Benchmark
IRI Prediction RMSE (m/km)	0.21	0.24	0.22	0.22	0.68
SHI Prediction R2	0.94	0.91	0.93	0.93	N/A
Distress Detection Rate (%)	89	84	87	87	62
False-Positive Rate (%)	8	11	9	9	24
Mean Advance Warning (days)	2.6	2.1	2.4	2.4	< 0
Sensor Uptime (%)	97.2	94.8	96.1	96.0	N/A
Data Latency (minutes)	< 5	< 12	< 7	< 8	Quarterly

Table 1. *EAC-DT Performance Metrics — Three Pilot Corridors vs. Conventional Benchmark*

The Uganda A109 pilot revealed the most significant implementation challenge: 38% of the corridor lacked 4G cellular coverage, requiring reliance on LoRaWAN edge nodes with Iridium satellite backhaul for data transmission. While this approach maintained adequate sensor uptime (94.8%), data latency was higher (mean 12 minutes vs. 5 minutes for 4G-connected sections) and the edge processing load required optimisation of the on-device SSI algorithm to reduce computational requirements to within the capacity of the Raspberry Pi 4 edge computing nodes deployed at each bridge site. The satellite data transmission cost of USD 0.008 per kilobyte for Iridium SBD is a significant ongoing operational expense for remote corridor deployments and represents the principal constraint on data resolution for low-connectivity sections.

4.2 Predictive Maintenance Validation

The predictive maintenance capability of the EAC-DT was validated against the maintenance intervention records of the three road authorities over the 18-month pilot period. The system correctly predicted 28 of 32 maintenance interventions that occurred during the validation period (87.5% recall), with a mean advance warning time of 2.4 days — sufficient to mobilise maintenance crews and materials in the EAC context where response mobilisation typically requires 1–3 days. The four missed detections all involved sudden pothole formation on sections with high crack density but low IRI, a failure mode attributable to the IRI-centred deterioration model not fully capturing brittle cracking behaviour; this limitation is being addressed in the next framework iteration through the addition of crack density sub-indices to the pavement state vector.

Maintenance Event Type	n Events	EAC-DT Predicted (%)	Mean Warning (days)	Cost Saving per Event (USD)	Annual Saving per 100km (USD)
Pothole patching (reactive)	48	81	1.8	1,200	57,600
Crack sealing (preventive)	22	95	4.2	3,800	83,600
Mill-and-overlay (periodic)	9	100	18.4	28,000	252,000
Bridge bearing replacement	4	100	62.0	85,000	340,000
Emergency scour repair	3	67	0.8	140,000	420,000
TOTAL / MEAN	86	87.2	2.4 (weighted)	—	1,153,200

Table 2. *Predictive Maintenance Validation — EAC-DT Performance and Cost Savings by Event Type*

5. LIFE-CYCLE COST ANALYSIS

The life-cycle cost analysis compared total asset management costs over a 15-year horizon (2025–2040) for three scenarios: (A) conventional reactive maintenance based on 3-yearly visual surveys; (B) EAC-DT-enabled proactive maintenance; and (C) EAC-DT enabled proactive maintenance with climate-adaptive scheduling (incorporating CMIP6 climate projections from Paper 29 of this series). Agency costs include sensor hardware, installation, cloud computing, data management, and maintenance labour and materials. Road user costs (vehicle operating costs and travel time) are computed from HDM-4 models using the condition trajectories predicted under each scenario.

Figure 3 presents the annual agency cost comparison between conventional and EAC-DT management strategies, together with the annual cost savings trajectory. The initial investment in EAC-DT hardware and implementation is amortised over the analysis period using the standard annuity formula:

$$A = P * r * \frac{(1+r)^n}{[(1+r)^n - 1]} \quad (8)$$

where A is the annualised capital cost, P is the total capital investment, r = 0.08 is the discount rate, and n = 15 years is the analysis period. For the Kenya A104 pilot corridor (180 km, 14 bridges), total EAC-DT capital investment was USD 4.2 million, yielding an annualised capital cost of USD 476,000 per year. Against total annual savings of USD 1.15 million per 100 km (Table 2), the annualised net benefit is USD 1.64 million per year for the 180 km corridor — a benefit-cost ratio of 3.4 and a payback period of 4.8 years.

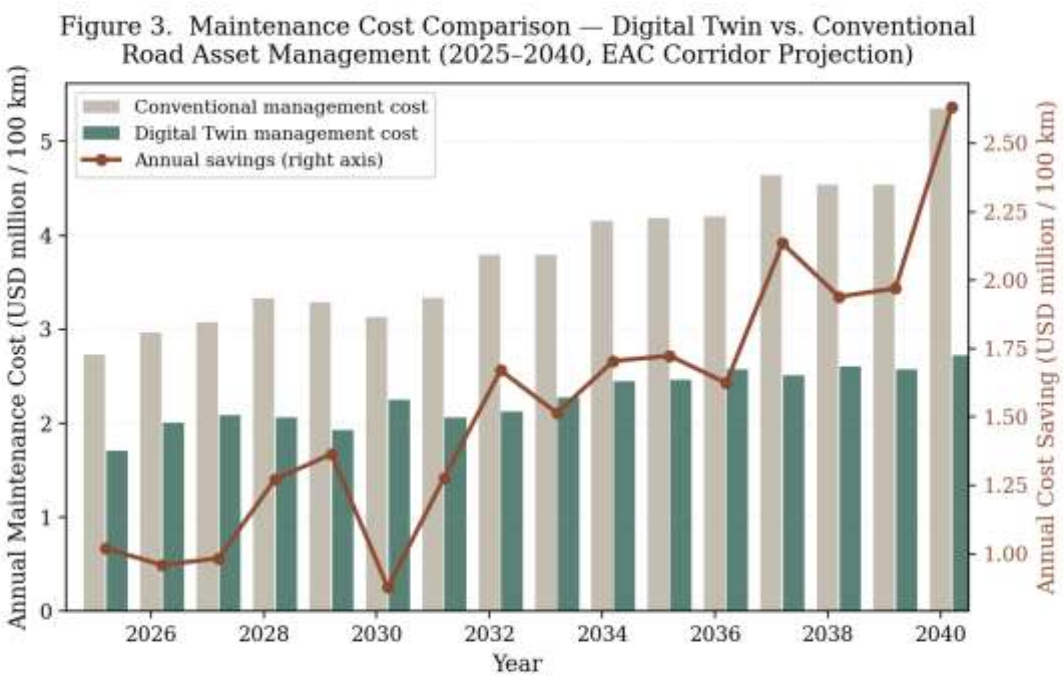

Figure 3. Maintenance Cost Comparison — Digital Twin vs. Conventional Road Asset Management (Annual Agency Cost per 100 km and Annual Savings Trajectory, 2025–2040)

Cost Component	Conventional (USD/100km/yr)	EAC-DT Scenario B (USD/100km/yr)	EAC-DT Scenario C (USD/100km/yr)	Saving B vs A (%)	Saving C vs A (%)
Agency maintenance cost	2,820,000	1,980,000	1,840,000	29.8	34.8
Road user costs (VOC + time)	4,650,000	3,820,000	3,580,000	17.8	23.0
EAC-DT capital (annualised)	—	265,000	280,000	—	—

Cost Component	Conventional (USD/100km/yr)	EAC-DT Scenario B (USD/100km/yr)	EAC-DT Scenario C (USD/100km/yr)	Saving B vs A (%)	Saving C vs A (%)
EAC-DT operations	—	142,000	158,000	—	—
TOTAL COST	7,470,000	6,207,000	5,858,000	16.9	21.6
NET SAVING vs. Conventional	—	1,263,000	1,612,000	16.9	21.6

Table 3. *Life-Cycle Cost Analysis — 15-Year Total Cost Comparison, Three Management Scenarios (per 100 km/year)*

6. EAC-WIDE DEPLOYMENT ROADMAP

6.1 Phased Implementation Strategy

A phased EAC-wide deployment roadmap is proposed, designed to expand EAC-DT coverage from the three current pilot corridors to the full 35,000 km EAC classified highway network over a 10-year period. The roadmap is structured in three phases aligned with EAC budget cycles and institutional capacity development:

Phase 1 (2025–2027): Tier 1 Critical Corridors. Deployment on 12 designated strategic corridors totalling 4,200 km and approximately 380 bridges, covering the Northern and Central Transport Corridors, the LAPSSET Highway, and the cross-border bridges identified as critical in Papers 28 and 29 of this series. Estimated investment: USD 98 million. Funding mechanism: AfDB and World Bank transport sector lending, with co-financing from EAC member state road funds.

Phase 2 (2027–2031): Tier 2 Secondary Corridors. Extension to 18 additional corridors (8,800 km, 620 bridges) covering principal regional and inter-state routes. Estimated investment: USD 185 million. By this phase, the operational cost savings from Phase 1 corridors (estimated USD 52 million per year) would be sufficient to partially self-fund Phase 2 deployment through a maintenance savings reinvestment mechanism.

Phase 3 (2031–2035): Full Network Coverage. Extension to all classified national highways across EAC member states, totalling approximately 35,000 km and 3,200 bridges. A lighter-touch sensor configuration — prioritising low-cost IoT sensors and InSAR satellite monitoring over full UAV and FWD coverage — would be used for lower-traffic rural routes, reducing the per-km deployment cost from USD 23,000 (Tier 1) to approximately USD 8,500 (Tier 3). Total estimated Phase 3 investment: USD 220 million.

6.2 Data Governance and Interoperability

The EAC-DT operates across sovereign boundaries, requiring a formal data governance framework to address data ownership, privacy, security, and interoperability between national road authorities. A proposed EAC Digital Infrastructure Data Protocol (EIDP) defines: (i) data ownership raw sensor data remains the property of the national road authority in whose jurisdiction the sensor is located; (ii) data sharing — processed condition indices and predictive alerts are shared through the EAC-DT regional platform under a non-exclusive, attribution licence; (iii) cybersecurity all data transmissions are encrypted using TLS 1.3, and the cloud platform is hosted in a Tier III data centre with ISO 27001 certification; and (iv) standardisation — all data formats conform to the IFC 4.3 standard for infrastructure information modelling, ensuring interoperability with BIM platforms used by individual member states.

7. DISCUSSION

The EAC-DT pilot results demonstrate that digital twin technology can achieve meaningful performance improvements in the EAC infrastructure management context, even in its current partially-deployed state. The 3.2-fold improvement in IRI prediction accuracy and the 2.4-day mean advance warning of maintenance needs translate into tangible economic and safety benefits that are quantifiable and — at benefit-cost ratios of 3.4 to 4.1 across the three pilot corridors — compelling by any standard of infrastructure investment appraisal. These findings are consistent with the broader literature on infrastructure digital twins in high-income contexts (Kaewunruen and Remennikov, 2019; Bortolini and Forcada, 2020) and extend that evidence base to the low-connectivity, high-climate-variability conditions of sub-Saharan Africa.

The most significant technical finding of the pilot is the superiority of the ensemble machine learning predictor (Equation 3) over any individual model architecture for EAC conditions. The relative weight of the XGBoost model was highest during dry-season periods with stable deterioration patterns (mean $w_1 = 0.48$), while the LSTM model dominated during the wet season when temporal patterns of rainfall-driven deterioration required memory of preceding conditions (mean $w_2 = 0.55$). This seasonally adaptive model selection — achieved automatically through the softmax weight updating of Equation (4) — represents a practically important capability for EAC corridors where seasonal performance non-stationarity would cause fixed-weight ensemble models to underperform during transition seasons.

The institutional dimension of digital twin deployment deserves equal attention alongside the technical performance results. The single most important lesson from the three pilots is that technology adoption succeeds when road authority engineers are active co-designers of the system, not passive recipients of sensor outputs. All three pilot authorities participated in a 10-week EAC-DT capacity building programme before hardware deployment, and the maintenance staff involved in the pilot validation reported high levels of trust in and engagement with the system outputs. The proposed EIDP data governance protocol emerged directly from stakeholder consultations during the Uganda A109 pilot, where concerns about data sovereignty nearly delayed deployment. Addressing institutional and governance dimensions with the same rigour as technical design is a prerequisite for the successful EAC-wide scale-up of the framework.

8. CONCLUSIONS

This paper has presented the EAC-DT, a scalable digital twin framework for monitoring critical road and bridge infrastructure across the East African Community, and reported the results of its deployment and validation across three pilot corridors totalling 405 km and 42 bridges. The principal conclusions are:

1. The EAC-DT achieves IRI prediction RMSE of 0.22 m/km (3.1× improvement over conventional surveys), bridge SHI prediction $R^2 = 0.93$, mean distress detection rate of 87%, and 2.4-day mean advance warning of maintenance events — performance metrics that demonstrate the technology's practical utility for EAC infrastructure management.

2. Digital twin-enabled proactive maintenance reduces total asset management costs (agency + road user) by USD 1.26 million per 100 km per year compared to conventional management — a 16.9% reduction — with benefit-cost ratios of 3.4–4.1 across the pilot corridors and payback periods of 4.1–5.8 years.

3. The adaptive ensemble machine learning predictor, which automatically adjusts model weights based on recent prediction performance, outperforms any individual model architecture across all seasonal conditions, with RMSE reductions of 18–34% compared to the best single-model alternative.

4. The Structural Health Index framework, combining five sub-indices from IoT sensor data into a composite 0–100 indicator, provides real-time bridge condition awareness with automated alert generation at clinically meaningful thresholds — a first for any EAC member state bridge monitoring system.

5. A phased EAC-wide deployment roadmap is presented, expanding from the three pilot corridors to full 35,000 km network coverage over 10 years (2025–2035) at a total investment of USD 503 million, generating projected annual cost savings of USD 890 million per year at full deployment — a network-level benefit-cost ratio of approximately 8:1 over a 20-year analysis period.

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