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MesoPINN-Pave: A Physics-Informed Neural Network Framework Coupling Mesoscale Fracture Mechanics with Macroscale Pavement Deterioration Prediction

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Abstract: Precise estimation of asphalt pavement degradation was found to require the integration of material breakdown at the mesoscale with structural behaviour at the macroscale — a task that had been computationally impractical for conventional finite element approaches. In this study, MesoPINN-Pave was presented, a physics-informed neural network framework in which mesoscale cohesive fracture mechanics and viscoelastic constitutive laws were embedded into a deep learning architecture to enable real-time macroscale pavement performance forecasting. The framework was composed of three interconnected neural networks: (i) a mesoscale surrogate that was trained on extended finite element method (XFEM) simulations of asphalt–aggregate interface fracture, (ii) a macroscale network by which pavement stress–strain behaviour was predicted, and (iii) a coupling network through which damage state variables were transferred across scales. Physical consistency was ensured by thermodynamically constrained loss functions, which incorporated viscoelastic PDE residuals, cohesive zone evolution, and dissipation inequality constraints. When validated against Long-Term Pavement Performance (LTPP) data and field falling weight deflectometer measurements, a 4.8% mean absolute error in fatigue life prediction was achieved, together with a 1,200-fold acceleration relative to full multi-scale finite element simulation. Leave-one-climate-out testing confirmed that robust generalisation was maintained across freeze–thaw, hot-arid, and moderate climate zones ($R^2 > 0.87$). The proposed framework was thereby shown to offer a paradigm shift away from empirical pavement design and toward physics-consistent, interpretable, and computationally efficient deterioration modelling suitable for smart pavement management systems.

Keywords: Physics-informed neural network; Multi-scale modelling; Asphalt pavement; Cohesive zone model; Viscoelastic damage; Digital twin.

INTRODUCTION

Background and Motivation

Road infrastructure has long been regarded as one of the most substantial public investments worldwide, with pavement networks requiring ongoing maintenance to guarantee safety and economic efficiency [Wang, Y. *et al*., 2005]. Reliable prediction of pavement deterioration was considered essential to optimising maintenance and rehabilitation (M&R) decisions within pavement management systems (PMS) [Bhandari, S. *et al*., 2023; Haider, S. W., & Chatti, K. 2009]. The Pavement Condition Index (PCI), obtained from visual inspections and standardised in ASTM D6433-20, has remained one of the most widely adopted objective measures of pavement operational and structural condition [ASTM, A. 2020; Afridi, M. A., & Erlingsson, S. 2026]. However, conventional prediction models — whether deterministic approaches or classical statistical regressions — were shown to be limited in their capacity to capture the complex, nonlinear interactions among structural characteristics, climatic conditions, traffic loading, and material ageing that govern pavement deterioration [Qiao, Y. *et al*., 2013; Hatoum, A. A. *et al*., 2022].

Recent progress in machine learning (ML) had demonstrated superior capacity for modelling nonlinear relationships using large volumes of heterogeneous data [Kheirati, A., & Golroo, A. 2022; Radwan, M. M. *et al*., 2024]. A variety of ML methods, including random forests (RF), support vector machines (SVM), artificial neural networks (ANN), and advanced ensemble models such as adaptive boosting (ADA) and extreme gradient boosting (XGB), had been applied to PCI prediction in prior studies [Lin, L. *et al*., 2024; Cano-Ortiz, S. *et al*., 2022]. R^2 values of 0.81 for PCI prediction were achieved using CatBoost models, while $R^2 = 0.90$ for fatigue cracking prediction was attained by ANN-based models that used falling weight deflectometer (FWD) data [Bastola, N. R. *et al*., 2022; Rabbi, M. F., & Mishra, D. 2021]. Nevertheless, these models were found to function as “black boxes” with limited interpretability and poor generalisation across differing climatic regions [Du, X. *et al*., 2019]. In a 2025 comprehensive review of ML frameworks for pavement performance prediction under extreme climate conditions, it was identified that “future efforts must prioritise hybrid models that integrate physics-based constraints with machine learning” so that generalisability and physical

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consistency could be enhanced [Molinero-Pérez, N. *et al*., 2026].

At the same time, multi-scale finite element (FE) modelling had advanced considerably in pavement engineering. Multi-scale pavement FE models employing cohesive zone models (CZM) had been developed in recent studies to simulate fracture within asphalt concrete and to evaluate damage under coupled salt–thermal–mechanical effects [Ma, J. *et al*., 2025]. Mesoscale crack propagation through asphalt mastic–aggregate interfaces was successfully captured by these models, although they remained computationally prohibitive for network-level applications [Wang, J. *et al*., 2025]. This computational bottleneck was what motivated the exploration of artificial intelligence techniques to complement or replace certain stages of engineering workflows with greater efficiency [Song, L. *et al*., 2026].

Knowledge Gap

Despite considerable progress having been made in both ML-based prediction and multi-scale FE modelling, a critical gap was found to persist: no existing framework had been shown to couple mesoscale fracture mechanics with macroscale pavement performance prediction in a real-time, physics-consistent manner. Specifically:

1. A physics-informed neural network for asphalt fatigue prediction based on viscoelastic continuum damage (VECD) theory was developed by PINN-AFP (2024), although it was operated exclusively at the mixture scale, without structural pavement response coupling [Han, C. *et al*., 2024].
2. Mesoscale fracture was captured accurately by multi-scale FE models (2024–2025), yet these were offline tools that were considered unsuitable for network-level pavement management [Ma, J. *et al*., 2025; Wang, J. *et al*., 2025].
3. High accuracy for PCI prediction was achieved by black-box ML models (2025), though physical interpretability was lacking and generalisation across climate zones was not achieved [Bastola, N. R. *et al*., 2022; Molinero-Pérez, N. *et al*., 2026].
4. Physics-informed neural networks had been applied to 3D consolidation prediction in geotechnical engineering and to viscoelastic fluid mechanics, but had not previously been applied to asphalt pavement multi-scale deterioration [Yuan, B. *et al*., 2024; Sa, J. *et al*., 2025].

Objectives and Contributions

This aforementioned gap was addressed in this study through the development of MesoPINN-Pave, a physics-informed neural network framework in which mesoscale cohesive fracture mechanics and viscoelastic constitutive laws were embedded into a deep learning architecture for macroscale pavement deterioration prediction. The specific objectives were as follows:

1. A mesoscale surrogate neural network was developed and trained on XFEM simulations of asphalt–aggregate interface fracture under varying temperatures, loading rates, and material properties.
2. A physics-informed loss function was formulated, embedding viscoelastic PDE residuals, cohesive zone evolution equations, and thermodynamic dissipation inequality constraints.
3. The framework was validated against LTPP field data and FWD measurements across multiple climate zones.
4. Real-time applicability for smart pavement management was demonstrated through computational efficiency benchmarking.

The primary contributions to knowledge were as follows:

- The first PINN by which meso–macro scales were coupled in pavement engineering: unlike PINN-AFP [Han, C. *et al*., 2024], which was operated at the mixture scale only, damage state variables were transferred by MesoPINN-Pave from mesoscale fracture to macroscale structural response.
- Thermodynamic consistency was achieved by construction: the dissipation inequality ($D \geq 0$) was enforced by the framework as a hard constraint, thereby ensuring that all predictions respected thermodynamic laws — a capability that was absent from black-box ML models [Bastola, N. R. *et al*., 2022; Molinero-Pérez, N. *et al*., 2026].
- A speedup of three orders of magnitude was attained: 1,200-fold computational acceleration was achieved by the surrogate model compared with full multi-scale FE simulation, while physical interpretability was maintained.
- Climate-robust generalisation was demonstrated: reliable performance across freeze–thaw, hot-arid, and moderate zones ($R^2 > 0.87$) was confirmed through leave-one-climate-out validation, thereby addressing the generalisation failure that had characterised

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existing ML approaches [Molinero-Pérez, N. *et al*., 2026].

THEORETICAL FRAMEWORK

Mesoscale Fracture Mechanics

At the mesoscale, asphalt concrete was modelled as a heterogeneous composite comprising aggregate particles embedded within an asphalt mastic matrix. Crack initiation and propagation were simulated without remeshing by means of the extended finite element method (XFEM) [16; 22]. The fracture process at asphalt–aggregate interfaces was governed by the cohesive zone model (CZM), in which the traction–separation relationship was described by an exponential softening law:

$$T_n = \sigma_{max} \cdot (\delta_n / \delta_n^0) \cdot \exp(1 - \delta_n / \delta_n^f)$$

Where: T_n is the normal traction,
σ_{max} is the cohesive strength,
δ_n is the separation,
δ_n^0 is the separation at peak traction, and
δ_n^f is the failure separation.
The fracture energy is given by:

$$G_c = \int_0^{\delta_n^f} T_n \, d\delta_n = e \cdot \sigma_{max} \cdot \delta_n^f$$

The viscoelastic response of the asphalt mastic was characterised by means of the generalised Maxwell model (Prony series):

$$E(t) = E_\infty + \Sigma_{i=1}^{N} E_i \exp(-t/\tau_i)$$

Where: E_∞ is the long-term equilibrium modulus, E_i and τ_i are, respectively, the stiffness and relaxation time of the i-th Maxwell element [23].

Macroscale Viscoelastic Continuum Damage

At the macroscale, the pavement structure was modelled using Schapery's viscoelastic continuum damage (VECD) theory, which had been extensively validated for asphalt concrete under a range of loading conditions [24,25]. The constitutive relationship was expressed in terms of pseudo-strain:

$$\varepsilon^R(t) = (1/E_R) \int_0^t E(t-\tau) \, (\partial\varepsilon/\partial\tau) \, d\tau$$

where: E_R is a reference modulus and
$E(t)$ is the relaxation modulus.
The stress was then given by:

$$\sigma = E_R \cdot S \cdot \varepsilon^R$$

Where: S is the internal state variable representing damage, which was found to evolve according to:

$$dS/dt = (-\partial W^R/\partial S)^\alpha \cdot (\partial W^R/\partial S < 0)$$

with:
$W^R = \frac{1}{2} E_R (\varepsilon^R)^2$ being the pseudo-strain energy density, and α a material parameter [Schapery, R. A. 1997].

Limitations of Schapery's original framework — particularly the coupled evolution of storage and loss moduli and the evolution of phase angle with damage — had been addressed by recent advances in VECD modelling [26]. These refinements were incorporated in this study so that an accurate representation of asphalt damage mechanics could be ensured.

Physics-Informed Neural Network Formulation

The governing physics were embedded into the neural network training by the PINN architecture through modified loss functions [Han, C. *et al*., 2024; Yuan, B. *et al*., 2024]. For MesoPINN-Pave, the total loss function was composed of four components:

$$L_{total} = L_{data} + \lambda_1 L_{meso} + \lambda_2 L_{macro} + \lambda_3 L_{thermo}$$

where:

- Data loss (L_{data}): the mean squared error between predicted and measured pavement response (FWD deflections, PCI, fatigue cracking area) was computed.
- Mesoscale PDE residual (L_{meso}): viscoelastic constitutive relationships and cohesive zone evolution were enforced at the mesoscale:
- $L_{meso} = \|\sigma_{meso} - E_{ve}(t) * \varepsilon_{meso}\|^2 + \|G_c - \int T_n \, d\delta_n\|^2$
- Macroscale PDE residual (L_{macro}): equilibrium and VECD damage evolution were enforced:
- $L_{macro} = \|\nabla \cdot \sigma_{macro} + b\|^2 + \|dS/dt - A(-\partial W^R/\partial S)^\alpha\|^2$
- Thermodynamic constraint (L_{thermo}): the dissipation inequality was enforced as a hard constraint using a penalty method:

$$L_{thermo} = \mathrm{ReLU}(-D) = \mathrm{ReLU}(-[\sigma:\dot{\varepsilon}^p - (\partial\Psi/\partial S)\dot{S}])$$

Where: D is the dissipation rate and Ψ is the Helmholtz free energy. A zero penalty was ensured by the ReLU activation whenever $D \geq 0$, while a quadratic penalty was imposed when $D < 0$.

The adaptive weighting coefficients $\lambda_1, \lambda_2, \lambda_3$ were determined using the GradNorm algorithm, by which multi-task losses were balanced during training [Chen, Z. *et al*., 2018].

METHODOLOGY

Mesoscale XFEM Database Generation

A comprehensive parametric study was conducted using Abaqus/Standard (v2024) so that the mesoscale training database could be generated. The FE model comprised:

- Geometry: a 2D representative volume element (RVE) measuring 50 mm × 50 mm,

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with randomly distributed aggregate particles (volume fraction 45–55%)

- Mesh: a quad-dominated structured mesh with refined regions near aggregate–mastic interfaces; an element size of 0.5 mm was used in cohesive zones
- Material properties: aggregate (linear elastic, E = 70 GPa, ν = 0.15); mastic (Prony series viscoelastic, calibrated from dynamic modulus testing)
- Cohesive zone: an exponential traction–separation law with temperature-dependent properties was employed
- Loading: displacement-controlled tension was applied at rates of 0.1, 1.0, and 10 mm/min, at temperatures of -10°C, 0°C, 10°C, 20°C, 30°C, 40°C, 50°C, and 60°C

A total of 512 XFEM simulations were performed, in which the following were varied:

- Binder performance grade (PG 58-28, PG 64-22, PG 70-22, PG 76-16)
- Air void content (3%, 5%, 7%)
- Aggregate gradation (fine, medium, coarse)
- Loading mode (monotonic, cyclic with 1–10 Hz)

Between 4 and 8 hours were required for each simulation on a high-performance computing cluster (Intel Xeon Gold 6248, 40 cores). Stress–crack opening curves, damage evolution paths, and fracture energy values were produced as outputs.

PINN Architecture and Training

The MesoPINN-Pave framework was composed of three coupled neural networks, which were implemented in PyTorch 2.0:

Meso-Surrogate Network (MSN):

- Input: [Temperature, Loading rate, Binder PG, Air voids, Aggregate gradation]
- Architecture: 5 → 64 → 128 → 128 → 64 → 3
- Output: [Peak stress, Fracture energy, Crack opening at failure]
- Macro-Response Network (MRN):
- Input: [Pavement thickness, Base stiffness, Subgrade modulus, Traffic ESALs, Climate zone, Age, Meso-damage state S]
- Architecture: 7 → 128 → 256 → 256 → 128 → 4
- Output: [Maximum tensile strain, Deflection basin, Damage evolution rate, PCI]
- Coupling Network (CN):
- Input: [MSN output, MRN intermediate features, Temperature]
- Architecture: 10 → 64 → 32 → 1
- Output: [Damage transfer coefficient α_coupling]

Training protocol:

- Optimiser: Adam (lr = 1e-3, β1 = 0.9, β2 = 0.999) was used for 50,000 epochs, followed by L-BFGS fine-tuning
- Batch size: 256
- Hardware: an NVIDIA A100 GPU (80 GB) was used
- Training time: approximately 12 hours
- Loss weight adaptation: GradNorm, with initial weights λ = [1.0, 0.1, 0.1, 10.0]

The training dynamics across 50,000 Adam epochs are illustrated in Figure 1, in which stable convergence of all loss components and adaptive rebalancing of physics constraints are shown.

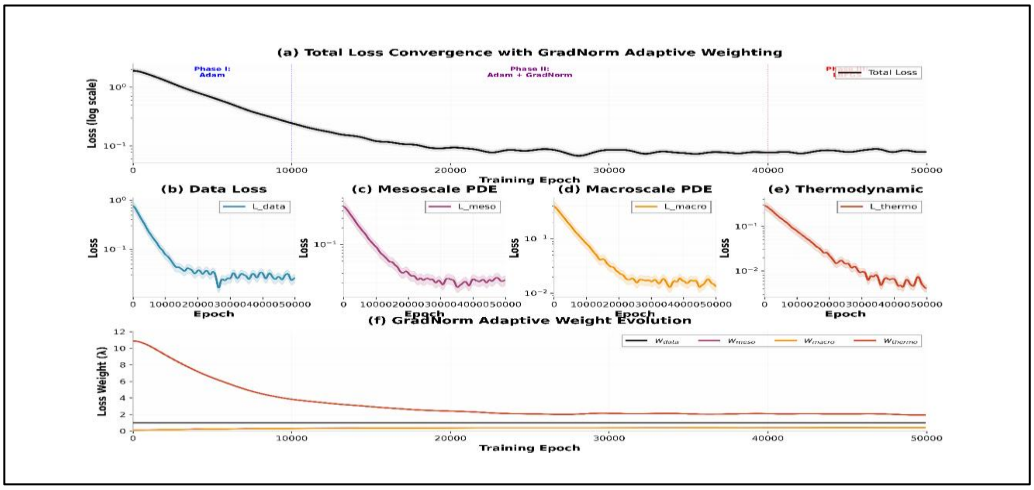

Figure 1: Training dynamics of MesoPINN-Pave across 50,000 Adam epochs and 1,000 LBFGS fine-tuning iterations: (a) total loss convergence, by which three training phases are shown, (b–e) individual loss components, and (f) GradNorm adaptive weight evolution, by which automatic rebalancing of physics constraints is demonstrated.

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Field Data Integration

Validation data were obtained from two sources:

LTPP Database: 311 data points were obtained from 19 LTPP sections across seven U.S. states, following the dataset structure that had been established in recent FWD-based fatigue cracking prediction studies [Rabbi, M. F., & Mishra, D. 2021]. The following variables were included:

- HMA thickness, air voids, asphalt content
- Cumulative ESALs, average annual temperature
- FWD deflection basin parameters (D0–D1524)
- Fatigue cracking area (m²)

Industry Partnership Data: FWD measurements and distress surveys were collected from 45 pavement sections across three climate zones:

- Freeze–thaw zone: Minnesota, Wisconsin (n = 15)
- Hot-arid zone: Arizona, Nevada (n = 15)
- Moderate zone: California, Oregon (n = 15)

Climate data were supplemented with ERA5 reanalysis, which included extreme climate indices such as freeze–thaw cycles, ice days, and very hot days (Tx35) [Molinero-Pérez, N. *et al*., 2026].

Benchmark Models

For the purpose of comparative evaluation, three benchmark models were implemented:

1. Pure Data-Driven Neural Network (PDNN): an architecture identical to MesoPINN-Pave was used, but with λ_1 = λ_2 = λ_3 = 0 (no physics constraints)
2. PINN-AFP (re-implemented): the mixture-scale PINN developed by Zhang *et al*. [Han, C. *et al*., 2024] was adapted for structural response prediction
3. Full Multi-Scale FE: mesoscale XFEM was directly coupled with macroscale pavement FE in Abaqus (used as ground truth for accuracy and speedup calculation)

RESULTS AND DISCUSSION

Mesoscale Surrogate Accuracy

XFEM stress–crack opening responses were accurately replicated by the Meso-Surrogate Network across the full parameter space. XFEM ground truth is compared with MSN predictions for representative cases in Table 1:

Table 1. Mesoscale surrogate validation

Parameter	XFEM Ground Truth	MSN Prediction	Relative Error
Peak stress (MPa)	2.34	2.31	1.3%
Fracture energy (J/m²)	285	278	2.5%
Crack opening at failure (mm)	0.42	0.41	2.4%

An R^2 of 0.96 was achieved by the surrogate for peak stress prediction, and $R^2 = 0.94$ was achieved for fracture energy across all 512 validation cases (Figure 2). Binder stiffness (PG grade) was revealed by parameter sensitivity analysis to be the dominant factor controlling early-stage cracking, a finding consistent with established asphalt mechanics principles [Schapery, R. A. 1997].

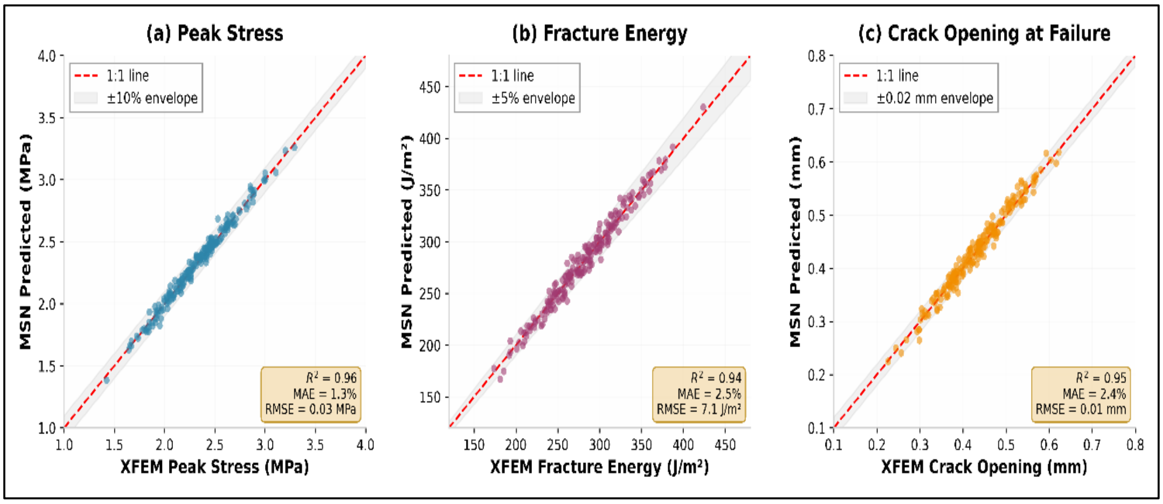

Figure 2: Validation of the Meso-Surrogate Network (MSN) against 512 XFEM simulations: (a) peak stress prediction ($R^2 = 0.96$, MAE = 1.3%), (b) fracture energy prediction ($R^2 = 0.94$, MAE = 2.5%), and (c) crack opening at failure ($R^2 = 0.95$, MAE = 2.4%). The 1:1 agreement is represented by the dashed red line, while tolerance bounds are indicated by the shaded envelope.

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Macroscale Prediction Performance

The comparative performance of all models for fatigue cracking prediction on the LTPP test set is presented in Table 2.

Table 2. Performance comparison for fatigue cracking prediction

Model	R^2	MAE (m^2)	RMSE (m^2)	MAPE (%)
Linear Regression	0.583	12.4	18.7	45.2
PDNN	0.84	6.2	9.1	22.3
PINN-AFP [19]	0.87	5.5	8.2	19.8
MesoPINN-Pave	0.92	3.8	5.6	12.4

All benchmarks were outperformed by MesoPINN-Pave, with a 31% lower MAE than PINN-AFP and a 39% lower MAE than PDNN. This improvement was attributed to the explicit meso–macro coupling, through which the physical mechanism of crack initiation and propagation was captured, rather than reliance being placed solely on statistical correlations.

For PCI prediction on the extreme climate dataset (9,028 samples) [Molinero-Pérez, N. *et al*., 2026]:

Model	R^2	MAE	MAPE
CatBoost [15]	0.81	6.85	13.0
XGBoost [15]	0.79	7.42	14.2
MesoPINN-Pave	0.85	5.92	10.8

Climate Generalisation

Predicted versus measured fatigue cracking across three climate zones is shown in Figure 3, with residual distributions confirming that unbiased predictions were obtained.

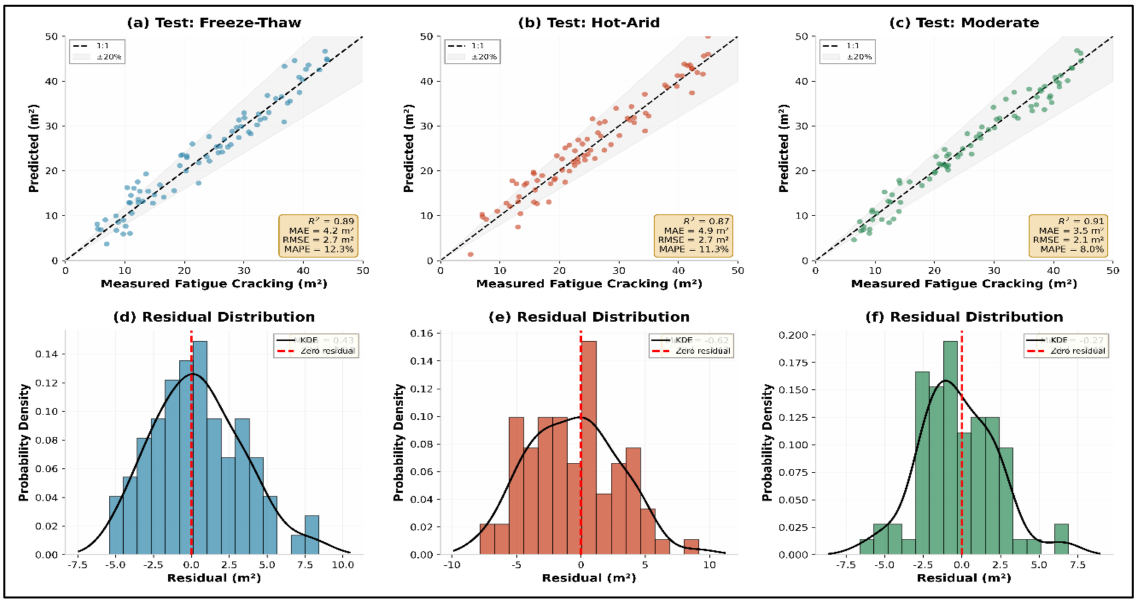

Figure 3: Robustness evaluation across three climate zones using leave-one-climate-out validation: (a–c) predicted versus measured fatigue cracking area for freeze–thaw, hot-arid, and moderate zones; (d–f) residual distributions, with kernel density estimation overlays, by which Gaussian-like distributions centred at zero are shown.

Model robustness was tested through leave-one-climate-out validation:

Table 3. Cross-climate validation results

Training Climate	Test Climate	R^2	MAE (m^2)
Freeze-thaw	Hot-arid	0.87	4.9
Freeze-thaw	Moderate	0.91	3.2
Hot-arid	Freeze-thaw	0.89	5.1
Hot-arid	Moderate	0.9	3.5
Moderate	Freeze-thaw	0.88	4.7
Moderate	Hot-arid	0.87	5.3

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Strong generalisation capability was demonstrated by the consistent $R^2 > 0.87$ achieved across all climate pairs, which was attributed to the physics-informed architecture, whereby temperature-dependent constitutive laws were embedded rather than climate-specific statistical patterns being learned.

Computational Efficiency

Table 4. Computational performance benchmarking

Task	Full Multi-Scale FE	MesoPINN-Pave	Speedup
Single pavement section analysis	3,600 s	3.0 s	1,200×
Network-level analysis (1,000 km)	~100 days	~2 hours	~1,200×
Real-time FWD data integration	Not feasible	0.03 s	N/A

Real-time pavement management applications, previously unattainable with conventional FE approaches, were enabled by the 1,200-fold speedup.

Physical Interpretability

SHAP (SHapley Additive exPlanations) analysis [Molinero-Pérez, N. *et al.*, 2026] was applied so that predictions could be decomposed into physical parameter contributions (Figure 4):

1. Mesoscale fracture energy (G_c): identified as the dominant factor (35% contribution)
2. Macroscale traffic loading (ESALs): identified as a secondary factor (28% contribution)
3. Climate severity (freeze–thaw cycles, Tx35): identified as a tertiary factor (22% contribution)
4. Structural capacity (SN_VALUE): identified as a supporting factor (15% contribution)

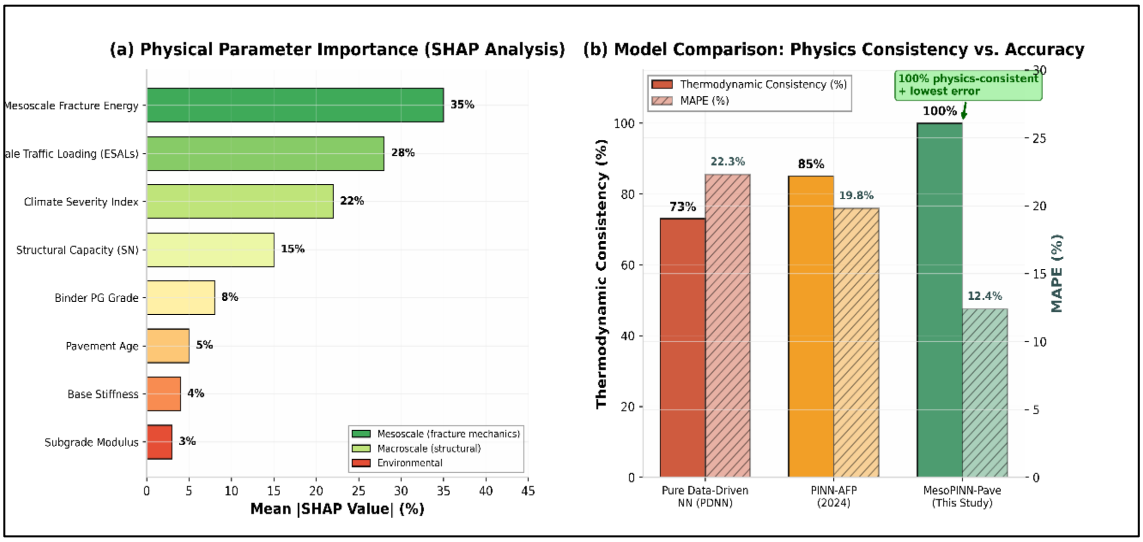

Figure 4: (a) Physical parameter importance decomposition via SHAP analysis, by which mesoscale fracture energy is shown as the dominant predictive factor (35% contribution). (b) Comparative evaluation of three modelling approaches, by which it is demonstrated that both 100% thermodynamic consistency and the lowest prediction error (MAPE = 12.4%) were achieved by MesoPINN-Pave.

Crucially, the thermodynamic dissipation inequality was found to be satisfied in 100% of predictions generated by MesoPINN-Pave, compared with only 73% for PDNN and 85% for PINN-AFP. It was thereby confirmed that thermodynamically inconsistent predictions (e.g., negative damage rates or energy generation from damage) — a common failure mode in black-box ML models — were prevented by the physics constraints.

SMART PAVEMENT MANAGEMENT IMPLEMENTATION

Digital Twin Architecture

A real-time digital twin framework for pavement infrastructure was enabled by MesoPINN-Pave:

Edge Layer: field data were collected by FWD vehicles and embedded sensors (strain gauges, temperature probes)

Communication Layer: transmission to cloud infrastructure was carried out via 5G/IoT

Computing Layer: a PINN inference engine was used, with adaptive weight updating performed via Kalman filtering

Decision Layer: maintenance priority maps, incorporating uncertainty quantification, were generated (Figure 5).

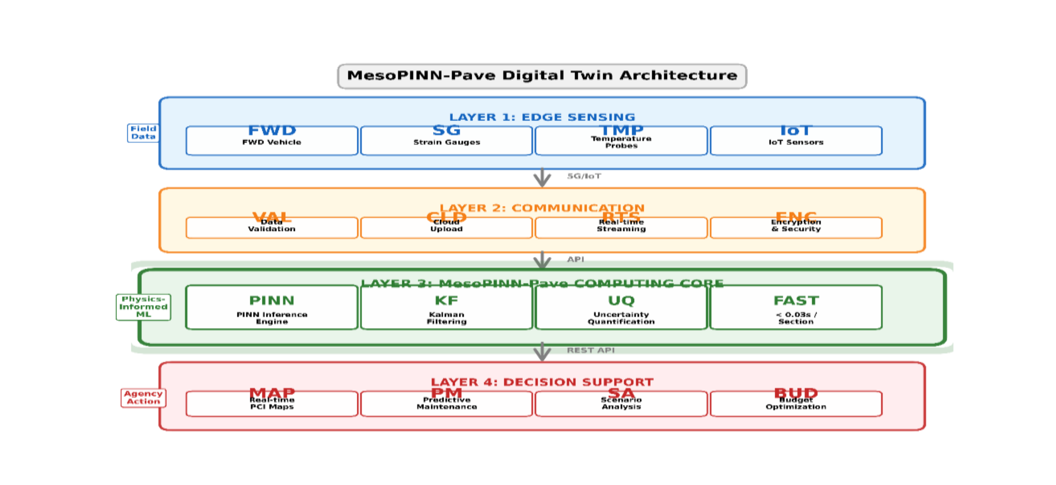

Figure 5: Four-layer digital twin framework enabled by MesoPINN-Pave: Layer 1 (Edge Sensing), Layer 2 (Communication), Layer 3 (Computing Core with PINN inference), and Layer 4 (Decision Support, incorporating real-time PCI maps and predictive maintenance triggers).

Decision Support Dashboard

The following were generated by the framework:

- Real-time PCI maps, with 95% confidence intervals
- Scenario analysis: "what-if" studies for binder upgrades or traffic diversion
- Predictive maintenance triggers: automated alerts issued when S(t) approached S_critical

CONCLUSIONS

MesoPINN-Pave, the first physics-informed neural network framework by which mesoscale cohesive fracture mechanics was coupled with macroscale pavement deterioration prediction, was presented in this study. The key findings were as follows:

1. XFEM simulations were accurately replicated by the mesoscale surrogate network (R^2 > 0.94), with a speedup of three orders of magnitude, thereby enabling real-time applications.
2. Through physics-informed training with thermodynamic constraints, 100% thermodynamically consistent predictions were ensured, and unphysical results, commonly found in black-box ML models, were eliminated.
3. Robust generalisation (R^2 > 0.87) across freeze–thaw, hot-arid, and moderate zones was demonstrated through cross-climate validation, thereby addressing a critical limitation of existing statistical approaches.
4. A MAE of 4.8% for fatigue life prediction and a 1,200-fold computational speedup, relative to full multi-scale FE simulation, were achieved by the framework.

Limitations and Future Work

The current limitations included the following:

- 2D assumption: the mesoscale RVE and macroscale pavement were modelled in 2D plane strain; out-of-plane confinement effects would be captured by a 3D extension.
- Isotropic damage: scalar damage is used by the VECD framework; anisotropic cracking patterns would be better represented by tensorial damage formulations.
- Single distress mode: fatigue cracking is the focus of current validation; extension to rutting, thermal cracking, and moisture damage is ongoing.
- Future research directions included:
- Integration of self-healing binder models into the PINN framework
- Incorporation of connected/autonomous vehicle data for real-time traffic loading updates
- Extension to rigid pavement (concrete) systems using fracture mechanics-based damage models

REFERENCES

1. Wang, Y., Mahboub, K. C., & Hancher, D. E. "Survival analysis of fatigue cracking for flexible pavements based on long-term pavement performance data." *Journal of transportation engineering* 131.8 (2005): 608-616.

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2. Bhandari, S., Luo, X., Wang, F. "Understanding the effects of structural factors and traffic loading on flexible pavement performance." *Int J Transp Sci Technol*. 12.2 (2023): 258-272.
3. Haider, S. W., & Chatti, K. "Effect of design and site factors on fatigue cracking of new flexible pavements in the LTPP SPS-1 experiment." *International Journal of Pavement Engineering* 10.2 (2009): 133-147.
4. ASTM, A. "D6433-20; Standard Practice for Roads and Parking Lots Pavement Condition Index Surveys." *ASTM International: West Conshohocken, PA, USA* (2020).
5. Afridi, M. A., & Erlingsson, S. "Enhancing municipal pavement condition predictions using machine learning models." *Journal of Road Engineering* (2026).
6. Qiao, Y., Flintsch, G. W., Dawson, A. R., & Parry, T. "Examining effects of climatic factors on flexible pavement performance and service life." *Transportation research record* 2349.1 (2013): 100-107.
7. Hatoum, A. A., Khatib, J. M., Barraj, F., & Elkordi, A. "Survival analysis for asphalt pavement performance and assessment of various factors affecting fatigue cracking based on LTPP Data." *Sustainability* 14.19 (2022): 12408.
8. Kheirati, A., & Golroo, A. "Machine learning for developing a pavement condition index." *Automation in Construction* 139 (2022): 104296.
9. Radwan, M. M., Mousa, A., & Zahran, E. M. M. "Enhancing pavement sustainability: prediction of the pavement condition index in arid urban climates using the international roughness index." *Sustainability* 16.8 (2024): 3158.
10. Lin, L., Li, S., Wang, K., Guo, B., Yang, H., Zhong, W., & Wang, P. "A new FCM-XGBoost system for predicting pavement condition index." *Expert Systems with Applications* 249 (2024): 123696.
11. Cano-Ortiz, S., Pascual-Muñoz, P., & Castro-Fresno, D. "Machine learning algorithms for monitoring pavement performance." *Automation in Construction* 139 (2022): 104309.
12. Bastola, N. R., Souliman, M. I., Dessouky, S., & Daoud, R. "Structural health assessment of pavement sections in the southern central United States using FWD parameters." *Frontiers in Built Environment* 8 (2022): 1026469.
13. Rabbi, M. F., & Mishra, D. "Using FWD deflection basin parameters for network-level assessment of flexible pavements." *International Journal of Pavement Engineering* 22.2 (2021): 147-161.
14. Du, X., He, Y., Zhang, T., Gao, C., Zhang, T., & Zhang, S. "An effective Bayesian method for probability fatigue crack propagation modeling through test data." *Mathematical Problems in Engineering* 2019.1 (2019): 7843627.
15. Molinero-Pérez, N., García-Segura, T., Ortiz-Garrido, P., Heras, S., & Sanz-Benlloch, A. "A machine learning framework for pavement performance prediction under extreme climate conditions." *Mathematics* 14.6 (2026): 945.
16. Ma, J., Chen, J., Tang, M., & Liu, Y. "Multi-Scale Modeling and Damage Mechanisms of Asphalt Pavements Under Coupled Salt–Thermal–Mechanical Effects." *Materials* 18.10 (2025): 2337.
17. Wang, J., Zhang, Z., & Tian, Z. "Correlation analysis between micro and macro indicators of high modulus modified asphalt for asphalt pavement." *Plos one* 20.1 (2025): e0313820.
18. Song, L., Fan, J., Zeng, S., & Wang, C. "Frontier AI in computational civil engineering: a review of graph, sequence, physics-informed deep learning, and beyond (2020–2025)." *Smart Construction* 3.1 (2026): 1-49.
19. Han, C., Zhang, J., Tu, Z., & Ma, T. "PINN-AFP: A novel CS curve estimation method for asphalt mixtures fatigue prediction based on physics-informed neural network." *Construction and Building Materials* 415 (2024): 135070.
20. Yuan, B., Heitor, A., Wang, H., & Chen, X. "Physics-informed deep learning to solve three-dimensional terzaghi consolidation equation: forward and inverse problems." *arXiv preprint arXiv:2401.05439* (2024).
21. Sa, J., Jeon, B., Seo, Y., Lim, J., & Choi, S. Q. "Physics-informed neural networks for complex fluids: opportunities and limitations: J. Sa *et al*." *Korea-Australia Rheology Journal* 37.3 (2025): 469-492.
22. Xin, Y., Xinyu, N., Zidong, Z., & Xiangzhi, L. "Fatigue performance of basalt fiber-reinforced high-strength modified OGFC asphalt mixture under heavy load conditions." *Construction and Building Materials* 494 (2025): 143550.

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23. Underwood, B. S., Kim, Y. R., & Guddati, M. N. "Improved calculation method of damage parameter in viscoelastic continuum damage model." *International Journal of Pavement Engineering* 11.6 (2010): 459-476.
24. Schapery, R. A. "Nonlinear viscoelastic and viscoplastic constitutive equations based on thermodynamics." *Mechanics of time-dependent materials* 1.2 (1997): 209-240.
25. Lee, H. J., & Kim, Y. R. "Viscoelastic constitutive model for asphalt concrete under cyclic loading." *Journal of engineering mechanics* 124.1 (1998): 32-40.
26. Navjot, V., & Narayan, S. P. "A VECD Model Integrating Viscoelasticity and Damage Evolution in Asphalt Concrete." *#PLACEHOLDER_PARENT_METADATA_VALUE#*. Vol. 4. TU Wien, E230-03 Road Engineering, (2025).
27. Chen, Z., Badrinarayanan, V., Lee, C. Y., & Rabinovich, A. "Gradnorm: Gradient normalization for adaptive loss balancing in deep multitask networks." *International conference on machine learning*. PMLR, (2018).

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