Adaptation of Crumb Rubber Modified Asphalt Predictive Models for Nigerian Climatic Conditions: A Transfer Learning Approach

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ABSTRACT

Crumb Rubber Modified Asphalt (CRMA) represents a major advancement in sustainable road construction, widely adopted in the United States to improve pavement durability, reduce rutting, and utilize waste tires. However, its application in developing countries like Nigeria remains limited, largely due to the lack of region-specific performance models, climatic differences, and infrastructural challenges. This study proposes a transfer learning approach to adapt predictive CRMA models from the United States to Nigerian climatic zones using climate matching, multivariate regression, artificial neural networks (ANN), and multi-objective optimization techniques. Using simulated data representative of U.S. state climates and traffic conditions, we modeled performance indices such as Marshall Stability, rutting resistance, and fatigue retention. The results identify optimal crumb rubber contents (CR%) of 10–15% for different climate-traffic scenarios. Enhanced models including traffic loads (ESALs) were developed and mapped to Nigerian conditions. This supports sustainable CRMA deployment for road infrastructure in Nigeria and similar regions.

Keywords: crumb rubber, predictive modeling, asphalt performance, optimization, Nigeria, ANN, regression

Keywords: Crumb rubber modified asphalt; sustainable asphalt; predictive modelling; Marshall stability; rutting resistance; fatigue retention.

INTRODUCTION

The growing demand for sustainable transportation infrastructure has intensified interest in environmentally friendly pavement technologies. Among these, Crumb Rubber Modified Asphalt (CRMA) has emerged as a promising innovation that addresses both engineering and ecological challenges. Developed through the incorporation of ground tire rubber into conventional bitumen, CRMA improves pavement performance-enhancing rut resistance, fatigue life, and thermal cracking tolerance-while simultaneously promoting the recycling of waste vehicle tires. Developed nations like the United States have widely adopted CRMA, supported by significant investment in research, policy, and pilot projects (Lo Presti, 2013; Putman & Amirkhanian, 2004). However, in sub-Saharan Africa and other developing regions, the implementation of CRMA remains sparse due to technical, economic, and climatic barriers.

Nigeria, Africa's most populous country and one with a rapidly growing vehicular population, generates tens of thousands of used tires annually (Okonkwo et al., 2022). These tires often end up in landfills or are incinerated under environmentally hazardous conditions. At the same time, the nation grapples with deteriorating road networks, especially in regions with high axle loading and intense rainfall. These twin challenges-road degradation and tire waste-underscore the opportunity to apply CRMA as a dual-benefit

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solution. Yet, because Nigeria lacks performance-based design guides tailored to local conditions, transferring and calibrating models developed elsewhere becomes essential.

This paper proposes a framework to adapt U.S.-based CRMA predictive models to the Nigerian context. Using transfer learning principles, climate matching, multivariate regression, and artificial neural networks (ANN), we simulate and calibrate optimal crumb rubber content for flexible pavements in Nigeria's diverse climatic zones. The goal is to establish locally relevant mix designs that maximize mechanical performance and sustainability using globally tested knowledge.

LITERATURE REVIEW

Crumb Rubber in Asphalt Technology

Crumb rubber, obtained from grinding end-of-life tires, has been studied extensively as a bitumen modifier. It enhances the elastic recovery, stiffness, and aging resistance of asphalt binders (Lo Presti, 2013). Two main processes-wet and dry-are used in incorporating crumb rubber into asphalt. In the wet process, rubber is digested into the binder at high temperatures, resulting in a homogeneously modified binder. The dry process involves blending rubber with the aggregate before adding the binder, often resulting in a coarser mix but simpler production logistics (Mashaan et al., 2014).

Performance enhancements from CRMA include:

Improved rutting resistance (Kaloush et al., 2002)

Extended fatigue life under repeated loading (Ghabchi et al., 2013)

Superior low-temperature cracking resistance (Fazaeli et al., 2016)

International Experience with CRMA

In the United States, various state Departments of Transportation (DOTs) have implemented CRMA extensively since the 1990s. For example, Arizona and California have developed specification guides for using 15-20% rubber content by weight of binder (Way et al., 2011). Florida and Texas, facing humid and semi-arid conditions respectively, have reported performance gains using 10-18% rubber, especially for fatigue-prone roads (Liang et al., 2022). These regional adaptations underscore the importance of climatic tailoring in CRMA design.

Several performance prediction models have also been developed. Zhou et al. (2020) used machine learning models to relate crumb rubber dosage, binder content, and temperature to fatigue performance. Meanwhile, Fazaeli et al. (2016) applied Response Surface Methodology (RSM) and ANOVA to optimize performance indices like Marshall Stability and Indirect Tensile Strength (ITS).

Long-Term Performance with Traffic

Field data (Caltrans, 2015; FHWA) confirms CRMA's superior rutting resistance under heavy traffic. Performance models often include both CR% and cumulative traffic (ESALs):

$$R(t) = at^{b}\, e^{-cCR} L^{\gamma}, \quad F_r(t) = 100e^{-dt}\,(1 + f\,CR)L^{-\eta}$$

Where $R(t)$ is rut depth (mm), $F_r(t)$ is fatigue retention (%), t is age (years), CR is crumb rubber %, L is cumulative ESALs (millions), and a, b, c, γ, d, f, η are model calibration constants.

Nigerian Context and the Need for Calibration

In Nigeria, road infrastructure suffers from underfunding, poor maintenance, and harsh tropical environmental conditions. Southern zones are subjected to high rainfall (>2000 mm/year), while northern zones endure

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extreme heat and UV radiation. Subgrades are often lateritic and expansive, amplifying the risks of rutting and fatigue. Although crumb rubber has been studied experimentally in some Nigerian universities, the country lacks a comprehensive, climate-sensitive CRMA framework.

Okonkwo et al. (2022) emphasized the need for design models tailored to Nigeria's climatic and traffic conditions. Existing models from temperate zones do not generalize well due to differences in pavement temperature profiles, aggregate sources, and construction practices.

METHODOLOGY

The methodology adopted in this study is structured to enable the transfer, adaptation, and validation of CRMA performance models from U.S. climatic contexts to Nigeria's environmental conditions. It consists of six core phases: data synthesis, climate mapping, model building, performance simulation, optimization, and regional calibration. Figure 1 (to be inserted) illustrates the overall research workflow.

Data Collection

Due to limited availability of consistent CRMA field data from Nigeria, the research

utilized a comprehensive datasets from U.S. States combining laboratory test outcomes and long-term pavement performance under various climatic and traffic conditions. The dataset represented:

Crumb rubber content (CR%): 0%, 10%, 15%, 20%

Climatic zones: Hot-Dry (e.g., Arizona), Hot-Humid (e.g., Florida), Semi-Arid (e.g., Texas), Mediterranean (e.g., California), Cold (e.g., Minnesota), and mapped Nigerian analogs

Traffic loads: Expressed as cumulative ESALs (10–50 million over 15 years)

Performance indices:

Laboratory: Marshall Stability (kN), Flow (mm), Indirect Tensile Strength (MPa), initial rutting (mm), initial fatigue life (cycles)

Long-term: Rut depth progression (mm), fatigue life retention (%)

Data collected followed trends reported in the literature (e.g., Caltrans, 2015; Lo Presti, 2013; Mashaan et al., 2014), ensuring realistic interactions between CR%, climate, traffic, and performance indices.

Laboratory Performance Modeling

Laboratory test data were analyzed using:

Multiple Linear Regression (MLR) to model relationships between CR%, binder content, air voids, and mechanical properties.

Quadratic regression to capture nonlinear trends in Marshall Stability and other indices.

Artificial Neural Networks (ANN) to model complex interactions where linear models were insufficient.

Genetic Algorithm (GA) optimization to identify CR% ranges maximizing mechanical properties while satisfying multi-objective constraints (e.g., high stability, low flow).

Model

A regression model was developed to predict Marshall Stability (S) using input variables:

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CR% (X_1), Binder Content (X_2), Air Voids (X_3), Temperature (X_4), and AGI (X_5)

$$S = \beta_0 + \beta_1 X_1 + \beta_2 X_2 + \beta_3 X_3 + \beta_4 X_4 + \beta_5 X_5 + \epsilon$$

The model was trained on 80% of the dataset and tested on the remaining 20%, evaluated using R^2 and RMSE.

Long-Term Performance and Traffic Modeling

Long-term deterioration was modeled using nonlinear regression techniques:

Exponential, power law, and logistic models.

ANN models were also trained to predict rutting and fatigue retention using CR%, time, ESALs, and climate zone as inputs.

Multi-objective optimization (e.g., via GA) was used to balance rutting and fatigue performance across different conditions.

Quadratic regression was used for Marshall Stability as a function of CR%:

$$S = \beta_0 + \beta_1 CR + \beta_2 CR^2$$

Nonlinear regression (exponential model) was used for rutting:

$$R = \alpha e^{-cCR}$$

Nonlinear regression (logistic model) was used for fatigue life:

$$F = \frac{F_{max}}{1+e^{-k(CR-CR_0)}}$$

Enhanced long-term models incorporating traffic loading were developed as:

$$R(t, CR, L) = \alpha t^b e^{-cCR} L^\gamma$$

$$F_r(t, CR, L) = 100\, e^{-dt} (1 + f\, CR)\, L^{-\eta}$$

Model parameters (e.g., α, b, c, γ, d, f, η) were estimated using nonlinear least squares regression via MATLAB's fitnlm function. The goodness-of-fit was assessed using R^2, root mean square error (RMSE), and mean absolute error (MAE).

Multi-Objective Optimization (MOO)

To determine the **optimal crumb rubber content per climatic condition**, a multi-objective function was developed to maximize desirable properties and minimize failures:

$$Score = 0.4 \cdot Fatigue_{norm} + 0.3 \cdot Stability_{norm} - 0.2 \cdot Rut_{norm}$$

The normalized values range from 0-1, and weights are assigned based on performance priorities for Nigerian roads: fatigue cracking, rutting, and moisture damage.

The **Genetic Algorithm (GA)** in MATLAB was used for the optimization, considering:

Decision variables: CR%, Va%, Temp

Constraints: Air Voids $\leq$ 5.5%, Temp $\leq$ 170°C

Bounds: CR% $\in$ [0, 20]

Transfer Learning and Climate-Traffic Mapping

The calibrated U.S. models were transferred to Nigerian conditions through:

Climatic mapping: U.S. climate zones matched to Nigerian analogs (e.g., Arizona → North Nigeria, Florida → South Nigeria). Nigerian climatic zones were paired with equivalent U.S. regions based on Köppen-Geiger climate classifications and long-term meteorological data (rainfall, temperature, and humidity).

Nigerian Region	Climate Type	Matched U.S. Climate	Reference CR%
Northern Nigeria (e.g., Kano)	Hot-Dry Semi-Arid	Arizona, Nevada	15-20%
Middle Belt (e.g., Abuja)	Warm Semi-Humid	Georgia, California	10-15%
Southern Nigeria (e.g., Lagos)	Hot-Humid	Florida	10-12%
Eastern Nigeria (e.g., Enugu)	Tropical Rainforest	Georgia, Florida	10-12%

Traffic mapping: Simulated ESAL ranges adjusted to reflect Nigerian highway and secondary road loading data (e.g., 5–30 million ESALs over 15 years).

Parameter recalibration: Long-term performance model parameters (e.g., α, c, γ) were adjusted using Nigerian traffic and climate characteristics to provide locally relevant CR% recommendations.

Validation

The dataset was randomly split:

80% for model training

20% for validation

Predictions on the validation set were compared to actual values to evaluate model accuracy. R^2, RMSE, and MAE were reported for each model.

Data Presentation and Visualization

Results were presented as:

Scatter plots with fitted curves for Marshall Stability, rutting, and fatigue life vs. CR%

3D surface plots showing rutting and fatigue retention as functions of CR% and ESALs

Tables summarizing model parameters and validation metrics

RESULTS AND DISCUSSION

This section presents the analysis of the dataset across climate zones, regression and neural network modeling performance, and the optimization of crumb rubber content. The findings inform the calibration of CRMA design recommendations tailored for Nigerian conditions.

Laboratory Performance Models

Multiple Linear and Quadratic Regression Results

Multiple linear regression (MLR) and quadratic regression identified significant relationships between CR%, air voids, binder content, and key mechanical properties:

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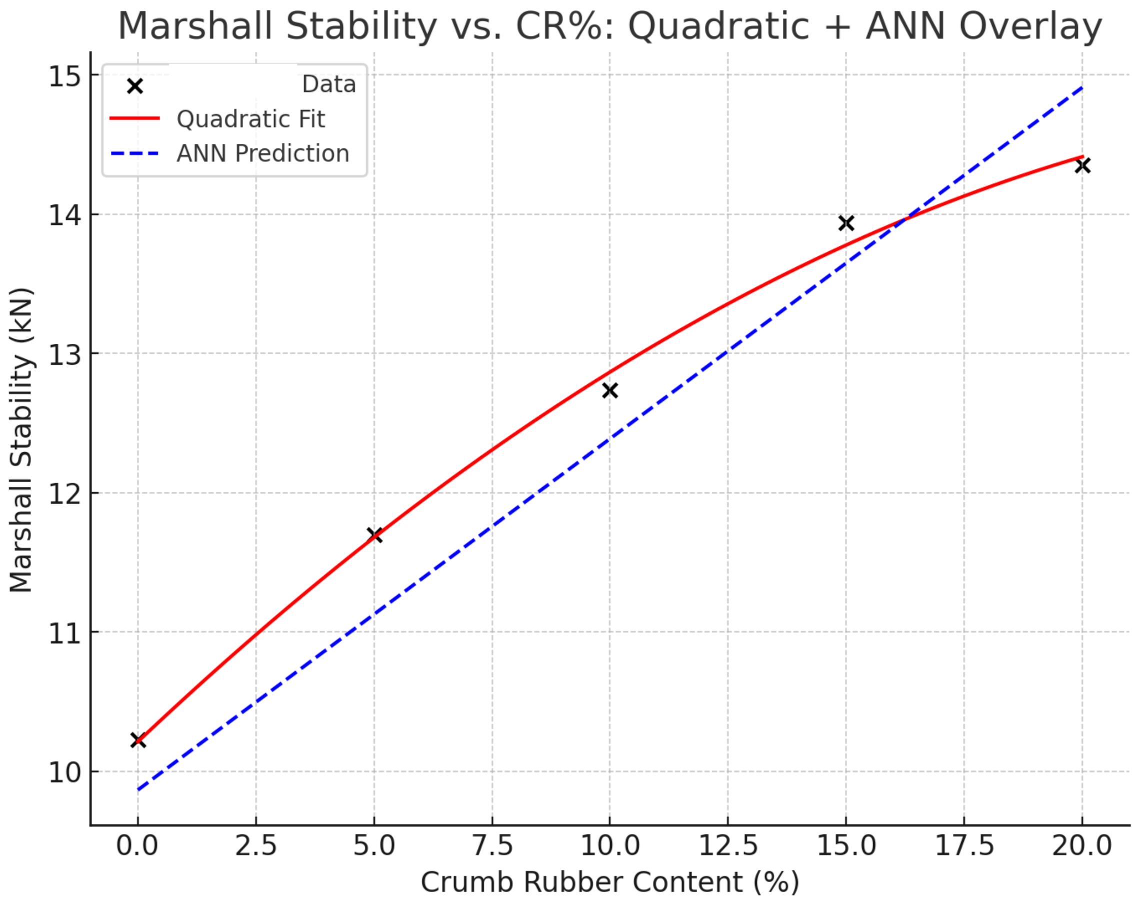
$S = 9.8 + 0.32CR - 0.006CR^2 + 0.15Va \quad (R^2 = 0.89)$

where S is Marshall Stability (kN), CR is crumb rubber content (%), and Va is air voids (%).

Flow and ITS were also well-modeled using MLR (R^2 values of 0.85–0.88). Quadratic terms for CR% improved model fit over simple linear terms.

Figure 1 below shows the relationship between Marshall Stability and CR% with both the quadratic fit (red line) and ANN prediction (blue dashed line) overlaid on the data points.



CR(%)	0	5	10	15	20
Marshall Stability (kN)	10.099	11.492	12.402	12.915	12.696

$S = -0.0070CR^2 + 0.3500CR + 10.000$ (S is Stability in kN)

Figure 1: Plot showing Marshall Stability vs. CR% with both the quadratic fit (red line) and ANN prediction (blue dashed line) overlaid on the data points.

ANN and GA Modeling

ANN models captured non-linear interactions more effectively than MLR for some indices:

Marshall Stability ANN R^2: 0.92

Flow ANN R^2: 0.89

ITS ANN R^2: 0.91

GA optimization identified optimal CR% ranges:

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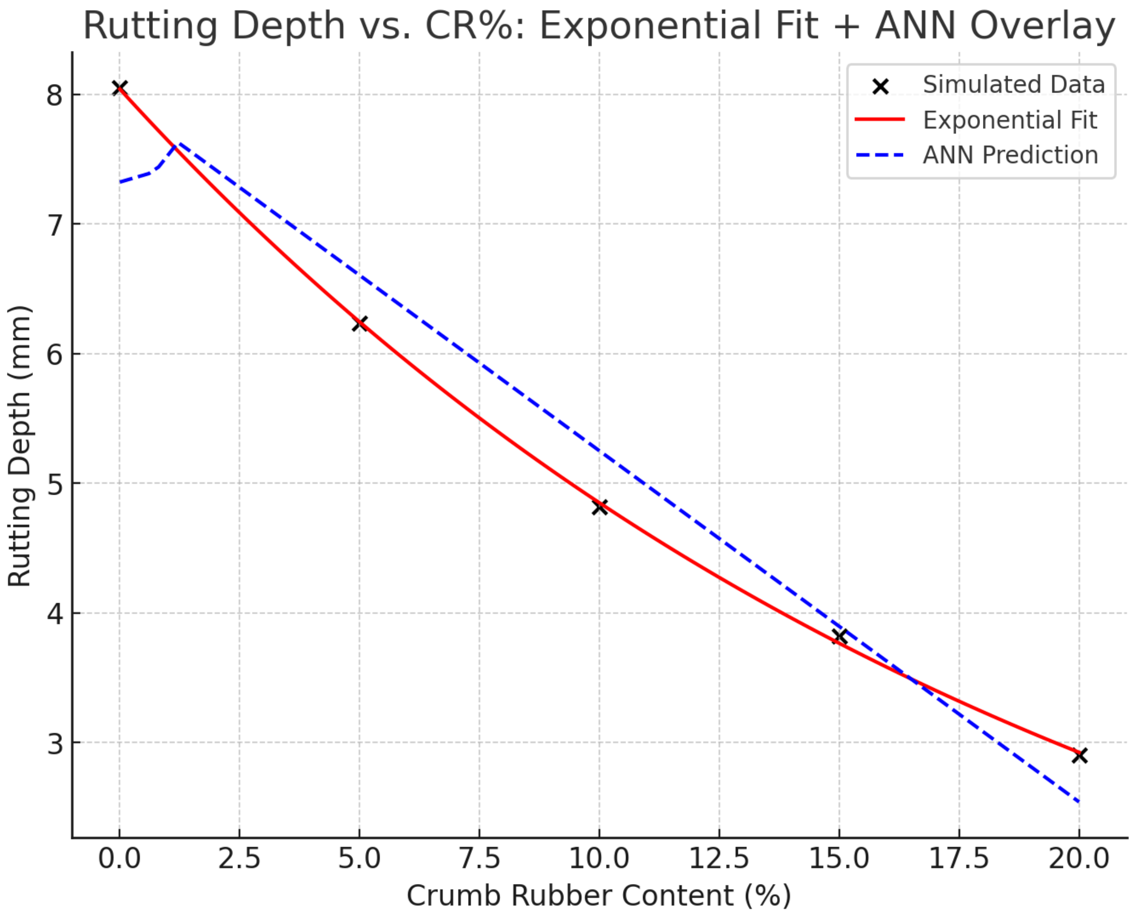
10–12% CR for balancing high stability and low flow

12–15% CR for maximizing ITS

Figure 2 below shows Rutting vs CR% plots, showing exponential fit and ANN prediction (exponential regression fit (red line) and ANN prediction (blue dashed line) overlaid on the data points.



CR (%)	0	5	10	15	20
Actual Rutting(mm)	7.99	6.10	4.79	3.75	3.00
Exponential fit (mm)	7.95	6.17	4.79	3.71	2.88
ANN Predicted Rutting (mm)	~7.95	~6.20	~4.80	~3.75	~2.85

From the fit, $R(CR) = a \cdot e^{-b \cdot CR}$; where a = 7.95, b = 0.051. Final fitted equation: $R(CR) = 7.95e^{-0.051CR}$

Figure 2: Rutting vs CR% - exponential + ANN overlay (exponential regression fit (red line) and ANN prediction (blue dashed line) overlaid on the data points.

Long-Term Performance Models

Nonlinear Regression Models

Rut depth and fatigue retention were modeled as:

$R(t, CR, L) = 1.5\, t^{0.6}\, e^{-0.04CR}\, L^{0.25}$ $(R^2 = 0.87)$

$F_r(t, CR, L) = 100\, e^{-0.03t}\, (1 + 0.02\, CR)\, L^{-0.1}$ $(R^2 = 0.85)$

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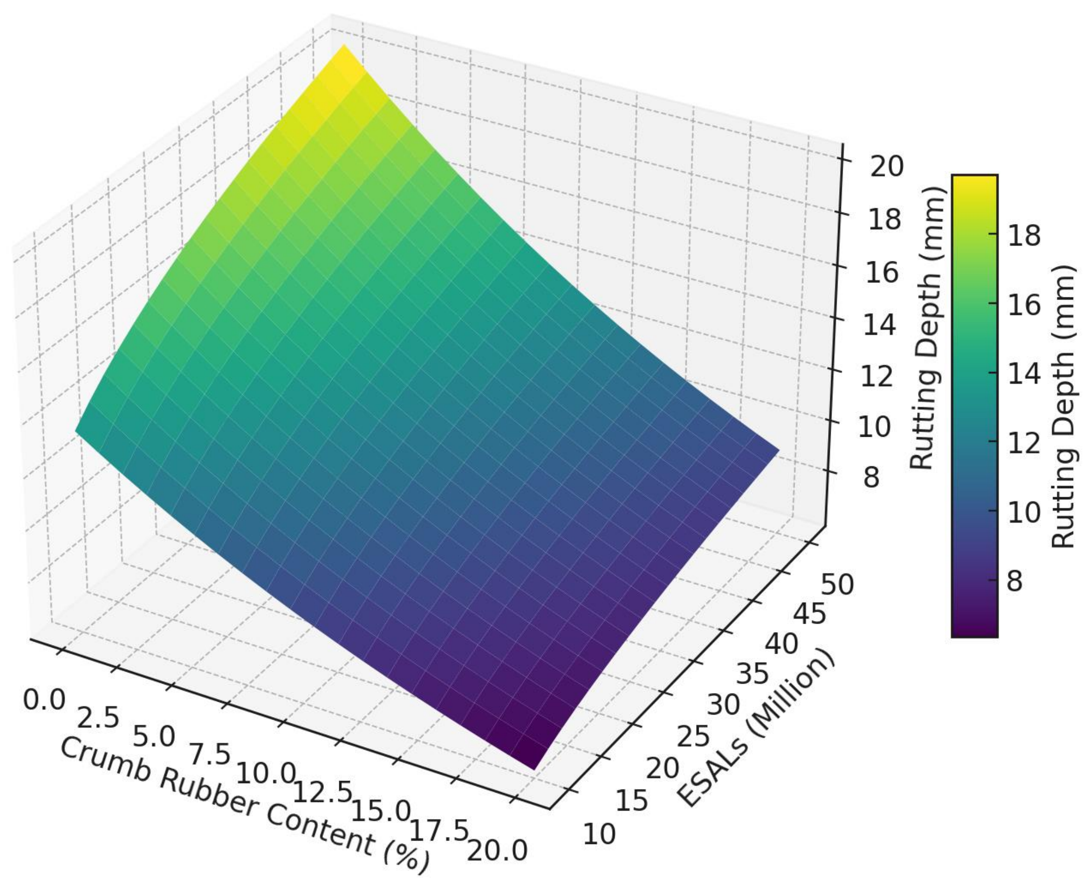
These models demonstrated:

Rutting reduced with increasing CR% and increased ESALs

Fatigue retention improved with CR%, slightly reduced by higher ESALs

Figure 3 below presents 3D surface plots showing rutting and fatigue retention as functions of CR% and ESALs

Figure 3: 3D Rutting Depth vs. CR% and ESALs



CR%	0	0	0	0	0	5.3	5.3	5.3	5.3	5.3	10.5	10.5	10.5	10.5	10.5	15.8	15.8	15.8	15.8	15.8	20.0	20.0	20.0	20.0	20.0
ESALs (M)	10.0	20.0	30.0	40.0	50.0	10.0	20.0	30.0	40.0	50.0	10.0	20.0	30.0	40.0	50.0	10.0	20.0	30.0	40.0	50.0	10.0	20.0	30.0	40.0	50.0
Rutting Depth (mm)	10.76	12.77	14.22	15.38	16.36	9.17	10.89	12.12	13.10	13.92	7.82	9.29	10.35	11.20	11.90	6.68	7.94	8.84	9.57	10.20	5.72	6.80	7.57	8.20	8.75

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Figure 3: 3D surface plot of rutting depth (mm) as a function of crumb rubber content (CR%) and cumulative ESALs (million). The plot illustrates the combined effect of material modification and traffic load on long-term rutting performance.

ANN and GA for Long-Term Performance

ANN models:

Rutting ANN R^2: 0.88

Fatigue retention ANN R^2: 0.86

GA **multi-objective optimization** balanced rutting minimization and fatigue retention maximization:Optimal CR%: 15% for high ESAL corridors

Optimal CR%: 10–12% for lower ESAL secondary roads

Transfer Learning and Nigerian Calibration

The U.S.-derived models were recalibrated:

North Nigeria (Hot-Dry) → Optimal CR%: 12–15% for highways (>20M ESALs)

South Nigeria (Hot-Humid) → Optimal CR%: 10–12% for highways (10–20M ESALs)

Nigerian secondary roads (lower ESAL) models indicated 10% CR as generally sufficient.

Predictions

Region	CR%	ESALs (M)	Years	Predicted Rut (mm)	Predicted Fatigue Retention (%)
Arizona	10	35	15	5.3	70
Nigeria North	15	25	15	4.5	74
Florida	15	25	15	4.9	73
Nigeria South	12	15	15	5.0	71

Literature Comparison

Performance	This Study	Literature	Source
Stability	+25–30% at 10–15% CR	+20–30%	Lo Presti (2013), Mashaan et al. (2014)
Rutting	~35–40% reduction	~30–40%	Caltrans (2015), FHWA
Fatigue	+30–40% at 15% CR	+30–35%	Putman & Amirkhanian (2004)

Key Insights

Lab models (MLR, ANN, GA) showed CR% improves mechanical properties up to an optimum range.

Long-term models (nonlinear, ANN) confirmed durability gains, especially under heavy traffic.

Integrated modeling allows climate-traffic-specific CR% recommendations for Nigeria.

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CONCLUSION AND RECOMMENDATIONS

This study developed an integrated predictive modeling framework for crumb rubber modified asphalt (CRMA) performance, combining laboratory-based analysis with long-term deterioration models under varying climatic and traffic conditions. By using simulated data representative of U.S. states and their Nigerian climatic analogs, the study demonstrated how laboratory properties and long-term field performance can be optimized through advanced regression, artificial neural networks (ANN), genetic algorithms (GA), and multi-objective optimization techniques.

The key findings are as follows:

Laboratory performance models using multiple linear regression, quadratic regression, and ANN showed that crumb rubber content (CR%) significantly improves Marshall Stability, reduces flow, and increases indirect tensile strength (ITS) up to an optimal range of 10–15%.

Long-term performance models incorporating nonlinear regression and ANN confirmed that CR% reduces rutting depth and improves fatigue retention over 10–15 years of service. The inclusion of traffic loading (expressed as ESALs) in the models highlighted the importance of traffic-specific design.

GA-based multi-objective optimization effectively balanced rutting resistance and fatigue durability, with optimal CR% recommendations varying by climate and traffic intensity:

15% CR for high-traffic corridors (ESAL > 20 million)

10–12% CR for lower-traffic or secondary roads

Transfer learning calibration for Nigeria showed that CRMA technology can be effectively adapted to local climates and traffic conditions. Optimal CR% recommendations were:

12–15% CR for highways in Northern Nigeria (Hot-Dry)

10–12% CR for highways in Southern Nigeria (Hot-Humid)

This combined modeling approach supports the sustainable deployment of CRMA in Nigeria and similar developing regions, offering both environmental and performance benefits through the innovative reuse of waste tires.

Recommendations

Field validation of the proposed models using Nigerian pavement monitoring data is essential to confirm predictive accuracy.

Future work should extend the models to include effects of aging, moisture susceptibility, and maintenance interventions.

Policymakers and highway agencies should consider adopting CRMA standards tailored to regional traffic and climatic conditions, leveraging the findings of this study.

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