Engineering and Technology Journal e-ISSN: 2456-3358

Volume 10 Issue 05 May-2025, Page No.- 5005-5023

DOI: 10.47191/etj/v10i05.29, I.F. – 8.482

Integrating Extreme Vertices Design and Genetic Algorithm to Enhance the Moisture Resistance of Bituminous Concrete Modified with Recycled High-Density Polyethylene

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ABSTRACT: This study combined Extreme Vertices Design (EVD) and Genetic Algorithm (GA) to improve the moisture resistance of HDPE-modified bituminous concrete by enhancing its tensile strength ratio (TSR). EVD was employed for mixture design, sensitivity analysis, and model development using regression techniques, which were validated through F-statistics, R^2, and mean absolute percentage deviation (MAP.D). GA was used to optimize the mixture components to further enhance the TSR. The TSR of HDPE-modified mixtures ranged from 82.73% to 95.82%, surpassing the ASTM and AASHTO thresholds, while the unmodified mixture had a TSR of 82.43%. HDPE-modified mixtures met or exceeded the 80% TSR requirement, with several exceeding 85%. The analysis identified key interactions, such as the positive effect of granite content on TSR and the negative impact of excess sand and bitumen. Optimal HDPE content was found to improve TSR up to a certain point, beyond which it reduced the mixture's cohesion. ANOVA indicated significant interactions between granite, bitumen, and HDPE in influencing TSR. The regression model demonstrated high predictive capability with an R^2 of 93.27% and a low MAP.D of 0.74%, confirming its adequacy. GA optimization yielded a TSR of 97.88%, significantly improving upon the unmodified mixture's performance. The optimized mixture, with specific proportions of granite, sand, bitumen, and HDPE, surpassed ASTM and AASHTO standards, showing the effectiveness of HDPE in enhancing both performance and sustainability in asphalt mixtures.

KEYWORDS: Extreme Vertices Design, Genetic Algorithm, High Density Polyethylene, Bituminous Concrete, Tensile Strength Ratio

1. INTRODUCTION

The growing environmental burden posed by plastic waste, particularly high-density polyethylene (HDPE), has prompted increasing interest in sustainable construction practices. In the field of flexible pavements, the integration of recycled HDPE into bituminous mixtures presents a promising strategy for both waste valorization and performance enhancement (Transportation Research Board, 2023; Al-Mansour & Al-Hadidy, 2023). Beyond environmental benefits, HDPE-modified asphalt mixtures have demonstrated improved resistance to moisture damage, one of the primary causes of premature pavement deterioration (Hamedi, 2023). This enhancement is attributed to the modification of surface chemistry at the asphalt-aggregate interface, which reduces surface free energy and increases hydrophobicity, thereby improving adhesion and minimizing moisture susceptibility (Hamedi, 2023; Kumar & Gupta, 2024). Furthermore, the inclusion of HDPE contributes to superior mechanical properties such as increased stiffness, rutting resistance, and fatigue life, all critical to pavement durability (Al-Mansour & Al-Hadidy, 2023). The recyclability of HDPE-modified asphalt mixtures also supports circular economy principles, allowing reclaimed materials to be reused without compromising structural integrity (Kumar & Gupta, 2024). As research continues to evolve, the use of recycled HDPE in asphalt mixtures not only aligns with sustainability goals but also offers tangible improvements in pavement performance (Lee & Kim, 2024; Sarang & Dalhat, 2024).

While HDPE offers potential performance gains in asphalt mixtures, identifying the optimal mixture proportions remains a complex challenge due to component constraints and nonlinear interactions. The Extreme Vertices Design (EVD) is particularly well-suited for mixture experiments with constrained variables, as it effectively maps the boundaries of the feasible formulation space (Zhao et al., 2021). EVD enables efficient exploration of the design space, focusing on extreme formulations where material performance is most likely to differ. Recent studies have applied EVD to optimize composite materials, demonstrating its efficacy in identifying optimal combinations within specified constraints (Abdel-Raheem et al., 2023). For example, Bakare et al. (2020) employed EVD in developing polymer-modified bituminous mixtures and found that this design approach significantly improved the prediction of mechanical properties under varying additive concentrations. Similarly, Al-Busaltan et al. (2022) applied EVD to evaluate the moisture sensitivity of polymer-asphalt composites, concluding that the design facilitated a more accurate representation of interactive effects among mix constituents. Moreover, Asif et al. (2023) emphasized the importance of EVD in sustainable pavement design, highlighting its utility in balancing recycled plastic content with durability and workability requirements. These findings support the growing consensus that EVD offers a robust framework for optimizing recycled material blends in flexible pavements.

To complement EVD's experimental efficiency, Genetic Algorithms (GAs) provide a robust optimization framework capable of handling nonlinear, multi-objective, and constrained design problems. Inspired by the principles of natural selection, GAs iteratively evolve a population of solutions, converging on optimal or near-optimal outcomes through operations such as selection, crossover, and mutation (Aly et al., 2022). In pavement engineering, GAs have been successfully applied to optimize mix designs incorporating recycled and warm-mix additives, achieving improved trade-offs between mechanical performance, durability, and sustainability metrics (Zhang et al., 2021). Moreover, hybrid models combining GAs with other computational techniques, such as artificial neural networks (ANNs) and response surface methodology (RSM), have been developed to predict and enhance the resilient modulus of fiber-reinforced asphalt concrete, showcasing the adaptability of GAs in managing complex interactions among mix components (Zhang et al., 2021). Recent work by Khalid et al. (2020) further demonstrates the potential of GA-ANN hybrids in predicting fatigue life and rutting performance in modified asphalt mixes. Similarly, Ghafoori and Kouchaki (2019) employed GAs in optimizing warm-mix asphalt compositions to minimize environmental emissions without compromising mechanical behaviour, reaffirming the algorithm's practicality in sustainable pavement material design.

This study thus, aims to integrate EVD and GA to optimize the formulation of recycled HDPE-modified bituminous concrete with respect to moisture resistance, as measured by tensile strength ratio (TSR). By combining design of experiments with intelligent optimization, the research seeks to identify the most effective blend of constituents to enhance durability, promote sustainability, and advance the performance of modified asphalt concrete pavements.

1.1 Extreme Vertices Design of Mixture Design Theory

Mixture design theory is employed when the response of interest is influenced by the relative proportions of components in a mixture, rather than their absolute amounts. Traditional factorial or response surface designs are not directly applicable due to the constraint that the sum of mixture components is typically fixed (e.g., to 1 or 100%) (Kristoffersen & Smucker, 2020).

Let $z_1, z_2..., z_q$ represent the proportions of q mixture components, then:

$$\sum_{i=1}^{q} z_i = 1; \quad 0 \leq z_i \leq 1 \qquad (1)$$

This constraint, Equation (1), defines a (q−1)-dimensional simplex within which feasible mixtures exist.

Extreme Vertices Design (EVD) is a specific approach used when the component proportions are further restricted by upper and/or lower bounds. The design space is no longer a regular simplex but an irregular polytope. EVD efficiently selects design points located at the "extreme vertices" or corners of this feasible polytope (Kristoffersen & Smucker, 2020). These extreme vertices represent compositions where the response is expected to vary the most, allowing for efficient model fitting.

For a mixture experiment with q, number of mixture components, $z = (z_1, z_2, \dots z_q)^T$, mixture vector (proportions of each mixture component), $L_i \leq z_i \leq U_i$, the range of each component with, L_i and U_i, being the lower and upper bound respectively, Equation (2) represents the general equation for the feasible region.

$$\chi = \{z \in R^q | \sum_{i=1}^{q} z_i , \ L_i \leq z_i \leq U_i, \ \forall i = 1, 2, \dots . q\} \qquad (2)$$

The feasible region, χ defined by the above constraints forms a convex polytope (a multidimensional polygon). The Extreme Vertices Design uses the vertices of this polytope as the design points, as presented by Equation (3)

$$\curlyvee = \{z^{(1)}, z^{(2)}, \dots \dots z^{(n)}\} \qquad (3)$$

Where, $x^j \in \chi$, are the extreme points that satisfy all the constraints and the mixture condition $\sum z = 1$. Figure 1 is a 2D representation of a three-mixture component EVD, with the feasible region explicitly shown.

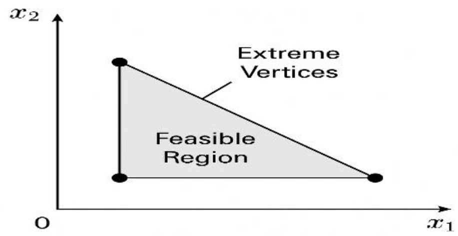

Figure 1. Simplex Plot for a three-mixture EVD

The most common response surface model fitted to EVD data is the Scheffe’s canonical polynomial models. For a second-degree model (quadratic), Scheffe’s polynomial model is presented by Equation (4)

$$Y = \sum_{i=1}^{q} \beta_i z_i + \sum_{i<j}^{q} \beta_{ij} z_i z_j + \epsilon \quad (4)$$

Where; Y is the response variable, βi are the linear coefficients, βij are the interaction coefficients, and ϵ is the random error term.

1.2 Genetic Evolutionary Algorithm for Optimization

Genetic Algorithms (GAs) are optimization techniques inspired by the principles of natural selection and genetics, as outlined by Charles Darwin. They use processes such as selection, crossover (recombination), and mutation to evolve solutions toward an optimal or near-optimal solution. GAs are especially useful for solving complex problems with large, non-linear, or discontinuous solution spaces, where traditional optimization methods often struggle (Sivanandam & Deepa, 2023).

The basic idea of GAs is to maintain a population of candidate solutions and evolve this population over successive generations. Each candidate solution (or chromosome) is evaluated using a fitness function that measures how good the solution is in terms of the optimization goal. GAs have been successfully applied in various fields, including engineering, machine learning, bioinformatics, and software optimization (Huang et al., 2024). Their ability to handle both continuous and discrete optimization problems and their robustness against local minima make them highly versatile (Mirjalili & Lewis, 2019; Sivanandam & Deepa, 2023).

Before the application of GAs, there must be fitness function (Equation 5), where the goal is to minimize an objective (fitness) function f(z), subject to constraints on the solution space S.

$$fitness\ function = min\ f(z)_{x \in S} \quad (5)$$

Where, $z = [z_1, z_2, \dots . z_n]$ is a candidate solution (or chromosome), representing the decision variables of the optimization problem, $f(z)$ is the fitness function that evaluates how good a solution z is and S is the feasible solution space, which could be continuous, discrete, or a combination of both.

Below are the steps involved in the application of GA for optimization;

1. Initialization; The GA process begins with the creation of an initial population of candidate solutions, often generated randomly to ensure diversity. Each individual in the population represents a potential solution to the fitness function. Let P_0 (Equation 6) be the initial population consisting of n individuals:

$$P_0 = \{z_1, z_2, \dots . z_n\} \quad (6)$$

Evaluate the fitness of each chromosome xi in the population using the fitness function $f(z_i)$.

2. Selection; During the selection phase of a genetic algorithm, individuals are chosen to serve as parents for the next generation based on their fitness scores. This process aims to favour the selection of individuals with higher fitness (i.e., superior solutions) over those with lower fitness levels. Various selection strategies exist to accomplish this, including Roulette Wheel Selection (RWS) and Tournament Selection (TS) (Rawat et al., 2022). In the RWS approach, an individual's chance of being selected is directly proportional to its fitness value, as defined in Equation (7).

$$p_i = \frac{f(z_i)}{\sum_{j=1}^{n} f(z)_i} \quad (7)$$

Where, $f(z_i)$ = fitness of individual z_i, $\sum_{j=1}^{n} f(z)_i$ = total fitness of the population

3. Crossover (Recombination); Crossover combines genetic information from pairs of parent individuals to produce offspring. This process introduces new genetic structures into the population, facilitating the exploration of the solution space. In single-point crossover, a random crossover point is chosen, and the parents' genetic material is exchanged at this point to create two offspring. If parent chromosomes are represented as binary strings, then:

$$Parent_1 = [z_1^{(1)}, z_2^{(1)}, \dots, z_c^{(1)}, z_{c+1}^{2}, \dots . z_n^{2}] \quad (8a)$$

$$Parent_2 = [z_1^{(2)}, z_2^{(2)}, \dots, z_c^{(2)}, z_{c+1}^{1}, \dots . z_n^{1}] \quad (8b)$$

Where, c is the crossover point. This operation creates two new offspring, $Child_1$ and $Child_2$

4. Mutation; Mutation introduces random changes to an individual chromosome with a low probability, μ. This helps maintain diversity in the population and prevents premature convergence to local minima. For an individual zi= $[z_1, z_2 \dots zn]$, mutation changes one of its genes, say z_k, by a small value δ, which is usually sampled from a uniform distribution (Equation 9).

$$z_k' = z_k + \delta,\ \delta \sim \mathcal{U}\ (-€,\ €) \quad (9)$$

Where; z_k' is the mutated gene, $\mathcal{U}$ (-€, €) is the uniform random distribution within the defined range, [-€, €]. The mutation probability $\mathcal{U}$, is typically set to a small value typically between, 0.01 to 0.1.

5. Replacement; After generating offspring through crossover and mutation, the new individuals replace some or all of the current population, depending on the replacement strategy. This step ensures the evolution of the population over successive generations (Huang et al., 2024).
6. Termination; The algorithm iteratively repeats the evaluation, selection, crossover, mutation, and replacement steps until a termination condition is met. Common termination criteria include reaching a maximum number of generations or achieving a satisfactory fitness level.

2. MATERIALS AND METHODS

2.1 Design of Research

This paper is structured into two main parts. The first part focuses on the experimental phase, where the Extreme Vertices Design (EVD) approach was utilized to formulate the experimental design for assessing the moisture resistance of high-density polyethylene (HDPE) modified bituminous concrete. A mixture regression model was subsequently developed based on the EVD, and sensitivity analysis was performed using response trace plot, 3D surface plot and ANOVA statistics to examine the influence of the mixture components and their interaction on moisture resistance. The second part of the study involves the application of a genetic algorithm, implemented in MATLAB, to optimize and improve the moisture resistance of the HDPE modified bituminous concrete.

2.2 Materials

The major materials used in this research are; Aggregates; granite of maximum size 12.5mm, and fine river sand, bitumen of PEN grade 60/70, and high-density polyethylene (HDPE) waste plastics.

1. **Aggregates**; Granite with a maximum particle size of 12.5 mm was utilized as the coarse aggregate. It was sourced from a local construction materials store in Choba, Port Harcourt, with the supplier indicating that the material originally came from the Akamkpa quarry site in Calabar. Fine river sand served as the fine aggregate in this study. It was collected from a sand fill site along the New Calabar River in the Choba area. Following collection, the sand was dried and sieved through a 4.75 mm mesh to remove dirt and other impurities. The properties of the aggregates are as summarized in Table 1. According to Table 1, both aggregates meet the requirements for uniform grading, with their coefficients of uniformity (Cu) and coefficients of curvature (Cc) falling within the acceptable range. The fineness modulus values were 4.25 for the granite and 3.54 for the sand, indicating the sand's appropriateness for construction use. Specific gravity measurements yielded values of 2.77 for the granite and 2.43 for the river sand.

Table 1. Properties of Aggregates

Properties	Classification Parameter	Description	Specification/ Code
1. **Gradation**		Both aggregates are classified as uniformly graded because Cu < 6 for fine river sand and Cu < 4 for granite	ASTM (2006)
Granite	$Cu = 1.82$, $Cc = 0.82$		
Fine River sand	$Cu = 3.947$, $Cc = 1.12$		
2. Zone of River sand	Zone II	Suitable for construction purposes	IS: 383-(1970)
3. **Fineness Modulus**			
Granite	Fineness modulus = 4.25	-	IS:2386-(1963)
Fine River Sand	Fineness modulus = 3.54	Coarse sand (Ok for construction purposes)	
3. **Specific gravity**			
Granite	$Gs = 2.77$	-	ASTM C128 (2015)
Fine River sand	$Gs = 2.43$		

2. **Bitumen**; Bitumen, commonly referred to as asphalt cement, was utilized as the primary binder in the preparation of the bituminous mixtures. It served as the base material into which HDPE was incorporated. The bitumen used in this study was of the 60/70 penetration grade and was procured from a reputable supplier at the

Mile 3 market in Port Harcourt. According to the supplier, the bitumen possessed a specific gravity of 1.09, a softening point of 53°C, a penetration value of 68, and a flash point temperature of 250°C.

3. **HDPE**; Waste oil plastic containers, identified as high-density polyethylene (HDPE), were used as the HDPE material in this study. The waste HDPE oil cans were collected from a mechanic workshop located in Choba, Port Harcourt. After collection, the plastics were thoroughly washed and shredded to facilitate easier melting during the production of the bituminous mixtures. The chemical formula of HDPE is $[C_2H_4]n$ as obtained Abdulfatai et al. (2024). The shreded HDPE is shown in Plate 1.

Plate 1. Pulverized HDPE

2.3 Methods

2.3.1 Preliminary Investigation

1. **Determination of Optimum Aggregate Blend (OAB);** The analytical or formula method of aggregate blending was applied to combine fine river sand and granite, using linear programming techniques via Excel Solver. The particle size distribution of both materials was compared to the standard job mix specifications outlined by FMWH (2016). The general equation for blending two aggregates is presented in Equation (10).

$$aA + bB = P \tag{10}$$

In this context, a and b denote the proportions of two different aggregate types, granite (A) and fine river sand (B), that pass through a specific sieve size. P represents the resulting gradation from the combined aggregates passing that sieve, which should either meet the specified job mix formula or align as closely as possible with the midpoint of the target range. A key constraint is that the sum of the optimal proportions (a and b) must equal 1, as expressed in Equation (11).

$$a + b = 1 \tag{11}$$

For n number of sieve sizes, Equation (10) becomes;

$$\left.\begin{array}{l} aA_1 + bB_1 = P_1 \\ aA_2 + bB_2 = P_2 \\ aA_3 + bB_3 = P_3 \\ \quad \cdot \\ \quad \cdot \\ aA_n + bB_n = P_n \end{array}\right\} \tag{12}$$

Manually solving Equation (12) to determine values for a and b is highly challenging. Effective computer programs are necessary for this task. Therefore, software such as Excel's Solver was used to obtain the OAB. These steps were followed during the optimization of OAB using excel solver;

i. The mid-point of the specified job mix for each sieve size was determined
ii. Sieve analysis was conducted on the different aggregates to obtain the gradation (percent finer than each) of the considered sieve size
iii. An initial or arbitrary value of a and b depending on the number of aggregates considered in that category was chosen
iv. Equation (10) was then applied to obtain the grading (P) for each of the considered sieve size
v. The difference between P and the mid-point of the job mix was calculated for the different sieve sizes
vi. These differences were then squared to obtain the square of differences (SD)
vii. The sum of squares of these differences (SSD) was then obtained
viii. Then finally excel solver was then employed for optimization process with;

the Objective function; Minimizing (SSD)
By changing variables; A and B
Subjecting to constraints; $a + b = 1$

$a, b, A, B \geq 0$

These steps were strictly followed in obtaining the optimum aggregate blend of dense asphalt concretes produced. On optimization, proportion of A was obtained as 54.5 % (a) and that of B as 45.5 % (b). The resulting blend aligns with the specified job mix formula, as clearly shown in Figure 1.

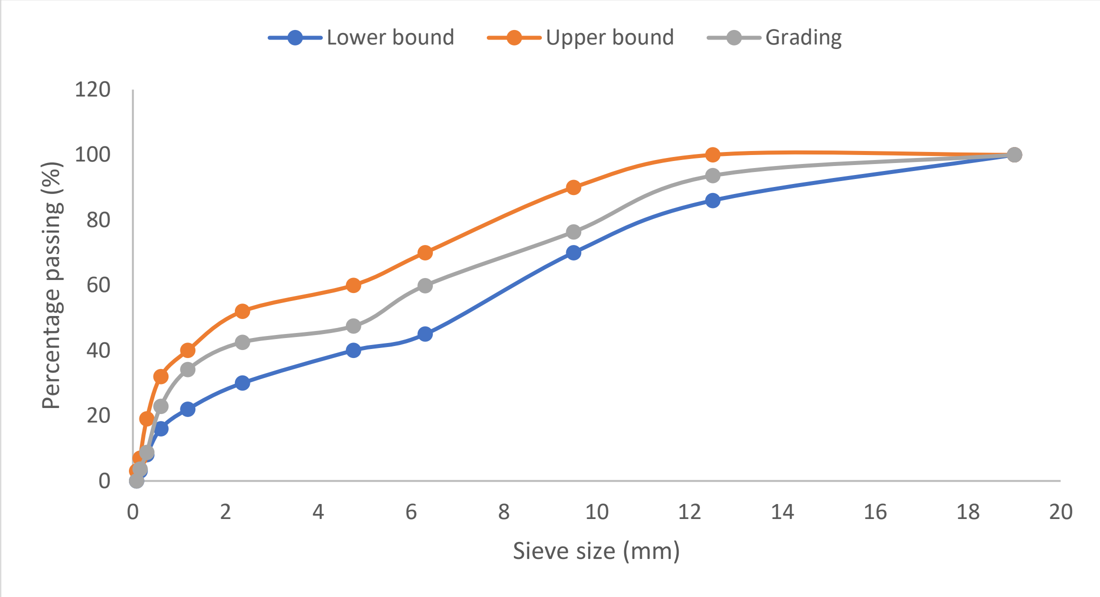

Figure 1. Gradation curves for OAB in Accordance to FMWH (2016)

2. **Determination of Optimum Bitumen Content (OBC);** The preliminary wet mix design employed the Marshall standard procedure to determine the optimum bitumen content. Specimens were compacted with 50 blows on each face, appropriate for medium traffic conditions, using a compaction hammer with a 450 mm free fall. Samples were prepared at a standard temperature of 60°C before undergoing density-void analysis and stability-flow testing. The bitumen content was initially set between 4% and 6% of the total mix weight, with the determined optimum aggregate blend (OAB) adjusted accordingly. For each subsequent trial, the bitumen content was increased by 0.5%, and the process was repeated. Graphical plots based on density-void analysis and stability-flow results were used to identify the optimum bitumen content (OBC) for the unmodified bituminous concrete mixtures, focusing on the relationships between bitumen content and corrected Marshall stability, voids in total mix (VTM), and unit weight, as illustrated in Figures 2 to 4. On application of Equation (13), the OBC was obtained as 5.95%, forming the basis for the main experimental mix design.

$$B_0 = \frac{B_1 + B_2 + B_3}{3} \tag{13}$$

Where; B_0 = Optimum Bitumen Content, B_1 = Percent bitumen content at maximum stability, B_2 = Percent bitumen content at maximum unit weight, B_3 = Percent bitumen content at 4% air voids in the total mix.

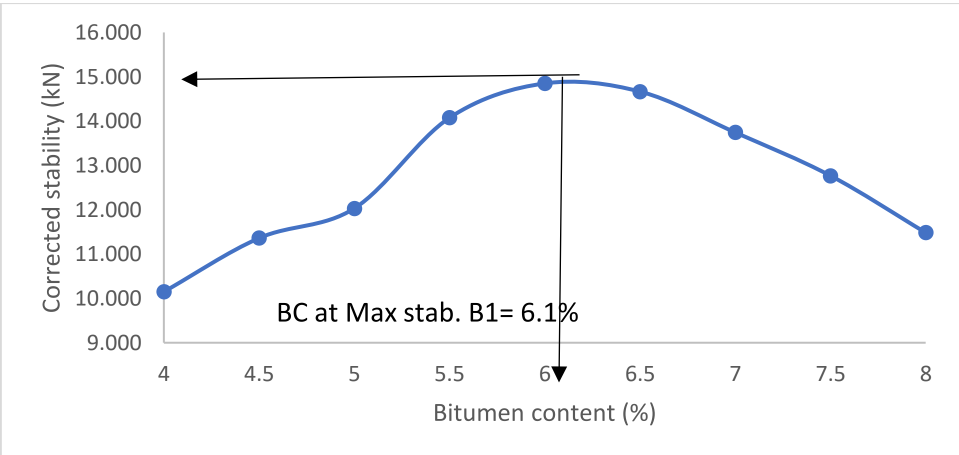

Figure 2. Corrected Stability vs % bitumen of unmodified bituminous mixtures

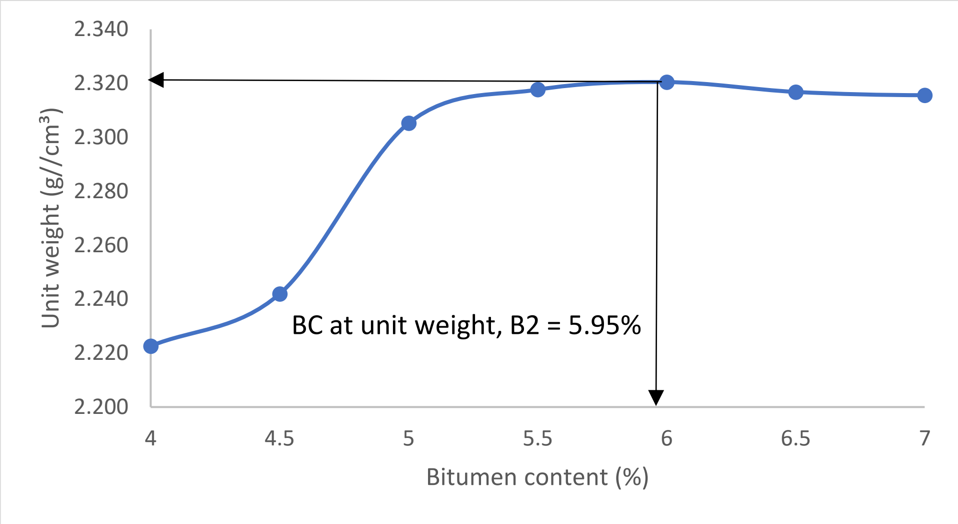

Figure 3. Unit weight vs % bitumen of unmodified bituminous mixtures

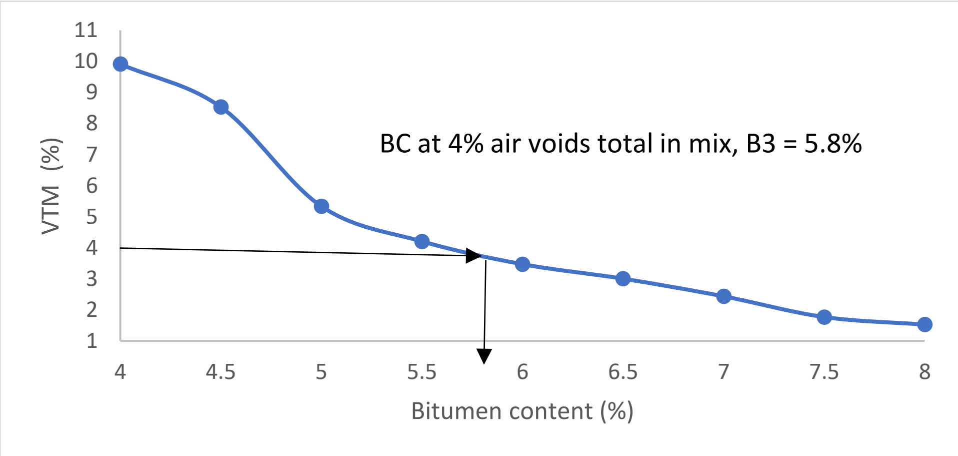

Figure 4. Percent air voids, VTM vs % bitumen of unmodified bituminous mixtures

2.3.2 Main Experimental Procedures

1. Extreme Vertices Design (EVD) Formulation for HDPE modified Bituminous Concrete

In designing the experiment for HDPE-modified bituminous mixtures, HDPE was incorporated as a partial replacement for bitumen. The optimum mix proportions for the unmodified bituminous concrete were determined to be 5.95% bitumen, 51.26% granite, and 42.79% fine river sand by total mix weight. Based on prior experience and previous studies, polymers like HDPE can replace up to 10% of the bitumen content, corresponding to about 0.6% of the total mix weight. With the addition of HDPE, it was assumed that the proportions of other constituents, such as granite and sand, might also be influenced. Accordingly, HDPE content was varied between 0 and 0.6% of the total mix, while bitumen content ranged from 5.35% to 5.95%. Granite content was adjusted between 51.26% and 51.58%, and sand content varied from 42.79% to 43.07% by total mix weight. The specified constraints for selecting mixture proportions are presented in Table 2. Using these bounds, Minitab software generated 15 different mixture designs for the HDPE-modified bituminous concrete, as shown in Table 3. The mixture proportions adhered to the constraint outlined in Equation (1).

Table 2. HDPE-modified Bituminous Concrete Mixtures Boundary Specifics for EVD Development

Constraints	Materials/constituents			
	Granite (%)	Sand (%)	Bitumen (%)	HDPE (%)
Lower bound	51.26	42.79	5.35	0
Upper bound	51.58	43.07	5.95	0.6

Table 3. EVD for HDPE-modified Bituminous Concrete Mixtures

Run order	Granite (%)	Sand (%)	Bitumen (%)	HDPE (%)
1	51.48857	42.85	5.435714	0.225714
2	51.48857	42.99	5.435714	0.085714
3	51.32857	42.99	5.435714	0.245714
4	51.48857	42.85	5.575714	0.085714
5	51.26	42.79	5.35	0.6
6	51.26	43.07	5.67	0
7	51.32857	42.85	5.735714	0.085714
8	51.26	42.79	5.95	0
9	51.39714	42.91	5.521429	0.171429
10	51.26	43.07	5.35	0.32
11	51.32857	42.85	5.435714	0.385714
12	51.58	43.07	5.35	0
13	51.58	42.79	5.63	0
14	51.58	42.79	5.35	0.28
15	51.32857	42.99	5.595714	0.085714

2. Production of HDPE modified Bituminous Concrete Samples

HDPE modified bituminous concrete specimens were prepared in accordance to the Marshall mix design procedure (ASTM D6927, 2015) and compacted with 50 blows on each face, appropriate for medium traffic conditions, using a compaction hammer with a 450 mm free fall. In preparing the samples, the aggregates, measured according to the developed EVD, were heated to 180°C, while the bitumen and HDPE were combined and heated to 140°C. These heated components were then thoroughly mixed at 180°C until a homogeneous mixture was achieved. This mixture was then placed into a preheated mold and compacted using a rammer with 50 blows on each side, at a temperature between 140°C and 150°C. specimens were preheated to 60°C, placed in a Marshall testing machine, and subjected to moisture resistance testing at a constant strain rate of 50.8 mm per minute. Plate 2 presents a cross section of some prepared HDPE modified bituminous concrete samples.

Plate 2. Samples of produced HDPE modified Bituminous Concrete

3. Moisture Resistance Testing of HDPE modified Bituminous Concretes

The moisture resistance of prepared HDPE modified bituminous concrete samples was determined through measurement of tensile strength ratio (TSR). Tensile strength ratio is evaluated by comparing the tensile strength of samples at wet and dry condition (Equation 14).

$$TSR = \frac{\sigma_{Tw}}{\sigma_{Td}} X\ 100 \tag{14}$$

Where; TSR = Tensile strength ratio

σ_{Tw} = Tensile strength at wet condition

σ_{Td}= Tensile strength at dry condition

The tensile strength of HDPE modified samples, which is a performance parameter that gives insight into how such sample can resist fatigue cracking, was measured using the splitting cylinder technique in accordance to ASTM D6931-22 (2022). The indirect tensile strength was evaluated mathematically using Equation (15).

$$\sigma = \frac{2P}{\pi D t} \qquad (15)$$

Where; P is equivalent to the failure load, D is the diameter or width of the HDPE modified bituminous concrete specimen and t represent the thickness of the specimen.

2.3.3 Sensitivity Analysis

The influence of the mixture components in the HDPE-modified bituminous mixtures on TSR was examined from two viewpoints: descriptively through 3D mixture surface plots and response trace plots, and quantitatively through ANOVA (P-statistics) analysis. This evaluation was carried out using Minitab software.

2.3.4 Mixture Regression Model for TSR of HDPE modified Bituminous Concrete

1. Model Formulation

For four-factor mixture components (q = 4), the second-degree mixture regression model for EVD (Equation 4) becomes;

$$Y = \beta_1 Z_1 + \beta_2 Z_2 + \beta_3 Z_3 + \beta_4 Z_4 + \beta_{12} Z_1 Z_2 + \beta_{13} Z_1 Z_3 + \beta_{14} Z_1 Z_4 + \beta_{23} Z_2 Z_3 + \beta_{24} Z_2 Z_4 + \beta_{34} Z_3 Z_4 \qquad (16)$$

Where;

Y = TSR of HDPE modified bituminous concrete

β_i, β_{ij} = Coefficients of the mixture quadratic regression model

Z_1 = Proportion of granite in the HDPE modified bituminous mixtures

Z_2 = Proportion of sand in the HDPE modified bituminous mixtures

Z_3 = Proportion of bitumen in the HDPE modified bituminous mixtures

Z_4 = Proportion of HDPE in the HDPE modified bituminous mixtures

In a short mathematical or matrix form, Equation (16) becomes;

$$Y = [Z_i][\beta_i] \qquad (17)$$

$[Z_i]$= shape function vector showing interaction between components

$[\beta_i]$ = model coefficient vector function

Y = vector of dependent variable or TSR

The coefficient vector or column matrix can be determined from least square estimator given by Equation (18)

$$[\beta_i] = \begin{bmatrix} \beta_1 \\ \beta_2 \\ \beta_3 \\ \beta_4 \\ \beta_{12} \\ \beta_{13} \\ \beta_{14} \\ \beta_{23} \\ \beta_{24} \\ \beta_{34} \end{bmatrix} = (Z^T Z)^{-1} Z^T Y \qquad (18)$$

Where; Z^T = transpose of the shape function or transpose of the matrix of components proportions.

The special consideration here is that Equation (18) is subjected to the constraints shown in Equation (1), hence, a case of a constrained mixture regression model suffices. Consequently, the coefficients in the constrained mixture regression model (Equation 16) were estimated or determined using least square method (Equation 18) via Microsoft excel.

2.Model Validation

TSR mixture regression model developed was subjected to F-distribution test and mean absolute percentage difference (MAP.D) statistics for validation.

F-distribution test; The F-statistics is given as the ratio of variances (Equation 19) between the predicted and experimental TSR values.

$$F = \frac{S_1^2}{S_2^2} \qquad (19)$$

Where; S_1^2 = Larger of both variances

S_2^2 = Smaller of both variances

S^2 is obtained from Equation (20)

$$S^2 = \frac{1}{n-1}\left[\sum (Y - \bar{Y})^2\right] \qquad (20)$$

Where: $\bar{Y}$= Average mean of response, Y

Y = Means of response

The following hypothesis were adopted;

Null Hypothesis: H_0 = there is no significant difference between the experimental and model TSR.

Alternate Hypothesis: H_1= there is a significant difference between the experimental and model TSR.

The null hypothesis is accepted when the F-value calculated in accordance to Equation (19) is less than tabulated value (from F-distribution table) and the model is declared adequate. Otherwise, the alternate hypothesis is accepted and the model is considered inadequate.

MAP.D Statistics; MAP.D simply quantifies the average relative difference between predicted or measured TSR and actual TSR in percentage terms. It is commonly used in forecasting, regression analysis, and comparing model accuracy. Equation (21) was used for the determination of MAP.D.

$$MAP.D = \frac{1}{n}\sum\left(\frac{/Experimental\ TSR - model\ TSR/}{Average\ of\ both\ responses} \times 100\right) \quad (21)$$

Where; n represents the number of data sets.

5.3.5 Genetic Algorithm of Components Optimization for Enhanced TSR

In developing the GA for the optimization of the components proportions to ensure enhanced TSR of HDPE modified bituminous concrete, the following steps were adopted while using the MATLAB programming software.

1. **Model block formulation**; A model block or script was created in the MATLAB environment to implement the developed mixture regression model for predicting the TSR of HDPE-modified bituminous concrete. The developed model is in the form of Equation (16) which in short form can be represented as;

$$Y = f\,(Z_1, Z_2, Z_3, Z_4) = f(Z) \quad (22)$$

   Where; Y = TSR of HDPE modified bituminous concrete, Z = mixture components to be optimized.

2. **Specification of constraints and number of mixture components**; In this step, the constraints applied to the fitness function (Equation 22) are explicitly defined and also the number of process parameters (mixture components) clearly stated. The fitness function can be formulated either for maximization or minimization, depending on the specific property of the bituminous concrete being optimized. In this study, the fitness function was maximized, as the objective was to improve the TSR of the HDPE-modified bituminous concrete. However, since the Genetic Algorithm (GA) by default performs minimization, a negative sign was applied to the fitness function to effectively convert the maximization task into a minimization one. The constrained optimization framework, originally given in Equation (1) and re-presented here as Equation (23) for clarity, was applied in this step as follows:

Objective Function;

$minimize: -f(Z$

Subject to;

$Z_1 + Z_2 + Z_3 + Z_4 =$

With bounds as;

$Z_1;\ 51.26\% \le Z_1 \le$

$Z_2;\ 42.79\% \le Z_2 \le 43.07\%$

$Z_3;\ 5.35\% \le Z_3 \le$

$Z_4;\ 0\% \le Z_4 \le 0.6$

3. **Implementation and running of the GA**; The Genetic Algorithm (GA) was configured using the 'gaoptimset' function to define parameters such as the number of generations and iteration processes. The GA toolbox in MATLAB was then employed to execute the optimization. Figure 5 represents the flow chart for the GA process.

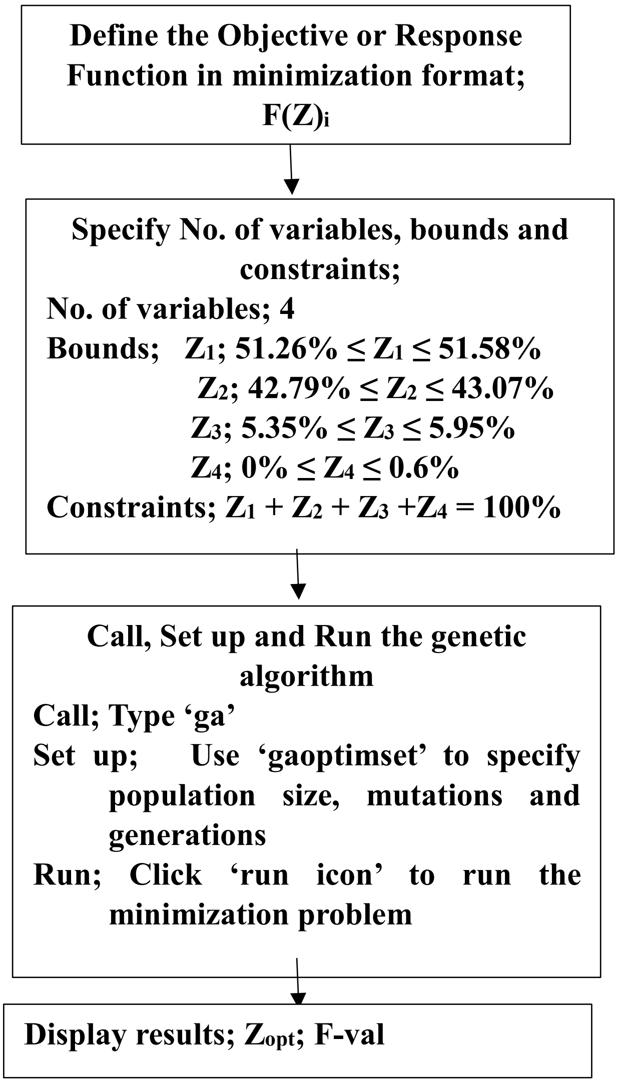

Figure 5. Flow chart for the GA process

3. RESULTS AND DISCUSSION

3.1 TSR of HDPE modified Bituminous Concrete

The tensile strength ratio (TSR) results for the HDPE-modified bituminous concrete are summarized in Table 4. The TSR values ranged from 82.734% to 95.816%. In comparison, the optimum unmodified bituminous concrete exhibited a TSR of 82.43%. These results indicate a significant improvement in moisture resistance for many of the HDPE-modified mixtures, particularly at the higher TSR values observed.

According to established specifications, moisture susceptibility performance requirements for asphalt mixtures typically demand minimum TSR thresholds. For instance, ASTM D4867 (2021) and AASHTO T283 (2020) both recommend a minimum TSR value of 80% for asphalt mixtures to be considered adequately resistant to moisture-induced damage. In some highway agency standards, even higher thresholds such as 85% are specified for more critical applications. In this study, all HDPE-modified mixtures met or exceeded the minimum ASTM and AASHTO criteria, with several mixtures significantly surpassing 85%, thereby affirming the suitability of HDPE modification for improving moisture resistance.

These findings are consistent with observations reported in recent research. Ameur et al. (2025) reviewed the use of plastic waste in asphalt mixtures and highlighted that HDPE modification enhances moisture resistance, fatigue life, and structural integrity of bituminous mixtures. Similarly, Ma et al. (2021) experimentally confirmed that the addition of HDPE to asphalt mixtures significantly increases water resistance, as indicated by elevated TSR values.

Patel and Modarres (2024) also reported that polyethylene-modified asphalt mixtures achieved TSR values up to 88.61%, demonstrating a substantial improvement compared to unmodified mixtures. In another recent study, Khan et al. (2024) showed that low-density polyethylene (LDPE) waste-modified asphalt mixtures consistently produced TSR values above 80%, reinforcing the effectiveness of polymer modification in enhancing resistance to moisture damage.

Comparing these studies with the present results, it is evident that the HDPE-modified bituminous concrete in this work not only satisfies but often exceeds the minimum performance requirements outlined by ASTM D4867 and AASHTO T283. Moreover, with TSR values reaching as high as 95.816%, the HDPE modification approach demonstrates potential for application in regions where high durability against moisture is critical, possibly offering better long-term pavement performance compared to conventional unmodified mixtures.

Table 4. Tensile Strength Ratio (TSR, %) Results of HDPE-Modified Bituminous Concrete

Run No.	Mix Proportions				Tensile Strength before Submergence	Tensile Strength after Submergence	TSR (%)
	Granite (%)	Sand (%)	Bitumen (%)	HDPE. P (%)			
1	51.489	42.850	5.436	0.226	944.22	904.72	**95.816**
2	51.489	42.990	5.436	0.086	619.17	577.39	**93.252**
3	51.329	42.990	5.436	0.246	856.38	790.20	**92.273**
4	51.489	42.850	5.576	0.086	539.18	505.49	**93.750**
5	51.260	42.790	5.350	0.600	475.72	408.88	**85.950**
6	51.260	43.070	5.670	0.000	447.65	377.58	**84.348**
7	51.329	42.850	5.736	0.086	521.50	470.14	**90.152**
8	51.260	42.790	5.950	0.000	541.08	447.65	**82.734**
9	51.397	42.910	5.521	0.171	794.10	736.55	**92.754**
10	51.260	43.070	5.350	0.320	709.70	655.99	**92.432**
11	51.329	42.850	5.436	0.386	634.50	556.65	**87.730**
12	51.580	43.070	5.350	0.000	375.95	341.42	**90.816**
13	51.580	42.790	5.630	0.000	406.45	379.86	**93.458**
14	51.580	42.790	5.350	0.280	766.85	689.00	**89.848**
15	51.329	42.990	5.596	0.086	719.03	643.97	**89.560**

3.2 Sensitivity Analysis of Mixture Components on TSR of HDPE Modified Bituminous Concrete

Figure 6 presents the 3D response surface plots illustrating the effects of mixture components on the tensile strength ratio (TSR) of HDPE-modified bituminous concrete. Distinct trends are observed for each component. An increase in granite content is associated with an increase in TSR, suggesting that higher granite proportions contribute positively to moisture resistance. Conversely, both sand and bitumen demonstrate a trend where higher proportions correspond to reduced TSR values, indicating a potential detrimental effect on moisture damage resistance when their contents exceed certain thresholds. For HDPE, the TSR initially improves as the HDPE content increases; however, beyond an optimal point, further HDPE additions result in a decline in TSR, suggesting that excessive HDPE may adversely affect the cohesion and durability of the mixture.

The trends observed in Figure 6 are corroborated by the response trace plot shown in Figure 7, which similarly confirms the influence patterns of granite, sand, bitumen, and HDPE on TSR. To maintain TSR values within the acceptable range of 80–90%, as determined from the contour plots (Figure 8), the component proportions must be carefully managed: granite between 51.2687–51.5855%, sand between 42.7984–43.0650%, bitumen between 5.36693–5.92802%, and HDPE between 0.0402394–0.579567%.

The Analysis of Variance (ANOVA) results presented in Table 5 reveal that interactions among mixture components predominantly influence TSR. The most significant interactions identified are granite*bitumen and granite*HDPE, with p-values of 0.146 and 0.189, respectively. Although these p-values are higher than the conventional significance threshold ($p < 0.05$), they suggest that component interactions still notably affect the TSR trends. Other interactions such as sand*bitumen, granite*sand, sand*HDPE, and bitumen*HDPE were found to be less influential, indicated by relatively larger p-values.

The findings align closely with recent studies. For instance, Ma et al. (2021) highlighted that the correct proportioning of aggregates and bitumen is essential for optimizing TSR and that excessive polymer (such as HDPE) contents can create internal stresses that diminish moisture resistance. Similarly, Ameur et al. (2025) noted that while low levels of plastic waste additives enhance the mechanical properties of asphalt mixtures, exceeding optimal limits can lead to reductions in durability indicators like TSR.

Patel and Modarres (2024) further emphasized that the interaction between aggregate and polymer-modified bitumen critically influences performance, particularly in wet conditions, corroborating the significance of component interaction effects seen in this study. Meanwhile, Khan et al. (2024) showed that balanced combinations of granite and polymer-modified binder are crucial in achieving the best TSR outcomes, supporting the emphasis placed on granite*bitumen and granite*HDPE interactions in the present findings.

In terms of specifications, ASTM D4867 (2021) and AASHTO T283 (2020) recommend that the TSR of asphalt mixtures should not fall below 80% to ensure acceptable moisture susceptibility resistance. The present results show that the properly balanced HDPE-modified mixtures can comfortably meet or exceed this threshold, confirming their potential for practical use under established standards.

Thus, the results not only validate the effectiveness of HDPE-modification in enhancing moisture damage resistance but also highlight the importance of careful mixture proportioning and interaction management, consistent with both recent research findings and international specifications.

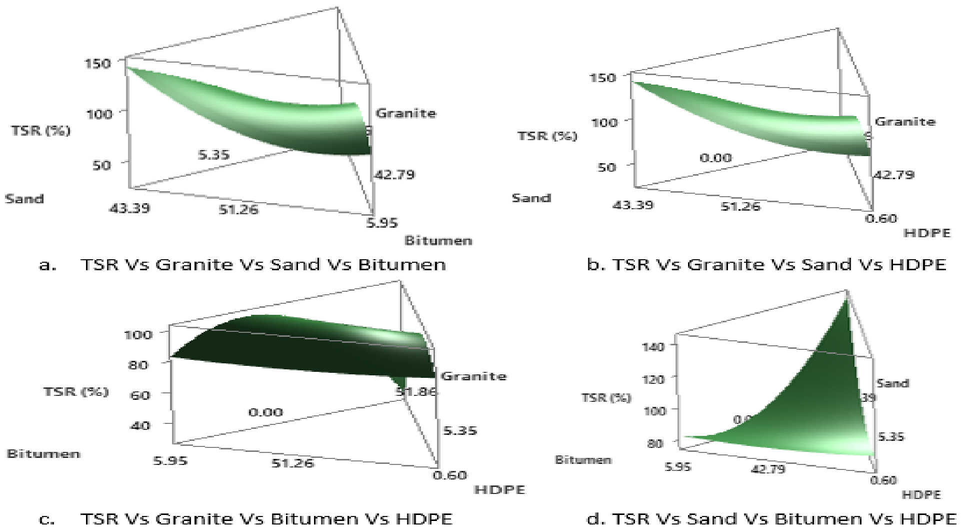

Figure 6. 3D Response Surface Plots for TSR of HDPE modified Bituminous Concrete

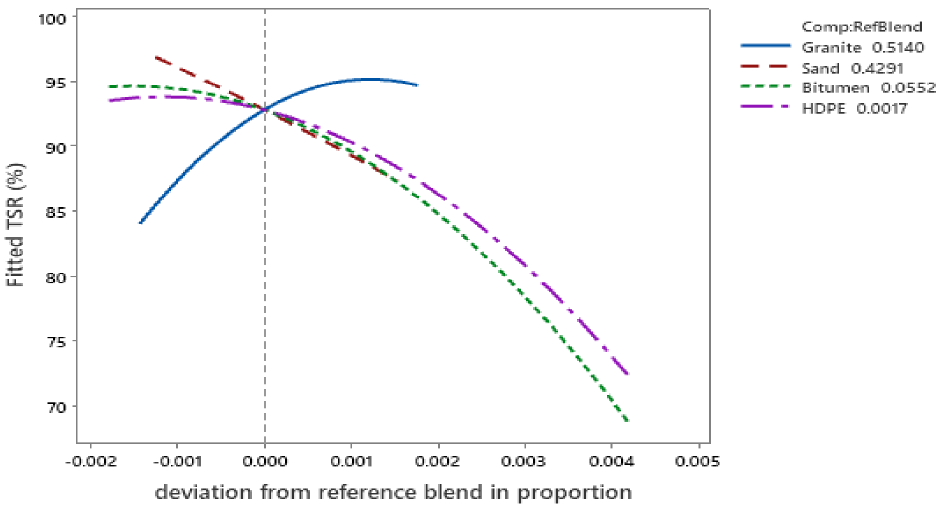

Figure 7. Response Trace Plot for TSR of HDPE modified Bituminous Concrete

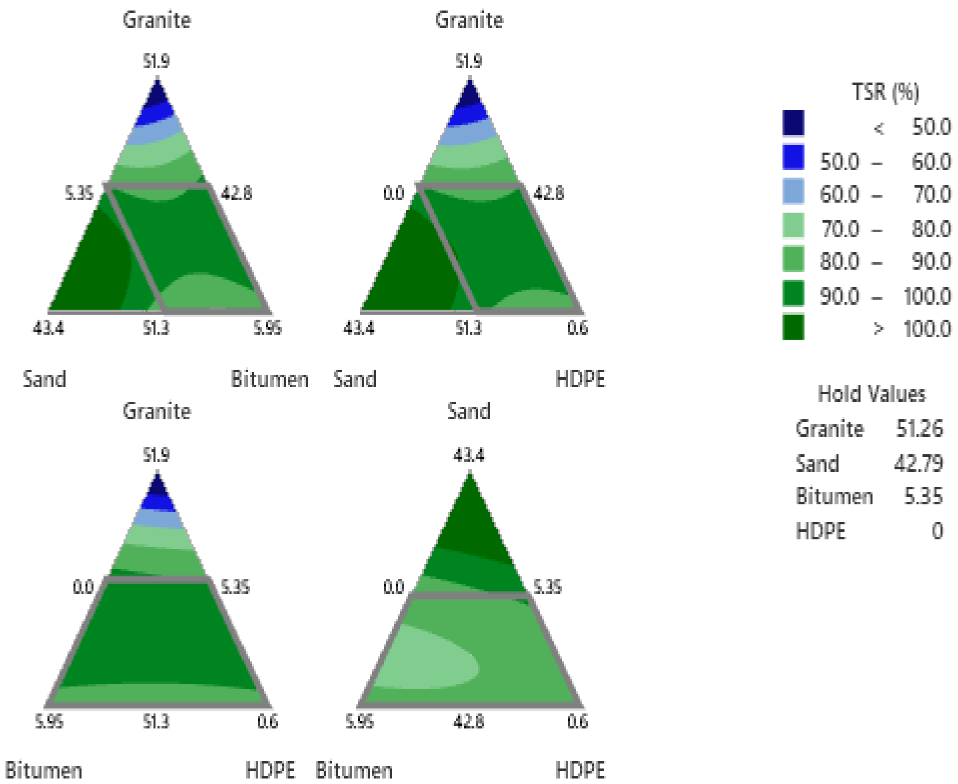

Figure 8. Contour Plots for TSR of HDPE modified Bituminous Concrete

Table 5. Analysis of Variance for TSR for HDPE modified Bituminous Concrete

Source	DF	Seq SS	Adj SS	Adj MS	F-Value	P-Value
Regression	9	181.598	181.598	20.1776	7.70	0.018
Linear	3	87.328	18.333	6.1111	2.33	0.191
Quadratic	6	94.270	94.270	15.7116	6.00	0.034
Granite*Sand	1	8.246	1.131	1.1307	0.43	0.540
Granite*Bitumen	1	33.665	7.763	7.7630	2.96	0.146
Granite*HDPE	1	32.018	6.042	6.0416	2.31	0.189
Sand*Bitumen	1	18.591	2.011	2.0106	0.77	0.421
Sand*HDPE	1	1.472	1.132	1.1322	0.43	0.540
Bitumen*HDPE	1	0.278	0.278	0.2778	0.11	0.758
Residual Error	5	13.103	13.103	2.6205		
Total	14	194.701				

3.3 Mixture Regression Model for Predicting TSR of HDPE Modified Bituminous Concrete

Table 6 presents the shape vector, Z and the experimentally determined TSR of HDPE-modified bituminous concrete samples. β or coefficient matrix as presented in Equation (24) was obtained by the application of Equation (18).

$$[\beta_i] = \begin{bmatrix} \beta_1 \\ \beta_2 \\ \beta_3 \\ \beta_4 \\ \beta_{12} \\ \beta_{13} \\ \beta_{14} \\ \beta_{23} \\ \beta_{24} \\ \beta_{34} \end{bmatrix} = \begin{bmatrix} -3724.490 \\ -427.563 \\ -7093.190 \\ -7484.870 \\ 88.74332 \\ 430.0049 \\ 379.3466 \\ -291.833 \\ -218.995 \\ -23.3007 \end{bmatrix} \quad (24)$$

By substituting these coefficient values into Equation (16), the mixture regression model for predicting the tensile strength ratio, TSR of HDPE-modified bituminous concrete was formulated, as presented in Equation (25).

$$TSR = -3724.490Z_1 - 427.563Z_2 - 7093.190Z_3 - 7484.870Z_4 + 88.74332Z_1Z_2 + 430.0049Z_1Z_3 + 379.3466Z_1Z_4 - 291.833Z_2Z_3 - 218.995Z_2Z_4 - 23.3007Z_3Z_4 \quad (25)$$

Table 7 presents the F-distribution test or analysis for the validation of the developed mixture regression model for predicting the TSR of HDPE-modified bituminous concrete. The obtained F-distribution value of 1.06 is far less than the

F-critical value of 2.48 obtained from the F-distribution table at 5 % level of significance and 14 degrees of freedom. Because F-calculated of 1.06 is less than the F-critical of 2.48, the null hypothesis is accepted and the model is considered adequate for the prediction of the tensile strength ratio, TSR of HDPE modified bituminous concrete.

To support the finding from the F-distribution statistics, Figure 9 presents the R^2 statistics for the verification of the derived TSR model for HDPE modified bituminous concrete. An R^2 value of 93.27%, insinuating that over 93% of the data within the considered simplex design space is explained by the derived model.

The MAP.D (Table 8) analysis comparing the predicted TSR values to their experimental counterparts, also revealed that the predicted values compared favourably with the experimental values. A MAP.D value of 0.74% was obtained. This suggests that the model predicts values that are not significantly different from the experimental values. This MAP.D value of 0.74% is very low and the model can be considered suitable for engineering applications.

Table 6; Shape Matrix or Vector of Components and TSR for HDPE-Modified Bituminous Concrete

Z_1	Z_2	Z_3	Z_4	Z_1Z_2	Z_1Z_3	Z_1Z_4	Z_2Z_3	Z_2Z_4	Z_3Z_4	Y = TSR (%)
51.489	42.850	5.436	0.226	2206.285	279.8772	11.62171	232.9204	9.671857	1.226918	**95.816**
51.489	42.990	5.436	0.086	2213.494	279.8772	4.413306	233.6814	3.684857	0.465918	**93.252**
51.329	42.990	5.436	0.246	2206.615	279.0074	12.61216	233.6814	10.56326	1.335633	**92.273**
51.489	42.850	5.576	0.086	2206.285	287.0856	4.413306	238.9194	3.672857	0.477918	**93.750**
51.260	42.790	5.350	0.600	2193.415	274.241	30.756	228.9265	25.674	3.21	**85.950**
51.260	43.070	5.670	0.000	2207.768	290.6442	0	244.2069	0	0	**84.348**
51.329	42.850	5.736	0.086	2199.429	294.406	4.399592	245.7754	3.672857	0.491633	**90.152**
51.260	42.790	5.950	0.000	2193.415	304.997	0	254.6005	0	0	**82.734**
51.397	42.910	5.521	0.171	2205.451	283.7857	8.810939	236.9245	7.356	0.946531	**92.754**
51.260	43.070	5.350	0.320	2207.768	274.241	16.4032	230.4245	13.7824	1.712	**92.432**
51.329	42.850	5.436	0.386	2199.429	279.0074	19.79816	232.9204	16.52786	2.096633	**87.730**
51.580	43.070	5.350	0.000	2221.551	275.953	0	230.4245	0	0	**90.816**
51.580	42.790	5.630	0.000	2207.108	290.3954	0	240.9077	0	0	**93.458**
51.580	42.790	5.350	0.280	2207.108	275.953	14.4424	228.9265	11.9812	1.498	**89.848**
51.329	42.990	5.596	0.086	2206.615	287.22	4.399592	240.5598	3.684857	0.479633	**89.560**

Where; Z_1= granite proportion; Z_2 = sand proportion, Z_3= bitumen proportion; Z_4 = HDPE proportion

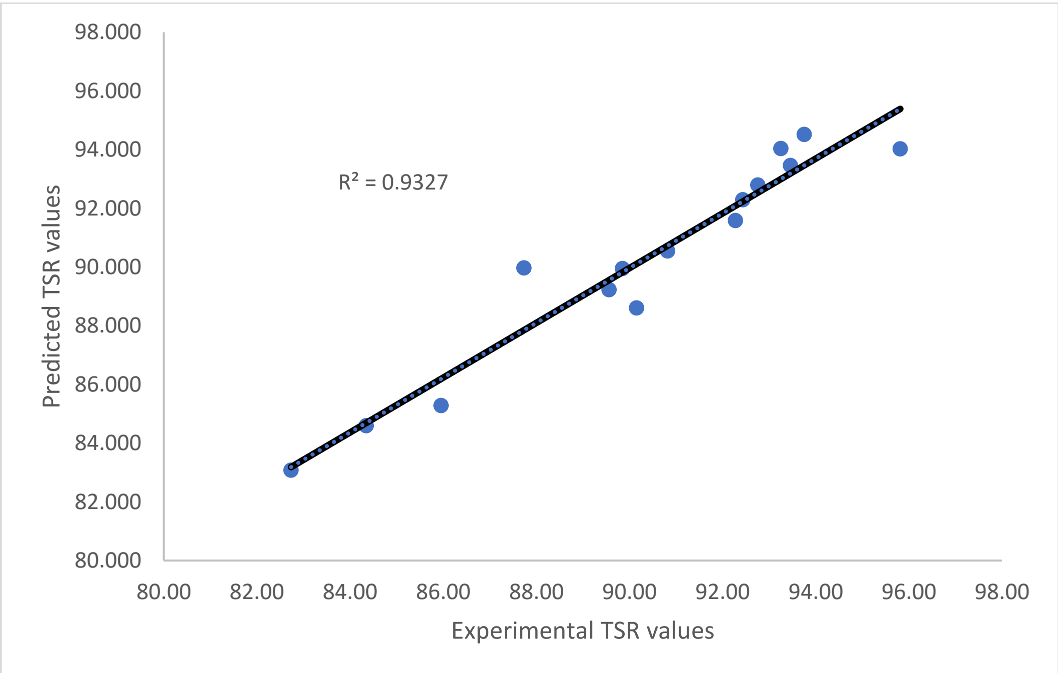

Figure 9. R^2 Statistics for TSR Model

Table 7. F-Distribution Statistics for Validation of TSR Model of HDPE-Modified Bituminous Concrete

Experimental TSR Values=Y_e	Predicted TSR Value= Yp	Y_e-$\hat{Y}_e$	Yp-$\hat{Y}$p	$(Y_e-\hat{Y}_e)^2$	$(Yp-\hat{Y}p)^2$
95.82	94.024	5.702	4.188	32.50995	17.54234
93.25	94.032	3.137	4.197	9.84318	17.61177
92.27	91.587	2.159	1.751	4.65946	3.06531
93.75	94.522	3.636	4.686	13.21940	21.95775
85.95	85.276	-4.164	-4.560	17.33671	20.79449
84.35	84.595	-5.766	-5.241	33.25049	27.46981
90.15	88.609	0.037	-1.227	0.00140	1.50533
82.73	83.083	-7.380	-6.753	54.46938	45.60285
92.75	92.795	2.639	2.959	6.96682	8.75841
92.43	92.290	2.318	2.455	5.37443	6.02536
87.73	89.974	-2.384	0.138	5.68388	0.01918
90.82	90.546	0.702	0.710	0.49305	0.50399
93.46	93.463	3.344	3.627	11.18096	13.15439
89.85	89.947	-0.266	0.111	0.07099	0.01238
89.56	89.227	-0.554	-0.609	0.30660	0.37087
$\hat{Y}_e$ = 90.114	$\hat{Y}$p = 89.836			∑= 195.36667	∑= 184.39424
Square of deviation of experimental TSR values from mean TSR value			S_e^2	**13.95476249**	
Square of deviation of predicted TSR values from mean TSR value			Sp^2	**13.171017**	
F- Calculated value, ratio of the two deviations (Equation 3.34), F-cal				**1.059505314**	

Table 8. MAP.D Statistics for Comparing Model to Experimental TSR Values of HDPE-Modified Bituminous Concrete

Experimental TSR Values=Y_e	Predicted TSR Value= Yp	ABS(Y_e - Yp) = B	(Y_e + Yp)/2 = C	B/C	(B/C)*100
95.816	94.024	1.792	94.920	0.01888	1.88761
93.252	94.032	0.781	93.642	0.00834	0.83395
92.273	91.587	0.686	91.930	0.00746	0.74633
93.750	94.522	0.772	94.136	0.00820	0.81981
85.950	85.276	0.675	85.613	0.00788	0.78807
84.348	84.595	0.247	84.471	0.00292	0.29221
90.152	88.609	1.543	89.380	0.01726	1.72590
82.734	83.083	0.349	82.908	0.00421	0.42097
92.754	92.795	0.042	92.774	0.00045	0.04491
92.432	92.290	0.142	92.361	0.00154	0.15369
87.730	89.974	2.244	88.852	0.02526	2.52583
90.816	90.546	0.271	90.681	0.00298	0.29839
93.458	93.463	0.005	93.460	0.00005	0.00511
89.848	89.947	0.099	89.897	0.00111	0.11054
89.560	89.227	0.334	89.394	0.00373	0.37319
Absolute percentage difference (AP.D)					11.02650
Mean Absolute percentage difference (MAP.D)					**0.7351**

3.4 Genetic Algorithm Based Optimization of Mixture Components for Enhanced TSR

Table 9 presents the pseudo code of the genetic algorithm for the maximization of the TSR of HDPE-modified bituminous concrete. The result of the optimization is hereby presented where the optimal mixture components proportions are represented by Equation (24) with the maximized TSR obtained as 97.877%.

$$Z_{opt} = \begin{bmatrix} Z_1 = 51.3353 \\ Z_2 = 43.0574 \\ Z_3 = 5.3501 \\ Z_4 = 0.2573 \end{bmatrix} \quad (24)$$

Equation (24) established the optimum proportions of the mixture components as follows: granite (Z_1) = 51.3353%, sand (Z_2) = 43.0574%, bitumen (Z_3) = 5.3501%, and HDPE (Z_4) = 0.2573%. The combination of these proportions resulted in a maximized tensile strength ratio (TSR) of 97.877%. Compared to the TSR of 82.43% for the unmodified bituminous concrete, this represents an impressive improvement of 18.74%. This significant enhancement highlights the effectiveness of HDPE as a polymeric additive capable of substantially improving the moisture resistance of bituminous mixtures. Similar trends were reported by Zhang et al. (2021), who found that HDPE modification led to increased density and better water resistance of asphalt mixtures by promoting stronger cohesive and adhesive bonding within the matrix.

Additionally, when compared to the highest TSR value of 95.816% obtained from the experimental observations under the Extreme Vertices Design (EVD) methodology, the Genetic Algorithm (GA) optimization achieved an even higher TSR of 97.877%. This improvement was associated with an increase in HDPE content from 0.226% to 0.2573%, reflecting a 13.85% increase in HDPE content that translated into an additional 2% rise in TSR performance. This emphasizes the sensitivity of TSR to slight adjustments in HDPE content and the precision of GA in identifying such optimum conditions.

The efficacy of GA in optimization is particularly notable. While traditional methods like EVD offer useful insights, they may not efficiently navigate complex nonlinear surfaces characterized by multiple interactions between mixture components. GA, on the other hand, as observed in this study and corroborated by Patel and Modarres (2024), effectively handles such complexities and identifies superior solutions by employing biologically inspired operators such as selection, crossover, and mutation. Their research also demonstrated that GA-based optimization yielded higher performance indices in plastic-modified asphalt mixtures compared to classical statistical approaches.

Comparing these findings with established specifications, ASTM D4867 (2021) and AASHTO T283 (2020) require a minimum TSR value of 80% to ensure sufficient moisture resistance in asphalt mixtures. The optimized HDPE-modified mixture with a TSR of 97.877% exceeds these specifications by a substantial margin, providing a robust confirmation of its enhanced durability and field performance potential. Furthermore, Khan et al. (2024) recently showed that modified asphalt mixtures incorporating LDPE and HDPE achieved TSR improvements in the range of 10–15%, reinforcing the consistency and reliability of the current study's results.

Thus, the present optimization not only meets the standard specification limits but also demonstrates a significant enhancement over typical performance improvements reported in the literature, highlighting the dual benefit of sustainable waste reuse and enhanced mechanical performance through HDPE modification.

Table 9. Pseudo code for the Optimization of Mixture Components of HDPE Modified Bituminous Concrete

```
% Tensile Strength Ratio Function
function y = TSRHDPEmBC(Z)
% Define the objective function to maximize
y = -(-(3724.490*Z(1))- (427.563*Z(2))- (7093.190*Z(3))- (7484.870*Z(4))+(88.74332*Z(1)*Z(2))+ (430.0049*Z(1)*Z(3))+ (379.3466*Z(1)*Z(4))- (291.833*Z(2)*Z(3))- (218.995*Z(2)*Z(4))- (23.3007*Z(3)*Z(4)));
end
%Constraint Function
function [c, c_eq]= TSRHDPEConstraints(Z)
c = [];
c_eq = Z(1)+ Z(2)+ Z(3)+ Z(4)- 100;
end
%main code for the maximization of the TSR of HDPE-mBC
ObjFcn = @TSRHDPEmBC;
nvars = 4;
LB = [51.26,42.79,5.35,0];
UB = [51.58,43.07,5.95,0.6];
ConsFcn = @TSRConstraints;

 % Set optimization options with increased MaxGenerations
options = gaoptimset('Generations', 100, 'Display', 'iter');
%call up the genetic algorithm
```

```
[Zopt, negTSRval] = ga(ObjFcn,nvars,[],[],[],[],LB,UB,ConsFcn);
 %Recover the maximum TSR value
TSRval = -negTSRval;
```

4. CONCLUSION

From the results and discussion of this study, the following conclusions are hereby put forward

i. HDPE-modified bituminous concrete showed a significant improvement in moisture resistance, with TSR values ranging from 82.734% to 95.816%, surpassing the minimum ASTM and AASHTO thresholds. The unmodified mixture had a TSR of 82.43%. All HDPE-modified mixtures met or exceeded the 80% requirement, with several exceeding 85%. These results align with recent studies confirming the benefits of HDPE in enhancing asphalt durability. The HDPE modification shows potential for applications where high moisture resistance is crucial. It offers a promising alternative to conventional unmodified mixtures for long-term pavement performance.

ii. The sensitivity analysis of mixture components on the TSR of HDPE-modified bituminous concrete revealed key trends in component interactions. Increasing granite content improves TSR, while excess sand and bitumen reduce TSR, indicating potential negative impacts on moisture resistance. HDPE content enhances TSR up to an optimal level, beyond which it decreases, suggesting that excessive HDPE can compromise mixture cohesion. The optimal component proportions were identified to maintain TSR within the acceptable range of 80–90%. ANOVA results emphasized the significant influence of granite*bitumen and granite*HDPE interactions on TSR. These findings align with recent studies and confirm the effectiveness of HDPE modification in improving moisture resistance, provided that the mixture is carefully proportioned. The results also meet ASTM and AASHTO specifications for moisture susceptibility, supporting the practical application of HDPE-modified mixtures in asphalt pavements.

iii. The mixture regression model for predicting the tensile strength ratio (TSR) of HDPE-modified bituminous concrete was derived using a coefficient matrix and the shape vector. The model was validated through an F-distribution test, where the calculated F-value of 1.06 was lower than the critical value of 2.48, confirming the model's adequacy. The R^2 value of 93.27% indicated that over 93% of the variance in the data was explained by the model, demonstrating its high predictive capability. Additionally, the model's performance was further supported by a low mean absolute percentage deviation (MAP.D) of 0.74%, suggesting minimal differences between the predicted and experimental TSR values. Overall, the model is deemed suitable for engineering applications in predicting the moisture resistance of HDPE-modified bituminous concrete.

iv. The GA optimization of the HDPE-modified bituminous concrete mixture resulted in an optimized TSR of 97.877%, a significant improvement from the unmodified bituminous concrete TSR of 82.43%. The optimal mixture proportions identified by GA were granite (51.3353%), sand (43.0574%), bitumen (5.3501%), and HDPE (0.2573%). This optimization highlighted the sensitivity of TSR to small variations in HDPE content in TSR. GA efficiently navigated complex interactions between mixture components. The optimized mixture not only surpassed the minimum TSR requirements set by ASTM D4867 (80%) and AASHTO T283 (80%) but also exceeded typical performance improvements seen in the literature. This emphasizes the dual benefits of HDPE modification, enhancing both the sustainability of waste reuse and the mechanical performance of the asphalt mixture.

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