



Sustainable Bio-Bitumen Formulation Using a Grey Relational Taguchi Approach with Waste Oils and Biochar

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Abstract: Pavement binder properties play a crucial role in road durability, yet conventional bitumen relies on depleting crude oil resources. This study explores a sustainable alternative by modifying 60/70 penetration grade bitumen with biochar (BC), waste engine oil (WEO), waste cooking oil (WCO), and phthalic anhydride (PA). A hybrid optimization framework combining Taguchi-based Grey Relational Analysis (GRA) with Principal Component Analysis (PCA) was applied using an L16 orthogonal array to evaluate multiple performance responses. The optimal formulation, consisting of 5% BC, 2% WEO, 1% WCO, and 0% PA, achieved a penetration of 102 dmm, ductility of 63 cm, a softening point of 50 °C, and an elastic recovery of 100%, meeting the standard requirements. While PA individually improved certain properties such as moisture resistance, its combined effect with other modifiers reduced overall performance, likely due to antagonistic interactions or chemical incompatibility. These findings underscore the need for advanced optimization methods that can address both synergistic and antagonistic effects in multi-component systems. The proposed PCA–Grey–Taguchi approach provides a systematic pathway for designing high-performance bio-bitumen, demonstrating the potential of waste-derived modifiers to deliver cost-effective, environmentally sustainable, and technically viable pavement binders for future road infrastructure.

Keywords: Bio-bitumen; biochar; waste engine oil; waste cooking oil; grey relational analysis

1. Introduction

The global infrastructure industry increasingly demands resilient and environmentally responsible materials that also meet stringent performance requirements [1]. Asphalt concrete remains a key component in road construction, providing durable and long-lasting surfaces [2]. Conventional asphalt mixtures primarily consist of aggregates, asphalt binders, and mineral fillers [3]. However, the transportation sector contributes significantly to greenhouse gas (GHG) emissions, with road traffic and construction activities accounting for 74% of the sector's emissions, which represent 32% of global totals [4]. The Sustainable Development Goals (SDGs), the Convention on Biological Diversity, and the Paris Agreement are just a few of the conventions that the Green Roads Toolkit will ensure roads comply with. It will also incorporate green road elements beyond the current hallmark of conventional

roads, which are connectivity, safety, and affordability [5-6]. In addition, extracting natural aggregates and disposing of construction waste impose substantial environmental burdens. Consequently, researchers are increasingly exploring sustainable alternatives, including the incorporation of waste-derived materials into asphalt mixtures, to reduce environmental impact and enhance pavement performance [3]. This study contributes to the development of "Green Roads," including climate-resilient, sustainable, and environmentally friendly pavement systems.

Bitumen is a black binding material used with aggregates in road construction. Due to its dark color, it contributes to the urban heat island effect under extreme temperatures, thereby exacerbating climate change, since it is derived from fossil fuels [7]. Bitumen is processed through fractional distillation and oxidation. Oxidation plays a vital role in producing various paving grades, and it must be carefully controlled to ensure that the cohesion and adhesion properties of bitumen conform to standards [8]. Its production is hazardous due to its low dielectric/micro-permittivity constant, high levels of polycyclic aromatic hydrocarbons (PAHs), and the presence of hydrogen sulfide and bromine [9]. Bitumen deposits are often located at relatively shallow depths, ranging from 0 to 500 m below the Earth's surface, which leads to subsurface water contamination and poses risks to human health and the environment. Moreover, extraction is cumbersome, complex, and time-consuming [10]. Global bitumen reserves are being consumed at an alarming rate of 100 million metric tonnes annually and are projected to last only another 46 years, since it is a non-renewable finite resource [11]. Another major factor challenging the future of bitumen is the decline in crude oil reserves and the associated fluctuations in cost. To meet increasing demands for strength under evolving wheel loads and resilience to thermal susceptibility, modification of bitumen is therefore essential. Polymer-modified bitumen (PMB) refers to the incorporation of elastomeric polymers into bitumen to reduce heat susceptibility and deformation under load [12]. PMBs are widely applied in high-performance pavement projects worldwide, particularly in areas requiring enhanced rutting resistance, elasticity, and durability [13]. However, their higher cost and potential for premature failure when interacting with certain hydrocarbon oils can limit broader adoption, especially in resource-constrained regions [12]. This study, therefore, aims to develop a cost-effective and sustainable alternative to traditional residual bitumen and PMB systems, addressing both performance and environmental objectives.

In this research, conventional 60/70 penetration grade bitumen is modified with biochar (BC), waste engine oil (WEO), waste cooking oil (WCO), and phthalic anhydride (PA) using a Taguchi-based design of experiments. These materials were selected to promote sustainability and circular economy principles in line with the Sustainable Development Goals, with the aim of mitigating climate change impacts. Biochar, an end-product of the thermochemical conversion of biomass waste, is produced globally in significant quantities. Its porous, irregular surface has been reported to enhance physicochemical bonding with bitumen, improving stiffness and stability [14]. WEO has been shown to act as a fluxing agent, reducing viscosity and improving workability, but may increase susceptibility to permanent deformation at high dosages. WCO can improve low-temperature flexibility but may reduce moisture resistance due to its polar compounds. While individual studies have examined these modifiers separately, limited research has optimized them in combination to capture synergistic benefits while mitigating antagonistic effects. This study addresses that gap by systematically evaluating their interactions, balancing performance, cost, emissions, and workability. Large volumes of solid biomass wastes, such as sugarcane bagasse, coconut copra, rice husks, and palm oil residues, are generated in Southeast Asia. Due to their low economic value, these wastes are often managed inefficiently, primarily through burning or uncontrolled decomposition, both of which contribute to environmental pollution [15]. Similarly, most WCO and WEO are disposed of in open dumps, causing serious environmental problems by releasing foul odors and contaminating soil and water with hazardous liquids [16-17]. The above-mentioned issues can be effectively addressed by employing these waste materials in bio-bitumen production. Process efficiency in material development is best achieved through optimisation, as traditional approaches that vary one factor at a time often overlook the interaction effects between components, increasing both cost and testing time. To address these challenges, statistical strategies such as the Design of Experiments (DoE) have been adopted to identify cause-and-effect relationships between variables and performance outcomes [18]. In this study, a Grey-Taguchi multi-objective optimisation approach was selected for its ability to handle multiple performance criteria, capture interaction effects, and determine the most effective

combination of bio-based modifiers for bitumen [19-20]. The method is implemented using Minitab software, which enables the design, statistical analysis, and ranking of factor levels to achieve optimal binder properties, incorporating a detailed experimental design and the integration of Taguchi, Grey Relational Analysis, and Principal Component Analysis.

A limited amount of research has examined the combined effects of biochar, waste cooking oil, and waste engine oil on key performance parameters, including penetration, ductility, softening point, and elastic recovery, using a Grey-Taguchi optimization approach with Principal Component Analysis (PCA) integration. Previous studies have examined the use of various additives in bio-bitumen formulations. By combining waste cooking oil, waste engine oil, and waste biochar in the synthesis of bio-bitumen and utilizing the Grey-Taguchi approach integrated with PCA, this work seeks to close this gap. By analyzing the crucial performance factors, this research aims to identify the optimal additive combination for producing high-performing and sustainable bio-bitumen formulations.

2. Methodology

2.1 Taguchi Analysis

The Taguchi method, developed by Genichi Taguchi, is a statistical design of experiments (DoE) framework that improves process robustness by systematically analysing factor effects through orthogonal arrays [27]. Its foundation lies in fractional factorial design, signal-to-noise (S/N) ratios as quality metrics, and the Quality Loss Function, which relates deviation from the target to performance loss [28-29]. In this framework, the S/N ratio is a key indicator, expressed either as a logarithmic measure of mean-to-variance [30] or as the ratio of wasted to required energy [31]. Regression analysis is further employed to evaluate relationships between input and output variables [31]. In this study, an L16 orthogonal array (OA) was employed to evaluate four factors—biochar (BC), waste engine oil (WEO), waste cooking oil (WCO), and phthalic anhydride (PA), each at four levels (4⁴). Factor ranges were defined as BC (0–15%), WEO (0–3%), WCO (0–3%), and PA (0–15%), based on prior literature and preliminary tests to balance stiffness, rutting resistance, workability, and fatigue performance [32]. The final ranges ensured that BC content did not induce brittleness, WEO/WCO avoided excessive softening, and PA levels provided sufficient reactivity without binder hardening. The L16 OA ensured equal representation of factor-level combinations, with all 16 trials conducted in randomised order to minimise experimental bias. Each test was carried out once per response, consistent with the Taguchi method's robustness. Binder properties were evaluated using standard protocols: Penetration (ASTM D5/IS 1203), Ductility (ASTM D113/IS 1208), Softening Point (ASTM D36/IS 1205), and Elastic Recovery (ASTM D6084). The S/N ratios were calculated using the “smaller-the-better” (STB) and “larger-the-better” (LTB) formulations shown in (1) and (2), where n denotes the number of trials and Y the measured response:

$$K_{ij} = -10 \log_{10} \left(\frac{1}{n} \sum_{j=1}^n Y_{ij}^2 \right) \text{ STB} \quad (1)$$

$$K_{ij} = -10 \log_{10} \left(\frac{1}{n} \sum_{j=1}^n \frac{1}{Y_{ij}^2} \right) \text{ LTB} \quad (2)$$

The factors and their corresponding levels are summarised in Table 1, and the complete L16 orthogonal array with experimental responses is presented in Table 2.

2.2 Grey-Taguchi Analysis (Multi-objective Optimization)

Grey Relational Analysis (GRA) was adopted in this study to overcome the limitation of the Taguchi method, which is restricted to single-objective optimization. Since the present work involves multiple performance characteristics—penetration, ductility, softening point, and elastic recovery—a hybrid Taguchi-GRA-Principal Component Analysis (PCA) framework was employed. In this approach, PCA was utilized to objectively assign weights to each response parameter, thereby avoiding arbitrary assumptions. By ensuring that each characteristic's contribution to the overall optimization is proportional to its statistical significance,

PCA provides a more robust weighting system. PCA performs an orthogonal transformation that converts correlated variables into a set of uncorrelated variables, known as principal components (PCs), which retain most of the variance in the dataset [12]. This methodology is widely adopted in multi-response optimization problems in engineering, as it effectively reduces dimensionality while preserving essential information, thereby enabling accurate Grey Relational Grading. In the present study, a hybrid Taguchi–GRA–PCA approach was adopted (Figure 1) to facilitate the multi-objective optimization of bio-bitumen formulations.

Table 1 Factors and their levels used in the Taguchi L16 orthogonal array

FACTORS	BC	WEO	WCO	PA
LEVEL 1	0	0	0	0
LEVEL 2	5	1	1	5
LEVEL 3	10	2	2	10
LEVEL 4	15	3	3	15

Table 2 L16 orthogonal array with factor–level combinations for all 16 experimental trials

Run	BC	WEO	WCO	PA	Penetration (dmm)	Ductility (cm)	Softening Point (°c)	Elastic Recovery (%)
1	0	0	0	0	52.3	70	50	97
2	0	1	1	5	106	31.3	62	98
3	0	2	2	10	122	36.8	65	97
4	0	3	3	15	51	26.8	58	94
5	5	0	1	10	149	30.2	50	93
6	5	1	0	15	156.3	33	52	92
7	5	2	3	0	161	49.5	60	95
8	5	3	2	5	151	41.5	52	95
9	10	0	2	15	66	35	58	94
10	10	1	3	10	80	55	46	96
11	10	2	0	5	80	58	45	96
12	10	3	1	0	102	63	50	100
13	15	0	3	5	78.33	51.2	59	91
14	15	1	2	0	78	53	56	99
15	15	2	1	15	105.33	33.5	62	95
16	15	3	0	10	127.66	33.8	60	96

Although the Taguchi method provides an optimal factor setting for single-response optimisation, it is limited when multiple performance criteria must be satisfied simultaneously. To address this limitation, the S/N ratios derived here were further processed using Grey Relational Analysis (GRA) integrated with Principal Component Analysis (PCA).

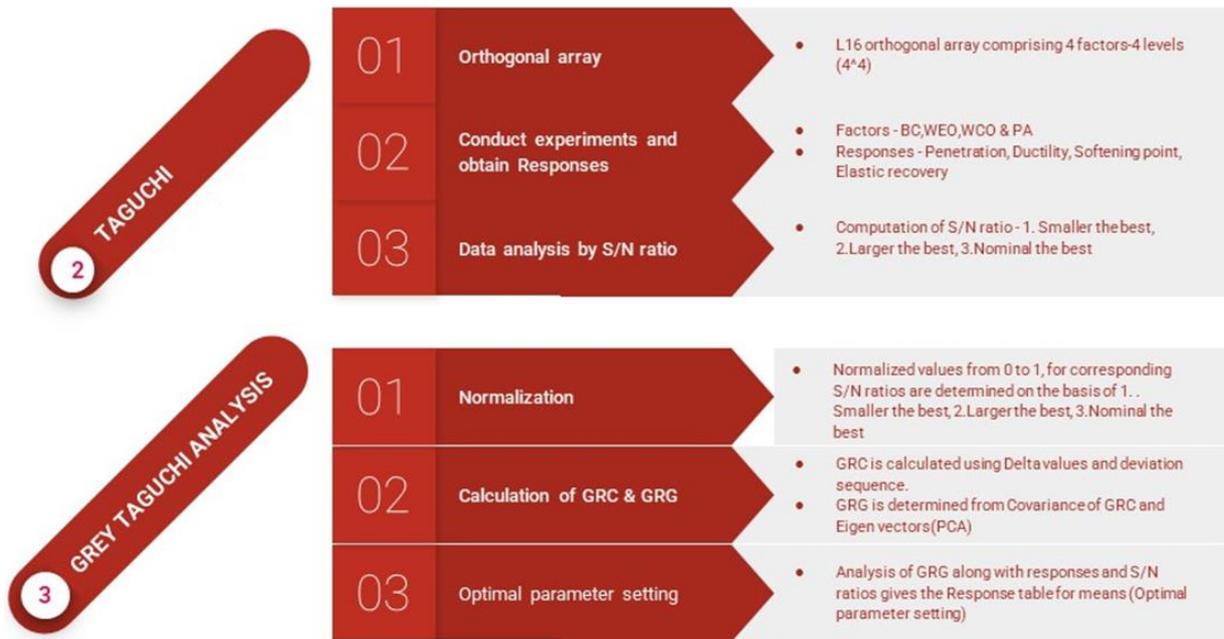


Figure 1. Roadmap for optimization of bio-bitumen using Grey-Taguchi technique

2.2.1 Optimization Using GRA

The signal-to-noise (S/N) ratios obtained from the Taguchi design (Section 2.1) were first normalized to a range of 0 to 1. For the “smaller-the-better” characteristic (penetration), normalization was performed using Equation (3):

$$X_i^*(k) = \frac{\max X_i^o(k) - X_i^o(k)}{\max X_i^o(k) - \min X_i^o(k)} \quad (3)$$

For the “larger-the-better” characteristics (ductility, softening point, and elastic recovery), normalization was performed using Equation (4):

$$X_i^*(k) = \frac{X_i^o(k) - \min X_i^o(k)}{\max X_i^o(k) - \min X_i^o(k)} \quad (4)$$

The normalized results are presented in **Table 3**.

The deviation sequence from the ideal value (1) was calculated as:

$$\Delta_{oi}(k) = |X_o^*(k) - X_i^o(k)| \quad (5)$$

The Grey Relational Coefficient (GRC) was then computed using Equation (6):

$$\xi_i(k) = \frac{\Delta_{min} + \psi \cdot \Delta_{max}}{\Delta_{oi}(k) + \psi \cdot \Delta_{max}} \quad (6)$$

Where ψ is the distinguishing coefficient (taken as 0.5), and Δ_{min} and Δ_{max} are the minimum and maximum deviation sequences, respectively.

Finally, the Grey Relational Grade (GRG) for each trial was obtained as:

$$\gamma_i(GRG) = \sum_{k=1}^n \omega_k \cdot \xi_i(k) \quad (7)$$

where ω_k represents the weight for the k-th response, determined from PCA eigenvectors.

Table 3. Normalized values for the deviation sequence

RUN ORDER	NORMALIZED VALUES			
	PENETRATION	DUCTILITY	SOFTENING POINT	ELASTIC RECOVERY
1	0.02	1.00	0.29	0.68
2	0.64	0.16	0.87	0.79
3	0.76	0.33	1.00	0.68
4	0.00	0.00	0.69	0.34
5	0.93	0.12	0.29	0.23
6	0.97	0.22	0.39	0.12
7	1.00	0.64	0.78	0.46
8	0.94	0.46	0.39	0.46
9	0.22	0.28	0.69	0.34
10	0.39	0.75	0.06	0.57
11	0.39	0.80	0.00	0.57
12	0.82	0.89	0.29	1.00
13	0.37	0.67	0.74	0.00
14	0.37	0.71	0.59	0.89
15	0.63	0.23	0.87	0.46
16	0.80	0.24	0.78	0.57

Table 4. Grey Relational Grading and Grey Relational Coefficient

Run Order	Grey Relational Coefficient					GRG	Rank
	Penetration	Ductility	Softening Point	Elastic Recovery			
1	0.34	1.00	0.41	0.61	0.65	3	
2	0.58	0.37	0.80	0.70	0.54	10	
3	0.67	0.43	1.00	0.61	0.62	4	
4	0.33	0.33	0.62	0.43	0.39	16	
5	0.88	0.36	0.41	0.39	0.54	11	
6	0.95	0.39	0.45	0.36	0.58	7	
7	1.00	0.58	0.70	0.48	0.72	2	
8	0.90	0.48	0.45	0.48	0.61	5	
9	0.39	0.41	0.62	0.43	0.44	15	
10	0.45	0.67	0.35	0.54	0.53	12	
11	0.45	0.72	0.33	0.54	0.55	9	
12	0.73	0.82	0.41	1.00	0.75	1	
13	0.44	0.61	0.65	0.33	0.53	13	
14	0.44	0.63	0.55	0.82	0.58	6	
15	0.58	0.39	0.80	0.48	0.53	14	
16	0.71	0.40	0.70	0.54	0.56	8	

The calculated GRG values and their corresponding rankings are shown in Table 4. The trial with the highest GRG value represents the optimal parameter combination. The response analysis and S/N ratio plots for the GRG, generated in Minitab, are summarized in Table 5 and Figure 2. Eigen Analysis of the covariance matrix was performed to extract the principal components, which quantify the contribution of each performance characteristic to the total variance. The resulting eigenvalues and eigenvectors (Tables 6 and 7) were used as weighting factors (ω_k) in Eq. (7) for Grey Relational Grade computation.

Table 5. Input factors, responses, and corresponding S/N ratios

Run	Penetration (dmm)	Responses										
		SNRA1	SNRA2	SNRA3	SNRA4	WEO	WCO	PA	SNRA1	SNRA2	SNRA3	SNRA4
1	52.3	-34.37	36.90	33.98	39.74	0	0	0	-34.37	36.90	33.98	39.74
2	106	-40.51	29.91	35.85	39.82	1	1	5	-40.51	29.91	35.85	39.82
3	122	-41.73	31.32	36.26	39.74	2	2	10	-41.73	31.32	36.26	39.74
4	51	-34.15	28.56	35.27	39.46	3	3	15	-34.15	28.56	35.27	39.46
5	149	-43.46	29.60	33.98	39.37	0	1	10	-43.46	29.60	33.98	39.37
6	156.3	-43.88	30.37	34.32	39.28	1	0	15	-43.88	30.37	34.32	39.28
7	161	-44.14	33.89	35.56	39.55	2	3	0	-44.14	33.89	35.56	39.55
8	151	-43.58	32.36	34.32	39.55	3	2	5	-43.58	32.36	34.32	39.55
9	66	-36.39	30.88	35.27	39.46	0	2	15	-36.39	30.88	35.27	39.46
10	80	-38.06	34.81	33.26	39.65	1	3	10	-38.06	34.81	33.26	39.65
11	80	-38.06	35.27	33.06	39.65	2	0	5	-38.06	35.27	33.06	39.65
12	102	-42.32	35.99	33.98	40.00	3	1	0	-42.32	35.99	33.98	40.00
13	78.33	-37.88	34.19	35.42	39.18	0	3	5	-37.88	34.19	35.42	39.18
14	78	-37.84	34.49	34.96	39.91	1	2	0	-37.84	34.49	34.96	39.91
15	105.33	-40.45	30.50	35.85	39.55	2	1	15	-40.45	30.50	35.85	39.55
16	127.66	-42.12	30.58	35.56	39.65	3	0	10	-42.12	30.58	35.56	39.65

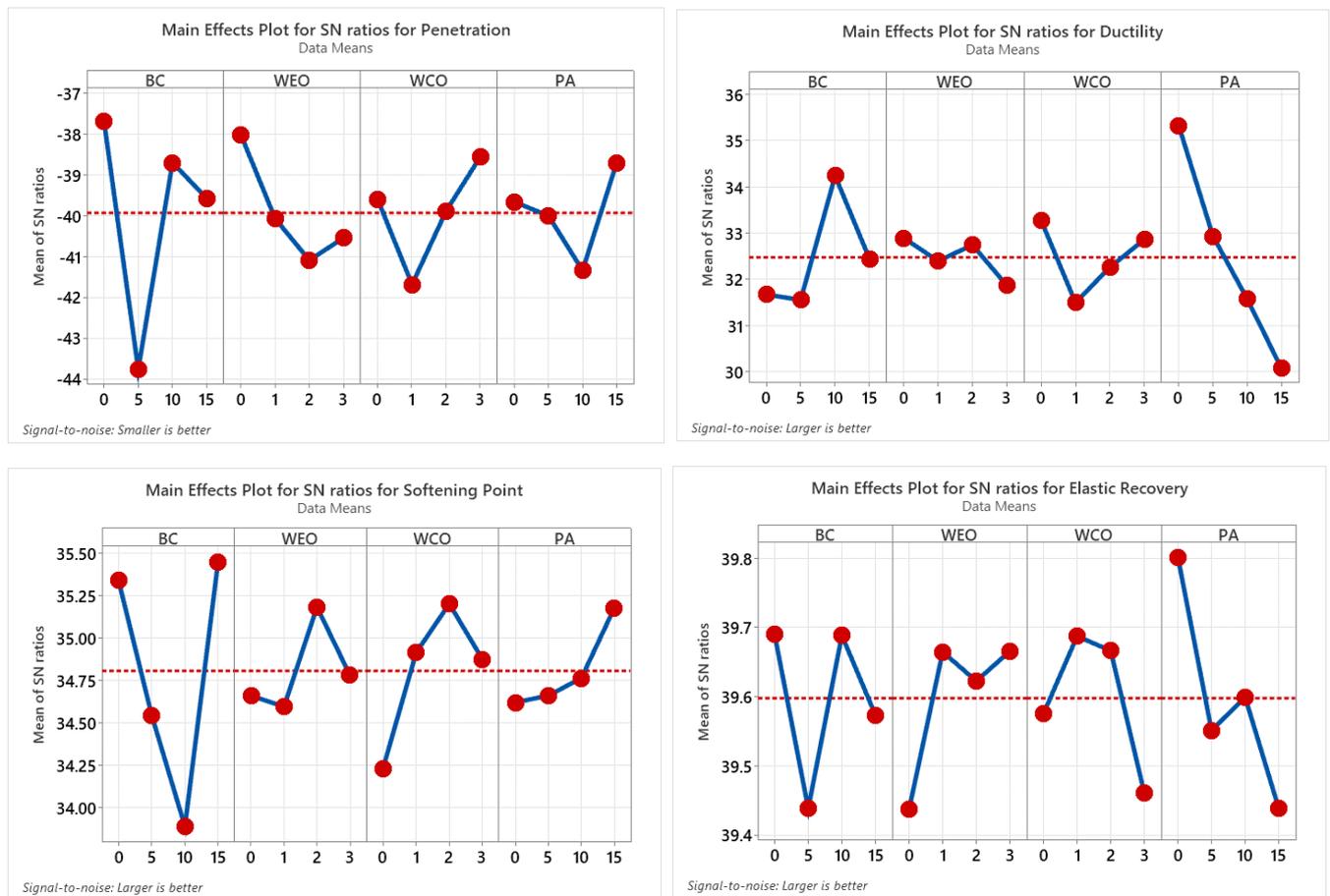


Figure 2. S/N ratio plots for responses

Table 6. Eigen vectors

Eigenvectors Variable	PC1	PC2	PC3	PC4
C1	0.57	-0.78	-0.20	0.159
C2	-0.63	-0.29	-0.12	0.709
C3	0.40	0.53	-0.57	0.48
C4	-0.34	-0.15	-0.79	-0.493

Table 7. Eigen analysis of the Covariance Matrix

Principal Component	PC1	PC2	PC3	PC4
Eigenvalue	0.068374	0.044395	0.030729	0.010365
Proportion	0.444	0.289	0.2	0.067
Cumulative	0.444	0.733	0.933	1

3. Results and Discussions

The levels of the input parameters or factors are determined through a combination of insights from literature reviews and laboratory experimentation on conventional bitumen. This process involves evaluating each input parameter or factor individually, one at a time. This study would require 256 (4⁴) experimental

runs because it has 4 components at 4 levels each. Fractional factorials offer a quicker option, but they require statistical knowledge that is not always available. A more effective approach is provided by orthogonal arrays, which enable smaller, less expensive tests with excellent reproducibility rates. In just 16 experimental runs, this research with 4 factors at 4 levels each can be completed with the right orthogonal array. For these 16 experimental runs, the laboratory tests were conducted to determine the following responses: Penetration, Ductility, Softening point, and Elastic recovery. Later, these values are analyzed in Minitab software to calculate S/N ratios for each response and are tabulated in Table 4. S/N ratios are calculated from Eq. 1. For instance, the S/N ratio for the first run order of Penetration, where the objective is "smaller-the-better," is required.

$$S/N = -10\log(52.32) = -34.37$$

Similarly, for the remaining responses, S/N ratios are calculated as "larger-the-better" using Eq. 2. For instance, the S/N ratio of the first run order of Ductility.

$$S/N = -10\log(1/702) = 36.90$$

S/N Ratio graphs are plotted for all 4 responses. The optimal value of the response can be determined from the graph that possesses the highest mean SNR. These graphs are shown in Figure 2. It has been found that for Penetration, the highest SNR is obtained at BC & WEO at 0%, WCO at 3%, and PA at 15%. For Ductility, the highest SNR was obtained at BC-10 %, WEO, WCO, and PA at 0%. For Softening Point, the highest SRN is obtained at BC – 15%, WEO – 2%, WCO 2%, and PA – 15%. Elastic recovery showed the highest SNR at BC – 0% & 10%, WEO – 3%, WCO – 1% and PA – 0%. Multiple regression analysis has been performed to examine these optimized outcomes further. The analysis indicates that binder composition significantly affects performance characteristics. For penetration, a higher BC content increases binder stiffness and reduces softness, while WEO functions as a fluxing agent, lowering viscosity. The inclusion of WCO at around 3% enhances plasticity without causing excessive softening, and PA at 15% contributes to elasticity while maintaining a relatively softer consistency. In terms of ductility, a BC content of 10% improves stiffness without resulting in excessive embrittlement. The absence of oils helps avoid over-softening, and the exclusion of PA prevents potential incompatibility issues. Regarding softening point, higher BC content (15%) enhances stiffness and thermal resistance, whereas small quantities of oils aid dispersion without compromising thermal stability. For elastic recovery, low PA content minimizes phase separation, and the combined effects of selected oil dosages promote chain mobility, thereby improving elasticity. Regression analysis can be used to establish a mathematical relationship between specific independent variables (response) and a dependent variable (predictor). As demonstrated, functions of independent variables may be used to express dependent variables in multiple regression.

$$Z = a_0 + a_1x_1 + a_2x_2 + a_3x_3 + \dots + a_nx_n$$

Where X1 to Xn are the independent variables, Z is the dependent variable, and a0 to an are the equation parameters for the linear relation. The coefficient of determination, also known as R², can be used to assess how well a linear model fits a particular set of observable data. To establish a link between the dependent and independent variables, statistical linear regression was performed in this study using MINITAB. Below is a discussion of the outcomes that were reached.

The relation between Penetration and the input parameters BC, WEO, WCO, and PA is given by the equation below.

$$\text{PENETRATION} = 104.9 - 0.43 \text{ BC} + 9.80 \text{ WEO} - 5.29 \text{ WCO} - 0.33 \text{ PA}$$

From this model, BC was identified as the most influential factor, accounting for 61.06% of the variation in penetration (calculated from the ANOVA sum of squares).

For ductility: DUCTILITY=57.28+0.383 BC-1.46 WEO-0.71 WCO-1.739 PA

PA had the greatest influence on ductility, contributing 59.29%.

For softening point: SOFTENING POINT=50.96-0.045 BC+0.63 WEO+1.38 WCO+0.225 PA

BC was the dominant factor for softening point, contributing 44.32%.

For elastic recovery: ELASTIC RECOVERY=96.92-0.0200 BC+0.700 WEO-0.400 WCO-0.2300 PA
PA contributed 38.07% to the variation in elastic recovery.

These results demonstrate that the parameters influencing each response differ, making single-objective optimization insufficient. To obtain an optimal combination that meets all performance criteria, Grey Relational Analysis (GRA) was applied to the S/N ratios from Taguchi (Table 5).

3.1 Normalization

The first step in this process is to normalize the data of all response characteristics using Equations 3 and 4. The normalized values and deviation sequence are tabulated in Table 3. The calculation of normalized values is given below for run order 1,

$$X_{iP}^*(1) = \frac{\max X_i^o(k) - X_i^o(k)}{\max X_i^o(k) - \min X_i^o(k)} = \frac{-34.15 - (-34.37)}{-34.15 - (-44.14)} = 0.02$$

$$X_{iD}^*(1) = \frac{X_i^o(k) - \min X_i^o(k)}{\max X_i^o(k) - \min X_i^o(k)} = \frac{(36.90) - (28.56)}{(36.90) - (28.56)} = 1.00$$

$$X_{iSP}^*(1) = \frac{X_i^o(k) - \min X_i^o(k)}{\max X_i^o(k) - \min X_i^o(k)} = \frac{(33.98) - (33.06)}{(36.26) - (33.06)} = 0.29$$

$$X_{iER}^*(1) = \frac{X_i^o(k) - \min X_i^o(k)}{\max X_i^o(k) - \min X_i^o(k)} = \frac{(39.74) - (39.18)}{(40) - (39.18)} = 0.68$$

The deviation sequences have been computed using Eq. 5, as a prerequisite for GRCs. Both the normalized values and the deviation sequence are tabulated and given in Table 3. The deviation sequence for run order 1 of all responses is computed as shown below:

$$\Delta_{oiP}(1) = |X_o^*(k) - X_i^o(k)| = |1 - 0.02| = 0.98$$

$$\Delta_{oiD}(1) = |X_o^*(k) - X_i^o(k)| = |1 - 1| = 0.00$$

$$\Delta_{oiSP}(1) = |X_o^*(k) - X_i^o(k)| = |1 - 0.29| = 0.71$$

$$\Delta_{oiER}(1) = |X_o^*(k) - X_i^o(k)| = |1 - 0.68| = 0.32$$

3.2 Computation of GRCs and GRGs

The GRC was calculated for each response characteristic using Equation 6 and the values of the deviation sequences listed in Table 3. In Equation 6, the value of the distinguishing coefficient, $\varphi = 0.5$, was substituted. Equation 7 was used to compute the GRGs after integrating the PCA methodology. Table 5 reports the calculated grey relation coefficients. The following is an example of the GRC calculation for run order 1:

$$\xi_{iP}(1) = \frac{\Delta_{min} + \psi \cdot \Delta_{max}}{\Delta_{oi}(k) + \psi \cdot \Delta_{max}} = \frac{0 + 0.5 \cdot 1}{0.98 + 0.5 \cdot 1} = 0.34$$

$$\xi_{iD}(1) = \frac{\Delta_{min} + \psi \cdot \Delta_{max}}{\Delta_{oi}(k) + \psi \cdot \Delta_{max}} = \frac{0 + 0.5 \cdot 1}{0.00 + 0.5 \cdot 1} = 1.00$$

$$\xi_{iSP}(1) = \frac{\Delta_{min} + \psi \cdot \Delta_{max}}{\Delta_{oi}(k) + \psi \cdot \Delta_{max}} = \frac{0 + 0.5 \cdot 1}{0.71 + 0.5 \cdot 1} = 0.41$$

$$\xi_{iER}(1) = \frac{\Delta_{min} + \psi \cdot \Delta_{max}}{\Delta_{oi}(k) + \psi \cdot \Delta_{max}} = \frac{0 + 0.5 \cdot 1}{0.32 + 0.5 \cdot 1} = 0.61$$

In Grey Relational Analysis (GRA), Principal Component Analysis (PCA) was applied to determine the relative importance of each performance characteristic objectively. PCA was performed on the normalized S/N ratio matrix by decomposing the covariance matrix into eigenvalues and eigenvectors (Table 3). The first two principal components were retained, explaining 90.3% of the total variance (PC1: 67.9%, PC2: 22.4%), which justifies their use for weighting. The weights for each response were calculated from the normalized square of the PC1 eigenvector loadings, as PC1 accounts for the majority of the data variance. These weights

were then applied to the Grey Relational Coefficients (GRCs) to compute the Grey Relational Grades (GRGs), integrating multi-response optimization effectively within the GRA framework. The array's constituents for each of the several performance attributes, as listed in Table 5, display the GRCs for each performance characteristic. Each eigenvalue's corresponding eigenvector is listed in Table 7, and the square of the principal component values of the respective eigenvectors yields the weighted contribution of each performance attribute. Furthermore, Table 7 indicates that up to 67.9% of the variation is attributed to the first main component, which accounts for the three performance criteria. Equation 7, which calculates the weighted value of each performance indicator, is used to compute grey relation grades (GRGs) with the introduction of PCA. Table 6 provides information about the GRGs and their corresponding ranks. The following is an example of a GRG calculation for experiment number 1 using Equation 7:

$$\gamma_i(\text{GRG}) = 0.34 * 0.32 + 1 * 0.40 + 0.41 * 0.16 + 0.61 * 0.12 = 0.65$$

The values of all the grey relational grades range from 0 to 1. A strong association is observed between the reference sequence and the comparability sequence as the GRG value approaches the maximum. The maximum GRG value in this study is obtained for the 12th run order with BC-10%, WEO – 3%, WCO – 1%, and PA – 0%. The corresponding test results are Penetration – 102 dmm, Ductility – 63cm, Softening point – 50 °C, and Elastic recovery – 100%. Furthermore, the optimum parameter setting for each factor is derived from the Response table for means. The optimum parameter setting (BC-5%, WEO-2%, WCO-1%, and PA-0%) has undergone a confirmatory test to assess the accuracy of the inquiry for penetration, Ductility, Softening point, and Elastic recovery.

4. Conclusion

This study presents a novel approach to developing sustainable, high-performance bio-bitumen binders by integrating waste oils and biochar, optimized using Grey-Taguchi analysis. The maximum Grey Relational Grade (GRG) was observed for the 12th run (BC-10%, WEO-3%, WCO-1%, PA-0%), achieving a penetration of 102 dmm, ductility of 63 cm, a softening point of 50°C, and an elastic recovery of 100%. An alternative “optimal” parameter set from the response table (BC-5%, WEO-2%, WCO-1%, PA-0%) was also validated, showing balanced improvements. While the 12th run showed slightly better individual properties, the chosen optimal set represents a practical compromise considering overall performance and process stability. The optimized binders meet existing standard specifications, demonstrating their potential for practical pavement use. Key limitations include the absence of long-term aging data and in-depth chemical analysis. The Grey-Taguchi results highlight that, despite all modifiers individually improving properties, PA at 0% was optimal due to possible antagonistic interactions with other additives. Future work should focus on detailed rheological, chemical, and durability studies, alongside cost and environmental assessments, to enable widespread application of bio-bitumen as a sustainable alternative in pavement construction.

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