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Utilizing a Hybrid Artificial Radial Basis Function Neural Network combined with Horse Herd Optimization Algorithm to Predict Red Mud-Modified Asphalt Mixture Properties using Marshall Mix Design

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ABSTRACT

This study investigated the use of red mud, an industrial waste material, as a sustainable alternative to conventional limestone fillers in asphalt mixtures, combined with the application of a novel predictive model. Utilizing a Radial Basis Function Neural Network optimized by the Horse Herd Optimization Algorithm (RBFNN-HOA), the research predicts key mechanical (Marshall stability, and Marshall flow) and volumetric properties of asphalt mixtures, including bulk density, air voids, voids in mineral aggregate, and voids filled with asphalt binder. Experimental work involved preparing and testing 30 asphalt mixture samples with varying red mud contents (0%, 25%, 50%, 75%, and 100%) and different asphalt contents (5.0, 5.5, and 6.0) under the Marshall mix design. The RBFNN-HOAmodel demonstrated exceptional predictive accuracy 99.97%, R^2 values exceeding 0.999 and minimal errors (e.g., RMSE < 0.0055, MAPE < 0.025% and SI < 0.00029), while variable importance analysis highlighted asphalt binder and red mud as critical input factors. This research highlights the dual advantages of employing advanced machine learning techniques and sustainable materials in asphalt design. The RBFNN-HOA model provides a reliable tool for predicting and optimizing asphalt mixture properties and reduces the need for extensive experimental work, thereby saving time and resources. Furthermore, the study supports the transition to a circular economy by demonstrating the effective use of red mud as a filler, achieving enhanced mechanical performance and environmental benefits.

Keywords: Industrial waste; red mud; Marshall mix design; sustainable pavement, artificial neural network

INTRODUCTION

The increasing global focus on sustainable construction practices has generated much interest in replacing raw materials with waste products (Babalghaith, Koting, Sulong, Karim & AlMashjary 2020; Khan et al. 2022; Shah, Min, Awang & Tey 2023; Maaze, Garg, Das & Shrivastava 2024). Due to the high need for materials, asphalt pavement is a good opportunity for agricultural industrial waste inclusion, also, this could provide for minimum environmental benefits (Kamaruzamana, Azahara, Kasima, Hairinb & Nadia 2025). An example of one of these by-products is red mud, a fine-grained, highly alkaline residue obtained when bauxite ore is treated to produce alumina (Zeng et al. 2020; Rooholamini, Bayat & Motevalizadeh 2024). Minerals such as iron oxide, silicon oxide, titanium dioxide, and sodium oxide are the main constituents of red mud. It has high alkalinity because of sodium hydroxide that is used in the process of extracting alumina (Archambo & Kawatra 2021). The alkaline nature represents a major environmental concern because it has the potential to degrade soil and water quality if left untreated (Gomes, Mayes, Rogerson, Stewart & Burke 2016).

Red mud is a waste product of extracting alumina from bauxite, an intermediate stage in aluminium manufacturing. Bauxite is then subjected to grinding and washing before the chemical extraction of alumina, with red mud being the primary waste product. This waste is generated in huge amounts, around 150 million tons a year globally, and is usually encased in tailings dams. For example, in Saudi Arabia, Maaden's aluminum production reflects a ratio of 2.65:1:2 for bauxite, alumina and red mud, signifying that more than half of the process yields waste (AlBoraikan, Bageri & Solling 2022) . The disposal of red mud has been a major challenge for several decades, with traditional storage methods giving rise to sporadic accidents and environmental pollution (Liu, Han, He, Gao & Yuan 2021). These challenges have spurred research and engineering to seek alternative uses for red mud and to minimize its environmental impact. Reuse in construction industry is one of the most promising scenarios (Morsali & Yildirim 2024).

Red mud, naturally existing in powder form, is well-suited as a filler in asphalt mixtures. Fillers play a crucial role in asphalt by filling voids between aggregate particles, creating denser and stiffer layers, and increasing the contact points between aggregates (Mohammed, Yousif & Zghair 2022; Khedaywi, Haddad & Alyaseen 2023). Moreover, fine mineral filler particles can form asphalt films that coat larger aggregates, influencing key performance aspects such as resistance to permanent deformation, fatigue cracking, and moisture susceptibility (Kandhal, Lynn & Parker 1998; Ali 2022).

Many studies are used to predict the properties of asphalt mixtures using different techniques (Dai et al. 2024; Wang et al. 2024; Ali, Abdualmtalab Abdualaziz, Milad, Abdalrhman, Al-Sabaeei, Abdulnaser M, Babalghaith, Ali Mohammed & Yusoff, Nur Izzi Md 2025; Babalghaith et al. 2025). Among these techniques, the use of machine learning offers a promising approach for predicting the properties of various materials (Alzaeemi, Sathasivam, Adebayo, Kasihmuddin & Mansor 2017; Ali, Abdualmtalab Abdualaziz, Milad, Abdalrhman, Al-Sabaeei, Abdulnaser M., Babalghaith, Ali Mohammed & Yusoff, Nur Izzi Md 2025). Machine learning applications are highly effective in developing models and expectations for the behavior and responses of asphalt mixture properties (Yaro et al. 2024).

Artificial Neural Networks (ANNs) is one of the most used machine learning applications for obtaining accurate predictions (Anuar, Khan, Ramli, Jidin & Othman 2021; Adwan et al. 2022; Ali et al. 2023). Common algorithms used in these applications include Generalized Regression Neural Networks (GRNN) (Wang & Peng 2018), Back-Propagation Neural Networks (BPNN) (Liao, Wang, Zhou, Liao & Huang 2012), Fuzzy Neural Networks (FNN) (Chen, Gooi, & Wang, 2013), and Radial Basis Function Neural Networks (RBFNN) (Oduro-Gyimah & BOATENG, 2021; Alzaeemi et al. 2023). These networks explore data and deliver equations for the predictive analysis. In particular, machine learning programs processes experimental observation data using optimization methods and validate the resulting model through laboratory experiments.

The ANN approach has found widespread applications in diverse domains of civil engineering. As an example, Sharifi and Tohidi (2014) employed a 3-layer back-propagation (BP) neural network for prediction of remaining buckling strength of localized corrosion plate girders made of steel. Their results validated the accuracy of the developed network. Wong (2018) also proposed a simple ANN method for predicting marine riser fatigue damage induced by vortex-induced vibration (VIV). Their final ANN model effectively predicted fatigue damage with superior efficiency in comparison to semi-empirical approaches.

Yaro et al. (2024) used a neural network (one hidden layer), which was able to predict the volumetric and Marshall properties of asphalt mixtures. The model accurately predicted the properties of Marshall with minimal prediction errors. However, there are no studies so far that evaluated the effects of asphalt mixture properties through a hybrid ANN model. This is the first study to use a hybrid ANN predictive model to confirm the hypothesis that using waste fillers in a Marshall mix can improve the properties of asphalt mixtures. The present study develops a predictive model utilizing a hybrid Artificial Neural Network referred to as Radial Basis Function Neural Network with Horse Herd Optimization Algorithm (RBFNN-HOA).

In this study, a RBFNN type of single hidden-layer feedforward network, was employed due to its well-established reputation as a forecasting model. According to Moody and Darken (1989), RBFNN was the first implemented feedforward neural network and has the advantage of learning more rapidly than a multilayer perceptron (MLP). Its widespread application across various fields is attributed to its simpler network architecture, faster learning process, and superior predictive capabilities (Sathasivam, Alzaeemi, Ismail, & VaniPachala, 2020). RBFNN can be used to solve a variety of issues in business, industry, and science. Besides, time series forecasting is one of the main ap-plications of RBFNN (Yan, Wang, Yu, & Li, 2005; Nguyen & Pham, 2024). The study utilized the horse hard optimization algorithm (HOAS) to train the RBFNN to achieve optimal performance and high accuracy in the predictive model RBFNN-HOA for Asphalt Mixture Properties. Horse Herd Optimization Algorithm (HOA), inspired by the social behavior of horse herds, is a swarm intelligence-based metaheuristic method designed to solve complex mathematical problems. It emulates the movement and interaction dynamics within a herd, including leadership and group cohesion. Similar to evolutionary algorithms, HOA begins with a random population of solutions and iteratively improves them over successive generations. However, unlike traditional evolutionary approaches, HOA does not use operators like crossover or mutation. Instead, it relies on updating positions based on the best-performing individuals and social influences (Basu, Kumar, & Basu, 2022). HOA has been successfully applied in various optimization domains, including training artificial neural networks (ANNs) and mechanical engineering design, due to its ability to achieve high accuracy and fast convergence. In this study, HOA is used to optimize the weights of RBFNN, minimizing training errors and improving predictive performance. By iteratively updating the output weights of the RBFNN, the algorithm achieves optimal performance in the predictive model. This method, referred to as RBFNN-HOA, ensures reliable training and high accuracy for the RBFNN, making it suitable for addressing real-world optimization problems. Given the limitations of conventional models in data-scarce environments, a more adaptive approach is proposed. This study introduces a hybrid modeling framework combining a RBFNN with the Horse Herd Optimization Algorithm (HOA), referred to as RBFNN-HOA, to predict the properties of asphalt mixtures incorporating industrial waste fillers. The RBFNN is selected for its effectiveness with small, nonlinear datasets, offering localized learning, resistance to overfitting, and efficient generalization capabilities (Jia, Zhao, & Ding, 2016). To further enhance predictive performance, HOA, a recent bio-inspired metaheuristic algorithm known for its effective balance between exploration and exploitation, is employed to optimize the network parameters (MiarNaeimi, Azizyan, & Rashki, 2021). Compared to traditional models such as Random Forest, SVM, and XGBoost, which often require larger datasets and rely heavily on manual or grid-based parameter tuning, the RBFNN-HOA model provides a more adaptive and accurate solution under data-constrained conditions. The proposed hybrid demonstrates superior robustness and adaptability, particularly in small-sample regression tasks, building upon prior work in both neural network modeling and metaheuristic optimization.

While linear or polynomial regression models are commonly used as initial steps in predictive modeling, they are often insufficient for capturing the complex, nonlinear behavior of asphalt mixtures, especially when modified with industrial waste fillers. Properties such as stability, flow, and stiffness are governed by several interacting variables, which violate the assumptions of linear models. Given these nonlinearities and the limited size of our dataset (30 samples), the study begins with a RBFNN-HOA, bypassing simpler regressors. RBFNNs offer a middle ground between simple linear models and computationally intensive deep learning networks, providing both flexibility and efficiency. The use of HOA further improves the model's adaptability and generalization. Prior studies confirm the effectiveness of metaheuristic-optimized RBFNNs in similar engineering applications with limited data (Jia et al. 2016; Noman, Al-Gheethi, Alzaeemi, Mohamed, & Gaik, 2024). Thus, the selected model provides a well-justified starting point for tackling the prediction task under the data and domain constraints of this study.

The objective of this study is to establish a prediction method to investigate the behavior of the waste fillers and asphalt binder on asphalt mixture. In this work, instead of a model to estimate individual mixture performance, it is proposed to characterize the parameter properties and ground the asphalt mixture as it is correlated with the parameter properties. It can be done by implementing different algorithms together with the Artificial Neural Network (ANN). Combination multiple with ANN is a new attempt to predict and ascertain the applicable relationships of parameters and their role in asphalt mixtures. Given that asphalt mixture analysis involves complex mixtures and non-linear relationships, the strength of ANN on such data is being utilized in this approach. However, building an efficient ANN model is not an easy task, it requires the selection of architecture, transfer functions, training algorithms, and other parameters very carefully. A three-layer feedforward neural network with a logistic transfer function in the hidden layer has often been regarded as an appropriate architecture to use for these applications (Al-Zamzami et al. 2024).

METHODOLOGY

The methodology of this study consists of two main parts, the experimental work and the artificial neural network model as described in detail in subsequent sections.

EXPERIMENTAL WORK

1. Materials used

The base binder, classified as penetration grade 60–70, was sourced from the Ras-Tanura Refinery in the Eastern Region of Saudi Arabia. Its physical properties are summarized in Table1.

TABLE 1. Asphalt binder properties

Property	Temp.	Unit	Value
Penetration	25°C	mm	67
Softening Point	-	°C	49.5
Ductility	25°C	cm	+ 100
Rotational Viscosity	165 °C	cps	239
Rotational Viscosity	135 °C	cps	510
Specific Gravity	25°C	-	1.025
Rolling Thin Film Oven	163°C	% wt loss	0.07

Limestone aggregates were sourced from the Al-Summan region, approximately 100 km west of Dammam. Their physical properties were thoroughly evaluated as shown in Table2. These properties highlight the suitability of the limestone aggregates for asphalt mixture applications.

TABLE 2. Aggregates properties

Parameter	Unit	Value
Abrasion loss	%	22.9
Sand equivalent	%	70.3
Clay lumps and friable particles	%	0.184
Coarse aggregates specific gravity	-	2.56
Coarse aggregates water absorption	%	1.93
Fine aggregates specific gravity	-	2.51
Fine aggregates water absorption	%	2.45

Asphalt wearing course with a nominal maximum aggregate size of 12.5 mm was selected, and the aggregate gradation with lower and upper limits as per the Ministry of Transport and Logistics Services (MOTLS) specifications in Saudi Arabia is depicted in Table 3.

TABLE 3. Aggregate gradation

Sieve Opening (mm)	Passing (%)	MOTLS specifications	
		Min.	Max.
19.0	100	100	100
12.5	95	90	100
9.5	83	76	90
4.75	62.5	50	75
2.36	43	28	58
1.18	23	12	34
0.075	6	2.0	10.0
Pan	0	0	0

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Limestone dust, sourced from the same origin as the aggregate, served as the primary filler in this study. Red mud, obtained from a local company's waste storage in Ras Al-Khair, Saudi Arabia, was also employed as a limestone filler replacement (Figure 1).

The particle sizes of the fillers were measured in micrometers (μm) using a particle size analyzer, while their chemical oxide compositions were determined using an X-ray fluorescence (XRF) spectrometer. Table 4 presents the physical properties and chemical composition of both fillers. The specific gravity of Red Mud (2.63) is slightly lower than that of Limestone (2.71), indicating a marginally lighter material density. The particle size distribution shows that Red Mud has finer particles (D_{10} = 2.13 μm, D_{50} = 0.32 μm, D_{90} = 23.7 μm) compared to Limestone (D_{10} = 4.32 μm, D_{10} = 0.3 μm, D_{90} = 27.8 μm), suggesting higher surface area and potential reactivity. Chemically, Red Mud is rich in Fe_2O_3 (27%) and Al_2O_3 (26%), along with considerable SiO_2 (17%) and CaO (8%), indicating its complex oxide composition and potential pozzolanic behavior. In contrast, Limestone mainly consists of CaO (81%) and SiO_2 (15%), reflecting its dominance as a calcium carbonate source.

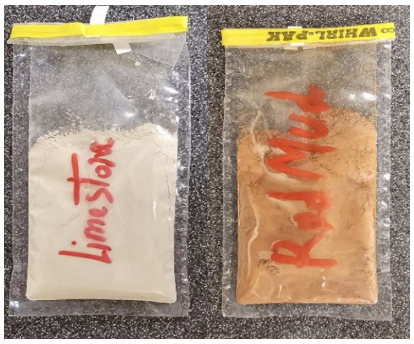

FIGURE 1. Fillers (limestone and red mud)

2. Experimental setup and design

The Marshall mix design method was employed in this study following the specifications of the Ministry of Transport and Logistic Services in Saudi Arabia. Five groups of asphalt mixtures were prepared with varying proportions of red mud (0%, 25%, 50%, 75%, and 100%) as a replacement for limestone dust. Additionally, hydrated lime (2 % of aggregate weight) was consistently added as a widely used antistripping additive, which is widely used worldwide for this purpose (Deb & Lakshman Singh, 2021; Yardım, Şitilbay, & Yılmaz, 2024). For sample preparation, 1100 grams of materials were measured based on the aggregate gradation. The aggregates and binder were heated to approximately 165°C for 2 hours, and all components were mixed using the dry process method. Asphalt binder contents of 5.0%, 5.5%, and 6.0% by total weight of the mix were added and thoroughly blended to achieve a uniform mixture.

The mixture was then placed into a preheated Marshall mould, lined with filter paper on both ends to prevent sticking, and compacted with 75 blows per side using a Marshall compactor. After compaction, the samples were cooled at room temperature for 24 hours, carefully removed from the mould using a jack, and stored in the laboratory for further testing.

The prepared samples were subjected to the Marshall test to determine the Marshall stability and Marshall flow. These mechanical properties provide insight into the load-bearing capacity and deformation resistance of the asphalt mixtures.

In addition to mechanical testing, the volumetric properties of each mix were calculated. The volumetric parameters include bulk density (BD), air voids (AV), voids in mineral aggregate (VMA), and voids filled with asphalt (VFA). These properties were computed using the following standard equations 1 to 6 in line with specifications ASTM/AASHTO procedures.

1. Bulk Density

$$BD = G_{mb} * \rho_w \tag{1}$$

$$G_{mb} = \frac{W_D}{W_{SSD} - W_{SUB}} \tag{2}$$

2. Air Voids

$$AV\ (\%) = \frac{(G_{mm} - G_{mb})}{G_{mm}} * 100 \tag{3}$$

$$G_{mm} = \frac{W_m}{W_m - W_w} \tag{4}$$

3. Voids in Mineral Aggregate

$$VMA\ (\%) = \left(1 - \frac{G_{mb} * P_S}{G_{sb}}\right) * 100 \tag{5}$$

4. Voids Filled with Asphalt Binder

$$VFA\ (\%) = \left(\frac{VMA - AV}{VMA}\right) * 100 \tag{6}$$

3. Data collected for ANN model

Based on the experimental design, 30 samples (2 replicates x 3binder content levels x 5 red mud content levels) were prepared. These samples were then tested for Marshall stability (MS), Marshall flow (MF), and various volumetric properties, including mixture bulk density (BD), air voids (AV), voids filled with asphalt binder (VFB) and voids in the mineral aggregate (VMA). The average results are recorded as shown in Table 5.

TABLE 4. Filler's properties

Materials	Specific gravity	Particle sizes, µm			Composition									
		D_{10}	D_{50}	D_{90}	Na_2O	Al_2O_3	SiO_2	P_2O_5	SO_3	K_2O	CaO	Tio_2	MnO	Fe_2O_3
Red Mud	2.63	23.7	2.13	0.32	18	26	17	0.2	1.9	0.1	8	1.3	0.2	27
Limestone	2.71	27.8	4.32	0.3	-	1.5	15	-	0.9	0.4	81	0.3	-	1.3

TABLE 5. Experimental results

Run	Input		Responses					
	AB	RM	BD	VMA	AV	VFB	MS	MF
	%	%	g/ml	%	%	%	KN	mm
1	5	0	2.227	16.47	5.55	66.31	9.67	3.29
2	5	0	2.222	16.67	5.77	65.36	10.74	3.24
3	5.5	0	2.267	15.44	3.22	79.17	11.13	3.46
4	5.5	0	2.267	15.41	3.18	79.34	11.13	3.56
5	6	0	2.286	15.18	1.74	88.57	10.89	3.61
6	6	0	2.278	15.47	2.07	86.62	10.73	3.54

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7	5	25	2.248	15.69	4.67	70.26	11.19	4.26
8	5	25	2.247	15.73	4.72	70.00	11.78	4.21
9	5.5	25	2.252	15.97	3.83	76.02	14.56	3.42
10	5.5	25	2.258	15.77	3.59	77.22	13.60	3.41
11	6	25	2.287	15.13	1.68	88.89	12.81	3.38
12	6	25	2.274	15.61	2.24	85.68	11.76	3.21
13	5	50	2.250	15.60	4.57	70.70	12.82	3.00
14	5	50	2.250	15.56	4.53	70.88	12.48	3.28
15	5.5	50	2.258	15.71	3.53	77.52	13.00	3.32
16	5.5	50	2.261	15.62	3.43	78.04	13.54	3.29
17	6	50	2.269	15.76	2.41	84.72	10.12	4.33
18	6	50	2.271	15.68	2.32	85.23	10.65	3.63
19	5	75	2.218	16.79	5.92	64.76	11.25	3.40
20	5	75	2.235	16.13	5.17	67.95	12.77	3.28
21	5.5	75	2.262	15.56	3.36	78.38	13.04	3.40
22	5.5	75	2.261	15.60	3.40	78.19	13.62	3.34
23	6	75	2.268	15.82	2.48	84.33	11.02	3.35
24	6	75	2.273	15.61	2.24	85.65	11.29	3.24
25	5	100	2.240	15.87	4.89	69.20	11.47	3.09
26	5	100	2.253	15.40	4.35	71.74	11.38	3.05
27	5.5	100	2.227	16.82	4.81	71.39	12.43	3.25
28	5.5	100	2.280	14.82	2.53	82.95	12.57	3.34
29	6	100	2.275	15.48	2.10	86.41	9.71	4.00
30	6	100	2.272	15.59	2.23	85.70	10.20	3.31

AB: Asphalt Binder, **RM**: Red Mud, **BD**: Bulk Density, **VMA**: Voids in Mineral Aggregate, **AV**: Air Voids, **VFB**: Voids Filled with Binder, **MS**: Marshall stability, **MF**: Marshall flow

As shown in Table 5, the inclusion of red mud consistently improved the stability of asphalt mixtures compared to mixtures without it. The highest stability was observed in mixtures with a binder content of 5.5%, after which further increases in binder led to a reduction in stability. Notably, all asphalt mixtures tested exceeded the 9.81 kN (1000 kg) minimum stability requirement set by the Saudi Arabian standard for the MOTLS (Ministry of Transport and Logistic Services, 2020). The enhancement is linked to the presence of cancrinite in red mud, which is rich in sodium (Na), aluminum (Al), and silicon (Si), and features finer particle sizes that provide a larger surface area. These properties improve the interaction between aggregate and binder by fostering stronger bonding, which in turn boosts strength. Regarding Marshall flow results did not show a clear pattern. However, all mixtures consistently fell within the recommended range of 2–4 mm, as per the same standard.

Regarding bulk density, the unit weight of the mixtures increases with higher binder content, accompanied by a decrease in air voids due to the asphalt binder filling these voids, thereby enhancing density. Table 5 illustrates the air void results for various asphalt mixtures with different binder contents, demonstrating a consistent trend: as the asphalt binder content increases, the air voids decrease. This occurs because the air voids are filled with asphalt binder, resulting in a lower percentage of air voids.

The voids filled with asphalt binder also show an upward trend with increasing binder content. Although the voids in mineral aggregate values for the mixtures do not exhibit a consistent pattern, all exceed the minimum requirement of 14% specified by the in Saudi Arabia (Ministry of Transport and Logistic Services, 2020). Based on the above findings, it can be concluded that red mud is suitable as a substitute for normal filler in asphalt mixtures up to 100% and fulfills the mixture specification criteria concerning the Marshall mix design.

The selection of the optimal binder content (OBC) for an asphalt mixture is critical to achieving a desirable equilibrium among its durability, strength, and workability. As stipulated by the MOTLS of Saudi Arabia (Ministry of Transport and Logistic Services, 2020), the OBC is defined as the average asphalt content yielding 4% air voids at both the maximum stability and maximum specific density. A target of 4% air voids is selected to balance durability and performance: an excessive amount of air voids may lead to cracking due to inadequate binder coverage on the aggregates, while too few air voids can cause rutting and binder bleeding (Zaltuom, 2018; Babalghaith et al. 2022). The OBC values of different mixtures incorporated with red mud is calculated and presented in Figure 2. The OBC for all mixtures, including those with red mud, consistently averaged 5.61±0.01% of the total mixture weight. This indicates that adding red mud as filler replacement did not affect the OBC, meaning it will not increase the amount of binder needed.

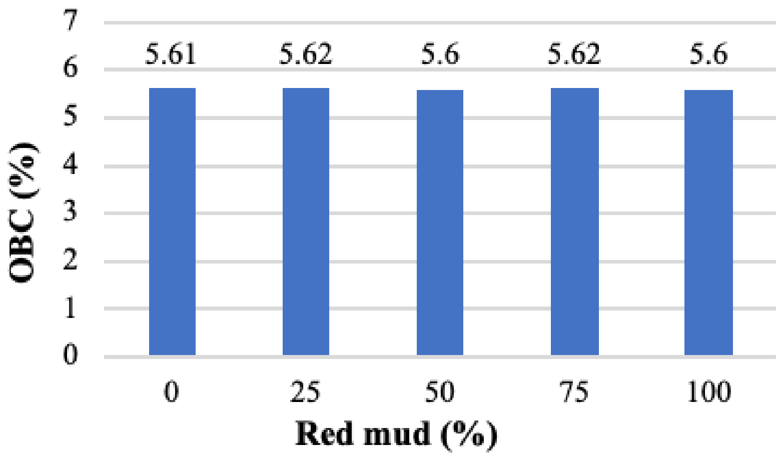

FIGURE 2. Optimum binder content

ARTIFICIAL NEURAL NETWORK MODEL

This study aims to present significant innovations by developing and validating the RBFNN-HOA model to predict the performance of asphalt mixtures containing industrial waste fillers. Based on the existing literature and the authors' expertise, previous studies investigating the behavior of asphalt mixture employing various characteristics are still few. This study employs novel qualities to comprehend the behavior of industrial waste fillers. Additionally, several influential attributes are utilized to enhance the accuracy of the results and get a comprehensive grasp of asphalt mixture behavior, enabling informed decision-making. Therefore, an RBFNN-HOA was used to assess the maximum capacity of the Marshall mix design. Based on the preliminary analyses and observations in experimental and numerical specimens, two parameters were identified as influencing the performance of asphalt mixtures. as the input factors for the model called Asphalt Binder (AB), and Red Mud (RM), which have an impact on six parameters (output) referred to as the Bulk Density (BD), Voids in Mineral Aggregate (VMA), Air Voids (AV), Voids Filled with Asphalt Binder (VFB), Marshall Stability (MS), and Marshall Flow (MF), as shown in Figure 3.

The use of only 30 experimental samples presents a challenge for machine learning due to risks of overfitting and limited generalizability. To address this, we employed a RBFNN combined with the HOA. RBFNNs are known for their suitability to small datasets owing to their localized learning properties and low model complexity (Buhmann, 2001). The Gaussian activation functions help avoid over-generalization by focusing learning within specific regions of the input space.

Regarding the selection of the activation function, Gaussian activation function has been employed because of the association properties of every radial unit as center, as well as width. The remaining activation functions like hyperbolic activation function and bipolar activation function, as well as Mc Culloch Pitts Activation Function, do not suit the presented RBFNN due to the given non-compatible classification interval. The activation function utilization has led to the RBFNN overfitting nature (Alzaeemi et al. 2023).

To further enhance the model's performance, HOA was used to optimize the network's output weights and spread parameters. As a recent bio-inspired optimizer, HOA simulates intelligent herd behavior and provides adaptive search capabilities that improve convergence and reduce the likelihood of local minima entrapment (MiarNaeimi et al. 2021). Previous work by Jia et al. (2016) demonstrated that even with datasets as small as 20–30 samples, hybrid models combining RBFNNs with metaheuristics (e.g., Genetic Algorithms) achieved high classification accuracy. This hybrid approach is particularly relevant in the field of asphalt materials engineering, where experimental sample collection can be expensive and time-consuming. Thus, our model is designed not only for predictive accuracy but also for practical feasibility in data-constrained scenarios.

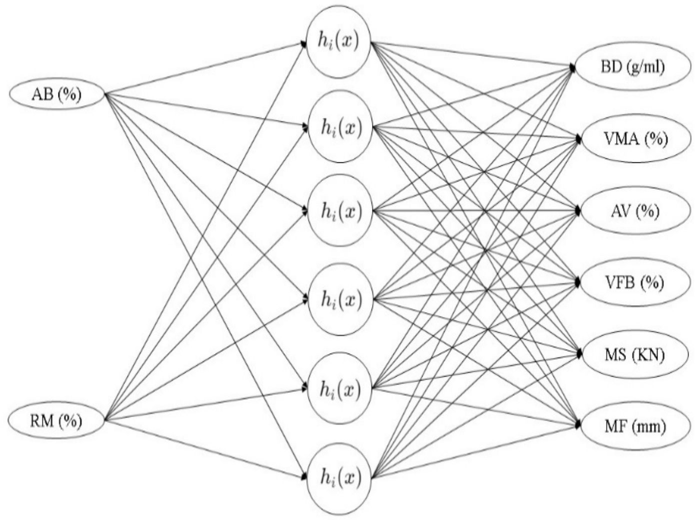

FIGURE 3. Structure of parameters affecting the behavior of the asphalt mixture using a hybrid ANN

This section will demonstrate the methodology of this study by using a hybrid neural network step by step using the following equations (7 to 12):

1. The RBFNN model design has three layers: the input layer, the hidden layer, and the output layer. As in this study, AB and RM are input in the input layer. These inputs represent material properties that influence asphalt performance. Flow to hidden layer using radial basis functions called Gaussian functions to transform the input data into a higher-dimensional feature space.

$$h_i(x) = e^{\left(-\frac{|x-c_i|^2}{2\sigma_i^2}\right)} \quad (7)$$

where c_i is the center of the hidden layer, and s_i is the width of the hidden layer.

The predicted parameters in the output layer are BD, VMA, AV, VFB, MS, and MF by using the following equation called the final output of RBFNN:

$$y = \sum_{i=1}^{m} w_i \, h_i(x) \quad (8)$$

where w_i is the output weight connecting the hidden neuron to the output neuron.

2. Initialize output weights in HOA. Each horse position represents a set of weights that connect the hidden layer to the output layer. For an RBFNN with:

$$w_i = (w_1, w_2, w_3, \ldots, w_n) \quad (9)$$

3. Updating weights using HOA as follows:

$$w_i^{t+1} = w_i^t + r_1 . \, (w_{leader} - w_i^t) \quad (10)$$

where w_i^t is the current weight vector for the i-th horse, w_{leader} is the weight vector of the leader, and r_1 is a random factor between 0 to 1.

4. Social cohesion update. In this step the horses update their weights by considering the influence of a neighboring horse:

$$w_i^{t+2} = w_i^{t+1} + r_2 . \left(w_j^t - w_i^{t+1}\right) \quad (11)$$

w_j^t is the Weight vector of a randomly selected neighboring horse and r_2 is a random factor between 0 and 1.

5. Exploration update. To avoid local optima, some horses explore new weight configurations:

$$w_i^{t+3} = w_i^{t+2} + r_3.V \tag{12}$$

where r_3 controls exploration intensity, V is the random vector that introduces diversity.

6. Final step to get the final output. The output weights optimized by HOA minimize the error in the RBFNN predictions and ensure high accuracy in predicting the six output parameters: BD, VMA, AV, VFB, MS, and MF.

Due to the limited size of the experimental dataset (n = 30), a conventional train–test split could have introduced high variance and unreliable performance estimates. Therefore, we adopted a k-fold cross-validation strategy, which is widely recommended for small-sample scenarios to ensure more reliable and generalizable evaluation results (Jia et al. 2016; Victor Wandera, Dennis, Mary Lemasulani, Njoka Grace, & Musyimi Daniel, 2024). Specifically, 5-fold cross-validation was employed: the dataset was randomly partitioned into five equally sized folds. In each iteration, four folds (80% of the data) were used to train the model, while the remaining fold (20%) served as the testing set. This process was repeated five times, ensuring that each sample was used once for validation. The final model performance was then reported as the average across all testing folds. The model achieved an average validation RMSE of 0.1732 with a standard deviation of 0.0754, demonstrating stable and reliable performance across all folds. This outcome confirms that the RBFNN-HOA model generalizes well, even when trained on limited data, and validates its suitability for small-sample regression tasks in civil engineering applications.

During each stage of model development, the performance of the RBFNN-HOA prediction model for each output was evaluated using various indices (shown in equations 13 to 17) , including the Coefficient of Determination (R^2), accuracy, Root Mean Square Error (RMSE), Mean Absolute Percentage Error (MAPE), Scatter Index (SI), with the Relative importance of input parameters for the output parameters.

$$R^2 = 1 - \frac{\Sigma(y\_acul - y\_pred)^2}{\Sigma(y\_acul - y\_mean)^2} \tag{13}$$

$$Accuracy = \frac{(Correct\ predictions)}{(Total\ predictions)} \tag{14}$$

$$RMSE = \sqrt{\frac{\Sigma\left|y_{acul} - y_{pred}\right|^2}{n}} \tag{15}$$

$$MAPE = 100 * \frac{\Sigma\left|y_{acul} - y_{pred}\right|}{\Sigma y_{acul}} \tag{16}$$

$$SI = RMSE/y\_mean \tag{17}$$

The RMSE assesses the accuracy of a model by considering the magnitude of the larger errors, specifically the squared difference between the actual and predicted values. Considering its absolute nature, the RMSE index is presented as a dimensionless value in the SI system. The R^2 index measures the strength of the linear relationship between the predicted and actual values. It is very responsive to any outliers or extreme data points.

RESULTS AND DISCUSSION

The results were discussed based on the output parameters as shown in the next subsections.

PREDICTION ERROR METRICS FOR BULK DENSITY

The RBFNN-HOA model demonstrated consistent performance in predicting BD, with low variation in error across multiple runs. This indicates the model's robustness and reliability in capturing the compaction behavior of asphalt mixtures as shown in Figure 4.

Figure 4 illustrates the result of the Hybrid Artificial Radial Basis Function Neural Network optimized with Horse Herd Optimization (RBFNN-HOA), which exhibits remarkable precision in forecasting the BD of asphalt mixes, including industrial waste fillers according to Marshall mix design. The model attains an RMSE of 0.000190 and a R^2 of 0.998613, indicating near-perfect predictions and accounting for 99.86% of the variability in BD values. The MAPE of 0.011673% and an accuracy of 99.38% underscore the model's dependability and exactness in reducing prediction mistakes. The scatter plot demonstrates a reliable linear correlation between actual and anticipated values, whilst the variable importance analysis indicates that AB has the most significant influence on BD, followed by RM. This methodology offers a resilient and sustainable technique for enhancing asphalt mixes, guaranteeing improved performance and effective use of industrial waste.

PREDICTION ERROR METRICS FOR VOIDS IN MINERAL AGGREGATE

The prediction errors for VMA remained within an acceptable range, reflecting the model's ability to handle structural parameters of the mix. Slight fluctuations suggest sensitivity to filler content, but overall accuracy remained high. In the dissection of Figure 5, the presentation of prediction error metrics for the RBFNN-HOA model in predicting VMA offers valuable insights into the model's accuracy and the influence of input variables. RBFNN-HOA achieves impressive performance in predicting VMA values in asphalt mixtures with industrial waste fillers under the Marshall mix design. The model demonstrates exceptional accuracy, with a RMSE of 0.007884 and a high R^2 value of 0.99, indicating that the model captures 99% of the variability in VMA values. The SI of 0.000501 and a MAPE of 0.070728% further highlights the model's ability to minimize prediction errors effectively. With an overall prediction accuracy of 98.9977%, the model is highly reliable in forecasting VMA. The variable importance analysis shows that RM and AB are the key contributors, ensuring accurate and sustainable asphalt mix designs.

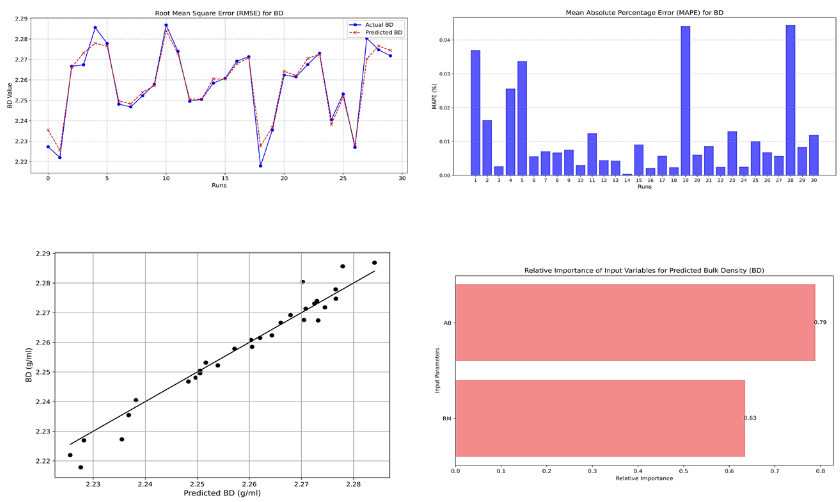

FIGURE 4. Prediction Error Metrics for Each Run of the RBFNHOA Model in BD

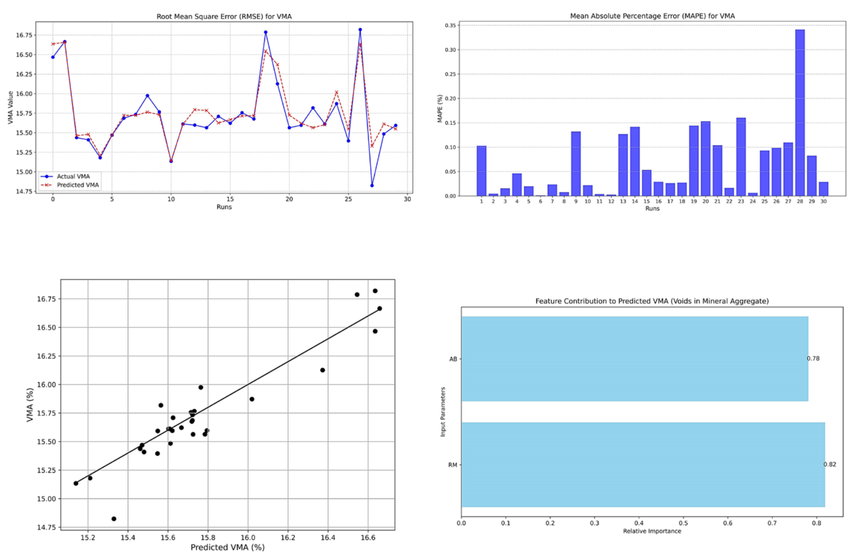

FIGURE 5. Prediction Error Metrics for Each Run of the RBFNHOA Model in VMA (%)

PREDICTION ERROR METRICS FOR AIR VOID

AV predictions showed minimal deviation, highlighting the model's strength in modeling volumetric properties. The low prediction error supports its applicability in optimizing air void targets during mix design as presented on Figure 6.

Figure 6 depicts the efficacy of RBFNN-HOA in forecasting AV in asphalt mixes using industrial waste fillers. The model's performance is characterized by an RMSE of 0.009318, a R^2 of 0.948529, and a MAPE of 0.428280%, demonstrating dependable and precise predictive capabilities, as it accounts for 94.85% of the variability in AV values. A SI of 0.002624, and a prediction accuracy of 94.75% further emphasise the model's efficacy. The lower left graph juxtaposes real and anticipated AV values throughout 30 iterations, demonstrating a strong correlation. The histogram graph shows MAPE values, indicating that most runs have low error levels, interspersed with occasional peaks that imply possible unpredictability. The scatter figure shows a reliable linear connection between anticipated and actual AV values, hence affirming model dependability. The bottom right bar chart illustrates the significance of input variables, highlighting the preeminent impact of AB at 0.91 in contrast to RM at 0.69. These results corroborate the model's capacity to enhance asphalt mix designs by pinpointing critical components influencing AV%.

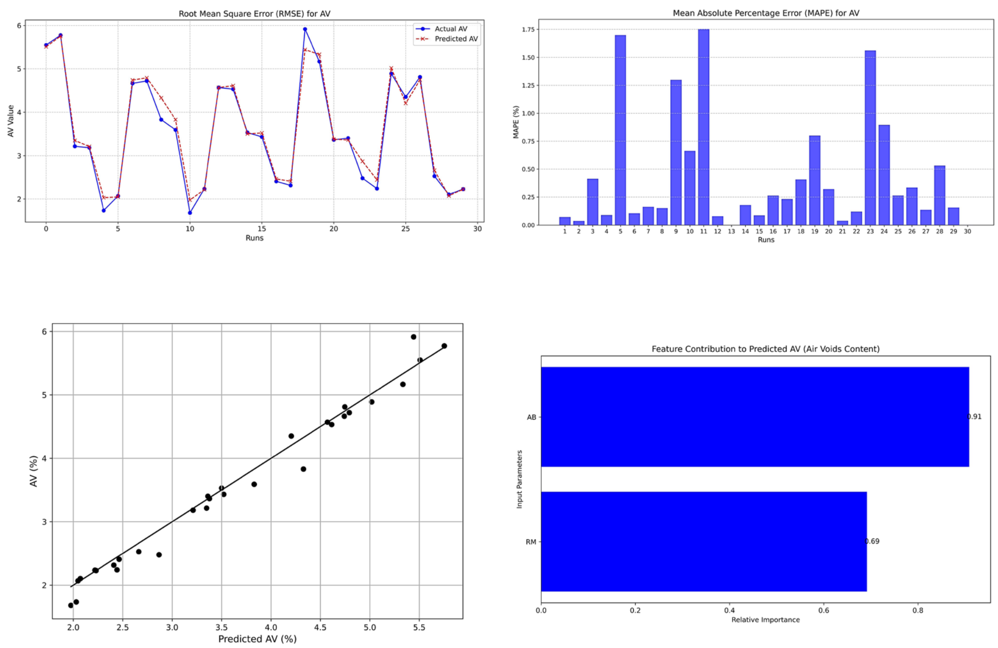

FIGURE 6. Prediction Error Metrics for Each Run of the RBFNHOA Model in AV (%)

PREDICTION ERROR METRICS FOR VOIDS FILLED WITH ASPHALT BINDER

For VFB, the model produced stable predictions across all runs. This suggests strong learning of binder distribution characteristics within the aggregate matrix as shown in Figure 7.

Figure 7 illustrates the prediction error metrics for RBFNN-HOA in predicting VFB for asphalt mixtures with industrial waste fillers. The model has remarkable performance, shown by an RMSE of 0.051108, a MAPE of 0.088317%, and a SI of 0.000659, signifying exceptional precision and negligible prediction mistakes. The R^2 value of 0.986810 indicates that the model accounts for 98.68% of the variability in VFB values, while a total prediction accuracy of 98.6823% underscores its dependability. The graph juxtaposes actual and anticipated VFB levels throughout 30 iterations, demonstrating a strong association. The histogram in the upper right shows MAPE values, indicating consistently low errors over most runs, with sporadic peaks that imply minor variability. The scatter figure illustrates a reliable linear correlation between the predicted and real VFB values, hence validating the model's accuracy. The bar chart in the bottom right illustrates the significance of input variables, indicating that AB has the greatest contribution at 0.93, while RM has a contribution of 0.67. The findings highlight the model's capacity to enhance asphalt mix designs, refine VFB forecasts, and facilitate the environmentally sustainable use of industrial waste fillers.

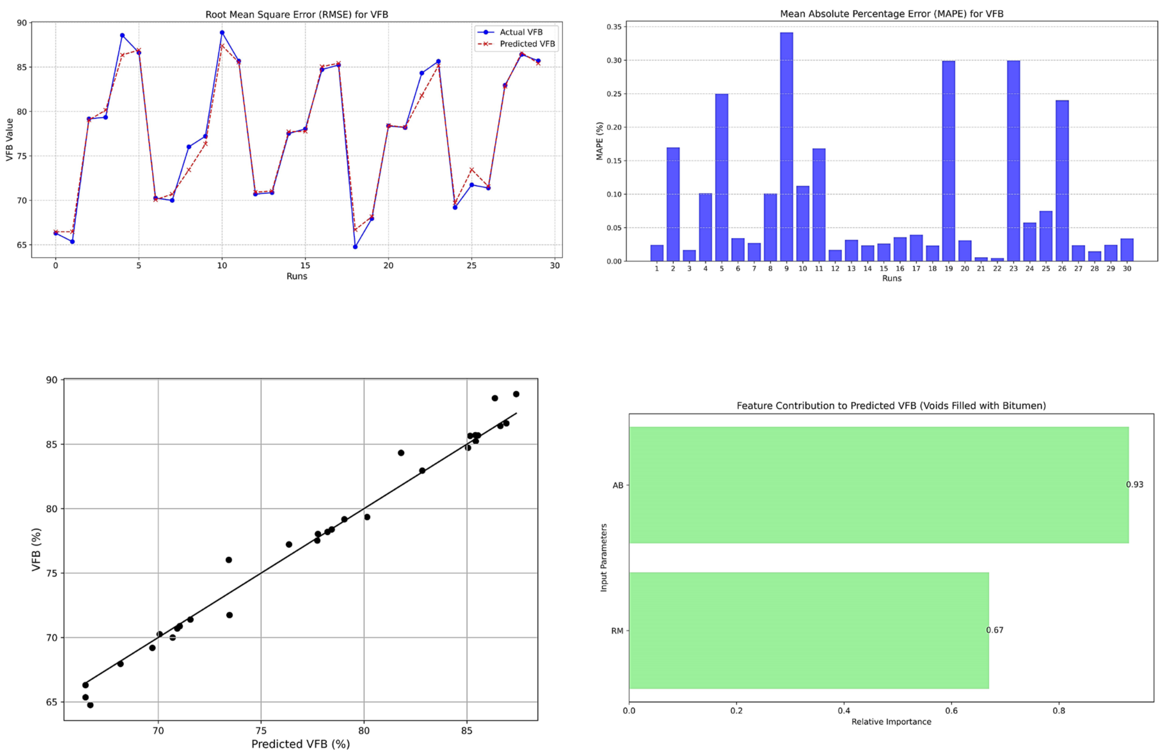

FIGURE 7. Prediction Error Metrics for Each Run of the RBFNHOA Model in VFB (%)

PREDICTION ERROR METRICS FOR MARSHALL STABILITY (MS)

The model effectively captured the variation in MS, with moderate but consistent error margins. These results confirm its suitability for strength-related predictions in modified asphalt mixes as exposed in Figure 8. It illustrates the prediction error metrics for the Radial Basis Function Neural Network, optimized using the Horse Herd Optimization Algorithm, in its attempt to forecast Marshall Stability values in kilonewtons for asphalt mixes, including industrial waste fillers. The model has remarkable predictive efficacy, with RMSE of 0.040622, MAPE of 0.496731%, and SI of 0.003449, indicating minimal prediction mistakes. The R^2 value of 0.930630 signifies that the model explains 93.06% of the variability in MS values, while an overall prediction accuracy of 93.1023% corroborates its dependability. The figure demonstrates a reliable connection between the actual and projected MS values throughout 30 runs, with minimal variations within an acceptable range. The histogram in the up-right displays MAPE values, suggesting that mistakes are mostly low but with considerable fluctuation in the predictions. The scatter figure in the lower left shows a distinct linear correlation between the anticipated and real MS values, supported by an almost linear regression line. The bar chart in the bottom-right corner depicts the importance of the input variables, with RM exhibiting the highest influence at 0.89, closely followed by AB at 0.71. The findings demonstrate that the model may significantly enhance asphalt mix designs by focusing on critical parameters that affect MS values, thereby improving performance and sustainability.

PREDICTION ERROR METRICS FOR MARSHALL FLOW (MF)

MF predictions exhibited slightly higher variability, likely due to the influence of material deformation properties. Nonetheless, the model maintained acceptable predictive performance across runs.

Figure 9 shows that the RBFNN-HOA model effectively predicts MF values in asphalt mixtures, demonstrating high accuracy and reliability. RM is the most influential factor affecting MF prediction accuracy, with a relative importance score of 0.86. This indicates that optimizing the proportion of RM in the mixture significantly impacts MF values. The model's performance is further supported by a low RMSE of 0.011644 and MAPE of 0.454092%. These metrics reflect minimal deviations between predicted and actual MF values, highlighting the model's accuracy. An SI of 0.003375 also underscores the model's precision and prediction consistency.

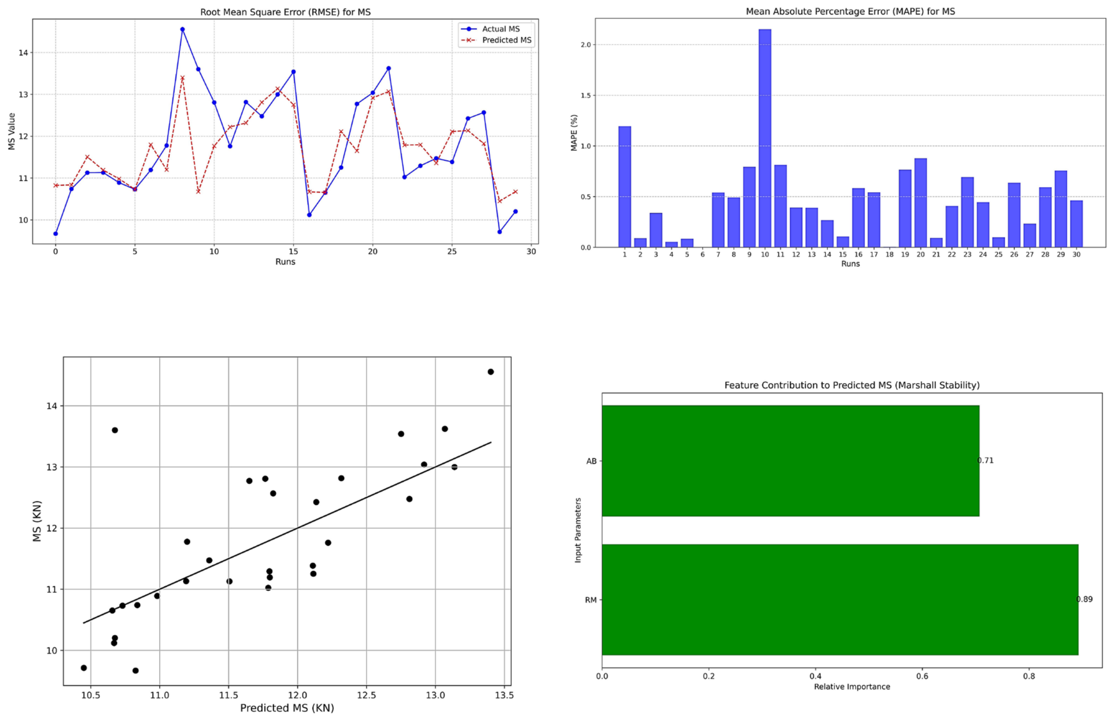

FIGURE 8. Prediction Error Metrics for Each Run of the RBFNHOA Model in MS (KN)

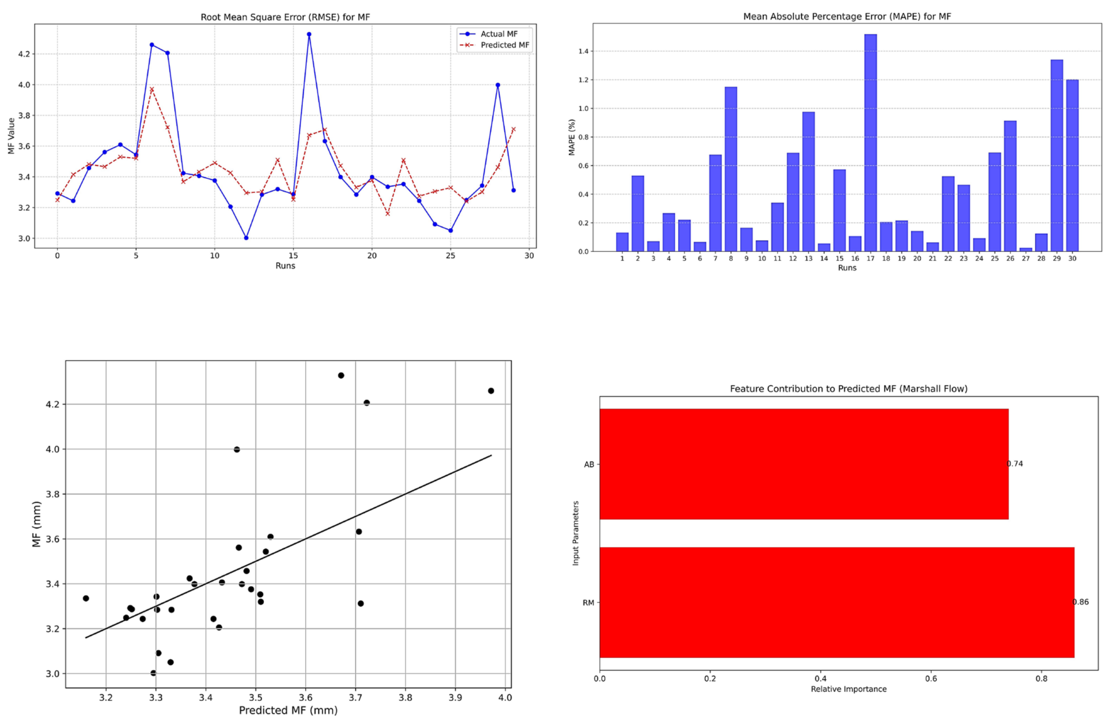

FIGURE 9. Prediction Error Metrics for Each Run of the RBFNN-HOA Model in MF (mm)

OVERALL PERFORMANCE VISUALIZATION OF THE RBFNN-HOA MODEL

The overall visualization illustrates balanced prediction accuracy across all target outputs. This supports the effectiveness of the RBFNN-HOA model as a generalized predictive tool for asphalt mixture design. The results of this study clearly demonstrate the accurateness, reliability, and stability of the RBFNN-HOA model to predict different properties of asphalt mixes included with fillers derived from industrial waste. Thus, this research comprehensively evaluates RBFNN-HOA based on different metrics and visualizations. By amalgamating these metrics and visualizations, a comprehensive assessment can be undertaken of the strengths of the RBFNN-HOA model, corroborating its viability as a reliable tool for asphalt mix design optimization and the advancement of sustainable construction methodologies.

The performance of RBFNN-HOA is extensively evaluated in Figure 10, which depicts its predicted accuracy and error distribution based on four major visualizations. Then, the scatter plot of Actual Vs Predicted Values exhibits linearity with points closely shelling red dashed line, indicating very small variation on granted for use with R^2 of 0.999578, i.e, 99.96% of the variance of the data. The Histogram of Prediction Errors shows symmetric, narrow distribution centered around zero confirming minimum prediction error, RMSE=0.005506, SI=0.000289 indicating a precise and reliable model. The bar chart for Model Performance parameters summarizes important parameters, including 99.97% accuracy and an extremely low MAPE of 0.025830%, capturing the model's precision and a handful of mistakes. The Actual vs expected values across the runs line plot illustrates that the actual as well as expected values remain consistently in line with each other across the predicted runs, reinforcing the stability and strength of the model.

The findings underscore the potential of the RBFNN-HOA model as a reliable alternative for achieving sustainability and efficiency in the design of materials, in particular for the incorporation in manufacturing asphalt. This improved prediction accuracy leads to better decisions, maximizing material characteristics, while its ability to evaluate the influence of recycled materials directly supports sustainability and resource conservation. The continual performance across many situations of the model shows its reliability and generalizability, thus reducing costs and waste by minimizing the need for trial-and-error studies. The study supports the need to use recycled content, enabling the transition to a circular economy and, therefore, the RBFNN-HOA model as a relevant tool to promote sustainable practices through the optimization of materials in construction.

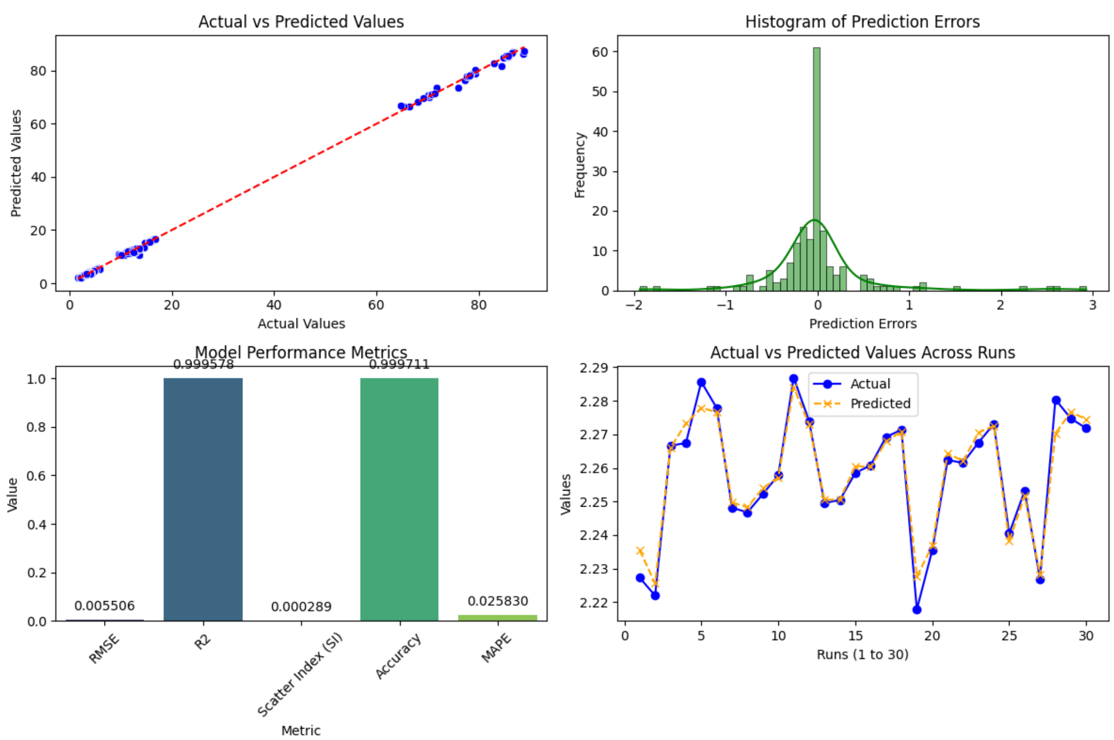

FIGURE 10. Visualizes RBFNN-HOA model's performance

CONCLUSION

This work studies the use of red mud, an industrial waste, as an environmental alternative to traditional limestone fillers in asphalt mixtures and the development of a new predictive model. Based on the findings analysis, it can be concluded that:

1. Based on the Marshall mix design criteria, red mud was found to be suitable for filler replacement in asphalt mixtures, up to 100%, while still meeting the design requirements according to the Ministry of Transport and Logistic Services specifications. These results can mitigate the adverse effects of waste on the environment and contribute to the development of pavement designs that are eco-friendly, sustainable, and green
2. Asphalt binder and red mud were identified as critical inputs influencing asphalt mixture properties, emphasizing their importance in optimizing sustainable mix designs. The relative importance analysis indicates that asphalt binder has the greatest influence on air voids (VA), voids filled with asphalt binder (VFB), and overall binder performance, while red mud has the most significant impact on voids in mineral aggregate (VMA), Marshall Stability (MS), and Marshall Flow (MF)
3. The Radial Basis Function Neural Network optimized using the Horse Herd Optimization Algorithm (RBFNN-HOA) demonstrated excellent predictive capability, achieving statistical values of $R^2 = 0.999578$, RMSE = 0.005506, and MAPE = 0.025830%. These results confirm the model's high reliability and accuracy in predicting the key properties of asphalt mixtures with minimal error, highlighting its potential as a powerful tool for performance prediction and optimization in asphalt mix design.
4. The proposed RBFNNHOA model demonstrated excellent consistency with different data sets and real time applications. Running through tests in triplicate reasserted its reliability, displayed with low Scatter Index values and closeness of predicted and actual values. The inclusion of the Horse Herd Optimization Algorithm prevents the model from falling into local optima traps while enabling it to converge quickly, attributes which make it especially useful in engineering. This stability along with computational efficiency makes it an attractive tool for practitioners looking to solve prediction problems.

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DECLARATION OF COMPETING INTEREST

None.

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