



PREDICTION OF COMPACTION PROPERTIES IN BIOPOLYMER-STABILIZED LATERITE SOILS USING ARTIFICIAL NEURAL NETWORK

Shailendra Pandurang Banne^{*1}, Pratima Vitthal Kalokhe², Ganesh Tarte³, Mugdha Kshirsagar⁴, Sudarshan Bobade⁵

^{1,2}Department of Civil Engineering, Pimpri Chinchwad College of Engineering, Nigdi, Pune 411044, India.

³Department of Applied Science and Humanities, Pimpri Chinchwad College of Engineering, Nigdi, Pune 411044, India.

⁴Department of Civil Engineering, Symbiosis Institute of Technology, Symbiosis International Deemed University, Pune 412115, India

⁵Department of Civil Engineering, Pimpri Chinchwad College of Engineering and Research, Ravet, Pune 412101, India

¹<https://orcid.org/0000-0001-5626-5508>, ²<https://orcid.org/0009-0009-1981-0218>, ³<http://orcid.org/0000-0002-7693-6548>,

⁴<https://orcid.org/0000-0001-5364-2064>, ⁵<http://orcid.org/0000-0001-7839-1855>

E-mail: *bannemtech@gmail.com, pratima.kalokhe@pccoepune.org, ganesh.tarte@pccoepune.org, mugdha@sitpune.edu.in, sudarshan.bobade@pccoer.in

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ABSTRACT

Biopolymers like xanthan gum, guar gum, cellulose, and chitosan, in varying proportions, can be used to stabilize weak laterite soil. By enhancing the soil's strength, resistance to erosion, and durability, these biopolymers improve its mechanical properties. This study presents artificial neural networks (ANN) to develop predictive models for estimating the Maximum Dry Density (MDD) and Optimum Moisture Content (OMC) of biopolymer-stabilized laterite soil, with model predictions validated against experimental results. The incorporation of various biopolymers particularly xanthan gum, guar gum, cellulose, and chitosan significantly improves the compaction characteristics of laterite soil, with notable increases in Maximum Dry Density (up to 27.46%) and varied effects on Optimum Moisture Content, depending on the biopolymer type and concentration. A previously made available database was utilized to develop the prediction models. The correlation coefficient (R-value) was employed as the standard for acceptable performance in neural network development. The ANN-based prediction model for MDD ($R = 0.941$) demonstrates the strongest correlation and best model fit. In comparison, the OMC model shows a slightly lower yet still commendable level of accuracy ($R = 0.925$).



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I. INTRODUCTION

Laterite soils, prevalent in tropical and subtropical regions, exhibit highly variable engineering properties due to factors such as mineral composition, degree of weathering, and moisture content [1]. Soil stabilization refers to improving the physical properties of soil to enhance its strength, load-bearing capacity, and resistance to erosion [2]. Biopolymers are natural polymers obtained from renewable sources like plants and microorganisms. They are widely used in fields such as soil stabilization [3]. In dry and semi-arid areas, biopolymers can enhance soil cohesiveness, vegetation germination, and water retention, resulting in favorable conditions for plants [4]. Biopolymers are a strong, safe, and eco-friendly alternative. They interact with soil and are more cost-effective than cement [5]. Understanding these properties is crucial for safe and cost-effective geotechnical design. To stabilize and comprehensively assess the research on using artificial neural networks to predict laterite soil characteristics, the present investigation investigated the use of biopolymers such as xanthan gum, guar gum, cellulose, and chitosan. Artificial neural networks (ANN) have become an effective method for predicting complex geotechnical behaviors recently [6]. Dhawale et al. provided a brief description of how artificial neural networks (ANNs) can be used to examine soil engineering characteristics such as optimum moisture content, maximum dry density, permeability, shear strength parameters, and unconfined compressive strength [7]. The data-driven method was more suited than the model-based one.

To address such challenges, computational approaches were used to create artificial neural networks (ANNs) that use artificial intelligence (AI) [8]. Regression models can only manage a single response, whereas artificial neural networks (ANN) can handle many outputs or replies, which is a major advantage when using ANN in process modeling [9]. The methodology and applications of the most current advances in artificial neural networks (ANN) in the field of geotechnical engineering were examined by a large number of researchers [10], [11].

1.1 STUDIES ON PREDICTION OF ENGINEERING PROPERTIES OF SOIL

Various methods, including regression analysis and neural networks, effectively predicted soil compaction characteristics with strong correlations ($R^2 = 0.70-0.95$). The derived equations were satisfactory, making them useful for preliminary project planning with time or budget constraints [12]. Researchers developed AI models using FN and MARS to predict MDD and UCS of cement-stabilized soil, outperforming traditional methods. The model is accurate and easy for engineers to use [13]. Abdel-Rahman [14] offers an ANN structure for determining the MDD and OMC, the two crucial parameters for compaction. An ANN-based model inspired the creation of empirical formulations to forecast the compaction properties of graded cohesionless soils. Many researchers used neural networks to link soil index properties to permeability, compaction, and shear strength. Their study of 580 data sets highlights the impact of compaction on permeability and bulk density on shear strength [15]. One study compares ANN and SVM models for predicting the MDD and UCS of cement-stabilized soil. Using key soil parameters, their analysis shows SVM outperforms ANN in accuracy [16]. Unconfined compression tests showed that copper slag improved UCS, especially in cement-stabilized soil. Samples had 0–6% cement and 0–25% copper slag. An ANN model with eight input variables accurately predicted results [17]. ANNs, particularly MLPs, predict soil-stabilizer mix MDD and OMC using soil properties and stabilizer details. Garson's method evaluates predictor importance, and trained models show reliable accuracy against experiments [18].

ANNs have been successfully used to predict OMC and MDD of cement kiln dust-stabilized black cotton soil, achieving high accuracy. Models like NN 10-5-1 and NN 10-7-1 showed strong correlation with experimental data, with R-values of 0.983 and 0.9884 [19]. MLP, RBF, and GP models were used to predict strength development in red earth (CL), brown earth (CH), and black cotton soil (CH) under varying water, cement, and curing conditions. These models effectively captured the complex relationships influencing soil strength [20]. Iyeke used artificial neural networks to predict lateritic soil shear strength in Delta State, Nigeria. Based on 83 samples, cohesion was 382 kN/m², and the friction angle ranged from 2 to 43 degrees. The best ANN models had 3-9-1 for cohesion and 3-11-1 for friction angle, outperforming empirical methods in accuracy [21]. Researchers modeled soil shear strength using ANN and soil index properties from Ranchi, Jharkhand. The model showed high accuracy, with a "d" value near unity and low RMSE, NMSE, MB, and FB [22]. Studies establish a link between soil index features and permeability, compaction, and soil shear strength. The results of the developed models and the experimental data demonstrate that the predictions are accurate to within a 95% confidence interval [15]. ANNs were developed to model shear stress (τ) and vertical strain (ϵ_v) in rubbers, while a GMDH-based prediction model provided closed-form equations. The ANN models achieved R-values of 0.9977 and 0.9994, while GMDH models had 0.9862 and 0.9942 [23]. The effective angle of shearing resistance (ϕ) is vital in geotechnical design but is costly and time-consuming to determine experimentally. Statistical and numerical models like GEP, ANN, and ANFIS help estimate it.

GEP outperforms ANN and ANFIS in training efficiency and prediction accuracy [12]. FN outperforms ANN based on R and E values, but SVM achieves the highest accuracy with superior R and E values [24]. Soil shear resistance was predicted using MR and ANNs (MLP, RBF, MNR, and MLR). Five models analyzed particle passing percentages, PI, and density. Prediction accuracy was evaluated using R, RMSE, MAE, and t-test [25]. A hyperbolic model was developed to predict unsaturated shear strength using matric suction, incorporating saturated soil parameters (c' , ϕ') and the ultimate apparent cohesion (C_{max}). This approach offers a practical alternative to complex suction-controlled tests [26]. An SVM model was developed to estimate soil cohesive resistance using six input variables. Validated over 200 simulations, it achieved high accuracy ($R = 0.9-0.95$), with moisture content, liquid limit, and plastic limit as key factors [27]. Experiments on sands yielded stress-strain correlations and internal friction angles. Eight ANN designs with three learning algorithms replicated the outcomes, showing ANN's potential for simulating shear development in granular soils with precise input and output parameters [28]. ANN, nonlinear multiple regression, and adaptive neuro-fuzzy inference systems were used to measure the angle of shearing resistance in uniform sands. Models trained on 132 shear box experiments demonstrated that a basic artificial neural network (ANN) can efficiently assess shearing resistance based on particle form, grain size distribution, and density factors [29].

1.2 STUDIES ON PREDICTION OF COMPACTION PARAMETERS OF SOIL

Soil classification characteristics are used to predict permeability, MDD, and OMC using ANN models. The models were trained on compaction and permeability data from 55 bentonite, limestone dust, sand, and gravel soil mixes. The results reveal that ANN models can accurately predict MDD, OMC, and permeability within 95% [30]. The models containing data from dams in Nigde, Turkey, correlated strongly ($r^2 = 0.70-0.95$) with experimental results, indicating their potential for project design under time and financial constraints [31]. Compaction determines and improves the engineering properties of construction soils. This study showed reliable models that connect liquid limit and compaction factors in the soils of the North Nicosia Kythrea group, achieving R^2 values above 75% and minimal error, making them suitable for early geotechnical designs [32]. A study utilized artificial neural networks to predict maximum dry density and moisture content using soil index properties, including plastic limit, liquid limit, fines, sands, gravels, and specific gravity. With 177 experimental datasets, a multilayer perceptron with backpropagation demonstrated superior accuracy compared to traditional prediction methods [33]. Compaction parameters like OMC and MDD are vital for earthworks design and quality control but require time-consuming testing. To address this, a study applied ANN and regression analysis to predict these parameters from basic soil properties, yielding promising results across various algorithms and validations [34].

A study uses ANN models to predict maximum dry density and optimum water content for nano-stabilized soils, surpassing statistical models by over 97% [35]. A study applied the MARS model to estimate soil compaction characteristics more efficiently than conventional laboratory methods. The model outperformed other machine learning techniques, identifying fine content and plastic limit as the most influential input parameters [36]. A study applied machine learning to evaluate the reliability of amended soils for housing developments using OMC, MDD, and UCS as indicators. Optimizable ensembles and neural networks effectively predicted OMC and UCS, but MDD predictions were less accurate [37]. A study developed regression models using sieve analysis and consistency limits to predict standard and modified Proctor compactions in cohesive soils. Modified Proctor results were accurately estimated through two-dimensional regression using Standard Proctor data and soil parameters [38]. A study examined the relationship between Atterberg limits and compaction parameters (OMC and MDD) in fine-grained soils along the Setit watercourse. Regression analysis of 40 samples revealed strong correlations, particularly with the liquid limit, aiding preliminary geotechnical evaluations [39]. An empirical study developed models to predict OMC and MDUW of fine-grained soils mixed with sand-sized tire-derived aggregates using 100 compaction tests. The models, based on unamended soil properties, showed strong statistical validity, offering an efficient alternative to extensive laboratory testing [40].

A study explored the use of grain size distribution and Atterberg limits to predict MDD and OMC through artificial neural networks. Among 240 ANN configurations, models with simpler architectures and hyperbolic tangent activation functions yielded the highest prediction accuracy [41]. A study developed predictive models for expansive soil compaction parameters using 195 datasets with gene expression programming (GEP) and multi-gene expression programming (MEP). Results showed GEP accurately predicted maximum dry density, while MEP outperformed in optimal moisture content prediction, offering a reliable alternative to conventional testing [42]. A study applied four soft computing algorithms to predict OMC and MDD, aiming to reduce reliance on time-consuming lab tests. Using a comprehensive soil index and compaction database, the Extreme Learning Machine (ELM) method achieved the highest prediction accuracy [43]. The present study aims to explore the application of ANN for predicting key compaction properties of laterite soils, providing a robust framework for rapid and reliable assessment in geotechnical engineering projects. Recent developments in sustainable soil stabilization have highlighted the promise of biopolymers like xanthan gum, guar gum, cellulose, and chitosan as environmentally friendly substitutes for traditional chemical stabilizers. To optimize geotechnical performance, this study presents a new method that combines biopolymer stabilization with ANN modelling to reliably and data-drivingly anticipate important compaction parameters.

II. MATERIALS AND METHODOLOGY

II.1 LATERITE SOIL

The laterite soil from Parshuram Ghat, Chiplun, Maharashtra, was taken from a sample pit that was 1 m deep for this study. Figure 1 depicts the location of the collected laterite soil. The particle sizes, specific gravity, compaction, CBR, and permeability of the soil are shown in Table 1. Based on IS: 1498–1970, the soil is Highly Compressible Silt (MH) because it has 28–31% sand, 20–24% silt, and 53–57% clay. The ranges of the LL, PL, and PI are 55–60%, 31–34%, and 24–26%, respectively. The optimum moisture content (OMC) and maximum dry density (MDD) for the heavy compression test are 14–17% and 1.52–1.60 g/cc, respectively. The soaked and unsoaked CBR values are 1.6–2.1% and 2.6–2.9 %, respectively. The soil's cohesion ranges from 0.14 to 0.16 kg/cm², with an internal friction angle of 14.20 to 16.30 degrees. When subjected to high compaction, the coefficient of permeability is measured to be 2.78×10^{-4} cm/s.



Figure 1: Map of Laterite Soil Sample Collection and Soil Collection Site (17°33'28.0"N, 73°29'53.0"E).

Source: Authors, (2026).

Table 1: Laterite Soil Properties.

Sr. No.	Properties	Value	Reference
1	Specific Gravity (G)	2.62-2.67	IS 2720 (Part-3) 1980
2	Distribution of Particle Size	53-57	IS: 2720 (Part-4): 1985
	a) Clay %	20-24	
	b) Silt %	28-31	
	c) Sand %		

3	Consistency Limits	55-60	IS 2720 (Part-5) 1985
	LL (%)	31-34	
	PL (%)	24-26	
	PI (%)	19-22	
	SL (%)		
4	IS Classification of Soil	MH	
5	Modified Proctor Test	14-17	IS 2720 (Part- 8) 1980
	a) OMC (%)	1.52-1.60	
	b) MDD (gm/cc)		
6	C. B. R Value (%)	1.6-2.1	IS 2720 (Part-16) 1987
	Soaked	2.6-2.9	
	Unsoaked		
7	Direct Shear Test	0.14-0.16	IS 2720 (Part-15) 1986
	Cohesion (kg/cm ²)	14.20-16.30	
	Angle of Internal Friction (Degree)		
8	Permeability (cm/sec)	2.78×10^{-4}	IS 2720 (Part-17) 1986

Source: Authors, (2026).

II.2 BIOPOLYMERS

In the present study, four biopolymers, like xanthan gum, guar gum, cellulose, and chitosan, were used with different dosages to investigate the effect on OMC and MDD of laterite soil.

Xanthan gum (XG): The bacteria *Xanthomonas campestris* produces xanthan gum, a biopolymer. Because it behaves as a hydrocolloid, people commonly use it to increase viscosity. Xanthan gum is often employed as a soil conditioner and binder to improve soil structure and prevent erosion [44]. The findings indicate that incorporating xanthan gum alters these compaction characteristics, which are crucial for understanding soil behavior post-stabilization [45]. A study investigated the influence of varying xanthan gum concentrations on the optimum moisture content (OMC) and maximum dry density (MDD) of soils. The findings highlight the optimal xanthan gum content for effective soil stabilization through detailed analysis of compaction behavior [46]. The behavior and strength properties of clayey soil stabilized by xanthan gum are assessed in this research. The study highlights the potential of xanthan gum as an environmentally friendly soil stabilizer by evaluating changes in soil parameters using both macro- and micro-scale experiments [47]. A study investigated the combined effects of xanthan gum and polypropylene fibers on clay, revealing notable improvements in geotechnical properties. The findings highlight xanthan gum's potential as an effective and eco-friendly soil stabilizer [48]. Xanthan gum, in particular, has shown significant influence on enhancing geotechnical properties across different soil types [49]. As the XG content increases, the soil's OMC decreases, suggesting that the xanthan gum-treated soil's ability to absorb water has improved. Furthermore, up to 3% of XG is added to laterite soil, after which its dry density decreases. When compared to untreated laterite soil, the MDD of laterite soil treated with 3% XG is 1.72 gm/cc, indicating a 28.36% increase [50].

Guar Gum (GG): Guar gum is a biopolymer, a naturally occurring polysaccharide that was taken from guar plant seeds. Because of its distinctive properties, it is a natural thickening and stabilizing agent widely employed in various industries. Guar gum is a soil binder in soil stabilization applications, increasing its cohesion and stability [51]. With the addition of guar gum up to 2%, both MDD and OMC values increase. Beyond this concentration, MDD decreases while OMC continues to rise, attributed to the hydrophilic nature of guar gum increasing water absorption [52]. A study examined the engineering behavior of soil treated with guar gum, observing a slight increase in dry density and a reduction in optimum moisture content with higher guar gum content. Additionally, the treatment significantly improved the soil's strength and stiffness over time [53]. A study examined the compressibility behavior of expansive soil stabilized with guar gum and found that a 2.5% dosage reduced MDD by 13.33% and increased OMC by 58.6%. These changes were attributed to the biopolymer's water absorption capacity and replacement of soil particles by guar gum strands [54]. A study on cohesionless soil stabilization using guar gum found that its hydrophilic nature enhances water absorption. The effect resulted in increased optimum moisture content (OMC) and decreased maximum dry density (MDD) in the soil-biopolymer mix [55]. Guar gum increases the dry unit weight up to 2%, after which it declines. At higher concentrations, the gum forms a highly viscous solution that coats and separates soil particles [56].

Cellulose (CL): Cellulose possesses diverse, prospective applications within geotechnical engineering, owing to its gelation characteristics, which can be harnessed to generate thickening agents and stabilizers. The MDD increases from 1.41 gm/cc to 1.65 gm/cc as cellulose content rises from 0% to 3%, while OMC decreases from 14.04% to 12.25%, indicating reduced moisture needed for optimal compaction [57]. Carboxymethyl cellulose (M-CMC), a brand-new soil stabilization additive that mixes polyacrylamide (PAM) and carboxymethyl cellulose (CMC) to treat silty sand [58]. Loess properties were evaluated using compressive and tensile strength tests. Carboxymethyl cellulose (CMC) levels were 0.5%, 1.0%, and 1.5%. Maximum dry density decreased with CMC [59]. carboxymethyl cellulose biopolymer as an environmentally friendly soil stabilizer [60].

Chitosan (CH): Decomposed chitin, or chitosan, is a component of crab exoskeletons and fungal cell walls. Typically, sodium hydroxide reacts with alkali to produce chitosan. The chitosan-based biopolymer is used in geo-environmental applications to enhance heavy metal absorption, reduce soil erosion, and improve clay stabilization through waste-derived solutions [61]. The study's findings, combined with chitosan's properties, suggest its potential as a short-term stabilizer for eco-friendly temporary geotechnical structures like working platforms [62].

Biopolymers like chitosan have been effectively used in geo-environmental applications, including soil stabilization. Studies show that chitosan improves the cohesion and mechanical strength of sandy soils, as evidenced by unconfined compression tests [63]. Chitosan-based biopolymers have shown potential in geo-environmental applications by improving soil stability, reducing hydraulic conductivity, and enhancing heavy metal absorption. A study using shrimp shell-derived chitosan (2%–8%) found improved clay strength under freeze-thaw cycles, with optimal performance at 6% due to electrical balance, influenced by moisture content and curing time [64]. A study explores xanthan gum and chitosan as eco-friendly clay soil stabilizers. We evaluate the effectiveness of the biopolymers using compaction tests and unconfined compression tests on the treated soil samples [65]. The effect of chitosan biopolymer on enhancing desert sand's geotechnical properties through cementation. Tests, including unconfined compression, direct shear, and electron microscopy, confirm its potential for soil stabilization. Results show a notable increase in shear strength up to 7% chitosan, with cohesion rising significantly at 1% and 2% concentrations [66]. In the present study, Laterite soil is combined with xanthan gum, guar gum, and cellulose biopolymer by the dry blending technique at concentrations of 1%, 2%, and 3% of the soil's weight. Chitosan biopolymer is incorporated into the laterite soil through the wet mixing process, in proportions of 0.15%, 0.30%, and 0.45% of the soil's weight, using acetic acid.

II.3 METHODOLOGY

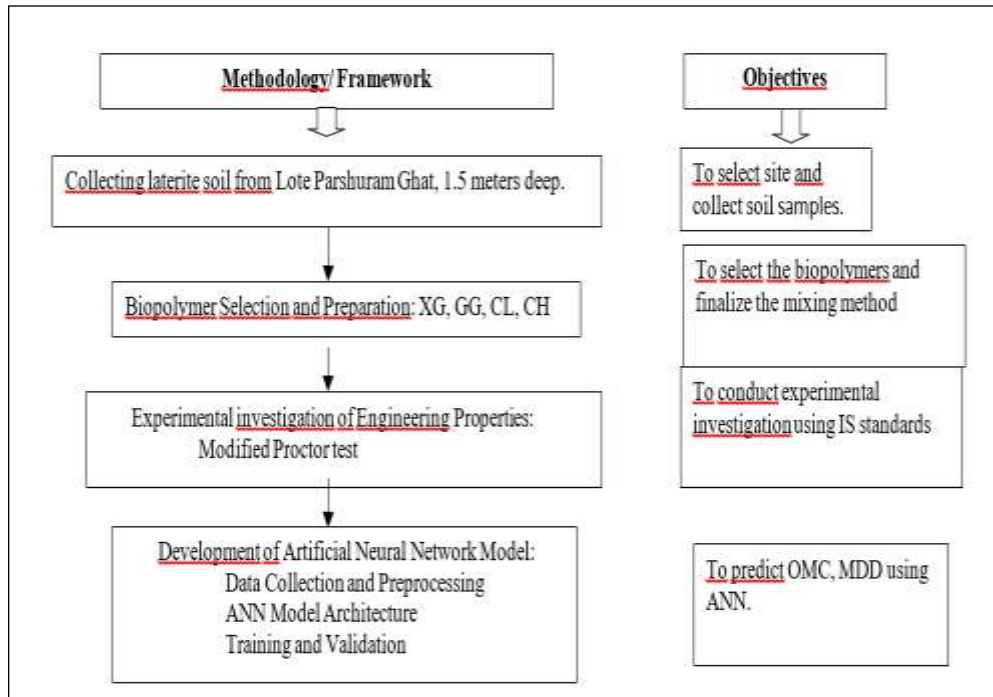


Figure 2: Methodology of present study.

Source: Authors, (2026).

III. EXPERIMENTAL INVESTIGATION

The Modified Proctor test determines how a specific soil sample compacts under controlled conditions. It assists engineers in determining the amount of compaction required to obtain the specified soil density and stability. The Modified Proctor test is instrumental in road construction. It helps engineers determine subgrade and base material compaction criteria, guaranteeing that the road can handle traffic loads and environmental stressors. When using admixtures in construction operations, mixing and compaction are crucial procedures this section emphasizes the need to investigate how incorporating biopolymers affects soil compaction behavior and its mixtures. Incorporating biopolymers into laterite soil can yield diverse implications on its engineering characteristics, encompassing the maximum dry density (MDD) and optimum moisture content (OMC).

III.1 EFFECT OF XANTHAN GUM BIOPOLYMER ON COMPACTION PARAMETERS

Maximum dry density increases as the xanthan gum biopolymer dosage increases. The varying compaction curves from the laterite soil under different dosages of xanthan gum biopolymer in the samples are shown in figure 3 while considering the maximum particle size. At optimum dosage (at 3%), the MDD was observed to be 1.68 g/cc (increased by 19.14%). In laterite soil, xanthan gum biopolymer can be a lubricant between soil particles. Higher addition rates result in less friction and more compact packing of the particles during compaction, raising the MDD. The capacity of soil particles to stick together, or cohesion, can be improved by xanthan gum biopolymer. When the dosage is increased, this greater cohesiveness may result in better compaction and a higher MDD. The optimum moisture content can also be affected by these changes. In this case, OMC slightly increases as xanthan gum dosage is increased. For the optimum dose of 3% xanthan gum, the OMC was 14.29% (increased by 1.78%).

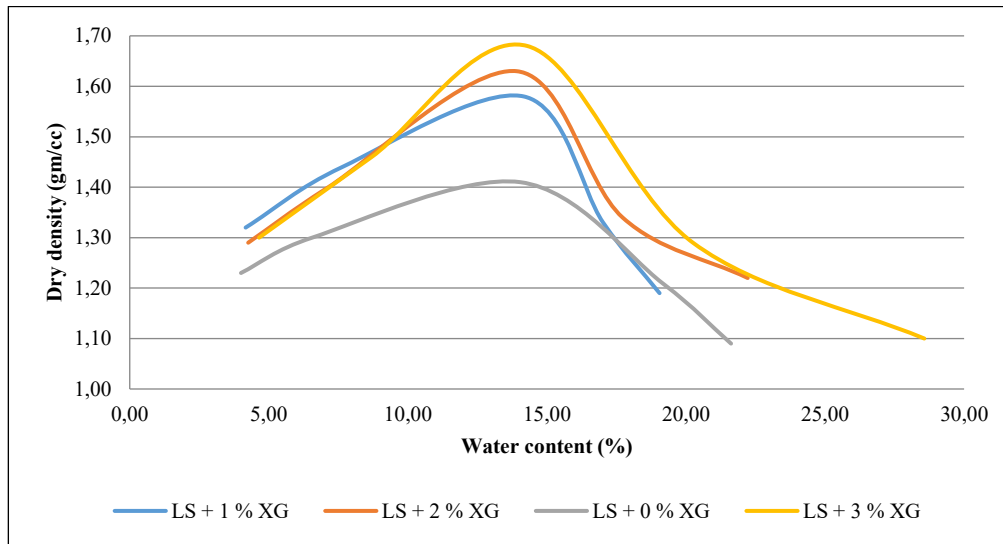


Figure 3: Moisture-density relationship of the laterite soil with xanthan gum.
Source: Authors, (2026).

III.2 EFFECT OF GUAR GUM BIOPOLYMER ON COMPACTION PARAMETERS

Guar gum reduced the optimum moisture content and increased the maximum dry density. The dry unit weight of laterite soil was increased by 27.46%, from 1.42 to 1.81 gm/cc, when the optimum concentration of 2% guar gum biopolymer was administered; however, subsequent additions resulted in a decrease. It can be a cohesive and binding agent when combined with laterite soil. Guar gum changes the way the soil's particles are arranged after being added. Minimizing void areas between soil particles may result in better particle packing. Higher densities during compaction may be the result of better particle packing. Guar gum is a high-carbon biopolymer that enhances soil structure cohesion when incorporated into laterite soil. The carbon component of guar gum can serve as a binder, stabilizing soil particles and preventing erosion. The varying compaction curves from the laterite soil under various guar gum biopolymer dosages of samples are shown in figure 4.

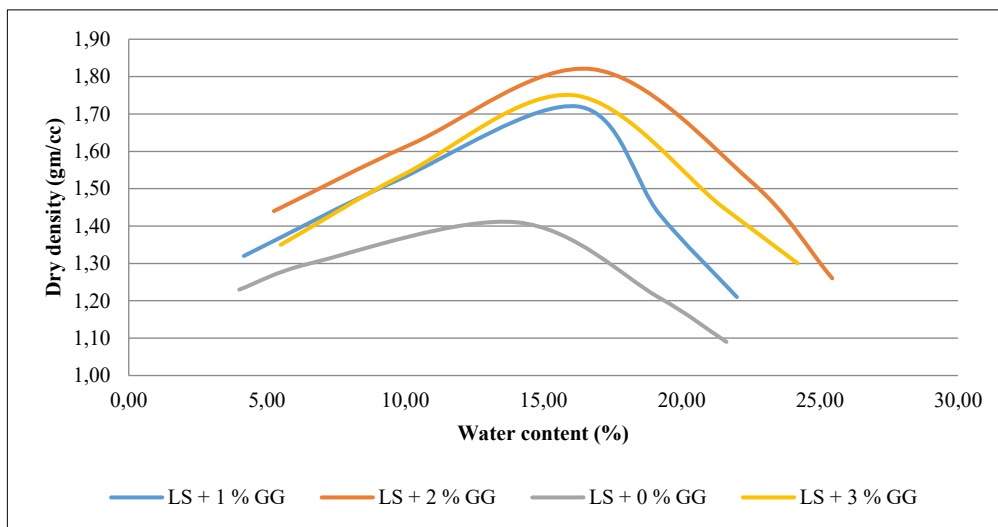


Figure 4: Moisture-density relationship of the laterite soil with guar gum.
Source: Authors, (2026).

III.3 EFFECT OF CELLULOSE BIOPOLYMER ON COMPACTION PARAMETERS

Conversely, cellulose may have a lower MDD due to its structural characteristics, such as lower molecular weight and different interaction mechanisms with the soil particles. Using cellulose can increase MDD while decreasing OMC. The dry density and moisture content results of compaction tests conducted on laterite soil are depicted in figure 5. The MDD value increases marginally from 1.41 gm/cc to 1.65 gm/cc as cellulose concentration increases from 0% to 3%; further cellulose addition reduces MDD slightly (1.62 gm/cc). These modifications are negligible. The results of the heavy compaction test also reveal that the OMC decreases from 14.04% to 12.25%.

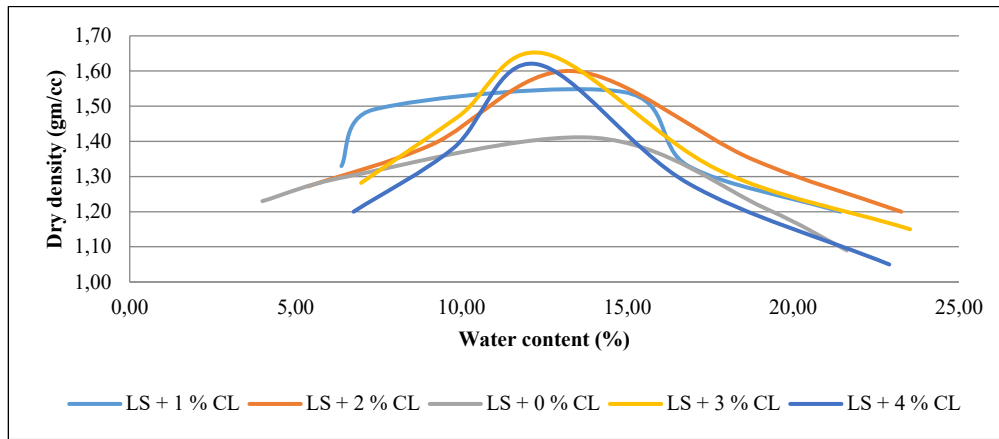


Figure 5: Moisture-density relationship of the laterite soil with cellulose.

Source: Authors, (2026).

III.4 EFFECT OF CHITOSAN BIOPOLYMER ON COMPACTION PARAMETERS

Chitosan biopolymer exhibits the highest MDD among the biopolymers studied, while cellulose has a lower MDD than other biopolymers. Chitosan is known for its strong bonding capabilities and high molecular weight, which may contribute to its ability to enhance soil compaction and increase MDD. The MDD value increases from 1.41 gm/cc to 1.92 gm/cc as chitosan concentration increases from 0% to 0.3%; further chitosan addition reduces MDD slightly (1.59 gm/cc). The data also shows that the OMC increases from 15.38% to 22.73% in the high compaction test. Adding a chitosan biopolymer solution improves the overall moisture content of the soil mixture, which could affect the OMC. The added moisture from the chitosan biopolymer solution changes the moisture-density relationship, resulting in a higher OMC. Figure 6 depicts the compaction curves for different dosages of chitosan biopolymer, and Figure 7 shows the photographs of modified proctor tests for OMC and MDD determination.

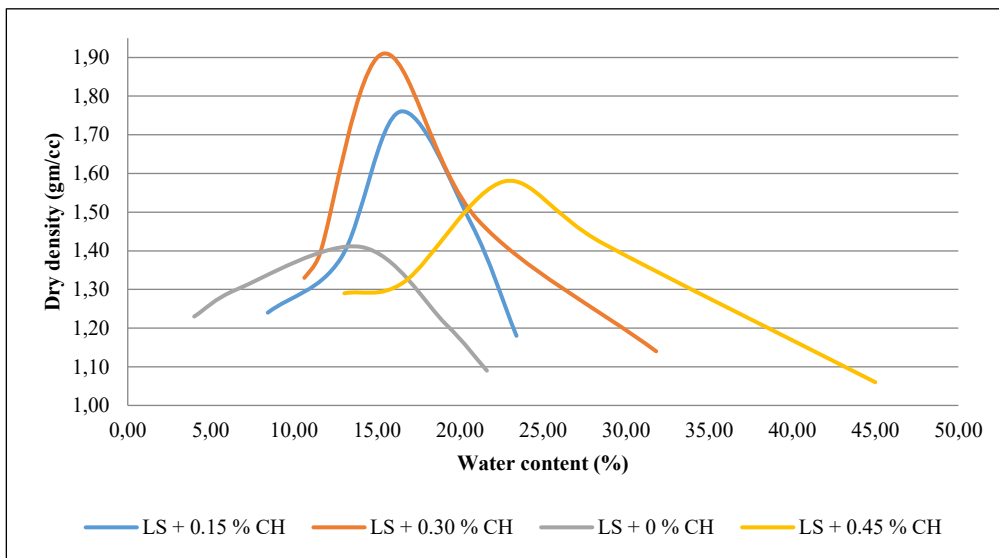


Figure 6: Moisture-density relationship of the laterite soil with chitosan.

Source: Authors, (2026).



Figure 7: Modified Proctor test on Laterite Soil.

Source: Authors, (2026).

IV. ANN

The study involved training and implementing ANN models using MATLAB 6.5. The created ANN models are compared to experimental data from laterite soil and soil combinations containing biopolymers such as xanthan gum, guar gum, cellulose, and chitosan to validate their predictive power. Biopolymers affect soil properties, making their integration important to the study. The comparison of predicted values and experimental findings tested the ANN models' ability to replicate real-world geotechnical behaviors. Even in complicated biopolymer-modified soil conditions, the ANN models have grasped the geotechnical parameter connections.

IV.1 OPTIMUM MOISTURE CONTENT (OMC)

Optimum moisture content is an essential feature in soil compaction that tells you the best amount of moisture in the soil so it can be packed down to its densest state. This trait is very important in engineering projects that need to compact soil to ensure structures built on or in it are stable and work well. This calculation to determine the Optimum Moisture Content (OMC) of soil used the percentage of fine grains, sand, and gravel, along with specific gravity (G), liquid limit, and plastic limit. The input values were sourced from external references. Figure 8 illustrates the construction of the ANN model is used to forecast the OMC of soil. The output layer contains a single neuron, as the output corresponds to the OMC. Various networks with differing quantities of hidden neurons were evaluated to ascertain the optimal amount of neurons in the hidden layer. The expected and desired outcomes were then compared. Ten neurons in a secret layer proved to be effective in this investigation.

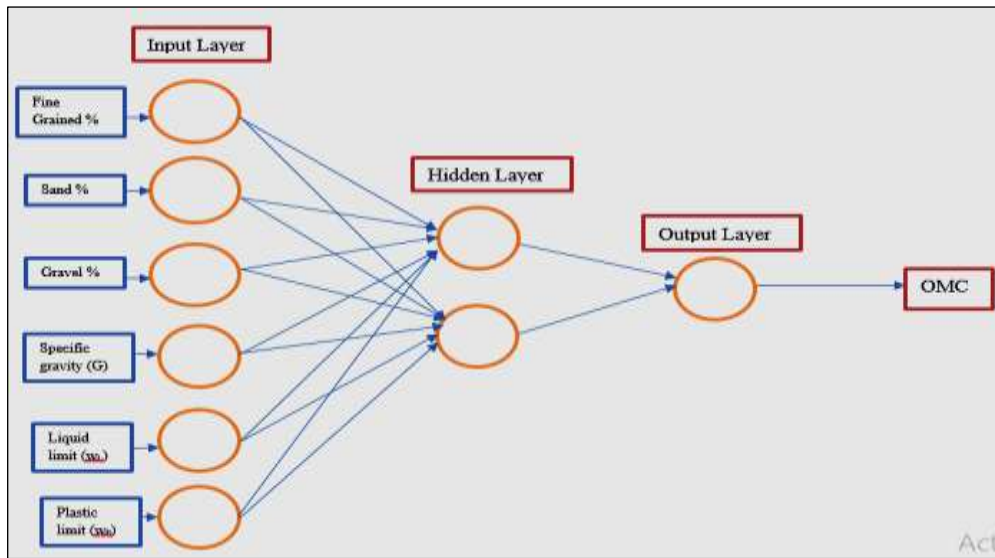


Figure 8: Architecture of an ANN model for estimating OMC.

Source: Authors, (2026).

The prediction of Optimum Moisture Content (OMC) is formulated as a supervised learning problem using an Artificial Neural Network (ANN). The model takes six geotechnical parameters as inputs:

- Fine-Grained Content (%) – x_1
- Sand Content (%) – x_2
- Gravel Content (%) – x_3
- Specific Gravity (G) – x_4
- Liquid Limit (wL) – x_5
- Plastic Limit (wP) – x_6

The ANN can be mathematically represented as:

$$\hat{y} = f(x_1, x_2, x_3, x_4, x_5, x_6)$$

Where:

- $\hat{y}$ is the predicted OMC
- f is the nonlinear mapping function learned by the ANN during training

If we consider a simple ANN with one hidden layer (as shown), the output can be written as:

$$\hat{y} = \phi_2 \left(\sum_{j=1}^m \omega_j^{(2)} \cdot \phi_1 \left(\sum_{i=1}^n \omega_{ji}^{(1)} x_i + b_j^{(1)} \right) + b_j^{(2)} \right)$$

Where:

- $n = 6$ (number of inputs)
- $m =$ number of hidden neurons (from diagram: 2)
- $\phi_1, \phi_2 =$ activation functions (e.g., sigmoid, ReLU, linear)
- $w_{ji}^{(1)}, w_j^{(2)} =$ weights for input-to-hidden and hidden-to-output connections
- $b_j^{(1)}, b^{(2)} =$ biases

The objective of the investigation was to predict the OMC of laterite soil and laterite soil that had been treated with various biopolymers at varying concentrations. The research aimed to establish a predictive model for OMC values under other conditions through comprehensive experimentation and analysis. The assessment included evaluating the correlation coefficient (R) between the actual measured OMC values and the OMC values predicted by the model. The obtained correlation coefficient (R) was calculated to be 0.925, indicating a robust statistical relationship between the predicted and measured OMC values. This high correlation coefficient is a testament to the accuracy and reliability of the predictive model developed in this study. Figure 9 shows the values of coefficients of relation in training, validation, and testing.

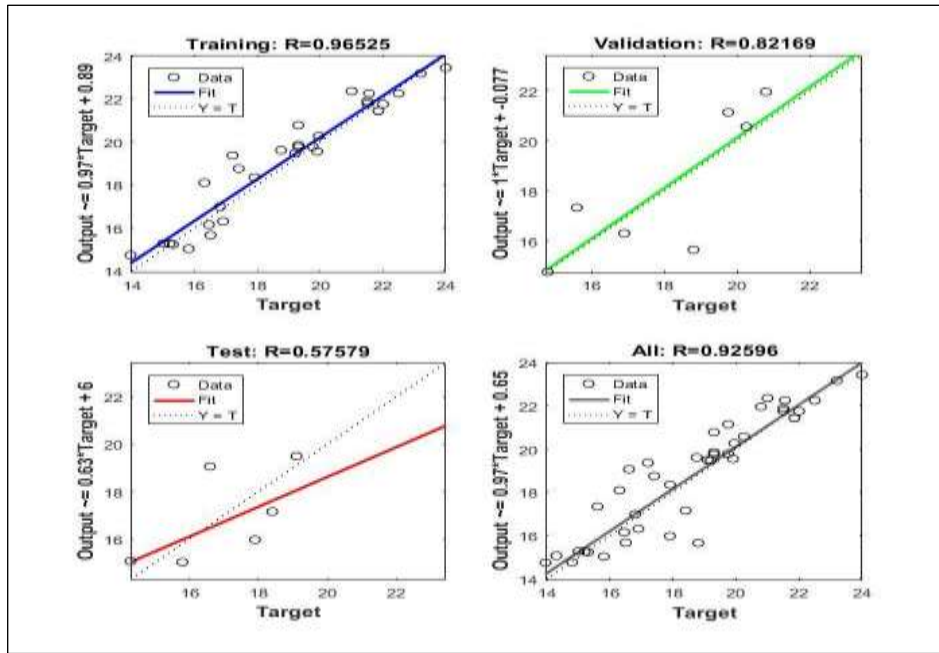


Figure 9: Regression graph for OMC prediction.

Source: Authors, (2026).

- **Training set:**

$$\hat{y} = 0.917 \cdot y + 0.89 \text{ With } R = 0.96525$$

- **Validation set:**

$$\hat{y} = 1.0 \cdot y + 0.077 \text{ With } R = 0.82169$$

- **Testing set:**

$$\hat{y} = 0.631 \cdot y + 6.0 \text{ With } R = 0.57579$$

- **Overall (All data):**

$$\hat{y} = 0.97 \cdot y + 0.65 \text{ With } R = 0.92596$$

Where R is the correlation coefficient, which measures linear correlation between predicted and actual values :

$$R = \frac{\sum (y_i - \bar{y})(\hat{y}_i - \bar{\hat{y}})}{\sqrt{\sum (y_i - \bar{y})^2 \sum (\hat{y}_i - \bar{\hat{y}})^2}}$$

Figure 10 shows the comparison between experimental results and predicted values of OMC in different soil combinations. From the results, it is observed that the results were almost the same, but the predicted values are slightly higher than the experimental results in all soil combinations.

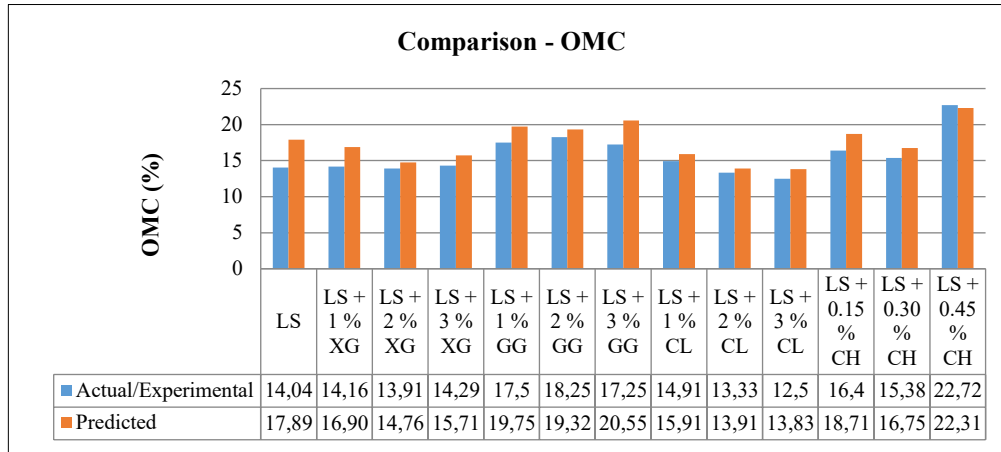


Figure 10: Comparison of experimental and predicted OMC values.

Source: Authors, (2026).

IV.2 MAXIMUM DRY DENSITY (MDD)

Maximum dry density (MDD) is the compression condition at which soil can reach its maximum density. At what is called the "optimum moisture content" (OMC), MDD takes place. Both MDD and OMC might change depending on the soil type and the amount of compaction force used in the test. The MDD, which derives from a compaction test, is a crucial metric in geotechnical engineering. It aids engineers in making educated decisions while planning and building civil engineering projects by indicating the maximum density that soil may reach under ideal compaction conditions. This study utilized variables such as fine-grained %, sand %, gravel %, specific gravity (G), liquid limit, and plastic limit to make an educated approximation as to the MDD of soil. The numbers used as inputs came from somewhere else. Soil MDD prediction using an ANN model is shown in figure 11. The MDD is the output; hence, there is just one neuron in the output layers. The hidden layer neuron count was determined by running many networks with varying numbers of hidden neurons and comparing the predicted and desired outcomes. A hidden layer consisting of 10 neurons performed admirably in this investigation.

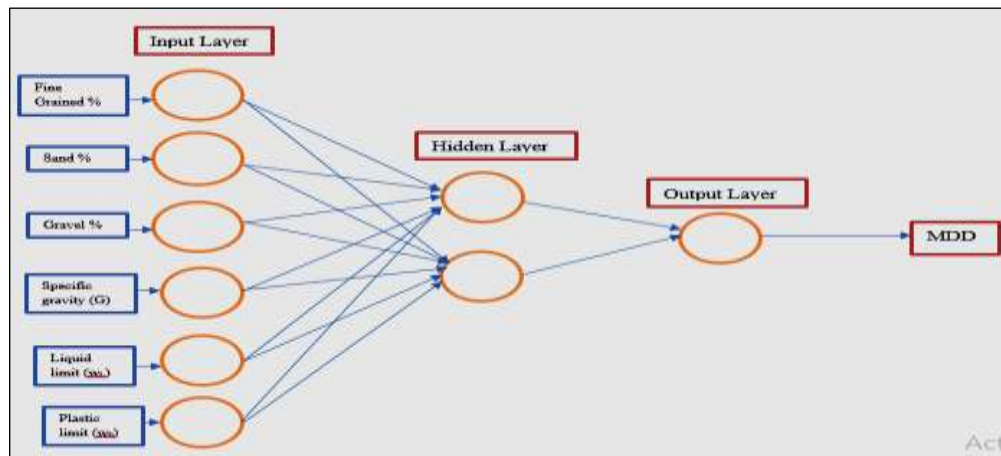


Figure 11: Architecture of an ANN model for estimating MDD.

Source: Authors, (2026).

Given the inputs:

- Fine-Grained Content (%): x_1
- Sand Content (%): x_2
- Gravel Content (%): x_3
- Specific Gravity (G): x_4
- Liquid Limit (LL): x_5
- Plastic Limit (PL): x_6

A **general linearized form** of the equation for MDD prediction, derived from ANN model behavior and regression trends, can be approximated as:

$$MDD = a_1x_1 + a_2x_2 + a_3x_3 + a_4x_4 + a_5x_5 + a_6x_6 + b$$

Where:

- $a_1, a_2, \dots, a_6$: weights (coefficients) learned by the neural network
- b : bias term

In the case of MDD, the coefficient correlation is 0.941, indicating a strong correlation between the experimental results and predicted results in all soil combinations. Figure 12 shows the regression analysis of MDD to check the model's accuracy.

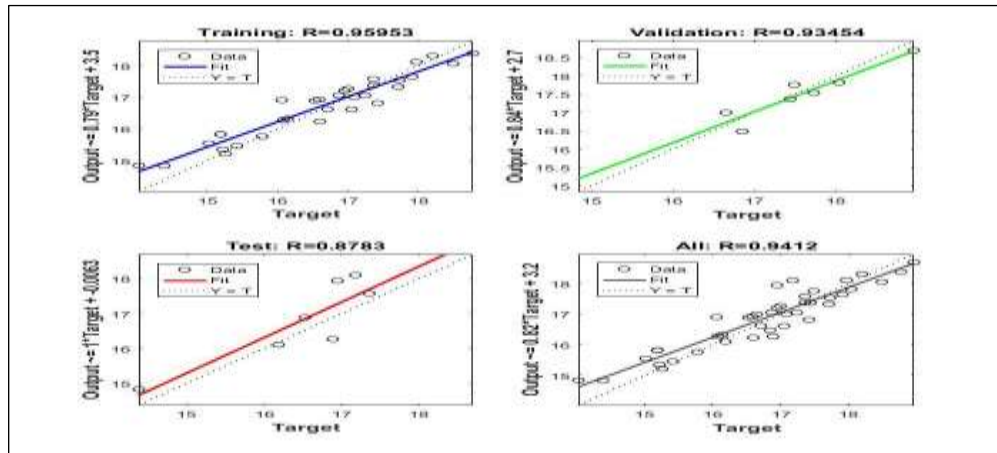


Figure 12: Regression graph for MDD prediction.
Source: Authors, (2026).

Each plot provides a **linear fit** between predicted (output) and actual (target) values. These can be used to report how well your model performed in different phases:

- **Training Phase:**

$$\text{Output} = 0.79 \cdot \text{Target} + 3.5 \quad (R = 0.95953)$$

- **Validation Phase:**

$$\text{Output} = 0.84 \cdot \text{Target} + 2.7 \quad (R = 0.93454)$$

- **Test Phase:**

$$\text{Output} = 1.0 \cdot \text{Target} - 0.0063 \quad (R = 0.8783)$$

- **Overall (All Data):**

$$\text{Output} = 0.82 \cdot \text{Target} + 3.2 \quad (R = 0.9412)$$

These **regression equations** and **correlation coefficients (R-values)** quantify the goodness of fit. A value of $R \approx 0.94$ indicates very strong correlation. Figure 13 shows the comparison between experimental results and predicted values of OMC in different soil combinations. The graph shows that the results were almost the same for all soil combinations.

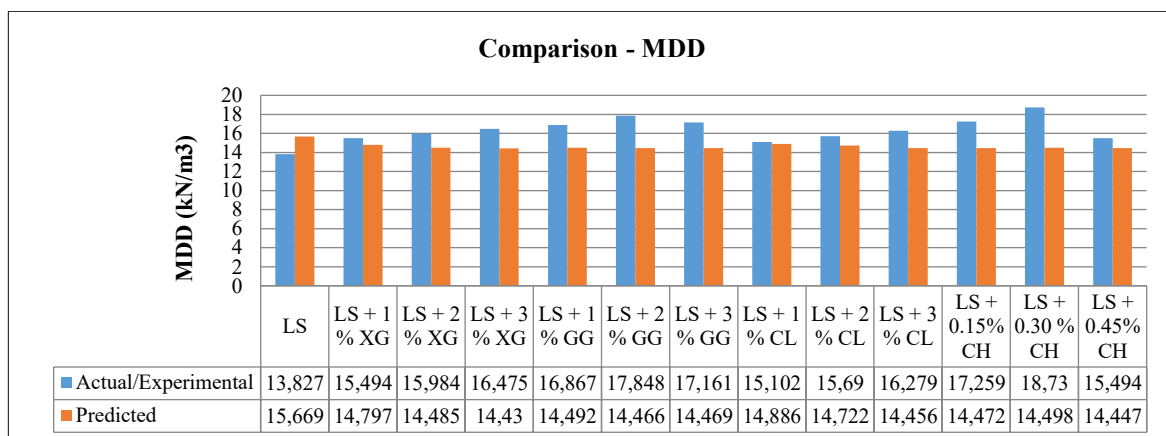


Figure 13: Comparison of experimental and predicted MDD values.
Source: Authors, (2026).

V. CONCLUSIONS

- The incorporation of xanthan gum biopolymer significantly enhances the compaction characteristics of laterite soil, with a 3% dosage yielding the optimal improvement—resulting in a 19.14% increase in Maximum Dry Density (MDD) and a modest 1.78% rise in Optimum Moisture Content (OMC)—due to improved particle lubrication, reduced internal friction, and enhanced cohesion.

- The incorporation of 2% guar gum biopolymer into laterite soil significantly enhanced its compaction characteristics, increasing the maximum dry density by 27.46% and reducing optimum moisture content, primarily due to improved particle packing and the cohesive, binding nature of the biopolymer.
- The addition of cellulose to laterite soil marginally increases the Maximum Dry Density (MDD) up to a concentration of 3%, while consistently reducing the Optimum Moisture Content (OMC), suggesting that cellulose can enhance compaction efficiency with minimal structural alteration.
- Chitosan biopolymer significantly enhances soil compaction, achieving the highest Maximum Dry Density (MDD) among the tested biopolymers, while also increasing the Optimum Moisture Content (OMC) due to its moisture-retention properties and strong bonding capacity.
- Artificial Neural Networks (ANNs) have proven effective in predicting the engineering characteristics of laterite soil, demonstrating strong model performance. The accuracy of soil property prediction using ANN heavily depends on the quality and comprehensiveness of input data.
- The ANN models were trained using key geotechnical parameters, including optimum moisture content (OMC), maximum dry density (MDD), clay content, gravel content, and specific gravity, ensuring a data-driven approach.
- The MDD prediction model achieved a high correlation coefficient ($R = 0.941$), indicating excellent agreement between predicted and experimentally measured values.
- The OMC model also performed well ($R = 0.925$), confirming that ANN can reliably model both moisture and density-related soil behaviors.
- The ANN predictions were validated through comparison with laboratory-obtained data, reinforcing the credibility and applicability of the developed models for practical soil analysis.

VI. AUTHORS CONTRIBUTION

Conceptualization: Shailendra Pandurang Banne, Pratima Vitthal Kalokhe.

Methodology: Shailendra Pandurang Banne, Pratima Vitthal Kalokhe

Investigation: Shailendra Pandurang Banne, Pratima Vitthal Kalokhe.

Discussion of results: Shailendra Pandurang Banne, Pratima Vitthal Kalokhe, Ganesh Tarte, Mugdha Kshirsagar, Sudarshan Bobade.

Writing – Original Draft: Shailendra Pandurang Banne, Pratima Vitthal Kalokhe.

Writing – Review and Editing: Shailendra Pandurang Banne, Pratima Vitthal Kalokhe, Ganesh Tarte, Mugdha Kshirsagar, Sudarshan Bobade.

Resources: Shailendra Pandurang Banne, Pratima Vitthal Kalokhe.

Supervision: Shailendra Pandurang Banne, Mugdha Kshirsagar, Sudarshan Bobade.

Approval of the final text: Shailendra Pandurang Banne, Pratima Vitthal Kalokhe.

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