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Assessment of Reinforced Slope Stability of Soils using Multiple Regression Models

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Abstract: Assessing the stability of slopes holds immense significance in geotechnical engineering. However, the conventional and soft computing methods used for this purpose come with notable challenges. Unlike the black-box nature of soft computing techniques such as artificial intelligence and fuzzy logic, employing traditional limit equilibrium procedures for slope stability assessment is often arduous and time-intensive. In contrast, multiple regression (MR) analysis emerges as a pragmatic alternative for evaluating slope stability. MR offers a simplified equation that can determine the critical factor of slope safety without the need for complex iterative processes. This utilization of MR models streamlines the assessment process, reducing both time and complexity and overall enhancing the evaluation process. In this study, we explored the accuracy of MR models in estimating slope stability using real-world field data. Our dataset comprises six key variables: unit weight, cohesiveness, internal friction angle, slope angle, slope height, and pore water pressure ratio. We constructed multiple regression models to assess their effectiveness in determining slope stability, accounting for both dry and wet slope conditions. The study successfully developed several multiple regression models for both dry and wet slopes. Furthermore, we employed performance metrics like Mean Square Error (MSE) and Coefficient of Determination (R2) to rigorously evaluate and validate the accuracy of these models in comparison to traditional limit equilibrium methods. The performance of the dry slopes R2 is 0.835 and wet slope of R2 value is 0.818.

Keywords: *Slope stability, Coefficient of determination, Mean Square Error, Artificial Intelligence, slopes.*

1.Introduction

The assessment of slope stability stands as a cornerstone in the field of geotechnical engineering, carrying profound implications for the safety and integrity of various civil engineering projects. Slope stability evaluations are instrumental in mitigating the risk of landslides, ensuring the structural soundness of embankments, and averting potentially catastrophic events. However, the traditional methodologies and soft computing approaches commonly employed for slope stability assessments are not without their challenges. Therefore, precise slope stability prediction has practical engineering value [1]. The slope engineering stability influencing elements have a very nonlinear connection. The system under examination is an open, dynamic, nonlinear system that consists of many complex and unexpected components. The technique of limit equilibrium [2] and numerical analysis techniques [3 - 6], are widely recognised as the conventional procedures used for the investigation of slope stability. For the evaluation of slope instabilities, soft computing techniques like Artificial Neural Networks (ANN) and fuzzy logic are currently being applied. However, the black box methodology of these methods causes problems. These conventional techniques must deal with a significant computing burden. Their stability calculation procedure in particular is laborious, making it challenging to satisfy the demands of

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accelerating slope designs. In the context of engineering mega-projects, particularly those including extensive slopes such as hydroelectric engineering, there is a prevalent demand for expeditious stability assessment and design at the initial stages of the design process. For the estimate and prediction of various parameters, multiple regression models are now often used across a diverse array of engineering disciplines, including geotechnical engineering. For geotechnical engineering systems, Zhang and Goh (2013) used the utilisation of multivariate adaptive regression splines in their study [7].

The contributions of the research are:

- This research introduces multiple regression (MR) analysis as a practical substitute for conventional and soft computing methods, simplifying slope stability assessments.
- MR models streamline the assessment process by providing a straightforward equation for critical factor determination, reducing time and complexity.
- The study utilizes real field data, including vital variables, ensuring applicability to diverse slope stability scenarios.

2.Related works

Traditional methods, rooted in limit equilibrium procedures, often entail intricate and time-consuming processes. On the other hand, contemporary soft computing techniques, like artificial intelligence and fuzzy logic, are often regarded as "black box" solutions, which may lack transparency and interpretability. In response to these challenges, this study explores an alternative approach: Multiple Regression (MR) analysis. MR analysis offers a pragmatic substitute for both traditional and soft computing methods in assessing slope stability. By providing a simplified equation, MR analysis can efficiently determine the crucial factor of slope safety without the need for complex and iterative procedures. This approach not only streamlines the assessment process but also enhances its overall efficiency. Multiple Regression (MR) approaches are a superior replacement for these techniques. The assessment of slope stability takes less time and is less complicated thanks to the use of MR, a method of statistics that provides a streamlined equation that can be used to compute the crucial component of slope safety without using any iterative procedures. In contrast to soft computing techniques, the well-established MR equation establishes a direct and transparent relationship between the independent variables and the dependent variables. Sayed et al. (2012) [8] and Esmaeili et al. (2014) [9] used multiple regression analysis to forecast backbreak in the context of rock blasting activities. Mojtahedi et al. (2019) [10] included four key variables, including slope height, slope angle, cohesiveness, and friction angle, as the primary factors. Gordan et al. (2016) [11] used five parameters as inputs in their study, namely slope height, angle, cohesiveness, angle of internal friction, and unit weight (or peak). Zhang and Goh (2016) [12] used multivariate regression analysis to evaluate the possibility for liquefaction. Sah et al. (1994) [13] and Erzin and Cetin (2013) [14] developed regression models for the purpose of forecasting slope stability. Sah et al. (1994) [13] created an empirical relationship for estimating slope stability using the greatest probability technique. The developed connection, however, is only applicable to a small number of slope failure types and is based on a small amount of data (46 cases). Erzin and Cetin (2013) [14] devised a multiple regression equation for slope stability prediction, but only tested its accuracy for a small number of soil parametric ranges (675 examples).

A large number of slopes (29112 examples in total) covering all conceivable slope configurations and soil characteristics were used to create MR models for the key FOS computation in the current study. For uniform dry slopes and saturated and slightly saturated slopes, two distinct equations have been constructed (i.e., wet slopes). By using real field data, the created models are further validated. These MR models were developed using IBM SPSS software.

Pre-processing of Data

MVI, or missing value imputation, is used in preprocessing. The only source of data used by a trainable automated classification decision-making process is a dataset. Conversely, the practical dataset often has an anomalously high percentage of missing values, which are often denoted by NaNs, null, blanks, undefined, or similar placeholders. A dataset's missing values must be removed or imputed in order to build a generic, reliable, and effective classification model. Several statistical and machine learning techniques are often employed to deal with missing data in an incomplete dataset, in contrast to the case deletion strategy. Therefore, this paper uses median-based statistical imputation techniques for MVI purposes.

Median-based statistical imputation techniques are a category of data imputation methods used in statistics and data analysis. These techniques involve replacing missing or incomplete data values with the median of the available data for that variable. The median is the middle value in a dataset when it is arranged in ascending or descending order, which makes it robust to outliers compared to other measures like the mean (average). Median-based imputation is commonly used in the preprocessing stage of data analysis. After imputation, the dataset can be analyzed using various statistical and machine learning techniques.

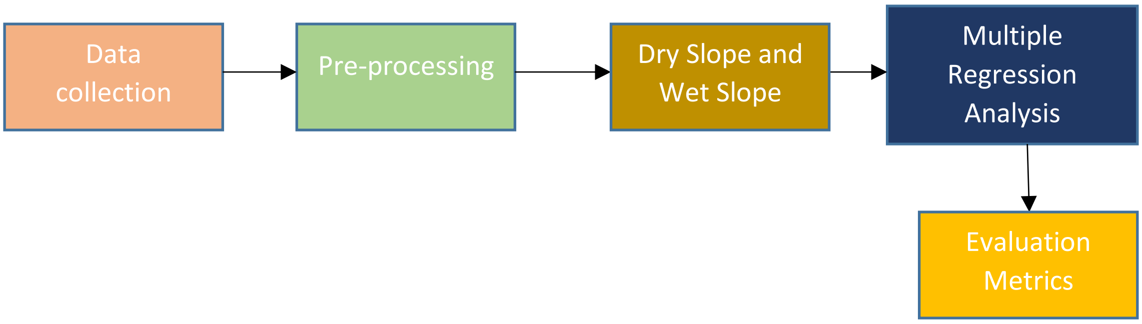

Fig 1. Proposed Block Diagram

3. Multiple regression model-based prediction

The statistical method known as multiple regression enables the analysis of a single dependent variable with a multitude of alternative independent variables. Multiple regression analysis is a statistical technique that involves using independent variables with known values to make predictions about a single dependent variable. Weights are used to show how much each predictor factor contributes to the overall prediction, and these weights are applied to each predictor value.

$$Y = \beta_1^* X_1 + \beta_2^* X_2 + \cdots + \beta_n^* X_n + C$$

Here, X1,..., Xn are the independent variables, while Y is the dependent variable. When determining the weights, a, b1... bn, the dependent variable is optimised for prediction using the collection of independent variables using regression analysis. This is often accomplished by least squares estimate. This methodology may be used for the analysis of multivariate time series data in situations where a single variable is dependent on many factors. The variable Y, which is the dependent variable, may be represented by a model that incorporates a collection of independent variables. The prediction of the value of Y may be made using Equation 1 at any given time, provided that the values of the independent variable are known. The stability of slopes is assessed in the current work using MR in cases where the slopes are dry, saturated, and partially saturated. (i.e., wet cases). In the instances of partial saturation and saturation, the geotechnical characteristics of soils (C, ϕ, β, γ, H, Γu) serve as the independent variables, while the FOS is the dependent variable. Conversely, in the dry scenario, the independent variables are (C, ϕ, β, γ, H), and the dependent variable is the FOS. The accuracy of the obtained MR equation is evaluated using R2 and MSE. The measure of association, or R2, represents the proportion of overlap between the answer variable and the calculated variable. The average of the squared discrepancies between the calculated value and the expected value is quantified by the mean squared error (MSE).

- It is essential that a linear connection exists between the independent and dependent variables. Additionally, it's crucial to look for outliers because MR is susceptible to their impacts. Scatter plots can be used to test this premise.
- In order to conduct a multiple linear regression analysis, it is necessary for the regression residuals to exhibit a normal distribution. Examining a histogram or a Q-Q-Plot will help you confirm this notion.
- Goodness-of-fit analyses including as Kolmogorov-Smirnov test, may similarly verify if a distribution is normal, but only on the residuals.
- Multiple linear regression assumes that the data is not multicollinear. Multicollinearity happens when

the levels of the independent variables are too high, of correlation with one another.

Data set description

The landform of the area, the physical and mechanical characteristics of of the soil and rocks, as well as external triggering variables like hydrogeological conditions, all have an impact on the stability of slopes. The FOS is a thorough metric for assessing slope stability. Since it is closely related to the soil's shear strength, the factor of safety (FOS) is a crucial component in the evaluation of slope stability. It is the ratio of the force causing a slope to slide to the resistance to slope sliding [15]. Numerous important factors, such as the unit weight, cohesiveness (C), and angle of internal friction, have an impact on the soil shear strength. Some researchers use the strength reduction approach [17] and the gravity increase methodology [16] to compute the (FOS). When evaluating the circumstances under which a slope is vulnerable to failure, a slope's geometric properties, namely the slope angle and slope height H, often play a critical role. The stability of the slope declines with increasing slope angle. The weight of the geotechnical is increased by water infiltration, and the soil's and rock's shear strength is decreased because of softening. All of these modifications have a negative impact on the stability of the slope. Consequently, the parameters pertaining to the geometry and geotechnical qualities of each slope are selected.

Estimation of variables

The characteristics that govern slope stability include unit weight (expressed in kN/m3), cohesiveness (measured in kPa), angle of internal friction (given in degrees), slope angle (also in degrees), slope height (measured in metres), and pore water pressure ratio [18]. There are, in theory, additional signs, but gathering them would present a significant obstacle before they could be used in real-world applications.

$$FOS = f(\gamma, C, \varphi, \beta, H, ru) \quad (1)$$

Multiple regression models are developed using a large amount of raw data. A sizable number of slopes (a total of 29112 instances) have been taken into account, with all feasible configurations and soil characteristics. Table 1 presents the data pertaining to dry instances, including a total of 14,112 cases. On the other hand, Table 2 provides information on wet cases, encompassing the same dataset of 15,000 cases. Both tables offer comprehensive details about the range of data that was considered for analysis. The stability condition, expressed as FOS, is assessed for every slope under consideration.

Table 1 Data ranges for dry cases

Parameter	Range	No of cases
Cohesion	10-45	7
Angle of friction	10°-40°	6
Angle of inclination	15°-50°	7
Unit weight	15-24	6
Height	6-54	8
Total number of case = 14112		

Table 2 Data ranges for Wet cases

Parameter	Range	No of cases
Cohesion	10-45	5
Angle of friction	10°-40°	5

Angle of inclination	15°-50°	5
Unit weight	15-24	4
Height	6-54	6
Γ_u	0-0.5	5
Total number of cases = 15000		

The determination of FOS for this broad collection of scenarios using traditional limit equilibrium approaches is a difficult undertaking due to the complexity and time-intensive aspects of the operation. As a result, the FOS was assessed using the stability chart technique. The Michalowski stability chart method, which is implemented in MATLAB code, is utilized to analyse the stability of several slopes. The use of lower limit kinematic analysis is employed inside the Michalowski stability chart technique (2002), which has been well validated. In this section, a total of 14,112 examples of dry slopes and 15,000 cases of wet slopes were examined in order to develop the MR model.

3.1 MR model for dry slopes

Therefore, an MR model has been created using the raw data generated by the Michalowski stability chart for evaluating the critical FOS for dry slopes. Data ranges from Table 1 are taken into consideration for the formulation of the MR equation because the MR model development demands a large amount of raw data. Prior to formulating the MR equation, it is essential to ascertain the fulfilment of the fundamental assumptions behind the equation.

Scatter plots have been generated to validate the assumption of linearity between the independent and dependent variables. The figures from 1 to 5 illustrate the linear connections between the independent and dependent variables. In this context, the variables C, β, γ, and H are considered as independent variables, while the FOS is regarded as the dependent variable. Figure 1 illustrates the correlation between the FOS and the parameter γ, while manipulating the variable ϕ. The constants C = 15, β = 25, and H = 10 are held fixed as independent and dependent variables.

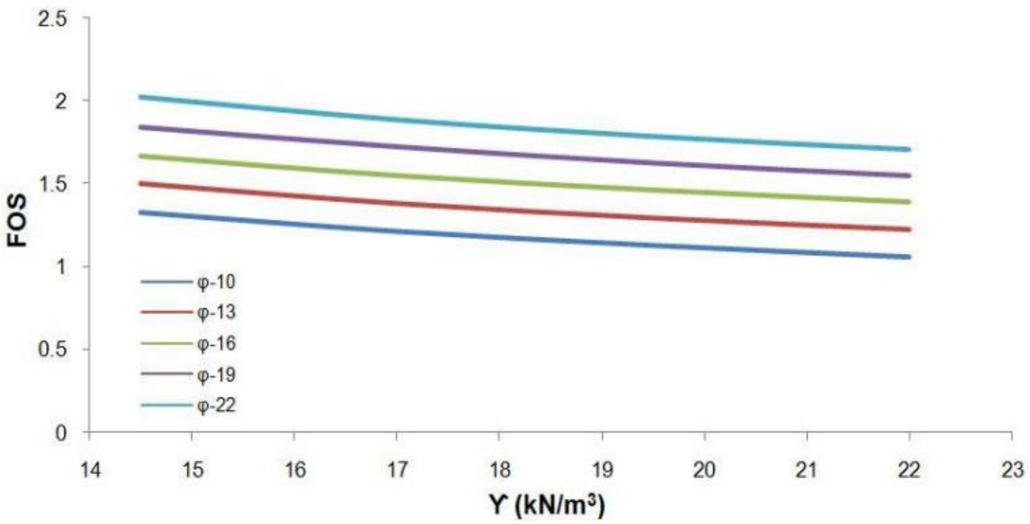

Fig 2. Connection between stability of slopes and unit weight of soils

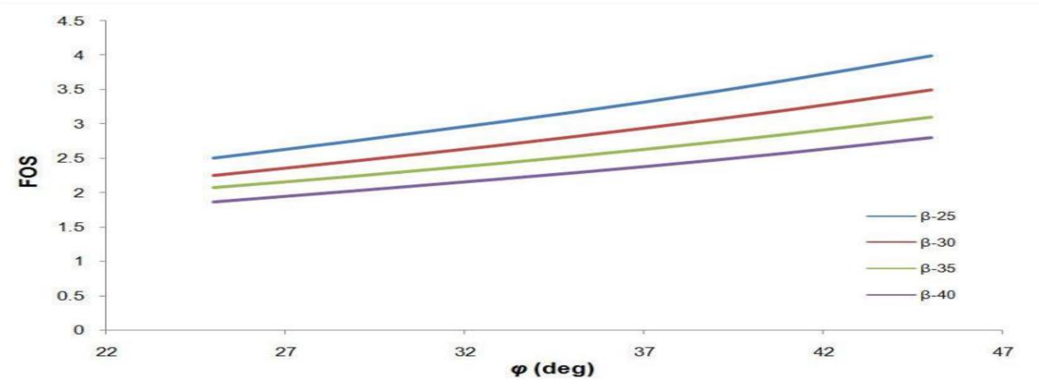

Fig 3. Connection between stability of slopes and angle of internal friction of soils ϕ

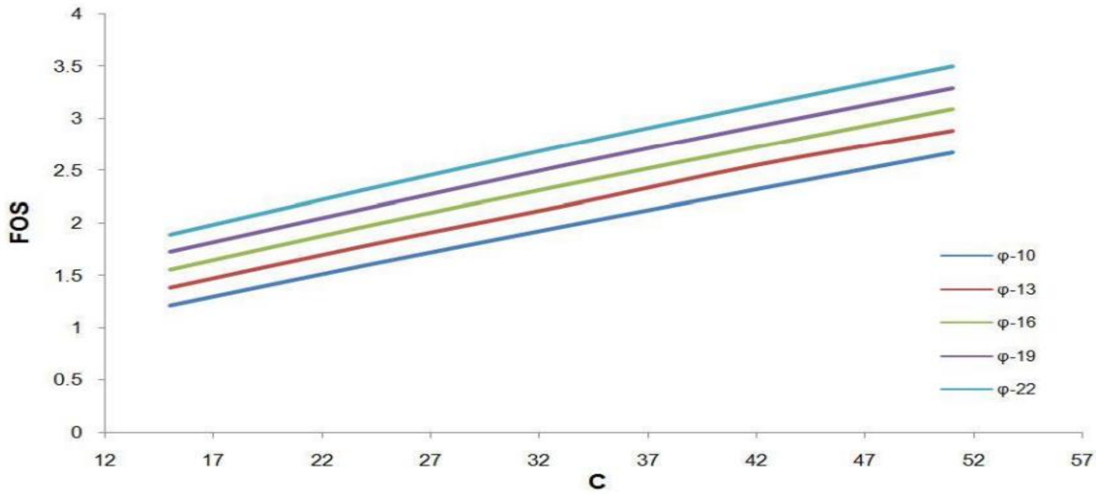

Fig 4. Relation between stability of slopes and cohesion of soils

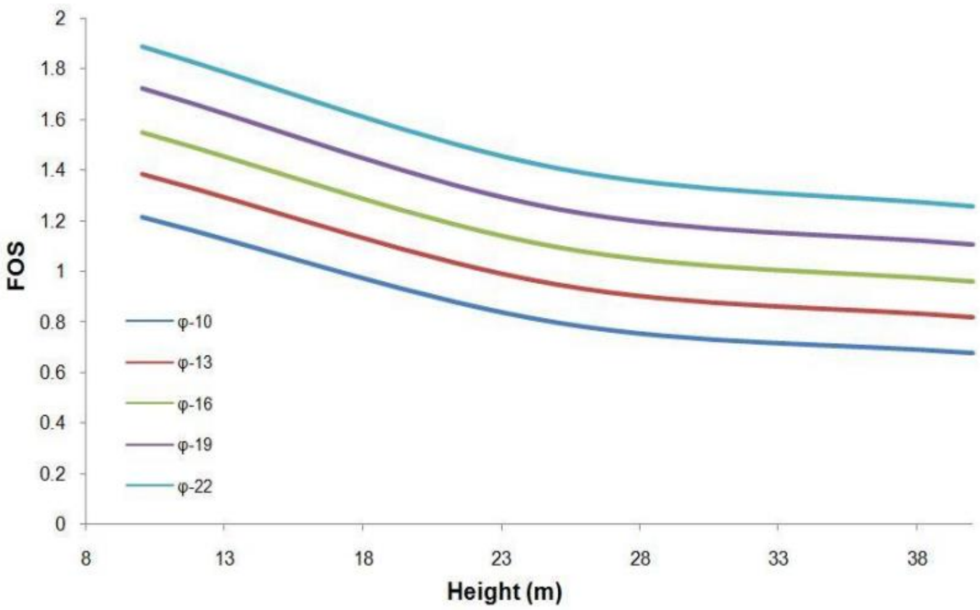

Fig 5. Relation between stability of slopes and height of the soils

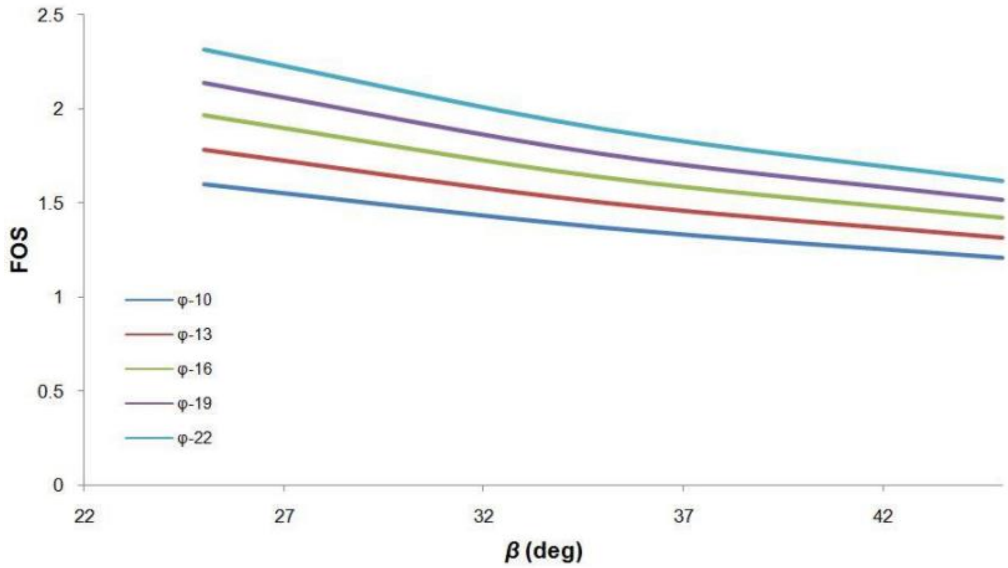

Fig 6. Relation between stability of slopes and slope angles

In a manner similar to the depiction in Figure 2, Figure 3 presents a visual representation of the correlation between FOS and the manipulation of one independent variable, while keeping the other independent variables constant at certain values (C = 10, γ = 14, H = 5). The relationship between FOS and C is depicted in Fig. 4 by changing while holding the other independent variables,γ = 17, β = 25, H = 10, constant. Figure 5 demonstrates the correlation between the FOS and the variable H, while keeping the other independent variables C = 15, β = 25, and γ = 17 constant. Figure 6 demonstrates the correlation between the FOS and the manipulation of the other independent variables, namely C = 24, γ = 17, and H = 10, which are held constant. The first assumption is satisfied as seen by the figures (Figs. 1–5), which demonstrate a linear relationship between the independent factors and the dependent variable.

The histogram in Fig. 7 is shown with a fitted normal curve to test the second supposition. The dependent variable FOS is shown in the figure to be regularly distributed.

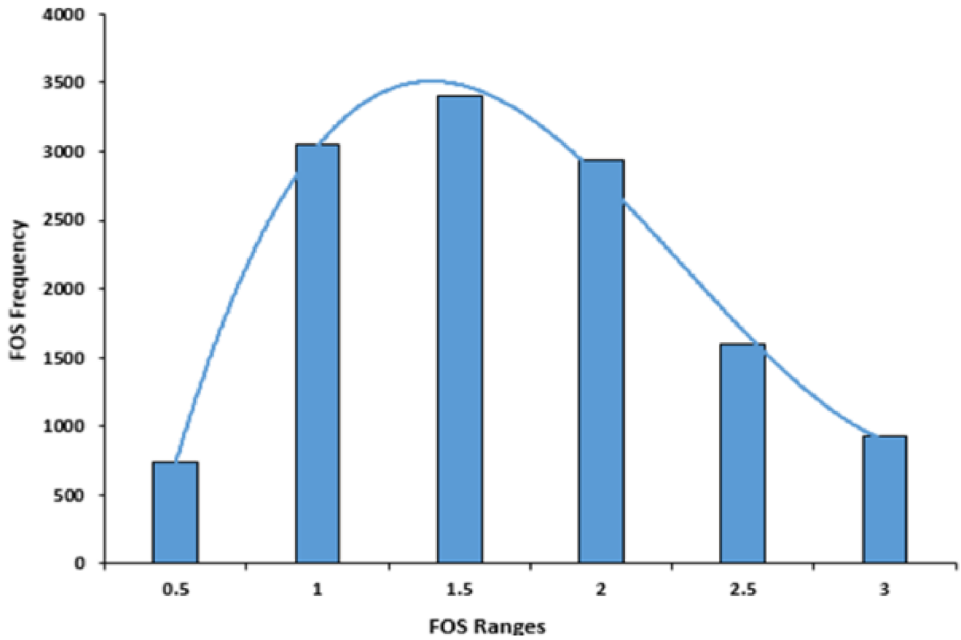

Fig 7. Normal distribution plot for dry cases

The Pearsons matrix is then used to determine whether multicollinearity exists in the data (i.e., the third assumption). When the independent variables are not independent of one another, multicollinearity arises. The ranges of collinearity are between 1 and -1. The number "1" denotes a strong relationship between the variables, whereas the value "0" denotes no relationship at all. If the sign is negative, it indicates a significant inverse correlation between the variables, thereby establishing the contrary as true. Table 4 presents the correlation coefficients pertaining to each of the independent variables. The table indicates a lack of multicollinearity or minimal multicollinearity among the independent variables.

Table 4 Multicollinearity to independent variable

	γ	ϕ	C	H	β β
γ	1	-0.011	-0.024	0.020	0.024
ϕ	-0.011	1	0.047	-0.083	-0.167
C	-0.024	0.047	1	-0.102	-0.059
H	0.020	-0.083	-0.102	1	0.112
β	0.024	-0.167	-0.059	0.112	1

The last homoscedasticity assumption, according to Osborne and Waters (2002) [19], states that the variance of the errors is constant at all levels of the independent variables. In other words, the researchers make the assumption that the mistakes are distributed consistently throughout the variables. Osborne and Waters (2002) recommended showing the standardised residuals against the standardised predicted values of the regression model as a way to visually evaluate homoscedasticity. Figure 8 displays the scatter plot for the cases that were thought to be dry. The criterion is verified by the figure, which shows that all residual errors are uniformly dispersed about zero.

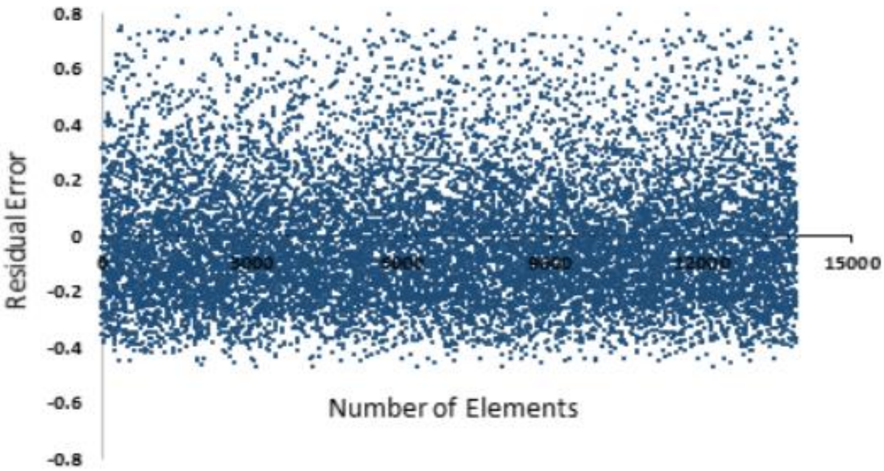

Fig 8. Homoscedasticity residual plot for dry cases

Using SPSS software, an MR model for dry slopes has been created after all fundamental assumptions have been verified. Eq. 1 presents the created MR model.

$$FOS = C * 0.0169 + \phi * 0.0208 - \beta * 0.0371 - H * 0.0371 + \gamma * 0.0208 + 2.4727 \quad (1)$$

The performance of the constructed multiple regression model is evaluated by using the data required for its creation, as shown in Table 1, and by generating a correlation diagram. Figure 9 displays the correlation plot illustrating the relationship between the FOS established using the stability chart technique and the FOS derived from the developed MR model.

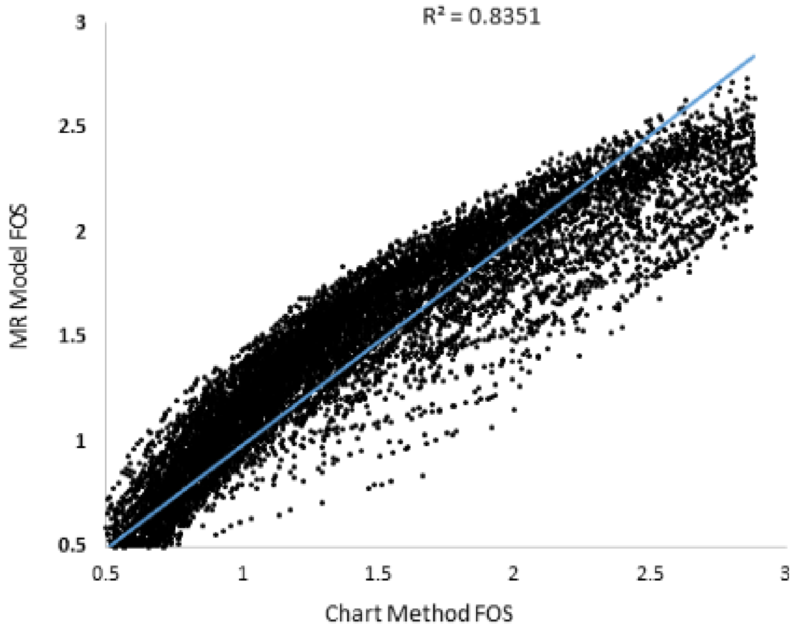

Fig 9. Correlation plot of training data for dry cases

The statistical estimation of the correlation between the two factors of interest is shown by the Coefficient of Determination R^2, which is calculated using Equation (2). The estimated FOS obtained by the MR model is found to be identical to the FOS calculated using the chart approach, as shown by the R2 value of 1. Nevertheless, this situation is considered ideal, as shown by Smith's (1986) assertion that R 2 value over 0.8 is seen favourable.

$$R^2 = \left[\frac{N\sum y*y' - (\sum y)(\sum y')}{\sqrt{[N\sum y^2 - (\sum y^2)][N\sum y'^2 - (\sum y')^2]}}\right]^2 \qquad (2)$$

$$MSE = \frac{1}{N}\sum_N^1 (y - y')^2 \qquad (3)$$

The Value Account for (VAF) encompasses variations and indices, and it is determined via the use of Equation 4. This calculation serves the purpose of regulating the predictive capability of the developed model's output. When the value of VAF approaches 100%, the associated error is minimised.

$$VAF = 100[1 - \frac{var\,(y-y')}{var(y)}] \qquad (4)$$

The evaluation of the disparity between predicted values generated by a model and the actual values obtained from the observed physical field under investigation is often conducted via the use of the root mean square error (RMSE). The aforementioned dissimilarities are often referred to as residuals, and the Root Mean Square mistake (RMSE) is a computational method that consolidates these residuals into a singular metric, so magnifying the mistake and effectively highlighting any discrepancies in Equation (5).

$$RMSE = \sqrt{\frac{1}{N}\sum_N^1 (y - y')^2} \qquad (5)$$

Where y is the FOS from the MR approach, y′ is the FOS from the stability chart method, N is the total number of cases, and var () is the variance.

The created MR model is confirmed by the derived Coefficient of determination R 2 value of 0.835, which shows high correlation between the two values (Smith 1986)[20] .

3.2 MR model for Wet slopes

For instances that are fully and partially saturated, a different MR equation has been created. The creation of the MR equation for both scenarios took into account a total of 15000 cases. The data is checked against all four major hypotheses listed in the Multiple Regression Model section before creating the multiple regression equation.

It is evident from Figs. 1–5 and 10 that link between the independent and dependent variables FOS is remarkably linear, satisfying the necessary linearity assumption. By varying while holding the other independent variables $C = 15$, $\beta = 25$, $\gamma = 17$, $H = 22$ constant, Fig. 11 illustrates the relationship between FOS and u. The normal distribution curve is used to confirm the normality of a dependent variable. The dependent variable's normal distribution plot is displayed in Fig. 12. The second premise is satisfactorily demonstrated by the figure, which shows that the dependent variable, FOS, is normally distributed.

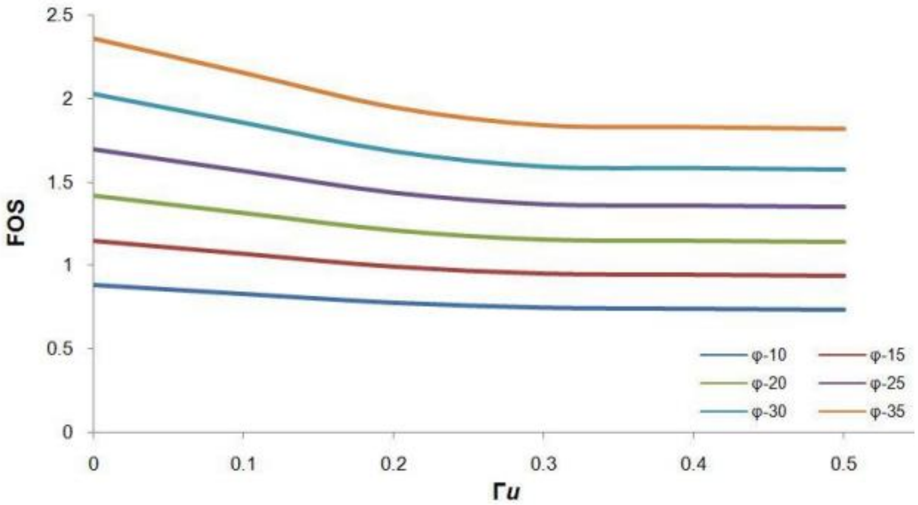

Fig 11. Relation between stability of slopes and pore water pressure Γu

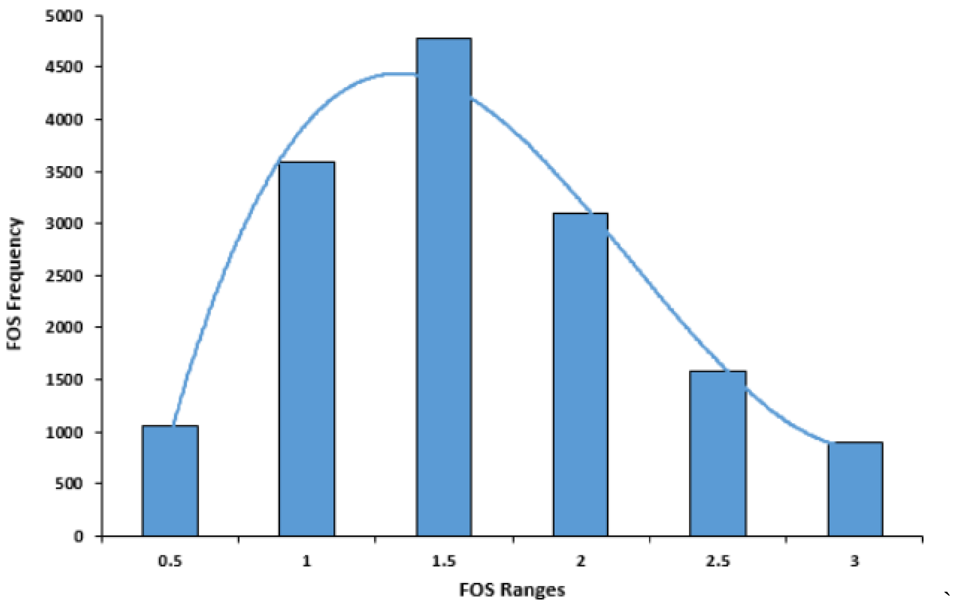

Fig 12. Normal distribution for wet case

The multicollinearity assumption is then confirmed using Pearson's matrix. Table 7 contains the correlation coefficients among all of the independent variables. To disregard the interdependence of the variables, these values must be less than 0.19, according to Osborne and Waters (2002). Table 7 exhibits little evidence of multicollinearity among the independent variables, hence providing support for the third premise of multicollinearity.

Table 4 Multicollinearity to independent variable

	H	β	C	ϕ	γ	Lu
H	1	0.023	0.031	-0.068	-0.109	0.111
β	0.023	1	0.011	-0.039	-0.033	0.047
C	0.031	0.012	1	-0.019	-0.029	0.012
ϕ	-0.068	-0.038	-0.019	1	-0.051	-0.129
γ	-0.109	-0.032	-0.029	0.051	1	-0.066
Lu	0.111	0.047	0.012	-0.129	-0.066	1

Fig. 13's scatter plot for the circumstances under consideration is shown to demonstrate how the homoscedasticity assumption can be verified. The image demonstrates that the residual errors exhibit a uniform distribution around zero, indicating an equitable distribution and confirming our initial assumption.

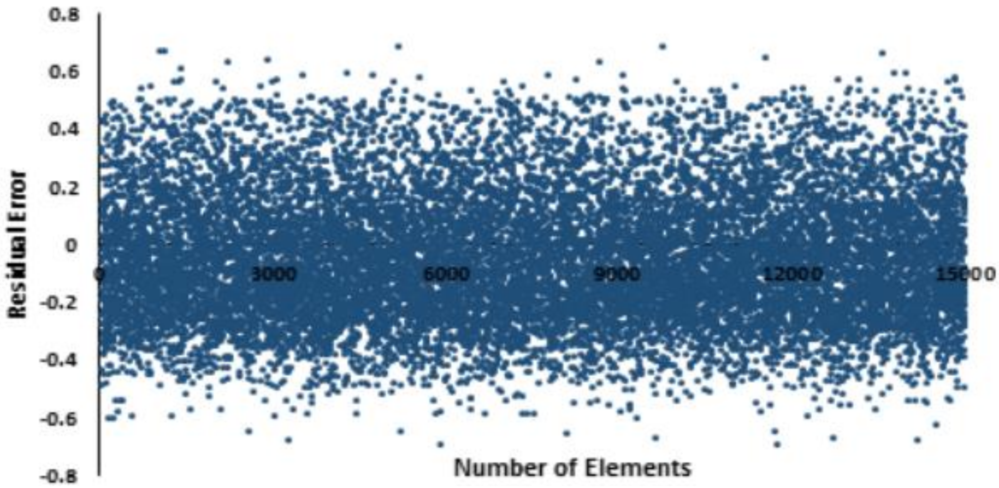

Fig 13. Homoscedasticity residual plot for wet cases

After confirming each of the four fundamental hypotheses, the MR equation for wet circumstances was created and is provided in Eq (6).

$$FOS = C * 0.0169 + \phi * 0.0208 - \beta * 0.0371 - H * 0.0371 - \gamma * 0.0208 - \Gamma_u * 0.6409 + 2.4727 \quad (6)$$

The FOS (Figure of Merit) of the dataset, consisting of 15,000 instances, used in the formulation of the MR (Multiple Regression) equation (as shown in Table 2), is determined using the chart method. Additionally, a correlation plot is shown, illustrating the relationship between the FOS acquired by the established MR model. The purpose of this action is to evaluate the efficacy of the formulated MR equation.

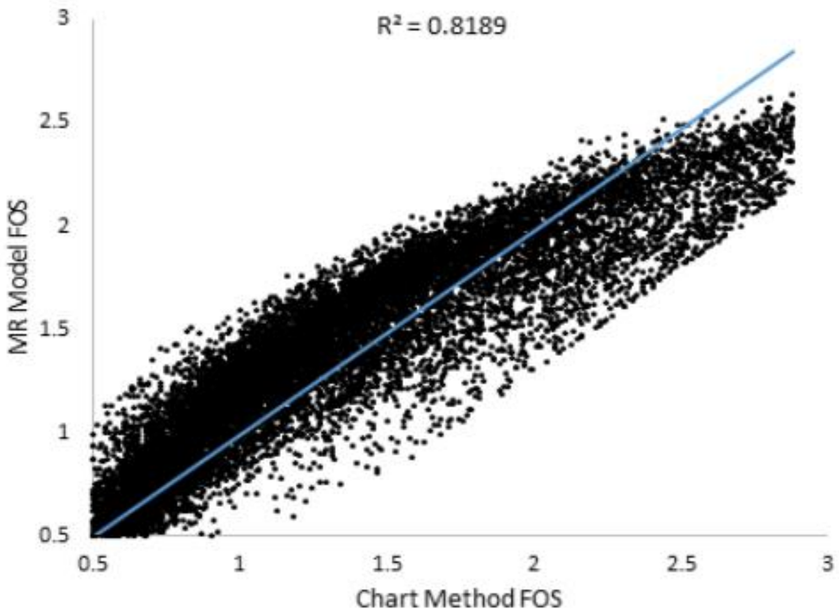

Fig 14 Correlation plot

The provided graph, labelled as Figure 14, displays a residual plot that assesses the homoscedasticity of wet instances. Figure 14 shows the correlation plot. The statistical estimate, namely the Coefficient of determination R2 value, confirms the validity of the developed MR model, with a computed value of 0.818. This numerical value indicates a strong association between the two fields of study.

4. Conclusion

Intelligent optimisation systems have been widely used in the field of slope deformation prediction. Many clever algorithms and technological tools have been combined to create new and improved models that anticipate slope deformation to a new degree of capacity. In the most recent research, a multiple regression model based on actual field data was developed and validated to evaluate slope stability. Many models of multiple regression have been created. In this instance, taking into account slopes that are both dry and wet. After a comparison study with conventional limit equilibrium techniques, it is shown that the created MR models have the capacity to predict the FOS of slopes with high accuracy in both dry and wet conditions. The models' usefulness is shown by this confirmation of their ability to estimate key FOS and detect slope instabilities in real-world scenarios. Furthermore, the MR models created in this work do not depend on any data specific to a certain area and span a broad range of parameter modifications. Therefore, any real slope may be immediately applied to the MR models that are developed. It's vital to remember that this study does not take nonlinearity's effects into account, even if the regression plots of the training data for both scenarios (shown in Figures 8 and 13) show nonlinearity. For this investigation, we are limited to developing a linear multiple regression equation. By considering the influence of these nonlinearities, it may be further enhanced as the study's future emphasis.

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