



Development of prediction models for strength behavior of MSWIA mixed with fiber and cement

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Abstract

Engineers are increasingly interested in using municipal solid waste incinerator ash (MSWIA) to construct different geotechnical structures. This practice not only helps manage waste but also positively impacts the environment. Stabilizing such wastes by adding admixture and reinforcing material significantly improves their load bearing capacity. This study investigates the strength behavior of the MSWIA mixed with cement and fiber, providing valuable insights for the practical application of these materials. Unconfined compressive strength (UCS) and split tensile strength (STS) tests were conducted to understand the behavior. The aspect ratio of the fiber, cement content, fiber content, and curing period varied during testing. The impact of individual variables was evaluated based on the results of the tests through sensitivity analysis. Further, a mathematical model based on the Artificial Neural network (ANN) and Multivariable linear regression model (MLRM) was developed, and results were compared. The coefficient of determination ‘ R^2 ’ for UCS in ANN was 0.996 and in STS was 0.995 while for MLRM, ‘ R^2 ’ was 0.94 for UCS and 0.93 for STS. From the results, it was found that the ANN can predict the strength better than MLRM. Also, a correlation between the UCS and STS for the MSWIA mixed with fiber and cement was established.

Keywords Artificial neural network · Unconfined compressive strength · Split tensile strength · Multilinear regression · Municipal solid waste incinerator ash

1 Introduction

The growing population generates enormous amounts of municipal solid waste (MSW). Managing such a massive amount of MSW is creating more significant challenges to society, especially in urban areas, due to the economic and environmental points of view (Chen et al. 2010).

Poor handling of MSW may create groundwater contamination, air pollution, soil pollution, etc. Presently, landfills for managing MSW are a convenient and cost-effective solution, but they create problems like soil and groundwater contamination, odor emission, etc. (Mukherjee et al. 2014; Luo et al. 2019). After incineration, MSW is dumped on the landfill when it changes into ash (Lo and Liao 2007). After changing into ash, the volume of MSW is reduced by up to 70–90% (Hjelmar 1996). During the incineration process, massive energy is generated (Allegrini et al. 2015). After the incineration of MSW, two forms of ash are generated, ‘bottom ash (BA)’ and ‘fly ash (FA)’ (Ferreira et al. 2003). It is found that the bottom ash is more than 80% in the MSWIA (Quina et al. 2018). Major constituents of MSWIA are oxides of Ca and Si, i.e., CaO and SiO₂. The other oxides are Al₂O₃, Fe₂O₃, Na₂O, and K₂O (Kirby and Rimstidt 1993; Luo et al. 2019).

MSWIA can be utilized for different purposes, such as construction materials, geotechnical structures, agriculture, etc. It contains lime and silicates, which can be used in cement production (Yakubu et al. 2018). Hamernik and Frantz (1991) have shown that MSWIA can be used as a replacement for cement in concrete. It can also produce ceramics and glass

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(Rokhvargher 1994). MSWIA can be used extensively to construct geotechnical structures like roads and embankments. One potential application of MSWIA in road pavement involves replacing sand and/or cement in cement-stabilized bases and subbases. Similarly, MSWIA can also be used in the construction of embankments. It can improve the stability of embankment (Ferreira 2003). The chemical composition and surface characteristics of the MSWIA can also be used for other purposes, such as agriculture, to support plants, as adsorbing materials, etc. (Rosen et al. 1994; Yang and Yang 1998).

Since MSWIA contains heavy metals, it is necessary to use them carefully; otherwise, they can threaten the environment. Quina et al. (2018) state that more leachable heavy metal is found in FA than in the BA. To minimize the toxic impact, MSWIA should be adequately treated. Different types of treatment processes can be used, such as solidification and stabilization, removing heavy metals with suitable techniques, etc. (Winter et al. 1994; Zhang et al. 2003; Chan et al. 2000). Among all these techniques, the stabilization technique is one of the most suitable and widely used technique (Bie et al. 2015).

Kamon et al. (2006) and Gao et al. (2011) have investigated the potential use of MSWIA for geotechnical applications. Stabilization with some cementitious and reinforcing material can improve the performance of MSWIA when used to construct geotechnical structures. Liu et al. 2022 have shown that due to the additional cementitious effect, the performance of MSWIA has improved. Researchers have shown that adding cement or lime to Soil or ashes like fly ash, rice husk ash, and others can improve their characteristics (Basha et al. 2005; Ahmad and Shah 2010; Kumar and Gupta 2015; Priyadarshree et al. 2021). Similarly, fiber reinforcement can improve soils properties (Kaniraj and Havanagi 2001; Gupta et al. 2018). Anburvel et al. (2023) present A systematic review of current soil stabilization methods. Incorporation of groundnut shell ash, rice husk ash, recycled aggregates, construction and demolition waste into soil stabilization and other civil engineering application were explored (Ng and Engelsen 2018; Sathiparan et al. 2023; Anburvel et al. 2023).

Studies to improve the performance of MSWIA for geotechnical purposes by adding different admixtures are very limited. Kamon et al. (2006) used coal ash to improve the MSWIA for geotechnical applications. Li et al. 2020 investigated the performance of MSWIA mixed with fiber in improving the performance of clay soil. Similarly, some other studies like Singh and Kumar (2017, 2019) Pastapure et al. 2022, etc. have used cement, fibers, and other admixtures to improve the performance of MSWIA. Some studies, like Singh and Kumar (2019), Kumar and Singh (2023), etc., have developed models based on MLR, ANN, and other techniques to predict strength. Studies have shown that the model

developed based on ANN is better than MLR, Singh and Kumar (2019). Prediction of the unconfined compressive strength (UCS) of cement-stabilized iron ore tailings have been done by using intelligent modeling techniques (Ghanizadeh et al. 2023). Multivariate adaptive regression splines (MARS) and Gaussian process regression (GPR) have been used to predict the UCS of stabilised soil (Ghanizadeh and Rahrovan 2019; Ghanizadeh and Naseralavi 2023).

The model based upon the ANN is developed in different studies mainly to predict the strength behavior of soil in compression. Considering this, the present study investigates the influence of fiber content, fiber aspect ratio, cement content, and curing period on the unconfined compressive strength (UCS) and split tensile strength (STS) of Municipal Solid Waste Incinerator Ash (MSWIA) composites incorporating cement and fiber. To predict the strength behavior of these composites under compression and tension, this research develops and compares two machine learning models: artificial neural networks (ANN) and multi-linear regression models (MLRM). Furthermore, a sensitivity analysis is employed to assess the relative importance of each investigated variable on UCS and STS. Further correlation between STS and UCS of the mix was developed.

2 Methodology

The details of the steps followed in the study are presented in Fig. 1. The main purpose of the present study is to develop the mathematical model to predict the UCS and STS of the MSWIA mixed with cement and fiber. For this purpose, the first laboratory tests were done to determine the UCS and STS of the mix. In laboratory testing, fiber content (FC), fiber aspect ratio (AR), cement content (CC), and curing periods

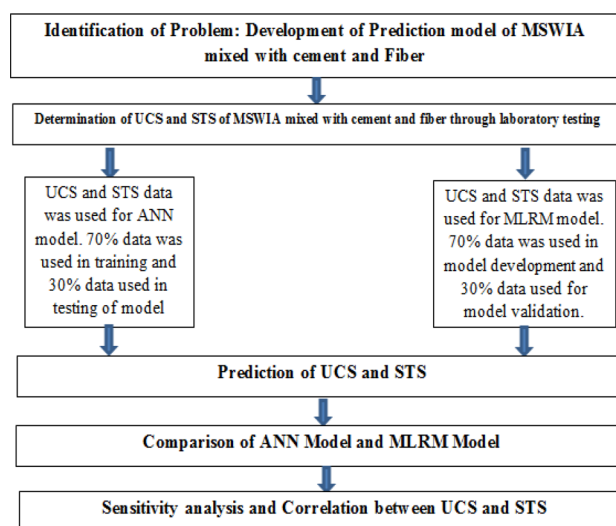


Fig. 1 Methodology adopted in the study

Table 1 Test series details

Test series	Mix	Fiber Content	Cement Content	Curing period (days)
A	MSWIA	–	–	–
B	MSWIA + fiber	FC = 0.25%, 0.5%, 0.75%, 1% AR = 200, 250, 300	–	–
C	MSWIA + cement	–	CC = 4%, 8%, 12%	CP = 0, 7, 28
D	MSWIA + cement + fiber	FC = 0.25%, 0.5%, 0.75%, 1% AR = 200, 250, 300	CC = 4%, 8%, 12%	CP = 0, 7, 28

(CP) were variables. The ANN and MLRM based model were developed with the help of laboratory data. For this purpose, all the data were split into two parts randomly. The first part contained 70% of the data, while the second contained 30%. The first part was used to develop the model, and the second was used to test or validate the model. Based on the developed model, predicted UCS and STS were determined. After this, a comparison of both of the models was done. After this, sensitivity analysis was done to determine the impact of the individual variables. Further details of the experimental investigation and model development are presented in the following section.

2.1 Details of experiments

The MSW ash was oven-dried at 105 °C before being combined with fiber and cement. To standardize the samples, any lumps in the dried ash were broken with a hammer and sieved through a 4.75 mm sieve. UCS and STS tests were conducted on MSWIA mixed with fiber and cement under three different series. The purpose of the evaluation of the UCS test was to evaluate the behavior of the mix under compressive load, while the purpose of the STS test was to evaluate the behavior of the mix under tension load. Table 1 details the series of tests conducted on different mixes. In series A, UCS and STS were conducted on the MSWIA alone. In series B, tests were conducted on the MSWIA mixed with fiber. Polypropylene fibers of 8 mm, 10 mm, and 12 mm were used. The aspect ratio of the fibers was 200, 250, and 300. FC in this series varied as 0.25%, 0.5%, 0.75%, and 1%. In Series C, tests were conducted on MSWIA mixed with cement. Cement content and curing period were varied in this series of tests. Cement content considered in this study was 4%, 8%, and 12%. The curing period considered in this study was 7 days and 28 days. The MSWIA, fiber, and cement mix tests were done on the test series D. All the samples were prepared on maximum dry density (MDD) and optimum moisture content (OMC). To determine the optimum moisture content (OMC), a sequence

of Standard Proctor compaction tests was performed on fabricating samples with varying percentages of cement and fiber. These tests were performed for each specific mix, considering the different proportions of cement and fiber. Since the addition of cement and fiber does indeed affect the OMC and maximum dry density (MDD), the changes in OMC for each combination were measured carefully to ensure accurate results. This approach allowed us to account for the variations caused by the admixtures and identify the OMC specific to each mix configuration.

This study used three types of material: MSWIA, fiber, and cement, as shown in Fig. 2. The MSWIA used in this study was obtained locally. The properties of the MSWIA used are presented in Table 2. The water absorption rate of the MSWIA used in this study is 21.48%. Polypropylene fiber used in this study was obtained from the locally available market. The properties of the polypropylene fiber used are presented in Table 3. Ordinary Portland cement, OPC grade 43, was used as cementitious material purchased from the local market. The specific gravity of cement was found to be 3.14. The soundness of cement was found to be 3 mm. The cement's initial and final setting time was 30 min and 600 min. Properties of cement used in this study shown in Table 4.

UCS and STS tests were performed on the MSWIA alone and with a mix of fiber and cement, as per IS 2720 (1999) part 10 and IS 5816 (1999), respectively. The cylindrical specimens were prepared with a standard size of 38 mm in diameter and 76 mm in height to determine the UCS and STS of specimens fabricated by varying percentages of cement and fiber. The specimens were prepared by compacting the mix design sample with their respective OMC. After compaction, the specimens were carefully extruded from the molds and cured in a controlled environment at room temperature for specific time period of 0, 7, and 28 days. The preparation of sample and testing of sample is shown in Fig. 3a–d. All the tests were conducted on the maximum dry density (MDD) and Optimum moisture content (OMC). Expression for the total weight of the mix prepared

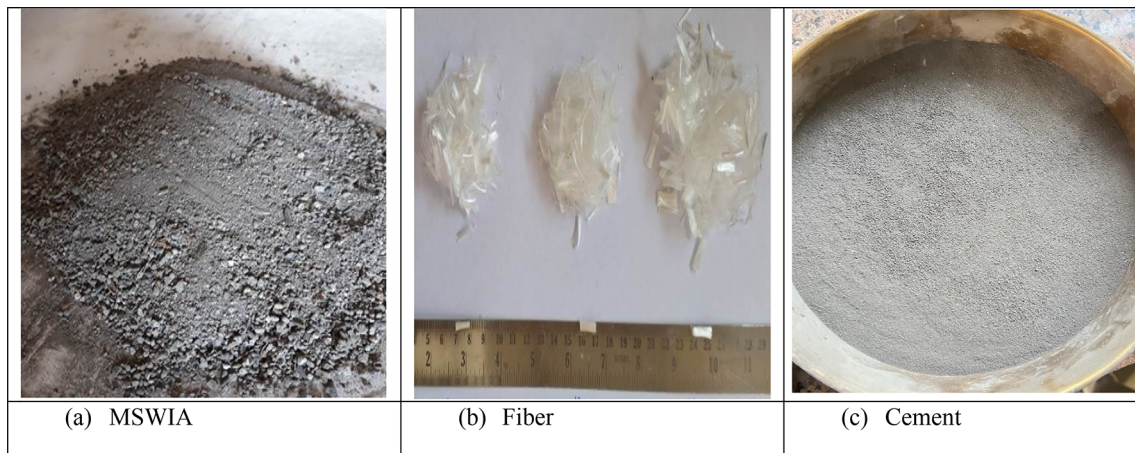


Fig. 2 Different materials used in this study

Table 2 Properties of MSWIA used in this study

Properties	Values
Specific gravity	2.26
Liquid limit (%)	37
Plastic limit (%)	NA
Maximum dry density (kN/m ³)	14.82
Optimum moisture content (%)	17.14
Sand fraction (%)	97.4
Silt and clay fraction (%)	2.6
Uniformity coefficient	8.228
Coefficient of curvature	0.812
Heavy metals (mg/kg)	
Cadmium	22.4
Lead	118.2
Nickel	6.5
Chromium	19.4

Table 3 Properties of fiber used in this study

Properties	Value
Specific gravity	0.91
Cut length (L)	8 mm, 10 mm, 12 mm
Diameter (D)	0.04 mm
Tensile strength (MPa)	600
Aspect ratio (L/D)	200, 250, 300

by MSWIA with fiber (W_{AF}) and cement (W_{AC}) can be expressed as follows.

$$W_{AF} = W_A + W_F \quad (1)$$

Table 4 Properties of cement used in this study

Properties	Value
Specific gravity	3.14
Consistency (%)	30
Soundness (mm)	3
Initial setting time (min)	32
Final setting time (min)	580

$$W_{AC} = W_A + W_C \quad (2)$$

W_A is the weight of ash, W_F is the weight of fiber, W_C is the weight of cement.

The expression for the total weight of the mix prepared by adding fiber and cement in MSWIA (W_{AFC}) can be expressed as follows.

$$W_{AFC} = W_A + W_F + W_C \quad (3)$$

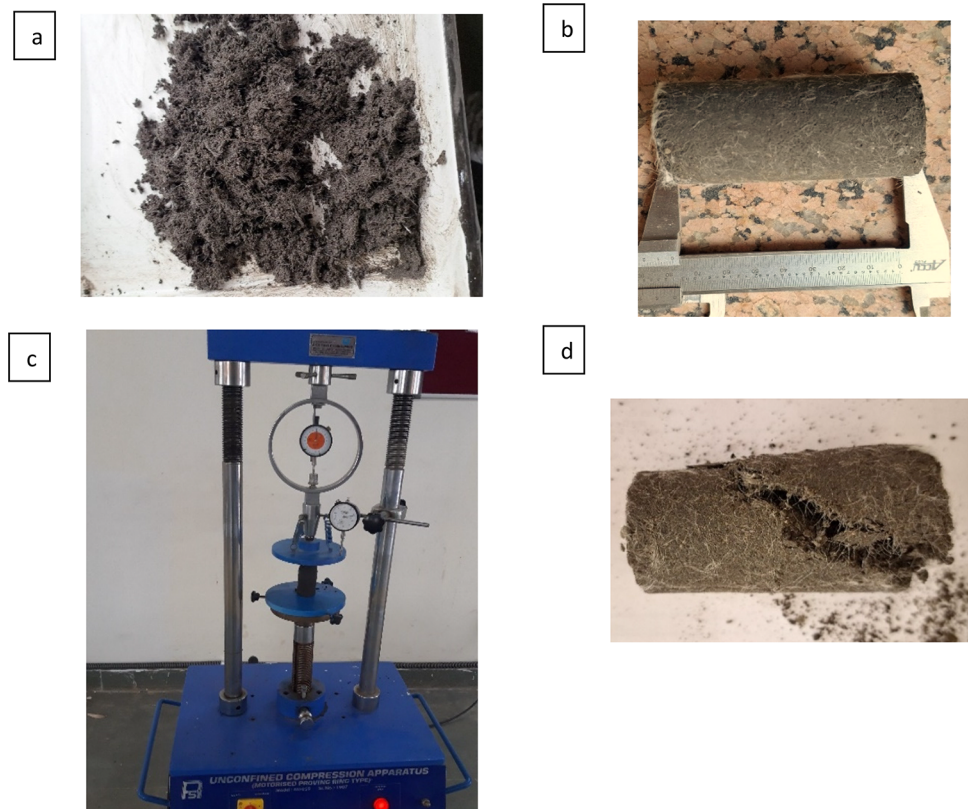
2.2 MLRM development

To develop a mathematical model to predict the UCS and STS based on multivariable linear regression (MLR), MSWIA content (MSWIAC), FC, AR, CC, and curing period were taken as independent variables. In contrast, UCS and STS were taken as dependent variables. A general equation for the MLRM can be written as:

$$Y = a_1 + a_2X_1 + a_2X_2 + \dots + a_nX_n + e \quad (4)$$

Here, Y is the dependent variable, X_i is the independent variables, a_i is the coefficient, and e is the error. The difference between the actual value obtained from the experiments

Fig. 3 (a, b) Preparation of UCS sample, (c) testing of sample (d) failure of UCS sample



and estimated from Eq. (4) is known as residue (e). The coefficients of the equation are determined by minimizing the sum of squared errors or residue. The expression can be written as follows.

$$\sum_{i=1}^n e^2 = \text{minimum} \quad (5)$$

Simultaneous, equations are developed using partial derivatives of e^2 to determine coefficients. The expression of the simultaneous equation can be expressed as (Ranjan et al. 1996):

$$AX = Y \quad (6)$$

A, X, and Y are matrices for unknown coefficients and independent and dependent variables. The unknown coefficient can be determined by the following expression.

$$A = X^{-1}Y \quad (7)$$

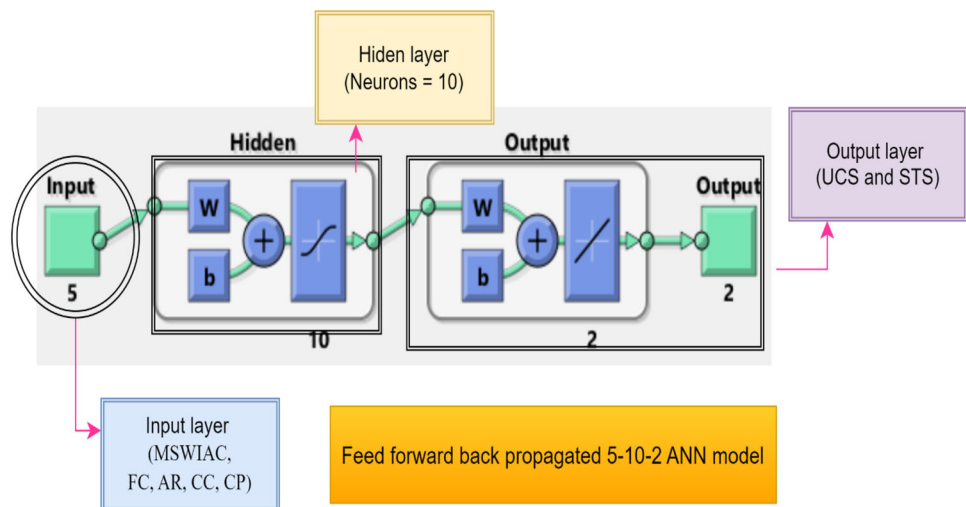
The value of the unknown coefficient is plotted in Eq. (4) to obtain a desirable equation to predict the magnitude of the dependent variable.

2.3 Development of ANN model

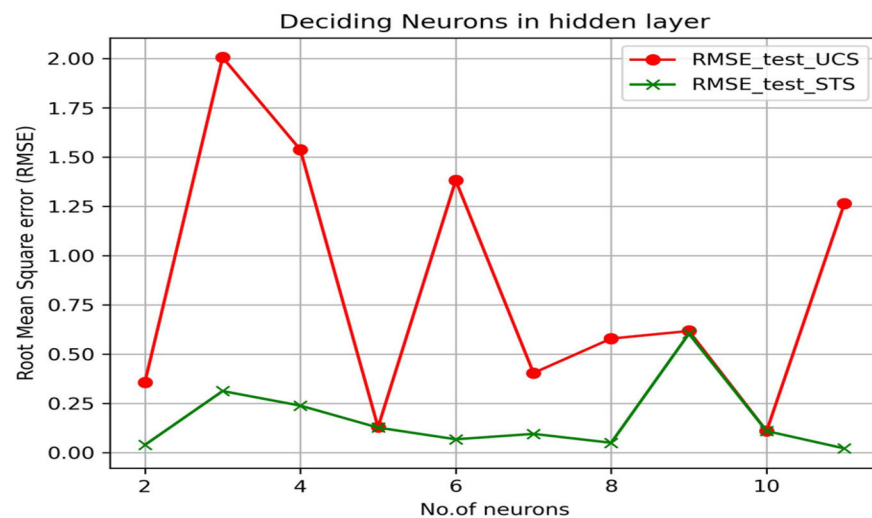
The development of ANN model is a complex and multi-step process. It starts from data preparation, architecture design, training of model and finally its evaluation. The main objective of developing ANN model is to predict results for unseen data. These models are capable of solving complex non-linear relationships and based on problem to be solved different types of ANN model can be selected. The algorithms used for training ANN are important as they are helpful in correct learning and optimization. Momentum constant and learning rates are varied in algorithm to improve the performance of model.

For developing the ANN model, first is selection of inputs and outputs. In these models' number of input and output can vary from one to many. During selection of inputs, it is important that the inputs are not redundant and all are independent to each other. For our study out of many variables monitored in lab, only 5 inputs (MSWIAC, FC, AR, CC and CP) were selected and 2 outputs (UCS, STS) were predicted. Other important feature of ANN model is the number of hidden layer and neurons in hidden layer. The inputs are connected through weights to the neurons in hidden layer and hidden layer to output layer. The activation or transfer function is used to activate the connections between input layer

Fig. 4 (a) Optimized ANN.
(b) RMSE during the testing phase at different neurons



(a) Optimized ANN



(b) RMSE during the testing phase at different neurons

and hidden layer and hidden layer and output layer. One hidden layer was used in ANN model in this study and transfer function between input layer and hidden layer was symmetric sigmoid transfer function and linear transfer function was used between hidden layer to output layer (Fig. 4a). Once the inputs, outputs and number of hidden layers is initialized, ANN model was programmed in MATLAB and after feeding input and output matrix, number of neurons in hidden layer were varied. In input and out matrix only 70% data was shown to model for training to make model learn while 20% for testing the model i.e. on unseen data and 10% for validation also unseen data.

The ANN model was trained and tested by varying neurons from 2 to 11 in the hidden layer. The selection of neurons in the hidden layer was based on Root Mean Square Error (RMSE) during the testing phases for prediction of UCS and

STS. The minimum difference of RMSE during the testing phase for UCS and STS is selected with good training performance. Figure 4b shows the variation of RMSE during the testing phase for UCS and STS, with minimum RMSE difference in the testing phase for both variables at 10 neurons in a hidden layer with good performance in the training phase. Thus, an architecture of 5–10–2 was finalized to predict the UCS and STS. The performance of the model using statistical indicators was identified as (i) mean absolute error (MAE), (ii) root mean square error (RMSE), (iii) correlation factor (CF), (iv) coefficient of determination (R^2) and (v) coefficient of efficiency (E) calculated over training and testing data for each zone as shown in Table 5 as per the Eqs. (8) to (12).

Table 5 Performance of the ANN model

Output	Phase	RMSE	MAE	CF	R ²	E
UCS	Training	0.1305	0.0176	0.9999	0.999	0.9998
	Testing	0.1089	0.0209	0.9999	0.996	0.9999
STS	Training	0.1022	0.0098	0.9999	0.996	0.9997
	Testing	0.1087	0.0195	0.9999	0.995	0.9999

$$MAE = \frac{1}{N} \sum_{i=1}^N |(U, S_m - U, S_p)| \quad (8)$$

$$RMSE = \left[\frac{\sum_{i=1}^N (U, S_m - U, S_p)^2}{N} \right]^{1/2} \quad (9)$$

$$CF = 1 - \left[\frac{\sum_{i=1}^N (U, S_m - U, S_p)^2}{\sum_{i=1}^N (U, S_m)^2} \right] \quad (10)$$

$$R^2 = 1 - \frac{\sum (U, S_m - U, S_p)^2}{\sum (U, S_m - \bar{U}, \bar{S}_m)^2} \quad (11)$$

$$E = 1 - \frac{\sum_{i=1}^N (U, S_m - U, S_p)^2}{\sum_{i=1}^N (U, S_m - \bar{U}, \bar{S}_m)^2} \quad (12)$$

where U, S_m is experimental UCS and STS, U, S_p is predicted UCS and STS value, $\bar{U}, \bar{S}_p$ is the mean of predicted value, and $\bar{U}, \bar{S}_m$ is the mean of the experimental value.

2.4 Sensitivity analysis

Sensitivity analysis estimates the effect of changes in attribute of a system model and its influence on the outcome of a model. It is done to understand the relative influence of independent variables on the dependent variable. This is helpful in identifying the influential variables and thus interpretability of model. This study evaluated the influence of fiber content, aspect ratio, cement content, and curing period on the UCS and STS of the mix through sensitivity analysis. For this purpose, the weight obtained from the ANN model was used. Weight plays a crucial role in the calculation. A larger weight magnitude for taken input indicates a stronger influence on the output. Garson (1991) and Priyadarshie et al. (2021) have similar methodologies for sensitivity analysis. The algorithm uses final and optimized connection weights between input layer and hidden layer and hidden layer and output layer. The sensitivity coefficient of each input towards output is calculated using Eq. (13)

$$Sensitivitycoeff_k(inp) = \frac{\sum_{h=1}^n (\frac{w_{ih} v_{ho}}{\sum_{i=1}^n w_{ih}})}{\sum_{i=1}^n (\sum_{h=1}^n \frac{w_{ih} v_{ho}}{\sum_{i=1}^n w_{ih}})} \quad (13)$$

where, $Sensitivitycoeff_k(inp)$ is for 'inpth' input variable; i, h, o means input layer, hidden layer and output layer neurons; n is total number of inputs. For carrying out sensitivity analysis the final weights of optimized model are used to make calculations.

2.5 Correlation between STS and UCS

UCS and STS for mix were evaluated using different tests. In this study, correlations between these two properties were evaluated. For this purpose, the first Pearson correlation coefficient was evaluated to check the level of correlation between UCS and STS. If it is found satisfactory, then a regression model is developed. The purpose of the regression model was to estimate the STS of MSWIA mixed with admixtures in a similar way as discussed above. The design mix used to prepare the specimen for UCS and STS is the same, while the UCS and STS values of the mix are considered as independent variables for modelling.

3 Results and discussion

The following section presents and discusses the laboratory testing results for UCS and STS, the model developed, and the sensitivity analysis results.

3.1 Results of UCS and STS

First, the 'Improvement factor (IF)' was calculated to present the experimental results obtained from the UCS and STS tests. The improvement factor was defined as the ratio of the peak UCS or STS of the mix to the UCS and STS of MSWIA alone. The UCS and STS of MSWIA alone were found to be 282 kPa and STS 22 kPa, respectively. These two values were used to calculate the IF of the mix.

Figures 5 and 6 depict the performance of MSWIA mixed with fiber. Figure 5 presents the impact of fiber content on the MSWIA. The results obtained from both UCS and STS have shown that the load bearing capacity of the mix increases with an increase in fiber content. Due to the inclusion of 0.25% of fiber, UCS improved by 17%, and STS improved by

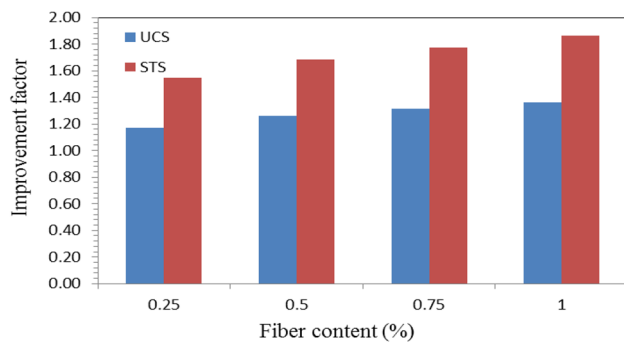


Fig. 5 Performance of MSWIA mixed with fiber with varying fiber content (AR = 200)

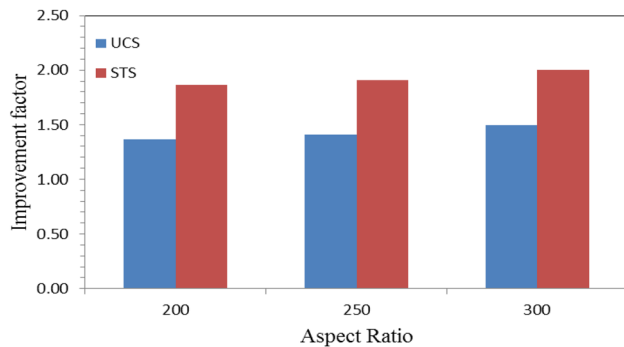


Fig. 6 Performance of MSWIA mixed with fiber with varying AR (FC = 1%)

more than 50%. Fiber binds the soil particle through particle binding through fiber and soil particle interaction. Further increase in the fiber content, i.e., from 0.25 to 1%, shows about a 16% increment in UCS and a 20% increment in STS. Similar behavior was reported by Pie and Le (2012), Tang et al. (2007), Priyadarshee et al. (2018), and others. The impact of AR on the performance of the MSWIA mixed with fiber is depicted in Fig. 6. UCS and STS increase with the increase in AR. Due to the increase in AR, the surface area of fiber increases; hence, the interaction between fiber and soil particles also increases. The improvement in interaction is the possible cause of improvement in UCS and STS. The optimum mix design with their respective value of UCS and STS is presented in Table 6.

Figures 7 and 8 show the stress–strain behavior of MSWIA mixed with cement. Figure 7 shows the impact of CC, and Fig. 8 shows the impact of CP. It can be observed that the peak stress of the mix increases with an increase in the cement content and curing period. When the cement was added to MSWIA, an increment of 1.8 to 2.5 times in the UCS and 2–3 times in the STS was found for a curing period of 7 days. When cement content increased from 4 to 8%, 1.3 times increment in UCS and 1.4 times increment in STS was found. Similar performance was observed for the 28-day

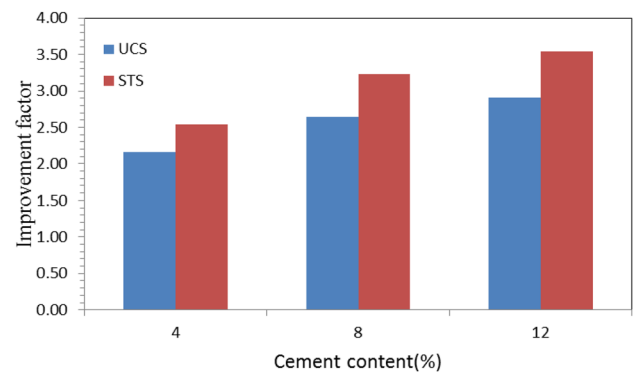


Fig. 7 Performance of MSWIA mixed with cement with varying cement content (CP = 28 days)

curing period. Further, it can be noted that the curing period significantly impacts the mix's UCS and STS. In 7 days, UCS was increased by 1.3 times, and in 28 days, it was increased by 1.5 times. STS was increased by 1.2 times in 7 days and 1.4 times in 28 days.

Figure 9 clearly shows the combined impact of cement and fiber on the performance of MSWIA concerning the individual performance of the admixture. It can be noted that the combined performance of cement and fiber is much higher than the individual performance of cement and fiber. Fiber reinforcement mobilizes the frictional component of the mix, while cement mobilizes the cohesion component of the mix. Due to this, when both are added, significant improvement takes place.

3.2 MLMR model

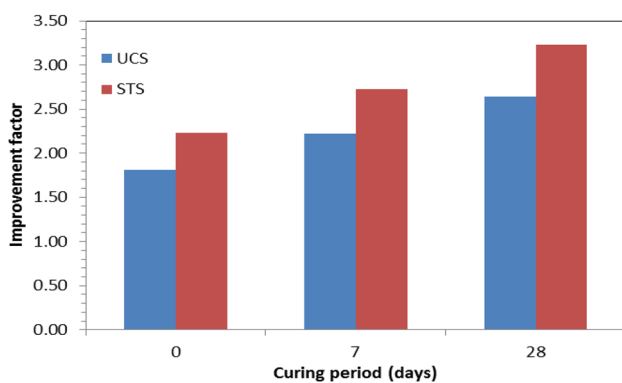
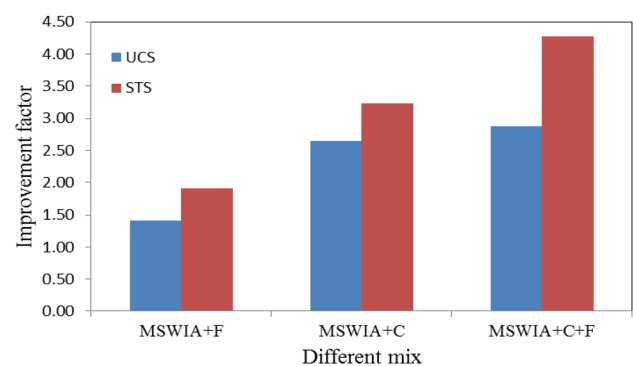
Based on the regression and considering the MSWIAC, FC, AR, CC, and CP as independent variables, prediction models for the mix's UCS and STS were developed. The coefficient of determination, 'R²,' was found to be 0.94 for Eq. 14 and 0.93 for Eq. 15. The scattered plots of the predicted and experimental values of UCS and STS are presented in Figs. 10 and 11, respectively. Both of the plots show that the scattering is not much. It shows that the present model can predict UCS and STS effectively. The prediction models are presented below:

$$UCS_{mix} = 5481.7 - 51.58 * MSWIAC + 0.01 * FC + 0.167 * AR - 26.84 * CC + 6.089 * CP \quad (14)$$

$$STS_{mix} = 770.27 - 7.453 * MSWIAC + 0.01 * FC + 0.048 * AR - 4.30 * CC + 0.723 * CP \quad (15)$$

Table 6 Optimum mix design

Sr. no.	Mix id	MSW ash %	Fiber %	Aspect ratio	Cement %	Curing days	UCS (kPa)	STS (kPa)
1	UT-MSWA	100	0	0	0	0	282	22
2	T-F _{0.5} + A ₁	99.5	0.5	200	0	0	356	37
3	T-F _{0.5} + A ₂	99.5	0.5	250	0	0	381	39
4	T-F _{0.5} + A ₃	99.5	0.5	300	0	0	397	41
5	T-F _{0.5} + A ₃ + C ₄	95.5	0.5	300	4	0	514	58
6	T-F _{0.5} + A ₃ + C ₈	91.5	0.5	300	8	0	592	68
7	T-F _{0.5} + A ₃ + C ₁₂	87.5	0.5	300	12	0	658	74
8	UT-MSWA	100	0	0	0	7	332	25
9	T-F _{0.5} + A ₁	99.5	0.5	200	0	7	422	42
10	T-F _{0.5} + A ₂	99.5	0.5	250	0	7	446	47
11	T-F _{0.5} + A ₃	99.5	0.5	300	0	7	463	48
12	T-F _{0.5} + A ₃ + C ₄	95.5	0.5	300	4	7	633	72
13	T-F _{0.5} + A ₃ + C ₈	91.5	0.5	300	8	7	714	82
14	T-F _{0.5} + A ₃ + C ₁₂	87.5	0.5	300	12	7	778	89
15	UT-MSWA	100	0	0	0	28	388	30
16	T-F _{0.5} + A ₁	99.5	0.5	200	0	28	504	53
17	T-F _{0.5} + A ₂	99.5	0.5	250	0	28	524	55
18	T-F _{0.5} + A ₃	99.5	0.5	300	0	28	541	57
19	T-F _{0.5} + A ₃ + C ₄	95.5	0.5	300	4	28	724	83
20	T-F _{0.5} + A ₃ + C ₈	91.5	0.5	300	8	28	808	93
21	T-F _{0.5} + A ₃ + C ₁₂	87.5	0.5	300	12	28	867	100

**Fig. 8** Performance of MSWIA mixed with cement with varying curing periods (CC = 8%)**Fig. 9** Performance of MSWIA mixed with different admixtures (FC = 1%, CP = 28 days, AR = 250, CC = 8%)

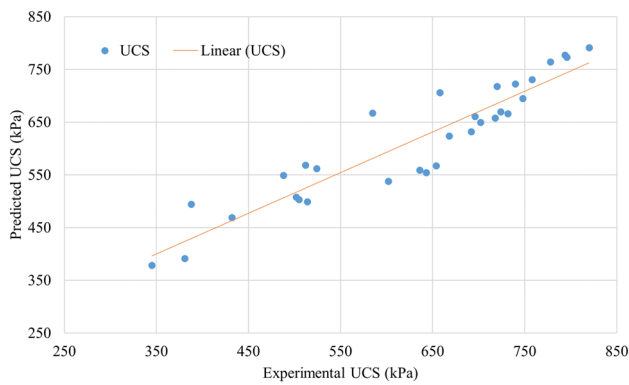


Fig. 10 Comparison of predicted and experimental value of UCS

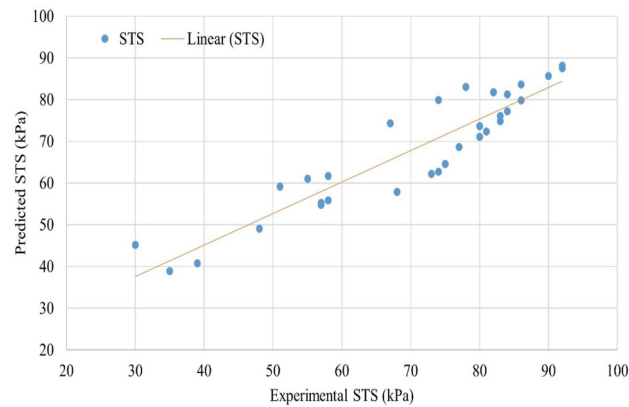


Fig. 11 Comparison of predicted and experimental value of STS

3.3 ANN model

In this study, the optimized feed-forward backpropagated ANN model was trained, tested and validated with topology 5-10-2. The model was trained using Levenberg Marquardt (LM) algorithm by adjusting the weights so that error between predicted and actual output can be minimized. In this study, feedforward back-propagated neural network was used for prediction of UCS and STS through ANN. The ANN model was trained with Levenberg–Marquardt (LM) algorithm with one input layer with 5 inputs and one hidden layer and one output layer with 2 outputs. The training was done with 70% data, 20% for testing and 10% for validation (Figs. 12, 13, 14).

A comparison between the model developed by MLRM and ANN shows that the prediction model developed by ANN can better predict UCS and STS.

3.4 Sensitivity analysis

MSWIAC, FC, AR, CC, and CP were considered for the sensitivity analysis. The result obtained from the sensitivity analysis is presented in Fig. 15, which presents the effect of

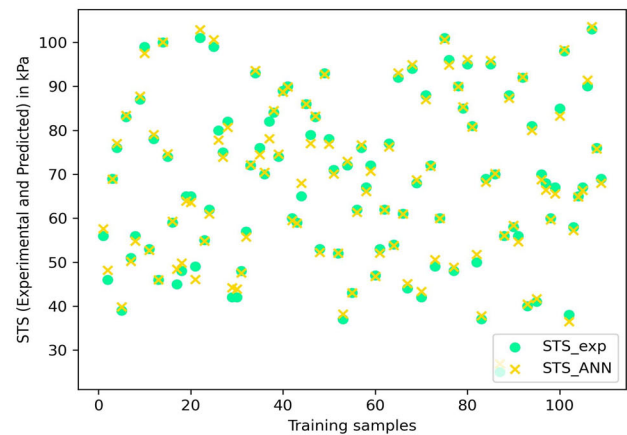
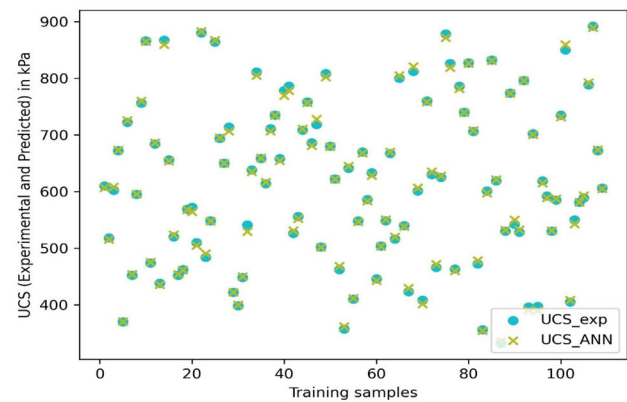


Fig. 12 Model performance during training

each input over outputs i.e. UCS and STS.

From Fig. 15, it is clear that curing days, effect the UCS and STS the most followed by fiber and cement content and it has been also highlighted by Sihag et al. (2019) that curing period is the most influencing parameter for prediction of UCS. The other study (Tinoco et al. 2021) have used 16 variables for prediction of UCS with cement content and cement dosage as separate inputs and fiber content and fiber dosage as separate and when added together for comparison effect of CC is 21.84% and FC is 14.07% which is comparable to present study. with contribution of cement content as aspect ratio has minimum effect on ICS and STS. But it is to be noted that the difference among each input variable with its impact over UCS and STS is between 3 to 4% hence all the inputs are significantly affecting the UCS and STS of MSWIA mixed with cement and fiber.

3.4.1 Parametric study

In order to know the effect of different inputs on UCS and STS parametric study was conducted and the results of the study are presented in Table 7. It can be said that when

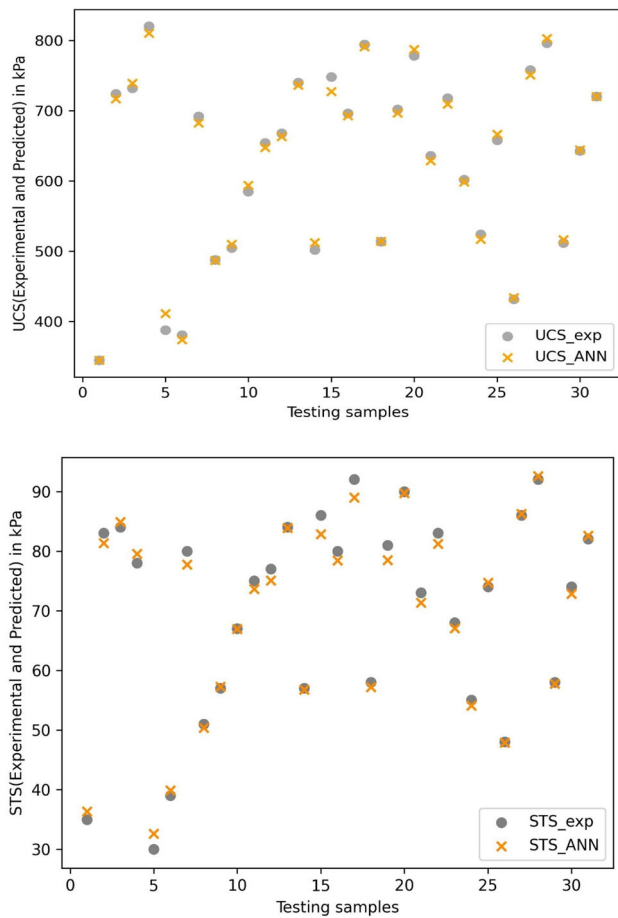


Fig. 13 Model performance during testing

MSWIAC and FC are analyzed for its relative impact on output, FC affects UCS and STS more as compared to MSWIAC. Cement content and fibre content affect the UCS and STS of mix.

3.5 Correlation between UCS and STS of mix

The Pearson correlation coefficient was evaluated before establishing correlation equations between UCS and STS. The magnitude of the coefficient is 0.987, indicating a strong correlation between UCS and STS exists. Considering this, two different regression models were developed to predict STS of mix (STS mix), as discussed above. The regression models developed are as follows:

$$STS_{mix} = -9.854 + 0.127 * UCS_{mix} \quad (16)$$

The coefficient of determination, ' R^2 ,' was found to be 0.95 for the above equation. Figure 16 shows the plot between UCS_{mix} and STS_{mix} . There is not much scattering, which indicates that the above expression can better predict STS. The above expression is very useful for predicting the STS

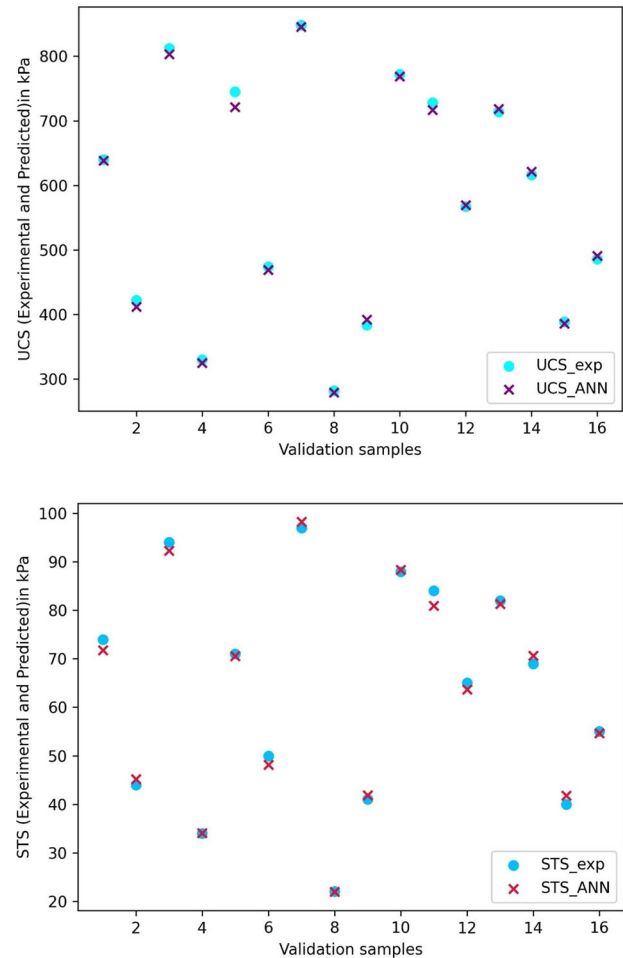


Fig. 14 Model performance during validation

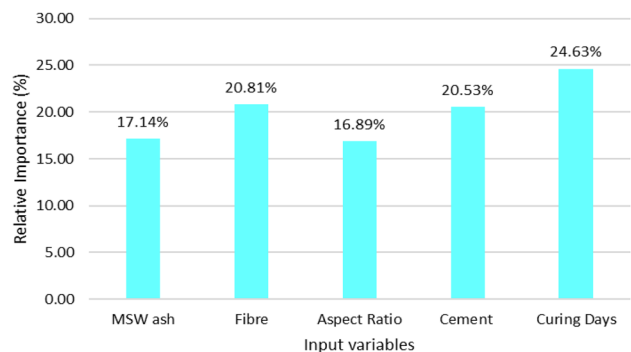
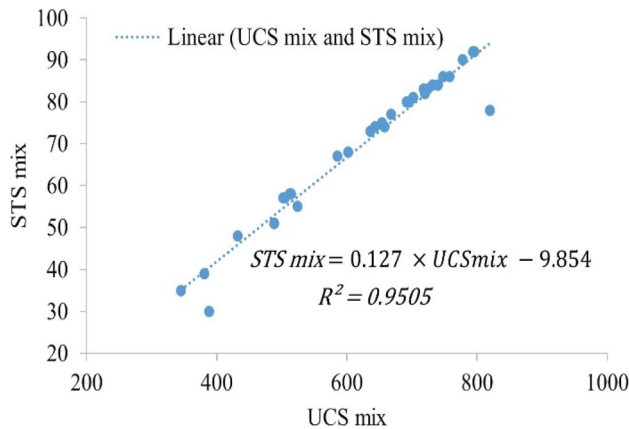


Fig. 15 Result of sensitivity analysis

of the mix without performing the test for STS and based on the UCS of the mix STS can be predicted.

Table 7 Effect of different input combination on output

Relative importance (%)	MSWIAC	FC	AR	CC	CP
MSWIAC	100.00				
FC	38.01	61.99			
AR	27.58	39.38	33.04		
CC	19.46	29.22	24.72	26.60	
CP	17.14	20.81	16.89	20.53	24.63

**Fig. 16** Comparison of predicted and experimental STS

4 Conclusions

A series of UCS and STS tests were conducted to evaluate the UCS and STS of MSWIA mix with cement and fiber. Based on the results, mathematical models were developed to predict the mix's UCS and STS. The important conclusions drawn from the analysis are as follows.

- Both fiber and cement can potentially improve the UCS and STS of MSWIA.
- Test results indicate that the aspect ratio of the fibre and cement percentages plays a crucial role in influencing the UCS values. Notably, the inclusion of 0.5% fiber content with an aspect ratio of 300, along with 8% cement, resulted in an improvement factor of 186% in UCS after 28 days of curing. The same combination increased split tensile strength (STS) by 210%.
- AR and CP also significantly impact the MSWIA mix with fiber and cement.
- The model developed by MLMR and ANN has the potential to predict the mix's UCS and STS. However, ANN can better predict this type of problems and single layer feed-forward neural network with LM algorithm can be used for solving.

- The advantage of ANN over MLMR model is that 2 outputs can be predicted simultaneously in ANN model.
- The correlation coefficient for the mix's UCS and STS is 0.987, which indicates a strong correlation between them. Also, a mathematical model developed to predict STS has shown satisfactory performance. Such a mathematical model will be helpful in predicting the STS without performing the test.
- For the optimum result in term of relative importance to find out the UCS and STS value, the FC, AR, CC, and CP has valuable impact of 20.81%, 16.89%, 20.53%, and 24.63% respectively.

Appendix

See Table 8.

The step-by-step process followed as per Garson (1991) is shown below:

Step 1: For each hidden neuron i , obtain the products X_{ih} where h is the weight corresponding to respective input and this is multiplied by absolute value of v_{ho} for each hidden neuron. Take example $X_{11} = 1.0177390 \times 0.287926 = 0.310209$.

Hidden layer neurons	Xih values				
	MSWIAC	FC	AR	CC	CP
Hidden 1	0.310209	0.043357	0.008132	0.395875	0.238169
Hidden 2	0.345107	0.153304	0.021242	0.062103	1.173147
Hidden 3	0.828421	0.504284	1.051529	0.861631	0.006109
Hidden 4	0.011307	0.019992	0.025306	0.0084	0.018144
Hidden 5	0.08667	0.107884	0.040729	0.305376	0.694572
Hidden 6	0.000766	0.048883	0.128259	0.098398	0.013816
Hidden 7	0.009341	0.205495	0.008581	0.058657	0.010409
Hidden 8	0.115798	0.103655	0.085994	0.091592	0.072261
Hidden 9	0.027968	0.109911	0.117144	0.024478	0.097039
Hidden 10	0.893401	0.191579	0.09689	0.474301	0.637324

Step 2 For every hidden neuron, divide X_{ih} by the sum of all input variables to obtain Y_{ih} . For example, $Y_{11} = 0.310209 / (0.310209 + 0.043357 + 0.008132 + 0.395875 + 0.238169) = 0.311535$.

Table 8 Weight and bias matrix connecting input layer and hidden layer and output layer

Hidden layer neurons	Weight matrix input and neuron (w_{ih})					Bias (b_{ih})	Output Layer (v_{ho})	Bias (b_{ho})	
	MSWIAC	FC	AR	CC	CP			UCS	STS
Hidden 1	1.077390	0.150585	− 0.028244	− 1.374918	0.827190	− 2.311060	− 0.287926	0.224461	− 0.550683
Hidden 2	− 0.953632	0.423624	0.058699	− 0.171609	3.241747	3.733600	0.361887		
Hidden 3	− 1.197983	− 0.729248	1.520621	− 1.246009	− 0.008835	1.681276	− 0.691513		
Hidden 4	− 0.803015	− 1.419853	1.797278	− 0.596585	1.288640	0.931251	− 0.014080		
Hidden 5	− 0.248839	0.309744	0.116938	0.876765	− 1.994185	0.079415	0.348299		
Hidden 6	− 0.008449	0.539222	1.414792	− 1.085401	0.152400	− 1.037078	0.090656		
Hidden 7	0.061327	− 1.349187	− 0.056338	0.385114	0.068344	1.109492	0.152310		
Hidden 8	1.240462	− 1.110384	0.921196	0.981168	0.774087	0.533138	0.093350		
Hidden 9	1.642097	− 6.453166	− 6.877835	− 1.437178	− 5.697464	11.173857	− 0.017032		
Hidden 10	− 0.875143	0.187664	0.094910	− 0.464608	0.624299	− 0.162132	1.020863		

Hidden layer neurons	Yih values				
	MSWIAC	FC	AR	CC	CP
Hidden 1	0.311535	0.043543	0.008167	0.397567	0.239188
Hidden 2	0.196653	0.087358	0.012105	0.035388	0.668496
Hidden 3	0.254744	0.155070	0.323351	0.264956	0.001879
Hidden 4	0.135980	0.240434	0.304346	0.101024	0.218215
Hidden 5	0.070165	0.087339	0.032973	0.247222	0.562301
Hidden 6	0.002640	0.168493	0.442086	0.339160	0.047621
Hidden 7	0.031936	0.702588	0.029338	0.200548	0.03559
Hidden 8	0.246745	0.220871	0.183239	0.195168	0.153977
Hidden 9	0.074277	0.291896	0.311105	0.065008	0.257714
Hidden 10	0.389537	0.083531	0.042246	0.206803	0.277883

Step 3: For each input, sum Yih to obtain Sensitivity. Say example,

$$S_{\text{MSWIAC}} = 0.311535 + 0.196653 + 0.254744 + 0.135980 + 0.070165 + 0.002640 + 0.031936 + 0.246745 + 0.074277 + 0.389537 = 1.714213.$$

	Sensitivity				
	MSWIAC	FC	AR	CC	CP
Total	1.714213	2.081123	1.688956	2.052844	2.462864

Step 4: Relative importance

Divide Sensitivity by the sum for all inputs to get the relative importance that can be attributed to the given input variable. For example,

$$\text{Relative Importance}_{\text{MSWIAC}} = (1.714213 \times 100) / (1.714213 + 2.081123 + 1.688956 + 2.052844 + 2.462864) = 17.142128.$$

	Input parameters				
	MSWIAC	FC	AR	CC	CP
Relative importance (%)	17.142128	20.811234	16.889559	20.528443	24.628636

Author contributions Author contributions: (1) Neelam Singh- Experimental work, Writing, (2) Akash Priyadarshree—Methodology, Literature (3) Sunayana- ANN model, MLR model, (4) Vikas Kumar- Conceptualization, Manuscript Writing.

Data availability No datasets were generated or analysed during the current study.

Declarations

Conflict of interest The authors declare no competing interests.

References

- Allegrini E, Vadenbo C, Boldrin A, Astrup TF (2015) Life cycle assessment of resource recovery from municipal solid waste incineration bottom ash. *J Environ Manag* 151:132–143
- Anburuvel A, Sathiparan N, Dhananjaya GMA, Anuruththan A (2023) Characteristic evaluation of geopolymer based lateritic soil stabilization enriched with eggshell ash and rice husk ash for road construction: an experimental investigation. *Constr Build Mater* 387:131659

- Basha EA, Hashim R, Mahmud HB, Muntohar AS (2005) Stabilization of residual soil with rice husk ash and cement. *Constr Build Mater* 19:448–453
- Bie R, Chen P, Song X, Ji X (2015) Characteristics of municipal solid waste incineration fly ash with cement solidification treatment. *J Energy Inst*. <https://doi.org/10.1016/j.joei.2015.04.006>
- Chan CCY, Kirk DW, Marsh H (2000) The behavior of AL in MSWfly ash during thermal treatment. *J Hazard Mater B* 76:103e111
- Chen X, Geng Y, Fujita T (2010) An overview of municipal solid waste management in China. *Waste Manag* 30:716–724
- Ferreira C, Ribeiro A, Ottosen L (2003) Possible applications for municipal solid waste fly ash. *J Hazard Mater B* 96:201–216
- Gao H, Liu J, Liu H (2011) Geotechnical properties of EPS composite soil. *Int J Geotech Eng* 5(1):11–19
- Ghanizadeh AR, Rahrovan M (2019) Modeling of unconfined compressive strength of soil-RAP blend stabilized with Portland cement using multivariate adaptive regression spline. *Front Struct Civ Eng* 13:787–799. <https://doi.org/10.1007/s11709-019-0516-8>
- Ghanizadeh AR, Naseralavi SS (2023) Intelligent prediction of unconfined compressive strength and Young's modulus of lean clay stabilized with iron ore mine tailings and hydrated lime using Gaussian process regression. *J Soft Comput Civ Eng* 7(4):1–23. <https://doi.org/10.22115/scce.2023.370814.1573>
- Ghanizadeh AR, Safi Jahanshahi F, Naseralavi SS (2023) Intelligent modelling of unconfined compressive strength of cement stabilised iron ore tailings: a case study of Golgohar mine. *Eur J Environ Civ Eng* 28(8):1759–1787. <https://doi.org/10.1080/19648189.2023.2276133>
- Gupta D, Priyadarshree A, Sharma SK, Singh H (2018) Behavior of cement-treated kaolin clay mixed with fiber and rice husk ash. *Int Res J Eng Technol* 5(2):250–255
- Hamernik JD, Frantz GC (1991) Strength of concrete containing municipal solid waste fly ash. *Mater J ACI* 88(5):508–517
- Hjelmar O (1996) Disposal strategies for municipal solid waste incineration residues. *J Hazard Mater* 47:345–368
- IS 2720 (Part-10) (1999) Methods of Test for Soils: Part 10, Determination of Unconfined Compressive Strength. New Delhi
- IS 5816 (1999) Method of test splitting tensile strength of concrete. New Delhi
- Kamon M, Ktsumi T, Sano Y (2006) MSW fly ash stabilized with coal ash for geotechnical application. *J Hazard Mater* 76(2):265–283
- Kaniraj SR, Havanagi VG (2001) Behavior of cement-stabilized fiber-reinforced fly ash-soil mixtures. *J Geotech Geoenviron Eng* 127(7):574–584
- Kirby CS, Rimstidt JD (1993) Mineralogy and surface properties of municipal solid waste ash. *Environ Sci Technol* 27:652–660
- Kumar A, Gupta D (2015) Behavior of cement-stabilized fiber-reinforced pond ash, rice husk ash-soil mixtures. *Geotext Geomembr*. <https://doi.org/10.1016/j.geotextmem.2015.07.010>
- Kumar S, Singh D (2023) Prediction of UCS and CBR of fiber-reinforced municipal solid waste incinerator bottom ash composites using experimental and machine learning methods. *Constr Build Mater*. <https://doi.org/10.1016/j.conbuildmat.2022.130230>
- Li L, Zang T, Xiao H, Feng W, Liu Y (2020) Experimental study of polypropylene fiber reinforced clay soil mixed with municipal solid waste incineration bottom ash. *Eur J Environ Civ Eng*. <https://doi.org/10.1080/19648189.2020.1795726>
- Liu Y, Ong DEL, Oh E, Liu Z, Hughes R (2022) Sustainable cementitious blends for strength enhancement of dredged mud in Queensland, Australia. *Geotech Res* 9(2022):65–82. <https://doi.org/10.1680/JGERE.21.00046/ASSET/IMAGES/SMALL/JGERE9-0065-F10.GIF>
- Lo HM, Liao YL (2007) The metal-leaching and acid-neutralizing capacity of MSW incinerator ash co-disposed with MSW in landfill sites. *J Hazard Mater* 142:512–551
- Luo H, Cheng Y, He D, Yang E (2019) Review of leaching behavior of municipal solid waste incineration (MSWI) ash. *Sci Total Environ* 668:90–103. <https://doi.org/10.1016/j.scitotenv.2019.03.004>
- Mukherjee S, Mukhopadhyay S, Hashim MA, Sen Gupta B (2014) Contemporary environmental issues of landfill leachate: assessment and remedies. *Crit Rev Environ Sci Technol* 45:472–590
- Ng S, Engelsen CJ (2018) Construction and demolition wastes. In: *Waste and supplementary cementitious materials in concrete*. Woodhead Publishing, pp 229–255
- Pastapure V, Singh D, Kumar S (2022) Engineering behavior of municipal solid waste incinerated bottom ash with the addition of lime. *Mater Today Proc*. <https://doi.org/10.1016/J.MATPR.2022.10.112>
- Pie O, Le TNH (2012) Effect of polypropylene fiber reinforcement on the mechanical behavior of silty clay. *Geotext Geomembr* 32:111–116
- Priyadarshree A, Chandra S, Kumar V (2021) Performance of grass ash with mix of black cotton soil and lime. *Innov Infrastruct Solut*. <https://doi.org/10.1007/s41062-021-00518-9>
- Priyadarshree A, Kumar A, Gupta D, Pushkarna P (2018) Compaction and strength behavior of tire crumbles-fly ash mixed with clay. *J Mater Civ Eng*. [https://doi.org/10.1061/\(ASCE\)MT.1943-5533.0002171](https://doi.org/10.1061/(ASCE)MT.1943-5533.0002171)
- Quina MJ, Bontempi E, Bogush A, Schlumberger S, Weibel G, Braga R, Funari V, Hyks J, Rasmussen E, Lederer J (2018) Technologies for the management of MSW incineration ashes from gas cleaning: new perspectives on recovery of secondary raw materials and circular economy. *Sci Total Environ* 635:526e542. <https://doi.org/10.1016/J.SCITOTENV.2018.04.150>
- Ranjan G, Vasan RM, Charan HD (1996) Probabilistic analysis of randomly distributed fiber-reinforced soil. *J Geotech Eng* 122(6):419–426
- Rokhvargher AE (1994) Environmental and waste management issues in the ceramic industry II. In: Bickford D, Bates S, Jain V, Smith G (eds) *Ceramic transactions*, vol 45. The American Ceramic Society, Westerville, pp 125–135
- Rosen CJ, Olson D, Bierman PM (1994) Swiss chard and Alfalfa responses to soils amended with municipal solid waste incinerator ash: growth and elemental composition. *J Agric Food Chem* 42(6):1361–1368. <https://doi.org/10.1021/jf00042a023>
- Sathiparan N, Anburuvel A, Selvam VV, Vithurshan PA (2023) Potential use of groundnut shell ash in sustainable stabilized earth blocks. *Constr Build Mater* 393:132058
- Singh D, Kumar A (2017) Performance evaluation and geo-characterization of municipal solid waste incineration ash material amended with cement and fiber. *Int J Geosynth Ground Eng* 3:16. <https://doi.org/10.1007/s40891-017-0094-6>
- Singh D, Kumar A (2019) Mechanical characteristics of municipal solid waste incineration bottom ash treated with cement and fiber. *Innov Infrastruct Solut* 4:61. <https://doi.org/10.1007/s41062-019-0247-7>
- Tang C, Shi B, Gao W, Chen F, Cai Y (2007) Strength and mechanical behavior of short polypropylene fiber reinforced and cement stabilized clayey soil. *Geotext Geomembr* 25:194–202
- Winter RM, Mallepalli RR, Hellem KP, Szydlowski SW (1994) Determination of As, Cd, Cr and Pb species form in a combustion environment. *Combust Sci Technol* 101(1e6):45e58
- Yakubu Y, Zhou J, Shu Z, Zhang Y, Wang W, Mbululo Y (2018) Potential application of pre-treated municipal solid waste incineration fly ash as cement supplement. *Environ Sci Pollut Res*. <https://doi.org/10.1007/s11356-018-1851-3>
- Yang GCC, Yang TY (1998) Synthesis of Zeolites from municipal incinerator fly ash. *J Hazard Mater* 62(1):75–89. [https://doi.org/10.1016/S0304-3894\(98\)00163-0](https://doi.org/10.1016/S0304-3894(98)00163-0)

Zhang RB, Chi Y, Lu YS et al (2003) Study on distribution characteristics of heavy metals from municipal solid waste incineration. *J Eng Therm* 24(1):149e152

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