Towards sustainability: Integrating experimental study and data-driven modeling for eco-friendly paver blocks containing plastic waste

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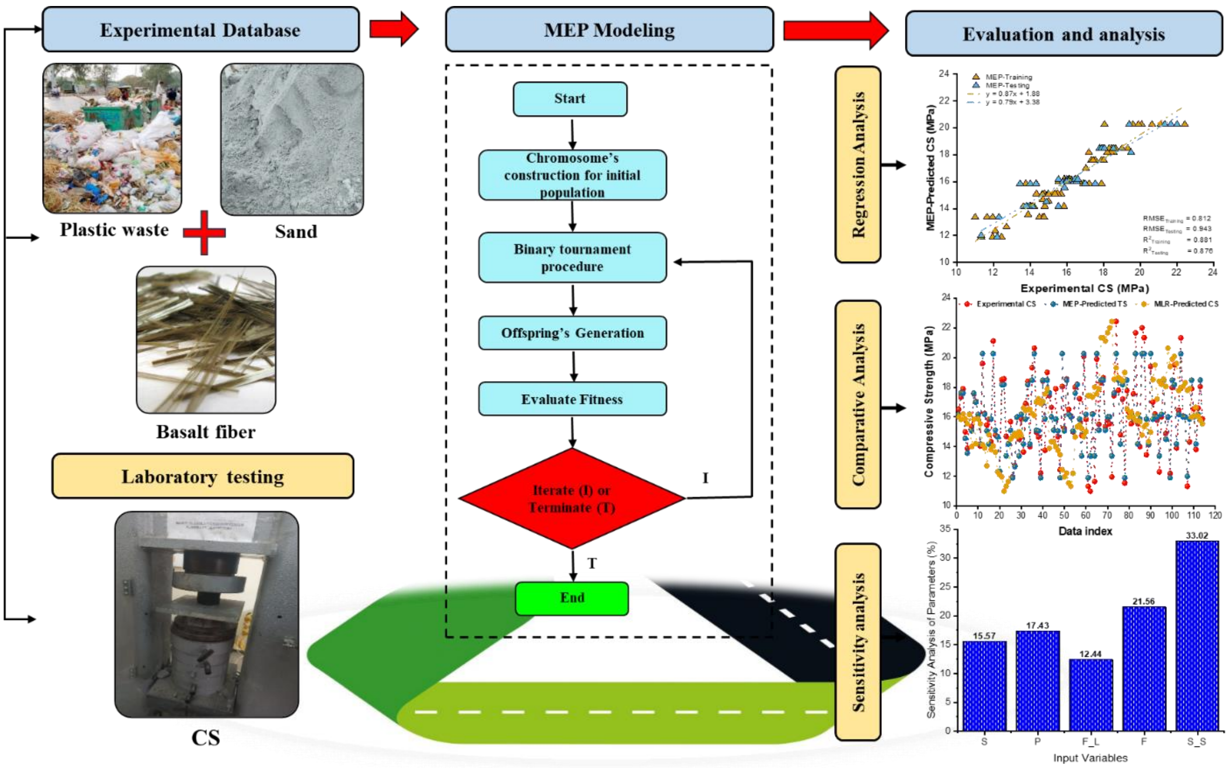
Abstract

Plastic waste poses a significant threat as a hazardous material, while the production of cement raises environmental concerns. It is imperative to urgently address and reduce both plastic waste and cement usage in concrete products. Recently, several experimental studies have been performed to incorporate plastic waste into paver blocks as a substitute for cement. However, the experimental testing can't be enough to optimize the use of waste plastic in pavers due to resource and time limitations. This study proposes an innovative approach, integrating experimental testing with machine learning to optimize plastic waste ratios in paver blocks efficiently. Initially, experimental investigations are performed to examine the compressive strength (CS) of plastic sand paver blocks (PSPB). Varied mix proportions of plastic and sand with different sizes of sand are employed. Moreover, to enhance the CS and meet the minimum requirements of ASTM C902-15 for light traffic, basalt fibers, a sustainable industrial material, are also utilized in the manufacturing process of environmentally friendly PSPB. The highest CS of 17.26 MPa is achieved by using the finest-size sand particles with a plastic-to-sand ratio of 30:70. Additionally, the inclusion of 0.5% basalt fiber, measuring 4 mm in length, yields further enhancement in outcome by significantly improving CS by 25.4% (21.65 MPa). Following that, an extensive experimental record is established, and multi-expression programming (MEP) is used to forecast the CS of PSPB. The model's projected results are confirmed by using various statistical procedures and external validation methods. Furthermore, comprehensive parametric and sensitivity studies are conducted to assess the effectiveness of the MEP-based proposed models. The sensitivity analysis demonstrates that the size of the sand particles and the fiber content are the primary factors contributing to more than 50% of the CS in PSPB. The parametric analysis confirmed the model's accuracy by demonstrating a comparable pattern to the experimental results. Furthermore, the results indicate that the proposed MEP-based formulation exhibits high precision with an R^2 of 0.89 and possesses a strong ability to predict. The study also provides a graphical user interface (GUI) to increase the significance of ML in the practical application of handling waste management The main aim of this research is to enhance the reuse of plastic waste to promote sustainability and economic benefits, particularly in producing green environments with integration of machine learning and experimental investigations.

Keywords: Compressive Strength, Plastic Waste, Basalt Fiber, Multi-Expression Programming, Paver Blocks, Graphical User Interface

Graphical abstract:



Abbreviations

PSPB	Plastic-sand paver blocks
CS	Compressive strength
ASTM	American Society for Testing and Materials
ML	Machine learning
LDPE	Low-density polyethylene
F	Fiber content
S	Sand
MEP	Multi expression programming
PW	Plastic waste
SVM	Support vector machine
R	Coefficient of correlation
OF	Objective function
ANN	Artificial neural network
PI	Performance Index
RMSE	Root means squared error.
ANFIS	Adaptive neuro-fuzzy inference system
MAE	Mean absolute error

1. Introduction

Efficiently managing solid waste remains a significant obstacle, especially in developing countries. PW is a sort of solid waste that is a matter of serious concern at both national and global levels. The issue of PW has been steadily increasing over the past four decades, with only a fraction of it currently being recycled. The widespread use of plastic, because of its adaptability and extended reliability, has resulted in the substantial creation of disposable plastic and the accompanying generation of garbage. The massive increase of PW in the ecosystem poses a significant risk to many aquatic creatures and the long-term viability of the natural world. Water pollution arises when polluted wastewater is discharged into aquatic environments such as oceans and rivers, in which it is exposed to solar radiation and the motions of water and waves [1], [2], [3]. An estimated 8 million metric tonnes of plastic are being dumped into the ocean, and it is expected that if this trend persists, garbage in the marine environment exceed the number of fish [4]. Microplastics produced during the degradation of plastic have been linked with health problems in animals as a result of the process of bioaccumulation and biomagnification [5]. Furthermore, PW can hinder the movement of water in sewer systems, leading to overflow and the rapid spread of insect parasites and waterborne diseases [6]. The global consistently expanding trend of plastic waste production from 1950 to 2015 is shown in **Fig. 1** [7]. Due to its inability to decompose, plastic has exacerbated various ecological challenges while posing additional risks to local communities.

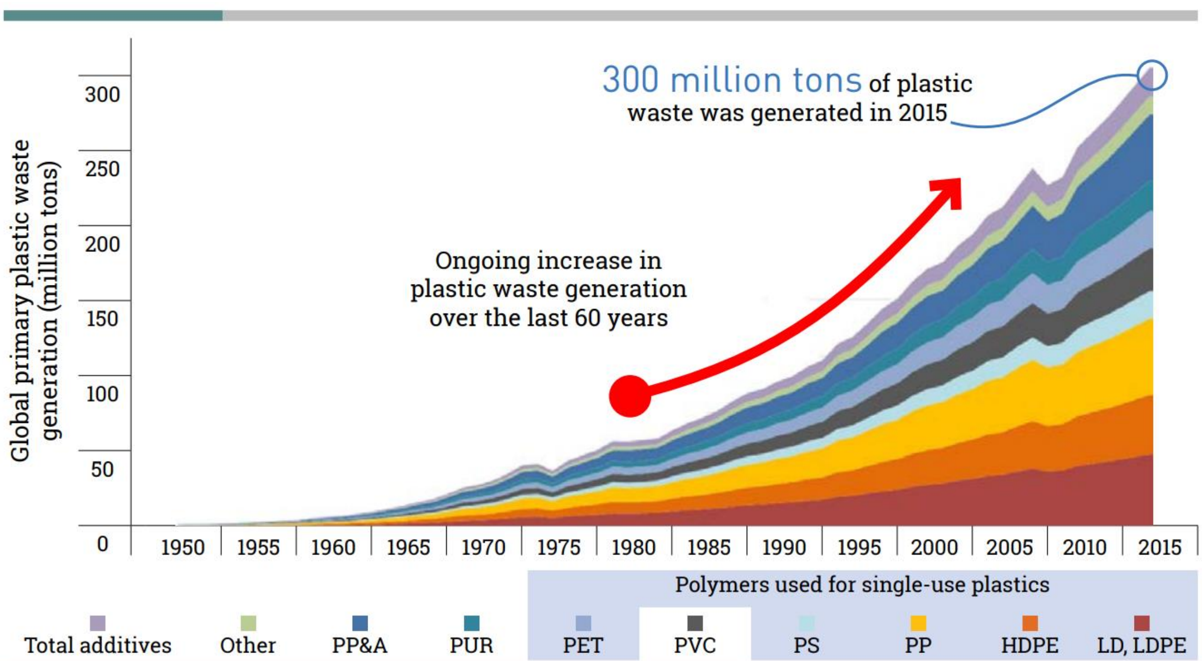


Fig. 1: Worldwide plastic waste production (1950-2015) [7].

Among the several approaches to managing PW, the conversion of plastic into a useful item is particularly beneficial. This approach not only decreases the need for new materials but also enhances the economic value of waste. Additionally, studies have indicated that recycling PW by stabilizing it in concrete or creating useful items using supplementary recycling has less detrimental effects on the environment compared to pyrolysis and incineration methods [8]. Paver blocks (PB) and bricks have also been produced using PW. For many years, Cement-based PB has been extensively used in pedestrian walkways, driveways, shipping yards, and roads [9]. However, scientists are worried about the growing production of concrete products and the subsequent release of CO_2, which poses a significant environmental risk. To preserve the planet, it is necessary to decrease the utilization of cement. This is because the manufacture of cement-based composites results in substantial releases of CO_2. Minimizing cement consumption can significantly decrease CO_2 emissions, with around 0.9 tonnes of CO_2 produced annually for every 1.0 tonnes of cement consumed [10]. The cement sector accounts for nearly 8% of all anthropogenic greenhouse gas emissions [11]. The conventional paver block (PB) utilizes 210 kg/m^3 of cement, resulting in significant CO_2 emissions [12]. The need to tackle numerous significant emissions originating from cement factories is crucial. Furthermore, concrete contains small amounts of crystalline silica, a material that can cause skin damage, lung irritation, and environmental pollution. Efforts should be made to find substitutes to decrease the usage of cement-based composites. Employing PW instead of cement as a binder material in concrete products is a viable option that can help reduce the use of cement and decrease the PW, which results in sustainable products [13].

In 2006, Pierre Kamsouloum first used a combination of PW and sand to manufacture pavement blocks. Agyeman et al. [14] stated that recycled PW can be used as a viable alternative to cement in the production of PB. Utilizing PW in construction projects has benefits in improving ecological sustainability [15]. Furthermore, the addition of PW in the PB leads to a 15% decrease in weight compared to a standard concrete block. The financial investigation reported that the PSPB has a 35.39% lower per unit cost than a typical concrete block [12]. Moreover, the CS of concrete PB is mainly influenced by the water-to-cement (w/c) ratio, the hydration process, the time of curing, and the properties of the concrete components used [16]. Eliminating cement from PSPB will result in the removal of both the water-to-cement ratio and the curing time, as there is no need for curing in the case of PSPB. It is important to highlight that PW is a thermoplastic substance that shows the property of being flexible and can assume any needed shape when exposed to heat. Nevertheless, as a thermoplastic substance, its strength decreases significantly as the temperature increases. Consequently, this study included basalt fibers as an addition to plastic-bonded sand paver to improve CS at elevated temperatures.

The strength of plastic blocks produced with PW is assessed to determine their performance. This assessment is influenced by various factors, such as the particular type, the composition, the content of plastic, the mix design, and the testing methodologies employed [17]. The PSPB responds in an anomalous manner when various mixed composites with additives like basalt fibers are utilized. In essence, an experimental study must be carried out for a complete understanding of the relationship between PSPB ingredients and their properties. However, conducting experimental studies could be a time-consuming and expensive process. Therefore, the availability of soft computing, along with experimental investigation, can accurately correlate influencing factors and properties of PSPB, which could be the best alternative to address the issue (of time and cost) and promote the re-utilization of PW for sustainability [18].

Recently, artificial intelligence (AI) approaches, such as multi-expression programming (MEP) [19], [20], support vector machine (SVM) [21], gene-expression programming (GEP) [22], [23], artificial neural network (ANN) [24] and Particle Swarm Optimization (PSO), have been extensively used to address issues related to complex construction materials [25], [26], [27]. Chou et al. [28] employed SVM and ANN to estimate the CS of high-strength concrete. The findings of the study showed that the proposed model had a significant prediction performance. In a different study by Trocoli et al. [29], the ANN was utilized to simulate the CS of recycled aggregate concrete, and they found that ANN models are reliable. Gupta [30] utilized SVM for forecasting the 28-day CS of high-strength concrete. They used a total of 371 data points from experimental findings and literature for model development. The findings confirm the efficacy of SVM-based modeling in forecasting the CS of high-performance concrete with an R^2 of more than 0.8. Amlashi et al. [31] explore the three ML techniques, namely, ANN, SVM, and ANFIS, optimized with PSO to estimate the CS and tensile strength of concrete incorporated with plastic waste. The outcomes indicate that ANN-PSO achieves a higher R^2 of 0.95 as compared to other techniques. Complex engineering problems are simplified due to the pattern recognition capabilities of these techniques [32]. Although these models found strong correlations, no mathematical equation was presented for real implementation due to the complex construction of these models, which is also considered to be one of the main obstacles preventing the method from being widely used [33]. In the majority of neural network-based approaches, a sophisticated mathematical formula is generated to estimate the output depending on the input parameters. Notably, neural networks (NN) may only perform for optimization problems under consideration since these techniques are referred to as black box models (BBM). Physical events or any data associated with the problem being addressed are not considered in BBM. Moreover, overfitting is another major issue found in ANN techniques [34]. In one of our earlier studies, Iftikhar et al. [35] employed GEP to estimate the CS of PSPB. The prediction was based on a dataset consisting of 135 measurements and seven input characteristics. The GEP models demonstrated a high degree of agreement with the findings, reaching R^2 values above 0.85. Parametric and sensitivity analyses were carried out to assess the validity of the suggested models. However, the GEP approach was limited in that it was unable to combine a few dissimilar datasets for model construction, hence restricting its utility. In order to improve the model's performance, it is necessary to remove the inconsistent data points from both the training and validation processes. Furthermore, genetic operators contain a single chromosome within their program and are appropriate when the input-output correlation is quite simple.

In recent years, an improved ML approach known as multi-expression programming (MEP) has been created to overcome the aforementioned drawbacks of ANN. MEP, an advanced form of genetic programming (GP), is considered superior to other evolutionary algorithms in its ability to produce accurate results even when the desired level of complexity is unknown [36]. The capacity of MEP to encode numerous chromosomes within a single computer program is a noteworthy indicator. The optimal chromosome is chosen as the definitive representation of the solution [37]. The pre-specification of the final expression form is necessary for other ML techniques [38], while the MEP evolving approach removes mathematical mistakes from the final expression. Compared with other ML techniques, the decoding process evolved in MEP is very simple.

Considering the benefits of MEP and the drawbacks of other ML models, this study employed the MEP technique for estimating the CS of PSPB. As per the author's knowledge, no studies have explored the use of both experimental and ML techniques to evaluate the CS of PSPB with basalt fiber as an additive. In the past, only experimental investigations or simple mathematical models were used, requiring a substantial investment of time and financial resources. Therefore, for the first time, this study integrates the experimental findings with MEP-based models to estimate and provide predictive equations for CS of PSPB. Firstly, experimental examinations were performed to assess the CS of PSPB. Varied mix proportions of plastic and sand with different sizes of sand were employed. Subsequently, an extensive experimental record was established, and the MEP technique was used to forecast the CS of PSPB. Various statistical methods and parametric and sensitivity analysis were performed to assess the models' effectiveness. This study aims to provide a sustainable alternative to cement by experimentally investigating the use of plastic waste instead of cement and providing an MEP-based simplified equation that can be applied in practice for pre-design purposes of PSPB.

2. Experimental analysis

2.1 Materials

2.1.1 Low-density polyethylene (LDPE)

In this study, the plastic type known as LDPE was utilized as a binding material in PSPB. The LDPE was obtained from the municipal authorities in Abbottabad, Pakistan. Following the collection process, the material was initially washed completely, cleaned, and dried to remove any pollutants that could hinder the melting process. In the end, the plastic material was transformed into small fragments using shredding. **Table 1** shows the characteristics of LDPE utilized in this investigation.

Table 1: Properties of LDPE.

Description	Value
Softening temperature	70 ^{o}C
Modulus of elasticity	0.6-1.4 GPa
Melting temperature	110 ^{o}C
Density	0.91 to 0.94 gm/cm^3

2.1.2 Natural fine aggregates (Sand)

The locally available sand was used as a fine material for the production of PSPB. Initially, two different types of sands were used to examine the impact of particle size on CS of PSPB. The properties of sand were assessed by conducting tests following the ASTM standards, as illustrated in **Table 2**. Specific gravity and sieve analysis tests were performed to ascertain the fineness modulus of both sands. A finer form of sand (Sand-1) was utilized for subsequent analysis.

Table 2: Properties of Sand.

Test type	Test Results		Standards
Sieve analysis	Sand-1	Sand-2	ASTM_C136
Water absorption	4.1%	5.3%	ASTM_C128
Specific gravity	2.64	2.67	ASTM _D854-02
Fineness Modulus (FM)	2.92	3.24	ASTM_C125

2.1.3 Basalt fibers

Basalt fiber is labeled as a green industrial material. Basalt fiber is formally known as the "21st-century non-polluting green material" [39]. Quarried basalt rock, when heated to a temperature of 1400 °C, results in the formation of molten basalt rock. Extrusion of these molten rocks through small holes can be used to form basalt fibers. Due to its property to withstand high temperatures, basalt fiber is generally used in applications like heat-insulated materials, vehicle braking systems, and flame-retardant materials [40]. Basalt can be used as an aggregate, fiber, mesh, and rebar. Being a multi-performance fiber, basalt fiber has several advantages [41]: it has high thermal resistance to heat, it is a waste and renewable material, it is very light in weight, and it increases the flexural and CS of paver blocks. The present study employed basalt fibers of two different lengths, specifically 4 mm and 12 mm. **Table 3** displays the chemical composition of the basalt fibers.

Table 3: Chemical composition of basalt fiber.

Compound	percentage by weight
MgO	1.3-3.7
K_2O	0.80-4.50
Fe_2O_3	4.0-9.5
Cao	5.21-7.80
$Al2O_3$	16.9 -18.2
Na_2O	2.51-6.4
SiO_2	51.6 -57.5

2.2 Mix design and sample preparation

The samples were produced by mixing LDPE and sand in a multi-stage procedure, as shown in **Fig. 2**. The LDPE material was initially melted in an exposed container to attain the intended flexibility. After being melted, it was properly blended with appropriate proportions of sand.

In the first stage, the impact of varying particle sizes of sand (d < 0.420 mm, 0.420 mmn< d < 0.595 mm, and 0.59 mm < d < 1.68 mm) on CS of PSPB was determined by keeping the exact proportions of plastic and sand (25% and 75%). During the second phase, the sand that showed the highest level of strength in the initial phase was mixed with LDPE in various proportions of plastic and sand (15:85, 20:80, 25:75, 30:70, 35:65 and 40:60). In the final stage, the mechanical characteristics of the PSPB were improved by adding basalt fibers of lengths 4 mm and 12 mm in different amounts (0.1%, 0.3%, 0.5%, 0.7%, and 1%) to the optimized specimens.

A total of 114 specimens were carefully produced, with a precise allocation of six specimens for each scenario, as shown in **Table 4**. A mixture comprised of liquefied plastic, fibers, and sand was carefully poured into cubic molds 50 mm in size that had been preheated and coated with lubricant. The molds were coated with lubricating oil to make it easier to demolding and were subjected to a temperature of 100°C to simplify the installation and compression of the specimens. Following 24 hours at ambient temperature, the specimens were evaluated for CS. The complete experimental procedure is described in **Fig. 2**.

This experimental study seeks to determine the most suitable sand grain sizes at a constant plastic-to-sand ratio and then investigate the optimum plastic-to-sand ratio using the chosen sand particle size. The plastic-to-sand ratio that yielded the best results was subsequently used in combination with basalt fibers of varied lengths and proportions to evaluate the CS of PSPB.

Table 4: Mix design for PSPB.

Description	**Code**	**Plastic content by weight %**	**Sand content by weight %**	**Particle size of sand**	**No of samples**
Effect of and grain size	S1	25	75	Dia < 0.42mm	6
	S2	25	75	0.59mm < Dia < 0.42mmm	6
	S3	25	75	1.68mm < Dia < 0.59mm	6
Varying Proportions of plastic-sand	P1	15	85	Dia < 0.42mm	6
	P2	20	80	Dia < 0.42mm	6
	P3	25	75	Dia < 0.42mm	6
	P4	30	70	Dia < 0.42mm	6
	P5	35	65	Dia < 0.42mm	6
	P6	40	60	Dia < 0.42mm	6
Basalt fiber of 4mm and 12mm in length with various proportions of fiber	F_i	30	70	Dia < 0.42mm	60

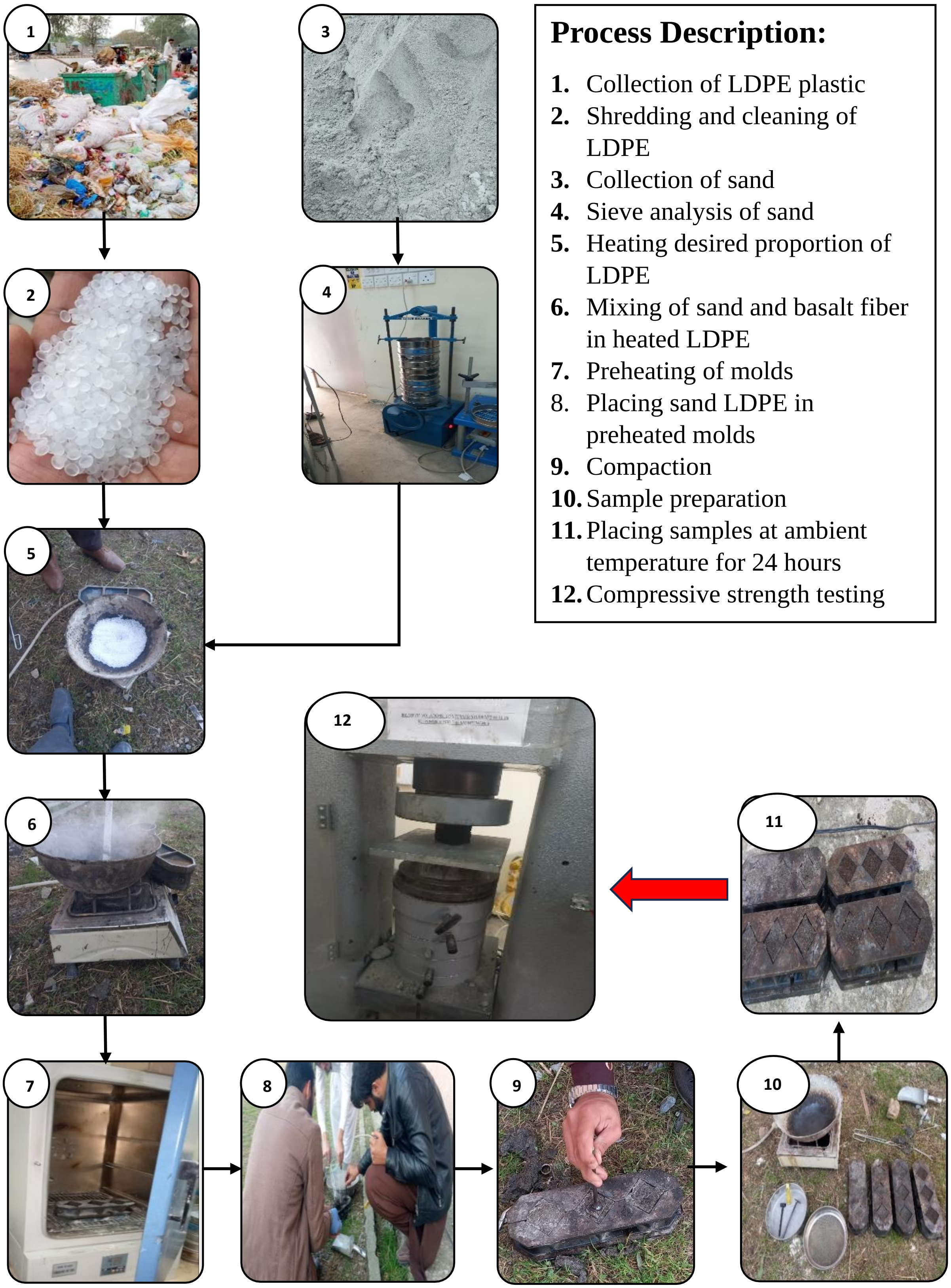


Fig. 2: Experimental program.

2.3 Compressive strength testing

The CS of PSPB was evaluated using a compressive testing machine (CTM). The test specimens were placed at room temperature for 24 hours and then tested following the guidelines provided by ASTM 109. Loading and strain rates of 20 MP/s and 10 mm/min were used as specified in ASTM standards. The Cubic size molds measuring 50 mm × 50 mm x 50 mm were utilized, as depicted in **Fig. 3**. Before testing, the CTM was provided with specific information regarding the area. Therefore, CTM automatically computes the amount of stress experienced by the specimen until it reaches its breaking point.

Fig. 3: Compressive strength testing

3. Machine learning analysis

The current study utilized multi-expression programming (MEP) to estimate the CS of paver blocks made with LDPE plastic waste. The method to develop MEP-based ML models is presented in **Fig. 4**.

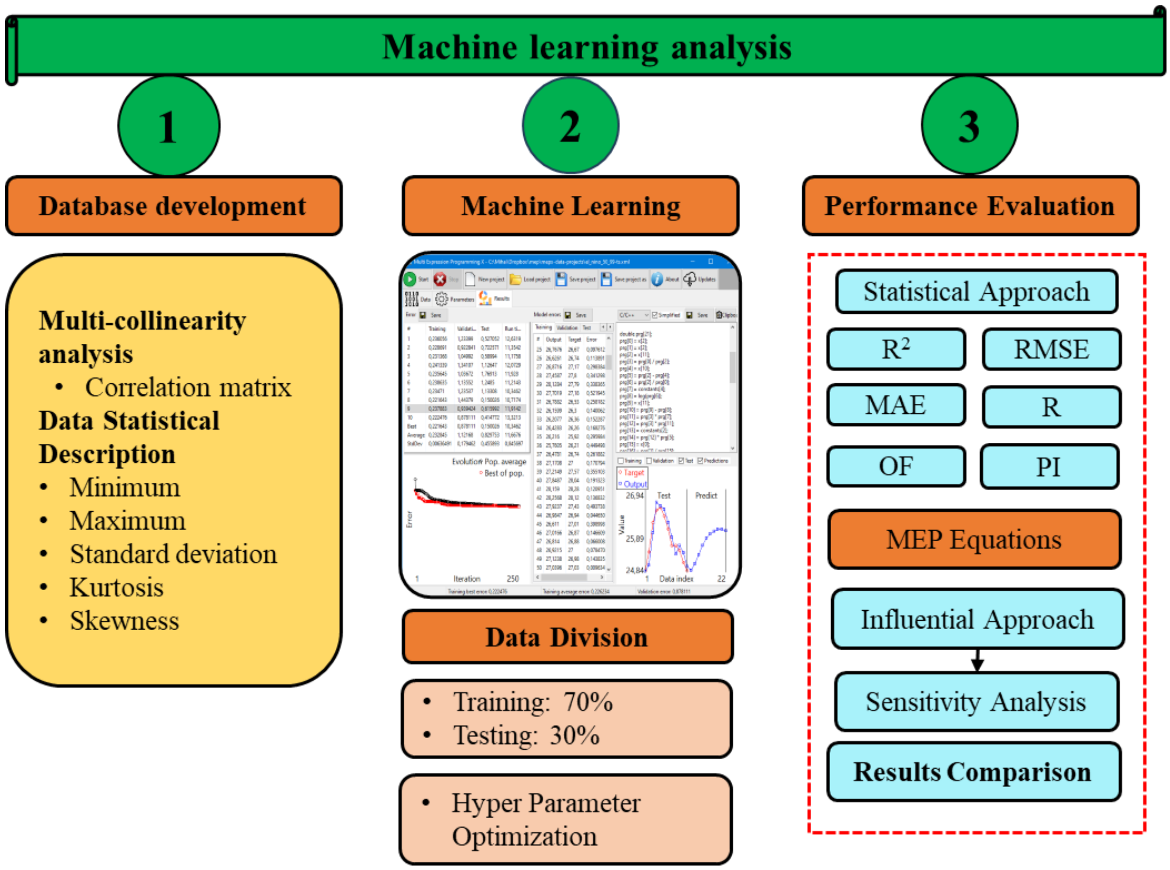


Fig. 4: The sequential MEP-based ML analysis used in the current study.

3.1 Multi expression programming (MEP)

Genetic programming-based soft computing techniques aim to provide precise and realistic mathematical equations for predicting outcomes based on preset parameters in the data input. Ferreira Ferreira (2001) initially suggested the genetic algorithm (GA), also known as genetic expressions. This algorithm was motivated by the Darwinian principle. Similarly, Cramer first proposed the idea of genetic programming (GP) [43]. Koza et al. [44] made significant advancements to the concept. The most important distinction between both approaches is that GP uses nonlinear parse trees compared to the fixed-length binary strings used in GA. Several distinct types of evolutionary algorithms have been developed in recent decades, with linearity being one of the most significant variations. Oltean proposed a linear variant of machine learning evolutionary algorithm called multi-expression programming (MEP). In MEP, each single entity can be expressed as a variable length [45] [46]. The assumption of linearity distinguishes the MEP technique from the GEP method. The MEP employs simplified decoding processes in comparison to the GP methodology and is given special weight when the complexity of the desired gene is unidentified [47]. In **Fig. 5**, the various steps of the MEP technique are illustrated. The MEP method's evaluation process includes creating a population of random chromosomes, selecting two parents using a binary competition procedure and reconfiguring them according to the possibility of crossover, mutating the selected parents to produce two offspring, and then the least effective population member is replaced with the best one. A linear form of string instructions made up of a combination of mathematical operators or terminal variables is used to express the results of MEP-based analysis [48].

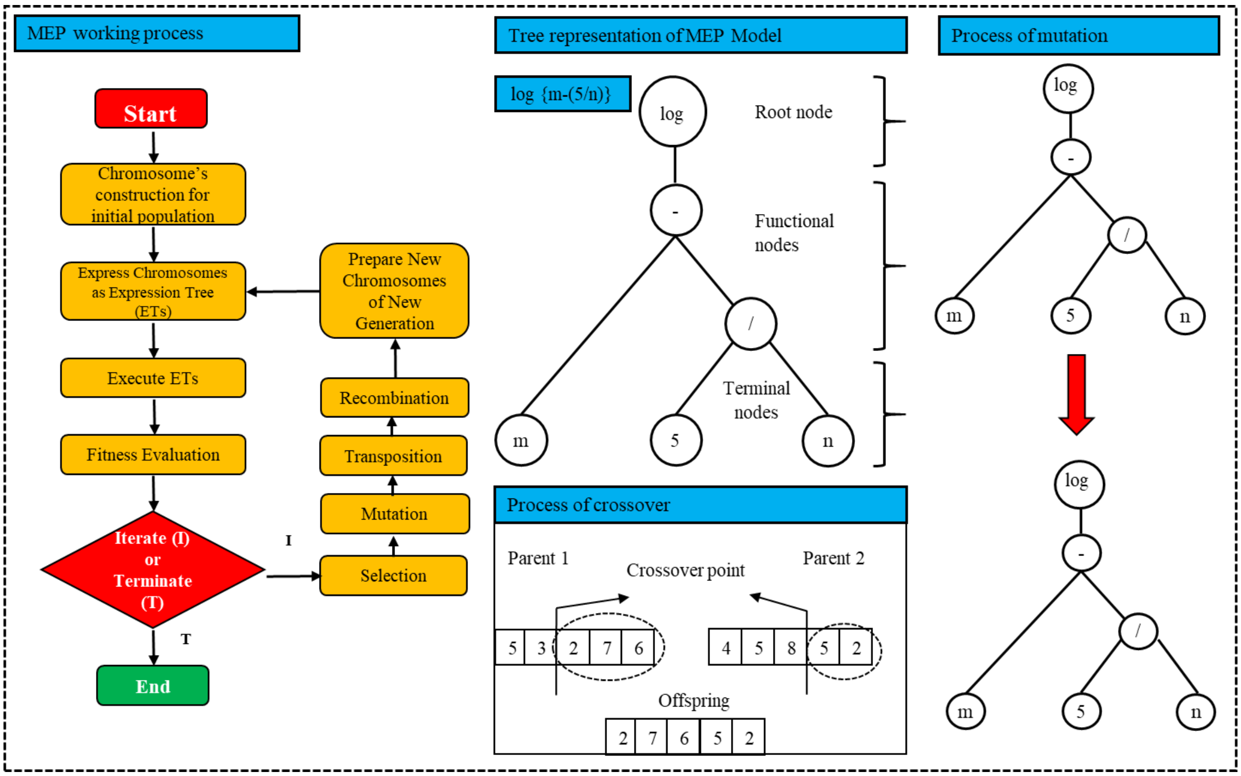


Fig. 5: Process flow diagram of MEP.

Numerous studies used the GEP approach and neural network methods to build an empirical model for the evaluation of various properties of structure materials. However, the inclusion of a linear variation feature of MEP makes it simple to distinguish between individual genotypes and phenotypes [49]. MEP is quite useful in material engineering, where the uncertainty of the intended equation is unknown, and a little variation in the concrete design variables may have a significant impact on concrete properties. In MEP, numerous solutions are encoded in a single linear chromosome, enabling the software to predict the result by looking at a larger area. MEP is capable of handling errors like incorrect expressions and division by zero and can convert into any terminal symbol to let the process proceed. This causes a gap in the chromosome's structure throughout the assessment procedure. The apparent advantages of MEP methods over other evolutionary computations would lead to the development of precise and reliable models for the field of material engineering [50]. The MEP models have been created in this study to formulate the CS of paver blocks incorporated with plastic waste. Developing a reliable, precise, and effective model will aid in using plastic waste as construction materials. These models could be viable options to resolve the issues related to the disposal of LDPE plastic waste. Additionally, sustainable construction will be prompted, and it would be useful in the savage of natural resources.

3.1.1 Database

A comprehensive data set for CS of PSPB was obtained by performing experimental testing in the laboratory. Raincloud plots with normal distribution curves were used to determine the potential outliers in the database, as shown in **Fig. 6**. As can be seen, only a few points deviated from the normal trend, so those were deleted. The total database comprises 114 data records for CS. All the input variables were considered to ensure the universality and precision of the proposed model. Input variables include sand content, fiber content, plastic content, and size and length of fiber used. Moreover, CS was considered as output for the development of the model. The performance and generalization capability of any model greatly depend on the distribution of input variables [51]. The frequency distribution histograms of input parameters can be seen in **Fig. 7**. It is obvious from contour plots that variables have higher frequencies, and the distribution of the input variables is not uniform. It is important to keep in mind that high variable frequencies are necessary for attaining a better model.

Additionally, **Table 5** provides a summary of the statistics indicators and ranges of the various variables included in the development of the models for CS, making the data analysis simple. It is clear that sand and plastic contents lie in the range of 1140 – 1615 kg/m^3 and 285 – 760 kg/m^3. Moreover, the values of CS lie in a range of 11 MPa – 22.43 MPa. A smaller standard deviation indicates that the majority of the values cluster closely around the mean value. Conversely, a greater standard deviation indicates a wider dispersion of data. Skewness refers to the extent to which the probability distribution of a variable differs from being symmetrical around the mean. As stated by reference [52], the optimal range for kurtosis values is between -10 and +10, which indicates the type of probability distribution. The statistical values of skewness and kurtosis indicate that the MEP-based models are viable for a wide range of input data, hence greatly increasing their potential applications. Furthermore, the entire database was divided into two distinct sections: the training area and the validation section. The predictive validity of the model was evaluated with the help of a validation database, and the overall development of the model was accomplished with the assistance of training data.

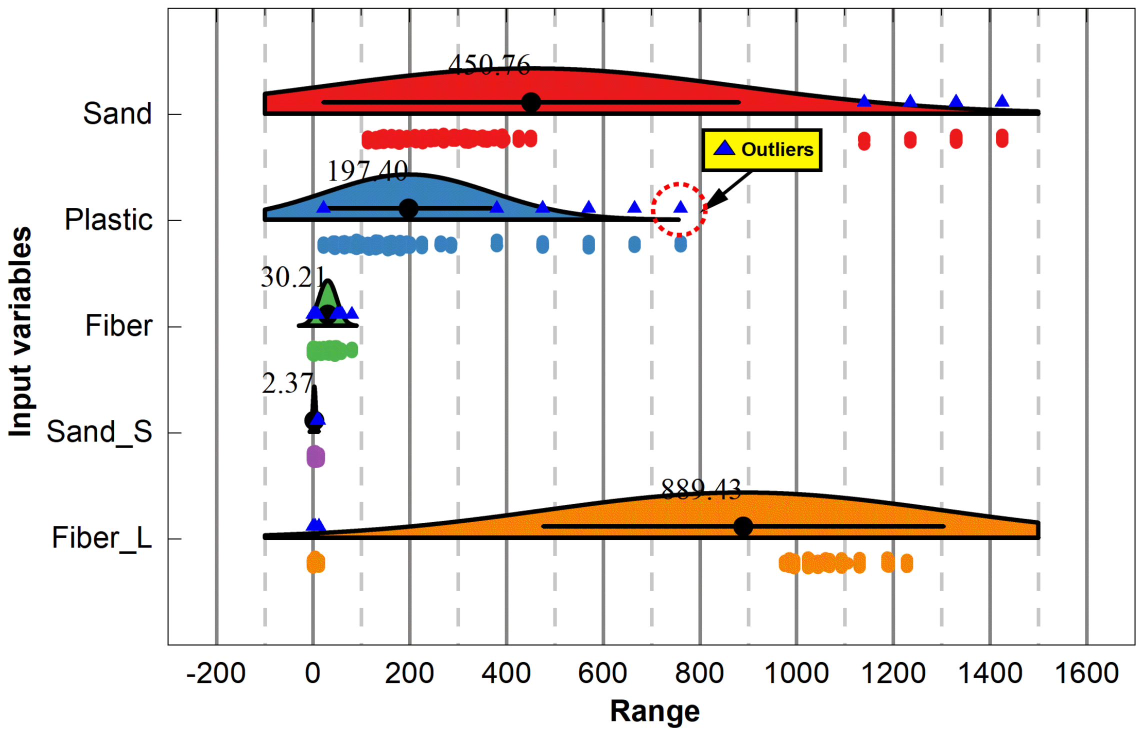


Fig. 6: Raincloud plots for outliers' detection.

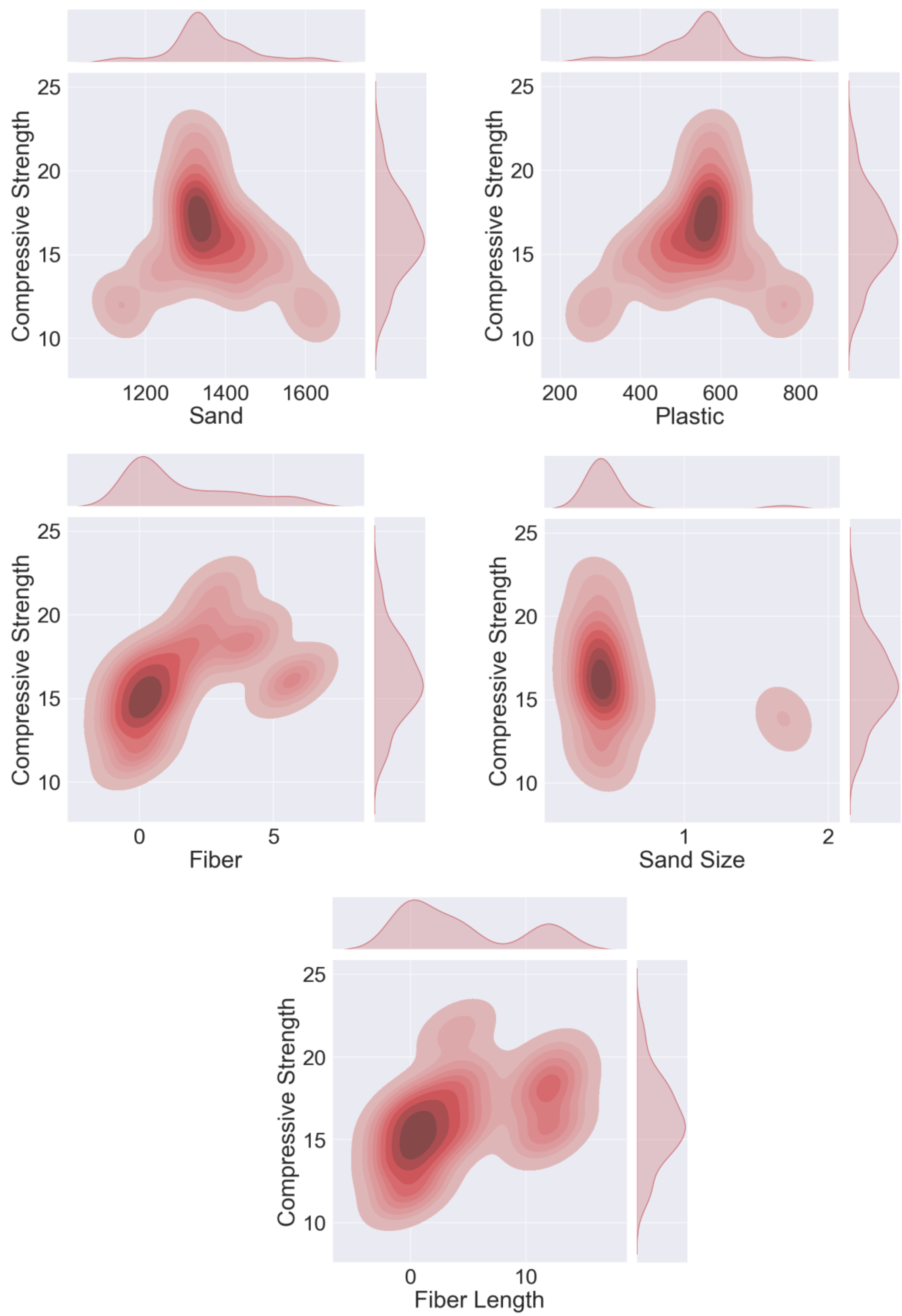


Fig. 7: Contour plots representing data distribution.

Table 5: Statistical description of the developed dataset.

Parameters	Sand (kg/m^3)	Plastic (kg/m^3)	Fiber (kg/m^3)	Sand Size (mm)	Fiber Length (mm)	CS (MPa)
Mean	1360.00	540.00	0.50	1.57	4.21	16.16
Sample Variance	9634.51	9634.51	0.08	3.88	24.59	6.26
Median	1330.00	570.00	0.42	0.63	4.00	15.99
Standard Error	9.19	9.19	0.03	0.18	0.46	0.23
Mode	1330.00	570.00	0.42	0.00	0.00	15.54
Standard Deviation	98.16	98.16	0.29	1.97	4.96	2.50
Kurtosis	1.47	1.47	4.12	-0.43	-1.12	-0.12
Minimum	1140.00	285.00	0.42	0.00	0.00	11.00
Skewness	0.51	-0.51	3.95	0.97	0.75	0.19
Range	475.00	475.00	1.27	5.70	12.00	11.43
Maximum	1615.00	760.00	1.69	5.70	12.00	22.43

3.1.2 MEP model development and assessment

As discussed earlier, to construct a reliable and widely applicable model, a number of MEP modeling parameters must be determined before the modeling process. Considering the prior recommendations, a hit-and-trial method was used in this study to select the best model-fitting parameters [53]. The size of the population determines how many programs will be included in the evolutionary process. If the population size of the model is large, the model will be complicated and precise and may take more time to converge. Overfitting of the model is a potential problem when a particular threshold has been reached. The procedure began with the assumption that there were ten distinct populations. For clarity, the function set considers just the four fundamental mathematical operators (+, -, x, and /). The accuracy level of the model greatly relies on the number of generations. The statistical mistakes in the algorithm would be reduced by running the program for several generations. The frequency with which offspring experience these genetic changes is measured by the crossover rate and mutation. In general, the crossover rate is between 50% and 95%. Numerous combinations of these parametric settings were tried, and optimum parametric settings were selected based on the prediction performance of the models, as displayed in **Table *6*.** Overfitting of the data is the major issue in ML-based models. To prevent this issue, it is suggested that the models should be trained on unseen data sets [54]. Following this, the whole data set has been separated into two parts, i.e., training and validation. Both of the data sets have been checked to make sure they have the same distribution. This work employed 70% and 30% of the dataset for training and validation, respectively. The proposed models performed well across both data sets. A commercially available software program, MEPX v1.0, was used to apply MEP models.

Table 6: MEP model Parameters settings

Genetic operators	
Generations	1000
Code-length	50
sub-population size	240
Arithmetic operations	+, −, ×, ÷
Sub-population count	10
Size of tournament	4
Crossover Probability	0.9
Fitness parameter	RMSE
Probability of mutation	0.01
Training data	70%
Validation data	30%

The first step in the model development is to produce an initial population of viable solutions. The iterative procedure is implemented, and each successive generation converges to the solution. Within the solutions population, each generation's fitness is continuously assessed. The MEP model will continue to develop until the predetermined fitness function, such as root mean squared error (RMSE) or R, no longer shows any indications of alteration. In order to address the problem of overfitting, the study additionally evaluates the objective function (OF). Suppose the findings of the model are not correct for both datasets (training and validation). In that case, the procedure is then rerun by progressively increasing both the number of subpopulations and their overall size. Following that, the model with the lowest OF is chosen to be the best one. It is important to remember that the evolving time of the number of generations has an influence on the correctness of the model. Due to the introduction of additional variables in such methods, a model may keep evolving continuously. However, in this study, the model was terminated after 1000 generations or when the variation in fitness value was smaller than 0.1%. The efficiency of the proposed models is determined by determining various statistical error indices. The metrics used in this analysis are the performance index (PI), the relative squared error (RSE), the relative root mean square error (RRMSE), the mean absolute error (MAE), and RMSE. Similarly, an alternative approach to mitigate overfitting is to select the optimal model by reducing the OF, as recommended by Iqbal et al. [55]. This methodology was chosen to address the problem in this study, and the term fitness function is used for OF. Es (1)-(6) shows the mathematical expressions for these statistical indices.

$$RMSE = \sqrt{\frac{\sum_{i=1}^{n}(exp_i - mod_i)^2}{n}} \quad (1)$$

$$MAE = \frac{\sum_{i=1}^{n}|exp_i - mod_i|}{n} \quad (2)$$

$$RSE = \frac{\sum_{i=1}^{n}(mod_i - exp_i)^2}{\sum_{i=1}^{n}(\overline{exp} - exp_i)^2} \quad (3)$$

$$RRMSE = \frac{1}{|\overline{exp}|}\sqrt{\frac{\sum_{i=1}^{n}(exp_i - mod_i)^2}{n}} \quad (4)$$

$$R = \frac{\sum_{i=1}^{n}(exp_i - \overline{exp}_i)^2 (mod_i - \overline{mod}_i)^2}{\sqrt{\sum_{i=1}^{n}(exp_i - \overline{exp}_i)^2 \sum_{i=1}^{n}(mod_i - \overline{mod}_i)^2}} \quad (5)$$

$$PI = \rho = \frac{RRMSE}{R} \quad (6)$$

$$OF = (\frac{n_T - n_v}{n})\rho_T + 2(\frac{n_v}{n})\rho_v \quad (7)$$

In the given expressions, exp_i and mod_i indicate the experimental and model anticipated outcomes. Whereas $\overline{mod_i}$ and $\overline{exp_i}$ signifies the average model anticipated and experimental outcomes, respectively, and n represents total occurrences. A model is considered accurate when it has a high R-value and minimal statistical errors. Alabduljabbar et al. [56] and Alyami et al [57] stated that an R-value of more than 0.8 indicates a strong connection between the anticipated and actual results. Since it is not affected by multiplying or dividing the outcome by a constant, it cannot be used as a solitary criterion for determining the overall effectiveness of the prediction models. The RMSE and MAE are indicators that are used to measure the average errors. However, each of these indicators has its own importance. RMSE gives greater importance to larger errors since they are squared before a mean is estimated. A high RMSE value shows that the number of estimates with high error is notably larger than anticipated and should be avoided. Meanwhile, MAE gives less importance to larger errors in comparison to the RMSE. Meanwhile, MAE gives less importance to larger errors in comparison to the RMSE. Both PI and OF have values that range between 0 and infinity. According to [58], the reliability of a ML model can be evaluated based on the value of PI and OF. A lesser value of OF indicates that the overall efficiency of a proposed model is better. As previously explained, several different trial runs were performed, and the model that produced the lowest OF is the one discussed in this study. In addition, external validation of the proposed model was done by using criteria given by various scholars [59].

4. Results and discussion

4.1 Experimental findings

4.1.1 Compressive strength

The laboratory-derived CS results of PSPB are depicted in **Fig. 8.** As discussed earlier in the first stage, the effect of sand particle size on CS was determined, as shown in **Fig. 8 (a)**. It can be seen that there is a reverse correlation between CS and sand particle size, indicating that as particle size increases, the CS decreases. This can be attributed to less cohesion between larger grain sizes due to increased contact area as compared to smaller grain sizes of sand [60]. The maximum CS was 15.93 MPa for the finest sand grain size of d < 0.420 mm at fixed a plastic-to-sand ratio of 25:75.

The influence of varying plastic-to-sand proportions on the CS of PSPB is illustrated in **Fig. 8 (b)**. It can be examined that an increase in the percentage of plastic content up to 30% results in a rise in CS. This can be explained by the fact that the optimal mixture was achieved with a plastic-to-sand ratio of 30:70. Whereas a further increase in plastic content results in a decline in CS. This decline in CS can be associated with an increase in the brittleness of the mixture due to the heating of plastic waste. The highest CS was observed as 17.26 MP at a plastic-to-sand ratio of 30:70.

In addition, varying proportions of basalt fiber (0.1%, 0.3%, 0.5%, and 1%) with lengths of 4mm and 12mm were used to further enhance the CS of PSPB, as depicted in **Fig. 8 (c and d)**. The optimum proportions of the plastic-to-sand ratio of 30:70 with a particle size of sand less than 0.42 mm, as achieved in the initial stages, were used to determine the influence of fiber content in PSPB. The findings indicate that the addition of basalt fiber increases CS up to a certain proportion and then decreases. The optimum results of CS with the basalt fiber of 4 mm in length were noted as 19.61 MPa, whereas in the case of 12 mm, the highest CS value was measured as 21.65 MPa at 0.5% fiber content. It can be noted that the use of 4 mm basalt fiber leads to a significant improvement in CS, with an increase of 25.4% as compared to 12 mm, which results in only 13% enhancement in CS. It is due to the fact that there is a restriction on the number of fibers that can be mixed because fibers with a higher aspect ratio and greater lengths reduce workability noticeably, making the mixing process more difficult, which in turn affects their CS [61]. It is worth mentioning that the typical CS of concrete paver blocks has been determined to be 19.8 MPa at 28 days' curing time [62]. The ASTM standard (ASTM C902-00) specifies that for light vehicular traffic, the CS of pavement bricks must be a minimum of 20.7 MPa (the mean of 5) and 17 MPa (individual). Therefore, plastic, sand, and basalt fibers proposed in this study can be efficiently utilized in low-traffic regions. The addition of basalt fibers with a length of 4 mm at an amount of around 0.5% in PSPB yields optimum outcomes.

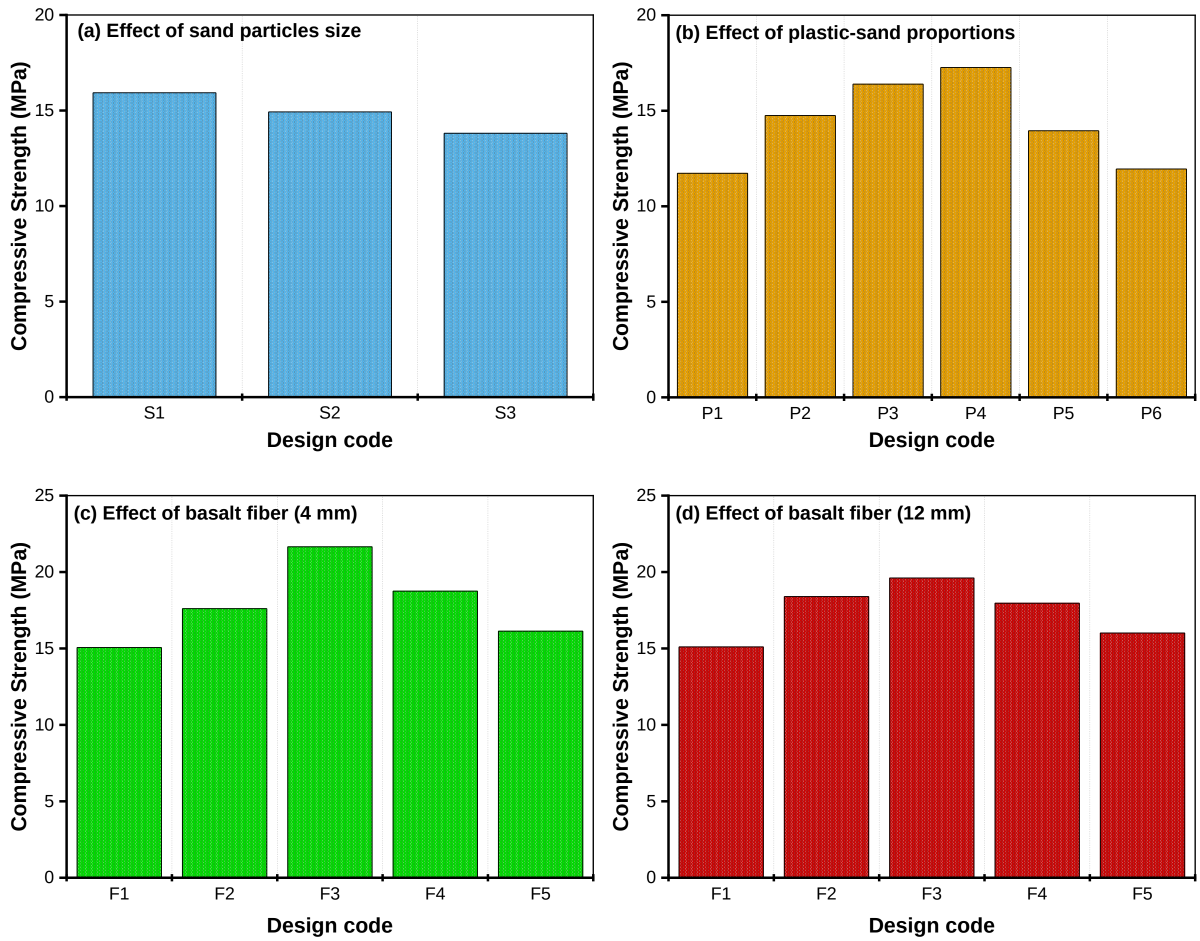


Fig. 8: CS test laboratory results

4.2 Machine learning results

4.2.1 MEP models predictive performance

Fig. 9 illustrates the comparison of the experimental and anticipated CS values of PSPB obtained from the optimum MEP-based model. The MEP model exhibited exceptional performance, with R^2 values of 0.88 and 0.87 during the training and evaluation stages, respectively. Ideally, the slope of the regression line should approach a value of 1. The slope values of 0.87 and 0.79 for the training and evaluation (testing) phases indicate a significant connection between the predicted and actual values in the established model. Moreover, the values demonstrate a high degree of similarity and closely align with the desired fit throughout both the training and evaluation phases. This suggests that the proposed model received adequate training and possesses a strong predictive capability, performing equally well on unfamiliar data. This also illustrates that the issue of overfitting the model has been much mitigated.

Additionally, in order to comprehend the statistical analysis for proposed models, absolute error analysis was performed, as shown in **Fig. 10**. It can be noted that the average error in the anticipated values for CS is 4.5 MPa, with a higher error value that does not exceed 11 MPa.

Overall, less than 5% of the total data points have an error value greater than 5 MPa. It is essential to emphasize the fact that the frequency of occurring maximum errors is substantially lower. Based on the above analysis, it can be stated that the developed MEP model for predicting the CS of PSPB can be used in the design process.

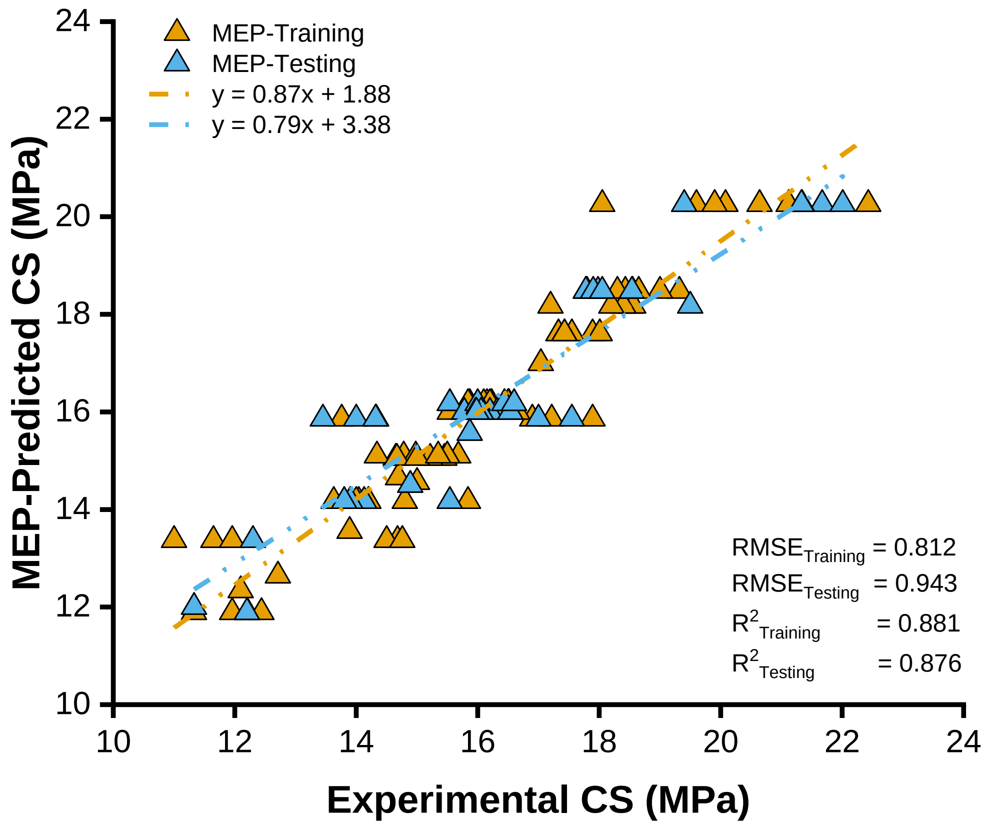


Fig. 9: Experimental Vs MEP-anticipated outcomes.

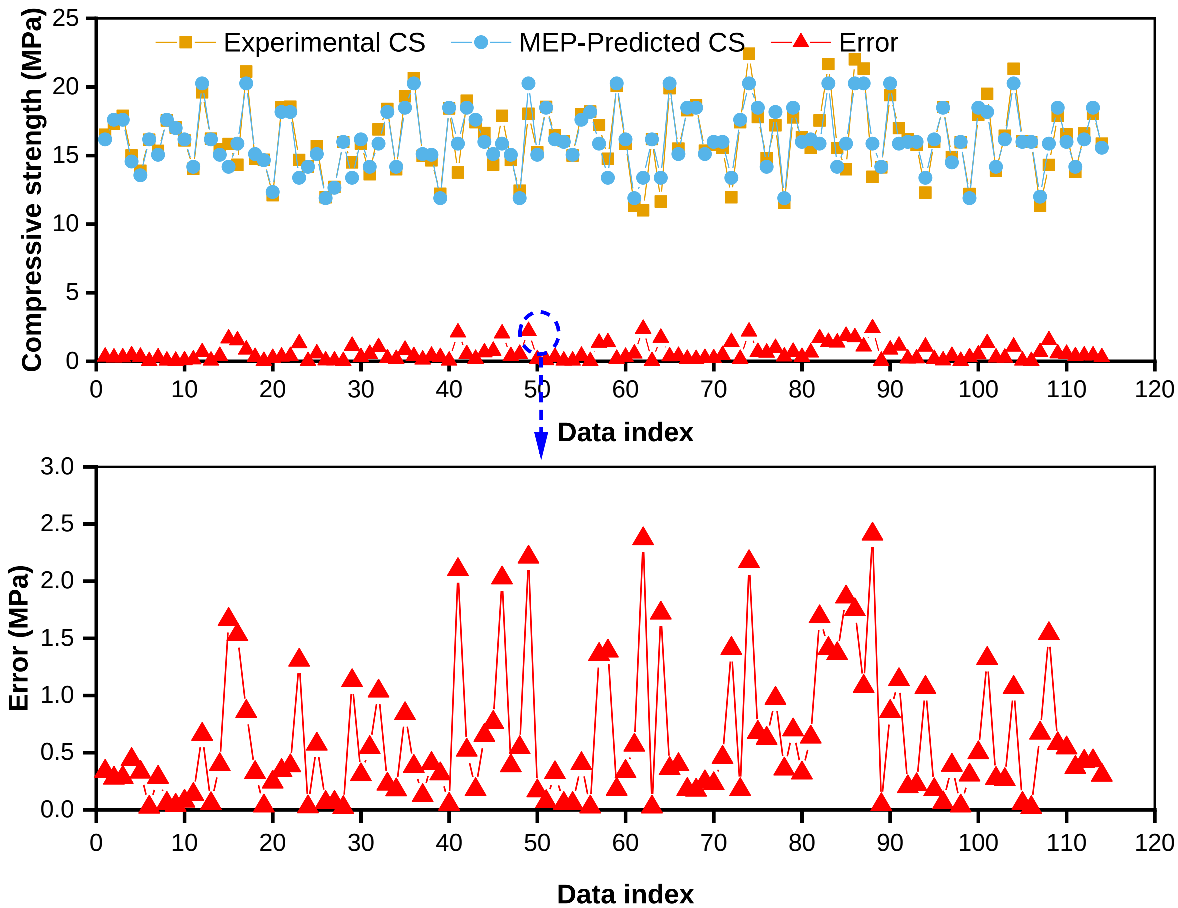


Fig. 10: Error distribution in MEP-anticipated CS results.

4.2.2 MEP-based formulations

After performing the statistical examination of various MEP trials, the optimum trial was chosen for additional analysis. The selected MEP model for CS was decoded to develop the empirical equations based on five input parameters. The development of equations used four arithmetic operators, namely subtraction (−), addition (+), multiplication (×), and division (÷), as previously mentioned. The explicit formulations are represented by the equations (7). These mathematical formulas can be used to estimate the CS of PSPB.

$$CS\ (MPa) = F + 42\,(S_s) - 16\,F^2 - 6\,(F.Ss^2)\frac{(-6 + P + 4.S - Ss)}{F + 4\,Ss} + 8\,F\,.Ss^2\,(-1 + 4.Fl)\,(-4 - 3\,(-6 + F)/4.S^2) \tag{8}$$

4.2.3 External validation of MEP model

The outcomes of statistical criteria employed for the external validation of the proposed models are shown in **Table 7.** Khan et al. [64] reported that for the proposed models to have a better level of precision, the slope of one of the regression lines (k or k') that pass through the center should be relatively near to one. For proposed models, these values can be noted as 0.947, which is in the acceptable range. Furthermore, if the values of the evaluation metrics (i.e., m and n) are less than

0.1, then they are regarded as adequate. A number of researchers have suggested that the squared coefficient ($R_o{}^2$) of experimental and estimated values should also be near to 1 [65]. It can be seen that all of the evaluated models lie in the recommended range of outcomes, making it obvious that the recommended models can satisfy the conditions for external verification. This demonstrates the MEP models' exceptional validity, predictive capability, and independent correlations between input and output.

Table 7: External validation of the MEP model.

S. No.	Equation	Model	Acceptable range
1	R	0.96	$R > 0.8$
3	$R'_o{}^2 = 1 - \frac{\sum_{i=1}^{n}(exp_i - mod_i{}^o)^2}{\sum_{i=1}^{n}(exp_i - exp_i{}^o)^2}$, $mod_i{}^o = k' \times exp_i$	0.961	$R'_o{}^2 \cong 1$
2	$R_o{}^2 = 1 - \frac{\sum_{i=1}^{n}(mod_i - exp_i{}^o)^2}{\sum_{i=1}^{n}(mod_i - mod_i{}^o)^2}$, $exp_i{}^o = k \times mod_i$	0.99	$R_o{}^2 \cong 1$
4	$k = \sum_{i=1}^{n} \frac{(exp_i \times mod_i)}{exp_i{}^2}$	0.971	$0.85 < k < 1.15$
5	$k' = \sum_{i=1}^{n} \frac{(exp_i \times mod_i)}{mo_i{}^2}$	1.032	$0.85 < k' < 1.15$
6	$m = \frac{(R^2 - R_o{}^2)}{R^2}$	0.0441	$m < 1$
7	$n = \frac{(R^2 - R'_o{}^2)}{R^2}$	0.0535	$n < 1$

4.2.4 Sensitivity and parametric analysis

While working with ML-based modeling, it is essential to carry out a wide range of assessments to validate that the indicated models are reliable and work efficiently when applied to a diverse set of data. In this study, sensitivity analysis (SA) and parametric analysis (PA) were done to ensure the validity of the proposed MEP models. Firstly, SA is studied to determine the relative effect of input variables (ingredients) on the outcome (i.e., CS) of the proposed MEP model. The SA is evaluated by using Eqs (9) and (10) for a given input parameter yi.

$$X_i = f_{max}(y_i) - f_{min}(y_i) \qquad (9)$$

$$SA = \frac{X_i}{\sum_{n}^{j=1} X_j} \qquad (10)$$

where $f_{max}(y_i)$ and $f_{min}(y_i)$, indicates the largest and minimum of the forecasted outcome, accordingly on the basis of the ith input variable, while the other input variables are kept constant at their mean values. When SA is performed on the entire dataset, it shows how sensitive a constructed model is to a particular change in the defined parameters. The outcomes of the SA are shown in **Fig. 11**. Among the five inputs being analyzed, the size of sand particles (S_S) and fiber content (F) have the greatest impact, contributing 33.02% and 21.56%, respectively, to the anticipated compressive strength (CS) of PSPB. Conversely, the sand content (S) and fiber length (F_L) are identified as the least influential factors, contributing just 15.57% and 12.44%, respectively, to the predicted CS. These findings are highly comparable with experimental outcomes, indicating the validity of the models.

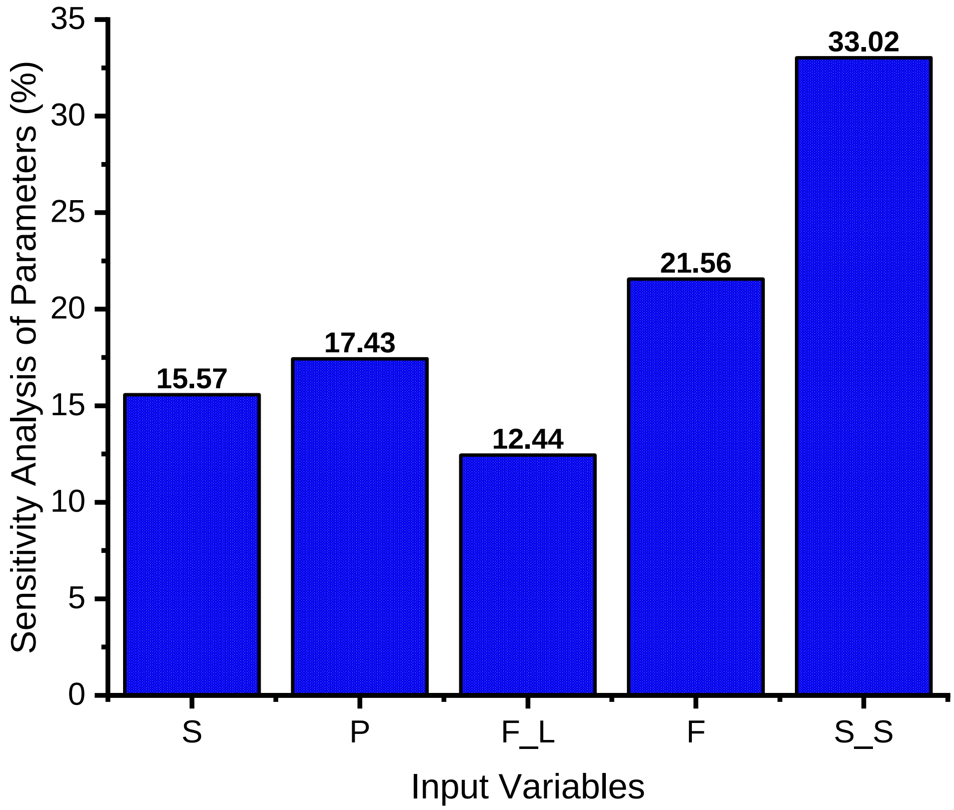


Fig. 11: Sensitivity analysis CS-MEP

To further evaluate the validity of the recommended models, PA, also known as monotonicity analysis, has been recommended by various research studies, and thus, it is also implemented in the presented study. In the parametric study, one input variable varied while the values for other input variables were fixed at their mean values. When these input features are combined with the MEP models that have been developed, it is possible to determine the corresponding change in the output parameters, such as CS. The pattern of CS with a corresponding input parameter is presented by fixing all other variables at their average scores across the full range of defined input variables. **Fig. 12** provides the findings of the parametric analysis for the created CS-MEP model. The CS of PSPB is considerably influenced by increasing the plastic concentration up to a certain limit and then decreasing. At first, the CS experiences a rapid rise as a result of the initial mixing of the preheated plastic and sand. Nevertheless, after the addition of 500 kg/m^3 of plastic, this graph approaches a state of near-constancy. The results align with the findings of [66] and [60], which indicate that an increase in the amount of plastic enhances the bonding between particles, increasing CS. The optimum amount of plastic content was noted as 28%, which is very near to the experimental findings which was 30%. The inverse relationship between the particle size of sand and the CS of PSPB was observed. It is clear that an increase in sand size results in a decline in CS due to greater contact area and lesser cohesion between particles. The same trend was also found in experimental investigations. Likewise, the fiber content significantly impacts the CS of PSPB. By maintaining all other input components at a similar level, the increase in fiber content up to 0.48% (3 kg/m^3) results in an increase in CS; further addition of fiber, leads to a decline in CS. These findings are well aligned with laboratory-derived outcomes. The prior research has already highlighted the identical impact of the fiber content on the CS of PSPB [67]. The sand content and fiber length have a relatively lower influence on the CS of PSPB. It can be noted that a fiber length of 4 mm has shown higher strength than 12 mm. In the case of sand content, the graph remains consistent with little increment in CS by decreasing sand initially and by increasing sand later.

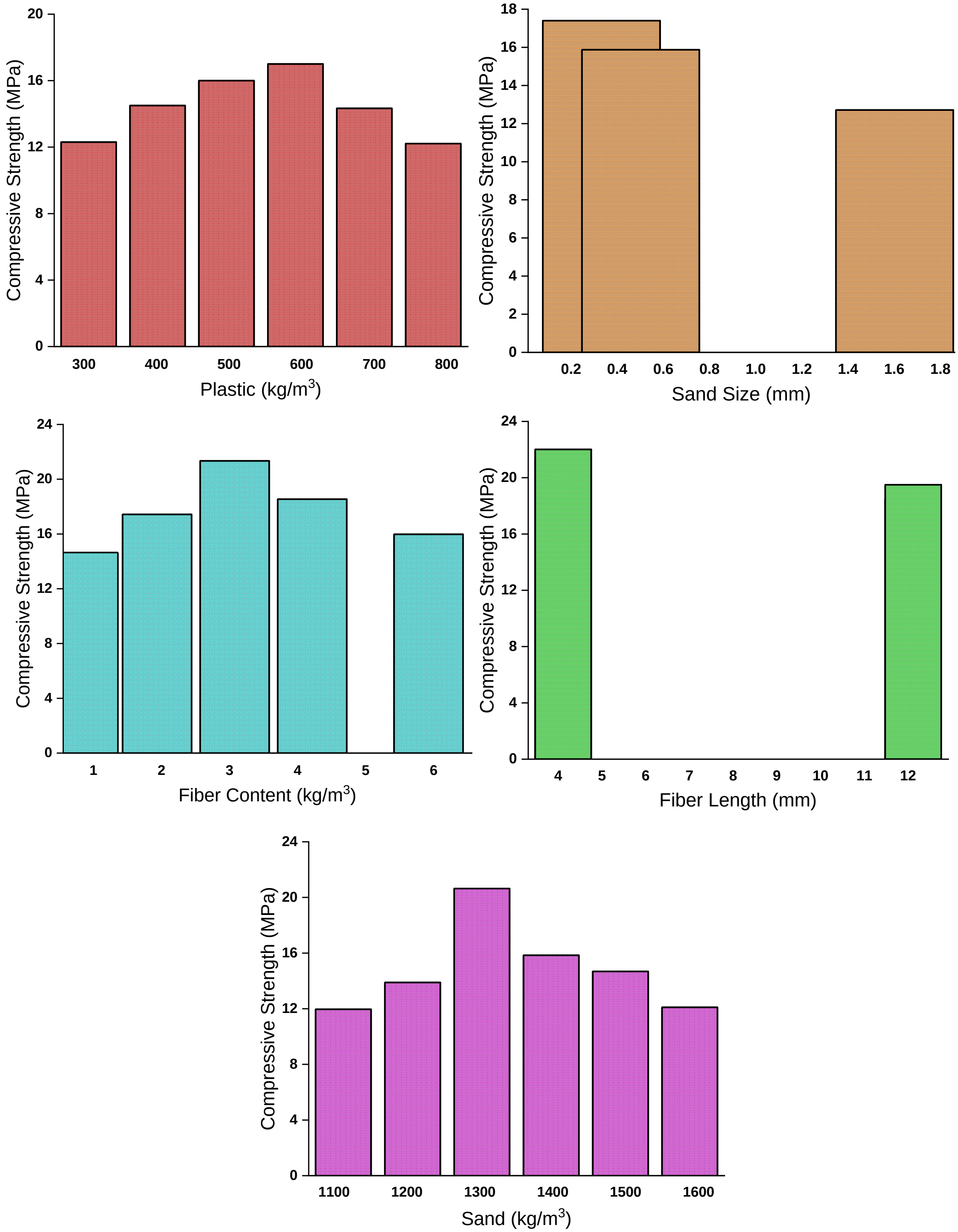


Fig. 12: Parametric analysis of input parameters

4.2.5 MEP model evolution and comparison with multi-linear regression (MLR)

The size of the database utilized for developing a model substantially affects the credibility of the model. Previous studies recommended that the ratio of recorded data points to the number of input parameters that were used in both the training and evaluation (testing) stages should exceed 5. In this study, this ratio is 23, which is much higher than the recommended values. The efficacy of the suggested model is examined by using statistical measures, as discussed in section 3.1.2, and the results are also compared with MLR, as shown in **Table 8**. It can be noted that MEP shows enhanced performance as compared to MLR, as is evidenced by a strong relationship between actual and anticipated values, exhibiting R values of 0.938 and 0.936 for the training and testing set of the CS-MEP as compared to MLR, which has R^2-value 0.861 and 0.825. The high efficiency and generalizability of the proposed MEP models are also indicated by substantially low values of MAE, RMSE, and RRSME across both sets. The RMSE for CS is close to 0.81 MPa and 0.944 MPa, whereas the values for the MLR model are 1.2 MPa and 0.97 MPa for the training and validation stages, respectively. The MAE values are 0.54 MPa and 0.724 MPa for MEP, while the MLR model has values around 0.8 MPa and 0.811 MPa. The values for PI are less than 0.20 for both the training and validation stages of MEP and MLR models. Therefore, the models have higher accuracy and prediction performance. Overall, based on comparison, it can be stated that MEP outperformed MLR with enhanced accuracy in terms of error analysis. The comparison among experimental, MEP, and MLR CS values is visually presented in **Fig. 13**. It is clear that there is a minor difference between the outcomes, which indicates the better efficacy of the proposed models.

Table 8 Statistical summary of MEP and MLR.

Model	Phase	R^2	RRMSE	RSE	RMSE	R	MAE	PI	OF
MEP-CS	Training	0.881	0.05	0.157	0.81	0.938	0.554	0.027	0.026
	Testing	0.876	0.057	0.084	0.944	0.936	0.724	0.029	
MLR-CS	Training	0.742	0.075	0.348	1.202	0.861	0.801	0.041	0.04
	Testing	0.681	0.055	0.481	0.97	0.825	0.812	0.03	

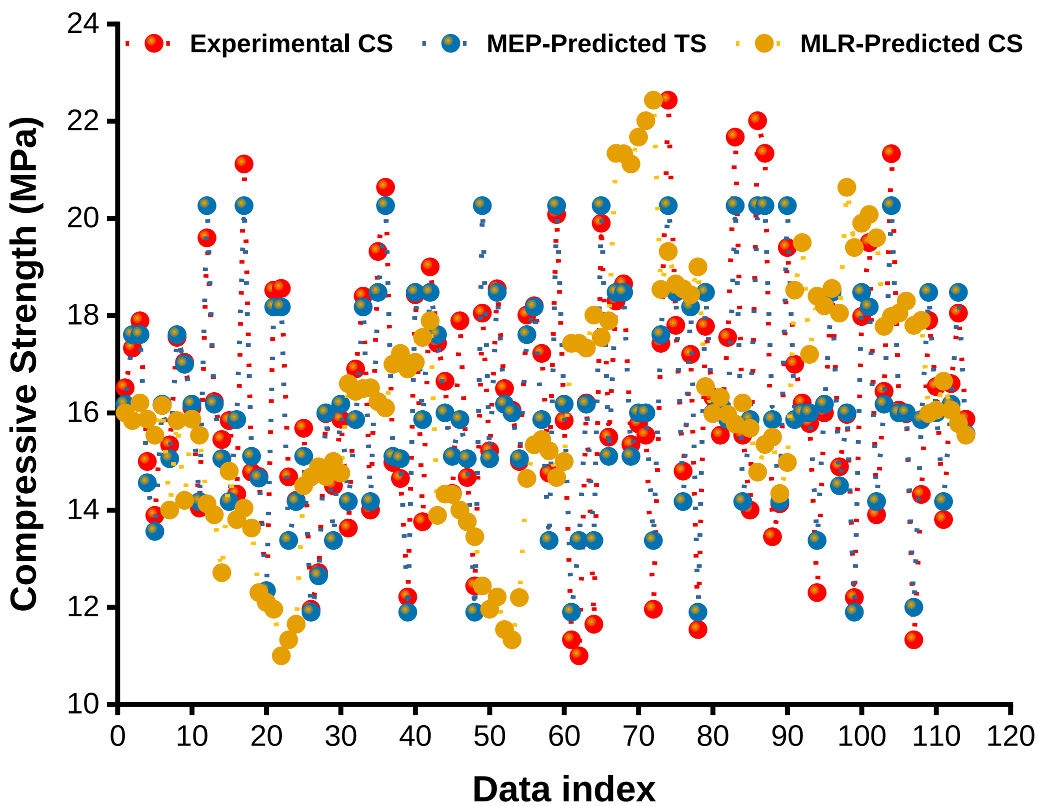


Fig. 13: Comparison between MLR and MEP models for CS.

4.2.6 Comparison with Literature

This study employs a data set from experimental investigations performed in the laboratory to create models, as previously stated. Therefore, there are no existing models with similar datasets to compare the effectiveness of the proposed models. Nevertheless, the outcomes of the present investigation are compared with alternative machine learning models that are constructed employing other databases on PSPB, as depicted in **Table 9**. The outcomes that result from the proposed model demonstrate a significant similarity to the findings reported in the available research for different models. The findings of this study demonstrate that equations derived from the MEP are reliable and useful pre-design predictors for the eco-friendly. The probable use of this innovation can significantly decrease time, expenditure, and allocation of resources, which represents a notable advancement for the corresponding field.

Table 9: Comparison of proposed models with existing literature.

Proposed models	Technique	Material used	R^2	RMSE	MAE	References
CS	**MEP**	**Plastic waste**	**0.891**	**0.94**	**0.554**	**This study**
CS	GEP	Plastic waste	0.87	1.171	1.001	Iftikhar, C. Alih, et al. [68]
CS	MEP		0.90	1.115	0.981	Iftikhar, C. Alih, et al. [68]
CS	GEP	Plastic waste	0.89	1.10	0.76	

4.2.7 Role of artificial intelligence in sustainable built environments

Artificial intelligence (AI) is essential in developing a sustainable environment by providing efficient waste management methods, such as using plastic trash as a construction material in concrete products. Previously, various AI applications have been successfully used to address the problems associated with the environment, such as waste management [69], [70]. AI-based models provide cost-effective and time-saving models with accurate estimations [71], [72]. Considering the above fact, this study utilized MEP-based ML models to make fast predictions and create mathematical formulas for determining the optimum use of waste plastic in producing paver blocks. MEP models provide economical methods for tackling difficulties related to reducing plastic waste, which enables their incorporation into practical applications. This novel method not only promotes ecologically sustainable environments but also demonstrates the adaptability of AI in enhancing resource efficiency in handling waste.

The present study utilizes extensive validation approaches such as statistical evaluations, comparison with MLR, and sensitivity analysis to assure the dependability of the MEP models. These approaches evaluate the precision and resilience of the prediction models, offering a thorough assessment of their performance. Utilizing these validation methodologies improves the credibility of the AI-based solutions used for eco-friendly environments. This study also provides a Graphical User Interface (GUI) based on the data gathered from the training database, which will be a useful tool for estimating the CS of plastic paver blocks and their desired elemental proportions. Users can utilize GUI to assess the CS of paver blocks by inputting certain parameters inside the defined data range of the research. The GUI enables easy access for users and encourages more usage of AI-driven waste management solutions for sustainable and effective resource utilization in building applications. The developed GUI is visually depicted in **Fig. 14**.

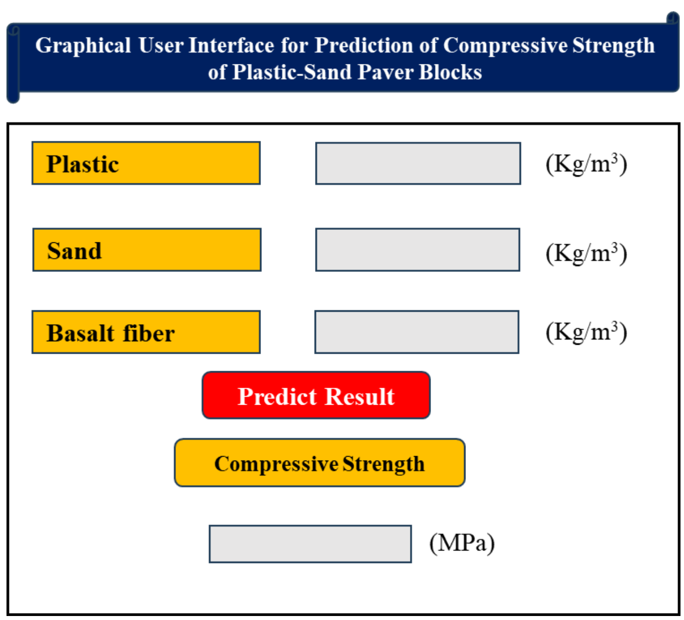


Fig. 14: GUI for estimating CS of PSPB.

5. Conclusion

This study presents comprehensive experimental testing to assess the viability of using plastic waste as an environmentally friendly alternative in paver blocks, addressing substantial concerns regarding plastic waste and CO_2 emissions associated with cement manufacture. Varied mix ratios of plastic and sand with different particle sizes of sand were employed. Additionally, to enhance the CS and meet the minimum acceptable level of ASTM C902-15 for light traffic, basalt fibers, a sustainable industrial material, were also utilized in the manufacturing process of environmentally friendly PSPB. Further, using experimental findings, an extensive database was created and used to create MEP-based models to estimate the CS of PSPB. The efficacy of MEP models was validated by using various statistical, sensitivity, and parametric evaluations. The following deductions can be made from this study.

a) In experimental findings, the impact of sand particle size on the CS of PSBC was initially determined. It was found that there is a negative correlation between CS and sand particle size.
b) Secondly, the influence of varying plastic-to-sand proportions on the CS was determined, and it was identified that that an increase in the quantity of plastic content up to 30% results in a rise in CS, whereas a further increase in plastic content results in a decline in CS.
c) The highest CS was observed as 17.26 MP at a plastic-to-sand ratio of 30:70 using the finest sand particle of $d < 0.420$ mm.
d) The inclusion of 0.5% basalt fiber, measuring 4 mm in length, yields further enhancement in outcome by significantly improving CS by 25.4% (21.65 MPa).
e) The proposed MEP model demonstrates outstanding results in accurately describing the correlations between the input characteristics and CS of PSPB, as indicated by the high R^2 of 0.89.
f) The sensitivity analysis showed that the size of sand particles and fiber content have the greatest impact, contributing 33.02% and 21.56%, respectively, to the anticipated CS of PSPB. The parametric analysis also validated the model performance by showing a similar trend to that found in the experimental findings.
g) MEP proposed a simplified closed-form mathematical formula and GUI for forecasting the CS of PSPB, which can contribute to sustainable practices by providing a design tool for using plastic waste as a sustainable alternative for cement in paver blocks.

6. Limitations and future work

Although this study provides valuable insights into the use of plastic in pavers through experimental investigations and machine learning optimization, it has several limitations. The proposed equations and the graphical user interface (GUI) are restricted to the range of inputs used in this study. This constraint limits the generalizability of our findings to broader applications.

In future work, it is recommended that the database be expanded to include a wider variety of parameters and conditions. This enhancement would allow for more robust modeling and optimization. Additionally, advanced machine learning techniques could be employed to improve predictive accuracy and model performance. Further, SHAP (SHapley Additive exPlanations) analysis can be conducted to gain deeper insights into the contributions of different parameters.

Credit statement:

Usama Asif: Conceptualization, Methodology, Software, Machine learning, Data Curation, Investigation, Validation, Writing-Original Draft, Writing – Review and Editing, Visualization**.** **Muhammad Faisal Javed:** Conceptualization, Methodology, Validation, Investigation, Writing – Review and Editing, Supervision. **Deema mohammed alsekait:** Project administration, Funding acquisition, Resources. **Diaa Salama AbdElminaam**: Investigation, Conceptualization, Resources. **Hisham Alabduljabbar:** Project administration, Funding acquisition, Resources.

Declaration of Competing Interest:

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Data availability:

Data will be made available on request.

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