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A machine learning-based genetic programming approach for the sustainable production of plastic sand paver blocks

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ABSTRACT

Plastic sand paver blocks (PSPB) provide a sustainable alternative by reprocessing plastic waste and decreasing reliance on environmentally hazardous materials such as concrete. They promote waste management and environmentally favorable building practices. This paper presents a novel method for estimating the compressive strength (CS) of plastic sand paver blocks based on gene expression programming (GEP) techniques. The database collected from the experimental work comprises 135 compressive strength results. Seven input parameters were involved in predicting the CS of PSPB, namely, plastic, sand, sand size, fiber percentage, fibre length, fibre diameter, and tensile strength of the fibre. Simplified mathematical expressions were used to figure out the CS. The results of GEP formulations showed that they were better in line with the experimental data, with R^2 values for CS of 0.89 (training) and 0.88 (testing). The models' performance was evaluated using sensitivity analysis and statistical checks. The statistical evaluations show that the actual and predicted values are closer together, which lends credence to the GEP model's capacity to forecast PSPB CS. The sensitivity analysis showed that sand size and fibre percentage contribute more than 50% of the CS in PSPB. In addition, the results demonstrate that the proposed models are accurate and have a robust capacity for generalization

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and prediction. This research can improve environmental protection and economic benefit by enhancing the reuse of PSPB in producing green ecosystems.

1. Introduction

Plastic is an incredible man-made innovation; nevertheless, its non-biodegradable nature has many negative environmental consequences. Pollution from plastic has grown to be the greatest challenge to contemporary civilization, resulting in environmental degradation and economic damage [1]. The enormous accumulation of plastic waste (PW) in the ecosystem has presented a threat to multiple aquatic organisms and the sustainability of the environment. Water pollution occurs when PW is dumped into bodies of water like rivers and seas, where it is subjected to the sun's rays and the forces of the water and the waves [2,3]. Microplastics formed by plastic's weathering have been linked to health issues in animals due to bioaccumulation and biomagnification [4,5]. Furthermore, PW can obstruct drains, which can lead to floods [6] and the proliferation of parasitic insects [1] and water-borne diseases. Some PW accumulates in aquatic habitats or is released there [7], and the large amount of PW that is typically disposed of instead of recycled has grown into an essential enthusiasm for creating effective PW management practises [8–10]. It's difficult to fathom the whole scale of the PW issue. Fig. 1 [11] from the research published in scientific advances, cited in the Forbes article from 2020, identifies the top 10 largest countries responsible for manufacturing more PW per person per nation. Because of its poor biodegradability, plastic has worsened a number of environmental difficulties while also posing hazards to locals.

Consequently, the increasing manufacturing of cement and the resulting emission of CO_2 are another severe environmental threat that environmentalists are concerned about. Cement usage must be reduced to protect the environment [12–14] since cement processing generates a comparable quantity of CO_2 when cement-based products like mortar, concrete, and PB. Reducing cement usage can dramatically reduce CO_2 productions, which accounts for around 0.9 tonnes of CO_2 for every 1.0 tonnes of cement [15]. About 8% of all manmade CO_2 emissions come from the cement industry [16]. The traditional paver block (PB) uses 210 kg/m^3 of cement, contributing to considerable CO_2 productions [17]. But using cement in PB manufacture as a bonding agent has resulted in global warming by releasing greenhouse gases [18]. Several significant emissions from cement facilities must be addressed [19]. These include dust, nitrogen oxides, carbon dioxide, and sulphur dioxide. Calcium oxide and lime also harm human tissue due to their cement concentration [20]. Additionally, concrete includes trace levels of crystalline silica, a substance that is abrasive to the skin and can irritate the lungs [18] and pollute the environment. Alternative materials should be sought in order to reduce cementitious material use. It is feasible to employ PW rather than cement as a binding medium, which will assist eliminate the PW and minimise the carbon footprint [21] and related health concerns.

Therefore, one alternative to using PW as a binding material is in manufacturing of paver blocks (PB)s [22]. PB is one of the most common solutions for flexible surface treatment applications. These blocks are comfortable to walk on, highly durable, easy to maintain, and aesthetically beautiful. PB in various forms and colours are available, which makes them immensely adaptable. Both residential and commercial premises can be used for these blocks. These PB are extremely easy to fit, and no extra installation equipment is required.

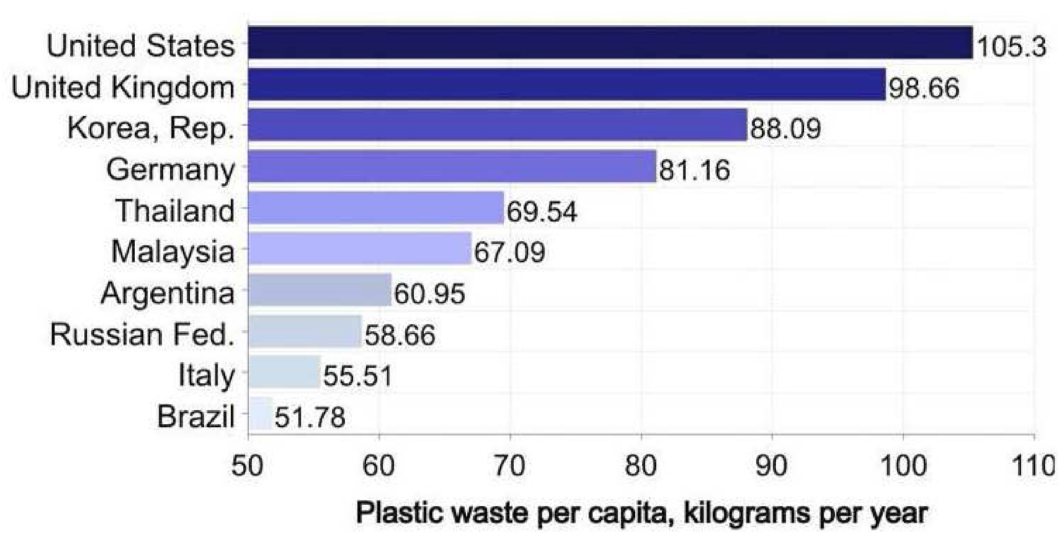

Fig. 1 – PW produced per person, per nation [11].

Besides, special care is not needed compared to concrete or asphalt surfaces. The blocks are clean and shiny with water washing. The most crucial feature of PB is their easy replacement, i.e., if one block is damaged, it can easily be replaced with another. Moreover, these PB can be used for pedestrians and traffic [23]. Also, having the property to absorb low water, these can be used in waterlogged areas [24]. Similarly, cement is the major component and is widely used in concrete PB; nevertheless, it is essential to reduce cement usage to reduce CO2 emissions [17]. Concrete PB has been widely utilized in pedestrian pathways, parking lots, container yards, and roadways for decades [25,26]. It takes time for cement to cure and reach its full strength, therefore using it is equally time-consuming [27]. Also, PB consumes a great deal of cement [17], thus minimising cement consumption is important.

Cement in PB can be reduced by using PW as a replacement [28,29]. In 2006, Pierre Kamsouloum of Cameroon made PB from sand and using recycled PW for the first time. Recycled PW can be utilized in place of cement as a binder in PB synthesis, according to Agyeman et al. [24]. Using PW in building projects is beneficial to environmental sustainability [7]. Similarly, the PW in the PB makes it 15% lighter than a concrete block [30]. The economic analysis shows that the unit cost of the cement-less plastic PB is 35.39% lesser compared to that of a typical concrete block [17]. Because of its lower weight and ability to prevent harmful impacts on the environment, a plastic paver is also more cost-effective. The importance of PSPB in the construction sector has been shown in Fig. 2.

The compressive strength (CS) of plastic concrete PB varies primarily based on the w/c ratio, the time the mixture is allowed to cure, and the type of plastic material utilized [31]. To deal with this scenario, removing the cement from plastic PB will also remove the w/c ratio and curing time. Also, concrete pavement blocks are prone to fracture when subjected to traffic loads (bending failure) [23]. The mechanical properties must be increased. As previously documented by researchers, incorporating fibres increases mechanical properties [32,33]. When deciding on a fibre, it's important to consider the needs for its final use [34]. Based on the availability and excellent mechanical properties of basalt fibre [35,36] and coconut fibres [37,38] have been studied in this research.

Before plastic sand blocks can be widely utilized in the construction sector, it is crucial to understand the link between the amounts of a mixture and its mechanical characteristics. Soft computing approaches have grown in favour of constructing factual models to boost the widespread usage of harmful materials in the construction sector. The latest developments in artificial intelligence (AI) have made it feasible to design precise and accurate models to resolve issues encountered in structural engineering [39–41]. The use of AI approaches is based on the use of natural tools such as fuzzy logic [42], support vector regression (SVR) [43], artificial neural networks (ANN) [44], genetic programming (GP) [45] and genetic algorithms (GA) [46]. These solutions handle the problem by training on the available data. The AI approaches can be used in engineering because they simplify complex patterns. Nonetheless, most of these solutions necessitate a predetermined foundation form, which requires substantial memory. Additionally, when these approaches are applied, the hidden neurons, which are found in vast numbers, hamper the formation of a real correlation between inputs and outputs. The ANN approach was used to forecast the concrete strength integrating rice husk ash (RHA) and reclaimed asphalt pavement (RAP) as partial replacements for OPC and sand, respectively [47]. ANN's predictive strength model demonstrated excellent unity with experimental data from 66 datasets. Another investigation on using ANN in self-compacting concrete (SCC) mix proportioning was examined [48]. While these models generated an excellent correlation, no empirical formulation was provided for practical use. This is due to the ANN model's complicated architecture, which is usually mentioned as a primary hurdle to the technique's widespread adoption [49]. The accuracy of ANN and GP modeling strategies for forecasting the punched shear strength of slabs of concrete was evaluated in this study [50]. Due to the intricacy of ANN models, it was established that they are prone to be overfitted when linked to the model values. Additionally, in these models, multicollinearity was reported. Further, it has been possible to forecast the mechanical properties of concrete using modified ANN methods when additional materials, such as silica fume and recycled aggregate been added to the mix. The properties forecasted were the CS (f'c) and the elastic modulus (Ec), respectively [51]. As a result, a complex relationship was developed, therefore. A specialized graphical user interface (GUI) was developed to facilitate the practical deployment of the concept [52].

Genetic programming (GP) is an effective soft computing technique that avoids assuming the past shape of an existing connection while creating a new modeling model [53]. Gene expression programming (GEP), a subset of genetic programming (GP), entails using linear chromosomes of a defined length to encode an elementary programme. GEP has the advantage of describing its results in simplified mathematical

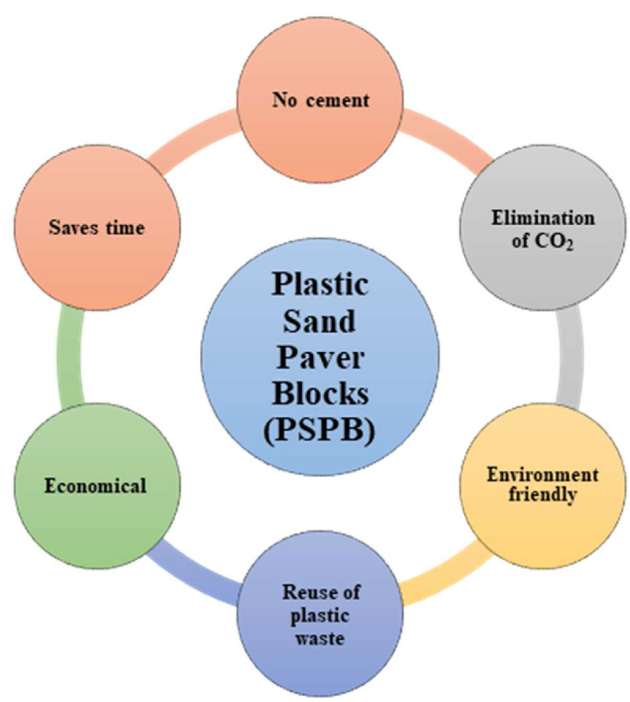

Fig. 2 – Importance of PSPB.

equations that are easier to use in the real world while providing a more accurate forecast. It has lately been adopted instead of more conventional prediction approaches, most notably in civil engineering [54–56].

Earlier researchers have focused on the experimental method for determining the optimal amount of plastic to utilize in PSPB to reach the desired standard strength [24,57]. Mechanical properties are critical when a material is employed in the construction industry. The availability of trustworthy equations to link the mixed proportion and mechanical properties of PSPB can help save money and time while promoting its use in the building sector. Literature reveals no GEP model has yet been identified for predicting the CS of PSPB composed of plastic, sand, and fibres. As a result, this work aims to close this research gap by utilizing the GEP approach to develop simplified empirical relationships capable of adequately predicting the CS of PSPB. Creating a precise model that correlates to the PSPB mixture proportion is crucial for saving time, money, and significantly reducing environmental impact. Consequently, the experimental data was compiled and utilized based on previously published work [22,58]. To evaluate the CS of PSPB, the GEP method was utilized. Based on the R^2 value, the difference between experimental and predicted CS, and errors assessment (MAE, MAPE, RMSLE, and RMSE), the results of the GEP model were evaluated. The GEP technique is more precise than ML algorithms for estimating the CS, according to prior studies [59–61]. Nevertheless, identifying and recommending the optimal ML strategy for predicting outcomes in various research fields is challenging due to the fact that the efficacy of an ML approach is highly dependent on the number of input parameters and datasets used to execute algorithms. The application of such algorithms will benefit the construction industry by fostering the development of rapid and cost-effective methods for testing material properties.

2. Research methodology

In the following part, we will examine the methodologies utilized in constructing empirical models of PSPB's mechanical features. After the brief explanation of GP and GEP, the research approach will be discussed in this investigation.

2.1. *Overview of GP and GEP*

Koza (1992) [62] explained how genetic and natural selection concepts might be used for GP [39,63]. It introduces non-linear structures (parse trees) instead of fixed-length binary strings to make GP a more versatile programming tool. The evolution of problem-solving computer programmes utilizes Darwinian reproduction and artificial analogues of natural genetic operators, including reproduction, crossover, and mutation, to tackle ill-defined challenges across several domains [62,64]. A strategy is developed at the reproduction stage to determine which programmes should be terminated. During the implementation phase, a predetermined proportion of the least suitable trees are removed, while the leftover trees are added to the population using the selected mechanism [65,66]. Sardemir (2010) [66] explains how the mutation approach restricts the model from premature convergence. Fig. 3 illustrates how a computer programme evolves to use the GP technique to resolve a problem.

The GP approach requires the specification of five significant parameters: a set of terminals, fitness measures, primitive functions, run controlling parameters, and a method for defining results and termination criteria [62,66]. Although GP represents three genetic operators, practically only tree crossover is used, resulting in a massive population of parse trees [62]. The other disadvantage of GP is the absence of an autonomous genome. GP cannot create basic and rudimentary expressions because its non-linear structures must serve as both genotype and phenotype [63].

GEP is a variant of GP suggested by Ferreira [63] and is established on the evolutionary population theory. It mixes essential linear chromosomes (GA) with parse trees. The required parameters correspond to those specified in the GP, namely the (a) fitness function, (b) terminal set, (c) terminal conditions, (d) function set, and (e) control parameters. During computer programme processing, this technique compares a character string having a fixed length to a parse tree of changing size in the GP. Individuals are recorded as fixed-length linear strings (genomes) that are then expressed as non-linear entities called expression trees (ETs). These ETs are tree-like structures resembling chromosomes in various sizes and forms [66]. This is analogous to claiming that GEP separates genotype and phenotype and that programming can use all evolutionary benefits [63]. A unique feature found in GEP is that, to the next generation, it transfers only the genome, eliminating the need to replicate and change the general structure, as all mutations occur inside a basic linear structure. Additionally, by a single chromosome, individuals are generated that contain many genes classed as head or tail [66]. Each GEP gene consists of a single variable of a defined length, terminal sets of constants, and functions for performing arithmetic operations. In the genetic code operator, each chromosome symbol corresponds precisely to the corresponding function or terminal, having a one-to-one link. The genetic process enables the evolution of chromosomal diversity in the GEP [39]. To deduce this information, a new language called Karva has been developed. The data required to create empirical relationships are encoded in the chromosomes. If the sequence of a gene is known, it is possible to deduce the exact phenotype and vice versa. This is referred to as Karva expression (K-expression) [63]. Karva's metamorphosis into the ET begins at the ET's leading position and continues throughout the string. ET may be translated to the K-expression by capturing nodes extending from the root to the deepest layer [53]. Because the range of ETs changes in the GEP algorithm, a precise amount of duplicated elements are present that are not used for genome mapping. As a result, the lengths of the GEP and K genes may or may not be equal.

The algorithm of GEP is depicted in Fig. 4. The procedure starts with producing random chromosomes of a set length for all individuals. After that, ETs express these chromosomes, and each fitness is determined. Physically acceptable individuals are picked to undergo the reproduction process. Several generations of iterations with new individuals are performed until the optimal solution is found. Genetic

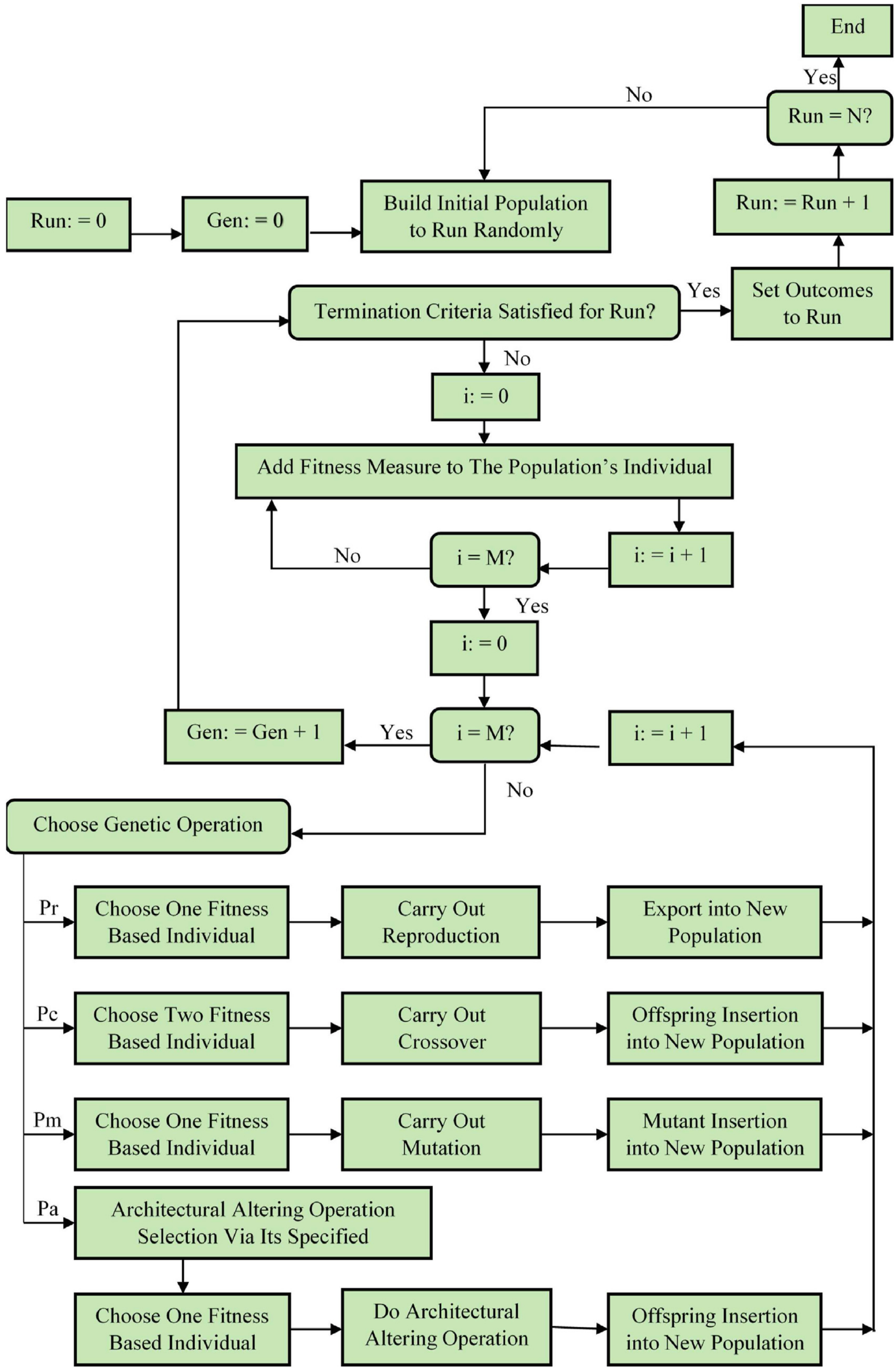

Fig. 3 – Flow chart of GP [67].

mechanisms such as reproduction, hybridization, and mutation are employed for population change.

2.2. *Data sample*

In our investigation, data collection was based on laboratory-based, genuine experimental testing. The PSPB was produced with a variety of plastic-to-sand ratios and sand diameters, as well as a variety of fibre percentages and lengths, including coconut and basalt fibres. Previously, experimental testing was performed to produce the dataset for modeling [22,58]. A total of 135 specimens have been tested in the laboratory to determine the CS. The frequency distribution and general data descriptions utilized to create the model are depicted in Fig. 5 and Table 1. The data collected from these results contain information about the amount of plastic (P), amount of sand (S), sand size (SS), percentage of fibre (F), fibre length (Fl), fibre diameter (Fd), the tensile strength of the fibre (Ft) and CS. Any model's performance is influenced by its distribution [50]. The parameters involved in this study, both input and output, are shown in Table 2. The trials which have given the best result are taken are processed further. In this research, efforts are made to test and train models utilizing the GEP technique. 70% of the dataset was used in the training of the models, and 30% of the data was used to test the models. The testing findings complement the experimental testing results for various models with excellent precision. Thus, the accuracy of the model is already validated and tested using testing data for different models utilized in the research. Moreover, researchers from a wide variety of fields have hypothesised that the success of the proposed model is heavily dependent on the proportion of data points to the total number of inputs [50,69]. The ratio should be greater than 5 for the optimal model [69] in order to test the efficacy of data points for determining the relationship between selected variables. In the present study, seven inputs were used to predict the CS of the PSPB, and the resulting ratio of 19.2 satisfies the criteria established by the researchers. The model was trained by training data through genetic evolution, and the built-in model was validated through test data or a validation set [54,70].

2.3. *Development of model and evaluation measures*

Before developing the model, selecting input factors is the initial step that can affect the attributes of PSPB. Each parameter in the dataset was thoroughly analyzed, and the

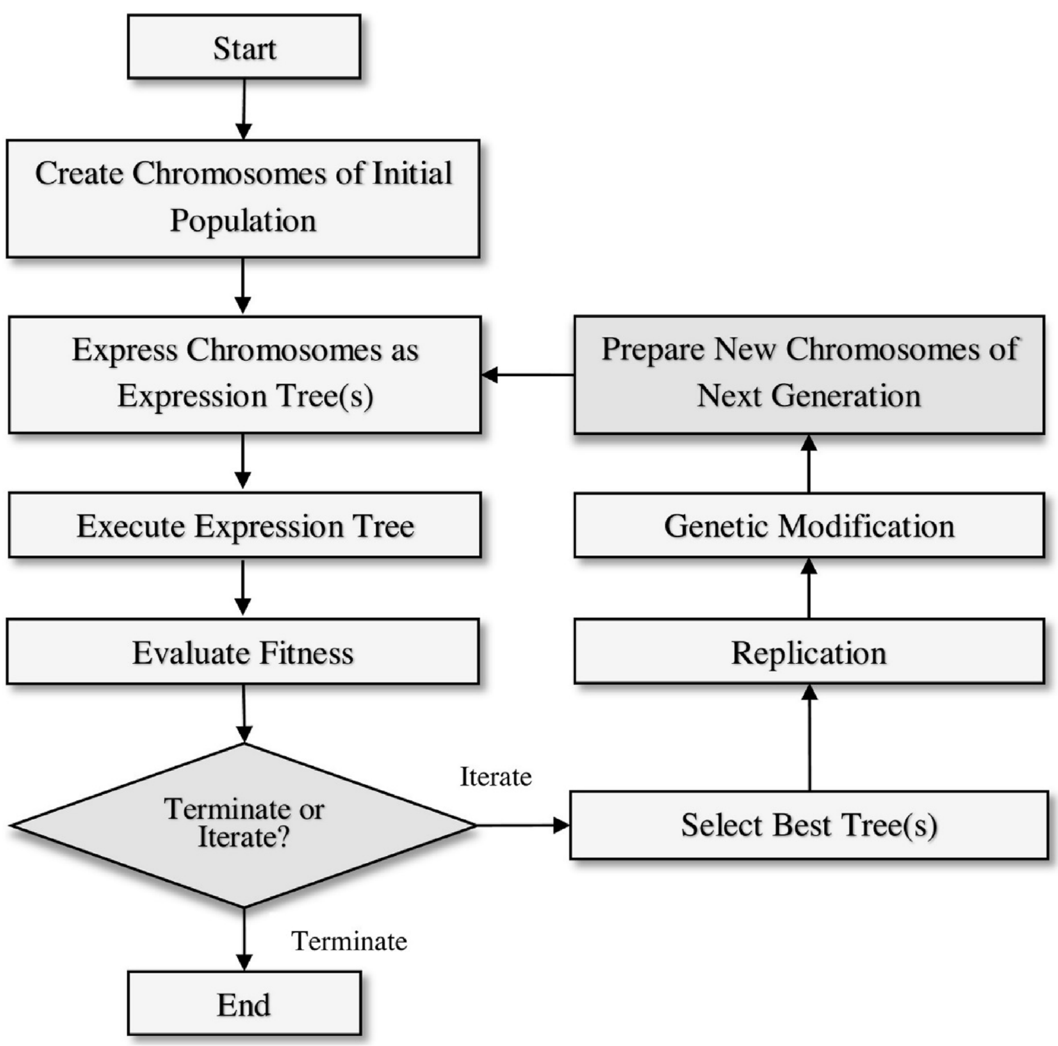

Fig. 4 – Flow chat of GEP [68].

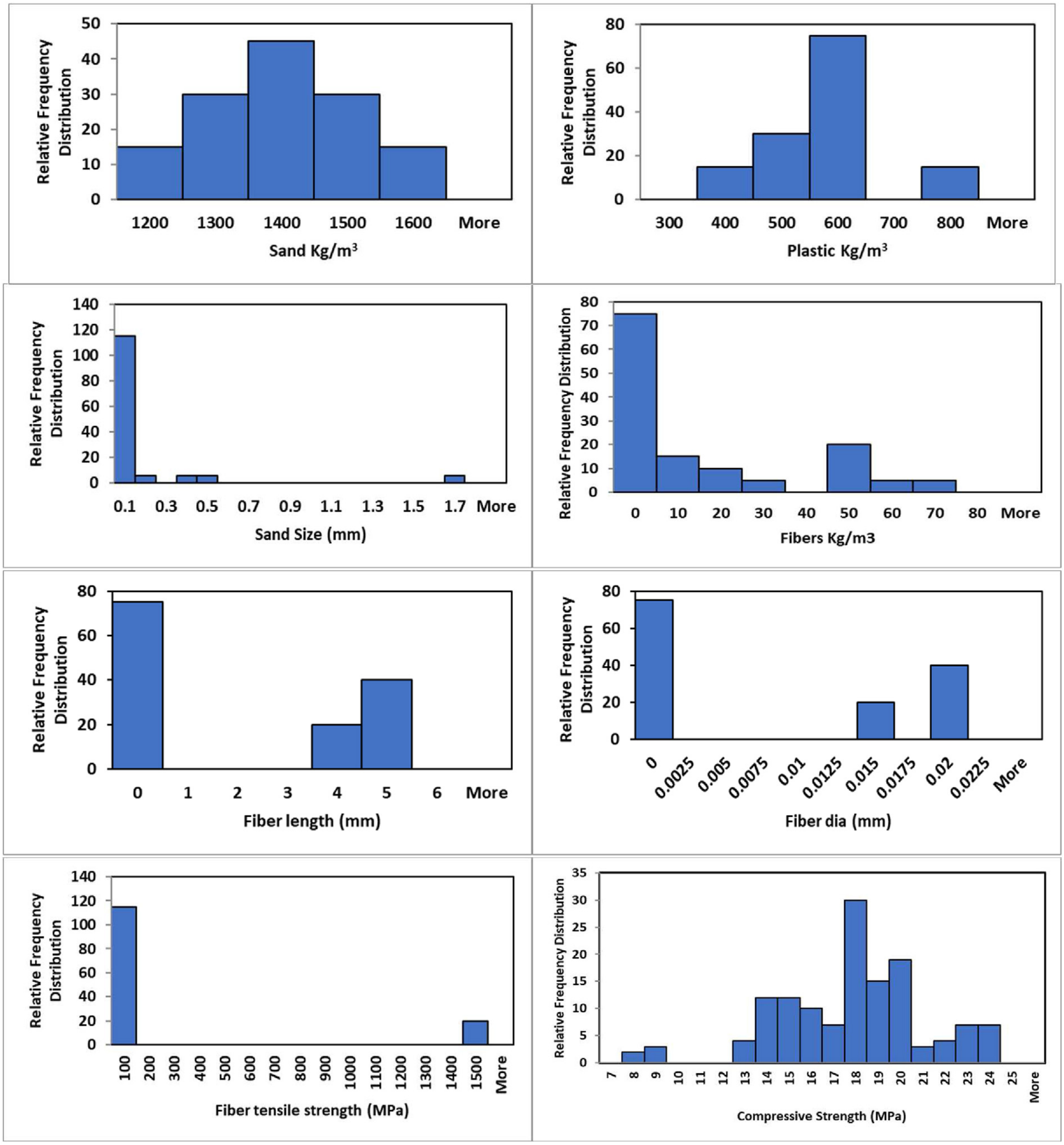

Fig. 5 – Frequency distribution of the data employed in model development.

effectiveness of many preliminary trials was evaluated to figure out which parameters have the greatest impact on the PSPB properties to develop a generalized link. As a result, it is assumed that the CS of PSPB is a function of the following factors, as shown in equation (1). It should be mentioned that multiple trials were conducted to determine the database's authenticity and consistency, as shown in Table 3.

$$f'c = f(P, S, SS, F, Fl, Fd, Ft) \quad (1)$$

It is essential to recognize that fitting parameters significantly influence the robustness and generalizability of the produced model. Using literature recommendations and multiple initial trials, the GEP algorithm's suitable parameters were determined [39]. The length of the programme is governed by the number of chromosomes in the population. Based on the extensiveness and variety of the prediction models available, the population size was determined to be 100. Based on the model's head size and gene count, the software's architecture calculates the difficulty of each term and the total number of sub-ETs. This research looked at eight-sided head sizes and a three-sided gene count. Listed in Table 4 are the model's GEP algorithm parameters.

The coefficient of correlation (R^2) is one of the most often used performance indicators. However, because R^2 is

Table 1 – Aspects of descriptive statistics for variables used in modeling.

Statistical details	Savnd	Plastic	Sand size	Fibres	F. Length	F. dia	fibre tensile
Mean	1343.28	550.91	0.16	12.81	2.07	0.01	220.74
Standard Error	8.89	8.49	0.03	1.70	0.20	0.00	44.29
Median	1330.90	572.10	0.08	0.00	0.00	0.00	0.00
Mode	1430.25	572.10	0.08	0.00	0.00	0.00	0.00
Standard Deviation	103.25	98.61	0.31	19.72	2.35	0.01	514.62
Sample Variance	10660.58	9724.87	0.10	389.01	5.52	0.00	264835.27
Kurtosis	−0.17	0.52	18.66	0.50	−1.89	−1.73	2.04
Skewness	−0.09	0.46	4.36	1.35	0.28	0.39	2.00
Range	381.40	381.40	1.62	66.75	5.00	0.02	1450.00
Minimum	1144.20	381.40	0.08	0.00	0.00	0.00	0.00
Maximum	1525.60	762.80	1.69	66.75	5.00	0.02	1450.00
Sum	181343.30	74373.00	22.15	1728.70	280.00	1.06	29800.00
Count	135.00	135.00	135.00	135.00	135.00	135.00	135.00

unaffected by multiplying or dividing output values by a constant, it cannot be used only to measure the model's ability to anticipate outcomes [53,71]. As a result, this study also calculates mean absolute error (MAE), root mean square error (RMSE), represent absolute percent error (MAPE), and root mean square logarithmic error (RMSLE). Eqs. (2)–(6) provide the mathematical formulations for these error functions and Table 5 shows the range of these statistical parameters, respectively.

$$R^2 = \frac{\sum_{i=1}^{n}(M_i - \overline{M}_i)(P_i - \overline{P}_i)}{\sqrt{\sum_{i=1}^{n}(M_i - \overline{M}_i)^2 \sum_{i=1}^{n}(P_i - \overline{P}_i)^2}} \tag{2}$$

$$MAE = \frac{1}{n}\sum_{i=1}^{n}|P_i - M_i| \tag{3}$$

$$RMSLE = \sqrt{\frac{1}{N}\sum_{i=1}^{N}(\log(yi+1) - \log(\hat{y}+1))^2} \tag{4}$$

$$RMSE = \sqrt{\frac{\sum_{i=1}^{n}(P_i - M_i)^2}{N}} \tag{5}$$

$$MAPE = \frac{1}{n}\sum_{i=1}^{n}\left|\frac{P_i - M_i}{P_i}\right| \tag{6}$$

where P_i = ith experimental output, M_i = $_w$ith model outputs, n = the total number of samples, $\overline{M}_i$ = average values of the experimental, and $\overline{P}_i$ = average value of the model outputs.

3. Results and discussion

Fig. 6 depicts the GeneXproTool-provided expression trees (ETs), which are decoded to yield an empirical expression for predicting the CS of PSPB. It employs only the four elementary arithmetic operators, namely, addition, division, subtraction, and multiplication. The basic expression that may be derived from these expression trees is represented by equation (7). Which is made up of separate variables, A (taken from Sub-ET 1), B (taken from Sub-ET 2), and C (taken from Sub-ET 3).

3.1. GEP formulation of PSPB for f′c

The f′c is formed using a model based on several genes and a head size of 3 and 8, respectively. The simplified equation used to estimate the CS, f′c, of PSPB in MPa is Equation (7). It consists of three variables, A, B, and C, represented by Equations (8)–(10).

$$f'c\ (MPa) = A + B + C \tag{7}$$

$$A = Ln\left(P - (8.40 \times Ft + F) - \frac{S}{7.25}\right) \tag{8}$$

$$B = \left(SS + FL - (294.62 \times Ft) - fd + \sqrt[3]{0.37 \times F}\right) \tag{9}$$

$$C = (5.63 - (Ln(SS) \times Ln(6.93)) + Ln(SS) + 6.33) \tag{10}$$

Using the dataset, the GEP CS model was used to predict CS. The efficacy of the model was assessed on both the training and testing datasets. Fig. 7a displays that the coefficient of determination (R^2) for the training model is 0.89. This indicates that the model can account for 89% of the variance in CS values among training data. The error distribution between the actual values and the model's predicted values for the training set is depicted in Fig. 7b. The mean error value of 0.762 MPa indicates a deviation of 0.762 MPa on average between the predicted and actual CS values in the training set. It is reported that the maximum and minimum discrepancies were 3.587 MPa and 0.001 MPa, respectively. Fig. 7c displays an

Table 2 – Input and output parameters of PSPB.

Parameters	Abbreviation
Input variables	
Plastic (kg/m^3)	P
Sand (kg/m^3)	S
Sand size (mm)	SS
Fibre percentage (kg/m^3)	F
Fibre length (mm)	Fl
Fibre diameter (mm)	Fd
Fibre tensile strength (MPa)	Ft
Output variable	
CS (MPa)	fc′

Table 3 – Details of the trials undertaken.

No. of Trials	Total Dataset	No. of inputs	No. of chromosomes	Head size	No. of Genes	Constants per Gene	Literals	Time (min)	Training Dataset		Validation Data Set	
									R^2	MAE	R^2	MAE
1	135	7	30	7	3	10	10	28	0.86	0.84	0.89	0.87
2			50	8	3	10	9	25	0.85	0.93	0.90	0.91
3			100	8	3	10	17	44	0.88	0.77	0.84	0.80
4			150	9	3	10	16	42	0.90	1.21	0.85	1.14
5			200	7	3	10	12	19	0.84	1.05	0.90	0.98
6			100	8	3	10	21	16	0.89	1.39	0.94	1.53
7			100	7	3	10	17	31	0.87	1.01	0.86	1.10
8			**100**	**8**	**3**	**10**	**11**	**33**	**0.89**	**0.76**	**0.88**	**0.75**
9			100	7	4	10	8	25	0.88	0.87	0.85	0.86
10			100	9	5	10	21	47	0.91	0.72	0.87	0.74

Table 4 – Configuration parameters for the designated GEP algorithm.

Parameters	Settings
General	f'c
Chromosome	100
Genes	3
Head size	8
Linking function	Addition
Function set	+, x, ÷, −

R^2 value of 0.88 for the testing model, indicating that the model can explain 88% of the variance in CS within the testing data. The error distribution for the testing set is illustrated in Fig. 7d. The testing model is reported to have an average error of 0.76 MPa, with a maximum error of 3.152 MPa and a minimum error of 0.002 MPa. The average error found between both the training and testing models was just 0.76 Mpa, indicating their success. The constructed model appropriately accounts for the effect of each of the seven input factors when predicting f'c for PSPB. The findings in Fig. 7 show a strong correlation, having the R^2 values of 0.89 and 0.88 for the training and test sets, respectively, indicating the model's superior performance. These high R^2 values indicate that the model adequately explains the variability in PSPB CS, suggesting that it can accurately predict the CS of plastic sand paver blocks. This information is useful for evaluating the structural integrity and durability of these blocks in various applications. The number of datasets used to develop the proposed models substantially affects their reliability [39]. The maximum number of specimens (i.e., 135 for f'c) was obtained from the experimental study, resulting in higher accuracy.

3.2. *Model validation*

According to the research findings, the quantity of data in the database should be no less than 3, the amount of data input, and ideally larger than 5, for effective models [50,69]. The ratio is much greater than 19 for f'c in this investigation. No GEP model estimating the CS of PSPB composed of plastic, sand, and fibres have been identified in the literature. As a result of this research, non-linear regression models for estimating the CS of PSPB were developed, and their findings were compared to those obtained using the GEP model. Therefore, R^2 was utilized for improved efficacy. If R^2 values are closer to one and add up to one, this indicates that the model applied maximal variability between input parameters. In RMSE, larger errors are professionally resolved as opposed to smaller ones. If the RMSE value is close to or equal to 0, it indicates that the prediction error is negligible [73]. However, optimal efficacy is not

Table 5 – Statistical parameter ranges and their associated error values [72].

Assessment Criteria	Range	Accurate model
MAE	[0, ∞)	smaller value, the better
RMSE	[0, ∞)	smaller value, the better
MAPE	[0, 0.5]	smaller value, the better
RMSLE	[0, ∞)	smaller value, the better
R^2 value	(0,1]	bigger value, the better

guaranteed in specific circumstances. Consequently, the MAE was also calculated. MAE is extraordinarily valuable if continuous and steady data are available [74]. The statistical deviations between the predicted values and the actual ones are laid out in Table 6. The results indicated that the MAE for GEP was 0.76 MPa, and the MAPE was 4.50%, while the RMSE, RMSLE, and R2 were 1.10, 0.002, and 0.89, respectively. According to the statistical measurements, the GEP model's ability to predict PSPB CS is supported by the fact that the actual and projected values are closer together. The GEP model beats other machine learning (ML) methods in terms of its capacity to determine a strong correlation between non-linear input and output variables [59,64].

3.3. *Sensitivity analysis*

The GEP model is subjected to a sensitivity analysis (SA). The SA establishes the relative contribution of each input

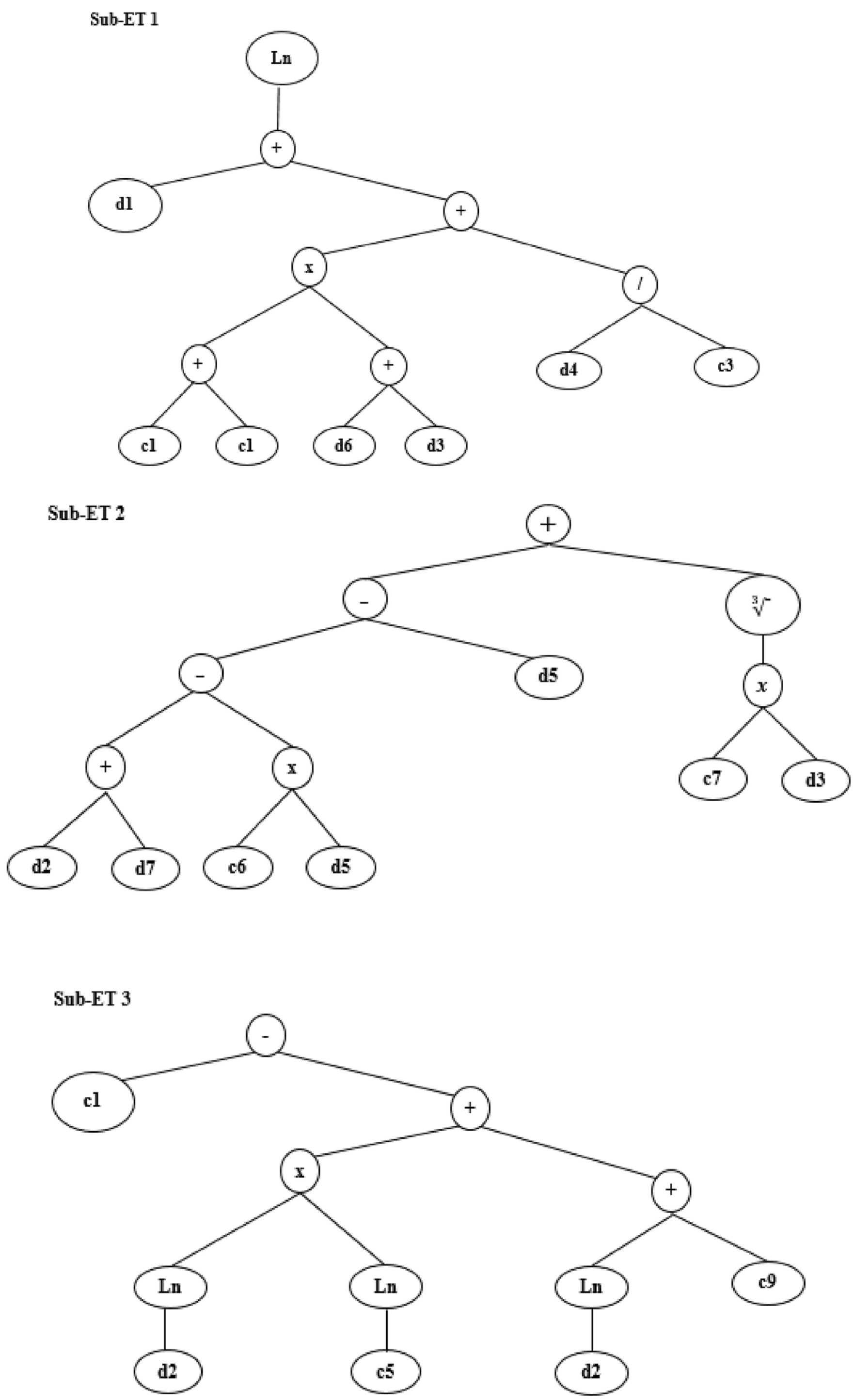

Fig. 6 – Expression tree with constants and variables for the GEP model of f'c for PSPB.

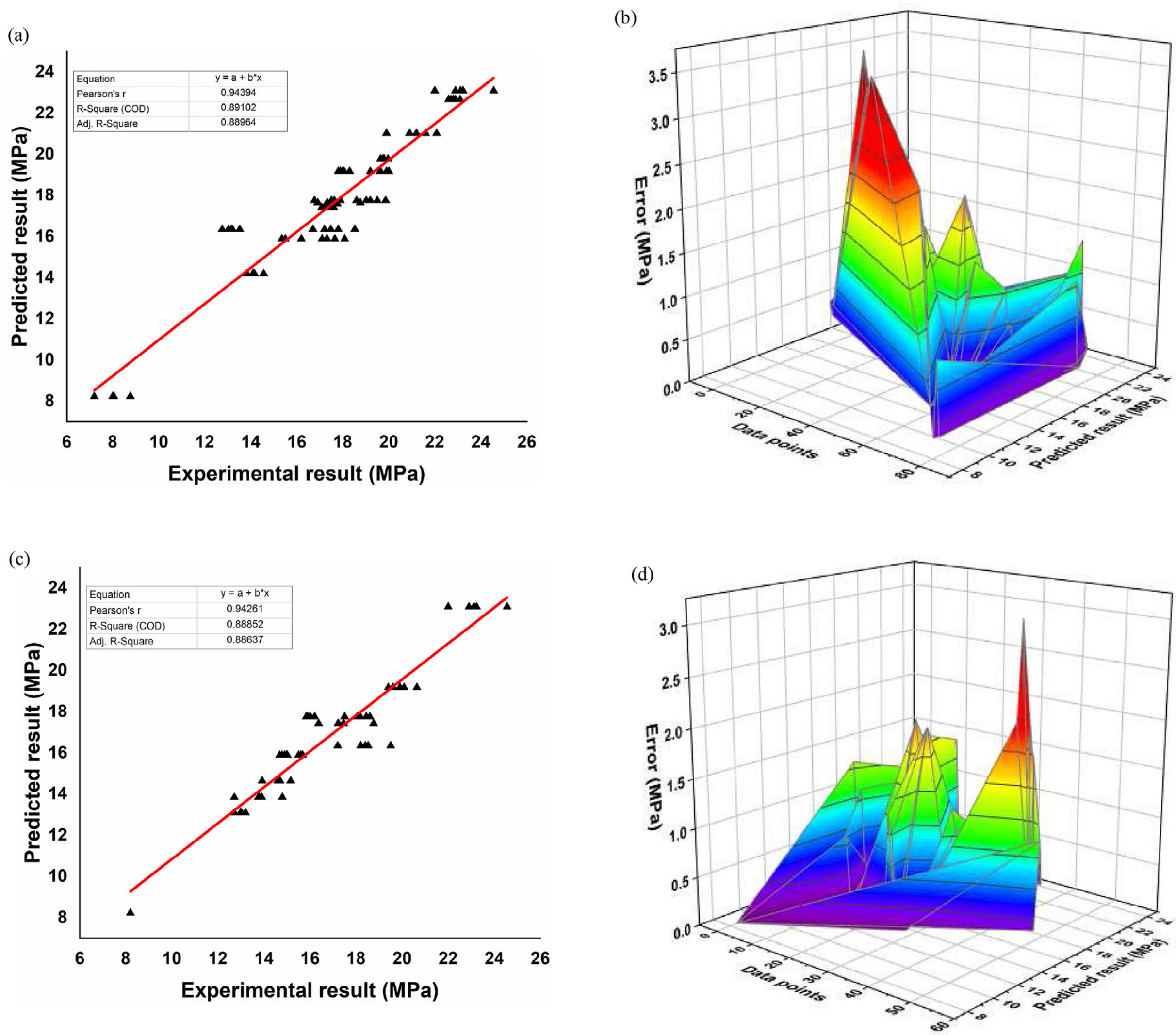

Fig. 7 – (a) GEP CS training model. (b) GEP CS error distribution of the training model. (c) GEP CS testing model. (d) GEP CS error distribution of the testing model.

parameter to the outcome. SA is technically implemented using equations (11) and (12).

$$N_i = f_{max}(x_i) - f_{min}(x_i) \tag{11}$$

$$SA = \frac{N_i}{\sum_{n}^{j=1} N_j} \tag{12}$$

where,

$f_{min}(x_i)$ = predicted model (minimum output).
$f_{max}(x_i)$ = predicted model (maximum output).

Table 6 – The GEP model's statistical error during the validation stage.

Models	CS
MAE	0.76
RMSE	1.10
RMSLE	0.002
MAPE	0.045
R^2 Value	0.89

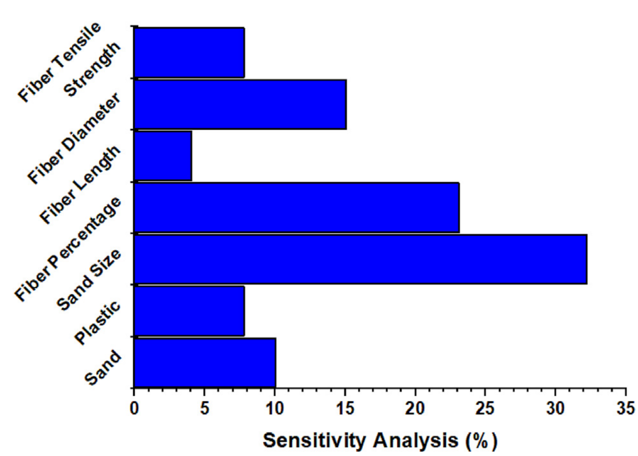

Fig. 8 – Input parameters contribution to CS.

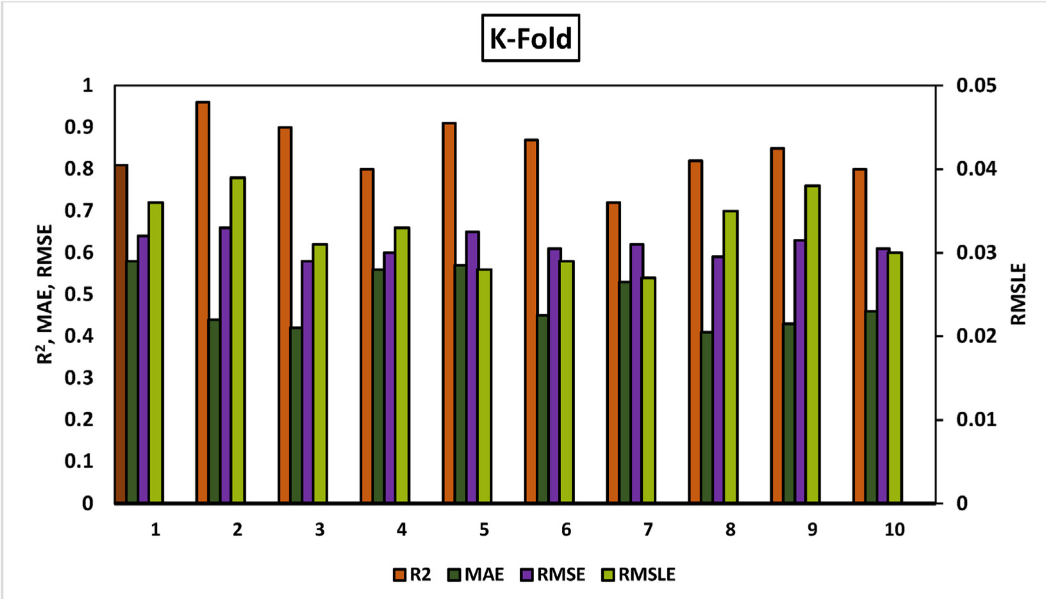

Fig. 9 – K-fold cross-validation statistical checks applied for CS for PSPB.

i = expressing the domain of the input variables while holding other variables constant.

As illustrated in Fig. 8, each parameter is critical in forecasting the CS of PSPB. Sensitivity analysis reveals that sand size and fibre percentage significantly impact the actual contribution of CS, which is greater than 50%. Previous researchers have indicated the same result, and it was revealed that increasing the size of the sand particle lowered the CS as porosity increased [57]. In contrast, finer sand and adding fibres enhanced the CS of PSPB [22]. This is why the sand size accounts for around 32.22% of the total, whereas fibre accounts for approximately 23.09%. The remaining five parameters' contributions are as follows: i.e., fibre tensile strength, fibre diameter, fibre length, plastic, and sand contribute about 7.78%,15.07%,4.03%,7.78%, and 10.02%, respectively.

3.4. *Cross-validation*

Evaluation of the actual efficacy of ML models is accomplished through the utilisation of a statistical method known as cross-validation. It is crucial to have a solid understanding of how well the models work. Because of this, a validation process needs to be carried out to determine the precision of the model's data. The database is shuffled arbitrarily and then divided into k subgroups for the k-fold validation test. The experimental results from the given study are evenly split into k^{10} data subsets. It employs nine of ten subsets, with the remaining one serving as a validation set. After that, ten repeats of the identical procedure are performed to obtain the mean accuracy of these ten repetitions. The tenfold cross-validation method is commonly considered as adequately representing the conclusion and validity of the model [72,75].

K-fold cross-validation is a method that may be utilized to investigate the test set for bias and variance reduction, namely (a) root mean square error (RMSE), (b) correlation coefficients (R^2), (c) root mean square logarithmic error (RMSLE) and (d) mean absolute error (MAE) are used to assess the cross-validation results for CS, as illustrated in Fig. 9. The CS model's k-fold cross-validation results revealed encouraging performance metrics. The average value of the coefficient of determination (R^2) was 0.84, with a maximum of 0.96 and a minimum of 0.72. This indicates that the model is able to account for a significant percentage of the variability that is present in the target variable. In addition, the mean absolute error (MAE) ranged from 0.41 to 0.58, with an average value of 0.48. The average value of the root mean square error (RMSE) was 0.61, with a maximum of 0.66 and a minimum of 0.58. These values represent the standard deviation of the model's prediction errors. The root mean square logarithmic error (RMSLE) yielded favorable results, averaging 0.032, with a maximum of 0.039 and a minimum of 0.027. Overall, these metrics indicate that the CS model accurately predicts the objective variable, thereby providing valuable insights into the field of the construction sector.

4. Conclusions

The GEP technique is used in this paper to offer formulations for predicting f'c from many essential parameters of PSPB. This is a novel approach for such situations. As CS is the primary characteristic of PB, no GEP model has been developed to evaluate the CS of PSPB. A significant and reliable database was built following a thorough experimental examination. Statistical indices such as R^2, RMSLE, RMSE, MAPE, and MAE were employed to evaluate the models. Based on the statistical parameter values, each model can correctly calculate the CS of PSPB. The GEP model's outcomes are explored. External validation and parametric analyses were also performed to ensure the results' accuracy.

The following are the specific outcomes of this study.

1. These results show that GEP models have higher accuracy in terms of forecasting.
2. GEP formulations produce findings more consistent with experimental data with R^2 values of 0.89 (training) and 0.88 (testing) for CS, respectively.
3. A CS equation for PSPB is obtained using the GEP model, which can be used to calculate the CS of PSPB.
4. To validate the k-fold validation findings, statistical measures such as R^2, MAE, RMSE, and RMSLE were employed. These parameters indicated that all of the models produced good outcomes.
5. The sensitivity analysis reveals that the model adequately predicts CS when the input parameters are used, with sand size and fibre percentage being the primary impacts in this study.

5. Future recommendation

This study proposed using GEP to predict the strength property of PSPB. The models created in this work are used to forecast the CS of PSPB. These models predicted PSPB strengths with high accuracy and reliability, as evidenced by statistical characteristics. A similar approach can be used to determine the PSPB's split tensile and flexural strengths. By utilizing machine learning techniques, it is possible to anticipate the strength properties of PSPB without casting them in the laboratory. However, the adoption of additional supervised machine learning algorithms would provide a more accurate estimate of the accuracy of the machine learning techniques used. Other ensemble machine learning techniques (for example, bagging, boosting, and Adaboost) may be more successful in predicting the CS of PSPB.

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.

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