

Review

# Gene Expression Programming (GEP) Modelling of Sustainable Building Materials including Mineral Admixtures for Novel Solutions

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**Abstract:** In this study, the employment of the gene expression programming (GEP) technique in forecasting models on sustainable construction materials including mineral admixtures and civil engineering quantities (e.g., compressive strength), was investigated. Compared to the artificial neural networks (ANN) based formulations, which are often too complicated to be used, GEP-based derived models provide estimation equations that are reasonably simple and may be used for practical design purposes and even for hand calculations. Many popular models, such as best-fitted curves based on regression analyses, multi-linear regression (MLR), multinomial logistic regression (MNLRL), and multinomial variate regression (MNVRL), can also be used for construction materials properties modeling. However, due to the nonlinearity and complexity of the target properties, the models established using linear regression analyses may not reveal the precise behavior. Additionally, regression models lack generality, and this comes from the fact that some functions are defined for regression in classical regression techniques; while in the GEP approach, there is no predefined function to be considered, and it reproduces or omits various combinations of parameters to provide the formulation that fits the experimental outcomes. If the input parameters can be evaluated through simple laboratory or rapid measurements, and also a comprehensive experimental database is made available, the models can be constructed with optimal flexibility. Flexibility in choosing the complexity and fitness functions, such as RMSE, MAE, and MSE, might lead to better performance of the approach and well-capturing the governing pattern behind the material's characteristics. There may be minor inaccuracies with this technique; however, the explicit mathematical expressions, which can be easily implemented in the design and analysis process, may cover the minor inaccuracies compared to ANN, support vector machine (SVM), and other intelligent approaches. Based on the presented study, sometimes it would be better to provide more than one GEP model and consider different combinations of input contributing variables to afford the possible initial feed for a more settled and comprehensive model. Mostly, GEP's strengths as a superior machine learning technique in modeling the behavior of construction materials including mineral admixtures, leading to innovative solutions in civil engineering, have been presented.

**Keywords:** gene expression programming (GEP); construction materials; mineral admixtures; concrete; soil; green admixtures; supplementary cementitious materials; mine waste reuse

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## 1. Introduction

With the increasing growth in the use of science and technology in solving everyday life problems, the need for methods that understand complex and ambiguous problems becomes greatly inevitable. Soft computing is an emerging collection of various methodologies aimed at finding a balance to poor precision, uncertainty, and unclear truth, by applying a collection of statistical, probabilistic, and optimization tools, in analyzing sets of data, classifying the data, identifying new patterns, and predicting next trends within the shortest convenient time. Soft computing has three main branches, which are genetic algorithms (GA), artificial neural networks (ANN), and fuzzy logic (FL); these branches tend to build intelligent and wiser machines that behave like the human mind and can answer questions explicitly and not just provide answers [1]. The application of soft computing in branches of civil engineering, such as geotechnical engineering, has been a breakthrough of the 21st century, with these techniques helping to solve different cumbersome mathematical problems in the space of seconds. Geotechnical engineering, as one of the most relevant branches of civil engineering, deals with the study of the engineering behavior of earth materials using the principles of soil mechanics and material engineering in finding lasting solutions to earth problems when it comes to the design of engineering works. The complexity accompanying geotechnical engineering has further led to the need to apply these soft computing techniques in solving earth problems such as swelling potentials of soils, as recorded by Alaneme et al. [2] and Onyelowe et al. [3] in the modeling change in volume properties of hydrated lime activated rice husk ash (RHA) modified soft soil using ANN. This study X-ray's the application of the ANN model in the estimation of the swelling and shrinkage potential and consistency indices of the stabilized soil. The input parameters are the soil-HARHA replacement ratio and Atterberg limit responses, while the shrinkage, clay activity, and swelling characteristics, were utilized as the network output parameters using Levenberg Marquardt (LM) training and feed-forward backpropagation (FFBP) algorithm with 5-9-6 network architecture. He recorded that the application of the ANN model in his research saved cost, made the best use of research materials, and was time efficient [4,5]. Kayadelen et al. [6] studied a model for the swelling potential of compacted soils, where an adaptive neuro-fuzzy model was applied to compacted soils sourced within Nigde, Turkey, with parameters such as the coarse grain fraction ratio, fine-grained fraction ratio, plasticity index, and maximum dry density, were presented to the model as input. The results obtained showed that the ANFIS model is a more reasonable model for calculating the swelling potential of soils. Furthermore, the use of soft computing in geotechnical engineering has been applied in the determination of mixture designs, predicting shallow foundations, predicting and modeling soil behaviors, and the study of pile cap resistance, etc. At the moment, soft computing-based techniques are becoming more popular in the field of geotechnical engineering, with several works on the application of neural networks and fuzzy logic, and little work done on the application of GA in this field.

In the present era of artificial intelligence and soft computing application to model engineering problems for a more sustainable smart solution, GEP has made a serious mark for its properties and usage. Gene Expression Programming (GEP) is an approach that takes a population of solutions and models, selects, and reproduces them based on fitness, and introduces genetic diversity using one or more genetic operators like recombination or mutation. Though the GEP can be likened to the GA and GP as the two still operate on the principle of population, the fundamental distinction among the three algorithms is dependent on the type of the individuals or models or solutions, as the case may be; individuals in GA are symbolic strings of fixed chromosomes, non-linear entities of various shapes and sizes exist in GP, and individuals in GEP are encoded in symbolic strings of

fixed chromosomes represented as GPs, this means that GEP is a combination of GA and GP [6]. The evaluation of soil liquefaction using the GEP model approach was studied by Goharzay et al. [7]. GEP was utilized to build several deterministic models to assess the occurrence of soil liquefaction in terms of liquefaction field performance indicator (LI) and factor of safety (Fs) using logistic regression and classification concepts. The results of their research back up the application of GEP as a green decision-making tool in engineering design for quantitatively examining liquefaction triggering thresholds. Armaghani et al. [8] proposed a GEP model for the estimation of tunnel boring machine (TBM) penetration rate in hard rock conditions. Several models were developed based on multiple inputs, and the best model was selected; it was further recorded that the GEP model is superior to linear multiple regression (LMR) in terms of applied performance indices. Mohammadzadeh et al. [9] utilized a GEP model to predict the compression index of fine-grained soils; GEP was employed to develop a model for predicting the coefficient of curvature (Cc) using the plastic limit (PL), liquid limit (LL), and coefficient of friction ( $\Phi$ ). The study analyzed 108 datasets containing Cc, PL, LL, and  $\Phi$ , and also used the same to train and validate the model; contrary to other models used in the estimation of Cc, the GEP model exposed highly nonlinear behavior and included a complex combination of influential input parameters furthermore revealing its good performance. Johari et al. [10] trained a GEP approach to the prediction of the maximum lateral displacement of a retaining wall in granular soil. The model's input parameters are the adjacent structure's effective period, the foundation's horizontal and rocking stiffness, the density, Young's modulus, and the friction angle of granular soil, as well as the thickness and height of the retaining wall. The model's predictions were compared to the actual data, and it showed good performance for predicting lateral displacements of structures in granular soils. Johari and Hooshmand Nejad [11] predicated soil-water characteristics using GEP, and the model was developed in two phases for control and validation. Both the data used in the first phase and the results used in the validation phase showed that the model was predicted with fair accuracy. Although there were some differences between the model estimation and the actual test data, a comparison of the proposed model's findings with traditional approaches revealed that it performed better in terms of soil water features prediction. Uysal [12] compared the GEP model to actual experimental values and the regression model in the estimation of the collapse potential of soils, and it was observed that GEP-based models are detected to be simpler methods to estimate the collapse potential. Jahed Armaghani et al. [13] studied the settlement of the rock socketed piles through a technique based on GEP. The findings showed that the GEP-based predictive model might be used to anticipate the settlement. The predominance of this model in forecasting pile settling is demonstrated by the coefficients of determination values of training and testing datasets, which were 0.872 and 0.861 for the GEP equation, respectively. This soft computing approach has proven to be very useful within the field of geotechnical engineering because it generally fits in and thrives, where other models have failed or have restricted abilities; hence, this study aims to effectively explore GEP around all corners of geotechnical engineering, how the language of genotypes is translated to that of the phenotypes with reference to geotechnical engineering and, therefore, the evaluation of sensitivity analysis and parametric study using the developed model. GEP is a type of evolutionary algorithms inspired by biological systems, the system is a complete genotype system, with expression trees of various sizes and forms recorded in fixed-length linear chromosomes. GEP chromosomes are multi-genic, storing many expression trees that will be arranged into a considerably more complex program, similar to GAs and GPs. So, just like life on earth's DNA/protein system, GEP's genes/trees system can not only explore all routes in the solution space, but it can also absolve to study higher levels of organization. GEP has two main players; the expression tree (ET) and also the chromosomes, and these can further be classified as phenotype and genotype, respectively. The genotypes are chromosomes that are simple entities; linear, relatively small, compact, and easy to manipulate genetically, while the phenotypes are exclusively the expression of their respective chromosomes. They are the objects on which

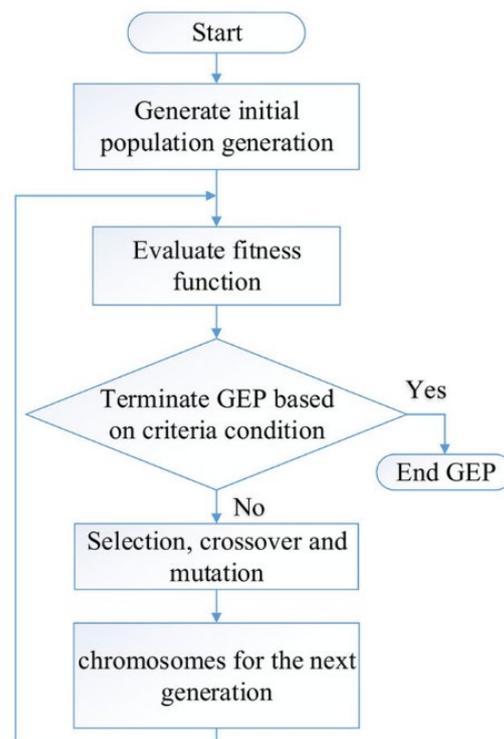
the selection occurs, and they are chosen to reproduce with change based on their fitness. In GEP, the interaction of chromosomes (genotype) and expression trees (phenotype) implies an unmistakable translation mechanism for translating chromosomal language into expression tree language (ETs) [14].

The application of GEP permits the chromosome can have more than one gene. These genes contain two types of information; the first type is stored in the head of the gene containing the data, which is employed in producing the overall GEP model, and the second is stored in the tail of the gene and used to generate future GEP models. The length of the tail can be calculated using the following expression:

$$t = h(n - 1) + 1 \quad (1)$$

where  $h$ ,  $t$ , and  $n$ , are the length of the head, length of the tail, and the number of arguments of the function with more arguments, respectively.

The process, as shown in Figure 1, starts with randomly generating chromosomes of a certain number of individuals (initial population). The procedure is continued until a good solution is found, or until a specific number of generations have passed [15–17]. The independent variables that are used as input variables in the model make up the terminal set. To utilize the GEP approach, the first step is to specify the terminal set.



**Figure 1.** Flowchart of GEP model.

The GEP technique uses an evolutionary process to choose the best program and individual. In each cycle, the chromosomes are updated and optimized using the genetic operators and fitness function, such as the GA. This procedure is repeated until all of the convergence requirements have been met. The major advantage of GEP over neural networks is that it proposes model equations, which are used to design and monitor the performance of civil engineering problems for sustainable utilization of construction materials. The aim of this research paper is to present an extensive review on the utilization of gene expression programming (GEP) and its algorithms in modeling construction materials including mineral admixtures, for sustainable and novel infrastructure development. Figure 2 shows the process of utilizing mining waste as building materials.



**Figure 2.** The process of utilizing mining waste as building materials.

**2. Concrete**

This section includes 17 different subsections, which are reported in Figure 3, and will be described in the following.



**Figure 3.** The studied subsections of concrete.

**2.1. High Strength Concrete (HSC)**

The basic ingredients of high strength concrete (HSC) mixtures are similar to conventional concrete, besides minerals and chemicals being adding to increase the compressive strength. Compressive strength is a critical property defining the HSC quality and depends on various parameters, including concrete mix design, type of materials and classifications, and the laboratory technicians’ skills in testing and preparation [18]. Many unknown factors are underlying the compressive strength prediction, making it challenging to achieve an accurate or analytical equation for concrete strength. The traditional concrete properties models may not be comprehensive and suitable for HSC strength due to their different responses [19]. Chou and Tsai [20] explained that the relationship between ingredients

and concrete properties is nonlinear, from which it can be concluded that the particular properties of HSC are not entirely found. Regression analysis can be used for the empirical estimation of concrete experimental results, including HSC strength. In addition to classical regression techniques, machine learning approaches such as ANN and GEP [21] can be implemented for predictions. GEP worked as a powerful method for the explicit formulations of concrete properties [22].

Abdollahzadeh et al. [18] presented two GEP models to predict the compressive strength of HSC. Assuming simplified composition for HSC preparations, cement, silica fume (SF), super plasticizer, fine aggregate, water, and coarse aggregate, were considered contributing predictors, and the 28-day compressive strength was considered the prediction target based on a dataset comprised of 159 mixes. Training and testing data partitioned 80% and 20%, respectively, were randomly chosen from the dataset. GEP was indicated as a powerful technique for HSC compressive strength prediction concerning the training results and testing data partitions compared to experimental values and error indicators. Farooq et al. [23,24] used GEP and random forest (RF) for the compressive strength prediction of HSC. Input parameters were cement content, water, fine and coarse, and admixture. Model performance evaluation was through statistical analyses using error indicators and benchmarks such as root mean squared error (RMSE), relative root mean squared error (RRMSE), mean absolute error (MAE), relative mean square error (RSE), and coefficient of determination ( $R^2$ ). The GEP approach resulted in a good match between actual experimental values and predictions, along with an empirical equation.

The cost of materials and CO<sub>2</sub> emissions are two critical and environmental challenges affecting HSC's long-term viability [25,26]. Wang [27] provided a calculating approach for SF-blended HSC mix design with an optimal overall cost based on different carbon prices. The concrete mixture and unit pricing were used to calculate the material cost and CO<sub>2</sub> emission value. GEP was used to assess the mechanical and workability qualities of concrete. GA was implemented for the optimal mixture search, considering different constraints, such as design compressive strength constraint, workability constraint, ratio constraints, and concrete volume constraint. The total cost of materials with the cost of CO<sub>2</sub> emissions was believed to be the GA optimization goal. Their technique may be used to build sustainable HSC materials with reduced material costs and CO<sub>2</sub> emissions. GEP was implemented as a practical approach for HSC properties reproduction.

## 2.2. Concrete Admixed with GGBFS

The sustainability characteristics of concrete depend on the performance and service life of the used binders. Traditional binders based on ordinary Portland cement (OPC) have performed well under a variety of situations; nevertheless, OPC manufacture, like that of other building materials, necessitates a large amount of energy consumption as a result of greenhouse gas emissions. Adopting cementitious materials as alternatives and reducing OPC use, such as using SF, fly ash (FA), ground granulated blast furnace slag (GGBFS), and natural pozzolans such as meta-kaolin, sustainability improvements might be attained [28–30]. The utilization of the supplemental cementitious materials must be done without jeopardizing the performance and serviceability characteristics of the structure [31]. GGBFS, also referred to as slag cement [32], undergoes hydration in the existence of water and alkali activators and can work similarly to Portland cement [33–35]. Akin and Abejide [32] adopted the GEP approach to predict the compressive strength of concrete admixed with GGBFS. It was indicated that GEP outperforms step-wise regression analysis and results in higher accuracy. Based on the acquired determination coefficient ( $R^2$ ) value and MSE of 0.94 and 5.15, respectively, it was stated that GEP is more accurate in the modeling of compressive strength for concrete admixed with GGBFS [32]. Shahmansouri et al. [36] implemented GEP to develop numerical models for predicting the compressive strength of geopolymer concrete (GPC), which is the concrete GGBFS. The database contains 351 specimens from 117 distinct mixes, with the five most effective factors evaluated as inputs: specimen age, natural zeolite (NZ), sodium hydroxide (NaOH) solution

concentration, GGBFS content, and SF. The compressive strength of GGBFS-based GPC was predicted using GEP simplified and realistic mathematical equations. The suggested equations' performance, high accuracy, and predictability, were evaluated by sensitivity and parametric analyses. GEP-based equations may encourage the reuse of GGBFS for GPC development, resulting in environmental and economic benefits.

### 2.3. Concrete Admixed with Meta-Kaolin

Meta-kaolin is created when kaolin clay is calcined at temperatures above 650°C. Kaolin or China clay refers to kaolinite-rich stones that have traditionally been used in the creation of porcelain. Kaolinite is crystalline in its raw state, and meta-kaolin is disordered mainly in its structure and, due to its fine particle nature, provides good characteristics as a mineral additive [37]. Meta-kaolin is not a binder material, but it is an extremely reactive pozzolan that combines effectively with lime in the presence of water to generate hydrated calcium and aluminum silicate compounds; therefore, it is an excellent synthetic pozzolan and can be potentially used for concrete production [38]. Akin et al. [31] proposed the compressive strength model of concrete admixed with meta-kaolin using GEP datasets, including laboratory results from different mix designs made of three different water binder ratios. The concrete's compressive strength was determined after 28 days of curing, and input variables were assumed to include meta-kaolin content, cement, water, and fine and coarse aggregate. R<sup>2</sup>-value from the GEP results was compared with that of conventional stepwise regression analysis. GEP R<sup>2</sup>-value was reported to be 0.95, which indicated a strong correlation between predicted and actual values, and the model could be a good alternative for the compressive strength of concrete admixed with Meta-kaolin.

### 2.4. Bagasse Ash (BA) Based Concrete

Bagasse is the fibrous waste from the sugarcane juicing process that can be burned as a fuel source to feed a boiler. As a result, sugarcane bagasse ash (SCBA) is a residue and is classified as a solid waste item that is typically disposed of in landfills [39,40]. Javed et al. [41] and Shah et al. [42] employed GEP for compressive strength prediction of sugarcane bagasse ash concrete (SCBAC). The compiled data encompassed different percentages of bagasse ash. GEP, MLR, and MNLR [40] approaches were used for SCBAC compressive strength modeling. The water-to-cement ratio, bagasse ash (BA) percent substitution, the quantity of coarse and fine aggregate, and cement content, were considered for the model input variables. Based on the various error and statistical criteria, i.e., Nash–Sutcliffe model efficiency coefficient (NSE), R<sup>2</sup>, and RMSE, the models' performance demonstrated a strong correlation between estimated and experimental values. With NSE and R<sup>2</sup> values greater than 0.8, GEP outclassed other MLR and MNLR for SCBAC compressive strength prediction. In the design mixes, cement content was the most sensitive parameter, followed by the w/c ratio based on the sensitivity analysis. The GEP-based simple derived equation can be used for the SCBAC compressive strength prediction.

### 2.5. Concrete with a Blend of Cement, Limestone, Slag, and Natural Pozzolans

Improving concrete sustainability is vital for producers and construction companies to reduce CO<sub>2</sub> emissions and materials' costs and maintain concrete mechanical properties, workability, and durability. Wang [43] suggested a straightforward method for determining the best FA and slag composition for blended concrete, taking into account material costs, strength, workability, carbon pricing, and carbonation durability. They used the GEP algorithm to forecast the strength and slump of the concrete, and the carbonation depth of the ternary blended concrete was computed using the efficiency factors of FA and slag. The GA was also utilized to discover the best combination under different limitations. The overall cost, material cost, and carbon pricing all increased as the concrete's strength increased, according to the findings. Slag blended and limestone concrete is another innovative material that belongs to limestone calcined clay cement concrete. Strength is an essential characteristic of structural concrete. Wang [44] studied ANN and GEP models to

estimate limestone and slag blended concrete. They introduced a GEP model comprised of the sum of three expression trees (ETs). ANN and GEP models' input parameters were mixing ingredients and ages, and the output was assumed to be the strength of the samples. The correlation coefficient (R) values of the GEP and ANN models were 0.98 and 0.99, respectively. Both GEP and ANN models can reliably predict the strength of ternary blended concrete. The flexural strength of these types of concretes is considered a significant engineering property of concrete. Wang [45] implemented ANN and GEP with different concrete mixes properties and curing ages as inputs to estimate the flexural strength. The correlation coefficient values of the ANN and GEP models reported as 0.99 and 0.98, respectively. Both GEP and ANN could reliably estimate the flexural strengths of ternary blended concrete.

#### *2.6. Concrete with Various Strength Classes of Cement*

Mermerdaş et al. [46] propose a prediction model for concretes' strength estimation, including various cement types and mix designs. The compressive strength of specimens, produced with three different cement types at different water rates to cement richness and cement ratios, was experimentally carried out. A statistical study was conducted on the experimental results, and the significance of the cement strength, w/c ratios, and cement content on the compressive strength of concrete was assessed. For the development of an explicit equation to estimate the compressive strength, GEP was benefited and also compared with the MLR method. The results showed that the specimens' compressive strength was significantly impacted by the type of cement and aggregate-to-cement ratio. The developed GEP model was accurate and showed a good correlation between experimental and estimated datasets.

#### *2.7. Glass Cullet Modified Concretes Compressive Strength*

In the research works by Gandomi et al. [47] and Mirzahosseini et al. [48], GEP was used to build the compressive strength prediction models using test results on 50mm mortar cubes containing glass powder. Sensitivity and parametric analyses were accompanied to estimate the effect of the predictor variables on compressive strength. Moreover, a comparative study with the classical regression models was performed. The GEP derived equations accurately characterized the compressive strength of concrete with ground glass fillers and outperformed the linear regression models. The simultaneous influence of many parameters, such as curing age, size distributions, glass compositions, and isothermal temperatures, was a significant element of the GEP suggested models. Compressive strength is sensitive to the curing temperature, curing age, and particle surface area, according to sensitivity and parametric analysis.

#### *2.8. Eco-Friendly Concrete Containing Natural Zeolite Compressive Strength and Electrical Resistivity*

Shahmansouri et al. [49] investigated the feasibility of applying the GEP method for predicting the compressive strength and electrical resistivity of concrete admixed with natural zeolite (NZ) to improve the durability and mechanical characteristics of the concrete. The compressive strength and electrical resistivity (ER) of the experimentally produced specimens at various ages were measured. Contributing input parameters, including the specimen age, cement, gravel water, sand, NZ, and admixture contents, were considered. The measured properties were compared with their predicted values, and the developed GEP models' great potential for estimating both compressive strength and ER of concrete containing NZ was indicated. When a concrete building is exposed to an adverse environment, the life cycle assessment (LCA) is more obvious. Shahmansouri et al. [50] studied the system boundaries of LCA of concrete mixtures. The samples were examined for sulphate attack and degradation, which is a common deterioration process in the Caspian Sea. The GEP method was used to forecast the strength loss and service life of the mixes. The results revealed that the mechanical and durability properties of NZ mixes

are superior to those of non-NZ combinations. The GEP approach was used to accurately anticipate the modified concrete's service life when exposed to a sodium sulphate assault based on the test findings.

### 2.9. Compressive Strength of "Roller Compacted Concrete Pavement" (RCCP)

There is a high expense in paving asphalt roads, and a huge amount of used oil pollutes the environment; hence, alternative technologies have to be used. "Roller-Compacted Concrete Pavement" (RCCP) is an accelerated construction rigid pavement that has reduced maintenance costs [51]. The higher aggregates and lower cement reduces the consistency of the RCCP; hence, it could be compacted using a roller compactor. The durability of RCCP was extensively studied due to low water absorption, proper compressive strength, and resistance to rising temperatures. Accordingly, it suffers less deformation under sustained loading [52]. Additionally, concrete pavement can resist frost cycles in cold zones, and prevent possible damage. Finally, using RCCP has no environmental impact due to its impermeability [53]. The neutral color of RCCP (gray) has a good coefficient of temperature absorption, which lowers the ambient temperature. Pozzolanic materials are usually used in RCCP due to their low cost and high strength [54]. Researchers [55,56] tested the applicability of geopolymer concrete in roller compacted concrete, among other uses. Generating models to accurately estimate the RCCP compressive strength would lead to a sustainable benefit, reducing both production time and cost besides optimal mix designing [54]. The RCCP using binder-based pulverized FA (PFA) powder was explored by Ashrafian et al. [54]. The PFA combines effectively with the gel created in concrete, increasing concrete hydration [57] and, as a result, increasing the density of the produced concrete and improving its chemical and mechanical characteristics. A comprehensive dataset of 235 test results collected from several studies was used for model development. Furthermore, MAE, RMSE,  $R^2$ , "Average Absolute Error" (AAE), "Performance Index" (PI), and "Objective Function" (OBJ), were implemented to evaluate the proposed GEP-based models. The results were verified using uncertainty and parametric studies. Moreover, a sensitivity investigation was also carried out to determine the importance of each input parameter on the RCCP compressive strength and revealed that sand content and water-to-binder ratio are the utmost significant predictors. The proposed GEP equation-based models were simple, robust, and straightforward to utilize, and consequently can be reliably used for RCCP strength estimation.

### 2.10. Self-Compacting Concrete (SCC)

When self-compacting concrete (SCC) is used in modern infrastructure development, it provides enormous benefits; SCC reduces energy use, labor costs, and building costs, etc. [58]. In order to avoid unnecessary repetition tests and extra material consumption, the development of models for estimating the strength characteristics of concrete can be beneficial. Some research works are available in modeling geopolymer concrete properties [59–64], in which GEP and ANN were implemented to estimate the properties of geopolymer concrete. GEP and ANN approaches were used by Awoyera et al. [65] to investigate the strength features of geopolymer SCC (GSSC). For the geopolymer process, these researchers used a 12M sodium silicate alkaline and sodium hydroxide solution with a ratio of 0.33 FA. FA was partially substituted with granulated blast furnace slag and SF in addition to the traditional material. The compressive strength, flexural strength, and the split tensile of hardened concrete, as well as filler ability and passage ability of new mixes, were all determined. Raw materials and fresh mix qualities were used as predictors, while strength attributes were used as the response. Both the ANN and GEP methods exhibited appropriate estimation of the experimental data, with negligible errors. However, GEP models could be preferred due to the development of simple equations [65]. The compressive strength of SCC containing FA was investigated using GEP by Özgür Deneme [66]. GEP models with different numbers of heads were implemented in the models' development. Two proposed established models were constructed utilizing cement,

water, FA, coarse and fine aggregate, superplasticizer, and the specimens' age, as input for the compressive strength evaluation. A total of 368 SCC mixtures were employed for training, and testing sets, and the models were validated using 148 sets for extra generality evaluation. The results achieved from the established models were compared with experimental values, and the previously proposed ANN model. The comparisons of the GEP models prediction results and experimental values strongly revealed that the results are very reliable with acceptable accuracy and correlation.

#### 2.11. Elastic Modulus of Concrete Containing FA

Two GEP models were introduced in Sarıdemir and Billir [67] research for predicting the elastic modulus ( $E_c$ ) of concrete containing FA. The proposed models are capable of elastic modulus prediction from the compressive strength of FA concrete and the amount of FA and compressive strength of FA concrete. The experimental results for 259 specimens, with 132 different concrete mixtures for the modeling, were collected from the literature [67]. The results were compared with the experimental results and formulas results given by some national building codes, which revealed that the outcomes of GEP-based equations are very reliable and well-agreed with the experimental results.

#### 2.12. Concrete Ultimate Strength under Triaxial Stress States

The inhomogeneous nature of concrete necessitates a more in-depth behavior investigation of this material under various loading configurations, due to its complexity. Different loading pathways should be investigated in this context in order to provide thorough behavioral knowledge. The general pathways explored by different researchers include uniaxial, biaxial, triaxial, and multiaxial (true-triaxial test). Closed-form equations were established by Gandomi et al. [68] and Babanajad et al. [69] to demonstrate the correlation between the compressive strength of concrete and primary stress components. Multiaxial stress states, also known as true-triaxial stress states, are a fact of life in construction, such as anchoring zones and shell structures [70]. Babanajad et al. [71] used a unique GEP feature to create computer-aided estimation models for concrete's multi-axial strength under true-triaxial stress. The suggested models connected true-triaxial concrete strength to mix design parameters and primary stresses without the requirement for time-consuming laboratory testing. External validation, as well as sensitivity investigation, were carried out using several performance criteria. The superior performance of the proposed model was demonstrated by comparing it to the other existing analytical models.

#### 2.13. Recycled Aggregate Concrete (RAC) Compressive Strength

Various types of recycled aggregate concrete (RAC) are employed by researchers and applied in construction toward sustainable development [72]. Accordingly, demolition and construction waste can be managed sustainably, while the misuse of natural construction resources would be significantly decreased, leading to the reduced environmental impact of concrete production [73]. However, RAC's primary drawbacks are its poor compressive strength and  $E_c$  [74]. Accurate prediction of the RAC compressive strength is necessary for design purposes and confidently allows using RAC in buildings and constructions. González-Taboada et al. [75] compiled a comprehensive database to provide a high precision model of recycled structural concrete's mechanical properties using the GP technique. For predicting RAC strength, Abdollahzadeh et al. [76] proposed 20 models for estimating the compressive strength of RAC containing SF by using GEP. Experimental data from 228 specimens made from 61 different combinations were gathered from the literature for model building. In the training phase, 80% of the data sets were used, with the remaining 20% being used in the testing phase. The cement content, age of specimens, water content, aggregates, recycled aggregates, SF, and amount of superplasticizer, were all arranged in a format of seven input parameters. The models demonstrate high consistency with experimental findings for compressive strength assessment of RAC containing SF, according to the training and testing results. Using the GEP approach, Gholampour et al. [77]

provided new empirical models for predicting RAC mechanical characteristics. Statistical indicators were used to show the findings of mechanical characteristics of RACs models. The suggested models' predictions agreed with the experimental test findings, indicating that, when compared to current models, GEP might offer better estimates of the mechanical characteristics of RACs.

Recycling and eliminating waste plastic products, such as polyethylene terephthalate (PET), from the environment are environmental concerns in urban areas. Using waste materials as a partial replacement for natural aggregate in concrete has shown to be a cost-effective solution to these materials' environmental issues. Ematzadeh et al. [72] examined the compressive strength of fiber-reinforced concrete (FRC) incorporating recycled PET chips subjected to high temperatures. The volume percentage of PET chips substituting natural sand, the volume ratio of steel fibers, and the temperature, were all thought to be relevant variables in the fabrication of 108 specimens. The use of PET in the concrete mix was shown to lower the compressive strength in the presence or absence of thermal stress. Using the GEP technique, a closed-form formula was established to estimate the compressive strength. In addition, the GEP model was validated by comparing the estimated and experimental outcomes, with the results indicating that the model predictions are very accurate and reliable.

#### 2.14. Green Concrete Incorporating Waste Materials

In order to re-cycle the "Waste Foundry Sand" (WFS), GEP models were studied by Iqbal et al. [78] to estimate the behavior characteristics of "Concrete Made with Waste Foundry Sand" (CMWFS). WFS is a significant contaminant produced from metal casting industries and can be classified as harmful material. An extensive dataset of mechanical characteristics of CMWFS was collected through the previous research comprised of 234 compressive, 163 split tensile strength tests in addition to 85 elastic modulus experimental results. The most important factors considered were the "Water-Cement" ratio (W/C), WFS%, "WFS-Cement" ratio (WFS/C), and WFS's modulus of fineness. The models' performance was evaluated by carrying out statistical analysis and comparing the results. The results indicated that GEP models can accurately predict mechanical properties with high generality capability. The findings might enhance the reuse of WFS for the development of green concrete and protect the environment, as well as financial providence. Green concrete compressive predictive models were developed by Murad et al. [79] using GEP. The models were developed for the compressive strength estimation of concrete, concrete mixed with FA, SF admixed concrete, and concrete with both SF and FA. The GEP models were established and validated using the database compiled from the literature. The  $R^2$ -value was implemented to evaluate the GEP models' performance. Acceptable  $R^2$ -values (greater than 0.8) and low RMSE and MAE achieved for GEP models indicate the capability of estimating the compressive strength of green concrete with reasonable accuracy.

#### 2.15. Lightweight Concrete Design

The use of lightweight concrete (LWC) in earthquake-resistant constructions is advantageous since the structures' weight and bulk are reduced. Providing references for three types of lightweight concretes, including clay and natural (mineral) pumice aggregates, was explored by Jafari and Mahini [80]. Using the aforementioned aggregates, 100 LWC specimens were constructed and examined in the lab. To obtain the compressive strength of a certain combination, three equations were constructed using GEP. When LWC mixtures are involved, comparing the actual and expected characteristics revealed that the recommended derivations are relevant and feasible for engineers.

#### 2.16. Recycled Rubber Concrete

Jalal et al. [81] studied the compressive strength prediction of rubber concrete composite containing SF, and zeolite (ZE) was investigated. Different forecasting models were developed using NMVR, ANN, GEP, ANFIS, and SVM. Closed-form formulations were

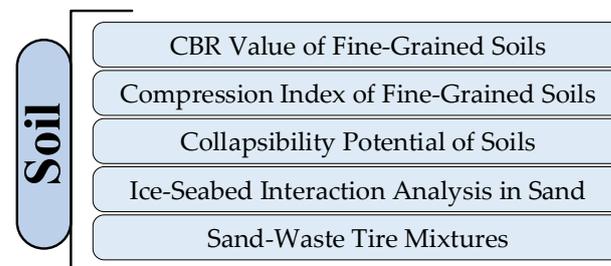
presented using NMVR, ANN, and GEP models. Performance indices, such as  $R^2$ , MAPE, and RMSE, were used to compare the performances of the models. Two GEP models were considered with different complexity in terms of the number of genes. Considering three and eight genes in GEP (I) and GEP (II) models,  $R^2$ -values of 0.93 and 0.95 were reported, respectively. In GEP (I), the cement variable was omitted automatically in the model evolution trend. This variable exclusion might be due to the inter-correlation cement with SF and ZE. Both models' accuracy was acceptable; however, the more complex model may lead to slightly higher precision (around 2%), which might be taken into account when the rough estimation of the compressive strength is not the case.

### 2.17. Shrinkage of Concrete including Mineral Admixtures

Mermerdaş et al. [82] derived a soft computing based mathematical model for predicting concretes shrinkage using GEP. The prediction parameter assigned to water-to-binder ratio, SF, FA content, cement, aggregate-to-binder ratio, compressive strength, type of shrinkage for shrinkage, and drying time. The obtained GEP model was compared to an available formula previously generated by ANN. Models were compared through some performance indices such as R, MAPE, MSE, and RMSE. An additional assessment of the performances was performed using an advanced statistical analysis method called "Wilcoxon on rank sum test", which indicates whether the obtained estimated and actual data are statistically equivalent or not, considering a specified level of significance. Although the constructed GEP model showed lower performance than the available ANN model, its simplicity in usage is preferable rather than the ANN one. Additionally, the statistical analyses proved that the proposed models' accuracy is good enough to be utilized for estimation purposes.

## 3. Soil

This section includes five subsections, which are reported in Figure 4, and will be described in the following.



**Figure 4.** The studied subsections of soil.

### 3.1. CBR Value of Fine-Grained Soils

The evaluation of subgrade soil strength is one of the most critical tests in evaluating the strength property concerning the adopted method for road pavement design. The "California Bearing Ratio" (CBR) is the most frequent parameter for flexible road pavement design. In situ or laboratory experiments of CBR are money and time-consuming and require skilled technicians. A soil sample CBR value evaluation via readily determinable physical and geotechnical parameters can be practical, which was investigated by Alam et al. [83] using the GEP approach. Taskiran [84] conducted a study to correlate the CBR of fine-grained soils from the southeast Anatolia region of Turkey by applying AI techniques. The CBR values using developed GEP and ANN models were evaluated. It was shown that both ANN and GEP learned the pattern between the CBR value and basic soil properties. Performed sensitivity analysis revealed that the maximum dry unit weight is the most influential parameter on CBR compared to plasticity index, sand content, liquid limit, optimum moisture content, fine-grained content, and gravel content. Statistical parameters such as  $R^2$ , MSE, and "Standard Deviation" (SD), were used to evaluate the accuracy of the

estimated results. Tenpe and Patel [85,86] established mathematical models to predict CBR using the various soil characteristics as independent variables using GEP and ANN models. The subgrade strength of both highways and roads depends on the “California bearing ratio” (CBR) value. Tenpe and Patel [85] attempted to develop models using SVM and GEP for CBR value prediction. A wide range of databases of different soils was used in the analysis. Consistency limits, particle size distribution, and compaction characteristics, were used as the input contributing variables. The benefit of SVM over others is working, based on statistical risk minimization. A comparison between SVM and GEP models indicated that the accuracy of SVM outperforms the GEP model. According to the statistical criteria, overfitting ratio of SVM was about 0.63, while it was about 1.02 for GEP model.

### 3.2. Compression Index of Fine-Grained Soils

The “Compression index” ( $C_c$ ) is a main factor in calculating the settlement of clay layers. Measuring ( $C_c$ ) value in the lab is an expensive and slow test and requires skilled labor. Mohammadzadeh et al. [9] investigated  $C_c$ 's prediction using basic soil parameters, such as the PL, LL, and initial void ratio ( $e_0$ ). The GEP model was established using a database that included 108 different data points, and a closed-form equation was derived for  $C_c$  as a function of PL, LL, and  $e_0$ . The GEP model's performance was assessed through the  $R^2$ , MAE, and RMSE, based on which the proposed model performed better compared to that of other models [87].

### 3.3. Collapsibility Potential of Soils

Collapsible soil is the soil that suffers a large reduction in volume when wetted, while subjected to continuous compressive pressure. It is one of the well-known causes of failure of soil-structure projects, such as earth dams and highway/railway embankments. Uysal [12] developed a GEP model to estimate the collapsibility potential in terms of sand-to-clay ratio or “coefficient of uniformity”, initial dry density, and water content besides wetting pressure. The precision of the GEP model was validated using laboratory experimental results and previous regression-based formulas, which indicated that the GEP model was more precise in predicting the collapsibility potential.

### 3.4. Ice-Seabed Interaction Analysis in Sand

Pipelines for the Arctic subsea are often buried for protection against the scour due to ice. Determining the maximum lateral displacement to guarantee both cost-effective design and operational integrity is the main challenge of the subsea pipeline industry in ice-prone zones. Considering a practical and cost-beneficiary solution for estimating the ice effect on buried pipelines, Azimi and Shiri [88] used the GEP approach to model the sub-gouge displacement in the sand. The main input parameters included dilation index, bearing pressure, attack angle, thickness of sub-gouge deformation, and soil depth. Accordingly, six GEP models were generated and tested by “K-fold” cross-validation technique. The accuracies of the developed GEP were compared with an ANN model, and a “Partial Derivative Sensitivity Analysis” (PDSA) was carried out to assess the key parameters' influence domain. It was shown that the GEP models could be a precise and more cost-effective alternative for estimating the ice-induced sub-gouge displacement [87].

### 3.5. Sand-Waste Tire Mixtures

Waste tires have become a main concern, and each year, the world produces more of these bulky materials. The problem could mostly be attributed to the world's increasing population and thus the demands for automotive transportation by vehicles, which lead to waste material being amassed after reaching the end of life. These waste and discarded bulky materials can be used to reinforce weak soils, slope stabilization, or, in the form of tire-derived aggregates (TDA), be implemented for the backfilling of retaining structures [89–93]. Soil-waste tire mixture showed more compressibility, less void ratio, and more attenuation than pure soil [94]. Edincliler et al. [95] investigated applications of the GEP and “Stepwise

Regression" (SR) for the estimation of shear modulus and damping ratio of the sand-rubber mixtures [92]. The damping ratio and shear modulus of geo-materials were measured through a series of cyclic triaxial tests, and the assumed input parameters in the generated GEP and SR models were confining pressures, strain, and type and content, of waste tires. The outcomes were the damping ratio and the shear modulus. The proposed GEP models ( $R^2$ -values of 0.94 and 0.95 for damping ratio and shear modulus, respectively) were perceived to be more precise than the SR models ( $R^2$ -values of 0.87 for shear modulus and 0.91 for damping ratio) [96].

#### 4. Mortar

This section includes four subsections, which are shown in Figure 5, and will be discussed in the following.



**Figure 5.** The studied subsections of mortar.

##### 4.1. Effect of "Nano Silica" (NS) and "Micro Silica" (MS) on Mortar Cement

Supplementary cementitious materials with high pozzolanic properties, or industrial waste materials, can change the microstructure of cement-based materials such as mortar, sandcrete, and concrete. It also enhances their mechanical characteristics [97]. Both NS and MS are the most efficient additives to change the microstructural configuration, which add to enhance the behavior of concrete and mortar because of their tiny particle size and pozzolanic reaction [96]. Machine learning techniques have been used to study the NS or MS in addition to a super plasticizer, which is the traditional way to minimize porosity and enhance both compressive strength and mortar durability. Tanyildizi and Çevik [98] reported that GEP was used to evaluate different combinations of considered factors to get the best fits to test results according to the correlation coefficient. GEP was used to predict the behavior of LWC with 0.0, 10.0, 20.0, and 30.0% of MS, subjected to a high level of temperature. Two models were developed, one using ANN and the other using GEP, as presented in the research work of [99], to estimate the effect of using NS and MS together on the characteristics of cement mortar. A total of 640 different design mixes were used to generate both ANN and GEP models, beside those, the 480 results of cube compressive strength test and the 96 results of bending strength test, were utilized to validate the two models. The two proposed models showed better accuracy levels than the current models. Finally, a study was conducted to investigate the impact of considering porosity as an input factor on the accuracy of the developed models.

##### 4.2. Impact of Porosity on Both Flexural and Compressive Strengths of Cement Mortar Having Micro and Nano Silica

Emamian and Eskandari-Naddaf [100] estimated the impact of porosity on the strength of mortar mixtures that include micro and nano-silica. Thirty-two (32) design mixes were tested for this purpose with different replacement proportions of "Nano-Silica" (NS) and "Micro-Silica" (MS) in individual and combined forms. "Field Emission Scanning Electron Microscopy" (FESEM) analysis was used to investigate the impact of the microstructure of NS and MS on the strength of the mortar. Additionally, both the flexural and compressive strength of mortar were forecasted using GEP and ANN models, which illustrated the impact of the porosity on the mortar strengths. A study was conducted on two conditions, the first without considering the porosity and the second considering it. ANN-I and GEP-I were generated in the first condition, while ANN-II and GEP-II were generated in the

second one. The results illustrated that using MS and NS together reduces the porosity and increases the strengths. Additionally, the results indicated that the second condition models (ANN-II and GEP-II) are more accurate than the first one.

The prediction and formulation of the hardened characteristics of cement mortar containing NS and MS together considering the “freeze-thaw” (F-T) cycles based on lab test results, were conducted by Emamian and Eskandari-Naddaf [101] to evaluate the capability of the GEP technique. A total of 32 design mixes with a cement content of 990–1200 grams, water/binder ratios between 0.4 and 0.5, sand/cement ratio of 2.67–3.22, MS/cement ratio of 0.0–0.16, and NS/cement ratio of 0.0–0.05, were prepared and tested. The targets in the GEP model were porosity ( $n$ ), compressive strength, and flexural strength with considering F-T cycles. The input dataset for the proposed GEP models were results extracted from the lab tests of this research. Minor differences were observed between the lab test results and the predicted values by the GEP model. The capability of the GEP technique to predict the characteristics of hardened cement mortar is proved by the generated predictive formulas.

In the Mahdinia et al. [102] study, 54 design mixes with a  $w/c$  ratio of 0.25–0.50,  $S/C$  ratio of 2.5–3.0, and “Cement Strength Classes” (CSC) of 32.5–52.5 MPa, were prepared and tested, then 270 specimens with ages between 3 and 28 days were prepared and tested. The GEP technique was utilized to estimate the strength of cement mortar. The impact of CSC on the mortar strength was investigated by developing two different GEP models, one with CSC as input and the other without it. The results illustrated that considering the CSC improves the prediction accuracy of mortar strength.

#### 4.3. Compressive Strength of Ferrosialate Based Geopolymer Mortars

A novel and efficient approach to forecasting the compressive strength of specimens of mortar by developing estimation formulas was proposed by Yeddula and Karthiyaini [103] in the present circumstances, where there is no code provision or standard method to design the mixture of “ferrosialate geopolymers”. It also studied the impact of different elements on increasing the strength of “ferrosialate geopolymers” regarding the traditional “FA/sialate geopolymers”. Precursors for geopolymerization materials like red mud (RM) and FA were used, and GEP was used for the model analytics. Ferrosialate mortar specimens showed compressive strength equal to 112.4% of the sialate mortar specimens with more dense microstructural composition and least binder unreacted stages. The optimum RM replacement ratio was 35% and 30% for ambient and oven curing, respectively. For the “ferrosialate geopolymers” that use RM as raw feed, the optimal dose aqueous solution of NaOH is 8 Moles, and again, oven curing gives a higher strength gain than ambient curing. Additionally, in “ferrosialate geopolymers”, the longer the curing period, the higher gained strength. The  $R^2$ -values for both developed GEP models were 0.88 and 0.92, respectively. The almost equal error percent of both training and validation datasets indicated the generality of the developed models.

#### 4.4. Compressive Strength of Lightweight Geopolymer Mortars

For the case of forecasting the compressive strength of lightweight geopolymer mortar (LWGM) with various types and amounts of binders with different curing regimes, Mermerdaş et al. [104] presented an inclusive study aimed at establishing a suitable mathematical model. Lightweight pumice aggregate and alkali activated powder materials are the main components of geopolymer binder. The experimental investigation collected 306 data samples, which were utilized to generate explicit model expressions for determining the compressive strength of LWGMs. The models were created using two methods. The first was a linear stepwise regression that was simplified. The GEP approach was the second way. Stepwise regression is a statistical method that evaluates the influence of each element on the resulting equation based on its strength. The probability effect of the F-distribution and the null hypothesis are used to determine this strength. The default probability value is 0.05 for each factor’s relevance. As a result, the program assesses each predictor’s likelihood and only includes those with values less than 0.05. A simplified linear regression equation

is introduced as a result of the contained predictors. Genetic programming, on the other hand, is a more advanced approach based on the principles of gene evolution. Each sort of binder's modeling is done separately. Equations based on granulated blast furnace slag and FA-based LWGM were generated as a result. Genetic algorithm-based modeling has been shown to have reliable potential in the evaluation of the strength of a network using these models.

## 5. Asphalt (Pavement)

This section includes seven subsections, which are shown in Figure 6, and will be discussed in the following.



**Figure 6.** The studied subsections of asphalt (pavement).

### 5.1. Viscosity Mixing Rule for Asphalt Blends

The binary blends of single hydrocarbons have inactive chemical and physical properties. It is normal to see that the properties of the mixture are different from the single hydrocarbons. Regardless of the single viscosity of the elements in the mixture, the total viscosity of the mixture depends on other factors, such as temperature, pressure, and the ratios of single components of the mixture [105].

The effect of mixture viscosity was investigated by different researchers to forecast the relation between elemental components and the binary blends. These mixture viscosity forecasting models, have shifted from conventional closed-form formulas to modern (AI) techniques. Modeling bi-mixtures of oils or petroleum blends have been attempted by various researchers employing artificial intelligence techniques. These AI techniques included least-squares "Support Vector Machine" (SVM) [106], "Particle Swarm Optimization" (PSO) combined with "Neuro-Fuzzy" "NF" inferences [107], and "Artificial Neural Network" (ANN) [108]. These techniques have their shortfalls as they do not produce formulas that can be used manually; in other words, they are "black box" techniques. However, "Gene Expression Programming" (GEP) is an (AI) technique that provides closed-form forecasting formulas as outcomes, which can easily be used manually. The (GEP)-based model to estimate the mixture viscosity was proposed by Eleyedath and Swamy [109] in a previous research work. Bi-mixtures were tested to measure their viscosity at different degrees of temperature to develop these expressions. The observed dataset was utilized to generate GEP model for mixture viscosity. A study was carried out to prove that the GEP model is more accurate than previous references.

### 5.2. Dynamic Modulus of Asphalt

Asphalt property is a key parameter as an input into the pavement design guide known as the Mechanistic Empirical Pavement Design Guide (MEPDG). This is employed to determine asphalt's mechanical properties. Previously, various researchers, such as Witczak and Fonseca [110] and Esfandiarpour and Shalaby [111], have evaluated the efficacy of the dynamic modulus of asphalt, within the framework of MEPDG. Researchers have advised employing regression-based methodologies to recalibrate different models for

local settings, since equations calibrated at the national/regional level performed poorly. Additionally, researchers have attempted to generate intelligent learning-based predictive models apart from these regression-based predictive ones. Some examples of such new evolutionary techniques include ANN, Classification and Regression Tree (CART), and GEP. Ceylan et al. [112] used the Witczak database, which contained 7400 data points from 346 hot mixed asphalt (HMA) combinations, to present an ANN-based dynamic modulus of the asphalt prediction model. Far et al. [113] used a long-term pavement performance database to construct a dynamic modulus of the asphalt forecasting model in a similar study. Due to ANN's black-box or hidden layer nature, it is only with the help of a computer that its models can be employed. This makes ANN models inefficient techniques for revealing the relationship between predictors and targets. Daneshvar and Behnood [114] employed a CART-based random forest technique to forecast the dynamic modulus of asphalt concrete commonly used in the northern US. Unfortunately, such a method has problems with: (i) higher calculation time; (ii) less interpretable decision tree (DT); (iii) slower forecasts; (iv) overfitting; and (v) subjectivity in selecting the number of trees. Conversely, GEP combines the merits and strengths of "Genetic Programming" (GP) and "Genetic Algorithm" (GA). Eleyedath and Swamy [109] presented a new technique, "Principal Component Analysis" (PCA), the "Gene Expression Programming" (GEP) technique, to estimate the asphalt concrete's dynamic modulus. A database of considered factors was used as inputs. The PCA technique was used to eliminate the input redundancy by reducing the dimensionality. Extracted "Principal Components" (PC's) were utilized to develop the first set of prediction models for the dynamic modulus. The second set of dynamic modulus prediction models were generated using the most effective factors to the individual PC's. Comparing the two sets shows that using factors as input directly in the model improves the prediction accuracy. Besides that, the achieved accuracy was better than the accuracies of the current regression-based formulas. The generality of the proposed model allows it to be applied to any new dataset.

### 5.3. Fracture Energy of Asphalt Mixtures

The asphalt mixture's fracture energy was estimated by Majidifard et al. [115]. They used both (GEP) and "Artificial Neural Network/Simulated Annealing" (ANN/SA) techniques. Both (ANN/SA) and (GEP) models were generated based on experimental test results, such as "disk-shaped compact tension" (DC (T)) test results for fracture energy. Various predictor factors, including "asphalt binder performance grading (PG)", "reclaimed asphalt pavement" (RAP), "reclaimed asphalt shingles" (RAS), asphalt content, crumb rubber content, aggregate size, test temperature, and aggregate gradation, were employed to formulate the fracture energy of asphalt. A procedure was proposed to transform the models' outputs into practical design formulas. A study was carried out to evaluate the impact of each predictor factor on fracture energy. According to the outcomes, the proposed design formula exhibited high accuracy in characterizing the fracture energy of asphalt mixtures. Due to its simplicity and superior accuracy, the GEP model is considered more practical than the ANN/SA model.

### 5.4. Rutting Depth of Asphalt Mixtures

Using (GEP), Majidifard et al. [116] presented a novel evolutionary model for forecasting the asphalt mixture's rutting depth. The test results of Hamburg were used to generate a GEP model. Ninety-six test results made up the database for different asphalt mixtures, with which the model was executed. The model was proposed with the following predictor variables: total asphalt binder recycling content; aggregate size; asphalt binder; mixture type; asphalt content; high-temperature performance grade (PG); and aggregate gradation. During validation, the model precision was assessed.

A study was carried out to benchmark the estimating accuracy of the GEP model against an ANN model. The model was able to mimic the mixture properties and testing

conditions. The model could be used in pre-design or to estimate the depth of rut of asphalt mixtures without lab tests.

#### 5.5. Effects of Aggregate Angularity on Asphalt Mixture Permanent Deformation

Using nonlinear GEP models, Gandomi et al. [47] studied the estimation of the flow number of asphalt concrete. In asphalt concrete pavements, the flow number has a relationship with rutting. Meanwhile, Gopalakrishnan et al. [117] proposed predictive models for hot mixed asphalt (HMA) dynamic modulus using the GEP technique. The study showed that the proposed models presented higher accuracies than the existing model by Witczak. Liu et al. [118] evaluated the HMA's dynamic modulus by also employing the GEP technique for mixtures of recycled asphalt shingles. It was also observed that the GEP model showed better prediction accuracy than the current prediction models. The advantage of GEP over ANN is that it provides a closed-form formula for pavement engineers.

It is important to note also that the shape of the aggregate has a great influence on the interlocking between the particles, also affecting the deformation performance of mixes. Leon and Ray [119] predicted asphalt concrete's permanent settlement with the amount of aggregate angularity by using (GEP) as an untraditional modeling approach. Original data was obtained through multiple lab experiments for estimating the permanent settlement of asphalt concrete. The GEP approach showed fair results in the forecasting of permanent settlements compared to current regression methods.

#### 5.6. Unconfined Compressive Behavior of Hot Mix Asphalt (HMA)

In order to predict the performance of materials during service life, the mechanical properties of such materials, like "Elastic tangential modulus" (Et) and "Unconfined Compressive Strength" (UCS), can be used. Leon and Ray [119] utilized the GEP method to evaluate the UCS of hot mix asphalt. The GEP and "Multiple linear regression" (MLR) techniques employed in the forecasting of UCS and Et showed good results. The "coefficient of determinations" ( $R^2$ ) for USC were 0.887 and 0.908 for MLR and GEP, respectively. Similarly, ( $R^2$ ) for Et were 0.785 and 0.648 for MLR and GEP, respectively. The developed models provided a fast, cheap, and flexible method to estimate the stress-strain relation of asphalt concrete without the need for experimental tests.

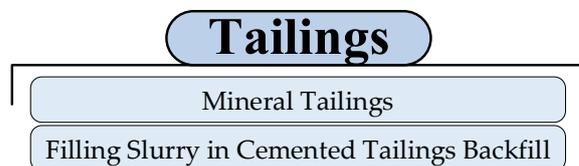
#### 5.7. The Service Life of Flexible Pavement (RSL)

The service life of pavement forecasting is a serious assignment of transportation engineering and road maintenance. The model forecasting of the RSL evaluates the duration that main pavement rehabilitation is necessary. The universal method or technique to forecast RSL includes using tests that are non-destructive. These tests, apart from being cost ineffective, disturb traffic flow, and compromise safety. In a previous study, Nabipour et al. [120] studied that the surface distresses of highway pavement are employed to evaluate the RSL to evaluate the challenges mentioned above. In order to put to work the suggested theory, 105 segments of flexible pavement were considered.

For every pavement segment, the "Pavement Condition Index (PCI)", surface damage extent, type, and severity, were evaluated. The RSL of the pavement was then evaluated using tests that are non-destructive, which included falling weight deflect meter (FWD) and "Ground-Penetrating Radar" (GPR). Afterwards, the datasets are compiled, and modeling is carried out to forecast RSL using three methods, which include SVR, optimized SVR by the Fruit Fly Optimization" algorithm (SVR-FOA), and GEP. All three modeling approaches forecast the RSL of the highway pavement by choosing the PCI as input parameter. The "Correlation coefficient" ( $R^2$ ), "Nash-Sutcliffe efficiency" (NSE), "Scattered index" (SI), and "Willmott's index" of agreement (WI) criteria, were used to test the behavior of the three methods deployed in this model exercise. At last, it was observed that GEP with  $R^2 = 0.874$ , NSE = 0.598, SI = 0.601, and WI = 0.807, had the best precision in forecasting the RSL of highway pavement.

## 6. Tailings

This section includes two subsections, which are shown in Figure 7, and will be discussed in the following.



**Figure 7.** The studied subsections of tailings.

### 6.1. Mineral Tailings

In the field of geotechnical and geo-environmental engineering, deposits of mineral tailing are one of the most significant issues. Tailings are mineral wastes that are fractured and wasted after the extraction and exploration of useful minerals. To investigate the geotechnical behavior of tailings, the tailing's void ratio is a main parameter, although as yet there has not been an empirical equation for predicting the tailing's void ratio. In previous related research, the waste mineral's void ratio was predicted using the (GEP) according to Heshmati et al. [121]. Meanwhile, considering the effective physical factors that influence the evaluation of this factor [122], eight different model equations were presented. An experimental database of about 113 laboratory data points gathered from literature was employed to generate the GEP models. The behavior of the generated GEP model was calculated using  $R^2$ , MAE, and RMSE. The outcomes showed that the best predicted "effective stress" ( $\sigma'$ ), "initial void ratio" ( $e$ ), have MAE = 0.109,  $R^2 = 0.92$ , and RMSE = 0.180. Lastly, a novel analytical formulation for the initial forecasting of the void ratio parameter is generated and suggested based on the analyses mentioned above.

### 6.2. Filling Slurry in Cemented Tailings Backfill

In most modern mines in China, cemented tailings backfill (CTB) has become a conventional mining technique. In order to meet the desired technical and economical design requirements, the parameters of the filling slurry are vital in designing a CTB. In a previous research presentation, Wang et al. [123] provided an approach to optimize the mix proportion of the filling slurry; GP and GA were used in this study. To create the unconfined CS (UCS), coursing degrees (CD), and slump data points, a series of tests were initially carried out. The GP results were employed in constraint conditions, which were crucial in optimization. The combination of the GA and GP revealed an excellent method for optimizing the CTB mix fraction in this investigation. The combined effect of GP and GA used in this study gives an engineering strategy for determining the CTB mix fraction.

Generally, beyond the fields of civil engineering and construction materials, GEP has been adapted to solving various other engineering and environmental problems, as presented by Sadeghi et al. [124,125]. The list is endless, but the present review work has presented an extensive search into the application of GEP, fundamentally as it affects major civil engineering problems and construction materials.

## 7. Concluding Remarks on the GEP Modeling

The following conclusions can be drawn:

- Like many other numerical approaches, GEP would involve advantages and shortcomings. The most significant distinction in GEP modeling is flexibility, which can be readily adopted, and evolutions can be initiated, incorporating user-selected or user-defined functions, constant ranges, and fitness functions. The outcome of the evolutions would lead to closed-form explicit formulations. If the input parameters can be evaluated through simple laboratory or rapid measurements, and a comprehensive experimental database was available, the models can be constructed.

- Compared to the ANN based formulations, which are often too complex to be used, GEP-based derived models provide estimation equations that are reasonably simple and can be used for practical design purposes, and can even be used for hand calculations. Many popular models, such as best-fitted curves based on regression analyses, MLR, MNLR, and MNVR, can be used for construction materials properties modeling. However, due to the nonlinearity and complexity of the target properties, the models developed using regression analysis may not reveal their precise nature. Besides, regression models may not considerably measure the additive component's effect on construction materials properties, such as concrete compressive strength. The lack of generality in regression models comes from the fact that some functions are defined for regression in classical regression techniques; while in the GEP approach, there is no predefined function to be considered, and it reproduces or omits various combinations of parameters to provide the formulation that fits the experimental outcomes.
- Flexibility in choosing the complexity and fitness functions, such as RMSE and MSE, might lead to better performance of the approach and well-capturing the governing pattern behind the material's characteristics. Thus, GEP can be accepted to be superior to conventional and classical regression techniques and ANN. Another merit of the GEP is the automatic feature selection in the evolution process. Input variables inter-correlated to other contributing parameters, or having minor contributions to the target, would be put aside and omitted automatically in the model evolution iterations. Different combinations of the input variables can be considered for GEP modeling with no specific pre-processing, which is not the case in ANN.
- The results of GEP based models may sometimes show lower accuracies when compared to artificial neural networks and support vector machines. In some cases, the lower precision might be attributed to the limited number of considered genes, chromosomes, and heads, which are the predefined characteristics in the GEP model development process. However, the explicit mathematical expressions, which can be easily implemented in the design and analysis process, may cover the minor inaccuracies compared to ANN and SVM approaches. Based on the presented review, it would sometimes be better to provide more than one GEP model and consider different combinations of input contributing variables to afford the possible initial feed for a more settled and comprehensive model.
- Research is ongoing on the topic of the present paper, and as a future study suggestion, the application of the Adaptive Neuro-Fuzzy Inference System (ANFIS) [81,126] could be further compared to the Gene Expression Programming (GEP) modeling.

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