Metaheuristic Based AI Approach Towards Strength Prediction of Strain Hardening Cementitious Composites (SHCC)

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DEDICATION

Dedicated to my beloved mother, father, brothers and the rest of the family and friends who have stood behind me till the accomplishment of this research.

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ABSTRACT

This research aims to create new empirical prediction models to assess the mechanical properties of strain hardening cementitious composites (SHCCs), to avoid the costly, and hectic experimental procedures that need enough time and require skilled investigators. Soft computing method adopted in this research is gene expression programming (GEP). This study compute five outputs, i.e., compressive strength (CS), first crack tensile stress (TS), first crack flexural stress (FS), first crack tensile strain (TST), and first crack flexural strain (FST). Wide-ranging records were considered from available literature with twelve parameters selected as the predictor variables. Important inputs of the study were cement percent weight (C%), fine aggregate percent weight (Fagg%), fly ash percent weight (FA%), water to binder ratio (W/B), super plasticizer percent weight (SP%), fiber amount percent weight (Fib%), length to diameter ratio (L/D), fiber tensile strength (FTS), fiber elastic modulus (FEM), environment temperature (ET), and curing time (CT). Correlation coefficient (R), and regression coefficient (R^2) were used in the deduction of the model's performance. In addition to this, the performance of the models was also established using relative root mean square error (RRMSE), mean absolute error (MAE), root squared error (RSE), root mean square error (RMSE), objective function (OBF), performance index (PI) and Nash-Sutcliffe efficiency (NSE). The resulting mathematical GP-based equations disclose the originality of GEP model. In addition to this, these equations are easy to understand and consistent. The objective function and performance index are also in accordance with the literature references. Consequently, all the proposed AI approaches has high generalization. The sensitivity analysis showed cement percentage, fine aggregate percentage and environmental temperature to be the most sensitive and significant variables for all the five models developed (CS, TS, FS, TST and FST). The result of this research can assist researchers, practitioners and designers in freely assessing SHCC; consequently, limiting environmental exposures. It will lead to sustainable, faster and safer construction from environment-friendly waste management point of view.

Keywords: Engineering cementitious composites (ECC); Compressive strength (CS); Tensile stress (TS); Flexural stress (FS); Tensile strain (TST); Flexural strain (FST); Artificial Intelligence (AI); Machine learning (ML); Gene Expression Programming (GEP).

TABLE OF CONTENTS

LIST OF FIGURES

LIST OF TABLES

LIST OF SYMBOLS AND ABBREVIATIONS

Symbol	Description
SHCC	Strain hardening cementitious composites
ECC	Engineering Cementitious Composites
OPC	Ordinary Portland Cement
C%	Cement Percentage By Weight
F_{agg} %	Fine Aggregate Percentage by weight
W/B	Water to Binder ratio
SP %	Super plasticizers percentage by weight
F_{ib}%	Fiber Amount percentage by weight
L/D	Length to Diameter Ratio
F_{TS}	Fiber Tensile Strength
F_{EM}	Fiber Elastic Modulus
ET	Environment Temperature
CT	Curing Time
AI	Artificial Intelligence
ANN	Artificial Neural Network
ANFIS	Adaptive narrow-Fuzzy interface system

RF	Random forest regression
MEP	Multi-Expression Programming
GA	Genetic Algorithm
GP	Genetic Programming
GEP	Gene Expression Programming
ET	Expression Tree
CS	Compressive Strength
TS	First Crack Tensile Stress
FS	First Crack Flexure Test
TST	First Crack Tensile Strain
FST	First Crack Tensile Strain
MAE	Mean Absolute Error
RSE	Root Squared Error
RMSE	Root Mean Squared Error
R	Coefficient of Correlation
RRMSE	Relative Root Mean Squared Error
PI	Performance Index

OBF	Objective function
NSE	Nash-Sutcliff efficiency
SA	Sensitivity Analysis
K	Slope of the Regression Line

CHAPTER 1

INTRODUCTION

Concrete is currently the most common material employed in the construction of constructions. Several structures remain in good functioning order, however owing to low material grade, poor maintenance, poor execution, and inappropriate design, several recent structures begin to exhibit indications of distress in a short period of time. As a result, most historic buildings require greater care and restoration, which may be accomplished with strain hardening cement composites.

A recently used concrete type has been giving satisfying results in construction and repair of engineering constructions; it is called engineered cementitious composites (ECC) or strain-hardening cementitious composites (SHCC) [1-5]. It has got, when compared to common concrete, a 300 to 500 times greater strain capacity [6]. Fracture widths of SHCC are less than 60 μm when subjected to high distortions. By giving this result, SHCC is solving long awaited solution to reinforced concrete construction and this is because of its high tensile ductility and compact crack width. [7-12]. Many researchers are conducting research on SHCC in different aspects, i.e., by varying the volume or type of fiber and trial situations. By using only less than 2% fiber by volume, SHCC provides excessive tensile strength, allowing the SHCC for high performance [13-19]. For a material to be used in actual for constructions, series of consistent efforts are needed to satisfy construction industry [20], as practical application is far different from design process of SHCC because it involves finite element analysis. In addition to this, shortage of professional staff is also hampering the application of SHCC [21]. The exponential growth of SHCC in many industrial practices is expected in the next decade. To optimize the use of SHCC, this research mainly focused on the development of the empirical prediction models for their mechanical properties using artificial intelligence techniques. Current study considers eleven controlling parameters, which is a quite challenging task and there exist higher chances of inaccuracy during lab testing. The development of these models will aid the designer and practitioners, to effectively utilize the SHCC in industrial practices.

1.1. Problem statement

Many experimental research studies carried out on the production of SHCC. Still there no proper mix design procedure developed till now. The mechanical properties of SHCC critically depend on several parameters like water content, curing temperature, curing time, aggregate, age of samples, and admixtures. Controlling all these variables simultaneously is a challenging task and there exist higher chances of inaccuracy during lab testing. However, AI based algorithms can be adopted to overcome these challenges. We need to formulize the compressive strength, first crack tensile stress, first crack flexural stress, first crack tensile strain, and first crack flexural strain of SHCC, as the experimental test are costly, time consuming and require skill investigators. In this research, one of the artificial intelligences (AI) techniques, gene expression programming (GEP) will be used to construct a mathematical model for the compressive strength, first crack tensile stress, first crack flexural stress, first crack tensile strain and first crack flexural strain of SHCC.

1.2. Objectives

Extensive research is available on the experimental determination of first crack tensile strain and first crack flexural strain of SHCC~~.~~ And still no proper mix design procedure is developed. There is a need to accurately formulize the compressive strength, first crack tensile stress, first crack flexural stress, first crack tensile strain and first crack flexural strain of SHCC. Keeping these points in mind, the following objectives are formulated.

I. To employ the machine learning (ML) technique for determining a model that can accurately predict the compressive strength, first crack tensile stress, first crack tensile strain, first crack flexural stress and first crack flexural strain of SHCC.

II. To evaluate the validity of the developed model using detailed statistical analysis along with sensitivity analysis.

1.3. Advantages of SHCC

The attractive features of strain hardening composite materials provide numerous benefits. It is obvious that the strength characteristics of SHCC are equivalent to that of high-performance concrete, whereas the energy absorbing capabilities, deformation, and crack width control are substantially enhanced due to the strain-hardening occurrence. SHCC can be used in scenarios where such qualities are significant in improving performances. All of such types of uses is described in detail below. The University of Michigan is now investigating the use of SHCC as a patch replacement substance.

To improve the endurance of steel and concrete flexural components, the authors developed a novel concept [4]. To reduce the fracture breadth, the structure allows utilisation SHCC's distinctive strain-hardening feature. In a typical reinforced concrete section, the composites are employed to substitute the construction mix which envelopes the primary reinforcement. This concept demonstrated that fracture widths at different loading circumstances may be reduced to levels that traditional steel reinforcing and frequently used concrete could not reach. According to these circumstances, it was found that hostile compounds could be prevented from migrating into the cementitious materials or reinforcements.

ECC is more widely known as bendable concrete. The compressive strength of ECC is 10-15% more than normal concrete (NC), while their tensile strain capacity is 300 times more than NC. The excellent energy-absorbing properties make it suitable for critical elements in seismic zones and design criteria for skyscrapers (see Figure 1.1.).

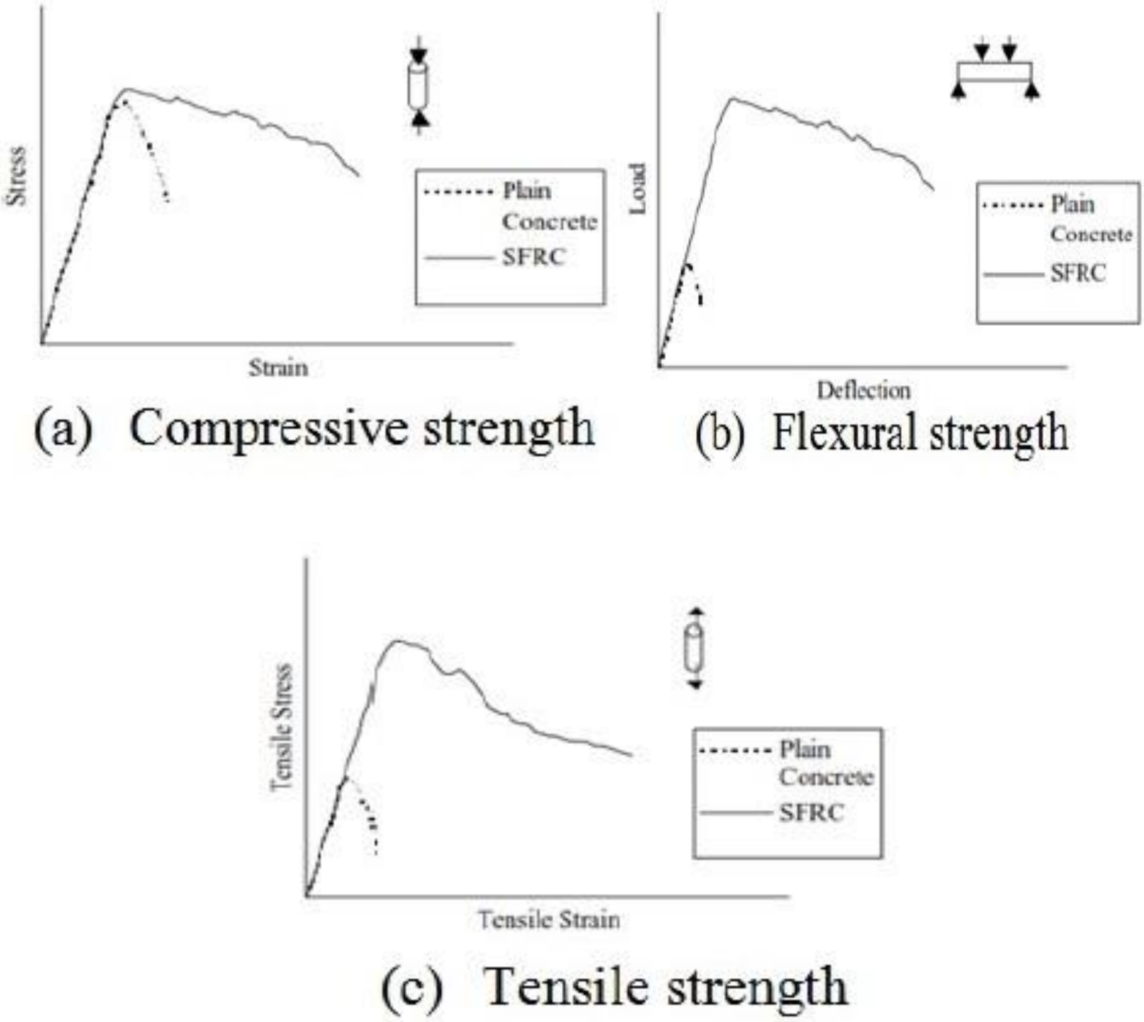


Figure 1.1. Performance of SHCC, (a) Stress strain curve of compressive strength, (b) Load deflection curve of flexural strength, (c) Stress strain curve of tensile strength

1.4. Areas of application

Cementitious composites with strain hardening SHCC looks at the different kind of fibre-reinforced concrete mixtures (FRCs) being used currently and proposes the development of a new category of FRCs having strain-hardening properties that are produced using standard tools. It is proved that such a material, known as engineered cementitious composites (ECCs), may be created using micro-mechanical concepts and exhibits considerable compressive strength, strain capacity, and strain-hardening in conventional high-strength concrete. including fracture toughness. SHCC spans exhibit substantial ductility either pre- or post-peak during shear and bending stresses.

Furthermore, the SHCC demonstrated peak in-sensitivity in double sided uni-axial samples, indicating the great dependability is possible inside this kind of composites. Mechanical characteristics of SHCC are isotropic. The material can be applied to cast-in-place or pre-cast structures due to its manufacturing adaptability, and broad classes of possible uses, including the ones requiring energy absorption and structural ductility have been noted as being appropriate for benefit of SHCC's special characteristics. Among the numerous conceivable uses are:

1.4.1. Structures subject to impact loads

- Light-weight durable bridge deck
- Pavement (reflective cracking, durability)

1.4.2. High energy absorption devices/structures

- Hybrid structures (RC/steel connection)
- Steel structures (joints)
- Seismic retrofits (dampers, shear walls)
- Earth Quick resilient constructions (beam-column connections, short span beam, columns)

1.4.3. Others

- FRP reinforced concrete structure
- Durable reparation material
- Concrete cover for durability
- Extruded products with mechanical capability
- Permanent formwork (additional steel-jacket for concrete columns).
- Radioactive left-over control.

1.5. Advantages of using AI techniques

Many research studies focused on the experimental route for analyzing the behavior of structural material following several test procedures. However, the use of machine learning (sub-part of AI), for predicting and analyzing different properties of concrete has exponentially increased in the last decade. These AI based prediction models help to avoid the costly, and hectic experimental procedures that need enough time and require skilled investigators. The use of AI can recognize the hidden pattern between the output/response parameter and the input variables being acquired from the experimental data. Thus provides the model for future prediction of the response parameter, which can be used as a benchmark.

1.6. Outline of thesis

The present research study is an effort to predict the mechanical properties of strain hardening cementitious composites by use of gene expression programming. The study includes five chapters; Introduction, Literature Review, Research Methodology, Results, Analysis and Discussion, in the end the main findings of the study are presented along with suggestions for future research.

Chapter 1 identifies the studied problem in relevance to the national needs. It includes the scope and objectives of the research. A brief description of what will be covered in each chapter is included.

Chapter 2 covers the detailed literature review of the strain hardening cementitious composites, its utilization in the construction industry, and the use of artificial intelligence techniques namely gene expression programming (GEP) to develop an effective and accurate GEP-based model for the estimation of mechanical properties of SHCC that are; compressive strength, first crack tensile stress, first crack tensile strain, first crack flexure stress and first crack flexure strain.

Chapter 3 covers the methodology followed in this research. This includes the collection of experimental data from the peer-reviewed published articles, the division of data, and the initial statistics of data. This chapter also explain the steps that are carried out to develop the GEP model. This includes the selection of input and output variables and pre-processing and determination of the GEP model's parameters. It also includes the details of the experimental setup.

Chapter 4 covers the overall results and discussion of the research. Which includes the translation of the expression tree into a mathematical expression for the development of a GEP model for the mechanical properties of SHCC that are; compressive strength, first crack tensile stress, first crack tensile strain, first crack flexure stress and first crack flexure strain, performance evaluation of the developed model via statistical criteria and the selected external validation criteria, and the analysis of model through sensitivity. In the end the performance of the model is also evaluated against linear and non-linear regression models.

Chapter 5 summarizes the main conclusions of this work and some suggestions for further research and development.

CHAPTER 2

LITERATURE REVIEW

A new category of concrete has been giving satisfying results in construction and repair of engineering constructions; it is called engineered cementitious composites (ECC) or strain-hardening cementitious composites (SHCC) [1-5]. It has got, when compared to common concrete, a 300 to 500 times greater strain capacity [6]. Fracture widths of SHCC are less than 60μm when subjected to high distortions. By giving this result, SHCC is solving long awaited solution to reinforced concrete construction and this is because of its high tensile ductility and compact crack width. [7-12]. Many researchers are conducting research on SHCC in different aspects, i.e., by varying the volume or type of fiber and trial situations. By using only less than 2% fiber by volume, SHCC provides excessive tensile strength, allowing the SHCC for high performance [13-19]. For a material to be used in actual for constructions, series of consistent efforts are needed to satisfy construction industry [20], as practical application is far different from design process of SHCC because it involves finite element analysis. In addition to this, shortage of professional staff is also hampering the application of SHCC [21]. Once the researcher's attention can be diverted toward SHCC, optimized use SHCC can increase many folds in practical industrial use.

In Civil Engineering, use of Artificial Intelligence (AI) is increasing day by day. Material design and technology researchers are drifting towards AI as a substitute of the conventional 'trial and error' method. In this method, instead of laboratory testing, to optimize materials qualities, emphasis is on learning from data [22-30]. For structural engineering as well, AI methods have progressed in the preparation of precise and particular models [31]. Some of the AI techniques used are artificial neural networks (ANNs), multilayer perceptron neural network (MLPNN), back-propagation neural network (BPNN), general regression neural network (GRNN), the there is a hybrid form of ANNs k-nearest neighbor (KNN)) i.e., adaptive neuro-fuzzy inference system (ANFIS). But potential for increasing AI's expansions is only available in Artificial Neural Networks (ANNs), even to a fact that they can beat individuals if adequate data is available to it [32,33]. But the problem lies in the compilation of this data; in case to get the most accurate results out of it [34]. Gathering this kind of heavy and widespread data is not only impossible at time but also time consuming and resource consuming [35-37].

Researchers have also worked on categorizing mathematical models [38-40]. They were categorized on given names of colors like white, black, or grey. White-box model were based on physical rules, black-box models were based on regressive data-driven systems and lastly grey-box models were logical systems. White-box model produced accurate interconnection, bringing extreme transparency while in black-box models functional form of correlations between variables is unknown and must be determined. Lastly, grey-box models were logical systems in which a statistical framework more successfully examines the performance of the system [41,42]. Due to its symbolic and simple picturing of physical phenomena, GEP is considered as a "grey box model" [43,44]. While ANNs and ANFIS are both categorized as 'black-box models' [43,45]. GEP models are helpful as they offer a brief mathematical formula for computing the dependent output parameter [46] that is why they are considered to achieve improved results than neural network-based ANN and ANFIS models in structural engineering [47,48].

This study was based on GEP considering above mentioned facts in mind. By doing so mechanical characteristics of SHCC, performance and efficiency of model was also evaluated. Genetic Programming (GP) was developed by Cramer in 1985, before being modified for by means of a variation of forms and sizes [36,47,49]. Lastly, Candida Ferreira developed the GEP in 1999 [46]. The GEP consists of simple, linear chromosomes. Length of chromosomes is fixed. This GEP can process and predict composite and nonlinear problems for answering regressions, modeling functions, predicting, detecting in data mining [50]. Another advantage is AI is that it frees the researcher from testing cost as data is retrieved from online resources or literature [46,50]. But that became disadvantage in this study, as very limited data is available for research in SHCC studies. Therefore, number of data samples mandatory shall be proportionate to the number of parameters examined [46,49]. As a result, number of inputs should be reduced as parameters utilized so as to get enough data for effective predicted performance. That is why Shi et al. [49] and Hossain et al. [36], limits the parameters in their study, and the models established are particular to that case, with only polyvinyl alcohol (PVA) fiber [49] or steel fiber [36] used in the reinforcement of SHCC.

With a dataset of 329 samples, the prime objective of the research was to establish GEP based prediction equations which can calculate the mechanical properties of SHCC. Important inputs of the study were cement percent weight (C%), fine aggregate percent weight (Fagg%), fly ash percent weight (FA%), water to binder ratio (W/B), super plasticizer percent weight (SP%), fiber amount percent weight (Fib%), length to diameter ratio (L/D), fiber tensile strength (FTS), fiber elastic modulus (FEM), environment temperature (ET), and curing time (CT), while the influencing outputs were compressive strength (CS), first crack tensile stress (TS), and first crack flexural stress (FS). To evaluate the appropriateness of the GEP models, statistical performance criteria such as root squared error (RSE), mean absolute error (MAE), Nash Sutcliffe efficiency (NSE), root mean square error (RMSE), relative root mean square error (RRMSE), correlation coefficient (R), and regression coefficient (R^2) were used. Moreover, sensitivity analysis was done, and the results were then gaged to categorize the majority of positive and negative input parameters.

CHAPTER 3

RESEARCH METHODOLOGY

In this chapter the methodology adopted for the for the empirical study of the collected data will be elaborated. The mechanical properties of SHCC that are; compressive strength, first crack tensile stress, first crack tensile strain, first crack flexure stress and first crack flexure strain are the main parameters in this research and all these factors depend on the materials and method employed in this research. Thus, the materials used and the detailed methodology implemented for the construction of the model will be discussed in this chapter.

3.1 Materials and Methods

Method used to develop empirical models for SHCC mechanical behavior will be discussed here. Introduction to GP and GEP will be given and research with proper technique will be discussed.

3.1.1. Genetic-programming and gene-expression-programming overview

GP was recommended by Koza in (1992), as a useful presentation of the models of genetics and biological selection [51-53]. GP is a flexible programming tool because it presents nonlinear structures (parse trees) as a substitute to unchanging length binary strings (used in genetic procedure). It is an independent methodology which answers problems by using Darwin's model of reproduction and notion of inherently arising genetic operators like re-production, re-combination and crossover [54].

In the reproduction stage, it eliminates the selected programs. In addition to this, in implementation stage a fixed proportion of trees with the bottom most fitness are destroyed, and based on the process selected the population is packed with the left over trees [55-57]. By doing so premature convergence is avoided. Five main parameters are used in GP namely, set of terminals, primitive functions , the fitness metrics, execution monitoring parameters, and outcome narrative technique, as well as execution closing conditions [57].

GP results in a vast inhabitants of parse trees instead of the fact that only one out three mutation is used i.e. crossover is used despite specification of mutation and reproduction [36]. Absence of an independent genome is also a disadvantage of GP; this makes GP to act as both genotype and phenotype. But basic and fundamental expressions can be created [58]. Another theorem-based variant of GP was created by Ferreira in 2006 [59]. This was a biological population evolutionary GP that merges both constant length (GA) as well as parse trees basic linear chromosomes with the same parameters as in GP. Throughout computer program processing, this method reflects a character string of a given length, in contrasted with the parse tree with shifting length in the GP. Expression trees (ETs) are lastly generated as nonlinear units of several sizes and forms by individuals coded as fixed-length linear strings (genome). Expression trees (ETs) are branching assemblies that replicate chromosomes [60]. Genotype and phenotype are separated in GEP, as a result programming can possibly get advantage from all evolutionary benefits [61]. Only genome transmission to the next generation is a prominent revision in GEP. It reduces the requirement to replace and alter the general structure as all mutations arise in a single linear framework. An added exclusive factor is that people are generated using particular chromosome composed of many genes that are subsequently categorized into tail and head [62]. Every gene in the GEP involves a variable, constants and mathematical operations. Variable length is defined, constants are designated via set of terminal, and mathematical operations as functions set. In the genetic structure operator, there is correlation between the chromosomal symbols and the corresponding function sets. At the chromosomes level, in the GEP, the genetic mechanism is made simpler by the evaluation of genetic variety [63]. Chromosomes stores the data required to create an empirical connection. Karva, a new language recently developed to deduce this data. Phenotype can be inferred if the sequence of the gene is available. This is known as K expression [64]. Karva's transition to the ET continues through the string before beginning with the leadership position in the ET. ET can be converted into the K-expression. The method to do so is by noting the nodes from the root layer to the deepest layer [65,66]. Definite number of redundant elements are also generated that are not consumed for genome mapping. This is because ETs fluctuation throughout the GEP method. Therefore, length of K expression and identity of the expression of the GEP can be variable. Generation of chromosomes of fixed length is the start of the process. After that, the chromosomes are then expressed as ETs. Fitness of ETs are examined before the start of reproduction process. Till the achievement of ideal solution, the iteration procedure is repeated with different individuals for numerous generations. Cross over, re production and mutation like genetic procedures are done for population conversion. The flow diagram of GEP is presented in Figure 3.1.

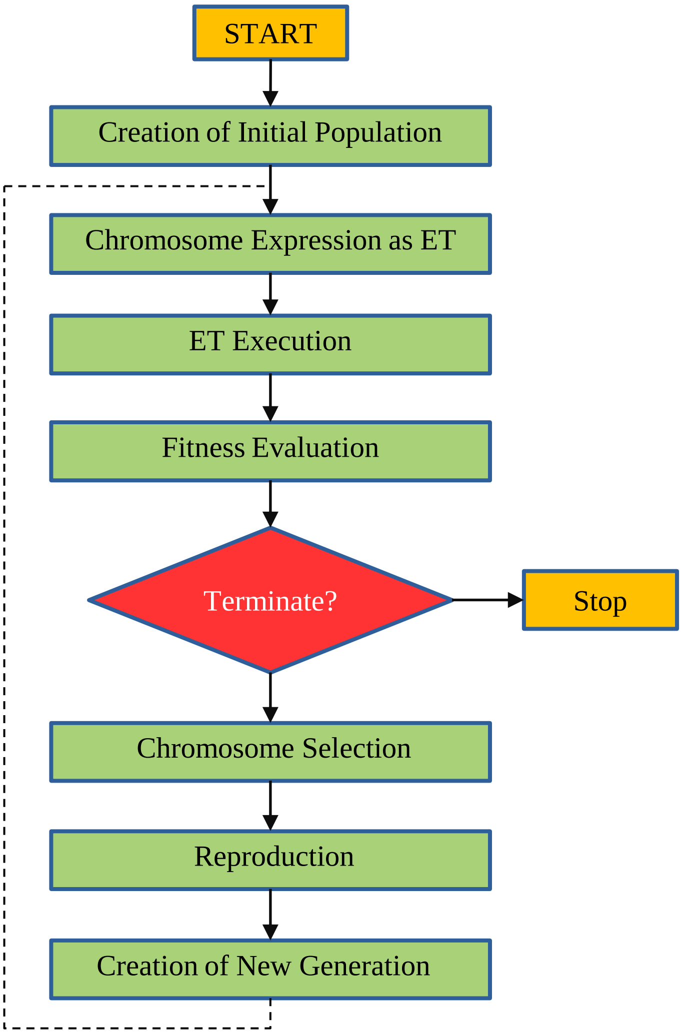


Figure 3.1. The systematic workflow of gene-expression-programming employed in current study

3.1.2 Data gathering and processing

Data retrieved from literature for this study includes, results of 182 Compressive strength (CS) (MPa), 50 first crack flexural stress (FS) (MPa), 97 first crack tensile stress TS (MPa), 107 first crack tensile strain (TST), and 38 first crack flexural strain (FST), of SHCC [62]. It also had 11 maximum noticeable explanatory variables for each response in accordance with mix-proportion of SHCC i.e., d0: Cement percent weight (C%), d1: Fine aggregate percent weight (Fagg%), d2: Fly Ash percent weight (FA%), d3: Water to Binder ratio (W/B), d4: Super Plasticizer percent weight (SP%), d5: Fiber Amount % weight (Fib%), d6: Length to diameter ratio (L/D), d7: Fiber Tensile Strength (FTS), d8: Fiber Elastic Modulus (FEM), d9: Environment Temperature (ET), d10: Curing Temperature (CT). Table 3.1 provides the descriptive statistical metrics i.e., skewness, minimum, mean, maximum, and standard deviation of the definite variables in a particular manner. Dependable and precise prediction within their maximum and minimum limits can be achieved by using the proposed models for the CS, TS, FS, TST and FST. Proximity to the mean value can be indicted by the lower value of standard deviation. This indicates the consistency of the data. Dispersion of the variables related to normal distribution is shown in skewness metrics. The skewness must lie between -3 and +3 [67-69] in order to reduce the deviation from the normal norm. The skewness here lies in the recommended range as shown in **Table 3.1** and **Table 3.2**. Multi-collinearity is one of the disadvantages of AI techniques [70]. This needs to be checked between the independent variables to escape the over fitting of data in the development of models [64]. The multi-collinearity metrics applied in this research are the variance inflation factor (VIF) and it's reciprocal i.e., tolerance. VIF has inverse relationship with multi-collinearity between inputs. As the VIF increases or tolerance decreases the less will be the likelihoods of multi-collinearity. Normally, the VIF is between 1 and $+\infty$. Tolerance must be greater than 0.2 and VIF less than 5 and in order to create smallest probabilities of multi-collinearity. For least chances of multi-collinearity, the VIF must be less than 5 with tolerance greater than 0.2 [71]. **Table 3.3** displays that VIF and tolerance both are in the suitable range assisting the dismissal of multicollinearity between the all the input variables. Therefore, in the course of modelling of TS, CS, and FS, there is zero probability of multi-collinearity occurrence.

Table 3.1. Statistical investigation of data sets exercised to develop models for compressive strength (CS), first crack tensile stress (TS), and first crack flexural stress (FS) of strain hardening cementitious composites using GEP

Parameters	CS (MPa)				TS (MPa)				FS (MPa)			
	Min.	**Max.**	**SD**	**Skew.**	**Min.**	**Max.**	**SD**	**Skew.**	**Min.**	**Max.**	**SD**	**Skew.**
Explanatory / Input												
Cement percentage by weight (C%)	0	0.538	0.105	1.733	0.093	0.511	0.091	1.119	0.028	0.639	0.131	0.792
Fine aggregate percentage by weight (F_{agg}%)	0	0.538	0.208	-0.054	0	0.446	0.099	-0.443	0	0.317	0.087	0.079
Fly Ash percentage by weight (FA%)	0.135	0.665	0.207	0.501	0	0.589	0.164	-0.973	0	0.646	0.234	0.351
Water to Binder ratio (W/B)	0.232	0.5	0.109	0.404	0.153	0.45	0.066	1.641	0.036	0.96	0.221	0.876
Super Plasticizer percentage by weight (SP%)	0	0.009	0.002	1.861	0	0.013	0.003	1.298	0	0.154	0.056	1.317
Fiber Amount percentage by weight (F_{ib}%)	0	0.041	0.007	1.671	0	0.013	0.005	-0.652	0	0.760	0.318	1.255
Length to diameter ratio (L/D)	18.181	1739	473.4	1.561	205.128	833.333	195.731	1.701	154.574	369.230	53.881	-0.210
Fiber Tensile Strength (F_{TS})	350	4200	1003.9	0.941	850	3000	526.549	1.343	15.3	40.104	10.08	0.704
Fiber Elastic Modulus (F_{EM})	4	363.54	70.815	1.790	6	110	25.211	1.432	33	684	279.669	0.861
Environment Temperature (ET)	20	650	206.8	1.620	20	20	0	1.123	20	20	0	1.223
Curing Time (CT)	1	30	11.101	-0.865	1	28	11.255	0.009	7	28	5.754	-3.192
Response / Output	**4.02**	**68**	**14.691**	**-0.317**	**1.47**	**4.75**	**0.755**	**-0.613**	**2.25**	**15.6**	**2.733**	**0.020**

CS: Compressive strength; TS: First crack tensile stress; FS: First crack flexural stress; Min.: Minimum value; Max.: Maximum value; SD: standard deviation; Skew.: Skewness

Table 3.2. Statistical investigation of data sets exercised to develop models first crack tensile strain (TST), and first crack flexural strain (FST) of strain hardening cementitious composites using GEP

Parameters	TST				FST			
	Min.	**Max.**	**SD**	**Skew.**	**Min.**	**Max.**	**SD**	**Skew.**
Explanatory / Input								
Cement percentage by weight (C%)	0.093	0.512	0.096	1.019	0.030	0.640	0.143	1.311
Fine aggregate percentage by weight (F_{agg}%)	0.000	0.447	0.101	-0.367	0.000	0.410	0.099	0.544
Fly Ash percentage by weight (FA%)	0.000	0.590	0.166	-0.927	0.000	0.650	0.229	-0.049
Water to Binder ratio (W/B)	0.153	0.450	0.064	1.507	0.038	1.000	0.208	2.171
Super Plasticizer percentage by weight (SP%)	0.000	0.012	0.003	1.329	0.000	0.150	0.061	0.859
Fiber Amount percentage by weight (F_{ib}%)	0.000	0.014	0.006	-0.432	0.000	0.760	0.348	0.826
Length to diameter ratio (L/D)	200.000	833.333	190.516	1.743	154.574	369.231	54.573	0.373
Fiber Tensile Strength (F_{TS})	850.000	3000.000	519.293	1.396	15.300	40.104	7.160	2.344
Fiber Elastic Modulus (F_{EM})	6.000	110.000	24.864	1.486	33.000	472.110	128.449	2.358
Environment Temperature (ET)	20.000	20.000	0.000	0	20.000	20.000	0.000	0
Curing Time (CT)	1.000	28.000	11.325	0.071	7.000	28.000	6.531	-2.679
Response / Output	**0.010**	**0.400**	**0.086**	**0.360**	**0.070**	**1.000**	**0.222**	**1.338**

TST: First crack tensile strength; FST: First crack flexural strength; Min.: Minimum value; Max.: Maximum value; SD: standard deviation; Skew.: Skewness

Table 3.3. Multi-collinearity analysis of considered explanatory or independent variables.

Independent variables (inputs)	**CS**		**TS**		**FS**		**TST**		**FST**	
	Tolerance	**VIF***	**Tolerance**	**VIF***	**Tolerance**	**VIF***	**Tolerance**	**VIF***	**Tolerance**	**VIF***
Cement percentage by weight (C%)	0.406	2.465	0.390	2.562	0.497	2.011	0.271	3.684	0.330	3.034
Fine aggregate percentage by weight (F_{agg}%)	0.311	3.216	0.194	5.145	0.122	8.209	0.118	8.473	0.266	3.764
Fly Ash percentage by weight (FA%)	0.188	5.314	0.149	6.719	0.229	4.368	0.154	6.488	0.190	5.273
Water to Binder ratio (W/B)	0.159	6.293	0.115	8.693	0.150	6.652	0.147	6.795	0.245	4.078
Super Plasticizer percentage by weight (SP%)	0.211	4.743	0.176	5.687	0.285	3.505	0.322	3.104	0.232	4.318
Fiber Amount percentage by weight (F_{ib}%)	0.292	3.427	0.305	3.281	0.272	3.671	0.647	1.546	0.175	5.716
Length to diameter ratio (L/D)	0.192	5.215	0.110	9.104	0.382	2.617	0.200	5.010	0.338	2.957
Fiber Tensile Strength (F_{TS})	0.117	8.547	0.125	8.029	0.183	5.461	0.447	2.235	0.266	3.753
Fiber Elastic Modulus (F_{EM})	0.132	7.600	0.127	7.859	0.282	3.551	0.180	5.542	0.326	3.070
Environment Temperature (ET)	0.294	3.403	0.313	3.192	0.109	9.177	0.159	6.290	0.296	3.381
Curing Time (CT)	0.443	2.257	0.651	1.537	0.177	5.656	0.629	1.590	0.861	1.161

*VIF: Variance inflation factor

3.1.3. Training hyper parameter

Fitting parameter`s role is very important in the effectiveness and simplification ability of established mathematical models. Frequent initial runs and references in literature were used to determine the optimized value of setting parameters encompassed in the GEP process [72]. The simple mathematical operators i.e., addition (+), multiplication (×), subtraction (-), and division (÷), are reflected in the function set for uncomplicatedness of the last expressions. Population size controls the running time of the program. Convergence time of model with higher chromosomes is more but it is also precise. But if the size is enlarged outside a definite boundary, matter of over fitting may also arise.

Number of populations was considered as 0, for each model at the early stage. Latter depending upon complexity and number, level were increased up to 250. Number of genes and head size is the development factor in the architecture of different models. Head size determines the complexity and number of genes commands the number of sub-ETs in the model. Number of gene was set as 3 and 4 in this research and three head sizes 10, 10 and 8 were selected. Possibility of the offspring to experience these genetic operations is indicated by the mutation, cross over. Finest combination was decided after several arrangements of these settings were started on the data. Selection was based on complete performance characteristics of the model as shown in **Table 3.4**.

Over fitting of the data is serious concern in the AI based modeling. Efficiency of the model is good on the actual data but decreases on the un-seen data. To escape the problem, it is suggested to check the generated models using a previously unexplored dataset that is known as testing dataset [36,65]. In the light of the above, the entire data has been distributed into train-set and test-set. The train-set data was recommended during modeling. The trained model is tested on testing set which was not used in the model establishment. Distribution of data was confirmed to be steady in both datasets. 70% and 30% of the data was used as training and testing in this research. On both datasets great performances was shown by the final models. GENXPro was used in application of GEP algorithm. GENXPro is commercially available computing package. Calculation of Initial population of feasible solutions is the starting point in this tool. With each generation, the process converges near the solution. In assessing the fitness of each generation, The GEP algorithm keeps on evolving till there is no variation in the pre-determine qualification function i.e., R or RMSE. In this research, objective function (OBF) is also assessed for every trained model. The purpose of this evaluation is to calculate the total productivity as it replicates the stimulus of R, RMSE and number of data-points. In case of low accuracy in model results, procedure is then repeated. This time size and number of subpopulations is slowly increased until the ultimate model is achieved on lowest OBF. However, over-fitting of the model accrued as performance of certain models on train-set was greater in comparison to performance of the test-set. This should be avoided because multiple performance indictors should be fulfilled by an optimal model.

Table 3.4. Hyper parameter tunning of developed models

Parameter	**Settings**				
General	**CS**	**TS**	**FS**	**TST**	**FST**
Chromosomes	200	250	100	400	120
Genes	4	4	3	4	4
Head size	10	10	8	10	12
Linking function	Addition	Addition	Addition	Addition	Addition
Function set	+, -, ×, ÷, Sqrt,3rt, Average of 2	+, -, ×, ÷, Sqrt,3rt, Average of 2	+, -, ×, ÷, Sqrt,3rt.	+, -, ×, ÷, 3rt.	+, -, ×, ÷, Sqrt,3rt, Average of 2
Normal constraint					
Constrain per gene	8	7	30	8	13
Data type	Floating	Floating	Floating	Floating	Floating
Lower bound	-10	-10	-10	-10	-10
Upper bound	10	10	10	10	10

Over fitting of the data is serious concern in the AI based modeling. Efficiency of the model is good on the actual data but decreases on the un-seen data. To escape the problem, it is suggested to check the trained model on an un-seen or testing dataset [36,65]. In the light of the above, the entire database has been distributed into training and testing set. The training data was recommended during modeling. The trained model is tested on testing set which was not used in the model development. Distribution of data was confirmed to be steady in both datasets. 70% and 30% of the data was used as training and testing in this research. On both datasets great performances was shown by the final models. GENXPro was used in application of GEP algorithm. GENXPro is commercially available computing package. Calculation of Initial population of feasible solutions is the starting point in this tool. With each generation, the process converges near the solution. In assessing the fitness of each generation, The GEP algorithm keeps on evolving till there is no variation in the pre-determine fitness function i.e., R or RMSE. In this research, objective function (OBF) is also assessed for every trained model. The purpose of this evaluation is to calculate the total productivity as it replicates the influence of R, RMSE and number of data-points. In case of low accuracy in model results, procedure is then repeated. This time number and size of subpopulation is slowly increased until the final model is achieved on minimum OBF. However, over-fitting of the model accrued as performance of certain models on training set was greater in comparison to performance of the testing set. This should be avoided because multiple performance indictors should be fulfilled by an optimal model.

3.1.4. Modeling evaluation metrics

Six analytical standard measure were used to forecast mechanical behavior of SHCC. These measures include correlation coefficient (R), coefficient of determination (R^2), relative squared error (RSE), root mean square error (RMSE), Nash-Sutcliffe efficiency (NSE), mean absolute error (MAE), and relative root mean square error (RRMSE) [36,73-75]. RRMSE also governs performance index (PI). Which is also one of the evaluating criteria and was determined here [65]. **Equation (3.1)-(3.7)** defined the above-mentioned determination.

$$RMSE = \sqrt{\frac{\sum_{i=1}^{n}(h_i - t_i)^2}{n}} \quad (3.1)$$

$$MAE = \frac{\sum_{i=1}^{n}|h_i - t_i|}{n} \quad (3.2)$$

$$RSE = \frac{\sum_{i=1}^{n}(t_i - h_i)^2}{\sum_{i=1}^{n}(\bar{h}_i - h_i)^2} \quad (3.3)$$

$$NSE = 1 - \frac{\sum_{i-1}^{n}(h_i - t_i)^2}{\sum_{i=1}^{n}(h_i - \bar{h}_i)^2} \quad (3.4)$$

$$RRMSE = \frac{1}{|\bar{h}|}\sqrt{\frac{\sum_{i=1}^{n}(h_i - t_i)^2}{n}} \quad (3.5)$$

$$R = \frac{\sum_{i=1}^{n}(h_i - \bar{h}_i)(t_i - \bar{t}_i)}{\sqrt{\sum_{i=1}^{n}(h_i - \bar{h}_i)^2 \sum_{i=1}^{n}(t_i - \bar{t}_i)^2}} \quad (3.6)$$

$$PI = \frac{RRMSE}{1 + R} \quad (3.7)$$

In the presented equations, hi and ti represents the i^{th} experimental or targeted outcome and model estimated outcomes, respectively. The $\bar{h}$i and $\bar{t}$i replicates the mean of the targeted outputs and mean of the model estimated outcomes, respectively. While the n shows the total number of instances or experiments deployed in the database. Relative correlation between the model and experimental outputs is determined by the performance of R. strong correlation is established if $R > 0.8$ [76]. But R is indifferent to division and multiplication of outputs [73]. Therefore, for better performance, R^2 was used. If R^2 values are closer and totaling unity, it suggests that the model applied maximum variability between the input parameters. Large errors are professionally solved in RMSE, in comparison with smaller. If RMSE value is nearer or equaling 0, it suggests insignificant error in prediction [77]. But ideal performance is not assured in specific situations. As a result, MAE was also calculated. MAE is vastly useful if continuous and smooth data is available [78,79]. To summaries, smaller values of NSE, RSE, MAE, RMSE, and RRMSE and signify greater R value signify a improved model calibration. Moreover, PI value nearer to zero recommends decent performance of the model [80]. higher testing errors and lesser training errors is observed because of too much training of the data points; resultantly, models over fits [81]. To overcome this, and choose the finest predictive model that will kill the over fitting issue, objective function (OBF) expressed as **Equation (3.8)** is minimized [81].

$$\mathrm{OBF} = \left(\frac{n_T - n_v}{n}\right) P_{iT} + 2\left(\frac{n_v}{n}\right) P_{iV} \tag{3.8}$$

Where, the letters ‘T’ and ‘V’ used in the subscript mentions the training and authentication points and n shows the total number of instances or experiments deployed in the database. Best predictive model is represented by lower value of OBF because it deliberates the purpose of R (correlation measure), RRMSE (error measure) and as well as the distribution effect of experiments in two different datasets. In this research, parameter having the minimum OBF was nominated amongst the 12 several arrangements of fitting parameters. In addition to this, external authentication of the developed model was also done. This is presented briefly in Table 3.4.

Table 3.4. External validation indicators for evaluation of developed models

Expression	Acceptable criteria	Reference
$k = \frac{\sum_{k=1}^{n}(e_k \times p_k)}{e_k^2}$	0.85 < *k* < 1.15	[73]
$k' = \frac{\sum_{k=1}^{n}(e_k \times p_k)}{p_k^2}$	0.85 < *k′* < 1.15	[73]
$R_m = R^2 \times \left(1 - \sqrt{\lvert R^2 - R_0^2 \rvert}\right)$	$R_m > 0.5$	[74]
$R_x = \lvert R_o^2 - R_o'^2 \rvert$	$Rx < 0.3$	[75]
Where;		
$R_o^2 = 1 - \frac{\sum_{k=1}^{n}(p_k - e_k^o)^2}{\sum_{k=1}^{n}\left(p_k - \overline{p_k^o}\right)^2};\ e_k^o = k \times p_k$	$R_o^2 \cong 1$	
$R_o'^2 = 1 - \frac{\sum_{k=1}^{n}(e_k - p_k^o)^2}{\sum_{k=1}^{n}\left(e_k - \overline{e_k^o}\right)^2};\ p_k^o = k' \times e_k$	$R_o'^2 \cong 1$	

CHAPTER 4

RESULTS AND DISCUSSION

The result of GEP algorithm is shown in form of expression tree in Figure 4.1, 4.3, 4.5, 4.7 and 4.9. These figures are for the models of CS, TS, FS, TST and FST, respectively. Empirical relationships were derived from encoding of these ETs. Where d0: Cement percent weight (C%), d1: Fine aggregate percent weight (Fagg%), d2: Fly Ash percent weight (FA%), d3: Water to Binder ratio (W/B), d4: Super Plasticizer percent weight (SP%), d5: Fiber Amount % weight (Fib%), d6: Length to diameter ratio (L/D), d7: Fiber Tensile Strength (FTS), d8: Fiber Elastic Modulus (FEM), d9: Environment Temperature (ET), d10: Curing Time (CT). The FS and TST contain six fundamental mathematical functions i.e., +, −, x, ÷, square root, and cubic root while for CS, TS, and FST contain average of two inputs as an extra function. While the random numerical constants chosen during modelling are represented in Table 4.1.

Table 4.1. Random Numerical Constant (RNC) used in developed GEP models

Developed model	Gene/Sub-expression tree	Value of constant
CS	Gene 1	C0 =11.396
		C4 = -2.688
	Gene 2	C1 = 14.450
	Gene 3	C3 = -4.054
		C2 = 6.363
		C4 = 11.530
	Gene 4	C2 = -12.210
		C5 = -6.912
TS	Gene 2	C6 = -7.173
		C3 = 10.339

		C1 = 8.904
	Gene 3	C6 = 5.830
		C4 = 11.530
		C0 = -5.780
	Gene 4	C3 = 1.434
FS	Gene 2	C15 = 6.569
	Gene 3	C3 = 9.198
TST	Gene 1	C5 = -23.23
	Gene 2	C0 = -10.94
		C7 = -4.11
		C3 = -8.64
	Gene 4	C2 = -8.65
FST	Gene 2	C6 = -5.26
		C12 = -6.97
	Gene 3	C12 = 2.03
	Gene 4	C5 = -8.62

4.1. Formulation of compressive strength (CS)

Number of genes and head size were considered as 4 and 10 in the model to formulate CS of SHCCs, predicted by simplified expressions extracted from the Figure 4, which can calculate CS up to 62.5 MPa. This is shown in Equation 4.1. Number of datasets greatly affects the proposed models [82]. Difference of model predictions and actual results for CS is shown in Figure 4.2. The graph also shows the expressions for regression lines of the two results. It is clear from fig that all twelve input parameters are precisely considered in the prediction. The slope of regression lines is 0.977 and 0.9508 which shows strong correlation between training and testing sets. To achieve precision maximum number of specimens i.e., 182 were taken from the existing literature.

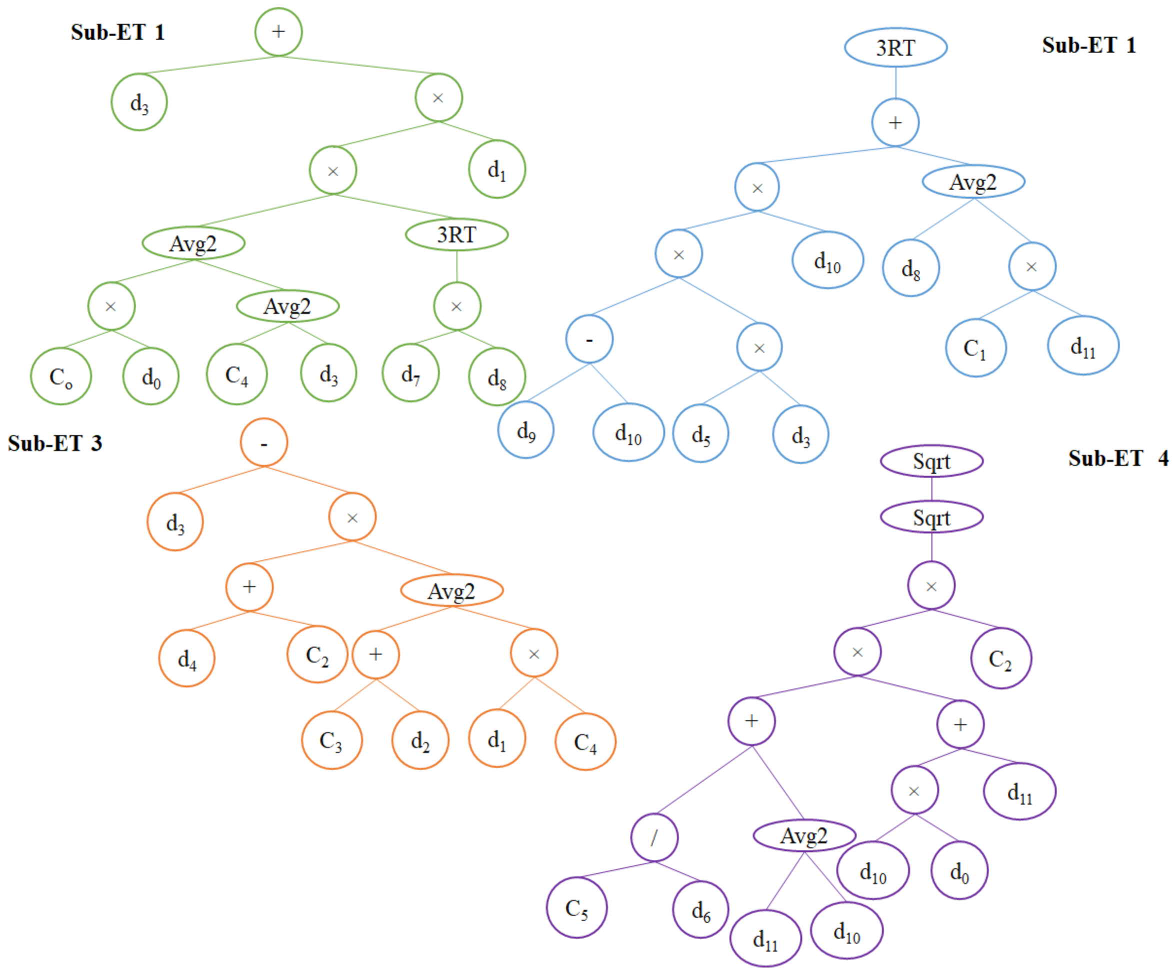


Figure 4.1. Expression trees for compressive strength

$$CS\ (MPa) = Y_1 + Y_2 + Y_3 + Y_4 \tag{4.1}$$

$$Y_1 = W/B + \left(\frac{(11.3967 * C\%) + \frac{((-2.6886) + W/B)}{2.0}}{2.0} * \sqrt[3]{\left(\frac{L}{D} * F_{TS}\right) * F_{agg}\%} \right) \quad 4.1(A)$$

$$Y_2 = \sqrt[3]{((F_{EM} - ET) * (F_{ib}\% * W/B)) * ET + \frac{(F_{TS} + (14.4508 * CT))}{2.0}} \quad 4.1(B)$$

$$Y_3 = W/B - \left((SP\% + 6.3683) * \frac{(((-4.0545) + FA\%) + (F_{agg}\% * 11.5301))}{2.0} \right) \quad 4.1(C)$$

$$Y_4 = \left(\left(-6.9128 + \frac{(CT + ET)}{2.0} \right) * ((ET * C\%) + CT) * (-12.2104) \right)^{1/4} \quad 4.1(D)$$

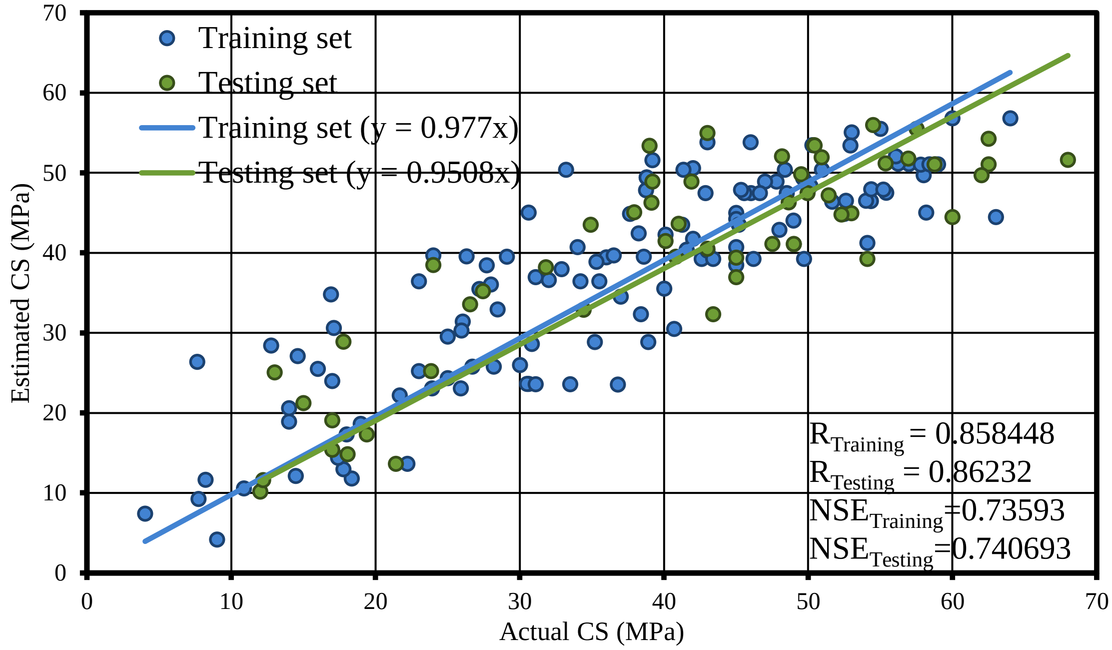


Figure 4.2. Regression plot of GEP model developed for compressive strength

4.2. Formulation of first crack tensile stress (TS)

Number of genes and head size were considered as 4 and 10 in the model to formulate TS, of SHCCs, as predicted by simplified expressions extracted from the Figure 4.3, which can calculate TS up to 4.75 MPa. This was done by using Equation 4.2. Difference of model predictions and actual results for TS are shown in Figure 4.4. Considerable reduction of statistical errors shows that the proposed model has precisely considered the influence of input parameters. Along with that TS was precisely predicted for a wide range of data. It is clear from figure that all twelve input parameters are precisely considered in the prediction. The slope of regression lines is 0.9831 and 1.0018 which shows strong correlation between training and testing sets, respectively.

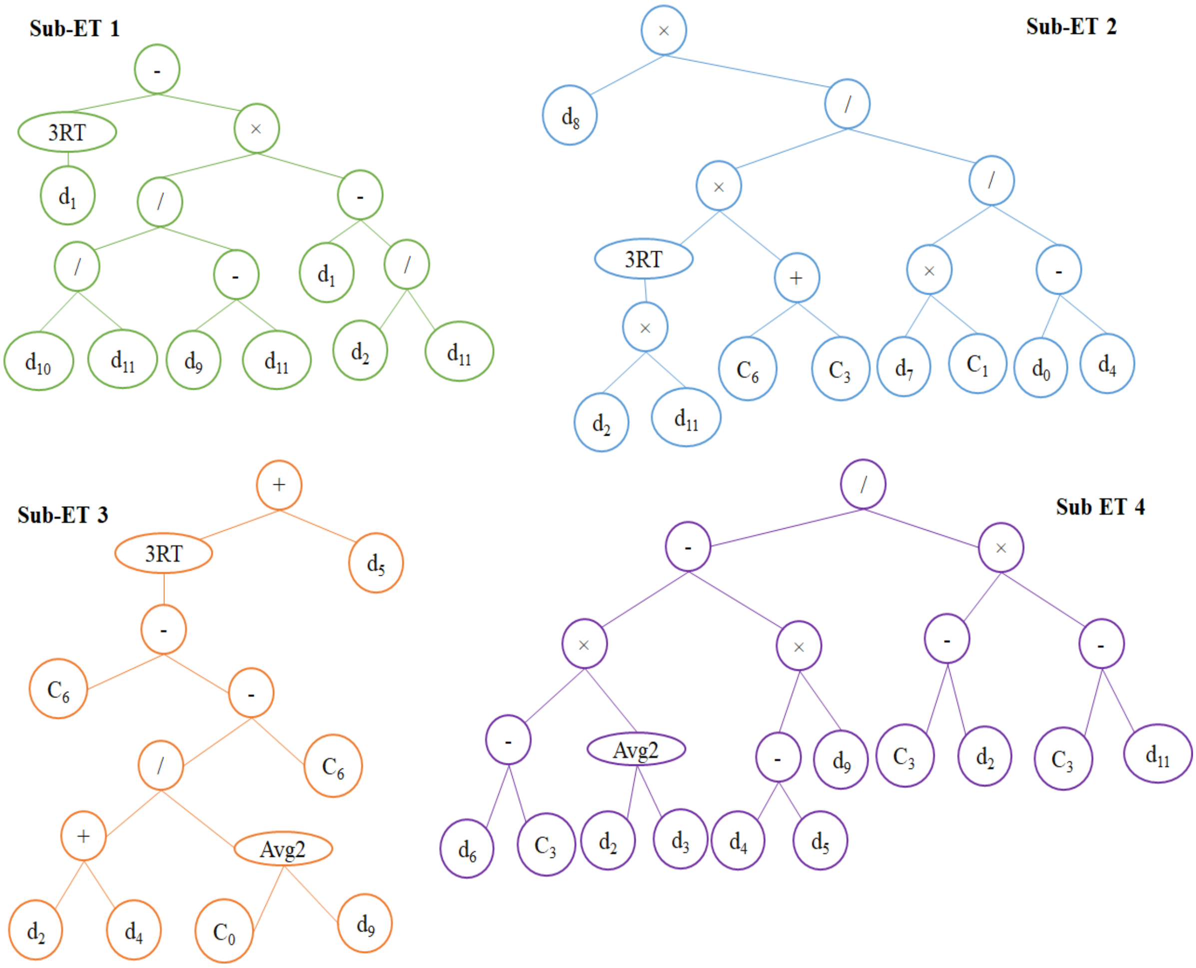


Figure 4.3. Expression tree for first crack tensile stress

$$Ts = Y_1 + Y_2 + Y_3 + Y_4 \tag{4.2}$$

$$Y_1 = \sqrt[3]{F_{agg}\% - \left(\frac{\frac{ET}{CT}}{F_{EM} - CT} * \left(F_{agg}\% - \frac{FA\%}{CT}\right)\right)} \tag{4.2(A)}$$

$$Y_2 = F_{TS} * \frac{\sqrt[3]{(FA\% * CT) * ((-7.1733) + 10.3390)}}{\frac{L/D * 8.9049}{C\% - SP\%}} \tag{4.2(B)}$$

$$Y_3 = \sqrt[3]{\left(5.8304 - \left(\left(\frac{(FA\% + SP\%)}{\frac{((-5.7804) + F_{EM})}{2.0}}\right) - 5.8304\right)\right) + F_{ib}\%} \tag{4.2(C)}$$

$$Y_4 = \frac{\left((-1.4340) * \frac{FA\% + W/B}{2.0}\right) - \left((SP\% - F_{ib}\%) * F_{EM}\right)}{(1.4340 - FA\%) * (1.4340 - CT)} \tag{4.2(D)}$$

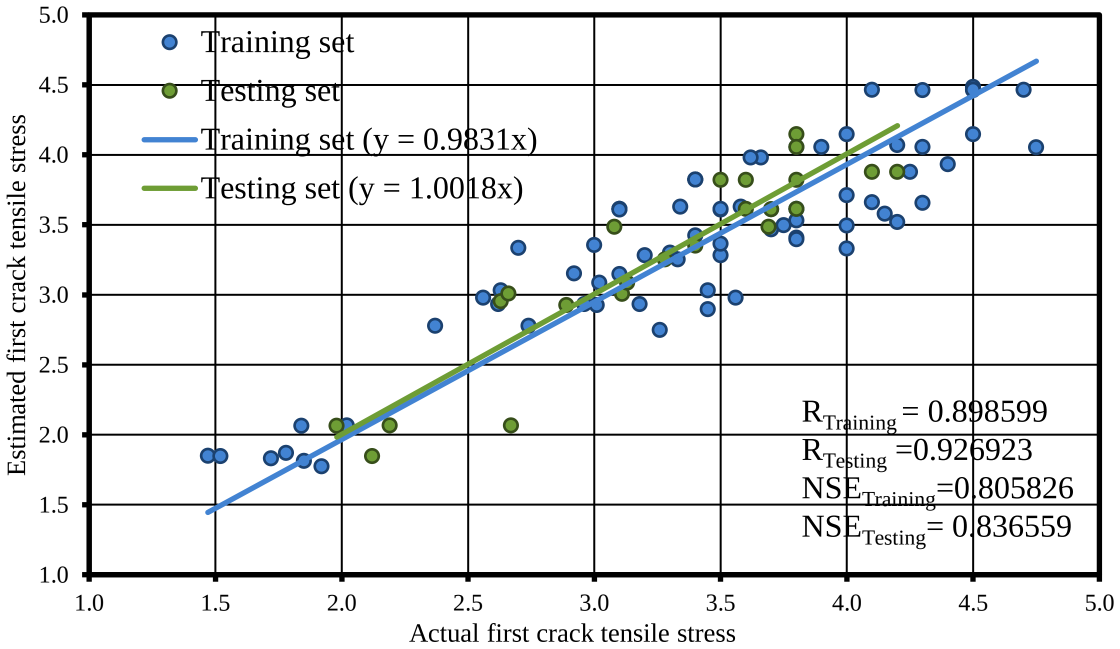


Figure 4.4. Regression plot of GEP model developed for first crack tensile stress

4.3. Formulation of first crack flexural stress (FS)

The number of genes and head size considered for the FS model was 3 and 8 respectively. Equation 4.3 shows the empirical relationship that is developed to calculate FS up to 15.6 MPa. This was done by decoding the ETs given in Figure 4.5. Genes with reduced complication of mathematical expression were considered. But considering its dependency on the distribution of data, the reduction of complexity cannot be relied on the number of functions. Compatibility of experimental and predicted results are shown in Figure 4.6. It is almost close to ideal fit as statistical errors are minimum. It is clear from figure that all twelve input parameters are precisely considered in the prediction. The slope of regression lines is 0.9759 and 0.8863 which shows strong correlation between training and testing sets, respectively.

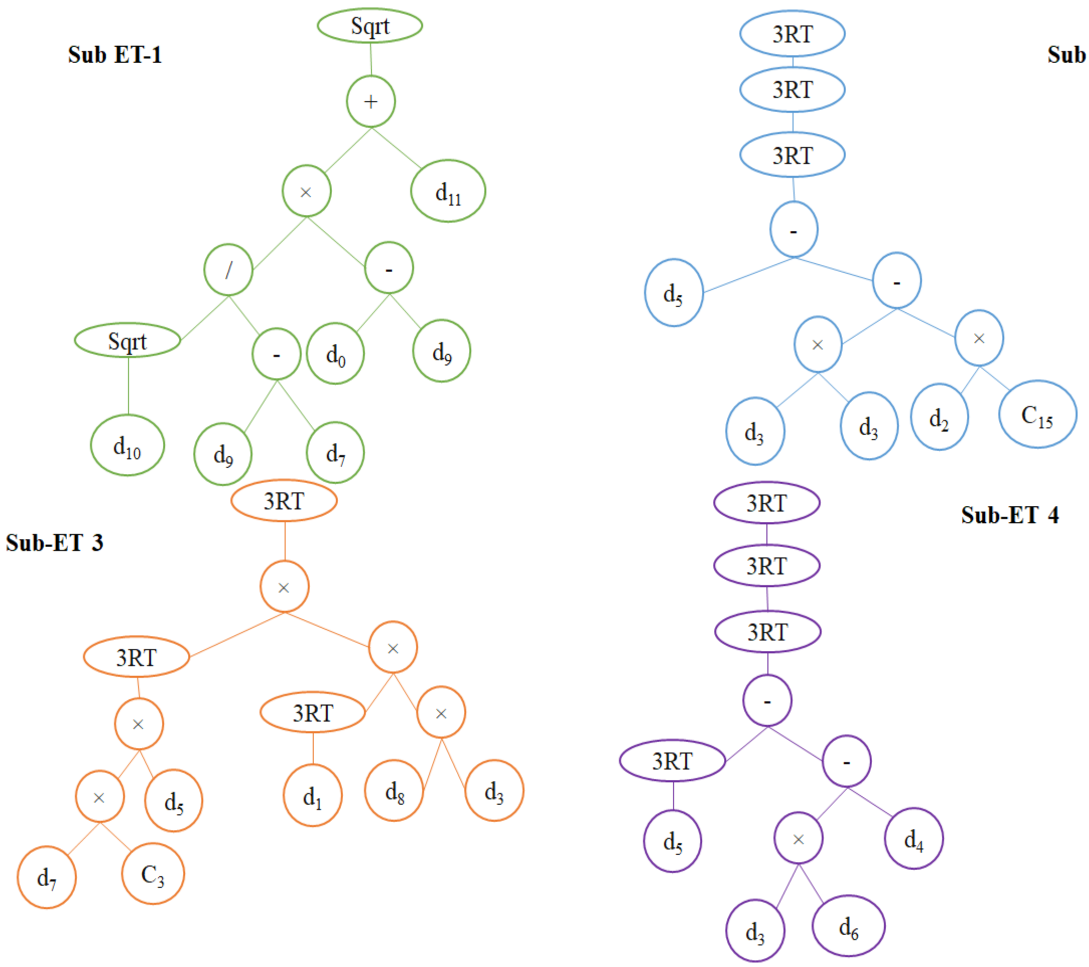


Figure 4.5. Expression trees for first crack flexural stress

$$FS = Y_1 + Y_2 + Y_3 + Y_4 \tag{4.3}$$

$$Y_1 = \sqrt[2]{\frac{\sqrt[2]{ET}}{F_{EM} - L/D} * (C\% - F_{EM}) + CT} \tag{4.3(A)}$$

$$Y_2 = \sqrt[9]{F_{ib}\% - \left((W/B)^2 - (FA\% * 6.5697)\right)} \tag{4.3(B)}$$

$$Y_3 = \sqrt[3]{\sqrt[3]{\left(\frac{L}{D} * 0.1985 * F_{ib}\%\right)} * \left(\sqrt[3]{F_{agg}\% * (F_{TS} * W/B)}\right)} \tag{4.3(C)}$$

$$Y_4 = \left(\sqrt[3]{F_{ib}\%} - \left((W/B) - SP\%\right)\right)^{1/9} \tag{4.3(D)}$$

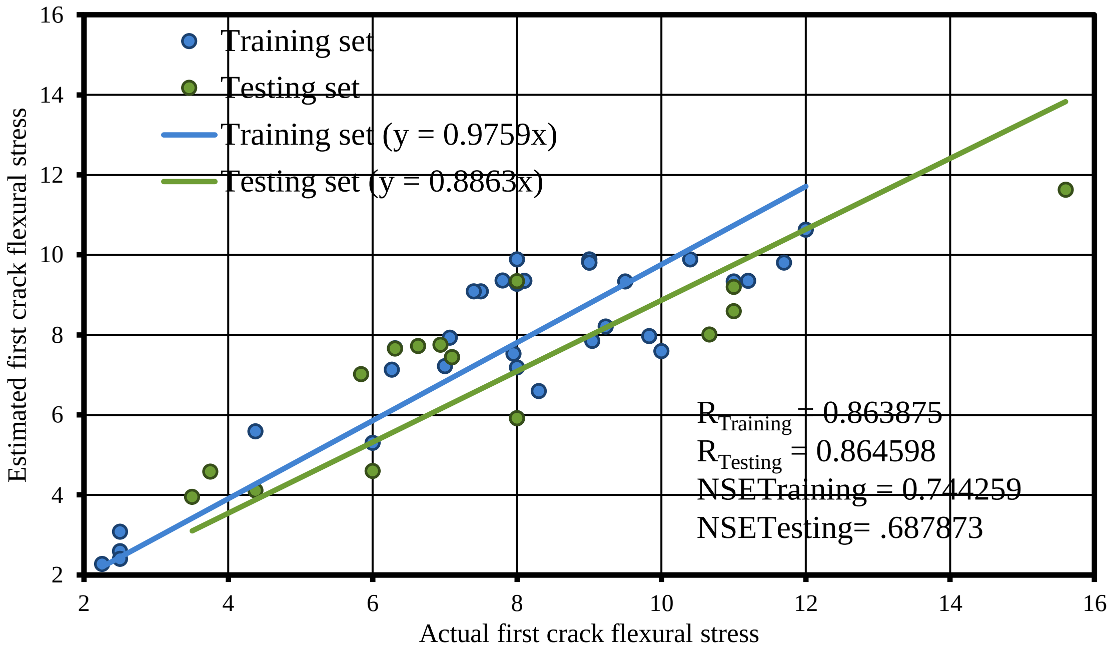


Figure 4.6. Regression plot of GEP model developed for first crack flexural stress

4.4. Formulation of first crack tensile stress (TST)

The number of genes and head size considered for the FS model was 4 and 8 respectively. Equation 4.1 shows the empirical relationship that is developed to calculate FS up to 15.6 MPa. This was done by decoding the ETs given in Figure 4.7. Genes with reduced complication of mathematical expression were considered. But considering its dependency on the distribution of data, the reduction of complexity cannot be relied on the number of functions. Compatibility of experimental and predicted results are shown in Figure 4.8. It is almost close to ideal fit as statistical errors are minimum. It is clear from figure that all twelve input parameters are precisely considered in the prediction. The slope of regression lines is 0.916 and 1.0384 which shows strong correlation between training and testing sets, respectively.

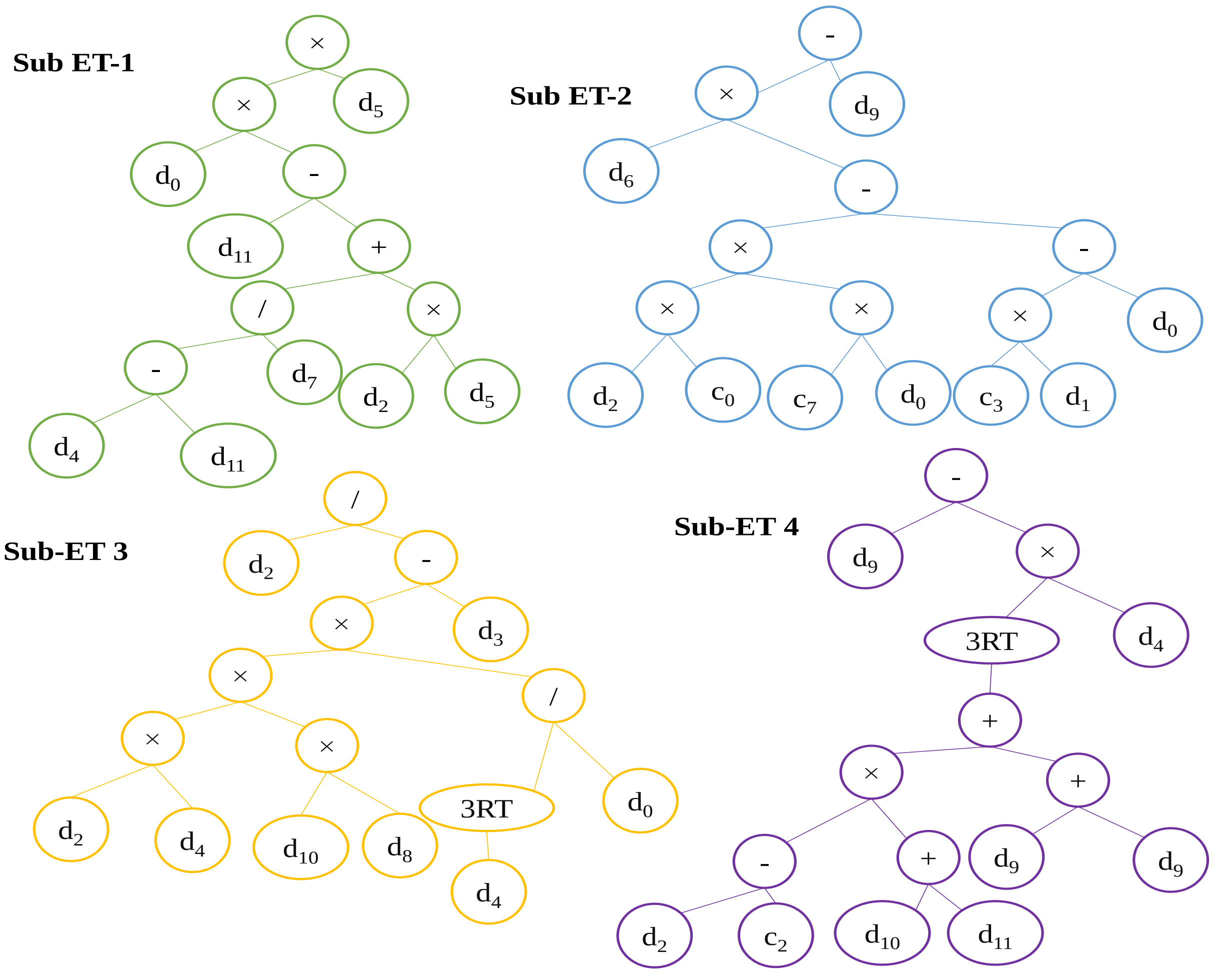


Figure 4.7. Expression trees for first crack flexural stress

$$FS = Y_1 + Y_2 + Y_3 + Y_4 \tag{4.4}$$

$$Y_1 = C\% * \left(CT - \frac{\frac{L}{D} - CT}{\frac{L}{D}} - 23.23 * FA\% \right) * F_{ib}\% \tag{4.4(A)}$$

$$Y_2 = \left(\left((44.96 * FA\% * C\%) - \left(\left(-8.64 * F_{agg} \right) - (C\%) \right) \right) \right) - F_{EM} \tag{4.4(B)}$$

$$Y_3 = \frac{FA\%}{\left(FA\% * SP\% * ET * F_{TS} * \frac{\sqrt[3]{SP\%}}{C\%} \right) - FA\%} \tag{4.4(C)}$$

$$Y_4 = (F_{EM}) - \left(\sqrt[3]{\left((FA\% - 8.66) * (ET - CT) \right) + (2 * F_{EM} * SP\%)} \right) \tag{4.4(D)}$$

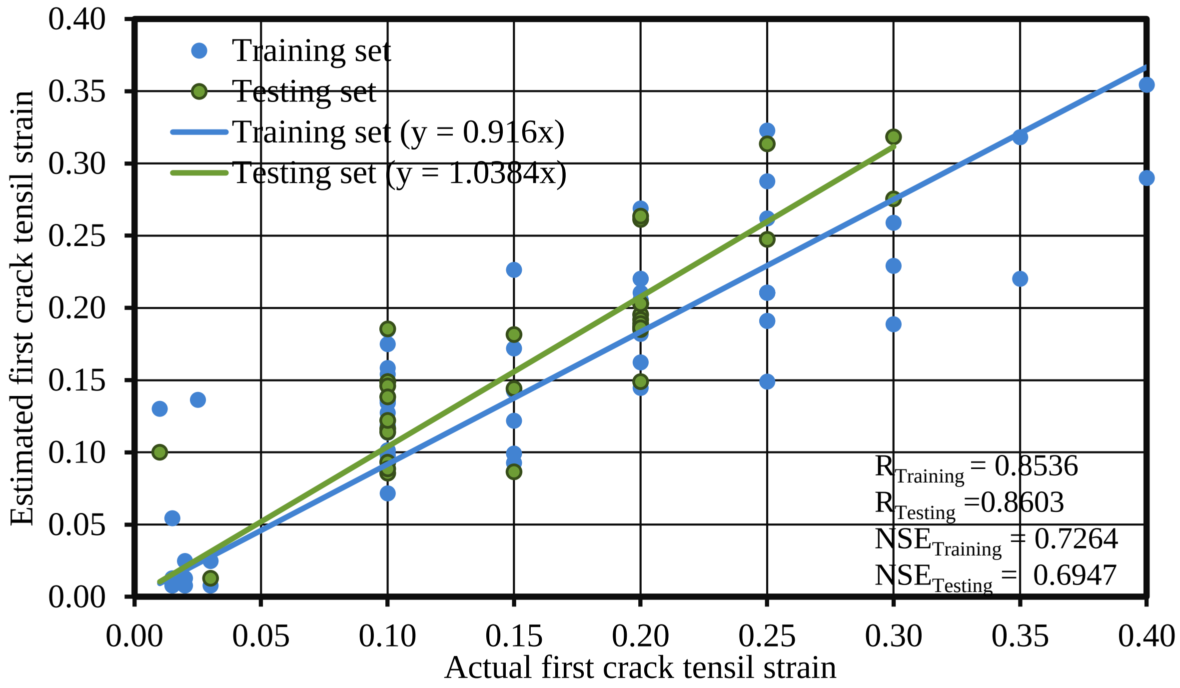


Figure 4.8. Regression plot of GEP model developed for first crack flexural stress

4.5. Formulation of first crack flexural strain (FST)

The number of genes and head size considered for the FS model was 4 and 12 respectively. Equation 4.5 shows the empirical relationship. This was done by decoding the ETs given in Figure 4.9. Genes with reduced complication of mathematical expression were considered. But considering its dependency on the distribution of data, the reduction of complexity cannot be relied on the number of functions. Compatibility of experimental and predicted results are shown in Figure 4.10. It is almost close to ideal fit as statistical errors are minimum. It is clear from figure that all twelve input parameters are precisely considered in the prediction. The slope of regression lines is 0.8454 and 0.9921 which shows strong correlation between training and testing sets, respectively.

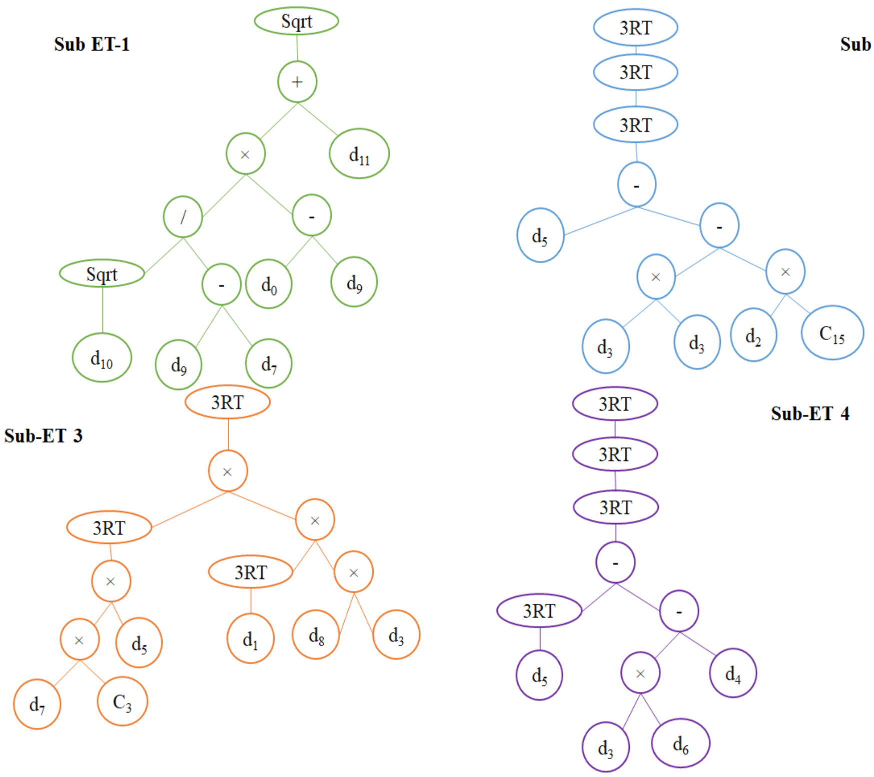


Figure 4.9. Expression trees for first crack flexural stress

$$FST = Y_1 + Y_2 + Y_3 + Y_4 \tag{4.5}$$

$$Y_1 = FA\% \tag{4.5(A)}$$

$$Y_2 = \sqrt[3]{\frac{4 * SP\%}{\left(\left(\left(\frac{(F_{EM} + CT)}{2} * (FA\% + F_{ib}\%)\right) + \sqrt[2]{C\%}\right) * \left((-5.266) + (F_{TS} + (-6.976))\right)\right)}} \tag{4.5(B)}$$

$$Y_3 = -\frac{(FA\%) * \left((SP\%) + \left((CT) * (F_{ib}\%)\right)\right)}{\frac{\left((F_{ib}\%) + (2.031)\right)}{2} - \left(\left(\frac{L}{D}\right) * (SP\%)\right)} \tag{4.5(C)}$$

$$Y_4 = (FA\%) * \left(\left(\left(\frac{W}{B}\right) * \left(\left(\left((ET) + (ET)\right) * \left(\frac{W}{B}\right)\right) - \left(\frac{\left((CT) + (-8.622)\right)}{2}\right)\right)\right) - \left((F_{agg}) * (FA\%)\right)\right) \tag{4.5(D)}$$

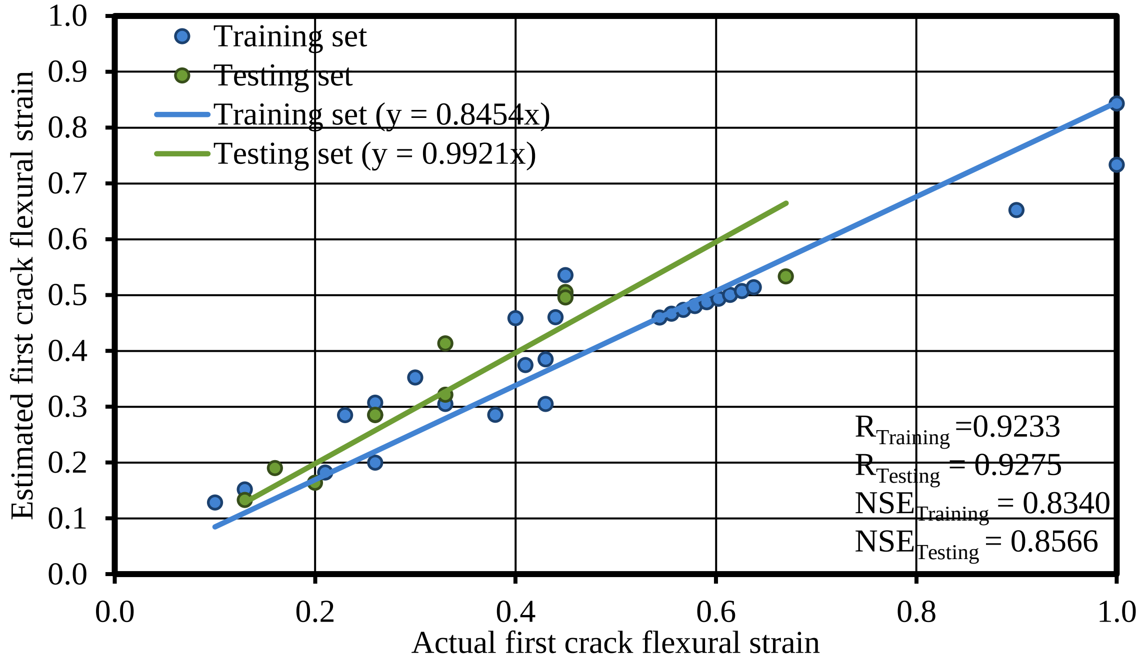
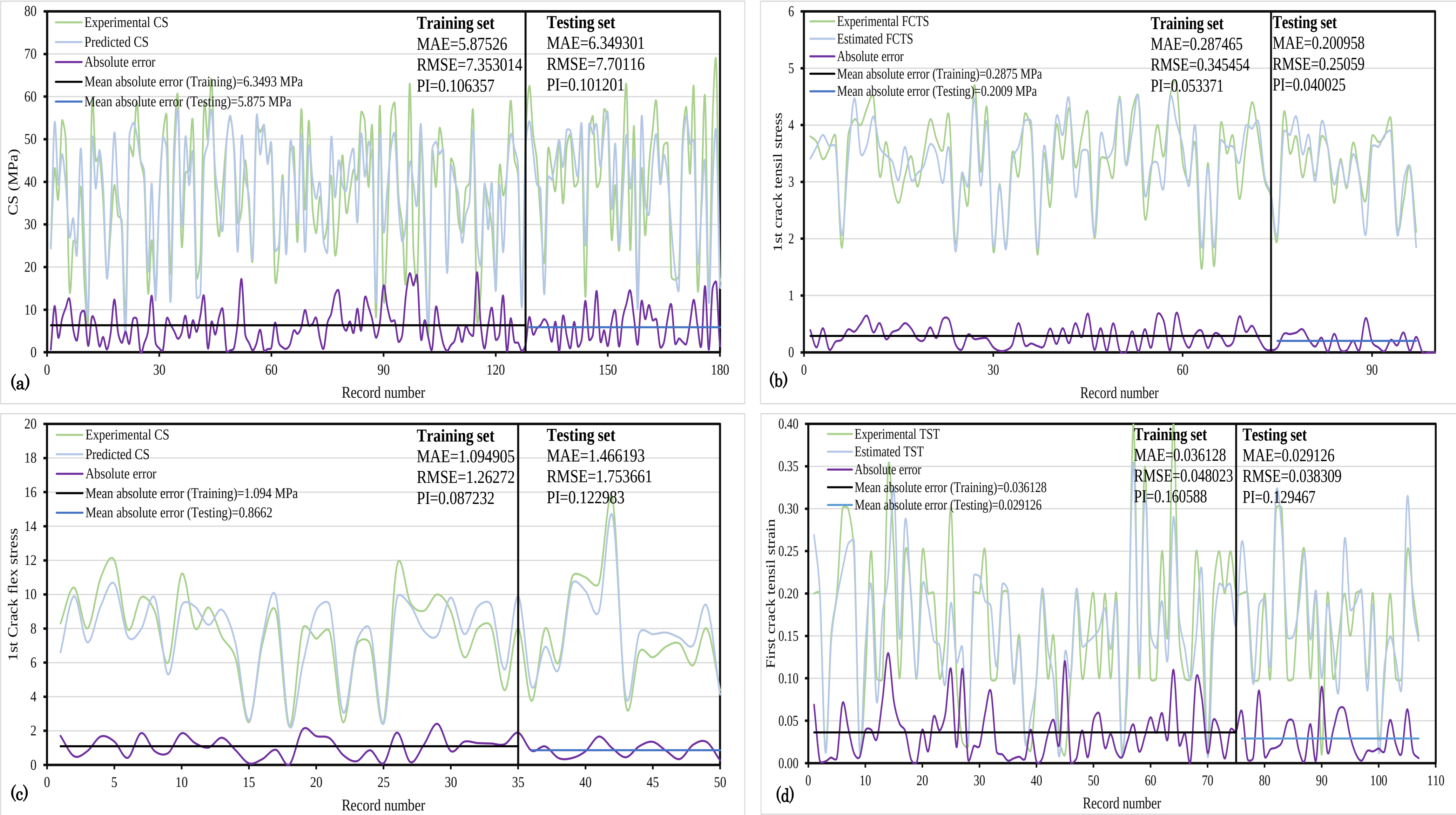


Figure 4.10. Regression plot of GEP model developed for first crack flexural stress

4.6. Performance evaluation of GEP model

For ideal models, researchers recommend the lowest ratio of data entries (total experimental results) to the number of inputs to be greater than 3 and for acceptable models it should at least equal 3 [65,76]. This value is far higher in this research. Tables 4.2 shows statistical parameters of the training and testing sets and reflects extraordinary correlation between the predicted and experimental. It also shows small error values as the models are trained efficiently. Testing values of RMSE, MAE and RSE for CS are 7.70116, 6.349301, and 0.259307 in comparison to training set of 7.353014, 5.87526 and 0.26407. The three parameters RMSE, MAE and RSE from TS model are 0.345454, 0.287405 and 0.104174 for the training phase and 0.25059, 0.200958 and 0.163441 for the testing phase, respectively. Likewise, the values of RMSE, MAE and RSE from FS model are 1.26272, 1.094905 and 0.255741 for training and 1.753661, 1.466193 and 0.312127 for the testing phase, respectively. A higher simplification ability and capacity to predict trustworthy outcomes for unseen data was obtained by keeping statistical measures similar for training, and testing sets. The statistical indices are excellently comparable for train, and test sets demonstrating a sophisticated generality to forecast consistent outcomes for unseen data or fresh instances. OBF values were 0.103298 for CS, 0.047042 for TS, 0.108682 for FS, 0.1419 for TST, and 0.1066 for FST. This near zero values indicate that matter of over fitting of data has been taken into account and also that all three models performed well.

Figure 4.11 shows predicted, and experimental outcomes mapped with absolute error. The purpose of this plot was to know the maximum error percentage in the models. It can be deducted from the graph that for CS maximum error was 18.751 MPa, minimum error was 0.0048 MPa was observed, and average error was 6.01591 MPa. Similarly, for TS maximum error was 0.696 MPa, minimum error was 0.001652 MPa and average value was 0.267 MPa. On the same pattern, maximum error was 3.969976 MPa and minimum error was 0.022328 MPa for FS; with an average error of 1.206 MPa. Moreover, less than 5 MPa error was noted in 80% of predicted CS outputs. Similarly, less than 1 MPa for 100% of TC and less than 4 MPa error for 100% of FS results were observed. Also, the performance index is less than 0.2 in all the three developed models indicating a higher predicting capability.



Experimental CS
Predicted CS
Absolute error
Mean absolute error (Training)=6.3493 MPa
Mean absolute error (Testing)=5.875 MPa
Training set
MAE=5.87526
RMSE=7.353014
PI=0.106357
Testing set
MAE=6.349301
RMSE=7.70116
PI=0.101201
CS (MPa)
Record number
(a)
Experimental FCTS
Estimated FCTS
Absolute error
Mean absolute error (Training)=0.2875 MPa
Mean absolute error (Testing)=0.2009 MPa
Training set
MAE=0.287465
RMSE=0.345454
PI=0.053371
Testing set
MAE=0.200958
RMSE=0.25059
PI=0.040025
1st crack tensil stress
Record number
(b)
Experimental CS
Predicted CS
Absolute error
Mean absolute error (Training)=1.094 MPa
Mean absolute error (Testing)=0.8662
Training set
MAE=1.094905
RMSE=1.26272
PI=0.087232
Testing set
MAE=1.466193
RMSE=1.753661
PI=0.122983
1st Crack flex stress
Record number
(c)
Experimental TST
Estimated TST
Absolute error
Mean absolute error (Training)=0.036128
Mean absolute error (Testing)=0.029126
Training set
MAE=0.036128
RMSE=0.048023
PI=0.160588
Testing set
MAE=0.029126
RMSE=0.038309
PI=0.129467
First crack tensil strain
Record number
(d)

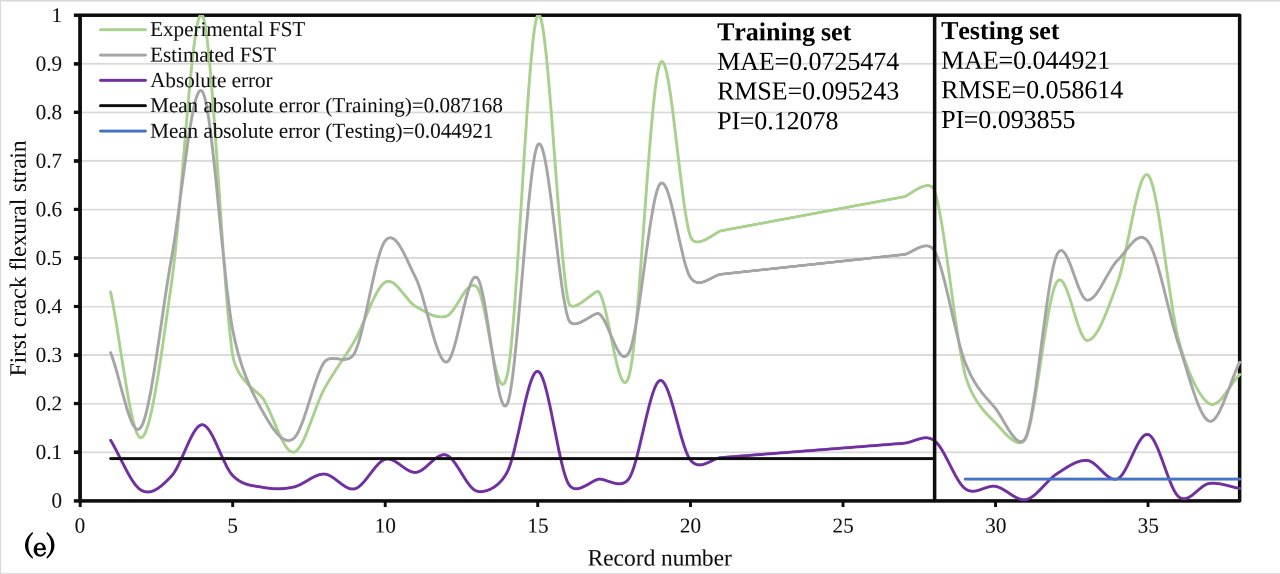


Figure 4.11. Absolute error plot of (a) compressive strength, (b) first crack tensile strength, (c) first crack flexural strength, (d) first crack tensile strain, (e) first crack flexural strain

Table 4.2. Evaluation of developed models using statistical indicators

Developed models		Statistical performance indicators									
		NSE	RMSLE	RMSE	MAE	RSE	RRMSE%	R	R^2	PI	OBF
CS	GEP Trn*	0.7359	0.0009	7.353	6.349	0.264	19.76	0.8584	0.7369	0.106	0.1032
	GEP Tst**	0.7406	0.0082	7.701	5.875	0.259	18.84	0.8623	0.7435	0.101	
TS	GEP Trn	0.8058	0.0043	0.345	0.287	0.194	10.13	0.8985	0.8074	0.053	0.0470
	GEP Tst	0.8365	0.0025	0.250	0.200	0.163	7.71	0.9269	0.8591	0.040	
FS	GEP Trn	0.7442	0.0148	1.262	1.094	0.255	16.25	0.8638	0.7462	0.087	0.1086
	GEP Tst	0.6878	0.0180	1.753	0.8662	0.312	22.93	0.8645	0.7475	0.122	
TST	GEP Trn	0.7264	0.0028	0.048	0.036	0.273	29.76	0.8535	0.7286	0.1606	0.1419
	GEP Tst	0.6947	0.0038	0.038	0.030	0.305	24.08	0.8602	0.7400	0.1294	
FST	GEP Trn	0.8340	0.0075	0.095	0.087	0.166	23.22	0.9233	0.8525	0.1208	0.1066
	GEP Tst	0.8566	0.0027	0.058	0.045	0.143	18.09	0.9275	0.8603	0.0939	

*Trn: Training set; **Tst: Testing set

4.7. External validation of developed models

For the external authentication, other checks are also done on proposed GEP models. In these checks, one includes that slope of one of the regression lines (k or k') passing through the origin should approach 1. This was recommended by several authors working in the area of machine learning [83]. This check when applied shows great accuracy of results as the slope of regression lines for 0.9508 for CS, 1.0018 for TS, 0.8863 for FS, 1.0384 for TST, and finally 0.9921 for FST.

Second check applied was that the coefficient between predicted and experimental values or squared correlation coefficient between the experimental and predicted values should also approach 1 [84]. Table 4.3 shows verification of the aforementioned check. Results show that proposed GEP models are not just correlation between the input and output parameters but actually they have the prediction ability; in addition to being precise.

Table 4.3. Evaluation of developed models using external validation

Developed GEP models	K	K'	R_o^2	$R_o'^2$	$R_o^2-R_o'^2$	R_m
CS	0.9508	1.0193	0.9700	0.7661	0.2039	0.5898
TS	1.0018	0.9925	0.9999	0.8273	0.1726	0.5369
FS	0.8863	1.0840	0.8112	0.7414	0.0698	0.5589
TST	1.038435	0.922552	0.989114	0.719406	0.269708	0.570707
FST	0.992149	0.981409	0.9995	0.850281	0.149219	0.539307

4.8. Sensitivity analysis

Equations (12) and (13) was used to perform sensitivity analysis to find that how the relative contribution of different variables affects the characteristics of SHCCs.

$$N_i = f_{max}(x_i) - f_{min}(x_i) \tag{12}$$

$$SA = \frac{N_i}{\sum_{n}^{j=1} N_j} \tag{13}$$

Where $f$max(xi) and $f$min(xi) represents maximum and minimum of the predicted output based on ith input domain, provided that others input parameters are kept constant at their mean values. It is quite evident from Figure 4.12 sensitivity analysis results that similar contribution of input factors was observed on the mechanical characteristics of SHCCs. The top three most contributing input variables are cement percentage, fine aggregate percentage and environmental temperature. The commutative contribution of the stated input variables were 60.97%, 53.99%, and 54.54%% in the GEP developed models for compressive strength, first crack tensile strength and first crack flexural strength, respectively. The input parameters related to fiber properties (i.e., fiber amount, length to diameter ratio of fiber, fiber tensile strength and fiber elastic modulus) also considerably affected the outcome of the GEP model with commutative contribution equals to 27.98%, 33.19, and 34.18% for compressive strength, first crack tensile strength and first crack flexural strength, respectively. On the other hand, for all the five developed models, water to binder ratio, fly-ash percentage, and superplasticizer percentage are the least contributing factor. This also seems correct in view of material engineering and in line with the previous work [6-10,12].

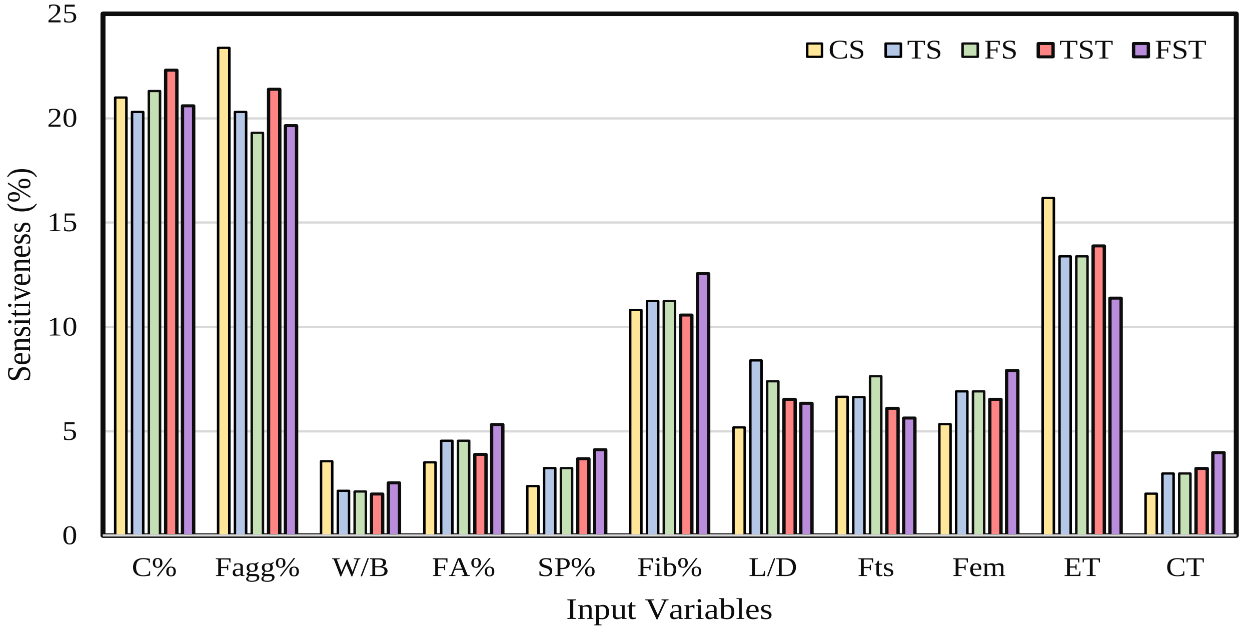


Figure 4.12. Sensitivity analysis of GEP models developed for compressive strength, first crack tensile stress, and first crack flexural stress.

CHAPTER 5

CONCLUSION AND RECOMMENDATION

5.1. Conclusion

The aim of this research work is to develop new empirical prediction models to assess mechanical properties of strain hardening cementitious composites (SHCCs). Soft computing method adopted in this research is gene expression programming (GEP). The research is to calculate five outputs, i.e., compressive strength (CS), first crack tensile stress (TS), first crack flexural stress (FS), first crack tensile strain (TST), and first crack flexural strain (FST). 182 data points for CS, 97 for TS, 50 for FS, 107 for TST and 38 for FST, were recorded from available literature that includes internationally published research papers. Five databases were created from this retrieved data.

1. It was observed that GEP formulated models can precisely calculate the mechanical properties with extraordinary accurateness. R2-value for CS was (0.736), for TS it was (0.898), and finally for FS it was (0.746).
2. Linear along with the nonlinear data was considered in calculation which indicates towards diversity of GEP approach. To reduce the complication in the suggested models, data preprocessing and division were used along with other measures. Similarly, sensitivity analysis helped a lot to overcome over-fitting issue. PI for CS was (0.106), and for TS it was (0.053) and finally for FS in was noted as (0.087); all almost equaling zero. Consequently, making it precise when compared to available literature.
3. MAE, RSE, RMSE, NSE, R, R^2, RMSLE, RRMSE%, PI, and OBF were used to analyze performance of all the models. Corresponding OBF values are 0.103, 0.047, and 0.108 for CS, TS, and FS. As a result it was established that developed models are effective and trustworthy methods for prediction of CS, TS, and FS.
4. An important point to note here is that the limitation of these generated models is the input parameters data range used for their formulation. They are only able to estimate within the

input parameters. If more data is available, these expressions can predict properties for a wider range. However, current model is still good enough to be engaged for future predictions in CS, TS, and FS. Not only are these techniques simple, quick, economical but it also led towards sustainable construction on concrete.

5.2. Recommendation for future study

To conclude, as per the results of the study, AI techniques are extremely helpful and precise tool for answering problems of materials and structural engineering, particularly problems with complicated mechanism. In addition to this, these techniques can be useful to an unseen data by generalizing these simplified mathematical expressions. It is recommended that the results of this study can be rechecked or verified with more recent data. In addition to this other AI methods such as Ensemble Random Forest (RF) regression, Gradient boosted (GB) trees, multi expression programming (MEP) and Support vector machines (SVMs) can be tried. These techniques are still not considered as reliable because of inborn limitations like model uncertainty, knowledge extraction and the model interpretability. Therefore, based on human expertise, a better knowledge of the hidden physical process is essential.

CHAPTER 6

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Appendix A. Dataset used for modeling the mechanical properties of strain hardening cementitious composites (SHCC).

Fine Agg. (% weight)	Fly ash (% weight)	Superplasticiser (% weight)	Fiber Amount (% weight)	Fiber Type	Fiber Diameter (Micro-Meter)	Fiber Length (mm)	Fiber Tensile Strength (MPa)	Fiber Elastic Modulus (GPa)	Environment Temperature	Water Curing	First crack tensile stress (TS)	First crack tensile strain (TST)	First crack flexural Stress (FS)	First crack flexural strain (FST)	Compressive strength (CS)
0.14	0.51	0.00	0.00	PVA	39.00	12.00	1620.00	43.00	20.00	28	5.00	0.40	3.75	0.45	27.20
0.14	0.51	0.00	0.00	PVA	39.00	12.00	1620.00	43.00	20.00	28	3.00	0.25	4.38	1.34	31.10
0.14	0.51	0.00	0.00	PVA	17.48	5.17	3261.60	337.69	20.00	28	3.00	0.30	3.50	0.45	31.80
0.14	0.51	0.00	0.00	PVA	11.44	3.26	3722.40	420.41	20.00	28	2.75	0.60	3.50	1.79	32.90
0.14	0.51	0.00	0.00	PVA	8.80	2.42	3924.00	456.60	20.00	28	3.10	0.20	2.25	0.45	33.70
0.14	0.51	0.00	0.00	PVA	39.00	12.00	1620.00	43.00	20.00	28	1.50	0.10	2.50	0.45	32.90
0.14	0.51	0.00	0.00	PVA	15.60	4.58	3405.60	363.54	20.00	28	2.75	0.30	2.50	0.45	35.30
0.14	0.51	0.00	0.00	PVA	10.31	2.90	3808.80	435.92	20.00	28	3.00	0.10	4.38	0.45	37.10
0.14	0.51	0.00	0.00	PVA	7.67	2.06	4010.40	472.11	20.00	28	2.20	0.10	2.50	0.45	37.80
0.37	0.00	0.00	0.00	PVA	39.00	12.00	1620.00	42.80	20.00	28	1.75	0.15	-	-	-
0.37	0.00	0.00	0.00	PVA	39.00	12.00	1620.00	42.80	20.00	28	1.85	0.15	-	-	-
0.37	0.00	0.00	0.00	PVA	39.00	12.00	1620.00	42.80	20.00	28	2.05	0.15	-	-	-
0.00	0.00	0.02	0.00	PE	38.00	12.70	2590.00	117.00	20.00	28	3.10	0.20	-	-	65.60
0.54	0.00	0.01	0.00	PE	38.00	12.70	2590.00	117.00	20.00	28	2.00	0.20	-	-	72.20

0.24	0.00	0.02	0.00	PE	38.00	12.70	2590.00	117.00	20.00	28	3.30	0.20	-	-	55.70
0.24	0.00	0.02	0.00	PE	38.00	12.70	2590.00	117.00	20.00	28	2.90	0.20	-	-	55.70
0.00	0.29	0.00	0.00	PVA	40.00	8.00	1600.00	41.00	20.00	28	6.90	0.10	11.00	0.20	92.40
0.00	0.28	0.00	0.00	PVA	40.00	8.00	1600.00	41.00	20.00	28	3.50	0.20	8.00	0.20	81.50
0.40	0.00	0.01	0.01	PVA	40.00	8.00	1600.00	41.00	20.00	28	-	-	-	-	42.00
0.22	0.33	0.01	0.01	PVA	40.00	8.00	1600.00	41.00	20.00	28	-	-	-	-	68.00
0.34	0.34	0.01	0.01	PVA	40.00	8.00	1600.00	41.00	20.00	28	-	-	-	-	40.80
0.34	0.34	0.01	0.01	PVA	40.00	8.00	1600.00	41.00	20.00	28	3.80	0.10	-	-	38.60
0.34	0.34	0.01	0.01	PVA	40.00	8.00	1600.00	41.00	20.00	28	-	-	-	-	36.50
0.34	0.34	0.01	0.01	PVA	40.00	8.00	1600.00	41.00	20.00	28	-	-	-	-	29.10
0.16	0.65	0.00	0.00	PVA	38.00	12.00	1600.00	42.00	20.00	7	2.75	0.20	6.00	0.40	-
0.16	0.64	0.00	0.00	PVA	38.00	12.00	1600.00	42.00	20.00	7	4.00	0.50	8.30	0.30	23.00
0.16	0.64	0.00	0.00	PVA	38.00	12.00	1600.00	42.00	20.00	7	3.70	0.10	11.00	0.70	26.00
0.16	0.64	0.00	0.00	PVA	38.00	12.00	1600.00	42.00	20.00	7	4.00	0.20	10.00	0.90	24.00
0.00	0.00	0.02	0.00	STEEL	150.00	6.00	2500.00	200.00	20.00	28	-	-	-	-	-
0.00	0.00	0.02	0.00	STEEL	150.00	6.00	2500.00	200.00	20.00	28	-	-	-	-	-
0.00	0.00	0.02	0.00	STEEL	150.00	6.00	2500.00	200.00	20.00	28	-	-	-	-	-
0.00	0.00	0.02	0.00	STEEL	150.00	6.00	2500.00	200.00	20.00	28	-	-	-	-	-
0.00	0.00	0.02	0.00	STEEL	150.00	6.00	2500.00	200.00	20.00	28	-	-	-	-	-
0.00	0.00	0.02	0.00	STEEL	150.00	6.00	2500.00	200.00	20.00	28	-	-	-	-	-

0.00	0.00	0.02	0.00	STEEL	150.00	12.00	2500.00	200.00	20.00	28	-	-	-	-	-
0.00	0.00	0.02	0.00	STEEL	150.00	16.00	2500.00	200.00	20.00	28	-	-	-	-	-
0.00	0.00	0.01	0.00	STEEL	150.00	20.00	2500.00	200.00	20.00	28	-	-	-	-	-
0.22	0.33	0.00	0.01	PVA	39.00	8.00	1620.00	42.80	20.00	27	4.70	0.30	-	-	62.50
0.22	0.42	0.00	0.01	PVA	39.00	8.00	1620.00	42.80	20.00	27	4.30	0.30	-	-	54.10
0.22	0.49	0.00	0.01	PVA	39.00	8.00	1620.00	42.80	20.00	27	3.70	0.20	-	-	36.80
0.22	0.33	0.00	0.01	PVA	39.00	8.00	1620.00	42.80	20.00	27	4.50	0.25	-	-	58.40
0.22	0.42	0.00	0.01	PVA	39.00	8.00	1620.00	42.80	20.00	27	4.75	0.50	-	-	46.20
0.22	0.49	0.00	0.01	PVA	39.00	8.00	1620.00	42.80	20.00	27	3.70	0.60	-	-	33.50
0.22	0.33	0.00	0.01	PVA	39.00	8.00	1620.00	42.80	20.00	27	4.30	0.40	-	-	57.80
0.22	0.42	0.00	0.01	PVA	39.00	8.00	1620.00	42.80	20.00	27	3.90	0.25	-	-	43.40
0.22	0.49	0.00	0.01	PVA	39.00	8.00	1620.00	42.80	20.00	27	3.10	0.10	-	-	31.10
0.22	0.33	0.00	0.01	PVA	39.00	8.00	1620.00	42.80	20.00	27	4.50	0.25	-	-	58.80
0.22	0.42	0.00	0.01	PVA	39.00	8.00	1620.00	42.80	20.00	27	3.80	0.20	-	-	49.70
0.23	0.49	0.00	0.01	PVA	39.00	8.00	1620.00	42.80	20.00	27	3.50	0.10	-	-	30.60
0.22	0.33	0.00	0.01	PVA	39.00	8.00	1620.00	42.80	20.00	27	4.10	0.35	-	-	59.00
0.22	0.42	0.00	0.01	PVA	39.00	8.00	1620.00	42.80	20.00	27	3.80	0.20	-	-	42.60
0.23	0.49	0.00	0.01	PVA	39.00	8.00	1620.00	42.80	20.00	27	3.10	0.30	-	-	30.50
0.26	0.00	0.00	0.00	PVA	39.00	12.00	1620.00	42.80	20.00	28	3.45	0.02	-	-	-
0.29	0.00	0.01	0.00	PVA	39.00	12.00	1620.00	42.80	20.00	28	3.18	0.02	-	-	-

0.35	0.00	0.01	0.00	PVA	39.00	12.00	1620.00	42.80	20.00	28	3.56	0.02	-	-	-
0.40	0.00	0.01	0.00	PVA	39.00	12.00	1620.00	42.80	20.00	28	3.97	0.02	-	-	-
0.29	0.00	0.01	0.00	PVA	39.00	12.00	1620.00	42.80	20.00	28	2.62	0.02	-	-	-
0.35	0.00	0.01	0.00	PVA	39.00	12.00	1620.00	42.80	20.00	28	2.56	0.02	-	-	-
0.40	0.00	0.01	0.00	PVA	39.00	12.00	1620.00	42.80	20.00	28	2.66	0.02	-	-	-
0.45	0.00	0.01	0.00	PVA	39.00	12.00	1620.00	42.80	20.00	28	3.45	0.02	-	-	-
0.29	0.00	0.01	0.00	PVA	39.00	12.00	1620.00	42.80	20.00	28	2.96	0.03	-	-	-
0.40	0.00	0.01	0.00	PVA	39.00	12.00	1620.00	42.80	20.00	28	3.11	0.03	-	-	-
0.45	0.00	0.01	0.00	PVA	39.00	12.00	1620.00	42.80	20.00	28	2.63	0.03	-	-	-
0.45	0.00	0.01	0.00	PVA	39.00	12.00	1620.00	42.80	20.00	28	3.39	0.03	-	-	-
0.27	0.00	0.01	0.00	PVA	39.00	12.00	1620.00	42.80	20.00	14	3.11	0.04	-	-	-
0.27	0.00	0.01	0.00	PVA	39.00	12.00	1620.00	42.80	20.00	14	2.63	0.01	-	-	-
0.27	0.00	0.01	0.00	PVA	39.00	12.00	1620.00	42.80	20.00	14	2.35	0.01	-	-	-
0.27	0.00	0.01	0.00	PVA	39.00	12.00	1620.00	42.80	20.00	14	2.90	0.01	-	-	-
0.27	0.00	0.01	0.00	PVA	39.00	12.00	1620.00	42.80	20.00	14	2.92	0.01	-	-	-
0.22	0.50	0.00	0.01	PVA	39.00	12.00	1600.00	42.00	20.00	1	2.63	0.01	-	-	17.00
0.22	0.50	0.00	0.01	PVA	39.00	12.00	1600.00	42.00	50.00	1	2.88	0.01	-	-	18.00
0.22	0.50	0.00	0.01	PVA	39.00	12.00	1600.00	42.00	100.00	1	3.39	0.01	-	-	17.00
0.22	0.50	0.00	0.01	PVA	39.00	12.00	1600.00	42.00	200.00	1	2.67	0.01	-	-	14.00
0.14	0.42	0.00	0.01	PVA	40.00	12.00	1600.00	42.00	20.00	28	2.75	0.00	-	-	38.80

0.14	0.41	0.00	0.04	STEEL	119.20	7.68	2608.00	155.12	20.00	28	2.89	0.00	-	-	40.10
0.14	0.41	0.00	0.04	STEEL	119.20	12.72	2608.00	155.12	20.00	28	3.32	0.00	-	-	45.00
0.14	0.42	0.00	0.01	PVA	40.00	12.00	1600.00	42.00	20.00	28	2.75	0.00	-	-	38.80
0.14	0.41	0.00	0.04	STEEL	119.20	7.68	2608.00	155.12	60.00	28	2.89	0.00	-	-	40.10
0.14	0.41	0.00	0.04	STEEL	119.20	12.72	2608.00	155.12	60.00	28	3.32	0.00	-	-	45.00
0.14	0.42	0.00	0.01	PVA	40.00	12.00	1600.00	42.00	60.00	28	-	-	-	-	-
0.14	0.41	0.00	0.04	STEEL	119.20	7.68	2608.00	155.12	60.00	28	-	-	-	-	-
0.14	0.41	0.00	0.04	STEEL	119.20	12.72	2608.00	155.12	60.00	28	-	-	-	-	-
0.14	0.42	0.00	0.01	PVA	40.00	12.00	1600.00	42.00	60.00	28	-	-	-	-	-
0.14	0.41	0.00	0.04	STEEL	119.20	7.68	2608.00	155.12	100.00	28	-	-	-	-	-
0.14	0.41	0.00	0.04	STEEL	119.20	12.72	2608.00	155.12	100.00	28	-	-	-	-	-
0.14	0.42	0.00	0.01	PVA	40.00	12.00	1600.00	42.00	100.00	28	-	-	-	-	-
0.14	0.41	0.00	0.04	STEEL	119.20	7.68	2608.00	155.12	200.00	28	-	-	-	-	-
0.14	0.41	0.00	0.04	STEEL	119.20	12.72	2608.00	155.12	100.00	28	-	-	-	-	-
0.14	0.42	0.00	0.01	PVA	40.00	12.00	1600.00	42.00	100.00	28	-	-	-	-	-
0.14	0.41	0.00	0.04	STEEL	119.20	7.68	2608.00	155.12	200.00	28	-	-	-	-	-
0.14	0.41	0.00	0.04	STEEL	119.20	12.72	2608.00	155.12	200.00	28	-	-	-	-	-
0.14	0.42	0.00	0.01	PVA	40.00	12.00	1600.00	42.00	150.00	28	-	-	-	-	-
0.14	0.41	0.00	0.04	STEEL	119.20	7.68	2608.00	155.12	400.00	28	-	-	-	-	-
0.14	0.41	0.00	0.04	STEEL	119.20	12.72	2608.00	155.12	200.00	28	-	-	-	-	-

0.22	0.33	0.00	0.01	PVA	39.00	12.00	1620.00	42.80	20.00	7	-	-	-	-	75.20
0.22	0.33	0.00	0.01	PVA	39.00	12.00	1620.00	42.80	20.00	7	-	-	-	-	70.30
0.22	0.48	0.00	0.00	PVA	35.00	12.00	1287.00	31.30	20.00	28	1.64	0.10	-	-	23.00
0.22	0.48	0.00	0.00	PVA	28.25	14.60	1929.60	137.04	20.00	28	2.43	0.20	-	-	30.00
0.22	0.48	0.00	0.00	PVA	23.75	8.01	2358.00	207.53	20.00	28	1.41	0.30	-	-	16.00
0.22	0.48	0.00	0.00	PVA	18.13	6.02	2893.50	295.65	20.00	28	1.32	0.60	-	-	13.00
0.17	0.34	0.00	0.23	PVA	18.13	6.02	2893.50	295.65	20.00	28	1.32	0.60	-	-	13.00
0.16	0.30	0.00	0.27	PVA	18.13	6.02	2893.50	295.65	20.00	28	1.32	0.60	-	-	13.00
0.14	0.21	0.00	0.35	PVA	18.13	6.02	2893.50	295.65	20.00	28	1.32	0.60	-	-	13.00
0.22	0.33	0.00	0.00	PVA	39.00	12.00	1620.00	42.80	20.00	28	-	-	-	-	53.00
0.23	0.45	0.00	0.00	PVA	39.00	12.00	1620.00	42.80	20.00	28	4.80	0.30	-	-	40.00
0.00	0.49	0.00	0.00	PE	38.00	38.00	2400.00	66.00	20.00	28	2.30	0.20	-	-	48.00
0.23	0.42	0.00	0.00	PVA	39.00	8.00	1600.00	42.80	20.00	1	1.72	0.15	-	-	-
0.23	0.42	0.01	0.00	PVA	39.00	8.00	1600.00	42.80	20.00	1	1.92	0.15	-	-	-
0.23	0.42	0.00	0.00	PVA	39.00	8.00	1600.00	42.80	20.00	1	1.78	0.15	-	-	-
0.23	0.42	0.00	0.00	PVA	39.00	8.00	1600.00	42.80	20.00	1	1.85	0.15	-	-	-
0.13	0.52	0.00	0.00	PVA	39.00	12.00	1600.00	40.00	20.00	28	2.00	0.10	-	-	14.20
0.13	0.53	0.00	0.00	PVA	39.00	12.00	1600.00	40.00	20.00	28	2.70	0.10	-	-	23.30
0.14	0.55	0.00	0.00	PVA	39.00	12.00	1600.00	40.00	20.00	28	3.00	0.10	-	-	47.20
0.14	0.55	0.00	0.00	PVA	39.00	12.00	1600.00	40.00	20.00	28	3.50	0.10	-	-	46.60

0.14	0.57	0.00	0.00	PVA	39.00	12.00	1600.0 0	40.00	20.00	7	3.20	0.10	-	-	42.40
0.14	0.57	0.00	0.00	PVA	39.00	12.00	1600.0 0	40.00	20.00	28	3.80	0.10	-	-	55.60
0.14	0.58	0.00	0.00	PVA	39.00	12.00	1600.0 0	40.00	20.00	7	3.30	0.10	-	-	49.40
0.14	0.58	0.00	0.00	PVA	39.00	12.00	1600.0 0	40.00	20.00	28	3.80	0.10	-	-	62.20
0.15	0.59	0.01	0.00	PVA	39.00	12.00	1600.0 0	40.00	20.00	7	4.00	0.10	-	-	58.70
0.22	0.33	0.00	0.01	PVA	39.00	8.00	1620.0 0	42.00	20.00	6	3.40	0.20	-	-	-
0.22	0.33	0.00	0.01	PVA	39.00	8.00	1620.0 0	42.00	20.00	6	3.40	0.20	-	-	-
0.22	0.33	0.00	0.01	PVA	39.00	8.00	1620.0 0	42.00	20.00	6	3.40	0.20	-	-	-
0.00	0.59	0.01	0.01	HTPP	12.00	10.00	850.00	6.00	20.00	7	1.47	0.20	-	-	39.00
0.00	0.59	0.00	0.01	HTPP	12.00	10.00	850.00	6.00	20.00	7	2.12	0.20	-	-	37.00
0.00	0.59	0.01	0.01	HTPP	12.00	10.00	850.00	6.00	20.00	28	1.84	0.20	-	-	45.00
0.00	0.59	0.00	0.01	HTPP	12.00	10.00	850.00	6.00	20.00	28	2.02	0.20	-	-	38.00
0.00	0.59	0.01	0.01	HTPP	12.00	10.00	850.00	6.00	20.00	1	3.26	0.20	-	-	30.00
0.00	0.59	0.00	0.01	HTPP	12.00	10.00	850.00	6.00	20.00	1	2.74	0.20	-	-	31.00
0.00	0.59	0.01	0.01	HTPP	12.00	10.00	850.00	6.00	20.00	28	1.98	0.20	-	-	49.00
0.00	0.59	0.00	0.01	HTPP	12.00	10.00	850.00	6.00	20.00	28	2.67	0.20	-	-	45.00
0.00	0.59	0.00	0.01	HTPP	12.00	10.00	850.00	6.00	20.00	1	2.37	0.20	-	-	36.00
0.00	0.59	0.00	0.01	HTPP	12.00	10.00	850.00	6.00	20.00	7	1.52	0.20	-	-	48.00
0.00	0.59	0.00	0.01	HTPP	12.00	10.00	850.00	6.00	20.00	28	2.19	0.20	-	-	69.00
0.22	0.33	0.00	0.01	PVA	39.00	12.00	1600.0 0	42.80	20.00	14	4.00	0.30	-	-	39.20
0.22	0.33	0.00	0.01	PVA	39.00	12.00	1600.0 0	42.80	20.00	28	4.40	0.25	-	-	62.50
0.22	0.42	0.00	0.01	PVA	39.00	12.00	1600.0 0	42.80	20.00	14	3.75	0.30	-	-	27.70
0.22	0.42	0.00	0.01	PVA	39.00	12.00	1600.0 0	42.80	20.00	28	4.10	0.25	-	-	54.10
0.22	0.42	0.00	0.01	PVA	39.00	12.00	1600	42.00	100.00	1	5.00	0.20	-	-	45.00
0.22	0.42	0.00	0.01	PVA	39.00	12.00	1600	42.00	200.00	1	4.50	0.10	-	-	43.00

0.22	0.42	0.00	0.01	PVA	39.00	12.00	1600	42.00	300.00	1	2.80	0.10	-	-	43.00
0.22	0.42	0.00	0.01	PVA	39.00	12.00	1600	42.00	400.00	1	2.40	0.10	-	-	36.00
0.22	0.42	0.00	0.01	PVA	39.00	12.00	1600	42.00	500.00	1	1.80	0.10	-	-	32.00
0.22	0.33	0.00	0.00	PVA	39.00	12.00	1620	42.80	20.00	1	5.50	0.10	-	-	-
0.22	0.43	0.00	0.00	PVA	39.00	12.00	1620	42.80	20.00	1	4.40	0.20	-	-	-
0.20	0.27	0.01	0.00	PE	26.00	18.00	3000.00	110.00	20.00	1	6.00	0.10	-	-	85.00
0.20	0.27	0.01	0.00	PE	26.00	18.00	3000.00	110.00	20.00	1	4.50	0.20	-	-	88.00
0.15	0.28	0.01	0.00	PE	26.00	18.00	3000.00	110.00	20.00	1	4.80	0.30	-	-	81.00
0.00	0.33	0.01	0.00	PE	26.00	18.00	3000.00	110.00	20.00	1	5.00	0.30	-	-	66.00
0.00	0.33	0.01	0.00	PE	26.00	18.00	3000.00	110.00	20.00	1	4.00	0.10	-	-	71.00
0.22	0.33	0.00	0.00	STEEL	192.70	16.30	1633.3	95.2	20.00	14	3.50	0.01	-	-	45.00
0.22	0.33	0.00	0.00	STEEL	192.70	16.30	1633.3	95.2	100.00	14	6.00	0.02	-	-	48.00
0.22	0.33	0.00	0.00	STEEL	192.70	16.30	1633.3	95.2	200.00	14	6.00	0.01	-	-	41.00
0.22	0.33	0.00	0.00	STEEL	192.70	16.30	1633.3	95.2	400.00	14	4.00	0.01	-	-	45.00
0.22	0.33	0.00	0.00	PVA	39.00	12.00	1600	42.80	20.00	14	4.50	0.03	-	-	42.00
0.22	0.33	0.00	0.00	PVA	39.00	12.00	1600	42.80	100.00	14	5.00	0.03	-	-	39.00
0.22	0.33	0.00	0.00	PVA	39.00	12.00	1600	42.80	200.00	14	3.00	0.01	-	-	43.00
0.23	0.39	0.00	0.00	PVA	39.00	12.00	1600	42.80	20.00	14	4.00	0.01	-	-	23.00
0.23	0.39	0.00	0.00	PVA	39.00	12.00	1600	42.80	100.00	14	4.00	0.01	-	-	24.00
0.23	0.39	0.00	0.00	PVA	39.00	12.00	1600	42.80	200.00	14	2.00	0.01	-	-	24.00
0.41	0.00	0.00	0.00	PVA	40.00	12.00	1620	42.8	20.00	0.17	3.00	0.20	0.00	0.00	23.60
0.41	0.00	0.00	0.00	PVA	40.00	12.00	1620	42.8	20.00	0.25	3.20	0.20	0.00	0.00	34.20
0.41	0.00	0.00	0.00	PVA	40.00	12.00	1620	42.8	20.00	0.5	3.40	0.20	0.00	0.00	37.00
0.41	0.00	0.00	0.00	PVA	40.00	12.00	1620	42.8	20.00	1	3.80	0.20	0.00	0.00	42.30
0.41	0.00	0.00	0.00	PVA	40.00	12.00	1620	42.8	20.00	3	4.40	0.20	0.00	0.00	44.70
0.41	0.00	0.00	0.00	PVA	40.00	12.00	1620	42.8	20.00	7	5.10	0.20	0.00	0.00	47.50
0.41	0.00	0.00	0.00	PVA	40.00	12.00	1620	42.8	20.00	14	5.20	0.20	0.00	0.00	50.80
0.41	0.00	0.00	0.00	PVA	40.00	12.00	1620	42.8	20.00	28	5.10	0.20	0.00	0.00	55.60
0.41	0.00	0.00	0.00	PVA	40.00	12.00	1620	42.8	20.00	60	5.40	0.20	0.00	0.00	56.80

0.22	0.33	0.00	0.00	PVA	39.00	12.00	1620	42.8	20.00	7	3.50	0.10	-	-	-
0.22	0.33	0.00	0.00	PVA	39.00	12.00	1620	42.8	20.00	7	3.80	0.25	-	-	-
0.22	0.33	0.00	0.00	PVA	39.00	12.00	1620	42.8	20.00	7	3.60	0.20	-	-	-
0.22	0.33	0.00	0.00	PVA	39.00	12.00	1620	42.8	20.00	7	3.80	1.20	-	-	-
0.22	0.33	0.00	0.00	PVA	39.00	12.00	1620	42.8	20.00	7	3.80	0.20	-	-	-
0.22	0.33	0.00	0.00	PVA	39.00	12.00	1620	42.8	20.00	7	3.10	0.10	-	-	-
0.22	0.33	0.00	0.00	PVA	39.00	12.00	1620	42.8	20.00	7	3.10	0.20	-	-	-
0.02	0.03	0.15	0.74	PVA	39.00	8.00	1620	42.00	20.00	28	-	-	11.7	0.23	62
0.02	0.03	0.15	0.74	PVA	39.00	8.00	1620	42.00	20.00	56	-	-	-	-	-
0.03	0.06	0.12	0.73	PVA	39.00	8.00	1620	42.00	20.00	28	-	-	9	0.13	53
0.03	0.06	0.12	0.73	PVA	39.00	8.00	1620	42.00	20.00	56	-	-	-	-	-
0.02	0.03	0.15	0.74	PVA	39.00	8.00	1620	42.00	20.00	28	-	-	7.5	0.43	61
0.02	0.03	0.15	0.74	PVA	39.00	8.00	1620	42.00	20.00	56	-	-	-	-	-
0.03	0.06	0.12	0.73	PVA	39.00	8.00	1620	42.00	20.00	28	-	-	8	0.38	52
0.03	0.06	0.12	0.73	PVA	39.00	8.00	1620	42.00	20.00	56	-	-	-	-	-
0.02	0.00	0.13	0.76	PVA	39.00	8.00	1620	42.00	20.00	28	-	-	15.6	0.25	69
0.02	0.00	0.13	0.76	PVA	39.00	8.00	1620	42.00	20.00	56	-	-	-	-	-
0.03	0.00	0.11	0.74	PVA	39.00	8.00	1620	42.00	20.00	28	-	-	8	0.21	67
0.03	0.00	0.11	0.74	PVA	39.00	8.00	1620	42.00	20.00	56	-	-	-	-	-
0.02	0.03	0.15	0.74	PVA	39.00	8.00	1620	42.00	20.00	28	-	-	9.00	0.07	60.00
0.02	0.03	0.15	0.74	PVA	39.00	8.00	1620	42.00	20.00	56	-	-	-	-	-
0.03	0.06	0.12	0.73	PVA	39.00	8.00	1620	42.00	20.00	28	-	-	10.40	0.26	47.00
0.03	0.06	0.12	0.73	PVA	39.00	8.00	1620	42.00	20.00	56	-	-	-	-	-
0.02	0.03	0.15	0.74	PVA	39.00	8.00	1620	42.00	20.00	28	-	-	9.00	0.26	59.00
0.02	0.03	0.15	0.74	PVA	39.00	8.00	1620	42.00	20.00	56	-	-	-	-	-
0.03	0.06	0.12	0.73	PVA	39.00	8.00	1620	42.00	20.00	28	-	-	7.40	0.10	45.00
0.03	0.06	0.12	0.73	PVA	39.00	8.00	1620	42.00	20.00	56	-	-	-	-	-
0.02	0.00	0.13	0.76	PVA	39.00	8.00	1620	42.00	20.00	28	-	-	12.00	0.16	69.00
0.02	0.00	0.13	0.76	PVA	39.00	8.00	1620	42.00	20.00	56	-	-	-	-	-
0.03	0.00	0.11	0.74	PVA	39.00	8.00	1620	42.00	20.00	28	-	-	8.00	0.13	67.00
0.03	0.00	0.11	0.74	PVA	39.00	8.00	1620	42.00	20.00	56	-	-	-	-	-

0.23	0.46	0.00	0.01	PVA	39.00	8.00	1600	42.00	20.00	7	-	-	-	-	53.4
0.23	0.45	0.00	0.01	PVA	39.00	8.00	1600	42.00	20.00	7	-	-	-	-	51.5
0.23	0.45	0.00	0.01	PVA	39.00	8.00	1600	42.00	20.00	7	-	-	-	-	50.9
0.26	0.39	0.00	0.01	PVA	39.00	8.00	1600	42.00	20.00	7	-	-	-	-	55.9
0.26	0.38	0.00	0.01	PVA	39.00	8.00	1600	42.00	20.00	7	-	-	-	-	53.6
0.25	0.38	0.01	0.01	PVA	39.00	8.00	1600	42.00	20.00	7	-	-	-	-	50.1
0.30	0.30	0.00	0.02	PVA	39.00	8.00	1600	42.00	20.00	7	-	-	-	-	58.1
0.29	0.29	0.01	0.02	PVA	39.00	8.00	1600	42.00	20.00	7	-	-	-	-	55.3
0.29	0.29	0.00	0.02	PVA	39.00	8.00	1600	42.00	20.00	7	-	-	-	-	52.8
0.36	0.05	0.01	0.00	PVA	39.00	12.00	1092	25.8	20.00	84	4.64	0.1	-	-	-
0.34	0.09	0.01	0.00	PVA	39.00	12.00	1092	25.8	20.00	84	4.58	0.1	-	-	-
0.26	0.26	0.01	0.00	PVA	39.00	12.00	1092	25.8	20.00	84	3.95	0.1	-	-	-
0.24	0.30	0.01	0.00	PVA	39.00	12.00	1092	25.8	20.00	84	4.42	0.1	-	-	-
0.22	0.34	0.01	0.00	PVA	39.00	12.00	1092	25.8	20.00	84	4.11	0.1	-	-	-
0.20	0.38	0.01	0.00	PVA	39.00	12.00	1092	25.8	20.00	84	3.69	0.1	-	-	-
0.40	0.00	0.01	0.01	PVA	39.00	12.00	1092	25.8	20.00	28	2.92	0.1	-	-	-
0.22	0.33	0.01	0.01	PVA	39.00	12.00	1092	25.8	20.00	84	3.3	0.1	-	-	-
0.38	0.27	0.01	0.01	PVA	39.00	12.00	1092	25.8	20.00	28	3.8	0.1	-	-	-
0.34	0.34	0.01	0.01	PVA	39.00	12.00	1092	25.8	20.00	28	3.69	0.1	-	-	-
0.45	0.12	0.01	0.02	PVA	39.00	12.00	1092	25.8	20.00	28	3.92	0.1	-	-	-
0.34	0.34	0.01	0.01	PVA	39.00	12.00	1092	25.8	20.00	28	3.08	0.1	-	-	-
0.22	0.33	0.00	0.01	PVA	39.00	8.00	1620	42.8	20.00	7	3.1	0.25	-	-	38.1
0.22	0.33	0.00	0.01	PVA	39.00	8.00	1620	42.8	20.00	7	4.1	0.25	-	-	50.2
0.22	0.33	0.00	0.01	PVA	39.00	8.00	1620	42.8	20.00	7	4.25	0.25	-	-	-
0.22	0.33	0.00	0.01	PVA	39.00	8.00	1620	42.8	20.00	7	4.2	0.25	-	-	-
0.22	0.33	0.00	0.01	PVA	39.00	8.00	1620	42.8	20.00	28	4.50	0.1	11	0.43	62.5
0.22	0.33	0.00	0.01	PVA	39.00	8.00	1620	42.8	20.00	28	4.20	0.2	9.5	0.33	58.9
0.22	0.33	0.00	0.01	PVA	39.00	8.00	1620	42.8	20.00	28	4.10	0.1	8	0.33	53.9
0.22	0.42	0.00	0.01	PVA	39.00	8.00	1620	42.8	20.00	28	4.20	0.20	11.20	0.41	54.10
0.22	0.42	0.00	0.01	PVA	39.00	8.00	1620	42.8	20.00	28	4.10	0.15	8.10	0.26	45.00
0.22	0.42	0.00	0.01	PVA	39.00	8.00	1620	42.8	20.00	28	3.60	0.25	7.80	0.36	40.70

0.22	0.33	0.00	0.01	PVA	39.00	8.00	1620	42.8	20.00	7	2.8	0.2	-	-	38.10
0.22	0.33	0.00	0.01	PVA	39.00	8.00	1620	42.8	20.00	14	3.8	0.2	-	-	50.20
0.22	0.33	0.00	0.01	PVA	39.00	8.00	1620	42.8	20.00	14	4	0.35	-	-	-
0.22	0.33	0.00	0.01	PVA	39.00	8.00	1620	42.8	20.00	14	4.5	0.2	-	-	-
0.22	0.42	0.00	0.01	PVA	39.00	8.00	1620	42.8	20.00	7	2.5	0.2	-	-	21.60
0.22	0.42	0.00	0.01	PVA	39.00	8.00	1620	42.8	20.00	14	3.5	0.25	-	-	36.30
0.22	0.42	0.00	0.01	PVA	39.00	8.00	1620	42.8	20.00	14	3.8	0.5	-	-	-
0.22	0.42	0.00	0.01	PVA	39.00	8.00	1620	42.8	20.00	14	3.6	0.25	-	-	-
0.22	0.33	0.00	0.01	PVA	39.00	12.00	1600	40.00	20.00	1	3.4	0.15	-	-	-
0.22	0.45	0.00	0.01	PVA	39.00	12.00	1600	40.00	20.00	1	3.1	0.2	-	-	-
0.32	0.00	0.00	0.00	STEEL	625.00	20.00	850.00	102.50	20.00	7	-	-	-	-	45.00
0.32	0.00	0.00	0.00	STEEL	625.00	20.00	850.00	102.50	20.00	28	-	-	-	-	49.00
0.32	0.00	0.00	0.00	STEEL	625.00	20.00	850.00	102.50	20.00	56	-	-	-	-	57.00
0.32	0.00	0.00	0.00	STEEL	625.00	20.00	850.00	102.50	20.00	90	-	-	-	-	58.00
0.32	0.22	0.00	0.00	STEEL	625.00	20.00	850.00	102.50	20.00	7	-	-	-	-	28.00
0.32	0.22	0.00	0.00	STEEL	625.00	20.00	850.00	102.50	20.00	28	-	-	-	-	34.00
0.32	0.22	0.00	0.00	STEEL	625.00	20.00	850.00	102.50	20.00	56	-	-	-	-	44.00
0.32	0.22	0.00	0.00	STEEL	625.00	20.00	850.00	102.50	20.00	90	-	-	-	-	48.00
0.32	0.32	0.00	0.00	STEEL	625.00	20.00	850.00	102.50	20.00	7	-	-	-	-	25.00
0.32	0.32	0.00	0.00	STEEL	625.00	20.00	850.00	102.50	20.00	28	-	-	-	-	37.00
0.32	0.32	0.00	0.00	STEEL	625.00	20.00	850.00	102.50	20.00	56	-	-	-	-	47.00
0.32	0.32	0.00	0.00	STEEL	625.00	20.00	850.00	102.50	20.00	90	-	-	-	-	50.00
0.32	0.43	0.00	0.00	STEEL	625.00	20.00	850.00	102.50	20.00	7	-	-	-	-	14.00
0.32	0.43	0.00	0.00	STEEL	625.00	20.00	850.00	102.50	20.00	28	-	-	-	-	25.00
0.32	0.43	0.00	0.00	STEEL	625.00	20.00	850.00	102.50	20.00	56	-	-	-	-	36.00
0.32	0.43	0.00	0.00	STEEL	625.00	20.00	850.00	102.50	20.00	90	-	-	-	-	37.00
0.32	0.54	0.00	0.00	STEEL	625.00	20.00	850.00	102.50	20.00	7	-	-	-	-	9.00
0.32	0.54	0.00	0.00	STEEL	625.00	20.00	850.00	102.50	20.00	28	-	-	-	-	12.00
0.32	0.54	0.00	0.00	STEEL	625.00	20.00	850.00	102.50	20.00	56	-	-	-	-	18.00
0.32	0.54	0.00	0.00	STEEL	625.00	20.00	850.00	102.50	20.00	90	-	-	-	-	23.00
0.00	0.00	0.02	0.00	STEEL	288.00	23.40	4500.0 0	360.00	20.00	28	3.50	0.25	-	-	-

0.00	0.00	0.02	0.00	STEEL	320.00	26.00	5000.00	400.00	20.00	28	4.00	0.20	-	-	-
0.00	0.00	0.02	0.00	PE	70.20	21.60	4698.00	142.20	20.00	28	2.20	0.35	-	-	-
0.00	0.00	0.02	0.00	PE	78.00	24.00	5220.00	158.00	20.00	28	1.50	0.20	-	-	-
0.00	0.00	0.02	0.00	STEEL	87.80	8.90	1772.00	115.80	20.00	28	2.40	0.10	-	-	-
0.00	0.00	0.02	0.00	STEEL	103.40	13.70	2816.00	147.40	20.00	28	2.50	0.10	-	-	-
0.00	0.00	0.02	0.00	STEEL	111.20	16.10	3338.00	163.20	20.00	28	3.20	0.20	-	-	-
0.00	0.00	0.02	0.00	STEEL	130.70	22.10	4643.00	202.70	20.00	28	2.90	0.20	-	-	-
0.26	0.00	0.01	0.00	STEEL	130.70	22.10	4643.00	202.70	20.00	28	3.75	0.20	-	-	-
0.00	0.00	0.02	0.00	STEEL	138.50	24.50	5165.00	218.50	20.00	28	2.50	0.20	-	-	-
0.00	0.00	0.02	0.00	STEEL	150.20	28.10	5948.00	242.20	20.00	28	3.25	0.20	-	-	-
0.00	0.00	0.02	0.00	STEEL	167.80	15.40	3022.00	215.80	20.00	28	4.10	0.10	-	-	-
0.00	0.00	0.02	0.00	STEEL	175.60	17.80	3544.00	231.60	20.00	28	3.50	0.10	-	-	-
0.00	0.00	0.02	0.00	STEEL	191.20	22.60	4588.00	263.20	20.00	28	3.00	0.20	-	-	-
0.26	0.00	0.01	0.00	STEEL	191.20	22.60	4588.00	263.20	20.00	28	4.00	0.20	-	-	-
0.00	0.00	0.02	0.00	STEEL	199.00	25.00	5110.00	279.00	20.00	28	2.80	0.15	-	-	-
0.00	0.00	0.02	0.00	STEEL	210.70	28.60	5893.00	302.70	20.00	28	2.80	0.20	-	-	-
0.00	0.00	0.02	0.00	STEEL	243.90	20.70	4011.00	307.90	20.00	28	3.00	0.10	-	-	-
0.00	0.00	0.02	0.00	STEEL	247.80	21.90	4272.00	315.80	20.00	28	3.10	0.05	-	-	-
0.00	0.00	0.02	0.00	STEEL	259.50	25.50	5055.00	339.50	20.00	28	3.10	0.15	-	-	-
0.26	0.00	0.01	0.00	STEEL	259.50	25.50	5055.00	339.50	20.00	28	5.20	0.10	-	-	-

0.00	0.00	0.02	0.00	STEEL	271.20	29.10	5838.00	363.20	20.00	28	3.00	0.20	-	-	-
0.00	0.00	0.02	0.00	STEEL	279.00	31.50	6360.00	379.00	20.00	28	3.20	0.30	-	-	-
0.00	0.00	0.02	0.00	STEEL	99.50	15.50	2555.00	139.50	20.00	28	2.50	0.20	-	-	-
0.00	0.00	0.02	0.00	STEEL	109.25	20.00	3207.50	159.25	20.00	28	2.80	0.25	-	-	-
0.00	0.00	0.02	0.00	STEEL	119.00	24.50	3860.00	179.00	20.00	28	2.50	0.20	-	-	-
0.00	0.00	0.02	0.00	STEEL	169.75	17.50	3152.50	219.75	20.00	28	3.40	0.10	-	-	-
0.00	0.00	0.02	0.00	STEEL	181.45	22.90	3935.50	243.45	20.00	28	3.30	0.20	-	-	-
0.66	0.00	0.00	0.00	Carbon	6.90	12.00	4200.00	240.00	21.00	30	-	-	-	-	52.92
0.66	0.00	0.00	0.01	Glass	14.00	12.00	1700.00	72.00	21.00	30	-	-	-	-	50.94
0.67	0.00	0.00	0.00	PP	18.00	12.00	350.00	4.00	21.00	30	-	-	-	-	55.40
0.67	0.00	0.00	0.00	PVA	660.00	12.00	900.00	23.00	21.00	30	-	-	-	-	47.80
0.66	0.00	0.00	0.00	Carbon	6.90	12.00	4200.00	240.00	100.00	30	-	-	-	-	58.75
0.66	0.00	0.00	0.01	Glass	14.00	12.00	1700.00	72.00	100.00	30	-	-	-	-	54.35
0.67	0.00	0.00	0.00	PP	18.00	12.00	350.00	4.00	100.00	30	-	-	-	-	58.18
0.67	0.00	0.00	0.00	PVA	660.00	12.00	900.00	23.00	100.00	30	-	-	-	-	54.33
0.66	0.00	0.00	0.00	Carbon	6.90	12.00	4200.00	240.00	450.00	30	-	-	-	-	49.50
0.66	0.00	0.00	0.01	Glass	14.00	12.00	1700.00	72.00	450.00	30	-	-	-	-	37.64
0.67	0.00	0.00	0.00	PP	18.00	12.00	350.00	4.00	450.00	30	-	-	-	-	38.23
0.67	0.00	0.00	0.00	PVA	660.00	12.00	900.00	23.00	450.00	30	-	-	-	-	48.98
0.66	0.00	0.00	0.00	Carbon	6.90	12.00	4200.00	240.00	650.00	30	-	-	-	-	27.43
0.66	0.00	0.00	0.01	Glass	14.00	12.00	1700.00	72.00	650.00	30	-	-	-	-	19.39
0.67	0.00	0.00	0.00	PP	18.00	12.00	350.00	4.00	650.00	30	-	-	-	-	18.96
0.67	0.00	0.00	0.00	PVA	660.00	12.00	900.00	23.00	650.00	30	-	-	-	-	21.68

0.66	0.00	0.00	0.01	Carbon	6.90	12.00	4200.00	240.00	21.00	30	-	-	-	-	50.43
0.66	0.00	0.00	0.01	Glass	14.00	12.00	1700.00	72.00	21.00	30	-	-	-	-	48.38
0.66	0.00	0.00	0.00	PP	18.00	12.00	350.00	4.00	21.00	30	-	-	-	-	49.94
0.66	0.00	0.00	0.00	PVA	660.00	12.00	900.00	23.00	21.00	30	-	-	-	-	39.19
0.66	0.00	0.00	0.01	Carbon	6.90	12.00	4200.00	240.00	100.00	30	-	-	-	-	56.98
0.66	0.00	0.00	0.01	Glass	14.00	12.00	1700.00	72.00	100.00	30	-	-	-	-	55.21
0.66	0.00	0.00	0.00	PP	18.00	12.00	350.00	4.00	100.00	30	-	-	-	-	52.99
0.66	0.00	0.00	0.00	PVA	660.00	12.00	900.00	23.00	100.00	30	-	-	-	-	51.66
0.66	0.00	0.00	0.01	Carbon	6.90	12.00	4200.00	240.00	450.00	30	-	-	-	-	49.64
0.66	0.00	0.00	0.01	Glass	14.00	12.00	1700.00	72.00	450.00	30	-	-	-	-	28.45
0.66	0.00	0.00	0.00	PP	18.00	12.00	350.00	4.00	450.00	30	-	-	-	-	34.42
0.66	0.00	0.00	0.00	PVA	660.00	12.00	900.00	23.00	450.00	30	-	-	-	-	41.56
0.66	0.00	0.00	0.01	Carbon	6.90	12.00	4200.00	240.00	650.00	30	-	-	-	-	26.56
0.66	0.00	0.00	0.01	Glass	14.00	12.00	1700.00	72.00	650.00	30	-	-	-	-	18.34
0.66	0.00	0.00	0.00	PP	18.00	12.00	350.00	4.00	650.00	30	-	-	-	-	18.05
0.66	0.00	0.00	0.00	PVA	660.00	12.00	900.00	23.00	650.00	30	-	-	-	-	17.40
0.66	0.00	0.00	0.01	Carbon	6.90	12.00	4200.00	240.00	21.00	30	-	-	-	-	50.40
0.66	0.00	0.00	0.02	Glass	14.00	12.00	1700.00	72.00	21.00	30	-	-	-	-	41.34
0.66	0.00	0.00	0.01	PP	18.00	12.00	350.00	4.00	21.00	30	-	-	-	-	48.50
0.66	0.00	0.00	0.01	PVA	660.00	12.00	900.00	23.00	21.00	30	-	-	-	-	41.90
0.66	0.00	0.00	0.01	Carbon	6.90	12.00	4200.00	240.00	100.00	30	-	-	-	-	56.22
0.66	0.00	0.00	0.02	Glass	14.00	12.00	1700.00	72.00	100.00	30	-	-	-	-	45.34
0.66	0.00	0.00	0.01	PP	18.00	12.00	350.00	4.00	100.00	30	-	-	-	-	52.50
0.66	0.00	0.00	0.01	PVA	660.00	12.00	900.00	23.00	100.00	30	-	-	-	-	48.64

0.66	0.00	0.00	0.01	Carbon	6.90	12.00	4200.00	240.00	450.00	30	-	-	-	-	49.82
0.66	0.00	0.00	0.02	Glass	14.00	12.00	1700.00	72.00	450.00	30	-	-	-	-	12.75
0.66	0.00	0.00	0.01	PP	18.00	12.00	350.00	4.00	450.00	30	-	-	-	-	25.95
0.66	0.00	0.00	0.01	PVA	660.00	12.00	900.00	23.00	450.00	30	-	-	-	-	40.69
0.66	0.00	0.00	0.01	Carbon	6.90	12.00	4200.00	240.00	650.00	30	-	-	-	-	26.05
0.66	0.00	0.00	0.02	Glass	14.00	12.00	1700.00	72.00	650.00	30	-	-	-	-	7.72
0.66	0.00	0.00	0.01	PP	18.00	12.00	350.00	4.00	650.00	30	-	-	-	-	17.76
0.66	0.00	0.00	0.01	PVA	660.00	12.00	900.00	23.00	650.00	30	-	-	-	-	14.47
0.66	0.00	0.00	0.01	Carbon	6.90	12.00	4200.00	240.00	21.00	30	-	-	-	-	50.28
0.65	0.00	0.00	0.02	Glass	14.00	12.00	1700.00	72.00	21.00	30	-	-	-	-	33.21
0.66	0.00	0.00	0.01	PP	18.00	12.00	350.00	4.00	21.00	30	-	-	-	-	45.55
0.66	0.00	0.00	0.01	PVA	660.00	12.00	900.00	23.00	21.00	30	-	-	-	-	46.99
0.66	0.00	0.00	0.01	Carbon	6.90	12.00	4200.00	240.00	100.00	30	-	-	-	-	55.35
0.65	0.00	0.00	0.02	Glass	14.00	12.00	1700.00	72.00	100.00	30	-	-	-	-	38.74
0.66	0.00	0.00	0.01	PP	18.00	12.00	350.00	4.00	100.00	30	-	-	-	-	52.30
0.66	0.00	0.00	0.01	PVA	660.00	12.00	900.00	23.00	100.00	30	-	-	-	-	39.13
0.66	0.00	0.00	0.01	Carbon	6.90	12.00	4200.00	240.00	450.00	30	-	-	-	-	50.14
0.65	0.00	0.00	0.02	Glass	14.00	12.00	1700.00	72.00	450.00	30	-	-	-	-	7.63
0.66	0.00	0.00	0.01	PP	18.00	12.00	350.00	4.00	450.00	30	-	-	-	-	17.76
0.66	0.00	0.00	0.01	PVA	660.00	12.00	900.00	23.00	450.00	30	-	-	-	-	30.84
0.66	0.00	0.00	0.01	Carbon	6.90	12.00	4200.00	240.00	650.00	30	-	-	-	-	23.85
0.65	0.00	0.00	0.02	Glass	14.00	12.00	1700.00	72.00	650.00	30	-	-	-	-	4.02
0.66	0.00	0.00	0.01	PP	18.00	12.00	350.00	4.00	650.00	30	-	-	-	-	12.21
0.66	0.00	0.00	0.01	PVA	660.00	12.00	900.00	23.00	650.00	30	-	-	-	-	10.87

0.22	0.33	0.00	0.01	PVA	39.00	8.00	1600.0 0	42.00	20.00	3	-	-	-	-	30.60
0.22	0.37	0.00	0.01	PVA	39.00	8.00	1600.0 0	42.00	20.00	3	-	-	-	-	26.30
0.22	0.40	0.00	0.01	PVA	39.00	8.00	1600.0 0	42.00	20.00	3	-	-	-	-	16.90
0.22	0.43	0.00	0.01	PVA	39.00	8.00	1600.0 0	42.00	20.00	3	-	-	-	-	17.10
0.22	0.44	0.00	0.01	PVA	39.00	8.00	1600.0 0	42.00	20.00	3	-	-	-	-	14.60
0.23	0.46	0.00	0.01	PVA	39.00	8.00	1600.0 0	42.00	20.00	3	-	-	-	-	17.00
0.23	0.47	0.00	0.01	PVA	39.00	8.00	1600.0 0	42.00	20.00	3	-	-	-	-	15.00
0.22	0.52	0.00	0.01	PVA	39.00	8.00	1600.0 0	42.00	20.00	3	-	-	-	-	8.20
0.22	0.33	0.00	0.01	PVA	39.00	8.00	1600.0 0	42.00	20.00	7	5.50	0.20	-	-	52.60
0.22	0.37	0.00	0.01	PVA	39.00	8.00	1600.0 0	42.00	20.00	7	4.70	0.20	-	-	47.50
0.22	0.40	0.00	0.01	PVA	39.00	8.00	1600.0 0	42.00	20.00	7	4.30	0.15	-	-	34.20
0.22	0.43	0.00	0.01	PVA	39.00	8.00	1600.0 0	42.00	20.00	7	4.15	0.15	-	-	38.40
0.22	0.44	0.00	0.01	PVA	39.00	8.00	1600.0 0	42.00	20.00	7	4.20	0.20	-	-	35.20
0.23	0.46	0.00	0.01	PVA	39.00	8.00	1600.0 0	42.00	20.00	7	3.70	0.10	-	-	26.70
0.23	0.47	0.00	0.01	PVA	39.00	8.00	1600.0 0	42.00	20.00	7	3.40	0.10	-	-	23.90
0.22	0.52	0.00	0.01	PVA	39.00	8.00	1600.0 0	42.00	20.00	7	3.50	0.15	-	-	21.40
0.22	0.33	0.00	0.01	PVA	39.00	8.00	1600.0 0	42.00	20.00	7	-	-	-	-	54.00
0.22	0.37	0.00	0.01	PVA	39.00	8.00	1600.0 0	42.00	20.00	7	-	-	-	-	49.00
0.22	0.40	0.00	0.01	PVA	39.00	8.00	1600.0 0	42.00	20.00	7	-	-	-	-	35.50
0.22	0.43	0.00	0.01	PVA	39.00	8.00	1600.0 0	42.00	20.00	7	-	-	-	-	43.40

0.22	0.44	0.00	0.01	PVA	39.00	8.00	1600.00	42.00	20.00	7	-	-	-	-	38.90
0.23	0.46	0.00	0.01	PVA	39.00	8.00	1600.00	42.00	20.00	7	-	-	-	-	28.20
0.23	0.47	0.00	0.01	PVA	39.00	8.00	1600.00	42.00	20.00	7	-	-	-	-	25.90
0.22	0.52	0.00	0.01	PVA	39.00	8.00	1600.00	42.00	20.00	7	-	-	-	-	22.20
0.00	0.00	0.03	0.00	PVA	39.00	12.00	1530.00	33.00	20.00	7	-	-	-	-	27.00
0.00	0.21	0.03	0.00	PVA	39.00	12.00	1530.00	33.00	20.00	7	-	-	-	-	26.00
0.00	0.00	0.03	0.00	PVA	39.00	12.00	1530.00	33.00	20.00	28	3.80	0.10	6.00	0.44	36.00
0.00	0.21	0.03	0.00	PVA	39.00	12.00	1530.00	33.00	20.00	28	4.00	0.10	7.00	0.44	29.00
0.00	0.00	0.03	0.00	PVA	39.00	12.00	1530.00	33.00	20.00	56	-	-	-	-	38.00
0.00	0.21	0.03	0.00	PVA	39.00	12.00	1530.00	33.00	20.00	56	-	-	-	-	37.00
0.22	0.40	0.00	0.00	PVA	39.00	12.00	1620.00	42.00	20.00	0	2.41	0.10	8.00	0.67	28.50
0.22	0.40	0.00	0.00	PVA	79.25	12.25	1927.50	82.10	20.00	0	2.69	0.10	10.67	1.00	27.90
0.22	0.40	0.00	0.00	PVA	32.50	12.00	1702.50	51.23	20.00	0	3.04	0.10	8.00	0.33	28.20
0.22	0.40	0.00	0.00	PVA	39.00	12.00	1620.00	42.00	20.00	0	2.20	0.10	6.27	1.00	26.60
0.21	0.00	0.01	0.00	UHMWPE	25.00	12.00	3000.00	100.00	20.00	28	-	-	-	-	105.00
0.34	0.00	0.02	0.00	UHMWPE	25.00	12.00	3000.00	100.00	20.00	28	-	-	-	-	106.00
0.40	0.00	0.02	0.00	UHMWPE	25.00	12.00	3000.00	100.00	20.00	28	-	-	-	-	115.00
0.43	0.00	0.02	0.00	UHMWPE	25.00	12.00	3000.00	100.00	20.00	28	-	-	-	-	100.00
0.20	0.00	0.01	0.00	UHMWPE	25.00	12.00	3000.00	100.00	20.00	28	-	-	-	-	97.50
0.34	0.00	0.01	0.00	UHMWPE	25.00	12.00	3000.00	100.00	20.00	28	-	-	-	-	100.00

0.40	0.00	0.01	0.00	UHMW PE	25.00	12.00	3000.0 0	100.00	20.00	28	-	-	-	-	105.00
0.43	0.00	0.02	0.00	UHMW PE	25.00	12.00	3000.0 0	100.00	20.00	28	-	-	-	-	95.00
0.20	0.00	0.01	0.00	UHMW PE	25.00	12.00	3000.0 0	100.00	20.00	28	-	-	-	-	82.50
0.33	0.00	0.01	0.00	UHMW PE	25.00	12.00	3000.0 0	100.00	20.00	28	-	-	-	-	90.00
0.39	0.00	0.01	0.00	UHMW PE	25.00	12.00	3000.0 0	100.00	20.00	28	-	-	-	-	95.00
0.42	0.00	0.01	0.00	UHMW PE	25.00	12.00	3000.0 0	100.00	20.00	28	-	-	-	-	90.00
0.21	0.00	0.02	0.00	UHMW PE	25.00	12.00	3000.0 0	100.00	20.00	28	-	-	-	-	120.00
0.37	0.30	0.01	0.01	PE	24.00	12.00	3000.0 0	110.00	20.00	2	3.66	0.10	-	-	63.00
0.30	0.33	0.01	0.01	PE	24.00	12.00	3000.0 0	110.00	20.00	2	3.58	0.10	-	-	62.00
0.22	0.37	0.00	0.01	PE	24.00	12.00	3000.0 0	110.00	20.00	2	3.33	0.10	-	-	60.00
0.22	0.36	0.00	0.01	PE	24.00	12.00	3000.0 0	110.00	20.00	2	3.13	0.10	-	-	57.50
0.21	0.36	0.00	0.01	PE	24.00	12.00	3000.0 0	110.00	20.00	2	2.89	0.10	-	-	46.00
0.37	0.30	0.01	0.01	PE	24.00	12.00	3000.0 0	110.00	20.00	2	3.62	0.10	-	-	60.00
0.30	0.33	0.01	0.01	PE	24.00	12.00	3000.0 0	110.00	20.00	2	3.34	0.10	-	-	58.00
0.22	0.37	0.00	0.01	PE	24.00	12.00	3000.0 0	110.00	20.00	2	3.28	0.10	-	-	64.00
0.22	0.36	0.00	0.01	PE	24.00	12.00	3000.0 0	110.00	20.00	2	3.02	0.10	-	-	55.00
0.21	0.36	0.00	0.01	PE	24.00	12.00	3000.0 0	110.00	20.00	2	3.01	0.10	-	-	43.00
0.14	0.00	0.00	0.01	PP	19.50	6.00	3700.0 0	684.00	20.00	0	-	-	7.10	-	71.71
0.13	0.00	0.00	0.01	PP	19.50	6.00	3700.0 0	684.00	20.00	0	-	-	7.95	-	57.00
0.13	0.00	0.00	0.01	PP	19.50	6.00	3700.0 0	684.00	20.00	0	-	-	5.84	-	44.06

0.14	0.00	0.00	0.01	PP	19.50	6.00	3700.00	684.00	20.00	0	-	-	6.31	-	54.57
0.14	0.00	0.00	0.01	PP	19.50	6.00	3700.00	684.00	20.00	0	-	-	6.94	-	44.59
0.13	0.00	0.00	0.01	PP	19.50	6.00	3700.00	684.00	20.00	0	-	-	9.04	-	50.72
0.14	0.00	0.00	0.01	PP	19.50	6.00	3700.00	684.00	20.00	0	-	-	7.10	-	71.71
0.24	0.00	0.00	0.01	PP	19.50	6.00	3700.00	684.00	20.00	0	-	-	6.63	-	54.57
0.32	0.00	0.00	0.01	PP	19.50	6.00	3700.00	684.00	20.00	0	-	-	7.07	-	60.10
0.14	0.00	0.00	0.01	PP	19.50	6.00	3700.00	684.00	20.00	0	-	-	6.31	-	54.57
0.24	0.00	0.00	0.01	PP	19.50	6.00	3700.00	684.00	20.00	0	-	-	9.83	-	48.18
0.32	0.00	0.00	0.01	PP	19.50	6.00	3700.00	684.00	20.00	0	-	-	9.23	-	43.30
0.27	0.00	0.00	0.00	Basalt	13.00	12.00	2600.00	85.00	20.00	28	-	-	-	-	54.49
0.27	0.00	0.00	0.00	Basalt	13.00	12.00	2600.00	85.00	20.00	28	-	-	-	-	56.07
0.27	0.00	0.00	0.00	Basalt	13.00	12.00	2600.00	85.00	20.00	28	-	-	-	-	46.03
0.27	0.00	0.00	0.00	Basalt	13.00	12.00	2600.00	85.00	20.00	28	-	-	-	-	46.63
0.27	0.00	0.00	0.00	Basalt	13.00	12.00	2600.00	85.00	20.00	28	-	-	-	-	37.92
0.27	0.00	0.00	0.00	Basalt	13.00	12.00	2600.00	85.00	20.00	28	-	-	-	-	45.18
0.27	0.00	0.00	0.00	Basalt	13.00	12.00	2600.00	85.00	20.00	28	-	-	-	-	34.92
0.27	0.00	0.00	0.00	Basalt	13.00	6.00	2600.00	85.00	20.00	28	-	-	-	-	48.16
0.27	0.00	0.00	0.00	Basalt	13.00	6.00	2600.00	85.00	20.00	28	-	-	-	-	42.88
0.27	0.00	0.00	0.00	Basalt	13.00	6.00	2600.00	85.00	20.00	28	-	-	-	-	41.26
0.26	0.00	0.00	0.00	Basalt	13.00	6.00	2600.00	85.00	20.00	28	-	-	-	-	50.91

0.26	0.00	0.00	0.00	Basalt	13.00	6.00	2600.00	85.00	20.00	28	-	-	-	-	56.94
0.26	0.00	0.00	0.00	Basalt	13.00	6.00	2600.00	85.00	20.00	28	-	-	-	-	51.40