MECHANICAL PROPERTIES AND OPTIMAL DESIGN OF GREEN CONCRETE INCORPORATING WASTE GLASS POWDER BASED ON GENE EXPRESSION PROGRAMMING

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"Mechanical Properties and Optimal Design Of Green Concrete Incorporating Waste Glass Powder Based On Gene Expression Programming"

Submitted by

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Declaration

I certify that this research work titled "Mechanical Properties and Optimal Design Of Green Concrete Incorporating Waste Glass Powder Based On Gene Expression Programming" is my own work. The work has not been presented elsewhere for assessment. The material that has been used from other sources has been properly acknowledged/referred.

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ABSTRACT

The ratio of production of waste glass annually throughout the world is around millions of tons. After transformation to waste, waste glass powder is usually dumped as landfill which is undesirable, as they are not biodegradable. In order to promote the usage of waste glass powder in concrete, Gene Expresion Programming (GEP) has been utilized in this research to develop empirical models and simplified equations to predict the mechanical properties of green concrete having waste glass powder as a partial replacement of cement. An extensive and reliable database was formed through a detailed literature review. The established dataset consists of 310 No.(s) of results for compressive strength, 129 No.(s) for split tensile strength and 45 No.(s) for flexural strength of GPC. Based on thorough study from literature, 9 No.(s) of influencing parameters were considered as input parameters for modelling. These parameters include %age of G.P added (%) as replacement of cement in concrete, Total Cementitious Materials (Cement & Glass Powder) Content (kg), Water Content (kg), Fine Aggregate Content (kg), Coarse Aggregate Content (kg), %age of SiO_2 in Glass Powder, %age of Al_2O_3 in Glass Powder, Maximum Size of Glass Powder Particles (microns) and Age of Sample (days). Proposed models and simplified mathetical equations can be safely used to predict the mechanical properties of GPC. The performance of the models is evaluated by conducting statistical analysis of the models. Also, models were re-validated by re-checking the mechanical properties on unseen data i.e. testing dataset. The results of analysis imitated that the proposed models have great prediction ability and produce correct results. The results of this study will encourage the use of waste glass powder in concrete leading to great benefits both in terms of economy and environmental safety.

1. INTRODUCTION

1.1. INTRODUCTION TO GLASS POWDER CONCRETE:

Manufacturing process of cement involves extensive amount of energy absorbtion and emission of large quantities of CO_2 in the atmosphere upto 150kg/m^2(Mounika et al., 2017). Manufacture of 1 Ton of cement results in emmission of about 1 ton of CO_2 and other greenhouse gases (Jena & Paikaray, 2018). The demand of cement is increasing annually which results in enhanced rate of CO_2 emission. Therefore, using waste materials in concrete in replacement of cement has become a necessity rather than an option. The ratio of production of waste glass annually throughout the world is around millions of tons. Glass does not produce pollution, so it doesn't damage the environment, but it can affect both humans and animals, if not treated with care because it does not decay. Glass is cheaper to store than reused, as conditioners require the cost of the renovation process (Singh Shekhawat & Aggarwal, 2007). Therefore, use of new skills/procedures is a must. The glass contains a variety of chemicals (Anwar, 2016). After it becomes a waste it is usually disposed as landfill which is undesirable, as they are not biodegradable (Mirzahosseini et al., 2019). The use of these products in the construction industry is the best choice due to the large number of construction sites around the world.

Waste glass can be utilized in concrete in two ways either as cement or fine aggregates are replaced to some extent. (Khan et al., 2021). Different researches have utilized waste glass powder in concrete. Different studies have proposed different results in form of percentage replacement for maximum performance of GPC owing to difference in experimental setup, conditions, quantities and types of materials used. The aim of this research is to optimize the mechanical properties of concrete in which waste glass powder has been used as a partial replacement of cement. A vast dataset of GPC having information on the selected input variables was established through an extensive literature review. Majority of the factors effecting the mechanical properties of GPC were taken into account by considering them as input parameters for modeling. The users will be able to predict mechanical properties of GPC by applying the proposed simplified mathematical expressions. Also, the users will be able to estimate the optimal percentage of glass powder as cement replacement for different ages of concrete for maximum strength and durability.

1.2. INTRODUCTION TO ARTIFICIAL INTELLIGENCE AND GENETIC ENGINEERING PROGRAMMING (GEP):

Artificial intelligence is that particular division of computer science which develops Softwares and programs with humanlike intelligence and is replacing classical modelling techniques to a large extent. Choosing the best technique for a particular situation with optimized results has never been easier and faster before but the use of Artificial Intelligence (AI) techniques have been found beneficial for cost and time saving. Also, they result in fastening the decision-making faster process and error reduction (Salehi & Burgueño, 2018). Quick decisions can be made even without repeated testing and with greater efficiency as compared to conventional methods.

There are many types of artificial intelligence (AI). These approaches have been used extensively for safe and reliable prediction of results through model development in engineering issues. Data is trained to get the solutions in these methods. The pattern recognition capability of AI processes can result in simplifying complex forms, thus working in the field of engineering. However, majority of these approaches require a pre-defined basic form thus requiring great memory. Similarly, the presence of a massive number of hidden neurons makes it hard to build a reliable relationship among predictors and responses using these mechanisms.

The genetic program was developed by Candida Ferreira in 1999 and is a breakthrough for Genetic Algorithms and Genetic Programming (Ferreira, 2002). GEP uses the same type of GP graphic representation but it creates Expression trees which represent a genome. Thus, GEP can provide new and effective solutions to natural calculations (Ferreira, 2002). Ferreira's proposed GEP which discovers the advantages of GA and GP; however, it defeats failures of both GA and GP (Abdulsalam et al., 2020). In this study, Genetic Expression Programming (GEP) will be utilized to predict mechanical properties of GPC which is a modification of Genetic Programming (GP) (Gholampour et al., 2017) and has many advantages over the typical modeling techniques. The main advantages of GEP which has been utilized and taken advantage in this study are as follows:

- GEP doesn't need an existing relationship/equation between the input variables to develop the model unlike other optimization algorithms (Iqbal et al., 2020), (Abdulsalam et al., 2020)
- Outputs can be represented in the form of easy mathematical equations which are appropriate for real-world applications with a high precision (Iqbal et al., 2020)
- GEP has self-optimization characteristics, (Saad & Malik, 2018) therefore, it can be utilized for predicting the optimal design of GPC
- The GEP takes into accounts the advantages of both GA and GP, however, overcomes the shortcomings of both the GA and GP (Abdulsalam et al., 2020)
- The accuracy of GEP models is high as compared to other regression models for example MLR (Multi-linear Regression) models (Abdulsalam et al., 2020)

GEP has been utilized in this study to predict and optimize the design of Waste glass powder concrete for achieving maximum performance. Waste Glass powder concrete is advantageous in following terms:

- For saving cost by reducing the cost of cement due to partial replacement of cement by glass waste powder (Islam et al., 2017) (Khmiri et al., 2012) (Özcan, 2012) (Mounika et al., 2017)
- For reducing CO_2 emissions and contributing to green construction (Islam et al., 2017), (Özcan, 2012), (Sayeeduddin & Chavan, 2016), (Hama et al., 2019), (Hussain & Chandak, 2015), (Mounika et al., 2017), (Vijayakumar et al., 2008), (Hendi et al., 2019)
- For achieving high and comparable strength of concrete in less cost (Islam et al., 2017), (Khmiri et al., 2012), (Özcan, 2012), (Khan et al., 2021), (Khan et al., 2021), (Tenpe & Patel, 2020), (Sayeeduddin & Chavan, 2016), (Hama et al., 2019), (Nayak & Raju, n.d.)(Hussain & Chandak, 2015), (Mounika et al., 2017), (Aliabdo et al., 2016), (Vijayakumar et al., 2008), (Eme & Nwaobakata, 2019), (Nayak & Raju, n.d.), (Hendi et al., 2019)
- For making the concrete durable (Islam et al., 2017) , (Özcan, 2012), (Khan et al., 2021), (Khan et al., 2021), (Sayeeduddin & Chavan, 2016), (Nayak & Raju,

n.d.)(Hussain & Chandak, 2015), (Eme & Nwaobakata, 2019), (Nayak & Raju, n.d.), (Hendi et al., 2019)

1.3. OBJECTIVES:

This study aims at:

i. Development of Reliable GEP reliable models and simple equations to predict the performance of GPC ($f_{c'}$, f_{st}, *and* f_b) to a maximum accuracy at different age and percentages of glass powder substitution
ii. Development of Reliable GEP models for $f_{c'}$, f_{st}, *and* f_b of Glass Powder Concrete

1.4. SIGNIFICANCE OF THIS STUDY:

Accessibility to trustworthy expressions/equations to find out the mechanical properties and design mix proportions of green concrete can result in both time and cost saving and also encourage the practice of utilizing waste glass powder in production of concrete. A comprehensive literature review was carried out on green concrete incorporating waste glass powder as a partial replacement of cement and it was noted that majority of literature consist of experimental data and there are rarely 1 or 2 models available to predict only compressive strength of green concrete incorporating waste glass powder as replacing cement (Khmiri et al., 2012). Also, no models are available till date to forecast the flexural and split tensile strength of Glass Powder Concrete. Furthermore, it was noted that the said models have focused on experimental route and are limited only to the small data obtained by experimentations during the same study. Thus, these models which were developed using the experimental data of a single study lacks the generalization capability to be applied on unseen data owing to different conditions and fugues.

No universal models are available for predicting mechanical properties of waste glass powder concrete based on Genetic Expression Programming till date. This topic has been selected to fill out this research gap and utilize GEP method to propose simple mathematical expressions to predict behavior of GPC with greater generalization ability. A large data from literature from different years have been considered in the development of these models which confirms that these models remain valid even for the unseen data. As compared to previous studies, these models will be able to predict properties of glass powder concrete (GPC) at different ages of samples and they include the combine effect of numerous parameters such as size of glass particles, composition of glass powder, effect of age and mix proportions on the properties of GPC.

1.5. RELEVANCE TO NATIONAL NEEDS:

Concrete, a major building material, is the most extensively used man-made material. (Aliabdo et al., 2016). Cost and environmental friendly construction is the need of every country. Waste management has become a significant issue in today's growing society (Tenpe & Patel, 2020). Utilizing waste glass powder in concrete industry helps in two ways. It facilitates in the re-use of powdered glass waste by using waste instead of valuable and expensive natural resources thus making it environment friendly, second, the production cost of concrete reduces when concrete incorporates waste glasses in replacement of cement. (Khan et al., 2021)

1.6. AREAS OF APPLICATION:

The predicted equations would be able to predict the properties of GPC with a higher precision in a shorter time and less cost. Waste Glass powder can be used everywhere for economical and green construction.

1.7. INTRODUCTION TO THIS THESIS REPORT:

This document has been prepared for academic purposes and presents the post graduate research carried out to predict mechanical properties of green concrete incorporating waste glass powder by partially replacing cement created with Gene Expression Programming.

- The first chapter is the introduction of the research.
- The second chapter describes the literature review already carried out in the field.
- The third chapter describes the research methodology and sequence.

- The 4th chapter represents the results and evalutaion of developed models. The last chapter presents the conclusions of the research.

2. LITERATURE REVIEW

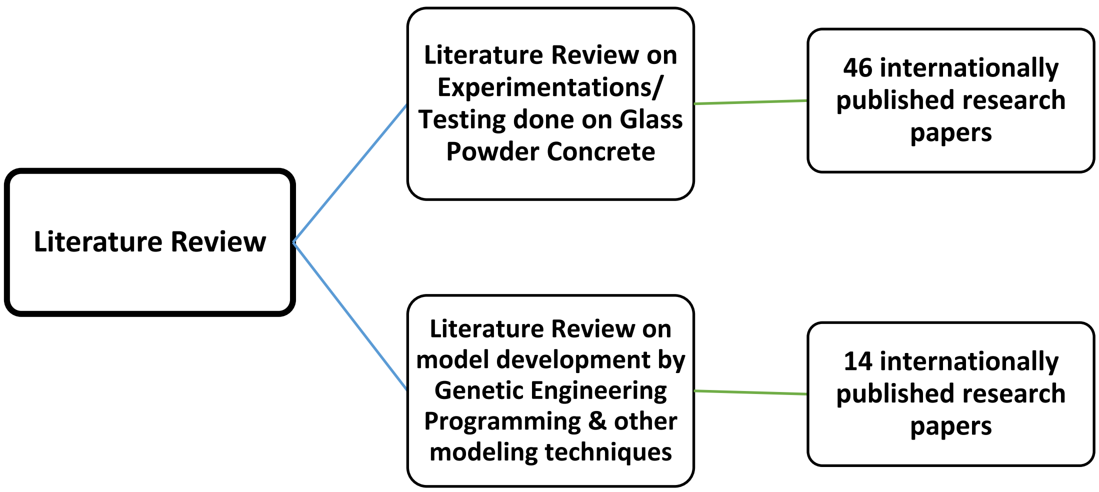


Figure 1: Literature Review

Stability of building materials is an important problem in the construction industry. (Özcan, 2012) Different researches have been conducted by replacing Portland cement with waste products with pozzolanic nature like Fly ash, Silica fume, Bagasse ash etc. Based on the chemical composition, glass powders could be stated as pozzolanic materials as per ASTM standards.(Islam et al., 2017) Therefore, waste glass powder may be utilized as a binder material by partially replacing cement (Sayeeduddin & Chavan, 2016). Many researches have been carried out using waste glass powder by replacing both cement and fine aggregates with it. The mechanical properties and durability of the cement-containing compounds have been the main focus of several studies. This chapter presents the published literature related to concrete containing waste glass powder either both in the form of experimentations and modelling/machine learning techniques.

Different researches have studied the effect of replacing cement with waste glass powder on different properties of concrete e.g. $f_{c'}$, f_{st},, f_b, Rapid chloride permeability (RCP), acidity etc. and accordingly proposed different %ages of optimum glass powder content to be added to glass powder concrete. Almost all the authors who have worked on Glass Powder Concrete have tested the glass powder concrete for its compressive strength and proposed ideal percentage of glass powder content to be added in concrete for best results. Given below is a summary of the research of different authors and their salient findings as given in Tables 1-3:

Name of Authors	Year of Publication	Salient Findings	Optimum GP content suggested by authors
Nathan Schwarz et. Al.,	2008	13% reduction in f_c' of GPC at optimum GP content	10%
Dr. G.Vijayakumar et. Al.,	2013	33.7% rise in f_c' of GPC at 40% replacement of cement by GP.	40%
N.Kumarappan	2013	17% rise in f_c' at suggested optimum GP content.	10%
Mahsa Kamali et. Al.,	2014	15% reduction in f_c' of GPC at optimum GP content of 30%	30%
T.Subramani et. Al.,	2015	1.5% rise in f_c' of GPC at suggested optimum GP content of 10%	10%
Mohd Vasique Hussain et. Al.,	2015	3% rise in Compressive Strength of GPC at optimum GP content of 10%	10%
Fasih Ahmed Khan et. Al.,	2015	12% reduction in f_c' of GPC at optimum GP content	15%
G. M. Sadiqul Islam et Al.,	2016	2% rise in f_c' of GPC at optimum GP content of 20%	20%
Ali A. Aliabdo et. Al.,	2016	9% rise in f_c' of mortars at optimum GP content	15%
Rakesh Sakale et. Al.,	2016	20% rise in f_c' of GPC at optimum GP content of 20%	20%
Mallikharjuna Rao Kelam et. Al.,	2017	22% rise in f_c' of GPC at optimum GP content	20%

Kolusu Maraiah Babu et. Al.,	2017	12% reduction in f_c' of GPC at optimum GP content of 20%	20%
Gurikini Lalitha et. Al.,	2017	36% rise in f_c' of GPC at optimum GP content of 10%	10%
Ankit Jena et. Al.,	2018	1% rise in f_c' of GPC at optimum GP content of 10%	10%
Sajedur Rahman et. Al.,	2018	6% rise in f_c' of GPC at optimum GP content of 20%	20%
D. B. Eme et. Al.,	2019	4% rise in f_c' of GPC at optimum GP content of 6%	6%
Miss. Shivani B. Mokal et. Al.,	2019	32% rise in f_c' of GPC at optimum GP content of 15%	15%

Table 1: Summary of Research carried out on Compressive Strength of GPC

Name of Authors	Year of Publication	Salient Findings	Optimum GP content
Shilpa Raju et. Al.	2014	22% increase in Split tensile Strength at Optimum GP content	20%
T.Subramani et. Al.,	2015	7% increase in Split tensile Strength at Optimum GP content	10%
Mohd Vasique Hussain et. Al.,	2015	10% increase in Split tensile Strength at Optimum GP content	10%
Prashant M. Shiyani et. Al.,	2015	5.48% increase in Split tensile Strength at Optimum GP content	10%
Ali A. Aliabdo et. Al.,	2016	6% increase in Split tensile Strength at Optimum GP content	15%
Bharat Nagar et. Al.,	2016	5.5% increase in Split tensile Strength at Optimum GP content	25%
Kolusu Maraiah Babu et. Al.,	2017	4.5% increase in Split tensile Strength at Optimum GP content	20%
Gurikini Lalitha et. Al.,	2017	10% increase in Split tensile Strength at Optimum GP content	10%

Sajedur Rahman et. Al.,	2018	3% increase in Split tensile Strength at Optimum GP content	30%

Table 2: Summary of Research on Split Tensile Strength of GPC

Name of Authors	**Year of Publication**	**Major Testings**	**Optimum GP content**
Dr. G.Vijayakumar et. Al.,	2013	100% increase in Flexural Strength at optimum GP content	40%
T.Subramani et. Al.,	2015	5% increase in Flexural Strength at optimum GP content	10%
Prashant M. Shiyani et. Al.,	2015	8.13% increase in Flexural Strength at optimum GP content	10%
Manoj Kumar et. Al.,	2016	14% increase in Flexural Strength at optimum GP content	20%
Bharat Nagar et. Al.,	2016	6% increase in Flexural Strength at optimum GP content	25%
Kolusu Maraiah Babu et. Al.,	2017	24% increase in Flexural Strength at optimum GP content	20%
Gurikini Lalitha et. Al.,	2017	10% increase in Flexural Strength at optimum GP content	10%

Table 3: Summary of Research carried out on Flexural strength of GPC

An overview of the optimum glass powder %ages proposed for optimal results of compressive strength during different years is given below:

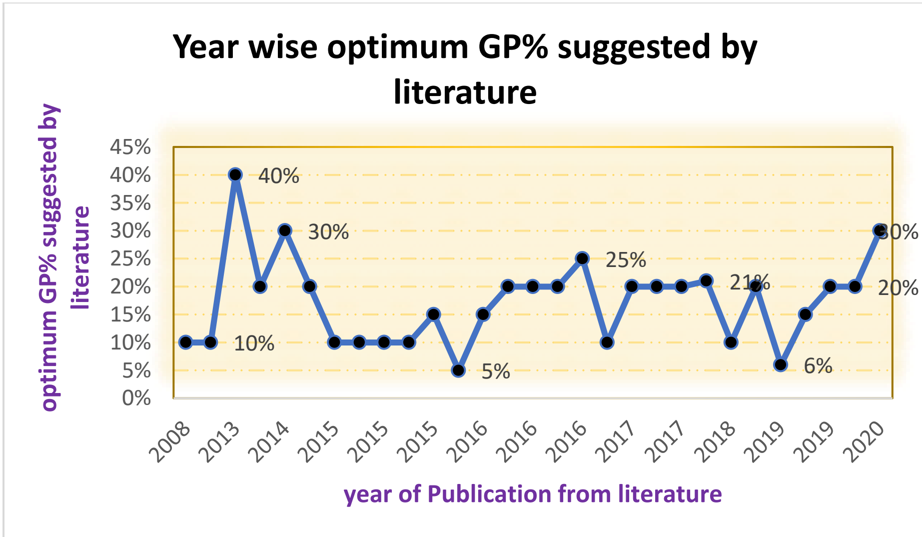


Figure 2: Year Wise optimum GP% suggested in literature

It can be seen from the above graph that different authors have concluded their researches with different optimum glass powder content starting from 5% to 40% to be added in concrete for maximum results. A pictorial summary of the frequency of different percentages of glass powder proposed by literature is given below:

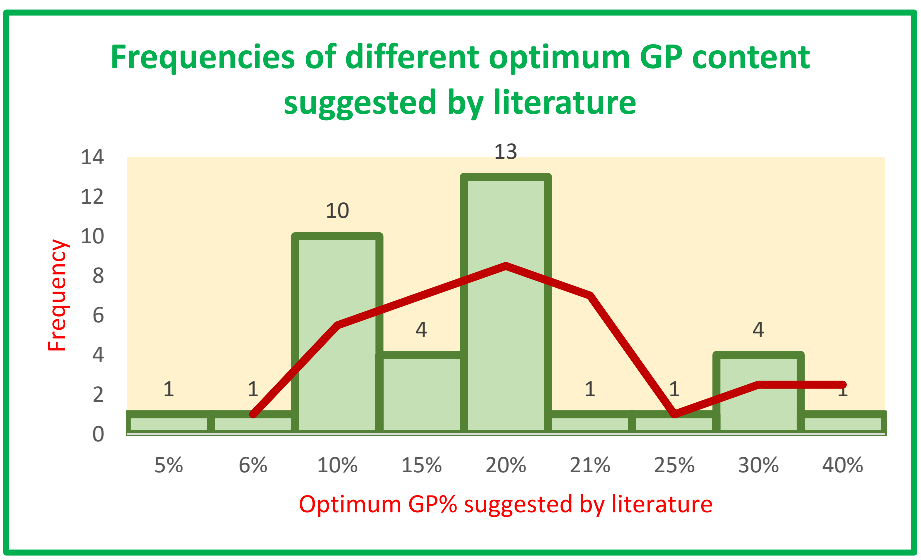


Figure 3: Frequency of different optimum GP content suggested by literature

Conflict of Researchers in proposing optimum glass powder percentage to be utilized in concrete highlights the need of a universal equation/ formulation for mix design of glass powder concrete. Different results proposed by different authors cause confusions for a new researcher who wants to utilize the technique with maximum results. Different machine learning techniques are utilized for this purpose for model development and prediction of results of different technologies

(Islam et al., 2017) carried research on compressive strength of both mortar and concrete specimens by replacing cement with waste glass powder up to an extent. They suggested the optimum glass content as 20% for compressive strengths for both mortar and concrete sample at age of 90 days. In addition, they concluded that the adding optimum glass content can increase the compressive strength by 2% as compared to controlled specimen and the cost of cement production can be decreased up to 14% and results in the reduced emission of CO_2 from cement production and protect the environment to a good extent.

(Khmiri et al., 2012) worked on the optimization of the mechanical properties of mortars by substitution of glass powder in place of cement and gave the output in the form of a cross mixture design, with three components i.e. % Portland cement, % of waste glass and % of silica fume and additional two variables including fineness and type of waste glass. This cross-mixture design was able to maximize the compressive strengths at age of 28 and 90 days. Their proposed cross mix design was to replace 20% of pure cement by 20 micro meter waste glass as it gives the maximum results for mechanical properties and helps in lowering cost of construction.

(Sayeeduddin & Chavan, 2016) carried research on both workability and f_c' of concrete specimens by replacing of cement with GP within some limit. They replaced cement with waste glass powder in different ratios starting from 0% to 40%. They found out that the adding waste glass powder decreases the concrete's workability. Optimum glass content was suggested as 15% due to maximum concrete strength at 15% replacement. Strength was found to be about 88.22 percent of the control mix at proposed optimum content of 15

(Hama et al., 2019) researched on the flexural performance of RCC beams containing waste glass powder. They settled that the beams containing waste glass resulted in increased load bearing capacity and improved flexural behavior at 10% and 15% replacement of cement with glass powder. In addition, it was concluded that replacement of cement by 15% glass powder will save 52.5 kg of cement for $1m^3$ volume of concrete thus resulting in significant cost savings.

(Raju & Kumar, 2015) experimented on both compressive strength and flexural strength of glass powder concrete. They concluded that concrete containing 20% cement in place of glass powder has higher strength.

(Mounika et al., 2017) focused on Strength Parameters of concrete with Partial Replacement of Cement by Glass Powder in their research. They concluded with the result that 20% replacement of cement with glass powder results in maximum compressive strength and 30% replacement of cement with glass powder results in minimum slump value which indicates good workability.

(Vijayakumar et al., 2008) researched on the effect of partially replacing cement with glass powder on f_c', f_{st} *and* f_b of concrete. The optimum GP% was suggested as 40% which results in enhancement of all strengths i.e. compressive strength, the split tensile strength and the flexural strength by 33.7%, 4.4% and 100% respectively.

(Eme & Nwaobakata, 2019) studied the effect of addition of powder glass, replacing cement in the concrete production process. It was found that the addition of powdered glass resulted in increase of both workability and strength. Therefore, replacement can be done in about 6% of powdered glass by weight of cement.

(Nayak & Raju, n.d.) learned the resistance of concrete-containing concrete from the attack of sulfate. They conclude that with or without sulphate, high strength and high resistance is obtained when 20% of the cement has been replaced by glass powder in concrete.

(Hendi et al., 2019) applied Artificial Neural Network to optimize the results of adding glass powder in concrete against alkali-silica reactions (ASR) and f_c' of self-consolidating concrete. The results showed reduction in f_c' by adding glass in concrete. However, it was found out that 30% substitution of cement by glass powder results in reduction of ASR by 52%.

(Raju & Kumar, 2015) tested both the mortar and concrete samples by replacing cement with glass powder in the proportion of 0% to 60% for both M25 grade and M30 grade of concrete. The w/c was 0.5 and 0.44 for M25 and M30 grade respectively. Compressive strength, split tensile strength, consistency and flexural strength of concrete containing waste glass powder were tested. The results presented betterment in the mechanical properties. The authors settled that the glass powder concrete is economical as compared to standard concrete.

(Subramani & Ram, 2015) worked on the effect of adding glass powder in place of cement both in mortars and in concrete and tested the mortars and concrete for their compressive, flexural and tensile strength. The results reported 10% increase in compressive strength of concrete at 10% replacement of cement with glass powder. Thus, this research suggested 10% as an optimum Glass powder content in concrete for best results. However, 15% was suggested as an optimum glass powder content in mortars based on results. The authors suggested the use of glass powder in concrete in order to play role in environmental protection.

(Jena & Paikaray, 2018) replaced the cement in concrete by glass in 0%, 5%, 10% & 15% respectively and determined its effects on f_c', f_{st}, f_b and workability at age of 7th, 28th and 45th days. In their research, they observed that addition of glass powder in concrete enhances the compressive, flexural and split tensile strengths of concrete at first till it becomes maximum at 10% replacement of cement by GP but after that, any further addition decreases the strength. Therefore, cement may be replaced safely up to 10% by glass powder without compromising on the f_c'.

(M & Chandru, 2016) partially replaced the cement with waste glass powder in the percentages of 30% to 50% and verified for its f_c' up to an age of 28 days. The authors concluded that using glass as a partial replacement of cement in concrete is a decent answer to problems related to waste glass disposal such as limited disposal space and increasing costs of disposing wastes. Also, using glass powder in concrete results in better quality of concrete both in terms of workability and compressive strength etc.

(Babu & Jayaram, 2017) studied the results of swapping cement in concrete by glass in an increment of 5% each starting from 5% and ending at 55% replacement of cement by waste glass powder. They tested for f_c', f_{st}, f_b, Acid Attack and Rapid Chloride Permeability (RCP) of Glass Powder Concrete

(Iqbal et al., 2020) utilized Genetic Expression Programming for modelling of concrete containing waste foundry sand. Models were developed for f_c', f_{st} and elastic modulus of concrete incorporating waste foundry sand. Performance evaluation of models developed by GEP was carried out and the results were found quite satisfactory. Also, simplified equations were developed for f_c', f_{st} and elastic modulus of concrete incorporating waste foundry sand.

(Gholampour et al., 2017) studied the mechanical properties of concrete containing recycled aggregate created by gene expression programming. GEP based equations were formulated for f_c', f_{st}, f_b and elastic modulus of Recycled Aggregate Concrete (RCA). Models were evaluated for their results and it was concluded that the proposed models are accurate and can be safely used for pre-designing RACs.

(Saad & Malik, 2018) utilized 1030 datasets from the available literature and used them to develop model for strength analysis of high-performance concrete created by Gene expression programming (GEP). Also, the authors compared the results of GEP with other Artificial Intelligence Technique i.e., RBF neural Network and the accuracy of the proposed GEP model was found to be higher i.e. 98.72% in comparison with RBF with an accuracy of 95.36%.

3. RESEARCH METHOLOGY

Following is the graphical representation of the research methodology:

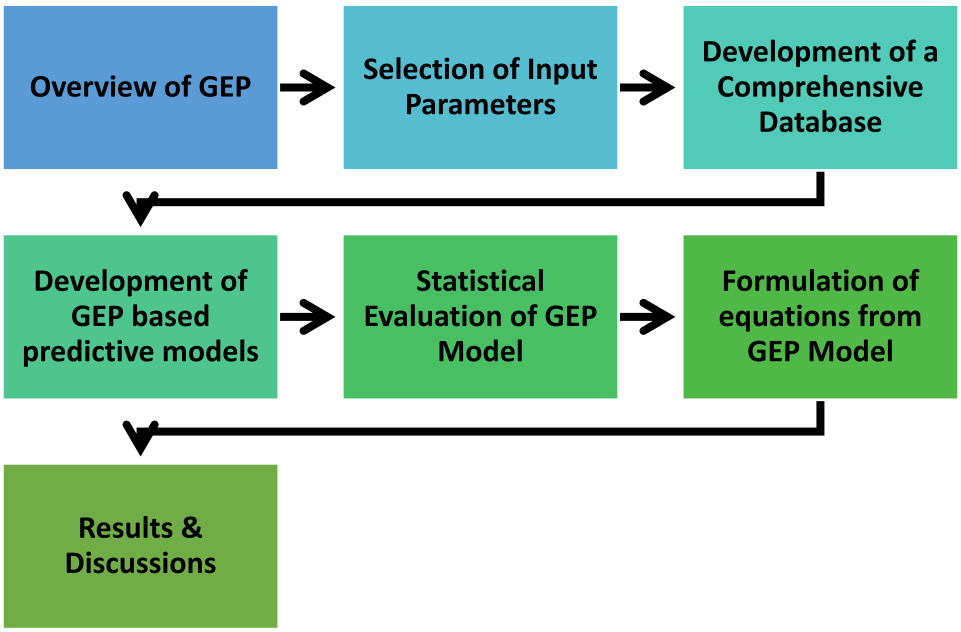


Figure 4: Research Methodology

3.1. OVERVIEW OF GENETIC EXPRESSION PROGRAMMING:

Gene expression programming (GEP) was proposed by Ferreira (Ferreira, 2002). It is an advancement of Genetic Programming (GP). In order to keep and transmit genetic information, GEP uses a chromosome of fixed length like a living organism whereas in GP uses non linear objects varying in sizes and shapes (Parse Trees). The chromosomes of GEP are then shown as expression trees.

A key characteristic of the GEP is the formation of chromosomes, which could represent any parse tree using the Karva language to examine and express data rooted in chromosomes. Chromosomes are then expressed as Expression trees (ET). The conversion of the Karva expression (k-expression) to the ET starts off evolved from the primary position in the ok-expression, as the root of the ET, and maintains thru the thread. so as to produce a thread, the ET is converted in contrast to K expression using nodes from the foundation layer to the inner most layer. Within the GEP algorithm, because of the previously defined period and consistency of genes and variability in ET corresponding length, there are numerous extra factors that do not paintings in the genome mapping system. consequently, the length of the K-expression may be much less or identical to that of the GEP type.

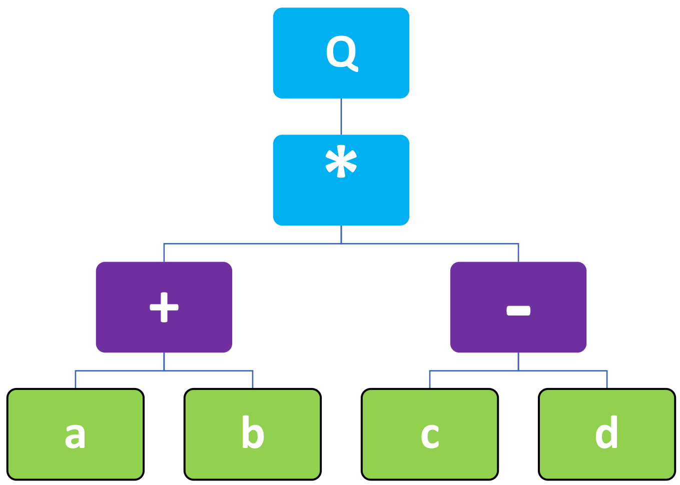


Figure 5: Example of an Expression Tree

$$\sqrt{(a+b)\times(c-d)},$$

Figure 6: Mathematical Expression of ET

The GEP method can be used in place of the outdated methods and is based on five different components: a function set, a terminal set, a fitness function, control parameters, and a terminal condition.

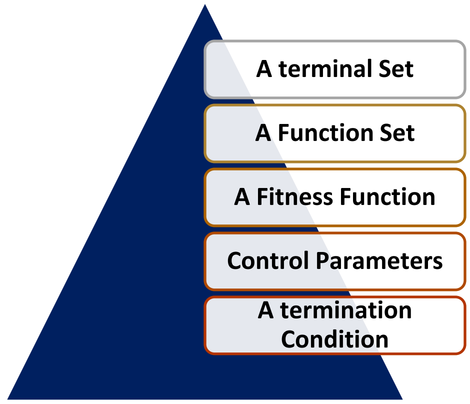


Figure 7: Components of GEP

3.2. SELECTION OF INPUT PARAMETERS:

A through and detailed literature review was carried out to carefully select the factors influencing the mechanical properties of Glass Powder Concrete (GPC). Strength of a normal conventional concrete usually depends upon its mix design proportions. Therefore, mix design proportions were taken as basic input parameters. One of the most factor for the strength analysis of Glass Powder Concrete was the percentage replacement of cement by waste glass powder. Detailed study from literature revealed that the size of glass particles also has significant effect on strength and durability of GPC. The size of the glass particles should be at least as fine as the cement powder for proper pozzolanic action for strength development (Nwaubani & Poutos, 2013). Glass particles of sizes less than 75µm contributes to better strength and durability (Mounika et al., 2017). Therefore, Maximum size of glass particles has also been considered as an input parameter for models' development.

Different types of glasses used in experimentations have found to be affecting the strength of GPC (Mirzahosseini et al., 2019). Therefore, in order to develop models with greater generalization capability, type of glass used has also been given its due weightage in the form of 2 input variables i.e. %age of SiO_2 and Al_2O_3 in glass particles which are two major components of chemical composition of glass. The effect of aging of concrete samples on its properties cannot be neglected. Hence, it has also been considered as an input parameter. After careful consideration, 9 No.(s) of input parameters were finalized and the models were developed for 3 No.(s) of output parameters. Given below is the graphical representation of both input and output variables considered for model development. Consequently, the mechanical properties of GPC can be presented as a function of following aspects:

f_c', f_{st} **and** f_f **= f (G.P%, TCM, W, F.A, C.A,** SiO_2**,** Al_2O_3**, D, A)**

where

TCM= Total cementitious Material (kg/m³)

D= Maximum Size of Glass powder particles (microns)

W= Water Content (kg/m³)

FA= Fine Aggregates (kg/m³)

CA= Coarse Aggregates (kg/m³)

GP%= Glass powder content as a percentage of Total cementitious materials (%)

SiO_2 *= Percentage of* SiO_2 *in glass particles (%)*

Al_2O_3*= Percentage of* Al_2O_3 *in glass particles (%)*

A= Age of Sample at testing (days)

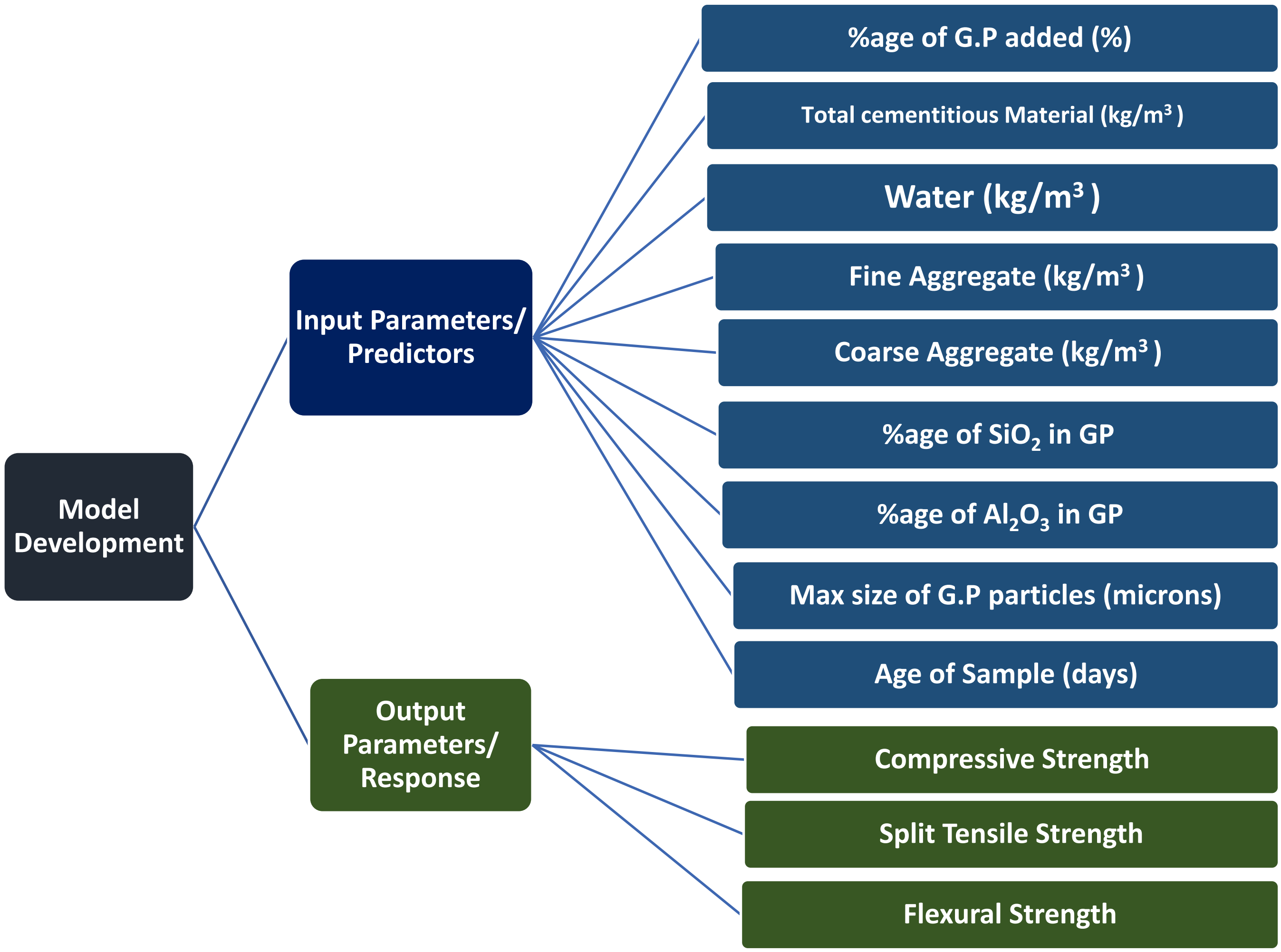


Figure 8: Input & Output Variables

3.3. DATA COLLECTION:

A vast literature consisting of several internationally published papers/journals was studied for the data collection. (Islam et al., 2017), (Mounika et al., 2017), (Aliabdo et al., 2016), (Vijayakumar et al., 2008), (Subramani & Ram, 2015), (Jena & Paikaray, 2018), (Kumarappan, 2013), (Mokal & Shirsath, 2019), (S. Kumar & Nagar, 2017), (Mounika et al., 2017), (Sakale et al., 2016), (Rahman & Uddin, 2018), (Lee et al., 2018), (Du & Tan, 2014), (Olutoge, 2016), (Eme & Nwaobakata, 2019), (Nayak & Raju, n.d.), (Hendi et al., 2019), (R. Kumar & Yadav, 2019), (M & Chandru, 2016), (Babu & Jayaram, 2017), (M. Kumar, 2016), (Bharat & Bhargava, 2016), (Hussain & Chandak, 2015). As data containing information about all input variables was required. Hence, the papers/journals with incomplete information such as lack of information on mix proportions, chemical composition of glass etc. were discarded and their data was not considered in the final database. The total dataset consists of 310 f_c', 129 f_{st} and 45 f_b data.

The collected database contains information about %age of Glass Powder substituted, Content of Total Cementitious Materials, Water Content, Fine Aggregates Content, Coarse Aggregates Content, %age of SiO_2 in Glass powder, %age of Al_2O_3 in Glass Powder, Maximum Size of Glass Particles and Age of Sample. The range of predictors and response parameters is shown below:

Input Variables	f_c'		f_{st}		f_b	
	Minimum	**Maximum**	**Minimum**	**Maximum**	**Minimum**	**Maximum**
G.P%	0	60	0	40	0	40
T.C.M (kg/m^3)	330	1440	350	1440	330	1440
W (kg/m^3)	157.5	878.4	157.5	878.4	174.9	619.2
F.A (kg/m^3)	608.19	4112	608.19	4112	608.19	2704
C.A (kg/m^3)	825	5288	992	5288	1184.8	3556.8
% age of SiO_2 in GP	66.8	98.1	70.22	72.61	67.33	98.1
%age of Al_2O_3 in GP	0.33	10.1	0.4	2.54	0.33	2.62
Max size of GP (microns)	45	300	75	150	75	150
Age of sample (days)	3	365	7	57	7	60

Table 4: Range of Input Parameters

Many trials were run for all of the 3 models to check the consistency of the compiled data. Data which variated more than 20% from the global trend were discarded. This resulted in 240 f_c', 119 f_{st} and 45 f_b data that were used for creation of models. The maximum size of glass powder particles was missing for a small number of data. Thus, mean value of D was assumed for those datasets. The dataset was partitioned into 3 sets; i.e. training data that was used for genetic evolution, validation data that was used for validation of the generalization capability of the developed models and the testing data was used to test the model on unseen data.

3.4. DEVELOPMENT OF GEP BASED MODELS:

The input parameters have already been selected as described above. The whole dataset for each model was shuffled randomly through GEP. GEP randomly divided the dataset into training and validation dataset. The 1st half of the validation dataset was separated as "Testing dataset" and discarded from the data used for model development. After separating the testing dataset, the remaining dataset was shuffled again. Random Shuffling was used in the GEP. Fitting parameters play a significant role in the development of an accurate model. Therefore, several trials were run to select the best fitting parameters. 1st trial for each model was run using the default settings of fitting parameters. Given below is the default setting of fitting parameters in GEP:

Sr. No.	Parameters	Settings
1	Chromosomes	30
2	Genes	4
3	Head Size	10
4	Linking Function	Addition

Table 5: Default Setting of Fitting Parameters in GEP

Different researches have adopted different parameters settings in literature. Different combinations of parameters settings were used by the authors. A brief is given below:

Sr. No.	Fitness Parameters	References
1	Chromosomes	10 (Saridemir, 2011) 20 (Özcan, 2012), (Saridemir, 2011) 30 (Beheshti Aval et al., 2017), (Farooq et al., 2020), (Shah et al., 2021) 50 (Beheshti Aval et al., 2017) 150 (Khan et al., 2021) 200 (Mousavi et al., 2012)
2	Genes	1 (Özcan, 2012) 2 (Saridemir, 2011)

		3 (Beheshti Aval et al., 2017), (Khan et al., 2021), (Mousavi et al., 2012) 4 (Beheshti Aval et al., 2017), (Shah et al., 2021), (Khan et al., 2021) 10 (Beheshti Aval et al., 2017)
3	Head Size	3 (Saridemir, 2011) 4 (Özcan, 2012), (Saridemir, 2011) 5 (Mousavi et al., 2012) 8 (Beheshti Aval et al., 2017), (Mousavi et al., 2012) 10 (Beheshti Aval et al., 2017), (Khan et al., 2021)
4	Linking Function	**Addition**: (Beheshti Aval et al., 2017), (Shah et al., 2021), (Khan et al., 2021) **Multiplication**: (Özcan, 2012), (Saridemir, 2011), (Khan et al., 2021), (Mousavi et al., 2012)

Table 6: Parameters Settings used in literature

In order to select the best fit model, different trials were run. Keeping all other parameters constant, each parameter was changed one by one and the results were analyzed. The running time of the program and complexity of model is controlled by number of chromosomes and head size respectively whereas number of genes control the number of sub Expression Tress in the model (Iqbal et al., 2020). First of all, all other settings except chromosomes were kept constant and chromosome's settings was changed starting from 10 to 200 as per suggestions from available literature. The results of Correlation Coefficient (R), R^2, Root Mean Square Error (RMSE), MAE etc. were compared and the chromosomes settings were selected which gave R and R^2 values close to 1 and error values close to zero. Same procedures were repeated for Head Size and number of genes and the best fit models were selected.

The final Settings for the best fit models for f_c', f_{st} and f_b are given below:

Sr. No.	Parameters	f_c'	f_{st}	f_b
1	Chromosomes	100	100	150
2	Genes	3	3	4
3	Head Size	10	10	10
4	Linking Function	Addition	Addition	Multiplication
5	Function Set	+, -, x, ÷	+, -, x, ÷	+, -, x, ÷

Table 7: Final Parameter Settings

Sr. No.	Numerical Constants	Settings for all 3 models
1	Constants per Gene	10
2	Data Type	Floating number
3	Lower Bound	-10
4	Upper Bound	10

Table 8: Numerical Constants Settings

Sr. No.	Genetic Operators	Settings for all 3 models
1	Mutation Rate	0.00138
2	Inversion Rate	0.00546
3	IS Transposition Rate	0.00546
4	RIS Transposition Rate	0.00546
5	One-point recombination Rate	0.00277
6	Two-point recombination Rate	0.00277
7	Gene Recombination Rate	0.00277
8	Gene Transposition Rate	0.00277

Table 9: Genetic Operators Settings

3.5. EVALUATION CRITERIA:

Correlation Coefficient (R) is the most commonly used performance measure but there are some limitations to it such that it is insensitive to multiplication and division of response values to a constant value. Therefore, Mean Squared Error (MSE), Root Mean Square Error (RMSE), Mean Absolute Error (MAE), Relative Absolute Error (RAE), Relative Squared Error (RSE) and Root Relative Squared Error (RRSE) have also been considered in this study.

4. RESULTS & DISCUSSIONS:

Models were run on the best fit settings and the results were analyzed and described in detail below:

4.1. COMPRESSIVE STRENGTH OF GPC:

The results of model developed for prediction of f_c' of Concrete incorporating waste glass powder is given below:

4.1.1. EXPRESSION TREE:

Given below is the expression tree developed through GEP for compressive strength of GPC. Input Variables have been represented in the ET by symbolic representation as given below:

Where;

d0: GP%= Glass powder content as a percentage of Total cementitious materials (%)

d1: TCM= Total cementitious Material (kg/m^3)

d2: W= Water Content (kg/m^3)

d3: FA= Fine Aggregates (kg/m^3)

d4: CA= Coarse Aggregates (kg/m^3)

d5: SiO_2 = Percentage of SiO_2 in glass particles (%)

d6: Al_2O_3= Percentage of $Al2O_3$ in glass particles (%)

d7: D=Maximum Size of Glass powder particles (microns)

d8: A= Age of Sample at testing (days)

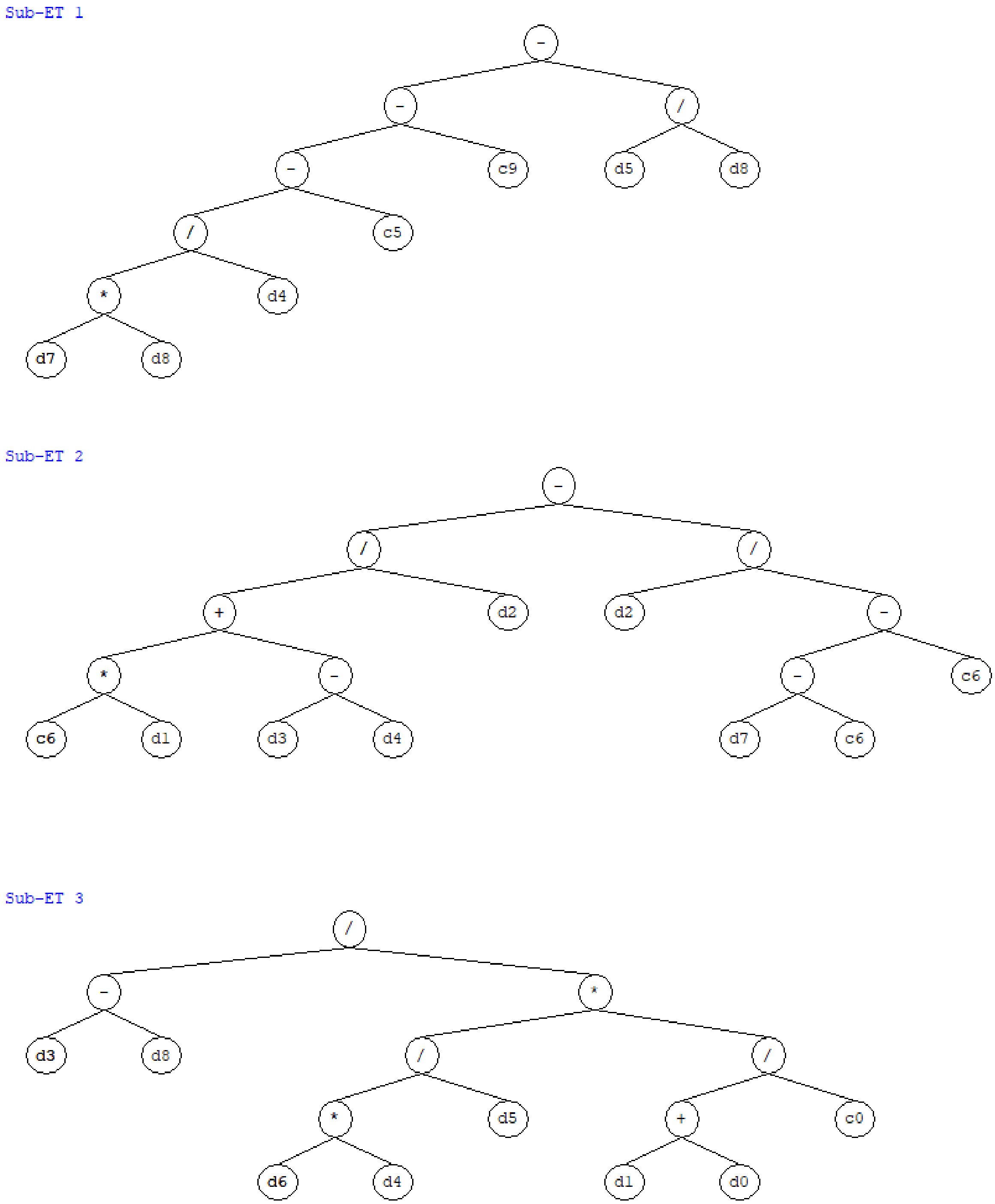


Figure 9: ET for compressive strength of GPC

4.1.2. FORMULATION OF EQUATIONS:

The model of fc' was formulated using gene as 3, therefore, the number of sub ETs are 3 as seen in the above given ET. The ET has been converted to simplified equations and these equations can be used to predict compressive strength of concrete incorporating different types of Glass powder at different ages of samples.

fc' (MPa)= A + B + C

Where

- $A = \dfrac{(F.A-A)}{\left(\frac{C.A\ x\ Al2O3}{SiO2}\right) x \left(\frac{TCM+GP\%}{84.31}\right)}$
- $B = \dfrac{14.42TCM+FA-CA}{W} - \dfrac{W}{D-28.84}$
- $C = \left(\dfrac{D\ x\ A}{CA}\right) - \left(\dfrac{SiO2}{A}\right) + 7.05$

And,

TCM= Total cementitious Material (kg/m³)

D= Maximum Size of Glass powder particles (microns)

W= Water Content (kg/m³)

FA= Fine Aggregates (kg/m³)

CA= Coarse Aggregates (kg/m³)

GP%= Glass powder content as a percentage of Total cementitious materials (%)

SiO_2 = Percentage of SiO_2 in glass particles (%)

Al_2O_3= Percentage of Al_2O_3 in glass particles (%)

A= Age of Sample at testing (days)

4.1.3. SENSITIVITY ANALYSIS/IMPORTANCE OF VARIABLES:

9 No.(s) of different input variables have taken into account for model development of Compressive strength of GPC. The ratio of influence of each parameter has been determined by sensitivity analysis. Among all variables, Water Content, TCM (Total Cementitious Materials), Age (A) and CA (Coarse Aggregate Content) seem to have the highest impact on Compressive Strength of GPC i.e. 24.32%, 19.15%, 16.22% and 15.62% respectively while D (maximum size of Glass powder particles) and FA(Fine Aggregates Content) has medium effect and %age of Glass Powder, SiO_2 and Al_2O_3 have low impact on Compressive Strength of Glass Powder concrete The importance of variables as predicted by GEP model is given below:

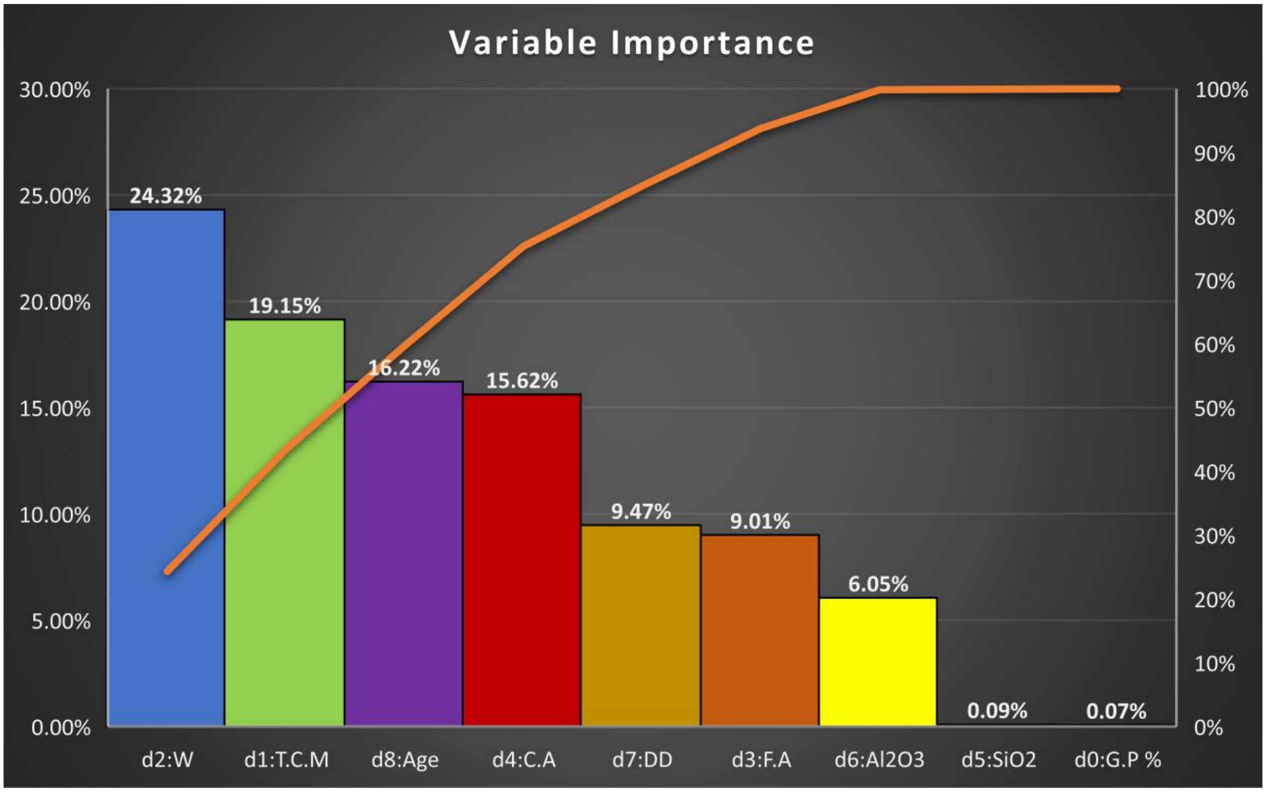


Figure 10: Importance of Variables for Compressive Strength

4.1.4. RELATIONSHIP OF INPUT VARIABLES WITH OUTPUT VARIABLES:

Parametric Analysis was also done in order to find out the relationship of all input variables with output variables. All the predictor variables were kept un-changed at their average values and the variation in compressive strength was noted for the increase of input variable from its least to highest value. The minimum, maximum and average values of input variables used for the development of the said relationships are given below:

Input Variables	**Minimum**	**Average**	**Maximum**
G.P%	0	16	60
T.C.M (kg/m^3)	330	644	1440
W (kg/m^3)	157.5	290	878.4
F.A (kg/m^3)	608.19	1031	4112
C.A (kg/m^3)	825	1592	5288
% age of SiO_2 in GP	66.8	72	98.1
%age of Al_2O_3 in GP	0.33	1.95	10.1
Max size of GP (microns)	45	100	300
Age of sample (days)	3	43	365

Table 10: Range of Input Variables for Compressive Strength

Graphical representation of relationships of input variables with their output variables are given below:

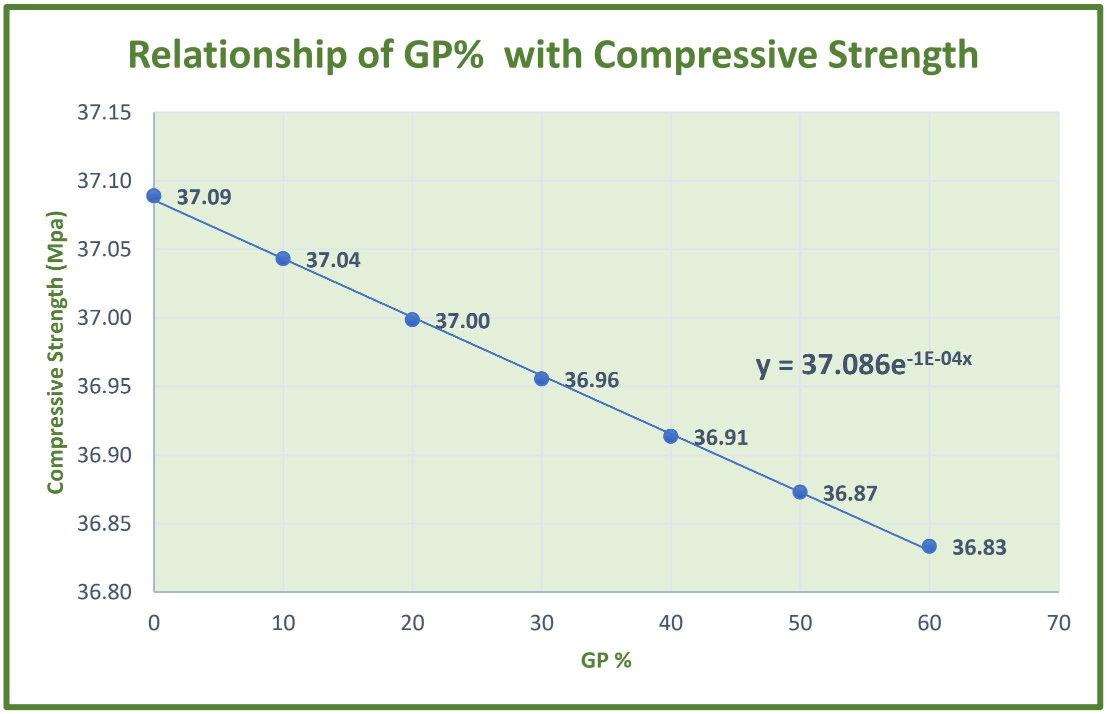


Figure 11: Relationship of GP% with Compressive Strength

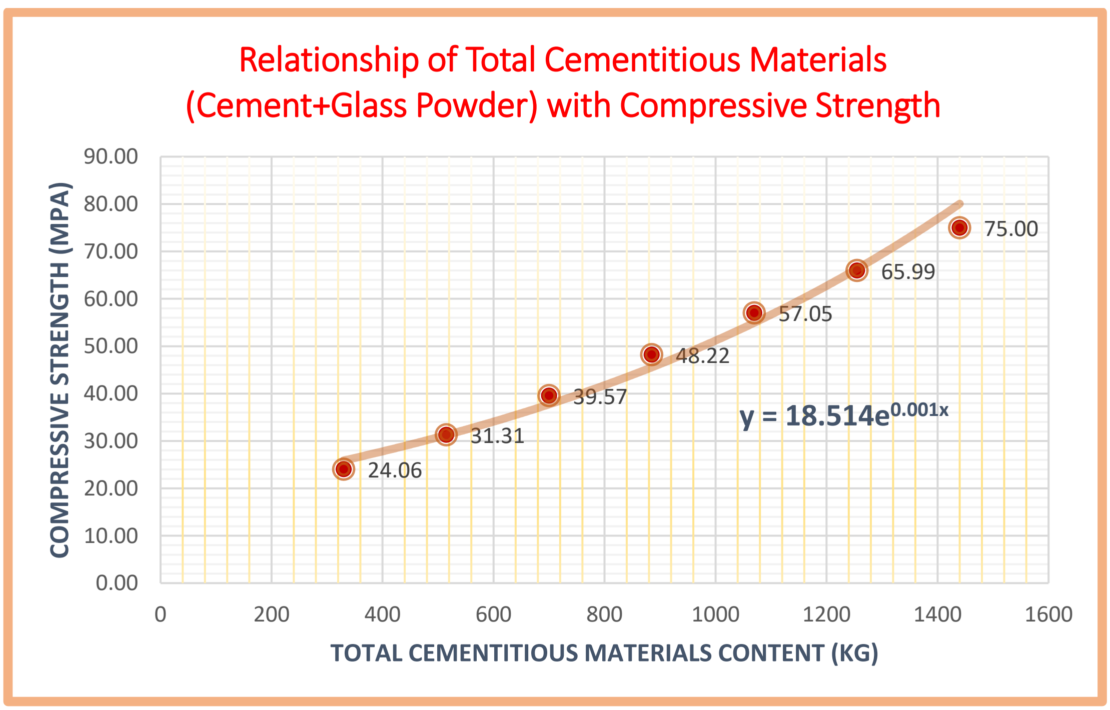


Figure 12: Relationship of TCM with Compressive Strength

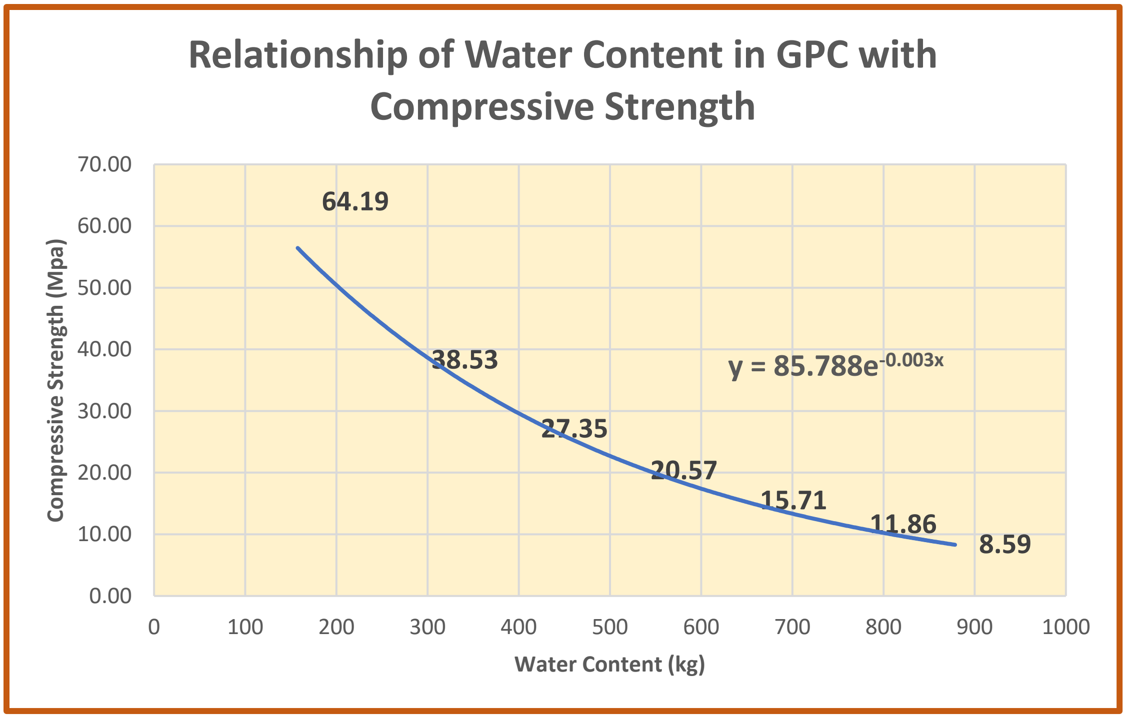


Figure 13: Relationship of Water Content with Compressive Strength of GPC

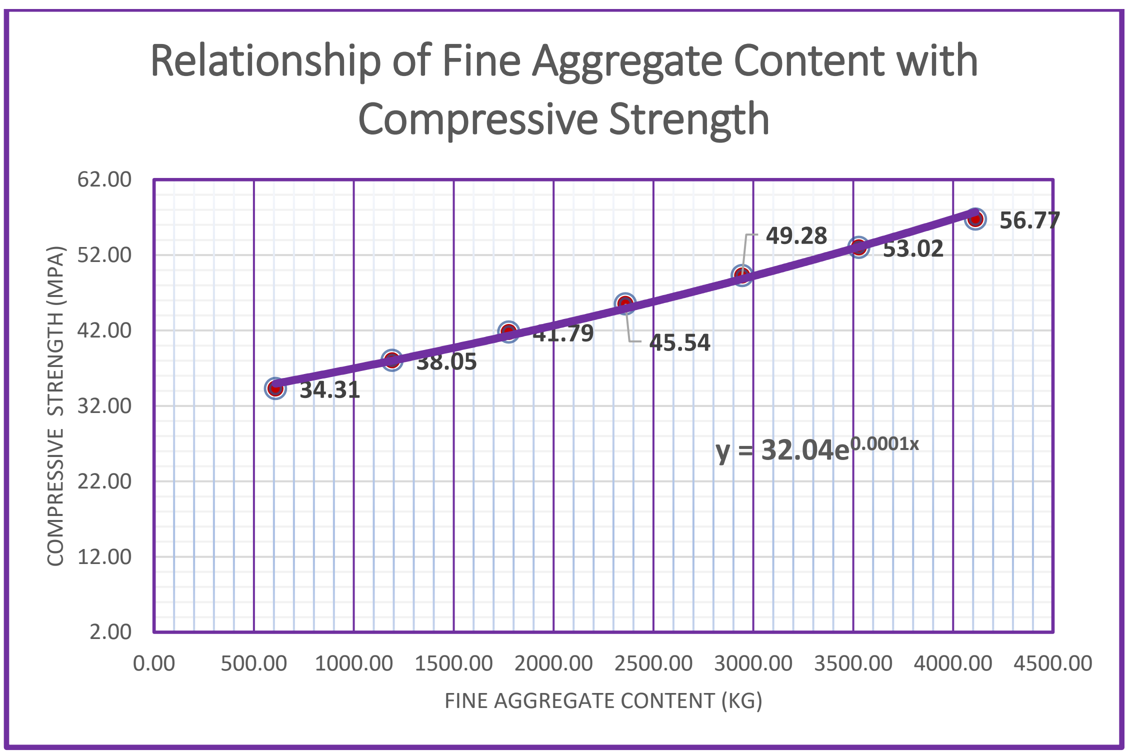


Figure 14: Relation of FA with Compressive Strength

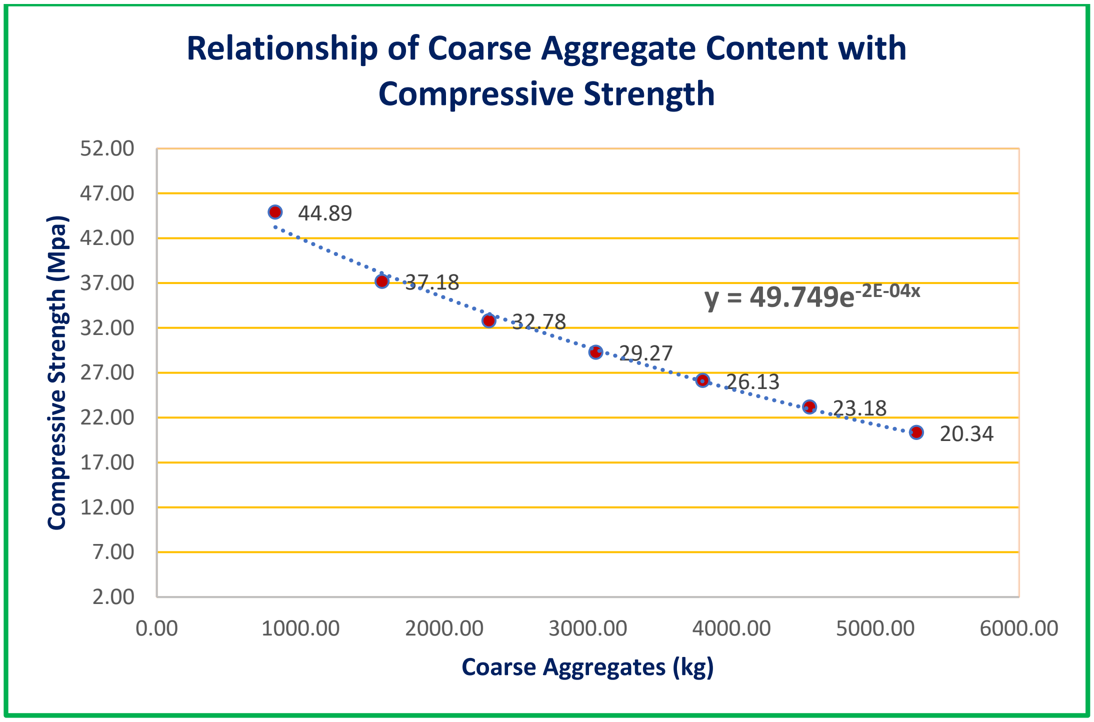


Figure 15: Relationship of CA with Compressive Strength of GPC

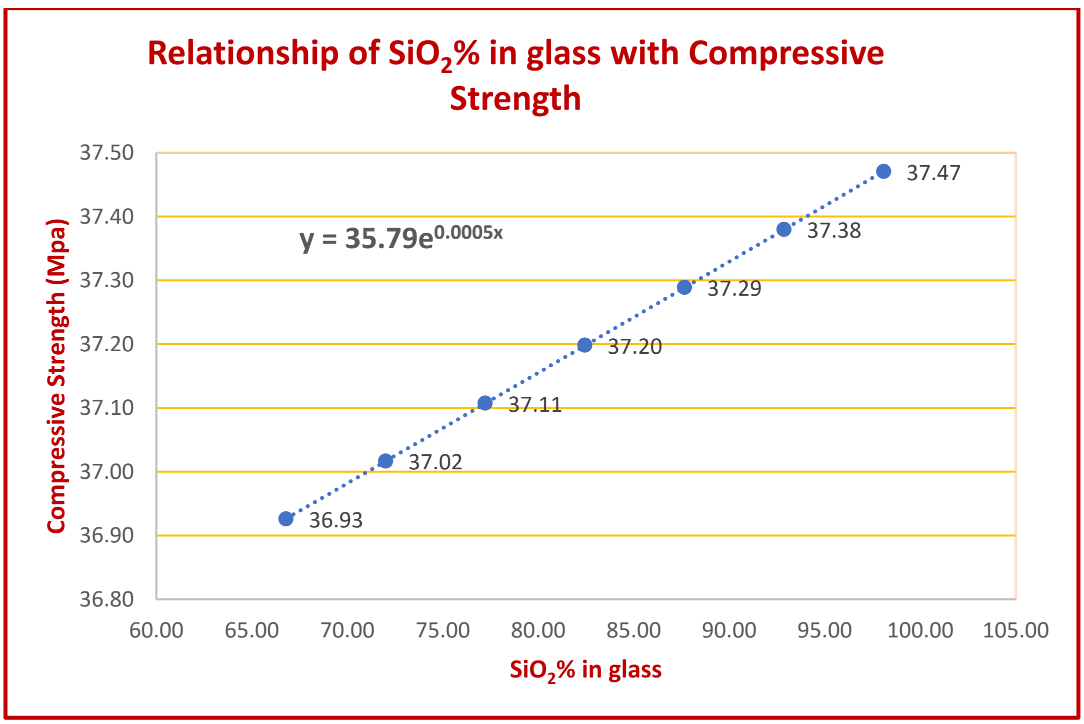


Figure 16: Relationship of Silica in GP with Compressive Strength of GPC

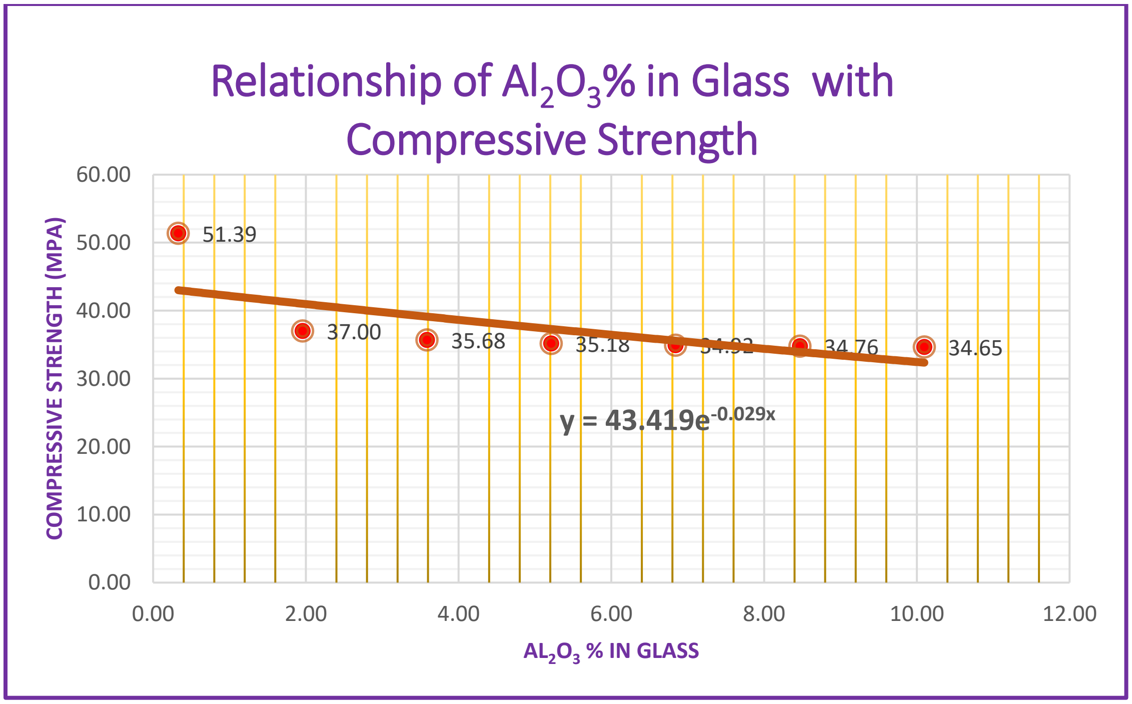


Figure 17: Relationship of Alumina in GP with Compressive Strength of GPC

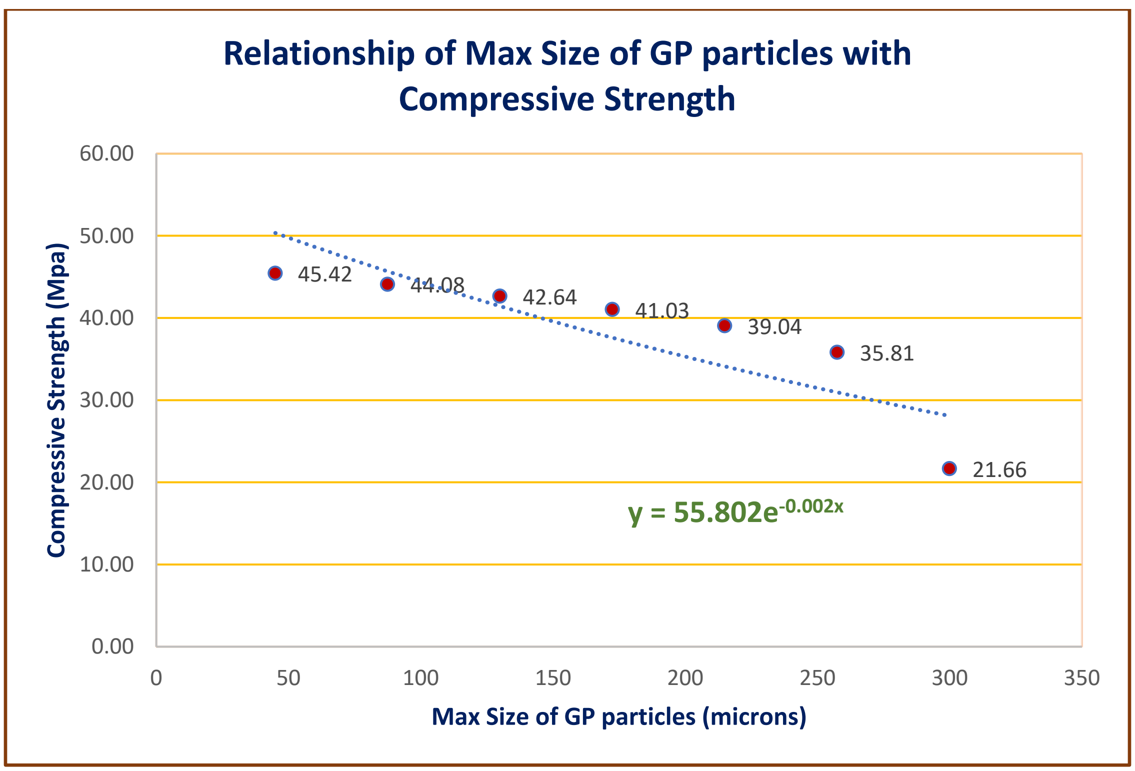


Figure 18: Relationship of Size of GP with Compressive Strength of GPC

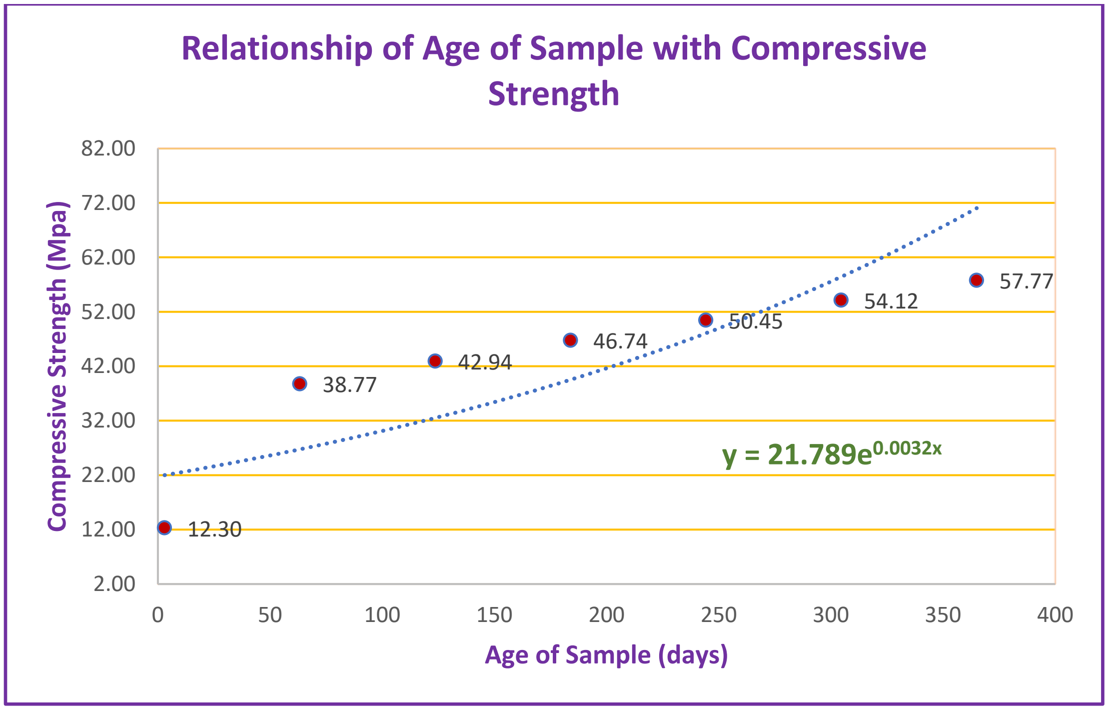


Figure 19: Relationship of Age of Sample with Compressive Strength of GPC

It has been noted that Glass powder content added as percentage of Total Cementitious Materials has mild effect on f_c' of GPC. The results have shown similar trends with the results of available literature. Majority of the authors have proposed the use of glass powder in concrete for the production of green concrete and promotion of environmental friendly construction. Some authors have reported a rise in f_c'of concrete up to a certain limit and then decrease occurs ((Raju & Kumar, 2015), (Mounika et al., 2017), (Aliabdo et al., 2016), (Vijayakumar et al., 2008), Eme & Nwaobakata, 2019), (Nayak & Raju, n.d.), (Gholampour et al., 2017), (Subramani & Ram, 2015), (Kumarappan, 2013), (Mokal & Shirsath, 2019), (Mounika et al., 2017), (M. Kumar, 2016), (Sakale et al., 2016), (Rahman & Uddin, 2018), (Kalakada et al., 2020)) while some have reported decrease in strength after replacing glass powder with cement (Sayeeduddin & Chavan, 2016), (R. Kumar & Yadav, 2019), (Babu & Jayaram, 2017), (Elaqra et al., 2019), (Schwarz et al., 2008), (Lee et al., 2018), (Du & Tan, 2014), (Olutoge, 2016). However, some authors have proposed the use of glass powder in concrete for the same strength or a minute improvement in strength in cheaper price (Islam et al., 2017), (Saad & Malik, 2018), (Subramani & Ram, 2015), (Jena & Paikaray, 2018), (Hussain & Chandak, 2015). This varies with the values of other input variables and different circumstances. The overall effect of addition of glass powder on f_c' of GPC has been determined through GEP model development and is shown in Figure 11. The results show that the strength varies with type of glass powder used and the percentage of glass powder doesn't significantly affect the compressive strength. A gradual decrease can be seen in f_c' with increase in % GP. The relative contribution of Glass powder percentage has been determined as 0.07% for f_c' of Glass Powder Concrete which is in agreement with the experimental results. Also, the addition of glass in concrete has been taken into account in the form of 4 input variables i.e. % of G.P added, Silica in GP particles, Alumina in GP particles and Size of GP particles. The cumulative effect of adding of glass powder can be seen by the influence of these 4 input variables.

4.1.5. COMPARISON OF TARGET AND MODEL VALUES:

The comparison of model values (predicted values) and target values (experimental data) for 3 data sets i.e. training, validation and testing has been shown in the figure 20. The points close to the regression line show that there is a close relationship between predicted and experimented values. Linear equations depicting the relationship between target and model values have also been developed for all 3 datasets as given below:

Training Dataset: y = 0.8811x + 4.2369

Validation Dataset: y = 0.9375x + 2.6185

Testing Dataset: y = 0.9312x + 2.652

Where x=y is an ideal fit.

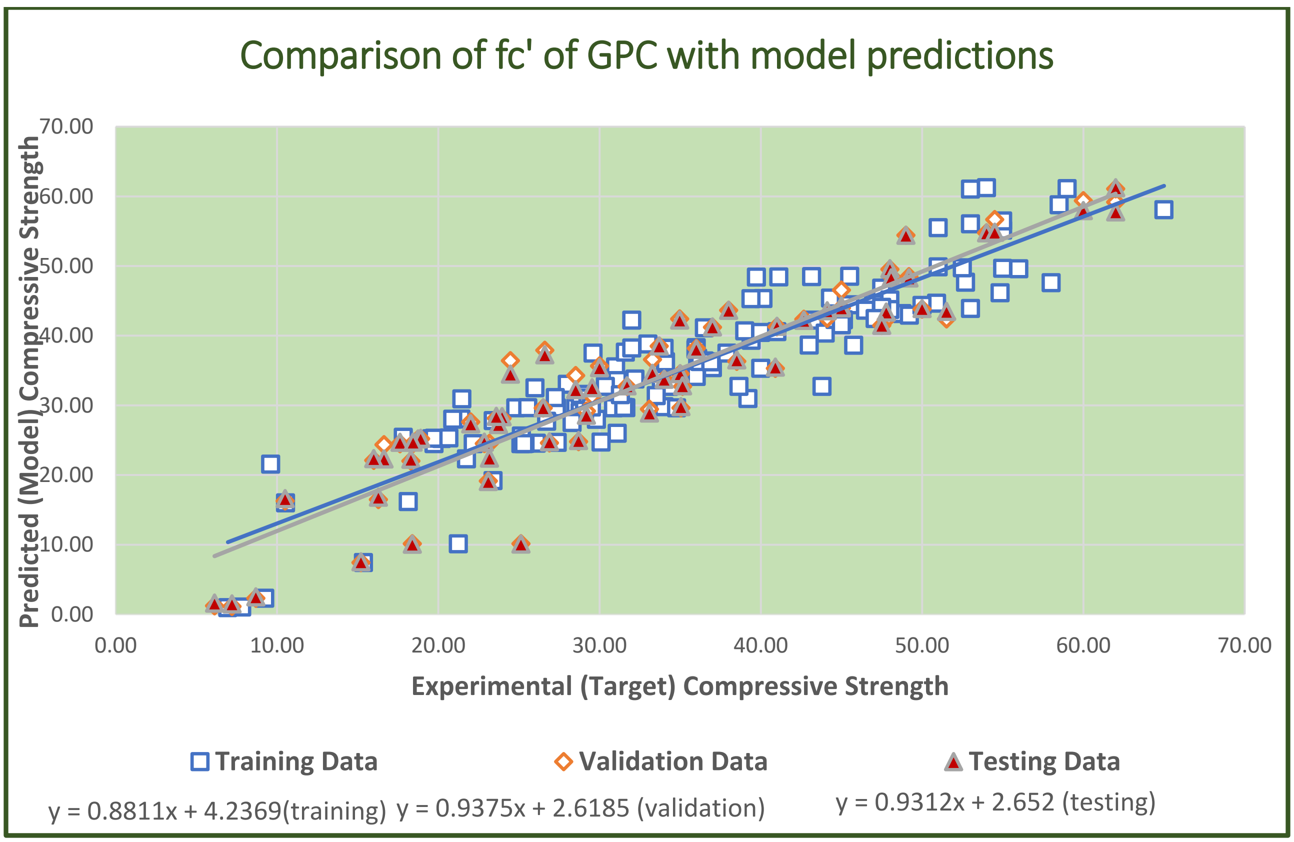


Figure 20: Comparison of Model & Target Values for f_c'

4.1.6. PERFORMANCE EVALUATION OF MODEL:

It has been suggested in literature that the ratio of total number of samples / databases to the total number of input variables should be three for satisfactory models and five for ideal models. In this study, this ratio is quite high i.e. 21 for model of Compressive Strength. Statistical Analysis for all 3 sets of data i.e. training, validation and testing data has been carried out and the results are shown in Table 12. It can be observed that high connection exists between target and model values and the values of errors are quite low. The values of MAE, RMSE and RSE for training sets have been recorded as 3.87, 4.82 and 0.156 respectively. The values of MAE, RMSE and RSE values for testing data have been recorded as 4.027, 4.999 and 0.131.

Evaluation Criteria	GEP Model			Remarks
	Training	Validation	Testing	
R	0.919	0.930	0.934	Strong Relation
R^2	0.845	0.865	0.873	Strong Relation
MAE	3.87	4.188	4.027	Acceptable
RMSE	4.82	5.204	4.999	Acceptable
RSE	0.156	0.142	0.131	Acceptable

Table 11: Statistical Evaluation of fc’ Model

It can be seen from the above table that the statistical measures for all 3 sets i.e. training, validation and testing data do not vary significantly and are effectively similar which reflects the adaptability of the model and it can be said that it can be safely applied to predict mechanical properties of unseen data.

Values of model, target and absolute errors were plotted to get an idea about the maximum error in the developed models as shown in Fig. 20. It can be observed that the actual experimental values are close to the values predicted by the models with an average error of 4 MPa, maximum error less than 10MPa. In addition, the rate of maximum error is very low. About 85% of dataset has been predicted with absolute error less than 7MPa.

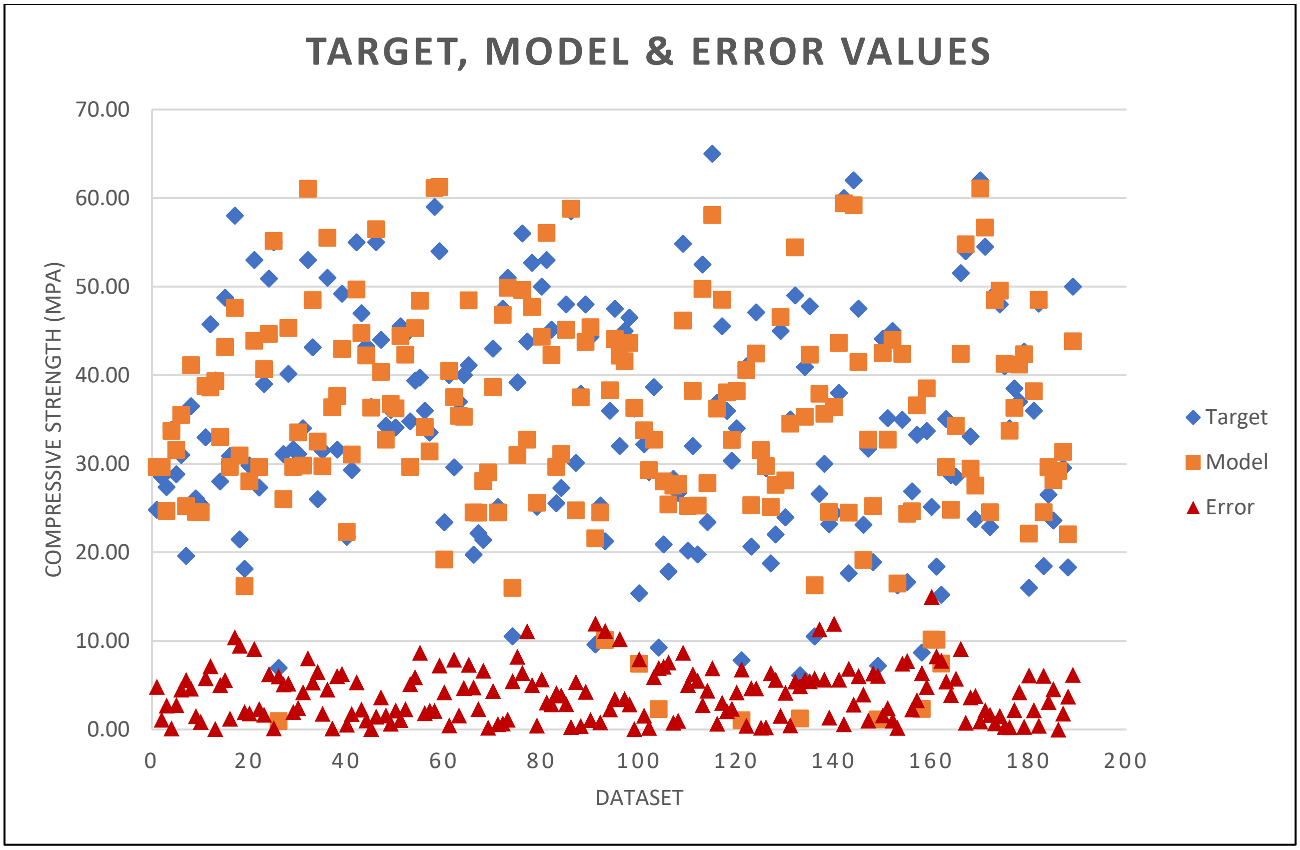


Figure 21: Representation of Target, Model & Error Values for fc'

4.2. SPLIT TENSILE STRENGTH OF GPC:

The results of model developed for prediction of Split Tensile Strength of Concrete incorporating waste glass powder is given below:

4.2.1. EXPRESSION TREE:

Given below is the expression tree developed through GEP for split tensile strength of GPC. Input Variables have been represented in the ET by symbolic representation as given below:

Where;

d0: GP%= Glass powder content as a percentage of Total cementitious materials (%)

d1: TCM= Total cementitious Material (kg/m³)

d2: W= Water Content (kg/m³)

d3: FA= Fine Aggregates (kg/m³)

d4: CA= Coarse Aggregates (kg/m³)

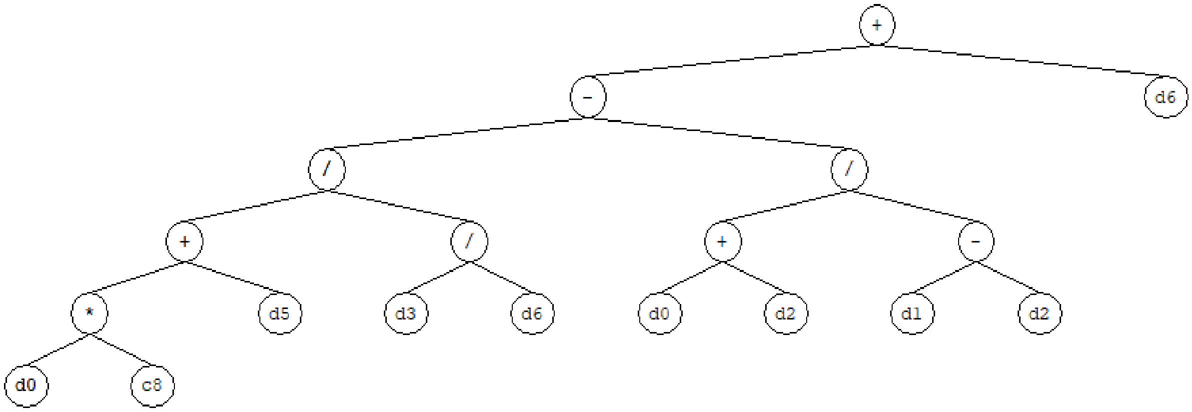
d5: SiO2 = Percentage of SiO2 in glass particles (%)

d6: Al2O3= Percentage of Al2O3 in glass particles (%)

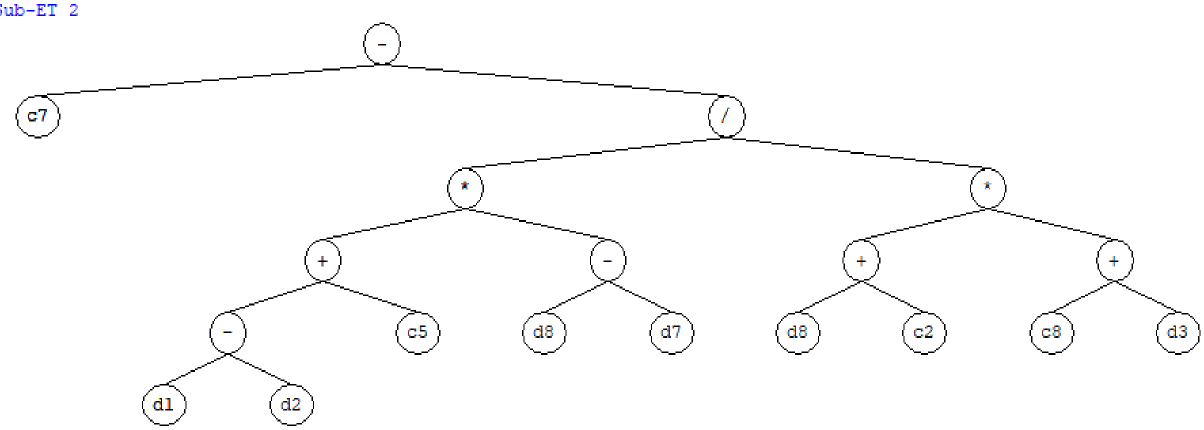
d7: D=Maximum Size of Glass powder particles (microns)

d8: A= Age of Sample at testing (days)

Sub-ET 1



Sub-ET 2



Sub-ET 3

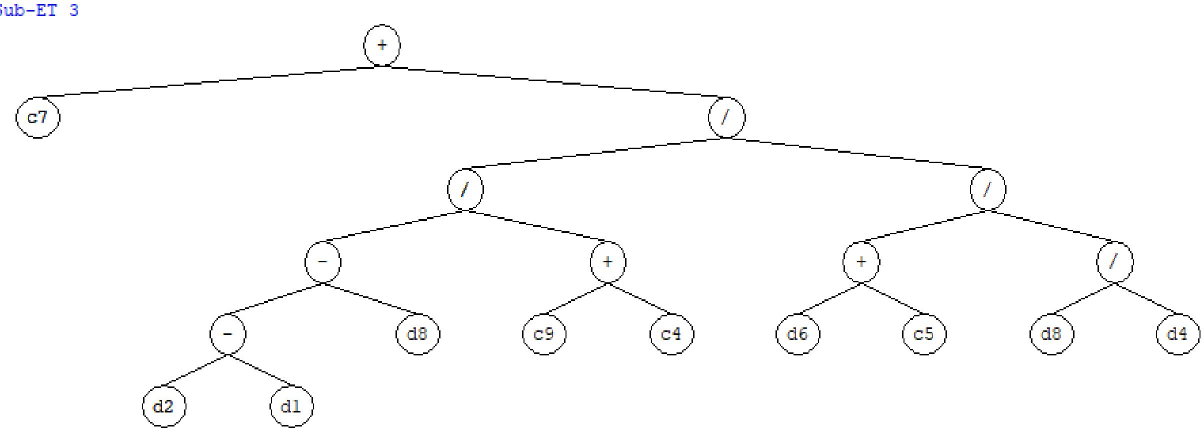


Figure 22: ET for Split Tensile Strength of GPC

4.2.2. FORMULATION OF EQUATIONS:

The model of fst was formulated using gene as 3, therefore, the number of sub ETs are 3 as seen in the above given ET. The ET has been converted to simplified equations and these equations can be used to predict split tensile strength of concrete incorporating different types of Glass powder at different ages of samples.

$$f_{st}\ (MPa) = A + B + C$$

where

- $A = \dfrac{(-3.753\ x\ GP\%) + SiO2}{\left(\frac{FA}{Al2O3}\right)} - \dfrac{(GP\% + W)}{(TCM - W)} - Al2O3$

- $B = 5.713 - \dfrac{\left((TCM - W) - 191.931\right)\ x\ (A - D)}{(A + 46.944)\ x\ (FA - 445.767)}$

- $C = \left(\left(\dfrac{W - TCM - A}{-4.454}\right) x \left(\dfrac{\left(\frac{A}{CA}\right)}{Al2O3 + 0.617}\right)\right) - 4.357$

And,

TCM= Total cementitious Material (kg/m³)

D= Maximum Size of Glass powder particles (microns)

W= Water Content (kg/m³)

FA= Fine Aggregates (kg/m³)

CA= Coarse Aggregates (kg/m³)

GP%= Glass powder content as a percentage of Total cementitious materials (%)

SiO_2 = Percentage of SiO_2 in glass particles (%)

Al_2O_3= Percentage of Al_2O_3 in glass particles (%)

A= Age of Sample at testing (days)

4.2.3. SENSITIVITY ANALYSIS/IMPORTANCE OF VARIABLES:

9 No.(s) of different input variables have taken into account for model development of Split tensile strength of GPC. The ratio of influence of each parameter has been determined by sensitivity analysis. Among all variables, TCM (Total Cementitious Materials), Water Content, Al_2O_3 and FA (Fine Aggregates) Content have the highest impact on Split Tensile Strength of GPC i.e. 29.97%, 18.65%, 18.25% and15.84% respectively while A (Age) and CA (Coarse Aggregate Content) have medium impact. However, %age of Glass Powder, SiO_2, and D (maximum size of Glass powder particles) have low impact on Split tensile Strength of Glass Powder concrete. The importance of variables as predicted by GEP model is given below:

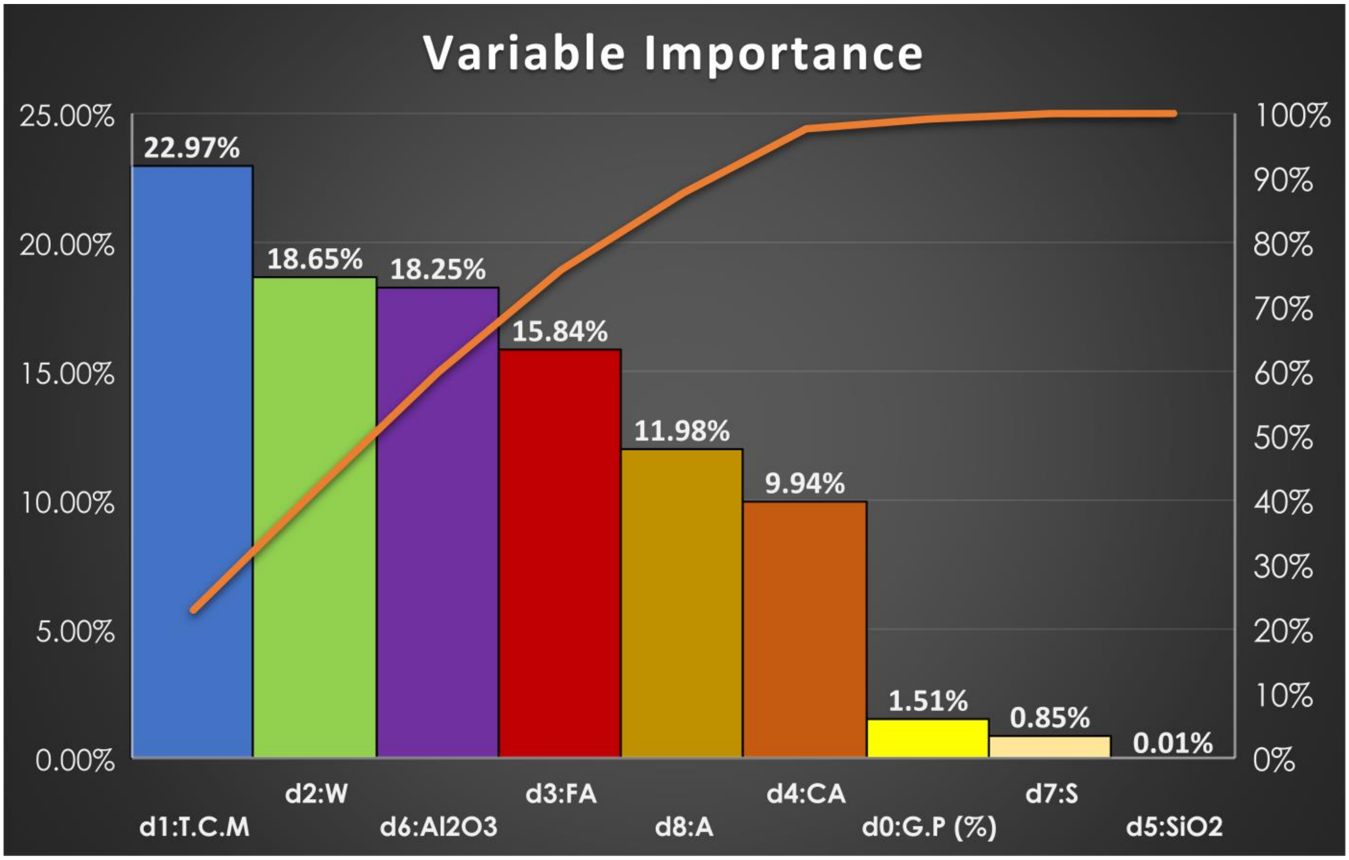


Figure 23: Importance of Variables for fst of GPC

4.2.4. RELATIONSHIP OF INPUT VARIABLES WITH OUTPUT VARIABLES:

Parametric Analysis was also done in order to find out the relationship of all input variables with output variables and all the predictor variables were kept unchanged at their average values and the variation in split tensile strength was recorded for the increase of input variable from its least to extreme value. The minimum, maximum and average values of input variables used for the development of the said relationships are given below:

Input Variables	**Minimum**	**Average**	**Maximum**
G.P%	0	15	40
T.C.M (kg/m^3)	350	663	1440
W (kg/m^3)	157.5	306	878.4
F.A (kg/m^3)	608.19	1160	4112
C.A (kg/m^3)	992	1765	5288
% age of SiO_2 in GP	70.22	71.65	72.61
%age of Al_2O_3 in GP	0.4	1.79	2.54
Max size of GP (microns)	75	88	150
Age of sample (days)	7	23	57

Table 12: Range of Input Variables for split tensile Strength

Graphical representation of relationships of input variables with their output variables are given below:

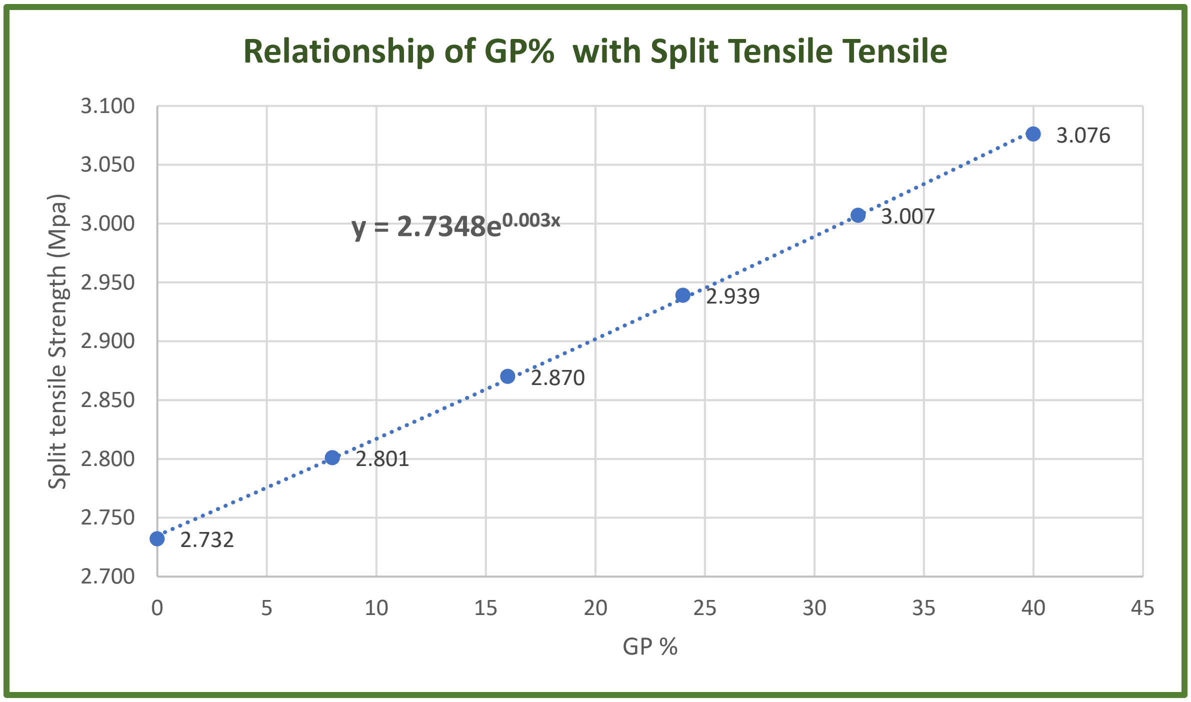


Figure 24: Relationship of GP with Split tensile Strength of GPC

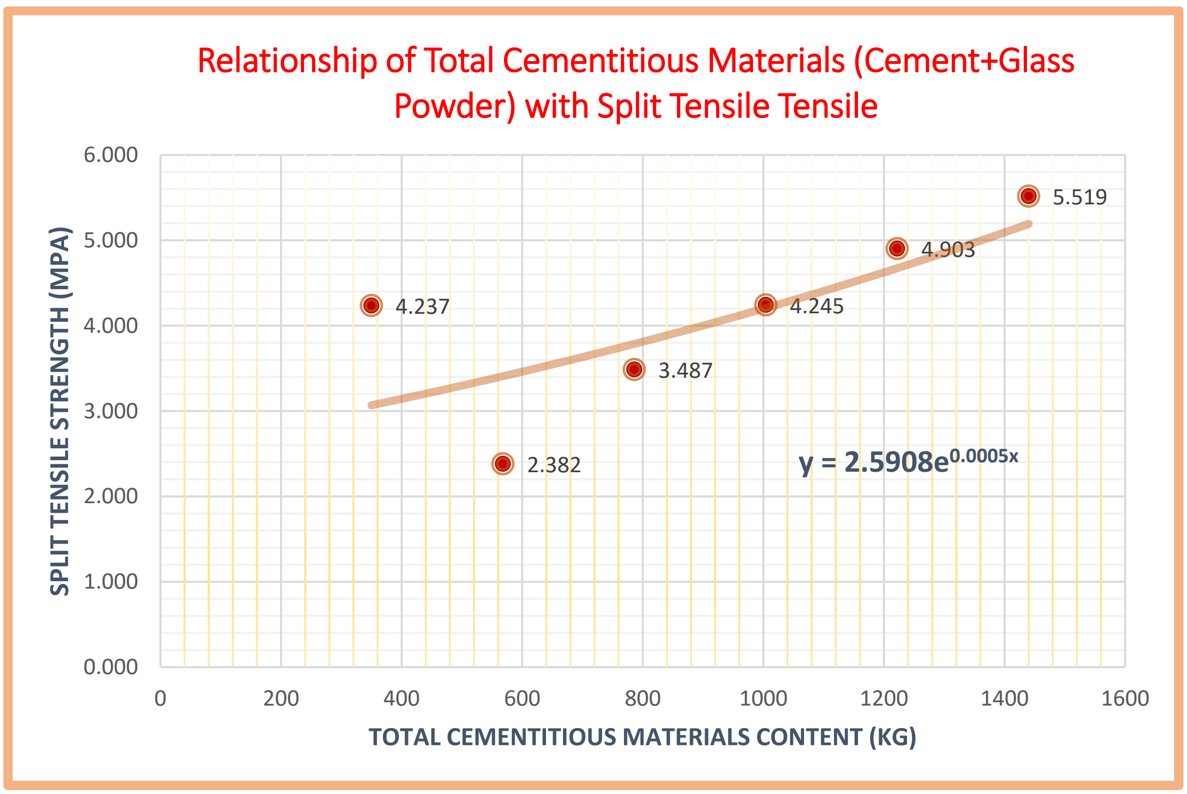


Figure 25: Relationship of TCM with Split Tensile Strength of GPC

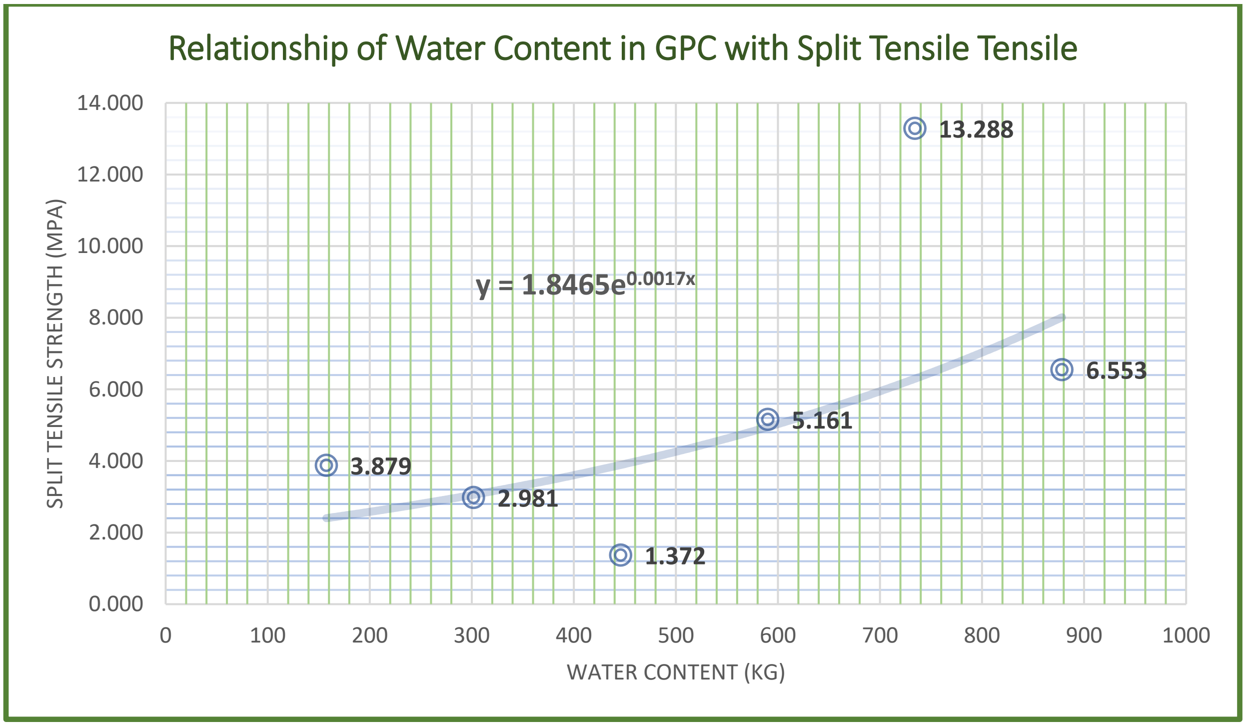


Figure 26: Relationship of Water content with Split Tensile Strength of GPC

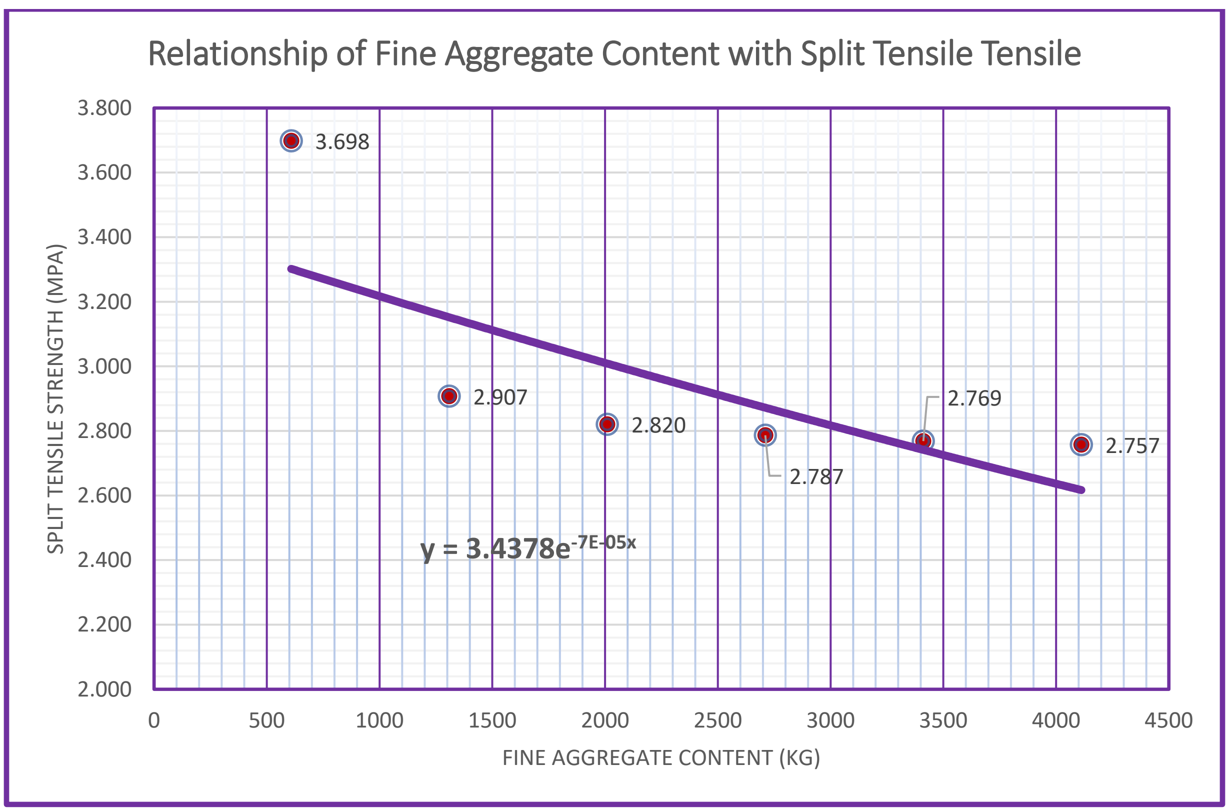


Figure 27: Relationship of FA content with Split Tensile Strength of GPC

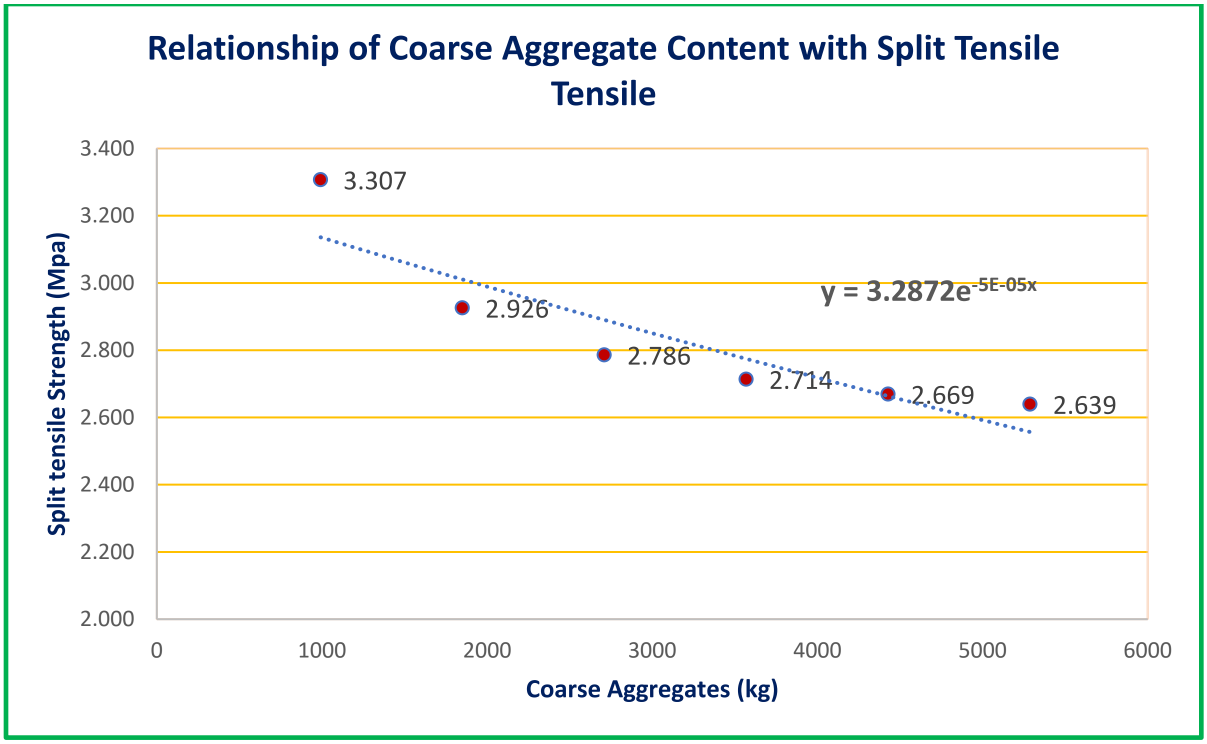


Figure 28: Relationship of CA content with Split Tensile Strength of GPC

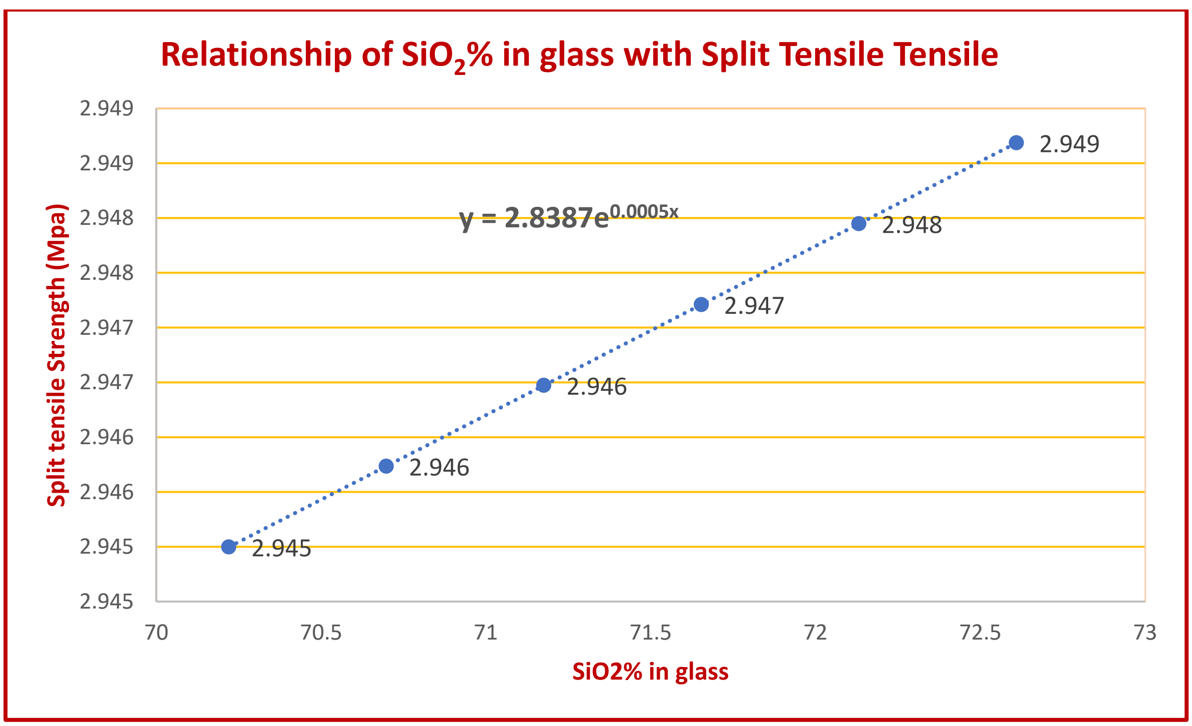


Figure 29: Relationship of Silica in GP with Split Tensile Strength of GPC

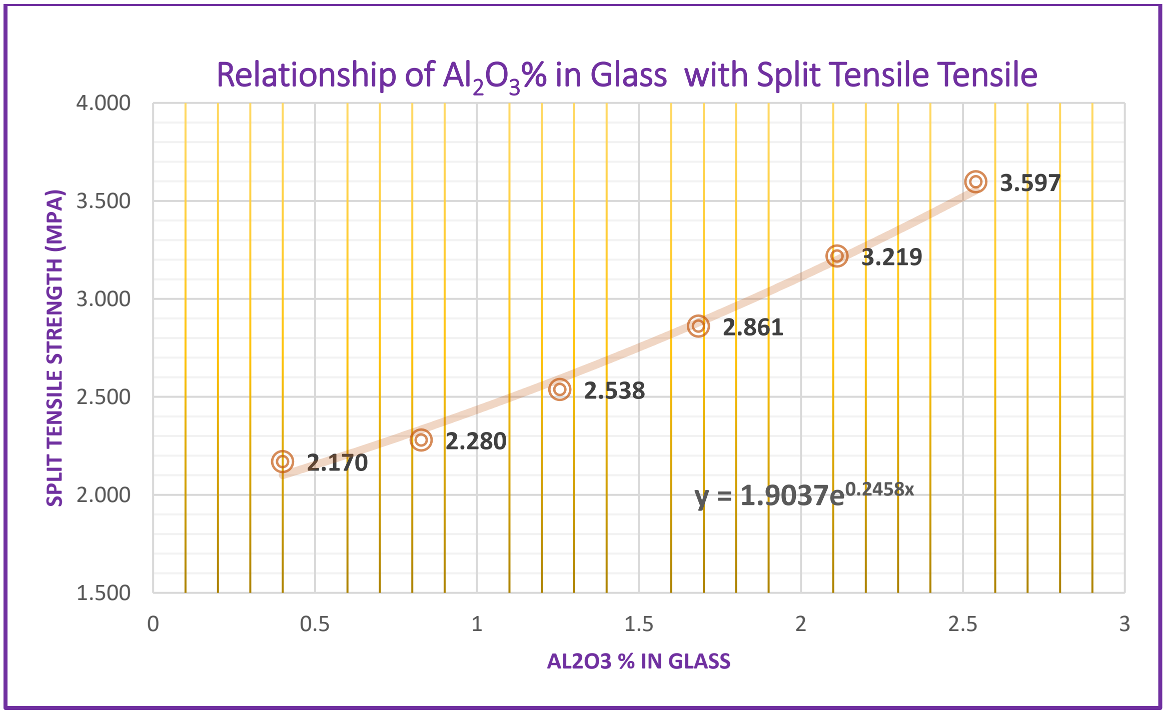


Figure 30: Relationship of Alumina in GP with Split Tensile Strength of GPC

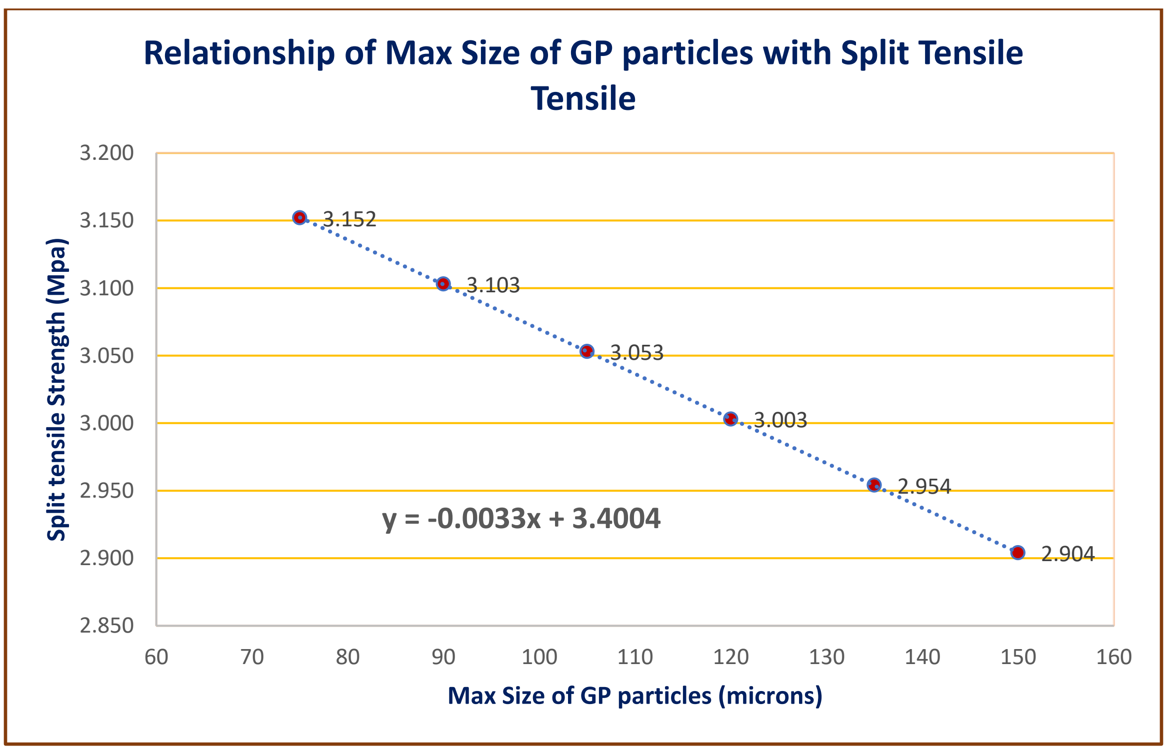


Figure 31: Relationship of Size of GP with Split Tensile Strength of GPC

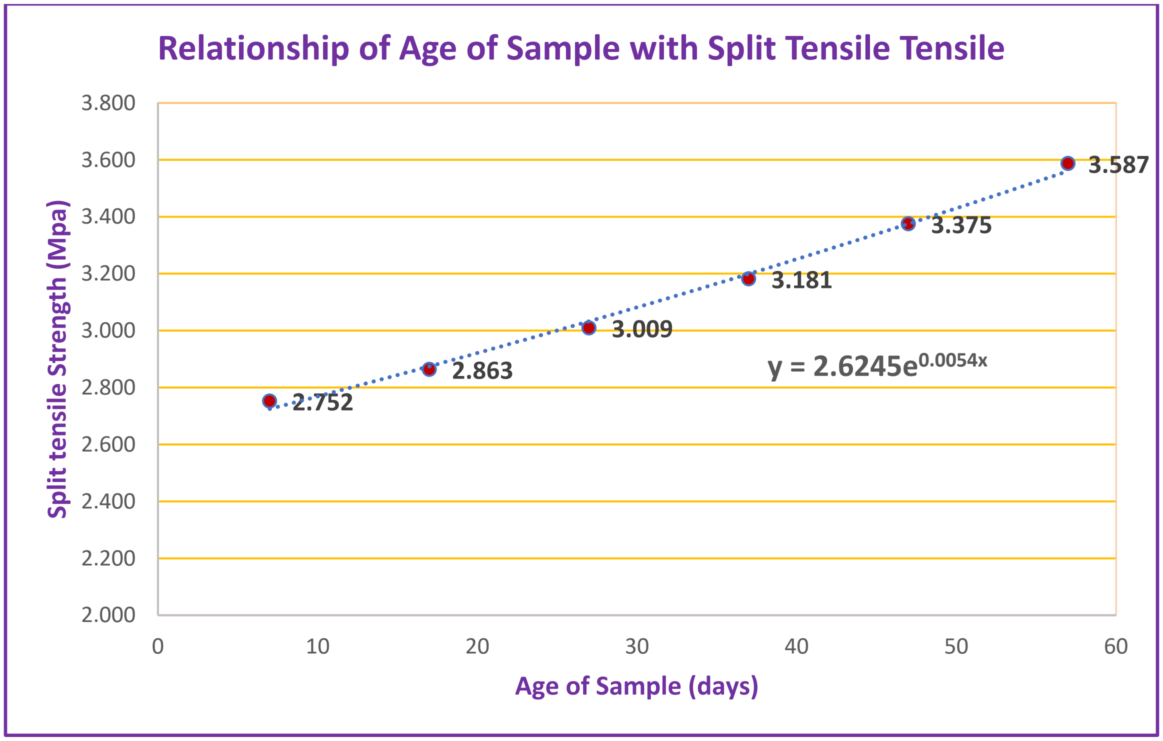


Figure 32: Relationship of Sample Age with Split Tensile Strength of GPC

It has been observed that Glass powder content added as percentage of Total Cementitious Materials has mild effect on Split Tensile Strength of GPC. The results have shown similar trends with the results of available literature. Majority of the authors have proposed the use of glass powder in concrete for the production of green concrete and promotion of environmental friendly construction. Authors have reported an increase in split tensile strength of concrete up to a certain limit and then decrease occurs (Vijayakumar et al., 2008), (Nayak & Raju, n.d.), (Subramani & Ram, 2015), (Aliabdo et al., 2016), (S. Kumar & Nagar, 2017), (Hussain & Chandak, 2015), (Babu & Jayaram, 2017), (Mounika et al., 2017), (Rahman & Uddin, 2018). Some authors have suggested minor while few have suggested major increase. This varies with the values of other input variables and different circumstances. The overall effect of addition of glass powder on Split tensile Strength of GPC has been determined through GEP model development. The results show that the strength varies with type of glass powder used and the percentage of glass powder doesn't significantly affect the split tensile strength. A gradual increase can be seen in Split tensile strength with increase in % GP. This is in agreement with the model results. The relative contribution of Glass powder percentage has been determined as 1.51% for Split Tensile Strength of Glass Powder Concrete which does not contradict with the test results from literature. Also, the addition of glass in concrete has been taken into account in the form of 4 input variables i.e. % of G.P added, Silica in GP particles, Alumina in GP particles and Size of GP particles. The cumulative effect of addition of glass powder can be seen by the influence of these 4 input variables which is 20% in case of Split tensile strength of GPC. It may be concluded that mix design proportions are the major influencing parameters for all types of strengths which is in confirmation with the experimental results.

4.2.5. COMPARISON OF TARGET AND MODEL VALUES:

The comparison of model values (predicted values) and target values (experimental data) for 3 data sets i.e. training, validation and testing has been shown in the figure 33. The points close to the regression line show that there is a close relationship between predicted and experimented values. Linear equations depicting the relationship between target and model values have also been developed for all 3 datasets as given below:

Training Dataset: y = 0.8707x + 0.3415

Validation Dataset: y = 0.8699x + 0.4148

Testing Dataset: y = 0.7904x + 0.6701

where x=y is an ideal fit.

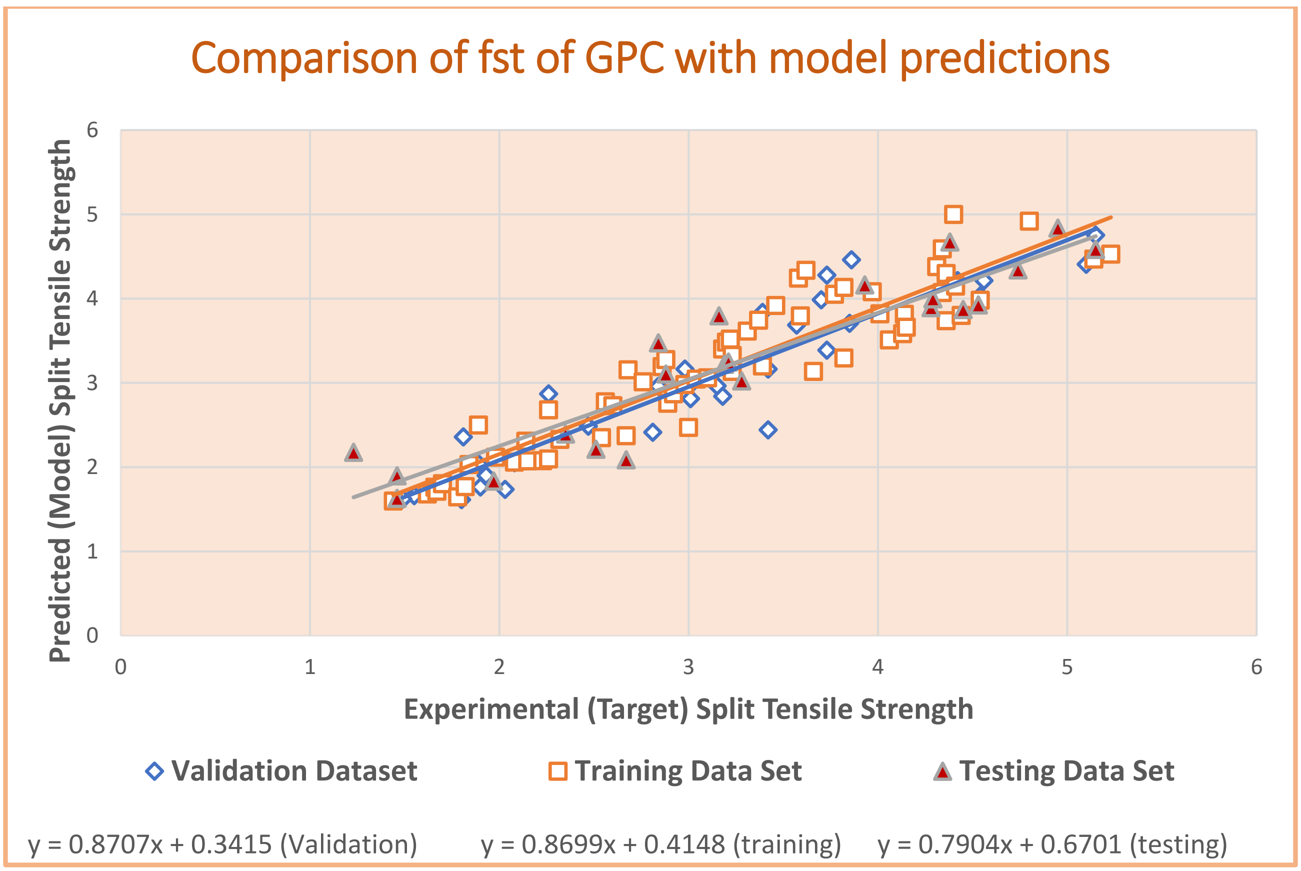


Figure 33: Comparison of Model & Target Values for Split tensile Strength of GPC

4.2.6. PERFORMANCE EVALUATION OF MODEL:

As already discussed in the section 4.1.6, the ratio of total number of samples / databases to the total number of input variables should be three for satisfactory models and five for ideal models (Iqbal et al., 2020). This ratio is significantly higher i.e. 12 for model of Split Tensile Strength. Statistical Analysis for all 3 sets of data i.e. training, validation and testing data has been carried out and the results are shown in Table 11. It can be observed that high correlation exists between target and model values and the values of errors are quite low. The results of MAE, RMSE and RSE for training sets have been recorded as 0.306, 0.43 and 0.130 respectively. The values of MAE, RMSE and RSE values for testing data have been recorded as 0.359, 0.429 and 0.136.

Evaluation Criteria	GEP Model			Remarks
	Training	Validation	Testing	
R	0.969	0.969	0.933	Strong Relation
R^2	0.939	0.94	0.871	Strong Relation
MAE	0.306	0.277	0.359	Acceptable
RMSE	0.43	0.433	0.429	Acceptable
RSE	0.13	0.134	0.136	Acceptable

Table 13: Statistical Evaluation of Model for fst of GPC

It can be seen from the above table that the statistical measures for all 3 sets i.e. training, validation and testing data do not vary significantly and are effectively similar which reflects the generalization capability of the model and it can be said that it can be safely applied to predict mechanical properties of unseen data.

Values of model, target and absolute errors were plotted to get an idea about the maximum error in the developed models as shown in Fig. 34. It can be observed that the actual experimental values are close to the values predicted by the models with an average error of 0.29 MPa, maximum error less than 0.7MPa. In addition, the rate of maximum error is very low. About 90% of dataset has been predicted with absolute error less than 0.6 MPa.

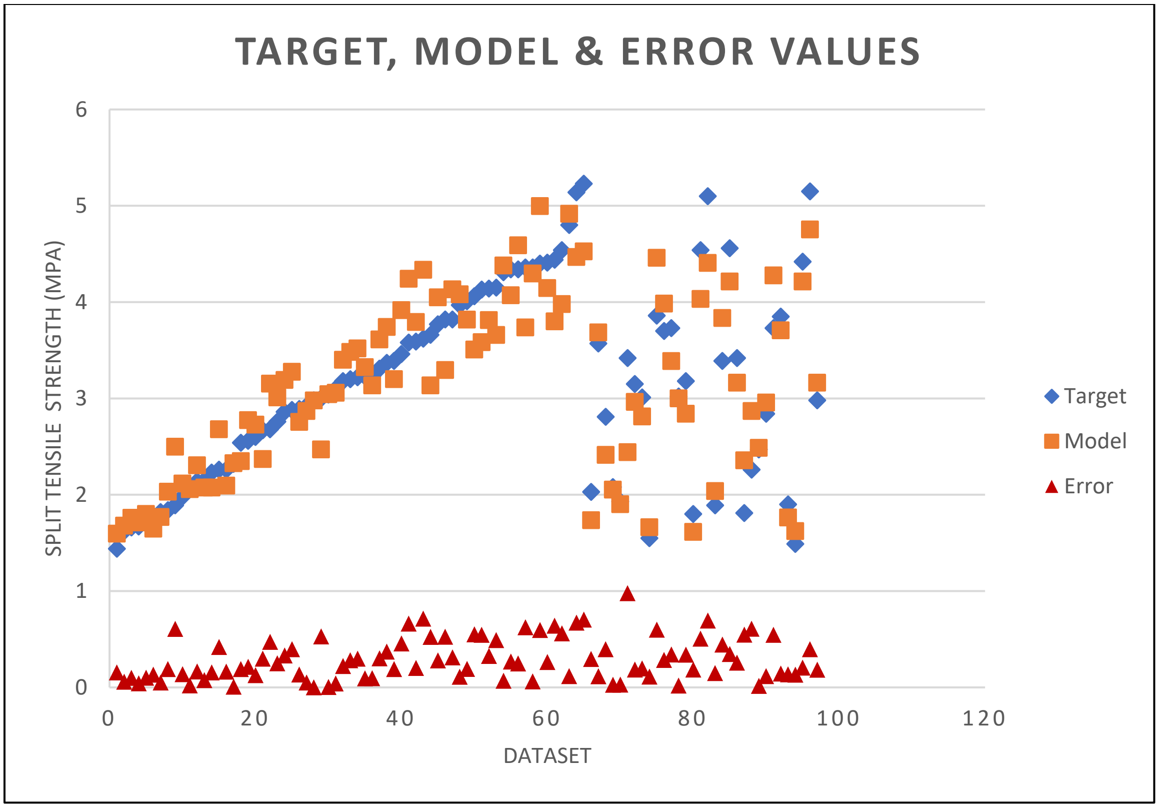


Figure 34: Target, Model & Error Values for Split tensile Strength of GPC

4.3. FLEXURAL STRENGTH OF GLASS POWDER CONCRETE:

The results of model developed for prediction of Flexural Strength of Concrete incorporating waste glass powder is given below:

4.3.1. EXPRESSION TREE:

Given below is the expression tree developed through GEP for flexural strength of GPC. Input Variables have been represented in the ET by symbolic representation as given below:

Where;

d0: GP%= Glass powder content as a percentage of Total cementitious materials (%)

d1: TCM= Total cementitious Material (kg/m^3)

d2: W= Water Content (kg/m^3)

d3: FA= Fine Aggregates (kg/m^3)

d4: CA= Coarse Aggregates (kg/m^3)

d5: SiO2 = Percentage of SiO_2 in glass particles (%)

d6: Al2O3= Percentage of Al_2O3 in glass particles (%)

d7: D=Maximum Size of Glass powder particles (microns)

d8: A= Age of Sample at testing (days)

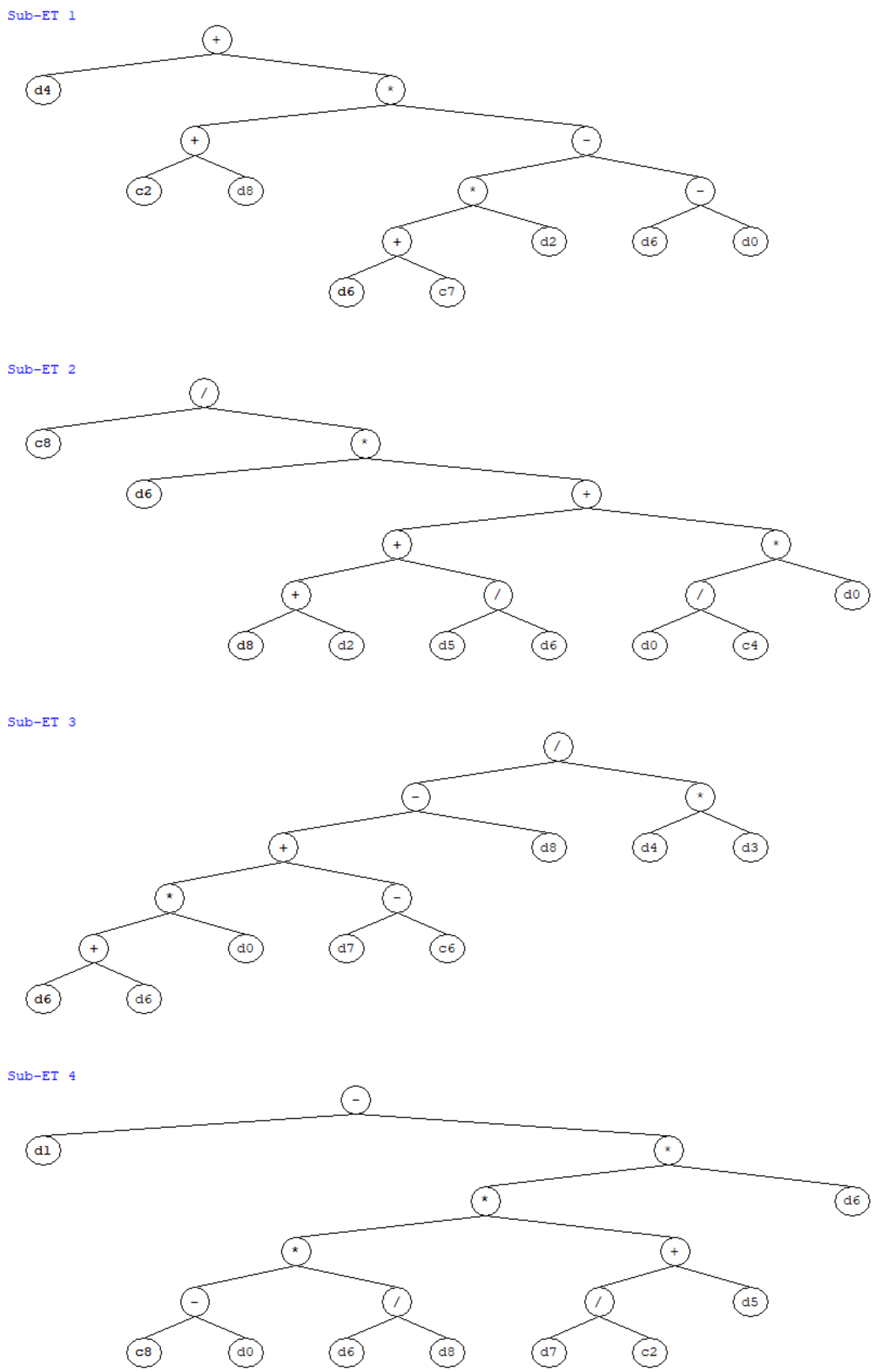


Figure 35: ET for Flexural Strength of GPC

4.3.2. FORMULATION OF EQUATIONS:

The model of fst was formulated using gene as 4, therefore, the number of sub ETs are 4 as seen in the above given ET. The ET has been converted to simplified equations and these equations can be used to predict split tensile strength of concrete incorporating different types of Glass powder at different ages of samples.

$$f_b\ (MPa) = A \times B \times C \times D$$

where

- $A = C.A + [(20.62 + A) \times ((5.59 + Al_2O_3) \times W) - Al_2O_3 + G.P\%]$
- $B = \frac{0.62}{Al2O3\ x\ \left(\left(A + W + \frac{SiO2}{Al2O3}\right) + \frac{GP^2}{3.83}\right)}$
- $C = \frac{(2\ x\ Al2O3\ x\ GP) + D + 20.52 - A}{F.A\ x\ C.A}$
- $D = T.C.M - [\ ((9.58 - G.P) \times \frac{Al2O3}{A}) \times (\frac{D}{-6.19} + SiO2) \times Al_2O_3\ ]$

And,

TCM= Total cementitious Material (kg/m³)

D= Maximum Size of Glass powder particles (microns)

W= Water Content (kg/m³)

FA= Fine Aggregates (kg/m³)

CA= Coarse Aggregates (kg/m³)

GP%= Glass powder content as a percentage of Total cementitious materials (%)

SiO_2 = Percentage of SiO_2 in glass particles (%)

Al_2O_3= Percentage of Al_2O_3 in glass particles (%)

A= Age of Sample at testing (days)

4.3.3. SENSITIVITY ANALYSIS/IMPORTANCE OF VARIABLES:

9 No.(s) of different input variables have taken into account for model development of Flexural Strength of GPC. The ratio of influence of each parameter has been determined by sensitivity analysis. Among all variables, CA (Coarse Aggregates Content), FA (Fine Aggregate Content), TCM (Total Cementitious Materials), and D (maximum size of Glass powder particles have the highest impact on Flexural Strength of GPC i.e. 17.57%, 17.56%, 17.43% and 13.03% respectively while, Al_2O_3 , %age of Glass Powder, A (Age) and Water Content have medium impact on Flexural Strength of Glass Powder concrete. However, SiO_2 has the least impact on Flexural Strength of Glass Powder Concrete. The importance of variables as predicted by GEP model is given below:

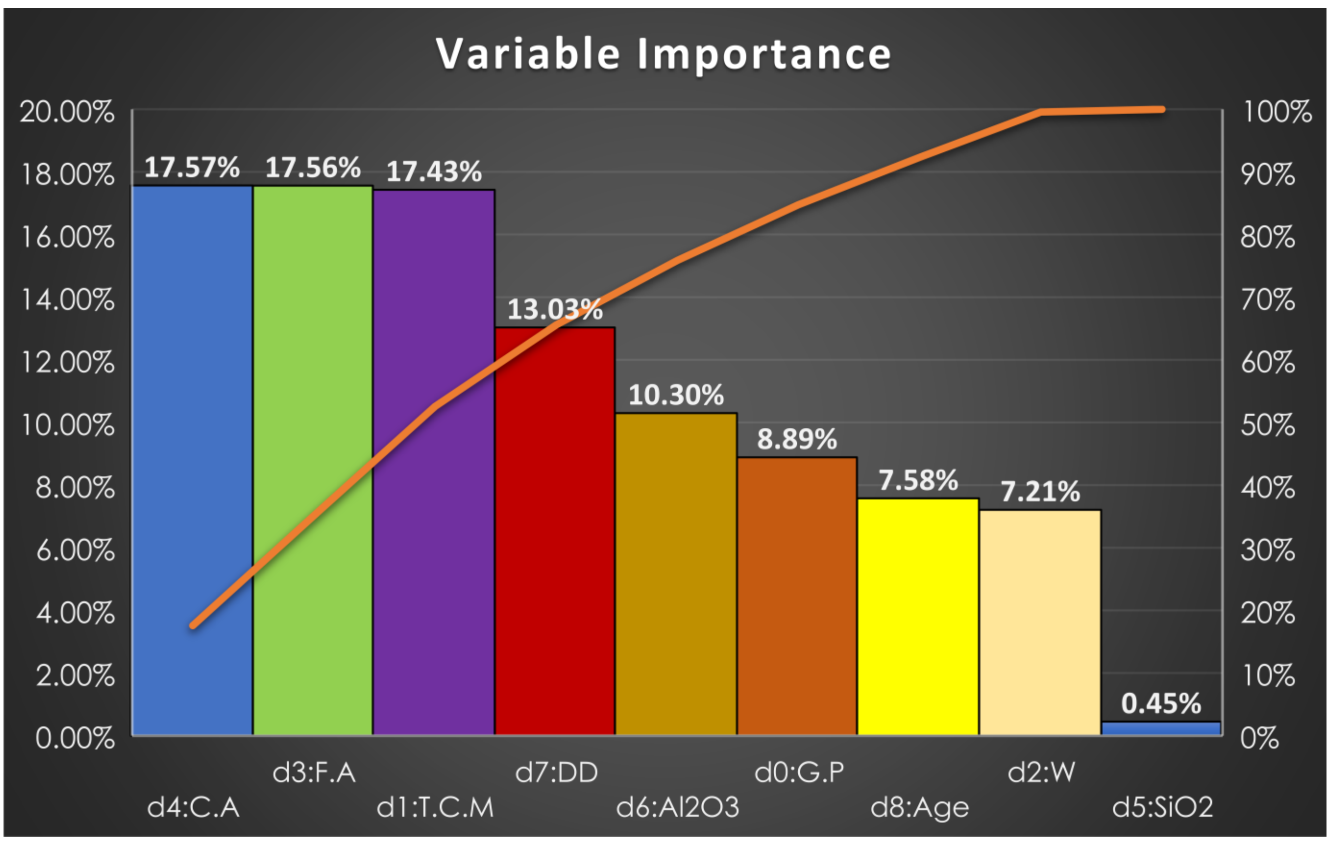


Figure 36: Importance of Variables for Flexural Strength of GPC

4.3.4. RELATIONSHIP OF INPUT VARIABLES WITH OUTPUT VARIABLES:

Parametric Analysis was also done in order to find out the relationship of all input variables with output variables. All the predictors variables were kept un changed at their average values and the variation in flexural strength was recorded for the increase of input variable from its lowest to highest value. The minimum, maximum and average values of input variables used for the development of the said relationships are given below:

Input Variables	**Minimum**	**Average**	**Maximum**
G.P%	0	18	40
T.C.M (kg/m^3)	330	834	1440
W (kg/m^3)	174.9	371	619.2
F.A (kg/m^3)	608.19	1209	2704
C.A (kg/m^3)	1184.8	2089	3556.8
% age of SiO_2 in GP	67.33	75	98.1
%age of Al_2O_3 in GP	0.33	1.1884	2.62
Max size of GP (microns)	75	119	150
Age of sample (days)	7	21	60

Table 14: Range of Input Variables for Model of Flexural Strength of GPC

Graphical representation of relationships of input variables with their output variables are given below:

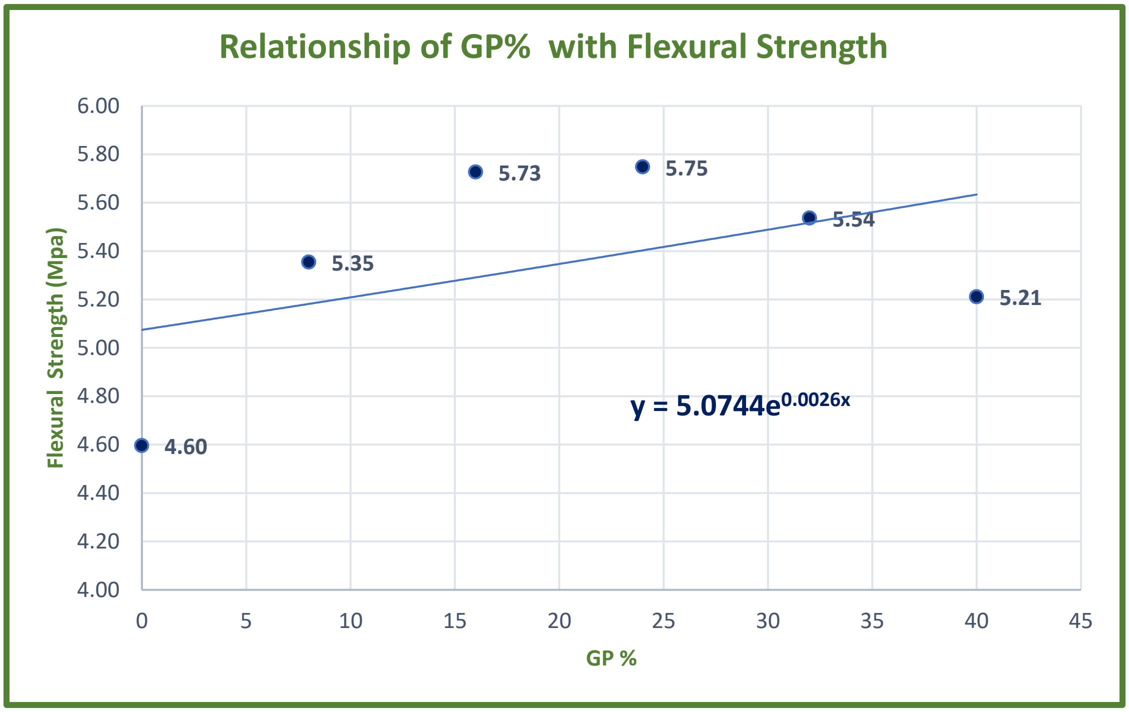


Figure 37: Relationship of GP% with Flexural Strength of GPC

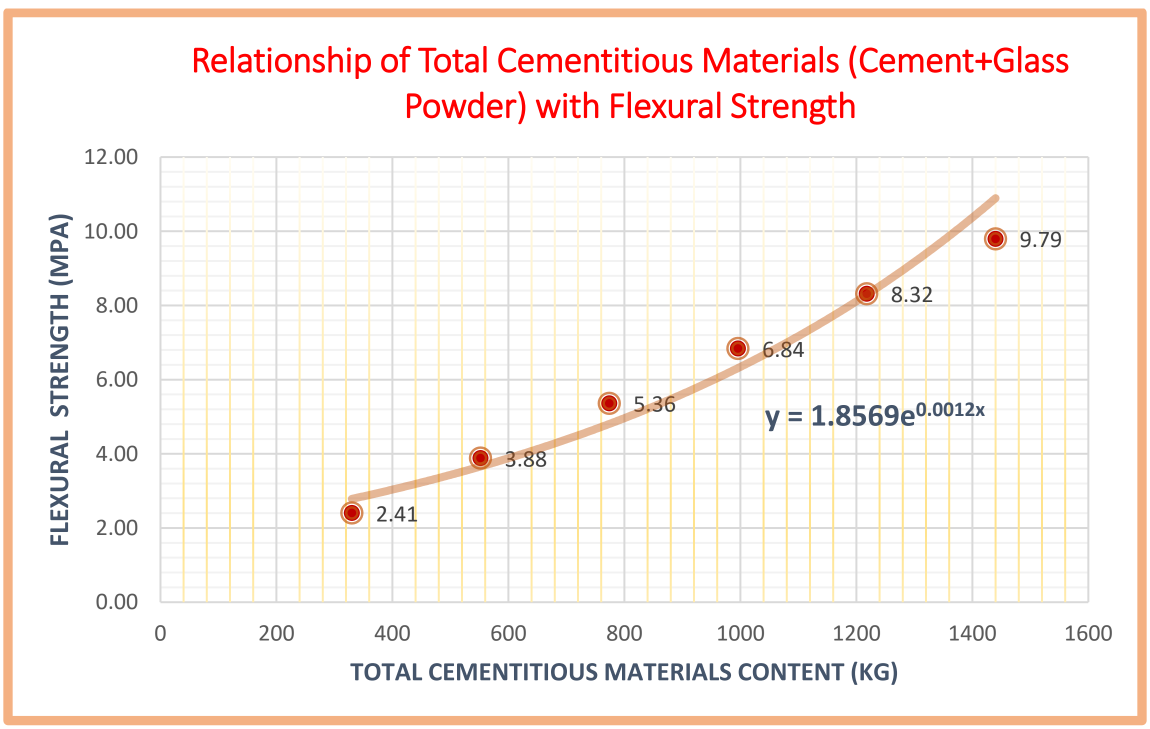


Figure 38: Relationship of TCM with Flexural Strength of GPC

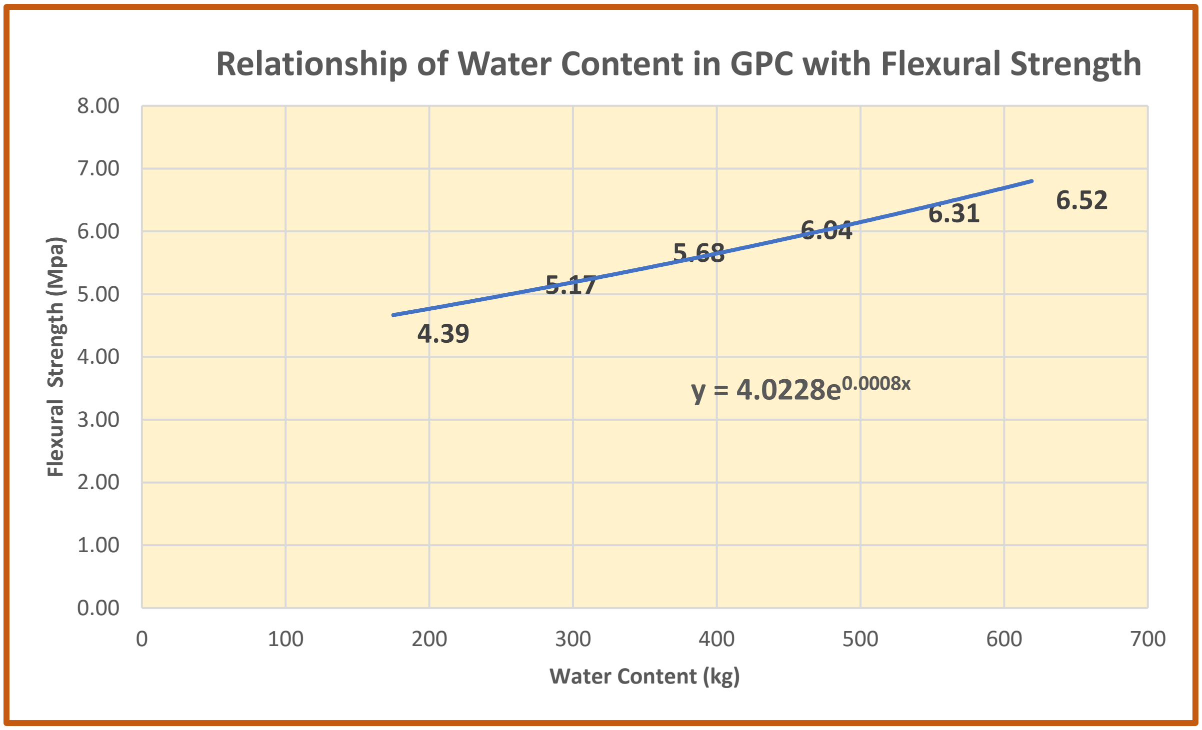


Figure 39: Relationship of Water Content with Flexural Strength of GPC

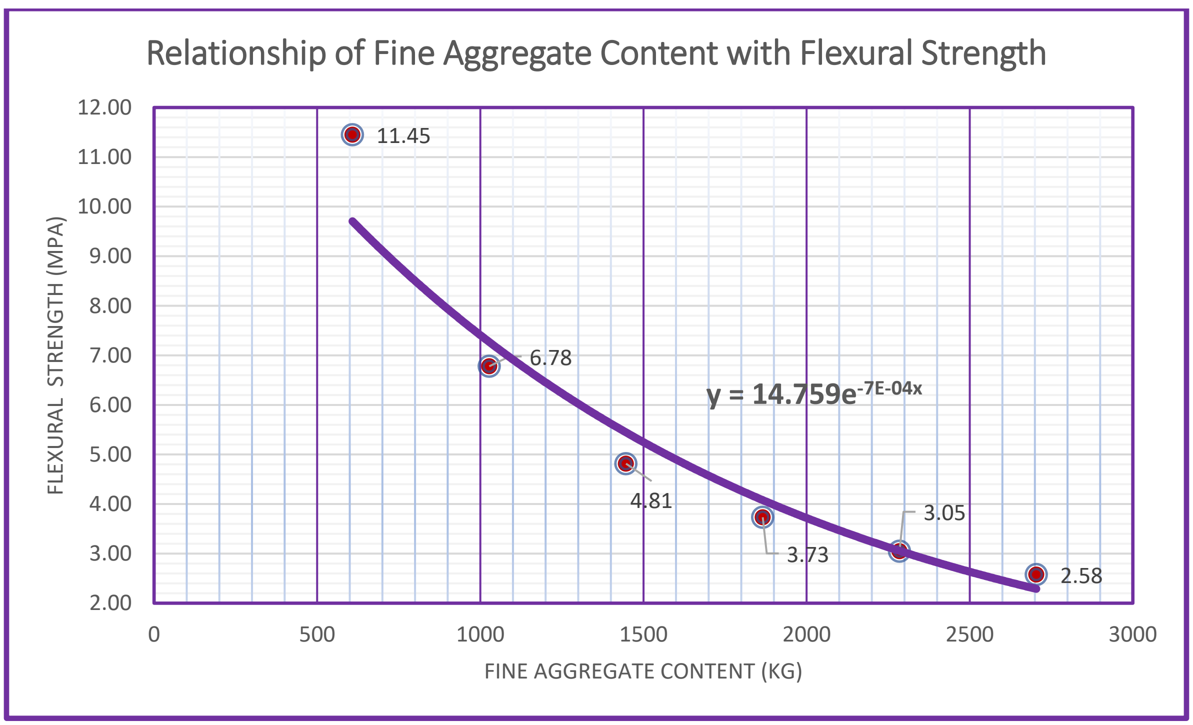


Figure 40: Relationship of FA with Flexural Strength of GPC

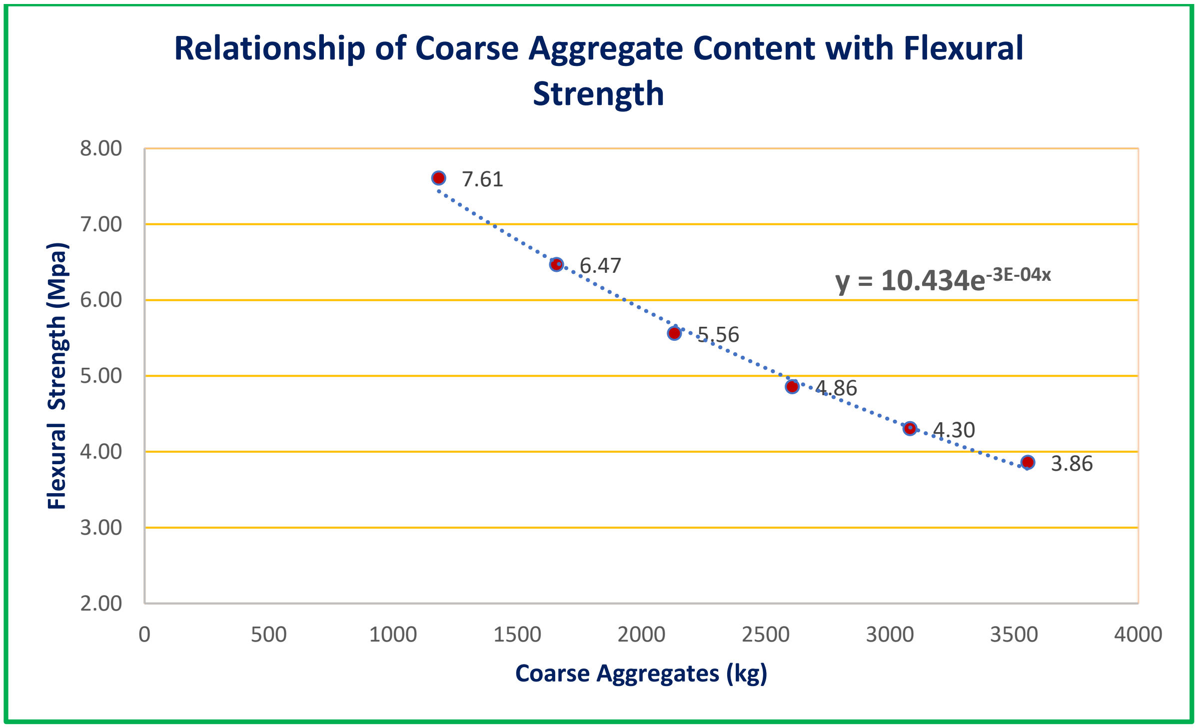


Figure 41: Relationship of CA with Flexural Strength of GPC

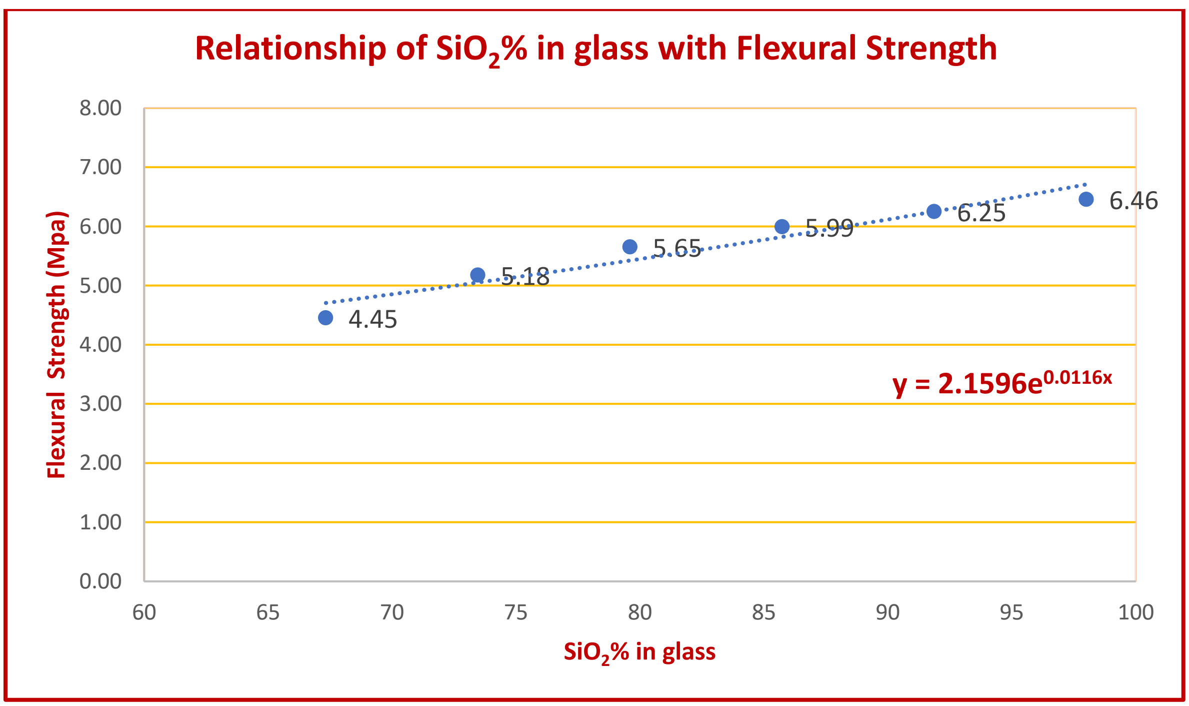


Figure 42: Relationship of SiO2 in GP with Flexural Strength of GPC

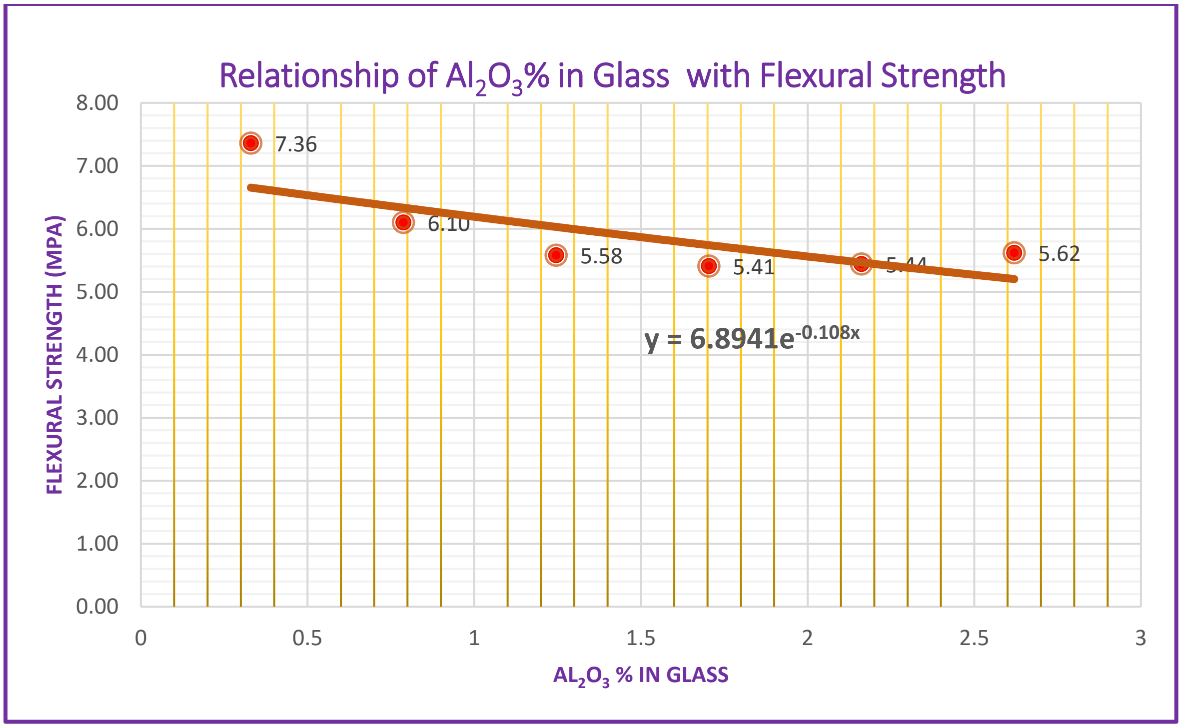


Figure 43: Relationship of Al2O3 with Flexural Strength of GPC

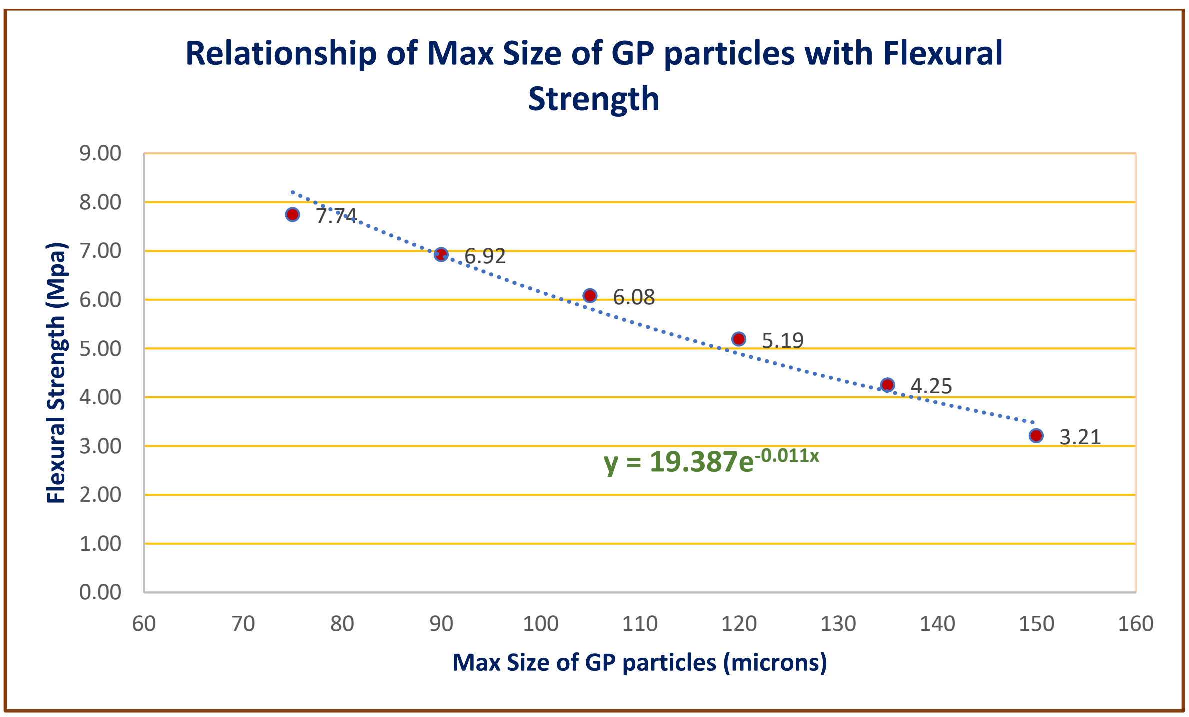


Figure 44: Relationship of Size of GP with Flexural Strength of GPC

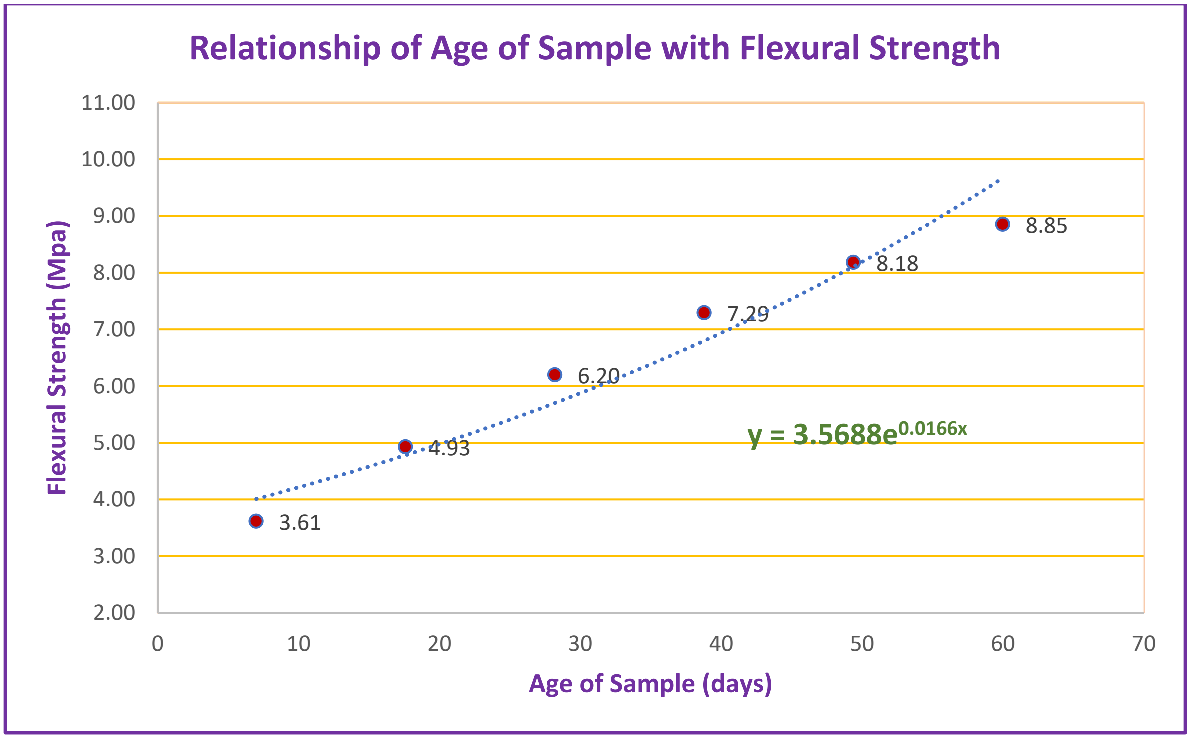


Figure 45: Relationship of Age of Sample with Flexural Strength of GPC

It has been observed that Glass powder content added as percentage of Total Cementitious Materials has noticeable effect on Flexural Strength of GPC. The results have shown similar trends with the results of available literature. Majority of the authors have proposed the use of glass powder in concrete for the production of green concrete and promotion of environmental friendly construction. Some authors have reported an increase in flexural strength of plain concrete up to a certain limit and then decrease occurs ((Raju & Kumar, 2015), (Mounika et al., 2017), (Aliabdo et al., 2016), (Vijayakumar et al., 2008), Eme & Nwaobakata, 2019), (Nayak & Raju, n.d.), (Gholampour et al., 2017), (Subramani & Ram, 2015), (Kumarappan, 2013), (Mokal & Shirsath, 2019), (Mounika et al., 2017), (M. Kumar, 2016), (Sakale et al., 2016), (Rahman & Uddin, 2018), (Kalakada et al., 2020)) while some have reported decrease in strength after replacing glass powder with cement (Sayeeduddin & Chavan, 2016), (R. Kumar & Yadav, 2019), (Babu & Jayaram, 2017), (Elaqra et al., 2019), (Schwarz et al., 2008), (Lee et al., 2018), (Du & Tan, 2014), (Olutoge, 2016).

The experimental results show an increase in flexural strength with an increase in % of glass powder added up to a certain extent. This is in agreement with the model results. The relative contribution of Glass powder percentage has been determined as 8.89% respectively for Flexural Strength of Glass Powder Concrete which agrees with the experimental results. Also, the addition of glass in concrete has been taken into account in the form of 4 input variables i.e. % of G.P added, Silica in GP particles, Alumina in GP particles and Size of GP particles. The cumulative effect of adding glass powder can be seen by the influence of these 4 input variables. It may be concluded that mix design proportions are the major influencing parameters for all types of strengths which is in confirmation with the experimental results.

4.3.5. COMPARISON OF TARGET AND MODEL VALUES:

The comparison of model values (predicted values) and target values (experimental data) for 3 data sets i.e. training, validation and testing has been shown in the figure 32. The points close to the regression line show that there is a close relationship between predicted and experimented values. Linear equations depicting the relationship between target and model values have also been developed for all 3 datasets as given below:

Training Dataset: y = 0.8707x + 0.3415

Validation Dataset: y = 0.8699x + 0.4148

Testing Dataset: y = 0.7904x + 0.6701

where x=y is an ideal fit.

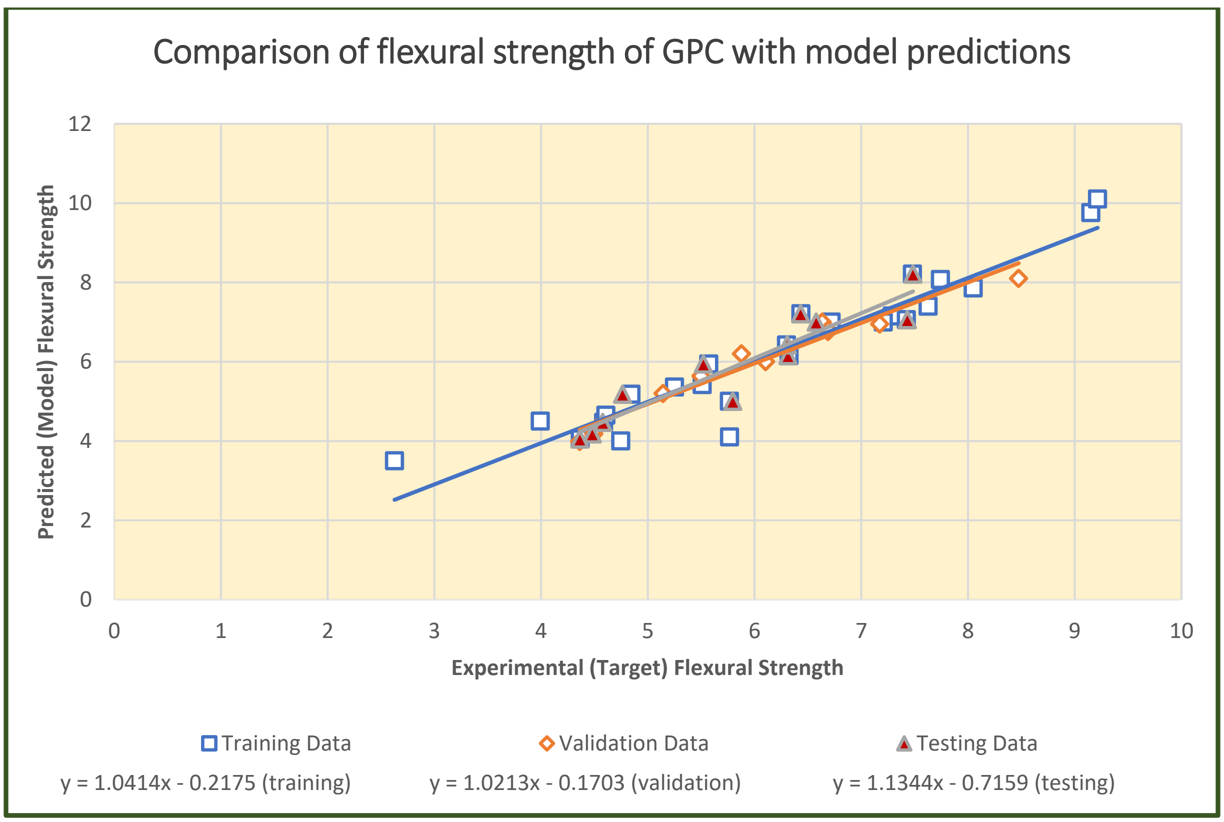


Figure 46: Comparison of Model & Target Values for flexural Strength of GPC

4.3.6. PERFORMANCE EVALUATION OF MODELS:

As already discussed in the section 4.1.6, the ratio of total number of samples / databases to the total number of input variables should be three for satisfactory models and preferably five for ideal models (Pavan & Todeschini, 2008). In this study, this ratio is higher i.e. 5 for model of Flexural Strength. Statistical Analysis for all 3 sets of data i.e. training, validation and testing data has been carried out and the results are shown in Table 11. It can be observed that high link exists between target and model values and the values of errors are quite low. The values of MAE, RMSE and RSE for training sets have been recorded as 0.439, 0.57 and 0.106 respectively. The values of MAE, RMSE and RSE values for testing data have been recorded as 0.359, 0.429 and 0.136.

Evaluation Criteria	GEP Model			Remarks
	Training	Validation	Testing	
R	0.945	0.98	0.938	Strong Relation
R^2	0.896	0.961	0.879	Strong Relation
MAE	0.439	0.221	0.411	Acceptable
RMSE	0.57	0.251	0.472	Acceptable
RSE	0.106	0.041	0.135	Acceptable

Table 15: Statistical Measures for flexural strength of GPC

It can be seen from the above table that the statistical measures for all 3 sets i.e. training, validation and testing data do not vary significantly and are effectively similar which reflects the generalization capability of the model and it can be said that it can be safely applied to predict mechanical properties of unseen data.

Values of model, target and absolute errors were plotted to get an idea about the maximum error in the developed models as shown in Fig. 47. It can be observed that the actual experimental values are close to the values predicted by the models with an average error of 0.37 MPa, maximum error less than 0.8MP. In addition, the rate of occurrence of maximum error is very low. About 80% of dataset has been predicted with absolute error less than 0.6 MPa.

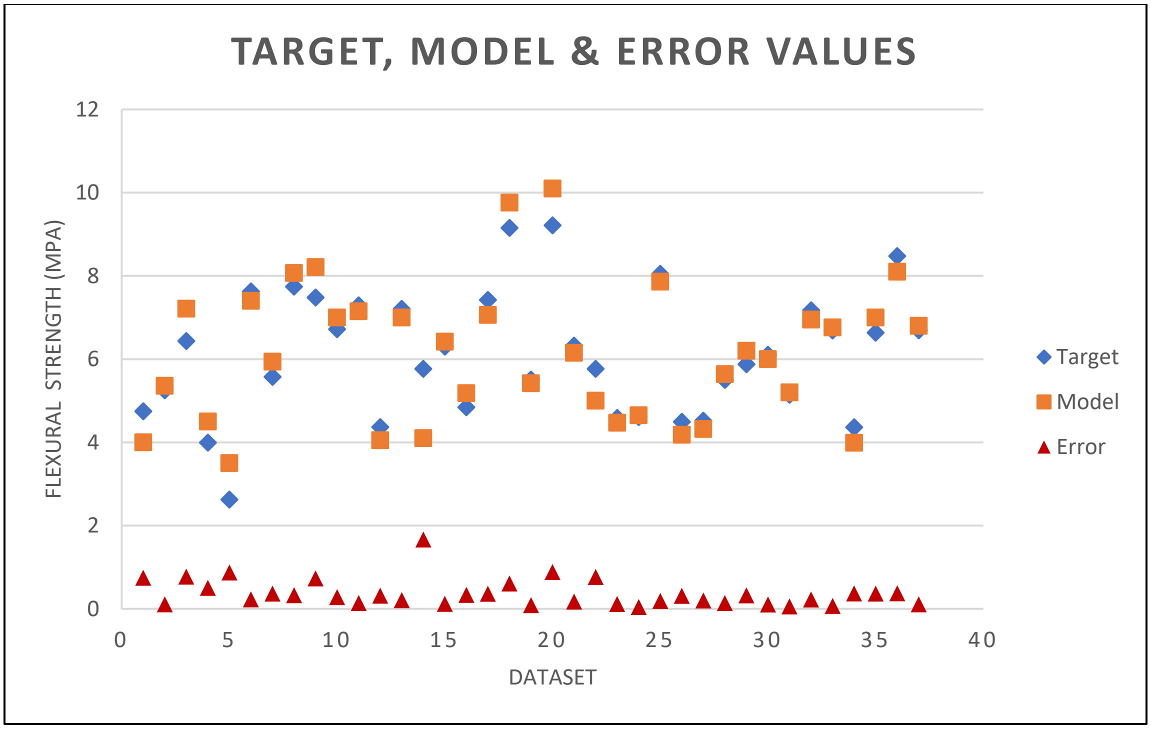


Figure 47: Taregt, Model & Error Values for Flexural Strength of GPC

4.4. STATISTICAL CHECKS:

Various statistical checks were also applied for the external validation of GEP models. A criterion suggested by Golbraikh suggests that the slope of regression line passing through the origin should be close to 1 (Golbraikh et al., 2003). It can be clearly seen in Table 6-8 that the slope of regression lines i.e. R is 0.924, 0.932 and 0.953 for f_c', f_{st} and f_b respectively. This shows high level of accuracy. In addition, different researchers have that the R^2 value through the origin should also be close to 1 (Roy & Roy, 2008). These external validation criteria have been summarized for all 3 models in Table 16.

Sr. No.	Condition	f_c',	f_{st}	f_b
1.	$0.8<R\approx1$ (Golbraikh et al., 2003)	0.924	0.932	0.953
2.	$0.8<R^2\approx1$ (Roy & Roy, 2008)	0.854	0.869	0.910

Table 16: Statistical Checks

4.5. COMPARISON WITH EXISTING MODELS:

To the best of author's knowledge, there are only 2 models already available to predict the compressive strength of Glass powder Concrete proposed in a single study (Mirzahosseini et al., 2019). There are several flaws/drawbacks in those models. The existing model proposed by Mirzahosseini et al., 2019 took into account only experimental results of the same study to develop the model. Hence, the model has no generalization capability and is not reliable to predict compressive strength of unseen data. In the model under discussion, effect of all influencing parameters e.g. concrete mix design ratio, w/c ratio etc. have not been considered. In addition, validity of model on unseen data was not checked. Whereas, the model developed in this study has addressed the flaws in the existing models to predict the compressive strength of glass powder concrete. The proposed model took into account experimental results of several studies so the model has great generalization capability and can be safely applied to predict the compressive strength of glass powder concrete. Effect of all major contributing factors including concrete mix design proportions, size and chemical composition of glass powder have been considered including mix proportion ratio of concrete, composition and size of glass powder, age of sample etc. Furthermore, validity of model on unseen data was checked and it was found to perform good on unseen data. A comparison of statistical measures for existing and model developed in this study to predict compressive strength of glass powder concrete is given below:

Statistical Measures	Existing Models				Developed Model	
	Model 1		Model 2			
	Training	Validation	Training	Validation	Training	Validation
R	0.81	0.81	0.81	0.73	0.919	0.93
RMSE	5.78	9.42	7.8	10.4	4.82	5.204
MAE	4.78	7.27	6.62	8.31	3.87	4.188

Table 17: Comparison with existing models

It can be clearly seen that the model developed in this study has better statistical measures i.e. R values of 0.919 and 0.93 as compared to 0.81 and 0.73. Also, the values of errors are less in the model developed in this study as compared to existing models.

To the best of author's knowledge, there are no models already available to predict both the split tensile strength and flexural strength of Glass powder Concrete.

5. CONCLUSIONS:

This study proposed the use of gene expression programming (GEP) method for creation of models for prediction of mechanical properties of concrete containing waste glass powder as a replacement of cement. The proposed models have been developed from a large database from experimental results available in literature. These models can be safely applied to a huge number of dataset and consider almost every influencing parameter. The results obtained from model are in agreement with the experimental results. The statistical checks applied to check the accuracy of models also confirmed the validation of models. These models have addressed the drawbacks/flaws of existing models. Also, the statistical measures for the proposed model are better than the existing models i.e. 0.93 as compared to 0.81 and 0.73, thus the proposed model seems to predict better results than the existing models. These models will be a source of promotion of use of waste glass powder in concrete and thus contributing towards green/sustainable construction. However, more research may be carried out for experimental re-validation of the predicted models may be carried out.

6. REFERENCES:

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