A Thesis on

ARTIFICIAL INTELLIGENCE IN THE PREDICTION OF VARIOUS CONCRETE PROPERTIES

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SUBMITTED BY

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DECLARATION

I declare that the research thesis entitled **“ARTIFICIAL INTELLIGENCE IN THE PREDICTION OF VARIOUS CONCRETE PROPERTIES”** is the bonafide research work carried out by me, under the guidance of **Mr**. **Tabish Izhar (**Assistant Professor**), Department of Civil Engineering, Integral University, Lucknow**. Further I declare that this has not previously formed the basis of award of any degree, diploma, associate-ship or other similar degrees or diplomas, and has not been submitted anywhere else.

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CERTIFICATE

It is Certified that the thesis entitled **"ARTIFICIAL INTELLIGENCE IN THE PREDICTION OF VARIOUS CONCRETE PROPERTIES"** *is being submitted by* ***Mr. Shailendra Kumar (Roll no: 2001431010)*** *in partial fulfillment of the requirement for the award of degree of Master of Technology (***Structural Engineering***) of Integral University, Lucknow, is a record of candidate's own work carried out by him/her under my supervision and guidance.*

The results presented in this thesis have not been submitted to any other university or institute for the award of any other degree or diploma.

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ABSTRACT

In this investigation the river sand was replaced with Quarry stone dust by 30% and 50% mix. Self- curing of concrete is enhanced by polyethylene glycol which increases hydration and strength properties of concrete. It also shows the effect of Polyethylene glycol on compressive strength, flexural strength with 0.4%, 0.6% & 0.8% percentage of PEG by weight of water were studied for 50% and 100% replacement of Quarry stone dust with M20 grades of concrete. The mix with % of PEG showed compressive strength marginally greater than the compressive strength of conventional concrete. The machine learning algorithm based on python is trained by the data available. Further, while predicting the strength of SCC the same data meant for SCC has been used to train in order to economies on computational effort. The compressive strengths & flexural strength of SCC estimated by the proposed algorithm are validated by experimental results.

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CHAPTER 1

INTRODUCTION

1.1 INTRODUCTION

Fresh water is a primary requirement for survival in our lives. . Cumulative activities of humans have led to the ecological imbalance in water availability and cause defects in ecosystem. India in its Nation Action Plan for Climate Change (NAPCC) along with Nation Water mission has pledged to increase the efficiency of water usage by 20%. Water is used mainly in concrete as it is a primary source for the hydration of cement. Water is the prime reason for the hardening of cement in concrete. The properties of concrete are determined mainly by its strength which is directly dependent on the W/C ratio. **Concrete is that the most generally used building material. It's the excellence of being shaped into desired form most handily. It's a man-made material consisting of ingredients like cement, fine aggregates, coarse aggregates,** Quarry stone dust **water and PEG.**

Crushed rock aggregates are more suitable for production of high strength concrete compared to natural gravel and sand. Crushed rock aggregates differ from sand and gravel in particle shape and surface texture and in the grading of fines. Crushed rock dust acts as filler and helps to reduce the total voids content in concrete.

Many parameters like Water Content, Cement content, Water Absorption, Replacement Ratio, Coarse & Fine Aggregate, Quarry stone dust and PEG are used to analyze the behavior of concrete.

Partial replacement of natural sand with Quarry stone dust materials can be reduced the burden on environment. Self-curing concrete helps in minimizing the wastage of water.

Python is very useful to develop an algorithm which is used as emerging AI tool in this investigation. The mechanical properties of concrete have been predicted by Machine learning Algorithm based on Python.

1.2 MATERIAL

1.2.1 Cement:

The cement is binding material for concrete which is used as ordinary Portland cement (OPC) grade 53 as per the coddle provision of IS: 12269.[21]

1.2.2 Aggregates

Major volume of concrete contains aggregates which are inert and less expensive and adds to the durability, strength of the concrete. The aggregate is a mixture of natural coarse and fine materials. The aggregates are mainly responsible for 70% of the strength gained by concrete. Natural aggregates are obtained from weathering action of rocks and artificial aggregates are obtained from crushing. Aggregates are classified as fine and coarse aggregates, fine aggregates are the aggregates which pass through 4.75 mm sieve whereas coarse aggregates are retained on 4.75 mm sieve. Coarse aggregates placement in concrete results in 30–40% void space which is filled by fine aggregates, where the voids left by fine aggregates is filled by still finer material like cement. Various specifications of aggregates are according to IS 383: 1970.[22]

1.2.3 Quarry Stone Dust

Crushed Quarry Dust is a fine material formed during the process of conversion of rock into aggregate and has particle size ranging from 4 mm to dust size (> 0.075mm).

1.2.4 Water

Water is responsible for hydration of cement and it is also responsible for workability, strength and durability of concrete. Water should be added in limited quantity whereas an excess of water added to the concrete leads to segregation. Water to cement ratio should be according to IS 456:2000[23]. Water used work for mixing should be as per IS 10262: 2019[24] whose pH is around 7.

1.2.5 Poly ethylene glycol (PEG)

PEG is a low molecular weight solvent use-full for substances which do not readily dissolve in water. PEG-n is a type of condensation polymer composed of ethylene oxide and water, where n refers to the average number of repeating oxyethylene groups.

On addition of PEG to concrete, it entraps the water particles by forming a shell of small thickness around the water molecules. The water will not be able to evaporate due to the shell formation around the water particles which reduces the rate of evaporation making the water available for the hydration process. Due to the availability of water in the early age of strength gain there will be a reduction in early age shrinkage cracks. This also helps in minimizing the need for external curing contributing to saving of water.

CHAPTER 2

LITERATURE REVIEWS

2.1 LITERATURE REVIEWS

1) **K. Liu et al. 2021(ELSEVIER); Prediction of carbonation depth for recycled aggregate concrete using ANN hybridized with swarm intelligence algorithms.{[1]**

This paper has been predict the carbonation resistance of recycled aggregate concrete (RAC) with machine learning models (ANN). It has taken 9 parameters (water content, cement content, water absorption, volume replacement ratio, temperature, relative humidity, concentration, curing time and exposure time) including environmental conditions. A dataset comprising 593 test data was used to train, validate and test machine learning models. The all dataset has been divided into three phase i.e.

a) Validation Phase

b) Training Phase

c) Testing Phase

Which are using these data as 15%, 70% and 15% respectively. Based on the review of the existing research, the data on the carbonation depth of RAC prepared with recycled fine aggregates or mineral admixtures were excluded since the available data volume was relatively low. The machine learning models used in this study were developed based on the WEKA workbench toolbox. Three standalone models (ANN, GPR and RF) and three hybrids ANN models were developed. The hybrid ANN models were called PSOANN, WOANN, and BASANN with weights and biases optimized by PSO, WO and BAS algorithm, respectively. Among all machine learning models, the WOANN model shows the best integral performance with the lowest OBJ value.

2) **O. Mohamed, M.Kewalramani, M.Ati et al. 2021(ELSEVIER); Application of ANN for prediction of chloride penetration resistance and concrete compressive strength.[2]**

Self-consolidating concrete has several advantages over conventional concrete such as minimized voids, ease of pour into congested formworks and complex shapes and absence of mechanical vibrations. One of the major problems with concrete structures is the corrosion of steel reinforcement due to penetration of chemicals like chloride. Standard tests to determine resistance of concrete to chloride ion penetration such as salt ponding test, bulk diffusion test and rapid chloride permeability test require 28–35 days. ANN developed for prediction of chloride penetration used 294 data points for training and validation. The four input parameters used for development of ANN were w/b ratio, cement content, FA or GGBS content and number of curing days to predict diffusion coefficient of chloride ion in concrete. This trained ANN was used to verify chloride penetration level of twenty experimentally evaluated SCC specimens of varied composition. Similarly, ANN developed for prediction of compressive strength used 1031 data points for training and validation of network. The study used two different w/b ratios of 0.65 and 0.45. It was observed that ANN with learning rate of 0.3, momentum of 0.5 and 5000 epochs resulted in the highest overall prediction accuracy of 95% for twenty experimentally evaluated chloride penetration levels of SCC specimens.

3) **M. J. Moradi, et al. 2021 (ELSEVIER); Predicting the compressive strength of concrete containing metakaolin with different properties using ANN.[3]**

Metakaolin is the anhydrous calcined form of the clay mineral kaolinite the proposed. Artificial Neural Network has been used in this paper. ANN with the GMDH model outcomes confirmed the high performance of the proposed ANN in predicting the compressive strength of concrete containing MK. Cement Content, Water Content, and aggregates (FA &CA) & metakaolin were used as a parameters. Compressive strength of concrete containing MK has been predict in this paper and Predicting accuracy in 7 and 28-days compressive strength with an MSE of 0.002 and 0.0017 respectively was achieved.

4) A.Ashrafian, et al.2020 (ELSEVIER); Compressive strength of Foamed Cellular Lightweight Concrete simulation: New development of hybrid artificial intelligence model.[4]

Foamed Cellular Lightweight Concrete (FCLC) was used as a material to find the compressive strength and novel self-adaptive and formula-based model called Multivariate Adaptive Regression Splines Optimized using Water Cycle Algorithm (MARS-WCA) is proposed for modeling fc based on mixture proportion had been used. The predictability performance of the proposed model was validated against well-established predictive models including linear model (e.g., MLR) and non-linear models (e.g., ANN, SVR, MARS) models for characteristic strength of concrete (fc) prediction.

The result indicated the superiority of the standard MARS model in comparison with the other developed linear and non-linear models.

5) Darko, Amos Chan, Albert P.C Adabre et al. 2020 (ELSEVIER); Artificial intelligence in the AEC industry: Scientometric analysis and visualization of research activities.[5]

In this paper, the first comprehensive scientometric study appraising the state-of-the-art of research on AI-in-the-AECI is presented. It is very important because Artificial intelligence (AI) is playing a core role in the Fourth Industrial Revolution (Industry 4.0), i.e., the digitalization era, wherein intelligent systems and technologies are used to create an active connection between the physical and virtual (digital) worlds. The present study used the science mapping method to analyze the literature on AI-in-the-AECI.

There are some limitations:-

They have been qualitative and based on manual appraisals.

Existing review studies have had narrowed perspectives, focusing on limited applications or on specific AI methods.

There is some Research methodologies used in AI:-

1. Science mapping tools selection
2. Data collection
3. Scientometric techniques

Because of growing interest in research applying AI techniques/algorithms/concepts to AEC problems are future directions.

6) **K. B. Ramkumar et al.2020 (ELSEVIER); A Review on Performance of Self-Compacting Concrete – Use of Mineral Admixtures and Steel Fibres with Artificial Neural.[6]**

Self-compacting concrete (SCC) has high value for deformability and segregation resistance, moderate viscosity and smaller yield stress. SCC has less voids when the fluidity of the concrete is better. SCC is another sort of High Performance Concrete (HPC) with isolation resistance and brilliant deformability. It has no requirement of compaction and vibration. Investigations of this paper to understand the micro structural and mechanical characteristics of the SCC mixture which contains ground granulated blast-furnace slag (GGBS), FA and MK.

This paper focuses on undertaking a review of SCC along with fibre reinforcement and cement replacement materials along with the role of ANN in predicting the optimum composition of SCC.

The Error level prediction in ANN is very less compared to linear regression.

7) **T. Udaya Banu,N.P. Rajamane, P.O Awoyera et al. 2020 (ELSEVIER); Strength characterization of self cured concrete using AI tools.[7]**

Author use in this study Ordinary Portland cement 53 grade, Coarse aggregate, super-plasticizer Conplast SP 430.To predict Compressive, tensile & flexure strength of concrete using ANN Techniques (Levenberg-Marquardt (L-M) process and Bayesian regularization (B-R)).

The conclusion of this research came the Regression value for compressive strength 0.97428 (for LM) and 0.96573 (for B-R) Regression Value for tensile strength 0.92865 0.95625 respectively for LM and BR. Regression values for flexure strength of 0.97558 and 0.90612 respectively.

8) **Trilok Gupta, K.A. Patel et al. 2019 (ELSEVIER); Prediction of Mechanical Properties of Rubberized Concrete Exposed to Elevated Temperature Using ANN.[8]**

Due to scarcity of natural sand, waste rubber tyre can be an alternate ingredient for replacement of conventional fine aggregates in the production of concrete. In this paper. Artificial neural network (ANN) approach has been used to find the mechanical properties of rubberized concrete.

This study was designed with shown bellow parameters-

1. Three different water to cement ratios :- 0.35, 0.45 and 0.55,
2. Variation in rubber fibers content :- 0%, 5%, 10%, 15%, 20% and 25%,
3. Elevated temperature:-150 °C, 300 °C, 450 °C, 600 °C and 750 °C
4. Exposure duration: - 30 min, 60 min and 120min.

Mean square error (MSE), root mean square error (RMSE),coefficient of correlation (R), average absolute deviation (AAD), coefficient of variation (COV) and sum of squared errors (SSE) are 0.000924, 0.03009, 0.992376, 6.074966, 7.998916 and 0.044256 respectively.

9) Ali Behnood, Emadaldin Mohammadi Golafshani 2018 (ELSEVIER); Predicting the compressive strength of silica fume concrete using hybrid artificial neural network with multi-objective grey wolves.[9]

Author studied compressive strength when silica fume as a partial replacement for OPC. Silica fume as a partial replacement for have many advantages like- reduced pressure on natural resources, reduced CO2 footprint and improved mechanical and durability properties of concrete. Silica Fume (SF), as one of the most widely used Supplementary Cementitious Materials (SCM), is a by-product of the smelting process in the silicon and ferrosilicon industry.

Hybrid artificial neural network with multi-objective grey wolves (MOGWO) has been used to Predicting the compressive strength of silica fume concrete. It was considered as a two-objective optimization problem. SF is considered as a super-fine SCM with an average particle size of less than 1μm.

The dataset used in their study included the experimental results had 48 concrete mixtures tested in their own laboratory. In this study, 70%, 15% and 15% of the collected data records were randomly selected and used for training, validating and testing the model respectively. It shows an acceptable performance with high accuracy and R value of 0.9617 for all data.

10) Akpinar & Adnan Khashman(2018) (ELSEVIER); Intelligent classification system for concrete Compressive Strength.[10]

Concrete elements of varying compressive strength classes and qualities, are required to be used for different purposes and under different environmental conditions so it is very important to know the intelligent classification system for concrete compressive strength.

The grade of the concrete dependent on many non-linear factors and it is often conventionally determined by using civil engineering methods involving the destruction of concrete samples. This study aims to propose a novel ANN approach for the concrete's compressive strength studies. The authors of this study would like to propose a model that will carry out "classification" of the determined strength values, as "low", "normal" and high".

The simulation was written in C-language and the implementation of the ANN model was carried out using a 3.2 GHz PC with 4GB of RAM, Windows 10 OS and Borland C++ compiler.

The overall correct classification result (CCR) value was 84.96% for 100,000 iterations. This study has innovatively suggested relatively much wider ranges of training periods, including the options of 100,000 and 400,000 iterations, in addition to the short training period alternative including 20,000 iterations.

Author summarized for this paper as:-

1. Merging the field of artificial intelligence with civil engineering applications.
2. Using a large dataset of 1030 cases.
3. Investigating learning method duration and establishing an optimum duration range.
4. Using binary coding to represent the single value reading of compressive strength.

NOTE:-Further works will involve adding more input attributes and investigating their effects on compressive strength classification

11) Sanjukta Sahoo, Trupti Ranjan Mahapatra 2018 (ESEVIER); ANN Modeling to study strength loss of Fly Ash Concrete against Long term Sulphate Attack.[11]

Author use commercially available ordinary Portland cement (43 grades) and class F fly ash collected from National Thermal Power Corporation (NTPC), Kaniha, were used in this study& aggregate and admixtures (poly carboxylic based super plasticizer) and the high sulphate soils, ground water and industrial waste water. He studied strength loss of Fly Ash Concrete against Long term Sulphate Attack and using ANN technique found Concrete Specimens Regression parameter are- Regression for Control Concrete (CC) Low Fly ash concrete(LFC), High Fly ash concrete(HFC) for water curing age at 28 days ,90 days & 180 days came more than 95%.

12) Henri Van Damme 2018 (ELSEVIER); Concrete material science: Past, present, and future innovations.[12]

Concrete facing tremendous challenges in terms of environmental impact, financial needs, societal acceptance and image. The exploration of radical changes in three aspects of

Concrete use basically:-

1. Reinforcement
2. Binder content
3. Implementation methods.

Few innovations like:-

1. Rebar-free reinforcement using non-convex granular media.
2. Compression-optimized concrete structures, using topology optimization, architectural geometry, and 3D-printing or origami-patterned formworks.
3. Truly digital concrete through the coupling of massive data collection and deep learning.

Author studied:-

1. Concrete: Material, system and icon.
2. Reinforced concrete.
3. Concrete formulation: The art of packing, flowing, and gluing grains.
4. Towards radical changes.

13) **Hadi Salehi, Rigoberto Burgueno 2018 (ELSEVIER); Emerging artificial intelligence methods in structural engineering.[13]**

The term “AI” was introduced at a workshop held in Dartmouth college in 1956Artificial intelligence (AI) is proving to be an efficient alternative approach to classical modeling techniques. AI refers to the branch of computer science that develops machines and software with human like intelligence. AI-based solutions are good alternatives to determine engineering design parameters when testing is not possible. different AI techniques, machine learning (ML), pattern recognition (PR), and deep learning (DL) have recently acquired considerable attention and are establishing themselves as a new class of intelligent methods for use in structural engineering.

Objective of this paper is to summarize techniques concerning applications of the noted AI methods in structural engineering developed over the last decade.

1. ML
2. PR
3. DL

Several terms are used in artificial intelligence which should know about that for easy understanding i.e.

1. Machine intelligence :- ML is often considered a synonym of AI
2. Cognitive computing: - CC able to solve problems in a form mimicking humans thinking and reasoning. It has an ability to interpret big data, dynamic training and adaptive learning.

Artificial intelligence in civil and structural engineering”, “pattern recognition structural Engineering”, “machine learning structural engineering”, “deep learning structural engineering”, “convolutional neural networks structural engineering”, and “computational intelligence” were used to search the databases.

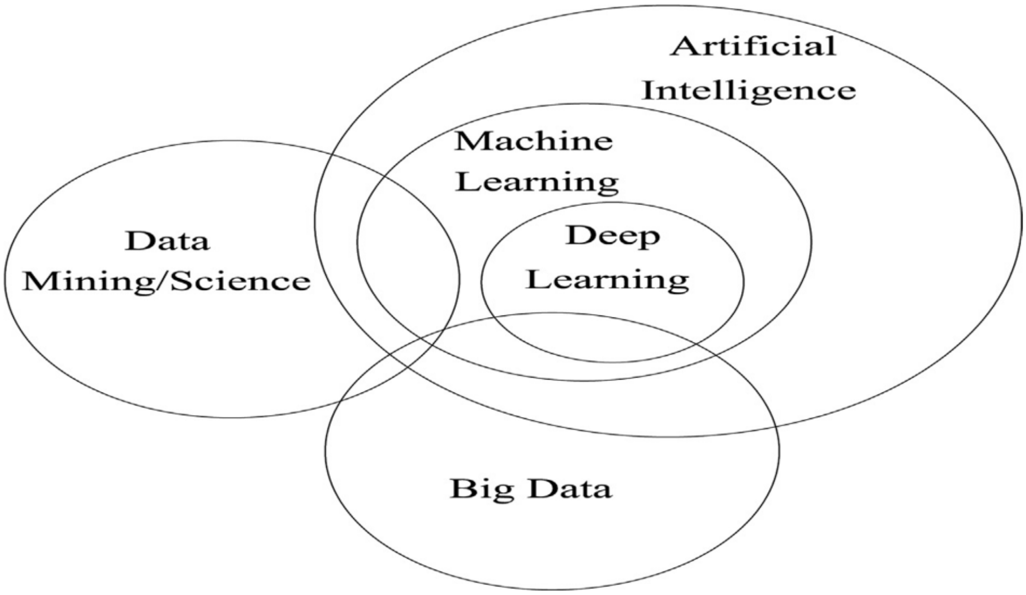


Fig. 2.1

Future Directions:-

The following sub-sections discuss future directions-

1. Data-driven SHM systems with self-powered sensing technology
2. Vision-based SHM systems and computational mechanics
3. SHM systems with IoT
4. Smart cities with IoT

Conclusions of this paper is the numerous AI methods, pattern recognition (PR), machine learning (ML), and deep learning (DL) have been increasingly adapted and used for SHM and damage identification, optimization, modeling concrete properties, structural identification, earthquake engineering etc.

14) M.R. Khosravani et al. 2018 (ELSEVIER); Prediction of dynamic properties of Ultra-High performance concrete by an artificial intelligence approach.[14]

Author use ultra-high performance concrete. It is new generation of concrete which exhibits higher strength and improved performance compared with traditional concrete. CBR methodology has been used in this paper to predict dynamic properties of UHPC. These predicted dynamic properties were-

1. Elastic modulus
2. Compressive strength
3. Tensile Strength

Note: - All under high rate of loading.

The high strain rate in the experimental practice on the UHPC material can be obtained by direct impact on the specimen, dropping of weight or employing split Hopkinson pressure bar (SHPB) device. Dynamic mechanical properties of UHPC materials and its variants are mainly determined through three experiments via SHPB:

1. Spalling test
2. Compression test
3. Brazilian test.

The prediction accuracy of this system is 81.5%.

15) Diab, Ahmed M. Diab,Hafez E.Elyamany, et al. 2014(AE Journal): Prediction of concrete compressive strength due to long term sulfate attack using neural network.[15]

Author divided this theory in two two phases-

Phase 1:- The validation of neural network to predict mortar and Concrete properties due to sulfate attack.

Phase 2:- Assessment of concrete compressive strength up to 200 years due to sulfate attack was considered.

The inputs of this studied were cement content, water cement ratio, C3A content, and sulfate concentration to predict the compressive strength loss after any certain age and sulfate concentration for different concrete compositions.

Parameters used in this paper are-

1. Water-to-binder ratio
2. Binder sand ratio
3. Metakaolin percentage
4. Age.

The used data were collected from 38 different documented published papers. Among those, 2000 records were used for training, testing, and validating phases of neural network models.

Result:- Prediction in this paper was done by Interpolation regression of concrete compressive strength using ANN.

The great performance to predict concrete properties subjected to sulfate attack where the minimum value of Regration R^2= 0.942.

16) **J.-s. chou , A.D. Pham (2013); Enhanced artificial intelligence for ensemble approach to predicting high performance concrete compressive strength.[16]**

The compressive strength of high performance concrete (HPC) is a highly nonlinear function of the proportions of its ingredients.This work evaluates the efficacy of ensemble models by comparing individual numerical models in terms of their performance in predicting the compressive strength of HPC.Since conventional material models, such those used to model the compressive strength of HPC, perform poorly in complex non-linear systems, scholars are constantly seeking to enhance prediction tools.

The proposed prediction and ensemble techniques are used to analysis of high performance concrete compressive strength.

Result:-

1. Prediction performance (R>93.3%)
2. Improved error rates from 4.2% from 69.7%.

17) **S. M. Mousavi, et al. (2011); A new predictive model for compressive strength of HPC using gene expression programming.[17]**

In this paper gene expression programming (GEP) is utilized to derive a new model for the prediction compressive strength of high performance concrete (HPC) mixes.

Author used these parameter for achieve own aim with the help of GEN Programming.

1. Water
2. Cement

3. Blast furnace
4. Slag
5. Fly ash
6. Super plasticizer
7. Coarse aggregate
8. Fine aggregate
9. Age of specimens

Conclusion: - Due to nonlinearity in the compressive strength behavior, the nonlinear GEP model produces better outcomes than the regression-based models.

18) B.K Raghu Prasad et al.(2008) (ELSEVIER); Prediction of compressive strength of SCC and HPC with high volume fly ash using ANN.[18]

An artificial neural network (ANN) is presented to predict a 28-day compressive strength of a normal and high strength self compacting concrete (SCC) and high performance concrete (HPC) with high volume fly ash.

It has excellent deformability and segregation resistance.

To predict compressive strength & slump SSC & HPC with the use of ANN technique.

In this paper some parameter were consider ie. Cement content, water/cement, water/binder, water/powder, fine aggregate/powder, coarse aggregate/powder, high range water reducer/powder, fly ash/binder and silica/binder ratio.

Result:-

Predicting the compressive strength of the training mixture is satisfactory with R2 = 0.92.

Slump value of the training mixture is satisfactory with R2 = 0.86.

19) D. Fan et al.(2021) (ELSEVIER); Precise design and characteristics prediction of Ultra-High Performance Concrete (UHPC) based on artificial intelligence techniques.[19]

Material used in this paper are Ultra-High Performance Concrete (UHPC) [Ordinary Portland Cement (OPC), Limestone Powder (LP), and Silica Fume (SF), River Sand (RS)]. To find the mechanical properties and durability of Ultra-High Performance

Concrete (UHPC). AI based technique Modified Andreasen and Andersen (MAA) model and Genetic Algorithm based Artificial Neural Network (GAANN) technique are used to predict these properties. And the result is found that Correlation coefficients (R2) = 0.95.

20) R. Ince (2003)(ELSEVIER); Prediction of fracture parameters of concrete by Artificial Neural Networks.[20]

Modeling of material behavior generally involves the development of a mathematical model derived from observations and experimental data.The main benefit in using an ANN approach is that the network is built directly from experimental data using the self-organizing capabilities of the ANN. In this paper the Two-Parameter Model (TPM) in the fracture of cementatious materials is modeled with a back-propagation ANN. In this study some Parameters are used like compressive strength, maximum aggregate size & water - cement ratio.These approaches primarily involve the fictitious crack model, the crack band model the Two-Parameter Model (TPM), the effective crack model, the size effect model and the peak load method. Contrary to LEFM, in which a single fracture parameter is used such as the critical stress intensity factor, these models need at least two experimentally determined fracture parameters to characterize failure of concrete structures.

Result:- The critical stress intensity factor as a fracture parameter of TPM depends on the compressive strength of a cementatious material.

2.2 INFERENCE

1) In self-curing concrete, ANN technique was used to determine the chloride penetration resistance and compressive strength with accuracy of 95%.
2) Compressive strength & Flexure strength of SCC and FCLC were examined using MLP and MLR, ANN respectively.
3) IN UHPC & HPC, MAA and CBR & GEP respectively were used to predict mechanical properties and durability of concrete.
4) Silica fume concrete used the ANN technology to investigate the compressive strength with regression coefficient greater than 0.96.

5) Waste rubber tire was used in place of fine sand to predict the mechanical properties of Rubberized Concrete Exposed to Elevated Temperature Using ANN.
6) Compressive strength of concrete containing metakaolin with different properties using ANN was also investigated.
7) Performance of Self-Compacting Concrete were integrated with the use of Mineral Admixtures and Steel Fibres. Artificial Neural Network Application using Self-Compacting Concrete, Admixtures (Polycarboxylate ether 0.2%), Steel Fibres by MLP technique to examine the compressive strength and flexural strength of concrete.
8) Mechanical properties of UHPC & Rubberized concrete has been predicted by using CBR, MAA, ANN & GAANN techniques respectively.

2.3 RESEARCH GAP

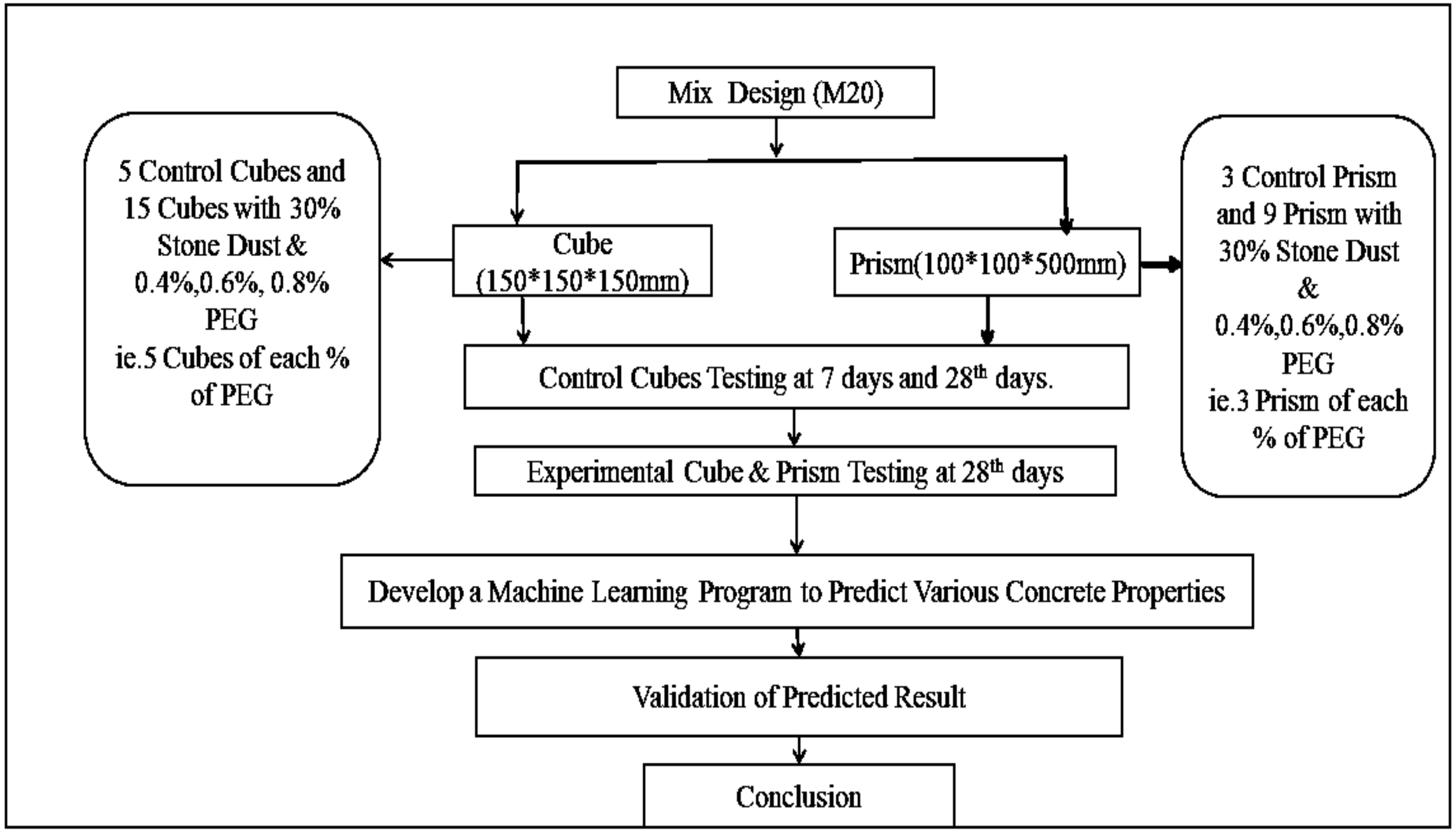
1. Rare work on flexural strength & tensile strength has been done on self curing concrete using machine learning algorithm.
2. A little work has been done yet to predict the compressive strength of self curing concrete with partial replacement of stone dust using AI technique.
3. Durability of self-curing concrete with stone dust partial replacement has been studied to predicted rarely using AI technique.

2.4 OBJECTIVE

Development of machine learning algorithm to predict the following properties of partial replaced stone dust self-curing concrete.

1. Compressive strength of concrete.
2. Flexure strength of concrete.

2.5 Methodology



Pathway of Research

Chapter 3

Experimental Study

3.1 Sieve Analysis of Course Aggregate

Mechanical sieving is the most commonly used method to determine the grading, i.e., particle size distribution, of course aggregate.

Basically, the sieving operation attempts to divide a sample of aggregate into fractions, each consisting of particles within specific size limits which is shown in Table no.-3.1

Table no.-3.1

Determination of Partical Size Distribution of Course Aggregate(IS 383 : 2016)

Total Weight of Aggregate = 5000 grams

IS Sieve Size(mm)	Weight Aggregate Retained				% age of total weight retained	Cumulative % age of total weight retained	%age Passing
	Determination No.						
	(i)	(ii)	(iii)	Avg.			
20	-	-	-	-	-	-	100
16	659	680	682	673.667	13.473	13.473	86.527
12.5	1352	1347	1363	1354.000	27.080	40.553	59.447
10	671	666	674	670.333	13.407	53.960	46.040
4.75	2209	2205	2220	2211.333	44.227	98.187	1.813
2.36	88	76	75	79.667	1.593	99.780	0.220

Conclusion : % Passing for Graded Aggregate of Nominal Size= 20mm.

3.2 Sieve Analysis of Fine Aggregate (Sand)

Mechanical sieving is the most commonly used method to determine the grading, i.e., particle size distribution, of fine aggregates (sand).

Basically, the sieving operation attempts to divide a sample of aggregate into fractions, each consisting of particles within specific size limits which is shown in Table no.-3.2

Table no.-3.2

Determination of Partical Size Distribution of Fine Aggregate (Sand)(IS 383 : 2016)

Total Weight of Aggregate = 1000 grms						
IS Sieve Size(mm)	**Weight Aggregate Retained**			**% age of total weight retained**	**Cumulative % age of total weight retained(CR)**	**%age Passing=100-CR**
	Determination No.					
	(i)	**(ii)**	**Avg.**			
10	0	0	0	0	0	100
4.75	68	72	70.000	7.00	7	93.000
2.36	129	135	132.000	13.20	20.20	79.800
1.18	231	181	206.000	20.60	40.80	59.200
600µ	176	194	185.000	18.50	59.30	40.700
300µ	314	325	319.500	31.95	91.25	8.750
150µ	61	55	58.000	5.80	97.05	2.950

Conclusion : Sand Corresponds to Grading Zone II

3.3 Sieve Analysis of Fine Aggregate (Stone Dust)

Mechanical sieving is the most commonly used method to determine the grading, i.e., particle size distribution, of fine aggregate (Stone Dust).

Basically, the sieving operation attempts to divide a sample of aggregate into fractions, each consisting of particles within specific size limits which is shown in Table no.-3.3

Table no.-3.3

Determination of Partical Size Distribution of Fine Aggregate(Stone Dust)(IS 383 : 2016)

Total Weight of Aggregate = 1000 grms						
IS Sieve Size(mm)	**Weight Aggregate Retained**			**% age of total weight retained**	**Cumulative % age of total weight retained(CR)**	**%age Passing=100-CR**
	Determination No.					
	(i)	**(ii)**	**Avg.**			
4.75	0	0	0.00	0.00	0.00	100.00
2.36	107	135	121.00	12.10	12.10	87.90
1.18	260	181	220.50	22.05	34.15	65.85
600µ	192	194	193.00	19.30	53.45	46.55
300µ	204	325	264.50	26.45	79.90	20.10
150µ	146	55	100.50	10.05	89.95	10.05
Pan	73	17	45.00	4.50	94.45	5.55

Conclusion : Sand corresponds to Grading Zone II

3.4 SPECIFIC GRAVITY & WATER ABSORPTION

3.4.1. Determination of Specific Gravity & Water Absorption of Course Aggregate (IS 2386 Part III: 1963)

In Ordinary Portland Cement Concrete, the specific gravity of the aggregate is used in calculating the percentage of voids and the solid volume of aggregates in computations of yield.

The water absorption is an important in determining the net water-cement ratio in the concrete mix.

Experiment of these two properties of course aggregate which is shown in Table.

Table no. 3.4.1

S. No.	**Descriptions**	**Sample**	
		i	**ii**
a	Weight of Basket & sample in water after 25 jolted (A1)	2293	2315
b	Weight of Empty Basket in Water (in grms) (A2)	1000	1000
c	Weight of Saturated Aggregate in Water After 24 hrs. (in grms.) (A)	1293	1305
d	Weight of Saturated Surface-Dry Aggregate in Air (in grms); (B)	2087	2082
e	Weight of Oven-Dry Aggregate after 24 hrs in Air (in grms); (C)	2082	2078
f	Specific Gravity = C/(B-A)	2.62	2.67
g	Apparent Specific Gravity = C/(C-A)	2.64	2.69
h	Water Absorption (% of dry weight) = 100*(B-C)/C	0.24	0.19
Average Value		**Specific Gravity**	**2.648**
		Apparent Specific Gravity	**2.66**
		Water Absorption	**0.216**

3.4.2 Determination of Specific Gravity & Water Absorption of Fine Aggregate (Sand) (IS 2386 Part III : 1963)

In Ordinary Portland Cement Concrete, the specific gravity of the aggregate is used in calculating the percentage of voids and the solid volume of aggregates in computations of yield.

The water absorption is an important in determining the net water-cement ratio in the concrete mix.

Experiment of these two properties of fine aggregate (sand) which is shown in Table. Table no. 3.4.2

S. No.	Descriptions	Sample	
		i	**ii**
A	Weight of sample taken (in grms)	511	513
B	Weight of Saturated Surface-Dry Sample Aggregate (in grms); (A)	518	519
C	Weight of Pycnometer or Gas Jar Containing sample and Filled With Distilled Water (in grms); (B)	1819	1820
D	Weight of Pycnometer or Gas Jar Filled With Distilled Water (in grms); (C)	1500	1500
E	Weight of Oven-Dry Sample (in grms); (D)	509	511
F	Specific Gravity = D/(A-(B-C))	2.558	2.568
G	Apparent Specific Gravity = D/(D-(B-C))	2.679	2.675
H	Water Absorption (% of dry weight) = 100*(A-D)/D	1.768	1.566
Average Value		**Specific Gravity**	**2.562**
		Apparent Specific Gravity	**2.677**
		Water Absorption	**1.666**

3.4.3 Determination of Specific Gravity & Water Absorption of Fine Aggregate (Stone Dust)(IS 2386 Part III : 1963)

In Ordinary Portland Cement Concrete, the specific gravity of the aggregate is used in calculating the percentage of voids and the solid volume of aggregates in computations of yield.

The water absorption is an important in determining the net water-cement ratio in the concrete mix.

Experiment of these two properties of fine aggregate (stone dust) which is shown in Table.

Table no. 3.4.3

S. No.	**Descriptions**	**Sample**	
		i	**ii**
A	Weight of sample taken (in grams)	525	530
B	Weight of Saturated Surface-Dry Sample Aggregate (in grams); (A)	521	526
C	Weight of Pycnometer or Gas Jar Containing sample and Filled With Distilled Water (in grams); (B)	1818	1822
D	Weight of Pycnometer or Gas Jar Filled With Distilled Water (in grms); (C)	1500	1500
E	Weight of Oven-Dry Sample (in grams); (D)	495	501
F	Specific Gravity = D/(A-(B-C))	2.44	2.46
G	Apparent Specific Gravity = D/(D-(B-C))	2.80	2.80
H	Water Absorption (% of dry weight) = 100*(A-D)/D	5.25	4.99
Average Value		**Specific Gravity**	**2.447**
		Apparent Specific Gravity	**2.80**
		Water Absorption	**5.346**

3.5 CONTROL MIX DESIGN

A-0 The mix proportioning for a concrete of M20 grade without PEG & Stone Dust is given below in **A-1** to **A-12**.

A-1 STIPULATIONS FOR PROPORTIONING

a) Grade designation: M20

b) Type of cement: PPC conforming to IS 1489 (Part 1)

c) Maximum nominal size of aggregate: 20 mm

d) Minimum cement content and maximum water-cement ratio to be adopted and/or: Moderate (RCC)

(For reinforced concrete) Exposure conditions as per Table 3 and Table 5 of IS 456

e) Workability: 75 mm (slump)

f) Method of concrete placing: Hand Placing

g) Degree of site control: Good

h) Type of aggregate: Crushed angular aggregate

j) Maximum cement content not including fly ash: 450 kg/m^3

k) Chemical admixture type: PEG

A-2 TEST DATA FOR MATERIALS

1. Cement used : PPC
2. Specific gravity of
   a) Specific gravity of cement : 3.15
   b) Coarse aggregate (at saturated surface dry (SSD) Condition) : 2.648
   c) Fine aggregate (Sand) (at saturated surface dry (SSD) Condition) : 2.562

4. Water absorption
   a) Coarse aggregate : 0.216%
   b) Fine aggregate(Sand) : 1.666%

5. Moisture content of aggregate [As per IS 2386 (Part 3)]

a) Coarse aggregate : Nil

b) Fine aggregate : Nil

6. Sieve analysis: (As per IS 383:2016)

a) Coarse aggregate (T-7) : Graded Aggregate of nominal size 20mm.

b) Fine aggregate (T-9)(Both Sand & Stone Dust) : Grading Zone II

A-3 TARGET STRENGTH FOR MIX PROPORTIONING

$f'ck = fck + 1.65\ S$

or

$f'ck = fck + X$

Whichever is higher.

Where,

f'ck = Target average compressive strength at 28 days,

fck = Characteristic compressive strength at 28 days,

S = Standard deviation

X = Factor based on grade of concrete.

(From Table 2, standard deviation, (S) = 4 N/mm^2 & From Table 1, X = 5.5)

Therefore, target strength using both equations, that is,

a) $f'ck = fck + 1.65\ S$

$f'ck = 20 + 1.65 \times 4 = 26.60\ N/mm^2$

b) $f'ck = fck + 5.5$

$f'ck = 20 + 5.5 = 25.5\ N/mm^2$

The higher value is to be adopted.

Therefore, target strength will be 26.60 N/mm^2.

A-4 APPROXIMATE AIR CONTENT

The approximate amount of entrapped air to be expected in normal (non-air-entrained) concrete is 1.0 % for 20 mm nominal maximum size of aggregate.(From Table 3)

A-5 SELECTION OF WATER-CEMENT RATIO

From Fig. 1, the free water-cement ratio required for the target strength of 31.60 N/mm^2 is 0.5 for OPC 43 grade curve. (For PPC, the strength corresponding to OPC 43 grade curve is assumed for the trial).

A-6 SELECTION OF WATER CONTENT

From Table 4, water content = 186 kg (for 50 mm slump) for 20 mm aggregate.

Estimated water content for 75 mm slump

= 186 + (3/100)*186

= 191.58 kg.

A-7 CALCULATION OF CEMENT CONTENT

Water-cement ratio = 0.5

Cement content = 191.58/0.5

Cement content = 383.16 kg/m^3

(From Table 5 of IS 456, minimum cement content for ‘Moderate’ exposure condition = 300 kg/m^3. Here 383.16 kg/m^3 > 300 kg/m^3)

Hence O.K.

A-8 PROPORTION OF VOLUME OF COARSE AGGREGATE AND FINE AGGREGETE CONTENT

From Table 5, the proportionate volume of coarse aggregate corresponding to 20 mm size aggregate and fine aggregate (Zone II) for water-cement ratio of 0.50 = 0.62.

Fine aggregate content = 1–0.62= 0.38.

A-9 MIX CALCULATIONS

The mix calculations per unit volume of concrete shall be as follows:

a) Total Volume = 1 m^3

b) Volume of entrapped air in wet concrete = 0.01 m^3

c) Volume of cement = (Mass of cement/Specific gravity of cement)*(1/1000).

   Volume of cement = (383.16/3.15)*(1/1000) =0.12164m^3

d) Volume of water = (Mass of water/Specific gravity of water)*(1/1000).

   Volume of water = (191.58/1)*(1/1000) =0.19158 m^3.

e) Volume of all in aggregate = [(a-b)-(c+d)]

   = [(1-0.01) – (0.12164 + 0.19158)]

   = 0.67678 m^3

f) Mass of Coarse Aggregate

   = Volume of all in aggregate × proportion of volume of CA × Specific gravity of CA × 1000

   = 0.67678×0.62×2.648 × 1000

   = 1111.110333 kg.

g) Mass of Fine Aggregate

   = Volume of all in aggregate × proportion of volume of Sand × Specific gravity of Sand × 1000

   Mass of Sand = 0.67678×0.38×2.562×1000

   = 658.8859 kg.

A-10 MIX PROPORTIONS FOR TRIAL NUMBER 1

a. Cement = 383.16 kg/m^3
b. Water = 191.58 kg/m^3
c. Sand (SSD) = 658.8859 kg/m^3
d. Coarse aggregate (SSD) = 1111.110333 kg/m^3
e. Free water-cement ratio = 0.5

A-11 ADJUSTMENT ON WATER, FINE AGGREGATE AND COARSE AGGREGATE (IF THE COARSE AND FINE AGGREGATE IS IN DRY CONDITION)

i. Fine Aggregate (Dry) = Mass of Sand in SSD condition/(1+ Water Absorption of Sand/100)

Sand (Dry) = 658.8859/(1+1.666/100) = 648.0887 kg/m³.

ii. Coarse Aggregate (Dry) = Mass of CA in SSD condition/(1+ WA of CA/100)

CA (Dry) = 1111.110333/(1+ 0.216/100) = 1108.715508 kg/m³.

The extra water to be added for absorption by coarse and fine aggregate,

1) For coarse aggregate = Mass of CA in SSD condition –mass of CA in dry condition

= 1111.110333–1108.715508 =2.39483 kg/m³

2) For fine aggregate

For; Sand = Mass of Sand in SSD condition – mass of Sand in dry condition

= 658.8859–648.0887=10.7972 kg/m³

The estimated requirement for added water,

Therefore, becomes

= 191.58+2.39483+10.7972= 204.77203 kg/m³

A-12 MIX PROPORTIONS AFTER ADUSTMENT FOR DRY AGGREGATES

a. Cement = 383.16 kg/m³
b. Water = 204.77203kg/m³
c. Sand (SSD) = 648.0887 kg/m³
d. Coarse aggregate (SSD) = 1108.715508 kg/m³
e. Free water-cement ratio = 0.5

3.6 EXPERIMENTAL MIX DESIGN 1

A-0 An example illustrating the mix proportioning for a concrete of M20 grade with 0.4% PEG & 30% Stone Dust is given below in A-1 to A-12.

A-1 STIPULATIONS FOR PROPORTIONING

a) Grade designation: M20

b) Type of cement: PPC conforming to IS 1489 (Part 1)

c) Maximum nominal size of aggregate: 20 mm

d) Minimum cement content and maximum water-cement ratio to be adopted and/or: Moderate (RCC)

(For reinforced concrete) Exposure conditions as per Table 3 and Table 5 of IS 456

e) Workability: 75 mm (slump)

f) Method of concrete placing: Hand Placing

g) Degree of site control: Good

h) Type of aggregate: Crushed angular aggregate

j) Maximum cement content not including fly ash: 450 kg/m3

k) Chemical admixture type: PEG

A-2 TEST DATA FOR MATERIALS

1) Cement used : PPC
2) Chemical admixture : PEG
3) Specific gravity of
    a) Specific gravity of cement : 3.15
    b) Coarse aggregate (at saturated surface dry (SSD) Condition) : 2.65
    c) Fine aggregate (Sand) (at saturated surface dry (SSD) Condition): 2.56
    d) Fine aggregate(Stone Dust) (at saturated surface dry (SSD) Condition :2.45
    e) Chemical admixture(PEG) : 1.1254
4) Water absorption
    a) Coarse aggregate : 0.216%

b) Fine aggregate(Sand) : 1.666%

c) Fine aggregate(Stone Dust) : 5.346%

5) Moisture content of aggregate [As per IS 2386 (Part 3)]

a) Coarse aggregate : Nil

b) Fine aggregate : Nil

6) Sieve analysis: (As per IS 383:2016)

a) Coarse aggregate (T-7) : Graded Aggregate of nominal size 20mm.

b) Fine aggregate (T-9) (Both Sand & Stone Dust) : Grading Zone II

A-3 TARGET STRENGTH FOR MIX PROPORTIONING

$f'ck = fck + 1.65\ S$

or

$f'ck = fck + X$

Whichever is higher.

where

$f'ck$ = Target average compressive strength at 28 days,

fck = Characteristic compressive strength at 28 days,

S = Standard deviation

X = Factor based on grade of concrete.

(From Table 2, standard deviation,(S) = 4 N/mm² & From Table 1, X = 5.5)

Therefore, target strength using both equations, that is,

a) $f'ck = fck + 1.65\ S$

$f'ck = 20 + 1.65 \times 4 = 26.60$ N/mm²

b) $f'ck = fck + 5.5$

$f'ck = 20 + 5.5 = 25.5$ N/mm²

The higher value is to be adopted.

Therefore, target strength will be 26.60 N/mm².

A-4 APPROXIMATE AIR CONTENT

The approximate amount of entrapped air to be expected in normal (non-air-entrained) concrete is 1.0 % for 20 mm nominal maximum size of aggregate.(From Table 3)

A-5 SELECTION OF WATER-CEMENT RATIO

From Fig. 1, the free water-cement ratio required for the target strength of 31.60 N/mm^2 is 0.5 for OPC 43 grade curve. (For PPC, the strength corresponding to OPC 43 grade curve is assumed for the trial).

A-6 SELECTION OF WATER CONTENT

From Table 4, water content = 186 kg (for 50 mm slump) for 20 mm aggregate.

Estimated water content for 75 mm slump

= 186 + (3/100)*186

= 191.58kg.

A-7 CALCULATION OF CEMENT CONTENT

Water-cement ratio = 0.5

Cement content = 191.58/0.5

Cement content = 383.16 kg/m^3

(From Table 5 of IS 456, minimum cement content for 'Moderate' exposure condition = 300 kg/m^3. Here 436 kg/m^3> 300 kg/m^3)

Hence O.K.

A-8 PROPORTION OF VOLUME OF COARSE AGGREGATE AND FINE AGGREGETE CONTENT

From Table 5, the proportionate volume of coarse aggregate corresponding to 20 mm size aggregate and fine aggregate (Zone II) for water-cement ratio of 0.50 = 0.62.

Therefore, corrected proportion of volume of-

Coarse aggregate for the water-cement ratio of 0.5=0.62

Fine aggregate content = 1–0.632= 0.38

Here, 30% Sand is replaced by Stone Dust

Final proportion of Sand= 0.266

Final proportion of Stone Dust= 0.114

A-9 MIX CALCULATIONS

The mix calculations per unit volume of concrete shall be as follows:

a) Total Volume = 1 m^3

b) Volume of entrapped air in wet concrete = 0.01 m^3

c) Volume of cement = (Mass of cement/Specific gravity of cement)*(1/1000).

   Volume of cement = (383.16/3.15)*(1/1000)=0.121634 m^3

d) Volume of water = (Mass of water/Specific gravity of water)*(1/1000).

   Volume of water = (191.58/1)*(1/1000) =0.19158 m^3.

e) Volume of chemical admixture PEG @ 0.4 percent by mass of cementitious material

   Volume of PEG = (Mass of chemical admixture / Specific gravity of admixture)*(1/ 1 000)

   Volume of PEG = (1.53264/1.1254)*(1/1000) = 0.00132 m^3.

f) Volume of all in aggregate = [(a-b)-(c+d+e)]

   Volume of all in aggregate = [(a-b)-(c+d+e)]

   = [(1-0.01) – (0.121634+0.192+0.00132)]

   = 0.675466 m^3

h) Mass of Coarse Aggregate= Volume of all in aggregate × proportion of volume of CA × Specific gravity of CA × 1000

   = 0.675466×0.62×2.648×1000

   = 1108.953 kg.

i) Mass of Fine Aggregate = Volume of all in aggregate × proportion of volume of Sand × Specific gravity of Sand × 1000

Mass of Sand = 0.675466×0.266×2.562×1000

= 460.32 kg.

j) Mass of Fine Aggregate = Volume of all in aggregate × proportion of volume of Stone Dust × Specific gravity of Stone Dust × 1000

Mass of Stone Dust = 0.675466×0.114×2.447153×1000

= 188.43843 kg.

A-10 MIX PROPORTIONS FOR TRIAL NUMBER 1

a. Cement = 383.16 kg/m³
b. Water = 191.58 kg/m³
c. Sand (SSD) = 460.32 kg/m³
d. Stone Dust (SSD) = 188.43843 kg/m³
e. Coarse aggregate (SSD) = 1108.953 kg/m³
f. Free water-cement ratio = 0.5

A-11 ADJUSTMENT ON WATER, FINE AGGREGATE AND COARSE AGGREGATE (IF THE COARSE AND FINE AGGREGATE IS IN DRY CONDITION)

i. Fine Aggregate (Dry) = Mass of Sand in SSD condition/(1+ Water Absorptionof Sand/100)
Sand (Dry) = 460.32 /(1+ 1.667/100)=452.7767 kg/m³.

ii. Fine Aggregate (Dry) = Mass of Stone Dust in SSD condition/(1+ WA of Stone Dust/100)
Stone Dust (Dry) = 188.43843/(1+ 5.346/100)=178.8757 kg/m³.

iii. Coarse Aggregate (Dry) = Mass of CA in SSD condition/(1+ WA of CA/100)
CA (Dry) = 1108.953/(1+ 0.216/100)=1106.5628kg/m³.

The extra water to be added for absorption by coarse and fine aggregate,

1) For coarse aggregate= Mass of CA in SSD condition –mass of CA in dry condition

= 1108.953 –1106.5628 = 2.3902kg/m³

2) For fine aggregate

i. For Sand = Mass of Sand in SSD condition – mass of Sand in dry condition
= 460.32-452.7767=7.5433kg/m³

ii. For Stone Dust = Mass of Stone Dust in SSD condition – mass of Stone Dust in dry condition
= 188.4384-178.8757 =9.5627kg/m³

The estimated requirement for added water, Therefore, becomes

= 191.58+2.3902+7.5433+9.5627=211.0762 kg/m³

A-12 MIX PROPORTIONS AFTER ADUSTMENT FOR DRY AGGREGATES

a. Cement = 383.16 kg/m³
b. Water = 211.07 kg/m³
c. Sand (SSD) = 452.7767 kg/m³
d. Stone Dust (SSD) =179.2603kg/m³
e. Coarse aggregate (SSD) = 1106.5628 kg/m³
f. PEG @ 0.4% by mass of cementitious material = ((0.4/100)*383.16)/1.1254= 1.36 lit/m³.
g. Free water-cement ratio = 0.5

3.7 EXPERIMENTAL MIX DESIGN 2

A-0 An example illustrating the mix proportioning for a concrete of M20 grade with 0.6% PEG & 30% Stone Dust is given below in A-1 to A-12.

A-1 STIPULATIONS FOR PROPORTIONING

a) Grade designation: M20

b) Type of cement: PPC conforming to IS 1489 (Part 1)

c) Maximum nominal size of aggregate: 20 mm

d) Minimum cement content and maximum water-cement ratio to be adopted and/or: Moderate (RCC)

(For reinforced concrete) Exposure conditions as per Table 3 and Table 5 of IS 456

e) Workability: 75 mm (slump)

f) Method of concrete placing: Hand Placing

g) Degree of site control: Good

h) Type of aggregate: Crushed angular aggregate

j) Maximum cement content not including fly ash: 450 kg/m3

k) Chemical admixture type: PEG

A-2 TEST DATA FOR MATERIALS

1) Cement used : PPC
2) Chemical admixture : PEG
3) Specific gravity of
    a) Specific gravity of cement : 3.15
    b) Coarse aggregate (at saturated surface dry (SSD) Condition) : 2.65
    c) Fine aggregate (Sand) (at saturated surface dry (SSD) Condition : 2.56
    d) Fine aggregate(Stone Dust in SSD Condition) : 2.45
    e) Chemical admixture(PEG) :1.1254
4) Water absorption
    a) Coarse aggregate : 0.216%
    b) Fine aggregate(Sand) : 1.666%
    c) Fine aggregate(Stone Dust) : 5.346%

5) Moisture content of aggregate [As per IS 2386 (Part 3)]
    a) Coarse aggregate : Nil
    b) Fine aggregate : Nil

6) Sieve analysis: (As per IS 383:2016)
    a) Coarse aggregate (T-7): Graded Aggregate of nominal size 20mm.
    b) Fine aggregate (T-9) (Both Sand & Stone Dust) : Grading Zone II

A-3 TARGET STRENGTH FOR MIX PROPORTIONING

f’ck = fck+1.65 S

or

f’ck = fck + X

Whichever is higher.

where

f’ck = Target average compressive strength at 28 days,

fck = Characteristic compressive strength at 28 days,

S = Standard deviation

X = Factor based on grade of concrete.

(From Table 2, standard deviation,(S) = 4 N/mm^2 & From Table 1, X = 5.5)

Therefore, target strength using both equations, that is,

a) f’ck = fck+1.65 S

f’ck = 20 +1.65 × 4 = 26.60 N/mm^2

b) f’ck = fck + 5.5

f’ck = 20 + 5.5 = 25.5 N/mm^2

The higher value is to be adopted.

Therefore, target strength will be 26.60 N/mm^2.

A-4 APPROXIMATE AIR CONTENT

The approximate amount of entrapped air to be expected in normal (non-air-entrained) concrete is 1.0 % for 20 mm nominal maximum size of aggregate.(From Table 3)

A-5 SELECTION OF WATER-CEMENT RATIO

From Fig. 1, the free water-cement ratio required for the target strength of 31.60 N/mm^2 is 0.5 for OPC 43 grade curve. (For PPC, the strength corresponding to OPC 43 grade curve is assumed for the trial).

A-6 SELECTION OF WATER CONTENT

From Table 4, water content = 186 kg (for 50 mm slump) for 20 mm aggregate.

Estimated water content for 75 mm slump

= 186 + (3/100)*186

= 191.58kg.

A-7 CALCULATION OF CEMENT CONTENT

Water-cement ratio = 0.5

Cement content = 191.58/0.5

Cement content = 383.16 kg/m³

(From Table 5 of IS 456, minimum cement content for ‘Moderate’ exposure condition = 300 kg/m³. Here 436 kg/m³> 300 kg/m³)

Hence O.K.

A-8 PROPORTION OF VOLUME OF COARSE AGGREGATE AND FINE AGGREGETE CONTENT

From Table 5, the proportionate volume of coarse aggregate corresponding to 20 mm size aggregate and fine aggregate (Zone II) for water-cement ratio of 0.50 = 0.62.

Therefore, corrected proportion of volume of-

Coarse aggregate for the water-cement ratio of 0.5=0.62

Fine aggregate content = 1–0.632= 0.38

Here, 30% Sand is replaced by Stone Dust

Final proportion of Sand= 0.266

Final proportion of Stone Dust= 0.114

A-9 MIX CALCULATIONS

The mix calculations per unit volume of concrete shall be as follows:

1) Total Volume = 1 m³
2) Volume of entrapped air in wet concrete = 0.01 m³

3) Volume of cement = (Mass of cement/Specific gravity of cement)*(1/1000).

   Volume of cement = (383.16/3.15)*(1/1000)=0.121634 m^3

4) Volume of water = (Mass of water/Specific gravity of water)*(1/1000).

   Volume of water = (191.58/1)*(1/1000) =0.19158 m^3.

5) Volume of chemical admixture PEG @ 0.4 percent by mass of cementitious material Volume of PEG = (Mass of chemical admix. / Specific gravity of admixture)*(1/1000)

   Volume of PEG = (2.29896/1.1254)*(1/1000) = 0.002043m^3.

6) Volume of all in aggregate = [(a-b)-(c+d+e)]

   Volume of all in aggregate = [(a-b)-(c+d+e)]

   = [(1-0.01) – (0.121634+0.19158+0.002043)]

   = 0.6754743 m^3

7) Mass of Coarse Aggregate= Volume of all in aggregate × proportion of volume of CA × Specific gravity of CA × 1000

   = 0.6754743×0.62×2.648×1000

   = 1107.7661kg.

8) Mass of Fine Aggregate = Volume of all in aggregate × proportion of volume of Sand × Specific gravity of Sand × 1000

   Mass of Sand = 0.675743×0.266×2.562×1000

   = 460.5135 kg.

9) Mass of Fine Aggregate = Volume of all in aggregate × proportion of volume of Stone Dust × Specific gravity of Stone Dust × 1000

   Mass of Stone Dust = 0.675743×0.114×2.447153×1000

   = 188.5157kg.

A-10 MIX PROPORTIONS FOR TRIAL NUMBER 1

a) Cement = 383.16 kg/m^3
b) Water = 191.58 kg/m^3
c) Sand (SSD) = 460.5135 kg/m^3
d) Stone Dust (SSD) = 188.5157kg/m^3

e) Coarse aggregate (SSD) = 1107.766kg/m³

f) Free water-cement ratio = 0.5

A-11 ADJUSTMENT ON WATER, FINE AGGREGATE AND COARSE AGGREGATE (IF THE COARSE AND FINE AGGREGATE IS IN DRY CONDITION)

a) Fine Aggregate (Dry) = Mass of Sand in SSD condition/(1+ Water Absorption of Sand/100)

Sand (Dry) = 460.5135/(1+ 1.667/100)=452.4575 kg/m³.

b) Fine Aggregate (Dry) = Mass of Stone Dust in SSD condition/(1+ WA of Stone Dust/100)

Stone Dust (Dry) =188.5157/(1+ 5.346/100)=178.9491kg/m³.

c) Coarse Aggregate (Dry) = Mass of CA in SSD condition/(1+ WA of CA/100)

CA (Dry) = 1107.766/(1+ 0.216/100)=1105.378383 kg/m³.

The extra water to be added for absorption by coarse and fine aggregate,

1) For coarse aggregate= Mass of CA in SSD condition –mass of CA in dry condition

= 1107.766–1105.378383 = 2.3876 kg/m³

2) For fine aggregate

a) For Sand = Mass of Sand in SSD condition – mass of Sand in dry condition

= 460.5135-452.4575 =8.056kg/m³

b) For Stone Dust = Mass of Stone Dust in SSD condition – mass of Stone Dust in dry condition

= 188.5157-178.9491=9.5666 kg/m³

The estimated requirement for added water,

Therefore, becomes

= 191.58+2.3876+8.056+9.5666=211.5902 kg/m³

A-12 MIX PROPORTIONS AFTER ADUSTMENT FOR DRY AGGREGATES

a) Cement = 383.16 kg/m³

b) Water = 211.5902 kg/m³

c) Sand (SSD) = 452.4575 kg/m³

d) Stone Dust (SSD) =178.9491kg/m^3

e) Coarse aggregate (SSD) = 1105.378383 kg/m^3

f) PEG @ 0.6% by mass of cementitious material = ((0.6/100)*383.16)/1.1254= 2.0428 lit/m^3.

g) Free water-cement ratio = 0.5

3.8 EXPERIMENTAL MIX DESIGN 3

A-0 An example illustrating the mix proportioning for a concrete of M20 grade with 0.8% PEG & 30% Stone Dust is given below in A-1 to A-12.

A-1 STIPULATIONS FOR PROPORTIONING

a) Grade designation: M20

b) Type of cement: PPC conforming to IS 1489 (Part 1)

c) Maximum nominal size of aggregate: 20 mm

d) Minimum cement content and maximum water-cement ratio to be adopted and/or: Moderate (RCC)

(For reinforced concrete) Exposure conditions as per Table 3 and Table 5 of IS 456

e) Workability: 75 mm (slump)

f) Method of concrete placing: Hand Placing

g) Degree of site control: Good

h) Type of aggregate: Crushed angular aggregate

j) Maximum cement content not including fly ash: 450 kg/m3

k) Chemical admixture type: PEG

A-2 TEST DATA FOR MATERIALS

1) Cement used : PPC
2) Chemical admixture : PEG
3) Specific gravity of
   a) Specific gravity of cement : 3.15
   b) Coarse aggregate (at saturated surface dry (SSD) Condition) : 2.65

c) Fine aggregate (Sand) (at saturated surface dry (SSD) Condition : 2.56

d) Fine aggregate(Stone Dust in SSD Condition) : 2.45

e) Chemical admixture(PEG) : 1.1254

4) Water absorption

a) Coarse aggregate : 0.216%

b) Fine aggregate(Sand) : 1.666%

c) Fine aggregate(Stone Dust) : 5.346%

5) Moisture content of aggregate [As per IS 2386 (Part 3)]

a) Coarse aggregate : Nil

b) Fine aggregate : Nil

6) Sieve analysis: (As per IS 383:2016)

a) Coarse aggregate (T-7) : Graded Aggregate of nominal size 20mm.

b) Fine aggregate (T-9) (Both Sand & Stone Dust) : Grading Zone II

A-3 TARGET STRENGTH FOR MIX PROPORTIONING

$f'ck = fck + 1.65\ S$

or

$f'ck = fck + X$

Whichever is higher.

where

$f'ck$ = Target average compressive strength at 28 days,

fck = Characteristic compressive strength at 28 days,

S = Standard deviation

X = Factor based on grade of concrete.

(From Table 2, standard deviation,(S) = 4 N/mm² & From Table 1, X = 5.5)

Therefore, target strength using both equations, that is,

a) $f'ck = fck + 1.65\ S$

$f'ck = 20 + 1.65 \times 4 = 26.60\ N/mm^2$

b) f’ck = fck + 5.5

f’ck = 20 + 5.5 = 25.5 N/mm²

The higher value is to be adopted.

Therefore, target strength will be 26.60 N/mm².

A-4 APPROXIMATE AIR CONTENT

The approximate amount of entrapped air to be expected in normal (non-air-entrained) concrete is 1.0 % for 20 mm nominal maximum size of aggregate.(From Table 3)

A-5 SELECTION OF WATER-CEMENT RATIO

From Fig. 1, the free water-cement ratio required for the target strength of 31.60 N/mm² is 0.5 for OPC 43 grade curve. (For PPC, the strength corresponding to OPC 43 grade curve is assumed for the trial).

A-6 SELECTION OF WATER CONTENT

From Table 4, water content = 186 kg (for 50 mm slump) for 20 mm aggregate.

Estimated water content for 75 mm slump

= 186 + (3/100)*186

= 191.58kg.

A-7 CALCULATION OF CEMENT CONTENT

Water-cement ratio = 0.5

Cement content = 191.58/0.5

Cement content = 383.16 kg/m³

(From Table 5 of IS 456, minimum cement content for ‘Moderate’ exposure condition = 300 kg/m³. Here 436 kg/m³> 300 kg/m³)

Hence O.K.

A-8 PROPORTION OF VOLUME OF COARSE AGGREGATE AND FINE AGGREGETE CONTENT

From Table 5, the proportionate volume of coarse aggregate corresponding to 20 mm size aggregate and fine aggregate (Zone II) for water-cement ratio of 0.50 = 0.62.

Therefore, corrected proportion of volume of-

Coarse aggregate for the water-cement ratio of 0.5=0.62

Fine aggregate content = 1–0.632= 0.38

Here, 30% Sand is replaced by Stone Dust

Final proportion of Sand= 0.266

Final proportion of Stone Dust= 0.114

A-9 MIX CALCULATIONS

The mix calculations per unit volume of concrete shall be as follows:

i. Total Volume = 1 m^3

ii. Volume of entrapped air in wet concrete = 0.01 m^3

iii. Volume of cement = (Mass of cement/Specific gravity of cement)*(1/1000).

   Volume of cement = (383.16/3.15)*(1/1000)=0.121634 m^3

iv. Volume of water = (Mass of water/Specific gravity of water)*(1/1000).

   Volume of water = (191.58/1)*(1/1000) =0.19158 m^3.

v. Volume of chemical admixture PEG @ 0.4 percent by mass of cementitious material

   Volume of PEG = (Mass of chemical admi. / Specific gravity of admixture)*(1/1000)

   Volume of PEG = (3.06528/1.1254)*(1/1000) = 0.002724m^3.

vi. Volume of all in aggregate = [(a-b)-(c+d+e)]

   Volume of all in aggregate = [(a-b)-(c+d+e)]

   = [(1-0.01) – (0.121634+0.19158+0.002724)]

   = 0.674062 m^3

vii. Mass of Coarse Aggregate= Volume of all in aggregate × proportion of volume of CA × Specific gravity of CA × 1000

$$= 0.674062 \times 0.62 \times 2.648 \times 1000$$

$$= 1106.648\text{kg.}$$

viii. Mass of Fine Aggregate = Volume of all in aggregate × proportion of volume of Sand × Specific gravity of Sand × 1000

Mass of Sand = 0.674062×0.266×2.562×1000

= 459.3678 kg.

ix. Mass of Fine Aggregate = Volume of all in aggregate × proportion of volume of Stone Dust × Specific gravity of Stone Dust × 1000

Mass of Stone Dust = 0.674062×0.114×2.447153×1000

= 188.0467kg.

A-10 MIX PROPORTIONS FOR TRIAL NUMBER 1

a) Cement = 383.16 kg/m³
b) Water = 191.58 kg/m³
c) Sand (SSD) = 459.3678 kg/m³
d) Stone Dust (SSD) = 188.0467 kg/m³
e) Coarse aggregate (SSD) = 1106.648 kg/m³
f) Free water-cement ratio = 0.5

A-11 ADJUSTMENT ON WATER, FINE AGGREGATE AND COARSE AGGREGATE (IF THE COARSE AND FINE AGGREGATE IS IN DRY CONDITION)

a) Fine Aggregate (Dry) = Mass of Sand in SSD condition/(1+ Water Absorption of Sand/100)

Sand (Dry) = 459.3678/(1+ 1.666/100)=451.478 kg/m³.

b) Fine Aggregate (Dry) = Mass of Stone Dust in SSD condition/(1+ WA of Stone Dust/100)

Stone Dust (Dry) = 188.0467/(1+ 5.346/100)=178.5038 kg/m³.

c) Coarse Aggregate (Dry) = Mass of CA in SSD condition/(1+ WA of CA/100)

CA (Dry) = 1106.648/(1+ 0.216/100)=1104.2627 kg/m³.

The extra water to be added for absorption by coarse and fine aggregate,

1) For coarse aggregate= Mass of CA in SSD condition –mass of CA in dry condition

= 1106.648-1104.2627=2.3853 kg/m³

2) For fine aggregate

a) For Sand = Mass of Sand in SSD condition – mass of Sand in dry condition
   = 459.3678-451.478=7.8898 kg/m³
b) For Stone Dust = Mass of Stone Dust in SSD condition – mass of Stone Dust in dry condition

   = 188.0467-178.5038=9.5429 kg/m³

The estimated requirement for added water,Therefore, becomes

= 191.58+2.3853+7.8898+9.5429 =211.398 kg/m³

A-12 MIX PROPORTIONS AFTER ADUSTMENT FOR DRY AGGREGATES

a) Cement = 383.16 kg/m³
b) Water = 211.398 kg/m³
c) Sand (SSD) = 451.478 kg/m³
d) Stone Dust (SSD) =178.5038kg/m³
e) Coarse aggregate (SSD) = 1104.2627 kg/m³
f) PEG @ 0.6% by mass of cementitious material = ((0.8/100)*383.16)/1.1254= 2.724lit/m³.
g) Free water-cement ratio = 0.5

CHAPTER 4

EXPERIMENTAL RESULTS

4.1 (A) Compressive strength test of concrete cubes M20 Grade (PEG =0.4% & Stone Dust = 30%)

Compressive testing shows how the material will react when it is being compressed. Compression testing is able to determine the material's behavior or response under crushing loads and to measure the plastic flow behavior and ductile fracture limits of a material. The experimental result of compressive strength as shown in table 4.1(A)

Cube no.	Wt. of cube(kg)	C/S Area	C/S Area of Cube(mm²)	Cast Date	Test Date	Age	Failure Load(N)	Compressive Strength(Mpa)
1	7.962	150*151	22650	31/3/2022	27/4/2022	28	607600	26.826
2	8.104	148*159	22200	31/3/2022	27/4/2022	28	544000	24.505
3	8.194	150*150	22500	31/3/2022	27/4/2022	28	580500	25.800
4	8.041	149*149	22201	31/3/2022	27/4/2022	28	544100	24.508
5	8.087	151*152	22952	31/3/2022	27/4/2022	28	676000	29.453
Avg. Compressive Strength (Mpa)								**26.218**

4.1 (B) Flexural strength test of concrete Prism M20 Grade (PEG =0.4% & Stone Dust = 30%)

Flexural testing shows how the material will react when it is being tensile. Flexural testing is able to determine the material's behavior or response under tensile loads and to measure the plastic flow behavior and brittle fracture limits of a material. The experimental result of Flexural strength as shown in table 4.1(B).

Prism no.	Wt. of Prism (kg)	C/S Area	C/S Area of Prism(mm²)	Cast Date	Test Date	Age	Failure Load(N)	Flexral Strength(Mpa)
1	11.457	100*100	10000	1/4/2022	27/4/2022	28	8130	3.256
2	11.372	100*100	10000	1/4/2022	27/4/2022	28	7890	3.195
3	11.509	100*100	10000	1/4/2022	27/4/2022	28	8610	3.448
Avg. Flexural Strength(Mpa)								**3.300**

Fig.4.1. Compressive Strength of Cube

Fig.4.2. Flexural Strength of Prism

4.2 (A) Compressive strength test of concrete cubes M20 Grade (PEG =0.6% & Stone Dust = 30%)

Compressive testing shows how the material will react when it is being compressed. Compression testing is able to determine the material's behavior or response under crushing loads and to measure the plastic flow behavior and ductile fracture limits of a material. The experimental result of compressive strength as shown in table 4.2(A)

Cube no.	Wt. of cube (kg)	C/S Area	C/S Area of Cube(mm^2)	Cast Date	Test Date	Age	Failure Load(KN)	Compressive Strength(Mpa)
1	7.848	149*151	22499	8/4/2022	5/5/2022	28	641400	28.508
2	8.172	150*149	22350	8/4/2022	5/5/2022	28	528100	23.628
3	8.097	150*150	22500	8/4/2022	5/5/2022	28	578100	25.693
4	8.07	149*150	22350	8/4/2022	5/5/2022	28	629300	28.157
5	8.203	150*150	22500	8/4/2022	5/5/2022	28	586100	26.049
Avg. Compressive Strength(Mpa)								**26.407**

4.2 (B) Flexural strength test of concrete Prism M20 Grade (PEG =0.6% & Stone Dust = 30%)

Flexural testing shows how the material will react when it is being tensile. Flexural testing is able to determine the material's behavior or response under tensile loads and to measure the plastic flow behavior and brittle fracture limits of a material. The experimental result of Flexural strength as shown in table 4.2 (B).

Prism no.	Wt. of Prism (kg)	C/S Area	C/S Area of Prism(mm^2)	Cast Date	Test Date	Age	Failure Load (KN)	Flexral Strength(Mpa)
1	11.45	100*100	10000	9/4/2022	6/5/2022	28	10.69	4.281
2	11.875	100*100	10000	9/4/2022	6/5/2022	28	9.5	3.805
3	11.589	100*100	10000	9/4/2022	6/5/2022	28	9.96	3.989
Avg. Flexural Strength (Mpa)								**4.025**

4.3 (A) Compressive strength test of concrete cubes M20 Grade (PEG =0.8% & Stone Dust = 30%)

Compressive testing shows how the material will react when it is being compressed. Compression testing is able to determine the material's behavior or response under crushing loads and to measure the plastic flow behavior and ductile fracture limits of a material. The experimental result of compressive strength as shown in table 4.3(A)

Cube no.	Wt. of cube(kg)	C/S Area	C/SArea of Cube(mm²)	Cast Date	Test Date	Age	Failure Load(N)	Compressive Strength(Mpa)
1	7.861	151*152	22952	9/4/2022	6/5/2022	28	745500	32.481
2	7.769	148*149	22052	9/4/2022	6/5/2022	28	578000	26.211
3	7.937	151*150	22650	9/4/2022	6/5/2022	28	692200	30.561
4	7.722	150*152	22800	9/4/2022	6/5/2022	28	771900	33.855
5	7.867	151*152	22952	9/4/2022	6/5/2022	28	736600	32.093
Avg. Compressive Strength (Mpa)								**31.040**

4.3(B) Flexural strength test of concrete Prism M20 Grade (PEG =0.8% & Stone Dust = 30%)

Flexural testing shows how the material will react when it is being tensile. Flexural testing is able to determine the material's behavior or response under tensile loads and to measure the plastic flow behavior and brittle fracture limits of a material. The experimental result of Flexural strength as shown in table 4.3(B).

Prism no.	Wt. of Prism(kg)	C/S Area	C/S Area of Prism(mm²)	Cast Date	Test Date	Age	Failure Load(N)	Flexral Strength (Mpa)
1	10.425	100*100	10000	12/4/2022	9/5/2022	28	9920	3.973
2	10.216	100*100	10000	12/4/2022	9/5/2022	28	9680	3.877
3	10.397	100*100	10000	12/4/2022	9/5/2022	28	9550	3.825
Avg. Flexural Strength (Mpa)								**3.892**

4.4 Training Datasheet for predicting compressive strength

In easy words the Compressive Strength of Concrete determines the quality of Concrete, we check it by standard crushing test on a concrete which are previous research paper results as shown in Table no. - 4.4

Cement	Water	Coarse	Sand	SD	PEG	Slump	CS
400	170	1054	732	0	0	67	38.63
400	170	1054	658.8	73.2	0	66	39.02
400	170	1054	585.6	146.4	0	68	39.13
400	170	1054	512.4	219.6	0	70	39.53
400	170	1054	439.2	289.8	0	67	39.12
339	152.5	1248	745	0	0	140	26
339	152.5	1248	670.5	74.5	0	135	27.5
339	152.5	1248	596	149	0	90	31
339	152.5	1248	521.5	223.5	0	138	33
339	152.5	1248	447	298	0	132	33.5
339	152.5	1248	372.5	372.5	0	138	29
339	152.5	1248	298	447	0	135	27.5
339	152.5	1248	223.5	521.5	0	140	25
339	152.5	1248	149	596	0	142	24.5
339	152.5	1248	74.5	670.5	0	145	23
339	152.5	1248	0	745	0	150	20
370	222	1210	583	0	0	132	26.7
397	222	1210	557	0	0	120	30.5
427	222	1210	530	0	0	110	36.17
463	222	1200	502	0	0	95	38.7
505	222	1185	473	0	0	65	44.43
388	233	1034	517	173	0	127	26.1
416	233	1035	496	166	0	115	31.2

448	233	1032	474	158	0	92	38
485	233	1025	451	151	0	68	42.4
530	233	1012	427	143	0	62	46.4
400	240	926	0	789	0	120	26.9
429	240	927	0	759	0	122	30.17
462	240	926	0	727	0	114	33.53
500	240	921	0	695	0	70	40.03
546	240	910	0	659	0	60	47.27
413	186	1243	632	0	0	52	32.63
413	186	1243	632	0	0.5	61	35.01
413	186	1243	632	0	1	73	35.71
413	186	1243	632	0	1.5	85	30.66
413	186	1243	632	0	2	94	29.59
413	186	1243	632	0	0	52	32.7
413	186	1243	632	0	0.5	61	35.01
413	186	1243	632	0	1	73	35.71
413	186	1243	632	0	1.5	85	30.66
413	186	1243	632	0	2	94	29.59
413	186	1243	632	0	0.1	64	33.65
413	186	1243	632	0	0.2	75	32.6
413	186	1243	632	0	0.3	87	35.68
413	186	1243	632	0	0.4	92	32.23
383.16	204.73	1089.5	646.07	0	0	78	33.3
383.16	204.73	1089.5	646.07	0	0	78	31.2
383.16	204.73	1089.5	646.07	0	0	78	30.6
383.16	204.73	1089.5	646.07	0	0	78	32.2
383.16	211.07	1106.56	452.78	179.26	1.36	80	28.83
383.16	211.07	1106.56	452.78	179.26	1.36	80	24.5

383.16	211.07	1106.56	452.78	179.26	1.36	80	25.8
383.16	211.07	1106.56	452.78	179.26	1.36	80	24.51
383.16	211.07	1106.56	452.78	179.26	1.36	80	29.45
383.16	211.59	1105.38	452.46	178.95	2.04	75	29
383.16	211.59	1105.38	452.46	178.95	2.04	75	26.1
383.16	211.59	1105.38	452.46	178.95	2.04	75	25.69
383.16	211.59	1105.38	452.46	178.95	2.04	75	28.16
383.16	211.59	1105.38	452.46	178.95	2.04	75	26.05
383.16	211.4	1104.26	451.48	178.5	2.72	90	25.48
383.16	211.4	1104.26	451.48	178.5	2.72	90	26.21
383.16	211.4	1104.26	451.48	178.5	2.72	90	30.56
383.16	211.4	1104.26	451.48	178.5	2.72	90	26
383.16	211.4	1104.26	451.48	178.5	2.72	90	32.09
383.16	211.06	1108.23	452.78	177.62	0	95	31.6
383.16	211.06	1108.23	452.78	177.62	0	95	33
383.16	211.06	1108.23	452.78	177.62	0	95	28.8
383.16	211.06	1108.23	452.78	177.62	0	95	32.7
383.16	211.06	1108.23	452.78	177.62	0	95	31.9
383.16	211.42	1078.62	303.08	336.53	1.36	78	25.9
383.16	211.42	1078.62	303.08	336.53	1.36	78	26.8
383.16	211.42	1078.62	303.08	336.53	1.36	78	26.5
383.16	211.42	1078.62	303.08	336.53	1.36	78	26.4
383.16	211.42	1078.62	303.08	336.53	2.04	100	26.9
383.16	211.42	1078.62	303.08	336.53	2.04	100	26.5
383.16	211.42	1078.62	303.08	336.53	2.04	100	24.7
383.16	211.42	1078.62	303.08	336.53	2.04	100	26.4
383.16	211.42	1078.62	303.08	336.53	2.04	100	24.3
383.16	211.42	1078.62	303.08	336.53	2.72	182	18

383.16	211.42	1078.62	303.08	336.53	2.72	182	16.8
383.16	211.42	1078.62	303.08	336.53	2.72	182	16.8
383.16	211.42	1078.62	303.08	336.53	2.72	182	19.4
383.16	211.42	1078.62	303.08	336.53	2.72	182	19.8

4.5 Training Datasheet for predicting Flexural Strength

In easy words the Flexural Strength of Concrete determines the quality of Concrete, we check it by standard crushing test on a concrete which are previous research paper results as shown in Table no. - 4.5

Cement	**Water**	**Coarse**	**Sand**	**SD**	**PEG**	**Slump**	**FS**
400	170	1054	732	0	0	67	4.29
400	170	1054	658.8	73.2	0	66	4.33
400	170	1054	585.6	146.4	0	68	4.35
400	170	1054	512.4	219.6	0	70	4.42
400	170	1054	439.2	289.8	0	67	4.34
339	152.5	1248	745	0	0	140	4.7
339	152.5	1248	670.5	74.5	0	135	5.2
339	152.5	1248	596	149	0	90	5.2
339	152.5	1248	521.5	223.5	0	138	5.9
339	152.5	1248	447	298	0	132	5.5
339	152.5	1248	372.5	372.5	0	138	5.4
339	152.5	1248	298	447	0	135	5.3
339	152.5	1248	223.5	521.5	0	140	4.8
339	152.5	1248	149	596	0	142	4.7
339	152.5	1248	74.5	670.5	0	145	4.3
339	152.5	1248	0	745	0	150	4.4
370	222	1210	583	0	0	132	3.53
397	222	1210	557	0	0	120	3.82

427	222	1210	530	0	0	110	4.56
463	222	1200	502	0	0	95	4.12
505	222	1185	473	0	0	65	4.57
388	233	1034	517	173	0	127	3.65
416	233	1035	496	166	0	115	3.8
448	233	1032	474	158	0	92	4.68
485	233	1025	451	151	0	68	4.24
530	233	1012	427	143	0	62	4.98
400	240	926	0	789	0	120	3.84
429	240	927	0	759	0	122	3.84
462	240	926	0	727	0	114	4.14
500	240	921	0	695	0	70	4.73
546	240	910	0	659	0	60	4.93
413	186	1243	632	0	0	52	4.6
413	186	1243	632	0	0.5	61	4.78
413	186	1243	632	0	1	73	5.36
413	186	1243	632	0	1.5	85	4.9
413	186	1243	632	0	2	94	4.55
413	186	1243	632	0	0	52	4.31
413	186	1243	632	0	0.5	61	4.69
413	186	1243	632	0	1	73	5.7
413	186	1243	632	0	1.5	85	6.65
413	186	1243	632	0	2	94	5.12
413	186	1243	632	0	0	52	4.31
413	186	1243	632	0	0.1	64	4.96
413	186	1243	632	0	0.2	75	5.7
413	186	1243	632	0	0.3	87	6.65
413	186	1243	632	0	0.4	92	5.12

383.16	204.73	1089.5	646.07	0	0	84	4.67
383.16	204.73	1089.5	646.07	0	0	84	4.9
383.16	204.73	1089.5	646.07	0	0	84	4.6
383.16	211.07	1106.56	452.78	179.26	1.36	86	3.26
383.16	211.07	1106.56	452.78	179.26	1.36	86	3.2
383.16	211.07	1106.56	452.78	179.26	1.36	86	3.45
383.16	211.59	1105.38	452.46	178.95	2.04	88	4.28
383.16	211.59	1105.38	452.46	178.95	2.04	88	3.81
383.16	211.59	1105.38	452.46	178.95	2.04	88	3.99
383.16	211.4	1104.26	451.48	178.5	2.72	110	3.97
383.16	211.4	1104.26	451.48	178.5	2.72	110	3.88
383.16	211.4	1104.26	451.48	178.5	2.72	110	3.83
383.16	211.06	1108.229	452.78	177.62	0	95	6.07
383.16	211.06	1108.229	452.78	177.62	0	95	4.1
383.16	211.06	1108.229	452.78	177.62	0	95	5.73
383.16	211.42	1078.62	303.08	336.53	1.36	78	1.94
383.16	211.42	1078.62	303.08	336.53	1.36	78	2.86
383.16	211.42	1078.62	303.08	336.53	1.36	78	2.732
383.16	211.42	1078.62	303.08	336.53	2.04	100	3.33
383.16	211.42	1078.62	303.08	336.53	2.04	100	3.26
383.16	211.42	1078.62	303.08	336.53	2.04	100	3.95
383.16	211.42	1078.62	303.08	336.53	2.72	182	3.95
383.16	211.42	1078.62	303.08	336.53	2.72	182	3.8
383.16	211.42	1078.62	303.08	336.53	2.72	182	3.86

CHAPTER 5

DISCUSSION

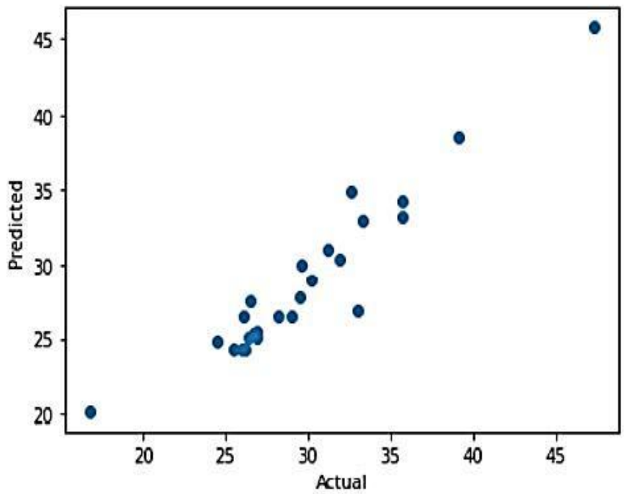
I have develop an algorithm in python to predict compressive strength and Flexural Strength of prepared mix design results based on previouse research data. I have use many libraries such as NUMPY, PANDAS, MATPLOTLIB, SKLEARN ect.

The reg.coeff. 0.877599042356055 which is very satisfactory as shown in Graph 5.1

Algorithm for Compressive Strength

```
import numpy as np
import pandas as pd
import matplotlib.pyplot as plt
import sklearn
from sklearn.model_selection import train_test_split
from sklearn import linear_model
from sklearn.linear_model import LinearRegression
from sklearn.preprocessing import PolynomialFeatures
df=pd.read_csv('DS_mtech1.csv')
df_x= df.iloc[:,:7]
df_y= df.iloc[:,7]
x_train,x_test,y_train,y_test=train_test_split(df_x,df_y,test_size=0.3,random_state=0,
shuffle=True)
ml=LinearRegression()
reg =ml.fit(x_train,y_train)
y_pred= ml.predict(x_test)
from sklearn.metrics import r2_score
r2_score(y_test,y_pred)
plt.scatter(y_test, y_pred)
plt.xlabel('Actual')
plt.ylabel('Predicted')
plt.show
reg.coef_
```

```
In [1]: import numpy as np
        import pandas as pd
        import matplotlib.pyplot as plt
        import sklearn
        from sklearn.model_selection import train_test_split
        from sklearn import linear_model
        from sklearn.linear_model import LinearRegression
        from sklearn.preprocessing import PolynomialFeatures
        from sklearn.metrics import r2_score

        df=pd.read_csv('New_DS_Mtech1.csv')

        df_x= df.iloc[:,:7]
        df_y= df.iloc[:,7]
        x_train,x_test,y_train,y_test= train_test_split(df_x,df_y, test_size= 0.3, randon

        ml=LinearRegression()
        reg = ml.fit(x_train,y_train)
        y_pred= ml.predict(x_test)

        r2_score(y_test,y_pred)
        plt.scatter(y_test, y_pred)
        plt.xlabel('Actual')
        plt.ylabel('Predicted')
        plt.show
        reg.coef_

Out[1]: array([ 0.10053979, -0.1371868 , -0.02290175, -0.01626216, -0.02144991,
               -2.29242728, -0.04136189])
```




```
In [2]: r2_score(y_test,y_pred)

Out[2]: 0.877599042356055
```

Graph 5.1

```
In [4]: df_x
Out[4]:
```

	Cement	Water	Coarse	Sand	SD	PEG	Slump
0	400.00	170.00	1054.00	732.00	0.00	0.00	67
1	400.00	170.00	1054.00	658.80	73.20	0.00	66
2	400.00	170.00	1054.00	585.60	146.40	0.00	68
3	400.00	170.00	1054.00	512.40	219.60	0.00	70
4	400.00	170.00	1054.00	439.20	289.80	0.00	67
...	...	...	...	...	...	...	...
78	383.16	211.42	1078.62	303.08	336.53	2.72	182
79	383.16	211.42	1078.62	303.08	336.53	2.72	182
80	383.16	211.42	1078.62	303.08	336.53	2.72	182
81	383.16	211.42	1078.62	303.08	336.53	2.72	182
82	383.16	211.42	1078.62	303.08	336.53	2.72	182

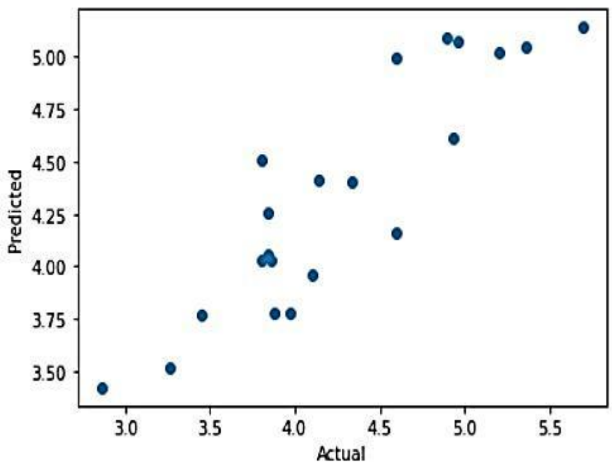
83 rows × 7 columns

```
In [3]: y_test,y_pred
Out[3]: (30    47.27
         53    29.45
         42    32.60
         59    25.48
         22    31.20
         38    35.71
         2     39.13
         55    26.10
         26    26.90
         8     33.00
         68    31.90
         13    24.50
         71    26.50
         76    26.40
         16    26.70
         27    30.17
         45    33.30
         57    28.16
         80    16.80
         73    26.90
         43    35.68
         60    26.21
         40    29.59
         62    26.00
         54    29.00
         Name: CS, dtype: float64,
         array([45.77880695, 27.85641828, 34.96771709, 24.36994337, 31.04009802,
                33.21649905, 38.54643462, 26.47191748, 25.46336746, 26.86462031,
                30.3519948 , 24.7667325 , 27.5920182 , 25.12320602, 25.35924242,
                28.91689322, 33.01911097, 26.47191748, 20.17268031, 25.12320602,
                34.24213165, 24.36994337, 30.05547203, 24.36994337, 26.47191748]))
```

Algorithm for Flexural Strength

The reg.coeff. 0.7753337003131175 which is very satisfactory as shown in Graph 5.2

```
In [1]: import numpy as np
        import pandas as pd
        import matplotlib.pyplot as plt
        import sklearn
        from sklearn.model_selection import train_test_split
        from sklearn import linear_model
        from sklearn.linear_model import LinearRegression
        from sklearn.preprocessing import PolynomialFeatures
        from sklearn.metrics import r2_score

        df=pd.read_csv('New_DS_Mtech1.csv')

        df_x= df.iloc[:,:7]
        df_y= df.iloc[:,7]
        x_train,x_test,y_train,y_test= train_test_split(df_x,df_y, test_size= 0.3, randon

        ml=LinearRegression()
        reg = ml.fit(x_train,y_train)
        y_pred= ml.predict(x_test)

        r2_score(y_test,y_pred)
        plt.scatter(y_test, y_pred)
        plt.xlabel('Actual')
        plt.ylabel('Predicted')
        plt.show
        reg.coef_

Out[1]: array([ 0.10053979, -0.1371868 , -0.02290175, -0.01626216, -0.02144991,
               -2.29242728, -0.04136189])
```




```
In [2]: r2_score(y_test,y_pred)

Out[2]: 0.7753337003131175
```

Graph 5.2

```
In [4]: df_x
```

Out[4]:

	Cement	Water	Coarse	Sand	SD	PEG	Slump
0	400.00	170.00	1054.00	732.00	0.00	0.00	67
1	400.00	170.00	1054.00	658.80	73.20	0.00	66
2	400.00	170.00	1054.00	585.60	146.40	0.00	68
3	400.00	170.00	1054.00	512.40	219.60	0.00	70
4	400.00	170.00	1054.00	439.20	289.80	0.00	67
...	...	...	...	...	...	...	...
65	383.16	211.42	1078.62	303.08	336.53	2.04	100
66	383.16	211.42	1078.62	303.08	336.53	2.04	100
67	383.16	211.42	1078.62	303.08	336.53	2.72	182
68	383.16	211.42	1078.62	303.08	336.53	2.72	182
69	383.16	211.42	1078.62	303.08	336.53	2.72	182

70 rows × 7 columns

```
In [3]: y_test,y_pred
```

```
Out[3]: (26    3.84
         27    3.84
         48    4.60
         22    3.80
         30    4.93
         51    3.45
         7     5.20
         59    4.10
         34    4.90
         69    3.86
         56    3.88
         28    4.14
         31    4.60
         42    4.96
         33    5.36
         55    3.97
         68    3.80
         62    2.86
         43    5.70
         4     4.34
         65    3.26
         Name: FS, dtype: float64,
         array([4.05612756, 4.25583887, 4.15731436, 4.5079613 , 4.61350603,
                3.76866082, 5.0207933 , 3.95969255, 5.08537074, 4.03265372,
                3.77987376, 4.41510152, 4.99468578, 5.07049768, 5.04802342,
                3.77987376, 4.03265372, 3.42305689, 5.13919058, 4.3995705 ,
                3.51428519]))
```

CHAPTER 6

CONCLUSIONS

This study is apparently the first to investigate the efficiency of the machine learning algorithm, which is based on python, for predicting the properties of SCC using several experimental datasets and for predicting SCC compressive strength with diverse additive materials from various laboratory works. The SCC behaviors have been developed based on the AI techniques. The accuracy of ensemble algorithm estimating SCC compressive strength was analyzed, and obtained results were validated by individual AI models and previous work.

Numerical modeling using this algorithm shows a great performance to predict concrete properties such as compressive strength & flexural strength subjected to different % ratio of Quarry stone dust (30% & 50%) as well as different % ratio of PEG(0.4%,0.6% & 0.8%) where the value of R^2 (regression coefficient) 0.8775 for compressive strength & 0.7753 for flexural strength.

This work confirms that the ensemble model effectively improves performance in predicting the properties of SCC and substantially reduces the amount of laboratory work required. Moreover, the proposed ensemble method can be used to optimize the quality of SCC mixtures and to reduce the time needed to design and validate mixtures. The proposed approach is implemented easily and has many potential applications in materials science. Experimental data for materials with characteristics resembling those of SCC might provide further evidence of the power of the ensemble models for solving different prediction problems. However, one significant limitation of this work is that it used default settings in the single and ensemble models. Therefore, further studies are needed to investigate parameters optimization in ensemble models for predicting SCC properties.

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