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**Research Article**

# Concrete strength prediction using artificial neural network and genetic programming

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**ABSTRACT**

Concrete is a highly complex composite construction material and modeling using computing tools to predict concrete strength is a difficult task. In this work an effort is made to predict compressive strength of concrete after 28 days of curing, using Artificial Neural Network (ANN) and Genetic programming (GP). The data for analysis mainly consists of mix design parameters of concrete, coefficient of soft sand and maximum size of aggregates as input parameters. ANN yields trained weights and biases as the final model which sometime may impediment in its application at operational level. GP on other hand yields an equation as its output making its plausible tool for operational use. Comparison of the prediction results displays the result the model accuracy of both ANN and GP as satisfactory, giving GP a working advantage owing to its output in an equation form. A knowledge extraction technique used with the weights and biases of ANN model to understand the most influencing parameters to predict the 28 day strength of concrete, promises to prove ANN as grey box rather than a black box. GP models, in form of explicit equations, show the influencing parameters with reference to the presence of the relevant parameters in the equations.

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## 1. Introduction

Concrete is a material with a mix of main constituents Cement, Aggregates and water. The properties of concrete depend on various parameters including the non-homogeneous nature of their components, different properties of various materials used and also the contradictory effects of some materials on the overall concrete performance. The strength of concrete are thus functions of relative magnitudes of these various concrete mixes. To ascertain the strength of concrete with use of these materials need extensive testing and time (28 day being standard) (Shetty, 2005). A need thus arises to use soft computing tools in prediction of concrete properties with acceptable performance which can reduce the consumption of materials and save time. Development of models using relevant soft computing tools can also help in designing the appropriate mix proportions for a required grade of concrete thus leading towards economic utilization of materials. Many researchers earlier have made an attempt to predict strength of concrete and other properties using techniques like Artificial Neural Network (ANN) (Mukherjee and Sudip, 1997; Meltem et al., 2008; Ni and Wang, 2000; Ahmet et al., 2006; Gorphade et al., 2014), Genetic Programming (GP) (Gandomia et al. 2014; Sarıdemir, 2010), Fuzzy systems etc. (Khademi et al. 2016; Khademi et al. 2017; Behfarnia and Khademi, 2017). ANN has been used in predicting the stress–strain behavior of concrete and ANN understands the relationship and the performance was superior to the existing mathematical models (Mukherjee and Sudip, 1997). ANN, Multiple Linear Regression (MLR) and Abram's law were used to predict concrete strength with input parameters as concrete mix proportions, Fresh Density and 7-days compressive strength, showing that MLR models are better in strength prediction of concrete than ANN models for models which include only the constituent materials and fresh concrete data and with early strength data in two models better prediction of strength by ANN models was seen (Meltem et al., 2008). ANN

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technique was used to predict the compressive strength of concrete with input parameters as water cement ratio, grade of cement, water dosage etc. The study shows that strength of concrete is direct proportion to the dosage of cement. Slight influence of sand to aggregate ratio on strength can be seen. Rules obtained by ANN models are consistent with those by laboratory work and exhibit good performance (Ni and Wang 2000). The applicability of ANN to predict the CS and slump of high strength concrete can be seen with ANN model with input parameters as water to binder ratio, fine aggregate ratio, water content, fly ash content etc. ANN shows reasonably good predictions with $R^2$ values as 99.8% and 99.25% in training set and 99.93% and 99.34% in test set for CS and slump, respectively (Ahmet et al., 2006). Prediction of the strength characteristics and workability and Young's modulus of High performance concrete was done using Genetic Algorithm based neural network models with an accuracy of about 95% (Gorphade et al. 2014). Linear genetic programming (LGP) technique was used in predicting strength capacity of Reinforced Concrete (RC) beams. The proposed design equation displays reliable estimations of the strength capacity of RC beams without stirrups and is also capable of capturing the underlaying physis of the same. The LGP model displays better outcomes than the existing building codes (Gandomia et al. 2014). Saridemir (2010) developed two models using gene expression programming (GEP) approach for predicting compressive strength of concretes with rice husk ash at the various ages from 1 to 90 days. The models in results for the testing and validation stages shows a good generalization capacity and low error values (Sarıdemir, 2010). Fuzzy Interference system and Regression analysis was also used to predict strength of concrete, displacement determination of reinforced building (Khademi et al., 2016; Khademi et al., 2017; Behfarnia and Khademi, 2017). Literature review thus signifies that ANN and GP are used in predicting strength but the use of properties of materials as additional input parameters and knowledge extraction from the weights and biases of ANN has been seldom done and discussed. The aim of the present study is thus to develop models predicting strength of concrete at 28 day with various input parameters, using soft computing techniques i.e. Artificial Neural Networks (ANN) and Genetic Programming (GP) and compare the performance of the same. ANN displays the output in form of weights and biases and Genetic Programming in form of equations. Knowledge extraction technique from ANN is used further and the influence of input parameter on output is studied and compared with the domain knowledge. Genetic Programming equations developed are significant in understanding the influence of input parameters.

In the further sections of the current work, basic concepts of artificial neural network, Knowledge extraction and Genetic Programming are discussed, followed by details of data used in the current study. Model development methodology is then presented followed by results and discussion. The current work ends with a conclusion.

## 2. Modeling Techniques

### *2.1. Artificial neural network (ANN)*

ANN is a soft computing technique is inspired by the biological network of human brain. Similar to working of biological network, Artificial Neural Network consists of basic three layers viz. input layer, hidden layer and the output layer. The input and output layers are connected to hidden layer by weights, biases and transfer functions. The error is computed with the difference between output and the target. This error is propagated back and the weight and biases are adjusted using optimization technique to minimize the error. The error optimization process is repeated for number of iterations till the desired accuracy is achieved. Once the desired accuracy is achieved, validation of the developed model is done on unseen data. Readers are referred to for details of ANN to Londhe et al. (2009).

### *2.2. Knowledge extraction from ANN*

ANN is said to be a performing tool, however little is known about what's happening inside it which can be slightly seen through Hinton diagram, and thus the performance of ANN is questioned many a times (Deshpande et al., 2014). It is difficult to monitor the relation between input and output parameters as the knowledge may not be extracted from the neural network and thus knowledge extraction is important. Rule extraction has three phases: decomposition, pedagogical, and eclectic (Kahramanli and Allahverdi, 2001). To obtain the influence of each input variable on the output of a trained feed-forward multilayer perceptron to estimate monthly runoff, Garson's model was used (Phukoetphim et al., 2014). However, it was seen that the magnitude and the nature of the contribution of the input parameters was not correctly displayed by Garson's algorithm. The models were developed with input parameters as maximum humidity, sunshine duration, maximum and minimum temperature and wind speed and pan evaporation (mm/day) as the output. Thus showing that this method of knowledge extraction is not applicable at least for evaporation modelling using ANN (Londhe and Shah, 2016). Thus to extract the knowledge locked up in the network, a new method was formulated by the authors. The new method suggests an algebraic sum of the influences of the inputs, which are obtained at two stages of the neural network programming. Hence, the method takes into consideration the signs of the weights extracted from the neural networks and thus would be able to give not only the magnitude but also nature of the influence of each input on the output. The procedure of obtaining the influence of inputs at both stages of programming and their summation is given in Appendix A (Londhe and Shah, 2016).

### *2.3. Genetic programming (GP)*

Genetic programming (GP) was inspired by biological evolution is a machine learning technique and based on principle of survival of fittest, to compute computer programs/ equations that solve a problem. It uses the principle of Darwinian natural selection to evolve a program. GP operates on parse trees to approximate the equation or computer program that best displays the output to input variables. To transfer one population of individuals into other one natural genetic operations like reproduction, mutation and cross-over are utilized in GP. The flowchart of GP is given in Fig. 1 below (Koza, 1992; Londhe and Dixit, 2012).

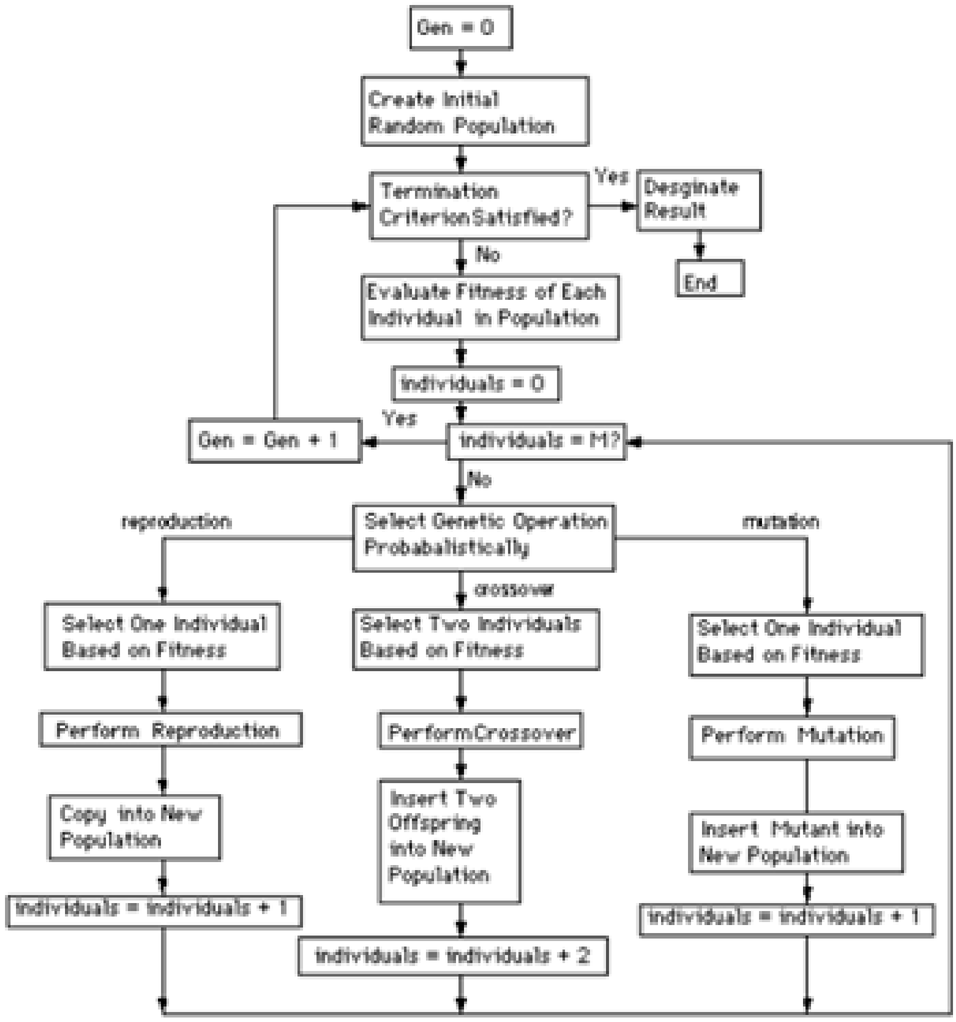


**Fig. 1.** Flowchart of genetic programming.

For details of the same readers are referred to Londhe and Dixit (2012). The three genetic operations are as follows:

**Reproduction:** An individual is chosen from the first population and is replicated exactly into the subsequent generation and the program which does not perform are removed. Fitness measure, selection, rank selection and tournament selection are few methods of selection from which individual are duplicated.

**Cross over:** Two parent results are selected and parts of their sub-tree are exchanged such that each function holds the property 'closure' (each tree member can transform all possible argument values).

**Mutation**: it provides diversity to the population. The mutation operator selects a node in the parse tree and replaces the branch at that node by a randomly generated branch. Perspective to portray GP as far as the structures that experiences adaptations are:

1. Initial structure generation
2. Fitness measure test which assesses the structure
3. Operations which change the structure
4. The state (memory) of the framework at each stage
5. The system for terminating the process

The system for designating the output and parameters that control the process. Linear representation of computer programming is used in linear genetic programming (LGP). Each individual (Program) in LGP is represented by a variable-length sequence of simple C language instructions, which operate on the registers or constants from predefined sets. The function set of the system can be composed of arithmetic operations (+, - , X, /), conditional branches, and function calls (f {x, xn, sqrt, ex, sin, cos, tan, log, ln}). The readers are further referred to Phukoetphim et al. (2014) and Londhe and Dixit (2012).

## 3. Modeling Data

A total of 149 data was collected from literature, which consists of testing the compressive strength of cylindrical samples with a diameter of 15 cm and a height of 30 cm are used (Kumar and Kumar, 2015; Oner and Akyuz, 2007; Lee et al., 2006). In addition, parameters such as the amount of 3/4 sand, 3/8 sand, cement, silt in kilograms, maximum sand size in millimeter, coefficient of fine sand, and water-cement ratio are used to determine the 28 day strength of concrete. The characteristics of used data have been illustrated in Table 1. The average mutual information (AMI) i.e. nonlinear relation of each parameter with the output and correlation coefficient of input parameter with output is also shown in Table 1 (Bhattacharya and Solomatine, 2005). The sample data used in the work is as shown in Table 2 below.

**Table 1.** Characteristics of Input and output parameters.

| Sr. No | Input Parameters | Range of Values (min-max) | AMI | Correlation coefficient | Mean |
|---|---|---|---|---|---|
| 1 | Cement Content (C) kg | 243-549 | 5.119 | 0.725 | 385.550 |
| 2 | Water cement ratio (WC) | 0.240-0.500 | 2.637 | -0.856 | 0.430 |
| 3 | Maximum size of Sand (MA) cm | 5.120-50 | 3.247 | 0.058 | 23.890 |
| 4 | Gravel (SA) kg | 559-1050 | 5.542 | -0.495 | 779.130 |
| 5 | Sand 3/8 (G1) kg | 303-523 | 4.323 | 0.085 | 427.050 |
| 6 | Sand ¾ (G2) kg | 365-693 | 4.358 | 0.042 | 563.310 |
| 7 | Coefficient of soft sand (FM) | 2.400-9.200 | 2.423 | -0.017 | 3.270 |
| | Output Parameter in kg/cm² | | | | |
| 1 | 28 day compressive strength of concrete kg/cm² (ST) | 173 -394 | - | | 279.270 |

**Table 2.** Sample of data used in the work.

| C (kg) | WC | MA (cm) | Gravel (SA) (kg) | Sand 3/8 kg G1 | Sand ¾ kg G2 | Coefficient of soft sand FM | 28 day compressive strength of concrete kg/cm² ST |
|---|---|---|---|---|---|---|---|
| 413 | 0.4 | 3.75 | 617 | 647 | 488 | 3 | 300 |
| 431 | 0.42 | 2.5 | 740 | 584 | 439 | 3.1 | 352 |
| 406 | 0.56 | 0.95 | 863 | 437 | 330 | 2.6 | 235 |
| 371 | 0.41 | 5 | 772 | 656 | 495 | 3.2 | 319 |
| 348 | 0.48 | 3.75 | 794 | 629 | 474 | 3.4 | 318 |
| 354 | 0.48 | 5 | 682 | 693 | 523 | 2.7 | 331 |
| 436 | 0.41 | 3.75 | 648 | 647 | 488 | 2.6 | 363 |
| 494 | 0.42 | 1.9 | 620 | 584 | 439 | 2.8 | 394 |
| 323 | 0.48 | 5 | 812 | 656 | 495 | 3.1 | 322 |
| 420 | 0.4 | 1.9 | 675 | 583 | 440 | 2.5 | 282 |

## 4. Methodology for Model Development

Four different models were developed in the current study using ANN and GP with common output as 28$^{th}$ day compressive strength of cylindrical concrete samples. The abbreviations used for the models developed are shown in Table 3. ANN1 and GP1 was developed with basic mix design parameters as Sand 3/8 (G1) in kg, Sand 3/4 (G2) in kg, Cement content (C) in kg, Gravel (SA) in kg and water cement ratio (WC) ratio as input parameters. ANN2 and GP2 were the new set of models developed with additional input parameters of coefficient of soft sand (FM) and maximum size of aggregate (MA) in cm as in ANN1 and GP1.

ANN models with 3 layers i.e. input, hidden and output layer were developed using MATLAB Neural Network toolbox. Development of ANN model was done with three layered "Feed forward Back propagation" network to predict the 28 day compressive strength of concrete and was trained till a very low performance error (mean squared error) was achieved. In order to determine the number of neurons in the hidden layer, the following experimental formula (Eq. (1)) was used (Bowden et al., 2005).

$$NH \leq 2N1 + 1\,, \qquad (1)$$

where NH is the maximum number of nodes in the hidden layer and N1 is the number of inputs. With regard to the fact that the number of obtained effective inputs is equal to 7, maximum number of nodes in the hidden layer is 15 (NH ≤ 15). All the networks were trained using Levernberg-Marquardt algorithm with 'log-sigmoid 'transfer functions in between first (input) and second (hidden) layer and 'linear' transfer function between the second and third layer (output). The data was normalized between 0 and 1. For developing equation using GP, GPKERNEL software was used. The various parameters which were decided for the same are as follows:
Population size: 500
Number of children to be produced: 500
Operators: exp(x), pow(x, 2), sqrt(x), (x + y), (x - y), (x * y), (x / y), pow(x, y).
Objective functions: Coefficient of determination and Root mean squared error
Maximum Subtree Mutation Size=15
Crossover rate=0.4

The data division was done as follows: 70% of data was used for training and 30% for testing which remains same for model development using ANN and GP techniques. The model's performance were assessed by statistical measures Normalized root mean squared error (NRMSE), correlation coefficient (R), Nash-Sutcliffe Efficiency (E) and Average absolute error (AARE) (Legates and McCabe, 1999; Dias and Pooliyadda, 2001).

**Table 3.** Abbreviations for the models developed using ANN and GP.

| Sr. No | Input Parameters | ANN Model | GP Model |
|---|---|---|---|
| 1 | G1, G2, C, SA, WC | ANN1 | GP1 |
| 2 | FM, G1, G2, C, SA, MA, WC | ANN2 | GP2 |

## 5. Results and Discussion

The current study makes an attempt to explore the applicability of models developed using ANN and GP for the prediction of 28 day concrete compressive strength with input parameters as: Sand 3/8 (G1) in kg, Sand 3/4 (G2) in kg, Cement content (C) in kg, Gravel (SA) in kg and water cement ratio (WC) ratio, coefficient of soft sand (FM) and maximum size of aggregate (MA).This section presents the comparative investigation of results obtained from ANN and GP approaches and quantitative assessment of the models. An investigation into understanding the influential parameters in predicting strength of concrete is done in the later stage. Mix design of concrete typically consists of calculation of proportions of materials used in concrete per cubic meter (Shetty, 2005). With the same view, ANN1 and GP1 model was developed with mix proportions of concrete as input parameters as shown in Table 4. The developed models were validated with 30% of testing data using error measures as shown in Table 4 below.

**Table 4.** Details and results of models developed.

| Sr. No | Input Parameters | Model | Architecture | R | NRMSE | AARE | E |
|---|---|---|---|---|---|---|---|
| 1 | G1, G2, C, SA, WC | ANN1 | 5:11:1 | 0.937 | 0.078 | 6.625 | 0.852 |
| 2 | G1, G2, C, SA, WC | GP1 | - | 0.917 | 0.147 | 12.816 | 0.478 |
| 3 | FM, G1, G2, C, SA, MA, WC | ANN2 | 7:15:1 | 0.941 | 0.078 | 6.674 | 0.854 |
| 4 | FM, G1, G2, C, SA, MA, WC | GP2 | - | 0.894 | 0.096 | 7.627 | 0.780 |

Table 4 shows that model ANN1 developed with mix design parameters as input parameters and architecture of 5:11:1, shows a better performance, with correlation coefficient R as 0.936, than GP1 model with same input parameters and R value as 0.917. Lower values of AARE and NRMSE and higher values of R and E for ANN1 indicate that the model can predict compressive strength of the mixes with high reliability as compared to GP1. ANN predicts the output better than GP in the current study but showcases a limitation of simplified equation which can be computed easily. Genetic programming (GP) on the other hand can provide an equation which can be used by a general user. The GP1 developed is as shown in Eq. (2):

$$ST=\left(\sqrt{(G_2+C)\sqrt{\left(C+\left((SA+C)\sqrt{\sqrt{G_1^{\,2}}}\right)\right)}+(C+(-4.3+C))}-\left(\left(\left(C+\sqrt{(C+SA)+WC}\right)+(C+G2)\right)^{WC}\right)-\left(Gt^{WC}\right)\right) . \quad (2)$$

The next set of models developed were ANN2 and GP2 with mix design parameters and coefficient of sand (FM) and Maximum size of aggregate (MA) as additional input parameters. Coefficient of soft sand i.e. fineness modulus of sand has an impact over the strength of concrete. An increase in fineness modulus of sand implies the increase coarsens of sand which can result further in decrease strength of concrete for given conditions (Shetty, 2005). Similarly maximum size of aggregate needs to be restricted to gain the required strength of concrete. With increase in size of aggregate (after a certain limit) increases the amount of voids in the concrete mix which can further lead to decrease in strength of concrete (Shetty, 2005). ANN2 with architecture of 7:15:1 displays a good performance with correlation coefficient as 0.941. The performance is also validated with other error measures as shown in Table 4.

Weights and bias developed for ANN2 is as shown in Appendix B.

The equation developed by GP2 is:

$$\mathbf{ST}=\frac{\sqrt{\left(\left(\sqrt{G1}\,\frac{MA^2}{\sqrt{SA}}\right)^2\right)+\left(\sqrt{\sqrt{C}}\cdot C\right)}\cdot\sqrt{\sqrt{\sqrt{\sqrt{FM}\cdot G2}+G2}}}{\sqrt{WC}}\,. \quad (3)$$

Eq. (3) developed using GP for GP2 shows the presence of all input parameters considered in the model and displays a satisfactory performance. Thus it can be said that ANN and GP models can be developed with acceptable performance when FM and MA are known. The table 4 below shows the sample of predictions done by developed ANN and GP model.

Thus the above study shows that ANN technique predicts 28 day strength of cylindrical concrete specimens better than GP technique in both the models. ANN builds an approximate function that matches a list of inputs to the desired outputs. In the process it adjusts the weights and biases to reach a predefined goal. This process makes ANN flexible and increases its performance as compared to GP. GP on other hand is based on evolutionary approach technique in which it does not involve any transfer function and evolves generations of 'offspring' based on the 'fitness criteria' and genetic operations. GP approach works with the concept of disregarding input parameters that do not that contribute beneficially to the model and thus based solely on 'fitness' criteria. In the process of building programs (through processes of mutation, crossover and reproduction), GP shows predictions which are slightly over predicted as compared to ANN (Refer Fig. 3 ) and thus GP shows a performance less as compared to ANN. Addition of material properties as Soft coefficient of sand and maximum size of aggregates as input parameters in developing ANN and GP models helps in predicting concrete strength is slightly better than the models with input parameters as mix design proportions. Though GP2 shows a reduction in R value as compared to GP1, the reduction is not very significant. Thus it can be said that inclusion of material properties as input parameters in development of models is beneficial for to capture the underlying phenomenon of the subject in detail. Figs. 2 and 3 show the scatter plot for ANN1 and GP2 respectively. The scatter plots for ANN1, ANN2 and GP2 do not exhibit an obvious under or over prediction. The trend of predicting concrete strength by GP1 is as shown in Fig. 4. It also shows ANN predicted values to be in tune with the Observed values but slight over prediction of strength in GP.

**Table 5.** Sample predictions and percentage errors for each model developed.

| Observed Values of 28 day strength in kg/cm$^2$ | Predictions | | | | | | | |
|---|---|---|---|---|---|---|---|---|
| | ANN1 | Error (%) | GP1 | Error (%) | ANN2 | Error (%) | GP2 | Error (%) |
| 226 | 246.287 | 8.237 | 283.966 | 20.413 | 249.273 | 9.336 | 243.822 | 7.309 |
| 211 | 209.299 | -0.813 | 226.662 | 6.910 | 225.757 | 6.537 | 193.845 | -8.850 |
| 279 | 318.718 | 12.462 | 332.281 | 16.035 | 325.924 | 14.397 | 284.525 | 1.942 |
| 321 | 295.755 | -8.536 | 324.072 | 0.948 | 303.561 | -5.745 | 272.882 | -17.633 |
| 326 | 306.208 | -6.464 | 325.658 | -0.105 | 311.104 | -4.788 | 280.927 | -16.045 |
| 285 | 281.224 | -1.343 | 329.124 | 13.407 | 277.351 | -2.758 | 307.824 | 7.415 |
| 249 | 239.717 | -3.873 | 272.051 | 8.473 | 239.819 | -3.828 | 233.114 | -6.815 |
| 347 | 355.604 | 2.419 | 358.385 | 3.177 | 354.858 | 2.214 | 341.444 | -1.627 |
| 343 | 348.216 | 1.498 | 355.938 | 3.635 | 344.578 | 0.458 | 327.756 | -4.651 |
| 231 | 244.655 | 5.581 | 282.097 | 18.113 | 242.194 | 4.622 | 237.336 | 2.670 |

Thus the above study shows that ANN technique predicts 28 day strength of cylindrical concrete specimens better than GP technique in both the models. ANN builds an approximate function that matches a list of inputs to the desired outputs. In the process it adjusts the weights and biases to reach a predefined goal. This process makes ANN flexible and increases its performance as compared to GP. GP on other hand is based on evolutionary approach technique in which it does not involve any transfer function and evolves generations of 'offspring' based on the 'fitness criteria' and genetic operations. GP approach works with the concept of disregarding input parameters that do not that contribute beneficially to the model and thus based solely on 'fitness' criteria. In the process of building programs (through processes of mutation, crossover and reproduction), GP shows predictions which are slightly over predicted as compared to ANN (Refer Fig. 3 ) and thus GP shows a performance less as compared to ANN. Addition of material properties as Soft coefficient of sand and maximum size of aggregates as input parameters in developing ANN and GP models helps in predicting concrete strength is slightly better than the models with input parameters as mix design proportions. Though GP2 shows a reduction in R value as compared to GP1, the reduction is not very significant. Thus it can be said that inclusion of material properties as input parameters in development of models is beneficial for to capture the underlying phenomenon of the subject in detail. Figs. 2 and 3 show the scatter plot for ANN1 and GP2 respectively. The scatter plots for ANN1, ANN2 and GP2 do not exhibit an obvious under or over prediction. The trend of predicting concrete strength by GP1 is as shown in Fig. 4. It also shows ANN predicted values to be in tune with the Observed values but slight over prediction of strength in GP.

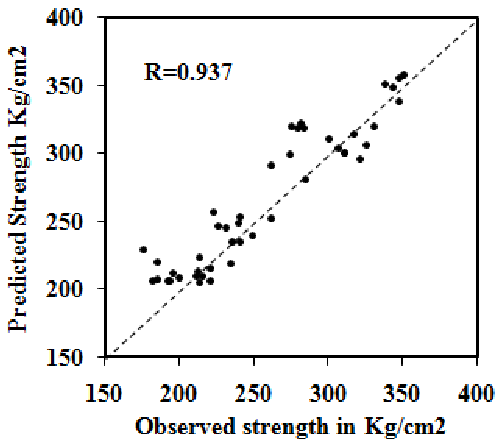


**Fig. 2.** Scatter plot for ANN1.

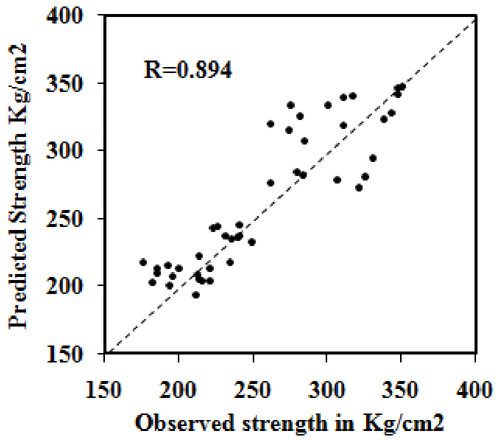


**Fig. 3.** Scatter plot for GP2.

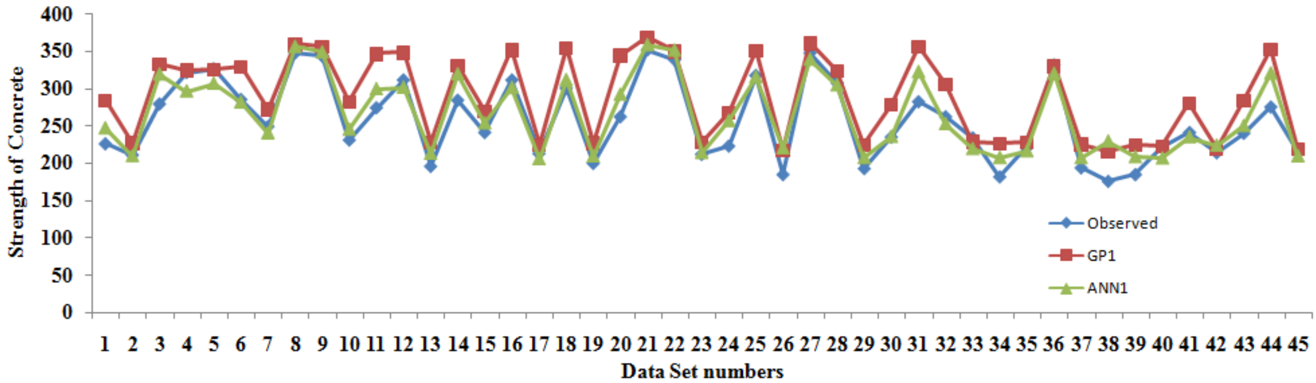


**Fig. 4.** Comparison between actual and predicted values for GP1.

### *5.1. Knowledge extraction*

Knowledge extraction as mentioned in the previous section is done to understand the influence of input parameter/s on the output. By using the procedure developed for extraction (Londhe and Shah, 2016), the histograms for model ANN1 and ANN2 were drawn and are shown in Figs. 5 and 6.

Fig. 5 show higher influence of C followed by SA, G2 and G1 content. A similar influence can also be seen in ANN2. Thus it can be said that inclusion of mix design parameters in respective proportions is important and its influence as per the domain knowledge is being calculated by ANN through judicious allocation of weights and biases. Strength of concrete is inversely proportional to water/cement ratio in hardened state (Shetty, 2005).

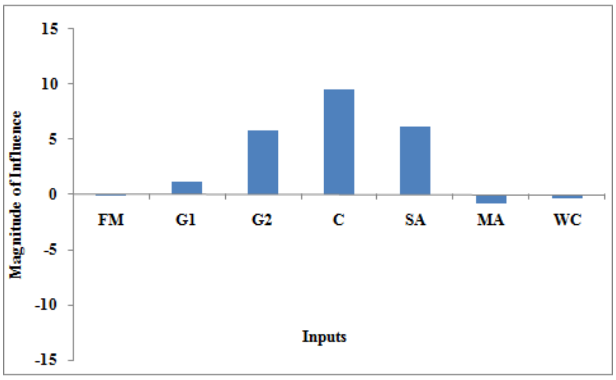


**Fig. 5.** Influence of inputs for ANN1.

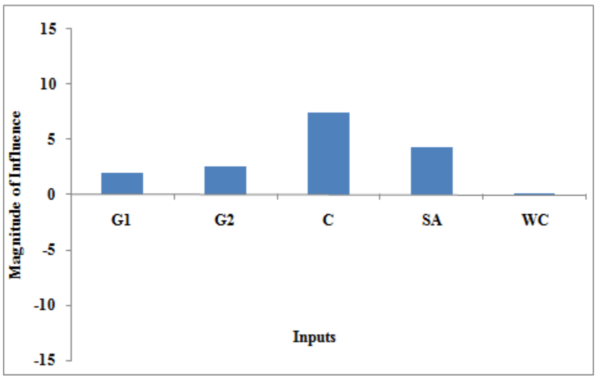


**Fig. 6.** Influence of inputs for ANN2.

For given cement content when the water cement ratio increases a decrease in the strength can be seen. This can be seen through negative influence of WC in ANN2. ANN1 however shows a direct influence of water to cement ratio on concrete strength; however the influence seen is of very small magnitude (01.3) as compared to other parameters. The magnitude of influence for Soft coefficient of sand (FM) and Maximum size of aggregate (MA) is also been shown by Fig. 6. Increase in soft coefficient of sand implies increase in coarseness of sand which shows a decrease in strength for a constant water cement ratio (Shetty, 2005). Also, lower strength of concrete is attributed towards the larger MA which gives lower surface area for developments of gel bonds. More heterogeneity in the concrete is seen when bigger aggregate size is used, which prevents the uniform distribution of load when stressed. Also internal bleeding can be seen and weaker the transition zone due to the development of micro cracks. This leads to lower compressive strength in concrete (Shetty, 2005; Neville, 2012). Thus it can be said that concrete strength is inversely proportional to the maximum size of aggregate, which can be seen from magnitude of influence for the said parameter. Knowledge extraction done by the said method thus can serve as a guideline towards input selection in development of ANN models. Genetic Programming on other hand evolves an equation or formula relating to the input and output variables. A major advantage of GP approach is its automatic ability to select input variables that contribute beneficially to the model and disregard those that do not. GP can thus reduce substantially the dimensionality of the input variables (Bishnoi, 2014). The equations developed in GP1 and GP2 shows the presence of all input parameters which are influential in predicting strength of concrete, which is also in tune with the fundamental knowledge of concrete technology. The inverse proportionality of WC with strength of concrete is shown in Eqs. (8) and (9).

## 6. Conclusions

Concrete being a complex material, modelling its behaviour is a difficult task. In the current work an attempt is made to predict strength of concrete using ANN and GP. Comparative analysis of ANN and GP techniques show that ANN predicts 28 day strength of concrete with good accuracy as compared to GP which can be evident from the higher R values. The performance statistics validated by lower NRMSE, E and RMSE values also show a good performance of ANN as compared to GP in all the models. Prediction of concrete strength can be done satisfactorily with the presence of mix design parameters i.e. mix proportions as input parameter and presence of material properties as FM and MA show slight increase the performance of models.

ANN shows the output in the form of weights and biases in which the knowledge about the problem is locked. Thus, analyzing the weights and biases in ANN and extracting the knowledge locked up in them done was done using the knowledge extraction model. This show that ANN1 and ANN2 show the influencing parameters as C and SA followed by G1 and G2 which is in tune with the basic domain knowledge. Thus ANN can't be just labelled as a black box and can be said as a Grey box. Genetic programming on the other hand displays the influence of input parameters through the presence of relevant parameters in the equation. Influence of WC ratio is shown as inverse in ANN1 which is as per the domain knowledge of concrete technology.

ANN thus predicts strength of concrete better than GP and can display the output in terms of weights and biases for a given set of input. ANN however has a limitation of not been able to provide standalone equations which can be done in GP. GP on the other hand is a powerful tool and can open a new field for efficient explicit equations of many civil engineering problems.

## Appendix A. Knowledge extraction from ANN

### *A.1. Input to hidden layer*

Fig. 7 shows the diagrammatic representation of a typical three layered feed forward network with 3 input neurons, 2 hidden neurons and 1 output neuron.

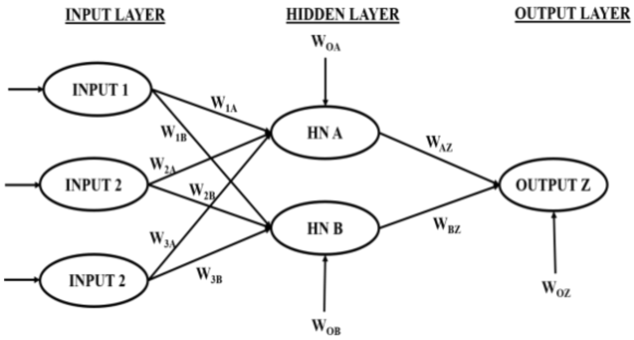


**Fig. 7.** Basic ANN architecture.

It can be seen from Fig. 7 that each hidden neuron in the hidden layer receives weights from all the inputs in the network. Thus, each hidden neuron contains a fraction of weight from each input. The fraction of a particular input can be calculated by taking a ratio of the weight of that particular input with the total weight from all inputs. For example, from Fig. 7, the fraction of first input in the first hidden neuron can be given by Eq. (4). Similarly, the fraction of each input on each of the hidden neurons can be calculated.

$$F_{1A} = W_{1A}/(W_{1A} + W_{2A} + W_{3A})\,. \tag{4}$$

When the network is trained, a bias ($W_{OA}$ and $W_{OB}$) is added to each hidden neuron. This bias can be divided into parts as per the fraction of weight of each input to that hidden neuron, thus assigning a part of bias to each of the input, through each of the hidden neurons. The bias assigned to the first input through the first hidden neuron can be calculated by Eq. (5).

$$W_{OA1} = W_{OA} \, X \, F_{1A}\,. \tag{5}$$

The total contribution of a particular input, on the hidden layer, can then be determined by addition of the fractions of its influence and fraction of the bias through all the hidden neurons. The total influence of input 1 can be calculated as given in Eq. (6).

$$C_1 = (F_{1A} + W_{OA1}) + (F_{1B} + W_{OB1})\,. \tag{6}$$

### *A.2. Hidden to output layer*

Each hidden neuron of the hidden layer is connected to the output with the layer weights. The layer weight from one hidden neuron to the output again, consists of fractions of each of the inputs that were calculated earlier. Thus, the layer weight from a hidden neuron to the output is again divided into parts as per the fractions of the influence of inputs in that particular hidden neuron. The contribution of the first input on the output through the first hidden neuron can be calculated by Eq. (7). Similarly, the contribution of the first input through all the hidden neurons can be calculated and their sum would give the total influence of that input on the output through the layer weights, as seen in Eq. (8). The total influence again would be a sum of these influences and the bias that is added to the output layer ($W_{OZ}$).

$$L_{1AZ} = W_{AZ} \text{ X } F_{1A} \,, \tag{7}$$

$$L_1 = L_{1AZ} + L_{1BZ} + W_{OZ} \,. \tag{8}$$

Thus, the total influence of the first input on the output can be given by Eq. (9).

$$I_1 = C_1 + L_1 \,. \tag{9}$$

The procedure is repeated for each of the inputs, and the results are plotted as histogram.

## Appendix B. Weights and biases for ANN2

| Input layer to hidden layer Weights | | | | | | | Bias | Hidden layer to output Weights | Bias |
|---|---|---|---|---|---|---|---|---|---|
| 0.1436 | 1.2858 | 5.267 | 7.6692 | 5.2026 | -0.2094 | 0.2353 | 0.017 | 0.2612 | -0.7919 |
| 0.135 | 1.2472 | 5.2313 | 7.6697 | 5.1958 | -0.2515 | 0.1693 | 0.0574 | 0.1753 | |
| 0.1321 | 1.2315 | 5.217 | 7.67 | 5.1932 | -0.2685 | 0.1428 | 0.073 | 0.1408 | |
| 0.1483 | 1.3058 | 5.2858 | 7.6687 | 5.2061 | -0.1877 | 0.2696 | -0.004 | 0.3046 | |
| 0.142 | 1.2808 | 5.2623 | 7.669 | 5.2016 | -0.2151 | 0.2263 | 0.0229 | 0.2489 | |
| 0.1381 | 1.2632 | 5.2459 | 7.6694 | 5.1985 | -0.2343 | 0.1961 | 0.0414 | 0.2099 | |
| 0.1457 | 1.2956 | 5.2761 | 7.6688 | 5.2042 | -0.199 | 0.2518 | 0.0072 | 0.2817 | |
| -0.1056 | 0.8213 | 4.6288 | 7.893 | 5.1426 | -0.852 | -0.4293 | 0.7573 | -0.1404 | |
| -0.136 | 0.8283 | 4.7946 | 7.7097 | 5.2305 | -0.7434 | -0.2797 | 0.6489 | -0.4352 | |
| -0.0251 | 0.8459 | 4.2365 | 8.2921 | 4.9021 | -1.1892 | -0.8141 | 1.2133 | 0.6226 | |
| -0.0633 | 0.8266 | 4.3872 | 8.1406 | 5.0034 | -1.047 | -0.6592 | 1.0104 | 0.3137 | |
| -0.0394 | 0.8376 | 4.2867 | 8.2415 | 4.9376 | -1.14 | -0.7614 | 1.1419 | 0.5168 | |
| 0.1108 | 0.9812 | 5.013 | 7.6632 | 5.1757 | -0.5143 | -0.2189 | 0.2808 | -0.3147 | |
| 0.1164 | 0.943 | 4.986 | 7.6614 | 5.1709 | -0.553 | -0.2749 | 0.3009 | -0.4033 | |
| 0.1107 | 0.9786 | 5.0112 | 7.6627 | 5.1756 | -0.5169 | -0.2224 | 0.2829 | -0.3198 | |

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