HASAN KALYONCU UNIVERSITY
GRADUATE SCHOOL OF
NATURAL & APPLIED SCIENCES

A STUDY ON EXPLICIT FORMULATION OF SORPTIVITY OF CONCRETES CONTAINING MINERAL ADMIXTURES

M. Sc. THESIS
IN
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FARMAN KHALIL GHAFFOORI
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A study on explicit formulation of sorptivity of concretes containing mineral admixtures

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In

Civil Engineering

Hasan Kalyoncu University

Supervisor

Assist. Prof. Dr. Kasım MERMERDAŞ

By

Farman Khalil GHAFFOORI

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T.C.
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Farman Khalil GHAFFOORI

ABSTRACT

A STUDY ON EXPLICIT FORMULATION OF SORPTIVITY OF CONCRETES CONTAINING MINERAL ADMIXTURES

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M.Sc. in Civil Engineering
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In this thesis, mathematical models derived from gene expression programming (GEP) and artificial neural network (ANN) were used for prediction of sorptivity of concretes. For this, 151 data samples were collected from the previous studies.The common predicttion parameters were selected as water-to-binder ratio (w/b), total binder content (B), compressive strength of 150 mm cube speciment at 28 days ($f_{c,28}$), aggregate-to-binder ratio (Agg./B) and age of concrete (A). Additionally, in order to evaluate the performance of the proposed models an experimental study was also conducted. The study was carried out on water cured and air cured concretes produced by w/b ratio of 0.45 with total binder content of 400 kg/m^3. Moreover, silica fume (SF) and fly ash (FA) were used in different replacement levels. Total 9 different concrete mixtures with binary and ternary blends of SF and FA were produced. Both of the proposed models were proved to be effective enough for prediction of sorptivity of concretes. However, NN models was more accurate than GEP model. Moreover, validation study also indicated that the proposed mathematical models can be utilized as reliable prediction tools for estimation of sorptivity of concretes.

Keywords: Sorptivity of concrete, Mineral admixtures, Artificial Neural Network, Gene Expression Programming.

ÖZET

MİNERAL KATKI İÇEREN BETONLARIN KILCAL SU GEÇİRİMLİLİĞİNİN AÇIK FORMÜLASYONU ÜZERİNE BİR ÇALIŞMA

GHAFFOORI, Farman Khalil
Yüksek Lisans Tezi, İnşaat Mühendisliği Bölümü
Tez Yöneticisi: Doç. Dr. Kasım MERMERDAŞ
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Bu tezde genetik programlama (GP) ve yapay sinir ağları (YSA) kullanılarak kılcal su geçirimliliğini tahmin eden matematiksel modeller türetilmiştir. Bunun için literaturde bulunan deneysel çalışmalar incelenerek 151 adet veri numunesi toplanmıştır. Ortak tahmin parametreleri olarak su-bağlayıcı oranı (w/b), toplam bağlayıcı miktarı (B), 150mm^3 lük küp numunenin 28 günlük basınç dayanımı, agrega-bağlayıcı oranı (Agg/B) ve betonun deney yaşı seçilmiştir. Bunun yanı sıra önerilen tahmin modellerinin performanslarını incelemek amacıyla deneysel bir çalışma da gerçekleştirilmiştir. Bu çalışmada 0.45 su-bağlayıcı oranına sahip 400 kg/m^3 toplam bağlayıcı ihtiva eden suda ve havada kür edilmiş betonlar kullanılmıştır. Ayrıca mineral katkı olarak silis dumanı (SD) ve uçucu kül (FA) çesitli ikame oranlarında kullanılmışlardır. Böylece ikili ve üçlü sistem mineral katkı içeren 9 adet beton üretilmiştir. Önerilen her iki modelin de kılcal su geçirimliliğinin tahmininde yeterince etkili oldukları görülmüştür. Ancak NN modelinin GEP modele göre daha doğru sonuçlar verdiği gözlenmiştir. Ayrıca deneysel doğrulama çalışmasından elde edilen sonuçlar da önerilen modellerin güvenilir tahmin araçları olarak kullanılabileceklerini göstermiştir.

Anahtar kelimeler: Betonun kılcal su geçirimliliği, Mineral katkılar,Yapay sinir ağları, Genetik programlama.

To my wife, son and daughter

Gashaw, Rezdar and Noor

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LIST OF SYMBOLS/ABBREVIATIONS

SC	Soft Computing
AI	Artificial Intelligence
FL	Fuzzy Logic
PR	Probabilistic Reasoning
NN	Neural Networks
ANN	Artificial Neural Networks
GA	Genetic Algorithms
GP	Genetic Programming
GEP	Gene Expression Programming
S	Sorptivity
MK	Metakaolin
CK	Calcined kaolins
FA	Fly Ash
SF	Silica Fume
GGBFS	Ground Granulated Blast Furnace Slag
PC	Portland Cement
PFA	Pulverised Fuel Ash
NR	Nonlinear Regression

ACI	American Concrete Institute
UPV	Ultrasonic Pulse Velocity
ASTM	American Society for Testing and Materials
SP	Superplasticizer
PCI	Prestressed/Precast Concrete Institute
PPC	Portland Pozzolana Cemen

CHAPTER 1

INTRODUCTION

1.1 General

Sorptivity, which is an index of moisture transport into unsaturated specimens, has been recognized as an important index of concrete durability, because the test method used for its determination reflects the way that most concretes will be penetrated by water and other injurious agents and it is an especially good measure of the quality of near surface concrete, which governs durability related to reinforcement corrosion. The sorptivity coefficient is essential to predict the service life of concrete as a structural and to improve its performance. (Al sheikh, 2013)

The measurement of sorptivity could be used as an indicator of durability. Sorptivity is a property associated with capillary effects.Sorption means water ingress into pores under unsaturated conditions due to capillary suction. The sorptivity test measures the ability of concrete to absorb water, where sorptivity (S) means the volume of water that is absorbed per unit of cross-section (i) in absorption time (t).To present the results, the sorptivity (S) was derived from the relationship between the volume of water absorbed per unit of cross-section (i) and the square root of time (t) using the following equation, Eq.(1)

$$S = \frac{i}{t^{1/2}} \qquad (1)$$

Where

i is the depth of penetrated water at different time intervals (mm), Ng et al. (2006)Soft Computing stands for system solutions based on soft computing techniques. Soft Computing is aimed to provide rapid publication of important and timely results on soft computing technologies intended as a fusion of the following research areas: Evolutionary algorithms and genetic programming neural science and neural net systems fuzzy set theory and fuzzy systems chaos theory and chaotic systems soft computing will be seen from various perspectives: mathematical system hard and soft ware (Math, 2013). Gene expression programming is a procedure that mimics biological evolution to create a computer program to model some phenomenon. Gene expression programming can be used to create many different types of models including decision trees, neural networks and polynomial constructs.

The term soft computing (SC) represents the combination of emerging problem solving technologies such as fuzzy logic (FL), probabilistic reasoning (PR), neural networks (NNs) and genetic algorithms (GA). Each of these technologies provides us with complementary reasoning and searching methods for solving complex, real-world problems (Bonissone, 1997)

A number of researchers utilized soft computing in their researches.For example, Nazari and Azimzadegan (2012) utilized two models based on artificial neural networks (ANN) and gene expression programming (GEP) for predicting splitting tensile strength and water absorption of concretes containing ZnO_2 nanoparticles at different ages of curing.To build these models, training and testing using experimental results for 144 specimens produced with 16 different mixture proportions were conducted. The used data in the multilayer feed forward neural networks models and input variables of genetic programming models are arranged in a format of eight input parameters that cover the cement content (C), nanoparticle content (N), aggregate type (AG), water content (W), the amount of superplasticizer (S), the type of curing medium (CM) and Age of curing (AC). According to these input parameters, in the neural networks and genetic programming models, the splitting tensile strength and water absorption values of concretes containing ZnO_2 nanoparticles were predicted. Although neural networks have predicted better results, genetic programming is able to predict reasonable values with a simpler method rather than neural networks.

Mermerdas et al. (2012) observed the strength of concretes incorporated with metakaolin and different types of calcined kaolins. Their study investigated the effects of metakaolin (MK) and calcined kaolins (CKs) on the compressive strength development of the concrete. For this, non purified ground kaolins obtained from different sources were thermally treated at specified conditions.

Four replacement levels (5%, 10% and 15%,) of CK and MK were assigned for concrete production. On the other hand, one plain mix without admixture was produced as reference. Compressive strength development of the concretes was observed at 3, 7, 28, and 90 days. The strength development of concretes was evaluated by statistical technique named GLM-ANOVA. Moreover, a prediction model was derived from gene expression programming (GEP) to illustrate and evaluate the parameters affecting the strength. The investigated parameters were SiO_2, Al_2O_3, kaolinite, and alunite contents, fineness of mineral admixture, age of concrete, and replacement level. The results showed that type of thermally treated kaolin, the replacement level,and age are very effective on the strength development of the concretes. The prediction model containing those seven parameters was compared with the experimental results and proved to be a handful tool for estimating compressive strength of concrete incorporated with commercial MK and calcined kaolins.

In this thesis, based on the collected data the sorptivity of concretes were predicted. The models were developed by using neural network and genetic programming which handle complex nonlinear relationships between various inputs and outputs.. Furthermore, FA and SF were used as a replacement for Portland cement (PC), in different range, to evaluate efficiency of the proposed models upon prediction of sorptivity. For this purpose, nine different concrete mixtures with w/b ratios of 0.45 were designed.

1.2 Outline

Chapter 1 Introduction

Chapter2 Literature review

Chapter 3 Analytical Modeling

Chapter 4 Experimental work

Chapter 5 Conclusion

CHAPTER 2

LITERATURE REVIEW

2.1 Introduction

The following literature review focuses on the capillary water absorption (Sorptivity) for concrete. Moreover, soft computing modelling and techniques (Artificial intelligence, Machine learning, Artificial Neural Network, Genetic Programming, Fuzzy Logic) are introduced. Information about application of artificial intelligence on civil engineering furthermore applications for concrete properties are also discussed.

2.2 Capillary water absorption

There is a strong interest in finding better ways of assessing the material properties of concretes which determine durability. The processes of deterioration in concrete are mediated largely by water. It is generally agreed that it would be a useful step forward to find a way of measuring a single material property which reflects the ability of a material to absorb and transmit water by capillarity. The sorptivity appears to be an especially useful property of this kind.

According to Hall (1989) the sorptivity is an easily measured material property which characterizes the tendency of a porous material to absorb and transmit water by capillarity. He reported the dependence of the sorptivity on initial water content, temperature and fluid properties. Moreover, he also discussed the initial surface absorption, the water absorption and the covercrete absorption tests in terms of the sorptivity.

Gonen and Yazicioglu (2007) investigated the influence of compaction pores on the sorptivity and the carbonation of concrete. To create various levels of compaction porosity (poor, medium and high) different techniques of compaction were used on concrete specimens at casting stage. Compressive strength, porosity, sorptivity coefficient, mass change due to carbonation and carbonation were tested in order to estimate the properties of concrete with various compaction pores. Test results showed that change in the compaction pores may significantly affect the carbonation rate and the sorptivity coefficient.

There are two engines controlling the uptake and transportation. Permeability, which is a measure of the flow under pressure in a saturated porous medium, and sorptivity, which characterizes the material's ability to absorb and transfer water through it by capillary sucking (Sabir et al., 1998)

According to study Bai et al. (2002) the variation in sorptivity with age of the water cured metakaolin–pulverised fuel ash (MK–PFA) and Portland cement–pulverised fuel ash–metakaolin (PC–PFA–MK) concrete for all cement replacement levels (10%, 20%, 30% and 40%) cured up to 18 months are given in Figure 2.1. In each situation, sorptivities are compared with those of the control PC concrete. Clearly sorptivity reduces systematically with an increase in curing period, and the gradients of the sorptivity versus age curves tend to reduce with an increase in MK content (Figure 2.1a and c). Moreover, at 28 days, the relevant sorptivity values are clearly reflected in the strength prices. Thus, the water-cured concretes with the highest sorptivities have the lowest strengths (i.e. the PC–PFA blended), as well as the concretes with the lowest sorptivities have the highest strengths (i.e. the PC–PFA–MK blends with the highest MK content).

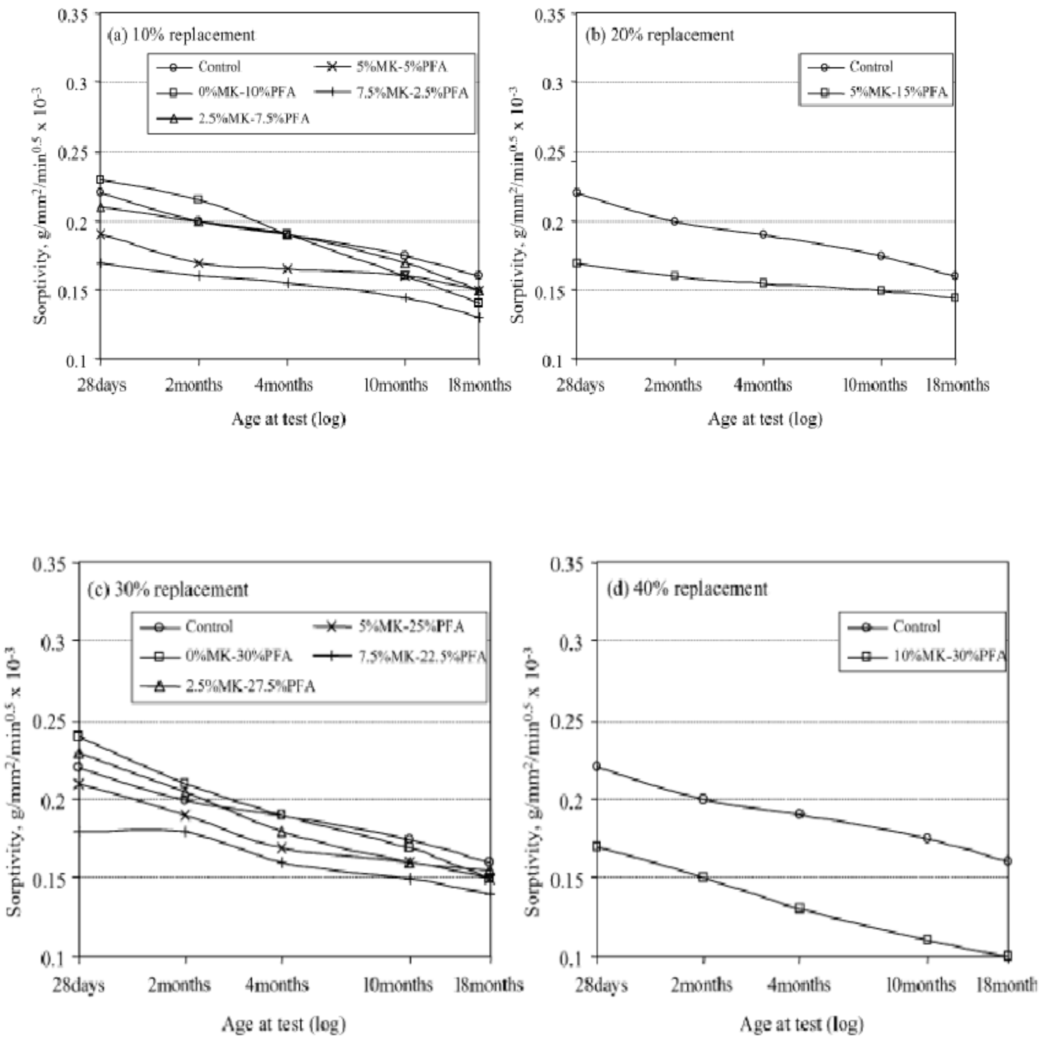


Figure 2.1 Sorptivity with age at 10%, 20%, 30% and 40% cement replacements for water-cured concrete (Bai et al., 2002)

In the study of Guneyisi and Mermerdas (2007) the variation in sorptivity with w/b ratio, concrete age, and curing condition for the plain and MK-modified concretes are given in Figure 2.2. It is obvious that sorptivity reduces systematically with an increase in curing time, and the gradient of the sorptivity tends to reduce with an increase in the replacement level of MK. At 28 days, the sorptivity values are obviously reflected in the strength values. Increasing the MK content reduced both the 28 and 90-day sorptivities of the concrete for the 0.55 w/b ratio and water-cured concretes. The sorptivity values of the concrete including MK were approximately from 2% to 36% and from 8% to 60% lower than that of the plain concretes at 28 and 90 days, correspondingly, depending on w/b ratio, the amount of MK used, and curing regime.

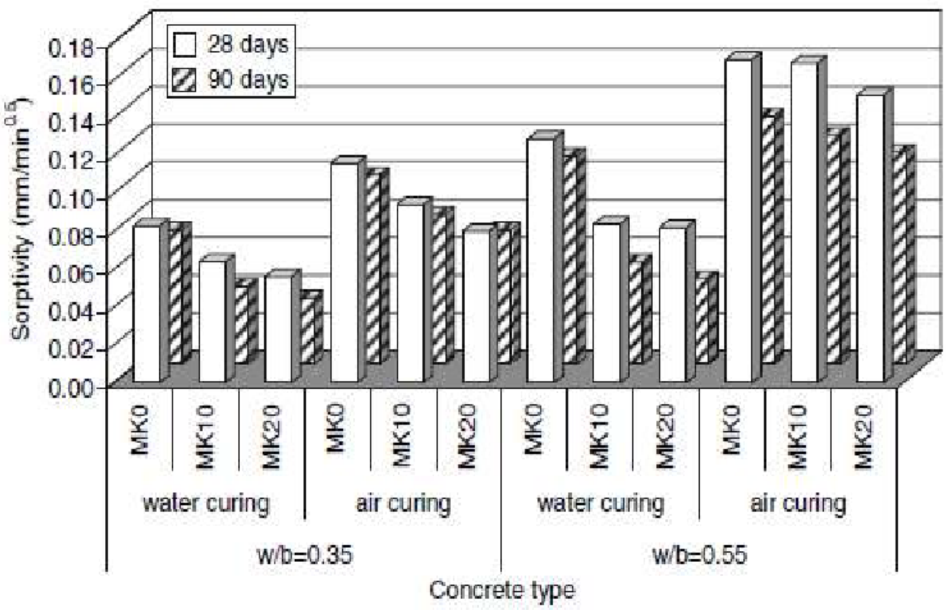


Figure 2.2 Variation in sorptivity of plain and MK-modified concretes to different curing regimes. (Guneyisi and Mermerdas, 2007)

Guneyisi et al. (2011) normalized water sorptivity of the concretes with respect to the control specimen. The sorptivity test consequences of the produced SCCs measured at 90 days. The plain control concrete had the highest sorptivity. Incorporating the mineral admixtures, continuously decreased the sorptivity of the SCCs, the lowest sorptivity index was measured for the concretes with the ternary blends of 15% MK and 45% GGBFS and the binary blends of 15% MK. The use of MK seemed to be much more effective in reducing the sorptivity due to the reduced pore volume. Using FA and/or GGBFS with MK gave a marked decrease in the sorptivity as well. It shown in Figure 2.3.

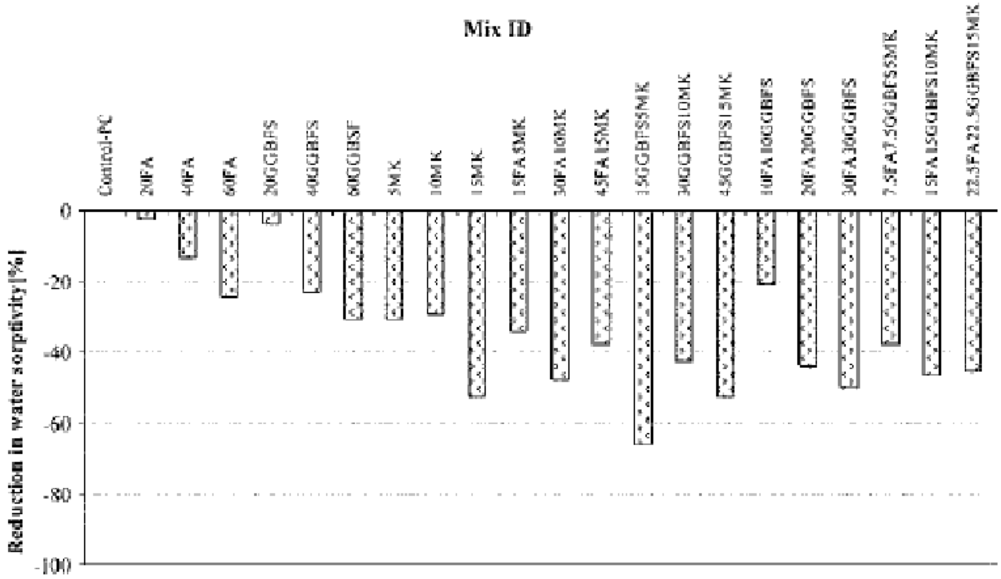


Figure 2.3 Normalized water sorptivity of concretes with respect to control specimen (Guneyisi et al., 2011)

Yerramala and Babu (2011) concluded the sorptivity of the low cement and high fly ash RCCs (RCC1 and RCC2) was higher than another concrete. Furthermore, it can also be seen that sorptivity of high cement and low fly ash RCCs (RCC5 and RCC6) was closely same as that of moderate cement and moderate fly ash RCCs (RCC3 and RCC4). As for permeability increase in cement content did not display any significant decrease in sorptivity in RCC5 and RCC6. Figure 2.4 gives a comparison between sorptivity and permeability of the concretes, nevertheless, of the amount of cement, fly ash percentage, and total cementations material and w/(c + f).

In general, very good correlation is noticed between the sorptivity and the permeability values. As both the parameters are functions of the porosity and pore system, permeability increased with sorptivity. Sorptivity of the concretes is demonstrated in Figure 2.5.

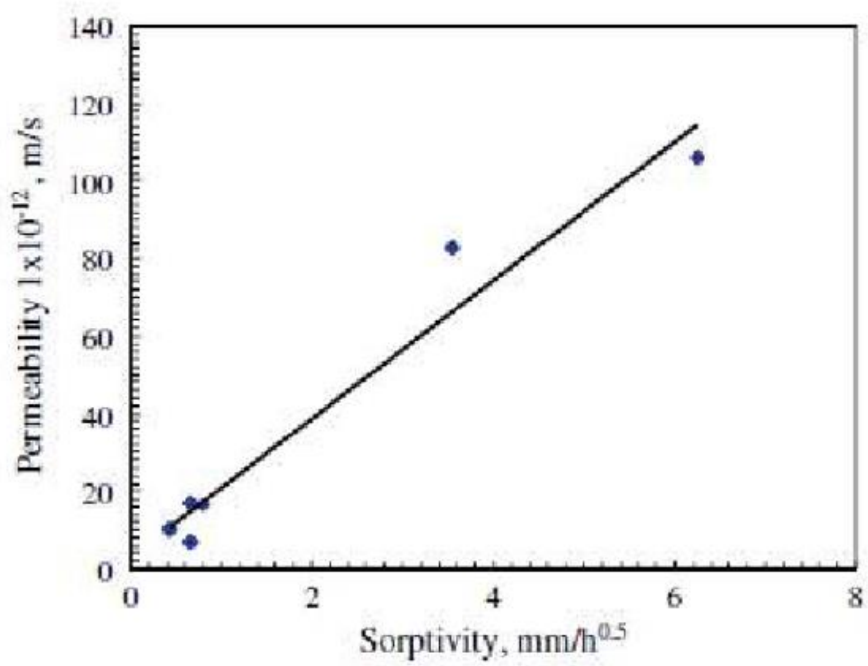


Figure 2.4 Relationship between permeability and Sorptivity (Yerramala and Babu, 2011)

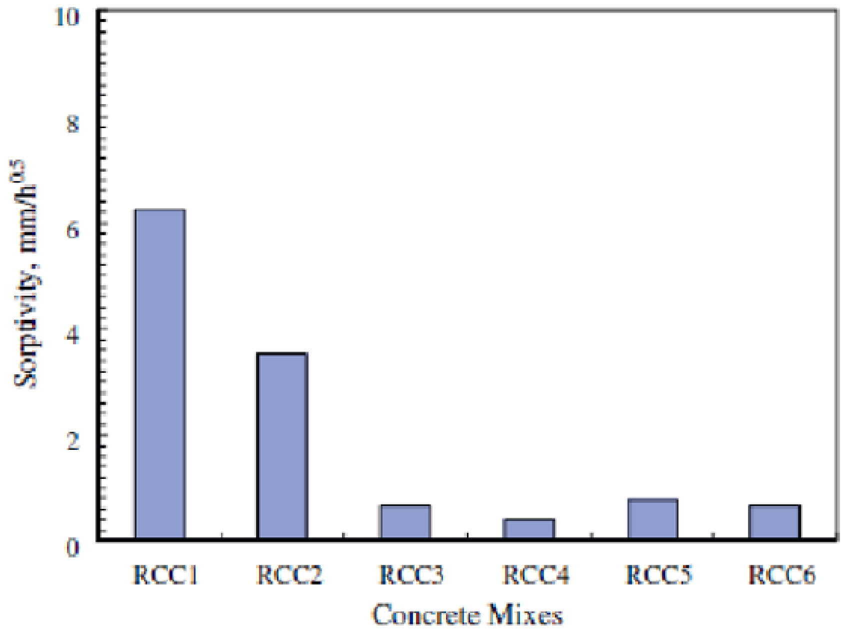


Figure 2.5 Sorption characteristics of the concretes (Yerramala and Babu, 2011)

2.3 Artificial intelligence

Artificial Intelligence (AI) techniques have been utilized as robust alternative technique for engineering analysis problems. Artificial intelligence emerged as a computers science discipline in the mid-1950s. Since then, a number of handful tools has been produced for practical use in engineering to figure out sophisticated problems which normally require human intelligence (Pham and Pham, 1999). AI can be described as the simulation of human intelligence on a machine, so that the machine effectively to identifies and uses the right part of Knowledge at a specified step of solving a problem. Therefore, AI alternatively might be defined as object orientation with computational models that can think and act rationally. AI has broad spectrum of research fields. It tackles various types of knowledge representation modes, different methods of intelligent search, various techniques for resolving fuzzy data and knowledge (Konar, 1999). Several AI tools that are widely utilized for engineering problems are knowledge-based systems, fuzzy logic, inductive learning, neural networks and genetic algorithms (Pham and Pham, 1999).

2.3.1 Origin

"[The automation of] activities that we associate with human thinking, activities such as decision-making, problem solving, learning ..."(Bellman, 1978)

"The exciting new effort to make computers think . . . *machines with minds*, in the full and literal sense" (Haugeland, 1985)

"The art of creating machines that perform functions that require intelligence when performed by people" (Kurzweil, 1990)

2.3.2 Current studies

According to Zadeh (1994) 'soft computing is a collection of methodologies that aim to exploit the tolerance for imprecision and uncertainty to achieve tractability, robustness, and low solution cost. Its principal constituents are fuzzy logic, neuro computing, and probabilistic reasoning. Soft computing is likely to play an increasingly important role in many application areas, including software engineering. The role model for soft computing is the human mind. The fuzzy logic, genetic algorithm, genetic programming, neural network can be accepted as the main techniques of soft computing.

Many researchers have been working on artificial intelligence such as:

- Mermerdaş, (2013) utilized artificial intelligence in his Ph.D. thesis it was an experimental investigation on the utilization of calcined impure Turkish kaolins as supplementary cementing material to improve mechanical and durability characteristics of concrete was presented. Microstructural characteristics of the raw kaolins were analyzed and the alteration in microstructural properties were monitored as a result of calcination process. And an analytical study was carried out to obtain explicit mathematical formulation for estimation of the concrete properties.
- In Master thesis by Ercan, (2006) performance analysis of decision tree algorithms on water-consumption domain was investigated. In today's world, learning is a process of computers as well as human being. "Learnable" systems and computers will become more important in following years and affect our lives in many ways. In his thesis, a survey has been carried out in the field of artificial intelligence, machine learning and especially on decision tree learning algorithms. Some of the decision tree learning algorithms was used to learn rules which are extracted from a dataset. The dataset that consists of water consumption of Ankara for one year and meteorological data of Ankara was used. The results indicate that which learning method is more efficient and have better performance.
- Çevik et al. (2008) utilized soft computing (SC) techniques for the prediction of shear capacity of RC beams without web reinforcement. Neural networks (NN), Genetic programming (GP) and nonlinear regression (NR) analysis are used as soft computing techniques. The proposed SC models are based on a wide range of experimental data gathered from literature. The accuracy of the proposed SC models are compared with current design codes (ACI-318, EC2 and LRFD) and found to be by far more accurate. Moreover the proposed NN, GP and NR models are also given in explicit form for practical

use.The overall performance of the proposed SC models in their study are quite satisfactory as compared to current design codes (ACI, EC2 and LRD).

- Yeh (2007) modelled the slump flow of high performance concrete using second order regressions and artificial neural networks. In that study, it was concluded that slump flow model based on ANN is much more accurate than that based on regression analysis.
- Hewayde et al. (2007) examined the feasibility of using artificial neural networks (ANNs) to predict the compressive strength of concrete and its degradation under exposure to sulphuric acid of various concentrations. Results showed that the ANN model successfully predicted the weight loss of concrete specimens subjected to sulphuric acid attack, not only for mixtures used in the training process, but also for new mixtures unfamiliar to the ANN model designed within the practical range of the input parameters used in the training process.
- Yeh (2006) investigated the potential of using design of experiments and artificial neural networks to determine the effect of fly ash replacements, from 0 to 50%, on the early and the late compressive strength, from 3 to 56 days, of low- and high-strength concrete, at water-cementations material ratios in the range of 0.3–0.7. It was reported that high correlations between the compressive strength and the component composition of concrete can be developed using the generalization capabilities of the neural networks.
- Kewalramani and Gupta (2006) conducted a study for prediction of compressive strength of concrete based on weight and UPV for two different concrete mixtures involving specimens of two different sizes and shapes as a result of the need for rapid test method for predicting long-term compressive strength of concrete. The prediction is done using multiple regression analysis and artificial neural networks. A comparison between two methods depicted that the artificial neural network can be used to predict the compressive strength of concrete more effectively.
- Sarıdemir (2014) developed the models by genetic programming for predicting the compressive strength values of cube (100 and 150 mm) and cylinder (100 _ 200 and 150 _ 300 mm) concrete containing fly ash at different proportions. The use of fly ash as a mineral admixture in the

manufacture of concrete has received considerable attention in recent years. For this reason, several experimental studies are carried out by using fly ash at different proportions replacement of cement in concrete. The experimental data of different mixtures are obtained by searching 36 different literatures to predict these models. In the set of the models, the age of specimen, cement, water, sand, aggregate, superplasticizers, fly ash and CaO are entered as input parameters, while the compressive strength values of concrete containing fly ash are used as output parameter. The training, testing and validation set results of the explicit formulations obtained by the genetic programming models show that artificial intelligent methods have strong potential and can be applied for the prediction of the compressive strength of concrete containing fly ash with different specimen size and shape.

- Gesoğlu et al. (2014) predicted the edge breakout shear capacity of single adhesive anchors post-installed into uncracked hardened concrete. For this purpose, an experimental database for the adhesive anchors compiled by the ACI Committee 355 was obtained and utilized to construct training and test sets so as to derive the closed-form solution by means of gene expression programming (GEP). The independent variables used for development of the prediction model were anchor diameter, type of anchor, edge distance, embedment depth, clear clearance of the anchor, type of chemical adhesive, method of injection of the chemical, and compressive strength of the concrete.
- Alqedra and Ashour (2005) proposed a feed forward back-propagation neural network model for predicting the shear capacity of anchor bolts located near a concrete edge. In the developed neural network, the neurons of the input layer represent the anchor outside diameter, concrete compressive strength, anchor embedment depth, and the edge distance from the anchor bolt to the edge of concrete in the direction of the shear force. One neuron is used in the output layer to repress the concrete shear capacity of the anchor bolts. Predictions of the concrete shear capacity of anchors using the trained neural network are in good agreement with experimental results and those calculated from the concrete capacity design method.

- Tarefder et al. (2005) constructed and applied a four-layer feed-forward neural network to determine a mapping associating mix design and testing factors of asphalt concrete samples with their performance in conductance to flow or permeability. The network is trained using the Levenberg-Marquardt algorithm. At the end of the study, it is believed that the developed ANN model will be a useful tool in the study of asphalt pavement construction and maintenance.
- Bai et al. (2003) developed a neural network model that provides effective predictive capability in respect of the workability of concrete incorporating metakaolin (MK) and fly ash (FA). The predictions produced reflect the effect of graduated variations in pozzolanic replacement in Portland cement (PC) of up to 15% MK and 40% FA.
- Jun et al. (2002) studied the feasibility of using a neural network as an adaptive synthesizer as well as an estimator to predict the chloride profiles diffused through concrete specimens. ANN predictions are in good agreement with the test results in both steady and unsteady states. Moreover, the investigation results demonstrate that the addition of fly ash and micro silica improves the resistance of mixtures to chloride diffusion. However, the addition of calcium nitrite solution degrades the improvement caused by the incorporation of these mineral admixtures, so calcium nitrite should be used in practical engineering with caution.
- Haj ali et al. (2001) developed an ANN model to predict the long-term expansion response of concrete cylinders while exposed to a 2.1% Na2SO4 solution. The experimental data used in that study was collected by the U.S. Bureau of Reclamation (USBR) during a long-term (40+ years), non-accelerated test program.
- The ANN was constructed such that it provided for the expansion of the concrete as an output while its input vector includes time and two mixture parameters: the water cement ratio (w/c), and the tricalcium aluminate content of the cement. At the end of the research, it was concluded that ANN could effectively learn and predict the expansion of the concrete samples within a practical range of the two mixture parameters, during a span of up to

40 years, despite the described limitations of using the USBR data for ANN training.

2.4 Use of Genetic programming on concrete properties

- The generated prediction model yielded correlation coefficients of 0.98 and 0.92 for training and testing data sets, respectively. Moreover, the performance of the proposed model was compared with the existing models proposed by American Concrete Institute (ACI) and Prestressed/Precast Concrete Institute (PCI). The analyses showed that the proposed GEP model provided much more accurate estimation of the observed values as compared to the other models.
- Nazari and Riahi (2011) predicted split tensile strength and percentage of water absorption of several types of concrete with and without TiO_2 nanoparticles by ANNs and GP. Totally 144 split tensile strength and 144% of water absorption data from 16 different concrete mixtures were collected, trained and tested by means of different models. The obtained results have been compared by experimental ones to evaluate the software power for predicting the properties of concrete.as shown in figs. 2.6-2.9

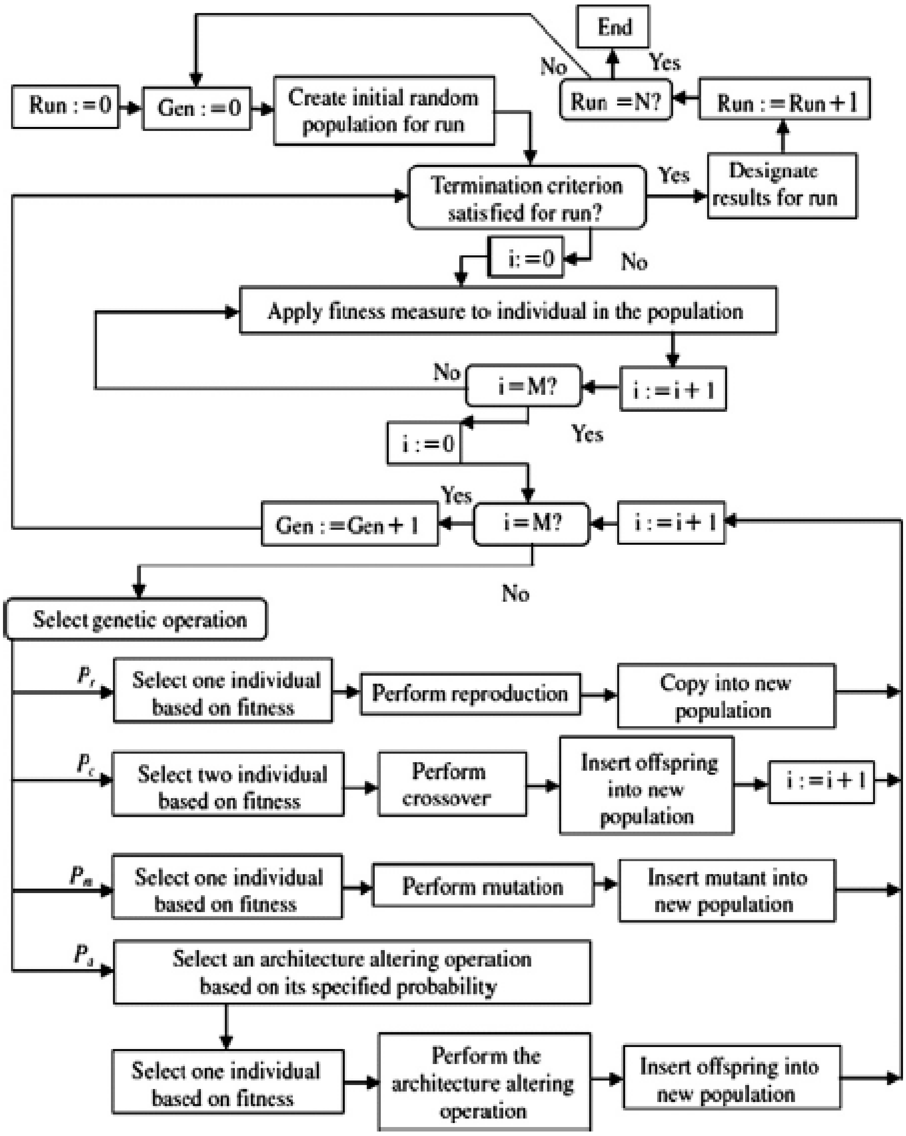


Figure 2.6 Genetic programming flowc harts. (Nazari and Riahi , 2011)

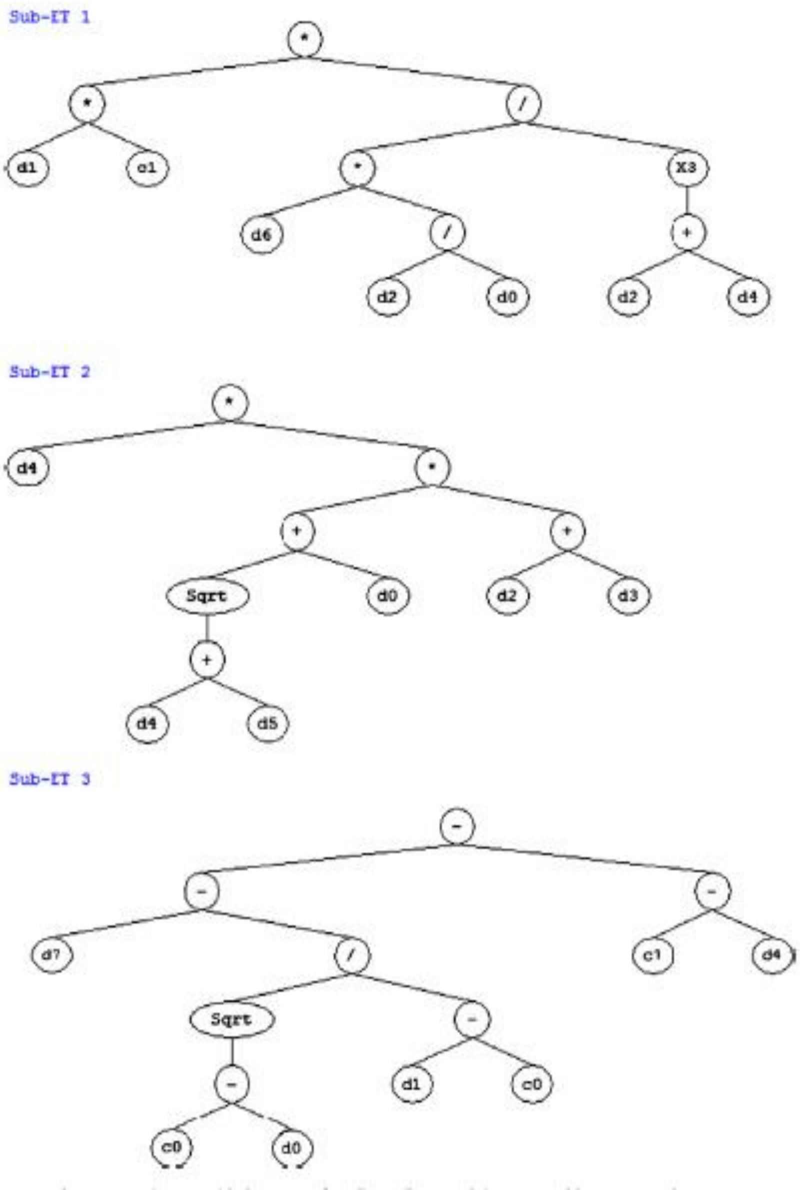


Figure 2.7 Expression tree with three genes for split tensile strength in GEP-I model. C0 = 3.24 and C1 = 11.32. (Nazari and Riahi, 2011)

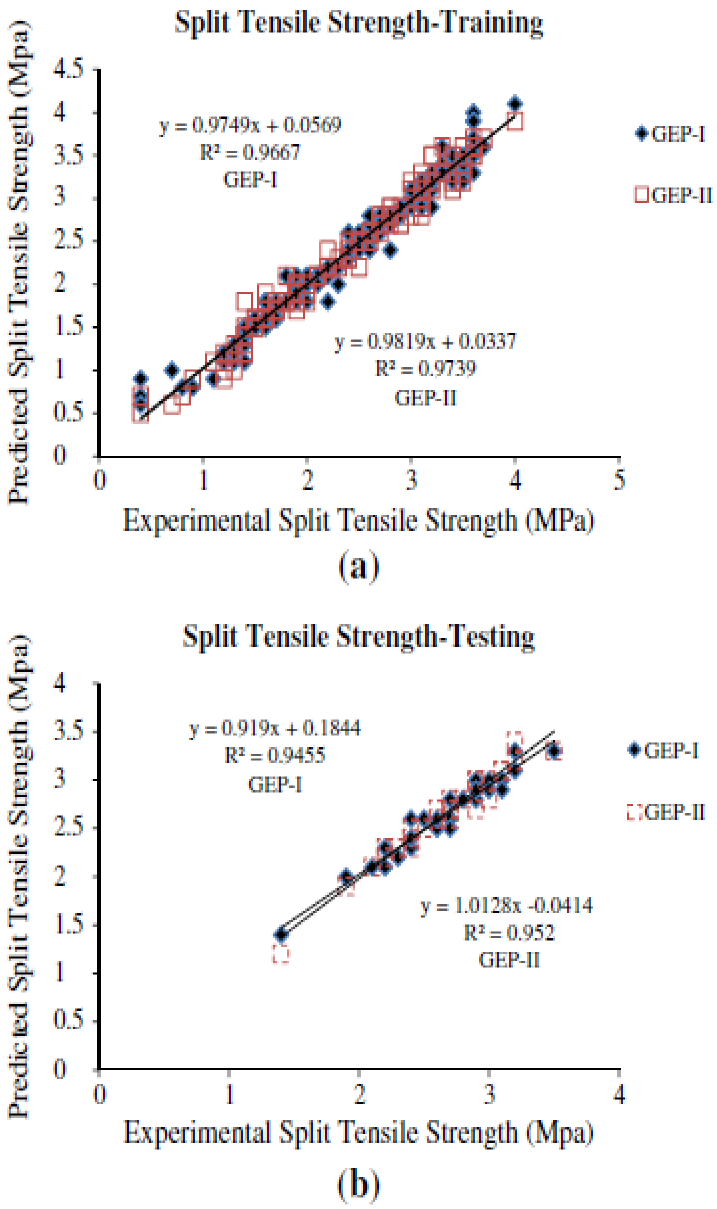


Figure 2.8 The correlation of the measured and predicted split tensile strengths in (a)Training and (b) testing phase for GEP models.(Nazari and Riahi , 2011)

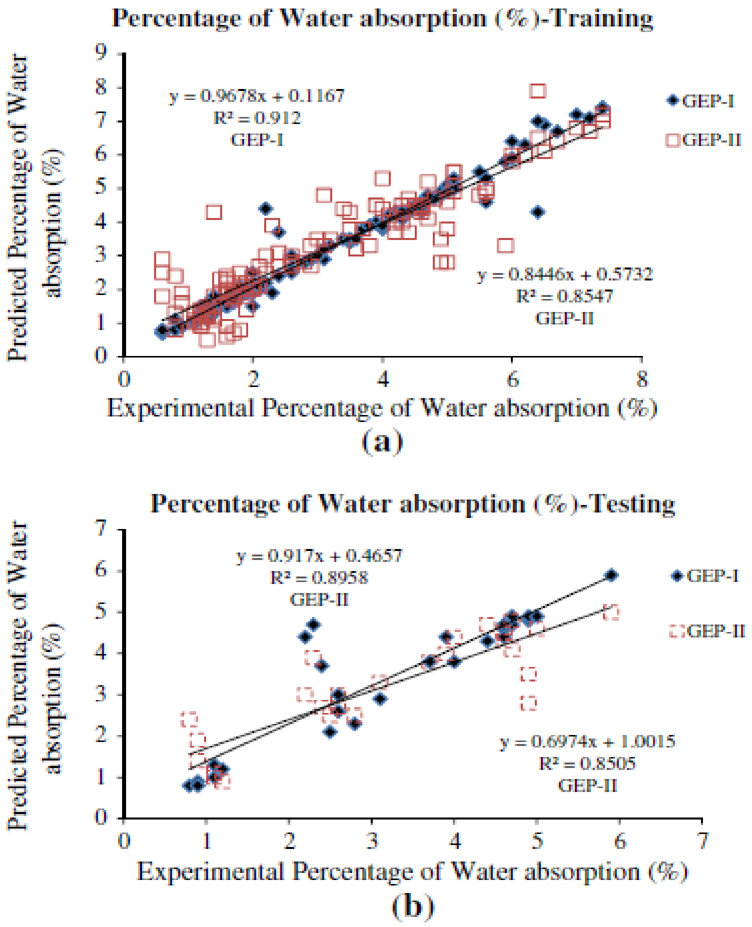


Figure 2.9 The correlation of the measured and predicted percentage of water absorption in (a) training and (b) testing phase for GEP models.(Nazari and Riahi , 2011).

2.5 Soft computing techniques

2.5.1 Artificial neural network

Artificial neural networks are computational systems that simulate the microstructure (neurons) of a biological nervous system. The most basic components of ANNs are modeled after the structure of the brain, and therefore even the terminology is borrowed from neuroscience. It is necessary to give a fundamental description of natural nerve system (Zhang and Friedrich, 2003).

The power of the brain comes from the numbers of these basic components and the multiple connections between them. All natural neurons have four basic components, which are dendrites, soma, axons, and synapses. In the brain, there is a flow of coded information (using electrochemical media, the so-called neurotransmitters) from the synapses towards the axon. The axon of each neuron transmits information to a number of other neurons. The neuron receives information at the synapses from a large number of other neurons. It is estimated that each neuron may receive stimuli from as many as 10,000 other neurons. Groups of neurons are organized into subsystems and the integration of these subsystems forms the brain. It is estimated that the human brain has got around 100 billion interconnected neurons (Kalogirou, 1999).

Inspired by biological neurons, ANNs are composed of simple elements operating in parallel, i.e. ANNs are the simple clustering of the primitive artificial neurons. This clustering occurs by creating layers, which are then connected to one another. How these layers connect may also vary. Basically, all ANNs have a similar topological structure. Some of the neurons interface with the real world to receive its input, and the other neurons provide the real world with the network's output. All the rest of the neurons are hidden from view. As in nature, the network function is determined largely by the interconnections between neurons, which are not simple connections, but some non-linear functions. Each input to a neuron has a weight factor of the function that determines the strength of the interconnection, and thus the contribution of that interconnection to the following neurons. ANNs can be trained to perform a particular function by adjusting the values of these weight factors between the neurons, either by the information from outside the network or by the neurons themselves in response to the input. This is the key to the ability of ANNs to achieve learning and memory (Zhang and Friedrich, 2003).

Artificial neural networks (ANN) have been developed as generalizations of mathematical models of biological nervous systems. A first wave of interest in neural networks (also known as connectionist models or parallel distributed processing) emerged after the introduction of simplified neurons by Mcculloch and Pitts (1943).

2.5.2 Genetic programming

Genetic programming (GP) is a search technique which allows the solution of problems by automatically generating algorithms and expressions. These expressions are coded or represented as a tree structure with its terminals (leaves) and nodes (functions) (Koza, 1992b).

Genetic programming is a domain-independent method that genetically breeds a population of computer programs to solve a problem. Specifically, genetic programming iteratively transforms a population of computer programs into a new generation of programs by applying analogs of naturally occurring genetic operations. The genetic operations include crossover (sexual recombination), mutation, reproduction, gene duplication, and gene deletion. Analogs of developmental processes that transform an embryo into a fully developed entity are also employed. Genetic programming is an extension of the genetic algorithm into the arena of computer programs (Koza, 2005).

Kisi et al. (2012) utilized the genetic programming (GP) technique for estimating the daily suspended sediment load in two stations in Cumberland River in U.S. Daily flow and sediment data from 1972 to 1989 were used to train and test the applied genetic programming models. The effect of various GP operators on sediment load estimation was investigated. The optimal fitness function, operator functions, linking function and learning algorithm were obtained for modeling daily suspended sediment. The GP estimates were compared with those of the Adaptive Neuro-Fuzzy Inference System (ANFIS), Artificial Neural Networks (ANNs) and Support Vector Machine (SVM) results, in term of coefficient of determination, mean absolute error, coefficient of residual mass and variance accounted for. The comparison results indicated that the GP is superior to the ANFIS, ANN and SVM models in estimating daily suspended sediment load.

Gene-Expression Programming (GEP) is a natural extension of Genetic Programming (GP) and was recently developed by Ferreira (2006). A standard GP is a search strategy based on the rules of natural genetic evolution (Castilho et al., 2005). The GP works with population of individuals each representing a possible solution to a given problem. Each candidate solution, or individual, is represented as a string of bits analogous to chromosomes and genes in the evolution theory. A fitness score is assigned to each individual (Al-Tabtabai and Alex, 1999). On the other hand a GEP starts with an expression tree (ET) written in the so-called Karva notation. For example, the algebraic expression given in equation 2.1 can be represented by an ET as shown in Figure 2.7

$$\left(c_0(d_0/d_4)\right) \times \sin\left(d_6(a\tan(d_3))\right) \tag{2.1}$$

To read the tree given in Figure 2.10, we start at the bottom and move up. The left leaf indicates d_0/d_4 as the lowest expression. It then is multiplied by c_0 to give the expression in the first set of parentheses. The right leaf starts with defining arctangent of d_3 which then is multiplied by d_6 and the resulting expression is then used as the argument to the sine function. The expressions from the two leafs are then multiplied to get the final expression. A GEP algorithm begins with the random values of parameters in the ET and applies standard genetic operations of selection, crossover, and mutation to find the best fit (Al-Tabtabai and Alex, 1999).

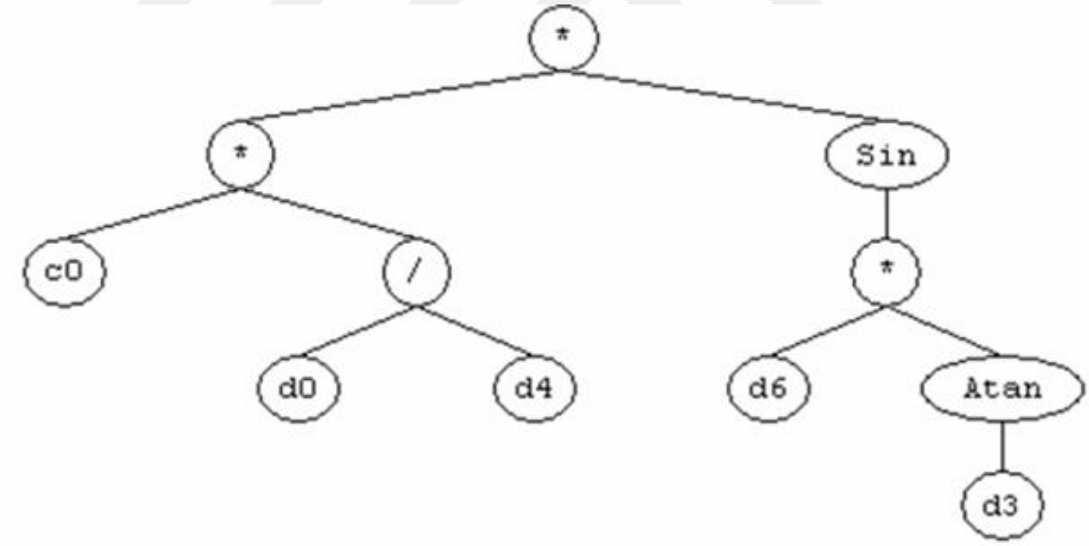


Figure 2.10 a typical example of the GEP expression tree.

2.5.3 Fuzzy logic

Tanyildizi and Coskun (2007) utilized fuzzy logic for prediction model for 3,7,14 and 28 days compressive strength of lightweight concrete made with scoria aggregate and fly ash under different curing conditions (standard and air curing) was devised. In mixtures containing fly ash, 15% of Portland cement by weight was replaced with fly ash. The specimens were cured in standard curing conditions at temperature 20±2 °C and air curing conditions at temperature 20±2 °C for periods of 3,7 ,14 and 28 days. Compressive strength and ultrasonic pulse velocity (UPV) were determined at the 3, 7, 14 and 28 days curing period. The obtained results close to each other .the results show that the fuzzy logic can be used to predict the compressive strength of lightweight concrete as shown in Figs. 2.11-2.16 and Tables 2.1-2.2 below.

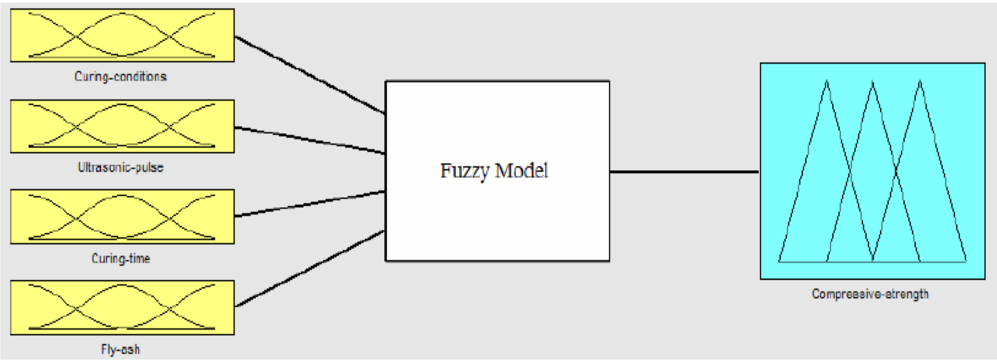


Figure 2.11 Block diagram used for fuzzy model.

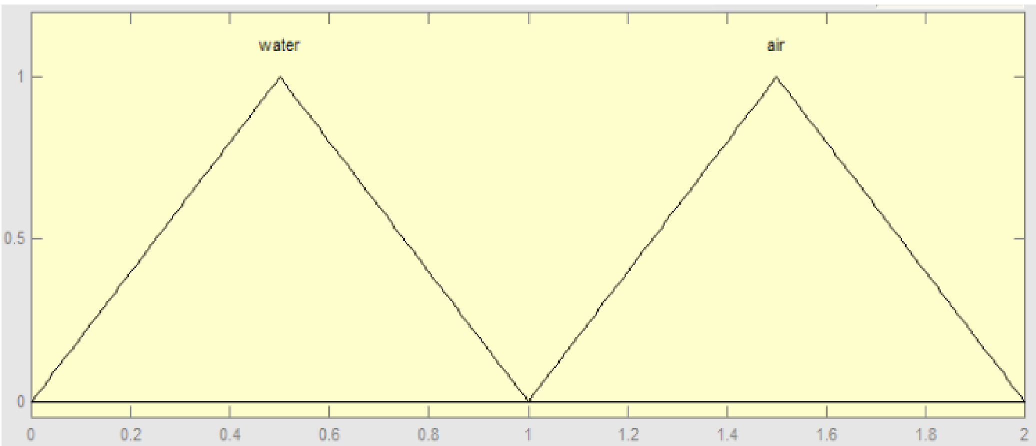


Figure 2.12 Fuzzy input membership functions used for curing conditions.

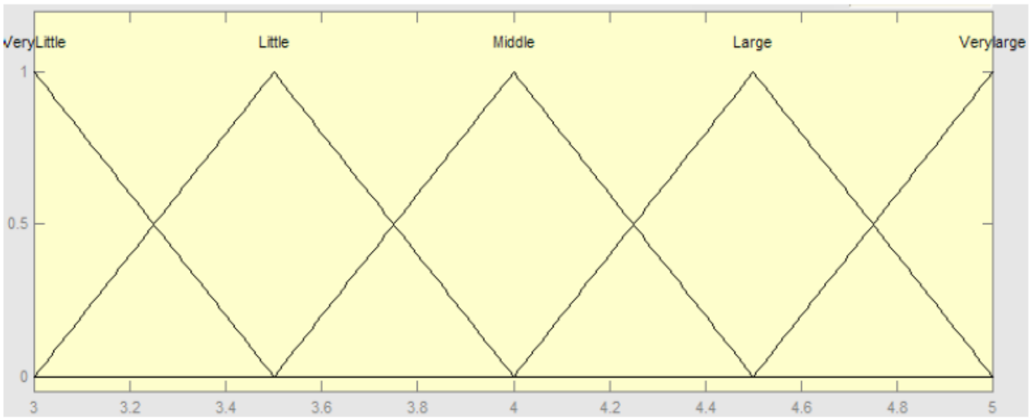


Figure 2.13 Fuzzy input membership functions used for ultrasonic pulse velocity (UPV).

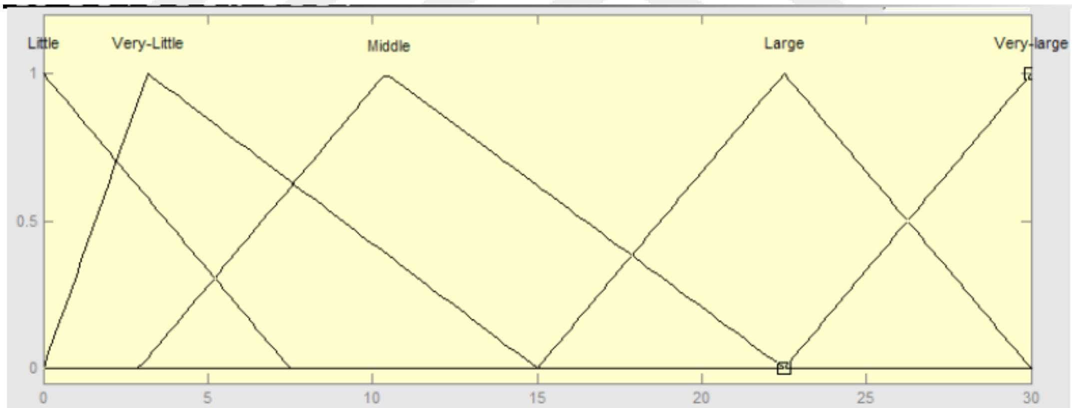


Figure 2.14 Fuzzy input membership functions used for curing times (days)

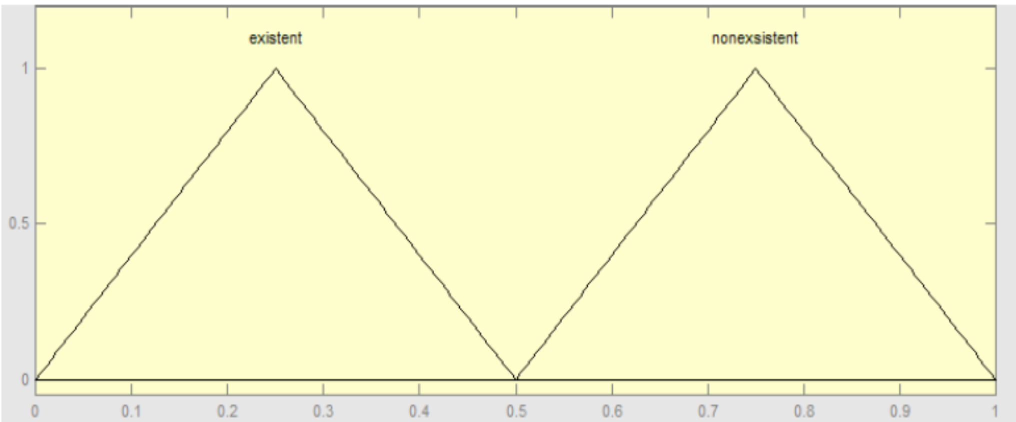


Figure 2.15 Fuzzy input membership functions used for flay ash.

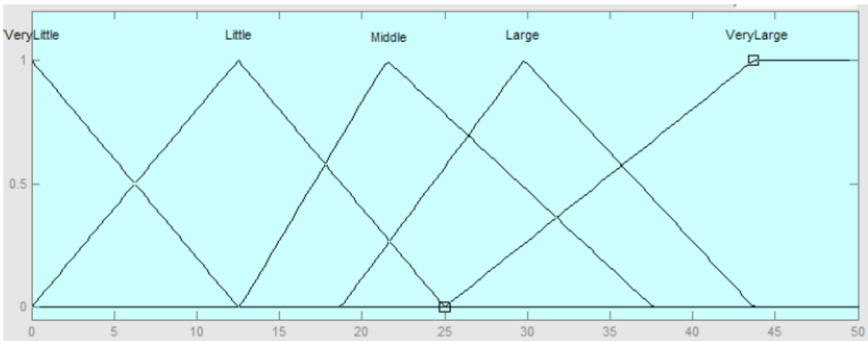


Figure 2.16 Fuzzy output membership functions used for compressive strength.

Table 2.1 Measured and predicted compressive strength results for water curing periods.

	3	**7**	**14**	**28**
Lightweight concrete	13.41	20.12	28.4	30.94
Fuzzy logic results for lightweight concrete	12.8	20.5	23.9	31.1
Lightweight concrete with fly ash	11.73	23 .99	29.9	33.99
Fuzzy logic results for lightweight concrete with fly ash	12	23.4	26.6	36.8

Table 2.2 Measured and predicted compressive strength results for air curing periods.

	3	**7**	**14**	**28**
Lightweight concrete	12.32	14.73	20.14	24.87
Fuzzy logic results for lightweight concrete	12.5	14	23.1	25
Lightweight concrete with fly ash	9.09	18.2	22.35	27.32
Fuzzy logic results for lightweight concrete with fly ash	10	21.8	24.2	31.1

2.6 Binary and Ternary blending systems of mineral admixture

Mullick (2007 a) discussed the main features of an ideal cement composition and the role of mineral admixtures in ideal cement systems. The one way to obtain the ideal cement system can be the use of fly ash, granulated slag or silica fume in requisite amounts as part replacement of OPC i.e. the use of binary and ternary cement blends. Concrete incorporating the industrial wastes like fly ash, slag and silica fume are more durable in aggressive environment. Enhanced durability of concrete results from denser micro-structure, strengthened aggregate-matrix interface, reduction in micro cracking and increased water-tightness (Mullick, 2007 b).

In ternary blend cement system, due to synergic effects, enhancement of some properties of concrete is more than superposition of the individual contribution for the respective proportions(Isaia et al., 2003). The synergic effect is due to physical and chemical effect of mineral admixtures. Isaia et al. (2003) investigated ternary systems incorporating fly ash and silica fume and found that the physical effect was presumably due to a higher content of particles smaller than 5 μm, whereas the chemical effect was associated with higher pozzolanic activity of the ternary system. Both effects were well reflected by increased compressive strength.

A number of researches demonstrated that the combined usage of SF and FA in ternary blend cement system resulted in overall improvements in mechanical properties. The combination of silica fume and FA results improvement in ternary blend concrete with early strength and long-term strength development (Thomas et al., 1999).

Jones et al. (1997) examined the chloride and carbonation durability performance of concrete containing ternary blended binders in comparison to OPC and binary blend of OPC+FA concrete. It has been shown that the chloride resistance of all the ternary binder concrete is significantly higher than corresponding OPC and binary mixes.

Other researchers (Elahi et al., 2010; Thomas et al., 1999; Shehata and Thomas, 2002; Khan, 2012; Hariharan et al., 2011) also reported that ternary blend of OPC+FA+SF has very high resistance to the ingress of chloride ions.

Soleymani and Ismail (2004) investigated the corrosion activity of steel embedded in two types of concrete, ordinary and high performance using different corrosion measurement methods like Tafel plot, linear polarization resistance, half-cell potential and chloride content methods. High performance concrete using silica fume showed lower corrosion activity level compared with OPC specimens.

Saraswathy and Song (2007) evaluated the corrosion resistance of Portland pozzolana cement (PPC) and fly ash blended cements in pre-cracked reinforced concrete slabs using various electrochemical tests like open circuit potential, linear polarization technique, free chloride measurement, alkalinity and weight loss measurements and concluded that PPC and fly ash replaced concrete showed better corrosion resistance than OPC.

Isaia et al. (2012) studied the statistical influence of type and content of mineral admixtures, water/binder ratio and compressive strength of binary and ternary concrete mixtures on microstructural characteristics and durability. Among the dependent variables, the mineral admixture content presented the highest significance followed by water/binder ratio, mineral admixture type and lastly the compressive strength. So, the effect of different replacement levels of mineral admixtures on different aspects of ternary blend cement system need to be thoroughly investigated to get optimum benefits of using mineral admixtures, as ternary blend concrete are the concrete of the present and future (Kumar and Kaushik, 2003).

Yazıcı (2007) performed a study to find out the effects of high volume FA replacement ratio on the properties of SCCs. In that study, cement was replaced by a Class C FA in various proportions from 30 to 60%. Similar tests were carried out with the incorporation of 10% SF to the same mixtures. The results showed that the compressive strength decreased with the increasing FA content at all ages. The compressive strength of control (0% FA) and 60% FA mixtures were 61.8 MPa and 28.4 MPa, respectively at 28 days. All mixes showed strength gain beyond 28 days and the control mixture reached to 72.5 MPa at 90 days while this value was 38 MPa for 60% FA content. However, it was possible to produce a SCC with a compressive strength value of 50 MPa with 30–40% FA replacement. 10% SF addition to the system positively affected the compressive strength and contributed to the production of SCC mixtures that develop high-mechanical properties incorporating high-volume of FA. At 30% and 40% FA replacement levels, compressive strength values even exceeded the compressive strength of the control specimens

CHAPTER 3

ANALYTICAL MODELLING

3.1 Introduction

An analytical model is a description of a system using mathematical concepts and language. The process of developing a mathematical model is termed mathematical modeling. Mathematical models are used not only in the natural sciences and engineering disciplines but also in the social sciences. Researchers use mathematical models most extensively. A model may help to explain a system and to study the effects of different components, and to make predictions about behavior (Wikipedia, 2008).

Several Artificial Intelligence AI tools that are widely utilized for engineering problems are knowledge-based systems, fuzzy logic, inductive learning, neural networks and genetic algorithms (Pham and Pham, 1999).

3.2 Genetic program

GP is a search technique which allows the solution of problems by automatically generating algorithms and expressions. These expressions are coded or represented as a tree structure with its terminals (leaves) and nodes (functions) (Koza, 1992). GP applies Genetic Algorithms (GAs) to a “population" of programs - typically encoded as tree-structures. Trial programs are evaluated against a “fitness function" and the best solutions selected for modification and re-evaluation. This modification evaluation cycle is repeated until a “correct" program is produced.

There are five major preliminary steps for solving a problem by using GP; (i) the set of terminals, (ii) the set of functions, (iii) the fitness measure, (iv) the values of the numerical parameters and qualitative variables for controlling the run, and (v) the criterion for designating a result and terminating a run (Koza, 1992).

The first major step in preparing to employ the GP paradigm is to identify the set of terminals to be used in the individual computer programs in the population. The major types of terminal sets contain the independent variables of the problem, the state variables of the system and the functions with no arguments. These types of terminal sets are given in a table by Koza (1992). The second major step is the set of functions; arithmetic operations, testing functions, (such as IF and CASE statements) and boolean functions. The third major step is fitness measure which identifies the way of evaluating how good a given program solves a particular problem. The terminals and the functions are the components of the programs which form the junctions in the tree. The choice of components of terminals and functions (the program) and the fitness function establishes the space that GP searches for. The fourth major step is the selection of certain parameters to control the runs. The control parameters contain the size of the population, the rate of crossover *etc*. The fifth and the last step is the criteria to terminate the run. For most of the problems, if the sum of the differences becomes zero (or reasonably close to zero), then, the solution is considered acceptable. The termination criterion is basically a rule for stopping. Characteristically the rule is to stop either on finding a program which solves the problem or after a certain number of generations.

Once the terminal and non-terminal operators are specified, it is possible to establish the types. Each node will have a type, and the construction of child expressions with crossover and mutation operations needs to follow the rules of the nodal type (Montana 1995), i.e., respect those grammatical rules specified by the user or investigator. Moreover, both specified operator sets must fulfill two requirements: closure and sufficiency. That is, it must be possible to build right trees with the specified operators, and the solution to the problem (the expression desired) must be able to be expressed by means of those operators.

The automatic program generation is carried out by means of a process derived from Darwin’s evolution theory, in which, after subsequent generations, new trees (individuals) are produced from old ones via crossover, copy, and mutation (Fuchs 1998; Luke and Spector 1998) Based on natural selection, the best trees will have more chances of being chosen to become part of the next generation. Thus, a stochastic process is established where, after successive generations, a well-adapted tree is obtained.

Gene expression programming (GEP) software used in this thesis is developed by Ferreira (2001). GEP is an extension to GP that evolves computer programs of different sizes and shapes encoded in linear chromosomes of fixed length. The chromosomes are composed of multiple genes, each gene encoding a smaller subprogram. Furthermore, the structural and functional organization of the linear chromosomes allows the unconstrained operation of important genetic operators such as mutation, transposition, and recombination. One strength of the GEP approach is that the creation of genetic diversity is extremely simplified as genetic operators work at the chromosome level. Another strength of GEP consists of its unique, multigenic nature which allows the evolution of more complex programs composed of several subprograms. As a result GEP surpasses the old GP system in 100–10,000 times (Ferreria 2001a,b, 2002). GeneXproTools 4.0, a GEP software developed by Ferreira (2001a,b) is used in this thesis.

The fundamental difference between GA, GP and GEP is due to the nature of the individuals, namely in GAs the individuals are linear strings of fixed length (chromosomes); in GP the individuals are nonlinear entities of different sizes and shapes (parse trees); and in GEP the individuals are encoded as linear strings of fixed length (the genome or chromosomes) which are afterwards expressed as nonlinear entities of different sizes and shapes (i.e. simple diagram representations or expression trees).

3.3 Neural network

ANNs technique is a data processing tool that mimics the function of the human brain and nerves built on the so-called neurons – processing elements – connected to each other. A biological neuron is made up of four main parts: dendrites, synapses, axon and the cell body (see Figure 3.1). The dendrites receive signals from other neurons. The axon of a single neuron serves to form synaptic connections with other neurons. The cell body of a neuron sums the incoming signals from dendrites. If input signals are sufficient to stimulate the neuron to its threshold level, the neuron sends an impulse to its axon. On the other hand if the inputs do not reach the required level, no impulse will occur.

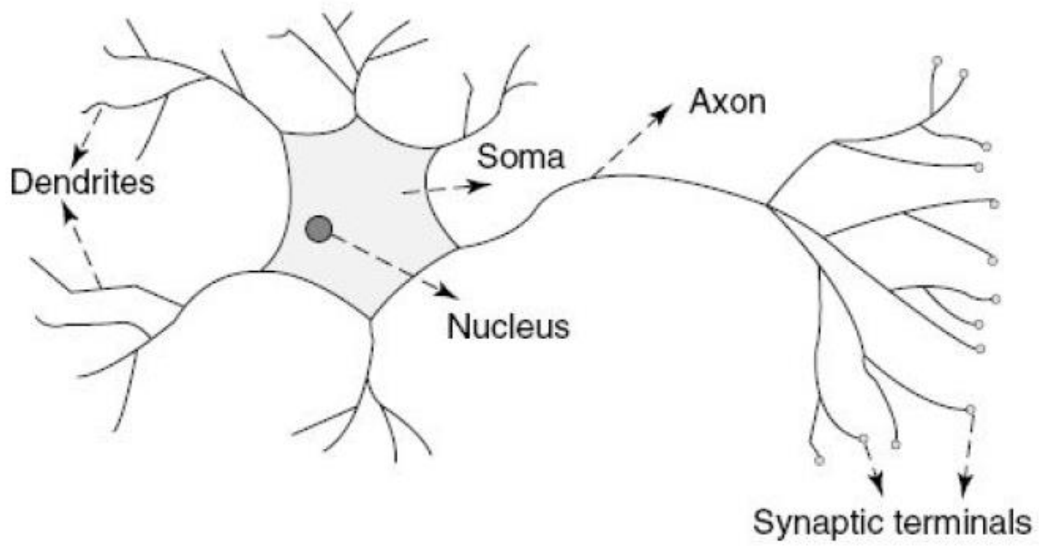


Figure 3.1 A simplified model of a biological neuron (Özbay, 2007)

Biological neuron model is also the basis of the artificial neuron model. Artificial neurons are organized in such a way that the structure resembles a network. This technique differs from the traditional data processing; it learns the relationship between the input and output data (Hecht-Nielsen, 1990). ANNs, like people, learn by example. An ANN is configured for a specific application, such as pattern recognition or data classification, through a learning process. Learning in biological systems involves adjustments to the synaptic connections that exist between the neurons.

ANN models have been used as an alternative method in engineering analysis and predictions during last two decades (Guven et al., 2006). ANNs mimic somewhat the learning process of a human brain. They operate requiring no detailed information about the system. Instead, they learn the relationship between the input parameters and the controlled and uncontrolled variables by studying previously recorded data.

ANNs have ability to handle large and complex systems with many interrelated parameters. They seem simply to ignore excess data that are of minimal significance and concentrate instead on the more important inputs (Kalogirou, 1999).

The basic element of a neural network is the artificial neuron as shown in Figure 3.2, which often consists of a body which acts as a basic function, with a set of inputs represented by the number of incoming links (Mcculloch-Pitts unit) or real values.

These values are passed to the neuron through abstract links, which might be associated with weights as in the case of synaptic weights in the biological neuron.

The neuron computed the function of the inputs, and emits an output value, which is transmitted to other components in the network. Hence, the artificial neurons can be thought as simplified versions of biological neurons or primitive analytical functions.

Artificial neuron consists of three main components; weights, bias, and an activation function. Each neuron receives inputs *xi* (*i* = 1, 2, …, *n*) attached with a weight *wij* (*j* ≥ 1) which shows the connection strength for a particular input for each connection.

Every input is then multiplied by the corresponding weight of the neuron connection and summed as

$$W_i = \sum_{j=1}^{n} W_{ij} x_j \qquad (3.1)$$

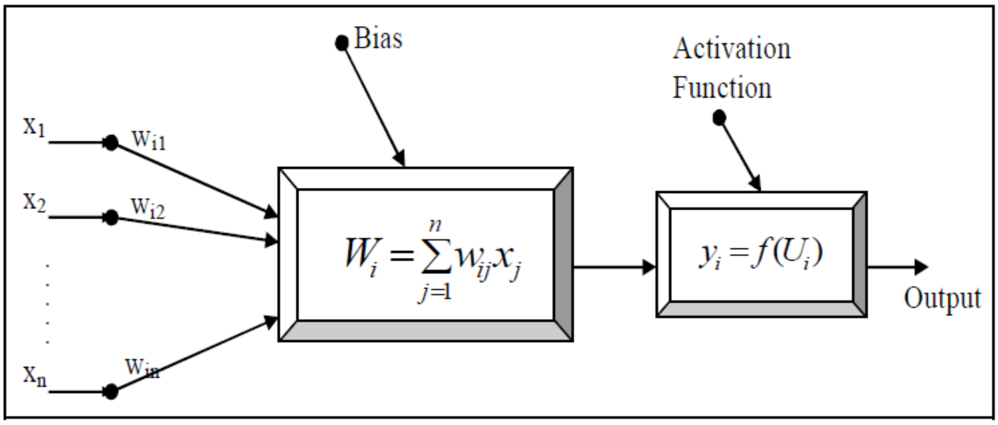


Figure 3.2 Basic elements of artificial neuron. (Özbay, 2007)

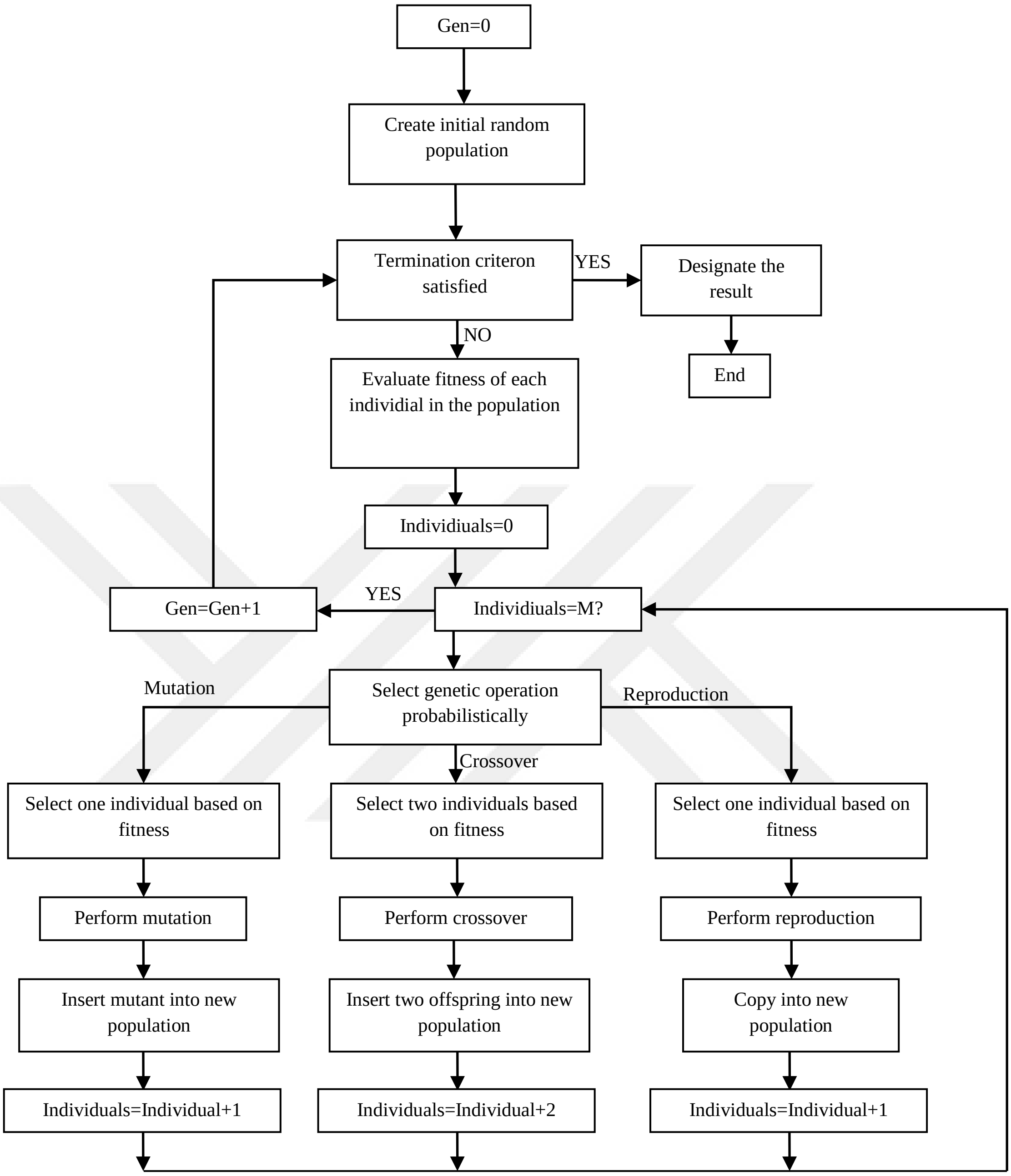


Figure 3.3 Flowchart for the genetic programming paradigm. (Zhao and Hancock, 1991)

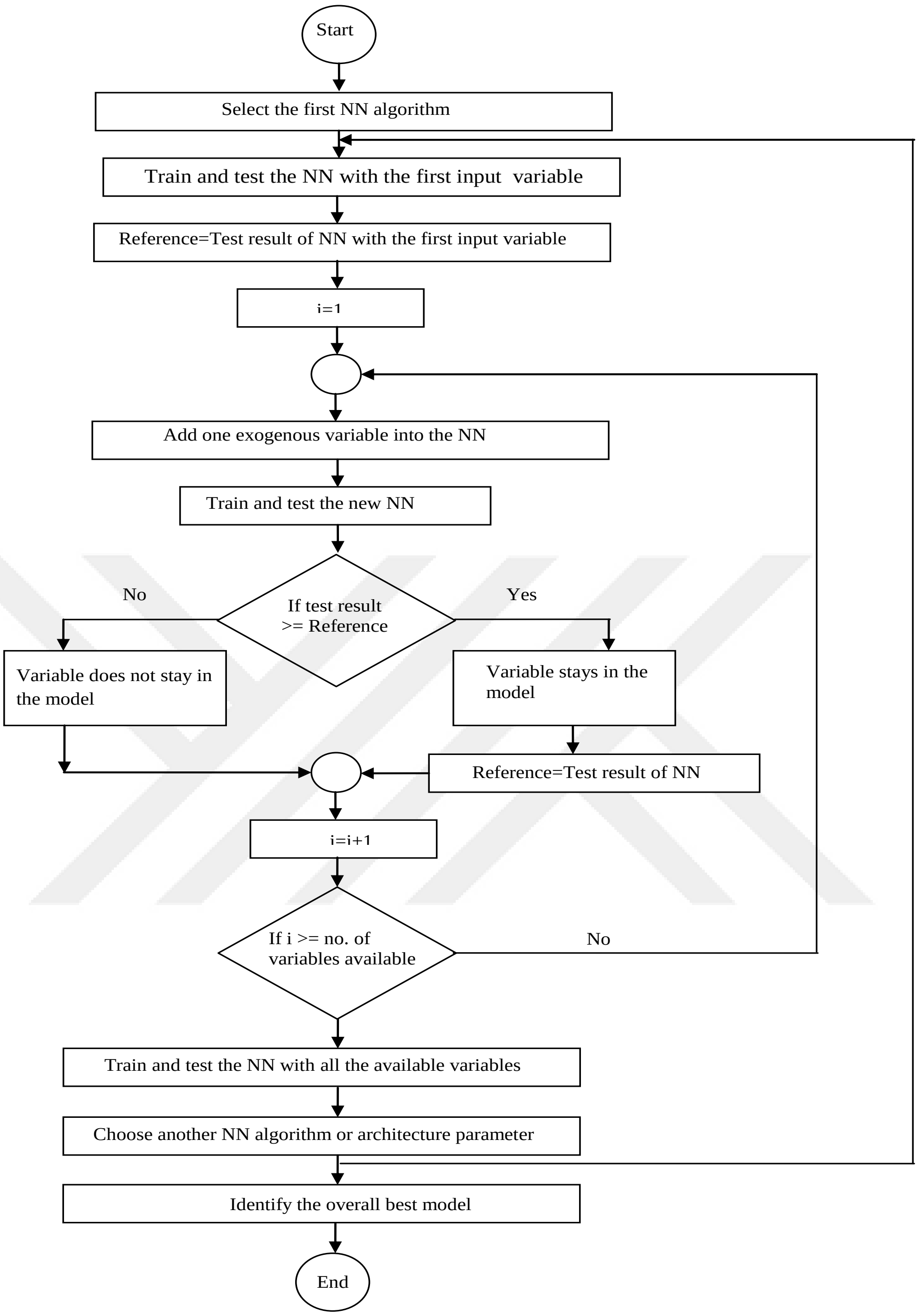


Figure 3.4 Forward strategy for selecting NN architecture and model. (Sušac et al. 2005)

3.4 Experimental database used for modeling

In order to develop a prediction model from GEP and NN a set of experimental data available in the technical literature has been utilized. In these studies, similar sorptivity testing methods were utilized to monitor the effects of different mineral admixtures at various replacement levels and with different combinations of blends on the sorptivity of concrete. The summary of the data set including thoroughly selected 151 data samples were shown in Table 3.1. The database was arbitrarily separated into two parts, namely training and sub-databases. The percentages of the sub-databases are 75% and 25% for training and testing respectively. Training database was utilized for the development of the prediction models while the test database was employed to observe the repeatability and robustness of the proposed models. To be more specific, the main role of training dataset is to adjust weights, while prevention of over fitting and confirmation of the actual predictive power of the model are functions of testing sets.

The input variables cover some mix design parameters, age of concrete at testing, and 28 day compressive strength of concrete. There is not any non-numeric input. The properties and range of the input parameters are also given in Table 3.1

Inputs,

d_0: Water to binder ratio; w/b,

d_1: Total binder content in kg/m^3; B,

d_2: Aggregate to binder ratio; Agg/B,

d_3: Compressive strength of concrete at the age of 28 days in MPa; f_c,

d_4: Age of concrete for sorptivity testing in days; A

The Summary of data base results are shown in the table 3.1.The detailed data is given in Appendix A.

Table 3.1 Summary of database

Data source (151)	Input					Output
	d_0	d_1	d_2	d_3	d_4	Y
	w/b	Total Binder	Aggregate/ Binder	fc@28,150 mm^3	Age	SORPTIVITY
Nath and Sarker (2011)	0.29-0.41	355-518	3.37-5.42	77.6-99.23	28-180	0.067-0.135
Bei et al.(2002)	0.50	390	4.6902-4.804	40.32-64.35	28-540	0.10-0.32
Atis and Karahan (2009)	0.35	400	3.507-4.727	60.7-81	28	0.0162-0.0565
Karahan and Atis (2011)	0.35	400	4.6275-4.7275	53-81.12	28	0.0163-0.043

3.5 Proposed Models

3.5.1 GEP Model

To clarify the GEP basis it is convenient to draft the fundamentals of GP. The GP reproduces computer programs to solve problems by executing the following steps (as described in Fig. 3.3):

(1) Generate an initial population of random compositions of the functions and terminals of the problem (computer programs);

(2) Execute each program in the population and assign it a fitness value according to how well it solves the problem;

(3) Create a new population of computer programs:

(i) Copy the best existing programs,

(ii) Create new computer programs by mutation,

(iii) Create new computer programs by crossover.

The prediction model derived from GEP is presented in Eq. 3.2. The GEP parameters used for derivation of the mathematical models are given in Table 3.1. As it can be seen from Table 3.1, in order to provide an accurate model, various mathematical operations were used.

The models developed by the software in its native language can be automatically parsed into visually appealing expression trees, permitting a quicker and more complete comprehension of their mathematical/logical intricacies. Figure 3.5 demonstrates the expression tree for the terms used in the formulation of the GEP model.

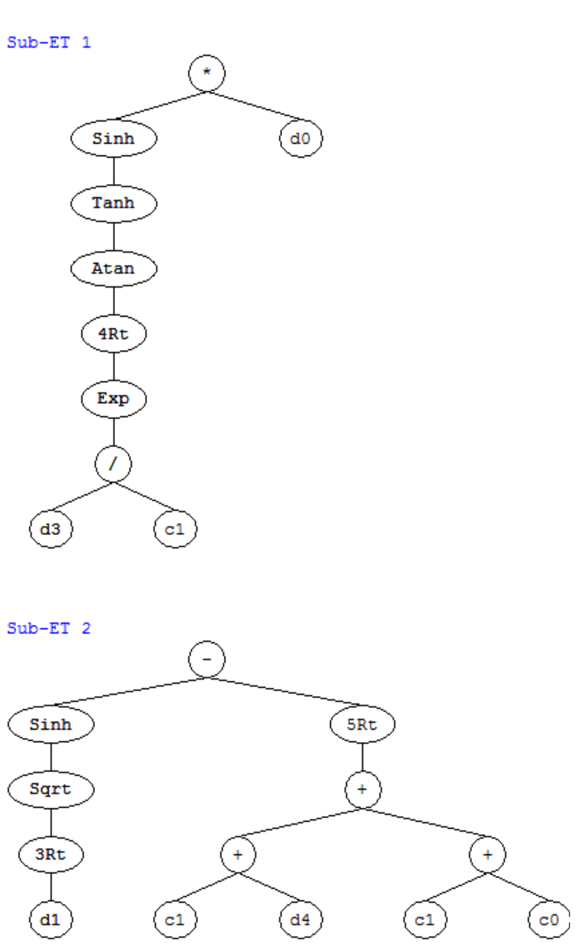


Figure 3.5 the expression tree for GEP model

Sub expressions for GEP model

Sorptivity S = $S_1 \times S_2 \times S_3 \times S_4$ (3.2)

Where S_1, S_2, S_3 And S_4 are sub expressions

$$S_1 = \sinh\left(\tanh\left[\arctan\left(\sqrt[4]{e^{\frac{d_3}{c_1}}}\right)\right]\right) \times d_0 \tag{3.3}$$

$$S_2 = \sinh\left(\sqrt[6]{d_1}\right) - \sqrt[5]{2(7.864777) + (4.222015) + d_4} \tag{3.4}$$

$$S_3 = d_0 \times \left(\frac{[\tanh(4.981659)]^3}{\arctan(d_2 - 2.192108)}\right)^2 \tag{3.5}$$

$$S_4 = \cos\left(\cos\left(\cos(8.963227) - \log(d_3) - \sin(d_2^2)\right)\right) \tag{3.6}$$

3.5.2 NN Model

In the NN architecture, there are 5 nodes in the input layer, corresponding to 5 prediction parameters, 7 nodes in the hidden layer, and one in the output layer corresponding to sorptivity index (*S*). Therefore, a 5-7-1 NN architecture, as shown in Figure 3.6, was obtained to construct the NN based model. The NN model used in this study can simply be expressed by Eq. 3.8. The details of input and/or layer weights, activation function (hyperbolic tangent), and biases are given in Eqs. 3.8-3.9. It should be emphasized that all numeric variables must be normalized to a range of [-1, 1] before being introduced to the NN. Therefore, one must enter the normalized values in the mathematical operations given in Eqs 3.10-3.12. It should also be taken into consideration that the final result obtained from Eq. 3.8 is in the normalized form which needs to be de-normalized according to Eq. 3.10 and normalization coefficients given in Table 3.2.

$$Sorptivity = 0.12258 + \sum_{n=1}^{7} [LW_i \times f(U_i)] \tag{3.7}$$

Where

Lw_i is layer weight matrix ,

U_i is numerical value of each node i,

f(x) is hyperbolic tangent (activation function)

$$Sorptivity = 0.12258 + \begin{bmatrix} -6.5693 \\ -1.2603 \\ 7.4333 \\ -0.2364 \\ 1.4499 \\ 1.1476 \\ 1.868 \end{bmatrix}^T \times \begin{bmatrix} f(U_1) \\ f(U_2) \\ f(U_3) \\ f(U_4) \\ f(U_5) \\ f(U_6) \\ f(U_7) \end{bmatrix}_{7\times1} \tag{3.8}$$

Where U_i values are numerical values of the nodes calculated according to the matrix operation given in Eq 3.9.

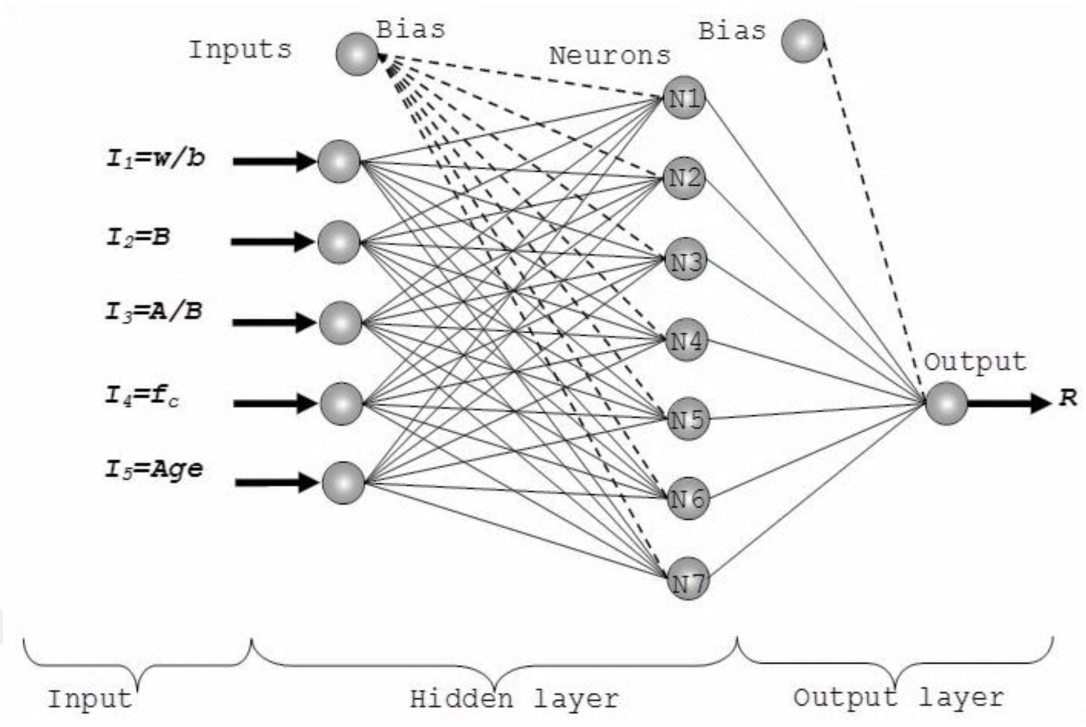


Figure 3.6 The architecture of NN model

$$\begin{bmatrix} 10.4461 & 3.996 & -12.5309 & -2.9381 & 0.0015 \\ -1.1441 & 1.4423 & 0.1448 & 0.4625 & 1.6408 \\ 6.1523 & 0.5357 & -7.2361 & -3.1199 & -0.0026 \\ -1.3587 & -2.7063 & 5.3446 & -1.9433 & 1.1693 \\ 0.1089 & -0.3923 & 0.9729 & -0.2607 & 1.2346 \\ -1.2823 & 1.2266 & -1.2457 & -0.0542 & -0.8298 \\ 1.6099 & -0.5328 & -1.1618 & 0.1492 & -0.8784 \end{bmatrix}_{7\times5} \times \begin{bmatrix} w/b \\ b \\ Agg/b \\ f_c \\ Age \end{bmatrix}_{5\times1} + \begin{bmatrix} -7.4168 \\ 4.3993 \\ -6.9137 \\ 0.0523 \\ 1.4033 \\ -1.9773 \\ 1.1699 \end{bmatrix}_{7\times1} = \begin{bmatrix} U_1 \\ U_2 \\ U_3 \\ U_4 \\ U_5 \\ U_6 \\ U_7 \end{bmatrix}_{7\times1} \tag{3.9}$$

Since nftool uses the normalized values in the range of [-1, 1], the input parameters were normalized by means of Eq. 3.10 in order to get the prediction results after execution of the training process of the NN. Moreover, the obtained results are also in the normalized form. Therefore, considering the Eq. 3.10 and the normalization coefficients *a* and *b* for outputs, de-normalization process is applied and the results are monitored.

Normalization of data

$$\beta_{normalized} = a\beta + b \tag{3.10}$$

Where

β is the actual input parameter or output value.

$\beta_{normalized}$ is the normalized value of input parameters or outputs ranging between [-1,1].

a and b are normalization coefficients given in the following equations.(Eq. 3.11,3.12) respectively.

$$a = \frac{2}{\beta_{\max} - \beta_{\min}} \qquad (3.11)$$

$$b = -\frac{\beta_{\max} + \beta_{\min}}{\beta_{\max} - \beta_{\min}} \qquad (3.12)$$

Where β_{max} and β_{min} are the maximum and minimum actual values of either inputs or outputs. They are shown in the table 3.2

Table 3.2 Normalization coefficients

Normalization parameter	W/B	Total binder (kg/m^3)	Agg/B	f_c,150mm^3@28 days (MPa)	Age (days)	Sorptivity Index (mm/min$^{0.5}$)
β_{max}	0.5	518	5.422535	99.23938	540	0.32
β_{min}	0.29	355	3.370656	38.09	28	0.016266
A	8.710831	0.01227	0.974716	0.032707	0.003906	6.584717
B	-3.35542	-5.35583	-4.28543	-2.2458	-1.10938	-1.10711

3.6 Results and Discussion of proposed models

The performance of the proposed GEP and NN prediction models is graphically demonstrated in Fig. 3.7 for the whole data sets. It seems that there is a good trend in the variation of the data between predicted and experimental data. Correlation coefficients equal to 0.98074 and Correlation coefficients equal to 0.90081 for NN model, thus indicating that GEP model strong correlation between actual and predicted values. Moreover, close values of the correlation coefficients may be considered as an evidence for the consistency and good fitness of the proposed model.

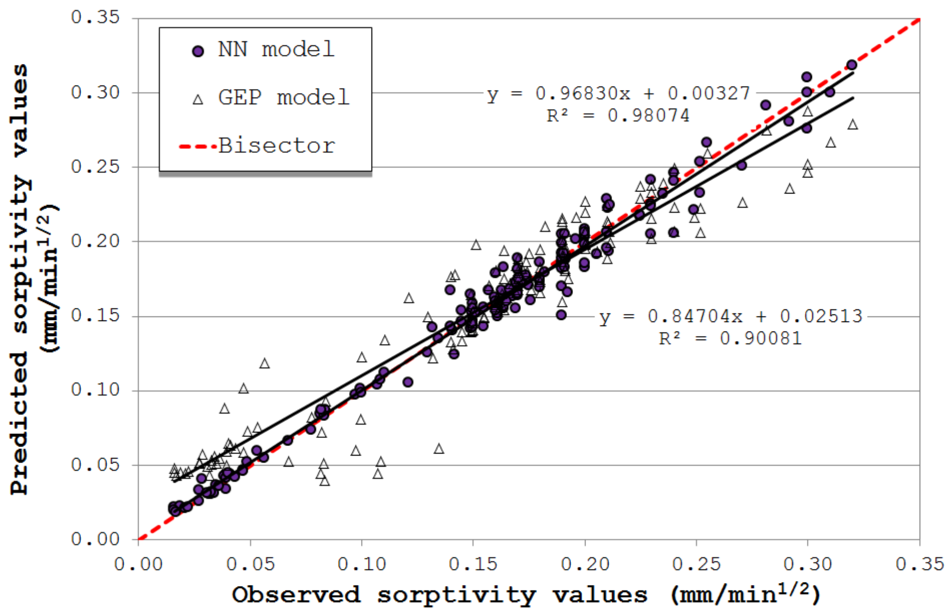
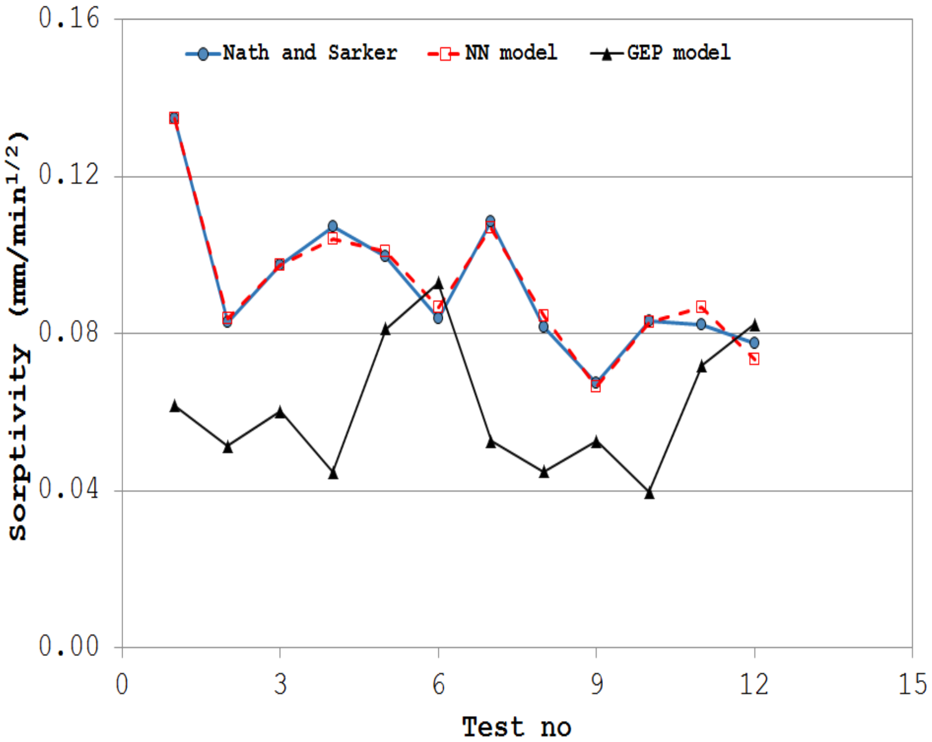
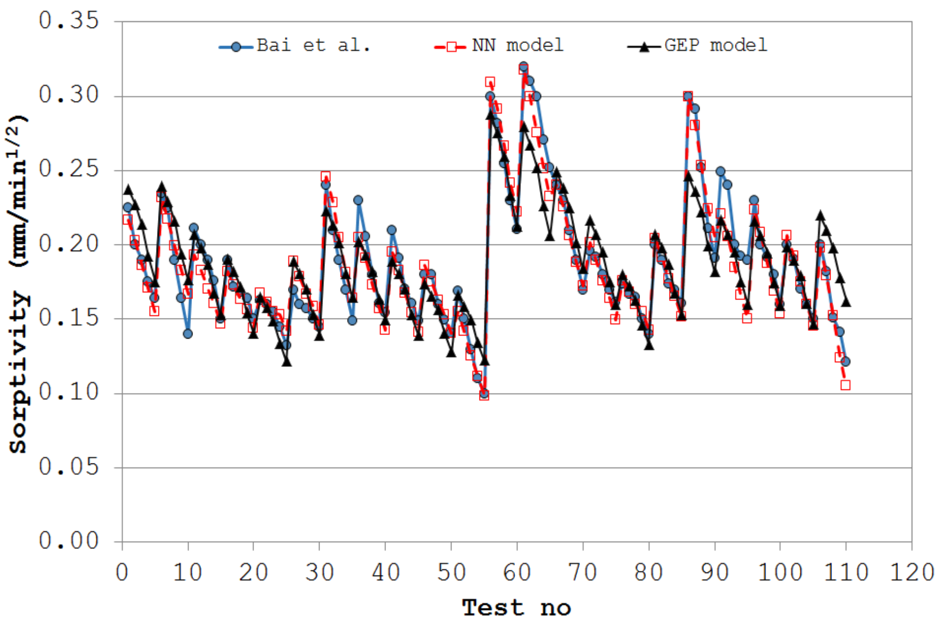


Figure 3.7 the performances of the proposed models

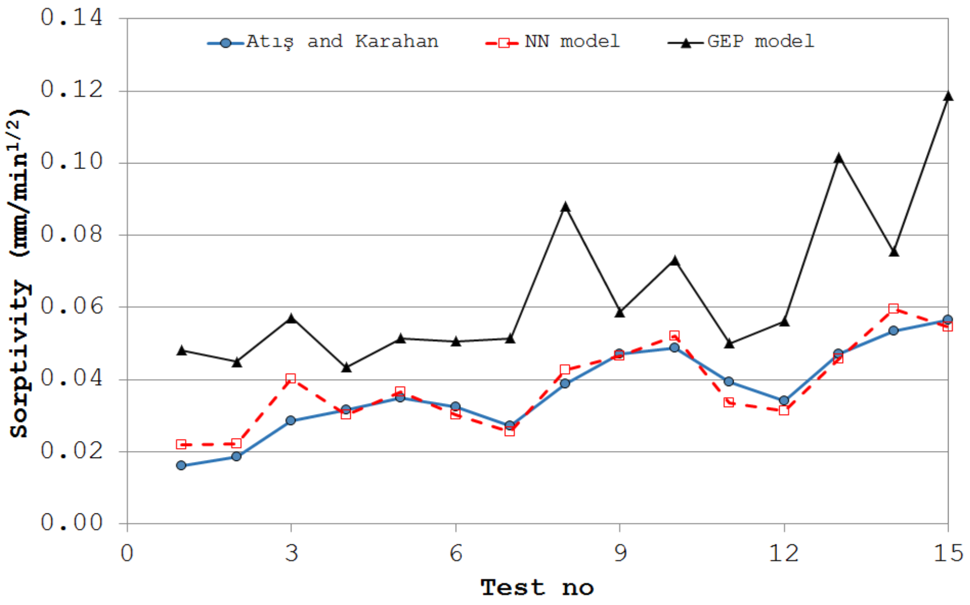
In the figure 3.8, comparison of the predicted results and the experimental values observed in the studies of Nath and Sarker (2011), Bai et al. (2002), Atış and Karahan (2009), and Karahan and Atış (2011) was shown.


Nath and Sarker
NN model
GEP model
Sorptivity (mm/min$^{1/2}$)
0.16
0.12
0.08
0.04
0.00
0
3
6
9
12
15
Test no

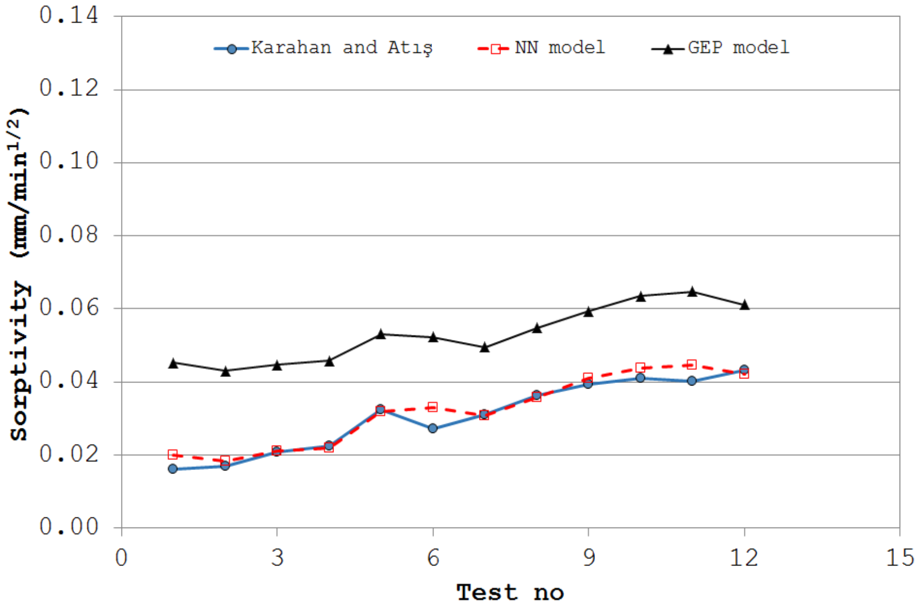
a)


Bai et al.
NN model
GEP model
Sorptivity (mm/min$^{1/2}$)
0.35
0.30
0.25
0.20
0.15
0.10
0.05
0.00
0
10
20
30
40
50
60
70
80
90
100
110
120
Test no

b)



c)



d)

Figure 3.8 Comparison of the predicted results and the experimental values observed in the studies of a) Nath and Sarker (2011), b) Bai et al. (2002), c)Atış and Karahan (2009), and d) Karahan and Atış (2011)

Figure 3.9 demonstrated the analysis of the average error between observed sorptivity and prediction results with respect to various intervals of sorptivity values. For the experimental sorptivity interval of 0.10-0.25 the highest errors were observed.

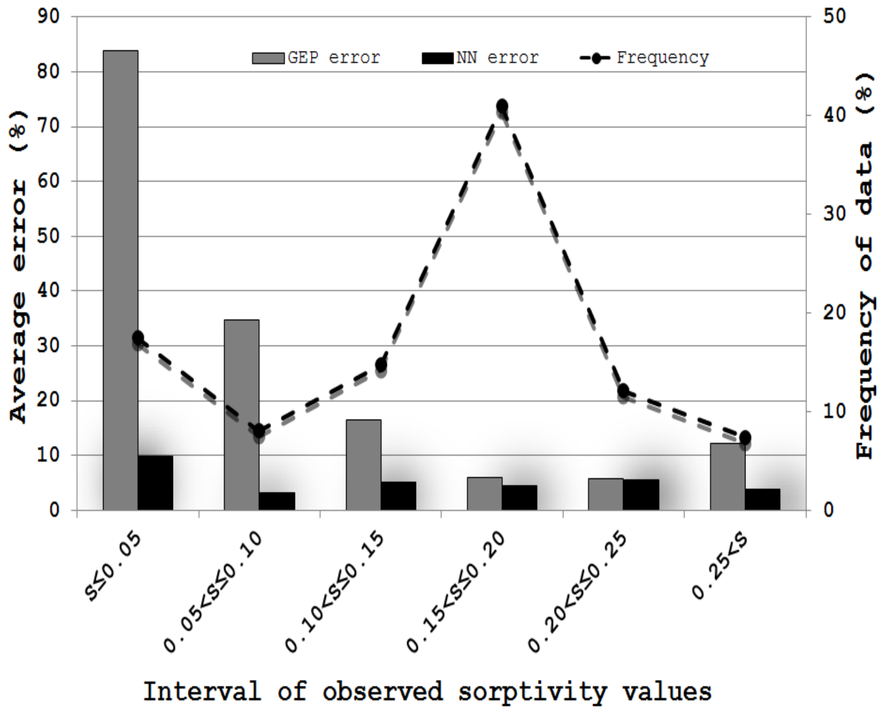


Figure 3.9 Error analyses of the proposed models Materials

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CHAPTER 4

EXPERİMENTAL WORK

4.1 Materials

4.1.1 Cement

CEM I 42.5 R type Portland cement having specific gravity of 3.14 and Blaine fineness of 327 m^2/kg was utilized for preparing the concrete production for compressive strength and Sorptivity testing. The chemical composition of the cement is shown in Table 4.1.

Table 4.1 Chemical compositions and physical properties of Portland cement, Fly ash and Silica fume.

Analysis Report (%)	Cement	Fly ash	Silica fume
CaO	62.58	4.24	0.45
SiO_2	20.25	56.2	90.36
Al_2O_3	5.31	20.17	0.71
Fe_2O_3	4.04	6.69	1.31
MgO	2.82	1.92	0
SO_3	2.73	0.49	0.41
K_2O	0.92	1.89	1.52
Na_2O	0.22	0.58	0.45
Loss on ignition	3.02	1.78	3.11
Specific gravity	3.14	2.25	2.2
Fineness (m^2/kg)	327(Blaine)	287(Blaine)	21080(Bet)

4.1.2 Fly ash

Fly ash (FA) used in the manufacture of lightweight aggregates was a class F type according to ASTM C 618 (2002) was supplied from Ceyhan Sugozu thermal Power Plant. It had a specific gravity of 2.25 g/cm^3 and the Blaine fineness of 287 m^2/ kg. A physical and chemical property of the fly ash is given in Table 4.1.

Figure 4.1 Photographic view of fly ash.

4.1.3 Silica fume

A commercial grade silica fume (SF) obtained from Norway was utilized in this study. It had a specific gravity of 2.2 g/cm^3 and the specific surface area (Nitrogen BET Surface Area) of 21080 m^2/kg. In Table 4.1, both the chemical analysis and physical properties of SF is provided.

Figure 4.2 Photographic view of silica fume.

4.1.4 Aggregate

The coarse aggregate (medium aggregate) used was river crushed stone gravel with a nominal size between of 2 and 8 mm.

As fine aggregate, a crushed limestone was used with a maximum size of 4 mm. The coarse aggregate (medium aggregate) had a specific gravity of 2.65 g/cm^3. The specific gravity of crushed limestone was 2.65 g/cm^3. The particle size gradation obtained through the sieve analysis and physical properties of the fine and coarse aggregates are presented in Table 4.2.

$$dp_i = 100 \times \sqrt{\frac{d_i}{d_{max}}} \tag{4.1}$$

Where

dp_i is percent passing from sieve size of "i".

d_i is sieve size.

d_{max} is the maximum aggregate size (16 mm for this study).

Table 4.2 Sieve analysis and physical properties of aggregate.

Sieve Analysis		
Sieve size (mm)	Passing %	
	C.S medium	C.S fine
16	100	100
8	64.36	100
4	3.01	94.58
2	0.78	59.91
1	0.78	41.74
0.5	0.78	27.11
0.25	0.78	19.07
Pan	0	0
Spec. Grav.	2.65	2.65

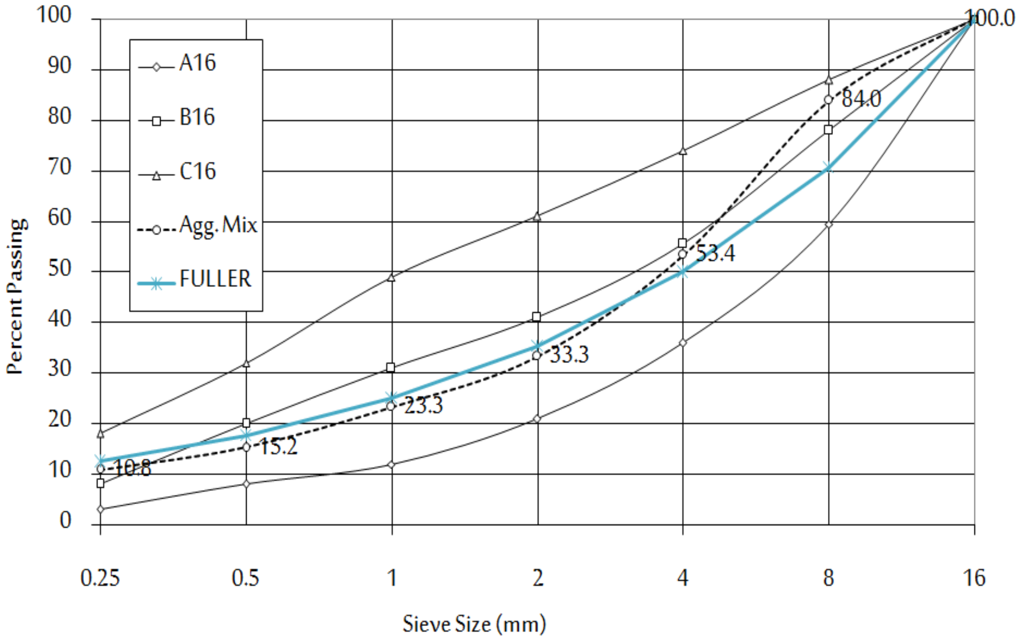

Figure 4.3 Grading of aggregate mix and reference curves.

4.1.5 Superplasticizer

A Sulphonated Naphthalene Formaldehyde type superplasticizer (SP) with a specific gravity of 1.19 and pH of 5.7 was used in all mixtures and used to achieve the target workability. The properties of superplasticizer are given in Table 4.3.

Table 4.3 Properties of superplasticizer

Properties	Superplasticizer
Name	Daracem 200
Color tone	Dark brown
State	Liquid
Specific gravity (kg/1)	1.19
Chemical description	Sulphonated Naphthalene Formaldehyde
Recommended dosage	% 1-2 (% binder content)

4.2 Mix proportions

A total of 9 mixtures were designed at 0.45 water/binder ratios (w/b). In the design of the all group concretes the total cementitious materials content was 400 kg/m3. In the production of such concretes the mineral admixtures used were FA and SF.

The mixture (SF0FA0) in Table 4.4 was designated as the control mixture which included only ordinary Portland cement as the binder while the remaining mixtures incorporated binary [(SF=0%, FA=10%), (SF=0%, FA=20%), (SF=5%, FA=0%), (SF=15%, FA=0%)], ternary [(SF=5%, FA=10%), (SF=5%, FA=20%), (SF=15%, FA=10%), (SF=15%, FA=20%),]. As shown in table 4.4.

Table 4.4 Concrete mixture proportioning at a w/b ratio of 0.45 (kg/m^3)

Mix codes / Materials	Mixture designations								
	SF0FA0	SF0FA10	SF0FA20	SF5FA0	SF5FA10	SF5FA20	SF15FA0	SF15FA10	SF15FA20
Cement	400	360	320	380	340	300	340	300	260
FA	0	40	80	0	40	80	0	40	80
SF	0	0	0	20	20	20	60	60	60
Water	180	180	180	180	180	180	180	180	180
Fine Aggregate	970.8	962.9	954.4	965.4	956.9	949.0	957.3	949.8	942.8
Coarse aggregate (Medium only)	812.7	806.0	798.9	808.1	801.0	794.3	801.3	795.1	789.2
Superplasticizer	4.4	3.2	2.4	6.4	5.6	4.4	8.0	6.4	4.4
Fresh unit weight	2367.9	2352.1	2335.7	2359.9	2343.5	2327.7	2346.7	2331.3	2316.4

4.3. Specimen Preparation and Curing

All concretes were mixed in accordance with ASTM C192 standard in a power driven rotating pan mixer with a 20 L capacity. All samples were poured into the steel moulds in two layers, each of which being vibrated for a couple of seconds.

After casting the moulded specimens were protected with a plastic sheet and left in the casting room for 24 hr. Thereafter, the samples were demolded and cured in water and air until the testing ages.

4.4 Test Methods

4.4.1 Compressive Strength

The compression test was carried out on the specimens by a 3000 kN capacity testing machine. Compressive strength test was conducted at the ages of 28 days on three 150 mm cube samples for each concrete mixture .The test way conducted per ASTM C39 (2005).

4.4.2 Sorptivity

The sorptivity test measures the rate at which water is drawn into the pores of concrete. For this, three test specimens having a dimension of 100x100x100 mm are employed. The specimens are dried in an oven at about 80 ^{o}C until constant mass and then allowed to cool to the ambient temperature in a sealed container. Afterwards, the sides of the specimens are coated by silicone and as shown in Fig. 3.9, the sorptivity test is carried out by placing the specimens on sharp edged rods in a tray such that their bottom surface up to a height of 5 mm is in contact with water. This procedure is considered to allow free water movement through the bottom surface. The total surface area of water within the tray should not be less than 10 times that of the specimen cross-sectional area. The specimens are removed from the tray and weighed at different time intervals up to 1 hour to evaluate mass gain. The volume of water absorbed is calculated by dividing the mass gained by the nominal surface area of the specimen and by the density of water. These values are plotted against the square root of time. The slope of the line of the best fit is defined as the sorptivity coefficient of concrete. For each test, the measurements are obtained from three specimens and the average values are reported. The test was conducted at the age of 28 days.

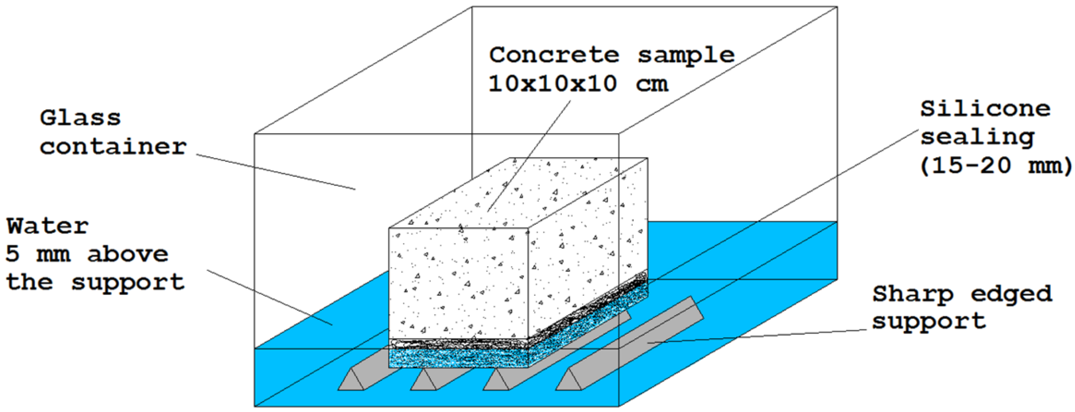

Figure 4.4 Sorptivity test set up

4.5 Results and Discussion

4.5.1 Compressive strength

The data concerning the variation of compressive strength with curing condition and mineral admixture for concretes incorporated with 0%, 10%, and 20% FA and 0%, 5%, 15% are given in Tables 4.5 and 4.6. The strength values for the plain in air cured and water cured are 66.44 and 78.53 MPa, respectively.

High compressive strength for concrete in the mix (SF5% ,FA0%) for air cured and water cured are 75.37 and 87.5 MPa, respectively.

The effect of SF on compressive strength of concrete is well observed in Figure 4.3. The figure indicated that there was an increase in compressive strength with the increase in SF content. This is more pronounced for concretes subjected to water curing (WC) is higher than to air cured. While added FA to concrete mixes, compressive strength systematically decreases.

Table 4.5 Compressive strength of air-cured concretes

SF content / FA content	SF0	SF5	SF15
FA0	66.44	75.37	71.67
FA10	62.77	69.62	67.9
FA20	38.09	64.11	65.27

Table 4.6 Compressive strength of water-cured concretes

SF Content / FA content	SF0	SF5	SF15
FA0	78.53	87.5	86.31
FA10	76.46	86.32	77.13
FA20	50.58	76.82	86.05

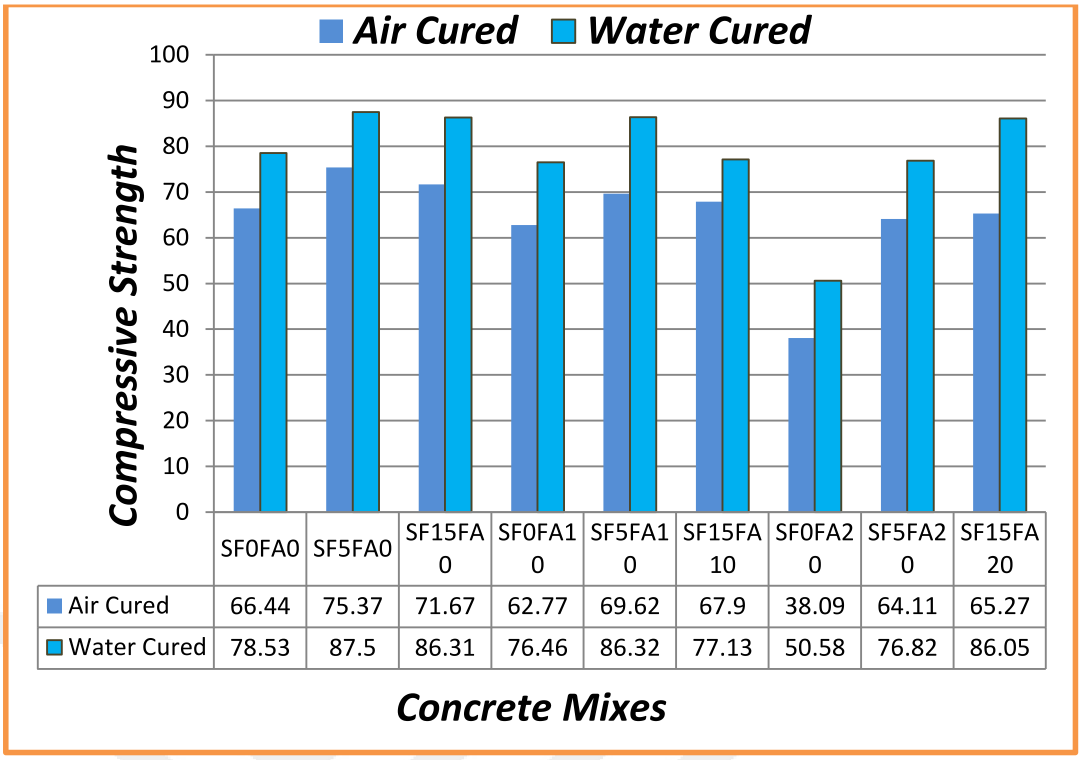

Figure 4.5 Compressive strength results for air and water cured.

4.5.2 Sorptivity result

4.5.2.1.Air cured concretes

The value of sorptivity illustrates the water mass uptake by concrete from the bottom surface based on water flowing into the concrete through large connected pores.

The change in sorptivity with air cured and diffrent ratio of SF and FA at age 28 days are given in Figure 4.4 and it can be noted that the sorptivity through (SF5%,FA10) is lowest value and (SF0%,FA20%) is highest value.

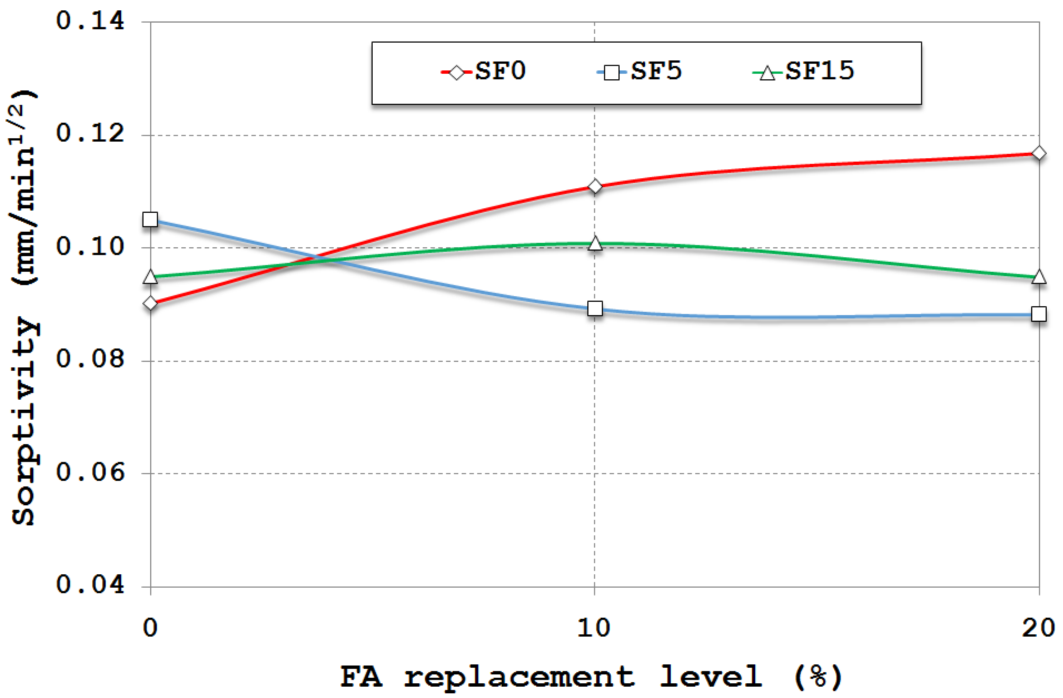

Figure 4.6 Experimental sorptivity air cured concretes.

4.5.2.2 Water cured concretes

The change in sorptivity with water cured and diffrent ratio of SF and FA at age 28 days are given in Figure 4.5 and it can be noted that the sorptivity through (SF5%,FA10) is lowest value and (SF0%,FA10%) is highest value.

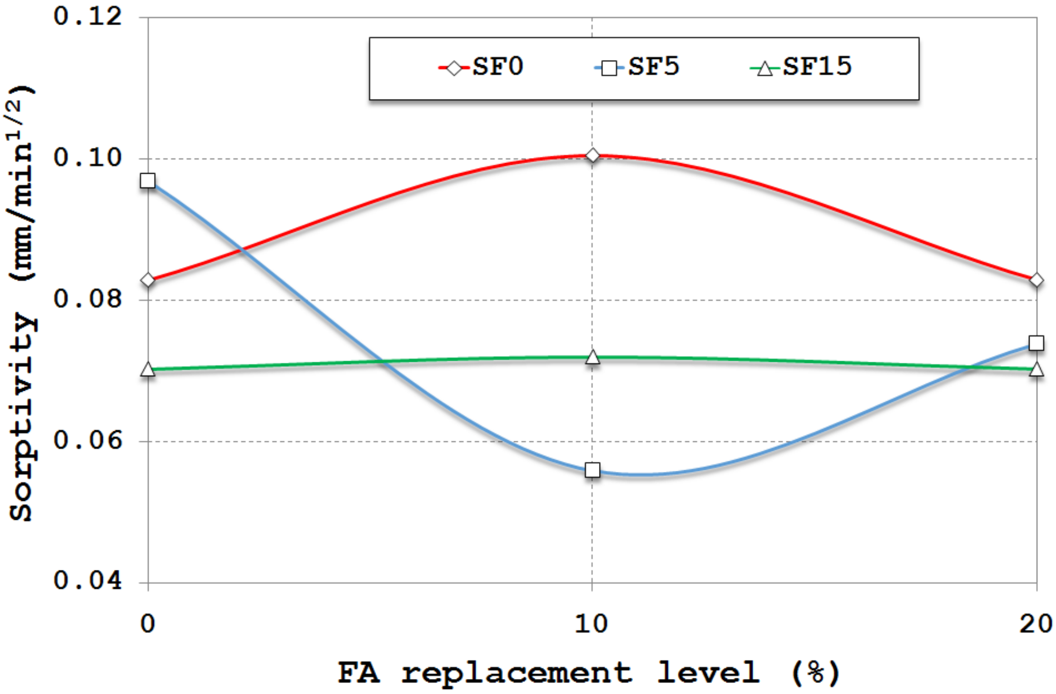

Figure 4.7 Experimental sorptivity water cured concretes.

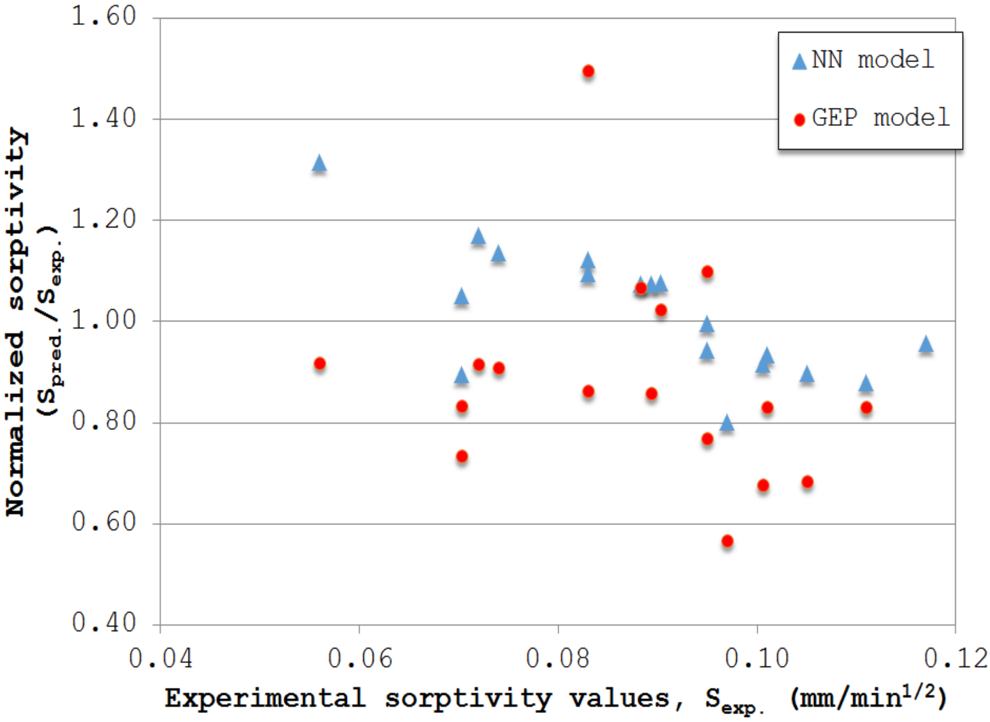

Figure 4.8 Experimental validation

The normalized sorptivity of the whole test data sets (18 samples) were illustrated in Figure 4.6 for comparison. As it can be seen from Fig.4.6 that most of the tested sorptivity values obtained from NN model within ±10% range of the target strength values. However, the values obtained from GEP model are mostly out of that range. Also, there is a prominent indication that the estimated strength values obtained from NN is more accurate and closer to the target values for concretes.both estimation models generally give higher results than actual ones. Nevertheless, even in this case, the values predicted by NN model are closer to the target values than that of NN model.

CHAPTER 5

CONCLUSION

In this thesis, explicit formulations of sorptivity of concretes incorporating mineral admixtures were presented. In the second stage of the study an experimental program was conducted to validate the proposed model. Based on the modelling and experimental studies the following conclusions can be drawn:

- Explicit formulation of sorptivity of concretes containing mineral admixtures was achieved. The proposed formulations are based on the most popular soft- computing techniques, namely gene expression programming (GEP) and artificial neural networks (NNs). To this aim, available experimental data presented in the existing literature we reused to derive those formulations. In order to evaluate their efficiency and advantages, the performance of the proposed models was compared to that provided by the collected data in the previous studies the correlation and accuracy of the proposed models are found to be good enough to be utilized for prediction purposes.
- A comparison with the existing analytical formulation for the collected data referred that the NN models provide better prediction results than the GEP model.
- Experimental study indicated that utilization of mineral admixtures like silica fume and fly ash effects the sorptivity behaviors of concretes significantly.
- When considering silica fume incorporated concretes produced in experimental stage, 5% silica fume and 0% replacement of fly ash was found to be the most effective substitution level for improving the concrete strength for 28 days for water-curing

.

- Sorptivity test results revealed that 10 and 20% replacement of fly ash with 5% replacement of silica fume at 28 day testing in air-cured condition. But in water-cured case sorptivity decreases due to 10% replacement of fly ash with 5% replacement of silica fume at 28 day.

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APPENDIX A: DATA BASE

Table A1 Data samples from Nath and Sarker (2011)

Source	No.	d_0 W/B	d_1 Total binder	d_2 Agg/B	d_3 fc @28 days 150mm cube	d_4 Age	Sorptivity
Nath and Sarker (2011)	1	0.41	355	5.42	81.85	28	0.135
	2	0.32	440	4.20	86.09	28	0.083
	3	0.31	440	4.20	77.60	28	0.097
	4	0.29	517	3.44	99.24	28	0.107
	5	0.29	517	3.39	82.38	28	0.100
	6	0.29	518	3.37	78.67	28	0.084
	7	0.41	355	5.42	81.85	180	0.108
	8	0.32	440	4.20	86.09	180	0.082
	9	0.31	440	4.20	77.60	180	0.067
	10	0.29	517	3.44	99.24	180	0.083
	11	0.29	517	3.39	82.38	180	0.082
	12	0.29	518	3.37	78.67	180	0.078

Table A2 Data samples from Bai et al. (2002)

Source	No.	d_0 W/B	d_1 Total binder	d_2 Agg/B	d_3 fc @28 days 150mm cube	d_4 Age	Sorptivity
Bai et al. (2002)	1	0.5	390	4.80	51.3	28	0.225
	2	0.5	390	4.80	51.3	60	0.200
	3	0.5	390	4.80	51.3	28	0.225
	4	0.5	390	4.80	51.3	60	0.200
	5	0.5	390	4.80	51.3	120	0.190
	6	0.5	390	4.80	51.3	300	0.175
	7	0.5	390	4.80	51.3	540	0.164
	8	0.5	390	4.77	49.5	28	0.235
	9	0.5	390	4.77	49.5	60	0.225
	10	0.5	390	4.77	49.5	120	0.190
	11	0.5	390	4.77	49.5	300	0.164
	12	0.5	390	4.77	49.5	540	0.140
	13	0.5	390	4.78	55.8	28	0.211
	14	0.5	390	4.78	55.8	60	0.200
	15	0.5	390	4.78	55.8	120	0.190
	16	0.5	390	4.78	55.8	300	0.176
	17	0.5	390	4.78	55.8	540	0.150
	18	0.5	390	4.78	58.95	28	0.190
	19	0.5	390	4.78	58.95	60	0.172
	20	0.5	390	4.78	58.95	120	0.168
	21	0.5	390	4.78	58.95	300	0.164
	22	0.5	390	4.78	58.95	540	0.150
	23	0.5	390	4.78	64.35	28	0.163
	24	0.5	390	4.78	64.35	60	0.160
	25	0.5	390	4.78	64.35	120	0.155
	26	0.5	390	4.78	64.35	300	0.145
	27	0.5	390	4.78	64.35	540	0.132
	28	0.5	390	4.75	56.25	28	0.170
	29	0.5	390	4.75	56.25	60	0.160
	30	0.5	390	4.75	56.25	120	0.157
	31	0.5	390	4.75	56.25	300	0.150
	32	0.5	390	4.75	56.25	540	0.145
	33	0.5	390	4.71	43.767	28	0.240

Table A2 (Continued)

Source	No.	d_0 W/B	d_1 Total binder	d_2 Agg/B	d_3 fc @28 days 150mm cube	d_4 Age	Sorptivity
Bai et al. (2002)	34	0.5	390	4.71	43.77	60	0.210
	35	0.5	390	4.71	43.77	120	0.190
	36	0.5	390	4.71	43.77	300	0.170
	37	0.5	390	4.71	43.77	540	0.149
	38	0.5	390	4.72	49.09	28	0.230
	39	0.5	390	4.72	49.09	60	0.206
	40	0.5	390	4.72	49.09	120	0.180
	41	0.5	390	4.72	49.09	300	0.161
	42	0.5	390	4.72	49.09	540	0.155
	43	0.5	390	4.72	51.54	28	0.210
	44	0.5	390	4.72	51.54	60	0.191
	45	0.5	390	4.72	51.54	120	0.170
	46	0.5	390	4.72	51.54	300	0.161
	47	0.5	390	4.72	51.54	540	0.149
	48	0.5	390	4.72	54.45	28	0.180
	49	0.5	390	4.72	54.45	60	0.180
	50	0.5	390	4.72	54.45	120	0.160
	51	0.5	390	4.72	54.45	300	0.150
	52	0.5	390	4.72	54.45	540	0.141
	53	0.5	390	4.69	50.31	28	0.169
	54	0.5	390	4.69	50.31	60	0.150
	55	0.5	390	4.69	50.31	120	0.130
	56	0.5	390	4.69	50.31	300	0.111
	57	0.5	390	4.69	50.31	540	0.100
	58	0.5	390	4.80	43.34	28	0.300
	59	0.5	390	4.80	43.34	60	0.282
	60	0.5	390	4.80	43.34	120	0.255
	61	0.5	390	4.80	43.34	300	0.230
	62	0.5	390	4.80	43.34	540	0.211
	63	0.5	390	4.77	43.49	28	0.320
	64	0.5	390	4.77	43.49	60	0.310
	65	0.5	390	4.77	43.49	120	0.300
	66	0.5	390	4.77	43.49	300	0.271
	67	0.5	390	4.77	43.49	540	0.252
	68	0.5	390	4.78	48.60	28	0.240

Table A2 (Continued)

Source	No.	d_0 W/B	d_1 Total binder	d_2 Agg/B	d_3 fc @28 days 150mm cube	d_4 Age	Sorptivity
Bai et al. (2002)	69	0.5	390	4.78	48.60	60	0.230
	70	0.5	390	4.78	48.60	120	0.210
	71	0.5	390	4.78	48.60	300	0.190
	72	0.5	390	4.78	48.60	540	0.169
	73	0.5	390	4.78	54.07	28	0.196
	74	0.5	390	4.78	54.07	60	0.192
	75	0.5	390	4.78	54.07	120	0.180
	76	0.5	390	4.78	54.07	300	0.170
	77	0.5	390	4.78	54.07	540	0.161
	78	0.5	390	4.78	61.06	28	0.174
	79	0.5	390	4.78	61.06	60	0.167
	80	0.5	390	4.78	61.06	120	0.165
	81	0.5	390	4.78	61.06	300	0.150
	82	0.5	390	4.78	61.06	540	0.140
	83	0.5	390	4.75	52.92	28	0.200
	84	0.5	390	4.75	52.92	60	0.190
	85	0.5	390	4.75	52.92	120	0.174
	86	0.5	390	4.75	52.92	300	0.170
	87	0.5	390	4.75	52.92	540	0.161
	88	0.5	390	4.71	40.32	28	0.300
	89	0.5	390	4.71	40.32	60	0.292
	90	0.5	390	4.71	40.32	120	0.252
	91	0.5	390	4.71	40.32	300	0.211
	92	0.5	390	4.71	40.32	540	0.191
	93	0.5	390	4.72	46.73	28	0.249
	94	0.5	390	4.72	46.73	60	0.240
	95	0.5	390	4.72	46.73	120	0.200

Table A2 (Continued)

Source	No.	d_0 W/B	d_1 Total binder	d_2 Agg/B	d_3 fc @28 days 150mm cube	d_4 Age	Sorptivity
Bai et al. (2002)	96	0.5	390	4.72	46.73	300	0.192
	97	0.5	390	4.72	46.73	540	0.190
	98	0.5	390	4.72	46.80	28	0.230
	99	0.5	390	4.72	46.80	60	0.200
	100	0.5	390	4.72	46.80	120	0.192
	101	0.5	390	4.72	46.80	300	0.180
	102	0.5	390	4.72	46.80	540	0.160
	103	0.5	390	4.72	49.68	28	0.200
	104	0.5	390	4.72	49.68	60	0.191
	105	0.5	390	4.72	49.68	120	0.170
	106	0.5	390	4.72	49.68	300	0.160
	107	0.5	390	4.72	49.68	540	0.150
	108	0.5	390	4.69	40.54	28	0.200
	109	0.5	390	4.69	40.54	60	0.182
	110	0.5	390	4.69	40.54	120	0.151
	111	0.5	390	4.69	40.54	300	0.142
	112	0.5	390	4.69	40.54	540	0.121

Table A3 Data samples from Atis and Karahan (2009)

Source	No.	d_0 W/B	d_1 Total binder	d_2 Agg/B	d_3 fc @28 days 150mm cube	d_4 Age	Sorptivity
Atis and Karahan (2009)	1	0.35	400	4.73	77.1	28	0.016
	2	0.333631	400	4.49	79.4	28	0.019
	3	0.318725	400	4.28	78.2	28	0.029
	4	0.292581	400	3.90	80.5	28	0.032
	5	0.270401	400	3.58	81	28	0.035
	6	0.35	400	4.69	67.8	28	0.033
	7	0.333631	400	4.45	69.4	28	0.027
	8	0.318725	400	4.23	68.3	28	0.039
	9	0.292581	400	3.86	71.7	28	0.047
	10	0.270401	400	3.54	72.7	28	0.049
	11	0.35	400	4.64	63.6	28	0.040
	12	0.333631	400	4.41	61.8	28	0.034
	13	0.318725	400	4.20	64.4	28	0.047
	14	0.292581	400	3.82	65	28	0.053
	15	0.270401	400	3.51	60.7	28	0.057

Table A4 Data samples from Karahan and Atis (2011)

Source	No.	d_0 W/B	d_1 Total binder	d_2 Agg/B	d_3 fc @28 days 150mm cube	d_4 Age	Sorptivity
Karahan and Atis (2011)	1	0.35	400	4.73	79.25	28	0.016
	2	0.35	400	4.73	81.125	28	0.017
	3	0.35	400	4.72	77.75	28	0.021
	4	0.35	400	4.72	76.875	28	0.022
	5	0.35	400	4.69	66.125	28	0.033
	6	0.35	400	4.68	65	28	0.027
	7	0.35	400	4.68	67	28	0.031
	8	0.35	400	4.67	61.875	28	0.036
	9	0.35	400	4.64	56.625	28	0.040
	10	0.35	400	4.64	53.75	28	0.041
	11	0.35	400	4.63	53	28	0.040
	12	0.35	400	4.63	55.375	28	0.043

Table A5 Data samples from current experimental data (2014)

Source	No.	d_0 W/B	d_1 Total binder	d_2 Aggregate/Binder	d_3 fc @28 days 150mm cube	d_4 Age	Sorptivity
Current experimental data (2014)	1	0.45	400	4.46	78.53	28	0.083
	2	0.45	400	4.46	66.44	28	0.090
	3	0.45	400	4.42	76.46	28	0.101
	4	0.45	400	4.42	62.77	28	0.111
	5	0.45	400	4.38	50.58	28	0.083
	6	0.45	400	4.38	38.09	28	0.117
	7	0.45	400	4.43	87.5	28	0.097
	8	0.45	400	4.43	75.37	28	0.105
	9	0.45	400	4.39	86.32	28	0.056
	10	0.45	400	4.39	69.62	28	0.089
	11	0.45	400	4.36	76.82	28	0.074
	12	0.45	400	4.36	64.11	28	0.088
	13	0.45	400	4.40	86.31	28	0.070
	14	0.45	400	4.40	71.67	28	0.095
	15	0.45	400	4.36	77.13	28	0.072
	16	0.45	400	4.36	67.9	28	0.101
	17	0.45	400	4.33	86.05	28	0.070
	18	0.45	400	4.33	65.27	28	0.095

Appendix B
Photographic views

Figure B 1 Photographic view of weight reading by sensitive balance

Figure B 2 Photographic view during concrete sorptivity test

Figure B 3 Photographic view of molded specimens

Figure B 4 Photographic view of demoulded specimens during air curing.

Figure B 5 Photographic view of compressive strength testing