FORECASTING THE COMPRESSIVE STRENGTH OF SELF-COMPACTING CONCRETES CONTAINING MINERAL ADMIXTURES BY ARTIFICIAL NEURAL NETWORKS

by

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LIST OF ABREVIATIONS

AI:	Artificial Intelligence
ANNs:	Artificial Neural Networks
BFG:	BFGS Quasi-Newton training function
FA:	Fly Ash
FL:	Fuzzy Logic
GA:	Genetic Algorithm
GMDH:	Group Method of Data Handling
GGBFS:	Ground Granulated Blast Furnace Slag
GUI:	Graphical User Interface
HC:	High Performance Concrete
HSC:	High Strength Concrete
I-PreConS:	Intelligent PREdiction system of CONcrete Strength
LM:	Levenberg – Marquardt training function
MSE:	Mean Square Error
MK:	Metakaolin
OPC:	Ordinary Portland Cement

RBE:	Radial Basis training function
RMSE:	Root Mean Square Error
RP:	Resilient Back-Propagation training function
SCC:	Self Compacting Concrete
SCG:	Scaled Gradient conjugate Back-Propagation training function
SF:	Silica Fume
SG:	Specific Gravity

RAMALAN KEKUATAN MAMPATAN KONKRIT TERPADAT SENDIRI YANG MENGANDUNGI BAHAN TAMBAH MINERAL MENGGUNAKAN JARINGAN SARAF TIRUAN

ABSTRAK

Kajian ini telah dijalankan untuk membangunkan jaringan saraf tiruan bagi meramal kekuatan mampatan konkrit terpadat sendiri yang mengandungi bahan tambah mineral. Ramalan dibahagikan kepada dua iaitu model jaringan saraf suapan kehadapan propagasi kembali dan model jaringan saraf terbalik. Bahagian pertama model boleh meramal kekuatan mampatan konkrit terpadat sendiri bukan sahaja berdasarkan data eksperimen, tetapi mengambil kira kadar campuran bahan tambah mineral. Disamping itu, jaringan yang dihasilkan berkebolehan meramal secara terbalik; iaitu ia berfungsi meramal secara dua-hala. Menggunakan kandungan bahan tambah mineral yang berlainan sebagai data masukan, model jaringan memberikan kekuatan konkrit pada umur 28 dan 90 hari sebagai output. Sebaliknya, model jaringan memberikan nisbah campuran sebagai output, apabila kekuatan mampatan pada umur 28 dan 90 hari dimasukkan sebagai data input. Lima fungsi latihan yang digunakan iaitu Levenberg-Marquardt (LM), BFGS Quasi-Newton (BFG), Scaled Gradient Conjugate Back-Propagation (SCG), Resilient Back-Propagation (RP), dan Radial Basis (RBE) di dalam merekabentuk model jaringan, didapati fungsi latihan LM adalah yang terbaik. Fungsi latihan ini memberikan purata kesalahan kuadrat terkecil untuk latihan dan pengujian bagi kekuatan mampatan pada umur 28, masing-masing 0.0048 dan 0.0348. Manakala bagi kekuatan mampatan pada umur 90 hari nilai yang diberikan adalah masing-masing

0.0034 dan 0.018, yang mana menunjukkan fungsi latihan LM adalah lebih tepat dari yang lain.

Grafik antara muka pengguna (GUI) telah direkabentuk supaya jaringan mudah digunakan oleh pengguna-pengguna tidak pakar. Dua program GUI telah direkabentuk untuk jaringan. GUI yang pertama, diintegrasikan di dalam program utama iaitu suapan kehadapan propagasi kembali (FeedForward back propagation) dan GUI kedua merangkumi suapan kehadapan propagasi kembali dan analisis terbalik secara serantak.

FORECASTING THE COMPRESSIVE STRENGTH OF SELF-COMPACTING CONCRETES CONTAINING MINERAL ADMIXTURES BY ARTIFICIAL NEURAL NETWORKS

ABSTRACT

This research was conducted to design an artificial neural network for predicting the compressive strength of self compacting concrete containing mineral admixtures. This prediction is divided into feed forward back propagation and reverse neural network model. The first part the model can predict the SCC compressive strength not only on experimental data but also on the every desired mineral admixture mix proportions. The network is able to pass the following way reversely. In other words, the network is acting as two-way routes. The first is the way which the starting point is amount of mineral admixtures (as input data) and the end point is the SCC compressive strength at 28 and 90 day (as desired output), the return way is vice versa. The network produces the mineral admixture mix proportion as the desired results (output) with the SCC compressive strength at 28 and 90 days as input data. By comparing the results using five training functions, Levenberg-Marquardt (LM), BFGS Quasi-Newton (BFG), Scaled Gradient Conjugate Back-Propagation (SCG), Resilient Back-Propagation (RP), and Radial Basis (RBE), in designing the network, it was found that LM training function is the best choice. The least network training and testing Mean Square Error for compressive strength at 28 days is respectively 0.0048 and 0.0348, also 0.0034 and 0.0118 for compressive strength at 90 days, respectively were obtained from LM training function which is much more accurate than others.

At the end, the Graphical User Interface (GUI) is designed to make the network as easy to use program for non-expert users. Two separate GUI programs were designed for the network. The first one is set to work on main program (FeedForward back propagation) and the second GUI covers all the desired results including the FeedForward back propagation and reverse analysis simultaneously.

CHAPTER 1

INTRODUCTION

1.1 Background of Study

All human activities affect the environment surrounding. The impact may be global, regional or local and may be immediate or may take years. Concrete is a construction material that consists of, in its most common form, cement, gravel, sand, and water. Concrete is the most highly used manmade product on earth. It is used to make pavements, building structures, foundations, motorways/roads, overpasses, parking structures, brick/block walls and footings for gates, fences and poles. Approximately six billion cubic meters of concrete are produced every year, which is one cubic meter per person on the earth. Concrete commands a $35 billion worldwide industry and employs, in the United States alone, 2 million people (Ji et al., 2006). Nowadays the international universities and research center around the world are working in the concrete fields because of these human needs.

In the recent years, application of artificial intelligence in concrete researches is gaining more acceptances. For example in the area of High Strength Concrete (HSC) and High Performance Concrete (HPC). Demir (2008), investigated the application of artificial neural networks (ANNs) to predict elastic modulus of normal and high strength concrete and Öztas et al., (2006) attempted to show possible applicability of neural networks (NN) to predict the compressive strength and slump of HSC. The usability of

Artificial Neural Networks (ANNs) to predict the compressive strength of steel fiber added lightweight concrete was studied by Altun et al., (2008) and Alshihri et al., (2009) investigated the application of ANNs to predict the compressive strength of lightweight concrete mixtures.

The topic of conventional concrete is more attractive for ANNs investigators. Bilim et al., (2009) presented artificial neural networks to predict the compressive strength of ground granulated blast-furnace slag concrete and found trustable output produced by the model. Kwon and Song (2009) developed back propagation neural network that can accurately predict the carbonation behavior in concrete. The analyzed experimental results and ANNs outputs were in good agreement. Lee (2003) developed the Intelligent PREdiction system of CONcrete Strength (I-PreConS) with artificial neural networks (ANNs) for predicting concrete strength.

Madandoust et al., (2010) generalized and developed group method of data handling (GMDH-type) neural network based on experimental data for predicting the compressive strength of concrete by means of non-destructive approach using Ultrasonic Pulse Velocity (UPV) method.

Ni and Wang (2000) proposed using multi - layer feed - forward neural networks (MFNNs) model to predict 28-day compressive strength of concrete.

Pala et al., (2007) investigated the applicability of ANNs for evaluating effects of fly ash and silica fume for a long period of time. ANNs program was written in MATLAB.

Bai et al., (2003) developed reliable and accurate ANNs model to predict workability of concrete incorporating metakaolin and fly ash. Ji et al., (2006) gained their goals to reduce the number of trial and error, save cost, laborers and time by creating an ANNs model to propose the concrete mix proportioning design algorithm. Dias and Pooliyadda (2000) in their study proposed back-propagation neural networks to predict the strength of ready mixed concrete and high strength concrete.

In the Self Compacting Concrete (SCC) territories a model of artificial neural networks was designed by Altin et al., (2008) for studying the characteristics of self-compacting concrete. The results of model were analyzed with SPSS statistical packet software and it has been found that the ANNs can be used as reliable modeling method for similar studies. Prasad et al., (2009) proposed a neural networks model to predict the compressive strength of Self Compacting Concrete (SCC) and High Performance Concrete (HPC) with high volume fly ash.

It was found by Gunneyisi et al., (2009) that the neural network models have a high prediction capability of Self Compacting Concrete (SCC) initial and final setting times with different concrete mixture constituents.

The lack of knowledge about application of ANNs in self compacting concrete was the main motivator for conducting this study. However, this study will cover compressive strength as one of the most important characteristics of SCC.

1.2 Problem Statement

All governments, from developed to developing countries are trying to stabilize and accelerate their development process respectively. It seems that in the last decades of the twentieth century, the concept of “sustainable development” was accepted by researchers as the best development model, all around the world. The fundamental axes of sustainable development are divided into: economy, society and environment (Adams, 2006).

It is clear that any quantitative or qualitative positive changes in the characteristics of concrete as a wide man made material can play an important role in sustainability. In this case, the golden triangles including time, budget and environment seems to be a good approach for investigating. The computer modeling is one of the offered solutions to this problem which is derived in this study as the use of Artificial Neural Networks to predict the compressive strength of self compacting concrete at 28 and 90 days.

The artificial neural networks solve very complex problems with the help of interconnected computing elements. Basically, the processing elements of a neural network are similar to the neurons in the brain, which consist of many simple computational elements arranged in layers (Yeh, 2007). The basic strategy for designing a neural network-based model for material behavior is the training of neural network on the result of a series of experiments using that material. If the experimental results contain the relevant information about the material behavior, then the training neural network will contain sufficient information about materials behavior to qualify as a material model. Such a train neural network not only would be able to reproduce the experimental results, but also it would be able to approximate the results in other experiments through its generalization capability (Jung and Jamshid, 2001).

1.3 Objectives

The objectives of this research have been set as follows:

i) To predict 28 and 90 days compressive strength of SCC samples by using neural network model.

ii) To predict the mineral admixtures mix proportions by using the desired 28 and 90 days compressive strength of SCC as input data.

iii) To design Graphical User Interface (GUI) for both main and reverse network for prediction of SCC characteristics.

1.4 Scope of Work

The following works are to be conducted in order to achieve the objectives of the study:

All experimental work done by Gunneyisi et al., (2009) with 65 mixtures will be used in this study. That study conducted to forecast the initial and final setting time of SCC containing mineral admixtures by ANNs. The data seems suitable to work on different phase with the same nature as ANNs atmosphere.

i) The prediction of 28 and 90 days compressive strength of SCC by using the best net of out 5 training functions namely Levenberg – Marquardt, BFGS Quasi-Newton, Scaled Gradient Conjugate Back-Propagation, Resilient Back-Propagation, and Radial Basis.

ii) The designing the GUI was based on LM training function which was achieved as the best net.

1.5 Thesis Outline

The thesis is subdivided into five chapters. Each chapter is briefly described as follows:

Chapter 1 gives a general background of the subject matter and serves as an introductory chapter. It incorporates the back ground of the study, problem statement, objectives of the research and a brief on the thesis outline.

Chapter 2 comprises of information relevant to this work. It includes background information on concrete characteristics, self compacting concrete, artificial intelligence, and the application of artificial neural networks in concrete research.

Chapter 3 devotes to the methodology adopted to achieve the objectives of the research. This includes investigation of the best network used for the prediction of self compacting concrete characteristics by using published experimental data.

Chapter 4 describes the details on modelling and programming. It also presents all steps in designing artificial neural network and comprises the results of the main proposed training functions to obtain the best network.

Chapter 5 contains the conclusions arrived at and gives the recommendations for future works.

CHAPTER 2

LITERATURE REVIEW

2.1 Introduction

The relevant literatures are discussed in this chapter. Initially, this chapter begins by giving a brief overview of the self-compacting concrete. Consequently, the concept of artificial intelligence is reviewed. Subsequently, the studies on all types of concrete by using artificial neural networks (ANNs) are presented. Finally, the applicability of ANNs in predicting the self compacting concrete characteristics is discussed.

2.2 Definition of Self-Compacting Concrete

Self-compacting concrete (SCC) is a type of concrete that does not require vibration for placing and compaction. It is completely filling the formwork and achieving maximum compaction by flowing under its own weight, even in the case of congested reinforcement. The homogeneity and density of hardened concrete are high and it has the same engineering properties and durability as normally vibrated concrete (Okamura and Masahiro, 2003).

In Europe, concrete that requires little vibration or compaction has been used since the early 1970s, but it was not until the late 1980's that SCC was developed in Japan (EFNARC, 2005). The concept of SCC refers to work of Okamura (1986) in Japan.

The fundamental study on the workability of concrete to develop SCC has been carried out by Ozawa and Maekawa at the University of Tokyo (Ozawa 1989, Okamura 1993 & Maekawan 1999). In civil works it was probably first used in Europe for transportation networks in Sweden in the mid 1990's. A rapid rate of concrete placement, with faster construction times and ease of flow around congested reinforcement are possible to be achieved by using SCC. The segregation resistance of SCC and fluidity, providing the potential for a superior level of finish and durability to the structure by ensuring a high level of homogeneity, uniform concrete strength and minimal concrete voids. The low water-cement ratio is often used in producing SCC which responsible for providing the potential for high early strength, earlier demoulding and faster use of elements and structures (EFNARC, 2005). The mechanical properties and durability of hardened concrete are the same as normally vibrated concrete but using SCC has many other advantages such as the followings:

i) To save time of construction period

ii) To make sure concrete compacted; especially in zones where vibrating compaction is difficult

iii) To remove noise caused by vibration: effective especially at concrete products plants (Okamura and Masahiro, 2003)

iv) SCC is believed to improve the durability relatively to vibrated concrete (this is due to the lack of damage to the internal structure, induced by the vibration).

2.3 Ingredients of SCC

The properties of concrete ingredients and mineral admixtures will be discussed in this part.

2.3.1 Cement

In the building and construction industries various types of cement are being used. The chemical compositions of these cements can vary considerably, but majority of concrete used today is made with Portland cement (Atkins, 2003).

The widespread availability, economic, versatility and adaptability are the most important reasons which promote Portland cement as the foremost among the construction materials used in civil engineering projects around the world (Mindess et al., 2003).

Nowadays, the most commonly used type of Portland cement is ASTM Type I, also known as Ordinary Portland Cement (OPC) which is used in general construction where no need special properties (Mohammed, 2009).

2.3.2 Water

The initial chemical reaction between cement and water is essential to produce concrete in addition water is also used to lubricate the mixture for easy placement and compaction. For the purpose of preventing destructive effects of some water ingredients such as silt, oil, sugar, chemicals or contamination, the drinking water from domestic water supply normally recommended as concrete mixing water. The water shall comply with requirements stipulated in codes of practice. According to British Standard Institution, added water should preferably be potable or clean, fresh and free of obvious contaminants. If mortar cubes made with water in question are at least equal to 90% of the compressive strength of the specimens made with distilled water, the water then can be considered acceptable for concrete making. Some specifications also accept water for making concrete if the PH value of the water lies between 6 and 8 and the water is free from organic materials (Mohammed, 2009).

2.3.3 Aggregates

Commonly, 70% to 80% of the volume of concrete is occupied by aggregates which have most consequential influence on its properties. They are granular materials, derived for the most part from natural rock (crushed stone, or natural gravels) and sands, although synthetic materials such as slags and expanded clay or shale are used to some extent (Mindess et al., 2003). In order to obtain a good concrete quality, aggregates should be hard and strong, free of undesirable impurities, and chemically stable (Garber and Hoel, 1988).

If impurities like silt, clay, dirt, or organic matter coat the surface of the aggregate, aggregate particles will be isolated from the surrounding concrete, causing a reduction in strength. Then aggregates should also be free of those impurities. Organic matter may interfere with the cement hydration on the other hand silt, clay and other fine materials will increase the water requirements of the concrete (Druta, 2003).

2.3.4 Fly Ash

Fly ash is a byproduct produced in electric power generating plants from burning pulverized coal. Mineral impurities in the coal (clay, feldspar, quartz, and shale) fuse in suspension and float out of the combustion chamber with the exhaust gases during combustion. When the fused material rises up, it cools and solidifies to glassy particles known as fly ash. Electrostatic precipitators or bag filters are usually used to trap and collect the fly ash from the exhaust gases. With some chemical differences, the fine powder does resemble with Portland cement. Chemical reaction between cement and water releases the byproduct calcium hydroxide which chemically reacts with fly ash to form cementitious products that improve many desirable properties of concrete. Cementitious properties are exhibited by all fly ashes to varying degrees depending on the chemical and physical properties of both the fly ash and cement (Basham et al., 2007).

In the past 50 years, the use of fly ash in concrete has grow up rapidly, for example the current usage in the United States is more than 6 million tons per annum (Manz, 1997). Many research workers have demonstrated that much higher levels (e.g. > 40%) of fly ash can be used to produce concrete with good mechanical properties and excellent durability. The use of such levels of fly ash has been restricted to special purposes such as large monolithic pours requiring temperature control or roller-compacted concrete, and for normal structural concrete the levels of between 40 to 60% fly ash can be successfully used (Dunstan et al., 1992).

The use of fly ash requires some special considerations and these are more important as the fly ash proportion in the mix increases. Although some cementitious properties can be exhibited by certain fly ashes. The cement hydration reactions typically occurs faster than that reaction and subsequently fly ash concrete does need more attention to moist curing during early ages (Hopkins et al., 2003).

2.3.5 Silica Fume

Silica Fume (SF) is a pozzolanic material and a by-product of the manufacture of silicon metal and ferro-silicon alloys. The process involves the reduction of high purity quartz (SiO_2) in electric arc furnaces at temperatures in excess of 2000°C. SF is a very fine powder consisting mainly of spherical particles or microspheres with mean diameter about 0.15 microns, with a very high specific surface area (15,000–25,000 m^2/kg). Each microsphere is on average 100 times smaller than an average cement grain (Dunster, 2009).

From the past, silicon and ferrosilicon producers had allowed the by-product silica fume to rise up into the atmosphere. Industries owners started to avoid that after being subjected to strong environmental regulations from their governments. They then had to find ways to minimize or eliminate the emission of these very fine dust particles. Moreover, the problem of handling such a fine powder was so difficult that even the most optimistic silicon producer could not at the time have conceived of the idea that one day they could take advantage of such a nuisance dust. The first interesting results obtained by the Scandinavians in usual concrete, the very impressive discoveries of Bache and co-workers in Denmark and significant research effort in the early 1980s in several other countries, resulted in the rapid acceptance of silica fume as a supplementary cementitious material for concrete almost everywhere in the world in less than 5 years (Aitcin, 1998).

The high level of fineness and practically spherical shape of silica fume results in good cohesion and improved resistance to segregation. However, silica fume is also very effective in reducing or eliminating bleed and this can give rise to problems of rapid surface crusting. This can result in cold joints or surface defects if there are any breaks in concrete delivery and also difficulty in finishing the top surface (EFNARC, 2005).

Proportions of silica fume in concrete mixtures generally vary from 5 to 20% by weight of cement, depending on the strength and workability requirements, although in special situations up to 30% has been used. However, water demand is greatly increased with increasing proportion of silica fume (Nawy, 2001).

2.3.6 Ground Granulated Blast Furnace-Slag

Ground Granulated Blast Furnace Slag (GGBFS) is a byproduct of the steel industry. Blast furnace slag is defined as “the non-metallic product consisting essentially of calcium silicates and other bases that is developed in a molten condition simultaneously with iron in a blast furnace’’ (ASTM C989 - 99, 2009).

In the iron industries, blast furnaces are inserted with iron ore, fluxing agents, and coke. Iron and molten slag are produced when the iron ore (including: iron oxides, silica and alumina) mixes together with the fluxing agents. Based on what type of slag needed the molten slag goes through a particular process. Slag which air-cooled has a rough finishing and larger surface area when compared to aggregates which allows it to bind well with Portland cements as in the matter of asphalt mixtures (Cervantes and Roesler, 2007).

The vitreous state of slag is a critical feature which must be checked carefully because its hydraulic properties are related to this feature. Some crystals could be present in the molten phase, upon quenching, the slag can be less reactive than hotter one which is more vitreous if the temperature of the slag was low. Well-quenched slags have a light yellow, beige or grey color while cold slags have a darker color from dark grey to dark brown. After separate grinding, slag can be blended with cement or by inter-grinding with clinker or it can be sold separately to concrete producers as a supplementary cementitious material (Aitcin, 1998).

Russell (1997) found out that reducing the need to use low alkali or sulfate-resistant Portland cements can be gained by using proper proportioning of slag cement. Russell's results showed that replacement of 20 to 30 percent of GGBFS by mass of the Portland cement can improve strength at later ages than 28 days.

Ozyildirim (2001) wanted to reduce the shrinkage and increase the flexural strength of the concrete. He made three concrete mixtures placed in the jointed plain concrete paving project in Newport News, Virginia. He selected two of the mixtures contained ground-granulated blast furnace slag as much as 30% by mass of the total cementitious material and the maximum water-cement ratio was 0.50 and third mixture contained Class F fly ash. At 28 days, flexural strengths were similar for fly ash and GGBFS concretes, but after 60 days those which contained slag were greater. The shrinkage values of concretes containing fly ash were slightly smaller than the value of concretes with slag.(Ozyildirim, 2001)

2.3.7 Metakolin

Metakaolin (MK) nowadays has been used as an effective and highly active pozzolan for the replacement of part of cement in concrete mixtures. It is very fine material prepared by calcining the kaolin clay in a furnace. The optimal temperature range of the dehydroxylation of kaolin is 700 – 800 °C (Qian and Li, 2001).

Between 100-200°C, clay minerals lose most of their adsorbed water. Between 500-800°C kaolinite becomes calcined by losing water through dehydroxilization. The dehydroxilization of kaolin to metakaolin is an endothermic process due to the large amount of energy required to remove the chemically bonded hydroxyl ions. Above this temperature range, kaolinite becomes metakaolin, with a two-dimensional order in crystal structure (Klimesch and Ray, 1998). The pozzolanic activity is the main characteristic of produced metakaolin for using in cement based system which defined as reactivity of material with hydroxide in the presence of water to form compounds that have cementitious properties (Ili et al., 2010).

Poon et al., (2006) investigated the relation between durability and mechanical properties of high performance MK and SF concretes to their microstructural characteristics. The concretes incorporated with MK or SF at water-to-binder (w/b) ratios of 0.3 and 0.5 and the compressive strength and chloride penetrability of the control were determined. They found that MK concrete has superior strength development and similar chloride resistance to SF concrete, and the MK concrete at a w/b of 0.3 has a lower porosity and smaller pore sizes than the control (plain) concrete.

Parande et al., (2008) studied corrosion behavior and mechanical property of carbon steel using metakaolin (5–20%) as partial replacement of ordinary Portland cement (OPC). They found that for improving the concrete mechanical properties, 15% replacement of metakaolin in OPC is the best proportion.

Cassagnabère et al., (2010) in their research, found the compressive strength of cement-based materials at both early (1 day) and later (28 days) ages under steam curing conditions by composing cements (clinker + slag) or combinations between clinker and mineral admixtures. They showed that MK is a very promising solution at a clinker replacement rate of 12.5–25% by mass. Compressive strength was significantly increased (1-day age) or practically the same as for reference mortars incorporating cement only (28-day age).

In their study, Khatib and Hibbert (2005) investigated the effect of incorporating GGBFS and MK on strength of concrete. Portland cement was partially replaced with 0–80% GGBS and 0–20% MK. The water to cementitious materials ratio was maintained at 0.5 for all mixes. During the early ages of curing, the strength increase because of the incorporation of metakaolin. They found that MK can compensate the decrease in compressive strength during the early ages of curing of GGBFS concrete.

2.4 Properties of Self-Compacting Concrete

The properties of self-compacting concretes depend on the material used in the mix design. These properties are divided into two phases: fresh and hardened states.

2.4.1 Properties of Fresh Concrete

The shape and texture of the aggregate particles are the main parameters which affect the water demand of self-compacting concrete (SCC). The rheological behavior of self-compacting concrete is different from normal concrete. Specifically, SCC flows under its own weight into all the spaces within the formwork. Slump flow or Orimet test can be conducted to measure workability. Total covering of the reinforcement by SCC can be reached by high fluidity and cohesion of the mixture (Neville, 1995).

The ability of SCC to flow through tight openings or obstructions like rebar but has to do so without bleeding or segregating (Sonebi, 2004). The paste and mortar viscosity as well as the maximum size of coarse aggregate are main parameters governing these properties.

Segregation resistance or stability is the ability to remain homogeneous while doing so (Memon et al., 2011). The segregation resistance is another important characteristic of SCC. Suitable segregation resistance can be reached if the aggregate particles distributions in the concrete are relatively equivalent at all levels and at all locations. It also means that concrete should not segregate in vertical and horizontal directions. Poor segregation resistance can cause high drying shrinkage, poor deformability and blocking around reinforcement as well as nonuniform compressive strength of concrete, hence it plays so important role for SCC (Bui et al., 2002).

2.4.2 Properties of Hardened Concrete

ACI 213R- 2003 gives values of standard cylinder compressive strength and its corresponding cement content. High cement content causes higher compressive strength. As in normal concrete, silica fume and other cementitious materials can be incorporated in SCC to improve the strength development (Neville, 1995). In general, SCC with the same water cement ratio will have higher strength compared with traditionally vibrated concrete (EFNARC, 2002).

In their study, (Sonebi et al., 2000) investigated the 28 days compressive strength and they found that the SCC compressive strength was completely affected by filler types and w/c ratio. Results of their research indicated that within the normal compliance range, using the limestone powder as filler rises up the strength of the SCC mixes in comparison with corresponding reference mixes. They showed that the SCC mix which contained GGBS as another type of filler instead of limestone powder, had lower strength at 1 and 7 days than the corresponding reference mix, but developed significantly higher strength at 28 days and beyond.

The strength development of the SCC with different curing conditions was also investigated. The results showed that the compressive strength of water-cured specimens is lighter than that of the air-cured specimens. However grade and the type of filler in the mixes influence of the extent of strength reduction due to the insufficient curing (i.e. in air) up to the age of 90 days. For example SCC mixes with limestone filler are less affected by air curing, and that air-cured strengths are reduced less than those of reference concretes. The strengths up to the age of 90 days are more affected by the air curing when GGBS was used as filler in SCC mixes.

2.5 Artificial Intelligence

In the 1940s and 50s, a handful of scientists from various fields (mathematics, psychology, engineering, economics and political science) began to discuss the possibility of creating an artificial brain.

The field of Artificial Intelligence (AI) research was founded as an academic discipline at the United State of America’s Dartmouth Conference in 1956. The proposal for the Dartmouth Conference of 1956, included this assertion: "every aspect of learning or any other feature of intelligence can be so precisely described that a machine can be made to simulate it". At the conference, Newell and Simon debuted the Logic Theorist and McCarthy persuaded the attendees to accept Artificial Intelligence as the name of the field. The 1956 Dartmouth conference was the moment that AI gained its name, its mission, its first success and its major players, and is widely considered the birth of AI.

AI is an artificial science which follows the classical hypothesis-and-test research paradigm and the study of developing computer programs that exhibit human-like intelligence (Durkin, 1994). Computers serve as laboratories for the conduction of AI experiments while programs serve as the experiments to answer questions in the natural world. A running program shows the response of nature to it. To validate the models of intelligent action, they undergo the process of design, construction, testing, and measurement of computer programs. AI is a broad status. It does not just study the mechanisms and models of intelligent actions but also the attributes of intelligent systems. In their study, Lea et al. (2005) stated that:

An intelligent system should be able to do the following:

(i) Exploit significant amounts of domain knowledge;

(ii) Tolerate error, unexpected and/or wrong input;

(iii) Use symbols and abstractions;

(iv) Exhibit goal-oriented behavior;

(v) Learn from the environment;

(vi) Operate in real time;

(vii) Communicate using natural language.

2.5.1 Expert System

Knowledge-based expert systems, or simply expert systems, use human knowledge to solve problems that normally would require human intelligence. These expert systems represent the expertise knowledge as data or rules within the computer. These rules and data can be called upon when needed to solve problems. Books and manuals have a tremendous amount of knowledge but a human has to read and interpret the knowledge for it to be used. Conventional computer programs perform tasks using conventional decision-making logic-containing little knowledge other than the basic algorithm for solving that specific problem and the necessary boundary conditions. This program knowledge is often embedded as part of the programming code, so that as the knowledge changes, the program has to be changed and then rebuilt. Knowledge-based systems collect the small fragments of human know-how into a knowledge-base which is used to reason through a problem, using the knowledge that is appropriate. A different problem, within the domain of the knowledge-base, can be solved using the same program without reprogramming. The ability of these systems to explain the reasoning process through back-traces and to handle levels of confidence and uncertainty provides an additional feature that conventional programming does not handle (Valentine and Arnhold, 2009).

An expert system has been defined by Professor Edward Feigenbaum (1960) of Stanford University as an early pioneer of experts systems technology, as: " … an intelligent computer program that uses knowledge and inference procedures to solve problems that are difficult enough to require significant human expertise for their solution " and another definition by Friederich and Gargano (1989) states that : "An expert system is a computer program that attempts to capture the knowledge and experience of one or more human experts in order to make such expertise available on demand to the user of the program".

Expertise is a highly specialized set of skills that have been honed in a particular situation for a specific purpose. Being an expert is quite different from having an education. A system is considered as an expert when it possesses the following characteristics (Jackson, 1999):

i) It contains knowledge.

ii) The knowledge must be focused upon a specific domain.

iii) This knowledge must be capable of solving problems directly.

In their investigation, Mohd Zain et al., (2005) described a prototype expert system that provides proportions of trial mix of High Performance Concrete (HPC) and recommendations on mix adjustment. The knowledge was acquired from various textual sources and human experts. The system was developed using hybrid knowledge representation technique. It is capable of selecting proportions of mixing water, cement, supplementary cementitious materials, aggregates and superplasticizer, considering the effects of air content as well as water contributed by superplasticizer and moisture conditions of aggregates. Similar to most expert systems, this system has explanation facilities, can be incrementally expanded, and has an easy to understand knowledge base.

2.5.2 Genetic Algorithm

A global optimization technique for highly dimensional, nonlinear, and noisy problems, the genetic algorithm is a stochastic search technique based on the mechanism of natural selection and natural genetics. Most genetic algorithm applications use fixed-length fixed-order bit strings to encode candidate solutions. However, there have been many experiments with other kinds of encodings, e.g., a multiple character genetic algorithm, a real-valued genetic algorithm, a continuous parameter genetic algorithm, and others (Lee et al., 2009).

It starts with initial set of random solutions called population. Each individual in the population is called a chromosome, representing a solution to the problem at hand. The evolution operation simulates the process of Darwinian evolution to create population from generation to generation. The success of genetic algorithm is founded in its ability to keep existing parts of solution and proceed with optimizing the non-optimal part. The approach is global since many samples from different parts of the solution space could be simultaneously examined. It gives more accurate results than other algorithms in the mix proportioning problem having many local solutions (Lim et al., 2004, Kamrani and Gonzalez, 2003, Yusuf et al., 2009).

In their study**,** Tanyildizi and Çevik (2010) used genetic algorithms programming to investigate the mechanical performance of lightweight concrete exposed to high temperature. Empirical genetic programming based equations for compressive and splitting tensile strength were obtained in terms of temperature, cement content, silica fume content, pumice aggregate content, water/cement ratio and super-plasticizer content. The conclusion of their work shows that the proposed genetic programming based equations are observed to be quite accurate as compared to experimental results.

Sarıdemi (2010) presented two models in gene expression programming (GEP) approach for predicting compressive strength of concretes containing rice husk ash. For building the models, experimental results for 188 specimens produced with 41 different mixture proportions were obtained from the literature. After comparing the results of training, testing and validation sets of the models with experimental results, it was found that for predicting compressive strength values of concretes containing rice husk ash, gene expression programming is a strong technique.

2.5.3 Fuzzy Logic

The concept of ‘’fuzzy set’’ was introduced by Zadeh (1967) who pioneered the development of fuzzy logic replacing Aristotelian logic which has two possibilities only. Fuzzy logic concept provides a natural way of dealing with problems in which the source of imprecision is the absence of sharply defined criteria rather than the presence of random variables (Demir, 2005). Fuzzy approach considers cases where linguistic uncertainties play some role in the control mechanism of the phenomena concerned. Herein, uncertainties do not mean random, probabilistic and stochastic variations, all of which are based on the numerical data. Zadeh has motivated his work on fuzzy logic with the observation that the key elements in human thinking are not numbers but levels of fuzzy sets. Further he saw each linguistic word in a natural language as a summarized description of a fuzzy subset at a universe of discourse representing the meaning of this word. In consequence, he introduced linguistic variables as variables whose values are sentences in a natural or artificial language (Sen, 1998).

In his study, Tanyildizi (2009) devised a fuzzy logic model to predict the bond strength of lightweight concrete containing mineral admixtures under different curing conditions. The results obtained from the fuzzy logic prediction model were compared with the average results of the experiments, and they were found to be remarkably close to each other. The results show that the fuzzy logic can be used to predict bond strength of lightweight concrete.

2.5.4 Neural Networks

Neural networks are discussed under the following subheadings.

2.5.4.1 Definition of Artificial Neural Network

Artificial intelligence is the study of how can programming achieve the intelligent behavior. It can be divided into two categories from the computational point of view. One is based on symbolism, and the other is based on connectionism. The symbols modeling in the past while recent intelligence models using network connections (Artificial Neural Networks) and associated weights have been successfully applied to many practical problems. In comparison with symbolic approach, the connectionist approach adopts the brain metaphor which suggests that intelligence emerges through a large number of interconnected processing elements in which any individual processing element performs a simple computational task (Foggia, 2001). The weights of the connections between processing elements encode the long term knowledge of a network. Artificial neural networks are viable computational models for a wide variety of problems. These include pattern classification, speech synthesis and recognition, adaptive interfaces between humans and complex physical systems, function approximation, image compression, associative memory, clustering, forecasting and prediction, combinatorial optimization, nonlinear system modelling, and control (Liu, 1996).

A general definition of an ANNs was given by Hecht-Nielsen (1988):

"A neural network is a parallel, distributed information processing structure consisting of processing elements (which can process a local memory and carry out localized information processing operations) interconnected together with unidirectional signal channels called connections. Each processing element has a single output connection which branches ("fan out") into as many collateral connections as desired (each carrying the same signal - the processing elements output signal). The processing element output signal can be of any mathematical type desired. All of the processing that goes on within each processing element must be completely local; that is, it must depend only upon the current values of the input signal arriving at the processing element via impinging connections and upon values stored in the processing element's local memory."

Another definition says that artificial neural networks are processor systems of information that have specified computational properties alike to those which have been presumed for biological neural networks. Artificial neural networks generalize the mathematical models of the human perception and neural biology. The imitation of the basis of conducting the organization of human brain forms the principles for their structural design and learning algorithms (Rivero et al., 2010). Artificial neural networks expose the ability to learn from the environment in an interactive fashion and show remarkable abilities of learning, recall, generalization and adaptation in the wake of changing operating environments. Biological neural systems are a formed and coordinated collection of billions of biological neurons. A simple biological neuron composed of a cell body which has a number of branched protrusions, called *dendrites*, and a single branch called the *axon* as shown in Figure 2.2 (Agatonovic-Kustrin and Beresford, 2000).