Artificial Neural Networks and Fuzzy Logic Applications in Modeling the Compressive Strength of Portland Cement

By

Sever CAN

A Dissertation Submitted to the
Graduate School in Partial Fulfillment of the
Requirements for the Degree of

MASTER OF SCIENCE

Department : Materials Science and Engineering
Major : Materials Science and Engineering

İzmir Institute of Technology
İzmir, Turkey

01 December, 2004

We approve the thesis of **Sever CAN**

Date of Signature

----------------------------------- **01.12.2004**

Assoc. Prof. Dr. Sedat AKKURT

Supervisor

Department of Mechanical Engineering

----------------------------------- **01.12.2004**

Prof. Dr. Muhsin ÇİFTÇİOĞLU

Head of Interdisciplinary

Materials Science and Engineering Program

----------------------------------- **01.12.2004**

Asst. Prof. Dr. Gürsoy TURAN

Department of Civil Engineering

----------------------------------- **01.12.2004**

Asst. Prof. Dr. Serhan ÖZDEMİR

Department of Mechanical Engineering

----------------------------------- **01.12.2004**

Asst. Prof. Dr. Fuat DOYMAZ

Department of Chemical Engineering

Head of Department of Materials Science and Engineering **01.12.2004**

Prof. Dr. Muhsin ÇİFTÇİOĞLU

ACKNOWLEDGEMENTS

I would like to express my sincere gratitude to my advisor, Assoc. Prof. Dr. Sedat AKKURT for his supervision, guidance and encouragement throughout this study.

I would like to appreciate deeply to my fiancée Pınar ÖZTÜRK for her help, support, encouragement and understanding.

I am grateful to Turkish Cement Manufacturers' Association (TÇMB) for their financial support throughout this study.

Special thanks to Sevdiye ATAKUL, Emre YALAMAÇ, Mücahit SÜTÇÜ and all my friends for their friendship, support and understanding.

Finally, I would like to thank my family for their support and encouragement all the time.

ABSTRACT

Portland cement production is a complex process that involves the effect of several processing parameters on the quality control of 28-day cement compressive strength (CCS). There are some chemical parameters like the C_3S, C_2S, C_3A, C_4AF, and SO_3 contents in addition to the physical parameters like Blaine (surface area) and particle size distribution. These factors are all effective in producing a single quantity of 28-day CCS. The long duration of 28 day CCS test provided the motivation for research on predictive models. The purpose for these studies was to be able to predict the strength instead of waiting for 28 days for the test to be complete. In this thesis, artificial intelligence (AI) methods like artificial neural networks (ANNs) and fuzzy logic were used in the modeling of the 28-day CCS. The two models were compared for their quality of fit and for the ease of application.

Quality control data from a local cement plant were used in the modeling studies. The data were separated randomly into two parts: the first one contained 100 data points to be used in training and the second part had 50 data points to be used in testing stages of the models. In this study, four different AI models were created and tested (3 ANN, 1 fuzzy logic). One of the ANN models (Model A) had 20 input parameters in 20x20x1 architecture with testing average absolute percentage error (AAPE) of 2.24%. The other ANN model (Model B) had four input parameters (SO_3, C_3S, Blaine and total alkali amount) in 4x4x1 architecture with AAPE of 2.41%. Both of the Model A and the Model B were created in the MatLAB® environment by writing a custom computer code. The last ANN model (Model C) actually refers to 72 different ANN models created in the MatLAB® neural networks toolbox. In order to obtain a model with the lowest error, different learning algorithms, training functions and architectures in combinations were tested. The lowest AAPE among these models appeared to be 2.31%. The fuzzy logic model (Model D) which had four input parameters (SO_3, C_3S, Blaine and total alkali amount) was created in the MatLAB® fuzzy logic toolbox. In order to write the fuzzy rules, the sensitivity analysis of the Model B was utilized. The AAPE of the Model D was 2.69%. The model was compared with the ANN models for its error levels and ease of application. The results indicated that through the application of fuzzy logic algorithm, a more user friendly and more explicit model than the ANNs could be produced within successfully low error margins.

ÖZ

Portland çimento üretimi, 28 günlük çimento basma dayanım (CCS) kalite kontrol testlerini etkileyen birçok süreç parametresinden oluşan karmaşık bir işlemdir. Bu parametreler C_3S, C_2S, C_3A, C_4AF ve SO_3 gibi kimyasal, Blaine (yüzey alanı) ve tanecik dağılımı gibi fiziksel faktörlerdir. Tüm bunlar, 28 günlük basma dayanımı ile test edilebilen çimentonun dayanımını oluşturan çok önemli faktörledir. 28 günlük CCS kalite kontrol testi, kalite kontrolü açısından uzun bir süreçtir. Bu yüzden de, bu uzun süreçten kurtulmak için çeşitli metotların arayışına gidilmiştir. Böylelikle, bu çalışmada 28 günlük CCS' yi modellemek için yapay zekâ metotlarından Yapay Sinirsel Ağ (ANNs) ve Bulanık Mantık (BM) kullanılmıştır. ANN ve BM modelleri karşılaştırılmıştır. Modelleme konusunda çalışan uzmanlaraın kolayca kullanabileceği bulanık mantık yaklaşımının, açık yapısı ve avantajları açıklanmaya çalışılmıştır.

Yerel bir çimento fabrikasından alınan kalite kontrol verileri modelleme çalışmalarında kullanılmıştır. Bu veriler, 100 veri seti modellerin öğrenme aşamasında ve 50 veri seti de modelin deneme aşamasında kullanılmak üzere iki kısma ayrılmıştır. Bu çalışmada, dört farklı yapay zeka modeli oluşturulmuştur ve denenmiştir (3 ANN, 1 BM). İçinde 20 girdi parametresi bulunan ANN modellerinden biri (Model A) %2.24 ortalama mutlak hata yüzdesi (AAPE) ve 20x20x1 mimarisinde tasarlanmıştır. İçinde 4 girdi parametresi (SO_3, C_3S, Blaine ve toplam alkali miktarı) bulunan diğer ANN modeli (Model B), %2,41 AAPE ile 4x4x1 mimarisine sahiptir. Bu iki model (Model A ve Model B) MatLAB® ortamında hazırlanmıştır. Son ANN modeli (Model C), MatLAB®Neural Network Toolbox içinde oluşturulmuş 72 farklı ANN modelini kapsamaktadır. Bu modelleri, en düşük hata ile çalıştırmak için farklı algoritmaların, öğrenme fonksiyonların ve mimarilerin kombinasyonları denenmiştir. En düşük AAPE, %2,31 olarak tespit edilmiştir. Son olarak, 4 girdi parametresi (SO_3, C_3S, Blaine ve toplam alkali miktarı) bulunan BM modeli (Model D), MatLAB®Fuzzy Logic Toolbox kullanılarak hazırlanmıştır. Bulanıklık kuralları yazılırken, Model B' deki girdi parametrelerinin hassasiyet çözümlemeleri kullanılmıştır. Model B'nin AAPE değeri %2,69 olarak bulunmuştur. Kullanılabilirliği ve hata seviyeleri açısından bu model, diğer ANN modelleri ile karşılaştırılmıştır. Sonuç olarak, hem uygulamada kullanıcıya rahatlık sağlaması ve kolay anlaşılır olması açısından, hem de düşük hata oranları bakımından BM modelinin, kurulan ANN modellerinden daha açık ve kolay tatbik edilebilir olduğu söylenebilir.

TABLE OF CONTENTS

LIST OF FIGURES

LIST OF TABLES

Chapter 1

INTRODUCTION

Portland cement is a binding material which has been widely used for more than fifteen decades. The basics of the production process remained almost the same since the patent for Portland cement was obtained in 1824 by Joseph Aspdin. The production is a complex process that involves the effect of several processing parameters on the quality control parameter of 28-day compressive strength. Examples for processing parameters are chemical parameters like the C_3S, C_2S, C_3A, C_4AF, and SO_3 contents in addition to the physical parameters like Blaine (surface area) and particle size distribution. These factors are all effective in producing a single strength quantity of 28-day compressive strength (CCS).

Many studies were performed to predict the 28-day CCS based on these parameters in addition to the 2 and 7-day CCS values (Mindess et al., 2002). The purpose was to accelerate the strength measurement for faster delivery of the product. The prediction studies included the extrapolation method, regression analysis methods, artificial neural networks (ANN) and fuzzy logic. The extrapolation method proposed by Tango involves the prediction of 28 days strength based on the 2 and 7 days strengths via the use of AMEBA method (de Siqueira Tango, 1998). Tsivilis and Parissakis, on the other hand, applied the stepwise regression analysis techniques to develop a mathematical model. The predicted variables in that study were 2, 7 and 28 days strengths as a function of chemical and physical parameters (Tsivilis et al., 1995). In a previous study of Fa-Liang, Fuzzy logic was proposed as a modeling technique of compressive strength development of cement (Fa-Liang, 1997). Akkurt et.al. also reported an ANN (Akkurt et al., 2003) and a fuzzy logic (Akkurt et al., 2004) model that predicts the 28-day CCS. More recently, Baykaşoğlu and his co-workers employed a Gene Expression Programming (GEP) technique for 28-day CCS prediction (Baykaşoğlu et al., 2004).

In Chapter 2 of this study, the chemistry, physical properties, the properties of mineralogical constituents like C_3S, C_2S, C_3A and C_4AF, production process and quality control parameters of Portland cement are briefly explained.

In Chapter 3, artificial intelligence (AI) methods like Artificial Neural Networks (ANNs) and fuzzy logic are presented. The components, architecture and learning algorithms of ANNs are explained. Also, the fundamentals and systems of fuzzy logic are given in this chapter.

Prediction modeling studies, like regression and other mathematical models are briefly explained in Chapter 4.

In Chapter 5, construction of the AI models that were created in this thesis, are explained.

In Chapter 6, the results of various models created in this study are discussed.

Chapter 2

PORTLAND CEMENT

There is a wide variety of cements that are used in construction and building industries, the most commonly used one being the Portland cement. The chemical compositions and physical properties of Portland cements are highly variable.

In this chapter a brief introduction to the history, chemistry, physical properties, mineralogy, hydration, production processes and quality control parameters of Portland cement is presented.

2.1. History of Modern Cement

In 1756, John Smeaton was told to rebuild the Eddystone Lighthouse in England. He made many experiments with different limes and pozzolans to overcome the problems caused by water. Finally he found that the best limestones for use in mortars were those containing a high proportion of clayey material (Mindess et al., 2002). Finally in 1824, Joseph Aspdin, a bricklayer and mason in Leeds, England, was the first who patented a product he named Portland cement. The name comes from the color of stone quarried from the Island of Portland (Bogue, 1955). The production of Portland cement with the modern techniques was first accomplished by Vicat in 1828 (Mindess et al., 2002).

2.2. Chemistry

There are four main constituents in Portland cement; calcium oxide “quicklime” (CaO), silica (SiO_2), alumina (Al_2O_3) and ferric oxide (Fe_2O_3) which are symbolized shortly as C, S, A and F, respectively. Other chemical compounds like magnesia (MgO), sulfur (S), alkalis (K_2O and Na_2O), carbon dioxide (CO_2) and water (H_2O) which are symbolized as M, S’, K, M, C’ and H respectively, are also present at amounts of 0 to 3.5% wt in portland cement (Czernin, 1980). The ASTM specifications for various Portland cement types are given in Table 2.1 (Bogue, 1955).

Table 2.1. Chemical Requirements for Portland cement According to ASTM Specifications C-150-53

Compound	Type I	Type II	Type III	Type IV	Type V
Silicon dioxide (SiO_2), min., %	——	21.0	——	——	——
Aluminum oxide (Al_2O_3), max., %	——	6.0	——	——	*a*
Ferric oxide (Fe_2O_3), max., %	——	6.0	——	0.5	*a*
Magnesium oxide (MgO), max., %	5.0	5.0	5.0	5.0	4.0
Calcium sulfate ($CaSO_4$) in hydrated portland cement mortar at 24±1/4 hr, expressed as SO_3, max. g/liter	0.5	0.5	0.5	0.5	0.5
Loss on ignition max., %	3.0	3.0	3.0	2.3	3.0
Insoluble residue, max., %	0.75	0.75	0.75	0.75	0.75
Tricalcium silicate (C_3S), max., %	——	50	——	35	50
Dicalcium silicate (C_2S), min., %	——	——	——	40	——
Tricalcium aluminate (C_3A), max., %	——	8	15	7	5

[a] The tricalcium aluminate (C_3A) shall not exceed 5%, and the tetracalcium aluminoferrite (C_4AF) plus twice the amount of tricalcium aluminate (C_3A) shall not exceed 20 %.

2.3. Physical Properties

The physical properties like air content in mortar, fineness, air permeability, expansion, strength (1, 3, 7 and 28 day) and time of setting are defined in ASTM C150 standard for Portland cement (Mindess et al., 2002). One of the most important properties of Portland cement is compressive strength (Mindess et al., 2002). Tensile and flexural strength values can also be measured but the results are not as reliable and reproducible as those of compressive strength measurements.

Compressive Strength: This is the most common measure of strength required by cement specifications. According to ASTM C109, specimen is molded in 2-in mortar cube with sand/cement ratio of 2.74:1 (using the standard Ottawa sand) at a water/cement ratio of 0.485 for all Portland cements. After the preparation of specimen, it is stored in water at 23 °C until tested. The compressive strength standards are given in Table 2.2 (Mindess et al., 2002). CEM I 42.5R type cement was used in the data collection of these thesis. According to the standards (ASTM C150), the compressive strength of this type cement cannot be less than 42.5 MPa.

Table 2.2. Compressive Strength Requirements of ASTM C150 Standard Specification for Portland cement

Compressive strength test	**Cement Type**							
	I	**IA**	**II**	**IIA**	**III**	**IIIA**	**IV**	**V**
1 day (MPa)	—	—	—	—	12.4	10.0	—	—
3 days (MPa)	12.4	10.0	10.3	8.3	24.1	19.3	—	8.3
7 days (MPa)	19.3	15.5	17.2	13.8	—	—	6.9	15.2
28 days (MPa)	—	—	—	—	—	—	17.2	20.7

Actually all types of cements have infinite time of hardening. Figure 2.1 shows strength development for different types of Portland cements as a function of time.

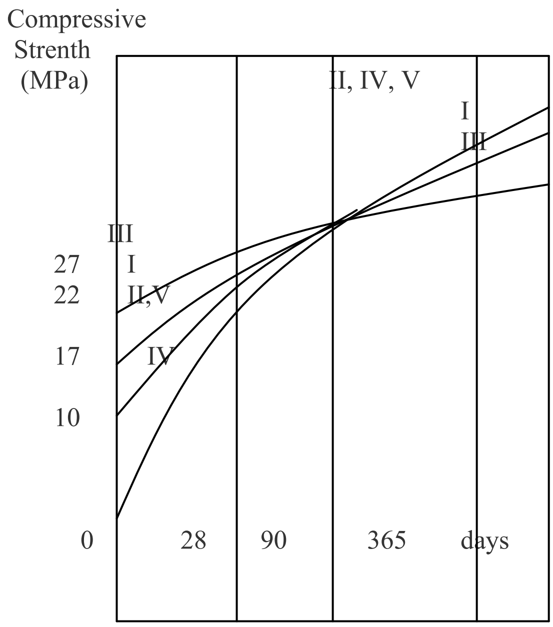


Figure 2.1. Compressive strength values for different Portland cement types in long term periods (Mindess et al., 2002)

The other important parameter of Portland cement is its fineness. The effect of fineness (Blaine) on the rate of hardening of Portland cement is due to the fact that the larger surface area allows earlier forming of cement gel. Therefore, initial strength will develop faster. For the first 7 days of hardening, fineness plays a more important role in hydration than chemistry (Czernin, 1980).

2.4. Mineralogy

There are four main phases in the Portland cement which are C_3S, C_2S, C_3A and C_4AF. The names and chemical formulas of all those phases are given in Table 2.3.

Table 2.3. Typical Mineralogical Compositions and Selected Properties of Portland Cements (Mindess et al., 2002)

Name	Formula	Items	Type of cement				
			I	II	III	IV	V
Tricalcium silicate (alite)	$3CaO.SiO_2$	C_3S	50	45	60	25	40
Dicalcium silicate (belite)	$2CaO.SiO_2$	C_2S	25	30	15	50	40
Tricalcium aluminate	$3CaO.Al_2O_3$	C_3A	12	7	10	5	4
Tetracalcium aluminoferrite	$4CaO.Al_2O_3.Fe_2O_3$	C_4AF	8	12	8	12	10
Gypsum [b]	$CaSO_4.2H_2O$	$CS'H_2$	5	5	5	4	4
[b] *Gypsum is added during the grinding of clinker*	Fineness (Blaine, m^2/kg)		350	350	450	300	350
	Comp. Strength-28-day (1day) (MPa)		27.6	27.6	(14)	(3)	(6)
	Heat of Hydration (7 days, J/g)		330	250	500	210	250

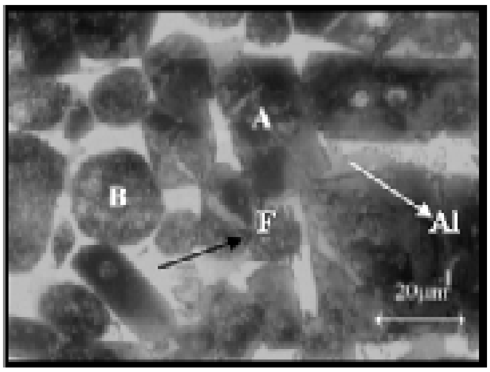


Figure 2.2. An Optical microscope image illustrating four main phase of polished and etched Portland cement clinker produced by Çimentaş A.Ş İzmir.

The micrograph of Portland cement clinker (Figure 2.2) illustrates the four main phase constituents in Portland cement. *A* is the alite, *B* donates the belite, *Al* is for tricalcium aluminate phase and *F* represents the tetracalcium aluminoferrite phase.

2.5. Hydration of Portland Cement

Final product, Portland cement, is in powder form and when water is added to the cement, a series of reactions produce hydrated forms of C_3S, C_2S, C_3A and C_4AF phases. The hydration products contribute to form the cement paste, which sets rapidly and develops the final rigid mass. Unrestrained high hydration rate releases high energy which may cause volume expansion of the structure and due to this expansion cracks may form (Czernin, 1980).

2.5.1. Hydration of Tricalcium and Dicalcium Silicates

The most dominating cement clinker phases that affect the hydration process are tricalcium and dicalcium silicates. The reactions are as follows;

$$2(3CaO.SiO_2) + 6H_2O \rightarrow 3CaO.2SiO_2.3H_2O + 3Ca(OH)_2 \quad (2.1)$$

$$2(2CaO.SiO_2) + 4H_2O \rightarrow 3CaO.2SiO_2.3H_2O \pm Ca(OH)_2 \quad (2.2)$$

The $Ca(OH)_2$ that is produced is known as portlandite and $3CaO.2SiO_2.3H_2O$, is named as tobermorite gel. Portlandite is the major product of hydration reaction (Schneider, 1991).

The amount of Portlandite produced from the C_2S reaction is about one-third the amount produced from the C_3S phase. The other difference is that the maximum rate of hydration for C_2S occurs around 40 days, when only about 20% of the C_2S has developed. That is why C_2S phase of Portland cement contributes to the late and continued strength of the cement (Schneider, 1991).

2.5.2. Hydration of Tricalcium Aluminate

Tricalcium aluminate reacts strongly with water to form the crystalline hydration products. And if no gypsum is added to cement, C_3A causes cement to set very quickly. The calcium sulfate in the gypsum reacts with C_3A to form a phase called ettringite (Schneider, 1991). The reaction is as follows;

$$3CaO.Al_2O_3 + 3(CaO.CaSO_4.2H_2O) + 26H_2O \rightarrow 6CaO.Al_2O_3.3CaSO_4.32\ H_2O \quad (2.3)$$

Gypsum acts as a retardant, and formation of ettringite prevents flash setting. Tetracalcium aluminoferrite follows the same hydration mechanism as C_3A (Mindess et al., 2002).

2.6. Production Process

In principle, the production of Portland cement is thought to be simple. Actually, it relies on the use of great amounts of raw materials. A mixture of limestone and clay is heated in a kiln to 1400 to 1600 °C, which is the temperature range where two materials interact and form calcium silicates. In practice, for desired quality of cement, great attention must be paid for every stage of manufacturing process. The manufacturing process of cement includes four basic operations; quarrying and crushing of raw materials, grinding to high fineness and carefully proportioning the mineral constituents, pyroprocessing the raw materials in a rotary calciner, and finally cooling and grinding the calcined product to obtain a fine powder (Schneider, 1991). Figure 2.3 represents the production process of cement.

2.6.1. Clinker Production

As shown in Figure 2.3 the raw materials are fed to a rotary kiln that is heated to temperatures as high as 1450 °C. The kiln output is known as clinker which is rapidly cooled to maintain the desired phase composition. The clinker is ground in tumbling ball mills to which additives like pozzolans and gypsum are incorporated into the cement powder.

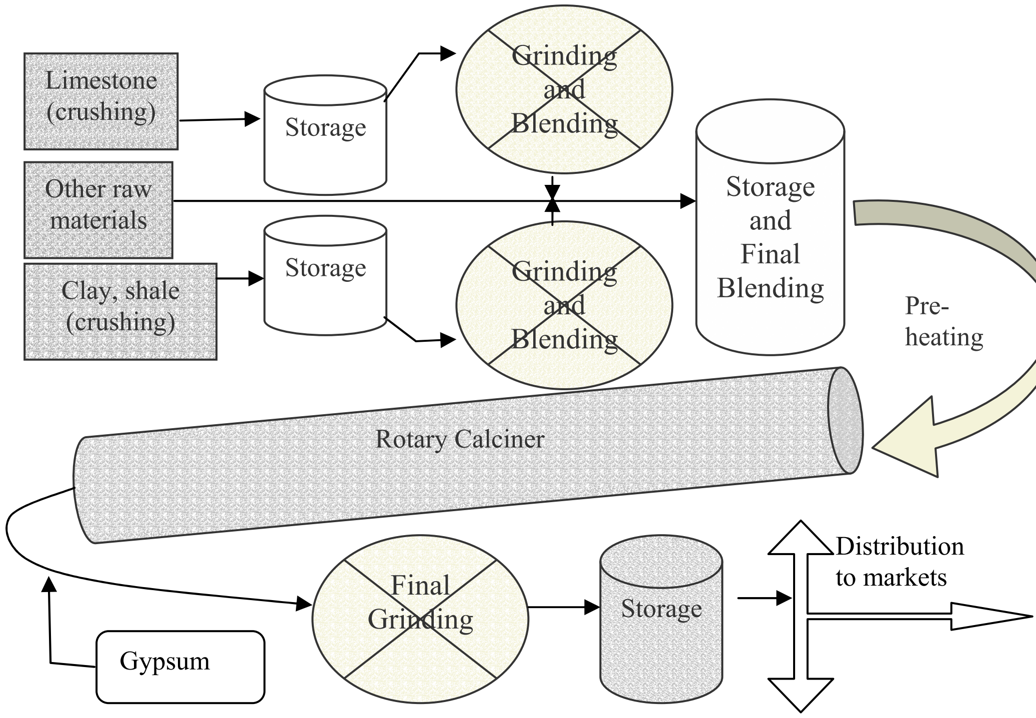


Figure 2.3. Scheme of Portland cement production (Mindess et al., 2002)

2.6.2. Additives

There are many admixtures to provide special properties of cement. Substances to modify the rate of reaction of cement are generally accelerators like soda, aluminium compounds, water-glass, high-alumina cements and various organic substances. Substances which reduce the need of water for concrete mix are plasticizers like ligninsulpho acids, hydroxylized carboxyl acids, zinc salts, borates, phosphates, polysaccharides, and certain silicones. There are air-entering agents like various kinds of oils and fats or resins. The final class of admixtures are water-repelling agents like calcium soaps, mineral oil emulsions etc.

2.7. Quality Control Parameters

Portland cement production is a complex process that involves tight control of many processing parameters. These parameters can be related to the chemical or physical properties of Portland cement or intermediate products (Table 2.4). Examples for chemical parameters are the percentages of phases like tricalcium silicate (C_3S), dicalcium silicate (C_2S), tricalcium aluminate (C_3A) and tetracalcium aluminoferrite (C_4AF). Other chemical constituents are silica (SiO_2), alumina (Al_2O_3), ferric oxide

(Fe_2O_3), calcium carbonate (CaO), sulfate (SO_3), magnesium oxide (MgO), alkalis (K_2O and Na_2O), aluminate modulus (%) (Al_2O_3/ Fe_2O_3), silicate modulus (%) (SiO_2/(Al_2O_3+ Fe_2O_3)), free lime (%) and Loss on ignition (%). In addition to the chemical parameters that have great effect on the quality of Portland cement, there are also some important physical parameters that must be considered. These are specific surface area (Blaine), in terms of cm^2/g and "Sieve residue on" 32 and 90 µm (%). The physical parameters measured using hardened cement are compressive strength (CCS) in terms of MPa, or N/mm^2, and Initial and Final setting time (hardening cement) in terms of minutes (Mindess et al, 2002). These chemical and physical parameters are shown in Table 2.4.

Table 2.4. The Chemical and Physical Parameters Measured During the Quality Control of Portland Cement

Chemical Parameters		**Physical Parameters**
C_3S (%)	C_2S (%)	Specific surface (Blaine) (cm^2/g)
C_3A (%)	C_4AF (%)	Sieve residue on (%) (32 and 90 µm)
Al_2O_3 (%)	SiO_2 (%)	Compressive strength (MPa (or N/mm^2))
SO_3 (%)	Fe_2O_3 (%)	Initial and Final setting time (min)
CaO (%)	MgO (%)	
K_2O and Na_2O (%)	Al_2O_3/ Fe_2O_3 (%)	
Free lime (%)	Loss on ignition (%)	
SiO_2/(Al_2O_3+ Fe_2O_3) (%)		

Chapter 3

NEURAL NETWORKS AND FUZZY LOGIC

Neural networks and fuzzy logic are the two most important concepts of artificial intelligence. They are useful in modeling or prediction of one or more variables, or simulation of a system.

3.1. Artificial Neural Networks (ANNs)

Artificial neural networks (ANNs) are one of the powerful data modeling tools motivated from the operation of human nervous system. ANN has a form of multiprocessor computing system, with simple processing elements (neurons), with a high degree of interconnection and simple scalar messages carried through the system. ANNs are very useful for problems where there exist no or only an incomplete algorithmic description. The main processing element is named as neuron (Figure 3.1).

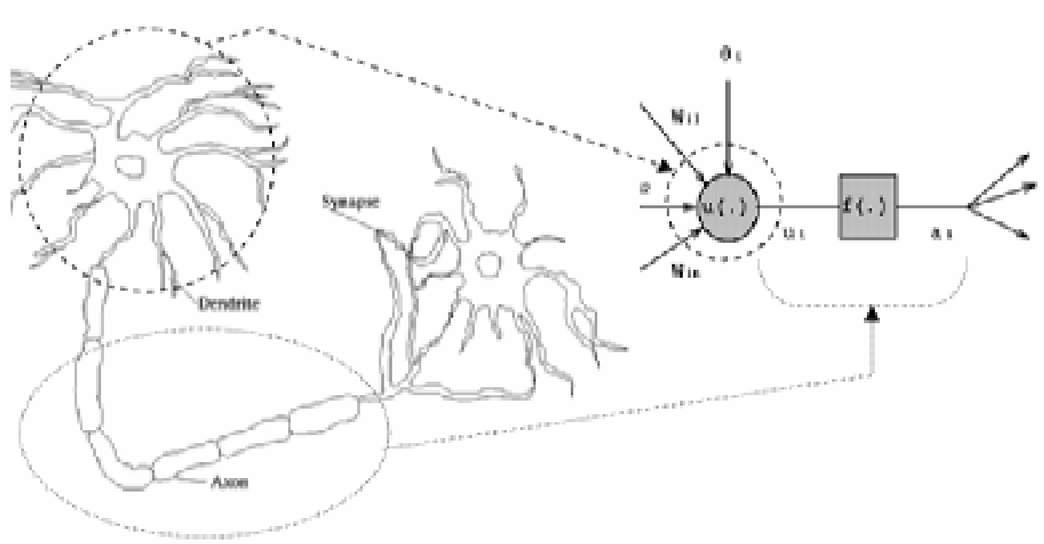


Figure 3.1. Schematic representations of the similarities between a human and an artificial neuron

The information that is contained in each neuron is first weighted (w_{ij}), and summed up as a net function (u_i). Then the value from that net function is transferred, by a transfer function ($f(u)$) with activation value (a_i), to the next neuron. Each input, therefore, is given a relative weight, which affect the impact of that input. They have adaptive coefficients that determine the strength of the input data (Nelson et al., 1994).

Net Functions: There are primarily two net functions that are used: linear-basis and radial-basis net functions. In linear-basis function (Eq. 3.1) u_i is summation of the weight (w_{ij}) from the ij^{th} neuron multiplied with the j^{th} input (x_j). Radial-basis function can be seen in Eq. (3.2).

$$u_i(w,x) = \sum_{j=1}^{n} w_{ij} x_j \qquad \text{Linear-basis function} \qquad (3.1)$$

$$u_i(w,x) = \sqrt{\sum_{j=1}^{n} (x_j - w_{ij})^2} \qquad \text{Radial-basis function} \qquad (3.2)$$

Transfer Functions: The sum of the weighted inputs becomes the input for an activation (transfer) function, which processes that input to a new output. There are mainly six transfer functions the commonly used one being the sigmoid transfer function (Eq. 3.3). It produces outputs in the interval of (0 to 1), and is continuous like its derivative. It's function is non-decreasing and monotonic (Nelson et al., 1994). Another widely used function is Gauss function which is shown in Eq. (3.4). Linear function calculates the output by the equation f(x) = αx where α is constant. Neurons with this type of transfer function result in linear approximations (Zurada, 1992). The other transfer functions are Step function, Ramp function and Hyperbolic tangent function.

$$f(u_i) = \frac{1}{1+e^{-u_i/\sigma}} \qquad \text{Sigmoid transfer function} \qquad (3.3)$$

$$f(u_i) = ce^{-u_i^2/\sigma^2} \qquad \text{Gauss function} \qquad (3.4)$$

3.1.1. The Network Architecture

An ANN consist of many neurons interconnected, and this net forms a processing system. Layers consist of processing elements that are known as neurons. Figure 3.2 shows a typical network with 4x4x1 architecture, which means 4 input neurons in the input layer, 4 neurons in the hidden layer and only one output in the output layer. Generally, the number of neurons in the hidden layer is limited with an upper value which is $N^H \leq (2N^I+1)$. N^H is the number of neurons in hidden layer, N^I is the number of neurons in input layer.

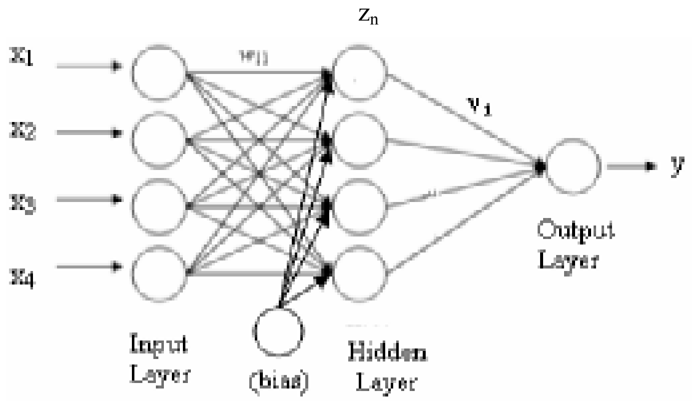


Figure 3.2. Schematic representation of a neural network (4x4x1 network architecture)

Neural networks could be single-layer or multi-layer networks. Single-layer neural network type has one layer of connection weights (Figure 3.2). Multi-layer neural network contains more than one layer of nodes between input and output neurons. ANNs do two major functions; they learn and recall. During the learning process, connection weights adapt to the knowledge they carry. Later, the adapted weights give an output with new, and independent from those of training, input data. This is a recall process which is employed for testing of the model or for sensitivity analysis.

3.1.2. Learning Algorithms

There are many learning algorithms like Feed forward back-propagation (BP), Kohonen self-organizing maps, The Widrow-Hoff rule, The Hopfield rule, Elman back-propagation, and Cascade-forward back-propagation (Haykin, 1999). One of the most widely used learning algorithms is Back-propagation (BP) learning.

BP algorithm includes two phases; forward pass and backward pass. In the forward pass, inputs are fed, transferred with weights, processed in the neurons and finally an output value is found. That value is compared with the actual value and the error is calculated. In backward pass, the same way as the forward pass is followed, by this way the error from the first pass is distributed through the weights (Base et al, 1996). The error from forward pass is optimized and the modification of the weights throughout the network is as:

$$v_{ij}^{new} = v_{ij}^{old} - \delta \frac{\partial E}{\partial v_{ij}} \tag{3.5}$$

where the δ is a positive constant term called learning rate and E is the error function.

3.2. Fuzzy Logic

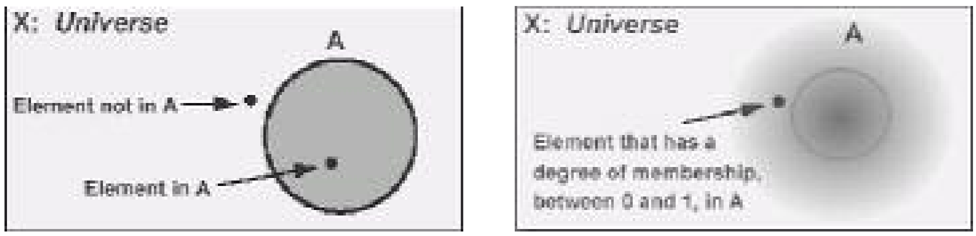
Fuzzy logic is a way to make machines more intelligent, enabling them to reason in a fuzzy manner like humans. Fuzzy models "think" the way as humans do (human-like thinking) and include verbal expressions instead of numbers. It is preferable when the mathematical problem is hard to derive, and when decisions have to be made with estimated values under incomplete information. First, it was proposed by Loutfi A. Zadeh in 1965 with the work "Fuzzy Set Theory" (Zadeh, 1965). In 1974, E. H. Mamdani at the University of London published "Application to Control Problems" working on fuzzy logic. Later, this intelligence technique was applied in many areas. The most successful areas of application are fuzzy control of physical or chemical parameters like temperature, electric current, flow of fluid, motion of machines etc. (Munakata, 1998). Some applications are Fuzzy washing machine (Panasonic); amount, type, dirtiness for water quality, water flow speed, and cycle times, Fuzzy vacuum cleaners (Matsushita), Fuzzy refrigerators (Sharp), Fuzzy fans, heaters, air conditioners, etc., Sendai Subway water tank, and Cameras & camcorders; focus, exposure, zoom, handshaking (Cheetham et al., 2001).

3.2.1. Fundamentals of Fuzzy Sets

Fuzzy logic includes concepts like fuzzy sets, membership functions, basic set operations like maximum and minimum operator, complement etc.

3.2.1.1. Fuzzy Set

It is quite different from the classical set. Fuzzy set allows an element to have a degree of membership between 0 and 1, whereas classical set allows an element to be or not to be a member of a set. In fuzzy set, if degree of membership is 0, it means the element belongs 0% to the set where if it is 1, the element belongs 100% to this set (Figure 3.3).



a) b)

Figure 3.3. Elements in classical (a) and fuzzy (b) set A (Larsen, 2003)

3.2.1.2. Membership function

Every element in a set is associated with a degree of membership. A membership function (MF) of a set maps each element to its degree. This degree is in [0,1] interval and is similar to the example of gray area between white and black. Figure 3.4 is an example membership function plot of youngness. Until the age of 25, all the elements have degree of membership 1, i.e. 100% young. After 25, the youngness decreases, and about the age of 70, the element has a degree of 0, which means 0% young (Munakata, 1998). The expression is given as:

$$\mu(x) = \{1.0 \textit{ for } 0<x<25 \textit{ or } 1/(1+((x-25)/5)^2) \textit{ for } x>25\} \quad (3.6)$$

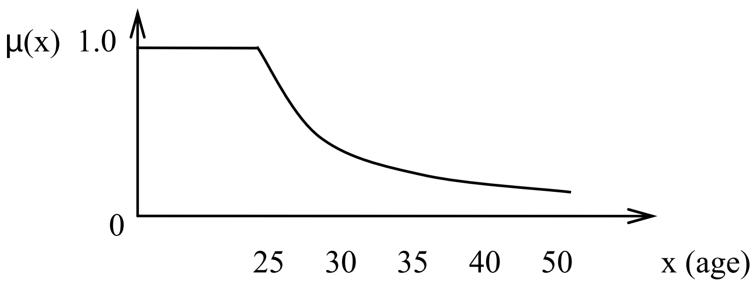


Figure 3.4. Membership function for youngness

Subset: In most cases of fuzzy logic problems, there exist subsets instead of only one set. In Figure 3.4, there is only one set for youngness. Other subsets like middle-aged and old can also be included. For instance, ages between 25 and 50 could be grouped as middle-aged, and the ages of 40 and above could be defined as the old group. These subsets can be constructed in various geometries, but the most popular one is triangular (Figure 3.5) geometry.

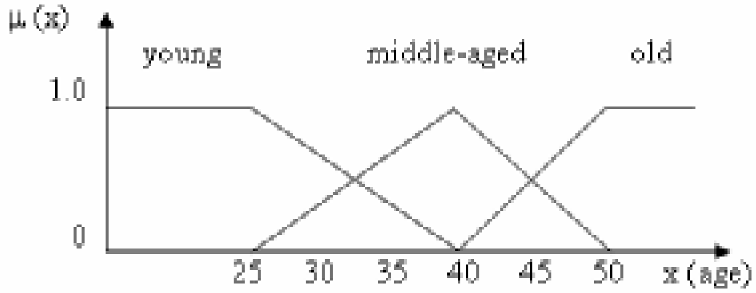


Figure 3.5. Triangular membership functions of youngness

Until the age of 25, μ *(x)* is totally 1, and each member of that group is 100% young. After 25, the "youngness" decreases, and finally at 40 there is no more a member to be defined as young. On the other hand, middle-aged category begins at 25, reaches top (members are totally middle-aged) at 40 and ends at 50 where there is no member defined as middle-aged. Beginning from 40, subset of being old, reaches maximum at age of 50, and after that age all the members are defined as 100% old. The boundaries of each subset could be defined in any desired combination.

3.2.1.3. Basic Fuzzy Set Operations

As in the classical sets, basic relations for fuzzy sets are defined.

Table 3.1. Correspondence Between Set Theory and Fuzzy Logic (Larsen, 2003)

Intersection	*Union*	*Complement*
$\mu_{A\cap B}(x) =$	$\mu_{A\cap B}(x) =$	$\mu_{\bar{A}}(x) =$
classical $\begin{cases} 1 & x \in A \cap B \\ 0 & x \notin A \cap B \end{cases}$	$\begin{cases} 1 & x \in A \cup B \\ 0 & x \notin A \cup B \end{cases}$	$\begin{cases} 1 & x \notin A \\ 0 & x \in A \end{cases}$
fuzzy $\min(\mu_A(x), \mu_B(x))$	$\max(\mu_A(x), \mu_B(x))$	$1 - \mu_A(x)$
AND	**OR**	**NOT**

Ordinary set operations like union, intersection and complement are valid for fuzzy sets, but with some differences. Table 3.1 compares these three operations for classical and fuzzy sets $\mu_{A,B}$ denotes the membership function of subsets A and B.

3.2.2. Fundamentals of Fuzzy Logic

Fuzzy logic, by using fuzzy sets deals with some verbal expressions and rules. Table 3.2 gives the correspondences between fuzzy set and fuzzy logic. Fuzzy implication is a relation in fuzzy logic; "IF A THEN B" or "IF A AND B THEN C". For example "IF young THEN small" is a fuzzy implication (Munakata, 1998). Fuzzy inference is another fundamental concept which is based on fuzzy implication and its compositional rule.

Table 3.2. Representing the Correspondences Between Fuzzy Set and Fuzzy Logic

Fuzzy Set	**Fuzzy Logic**
Degree of membership	Truth value of proposition
$\cap$	AND
$\cup$	OR
complement	NOT

3.2.3. Fuzzy Systems

A general fuzzy system basically has four components; fuzzification, fuzzy rule base, fuzzy output engine and defuzzification. The fuzzy system is shown in Figure 3.6.

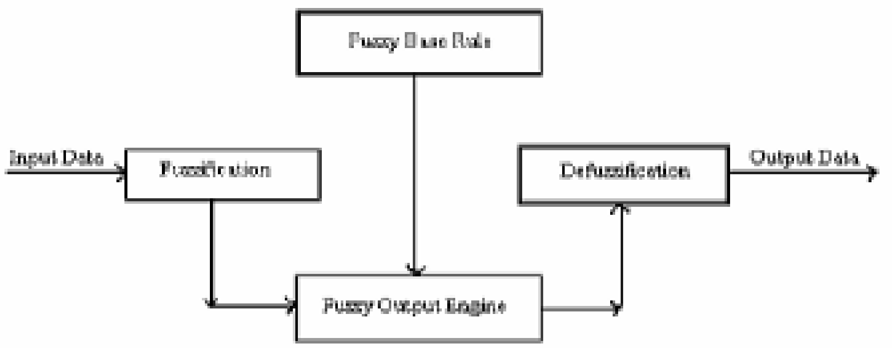


Figure 3.6. A Typical fuzzy system for fuzzy logic modeling process

3.2.3.1. Fuzzification

Fuzzification converts each piece of input data to degrees of membership by a lookup in one or more several membership functions, and assumes values between 0 and 1 inclusive. Intuition, inference, rank ordering, neural networks, genetic algorithms, and inductive reasoning can be ways to assign membership values or functions to fuzzy variables (Munakata 1998). Fuzzy membership functions may take many forms, but in practical applications simple linear functions such as triangular ones are preferable.

3.2.3.2. Fuzzy Rule Base

Fuzzy rule base contains rules that include all possible fuzzy relations between inputs and outputs. These rules are expressed in the IF-THEN format. In the fuzzy approach there are no mathematical equations. The model parameters, uncertainties, non-linear relationships, and model complications are included in the descriptive fuzzy inference procedure in the form of IF-THEN statements. There are basically two kinds of fuzzy rules: Mamdani and Sugeno (Jantzen, 1999).

3.2.3.3. Fuzzy Inference Engine

Fuzzy inference engine takes into account all the fuzzy rules in the fuzzy rule base and learns how to transform a set of inputs to corresponding outputs. There are basically two kinds of inference operators: minimization (min) and product (prod). Both methods, in general, work well (Jantzen, 1999). If there is a system "IF A THEN B", $B(y)=A(x)^{\circ}R(x,y)$ can be written where "°" is the compositional operator which indicates a compositional rule of inference (Simoes, 2003). For the purpose of practical computation, it can also be written in terms of the membership functions of the respective sets:

$$\mu B(y) = \text{MAX}\ [\text{MIN}(\mu_A(x), \mu_R(x,y))]\ x \in E1 \qquad (3.10)$$

$$\mu B(y) = \text{MAX}\ [\mu_A(x)\ .\ \mu_R(x,y)]\ \ x \in E1 \qquad (3.11)$$

where Eq. (3.10) is for min and Eq. (3.11) is for prod operators.

3.2.3.4. Defuzzification

Defuzzification converts the resulting fuzzy outputs from the fuzzy inference engine to a number. There are many defuzzification methods such as centre of gravity (COG) (centroid), bisector of area (BOA), mean of maxima (MOM), leftmost maximum (LM), rightmost maximum (RM), and so on. (Jantzen, 1999; Şen, 1999). The most commonly used one is the centroid method as expressed in Eq. (3.12) (Jantzen, 1999)

$$K_x^* = \frac{\sum_i \mu(K_{xi})\ K_{xi}}{\sum_i \mu(K_{xi})} \tag{3.12}$$

Where K_x^* is the defuzzified output value, K_{xi} is the output value in the i^{th} subset, and $\mu(K_{xi})$ is the membership value of the output value in the i^{th} subset. For the continuous case, the summations in Eq. (3.12) are replaced by integrals.

Chapter 4

PREVIOUS MODELS FOR CEMENT STRENGTH PREDICTION

Cement strength is an important parameter that depends on a large number of factors. This dependence has been widely investigated from many aspects. Examples for such studies include statistical techniques for various regression analysis, analytical techniques, artificial intelligence techniques and more recently gene expression programming. The statistical techniques are limited by the lack of controlled experiments because of the complexity of the cement production process. The methods like fuzzy logic, artificial neural networks (ANN), genetic algorithm (GA), and gene expression programming (GEP) were also used individually or in combinations.

Akkurt et al., used GA-ANN in the modeling of CCS (Akkurt et al., 2003). Akkurt et al., also worked on the CCS prediction using a combination of ANN and fuzzy systems (Akkurt et al., 2004). Wang et al, used only ANN in CCS prediction for concrete (Wang et al., 2000). Fuzzy logic was used for the same goal of prediction of CCS by Fa-Liang in 1997. Tango used an extrapolation technique he named AMEBA (regression method) in his work to simulate the compressive strength tests (Tango, 1998). More recent work was done by Baykaşoğlu and his co-workers to predict cement strength by using the GEP method (Baykaşoğlu et al., 2004).

In the study of Tango, the basis for the AMEBA Method was presented. A strength-time function was used to extrapolate the predicted cementitious material strength for a late (ALTA) age, based on two earlier age strengths; medium (MEDIA) and low (BAIXA) ages. The experimental basis for the method was the data from a Brazilian laboratory and the field, including a long-term study on concrete, research on limestone, slag, and fly-ash additions, and quality control data from a cement factory. The method applicability was also verified for high-performance concrete with silica fume. The equation for the AMEBA method is as:

$$f_{ca} = f_{cm}^{\ AMEBA} / f_{cb}^{(AMEBA-1)} \qquad (4.1)$$

where f_{ca} is the concrete compressive strength at a late (alta) age; f_{cm} is the concrete compressive strength at a medium (media) age; f_{cb} is the concrete compressive strength at an early (baixa) age; and AMEBA is a function depending on the late, medium, and early ages, and an adjusting exponent is as:

$$\text{AMEBA} = [(1/t_a^n) - (1/t_b^n)]/[(1/t_m^n) - (1/t_b^n)] \quad (4.2)$$

where t_a, t_m, and t_b are, respectively, the late, medium and early ages; and n is the adjusting exponent, which depends on material characteristics and test conditions. Using the AMEBA method, and only needing to know the type of cement used, the author claims that it has been possible to predict strengths satisfactorily, even without the preliminary tests which are required in other methods (de Siqueira Tango, 1998).

Fa-Liang used fuzzy logic techniques for 28-day CCS prediction. In his study two models were used for fuzzy pattern recognition: Distance and Similarity models. These were mathematical models that were used to predict 6 different sets of data from different plants. Parameters like SO_3, slag, fineness were inputs in prediction models. The results were compared with the results from the regression model. The results for fuzzy model in root mean square error were between 1.42 and 1.78 where the results of the regression model was in 2.10-3.00 range (Fa-Liang, 1997).

Wang et al. employed ANNs in prediction of 28-day compressive strength of concrete. They constructed a model in 11x7x1 architecture, and ran the learning part for 5000 iterations. Two batches of data were used; the first from the laboratory study and the second obtained from a plant. 50 data were used in learning and 15 in testing part of the study for both laboratory and plant data. The average percentage relative error results were found to be 1.15% and 1.8% for the first and the second models, respectively. They pointed out that ANN models could be constructed to provide quick results for 28-day CCS based on some factors. Also they claimed that ANN models showed good prediction accuracy (Wang et al., 2000).

In the study of Akkurt et al., CCS was modeled and the results were reported. They used plant data for the chemical and physical properties of the cement that were collected for 6 months from a local cement manufacturer. The training and testing data were separated from the complete original data set by the use of GAs. A GA–ANN model based on the training data of the cement strength was created. ANN model was feed-forward back propagation (BP) type with 20x20x1 architecture i.e. it had 20 input parameters, 20 neurons in the hidden layer and the 28-day CCS as a single output. During the training of the model 40000 iterations were run. The model was tested with

50 sets of data and the average percentage error was calculated to be 2.24%. The model was subjected to sensitivity analysis to predict the response of the system to different values of the factors affecting the strength. The plots obtained after sensitivity analysis indicated that increasing the amount of C_3S, SO_3 and surface area (Blaine) led to increased strength within the limits of the model. C_2S decreased the strength whereas C_3A decreased or increased the strength depending on the SO_3 level (Akkurt et al., 2003).

In another study of Akkurt et al., a fuzzy logic prediction model for the 28-day CCS under standard curing conditions was created. Data collected from a cement plant were used in the model construction and testing. The input variables of alkali, Blaine, SO_3, and C_3S and the output variable of 28-day CCS were fuzzified. Triangular membership functions were employed for the fuzzy subsets. The Mamdani fuzzy rules relating the input variables to the output variable were created by the ANN model, and were laid out in the If-Then format. Product (prod) inference operator and the centre of gravity (centroid) defuzzification methods were employed. The fuzzy system can be seen in Figure 3.6. The average percentage error of the prediction of 50 data points of the 28-day CCS data by the developed fuzzy model was reported to be 2.69%. The model was compared with the ANN model for its error levels and ease of application. The results indicated that through the application of the fuzzy logic algorithm, a more user friendly and more explicit model than the ANNs could be produced within successfully low error margins (Akkurt et al., 2004).

Chapter 5

MODEL CONSTRUCTION

Data collected from a local cement plant for a period of six months were employed in this thesis. Four different modeling studies were performed using this data:

(1) The ANN model with 20 input parameters (labeled in this study as Model A),

(2) The ANN model with four input parameters for fuzzy rule creation (labeled in this study as Model B),

(3) The ANN model with four input parameters on MatLAB® Neural Networks toolbox (labeled in this study as Model C),

(4) the fuzzy model (labeled in this study as Model D).

The ANN model (the model A) was created in a previous study with 20 input parameters for the same data set (Akkurt et al., 2003). In this study, however, 20 parameters would have been too high for a fuzzy model so a separate model (Model B) with 4 input variables was created. This new 4 variable ANN model (Model B) was then subjected to sensitivity analysis which helped create the rules for the fuzzy model (Model D). Further study was conducted on the four variable ANN model on MatLAB® Neural Network toolbox to see if the selection of different learning algorithms could yield lower error levels (Model C). The model D was the fuzzy logic equivalent of the Model B because they were generated from the same set of parameters using the same data.

5.1. Data Collection

The data were collected from a local cement plant that uses strength testing for process control. The data belonged to the period between the months of January and July 2001. Cement strength testing was carried out according to European standard EN 197-1 (CEN, 2000). Pre-manufactured sand with controlled particle size distribution and chemical composition was mixed with known amounts of cement and water. The mixture was molded into rectangular shapes (4x4x16 cm) and stored in a humidity cabinet at >90% relative humidity and 20 ± 1 °C for 24 h. Standard curing samples were stored in a water bath for 1, 6 and 27 more days for compressive strength testing.

The type of cement used in this research was Cem I 42.5R European standard EN 197-1. In all types of strength tests, six identical sample bars were tested for better statistics (see Tables A.1 and A.2 in App.A).

The original data of 150 data points were for 20 input parameters and one output parameter. However, the Models (B, C and D) were constructed to use 4 input and one output parameters. The parameter selection and reduction of data were done as explained below.

Data reduction: 150 data points of 20 inputs and one output parameter data were needed to be reduced into 4 inputs and one output parameter data points. Because the fuzzy logic model required rule sets that contain all possible combinations of parameter levels, only up to 4 parameters appeared to be reasonable in this study. The data for 4 inputs and one output parameters used in the modeling are given in Appendix A (Tables A.3 and A.4). Considering that each parameter had 3 to 4 subsets in the membership functions, a total number of combinations would be 108. If the original data with 20 parameters had been used, this number would have been $3^{20} \approx 3.5$ billion combinations. Writing of fuzzy rule sets for this many sets would be, obviously, impractical. Therefore, an ANN model (Model B) using the data generated by reduction of the original data set was used. Table 5.1 shows the parameters and their ranges used in this study. These four input parameters were selected based on the information in the literature (Mindess et al., 2002, Lea, 1971). Care was taken to select both physical and chemical parameters.

Table 5.1. The Input and Output Variables Used in Model Construction for Model B, C and D

Code	**Inputs**	**Data Range Used in Modeling**		
		Minimum	**Average**	**Maximum**
x_8	C_3S (%)	51.70	60.69	68.30
x_5	SO_3 (%)	2.2	2.7	3.1
x_{18}	Blaine (cm^2/g)	3120.0	3657.8	4100.0
$x_{(14+15)}$	Total alkali (%)	0.80	0.99	1.10
y	CCS (MPa)	47.60	53.14	58.40

5.2. ANN Models

Three different ANN models were considered in this research. The first (Model A) and the second (Model B) models were created on MatLAB® environment by using a custom program code that was written by Akkurt and Özdemir in previous studies (Akkurt et al., 2003, Akkurt et al., 2004). As shown in Table 5.2. the model A was created with 20 input parameters while the models B and C had only 4 input parameters. Another important point to note here is that the model C was subjected to numerous changes in the modeling conditions like the number of hidden layers, different learning algorithms apart from BP, and the number of hidden layer neurons. The purpose was to make sure that model B was sufficient for fuzzy rule creation.

Table 5.2. ANN Models Used in this Research

ANN Model	Number of Inputs	Model Created by	Model Constructed Using the Following Software
A	20	Akkurt, Özdemir, Tayfur, Akyol (Akkurt et al., 2003)	Custom computer program code written by the authors
B	4	Akkurt,Tayfur, Can (Akkurt et al., 2004)	Custom computer program code written by the authors
C	4	Can	MatLAB® NN Toolbox

5.2.1. The Model A

In the previous study of Akkurt et al., the ANN architecture was of feed-forward type composed of three layers. There were 20 neurons in the input layer for the 20 input variables. The middle layer had 20 neurons. In the output layer, one neuron was used for the output variable of cement strength. The input variables, their means and ranges are listed in Table 5.3. Bias term was not used during modeling but a momentum term was used to help obtain faster convergence during iterations. There were a total of 150 data points each with 21 components ($x_1, x_2, \ldots, x_{20}; y$) 20 of which were the input variables whereas the 21^{th} one was the output variable (Table 5.3).

The data were standardized in the interval [0.1, 0.9] using the following equation;

$$x_i = 0.1 + 0.8\,(x_i - x_{min\,i}) / (x_{max\,i} - x_{min\,i})$$

where $x_{max\,i}$ and $x_{min\,i}$ are the maximum and minimum values of the i^{th} node in the input layer for all the feed data vectors, respectively. Before the application to the problem, networks were first trained. The difference between the target output and the calculated model output at each output neuron was minimized by adjusting the weights and biases through some training algorithm. During training, a neuron receives inputs from a previous layer, weights each input with a prearranged value, and combines these weighted inputs.

Table 5.3. The Variables Used in the Construction of the Model A (Akkurt et al., 2003)

Code	**Input variable**	**Data used in model building**		
		Minimum	**Average**	**Maximum**
x_1	SiO_2 (%)	18.60	19.54	20.40
x_2	Al_2O_3 (%)	4.60	5.07	5.70
x_3	Fe_2O_3 (%)	3.50	3.64	4.00
x_4	CaO (%)	62.70	64.10	65.30
x_5	SO_3 (%)	2.20	2.70	3.10
x_6	Loss in ignition (%)	1.30	1.87	2.70
x_7	Free Lime (%)	0.60	1.13	1.70
x_8	C_3S (%)	51.70	60.96	68.30
x_9	C_2S (%)	3.60	10.01	18.30
x_{10}	C_3A (%)	6.30	7.29	8.90
x_{11}	C_4AF (%)	10.60	11.05	11.80
x_{12}	Alimunate modulus (Al_2O_3/Fe_2O_3)	1.30	1.39	1.60
x_{13}	Silicate modulus ($SiO_2/(Al_2O_3 + Fe_2O_3)$)	2.00	2.24	2.50
x_{14}	Na_2O (%)	0.10	0.21	0.30
x_{15}	K_2O (%)	1.70	0.78	0.80
x_{16}	Initial setting time (min)	95.00	156.77	225.00
x_{17}	Final setting time (min)	150.00	248.00	365.00
x_{18}	Specific surface (cm^2/g)	3120.00	3657.80	4100.00
x_{19}	Sieve residue on 90 μm (%)	0.10	0.72	2.40
x_{20}	Sieve residue on 32 μm (%)	8.20	15.52	25.50
y	Compressive strength (Mpa (or N/mm^2))	47.60	53.14	58.40

The combination of weighted inputs is presented as:

$$u_i(w,x) = \sum_{j=1}^{n} w_{ij} x_j$$

where u_i is the summation of the weighted input for the ith neuron, x_j is the input from the j_{th} neuron to the i_{th} neuron, and w_{ij} is the weight from the i_{th} neuron in the previous layer to the j_{th} neuron in the current layer. The u_i is passed through a transfer function to determine the level of activation. If the activation of a neuron is strong enough, it produces an output that is send as an input to other neurons in the successive layer.

Sigmoid function was employed as an activation function in the training of the network.

$$f(u_i) = \frac{1}{1 + e^{-u/\sigma}}$$

The program was introduced to run for 40,000 iterations and the optimal weights were calculated. The trained model was tested by comparing it to actual measured data that forms the group of 50 data points sorted after the application of GAs, and the testing results with an average error (AAPE) of 2.24%.

5.2.2. The Model B

In this study, in order to create the fuzzy rule sets and their membership functions, a new ANN model was created following the same procedures followed in the previous study (Akkurt et al., 2003). The only exception was that the new ANN model had four input parameters [% C_3S, % SO_3, % total alkali, and Blaine (cm^2/g)] and one output parameter of 28-day compressive strength (N/mm^2) (see Table 5.1.) as opposed to more than 20 for the model A. The reason for lowering the number of parameters was explained in the "Data reduction" part of section 5.1.

These parameters (C_3S, SO_3, total alkali, and Blaine) were believed to represent the more important factors regarding compressive strength based on the sensitivity analysis done on our previous model (Akkurt et al., 2003). As shown in Figure 5.1, the newly constructed ANN model had three layers: input, hidden, and output. The input and hidden layers had four neurons, while the output layer had only one neuron. Bias term was not used in training. Learning rate was 0.01. The model was trained for 20,000 iterations. Bias term was not used during modeling but a momentum term was used to help obtain faster convergence during iterations. There were a total of 150 data points each with 5 components (x_8, x_5, x_{18}, $x_{(14+15)}$; y). x_i stands for the input and y stands for the output variable. The reduction in the number of input parameters from 20 to 4 resulted in a slight increase in the percentage testing error, as already expected, for the new ANN model (average absolute error 2.41%).

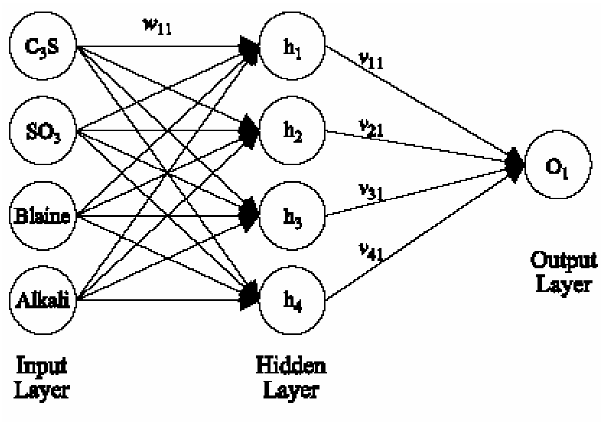


Figure 5.1. The ANN architecture of the Model B

The model B was constructed in order to make the sensitivity analysis which helped create the fuzzy rules. The model was used to predict CCS values for pairs of input parameters, and the CCS results were plotted in pairs of input parameters. Some of those sensitivity analysis plots were given in Figures 5.2-5.5.

Sensitivity Analysis: Sensitivity analysis was performed by feeding input parameters at varying levels into the developed model and producing prediction outputs of cement strength. The whole range of each input parameter was divided into 10 equal parts to have a continuous plot for factor effects. These ranges are listed in Table 5.4 and are the same as for training data because the model cannot be used to predict strength values for input parameter ranges for which it was not trained. In order to make sensitivity analysis with two parameters, the rest of the two parameters of total four were held constant at the average values of their ranges.

Table 5.4. Ranges of the Input Parameters Used in Sensitivity Analysis

Parameter	Range used in Sensitivity Analysis
C_3S (%)	51.66 - 68.35
SO_3 (%)	2.15 - 3.12
Blaine (%)	3120 - 4100
Total Alkali (%)	0.85 - 1.12

Figures 5.2-5.5, based on the results of prediction runs of the model, show the effects of two parameters at a time on each surface plot of the cement strength. The effect of SO_3 and surface area (Blaine) on cement strength is shown in Figure 5.2.

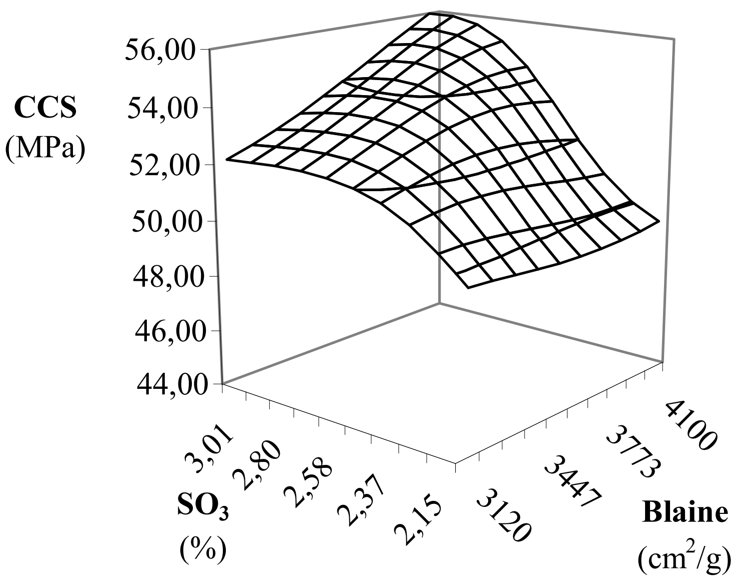


Figure 5.2. Effect of SO_3 and Blaine on CCS

As can be seen in Figure 5.2, increasing Blaine level, together with increasing SO_3, causes CCS to increase. The effect of increasing SO_3 was more significant at higher levels of Blaine. The combined effects of C_3S and Blaine on strength are shown in Figure 5.3.

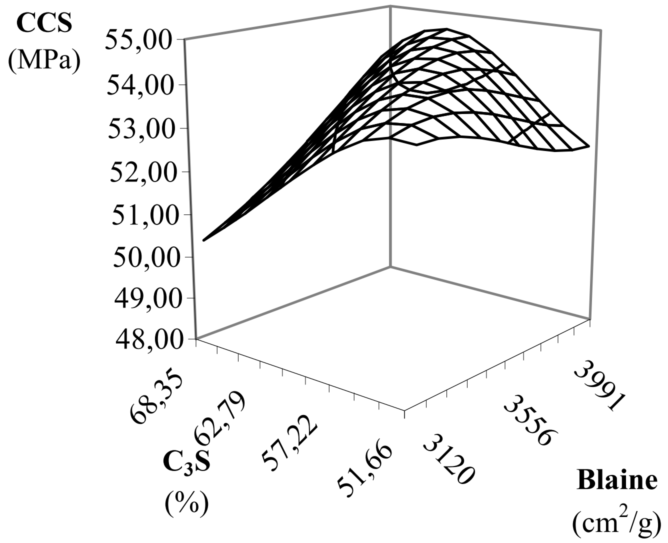


Figure 5.3. Effect of C_3S and Blaine on cement compressive strength

As can be seen in Figure 5.3, increasing Blaine increases strength at high levels of C_3S. The reverse is true at low levels of C_3S.

Figure 5.4 shows the effects of SO_3 and total alkali on cement compressive strength. From the Figure 5.4, it could be said that individually total alkali amount does not affect strength much.

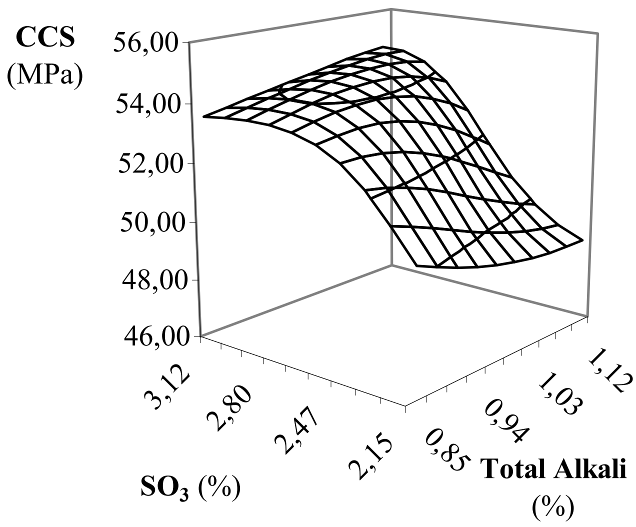


Figure 5.4. Effect of SO_3 and Total Alkali on cement compressive strength

Figure 5.5 show the effects of Blaine and Total Alkali on strength. Increasing in range of Blaine, with low levels of Total Alkali, cause strength to increase. However, while alkali amount increases, strength tends to decrease. At lower ranges for Blaine, changes of alkali amount do not affect strength significantly.

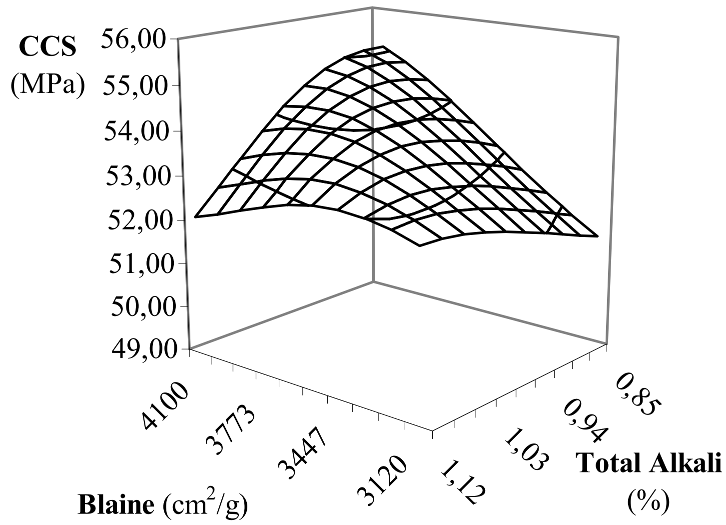


Figure 5.5. Effect of Blaine and Total Alkali on cement compressive strength

5.2.3. The Model C

In order to observe the effects of various combinations of parameters, the learning algorithms, training functions and different architectures were changed in the model C study. The model C, in fact, refers to a total of 72 separate models that were created for the purpose of finding out the best possible combination of conditions. These new models using different learning algorithms, training functions and different architectures were constructed by using MatLAB® neural network toolbox. Four different learning algorithms like Feed-forward BP, Elman BP, Time-delay BP and Cascade-forward were tested. Three training functions, which were TRAINLM, TRAINGD and TRAINGDA, were used in the modeling. The models were constructed to have 4 neurons in the input layer for the 4 input variables (C_3S, SO_3, total alkali and Blaine). They had either 1 or 2 hidden layers each containing 3-5 neurons. Considering 4 types of algorithms, 3 types of training functions, 2 numbers of hidden layers, and 3 numbers of neuron variations in the hidden layers(s), the total number of combinations for the models was 72. One neuron in the output layer was used for the output variable of 28-day CCS.

The errors for some of the ANN models can be seen in chapter 6. All results for these 72 models are given in Appendix B (Table B.1).

5.3. The Fuzzy Logic Model (Model D)

ANN models are reliable but they are also "black-box" models. The user cannot interrupt and change the model easily during the operations. All that the model offers is a weight matrix that defines the weights of interlayer connections, which are optimized after thousands of iterations. In order to create simpler model for the prediction of cement compressive strength, fuzzy logic techniques were used. The collected plant data are always associated with some error, which makes the fuzzy approach more suitable (Fa-Liang, 1997). First of all, the fuzzy approach provides possible rules relating input variables to the output variable; hence, it is more in-line with human thought. Therefore, plant operators can rapidly develop their own set of rules to test for their fit for the fuzzy model. This makes the fuzzy approach more user-friendly.

5.3.1. Rule Creation

Fuzzy logic rules are verbal expressions in "IF-THEN" format like IF low AND very low THEN hot. For the model of this study 4 input variables (C_3S, SO_3, total alkali and Blaine) and one output (28-day CCS) parameters were used. The aim was to create such rules that will relate 4 inputs with the output verbally. For this purpose, the sensitivity analysis graphs obtained from the new 4 parameter ANN model were used (see Figures 5.2-5.5). By using these sensitivity analysis results, the ranges of inputs and outputs were defined (see Figure 5.6). These defined ranges were also used in membership function creation explained in section 5.3.2. Table 5.4 shows a random selection of 10 of the total 108 rules. The whole rule table is given in Appendix B (Table B.2).

Table 5.5. A Random Selection of 10 Rule Sets from the Total 108 Rule Sets

$\%SO_3$	$\%C_3S$	Blaine	% Alkali	CCS
M	L	L	M	M
M	M	L	L	L
H	L	M	L	M
L	L	H	M	VL
L	VL	H	M	VL
H	H	L	M	L
H	VL	H	H	M
H	VL	L	L	H
H	H	M	M	M
M	VL	H	H	L

VL: *Very low,* L: *Low,* M: *Medium,* H: *High*

5.3.2. Membership Functions

In this study, five membership functions (mfs) were created: four for inputs and one for the output. The numbers of subsets were selected for each mf using the range for each parameter (Table A3, App.A). Since the number of fuzzy rules is obtained by multiplication of all subsets of input mfs, increasing the number of subsets for inputs would make the rule creation stage of modeling impractical (Model D had 108 rules generated via multiplication of the number of subsets in input mfs).

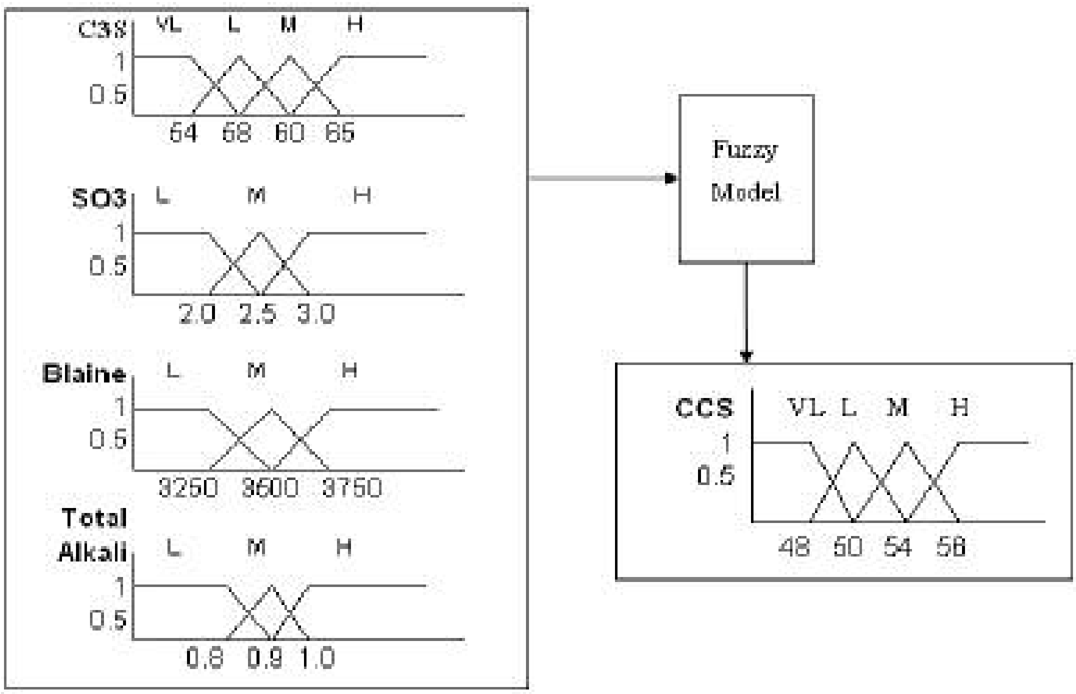


Figure 5.6. Membership functions for input and output parameters used in the model

5.3.3. The System of the Fuzzy Logic Model

Each membership function for inputs and output was created in MatLAB® fuzzy logic toolbox. Mamdani rules (see Table B.2 in App.B)) were defined and Prod method was chosen for fuzzy inference engine. In defuzzification part of the model, in order to obtain defuzzified results, COG (centroid) method was applied. Figure 5.7 illustrate the fuzzy system created in this study.

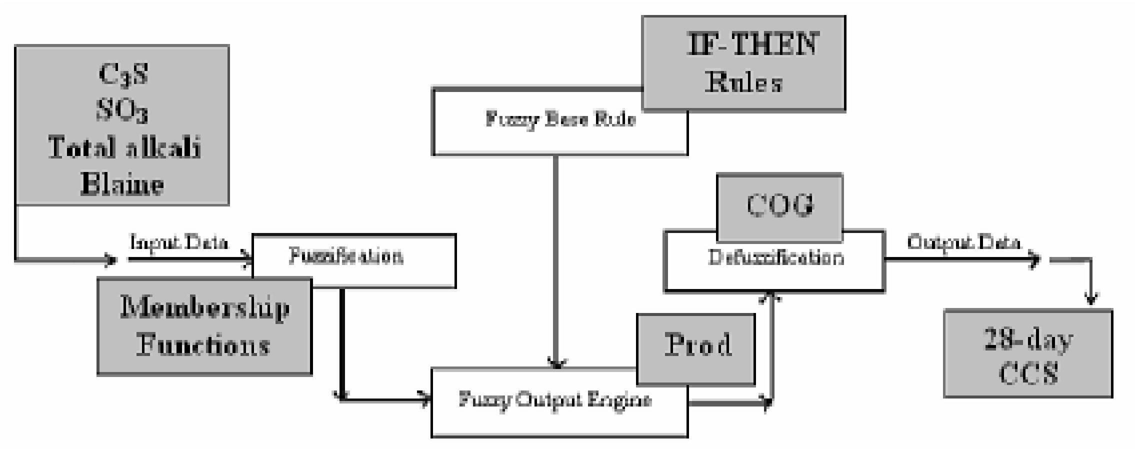


Figure 5.7. The fuzzy system created in MatLAB® fuzzy logic toolbox

The 50 sets of input data were fed into the model and as a result, 50 sets defuzzified output values were obtained from the model. These were predicted 28-day CCS values which were then compared with actual 50 sets 28-day CCS data. The average absolute error of the model was 2.69% which was a little bit higher than the error of the 4-input parameter ANN model (2.41%).

5.3.4. Testing Different Fuzzy Logic Models

In this study, other fuzzy logic models with different membership function geometries like GAUSS, GAUSS2, GBELL, PI, PSIG and TRAP were tested in MatLAB® fuzzy logic toolbox. Also, different defuzzification methods in the toolbox like bisector, mom, lom and som were tested. Totally 34 model combinations were created and the testing errors calculated. These results can be found in chapter 6 of this study.

Chapter 6

RESULTS AND DISCUSSION

In this thesis, four different artificial intelligence (AI) models were employed to predict the 28-day cement compressive strength (CCS). The original data was composed of 150 sets 20 input parameters and one output parameter, each. The data was obtained from a local cement plant's quality control laboratory. The as-received data was used for the Model A while the reduced data with four input parameters was used for Models B, C and D (Table A.1 and A.2 in App.A) Models A, B and C were constructed using ANN techniques, and Model D was created using fuzzy logic techniques. 150 sets of data was first of all split into two sets: The first set being used for training of AI models; and the second 50 sets for testing the quality of the model. In order to make a comparison of the performance of the models, the error measures of absolute average percentage error were computed for each model, and these are summarized in Table 6.1.

Model A was created on MatLAB® environment using a custom computer code that was written in a previous study (Akkurt et al., 2003). The model had 20 input parameters and one output parameter for CCS. The average absolute percentage error (AAPE) for the testing data was 2.24%, which was successfully low (Table 6.1.).

Table 6.1. The Testing Errors of Artificial Intelligence Models Created in this Study

The Artificial Intelligence Model	Minimum Absolute Percentage Error, AAPE (%)	Average Absolute Percentage Error, AAPE (%)	Maximum Absolute Percentage Error, AAPE (%)
ANN Model A	0.02	2.24	8.67
ANN Model B	0.02	2.41	8.91
ANN Model C	0.14	2.31*	7.85
Fuzzy Model D	0.19	2.69	8.65

**the lowest error value obtained from one of the 72 ANN models that were created in MatLAB® NN toolbox as part of the Model C study.*

Model B was created the same way as the Model A but the only difference was that it included only four input parameters which were C_3S, SO_3, total alkali amount and the surface area (Blaine) as opposed to 20 for the former model. The data used in the creation of Model B were the reduced data. The AAPE for Model B was 2.41%. This quantity was higher than the 2.24% achieved for the Model A for 20 input parameters. This increase in the error was a result of parameter elimination from 20 to 4. Variation caused by eliminated parameters was added to total error variance. The Model B was also used in rule creation for the fuzzy model (Model D). The sensitivity analysis is explained and discussed in section 5.2.2.

The Model C was actually a group of 72 separate ANN models that were created for the purpose of finding out the best possible combination of conditions. Those models using different learning algorithms, training functions and different architectures were created in MatLAB® NN toolbox. Some selected results for AAPE values are given in Table 6.2. A complete listing of the error values is given in Appendix B (Table B.1). The lowest AAPE of 2.31% was obtained in the model number 50 with the architecture of 4x(4x4)x1 (4 input neurons, 4 neurons in both 2 hidden layers and 1 output). The algorithm type was Elman back propagation (BP) where learning function was TRAINGD. The error of 2.31% was still higher than the error of Model A, but when compared with Model B (2.41%), it could be stated that the changes of architecture, algorithm and learning functions may result in models with improved precision.

Table 6.2. Some Selected ANN Models Created in MatLAB® NN Toolbox as part of Model C and Their AAPE Values.

Network number	**Number of Layers**	**Number of Neurons**	**Algorithm Type**	**Learning Function**	**Average Error (%)**
2	1	4	Feed-forward BP	TRAINLM	2.52
12	1	5	Elman BP	TRAINLM	3.39
29	1	4	Cascade-forward BP	TRAINLM	4.40
39	2	5	Feed-forward BP	TRAINLM	2.72
50	2	4	Elman BP	TRAINGD	2.31
56	2	4	Time-delay BP	TRAINLM	3.36

The developed fuzzy logic-based model (Model D) was applied to predict 50 sets of the 28-day cement strength data (Table A.4 in App.A). The Model D was created by using the MatLAB® fuzzy logic toolbox. The prod and centroid methods were employed as the inference operator and defuzzification methods, respectively. The AAPE of the Model D was 2.69% (Table6.1). The fuzzy model, perhaps, could have resulted in lower percentage errors than 2.69% if it had been constructed with more than four input parameters. However, such a slight improvement might not have been worth the effort to create a very complicated fuzzy model. The number of fuzzy rules for 20 input parameters would result in nearly 3.5 billion combinations, which made the model creation illogical. Some other membership function (mf) geometries and defuzzification methods in MatLAB® FL toolbox were employed for the same testing data. The results were summarized in Table 6.3. The lowest AAPE value (2.64%) was obtained from the model using COG (centroid) defuzzification method and GAUSS2 mf geometry in the MatLAB® FL toolbox. However, if this result was compared with the AAPE result of the Model D, which used TRI (triangular) mf geometry, it could be said that there was no significant difference of using Gaussian mf geometry.

Table 6.3. Testing AAPE of the Fuzzy Logic Models Created in MatLAB® FL Toolbox with Various Defuzzification Methods and Membership Functions

		Defuzzification Method									
		COG		**Bisector**		**mom**		**lom**		**som**	
Membership Function Geometries	**GAUSS**	min	0.00	min	0.00	min	0.00	min	0.00	min	0.00
		avg	2.70	avg	2.70	avg	3.21	avg	3.48	avg	3.59
		max	9.01	max	9.37	max	10.22	max	11.86	max	12.27
	GAUSS2	min	0.00	min	0.37	min	0.00	min	0.18	min	0.00
		avg	2.64	avg	2.78	avg	3.29	avg	3.53	avg	3.73
		max	8.73	max	8.83	max	9.61	max	11.86	max	11.01
	GBELL	min	0.20	min	0.00	min	0.00	min	0.18	min	0.00
		avg	2.92	avg	3.15	avg	3.38	avg	4.13	avg	4.15
		max	9.73	max	9.91	max	9.73	max	10.71	max	11.13
	PI	min	0.18	min	0.18	min	0.00	min	0.00	min	0.00
		avg	2.72	avg	2.90	avg	3.29	avg	3.53	avg	3.68
		max	8.83	max	8.83	max	9.61	max	12.07	max	11.19
	PSIG	min	0.18	min	0.00	min	0.00	min	0.00	min	0.18
		avg	2.65	avg	2.70	avg	3.30	avg	3.62	avg	3.69
		max	8.90	max	8.73	max	9.61	max	11.86	max	11.01
	TRAP	min	0.19	min	0.20	min	0.00	min	0.00	min	0
		avg	2.66	avg	2.76	avg	3.29	avg	3.53	avg	3.68
		max	8.65	max	8.83	max	9.61	max	12.07	max	11.19
	TRI	min	0.19	max	8.65	min	0.00	min	0.00	min	0.00
		avg	2.69	avg	2.73	avg	3.29	avg	3.54	avg	3.60
		max	8.65	min	0.00	max	9.61	max	12.07	max	11.19

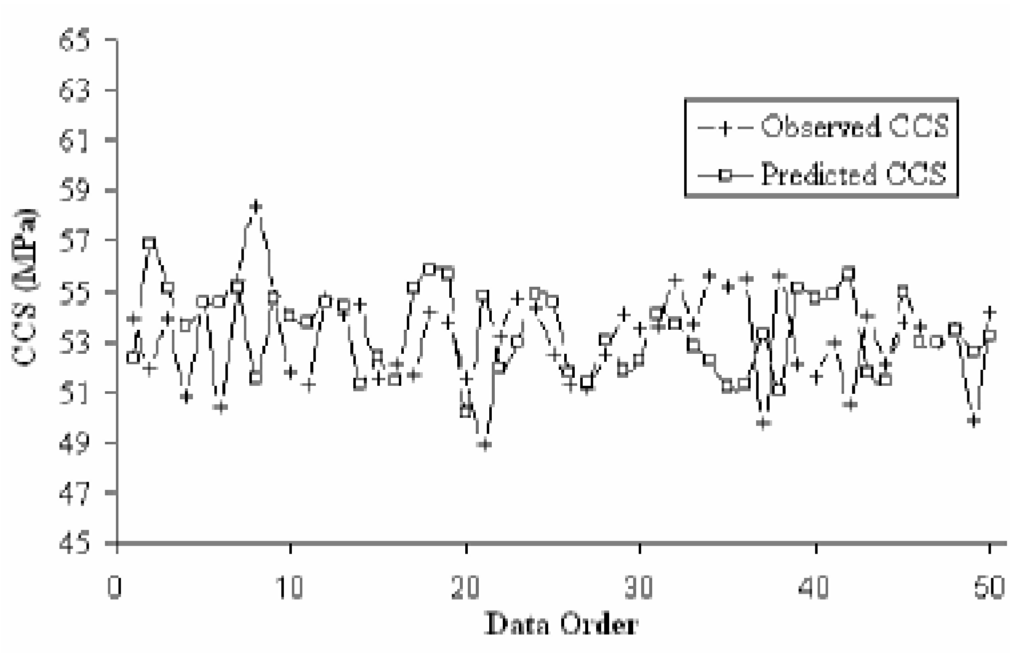


Figure 6.1. Observed and predicted values for 28-day CCS of Model A

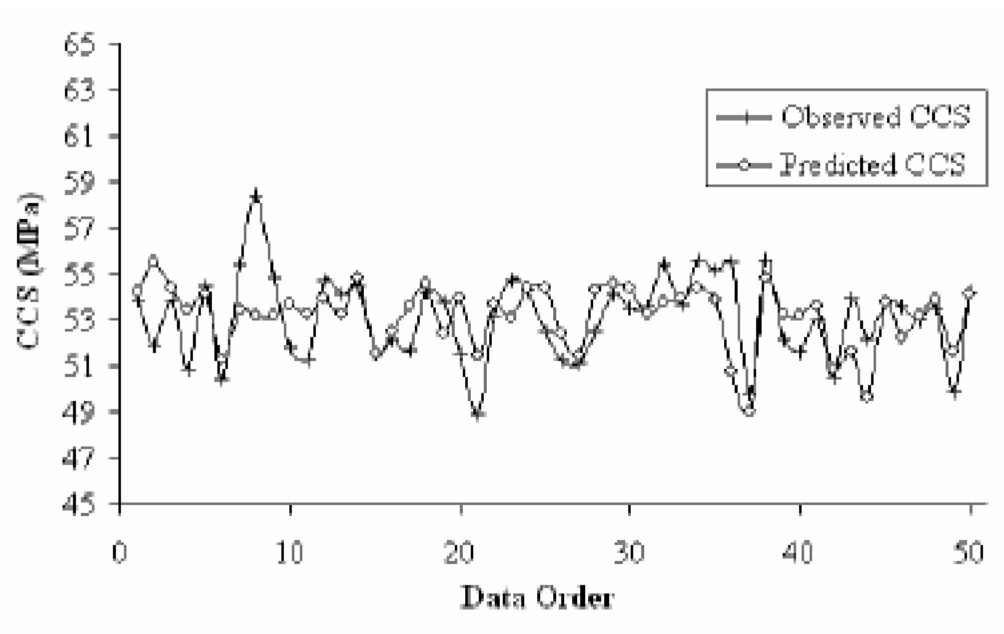


Figure 6.2. Observed and predicted values for 28-day CCS of Model B

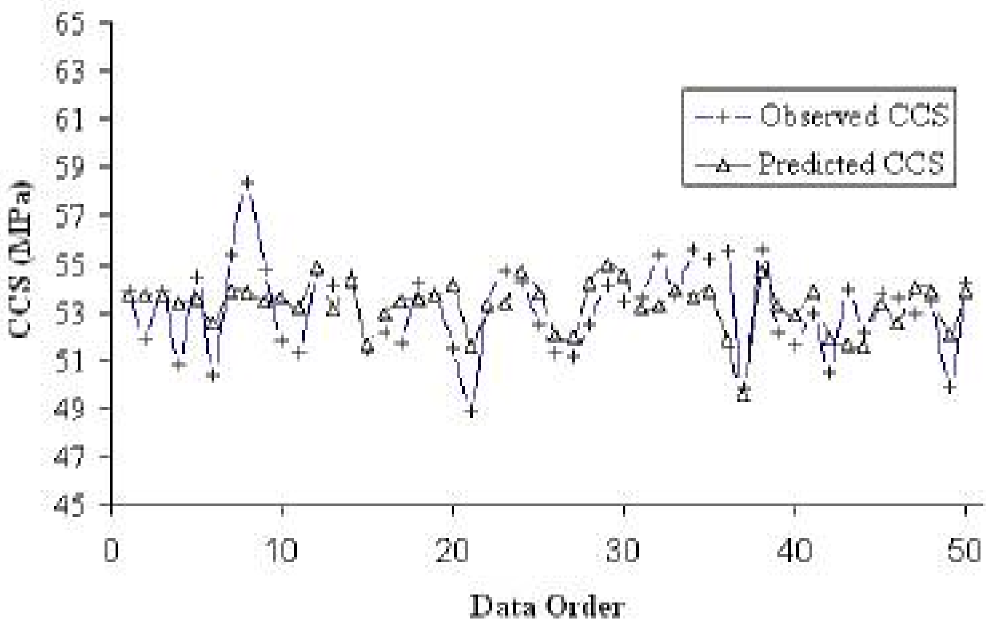


Figure 6.3. Observed and predicted values for 28-day CCS of Model C

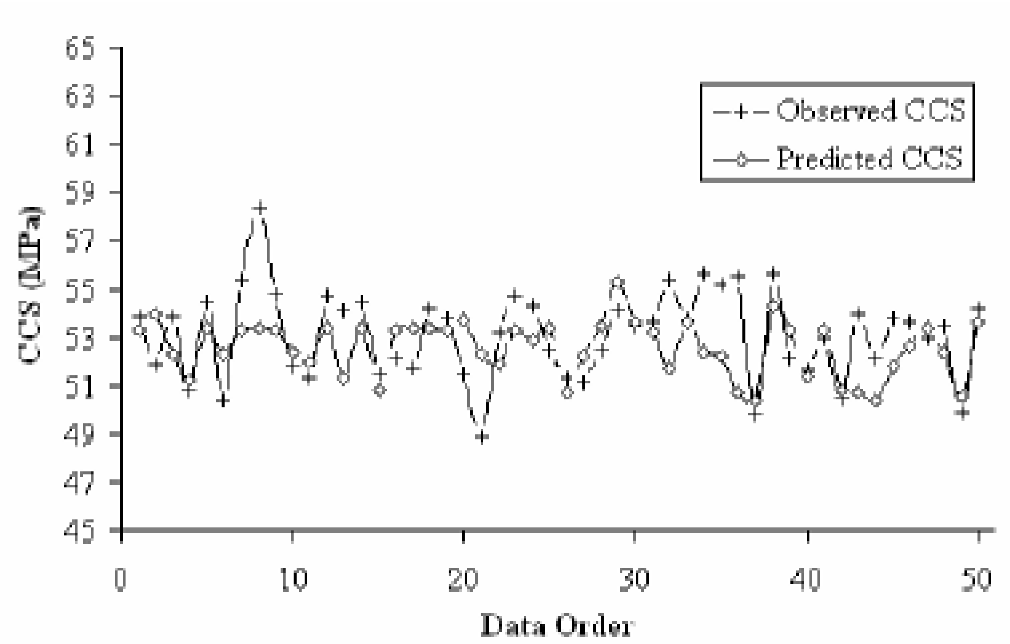


Figure 6.4. Observed and predicted values for 28-day CCS of Model D

The observed 28-day CCS values of 50 data testing set were compared with the predicted 28-day CCS values for the models A, B, C and D in the Figures 6.1 to 6.4 respectively.

Errors (AAPE) of the models A, B, C and D were calculated following equation:

$$\text{AAPE} = \frac{1}{N}\Sigma\frac{|observedCCS - predictedCCS|}{opservedCCS}x100\,\%$$

The strength measurements of brittle materials, like cement mortar, are always associated with a distribution. Such measurements never provide the same exact strength quantity after repeated tests. Therefore, the fuzzy approach is well suited for such samples. Another advantage of the fuzzy logic is that all the rules are written verbally, much like human thought. Fuzzy logic allows the rules to be changed, membership functions to be modified as the way programmer wants to do. ANN models, on the other hand, are black box models including matrices of weights, numbers etc., and are not immediately visible to the user. Plant operators may easily adapt to the verbal rule creation process, rather than dealing with the numbers, and create their own fuzzy logic models.

Chapter 7

CONCLUSIONS

In this thesis, prediction of 28-day compressive strength of Portland cement by using artificial intelligence techniques like Artificial Neural Networks (ANNs) and fuzzy logic was accomplished. The data obtained from a quality control laboratory of a local cement plant were used in the modeling studies. Four different artificial intelligence models were created; three of them were ANN models and one fuzzy logic model. An ANN model (Model A), created in MatLAB® environment by writing a custom code, which had 20 input parameters in 20x20x1 architecture resulted in absolute average percentage error (AAPE) of 2.24%.

Another ANN model (Model B), also created in MatLAB® environment, had 4 input parameters of C_3S, SO_3, total alkali amount and Blaine, and it was constructed in 4x4x1 architecture. AAPE of this model was 2.41%. This increase in the error (with respect to the Model A) was a result of parameter elimination from 20 to 4. Variation caused by eliminated parameters was added to total error variance. The Model B was also used for sensitivity analysis in the fuzzy rule creation stage of the fuzzy model construction.

The last ANN model (Model C) had 4 input parameters: C_3S, SO_3, total alkali amount and Blaine. There were 72 separate models created in MatLAB® Neural Networks Toolbox. The aim was to study the effect on the error of combining different learning algorithms, training functions and architectures. The 50th model in Model C (see Table B.1 in App.B) resulted in the lowest AAPE of 2.31%. Elman-BP was the learning algorithm in this model with 4x(4x4)x1 architecture. The model was trained using TRAINGD function.

The fuzzy logic model (Model D) was created in MatLAB® Fuzzy Logic Toolbox. The model had 4 input parameters (C_3S, SO_3, total alkali amount and Blaine), and the fuzzy rules were created by using the Model B for the sensitivity analysis. The AAPE of this model was 2.69%.

Successful predictions of the observed cement strength by the Model D indicated that fuzzy logic could be a useful modeling tool for engineers and research scientists in the area of cement and concrete. Since the cement data are always associated with a distribution, fuzzy approach could be more suitable than the ANN. Although the fuzzy model yielded slightly higher error than the ANN models, the human-like thinking approach of its explicit nature may grant its use by cement professionals for prediction purposes.

RECOMMENDATIONS FOR FUTURE WORK

The fuzzy logic model (Model D) generated in this study can be subjected to sensitivity analysis for observation of the effects of processing parameters on the 28-day CCS. Such a study would provide a visual inspection tool for potential users in cement plants. Also further study can be done to adapt the model to monitor and to control the production process. Other potential studies can be done on the use of the same methodology for modeling clinkering or milling shops in cement plants.

REFERENCES

S. Akkurt, S. Özdemir, G. Tayfur and B. Akyol, "The use of GA–ANNs in the modelling of compressive strength of cement mortar" , *Cement and Concrete Research, 33,* (2003), 973-979

S. Akkurt, G. Tayfur, S. Can, "Fuzzy logic model for the prediction of cement compressive strength" , *Cement and Concrete Research 34,* (2004), 1429– 1433

ASTM C150, Annual Book of ASTM Standards, Vol. 14.02

A. Baykaşoğlu, T. Dereli and S. Tanış, "Prediction of cement strength using soft computing techniques", *Cement and Concrete Research* 34*,* (2004), 2083- 2090

N.K. Base and P. Liang, "Neural Network Fundamentals with Graphs, Algorithms and Applications", McGraw-Hill, Singapore, (1996)

R.H. Bogue., "The Chemistry of Portland Cement", Reinhold Publishing Corp., New York, (1955)

B. Cheetham, K. Goebl, "http:// www.cs.rpi.edu / courses / fall01 / soft-computing / pdf /fuzzy_applications.pdf", 2001

W. Czernin., "Cement Chemistry and Physics for Civil Engineers" , Bauverlag, Berlin, (1980)

European Committee for Standardization (CEN), Cement Part 1: Composition, specifications and conformity criteria for common cements, European Standard EN 197-1, June 2000.

G. Fa-Liang, "A new way of predicting cement strength-fuzzy logic", *Cement and Concrete Research 27*, (1997) ,883–888.

S. Haykin, Neural Networks a Comprehensive Foundation, Prentince Hall, (1999).

J. Jantzen, "Design of fuzzy controllers", Technical Report (No:98-E864) Department of Automation, Technical Univ. of Denmark, (1999)

H. L. Larsen "http:// www.cs.aue.auc.dk /~legind / IRspring2004 / artikler / 03_Fuzzy QA2.pdf", 2003

F.M. Lea, "Chemistry of Cement and Concrete", Chemical Publishing, New York, (1971)

S. Mindess, J.F. Young and D. Darwin, "Concrete", Prentice Hall, (2002)

T. Munakata, "Fundamentals of the New Artificial Intelligence: Beyond Traditional Paradigms", Springer-Verlag, New York, (1998)

M.M. Nelson and W.T. Illingworth, "A Practical Guide to Neural Nets", Addison Wesley, USA, (1994)

S.J. Schneider., "ASM Engineered Materials Handbook", Volume:4, Ceramic and Glasses, The Materials Information Society, (1991)

M. G. Simoes, "egweb.mines.edu / msimoes / tutorials /Fuzzy_tutorial/ Module_1.pps", 2003

C.E. de Siquera Tango, "An extrapolation method for compressive strength prediction of hydraulic cement products" , *Cement and Concrete Research 28,* (1998), 969–983.

S. Tsivilis, G. Parissakis, A mathematical-model for the prediction of cement strength, Cement and Concrete Research 25, (1995), 9 – 14.

J.-Z. Wang, H.-G. Ni, "Prediction of compressive strength of concrete by neural Networks", *Cement and Concrete* Research 30 , (2000), 1245–1250.

L.A. Zadeh "Fuzzy sets" , *Information and Control* 8, (1965), 338-352 J.M. Zurada, "Introduction to Artificial Neural Systems", West Publishing, (1992)

APPENDIX A

Table A.1. All of the real plant data used in modeling of the ANN Model A (1)

NUMKOD	NUMTH1	SIO2	AL2O3	FE2O3	CAO	SO3	LSSONIGN	FREECAO	C3S	C2S	C3A	C4AF
P425	10102	19.72	5.06	3.58	64.13	2.48	1.43	1.07	60.66	10.78	7.33	10.91
P425	10103	19.58	4.81	3.58	64.38	2.62	2.10	1.04	64.11	7.78	6.69	10.89
P425	10104	19.63	4.92	3.58	64.44	2.42	2.07	0.89	64.42	7.68	7.00	10.88
P425	10105	19.45	4.98	3.57	64.21	2.42	2.04	1.11	63.51	7.86	7.17	10.86
P425	10106	19.68	5.03	3.56	64.06	2.31	1.90	0.80	62.47	9.29	7.33	10.82
P425	10108	19.46	5.07	3.56	64.22	2.47	2.01	0.96	63.48	7.91	7.40	10.83
P425	10109	19.51	5.14	3.60	63.63	2.47	1.86	1.00	59.95	10.69	7.54	10.96
P425	10110	19.42	4.98	3.57	63.75	2.51	2.11	0.99	62.13	8.81	7.17	10.85
P425	10111	19.46	4.91	3.55	63.76	2.51	2.16	1.00	62.41	8.70	6.98	10.81
P425	10112	19.58	5.16	3.59	63.63	2.59	1.62	0.81	59.77	11.04	7.60	10.93
P425	10113	19.79	5.09	3.54	63.68	2.52	1.50	0.96	58.47	12.64	7.49	10.77
P425	10115	19.60	4.93	3.53	64.09	2.47	1.69	1.06	62.42	9.10	7.08	10.76
P425	10116	19.69	5.19	3.56	63.62	2.54	1.36	1.18	57.41	13.12	7.73	10.82
P425	10117	19.61	4.98	3.53	63.82	2.77	1.42	1.24	59.30	11.49	7.22	10.75
P425	10118	19.61	4.89	3.54	63.91	2.75	1.58	1.02	61.23	10.01	6.96	10.79
P425	10119	19.79	4.97	3.56	63.95	2.71	1.50	0.95	59.91	11.53	7.15	10.83
P425	10120	19.62	4.85	3.53	63.95	2.80	1.94	1.03	61.41	9.92	6.88	10.75
P425	10122	19.67	4.93	3.54	64.41	2.70	1.94	0.83	63.43	8.53	7.06	10.79
P425	10123	19.84	4.99	3.58	64.05	2.54	1.90	1.18	59.30	12.14	7.15	10.90
P425	10124	19.79	5.00	3.63	64.67	2.33	1.96	1.06	63.14	9.09	7.11	11.06
P425	10125	19.66	4.86	3.60	64.25	3.00	2.05	0.74	62.81	8.98	6.77	10.97
P425	10126	19.85	4.71	3.63	64.46	2.41	2.03	0.80	64.55	8.21	6.34	11.04
P425	10127	19.93	4.83	3.66	63.88	2.77	2.19	1.23	58.06	13.33	6.61	11.13
P425	10129	19.67	4.87	3.68	64.65	2.70	2.02	0.84	64.60	7.65	6.69	11.19
P425	10130	19.54	4.80	3.60	63.64	2.72	2.04	1.15	60.73	10.22	6.64	10.94
P425	10131	19.55	4.86	3.56	63.67	2.77	2.26	1.04	60.72	10.25	6.86	10.84
P425	10201	19.51	5.00	3.55	63.43	2.68	1.93	1.09	59.19	11.29	7.24	10.80
P425	10202	19.47	4.87	3.59	63.40	2.58	2.13	1.03	60.70	10.03	6.84	10.92
P425	10203	19.56	4.95	3.59	63.54	2.22	1.45	1.12	60.77	10.23	7.04	10.93
P425	10205	19.68	5.17	3.62	63.22	2.44	1.58	1.12	56.38	13.88	7.58	11.02
P425	10206	19.63	4.96	3.60	63.99	2.64	1.80	1.00	61.26	10.05	7.05	10.95
P425	10207	19.47	5.06	3.51	63.45	2.72	1.64	1.04	59.32	11.07	7.49	10.67
P425	10208	19.45	5.07	3.51	63.48	2.72	1.41	1.17	59.00	11.26	7.49	10.68
P425	10209	19.83	5.04	3.56	64.67	2.83	1.50	1.04	61.24	10.67	7.34	10.84
P425	10210	19.42	4.87	3.48	64.20	2.81	1.72	1.14	63.47	7.79	7.01	10.59
P425	10212	19.62	4.90	3.52	64.05	2.75	1.80	1.00	61.80	9.62	7.02	10.72
P425	10213	19.74	4.99	3.52	64.81	2.82	1.63	1.37	61.65	10.09	7.26	10.71
P425	10214	19.52	5.26	3.57	63.51	2.69	1.96	1.32	56.77	13.12	7.91	10.85
P425	10215	19.83	5.47	3.55	63.87	2.93	1.97	1.07	54.79	15.52	8.48	10.81
P425	10216	19.67	5.57	3.50	63.66	2.78	1.41	1.14	54.66	15.16	8.86	10.64
P425	10217	19.95	5.49	3.65	64.93	2.60	1.35	0.97	59.28	12.47	8.37	11.11
P425	10219	19.41	5.36	3.55	64.12	2.73	1.79	1.01	60.57	9.96	8.18	10.81
P425	10220	19.67	4.98	3.63	64.69	2.90	2.03	0.95	63.04	8.85	7.06	11.05
P425	10221	19.86	5.17	3.55	63.89	2.64	1.68	1.30	56.54	14.29	7.68	10.81
P425	10222	19.62	5.20	3.54	63.74	2.92	1.52	1.00	57.97	12.53	7.80	10.76
P425	10223	19.77	5.30	3.58	64.41	2.84	1.58	1.07	58.75	12.35	7.99	10.90
P425	10224	19.57	5.30	3.56	63.73	2.69	1.84	1.07	58.00	12.35	8.03	10.83
P425	10226	19.45	5.01	3.95	63.59	3.02	1.57	0.90	60.03	10.48	7.27	10.81
P425	10227	19.44	4.85	3.51	64.12	2.93	1.61	0.92	63.62	7.73	6.90	10.70
P425	10228	19.51	4.98	3.56	63.86	2.52	2.29	1.06	61.67	9.42	7.17	10.82

NUMKOD	NUMTH1	SIO2	AL2O3	FE2O3	CAO	SO3	LSSONIGN	FREECAO	C3S	C2S	C3A	C4AF
P425	10301	19.66	5.12	3.55	63.80	2.78	1.80	1.41	57.22	13.19	7.56	10.80
P425	10302	19.76	5.25	3.56	63.85	2.79	1.86	1.66	54.71	15.37	7.89	10.84
P425	10303	19.65	5.09	3.59	64.62	2.71	2.08	0.95	62.77	8.98	7.42	10.94
P425	10309	19.74	5.25	3.62	63.74	2.95	1.91	1.04	56.35	14.04	7.79	11.03
P425	10310	20.00	5.00	3.47	64.93	2.79	1.45	1.02	61.70	10.80	7.37	10.55
P425	10312	19.99	5.00	3.47	65.08	2.90	1.69	1.04	61.97	10.56	7.37	10.56
P425	10313	19.89	4.84	3.48	64.84	2.89	1.41	1.02	62.92	9.55	6.93	10.60
P425	10314	20.01	5.01	3.50	64.53	2.35	1.36	1.05	60.96	11.38	7.36	10.66
P425	10315	19.72	4.78	3.52	64.74	2.75	1.31	1.15	64.04	8.23	6.70	10.72
P425	10316	19.69	4.59	3.48	64.50	2.88	1.63	1.14	64.34	7.90	6.26	10.60
P425	10317	19.80	4.68	3.49	64.64	2.73	2.56	1.09	64.03	8.44	6.50	10.63
P425	10319	20.40	4.83	3.47	63.89	2.95	2.06	1.28	54.03	17.71	6.93	10.57
P425	10320	19.86	4.63	3.52	64.71	2.81	1.43	1.18	63.59	8.96	6.30	10.71
P425	10321	19.85	4.76	3.56	64.49	2.64	1.40	0.97	63.15	9.27	6.57	10.84
P425	10322	19.74	4.84	3.53	64.15	2.56	1.34	0.58	63.95	8.34	6.85	10.73
P425	10323	20.08	4.89	3.53	63.84	2.73	1.70	0.55	59.39	12.77	6.97	10.75
P425	10324	19.80	4.76	3.58	64.73	2.33	2.16	1.04	65.09	7.66	6.55	10.89
P425	10326	19.89	4.75	3.55	64.60	2.93	1.57	0.83	63.15	9.38	6.58	10.81
P425	10327	19.82	4.85	3.56	64.88	2.44	1.76	0.96	64.94	7.82	6.84	10.82
P425	10328	19.98	4.75	3.60	64.98	2.56	1.43	0.91	64.64	8.53	6.49	10.95
P425	10329	19.87	4.83	3.59	64.58	2.52	1.52	1.00	62.89	9.53	6.72	10.93
P425	10330	20.34	5.16	3.68	65.31	2.30	1.44	1.09	60.40	12.75	7.45	11.19
P425	10331	19.97	5.00	3.65	64.76	2.30	1.53	0.91	62.76	9.90	7.09	11.10
P425	10402	19.55	4.99	3.59	63.88	2.65	1.97	0.94	61.41	9.71	7.16	10.93
P425	10403	19.62	5.00	3.62	64.31	2.89	1.90	1.23	60.75	10.41	7.11	11.01
P425	10404	19.72	4.81	3.61	64.80	2.82	1.86	1.05	64.07	8.21	6.65	10.98
P425	10405	19.86	4.70	3.63	65.04	2.74	1.62	1.12	64.76	8.08	6.31	11.04
P425	10406	19.66	4.72	3.61	64.81	2.87	1.73	1.00	65.28	7.13	6.40	10.99
P425	10407	19.73	4.88	3.61	64.41	2.71	1.78	1.32	61.17	10.43	6.84	10.98
P425	10409	19.81	4.85	3.62	64.61	2.88	1.52	1.06	62.20	9.89	6.73	11.00
P425	10410	19.58	4.74	3.61	64.61	2.78	1.90	1.02	65.08	7.05	6.46	10.99
P425	10411	19.81	4.77	3.64	64.99	2.30	1.72	1.19	65.40	7.44	6.47	11.08
P425	10412	20.04	4.83	3.70	64.58	2.34	1.44	1.19	61.31	11.21	6.55	11.26
P425	10413	19.75	4.89	3.65	64.11	2.25	1.73	1.64	59.69	11.60	6.79	11.11
P425	10414	19.80	4.86	3.66	64.41	2.15	1.66	1.51	61.60	10.29	6.71	11.12
P425	10416	19.71	5.17	3.58	64.17	2.77	1.76	1.50	57.50	13.14	7.66	10.89
P425	10417	19.93	5.12	3.71	64.51	2.36	1.33	1.27	59.54	12.21	7.30	11.29
P425	10418	19.43	4.96	3.66	64.32	2.76	1.60	1.30	62.46	8.58	6.97	11.12
P425	10420	19.52	5.17	3.61	64.51	2.48	2.50	1.21	62.33	8.95	7.59	11.00
P425	10421	19.54	4.93	3.60	64.88	2.68	2.53	1.27	64.47	7.39	6.98	10.97
P425	10425	19.28	4.94	3.67	64.41	2.53	2.56	1.68	63.18	7.61	6.90	11.17
P425	10426	19.43	4.85	3.78	64.59	2.66	2.35	1.27	64.53	7.03	6.47	11.49
P425	10428	19.36	4.89	3.71	64.80	2.57	2.48	1.34	65.77	5.88	6.66	11.30
P425	10430	19.26	4.99	3.76	64.46	2.53	2.40	1.21	65.03	6.16	6.86	11.43
P425	10501	19.27	4.93	3.69	64.35	2.53	2.57	1.31	64.58	6.52	6.82	11.23
P425	10502	19.37	4.84	3.70	64.69	2.68	2.43	1.26	65.58	6.05	6.57	11.26
P425	10503	19.57	5.09	3.80	64.33	2.56	1.92	1.25	61.16	9.96	7.06	11.57
P425	10505	19.19	5.02	3.69	63.86	2.80	2.47	1.37	61.62	8.52	7.06	11.23
P425	10507	19.55	5.08	3.84	64.86	2.37	2.03	1.38	63.45	8.18	6.94	11.71
P425	10508	19.30	4.86	3.79	64.28	2.84	2.06	1.40	63.17	7.68	6.46	11.54
P425	10509	19.32	5.17	3.73	64.18	2.84	2.09	1.14	61.64	8.88	7.40	11.34
P425	10510	19.48	5.00	3.79	64.23	2.81	1.81	1.01	62.31	8.83	6.85	11.52
P425	10511	19.47	5.02	3.78	64.50	2.82	1.89	1.24	62.36	8.78	6.92	11.49
P425	10512	19.63	4.96	3.79	64.82	2.94	1.89	1.02	63.48	8.38	6.73	11.53
P425	10514	19.33	5.12	3.77	64.03	2.75	1.90	1.49	60.03	10.14	7.20	11.47
P425	10515	19.22	5.05	3.74	63.90	2.70	1.90	1.23	62.07	8.29	7.04	11.39
P425	10516	19.34	5.16	3.77	64.43	2.95	2.32	1.35	61.30	9.21	7.30	11.48
P425	10517	19.51	5.04	3.69	64.02	2.58	2.03	1.35	60.35	10.40	7.13	11.22

NUMKOD	NUMTH1	SIO2	AL2O3	FE2O3	CAO	SO3	LSSONIGN	FREECAO	C3S	C2S	C3A	C4AF
P425	10518	19.60	5.05	3.66	64.78	2.70	2.13	1.57	61.48	9.81	7.20	11.12
P425	10519	19.15	4.93	3.65	63.63	2.81	2.17	1.42	61.33	8.64	6.89	11.11
P425	10521	19.28	5.03	3.67	63.80	2.81	2.03	1.27	60.98	9.26	7.11	11.18
P425	10522	18.98	4.89	3.64	63.12	2.81	2.14	1.36	61.07	8.35	6.81	11.08
P425	10523	19.31	5.15	3.67	62.74	2.71	1.68	1.33	55.65	13.37	7.44	11.16
P425	10524	19.39	5.03	3.67	62.93	2.80	1.44	1.30	56.53	12.93	7.12	11.18
P425	10525	19.64	5.39	3.67	64.08	2.68	1.42	1.37	56.87	13.42	8.07	11.18
P425	10526	19.36	5.42	3.68	63.87	2.62	1.50	1.25	58.66	11.25	8.13	11.19
P425	10528	19.52	5.32	3.64	64.12	2.81	1.56	1.59	57.25	12.79	7.93	11.08
P425	10529	19.79	5.30	3.76	64.54	2.35	1.50	1.04	60.39	11.19	7.68	11.45
P425	10530	19.36	5.32	3.73	63.60	2.77	1.77	1.12	58.26	11.55	7.78	11.36
P425	10531	19.55	5.39	3.76	63.88	2.87	1.66	1.30	56.47	13.44	7.92	11.43
P425	10601	19.24	5.62	3.73	63.23	2.78	1.72	1.05	55.93	12.96	8.58	11.34
P425	10602	19.20	5.40	3.73	63.32	2.83	1.77	1.24	57.10	11.97	8.02	11.34
P425	10605	19.22	5.28	3.72	64.01	2.37	1.77	1.31	61.67	8.57	7.68	11.33
P425	10606	19.43	5.33	3.77	64.51	2.39	1.82	1.21	62.00	8.93	7.76	11.46
P425	10607	18.99	5.41	3.79	63.43	2.99	1.83	1.16	58.89	10.00	7.91	11.54
P425	10608	19.31	5.32	3.80	63.73	3.02	1.79	0.81	59.65	10.35	7.67	11.55
P425	10609	19.19	5.38	3.79	63.26	3.00	1.86	1.35	56.05	12.74	7.83	11.54
P425	10611	19.08	5.57	3.79	62.90	3.06	1.74	0.91	55.81	12.60	8.35	11.52
P425	10612	19.12	5.53	3.85	63.83	2.85	1.71	1.01	59.57	9.89	8.15	11.72
P425	10613	18.88	5.53	3.83	62.86	3.11	1.95	1.29	55.64	12.16	8.17	11.66
P425	10614	19.27	5.67	3.86	63.71	2.71	1.73	0.95	57.67	11.75	8.50	11.73
P425	10615	19.16	5.49	3.87	63.75	2.64	1.84	0.97	60.05	9.62	7.99	11.79
P425	10616	18.80	5.25	3.86	63.47	3.03	1.87	1.32	60.69	8.11	7.38	11.76
P425	10618	18.74	5.45	3.83	63.31	2.89	1.85	1.24	59.93	8.53	7.96	11.66
P425	10619	19.31	5.59	3.88	63.80	2.99	1.87	1.36	55.84	13.25	8.28	11.74
P425	10620	18.78	5.55	3.84	63.50	2.99	2.42	0.89	60.91	7.88	8.20	11.69
P425	10621	18.77	5.63	3.69	63.27	3.12	2.36	1.01	58.78	9.47	8.68	11.24
P425	10622	18.60	5.50	3.70	62.83	3.07	1.76	1.12	58.90	8.88	8.32	11.26
P425	10623	18.89	5.37	3.78	63.47	3.01	2.20	0.86	61.28	7.92	7.83	11.51
P425	10625	19.06	5.33	3.63	63.66	3.03	2.29	1.04	60.42	9.06	8.00	11.03
P425	10626	19.03	5.33	3.57	63.54	2.96	2.36	1.10	60.19	9.16	8.09	10.87
P425	10627	19.15	5.41	3.52	63.71	2.79	2.54	1.32	59.13	10.29	8.37	10.72
P425	10628	19.11	5.27	3.55	63.88	2.93	2.34	1.06	61.70	8.22	7.96	10.81
P425	10629	19.32	5.35	3.49	64.11	3.03	2.37	1.12	60.04	10.10	8.27	10.62
P425	10630	19.36	5.45	3.49	63.95	3.03	2.17	1.05	58.70	11.21	8.54	10.61

Table A.2. All of the real plant data used in modeling of the ANN Model A (2)

NUMTH1	ALMODUL	SMODUL	KIRECS	INSETTIM	FINSETTIM	BLAINE	SIRON90	SIRON32	28CCS
10102	1.41	2.28	98.23	140.00	235.00	3520.00	2.00	23.20	52.70
10103	1.34	2.33	99.54	175.00	290.00	3610.00	0.80	21.00	50.60
10104	1.38	2.31	99.44	150.00	230.00	3680.00	1.00	21.00	50.70
10105	1.40	2.27	99.74	150.00	250.00	3630.00	1.50	22.00	49.00
10106	1.42	2.29	98.56	140.00	235.00	3470.00	1.50	24.00	49.50
10108	1.42	2.26	99.54	170.00	265.00	3540.00	1.10	22.20	51.30
10109	1.43	2.23	98.21	170.00	335.00	3490.00	0.80	17.60	52.20
10110	1.40	2.27	99.05	170.00	290.00	3420.00	0.80	23.20	51.50
10111	1.38	2.30	99.08	150.00	260.00	3590.00	0.90	20.40	51.50
10112	1.44	2.24	97.75	170.00	320.00	3560.00	1.30	19.10	52.80
10113	1.44	2.30	97.16	140.00	260.00	3580.00	1.00	15.80	52.50
10115	1.39	2.31	99.00	195.00	365.00	3480.00	0.90	17.00	51.10
10116	1.46	2.25	97.31	150.00	260.00	3390.00	1.70	24.40	50.50

NUMTH1	ALMODUL	SMODUL	KIRECS	INSETTIM	FINSETTIM	BLAINE	SIRON90	SIRON32	28CCS
10117	1.41	2.30	98.09	160.00	275.00	3500.00	0.80	14.00	51.80
10118	1.38	2.32	98.43	150.00	330.00	3580.00	1.00	13.60	54.30
10119	1.40	2.32	97.61	170.00	345.00	3520.00	1.10	13.00	52.00
10120	1.37	2.34	98.47	150.00	290.00	3510.00	0.90	13.50	55.00
10122	1.39	2.32	98.92	190.00	350.00	3580.00	0.70	14.10	53.60
10123	1.39	2.31	97.66	135.00	260.00	3750.00	0.60	16.50	55.50
10124	1.38	2.29	99.02	150.00	285.00	3580.00	1.30	23.60	50.10
10125	1.34	2.32	98.47	170.00	330.00	3750.00	1.10	19.50	54.10
10126	1.30	2.38	98.85	150.00	300.00	3570.00	1.20	21.20	48.90
10127	1.32	2.35	96.99	135.00	275.00	3570.00	0.70	20.70	51.40
10129	1.32	2.30	99.29	160.00	280.00	3560.00	0.50	19.00	52.40
10130	1.33	2.33	98.43	130.00	240.00	3720.00	0.80	22.10	52.40
10131	1.37	2.32	98.30	155.00	235.00	3740.00	0.60	18.70	55.20
10201	1.41	2.28	97.95	160.00	270.00	3690.00	0.70	18.20	52.50
10202	1.36	2.30	98.39	190.00	290.00	3770.00	0.60	19.20	52.80
10203	1.38	2.29	98.50	155.00	290.00	3520.00	2.10	23.80	49.80
10205	1.43	2.24	96.79	140.00	270.00	3560.00	1.50	24.00	50.20
10206	1.38	2.29	98.41	150.00	260.00	3560.00	0.90	18.80	53.80
10207	1.44	2.27	98.05	135.00	250.00	3550.00	0.70	10.00	55.10
10208	1.44	2.27	98.16	145.00	285.00	3580.00	0.90	13.50	55.30
10209	1.42	2.31	98.25	155.00	285.00	3390.00	0.60	12.30	53.60
10210	1.40	2.33	99.78	190.00	290.00	3740.00	0.60	18.70	55.30
10212	1.39	2.33	98.62	135.00	240.00	3630.00	1.40	21.60	51.30
10213	1.42	2.32	99.04	155.00	240.00	3630.00	0.80	21.20	53.50
10214	1.48	2.21	97.57	155.00	260.00	3620.00	0.40	18.00	53.80
10215	1.54	2.20	96.17	145.00	230.00	3680.00	0.50	21.30	51.90
10216	1.60	2.17	96.54	125.00	230.00	3590.00	1.80	23.40	53.50
10217	1.50	2.18	97.55	140.00	240.00	3450.00	2.30	23.50	51.60
10219	1.51	2.18	98.79	145.00	250.00	3640.00	0.60	19.20	53.70
10220	1.37	2.28	98.95	150.00	280.00	3700.00	0.60	19.00	51.20
10221	1.45	2.28	96.91	135.00	255.00	3610.00	1.80	17.20	49.90
10222	1.47	2.25	97.35	120.00	230.00	3430.00	0.50	12.70	55.00
10223	1.48	2.23	97.62	140.00	285.00	3360.00	0.60	13.80	52.10
10224	1.49	2.21	97.61	160.00	260.00	3420.00	0.80	16.10	53.20
10226	1.41	2.27	98.07	140.00	330.00	3450.00	0.70	12.60	55.10
10227	1.38	2.32	99.42	135.00	235.00	3490.00	0.50	18.50	51.90
10228	1.40	2.29	98.85	145.00	255.00	3330.00	0.40	17.50	51.00
10301	1.44	2.27	97.59	130.00	305.00	3620.00	0.80	20.20	51.70
10302	1.47	2.24	96.98	120.00	180.00	3770.00	1.40	22.20	47.60
10303	1.42	2.26	98.98	135.00	240.00	3900.00	1.30	17.10	53.90
10309	1.45	2.22	96.64	160.00	290.00	3370.00	0.70	11.30	52.50
10310	1.44	2.36	98.17	135.00	220.00	3630.00	0.70	13.70	54.70
10312	1.44	2.36	98.32	95.00	175.00	3720.00	0.30	12.70	54.30
10313	1.39	2.39	98.67	110.00	180.00	3770.00	0.60	18.30	51.80
10314	1.43	2.35	97.92	150.00	230.00	3160.00	0.70	16.30	54.20
10315	1.36	2.38	99.48	155.00	220.00	3740.00	1.10	20.40	49.70
10316	1.31	2.44	99.51	160.00	240.00	3540.00	0.40	8.20	57.00
10317	1.34	2.42	99.22	150.00	235.00	3640.00	1.30	15.00	56.50
10319	1.39	2.46	95.01	180.00	285.00	3530.00	0.80	13.00	53.90
10320	1.31	2.44	99.05	150.00	235.00	3680.00	0.60	13.10	53.00
10321	1.33	2.39	98.63	150.00	230.00	3540.00	1.50	19.30	52.10
10322	1.37	2.36	98.57	195.00	275.00	3650.00	1.00	17.70	55.10
10323	1.38	2.39	96.33	180.00	270.00	3650.00	1.00	14.50	53.20
10324	1.33	2.38	99.56	180.00	240.00	3930.00	0.30	16.00	50.70
10326	1.34	2.40	98.36	205.00	285.00	3750.00	1.00	16.00	52.70
10327	1.36	2.36	99.43	160.00	215.00	3900.00	1.10	19.00	49.90
10328	1.32	2.39	98.90	160.00	225.00	3850.00	1.00	20.00	50.80
10329	1.34	2.36	98.59	180.00	260.00	3680.00	1.40	21.50	50.60

NUMTH1	ALMODUL	SMODUL	KIRECS	INSETTIM	FINSETTIM	BLAINE	SIRON90	SIRON32	28CCS
10330	1.40	2.30	97.37	165.00	210.00	3530.00	1.20	21.60	49.80
10331	1.37	2.31	98.38	150.00	190.00	3580.00	0.70	20.80	51.10
10402	1.39	2.28	98.51	175.00	210.00	3840.00	0.90	23.30	52.50
10403	1.38	2.28	98.60	155.00	200.00	3650.00	0.80	23.10	50.60
10404	1.33	2.34	99.32	145.00	205.00	3770.00	0.80	22.80	52.80
10405	1.29	2.39	99.41	150.00	220.00	3560.00	0.80	19.80	52.60
10406	1.31	2.36	99.73	150.00	210.00	3710.00	0.60	19.00	51.00
10407	1.35	2.32	98.66	170.00	235.00	3610.00	1.70	18.20	51.70
10409	1.34	2.34	98.50	190.00	255.00	3670.00	0.60	17.90	51.90
10410	1.31	2.34	99.82	165.00	225.00	3760.00	0.70	18.80	52.20
10411	1.31	2.36	99.89	175.00	220.00	3730.00	0.60	19.10	48.90
10412	1.31	2.35	98.00	160.00	210.00	3780.00	1.20	18.50	50.40
10413	1.34	2.31	98.55	175.00	225.00	3890.00	0.60	13.80	52.10
10414	1.33	2.32	99.00	150.00	220.00	3590.00	0.90	21.00	50.80
10416	1.44	2.25	97.79	180.00	240.00	3680.00	0.50	12.80	55.00
10417	1.38	2.26	97.82	170.00	235.00	3630.00	2.40	25.50	49.50
10418	1.36	2.25	99.61	155.00	210.00	3770.00	1.60	20.70	52.00
10420	1.43	2.22	99.46	140.00	200.00	3910.00	0.90	15.60	53.60
10421	1.37	2.29	100.18	140.00	205.00	4030.00	0.70	14.20	53.70
10425	1.35	2.24	100.71	165.00	230.00	4010.00	0.50	13.90	52.10
10426	1.29	2.25	100.23	150.00	235.00	4060.00	0.30	11.70	54.60
10428	1.31	2.25	101.00	150.00	220.00	4050.00	0.40	12.60	53.00
10430	1.33	2.20	100.70	180.00	225.00	4070.00	0.50	12.70	54.70
10501	1.34	2.23	100.67	155.00	220.00	4090.00	0.40	12.50	54.80
10502	1.31	2.27	100.75	145.00	220.00	4080.00	0.40	13.70	55.20
10503	1.34	2.20	98.85	130.00	210.00	4000.00	0.30	10.50	57.50
10505	1.36	2.20	99.78	155.00	245.00	4100.00	0.20	10.60	55.70
10507	1.32	2.19	99.94	175.00	235.00	3990.00	1.00	17.60	49.40
10508	1.28	2.23	100.10	175.00	260.00	3850.00	0.30	10.10	54.50
10509	1.39	2.17	99.32	145.00	225.00	3840.00	0.20	10.10	58.20
10510	1.32	2.21	98.99	160.00	245.00	3640.00	0.20	9.70	55.40
10511	1.33	2.21	99.40	185.00	240.00	3590.00	0.20	8.60	58.40
10512	1.31	2.24	99.21	165.00	250.00	3540.00	0.10	9.00	54.60
10514	1.36	2.17	99.17	170.00	255.00	3540.00	0.20	10.00	56.60
10515	1.35	2.19	99.67	150.00	220.00	3690.00	0.30	8.60	53.40
10516	1.37	2.16	99.46	145.00	195.00	3580.00	0.20	9.60	54.70
10517	1.37	2.23	98.80	145.00	235.00	3680.00	0.30	9.70	54.10
10518	1.38	2.25	99.48	140.00	200.00	3660.00	0.30	9.20	52.80
10519	1.35	2.23	99.75	150.00	220.00	3850.00	0.20	8.20	55.60
10521	1.37	2.21	99.25	180.00	270.00	3700.00	0.20	9.70	54.20
10522	1.34	2.22	99.78	185.00	260.00	3720.00	0.30	11.40	54.20
10523	1.41	2.19	97.30	170.00	275.00	3620.00	0.10	8.80	54.20
10524	1.37	2.23	97.39	170.00	255.00	3620.00	0.30	10.00	54.30
10525	1.47	2.17	97.56	155.00	210.00	3580.00	0.30	10.70	54.50
10526	1.47	2.13	98.48	175.00	255.00	3720.00	0.40	11.10	55.00
10528	1.46	2.18	98.18	180.00	240.00	3560.00	0.30	10.10	53.90
10529	1.41	2.18	98.09	150.00	260.00	3120.00	0.50	12.20	52.50
10530	1.43	2.14	98.02	165.00	215.00	3570.00	0.40	10.80	52.20
10531	1.43	2.14	97.39	170.00	260.00	3650.00	0.30	11.80	55.80
10601	1.51	2.06	97.41	170.00	245.00	3620.00	0.60	11.20	55.60
10602	1.45	2.10	98.05	160.00	230.00	3540.00	0.30	10.70	55.70
10605	1.41	2.13	99.83	225.00	300.00	3630.00	0.30	11.30	53.60
10606	1.41	2.13	99.51	190.00	280.00	3490.00	0.20	11.00	54.00
10607	1.42	2.06	98.91	150.00	240.00	3540.00	0.40	11.20	53.50
10608	1.40	2.12	98.12	225.00	295.00	3520.00	0.50	13.00	52.30
10609	1.42	2.09	97.77	150.00	230.00	3400.00	0.60	14.50	52.70
10611	1.47	2.04	97.29	170.00	240.00	3420.00	0.50	13.50	53.70
10612	1.43	2.04	98.80	155.00	235.00	3620.00	0.40	13.00	56.10

NUMTH1	ALMODUL	SMODUL	KIRECS	INSETTIM	FINSETTIM	BLAINE	SIRON90	SIRON32	28CCS
10613	1.44	2.01	98.05	145.00	260.00	3510.00	0.60	15.50	54.50
10614	1.47	2.02	97.86	160.00	240.00	3480.00	0.50	13.50	55.40
10615	1.42	2.05	98.84	155.00	255.00	3380.00	0.30	14.00	52.50
10616	1.36	2.06	100.01	160.00	240.00	3840.00	0.30	12.00	55.60
10618	1.42	2.02	99.82	175.00	235.00	3530.00	0.50	13.30	53.20
10619	1.40	2.05	97.68	190.00	245.00	3590.00	0.50	12.60	52.80
10620	1.44	2.00	99.67	155.00	245.00	3830.00	0.40	11.70	55.30
10621	1.53	2.01	99.16	95.00	150.00	3830.00	0.40	10.60	58.30
10622	1.49	2.02	99.54	135.00	220.00	3650.00	0.40	11.60	55.10
10623	1.42	2.06	99.49	150.00	230.00	3600.00	0.40	12.50	53.10
10625	1.47	2.13	99.23	150.00	255.00	3800.00	0.50	12.20	54.10
10626	1.49	2.14	99.30	130.00	240.00	3760.00	0.40	11.00	54.00
10627	1.53	2.14	99.15	150.00	250.00	3660.00	0.40	11.50	55.80
10628	1.48	2.17	99.69	150.00	250.00	3680.00	0.30	11.20	56.90
10629	1.53	2.19	98.91	170.00	250.00	3370.00	0.40	8.50	54.10
10630	1.56	2.17	98.29	140.00	250.00	3550.00	0.50	11.10	51.50

Table A.3. 100 training data sets used in the training of Models B and C

SO_3	C_3S	Alkali	Blaine	28 CCS
3	60.9	0.9	3830	55.3
2.5	60.7	1.1	3520	52.7
2.4	64.4	1.1	3680	50.7
2.4	63.5	1.1	3630	49
2.3	62.5	1.1	3470	49.5
2.6	64.1	1.1	3610	50.6
2.8	56.5	0.8	3620	54.3
2.5	62.1	1	3420	51.5
2.8	54.7	1.1	3590	53.5
2.6	59.8	1.1	3560	52.8
2.5	58.5	1	3580	52.5
2.5	62.4	1.1	3480	51.1
2.8	58.7	1	3360	52.1
2.7	59.9	1.1	3520	52
2.7	61.2	1.1	3580	54.3
2.7	62.8	1.1	3900	53.9
2.8	61.4	1.1	3510	55
2.7	63.4	1.1	3580	53.6
2.2	61.6	0.9	3590	50.8
2.3	63.1	1.1	3580	50.1
3.1	58.9	0.9	3650	55.1
2.4	64.5	1.1	3570	48.9
3.1	58.8	1	3830	58.3
2.5	60	1.1	3490	52.2
2.7	60.7	1.1	3720	52.4
2.7	61.5	1	3660	52.8
2.7	59.2	1.1	3690	52.5
2.6	60.7	1.1	3770	52.8
2.6	60	0.9	3380	52.5
2.9	61.7	0.9	3680	56.9
2.6	61.2	0.9	4000	57.5
2.7	59.3	1.1	3550	55.1
2.7	59	1.1	3580	55.3
2.8	61.2	1.1	3390	53.6
2.8	63.5	1.1	3740	55.3
2.9	59.9	0.9	3530	53.2
2.9	62.2	0.9	3670	51.9
3	60.4	1	3800	54.1
2.9	59.6	0.9	3620	56.1
2.9	56.5	1	3650	55.8
2.9	63.1	1	3750	52.7
2.7	60.6	1	3640	53.7

SO_3	C_3S	Alkali	Blaine	28 CCS	
2.9	63	1	3700	51.2	
2.6	51.7	1	4060	53.3	
2.9	63.5	0.9	3540	54.6	
2.8	58.1	1.1	3570	51.4	
2.4	63.5	0.9	3990	49.4	
3	60	1.1	3450	55.1	
2.5	61.7	1	3330	51	
2.8	61.3	0.9	3850	55.6	
2.8	57.2	1	3620	51.7	
2.8	54.7	1.1	3770	47.6	
3	60.2	0.9	3760	54	
2.7	60	1	3540	56.6	
2.8	59.1	0.9	3660	55.8	
2.9	64.3	1	3540	57	
2.9	62.9	1	3770	51.8	
2.4	61	0.9	3160	54.2	
2.7	64	1	3740	49.7	
2.9	58	0.9	3430	55	
2.7	64	1	3640	56.5	
2.7	67.1	0.9	4050	53.9	
2.4	56.4	1.1	3560	50.2	
2.8	57.1	1	3540	55.7	
2.6	64	1	3650	55.1	
2.7	59.4	1	3650	53.2	
2.3	65.1	1	3930	50.7	
3	55.8	1	3590	52.8	
2.8	62.5	0.8	3770	52	
2.8	61.7	1	3630	54.7	
2.5	62.9	0.9	3680	50.6	
2.3	60.4	1	3530	49.8	
2.6	58.7	0.8	3720	55	
2.8	61.6	1	4100	55.7	
2.9	60.7	0.9	3650	50.6	
2.8	64.1	0.8	3770	52.8	
2.7	64.8	1	3560	52.6	
2.9	65.3	1	3710	51	
2.8	61.6	1	3840	58.2	
2.9	63.6	1	3490	51.9	
2.8	65.1	0.9	3760	52.2	
3	60	0.9	3370	54.1	
2.8	61.1	0.9	3720	54.2	
3	61.3	0.9	3600	53.1	
2.7	64.6	1.1	3560	52.4	
2.8	57.5	1	3680	55	
2.4	59.5	0.8	3630	49.5	
2.6	67.6	1	4050	54	
2.3	68.3	0.9	3890	52.9	
3	59.7	0.9	3520	52.3	
2.7	64.5	0.9	4030	53.7	
3	56	0.9	3400	52.7	
2.6	56.5	1.1	3610	49.9	
2.8	58.3	1	3570	52.2	
2.7	64.5	1	4060	54.6	
2.6	61.3	1.1	3560	53.8	
2.8	63.2	1	3850	54.5	
2.4	60.4	0.9	3120	52.5	
2.7	62.1	1	3690	53.4	
2.7	65.6	0.9	4080	55.2	
2.2	**51.7**	**0.8**	**3120**	**47.6**	min
3.1	**68.3**	**1.1**	**4100**	**58.3**	max
2.71	**61.11**	**0.99**	**3651.8**	**53.14**	average

Table A.4. 50 testing data sets used in the testing of Models B, C and D

SO_3	**C_3S**	**Alkali**	**Blaine**	**28 CCS**	
3	54	1.1	3530	53.9	
2.9	54.8	0.9	3680	51.9	
2.8	57.3	1	3560	53.9	
2.6	64.6	1	3850	50.8	
2.7	56.9	0.8	3580	54.5	
2.3	61.3	0.9	3780	50.4	
2.8	62.3	0.9	3640	55.4	
2.8	62.4	0.9	3590	58.4	
2.5	64.6	0.8	4090	54.8	
2.8	59.3	1.1	3500	51.8	
2.7	61.8	1.1	3630	51.3	
3	61.3	1	3580	54.7	
2.6	60.4	1	3680	54.1	
3.1	55.6	1	3510	54.5	
2.5	62.4	1.1	3590	51.5	
2.6	63.1	0.9	3540	52.1	
2.7	61.2	0.9	3610	51.7	
2.7	55.6	0.9	3620	54.2	
2.6	67.3	0.8	4020	53.8	
3	58.7	0.9	3550	51.5	
2.3	65.4	0.9	3730	48.9	
2.7	58	1	3420	53.2	
2.5	65	0.8	4070	54.7	
2.9	62	1	3720	54.3	
2.7	61.4	0.9	3840	52.5	
2.5	63.5	1	3540	51.3	
2.3	62.8	0.9	3580	51.1	
3	56.4	1.1	3370	52.5	
3	62.8	1.1	3750	54.1	
3	58.9	1	3540	53.5	
2.5	62.3	0.9	3910	53.6	
2.7	57.7	1	3480	55.4	
3.1	55.8	0.9	3420	53.7	
2.8	55.9	1	3620	55.6	
2.8	60.7	1.1	3740	55.2	
2.5	59.3	1.1	3750	55.5	
2.2	60.8	1.1	3520	49.8	
3	60.7	0.9	3840	55.6	
2.5	63.2	0.9	4010	52.1	
2.6	59.3	1	3450	51.6	
2.6	65.8	0.9	4050	53	
2.5	57.4	1.1	3390	50.5	
2.4	62	1	3490	54	
2.2	59.7	1	3890	52.1	
2.7	56.8	1	3620	53.8	
2.4	61.7	0.9	3630	53.6	
2.8	63.6	0.9	3680	53	
2.8	61.6	1.1	3630	53.5	
2.4	64.9	1	3900	49.9	
2.8	61	0.9	3700	54.2	
2.2	**54**	**0.8**	**3370**	**48.9**	min
3.1	**67.3**	**1.1**	**4090**	**58.4**	max
2.68	**60.63**	**0.97**	**3670.6**	**53.16**	average

APPENDIX B

Table B.1. The testing error results of the ANN Model C constructed by MatLAB®
Neural Network Toolbox

Network number	Number of Layers	Number of Neurons	Algorithm Type	Training Function	AAPE (%)
1	1	3	Feed-forward BP	TRAINLM	2.96
2	1	4	Feed-forward BP	TRAINLM	2.52
3	1	5	Feed-forward BP	TRAINLM	3.68
4	1	3	Feed-forward BP	TRAINGD	2.62
5	1	4	Feed-forward BP	TRAINGD	2.78
6	1	5	Feed-forward BP	TRAINGD	2.59
7	1	3	Feed-forward BP	TRAINGDA	2.36
8	1	4	Feed-forward BP	TRAINGDA	2.45
9	1	5	Feed-forward BP	TRAINGDA	2.61
10	1	3	Elman BP	TRAINLM	2.93
11	1	4	Elman BP	TRAINLM	3.21
12	1	5	Elman BP	TRAINLM	3.39
13	1	3	Elman BP	TRAINGD	2.35
14	1	4	Elman BP	TRAINGD	2.84
15	1	5	Elman BP	TRAINGD	3.03
16	1	3	Elman BP	TRAINGDA	2.58
17	1	4	Elman BP	TRAINGDA	2.38
18	1	5	Elman BP	TRAINGDA	3.06
19	1	3	Time-delay BP	TRAINLM	2.78
20	1	4	Time-delay BP	TRAINLM	3.04
21	1	5	Time-delay BP	TRAINLM	4.22
22	1	3	Time-delay BP	TRAINGD	2.48
23	1	4	Time-delay BP	TRAINGD	2.36
24	1	5	Time-delay BP	TRAINGD	2.81
25	1	3	Time-delay BP	TRAINGDA	2.43
26	1	4	Time-delay BP	TRAINGDA	2.53
27	1	5	Time-delay BP	TRAINGDA	2.71
28	1	3	Cascade-forward BP	TRAINLM	3.33
29	1	4	Cascade-forward BP	TRAINLM	4.40
30	1	5	Cascade-forward BP	TRAINLM	4.24
31	1	3	Cascade-forward BP	TRAINGD	2.43
32	1	4	Cascade-forward BP	TRAINGD	2.33
33	1	5	Cascade-forward BP	TRAINGD	3.04
34	1	3	Cascade-forward BP	TRAINGDA	2.37
35	1	4	Cascade-forward BP	TRAINGDA	3.17
36	1	5	Cascade-forward BP	TRAINGDA	2.79
37	2	3	Feed-forward BP	TRAINLM	2.55
38	2	4	Feed-forward BP	TRAINLM	3.60
39	2	5	Feed-forward BP	TRAINLM	2.72
40	2	3	Feed-forward BP	TRAINGD	2.80
41	2	4	Feed-forward BP	TRAINGD	2.42
42	2	5	Feed-forward BP	TRAINGD	2.43
43	2	3	Feed-forward BP	TRAINGDA	2.78
44	2	4	Feed-forward BP	TRAINGDA	2.84
45	2	5	Feed-forward BP	TRAINGDA	2.80
46	2	3	Elman BP	TRAINLM	3.34
47	2	4	Elman BP	TRAINLM	3.09
48	2	5	Elman BP	TRAINLM	6.57
49	2	3	Elman BP	TRAINGD	2.55
50	2	4	Elman BP	TRAINGD	2.31
51	2	5	Elman BP	TRAINGD	2.61
52	2	3	Elman BP	TRAINGDA	2.53

Network number	Number of Layers	Number of Neurons	Algorithm Type	Training Function	AAPE (%)
53	2	4	Elman BP	TRAINGDA	2.98
54	2	5	Elman BP	TRAINGDA	2.45
55	2	3	Time-delay BP	TRAINLM	2.89
56	2	4	Time-delay BP	TRAINLM	3.36
57	2	5	Time-delay BP	TRAINLM	4.46
58	2	3	Time-delay BP	TRAINGD	2.50
59	2	4	Time-delay BP	TRAINGD	2.40
60	2	5	Time-delay BP	TRAINGD	2.52
61	2	3	Time-delay BP	TRAINGDA	2.58
62	2	4	Time-delay BP	TRAINGDA	2.35
63	2	5	Time-delay BP	TRAINGDA	2.77
64	2	3	Cascade-forward BP	TRAINLM	4.95
65	2	4	Cascade-forward BP	TRAINLM	4.81
66	2	5	Cascade-forward BP	TRAINLM	3.60
67	2	3	Cascade-forward BP	TRAINGD	2.53
68	2	4	Cascade-forward BP	TRAINGD	2.35
69	2	5	Cascade-forward BP	TRAINGD	2.60
70	2	3	Cascade-forward BP	TRAINGDA	2.64
71	2	4	Cascade-forward BP	TRAINGDA	2.88
72	2	5	Cascade-forward BP	TRAINGDA	2.84

Table B.2. 108 Fuzzy rules (Mamdani rules) used in the fuzzy logic model D

SO_3	C_3S	Blaine	Total Alkali	28-day CCS
L	VL	L	L	L
L	VL	L	M	VL
L	VL	L	H	VL
L	VL	M	L	L
L	VL	M	M	VL
L	VL	M	H	VL
L	VL	H	L	L
L	VL	H	M	VL
L	VL	H	H	VL
L	L	L	L	L
L	L	L	M	L
L	L	L	H	VL
L	L	M	L	L
L	L	M	M	L
L	L	M	H	VL
L	L	H	L	L
L	L	H	M	VL
L	L	H	H	VL
L	M	L	L	L
L	M	L	M	L
L	M	L	H	VL
L	M	M	L	L
L	M	M	M	L
L	M	M	H	VL
L	M	H	L	L
L	M	H	M	L
L	M	H	H	VL
L	H	L	L	L
L	H	L	M	L
L	H	L	H	VL
L	H	M	L	L
L	H	M	M	L
L	H	M	H	VL
L	H	H	L	L
L	H	H	M	L
L	H	H	H	VL
M	VL	L	L	M

SO_3	C_3S	Blaine	Total Alkali	28-day CCS
M	VL	L	M	M
M	VL	L	H	L
M	VL	M	L	M
M	VL	M	M	M
M	VL	M	H	L
M	VL	H	L	M
M	VL	H	M	M
M	VL	H	H	L
M	L	L	L	M
M	L	L	M	M
M	L	L	H	L
M	L	M	L	M
M	L	M	M	M
M	L	M	H	L
M	L	H	L	M
M	L	H	M	M
M	L	H	H	L
M	M	L	L	L
M	M	L	M	L
M	M	L	H	L
M	M	M	L	L
M	M	M	M	M
M	M	M	H	L
M	M	H	L	M
M	M	H	M	M
M	M	H	H	L
M	H	L	L	L
M	H	L	M	L
M	H	L	H	L
M	H	M	L	L
M	H	M	M	M
M	H	M	H	L
M	H	H	L	M
M	H	H	M	M
M	H	H	H	L
H	VL	L	L	H
H	VL	L	M	H
H	VL	L	H	M
H	VL	M	L	H
H	VL	M	M	H
H	VL	M	H	M
H	VL	H	L	H
H	VL	H	M	H
H	VL	H	H	M
H	L	L	L	M
H	L	L	M	M
H	L	L	H	M
H	L	M	L	M
H	L	M	M	H
H	L	M	H	H
H	L	H	L	H
H	L	H	M	H
H	L	H	H	M
H	M	L	L	L
H	M	L	M	M
H	M	L	H	M
H	M	M	L	M
H	M	M	M	M
H	M	M	H	M
H	M	H	L	H
H	M	H	M	H
H	M	H	H	H
H	H	L	L	L
H	H	L	M	L
H	H	L	H	M
H	H	M	L	L
H	H	M	M	M
H	H	M	H	M
H	H	H	L	M
H	H	H	M	M
H	H	H	H	H