ANN PREDICTION OF UNCONFINED COMPRESSIVE STRENGTH DEVELOPMENT OF CEMENT MORTAR

A THESIS SUBMITTED TO THE GRADUATE SCHOOL OF APPLIED SCIENCE OF NEAR EAST UNIVERSITY

By
YARED BERHANU NEGEWO

In Partial Fulfilment of the Requirement for the Degree of Masters of Sciences in Civil Engineering

NICOSIA, 2019

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Approval of Director of Graduate School of

Applies Sciences

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I, the understand, declare that this thesis is my own work, has not been submitted for a degree in any universities and all references used for the thesis has been duly acknowledged.

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To my parents…

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ABSTRACT

This research representing the implementation of ANN prediction on cement mortar's unconfined compressive strength. To investigate these, two conditions were performed with and without considering cement type I as input variable ANNI and ANNII respectively to obtain the required goal. ANN I contain nine input material such as Day, cement type I, magnesium oxide (MgO), pulverized fly ash, slag, lime, bulk density (BD), water/solid ratio and waste addition. ANN II was predicted without considering the cement type I to assess the impact of cement type I on mortar's compressive strength. To compute these above 300 neural network trials above fourteen modelings with the different combinations were conducted by using sigmoid and Tanh ANN activation function.

According to the result obtained the ANN and experimental results show a good agreement. DC and RMSE values were calculated for all neural network models. Finally, the obtained result shows the cement type-I highly affect the cement mortar's unconfined compressive strength and it's the most important parameter.

Keywords: Experimental results; ANN prediction; cement type I; Unconfined compressive strength; sigmoid activation function

ÖZET

Bu araştırma, ANN analizlerini çimento harçının sınırlandırılmamış basınç dayanımı üzerindeki uygulamasının sonuçlarnı anlatıyor. Bunları araştırmak için, sırasıyla çimento tipi I ile birlikte giriş değişkeni ANNI ve ANNII olarak düşünülmeden iki koşul gerçekleştirildi. ANN I; Gün, çimento tipi I, magnezyum oksit (MgO), pulverize uçucu kül, cüruf, kireç, kütle yoğunluğu (BD), su / katı oranı ve atık ilavesi gibi dokuz girdi maddesi içerir. Bunları hesaplamak için, yaklaşık 300 sinir ağı denemesi, farklı kombinasyonlu on dört modelin üzerinde sigmoid ve Tanh ANN aktivasyon fonksiyonu kullanılarak yapıldı.

Elde edilen sonuçlara göre YSA ve deney sonuçlarının iyi bir şekilde anlaşıldığı görülmüştür. DC ve RMSE değerlerinin belirlenmesi tüm sinir ağı modelleri için hesaplandı. Son olarak, elde edilen sonuç çimento mukavemet sınıfının havanın sınırlandırılmamış basınç mukavemetini oldukça etkilediğini ve bunun en önemli parametre olduğunu göstermektedir.

Anahtar kelimeler: Deneysel sonuçlar; YSA tahmini; çimento tipi I; Kapalı basınç direnci; sigmoid aktivasyon işlevi

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LIST OF ABBREVIATIONS

ANN:	Artificial Neural Network
BD:	Bulk density
CCS:	Cement Compressive Strength
CEM:	Type I Cement Strength Class
DC:	Determination Coefficient
Fc:	Compressive Strength of Cement Mortar
HAC:	High Alumina Cement
LHC:	Low Heat Cement
MLR:	Multi-Linear Regression
PFA:	Pulverised Fly Ash
PPC:	Pozzolana Portland cement
RHC:	Rapid Hardening Cement
RMSE:	Root Mean Square Error
S/C:	Sand to Cement Ratio
SG:	Specific Gravity
SSC:	Speed Setting Cement
UCS:	Unconfined Compressive Strength
W/C:	Water to Sand Ratio
WC:	White Cement
W/S:	water/solid ratio

CHAPTER 1
INTRODUCTION

1.1 Background

Cement mortar is a combination material consists of several materials such as cement, sand (fine aggregates), water and when needed additives. The proportions, as well as properties of those materials, can affect the properties and strength of the cement mortar (Minafò & La Mendola, 2018; Eskandari-Naddaf & Kazemi, 2017). According to several studies conducted as experimental study reveals that the proportion of sand to cement (s/c), cement strength class, water to cement (w/c), aggregate size, and several additives (superplasticizer), shape and size of the sample are some factors that impact the physical and mechanical properties of a mortar. Among these factors, the cement strength types highly impact on the compressive strength of the cement mortar. However, cement has different compressive strength class standards such as 32.5, 42.5, 52.5 MPa which can be manufactured and useful in different construction structural sites with the same curing time (Mahdinia, Eskandari-Naddaf, & Shadnia, 2019). The highest compressive strength (Fc) of mortar can be evaluated after the curing of 28 days (Zak, Ashour, Korjenic, Korjenic, & Wu, 2016).

Cement is a fine grey matter prepared from major clay and calcined lime. Clay is used to having alumina land silica and iron oxides. Lime contains calcium oxides. Cement production can be made from clay and lime burned at clinker compound at temperatures of 1500 ^{0}C. Cement contains several clinker compounds such as Celite (tricalcium aluminate), tricalcium silicate, Belite (dicalcium silicate), Brownmillerite (tetra calcium ferrite), Sodium Oxide, Potassium Oxide, and Gypsum (Dunuweera & Rajapakse, 2018a).

The cement mortar can be produced from several types of cement such as pozzolana Portland cement, ordinary Portland cement, and other cement mixes with the sand(fine aggregate), water and some admixtures (Tosti, van Zomeren, Pels, Dijkstra, & Comans, 2019). Portland cement can be manufactured from clays with several chemical analysis Al_2O_3, SiO_2, CaO, Fe_2O_3, SO_3, Na_2O, MgO, LOI, K_2O, F.CaO, C3S and C3A (Eskandari-Naddaf & Kazemi, 2017).

Different conditions and specifications are used to get a better strength development of a mortar. Therefore, an alternative method was developed to simulate different properties and conditions to achieve better strength development rather than testing and analyzing every single mix batch by laboratory work. The compressive strength of concrete and mortars can be evaluated by different software such as fuzzy logic, electrical resistivity measurement and Artificial Neural network (ANN) can be used. However, among these methods, ANN is the most popular and common one which is exploited to solve the compressive strength of mortar and other more complex problems which are difficult to solve such as self compacted mortar, lightweight mortar, sulfate resistance concrete, admixtures, and many others. Microstructures of mortar's compressive strength can be found at different curing ages including 1,7,14,21,28 days, respectively (Eskandari-Naddaf & Kazemi, 2017).

ANN can be used for various modeling of cement mortar mix designs and proportions. However, the cement mortar with different cement to sand, cement strength, and water to cement ratio at the age of 7, 14, 28 days. The ANN model is capable of achieving the accurate value and approach in parallel to the laboratory-based experimental work results (Eskandari et al., 2016).

ANN can be exploited to connect nonlinear and complex systems based on correct and related input and output values. In mortar cement design and model; the quality of ANN is based on the input data and ratio of mixtures such as sand to cement (s/c), water to cement (w/c), fine aggregate and also depends on the individual materials such as water, sand, cement types, and compressive strength. The good concord between the microstructures and compressive strength can be done by using the nonlinear ANN modeler tools. The outputs of ANN results are in between -1 and 1 (Eskandari-Naddaf & Kazemi, 2017).

1.2 Objective of the Research

The general aim of this research is to evaluate the prediction of the ANN model on the impact of cement type I on the unconfined compressive strength development of cement mortars. With the specific objective of to assess the ANN model accuracy predict the compressive strength of cement and evaluate the impact of each input material on the output unconfined compressive strength as well as to make a comparison between the ANN models and experimental data to show good agreement amongst them.

1.3 Significance of the Study

The research entitles the prediction of ANN on the impact of cement strength class on the compressive strength of cement mortar, accurately predict of the cement compressive strength on the cement mortar compressive strength by using ANN modeling, to compare the good correspondence between the laboratory test and ANN model, by using ANN to perform the improved cement compressive strength which can be used as reference for further research works.

1.4 Scope and Limitations

While this research will touch upon ANN prediction of unconfined compression strength of cement mortar and its impact of cement strength class; the experimental results/data were obtained from (B. Cubukcuoglu, 2012) including nine materials as input materials such as Day, proportions of cement (CEM), magnesium oxide (MgO), pulverized fly ash (PFA), slag, lime, bulk density (BD), water/solid ratio, waste addition ratio and unconfined compressive strength as output variables. There are many different categories of ANN activations functions such as sigmoid, hyperbolic tangent function, linear function, and others. Among them, sigmoid feed forwarded neural network function was used in this research because of the sigmoid function is the most appropriate for accurate prediction in construction material especially for compressive strength of the material. Finally, the ANN prediction of the material was conducted by omitting each material as input variables to assess the outcome of each material on the compressive strength of cement mortar.

1.5 Thesis Organization

This thesis contains five chapters.

Chapter 1- Introduction: This chapter contains background information about the theme, statement of the problem, the significance of the problem, scope and limitation, and finally thesis organization.

Chapter 2- Literature Review: Literature was reviewed on materials used to provide mortar with their properties, factors affecting compressive strength development of cement mortar, compressive strength of cement mortar at different ages, the effect of curing time on the strength of cement mortar, experimental work undertaken on cement mortar compressive strength, Artificial Neural System (ANN), the ANN training procedure, the ANN model and experimental results and output compatibility and achievements.

Chapter 3-Research Methodology: Deals with an introduction, research approach, research method source, and nature of data, Artificial Neural Network, data processing and analyzing, steps to modeling an ANN.

Chapter 4- Results and Discussions: Deals a brief discussion based on Experimental results obtained from (B. Cubukcuoglu, 2012) prediction of ANN on the influences of cement type I on unconfined compressive strength with other aspect ratio of cement type I, lime, magnesium oxide (MgO), PFA, slag, waste addition, water to solid and bulk density as input data and unconfined compressive strength as output data.

Chapter 5-Conclusions and Recommendations: Deals with the conclusion and recommendations based on the result gained from ANN modeling.

CHAPTER 2
LITERATURE REVIEW

2.1 Introduction

Compressive strength is the tendency that the material resists the compression failure under the impact of compression forces. It is the most parameter that determines the performance of material strength. Mortar can be made from the combination of several raw materials such as cement, sand (fine), admixture, water, and some chemicals. The proportions mixes and properties of those materials can high influences on the strength and properties of cement mortar. According to several studies conducted the experimental results shows that the proportion of sand to cement (s/c), cement strength class, water to cement (w/c), aggregate grading, several additives such as superplasticizer, shape, and size of the sample are some factors influences the mechanical and physical properties of cement mortar (Mahdinia, Eskandari-Naddaf, & Shadnia, 2019).

Cement mortar can be composite materials contain cement, sand, fine aggregate, water, admixture, and chemicals. The mix design of those materials can affects the properties of concrete. Mix design contains the combination or proportion of several materials such as sand to cement ratio, water to cement ratio, cement: sand: aggregate ratio, quality of water, the chemical composition of cement, physical properties of materials such as specific gravity, shape, and soundness of aggregate and others factors. The mix design can directly affect the compression strength of mortar. However, mortar is the most and essential construction materials that can resist compression strength than other materials (Mahdinia et al., 2019).

There are several types of cement depending on raw materials properties, manufacturing process, chemical and physical composition and other various properties such as ordinary Portland cement, fly ash cement pozzolana Portland cement, and others. However, ordinary Portland cement (OPC) can be manufactured from cementations materials such as silica fume (SF), granulated blast furnace slag, fly ash and others (Verian, Ashraf, & Cao, 2018)

Portland cement can be used as binding materials. The workability of cement mortar can be depending on mix design factors such as cement to sand ratio, cement strength class, w/c ratio, and some admixtures. The types of cement can influence the properties of mortar (Kurda, de Brito, & Silvestre, 2018).

Portland cement can be produced from several raw materials such as and have different classes depending on their chemical composition such as Al_2O_3, MgO, SiO_2, Fe_2O_3, SO_3, K_2O, LOI, CaO, Na_2O, F.CaO, C3S, C3A. Depend on the percentage of their production there different categories of cement strength such as C32.5, C42.5, C52.5, and other cement class. (Eskandari-Naddaf & Kazemi, 2017) and (Islam, et.al 2017).

The compression strength of cement mortar can be depending on several factors such as material properties, mix design, water to cement ratio, curing time and other factors. Curing time plays a great role in concrete strength. The molded cement mortar has different strengths at a different age. According to ASTM concrete can get the maximum compression strength at 28 days and 65% curing gain at 7 days (Zhang, Tam, & Leow, 2003). To analyze the mechanical, mixture and other properties material strength un axial compression strength test should be used (Correia et al., 2017).

water to cement ratio is the major factor that influences the properties and strength of the mortar. High water to cement ratio can cause the shrinkage by causing more evaporation at high temperature and also cause the segregation of concrete during molding of cement mortar. The Portland cement concrete incorporates with silica fume can because shrinkage, when it is not mixed ratio, is not appropriate. The shrinkage increased when the water to cement ratio (0.26 to 0.35) and also when the silica fume increased (range of 1 to 10%) (Zhang et al., 2003).

The surface soluble water contains several materials such as magnesium, potassium, calcium affect the properties of concrete both internals and externals. The internal source of cement mortar can be affected due to several materials such as cement composition chemicals, wastewater (water from industrial), the contaminated aggregate can affect the concrete strength and properties (Sahoo & Mahapatra, 2018).

The Artificial Neural Network (ANN) is a software used to analyze and predicts several complex formulas. However, ANN can be used in predictions of cement mortar compressive strength that produced from several combinations of the mixture and is difficult to calculate. Cement mortar can be produced from several mixtures of materials such as cement, water, sand, admixtures, and other chemicals. However, all material has different properties cement have different compressive strength class and also other materials have their properties. The ANN can be used to predict the compressive strength of several admixtures and used to relate their properties (Eskandari-Naddaf & Kazemi, 2017). The ANN is mainly widely used in mortar analysis nowadays and it can reduce the time and cost (Mahdinia et al., 2019).

Neural system based techniques are utilized in tackling exceptionally non-straight issues where the complex material science of the framework presents a restrictive computational cost. The greatly parallel system framed by connecting the contributions to the yields uses versatile weight capacities for each and corresponds them to the yield. The calculation can likewise persistently train itself with extra informational collections to improve the exactness of the forecasts when contrasted with most static models coming about because of factual examinations. ANN has been utilized in impersonating learning and preparing like the human mind and has discovered broad application in taking care of confounding issues in picture handling, design acknowledgment, and fitting multivariable information yield connections (Goyal & Garimella, 2019).

ANN is formulated using a set of training, validation and test data points. In this study, the input parameters to the net are several independent variables, while the output is a desirable calculated state variable. MATLAB® Neural Network Toolbox is used to train the network and develop the model (Goyal & Garimella, 2019).

2.2 Cement Mortar

Cement mortar can be produced from the combination of several raw materials such as cement, sand, (fine aggregate), admixture, water, and some chemicals. The strength of cement is the major factors influence the strength of mortar. Several factors influences the properties and strength of mortar such water to cement ration, mixing proportion ratio, sand to cement ratio, quality of water, the shape of aggregate and other factors (Eskandari-Naddaf & Kazemi, 2017).

2.2.1 Cement

Cement is originally a binder material produced from raw materials of clay and some chemicals such asAl_2O_3, MgO, SiO_2, Fe_2O_3, SO_3, K_2O, LOI, CaO, Na_2O, F.CaO, C3S, C3A. The mix and proportion of these raw materials can change the compressive strength of cement (Eskandari-Naddaf & Kazemi, 2017).

Cement is a fine material made with clay and calcined lime as real fixings. The clay utilized gives alumina, silica, and iron oxide. While calcined lime fundamentally gives calcium oxide. In mortar assembling, crude cement materials are gotten by impacting rock quarries by exhausting the stone and setting off explosives. These divided rocks are at that point transported to the plant and put away independently in storehouses. They are then conveyed, independently, through chutes to pulverizes where they are then pulverized or beat to chunks of ~1/2 (Dunuweera & Rajapakse, 2018).

Table 2.8: Composition of the cement clinker (Dunuweera & Rajapakse, 2018)

Compound	Formula	Notation	wt.%
Celite (tricalcium aluminate)	$Ca_3Al_2O_6$ [$3CaO \cdot Al_2O_3$]	C3A	10
Brownmillerite (tetracalcium aluminoferrite)	$Ca4Al_2Fe_2O_{10}$ [$4CaO \cdot Al_2O_3 \cdot Fe_2O_3$]	C4AF	8
Belite (dicalcium silicate)	Ca_2SiO_4 [$2CaO \cdot SiO_2$]	C2S	20
Alite (tricalcium silicate)	Ca_3SiO_5 [$3CaO \cdot SiO_2$]	C3S	55
Sodium oxide	Na_2O	N	2
Potassium oxide	K_2O	K	2

2.2.2 Types of cement

There are more than ten unique kinds of cement that are utilized in development purposes, and they vary by their creation also, are made for various composition. These are rapid hardening cement(RHC), low heat cement(LHC), high-alumina cement (HAC), speedy setting cement (SSC), sulphate-resistance cement (SRC), blast furnace slag cement (BFSC), pozzolanic cement , white cement (WC), air-entraining cement (AEC), and hydrophobic cement (HPC). RHC has expanded the lime content contrasted with the Portland cement (PC). The reason for having high lime content is to achieve high quality in ahead of scheduled days. It is utilized in solid when the formwork is to be evacuated early. Since solidifying of the cement is because of the development of $CaCO_3$ by engrossing barometrical CO_2 by CaO, expanded CaO results in expanded $CaCO_3$ development even at the early stage to result in quick solidifying (Dunuweera & Rajapakse, 2018).

Analysts have been concentrating on growing progressively feasible cementations frameworks to check the negative ecological effects and crumbling of concrete structures related to ordinary Portland concrete (OPC). A few endeavors have been made to create manageable folios using pozzolans, for example, slag, silica smolder (SF), palm oil fuel ash (POFA) and fly Ash remains (FA) (Hossain, Karim, Hasan, Hossain, & Zain, 2016). Cement compressive strength can be affected by several factors among the PH value of cement can be one of the major factors that influence the compressive strength of cement mortar (Tosti, van Zomeren, Pels, Dijkstra, & Comans, 2019).

Table 2.9: Composition of components as wt. % used to make different types of cements (Dunuweera & Rajapakse, 2018)

Component	**Portland cement**	**Siliceous fly ash**	**Calcareous cement**	**Slag cement**	**Fume silica**
SiO_2	21.9	52	35	35	85–97
Al_2O_3	6.9	23	18	12	0
Fe_2O_3	3.9	11	6	1	0
CaO	63.0	5	21	40	<1
MgO	2.5	0	0	0	0
SO_3	1.7	0	0	0	0
SSA (m2·g−1)	0.37	0.42	0.42	0.4	15–30
SG	3.15	2.38	2.65	2.94	2.22

SG =specific gravity; SSA = specific surface area

2.2.2.1 Pozzolana portland cement (PPC)

General utilization of the pozzolana Portland cement, Calcareous (ASTM C618 Class C) Fly Ash, Siliceous (ASTM C618 Class F) Fly Ash, silica smolder and slag cement in cement is as essential folio, concrete substitution, cement substitution, and property enhancer, individually (Dunuweera & Rajapakse, 2018). Some admixtures used in Portland cement hydration production could be utilized as an alternative of normal gypsum in the creation of pozzolana Portland cement to manage the hydration response time of mortar (Islam et al., 2017).

Table 2.10: physical and chemical properties of portland cement (Eskandari-Naddaf & Kazemi, 2017)

Chemical composition analysis%

CEM	SO_2	Al_2O_3	Fe_2O_3	CaO	MgO	SO	Na_2O	K_2O	LOI	F.Co	C3A
C32.5	20.4	4.56	3.4	62.1	1.93	2.3	0.3	0.7	2.2	1.3	6.3
C42.2	20.2	4.6	3.5	16	1.94	2.4	0.3	0.7	2.7	1.3	6.3
C52.2	21	4.7	3.52	16.1	1.93	2.4	0.3	0.6	1.3	1.2	6.5

Table 2.11: Physical properties of cement

Physical properties		
Specific gravity (ton/m^3)	**Sieve residue on 90mm (%)**	**Blaine test (cm^2/gr)**
3.13	0.9	3000
3.13	0.8	3050
3.15	0.1	3600

The chemical properties contents (Al_2O_3, MgO, SiO_2, Fe_2O_3, SO_3, K_2O, LOI, CaO, Na_2O, F.CaO, C3S, C3A) physical properties(specific properties, sieve), sand to cement ratio, water to cement ratio, of the materials influence the strength of cement. However, water-cement (w/c) ratio can highly influence the strength of mortar (Eskandari-Naddaf & Kazemi, 2017).

2.2.2.2 Admixture

Admixtures generally in compound synthesis and many carry out greater than one capacity. There are two essential sorts of admixtures are accessible: mineral and compound admixtures. However, all the admixtures can be utilized in solid development should satisfy particulars; experiment ought to be made to assess how the admixture will influence the properties of cement mortar. The adequacy of the admixture depends on factors, for example, brand, type, and measure of concrete materials; total shape water content, gradation, extents; droop; blending time; and temperature of the concrete (Mansor, Borg, M Hamed, Gadeem, & Saeed, 2018).

2.2.2.3 Fine aggregate

Cement mortar is a blend of cementitious material, fine aggregate, water, chemical admixtures, and other materials. Total is regularly viewed as an inactive filler, which represents 60 to 80 percent of the volume and 70 to 85 percent of the heaviness of cement mortar(The Pennsylvania State University, 2014).

Aggregate is classified into two unique sorts, coarse and fine. Coarse aggregate is normally more prominent than 4.75 mm (held on a No. 4 strainer), while fine aggregate is under 4.75 mm (passing the No. 4 sifter). The compressive total quality is a critical factor in the determination of total. While deciding the quality of typical cement mortar, most concrete totals are a few times more grounded than alternate segments in cement and in this way not a factor in the quality of ordinary quality cement. Lightweight aggregate cement might be more impacted by the compressive quality of the totals. Other physical and mineralogical properties of the total must be known before blending cement to acquire an alluring blend. These properties incorporate shape and surface, estimate degree, dampness content, explicit gravity, reactivity, soundness and mass unit weight. These properties alongside the water/cement material proportion decide the quality, usefulness, and sturdiness of cement. Mortar is increasingly serviceable when the smooth and adjusted total is utilized rather than harsh precise or lengthened total. Most common sands and rock from riverbeds or seashores are smooth and adjusted and are incredible aggregate (The Pennsylvania State University, 2014).

2.3 Cement Mortar Properties

Droop test as indicated by ASTM C143 (1978) was done on the crisp cement whereas tests for compressive quality and flexural elasticity, was done on solidified cement (Ahmed et al., 2016). The compressive strength of cement mortar can be increased gradually from fresh up to become strength time that is at the typical age of 3,7,14 and 28 days. However, the maximum compressive strength can be obtained at the age of 28 days (Warudkar et.al.,2017).

2.4 Factors Affect the Compressive Strength of Cement Mortar

Cement mortar is a combination of several mixes. The response of the combination of cement with water prompts setting and mortar (Le, Poh, Wang, & Zhang, 2017). Cement mortar is a critical basic material being utilized in the greater part of the development setting time and business and it has two main vital properties. The mix of the underlying mineral materials ought to have a specific creation to lead an appropriate setting time and compressive quality after passing through high temperatures in the heater and afterward mixed with water. The specific arrangement of the materials is being evaluated by various mechanisms, for example, Al_2O_3, SiO_2 or water quality, and mix proportions. However, this modulus decides the amount of basic materials piece to complete an appropriate quality and the setting time as well (Abolpour, et.al., 2015).

Some ongoing articles have depicted the impact of different parameters on the quality of the mortar utilizing fuzzy logic. Anyway, the factual investigation has been utilized once in a while to examine the impact of crude materials synthesis on setting time and quality of cement. According to the previous examination, the fuzzy logic show was planned and upgraded to gauge compressive quality at 28 days of cements mortar. Information factors of the fluffy rationale show were the water to cement ratio proportion and also coarse aggregate to fine aggregate proportion, while the maximum compressive strength was 28 days of cement compressive strength (Abolpour et al., 2015). The main role of gypsum is as added cement mortar and they appear reaction to lessen the setting time of the cement mortar and becoming to very decreases quality(Zak, Ashour, Korjenic, Korjenic, & Wu, 2016).

The cement compressive strength was researched in a portion of the past experimental investigations through four clinker stages, with the weight percent several clinkers of SiO_2, CaO, Fe_2O_3 segments, and Al_2O_3. The other beginning materials, for example, MgO, Cl, Na_2O, SO_3 and K_2O which as a rule have low quantity percent of cement, and also can affect the CCS. The cement physical properties, for example, Blaine esteem likewise especially affect the CCS and IST. The Blaine estimations of the underlying materials show the particular surface zone and furthermore the volume of the concrete particles. The job of this physical properties parameter on the CCS ought to be explored a reasonable predictive of the model for these two targeted parameters (Abolpour et al., 2015).

Compressive strength of cement compressive strength can be affected by several factors such as aggregate porosity, sand to cement ratio, water to cement ratio, load parameter, curing time temperature, hydration, admixtures, mix design are some factors affecting the compressive strength of concrete (Chaunsali, et.al.,2018).

2.4.1 Water to cement ratio

Mortar develops up to its quality and strength through gradual hydration of the cement and expansion to shape an unpredictable arrangement of hydrates (Onwuka, Awodiji, & U, 2015). The underlying that the cement mortar fixes its strength through hydration cement mortar particles into a frail structure encompassed by the water-filled space. When the ratio of water to cement is high the cement mortar quality will become shrinkage, poor strength, low quality, and low toughness. However, the proportion of water to cement should be at balanced as per ASTM standards. The hydration process is mainly depending on the cement types, chemical compositions, rate of hydrations of the cements and environments as well (Apebo, Shiwua, Agbo, Ezeokonkwo, & Adeke, 2013).

According to the previous study shows as the ratio decreases from 0.33 to 0.50, the compressive strength quality can be increased from 34.4% to 35.2% respectively. However the maximum quality can be obtained from the mix design of 1:2:4 that is about 23.71N/mm^2 at the water to cement mix ratio of 0.5 at the age of 28 days (Apebo et al., 2013).

Reducing the amount of water in cement mortar mixes proportions was used to provide a higher thickness. However, reducing the amount of water can be at an adequate level and it should be enough for cement mortar hydrations process (Mansor et al., 2018).

So to keep the most useful of cement mortar mix it is important to provide and determine the appropriate mix design of the materials and also it's important to provide a good estimation of water to cement ratio and other material quantity (Mansor et al., 2018).

In case if the amount of water is maximum or high in mortar it is possible to reduce the amount of water by adding water reducers such as Type A, Type D water-reducer and Type F high range water reducer as per ASTM C 494/C 494M – 04. However, those high water reducer can be used to reduce the amount of water in cement mortar and provide good water to water-cement ratio. Reducing the amount of water in mortar can be used for stiff the mortar strength and also reduce segregation during placement of cement mortar. Water reducer is one of the most admixtures in cement mortar and used to utilize the properties of mortar and used to provide the most successful than normal without water reducer admixtures cement mortar. Water reducer can be used in a situation where the placement, transportations, mixing, and difficult climate conditions (Mansor et al., 2018).

Numerous essential attributes of cement have impacted the proportion of water to cement ratio utilized the blend. By decreasing the amount of measure of water, the cement glue becomes higher thickness, which results can be higher glue quality and henceforth the higher compressive strength quality and also reduce the penetrability of liquid. Diminishing the amount of water content in a mortar mix ought to be done in such a way in this way, that total mortar hydration may happen and adequate usefulness of cement is kept up for arrangement and solidification amid development (Mansor et al., 2018).

2.4.2 Mix proportion

Mix ingredients for different mixes can change the proportion of cement mortar. The mix proportion contains cement gradient, water to cement ratio, sand to cement, silica fume, the chemical composition of cement and other factors that can change the properties of cement mortar (Ahmed, Mallick, & Abul Hasan, 2016).

2.4.3 The impact of chemical admixture and water to cement ratio on compression strength of mortar

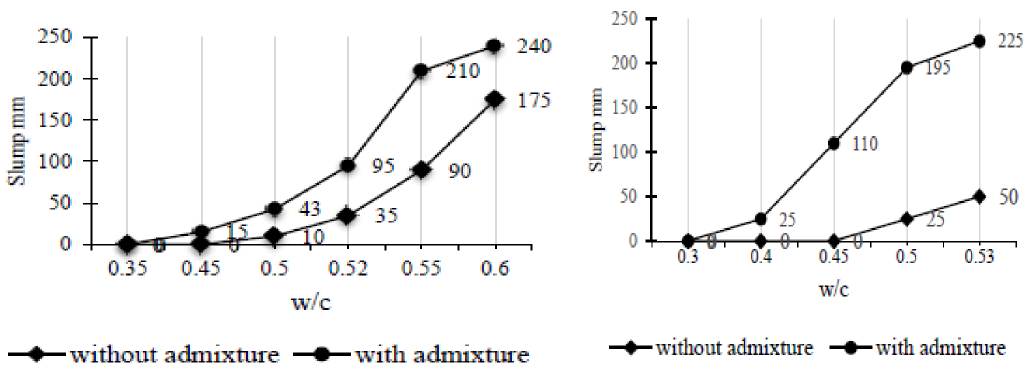
The chemical admixtures, curing days, sand to cement, water to cement ratio are some factors that affect the compression strength of cement mortar (B. Cubukcuoglu, 2018).

Table 2.12: Observations and results of using type a chemical admixture with various w/c ratio (Mansor et al., 2018)

Workability slump (mm)				Compressive strength (MPa)			
Admix %Cem	**w/c %**	**Without admix**	**With admix**	**Without admix**	**With admix**	**7 days**	**28 days**
1.5	0.3	Very low	Very low	0	0	7.5	11
	0.4	Very low	Low	0	25	31.4	47.6
	0.45	Very low	Medium	0	110	41.2	45.6
	0.5	Low	High segregation	25	195	37	45.7
	0.53	Low	High segregation	50	225	31.2	43
1.0	0.45	Very low	Low	0	15	25.6	31.7
	0.5	Very low	Low	10	45	26.8	30.7
	0.52	Low	Medium	35	95	24	33
	0.55	Medium	High segregation	90	210	29.7	39
	0.6	High	High segregation	175	240	27	38.5

Admix=Admixture Cem=cement w/c=water to cement ratio

Results demonstrated that for the 1.5% Type an admixture of the slump of 110 mm should be accomplished with the 0.45 w/c proportion contrasted with the zero slumps without the admixture. At similar rates, the age of 28 days compressive quality were recorded about 45.6 MPa. The higher compressive quality of the 47.6 MPa was accounted for 1.5% admixture and 0.4% water to cement ratio proportion with low usefulness. For the admixture of 1.0% and 0.45 water to cement ratio mix neither decent usefulness nor a decent compressive quality was accomplished, contrasting with the 1.5% admixture blend (Mansor et al., 2018).



a) 1.0% admixture

b)1.5% admixture

Figure 2.8: Slump with and without type A admixture (Mansor et al., 2018)

According to several studies shows the compressive strength of cement depending on various factors such as curing days, mix proportions, Aggregate size and shapes, and others. After concentrated every single exploratory datum the bond content in the blend is expanding, the proportion of barrel to block quality is in the event of 10mm total than 20mm total is additionally increasing. It was seen that the quality connection differs with the dimension of the superiority of cement. For higher value, the contrast between the quality of mortar shape and hollow is getting to be tight, for the higher quality, it is almost 1.00 (Akinpelu, Odeyemi, Olafusi, & Muhammed, 2019).

2.5 Compressive Strength of Cement Mortar at Different Ages

The figure 2.2 demonstrates the impact of the period of cement on the compressive quality. Since the synthetic response of the geopolymer gel is because of the generously quick polymerization process, the compressive quality does not change with the time of cement (Suraneni, Bran Anleu, & Flatt, 2016). This perception is as opposed to the notable conduct of OPC mortar, which experiences the hydration process and thus picks up quality after some time (Hardjito, et.al, 2007).

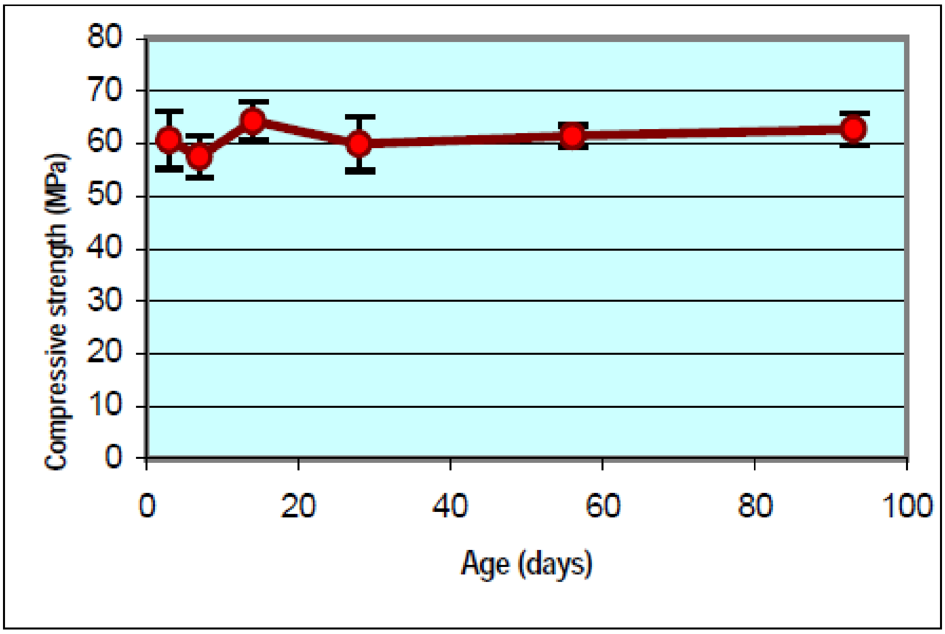


Figure 2.9: Compressive strength of the cement mortar at different ages (Hardjito et al., 2007)

2.6 The Effect of Curing Time on the Strength of Cement Mortar

The figure 2.3 demonstrates the impact of restoring time on compressive quality. Longer restoring time improves the polymerization procedure bringing about higher compressive quality (Hardjito et al., 2007).

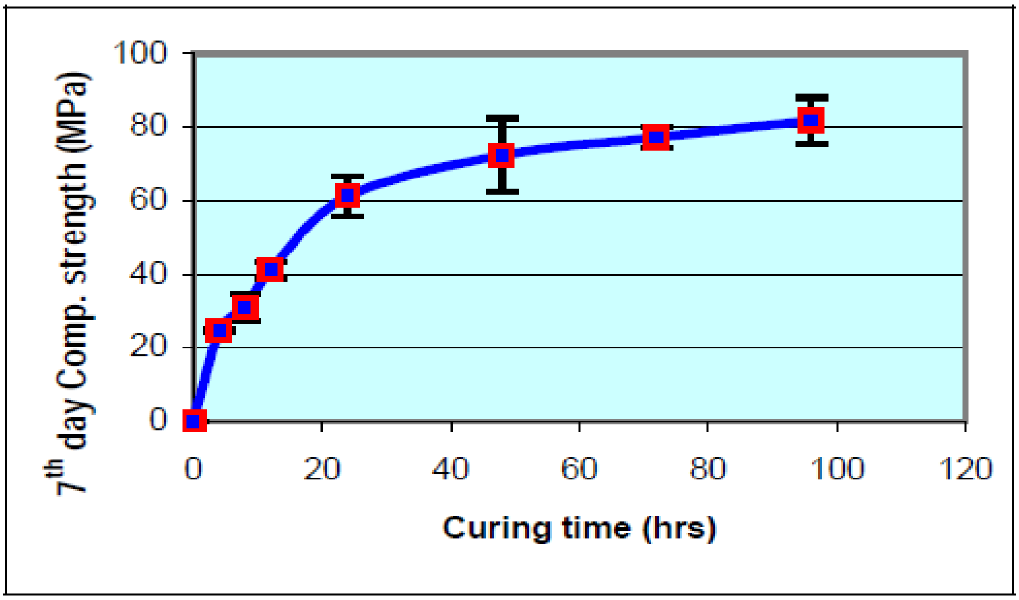


Figure 2.10 : The effect of curing time on cement mortar strength (Hardjito et al., 2007)

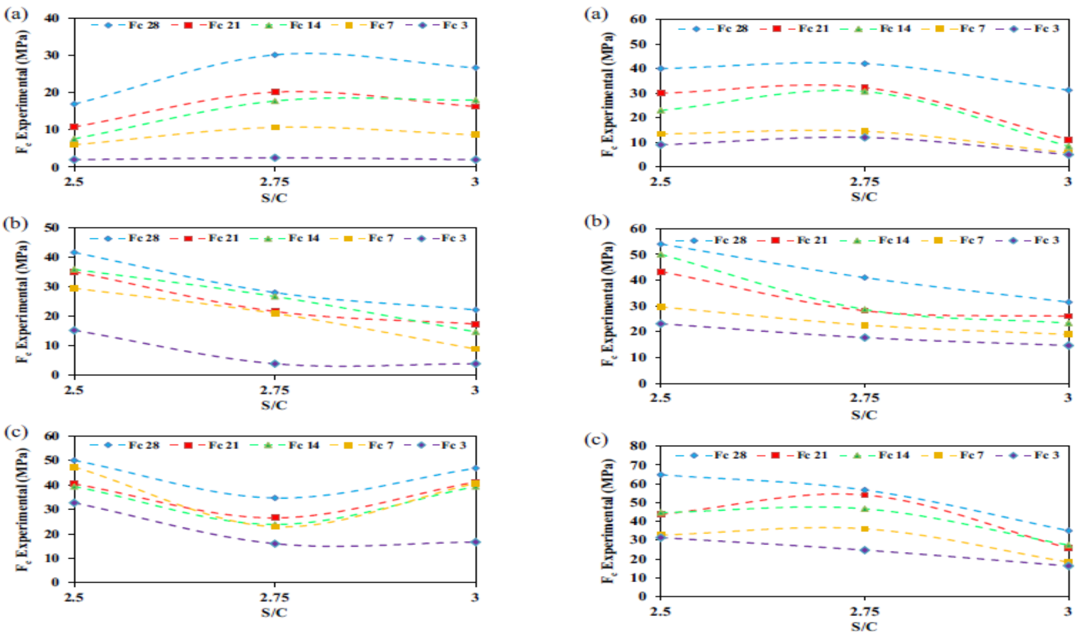
2.7 Experimental Done on Cement Mortar Compressive Strength

There are many experiments were conducted on the influences of cement compressive strength class on the cement mortar strength. Most of the experiments were done on the mix design, materials properties, and proportions of materials. As discussed in the section 2.2 the factors for productions of cement mortar includes the cement, water, sand (fine aggregate) and admixtures. The proportions that material can give different cement mortar strength depending on their quality and proportions. The cement strength contains 32.5, 42.5, 52.5 MPa water to cement ratio contains different ratios while sand to cement ratio as well. High water reducer admixtures can be also used to enhance the compressive strength by reducing the amount of water. Different experimental can be held on cement mortar at different combinations of those materials and discussed below (He, Chen, Hayatdavoudi, Sawant, & Lomas, 2019).

Regarding cement mortar compressive strength several experiments were conducted as follows:

Experiment 1

The laboratory experiment was done on the combination of several materials with different ages of the specimen and also on different proportions to evaluate the maximum mortar compressive strength. The materials used contain different cement type I, sand with different proportions with cement, water with different proportions. The experiment was checked on the age of three, seven, fourteen, twenty-one and twenty-eight days to obtain the maximum compressive strength. Accordingly, the maximum compressive strength obtained at the age of 28 days at the sand to cement ratio of 2.5 with cement strength class of 52.5MPa and water to cement ratio of 3 (Eskandari-Naddaf & Kazemi, 2017).



: **Figure 2.11:** Relation of compressive strength (Fc) and sand to cement(s/c) ratios for w/c 0.25,0.3 with cement strength classes of strength classes of 32.5 (a), 42.5 (b) and 52.5 (c) MPa (Eskandari-Naddaf & Kazemi, 2017)

Experiment 2

The mortar compressive strength can be affected by several factors such as material quality, mix proportions, chemical admixtures, and other factors. Among them, cement strength class is the factor affecting the compressive strength of mortar. According to the experimental done on the mortar with the mix of several materials such as cement type I, sand, superplasticizer, chemical admixtures, sodium chloride and water with different proportions with cement in 150x150x150mm cubic shows, the cement strength class is the main factor affecting the mortar strength. So the maximum mortar strength was obtained in the table 2.6 at 32.5MPa cement type, 5% of sodium chloride and 0.6 water to cement ratio (Eskandari, Gharouni, & Mahdi, 2016).

Table 2.13: Mix proportions of mortar (Eskandari et al., 2016)

Mix, No	**Cement type I**	**W/C**	**C**	**Fa/C**	**C/Fa+W**	**Compressive strength**		
						0%NaCl	5%NaCl	10%NaCl
1	325	0.3	700	3	0.303	46	58.75	51.56
2	325	0.3	700	2.5	0.357	45	53.43	49.68
3	325	0.4	700	3	0.294	42	54.37	47.81
4	325	0.4	700	2.5	0.344	40	53.75	47.18
5	325	0.6	700	3	0.278	35	79.67	45.12
6	325	0.6	700	2.5	0.322	24	66.56	42.62
7	425	0.3	700	3	0.303	73	57.4	55.13
8	425	0.3	700	2.5	0.357	72	56.1	54.36
9	425	0.4	700	3	0.294	62	55.4	52.9

Table 2.6 continued

Mix, No	Cement type I	W/C	C	Fa/C	C/Fa+W	Compressive strength		
						0%NaCl	5%NaCl	10%NaCl
10	425	0.4	700	2.5	0.344	60	53.95	52.4
11	425	0.6	700	3	0.278	49	53.3	51.9
12	425	0.6	700	2.5	0.322	45	52.51	50.7

Experiment 3

According to the experimental conceded on the mortar strength with the mixtures of several materials such as cement type I, sand that can pass through the sieve of 4.75mm, superplasticizer, and high range water reducers and with different ratio of water to cement. The cement strength class plays a great role in the mortar strength. The experimental done on molded 150x150 x150mm and stay in the specimen for 28 days.

Table 2.14: Mix proportions of ferrocement mortar (Eskandari et al., 2016)

Mix ,No	CEM	W/C	C	Fa/c	C/Fa+W		Compressive strength		
						HRWR	Spec1	Spec.2	Spec.3
1	325	0.3	700	3	0.303	6	44.5	46.3	47.1
2	325	0.3	700	2.5	0.357	6	41.2	45.5	48.5
3	325	0.4	700	3	0.294	4	38	44.2	43.8
4	325	0.4	700	2.5	0.344	4	38.4	40.8	40.8
5	325	0.6	700	3	0.278	0	31.2	36	37.8
6	325	0.6	700	2.5	0.322	0	21.5	24	26.5
7	425	0.3	700	3	0.303	6	68.4	70.1	80.5
8	425	0.3	700	2.5	0.357	6	69	72.9	74.1
9	425	0.4	700	3	0.294	4	59.3	61	65.7
10	425	0.4	700	2.5	0.344	4	56	60.7	63.3
11	425	0.6	700	3	0.278	0	46.3	48.1	52.6
12	425	0.6	700	2.5	0.322	0	41.8	44.7	48.5

2.8 Artificial Neural Network (ANN)

The Artificial neural system (ANN) can be turned out to be an amazing asset in displaying the informational collections and giving headings to information examination. The systems can be envisioned the thick parallel relationship between the neurons. The neurons speak to the procedure parameters amid the investigations. The procedure inputs add to the yield in various measures (Sahoo & Mahapatra, 2018).

2.8.1 The ANN training procedure

The ANN Model advancement for the compressive quality of cement beneath sulfate presentation was done allowing for water relieving age about days, the sulfate introduction several periods maybe (in months) and concrete % in bond fine aggregate FA blend as hubs in information layer. However, These in EXCEL are the standardized information input taken amid the test. The standardization has been finished utilizing the equation (Sahoo & Mahapatra, 2018).

ANN and Mat lab measurable programming was utilized to examine and explore the impact of the inputs of cement, water concrete proportion, POFA and the superplasticizer (SP) on the solidified properties compressive strength at the age of 7, 28 and 90 days (Ofuyatan & Edeki, 2018)

The ANN can be used in civil engineering to analysis many complex mathematical problems easily. By using the ANN it is possible to determine the compression strength of concrete by testing at different material properties with different ratios and also possible to determine the relationship between each test result and also used to compute the maximum compression strength of cement at appropriate mix ratio. According to the previous study, ANN can perform the weight ages and inclinations processed as demonstrate towards the predicting of the compressive quality of cement at differed fly slag structure, water restoring days and sulfate introduction period. The trial information and anticipated information have appeared in the figure 2.5 for various solid examples at water relieving at 28 days. The figure portrays closeness among the test and anticipated information. The figure below presents relapse and approval plots building up closeness among trial and model anticipated consequences of 28 days with water restored mortar (Sahoo & Mahapatra, 2018).

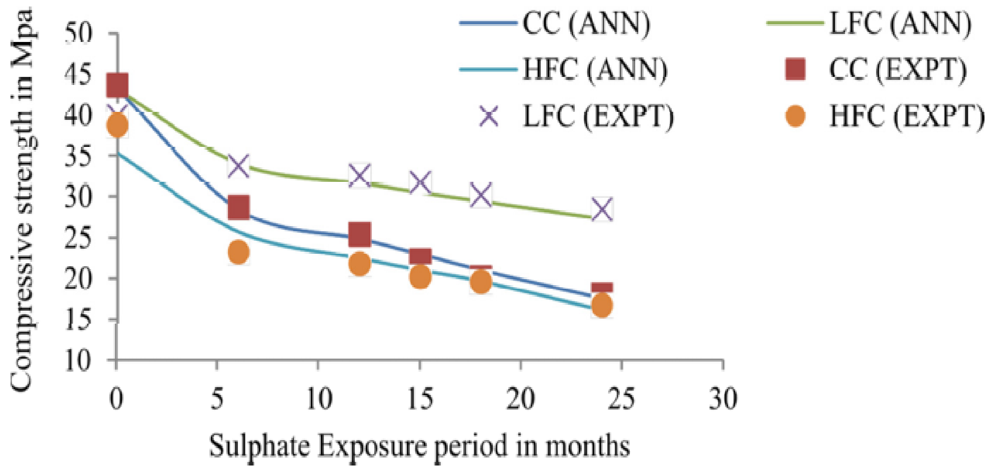


Figure 2.12: The experimental and the ANN Predicted Fc for the mortar specimen water Cured for 28 days.

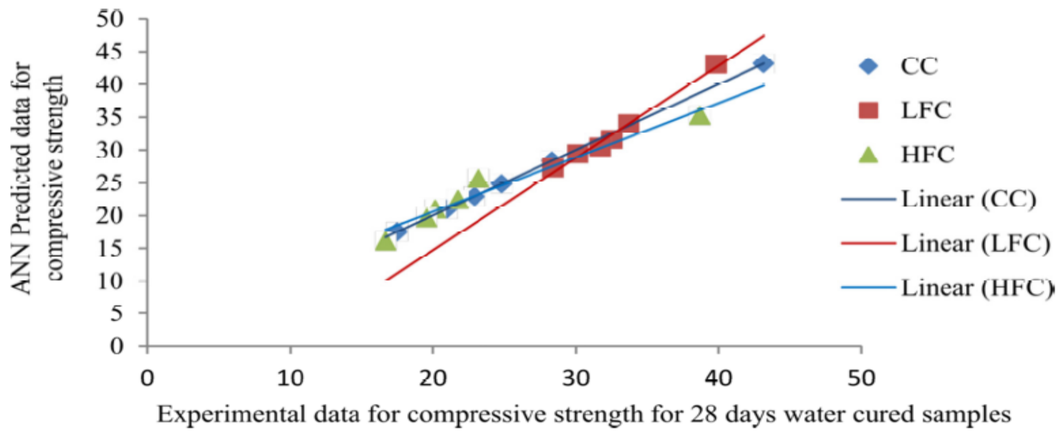


Figure 2.13: The experimental data and ANN predicted compressive strength for 28 days

2.9 The ANN Model and Experiments Results Output Compatibility

According to studies shows the correlation of the experimental results as well as predicted consequences of several layers feed-forwarded neural system fruitful results were obtained. Accordingly the experimental was done on the mortar compressive strength by mixing several materials then laboratory test was done on several days to obtain maximum compressive strength with different material proportions. Similarly, the ANN prediction was also done on the same data obtained from experiments the result obtained was compatible or similar to that of the experimental (Eskandari-Naddaf & Kazemi, 2017).

According to experimental 1 explained the two predictions were done that is ANN1 and ANN2.ANN1 considering the cement compressive strength class with other factors input and ANN2 without considering the cement compressive strength. However, the result of ANN can depend on the accuracy of the data. The input data was the sand to cement (s/c), water to cement (w/c), age of the specimen, cement compressive strength, and High water reducer (HRWR) and the output of mortar compressive strength. If the values of correlation train, validation test, total data coefficient are closed to each other there is less error and more reliable.

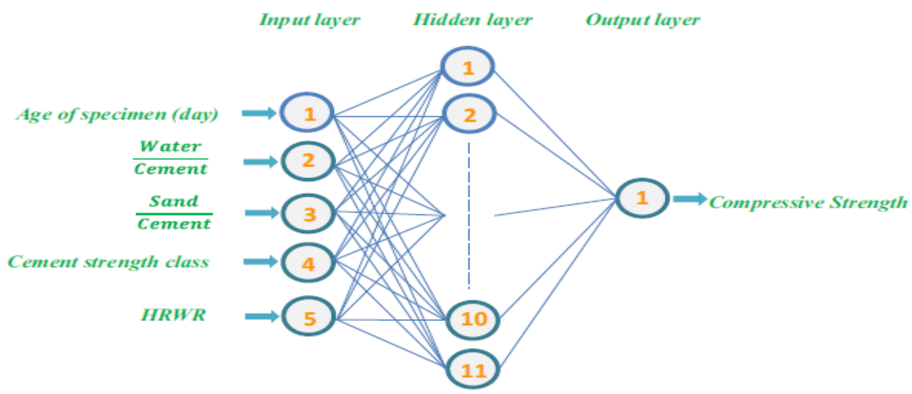


Figure 2.14: ANN-I architecture for prediction the Fc of cement mortar

The execution in predicting the compressive quality of the preparation blend is agreeable with $R^2 = 0.94$ (Eskandari-Naddaf & Kazemi, 2017).

2.10 Conclusions

Compressive strength is the tendency that the material resists the compression failure under the impact of compression forces. Compressive strength can be the most parameter that determines the performance of material strength. Mortar can be made from the combination of several raw materials such as cement, sand (fine aggregate), admixture, water, and some chemicals.

The cement strength class is the main factors influence the compressive strength of mortar. Several factors affect the properties and strength of mortar such as sand to cement ratio, mixing proportion ratio, water to cement ration, quality of water, and other factors. Cement mortar can be composite materials contain cement, sand, water, admixture, and chemicals. The mix design of those materials can affects the properties and strength of the concrete**.**

There several types of cement materials depending on their chemical, physical components such as pozzolana Portland cement, ordinary Portland cement, and others. Ordinary Portland cement (OPC) can be manufactured from cementations materials such as fly ash, silica fume (SF), ground granulated blast furnace slag (GGBFS), whereas, pozzolana Portland cement can be produced from several raw materials and have different classes depending on their chemical composition such as Al_2O_3, MgO, SiO_2, Fe_2O_3, SO_3, K_2O, LOI, CaO, Na_2O, F.CaO, C3S, C3A). Depend on the percentage of their production their different categories of cement strength such as C32.5, C42.5, C52.5, and other cement class. Those cement class can have the compression strength of 32.5, 42.5, and 52.5 Mpa respectively. The chemical admixtures, curing days and water to cement ratio are the main factors influence the compression strength of concrete.

The Artificial neural system (ANN) has turned out to be an amazing asset in displaying the informational collections and giving headings to information examination. ANN and Mat lab measurable programming was utilized to examine and explore the impact of the parameters such as cement, water to cement proportion, and superplasticizer (SP) on the solidified properties and compressive strength quality at the age of 7, 28 and 90 days.

The compression strength correlation of experimental and ANN predicted consequences of the different mix proportions within the age of 3, 7, 14, 21, and 28 days compressive strength. According to the showed the experimental and ANN prediction was almost the same approach results of cement mortar compressive strength.

CHAPTER 3

METHODOLOGY

3.1 Introduction

A research methodology is a technique used to choose, identify, process and analyze a specific topic. This research was focused on the ANN prediction of unconfined compressive strength of cement mortar, the influence of cement type I. The main objective of this research was to evaluate the impact of cement type I on the unconfined compressive stress of cement mortar. However, different types of aspects and methods were conducted during my research.

The summary of the research process steps was tabulated as in figure 3.1

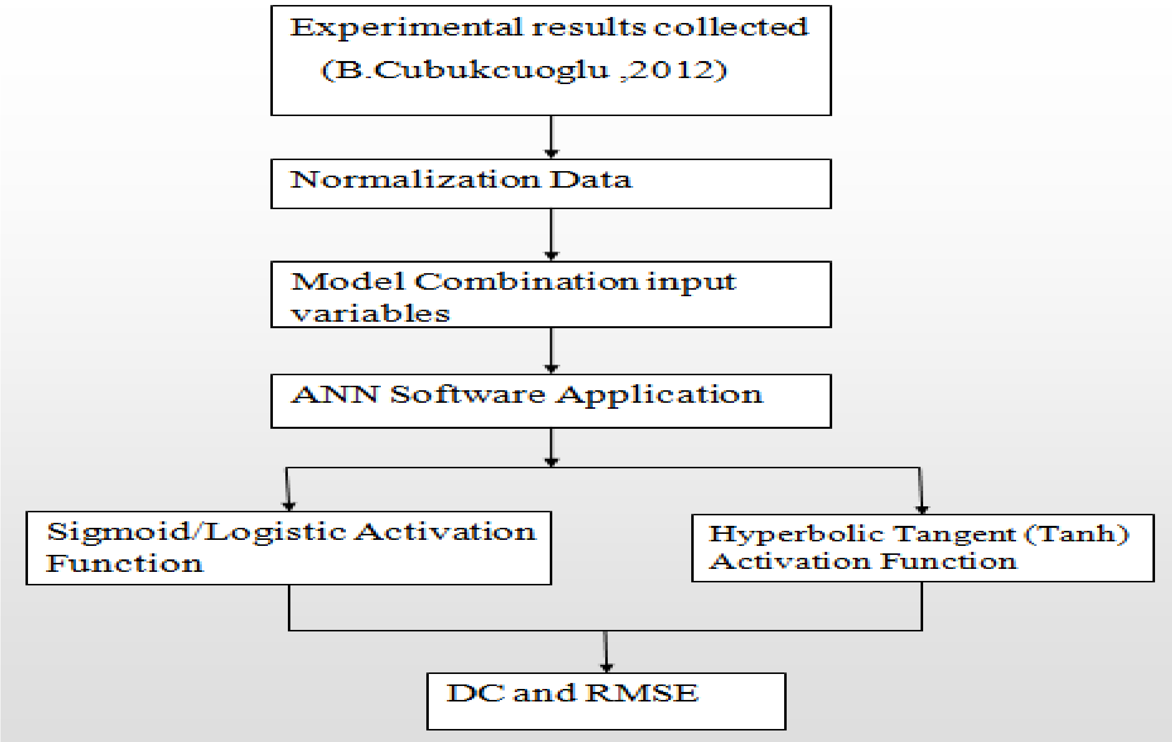


Figure 3.1: Research process steps

3.2 Research Approach

Research is a systematic process and diligent, active, revise the fact behaviour, theories, events, a particular application and interpret with the help of laws, facts or theories. However, the scope of the research is to produce new knowledge.

The research principles contain main different forms

1. Constructive research:-for any problem new solution can be developed
2. Explanatory research: is testing the theories and hypothesis that explain how, when, and why event engage as it does
3. Empirical research: empirical evidence on the possibility of an existing resolution to a problem can be provided

In this study, the main purpose is to evaluate the result of the cement type I on the unconfined compressive strength. To evaluate these: experimental results and ANN software analysis can be conducted. The ANN modeling was also conducted to compute the compressive strength gain from the laboratory and finally, the comparison was made between the investigational results and ANN modeling was conducted.

The empirical method is the type of research method which is used to answer particular problems depends on the collected data. However, the empirical method is mainly used in academic research and useful for industrial researches. Empirical theory starts with the previous theory, in which the researcher develops to predict and explain what will happen in the real world. The research to be empirically tested the research issue should be transformed into a theoretical model, consisting of a theoretical construct causal relationship and the observed variables. Hence the idea of research is to testes the theory and possibly process.

The theoretical model generally developed based on the investigation of the literature review. The theoretical model is the basis for both collecting and analyzing data and can be modified as a result of the researches. The first step made during the research was to have an overall idea and pictures of the research areas. The overall idea about the research is to evaluate the best prediction of ANN on mortar’s unconfined compressive strength with an inappropriate mix of material at a suitable proportion and to predict the ANN modeling with the experimental results.

3.3 Research Method

The research method used for collecting, processing, and analysis of the gathered information can be either a qualitative or quantitative method. The research is focused on the impact of cement type I on mortar's unconfined compressive strength. However, the research is to answer the following question.

- To evaluate the prediction of the ANN model on the impact of cement type I on mortar's unconfined compressive.
- To assess the ANN model accurately predict unconfined compressive strength.
- To compare the ANN model with experimental results shows good agreement.

The following step should be carried out to attempt the research question

1. Literature review
2. Reviewed experimental output and ANN software Application
3. ANN model accurately predict the unconfined compressive strength of mortar
4 Conclusions

The literature review part was discussed in detail in chapter two to supports the idea of this research regarding the ANN prediction of cement type I on unconfined compression strength. The experimental results were tabulated in Appendix1a and the overall experimental results were gain from (B. Cubukcuoglu, 2012). By using experimental data the ANN were conducted to predict the unconfined compressive strength by using different combinations. After the trial of different models and combination inputs variables, the best RMSE and DC were selected. Finally based on the gained result from ANN prediction the conclusion was developed.

3.4 Artificial Neural Network

ANN is software that analyzes the complex data to relate all the data and output the results between them. ANN has different data that is input data, hidden neuron, and output. The input data can be the data given to them as input to the ANN and the output is the final results of the combination among the inputs. The correlation among the input and output can be nonlinear ration ship data between both input and output there is the hidden neuron. However, all data can be interrelated to each other and it used to model among the non-related input parameters. The relation among all the input can record and arrange in feed-forward networks. In this study, the feed-forward network was used to model the output.

3.5 Data Processing and Analyses

After all, the proportion of mix of materials laboratory test was done at different age of 7, 14, 21, and 28 days respectively. Based on the result gained from laboratory test the ANN modeling was conducted and finally, the comparison between experimental and ANN were conducted. Finally, based on both ANN and experimental result the conclusion will be developed.

There are two categories of ANN connection pattern such as feed forwarded neural network and recurrent. The feed forwarded neural network (FFNN) is the best function that provides the correct output of the network every pattern. However, FFNN is adjusted to the correct output that containing inputs, hidden and output which contain multi-layer preceptors. Feed-forward has three main functions such as hard linear, sigmoid, and hyperbolic tangent. Sigmoid feed-forward is the main and best type of FFNN which used to decrease the error and the most effective types of ANN prediction. In this research, the sigmoid feed forwarded types were selected to keep the precision of the output and prediction of the mortar compressive strength.

3.6 Steps to Modeling an ANN

To predict the ANN on the impact of cement type I on unconfined compressive strength mortar, several procedures were conducted

- Input parameter: are tabulated in a table 3.1, there are nine different material combinations with one output. The output is the unconfined compressive strength. However, a different model of input materials was conducted to evaluate the best predictions of ANN.

Table 3.1: Input and output variables used in the ANN predictions

Input variables	Output variables
Day, CEM, Lime, MgO, PFA, slag, waste addition, W/S, BD	UCS (MPa) unconfined Compressive strength of cement mortar

- Data gathering process: was done by considering the quality and quantity of data. However, the accuracy of data is used to evaluate the exact prediction value of ANN so the data should be safe quantity means it should be economical.
- Data pre-processing: The data pre-processing means that the data should be normalized which mean that the value of all input and output should be between -1 and 1
- Data normalization

The input and output transformation can be normalized by using the equations as follows.

$$X=(X-X_{min})/(X_{max}-X_{min}) \tag{3.1}$$

Where X_{min} is the minimum value of the all correspondent of the input

X_{max} is the maximum value of the all correspondent of the output

X is the ith after being normalized variable

The input data should be normalized and should be between 0 and 1 and also the ANN output should be between 0 and 1. The normalized data were tabulated in appendix 1a.

3.6.1 ANN activation function

ANN Activation function is a computational network, the activations functions of nodes define the output of that node given an input or set of input. There are several types of ANN activation functions among there four more common types of ANN activations such as:

- Sigmoid or logistic ANN activation functions
- Hyperbolic tangent (Tanh) ANN activation functions
- Relu ANN activation functions
- ArcTan ANN activation functions

1. Sigmoid or logistic ANN activation functions

Sigmoid or logistic is the most sophisticated, popular and common type of AAN activation function. The output is between 0 and 1 if the result is zero-mean the function is not firing, and if the output is 1 mean the output is fully saturated fired. However, the sigmoid output is not zero centered.

The mathematical notation of Sigmoid functions is 0< output <1

$F(x) = 1/ (1-e^{-z})$ (3.2)

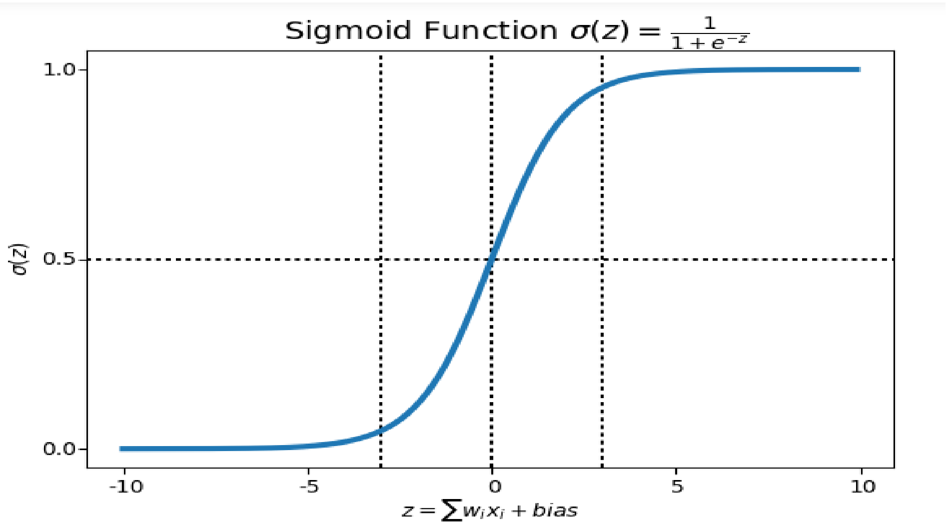


Figure 3.2: Sigmoid feed-forwarded neural network output activation function

$Z = \Sigma_{i=1}^{m} w_i x_i + bias$ (3.3)

Input * weight + bias =ANN Activation

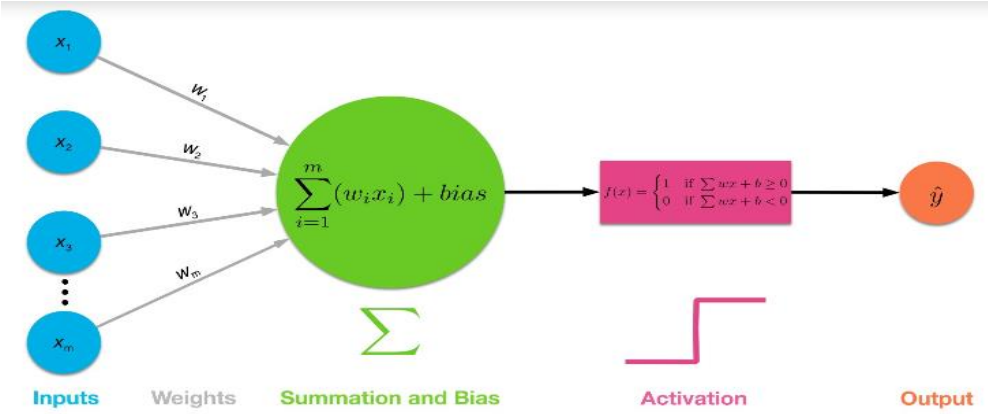


Figure 3.3: procedure of perception of ANN modelling

2. Hyperbolic tangent (Tanh) ANN activation functions

Hyperbolic tangent (Tanh) is also one of the most commonly used types of ANN activations. The range of output can be between -1 and 1.

Tanh ANN activation function has the mathematical notation of

$$F(x) = \frac{2}{1+e^{\wedge}(-2x)} - 1 \tag{3.4}$$

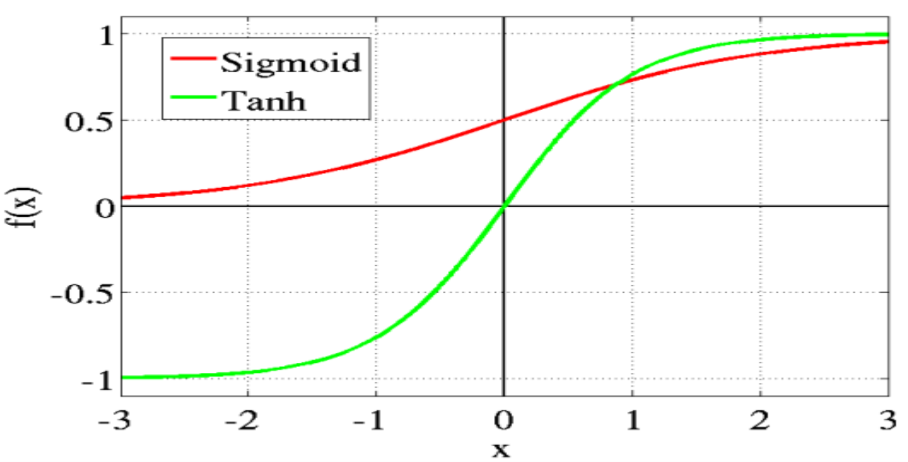


Figure 3.4: Tanh and sigmoid ANN activation function graph

Both Hyperbolic tangent (Tanh) and sigmoid ANN function are used feed forwarded neural networks

3.7 Determination Coefficient (DC) and Root Mean Square Error (RMSE)

In the Construction of the training and verification model, the model should have acceptable DC and RMSE with the verification.

During ANN trial both DC and RMSE analyzed as follows

- The value of training, validation, and test data was used 70% training, 30% test to evaluate the DC and RMSE.
- The DC and RMSE can be determined by using the formula:

$$R^2 = 1 - \frac{\sum(\hat{y}_i - y_i)^2}{\sum(y_i - \bar{y})^2} \quad (3.5)$$

$$RMSE = \sqrt{\sum(\hat{y}_i - y_i)^2} \quad (3.6)$$

Where R^2: coefficient of determination

$\hat{y}$: *predicted y values*

$\bar{y}$: *avg observed y values*

y: *observed y values*

3.8 Multi Linear Regression Mathematical Development

A multi linear regression model is mathematical modeling to express a linear correlation among one or more dependent and independent variables. The independent variables were used to calculate the dependent variables.

The Multi linear regression model is given by the formula of:

$$Y=b_o+b_1x_1+b_2x_2+b_3x_3+\ldots+b_ix_i \quad (3.7)$$

Where: xi =value of the i_{th} predictors

b_o= constant of regression

b_i=the coefficient of the i^{th} predictor

CHAPTER 4
RESULTS AND DISCUSSIONS

4.1 Introduction

In this section to compute the impact of cement type I on cement mortar's strength, sigmoid activation neural network with many models and trials of the neural network were mainly conducted. Hyperbolic tangent (Tanh) function prediction of ANN modeling was performed to compare with experimental and sigmoid results. The experimental results can be gained from (B. Cubukcuoglu, 2012) as tabulated in appendix 1a. The experiment was done by using nine various materials were mixed to get the upper limit mortar's strength. The materials exploited in experimental are cement type I, lime, magnesium oxide, pulverized fly ash, slag, waste addition, sand and bulk density were conducted on this experiment to assess the highest mortar's strength.

4.2 Pre data Processing and ANN Preparation

In this research, the sigmoid FFNN activation function was used. The total number of input contains nine parameters such as Day, cement type I, magnesium oxide (MgO), pulverized fly ash, slag, lime, bulk density (BD), water/solid ratio, waste addition ratio were used and the output of strength. The aim of ANN anticipation is can be to find out the impact of different input variables combination on the compressive strength.

However, it is essential to check by considering a different blend of input variables to evaluate which factor of input is very important for mortar's strength and also to assess which input variables are no so important and also to evaluate factors not impact the cement mortar's strength. Accordingly, about fourteen models and thirty ANN predictions with more than 300 neuron prediction trials with determination (DC), with different neural networks and also above 300 different outputs of compressive strength with a graph of validation, training, total data, and test were conducted.

The detail combination of different input variables with a model of cement mortar was revealed in table 4.1. However, the main idea of the category the input variables in different combination or model are to evaluate the influences of each material on the output to evaluate the economic viability of material combinations. As the model tabulated in table 4.1 model 1 contains the two combination materials, model 2 contains three material combinations and so on. The main purpose was to weigh up the ANN prediction output and to evaluate the impact of each material on output.

Table 4.1: Model combination of different input variables and ANN number format

Model no	**Input Variables**	**Explanation**
Model 1	Day , CEM	Two materials combinations
	Day ,Lime	
	Day, MgO	
	Day, PFA	
	Day, Slag	
	Day, BD	
Model 2	Day ,Lime, CEM	Three materials combinations
	Day, MgO, CEM	
	Day, PFA, CEM	
	Day, slag, CEM	
	Day, BD, CEM	
Model 3	Day, MgO, CEM, PFA	Four materials combinations
	Days, BD, Wa, W/s	

Table 4.1 continued

Model no	Input Variables	Explanation
	Day, Slag, CEM, PFA	
	Day, BD, CEM, PFA	
Model 4	Day, MgO, CEM, PFA, slag	Five materials combinations
	Day, BD, CEM,PFA, slag	
Model 5	Day, MgO, CEM, PFA, slag, BD	Six materials combinations
Model 6	Day , MgO, PAF, S, BD, w/s, Wa, L	CEM missing
Model 7	Day ,CEM, MgO, PAF, S, BD, w/s, Wa, L	All materials combinations
Model 8	Day, CEM ,L, MgO, PFA, Slag, Wa, W/s	BD missing
Model 9	Day ,CEM, MgO, PAF, slag, BD, W/s, lime	Wa missing
Model 10	Day ,CEM, MgO, PAF, BD, W/s, Wa, lime	Slag missing
Model 11	Day ,CEM, MgO, PAF, slag, BD, Wa, lime	w/s missing
Model 12	Day ,CEM, MgO, slag, BD, W/s, Wa, lime	PFA missing
`model 13	Day ,CEM, MgO, PAF, slag, BD, w/s, Wa	Lime missing
Model 14	CEM, MgO, PAF, slag, BD, w/s, wa, lime	Days missing

Where: D=day, C=cement type I, Mg=magnesium oxides, Bd=bulk density,
Pfa= pulverized fly ash, S=slag, w/s=water to solid ratio, Wa=waste addition, and L=lime.

These researches were conducted by considering the cement type I and without considering the cement type I. However, due to using different input parameters by missing several variables different models were developed such as ANN1, ANN2, ANN3 and so on by changing the input data. Depending on this different modeling different outputs were conducted. The exact prediction ANN value can be evaluated from the ANN output. The precision of output contingent on the precision of the input parameters. So the input data should be accurate to evaluate the prediction of ANN with the experimental results. The input variable such as Day, cement type I, magnesium oxide (MgO), pulverized fly ash (PFA), slag, lime, bulk density(BD), water/solid ratio, waste addition ratio parameter should be accurate to obtain the compressive strength with the ANN predictions.

70% of input was the training whereas 30% input can be testing the ANN data model arrangement and the data can be selected randomly. The overall input data are nine parameters. The hidden neuron was tested between the ranges start from 2 to 20 hidden neurons for all combination data because the neural network number little more than input variables and the value of training, validation, overall data, and test R-value should be related to each other. In ANN prediction the ANN 9-n-1 or ANN I where n is hidden neuron network, nine input variables, and one output. During ANN prediction if the correlation value is related to one and if the testing, validations, and training are nearer to 1 and the error is minimum the prediction is more accurate (Eskandari-Naddaf & Kazemi, 2017).

4.3 ANN Input, Hidden, and Output Layer Modeling

The experiments were conducted on nine different construction materials such as day, cement type I, magnesium oxide (MgO), pulverized fly ash, slag, lime, bulk density, water/solid ratio, waste addition ratio. The combination of these materials can give various compressive strength and each input variable can affect the result of the mortar's compressive strength. However, by combining these all materials various factors affect the mortar's compressive strength such as day of the specimen, cement type I, the proportion of water, the amount proportion of all inputs and other factors that can impact the strength of mortar. So the ANN can be exploited to predict impact or affect each material on the final mortar's compressive strength. As mentioned in table 4.1 model one was evaluated by considering the two input variables without considering the other inputs and the final compressive strength output ANN prediction was discussed below in detail. ANN I was done by combining all nine input construction materials and also many different hidden layers for all neural numbers there are only one output layers. Figure 4.1 contains the ANN I input layer, hidden layers and output layers modeling of the mortar's compressive strength.

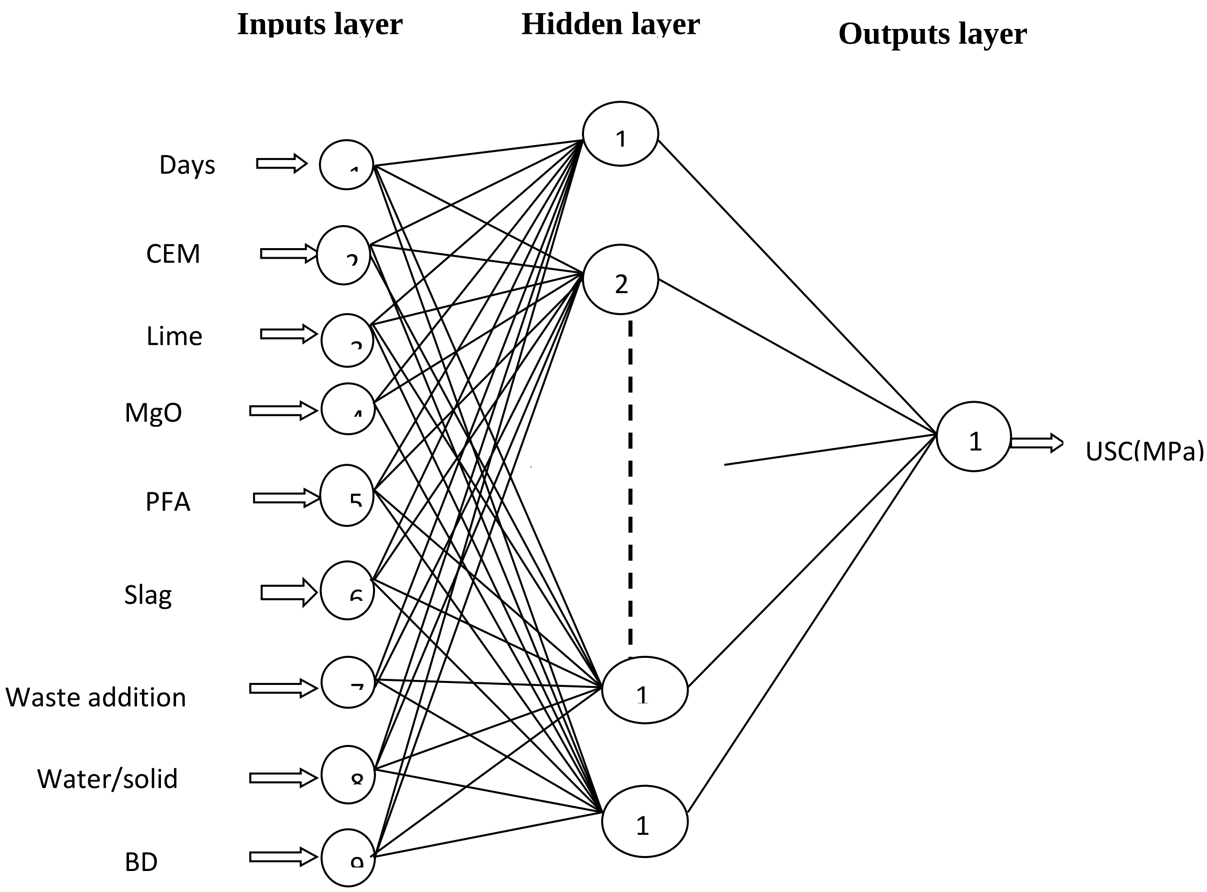


Figure 4.1: ANN I prediction model for cement mortar’s compressive strength

4.4 Evaluation of Experimental Output and ANN Prediction

The cement mortar’s compressive strength was conducted both experimentally and ANN prediction output. Different combinations of input variables and output results were done for each combination model in table 4.1. For each input variable the ANN prediction output, DC, RMSE, and the training, validation, test and total data was done by changing the neural network number and the detailed result for each data was conducted in detail refer the appendix.

Table 4.2: The maximum DC and minimum RMSE values from all models

Model	**Input**	**Structure**	**70% of Data**		**30% of Data**	
			DC	**RMSE**	**DC**	**RMSE**
Model 1	DC	2-2-1	0.386683	1.74335	0.44238	1.25904
	D,L	2-14-1	0.24715	1.93150	0.29320	1.41748
	D ,Mg	2-20-1	0.06917	2.14771	0.88606	2.48190
	D, Pf	2-10-1	0.09074	2.12268	0.2740	1.43660
	D,S	2-6-1	0.34231	1.80531	0.38206	1.32538
	D, Bd	2-10-1	0.18173	2.01368	0.18509	1.52203
Model 2	D,L,C	3-5-1	0.601507	1.40525	0.36298	1.34568
	D, Mg, C	3-2-1	0.400970	1.72293	0.53087	1.15481
	D, Pf, C	3-2-1	0.404371	1.71803	0.41524	1.28931
	D,S, C	3-12-1	0.664571	1.28927	0.55174	1.12883
	D, Bd, C	3-5-1	0.511988	1.555101	0.53464	1.15017
Model3	D,Mg,C,Pf	4-20-1	0.441466	1.66367	0.40389	1.30176

Table 4.2 continued

Model	**Input**	**Structure**	**70% of Data**		**30% of Data**	
			DC	**RMSE**	**DC**	**RMSE**
	D,S, C, Pf	4-5-1	0.765704	1.07752	0.76146	0.82347

	D,Bd,C,Pf	4-4-1	0.85692	0.84201	0.77193	0.80519
Model 4	D, Mg,C, Pf ,S	5-10-1	0.50990	1.55849	0.62442	1.03322
	D, Bd, C, Pf, S	5-4-1	0.92324	0.616729	0.80504	0.74444
Model 5	D, Mg, C, Pf, S, Bd	5-20-1	0.924103	0.613274	0.88599	0.569278
Model 6	D,L,MgO,Pf,S, Wa,Ws,Bd	8-18-1	0.963292	0.287742	0.86748	0.613767
Model 7	**D,C,L, Mg, Pf, S,Wa, Ws, Bd**	**9-18-1**	**0.976146**	**0.343808**	**0.91594**	**0.48881**
Model 8	D,C,L,Mg,PfaS ,Wa,Ws	8-8-1	0.951326	0.491123	0.8362	0.4256
Model 9	D,C,L,Mg,PfaS ,Bd,Ws	8-4-1	0.910540	0.6658	0.89584	0.54414
Model 10	D,C,L,Mg,PfaB d,Ws,Wa	8-4-1	0.8823	0.76358	0.7805	0.7897
Model 11	D,C,L,Mg,PfaB d,Wa,S	8-4-1	0.94588	0.51785	0.757954	0.82950
Model 12	D,C,L,Mg,Bd Wa,S,Ws	8-10-1	0.8660	0.41023	0.8728	0.6012

Table 4.2 continued

Model	**Input**	**Structure**	**70% of Data**		**30% of Data**	
			DC	**RMSE**	**DC**	**RMSE**

Model 13	C,L,Bd,Wa,SWs ,Pfa ,Mg	8-6-1	0.8759	0.78403	0.77527	0.7992
Model 14	D,C,Mg,Bd,Wa ,S,Ws,Pfa	8-2-1	0.8660	0.81486	0.71846	0.8946
Model 15	D, BD, Wa, w/s	4-12-1	0.7236	1.16752	0.67163	1.3863

Where: D=day, C=cement type I, Mg=magnesium oxides, Bd=bulk density, Pfa= pulverized fly ash, S=sand, W/s=water to solid ratio, Wa=waste addition, and L=lime.

Table 4.2 the maximum determination coefficient and RMSE were conducted for each input variable many different neural networks was done and among them, the best maximum approach DC and minimum RMSE were selected comparatively.

However, DC and RMSE were done by using 70% of training and 30% of the test. From table 4.2 for model 1 day and cement type, I (D, C) as input variables, the comparatively maximum determination coefficient, and minimum RMSE can be gain from the trail at the structure (2-2-1) that is 2 input (D, C), 2 neural networks, and 1 output. For these input variables, the DC and RMSE values can be 0.3866 and 1.74335 respectively for 70% training and for 30% test the value of DC and RMSE can be 0.4413 and 1.259 respectively. However, to find out the best prediction of ANN results the determination coefficient (DC) should be the approach to 1 and the RMSE can behave minimum value. So for f(D, C), input variables the DC value is very low and RMSE value is very high from this result we can understand that only specimen day and cement type I (D, C) cannot be enough for compressive its below the expected value cannot be considered.

Similarly, for all model 1 input available such as (D, L) the maximum DC and RMSE can be at structures of 2 input, 14 networks, and 1 output (2-14-1) and DC value is very low and RMSE value can be very high. Similarly, the DC and RMSE values were calculated for model 1 and the 70 % training and30% test were conducted in the table 4.2. The results of all model 1 were below the expected value it means we need more input variable data.

The other input variable can be done on model 2 with three different input variables such as f(D,C,L), f(D, MgO, C), f(D, Pf, C), f(D,S,C), f(D, Db, C) the determination coefficient and the RMSE value was conducted for all input variables, for each variable several trails were done by changing the values of network number among them the best prediction and Maximum DC and minimum RMSE were conducted in a table below 4.2. Accordingly, for model 2 input f(D, C, L) the structure 3-5-1 which is three input, 5 networks, and 1 output is comparatively the best prediction among the rest network. The best 70% training value of DC and RMSE is 0.6015 and 1.40525 respectively and for 30% test the DC and RMSE value was 0.3629 and 1.34568 respectively this shows that the model 2 is better than model 1 and the quantity of input is still below the required that is very low DC and maximum RMSE value and this perdition shows more input data should be needed to match with the experimental results. Similarly, all model 2, DC and RMSE value is not compatible with the cement mortar's compressive strength. The comparative maximum DC and lower RMSE were computed in Table 4.2 below and the detail of all networks can be computed in the appendix.

Model 3 was conducted on a combination of four different variables in table 4.2 the maximum value DC and lower value RMSE was calculated. Model 3 is better than model 1 and model 2 because of more important input variables for cement mortar's compressive strength. Model 3 contains function f(D, Mg, C, Pf), f(D, S, C, Pf), and f(D, Db, C, Pf) for each input variable material many networks were conducted with DC and RMSE among the for each combination the maximum DC and minimum RMSE was calculated in table 4.2 for 70% training and 30% test. Hence for each combination different input variables were calculated from all model 3 combination DC and RMSE result the f (D, Bd, C, Pf) is comparatively better values that are 70% DC of 0.8569 and RMSE 70% of 0.8420 and 30% test DC value of 0.7719 and 30% RMSE of 0.8051 this shows that those variable are more important than the other variable and also that variable can impact on the mortar's compressive strength. As the DC values approach to 1 the values of RMSE becomes minimum and are more reliable.

Model 4 contains the function input variables f (D, Mg, C, Pf, S) and f (D, Bd, C, Pf, S) the highest value of DC and RMSE can be conducted in table 4.2. For the f (D, Mg, C, Pf, S) the 70% of training DC were 0.5099 and RMSE 1.5584 and the 30% test DC and RMSE can be 0.6244 and 1.0332 respectively. For input variables of (D, Bd, C, Pf, S) the DC and RMSE values for training 70% are 0.9232 and 0.6167 respectively and for 30% of DC and RMSE values are 0.8859 and 0.5962 respectively. However when we compare the results of the f (D, Mg, C, Pf, S) and f (D, Bd, C, Pf, S) ,the f (D, Bd, C, Pf, S) DC and RMSE values are better than the (D, Mg, C, Pf, S) values this shows that BD input materials are more important than the MgO. Model 4 is quite better than model 1, 2 and 3 because of the maximum DC and less RMSE values than the other models.

Model 5 contains the variables f (D, Mg, C, Pf, S, Bd) that are five input variables. However, the determinacy coefficient (DC) value is better than the rest model 1, 2, 3 and 4 and the RMSE values are less than the rest model as well. The 70% training values of DC and RMSE are 0.9241 and 0.6132 respectively and the 30% test of DC and RMSE values are 0.8859 and 0.5692 respectively. When we contrast with another model this model more reliable than the rest model 1,2,3 and 4.From this we understand that the cement type I, slag, bulk density, and the age of specimen are the main critical material for mortar's compressive strength.

Model 6 contains the combination of six input variables such as CEM, slag, lime, waste addition, w/s, BD MgO, and PFA are more reliable input variables models. The curing time of mortar is the main important parameter for the mortar's compressive strength. However; the ANN results predict that model six better than models 1,2,3,4 and 5 from this prediction we realize that the added variables w/s, and waste addition are important for the cement mortar's compressive strength. Hence, the results show the 70% training values of DC and RMSE values are 0.9832 and 0.2877 and also the 30% test results of DC and RMSE value are 0.8674 and 0.6137 respectively. When we compare the results the DC value is maximum and RMSE values are less.

Model 7 contains nine variable inputs such as specimen day, cement type I, lime, MgO, PFA, slag, waste addition, w/s, BD. The ANN prediction for this material was more reliable than the rest of all predictions and the output gain from ANN can be almost similar to the experimental results. Compared all ANN prediction the model 7 that contain nine input variables is the maximum Determination coefficient (DC) values and less RMSE values. The 70% training value of DC and RMSE values are 0.9922 and 0.1962 and the 30% test value of DC and RMSE values are 0.8922 and 0.5533 respectively. From all model 7, ANN prediction is the best prediction value and the70% training value of DC is almost approach to the 0.9922 ~ 1 and the 30% test value of DC is 0.8922 ~1. The RMSE value of 70% training was 0.1962 and for 30% test RMSE value was 0.5533 comparatively minimum value. So from all trials, we realize that the ANN prediction was exactly approached to the experimental values. The detail trial values of output, graphs, DC and RMSE refer to appendix1a. The determination coefficient and RMSE can be resolute by using the formula mentioned in chapter three equations 3.5 and 3.6 respectively.

The prediction for Model 8 was done for eight inputs without bulk density. However, bulk density affects the output of the mortar's compressive strength. Similarly, model 9, 10, 11, 12, 13, and 14 was done by omitting of waste addition, slag, water solid ratio, PFA, lime, and days respectively. However, waste addition, slag, and water solid ratio, PFA and lime are highly impacted by the cement mortar's compressive strength. This shows that all these materials applied to boost the cement mortar's unconfined compressive strength.

4.5 Compressive strength of cement Mortar, Correlation among Experimental and ANNI Output

Compressive strength is the tendency which material resist under the failure of the axial load. However, the can be influenced by several factors such as material mix proportions, cement type, water proportions, and other factors. According to the ANN prediction, the final best results of the unconfined cement strength were obtained from ANN I on the structures of ANN9-18-1 that is at nine inputs variables, 18 neural networks and one output. The result gained from prediction can be in table 4.3. As a result, the experimental prediction was almost very similar and the final determination coefficient obtained is 0.97614$\simeq$1 almost approach to 1 this shows that the obtained results are almost very nice and compatible and also acceptable. The other is the ANN result outcome from figure 4.3 that the overall data at ANN I was 0.97904 with the training value of 0.999777, validation of 0.98588 and test 0.98317. The result obtained was very approach to 1 and this shows that all input data is accurate and also very high mortar's compressive strength.

The correspondence between the experimental & predictions can be obtained in table 4.3. However, the result obtained on the cement mortar's compressive strength for both predictions can be almost similar value. The Figure 4.2 explain the correlation compressive strength from experimental and ANN I prediction can be drawn in figure 4.2. As from the figure 4.2 the result obtained was almost similar and the ANN prediction was successful results.

Table 4.3: The cement mortar′s compressive strength of experimental and ANN I output Prediction

No data	Experimental UCS (MPa)	ANN I (MPa) simulation	No Data	Experimental UCS (MPa)	ANN I (MPa) simulation
1	0.4577	0.4571	64	0.0052	0.0018
2	0.0164	0.0205	65	0.6596	0.6595
3	0.4419	0.442	66	0.0405	0.0409
4	0.1150	0.1155	67	0.3920	0.392
5	0.1338	0.099	68	0.2113	0.2361
6	0.3099	0.3092	69	0.0305	0.029
7	0.1831	0.185	70	0.0054	0.0065
8	0.2588	0.2584	71	0.0563	0.0573

Table 4.3 continued

No Data	Experimental UCS (MPa)	ANN I (MPa) simulation	No Data	Experimental UCS (MPa)	ANN I (MPa) simulation
9	0.1667	0.1671	72	0.2271	0.227

10	0.0986	0.0968	73	0.4085	0.4083
11	0.1567	0.1267	74	0.1831	0.2524
12	0.0651	0.0649	75	0.0063	0.0095
13	0.0070	0.0107	76	0.6643	0.7113
14	0.0035	0.0057	77	0.5939	0.5977
15	0.0117	0.0138	78	0.0563	0.0522
16	0.0094	0.0019	79	0.2412	0.2412
17	0.0189	0.0145	80	0.1948	0.195
18	0.0117	0.0102	81	0.0352	0.0185
19	0.3826	0.3749	82	0.0124	0.0113
20	0.0563	0.0555	83	0.4038	0.3946
21	0.0221	0.0329	84	0.1925	0.2106
22	0.0282	0.0305	85	0.1279	0.118
23	0.1127	0.0452	86	0.9507	0.6609
24	0.0270	0.016	87	0.0123	0.0079
25	0.1690	0.1695	88	0.0094	0.0184
26	0.3545	0.3541	89	0.4296	0.4199
27	0.0199	0.0045	90	0.1291	0.1272
28	0.0563	0.063	91	0.0019	0.004

Table 4.3 continued

No Data	Experimental UCS (MPa)	ANN I (MPa) simulation	No Data	Experimental UCS (MPa)	ANN I (MPa) simulation

29	0.8920	0.8908	92	0.5986	0.9956
30	0.2623	0.2622	93	0.4859	0.4933
31	0.1432	0.1424	94	0.0034	0.0053
32	0.7254	0.7258	95	0.1197	0.1228
33	0.2981	0.2884	96	0.2254	0.2253
34	0.0474	0.0436	97	0.1737	0.1761
35	0.2840	0.2811	98	0.0035	0.0017
36	0.3826	0.3825	99	0.9296	0.9296
37	0.0563	0.0291	100	0.0352	0.036
38	0.1620	0.1557	101	0.8380	0.7127
39	0.0164	0.0155	102	0.3239	0.3335
40	0.4178	0.4181	103	0.0253	0.0284
41	1.0000	0.9988	104	0.3996	0.3993
42	0.7835	0.7837	105	0.9601	0.9572
43	0.0239	0.0184	106	0.3873	0.3865
44	0.0634	0.0633	107	0.0798	0.0808
45	0.0687	0.0579	108	0.2324	0.2553
46	0.0000	0.0063	109	0.0175	0.017
47	0.2136	0.2131	110	0.0282	0.0236
48	0.0516	0.0505	111	0.2136	0.2134

Table 4.3 continued

No	Experimental	ANN I (MPa)	No	Experimental	ANN I (MPa)

Data	UCS (MPa)	simulation	Data	UCS (MPa)	simulation
49	0.1526	0.1374	112	0.1995	0.2007
50	0.0962	0.0972	113	0.4272	0.6027
51	0.8310	0.8316	114	0.0059	0.0134
52	0.8873	0.999	115	0.0329	0.0302
53	0.1667	0.1682	116	0.2230	0.2229
54	0.1197	0.1194	117	0.3028	0.2934
55	0.0757	0.024	118	0.0986	0.0958
56	0.0511	0.0097	119	0.0880	0.0957
57	0.0119	0.0128	120	0.1831	0.2417
58	0.5282	0.5283	121	0.2300	0.306
59	0.0035	0.0019	122	0.1039	0.0158
60	0.5657	0.6306			
61	0.1408	0.1419			
62	0.2254	0.2082			
63	0.0282	0.0264			

Figure 4.2 the prediction of ANNI by considering all material as in input variables. Hence the experimental output prediction results show the good relationships and have almost similar values.

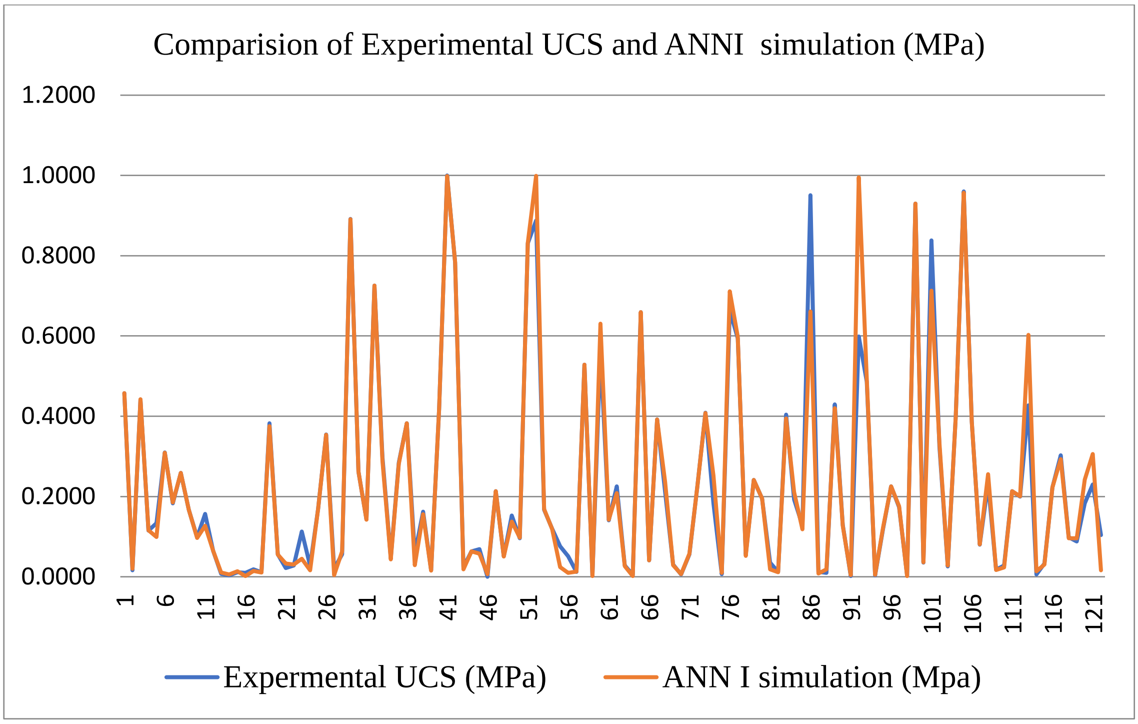


Figure 4.2: Cement mortar's compressive strength correlation between the experimental result and ANN I output logistic activation function

Figure 4.2 was obtained from the experimental data and ANN simulation data. However, to compare both ANNI simulation and experimental data all nine input material was included. Accordingly, from the graph, the experimental and ANN simulation showed a good approach almost the value with minimum differences.

Table 4.4 explain the ANN I results of training, validation, test, and total data. The ANN I trial was done for 24 times from the table starting from the network 2 to the other network. The result obtained was almost approached to each other and all result was successful ANN prediction trial because of the results was the approach to 1 among the trial network number 18 is the most reliable than the other results. The graph in figure 4.4 the results of ANNI prediction is almost similar value and the obtained prediction was successful.

Table 4.4: The DC of training, validation, test, total data for ANNI logistic /sigmoid activation function

Number of Neurons	Training	Validation	Test	Total data
2	0.85376	0.95368	0.94999	0.88122
4	0.98523	0.92435	0.972	0.97833
6	0.99125	0.98755	0.97556	0.98731
7	0.9946	0.95265	0.95686	0.97842
8	0.99161	0.93832	0.88122	0.95845
9	0.99113	0.95153	0.97957	0.98447
10	0.99154	0.94069	0.98618	0.983
11	0.98147	0.95917	0.78195	0.93776
12	0.98877	0.96704	0.93152	0.97339
13	0.99389	0.97217	0.89466	0.97001
14	0.98577	0.99819	0.93913	0.9792
16	0.99154	0.98708	0.84172	0.96008
18	**0.999778**	**0.98588**	**0.98317**	**0.97904**
19	0.9809	0.9767	0.9374	0.97344
20	0.98864	0.9069	094114	0.96767
21	0.99455	0.96416	0.87133	0.97522
22	0.97098	0.92083	0.80973	0.93384
24	0.99764	0.94731	0.75968	0.94471

Figure 4.3 was obtained from the data tabulated in table 4.4 to show the values of training, test, validations, and total data directly obtained from the ANNI simulations to select the best approach among them based on the neural network numbers. Accordingly, neuron number 18 shows a maximum value and good approach between training, test, validations, and total data with the values of 0.999778, 0.98317, 98588, 0.97904 respectively.

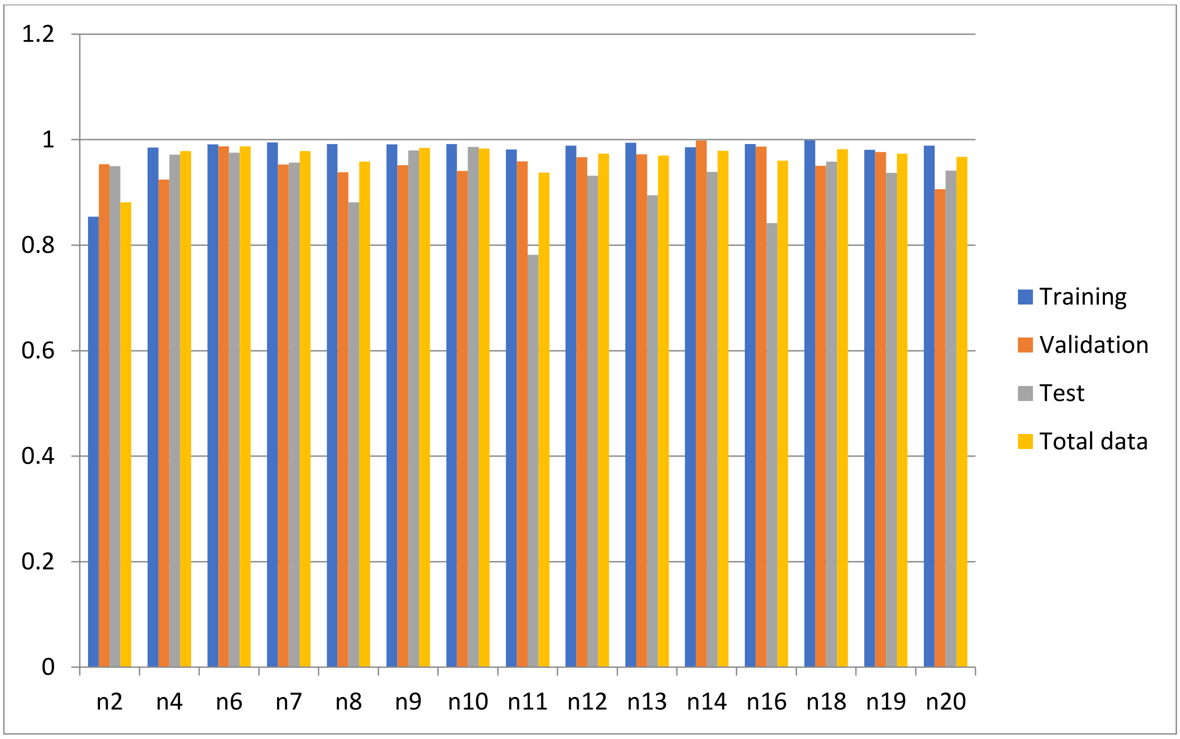


Figure 4.3: ANNI training, validation, test, total data ANN I (logistic /sigmoid) activation function

From figure 4.4 the ANN prediction obtained results show that the best ANN prediction among the other results. The obtained results were almost approach to 1 and are more reliable results and show the successful ANNI with the result of training, test, validations, and total data with the values of 0.999778, 0.98317, 98588, 0.97904 respectively.

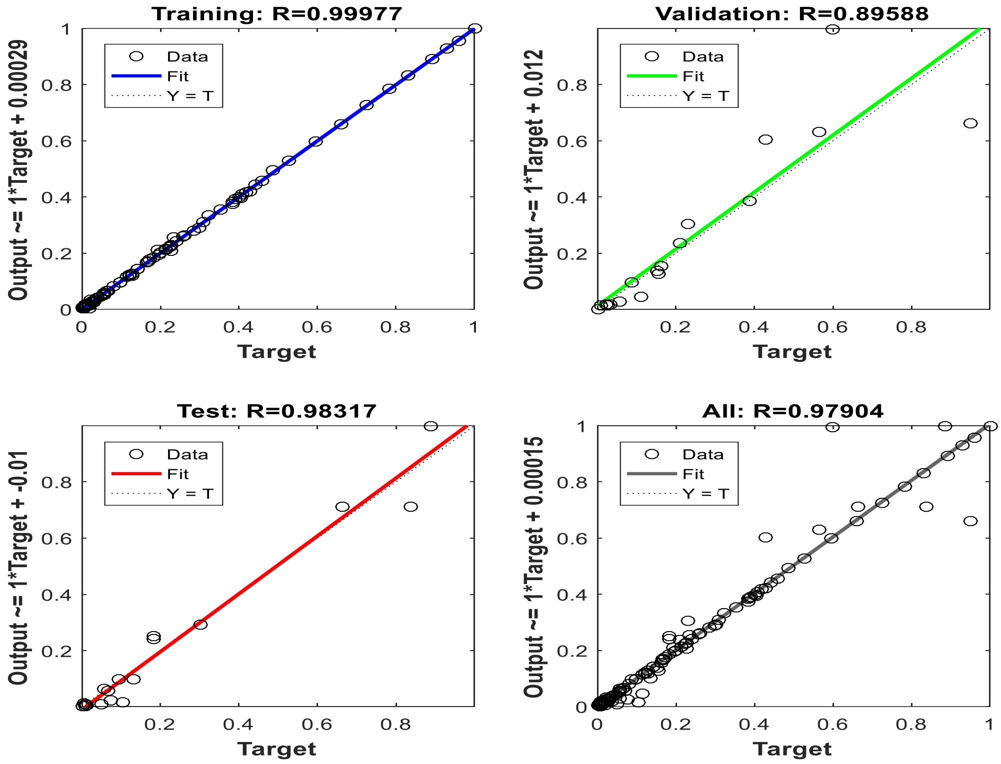


Figure 4.4: ANN I graph training, validation, test and all data for nine combinations input at neuron number 18 by using a (sigmoid or logistic) activation function

4.6 Determination Coefficient (DC) and Root Mean Square Error (RMSE) of ANN I

DC and RMSE can be gain from the formula mentioned in chapter three section 3.6 equation 3.5 and 3.6 respectively. The cement mortar's compressive strength obtained from the ANN prediction output were more accurate the DC and RMSE randomly selected data 70% training was calculated in table 4.5 and 30% testing data ANN I also calculated and tabulated in table 4.5 and also the graph below the 70% of DC and RMSE as well as 30% test values of DC and RMSE were constructed figure 4.5 and 4.6 respectively. The DC value of obtained from all ANN I is almost above 0.9 and this is more consistent and shows the obtained result, as well as the input data, was very accurate data and the RMSE value was very low compared to other model and ANN I is more consistent and correct prediction of cement mortar's compressive strength.

As the obtained result in table 4.5, among overall neurons for ANNI 70% of data the maximum DC and minimum RMSE values obtained at neuron number 18 with DC and RMSE values of 0.976146 and 0.343808 respectively. However, for 30% of data the maximum DC and minimum RMSE was obtained at neuron number 10 with DC and RMSE values of 0.97757 and 0.2525 respectively.

Table 4.5: DC and RMSE value of randomly selected 70 % and 30%of data of the ANNI (sigmoid /logistic) activation function

	Training 70% of Data		**Test (30%) of Data**	
Neurons	**DC**	**RMSE**	**DC**	**RMSE**
2	0.854759323	0.84837517	0.614888376	1.046319703
4	0.95632757	0.465208345	0.957484284	0.347652884
6	0.975014031	0.351877841	0.972671773	0.278725575
7	0.950549822	0.495025699	0.967243853	0.305152898
8	0.90704457	0.678705208	0.935710206	0.427505896
9	0.964844603	0.417387866	0.969990726	0.292077993
10	0.959154346	0.449900775	**0.977571515**	**0.252505628**
11	0.973252662	0.364069331	0.901135774	0.530140125
12	0.954061906	0.477122946	0.928475031	0.450920449
13	0.927640326	0.598814238	0.95999667	0.337224535
14	0.959776252	0.446462603	0.952310581	0.368198577
16	0.970588919	0.381767813	0.829755424	0.695677138
18	**0.976146844**	**0.343808601**	0.941252566	0.408663211

Table 4.5 continued

20	0.958109567	0.455618386	0.915947055	0.488818414
21	0.93830591	0.552924201	0.928747276	0.450061462
22	0.9693259	0.330688812	0.901831087	0.528272595

Figure 4.5 70% of data DC and RMSE for ANNI based on the result tabulated in table 4.5. Accordingly, the obtained DC was above 0.9 with minimum RMSE value. The obtained result shows the DC was an approach to 1 which is a more reliable value with a minimum RMSE.

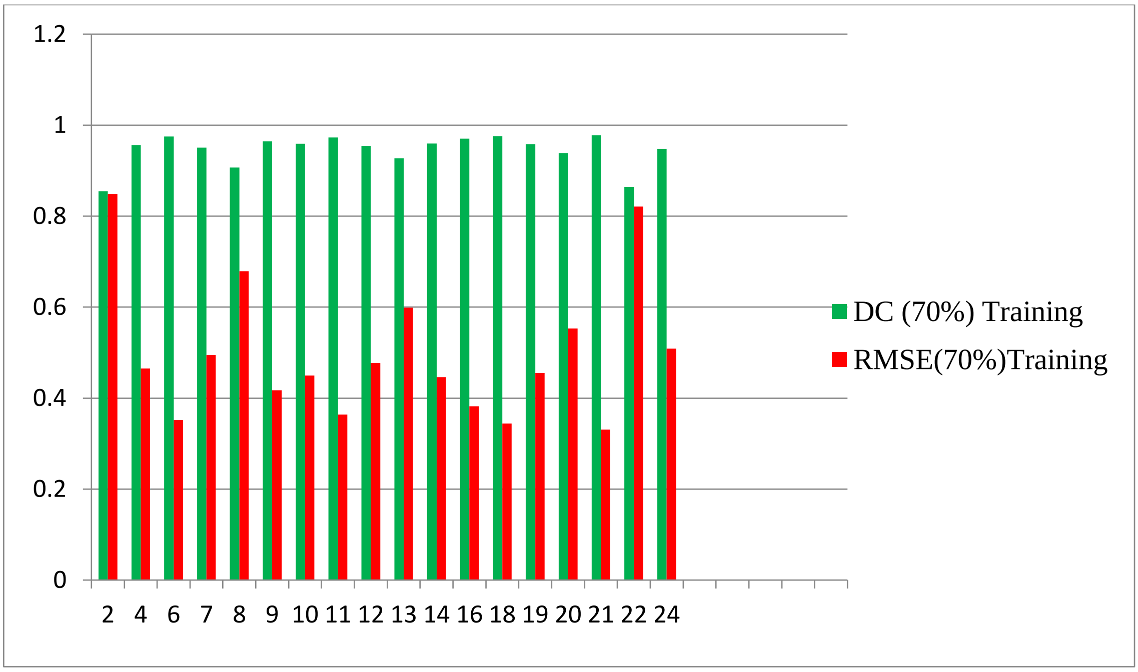


Figure 4.5:70 % of Data DC and RMSE for ANNI (sigmoid/logistic) function Activation

Figure 4.6 explain 30% of data DC and RMSE for ANNI based on the result tabulated in table 4.5. Accordingly, the obtained DC was above 0.9 with minimum RMSE value. The obtained result was the DC was an approach to 1 which is a more reliable value with a minimum RMSE

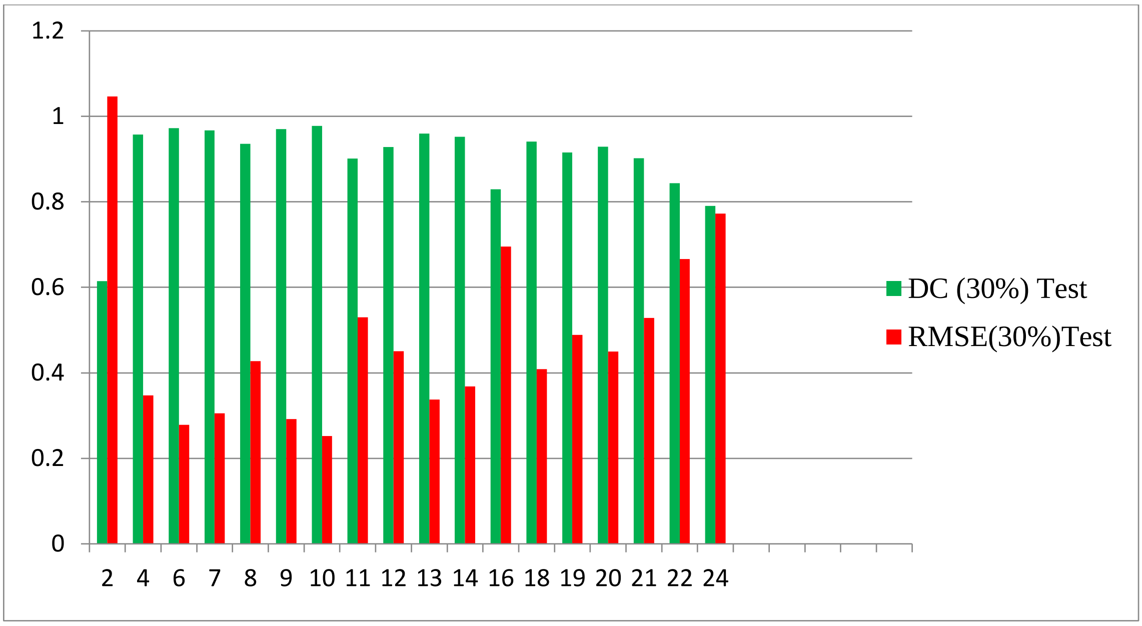


Figure 4.6: 30% data of DC and RMSE of ANN I (sigmoid/logistic) activation Function

4.7 Comparison between ANNI and ANN II Prediction of DC and RMSE (Sigmoid /Logistic) Activation Function

ANN I contain the combination of all nine input variables and the ANN II prediction contains eight input variables without cement type I. However, cement type-I is the foremost factor that influences the cement mortar's strength. The aim of ANN II without cement type I was to assess the impact of cement type I on the cement mortar's compressive strength by using the prediction of ANN predictions. The difference is visible that without cement type I, it's difficult to think about cement mortar's compressive strength and it's important to assess by using the ANN prediction. The ANN II prediction of DC and RMSE results showed in Table 4.6 explains the 70% of training and 30% test of the DC and RMSE.

According to the obtained results the ANNI has maximum DC and minimum RMSE value than ANNII at the same neuron number. The 70% data of DC and RMSE value of ANNI was 0.976146 and 0.3438 at neuron number 18 whereas, for ANNII the obtained value 70% data of DC and RMSE was 0.96598 and 0.4105 at neuron number 18. The 30% data of ANNI was DC and RMSE of 0.97757 and 0.2525 respectively at neuron 10. Whereas, for ANNII the DC and RMSE were 0.925402 and 0.460506 respectively at neuron 10. Generally, ANNI has maximum compressive strength than ANNII (without cement type I)

Table 4.6: 70% of data training and 30% of data test value DC and RMSE output ANN II (sigmoid/logistic) activation function

	Training 70% of Data		**Test (30%) of Data**	
Neurons	**DC**	**RMSE**	**DC**	**RMSE**
2	0.924577	0.611356	0.885666	0.570109
4	0.983292	0.287742	0.867485	0.613767
6	0.959747	0.446627	0.846563	0.660443
8	0.964945	0.416789	0.930762	0.443654
10	0.872394	0.795204	**0.925402**	**0.460506**
12	0.971634	0.374925	0.84062	0.673112
14	0.961504	0.436769	0.943495	0.400789
16	0.97671	0.339728	0.863788	0.62227
18	**0.965982**	**0.410583**	0.952954	0.365705
20	0.969779	0.386991	0.951357	0.371862

The figure 4.8 explain the ANN II prediction the not reliable as the ANN I of figure 4.4. So we can reason out that the cement type I highly affect the cement mortar's compressive strength. As the figure 4.2 ANNI the experimental and ANNI was almost exactly have the same results. Whereas the ANNII was not shows equal approach with the experimental results. However, the cement type I has affect the compressive strength of mortar.

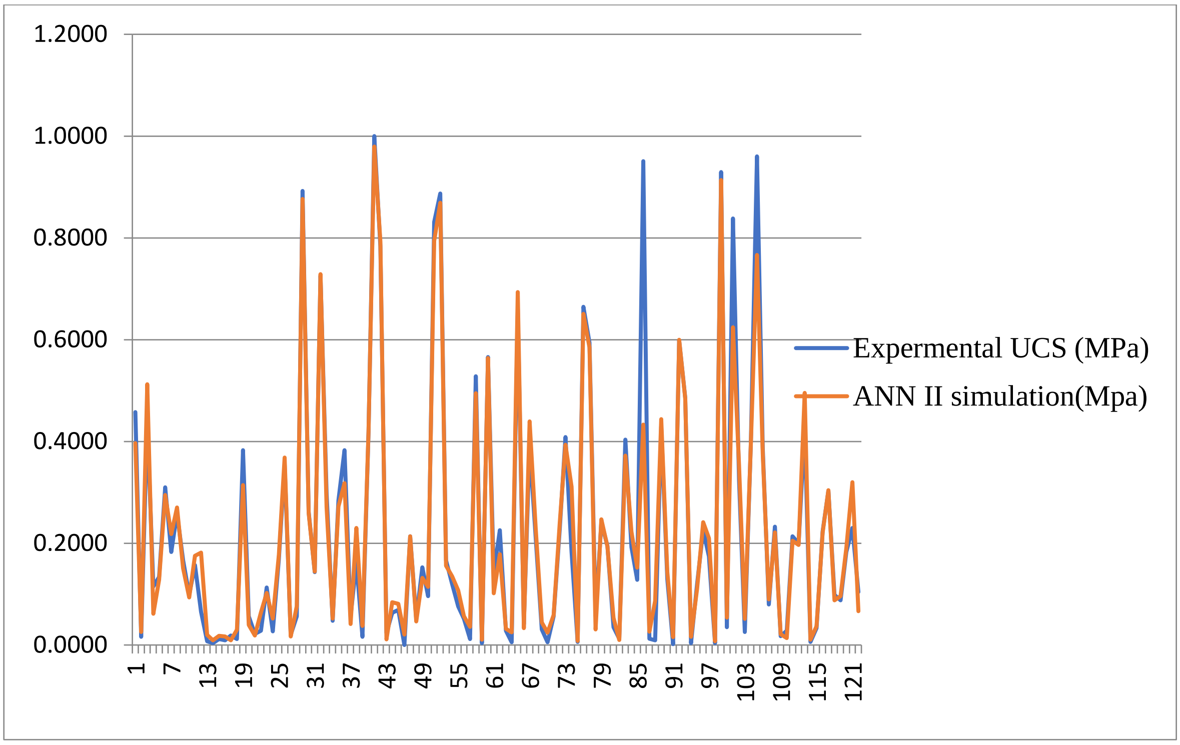


Figure 4.7: Evaluation of experimental result with ANN-II predicted the compressive strength (sigmoid/logistic) activation function

The figure 4.8 was the prediction of mortar's compressive strength without cement type I. However, the figure 4.8 contains the output training, validation, test, and all data were the prediction line and is not follows the line of the prediction. This shows that the cement type-I affect the mortar's compressive strength. When comparing the obtained results figure 4.4 the ANNI has the best combination materials than ANNII. Figure 4.8 contains the training, test, validations, and total data with the results 0.98081, 0.90935, 0.96944, and 0.95407 respectively of ANNII prediction at neuron number 18 the same structures with ANNI. Comparing with figure 4.4 the ANNII fewer values than the ANNI which shows the impact of cement type I on the mortar.

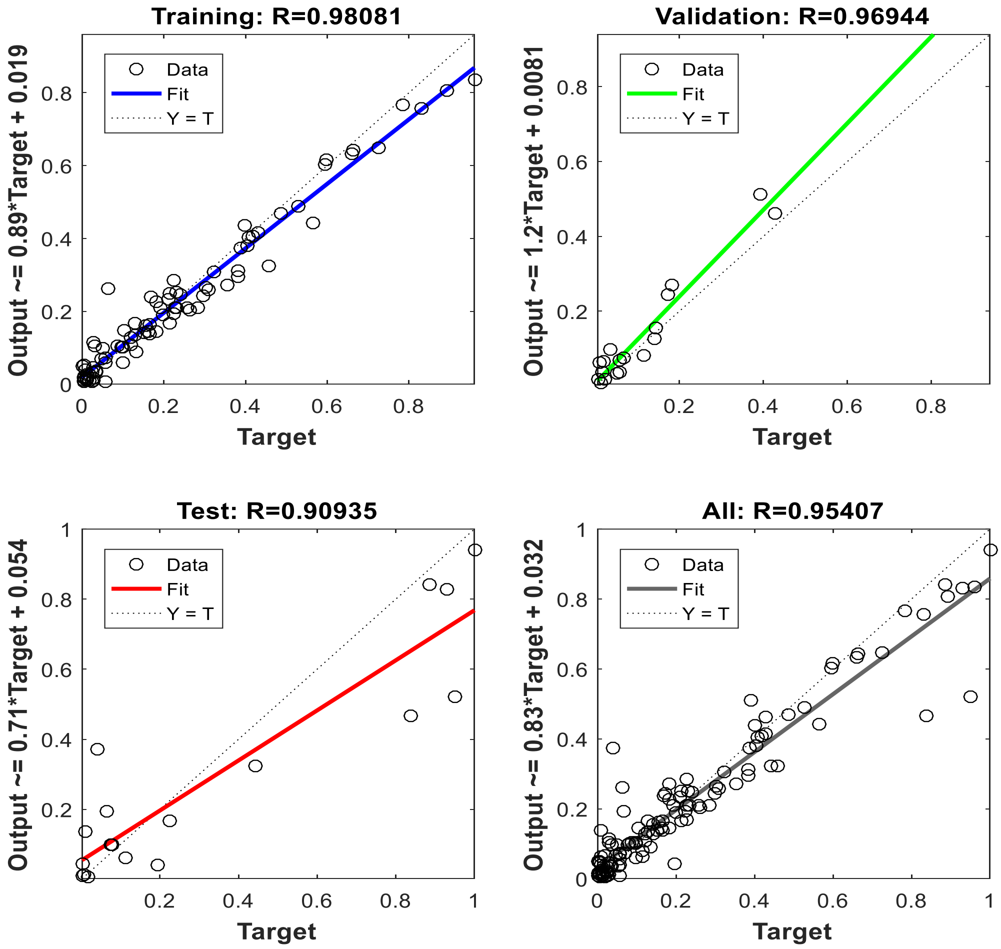


Figure 4.8: ANN II training, validation, test, and total data values (sigmoid/logistic) activation function at neuron18.

4.8 Prediction of ANN by Using Hyperbolic Tangent (Tanh) Activation Function

Hyperbolic Tangent (Tanh) activation function output is a range of -1 and 1 and also FFNN similar to a sigmoid activation function. In this train, 70% were training and a 30% test. The result of this train in table 4.8, the DC on neuron number 18 can be DC= 0.999 which is the approach to 1 and the MSE can be too small which is very approach to zero this shows the prediction is more reliable with very minimum error and also shows the experiment was very accurate. However, in sigmoid activation function the training 0.9989, validation 0.95031, and test 0.95825 which is almost equal to Tanh activation value. From this, we understand that both Tanh and sigmoid activation function predict similar values.

Tanh activation functions show a good approach to 1 with testing, validation, and training value of 0.999 which is greater than logistic values. Tanh has a good approach than logistic activation functions.

Table 4.7: ANNI prediction MSE and R value Tanh activation

	MSE	**DC**
Training	$2.47 \times e^{-11}$	0.9999
validation	$4.948 \times e^{-11}$	0.9999
Testing	$4.13 \times e^{-10}$	0.9999

The figure 4.9 contains the prediction of ANNI by considering all variables as input variables and the overall prediction DC=0.9788 which is the approach to 1. However, the graph prediction line is fit to the line; data matches in the same line this also shows the experimental result is very accurate.

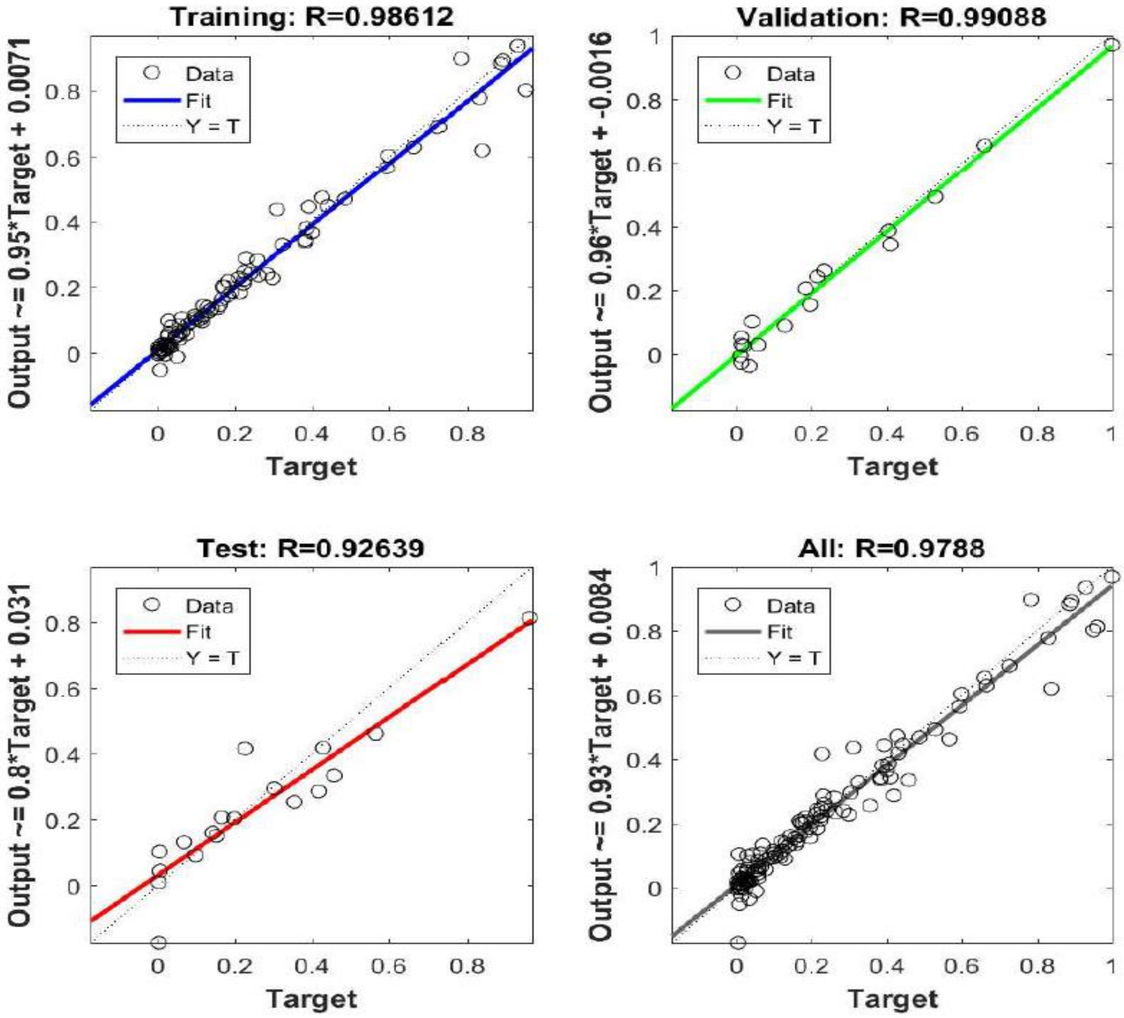


Figure 4.9: ANNI prediction by considering all input variables by using (Tanh) activation function

Comparing with table 4.4 because of both ANNI prediction with different activation functions Tanh and logistic. By using Tanh the training 0.98612, test 0.9263, validation of 0.99088, and total data of 0.9788 results whereas, by using sigmoid activation function the training 0.9989, validation 0.95031, and test 0.95825. The obtained results were very approached to each other all results were above 0.9 which is a good approach and good materials combinations.

ANN II prediction was done using Tanh initiate function by ignoring the cement type I as input variables. Table 4.8 contain the mean square error (MSE) and DC. When we comparing the results with ANNI Tanh, ANNII has more error and the R values are less than ANNI. However, this shows that cement type I can highly affect the unconfined cement mortar's compressive strength.

The obtained results of DC value for ANNII less than ANNI. The training, validation and testing results for ANNI was 0.999 and training 0.9286, testing 0.9216, and validation 0.9789. Cement type I shows the impact on compressive strength.

Table 4.8: ANN II prediction MSE and R value using Tanh activation function

	MSE	DC
Training	9.37x e^{-3}	0.9286
validation	6.27x e^{-3}	0.9789
Testing	1.72 x e^{-3}	0.9216

Figure 4.10 contains, the training, validation, test prediction does not match with the fitting line. However, this shows that cement type I can highly affect the mortar's compressive strength. As the figure 4.10 obtained result contains the ANNII of training 0.9286, test 0.9266, validation 0.9718, and total data 0.9337 by using Tanh and also the ANNII of training 0.9808, test 0.9093, validation 0.9694, and total data 0.95407 by using logistic activation. The obtained results in both case approach to each other.

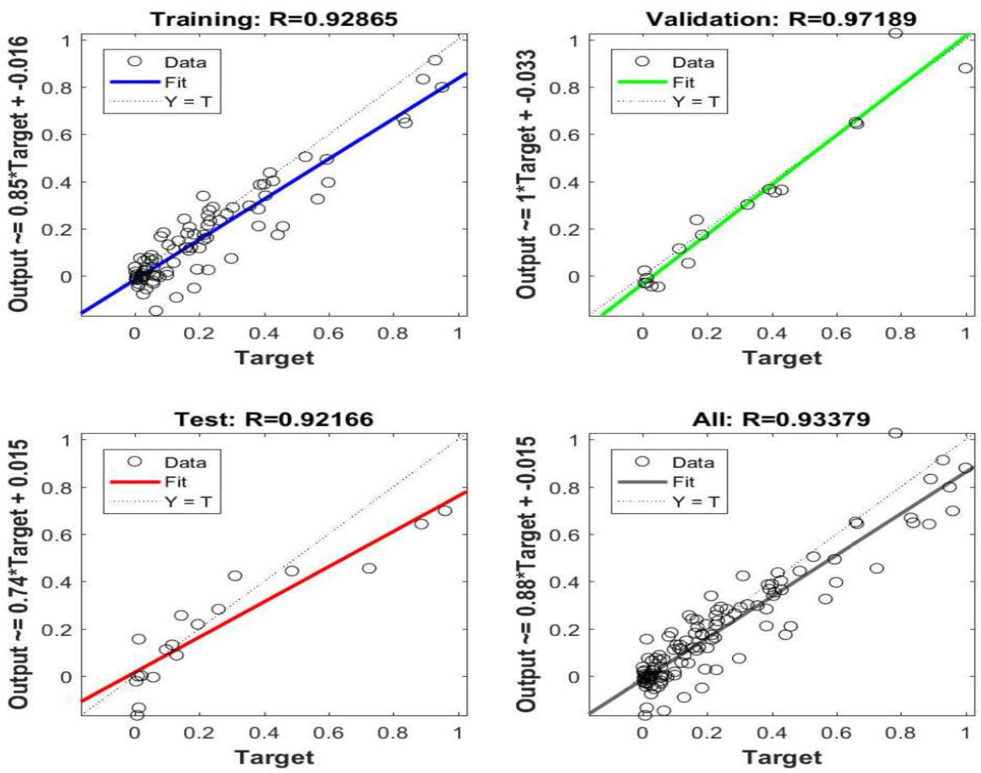


Figure 4.10: ANN-II prediction without considering cement type I as input variable using Tanh

4.9 Comparison of Experimental Result with ANNI Using (sigmoid and Tanh) Activation Functions

The figure 4.8 the experimental results with ANNI prediction by using both activation functions. According to the results shows the experimental results are almost exactly similar to the prediction of ANN I. However, the sigmoid & Tanh activation gives almost similar results. Hence, we can reason out that the experimental result is perfect and also ANNI can be the best reliable to predict in every construction material concrete and mortar mix design.

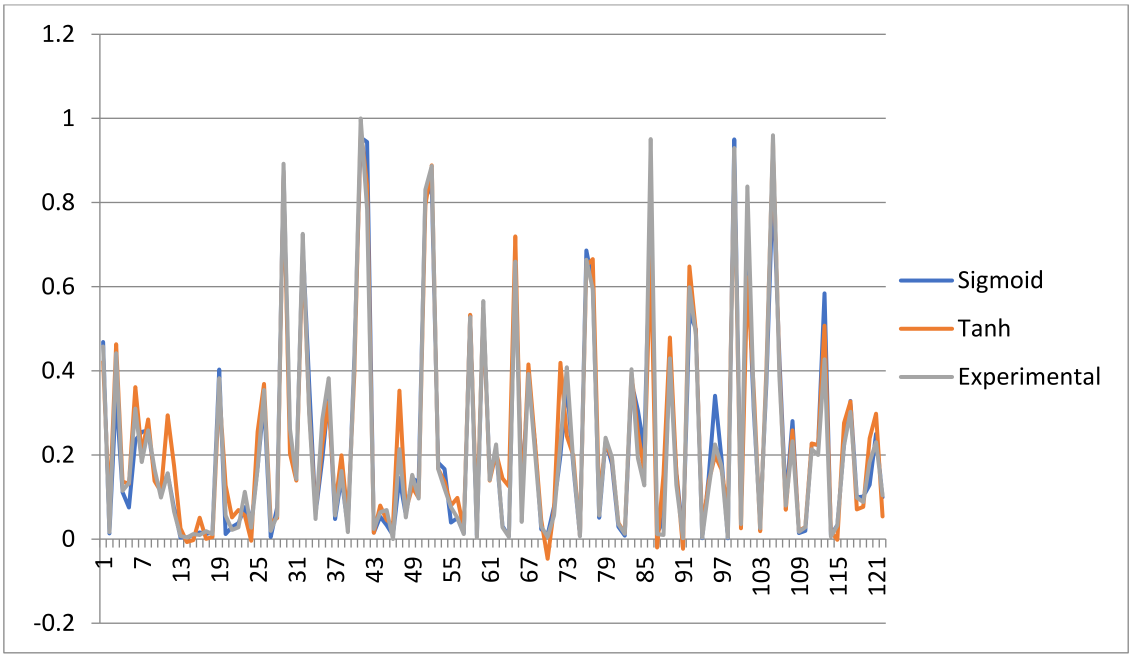


Figure 4.11: Comparison of experimental result with ANNI prediction by using Sigmoid & Tanh functions

Generally, the sigmoid and Tanh activation functions show a good approach with the experimental results and the obtained results in all methods showed a maximum compressive strength with maximum DC and minimum RMSE.

4.10 Mathematical Equation Development for UCS of Cement Mortar by Using Multi Linear Regression Model`

A multi-linear regression model is mathematical modeling to express a linear correlation among one or more dependent and independent variables. The independent variables were used to calculate the dependent variables.

The Multi-linear regression model is given by the formula of:

$$Y = b_o + b_1x_1 + b_2x_2 + b_3x_3 + \cdots + b_ix_i \quad (4.1)$$

Where: X_i: value of the ith predictors

b_o: constant of regression

b_i: the coefficient of the ith predictor

Similarly, the mathematical regression equation was developed for unconfined compressive strength by using multi-linear regression model

Among different combinations, the best regression model was selected based on the R^2 value. The summary of the multi-linear regression equation developed for unconfined compressive strength as follows:

$$UCS(MPa) = 0.0159 + 0.1591Day + 0.818\,CEM \tag{4.2}$$

$$UCS(MPa) = -0.0564 + 0.1592Day + 0.2877\,slag + 0.8884\,CEM \tag{4.3}$$

$$UCS(MPa) = 0.1221 + 0.1594\,Day + 0.3535\,slag + 0.9535\,CEM + 0.1958\,PFA \tag{4.4}$$

$$UCS(MPa) = 0.1757 + 0.1594Day + 0.1057\,MgO + 1.0061\,CEM + 0.2493PFA + 0.4071slag \tag{4.5}$$

$$UCS(MPa) = 0.9198 + 0.645BD + 0.1694Day - 0.7205MgO - 0.843PFA - 1.0289\,slag - 0.3632\,L - 0.4445Wa - 0.732w/s \tag{4.6}$$

$$UCS(MPa) = 0.0768 + 0.645BD + 0.1694Day + 0.1224MgO - 0.1859Slag + 0.480L - 0.4445Wa - \frac{0.732w}{s} + 0.8430CEM \tag{4.7}$$

$$UCS(MPa) = 0.2914 + 0.1603\mathrm{Day} + 0.9019\mathrm{CEM} + 0.306\mathrm{Lime} + 0.1116\mathrm{MgO} - 0.0946\mathrm{PFA} - 0.2481\mathrm{Wa} - 0.783\mathrm{w/s} \tag{4.8}$$

$$UCS(MPa) = 0.5098 + 0.1542\mathrm{Day} + 0.7402\mathrm{CEM} - 0.136\mathrm{L} - 0.1383\mathrm{MgO} - 0.2911\mathrm{PFA} - \frac{0.577\mathrm{w}}{\mathrm{s}} - 0.408\mathrm{BD} \tag{4.9}$$

$$UCS(MPa) = -0.109 + 0.1694\mathrm{Day} + 1.0289\mathrm{CEM} + 0.666\mathrm{L} + 0.3083\mathrm{MgO} + 0.1859\mathrm{PFA} - \frac{0.732\mathrm{w}}{\mathrm{s}} + 0.645\mathrm{BD} - 0.4445\mathrm{Wa} \tag{4.10}$$

$$UCS(MPa) = -0.186 + 0.1704\mathrm{Day} + 0.7407\mathrm{CEM} + 0.063\mathrm{L} - 0.0402\mathrm{MgO} + 0.1747\mathrm{PFA} + 0.754\mathrm{BD} - 0.3827 \quad (4.11)$$

$$UCS(MPa) = 0.0768 + 0.1694\mathrm{Day} + 0.8430\mathrm{CEM} + 0.48\mathrm{L} + 0.1224\mathrm{MgO} + 0.645\mathrm{BD} - 0.4445\mathrm{Wa} - 0.185\mathrm{slag} - 0.732\mathrm{w/s} \quad (4.12)$$

$$UCS(MPa) = 0.557 + 0.1694\mathrm{Day} + 0.3632\mathrm{CEM} - 0.3573\mathrm{MgO} + 0.645\mathrm{BD} - 0.445\mathrm{Wa} - 0.666\mathrm{slag} - 0.732 - 0.48\mathrm{PFA} \quad (4.13)$$

$$UCS(MPa) = 0.64 + 0.398\mathrm{CEM} - 0.3331\mathrm{MgO} + 0.552\mathrm{BD} - 0.4154\mathrm{Wa} - 0.611\mathrm{slag} - \frac{0.737\mathrm{w}}{\mathrm{s}} - 0.466\mathrm{PFA} \quad (4.14)$$

Where: $USC\ (MPa)\ = unconfined\ compressive\ strength(MPa)$

$L = lime$

$BD = Bulk\ density$

$W/s = water\ to\ solid\ ratios$

$Wa = Waste\ addition$

The table explains the best MLR value from each model based on the R2 value. However, as the number of input variables increase, the value of R also increased. Similarly, the value of ANNI or model 7 combinations of all nine input materials was the maximum R^2 value that is 81.78%. The R^2 value for model 6 or ANN II which is without considering the cement type I is less than that of ANNI that is 75.02% is less than 81.78% this shows the cement type I important materials to enhance the compressive strength of cement mortar which shows good approach with the ANN predictions.

Table 4.9: The summary of the best MLR of unconfined compressive strength mortar

Models	Input variables	R^2 value
Model 1	D,C	39.45%
Model 2	D,C,S	57.08%
Model 3	D, S, C, PFA	64.32%
Model 4	D, MgO, PFA, S	65.89%
Model 5	D, MgO, PFA, S,BD	67.16%
Model 6	D, MgO, PFA, S,BD, Wa, W/s, L	75.02%
Model 7	D, MgO, PFA, S,BD, Wa, W/s, L,C	**81.78%**
Model 8	D, C, L, MgO, PFA, S, Wa, Ws	78.88%
Model 9	D,C,L,MgO,PFAS,Bd,Ws	71.48%
Model 10	D,C,L,MgO,PFABd,Ws,Wa	81.21%
Model 11	D,C,L,MgO,PFABd,Wa,S	75.02%
Model 12	D, C, L, MgO, Bd, Wa, S, Ws	81.00%
Model 13	C, L, Bd, Wa, SWs, PFA , MgO	80.48%
Model 14	D, C, MgO, Bd, Wa, S, Ws ,PFA	72.71%

The figure 4.12 is the best MLR among all other models 7. The obtained results show a good approach of MLR prediction with the actual value of unconfined compressive strength of cement mortar. Similarly, the results obtained from the ANN prediction also shows a good approach value with the actual value of UCS obtained from the experiment.

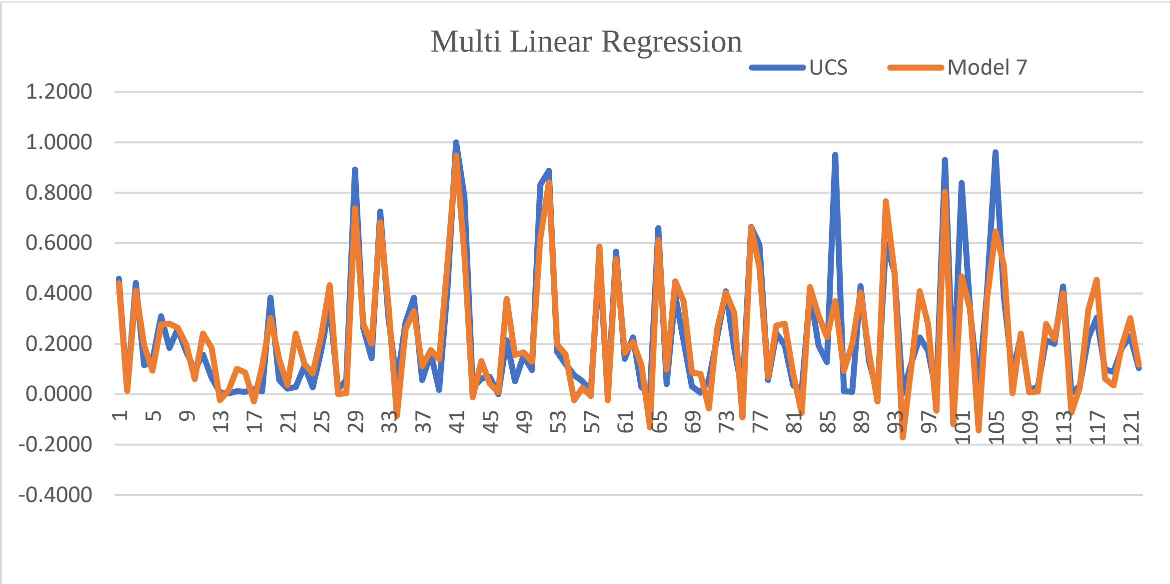


Figure 4.12: MLR prediction for model 7 or ANNI with actual unconfined compressive strength of cement mortar

4.11 The Compositions and Properties of Input Materials used in UCS Cement Mortar Development

There are nine different materials mixed to increase the compressive strength of cement mortar. Every material has its physical, chemical, and mechanical properties. Among the cement type, I a normal cement and the most commonly used type of cement. Cement type I was manufactured by combining several materials such as clay with MgO, Al_2O_3, Fe_2O_3, SiO_2, C3S, C2S, C3A C4AF, and SO_3.

Pulverized fly ash is one of the materials used to enhances the compressive strength of cement mortar and is manufactured from coal combustion production.PFA is manufactured from SiO_2, Al_2O_3, CaO, and Fe_2O_3. Slag is also one of the most important materials to increase the compressive strength of cement mortar. However, the slag is the by-product of Iron and a mixture of Fe_2O_3, SiO_2, and metal sulfite. Slag is also used to assist temperature control and also minimize the re-oxidization of the final liquid. Bulk density is an important characteristic of materials and it is the mass of the material related to a specific volume. Water to solid ratio is the proportion of water to total solid particles and it should at desired ratio to get the required compressive strength.

Generally, the materials such as slag, MgO, PFA, and lime are the materials that highly enhance unconfined compressive strength because those materials have almost the same material properties with cement type-I compositions. However, according to the result obtained from ANN II the value of determination coefficient, RMSE, training value, total data, and test values are above 0.9. The obtained value was a good approach and can be used as cement type I as an alternative. Moreover, these materials are environmentally friendly, safe and cost-effective.

CHAPTER 5
CONCLUSIONS AND RECOMMENDATIONS FOR FUTURE WORKS

5.1 Conclusions

This research was representing on the implementation of ANN prediction on cement mortars of unconfined compressive strength development. Addition of cement type I improve /increase the mortar's compressive strength. The Sigmoid, Tanh ANN activation function, and Multi-Linear Regression were conducted. ANN9-18-1 network was chosen as ANNI depending on the DC and MSE. By eliminating cement type I from the input parameter as ANN II with similar architecture ANN8-18-1 to evaluate the influence of cement type I on unconfined compressive strength. From the ANN investigation, the following conclusion was made.

- The determination coefficient for ANNI model appear shows an acceptable range total data of DC=0.979 by using both logistic and 0.9788 by using Tanh activation functions
- For ANNII the determination coefficient was R^2= 0.9504 but the graph is not so valid it does not fit with actual valid line and the neuron network is spread out
- To verify the performance of ANNI by using 70% of data training the DC was greater than 0.9 which is 0.97614 and RMSE was 0.343 which is minimum error this shows a good agreement and 30% of data test,the DC 0.97757 and RMSE 0.2525.
- The result obtained from multi-linear regression R^2=81.78% from ANN I with minimum error.
- For ANNII the determination coefficient was DC= 0.9659. However, materials such as slag, MgO, PFA, and lime are the materials that highly enhance unconfined compressive strength.

As a result of the cement type I can be a significant parameter and should be considered in the ANN model as well as, it is an important material for enhancing the cement mortar's unconfined compressive strength.

5.2 Recommendations

This research will be helpful for further researcher to use as references and also to found the better results of the prediction of cement strength classes on cement mortar and also to found best material combination with high cement mortar's compressive strength.

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APPENDICES

APPENDICE 1a

Normalized experimental data and all DC and RMSE calculation values for all networks

Table1.a: Experimental cement mortar input variables and normalized data

Day	CEM	Lime	MgO	PFA	Slag	waste addition	W/s	BD (g/cm3)	UCS (MPa)
0.0000	0.1279	0.0000	0.0000	0.0000	0.8721	0.0000	0.0000	0.6481	0.4577
0.0000	0.0698	0.0000	0.0000	0.9302	0.0000	1.0000	0.1000	0.6121	0.0164
1.0000	0.2209	0.0000	0.0000	0.0000	0.7791	1.0000	0.1000	0.9934	0.4419
0.0000	0.2209	0.0000	0.0000	0.7791	0.0000	0.5714	0.1000	0.4002	0.1150
0.4286	0.0698	0.0000	0.0000	0.9302	0.0000	0.5714	0.1000	0.3299	0.1338
0.4286	0.0698	0.0000	0.0000	0.0000	0.9302	0.5714	0.0000	0.7676	0.3099
0.4286	0.0349	0.0000	0.0000	0.0000	0.9651	0.0000	0.0600	0.5029	0.1831
0.4286	0.2209	0.0000	0.0000	0.7791	0.0000	0.5714	0.1000	0.3965	0.2588
0.4286	0.4186	0.5814	0.0000	0.0000	0.0000	0.0000	0.9000	0.1138	0.1667
0.4286	0.0698	0.0000	0.9302	0.0000	0.0000	0.0000	0.6000	0.2737	0.0986
0.4286	0.2209	0.0000	0.0000	0.7791	0.0000	1.0000	0.1000	0.6547	0.1567
1.0000	0.0698	0.0000	0.0000	0.9302	0.0000	1.0000	0.1000	0.6136	0.0651
0.0000	0.0698	0.0000	0.0000	0.0000	0.9302	1.0000	0.1000	0.8231	0.0070
0.0000	0.0698	0.9302	0.0000	0.0000	0.0000	1.0000	0.7000	0.6052	0.0035
1.0000	0.0698	0.9302	0.0000	0.0000	0.0000	0.5714	0.7000	0.1796	0.0117
0.0000	0.2209	0.0000	0.7791	0.0000	0.0000	1.0000	0.3000	0.6062	0.0094
0.4286	0.0000	1.0000	0.0000	0.0000	0.0000	0.0000	0.9000	0.0000	0.0189
1.0000	0.0698	0.9302	0.0000	0.0000	0.0000	0.0000	0.9000	0.0302	0.0117

Table cont…

0.4286	0.1279	0.0000	0.0000	0.8721	0.0000	0.0000	0.1000	0.1819	0.3826
0.0000	0.2209	0.0000	0.0000	0.0000	0.7791	1.0000	0.1000	0.8357	0.0563
0.4286	0.1279	0.8721	0.0000	0.0000	0.0000	0.0000	0.9000	0.0293	0.0221
0.0000	0.2209	0.0000	0.7791	0.0000	0.0000	0.5714	0.3000	0.5511	0.0282
0.0000	0.4186	0.5814	0.0000	0.0000	0.0000	0.0000	0.9000	0.1085	0.1127
0.0000	0.2209	0.7791	0.0000	0.0000	0.0000	0.0000	1.0000	0.2757	0.0270
1.0000	0.0698	0.0000	0.0000	0.9302	0.0000	0.5714	0.1000	0.3889	0.1690
0.4286	0.4186	0.0000	0.5814	0.0000	0.0000	0.0000	0.5000	0.3494	0.3545
0.0000	0.2209	0.7791	0.0000	0.0000	0.0000	0.5714	0.7000	0.2016	0.0199
0.0000	0.0698	0.0000	0.9302	0.0000	0.0000	0.0000	0.6000	0.3007	0.0563
0.4286	0.4186	0.0000	0.0000	0.0000	0.5814	0.0000	0.0600	0.6009	0.8920
0.4286	0.2209	0.0000	0.7791	0.0000	0.0000	0.5714	0.3000	0.4979	0.2623
1.0000	0.1279	0.0000	0.8721	0.0000	0.0000	0.0000	0.6000	0.2758	0.1432
0.0000	0.4186	0.0000	0.0000	0.0000	0.5814	0.0000	0.0600	0.6264	0.7254
0.0000	0.0698	0.0000	0.0000	0.0000	0.9302	0.0000	0.0000	0.5977	0.2981
0.4286	0.0000	0.0000	1.0000	0.0000	0.0000	0.0000	0.7000	0.2401	0.0474
1.0000	0.0000	0.0000	0.0000	1.0000	0.0000	0.0000	0.1000	0.1304	0.2840
0.0000	0.2209	0.0000	0.0000	0.7791	0.0000	0.0000	0.1000	0.2179	0.3826
1.0000	0.2209	0.7791	0.0000	0.0000	0.0000	0.0000	1.0000	0.0570	0.0563
0.4286	0.0698	0.0000	0.9302	0.0000	0.0000	0.5714	0.3000	0.5054	0.1620
1.0000	0.1279	0.8721	0.0000	0.0000	0.0000	0.0000	0.9000	0.0388	0.0164
1.0000	0.4186	0.0000	0.5814	0.0000	0.0000	0.0000	0.5000	0.3315	0.4178

Table cont…

1.0000	1.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.5000	0.3480	1.0000
1.0000	0.2209	0.0000	0.0000	0.0000	0.7791	0.5714	0.0000	0.8087	0.7835
0.4286	0.0349	0.9651	0.0000	0.0000	0.0000	0.0000	0.9000	0.0069	0.0239
1.0000	0.0698	0.0000	0.9302	0.0000	0.0000	1.0000	0.3000	0.5844	0.0634
0.4286	0.0698	0.0000	0.0000	0.0000	0.9302	1.0000	0.1000	0.8141	0.0687
0.4286	0.0698	0.9302	0.0000	0.0000	0.0000	0.5714	0.7000	0.1864	0.0000
0.0000	0.2209	0.0000	0.0000	0.0000	0.7791	0.5714	0.0000	0.7970	0.2136
1.0000	0.2209	0.7791	0.0000	0.0000	0.0000	0.5714	0.7000	0.1796	0.0516
1.0000	0.0698	0.0000	0.9302	0.0000	0.0000	0.0000	0.6000	0.2888	0.1526
0.0000	0.0000	0.0000	0.0000	1.0000	0.0000	0.0000	0.0600	0.1480	0.0962
0.4286	0.4186	0.0000	0.0000	0.5814	0.0000	0.0000	0.1000	0.2925	0.8310
0.4286	1.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.5000	0.3336	0.8873
0.4286	0.0000	0.0000	0.0000	1.0000	0.0000	0.0000	0.0600	0.1404	0.1667
0.0000	0.0349	0.0000	0.0000	0.9651	0.0000	0.0000	0.0600	0.1481	0.1197
0.4286	0.0698	0.0000	0.0000	0.9302	0.0000	1.0000	0.1000	0.4427	0.0757
0.4286	0.0698	0.0000	0.9302	0.0000	0.0000	1.0000	0.3000	0.5695	0.0511
1.0000	0.2209	0.7791	0.0000	0.0000	0.0000	1.0000	0.7000	0.2226	0.0119
1.0000	0.1279	0.0000	0.0000	0.0000	0.8721	0.0000	0.0000	0.6095	0.5282
0.0000	0.0698	0.0000	0.9302	0.0000	0.0000	1.0000	0.3000	0.6052	0.0035
0.0000	0.2209	0.0000	0.0000	0.0000	0.7791	0.0000	0.0000	0.6493	0.5657
0.0000	0.2209	0.0000	0.7791	0.0000	0.0000	0.0000	0.5000	0.2664	0.1408
0.4286	0.0349	0.0000	0.0000	0.9651	0.0000	0.0000	0.1000	0.1585	0.2254

Table cont…

0.0000	0.2209	0.0000	0.0000	0.7791	0.0000	1.0000	0.1000	0.5768	0.0282
0.4286	0.0698	0.9302	0.0000	0.0000	0.0000	1.0000	0.7000	0.2650	0.0052
0.4286	0.2209	0.0000	0.0000	0.0000	0.7791	0.0000	0.0000	0.6534	0.6596
1.0000	0.2209	0.0000	0.7791	0.0000	0.0000	1.0000	0.3000	0.3608	0.0405
0.0000	0.4186	0.0000	0.0000	0.5814	0.0000	0.0000	0.2000	0.2554	0.3920
1.0000	0.2209	0.0000	0.7791	0.0000	0.0000	0.0000	0.5000	0.3219	0.2113
0.0000	0.0698	0.0000	0.9302	0.0000	0.0000	0.5714	0.3000	0.4810	0.0305
1.0000	0.0000	1.0000	0.0000	0.0000	0.0000	0.0000	0.9000	0.0208	0.0054
0.4286	0.0349	0.0000	0.9651	0.0000	0.0000	0.0000	0.7000	0.2451	0.0563
1.0000	0.0698	0.0000	0.0000	0.0000	0.9302	1.0000	0.1000	1.0000	0.2271
1.0000	0.2209	0.0000	0.7791	0.0000	0.0000	0.5714	0.3000	0.5411	0.4085
1.0000	0.2209	0.0000	0.0000	0.7791	0.0000	1.0000	0.1000	0.6342	0.1831
0.0000	0.0000	1.0000	0.0000	0.0000	0.0000	0.0000	0.9000	0.0156	0.0063
1.0000	0.2209	0.0000	0.0000	0.0000	0.7791	0.0000	0.0000	0.5792	0.6643
1.0000	0.2209	0.0000	0.0000	0.7791	0.0000	0.0000	0.1000	0.2224	0.5939
0.4286	0.2209	0.7791	0.0000	0.0000	0.0000	0.0000	0.9000	0.0275	0.0563
1.0000	0.0698	0.0000	0.9302	0.0000	0.0000	0.5714	0.3000	0.5071	0.2412
1.0000	0.4186	0.5814	0.0000	0.0000	0.0000	0.0000	0.9000	0.0945	0.1948
0.4286	0.2209	0.7791	0.0000	0.0000	0.0000	0.5714	0.7000	0.2082	0.0352
0.0000	0.0349	0.9651	0.0000	0.0000	0.0000	0.0000	0.9000	0.0232	0.0124
0.4286	0.0698	0.0000	0.0000	0.0000	0.9302	0.0000	0.0000	0.6049	0.4038
0.0000	0.0349	0.0000	0.0000	0.0000	0.9651	0.0000	0.0000	0.5971	0.1925

Table cont…

0.0000	0.0000	0.0000	0.0000	0.0000	1.0000	0.0000	0.0000	0.5213	0.1279
1.0000	0.0698	0.0000	0.0000	0.0000	0.9302	0.5714	0.0000	0.7623	0.9507
1.0000	0.0349	0.9651	0.0000	0.0000	0.0000	0.0000	0.9000	0.0211	0.0123
0.0000	0.0698	0.0000	0.0000	0.0000	0.9302	0.5714	0.0000	0.7599	0.0094
1.0000	0.1279	0.0000	0.0000	0.8721	0.0000	0.0000	0.1000	0.1908	0.4296
0.0000	0.0698	0.0000	0.0000	0.9302	0.0000	0.0000	0.1000	0.1483	0.1291
1.0000	0.0698	0.9302	0.0000	0.0000	0.0000	1.0000	0.7000	0.2737	0.0019
0.0000	1.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.5000	0.3290	0.5986
0.4286	0.1279	0.0000	0.0000	0.0000	0.8721	0.0000	0.0000	0.6040	0.4859
0.0000	0.2209	0.7791	0.0000	0.0000	0.0000	1.0000	0.7000	0.2297	0.0034
0.4286	0.1279	0.0000	0.8721	0.0000	0.0000	0.0000	0.6000	0.2738	0.1197
1.0000	0.0349	0.0000	0.0000	0.0000	0.9651	0.0000	0.0000	0.4841	0.2254
0.4286	0.0000	0.0000	0.0000	0.0000	1.0000	0.0000	0.0000	0.4896	0.1737
0.0000	0.0698	0.9302	0.0000	0.0000	0.0000	0.5714	0.7000	0.1834	0.0035
1.0000	0.4186	0.0000	0.0000	0.0000	0.5814	0.0000	0.1000	0.5986	0.9296
0.0000	0.0349	0.0000	0.9651	0.0000	0.0000	0.0000	0.7000	0.2620	0.0352
0.4286	0.2209	0.0000	0.0000	0.0000	0.7791	0.5714	0.0000	0.8238	0.8380
1.0000	0.0698	0.0000	0.0000	0.9302	0.0000	0.0000	0.1000	0.1572	0.3239
0.0000	0.0000	0.0000	1.0000	0.0000	0.0000	0.0000	0.7000	0.2640	0.0253
1.0000	0.2209	0.0000	0.0000	0.7791	0.0000	0.5714	0.1000	0.4174	0.3996
1.0000	0.4186	0.0000	0.0000	0.5814	0.0000	0.0000	0.1000	0.1864	0.9601

Table cont…

1.0000	0.0698	0.0000	0.0000	0.0000	0.9302	0.0000	0.0000	0.5877	0.3873
1.0000	0.0000	0.0000	1.0000	0.0000	0.0000	0.0000	0.7000	0.2299	0.0798
0.4286	0.0698	0.0000	0.0000	0.9302	0.0000	0.0000	0.1000	0.1644	0.2324
0.0000	0.1279	0.8721	0.0000	0.0000	0.0000	0.0000	0.9000	0.0995	0.0175
0.4286	0.0698	0.9302	0.0000	0.0000	0.0000	0.0000	0.9000	0.0234	0.0282
0.4286	0.2209	0.0000	0.7791	0.0000	0.0000	0.0000	0.5000	0.3316	0.2136
0.0000	0.1279	0.0000	0.0000	0.8721	0.0000	0.0000	0.1000	0.1659	0.1995
0.4286	0.2209	0.0000	0.0000	0.7791	0.0000	0.0000	0.1000	0.2146	0.4272
0.0000	0.0698	0.9302	0.0000	0.0000	0.0000	0.0000	0.9000	0.0057	0.0059
0.0000	0.0698	0.0000	0.0000	0.9302	0.0000	0.5714	0.1000	0.3366	0.0329
0.0000	0.4186	0.0000	0.5814	0.0000	0.0000	0.0000	0.5000	0.3106	0.2230
1.0000	0.0000	0.0000	0.0000	0.0000	1.0000	0.0000	0.0000	0.6114	0.3028
0.0000	0.1279	0.0000	0.8721	0.0000	0.0000	0.0000	0.6000	0.3251	0.0986
1.0000	0.0349	0.0000	0.9651	0.0000	0.0000	0.0000	0.7000	0.2383	0.0880
0.4286	0.2209	0.0000	0.0000	0.0000	0.7791	1.0000	0.1000	0.8065	0.1831
1.0000	0.0349	0.0000	0.0000	0.9651	0.0000	0.0000	0.1000	0.1545	0.2300
0.4286	0.2209	0.0000	0.7791	0.0000	0.0000	1.0000	0.3000	0.5441	0.1039

Model 1

Table 2.a: Day, cement type I 70% training and 30% test values of ANN prediction output

	Training (70%)		Testing (30%)	
N	DC	RMSE	DC	RMSE
2	**0.386684**	**1.743355557**	**0.442380478**	**1.259041585**
4	0.375638	1.7589844	0.194942959	1.5128101
6	0.2782483	1.891201	0.39553839	1.3108574
8	-0.376999	2.6122254	0.969881477	1.518504627

Table 3.a: Day and Lime 70% training and 30% test values of ANN prediction output

	Training (70%)		Testing (30%)	
N	DC	RMSE	DC	RMSE
2	-0.0140206	2.241646916	-0.022168323	1.704638524
4	0.24476698	1.934569334	0.151969356	1.552661781
6	0.20337695	1.986873643	0.265477671	1.445019112
8	0.2357526	1.946080502	0.318545195	1.391840979
10	0.233827257	1.948530309	0.298152483	1.412513066
14	**0.247155927**	**1.931507215**	**0.293205686**	**1.417482199**

Table 4.a: Day and MgO 70% training and 30% test values of ANN prediction output

	Training (70%)		Testing (30%)	
N	**DC**	**RMSE**	**DC**	**RMSE**
2	0.045725234	2.174605774	0.24143998	1.468473334
6	-0.030763218	2.260077195	0.219320255	1.489729939
10	-0.048787146	2.27975142	0.219071749	1.489967025
14	-0.389760196	2.624301637	-0.101158067	1.769277369
20	**0.069176515**	**2.147719117**	**0.886067997**	**2.481907441**

Table 5.a: Day and PFA 70% training and 30% test values of ANN prediction output

	Training (70%)		Testing (30%)	
N	**DC**	**RMSE**	**DC**	**RMSE**
10	**0.09074927**	**2.122685465**	**0.274011456**	**1.43660037**
15	0.025039707	2.198048552	0.287903018	1.422789536
20	0.009594514	2.215390737	0.218332989	1.490671615
25	-0.206999287	2.445667001	-0.068238425	1.742630006
30	0.039038312	2.182211567	0.203779487	1.504484685

Table 6.a: Day and Slag 70% training and 30% test values of ANN prediction output

	Training (70%)		**Testing (30%)**	
N	**DC**	**RMSE**	**DC**	**RMSE**
4	0.043055753	2.177645262	0.127891812	1.574549332
6	**0.342311839**	**1.805318484**	**0.382062269**	**1.32538926**
10	0.33713363	1.812411502	0.394340885	1.312155239
20	0.033102704	2.188940666	0.398566166	1.307570211

Table 7.a: Day and BD 70% training and 30% test values of ANN prediction output

	Training (70%)		**Testing (30%)**	
N	**DC**	**RMSE**	**DC**	**DC**
2	0.132543598	2.073326245	0.271546361	1.439037292
4	0.132696347	2.073143693	0.337146211	1.372713679
10	**0.181732664**	**2.013684488**	**0.185095181**	**1.522034627**
15	-0.665216741	2.872626754	0.001399963	1.684871867
20	0.104451539	2.106630476	0.229698143	1.479795023

Model 2

Table 8.a: Day, MgO ,CEM 70% training and 30% test values of ANN prediction output

	Training(70%)		Test (30%)	
N	**DC**	**RMSE**	**DC**	**RMSE**
2	**0.400970857**	**1.722930633**	**0.53087879**	**1.154818212**
6	0.382857449	1.748785575	0.491359712	1.202476142

Table 9.a: Day, Bd, CEM 70% training and 30% test values of ANN prediction output

	Training (70%)		Testing (30%)	
N	**DC**	**RMSE**	**DC**	**RMSE**
2	**0.511988656**	**1.555101626**	**0.534645987**	**1.150172082**
6	0.508342406	1.560900402	0.54381909	1.138779509
10	0.046434414	2.173797583	0.492949409	1.200595571
15	0.40622634	1.71535606	0.510623091	1.179486099
20	-0.074083817	2.307081324	0.594615964	1.073505839

Table 10.a: Day, slag, CEM 70% training and 30% test values of ANN prediction output

	Training (70%)		Testing (30%)	
N	**DC**	**RMSE**	**DC**	**RMSE**
2	0.633525502	1.347614564	0.556660504	1.12263687
8	0.640539171	1.334656797	0.59967231	1.066789925
12	**0.664571078**	**1.289270573**	**0.551749363**	**1.128837811**

20	0.65235471	1.31253832	0.643532781	1.006655542

Table 11.a: Day, PFA , CEM 70% training and 30% test values of ANN prediction output

	Training (70%)		**Testing (30%)**	
N	**DC**	**RMSE**	**DC**	**RMSE**
2	**0.40437198**	**1.718032507**	**0.415246021**	**1.289310985**
8	0.313355434	1.844632306	0.426634598	1.276694042
12	0.398277703	1.72679932	0.382992943	1.324390801
20	0.126936376	2.080016422	0.445577509	1.255427131

Table12.a: Day, Lime, CEM 70% training and 30% test values of ANN prediction output

	Training (70%)		**Testing (30%)**	
N	**DC**	**RMSE**	**DC**	**RMSE**
5	**0.601507818**	**1.405250405**	**0.362987738**	**1.345689879**
10	0.575303532	1.450718473	0.502051646	1.189770621
15	0.58122661	1.440566648	0.584762994	1.086473444
20	0.570277471	1.459277474	0.550928741	1.129870632

Model 3

Table 13.a: Day, MgO, CEM, PFA 70% training and 30% test values of ANN prediction output

	Training (70%)		**Testing (30%)**	
N	**DC**	**RMSE**	**DC**	**RMSE**
2	0.394444174	1.732291244	0.403466182	1.302232784
4	0.375525034	1.759143765	0.402346818	1.303453997
10	0.40363025	1.719101898	0.517763377	1.170849797
15	0.40363025	1.719101898	0.517763377	1.170849797

Table 14.a: Day, BD, CEM, PFA 70% training and 30% test values of ANN prediction output

	Training (70%)		**Testing (30%)**	
N	**DC**	**RMSE**	**DC**	**RMSE**
2	0.760570368	1.089263036	0.719040784	0.893702003
5	**0.76570407**	**1.077522107**	**0.76146394**	**0.823470624**
10	0.543982851	1.503261048	0.447517142	1.253229166
15	0.738824788	1.137652944	0.742220127	0.856043023

Table 15.a: Day, BD, CEM, PFA 70% training and 30% test values of ANN prediction output

	Training (70%)		**Testing (30%)**	
N	**DC**	**RMSE**	**DC**	**RMSE**
2	0.803999807	0.985535033	0.707762384	0.911463219
4	**0.856929691**	**0.84201257**	**0.771932856**	**0.805197563**
10	0.406754864	1.714592462	0.514611731	1.174669595
15	0.728111077	1.160752357	0.785320074	0.781208228
20	0.672813591	1.273331388	0.703769975	0.917668084

Model 14

Table 16.a: Day, MgO, CEM, PFA, slag 70% training and 30% test values of ANN prediction

	Training (70%)		**Testing (30%)**	
N	**DC**	**RMSE**	**DC**	**RMSE**
4	-0.01317893	2.240716393	0.081612538	1.615786826
10	**0.509905811**	**1.558416699**	**0.624427559**	**1.033279822**
15	0.425808467	1.686833467	0.624399976	1.033317765
20	0.412162278	1.706760341	0.492378744	1.20127099

Table 17.a: Day, BD, CEM, PFA, slag 70% training and 30% test values of ANN prediction output

	Training (70%)		Testing (30%)	
N	DC	RMSE	DC	RMSE
2	0.671311554	1.276250826	0.599469693	1.067059856
4	**0.923245749**	**0.616729946**	**0.805049948**	**0.744445258**
10	0.906470951	0.680796128	0.784368759	0.782937206
15	0.899085306	0.707165427	0.752903975	0.838115687
20	0.805185607	0.982549268	0.527358318	1.159143221

Model 5

Table 18.a: Day, MgO, CEM, PFA, slag, BD 70% training and 30% test values of ANN prediction output

	Training(70%)		**Testing (30%)**	
N	**DC**	**RMSE**	**DC**	**RMSE**
2	0.876473316	0.782391654	0.708979563	0.909563102
4	0.888091713	0.744689003	0.744099619	0.852916578
10	0.901013561	0.700376665	0.700353379	0.922944917
20	**0.924103531**	**0.613274072**	**0.885999167**	**0.569278919**

Model 7

Table 19.a: Date, CEM, MgO, PFA, slag, BD, water/solid, waste addition, lime 70% training and 30% test values of ANN prediction output

	Training (70%)		**Testing (30%)**	
N	**DC**	**RMSE**	**DC**	**RMSE**
2	0.854759323	0.84837517	0.614888376	1.046319703
4	0.95632757	0.465208345	0.957484284	0.347652884
6	0.975014031	0.351877841	0.972671773	0.278725575
7	0.950549822	0.495025699	0.967243853	0.305152898
8	0.907044577	0.678705208	0.935710206	0.427505896
9	0.964844603	0.417387866	0.969990726	0.292077993
10	0.959154346	0.449900775	0.977571515	0.252505628
11	0.973252662	0.364069331	0.901135774	0.530140125
12	0.954061906	0.477122946	0.928475031	0.450920449
13	0.927640326	0.598814238	0.95999667	0.337224535
14	0.959776252	0.446462603	0.952310581	0.368198577
16	0.970588919	0.381767813	0.829755424	0.695677138
18	0.976146844	0.343808601	0.941252566	0.408663211
19	0.958109567	0.455618386	0.915947055	0.488818414
20	0.93830591	0.552924201	0.928747276	0.450061462
21	0.97793259	0.330688812	0.901831087	0.528272595
22	0.863856827	0.821375512	0.843882665	0.666187769

24	0.947787216	0.508665453	0.790204881	0.772269316
26	0.633263137	0.348096868	0.678028239	0.656709269
28	0.971792616	0.373873964	0.945180852	0.394763719
30	0.968447552	0.395421564	0.963151125	0.323655662

Model 8

Table 20.a: Day, CEM, Lime, MgO, PFA, Slag, Waste addition and water to solid without addition of Bulk Density 70% training and 30% test values of ANN prediction output

	Training(70%)		**Testing(30%)**	
n	**DC**	**RMSE**	**DC**	**RMSE**
2	0.911800858	0.661113458	0.799131273	0.755661427
4	0.926985774	0.367820945	0.838274189	0.6780485
6	0.278248311	1.891201141	0.904536812	0.52094162
8	**0.951326332**	**0.491123659**	**0.836254815**	**0.425691307**
10	0.863954003	0.422641695	0.88382383	0.214441551
14	0.850927059	0.493133902	0.913129847	0.496942778

Model 9

Table 21.a: Date, CEM, MgO, PFA, slag, BD, water/solid, lime: without waste addition 70% training and 30% test values of ANN prediction output

	Training(70%)		**Testing(30%)**	
n	**DC**	**RMSE**	**DC**	**RMSE**
2	0.899504313	0.705695794	0.825993362	0.70332167
4	**0.910540035**	**0.665822059**	**0.895844309**	**0.54414243**
6	-0.456437479	2.686517908	-0.324317434	1.940292201
8	0.826498764	0.293221022	0.819506853	0.716310717
10	-0.788057082	2.976696155	-0.859616568	2.29923199

Model 10

Table 22.a: Date, CEM, MgO, PFA, BD, water/solid, waste addition, lime: without slag 70% training and 30% test values of ANN prediction output

	Training(70%)		Testing(30%)	
N	**DC**	**RMSE**	**DC**	**RMSE**
2	0.881948533	0.764855707	0.786956736	0.77822467
4	**0.88233977**	**0.763587242**	**0.780596261**	**0.789756305**
8	0.863196714	0.427058249	0.875215723	0.265435629
10	0.878698191	0.324901757	0.892820333	0.142864147

Model 11

Table 23.a: Date, CEM, MgO, PFA, slag, BD, waste addition, lime: Without w/s 70% training and 30% test values of ANN prediction output

	Training(70%)		Testing(30%)	
N	**DC**	**RMSE**	**dDC**	**RMSE**
2	0.896172385	0.717299049	0.680224293	0.953441001
4	**0.945883991**	**0.517853239**	**0.757954401**	**0.829506293**
6	0.869385285	0.389501317	0.886969184	0.566851789
8	0.840656371	0.542289089	0.844004067	0.398978354
10	0.826901346	0.601864193	0.842318089	0.669517644

Model 12

Table 24.a: Date, CEM, MgO, slag, BD, water/solid, waste addition, lime: without PFA 70% training and 30% test values of ANN prediction output

	Training (70%)		Testing (30%)	
N	**DC**	**RMSE**	**DC**	**RMSE**
2	0.815447719	0.647301303	0.748552344	0.845463544
4	0.836889324	0.559236145	0.803859145	0.52278736
6	0.849970921	0.497914838	0.886778876	0.567328787
10	**0.866040012**	**0.410230156**	**0.8728156**	**0.601295583**

Model 13

Table 25.a: Date, CEM, MgO, PFA, slag, BD, water/solid, waste addition, lime: without Day 70% training and 30% test values of ANN prediction output

	Training (70%)		Testing (30%)	
N	DC	RMSE	DC	RMSE
2	0.523174868	1.537175258	0.507070451	1.183759606
4	0.858319861	0.837911794	0.721092232	0.890433304
6	**0.875955358**	**0.784030253**	**0.775272635**	**0.799280227**
8	0.791816597	1.015703311	0.55224216	1.12821713
10	0.848944019	0.502999008	0.839664059	0.4141514

Model 14

Table 26.a: CEM, MgO, PFA, slag, BD, water/solid, waste addition, lime: without Day 70% training and 30% test values of ANN prediction output

	Training (70%)		Testing (30%)	
N	DC	RMSE	DC	RMSE
2	**0.866005962**	**0.814866671**	**0.718461096**	**0.894623491**
4	0.849734749	0.862925092	0.705335451	0.915240088
6	0.770086356	1.067397519	0.509411844	1.180944858
8	0.869479581	0.804235143	0.564960169	1.1120789
10	0.806915189	0.978177959	0.714785275	0.900444731

APPENDIX 1b

The ANN graph for each model of maximum DC and RMSE value and good approach of neural training, validation, Test and all data values

Model 1

N20

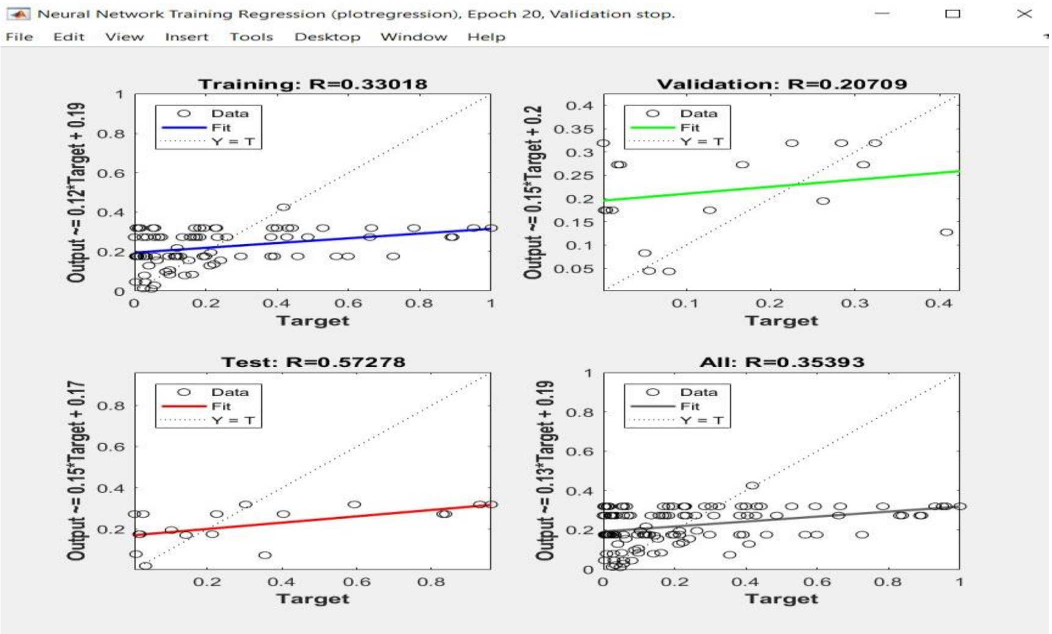

Figure 1.b: Day and MgO good approach of neural training, validation, Test and all data values

Day, Lime .N14

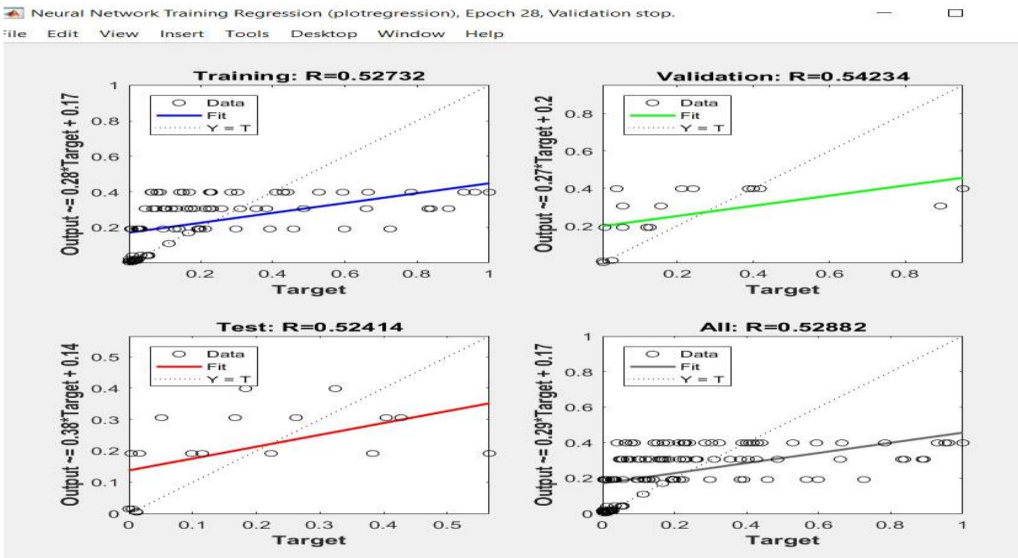

Figure 2.b: Day and Lime good approach of neural training, validation, Test and all data values

N10

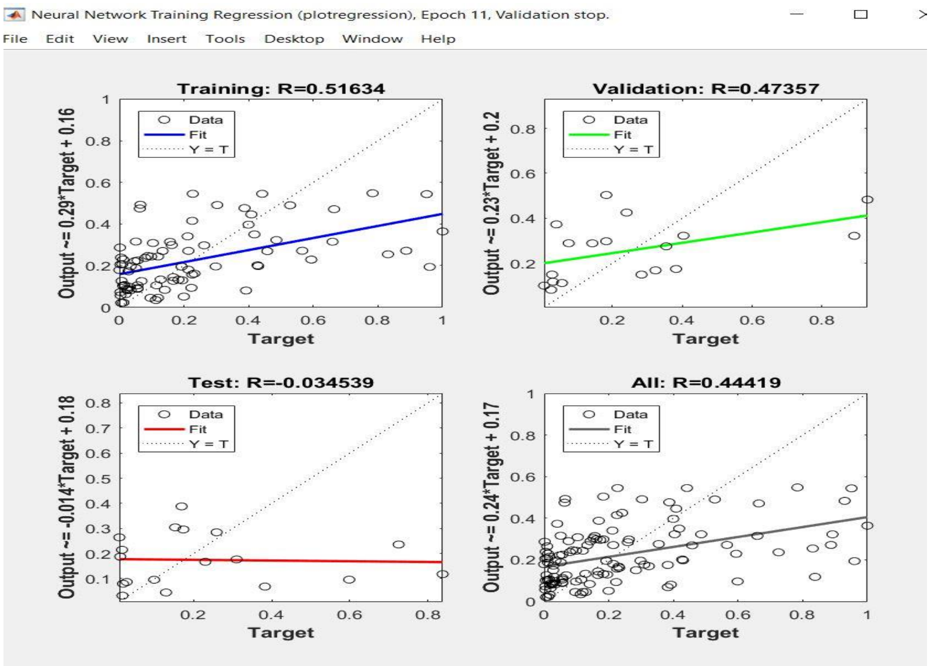

Figure 3.b: Day and bulk density good approach of neural training, validation, Test and all data values

N10

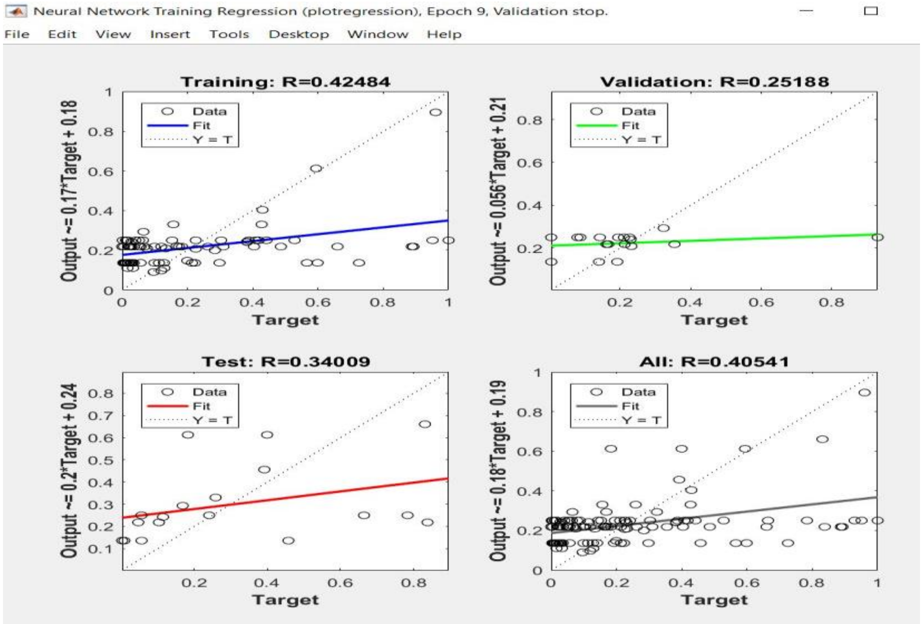

Figure 3.b: Day and PFA good approach of neural training, validation, Test and all data values

Model 2

N2

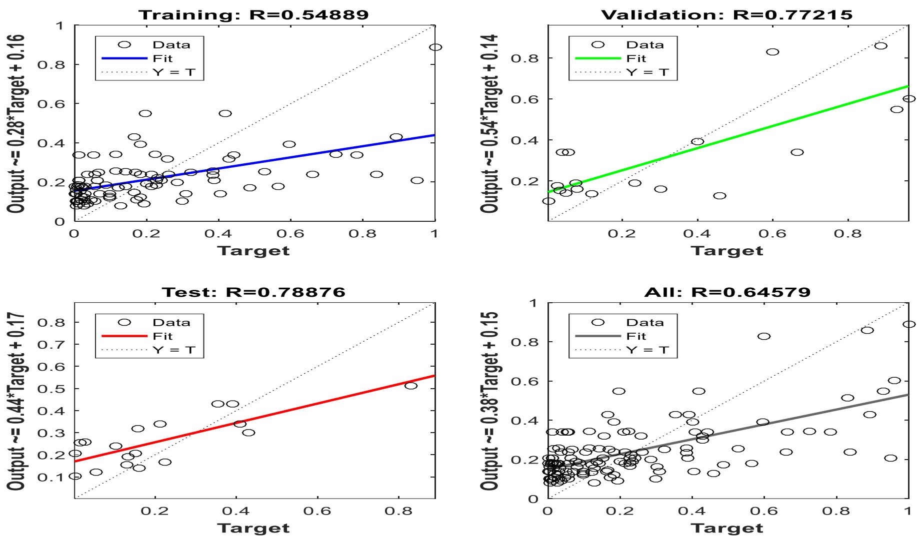

Figure 4.b: Day, PFA, CEM good approach of neural training, validation, Test and all data values

N12

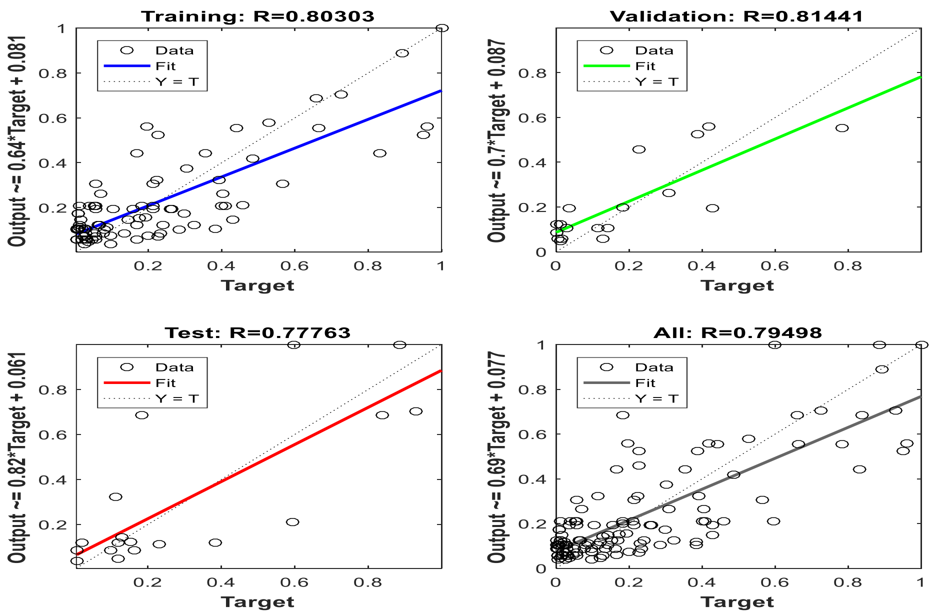

Figure 5.b: Day, slag, CEM good approach of neural training, validation, Test and all data value

N2

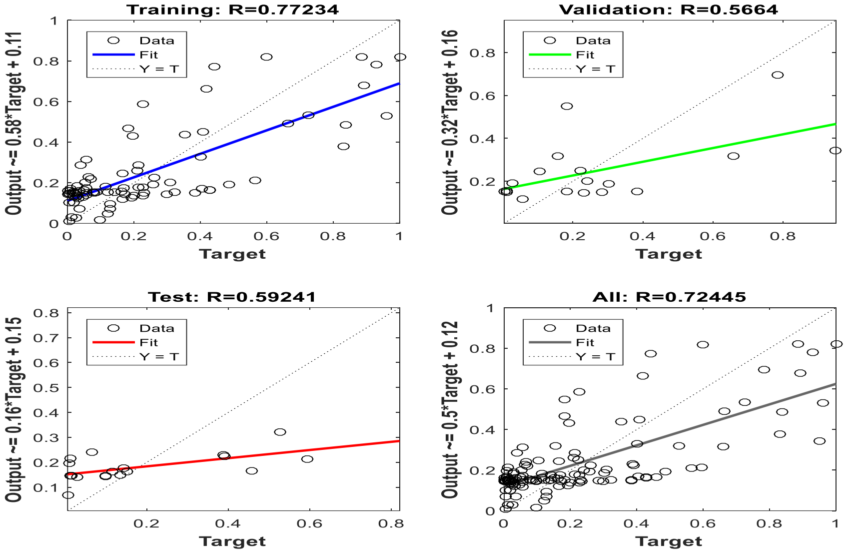

Figure 6.b: Day, BD, CEM good approach of neural training, validation, Test and all Data value

N2

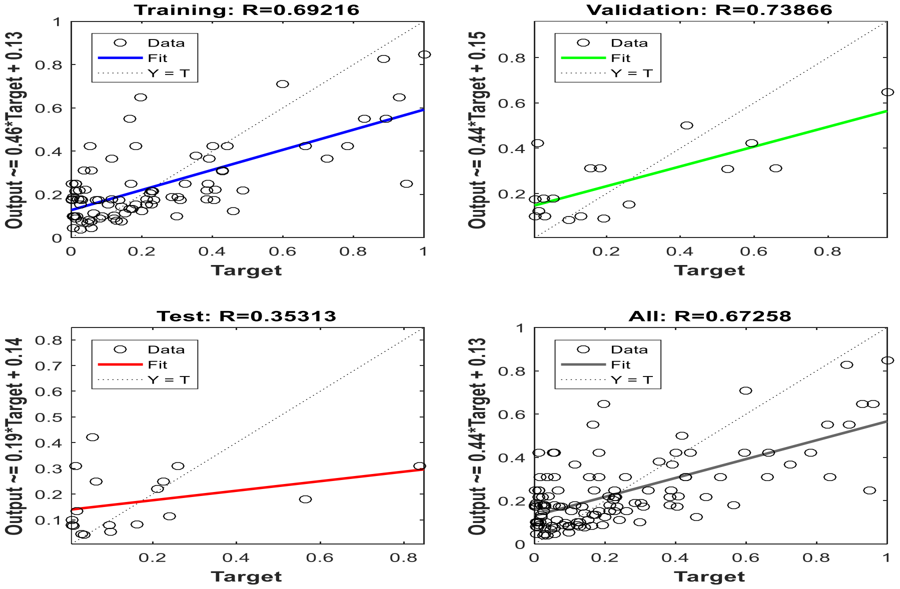

Figure 7.b: Day, Mgo, CEM good approach of neural training, validation, Test and all

data value

N5

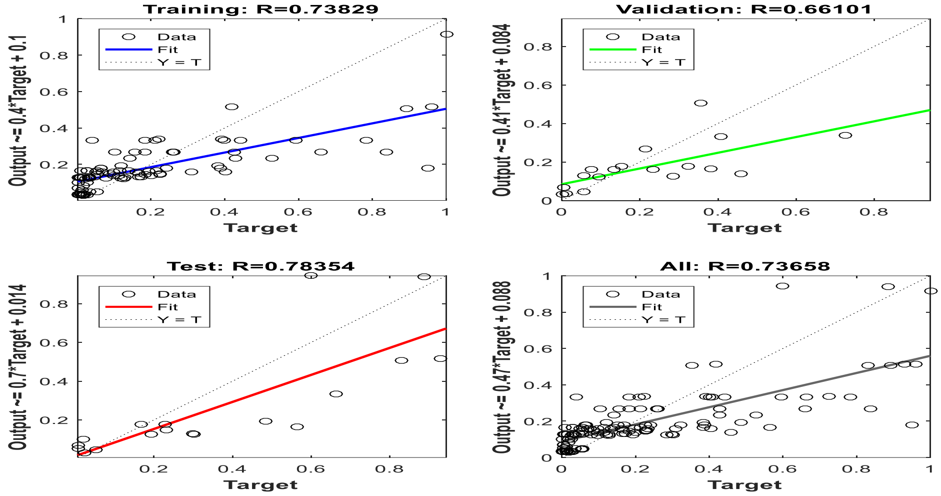

Figure 8.b: Day, lime, CEM good approach of neural training, validation, Test and all data value

Model 3

N10

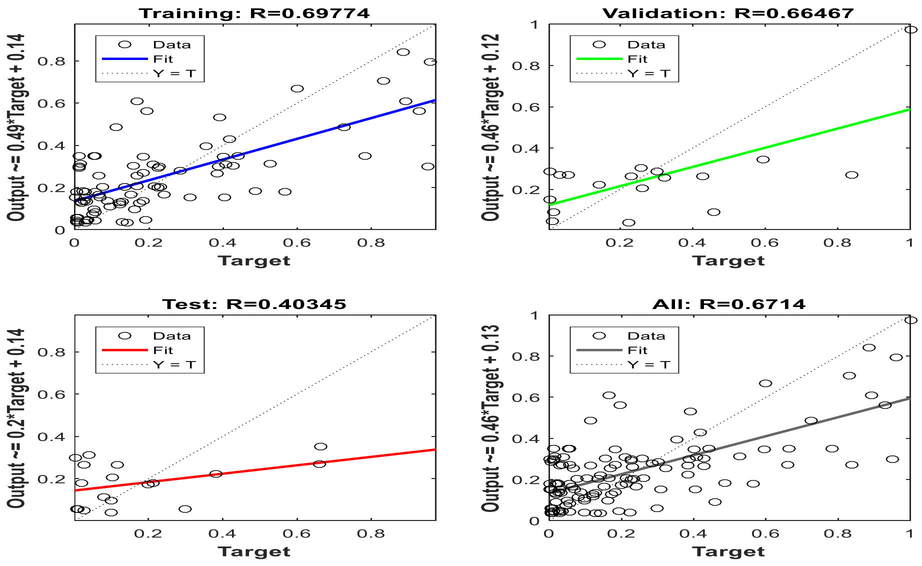

Figure 9.b: Day, MgO, CEM, PFA good approach of neural training, validation, Test and all data value

Model 4

N4

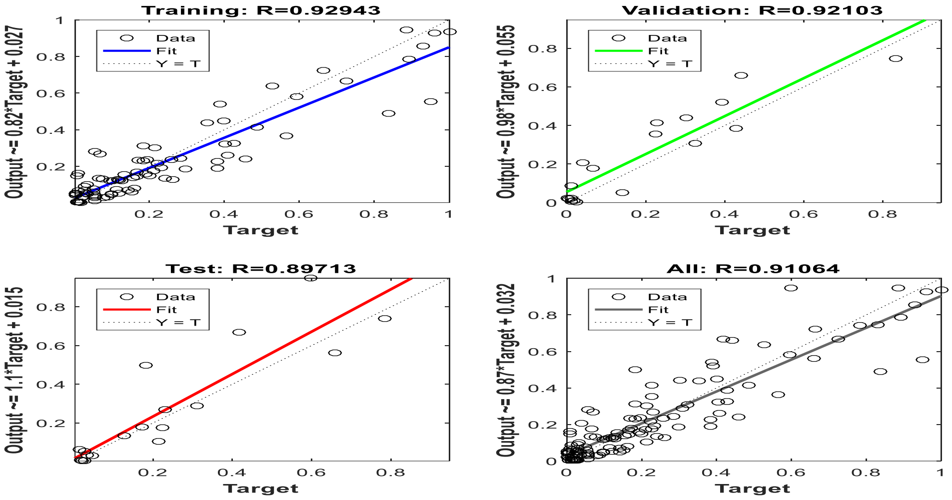

Figure 10.b: Day, BD, CEM, PFA, slag good approach of neural training, validation, Test and all data value

N10

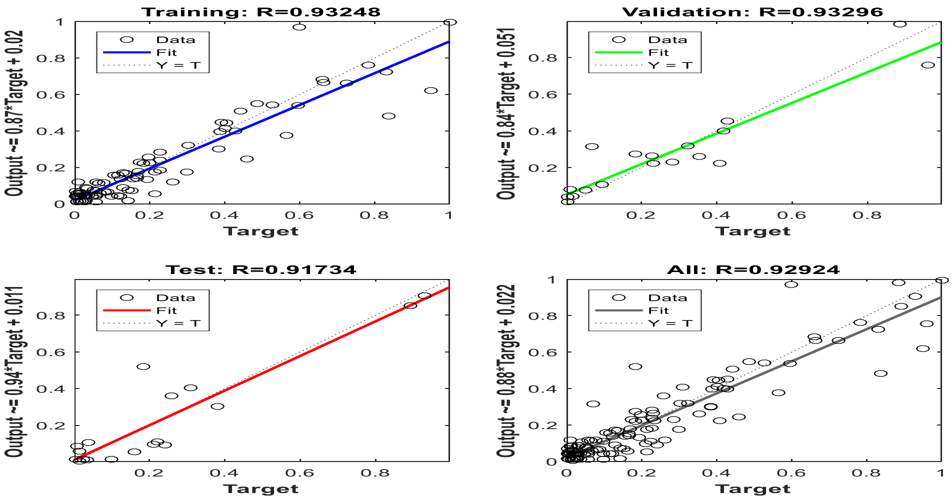

Figure 11.b: Day, MgO, CEM, PFA, Slag good approach of neural training, validation, Test and all data value

Model 5

N20

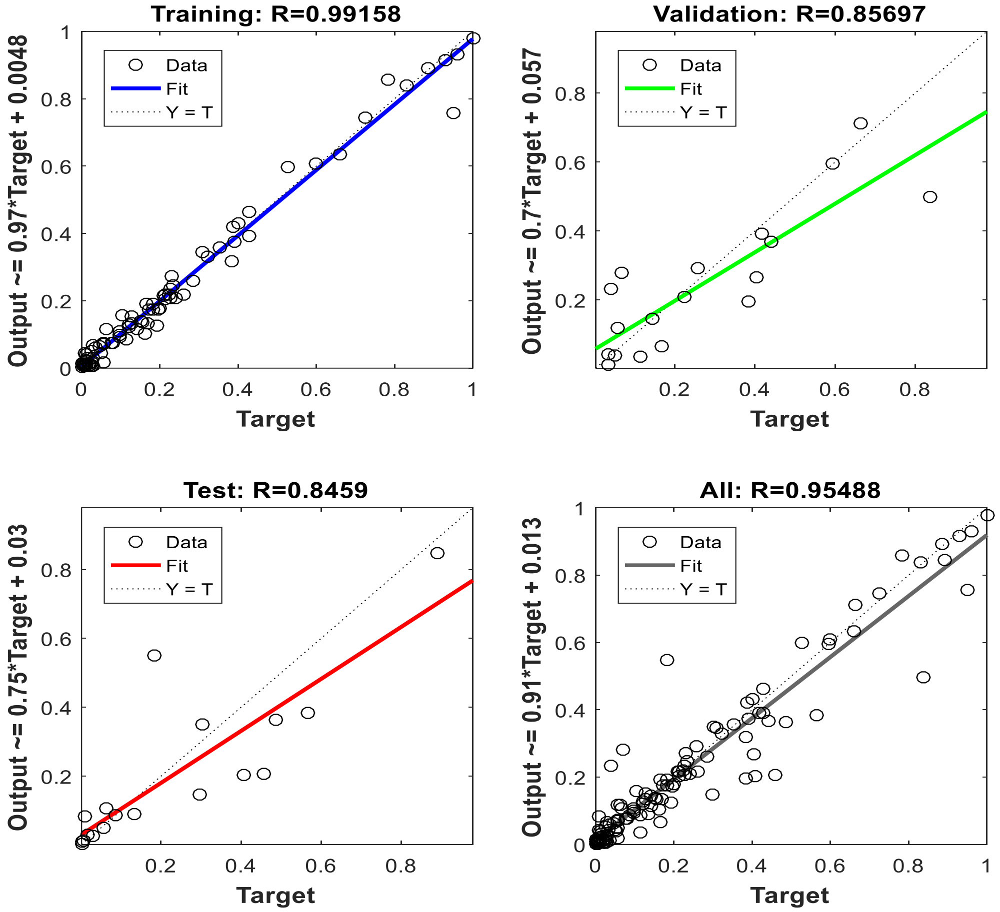

Figure 12.b: Day, MgO, CEM, PFA, Slag, BD good approach of neural training, validation, Test and all data value

Model 6

N18

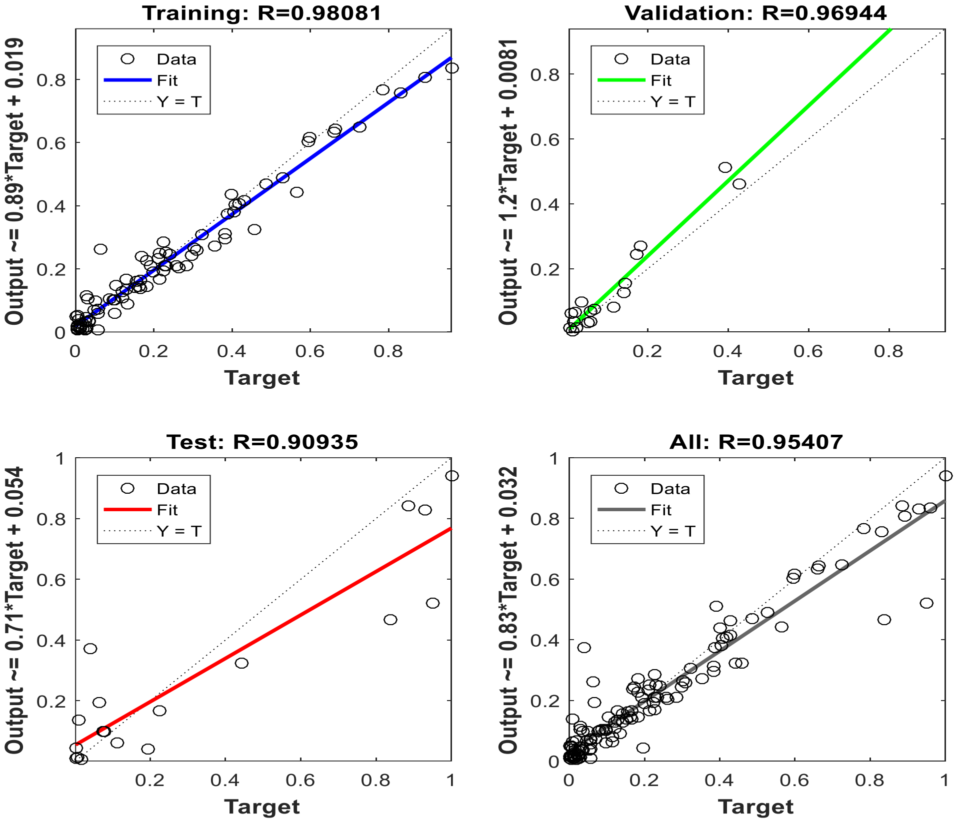

Figure 13.b: Day, Lime, MgO, PFA, Slag, Waste Addition, W/S, BD good approach of neural training, validation, test and all data value

Model 7

N18

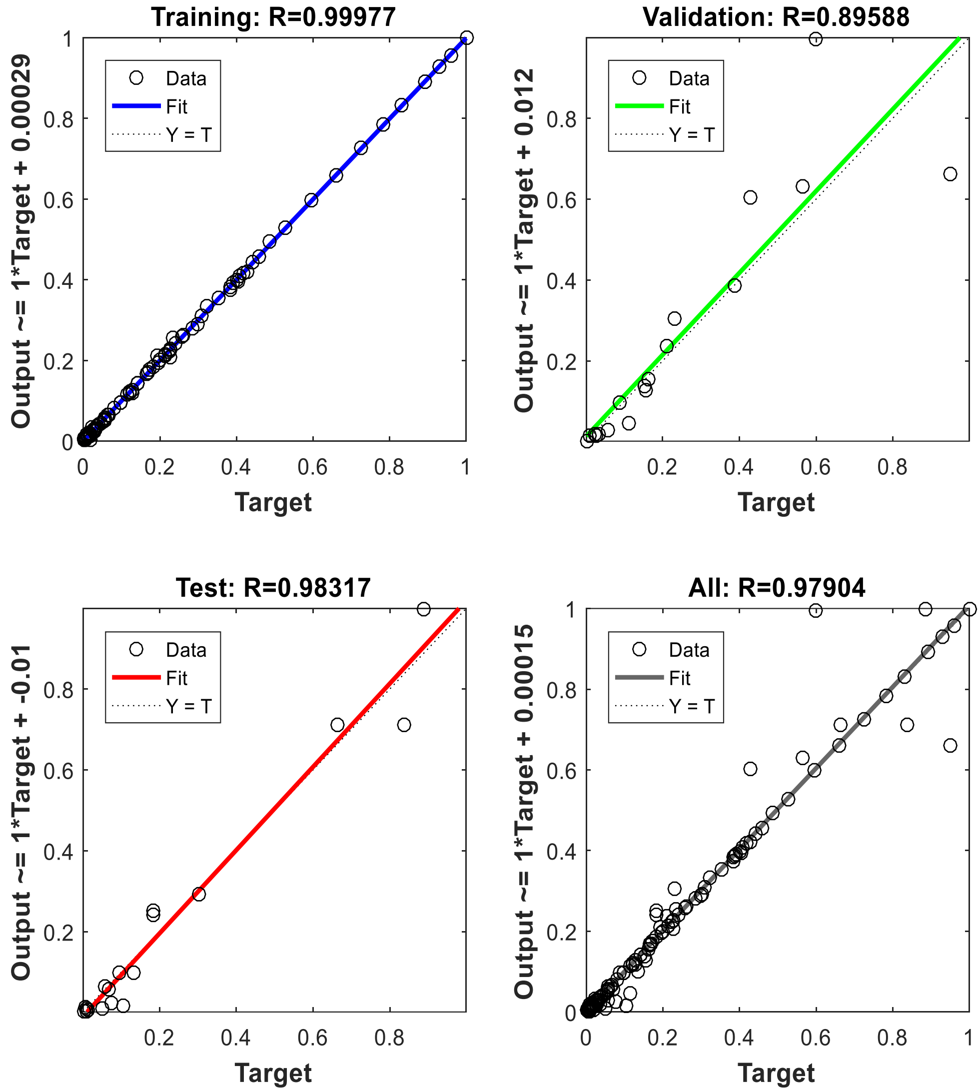

Figure 14.b: Day, CEM, Lime,MgO, PFA,Slag, Waste Addition, W/S, BD good approach of neural training, validation, test and all data value

Model 8

N8

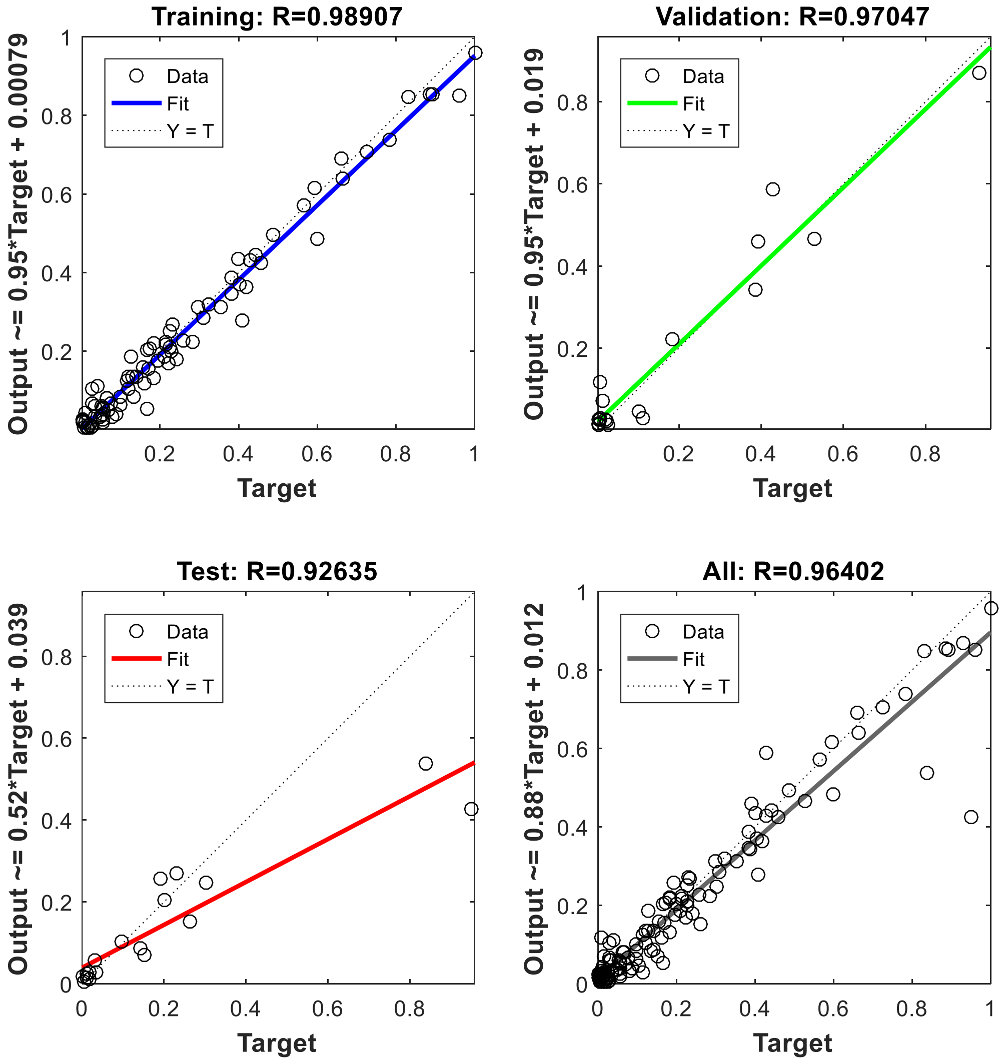

Figure 14.b: Day, CEM, Lime, MgO, PFA, Slag, Waste addition and water to solid without addition of Bulk Density good approach of neural training, validation, test and all data value

Model 9

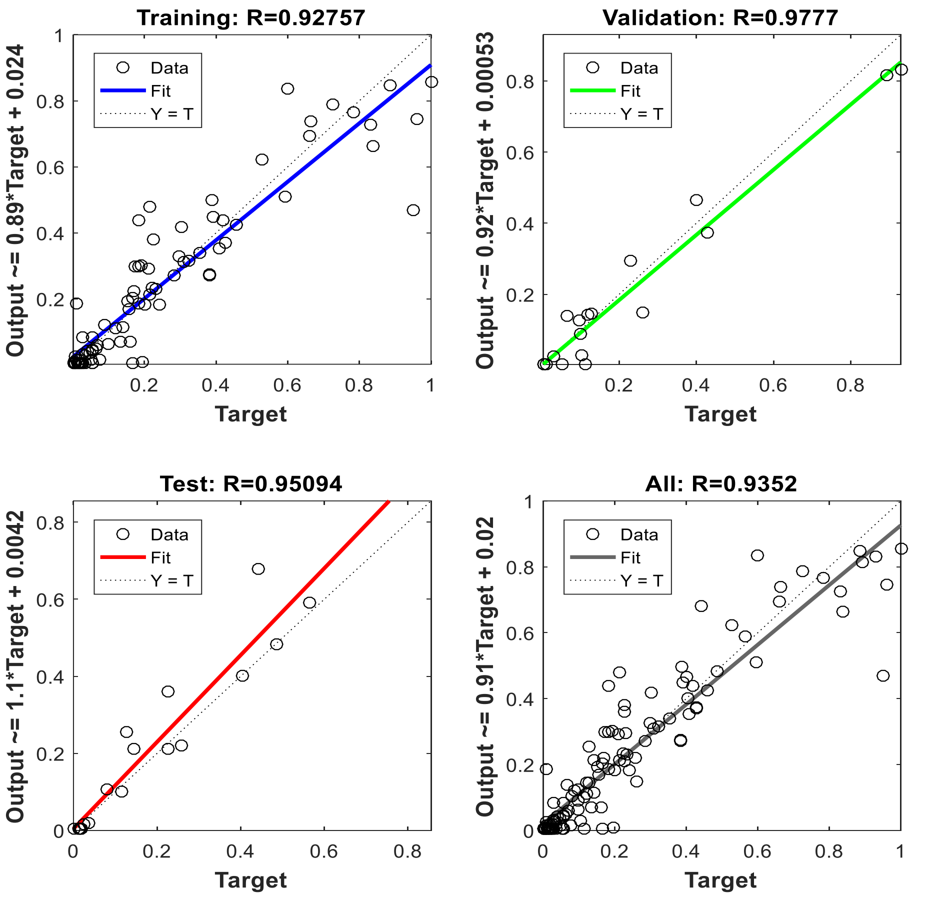

Figure 15.b: Date, CEM, MgO, PFA, slag, BD, water/solid, lime: without waste addition good approach of neural training, validation, test and all data value

Model 10

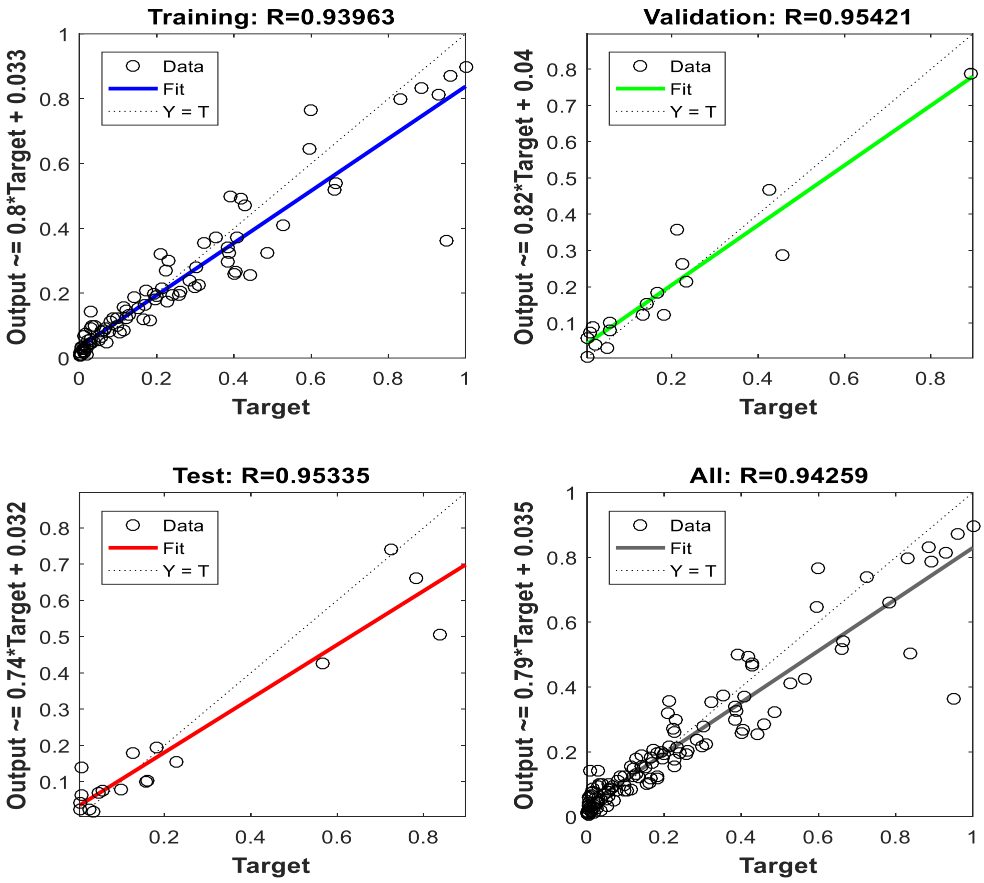

Figure 16.b: Date, CEM, MgO, PFA, BD, water/solid, waste addition, lime: without slag good approach of neural training, validation, test and all data value

Model 11

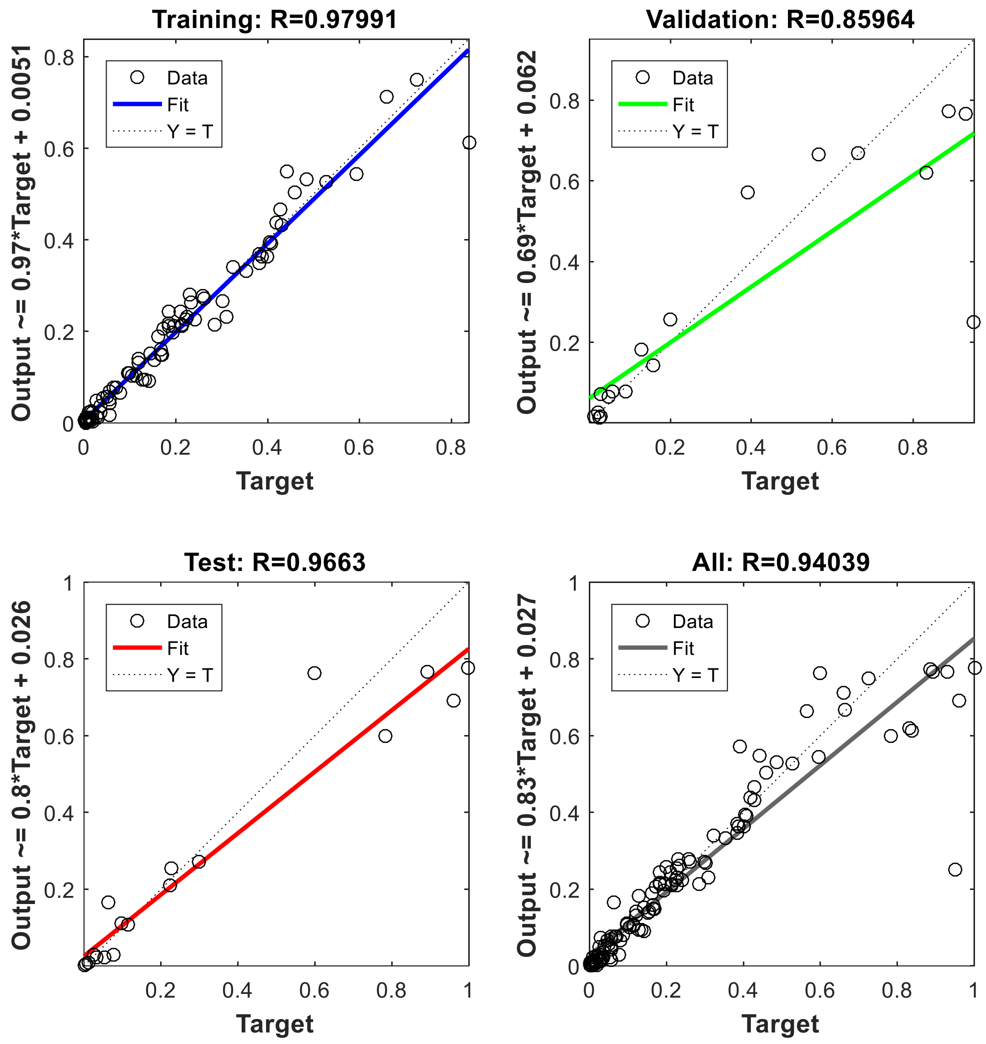

Figure 17.b: Date, CEM, MgO, PFA, slag, BD, waste addition, lime: Without w/s good approach of neural training, validation, test and all data value

Model 12

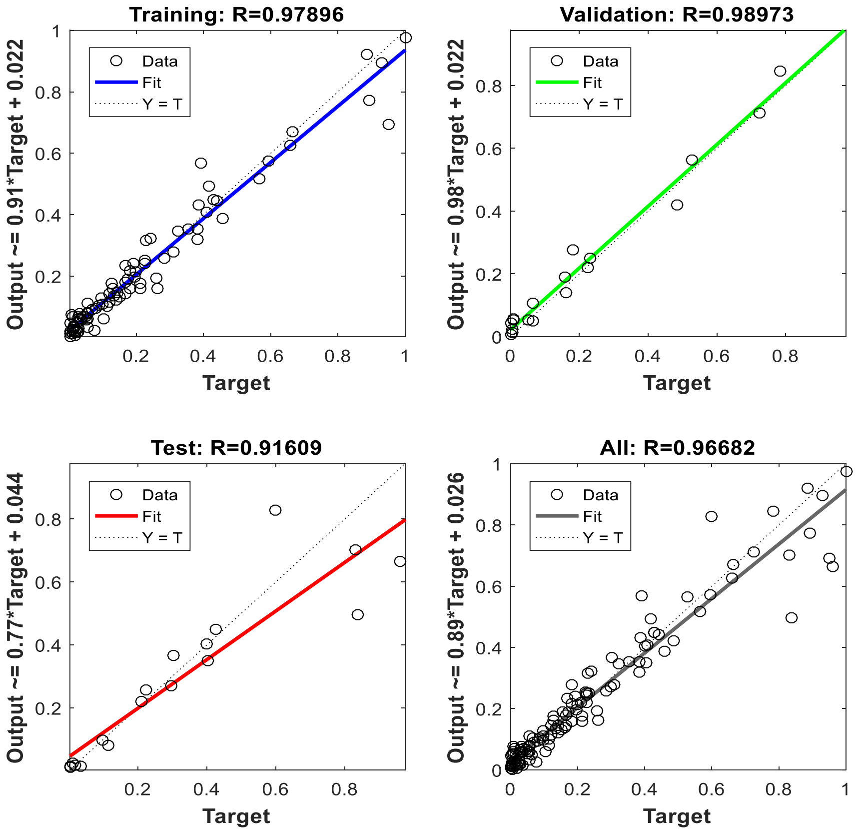

Figure 18.b: good Date, CEM, MgO, slag, BD, water/solid, waste addition, lime: without PFA approach of neural training, validation, test and all data value

Model 13

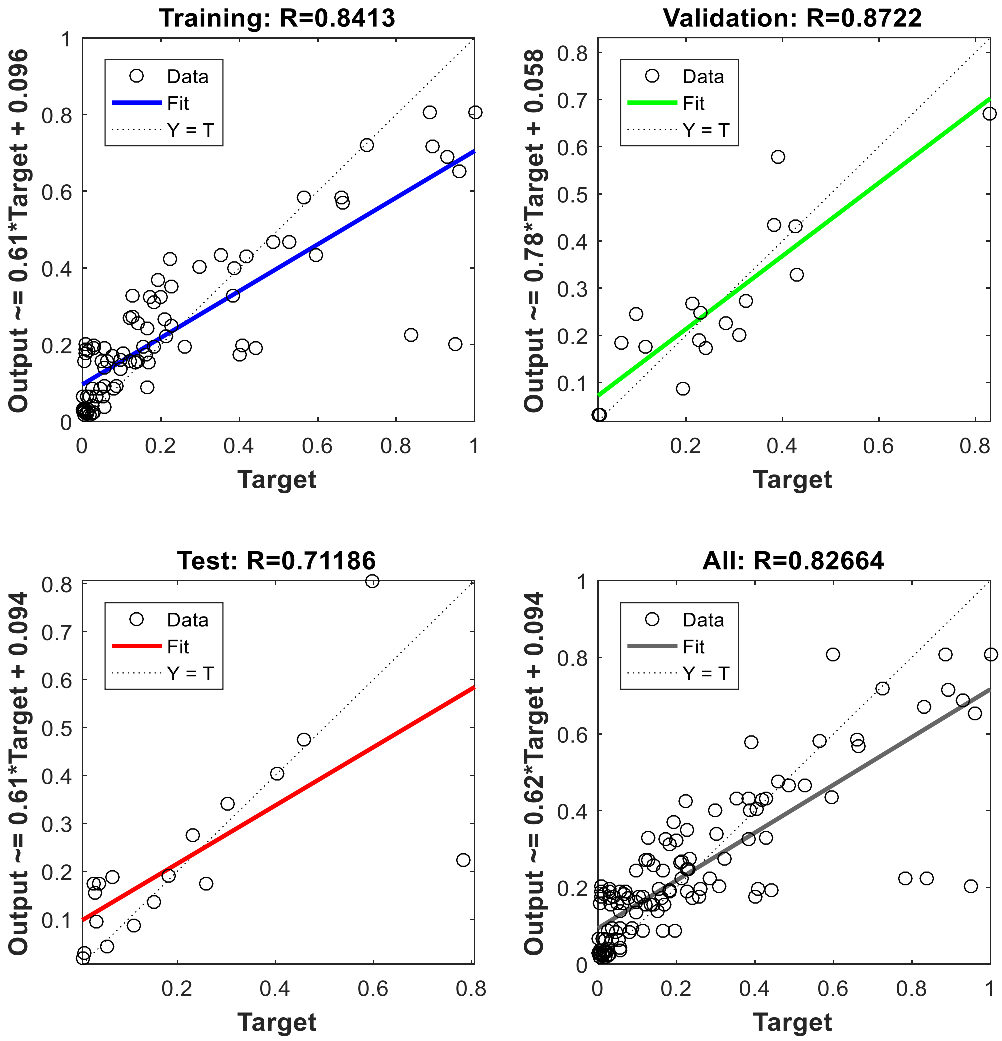

Figure 19.b: Day, CEM, MgO, PFA, slag, BD, water/solid, waste addition: without lime approach of neural training, validation, test and all data value

Model 14

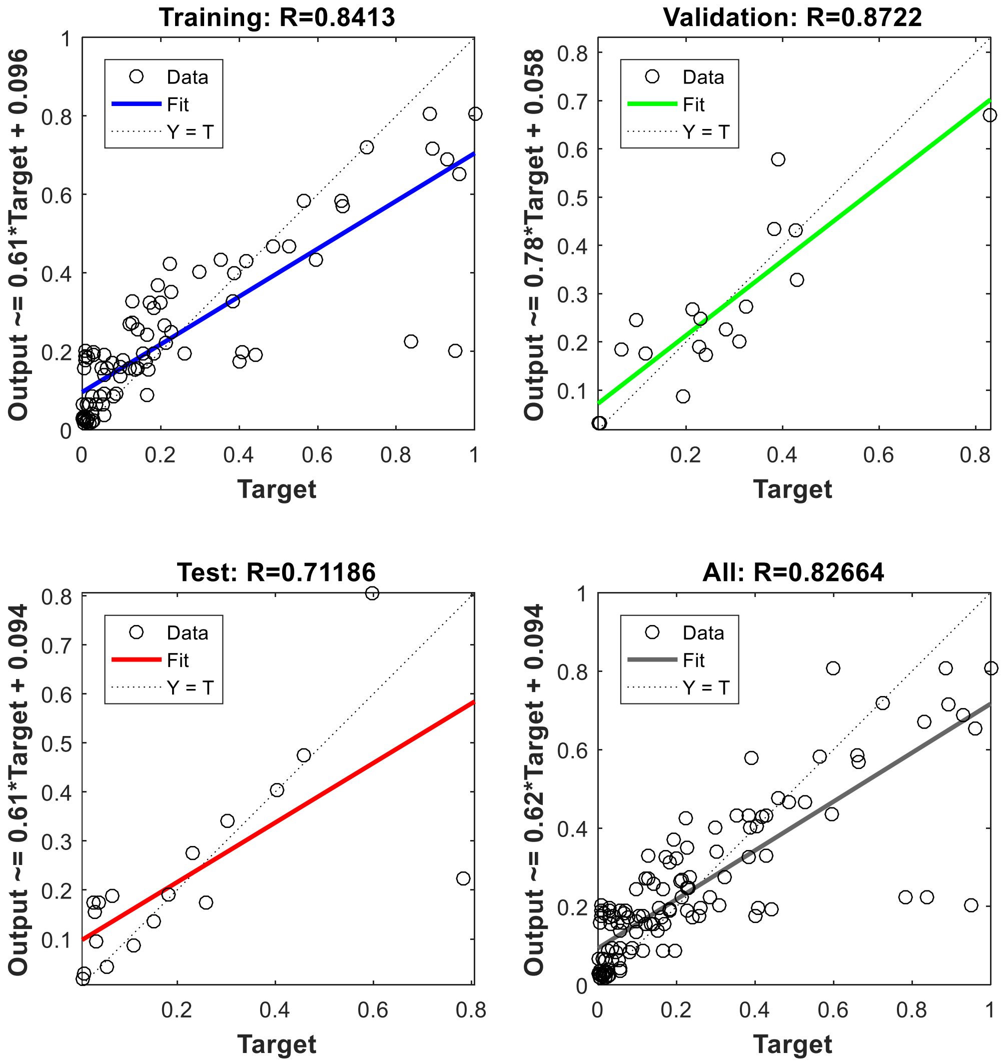

Figure 20.b: CEM, MgO, PFA, slag, BD, water/solid, waste addition, lime: without Day approach of neural training, validation, test and all data value