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Marshall Test Results Prediction

Using Artificial Neural Network

By

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DECLARATION

I certify that all the material in this thesis that is not my own work has been identified, and that no material is included for which a degree has previously been conferred on me.

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We certify that we have read the present work and that in our opinion it is fully adequate in scope and quality as thesis towards the partial fulfillment of the Master Degree requirements in

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All thanks to ALLAH the most gracious the most merciful who gives me the strength to accomplish this research and give a small part of his great knowledge.

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Abstract

Hot Mix Asphalt (HMA) is the most common type of pavements used in Egypt and around the world. Several factors can affect the pavement performance. A good understanding of these factors would enable pavement experts to build smooth, cost effective, and long-lasting pavement that requires little maintenance and satisfies user needs. Several methods can be used to design the (HMA). Among these methods is the Marshall Test Method developed originally by Bruce Marshall and widely used around the world.

Marshall Test method used also for quality control and quality assurance of (HMA) but it takes long time about 24 hours.

Extraction and Sieve Analysis Tests which take short time about 20 minutes used to check adaptation of the (HMA) in site which previously designs by Marshall Test Method.

The main objective of this research is to develop a simple Artificial Neural Network (ANN) simulation model to predict the future Marshall Test Results depending on previously recorded data from Extraction and Sieve Analysis Tests.

Table of Contents

List of Figures

List of Figures (Cont'd)

List of Tables

Chapter One

INTRODUCTION

Chapter1

INDRODUCTION

1.1 Overview

Asphalt pavement is spread method to pave highways, airports and parking lots because of their ability to provide improved ride quality, reduce pavement distresses, reduce noise levels, reduce life-cycle costs, and provide long-lasting service. Hot mix asphalt (HMA) is most common asphalt mixes; it is a combination of different sized aggregates and asphalt cement, which binds the mixture together. HMA is generally composed of 93 to 97 percent by weight of aggregate and 3 to 7 percent asphalt cement.

The most popular method used to design the Hot Mix Asphalt (HMA) especially in Egypt is Marshall Mix design (AASHTO T-245), The Marshall method seeks to select the asphalt binder content at a desired density that satisfies minimum stability and range of flow values (Khanfar and Kholoqui,2007). The Marshall method uses several trials of aggregate-asphalt binder blend (typically 5 blends with 3 samples each for a total of 15 specimens), each with a different asphalt binder content. Then, by evaluating each trial blend performance, optimum asphalt binder content can be selected.

For product acceptance, quality assurance, process quality control and research the Extraction and Sieve Analysis ASTM(D-2172&D-136) test method used to determine the asphalt content of hot mix asphalt, the asphalt content is expressed as a percent by dry weight of extracted aggregate corrected for asphalt mix moisture content and extractor error. The sieve analysis test applied for determination of the particle size distribution of aggregate extracted from asphalt mixtures. Extraction and sieve analysis test take short time to operated, so the results can be used to estimate the Marshall Test results.

Stability of asphalt concrete determines the performance of the highway pavement. Low stability in asphalt concrete may lead to various types of distress in asphalt pavements(Ozgan.,2011).

1.2 Research Objectives

This research deals with the target to develop a simple Artificial Neural Network (ANN) simulation model to predict the future Marshall Test Results (stability, flow, density and air voids ratio) depending on previously recorded data from Extraction and Sieve Analysis Tests the research has 4 main objectives:

1. Identify the factors affecting the results of Marshall Test separately depending on related Sieve Analysis and Extraction tests.

2. Use state-of-the-art techniques, such as Genetic Algorithms and feed-forward Back propagation, for optimization and training of the Neural Networks to determine the optimum Neural Network model that accommodates the identified parameters.

3. Promote the application of the Neural Networks approach in the construction domain by presenting it in a simple spreadsheet format that is customary to construction practitioners.

4. Develop a simple tool for Marshall Test results prediction using the resulting Neural Network model.

1.3 Research Methodology

The approach used to arrive at the study objectives can be summarized in the following steps:

1. Review the theory and current developments in Marshall Test, Sieve Analysis tests, Extraction tests and Neural Networks that relate to the system modules. This helps identify, for each module, the most appropriate procedure applicable to the system.
2. Collect and organize real and accurate data related to Marshall Tests, Sieve Analysis tests and Extraction tests.
3. Develop the Marshall Test results estimation system in a modular architecture with several components (Figure 1.1).
4. Identify the qualitative factors which need to be considered in the Marshall Test results estimation.

5. Study the applicability of Neural Networks to the problem at hand; accordingly, develop the Marshall Test results estimation system.

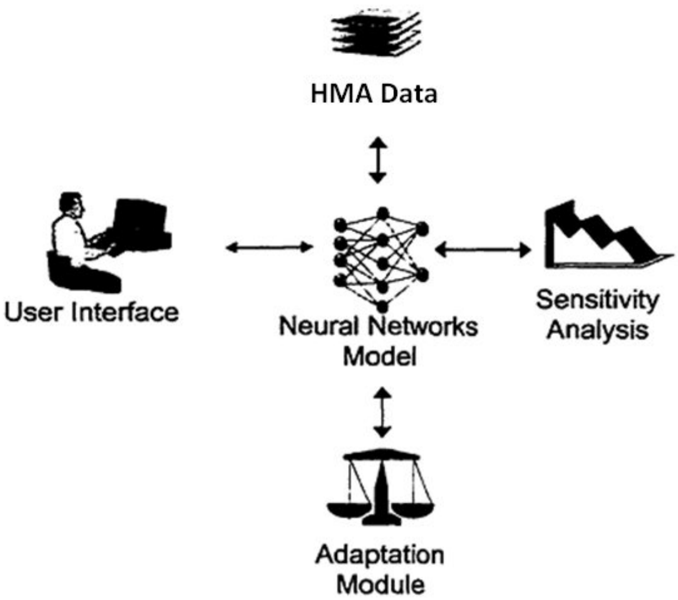


Figure 1.1 Components of Marshall Test Results Estimation System

1.4 Thesis organization

The thesis is divided into five chapters:

- Chapter one gives an introduction about the research and the procedure of the work.
- Chapter two contains a literature review about the Marshall, extraction, sieve analysis tests and introduction to neural network.
- Chapter three describes the methodology of classifying the collected data.
- Chapter four presents models prediction and data analysis.
- Chapter five presents the summary and conclusions.

Chapter Two

LITERATURE REVIEW

Chapter2

LITERATURE REVIEW

2.1 Background

The origin of roads dates back to the period before the advent of recorded history. With the desire to hunt animals for food, the ancient man began to form pathways and tracks to facilitate his movements. As civilization advanced, the growth of agriculture took place and human settlement to another, tracks were formed. These tracks might have been the skeletal framework of the modern highways.

The next major event to revolutionaries transport was the invention of the wheel (approx. 3500-5000 BC). Man soon saw the advantages of an axle joining two wheels and began to build two-wheeled and four-wheeled carts and chariots. The art of road-building soon began with the need to provide a hard durable surface to withstand the abrading effect of the wheels.

Many civilizations have been known for their excellence and attainments in road building. The streets of city of Babylon are known to have been paved one or two kilometer in length and 10-20 meter in width. It was paved with stone slabs which rested on a few layers of bricks jointed with bitumen.

The construction of the Great Pyramid in Egypt, about 3000 BC, was facilitated because of a good road for transporting huge stone blocks from the Nile River bank to the construction site of the pyramids.

The Roman civilization is well-known for the good road system it built. The 100,000 km roads network served military and administrative purposes. Some of the modern highways of Europe are aligned generally along the routes of the Roman Era. The top layers of the pavements consisted of flat stones. Lime mortar was used to cement the stones (figure 2.1.)

The Persians built the Royal Persian Road, connected Turkey to the Persian Gulf. This road served both trade and military purposes (Kadyali and Lal,2008).

Figure 2.1 Old Roman Road (Kadyali and Lal,2008)

2.2 Modern Highway Engineering

The industrial revolution in Europe created accelerated demand for transport in that continent. Wheeled coaches began to make their appearance on the roads in the sixteenth century. The disruption of the road bed caused by the movement of animal drawn passenger coaches and goods wagons gave a spurt to scientific design of roads.

Pierre Tresaguet, the Inspector General of roads in France, was the first to recognize the importance of drainage of roads and its methodical maintenance (Kadyali and Lal,2008). He appreciated the role of moisture in soils and pavements and how moisture affects the performance of road beds. Camber began to be rightly called the father of modern highway engineering.

The name of Johan Metcalf is associated with the art of building good and stable roads in Britain in the latter part of the eighteenth century (Kadyali and Lal,2008). He used boulders to achieve strong foundations for roads and spread gravel as a surface layer. He pioneered the construction of good roads on soft ground, using a sub-base of bundles of heather.

Thomas Telford is yet another illustration name in highway engineering, immortalized by naming the hand –packed boulder foundation of roads as Telford base.

The construction technique held the sway for nearly 150 years since Telford introduced it in the early part of the nineteenth century (Kadyali and Lal,2008).

A run of names of eminent highway engineers is incomplete without John Mc Adam's. He was a Scottish road builder who was influenced road construction so profoundly that the term "macadam" is frequently used in pavement specification even to this day. His two important principles of good road construction were:

- It is the native soil that supports the traffic load ultimately, and when the soil is maintained in dry state it can carry heavy loads without settlement.
- Stones which are broken to small angular pieces and compacted can interlock with each other and form a hard surface.

Thus, Mc Adam's specifications were at variance with Telford's in that small pieces of stones with angular faces were favored than larger hand-packed boulders. He was reported to give a practical hint to engineers in selecting the size of stones; the size is good if the stone cane be put into the mouth. How valid his advice is even to this day! Apart from the innovative specifications he introduced, Mc Adam is also remembered for his foresight in urging the creation of a central highway authority to advice and monitors all matters relating to roads in Britain. (Figure 2.2) gives the cross-sections of some of the early roads.

A significant development which revolutionized road construction during the nineteenth century was the steam road roller introduced by Eveling and Barford.

The development Portland cement in the first few decades of the nineteenth century by Aspdin and Johnson facilitated modern bridge construction and use of concrete as a pavement material (Kadyali and Lal,2008).

Tars and asphalts began to be used in road construction in the 1830s, though it was pneumatic tyre vehicle which gave real push to the extensive use of bituminous specifications.

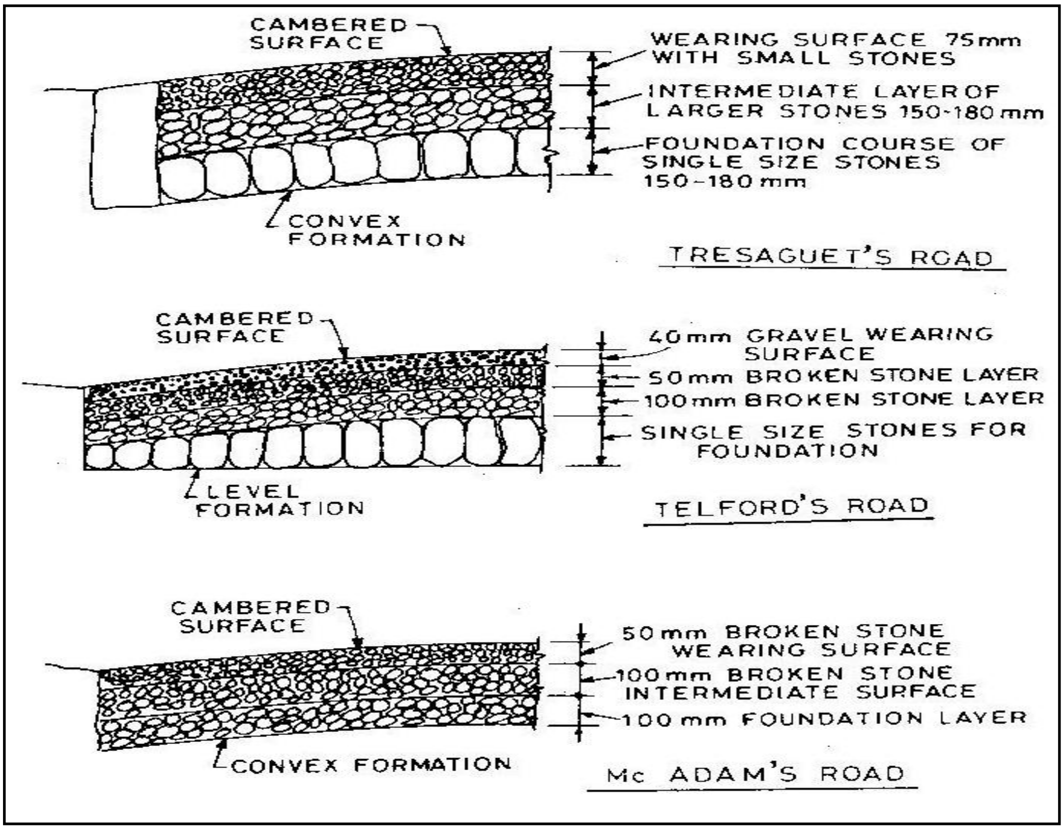


Figure 2.2 Cross-Sections of Some of the Early Roads. (Kadyali and Lal,2008).

2.3 Pavement Types

Roads comprised many parts that can be discussed; the most important part is the pavement. Basically, pavement can be categorized to two groups flexible and rigid. Flexible pavements are those which are surfaced with bituminous (or asphalt) materials. These can be either in the form of pavement surface treatments such as a Bituminous Surface Treatment, generally found on lower volume roads or, Hot Mix Asphalt (HMA) surface courses, generally used on higher volume roads. These types of pavements are called flexible since the total pavement structure bends due to traffic loads. A flexible pavement structure is generally composed of several layers of materials which can accommodate this flexing. On the other hand, rigid pavements are composed of a Plain Concrete (PC) surface course.

Such pavements are basically harder than flexible pavements due to the high modulus of elasticity of the PC material. Further, these pavements can have reinforcing steel, which is generally used to reduce or eliminate joints (Department of Transportation USA, 2011), as shown in Figure2.3.

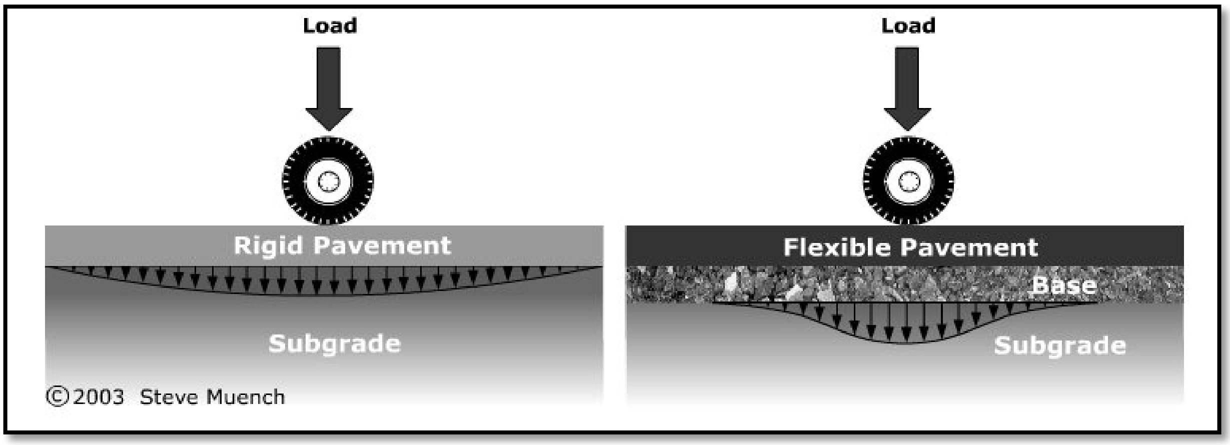


Figure2.3 Rigid and Flexible Pavement Load Distribution*(W. and Lenz, 2011)*

2.4 Hot Mix Asphalt Pavement

Asphalt pavements are composed of skeleton of coarse and fine aggregates and a filler of aggregate dust, asphalt cement as a binder and air voids as shown in Figure 2.4. Three groups of aggregates are usually used in asphalt concrete mix design. These are coarse aggregate, fine aggregate and mineral filler.

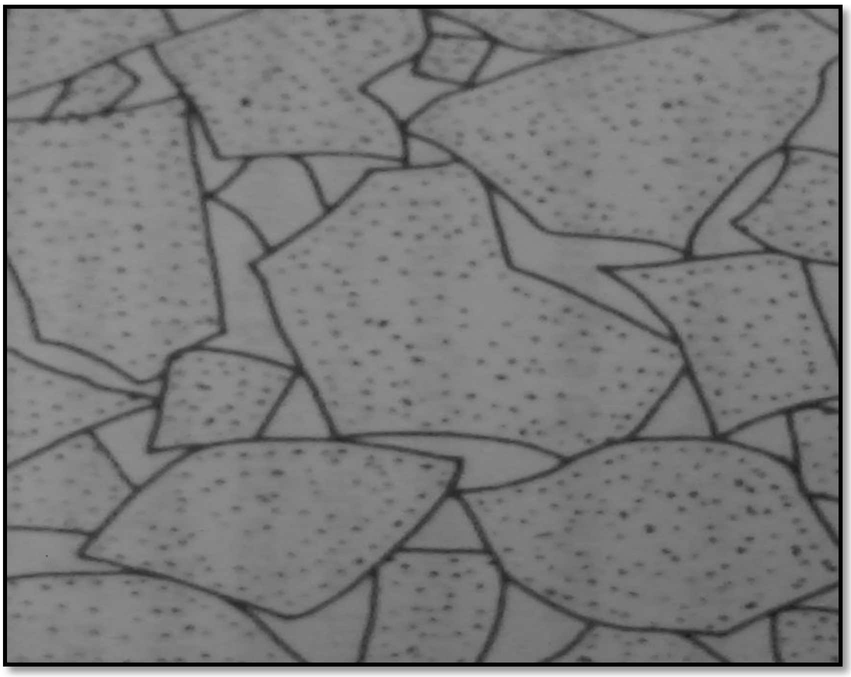


Figure2.4 Diagram Aggregate Frame Work with Asphalt Binder and Air Voids(Kadyali and Lal,2008).

A successful flexible pavement must have several desirable properties. These are stability, durability, safety (skid-resistance) and economy. Because of the binding property of asphalt cement, it is the most important constituent in asphalt concrete mix. Quality control of asphalt cement is always required and essential for successful mix performance. Some of these control quality tests are performance grading (PG), penetration, softening point, ductility, flash point, thin- film oven test, solubility, viscosity, etc. Asphalt content is a very important factor in the mix design and has a bearing on all the characteristics of a successful pavement. Various mix design procedures are used for finding out the "optimum" asphalt content.

2.5 Hot Mix Asphalt Design Methods

All of (HMA) design methods must govern the following considerations:

1. The binder content should be sufficient to impart the maximum stability. For a given mix grading, there is an optimum binder content that produce maximum stability.

2. The binder content should be to impart workability to the mix to facilitate its placement.

3. The voids in the aggregates should partly fill by bitumen and partly left unfilled. The unfilled voids will act a reservoir of space for the expansion of the asphalt during hot days and for a slight amount of additional compaction under traffic loading. Overfilling of the voids with binder may result in bleeding of asphalt and should be avoided.

4. The durability of the pavement is governed by the binder content. The higher the binder content, the more durable is the mix.

   Some of the above considerations are conflicting in requirements. Therefore, the selection of the binder content has to be a judicious compromise.

There are four popular methods of (HMA) design(Kadyali and Lal,2008):

- Marshall method
- Hubbard-Field method

- Hveem method
- Smith traxial method

Each of the above methods is associated with a set of design criteria for the properties of the mix. The Marshall method is the most popular in Egypt and is described below.

2.6 Marshall Method

The Marshall method of mix design has been widely used with satisfactory results. It was developed originally by Bruce Marshall of the Mississippi State Highway Department. The U.S. corps of engineers had been later developed and adopted it.

2.6.1 Specimen Preparation

The test is relatively a simple one and uses simple apparatus. In the test a sample specimen 4in in diameter and 2½in high is prepared by compacting in a mould on both faces with a compacting hammer shown in Figure 2.5. That weighs 10lb and has a free fall of 18in depending upon the design traffic condition

- For heavy traffic use 75 strokes at both sides of sample
- For medium traffic use 50 strokes at both sides of sample
- For light traffic use 35 strokes at both sides of sample

After overnight curing, the density and voids are determined and the specimen is heated to 140ºF (60ºC) for the Marshall Stability and flow tests. Our study will be made on heavy loading criteria.

The specimen is then placed in a cylindrically shaped split breaking head and is loaded at a rate of 2in/min. The maximum load registered during the test in Newton or pounds is designated as the Marshall stability of the specimen. The stability we want to get is bigger than or equals 750Kg.

2.6.2 Determination of Marshall Stability and Flow

The stability gained from the apparatus is in divisions. This value should be evaluated in Kg for the standard height of a specimen which equals 63.5mm (2.5”). The height of the specimen may not be standard, so a correction factor must be multiplied by the stability value we gained. We use the following equation:

$$Stability(Kg) = Stability(div.) \times 1.64$$
$$Stability_{corrected} = Stability(Kg) \times C$$

Where:

C: Factor of height

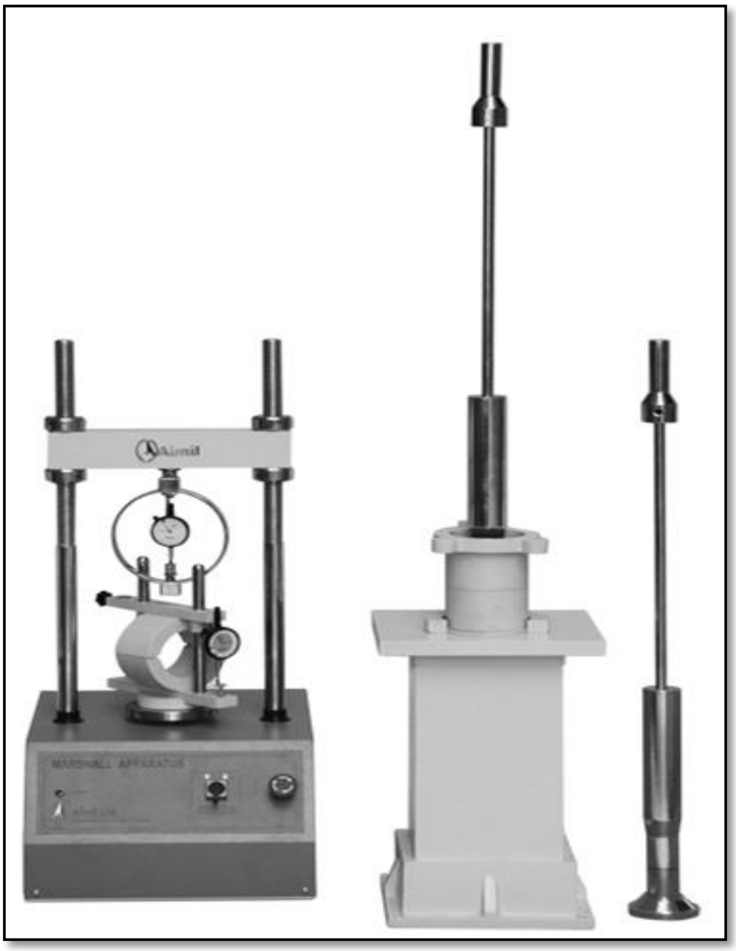


Figure2.5 Marshall Stability Test Apparatuses (Mfg,2014)

The amount of movement, or strain, occurring between no load and the maximum load, in units of 0.01in, is the flow value of the specimen. The specimen needed to be flexible, not too hard so it will disintegrate or not too liquid. The limits of flow are 0.8”-0.16” (2 – 4 mm).

2.6.3 Determination of properties of HMA

Durability is needed for an asphalted specimen. This is measured by finding the voids percentage in the specimen, or the Voids in Mix. These voids are the voids in the mix after compaction having the range of 3-5% with 4% for medium load. Less than 3% voids ratio means no enough space for bitumen to fill the sample and carry the load. While more than 5% ratio means a very high porous specimen, thus, ease for water and air to flow inside and therefore lead to segregation.

It has been noticed that after long term use of the road, the voids ratio will decrease because of compression under load. So a correction for the limit is used, that is (4-6) % so that the voids ratio will go back to its original limit after compaction. There are five measurements we can use them:

The theoretical specific gravity *Gt*. the bulk specific gravity of the mix *Gm*. percent air voids *Vv*. percent volume of bitumen *Vb*. percent void in mixed aggregate *VMA* and percent voids filled with bitumen *VFB*.

These calculations are discussed next. To understand these calculations a phase diagram is given in (Figure 2.6).

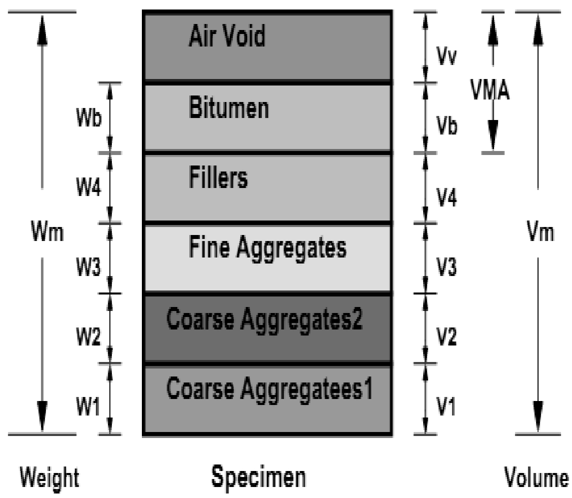


Figure2.6 Marshall Mould (Mathew and Krishna Rao,2006)

2.6.4 Theoretical specific gravity of the mix *Gt*

Theoretical specific gravity Gt is the specific gravity without considering air voids, and is given by:

$$G_t = \frac{W_1 + W_2 + W_3 + W_b}{\frac{W_1}{G_1} + \frac{W_2}{G_2} + \frac{W_3}{G_3} + \frac{W_b}{G_b}} \quad (1)$$

Where,

W1 is the weight of coarse aggregate in the total mix,

W2 is the weight of fine aggregate in the total mix,

W3 is the weight of filler in the total mix,

Wb is the weight of bitumen in the total mix,

G1 is the apparent specific gravity of coarse aggregate,

G2 is the apparent specific gravity of fine aggregate,

G3 is the apparent specific gravity of filler

Gb is the apparent specific gravity of bitumen,

2.6.5 Bulk specific gravity of mix Gm

The bulk specific gravity or the actual specific gravity of the mix Gm is the specific gravity considering air voids and is found out by:

$$G_m = \frac{W_m}{W_m - W_w} \quad (2)$$

Where,

Wm is the weight of mix in air,

Ww is the weight of mix in water,

2.6.6 Air voids percent *Vv*

Air voids *Vv* is the percent of air voids by volume in the specimen and is given by:

$$V_v = \frac{(G_t - G_m)100}{G_t} \qquad (3)$$

Where

Gt is the theoretical specific gravity of the mix, given by equation (1).

Gm is the bulk or actual specific gravity of the mix given by equation (2).

2.6.7 Percent volume of bitumen *Vb*

The volume of bitumen *Vb* is the percent of volume of bitumen to the total volume and given by:

$$V_b = \frac{\frac{W_b}{G_b}}{\frac{W_1+W_2+W_3+W_b}{G_m}} \qquad (4)$$

Where,

W1 is the weight of coarse aggregate in the total mix,

W2 is the weight of fine aggregate in the total mix,

W3 is the weight of filler in the total mix,

Wb is the weight of bitumen in the total mix,

Gb is the apparent specific gravity of bitumen,

Gm is the bulk specific gravity of mix given by equation (2).

2.6.8 Voids in mineral aggregate VMA

Voids in mineral aggregate VMA is the volume of voids in the aggregates, and is the sum of air voids and volume of bitumen, and is calculated from

$$VMA = Vv + Vb \qquad (5)$$

Where,

Vv is the percent air voids in the mix, given by equation (3).

Vb is percent bitumen content in the mix, given by equation (4).

2.6.9 Voids filled with bitumen VFB

Voids filled with bitumen VFB is the voids in the mineral aggregate frame work filled with the bitumen, and is calculated as:

$$VFB = \frac{V_b \times 100}{VMA} \tag{6}$$

Where,

Vb is percent bitumen content in the mix, given by equation (4).

VMA is the percent voids in the mineral aggregate, given by equation (5).

An additional useful term is Stiffness.

$$Stiffness = \frac{Stability}{Flow}$$

2.7 Controlling Quality During Construction

2.7.1 Frequency of tests for quality control

Quality control during construction is necessary to ensure that the pavement is constructed so as to meet the various requirements of specifications and design documents. Such a quality control involves a variety of tests to be conducted during construction with regular frequency and obtaining all the relevant construction data for statistically processing the test results. The different types of tests to be conducted and their repetitions for earthwork , granular sub bases and base courses, pavement layers involving bituminous and cement concrete construction work are given in table 2.1 below.

Table 2.1 Frequency of tests for quality control(Kadyali and Lal,2008).

NO.	Item of work	Test	Frequency	Rate	Notes
1	Earthwork	Soil particle size, Atterberg Limits	1-2 tests	8000 m^3	
		C.B.R on a set of 3 specimens	1 test	3000 m^3	
		Natural moisture content	1 test	250 m^3	
		Moisture content before compaction	2-3 tests	250 m^3	
		Dry density of compacted area	1 test	1000 m^3	Embankments to be increased to one test per 500-1000 m3 for sub grade layers.
2	Gravel sub-base	Gradation, plasticity	1 test	200 m3	
		Moisture content	1 test	250 m3	
		Density	1 test	500 m3	
3	Lime – soil	Purity of lime	1 test	5Ton	
		Lime content, moisture content	1 test	250 m^2	

3	Lime – soil	Density	1 test	500 m^2	
4	Water-bound macadam	Los Angeles Abrasion or Aggregate Impact Value, Flakiness Index	1 test	200 m^3	
		Grading of materials	1 test	100 m^3	
		Plasticity of binder	1 test	25 m^3	
5	Bituminous Macadam	Los Angeles Abrasion Value or Aggregate	1 test	50-100 m^3	
		Mix grading, binder content, aggregate gradation	2 tests	day	
6	Surface dressing and premix carpet	Los Angeles Abrasion Value or Aggregate Impact Value, Stripping Value, Flakiness Index Water absorption	1 test	50 m^3	
		Grading of aggregate	1 test	25 m^3	
		Rate of spread of binder and aggregate for surface dressing	1 test	500 m^3	
		Binder content for premix carpet	2 test	day	

7	Hot mix Asphalt	Los Angeles Abrasion Value or Aggregate, Impact Value, Stripping Value, Water absorption, Flakiness Index	1 test	50-100 m^3	
		Sieve analysis for filler	1 test	100 ton of mix	
		Mix grading, binder content	1 test	100 ton	min. 3 tests per day
		Stability and flow Thickness and density	3 Marshall Specimens	1000 ton	
8	Cement concrete pavement	Gradation of aggregate Cement, physical and chemical Concrete strength	1 test		
		Los Angeles Abrasion Value or Aggregate	1 test		
		Impact Value, Soundness	1 test		

8	Cement concrete pavement	Workability	3 cube/beam samples for each 7 days and 28 days	30 m^3	
		Concrete strength on hardened concrete	2 cores	30 m^3	

2.7.2 Scope at Hot mix asphalt Q.C frequency

According to the previous table at Hot Mix Asphalt section it shown that for controlling quality during construction Mix grading (sieve analysis) and binder content (bitumen extraction) were conducted minimum 3 tests per day or one test per 100T of mix, Stability and flow (Marshall test) (AASHTO-T245,2006) conducted also 3 specimens per 100T of mix, so those tests are daily tests in site which can be correlated together .

2.8 Sieve Analysis for Fine and Coarse Aggregates

This test method determines the particle size distribution of fine and coarse aggregates by sieving. The No. 4 sieve is designated as the division between the fine and coarse aggregate Figure 2.7.

2.8.1 Procedure:

Dry the sample according to T 255 at a temperature of 230 ± 9°F (110 ± 5°C). Select sieves to furnish the information required by the specifications covering the material to be tested. Use of additional sieves may be desirable to prevent the required sieves from becoming overloaded.

The quantity retained on any sieve, with openings smaller than the No. 4 sieve, at the completion of the sieving operation shall not exceed 4 g per sq.in. of sieving surface area. If this occurs it is considered overloading of the sieve. The overload amount for an 8" diameter sieve is 200 g.

Figure2.7 The Sieve Shaker with a Stack of Sieves.(instruments,2014)

Table 2.2 Shows different size sieves of the maximum allowable quantities of material retained on a sieve (AASHTO-T-27,2006).

Table 2.2 Different Size Sieves of the Maximum Allowable Quantities of Material Retained on a Sieve*(AASHTO-T-27,2006)*.

MAXIMUM ALLOWABLE QUANTITY OF MATERIAL RETAINED*		
Sieve Opening Size	8" Diameter Sieve	14" Square Sieve
2" (50 mm)	7.9 lbs (3.6 kg)	33.7 lbs (15.3 kg)
1½" (37.5 mm)	6.0 lbs (2.7 kg)	25.4 lbs (11.5 kg)
1" (25.0 mm)	4.0 lbs (1.8 kg)	17.0 lbs (7.7 kg)
3/4" (19.0 mm)	3.1 lbs (1.4 kg)	12.8 lbs (5.8 kg)
1/2" (12.5 mm)	2.0 lbs (0.89 kg)	8.4 lbs (3.8 kg)
3/8" (9.5 mm)	1.5 lbs (0.67 kg)	6.4 lbs (2.9 kg)
No. 4 (4.75 mm)	0.7 lbs (0.33 kg)	3.3 lbs (1.5 kg)

2.8.2 Calculation:

Add the non-cumulative weight retained on the largest sieve to the weight retained on the next smallest sieve and record in the cumulative column.

Calculate the percent retained on each sieve by dividing each weight by the original total dry weight and multiply by 100. This is the percent retained. Subtract each of these values from 100 to obtain the percent passing each sieve. Continue this process for each sieve. The equations are as follows:

Percent retained on sieve = (Cumulative weight/Total weight) x 100

Percent passing = 100 - Percent retained on sieve

This calculation is completed for both the course and fine aggregate.

If an accurate determination of the amount of material passing the No. 200 was accomplished by performing T 11, subtract the weight after wash from the original weight and record as wash loss.

Sum the cumulative weight retained on the No. 200, the weight of the Minus No. 200 material, and the wash loss, and record as the weight check.

To calculate the percent passing of the total sample for the fine portion of the aggregate, multiply the percent passing the sieve No. 4 multiply by the percent passing on each individual. Sieve in the fine aggregate portion and divide by 100. The equation is as follows:

Percent total sample = [(Percent passing No.4) x (Percent passing smaller sieve)]/100

Final calculations of percentages passing are reported to the nearest whole number with the exception of the No. 200 which is reported to same significant digit as specified by the specification for the class of aggregate.

For both the Plus No. 4 and Minus No. 4, compare the original weight to the weight check. Subtract the smaller value from the larger value, divide the result by the original weight, and multiply by 100, to obtain the percent difference. For acceptance purposes, the two must not differ by more than 0.3%.

2.9 Bitumen Extraction Test

The method described is a procedure used to determine the bitumen content of bitumen aggregate mixtures according to(ASTM-D2127).

2.9.1 Apparatuses and materials:

- Centrifuge extractor with a bowl. The extractor must be capable of rotating the bowl at controlled variable speeds up to 3600 rpm as shown in Figure 2.8.
- Paper or felt filter rings to be placed on the rim of the bowl and beneath the bowl lid.
- Scale capable of weighing to 2500 g at 0.1 g accuracy.
- Heating equipment such as electric stove.
- 500 ml cup or beaker.
- Hand Tools - spatula, small brush, scoop, large pan for collection of a representative bitumen mix sample, pan for test sample.
- Container for collection of bitumen laden solvent thrown from the bowl during extraction.
- Solvents - suggested materials are benzene or Carbon Tetra chloride.

Figure2.8 Bitumen Extractor (Centrifuge Extractor)*(Mfg,2014)*

2.9.2 Procedure

A representative sample about 400gm is exactly weighed and placed in the bowl of the extraction apparatus and covered with commercial grade of benzene. Sufficient time (not more than 1 hour) is allowed for the solvent to disintegrate the sample before running the centrifuge.

The filter ring of the extractor is dried, weighed and then fitted around the edge of the bowl. The cover of the bowl is clamped tightly. A beaker is placed below to collect the extract.

The machine is revolved slowly and then gradually, the speed is increased to a maximum of 3600 r.p.m. The speed is maintained till the solvent ceases to flow from the drain. The machine is allowed to stop and 200 ml. of the benzene is added and the above procedure is repeated.

A number of 200 ml. solvent additions (not less than three) are used till the extract is clear and not darker than a light straw color.

The filter ring from the bowl is removed, dried in air and then in oven to constant weight at 115o C and weighed. The fine materials that might have passed through the filter paper are collected back from the extract preferably by centrifuging. The material is washed and dried to constant weight as before.

2.9.3 Calculation

The percentage of binder (binder content) in the sample is calculated as follows:

Percentage binder on the total mix $= \frac{W1-(W2+W3+W4)}{W1}$

Where W1 = weight of sample

W2 = weight of the sample after extraction

W3 = weight of fine material, recovered from the extract

W4 = increase in weight of the filter ring

2.9.4 Application of testes

The bitumen content of bitumen-aggregate mixtures as determined by the described test method is used for

- Product acceptance.
- Quality assurance.
- Quality control
- Research activities.

2.10 Modern Prediction Techniques

Different fields of engineering aims to estimate final results from previous recorded data. There are many kinds of prediction techniques such as:

- Artificial neural network.
- Linear and multiple regressions.
- Hypothetical frame work.

Generally, the first artificial neural network (ANN) paper in civil engineering area was published in 1989 (Adeli ,et al.,2001). (Adeli ,et al.,2001) identified the neural networks as “a function of the biologic neural structures of the central nervous system.”

Previously, researchers in the area of civil engineering used ANNs as a reliable tool for simulation and regression analysis. According to (Flood,2006), the artificial neural networks have been identified as the more flexible and precise method for all academic researches and some practical achievements. Flood pointed out the artificial neural network as reasonable and interesting research implemented in computer based civil engineering. However, the researchers are challenged to come up with a complete and convincing prediction model in the future (Flood,2006).

According to(Adeli and Wu,1998), a regularization neural network model was created to forecast the estimated construction cost of projects.

Another publication implements the back propagation network (BPN) model based on genetic algorithms to estimate construction projects cost(Kim ,et al.,2004).

(Kim ,et al.,2004)attempted to construct prediction models by two distinct methods; back propagation network (BPN) genetic algorithm and trial and error comparing the result. This attempt concluded that a BPN model incorporating a genetic algorithm determines reliable and accurate construction estimation compared to the trial and error method.

The artificial neural network methods and models represent broad usage in terms of simulation and statistical analysis in science and arts. A research was accomplished in terms of framework to develop, train, and test neural network to predict concrete activities estimation (Ezeldin and Sharara,2006). This attempt identified the influential factors in concrete activities and developed a prediction model based on the identified parameters.

The data used for accomplishment of this research was collected in Egypt. As a result of this research, the identification of influential factors demonstrates reasonable improvement to predict future values.

On the other hand, distinct to ANNs, models were developed based on **linear regression analysis** to predict the construction projects costs. An attempt of regression modeling used 286 records of data in the United Kingdom to develop forecasting models (Lowe ,et al.,2006). The models were created based on; cost/m2, log of cost and log of cost/m2. In this analysis backward and forward stepwise analysis was preferred. In addition, regression analysis and bootstrap methods were also implemented for the conceptual estimation of costs. The author concluded the advantage of this method as both techniques used for the same inputs with fewer assumptions(Lowe ,et al.,2006).

Also, (Sonmez 2004), emphasized advantages and disadvantages of conceptual cost estimation methods. In this investigation intangible cost models were developed based on regression analysis and neural networks to compare the method reliability. The researcher of this paper eager was to use simultaneously the regression analysis and neural network a leading step to the future of more realistic expectation and better strategies. A reliable advantage of simultaneously using both methods demonstrates the convenience of accuracy.

The third technique, a **hypothetical frame work** was performed to identify the critical issues of effective cost judgment during each stage of project (Liu ,et al.,2007). This work has classified the critical issues and relationship between the dependent and independent factors. (Liu ,et al.,2007), concluded the approach to be helpful for future construction companies to control the critical factors for an effective predicted estimation. In another attempt,(Skitmore and Ng,2003), developed several models based on 93 construction projects to predict the actual construction time. This analysis identified the influential parameters in project duration prediction as the method of contractors‟ selection of imprecise contract phase and sum, and cost based on the risk and doubts of different segments (Skitmore and Ng,2003). In another hand, an investigation was performed to incorporate the parametric and probabilistic cost assessment procedures as well (Sonmez 2004).

2.11 Introduction to Neural Networks

Based on many techniques and methods used to maintain the previous data and develop future forecasting models, mathematical regression analysis have been widely used(Aasadullah. Attal,2010). Based on the statistical analysis "Artificial Neural Networks (ANN) recently been broadly used to model some of the human activities in many areas of science and engineering" (Rafiq ,et al.,2001). Nevertheless, the previous historical data and expert represents crucial implements for future improvement.

According to (Moselhi ,et al.,1991), currently there have been several artificial intelligences such as expert systems, robotics , and neural networks used for statistical analysis. In this study, expert system was identified as an attempt to model the problem solution based on the capability of human brain. On the other hand, neural network efforts to model the brain learning, thinking, storage, and retrieval of information, as well as associative recognition" (Moselhi ,et al.,1991). Therefore, this research attempts to identify the input-output relationship and improve future highway construction data forecasts based on nonlinear ANNs and linear regression analysis.

A research pointed out that: "Artificial Neural Networks (ANNs) are mathematical models, which are biologically inspired to imitate the primitive cognitive functionality of the human brain" (Young II ,et al.,2008). The artificial intelligence model names machine learning represents data-driven is capable of showing complex input and output non-linear relationships (Young II ,et al.,2008).

Since the ANNs have been identified as universal approximator (Reed and Marks,1998), therefore a structured approach was performed to develop the non-linearity of modeling.

Artificial neural networks represent a combination of several layers of interconnecting processing elements named neurons (Young II ,et al.,2008). Also, activation functions applied with neurons to control the signals passing through the network. A Neuron represents a systematic unit correlating input-output or by another word "an artificial neuron is a single processing element in an ANN" (Young II ,et al.,2008). More clearly, an artificial neuron presents a device with many inputs and one output. Generally, the architecture of ANNs contains several parts as: input, controlling weights, summation, and output. A simple structure of an artificial neural network is shown in Figure 2.9. An artificial neuron is a unit processing element contains a single perceptron to compute the output of network by forming linear combination of activation functions and weights.

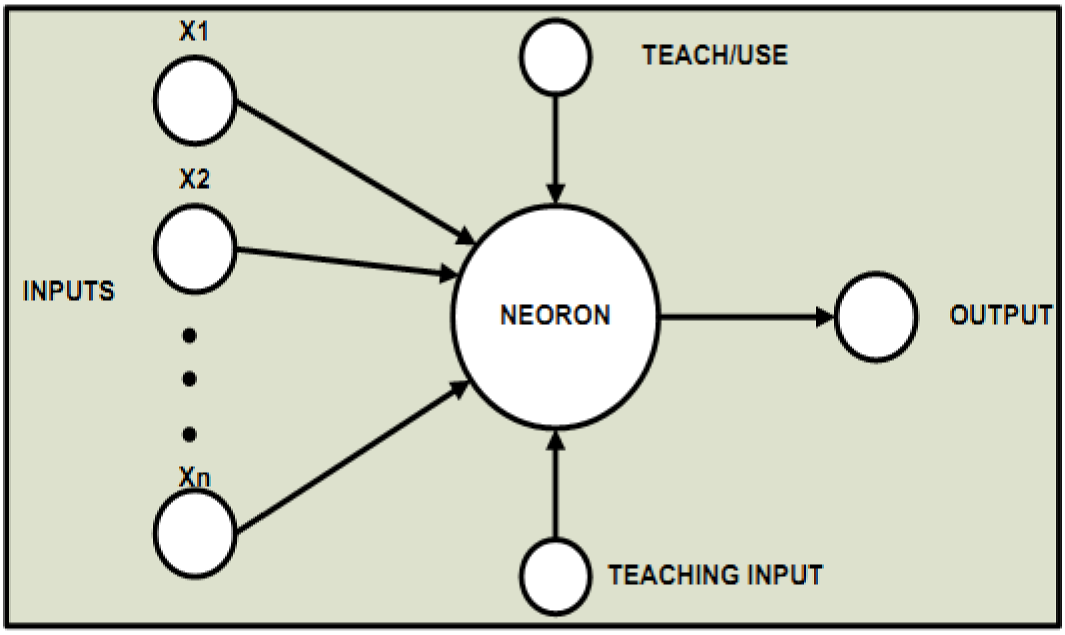


Figure2.9 Simple Neuron(Young II ,et al.,2008).

Where in figure 2.9; x1, x2,…,xn,m are inputs

- w1, w2,…wm represent connection weights
- B represents bias
- Y is dependent variable

In terms of the structure of ANNs, there have been several types of activation functions used in ANN table 2.3 (Young II ,et al.,2008). ANNs contains many types of applications used based on types of problems. The more related application types of ANNs in engineering area represents: adaptive controller, interpretation system, machining feature recognition system, image classification system, and a pump design system (Garrett et al., 1993). In addition to that, other applications used in engineering, formed in the following list:

1. Stochastic contains the approximation ability(Belli ,et al.,1999).
2. Functional networks for in real-time flood forecasting- a novel application (Bruen and Yang,2005).
3. Genetic algorithms (GA) for the permeability estimation of the reservoir, fuzzy neural networks for the design of industrial roofs (Rajasekaran ,et al.,1996).
4. Back-propagation learning algorithm used in a research for prestressed concrete pile (Tam ,et al.,2004).
5. Discrete - event simulation used for modeling of construction processes(Flood and Worley,1995).
6. Fuzzy neural inference model used for conceptual construction cost estimation (Cheng ,et al.,2009).

Also, a research was provided to develop a neural network based on decision making system –neuro mode for an industrial plant (Murtaza and Fisher,1994). In this research, several major attributes categorized to provide the decision based on Neural Networks (NN) represents; plant location, environmental and organizational, labor-related, plant characteristics and project risks (Murtaza and Fisher,1994).

In addition, an experimental assessment of neural network was accomplished for nonlinear time-series forecasting(Zhang ,et al.,2001). This research concluded the neural network is a reliable tool for forecasting nonlinear time series. The impact of input, hidden layers, and output nodes were practically examined (Zhang ,et al.,2001).

The ability of ANNs to adapt different types of problems based on activation functions represents a critical flexibility. These functions experimentally change based on the placed independent variables in model and expected outputs. The mathematical activation functions used in ANNs to interpret the data between layers and input-output placed in table 2.3.

The NN approach with simulated data showed a promising result. However, according to(Chao and Skibniewski,1995) , several assumptions have been used in the simulation modeling which might cause low precision.

Accordingly, a procedure was developed based on the neural networks model to escalate the highway construction costs over time considering highway construction cost index (Wilmot and Mei,2005). The influential terms in this cost index model represent the costs of: construction material, labor, equipment, and the time of notice to proceed.

Based on the mentioned flexibility of ANNs, a neural networks data-base was accomplished to estimate the construction operation productivity (Chao and Skibniewski,1994). This attempt examined an excavation process by excavator and concluded that neural networks are an efficient tool for construction productivities estimation. Also, a neural network based approach was developed to forecast the acceptability of new construction technology(Chao and Skibniewski,1995).

In this study a neural network model and linear regression models were simultaneously developed to evaluate labor productivity in construction projects but ANNs came up with reasonable higher accuracy compared to regression analysis(Sonmez and Rowings,1998). This model was examined on concrete pouring, formwork, and concrete finishing tasks. The general mathematical equation used for calculation of network is presented in the following equation:

$$\sum_{k=1}^{K} W_k \cdot s_o \left(\sum_{i=1}^{n} W_{ki} \cdot x_i + W_{ko}\right) + w_o$$

Where, in this equation

Wki is the controller weight of input i to the hidden layer k, So is the hidden layer-output activation function, xi is the input i,

Wko is the weight of hidden layer to output.

Wk, Wo is the respectively weight of input k, hidden layer to output on the same example.

Table 2.3 Common Activation Functions in ANNs ***(Adapted from Young II et al, 2008)***

Activation Functions	Definitions	Range
Linear	x	(-∞, +∞)
Sigmoid	$\frac{1}{(1-e^{-x})}$	(0 , 1)
Hyperbolic	$\frac{e^{x}-e^{-x}}{(e^{x}+e^{-x})}$	(-1 , 1)
Exponential	e^{-x}	(0 , ∞)
Soft max	$\frac{e^{-x}}{\sum_i x_i}$	(0 , 1)
Unit Sum	$\frac{x}{\sum_i x_i}$	(0 , 1)
Square Root	$\sqrt{x}$	(0 , ∞)
Sine	Sin(x)	(0 , 1)
Ramp	$\begin{cases} 1, x \leq -1 \\ x, -1 < x < 1 \\ 1, x \geq 1 \end{cases}$	(-1 , 1)
Step	$\begin{cases} 0, x < 0 \\ 1, x \geq 0 \end{cases}$	(0 , 1)

Where in this equation: Yi represents the observed value and Ŷi is the mean value. The sub i represents an integer from 1 to n.

The mathematical equation used for mean square error is formulated in the following equation:

$$MSE = \frac{\sum(Y_i - \hat{Y}_i)^2}{n}$$

Where Yi is the observed value and Ŷi is predicted value, and i is an integer varying from 1 to n. In this equation instead of n (Y-Ȳ)2 is used in some analysis to determine the final error.

Based on the mentioned information, a method was derived to combine some of the recent useful methods and traditional symbolic systems to develop the reliability of prediction and classification models(Fletcher and Hinde,1995). This research pointed out the neural networks as a reliable tool for highway Marshall Test prediction. The architecture of an ANNs model approximate assumed for this prediction model is shown in Figure 2.10.

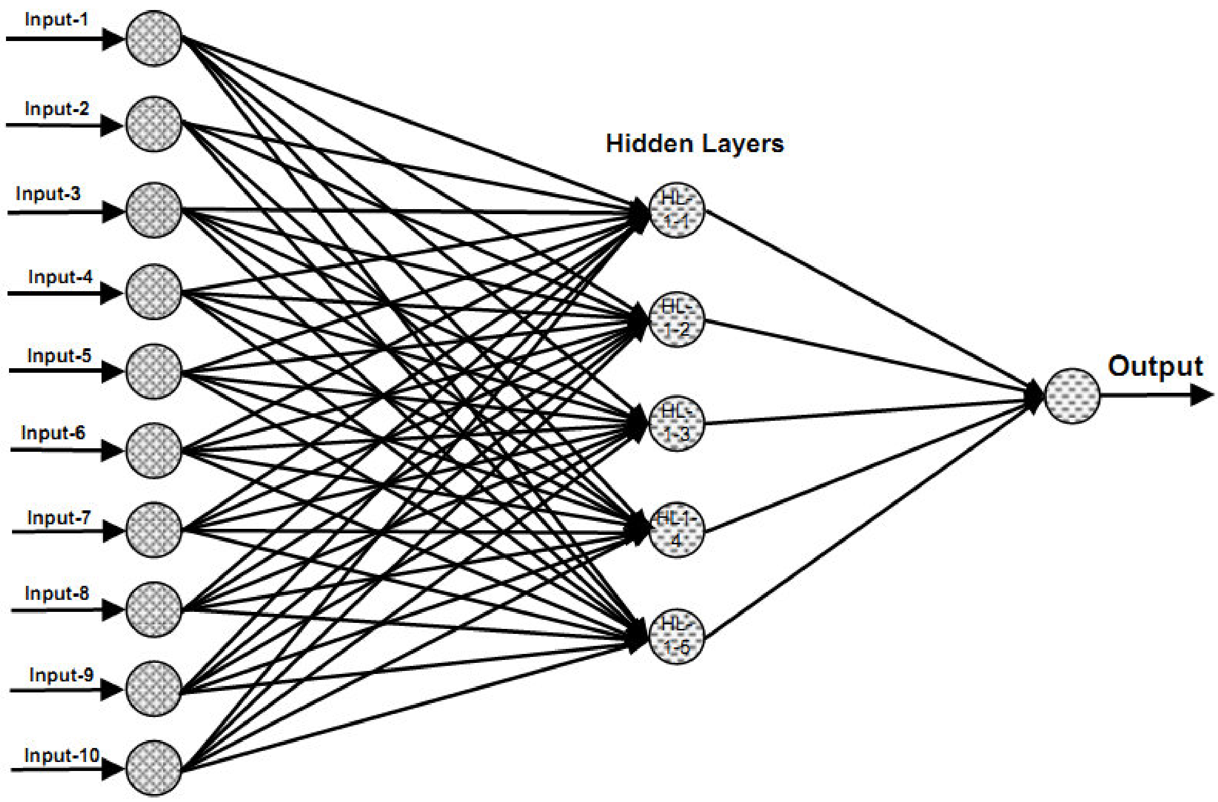


Figure2.10 Simple Architecture of Prediction Model Based on ANNs

There are several types of artificial neural networks and regression analysis software to classify or predict the future values based on the past data. The models developed in this research based on the knowledge and calculation and procedure respectively based on the Neuro Solutions for Excel and Automated Neural system of STATISTICA for ANNs and Minitab and multiple regression of STATISTICA for stepwise regression analysis. However, the results of models that placed in this research entirely calculated by Automated Networks (ANs). The reason for the choosing of ANs for the calculation of these models represents the ability of the system that calculating the model faster and most importantly automatically choosing.

$$S_{ki,\,abs} = \frac{\sum_{j-1}^{p}\left|s_{ki}^{(p)}\right|}{p}$$

Where, Ski, abs is the average sensitive absolute value of partial derivative of output k with respect to input i, and p is the number of samples.

2.12 Historical Background of Neural Network Applications in Pavement Engineering

Very detailed information about the applications of traffic engineering can be found in the relevant literature (Tapkın,2004). At this point, it is important to state out, one by one, the relevant important neural network applications in the pavement engineering area.

In a study by (Ritchie ,et al.,1991), a system that integrates three artificial intelligence technologies: computer version, neural networks and knowledge-based system in addition to conventional algorithmic and modeling techniques were presented. (Ritchie ,et al.,1991) used neural network models in image processing and pavement crack detection.(Gagarin ,et al.,1994) discuss the use of a radial-Gaussian-based neural network for determining truck attributes such as axle loads, axle spacing and velocity from strain-response readings taken from the bridges over which the truck is traveling.

(Eldin,1995) describe the use of a back propagation (BP) algorithm for condition rating of roadway pavements. They report very low average error comparing with a human expert determination , (Cal,1995) uses the back propagation algorithm for soil classification based on three primary factors: plastic index, liquid limit, water capacity, and clay content. (Razaqpur ,et al.,1996) present a combined dynamic programming and Hopfield neural network bridge-management model for effi-allocation of a limited budget to bridge projects over a given period of time.

The time dimension is modeled by dynamic programming, and the bridge network is simulated by the neural network. (Roberts and Attoh-Okine,1998) use a combination of supervised and self-organizing neural networks to predict the performance of pavements as defined by the International Roughness Index.(Tutumluer and Seyhan,1998) investigated neural network modeling of anisotropic aggregate behavior from repeated load triaxial tests.

The BP algorithm is used by (Owusu-Ababia,1998) for predicting flexible pavement cracking and by (Alsugair and Al-Qudrah,1998) to develop a pavement-management decision support system for selecting an appropriate maintenance and repair action for a damaged pavement.

(Kim and Kim,1998) used artificial neural networks for prediction of layer module from falling weight deflectometer (FWD) and surface wave measurements.

(Shekharan,1998) studied the effect of noisy data on pavement performance prediction by an artificial neural network with genetic algorithm.

(Attoh-Okine,2001) uses the self-organizing map or competitive unsupervised learning model for grouping of pavement condition variables (such as the thickness and age of pavement, average annual daily traffic, alligator cracking, wide cracking, potholing, and rut depth) to develop a model for evaluation of pavement conditions.

(Lee and Lee,2004) present an integrated neural network-based crack imaging system to classify crack types of digital pavement images which includes three types of neural networks: image-based neural network, histogram-based neural network and proximity-based neural network.

In an article by (Mei ,et al.,2004), it is presented a computer-based methodology with which one can estimate the actual depths of shallow, surface-initiated fatigue cracks in asphalt pavements based on rapid measurement of their surface characteristics.

(Ceylan ,et al.,2005) has investigated the use of artificial neural networks as pavement structural analysis tools for the rapid and accurate prediction of critical responses and deflection profiles of full-depth flexible pavements subjected to typical highway loadings.

(Bosurgi and Trifiro,2005) has described a procedure that has been defined to make use of the available economic resources in the best way possible for resurfacing interventions on flexible pavements by using artificial neural networks and genetic algorithms.

Chapter Three

DATA COLLECTION TECHNIQUES AND CLASSIFICATION

Chapter 3

DATA COLLECTION TECHNIQUES AND CLASSIFICATION

3.1 Introduction

This chapter outlines the data sources and parameters used in the analytical work of this research. Collecting data is the most difficult and critical part for its importunacy in the research which all the work is depending on it. On this research the data is extracted from real laboratory and site experimental.

3.2 Description of Data

The data in this thesis was collected and extracted from two main processes:

- Job mix design tests process
- Quality control tests process

From (HMA) of highway project (BaniSwef-El-Minya - Assyutfree way Project) constructed in Upper Egypt. The satellite image below (Figure3.1) shows the location of the highway which parallel to the old road at the east bank of Nile River.

This project was about 320 km long , about 121 km from Baniswef city to El-Minya city and about 121 km from El-Minya city to Assyut city .

The cross section (Figure3.2) was three lanes for each way with 2.5 m outer paved shoulders, 0.75m inner paved shoulders, 20 m median with total width 52 m, the project has a huge quantity of earth moving working, it was about 37 million m3 of fill and 11million m^3 of cut, the paving work had about 19 million m^2 of (HMA).

3.2.1 Data collection

Data were collected from two main sources:

- Different trials of job mix for (HMA) design which was done at laboratory.
- Quality control actual tests which were done mainly at site.

Figure 3.1 The Layout of the Highway

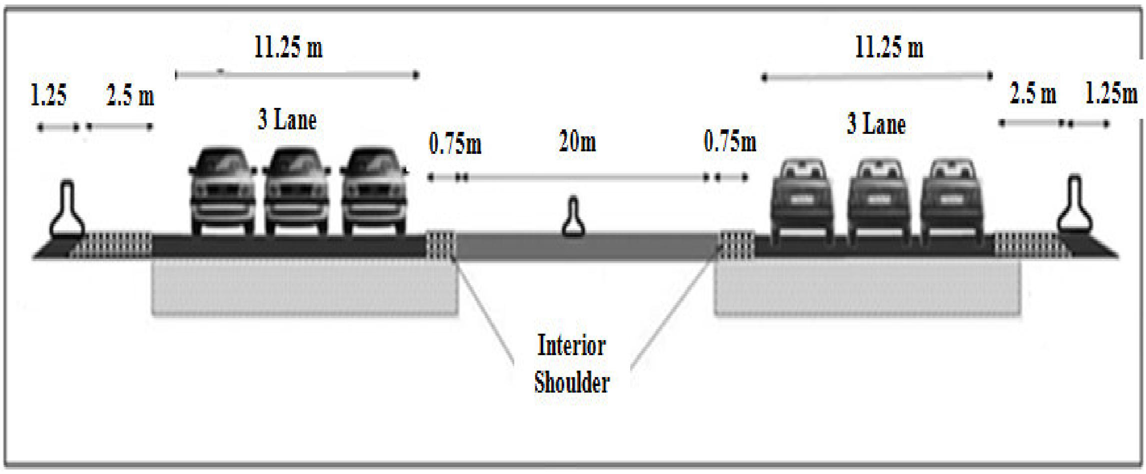


Figure 3.2 The Typical Cross Section of the Highway

3.2.2 Job mix of asphalt

Marshall Specimens were fabricated in the laboratory utilizing75 blows on each face representing heavy traffic conditions according to (AASHTO-T245,2006). The standard 60/70 penetration bitumen was modified in the laboratory.

Marshall Stability and flow tests were done on these asphalt samples. These tests were considered to be adequate to clarify the positive effect of different mixes on asphalt concrete. In laboratory test program, continuous aggregate gradation has been used to fit the gradation limits for wearing course set by Highway Technical Specifications of General Association of Egypt Highways and Bridges (Highway Technical Specifications, 1998). The aggregate was calcareous type crushed stone obtained from a local quarry and 60/70 penetration bitumen obtained from a local refinery (El-Nasr Company) in Suez city was used for preparation of the Marshall specimens.

Physical properties of the bitumen samples are given in Table 3.1. The physical properties of coarse and fine aggregates are given in Table 3.2. The apparent specific gravity of aggregate size 2 and 1 are 2.684 t /m^3 and 2.681 t /m^3 and sand is 2.728 t/m^3, Aggregate gradation for the bituminous mixtures tested in the laboratory has been selected as an average of the wearing course Type 2 gradation limits given by General Association of Egypt Highways Table 3.3.

Table 3.1. Physical Properties of Asphalt Cement

Properties of the asphalt	Range	Specs. Used
Penetration Grade	60 / 70 mm	ASTM D 5
Penetration at 25^{o} C	64 mm	ASTM D 5
Specific Gravity	1.07 gm/cm^3	ASTM D 70
Softening Point	50^{o} C	ASTM D 36
Loss in Heating	2 %	ASTM D 6
Flash Point	314^{o} C	ASTM D 92
Fire Point	326^{o} C	ASTM D 113
Ductility (5 cm/dk)	> 100 cm	ASTM D 113
Viscosity at (135^{o}C)	0.418 Pa s	ASTM D 88
Viscosity at (165^{o}C)	0.112 Pa s	ASTM D 88

Table 3.2. Physical Properties of Aggregate

Tested Property	Specs. Used	Limits	Aggregate Size		
			Size 2 (25-12)mm	Size 1 (12-5) mm	Crushed Sand
Abrasion (L.A.)	ASTM C131	Max 32%	23.7	24.3	—
Water absorption	ASTM C127	Max 2%	1.1	1.3	1.7
Specific Gravity(t/m^3)	ASTM C127& C128	—	2.684	2.681	2.728
Flat and Elongation	ASTM D693	Max 8%	4.3	5.1	—
Stripping	ASSHTO T 283	Max 3%	No stripping		

Table 3.3.General Aggregate Gradation Limits

Sieves No.	Limits of project technical Specifications	
	Lower Limit	**Upper Limit**
"1	100	100
"3/4	80	100
"1/2	70	90
"3/8	60	80
#4	48	65
#8	35	50
#30	19	30
#50	13	23
#100	7	15
#200	3	8

3.2.3 Marshall Mix design

The sheet of job mix formula (JMF) design of wearing contain a table and graph, the table in second column shows the percentage of passing aggregate from sieves (table 3.4)., which must be inside the limits of general specifications of aggregate gradation (table 3.2).

The graph in (figure 3.3) shows the upper and lower limits of project technical specifications, which the (JMF) line must be among them also.

Appendix B shows the real JMF excel spread sheet from highway project (BaniSwef-El-Minya – Assyut free way)

Table 3.4.The percentage of passing aggregate from sieves

Gradation of the proposal JMF wearing Course			
Sieves No.	JMF (Total)	JMF tolerance	
		Lower Limit	Upper Limit
"1	**100**	**100**	**100**
"3/4	**97.2**	**93.2**	**100**
"1/2	**78.7**	**74.7**	**82.7**
"3/8	**69.7**	**65.7**	**73.7**
#4	**58.1**	**55.1**	**61.1**
#8	**44.3**	**41.3**	**47.3**
#30	**22.5**	**19.5**	**25.5**
#50	**14.3**	**12.3**	**16.3**
#100	**7.7**	**5.7**	**9.7**
#200	**5.2**	**4.2**	**6.2**

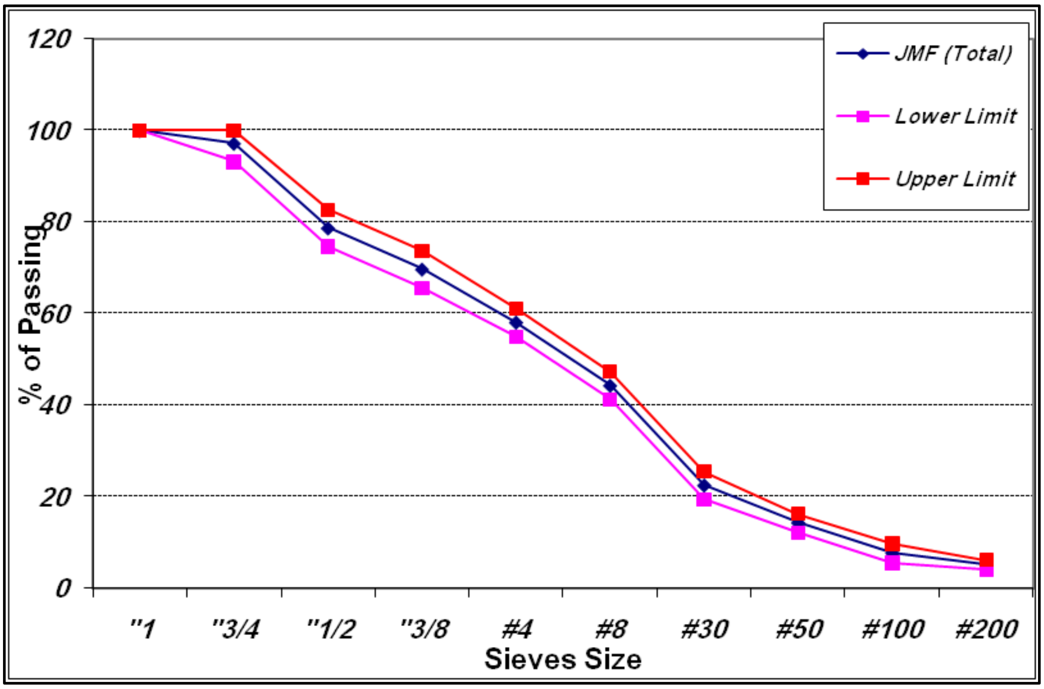


Figure 3.3 shows the JMF , upper and lower limits of project.

The test specimens were prepared with varying bitumen content with 0.25% to 0.5% increment for about 4 specimens (table 3.5). The maximum load at failure was the stability value. A flow meter records the strain at the maximum load when failure occurs. The density and void analysis were then done. The following graphs are drawn:

- Marshall Stability vs. bitumen content
- Flow value vs. bitumen content
- Air voids ratio vs. bitumen content
- Density vs. bitumen content

Figure.3.4 shows these graphs, for these curves, the bitumen content is determined depending on the following conditions:

- Point of maximum stability
- Point of maximum density
- Specifications Limits of project about air voids ratio and voids filled with bitumen (table 3.6).

Table 3.5 Marshall Test properties of wearing layer

Test Performed	Bitumen Content %			
	5.0%	5.5%	5.75%	6.0%
Marshall Stability (N)	1061	1154	1370	1317
Flow (inch)	11	12	13	13
Unit Weight (g/cm^3)	2.312	2.322	2.338	2.344
Theoretical specific weight (Gmm)	2.453	2.422	2.414	2.406
Air Voids (%)	5.7	4.1	3.2	2.6

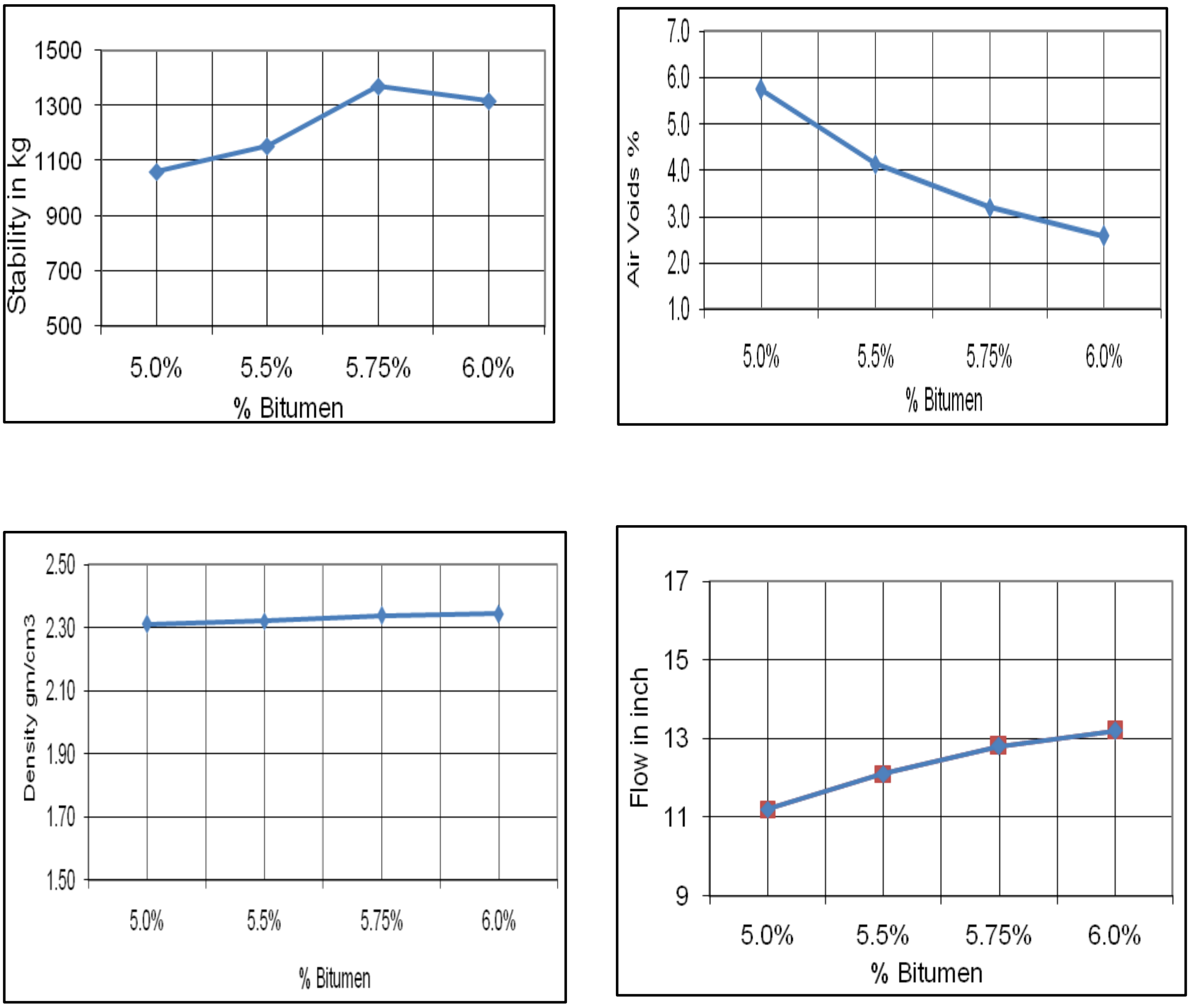


Figure.3.4 Marshall, Flow, Air voids and density vs. bitumen content

3.3 Quality Control Tests

Quality control during construction is necessary to ensure that the pavement is constructed so as to meet the various requirements of specifications and design documents.

General specification of (BaniSwef-El-Minya - Assyutfree way Project) shown in the table 3.6 of HMA wearing layer must be achieved.

Table 3.6 General Specification of HMA

Test Performed	Limits of Project Technical Specification
Marshall Stability (Kg)	**Min. 800**
Air Voids (%)	**3-5**
VMA (%)	**Min. 14**
VFB (%)	**60-75**
Flow (1/100 inch)	**8--16**

According to (table 2.1) Frequency of tests for quality control as previously explained in chapter 2 , it shown that Sieve analysis (Grading) and Bitumen content (Extraction) have a frequency of One test per 100T of mix, min. 3 tests per day, Extraction experiments were conducted according to (ASTM-D2127) by using the centrifuge extractor to determine the bitumen quantity for all of the asphalt core samples. In these experiments, three-chloral ethylene was used to decompose the bitumen from aggregates in the asphalt core samples that was taken during the (HMA) laying process. Gradation test method determines the particle size distribution of fine and coarse aggregates by sieving The No. 4 sieve is designated as the division between the fine and coarse aggregate. Also according to the same (table 2.1) it was 3 Marshall Specimens per 100T of mix, (Appendix B) shows the sample of actual site excel sheets used to prepare the data

The results taken from Extraction, Sieve Analysis and Marshall Tests for the same sample of (HMA) during the quality control test process shows in (Figure 3.5).Marshall test take long time about 24 hours however, Extraction and Sieve Analysis test take short time about 20 minutes.

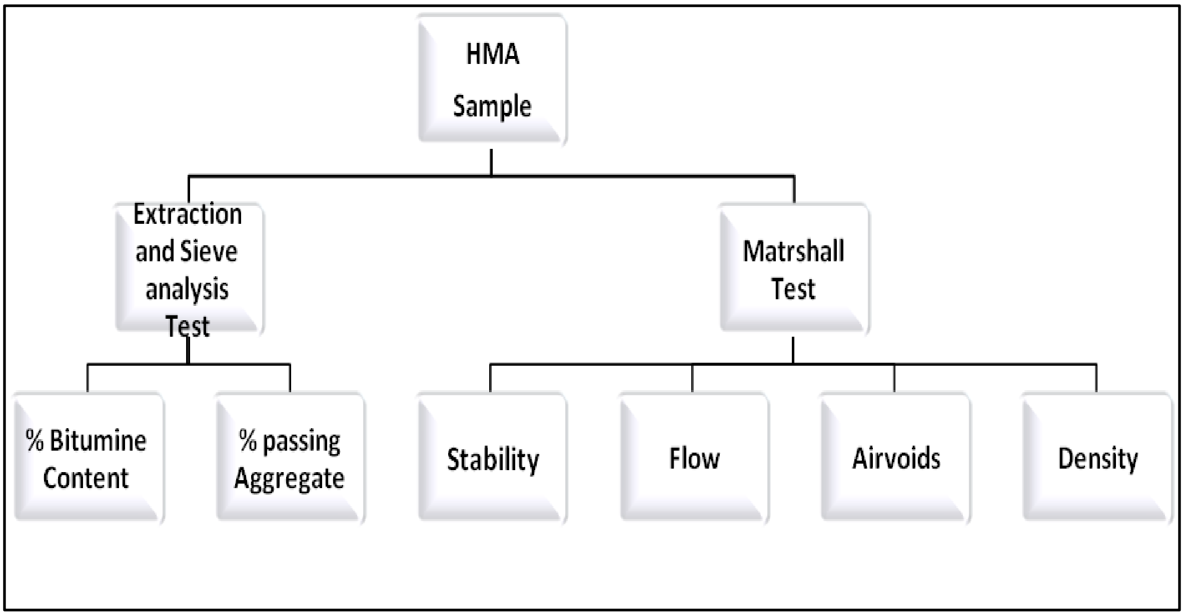


Figure 3.5 Results obtaining from quality control tests

3.4 Summary of the Collected Data

This part deals with preparing the database needed for the models development. asphalt mix samples were taken from the site before compaction. In order to get a wide range of aggregate gradation and asphalt content, the samples were obtained from different sites in the project representing two different types of asphalt concrete mixes. Each mix sample was divided into two parts. The extraction test was performed on the first part in order to get the aggregate gradation and asphalt cement content. On the other hand, the second part was used to prepare cylindrical specimens. The specimens were then tested by Marshall Apparatus to get their stabilities and flows. Table 3.7 summarizes the output data of the experimental investigation which include the minimum and maximum values obtained for the following items:

- Percentage of passing from each sieve size.
- Percentage of asphalt content (aggregate weight base).
- Marshall Stability.
- Marshall Flow.
- Air Void Ratio
- Density

Table 3.7 Summary of the Collected Experimental Data

Test	Minimum Value	Maximum Value
Extraction Test		
• %passing from sieve 1”	100	100
• %passing from sieve 3/4”	93.100	98.09
• %passing from sieve 1/2”	54.180	77.50
• %passing from sieve no .4	35.781	60.87
• %passing from sieve no .8	22.716	46.81
• %passing from sieve no .30	9.821	25.1
• %passing from sieve no .50	6.746	16.07
• %passing from sieve no .100	3.928	9.49
• %passing from sieve no .200	1.456	5.42
• % of bitumen content	4.431	6.0
Marshall Test		
• Marshall Stability (kg)	1019	1369.50
• Marshall Flow (1/100 inch)	10.80	13.33
• Air void ratio	2.596	6.89
• Density (gm/cm^{3})	2.249	2.54

Chapter Four

MODEL DEVELOPMENT

AND ANALYSIS

Chapter 4

MODEL DEVELOPMENT AND ANALYSIS

4.1 Introduction

Data analysis plays a great roll at any research; a simple neural network (ANN) simulation has been developed in a spread sheet format that is customary to many highway construction practitioners. The weights that produced the best Marshall Test results (stability, flow, density and air voids ratio) for the historical cases were used to find the optimum (ANN). To facilitate the use of this (ANN) on new projects, a user friendly interface was developed using spreadsheet to simplify user input and automate Marshall Test results predication.

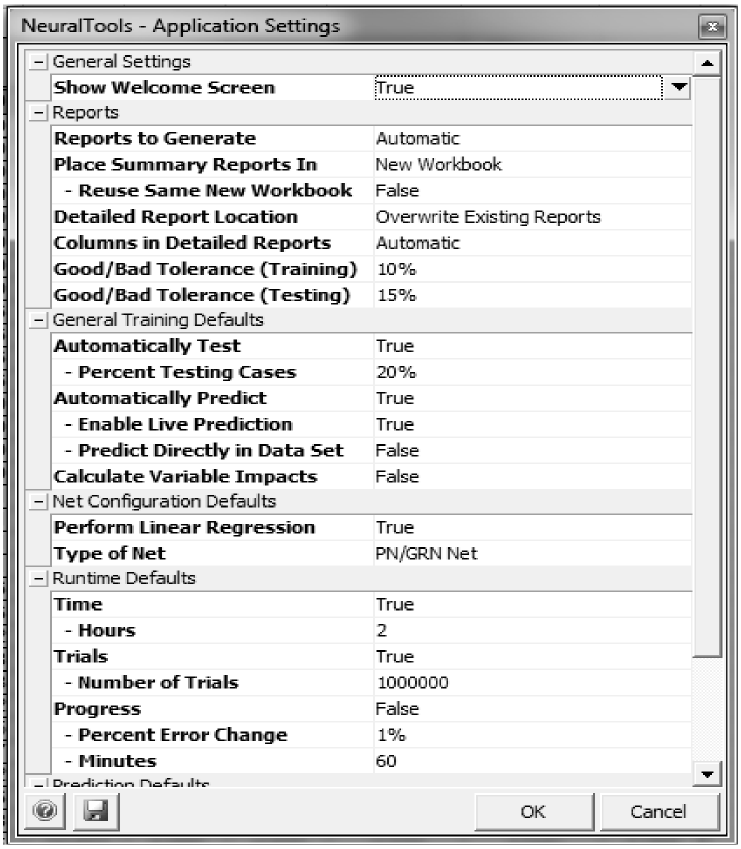
To start the investigation, simple (ANN) commercial software (Neural Tools 5.5.0) for Microsoft Excel was used. Marshall Test results were predicted and preferences were set to train 80% of cases and test the remaining 20%.

4.2 Neural Tools program

Acceptance errors were set to 10% for testing and 15% for training, (Figure 4.1) showing the application settings.

At Data set manager ribbon, all sieves and bitumen percentage set as independent variables, Marshall Test Results (Stability, Flow, Air voids and Density) set as dependent variable. After run the program the report shown in (Figure 4.2) clarify the availability of using prediction.

Results showed that it was possible to achieve errors less than 10% for testing and 15% for training, thereby suggesting that the ANN can be used to Marshall Test results with good accuracy.

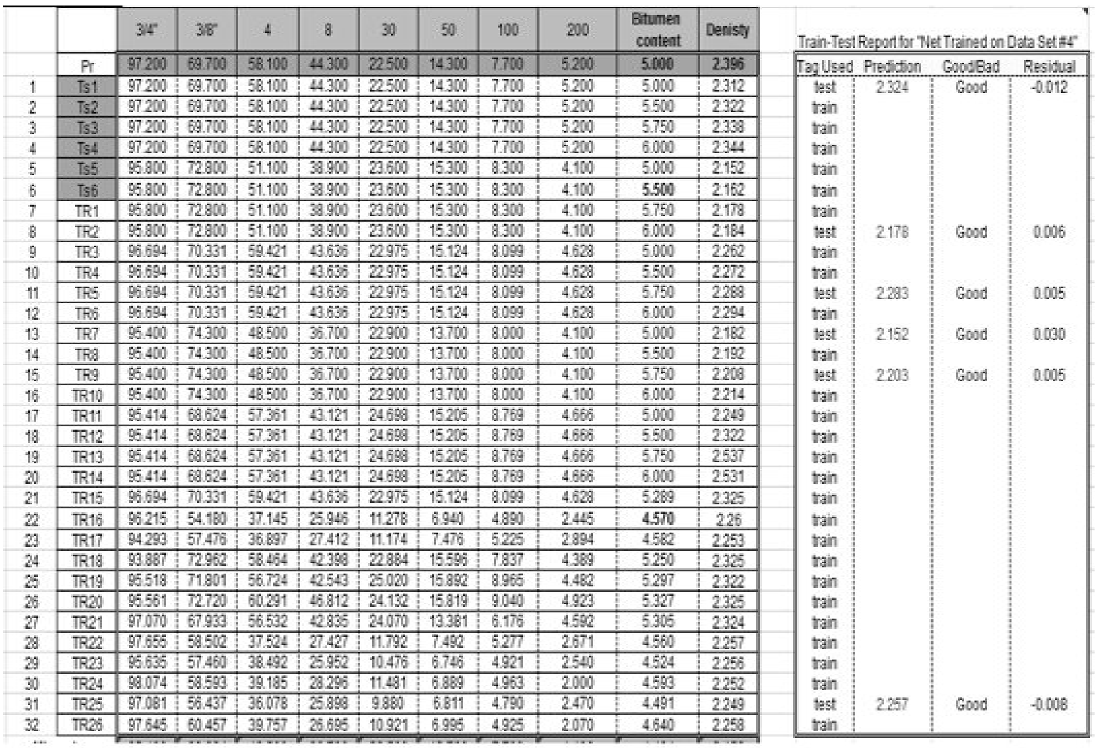


NeuralTools - Application Settings

General Settings	
Show Welcome Screen	True
Reports	
Reports to Generate	Automatic
Place Summary Reports In	New Workbook
- Reuse Same New Workbook	False
Detailed Report Location	Overwrite Existing Reports
Columns in Detailed Reports	Automatic
Good/Bad Tolerance (Training)	10%
Good/Bad Tolerance (Testing)	15%
General Training Defaults	
Automatically Test	True
- Percent Testing Cases	20%
Automatically Predict	True
- Enable Live Prediction	True
- Predict Directly in Data Set	False
Calculate Variable Impacts	False
Net Configuration Defaults	
Perform Linear Regression	True
Type of Net	PN/GRN Net
Runtime Defaults	
Time	True
- Hours	2
Trials	True
- Number of Trials	1000000
Progress	False
- Percent Error Change	1%
- Minutes	60

OK Cancel

Figure 4.1 Neural Tools application settings



Train-Test Report for "Net Trained on Data Set #4"

		3/4"	3/8"	4	8	30	50	100	200	Bitumen content	Denisty	Tag Used	Prediction	Good/Bad	Residual
	Pr	97.200	69.700	58.100	44.300	22.500	14.300	7.700	5.200	5.000	2.396				
1	Ts1	97.200	69.700	58.100	44.300	22.500	14.300	7.700	5.200	5.000	2.312	test	2.324	Good	-0.012
2	Ts2	97.200	69.700	58.100	44.300	22.500	14.300	7.700	5.200	5.500	2.322	train			
3	Ts3	97.200	69.700	58.100	44.300	22.500	14.300	7.700	5.200	5.750	2.338	train			
4	Ts4	97.200	69.700	58.100	44.300	22.500	14.300	7.700	5.200	6.000	2.344	train			
5	Ts5	95.800	72.800	51.100	38.900	23.600	15.300	8.300	4.100	5.000	2.152	train			
6	Ts6	95.800	72.800	51.100	38.900	23.600	15.300	8.300	4.100	5.500	2.162	train			
7	TR1	95.800	72.800	51.100	38.900	23.600	15.300	8.300	4.100	5.750	2.178	train			
8	TR2	95.800	72.800	51.100	38.900	23.600	15.300	8.300	4.100	6.000	2.184	test	2.178	Good	0.006
9	TR3	96.694	70.331	59.421	43.636	22.975	15.124	8.099	4.628	5.000	2.262	train			
10	TR4	96.694	70.331	59.421	43.636	22.975	15.124	8.099	4.628	5.500	2.272	train			
11	TR5	96.694	70.331	59.421	43.636	22.975	15.124	8.099	4.628	5.750	2.288	test	2.283	Good	0.005
12	TR6	96.694	70.331	59.421	43.636	22.975	15.124	8.099	4.628	6.000	2.294	train			
13	TR7	95.400	74.300	48.500	36.700	22.900	13.700	8.000	4.100	5.000	2.182	test	2.152	Good	0.030
14	TR8	95.400	74.300	48.500	36.700	22.900	13.700	8.000	4.100	5.500	2.192	train			
15	TR9	95.400	74.300	48.500	36.700	22.900	13.700	8.000	4.100	5.750	2.208	test	2.203	Good	0.005
16	TR10	95.400	74.300	48.500	36.700	22.900	13.700	8.000	4.100	6.000	2.214	train			
17	TR11	95.414	68.624	57.361	43.121	24.698	15.205	8.769	4.666	5.000	2.249	train			
18	TR12	95.414	68.624	57.361	43.121	24.698	15.205	8.769	4.666	5.500	2.322	train			
19	TR13	95.414	68.624	57.361	43.121	24.698	15.205	8.769	4.666	5.750	2.537	train			
20	TR14	95.414	68.624	57.361	43.121	24.698	15.205	8.769	4.666	6.000	2.531	train			
21	TR15	96.694	70.331	59.421	43.636	22.975	15.124	8.099	4.628	5.289	2.325	train			
22	TR16	96.215	54.180	37.145	25.946	11.278	6.940	4.890	2.445	4.570	2.26	train			
23	TR17	94.293	57.476	36.897	27.412	11.174	7.476	5.225	2.894	4.582	2.253	train			
24	TR18	93.887	72.962	58.464	42.398	22.884	15.596	7.837	4.389	5.250	2.325	train			
25	TR19	95.518	71.801	56.724	42.543	25.020	15.892	8.965	4.482	5.297	2.322	train			
26	TR20	95.561	72.720	60.291	46.812	24.132	15.819	9.040	4.923	5.327	2.325	train			
27	TR21	97.070	67.933	56.532	42.835	24.070	13.381	6.176	4.592	5.305	2.324	train			
28	TR22	97.655	58.502	37.524	27.427	11.792	7.492	5.277	2.671	4.560	2.257	train			
29	TR23	95.635	57.460	38.492	25.952	10.476	6.746	4.921	2.540	4.524	2.256	train			
30	TR24	98.074	58.593	39.185	28.296	11.481	6.889	4.963	2.000	4.593	2.252	train			
31	TR25	97.081	56.437	36.078	25.898	9.880	6.811	4.790	2.470	4.491	2.249	test	2.257	Good	-0.008
32	TR26	97.645	60.457	39.757	26.695	10.921	6.995	4.925	2.070	4.640	2.258	train			

Figure 4.2 Marshall Test results prediction using ANN (NeuroTools 5.5 screenshot)

4.3 ANN's Data Entry

The data entry organized to give respectable results from the analysis. Simple figure Figure4.3 summarizes the way to collect and mix four results from Marshall Test experiments (Stability, Flow, Air Void ratio, Density) used in this research with Gradation and Extraction experiments in ANN system.

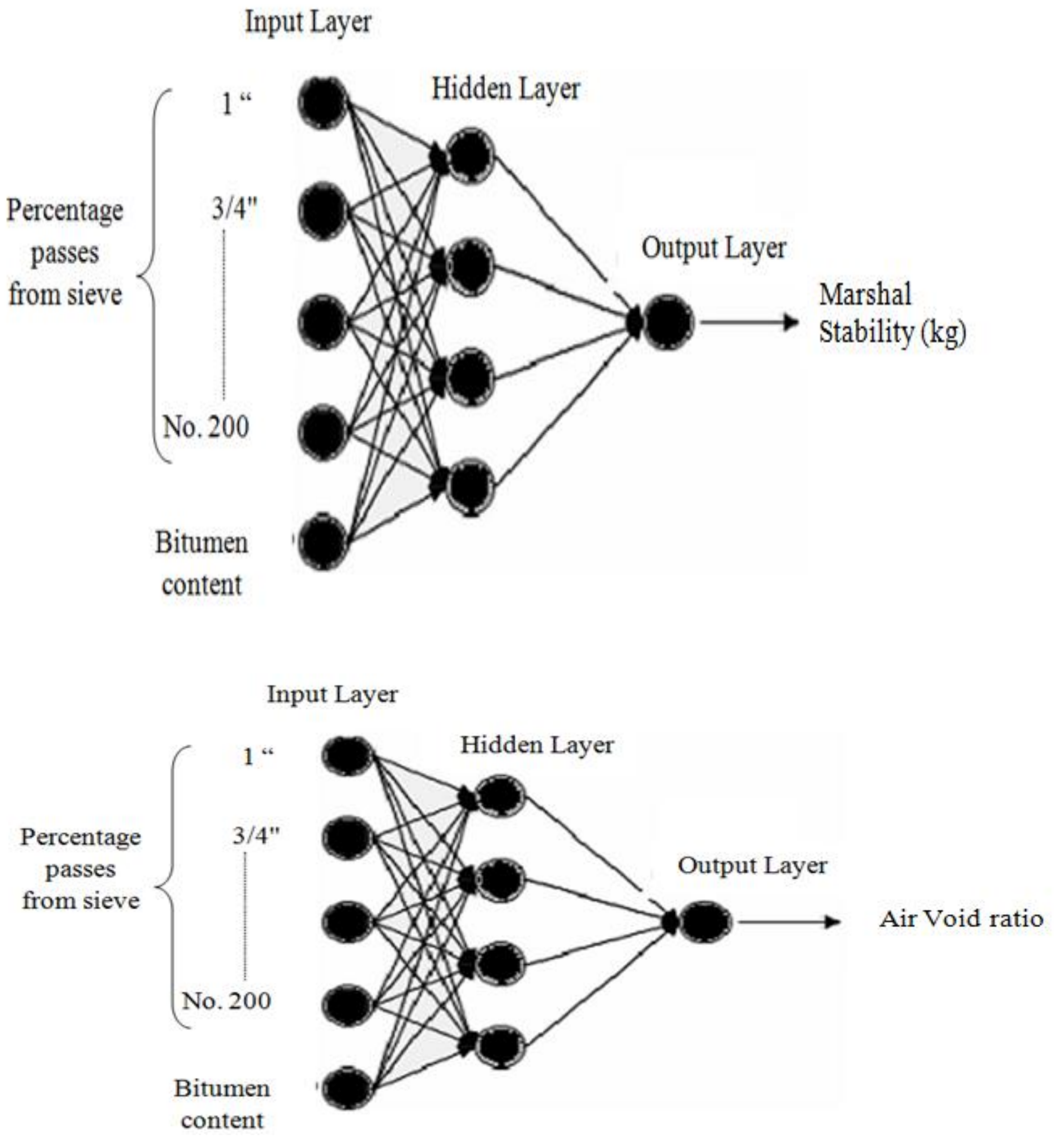
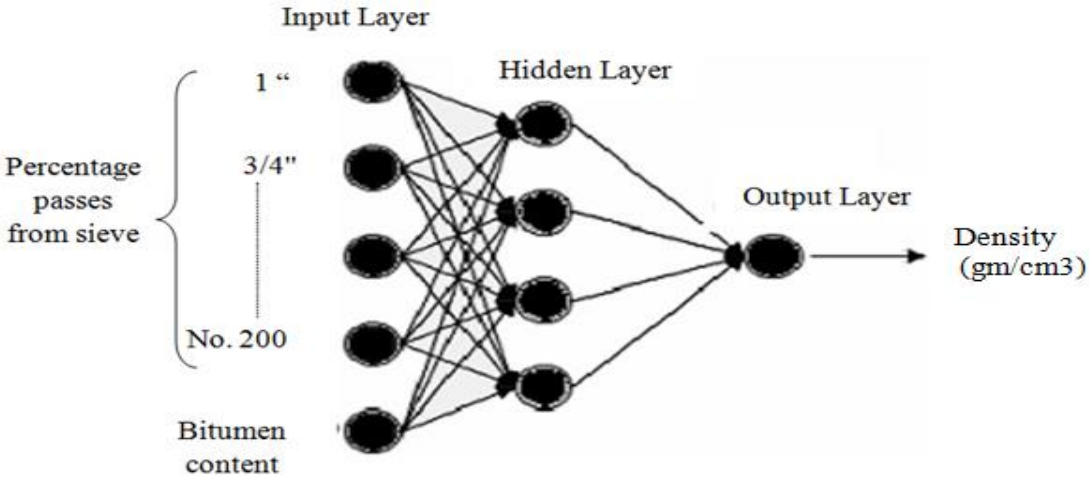


Figure 4.3 Neural Network System architect



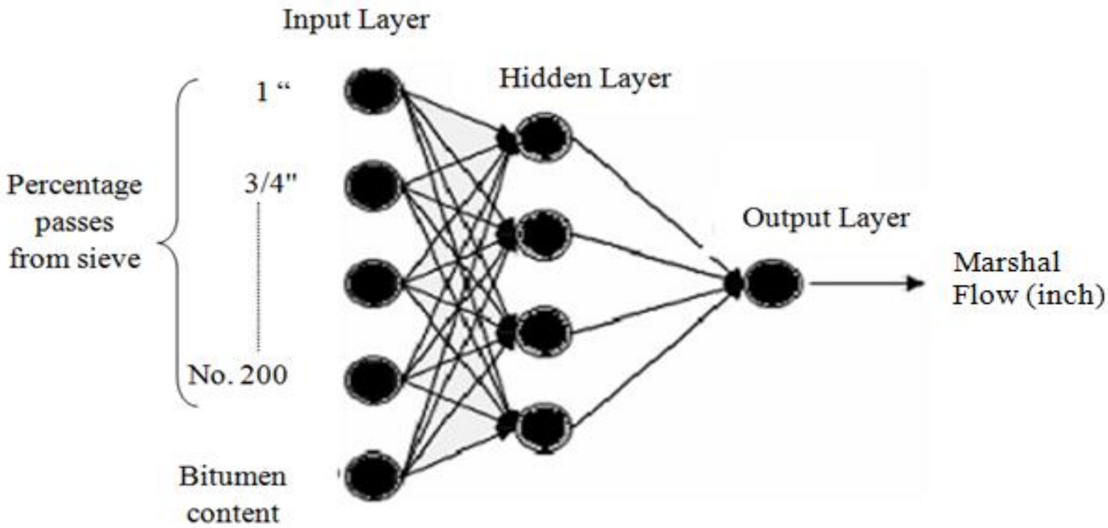


Figure 4.3 Neural Network System architect (cont.)

4.4 ANN Architecture

The choice of ANN architecture depends on a number of factors such as the nature of the problem, data characteristics and complexity, the number of sample data, etc. ANN architecture was chosen after several trial and errors.

Some recommendations from previous research work, for example, Hegazy T. et. al (1994) heuristically suggested that the number of hidden nodes should be set as one-half of the total input and output nodes. The other suggestions by Nikola K., (1998) involved on how to choose network parameters in a situation where the training set is clustered in groups with similar features.

The number of these groups can be used to choose the number of hidden layers, the minimum number of hidden nodes should be $h \geq (p-1) / (n+2)$, where p is the number of the training examples and n is the number of the inputs of the networks. In a situation where the training data are sparse and do not contain any common features, the number of connections might need to be close to the number of training examples in order for the network to reach a convergence.

The greater the number of hidden nodes in a network, the more characteristics of the training data it will capture, but more time will be consumed in learning procedure. Transfer function, learning rule, stop criteria and training characteristics were chosen after literature survey and also FAQ on ANNs maintained by (Sodikov,2005)

Choosing numbers of hidden layers in this thesis is depending in many trials and errors trials, it is found that two hidden layers with five nodes in first hidden layer and one node in second layer.

4.5 ANN Excel Spreadsheet

Since their introduction in early 1980s, spreadsheet programs have been among the most easy-to-use software programs that include powerful data management capabilities.

The use of spreadsheets in construction has, therefore, been customary to many practitioners and several applications, particularly in cost estimation, were developed in their familiar spreadsheet format (Pickard,1997). In the present developments, the use of a spreadsheet program has brought several benefits to the development process and presumably to the end user. It was possible to simulate the ANN process in a transparent form, further more it can be optimized using spreadsheet tools.

This presents NNs as a viable tool for use in construction by adjusting the developed template to other applications.

Also, spreadsheets incorporate many powerful features including formula computations and unlimited customization tools that are easy to use. The user, therefore, does not have to program any routines for creating reports and printing results. In addition, newer versions of spreadsheet programs have included powerful data management techniques and scenario-management capabilities. They have also included links to the Internet to present information and allow the sharing of files among work groups. Their capabilities offer many general-purpose features that can be used to develop modules to integrate with existing one to form global solutions. Users can also select among many add-in modules available on the market to extend spreadsheet capabilities.

A general structure of a multi-layer ANN was shown (Figure 4.4).Such a neural network contains three layers: input layer, hidden layer(s) and output layer (Rumelhart & McClelland, 1986). Each layer is composed of several neurons. The number of neurons in the input and output layers depends on the system dynamics and the desired accuracy. All the neurons in adjacent layers are interconnected (Ozgan.,2011).

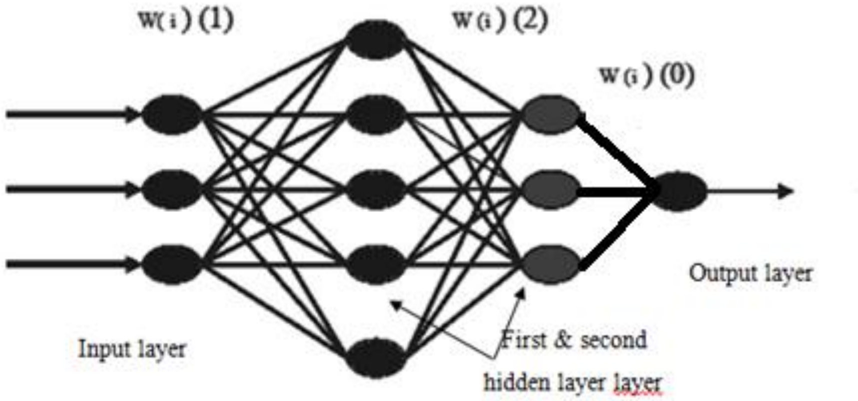


Figure 4.4 Description of Neural Network System(Ozgan.,2011)

As a simple approach to (ANN) modeling, an excel spreadsheet simulation of a three layer including (input layer, hidden layer, and output layer). (ANN) with one output node was illustrated to Excel sheet (Figure. 4.4). The excel spreadsheet represents a template for three hidden layers (ANN) that is suitable for most applications (Hegazy et al. 1994b). The processing of the template incorporates seven steps, following the widely known back-propagation formulation (Rumelhart ,et al.,1986).

According to (Hegazy.T. and Ayed.A.,1998) the general structure and forward computations of (ANN) was presented in (Figure 4.5) the seven steps as follows:

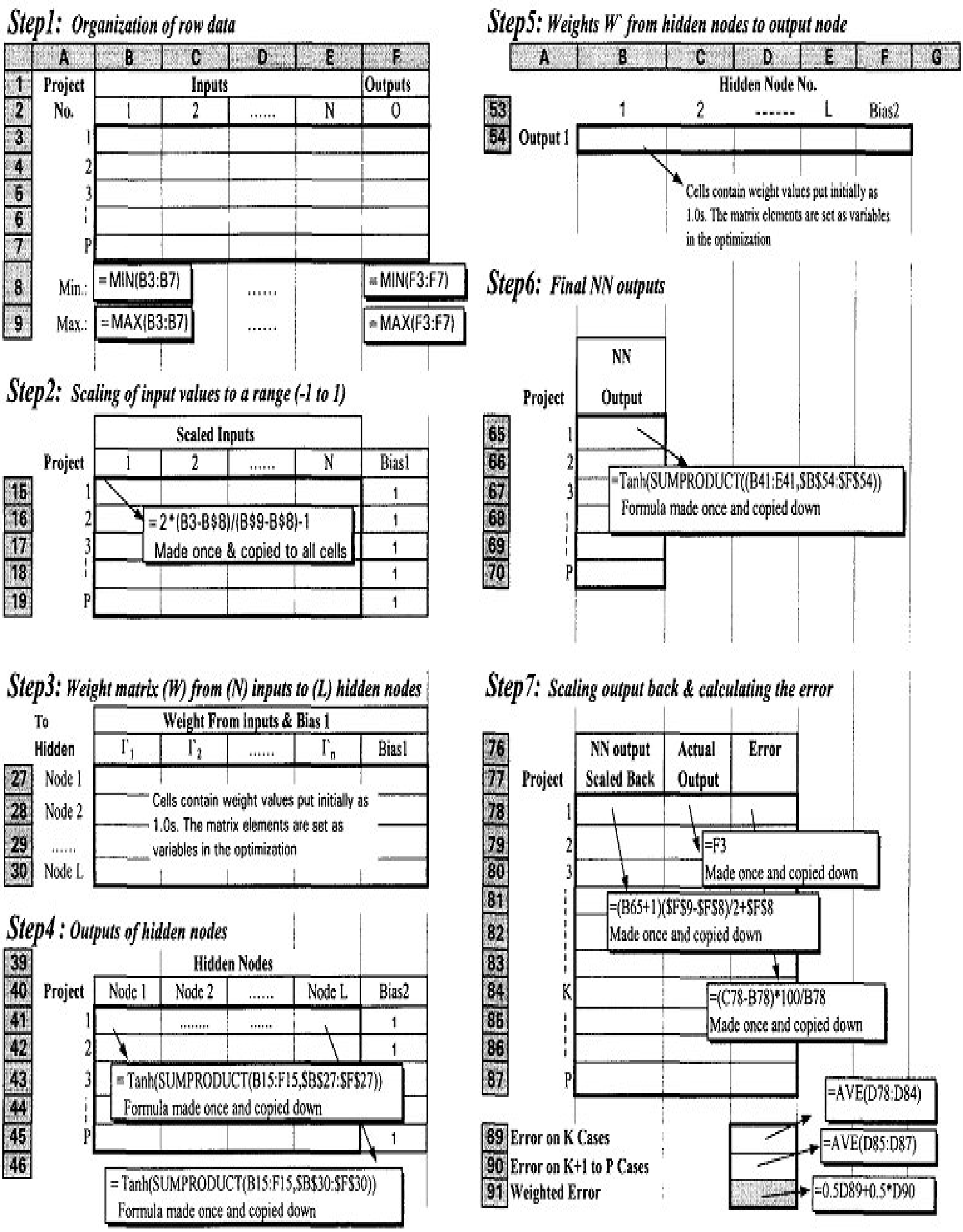


Figure 4.5: Spread Sheet Simulation of Three-Layer NN with One Output Node*(Hegazy.T. and Ayed.A.,1998).*

Step 1. Data Organization , through this process, as a preliminary stage to ANN modeling, we collect data from extraction and Marshall tests from different locations (BaniSwef-ElMinya - Assyutfree way Project) and two different layers (binder and wearing) to make a variety data in the spreadsheet which it will be appear in accuracy of the model results.

The data is first collected from extraction and gradation tests (sieve numbers and bitumen content) and organized in rows, then we got the corresponding Marshall test (stability, flow and air void ratio) but each of them putted in a different sheet with the same corresponding (sieve numbers and bitumen content).for each variable (Figure 4.6), the minimum and maximum values were also put in spreadsheet formulas to be used in step 2.

Step 2. Data Scaling, in this step, the input data part of the first matrix is scaled to a range from [-1 to 1] to suit (ANN) processing. It was computed by constructing the second matrix with linear formula for scaling the values of the first matrix (Hegazy.T. and Ayed.A.,1998)**.**, as follows:

$$\textbf{\textit{Scaled Value}} = \frac{\textbf{\textit{2 x (Unscaled Value – Column Min.)}}}{\textbf{\textit{(Column Max.– Column Min.)}}} \textbf{\textit{-1}} \qquad \textbf{\textit{(1)}}$$

This scaling formula is written only one cell, and then copied to all cells in the scaling matrix(Figure 4.7).

Step 3. Weight matrix (W), the third step to construct and initialize the weight matrix between the inputs and the hidden layers. All inputs were fully connected to the hidden nodes. All the values of the in weight matrix are considered variables to be determined in (ANN) modeling (Figure 4.8). Through preliminary experimentation, it was found that setting the initial weight values to a range (0.5 to 1) is appropriate for inputs scaled to a range (-1 to 1) (Hegazy.T. and Ayed.A.,1998).

Step 4. Output of Hidden Nodes, this step is to allow the hidden nodes to process the input data and produce values to be forwarded to the next layer. According to (ANN) processing (Figure 1), each hidden node j receives activation *Xj*, which is sumproduct formula of scaled inputs by their associated connection weights. Accordingly, each hidden node produces an output *Xjj* that is a function of its activation, as follows:

$$Xj = \sum_{I-1} (Xj x Wjj) \qquad (2)$$

$$Xjj = \tanh (Xj) \qquad (3)$$

Tanh function has shown the best results (Hegazy.T. and Ayed.A.,1998) As shown in Step 4 of (Figure 4.5), a formula was written for the first row of all hidden nodes and then copied to the down cells(Figure 4.9).

Step 5. Weight Matrix (*W*`), similar to the weight matrix constructed in step 3, a second matrix was constructed to connect the (*L*) hidden to the single output node.

These weights are additional variables in the model and were initialized as previously described (Figure 4.10).

Step 6. Finally (ANN) Output, similar to step 4, the output of the (ANN) is computed by calculating the sum product (*Y*) of each hidden node by its connection weight and then processing this value through the tanh function as follows(Figure 4.11):

$$Y = \sum_{I=1}^{L} (Xjj \ x \ Wjj) \qquad (4)$$

$$\text{Output of ANN} = \tanh (Xj) \qquad (5)$$

Step 7. Scaling Back (ANN) Output and Calculating the Error, in this step, the ANN output is scaled back to the original range of values using the reverse of equation (1) (Hegazy and Ayed el al.1998) as follows:

$$\text{OutputScaled back} = \frac{(\text{Output Value} + 1) x (\text{Max. Output} - \text{Min. Output})}{2} \qquad (6)$$

To calculate a measure of the (ANN) performance, a column is constructed for determining the error between the actual outputs and (ANN) outputs as follows:

$$\textit{ESTIMATING ERROR (\%)} = \frac{\textit{(ANN OUTPUT} - \textit{ACTUAL OUTPUT)}}{\textit{ACTUAL OUTPUT}} \times 100 \qquad (7)$$

It is also possible in the (ANN) simulation to use some cases for training and others for testing. The average error of each group of cases can be calculated in a different cell and then combined in a cell that calculates the performance measure of the (ANN), for example:

Weighted Error (%)

= 0.5 (Test Average Error) + 0.5(Training Average Error) (8)

Where weight of 0.5 were assumed for illustration. This approach gives more emphasis to the test cases which are usually a small numbers compared to training cases, to ensure good performance and avoid overtraining (Hegazy.T. and Ayed.A.,1998).

4.6 Neural Network Implementation

Relevant data from job mix and quality control tests for the (Bani Swef-ElMinya – Assyut free way Project) were collected and organized in a four spread sheets (Figure 4.6),

- Sieve aggregate analysis and bitumen content corresponding to specimen stability.
- Sieve aggregate analysis and bitumen content corresponding to specimen Flow.
- Sieve aggregate analysis and bitumen content corresponding to specimen Air Void and
- Sieve aggregate analysis and bitumen content corresponding to specimen Density.

	3/4"	3/8"	4	8	30	50	100	200	Bitumen content	Stability.
Pr	97.200	69.700	58.100	44.300	22.500	14.300	7.700	5.200	**5.500**	**1223.665**
Ts1	97.200	69.700	58.100	44.300	22.500	14.300	7.700	5.200	5.000	1059.878
Ts2	97.200	69.700	58.100	44.300	22.500	14.300	7.700	5.200	5.500	1212.345
Ts3	97.200	69.700	58.100	44.300	22.500	14.300	7.700	5.200	5.750	1369.501
Ts4	97.200	69.700	58.100	44.300	22.500	14.300	7.700	5.200	6.000	1316.881
TR1	95.800	72.800	51.100	38.900	23.600	15.300	8.300	4.100	5.000	982.306
TR2	95.800	72.800	51.100	38.900	23.600	15.300	8.300	4.100	**5.500**	1134.773
TR3	95.800	72.800	51.100	38.900	23.600	15.300	8.300	4.100	5.750	1291.929

	3/4"	3/8"	4	8	30	50	100	200	Bitumen content	Flow
Pr	97.200	69.700	58.100	44.300	22.500	14.300	7.700	5.200	**5.500**	**12.337**
Ts1	97.200	69.700	58.100	44.300	22.500	14.300	7.700	5.200	5.000	11.200
Ts2	97.200	69.700	58.100	44.300	22.500	14.300	7.700	5.200	5.500	12.100
Ts3	97.200	69.700	58.100	44.300	22.500	14.300	7.700	5.200	5.750	12.800
Ts4	97.200	69.700	58.100	44.300	22.500	14.300	7.700	5.200	6.000	13.200
TR1	95.800	72.800	51.100	38.900	23.600	15.300	8.300	4.100	5.000	11.049
TR2	95.800	72.800	51.100	38.900	23.600	15.300	8.300	4.100	**5.500**	11.500
TR3	95.800	72.800	51.100	38.900	23.600	15.300	8.300	4.100	5.750	12.620

	3/4"	3/8"	4	8	30	50	100	200	Bitumen content	AirVoids
Pr	97.200	69.700	58.100	44.300	22.500	14.300	7.700	5.200	**5.500**	**3.086**
Ts1	97.200	69.700	58.100	44.300	22.500	14.300	7.700	5.200	5.000	5.748
Ts2	97.200	69.700	58.100	44.300	22.500	14.300	7.700	5.200	5.500	3.293
Ts3	97.200	69.700	58.100	44.300	22.500	14.300	7.700	5.200	5.750	2.869
Ts4	97.200	69.700	58.100	44.300	22.500	14.300	7.700	5.200	6.000	2.756
Ts5	95.800	72.800	51.100	38.900	23.600	15.300	8.300	4.100	5.000	5.518
Ts6	95.800	72.800	51.100	38.900	23.600	15.300	8.300	4.100	**5.500**	3.213
TR1	95.800	72.800	51.100	38.900	23.600	15.300	8.300	4.100	5.750	2.678
TR2	95.800	72.800	51.100	38.900	23.600	15.300	8.300	4.100	6.000	2.347
TR3	96.694	70.331	59.421	43.636	22.975	15.124	8.099	4.628	5.000	5.598

	3/4"	3/8"	4	8	30	50	100	200	Bitumen content	Denisty
Pr	97.200	69.700	58.100	44.300	22.500	14.300	7.700	5.200	**5.500**	**2.290**
Ts1	97.200	69.700	58.100	44.300	22.500	14.300	7.700	5.200	5.000	2.312
Ts2	97.200	69.700	58.100	44.300	22.500	14.300	7.700	5.200	5.500	2.322
Ts3	97.200	69.700	58.100	44.300	22.500	14.300	7.700	5.200	5.750	2.338
Ts4	97.200	69.700	58.100	44.300	22.500	14.300	7.700	5.200	6.000	2.344
TR1	95.800	72.800	51.100	38.900	23.600	15.300	8.300	4.100	5.000	2.152
TR2	95.800	72.800	51.100	38.900	23.600	15.300	8.300	4.100	**5.500**	2.162
TR3	95.800	72.800	51.100	38.900	23.600	15.300	8.300	4.100	5.750	2.178

Figure 4.6 Organization of data from Extraction, Sieve Analysis and Marshall Tests

	3/4"	3/8"	4	8	30	50	100	200	Bitumen content	Stability.
Pr	1.000	-0.621	0.758	1.000	-1.000	-0.250	-1.000	1.000	0.000	0.198
Ts1	1.000	-0.621	0.758	1.000	-1.000	-0.250	-1.000	1.000	-1.000	-0.615
Ts2	1.000	-0.621	0.758	1.000	-1.000	-0.250	-1.000	1.000	0.000	0.142
Ts3	1.000	-0.621	0.758	1.000	-1.000	-0.250	-1.000	1.000	0.500	0.922
Ts4	1.000	-0.621	0.758	1.000	-1.000	-0.250	-1.000	1.000	1.000	0.661
TR1	-0.556	0.471	-0.524	-0.421	0.001	1.000	0.122	-1.000	-1.000	-1.000
TR2	-0.556	0.471	-0.524	-0.421	0.001	1.000	0.122	-1.000	0.000	-0.243
TR3	-0.556	0.471	-0.524	-0.421	0.001	1.000	0.122	-1.000	0.500	0.537

Figure 4.7 Scaling of data

	3/4"	3/8"	4	8	30	50	100	200	Bitumen content
HN1	9.63E+09	2.11E+08	-2.2E+09	-1E+09	-1.6E+09	-1.5E+09	-1.2E+09	-3.8E+09	3.04E+09
HN2	-1.6E+09	1.58E+09	8.26E+09	6.09E+08	1.61E+09	3.39E+08	-1.4E+09	4.74E+09	9.13E+09
HN3	-5.9E+09	1.18E+09	7.05E+08	8.19E+08	-3E+07	-5E+08	-3.2E+07	2.23E+09	7.5E+09
HN4	-6.3E+08	-9.8E+09	2.18E+09	-2.5E+09	-9.6E+08	-2E+09	-1.6E+09	4.96E+08	-7.9E+07
HN5	-2.2E+08	-2.9E+08	-1.4E+08	-1E+10	-5.5E+08	2.06E+09	6E+09	-5.9E+08	-9.4E+09

Figure 4.8 Weights of 5 hidden neurons

	HN1	HN2	HN3	HN4	HN5
Pr	1	1	-1	1	-1
Ts1	1	-1	-1	1	-1
Ts2	1	1	-1	1	-1
Ts3	1	1	1	1	-1
Ts4	1	1	1	1	-1
TR1	-1	-1	-1	-1	1
TR2	-1	-1	1	-1	1
TR3	1	-1	1	-1	1

Figure 4.9 Outputs of hidden neurons

	HN1	HN2	HN3	HN4	HN5
HN22	0.332943	0.414857	0.72081	0.582095	0.408374

Figure 4.10 Weights of 5 hidden neurons to 1 output

NN output	
Pr	0.198059
Ts1	-0.55737
Ts2	0.198059
Ts3	0.927798
Ts4	0.927798
Ts5	-0.9278
Ts6	-0.19806
TR1	0.434292
TR2	0.444754
TR3	-0.44475

Figure 4.11 Neural network Output

NN output Scaled back		Actual Stability.		% Errors
Pr	1223.665	Pr		
Ts1	1071.478	Ts1	1059.88	1.09
Ts2	1223.665	Ts2	1212.34	0.93
Ts3	1370.678	Ts4	1369.50	0.09
Ts4	1370.678	Ts5	1316.88	4.09
Ts5	996.8517	Ts6	982.31	1.48
Ts6	1143.864	Ts7	1134.77	0.80
TR1	1271.257	Ts8	1291.93	1.60
TR2	1273.364	TR1	1239.31	2.75
TR3	1094.165	TR2	1016.33	7.66

Figure 4.12 Scaling back and calculating the error

4.7 Determining NN Weights

Once the Excel spreadsheet has been set up with initial weights of [0 to 1], it was apparent that overall performance indicator of cell (I 195) (Figure 4.13) showing a very high error value. Because all formulas in the template are functions of the weights, the next step was to determine the (ANN) weight values that would optimize (ANN) performance. In this thesis genetic algorithm (GA) technique using Evolver 5.5 optimization add-in for Microsoft Excel software from Palisade Corporation was used. The details of (GA) are provided as follow:

TR24	0.99143		TR24	6.874262	TR24	4.75	44.72
TR25	0.994792		TR25	6.881485	TR25	4.6	49.60
TR26	-0.99636		TR26	2.603343	TR26	6.4	59.32
TR27	-0.99634		TR27	2.603373	TR27	6.4	59.32
TR28	-0.99637		TR28	2.603322	TR28	6.5	59.95
TR29	-0.99631		TR29	2.603445	TR29	6.4	59.32
TR30	-0.9964		TR30	2.603253	TR30	6.6	60.56
TR31	-0.9964		TR31	2.603258	TR31	6.4	59.32
TR32	-0.9965		TR32	2.603039	TR32	6.5	59.95
TR33	-0.99642		TR33	2.603216	TR33	6.4	59.32
TR34	0.994305		TR34	6.880439	TR34	4.75	44.85
				Testing error		66.41	
				Traning error		66.78	
				Weighted Error		66.60	

Figure 4.13 (ANN) Templates

4.7.1 Genetic Algorithm (GA) technique

This technique is fundamentally different from traditional simplex based algorithms such as the one used by Excel Solver. It uses the method of evolution, specifically survival of the fittest. The theory behind (GA) is that a population of a certain species will, after many generations of random evolution, adapt to live better in its environment. (GA) solved optimization problems in the same fashion. First, a population of possible solutions to the problem is created. Individuals in the population are then allowed to randomly breed, a process called crossover, until the fittest offspring (the one that solves the problems best) is generated. After a large number of generations, a population eventually emerges wherein the individuals will provide an optimum or close to optimum solution (Hegazy.T. and Ayed.A.,1998).

4.7.2 Evolver

For the case study at hand, commercial (GA) software (Evolver5.5 optimization) was used to find the optimum originals weights at step 3 and step 5 (Figure 4.14) of the model.

Since, the training of the back-propagation network is performed by Evolver, a brief description about the software and the data input is given below.

Evolver uses a proprietary set of genetic algorithms to search for optimum solutions to a problem, along with probability distributions and simulation to handle the uncertainty present in model. Genetic algorithms are used in Evolver to find the best solution for model.

Step3 :Weights of 5 hidden neurons

	3/4"	3/8"	4	8	30	50	100	200	Bitumen content	
HN1	0.409446	0.548448	0.035205	0.50331	0.359908	0.003636	0.288565	0.529799	0.837114	Layer 1
HN2	0.092432	0.171751	0.102081	0.213943	0.533312	0.182971	0.858888	0.852815	0.980897	
HN3	0.247777	0.942019	0.27612	0.350308	0.495475	0.056454	0.606461	0.39369	0.558345	
HN4	0.352202	0.890275	0.027824	0.230818	0.296332	0.82264	0.210413	0.398612	0.104975	
HN5	0.114068	0.231615	0.216931	0.967526	0.708307	0.456648	0.698963	0.795007	0.916145	

Step 5 :Weights from 5 Hidden Neurons to 1 Output

	HN1	HN2	HN3	HN4	HN5
HN22	0.332943	0.414857	0.72081	0.582095	0.408374

Figure 4.14 Original Weights of the Spread Sheets

Genetic algorithms mimic Darwinian principles of natural selection by creating an environment where hundreds of possible solutions to a problem can compete with one another, and only the "fittest" survive. Just as in biological evolution, each solution can pass along its good "genes" through "offspring" solutions so that the entire population of solutions will continue to evolve better solutions. The terminology used when working with genetic algorithms is often similar to that of its inspiration. Crossover functions help focus the search for solutions, "mutation" rates help diversify the "gene pool", and evaluate the entire "population" of solutions or "organisms". (Cell I 154) representing the (ANN) training weighted error was selected to be minimized. The screen model definition at Evolver adjustable cells ranges (Figure.4.15) containing the optimization variables were also specified as the two weight matrices. Adjustable cells founded that the range from (-1000000 to 1000000) gives satisfied results, at the same screen constraints was founded from (0 to 10) for testing trials and (0 to 15) for training trials.

At setting screen (Figure4.16) after many trials it was founded that 100000 trials and progress maximum change 0.01% with number of trials 5000 give acceptable results.

During the (GA) optimization, Evolver options can be used to enhance the results. For example, population size affects processing time because the fitness function must be calculated for every individual in every generation. A population size 50 was found as a good number to start with. The number can be increased later during the optimization process. Chromosome length presents the level of accuracy needed for the adjustable cells.

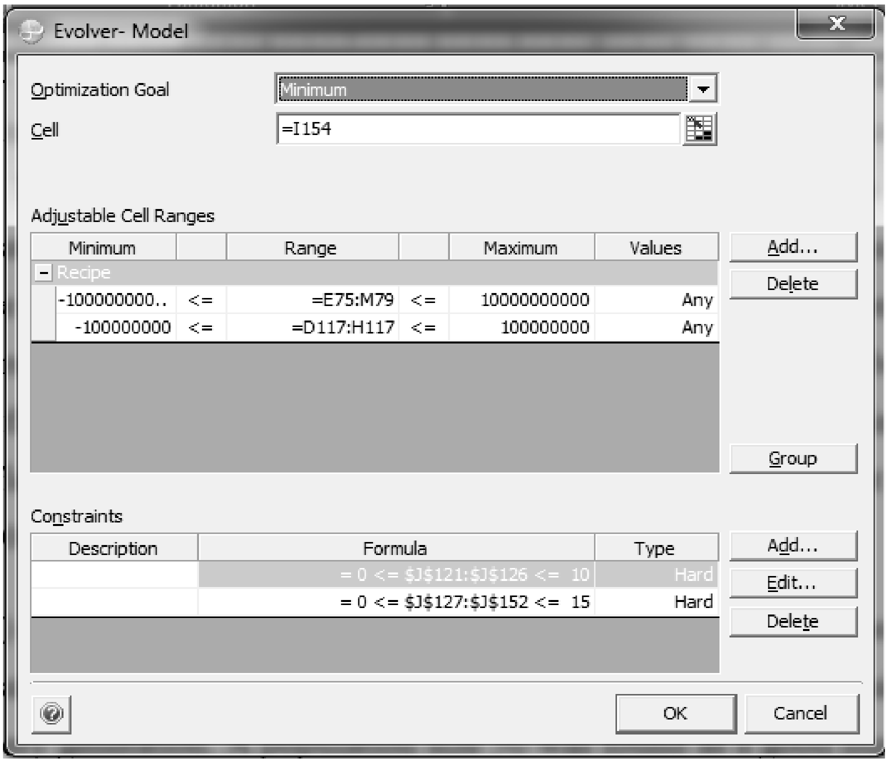


Figure 4.15 Evolver Model Definition Screen

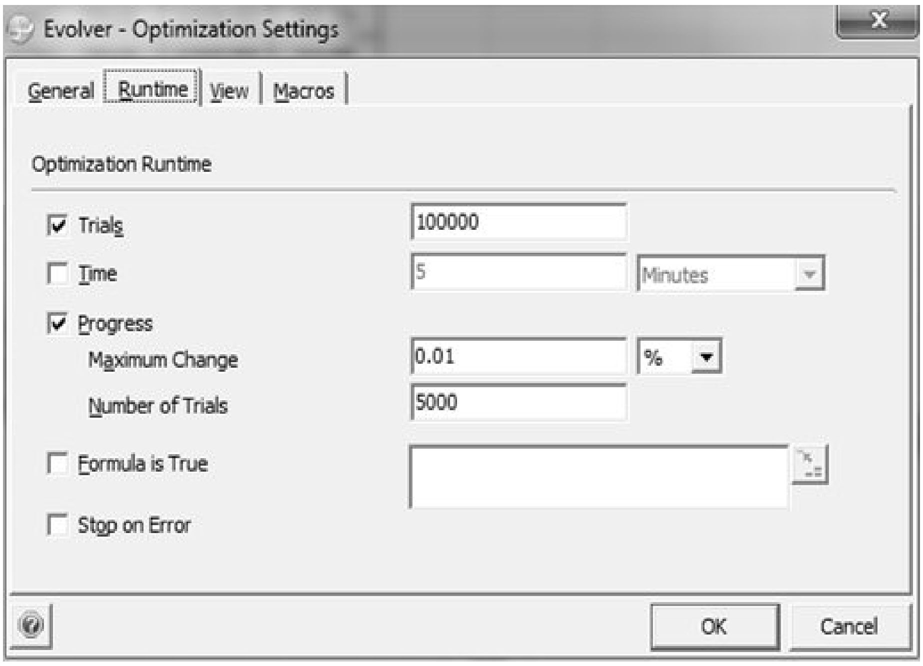


Figure 4.16 Evolver Optimization Setting Screen

Appendix C shows the sample report of optimization process using Evolver, the report was appeared automatically after the end of optimization process in a single sheet.

The most remarkable results in this report are no. of valid trials, no. of total trials, original value, best value found, reason optimization stop and total optimization time.

4.8 Comparing experimental results with the ANN model

The Marshall Test Results data (Stability, Flow, Air Void, and Density) were presented on charts (Figures 4.17- 4.20) shows the big different between experimental and predicted results before Genetic Algorithm running.

Furthermore, the results comparison by the error percentage is the main focus and can be computed by

Error% =Absolute ((experimental – Predicted)/experimental)*100

After the end of the optimization process at each sheet it founded that difference chart between the experimental and predicted results error was minimized. (Figures from. 4.17 to 4.20) show this.

Comparison of the results yields that Evolver is effective in modeling the problem and its predictions' is close to real data.

If the previous recorded data (input data) increase, the error percentage decrease and more accurate Marshall Test results (output data) will be gained.

4.9 Analysis

4.9.1 Average Error

After the ANN model has been developed, it seems in (Figure.4.21) that the weighted error in all Marshall Results was acceptable; it had maximum error not exceed 3.99% at stability, 2.38% at flow, 9.46%at air voids and 2.41%at density.

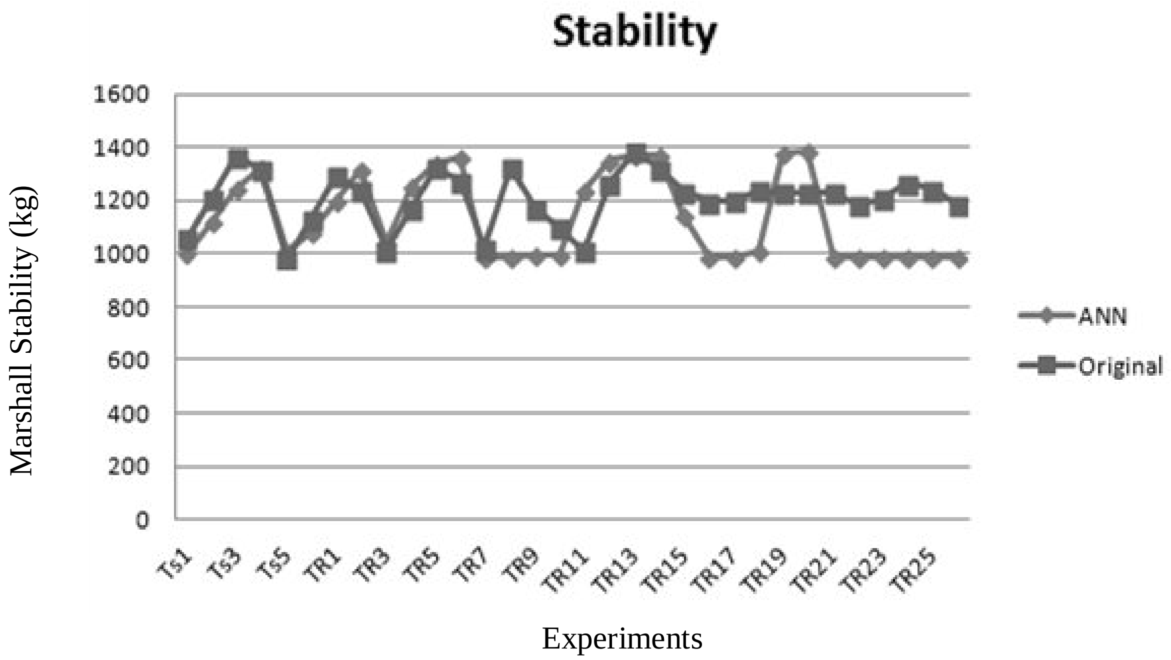


Figure 4.17.a Stability Before Optimization.

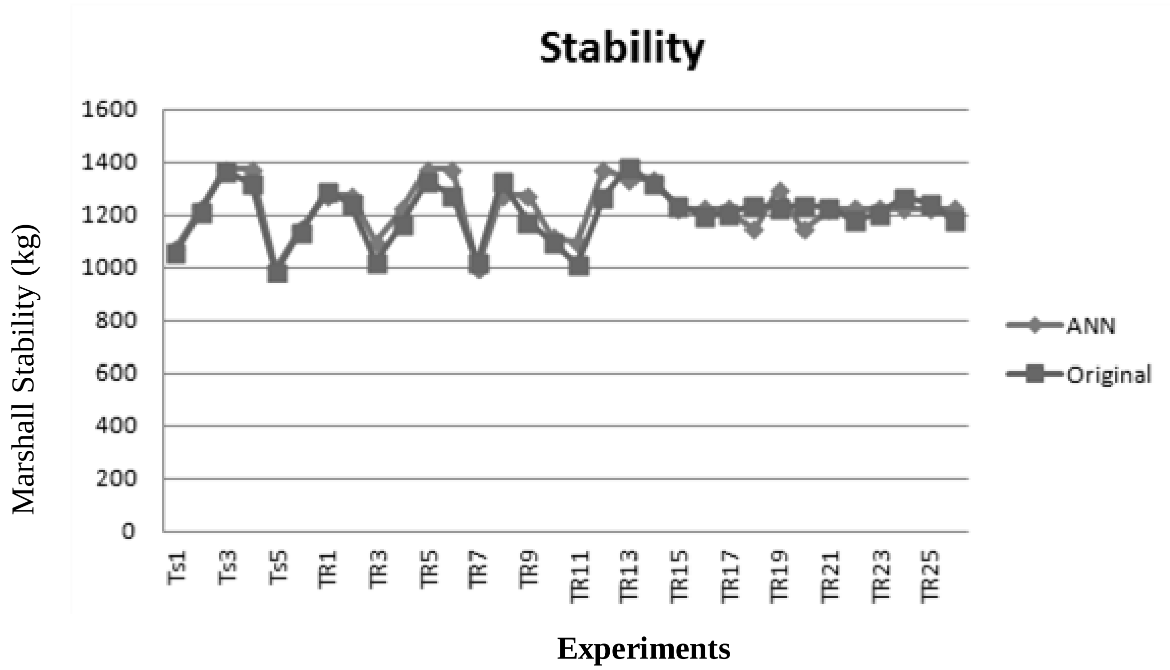


Figure 4.17.b Stability After Optimization.

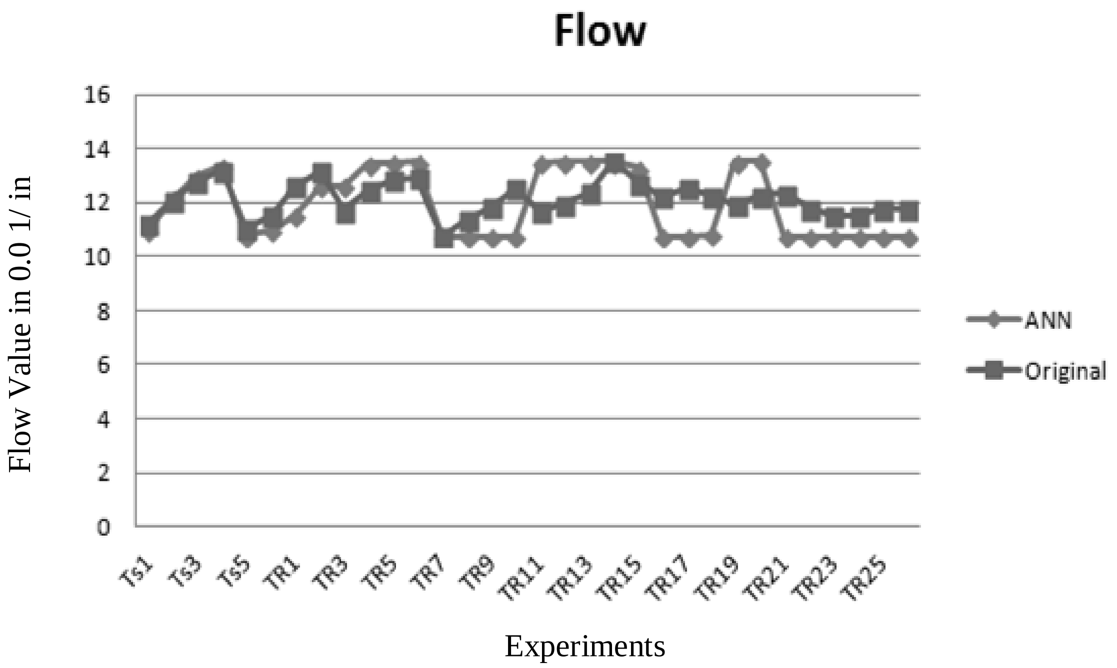


Figure 4.18.a Flow Before Optimization.

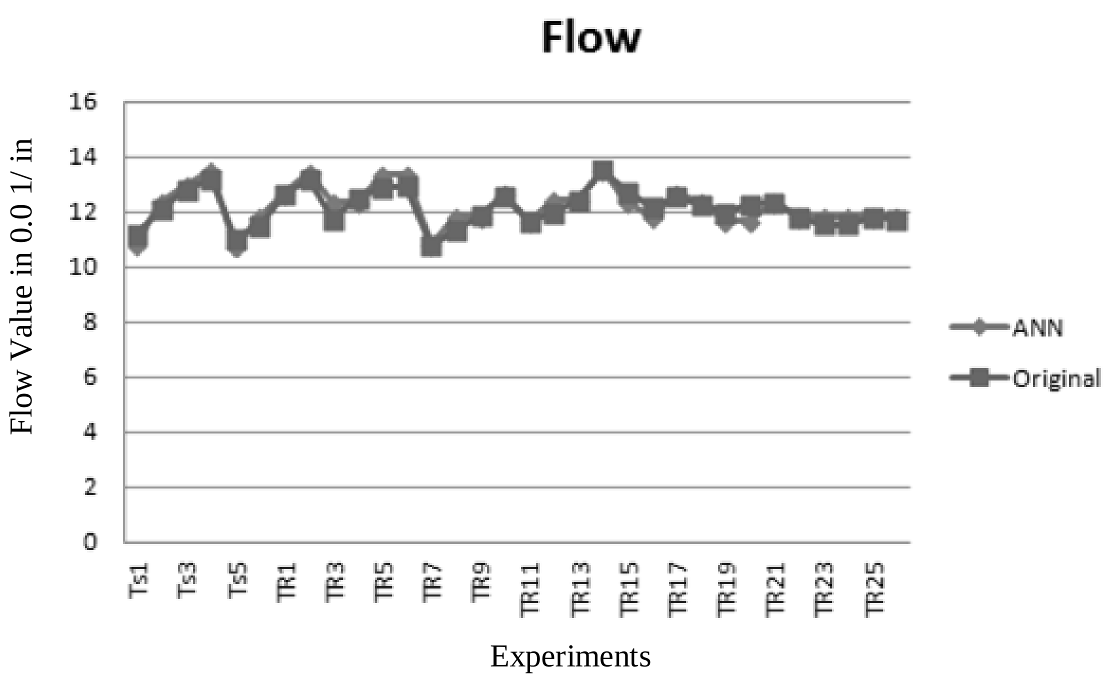


Figure 4.18.b Flow After Optimization.

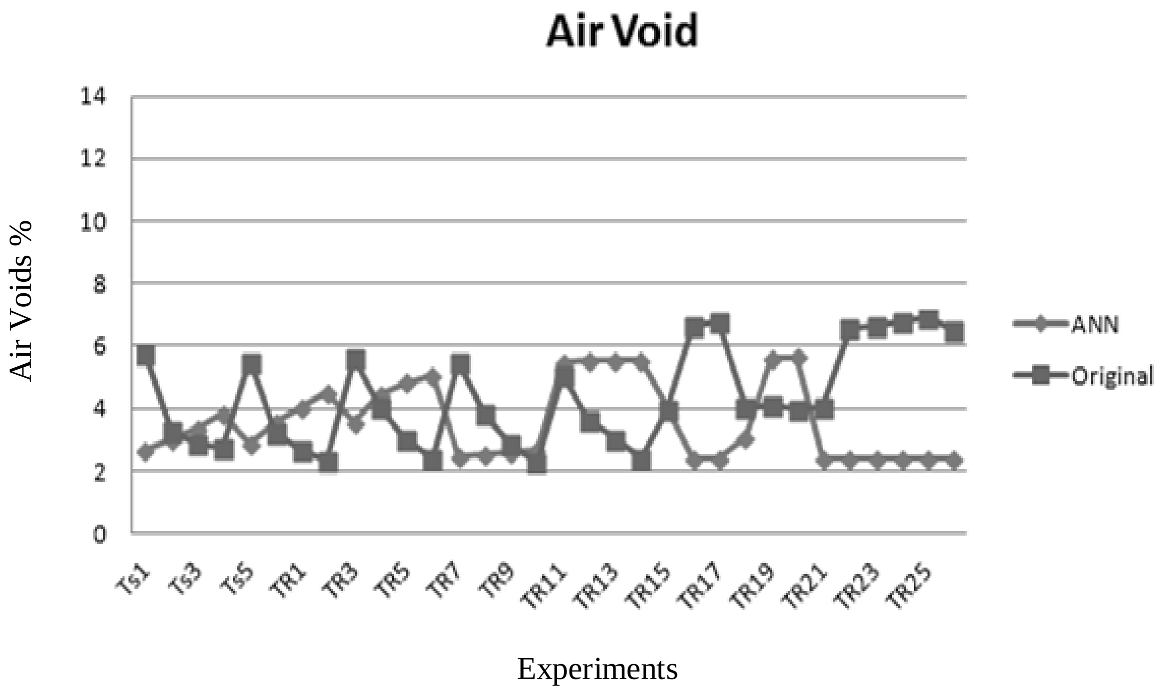


Figure 4.19.a Air Void Before Optimization.

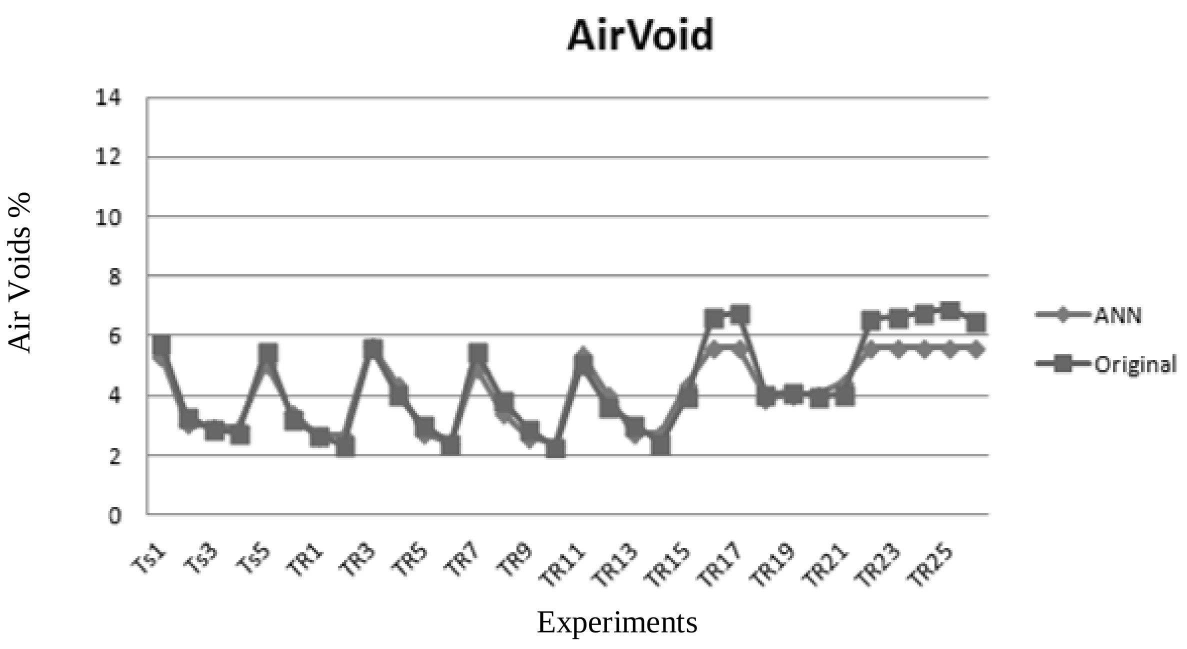


Figure 4.19.b Air Void After Optimization.

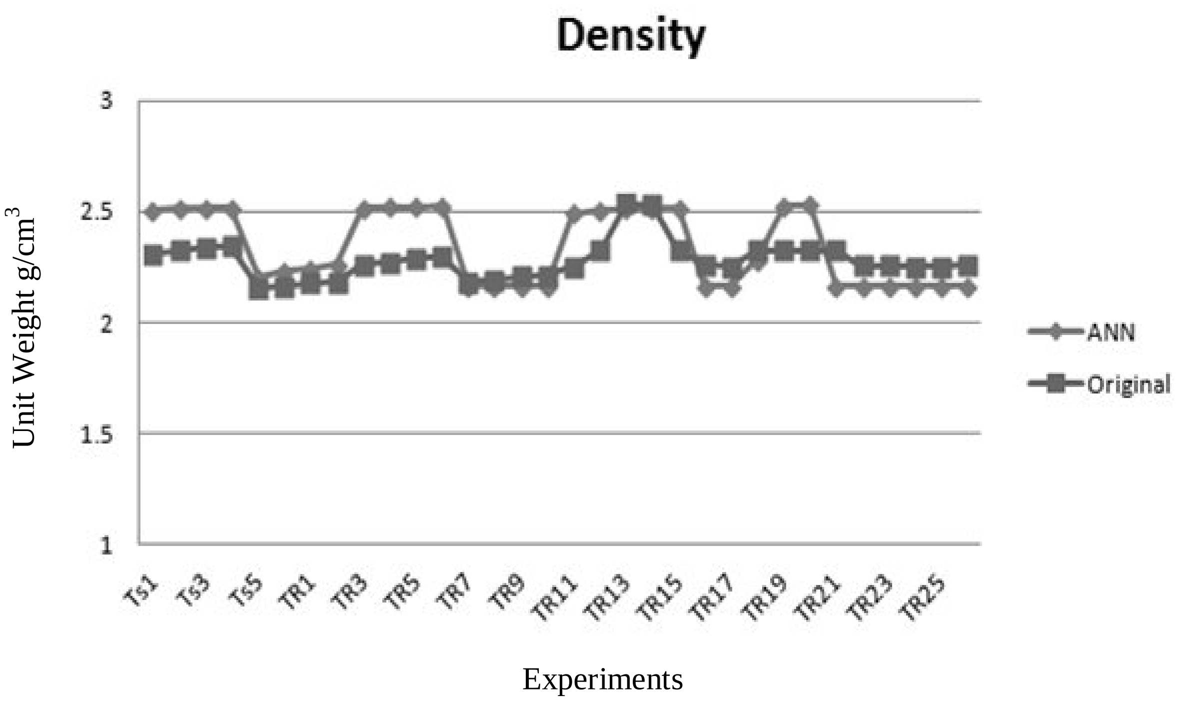


Figure 4.20.a Density Before Optimization.

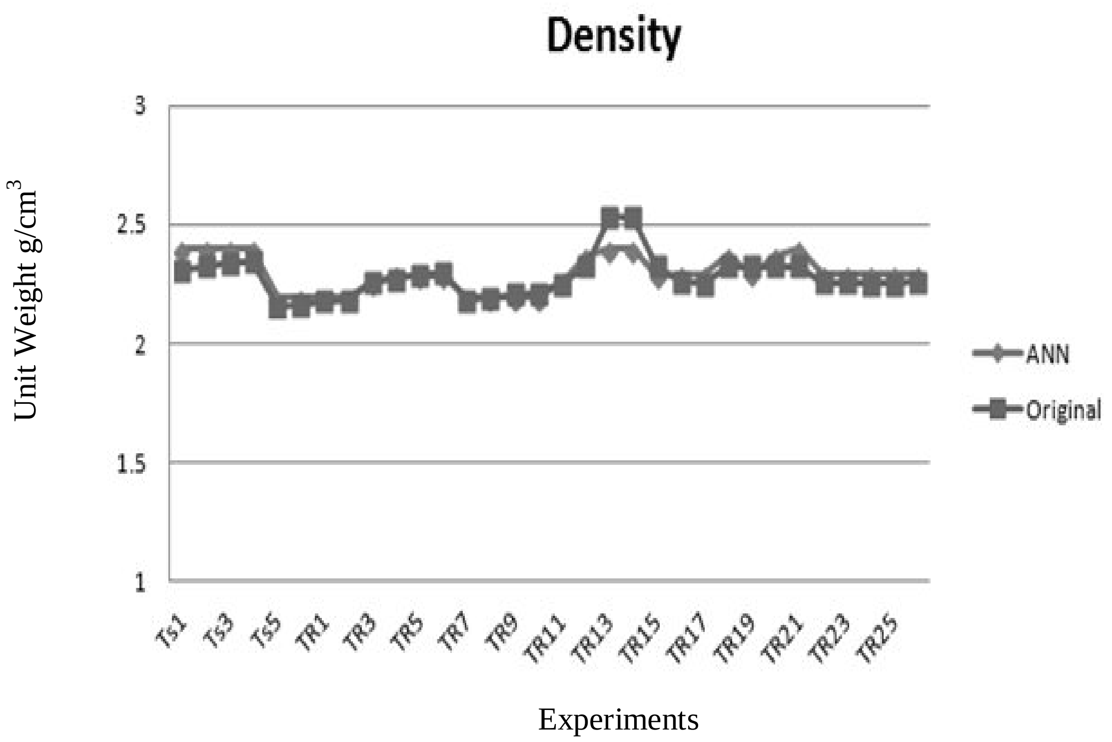


Figure 4.20.b Density After Optimization.

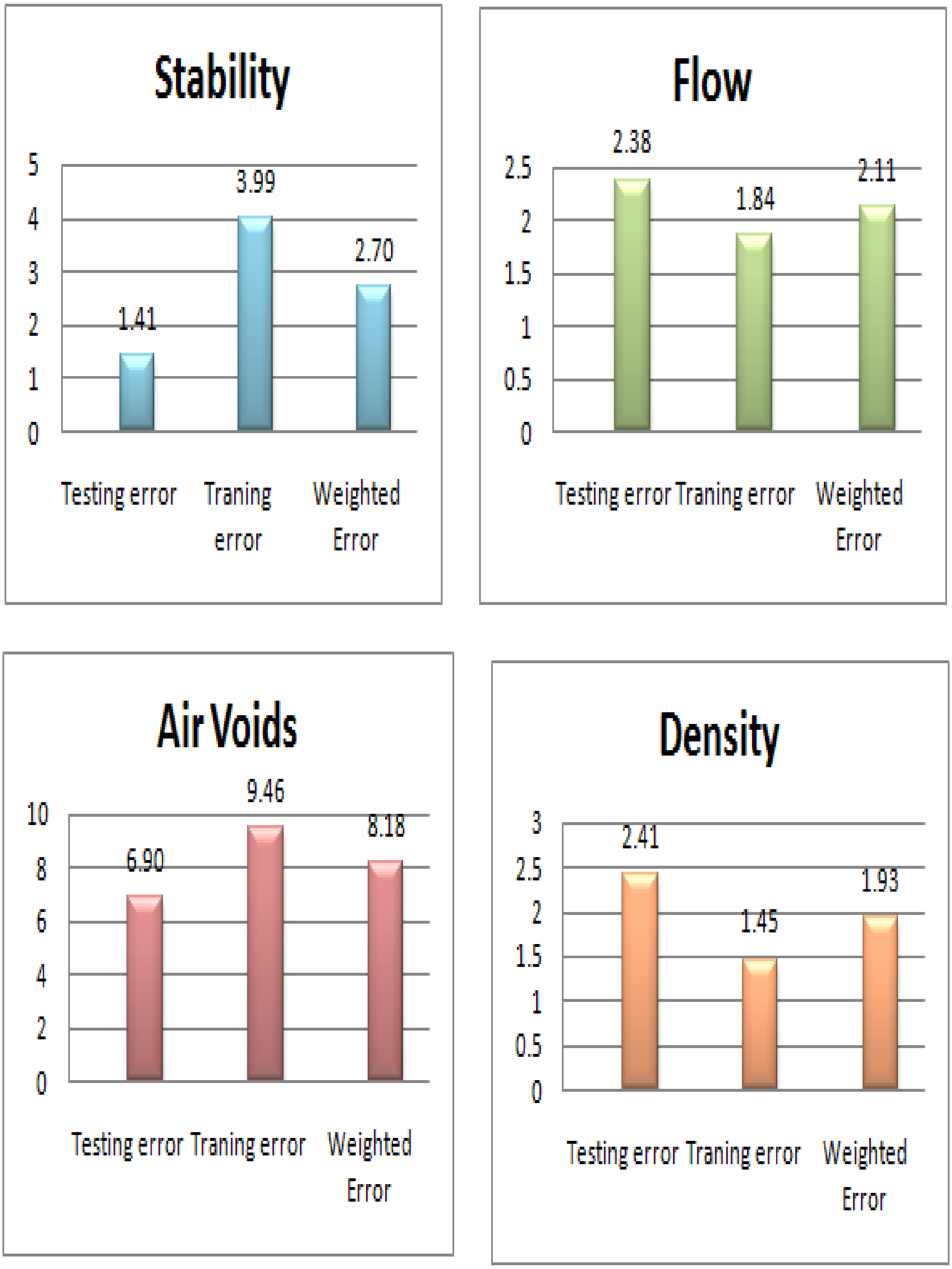


Figure 4.21 The ANN Model After Developed Error

4.9.2 Detailed Error analysis

A detailed error analysis was also performed and is shown in (Figure 4.21.a, b, c, d), which illustrates the error distribution for both the training and testing cases.

As shown for table (4.1) training error percentage, more than 55.77% less than 3 %, 14.43% between 5-7%, 17.3% between 5-7% and less than 1% between 7 – 10 %

As shown for table (4.1) testing error percentage, more than 58.35% less than 3 %, 21.79% between 5-7%, 3.845% between 5-7% and less than 1% between 7 – 10 %

Table 4.1 Summary of Training and Testing Error

Training Error %	**Stability**	**Flow**	**Air voids**	**Density**	**Average**
0-3%	42.31	73.08	19.23	88.46	55.77
3-5%	26.92	19.23	7.69	3.85	14.43
5-7%	26.92	7.69	26.92	7.69	17.3
7-10%	3.85	0	0	0	0.925
Testing Error %	**Stability**	**Flow**	**Air voids**	**Density**	**Average**
0-3%	83.33	66.67	16.67	66.67	58.35
3-5%	16.67	33.33	3.85	33.33	21.79
5-7%	0	0	15.38	0	3.845
7-10%	0	0	0	0	0

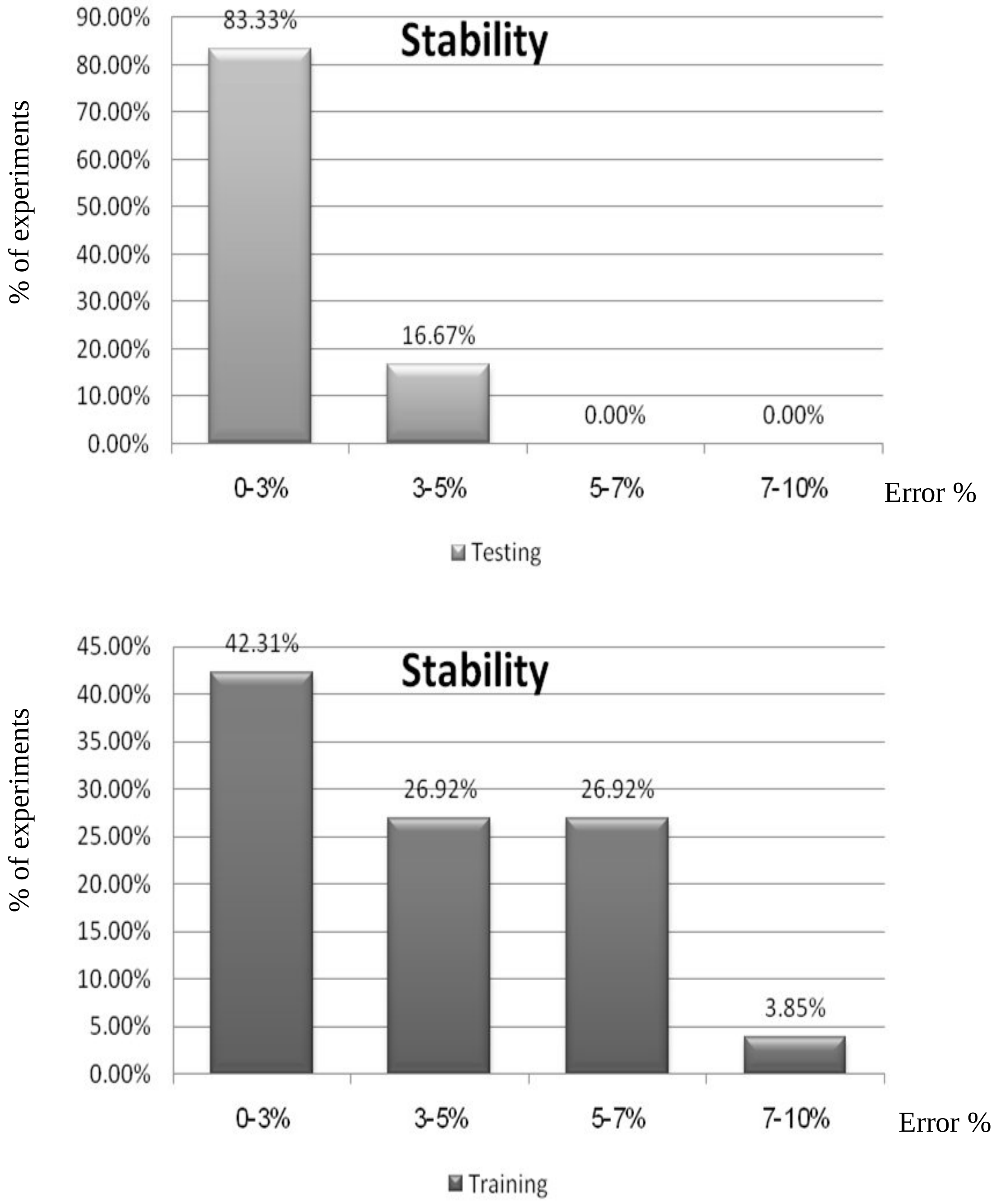
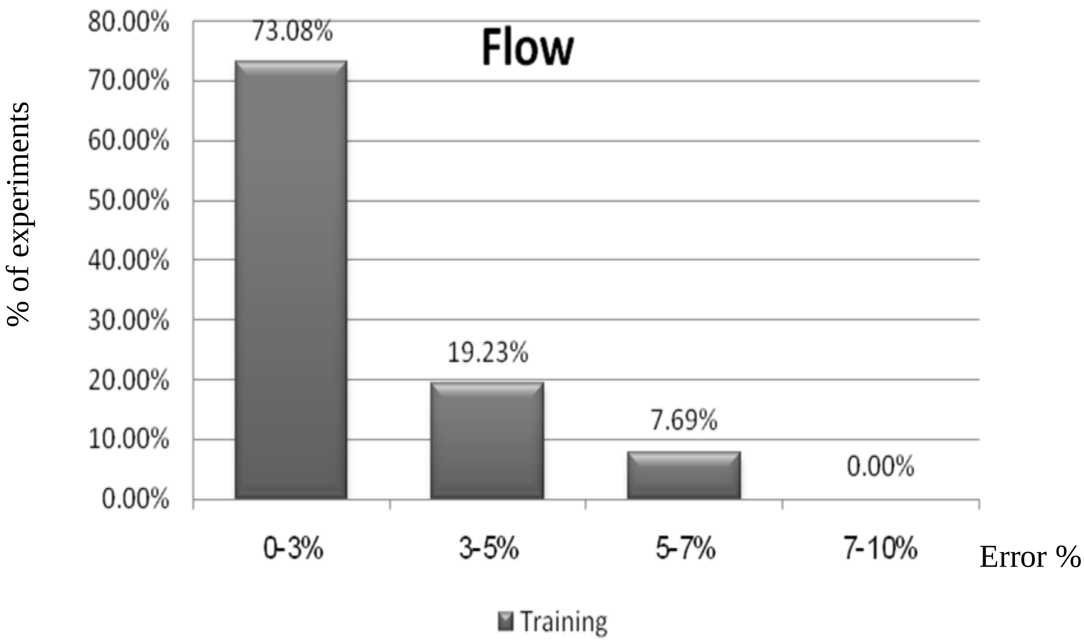


Figure 4.22.a Error distribution, Training and Testing sets



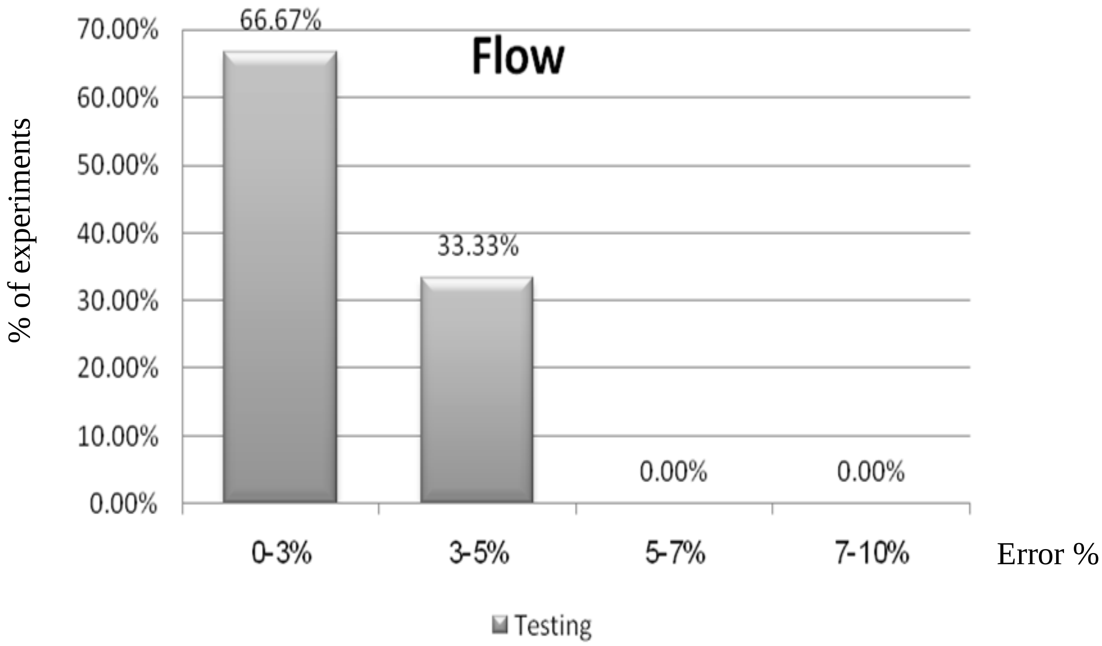


Figure 4.22.b Error distribution, Training and Testing sets

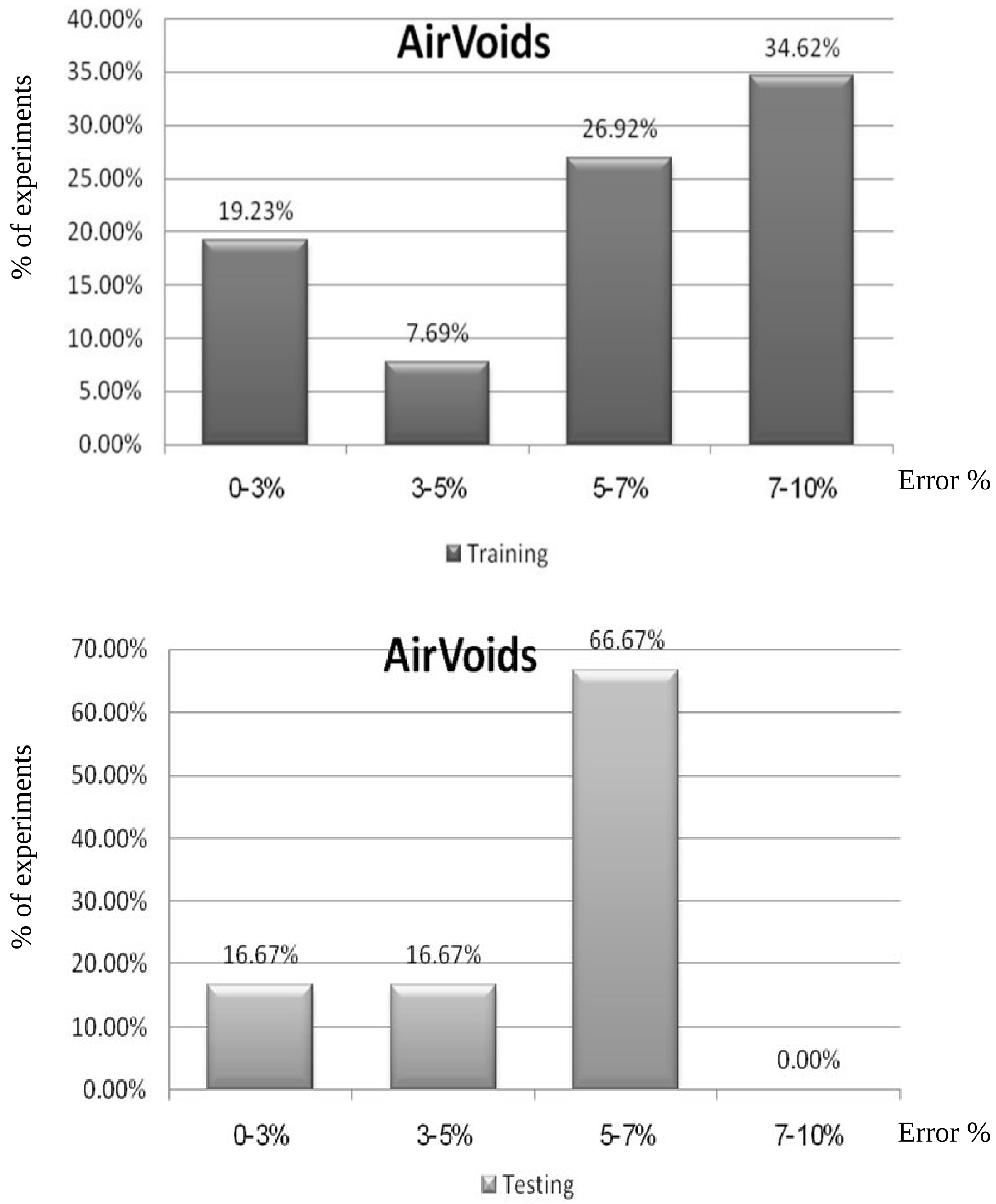
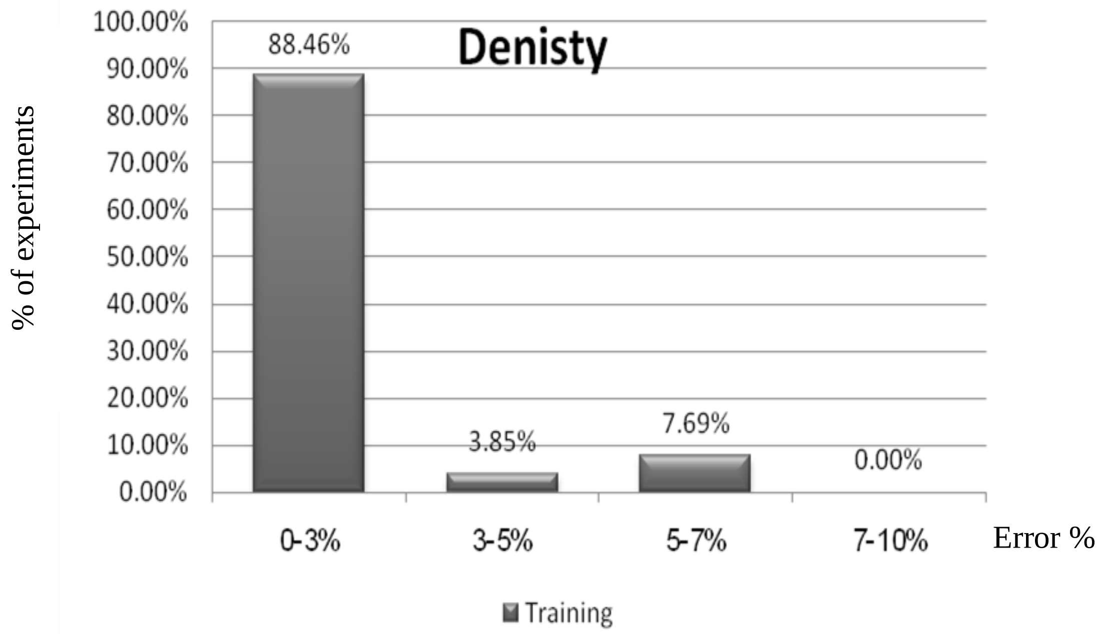


Figure 4.22.c Error distribution, Training and Testing sets



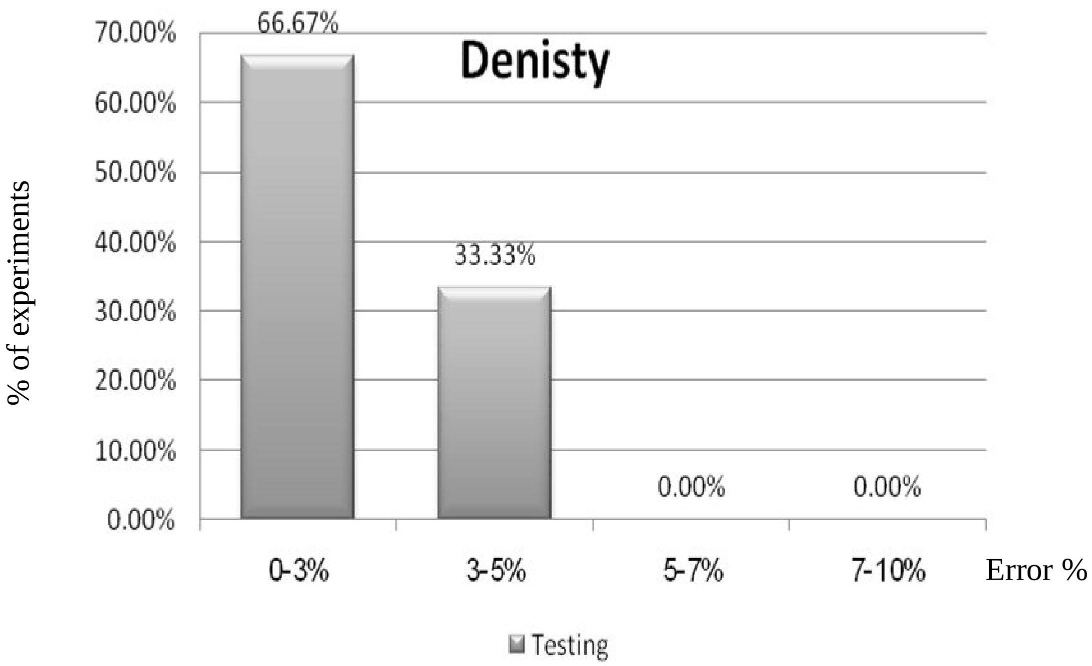


Figure 4.22.d Error distribution, Training and Testing sets

4.10 Validating of the model

Once the ANN model has been developed, it can be put to actual new sieve and bitumen percentages use in predicting the Marshall Results for new (HMA).(Figure 4.23) shows estimation screen for new (HMA), Marshall Results (stability, flow, air voids and density) linked to previous ANN models individually.

Estimated Results

Please enter all of sieve size passing % and bitumen content to automaically estimate Marshal test result

1"	3/4"	3/8"	4	8	30	50	100	200	Bitumen content	Stability.	Flow(1/100)	air voids	denisty
100	97.2	69.7	58.1	44.3	22.5	14.3	7.7	5.2	5	1071.48	10.86	5.34	2.40

Figure 4.23 Estimation Screen for New Marshall Results

Data collected from another two projects to validate the model, sixteen experiments from ”Orascome Company” and fourteen experiments from the ”General Nile Company”, Table 4.2 illustrated maximum and minimum pass sieve percentage and Marshall Test results data from two projects.

Table 4.2 The Characteristics of HMA

Test	Project 1		Project 2	
	Minimum Value	Maximum Value	Minimum Value	Maximum Value
Extraction Test				
• %passing from sieve 1”	100	100	100	100
• %passing from sieve 3/4”	94.29	98.09	93.1	96.4
• %passing from sieve 3/8”	54.76	60.48	70	77.5

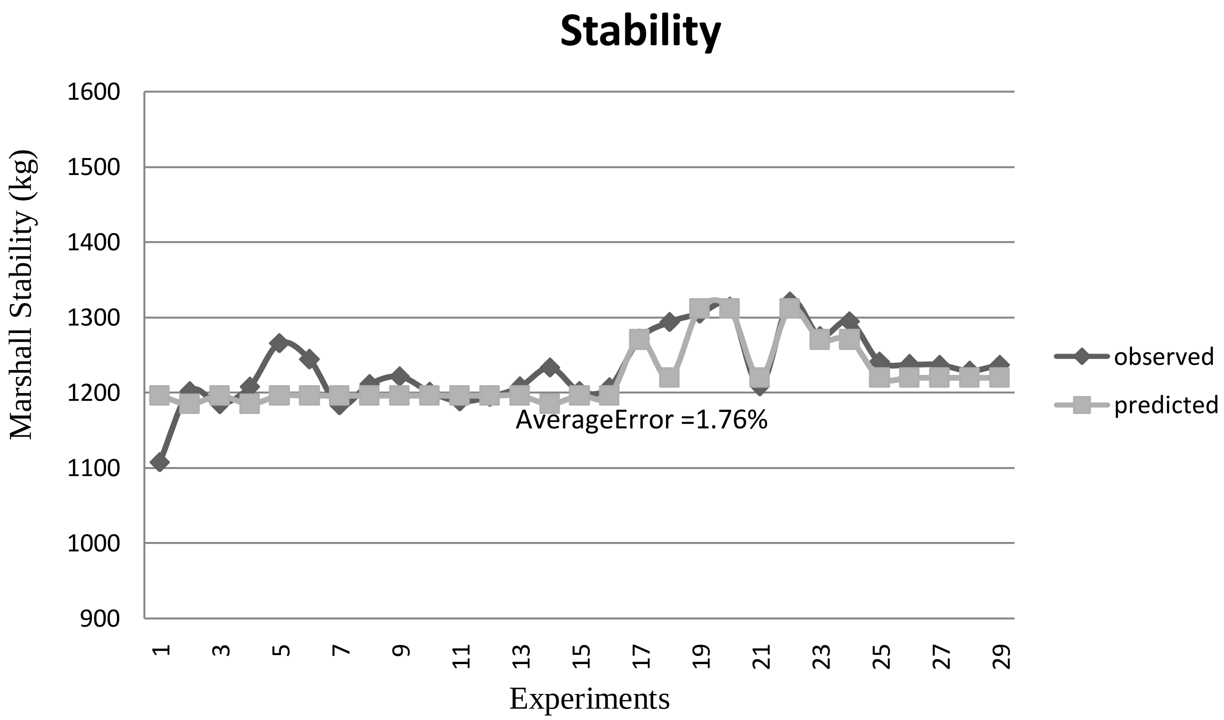
• %passing from sieve no .4	36.07	39.75	48.5	51.1
• %passing from sieve no .8	25.21	28.29	35.8	38.9
• %passing from sieve no .30	9.88	11.89	20.5	25.2
• %passing from sieve no .50	6.75	7.83	13.4	15.9
• %passing from sieve no .100	4.77	5.71	7.4	8.3
• %passing from sieve no .200	2	2.96	3.2	4.1
• % of bitumen content	4.4	4.7	5.22	5.36
Marshall Test				
• Marshall Stability (kg)	1107.7	1265.73	1208.2	1321.2
• Marshall Flow (1/100 inch)	11.3	12.53	10.8	11.6
• Air void ratio	6.39	6.9	2.83	4.8
• Density (gm/cm^3)	2.25	2.3	2.34	2.61

Previous experiments inserted to the Estimation screen to predict the results, (Figure 4.24) shows the percentage of average error after using the model to predict Marshall Test results data, following equations 1&2 show calculations of the average error.

$$\boldsymbol{Estimating\ Error}\ (\%)\ = \frac{(\boldsymbol{ANN\ OUTPUT} - \boldsymbol{Actual\ Output})}{\boldsymbol{Actual\ Output}} \times \mathbf{100}$$

$$\boldsymbol{Average\ ERROR}\ = \frac{\sum_{i=1}^{n} \boldsymbol{Estimating\ Error}}{\boldsymbol{n}}$$

Where n is number of experiments.



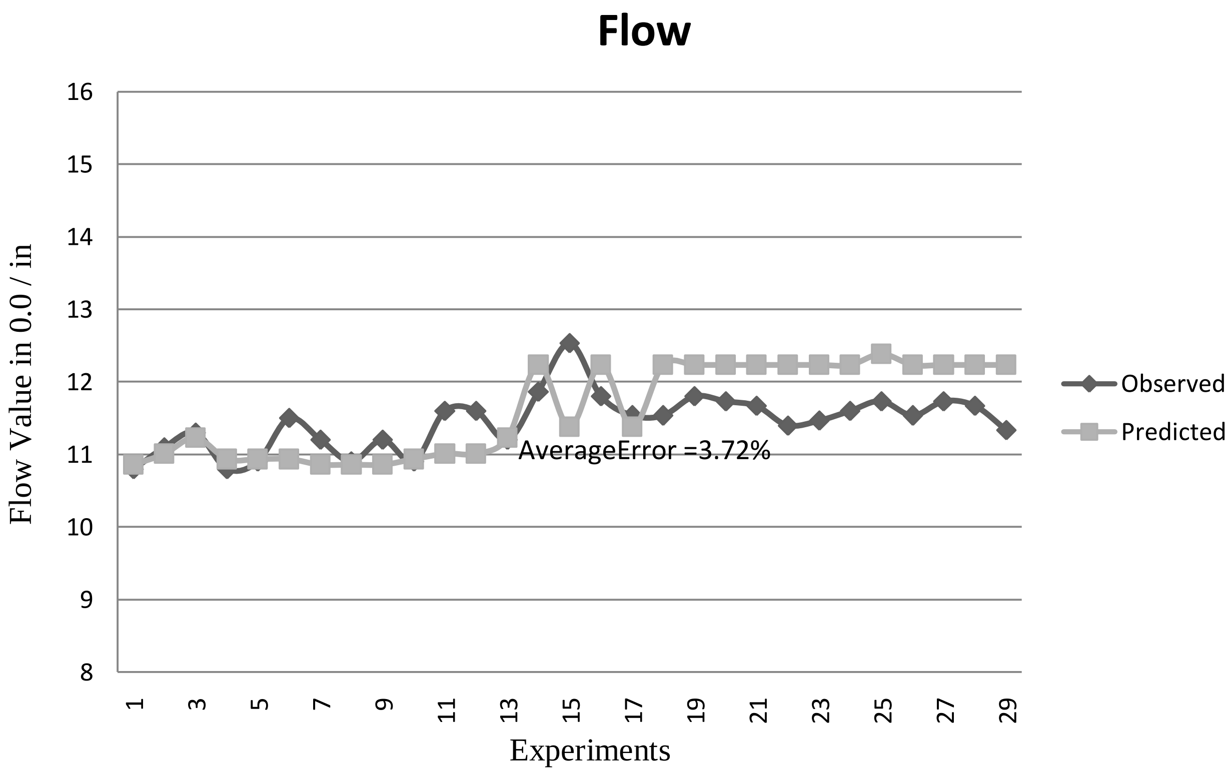
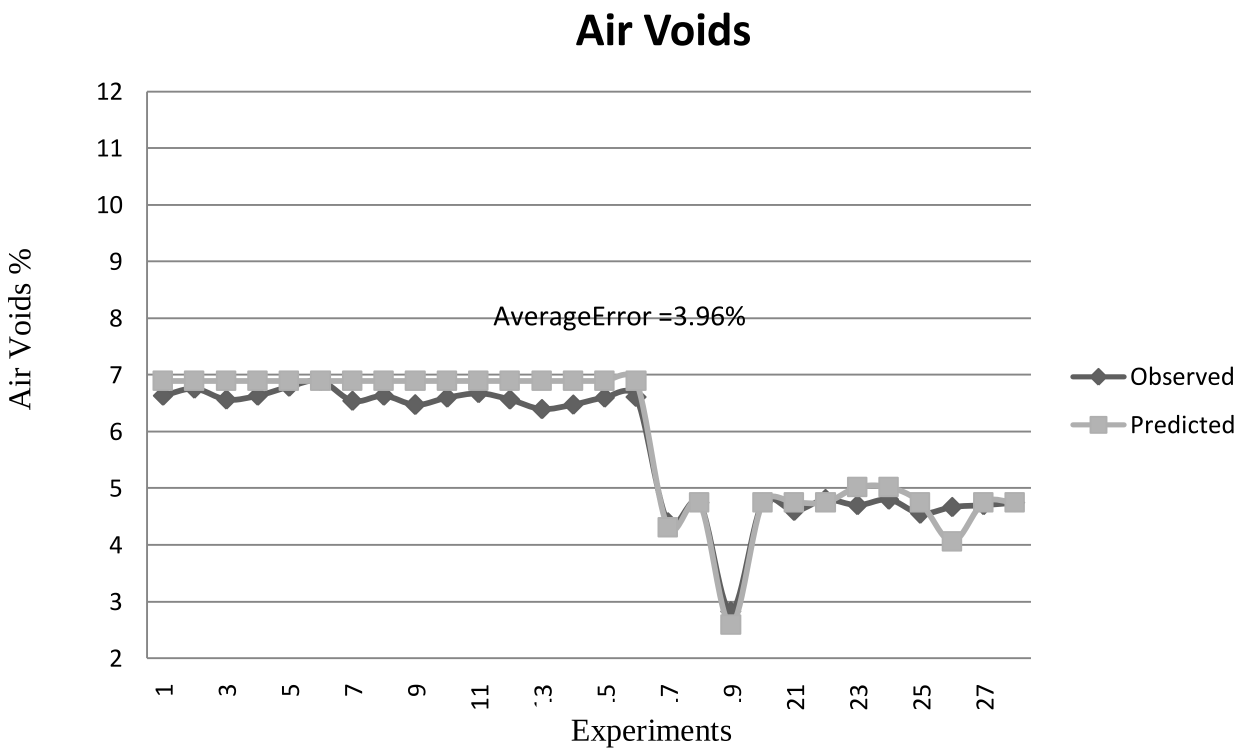


Figure 4.24 The Percentage of Error of Projects



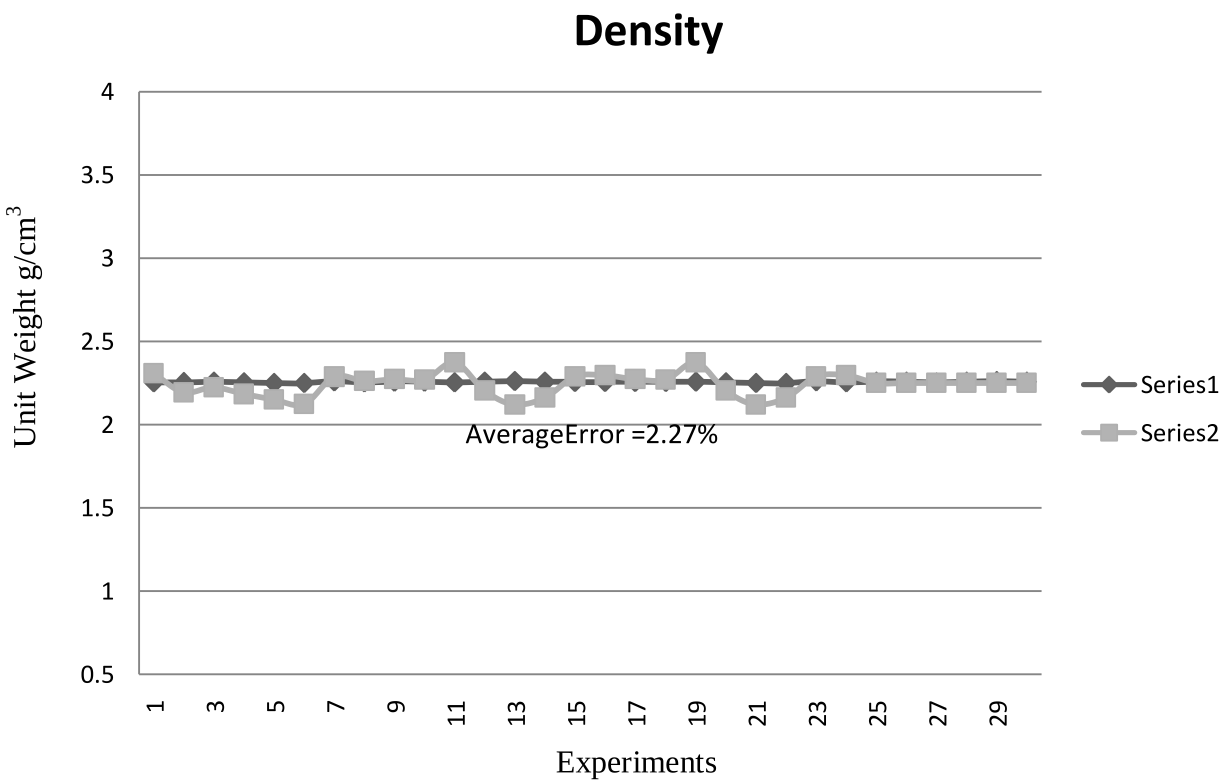


Figure 4.24 The Percentage of Error of Projects (cont.)

4.11 Summary

This chapter demonstrates the seven steps ANN model with two hidden layers using Microsoft Excel were suitable for organization of data.

Genetic Algorithm commercial software (Evolver 5.5) used to detect the suitable weights of hidden layers. Detailed error analysis shown in (table 4.1) illustrated it were acceptable.

The proposed model is valid among the ranges (maximum and minimum values) of the previously recorded experimental database which illustrated in (table 3.7) to predict a future Marshall Test results.

The model validated by thirty experiments goes between ranges and the errors were acceptable (Figure 4.25).

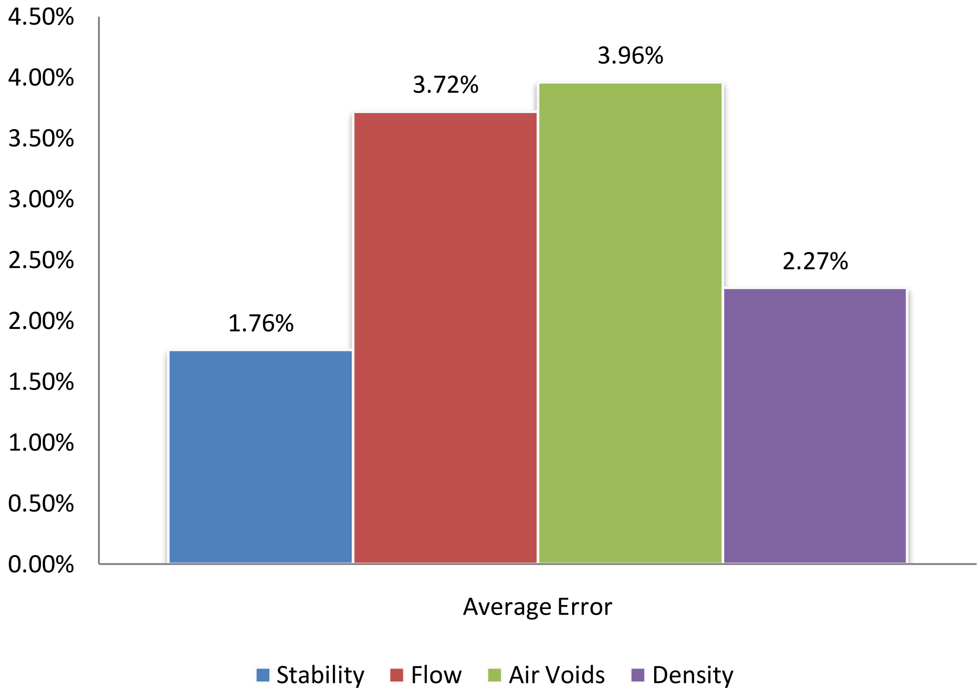


Figure 4.25 Error percentage of validating experiments

Chapter Five

CONCLUSION AND RECOMMENDATIONS

Chapter 5

CONCLUSION AND RECOMMENDATIONS

5.1 Introduction

The thesis is presented in five chapters encircling the whole research; this chapter reveals the summary of the study, also the chapter cites the appropriate current recommendations, which the researcher developed based on the research study.

The Extract, Sieve Analysis and Marshall Tests recorded data are the most important tests to control the quality in any pavement projects according to the quality control specifications of these projects.

The study demonstrates the benefits of using Artificial Neural Network technique for prediction of future depends on previous recorded data. thesis presents a model to predict Marshall Test Results depending on Extract and Sieve Analysis Test data. Modeling the Marshall Test Results of (HMA) is very important in quality control process without carrying out destructive tests which takes too much time and human effort.

The structure of a simple Artificial Neural Network (ANN) was simulated using a spreadsheet program (Excel) to provide a transparent and simplified representation of this technique.

Genetic Algorithm commercial software (Evolver 5.5) used to optimize the weights of (ANN) then to get a reasonable percentage error results.

The model allows the user to input sieve size passing percentage from sieve analysis test and bitumen content from extraction test then automatically get the Marshall Test results.

5.2 Conclusion

Based on the results of the developed models and from the experiences gained in this work it was concluded that:

- Using same kind of (HMA) (wearing, binder….etc.) to predict Marshall Test results at the (ANN) model give more accurate results.

- It founded that there is a great effect of percentage of bitumen in (HMA) characteristic especially in stability.

- The proposed model is valid for the ranges of the experimental database which it was shown at (table 3.7) used for (ANN) modeling.

- The Marshall Test results of the (HMA) was nonlinear, the proposed (ANN) method had the ability to model it. The ability of (ANN) method to model nonlinear data indicates that the model can also be used for hot mix asphalt designs.

5.3 Recommendations

First of all, the compilation, evaluation, and accuracy of historical data demanded for the development of the future Marshall Test results prediction models represents the most critical part of the research work.

The following recommendations will be useful to develop the model in the future.

- Increasing input trials data especially experimental Marshall Test with different percentage of bitumen and sieve passing will reduce the error of the model.
- In the future new factors like (temperature, kind of aggregate, characteristics of bitumen …etc) need to be inserted to the model to improve the predication process.
- Using microprogramming to enhance the interface of Microsoft Excel will be useful
- Using the model to predict pass sieve percentage dependent on Marshall Test characteristics which the project need.

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Appendix A

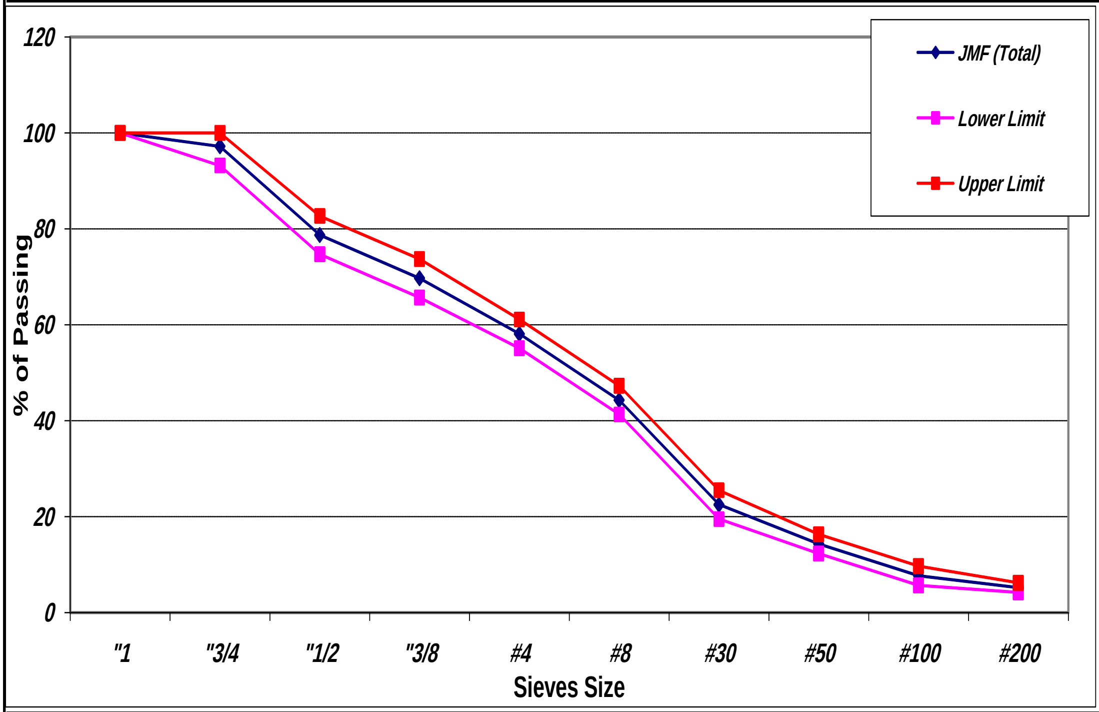
El Minia - Assute free way

Lab. Division

Bituminous Mix Design (wearing Course)25mm

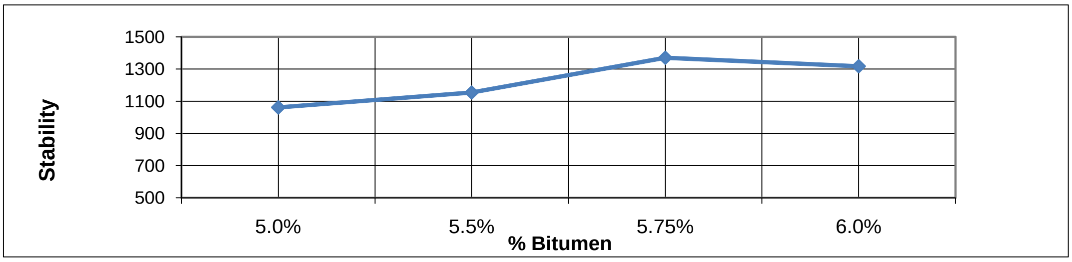
Gradation of the proposal JMF wearing Course

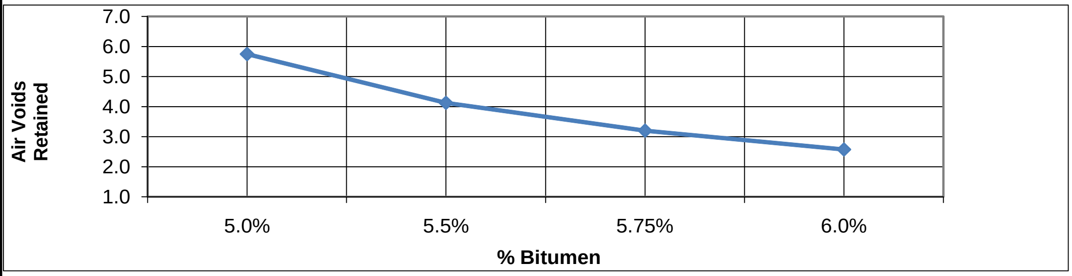
Sieves No.	JMF (Total)	JMF tolerance		Limits of project technical Specifications	
		Lower Limit	Upper Limit	Lower Limit	Upper Limit
"1	100	100	100	100	100
"3/4	97.2	93.2	100	80	100
"1/2	78.7	74.7	82.7	70	90
"3/8	69.7	65.7	73.7	60	80
#4	58.1	55.1	61.1	48	65
#8	44.3	41.3	47.3	35	50
#30	22.5	19.5	25.5	19	30
#50	14.3	12.3	16.3	13	23
#100	7.7	5.7	9.7	7	15
#200	5.2	4.2	6.2	3	8

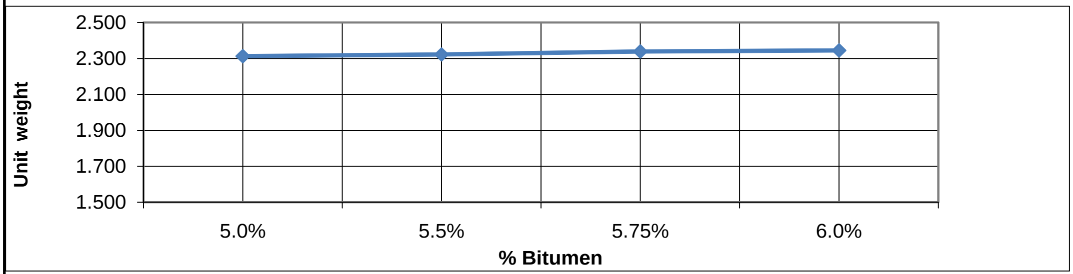


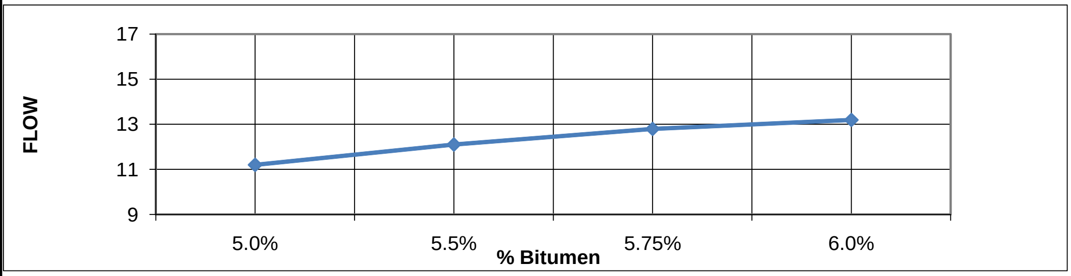
Marshall Propeties for WEARING

Test Performed	Bitumen Content %			
	5.0%	5.5%	5.75%	6.0%
Marshal Stability (N)	1061	1154	1370	1317
Flow	11	12	13	13
Unit Weight (g/cm3)	2.312	2.322	2.338	2.344
Theoretical specific weight (Gmm)	2.453	2.422	2.414	2.406
Air Voids (%)	5.7	4.1	3.2	2.6









Appendix B

El minia - Assute free way Project

EXTRACTION & GRADATION

Date :	12/1/2011	Location :	M R W
Type of mix. :	wearing	Station :	- (0+200) to (1+330)
Sample no.	2	Sample station :	(0+250)

A) MIX TEMPERATURE : 148°C

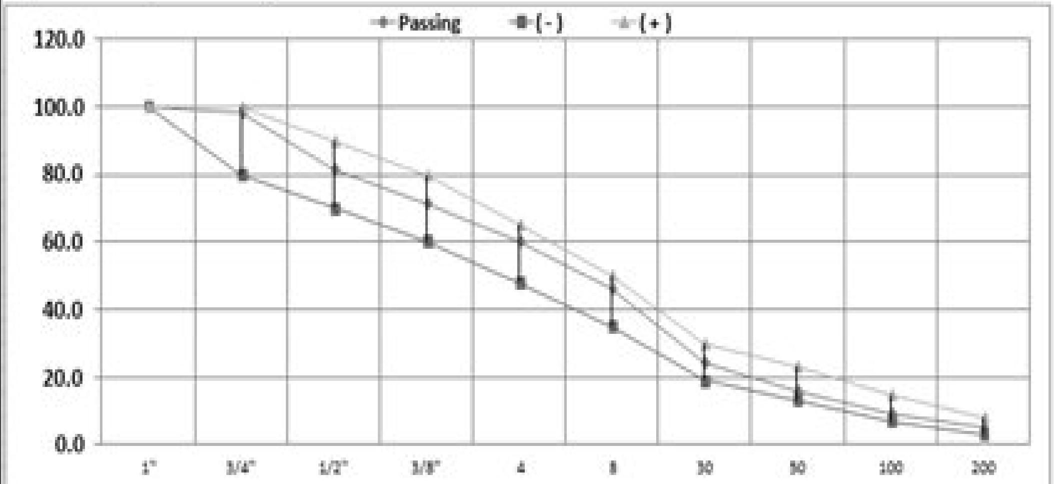
B) BITUMEN CONTENT:

a- Wt. before extraction.	=	1315	gm	e-	Wt.of agg. retaind	=	6	gm
b- Wt. after extraction.	=	1243	gm	f-	Total wt.extract. Agg	=	1249	gm
c- Wt. of filter & agg.	=	28	gm	g-	Wt.of bit (a-f)	=	66	gm
d- Initial wt. filter.	=	22	gm	h-	% Bit. 100	=	5.28	%

C) GRADATION OF AGGREGATES :

wt.of sample = 1249 gm

SIEVE SIZE	WT. OF RETAINED	% RETAINED	% PASSING	JMF			General spec.		notes
				JMF -	blend	JMF+	(-)	(+)	
1"	0	0.0	100.0	100	100	100.0	100	100	
3/4"	24	1.9	98.1	93.2	97.2	100.0	80	100	
1/2"	234	18.7	81.3	74.7	78.7	82.7	70	90	
3/8"	355	28.4	71.6	65.7	69.7	73.7	60	80	
4	495	39.6	60.4	55.1	58.1	61.1	48	65	
8	672	53.8	46.2	41.3	44.3	47.3	35	50	
30	944	75.6	24.4	19.5	22.5	25.5	19	30	
50	1050	84.1	15.9	12.3	14.3	16.3	13	23	
100	1135	90.9	9.1	5.7	7.7	9.7	7	15	
200	1187	95.0	5.0	4.2	5.6	6.2	3	8	
pan	1247								



Elminia - Assuit FreeWay

Marshal Test

Location : (Maine road Weast)   Date of sample : 2-10-2010

Mix type : Wearing mix   bit. 5

No.	Wt. in air (gm)	wt. in water (gm)	wt.after 2 minutes(gm)	volume(cm3)		density (ton/m3)	Gmm. (ton/m3) by vacume	air voids	Marshal		Stability.	Flow (1/100)	VMA%	VFB%	average Stability
				volume	Correction				Reading(mm)	Convert(N)					
1	1243.1	704	1244.7	540.7	0.93	2.299	2.453	6.3	1.05	11360	1077	12.0	12.2	48.8	1060
2	1247.6	706	1249.1	543.1	0.93	2.297		6.4	1.02	11040	1047	12.8	12.3	48.4	
3	1252.8	709	1253.9	544.9	0.93	2.299		6.3	1.03	11140	1056	13.6	12.2	48.8	
average						2.298		6.3			1060	12.8	12.3	48.7	

Q.C. Eng.Comment : ....

Appendix C

Optimization Summary Report

Evolver: Optimization Summary

Performed By: keno
Date: 14 أبريل، 2013 10:52:41 م
Model: ANN11.xlsx

Goal	
Cell to Optimize	Stability!$I$195
Type of Goal	Minimum

Results	
Valid Trials	100000
Total Trials	100000
Original Value	35.86
+ soft constraint penalties	0.00
= result	35.86
Best Value Found	3.99
+ soft constraint penalties	0.00
= result	3.99
Best Simulation Number	98702
Time to Find Best Value	0:33:10
Reason Optimization Stopped	Number of trials
Time Optimization Started	14/04/2013 22:19
Time Optimization Finished	14/04/2013 22:52
Total Optimization Time	0:33:31
Adjustable Cell Values	Stability!$E$96
Original	481227.0883
Best	-667644.842
Adjustable Cell Values	Stability!$F$96
Original	542696.0173
Best	-1000000
Adjustable Cell Values	Stability!$G$96
Original	471999.6587
Best	-1000000
Adjustable Cell Values	Stability!$H$96
Original	91688.2801
Best	-1000000
Adjustable Cell Values	Stability!$I$96
Original	-84678.95351
Best	-1000000
Adjustable Cell Values	Stability!$J$96
Original	-543506.6512
Best	-1000000
Adjustable Cell Values	Stability!$K$96
Original	-401556.1278

Best	981596.817
Adjustable Cell Values	Stability!$L$96
Original	-695885.4026
Best	-298226.386
Adjustable Cell Values	Stability!$M$96
Original	-654449.3884
Best	-1000000
Adjustable Cell Values	Stability!$E$97
Original	-184507.5618
Best	1000000
Adjustable Cell Values	Stability!$F$97
Original	-850209.9263
Best	-1000000
Adjustable Cell Values	Stability!$G$97
Original	-485474.0749
Best	-270925.271
Adjustable Cell Values	Stability!$H$97
Original	12171.50179
Best	-738747.6289
Adjustable Cell Values	Stability!$I$97
Original	-276038.779
Best	-1000000
Adjustable Cell Values	Stability!$J$97
Original	292610.1537
Best	-1000000
Adjustable Cell Values	Stability!$K$97
Original	-50952.10671
Best	652979.0966
Adjustable Cell Values	Stability!$L$97
Original	464245.9601
Best	-699619.6572
Adjustable Cell Values	Stability!$M$97
Original	705731.1289
Best	-1000000
Adjustable Cell Values	Stability!$E$98
Original	-412019.495
Best	-197552.6021
Adjustable Cell Values	Stability!$F$98
Original	931316.3775
Best	168056.6186
Adjustable Cell Values	Stability!$G$98
Original	44429.67224
Best	-110211.9856
Adjustable Cell Values	Stability!$H$98
Original	211005.0608
Best	-1000000
Adjustable Cell Values	Stability!$I$98
Original	890810.9687
Best	891665.669
Adjustable Cell Values	Stability!$J$98

Original	89329.35443
Best	71850.41648
Adjustable Cell Values	Stability!$K$98
Original	-527819.3597
Best	118080.121
Adjustable Cell Values	Stability!$L$98
Original	-30536.10942
Best	616137.7628
Adjustable Cell Values	Stability!$M$98
Original	354764.8063
Best	849568.3371
Adjustable Cell Values	Stability!$E$99
Original	648524.9662
Best	-166361.7483
Adjustable Cell Values	Stability!$F$99
Original	510350.7485
Best	532979.0609
Adjustable Cell Values	Stability!$G$99
Original	-308511.3307
Best	423463.349
Adjustable Cell Values	Stability!$H$99
Original	751127.3864
Best	818826.4182
Adjustable Cell Values	Stability!$I$99
Original	119375.4664
Best	408093.1355
Adjustable Cell Values	Stability!$J$99
Original	541719.1019
Best	-1000000
Adjustable Cell Values	Stability!$K$99
Original	-12960.20762
Best	102758.8273
Adjustable Cell Values	Stability!$L$99
Original	466610.5678
Best	113449.3654
Adjustable Cell Values	Stability!$M$99
Original	-619005.9152
Best	-704622.2875
Adjustable Cell Values	Stability!$E$100
Original	-175163.8372
Best	1000000
Adjustable Cell Values	Stability!$F$100
Original	443258.0568
Best	-1000000
Adjustable Cell Values	Stability!$G$100
Original	-100683.932
Best	-794015.114
Adjustable Cell Values	Stability!$H$100
Original	-731720.5365
Best	-416692.514

Adjustable Cell Values	Stability!$I$100
Original	-47382.96429
Best	-1000000
Adjustable Cell Values	Stability!$J$100
Original	-347114.4203
Best	-1000000
Adjustable Cell Values	Stability!$K$100
Original	931986.8102
Best	826021.4979
Adjustable Cell Values	Stability!$L$100
Original	119958.1937
Best	319783.3765
Adjustable Cell Values	Stability!$M$100
Original	-182259.7557
Best	-1000000
Adjustable Cell Values	Stability!$D$147
Original	0.332931478
Best	0.332931478
Adjustable Cell Values	Stability!$E$147
Original	0.415717188
Best	0.415717188
Adjustable Cell Values	Stability!$F$147
Original	0.722272087
Best	0.722272087
Adjustable Cell Values	Stability!$G$147
Original	0.580635592
Best	0.580635592
Adjustable Cell Values	Stability!$H$147
Original	0.406879122
Best	0.406879122

Adjustable Cells	
Description	
Solving Method	Recipe
Mutation Rate	0.1
Crossover Rate	0.5
Cell Range	-1000000 <= Stability!$E$96:$M$100 <= 1000000
Cell Range	-1000000 <= Stability!$D$147:$H$147 <= 1000000
Operators (scores)	Default parent selection (0.2249)
	Default mutation (0.1109)
	Default crossover (0.1738)
	Default backtrack (0.2751)
	Arithmetic crossover (0.0446)
	Heuristic crossover (0.0064)
	Cauchy mutation (0.0769)
	Boundary mutation (0.0034)
	Non-uniform mutation (0.0336)
	Linear (0.0503)
	Local search (0.0000)

Optimization Settings	
General	
Population Size	50
Optimization Random Number Seed	8456013 (Chosen Randomly)
Optimization Runtime	
Trials	TRUE
Trial Count	100000
Time	FALSE
Progress	FALSE
Formula	FALSE
Stop on Error	FALSE
View	
Minimize Excel at Start	FALSE
Show Excel Recalculations	Every New Best Trial
Keep Log of All Trials	TRUE
Macros	
At Start of Optimization	N/A
Before Recalculation	N/A
After Recalculation	N/A
After Storing Output	N/A
At End of Optimization	N/A

ملخص الرسالة

الرصف الاسفلتى يعد اهم و اشهر وسائل الرصف فى مصر لجميع اشكال الرصف سواء فى الطرق او المطارات او مناطق الانتظار و تتكون الخلطة الاسفلتية تقريبا من 93% الى 97% من الركام المتدرج ومن 7% الى 3% من البيتومين الساخن.

تعد طريقة مارشال لتصميم الخلطة الاسفلتية من اشهر الطرق المستخدمة بمصر و تختص هذه الطريقة فى تحديد مكونات الخلطة الاسفلتية من الركام و نسبة البيتومين لتحقيق الخواص المطلوبة للخلطة من الثبات و الانسياب و نسبة الفراغات الهوائية و الكثافة و هذه النتائج يتم الوصول اليها بعد اجراء العديد من التجارب بمحتويات مختلفة من البيتومين ويتم استنتاج النتائج بطريقة التجربة و الخطأ، هذه النتائج ترتبط بعلاقة غيرمباشرة بعدة عوامل اهمها تدرج الركام و محتوى الخلطة الاسفلتية من البيتومين .

بعد قبول الخلطة الاسفلتية و اثناء سير العمل يتم اجراء اختبارات مارشال و الاستخلاص و التدرج فى الموقع و المعمل دوريا و ذلك لقبول الخلطة وضبط الجودة حيث يختص اختبار مارشال بقارنة نسب الثبات و الانسياب و نسبة الفراغات الهوائية و الكثافة بالخلطة التصميمية و الاستخلاص فى تحديد النسبة المئوية لمحتوى البيتومين بالخلطة و يختص اختبار التدرج تحديد نسب توزيع احجام الركام بالخلطة. تتميز اختبارات الاستخلاص و التدرج بسرعة اجراءها فى الموقع .

السنوات الاخيرة اظهرت استخدامات الشبكة العصبية الاصطناعية كاحد اساليب الذكاء الصناعى فى الهندسة المدنية كبديل لطرق التوقعات الاعتيادية و اظهرت نجاح ملحوظ و لذلك فان **الهدف الرئيسى من البحث هو استحداث نموذج قادر على توقع نتائج تجربة مارشال السالف ذكرهم بدلالة نسبة البيتومين فى الخلطة (تجربة الاستخلاص) و تدرج الركام (تجربة التدرج) .**

تم بالفعل تجميع تجارب مارشال و تجارب استخلاص و تدرج من عدة مشاريع منفذة بمصر و عدة شركات مقاولات وتم عمل نموذج الشبكة العصبية الاصطناعية على ملف اكسيل و اظهرت النتائج النهائية نسبة خطأ صغيرة و مقبولة.

يتم تجميع تجارب عديدة من تجربتى التدرج و الاستخلاص و التى يتم تنفيذ بسرعة سواء فى الموقع او المعمل و تجربة مارشال لنفس الخلطة لإعداد قاعدة بيانات و ربطهم بالشبكة العصبية الصناعية و ذلك لتوقع نتائج تجربة مارشال المستقبلية بدون اجراءها بدلالة تجربتى التدرج و الاستخلاص .

تم تقسيم هذه الرسالة الى خمسة فصول كالاتى :

الفصل الاول : مقدمة تشمل ملخص قصير عن فكرة الرسالة واهدافها و طريقة العمل.

الفصل الثانى : تاريخ الاعمال السابقة بالنسبة للطرق و طرق التصميم المختلفة والتركيز على طريقة تجربة مارشال و مقدمة عن الشبكة العصبية الصناعية و استخداماتها.

الفصل الثالث : طريقة تجميع المعلومات من تجارب مارشال و التدرج و الاستخلاص و ترتيبها فى ملف برنامج اكسيل.

الفصل الرابع : و يتحدث عن طريقة عمل ملف الاكسيل و استخدام الشبكة العصبية الصناعية لتقليل خطأ توقع نتائج تجربة مارشال بدلالة تجربتى التدرج و الاستخلاص.

الفصل الخامس : و يختص بملخص الرسالة مع وضع مقترحات و توصيات للاعمال المستقبلية.

الاكاديمية العربية للعلوم و التكنولوجيا و النقل البحرى

كلية الهندسة و التكنولوجيا

قسم هندسة التشيد و البناء

توقع نتائج تجربة مارشال باستخدام الشبكة العصبية الصناعية

اعداد

عـمـرو القنــــاوى جـمعه

رسالة مقدمة للاكاديمية العربية للعلوم و التكنولوجيا والنقل البحرى لإستكمال متطلبات نيل درجة

الماجستير

فى

هندسة التشيد و البناء

إشراف

ا.د.م أكرم سلطان قطب

قسم التشييد و البناء

كلية الهندسة

الاكاديمية العربية للعلوم و التكنولوجيا

و النقل البحرى

ا.د. خالد أنور قنديل

قسم الأشغال العامة

كلية الهندسة

جامعة عين شمس

ديسمبر 2014