ARAB ACADEMY FOR SCIENCE, TECHNOLOGY AND MARITIME TRANSPORT
(AASTMT)

College of Engineering and Technology
Construction and Building Engineering Department

Marshall Test Results Prediction
Using Artificial Neural Network

By

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A thesis submitted to AASTMT in partial Fulfillment of the requirements for the
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In

CONSTRUCTION AND BUILDING ENGINEERING

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December 2014
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.

The contents of this thesis reflect my own personal views, and are not necessarily endorsed by the University.

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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.

This work is dedicated to my Father and Mother souls, Mercy of ALLAH upon them, who they were and still the source of my inspiration, encouragement, guidance and happiness.

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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.
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Chapter One

INTRODUCTION
Chapter1

**INTRODUCTION**

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.

![Diagram of 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).
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 McAdam’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, McAdam’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.
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 Figure 2.3.
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
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 140°F (60°C) 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:
\[
\text{Stability}(Kg) = \text{Stability(div.)} \times 1.64
\]

\[
\text{Stability}_{\text{corrected}} = \text{Stability}(Kg) \times C
\]

Where:

C: Factor of height

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 $G_t$, the bulk specific gravity of the mix $G_m$, percent air voids $V_v$, percent volume of bitumen $V_b$, percent void in mixed aggregate $V_{MA}$ and percent voids filled with bitumen $V_{FB}$.

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

![Figure 2.6 Marshall Mould (Mathew and Krishna Rao, 2006)](image_url)

### 2.6.4 Theoretical specific gravity of the mix $G_t$

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

\[
G_m = \frac{W_m}{W_m - W_w}
\]

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:
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 $V_b$

The volume of bitumen $V_b$ is the percent of volume of bitumen to the total volume and given by:

$$V_b = \frac{W_b}{W_1 + W_2 + W_3 + W_b} \times \frac{G_b}{G_m}$$  \hspace{1cm} (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

$$VMA = V_v + V_b$$  \hspace{1cm} (5)

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

V_b 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:

\[ V_{FB} = \frac{V_b \times 100}{VMA} \]  \( (6) \)

Where,

V_b 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.

\[ \text{Stiffness} = \frac{\text{Stability}}{\text{Flow}} \]

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).

<table>
<thead>
<tr>
<th>NO.</th>
<th>Item of work</th>
<th>Test</th>
<th>Frequency</th>
<th>Rate</th>
<th>Notes</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>Earthwork</td>
<td>Soil particle size,</td>
<td>1-2 tests</td>
<td>8000 m³</td>
<td></td>
</tr>
<tr>
<td></td>
<td></td>
<td>Atterberg Limits</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td></td>
<td>C.B.R on a set of 3</td>
<td>1 test</td>
<td>3000 m³</td>
<td></td>
</tr>
<tr>
<td></td>
<td></td>
<td>specimens</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td></td>
<td>Natural moisture</td>
<td>1 test</td>
<td>250 m³</td>
<td></td>
</tr>
<tr>
<td></td>
<td></td>
<td>content</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td></td>
<td>Moisture content before</td>
<td>2-3 tests</td>
<td>250 m³</td>
<td></td>
</tr>
<tr>
<td></td>
<td></td>
<td>compaction</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td></td>
<td>Dry density of compacted</td>
<td>1 test</td>
<td>1000 m³</td>
<td>Embankments to be increased to one test per 500-1000 m³ for sub grade layers.</td>
</tr>
<tr>
<td></td>
<td></td>
<td>area</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>2</td>
<td>Gravel sub-base</td>
<td>Gradation, plasticity</td>
<td>1 test</td>
<td>200 m³</td>
<td></td>
</tr>
<tr>
<td></td>
<td></td>
<td>Moisture content</td>
<td>1 test</td>
<td>250 m³</td>
<td></td>
</tr>
<tr>
<td></td>
<td></td>
<td>Density</td>
<td>1 test</td>
<td>500 m³</td>
<td></td>
</tr>
<tr>
<td>3</td>
<td>Lime – soil</td>
<td>Purity of lime</td>
<td>1 test</td>
<td>5Ton</td>
<td></td>
</tr>
<tr>
<td></td>
<td></td>
<td>Lime content, moisture</td>
<td>1 test</td>
<td>250 m²</td>
<td></td>
</tr>
<tr>
<td></td>
<td></td>
<td>content</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>Material Type</td>
<td>Test Item</td>
<td>Tests</td>
<td>Sample Size</td>
<td></td>
</tr>
<tr>
<td>---</td>
<td>---------------------------------------</td>
<td>---------------------------------------------------------------------------</td>
<td>-------</td>
<td>-------------</td>
<td></td>
</tr>
<tr>
<td>3</td>
<td>Lime – soil</td>
<td>Density</td>
<td>1 test</td>
<td>500 m³</td>
<td></td>
</tr>
<tr>
<td>4</td>
<td>Water-bound macadam</td>
<td>Los Angeles Abrasion or Aggregate Impact Value, Flakiness Index</td>
<td>1 test</td>
<td>200 m³</td>
<td></td>
</tr>
<tr>
<td></td>
<td></td>
<td>Grading of materials</td>
<td>1 test</td>
<td>100 m³</td>
<td></td>
</tr>
<tr>
<td></td>
<td></td>
<td>Plasticity of binder</td>
<td>1 test</td>
<td>25 m³</td>
<td></td>
</tr>
<tr>
<td>5</td>
<td>Bituminous Macadam</td>
<td>Los Angeles Abrasion Value or Aggregate</td>
<td>1 test</td>
<td>50-100 m³</td>
<td></td>
</tr>
<tr>
<td></td>
<td></td>
<td>Mix grading, binder content, aggregate gradation</td>
<td>2 tests</td>
<td>day</td>
<td></td>
</tr>
<tr>
<td>6</td>
<td>Surface dressing and premix carpet</td>
<td>Los Angeles Abrasion Value or Aggregate Impact Value, Stripping Value, Flakiness Index</td>
<td>1 test</td>
<td>50 m³</td>
<td></td>
</tr>
<tr>
<td></td>
<td></td>
<td>Water absorption</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td></td>
<td>Grading of aggregate</td>
<td>1 test</td>
<td>25 m³</td>
<td></td>
</tr>
<tr>
<td></td>
<td></td>
<td>Rate of spread of binder and aggregate for surface dressing</td>
<td>1 test</td>
<td>500 m³</td>
<td></td>
</tr>
<tr>
<td></td>
<td></td>
<td>Binder content for premix carpet</td>
<td>2 tests</td>
<td>day</td>
<td></td>
</tr>
<tr>
<td>7</td>
<td>Hot mix Asphalt</td>
<td>Los Angeles Abrasion Value or Aggregate, Impact Value, Stripping Value, Water absorption, Flakiness Index</td>
<td>1 test</td>
<td>50-100 m³</td>
<td></td>
</tr>
<tr>
<td>7</td>
<td>Hot mix Asphalt</td>
<td>Sieve analysis for filler</td>
<td>1 test</td>
<td>100 ton of mix</td>
<td></td>
</tr>
<tr>
<td>7</td>
<td>Hot mix Asphalt</td>
<td>Mix grading, binder content</td>
<td>1 test</td>
<td>100 ton</td>
<td>min. 3 tests per day</td>
</tr>
<tr>
<td>8</td>
<td>Cement concrete pavement</td>
<td>Stability and flow</td>
<td>3 Marshall Specimens</td>
<td>1000 ton</td>
<td></td>
</tr>
<tr>
<td>8</td>
<td>Cement concrete pavement</td>
<td>Gradation of aggregate</td>
<td>1 test</td>
<td></td>
<td></td>
</tr>
<tr>
<td>8</td>
<td>Cement concrete pavement</td>
<td>Cement, physical and chemical</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>8</td>
<td>Cement concrete pavement</td>
<td>Concrete strength</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>8</td>
<td>Cement concrete pavement</td>
<td>Los Angeles Abrasion Value or Aggregate</td>
<td>1 test</td>
<td></td>
<td></td>
</tr>
<tr>
<td>8</td>
<td>Cement concrete pavement</td>
<td>Impact Value, Soundness</td>
<td>1 test</td>
<td></td>
<td></td>
</tr>
</tbody>
</table>
### 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.

<table>
<thead>
<tr>
<th>#</th>
<th>Test Description</th>
<th>Sample Quantity</th>
<th>Volume</th>
</tr>
</thead>
<tbody>
<tr>
<td>8</td>
<td>Cement concrete pavement</td>
<td>Workability</td>
<td>3 cube/beam samples for each 7 days and 28 days</td>
</tr>
<tr>
<td></td>
<td>Concrete strength on hardened concrete</td>
<td>2 cores</td>
<td>30 m³</td>
</tr>
</tbody>
</table>
Figure 2.7 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).

<table>
<thead>
<tr>
<th>Sieve Opening Size</th>
<th>8&quot; Diameter Sieve</th>
<th>14&quot; Square Sieve</th>
</tr>
</thead>
<tbody>
<tr>
<td>2&quot; (50 mm)</td>
<td>7.9 lbs (3.6 kg)</td>
<td>33.7 lbs (15.3 kg)</td>
</tr>
<tr>
<td>1 1/2&quot; (37.5 mm)</td>
<td>6.0 lbs (2.7 kg)</td>
<td>25.4 lbs (11.5 kg)</td>
</tr>
<tr>
<td>1&quot; (25.0 mm)</td>
<td>4.0 lbs (1.8 kg)</td>
<td>17.0 lbs (7.7 kg)</td>
</tr>
<tr>
<td>3/4&quot; (19.0 mm)</td>
<td>3.1 lbs (1.4 kg)</td>
<td>12.8 lbs (5.8 kg)</td>
</tr>
<tr>
<td>1/2&quot; (12.5 mm)</td>
<td>2.0 lbs (0.89 kg)</td>
<td>8.4 lbs (3.8 kg)</td>
</tr>
<tr>
<td>3/8&quot; (9.5 mm)</td>
<td>1.5 lbs (0.67 kg)</td>
<td>6.4 lbs (2.9 kg)</td>
</tr>
<tr>
<td>No. 4 (4.75 mm)</td>
<td>0.7 lbs (0.33 kg)</td>
<td>3.3 lbs (1.5 kg)</td>
</tr>
</tbody>
</table>
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:

\[
\text{Percent retained on sieve} = \left(\frac{\text{Cumulative weight}}{\text{Total weight}}\right) \times 100
\]

\[
\text{Percent passing} = 100 - \text{Percent retained on sieve}
\]

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:

\[
\text{Percent total sample} = \left(\frac{\text{Percent passing No.4} \times \text{Percent passing smaller sieve}}{100}\right)
\]

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.

![Figure 2.8 Bitumen Extractor (Centrifuge Extractor) (Mfg, 2014)](image-url)
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:

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

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 tests

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 framework.

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 framework 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.

Where in figure 2.9;  \( x_1, x_2, \ldots, x_n, m \) are inputs

- \( w_1, w_2, \ldots, w_m \) 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:

2. Functional networks for in real-time flood forecasting- a novel application (Bruen and Yang, 2005).
5. Discrete-event simulation used for modeling of construction processes (Flood and Worley, 1995).

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)*

<table>
<thead>
<tr>
<th>Activation Functions</th>
<th>Definitions</th>
<th>Range</th>
</tr>
</thead>
<tbody>
<tr>
<td>Linear</td>
<td>$x$</td>
<td>$(-\infty, +\infty)$</td>
</tr>
<tr>
<td>Sigmoid</td>
<td>$\frac{1}{1 - e^{-x}}$</td>
<td>$(0, 1)$</td>
</tr>
<tr>
<td>Hyperbolic</td>
<td>$\frac{e^x - e^{-x}}{e^x + e^{-x}}$</td>
<td>$(-1, 1)$</td>
</tr>
<tr>
<td>Exponential</td>
<td>$e^{-x}$</td>
<td>$(0, \infty)$</td>
</tr>
<tr>
<td>Soft max</td>
<td>$\frac{e^{-x}}{\sum_i x_i}$</td>
<td>$(0, 1)$</td>
</tr>
<tr>
<td>Unit Sum</td>
<td>$\frac{x}{\sum_i x_i}$</td>
<td>$(0, 1)$</td>
</tr>
<tr>
<td>Square Root</td>
<td>$\sqrt{x}$</td>
<td>$(0, \infty)$</td>
</tr>
<tr>
<td>Sine</td>
<td>$\sin(x)$</td>
<td>$(0, 1)$</td>
</tr>
<tr>
<td>Ramp</td>
<td>$\begin{cases} 1, &amp; x \leq -1 \ x, &amp; -1 &lt; x &lt; 1 \ 1, &amp; x \geq 1 \end{cases}$</td>
<td>$(-1, 1)$</td>
</tr>
<tr>
<td>Step</td>
<td>$\begin{cases} 0, &amp; x &lt; 0 \ 1, &amp; x \geq 0 \end{cases}$</td>
<td>$(0, 1)$</td>
</tr>
</tbody>
</table>

Where in this equation: $Y_i$ represents the observed value and $\hat{Y}_i$ 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-Ŷ)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.

![Figure 2.10 Simple Architecture of Prediction Model Based on ANNs](image)

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.

\[ S_{ki, \text{abs}} = \frac{\Sigma_{j=1}^{p} |S_{ki}^{(p)}|}{p} \]

Where, \( S_{ki, \text{abs}} \) 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.

(Atttoh-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.


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 m³ of cut, the paving work had about 19 million m² 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
3.2.2 Job mix of asphalt

Marshall Specimens were fabricated in the laboratory utilizing 75 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

<table>
<thead>
<tr>
<th>Properties of the asphalt</th>
<th>Range</th>
<th>Specs. Used</th>
</tr>
</thead>
<tbody>
<tr>
<td>Penetration Grade</td>
<td>60 / 70 mm</td>
<td>ASTM D 5</td>
</tr>
<tr>
<td>Penetration at 25°C</td>
<td>64 mm</td>
<td>ASTM D 5</td>
</tr>
<tr>
<td>Specific Gravity</td>
<td>1.07 gm/cm³</td>
<td>ASTM D 70</td>
</tr>
<tr>
<td>Softening Point</td>
<td>50°C</td>
<td>ASTM D 36</td>
</tr>
<tr>
<td>Loss in Heating</td>
<td>2 %</td>
<td>ASTM D 6</td>
</tr>
<tr>
<td>Flash Point</td>
<td>314°C</td>
<td>ASTM D 92</td>
</tr>
<tr>
<td>Fire Point</td>
<td>326°C</td>
<td>ASTM D 113</td>
</tr>
<tr>
<td>Ductility (5 cm/dk)</td>
<td>&gt; 100 cm</td>
<td>ASTM D 113</td>
</tr>
<tr>
<td>Viscosity at (135°C)</td>
<td>0.418 Pa s</td>
<td>ASTM D 88</td>
</tr>
<tr>
<td>Viscosity at (165°C)</td>
<td>0.112 Pa s</td>
<td>ASTM D 88</td>
</tr>
</tbody>
</table>

Table 3.2. Physical Properties of Aggregate

<table>
<thead>
<tr>
<th>Tested Property</th>
<th>Specs. Used</th>
<th>Limits</th>
<th>Aggregate Size</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td></td>
<td></td>
<td>Size 2 (25-12)mm</td>
</tr>
<tr>
<td>Abrasion (L.A.)</td>
<td>ASTM C131</td>
<td>Max 32%</td>
<td>23.7</td>
</tr>
<tr>
<td>Water absorption</td>
<td>ASTM C127</td>
<td>Max 2%</td>
<td>1.1</td>
</tr>
<tr>
<td>Specific Gravity</td>
<td>ASTM C127 &amp;</td>
<td>__</td>
<td>2.684</td>
</tr>
<tr>
<td></td>
<td>C128</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Flat and</td>
<td>ASTM D693</td>
<td>Max 8%</td>
<td>4.3</td>
</tr>
<tr>
<td>Elongation</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Stripping</td>
<td>ASSHTO T 283</td>
<td>Max 3%</td>
<td>No stripping</td>
</tr>
</tbody>
</table>
Table 3.3. General Aggregate Gradation Limits

<table>
<thead>
<tr>
<th>Sieves No.</th>
<th>Limits of project technical Specifications</th>
<th>Lower Limit</th>
<th>Upper Limit</th>
</tr>
</thead>
<tbody>
<tr>
<td>&quot;1</td>
<td></td>
<td>100</td>
<td>100</td>
</tr>
<tr>
<td>&quot;3/4</td>
<td></td>
<td>80</td>
<td>100</td>
</tr>
<tr>
<td>&quot;1/2</td>
<td></td>
<td>70</td>
<td>90</td>
</tr>
<tr>
<td>&quot;3/8</td>
<td></td>
<td>60</td>
<td>80</td>
</tr>
<tr>
<td>#4</td>
<td></td>
<td>48</td>
<td>65</td>
</tr>
<tr>
<td>#8</td>
<td></td>
<td>35</td>
<td>50</td>
</tr>
<tr>
<td>#30</td>
<td></td>
<td>19</td>
<td>30</td>
</tr>
<tr>
<td>#50</td>
<td></td>
<td>13</td>
<td>23</td>
</tr>
<tr>
<td>#100</td>
<td></td>
<td>7</td>
<td>15</td>
</tr>
<tr>
<td>#200</td>
<td></td>
<td>3</td>
<td>8</td>
</tr>
</tbody>
</table>

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

<table>
<thead>
<tr>
<th>Sieves No.</th>
<th>JMF (Total)</th>
<th>JMF tolerance</th>
<th>Lower Limit</th>
<th>Upper Limit</th>
</tr>
</thead>
<tbody>
<tr>
<td>&quot;1&quot;</td>
<td>100</td>
<td>100</td>
<td>100</td>
<td></td>
</tr>
<tr>
<td>&quot;3/4&quot;</td>
<td>97.2</td>
<td>93.2</td>
<td></td>
<td>100</td>
</tr>
<tr>
<td>&quot;1/2&quot;</td>
<td>78.7</td>
<td>74.7</td>
<td></td>
<td>82.7</td>
</tr>
<tr>
<td>&quot;3/8&quot;</td>
<td>69.7</td>
<td>65.7</td>
<td></td>
<td>73.7</td>
</tr>
<tr>
<td>#4</td>
<td>58.1</td>
<td>55.1</td>
<td></td>
<td>61.1</td>
</tr>
<tr>
<td>#8</td>
<td>44.3</td>
<td>41.3</td>
<td></td>
<td>47.3</td>
</tr>
<tr>
<td>#30</td>
<td>22.5</td>
<td>19.5</td>
<td></td>
<td>25.5</td>
</tr>
<tr>
<td>#50</td>
<td>14.3</td>
<td>12.3</td>
<td></td>
<td>16.3</td>
</tr>
<tr>
<td>#100</td>
<td>7.7</td>
<td>5.7</td>
<td></td>
<td>9.7</td>
</tr>
<tr>
<td>#200</td>
<td>5.2</td>
<td>4.2</td>
<td></td>
<td>6.2</td>
</tr>
</tbody>
</table>

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**

<table>
<thead>
<tr>
<th>Test Performed</th>
<th>Bitumen Content %</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>5.0%</td>
</tr>
<tr>
<td>Marshall Stability (N)</td>
<td>1061</td>
</tr>
<tr>
<td>Flow (inch)</td>
<td>11</td>
</tr>
<tr>
<td>Unit Weight (g/cm³)</td>
<td>2.312</td>
</tr>
<tr>
<td>Theoretical specific weight (Gmm)</td>
<td>2.453</td>
</tr>
<tr>
<td>Air Voids (%)</td>
<td>5.7</td>
</tr>
</tbody>
</table>
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 (BaniSweif-El-Minya - Assyut-free way Project) shown in the table 3.6 of HMA wearing layer must be achieved.
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.
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).
- Air Void Ratio
- Density
<table>
<thead>
<tr>
<th>Test</th>
<th>Minimum Value</th>
<th>Maximum Value</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Extraction Test</strong></td>
<td></td>
<td></td>
</tr>
<tr>
<td>%passing from sieve 1”</td>
<td>100</td>
<td>100</td>
</tr>
<tr>
<td>%passing from sieve 3/4”</td>
<td>93.100</td>
<td>98.09</td>
</tr>
<tr>
<td>%passing from sieve 1/2”</td>
<td>54.180</td>
<td>77.50</td>
</tr>
<tr>
<td>%passing from sieve no .4</td>
<td>35.781</td>
<td>60.87</td>
</tr>
<tr>
<td>%passing from sieve no .8</td>
<td>22.716</td>
<td>46.81</td>
</tr>
<tr>
<td>%passing from sieve no .30</td>
<td>9.821</td>
<td>25.1</td>
</tr>
<tr>
<td>%passing from sieve no .50</td>
<td>6.746</td>
<td>16.07</td>
</tr>
<tr>
<td>%passing from sieve no .100</td>
<td>3.928</td>
<td>9.49</td>
</tr>
<tr>
<td>%passing from sieve no .200</td>
<td>1.456</td>
<td>5.42</td>
</tr>
<tr>
<td>% of bitumen content</td>
<td>4.431</td>
<td>6.0</td>
</tr>
<tr>
<td><strong>Marshall Test</strong></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Marshall Stability (kg)</td>
<td>1019</td>
<td>1369.50</td>
</tr>
<tr>
<td>Marshall Flow (1/100 inch)</td>
<td>10.80</td>
<td>13.33</td>
</tr>
<tr>
<td>Air void ratio</td>
<td>2.596</td>
<td>6.89</td>
</tr>
<tr>
<td>Density (gm/cm³)</td>
<td>2.249</td>
<td>2.54</td>
</tr>
</tbody>
</table>
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.
Figure 4.1 Neural Tools application settings

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 Figure 4.3 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
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:

\[
\text{Scaled Value} = \frac{2 \times (\text{Unscaled Value} - \text{Column Min.})}{(\text{Column Max.} - \text{Column Min.})} - 1
\] (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 \(X_j\), which is sumproduct formula of scaled inputs by their associated connection weights. Accordingly, each hidden node produces an output \(X_{jj}\) that is a function of its activation, as follows:
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):

$$Y = \sum_{j=1}^{L} (X_{jj} \times W_{jj})$$  \hspace{1cm} (4)

$$Output \ of \ ANN = tanh \ (X_{j})$$  \hspace{1cm} (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:

$$Output \ scaled \ back = \frac{(Output \ Value + 1) \times (Max. \ Output - Min. \ Output)}{2}$$  \hspace{1cm} (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:

\[
\text{ESTIMATING ERROR (\%)} = \left( \frac{\text{ANN OUTPUT} - \text{ACTUAL OUTPUT}}{\text{ACTUAL OUTPUT}} \right) \times 100
\]  

(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:

\[
\text{Weighted Error (\%)} = 0.5 (\text{Test Average Error}) + 0.5 (\text{Training Average Error})
\]  

(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.
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<th>3/8&quot;</th>
<th>4</th>
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Figure 4.6 Organization of data from Extraction, Sieve Analysis and Marshall Tests
Figure 4.7 Scaling of data

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<tr>
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<th>3/8''</th>
<th>4</th>
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Figure 4.8 Weights of 5 hidden neurons

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<th>HN3</th>
<th>HN4</th>
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Figure 4.9 Outputs of hidden neurons

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<th>HN5</th>
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<td>0.408374</td>
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</table>

Figure 4.10 Weights of 5 hidden neurons to 1 output
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:
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.

<table>
<thead>
<tr>
<th>Step 3: Weights of 5 hidden neurons</th>
<th>3/4th</th>
<th>3/8th</th>
<th>4</th>
<th>8</th>
<th>30</th>
<th>50</th>
<th>100</th>
<th>200</th>
<th>Bitumen content</th>
</tr>
</thead>
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</table>

**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 (Figure 4.16) 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

\[ \text{Error\%} = \text{Absolute} \left( \frac{\text{experimental} - \text{Predicted}}{\text{experimental}} \right) \times 100 \]

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

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<th>Training Error %</th>
<th>Stability</th>
<th>Flow</th>
<th>Air voids</th>
<th>Density</th>
<th>Average</th>
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<td>5-7%</td>
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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 automatically estimate Marshall test result

<table>
<thead>
<tr>
<th>1&quot;</th>
<th>3/4&quot;</th>
<th>3/8&quot;</th>
<th>4</th>
<th>8</th>
<th>30</th>
<th>50</th>
<th>100</th>
<th>200</th>
<th>Bitumen content</th>
<th>Stability</th>
<th>Flow(1/100)</th>
<th>air voids</th>
<th>density</th>
</tr>
</thead>
<tbody>
<tr>
<td>100</td>
<td>97.2</td>
<td>69.7</td>
<td>58.1</td>
<td>44.3</td>
<td>22.5</td>
<td>14.3</td>
<td>7.7</td>
<td>5.2</td>
<td>5</td>
<td>1071.48</td>
<td>10.86</td>
<td>5.34</td>
<td>2.40</td>
</tr>
</tbody>
</table>

**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**

<table>
<thead>
<tr>
<th>Test</th>
<th>Project 1</th>
<th>Project 2</th>
</tr>
</thead>
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<tr>
<td></td>
<td>Minimum Value</td>
<td>Maximum Value</td>
</tr>
<tr>
<td>Extraction Test</td>
<td></td>
<td></td>
</tr>
<tr>
<td>%passing from sieve 1”</td>
<td>100</td>
<td>100</td>
</tr>
<tr>
<td>%passing from sieve 3/4”</td>
<td>94.29</td>
<td>98.09</td>
</tr>
<tr>
<td>%passing from sieve 3/8”</td>
<td>54.76</td>
<td>60.48</td>
</tr>
</tbody>
</table>
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.

\[
Estimating\ Error\ (\%) = \frac{(ANN\ OUTPUT - Actual\ Output)}{Actual\ Output} \times 100
\]

\[
Average\ ERROR = \frac{\sum_{i=1}^{n} Estimating\ Error}{n}
\]

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).

![Average Error](image)

**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.
REFERENCES


ASTM-D2127 Method of Test for Bitumen Content of Paving Mixtures by Centrifuge (Withdrawn 1964).


Tutumluer, E. and U. Seyhan (1998). Neural network modeling of anistropic aggregate behavior from repeated load triaxial tests. transportation research board 77th annual meeting. Washington, DC, USA.


Appendix A

El Minia - Assute free way
Lab. Division

Bituminous Mix Design (wearing Course) 25mm

Gradation of the proposal JMF wearing Course

<table>
<thead>
<tr>
<th>Sieves No.</th>
<th>JMF (Total)</th>
<th>JMF tolerance</th>
<th>Limits of project technical Specifications</th>
</tr>
</thead>
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<td></td>
<td></td>
<td>Lower Limit</td>
<td>Upper Limit</td>
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<td>100</td>
<td>100</td>
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<tr>
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<td>93.2</td>
<td>100</td>
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<td>61.1</td>
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<td>7.7</td>
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<tr>
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<td>4.2</td>
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![Graph](image)

-88-
## Marshall Properties for WEARING

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<tr>
<th>Test Performed</th>
<th>Bitumen Content %</th>
<th>5.0%</th>
<th>5.5%</th>
<th>5.75%</th>
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<td>1154</td>
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<td>Flow</td>
<td></td>
<td>11</td>
<td>12</td>
<td>13</td>
<td>13</td>
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<td>Unit Weight (g/cm³)</td>
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<td>2.322</td>
<td>2.338</td>
<td>2.344</td>
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<tr>
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<td>4.1</td>
<td>3.2</td>
<td>2.6</td>
</tr>
</tbody>
</table>

### Graphs

- **Stability**
  - X-axis: % Bitumen
  - Y-axis: Stability

- **Air Voids Retained**
  - X-axis: % Bitumen
  - Y-axis: Air Voids

- **Unit weight**
  - X-axis: % Bitumen
  - Y-axis: Unit weight

- **FLOW**
  - X-axis: % Bitumen
  - Y-axis: FLOW
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:
- Wt. before extraction = 1315 gm  e- Wt. of agg. retained = 6 gm
- Wt. after extraction = 1243 gm  f- Total wt. extract. Agg = 1249 gm
- Wt. of filter & agg. = 28 gm  g- Wt. of bit (a-f) = 66 gm
- Initial wt. filter. = 22 gm  h- % Bit. 100 = 5.28 %

C) GRADATION OF AGGREGATES:
wt. of sample = 1249 gm

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<tr>
<th>SIEVE SIZE</th>
<th>WT. OF RETAINED</th>
<th>% RETAINED</th>
<th>% PASSING</th>
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<th>General spec.</th>
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<td>JMF+ (-) (+)</td>
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<td>5.6 6.2</td>
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-90-

Diagram showing gradation and specifications.
**Elminia - Assuit FreeWay**

**Marshal Test**

<table>
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<th>No.</th>
<th>wtr. in air (gms)</th>
<th>wtr. in water (gms)</th>
<th>mattr. in mg</th>
<th>rel. volume (cm³)</th>
<th>density (tonnes)</th>
<th>comp. (kilo cm²) by vacuum</th>
<th>Marshall Stability</th>
<th>Flow (1/100)</th>
<th>VMA%</th>
<th>YFB%</th>
<th>average density</th>
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<td>1.03</td>
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<td>13.6</td>
</tr>
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</table>

**Average**

|                |                   |                     |             |                   |                     |                         | 6.3              | 1060       |      |      | 48.7 |

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

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## Appendix C

### Optimization Summary Report

**Evolver: Optimization Summary**

**Performed By:** keno  
**Date:** 14 أثشيم، 2013 10:52:41  
**Model:** ANN11.xlsx

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<td>Type of Goal</td>
<td>Minimum</td>
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<td>Total Trials</td>
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<td>+ soft constraint penalties</td>
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<td>= result</td>
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<td>Best Value Found</td>
<td>3.99</td>
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ملخص الرسالة

الرصاص الأسفلتي يعد أهم و أشهر وسائل الرصاص في مصر لجميع أشكال الرصاص سواء في الطرق أو المطارات أو مناطق الانتظار و تتكون الخلطة الأسفلتية تقريبا من 93% إلى 97% من الركام المدجج ومن 7% إلى 3% من البيتومين الساخن.

تعد طريقة مارشال لتصميم الخلطة الأسفلتية من أشهر الطرق المستخدمة بصرح و تختص هذه الطريقة في تحديد مكونات الخلطة الأسفلتية من الركام و نسبة البيتومين لتحقيق الخواص المطلوبة للخلطة من الأشياء و أساليب و نسبة الفراغات الهوائية و الكاففة و هذه النتائج يتم الوصول إليها بعد إجراء العديد من التجارب بمحطات مختلفة من البيتومين و يتم استنتاج النتائج بطريقة التجربة و الخطأ، هذه النتائج ترتبط بعلاقة غير مباشرة بعدة عوامل أهمها تدرج الركام و محتوى الخلطة الأسفلتية من البيتومين.

بعد قبول الخلطة الأسفلتية و أثناء سير العمل يتم إجراء اختبارات مارشال و الاستخلاص و التدرج في الموقع و المعمل دوريا و ذلك لضمان الخلطة وضفت النجاح حيث يختص اختبار مارشال بقياس نسبة هذه الأشياء و أساليب و نسبة الفراغات الهوائية و الكاففة للخلطة و إستخلاص و اختبارات في تعديل النسبة المندوبة لخفض البيتومين و الخلطة و اختصار اختبار التدرج يعتمد على توزيع احمام الركام بالخلطة. تميز اختبارات الاستخلاص و التدرج بسرعة إجراءها في الموقع.

السنوات الأخيرة أظهرت استخدامات الشبكة العصبية الاصطناعية كأداة أساليب الذكاء الصناعي في الهندسة المدنية كبديل لطرق التوقعات الاعتمادية و اظهرت نجاح مجراه و ذلك فإن الهدف الرئيسي من البحث هو استحداث نموذج قادر على توقع نتائج تجربة مارشال السافل ذكرهم بدالة نسبة البيتومين في الخلطة (تجربة الاستخلاص) و تدرج الركام (تجربة التدرج).

تم الفعلي تجميع تجارب مارشال و تجارب استخلاص و تدرج من عدة مشاريع منفذيه بصرح و عدة شركات مقابلات وتم عمل نموذج الشبكة العصبية الاصطناعية على ملف أكسيل و أظهرت النتائج النهائية نسبة خطأ صغيرة و مقولة.

تم تجميع تجارب عديدة من تجربتي التدرج و الاستخلاص التي تم تنفيذ بسرعة سواء في الموقع و المعمل و تجريب مارشال نفس الخلطة لإعداد قاعدة بيانات وربطهم بالشبكة العصبية الصناعية وذلك لتوقع نتائج تجربة مارشال المستقبلية بدون إجراءها بدلالة تجربة التدرج و الاستخلاص.

تم تفسير هذه الرسالة إلى خمسة فصول كالتالي:

الفصل الأول: مقدمة تشمل ملخص قصير عن فكرة الرسالة و أهدافها و طريقة العمل.

الفصل الثاني: تاريخ الأعمال السابقة بالنسبة للطرق و طرق التصميم المختلفة و التركيز 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 في ملف برنامج أكسيل.
الفصل الرابع: و يتحدث عن طريقة عمل ملف الاكسيل و استخدام الشبكة العصبية الصناعية لتقليل خطأ توقع نتائج تجربة مارشال بدالة تجربتي التدرج و الاستخلاص.

الفصل الخامس: و يختص بملخص الرسالة مع وضع مقترحات و توصيات للاعمال المستقبلية.
الاكاديمية العربية للعلوم والتقنية والنقل البحري
كلية الهندسة والتكنولوجيا
قسم هندسة التشييد والبناء

توجه نتائج تجربة مارشال باستخدام الشبكة العصبية الصناعية

إعداد
عمرو القناعي جمعه

رسالة مقدمة للاقاديمية العربية للعلوم والتكنولوجيا والنقل البحري لاستكمال متطلبات نيل درجة الماجستير
في
هندسة التشييد والبناء

إشراف

د. د. ك. سلطان قطب
قسم التشييد والبناء
كلية الهندسة
الاكاديمية العربية للعلوم والتكنولوجيا
و النقل البحري

جامعة عين شمس

ديسمبر 2014