Predicting Marshal Flow and Marshal Stability of Asphalt Pavements using Multi Expression Programming

By

Hamad Hassan Awan

(00000274336)

Department of Transportation Engineering,

School of Civil and Environmental Engineering (SCEE),

National University of Sciences and Technology (NUST),

Islamabad, Pakistan.

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Hamad Hassan Awan

(00000274336)

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Thesis Supervisor

Dr. Arshad Hussain

Department of Transportation Engineering,

School of Civil and Environmental Engineering (SCEE),

National University of Sciences and Technology (NUST),

Islamabad, Pakistan.

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Examination Committee Members

1. Name: Dr. Sameer ud Din Signature:_______________

2. Name: Dr. Muhammad Asif Khan Signature:_______________

Supervisor's name: Dr. Arshad Hussain Signature:_______________

Date: _________

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Head of Department

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DEDICATION

This thesis is dedicated to my Beloved, Exceptional, Sweet, Loving, and Caring

Parents

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ABSTRACT

The most widely used method for mix design of asphalt pavements in Pakistan is Marshall Mix Design Method (MMDM) which is based on Asphalt Institute MS-2 in accordance with National Highways Authority's general specifications. The type and amount of bitumen, as well as the grading characteristics of aggregates, dictates the MMDM. The traditional method of obtaining optimum bitumen content and the relevant parameters entails time-consuming, complicated and expensive laboratory procedures and require skilled personnel. Likewise, it is becoming increasingly vital to use new and advanced methodologies for the design and quality control of Marshall parameters. Therefore, this research study uses innovative and advance machine learning technique named Multi Expression Programming (MEP) to develop empirical predictive models for the Marshall parameters i.e. Marshall Flow (MF) and Marshall Stability (MS) for Asphalt Base Course (ABC) and Asphalt Wearing Course (AWC) of flexible pavements. The comprehensive, reliable and wide range of datasets from various road projects of Pakistan were produced for MMDM. The collected datasets contain the 253, and 343 results of MMDM for ABC and AWC, respectively. Eight input parameters were considered for modeling the output parameters i.e. MS and MF. The overall performance of the models was evaluated using statistical measures such as mean absolute error (MAE), root mean square error (RMSE), correlation coefficient (R), relative root mean square error (RRMSE), performance index (ρ), root square error (RSE), and objective function (OF). The relationship between input and output parameters was determined by performing parametric analysis, and the results of trends were found to be consistent with earlier research findings stating that the developed predicted models are well trained. The results revealed that developed models are superior and efficient with respect to prediction and generalization capability for output parameters of MMDM as evident by R (in this case>0.90) for both ABC and AWC.

Key Words: Multi Expression Programming (MEP), Marshall Mix Design Method (MMDM), Marshall Flow (MF), and Marshall Stability (MS).

Table of Contents

List of Figures

List of Tables

List of Abbreviations

MMDM	Marshal Mix Design Method
M3DM	Modified Marshal Mix Design Method
NHA	National Highway Authority
MS	Marshall Stability
MF	Marshall Flow
MQ	Marshall Quotient
ASTM	American Society for Testing and Materials
GP	Genetic Programming
EAs	Evolutionary Algorithms
MEP	Multi Expression Programming
ABC	Asphalt Base Course
AWC	Asphalt Wearing Course
Ps(%)	Percentage of Aggregates
Pb(%)	Percentage of Asphalt Content
Gmm	Theoretical Maximum Specific Gravity of Paving Mix
Gmb	Bulk Specific Gravity of Compacted Aggregate
Gsb	Bulk Specific Gravity of Aggregate
Va(%)	Air Voids
VMA(%)	Voids in Mineral Aggregates
VFA(%)	Voids Filled by Bitumen
AI	Artificial Intelligence
HMA	Hot Mixed Asphalt
USA	United States of America
UK	United Kingdom
GEP	Gene Expression Programming
SVM	Support Vector Machine
ANN	Artificial Neural Networks
ANFIS	Adaptive Neuro-Fuzzy Inference System
LS-SVM	Lest-Square Support Vector Machine
FL	Fuzzy Logic

MLSL	Multiple Lease Square Regression
AASHO	American Association of State Highway Officials
PSR	Pavement Serviceability Ratio
MART	Multiple Additive Regression Trees
MLPNN	Multilayer Perception Neural Networks
SMA	Stone Matrix Asphalt
MAE	Mean Absolute Error
MSE	Mean Square Error
OF	Objective Function
RMSE	Root Mean Square Error
R	Correlation Coefficient
R^2	Coefficient of Determination
MARS	Multivariate Adaptive Regression
NN	Neural Networks
OBC	Optimum Bitumen Content
LMBP	Lavenberg Marquardt Back Propagation
GA	Genetic Algorithm
BBA	Black Box Algorithms
JMF	Job Mix Formula
NHA	National Highway Authority
AASHTO	American Association of State Highway and Transportation Officials

CHAPTER 1: INTRODUCTION

1.1. BACKGROUND

The parameters for Mix Design of Asphalt Concrete are used to grade characteristics of aggregates, and the types and percentages of bitumen used. The key methods used for mix design of asphalt are [1]; Marshal Method; Bruce Marshall in 1930s developed the procedure for design, of Mississippi Highway Department.

Modified Marshall Method; modification and improvement in Marshal Method by, the US Corps of Engineers, in 1950s, through extensive correlation and research.

Hveem Mix Design; Francis Hveem in 1930s, developed it which is similar to Marshall Method, except introduction of kneading compactor in Hveem Method by acknowledging the need to perform mechanical test in order to evaluate the mix's performance.

Superpave Mix Design; replacement of compaction devices with gyratory compactor, in order to determine volume properties and optimum content of binder.

Marshal Mix design was practiced by almost, 75% of state high agencies before 1990s, prior to development of Superpave mix design. Asphalt pavement is most commonly used in Pakistan and several other countries. Presently, in Pakistan, the common methods used for mix design of asphalt are Marshal Mix Design Method (MMDM) and Modified Marshall Mix Design Method (M3DM) as endorsed by asphalt institute MS-02 corresponding to general specification 1998 of the department of National Highway Authority (NHA), Pakistan [2].

The aim of the mix design for asphalt concrete suitable gradation of aggregates and adequate binder for asphalt, such that the mixture can accommodate the following characteristics easily [1];

- Sufficient content of asphalt for better durability
- Sufficient stability of mixture to withstand traffic to avoid distortion
- Presence of sufficient air voids, to avoid loss of stability and bleeding, due to increased ambient temperature and traffic, in the total mix.
- To prevent the permeability of air and water to the surface of pavement, maximum void content.

- To prevent segregation, but adequate workability, for efficient placement, avoiding the sacrifice in performance and stability.
- Properties of aggregates like hardness and texture, for provision of skid resistance in adverse weather conditions.

MS, and MF are the significant features in Marshal Mix Design. MS is very critical in design of wearing course. The ability to resist rutting and shoving is known as stability of pavement. Flow is regarded as property which is opposite to stability. Flow determines the elsto-plastic characteristics of asphalt concrete. The capability of asphalt concrete to adjust with the gradual movements and settlement in the subgrade without having crack [3, 4]. The ratio of MS to MF, is known as Marshall Quotient (MQ), which measures material's resistance against permanent deformation [5]. The above parameters are calculated with trial and error approach.

1.2. PROBLEM STATEMENT

The development and construction of roadways play a significant role in the cultural and economic development process. However, due to rapid development of asphalt pavements, and the high costs pertaining to construction and maintenance, it has become the need of the hour to use the advanced and innovative methodologies in asphalt mix design, when the quality of asphalt is becoming more obvious and evident. In case of Marshall Mix Design, MF and MS are only value that could be obtained physically, at the end of the tests. Other factors, such as theoretical specific gravity (Gmm), specific gravity of mixture (Gmb), void filled with asphalt (VFA %), void in mineral aggregates (VMA %), and air void (Va %) can be calculated by extra calculations. Hence, if the parameters i.e. Marshall Flow and Marshall Stability can be determined, for a standard mix, by some other sources or means, then the remaining parameters can easily be determined with use of mathematical equations.

To avoid problems and make the process intelligible, easy and straightforward, many researchers have used techniques of Artificial Intelligence (AI) to determine the values of MF and MS in the Marshall Mix Design used for asphalt mixtures, which are the major output parameters.

The tests used for Marshall mixed design are time consuming, hectic, and need the expertise of skilled operator to handle test equipment, with zero mathematical relation to predict the mathematical values of MF and MS. Hence researchers have used various AI techniques to predict the MS and MF which in our case, are the major output parameters. This research is based on AI technique i.e. MEP to predict these parameters i.e. MF and MS.

1.3. RESEARCH OBJECTIVES

The objectives of this research study are listed below;

1. Establishment of comprehensive database for Marshall Mix Designs that are being used in various projects in Pakistan.
2. To develop a Multi Expression Programing (MEP) based model to predict the MF and MS parameters for the samples of Hot Mixed Asphalt (HMA).
3. To evaluate and assess the fitness and accurateness of developed MEP model with the help of validation criteria and statistical checks suggested in the literature.
4. To carry out the parametric analysis to investigate about the relationship between output and input parameters.

1.4. SCOPE OF THE STUDY

The focus of this study is to acquire the datasets from different road projects in Pakistan. The main output parameters of Marshall Mix Design i.e. MS and MF are assessed in this study. The characteristics of materials that have been used in the projects i.e. aggregate types and properties are assessed. The selection of input parameters for MEP modeling and reviewing the results of the models.

1.5. THESIS ORGANIZATION

This research thesis is organized in 05 Chapters. A brief description of each Chapter is given below:

Chapter 1 includes the overall background of various mix designs used for asphalt pavements, problem statement, objective, and scope of this research study.

Chapter 2 includes the literature review for Marshal Mix Design, Marshall Stability, and Marshall Flow. This chapter explains about MEP and its advantages of other AI techniques. At the end a vast and comprehensive literature review on various past studies conducted in the field of pavement engineering and especially to estimate the MS and MF of asphalt pavements.

Chapter 3 includes the approach methodology adopted for this research study to achieve the objectives of this study with experimental database, modelling approach.

Chapter 4 includes the explanation of results and analysis following the approach methodology presented in chapter 3. The performance evaluation of all the developed models is evaluated and compared.

Chapter 5 includes the summary of main conclusions derived from this research study with some suggestions for future research and development.

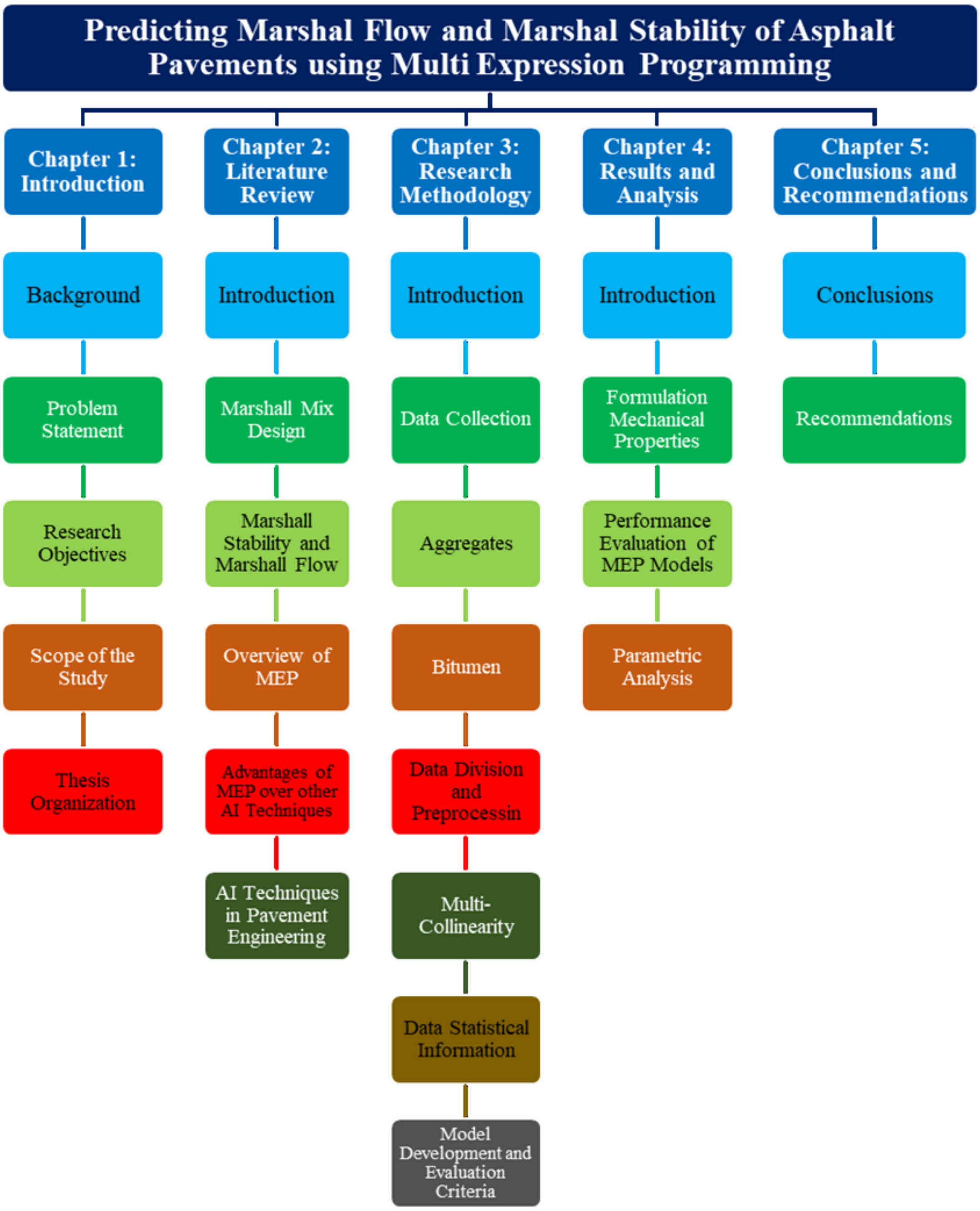

Figure 1-1: Thesis Organization

CHAPTER 2: LITERATURE REVIEW

2.1. INTRODUCTION

The quality of asphalt pavements largely depend upon the quality of asphalt concrete. Marshall Mix Design, Asphalt Institute Triaxle, Superpave, Hveem, and Hubbard Field methods are used are one of many methods for asphalt mix designs. The most extensively used methods all over the world are Marshal, Hveem, and Superpave mix designs [6].

The goals of any method used to design asphalt concrete mix is to work out the most suitable proportions of asphalt cement and aggregates. The primary differences between the Superpave and Marshall mix design methods is the approach to select materials, method of compaction, dimensions of specimen, selection of void analysis, and specifications. Pakistan comes in the list of those few countries where both Marshall Method and Modified Marshall Method are prevalent.

2.2. MARSHALL MIX DESIGN

To carry out heavy loads and aircrafts' large tire pressures, asphalt concrete was introduced to world by the USA. In UK, it was termed as Marshall Asphalt when using for airfields. An engineer of highways, in the Mississippi State Highway Department, in 1939, named Bruce Marshall developed the procedure for Marshall Mix Design which then later was modified in 1943 by US Army Corps of Engineers after extensive research, and in 1958 standardized by American Society for Testing and Materials (ASTM) with ASTM D 1559 as designation, adopted and utilized in various countries of the world [7, 8].

These procedure are given in:

- ASTM D6926, "Preparation of bituminous mixtures using Marshall Apparatus".
- ASTM D6927, "Standard test method for Marshall Stability and flow of bituminous mixtures".
- AASHTO T245, "Resistance to plastic flow of bituminous mixtures using Marshall Apparatus".

The Marshall Tests consists of cylindrical specimen having dimensions of 102mm diameter and 64 mm of height, compacted using standard hammer, in cylindrical mold. These specimen is compacted according to applicable loading conditions. For streets and roads having low tire pressures, two faces of materials are compacted with the help of 45.72 cm long hammer with weight of 4.53 kg, in 50 blows. For the tire pressure of 200 psi, each face of the materials is compacted with 75 blows. Then these specimen are tested against the resistance to deformation at 60ºC with the load applied at the constant rate (50.8 mm/min), in a test rig. Entire circumference of the specimen is not confined by jaws of the loading rig but the majority, and top and bottom of the cylinder remains unconfined [9].

The main aim of any mix design is to find best possible blend of asphalt cement with aggregates as component of the asphalt pavement for a long term performance. The mix design consists of a number of processes to be performed in the laboratory in order to determine the proportions of the mix's ingredient which will be used in asphalt concrete. These procedures are performed to select the most suitable amount and category of asphalt cement to be used as a binder for the specific type of gradation, as well as to identify the appropriate proportions of the aggregate sources to accomplish the adequacy in selection of mineral gradation. When the asphalt mixture are properly designed, they can perform very well under various climatic and load condition for many years.

Viscoelasticity, temperature susceptibility, and aging characteristics of asphalt binder content all play an important role in the behavioral performance of asphalt mixtures.

The simplified or original Marshall Method is suitable for mixtures with maximum aggregate size of 1 in (25 mm) or smaller. While Modified Marshall Method is used for the aggregates whose diameter size reaches up to 38 mm (1.5 in).

The first step in Marshall Mix Design Method (MMDM) is to prepare the specimen. A number of steps are being taken to prepare the specimen which are given below;

- Physical requirements of the project should be met by the recommended materials.
- Project's specification criteria should be met by the blend of aggregates.
- To perform the density and void analysis, the bulk specific gravity, and specific gravity of entire aggregates are determined.

- Marshall Method uses standard test specimen with height of 2.5 in (64 mm) with 4 in (102 mm) diameter. The mixture of asphalt and aggregates is heated, mixed, and compacted in accordance with the specific set of instructions. A analysis of density–voids and stability–flow of compacted test specimen are the two major aspects of the MMDM.

To determine the optimum asphalt content, in MMDM, for a particular gradation or blend of aggregates, various sets of test specimen with the different ranges of asphalt contents are developed in order to get the well-defined correlations of test data curves. Planning of asphalt content should be in such a way that they have increments of 0.5 percent with two number of asphalt content below and above the estimated design value, at least. Haveem method's centrifuge kerosene equivalency and oil soak tests could also be carried out to determine the "projected design" asphalt content, or with a mathematical method.

MS and MF are the properties that are determined from the MMDM. In simple words, MS is the maximum load resisted by the specimen before its failure, while MF is the deformation occurred in the specimen during the application of the load.

Each of the compacted test specimen goes through these tests and analysis in the MMDM as stated in order below;

- Calculation of specimen height
- Determination of Bulk Specific Gravity
- Investigation about voids and density
- Tests for stability and flow

As soon as the specimen which are freshly compacted are prepared, the test for bulk specific gravity should be performed. This test is conducted in accordance with ASTM D1188, "Standard Test Method for Bulk Specific Gravity and Density of Compacted Bituminous Mixtures Using Coated Samples" or in accordance with ASTM D2726, "Standard Test Method for Bulk Specific Gravity and Density of Non-Absorptive Compacted Bituminous Mixtures".

The following equipment are needed for preparation of test specimen:

- Mould Assembly: cylindrical moulds having diameter of 10cm, and height of 7.5 cm with collar extension and base plate.

- Sample Extractor: for removal of compressed sample form mould.
- A hammer and a pedestal for compaction.
- Breading head.
- A loading machine.
- Flow meter, thermometers, and a water bath.

The MS of the test specimen is defined as the resistance to maximum load that a standard test specimen will attain when tested at 60 ºC (140 ºF). The MF is the overall deformation in the sample from no load to maximum load during stability test, measure in units of 1/100 in (0.25 mm) [1].

The MMDM has achieved incredible admiration as an evaluation and design method for HMA used in highways and airports. It is relevant for both field control operations and laboratory mix design. Furthermore, this method adopts several types of gradations such as stone matrix and dense graded asphalt [10].

Even with some flaws, the MMDM is used as method for mix design throughout the world for it application range [11]. Stability of asphalt determines how well a roadway surface will perform. Several types of discomforts in asphalt are triggered due to low stability of asphalt [12, 13].

Fatigue cracking is regarded as the critical distress in asphalt concrete caused due to repetitive loading. The bitumen content, stiffness of mix, viscosity of bitumen, bitumen softening point, meteorological variables, and aggregate grading all affect the stability of asphalt [14]. The optimal value for Marshall Flow (MF) is hard to determine, however, its acceptable upper and lower could be defined. For example when the flow goes beyond the upper limit at the optimum binder content, it is termed as unstable or overly plastic, while on the other hand, if it is below lower limit, then mix is considered as brittle [15]. The stability of the mix increases with the increase in bitumen's proportion up to an optimum level, after which it starts to drop, while the flow value keeps increasing the increase in proportion of the bitumen [16]. The increase of asphalt content beyond the optimum level results in an exceptionally thick coating of asphalt over the particles of aggregates, reducing the mix stability. The characteristics of the aggregates used in the mix play a vital role to determine this limit [17].

The stability of the mix is determined by it cohesiveness and internal friction. Cohesiveness is the measure of bitumen's binding strength, while internal friction is a measure that indicates friction resistance and aggregate interlocking, and flow is measurement of specimen's deformation measured at increments of 0.25 mm. A mixture, under traffic, will certainly deform permanently if the flow values are high, whereas the mixture with low flow values will contribute to more than normal voids, insufficient asphalt to afford longevity, and probability of asphalt will increase, due to mixture's fragility, for premature cracking [18].

The Gmm and Gmb for asphalt specimen are calculated in accordance with ASTM D2401 and ASTM D2726, respectively. Using these values from experiments, the volumetric characteristics of asphalt specimen, i.e. Va (%),VMA (%), VFA (%) as percentage of VMA, Gsb, Ps (%), are determined using the following equations;

$$V_a = \frac{(G_{mm} - G_{mb})}{G_{mm}} \times 100$$

$$VMA = 100 - \frac{(G_{mm} - G_{mb})}{G_{mm}}$$

$$VFA = \frac{100(VMA - V_a)}{VMA}$$

2.3. MARSHALL STABILITY AND FLOW

The two major outputs of Marshall Mix Design, are the stability ratings, which designate a sample of asphalt concrete, the maximum load resistance to external diametrical load which is applied at a rate of 2 in/min (50.8 mm//min), and flow is recorded at increments of 0.01 in (0.25 mm), which denotes the specimen's plastic deformation at the maximum load applied [9].

When a standard test specimen attains maximum resistance to load in Newtons (lb) at temperature of 60ºC (140ºF) is known as the stability of the specimen. The values of flow is acquired from the total deformation of the specimen in between zero load and point when the load is maximum, in units of 0.25 mm (1/100 in), during the stability test [9]. How well the surface of roadway performs depend on the value of asphalt stability. A number of distresses are caused in asphalt pavement due to low value of asphalt concrete [12, 13].

A significant concern about distresses in asphalt pavements is fatigue cracking, which is caused due to repetition of loads. The mix's stiffness, content of bitumen, softening point of bitumen, method of construction, meteorological variables and gradation of aggregates are factors the effect the stability of asphalt stability [14]. The optimal value for Marshall Flow (MF) is hard to determine, however, its acceptable upper and lower could be defined. For example when the flow goes beyond the upper limit at the optimum binder content, it is termed as unstable or overly plastic, while on the other hand, if it is below lower limit, then mix is considered as brittle [15].

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2.4. OVERVIEW OF MEP

Encouraged by Darwin's theory of evolution, Genetic Programming (GP) [19, 20] is an emerging subclass of Evolutionary Algorithms (EAs) [21]. Generally, GP can be defined as machine learning technique which explores program space as a substitute to data space [19]. In the previous decade, a certain variant of GP, named Multi Expression Programming (MEP) was proposed in which linear representation of chromosomes is used [22]. Multiple computer programs could be encoded in a single chromosome, for a problems, making it the special ability of MEP. MEP technique has the ability to outperform similar approaches significantly which are based on numerical experiments. MEP could be used as an efficient substitute to traditional GP (tree-based) approaches [23]. Despite the fact that MEP has significant advantages over other approaches, it has been merely utilized in civil engineering tasks and in the field of pavement engineering its applications are near to none.

Koza [19] introduced GP to world which is a branch of EA that develops computer programs by utilizing the Darwinian principle of natural selection to solve a problem. GP was presented as an extension to genetic algorithms, which represents programs as tree structures and are expressed in programming language named LISP [19]. GP has successful been utilized in some of pavement engineering problems [24-28].

Otlean and Dumitrescu developed MEP which is a branch of GP [22]. Linear chromosome are used in MEP for encoding of solution with a distinctive ability to encode several solutions (computer program) into a single chromosome. The best encoded solution to represent chromosome is chosen according individual's fitness values. The first step of MEP procedure is to create random population of individuals. For development of best output expression from the dataset containing input and outputs with certain number of generations, following steps are used by MEP until a condition to terminate the process is reached [29]:

- Selection of two parents with the help of binary tournament procedure and their recombination with probability of fixed crossover.
- Acquiring of two offspring by recombining the two parents.
- Mutation of offspring and then replacement of the worst individual with best of them, in the current population (if the worst individual is weaker than the offspring in the present population).

The representation of MEP is similar to Pascal and C compliers and their way of translating the mathematical expression into machine code [30]. The length of chromosome in MEP is specified by number genes per chromosome which is constant. Each gene encodes the functional symbol (an element in function set F) or terminal (an element in terminal set T). Pointers are included in the gene towards the function that encodes a function. Function parameters must contain indices of lower values as compared to the function in the chromosome itself. As specified by the scheme of proposed representation, first symbol must be a terminal symbol in chromosome.

An illustration of chromosome in MEP is described below. It ought to be noted that number on the left side represent gene labels that are not associated with chromosome. By using F = {×, /, +} as arithmetic operators, and T = {a_1, a_2, a_3, a_4} as set of terminals, the example is given as follows:

1: a_1

2: a_2

3: / 1, 2

4: a_3

5: × 3, 4

6: a_4

7: + 5, 6

The interpretation of individuals in MEP into computer programs could be achieved by reading chromosome from top to down and starting with top position. Terminal symbol characterizes a straightforward expression and all the function symbols defines a complex expression acquired by connection of operands indicated by positions of argument with the current function symbol [29]. In the current illustration, genes 1, 2, 4, and 6 are encoding simple expressions created by single terminal symbol. These expressions are

$E_1 = a_1$

$E_2 = a_2$

$E_4 = a_4$

$E_6 = a_6$

Gene 3 represents the operation "/" on the operands at positions 1 and 2. Hence, gene 3 is encoding

$E_3 = a_1 / a_2$

Gene 5 represents the operation "+" on the operands at positions 3 and 4. Hence, gene 5 is encoding

$E_5 = (a_1 / a_2) \times a_3$

Gene 7 represents the operation "×" on the operands at positions 5 and 6. Hence, gene 5 is encoding

$E_7 = ((a_1 / a_2) \times a_3) + a_4$

To select one of these expressions (E_1, E_2,…, E_6) to represent chromosome, various solutions are encoded in a single chromosome. The number of expressions encoded by each of MEP chromosome is equal to number of genes (length of chromosome). In light of its ability to represent multi expressions, each MEP chromosome might be taken as a forest of trees instead of a single tree, as considered in GP. Figure 2-1 exhibits encoded forest of expressions as presented in above MEP chromosome. Each expression could be considered as a potential solution to this problem. The fitness of every expression encoded in MEP chromosome can be defined as fitness of best expression encoded by that chromosome. In order to solve the problems of symbolic regression, the fitness (f_i) of MEP chromosome might be calculated utilizing the following equation [23]:

$$f_i = \min_{i=1,m}\left\{\sum_{j=1}^{n}\left|E_j - O_j^i\right|\right\}$$

where n is the number of cases for fitness, E_j is the estimated value for the fitness case j, O_j^i is the returned value for the j^{th} fitness case by the i^{th} expression encoded in current chromosome, and m is number of chromosome genes.

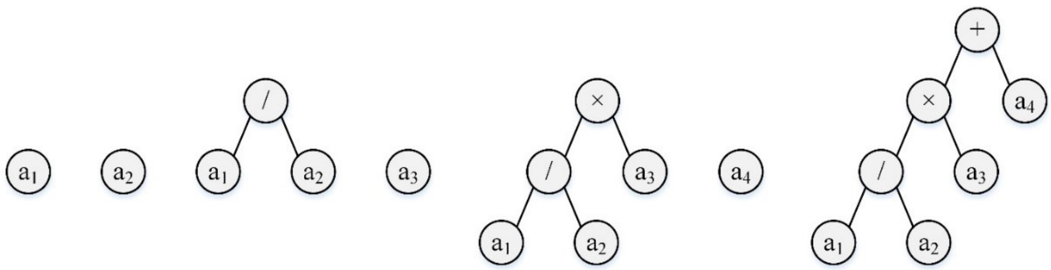

Figure 2-1: Forest of Expression in the Exampled MEP Chromosome

The main objective of this research study is to utilize the MEP approach to predict the output parameters of MMDM i.e. MS and MF.

2.5. ADVANTAGES OF MEP OVER OTHER AI TECHNIQUES

The basic purpose modelling based on computations is to predict a practical and correct mathematical expression to predict outputs based on the pre-defined input variables. Koza (1992) developed the GP based on Darwinian principle of natural selection which is an extension to genetic algorithm (GA) [19]. The major difference amongst these methods is replacement of binary strings of fixed length used in GA with the non–linear parse trees of GP. In recent decade, numerous diverse procedures of EA's have been suggested with linearity as key variant amongst them. Otlean proposed that in case of MEP, individuals could be represented by variable length entities [22, 23]. The simulation output of MEP can be defined as instructions of linear strings which are amalgamation of mathematical operators (functions) or variables (terminals). The steps that imply in the execution process of MEP are shown in Figure 2-2. The algorithm of MEP in its evolution process includes generating the random population of the chromosomes, selecting two parents with the use of binary tournament procedure then recombining them a probability of fixed cross-over, generating two off-spring by recombining the parents that are selected, mutation of off-springs and then replacement of worst individuals with best ones in the population. This process runs in a cycles and terminates until the achievement of convergence. [23, 31].

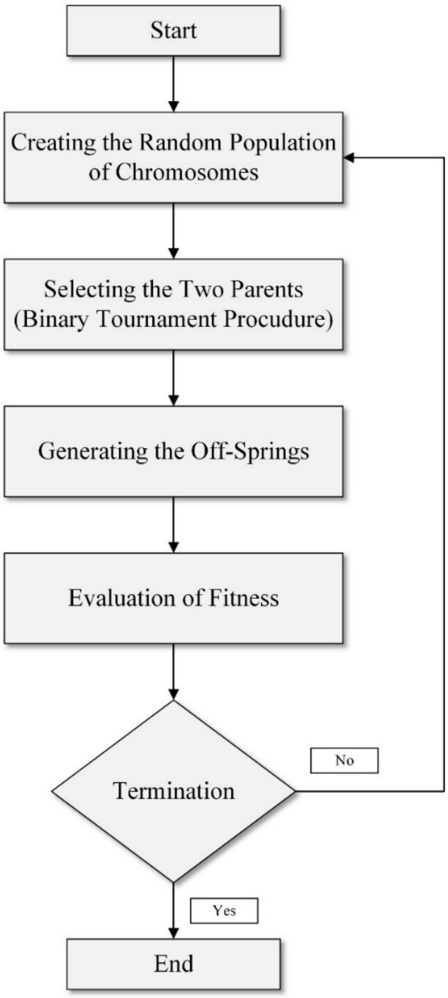

Figure 2-2: Schematic Diagram of MEP Algorithm

In recent decade, the majority of research studies have put their focus on GEP and NN in order to model the MS and MF, the output parameters of MMDM. Although, MEP has certain advantages over similar algorithms. Usually, a large database is utilized to model MS and MF of MMDM. In GP, the utilization of genetic tree cross-over operator results in creation of parse tree with large population which in return leads to increased simulation time and requirement large memory [19]. Additionally, GP's non-linear structure works as phenotype and genotype which make it challenging for the algorithm devise a suitable mathematical expression needed for the desired properties. [32]. However, the inclusion of linear variant in MEP enables it to easily distinguish between the phenotype and genotype of an individual. [33]. There is a threshold limit in the accomplishment rate of GP, by increasing the number of genes in the chromosomes.

Overfitting is likely to appear beyond the threshold limit limiting the applications of model in the construction industry [34-36]. On the other side where complexity of targeting model expression is not known which is most common problem in material engineering, MEP is predominantly more beneficial, where a slight variation in input parameters have a significant impact on the output parameters [23]. In MEP, the encoding of multiple solutions in single chromosome and linearity of chromosomes enables model to search broader space for prediction of output parameters. The evident benefits of MEP over EAs mentioned above will result in creation of the more precise models in field of pavement engineering.

The applications of MEP has been near to none in field of pavement engineering to predict the output parameters of MMDM i.e. MF and MS, despite its obvious advantages. However some studies has used NN for dense bituminous mixtures modified with polypropylene [37], to model the MS of asphalt concrete [38], to model stiffness modulus and MS of HMA [39], to model MF and MS of asphalt concrete with progressive conditions of temperature [40] model the MS of expanded clay aggregates used in light asphalt concrete [41], using ANFIS to model MS for fiber reinforced asphalt mixtures [42], us of fuzzy logic to predict MS of expanded clay aggregated used in lightweight asphalt concrete [43], using Multiple Additive Regression Trees to predict MS of asphalt concrete [44], using SVM to predict MS of stone matrix asphalt [45], using GP to model parameters of flexible pavement [24].

In the current study, model to predict the output parameters of MMDM i.e. MS and MF are developed using MEP. The modeling is combined with detailed parametric and statistical assessment to warrant the accuracy, precision and efficiency of the model. The availability of trustworthy and consistent models will endorse the employment of MEP technique in the construction and pavement industry as it will bypass the hectic and time consuming experimental procedures used for MMDM. This would contribute towards the reduction of time for testing and promote the use of MEP technique in the construction and pavement industry. Additionally, the current methodology for modeling will pave the way to for the similar complex modeling engineering phenomenon accurately.

The distinguishing features of a common AI technique, ANN, have been used widely to model development of the MS and MF of asphalt concrete. [24, 37-56]. These algorithms with their abilities to recognize patterns result in simplified engineering problems that are complex in nature. [57]. It is also worth noticing that NN is labelled as Black Box Algorithms (BBA) and could perform well only over a specific set of problems being under consideration for optimization. BBA don't take into consideration any physical phenomenon or data information of problem under evaluation. [29]. The majority of ANN procedures slack in a way that a complex numerical expression is created for prediction of output parameters based on input parameters. Models bases on ANN technique are considered as a linear correlation of input parameters with that of output parameters or relationship in them is pre–defined base function [58]. To minimize the effects of these issues, a number of EA such as GEP, SVM, ANFIS are being used for modeling output parameters for MMDM [24, 42, 45, 52]. The benefits of these EA is high generalization, developing practical mathematical expression, and high capability of prediction.

In response to cater the problems associated with the above mentioned deficiencies of NN, a more advanced technique named MEP has been introduced for modelling. The capacity to encode several chromosomes (expressions) in a single program of computer is the eminent feature of MEP. The best of selected chromosome is chosen for ultimate representation of solution [23]. MEP is considered to be the improved version of GP having the capability to predict more accurate and precise results compared to other EA's where the complication of the target is unknown. [59]. Dissimilar to various other AI algorithms, it is not compulsory to specify in advance the final form of expression in MEP. The evolution process of MEP is capable to read and eliminate the mathematical errors from final expression. Compared to other AI techniques, the decoding procedure of MEP is straightforward. Despite the clear and evident benefits of MEP over other EAs, it has been seldom utilized in civil engineering's field, and especially in field of pavement engineering, the utilization of MEP is seen near to nowhere.

In the current research study, the parameters of MMDM have been modelled depending upon the parameters that are more influencing. An enormous database was collected from the construction industry of Pakistan. The database was then divided into three parts for training, validation, and testing in order to guarantee that the model is well trained. By conducting parametric analysis and an in depth statistical error checks, the efficiency of the model was evaluated, for the assurance of model's reliability and generalization.

2.6. ARTIFICIAL INTELLIGENCE TECHNIQUES IN PAVEMENT ENGINEERING

MMDM is used most frequent in design of Hot Mixed Asphalt (HMA). The major design parameters of MMDM are MF and MS. A number of pavement engineering research studies have used AI techniques such as Genetic Programming (GP), Artificial Neural Networks (ANN), Support Vector Machine (SVM), Gene Expression Programming (GEP), and Adaptive Neuro-Fuzzy Inference System (ANFIS) as an alternative tools to traditional prediction approaches.

The major goal of this research study was to create MEP models. The models will assess the MS and MF of ABC and AWC as a function of components of asphalt cement and mix gradations. The coefficient of determination and root mean square error (RMSE) for MS of ABC were 0.97 and 44.91 kg, for MF of ABC were 0.97 and 0.81 (0.01 in), for MS of AWC were 0.94 and 35.86 kg, and for MF of AWC were 0.97 and 0.43 (0.01 in), respectively. Based on bitumen content and mix gradations, it was concluded that MEP could be a suitable method for modeling of MS and MF of ABC and AWC [60].

With the advancement in the field of AI techniques, the new, accurate, and updated models for pavement engineering have been introduced [24, 37, 61].

Baldo et. al. [39] used laboratory data for modeling HMA parameters to predict the MS, Marshall Quotient (MQ), and stiffness modulus based on the multiple layer structures of ANN. In the lab, 129 specimens were made with various aggregate and bitumen types. Aggregate and various types of bitumen were used as input parameters. The main aspect of this study is that instead of using the traditional strategy of separating the available data into testing and training, five–fold cross validation was employed in ANN model selection technique based on k–fold cross validation. They stated that, depending upon the mechanical parameters, use of development of multiple layer structure could be helpful.

Khuntia et. al. [46] stimulated the MS of polyethylene modified asphalt specimen with lest-square support vector machine (LS-SVM) and ANN. The results of laboratory validated the incorporation of polyethylene to improve the MS, MF and air voids of the specimen. They used two simulation methods with bitumen, aggregate, and polyethylene as input parameters for prediction of MS, MF, and air void's percentage. When compared the results of two models for accuracy, ANN based model performed well than the LS-SVM based model.

Ceylan et. al. [47] has investigated about the applications of ANN as tool to analyze pavement structures for accurate and rapid prediction of deflection profiles and critical responses for full depth pavements under typical highway loading conditions. Ceylan et. al. [48] also successfully predicted the dynamic modulus of HMA using ANN.

Ozgan [49] predicted the MS of asphalt concrete underlying various temperatures and exposure with statistical method and Fuzzy Logic (FL).

Tapkin et. al. [37] used Neural Network to predict the results of Marshall tests for polypropylene based modified dense bituminous mixtures. The results of Tapkin el. al. showed that the approach could be useful to predict the values of MS, MF and MQ without carrying destructive tests taking too much time with large human effort, for predetermined testing conditions and specific type of asphalt mixtures.

Acceptable performance of ANN models is the main attraction for their application but one of the shortcomings is problem with generalization for traditional ANN based models [50]. The development of models by ANN can over-fit the data. Moreover, the utmost difficult task to carry out in studies using ANN is finding optimal number of neurons and layers in hidden layers with trial and error approach to find optimal architecture of network [37, 51].

Yan et. al. [52] used SVM to compare it with GEP, and Multiple Lease Square Regression (MLSL) to predict the flow number. Another research study conducted by Ke-zhen et. al [62] used models of SVN, ANN, and American Association of State Highway Officials (AASHO) to predict the pavement serviceability ratio (PSR) of flexible pavement.

Tsompanakis et. al. [44] investigated about the prediction of stability using Multiple Additive Regression Trees (MART) model. Input parameters in their study were gradation of aggregates, bitumen content, and MF while the output parameter was MS. They compared the results of MART's model with Multilayer Perception Neural Networks (MLPNN). They noticed that MLPNN model was under-predicting the values of MS while the MART model was over-predicting the values.

Morova et. al [42] developed an ANFIS model for predicting MS of basalt fiber reinforced asphalt concrete mix. Input parameter were fiber (Basalt) ratio percentage and bitumen percentage where output parameter was MS. They randomly chose 29 experimental data as training, whereas for testing 7 data were chosen. The statistical checks were applied to evaluate the ANFIS model.

Nguyen et. al. [45] prepared samples of stone matrix asphalt (SMA) in laboratory and generated data sets in which input parameters were bitumen content, coarse aggregate, and cellulose, whereas the output parameters were MS, MF and MQ. Models of ANFIS improved by and SVM, Genetic Algorithm (GAANFIS), Particle Swarm Optimization (PSOANFIS), were developed and compared. They developed and utilized 60 groups of stone matrix asphalt (SMA) in the laboratory and then utilized them to generate datasets. The models were validated using a variety of criteria such as MAE, RMSE, and others. The results showed that all of the proposed AI models worked well in forecasting the MS of SMA materials, however the SVM outperformed the other techniques in this study.

Shah et. al. [40] has developed a model for predicting MS of asphalt with two types of aggregates based on their mineralogy at four testing temperatures ranging from 25 ºC to 60 ºC using ANN methodology. MS, MF, stiffness, and indirect tensile strength were all the output parameters, while temperature, aggregate type, space volume, ultrasonic pulse velocity–time, and specimen's SSD were the input parameters. According to investigation, the aggregate type, temperature, space volume, and ultrasonic pulse velocity–time all have a direct effect on output. The proposed model's accuracy was tested using R^2, and RMSE. In both, training and testing R^2 values were found to be within acceptable limits. The maximum stability's value was identified at 25 ºC, whereas the lowest stability value was identified at 60 ºC.

Ozgan [38] used ANN technique to model the MS of asphalt concrete for changing temperature, physical properties, and exposure periods. Changing temperatures, physical properties, and exposure periods, were used as input parameters, whereas MS was used as an output parameter. Exposure times of 1.5, 3, 4.5, and 6 h, as well as temperatures of 30ºC, 40ºC, and 50ºC were chosen to evaluate the MS of asphalt concrete depending on physical parameters, exposure period, and ambient temperature. The stability of the asphalt samples deteriorated by 40.16 % at 30ºC after 1.5h and 62.39 % after 6h at a temperature of 17 ºC, according to the findings. After 1.5 hours at 40 ºC, the drop was 74.31%, and after 6 hours, it was 78.10%. After 1.5 hours at 50 ºC, the asphalt's stability had dropped by 83.22%, and after 6 hours, it had dropped by 88.66%.

Azarhoosh et. al. [24] used a Genetic Programming (GP) technique to predict MMDM's parameters of asphalt mix. In addition, to analyze the models offered by the GP approach, multiple models of linear regression were used as base model. The aggregate index, particle texture and shape and the viscosity and amount of the bitumen were all input parameters. The results showed that proposed models are more effective than the expensive laboratory method and GP models with minimum error and correlation coefficients > 0.9 can predict MMDM's parameters with reasonable accuracy. The particle index values of coarser grading aggregates are higher than those of finer grading aggregates which is valid for all types of aggregates. The bitumen amount and the particle index have the most influence among the independent factors used to forecast the parameters of the MMDM.

Ghanizadeh et. al. [53] developed a Multivariate Adaptive Regression Spline (MARS) model to predict the MF of asphalt mix based on the MMDM parameters. Data set comprised of 118 samples of flow number for different asphalt mix were employed. Input parameters were percentage of coarse and fine aggregates, air void, voids in mineral aggregate, and MS and whereas output parameters was MF of asphalt mix. The coefficient of determination for the MARS model was above 0.96. The parametric analysis of the developed model indicated that the results of model were in accordance with the actual behavior of the asphalt mixtures. Statistical checks were used to assess the suggested model's accuracy, generalization, and prediction capabilities. Therefore, the developed model can be used to predict the flow number without conducting any field tests but can only base on the MMDM parameters.

Alawi and Rajab [54] used Neural Networks (NN) in determination of optimum bitumen content (OBC), MS and MQ of asphaltic concrete mixtures. During construction, samples were taken from several locations in the Mecca area and examined in laboratories for bitumen content, aggregate gradation, MS, and MQ determination. On the basis of the data gathered, typical models for asphaltic concrete mixtures were developed. Validation was performed on a portion of the data set. For optimum bitumen content, MS, and MQ, the successful NN mode has the highest correlation values of 0.970, 0.969, and 0.862 respectively. Engineers can use this model to estimate the optimum bitumen content, MS, and MQ of asphaltic concrete mixtures without having to conduct costly and time-consuming experiments, according to the findings.

Saffarzadeh and Heidaripanah [55] used ANNs as a Levenberg Marquardt Back Propagation (LMBP) training technique to model the fluctuation in MS with asphalt content. The percentage of crushed aggregates, the Ps (%) passed through sieve # ½, 4, 8, 30, 50, and 200 inch and Pb (%) were all input parameters whereas MS was the output parameter. There were 110 samples in the data set. There were 85 datasets utilized in training and 25 datasets utilized in testing. A little variance in training error (MSE) can generate a big difference in simulation competence (R).

The greatest generalization capability of each network with certain number of neurons in hidden layer was determined in the first stage. When these maximum values were compared, it was clear that the hidden layer network with 8 neurons had the best generalization ability. The fluctuation of MS with asphalt content was simulated in the second stage by doing a sensitivity analysis on the network with highest generalization ability.

Serin Sercan et al. [43] used Fuzzy Logic (FL) technique to predict MS of light–asphalt–concrete that was fabricated utilizing expanded clay and had different mix properties. The Pb (%), the transition speed of ultrasound (μs), and the unit weight were all input parameters whereas MS was the output parameter (kg). The model was created using 13 experimental results. The experimental findings were compared to the outcomes predicted by the FL model using the R^2 and RMSE criteria. The RMSE and R^2 values were found to be 19.25 and 0.7758, respectively, when the results were compared.

Serin et. al. [56] developed models using regression analysis and ANN approaches for estimation of compressive strength of asphalt concrete as a function of bituminous quantity. The compressive strength was evaluated after 45 Marshall samples were made and a MS experiment was conducted. The model's results were compared to the outcomes of the experiments. The performance of developed models in terms of prediction was compared and evaluated. As a result it was discovered that using the developed ANN model, it is possible to estimate the compressive strength of asphalt concrete as a function of bituminous amount and that the ANN model is more fruitful than the regression model in estimating the compressive strength of asphalt concrete.

2.7. SUMMARY

This chapter includes the introduction of MMDM, MS, MF, overview of MEP techniques and its advantages over other AI techniques followed by a comprehensive literature review of various AI techniques in the field of Pavement Engineering.

CHAPTER 3: RESEARCH METHODOLOGY

3.1. INTRODUCTION

In this chapter the methodology adopted for the empirical study of the collected data will be elaborated. MS and MF are the main output parameters of MMDM tests. To save time and cost of skilled personnel, it is the need of the hour to develop precise and accurate expressions.

3.2. DATA COLLECTION

The data for MMDM is compiled from various construction companies working on various road projects in Pakistan. The comprehensive dataset is compiled of values from 25 different road projects of Pakistan for ABC and AWC. The database consists of 253 dataset for ABC and 343 dataset for AWC. To ensure accurate and universal models, all variable datasets were collected. The Marshall Tests were conducted in established laboratories of various construction companies of Pakistan duly approved by Pakistan Engineering Council (PEC) in accordance with standard ASTM D6927-96.

3.3. AGGREGATES

The aggregates used in this research study are from various quarries all over Pakistan i.e. Kohat, Pathar Garh, Aamri, Chondiko, Daraban, Margalla, Babuzai, Sargodha, Sadu Khel, Khan Pur, and Shah Khalid. The aggregates from these quarries were used in various periodic maintenance projects of national motorways and highways of Pakistan i.e. M10, E-35, N-5, N-35, N-55, N-70, N-75, and construction of various national and provincial roads in Pakistan i.e. Haripur Bypass, Mardan Ring Road, Provincial Highway S-IA, and Peshawar Northern Bypass.

The gradation curves of aggregates for all of the projects used in the datasets lie within the lower and upper range of NHA's general specifications, Table No 305.2. Aggregate sizes ranging from 50mm to 0.075 mm were used. The blending of aggregates used in Job Mix Formula (JMF) for ABC and AWC adopted for the projects and obtained from particle size distribution are shown in Tables below;

Table 3-1: Blending of Aggregates for Asphalt Base Course

Aggregate Type	Asphalt Base Course Blend				
1 (ABC)	Particles Size (mm)	20-50	10-20	05-10	00-05
Kohat	%	34	24	17	25
2 (ABC)	Particles Size (mm)	20-38	10-20	05-10	00-05
Pathar Garh	%	35	20	15	30
3 (ABC)	Particles Size (mm)	20-50	10-20	05-10	00-05
Aamri	%	31	22	16	31
4 (ABC)	Particles Size (mm)	25-38	12-25	05-12	00-05
Choondiko	%	31	26	13	30
5 (ABC)	Particles Size (mm)	20-38	10-20	05-10	00-05
Daraban	%	34	20	17	29
6 (ABC)	Particles Size (mm)	20-38	10-20	05-10	00-05
Margalla	%	38	20	14	28
7 (ABC)	Particles Size (mm)	22-38	13-22	05-13	00-05
Babuzai	%	29	17	20	24
8 (ABC)	Particles Size (mm)	25-38	10-25	05-10	00-05
Sadu Khel	%	27	32	5	36
9 (ABC)	Particles Size (mm)	25-38	13-25	05-13	00-05
Margalla	%	35	10	17	38
10 (ABC)	Particles Size (mm)	22-38	13-22	05-13	00-05
Babuzai	%	29	17	20	34
11 (ABC)	Particles Size (mm)	20-38	10-20	05-10	00-05
Khan Pur	%	33.00	20.00	15.00	32.00
12 (ABC)	Particles Size (mm)	25-50	12-25	05-12	00-05
Choondiko	%	30.00	30.00	10.00	30.00

Table 3-2: Blending of Aggregates for Asphalt Wearing Course

Aggregate Type		Asphalt Wearing Course Blend		
1 (AWC)	Particles Size (mm)	12-20	05-12	00-05
Pathar Garh	%	32	28	40
2 (AWC)	Particles Size (mm)	10-20	05-10	00-05
Shah Khalid	%	35	29	36
3 (AWC)	Particles Size (mm)	10-20	05-10	00-05
Daraban	%	39	22	39
4 (AWC)	Particles Size (mm)	10-20	05-10	00-05
Sargodha	%	40	25	35
5 (AWC)	Particles Size (mm)	20-25	12-20	05-12
Margalla	%	7	28	25
6 (AWC)	Particles Size (mm)	12-20	05-12	00-05
Kacha Morh	%	38	24	38
7 (AWC)	Particles Size (mm)	12-20	05-12	00-05
Margalla	%	32	30	38
8 (AWC)	Particles Size (mm)	19-25	13-19	05-13
Aamri	%	17	17	31
9 (AWC)	Particles Size (mm)	12-20	05-12	00-05

Aggregate Type		Asphalt Wearing Course Blend		
Margalla	%	25	35	40
10 (AWC)	Particles Size (mm)	10-20	05-10	00-05
Sadu Khel	%	43	38	39
11 (AWC)	Particles Size (mm)	10-20	05-10	00-05
Margalla	%	29	32	39
12 (AWC)	Particles Size (mm)	10-20	05-10	00-05
Babuzai	%	39	35	26
13 (AWC)	Particles Size (mm)	10-20	05-10	00-05
Khan Pur	%	33	26	41
14 (AWC)	Particles Size (mm)	10-20	05-10	00-05
Choondiko	%	30	34	36
15 (AWC)	Particles Size (mm)	10-20	05-10	00-05
Choondiko	%	30	32	38

Physical properties of aggregates specific gravities, absorption, loss angeles abrasion, soundness, clay lumps, average sand equivalent, and flakiness and elongation index are enlisted in Tables below. Aggregates used in these projects has satisfied the general specifications of NHA [2].

Table 3-3: Physical Properties of Aggregates for ABC

Data No.	Loss Angeles Abrasion (%)	Soundness (%)	Clay Lumps	Average Sand Equivalent (%)	Flakiness and Elongation (%)
1 (ABC)	26.4	3.83	0.13	62.0	5.5
2 (ABC)	16.8	2.60	0.44	78.6	1.4
3 (ABC)	22.4	3.56	0.13	61.4	4.5
4 (ABC)	25.0	2.43	0.27	61.5	3.7
5 (ABC)	22.0	1.33	0.17	57.0	8.6
6 (ABC)	22.3	4.10	0.38	86.4	5.2
7 (ABC)	19.8	1.48	0.07	61.0	7.7
8 (ABC)	17.6	2.55	0.27	63.0	9.4
9 (ABC)	19.9	2.71	0.24	70.1	7.4
10 (ABC)	19.7	2.55	0.27	67.2	2.9
11 (ABC)	16.2	2.40	0.17	75.4	1.7
12 (ABC)	23.1	2.69	0.38	59.0	4.0

Table 3-4: Physical Properties of Aggregates for AWC

Data No.	Loss Angeles Abrasion (%)	Soundness (%)	Clay Lumps	Average Sand Equivalent (%)	Flakiness and Elongation (%)
1 (AWC)	18.6	3.11	0.12	79.3	1.50
2 (AWC)	22.8	3.62	0.18	60.0	5.70
3 (AWC)	19.5	2.80	0.23	55.0	6.10
4 (AWC)	25.1	1.85	0.33	47.3	9.40

Data No.	Loss Angeles Abrasion (%)	Soundness (%)	Clay Lumps	Average Sand Equivalent (%)	Flakiness and Elongation (%)
5 (AWC)	17.0	3.26	0.17	70.0	1.80
6 (AWC)	22.4	2.89	0.50	78.8	4.87
7 (AWC)	16.2	2.55	0.22	62.3	1.10
8 (AWC)	21.2	2.15	0.75	63.0	3.25
9 (AWC)	22.8	1.79	0.37	57.0	6.20
10 (AWC)	22.2	1.23	0.19	63.0	9.40
11 (AWC)	21.9	2.87	0.28	61.3	6.28
12 (AWC)	18.4	4.73	0.93	66.2	3.99
13 (AWC)	19.3	3.11	0.16	75.3	1.80
14 (AWC)	24.0	2.53	0.24	56.0	3.80
15 (AWC)	23.0	1.61	0.16	62.0	3.67

Table 3-5: Specific Gravities and Absorption for ABC

Data No.	Coarse Aggregates				Fine Aggregates			
	Bulk Specific Gravity (OD)	Bulk Specific Gravity (SSD)	Apparent Specific Gravity	Absorption (%)	Bulk Specific Gravity (OD)	Bulk Specific Gravity (SSD)	Apparent Specific Gravity	Absorption (%)
1 (ABC)	2.680	2.697	2.727	0.66	2.654	2.686	2.742	1.20
2 (ABC)	2.693	2.704	2.731	0.69	2.677	2.685	2.700	0.99
3 (ABC)	2.618	2.640	2.679	0.88	2.699	2.732	2.792	1.10
4 (ABC)	2.618	2.640	2.679	0.88	2.702	2.735	2.795	1.10
5 (ABC)	2.721	2.741	2.776	0.74	2.669	2.720	2.813	1.91
6 (ABC)	2.635	2.657	2.696	0.63	2.657	2.689	2.745	1.20
7 (ABC)	2.758	2.771	2.796	0.50	2.697	2.734	2.800	1.37
8 (ABC)	2.654	2.675	2.709	0.76	2.602	2.639	2.703	1.43
9 (ABC)	2.682	2.701	2.734	0.63	2.652	2.687	2.749	1.33
10 (ABC)	2.670	2.688	2.719	0.68	2.654	2.678	2.728	1.09
11 (ABC)	2.681	2.702	2.738	0.78	2.662	2.687	2.730	0.93
12 (ABC)	2.659	2.674	2.700	0.57	2.646	2.669	2.726	1.26

Table 3-6: Specific Gravities and Absorption for AWC

Data No.	Coarse Aggregates				Fine Aggregates			
	Bulk Specific Gravity (OD)	Bulk Specific Gravity (SSD)	Apparent Specific Gravity	Absorption (%)	Bulk Specific Gravity (OD)	Bulk Specific Gravity (SSD)	Apparent Specific Gravity	Absorption (%)
1 (AWC)	2.623	2.645	2.681	0.83	2.627	2.658	2.711	1.18
2 (AWC)	2.664	2.685	2.721	0.79	2.674	2.709	2.773	1.34
3 (AWC)	2.668	2.687	2.721	0.73	2.635	2.685	2.774	1.91
4 (AWC)	2.752	2.763	2.792	0.60	2.715	2.726	2.750	1.30
5 (AWC)	2.623	2.645	2.681	0.83	2.627	2.658	2.711	1.18
6 (AWC)	2.675	2.690	2.720	0.65	2.676	2.707	2.760	1.14

Data No.	Coarse Aggregates				Fine Aggregates			
	Bulk Specific Gravity (OD)	Bulk Specific Gravity (SSD)	Apparent Specific Gravity	Absorption (%)	Bulk Specific Gravity (OD)	Bulk Specific Gravity (SSD)	Apparent Specific Gravity	Absorption (%)
7 (AWC)	2.667	2.690	2.729	0.86	2.616	2.644	2.690	1.05
8 (AWC)	2.641	2.663	2.697	0.66	2.627	2.658	2.707	1.22
9 (AWC)	2.646	2.666	2.701	0.76	2.612	2.642	2.693	1.15
10 (AWC)	2.689	2.712	2.752	0.86	2.644	2.681	2.746	1.41
11 (AWC)	2.651	2.673	2.709	0.76	2.618	2.648	2.700	1.14
12 (AWC)	2.635	2.655	2.676	0.79	2.654	2.692	2.736	1.14
13 (AWC)	2.628	2.649	2.643	0.83	2.629	2.682	2.705	1.08
14 (AWC)	2.661	2.678	2.707	0.65	2.633	2.667	2.725	1.28
15 (AWC)	2.616	2.639	2.678	0.90	2.699	2.728	2.779	1.07

3.4. BITUMEN

Bitumen is the key component of asphalt concrete which acts as adhesive material. It is termed as viscoelastic materials having properties of both viscous and that of elastic materials. The properties of viscosity, or elasticity, or visco-elasticity depends majorly on temperature and loading time.

In this study, the bitumen of penetration grade 60/70 was used for all the projects. The bitumen was obtained from various oil refineries of Pakistan i.e. Parco, Attock Oil Refinery, National Refinery Limited, and Attock Petroleum Limited. In order to control the consumption of bitumen, conventional tests i.e. specific gravity of bitumen, softening point test, flash and fire point tests, ductility and penetration tests were performed according to standards of AASHTO and their results for ABC and AWC are shown in Tables below

Table 3-7: Test Results of Bitumen Binder for ABC

Data No.	Bitumen (Grade 60-70)					
	Bitumen Specific Gravity	Softening Point (ºC)	Flash Point (ºC)	Fire Point (ºC)	Ductility (cm)	Penetration (tenth of mm)
1 (ABC)	1.020	49.0	252	287	100+	61.0
2 (ABC)	1.023	50.2	279	301	100+	63.8
3 (ABC)	1.021	47.9	283	303	100+	65.0
4 (ABC)	1.020	48.6	278	298	100+	65.0
5 (ABC)	1.020	50.0	255	292	100+	65.0
6 (ABC)	1.023	50.5	279	305	100+	65.6
7 (ABC)	1.024	48.0	288	303	100+	66.1

Data No.	Bitumen (Grade 60-70)					
	Bitumen Specific Gravity	Softening Point (ºC)	Flash Point (ºC)	Fire Point (ºC)	Ductility (cm)	Penetration (tenth of mm)
8 (ABC)	1.023	47.0	266	274	100+	68.0
9 (ABC)	1.021	48.3	267	285	100+	64.2
10 (ABC)	1.022	47.6	284	315	100+	66.0
11 (ABC)	1.023	49.3	269	280	100+	65.5
12 (ABC)	1.018	49.4	274	281	100+	66.0

Table 3-8: Test Results of Bitumen Binder for AWC

Data No.	Bitumen (Grade 60-70)					
	Bitumen Specific Gravity	Softening Point (ºC)	Flash Point (ºC)	Fire Point (ºC)	Ductility (cm)	Penetration (tenth of mm)
1 (AWC)	1.022	50.2	276	291	100+	62.8
2 (AWC)	1.024	48.0	313	338	100+	62.0
3 (AWC)	1.021	47.5	308	334	100+	63.5
4 (AWC)	1.020	45.0	301	328	100+	63.0
5 (AWC)	1.022	50.0	275	306	100+	64.8
6 (AWC)	1.021	50.1	276	295	100+	65.3
7 (AWC)	1.021	49.6	259	273	100+	64.8
8 (AWC)	1.022	46.7	264	286	100+	64.0
9 (AWC)	1.020	46.0	271	303	100+	66.0
10 (AWC)	1.023	47.0	266	274	100+	68.0
11 (AWC)	1.021	48.3	267	285	100+	64.2
12 (AWC)	1.022	47.6	284	315	100+	66.0
13 (AWC)	1.023	49.7	274	297	100+	63.7
14 (AWC)	1.018	50.4	276	296	100+	66.0
15 (AWC)	1.016	48.0	278	300	100+	67.0

3.5. DATA DIVISION AND PREPROCESSING

A dataset of 253 samples for ABC and 343 for AWC was collected for development of models employing MEP approach. The model's efficiency is dependent on the distribution of the datasets [63]. The accuracy of newly constructed model for prediction majorly depends on (a) size of data (b) characteristics of data and (c) relationship between input and output parameters [64]. From literature, it is observed that if input parameters are considered in excess which have low correlation with output parameters, then it can escalate the complexity of model putting adverse effects on the performance of models [65]. The collected dataset contains information about Ps (%), Pb (%), Gmb, Gsb, Gmm, Va (%), VMA (%), VFA (%), MS and MF.

Finally, eight input parameters were selected for development of MEP models. For training of MS and MF of ABC 70% of data (177 data points) was used while 15% (38 data points) was used testing and 15% (38 data points) was used for validation of the developed models. Whereas, for training of MS and MF of AWC 70% of data (241 data points) was used while 15% (51 data points) was used testing and 15% (51 data points) was used for validation of the developed models.

3.6. MULTI- COLLINEARITY

The multi-collinearity problem, which develops owing to the inter-dependence of input parameters, is prevalent issue in applications of machine learning algorithms [66]. It has potential to raise the strength of relationships among variables, lowering the efficiency of the models being developed. It has advocated that the R among two input parameters should be less than 0.8 to prevent this problem [67]. R is calculated for all input parameter combinations, as shown in Table 0-1 and 0-2. The Table 0-1 and 0-2 shows that whether positive or negative, R is smaller than the stipulated limit i.e. 0.8, indicating that there would be no risk of multi-collinearity amongst input parameters during modelling.

3.7. DATA STATISTICAL INFORMATION

The generalization ability of the developed models is influenced by the distribution of their input variables. Frequency histograms are provided in Figure 0-1 and 0-2 in Appendix A for ABC and AWC datasets, respectively. The distribution of input parameters is not uniform, and frequencies of input parameters are adequately high, as shown in Figure 0-1 and 0-2 in Appendix A. It is important to keep in mind that if variables have high frequencies, the chances of getting a better model are increased. The table 0-3 and 0-4 in Appendix A provides statistical range of input data of the datasets for ABC and AWC, respectively, in order to present data in more comprehensible manner. The tables show the units of parameters, data centre (mean and median), most frequent values (mode), dispersion (standard deviation, sample variance and coefficient of variance), data extremes (minimum and maximum), and shapes of distribution (kurtosis and skewness), making data interpretation relatively straightforward. The table 0-3 and 0-4 in Appendix A show that Pb (%) ranges from 2.5-5.0, and 2.5-5.5 for ABC and AWC, respectively. The statistics of the datasets demonstrates that, suggested machine learning models are applicable to a large range of input data, enhancing their utility. It should be noted that only few research studies have predicted MS and MF separately for ABC and AWC. As a result, distinct datasets have been compiled for ABC and AWC and considered for respective development of models.

3.8. MODEL DEVELOPMENT AND EVALUATION CRITERIA

Several fitting input parameters are required in MEP which need to be identified before model development for a generalized and robust model. The fitting input parameters are carefully chosen keeping in sight the recommendations made previously and with trial and error approach [68]. The size of population specifies the number of programs which needs to be evolved. A model developed with high size of population might be relatively accurate but it would be complex and might take longer time to converge. Although, as size increases beyond a threshold limit, issue may arise, regarding the overfitting of the model.

Table 3-9: Parameters Setting for MEP Model

Parameters Setting for MEP Model	
Number of Subpopulations	50
Subpopulation Size	100
Code Length	50
Crossover Probability	0.9
Crossover Type	Uniform
Mathematical Operators	$+, -, \times, \div, Power, Sqrt, Exp, Sin, Cos, Tan$
Mutation Probability	0.01
Tournament Size	2
Functions	0.5
Variables	0.5
Number of Generations	1000

At the beginning, sub-population size of 10 and 100 number of generations were considered for initiation of the project with basic mathematical parameters i.e. subtraction, addition, division, and multiplication. The parameters including subpopulation, and number of generation were gradually increased in trials by addition of mathematical parameters in the models to reduce the error size. The final selection of parameters for 4 models, based on acceptable error range, are shown in Table 3-9 aobve.

The accuracy level which model's algorithm should achieve is determined by the number of generations prior to its termination. The larger the number of generations in a run, the minimum the statistical errors will be. Likewise, crossover and mutation rate indicates the offspring's probability of undergoing these genetic operations. Range for rate of cross over lies between 50%–95%. Various combination of these settings were tested on data sample and optimum combination was chosen based on model's performance attributes, which are shown in Table 3-9 above. Overfitting of the data is one of major challenges in AI based modelling. The model's efficiency is high, when using the original data but the efficiency reduces considerably when un–seen data is used. To avoid this issue, it is recommended that trained model be tested on testing or un–seen dataset [69, 70]. Consequently, the entire dataset was randomly divided into sets of training, validation and testing. In modeling, datasets of training and validation were processed. The validation model was then tested on the testing dataset which was not included in the development of the model. The distribution of data in all three datasets was assured to be consistent. For the current research study, 70%, 15%, and 15% of the data were used for training, testing, and validation, respectively. On all three datasets, the final developed models outperformed the competition. MEPX v 2021.08.05.0-beta, a commercially available computing tool, was used to implement the MEP algorithm.

The selection of influential input parameters for prediction of output parameters is the starting step in development of a model. In order to develop the model, the parameters affecting MS and MF of the MMDM were selected. Numerous trials were made and the results were calculated to assess best and simplest influencing parameters for the development of model. The equations below are used to MS and MF of ABC and AWC of asphalt pavements.

$$MS = f(P_s(\%), P_b(\%), G_{mb}, G_{sb}, G_{mm}, V_a(\%), VMA(\%), VFA(\%))$$

$$MF = f(P_s(\%), P_b(\%), G_{mb}, G_{sb}, G_{mm}, V_a(\%), VMA(\%), VFA(\%))$$

Where,

P_s (%): Percentage of Aggregates

P_b (%): Percentage of binder content

Gmb: Bulk Specific Gravity of Compacted Aggregate

Gsb: Bulk Specific Gravity of Aggregate

Gmm: Max Specific Gravity Paving Mix

Va (%): Percentage of Air Voids

VMA (%): Voids in Mineral Aggregates

VFA (%): Voids Filled by Bitumen

The algorithm begins by creating population of most possible solutions. The process of the algorithm is iterative, and with each generation, it gets closer to the solution. Within the solution population, each generation's fitness is assessed. The algorithm of MEP continues to advance unit the pre–specified fitness function i.e. RMSE or R, remains unchanged. For each trained model, the objective function (OF) is also assessed in this research study, because it reflects the impact of RMSE, R and frequency of data points, to quantify the overall efficiency. If the results of the model for the three datasets (i.e. training, testing, and validation) are not accurate, the process is repeated, by increasing the size and number of subpopulations, incrementally. After that, the final model is chosen based on minimum OF. However, it was determined that certain models performed better on the training sets than on the testing set, indicating over–fitting of the model, which should be dodged. It's worth noticing that number of generations it takes for a model to evolve has an in impact on mode's accuracy. A model would keep evolving indefinitely in these types of algorithms due to induction of additional variables into the system. The model, in this research study was terminated at thousand (1000) generations or at point when change in the fitness function was < 0.1 percent. Furthermore, an ideal model should meet the criteria for several performance indicators, as elaborated in the following discussion.

The effectiveness of model is assessed by calculating several statistical measures. These statistical errors include R, MAE, RMSE, relative squared error (RSE), RRMSE, and ρ. Moreover, another strategy to prevent model's over–fitting is to choose an optimal model by reducing the OF, as advocated by Azim et. al. [66].

In the current research study, this technique was used, and this OF is referred to as fitness function. These statistical checks have the following expressions 3-1 – 3-7:

$$R = \frac{\sum_{i=1}^{n}(x_i - \bar{x}_i)(p_i - \bar{p}_i)}{\sqrt{\sum_{i=1}^{n}(x_i - \bar{x}_i)^2 \sum_{i=1}^{n}(p_i - \bar{p}_i)^2}} \qquad \text{Equation (3-1)}$$

$$MAE = \frac{\sum_{i=1}^{n}|x_i - p_i|}{n} \qquad \text{Equation (3-2)}$$

$$RMSE = \sqrt{\frac{\sum_{i=1}^{n}(x_i - p_i)^2}{n}} \qquad \text{Equation (3-3)}$$

$$RSE = \frac{\sum_{i=1}^{n}(p_i - x_i)^2}{\sum_{i=1}^{n}(\bar{x}_i - x_i)^2} \qquad \text{Equation (3-4)}$$

$$RRMSE = \frac{1}{|\bar{x}|}\sqrt{\frac{\sum_{i=1}^{n}(x_i - p_i)^2}{n}} \qquad \text{Equation (3-5)}$$

$$\rho = \frac{RRMSE}{1 + R} \qquad \text{Equation (3-6)}$$

$$OF = \left(\frac{n_T - n_{TE}}{n}\right)\rho_T + 2\left(\frac{n_{TE}}{n}\right)\rho_{TE} \qquad \text{Equation (3-7)}$$

Where p_i, x_i, $\bar{p}_i$ and $\bar{x}_i$, denote the i^{th} predicted, experimental, mean predicted and mean experimental values, respectively and n denotes total number of values in the dataset used for development of models. The training and testing sets are denoted by abbreviations T and TE, respectively. An accurate model has a high R value while the statistical errors are low. R has been recommended by the researchers to assess the linear dependency among input and output parameters [71] with a value greater than 0.8 indicating a decent correlation between experimental and predicted values [72, 73]. Due to insensitivity of R with "/" or "×"of output with constant, it could not be considered solely as a measure of overall model efficiency. The average magnitude of errors can be measured using MAE and RMSE. Both of these parameters, however, have their individual implication. In RMSE, errors are squared before average is estimated, giving larger errors more weight. A high RMSE value indicates that the amount of high-error predictions is significantly more than the expected, and should be excluded. MAE, on the other hand, gives large errors a low weight and is always smaller than RMSE. Likewise, Despotovic et. al. (2016)

recommended that, a model is considered to be excellent if, RRMSE values are between 0.10 and 0, and good if the value is between 0.20 and 0.11 [74]. The range of values for ρ and OF is 0–infinity. If the values of OF and ρ are less than 0.2, the model can be considered as good [63]. While using OF, it should be noted that OF considers three factors at the same time i.e. R, RRMSE, and the relative % of data in various datasets (training and testing). As a result, a low value of OF indicates that the model's overall performance is superior. As stated previously, numerous trial runs were carried out and the models having the lowest values of OF are being stated in this research study. Additionally, validation of the developed models was also carried out using criteria suggested by various researchers, which are described in Table 3-10 below;

Table 3-10: External Validation of Models

S. No.	Equation	Condition	Suggested by
1	$k = \frac{\sum_{i=1}^{n}(x_i \times p_i)}{\sum_{i}^{n} p_i^2}$	$0.85 < k < 1.15$	Golbraikh and Tropsha, 2002
2	$k' = \frac{\sum_{i=1}^{n}(x_i \times p_i)}{\sum_{i=1}^{n} x_i^2}$	$0.85 < k' < 1.15$	Golbraikh and Tropsha, 2002
3	$R_m = R'^2_0 \times \left(1 - \left\lvert\sqrt{R'^2_0 - R^2_0}\right\rvert\right)$	$R_m > 0.5$	Roy and Roy, 2008
	$R_0^2 = 1 - \frac{\sum_{i=1}^{n}(p_i - x_i^{r0})^2}{\sum_{i=1}^{n}(p_i - \overline{p_i})^2}$	$R_0^2 \cong 1$	
	$R'^2_0 = 1 - \frac{\sum_{i=1}^{n}(x_i - p_i^{r0})^2}{\sum_{i=1}^{n}(x_i - \overline{x_i})^2}$	$R'^2_0 \cong 1$	
	$x_i^{r0} = k \times p_i$		
	$p_i^{r0} = k' \times e_i$		

3.9. SUMMARY

This chapter focused on the research methodology adopted for the current research study. In this chapter the procedure of data collection with the properties of aggregates and bitumen have been discussed. This chapter also includes data division and preprocessing, multi-collinearity discussion, data statistical information followed by model development and evaluation criteria.

CHAPTER 4: RESULTS AND ANALYSIS

4.1. INTRODUCTION

The models for MS and MF of ABC, and AWC, respectively were developed using MEP programming in MEPX v 2021.08.05.0-beta as already explained in chapter 3. The results obtained from the equations obtained from the developed models and their analysis is described in this chapter.

4.2. FORMULATION OF MECHANICAL PROPERTIES

The decoded mathematical equations for the calculation of corresponding properties based on eight input parameters are taken from MEP for ABC and AWC. The explicit expressions for MS and MF of ABC, and MS and MF of AWC, respectively, are shown in equations 8-11 below;

$$\mathrm{ABC-MS} = \left(\mathrm{a} + \left(\left(\mathrm{a} + \left(\left((2\mathrm{d} \times \sqrt{2\mathrm{d}}) + \mathrm{b} \right) - \left(\left((2\mathrm{f}) + \left((\sin(2\mathrm{d}) - \sin(\mathrm{d})) \times 2\mathrm{d} \right) \right) - \tan(2\mathrm{f}) \right) \right) \right) - (\mathrm{e} \times \tan(\mathrm{d}^2)) \right) \right) + \mathrm{a} \qquad \text{Equation (4-1)}$$

where

$$a = tan\left(e^{e^{(sin(P_S(\%)) - sin(2P_S(\%)))}}\right)$$

$$b = tan\big(tan\big(tan\big(P_s(\%) \times P_s(\%)\big)\big)\big)$$

$$c = V_a(\%) - VFA(\%)$$

$$d = P_s(\%)$$

$$e = P_b(\%)$$

$$f = (2d + sin(2d)) + (c)$$

$$\mathrm{ABC-MF} = \left(\left(\frac{e^{\frac{a}{c}} + \cos(a) + b + d}{e + \sin(b)} - \sin(\cos(a) \times a)\right) - \frac{\frac{f}{\cos(a) \times a + a}}{\cos(a) \times a}\right) - \sin(b) \qquad \text{Equation (4-2)}$$

where

$$a = {G_{sb}}^{G_{sb}} + {G_{sb}}^{G_{sb}}$$

$$b = e^{cos(a)^{G_{mm}}}$$

$$c = \frac{VFA(\%)}{G_{mm}}$$

$$d = VFA(\%) \times P_b(\%)$$

$$e = \sqrt{VFA(\%) \times P_b(\%)}$$

$$f = VFA(\%) + G_{mm}$$

$$\mathrm{AWC-MS} = (\cos(c) \times h) + \left(\left((2i - a) + \left((\cos(f) \times g) + \left((c \times d) + \tan(c)\right)\right)\right) + \cos(f) \times h\right) \qquad \text{Equation (4-3)}$$

where

$$a = P_s(\%) + cos\left(VMA(\%)\right)$$

$$b = cos\left(VMA(\%)\right) + cos\left(VMA(\%)\right)$$

$$c = e^{G_{sb}}$$

$$d = P_s(\%) + sin(a - b)$$

$$e = P_b(\%)$$

$$f = VMA(\%)$$

$$g = P_s(\%)$$

$$h = e \times \left(a - (d - f)\right)$$

$$i = (sin(g) \times d) + \sqrt{b}$$

$$\mathrm{AWC-MF} = \left(\left(b - (\sin(a) - c)\right) - d\right) + \frac{\sin(\sin(c))}{(\tan(\sin(a)) + e)^{(b + \sin(a)) - f}} \qquad \text{Equation (4-4)}$$

where

$$a = e^{G_{sb}}$$

$$b = G_{mb}$$

$$c = VMA(\%)$$

$$d = V_a(\%)$$
$$e = G_{mm}$$
$$f = e^{sin\left(e^{e^{G_{sb}}}\right)}$$

The comparison between experimental and predicted values of MS and MF of ABC, and MS and MF of AWC are shown in figures 4-1 – 4-4 below for all datasets. Additionally, regression line expression are also displayed in these graphs. For an ideal scenario, the slope of the regression line should be close to one (1). It can be inferred from the figures 4-1 – 4-4 below that the developed models have significant correlation between predicted and experimental data as evident by the slopes of 0.9742, 0.9759, and 0.9624 for training, validation, and testing, respectively for MS of ABC, 0.9742, 0.9759, and 0.9624 for training, validation, and testing, respectively for MF of ABC, 0.9530, 0.9714, and 0.9029 for training, validation, and testing, respectively for MS of AWC, and 0.9581, 0.9783, and 0.9727 for training, validation, and testing, respectively for MF of AWC. The models developed, have been well trained on input parameters in order to effectively predict the values of MS and MF for ABC and AWC, respectively. Furthermore, the data points for all three datasets, the results are quite comparable to one another and close to ideal fit, showing that the models have been well trained and possess strong generalization capability i.e. the performance of the models on unseen data will be equally well. The models have performed exceptionally well on the testing data. This demonstrates that the problem regarding the over fitting of the data points employed for modelling has been greatly removed in all the models. Moreover, the number of data points employed for such empirical models has a significant impact the applicability and accuracy of such models [75]. The largest number of points i.e. 241 have been chosen in the collated database for MS and MF of AWC, hence minimum errors with high accuracy have been achieved.

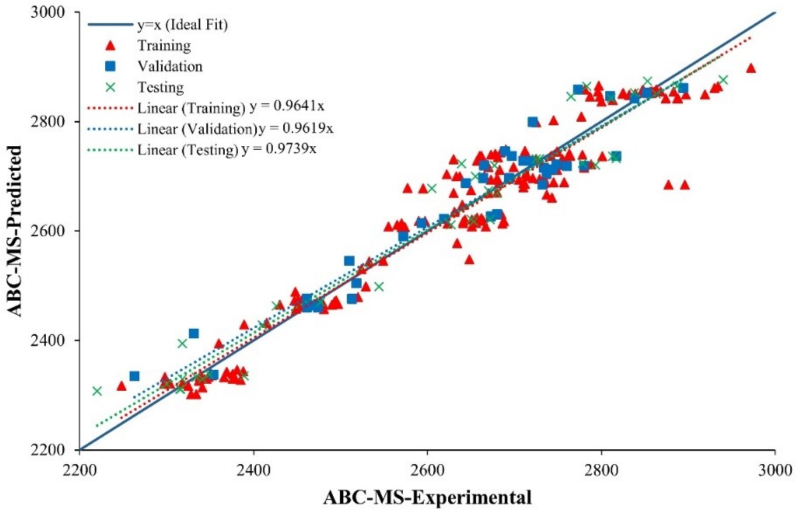

Figure 4-1: Comparison b/w Experimental and Predicted Values of ABC-MS

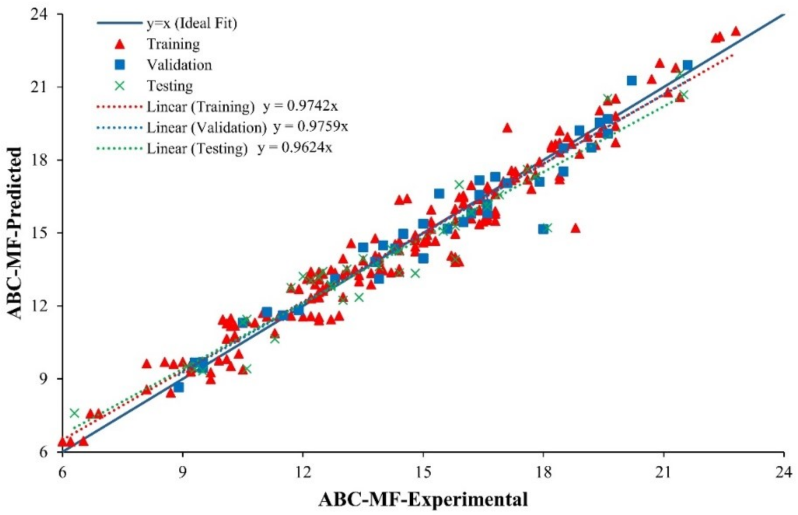

Figure 4-2: Comparison b/w Experimental and Predicted Values of ABC-MF

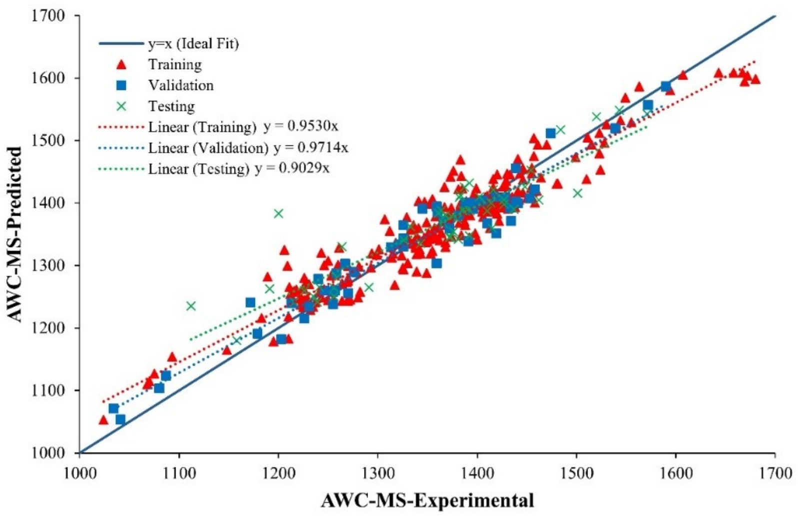

Figure 4-3: Comparison b/w Experimental and Predicted Values of AWC-MS

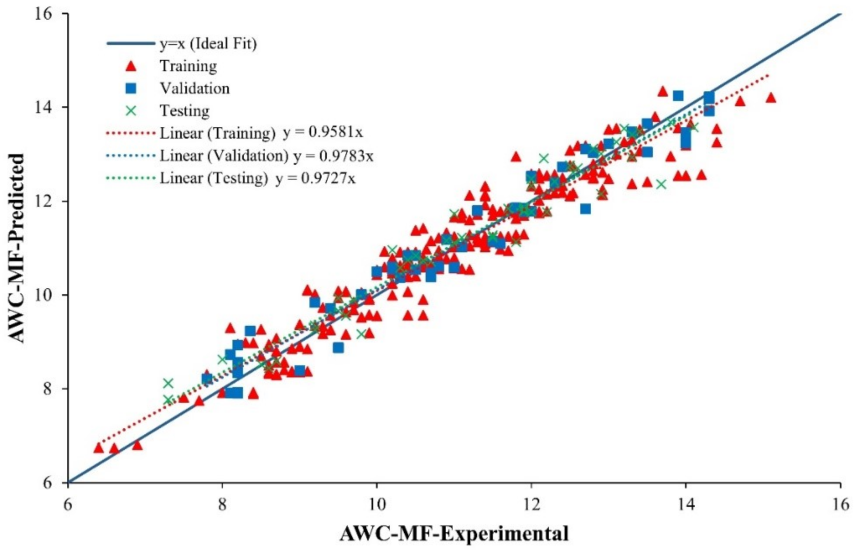

Figure 4-4: Comparison b/w Experimental and Predicted Values of AWC-MF

4.3. PERFORMANCE EVALUATION OF MEP MODELS

The amount of datasets used in developing models are also very important because reliability of developed models is dependent on these. The literature recommends a ratio greater than 5 for the number of data points to number of input parameters used in both training and un–seen (testing and validation) stages [63]. For the training stage, the ABC and AWC models have a ratio of 22.13 and 30.13, respectively. While for testing stage, the ABC and AWC models have values of 5.75 and 6.38, respectively. Statistical measure such as MAE, R, RSE, RMSE, RRMSE, ρ, and OF are used to assess performance of the developed models, as explained in Chapter 4. Table 4-1 below shows the results of these statistical checks for training, testing, and validation for ABC and AWC models.

Table 4-1: Statistical Measures for Training, Testing, and Validation

Model	Dataset	R	MAE	RMSE	RSE	RRMSE	ρ	OF
ABC-MS	Training	0.96	36.30	46.62	0.07	0.01	0.004	0.033
	Validation	0.96	33.51	41.39	0.08	0.03	0.017	
	Testing	0.97	36.94	46.71	0.06	0.03	0.017	
ABC-MF	Training	0.97	0.62	0.80	0.05	0.01	0.004	
	Validation	0.98	0.53	0.73	0.05	0.04	0.018	
	Testing	0.96	0.71	0.90	0.09	0.03	0.017	
AWC-MS	Training	0.95	26.65	33.72	0.13	0.01	0.003	0.046
	Validation	0.97	24.64	30.55	0.07	0.02	0.012	
	Testing	0.90	29.59	43.32	0.29	0.03	0.015	
AWC-MF	Training	0.96	0.37	0.47	0.09	0.01	0.003	

Model	Dataset	R	MAE	RMSE	RSE	RRMSE	ρ	OF
	Validation	0.98	0.34	0.40	0.05	0.02	0.012	
	Testing	0.97	0.31	0.41	0.06	0.03	0.013	

It is seen form the table that experimental and predicted values have strong correlation, as manifested by R of 0.96, 0.97, 0.95, and 0.96 for training, 0.96, 0.98, 0.97, and 0.98 for validation, and 0.97, 0.96, 0.90, and 0.97 for testing datasets of ABC-MS (MS of ABC), ABC-MF (MF of ABC), AWC-MS (MS of AWC), and AWC-MF (MF of AWC) models, respectively.

The results of RSE, MAE, and RMSE for all three datasets are considerably low and close, which indicates the model's strong generalization capacity and high accuracy. The MAE is 36.30, 33.5, and 36.94 for ABC-MS, 0.62, 0.53, and 0.71 for ABC-MF, 26.65, 24.64, and 29.59 for AWC-MS, and 0.37, 0.34, and 0.31 for AWC-MF, for all three datasets, respectively. The values of RMSE, for ABC-MS are 46.62, 41.39 and 46.71, for ABC-MF are 0.80, 0.73, and 0.90, for AWC-MS are 33.72, 30.55, and 43.22, and for AWC-MF are 0.47, 0.40, and 0.41, respectively for all three datasets. The results revealed that the values of MAE are lower than RMSE, indicating that criteria of analysis described in Chapter 4 is satisfied. The models developed for estimation of ABC-MS, ABC-MF, AWC-MS and AWC-MF can be labeled as excellent, based on RRMSE estimates as values are less 0.10, i.e., 0.01, 0.03, and 0.03 for ABC-MS, 0.01, 0.04, and 0.03 for ABC-MF, 0.01, 0.02, and 0.03 for AWC-MS, and 0.01, 0.02, 0.03, respectively for three datasets of all models.

The results of ρ less than 0.20 for all three datasets of the all four developed models, demonstrating that all four developed models are consistent and have the capability to forecast output parameters.

For ABC and AWC models, the values of OF are 0.033 and 0.046, respectively. These values are almost near to zero, verifying overall performance and demonstrating that problems regarding the overfitting for the proposed models has been addressed properly.

To analyze the statistics of absolute errors, the datasets for all four developed models are plotted in Figures 4-5 – 4-8 below together with absolute errors in respective points of datasets. The mean error in predicted values for ABC-MF and AWC-MF is 0.62 and 0.35, with a maximum error of 3.59 and 1.64, respectively.

Out of 253 data points for ABC-MS, only 5 points have value greater than 100 kg which accounted for 1.58% of the total data points while for AWC-MS only 8 points have value greater than 80 kg out of 343 data points which accounts for 2.33% of the total data points. According to the findings, it was concluded that for ABC-MS, ABC-MF, AWC-MS, and AWC-MF 85% of the results have errors less than 67 kg, 1.05 (0.01 in), 48 kg, and 0.63 (0.01 in), respectively.

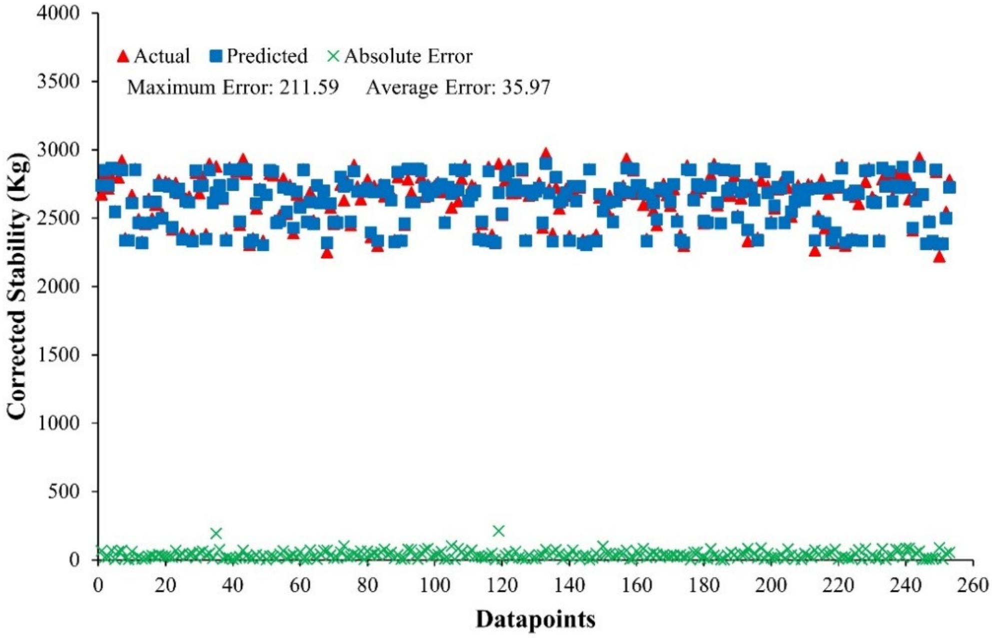

Figure 4-5: Absolute Errors of ABC-MS

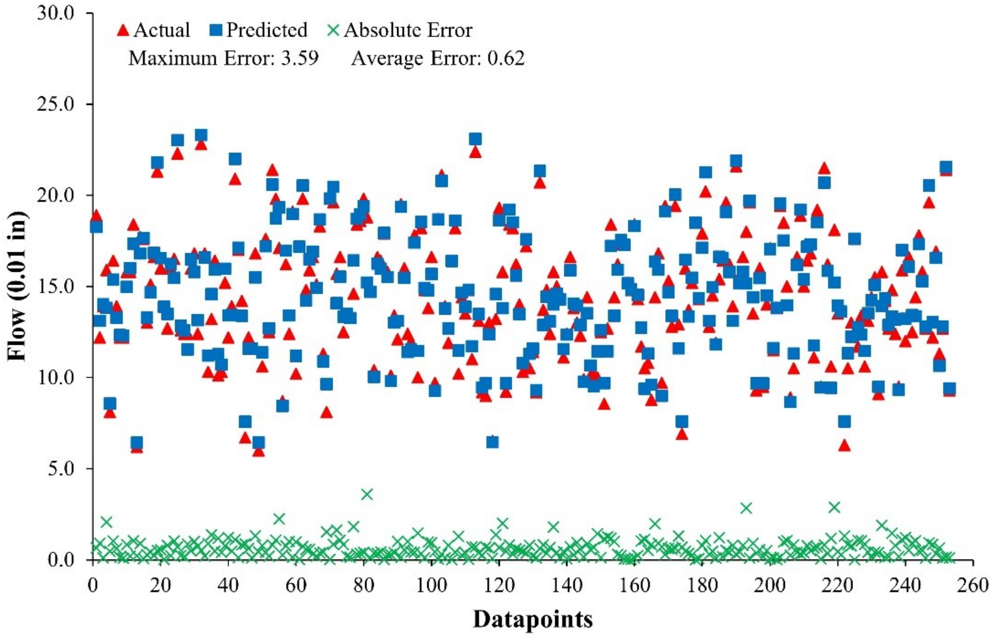

Figure 4-6: Absolute Errors of ABC-MF

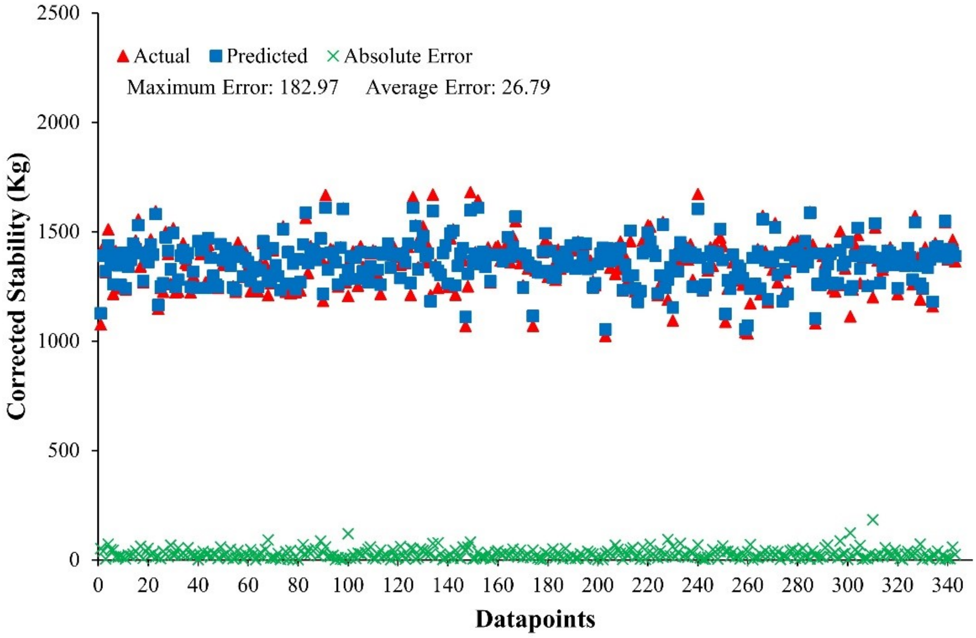

Figure 4-7: Absolute Errors of AWC-MS

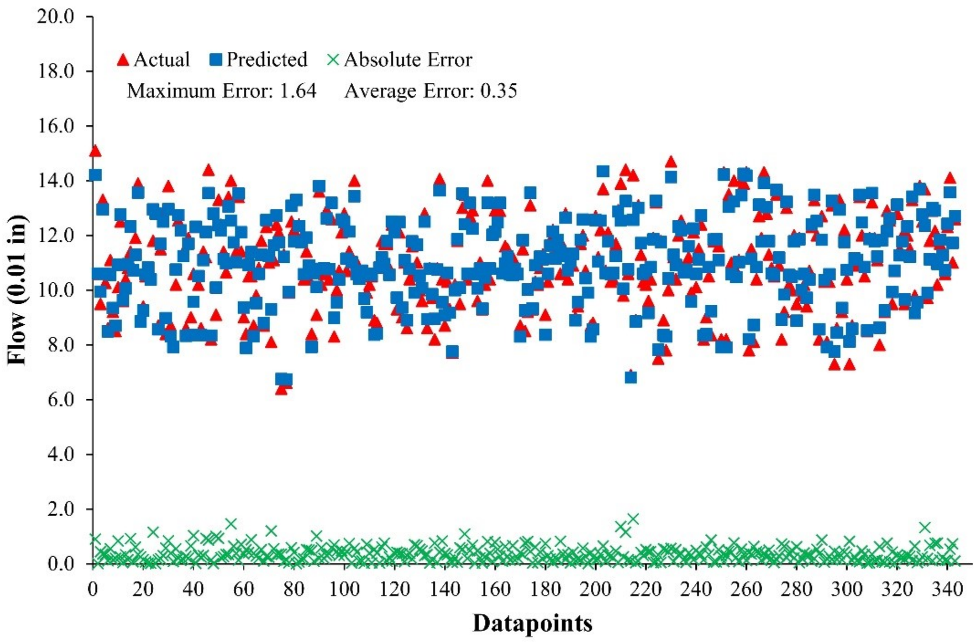

Figure 4-8: Absolute Errors of AWC-MF

Table 4-2 below shows the results of the additional criteria utilized external validation of the developed models. The slopes of the regression lines (k' or k) running through the origin have been suggested to be close to one [76]. A confirm indicator (Rm) proposed by Roy and Roy (2008), as a measure of model's external predictability. When Rm>0.5, this criteria is satisfied [77]. Table 4-2 below indicates the all four models fulfill the criteria considered in external validation of models indicating that the all the models are credible and they are not just a mere correlation of input and output parameters.

Table 4-2: Results of External Validation

Model	k	k'	Rm	R20	R'20
ABC-MS	1.0008	0.9989	0.9887	0.9999	0.9997
ABC-MF	0.9996	0.9975	0.9894	1.0000	0.9999
AWC-MS	0.9994	1.0000	0.9913	0.9999	1.0000
AWC-MF	0.9985	1.00	1.0000	1.0000	1.0000

4.4. PARAMETRIC ANALYSIS

In the case of models development based on AI, numerous analysis are required to guarantee that models are strong and perform well across a variety of data sets. Higher performance on the current datasets i.e. training, validation and testing does'nt imply that the models are superior overall. Parametric analysis has been developed by numerous researchers, and is used in this research study, to determine whether models are well–trained and not just a correlation between input and output parameters. All the input parameters are set to their mean value, the output variation is plotted against the variation in one of the input parameters over its entire range. This procedure is carried out for each of input parameters separately. The results of the parametric analysis for MS of ABC and AWC, and MF of ABC and AWC for their respective developed models are shown in Figures 4-9 and 4-10, respectively.

It must be kept in mind that the equations of MS and MF of ABC and AWC as developed by MEP does not use all the input parameters in each equation. The MEP algorithms has chosen those input parameters which have given the best results. Based on the developed equations of MEP models following Table 4-3 is shows the effectiveness of input parameters in each of models. Only those parameters are drawn in Figures 4-9 and 4-10 which are being used in the equations developed by MEP and have significant impact on the output parameters.

Table 4-3: Significant Effect of Parameters in Developed Models

Input Parameters	MS-ABC	MF-ABC	MS-AWC	MF-AWC
Ps (%)	Yes	No	Yes	No
Pb (%)	No	Yes	No	No
Gmb	No	No	No	Yes

Input Parameters	MS-ABC	MF-ABC	MS-AWC	MF-AWC
Gsb	No	Yes	Yes	Yes
Gmm	No	No	No	No
Va (%)	Yes	No	No	Yes
VMA (%)	No	No	Yes	Yes
VFA (%)	Yes	Yes	No	No

4.4.1. Marshall Stability Analysis

Figure 4-9 shows that as Ps (%), Pb (%), and Va (%) increases, MS increases to a point and subsequently drops. Additionally, it has been witnessed in the collected datasets that when Ps (%), Pb (%), and Va (%) increase, first increases and then drops. MS is likewise seen to decrease linearly when Gsb, and VMA (%) increase. The collected dataset also show that as Gsb, and VMA increases, MS decreases. MS increases linearly as VFA (%) increases. In addition it has been observed in the collected data sets that when VFA (%) increases, so does MS. Previous research studies have found similar trends in parametric analysis of MS [37].

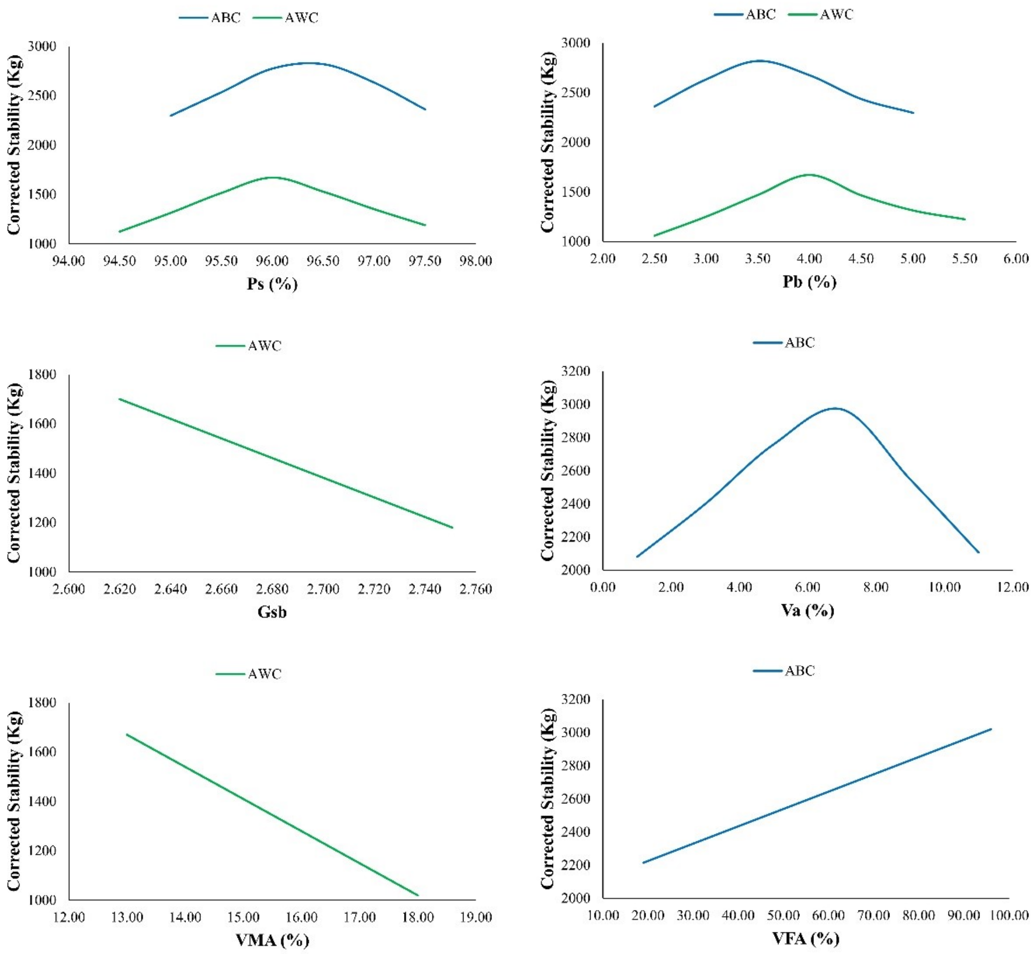

Figure 4-9: Parametric Analysis of MS-ABC-AWC

4.4.2. Marshall Flow Analysis

MF increases with increasing Pb (%), Gmb, and VFA (%), as shown in Figure 4-10. In the collected datasets, it was also discovered that when Pb (%), Gmb, and VFA (%) increases, so does MF. MF decreases linearly when Gsb, Gmm, Va (%), and VMA (%) increase. The collected datsets also show that as Gsb, Gmm, Va (%), and VMA (%) increase, MF decreases. Previous research studies have found similar trends in parametric analysis of MS [37].

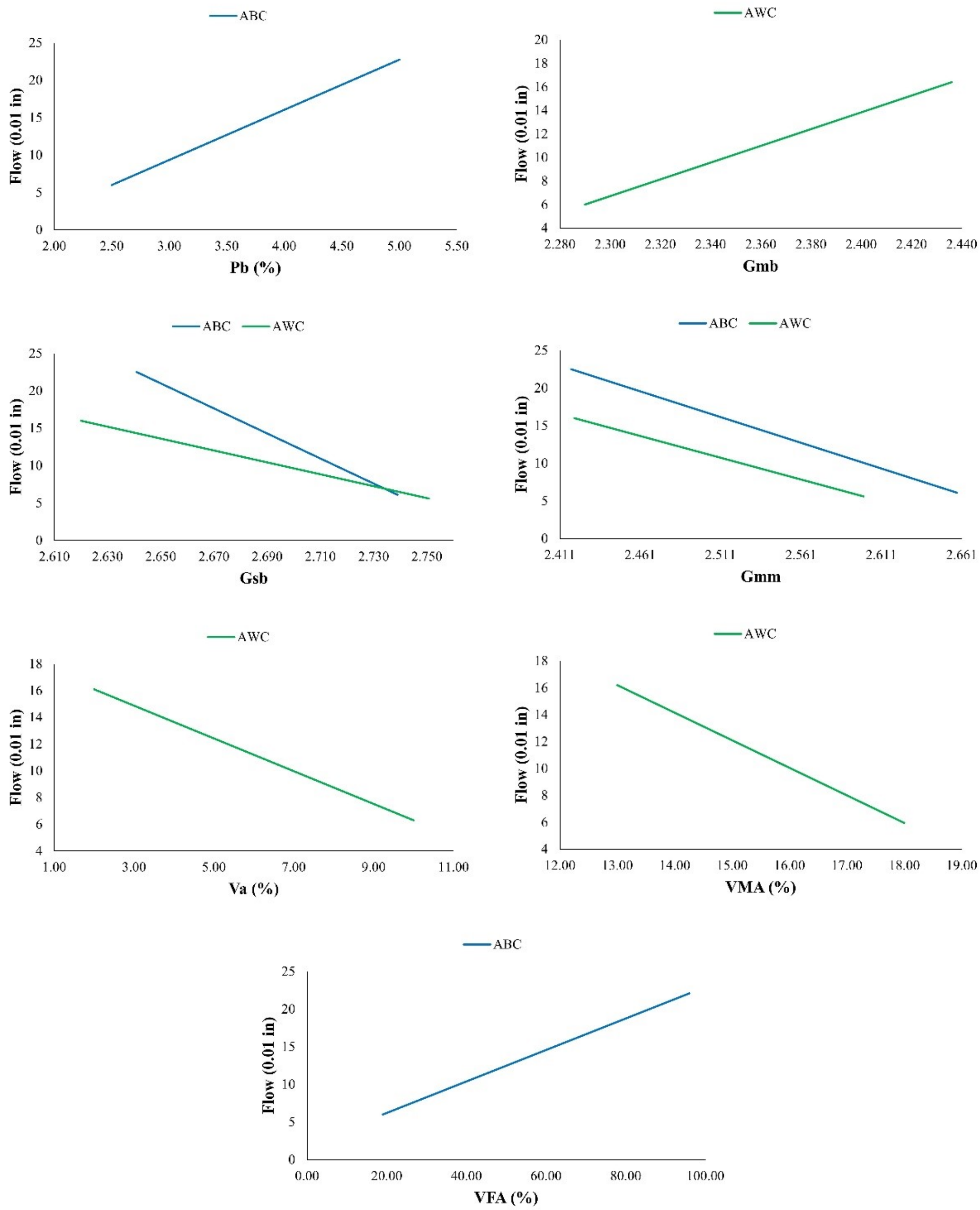

Figure 4-10: Parametric Analysis of MF-ABC-AWC

4.5. SUMMARY

In this chapter results and discussion are presented. All the results are represented in tables, figures and graphs as necessary. This chapter starts with formulation of mechanical properties followed by performance evaluation of MEP models and ends at parametric analysis for MS and MF of the developed models.

CHAPTER 5: CONCLUSIONS AND RECOMMENDATIONS

5.1. INTRODUCTION

This research study utilizes MEP, an innovative AI technique in the area of pavement engineering to develop predictive models for MS and MF of MMDM for ABC and AWC of flexible pavements. For this reason, wide and comprehensive datasets were produced from various projects of Pakistan. The researchers developed high-precision models, the following are the main conclusions of this research study;

5.2. CONCLUSIONS

- The developed models have produced results which are consistent with the experimental data and function equally well on unknown data.
- Various performance measure such as RMSE, RRMSE, R, RSE, MAE were used to assess the reliability and correction of the developed models. Furthermore, OF and ρ that the developed models are highly generalized, with the issue of overfitting effectively addressed. The results of statistical parameters validates the accuracy of the proposed MEP developed models.
- The value of R lies in between 0.90 and 0.98 for MS and MF of ABC and AWC. The range MAE ranges from 24.64 kg to 36.94 for MS of ABC and AWC, while it ranges from 0.31 (0.01 in) TO 0.71 (0.01 in) for MF of ABC and AWC.
- The developed models also met a number of external validation criteria taken from literature.
- The models developed, has the capability to predict the trends of and has incorporated input parameters successfully to predict the trends of MS and MF for flexible pavements, as revealed form parametric study.
- It is convincing from the modeling approach being proposed i.e. MEP in conjunction with validation parameters, that MEP can be utilized for predicting the Marshall parameters.

5.3. RECOMMENDATIONS

- It is suggested that different other AI techniques such SVM, Ensemble random forest regression, eXtreme gradient boosting (XGBoost), GEP, and ANFIS be used to predict MS and MF and then compared to each other to see which AI technique is more efficient to predict MS and MF.

- It is recommended that bitumen with different penetration grades such as 85/100, and 45/50, be tested on AI based Marshall parameters modelling.
- The most influential parameter in MMDM is grading of aggregates, whereas the impact of grading on MMDM has be discussed by various researchers. Hence, finding the influence of different types of grading on Marshall parameters using various AI methods, is also recommended.

5.4. SUMMARY

The study was conducted to predict the MS and MF of asphalt pavements using MEP technique. This chapter concluded the major results obtained from this research study followed by recommendations for the studies to be conducted in future.

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Appendix: A

Table 0-1: Correlation of Input Parameters for ABC

	Ps (%)	***Pb (%)***	***Gmb***	***Gsb***	***Gmm***	***Va (%)***	***VMA (%)***	***VFA (%)***
Ps (%)	1.00	-1.00	-0.15	0.01	0.59	0.76	-0.28	-0.84
Pb (%)	-1.00	1.00	0.15	-0.01	-0.59	-0.76	0.28	0.84
Gmb	-0.15	0.15	1.00	0.68	0.50	-0.48	-0.65	0.32
Gsb	0.01	-0.01	0.68	1.00	0.63	-0.03	-0.01	0.03
Gmm	0.59	-0.59	0.50	0.63	1.00	0.52	-0.40	-0.64
Va (%)	0.76	-0.76	-0.48	-0.03	0.52	1.00	0.24	-0.96
VMA (%)	-0.28	0.28	-0.65	-0.01	-0.40	0.24	1.00	0.02
VFA (%)	-0.84	0.84	0.32	0.03	-0.64	-0.96	0.02	1.00

Table 0-2: Correlation of Input Parameters for AWC

	Ps (%)	***Pb (%)***	***Gmb***	***Gsb***	***Gmm***	***Va (%)***	***VMA (%)***	***VFA (%)***
Ps (%)	1.00	-1.00	-0.37	0.09	0.68	0.93	-0.09	-0.95
Pb (%)	-1.00	1.00	0.37	-0.09	-0.68	-0.93	0.09	0.95
Gmb	-0.37	0.37	1.00	0.68	0.35	-0.50	-0.30	0.46
Gsb	0.09	-0.09	0.68	1.00	0.70	0.08	0.31	-0.02
Gmm	0.68	-0.68	0.35	0.70	1.00	0.64	-0.09	-0.65
Va (%)	0.93	-0.93	-0.50	0.08	0.64	1.00	0.16	-0.99
VMA (%)	-0.09	0.09	-0.30	0.31	-0.09	0.16	1.00	0.00
VFA (%)	-0.95	0.95	0.46	-0.02	-0.65	-0.99	0.00	1.00

Table 0-3: Statistical Range of Input and Output Data of the ABC

Parameters	Unit	Mean	Standard Error	Median	Mode	Standard Deviation	Sample Variance	Coefficient of Variation	Kurtosis	Skewness	Range	Minimum	Maximum
MS	Kg	2630	11.07	2670	2680	176.15	31027.694	6.70	-0.816	-0.433	752.000	2220	2972
MF	0.01 in	14.50	0.22	14.40	17	3.51	12.31	24.20	-0.460	-0.037	16.800	6.00	22.80
Ps (%)	%	96.50	0.04	96.50	97	0.62	0.389	0.65	-0.573	-0.143	2.500	95.00	97.50
Pb (%)	%	3.50	0.04	3.50	4	0.62	0.389	17.79	-0.573	0.143	2.500	2.50	5.00
Gmb	g/cm3	2.400	0.00	2.401	2	0.042	0.002	1.731	-0.578	0.199	0.177	2.306	2.483
Gsb	g/cm3	2.677	0.00	2.676	3	0.031	0.001	1.164	-0.625	0.783	0.097	2.641	2.738
Gmm	g/cm3	2.542	0.00	2.540	3	0.045	0.002	1.769	0.608	0.139	0.240	2.418	2.658
Va (%)	%	5.58	0.10	5.25	6	1.64	2.696	29.41	0.637	0.585	9.327	1.27	10.60
VMA (%)	%	13.48	0.07	13.37	15	1.12	1.263	8.34	0.461	0.727	5.669	11.23	16.89
VFA (%)	%	58.57	0.73	59.73	62	11.66	135.975	19.91	0.624	-0.418	69.408	19.89	89.30

Table 0-4: Statistical Range of Input and Output Data of the AWC

Parameters	Unit	Mean	Standard Error	Median	Mode	Standard Deviation	Sample Variance	Coefficient of Variation	Kurtosis	Skewness	Range	Minimum	Maximum
MS	Kg	1358	5.91	1372	1410	109.40	11968.281	8.06	0.838	-0.129	656.000	1024	1680
MF	0.01 in	10.97	0.09	10.90	10	1.70	2.876	15.46	-0.476	-0.057	8.700	6.40	15.10
Ps (%)	%	95.94	0.04	95.90	96	0.66	0.431	0.68	-0.472	0.083	3.000	94.50	97.50
Pb (%)	%	4.06	0.04	4.10	4	0.66	0.431	16.16	-0.472	-0.083	3.000	2.50	5.50
Gmb	g/cm3	2.363	0.00	2.355	2	0.032	0.001	1.344	-0.474	0.413	0.141	2.290	2.431
Gsb	g/cm3	2.660	0.00	2.655	3	0.033	0.001	1.238	1.744	1.486	0.126	2.625	2.751
Gmm	g/cm3	2.501	0.00	2.495	2	0.038	0.001	1.507	-0.212	0.497	0.172	2.427	2.599
Va (%)	%	5.50	0.08	5.25	5	1.53	2.343	27.82	-0.155	0.646	7.649	2.20	9.85
VMA (%)	%	14.79	0.04	14.68	14	0.72	0.519	4.87	1.192	0.692	4.142	13.24	17.39
VFA (%)	%	62.81	0.54	63.89	64	10.06	101.208	16.02	-0.355	-0.498	48.836	34.82	83.65

The distribution of input parameters for ABC are shown in Figure 0-1 below;

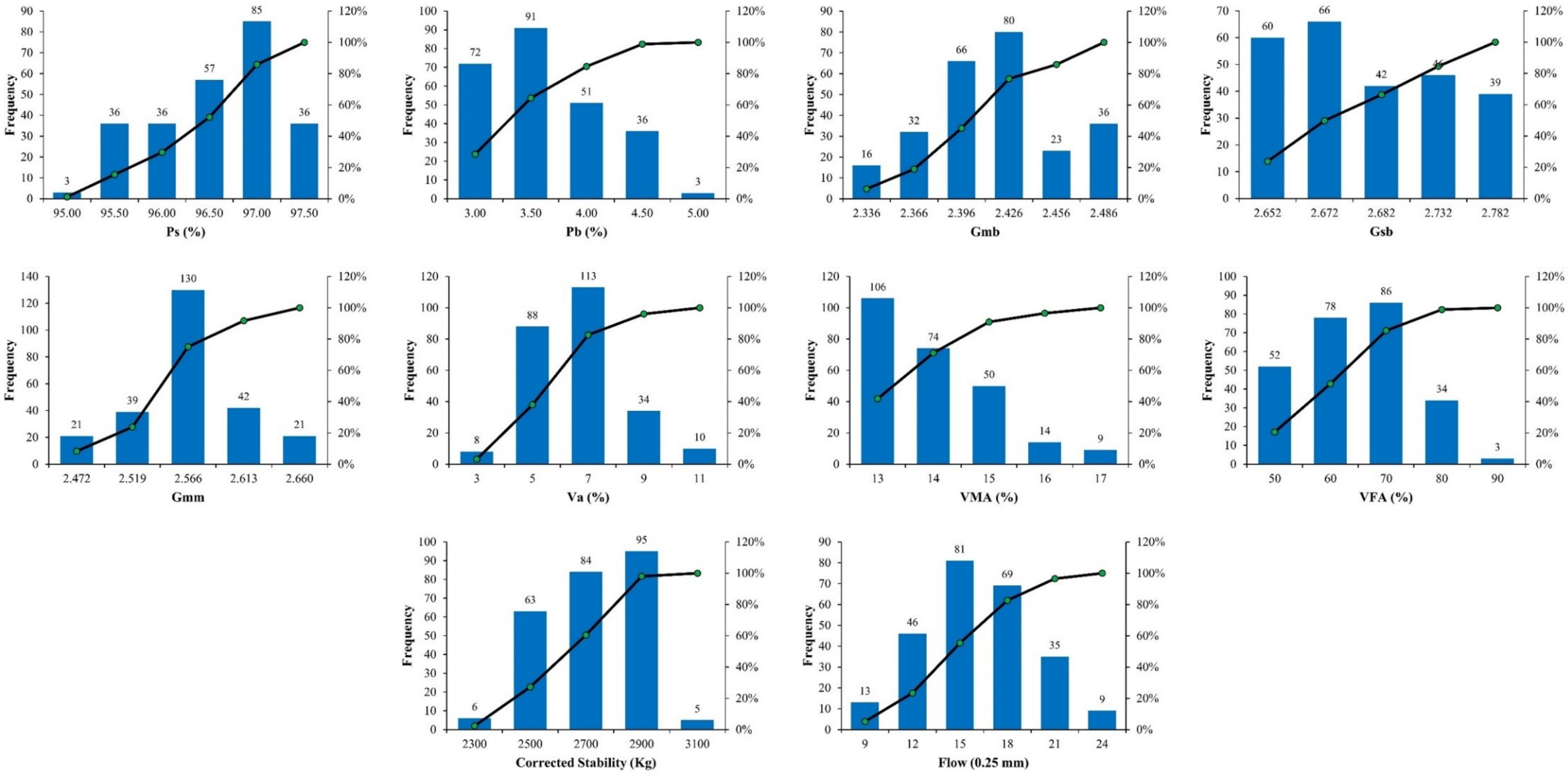

Figure 0-1: Distribution of Input Parameters for ABC

The distribution of input parameters for AWC are shown in Figures 0-2 below;

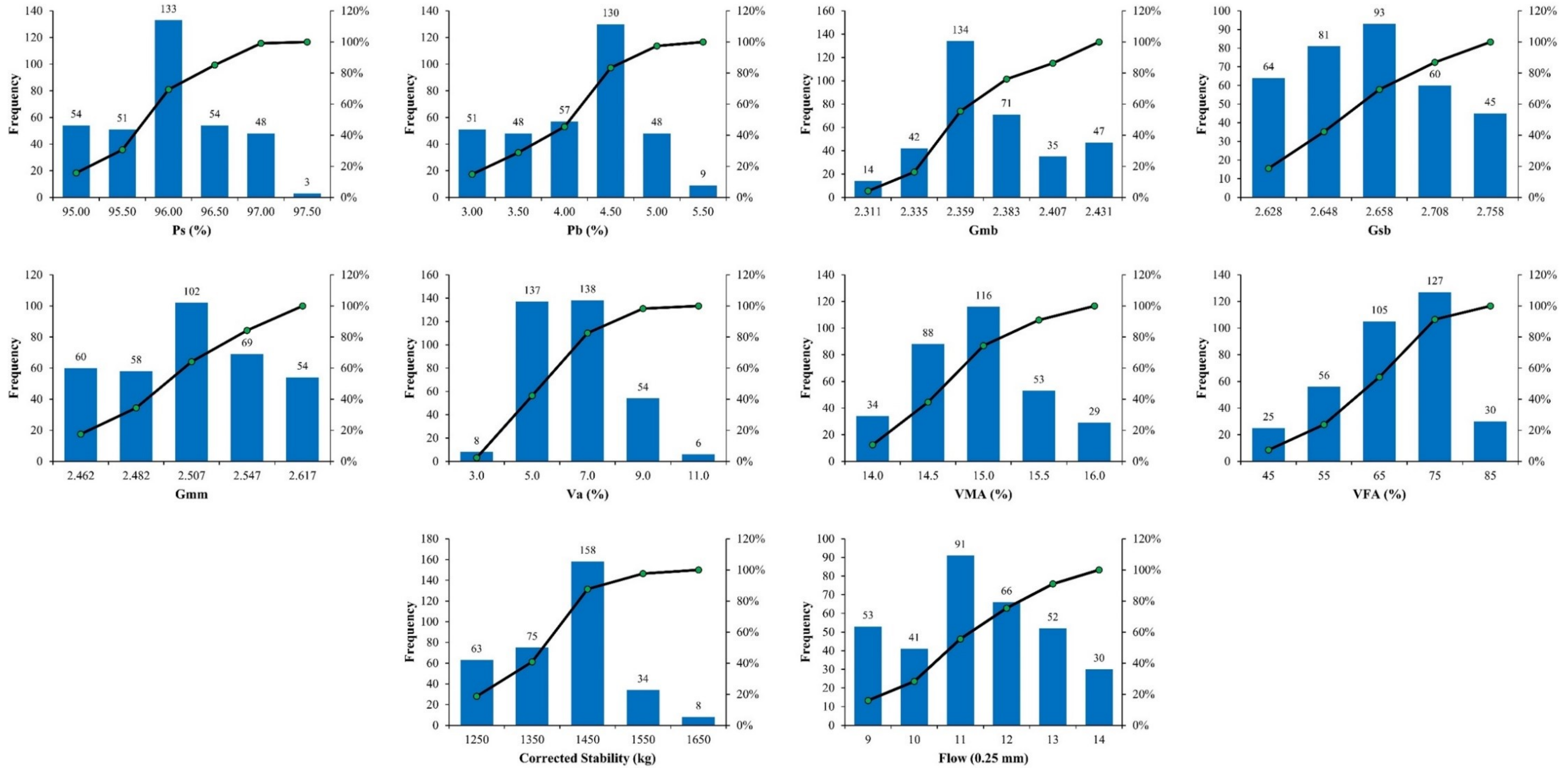

Figure 0-2: Distribution of Input Parameters for AWC