Fall 2021

Balancing fracture and fatigue performance in asphalt pavements: A hybrid mechanistic and statistical modelling approach

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BY

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DISSERTATION

Submitted to the University of New Hampshire
in Partial Fulfillment of
the Requirements for the Degree of

Doctor of Philosophy
In
Civil and Environmental Engineering

September 2021

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On 7/27/2021

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DEDICATION

To my parents. For believing in me and supporting me to follow my dreams. There was not a minute that went by that I was not thinking about you these last three years. I love you and I will see you soon!

ACKNOWLEDGEMENTS

First and foremost, to my advisor and role model Dr. Eshan Dave. This could not have been accomplished without your endless support. Thank you for challenging me every day to become better and encouraging me every step of the way. I learned far more than just Pavement Engineering from you. I was, am, and will be your student and trying to learn more and more from you. You are a true gentleman and scholar.

I also want to thank my other advisor Professor Jo Sias. Thank you for being a mentor and always providing sound answers to my questions. You were an incredible guide for every student involved in our group and I do not have a word to express how grateful I am that I had a chance to work as your student. Thank you for all the time you spent helping us.

I would like to thank my dissertation committee members, Dr. Navneet Garg, Dr. Philip Ramsey and Dr. Majid Ghayoomi for your invaluable feedback and guidance throughout this process.

The UNH technology service center, Kevan Carpenter, John Ahern and Noah Macadam were a key part in our research. They consistently supported us by being an incredible technological support, keeping our research moving forward. Thanks for being available all the time to help us.

The asphalt material research group at UNH Dr. Reyhaneh Rahbar-Rastegar, Dr. Mirkat Oshone, Dr. Rasool Nemati, Dr. Yaning Qiao, Dr. Runhua Zhang, Dr. Francesco Preti, Katie Haslet, Chibuike Ogbo, Farah Zaremotekhases, Miranda Chiappini, Anh Tran, Wei Fang and Zheng Wang. I consider you all as family, the time we spent together was a blessing.

Thank you to all my friends outside of the UNH, Joe Towle, Shayan Hassantabar, Parisa Sarzaeim, and Ahmad Mehrabi for all your support during the process.

TABLE OF CONTENTS

DEDICATION .... **iv**

ACKNOWLEDGEMENTS .... **v**

TABLE OF CONTENTS .... **vi**

LIST OF TABLES .... **x**

LIST OF FIGURES .... **xi**

ABSTRACT .... **xiii**

CHAPTER 1 .... **1**

1.1 Motivation and Background 1

1.2 Objective 5

1.3 Overall Research Approach 6

1.4 Organization of the dissertation 9

Reference 13

CHAPTER 2 .... **14**

2.1 Performance Based Specifications and Balanced Mix Design Process 14

2.2.1 History of Asphalt Mix Design 14

2.2.2 Balanced Mix Design Approach 17

2.2.3 The Current Practice of Balanced Mix Design 21

2.2 Laboratory Testing 23

2.2.1 Complex Modulus Testing (E*) 24

2.2.2 Direct Tension Cyclic Fatigue testing (DTCF) 26

2.2.4 Semi-circular Bend (SCB) Testing 28

2.2.3 Disk-shaped Compact Tension (DCT) Testing 29

2.3 Statistical Analysis and Prediction Models 30

Reference 35

CHAPTER 3 .... **39**

3.1 Chapter Introduction 39

3.2 Methodology and Results 40

Reference 43

CHAPTER 4 .... **44**

4.1 Chapter Introduction 44

4.2 Test Data 48

4.3 Data Analysis Method 54

4.3.1 Full Quadratic Model (FQM) 55
4.3.2 Artificial Neural Network (ANN) Method 57
4.3.3 Self-validated Ensemble Modelling (SVEM) 58
4.4 Results and Discussion 61
4.4.1 Full Quadratic Model (FQM) 61
4.4.2 Artificial Neural Network (ANN) Model 63
4.4.3 Self-validated Ensemble Modelling (SVEM) 67
4.4.4 Model Comparison 69
4.4.5 Sensitivity Analysis 70
4.4.6 Web-based Fracture Energy Prediction Model 72
4.4.7 Model Evaluation 75
4.5 Summary and Conclusion 76
Reference 79
CHAPTER 5 83
5.1 Chapter Introduction 83
5.2 Methodology 86
5.2.1 Laboratory Testing 86
5.2.2 Test Data 87
5.3 Data Analysis Method 89
5.3.1 Self-validated Ensemble Modelling (SVEM) 90
5.3.2 Boosted Tree 90
5.3.3 Random Forest 91
5.3.4 Support Vector Machine 92
5.3.5 Model Calibration 94
5.3.6 Hyperparameter tuning 94
5.4 Results and Discussion 95
5.4.1 Self-validated Ensemble Modelling (SVEM) 95
5.4.2 Machine Learning Algorithms 98
5.4.3 Model Comparison 100
5.4.4 Web-based Prediction Model 105
5.5 Summary and Conclusion 107
Reference 108
CHAPTER 6 111
6.1 Chapter Introduction 111
6.2 Test Data 113
6.3 Methodology 113

6.4 Data Analysis Method 117
6.5 Results and Discussion 118
6.5.1 Self-validated Ensemble Modelling (SVEM) 118
6.5.2 Machine Learning Algorithms 120
6.5.3 Model Comparison 123
6.5.4 Sensitivity Analysis 126
6.5.5 Web-based Prediction Model 128
6.6 Cracking Balance Design Diagram 133
6.5 Summary and Conclusion 137
Reference 140
CHAPTER 7...141
7.1 Summary 141
7.2 Conclusions 145
7.2.1 Exploration of cracking-related performance-based specification (PBS) indices for airfield asphalt mixtures 145
7.2.2 Fracture Properties Prediction Models 146
7.2.3 Fatigue Properties Prediction Models 147
7.3 Future Extensions 148
7.3.1 Exploration of cracking-related performance-based specification (PBS) indices for airfield asphalt mixtures 149
7.3.2 Cracking prediction model 149
APPENDICES...151
Appendix A: Paper 1 (Chapter 3) 152
Abstract 153
Introduction 154
Motivation and Objective 155
Materials and Methods 156
Materials 156
Specimen Fabrication 157
Testing and Analysis Methods 157
Pavement Performance Prediction: FAARFIELD and FlexPAVE ™ 158
Results and Discussion 159
Linear Viscoelastic (LVE) Properties 159
Fracture Properties 161
Fatigue Properties 162
Fatigue Performance based on FAARFIELD 164

Fatigue Performance Prediction from FlexPAVE^{TM} 165
Correlation between asphalt mixtures fatigue properties performance 167
Summary and Conclusion 170
Acknowledgement 171
Author Contribution Statement 171
Conflict of Interest Statement 171
References 172

LIST OF TABLES

Table 1-1 Status of the technical papers culminating from this doctorate research. 12
Table 2-1 DOT responses on existing mix design criteria [9] 23
Table 2-2 Asphalt contractor responses on existing mix design criteria [9]................................ 23
Table 4-1 Effective asphalt mix variables for fracture energy 48
Table 4-2 Different variables in each group for statistical analysis... 53
Table 4-3 Descriptive statistics of variables on this study... 54
Table 4-4 Statistical values of ANN model for groups A, B, and C.. 64
Table 4-5 Model comparison in terms of prediction accuracy and errors 70
Table 4-6 Model comparison in terms of prediction accuracy and errors 76
Table 5-1 Descriptive statistics of variables on this study... 88
Table 5-2 Hyper parameters for machine learning techniques 95
Table 5-3 C_{11} prediction model comparison in terms of prediction accuracy and errors 103
Table 5-4 C_{12} prediction model comparison in terms of prediction accuracy and errors 104
Table 6-1 E* prediction model [4].. 116
Table 6-2 Alpha prediction model comparison in terms of prediction accuracy and errors....... 125
Table 6-3 D^R prediction model comparison in terms of prediction accuracy and errors............ 126
Table 6-4 variables recommended range for prediction models.. 132
Table 6-5 Recommended threshold values for S_{app} and G_f.. 134
Table 6-6 Selected mixtures and mix variables to be used in CBDD.. 136
Table 0-1 Test Lane Asphalt Mixtures and Pavement Structure 157
Table 0-2 Traffic Data Information 159
Table 0-3 Asphalt mixtures ranking based on performance indices and simulation results....... 168
Table 0-4 Average percent discrepancy.. 168

LIST OF FIGURES

Figure 1-1 Overall research approach 8
Figure 2-1 Volumetric vs Balanced mix design [10] 18
Figure 2-2 The first approach, Volumetric design with performance verification [9] 19
Figure 2-3 The second approach, Performance modified volumetric design [9] 20
Figure 2-4 The third approach, Performance design [9] 21
Figure 2-5 U.S. map of current use of BMD approaches [9] 22
Figure 2-6 AMPT and complex modulus testing configuration 25
Figure 2-7 Fatigue test specimen and configuration in AMPT 26
Figure 2-8 DCT test specimen and configuration in UTM 30
Figure 4-1 Fracture energy vs. low temperature cracking [11] 45
Figure 4-2 Mix design and production phases and experimental data for statistical analysis 52
Figure 4-3 Schematic of data at each stage for model development and evaluation 55
Figure 4-4 Auto-validation weigh vs Training Weight 59
Figure 4-5 SVEM workflow diagram [41] 60
Figure 4-6 Actual vs Predicted fracture energy based on augmented FQM i) Group A, ii) Groups A and B, iii) Groups A, B, and C 62
Figure 4-7 ANN architecture diagram for groups A, B, and C 65
Figure 4-8 Actual vs Predicted fracture energy based on ANN i) Group A, ii) Groups A and B, iii) Groups A, B, and C 66
Figure 4-9 Actual vs Predicted fracture energy based on SVEM technique i) Group A, ii) Groups A and B, iii) Groups A, B, and C 68
Figure 4-10 Effect of each variable on fracture energy 72
Figure 4-11 Fracture energy prediction tool 74
Figure 4-12 Actual vs Predicted fracture energy based on SVEM and GEP models 76
Figure 5-1 schematic of testing and data analysis procedures 87
Figure 5-2 Actual vs Predicted C_{11} coefficient based on SVEM technique a) Adaptive Lasso, b) Forward selection 96
Figure 5-3 Actual vs Predicted C12 coefficient based on SVEM technique a) Adaptive Lasso, b) Forward selection, c) Elastic net 97
Figure 5-4 Actual vs Predicted C_{11} coefficient based on machine learning technique a) Boosted Trees, b) Random Forest, c) Support Vector Machine 99
Figure 5-5 Actual vs Predicted C_{12} coefficient based on machine learning technique a) Boosted Trees, b) Random Forest 100
Figure 5-6 Example of core location selection. 106
Figure 6-1 schematic of testing and data analysis procedures 117
Figure 6-2 Actual vs Predicted alpha based on SVEM technique a) Forward selection, b) Elastic net 119
Figure 6-3 Figure 6-3 Actual vs Predicted D^R values based on SVEM technique a) Adaptive Lasso, b) Elastic net 120
Figure 6-4 Actual vs Predicted alpha based on machine learning technique a) Boosted Trees, b) Random Forest 122
Figure 6-5 Actual vs Predicted D^R values based on Random Forest machine learning technique 123

Figure 6-6 Effect of each variable on fatigue properties of asphalt mixtures............................ 128
Figure 6-7 S_{app} prediction tool 131
Figure 6-8 Figure 6-8 Variables profiler for G_f prediction model developed in chapter 4......... 131
Figure 6-9 Distribution of four variables for mixtures with the lowest PGLT........................... 133
Figure 6-10 Cracking balance design diagram 134
Figure 6-11 Demonstration of the CBDD usefulness in mix design level 137
Figure 0-1 a) Dynamic modulus mastercurve at 21.1°C reference temperature, b) Phase angle mastercurve at 21.1°C reference temperature.. 160
Figure 0-2 Glover-Rowe Parameter at the frequency of 5 Hz at 20°C...................................... 161
Figure 0-3 a) Fracture energy for asphalt mixtures measured from SCB test; b) Flexibility index for asphalt mixtures measured from SCB test (dashed line represent the threshold value).. 162
Figure 0-4 a) Number of load cycles at G^R=100 for asphalt mixtures; b) Amount of average drop in material integrity per load cycle until failure; c) S_{app} values; d) Number of load cycles at C^S_{Nf}=100... 163
Figure 0-5 a) FAARFIELD predicted damage in the asphalt layer; b) Allowable number of departures at the end of design period. 165
Figure 0-6 Damage contours within the pavement cross section 166
Figure 0-7 Predicted fatigue damage within the pavement (total damage is separated using two colors to show the bottom-up and top-down damage)....................................... 167
Figure 0-8 Pearson's correlation coefficients 169

ABSTRACT

Balancing fracture and fatigue performance in asphalt pavements: A hybrid mechanistic and statistical modelling approach

The asphalt mix design and evaluation approaches are divided into two main categories as empirical and mechanistic-empirical (M-E) methods. The empirical methods are based on empirical observations of in-service pavement performance, and they do not take into account engineering properties or failure criteria. The M-E methods were introduced as a new generation for design and evaluation approaches that consider fundamental mixture properties such as material stiffness to determine the pavement's structural response. However, the need for expensive and time-consuming performance-based laboratory tests and local calibration makes the M-E methods unsuitable for routing design. In addition, during the last few years, the asphalt paving industry has been consistently tried to improve pavement performance by introducing new types of materials in asphalt mixtures. Regardless of all the positive effects of innovative materials on mix performance, the M-E design and evaluation methods might not be able to fully capture the benefits that may be achieved through using these materials. It likely stems from the fact that the M-E methods only utilize mix stiffness to evaluate the performance with respect to different distresses. Therefore, a methodology needs to be developed within the framework of current design and evaluation approaches to consider the mixture performance and the impact of innovative materials on pavement performance.

This dissertation research aimed to assess the mixture properties indices that can be implemented in performance-based design methods. The proposed endeavor will yield a more precise evaluation of the innovative materials impact on asphalt mixture performance through

consideration of the viscoelastic nature of asphalt mixtures to determine mechanistic damage effect.

Furthermore, several prediction models for a simplified viscoelastic continuum damage-based fatigue index (as crack initiation phase) and mixture fracture energy (as crack propagation phase) were developed to investigate asphalt mixture performance with respect to cracking. The models include the simultaneous impact of various mix variables that are available during the mix design process. Thus, they can be used as a predesign tool to investigate mixtures' cracking properties without the need for any performance laboratory test data.

Finally, a cracking balance design diagram (CBDD) was generated with a combination of prediction models for crack initiation and propagation. The CBDD helps toward better identification of cracking performance considering the simultaneous effects of both cracking phases in a single diagram.

CHAPTER 1

INTRODUCTION

1.1 Motivation and Background

Asphalt concrete pavements (including both highways and airports) are a vital component of the global economy and social wellbeing. According to information from the World Bank, the number of vehicles on roads around the world are projected to double to 2 billion by 2050. Moreover, some one billion people in underdeveloped nations do not have reliable access to roads, drastically limiting their economic prospects as well as access to necessities such as education and medicine [1]. This is also true for airfield pavement systems as the total economic output of commercial airports in U.S. exceeded $1.4 trillion in 2017. This number includes more than 11.5 million jobs with more than $428 billion of payrolls [2]. Considering these numbers along with the rapid global urbanization and industrialization in many parts of the world, necessitate the development of improved asphalt concrete pavements to accommodate the changing global situation.

The proposed endeavor in this dissertation will have broad implications for the field of pavement engineering and, by extension, the nation. For instance, transportation of goods on U.S. roads is a major industry with a large impact on the national economy. According to a recent report from the American Trucking Associations, the trucking industry posted nearly $800 billion in revenues in 2018 alone. In that year, trucks moved more than 70% of all of the freight in the nation. Furthermore, the trucking industry as a whole employs nearly 8 million people, including some 3.5 million drivers [3]. Moreover, based on the Air Carrier Activity Information System (ACAIS) data base, all-cargo landed wights in U.S. by average increased more than 14% from 2018 to 2019.

This number is more than 45% for average number of passenger (enplanement) at all commercial service airports in the U.S. between 2018 and 2019 [4]. These figures illustrate how crucial America's network of roads (highway and airfield) is to the nation's economic success. Poor quality asphalt concrete pavements reduce roads quality and serviceability time, which raise the price of transport and negatively affect economic growth.

Cracking in asphalt pavements is one of the significant problems in cold regions, especially northern half of the United States. United States Departments of Transportation (USDOT) and State Transportation Agencies have been substantially investing in development of new procedures to predict cracking performance of asphalt mixtures and consequently of pavements.

In general, cracking can be classified into load-associated and non-load-associated categories, and it is being generated when principal stresses exceed material strength. Microcracks first form in asphalt mixtures as the crack initiation phase. After crack initiation in the field, loads are still being applied on the pavements and then due to excessive tensile stress, microcracks will grow and incorporate to macro cracks (known as crack propagation phase), which can lead to structural failure in asphalt pavements [5]. The presence of microcracks would result in stress intensification and lower the pavement stiffness. Thus, using the magnitude of stress and strain as a classical mechanistic analysis approach may not be appropriate to analyze cracked materials. In such conditions, fracture mechanics can be used, which is concerned primarily with the distribution of stresses and displacements in the vicinity of a crack tip to model crack propagation in materials.

Researchers and asphalt agencies have developed several properties and performance-based laboratory tests to assess the cracking resistance of asphalt mixtures. None of them, however, can fully capture the asphalt mixture cracking resistance. The main problem with the current asphalt mixtures cracking laboratory tests is they either consider the initiation phase or propagation phase to evaluate the cracking resistance of mixtures, but usually do not consider both. For example, direct tension cyclic fatigue testing (DTCF) is used as a performance-based test to determine the damage characteristics of asphalt mixtures based on the simplified viscoelastic continuum damage (S-VECD) approach [6]. In the DTCF test, failure is defined as the number of load cycles where a sudden drop can be observed in the phase angle during continued loading, which shows the presence of microcracks in the material. The test, however, is not going any further than crack initiation and the amount of total damage (S), which is related to the number and magnitude of micro-cracks (which then will be linked to make macrocracks), as well as macrocrack propagation in mixtures cannot be precisely taken into account by this method. As opposed to the DTCF test, fracture tests such as semi-circular bend (SCB) and disk-shaped compact tension (DCT) test consider macrocrack propagation (second phase of racking). However, these tests are being conducted on already notched specimens which means the micro-crack formation step (initial phase of cracking) is totally skipped in these methods. As a consequence, they may not be able to fully capture the behavior of the materials with respect to cracking.

A reliable cracking prediction model should take into account both crack initiation and propagation to capture the full range of material behaviors. First, a viscoelastic continuum damage-based model needs to be implemented to account for the effects of loading prior to cracking and at the crack initiation time; second, a fracture-based model to predict crack propagation over time. The results of cracking performance-based laboratory tests can then be plugged into pavement performance prediction models to capture the real potential for distress with respect to different pavement structures, loading types, environmental conditions, to name but a few. However, asphalt mixture performance tests need a considerable amount of time and effort in terms of materials availability, test specimen preparation, and might be cost and time prohibitive for majority of pavement projects.

Moreover, during the last few decades, significant improvements in production and construction technologies of asphalt mixtures (such as utilizing innovative materials) as well as properties and performance assessment methods have been made and implemented to reduce the potential of distresses in asphalt concrete pavements. Despite notable positive impacts and economic benefits, innovative mixtures face certain challenges due to the limitations of current pavement design and evaluation approaches and they need to be more researched and developed. Innovative materials may alter asphalt pavement perfromnace in a manner that would indicate detrimental changes to performance using current analysis methods but in practice have shown substantial performance enhancement. In many cases, current pavement design and evaluation methods might not be able to fully capture the benefits that may be achieved through the use of innovative materials in asphalt pavements specially in airfield pavements design. The airfield asphalt mixture design and performance evaluation have not been substantially improved (as compared to highway) to compensate for the high tire pressures and complicated gear configuration of the airplanes. Currently, the Federal Aviation Administration (FAA) acknowledges the absence of guidance on the use of innovative materials such as recycled materials or newer construction techniques such as warm mix asphalt (WMA) in airfield pavements.

New performance-based pavement design and evaluation approaches are currently under development, but these are not mature enough to be widely accepted or implemented and are often not appropriate for routine design. Eventually, advanced performance-based approaches to pavement design will address the challenges related to precise performance evaluation of pavements. However, there is an immediate need to develop a methodology framework by which performance of mixtures can be appropriately evaluated within the framework of existing design approaches which are currently implemented by asphalt agencies and DOTs.

The research proposed herein will fill this gap by developing a methodology by which laboratory measured performance index parameters can be integrated with existing design approaches to reliably credit enhanced performance of innovative asphalt mixtures as well as better identification of cracking perfromnace with taking into account the whole cracking phases in a single prediction model. In this dissertation, performance properties indexes which can be accommodated in performance-based design and analysis methods were proposed which can help towards more precise monitoring of pavement distress appearance time (specially for airfield pavements) through combination of performance-based laboratory tests and analysis techniques that take into account the viscoelastic nature of asphalt mixtures to incorporate mechanistic damage effects on asphalt pavements. Moreover, distress prediction models were developed which can be implemented as a prediction tool to investigate the susceptibility of asphalt mixtures to cracking when a limited amount of data is available and testing is not feasible to capture mixture performance. The developed prediction models can be used either even prior to conventional volumetric mix design or can be accommodated as a performance-based specification (PBS) in performance-based mix design process. A comprehensive literature review of mix design methods history will be presented in chapter 2 of this dissertation.

1.2 Objective

The principal objectives of this research are to:

- Propose suitable laboratory performance tests and performance indices that can be adopted in performance related mix design and evaluation approaches to address cracking performance of airfield pavement constructed using WMA and recycled materials.
- Develop comprehensive machine learning based prediction models for asphalt mixture properties which are relevant to damage development to capture both crack initiation and propagation phases.
- Develop a cracking balance diagram based on fracture mechanics and viscoelastic continuum damage theories that can be adopted as a predesign tool.
- Conduct sensitivity analysis to investigate the effect of different variables on mixture cracking properties.

1.3 Overall Research Approach

In In order to fulfill the dissertation objectives a number of research efforts are undertaken to evaluate the cracking performance of asphalt mixtures. The research approach used in this dissertation work generally includes:

a) Conduction performance evaluation of airfield asphalt mixture using FAA conventional design program (FAARFIELD) and S-VECD based model (FlexPAVETM) and compare the results with test sections data to investigate the reliability of each method.

b) Data gathering (the results of all performance-based laboratory tests will be collected and categorized into appropriate subsets that can be used as inputs for prediction models)

c) Using linear regression models, artificial neural network, conventional machine learning in techniques such as boosted tress, ransom forest and support vector machine, as well as state of the art machine learning based mode (Fractionally weighted bootstrapping and auto validation technique) to predict cracking prediction models.

d) Development of cracking balance diagram as well as conducting sensitive analysis to assess the effect of different variables on test results.

Figure 1-1 presents a simplified process diagram of the overall research approach. The detailed discussion of each facet will be presented next.

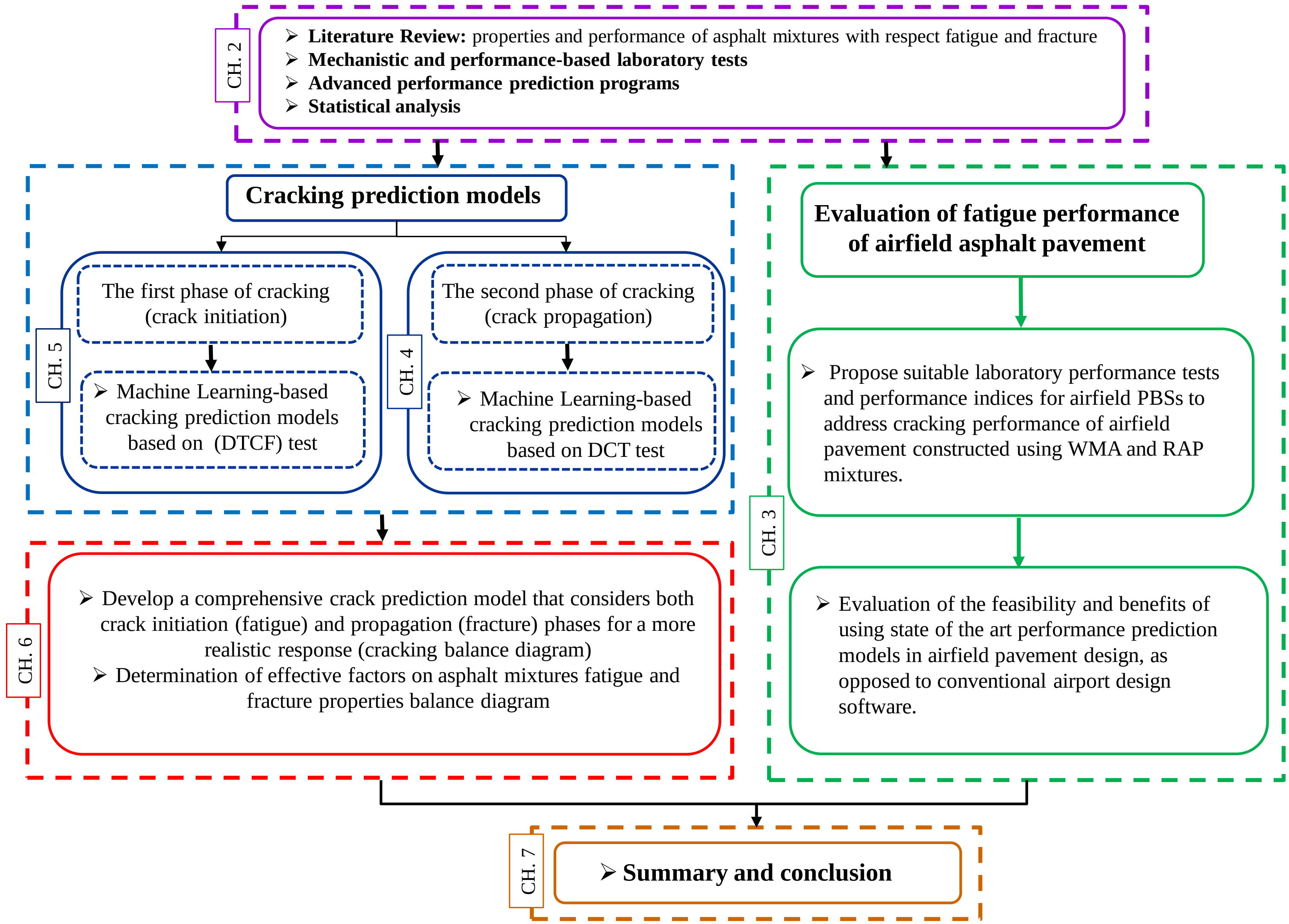

Figure 1-1 Overall research approach

1.4 Organization of the dissertation

Chapter 1 is dedicated to a general introduction as well as motivations and objective for this research.

Chapter 2 is an extended literature review on topics such as asphalt mixture performance-based mix design. Followed by a description of the different mechanistic and performance-based laboratory tests, as well as the advanced prediction programs that are employed to characterize the asphalt mixtures' cracking performance within the structure, climate and traffic conditions.

Chapter 3 Introduces suitable laboratory performance tests and performance indices that can be adopted in airfield performance-based specifications (PBSs) to address cracking performance of airfield pavement constructed using WMA and RAP mixtures. In addition, predicted fatigue performance of airfield pavement based on highway PBSs will be compared with test section data to validate the finding as well as to evaluate of the feasibility and benefits of using state of the art performance prediction models in airfield pavement design, as oppose to conventional airport design software like FAARFIELD.

Chapter 4 Focuses on developing comprehensive models to predict the fracture properties of asphalt mixtures at low temperatures as the final phase of cracking (crack propagation). To this aim, machine learning methods were used to propose the prediction models to predict mixtures' fracture energy as one of the Disk-shaped compact test outcomes. The machine learning algorithms will be calibrated using a set of DCT fracture energy data for asphalt mixtures. A key feature of the proposed models will be that they include simultaneous effects of various testing, binder and aggregate-related parameters, along with modern asphalt ingredients such as recycled materials. The derived model can be incorporated to a programmed spreadsheet for use in routine pre-design practice.

Chapter 5 is intended to propose machine learning-based prediction models for asphalt mixtures' fatigue properties to assess the initial cracking phase (crack initiation). In this chapter, direct tension cyclic fatigue (DTCF) test results were collected for 47 asphalt mixtures. The damage characteristics curve (DCC) was employed as the main outcome of simplified viscoelastic continuum damage (S-VECD) theory. Two coefficients (C_{11} and C_{12}) were determined as determinant factors of DCC shape, and the models were formulated in terms of typical influencing mixture properties variables such as asphalt binder performance grade (PG), mixture type, aggregate size, aggregate gradation, asphalt content, total asphalt binder recycling content, and test parameters like temperature and number of cycles. The developed prediction models were then used in chapter 6 to develop a final prediction model for S_{app} as fatigue properties index based on S-VECD theory. In addition to C_{11} and C_{12} coefficients, prediction models for D^R value which is the amount of average drop in material integrity per load cycle and alpha which is the maximum slope of the relaxation modulus in log–log scale were developed in chapter 6. An established dynamic modulus prediction model was also selected based on literature to be incorporated in final fatigue properties prediction model in chapter 6.

Moreover, the chapter 6 introduces a cracking balance design diagram that considers both crack initiation (fatigue) and propagation (fracture) phases for a more realistic response. To this aim, the developed prediction models in chapters 4, 5, and 6 were combined and the final model includes simultaneous effects of various asphalt mixture ingredients, mixture physical and mechanical properties, and innovative materials in the asphalt industry such as polymer modifiers and recycled materials.

In addition, this chapter focuses on the determination of effective factors on asphalt mixtures fatigue and fracture properties balance diagram, which will be developed in chapter 6.

As opposed to current asphalt mixtures specifications, which allow researchers to assess the effect of variables only on one type of distresses at a time, a sensitivity analysis were performed to distinguish the parameters with higher contributions in the final models along with the correlation direction of effective variables.

Chapter 7 summarizes the findings of the research and the contribution of the study to the body of knowledge. In addition, the limitations of the study as well as recommended future work were discussed.

Details of research efforts and corresponding results and discussion from Chapters 3 through 6 of this dissertation will be in the form of peer-reviewed journal manuscripts. The status of these papers is indicated in Table 1-1.

Table 1-1 Status of the technical papers culminating from this doctorate research.

Chapter	Paper	Journal	Status
3	Exploration of Cracking-related Performance-based Specification (PBS) Indices for Airfield Asphalt Mixtures	Journal of Transportation Engineering (ASCE)	Submitted
4	Developing a prediction model for fracture energy of asphalt mixtures using machine learning approach	International Journal of Pavement Engineering	In preparation
5	Machine learning-based prediction models for damage characteristics curve of asphalt mixtures based on simplified viscoelastic continuum damage mechanics	Road Materials and Pavement Design	In preparation
6	Development of a balanced cracking diagram for asphalt mixtures cracking resistance based on fracture and viscoelastic continuum damage theories	Road Materials and Pavement Design	In preparation

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CHAPTER 2

LITERATURE REVIEW

2.1 Performance Based Specifications and Balanced Mix Design Process

The main goal of asphalt mix design is to find an appropriate combination of asphalt binder and aggregates such that the final product provides sufficient stability to withstand traffic loading under different climatic conditions. The Marshall, Hveem, and Superpave methods are among the most commonly used techniques to design asphalt mixtures. Many research studies are being conducted to develop a performance-based mix design, and this approach is not entirely new, which stems from existing asphalt mix design methods. This is a current active area of research, and while some performance-based approaches have been introduced, they have not yet been widely accepted or implemented. Understanding the history of mix design is inevitable to realize performance-based design techniques. In the following sections, the history of asphalt mix design, as well as balance mix design, will be presented.

2.2.1 History of Asphalt Mix Design

The Hveem mix design technique was developed in the late 1920s to determine the optimum amount of asphalt content based on aggregate absorption and surface area. The Hveem method measures the stability of mixtures as a function of mix cohesion and friction between aggregate particles via Hveem stabolometer. A compressive load is being applied with a predefined increasing rate to a compacted asphalt mixture specimen, and mechanical properties are determined to measure the amount of optimum binder content [1]. Hveem design process did not consider mixtures air void level in mix design until the 1990s, and most of the asphalt mixtures that were designed with this method are found to be dry and prone to fatigue cracking [2].

In the early 1940s, the Marshal method was developed to determine the optimum amount of asphalt binder in mixtures based on maximum stability, air void level, and maximum density. The U.S. Army Corps of Engineers subsequently implemented Marshal mix design during World War II to design mixtures for airports. This method has been validated with the determination of void in mineral aggregates (VMA) and mixture flow. It has been wildly observed that the Marshal mix design will lead to a higher amount of asphalt binder in mixtures as compared to the Hveem method [2]. Until the early 1900s, both Hveem and Marshal mix design procedures were commonly utilized before the introduction of the Superpave procedure.

The Superpave method was developed as a performance-related mix design method in 1993 as a part of the Strategic Highway Research Program (SHRP). While several performance-based laboratory tests were accommodated in the design process, the entire design procedure was too complex, and none of the state departments of transportation (DOTs) accepted to use the Superpave method in their design procedures.

The Superpave method has three levels of mix design, with level 1 being the least complex and level three being the most complex levels [3]. Level 2 and Level 3 mix designs were supposed to include performance-based specifications (PBS); however, PBSs were never implemented in the procedure. The level 1 design is currently being used as the Superpave mix design practice. This level includes proportioning of the asphalt binder and aggregates based on aggregate empirical properties and volumetric properties of a mixture such as air voids, densities, voids filled with asphalt (VFA), and VMA. Over the years, asphalt agencies realize that the measurement of these properties is widely variable, which may lead to the faulty calculation of the optimum amount of asphalt binder in the mixture. Asphalt mixtures designed with a high amount of binder are more prone to permanent deformation (rutting), while mixtures with low binder content are more susceptible to cracking-related distresses [4].

Moreover, the asphalt paving industry has consistently been seeking to improve the performance of asphalt mixtures through the use of innovative materials (such as fibers, newer types of chemical modifiers, newer material processing techniques, reclaimed asphalt pavement (RAP)). Despite notable positive impacts and economic benefits, innovative mixtures face certain challenges due to the limitations in the current mix design approaches. The impact of these innovative materials on asphalt mixture performance has not been widely understood. Various types of modifiers and additives have been introduced and investigated by researchers and agencies; this research has shown that these may have different effects on mixture properties and performance both in the field and laboratory with respect to various distresses. Some innovative materials may alter the material stiffness, others may change the resistance to plastic deformation, fatigue, or fracture under higher loads/strains, while others may alter properties in both the linear viscoelastic (LVE) and damage range [5]. Rooholamini et al. (2019) demonstrated that a particular polymer increased mixture stiffness and fatigue properties at intermediate temperatures, but negatively impacted thermal cracking properties at low temperatures [6]. Ziari et al. (2019) showed that polyolefin-glass fibers improved rutting resistance of mixture but no consistent trend of enhancement for fatigue and fracture properties [7], and in a separate study showed that polyolefin-aramid fibers at appropriate dosages improved both rutting resistance and cracking performance of the evaluated mixtures [8]. These and other examples clearly illustrate that in addition to volumetric properties measurements, the performance-based laboratory tests should be accommodated in mix design procedures to ensure anticipated field performance of asphalt pavements with respect to different distresses.

2.2.2 Balanced Mix Design Approach

An expert task group was formed by the Federal Highway Administration (FHWA) to develop a Balanced Mix Design (BMD) procedure [9]. The BMD was defined as using performance-based laboratory tests in the asphalt mix design process to take into account several modes of distress while considering traffic, location within the pavement, climate, and mix aging. Figure 2-1-1 shows the difference between the conventional volumetric asphalt mix design process and the proposed BMD.

In volumetric mix design, a predefined compaction effort is being applied to asphalt mixtures to determine the optimum amount of binder content while mix air void reaches to 4%, and this method does not take into account the performance-based properties of asphalt mixtures. The BMD, however, includes both volumetric properties and performance properties. Based on figure 2-1, the binder content determined by the balanced mix design is between 6.2% and 6.7%, which satisfies both rutting and cracking criteria. On the other hand, the volumetric mix design process yields 5.7% binder content. Comparing the measured binder content based on volumetric approach with BMD shows 5.7% binder content would meet the rutting criterion, while it does not satisfy the cracking threshold.

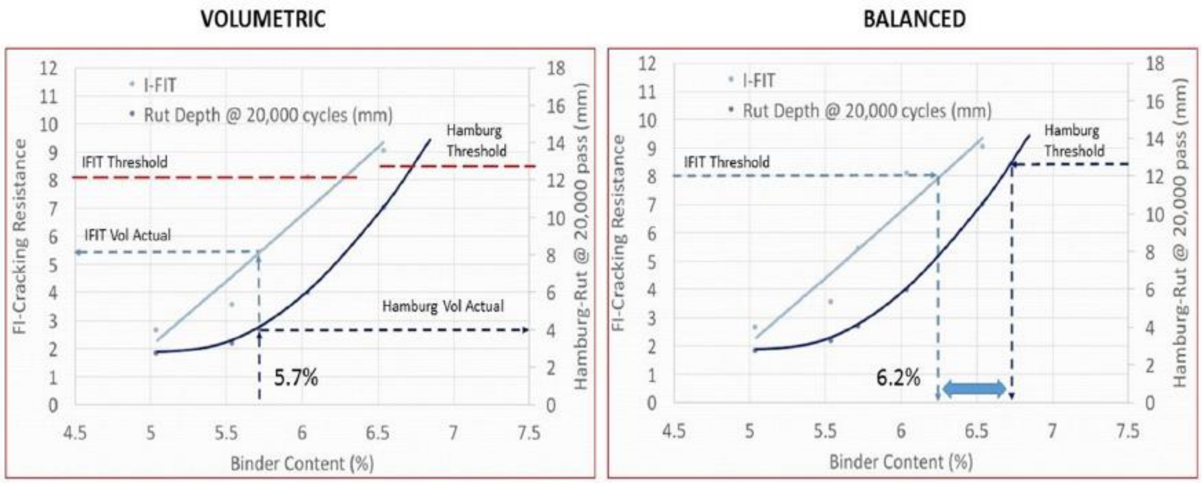

Figure 2-1 Volumetric vs Balanced mix design [10]

Three potential approaches to utilize BMD were also proposed by the FHWA group [9]. These approaches are described as follows:

The first Approach: Volumetric Design Method with Performance Verification. This approach is based on the Superpave mix design and is the most commonly researched and implemented mix design method by asphalt agencies. In this method, the asphalt mixture is first designed with the conventional volumetric mix design and then validated using performance-based tests. If the mixture does not satisfy volumetric and performance properties, the mix design process should be repeated. Mixtures can be adjusted through binder source and grade, aggregate source and gradation, and/or additives in the mixtures. Several state DOTs such as Texas, Wisconsin, New Jersey, Louisiana, and Illinois DOTs implement this approach in their mix design procedure. Figure 2-2 shows mix design process using the first approach.

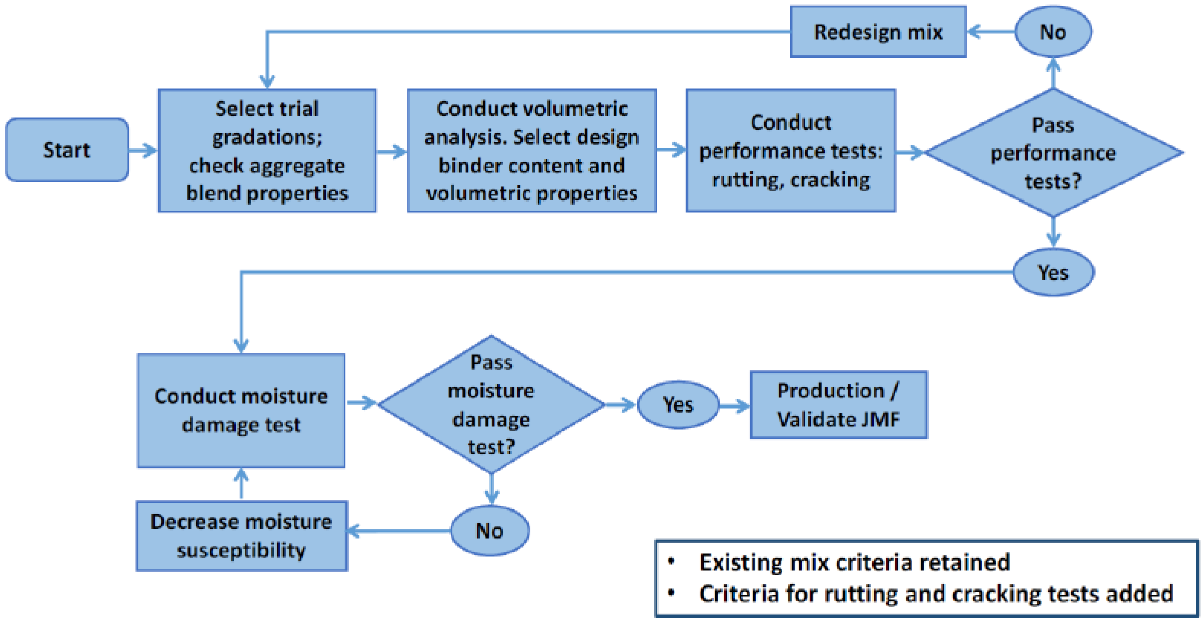

Figure 2-2 The first approach, Volumetric design with performance verification [9]

The second approach: Performance-Modified Volumetric Asphalt Mix Design. In the second approach, performance-based properties need to be satisfied, while volumetric measurement requires are not strictly enforced. The Superpave method is used to determine the initial blend of asphalt binder and aggregates. The properties of asphalt mixture are then adjusted to satisfy the performance-based tests requirements. This approach is currently being used in California. Figure 2-3 demonstrates the second approach procedure.

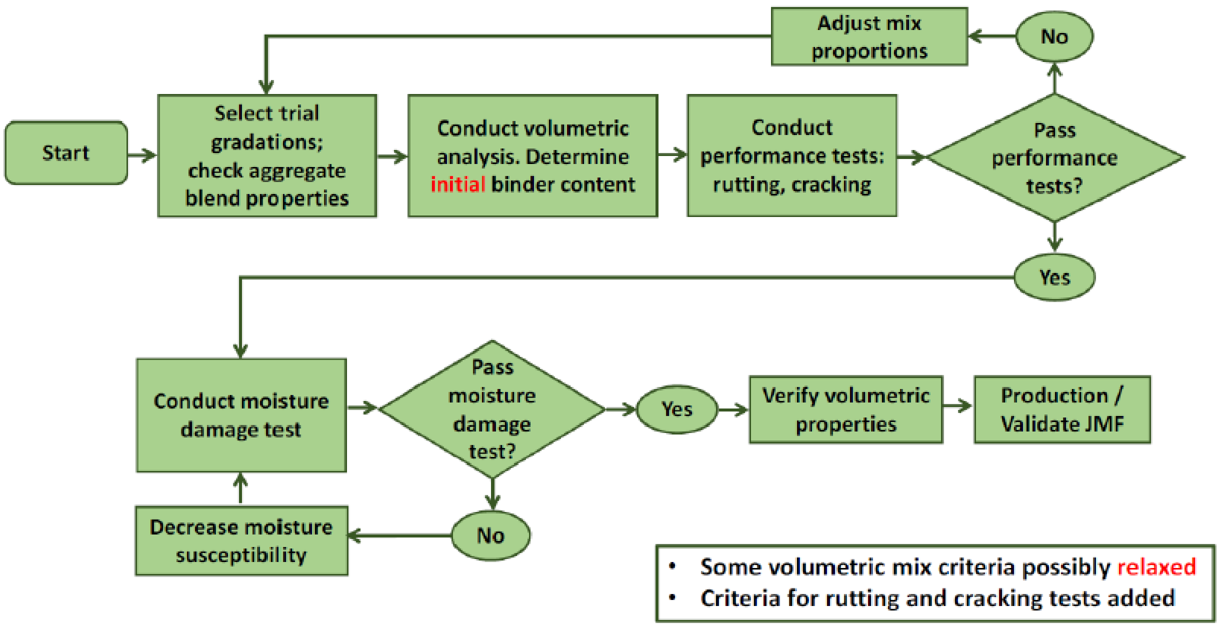

Figure 2-3 The second approach, Performance modified volumetric design [9]

The third approach: Performance Design. In this approach, performance-based tests are conducted on several trial mixtures, and the volumetric measurements in the mix design procedure are entirely skipped or limited, as shown in Figure 2-4. The objective of this approach is to meet the performance-based test criteria using different mixture components. While a minimum amount of volumetric measurement criteria may be set for asphalt binder and aggregates properties, some volumetric criteria such as VFA, VMA, minimum asphalt binder content, and aggregate gradation might still be utilized as a mix design guideline (not design criteria). This method can be rewarding for state DOTs and asphalt agencies because of the provided flexibility in the asphalt mix design. This approach, however, is not currently being implemented by any state DOTs because there are no knowledge and/or pavement field data available for validation of this method. The presence of innovative materials in asphalt mixtures is expected to be encouraged by this approach. However, a significant amount of research and test section data are necessary before using a high-risk method such as this approach in mix design procedures.

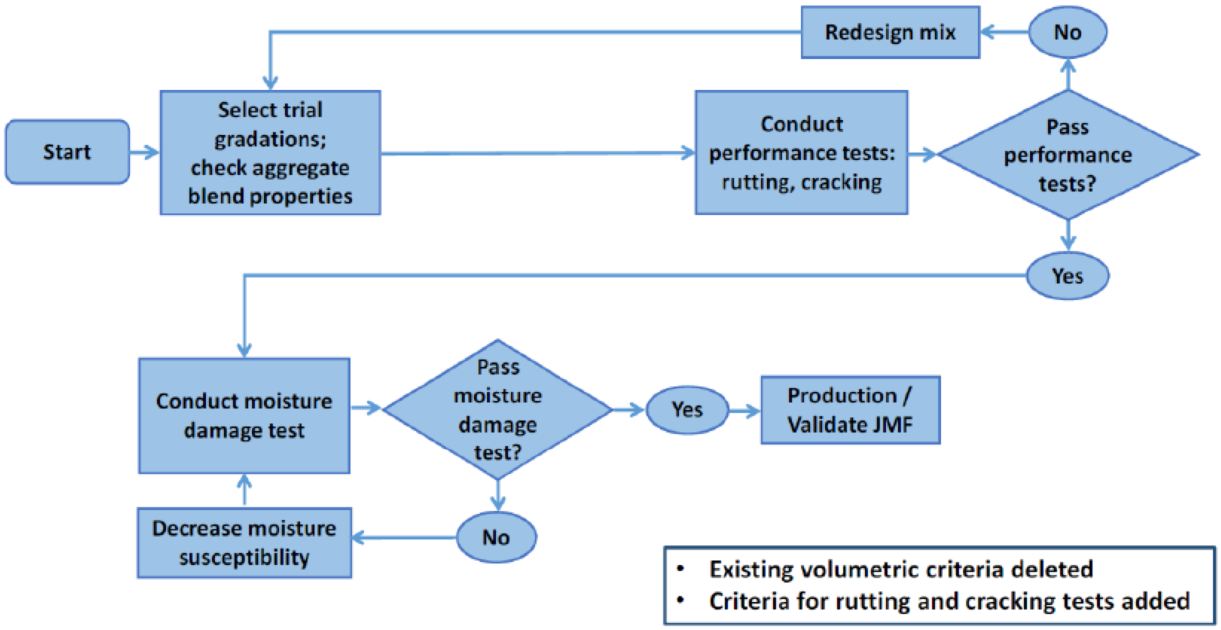

Figure 2-4 The third approach, Performance design [9]

2.2.3 The Current Practice of Balanced Mix Design

The feasibility of utilizing performance-based laboratory tests in asphalt mixture mix design procedure has been investigated by several state agencies. Figure 2-5 shows the states that implement the different approaches of BMD in their asphalt mix design procedures.

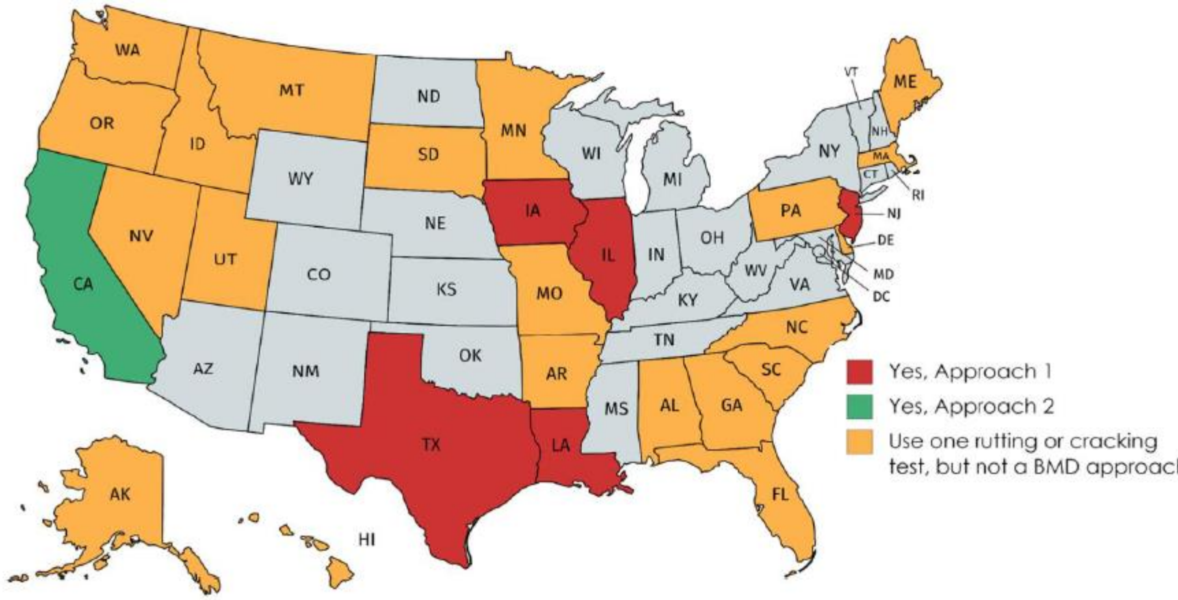

Figure 2-5 U.S. map of current use of BMD approaches [9]

A survey conducted by National Center for Asphalt Technology (NCAT) showed that 63% of state DOTs think VFA requirements should either be relaxed in or entirely eliminated from the current volumetric asphalt mix design (table 2-1). Table 2-2 shows, this number increase to 69% based on asphalt contractor responses [9].

As opposed to VFA, there is no consensus between DOTs and asphalt contractors on VMA. While 67% of DOTs think the VMA could be kept in the mix design process as a reflective parameter of pavement long-term performance, 64% of asphalt contractors believe VMA should be relaxed or eliminated as it does not have a critical effect on the mix design process. It worth mentioning that aggregate bulk specific gravity needs to be measured prior to VMA calculation, and high variability has been widely observed in aggregate bulk specific gravity calculation, which might lead to questionable VMA measurement [9]. About 54% of state DOTs think that dust to binder ratio should not be changed in the mix design process; this number drops to 46% when the responses of asphalt contractors are evaluated. The TSR parameter is considered as an effective parameter in asphalt mix design by the majority of both state DOTs and asphalt contractors, and they think this parameter should be kept in the mix design procedure.

Table 2-1 DOT responses on existing mix design criteria [9]

Mix Design Criteria	No Change	Relaxed	Eliminated
$\%G_{mm}$ @ Ni	19%	36%	45%
$\%G_{mm}$ @ Nm	22%	37%	41%
VFA	37%	39%	24%
Va	53%	42%	5%
D/A Ratio	54%	34%	12%
TSR	63%	15%	23%
VMA	67%	24%	10%

Table 2-2 Asphalt contractor responses on existing mix design criteria [9]

Mix Design Criteria	No Change	Relaxed	Eliminated
$\%G_{mm}$ @ Ni	13%	28%	59%
$\%G_{mm}$ @ Nm	19%	27%	54%
VFA	31%	43%	26%
Va	47%	53%	6%
D/A Ratio	33%	49%	18%
TSR	51%	23%	26%
VMA	36%	53%	11%

2.2 Laboratory Testing

The experimental campaign in this research includes complex modulus (E*), direct tension cyclic fatigue (DTCF), and disk-shaped compact tension (DCT).

2.2.1 Complex Modulus Testing (E)*

Complex modulus testing was carried out on asphalt mixtures in accordance with AASHTO T 342, standard method of test for determining dynamic modulus of hot mix asphalt (HMA) [10]. Three cylindrical specimens with 150 mm height and 100 mm diameter were tested for each mixture at different temperatures (4°, 20°, and 35° C) and frequencies (25, 10, 5.0, 1.0, 0.5, and 0.1 Hz) to capture the rheological behavior of asphalt mixtures in the linear range. The Asphalt Mixture Performance Tester (AMPT) equipment was used to conduct the test. Figure 2-6 shows the AMPT equipment at the UNH lab and a complex modulus specimen in the test chamber. Dynamic modulus and phase angle can be calculated from measured stresses and strains as shown in equations 1 and 2, respectively.

$$|E^*| = \frac{\sigma_{amp}}{\varepsilon_{amp}} \quad (1)$$

Where:

$|E^*|$ = dynamic modulus (psi)

σ_{amp} = amplitude of applied stress (psi)

ε_{amp} = amplitude of strain response (in/in)

$$\delta = 2\pi f \Delta t \quad (2)$$

Where:

δ = phase angle (degrees)

f = load frequency (Hz)

Δt = the time lag between peak stress and peak strain

Dynamic modulus and phase angle were calculated as test outputs and RHEA® software was used to construct the master curves based on the time-temperature superposition principle. For the completeness of the study, black space diagram was also plotted based on the results of dynamic modulus and phase angle.

The Glover–Rowe mixture parameter (G-R_m) was determined to evaluate the cracking properties of asphalt mixtures in a linear range of material response at intermediate temperature. Results of the complex modulus test were utilized to determine the G-R_m using equation (3) [11]. The G-R_m parameter was calculated at 20°C and a frequency of 5 Hz following the NCHRP 09-58 project [12,13].

$$G - R_m = \frac{|E^*|(cos\delta)^2}{sin\delta} \quad (3)$$

Figure 2-6 AMPT and complex modulus testing configuration

2.2.2 Direct Tension Cyclic Fatigue testing (DTCF)

To investigate the damage characteristics of asphalt mixtures, DTCF fatigue testing was performed on specimens in accordance with AASHTO TP 107, standard method of test for determining the damage characteristic curve and failure criterion using the AMPT [14]. At least three replicates with 130 mm height and 100 mm diameter were tested for each mixture. The tests were conducted at 20°C and 225 microstrain, 250 microstrain and 300 microstrain peak to peak on specimen strain levels to get a range of number of cycles to failure (N_f). The test was conducted by applying sinusoidal tensile loading at a frequency of 10 Hz in crosshead-controlled mode until failure. Failure is defined as the cycle where a sudden decrease can be observed in the phase angle during continued loading. Figure 2-7 shows a prepared DTCF test specimen and configuration of a specimen in the test chamber.

Figure 2-7 Fatigue test specimen and configuration in AMPT

Fatigue Parameters

The S-VECD approach developed by Underwood and Kim (2010) was used to analyze the fatigue test results using data acquired during complex modulus and fatigue tests. Four parameters have been used to investigate the fatigue properties of asphalt mixtures:

1: G^R is the rate of the average reduction in material integrity and can be computed through equation (4). The number of load cycles at $G^R = 100$ is usually used to rank mixtures with respect to expected fatigue performance. The higher the G^R is, the better the fatigue resistance of mixture is expected to be. [15].

2: D^R is the amount of average drop in material integrity (1-C), per load cycle until failure. D^R value can be measured using equation (5). Mixtures with a higher D^R value would be expected to have better fatigue resistance [16].

3: S_{app} is defined as the amount of damage accumulation (S) when pseudo-stiffness equals $1\text{-}D^R$ and can be calculated using equation (6). A higher value of S_{app} indicates that mixture has better fatigue resistance [17].

4: C^S_{Nf} is a recently developed fatigue parameter based on the rate of damage growth in asphalt mixtures and can be calculated using equation (7). A mixture with higher C^S_{Nf} suggests better fatigue resistance. [18].

$$G^R = \frac{\int_0^{N_f} w_c{}^R}{N_f{}^2} \qquad (4)$$

$$D^R = \frac{\int_0^{N_f} (1-C)}{N_f} \qquad (5)$$

$$S_{app} = 1000^{\frac{\alpha}{2}-1} \frac{a_T{}^{1/(\alpha+1)} (\frac{D^R}{C11})^{\frac{1}{C12}}}{|E^*|^{\frac{\alpha}{4}}} \qquad (6)$$

$$C_{N_f}{}^{S} = \frac{\int_0^{N_f}(1-C)dN}{S_f} \times m \quad (7)$$

Where:

${w_c}^R$ = Dissipated pseudo energy per load cycle

N_f = Number of load cycles to failure

C = Pseudo stiffness

C_{11}, C_{12} = model coefficients of the damage characteristic curve

α = material constant that can be calculated from the maximum slope of the relaxation modulus in log–log scale

a_T = shift factor

E* = dynamic modulus (kPa) at 10 Hz and the reference temperature.

S_f = accumulated damage at failure

m = Unit correction factor

2.2.4 Semi-circular Bend (SCB) Testing

In order to evaluate the fracture properties of the asphalt mixtures at intermediate temperatures, the Semi-Circular Bend test was conducted following the test procedure in AASHTO TP 124 standard method of test for determining the fracture potential of asphalt mixtures using the Illinois flexibility index test (I-FIT) [19]. The test was performed using the line-load displacement method with monotonic loading with a rate of 50 mm/min at 25°C. The fracture energy (G_f) and the flexibility index (FI) were calculated from the SCB test. The fracture energy (G_f) indicates the material's overall capacity to resist cracking (equation 8). The FI (equation 9) is calculated from the post-peak slope of the load-displacement curve in the fracture test and G_f. Generally, the FI provides a means to rank cracking resistance. Higher the G_f and FI values indicate better expected cracking resistance of a mixture [20]. The current recommended threshold value for FI to distinguish asphalt mixtures with good performance from mixtures with bad performance is eight [21].

$$G_f = \frac{Area\ under\ loaD{-}displacement\ curve\ (Farcture\ work)}{Fracture\ Area} \tag{8}$$

$$FI = \frac{G_f}{Slope\ at\ post\ peak\ inflection\ point} \tag{9}$$

2.2.3 Disk-shaped Compact Tension (DCT) Testing

The disk-shaped compact tension (DCT) test was carried out in accordance with ASTM D7313 to investigate the fracture properties of asphalt mixtures at low temperatures [22]. Crack mouth opening displacement (CMOD) was utilized to measure displacements (with a rate of 1 mm/min) on the sample under monotonic load. The DCT testing temperature was determined based on the in-service location (10°C+PGLT) using the MERRA climatic data source in InfoPave LTPP program. At least three replicates with 50 mm height and 150 mm diameter were tested for each asphalt mixture using the universal testing machine (UTM). Peak load and G_f were determined from the DCT test to evaluate the cracking resistance of asphalt mixtures at low temperatures [23]. Based on literature a proposed threshold value for G_f is 400 J/m2 [24]. Asphalt mixtures with fracture energy higher than 400 J/m2 are expected to have minimal thermal cracking compared to mixtures with fracture energies below the threshold. Figure 2-8 shows the DCT test specimen in a UTM chamber.

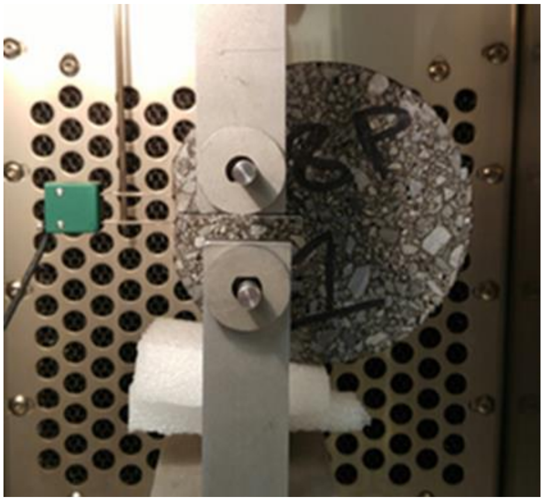

Figure 2-8 DCT test specimen and configuration in UTM

2.3 Statistical Analysis and Prediction Models

In fact, a challenge with prediction model development is to find the most suitable factors and simulation techniques that can predict future performance. Regression analysis is among the basic statistical techniques for this purpose. Box and Wilson (1951) conducted a study on process characterization and prediction that has been known as the pioneer of full quadratic models (FQM) [25]. The FQM contains the main effects, all two-way interactions, and quadratic effects as shown in equation 10, and this is yet the gold standard for building process models, especially for production, and the process is known today as the response surface model.

$$Y = \beta_0 + \beta_1 X_1 + \beta_2 X_2 + \beta_{12} X_1 X_2 + \beta_{11} {X_1}^2 + \beta_{22} {X_2}^2 \qquad (10)$$

Where:

X_1 and X_2 = Experimental factors

β = Model coefficient

FQMs are good second-order approximations to unknown response functions. However, Cornell and Montgomery (1996) showed they often are a poor approximation to the response surface over the entire design region, and then they raised the fact that the FQM often is inadequate to characterize a design space [26]. In other words, there is a great deal of nonlinearity that leads to response surfaces with pronounced compound curvature in different regions. Thus, the FQM simply cannot deal with it. Cornell and Montgomery proposed augmenting the FQM, and they added more terms in the model, such as quadratic by linear, linear by quadratic, and even quadratic by quadratic interactions. Equation 11 shows an augmented FQM with two variables. Based on the results, they claimed that these models approximate design regions better than FQMs.

$$Y = FQM + \beta_{112}{X_1}^2X_2 + \beta_{122}X_1{X_2}^2 + \beta_{1122}{X_1}^2{X_2}^2 \tag{11}$$

While the augmented FQM does a better job compare to the FQM model, there is a drawback for using this approach to develop prediction models. The addition of new terms to FQM will lead to a very large model that even makes a big model such as central composite design (CCD) supersaturated. It means there are more unknowns (p) than observations to fit the models. For example, an FQM with 13 experimental factors will have 105 terms. While the number of terms for an augmented FQM with the same amount of experimental factors would be 339.

With the improvement of the computational capacity of computers, researchers are utilizing some state-of-the-art statistical analysis techniques such as machine learning (ML) and deep learning (DL) to deal with saturated models with a limited amount of experimental observations [27]. Some of the useful ideas in these techniques stem from drawbacks in linear regression models. In 1996 Leo Brieman conducted a research study that was the start of a new era in prediction algorithms [28]. He pointed out that almost all model-building algorithms for prediction (such as forward selection, lasso, best subsets regression, etc.) are inherently unstable.

Being unstable means small perturbations in the data can result in wildly varying models. Although Brieman did not have a proper tool to conduct an extensive amount of statistical analysis, he showed fitting a large number of models on data set and then using the average of all models has some potentials to deal with supersaturated models. The idea that Brieman proposed is now commonly accepted in machine learning and deep learning techniques that is the idea of ensemble modeling and model averaging. Every predictive model needs a training set to fit the model, then it requires an additional or validation set of data to test the model to see how well it would predict. To demonstrate that ensemble modeling can improve prediction performance by reducing the effect of model instability on the model, Breiman conducted a simulation study. However, data sets with a limited amount of observations do not have additional trials available to be served as a validation set, and Brieman was stuck on this point.

Lemkus et al. used the Brieman idea and proposed self-validated ensemble modeling based on fractionally weighted bootstrapping technique and model averaging to deal with super saturated models with a limited amount of data [29]. They claimed a prediction model could use the same data set as both training and validation sets. The model takes the original data, copies it as the auto validation set, and then assigns random weights to the observations. The model creates exponentially distributed weights by the probability integral transform such that it drives anticorrelation between the training set and the auto validation set. The first prediction formula will be developed based on initial weights. The model saves the first formula and then assigned other sets of randomly anticorrelated weights to data set and develops the second prediction formula. Note that for the second run, a different set of main effects and interactions were chosen, and their regression coefficients are different this time. It does the iteration hundreds or thousand of times, and the final prediction model would be the average across all the prediction formulas. More details of this method can be found in chapter 4 of this dissertation.

The ML is a subset of artificial intelligence (IL) and inspired by the process of biological learning. The ML uses algorithms to train computers to learn like a human brain from a data set without any prior knowledge about the relationship between data [30]. The ML contains different algorithms, such as support vector machines (SVM), random forest, ANN, etc. As one of the subsets of ML, ANN has gained much attention to predict materials properties, and several research studies have shown this technique is useful for applications in civil engineering [21-38]. Cooper et al. [39] utilized an ANN model to predict cracking properties of asphalt mixtures using semicircular bend (SCB) specimens, and they claimed that the ANN technique could predict the critical strain energy release rate with an acceptable level of accuracy. Zavrtanik et al. [40] incorporated both ANN and regression models to predict air void levels in asphalt mixtures. They considered different variables such as density of aggregates, binder content, aggerate gradation (sieve analysis), and air void content for 17,296 asphalt mixtures. The author concluded that the ANN model is more effective than the regression model to predict the air void level in asphalt mixtures. Venudharan et al. [41] investigated ANN models' liability to predict the rubberized binders rutting performance. Based on the results, they concluded that ANN models are appropriate techniques to predict the performance of asphalt rubber with respect to cracking. Although the ANN techniques have been proven to have reliable performance, they are black-box tools, which means they are unable to generate practical equations for models [42]. Moreover, ANN techniques are susceptible to stuck in local minimums while the model is trying to find the optimum solution path. To prevent ANN models from being stuck in local minima, the training process can be integrated with a powerful optimization algorithm; however, using optimization tools makes the ANN models more computationally expensive and complicated [43-48].

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CHAPTER 3

Exploration of Cracking-related Performance-based Specification (PBS) Indices for Airfield Asphalt Mixtures (Paper 1, Appendix A)

3.1 Chapter Introduction

Airfield pavements are a critical component of airport infrastructure that accounts for significant proportion of the operational budget due to factors such as maintenance needs and construction timing and its impacts on operations. Asphalt concrete mixtures make up the top layer(s) of flexible airfield pavements. They are subjected to extreme loading and climatic conditions and, as a result, undergo different types of distresses [1]. These distresses not only lead to a significant need for maintenance and rehabilitation, they can also cause major safety problems. Problems associated with the surface roughness and friction as well as foreign object debris (FOD) can cause severe damage to aircraft leading to hazardous operating conditions. To address these issues, it is necessary to improve the overall functionality of the pavements through the specification of high-quality distress-resistant asphalt mixtures that can tolerate heavy aircraft loads under different climatic conditions.

In the last few decades, significant improvements in production and construction technologies of asphalt mixtures have been made to lower costs and distresses potential of highway pavements. Fundamental and engineering properties of asphalt concrete mixtures (e.g., fatigue, modulus, creep properties) can be determined using performance-based lab tests. The main reason for conducting these tests is to address common distresses in pavements such as cracking and permanent deformation (rutting). These properties have been shown to better correlate with pavement performance as opposed to traditional approaches of mixture compositions and volumetric measures. The use of performance properties in material specifications has led to the development of performance-based specifications (PBS) that are now being utilized in highway construction. The use of reclaimed asphalt pavement (RAP) and warm mix asphalt (WMA) technologies in highway construction have been shown to reduce overall construction cost while maintaining comparable and, in some cases, enhanced performance. However, the application of these technologies for airfield pavements has not been widely investigated. Since the type and magnitude of the loads, as well as a number of load repetitions, are quite different between highways and airfields, there is an urgent need to assess suitable performance-properties and their thresholds for developing PBS for airfields. Furthermore, the performance of airfield asphalt mixtures with the incorporation of RAP and WMA technologies needs further investigation.

3.2 Methodology and Results

This research used three types of warm mix asphalt (WMA), along with a mix of WMA and reclaimed asphalt pavement (RAP), to assess the cracking performance of WMA and RAP mixtures for airfield pavements and to explore performance-based airfield asphalt mix specifications. Fundamental properties of these mixtures were investigated through advanced performance-based laboratory testing methods such as complex modulus, semi-circular bend (SCB), and direct tension cyclic fatigue (DTCF) tests. Laboratory measured properties were utilized as inputs in advance performance prediction software (i.e., FAARFIELD [2, 3] and FlexPAVETM) to evaluate mixture performance during the design period. In addition, percent discrepancy and Pearson's correlation coefficient were utilized to compare the cracking performance indices and predicted pavement cracking performance to investigate which laboratory test(s) and property threshold(s) would be viable to be implemented in PBSs. Based on the results of complex modulus and SCB tests, it was found that organic additive and RAP tend to increase mixture susceptibility to fracture. In contrast, chemical and hybrid additives showed statistically similar fracture properties as compared to the control mixture. According to the results of the DTCF test, all fatigue indices ranked asphalt mixtures in different ways, which emphasizes the importance of using performance prediction programs to investigate mixture fatigue performance as opposed to the use of laboratory-measured index properties as a standalone parameter. The results of FAARFIELD software demonstrated that utilization of WMA and RAP would increase the fatigue damage in the pavement except for the chemical WMA additive. Moreover, based on the results of FlexPAVETM, it was concluded that chemical and organic additives improve mixture fatigue performance. While hybrid additive and RAP seemed to worsen the fatigue properties. Based on the results of statistical analysis, none of the performance-based laboratory test parameters show a promising correlation with the results of FAARFIELD. It was also found there is a moderate positive relationship between predicted damage in asphalt mixtures using FlexPAVETM and FAARFIELD software. The contradictory results of laboratory tests and pavement performance simulation show the Federal Aviation Administration (FAA) current asphalt pavement thickness design procedure lacks a usable model of fatigue cracking in its standard design program (FAARFIELD).

It should be noted that the Federal Aviation Administration's National Airport Pavement and Materials Research Center (NAPMRC) constructed several test sections with study mixtures to evaluate the performance of the same mixtures that were utilized in this study using an airport heavy vehicle simulator (HVS-A). The availability of field performance data will enable researchers to validate their findings. As the future extension of this study, a comparison will be made between the mixture predicted performance and accelerated pavement test data (pavement performance under APT) to determine the accuracy of the prediction. In addition, to evaluate the feasibility and benefits of using state-of-the-art performance prediction models in airfield pavement design, as opposed to conventional airport design software.

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CHAPTER 4

Developing a prediction model for fracture energy of asphalt mixtures using machine learning approach

4.1 Chapter Introduction

Thermal cracking is one of the most common distresses in asphalt pavements, which usually occurs due to higher tensile stresses in asphalt concrete due to high cooling rates and low temperatures [1,2]. Therefore, it is vital to evaluate the cracking resistance of asphalt mixtures using appropriate methods. Fracture mechanics concepts are useful to analyze fracture properties of asphalt mixtures. Disk-shaped compact tension (DCT) test is one of the most common fracture tests in pavement engineering [3-7].

The DCT test uses a notched specimen that is loaded in tensile mode using a controlled crack-mouth opening displacement (CMOD) rate of 1 mm/minute. Using the data from the test, fracture work is calculated as the area under the load-CMOD curve. Fracture work is further converted to fracture energy (G_f) by normalizing it with respect to the fractured face area (equation 1). The peak load and fracture energy are two primary material characteristics calculated from DCT test. The test procedure is standardized as ASTM D7313 [8]. In order to improve the repeatability of this test and refine the testing procedures, the Minnesota Department of Transportation (MnDOT) has supplemented the ASTM D7313 specifications with MnDOT-modified test procedures that has added constraints on specimen dimension tolerances, machine calibration requirements, and specimen test temperature control and conditioning, more details are available elsewhere [9]. Furthermore, a detailed investigation has been conducted to improve the precision and confidence level in the asphalt mixture low temperature fracture energy measurement using the DCT test in previous work [10].

$$G_f = \frac{Area\ under\ load{-}CMODcurve\ (Fracture\ work)}{Fracture\ Area} \tag{1}$$

Several studies have shown that fracture energy has a reasonable correlation with field cracking performance [11-14]. Therefore, it has been utilized in performance-based specifications to capture asphalt mixture performance with respect to low temperature cracking [15]. Buttlar et al. determined the correlation between the amount of transverse cracking in field sections for Missouri, Minnesota, Illinois, and Wisconsin and calculated fracture energy based on DCT test for corresponding asphalt mixtures (figure 4-1) [11]. Based on the results, they claimed that there is a strong correlation between low temperature cracking and fracture energy.

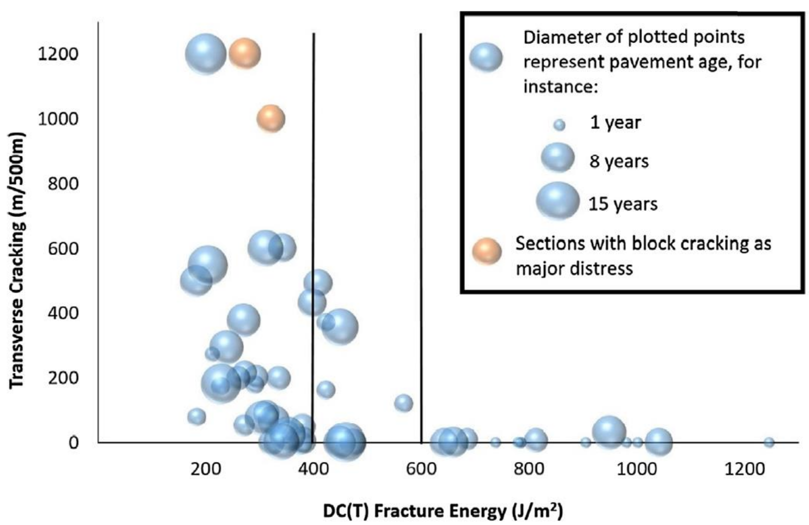

Figure 4-1 Fracture energy vs. low temperature cracking [11]

Although performance-based tests showed a promising correlation with asphalt pavement field performance, these tests have some limitations, such as they might be cost/time prohibitive, and mixture components are not available before the mix design process. Asphalt producers and departments of transportation (DOTs) that want to incorporate performance-based design need to come up with a trial mix design and prepare mixtures for performance tests, which requires in significant resources (money, time, and personnel).

New performance-related evaluation approaches are currently under development, but these are not mature enough to be widely accepted or implemented and are often not appropriate for the routine design. Thus, it is necessary to develop a relationship between estimated and/or known asphalt mixture components and performance-based test outcomes that can be used as a predesign tool, leading to considerable savings in time and cost of mixture fabrication. In addition, asphalt mixtures variables are often not the same during the mix design process and actual production process. Therefore, an efficient and helpful prediction model needs to be capable of predicting performance-based test outcomes based on mix design parameters and have the capability to be able to accommodate asphalt mixture production variabilities.

With the improvement of the computational capacity of computers during the last few decades, researchers have been utilizing different statistical analysis techniques such as regression-based models, machine learning (ML), and deep learning (DL) techniques to develop properties and performance prediction models based on experimental observations [16]. Cooper et al. [17] utilized an ANN model to predict cracking properties of asphalt mixtures using semicircular bend (SCB) specimens, and they claimed that the ANN technique could predict the critical strain energy release rate with an acceptable level of accuracy. Zavrtanik et al. [18] incorporated both ANN and regression models to predict air void levels in asphalt mixtures. They considered different variables such as density of aggregates, binder content, aggerate gradation (sieve analysis), and air void content. The authors concluded that the ANN model is more effective than the regression model to predict the air void level in asphalt mixtures. Venudharan et al. [19] investigated ANN model liability to predict a rubberized binder's rutting performance. Based on the results, they concluded that ANN models are appropriate techniques to predict the performance of asphalt rubber with respect to cracking. Majidifard et al. [20] utilized an innovative ML method called gene expression programming (GEP) and a hybrid ANN model to predict the fracture energy of asphalt mixtures. They concluded that the GEP model seems to be more practical as compared to the hybrid ANN model.

In fact, a challenge with prediction model development is to find the most suitable factors and simulation techniques that can predict future performance. Asphalt mixture performance depends upon several factors such as aggregate type, binder type, air void content, and production techniques. However, most of the developed prediction models to date either do not include all important variables, or may be computationally expensive and are therefore not suitable to be implemented in predesign procedures [15, 21]. According to the nature of experimental observation (lab test results), each variable might have an influence on the test results and removing even a few observations or variables can cause the main effects and interactions to collapse and creates an "ill-fitted" model. In these cases, prediction models only work within the circumstances they are developed under and using a different data set will cause a significant error in those models. Table 4-1 shows a summary of effective variables on fracture energy based on the literature review.

Table 4-1 Effective asphalt mix variables for fracture energy

Authors	Variables Investigated
Blankenship and Zeinali [22]	Binder PG grade
	Polymer and rubber modification
Li et al. [23]	Test temperature
	Aggregate source
Behnia et al. [24]	Recycled materials (RAP)
Dave et al. [25]	Type of binder modification
	RAP
	Low temperature binder grade
Buttlar et al. [26]	Aggregate type
	Aggregate gradation
	Binder PG grade
Zegeye et al. [27]	Type of binder modification
Mogawer et al. [28]	Type of binder modification
Oshone et al. [29]	RAP Effective binder content Air void Asphalt film thickness (AFT) Void in mineral aggregates Binder PG grade

Based on this motivation, the objectives of this study are as follows:

(a) To develop a precise yet computationally low-cost low-temperature property prediction model using different statistical methods.

(b) To determine how prediction capabilities can be impacted when mix design data is used as opposed to actual production data.

(c) To determine which mixture attributes are most important to low temperature fracture property

4.2 Test Data

Asphalt mixtures were designed at MnDOT based on the Superpave mix design procedure. The mix design includes selection of asphalt binder and aggregate types and recycle material content, and then proportioning of the asphalt binder and aggregates based on design traffic data, aggregate empirical properties, and volumetric properties of a mixture such as air voids, densities, voids filled with asphalt (VFA), and VMA. After mix design process, asphalt mixtures were constructed as field pavements and job mix formula including stockpile blending, recycle material content, virgin binder content was measures to be compared with the proportioning data at the mix design phase. Loose mix samples were taken at construction stage and compacted at laboratory to measure mix volumetric properties as well as to conduct performance related lab test on asphalt mixtures. Figure 4-2 shows a schematic of mix design and actual production phases data and how they were used in analysis for this study.

DCT test (ASTM D7313/MnDOT modified) was conducted on 71 plant-produced lab-compacted (actual production) asphalt mixtures with the short-term aging condition at MnDOT, and fracture energy was calculated as the primary outcome of the test. The fracture energy of each mixture represents the average value of 12 replicate specimens. In addition to the actual production, mix design data were also collected to be utilized as a validation data set for prediction model as well as to investigate how different a low temperature cracking performance property would be if mix design info were used as opposed to actual production data for prediction.

In this study, all mix information at the mix design and production stage were categorized into three groups to determine the minimum amount of mix information that one needs to utilize to be able to predict asphalt mixture fracture properties into a certain level of reliability. Different groups were selected based on the availability of data during the mix design procedure. Group A is represents variables that are typically known during the planning stage and contains information that the designer would know at the first step of mix design. All design variables in group B are available at the early stages of mix design and can be determined without the need for any specific lab mixing or compaction of asphalt mixture. Group C includes information that is available at the final stage of mix design. Some of the variables such as asphalt film thickness (AFT), equivalent single axle load (ESAL), and maximum aggregate size might not be very well-known outside of the U.S. Therefore, these variables are elaborated upon hereunder.

AFT is the ratio of effective volume of asphalt binder to the aggregate surface area and can be calculated using equation 2.

$$T_f = \frac{V_{asp}}{SA \times W} \times 1000 \qquad (2)$$

Where:

T_f = Average film thickness (μm)

V_{asp} = Volume of effective asphalt binder (L)

SA = Aggregate surface area (m^2/kg)

W = aggregate weight (kg)

The ESAL concept was developed at early 1960 by American association of state highway officials (AASHO) to convert induced damage by wheel loads with different repetition and magnitudes to damage from an standard wheel load. The most commonly implemented equivalent load in the U.S. is 80 kN which comes from single axle dual tire configuration. Equation 3 shows ESAL calculation. More details on ESAL calculation can be found here [30, 31].

$$ESAL = (ADT)(T)\left(T_f\right)(G)(D)(L)(365)(Y) \qquad (3)$$

Where:

ADT = Average daily traffic

T = Truck percent

T_f = Truck factor

G = Growth factor

D = Directional distribution factor

L = Lane distribution factor

Y = Number of design years.

Based on the Superpave definition, maximum aggregate size is one sieve size larger than nominal maximum aggregate size (NMAS). The NMAS is the one sieve size larger than the first sieve on which more than 10% of aggregates would retain. More information can be found in hot mix asphalt materials, mixture design and construction book [32].

Tables 4.2 and 4.3 show different groups and available information within each group and descriptive statistics of each variable, respectively.

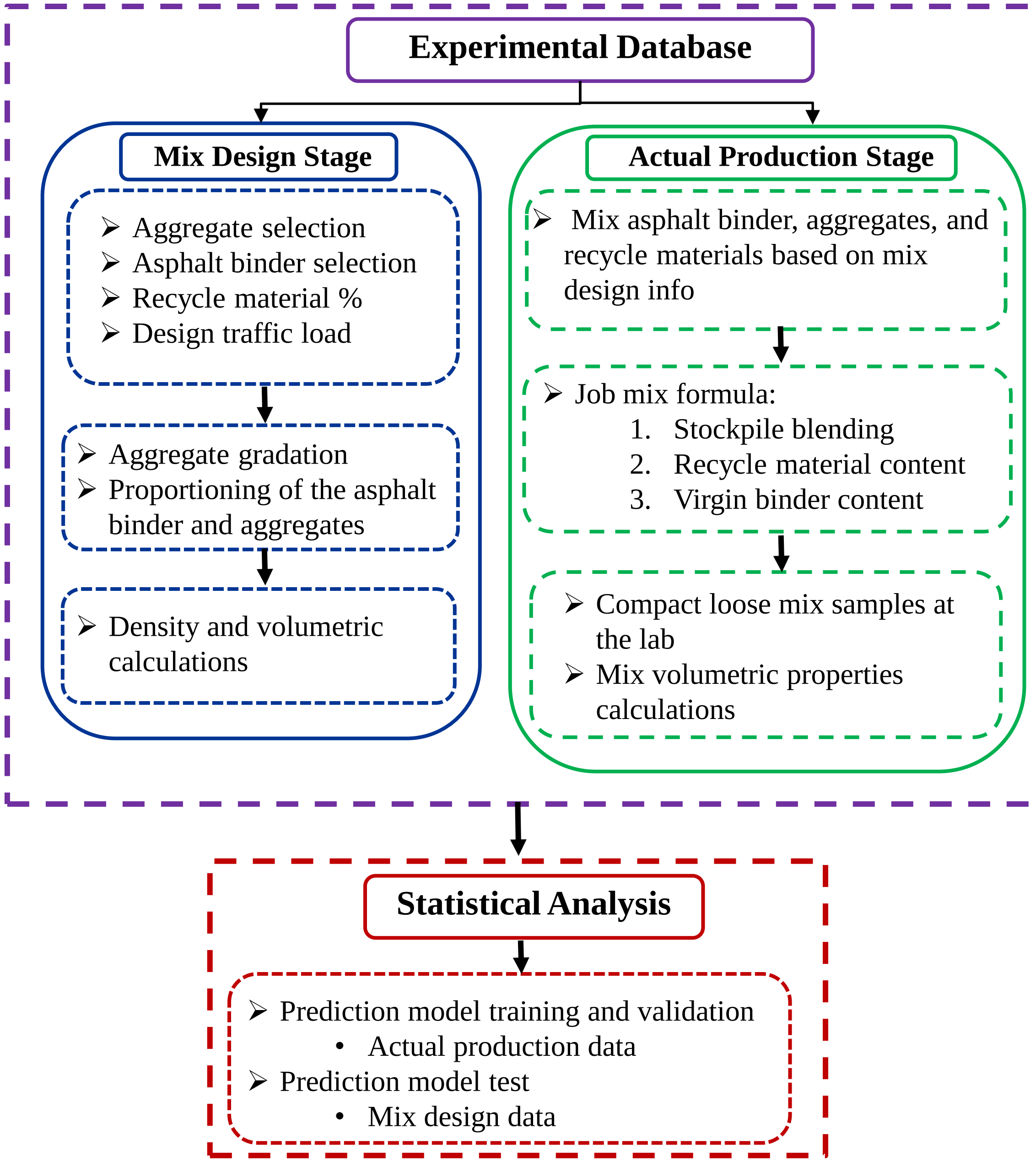

Figure 4-2 Mix design and production phases and experimental data for statistical analysis

Table 4-2 Different variables in each group for statistical analysis

Variables	Group
High temperature binder grade (PGHT)	A
Low temperature binder grade PGLT	
Maximum Aggregate Size (mm)	
Design traffic load (ESALs)	
Total binder content (AC %)	
RAP (%)	
Percent passing 3/8 in. for combined gradation (%)	B
Percent passing #4 sieve for combined gradation (%)	
Percent passing #200 sieve for combined gradation (%)	
Void in mineral aggregates (VMA)	C
Asphalt film thickness (AFT)	
Maximum specific gravity (G_{mm})	
Bulk specific gravity (G_{mb})	
Aggregate specific gravity (G_{sb})	

Table 4-3 Descriptive statistics of variables on this study

Variable	N	Mean	Std Dev	Sum	Minimum	Maximum
PGHT	71	58.4	1.5	4148	58	64
PGLT	71	-28.4	1.5	-2018	-34	-28
Maximum Aggregate Size (mm)	71	17.1	2.3	1212	12.5	19
Design ESALs (million)	71	6.3	4.5	450	3	30
Binder Content, P_b (%)	71	5.2	0.3	373	4.1	6
RAP%	71	22.6	2.9	1605	15	30
Particle Size 3/8 in. (%)	71	86.4	6.1	6135	73	98
Particle Size #4 (%)	71	65.8	4.2	4670	51	77
Particle Size #200 (%)	71	4.6	0.5	324	2.8	5.5
VMA (%)	71	14.9	0.7	1056	13	16.3
AFT (micron)	71	8.6	0.5	613	7.5	10.4
G_{mm}	71	2.488	0.017	177	2.441	2.523
G_{mb}	71	2.389	0.020	170	2.335	2.434
G_{sb}	71	2.658	0.021	189	2.605	2.700

4.3 Data Analysis Method

AFQM, ANN, and an innovative machine learning technique called SVEM were utilized to develop prediction models based on different variables. Mix information at the production stage was used to train and validate the prediction models. Moreover, the mix design data of the corresponding mixtures were used to test the model and assess how prediction capabilities can be impacted when mix design data is used as opposed to actual production data (as shown in figure 4-3). In this study, the efficiency of trained models was evaluated using correlation of determination (R^2) (equation 4), root average square error (RASE) (equation 5), and the absolute average error (AAE) (equation 6).

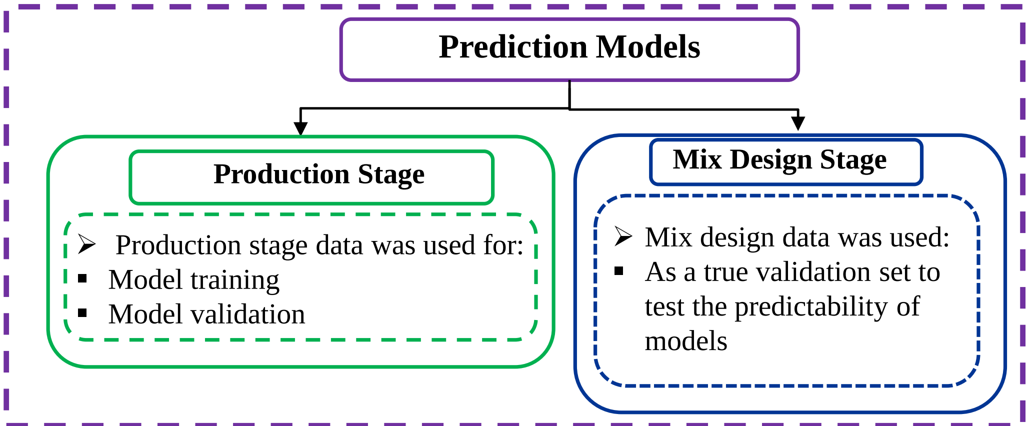

Figure 4-3 Schematic of data at each stage for model development and evaluation

$$R^2 = \frac{(\sum_{i=1}^{N}(M_i - \bar{M}_i)(T_i - \bar{T}_i))^2}{\sum_{i=1}^{N}(M_i - \bar{M}_i)^2 \sum_{i=1}^{N}(T_i - \bar{T}_i)^2} \qquad (4)$$

$$RASE = \sqrt{\frac{\sum_{i=1}^{N}(M_i - T_i)^2}{n}} \qquad (5)$$

$$AAE = \frac{\sum_{i=1}^{n}|M_i - T_i|}{n} \qquad (6)$$

Where:

M_i = Measured output

T_i = Predicted output

$\bar{M}_i$ = Average of measured outputs

$\bar{T}_i$ = Average of predicted outputs

n= Number of samples

4.3.1 Full Quadratic Model (FQM)

The FQM is a subset of regression models which contains the main effects, all two-way interactions, and quadratic effects of variables to predict the outcome, as shown in equation (7) [33].

$$FQM\ (Y) = \beta_0 + \beta_1 X_1 + \beta_2 X_2 + \beta_{12} X_1 X_2 + \beta_{11} {X_1}^2 + \beta_{22} {X_2}^2 \qquad (7)$$

Where:

$X_{1, \dots, n}$ = Variables

B = Model coefficient

The FQM, however, might not be able to capture all the interaction between variables because it is limited to second-order approximations to the unknown response function. To deal with this issue, the FQM can be augmented with more interactions such as quadratic by linear, linear by quadratic, and even quadratic by quadratic interactions, as shown in equation (8) [34].

$$AFQM(Y) = FQM + \beta_{112} {X_1}^2 X_2 + \beta_{122} X_1 {X_2}^2 + \beta_{1122} {X_1}^2 {X_2}^2 \qquad (8)$$

Where:

FQM = Full quadratic model

An augmented FQM was utilized in this study to assess the impact of various parameters on the fracture energy of asphalt mixtures. A response surface model (RSM) was adopted in JMP® Pro software, and the model was then augmented by adding 3rd degree polynomial terms to the model. 80% of data was selected randomly for training the model, and 20% was used for validation purposes. Once prediction models were developed, mix design data were used for corresponding mixtures as a true validation set (test set) to examine the model's reliability. All analyses were conducted on variables in group A, the combination of variables in groups A and B, and the combination of all variables in groups A, B, and C to determine the minimum amount of experimental observations needed for specified reliability in the prediction model.

4.3.2 Artificial Neural Network (ANN) Method

ANN is a subfield of machine learning where the algorithms are inspired by the structure of the human brain. Neural networks take in data, train themselves to recognize the patterns in the data, and then predict the outputs for a new set of similar data [35]. ANN models are powerful tools to solve complex nonlinear problems and analyze complicated data sets [36]. Neural networks are made up of layers of neurons. The first layer is called the input layer, which receives the input. The output layer predicts the final output, and in between exist the hidden layers which perform most of the required computations.

In this study, a multilayer feed-forward back-propagation neural network model was created in JMP® Pro software. Data normalization was done by mapping the data set to the range of (0,1). K-fold cross-validation was used to prevent overfitting of the model, and the dataset is divided into k subsamples with equal sizes [37]. K-1 subsamples were used to train the prediction model, and a remaining subsample was used to validate the model. The process was then repeated K times for cross-validation with using each subsample exactly once as the experimental data. Considering the amount of experimental observations (71) in this work, 5 folds were used for model validation. The mix design info was then utilized to test the final model.

The accuracy of ANN models depends on the network's architecture; however, there is no general rule to select the numbers of hidden layers as well as the number of neurons in each hidden layer. Besides, the initial weights of variables were randomly chosen during the training process. Consequently, there is a possibility that the algorithm falls into local minimum points [38]. In this study, to prevent the model from being stuck in local minimums, the first ANN structure was used with one hidden layer and different numbers of neurons (1 to 100). Then, the networks were tested through 5 iterations, and average results were recorded. The models were then compared with respect to the maximum coefficient of determination and minimum error. The same steps were then repeated for a network with two hidden layers, and the optimum structure was selected by comparing the statistical results of different models [39].

4.3.3 Self-validated Ensemble Modelling (SVEM)

This study utilized a new model-fitting method called fractionally weighted bootstrapping and auto validation (FWB+AV) method. This method keeps the design structure intact while simultaneously incorporating a weight re-sampling scheme [40]. In order to use this model, a new JMP® pro software add-in called self-validated ensemble modelling (SVEM) was used [41]. The SVEM is a new method to extract more insights with fewer experimental observations and build more accurate predictive models from small data sets [41]. As a result, SVEM validates prediction models without reduction or removal of any runs in the model. In this method, generalized bootstrapping implements random exponential weights with a mean of 1.0 [42]. Such that, a set of random uniform weight (0,1) is being generated with the same size as the data set, then the weighting scheme utilizes exponentially distributed inverse probability transform for a fractional wight generation. Equation 9 [41] represents the computation of the weights. Figure 4-4 shows the inverse correlation between training and validation weights based on the auto-validation approach.

$$\begin{aligned} &Generate:\ u_i \sim U\,[0.1] i = 1 \dots N \\ &Training\ FW's:\ w_{T,i} = F^{-1}\,(u_i) i = 1 \dots N \\ &Auto - Validation\ FW's:\ w_{V,i} = F^{-1}\,(1-u_i) i = 1 \dots N \end{aligned} \tag{9}$$

Where:

U [0, 1]i = uniform distribution on the interval (0, 1)

w_T = Training Weight

FW = Fractional Weight

F = the cumulative distribution function for an exponential distribution with mean 1

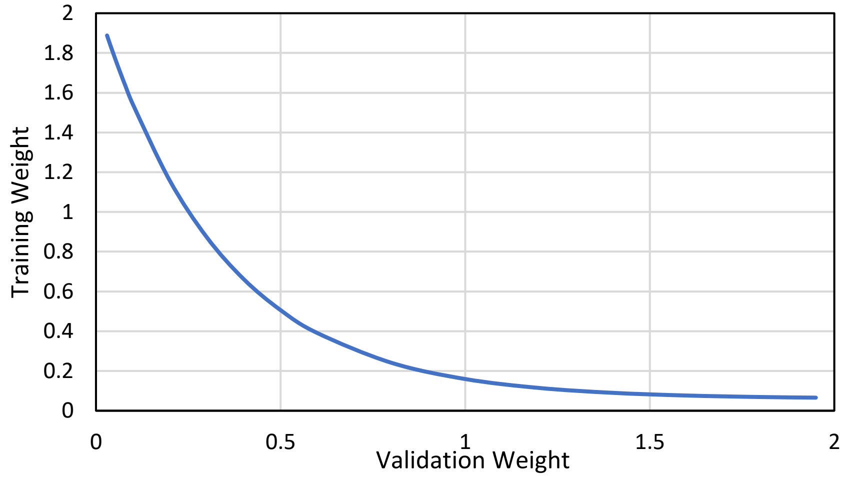

Figure 4-4 Auto-validation weigh vs Training Weight

Once both the training and auto-validation sets have been assigned random weights, a selected prediction algorithm will be applied to the training set. The prediction algorithms then choose the best model based on the minimum mean squared error (MMSE) for the auto-validation set. The selected model will be stored for final model inclusion. The procedure will then be repeated for a number of iterations that is specified by the user. Algorithm 1 shows the SVEM analysis steps where Mi represents the ith row in the matrix.

Algorithm 1: SVEM [41]

$\boldsymbol{Results}$: $\hat{\beta}_{SVEM}$

$\boldsymbol{for}\ i = 1 : n\hat{B}\ do$

$\quad Generate\ \ \tilde{w}_T , \tilde{w}_V ;$

$\quad Fit\ model\ \ f(X, \tilde{w}_T , \tilde{w}_V\ Y);$

$\quad Calculate\ SSE^V(\beta) = argmin\ \sum_i \tilde{w}_{V,i}(y_i - \hat{f}(X, \beta))^2;$

$\quad Select\ \hat{\beta} = argmin\ [SSE^V(\beta)];$

$\quad M_i\ \leftarrow \hat{\beta};$

$\boldsymbol{End}$

$Bag\ (M) \rightarrow\ \hat{\beta}_{SVEM}$

Where:

β = Model outcome

wT = Training weight

wv = Validation weight

SSE = Sum of squared estimate of errors

argmin () = The function that returns indices of the min element of the array in a particular axis

Bag = Bagging function

For M iterations, the Mfinal matrix contains all fitted models along with the coefficient estimates that were created for the final model. The model takes into account all possible terms with zeroing the associated coefficient value of variables that did not get selected for each FWB iteration. Figure 4-5 demonstrates a succinct diagram that illustrates the SVEM algorithm

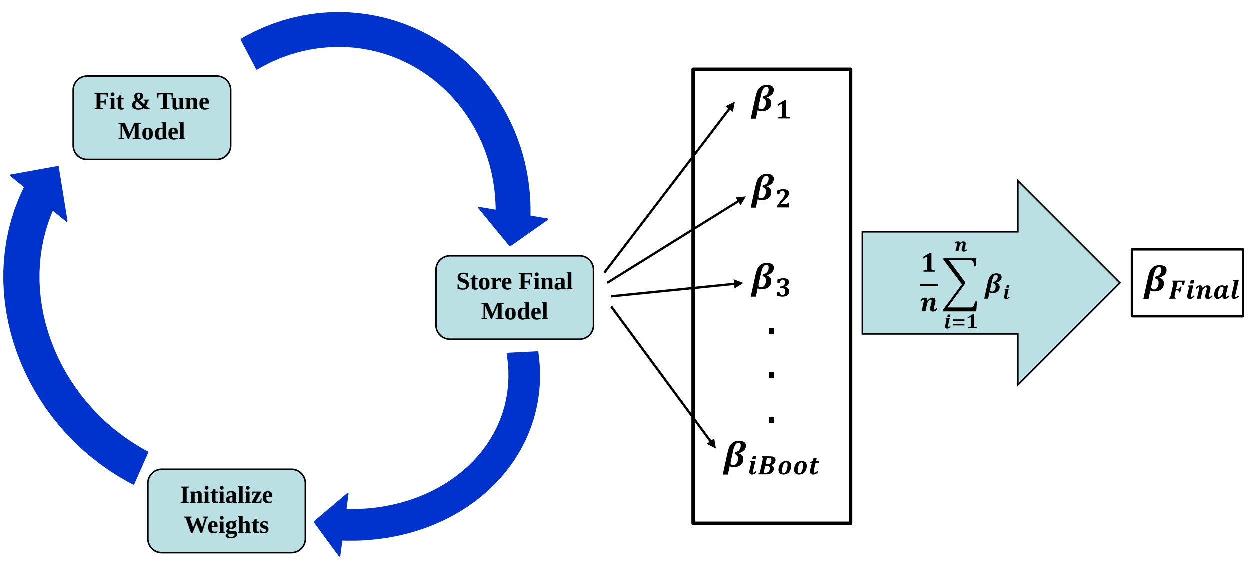

Figure 4-5 SVEM workflow diagram [41]

4.4 Results and Discussion

4.4.1 Full Quadratic Model (FQM)

An augmented FQM was used to predict the fracture energy based on variables in group A, the combination of variables in groups A and B, and the combination of variables in groups A, B, and C, and the results are presented in figures 4-6 i, ii, and iii, respectively. The results show that the accuracy of the model increases as group B variables are combined with variables in group A. while the accuracy of the model based on mix design data decreases (test set). The prediction model based on the combination of all groups together showed lower accuracy for all training, validation, and test sets as compared to the prediction model based on the combination of groups A and B. It could be related to the higher amount of data points for combination of all groups together which makes the model supersaturated and unstable and decreases the reliability of regression models to predict the test outcome. It can be concluded that having additional variables for the FQM, may not necessarily improve the predictability of the model.

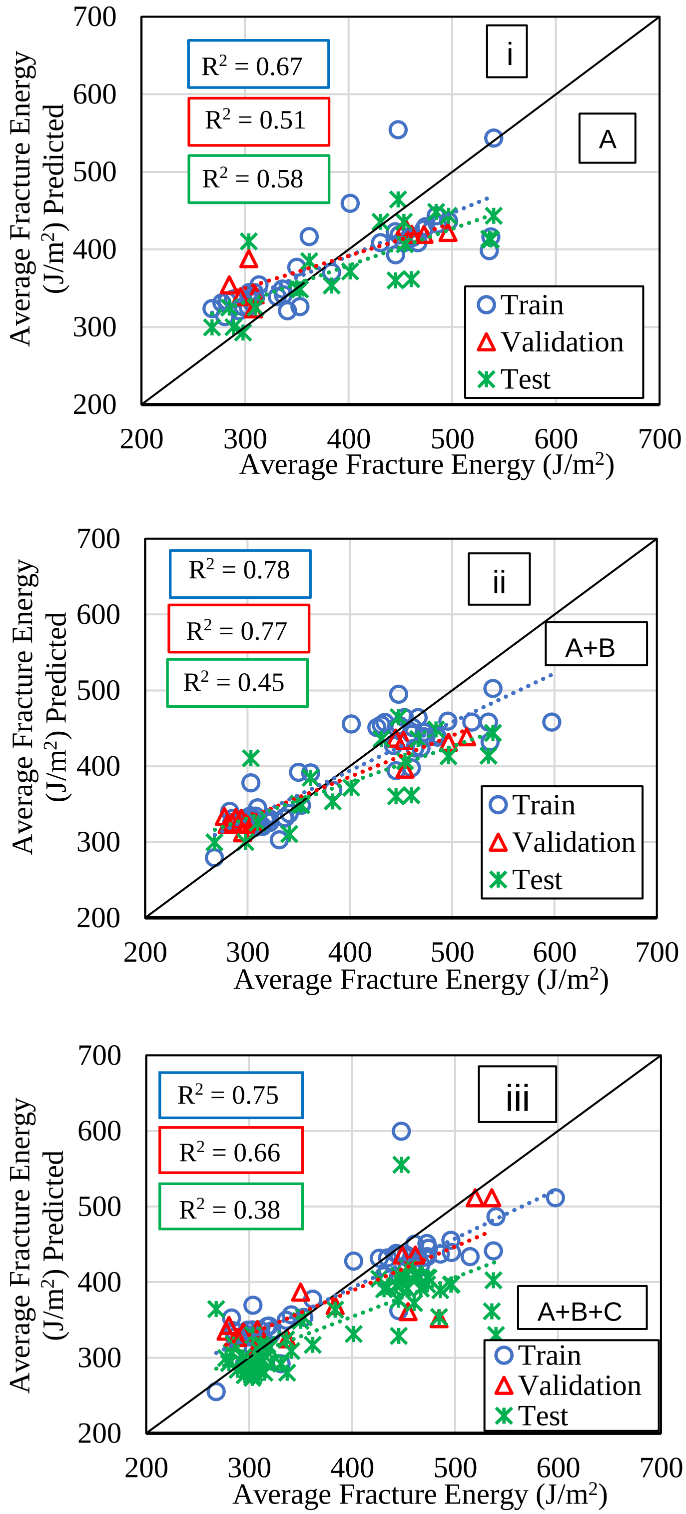

Figure 4-6 Actual vs Predicted fracture energy based on augmented FQM i) Group A, ii) Groups A and B, iii) Groups A, B, and C

4.4.2 Artificial Neural Network (ANN) Model

Several model structures with different neurons in the hidden layer were utilized to determine the optimum ANN architectures to predict fracture energy. The best models were then validated using K-fold cross-validation techniques. In addition, mix design data was used as a test set to investigate the reliability of the model. Table 4-4 shows R-squared values and model error for different models for the combination of groups A, B, and C. Based on the results, the best model structure for the combination of all groups was found to be 14-100-1. Figure 4-7 demonstrates a model architecture diagram with 14 inputs, 1 hidden layer with 100 neurons, and 1 outcome. ANN models are complex and computationally expensive and level of complexity can be visualized by the number of neurons and number of required calculations between layers in figure 4-6. Figures 4-7 i, ii, and iii show predicted vs. actual fracture energies based on ANN for group A, the combination of group A and B, and the combination of groups A, B, and C, respectively. In general, it can be concluded that ANN can predict fracture energy of asphalt mixtures with high accuracy. The model accuracy increases (especially for the training set and test set) as more input variables are added to the model.

Table 4-4 Statistical values of ANN model for groups A, B, and C

ANN architectures	Train		Validation	
	R^2	RASE	R^2	RASE
14-1-1	0.88	29.92	0.64	74.20
14-2-1	0.93	22.62	0.72	65.57
14-3-1	0.97	15.99	0.93	21.62
14-4-1	0.88	36.36	0.99	6.04
14-5-1	0.95	21.28	0.92	23.24
14-6-1	0.97	15.33	0.97	12.23
14-7-1	0.95	18.53	0.81	54.33
14-8-1	0.85	38.81	0.99	4.03
14-9-1	0.98	10.57	0.67	73.78
14-10-1	0.97	15.85	0.95	26.22
14-15-1	0.98	11.26	0.76	59.88
14-20-1	0.73	51.72	0.96	15.77
14-25-1	0.96	15.84	0.91	36.95
14-30-1	0.96	16.21	0.35	99.84
14-35-1	0.82	42.80	0.99	2.52
14-40-1	0.77	47.52	0.99	7.38
14-45-1	0.45	73.79	0.99	3.20
14-50-1	0.80	44.60	0.99	1.90
14-60-1	0.97	14.37	0.52	85.21
14-70-1	0.97	13.58	0.62	76.41
14-80-1	0.98	13.06	0.98	11.44
14-90-1	0.97	15.28	0.61	76.71
14-100-1	**0.99**	**10.49**	**0.98**	**11.42**

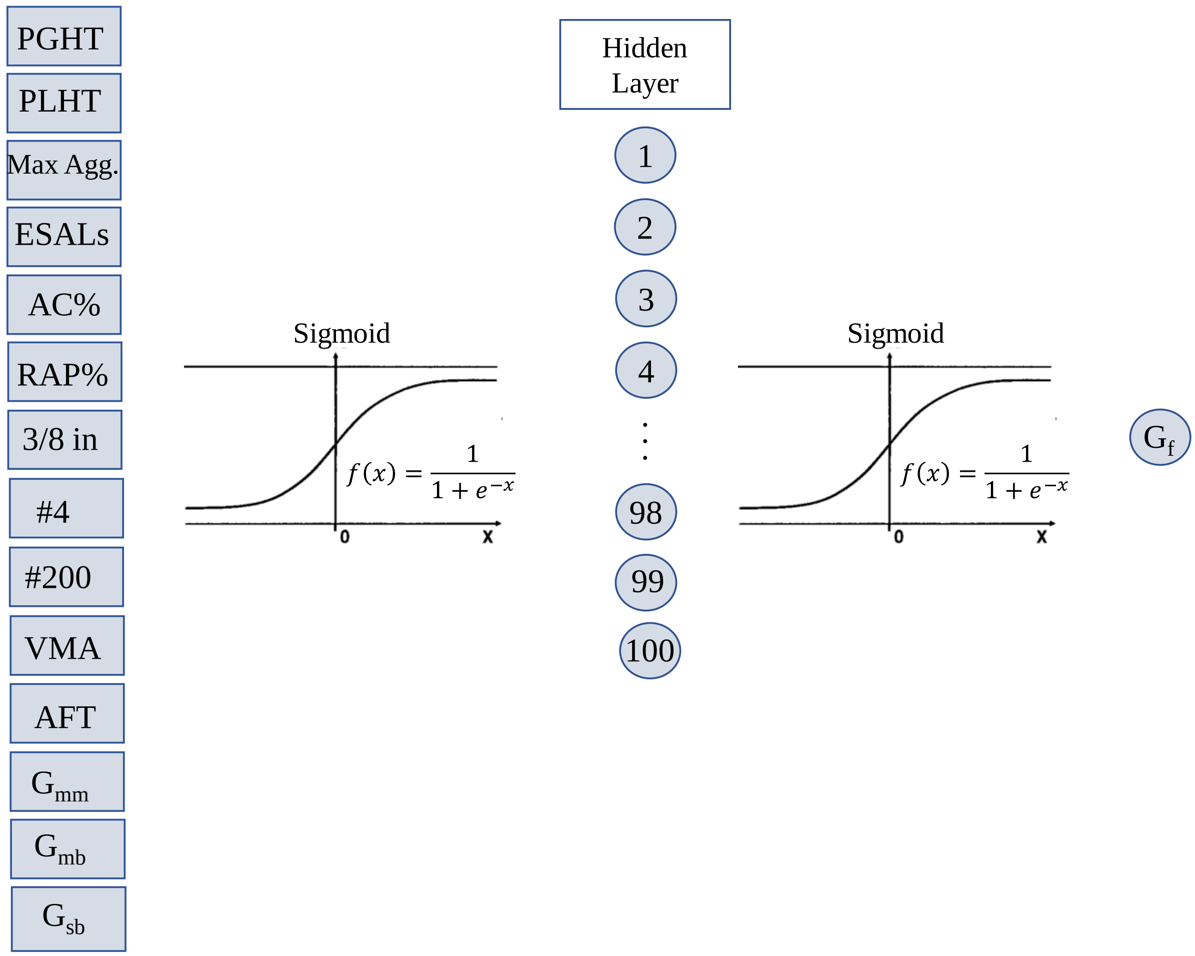

Figure 4-7 ANN architecture diagram for groups A, B, and C

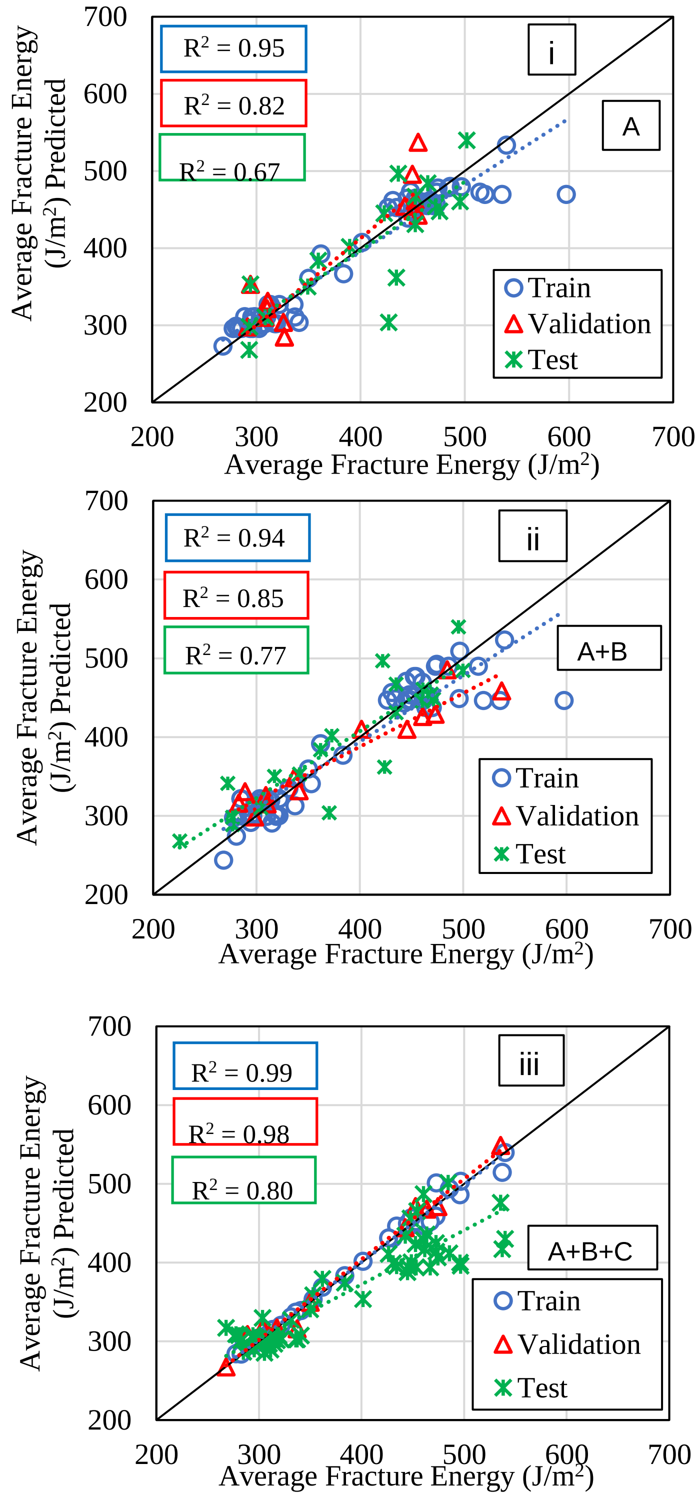

Figure 4-8 Actual vs Predicted fracture energy based on ANN i) Group A, ii) Groups A and B, iii) Groups A, B, and C

4.4.3 Self-validated Ensemble Modelling (SVEM)

The same augmented FQM as regression analysis was used for the SVEM. Each model was run for a different number of iterations, and it was found that 250 iterations would lead to the most optimum results, and the final models are presented as the average of 250 model runs. Figures 4-8 i, ii, and iii show the actual vs. predicted fracture energy for group A, the combination of groups A and B, and the combination of groups A, B, and C, respectively. According to the results, the SVEM technique is able to develop reliable prediction models even only with variables in group A. Combination of variables in groups A and B increases the accuracy of training and validation sets, while it lowers the accuracy of the test set. Although the accuracy of prediction models based on variables for the combination of groups A and B and the combination of all groups is comparable, using all variables increases the test set accuracy. This means utilizing more variables results in a more stable model and increases prediction capability even if mix design data is used as opposed to production data.

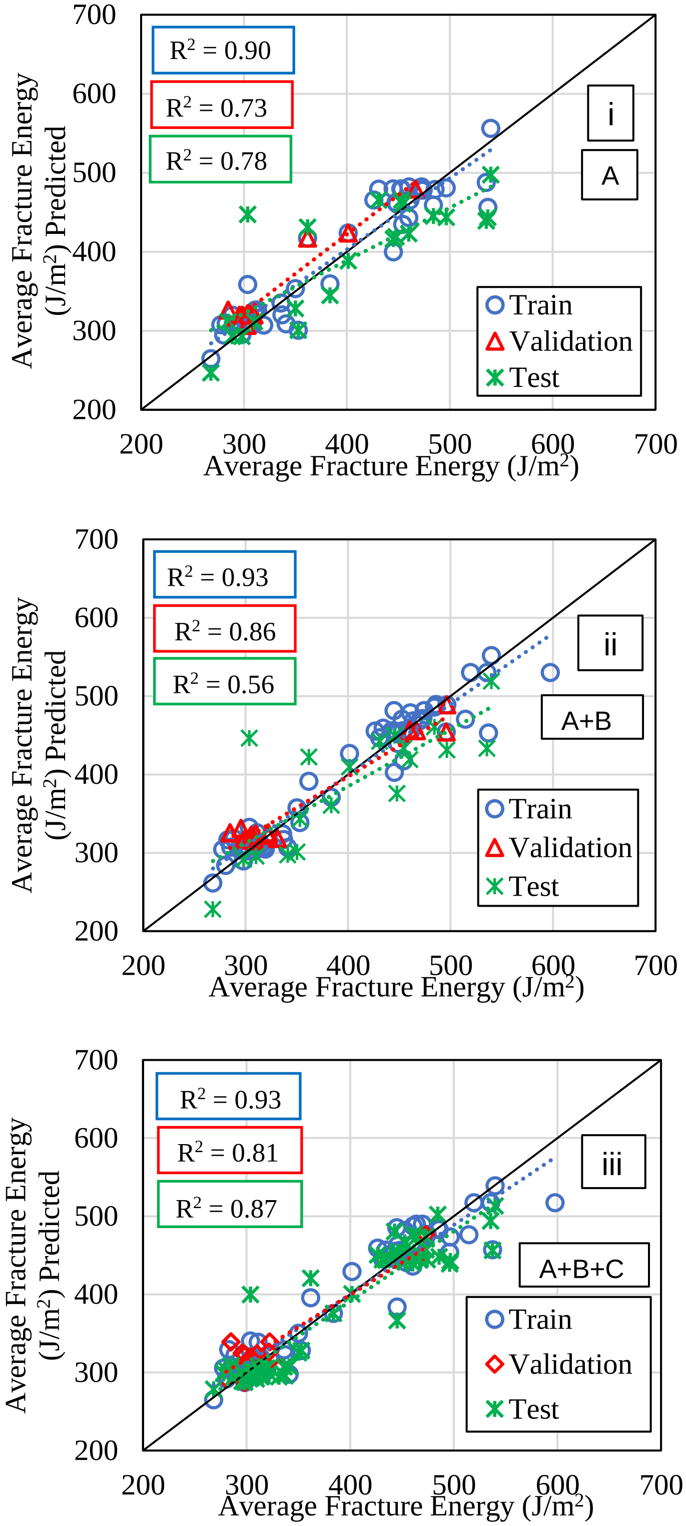

Figure 4-9 Actual vs Predicted fracture energy based on SVEM technique i) Group A, ii) Groups A and B, iii) Groups A, B, and C

4.4.4 Model Comparison

All prediction models in this study were compared in terms of variation between actual test data and predicted fracture energy and amount of error in the models (table 5). Color coding has been utilized in table 5 to better visualize the differences between model performance with green indicating better performance and red indicating worse performance. As expected, the augmented FQM shows the highest amount of error and lowest accuracy among all prediction models. Using SVEM technique substantially improves the model accuracy and lowers the error, which demonstrates this technique's efficiency even with a limited amount of data. Both SVEM and ANN models show promising and comparable results in terms of fracture energy prediction model accuracy and error with the ANN model having slightly better results for the combination of all groups together. The ANN implemented 100 neurons in the hidden layer and considering that it uses non-linear techniques to predict the test outcome, the model would be time-consuming and computationally expensive (for example, a 1000 neuron model with 1 hidden layer in this study required approximately 45 minutes of time to complete analysis on a standard windows mid-range laptop computer). Moreover, since the ANN does not provide a final prediction equation, it would not be very suitable to be used as a predesign prediction tool, and it requires more familiarity with data analysis. On the other hand, the SVEM technique utilizes a linear approach, which shows comparable precision to the ANN model but is less computationally expensive and does not require data analysis knowledge prior to implementing the final prediction model. The SVEM models based on the group A and B variables and combination of all variables have comparable predictability. This shows a reliable and precise prediction of fracture energy can be obtained only with variables available at the early stage of mix design when conducting laboratory tests to measure physical and volumetric properties of asphalt mixtures may not be feasible.

Table 4-5 Model comparison in terms of prediction accuracy and errors

Group	Statistical Parameter								
	R-Squared			RASE			AAE		
	Train	Validation	Test	Train	Validation	Test	Train	Validation	Test
	FQM								
A	0.67	0.51	0.58	58.88	56.22	70.42	46.60	51.68	52.97
A+B	0.78	0.77	0.45	40.28	42.86	58.69	30.96	38.21	44.79
A+B+C	0.75	0.66	0.38	43.32	51.97	64.20	33.32	39.30	47.66
	ANN								
A	0.95	0.82	0.67	18.41	37.17	43.63	13.66	27.46	32.27
A+B	0.94	0.85	0.77	23.99	32.88	36.95	17.61	24.67	29.90
A+B+C	0.99	0.98	0.80	10.49	11.42	41.86	6.15	8.10	31.04
	FWB+AV								
A	0.90	0.73	0.78	30.69	24.74	50.77	23.37	19.59	37.93
A+B	0.93	0.86	0.56	23.23	24.17	52.34	16.58	19.50	39.22
A+B+C	0.93	0.81	0.87	26.33	25.12	28.94	19.32	19.62	21.09

4.4.5 Sensitivity Analysis

Sensitivity analysis was conducted using JMP® Pro software to assess the effect of each variable on the final prediction model. It is worth noting that the evaluation was conducted withing the range of values for the variables assessed in this study as shown in table 3. Figure 4-10 shows the results of sensitivity analysis. Based on the results, design traffic level has the highest impact on fracture energy. The results make sense because higher traffic volume requires mixtures to be designed with higher amount of crushed aggregate in the mix design as well as higher compaction levels which increases fracture energy of asphalt mixtures. Three levels of design traffic (levels

3, 4, and 5 based on MnDOT definition) were used in this study. Between levels 3 and 4, the required amount of crushing in coarse aggregates would change (55% coarse aggregate by weight need at least one crushed face for level 3 whereas 85% require two crushed faces and 80% require at least one crushed face). There are no sand equivalency requirements for fine aggregate for level 3 and also required amount of fine aggregate angularity is lower for level 3 (42% for wear courses) as opposed to level 4 (44% for wear course). Lastly, level 4 mixtures are designed with 90 gyrations as opposed to level 3 mixtures which are designed with 60 gyrations. This means that level 3 mixes often have significantly larger amount of rounded aggregate particles (such as, natural sand and gravels), and lower amount of compactive effort that impacts the aggregate interlocking, both these aspects are expected to impact the fracture energy of mix.

According to the results, gradation of fine aggregates (smaller than sieve #4) and total binder content have a very small (insignificant) impact on the fracture energy (less than 1%). The results are not entirely unexpected since volumetric measures such as, VMA and AFT represent actual binder availability or need within the mixtures and these depend significantly on the type and gradation of aggregates. Although total binder content has a negligible effect on the fracture energy, binder PGLT was found to be the second most effective variable on mixture fracture energy. At low temperatures, the fracture energy significantly depresses when temperatures approach the glass transition temperature of the binder. Asphalt binders with lower PGLT have lower glass transition temperature and thus the observed trend is expected. In addition, a lower PGLT provides higher flexibility and ductility at low temperatures and as a result a softer binder has higher fracture energy as compared to a stiff binder.

It can also be concluded that almost 89% of the predicted model can be represented with variables from groups A and B, meaning that these variables and interactions between them define about 90% of the predictability of model. This emphasizes the finding in previous sections that even before conducting any laboratory tests to measure physical and volumetrics properties of asphalt mixtures, the low temperature fracture energy can be predicted with a high reliability.

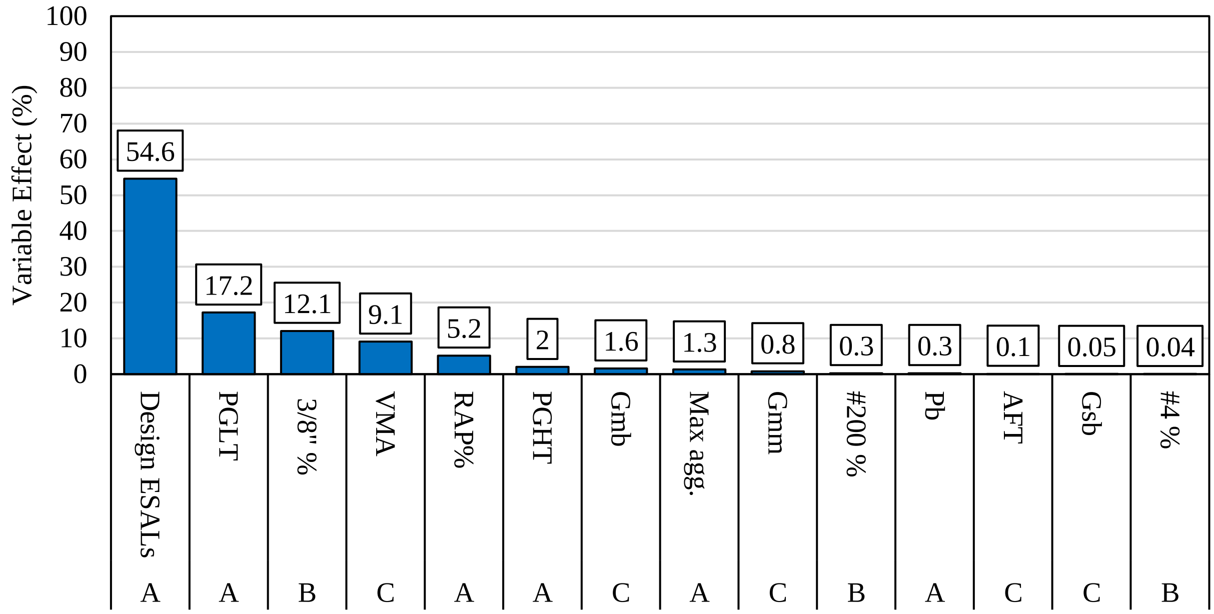

Figure 4-10 Effect of each variable on fracture energy

4.4.6 Web-based Fracture Energy Prediction Model

Based on the model error, the accuracy of prediction, and computational time and cost, prediction models based on SVEM techniques were selected as the final fracture energy prediction models. A web-based prediction tool was developed based on the final prediction equations for all three levels (group A, combination of groups A and B, and combination of groups A, B, and C) as a predesign prediction tool (figure 4-11). Researchers and asphalt agencies can choose the most suitable model based on their preference and availability of data. When testing is not feasible, these models ensure prediction of fracture energy with certain levels of accuracy even with a limited amount of data. The final model has been converted into a web-based tool that can be found on https://mdscrackpredictor.com/. It should be mentioned that the proposed prediction models are not based on mechanistic evaluation of mixture behavior, and they are mostly suitable for the considered range of predictor variables in this study. The author would not recommend extrapolation of the models at this time. While the particular developed models are only applicable for range of variables in the data set, this paper provides framework on how to develop accurate prediction models using SVEM technique.

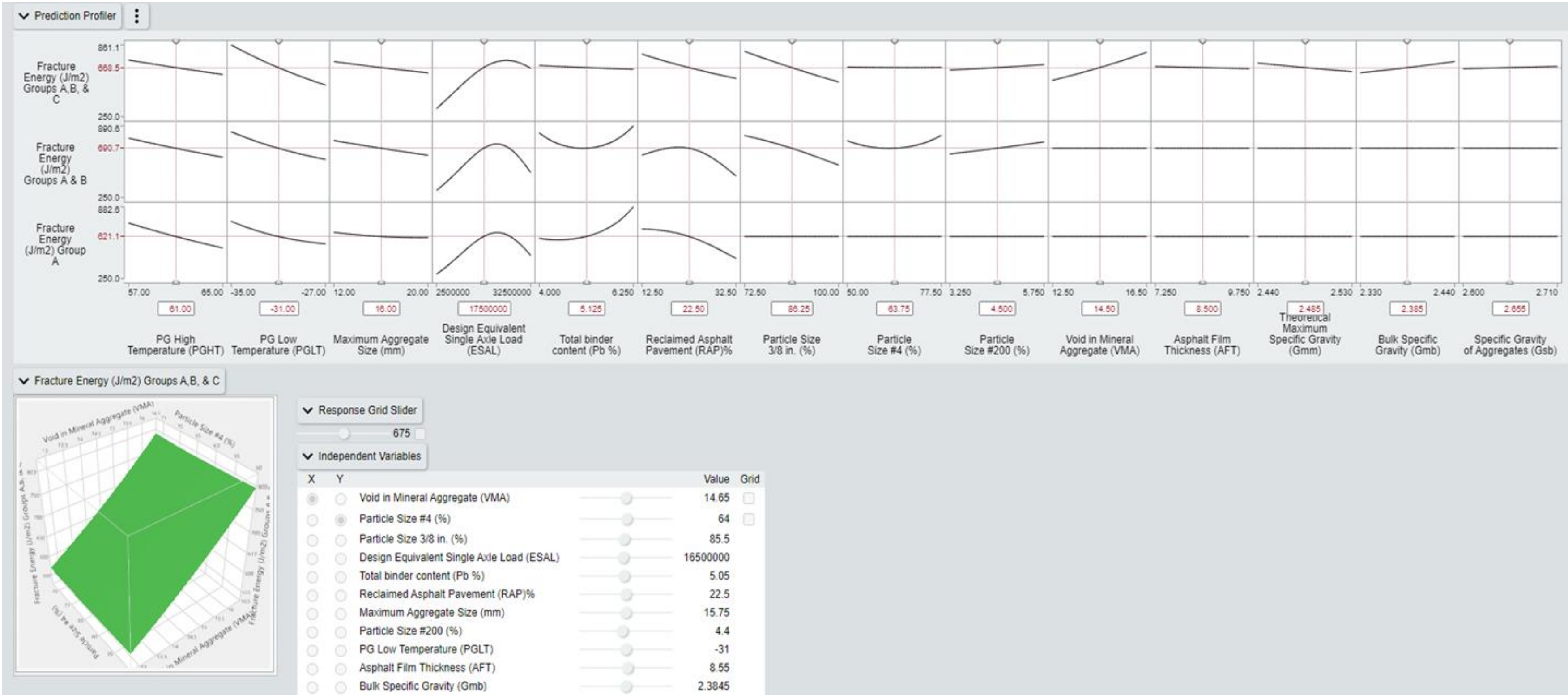

Figure 4-11 Fracture energy prediction tool

4.4.7 Model Evaluation

The performance of the developed prediction model in this dissertation was compared with a published fracture energy prediction model by Majidfar et al. [34] to evaluate the predictability of the model. Majidfar et al. used gene expression programming (GEP) as a machine learning method and recommended the model for predesign purposes when testing is not feasible. Mix design data that was not involved in any step of model development in this work (test set) was used to compare the performance of two models. The GEP model utilizes fewer mix variables and is accurate for a narrower range of variables as compared to the SVEM model in this work. Therefore, only mixtures for which mix variables meet the GEP model requirements were selected. Figure 4-12 shows actual fracture energy vs. predicted fracture energy based on SVEM and GEP models. Based on the results, SVEM has better accuracy than GEP. While the accuracy of the GEP model is not low, the model is extremely biased that emphasized coefficient of determination cannot be used solely to compare model performance. In addition to the coefficient of determination, RASE and AAE were used for the models comparison, and table 4-6 shows the results. The SVEM model has a significantly lower error with respect to both RASE and AAE. The high amount of error in the GEP model could be related to the fact that this model only considers a few mix variables with a narrow range which means the model would result the same amount of fracture energy for most of the mixture in this work without considering all influential variables.

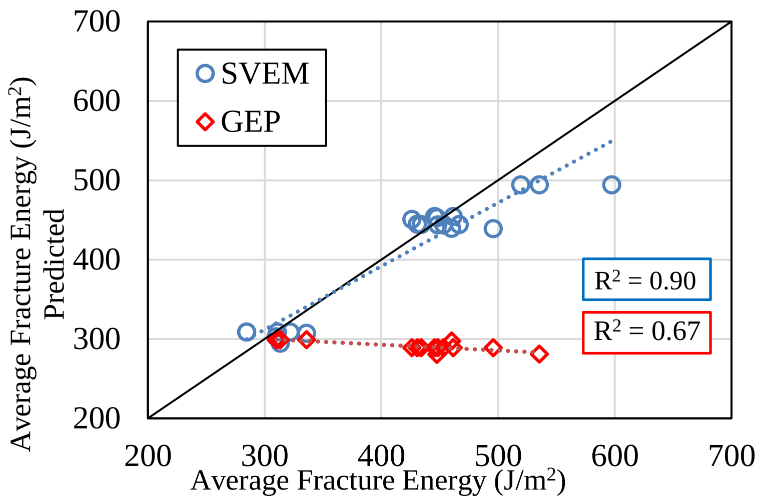

Figure 4-12 Actual vs Predicted fracture energy based on SVEM and GEP models

Table 4-6 Model comparison in terms of prediction accuracy and errors

Model	Statistical Parameter		
	R-Squared	RASE	AAE
SVEM	0.90	31.53	22.45
GEP	0.67	157.28	129.77

4.5 Summary and Conclusion

In this study, FQM, ANN, SVEM statistical analysis methods were utilized to predict the low temperature fracture energy of asphalt mixtures corresponding to temperature equal to asphalt binder PGLT+10°C. Prediction models were developed using an experimental database including 71 different asphalt mixtures with 12 replicate specimens for each mixture. The models include the simultaneous impact of various predictor variables such as asphalt binder and aggregate types, recycled material content, proportioning of the asphalt binder and aggregates based on design traffic data, mixture volumetric properties such as air voids, densities, AFT, VFA, and VMA.

Values determined from plant produced materials were used for training and validation of prediction models. In addition to actual production data, mix design data was also collected to test the predictability of the proposed models. The dataset was then divided into three subgroups based on the availability of the data during the mix design process to determine the minimum amount of data that needs to be collected for a reliable performance prediction. Sensitivity analysis was conducted to determine the effect of each variable on the model outcome. Based on the obtained results, the following conclusions can be drawn:

- While, adding more variables increases prediction models accuracy, the predictability of the AFQM decreased using all variables in groups A, B, and C. This is likely related to saturation of the regression model and shows that model accuracy may not necessarily be improved with more variables.
- Both ANN and SVEM showed comparable predictability in the models. However, ANN models were found to be time-consuming and computationally more expensive than the models developed using the SVEM technique. Also, SVEM does not require a predefined functional structure of the model to predict the outcome, which leads to a simpler functional structure and increased practicality.
- The sensitivity analysis results showed that design traffic level (aggregate angularity, aggregate plastic fines amount and mix compaction levels), PGLT, percent passing 9.5 mm sieve, and VMA the most effective factors as compared to other variables in this study. In addition, predictor variables in groups A and B can explain almost 91% of the variation in predicted fracture energy, which means that based on the SVEM models, fracture energy can be predicted with high reliability even before measuring mixture properties and conducting laboratory tests.

- Three web-based prediction models were developed based on the SVEM technique that can be utilized as asphalt mixture predesign tool. The models enable users to predict asphalt mixture susceptibility to low temperature cracking with high reliability when testing is not feasible and/or a limited amount of data is available during the mix design process.

Overall, designing a mix with acceptable performance with respect to thermal cracking may be cost prohibitive. Using the developed empirical prediction models in this study will result in monetary and time saving for such a design process.

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CHAPTER 5

Machine learning-based prediction models for asphalt mixtures fatigue cracking resistance

5.1 Chapter Introduction

The asphalt paving industry has consistently been seeking to improve the performance of asphalt mixtures through the use of different techniques (such as using newer types of chemical modifiers and newer material processing techniques). Despite notable positive impacts and economic benefits, these mixtures face certain challenges due to the limitations of current pavement design and evaluation approaches. Both empirical and mechanistic-empirical (M-E) design methods typically consider material stiffness in differentiating mixture performance with respect to different distresses. However, some innovative materials may minimally change stiffness but substantially improve resistance to rutting and/or cracking. Others may change stiffness in a manner that would indicate detrimental changes to performance using current analysis methods but, in practice, have shown substantial performance enhancement. In many cases, current pavement design and evaluation methods cannot adequately quantify the benefits that may be achieved through the use of innovative mix production techniques in asphalt pavements. Therefore, pavement design and evaluation approaches should incorporate performance-based properties to accurately represent the true performance differences to be expected under realistic loading and environmental conditions [1,2].

The AASHTO 1993 empirical pavement design methodology is currently used by many agencies to design and evaluate flexible pavements. This methodology uses a single-layer coefficient value to represent the ability of each layer to provide structural capacity for the pavement [1]. Layer coefficients are determined based on the stiffness of the material and the layer within the pavement structure where the material will be used [3, 4]; however, this relationship is currently based solely on empirical observations of in-service pavement performance, and it is not related to engineering properties or failure criteria. Consequently, traditionally determined layer coefficients may not be able to appropriately quantify the structural and performance contribution of a material to arrive at optimized pavement design [1,5-8]. To address these challenges, a recent study by the New Hampshire Department of Transportation (NHDOT), has applied performance index parameters to develop performance incorporated layer coefficients. The lab-measured index parameters have been utilized to modify structural coefficients of the asphalt mixtures through different mechanistic and performance-based measurements. New layer coefficients can be determined based on specific distresses or a standardized distress index parameter such as the International Roughness Index (IRI) to account for a range of field variables. Modified layer coefficients that incorporate performance-based properties allow for more efficient and optimized pavement design and evaluation for reliable use of innovative asphalt mixtures [9].

M-E methods have been introduced as the next generation of design procedures and directly use rate and temperature-dependent modulus values along with traffic data and climatic conditions as inputs in mechanistic, structural models (layered elastic analysis) to calculate stresses and strains within a pavement structure. Empirically based transfer functions are then employed to convert stresses and strains to expected values of distress (e.g., rutting and cracking). Failure in the pavement is defined when pavement distress reaches the predefined threshold [1, 10, 11]. Common advanced simulation and design software such as AASHTOWare™ Pavement ME Design and MnPAVE, which are built upon M-E methods, employ modulus values measured in the linear viscoelastic (LVE) range [12-15]. Consequently, M-E procedures are not able to distinguish between materials with the same stiffness/modulus but different properties with respect to different distresses [2,16]. Construction of multiple field test sections and performance monitoring over time could be used to calibrate new transfer functions specifically for individual innovative materials but requires substantial time and effort. In addition, since M-E methods are not able to capture mixture properties outside of the LVE range, even locally calibrated transfer functions within the current system would not be able to represent the effects of newer innovative approaches.

To overcome these limitations, the simplified viscoelastic continuum damage (S-VECD) approach was developed by Underwood and Kim (2010) and showed promising results as an asphalt mixture fatigue cracking characterization tool [17, 18]. In addition to LVE properties, the S-VECD theory utilizes the damage evolution law to capture the fatigue properties of material outside of the linear range with respect to the amount of accumulated damage in a mixture. The main outcome of S-VECD theory is the damage characteristic curve (DCC) which is fundamental mix property and independent of loading mode and test temperature. The DCC represents the relationship between the asphalt mixture's material integrity (called the Pseudo stiffness, C) and the level of damage over time, S due to the loading cycle (N) [19]. Important information such as the rate and amount of accumulated damage and the mixture terminal integrity before the crack localization can be provided with the DCC cure that can be used as inputs in structural models to assess asphalt mixtures performance with respect to cracking.

The objectives of this chapter of dissertation are as follows:

- Find the best fit for DCC based on S-VECD analysis approach
- To develop a precise prediction models for DCC curve model coefficients using different statistical methods.

5.2 Methodology

5.2.1 Laboratory Testing

The experimental campaign in this chapter includes complex modulus (E*) and direct tension cyclic fatigue (DTCF) tests.

Complex modulus testing was carried out on asphalt mixtures in accordance with AASHTO T 342, the standard method of test for determining dynamic modulus of hot mix asphalt (HMA) [20]. Three cylindrical specimens with 150 mm height and 100 mm diameter were tested for each mixture at different temperatures and frequencies to capture the rheological behavior of asphalt mixtures in the linear range. The asphalt mixture performance tester (AMPT) equipment was used to conduct the test. Dynamic modulus and phase angle were calculated as test outputs, and RHEA® software was used to construct the master curves based on the time-temperature superposition principle.

To investigate the fatigue damage characteristics of asphalt mixtures, DTCF fatigue testing was performed on specimens in accordance with AASHTO TP 107, the standard method of test for determining the damage characteristic curve and failure criterion using the AMPT [21]. At least three replicates with 130 mm height and 100 mm diameter were tested for each mixture. The tests were conducted at, at least three different peak to peak on specimen strain levels to get a range of number of cycles to failure (N_f). The test was conducted by applying sinusoidal tensile loading at a frequency of 10 Hz in crosshead-controlled mode until failure. Test temperature was determine based on asphalt binder PG using equation (1).

$$DTCF\ test\ temperature = \left(\frac{PGHT - PGLT}{2}\right) - 3 \tag{1}$$

The S-VECD approach developed by Underwood and Kim (2010) was used to analyze the fatigue test results using data acquired during complex modulus and fatigue tests. The C-S curve was plotted as a S-VECD based fatigue properties using FlexMAT^{TM} software. Figure 5-1 shows a schematic of testing and data analysis procedures and how the results were used in statistical analysis for this study.

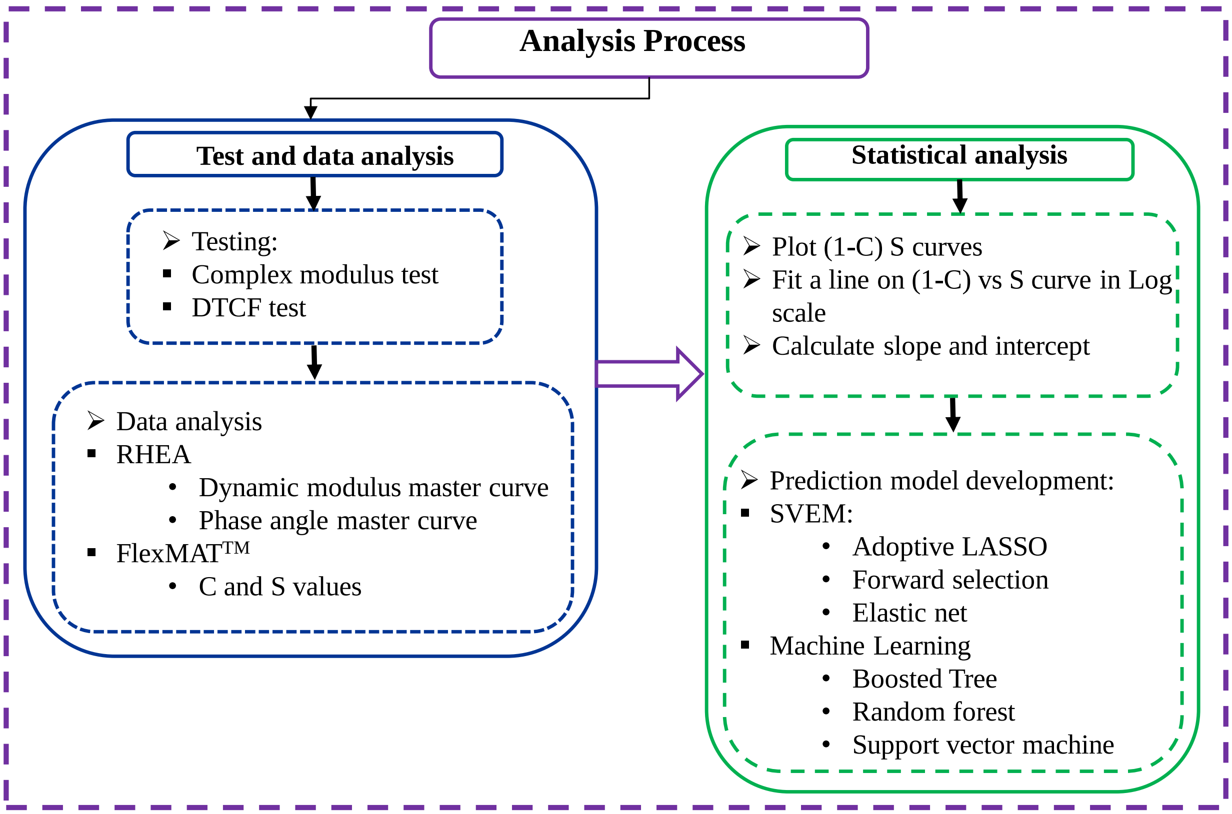

Figure 5-1 schematic of testing and data analysis procedures

5.2.2 Test Data

A set of 47 mixtures were used to assess their fatigue cracking properties based on S-VECD theory. Asphalt mixtures were designed based on the Superpave mix design procedure. The mix design variables include a selection of asphalt binder and aggregate types and recycle material content, and then proportioning of the asphalt binder and aggregates, aggregate empirical properties, and volumetric properties of a mixture such as air voids, densities, voids filled with asphalt (VFA), and VMA. The mix design variables were then used as inputs of the prediction model to determine their relationship with the C-S curve as an S-VECD based fatigue properties. Tables 5.1 shows descriptive statistics of each variable.

Table 5-1 Descriptive statistics of variables on this study

Variable	N	Mean	Std Dev	Sum	Minimum	Maximum
PGHT	47	63.91	7.77	2428.40	52	81
PGLT	47	-27.07	4.19	-1028.50	-34	-22
NMAS (mm)	47	13.39	3.98	508.75	4.8	19.0
Binder Content %	47	5.41	0.59	205.76	4.5	7.0
RAP%	47	11.14	10.89	423.50	0	31.3
Particle Size 3/8 in. (%)	47	85.06	9.71	3232.20	66	100
Particle Size #4 (%)	47	60.71	10.95	2306.90	43	94
Particle Size #200 (%)	47	4.15	1.71	157.68	0.9	8.5
VMA	47	16.14	1.29	613.44	14.1	20.2
AFT	47	9.83	1.73	373.55	6.7	13.7
G_{mm}	47	2.541	0.101	96.572	2.357	2.710
G_{mb}	47	2.397	0.106	91.080	2.180	2.580
GSB	47	2.757	0.112	104.746	2.650	2.961

5.3 Data Analysis Method

The pseudo stiffness (C) and corresponding damage (S) values were determined based on S-VECD theory and (1-C) vs S curves were plotted for each mixture using polynomial function. The slope and intercept of each curve were calculated in Log scale as determinant factors of the curve shape. Two parameters where then defined as follows:

$C_{11}= 10^{(\text{intercept})}$

$C_{12}=$ slope

The C_{11} and C_{12} parameters were used for statistical analysis to develop prediction models based on mix variables that introduced in the previous section. Equation 2 shows fitted curve equation based on C and S values.

$$C = 1 - C_{11} \times S^{C_{12}} \tag{2}$$

Several statistical analysis methods such as fractionally weighted bootstrapping + auto validation, boosted tree, random forest, and support vector machine were utilized to develop prediction models based on different variables. Thirty-seven (37) mixtures were selected randomly to be used as training and calibration of the models. Distribution of randomly selected mixtures were checked in order to make sure the training set is balance and true representative of the whole dataset. Ten mixtures that were not involved in any steps of model development where used as true validation set to assess the predictability of the models. In this study, the efficiency of trained models was evaluated using correlation of determination (R2) (equation 3), root average square error (RASE) (equation 4), and the absolute average error (AAE) (equation 5).

$$R^2 = \frac{(\sum_{i=1}^{N}(M_i - \bar{M}_i)(T_i - \bar{T}_i))^2}{\sum_{i=1}^{N}(M_i - \bar{M}_i)^2 \sum_{i=1}^{N}(T_i - \bar{T}_i)^2} \tag{3}$$

$$RASE = \sqrt{\frac{\sum_{i=1}^{N}(M_i - T_i)^2}{n}} \tag{4}$$

$$AAE = \frac{\sum_{i=1}^{n}|M_i - T_i|}{n} \tag{5}$$

Where:

M_i = Measured output

T_i = Predicted output

$\bar{M}_i$ = Average of measured outputs

$\bar{T}_i$ = Average of predicted outputs

n= Number of samples

5.3.1 Self-validated Ensemble Modelling (SVEM)

Fractionally weighted bootstrapping and auto validation (FWB+AV) method (as described in chapter 4 of this dissertation) was used to predict C_{11} and C_{12} parameters based on mix variables. Adaptive LASSO, forward selection, and elastic net models were utilized as linear regression models using SVEM add-in in JMP® pro software.

5.3.2 Boosted Tree

Boosted trees is a machine learning technique for both regression and classification problems. The Boosted trees model combines weak learning models (each tree) to a strong single prediction model by optimization of differentiable loss function [22,23]. The boosting process modifies a model S_n by adding an estimator k such that the new model predicts the mean of the response variable (y) at each step of boosting process (n). The model then calculates the square error loss function (L_b) by fitting the k parameter to the residual y-S_n(x). At the end, the prediction model (S_n(x)) will be modified by performing gradient descent at each boosting step for a data set [24]. Equation 6 shows model refining process. The model then utilizes the ensemble technique by averaging all prediction outcomes from each tree. Generally, tree based models could be inherently unstable based on the data set and the reason of ensumbling is to make accurate and stable model out of several weak models. In this study, different number of layers (20, 50, 100, 200, 500, 1000) were utilized in boosted tress to select the best model with respect to their predictability performances. Three splits per tree were selected with a learning rate of 0.1.

$$S_{n+1}(x) = S_n(x) + k(x) = y$$

$$L_b = \frac{1}{2}[y - S(x)]^2 \qquad (6)$$

$$S_n(x) \leftarrow S_n(x) - \delta \frac{L_b}{S_n(x)}$$

Where:

y = Response variable mean

L_b = Square error loss function

δ = learning rate

5.3.3 Random Forest

The random forest, also known as the bootstrap forest, is an ensemble learning prediction technique in machine learning [24]. The model can address both regression and classification tasks by creating several trees, and then the mean of the regression or mode of classification for each individual tree can be employed in prediction after learning. Each tree in the model grows on a bagging sample or bootstrap aggregation that is obtained by sampling the data with replacement. During the growth of a tree, the best split variable at each node is selected from a randomly drawn smaller number of variables from a data set. The random forest analysis then combines decision trees to develop a powerful "forest".

Considering a training set with input variables X=x_1,x_2,…,x_n and output variables Y= y_1, y_2,…, y_n, the bootstrap aggregation procedure repeats N times. Each time the model fits trees to random sample replacing the training set. For a particular bag n, where n=1, 2, …, N, the samples with replacement are from set N (X, Y) with a training sample as (X_n,Y_n). The model will train the regression tree (f_n) based on the training sample for each bag (X_n,Y_n). After training, the model calculates the average of the predictions for all individual prediction models from each bag as a final prediction model, as shown in equation 7 [24]. In this work, different number of trees in forest (20, 50, 100, 200, 500, 1000) were utilized to select the best model with respect to their performances. Bootstrap sample rate was selected to be one, and ten terms samples were selected per split in trees.

$$\hat{f} = \frac{1}{N}\sum_{n=1}^{N} f_n(x) \qquad (7)$$

5.3.4 Support Vector Machine

Support vector machine (SVM) is a machine learning tool that solves a problem using the minimization of structural risk concept to minimize the upper bound of predicted risk. The model was initially developed for classification solutions and, afterward, has been advanced to solve regression problems [25]. The SVM separates the positive and negative values using a functionally produced hyperplane. Considering a training set (x1,y1), (x2,y2),...,(xn,yn), the SVM performs a nonlinear function to convert an initial space in a dataset to a multi-dimensional space using the function of Ø(x) = (Ø1(x), Ø2(x),…, Øn(x)). Equation 8 shows the nonlinear function F calculation [26].

$$f(x) = w^T \emptyset(X) + b$$

$$\begin{cases} \min \frac{1}{2}(\|w\|^2 + CR_e) \\ R_e = \frac{1}{n}\sum_{i=1}^{n} L(y_n, f(x_n)) \end{cases} \qquad (8)$$

Where:

C = Regularization constant

$\|\omega\|^2$ = Regularization term that shows the confidence interval

R = Loss function empirical error

Equation (8) which is the optimization concept, can be supplementary converted to and essential objective function using equation 9.

$$\begin{cases} \min \frac{1}{2}(\|w\|^2 + C\sum_{i=1}^{n}(\varphi_i - {\varphi^*}_n)) \\ \begin{cases} y_n\omega^T\emptyset(x_n) - b \leq \varepsilon + {\varphi^*}_n \\ \omega^T\emptyset(x_n) + b - y_n \leq \varepsilon + {\varphi^*}_n \\ \varphi_n, {\varphi^*}_n > 0 \end{cases} \end{cases} \tag{9}$$

Where:

$\varphi_n, {\varphi^*}_n$= positive slack variables

ε = tube size

The constant C determines the trade-off between the extent up value and the flatness that can tolerate deviations larger than ε. For dual optimization problems, Lagrangian multipliers can be introduced. Equation 10 shows dual optimization process with Lagrangian multipliers and maximizing equation (9).

$$\begin{cases} \frac{1}{2}\sum_{i,j=1}^{l} (a_i - {a^*}_i)(a_j - {a^*}_j) \times K(x_i, x_j) - \varepsilon\sum_{i=1}^{n}(a_i - {a^*}_i) + \sum_{j=1}^{n} y_i(a_i - {a^*}_i) \\ s.t \begin{cases} \sum_{i=1}^{n}(a_i - {a^*}_i) \\ a \leq a_i,\ a_i \leq C \end{cases} \end{cases} \tag{10}$$

Where:

$k(xi, xj) = \emptyset T(xi)\ \emptyset(xj)$ is called the kernel function.

$$K(x, x_i) = \exp(-\gamma\|x - x_i\|^2)$$

Where:

γ , d = kernel parameters

An explicit formation of the nonlinear mapping can be avoided by developing kernel based SVM models. Kernels based models enable the operation in low-dimensional feature space to significantly reduce the computational load instead of operating in high dimensional input space. In this study radial basis function (RBF) kernel was used to develop prediction model.

5.3.5 Model Calibration

K-fold cross-validation was utilized to calibrate the regression models. The dataset is divided into k subsamples with equal sizes. K-1 subsamples were used to train the prediction model, and a remaining subsample was used to validate the model. The process was then repeated K times for cross-validation with using each subsample exactly once as the experimental data. In this study, five folds were used for model calibration.

5.3.6 Hyperparameter tuning

The hyperparameters of the three ML models (boosted trees, random forest, and SVM) are tuned using an auto-tunning model in JMP® pro software. Hyperparameters were tuned in a specific predefined range such that RMSE was determined for each set of hyperparameters, and the combination of hyperparameters with the lowest RMSE was selected as the final model. It should be noted that the mixtures that were used as true validation set were not involved in any step of model training and hyperparameter tuning. Table 5-2 shows the hyperparameter for each model.

Table 5-2 Hyper parameters for machine learning techniques

ML Models	Hyperparameters	Definition
Boosted Trees	Layer_num	Number of layers
	Split	Number of splits per tree
Random Forest	Tree_num	Number of trees in the forest
	Terms_split	Number of terms samples per split
SVM	C	Penalty term coefficient
	gamma	Gamma in gaussian kernel

5.4 Results and Discussion

5.4.1 Self-validated Ensemble Modelling (SVEM)

Different regression analysis methods such as adaptive Lasso (AL), forward selection (FS), and elastic net (EN) were used for the SVEM to predict C_{11} and C_{12} coefficients. The response surface method was used to capture all interactions between variables and their effect on the outcome. Each model was run for a different number of iterations (20, 50, 100, 200, 500, and 1000), and the model with the best performance with respect to the true validation set for each method is presented in these sections. It should be noted that models with overfitting and/or a high amount of bias were excluded from the final results.

Figures 5-2 a and b show the actual vs. predicted C_{11} coefficient based on AL (100 iterations) and FS (50 iterations) techniques, respectively. According to the results, the FS model has higher predictability for both the training set and true validation set as compared to AL. In addition, the fitted model based on FS is less biased than AL.

Figures 5-3 a-c show the actual vs. predicted C12 coefficient based on AL (20 iterations), FS (100 iterations), and EN (50 iterations) techniques, respectively. The results show FS has the highest accuracy among other models for both training and true validation sets. AL and EN showed comparable performance, with EN having a lower biased result as compared to the AL model.

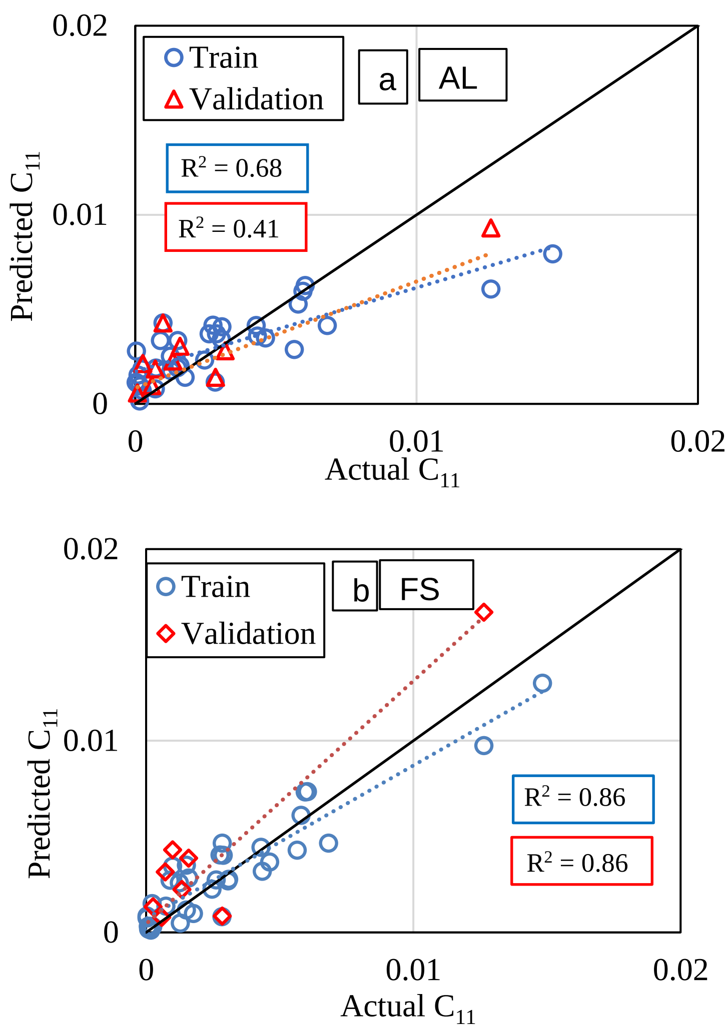

Figure 5-2 Actual vs Predicted C_{11} coefficient based on SVEM technique a) Adaptive Lasso, b) Forward selection

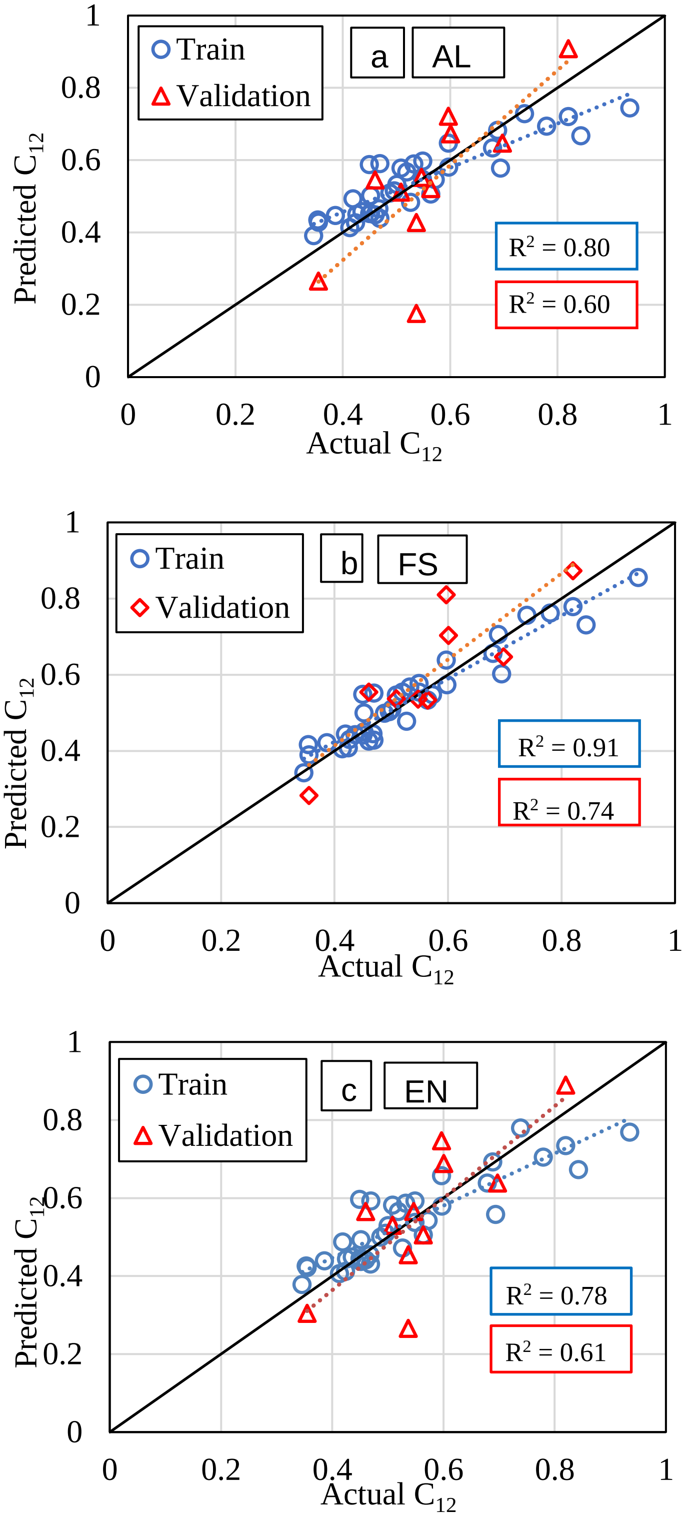

Figure 5-3 Actual vs Predicted C12 coefficient based on SVEM technique a) Adaptive Lasso, b) Forward selection, c) Elastic net

5.4.2 Machine Learning Algorithms

Different machine learning algorithms such as boosted trees (BT), random forest (RF), and support vector machine (SVM) were used to predict C_{11} and C_{12} coefficients.

Each model was run for a different number of layers or trees or iterations (20, 50, 100, 200, 500, and 1000), and the model with the best performance with respect to the true validation set for each method is presented in these sections. It should be noted that models with overfitting and/or a high amount of bias were excluded from the final results.

Figures 5-4 a-c show the actual vs. predicted C_{11} coefficient based on BT (100 layers), RF (500 trees), and SVM (20 iterations) techniques, respectively. According to the results, both BT and RF models have very high prediction accuracy and low bias. The BT model has more precise predictability with respect to the true validation set than the RF. The SVM model showed relatively high accuracy for training set prediction, while the true validation fit was highly biased. The results are expected based on the definition of the SVM model, which was developed for classification problems and then mathematically modified to be utilized in regression problems. The other reason could be related to the true validation set that was completely isolated during the model development process. Considering the amount of data points for the true validation set (10), a highly biased fit based on SVM was not surprising.

Figures 5-5 a and b show the actual vs. predicted C_{12} coefficient based on BT (200 layers) and RF (500 trees), respectively. The results demonstrate that both BR and RF fit a very accurate model on the training set with R-squared higher than 0.99. The BT technique showed more reliable prediction with respect to the true validation set as compared to RF.

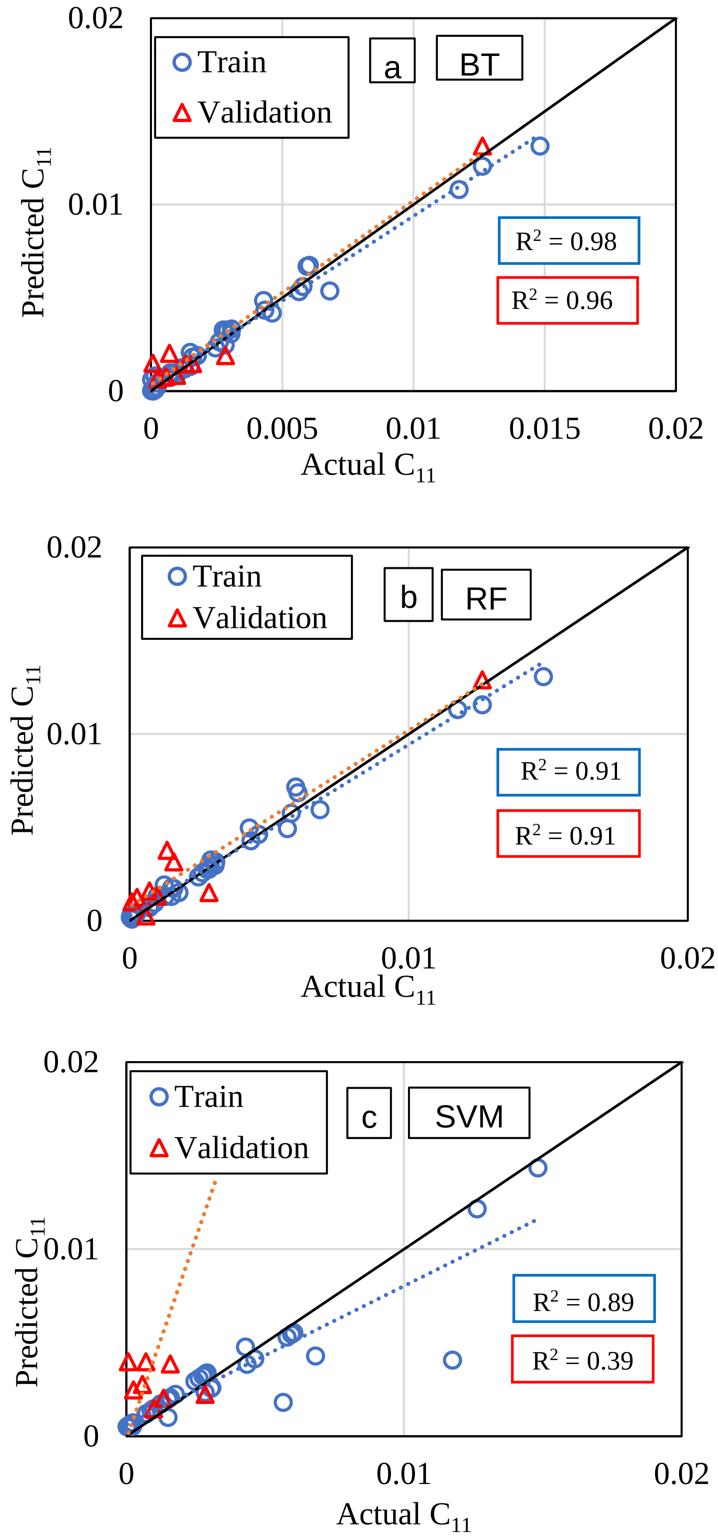

Figure 5-4 Actual vs Predicted C_{11} coefficient based on machine learning technique a) Boosted Trees, b) Random Forest, c) Support Vector Machine

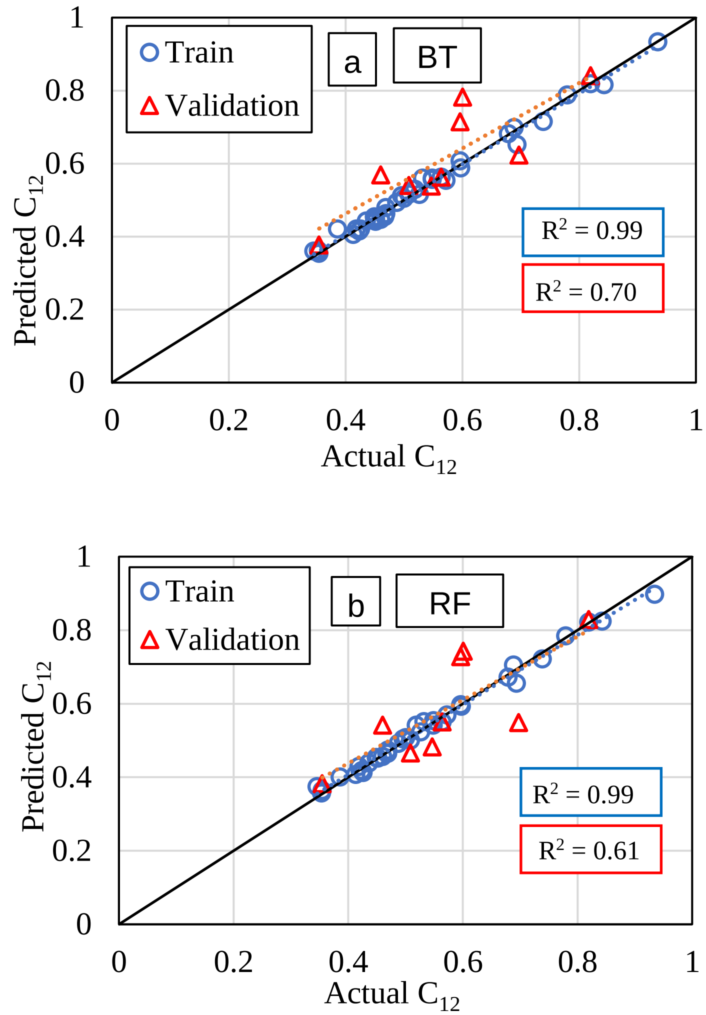

Figure 5-5 Actual vs Predicted C_{12} coefficient based on machine learning technique a) Boosted Trees, b) Random Forest

5.4.3 Model Comparison

All prediction models in this study were compared in terms of variation between actual test data and predicted C_{11} and C_{12} coefficients and amount of error in the models. Table 5-3 shows the models' predictability for the C_{11} coefficient. Among SVEM models, FS showed higher accuracy and lower errors in both training and true validation sets. Moreover, it can be concluded that increasing the number of iterations in SVEM does not necessarily improve model predictability as the model accuracy decrease and error increase after a certain number of iterations. The BT has the best performance among all models in this study following by the RF technique. Considering the isolation of true validation set during the model development, both BT and RF are able to fit very accurate models with different layers and a number of trees on the training set with high R-squared and low error. As expected, the SVM does not show a good performance with respect to true validation set predictability, and the models with a different number of iterations have comparable accuracy and error that shows increasing the number of iterations only changes the hyperparameters of the model and does not have any considerable effect on model performance. The results for all iterations are presented here for the sake of completeness. The SVM model was run up to 500 iterations instead of 1000 iterations because the model's predictability is almost constant with a significantly higher run time for the model with 1000 iterations. The prediction model based on the BT technique with 100 layers was selected as the final prediction model for the C_{11} coefficient.

Table 5-4 shows the models' predictability for the C_{12} coefficient. Almost all techniques have accurate models for training set with BT and RF having the most accurate with lowest error models. However, the performance of a prediction model should be judged based on the validation set. The FS with 100 iterations showed the most accurate fit with the lowest error for the true validation set. While increasing the number of iterations for FS, improved the predictability of the model for training set, increasing the number of iterations for FS from 100 to 200 decreases the model accuracy by almost 36% and increases the average of the errors in the model by 33% which emphasizes that number of iteration can play a significant role in SVEM technique. Based on models' performances, forward selection with 100 iterations was selected as the C_{12} final prediction model.

Table 5-3 C_{11} prediction model comparison in terms of prediction accuracy and errors

Number of Layers	Statistical Parameter					
	R-Squared		RASE		AAE	
	Train	True Validation	Train	True Validation	Train	True Validation
Adaptive Lasso						
20	0.56	0.34	2.20E-03	2.80E-03	1.50E-03	2.00E-03
50	0.59	0.17	2.10E-03	3.10E-03	1.40E-03	2.10E-03
100	0.68	0.41	2.10E-03	2.65E-03	1.40E-03	2.00E-03
200	0.58	0.4	2.20E-03	2.60E-03	1.40E-03	1.90E-03
500	0.6	0.31	2.10E-03	2.80E-03	1.40E-03	2.00E-03
1000	0.61	0.31	2.10E-03	2.80E-03	1.40E-03	2.00E-03
Forward Selection						
20	0.84	0.81	1.30E-03	2.30E-03	1.00E-03	2.00E-03
50	0.86	0.86	1.20E-03	2.30E-03	1.00E-03	2.10E-03
100	0.85	0.7	1.30E-03	2.30E-03	1.00E-03	2.00E-03
200	0.84	0.72	1.30E-03	2.30E-03	1.00E-03	2.00E-03
500	0.84	0.71	1.30E-03	2.20E-03	1.00E-03	2.00E-03
1000	0.85	0.73	1.30E-03	2.20E-03	1.00E-03	2.00E-03
Boosted Trees						
20	0.77	0.8	1.67E-03	1.70E-03	1.20E-03	1.30E-03
50	0.88	0.89	1.20E-03	1.20E-03	8.00E-04	1.00E-03
100	0.98	0.96	5.22E-04	8.00E-04	4.00E-04	6.00E-04
200	0.99	0.95	2.69E-04	9.00E-04	2.00E-04	7.00E-04
500	1	0.94	8.83E-05	9.00E-04	0.00E+00	7.00E-04
1000	0.99	0.94	3.44E-04	9.00E-04	3.00E-04	7.00E-04
Random Forest						
20	0.93	0.63	1.80E-03	2.10E-03	1.10E-03	1.50E-03
50	0.92	0.88	3.00E-04	1.20E-03	4.00E-04	1.00E-03
100	0.93	0.88	1.00E-04	1.20E-03	5.00E-04	1.00E-03
200	0.91	0.9	3.00E-04	1.10E-03	2.00E-04	9.00E-04
500	0.91	0.91	3.00E-04	1.00E-03	2.00E-04	9.00E-04
1000	0.93	0.9	1.00E-04	1.10E-03	3.00E-04	9.00E-04
SVM						
20	0.88	0.39	1.65E-03	6.80E-03	8.00E-04	3.70E-03
50	0.89	0.39	1.57E-03	7.70E-03	8.00E-04	4.20E-03
100	0.89	0.39	1.50E-03	7.70E-03	8.00E-04	4.20E-03
200	0.89	0.39	1.58E-03	7.70E-03	8.00E-04	4.20E-03
500	0.89	0.39	1.58E-03	7.70E-03	8.00E-04	4.20E-03

Table 5-4 C_{12} prediction model comparison in terms of prediction accuracy and errors

Number of Layers	Statistical Parameter					
	R-Squared		RASE		AAE	
	Train	True Validation	Train	True Validation	Train	True Validation
Adaptive Lasso						
20	0.80	0.60	6.38E-02	1.32E-01	4.80E-02	9.37E-02
50	0.76	0.49	6.98E-02	1.27E-01	5.17E-02	8.63E-02
100	0.83	0.40	5.86E-02	2.10E-01	4.62E-02	1.30E-01
200	0.83	0.25	5.89E-02	3.01E-01	4.64E-02	1.56E-01
500	0.82	0.32	5.96E-02	2.51E-01	4.69E-02	1.41E-01
1000	0.82	0.39	5.98E-02	2.08E-01	4.69E-02	1.26E-01
Forward Selection						
20	0.92	0.65	3.93E-02	8.00E-02	3.17E-02	5.83E-02
50	0.91	0.70	4.14E-02	7.60E-02	3.22E-02	5.84E-02
100	0.91	0.74	4.33E-02	7.05E-02	3.34E-02	5.85E-02
200	0.98	0.47	2.06E-02	1.06E-01	1.51E-02	8.66E-02
500	0.98	0.46	1.89E-02	1.06E-01	1.41E-02	8.70E-02
1000	0.99	0.47	1.72E-02	1.06E-01	1.27E-02	8.67E-02
Elastic Net						
20	0.80	0.51	6.38E-02	8.85E-02	4.88E-02	7.66E-02
50	0.78	0.61	6.66E-02	7.91E-02	5.02E-02	6.90E-02
100	0.86	0.49	5.23E-02	8.97E-02	4.19E-02	7.76E-02
200	0.82	0.51	5.95E-02	8.84E-02	4.67E-02	7.64E-02
500	0.82	0.53	5.92E-02	8.60E-02	4.67E-02	7.44E-02
1000	0.82	0.55	5.94E-02	8.41E-02	4.66E-02	7.22E-02
Boosted Trees						
20	0.79	0.31	6.54E-02	1.00E-01	4.57E-02	9.64E-02
50	0.92	0.59	3.91E-02	8.00E-02	3.03E-02	7.23E-02
100	0.97	0.63	2.51E-02	8.00E-02	2.04E-02	5.82E-02
200	0.99	0.70	1.42E-02	8.00E-02	1.09E-02	5.85E-02
500	1.00	0.68	1.68E-02	9.00E-02	3.40E-03	6.20E-02
1000	0.98	0.66	1.79E-02	8.00E-02	1.41E-02	5.83E-02
Random Forest						
20	0.90	0.44	4.47E-02	1.06E-01	3.37E-02	9.15E-02
50	0.95	0.55	3.15E-02	9.46E-02	2.19E-02	7.85E-02
100	0.95	0.55	3.19E-02	9.41E-02	2.33E-02	8.09E-02
200	0.99	0.59	1.38E-02	9.12E-02	9.50E-03	7.47E-02
500	0.99	0.61	1.39E-02	9.03E-02	9.70E-03	7.35E-02
1000	0.95	0.54	3.05E-02	9.36E-02	2.27E-02	7.98E-02

5.4.4 Web-based Prediction Model

Based on the models' error, the accuracy of prediction, and computational cost prediction models based on BT with 100 layers and FS based on SVEM technique with 100 iterations were selected as final prediction models for C_{11} and C_{12} coefficients, respectively. A web-based prediction tool was developed based on the final prediction equations for both C_{11} and C_{12}. Users can directly input the variables and these models ensure to DCC curve coefficients with certain levels of accuracy even with a limited amount of data. Figure 4-10 shows the prediction tool for C_{11} and C_{12}.

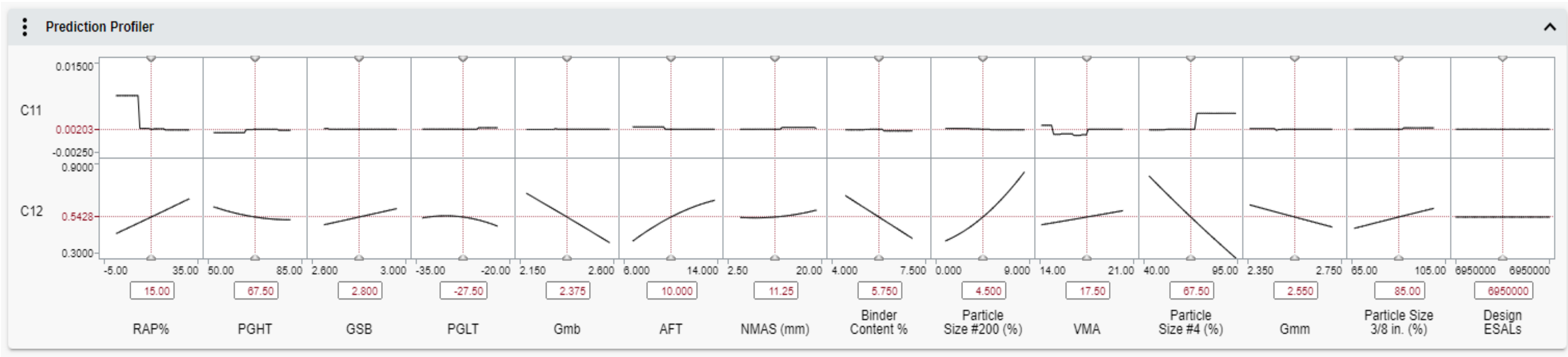

Figure 5-6 Example of core location selection.

5.5 Summary and Conclusion

To overcome the limitation of current mix design and evaluation methods, S-VECD approach was utilized in this chapter to assess the fatigue properties of asphalt mixtures outside of the linear range. The DCC was selected as the main outcome of S-VECD theory that shows the materials integrity with corresponding level of damage in the material. C_{11} and C_{12} were chosen as DCC curve coefficient and a set of 47 mixtures including at least 3 replicate specimens for each mixture was utilized to develop prediction models for C_{11} and C_{12} coefficients. Several regression-based models such as AL, FS, and EN were selected to be used with SVEM technique in JMP® Pro software. Furthermore, BT, RF, and SVM were employed as machine learning based model to develop prediction models. The prediction models were formulated based on available mix variables during mix design process.

Based on the obtained results, the following conclusions can be drawn:

- In general, increasing the number of iterations for the SVEM technique does not necessarily increase model accuracy and can yield highly biased prediction models.
- The FS technique showed more promising results among other SVEM models in this study that show FS's ability to deal with small datasets using the self-validation technique.
- Machine learning techniques have different performances based on the number of data points in the dataset. Using a small dataset might yield an overfitted model, which necessitates the need for true validation set to evaluate the model's accuracy.
- Web-based prediction models were developed for C_{11} and C_{12}. These models can be utilized to determine the DCC curve coefficients based on asphalt binder and mix variables available during the mix design process.

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CHAPTER 6

Development of a balanced cracking diagram for asphalt mixtures cracking resistance based on fracture and viscoelastic continuum damage theories

6.1 Chapter Introduction

As discussed in chapter five of this dissertation, the S-VECD analysis method has gained widespread attention among researchers as a reliable method to investigate mixture susceptibility to cracking. In the previous chapter, prediction models were developed for two parameters (C_{11} and C_{12}) as the damage characteristic curve (DCC) coefficients. While this curve shows the amount of internal damage in materials to get to a certain loss of integrity, it cannot rank mixtures with respect to cracking resistance. The damage characteristic curve should be plugged into pavement analysis models to capture the fatigue cracking performance of asphalt mixture in the context of pavement structure under traffic and environmental loads. In the last few years, researchers have consistently endeavored to develop performance properties indices based on the S-VECD theory to rank asphalt mixtures in terms of their fatigue cracking properties. Currently, four fatigue properties parameters have been developed such as G^R, D^R, S_{app}, and C^S_{Nf} that were defined in chapter 2 of this dissertation.

Based on the simplified viscoelastic continuum damage (S-VECD) theory, the magnitude of microcracks in the asphalt mixture is quantified using the amount of damage (S). Neither G^R nor D^R indices take the amount of damage into account. As opposed to G^R and D^R, S_{app} incorporates damage growth magnitude at the average integrity of mixture to investigate fatigue resistance of asphalt mixtures. In addition, the C^S_{Nf} is based on damage growth rate in which accumulated damage at failure as well as an accumulated decrease in material integrity are taken into consideration [1]. Therefore, both S_{app} and C^S_{Nf} are expected to have a good correlation with mixture fatigue properties. The C^S_{Nf} parameter has been recently proposed and adopted in few research projects. The S_{app}, on the other hand, is currently being implemented in a performance-based framework by some states' DOTs and asphalt agencies [2]. Therefore, the S_{app} was selected to be used as a fatigue performance index in this chapter. A prediction model was developed for S_{app}, and a cracking balance design diagram was generated based on fracture energy (G_f) prediction model in chapter 4 of this dissertation and S_{app} prediction model in this chapter to assess the cracking properties of asphalt mixtures at low and intermediate temperatures based on different mix variables. Finally, a sensitivity analysis was conducted to determine the effective factors on both fracture and fatigue cracking resistance of asphalt mixtures.

The objectives of this chapter of dissertation are as follows:

(a) To develop a precise prediction models for S_{app} as a mixture fatigue property based on S-VECD theory

(b) Develop a cracking balance design diagram based on the prediction model at chapter 4 and chapter 6 of this dissertation

(c) Sensitivity analysis to determine the effect of variable on fatigue cracking properties as well as to determine effective variables on both fracture and fatigue susceptibility of asphalt mixtures

6.2 Test Data

A set of 47 mixtures as discussed in chapter 5 of this dissertation were used in this study. Complex modulus (E*) and direct tension cyclic fatigue (DTCF) tests were conducted, and test results were utilized to determine S_{app} as mixture fatigue properties index based on S-VECD theory.

6.3 Methodology

A Fatigue cracking susceptibility of materials is a complex phenomenon. It depends on several factors, such as material stiffness (modulus) and the ability of a material to absorb energy without failure (toughness). Under the same load amplitude, a material with a lower modulus will have a higher induced strain level as compared to a material with a higher modulus. Considering the same toughness for these two materials, the higher strain level in the material with a lower modulus will yield shorter fatigue life. If the induced strain levels in the materials are same, but they have different toughness values, the material with higher toughness would yield to longer fatigue life [3]. Many materials with high susceptibility to cracking either have a low modulus value with high toughness or a high modulus value with a low toughness level. Thus, an appropriate fatigue cracking parameter should be used to take into account the effect of both modulus and toughness on mixture susceptibility to fatigue cracking.

Recently, the S_{app} was developed by Wang. et al. [3] to account for the modulus and the toughness of asphalt mixtures as two main effective factors on cracking susceptibility of asphalt mixture. Equation 1 shows S_{app} calculation with respect to material stiffness and induced damage in the material under loading based on S-VECD theory.

$$S_{app} = 1000^{\frac{\alpha}{2}-1} \frac{a_T{}^{1/(\alpha+1)} (\frac{D^R}{C11})^{\frac{1}{C12}}}{|E^*|^{\frac{\alpha}{4}}} \tag{1}$$

In this equation α is a material constant that can be calculated from the maximum slope of the relaxation modulus in log–log scale based on complex modulus test results.

a_T is the shift factor based on time-temperature superposition concept and it should be computed at the reference temperature of direct tension cyclic fatigue (DTCF) test that is the average of the asphalt binder PG minus 3°C.

D^R is S-VECD based parameter that is the amount of average drop in material integrity (1-C), per load cycle until failure of material. D^R can be used to determine the number of load cycles when a macrocrack forms in the mixture and indicates material toughness. Equation 2 shows D^R value calculation.

$$D^R = \frac{\int_0^{N_f} (1-C)}{N_f} \tag{2}$$

Where:

C = Material integrity (1 is being intact and 0 everything is fallen apart)

N_f = Number of load cycle

C_{11} and C_{12} are model coefficients of damage characteristic curve (DCC) to take into account the modulus effect using the position of curve (as discussed in chapter 5). The DCC curve can predict the damage evolution in the material under fatigue loading.

E* is asphalt mixtures dynamic modulus (kPa) at 10 Hz and the reference temperature. The term has been recently added to the S_{app} equation as a semi-empirical modification to take into account the effect of long-term aging on mixture damage behavior.

The development of the S_{app} prediction model was done in several steps. Two prediction models for C_{11} and C_{12} coefficients were developed in chapter 5 of this dissertation. The same statistical analysis methods as discussed in chapter 5 were used in this chapter to develop prediction models for D^R and α. To determine the dynamic modulus of mixtures, a developed E* prediction model by Nemati. et al. [4] was utilized in this work and the modulus of each mixture was determined at 10 Hz and the temperature that DTCF test was conducted (using the DTCF test temperature would eliminate the effect of a_T on S_{app} calculation. The proposed model, predicts asphalt mixture dynamic modulus based on a generalized regression model using asphalt mix properties available during the mix design process, making it a good candidate to be employed in S_{app} prediction model development in this chapter. Table 6-1 shows the E* prediction model employed in this study. Equation 3 shows the final equation to predict S_{app}.

Table 6-1 E* prediction model [4]

(|E*|) Predictive Model				
	Active Factors (a_i)	**Coefficient (b_i)**	**Std Error**	**Prob > ChiSquare**
1	Intercept	6.7176428	0.0976212	<0.0001
2	Log (Temperature)	-1.390417	0.007481	<0.0001
3	Log(Frequency)	0.2716079	0.0021966	<0.0001
4	(Log (Temperature)-1.20037)*(Log (Temperature)-1.20037)	-1.395977	0.0207529	<0.0001
5	(Log (Temperature)-1.20037)*(Log (Frequency)-0.26115)	0.1726025	0.0054005	<0.0001
6	Va%	-0.034862	0.0011471	<0.0001
7	PGLT	0.0308918	0.0013407	<0.0001
8	RAP%	0.0029715	0.0001347	<0.0001
9	AC%	-0.067239	0.0047671	<0.0001
10	(Log (Temperature)-1.20037)*(PGHT-60.3887)	-0.012624	0.001892	<0.0001
11	(Log (Temperature)-1.20037)*(PGLT+28.9976)	0.0222484	0.0034946	<0.0001
12	(Log (Temperature)-1.20037)*(RAS%-0.88064)	0.0081275	0.001892	<0.0001
13	NMAS	-0.004575	0.001164	<0.0001
14	RAS%	0.0025448	0.0007382	0.0006
15	PGHT	-0.000955	0.0008396	0.2555

$$Log(E^*) = \sum_{i=1}^{15} a_i b_i$$ where: a_i= Coefficient and d_i = values of active factors (3)

$$S_{app} = 1000^{\frac{\alpha}{2}-1} \frac{(\frac{D^R}{C_{11}})^{\frac{1}{C_{12}}}}{|E^*|^{\frac{\alpha}{4}}} \tag{3}$$

The final prediction model for S_{app} consists of 5 prediction models based on asphalt binder and aggregate types, recycle material content, proportioning of the asphalt binder and aggregates, aggregate empirical properties, and volumetric properties of a mixture. Figure 6-1 shows a schematic of data analysis procedures and cracking balance design diagram development for this study.

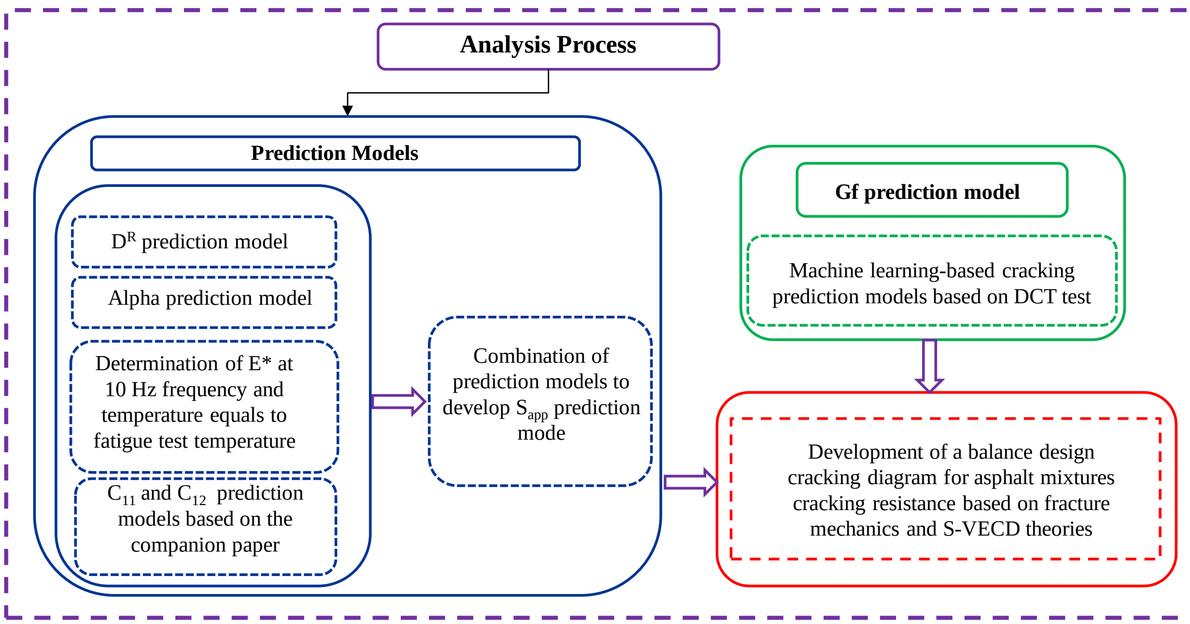


Figure 6-1 schematic of testing and data analysis procedures

6.4 Data Analysis Method

The same statistical analysis method as discussed in chapter 5 was used in this chapter. The predictability of models was evaluated using correlation of determination (R^2), root average square error (RASE), and the absolute average error (AAE) and the models with the best performance with respect to true validation set for each method were presented in these sections. It should be noted that models with overfitting and/or high amount of bias were excluded from the final results.

6.5 Results and Discussion

6.5.1 Self-validated Ensemble Modelling (SVEM)

As discussed in chapter 5 of this dissertation, adaptive Lasso (AL), forward selection (FS), and elastic net (EN) were used for the SVEM with different numbers of iterations to predict alpha and D^R values. The response surface method was used to capture all interactions between variables and their effect on the outcome. The model with the best performance with respect to the true validation set for each method is presented in these sections.

Figures 6-2 a and b show the actual vs. predicted alpha, based FS (200 iterations) and EN (100 iterations) techniques, respectively. Based on the results, the FS model has higher predictability for both the training set and true validation set as compared to EN. In addition, the fitted model based on FS is less biased than AL.

Figures 6-3 a-c show the actual vs. predicted D^R values based on AL (200 iterations) and EN (100 iterations) techniques, respectively. The results show EN has a higher accuracy for both training and true validation sets as compared to AL. The Lasso would eliminate features to reduced overfitting in the model. The EN combines Lasso and Ridge regression models for feature elimination ad reduction of feature coefficient in the model (based on Ridge mode) to improve the predictability of the model. Considering the small data set with high number of variables and using response surface to capture all interactions between variables it was expected that EN would yield a more accurate prediction model as compared to AL.

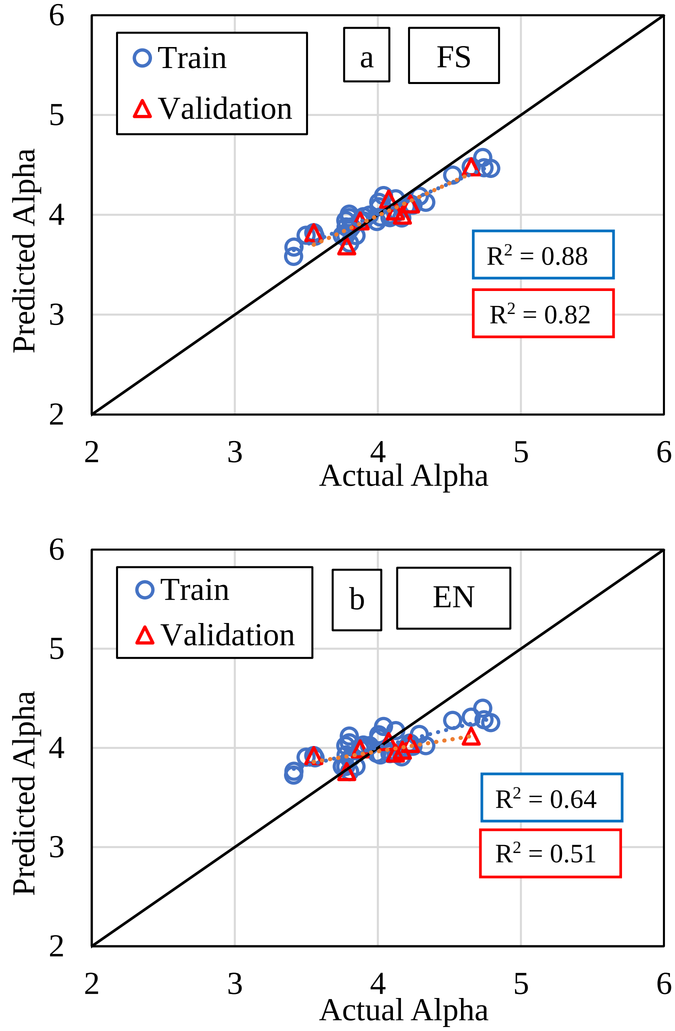
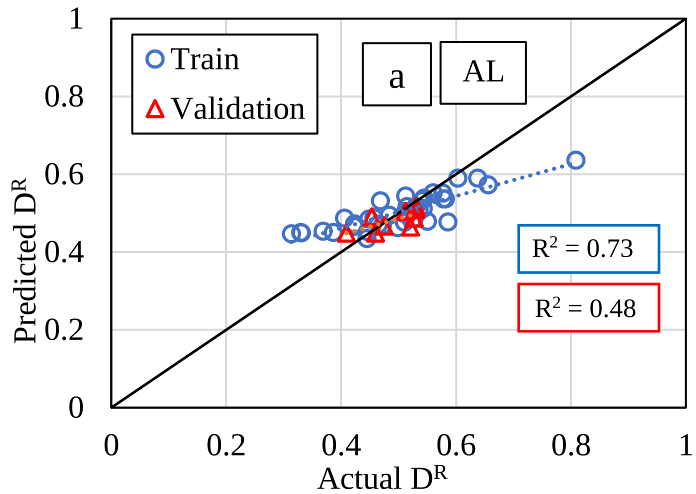


Figure 6-2 Actual vs Predicted alpha based on SVEM technique a) Forward selection, b) Elastic net



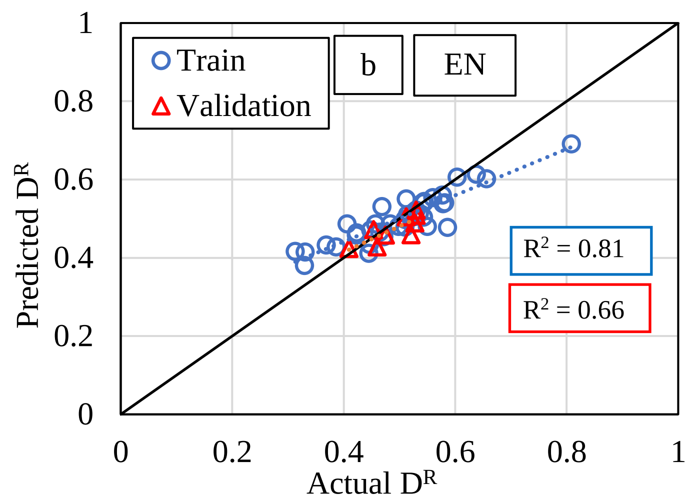


Figure 6-3 Figure 6-3 Actual vs Predicted D^R values based on SVEM technique a) Adaptive Lasso, b) Elastic net

6.5.2 Machine Learning Algorithms

Figures 6-4 a and b show the actual vs. predicted alpha based on BT (200 layers), RF (500 trees) techniques, respectively. According to the results, both BT and RF models have high prediction accuracy and low bias for the training set, with the RF model having more accuracy and lower error. On the other hand, the BT model has better predictability in terms of true validation set as compared to the RF model.

Figure 6-5 presents the actual vs. predicted D^R values based on RF with 1000 trees. The results show that RF could predict D^R values for the training set with high accuracy and low error in the model. For the true validation set, however, as expected, the model is less accurate. Neither BT nor SVM model could predict D^R values based on the data set in this study. The size of the data set would yield overfitted or highly biased models.

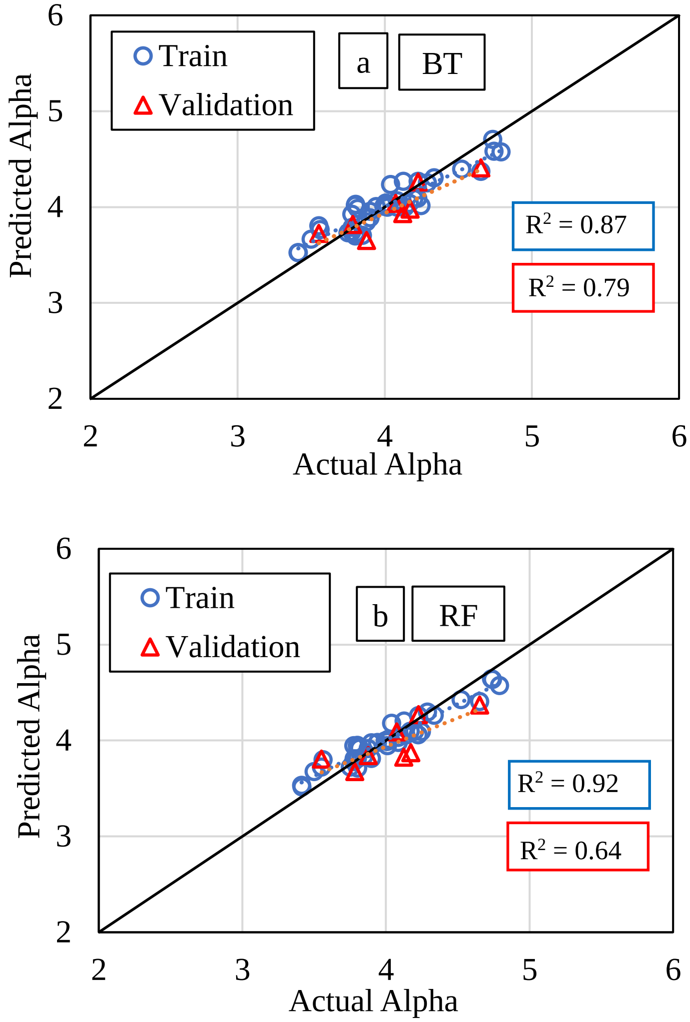


Figure 6-4 Actual vs Predicted alpha based on machine learning technique a) Boosted Trees, b) Random Forest

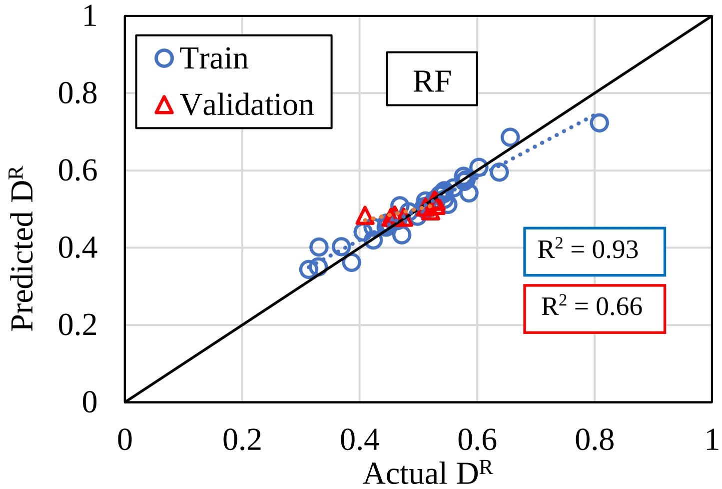


Figure 6-5 Actual vs Predicted D^R values based on Random Forest machine learning technique

6.5.3 Model Comparison

All prediction models in this study were compared in terms of variation between actual test data and predicted alpha and D^R values and amount of error in the models. Table 6-2 shows the models' predictability for alpha. Among SVEM models, FS showed higher accuracy and lower errors in both training and true validation sets. Both BT and RF techniques showed accurate models with low error after 200 layers and 200 trees in the forest, respectively. The BT with 200 or more layers can predict alpha values based on true validation set with a relatively accurate model and low error in the model. In contrast, the accuracy of a prediction model for a true validation set drops significantly. In terms of true validation set predictability, FS has the best performance among all models, which shows based on the dataset in this study, the self-validation technique might be the best way to deal with small data points. It should be noted that selecting the best regression model with the optimum number of iterations based on the size of the dataset, number of variables in the model, and variation in data point is critical to develop prediction model using SVEM technique as the elastic net has low accuracy and AL was highly biased and overfitted.

Table 6-3 shows the models' predictability for D^R values. The RF showed the most accurate prediction model with the least error for the training set among all models in this study. None of the models showed a reliable prediction model with respect to model performance. Both EN (100 iterations) and RF (1000 trees) have the same prediction model accuracy based on the true validation set. The RF with 1000 trees in the forest was selected as the final prediction model for D^R because of a slightly lower error in the model as compared to EN. It should be emphasized that developing a prediction model for D^R based on the small dataset was a challenging task in this work. Because D^R is the amount of average drop in material integrity at each load cycle and could be a unique feature for each material and might have more determinant variables than the variables that used in this study. The D^R model needs to be adjusted based on more data points for a more reliable prediction model.

Table 6-2 Alpha prediction model comparison in terms of prediction accuracy and errors

Number of Layers	Statistical Parameter					
	R-Squared		RASE		AAE	
	Train	True Validation	Train	True Validation	Train	True Validation
Forward Selection						
20	0.86	0.60	1.59E-01	2.04E-01	1.37E-01	1.70E-01
50	0.89	0.73	1.54E-01	1.76E-01	1.32E-01	1.47E-01
100	0.87	0.81	1.56E-01	1.53E-01	1.34E-01	1.39E-01
200	0.88	0.82	1.54E-01	1.47E-01	1.32E-01	1.32E-01
500	0.89	0.80	1.46E-01	1.49E-01	1.27E-01	1.36E-01
1000	0.85	0.60	1.57E-01	2.04E-01	1.38E-01	1.71E-01
Elastic Net						
20	0.51	0.55	2.39E-01	2.08E-01	2.06E-01	1.71E-01
50	0.52	0.50	2.37E-01	2.19E-01	2.00E-01	1.78E-01
100	0.64	0.51	2.01E-01	2.16E-01	1.80E-01	1.77E-01
200	0.52	0.48	2.37E-01	2.23E-01	2.00E-01	1.81E-01
500	0.50	0.49	2.43E-01	2.21E-01	2.05E-01	1.78E-01
1000	0.50	0.46	2.43E-01	2.29E-01	2.11E-01	1.89E-01
Boosted Tree						
20	0.34	0.52	2.77E-01	2.13E-01	2.14E-01	1.76E-01
50	0.56	0.63	2.28E-01	1.88E-01	1.79E-01	1.58E-01
100	0.75	0.62	1.71E-01	1.90E-01	1.41E-01	1.64E-01
200	0.87	0.79	1.34E-01	1.41E-01	1.08E-01	1.12E-01
500	0.93	0.78	9.34E-02	1.46E-01	7.52E-02	1.19E-01
1000	0.78	0.79	1.51E-01	1.43E-01	3.90E-02	1.48E-01
Random Forest						
20	0.68	0.35	1.94E-01	2.49E-01	1.57E-01	2.02E-01
50	0.67	0.49	1.96E-01	2.22E-01	1.63E-01	1.78E-01
100	0.67	0.49	1.95E-01	2.22E-01	1.64E-01	1.77E-01
200	0.90	0.56	1.11E-01	2.05E-01	9.03E-02	1.66E-01
500	0.92	0.64	1.13E-01	1.86E-01	9.20E-02	1.62E-01
1000	0.89	0.64	1.13E-01	1.87E-01	9.33E-02	1.53E-01

Table 6-3 D^R prediction model comparison in terms of prediction accuracy and errors

Number of Layers	Statistical Parameter					
	R-Squared		RASE		AAE	
	Train	True Validation	Train	True Validation	Train	True Validation
Adaptive Lasso						
20	0.45	0.24	6.93E-02	3.67E-02	4.92E-02	3.08E-02
50	0.48	0.20	6.75E-02	3.75E-02	4.90E-02	3.16E-02
100	0.44	0.33	7.02E-02	3.47E-02	5.01E-02	2.83E-02
200	0.73	0.48	5.29E-02	3.10E-02	3.39E-02	2.61E-02
500	0.60	0.45	5.95E-02	3.20E-02	4.35E-02	2.71E-02
1000	0.60	0.45	5.93E-02	3.20E-02	4.33E-02	2.73E-02
Elastic Net						
20	0.51	0.39	6.56E-02	3.01E-02	4.71E-02	4.31E-02
50	0.61	0.48	5.81E-02	6.01E-02	4.23E-02	3.93E-02
100	0.81	0.66	3.28E-02	2.65E-02	3.04E-02	2.23E-02
200	0.77	0.53	4.58E-02	5.00E-02	3.78E-02	3.12E-02
500	0.71	0.55	5.05E-02	4.94E-02	3.81E-02	3.47E-02
1000	0.71	0.55	5.07E-02	5.01E-02	3.82E-02	3.54E-02
Random Forest						
20	0.88	0.28	3.25E-02	3.73E-02	2.37E-02	3.93E-02
50	0.95	0.34	1.49E-02	3.45E-02	1.01E-02	2.97E-02
100	0.98	0.63	1.37E-02	2.89E-02	9.40E-03	2.27E-02
200	0.98	0.53	1.37E-02	3.12E-02	9.70E-03	2.67E-02
500	0.98	0.55	1.39E-02	3.06E-02	9.70E-03	2.55E-02
1000	0.93	0.66	2.69E-02	2.57E-02	1.91E-02	2.16E-02

6.5.4 Sensitivity Analysis

Sensitivity analysis was conducted using JMP® Pro software to assess the effect of each variable on the final prediction model. Figure 6-6 shows the results of sensitivity analysis. Based on the results, percent of aggregate smaller than 4.75 mm and aggregate percent smaller than 0.75 mm, aggregate bulk specific gravity, asphalt binder content, and asphalt film thickness have a higher impact on fatigue properties as compared to other variables. The effects of these factors cannot be decoupled from each other. A higher amount of aggregates smaller than 4.75 would yield a more dense mixture with higher binder content which would be expected to have better fatigue life. Higher filler or material smaller than 0.75 mm would increase the stiffness of the mixture and decrease air void in the mixture that would increase the fatigue cracking susceptibility. The same finding of the air void levels effect on the S-VECD fatigue test was reported by Zeiada et al [5]. It is worth noting that the finding is counterintuitive to what is actually happening in the field, as higher air void levels lead to higher rates of pavement deterioration [6, 7]. More binder content in the mixture would increase the ability of a mixture to absorb energy without failure by higher viscosity and lower elasticity. Therefore, it increases the fatigue life of mixtures. Inadequate asphalt film thickness around aggregates due to insufficient asphalt binder decreases the mixture tensile properties, therefore, yield to higher fatigue cracking susceptibility. Among the other parameters with lower effects than the four factors as mentioned earlier, NMAS and RAP% can be pointed out as it has been proven that they affect mix fatigue properties. For example, higher NMAS and higher RAP % mean a stiffer mixture with less amount of binder content for higher NMAS with probably higher fatigue cracking susceptibility.

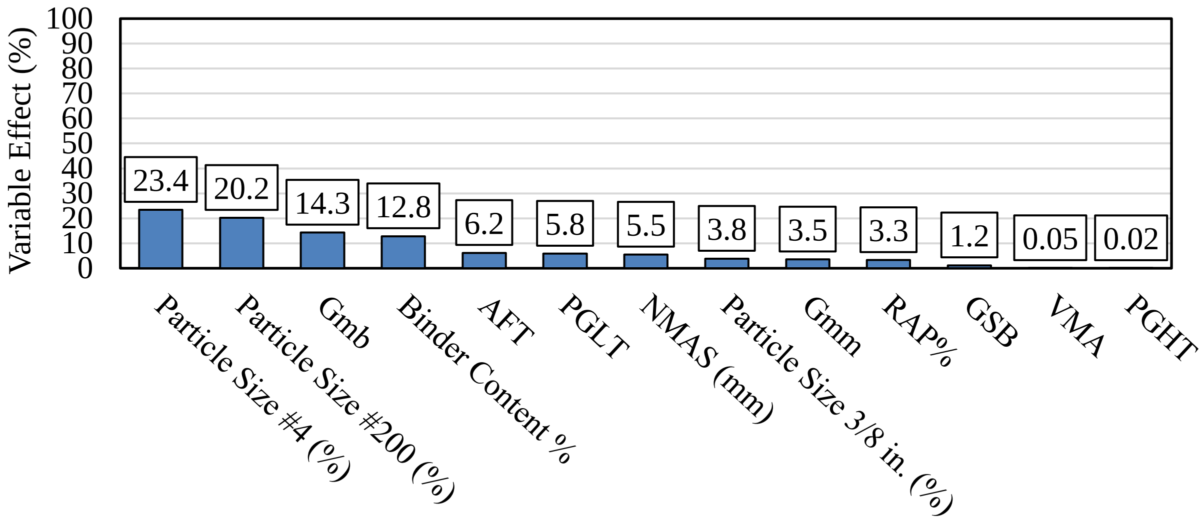


Figure 6-6 Effect of each variable on fatigue properties of asphalt mixtures

6.5.5 Web-based Prediction Model

The best prediction models in terms of model performance were selected in chapter 5 and chapter 6 of this dissertation and combined to develop a final prediction model for S_{app} as an indicator of fatigue cracking susceptibility of asphalt mixtures. The C_{11} and C_{12} prediction models were developed in chapter 5. In this chapter, alpha and D^R prediction models were developed. To predict E* at 10 Hz frequency and the same temperature as DTCF test temperature, a published prediction model by Nemati. et al. [4] was employed in this work. All models were combined based on the S_{app} equation that yields a complex final prediction model with five layers of prediction. A web-based prediction tool was developed based on the final prediction equations as a predesign prediction tool. Researchers and asphalt agencies can use the model to predict the susceptibility of a mixture to fatigue cracking even during the mix design process. Figure 6-7 shows the prediction tool that users can simply change the input variables, and the software will predict the S_{app}.

The proposed prediction model for fracture energy in chapter 4 of this dissertation was run on the data set that used to develop prediction models for chapters 5 and 6, and variables profiler was plotted to determine how different variables affect mixture cracking properties (direction of correlation). Figure 6-8 shows the variable profiler for G_f and S_{app}. Based on the results, higher G_{mb}, lower percent passing of sieve 3/8 in, lower RAP%, lower NMAS, and higher VMA up to 17% would decrease mixture susceptibility with respect to both fatigue and fracture cracking. There are some parameters that have opposite effects on fracture and fatigue cracking. Warmer PGLT (less negative), higher G_{mm}, warmer PGHT, and lower percent passing of sieve #200 increase mixture susceptibility to low temperature cracking and, at the same time, decrease susceptibility to fatigue cracking. Therefore, these parameters should be selected with caution in a range that keeps the balance between low temperature and fatigue cracking. The useful range depends on the data set distribution and content. Using different data sets might change the useful range for balance cracking properties. That is why no specific limits have been recommended in this dissertation.

Based on the profiler, the effect of some variables on fatigue and/or fracture properties of the mixture runs contrary to the widely accepted proposition based on literature. It stems from the fact that the response surface shows the effect of each variable as well as the interaction between variables' effects, and they cannot be decoupled from each other. For example, colder PGLT means a less stiff binder that would absorb more energy that yield less fatigue susceptibility compared to a stiffer binder. This is true when all other variables are constant. The distribution plot of variables was plotted for deeper interpretation of observed behavior, and samples with the coldest PGLT were highlighted, as shown in figure 6-9.

It can be clearly observed that mixtures with the coldest PGLT have relatively high NMAS, low binder content, high amount of RAP which in combination deteriorates the fatigue properties of mixtures. This example shows the response surfaces should not be interpreted considering only one variable at a time, and using another data set with a different variable range might change the shape of the response surface. The E* was selected as inputs in the final prediction models; however, it was formulated based on mix variables for the sensitivity analysis. Thus, the profiler does not show the effect of E* on fatigue and fracture properties. Moreover, the profiler shows jumps in response surface of some variables such as VMA, RAP, and particle size #4 sieve. The observed pattern has nothing to do with the model predictability. It is related to the existing gap in variable ranges used in this study and the type of developed prediction models. In general, tree-based models such as boosted trees and random forests are more prone to show jumps in response surface if a gap exists in the data set. Using more data points within the available range of variables in this study helps toward a more smooth response surface.

It should be noted that all the prediction models were developed based on a limited range of variables, and they are only applicable for a specific range of variables in the data set that used in this work, and model extrapolation would not be recommended at this time. A recommended range of variables in which the models are valid is set as the web-based model's minimum and maximum thresholds, and users should follow these thresholds while using the models. Table 6-4 also shows the recommended range for each variable.

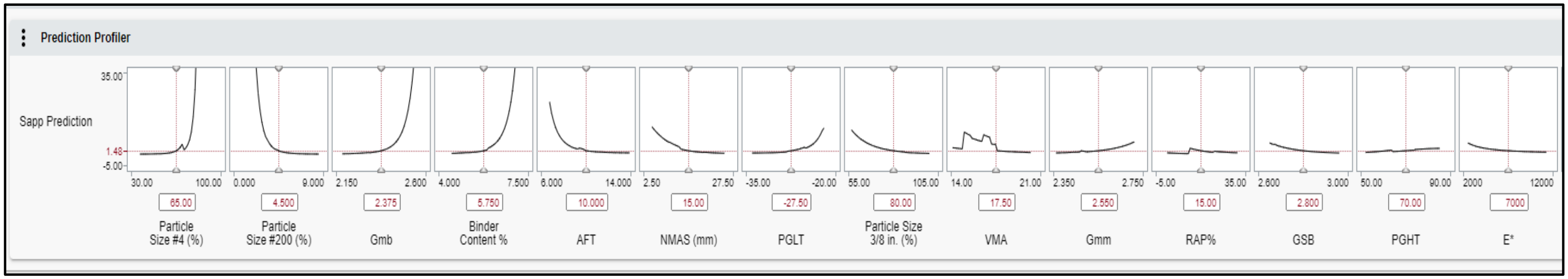


Figure 6-7 S_{app} prediction tool

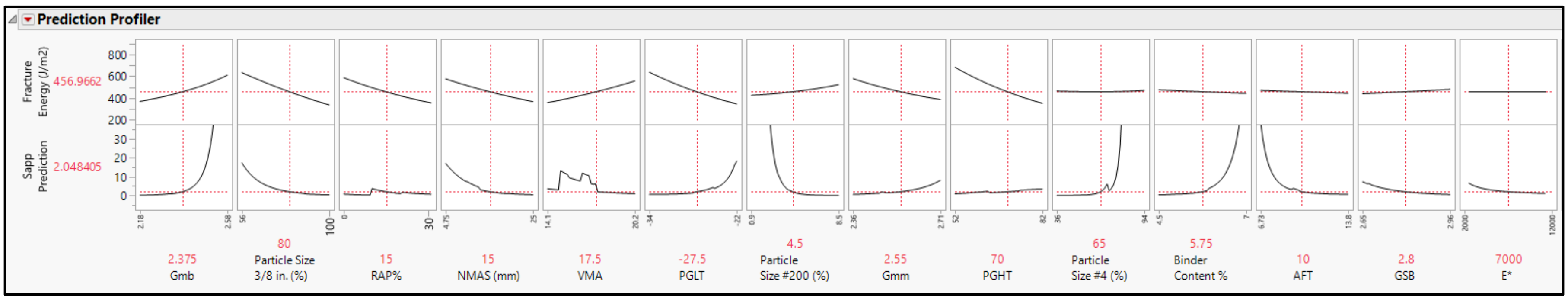


Figure 6-8 Figure 6-8 Variables profiler for G_f prediction model developed in chapter 4

Table 6-4 variables recommended range for prediction models

Variable	Minimum	Maximum
G_{mb}	2.18	2.58
Particle Size 3/8 in. (%)	56	100
RAP%	0	31
Maximum Aggregate Size (mm)	4.75	25
VMA (%)	14.1	20.2
PGLT	-22	-34
Particle Size #200 (%)	0.9	8.5
G_{mm}	2.36	2.71
PGHT	52	82
Particle Size #4 (%)	36	94
Binder Content, P_b (%)	4.5	7
AFT (micron)	6.73	13.8
G_{sb}	2.65	2.96
E*	2000	12000

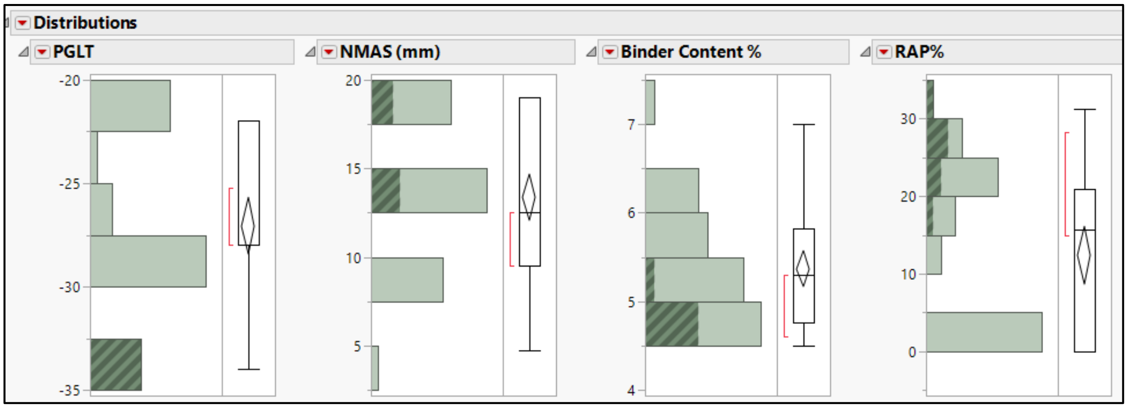


Figure 6-9 Distribution of four variables for mixtures with the lowest PGLT

6.6 Cracking Balance Design Diagram

The G_f prediction model based on the results of chapter 4 of this dissertation and the S_{app} prediction model based on the results of this chapter were combined as a 2-D scatter plot to form a cracking balance design diagram (CBDD). Figure 6-9 demonstrates a plot known as the "performance-space diagram" [8], specifically in this case, a "Fracture-Fatigue properties" plot. The CBDD plot allows the simultaneous evaluation of the cracking properties of asphalt mixtures at low and intermediate temperatures. Threshold values (as shown with horizontal and vertical lines in figures 6-9) were utilized to differentiate asphalt mixtures in terms of their cracking susceptibility. The threshold values in the diagram were selected based on published literature [3, 9]. Table 6-4 shows threshold values for S_{app} and G_f.

The best overall performing asphalt mixture will be shown in the top-right corner of the performance space diagram (high G_f and high S_{app}). On the other hand, the lower-left section of the diagram represents mixtures with high cracking susceptibility. The developed model can be implemented as a predesign tool in conventional volumetric mix design procedure to capture cracking resistance of mixture before the actual construction phase, as well as performance-based mix design approaches when conducting performance-based tests is not feasible.

Table 6-5 Recommended threshold values for S_{app} and G_f

Traffic (million ESALs)	Limits
Less than 10	$S_{app} > 8$
Between 10 and 30	$S_{app} > 24$
Greater than 30	$S_{app} > 30$
Greater than 30 and slow traffic	$S_{app} > 36$
N.A.	$G_f \geq 400$ J/m^2

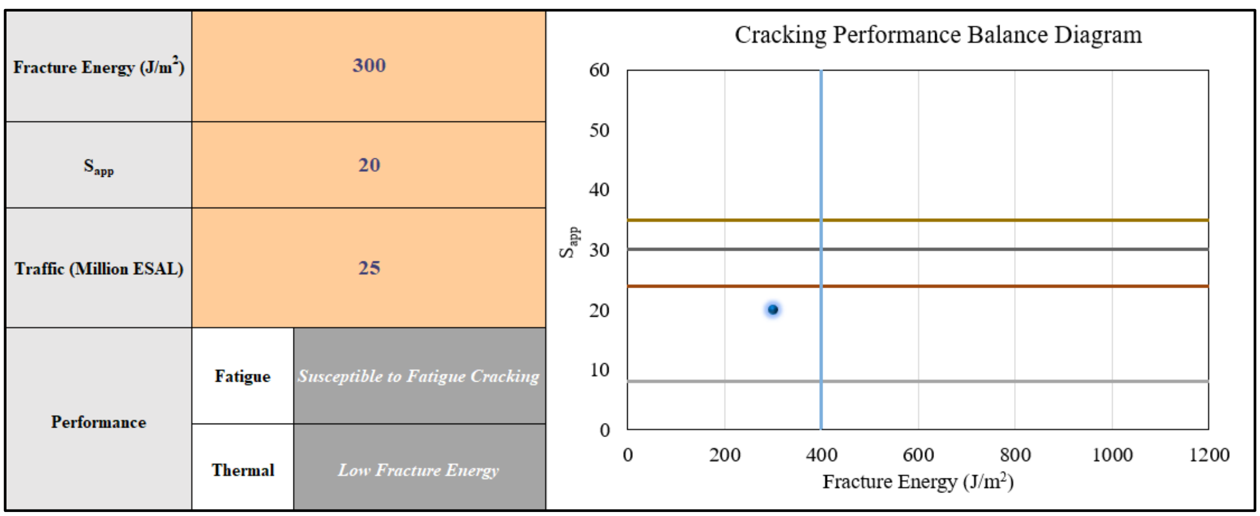


Figure 6-10 Cracking balance design diagram

Four mixtures were selected with different fatigue and fracture properties intentionally to show how CBDD differentiates mixtures based on their properties, as shown in figure 6-11. In this figure, mix A shows good properties with respect to both fatigue and fracture. Mix B has good fracture properties, but it failed to meet the fatigue threshold. Mix C, on the other hand, has good fatigue properties but is susceptible to fracture cracking. Mix D was unable to meet both fatigue and fracture thresholds that shows this mix is susceptible to both types of cracking. Different variables were selected randomly and changed based on sensitivity analysis to demonstrate how mix cracking properties can be improved using developed prediction models in this dissertation, as shown in table 6-6. For the presentation proposes in this section, only eight variables are presented in table 6-6. However, for actual design, all variables should be considered to capture the effects of all variables on mix properties.

For mix B, percent passing of sieve 3/8" was selected and decreased from 100% to 95% that moved mix B to the new position in the CBDD (B′), with improving both S_{app} and G_f values. For mix C, percent passing of sieve 3/8" and RAP% were selected and decreased to 75% AND 15%, respectively, to evaluate the simultaneous effects of two variables on mix cracking properties. The result showed improvement in fracture and fatigue properties with a more pronounced increase in S_{app} value (point C′). To improve mix D cracking properties, G_{mb} was increased to 2.33, and the percent passing of sieves 3/8" and #200 were decreased to 90% and 3%, respectively. Based on the results, mix D passed both fatigue and fracture thresholds with new variables (point D′). This example showed CBDD can be used at the mix design level to ensure the mix design will yield a mixture with good cracking properties.

Table 6-6 Selected mixtures and mix variables to be used in CBDD

Mix	**G_{mb}**	**Particle Size 3/8 in. (%)**	**RAP %**	**NMAS (mm)**	**VMA**	**PGLT**	**G_{mm}**	**Particle Size #200 (%)**	**G_f**	**S_{app}**
A	2.58	74.4	0	19	16.8	-22	2.71	4.2	469.75	21.13
B	2.18	100	0	4.75	20.2	-28	2.36	8.5	839.2	5.65
B'	2.18	**95**	0	4.75	20.2	-28	2.36	8.5	**903.01**	**15.02**
C	2.5	84	18.5	12.5	15.6	-28	2.70	4	328.72	16.67
C'	2.5	**75**	**17**	12.5	15.6	-28	2.70	4	**418.14**	**39.07**
D	2.31	97	25	9.5	14.9	-28	2.48	4	375.93	2.53
D'	**2.33**	**90**	25	9.5	14.9	-28	2.48	**3**	**415.28**	**19.5**

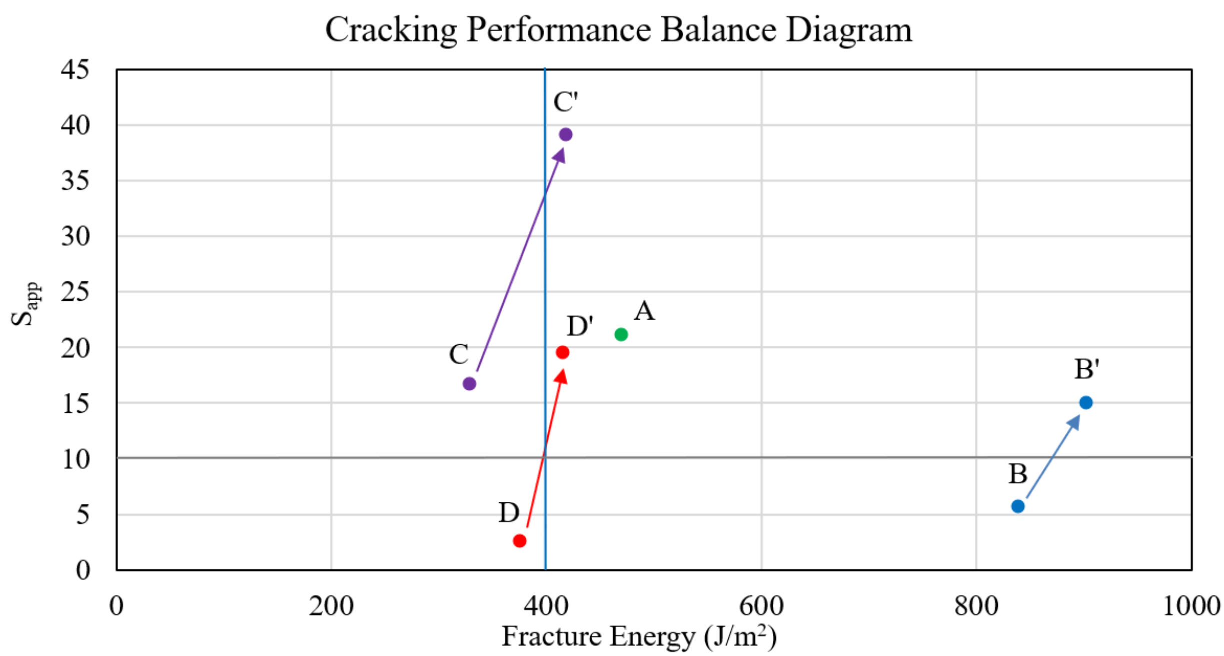


Figure 6-11 Demonstration of the CBDD usefulness in mix design level

6.5 Summary and Conclusion

In this chapter of the dissertation, prediction models were developed for S_{app} as S-VECD based fatigue index that can differentiate asphalt mixture with respect to their fatigue properties. The same set of mixtures as mixtures in chapter 5 of this dissertation was used. Several prediction models were developed for D^R (the amount of average drop in material integrity per load cycle) and alpha (maximum slope of the relaxation modulus) using the same statistical analysis that explained in chapter 5. In addition, the prediction models for C_{11} and C_{12} (based on chapter 5 of this dissertation), and a stablished E* prediction model based on literature were employed in this chapter for the final prediction model of S_{app} parameter. The prediction models for S_{app} and Fracture energy (G_f) were combined to create CBDD. Moreover, a sensitivity analysis was conducted to investigate the effective variables toward the cracking balance mix design. Based on the obtained results, the following conclusions can be drawn:

- The SVEM technique does not necessarily yield accurate prediction models, and different regression models and different numbers of iterations need to be used to find out the best model with respect to the dataset.
- Since SVM was generated to deal with classification problems, it might not be a good candidate to be used in regression problems with a small dataset. The SVM yield highly biased models with respect to the true validation set.
- While the developed prediction model for D^R is the most accurate model based on the dataset in this word, the model needs to be further adjusted using more data points.
- A Web-based prediction model was developed for S_{app}. The model can be used as predesign tool to assess mixtures fatigue properties based on available mix data during the mix design process.
- Sensitivity analysis results showed that percent passing of #4 and #200 sieves, aggregate bulk specific gravity, and asphalt binder content have the highest impact on asphalt mixture fatigue properties, among other variables in this study.
- The developed CBDD can be used for a more precise evaluation of mixture cracking properties by considering both initiation and propagation phases of cracking.
- The particular developed models are only applicable for a range of variables in the data set, and model extrapolation would not be recommended at this time.
- The sensitivity analysis of CBDD showed higher G_{mb}, lower percent passing of sieve 3/8 in, lower RAP%, lower NMAS, and higher VMA up to 17% improve asphalt mixture

cracking properties with respect to both fatigue (initiation) and fracture (propagation) cracking. At the same time, less negative PGLT, higher G_{mm}, higher PGHT, and lower percent passing of sieve #200 improve mixture fatigue properties and deteriorate mixture fracture properties. These parameters should be kept in a range that makes a balance between fatigue and fracture cracking.

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CHAPTER 7

SUMMARY, CONCLUSIONS, RECOMMENDATIONS AND FUTURE EXTENSIONS

7.1 Summary

Cracking is one of the most significant deterioration modes in asphalt pavement, particularly in colder areas that affect roads' ride quality and longevity. Cracking can occur in different forms, such as fatigue cracking under cyclic traffic loading in any climatic conditions, block cracking with cyclic environmental conditions, especially after long-term aging has occurred, and reflective cracking under traffic and environmental loading.

Generally, asphalt mix design procedures should take into account the performance of asphalt mixture with respect to different distresses under traffic and environmental loading. However, most current pavement design methods are not structured to easily accommodate the analysis of material performance in design procedure as the majority of existing design systems only use a measure of stiffness to distinguish properties or performance of asphalt mixtures. This was suitable to differentiate conventional asphalt mixtures used primarily during the development of these design approaches; however, the actual field performance for mixtures is not always adequately captured by stiffness measurements alone. Mixtures with similar stiffness can have significantly different capacities to resist cracking or permanent deformation. Therefore, pavement design and evaluation approaches should incorporate performance-based properties to accurately represent the true performance differences to be expected under realistic loading and environmental conditions [2,3]. This is currently an active area of research. While various performance-based approaches have been introduced (e.g., FHWA Performance Engineered Mixture Design (PEMD) and Performance Related Specifications (PRS)), they have not yet been widely accepted or implemented. They would not be used for routine design because they need performance-based laboratory test results that can be accommodated in the design process. Conduction performance-based laboratory tests would be time-consuming and expensive and might not be a viable option for all cases due to existing limitations for each specific project. Furthermore, performance-based mix design methods need to be locally calibrated for each project based on the available material and environmental and traffic conditions.

In addition to performance-based mix design procedures, the asphalt pavement industry has consistently endeavored to extend pavement life by introducing innovative materials to improve the performance, sustainability, and cost-effectiveness of asphalt concrete materials [1]. Extensive evaluation and characterization of innovative materials have been conducted in the laboratory using various testing and analysis approaches. However, many agencies are reluctant to implement widespread use of innovative materials until they have a proven track record of performance in the field. Part of the reason is the lack of a well-established framework for quantifying the benefits of innovative materials within existing pavement design and analysis approaches. For instance, the current airfield pavement design and performance evaluation software (FAARFIELD) acknowledges the absence of guidance on the use of new types of materials in asphalt pavement such as recycled materials or modifiers and innovative construction techniques such as utilizing warm mix asphalt (WMA) in airfield pavement. Moreover, the current cracking model in FAARFIELD software for flexible pavements might not be able to capture the actual mixture performance with respect to top-down and thermal cracking as it only considers the tensile strain at the bottom of the asphalt layer.

Finally, performance-based design and evaluation approaches will be tailored to consider the materials performance with respect to different distresses. However, there is immediate need to adjust the existing design frameworks to accommodate the performance of asphalt mixtures as well as to evaluate the effect of the innovative material on pavement performance. This will give agencies and designers a tool by which to select the most efficient mixture for a specific situation and appropriately design the pavement structure to perform satisfactorily under the given design and environmental loads.

In order to fulfill this aim, six asphalt mixtures, including hot mix asphalt (HMA), three types of warm mix asphalt (WMA), along with a combination of WMA and reclaimed asphalt pavement (RAP), were obtained from ongoing research at the Federal Aviation Administration's National Airport Pavement and Materials Research Center (NAPMRC). Laboratory performance-based tests were conducted to evaluate mixtures cracking properties, and the test results were then utilized as pavement performance prediction software (FlexPAVE™ and FAARFIELD) inputs to assess mixture fatigue cracking properties in the context of pavement. The predicted fatigue cracking performance based on two software and fatigue properties indices based on laboratory tests were compared with each other to investigate which laboratory test(s) and property threshold(s) would be viable to be implemented in airfield pavement performance-based specifications.

In addition, several statistical analysis methods were utilized to develop prediction models for low-temperature fracture energy (G_f) as an indicator of low temperature cracking susceptibility of asphalt mixtures as well as S_{app} parameter based on simplified viscoelastic continuum damage (S-VECD) theory as representative of mixtures fatigue cracking susceptibility.

The G_f prediction models were developed using a set of 71 mixtures with 12 replicate specimens for each mixture. An experimental database including 47 different asphalt mixtures with at least three replicate specimens for each mixture was used to assess their fatigue cracking properties based on S-VECD theory.

The models include the simultaneous impact of various predictor variables such as asphalt binder and aggregate types, recycled material content, proportioning of the asphalt binder and aggregates based on design traffic data (for G_f model), mixture empirical and volumetric properties such as air voids, densities, VFA, and VMA.

Several prediction models were developed and combined with an already established dynamic modulus prediction modulus to form the final S_{app} prediction model. The developed prediction models are as follow:

• Two prediction models based on damage characteristic curve (DCC) coefficients (C_{11} and C_{12}) as the main outcome of S-VECD theory

• D^R value prediction model (amount of average drop in material integrity per load cycle)

• Alpha prediction model (the maximum slope of the relaxation modulus)

Furthermore, a cracking balance design diagram was developed based on G_f and S_{app} prediction models to be used as a predesign tool to evaluate mixture cracking susceptibility only with the information available during the mix design process. The cracking balance design diagram considers both phases of cracking (crack initiation and propagation) using S-VECD and fracture mechanics theories.

Finally, sensitivity analysis was conducted to determine the most effective variables on both low temperature and fatigue cracking properties of asphalt mixtures.

7.2 Conclusions

Throughout this doctorate research, a number of significant findings were inferred. A summary of key conclusions from the research efforts are as following:

7.2.1 Exploration of cracking-related performance-based specification (PBS) indices for airfield asphalt mixtures

- The addition of an organic WMA additive and RAP increased asphalt mixture stiffness and decreased relaxation capability. In addition, they seemed to worsen fracture properties of asphalt mixtures at both intermediate and low temperatures.
- Based on the direct tension cyclic fatigue (DTCF) test results, a poor correlation was found between all four fatigue parameters, which can be attributed to the fact that performance of mixtures with respect to fatigue cracking cannot be assessed solely based on laboratory measurements and combination of the mixtures lab measured properties with the pavement structure, environmental condition, and traffic data is crucial to investigate the fatigue performance.
- The contradictory results of performance-based laboratory tests and pavement performance simulation show the Federal Aviation Administration (FAA) current asphalt pavement thickness design procedure lacks a usable model of fatigue cracking in its standard design program (FAARFIELD). The major flaw in fatigue modeling of FAARFIELD is that it does not take into account many significant factors (such as mix properties) in the design process,

and it might lead to unrealistic pavement structural design. Therefore, a performance-based specification needs to be developed based on the nonlinear viscoelastic properties of asphalt mixtures along with other effective factors such as aging to capture the proper fatigue performance limit in the airfield pavement design model.

- The results of the simulation with the FlexPAVETM showed that fatigue failure in pavements could happen due to both top-down and bottom-up cracking. A reasonable correlation was found between total damage in the pavement and top-down cracking damage. While the results of bottom-up cracking are relatively comparable.

- Based on the statistical analysis results, C^{S}_{Nf} and flexibility index (FI) cracking performance indices have the most similar ranking sequence and a moderate negative relationship with the predicted damage of FlexPAVETM and FAARFIELD, respectively. On the other hand, S_{app} was found to have the highest percent discrepancy and a strong negative relationship with FI values.

7.2.2 Fracture Properties Prediction Models

- In general, adding more variables increases prediction models' accuracy. However, the predictability of the full quadratic model (FQM) decreased using all variables in groups A, B, and C. This is likely related to saturation of the regression model and shows that model accuracy may not necessarily be improved with more variables.

- Both ANN and SVEM showed comparable predictability in the models. However, ANN models were found to be time-consuming and computationally more expensive than the models developed using the SVEM technique. Also, SVEM does not require a predefined functional structure of the model to predict the outcome, which leads to a simpler functional structure and increased practicality.

- The sensitivity analysis results showed that design traffic data, PGLT, percent passing 3/8 in sieve, and VMA the most effective factors as compared to other variables in this study. In addition, predictor variables in groups A and B can explain almost 91% of the variation in predicted fracture energy, which means that based on the SVEM models, fracture energy can be predicted with high reliability even before measuring mixture properties and conducting laboratory tests.

- Three web-based prediction models were developed based on the SVEM technique that can be utilized as a predesign tool. The models enable users to predict asphalt mixture susceptibility to low temperature cracking with high reliability when testing is not feasible and/or a limited amount of data is available during the mix design process.

7.2.3 Fatigue Properties Prediction Models

- Not all regression models would yield a promising result based on SVEM techniques. In addition, increasing the number of iterations does not necessarily improve the performance of the model. Several models with different numbers of iterations need to be implemented to find out a model with the best performance.

- Forward selection showed the most promising results based on SVEM techniques that show, although this technique is based on linear regression models. It can deal with small datasets using the self-validation technique.

- Support vector machine might not be a good candidate to be used in regression problems with a small amount of data

- Based on sensitivity analysis results, percent of aggregate smaller than 4.75 mm and aggregate percent smaller than 0.75 mm, aggregate bulk specific gravity, and asphalt binder content have the highest impact on fatigue properties, among other variables.

- Sensitivity analysis of cracking balance diagram showed that higher G_{mb}, lower percent passing of sieve 3/8 in, lower RAP%, lower NMAS, and higher VMA up to 17% decrease mixture cracking susceptibility at both intermediate and low temperatures. In contrast, higher PGLT (less negative), higher G_{mm}, higher PGHT, and lower percent passing of sieve #200 increase mixture susceptibility to low temperature cracking and, at the same time, decrease susceptibility to fatigue cracking. Thus, these parameters should be selected in a range that keeps the balance between low temperature and fatigue cracking.

- The developed cracking balance design diagram in this dissertation can be used as a predesign tool to investigate mixture cracking properties. Users can input variables based on their available data and/or desired variables. The predicted cracking properties will then be calculated and shown on the diagram. It should be mentioned that the proposed prediction models are not based on mechanistic evaluation of mixture behavior, and they are mostly suitable for the considered range of predictor variables in this study. The extrapolation of the models is not recommended at this time.

7.3 Future Extensions

The study conducted in this doctoral thesis will be further extended. Some examples of the future works that can be conducted as a future extension of this research are as follow:

7.3.1 Exploration of cracking-related performance-based specification (PBS) indices for airfield asphalt mixtures

- The current NAPMRC experiment consists of three different test sections for each lane. All test sections were instrumented with asphalt strain gages (ASG), earth pressure cells (EPC), thermocouples (TC), and Moisture Gages (MG) to record asphalt mixture critical responses and evaluate pavement behavior. Field distress data will be obtained for rutting and cracking for all test sections. The lab performance testing data will then be compared with field performance results to establish which performance test would be appropriate to determine airfield pavement behavior. All asphalt mixtures will be ranked based on their rutting, fatigue, and cracking performances for plant-produced lab compacted mixtures and test section performance. Moreover, the correlation between performance indices from lab test results and field distress data will be investigated.

7.3.2 Cracking prediction model

- All the conclusions were made based on the laboratory test results of unaged asphalt mixtures. Aging level, however, plays a significant role in mixtures properties. Some properties might get improved, while some may get worse as aging increases in asphalt mixtures. As a consequence, there is a potential that performance prediction models under-predict the amount of cracking without the inclusion of age-related property evolution. Therefore, asphalt mixtures need to be evaluated at the aged condition to assess the mixture properties in the long-term aging condition.

- More laboratory test results need to be utilized to future validate the prediction models and to improve model accuracy. Any necessary adjustment on the developed model should be made by retuning the hyperparameters. The predictive models can be improved even by more varying types of aggregate, asphalt binders, and innovative materials. With expanding datasets, the prediction models can be categorized into different groups with more normally distributed data point to increase predictability of the models.
- By utilizing more datapoints, more complex models such as artificial neural network can be employed to better predict the nonlinear algorithm withing dataset.
- Test sections are constructed for some of study mixtures in this dissertation. The test sections will continue to be monitored and field distress data will be collected to calibrate the prediction models.
- Wider range of mix characteristics can be utilized to further expand the range in which prediction model are valid.

APPENDICES

Appendix A: Paper 1 (Chapter 3)

Exploration of Cracking-related Performance-based Specification (PBS) Indices for Airfield Asphalt Mixtures

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Abstract

The purpose of this study is to assess cracking performance of warm-mix asphalt (WMA) and reclaimed asphalt pavement (RAP) mixtures for airfield pavements and to explore performance-based airfield asphalt mix specifications. Fundamental properties of these mixtures were investigated through performance-based laboratory tests such as complex modulus, semi-circular bend (SCB), and direct tension cyclic fatigue (DTCF) tests. Moreover, performance prediction software (i.e., FAARFIELD and FlexPAVE^{TM}) were utilized to evaluate mixture performance during the design period. Based on the complex modulus and SCB tests results, organic additive and RAP tend to increase mixture susceptibility to fracture. Results of the DTCF test showed that fatigue indices ranked mixtures in different ways, which emphasizes the importance of using performance prediction programs to investigate mixture fatigue performance. The results of performance prediction indicated that utilization of hybrid WMA additive and RAP would increase airfield pavements fatigue damage. The contradictory results of laboratory tests and pavement performance simulation show the airfield current asphalt pavement thickness design procedure lacks a usable model of fatigue cracking in its standard design program (FAARFIELD).

Keywords: Airfield Pavement, Warm Mix Asphalt (WMA), Reclaimed Asphalt Pavement (RAP), Fatigue Cracking, FAARFIELD, FlexPAVE^{TM}, Performance Prediction.

Introduction

Airfield pavements are subjected to significantly heavier loading as compared to highway pavements as a function of the weight of the aircrafts and aircraft braking as well as operation of aircrafts with different gear configurations and very high tire pressures. As a result, they undergo different types of distresses. These distresses may require a significant amount of time and cost for maintenance and rehabilitation, and can also cause major safety problems. Problems associated with surface roughness and friction, as well as foreign object debris (FOD), can cause severe damage to aircraft leading to hazardous operating conditions. In order to address these issues, it is necessary to improve the overall functionality of airfield pavements through designing high-quality distress resistant asphalt mixtures that can tolerate heavy aircraft loads under different climatic conditions [1, 2].

During the last few decades, significant improvements in technologies and understanding of asphalt mixtures performance have been made to lower costs and the potential of distress in highway pavements. Fundamental and engineering properties of asphalt concrete mixtures (e.g., fatigue resistance, modulus, rheological properties) can be determined using performance-based lab tests. The main reason for conducting these tests is to address the different distresses in pavements, such as cracking and permanent deformation (rutting). These mixture properties have been shown to better correlate to asphalt pavement performance than traditional approaches of relying on mixture compositions and volumetric measures [3]. The use of performance properties in material specifications has led to the development of performance-based specifications (PBSs) that are now being utilized in highway construction.

The use of reclaimed asphalt pavement (RAP) and warm mix asphalt (WMA) technologies in highway construction have been shown to reduce overall construction cost while maintaining comparable and, in some cases, enhanced performance [4]. However, the application of these technologies in airfield pavements in the context of performance-based specifications has not been widely investigated. Since the type and magnitude of the loads, as well as the number of load repetitions, are quite different between highways and airfields, there is an urgent need to evaluate performance properties for airfield asphalt pavements with the incorporation of RAP and WMA technologies. Furthermore, there is a need to investigate a suitable threshold for performance properties that can be used in PBSs for airfields.

A number of research studies have been conducted to assess the possibility of using WMA in airfield pavements. The results showed that WMA mixtures are more prone to moisture damage, and they also have higher rutting potential than hot mix asphalt (HMA) mixtures in airfield pavement [5]. The test temperature has more effect on the rutting performance of asphalt mixtures than other factors such as environmental aging and tire pressure [6]. Su et al. claimed that based on laboratory test results, WMA could not be a good alternative for HMA to use in airfield pavement rehabilitation [7]. It has also been reported that WMA has moderately lower resilient modulus and marshal stability than HMA. On the other hand, the relative density of field cores is modestly higher in WMA compared to HMA [8]. These previous studies did not extensively focus on cracking performance evaluation.

In a study conducted by Shoenberger et al., the performance of recycled asphalt pavements for different airports was investigated. The results showed that the recycled asphalt mixtures are susceptible to rutting and most of the distress found in recycled asphalt pavements was climatic and environmental-related, not load associated [9]. Asphalt mixtures containing RAP have slightly higher stiffness, higher dynamic modulus and lower surface friction than asphalt mixtures without

RAP; however, the maximum amount of RAP in airfield pavements should not exceed 30% in HMA in order to meet all specified requirements for virgin asphalt mixtures [10,11].

Since both WMA and RAP are relatively new concepts in airfield pavements, a few studies have investigated the performance of WMA mixtures containing RAP. Guercio et al. compared the performance of WMA-RAP and HMA mixtures with respect to fatigue cracking and rutting for airfield pavements. Results showed that HMA has better performance against fatigue and rutting than WMA-RAP asphalt mixtures [12]. Mejías-Santiago et al. investigated the moisture susceptibility of different types of WMA containing RAP. Results showed that using WMA with a high amount of RAP can improve mixture's moisture damage resistance. In addition, moisture susceptibility of WMA-RAP mixtures is related to mixing and compaction temperatures [13].

Incorporation of new materials such as warm mix additives and RAP in asphalt mixture design required specific PBSs, which considers all possible aspects to achieve a balance of asphalt mixtures performance with respect to various distress mechanisms. Among different asphalt mixtures performance properties, moisture resistance, stiffness, deformation resistance (ie. shoving and rutting resistance), thermal cracking, and fatigue cracking have been the focus of research studies. In some cases, several laboratory performance-based tests such as flexural beam fatigue, Hamburg Wheel Tracking Device (HWTD), Asphalt Pavement Analyzer (APA), bending beam rheometer have been commonly utilized to support asphalt mixtures' PBSs. [14]. Jamieson and White proposed a PBS to use stone mastic asphalt as an airfield ungrooved runway surface. They used volumetric and constituent material properties, and requirements for fatigue resistance, resistance to deformation, surface texture, and durability as required performances in PBSs [15].

Motivation and Objective

Based on previous research studies, it has been shown that some modifiers may have different impacts on airfield pavements performance with respect to different distresses. Results of a study conducted by Bennert showed rutting performance of airfield asphalt mixtures was improved with modification. On the other hand, modification deteriorated the fatigue performance of asphalt mixtures [16]. Although the current airfield pavement design procedure includes fatigue in the asphalt layer and rutting in the subgrade, most airfield pavements are designed based on subgrade rutting criteria. Which shows, in many cases, current pavement design methods cannot adequately quantify the performance change that may be achieved through the use of modification in airfield asphalt pavements. Therefore, there is an immediate need to develop a performance-based specification by which modified mixtures can be appropriately evaluated within existing airfield pavement design methodologies. It is worth mentioning that several research studies have been conducted because of the concerns of fatigue in airfield pavements and its considerations and focused on necessary parameters for airfield pavement structural design [17,18]. In this study, however, the main focus is identifying performance measures indices that can be used for material specification purposes to address limitations in the current airfield pavement design procedure.

The objective of this research is to propose suitable laboratory performance tests and performance indices that can be adopted in PBSs to address cracking performance of airfield pavement constructed using WMA and RAP mixtures. To accomplish this objective, cracking properties of WMA, RAP mixtures, and traditional P401 hot-mixed asphalt are evaluated using performance based laboratory tests and long-term pavement cracking performance is predicted using advanced mechanistic based simulation software. Finally, comparisons are made between mixture performance indices and predicted pavement performance to propose suitable tests and performance properties that can be adopted in PBSs. Three types of WMA, along with a combination of WMA and RAP mixtures, as well as P401 hot-mixed asphalt were utilized in this study. This research effort will pave the road for designers and agencies to better understand actual behaviour of airfield pavements under given traffic and environmental loads based on laboratory tests.

Materials and Methods

Materials

This study includes six asphalt mixtures which were obtained from ongoing research at the Federal Aviation Administration's National Airport Pavement and Materials Research Center (NAPMRC). These represent six different airfield pavement test lanes that were constructed during spring 2019, including one lane with hot mix asphalt (HMA), three lanes with WMA, and two lanes with WMA+RAP. The RAP content used was 20% by total mixture weight. Two Superpave performance-graded asphalt binders, a PG 76-22 and a PG 64-22 (with latex), were used in this study. HMA and WMA sections (four outdoor lanes) were constructed using the PG 76-22 asphalt binder, and the PG 64-22 and latex was used to build WMA+RAP lanes (two indoor lanes). Chemical, organic, and hybrid additives were utilized to represent different available technologies to produce WMA. All test lanes consisted of 8 inches P-209 crushed stone base layer, 12 inches P-154 subbase layer, and sandy subgrade with CBR of 20 [19]. Performance data from the test lanes is not currently available due to unavoidable delays in testing. Table 1 shows the mixture type for each test lane.

Table 0-1 Test Lane Asphalt Mixtures and Pavement Structure

Lane Number	Mixture Type (Lift thickness)	Base Layer	Subbase Layer	Subgrade
Lane 1	Mix A: PG 76-22, Control, HMA (P-401) (9 inch)	P-209 Crushed Aggregate Base Course (8 inch)	P-154 Subbase Course (12 inch)	Sandy Subgrade (CBR 20)
Lane 2	Mix B: PG 76-22, WMA, Chemical additive (9 inch)			
Lane 3	Mix C: PG 76-22, WMA, Organic additive (9 inch)			
Lane 4	Mix D: PG 76-22, WMA, Hybrid additive (9 inch)			
Lane 5	Mix E: PG 64-22, WMA, Organic additive, with Latex modifier (3 inch) Mix F: PG 64-22, WMA, Organic additive, with Latex modifier, RAP (6 inch)			
Lane 6	Mix F: PG 64-22, WMA, Organic additive, Latex, RAP (9 inch)			

Specimen Fabrication

Loose plant-produced asphalt mixtures provided by NAPMRC were compacted to a target air void content of 5%±0.5% as measured on final laboratory test specimens, which is a common in-place air void content in airport pavements. In order to achieve consistency among mixtures a reasonable reheating protocol was used as follow:

(1) Buckets were placed in preheated oven set at mixing temperature minus 10°C for two hours
(2) Mixtures were transferred to pans
(3) Mixtures were placed at compaction temperatures for two hours

Testing and Analysis Methods

The experimental campaign in this research includes complex modulus test, semi-circular bend (SCB) test, and direct tension cyclic fatigue (DTCF) test.

Linear viscoelastic properties of asphalt mixtures were investigated through complex modulus test following AASHTO T 342 test specification. Testing was conducted using an asphalt mixture performance tester (AMPT) at 4.4, 21.1, 37.8°C temperature with loading frequencies of 0.1, 0.5, 1, 5, 10, 25 Hz at each temperature. Measured stresses and strains for each mixture were utilized to construct the dynamic modulus and phase angle mastercurves using RHEA® software based on the time-temperature superposition principle. In addition, the (G-R_m) parameter was determined to assess the asphalt mixture's cracking performance. The mixture's Glover–Rowe parameter (G-R_m) is also determined from complex modulus test results using equation 1 [20]. In this study, the G-R_m parameter was calculated at the frequency of 5 Hz at 20°C in accordance with the NCHRP 09-58 project [21, 22].

(1)

Where:
E^* is dynamic modulus (MPa) and is phase angle (degrees).

SCB test was conducted to evaluate fracture characteristics of asphalt mixtures at intermediate temperatures. The SCB test was performed using the load line displacement method in accordance with AASHTO TP 124 with the universal testing machine (UTM) at 25ºC. Fracture energy and flexibility index (FI) were calculated based on the SCB test data using IFIT software developed by Illinois Center of Transportation (ICT). Currently, an FI value of eight (8) has been recommended by the Illinois Department of Transportation as a threshold value to distinguish asphalt mixtures with acceptable cracking performance from mixtures with inferior cracking performance [23].

To assess the fatigue properties of asphalt mixtures, DTCF test was conducted in accordance with AASHTO TP 107 using an AMPT. Asphalt mixture specimens were tested at 200, 225, and 250 microstrain. Test data were analyzed using FHWA's FlexMAT™ software, the analysis is based on the simplified viscoelastic continuum damage (S-VECD) approach [24]. Four performance-based fatigue indices (G^R, D^R, S_{app}, and) were calculated to determine mixture properties with respect to fatigue cracking [25-27].

Pavement Performance Prediction: FAARFIELD and FlexPAVE ™

In this study, the expected field performance of the mixtures during and at the end of pavement service life was investigated using FAARFIELD (version 1.42) and FlexPAVE™ software. FAARFIELD is a mechanistic-empirical (M-E) airport pavement thickness design program developed by the Federal Aviation Administration (FAA). It incorporates layered elastic analysis for flexible pavements to determine critical pavement responses. FAARFIELD determines the structural fatigue life of pavement through cumulative damage factor (*CDF*). It computes a separate CDF for each failure mode – subgrade failure and HMA failure. HMA failure model included in the design procedure is based on the ratio of dissipated energy change (RDEC) concept using flexural stiffness [28]. In this research, a frequency of 3.2 Hz was selected to convert dynamic modulus data to flexural stiffness based on the speed of Heavy vehicle simulator for airports (HVS-A) on test sections. In addition, FAARFIELD utilizes resilient modulus to investigate asphalt layer properties. Equation 2 was implemented to convert dynamic modulus to resilient modulus with respect to tire radius and loading speed (3 mph), which resulted in dynamic modulus selection at a frequency of 0.5 Hz at 21.1°C. Note that FAARFIELD utilizes the horizontal strain at the bottom of the asphalt layer to investigate accumulated fatigue damage in the pavement. Thus, it would be able to capture only bottom-up fatigue cracking performance.

In addition to FAARFIELD, the amount of fatigue cracking damage was also determined using the FlexPAVE™ program. The FlexPAVE™ incorporates a three-dimensional layered system in conjunction with the simplified viscoelastic continuum damage (S-VECD) model to assess mechanistic properties of mixtures such as strains and stresses, under assigned traffic load and various climatic conditions. A cumulative damage model has been incorporated in the FlexPAVE™ to investigate accumulated damage in the pavement cross-section [29]. Due to adoption of finite element model and use of continuum damage approach, FlexPAVE™ is able to determine fatigue damage throughout the asphalt layer, thus is able to distinguish between top-down and bottom-up fatigue cracking potential.

To analyze pavement performance, test lane structures were replicated in the software and the measured material properties based on complex modulus and DTCF tests have been input to predict the fatigue performance of asphalt pavements. All layers beneath the asphalt layer were considered to be linear elastic and precomputed modulus values based on FAARFIELD were assigned to these layers. The elastic moduli of layers the beneath asphalt layer were 75 ksi for base and 40 ksi for subbase, and 30 ksi for subgrade layer. These moduli value are selected by FAARFIELD as default values for the materials types (P-209, P-154 and Subgrade with CBR of 20). HVS-A was used for traffic loading with total departures of 200,000 at the end of design life as shown in table 2. Moreover, 20°C has been used in the simulation to predict performance of asphalt pavements with respect to fatigue cracking. This pavement temperature was chosen since the HVS testing at NAPMRC is being conducted in temperature-controlled manner at 20°C. Also, for the sake of comparison between asphalt mixtures performance using statistical analysis, the fatigue performance of lane five has been also predicted using only one mixture (i.e., 64-22, WMA, Organic (L)) in addition to analysis of as-built structure for this lane.

Where:
S is loading speed (m/s) and a is average tire radius (m).

Table 0-2 Traffic Data Information

Load	Gross Wt. (lbs.)	Annual Departures	Total Departures	Tire Pressure (psi)	Test Speed mph
HVS-A	61,300	10,000	200,000	254	3

Results and Discussion

Linear Viscoelastic (LVE) Properties

Figures 1a and 1b show dynamic modulus and phase angle master curves for asphalt mixtures in this study. The results are shown as an average value of three replicates. According to the results, WMA with an organic additive (PG 76-22), and WMA with an organic additive, latex-modified binder and RAP (PG 64-22) have higher stiffness and lower phase angle (relaxation capability) compared with other mixtures; this indicates that these mixture may be more susceptible to cracking. The behavior of WMA with organic additive was expected, and it likely stems from the chemical interaction of organic additive with asphalt binder (polymer effect), especially during laboratory reheating process. WMA with an organic additive and latex (PG 64-22) has the lowest stiffness and highest relaxation capability among all mixtures, shows the positive effect of latex with respect to decreasing asphalt mixture susceptibility to cracking. The area under the curve was determined for each mixture, and Kruskal-Wallis test was used as a non-parametric statistical test to investigate if there is a statistically significant difference between the area under the curve for mixtures. WMA mixtures with chemical and hybrid additives, and control mixture showed statistically similar values of dynamic modulus and phase angle, meaning that neither of these additives has a significant effect on asphalt mixture LVE properties.

Figure 2 depicts the G-R_m parameter for asphalt mixtures. According to the results, an organic WMA additive increased the G-R_m value of the control mixture by 29%, which indicates higher cracking susceptibility of the mixture with an organic additive. At the same time, there is no statistically significant difference in G-R_m values between both chemical and hybrid additives and control mixture. Although WMA with an organic additive and latex (PG 64-22) was found to be the best mixture in terms of cracking susceptibility among all the mixtures, addition of RAP increased its G-R_m value by 27%, which shows that RAP deteriorates mixture cracking susceptibility.

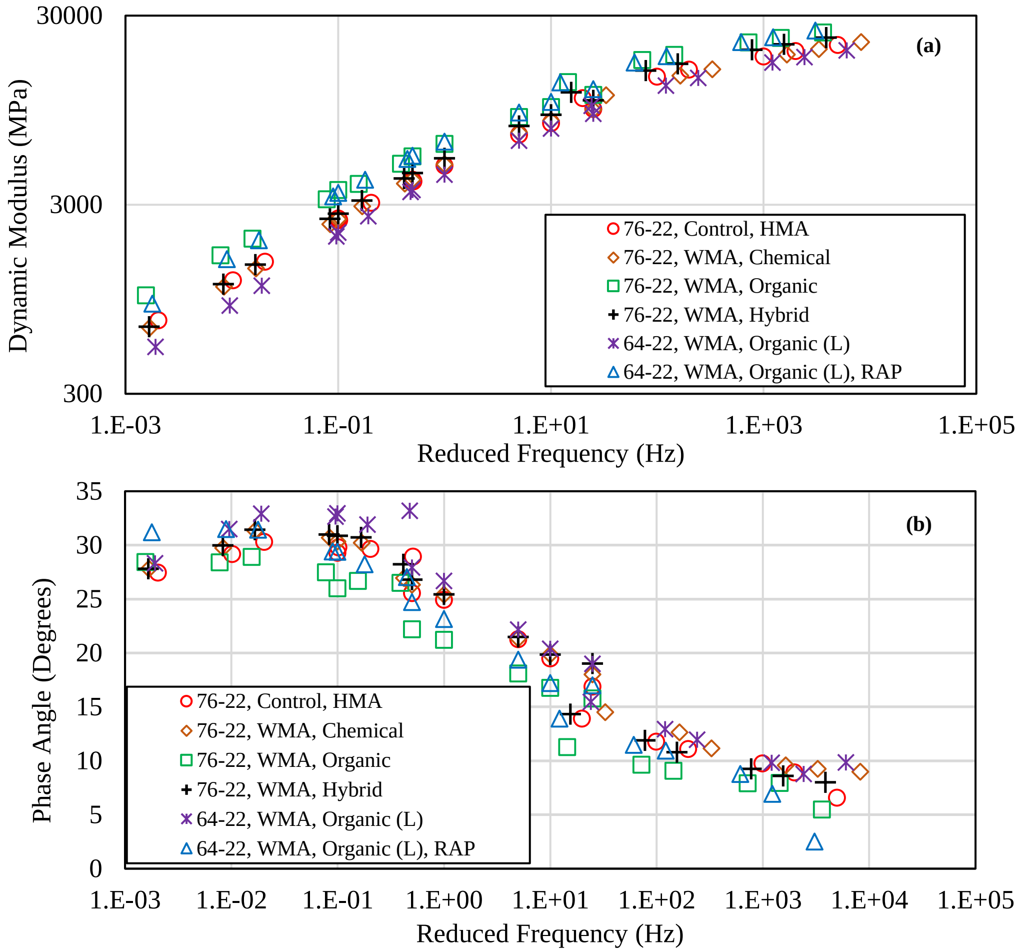

Figure 0-1 a) Dynamic modulus mastercurve at 21.1°C reference temperature, b) Phase angle mastercurve at 21.1°C reference temperature

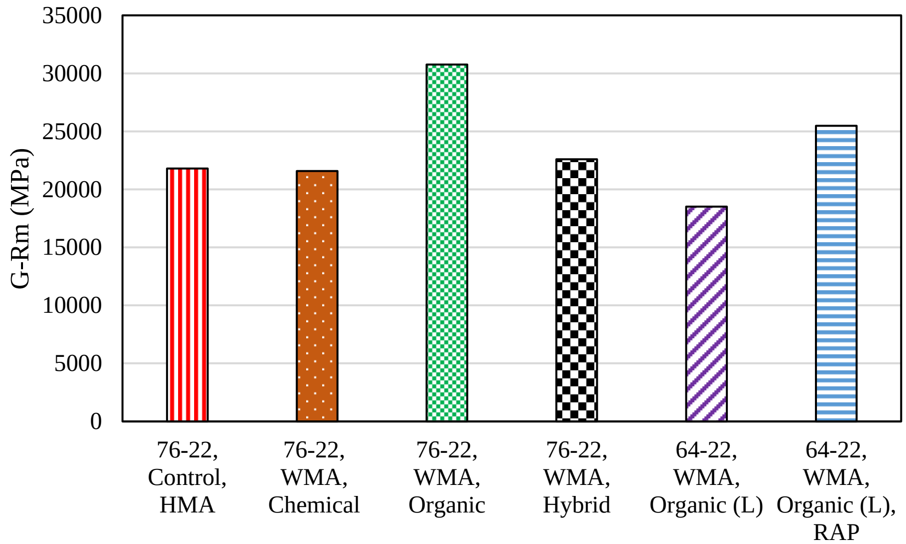

Figure 0-2 Glover-Rowe Parameter at the frequency of 5 Hz at 20°C

Fracture Properties

Figures 3a and 3b show the average fracture energy and the FI parameter for asphalt mixtures. At least three replicates were tested for each mixture, and the results are shown as an average value of replicates. The error bars in the results represent one standard deviation interval.

The fracture energy and FI values showed similar trends, except WMA with an organic additive (PG 64-22) and latex. Based on the results of both criteria, WMA with an organic additive (PG 76-22) has the worst cracking resistance at intermediate temperatures, which was also shown with the G-R_m parameter. According to the fracture energy, WMA with a chemical additive (PG 76-22) showed the best cracking resistance. According to the FI results, all mixtures failed to meet the threshold except the WMA with an organic additive and latex (PG 62-22). It is worth mentioning that the threshold value was developed for highway pavement based on different loading and temperature conditions for various types of asphalt mixtures in Illinois, and there is a potential that the same threshold may not be appropriate for other types of asphalt mixtures at other locations and it was used to compare airfield asphalt mixtures in this study. Based on the FI, WMA with an organic additive and latex (PG 64-22) has the best fracture properties, which may be attributed to the improvement of relaxation capability of the mixture due to the presence of latex. On the other hand, the addition of RAP deteriorates mixture fracture properties as it increases mixture stiffness and decreases relaxation capability. Since the utilization of an organic additive leads to fracture properties deterioration, it can be concluded that latex plays the most important role in passing the FI threshold.

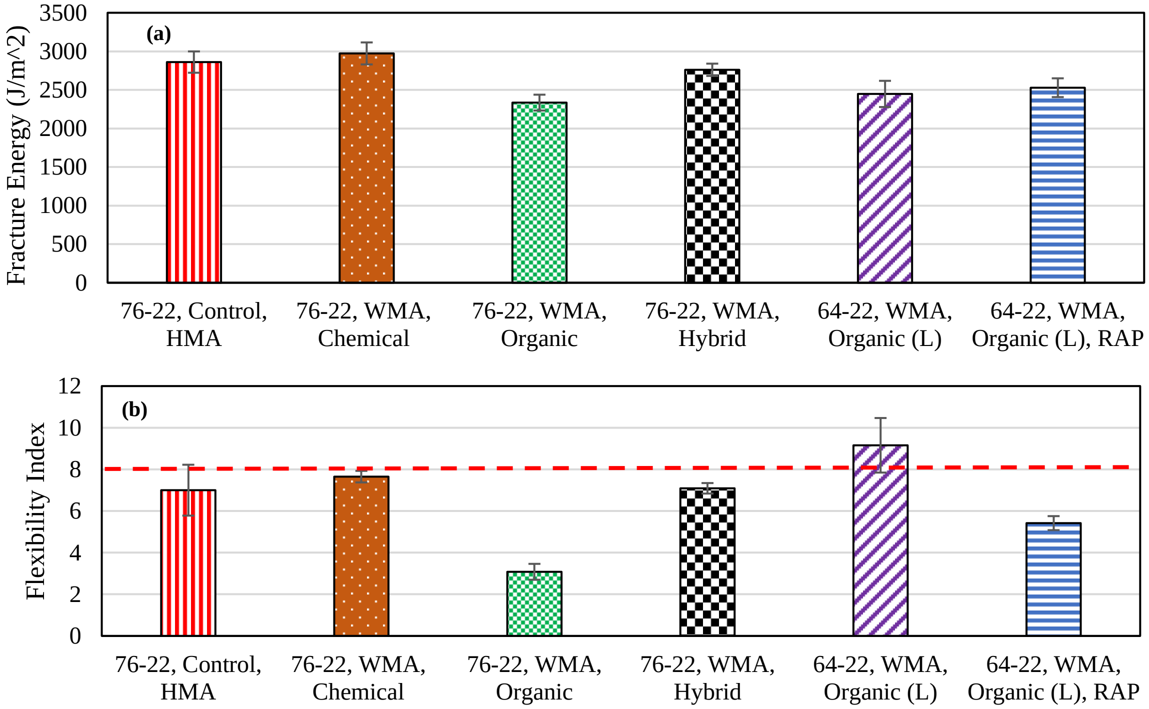

Figure 0-3 a) Fracture energy for asphalt mixtures measured from SCB test; b) Flexibility index for asphalt mixtures measured from SCB test (dashed line represent the threshold value)

Fatigue Properties

Four fatigue performance indices were utilized to evaluate mixture properties with respect to fatigue cracking. At least three replicates have been used for each mixture and Figures 4a-4d present the average results of N_f @ $G^R = 100$, D^R, S_{app}, and N_f @ $C^S_{Nf}=100$, respectively. Based on the results it can be concluded that all four indices ranked asphalt mixtures in quite different ways. Such that, WMA with a chemical additive (PG 76-22) is shown to have the best fatigue properties with respect to G^R and D^R parameters, whereas it has been ranked the 3rd and the 2nd best mixture based on S_{app}, and C^S_{Nf}, respectively. The same observation can also be made for other asphalt mixtures in this study.

The main reason for the discrepancy between these indices could be related to their definitions. Based on the S-VECD theory, the magnitude of microcracks in asphalt mixture is quantified using the amount of damage (S); neither G^R nor D^R indices take the amount of damage into account. On the other hand, S_{app} incorporates damage growth magnitude at average integrity of mixture to investigate fatigue resistance of asphalt mixtures. Damage accumulation, however, is not a linear phenomenon, and utilization of an average value might lead to an unrealistic fatigue resistance indicator. As opposed to other indices, the C^S_{Nf} criterion is based on damage growth rate in which accumulated damage at failure as well as accumulated decrease in material integrity are taken into consideration [30]. Therefore, the C^S_{Nf} is expected to have good correlation with the results of performance prediction software. Based on the discussion mentioned above, it can be deduced that current fatigue parameters might be insufficient to evaluate and rank asphalt mixture fatigue performance as a standalone parameter. Therefore, laboratory measured properties need to be incorporated in performance prediction software to better evaluate the expected performance with respect to fatigue cracking.

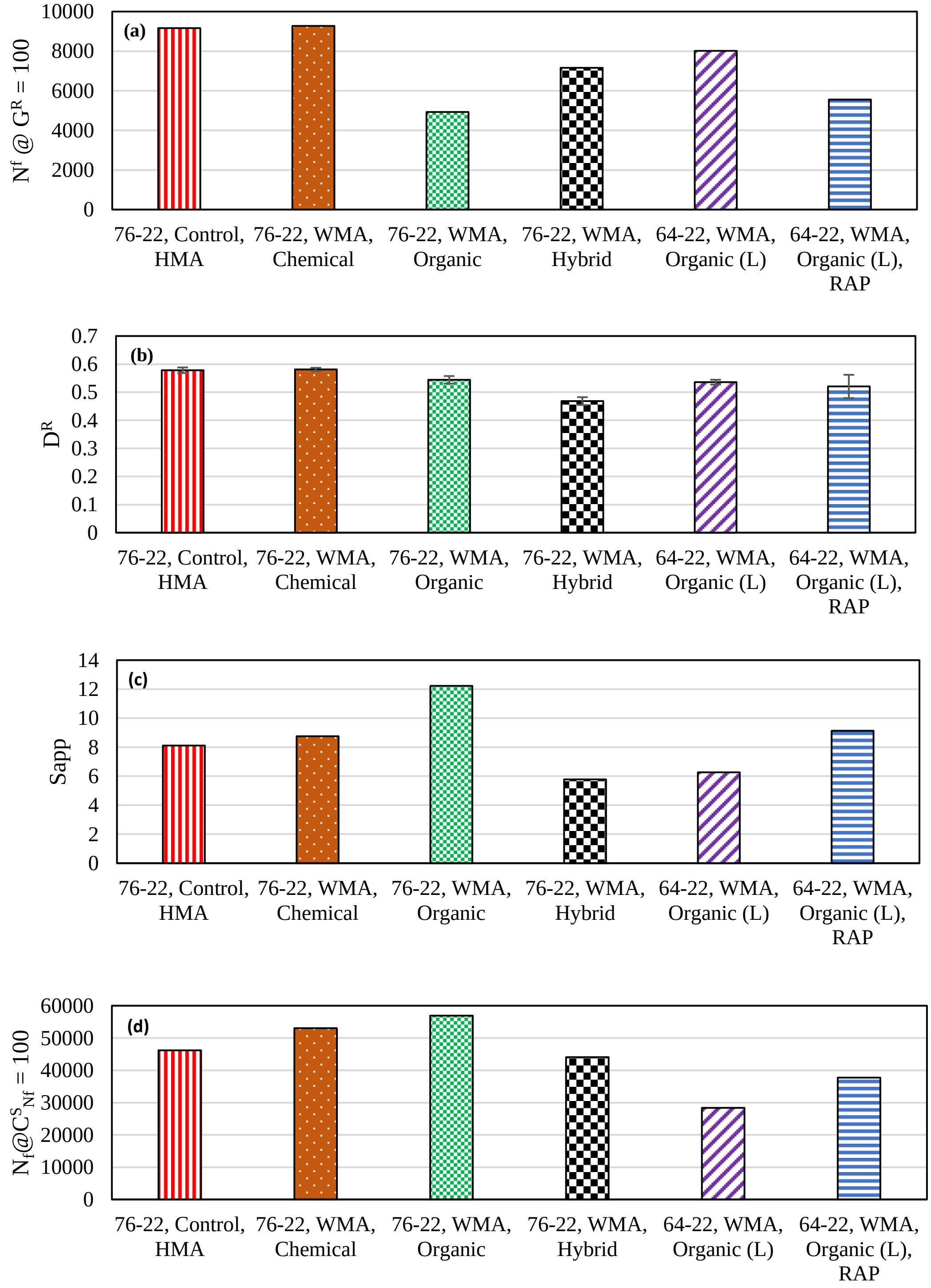

Figure 0-4 a) Number of load cycles at G^R=100 for asphalt mixtures; b) Amount of average drop in material integrity per load cycle until failure; c) S_{app} values; d) Number of load cycles at C^S_{Nf}=100

Fatigue Performance based on FAARFIELD

The amount of accumulated damage with respect to bottom-up fatigue cracking has been calculated for each lane based on the ratio of dissipated energy change (RDEC) concept and is plotted in figure 5a. Based on the results, lane two has the lowest fatigue damage among all lanes, which indicates that the utilization of chemical additive improves pavement fatigue performance. Incorporating hybrid and organic additives appear to deteriorate mixture fatigue performance as compared to the control mixture. Lane six is shown to have the highest amount of damage, followed by lane five. The high amount of damage in both lanes five and six can be attributed to the presence of RAP in the asphalt pavement.

In addition, the allowable number of departures was calculated for each lane based on the CDF in the asphalt layer. Figure 5b shows number of allowable departures with respect to fatigue cracking. Lane two holds the highest number of departures among all test lanes. However, the improvement is only 2.63% compared to lane one, meaning that WMA with a chemical additive is not substantially better than the control mixture. As expected, based on the fatigue damage results, the control mixture has outperformed asphalt pavements with hybrid and organic WMA additives, as well as the combination of WMA and RAP. Lane six is shown to have a lower number of departures compare to lane one by more than 21%. The results suggest that the incorporation of RAP along with WMA with an organic additive, could substantially worsen the pavement fatigue performance.

It should be noted that the CDF values are all below 0.5, meaning that no matter how good or bad the asphalt mixture fatigue performance is, the subgrade will fail due to rutting first, and the subgrade governs the design. The FAARFIELD will predict lower fatigue life for asphalt mixtures with a higher modulus. This does not take into account the type of binder, and consequently, any such analysis is fundamentally limited by the assumption that more stiffness means lower fatigue resistance [31]. That might not be true because a polymer can add stiffness and, at the same time, improve fatigue and fracture resistance of asphalt mixtures.

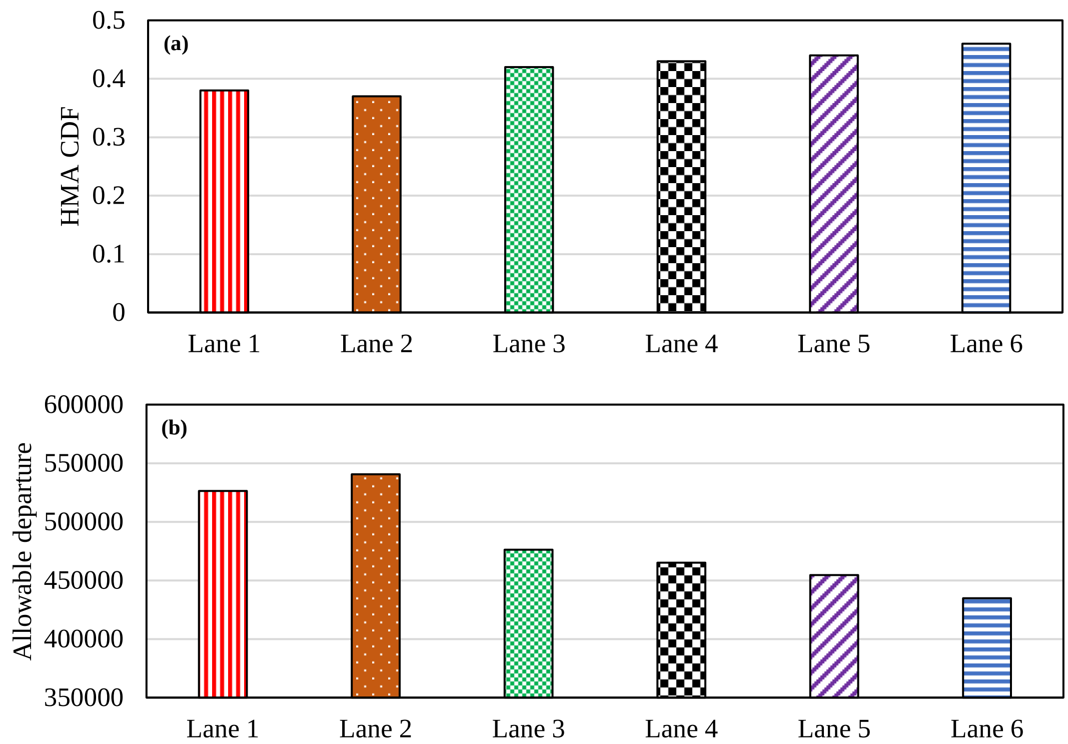

Figure 0-5 a) FAARFIELD predicted damage in the asphalt layer; b) Allowable number of departures at the end of design period.

Fatigue Performance Prediction from FlexPAVE^{TM}

Predicted fatigue performance of the test lanes using FlexPAVE^{TM} are presented in this section. Figure 6 demonstrates damage contours in lane one as an example to illustrate the predicted damage growth within the pavement. Based on the figure 6, it can be observed that fatigue damage occurs in the pavement due to both bottom-up and top-down cracking. Therefore, the results of the FlexPAVE^{TM} software are representative of what may be happening in the field and therefore the overall level of distress or relative performance.

The reference cross sectional area in FlexPAVE^{TM} is defined as two overlapping triangles which form two trapezoids within the asphalt layer thickness. The top inverted trapezoid has a 170 cm wide based (surface of asphalt layer) and the bottom trapezoid has a 120 cm wide base (bottom of asphalt layer). The percent damage is measured as the accumulated damage factors within the reference area (two trapezoid) divided by the whole area of reference cross section [29]. Figure 7 indicates the total accumulated damage in the test lanes at the end of design life. The results suggest that the utilization of WMA with a chemical and an organic additive could improve pavement fatigue performance. However, WMA with a hybrid additive and combination of WMA with an organic additive and RAP deteriorate the fatigue performance. It is commonly known that asphalt mixtures containing RAP will be more susceptible to fatigue cracking. Therefore, the exhibition of the highest amount of fatigue cracking in lane six is expected due to the inherent brittle pre-aged mixture in this test lane.

To compare the amount of fatigue damage at the top and the bottom of the asphalt layer, percent damage was calculated for the top and bottom trapezoids separately and is shown in Figure 7 with different colors. The results indicate that all test lanes will experience significantly more bottom-up cracking compared to top-down cracking at the end of the design period. The same trend as the total damage can be observed for the top-down cracking. On the other hand, lane one, lane two, lane three, and lane five are shown to have comparable results with the lowest amount of damage due to the bottom-up cracking, and lane six has the highest damage percent followed by lane four.

Although top-down cracking is evident from the FlexPAVE^{TM} simulations, the amount of top-down cracking is low. However, it is known that a considerable amount of top-down cracking will occur in actual field pavements due to much higher aging levels in the top portion of pavements as well as significant redistribution of stress on top of the pavements. The current version of FlexPAVE™ neither considers aging in the fatigue simulation, nor does it update the asphalt mixture stiffness with an accumulation of damage in the pavement [32]. Therefore, without inclusion of age-related property evolution the FlexPAVE^{TM} is expected to under-predict the amount of top-down fatigue damage. With regards to the aforementioned concerns, as the next step of this research study, different levels of aged asphalt mixtures will be utilized for a more reliable performance prediction with respect to cracking. The severity of predicted damage from top-down cracking is expected to increase after the aging model is included in the simulation process.

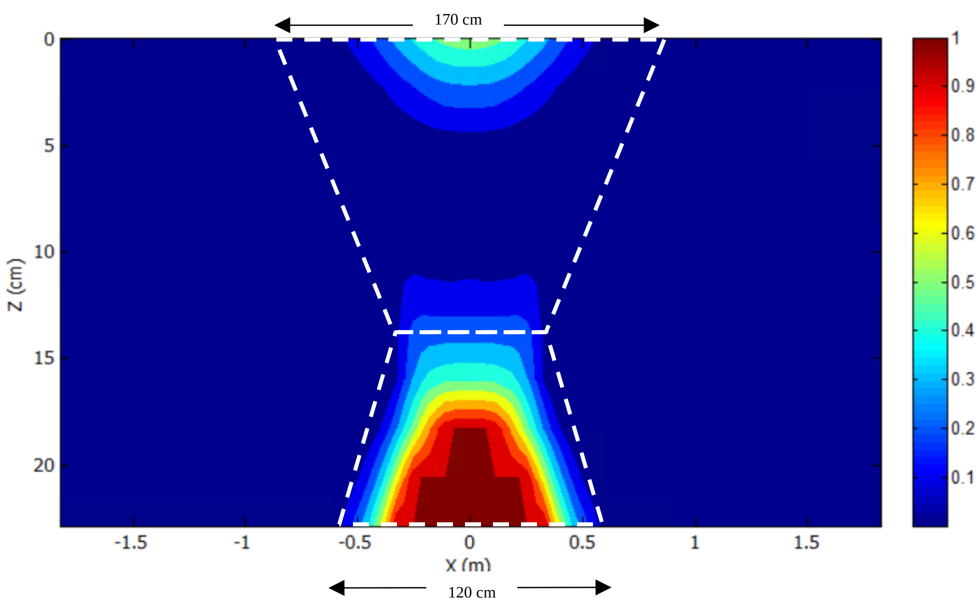

Figure 0-6 Damage contours within the pavement cross section

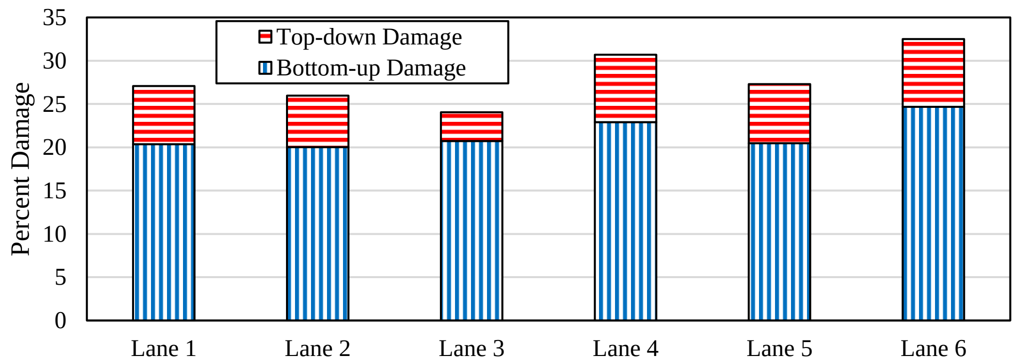

Figure 0-7 Predicted fatigue damage within the pavement (total damage is separated using two colors to show the bottom-up and top-down damage)

Correlation between asphalt mixtures fatigue properties performance

The correlation between performance indices and predicted pavement cracking performance was investigated to determine which performance parameter(s) would be viable for predicting relative pavement fatigue performance. Asphalt mixtures were first ranked based on different performance indices and predicted performance, as shown in table 3. Next, to determine how different asphalt mixtures have been ranked based on their properties and performance, percent discrepancy was introduced [3]. Each mixture's ranking was compared with other mixtures to determine the absolute difference value of the ranking and then normalized with respect to the maximum possible ranking difference. For example, based on G^R, WMA with an organic additive (PG 76-22) is ranked 6^{th}, while it has been ranked as the 3^{rd} best asphalt mixture with respect to D^R values The percent discrepancy between these two indices can be defined as the absolute ranking difference (i.e., |6-3|=3) divided by the maximum possible difference in the ranking (i.e., 6-1=5). The lower percent discrepancy means parameters rank asphalt mixtures similarly. The average percent discrepancy of all asphalt mixtures was determined, and the value for each pair is presented in table 4.

The results suggest that the least discrepancy exists between predicted damage based on FlexPAVE™ and C^s_{Nf} parameter (13.33%) among all parameters. The results of FAARFIELD have the best correlation with FI values based on the SCB test, with a percent discrepancy of 20%. In addition, the percent discrepancy between asphalt mixtures ranking based on the results of two performance prediction software is as low as 20%. On the other hand, the percent discrepancy between S_{app} and all other parameters and results are quite high. So much so that S_{app} has the highest percent discrepancy with G^R parameter as well as FI (53.33%).

Table 0-3 Asphalt mixtures ranking based on performance indices and simulation results

Mixture	G^R	D^R	S_{app}	C^S_{Nf}	FI	FAARFIELD	FlexPAVE™
76-22, Control, HMA	2	2	4	3	4	3	3
76-22, WMA, Chemical	1	1	3	2	2	2	2
76-22, WMA, Organic	6	3	1	1	6	4	1
76-22, WMA, Hybrid	4	6	6	4	3	5	5
64-22, WMA, Organic (L)	3	4	5	6	1	1	4
64-22, WMA, Organic (L), RAP	5	5	2	5	5	6	6

Table 0-4 Average percent discrepancy

	G^R	D^R	S_{app}	C^S_{Nf}	FI	FAARFIELD	FlexPAVE™
G^R	N/A	20.00	53.33	33.33	20.00	26.67	33.33
D^R		N/A	33.33	26.67	40.00	26.67	20.00
S_{app}			N/A	26.67	53.33	46.67	26.67
C^S_{Nf}				N/A	40.00	33.33	13.33
FI					N/A	20.00	40.00
FAARFIELD						N/A	20.00
FlexPAVE™							N/A

Pearson's correlation coefficient was utilized to investigate direction and strength of any possible correlation between pairs with the highest and lowest percent discrepancy values. According to figure 8, C^s_{Nf} and FI performance indices have a moderate negative relationship with mixture cracking performance based on FlexPAVE™ and FAARFIELD software, respectively. It was also found there is a moderate positive relationship between predicted damage in asphalt mixtures using FlexPAVE™ and FAARFIELD software. S_{app} is shown to have a strong and moderate negative relationship with FI and G^R performance indices, respectively. The correlation between S_{app} and FI parameters is quite interesting, and it was not expected. Based on continuum damage mechanics, macro cracks form with localization and evolution of micro-cracks. S_{app} is the only fatigue performance parameter that incorporates damage (S) to quantify the magnitude of micro-cracks in asphalt mixtures. The strong correlation between S_{app} and FI supports the hypothesis that accumulation of damage needs to be taken into account in order to investigate the performance of asphalt mixtures with respect to cracking.

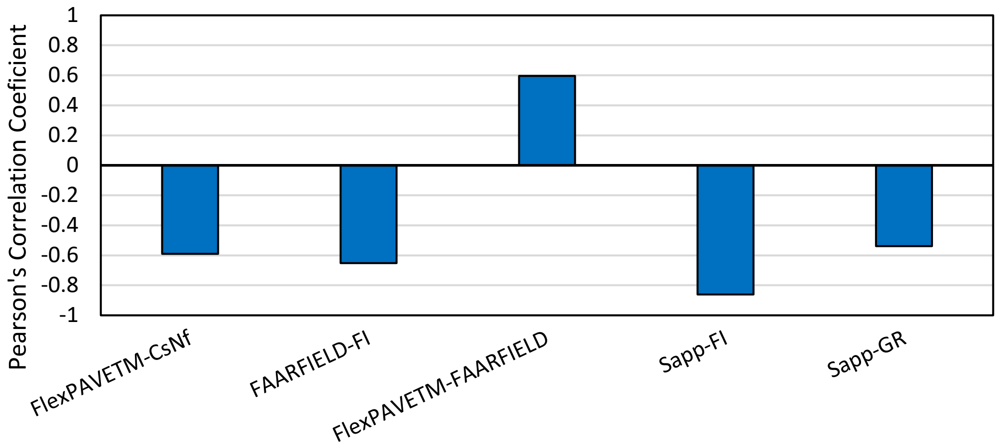

Figure 0-8 Pearson's correlation coefficients

Summary and Conclusion

The objective of this research study was to evaluate the cracking properties of WMA, combination of WMA and RAP, and P401 HMA at airfield pavements via complex modulus, SCB, and DTCF tests to predict the performance of these mixtures with respect to fatigue cracking using advanced performance simulation and prediction software such as FAARFIELD and FlexPAVE^{TM}. In addition, percent discrepancy and Pearson's correlation coefficient were utilized to compare the cracking performance indices and predicted pavement cracking performance to investigate which laboratory test(s) and property threshold(s) would be viable to be implemented in PBSs. Based on the obtained results, the following conclusions can be drawn:

- The addition of an organic WMA additive and RAP increased asphalt mixture stiffness and decreased relaxation capability. In addition, they seemed to worsen fracture properties of asphalt mixtures at both intermediate and low temperatures.
- Based on the DTCF test results, a poor correlation was found between all four fatigue parameters which can be attributed to the fact that performance of mixtures with respect to fatigue cracking cannot be assessed solely based on laboratory measurements and combination of the mixtures lab measured properties with the pavement structure, environmental condition, and traffic data is crucial to investigate the fatigue performance.
- The contradictory results of performance-based laboratory tests and pavement performance simulation show the FAA current asphalt pavement thickness design procedure lacks a usable model of fatigue cracking in its standard design program (FAARFIELD). The major flaw in fatigue modeling of FAARFIELD is that it does not take into account many significant factors (such as mix properties) in the design process, and it might lead to unrealistic pavement structural design. Therefore, a performance-based specification needs to be developed based on the nonlinear viscoelastic properties of asphalt mixtures along with other effective factors such as aging to capture the proper fatigue performance limit in the airfield pavement design model.
- The results of the simulation with the FlexPAVE^{TM} showed that fatigue failure in pavements could happen due to both top-down and bottom-up cracking. A reasonable correlation was found between total damage in the pavement and top-down cracking damage. While the results of bottom-up cracking are relatively comparable.
- Based on the results of statistical analysis C^{s}_{Nf} and FI cracking performance indices showed the most similar ranking sequence and a moderate negative relationship with the predicted damage of FlexPAVE^{TM} and FAARFIELD, respectively. On the other hand, S_{app} was found to have the highest percent discrepancy and a strong negative relationship with FI values.

It should be emphasized again; all the conclusions presented here were made based on the simulation and prediction of unaged asphalt mixtures.The availability of field performance data will enable researchers to validate their findings. Future work will focus on investigating asphalt mixtures performance with respect to fatigue cracking at several aging levels. Performance-based laboratory tests, along with advance performance simulation programs such as FlexPAVE^{TM}, will be utilized to predict mixture performance with consideration of aging. A comparison will be made between the mixture predicted performance and accelerated pavement test data (pavement performance under APT) to determine the accuracy of the prediction.

Acknowledgement

This research was supported by the airport cooperative research program graduate research award (ACRP-GRA). The authors would like to sincerely thank the FAA's NAPMRC for providing materials for this study. Besides, the authors would also like to gratefully acknowledge the ACRP-GRA panel members for their invaluable guidance and feedback.

Author Contribution Statement

The authors confirm contribution to the paper as follows: study conception and design: D. Mirzaiyanrajeh, E.V. Dave, J.E. Sias and N. Garg; data collection and analysis: D. Mirzaiyanrajeh; initial manuscript draft preparation: D. Mirzaiyanrajeh; all authors contributed to interpretation of results, review and editing of manuscript.

Conflict of Interest Statement

There is no conflict of interest.

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