

PHYSICAL AND MECHANICAL BEHAVIOR OF TIRE DERIVED GEOMATERIALS AND THEIR MODELING USING ARTIFICIAL INTELLIGENCE

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**Physical and Mechanical Behavior of Tire Derived
Geomaterials and Their Modeling Using
Artificial Intelligence**

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August, 2018

**Physical and Mechanical Behavior of Tire Derived
Geomaterials and Their Modeling Using
Artificial Intelligence**



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In Partial Fulfillment of the Requirements
For the Degree Of
Doctor of Engineering

By

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August, 2018

DEDICATION

TO MY MOTHER, MOONES

Who has shared in all my happiness and sorrows, failures and achievements; and whose love, unbiased support and devotion have been the strength of my endeavor.

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CERTIFICATE

The undersigned hereby certify that they have read and recommended to the Graduate School of Engineering for the acceptance of this thesis entitled, “*Physical and Mechanical Behavior of Tire Derived Geomaterials and Their Modeling Using Artificial Intelligence*” by **Siavash Manafi Khajeh Pasha** in partial fulfillment of the requirements for the degree of **Doctor of Engineering**.

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ABSTRACT

The use of scrap tire derived materials (STDM) such as tire chips, shreds and powders has rapidly been adopted in civil engineering applications, with the objective of preserving our ecosystem and reducing construction costs. Considerable research has been devoted to explore the behaviour of sand-STDM as a conventional tire derived geomaterials in geotechnical applications such as lightweight fills for embankments, backfills and liquefaction protection layers for residential houses. However, high compressibility and low stiffness of mixture may lead to differential settlements and inadequate bearing capacity. This may undermine the serviceability of geo-structures built on these materials and increase construction and maintenance costs. Gravel has low compressibility, high permeability (same as STDM) and stiffness and can be considered as a suitable alternative material for sand in soil-STDM mixture. However, so far, no study has been conducted to investigate the physical and mechanical behaviour of gravel-STDM mixture as a new tire derived geomaterials. Modelling soil behaviour plays a key role in successful numerical simulation of the behaviour of geotechnical structures. Existing conventional material models are in capable of capturing the stress-strain behaviour of the tire derived geomaterials. Therefore, there is a need for developing a new suitable material model that is capable of modelling complex behaviour of tire derived geomaterials.

The purpose of this study is to (1) identify important parameters affecting physical and mechanical behaviour of gravel-tire chips mixture (GTCM) using experimental

programs, (2) evaluate the effectiveness of GTCM in mitigating the earthquake induced liquefaction, (3) develop a constitutive material model for the reinforced soil using Artificial Intelligence (AI) .

In experimental approach, a series of consolidated drained (CD) and consolidated undrained triaxial compression tests were conducted on gravel-tire chips mixture to evaluate the effect of different parameters such as tire chips size and mixing percentage of gravel-tire chips on physical properties, stress-strain, shear strength, and dilatancy behaviour of GTCM. In addition, the evolution of dynamic characteristics and liquefaction potential were assessed by performing a series of CU cyclic triaxial tests on GTCM.

In numerical approach, an artificial neural network (ANN) model was developed to simulate packing density of GTCM. Furthermore, support vector machine (SVM) and ANN machine learning techniques were employed to predict dynamic characteristics of GTCM using database obtained from experimental analysis. In this thesis, a new ANN based constitutive material model was also introduced to capture complex stress-strain behaviour of GTCM using laboratory test results. The model then is validated against independent data base and used to generalize stress strain behaviour of GTCM.

This dissertation comprises 8 chapters. The contents of each chapter are as follows:

Chapter 1 describes the research background and motivation. It highlights the environmental issues associated with scrap tires disposal. It discusses the existing challenges related to utilization of preceding reinforcing techniques such as sand-STDMS and sheds light on the importance of introducing alternative materials such as GTCM. In addition, it discusses drawbacks of existing material models for reinforced

soil with STDMS and importance of developing new material model for these mixtures.

The objective and originality of this research were also presented in the chapter.

Chapter 2 presents physical and chemical properties of materials used in this research.

A series of maximum and minimum void ratio tests were conducted and a new empirical expression was introduced to determine the void ratio characteristics of binary mixture of GTCM in terms of particle size ratio and volumetric fraction of gravel (GF). Chemical composition of gravels was also examined using x-ray fluorescence spectrometer test.

Chapter 3 provides past research works on static behaviour of soil-STDMS and examines mechanical behaviour of GTCM using consolidated drained and undrained triaxial compression tests. The effects of volumetric fraction of gravel, particle size ratio of tire chips to gravel, relative density, and confining pressure on stress-strain and dilatancy behaviour of GTCM were investigated. A new formula was proposed to estimate initial tangent modulus and dilatancy of GTCM. It was found that the parameters such as GF, particle size ratio of tire chips to gravel, and confining pressure have significant impact on shear strength and dilatancy of GTCM.

Chapter 4 provides a summary of the past research works related to the dynamic behaviour of soil-STDMS mixture and examines the liquefaction resistance and dynamic characteristics of GTCM determined by laboratory cyclic triaxial testing. It was observed that shear modulus and liquefaction resistance are significantly influenced by the confining pressure and volumetric fraction of gravel in mixture.

Chapter 5 discusses issues associated with the mathematical modelling of void ratio characteristics of binary mixture comprises of stiff gravel and soft tire chips particles.

A new model using ANN is developed to estimate maximum and minimum void ratio of GTCM. The results provided the evidence of ANN based model's capability to capture and generalize complex void ratio characteristics of GTCM. Furthermore, proposed model yielded better performance over the conventional mathematical models for estimating void ratio of binary mixture.

Chapter 6 discusses the limitation of current models for predicting dynamic properties of reinforced soil with STDMS. It proposes novel models for estimating dynamic characteristics of GTCM using ANN and SVM techniques. The models then are validated against independent testing datasets. It was observed that ANN based model yields better performance on generalization of dynamic properties of GTCM in comparison to that of SVM.

Chapter 7 presents a new ANN based approach for constitutive modelling of Geomaterials. The model was trained, validated and tested using database obtained from CD triaxial tests on GTCM specimens. Comparison between ANN based material model prediction, plasticity soil model and the independent experimental data revealed the exceptional capabilities of the proposed methodology in mapping the very complicated behaviour of reinforced soil.

Chapter 8 concludes the results and achievements of the research and presents recommendation for the future studies.

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TABLE OF CONTENTS

	ABSTRACT	i
	ACKNOWLEDGMENT	v
	TABLE OF CONTENT	ix
	LIST OF FIGURES	xv
	LIST OF TABLES	xxiii
	NOMENCLATURE AND ABBREVIATIONS	xxv
1	CHAPTER 1 Introduction	1
	1.1 Background of the study	1
	1.1.1 Waste tire generation and environmental impacts	1
	1.1.2 Application of scrap tire in civil engineering	2
	1.1.3 Ground improvement using sand-STDMS mixture	5
	1.1.4 Gravel-tire chips mixture technique as novel ground improvement approach.....	7
	1.1.5 Material models for reinforced soil with STDMS.....	8
	1.2 Objectives of study.....	9
	1.3 Original contributions to the knowledge.....	9
	1.4 Thesis organization	11
	References.....	13
	CHAPTER 2 Physical Properties of Gravel Tire Chips Mixture	18

2.1 Introduction	18
2.2 Grain size distribution and material classifications.....	19
2.2.1 Gravel	19
2.2.2 Tire chips.....	21
2.3 Weight volume relationships for Gravel Tire Chips Mixture	23
2.4 Specific gravity.....	25
2.5 Void ratio of granular mixture	25
2.6 Chemical composition of gravel using X-Ray Fluorescence Spectrometer	31
2.7 Summary and Conclusion	34
References.....	35

CHAPTER 3 Mechanical behaviour of gravel-tire chips mixture using static triaxial

compression tests.....	38
3.1 Introduction	38
3.2 Apparatus, equipment and layout of experiments for monotonic triaxial testing	39
3.2.1 Selection of parameters and layout of experimental tests.....	39
3.2.2 Triaxial testing apparatus	40
3.2.3 Specimen preparation.....	41
3.3 Results and Discussion.....	45
3.3.1 Shear strength and deformation characteristics of GTCM.....	45
3.3.1.1 Effect of fraction of gravel in GTCM (GF).....	45
3.3.1.2 Effect of confining pressure.....	49
3.3.1.3 Effect of relative density.....	56

3.3.1.4 Effect of tire chips- gravel particle size ratio (D_R/D_G).....	59
3.3.1.5 Effect of drainage boundary condition.....	62
3.3.2 Tangent modulus.....	65
3.3.3 Mohr strength criterion of GTCM	68
3.3.4 Stress-dilatancy.....	70
3.4 Conclusion and summary.....	73
References.....	76
CHAPTER 4 Dynamic characteristics and liquefaction resistance of gravel tire chips mixture	78
4.1 Introduction.....	78
4.2 Apparatus, Equipment and Layout of Experiments for Cyclic Triaxial Testing.....	80
4.2.1 Selection of parameters and layout of experimental tests	80
4.2.2 Cyclic Triaxial testing apparatus	81
4.2.3 Specimen preparation	83
4.2.4 Mathematic formulae for the analysis of undrained cyclic triaxial tests	85
4.3 Results and discussion	86
4.3.1 Stress paths	86
4.3.1.1 Effect of gravel fraction.....	86
4.3.1.2 Effect of confining pressure.....	87
4.3.2 Liquefaction resistance of GTCM	92
4.3.2.1 Effect of gravel fraction.....	92

4.3.2.2 Effect of the confining pressure (σ'_3).....	94
4.3.3 Shear modulus and damping ratio of GTCM.....	97
4.3.3.1 Effect of gravel fraction.....	97
4.3.3.2 Effect of the confining pressure.....	100
4.4 Summary and conclusion	101
References.....	102

CHAPTER 5 Modelling Packing Density of Granular Mixtures: An Artificial

Intelligence Approach.....	105
5.1 Introduction	105
5.2 Material properties and testing programs	107
5.3 Results and discussion.....	108
5.4 Artificial intelligence	110
5.5 Artificial Neural Network model.....	112
5.5.1 Outline of Artificial Neural Network (ANN).....	112
5.5.1.1 Artificial neural network topology.....	114
5.5.1.2 Types of learning.....	116
5.5.1.3 Feedforward Neural Network with back propagation algorithm.....	117
5.5.2 Artificial Neural Network model for packing density of granular mixture with tire chips	119
5.5.3 Assessing performance of model over training, validation and testing data sets	122
5.6 Summary and Conclusion	126

References.....	127
CHAPTER 6 Estimating Dynamic Properties of Granular Mixtures with Tire Chips	
Using Artificial Intelligence.....	130
6.1 Introduction.....	130
6.2 Artificial intelligence model.....	133
6.2.1 Support Vector Machines.....	133
6.2.1.1 Application of SVMs in civil and geotechnical engineering.....	134
6.2.1.2 Basics of Statistical Learning Theory.....	136
6.2.1.2.1 Classification Problem.....	136
6.2.1.2.2 Empirical risk minimization.....	136
6.2.1.2.3 Structural Risk Minimization.....	137
6.2.1.2.4 VC dimension.....	138
6.2.1.2.5 Linear Classification.....	139
6.2.1.2.6 Maximizing Margin between the classes.....	140
6.2.1.2.7 Lagrangian formulation.....	141
6.2.1.3 Nonlinear classification.....	142
6.2.2 Support Vector Regression (SVR)	143
6.2.2.1 SVR model development and database preparation.....	145
6.2.2.2 Results of SVR model and discussion.....	146
6.2.3 Artificial Neural Network model	150
6.2.3.1 ANN model development and database preparation.....	151
6.3 Summary and Conclusion	157
References.....	158

CHAPTER 7 Modelling stress-strain behaviour of granular mixture with STDMS.

.....	162
7.1 Introduction	162
7.2 Artificial intelligence based material modelling	165
7.3 Developing ANN based material model for granular material mixed with STDM.....	166
7.3.1 Database for developing ANN model	166
7.3.2 ANN modelling procedure	166
7.3.3 Performance of neural network.....	171
7.3.4 ANN models simulations ad predictions.....	175
7.4 Parametric analysis.....	183
7.5 Relative importance of the input parameters.....	185
7.6 Summary and conclusions.....	186
References.....	188
CHAPTER8 Conclusions and future work.....	191
8.1 Conclusions.....	191
8.2 Future work.....	195

LIST OF FIGURES:

Figure 1.1 Scrap tires recycling status in japan from 2009 to 2016.....	2
Figure 1.2 Types of STDMS: (a) granular rubbers (b) tire chips (c) tire shreds (Hazarika 2012).....	3
Figure 1.3 Application of STDMS in civil and geotechnical engineering: (a) backfill for retaining wall (b) slope stabilization (c) lightweight fill for embankment (d) Landfill leachate system (CODRR 2018).....	4
Figure 1.4. Flow chart this thesis.....	17
Figure 2.1 Particle size distribution of gravel materials	20
Figure 2.2 Gravel samples: (a) G1 (b) G2	20
Figure 2.3 Particle size distribution of tire chips materials.....	21
Figure 2.4 Tire chips samples: (a) TCH1 (b) TCH2 (c) TCH3	22
Figure 2.5 Variation of specific gravity of GTCM $G_{s,GTCM(x_0)}$, $(D_{50,R}/D_{50,G}) \approx 1.2$	26
Figure 2.6 (a) Schematic view of vibratory test apparatus (source: JGS-0162) (b) Sample of GTCM after conducting maximum void ratio	26
Figure 2.7 Void ratio of GTCM: a) $D_{50,Large}/D_{50,Small} \gg 1.2$ or $\ll 1.2$ b) $D_{50,Large}/D_{50,Small} \approx 1.2$	28
Figure 2.8 (a) Schematic diagram of the XRF and its components (Young et al. 1983) (b) Energy dispersive XRF spectrometer at the center of advanced instrumental analysis of Kyushu University	31

Figure 3.1 Schematic view of triaxial apparatus	41
Figure 3.2 Split mold and rubber membrane: (a) Front view (b) upper view	43
Figure 3.3 Checking the degree of saturation (B-value)	44
Figure 3.4 Effect of fraction of gravel on a) Deviatoric stress-axial strain b) Volumetric strain-axial strain behaviour of GTCM.....	47
Figure 3.5 Effect of tire chips particle size on a) Deviatoric stress-axial strain b) Volumetric strain-axial strain behaviour of GTCM	48
Figure 3.6 Effect of confining pressure on a) Deviatoric stress-axial strain b) Volumetric strain-axial strain behaviour of GTCM with $G_f=100\%$ and $D_r=50\%$	50
Figure 3.7 Definition of particle breakage based on the Hardin method (1985).	51
Figure 3.8 Particle size distribution curves before and after the triaxial test (a) G1 (b) G2	52
Figure 3.9 Influence of confining pressure on a) deviatoric stress-axial strain b) Volumetric strain-axial strain behaviour of GTCM with $G_f=0\%$ (TC1) and $D_r=50\%$	53
Figure 3.10 Influence of confining pressure on a) deviatoric stress-axial strain b) Volumetric strain-axial strain behaviour of GTCM with $G_f=88\%$ (TC1) and $D_r=50\%$	54
Figure 3.11 Influence of confining pressure on a) Deviatoric stress-axial strain b) Volumetric strain-axial strain behaviour of GTCM with $G_f=55\%$ (TC1) and relative density $D_r=50\%$	55

Figure 3.12 Influence of relative density on a) Deviatoric stress-axial strain b) Volumetric strain-axial strain behaviour of GTCM with $G_f=100\%$ ($D_R/D_G \approx 1.2$) and effective confining pressure of ($\sigma_3 = 100\text{kN/m}^2$).....	57
Figure 3.13 Influence of relative density on a) Deviatoric stress-axial strain b) Volumetric strain-axial strain behaviour of GTCM with $G_f=55\%$ ($D_R/D_G \approx 1.2$) and effective confining pressure of ($\sigma_3 = 100\text{kPa}$)	58
Figure 3.14 Influence of relative density on a) Deviatoric stress-axial strain b) Volumetric strain-axial strain behaviour of GTCM with $G_f=55\%$ ($D_R/D_G \approx 1.2$) and effective confining pressure of ($\sigma_3 = 100\text{kPa}$)	59
Figure 3.15 Influence of tire chips-gravel particle size ratio on a) Deviatoric stress-axial strain b) Volumetric strain-axial strain behaviour of GTCM with different G_f at effective confining pressure of $\sigma_3 = 100\text{ kN/m}^2$ and $D_r=50\%$	61
Figure 3.16 The effect of tire chips- gravel particle size ratio on normalized shear strength $\tau_f(G_f = X\%)/\tau_f(G_f = 100\%)$ of GTCM with different G_f at effective confining pressure of $\sigma_3 = 100\text{ kN/m}^2$ and $D_r=50\%$	62
Figure 3.17 The effect of drainage condition on a) deviatoric stress-axial strain b) Volumetric strain and pore water pressure-axial strain behaviour of GTCM with $G_f=100\%$ and effective confining pressure of	

($\sigma_3 = 100\text{kPa}$).....	63
Figure 3.18 The effect of drainage condition on a) Deviatoric stress-axial strain b) Volumetric strain and water pore pressure axial strain behaviour of GTCM with $G_f=88\%$ and $G_f=55\%$ ($R \approx 1.2$) and effective confining pressure of ($\sigma_3 = 100\text{kPa}$).....	64
Figure 3.19 Variation of initial tangent modulus versus G_f (%) in the GTCM with $D_{50,r}/D_{50,G}=1$ at $\sigma_{3c} = 100 \text{ kPa}$ and $D_r = 50\%$	67
Figure 3.20 Variation of initial tangent modulus versus confining pressure (σ_{3c}) in the GTCM with $D_{50,r}/D_{50,G}=1$ at $\sigma_{3c} = 100 \text{ kPa}$ and $D_r = 50\%$	67
Figure 3.21 The Mohr's stress circles and failure envelope of GTCM with $D_{50,r}/D_{50,G}=1$ and $D_r = 50\%$ (a) $G_f=100\%$ (b) $G_f=55\%$	69
Figure 3.22 Evolution of shear strength parameters of GTCM with gravel fraction, $D_{50,r}/D_{50,G} \approx 1.2$ and $D_r = 50\%$	70
Figure 3.23 Stress-Dilatancy of the gravel at different relative density and confining pressure: (a) G1 (b) G2	72
Figure 3.24 Stress-Dilatancy of the G1TCH1 mixture with different G_f at $D_r = 50\%$ and $\sigma_3 = 100 \text{ kN/m}^2$	72
Figure 3.25 The relationship between the stress ratio and minimum dilatancy: (a) G1TCH1 (b)G2TCH2 and G2TCH3	73
Figure 4.1 Schematic view of triaxial apparatus	82
Figure 4.2 Cyclic stress paths of GTCM at $\text{CSR} = 0.3$ and $D_r =$ 50% and $\sigma_3 = 100\text{kN/m}^2$: (a) $G_f = 100\%$; (b) $G_f = 87\%$..	88

Figure 4.3 Cyclic stress paths of GTCM at $CSR = 0.3$ and $Dr=50\%$ and $\sigma_3 = 100\text{kN/m}^2$: (a) $GF=44\%$; (b) $GF=33\%$	89
Figure 4.4 Cyclic stress paths of GTCM with $GF=100\%$ at $Dr=50\%$ and $CSR = 0.35$: (a) $\sigma_3 = 50 \text{ kN/m}^2$; (b) $\sigma_3 = 100 \text{ kN/m}^2$	90
Figure 4.5 Cyclic stress paths of GTCM with $GF=100\%$ at $Dr=50\%$ and $CSR = 0.35$: (a) $\sigma_3 = 50 \text{ kN/m}^2$; (b) $\sigma_3 = 100 \text{ kN/m}^2$	91
Figure 4.6 The effect of gravel fraction on the evolution of excess pore water ratio of GTCM with different GF at $Dr=50\%$, $CSR=0.3$, $\sigma_3 = 100 \text{ kN/m}^2$: (a) $GF=87\%$; (b) $GF=44\%$ (c) $GF=30\%$	93
Figure 4.7 Number of cycles to liquefaction versus the CSR at various $GF(\%)$..	94
Figure 4.8 The effect of effective confining pressure on the evolution of excess pore water ratio of GTCM versus number of cycles at $GF=30\%$, $Dr=50\%$ and $\sigma_d/2\sigma_{3c} = 0.35$: (a) $\sigma_3 = 50 \text{ kN/m}^2$; (b) $\sigma_3 = 100\text{kN/m}^2$	95
Figure 4.9 Number of cycles to liquefaction versus the CSR at various effective confining pressures (σ_3).....	96
Figure 4.10 Definition of cyclic shear modulus and damping ratio.....	98
Figure 4.11 The evolution of shear modulus versus number of cycles for GTCM at different gravel fractions (GF) : (a) $30\%\leq GF\leq 100\%$ (b) $30\%\leq GF\leq 44\%$	99
Figure 4.12 Effect of gravel fraction on damping ratio of GTCM	100
Figure 4.13 The effect of confining pressure on shear modulus of GTCM with $GF=100\%$ and $GF=30\%$ at $CSR=0.4$	101

Figure 5.1	Schematic diagram of theoretical variation of minimum void ratio in binary mixture with percentage of fine particles in mixture....	108
Figure 5.2	Minimum void ratio of GTCM with $D_{50,R}/D_{50,G}=0.35$	109
Figure 5.3	Neuron in human nervous system and its connection (wikispace.com)	112
Figure 5.4	McCulloch and Pitts' ANN model	113
Figure 5.5	Activation functions: (a) sigmoid (b) hyperbolic tangent (c) arctangent (d) linear function (e) step function (f) Gaussian radial function.....	114
Figure 5.6	Architecture of a neural network.....	115
Figure 5.7	Topology of neural networks: (a) Feedforward (b) Recurrent	116
Figure 5.8	Backpropagation neural network	117
Figure 5.9	Architecture of proposed ANN model	120
Figure 5.10	Comparison of ANN simulation with experimental data: (a) $D_{50,R}/D_{50,G} = 1.2$; (b) $D_{50,R}/D_{50,G} = 0.35$	124
Figure 5.11	Performance of the ANN Model over: (a) Training; (b) Validation (c) Testing datasets.....	125
Figure 5.12	Comparison of ANN simulation with experimental data for GTCM with $D_{50,R}/D_{50,G} = 3.35$	125
Figure 6.1	Correlation between empirical risk, expected risk, VC dimension (Ech-Cherif et al. 2002).....	138
Figure 6.2	Example of binary classification.....	139
Figure 6.3	Optimal plane that maximizes the margin ϕ	140
Figure 6.4	Nonlinear mapping of linearly inseparable data into higher	

dimensional space to make them linearly separable	142
Figure 6.5 Linear SVM regression.....	144
Figure 6.6 Comparison between observed and predicted values of shear modulus for training data sets using SVR: (a) GF=55%, $(\sigma_d/2\sigma_3)=0.25$; (b) GF=44%, $(\sigma_d/2\sigma_3)=0.3$	148
Figure 6.7 Comparison between observed and predicted values for new testing data sets using SVM at GF=87%, $(\sigma_d/2\sigma_3)=0.25$: (a) Shear modulus (b) Damping ratio.....	149
Figure 6.8 Architecture of ANN model.....	152
Figure 6.9 Performance of the ANN Model over: (a) Training; (b) Validation (c) Test datasets	154
Figure 6.10 Comparison between observed and predicted values of the shear modulus for independent testing dataset using ANN at GF=87%, $(\sigma_d/2\sigma_3)=0.25$ (b) Performance of the ANN Model over independent testing dataset	156
Figure 7.1 Architecture of neural network (a) ANN-q (b) ANN- εv	172
Figure 7.2 Performance of the proposed ANN models during training (a) ANN-q (b) ANN- εv	173
Figure 7.3 Performance of the ANN-q Model over: (a) Training; (b) Validation (c) Testing datasets	174
Figure 7.4 Performance of the ANN- εv Model over: (a) Training; (b) Validation (c) Testing datasets	175

Figure 7.5 Comparison between experimental data and simulation of the (a) ANN-q and (b) ANN- ϵ_v for G2TCH3 specimens at $D_r=50\%$ and $\dot{\sigma}_{3c}=100 \text{ kN/m}^2$	176
Figure 7.6 Hyperbolic stress-strain relationship for standard drained triaxial test (Schanz 1999).....	178
Figure 7.7 The ANN and HS models results for simulation of (a) deviatoric stress- axial strain (b) volumetric strain-axial strain behavior of G1TCH1 with GF=55% at $D_r=50\%$ and $\dot{\sigma}_{3c}=100 \text{ kN/m}^2$	180
Figure 7.8 The ANN and HS models results for simulation of (a) deviatoric stress- axial strain (b) volumetric strain-axial strain behavior of G2TCH3 with GF=40% at $D_r=50\%$ and $\dot{\sigma}_{3c}=100 \text{ kN/m}^2$	181
Figure 7.9 Performance of ANN-q over training dataset (a) GF=55% (b) GF=40%.....	182
Figure 7.10 Performance of ANN- ϵ_v over training dataset (a) GF=55% (b) GF=40%.....	182
Figure 7.11 The effect of GF in G1TCH1 using (a) ANN-q and (b) ANN- ϵ_v model.....	184
Figure 1.1 Procedure for identifying relative importance of input variables..	186

LIST OF TABLES

Table 2.1 Different combination of gravel and tire chips in GTCM.....	24
Table 2.2 Calibrated parameters of max and min void ratio of GTCM	30
Table 2.3 Chemical composition of materials G1 and G2	33
Table 2.4 Weathering indices evaluated in this study	34
Table 3.1 GTCM specimens testing conditions and list of parameters.....	40
Table 3.2 Calibration parameters and constants for initial tangent modulus of GTCM	66
Table 4.1 GTCM specimens testing conditions and list of parameters.....	81
Table 6.1 Optimal values of penalty parameter, loss function, and kernel parameter for SVR model development.....	146
Table 6.2 Statistical performance of all models over the training data sets.....	147
Table 6.3 Statistical Performance of all models over the independent testing data sets	150
Table 7.1 Summary of triaxial tests used for training the ANN model.....	167
Table 7.2 Feature of training database for ANN model	170
Table 7.3 Hardening soil model parameters for GTCM specimens.....	178
Table 1.1 Relative importance of input variables on the output of (ANN-q)....	186

NOMENCLATURE

Basic SI units are given in parentheses.

$D_{50,R}$	Mean grain size of rubber particles (mm)
$D_{50,G}$	Mean grain size of gravel particles (mm)
D_r	Relative density of gravel, GTCM (mm)
V_{Gravel}	Volume of Gravel in mixture (m ³)
V_T	Total Volume of gravel-tire chips particles in mixture (m ³)
σ'_{3c}	Effective Confining pressure (KN/m ²)
D	Dilatancy rate
D_s	Diameters of sand particles (mm)
D_t	Diameters of STDN particles (mm)
D_{tr}	Diameter of sample in triaxial test (mm)
$D_{50,G1}$	Mean grain size of gravel, G1 (mm)
$D_{50,G2}$	Mean grain size of gravel, G2 (mm)
U_c	Coefficient of uniformity (Dimensionless)
G_s	Specific gravity of soil (Dimensionless)
$D_{50,Large}$	Mean grain size of geomaterial with large particles (mm)
$D_{50,Small}$	Mean grain size of geomaterial with small particles (mm)
$D_{50,S}$	Mean grain size of soil (mm)
$\chi_0, \chi_1, \chi_2, \chi_3, \chi_4, \chi_5, \chi_6$	Calibration parameters for $e_{max,GTCM}$

$\theta_0, \theta_1, \theta_2$	and $e_{min,GTCM}$ (Dimensionless) Calibration parameters for $e_{max,GTCM}$ and $e_{min,GTCM}$ (Dimensionless)
Δu	Pore water pressure (kN/m ²)
$\Delta \sigma_3$	Increment of effective confining pressure (kN/m ²)
D_r	Relative density of gravel tire chips mixture (Dimensionless)
B_r	Relative breakage ratio (Dimensionless)
B_t	Total breakage (Dimensionless)
B_p	Breakage potential (Dimensionless)
X	Percentage of gravel fraction in mixture (%)
K_i	Modulus number for tangent modulus (Dimensionless)
K_0	Modulus number for tangent modulus at GF=0% (Dimensionless)
P_a	Atmospheric pressure (kN/m ²)
n	Exponent number (Dimensionless)
$K_{i,GTCM}$	Modified modulus number for tangent modulus (Dimensionless)
C_d	Shear envelope apparent cohesion (kN/m ²)
ϕ_p	Shear envelope friction angle (Degree)
τ_f	Shear strength of gravel tire chips mixture at failure (kN/m ²)
e_{GTCM}	Void ratio of GTCM at relative density of D_r (Dimensionless)
$e_{max,GTCM}$	Maximum void ratio of GTCM at given GF (Dimensionless)
$e_{min,GTCM}$	Minimum void ratio of GTCM at given

q	GF (Dimensionless)
ϵ_a	Deviatoric stress (kN/m ²)
B	Axial strain (%)
ϵ_v	Skempton's B value (Dimensionless)
	Volumetric strain (%)

ABBREVIATIONS

GTCM	Gravel Tire Chips Mixture
GF	Gravel Fraction
STDm	Scrap Tire Derived Materials
G1	Gravel Type 1
G2	Gravel Type2
TCH1	Tire Chips Type1
TCH2	Tire Chips Type2
TCH3	Tire Chips Type3
CD Triaxial	Consolidated Drained Triaxial Compression Test
CU Triaxial	Consolidated Undrained Triaxial Compression Test
SSA	specific surface area
JATMA	Japan Automobile Tyre Manufacturers Association
SP	Poorly graded sand
AR	Aspect ratio of Tire derived materials
TCR	Tire crumbs
SW	Well graded sand
RD	Relative density
CE	Compaction effort
SS	Size of STDm
TO	Tire chips orientation
TT	Tire chips type

CHAPTER 1

INTRODUCTION

1.1 BACKGROUND OF THE STUDY

1.1.1 WASTE TIRE GENERATION AND ENVIRONMENTAL IMPACTS

Tires are removed from service and disposed as scrap tires when they are no longer suitable for use on the vehicles. Tires are considered as highly durable and non-degradable materials. Scrap tires in large quantity and volumes may consume a large space when they are disposed in open landfills. Furthermore, disposal of the scrap tires in landfills may pose serious threat to ecosystems by providing a suitable breeding habitat for flies and other insidious creatures and increasing the risk of fire. Japan currently have strict law and regulation which deal with scrap tires and bans them from disposing in landfills. Therefore, recycling of scrap tires considered to be ultimate solution to reduce the amount of tires stockpiled in landfills and help save our ecosystem. In 2016, 997000 tonnes in weight scrap tires were generated in Japan which was 0.3% less than the previous year. Fig. 1.1 shows the status on scrap tires recycling in Japan from 2009 to 2016. In 2016, more than 69% of these scrap tires were used as a fuel source for energy production in concrete and paper manufacturing companies and less than 17% were reused for the production of industrial and engineering

applications. However, thermal recycling of scrap tires can increase emission of CO₂ to the atmosphere which can cause global warming. Therefore, reusing of scrap tires is considered to be preferred option to prevent environmental issues created by thermal recycling.

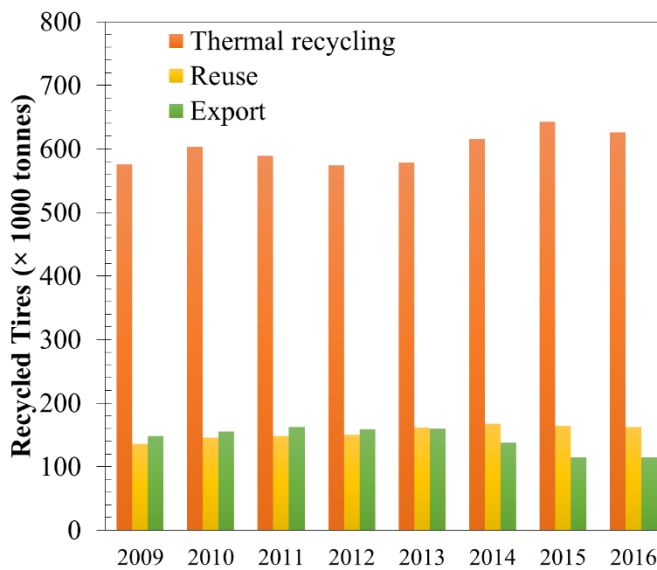


Figure 1.1 Scrap tires recycling status in Japan from 2009 to 2016

1.1.2 APPLICATION OF SCRAP TIRE IN CIVIL ENGINEERING

Scrap tires have unique engineering properties such as: low unit weight, low bulk density, high hydraulic conductivity, and high elastic deformability (Humphrey and Manion 1992; Ahmed 1993; Edil and Bosscher 1994). Therefore, they can be adopted in civil and geotechnical applications as a whole or Scrap Tire Derived Materials (STDMS). STDMS are classified into several categories according to their shape and sizes.

A photograph of different types of STDMs is presented in Fig. 1.2. In general, granulated rubbers particle size range between 0.3mm to 10mm and tire chips 10 mm to 50 mm and tire shreds 50mm to 305 mm. STDMs are also categorized as three dimensional geosynthetic. Because they act in three dimensions when they are used as geosynthetics in civil engineering projects (Hazarika et al. 2010b). Examples of STDMs use in civil engineering applications are shown in Fig. 1.3 and include: retaining wall and bridge abutment backfills (Reid et al. 1998), fills for lightweight embankment and caissons (Humphrey and Manion 1992; Masad et al. 1996; Lee et al. 1999; Garga and O'Shaughnessy 2000; Hazarika et al. 2008), landfill liners (Kaushik et al. 2015; Kaushik et al. 2017) and slope stabilization (Poh and Broms 1995). However pure STDMs are highly compressible and may undermine long term serviceability and performance of heavy geo-structures constructed on this materials (Humphrey and Manion 1992; Edil and Bosscher 1994). Therefore, the use of pure STDMs are limited to light weight and generally non-structural applications.



Figure 1.2 Types of STDMs: (a) granular rubbers (b) tire chips (c) tire shreds
(Hazarika 2012)



Figure 1.3 Application of STDMs in civil and geotechnical engineering: (a) backfill for retaining wall (b) slope stabilization (c) lightweight fill for embankment (d)

Landfill leachate system (CDORR 2018)

In recent years, the use of soil-STDMs mixture has been promoted with the goal of reducing undesirable environmental impact of disposing tires, finding solution for drawbacks of using pure STDMs and improving physical and mechanical behavior of soils. It was reported that using STDMs together with soil can significantly reduce compressibility of STDMs. Clay- STDMs mixture as a stabilizer (Cabalar et al. 2014) and countermeasure for extreme shrinkage and cracks (Soltani Jigheh et al. 2014); and fly ash-STDMS as an soil reinforcement are some of the methods that have been studied thoroughly so far. Recent research has focused on the use of sand and STDMS mixtures.

Sand-STDMS mixtures were found to have interesting engineering properties such as low unit weight, reduced compressibility in comparison to the pure STDMS and better compaction performance (Ahmed 1993). Brief summary of studies on the application and mechanical behavior of sand-STDMS is provided in following section.

1.1.3 GROUND IMPROVEMENT USING SAND-STDMS MIXTURE

The effect of addition of STDMS either in the form of very large size tire shreds or strips (e.g. Edil and Bosscher 1994; Foose et al. 1996; Zornberg et al. 2004; Gotteland et al. 2005; Kaushik et al. 2015; Mashiri et al. 2015; Kaushik et al. 2017) and tire crumbs or chips with relatively small particles (e.g. Ahmed 1993; Masad et al. 1996; Youwai and Bergado 2003; Kawata et al. 2007; Lee et al. 2007; Sheikh et al. 2013; Ehsani et al. 2017) on physical and mechanical behaviour of sand has already been investigated extensively in literature review. Several applications for the use of STDMS in geotechnical engineering has been introduced so far. Lightweight fills for embankments (Yoon et al. 2006) and base isolation for buildings (Tsang 2008) are just examples of using these materials in civil engineering application.

Liquefaction induced damages such as excessive settlements under residential houses, dike collapse and floating of manholes has been widely observed during recent strong earthquakes in Japan such as “The 2011 earthquake off the Pacific coast of Tōhoku”. Utilization of STDMS especially in the form of tire chips was found to be effective novel economic and environmental friendly technique in mitigating liquefaction potential of sandy soil (Uchimura et al. 2007; Hazarika et al. 2010a; Fuchiyama and Konja 2016). The seismic performance of small scale quay wall

backfilled with reinforced materials comprises of sand-tire chips mixture was investigated by (Hazarika et al. 2007). They found out that utilization of sand-tire chips mixture reduces liquefaction susceptibility of backfill. Furthermore, the incremental dynamic earth pressure on soil structure was reduced remarkably. Despite aforementioned advantages of utilization of sand-tire chips mixture in civil engineering application, this technique suffers from many drawbacks.

These materials are highly compressible and have a low elastic modulus which may cause a high differential settlement, and an inadequate bearing capacity of foundation. (Anvari and Shooshpasha 2016) conducted a series of model footing tests on reinforced sand with different sizes of granulated rubber. They found the bearing capacity of reinforced sand with rubber might be less than of that sand especially when rubber inclusion is over 10% in mixture. It has also been reported that using sand as host material may decrease permeability of soil-STDm system (Humphrey et al. 1993) and undermine stability and serviceability of structures constructed on these materials.

Moreover, the availability and cost efficiency need to be taken into account when a host material is selected for the civil engineering projects. In order to avoid segregation of STDm and soil particles with different density, STDms should be cut into smaller pieces when they are mixed with sandy soil. This may increase the implementation costs. Therefore, while recycling scrap tires needs to be encouraged by providing a ground for utilization of STDms as environmentally friendly materials in civil engineering projects on the one hand, a new technique needs to be developed to address drawbacks of existing technique on the other hand.

1.1.4 GRAVEL-TIRE CHIPS MIXTURE TECHNIQUE AS NOVEL GROUND IMPROVEMENT APPROACH

Ground improvement using Gravel-Tire Chips Mixture (GTCM) as a novel approach was introduced with the goal of compensating for the limitations of preceding methods (Niiya et al. 2012; Hazarika and Abdullah 2016). Replacing gravel with sand increases permeability of reinforced mixture (Kaushik et al. 2015). A series of 1g model shaking table tests were conducted by (Chu et al. 2016) to evaluate dynamic performance of an inclusion layer made of GTCM which were placed horizontally under the foundation of residential house model. They found out that when a GTCM reinforced layer with a GF=50% and thickness of 10 cm (2 m in prototype) is placed under the foundation of house model, the rise in the excess pore water pressure could be remarkably restrained. Moreover, earthquake induced settlement of structure was significantly reduced due to the enhanced bearing capacity in comparison to that of unreinforced model.

Numerical analysis on the performance of horizontal reinforcing layer under the shallow foundation of residential houses revealed that the settlement of shallow foundation was reduced with the width ratio of reinforcement layer to foundation. Furthermore, liquefaction susceptibility and liquefaction induced settlements are reduced when a reinforced layer of 2m in thickness with gravel fraction of 50% is placed under the foundation (Hazarika et al. 2018).

GTCM might be a promising replacement for STDm and sand-STDm mixtures. Prior to apply these materials in civil engineering projects, the mechanical behaviour of GTCM should be thoroughly investigated. Until now, the physical and mechanical

properties of GTCM are largely unknown.

1.1.5 MATERIAL MODELS FOR REINFORCED SOIL WITH STDMS

In spite of the fact that many studies have been conducted on the behaviour of reinforced soil with STDMS, very limited mathematical material models have been developed to capture behaviour of reinforced soil. A very first material model for sand-tire chips mixture was developed by (Lee et al. 1999) using the hyperbolic model of (Duncan 1980). All 7 parameters of model were calibrated against experimental data. However, the model was not able to capture the residual strength behaviour, plastic strain and volumetric strain behaviour of reinforced soil. A hypo-plasticity material model, based on the critical state framework was developed for sand-tire chips mixture by (Youwai and Bergado 2003). Their model had difficulties in capturing post peak shear strength and volumetric strains at higher axial strains. Because most of their specimens were experienced critical state even at axial strain level as high as 25%.

Furthermore, model consisted of 10 parameters that need to determine by fitting the experimental data for each mixing ratio under different confining pressures. The large number of parameters involved in developing mathematical material model of reinforced soil on the one hand and unconventional stress-strain behaviour of reinforced soil with STDMS are some of difficulties in developing proper material models for these materials. Therefore, the encouraging efforts for developing material modelling of reinforced soil with STDMS which can address complex behaviour of reinforced soil such as yielding, plastic deformation, softening, volume change is still needed.

1.2 OBJECTIVES OF STUDY

The aim of this research is to increase existing knowledge about the behaviour of Gravel-Tire Chips Mixture (GTCM) as a novel soil improvement technique and promote the use of STDs in civil engineering projects by thoroughly examining physical, static and dynamic behaviour of these mixtures. The main objective of this study are as follows:

- 1) To evaluate the factors affecting physical characteristics of GTCM
- 2) To determine the major factors affecting static behaviour of GTCM and evaluate the influence of those factors on the behaviour zones of GTCM
- 3) To evaluate the influence of different parameters on dynamic characteristics and liquefaction resistance of GTCM
- 4) To model packing density of GTCM using artificial intelligence
- 5) To predict dynamic properties of GTCM using artificial intelligence
- 6) To model stress-strain behaviour of GTCM using artificial intelligence

1.3 ORIGINAL CONTRIBUTIONS TO THE KNOWLEDGE

In the present study, physical, static and dynamic behaviour of gravel-tire chips mixture were thoroughly investigated which were largely unknown until now. Furthermore, an attempt has been made to introduce a novel artificial intelligence based material model as an alternative to conventional mathematical model. Two methods were used to achieve the goal: experimental approach and numerical approach. Some of the findings of this study which are considered to be original

contributions to the knowledge are as follows:

- 1- Void ratio characteristics of binary mixture of gravel and tire chips is presented considering important parameter affecting physical properties of GTCM which was not studied before. Furthermore, a new empirical equation was proposed to predict void ratio characteristics of mixture. (Chapter 2)
- 2- The behaviour zones of GTCM was introduced considering different influential parameters affecting mechanical behaviour of GTCM. (chapter 3)
- 3- A new semi-empirical formula was proposed to predict initial tangent modulus and stress-dilatancy relationship of GTCM, considering most important factor affecting mechanical behaviour of mixture (chapter 3).
- 4- Liquefaction resistance of GTCM were investigated using CU cyclic triaxial for the first time. In addition, dynamic properties of GTCM were investigated at the medium to the large shear strain levels (Chapter 4).
- 5- A new model was proposed to simulate packing density of binary mixture of soft and rigid particles using artificial intelligence approach (Chapter 5).
- 6- A new model was introduced to predict shear modulus and damping ratio of granular mixture with STDm using artificial neural network and support vector machine techniques (Chapter 6).
- 7- A new material model was introduced to simulate stress-strain and volumetric strain behaviour of granular mixture with STDm using artificial neural network (Chapter 7)

1.4 THESIS ORGANIZATION

This dissertation comprises 8 chapters. The contents of each chapter are concisely summarized as follows (Fig. 1.4):

Chapter 1 describes the research background and motivation. It highlights environmental issues associated with scrap tires disposal. It discusses existing challenges related to utilization of preceding reinforcing techniques such as sand-STDMS and sheds light on the importance of introducing alternative materials such. In addition, it discusses drawbacks of existing material models for reinforced soil with STDMS and importance of developing new material model for these mixtures. The objective and originality of research were also presented in the chapter.

Chapter 2 presents physical and chemical properties of materials used in this research. A series of maximum and minimum void ratio tests were conducted and a new empirical expression was introduced to determine the void ratio characteristics of binary mixture of GTCM in terms of particle size ratio and volumetric fraction of gravel (GF). Chemical composition of gravels were also examined using x-ray fluorescence spectrometer test.

Chapter 3 provides past research works on static behaviour of soil-STDMS and examines mechanical behaviour of GTCM using CD and CU compression triaxial tests. The effect of volumetric fraction of gravel, particle size ratio of tire chips to gravel, relative density, and effective confining pressure on stress-strain and dilatancy behaviour of GTCM was investigated. A new formula was proposed to estimate initial tangent modulus and dilatancy of GTCM. It was found that the parameters such as volumetric fraction of gravel, particle size ratio of tire chips to gravel, and effective

confining pressure have significant impact on shear strength and dilatancy behaviour of GTCM.

Chapter 4 provides a summary of past research works related to the dynamic behaviour of soil-STDMS mixture and examines the liquefaction resistance and dynamic characteristics of GTCM determined by laboratory cyclic triaxial testing. It was observed that shear modulus and liquefaction resistance are significantly influenced by the effective confining pressure and volumetric fraction of gravel in mixture.

Chapter 5 discusses issues associated with mathematical modelling of void ratio characteristics of binary mixture comprises of stiff (gravel) and soft (tire chips) particles. A new model using ANN is developed to estimate maximum and minimum void ratio of GTCM. The results provided the evidence of ANN based model capability to capture and generalize complex void ratio characteristics of GTCM. Furthermore, proposed model yielded better performance over the conventional mathematical models for estimating void ratio of binary mixture.

Chapter 6 discusses the limitation of current models for predicting dynamic properties of reinforced soil with STDMS. It proposes novel models for estimating dynamic characteristics of GTCM using ANN and SVM techniques. The models then are validated against “unseen” datasets. It was observed that ANN based model yields better performance on generalization of dynamic properties of GTCM in comparison to that of SVM.

Chapter 7 presents a new ANN based approach for constitutive modelling of reinforced soil with tire chips. The model was trained, validated and tested using

database obtained from CD triaxial tests on GTCM specimens. Comparison between ANN based material model prediction and the experimental data revealed the exceptional capabilities of the proposed methodology in mapping the very complicated behaviour of reinforced soil.

Chapter 8 concludes the results and achievements of the research and presents recommendation for the future studies.

REFERENCES

- Ahmed, I. 1993. Laboratory Study on Properties of Rubber-Soils, *Joint Highway Research Project. Indiana Department of Transportation and Purdue University, West Lafayette, Indiana*.
- Anvari, S. M. & Shooshpasha, I. (2016). Influence of size of granulated rubber on bearing capacity of fine-grained sand. *Arabian Journal of Geosciences*, 9(18): 707.
- Cabalar, A. F., Karabash, Z. & Mustafa, W. S. (2014). Stabilising a clay using tyre buffings and lime. *Road Materials and Pavement Design*, 15(4): 872-891.
- Chu, C., Hazarika, H. & Ishibashi, I. Experimental evaluation of the tire chips and gravel mixed reinforced layer on preventing liquefaction under residential building. *7th Japan-Taiwan Workshop on Geotechnical Hazards from Large Earthquakes and Heavy Rainfall*, Pingtung, Taiwan. 2016, pp. 100-102.
- Duncan, J. (1980). Strength, stress-strain and bulk modulus parameters for finite element analyses of stresses and movements in soil masses. *Report No. UCB/GT/80-01, University of California*.
- Edil, T. & Bosscher, P. (1994). Engineering Properties of Tire Chips and Soil Mixtures. *Geotechnical Testing Journal*, 17(4): 453-464.
- Ehsani, M., Shariatmadaria, N. & Mirhosseini, S. (2017). Experimental study on behavior of soil-waste tire mixtures. *Scientia Iranica. Transaction A, Civil Engineering*, 24(1): 65.
- Foose, G. J., Benson, C. H. & Bosscher, P. J. (1996). Sand Reinforced with Shredded Waste Tires. *Journal of Geotechnical Engineering*, 122(9): 760-767.
- Fuchiyama, M. & Konja, A. (2016). Compression and shear behavior of tire chips and

- prevention effect of liquefaction. *Japanese Geotechnical Society Special Publication*, 2(61): 2086-2089.
- Garga, V. K. & O'Shaughnessy, V. (2000). Tire-reinforced earthfill. Part 1: Construction of a test fill, performance, and retaining wall design. *Canadian Geotechnical Journal*, 37(1): 75-96.
- Gotteland, P., Lambert, S. & Balachowski, L. (2005). Strength characteristics of tyre chips-sand mixtures. *Studia geotechnica et mechanica*, 27(1-2): 55-66.
- Hazarika, H. (2012). Earthquake resistant reinforcement of coastal structure using recycle material from waste tires. *Expected Materials for the Future*, 12(4): 34-41.
- Hazarika, H. & Abdullah, A. (2016). Improvement effects of two and three dimensional geosynthetics used in liquefaction countermeasures. *Japanese Geotechnical Society Special Publication*, 2(68): 2336-2341.
- Hazarika, H., Hyodo, M. & Yasuhara, K. (2010a). Investigation of tire chips-sand mixtures as preventive measure against liquefaction. *Ground Improvement and Geosynthetics*, pp.338-345.
- Hazarika, H., Kohama, E. & Sugano, T. (2008). Underwater Shake Table Tests on Waterfront Structures Protected with Tire Chips Cushion. *Journal of Geotechnical and Geoenvironmental Engineering*, 134(12): 1706-1719.
- Hazarika, H., Yasuhara, K., Kikuchi, Y., Karmokar, A. K. & Mitarai, Y. (2010b). Multifaceted potentials of tire-derived three dimensional geosynthetics in geotechnical applications and their evaluation. *Geotextiles and Geomembranes*, 28(3): 303-315.
- Hazarika, H., Yokota, H., Endo, S. & Kinoshita, T. (2018). Cascaded Recycle of Waste Tires—Some Novel Approaches Toward Sustainable Geo-Construction and Climate Change Adaptation. In: Krishna, A. M., Dey, A. & Sreedeeep, S. (eds.) *Geotechnics for Natural and Engineered Sustainable Technologies: GeoNEst*. Singapore: Springer Singapore.
- Humphrey, D. N. & Manion, W. P. (1992). Properties of tire chips for lightweight fill. Grouting, *Soil Improvement and Geosynthetics*, ASCE, pp. 1344-1355.
- Kaushik, M. K., Kumar, A. & Bansal, A. (2015). Performance Assessment of Gravel–Tire Chips Mixes as Drainage Layer Materials Using Real Active MSW Landfill Leachate. *Geotechnical and Geological Engineering*, 33(4): 1081-1098.
- Kaushik, M. K., Kumar, A. & Bansal, A. (2017). Performance of tire chips–gravel combinations with nonwoven geotextile and encapsulated tire chips layers used as filter/separator under incremental stress levels. *European Journal of Environmental*

and Civil Engineering, 1-34.

- Kawata, S., Hyodo, M., Orense, P., Yamada, S. & Hazarika, H. (2007). Undrained and drained shear behavior of sand and tire chips composite material. Proceedings of the international workshop on scrap tire derived geomaterials—opportunities and challenges, Yokosuka, Japan, pp. 277-283.
- Lee, J.-S., Dodds, J. & Santamarina, J. C. (2007). Behavior of Rigid-Soft Particle Mixtures. *Journal of Materials in Civil Engineering*, 19(2): 179-184.
- Lee, J. H., Salgado, R., Bernal, A. & Lovell, C. W. (1999). Shredded Tires and Rubber-Sand as Lightweight Backfill. *Journal of Geotechnical and Geoenvironmental Engineering*, 125(2): 132-141.
- Masad, E., Taha, R., Ho, C. & Papagiannakis, T. (1996). Engineering Properties of Tire/Soil Mixtures as a Lightweight Fill Material. *Geotechnical Testing Journal*, 19(3): 297-304.
- Mashiri, M. S., Vinod, J. S., Sheikh, M. N. & Tsang, H. H. (2015). Shear strength and dilatancy behaviour of sand-tyre chip mixtures. *Soils and Foundations*, 55(3): 517-528.
- Niiya, F., Hazarika, H., Yasufuku, N. & Ishikura, R. Cyclic frictional behavior of two and three dimensional geosynthetics used in liquefaction countermeasure. the 5th Taiwan-Japan Joint Workshop on Large Earthquakes and Heavy Rainfall, Tainan, Taiwan:CD-ROM., 2012, pp.
- Poh, P. S. H. & Broms, B. B. (1995). Slope Stabilization Using Old Rubber Tires and Geotextiles. *Journal of Performance of Constructed Facilities*, 9(1): 76-79.
- California Department of Resources Recycling and Recovery, Tire derived aggregate uses. 2018. *Tire derived aggregate uses*. Available: <http://www.calrecycle.ca.gov/tires/TDA/Uses/default.htm> [Accessed 2017/06].
- Reid, R. A., Soupir, S. P. & Schaefer, V. R. (1998). Mitigation of void development under bridge approach slabs using rubber tire chips. *Recycled Materials in Geotechnical Applications*. ASCE, pp. 37-50.
- Sheikh, M. N., Mashiri, M. S., Vinod, J. S. & Tsang, H.-H. (2013). Shear and Compressibility Behavior of Sand&Tire Crumb Mixtures. *Journal of Materials in Civil Engineering*, 25(10): 1366-1374.
- Soltani Jigheh, H., Asadzadeh, M. & Marefat, V. (2014). Effects of tire chips on shrinkage and cracking characteristics of cohesive soils. *Turkish Journal of Engineering and Environmental Sciences*, 37(3): 259-271.
- Tsang, H. H. (2008). Seismic isolation by rubber–soil mixtures for developing

- countries. *Earthquake Engineering & Structural Dynamics*, 37(2): 283-303.
- Uchimura, T., Chi, N., Nirmalan, S., Sato, T., Meidani, M. & Towhata, I. (2007). Shaking table tests on effect of tire chips and sand mixture in increasing liquefaction resistance and mitigating uplift of pipe. Proceedings, international workshop on scrap tire derived geomaterials—opportunities and challenges, Yokosuka, Japan, pp. 179-186.
- Yoon, S., Prezzi, M., Siddiki, N. Z. & Kim, B. (2006). Construction of a test embankment using a sand–tire shred mixture as fill material. *Waste Management*, 26(9): 1033-1044.
- Youwai, S. & Bergado, D. T. (2003). Strength and deformation characteristics of shredded rubber tire – sand mixtures. *Canadian Geotechnical Journal*, 40(2): 254-264.
- Zornberg, J. G., Cabral, A. R. & Viratjandr, C. (2004). Behaviour of tire shred – sand mixtures. *Canadian Geotechnical Journal*, 41(2): 227-241.

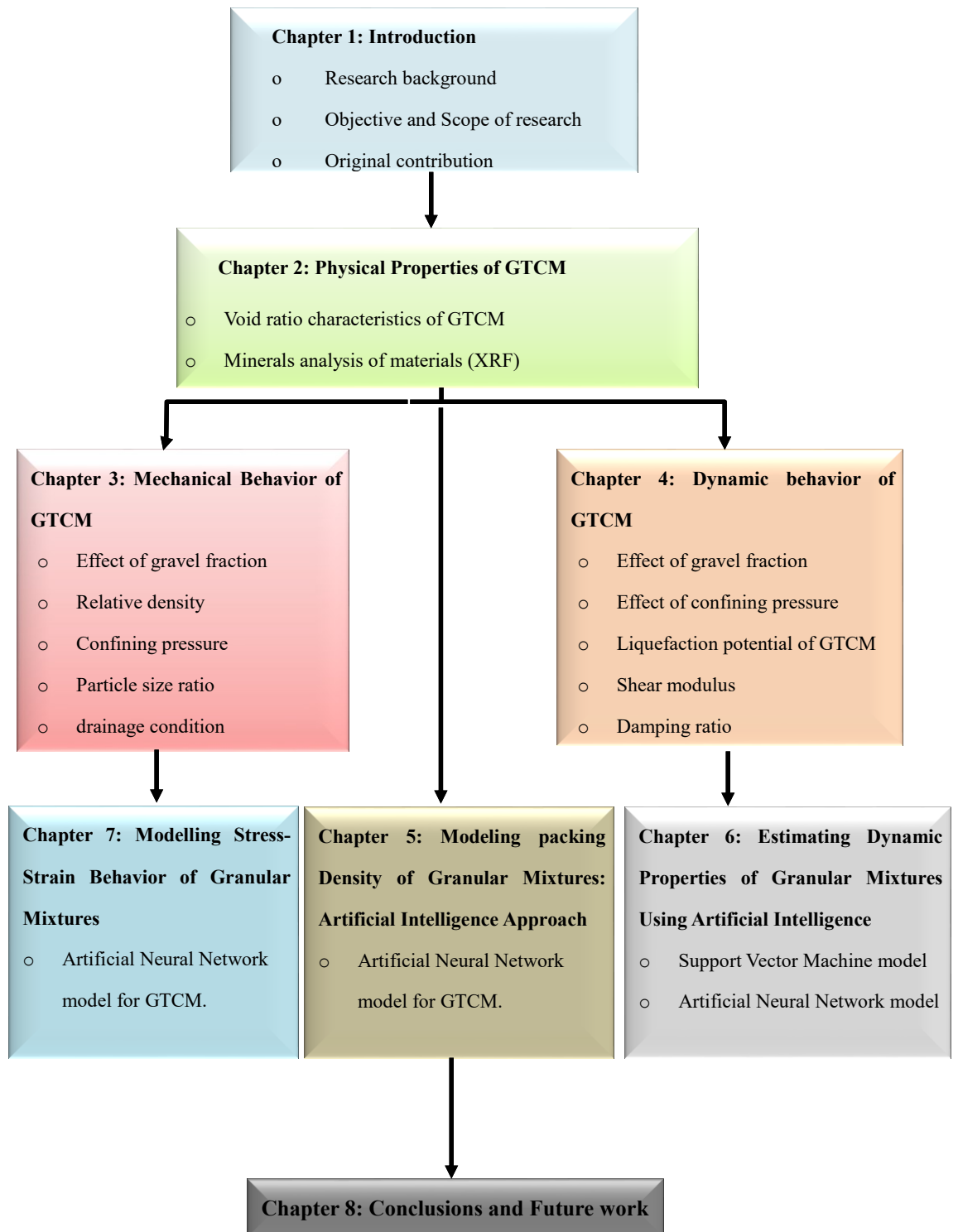


Figure 1.4 Flow chart this thesis

CHAPTER 2

PHYSICAL PROPERTIES OF GRAVEL-TIRE CHIPS MIXTURE

2.1 INTRODUCTION

A comprehensive examination of physical properties of gravel, tire chips and chemical composition of materials are required in order to fully understand the mechanical behavior of granular mixtures reinforced with Scrap Tire Derived Materials (STDM) subjected to static and cyclic loading. This chapter presents different experimental investigations and testing methodologies used to examine the physical properties of gravel and gravel-tire chips mixtures.

Geotechnical properties of granular mixtures would influence the stability of civil engineering structures built in or on these materials. The mechanical behavior of granular materials mixed with tire chips at the micro or macro-scale strongly depends on the individual characteristics of soil and tire chips and their interaction within the mixture. Therefore, physical and chemical characteristics of gravel and tire chips such as grain size distribution, specific gravity, packing density and mineralogy need to be thoroughly examined.

In this chapter the methods used to prepare specimen for experimental investigations are explained in details. In addition, the procedure and equipment utilized to conduct each test is given along with the theoretical or empirical expression

used to temperate the test results.

2.2 GRAIN SIZE DISTRIBUTION AND MATERIAL CLASSIFICATIONS

2.2.1 GRAVEL

In this study the grain size distribution and classification of gravel materials were determined by a sieving analysis conducted according to JGS-0051 (2009). Two sets of gravel (G1 and G2) were examined in order to study the impact of gravel particle characteristics on the overall mechanical behaviour of GTCM. Particle size distributions of gravel is plotted in Fig. 2.1. The coefficient of uniformity (U_c) and coefficient of curvature (U_c) are defined by Eq. 2.1 and Eq. 2.2 respectively. Both sets of gravel were carefully selected and sieved in such a way that the inclination of G2 becomes similar to that of G1 with relatively close mean grain size ratio ($D_{50,G1} \approx D_{50,G2} = 4.3$ mm) and coefficient of uniformity $U_c \approx 2.17$ and $U_c \approx 1$. Both G1 and G2 gravels are classified as poorly graded (GP) according to JGS-0051 (2009). It is worth nothing that G2 has weaker sub-angular sharp particles compared to G1. A picture of gravel samples is presented in Fig. 2.2.

$$U_c = \frac{D_{60}}{D_{10}} \quad (2.1)$$

$$U_c = \frac{(D_{30})^2}{D_{10} \times D_{60}} \quad (2.2)$$

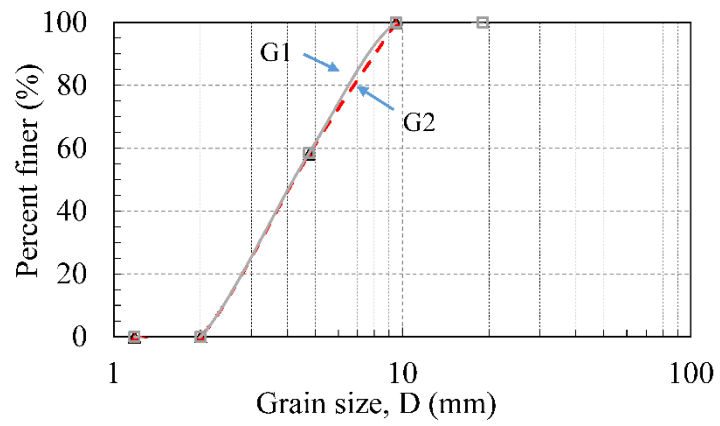


Figure 2.1 Particle size distribution of gravel materials

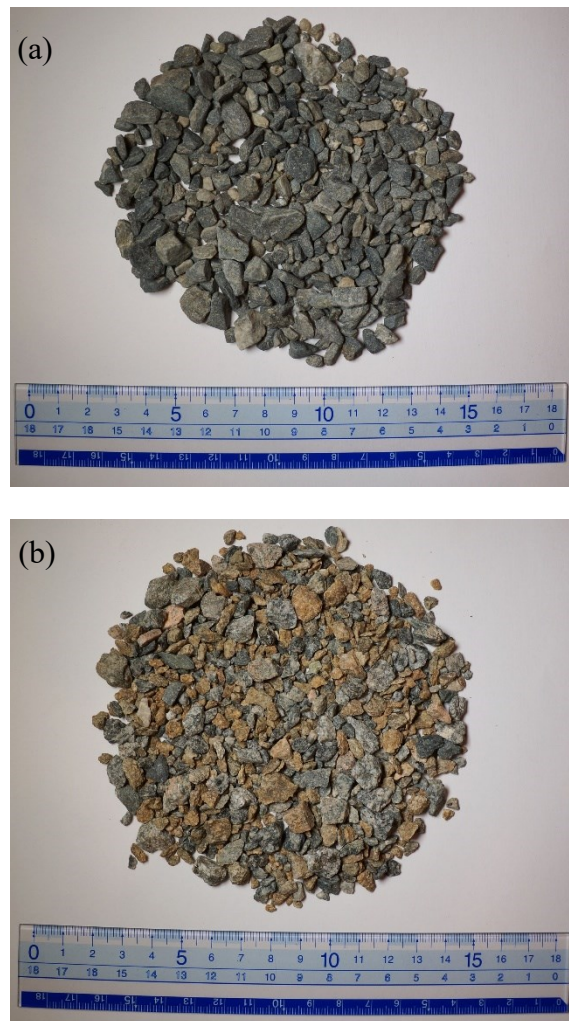


Figure 2.2 Gravel samples: (a) G1 (b) G2

2.2.2 TIRE CHIPS

In this study the grain size distribution and classification of tire chips materials were determined by a sieving analysis conducted according to JGS-0051 (2009) and ASTM 6270-17 standard. The tire chips materials used in this study were made of scrap tires and do not contain any steel belts or fiber. Three sets of tire chips (TCH1, TCH2 and TCH3) were used in this study. The STDMS of present study are classified as granulated rubber and tire chips according to ASTM 6270-17 standard . TCH1 has uniformity coefficient of $U_c \approx 2.2$ and $U_\epsilon \approx 0.94$. The materials TCH2 and TCH3 have a similar uniformity coefficient of $U_c \approx 1.4$ and $U_\epsilon \approx 0.95$. Particle size distributions of tire chips can be seen in Fig. 2.3. A picture of gravel samples is presented in Fig. 2.4.

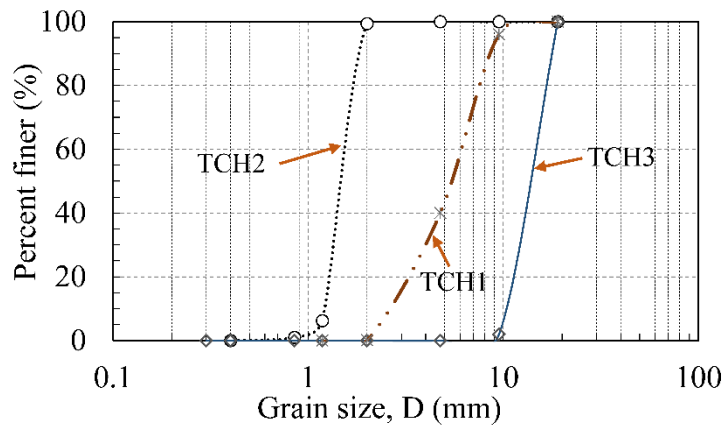


Figure 2.3 Particle size distribution of tire chips materials

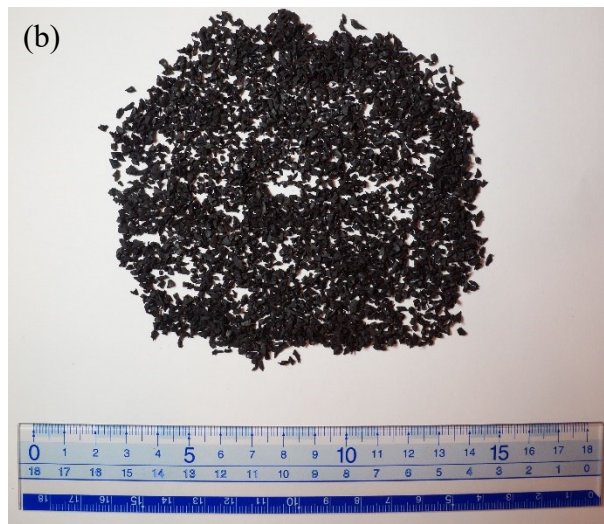


Figure 2.4 Tire chips samples: (a) TCH1 (b) TCH2 (c) TCH3

2.3 WEIGHT VOLUME RELATIONSHIPS FOR GRAVEL TIRE CHIPS MIXTURE

In order to proceed with analysis of experimental test results, weight-volume relationship for Gravel Tire Chips Mixture (GTCM) as binary material needs to be defined. In this study, the proportion of gravel was determined by the two means, mass proportion of tire chips (x_θ) and volume proportion of gravel (G_F) in GTCM mixture as follows:

$$x_\theta = \frac{m_{TC}(x_\theta)}{m_T(x_\theta)} \quad (2.3)$$

$$G_F = \frac{V_G(x_\theta)}{V_s(x_\theta)} \quad (2.4)$$

Where $m_{TC}(x_\theta)$ and $m_T(x_\theta)$ are the mass of Tire Chips (TC) and total mass of mixture in (kg) respectively. $V_G(x_\theta)$ and $V_T(x_\theta)$ are the Volume of gravel and total volume for GTCM with $x_\theta(\%)$ tire chips in mixture. $V_s(x_\theta)$ is the volume of gravel and tire chips particles. The total volume ($V_T(x_\theta)$) of GTCM at x_θ proportion of tire chips can be obtain by following expression:

$$V_T(x_\theta) = \frac{(1+e(x_\theta))M_T(x_\theta)}{G_{s,GTCM}(x_\theta)} \times \left(\frac{g}{\gamma_w}\right) \quad (2.5)$$

Where $e(x_\theta)$ is void ratio of GTCM at given tire chips proportion in mixture. $G_{s,GTCM}(x_\theta)$ is the specific gravity of GTCM at given tire chips proportion in mixture. g and γ_w are the gravity constant (m/s^2) and unit weight of water (kN/m^2) respectively. Total volume of gravel tire chips mixture $V_T(x_\theta)$ corresponds to the volume of gravel and tire chips particles ($V_s(x_\theta)$) plus volume of voids ($V_v(x_\theta)$) at given tire chips proportion in mixture. Volume of GTCM particles ($V_s(x_\theta)$) can be calculated as follows:

$$V_s(x_\theta) = \frac{M_T(x_\theta)}{G_{s,GTCM}(x_\theta)} \times \left(\frac{g}{\gamma_w}\right) = \frac{m_{TC}(x_\theta)}{G_{s,GTCM}(x_\theta)} \times \left(\frac{g}{\gamma_w}\right) + \frac{m_G(x_\theta)}{G_{S,G}} \times \left(\frac{g}{\gamma_w}\right) \quad (2.6)$$

Where $m_G(x_\theta)$ and $G_{S,G}$ are the mass of gravel at given proportion of tire chips in mixture and specific gravity of gravel respectively.

Specific gravity of GTCM $G_{s,GTCM}(x_\theta)$ can be expressed by rearranging the Eq. 2.3 and 2.6 in terms of specific gravity of gravel ($G_{S,G}$) and tire chips $G_{S,TC}$ as well as proportion of tire chips in mixture (x_θ) as follows:

$$G_{s,GTCM}(x_\theta) = \frac{1}{\left(\frac{1-(x_\theta)}{G_{S,G}}\right) + \left(\frac{x_\theta}{G_{S,TC}}\right)} \quad (2.7)$$

In this study three mean different mean particle size ratio of tire chips to gravel ($D_{50,R}/D_{50,G}$) were taken into account to investigate the effect of particle characteristics of GTCM on physical properties and mechanical behaviour of GTCM. GTCM samples of this study are classified in three mixture groups according to the host gravel and tire chips material used in each mixture. The symbols used to denote each groups reflect the type of the gravel and tire chips used in each mixture (Table. 2.1).

Where $D_{50,R}$ and $D_{50,G}$ are mean particle size of tire chips and gravel, respectively.

Table 2.1 Different combination of gravel and tire chips in GTCM

Mixture	Host	Tire chips	Gravel Fraction	($D_{50,R}/D_{50,G}$)
group	gravel		(Gr)	
G1TCH1	G1	TCH1	0-100%	1.2
G2TCH2	G2	TCH2	0-100%	0.35
G2TCH3	G2	TCH3	0-100%	3.35

2.4 SPECIFIC GRAVITY

The specific gravities (G_s) of gravel and tire chips samples were determined according to JGS-0111 and ASTM 6270-17 recommendations. Six different subsamples of oven dried materials were selected for each sets of gravels (G1 and G2). It is worthwhile to mention that the samples were soaked for at least 24-48 hours, in order to ensure all pores are fully saturated.

The specific gravities of gravel G1 and G2 are 2.81 and 2.78, respectively. TCH1, TCH2 and TCH3 have specific gravities of 1.17, 1.14 and 1.15, respectively. These values are in accordance with the specific gravity of various types of STDm reported in literatures and that vary between 1.02-1.27 with an average of 1.15 (Bressette 1984; Humphrey and Manion 1992; Yang et al. 2002). Once we obtained the specific gravity of tire chips ($G_{s,TC}$) and gravel, specific gravity of GTCM can be determined in terms of proportion of tire chips (x_θ) in mixture according to Eq. 2.7. Specific gravity of GTCM with mean particle size ratio of tire chips to gravel ($D_{50,R}/D_{50,G}$) $\approx$ 1.2 as a representative mixture of GTCM is plotted in Fig. 2.5.

2.5 VOID RATIO OF GRANULAR MIXTURE

In this study, a series of vibratory tests were conducted on gravel and GTCM mixtures according to JGS-0161 standard . In order to obtain a desired ratio of gravel to tire chips, gravel and tire chips were weighed separately and then mixed together by hand. The mixture was then placed into the mold with a 30 cm diameter 30 cm height.

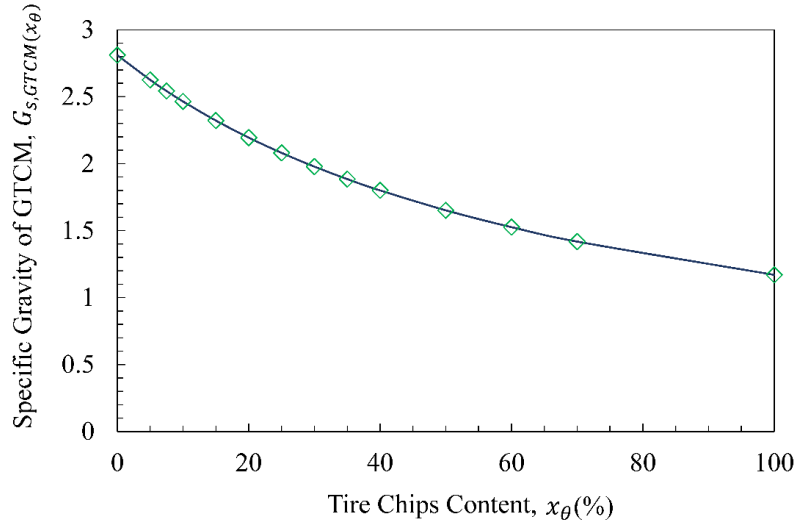


Figure 2.5 variation of specific gravity of GTCM $G_{s,GTCM}(x_{\theta})$,

$$(D_{50,R}/D_{50,G}) \approx 1.2$$

Minimum void ratio of GTCM samples were obtained by compacting materials in five layers. Vertical vibration at frequency of 50 Hz is applied to the surface of each layers using a vibrator with a total weight of 14 Kg that can generate total trust force of 3.45 kN (see Fig. 2.6). Note that for a given gravel fraction, represented values are the averages of at least three to five vibratory tests on GTCM samples.

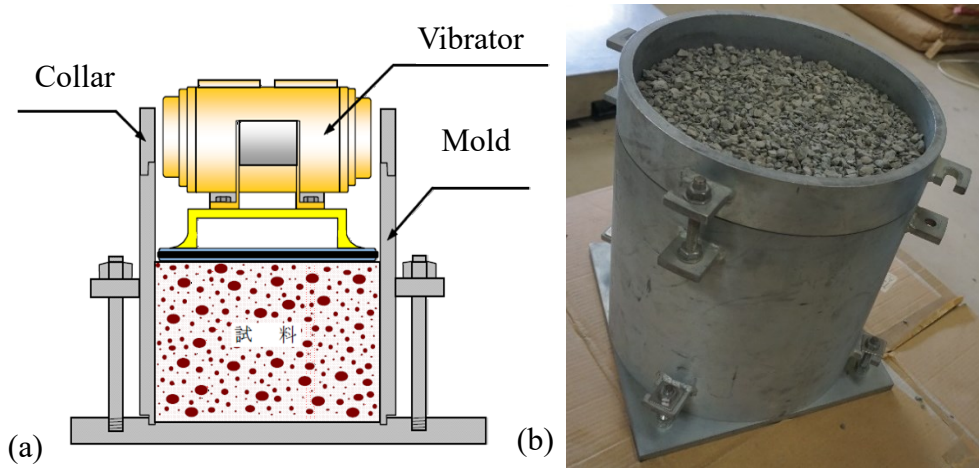


Figure 2.6 (a) Schematic view of vibratory test apparatus (source: JGS-0162)

(b) Sample of GTCM after conducting maximum void ratio

Variation of maximum and minimum void ratio of GTCM with different volumetric proportion of gravel (G_f) and particle size ratio ($D_{50,Large}/D_{50,Small}$) is shown in Fig. 2.7. Experimental (Ueda et al. 2011; Hsiao et al. 2015) and numerical studies (Chang and Meidani 2013; Zhou et al. 2016; Ng et al. 2017) on granular mixtures with different size and shape particles proved that the content of fine and coarse material impacts the mechanical behaviors and packing properties of binary mixtures, such as: void ratio, packing density and shear strength.

Previous studies (Chang and Meidani 2013; Zhou et al. 2016) have shown three different packing states exist for large particles in binary mixtures. These states correspond to the amount of fine content in mixture and are as follows: floating state, non-floating states and transitional state.

In non-floating state, voids between large particles are filled with small particles by increasing small particles content in mixture. Large particles are in contact with each other within the granular structure, thus forces in the system are primarily carried through the large grains contact.

In floating state, small particles prevent contact between the large particles. Contact force chains are primarily formed and carry force through small grain contact. In transitional state, classifying the binary mixture as small particle dominated or large particle dominated is very difficult. Voids are filled by small particles but do not fully separate large particles. Large particle content in transitional state mixtures is function of parameters such as particles shape and particle size ratio.

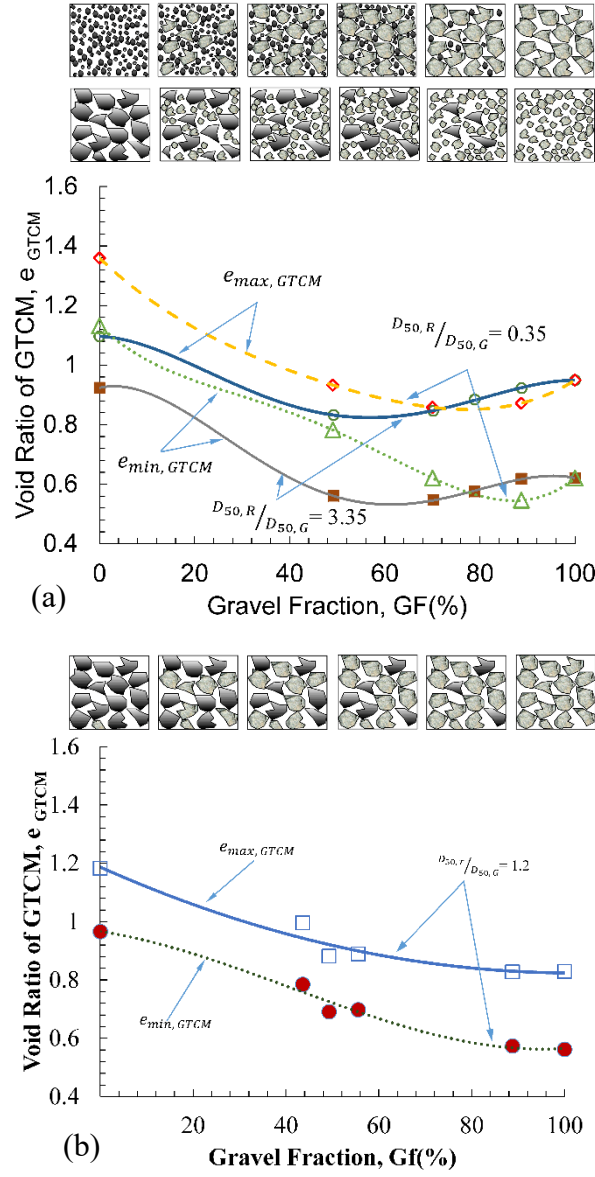


Figure 2.7 Void ratio of GTCM: a) $D_{50, Large}/D_{50, Small} \gg 1.2$ or $\ll 1.2$

b) $D_{50, Large}/D_{50, Small} \approx 1.2$

It is shown that optimum percentage of fine particles, where there is a minimum of voids in the binary mixtures, is obtained in the transitional state (Simpson and Evans 2016). It has been reported that the packing density of binary mixture with non mono-size particles increases with an increase in particle size ratio ($D_{50, Large}/D_{50, Small}$)

(McGeary 1961). The value of minimum void ratio depends on intrinsic properties of soil, such as: fine contents, particle shape, particle size distribution and packing method (Cho et al. 2006).

Minh et al. (2014) reported that once binary mixtures reach their densest possible state, where the mixture is approximately 30 percent fine content, small particles fill voids between large particles. The addition of more small particles beyond this state will cause the large particles to separate from each other and will create more contacts between the fine contents.

For the G2TCH2 mixture with $(D_{50,R}/D_{50,G})=0.35$, the minimum value of both maximum and minimum void ratios is achieved when $GF \cong 80\%$. This finding is in agreement with the values reported by Li et al. (2016) on sand-rubber with particle size ratio of $(D_{50,R}/D_{50,S})=0.25$.

For G2TCH3 mixture with $(D_{50,R}/D_{50,G})=3.35$, the minimum value of maximum and minimum void ratio curves occur with a GF around 50%. This value is in agreement with those reported by Kim and Santamarina (2008) and Mashiri et al. (2015) on sand- tire chips mixture with $(D_{50,R}/D_{50,S})=10$ and $(D_{50,R}/D_{50,S})>20$. For the GTCM with particle size ratio of $(D_{50,R}/D_{50,G})=1.2$, minimum and maximum void ratio of GTCM decreases with increasing gravel fraction. Because large particles are surround with small particles of the same size, no packing phenomena occurs. Similar trends have been reported by Li et al. (2016).

The following relationship has been established to define maximum and minimum void ratio of GTCM in terms of GF (%) and $(D_{50,R}/D_{50,G})$.

$$e_{\max,GTCM}, e_{\min,GTCM} = \chi_0 + \chi_1 / (1 + \chi_2 (\Psi)^2 + \chi_3 (\Psi)^4 + \chi_4 (\Psi)^6) \quad (2.8)$$

$$\Psi = (GF(\%) - \chi_5) / \chi_6 \quad (2.9)$$

$$\chi_i = f(D_{50,R}/D_{50,G}) = \theta_0 + \theta_1 (D_{50,R}/D_{50,G}) + \theta_2 (D_{50,R}/D_{50,G})^2; i: 0:6 \quad (2.10)$$

Where $e_{\max,GTCM}$ and $e_{\min,GTCM}$ are maximum and minimum void ratio of GTCM. And χ_i particle size ratio function. $\theta_0, \theta_1, \theta_2$ are calibration parameters for $D_{50,G} \approx 4.3mm$ and $0.35 \leq (D_{50,R}/D_{50,G}) \leq 3.35$. All Calibration parameters are presented in Table. 2.2.

Table 2.2 Calibrated parameters of max and min void ratio of GTCM

Plot	Parameter	χ_0	χ_1	χ_2	χ_3	χ_4	χ_5	χ_6
$e_{\min,GTCM}$	θ_0	1.39	-0.86	7.18	-15.47	46.53	74.58	122.08
	θ_1	-0.48	0.52	-8.15	25.32	-111.19	34.93	-66.33
	θ_2	0.11	-0.12	2.17	-10.10	61.79	-11.57	21.44
$e_{\max,GTCM}$	θ_0	17.35	-2.94	-5.32	7.2	-8.32	1319.72	1480.4
	θ_1	-19.86	4.43	6.88	-10.88	22.4	-1406.68	-1659.2
	θ_2	5.32	-1.9	-1.64	3.2	-6.4	317.42	402.68

2.6 CHEMICAL COMPOSITION OF GRAVEL USING X-RAY FLUORESCENCE SPECTROMETER

X-Ray Fluorescence (XRF) is a powerful non-destructive analytical tool for elemental analysis and chemical analysis of materials such as ceramics, glasses, soil, building materials. XRF apparatus consists of three main components, a X-Ray source, compartment for holding a sample and analyser. The unit used in this study is a Shimadzu EDX-7000 (2015) energy dispersive XRF spectrometer (see Fig. 2.8). Rh target tube that can operate at maximum 50 kv and $1\mu\text{A}$ is the X-Ray source of this device. Primary X-Rays are generated by the X-Ray source and emitted at the sample's surface. When the atoms in samples receive X-Ray beams, they react and generate a secondary beam that can be detected by detector. The analyser processes the data to generate a spectrum correlating the X-Ray's intensity and their energy.

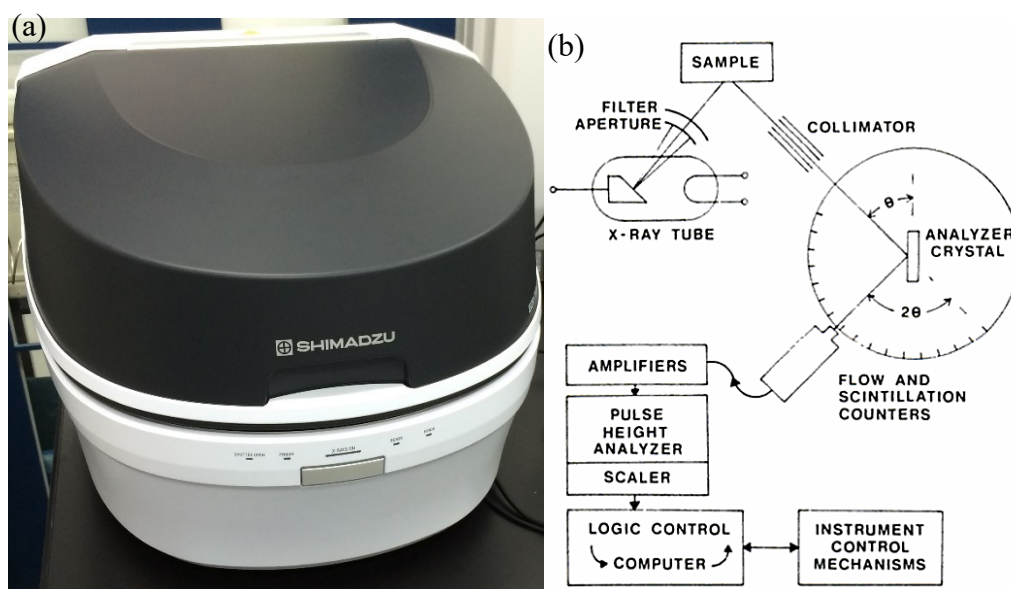


Figure 2.8 (a) Schematic diagram of the XRF and its components (Young et al. 1983)

(b) Energy dispersive XRF spectrometer at the center of advanced instrumental analysis of Kyushu University (Shimadzu Corporation EDX 7000)

Then the analyser uses the obtained information to calculate the composition of elements in the sample. Accurate quantitative XRF analysis requires a homogeneous and very fine and flat samples. In this study two sets of samples (which each set contains 3 samples) were prepared from gravel materials G1 and G2. It should be noted that oven dried samples were crushed, grounded and then mixed together carefully. Then samples were passed through a sieve at 100 μm , in order to increase the precision of analysis. Composition of gravel materials G1 and G2 obtained from the XRF test is shown in Table 2.3. The XRF analyses reported showed the presence of major amounts of quartz, plagioclase, feldspar, biotite, muscovite, and some chlorite. As it can be seen in Table 2.3, silicon dioxide, or silica (SiO_2) and Aluminium oxide (Al_2O_3) are the two major chemical compounds of G1 and G2 gravels which also are most common constituent minerals in silica (quartz) gravel and sands. Comparison of XRF results between samples G1 and G2 shows that G2 is richer in Aluminium Oxides which is usually produced during the weathering process.

Chemical weathering indices were used for evaluating weathering of parent rock and soil development. For each sample of gravel, five different indices were used to incorporate bulk major element oxide chemistry into single value. Table 2.4, outlines the indices evaluated in this study.

Table 2.3 Chemical composition of materials G1 and G2

Oxides	G1	G2
SiO ₂	55.7	60.0
Al ₂ O ₃	15.3	16.4
Fe ₂ O ₃	10.3	7.7
CaO	9.4	6.4
MgO	5.3	3.9
K ₂ O	1.9	3.2
Na ₂ O	0.0	1.0
TiO ₂	1.4	0.8
MnO	0.3	0.2
SO ₃	0.3	0.1
V ₂ O ₅	0.1	0.0
Others	0.2	0.3

As is displayed in Table 2.4, G1 and G2 yield almost same Ruxton weathering index (R). However this index was found to be not suitable for rocks that contains smectite and vermiculite as weathering by-products. Comparison between the values of weathering indices CIA, CIW and PIA of G1 and G2 suggests that G2 is slightly weathered than G1.

Table 2.4 Weathering indices evaluated in this study

index	Expression	Trend (increase in weathering)	G1	G2	Reference
R	SiO_2/Al_2O_3	Negative	3.64	3.65	(Ruxton 1968)
CIA	$[Al_2O_3/(Al_2O_3 + CaO + Na_2O + K_2O)]$	Positive	0.58	0.6	(Nesbitt and Young 1982)
CIW	$[Al_2O_3/(Al_2O_3 + CaO + Na_2O)]$	Positive	0.62	2.62	(Harnois 1988)
PIA	$(Al_2O_3 - K_2O)/(Al_2O_3 + CaO + Na_2O - K_2O)$	Positive	0.58	0.64	(Jayawardena and Izawa 1994)

2.7 SUMMARY AND CONCLUSION

The physical properties and chemical composition of gravel, tire chips and GTCM are thoroughly examined by running series of experimental testing programs and presented in this chapter. Sieve analyses were conducted to obtain the grain size distribution and classification of materials used in this study. The effect of mean size particle ratio of tire chips to gravel ($D_{50,R}/D_{50,G}$) and GF(%) on packing density of GTCM binary material has also been investigated. The specific gravity of GTCM was

found to be highly influenced by tire chips content in mixture.

The variation of minimum and maximum void ratio with respect to gravel fraction was found to be highly sensitive to the particle size ratio of tire chips to gravel ($D_{50,R}/D_{50,G}$).

For the binary materials with particle size ratio ($D_{50,R}/D_{50,G}$) >1.2 or ($D_{50,R}/D_{50,G}$) <1.2 , the value of maximum and minimum void ratio of GTCM versus gravel fraction were found to be at a minimum when the gravel fraction was at the optimal percentage in mixture. This gravel fraction value is the threshold where large particles in mixture are completely surrounded by small particles. At this point, adding additional small particles to the mixture will separate large particles further and increase the void ratio of binary mixture.

REFERENCES

- ASTM D6270-12: Standard Practice for Use of Scrap Tires in Civil Engineering Applications, ASTM International. West Conshohocken, PA, USA.
- JGS 0051-2009, Method of classification of geomaterials for engineering purposes, Japanese Geotechnical Society.
- JGS 0161-2009, Test method for minimum and maximum densities of sands, Standards of the Japanese Geotechnical Society, Japanese Geotechnical Society.
- Bressette, T. 1984. Used Tire Material as an Alternate Permeable Aggregate, Report No.FHWA/CA/TL-84/07, Office of Transportation Laboratory, California Department of Transportation, Sacramento, California.
- Chang, C. S. & Meidani, M. (2013). Dominant grains network and behavior of sand–silt mixtures: stress–strain modeling. *International Journal for Numerical and Analytical Methods in Geomechanics*, 37(15): 2563-2589.
- Cho, G.-C., Dodds, J. & Santamarina, J. C. (2006). Particle Shape Effects on Packing Density, Stiffness, and Strength: Natural and Crushed Sands. *Journal of Geotechnical and Geoenvironmental Engineering*, 132(5): 591-602.
- Harnois, L. (1988). The CIW index: A new chemical index of weathering. *Sedimentary*

- Geology*, 55(3): 319-322.
- Hsiao, D.-H., Phan, V. T.-A., Hsieh, Y.-T. & Kuo, H.-Y. (2015). Engineering behavior and correlated parameters from obtained results of sand–silt mixtures. *Soil Dynamics and Earthquake Engineering*, 77:137-151.
- Humphrey, D. N. & Manion, W. P. Properties of tire chips for lightweight fill. Grouting, soil improvement and geosynthetics. ASCE, 1992, pp. 1344-1355.
- Jayawardena, U. d. S. & Izawa, E. (1994). A new chemical index of weathering for metamorphic silicate rocks in tropical regions: A study from Sri Lanka. *Engineering Geology*, 36(3): 303-310.
- Kim, H. K. & Santamarina, J. C. (2008). Sand–rubber mixtures (large rubber chips). *Canadian Geotechnical Journal*, 45(10): 1457-1466.
- Li, B., Huang, M. & Zeng, X. (2016). Dynamic Behavior and Liquefaction Analysis of Recycled-Rubber Sand Mixtures. *Journal of Materials in Civil Engineering*, 28(11): 04016122.
- Mashiri, M. S., Vinod, J. S., Sheikh, M. N. & Tsang, H. H. (2015). Shear strength and dilatancy behaviour of sand-tyre chip mixtures. *Soils and Foundations*, 55(3): 517-528.
- McGeary, R. K. (1961). Mechanical Packing of Spherical Particles. *Journal of the American Ceramic Society*, 44(10): 513-522.
- Minh, N. H., Cheng, Y. P. & Thornton, C. (2014). Strong force networks in granular mixtures. *Granular Matter*, 16(1): 69-78.
- Nesbitt, H. W. & Young, G. M. (1982). Early Proterozoic climates and plate motions inferred from major element chemistry of lutites. *Nature*, 299:715.
- Ng, T.-T., Zhou, W. & Chang, X.-L. (2017). Effect of Particle Shape and Fine Content on the Behavior of Binary Mixture. *Journal of Engineering Mechanics*, 143(1): C4016008.
- Roaldset, E. (1972). Mineralogy and geochemistry of Quaternary clays in the Numedal area, southern Norway. *Norsk Geologisk Tidsskrift*, 52:335-369.
- Ruxton, B. P. (1968). Measures of the Degree of Chemical Weathering of Rocks. *The Journal of Geology*, 76(5): 518-527.
- Simpson, D. C. & Evans, T. M. (2016). Behavioral Thresholds in Mixtures of Sand and Kaolinite Clay. *Journal of Geotechnical and Geoenvironmental Engineering*, 142(2): 04015073.
- Ueda, T., Matsushima, T. & Yamada, Y. (2011). Effect of particle size ratio and volume fraction on shear strength of binary granular mixture. *Granular Matter*, 13(6): 731-

742.

- Yang, S., Lohnes, R. & Kjartanson, B. (2002). Mechanical Properties of Shredded Tires. *Geotechnical Testing Journal*, 25(1): 44-52.
- Young, H. W., Boybay, M., Young, J. C. & Demirel, T. (1983). X-Ray Fluorescence Spectrometry for Analysis of Fly Ash Column Leachates. Hazardous and Industrial Solid Waste Testing: Second Symposium. ASTM International.
- Zhou, W., Xu, K., Ma, G., Yang, L. & Chang, X. (2016). Effects of particle size ratio on the macro- and microscopic behaviors of binary mixtures at the maximum packing efficiency state. *Granular Matter*, 18(4): 81.

CHAPTER 3

MECHANICAL BEHAVIOUR OF GRAVEL-TIRE CHIPS MIXTURE USING STATIC TRIAXIAL COMPRESSION TESTS

3.1 INTRODUCTION

Recycling the scrap tyres as a waste material of industrial activities are highly encouraged recently, because it helps reduction of CO₂ emission to atmosphere and leads to restoration of our ecosystems. Due to advantageous physical and mechanical characteristics of STDm, worldwide use of these materials in civil and geotechnical applications such as light weight backfills, drainage, and leachate layers has been increasing steadily. Design, construction and maintenance of structures built on these materials needs a proper understanding of how different parameters affect the mechanical behaviour of STDm and STDm soil mixtures.

Some studies have already reported the effect of different parameters on monotonic behaviour of sand-tire shreds (e.g. Foote et al. 1996; Zornberg et al. 2004; Gotteland et al. 2005; Kaushik et al. 2015; Mashiri et al. 2015). However the main objective of this chapter is to understand the mechanical behaviour of GTCM that was introduced by Hazarika and Abdullah (2016) with the goal of compensating for the mechanical limitations of sand-tire chips mixture.

This chapter presents the results of a series of consolidated drained (CD) and

undrained (CU) triaxial compression tests performed on gravel- tire chips mixtures. The effect of different parameters on stress-strain as well as dilative behaviour of GTCM is also examined. The method used to prepare the specimen for triaxial apparatus is described in details. The procedure and equipment used to conducted triaxial tests along with the mathematical expressions to analyse the test results are also addressed in this chapter.

3.2 APPARATUS, EQUIPMENT AND LAYOUT OF EXPERIMENTS FOR MONOTONIC TRIAXIAL TESTING

One of the objectives of this study is to investigate monotonic behaviour of GTCM using triaxial apparatus. In this section, first the most important determinative parameters on mechanical behaviour of GTCM are introduced and then layout of experimental triaxial tests are presented in detail. In addition, the specimen preparation and testing method for triaxial compression tests such as specimen setup, saturation, and consolidation is also thoroughly addressed.

3.2.1 SELECTION OF PARAMETERS AND LAYOUT OF EXPERIMENTAL TESTS

Understanding the monotonic behaviour of GTCM binary mixture requires determination of the major parameters affecting stress-strain and dilative behaviour of this material. However, to the best of author's knowledge, no study can be found in literature investigating influential parameters on the mechanical behaviour of gravel-tire chips mixture.

Therefore, this study aims to investigate the effects of particle characteristics, tire

chips–gravel particle size ratio ($D_{50,R}/D_{50,G}$), degree of compaction (D_r), gravel fraction ($GF = V_{Gravel}/V_T$) in gravel-tire chips mixture (GTCM), effective confining pressure (σ'_{3c}) and drainage boundary condition on shear strength and deformation characteristic of gravel and GTCM. Table 3.1 lists the parameters and testing conditions on the gravel tire chips mixture.

Table 3.1 GTCM specimens testing conditions and list of parameters

List of parameter/ Testing condition	Range of variation
Gravel fraction ($GF = V_{Gravel}/V_T$), %	0-100
Tire chips–gravel particle size ratio($D_{50,R}/D_{50,G}$)	0.35, 1.2, 3.35
Degree of compaction (D_r),%	35, 50, 75
Effective confining pressure (σ'_{3c}), kN/m ²	50, 100, 150, 200
Drainage boundary condition	Drained, Undrained

3.2.2 TRIAXIAL TESTING APPARATUS

The triaxial compression tests were performed in monotonic triaxial compression system by Marutani Testing Machine Company. The machine equipped with displacement transducer with resolution of 0.1 microns, triaxial load cell with the maximum axial load capacity of +/- 10 kN and the volume change measuring transducer with capacity of 250 cm³. The triaxial system is facilitated by a 6-channel data with 16bit data acquisition.

A code written in Visual basic environment was used for data acquisition and

controlling servo- electric loading systems. The schematic view of triaxial apparatus and equipment is shown in Fig. 3.1. The triaxial apparatus could conduct test on specimens of 38 to 100mm in diameters.

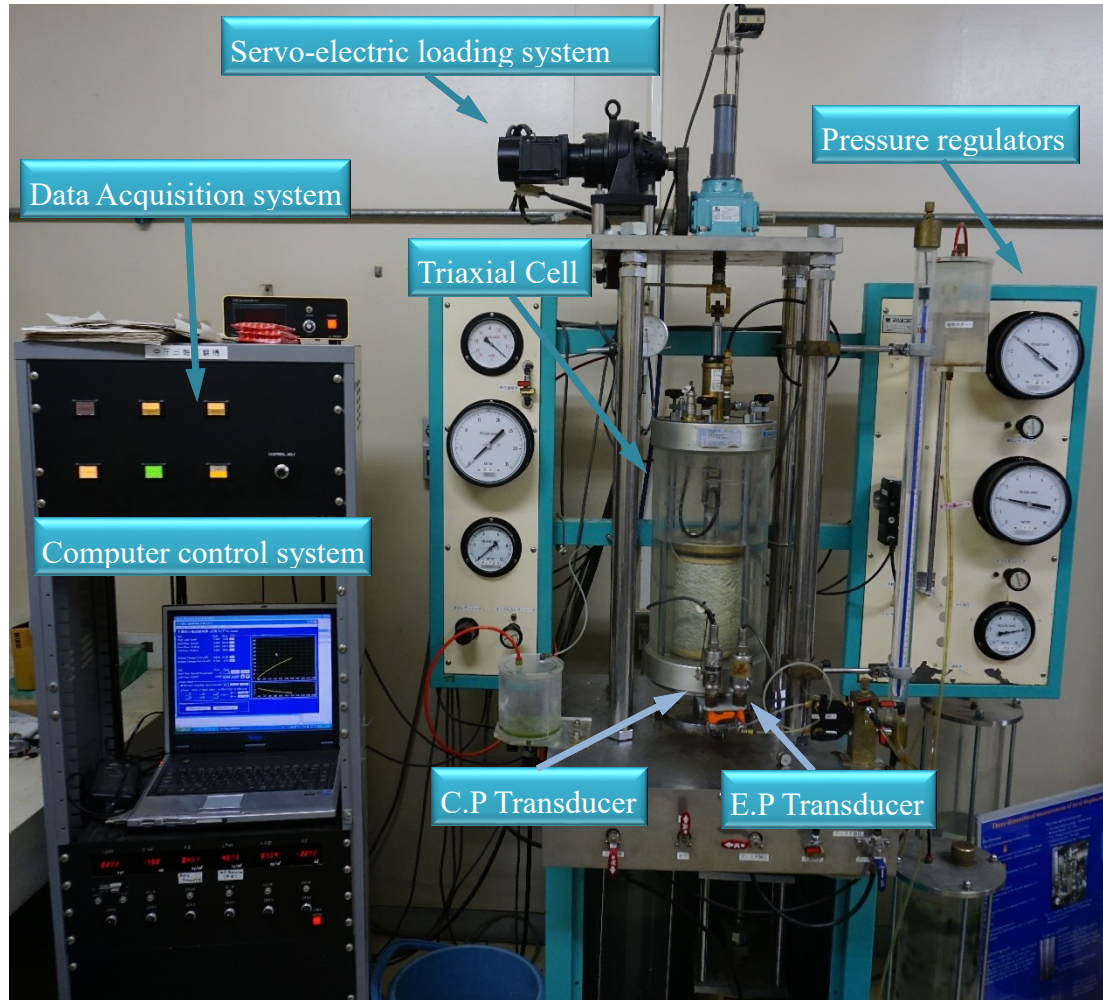


Figure 3.1 Schematic view of triaxial apparatus

3.2.3 SPECIMEN PREPARATION

The gravel and GTCM specimens tested in the triaxial apparatus are prepared in a split mold with an inner diameter of 100.6mm and height of 200mm. The specimens are isolated from the cell fluid by a non-porous latex rubber membrane (with the

thickness of 0.3mm) attached to the base of triaxial set up. In addition, a porous stone and a filter paper were embedded in each of the end plates, in order to provide a support at both ends of sample and enable free passage of water. A drainage inlet is embedded in pedestal to connect the water in the specimen with an external back pressure controller and pore water pressure transducer.

In First step, the membrane was secured in place by rubber bands and O-rings around the pedestal. Split mold was placed around the membrane and fixed in place with a pair of fasteners. At the next step, a small vacuum was applied to the mold. This vacuum seals the membrane to the mold's wall and decreases friction between soil and membrane (see Fig 3.2). Then the first filter paper was placed on top of porous stone.

In order to have homogenous samples, the under-compaction method was used for preparation of specimens (Ladd 1978). The method was proposed to overcome the non-uniformity produced by soil compaction in which the compaction of top layers might further densify the soil in the below layers. Basically in this method each layer is typically compacted to lower density than desired one by a preset value.



Figure 3.2 Split mold and rubber membrane: (a) Front view (b) upper view

Mixtures of desired relative densities were obtained by measuring weights of gravel and tire chips, then they were mixed carefully by hand, placed into the mold and compacted into 10 layers. Another filter paper was placed on the top of sample and top cap was fixed in place by three bolts. At the next stage, membrane fold over around the top cap and sealed in place with rubber bands and O-rings. A small vacuum is applied to the drainage lines to create an effective confining pressure on the specimen before removing the forming mold. At the next step, the dimension of specimen was carefully measured with resolution of 0.1 mm.

The triaxial cell mounted on the apparatus and filled with water. Before starting the saturation process, CO_2 was allowed to flow through with a slow rate from bottom of specimen and flush out air trapped in specimen. Samples were saturated by allowing

de-aired water to flow through from bottom of the sample. The back pressure technique was adopted to enhance the degree of saturation of samples. The cell pressure and back pressure were simultaneously increased by an increment of 5 kPa per minute to maintain the effective confining pressure constant. A 200 kPa backpressure was found to be sufficient to dissolve any small amount of air in the pore water. In this study, the degree of saturation was measured by closing the back pressure inlet and increasing the cell pressure gradually by 50 kPa in very small steps (1 kPa). Then Skempton's B value is calculated from Eq. 3.1. Full saturation was assumed to be achieved when Skempton's B parameter ($\Delta u / \Delta \sigma_3$) was greater than 0.95 (see Fig 3.3).

$$B = \Delta u / \Delta \sigma_3 \quad (3.1)$$

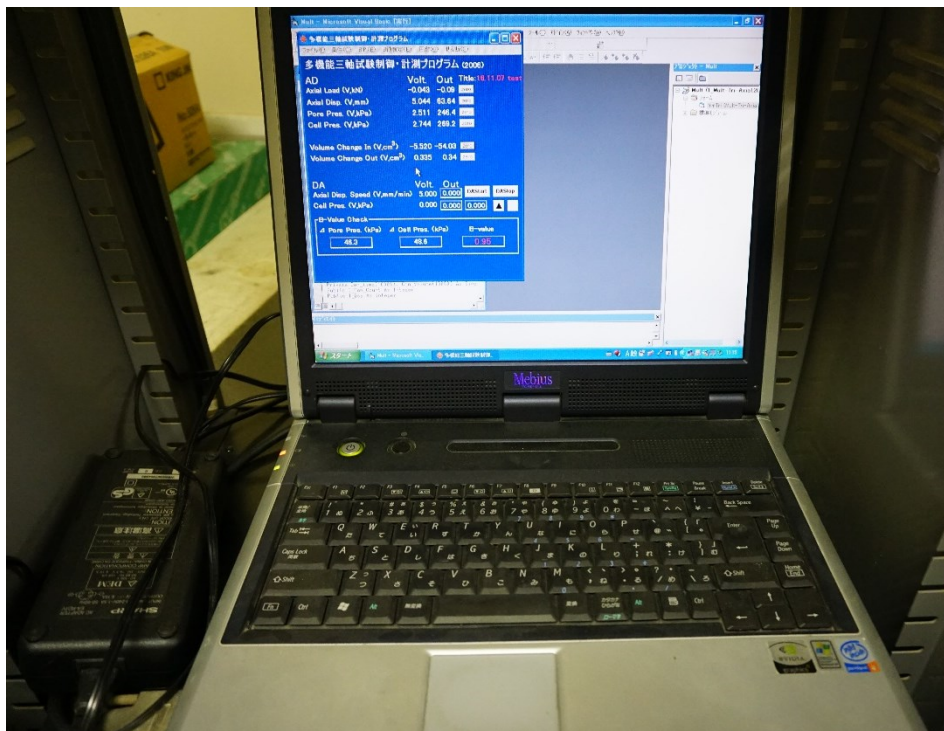


Figure 3.3 Checking the degree of saturation (B-value)

An isotropic consolidation pressure was applied to samples, while maintaining constant initial backpressure (200 kN/m²). The triaxial compression tests were performed with a constant axial strain rate of 0.1 %/min until an axial strain of 20% was attained. A low strain rate was used to prevent large pore pressures developed under drained conditions (Bishop and Blight 1963; Lade 2016). Following the triaxial testing, specimen was carefully removed from triaxial setup, then dried for determining the mass for dry unit weight calculations.

3.3 RESULTS AND DISCUSSION

3.3.1 SHEAR STRENGTH AND DEFORMATION CHARACTERISTICS OF GTCM

3.3.1.1 Effect of fraction of gravel in GTCM (GF)

The influence of tire chips inclusion on deviatoric stress and volumetric strain versus axial strain of GTCM with different gravel fraction at relative density $D_r=50\%$, confining pressure (σ'_{3c}) of 100 kN/m² and particle size ratio ($D_{50,R}/D_{50,G}$) ≈ 1.2 is illustrated in Fig. 3.4. it should be noted that, following mathematical formulas are used for the analysis of the triaxial test results:

$$\varepsilon_1(\%) = \frac{\Delta L_1}{L_1}, \varepsilon_3(\%) = \frac{\Delta L_3}{L_3}, \varepsilon_v(\%) = \frac{\Delta V}{V_0} \quad (3.2)$$

$$\varepsilon_v(\%) = \varepsilon_1 + 2\varepsilon_3 \quad (3.3)$$

$$\varepsilon_3 = \frac{1}{2}(\varepsilon_v - \varepsilon_1) \quad (3.4)$$

Where ε_1 , ε_3 and ε_v are axial strain, radial strain and volumetric strain respectively.

$$\sigma'_3 = \sigma_3 - \Delta u \quad (3.5)$$

$$q = \sigma_1 - \sigma'_3 \quad (3.6)$$

$$\varepsilon_q = \frac{2}{3} \times (\varepsilon_1 - \varepsilon_3) \quad (3.7)$$

$$\dot{p} = \frac{(\sigma_1 + 2\sigma'_3)}{3} \quad (3.8)$$

$$\eta = \frac{q}{\dot{p}} \quad (3.9)$$

Where σ_3 (kN/m²), σ'_3 (kN/m²) and Δu (kN/m²) are confining pressure, effective confining pressure and excess pore water pressure respectively. q (kN/m²) and ε_q (%) are deviatoric stress and strain respectively. $\dot{p}$ (kN/m²) and η are effective mean stress and stress ratio respectively. As seen in Fig. 3.4, peak deviatoric stress decreases and corresponding axial strain increases with decreasing gravel fraction in mixture.

As seen in Fig 3.4, For GF>83%, GTCM samples exhibit gravel like behavior with distinct peak shear strength where essentially gravel particles forms GTCM soil matrix and stresses are mainly transmitted through gravel to gravel contacts. Moreover, it can also be observed from the volumetric strain curves that the tendency for dilation is much more for gravel sample (GF=100%) than GTCM with lower gravel fraction. For GF<55%, soil matrix is dominated by tire chips particles. Tire chips like behavior is evident where force networks are mainly formed between tire chips particles. At this percentage of GF, GTCM shows significant reduction in shear strength due to very low stiffness of tire chips particles. As expected completely linear contractive behavior was observed for samples in this range.

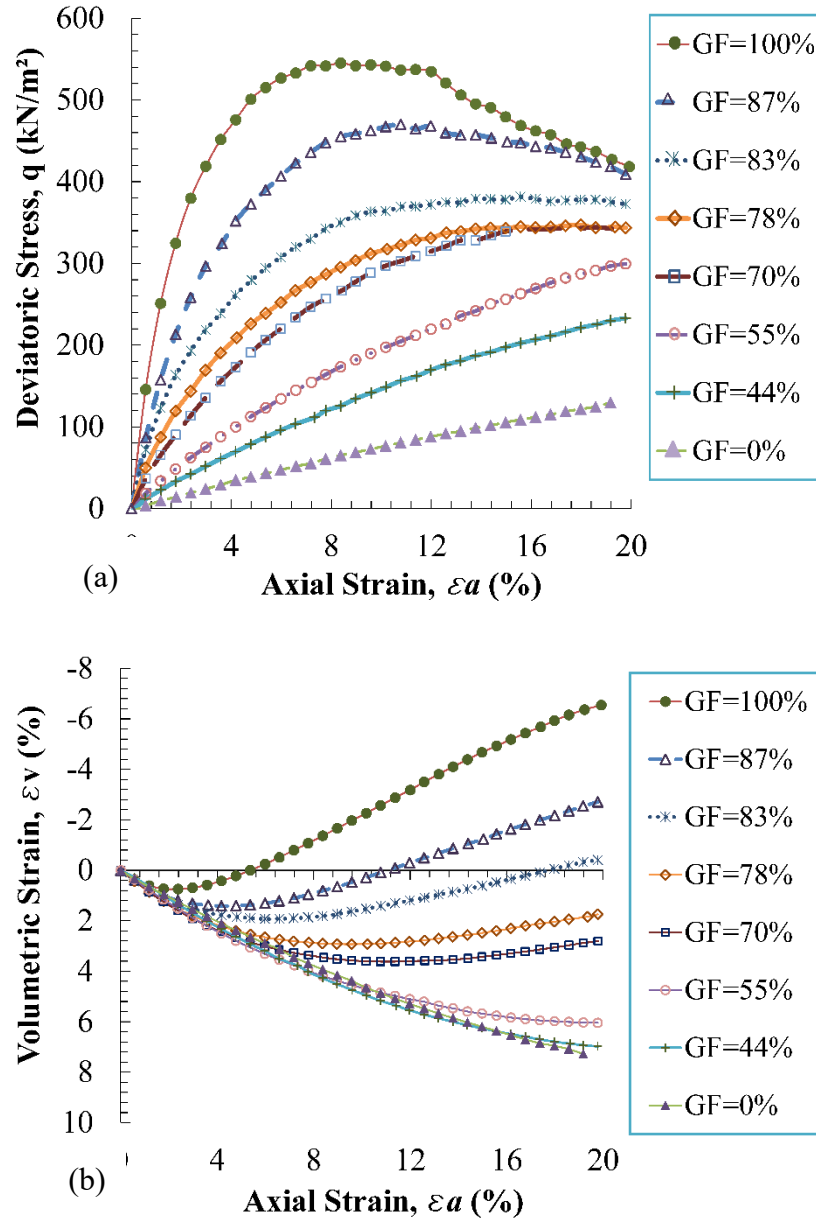


Figure 3.4 Effect of fraction of gravel on a) Deviatoric stress-axial strain b)

Volumetric strain-axial strain behaviour of GTCM

For GTCM with $55\% < G_f < 83\%$, transitional state where it is very difficult to classify whether binary mixture is tire chips dominated or gravel dominated, Samples sustained large deformation without exhibiting well-defined peak deviatoric stress. In

addition, this state GTCM shows slightly dilative behavior followed by clear contractive behavior. Deviatoric stress and volumetric strain versus axial strain curves of TCH 1, TCH 2 and TCH3 samples are plotted in Fig. 3.5a and Fig.3.5b.

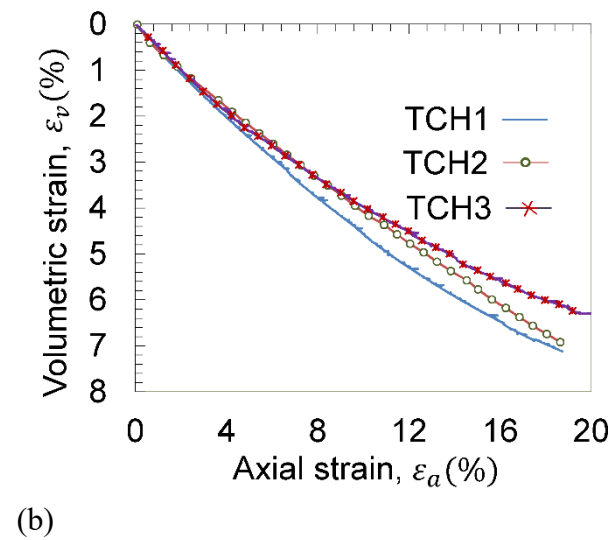
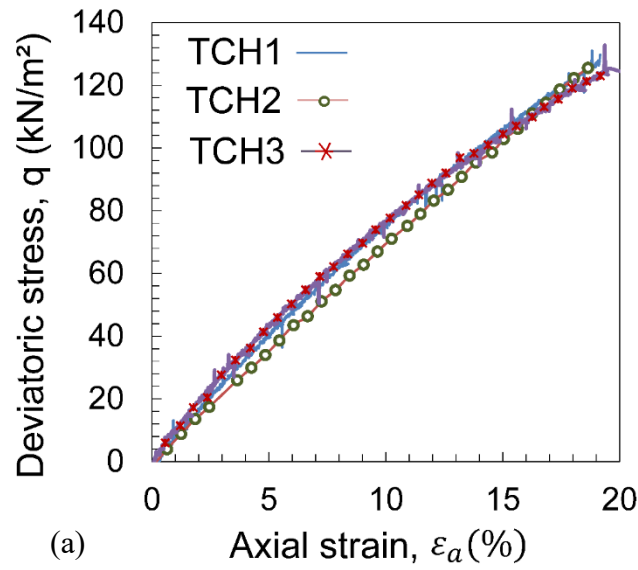


Figure 3.5 Effect of tire chips particle size on a) Deviatoric stress-axial strain

b) Volumetric strain-axial strain behavior of GTCM

The behavior of TCH2 and TCH3 sample with fine and coarse particles during shearing is similar to that of TC1. It can be concluded that shear strength of tire chips is nearly independent of particle size. Similar results have been reported by other researches (Benda 1995; Yang et al. 2002).

3.3.1.2 Effect of confining pressure

Fig.3.6 presents the effect of confining pressure on the shear strength and dilative behavior of pure gravels, G1 and G2. As mentioned previously, G1 and G2 have similar particle size distribution. It is evident that G1 specimens show more dilative behavior in comparison to that of G2. In addition, peak shear strength of G1 samples are 8% and 13% greater than that of G2 at confining pressures of 50 and 100 kN/m², respectively, and yield similar residual shear strength at the axial strain of 20%.

However, G1 exhibited remarkably greater peak shear strength as well as residual shear strength in comparison to that of G2 at the effective confining pressure of 200 kN/m². As mentioned, G2 has more sub-angular sharp aggregates, so it is more susceptible to particle breakage even at lower confining pressure (Lade et al. 1996; Agustian and Goto 2008) .

Particle size distribution was analyzed at the end of triaxial test. Relative breakage was assessed by using Hardin method as follows (Hardin 1985).

$$B_r = B_t/B_p \quad (3.10)$$

Where B_p is the potential breakage and B_t is the total breakage, as shown in Fig. 3.7.

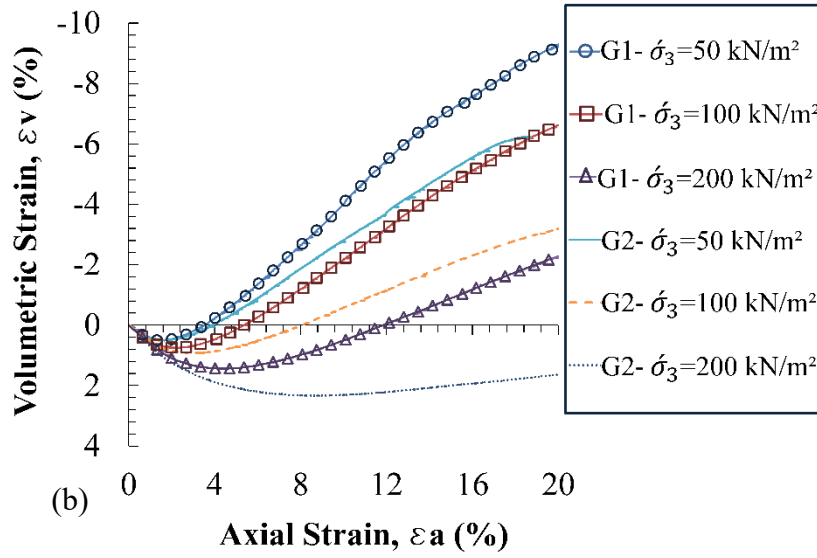
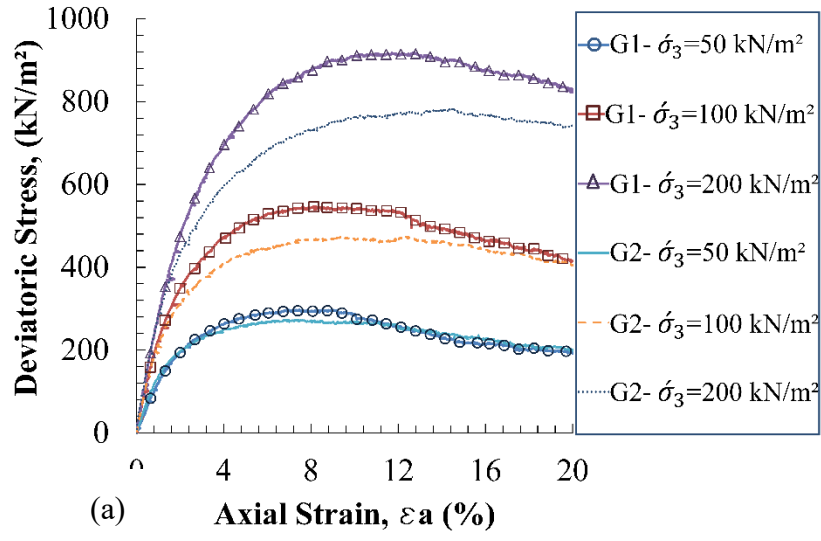


Figure 3.6 Effect of confining pressure on a) Deviatoric stress-axial strain b)

Volumetric strain-axial strain behaviour of GTCM with $G_f=100\%$ and $D_r=50\%$.

The relative breakage of B_r of 0.017 and 0.059 are obtained for gravel G1 and G2, respectively, at confining pressure of 200 kN/m².

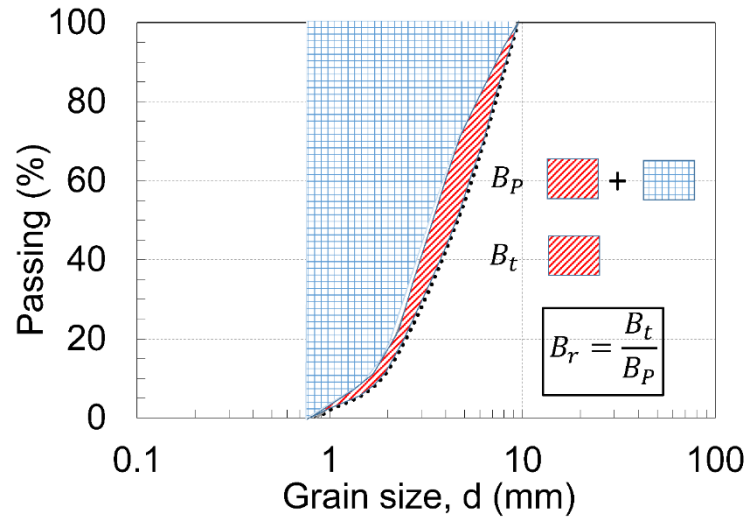


Figure 3.7 Definition of particle breakage based on the Hardin method (1985).

As can be seen from Fig. 3.8, the results show that G1 had insignificant particle breakage in comparison to that of G2 which can be one reason why G1 exhibits high peak shear strength and dilative behavior (Lade et al. 1996; Shahnazari and Rezvani 2013; Liu et al. 2016).

The effect of confining pressure on deviatoric stress and volumetric strain of pure tire chips (TC1) is shown in Fig. 3.9. Pure tire chip samples exhibit nearly linear stress-strain behaviour for the confining pressures considered in this study.

In addition, volumetric strain decreases with increased confining pressure and furthermore, fully contractive and linear behavior was observed for samples under different confining pressure.

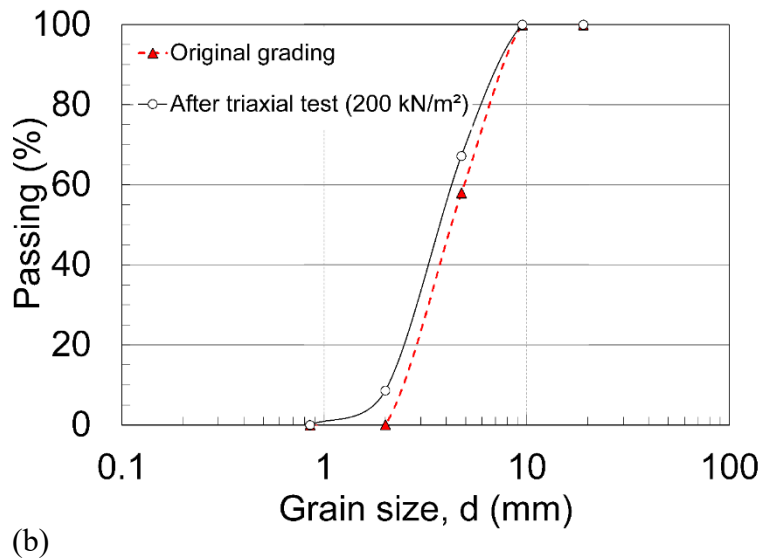
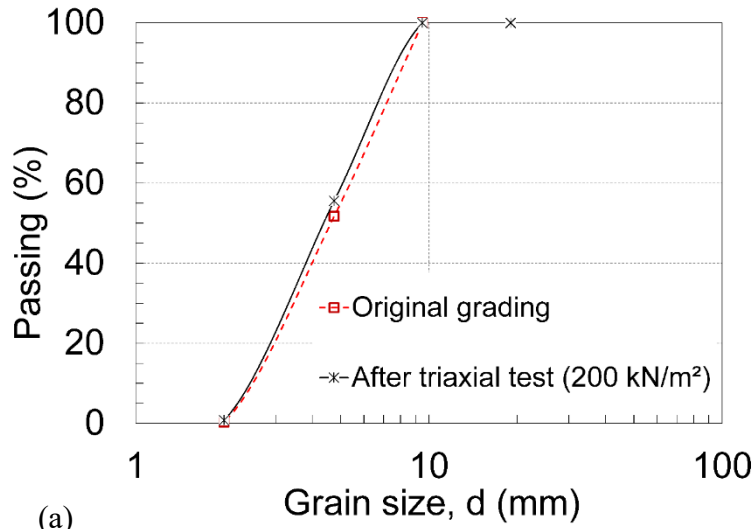


Figure 3.8 Particle size distribution curves before and after the triaxial test

(a) G1 (b) G2

Fig. 3.10 and Fig. 3.11 are the plots of deviatoric stress and volumetric strain against axial strain for GTCM specimens with GF=88% and GF=55% at relative density of $D_r=50\%$ and under different confining pressures.

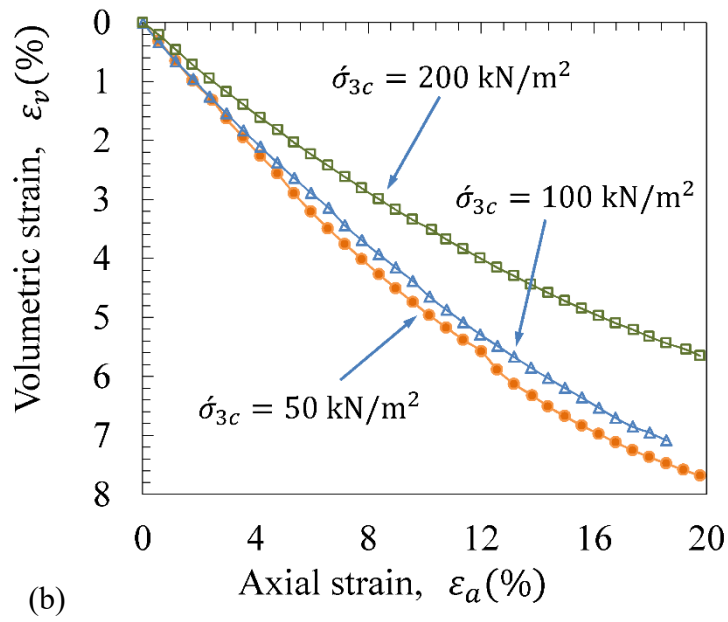
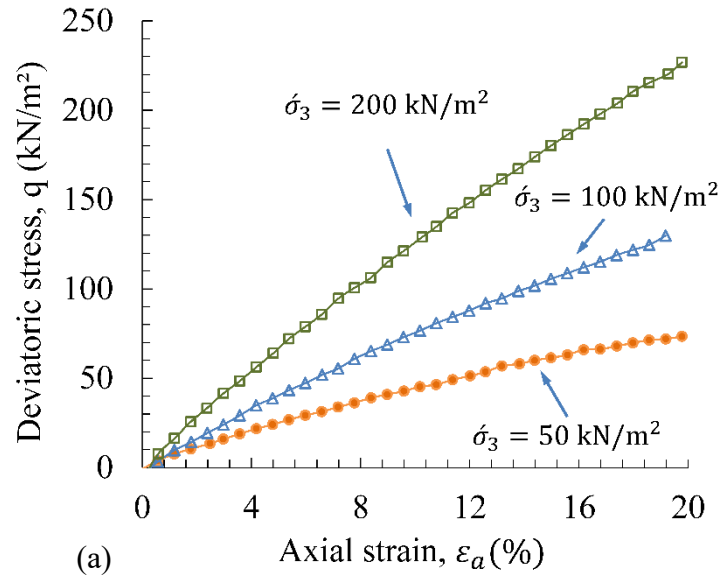


Figure 3.9 Influence of confining pressure on a) deviatoric stress-axial strain b) Volumetric strain-axial strain behaviour of GTCM with $G_f=0\%$ (TC1) and $D_r=50\%$.

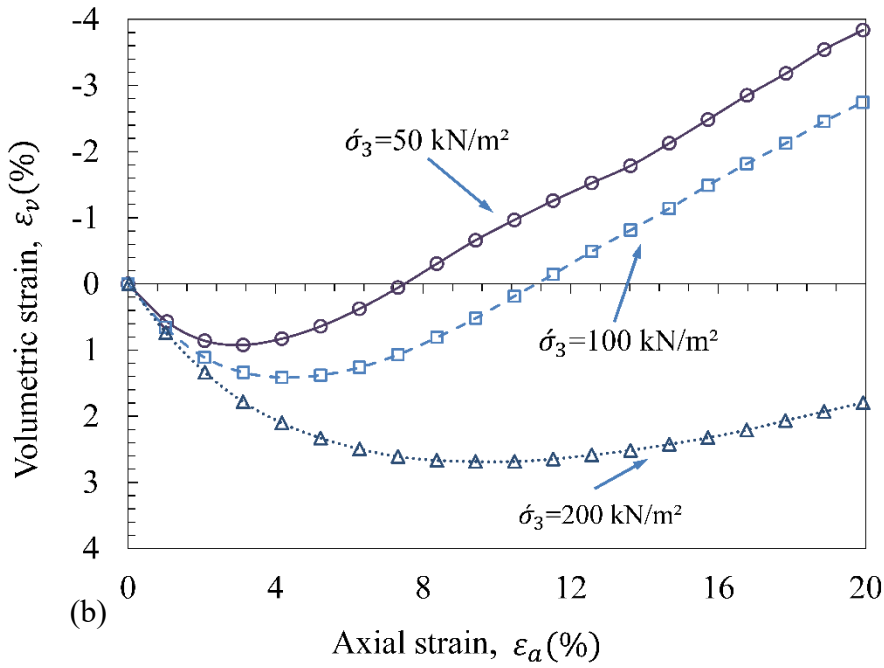
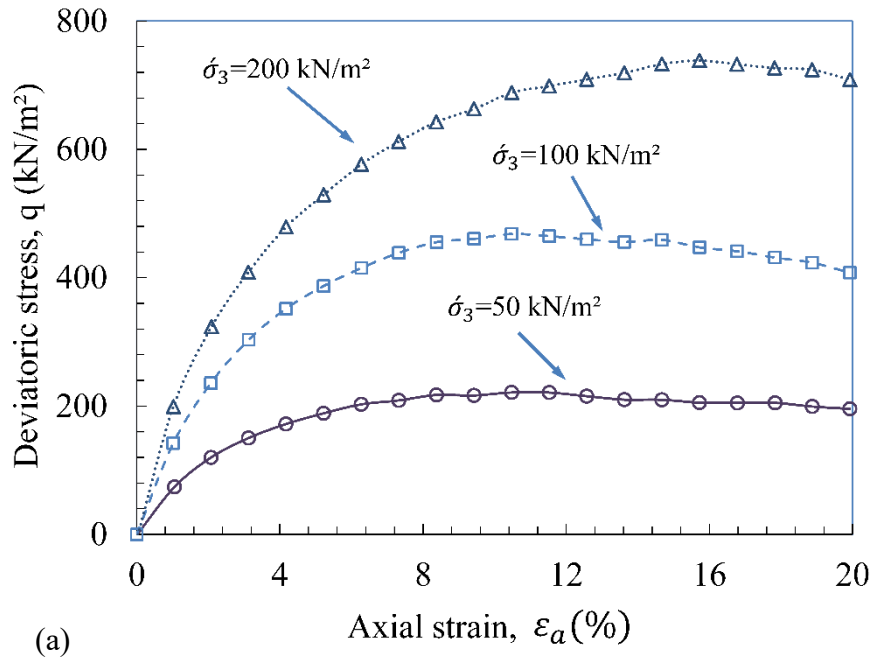
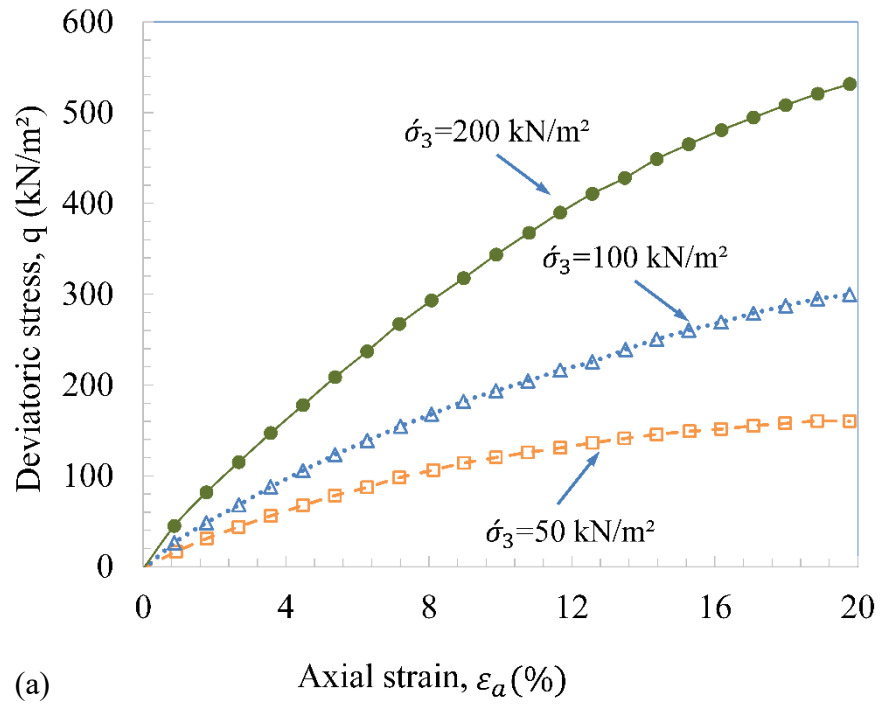
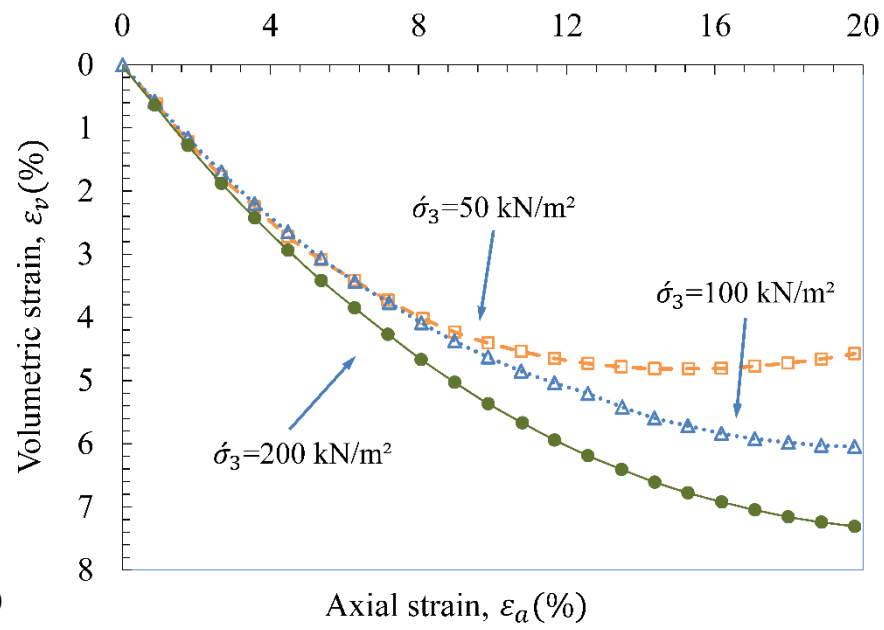


Figure 3.10 Influence of confining pressure on: (a) deviatoric stress-axial strain (b) Volumetric strain-axial strain behavior of G1TCH1 mixture at GF=87% and $D_r=50\%$.



(a)



(b)

Figure 3.11 . Influence of confining pressure on: (a) Deviatoric stress-axial strain (b) Volumetric strain-axial strain behavior of G1TCH1 mixture at GF=55% and $D_r=50\%$.

Pressure sensitivity of shear strength and volumetric strain behavior of GTCM can be investigated by considering relative movements between gravel and tire chips particles. Unlike rigid gravel particles, tire chips particles are highly deformable.

In GTCM samples, grain movements are a combination of particle slippage, rearrangement, crushing and deformation of tire chips particles. At high effective confining pressures, dilatancy is considerably suppressed due to the gravel particles crushing and deformation of tire chips particles rather than slippage and rearrangement of grains, which cause an increasing tendency for compression (see Fig.3.10).

As is evident, increases in confining pressure resulted in increased shear strength and deformation and consequently, an increase of axial strain at failure. GTCM specimens with GF=55% experienced contraction, which is followed by marginal dilation at higher axial strains. This contractive behavior was elevated by confining pressure due to deformation of tire chips particle and reduction of slippage and rearrangement of tire chips and gravel particles which decreased the dilatancy of GTCM (see Fig.3.11).

Aforementioned results are consistent with the findings from previous studies on mechanical behaviour of sand-tire chips mixtures (ex. (Zornberg et al. 2004; Sheikh et al. 2013; Noorzad and Raveshi 2017)).

3.3.1.3 Effect of relative density

The effect of relative density on deviatoric stress and volumetric strain against axial strain of GTCM with GF=100%, GF=55% and GF=0% are shown in Fig. 3.12, 13 and 14.

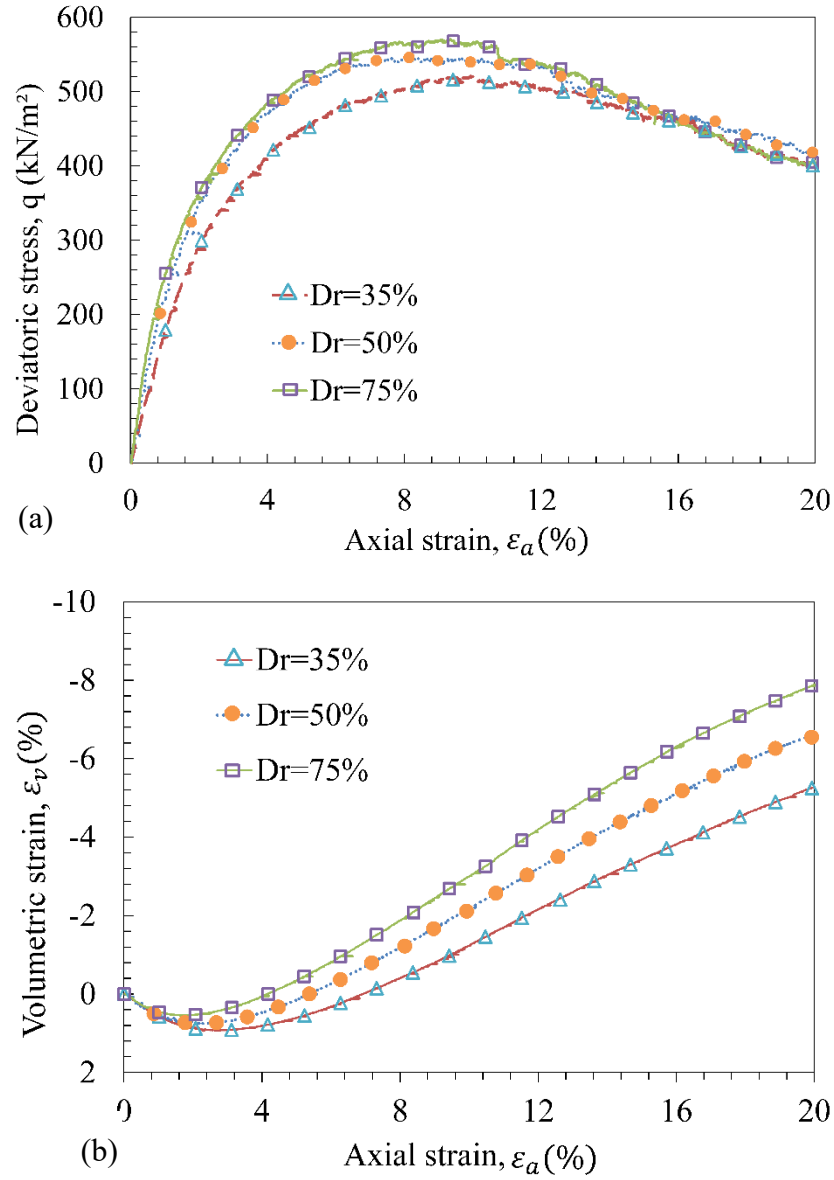


Figure 3.12 Influence of relative density on: (a) Deviatoric stress-axial strain (b)

Volumetric strain-axial strain behavior of G1TCH1 mixture with GF=100% at $\sigma_{3c} =$
100 kN/m².

Peak deviatoric stresses of GTCM specimens with Gf=100% increase 5% and 10% as the relative density of the mixture used increases from 35% to 50% and then to 75%, respectively while the effective confining pressure is 100 kN/m².

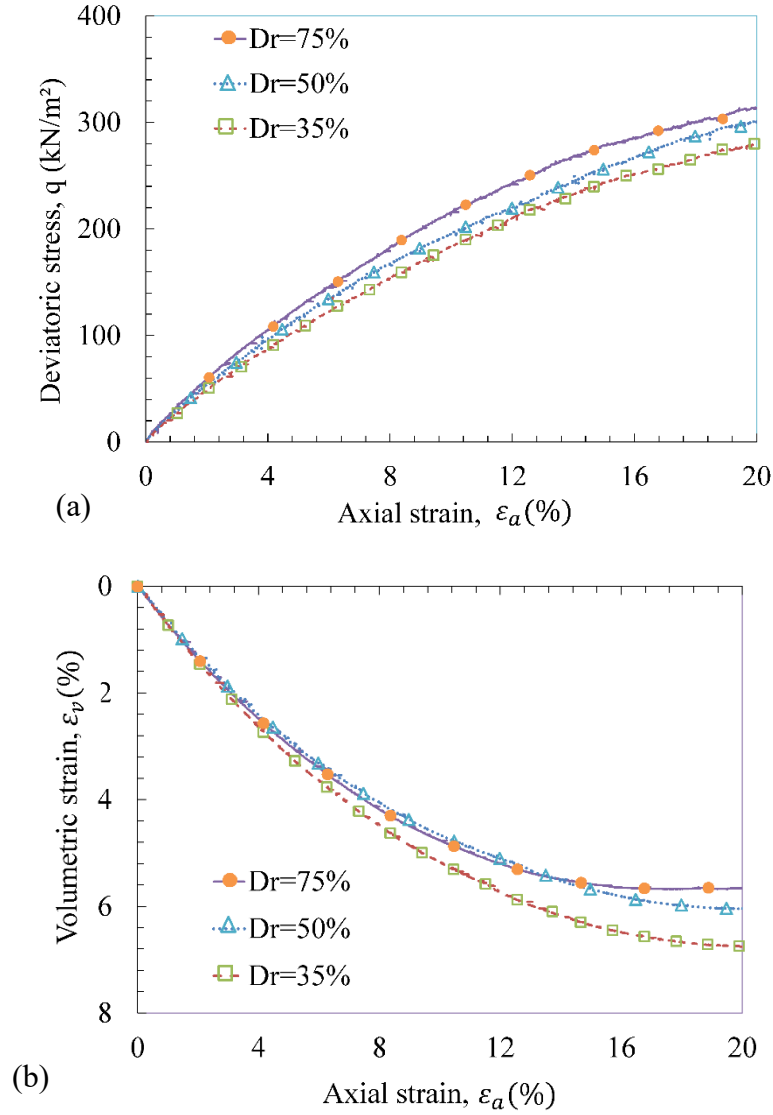


Figure 3.13 Influence of relative density on (a) Deviatoric stress-axial strain (b)

Volumetric strain-axial strain behavior of G1TCH1 mixture with GF=55% at $\sigma_3 =$
100 kN/m².

As can be seen from Fig. 3.13, dilation increases with an increase in relative density. The effect of relative density on shear and volumetric strain versus axial strain of GTCM specimens decreases with decreasing gravel fraction in mixture. As seen in Fig. 3.14, relative density has almost no influence on shear strength and dilatancy of GTCM with GF=0%.

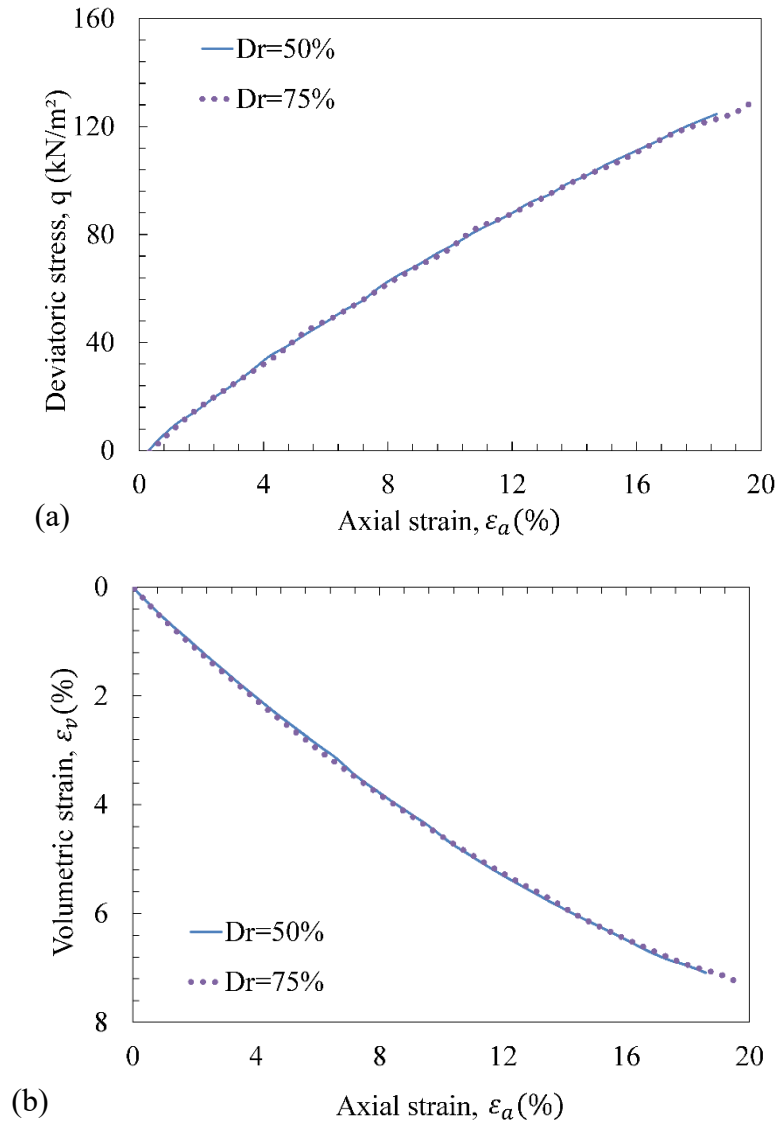


Figure 3.14 Influence of relative density on (a) Deviatoric stress-axial strain (b)

Volumetric strain-axial strain behavior of TCH1 at at $\dot{\sigma}_3 = 100 \text{ kN/m}^2$.

3.3.1.4 Effect of tire chips- gravel particle size ratio

Fig. 3.15 demonstrates the effect of $(D_{50,R}/D_{50,G})$ on stress-strain and dilation behavior of GTCM with different GF at a relative density of 50% and confining pressure of 100 kN/m^2 . G2TCH3 exhibits higher shear strength and dilation in comparison to that of G2TCH2. For GTCM specimens with $(D_{50,R}/D_{50,G})=3.35$, the

boundaries of gravel-tire chips like and tire chips like behavioral zones were moved toward lower values of gravel fraction in comparison to that of $(D_{50,R}/D_{50,G})=1.2$. For G2TCH3 mixture, specimens with $GF \geq 70\%$, $40\% \leq GF < 70\%$, and $GF < 40\%$ showed the features of gravel like behavior, gravel-tire chips like behavior and tire chips like behavior respectively.

Shear strength of GTCM with different gravel fraction ($GF=X\%$) was normalized by the shear strength of pure gravel ($GF=100\%$) at failure and is shown in Figure 3.16. It can be seen that GTCM specimens with $(D_{50,R}/D_{50,G})=3.35$ yields greater shear strength at failure in comparison to that of $(D_{50,R}/D_{50,G})=0.35$ and $(D_{50,R}/D_{50,G})=1.2$. As mentioned in previous sections, the packing phenomena occurred in GTCM samples with $(D_{50,R}/D_{50,G})=0.35$ and $(D_{50,R}/D_{50,G})=3.35$ in which void ratio continued to decrease as the percentage of small particles in the mixture increase to the optimal percentage. Therefore, it is possible that small particles provide lateral support for large particles by filling the voids between them and prevent particle slippage and buckling.

The percentage and size of tire chips in the mixture have significant impact on micro and macro mechanical behavior of specimens (Evans and Valdes 2011; Changho et al. 2014; Perez et al. 2017a; Lopera Perez et al. 2017b). However, the overall mechanical behavior of GTCM at micro-scale depends on gravel-gravel contacts rather than gravel-tire chips and tire chips-tire chips contacts. For GTCM specimens with particle size ratio of $(D_{50,R}/D_{50,G})=3.35$, gravel-gravel contacts outnumber gravel-tire chips and tire chips-tire chips contacts at GF higher than 70% and contributes effectively in transmission of stresses within the specimen. This would result in a system that can

sustain higher peak deviatoric stress at the macro-scale (Perez et al. 2017a; Perez et al. 2017b). On the other hand for GTCM specimens with $(D_{50,R}/D_{50,G})=1.2$ at $GF<87\%$, gravel-tire chips and tire chips-tire chips contacts provide more contribution to transmission of deviatoric stress.

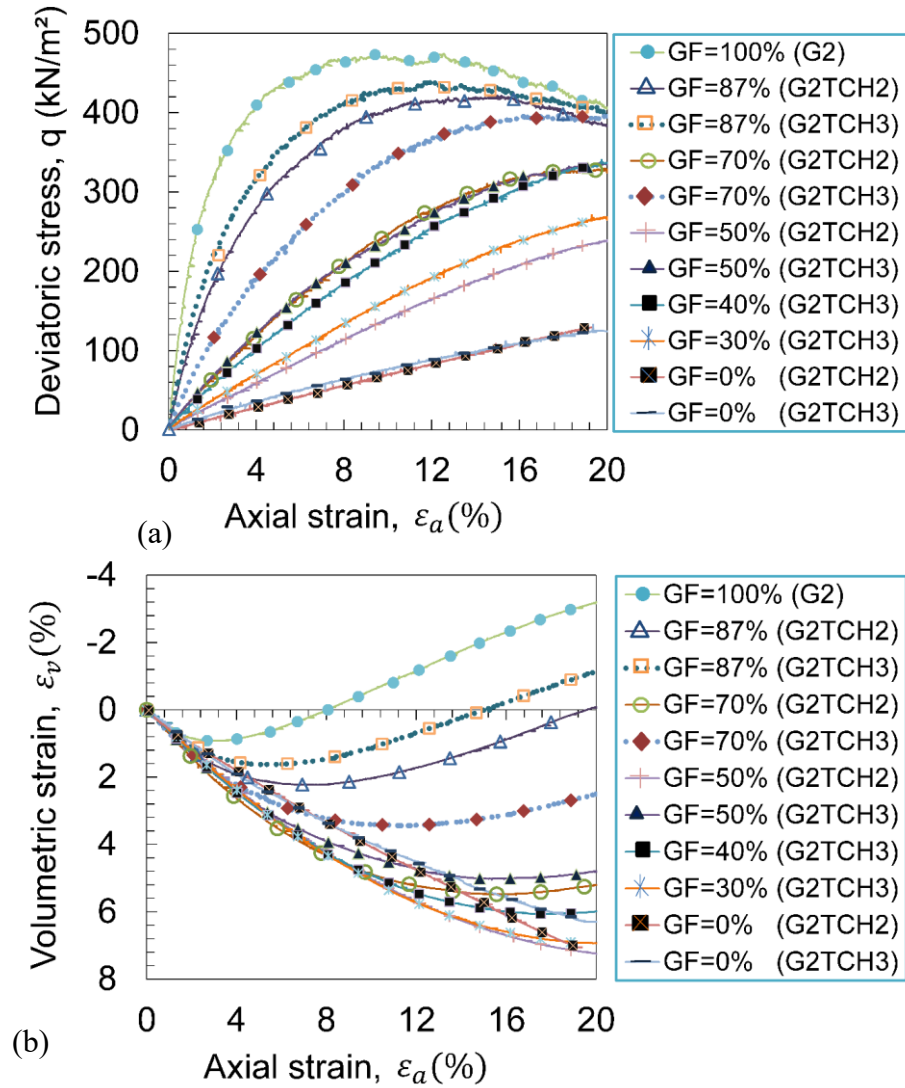


Figure 3.15 Influence of tire chips-gravel particle size ratio on: (a) Deviatoric stress-axial strain (b) Volumetric strain-axial strain behavior of GTCM with different GF at

$$\sigma_{3c} = 100 \text{ kN/m}^2 \text{ and } D_r=50\%.$$

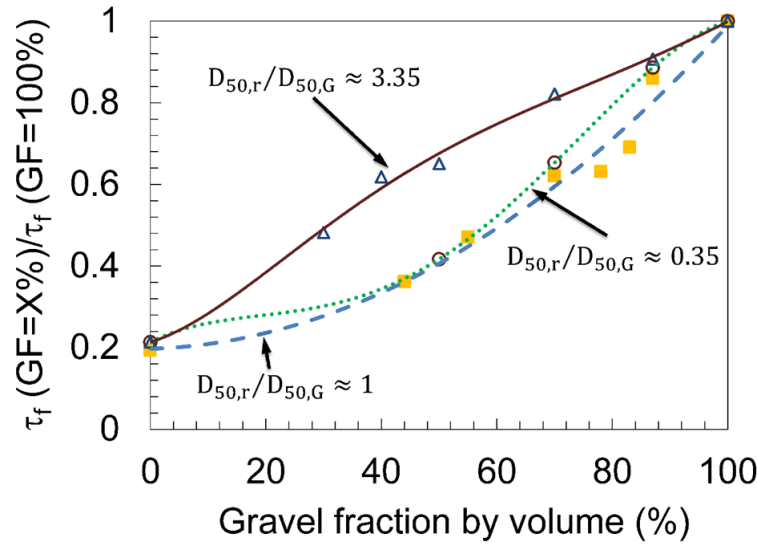


Figure 3.16 The effect of tire chips- gravel particle size ratio on normalized shear strength $\tau_f(\text{GF} = \text{X}\%)/\tau_f(\text{GF} = 100\%)$ of GTCM with different GF at $\sigma_{3c} = 100 \text{ kN/m}^2$ and $D_r=50\%$.

Therefore, force chain networks are formed through the contact between gravel particles rather than gravel-tire chips particles, and induce higher shear strength at failure.

3.3.1.5 Effect of drainage boundary condition

In order to study the effect of drainage boundary condition on stress and dilatancy behavior of binary mixture, a series of consolidated undrained triaxial compression tests were conducted on gravel (G1) and GTCM with different gravel fractions. The consolidated drained and undrained tests are indicated by the symbols “CD” and “CU”, respectively (see Fig. 3.17 and 18).

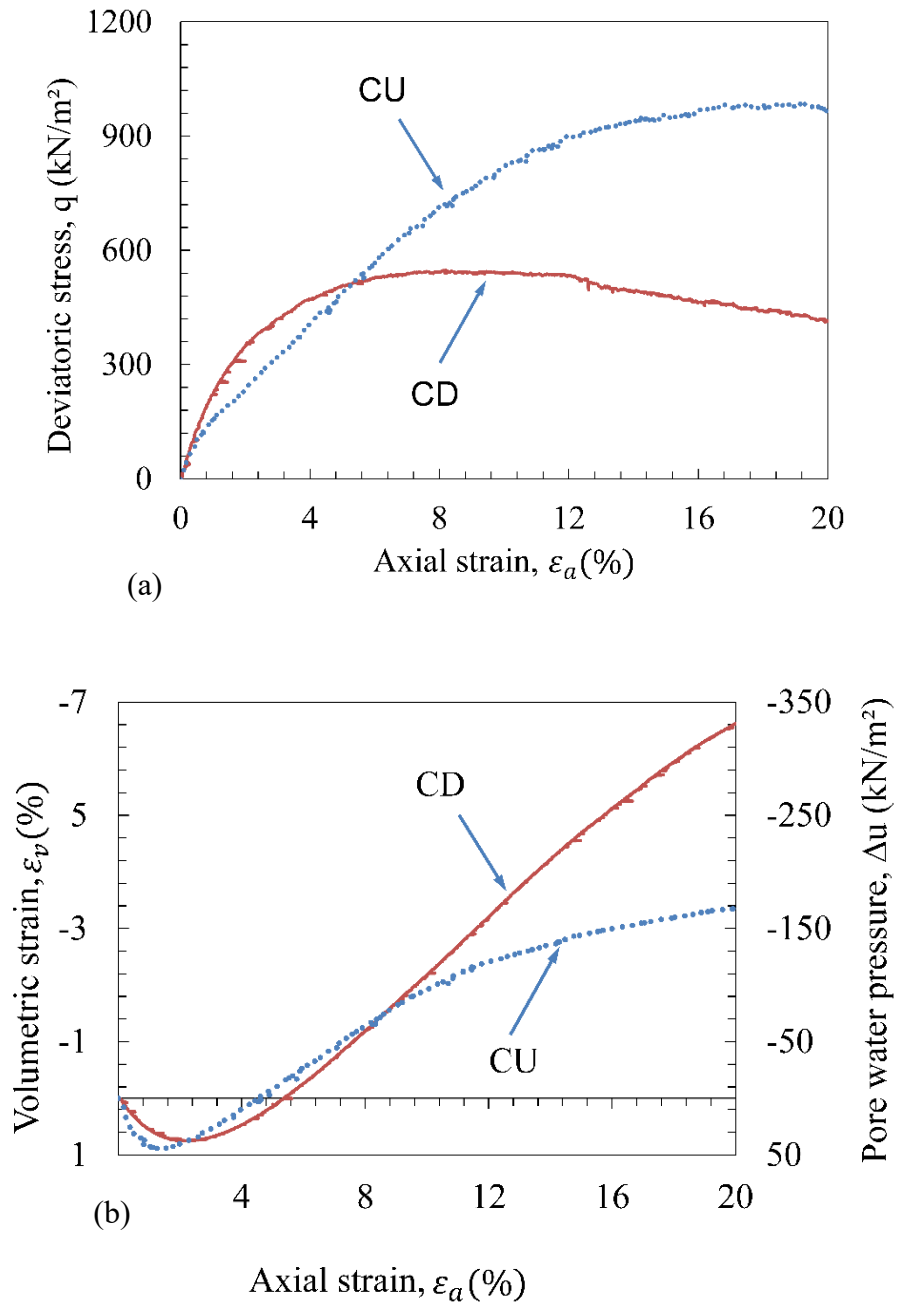


Figure 3.17 The effect of drainage condition on: (a) deviatoric stress-axial strain (b) Volumetric strain and pore water pressure-axial strain behavior of G1 at $D_r = 50\%$ and

$$\sigma_{3c} = 100 \text{ kN/m}^2.$$

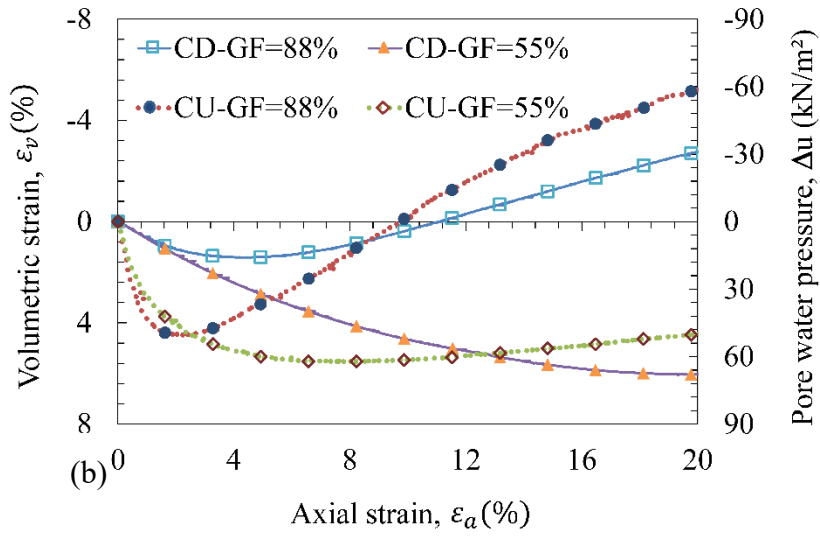
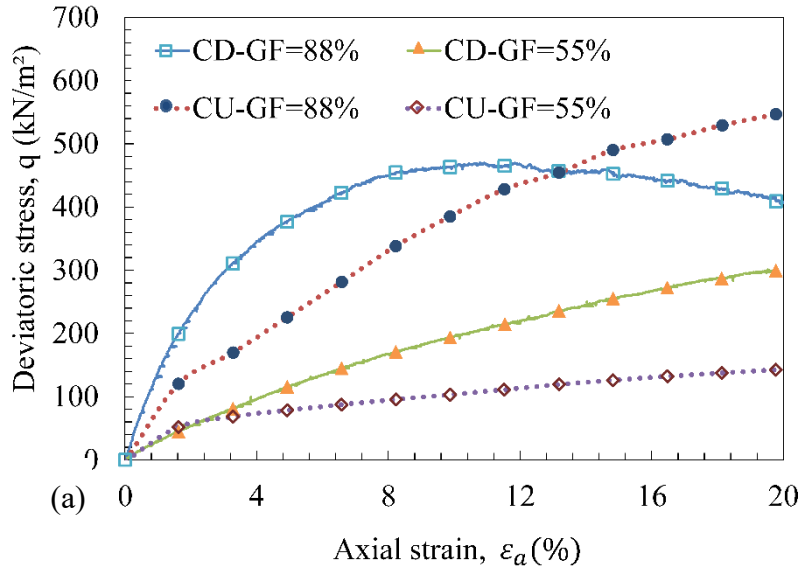


Figure 3.18 The effect of drainage condition on: (a) Deviatoric stress-axial strain

(b) Volumetric strain and pore water pressure axial strain behavior of GTCH1

mixture with GF=87% and GF=55% at $D_r = 50\%$ and $\sigma_{3c} = 100 \text{ kN/m}^2$.

It is evident that the axial strain required to mobilize peak deviatoric stresses are higher in the case of undrained samples in comparison to that of drained ones, and

furthermore the softening behavior was not as clear as the drained tests. The peak deviatoric stress of the undrained GTCM sample with GF=100% was 80 percent higher than the drained sample. As is mentioned earlier, gravel like behaviour was observed in the case of GTCM sample with GF=88%.

As seen in Fig. 3.18, peak undrained deviatoric stress at failure is 20% higher than that of the drained sample. Additionally in the undrained sample, water pore pressure changes from positive to negative where dilatancy changes from positive to negative in the drained sample.

In the case of GTCM with GF=55%, the buildup of water pore pressure during undrained shear loading causes reduction in stiffness and undrained peak shear strength up to almost 50% of the drained one.

3.3.2 TANGENT MODULUS

Initial tangent modulus, or initial slope, of the stress-strain plot of soil has been extensively studied. Based on theoretical considerations and large number of experiments, (Janbu 1963) found that initial tangent modulus can be estimated as function of effective confining pressure (Eq.3.12).

$$E_i = K_i \times P_a \times (\sigma_{3c}/P_a)^n \quad (3.11)$$

Where P_a is atmospheric pressure, K_i is modulus number and n is exponent number. For use in this study, Equation 3.5 was modified to include the effect of tire chips inclusion in GTCM on the value of the initial tangent modulus and is expressed by the following equation:

$$E_{i,GTCM} = K_{i,GTCM} \times P_a \times (\sigma_{3c}/P_a)^{n_r} \quad (3.12)$$

$$K_{i,GTCM} = K_0 + \alpha \times (G_f)^\beta \quad (3.13)$$

Where $K_{i,GTCM}$ is modified modulus number and was found to be function of gravel fraction (GF), n_r is an exponent number for a given relative density D_r and tire chips to gravel particle size ratio ($D_{50,R}/D_{50,G}$), K_0 is modulus number at GF=0%, α and β are calibration parameters (Table 3.2). As is evident from Fig. 3.19 and Fig. 3.20, predicted values were congruent with experimental values.

It can be observed from Fig. 3.19 that the effect of gravel fraction on initial tangent modulus was significantly reduced with the tire chips content in the mixture, especially for GTCM specimens with GF<55% where the tire chips form the skeleton of the material matrix.

As the effective confining pressure increases, contact between particles increases, which ultimately increases in the value of the initial tangent modulus in GTCM samples (see Fig. 3.20).

Table 3.2 Calibration parameters and constants for initial tangent modulus of GTCM

	D_r (%)	K_0	α	β	n_r
GTCM ($D_{50,r}/D_{50,G}=1$)	50	1.5633	240.23	3.1464	0.6526
GTCM ($D_{50,r}/D_{50,G}=0.35$)	50	5	218.47	6.7485	0.55

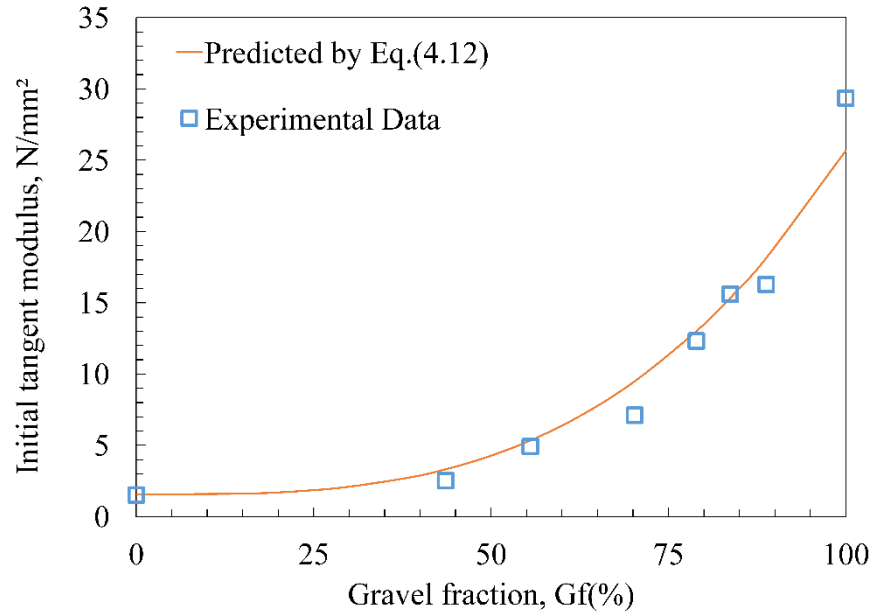


Figure 3.19 Variation of initial tangent modulus versus Gf (%) in the GTCM with

$$D_{50,r}/D_{50,G}=1.2 \text{ at } \sigma_{3c} = 100 \text{ kPa and } D_r = 50\% .$$

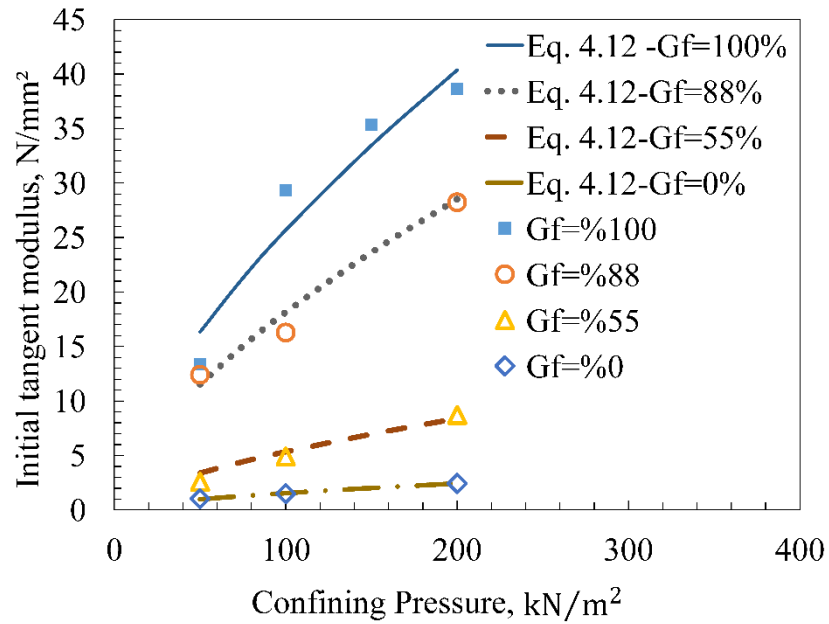


Figure 3.20 Variation of initial tangent modulus versus confining pressure (σ_{3c}) in

the GTCM with $D_{50,r}/D_{50,G}=1.2$ at $\sigma_{3c} = 100 \text{ kPa}$ and $D_r = 50\%$.

3.3.3 MOHR STRENGTH CRITERION OF GTCM

Shear strength of GTCM can be obtained using Mohr-Coulomb failure concept as follows:

$$\tau = c + \sigma \tan \phi \quad (3.14)$$

τ is the maximum shear stress and σ is the normal stress on the failure plane. The parameter c is the cohesion and ϕ is the friction angle of the soil, both empirical constants should be obtained from results of experiments.

Fig. 3.21 displays the Mohr circles of representative gravel (G1) with $D_r=50\%$ and GTCM ($D_{50,R}/D_{50,G} \approx 1.2$ with $G_f=55\%$). In the case of GTCM with $G_f=100\%$, the rise in the effective confining pressure (σ'_{3c}) gradually increases the particle crushing rate and eventually reduces the friction angle corresponding to peak shear strength. This can be seen as the apparent cohesion intercept (c_d) on shear strength-principle stress plot.

The effect of gravel fraction on shear strength parameters of GTCM with particle size ratio of ($D_{50,R}/D_{50,G} \approx 1.2$ and $D_r=50\%$ over the considered range of the effective confining pressure for the present study is plotted in Fig. 3.22, which depicts peak friction angle ϕ_p consistently decreases with decreasing gravel fraction in mixture. On the other hand, apparent cohesion intercept (c_d) increases with decreasing gravel fraction from 100 to 50% and continues to decrease with further decrease in gravel fraction.

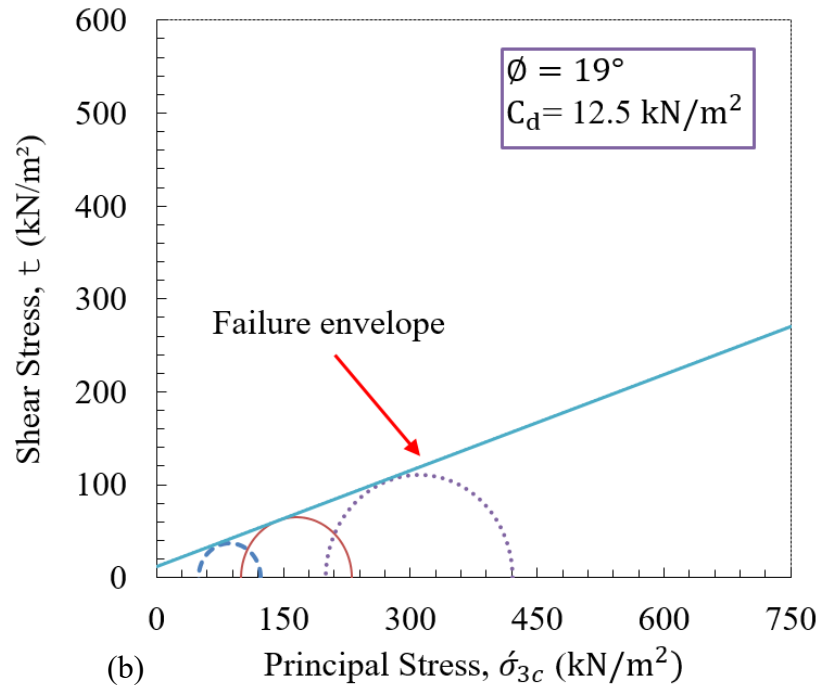
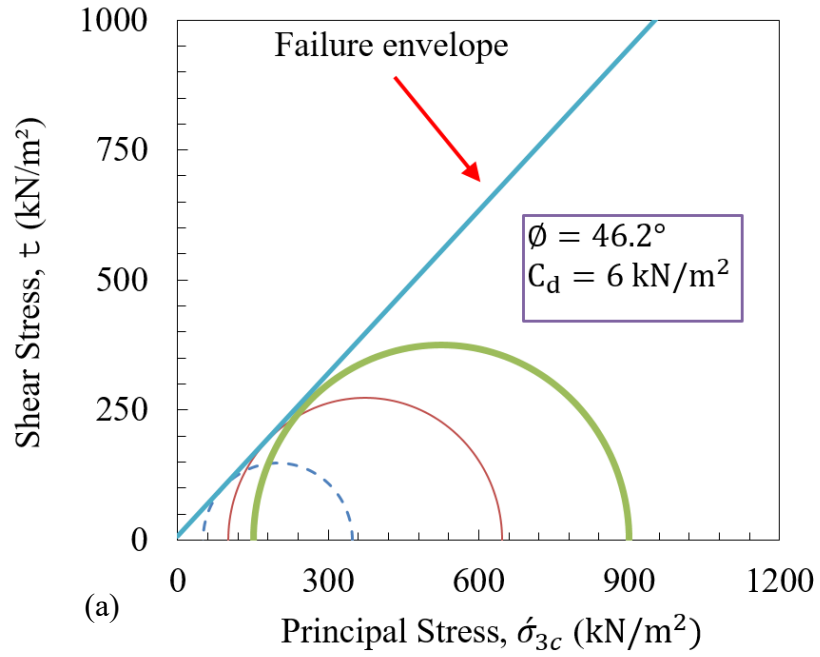


Figure 3.21 The Mohr's stress circles and failure envelope of GTCM with

$D_{50,r}/D_{50,G}=1.2$ and $D_r = 50\%$ (a) $G_f=100\%$ (b) $G_f=55\%$.

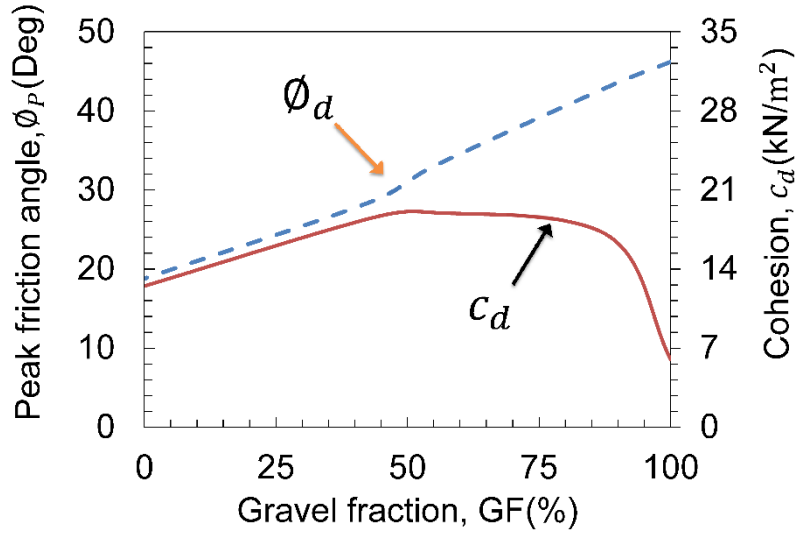


Figure 3.22 Evolution of shear strength parameters of GTCM with gravel

fraction, $D_{50,r}/D_{50,G} \approx 1.2$ and $D_r = 50\%$

3.3.4 STRESS-DILATANCY

Dilatancy is the principle characteristic of soil behavior which represents the tendency of soils to change volume during the shearing. Most elasto-plastic models incorporates stress-dilatancy relationship to predict soil behavior. However, limited studies can be found in literature to investigate stress-dilatancy feature of reinforced soil with STDm (e.g. Mashiri et al. 2015). The dilatancy rate ($\dot{D}$) was employed to characterize the stress-dilatancy feature of GTCM and can be expressed as follows:

$$\dot{D} = d\varepsilon_v/d\varepsilon_d \quad (3.15)$$

Where $d\varepsilon_v$ and $d\varepsilon_d$ are the volumetric and deviatoric strain increments, respectively. Figure 3.23 shows the stress ratio η plotted versus the dilatancy rate $\dot{D}$ of gravel G1 and G2 at the different relative density and effective confining pressure (σ'_{3c}). The results indicate an initial contraction ($\dot{D} > 0$) followed by dilation behavior

($\dot{D} < 0$). G1 exhibits slightly higher dilation tendency than G2 at higher stress ratio. It is evident from Figure 3.21 that the maximum stress ratio and dilatancy at peak state decreases with increasing (σ'_{3c}). Furthermore, the dilation of both gravel G1 and G2 slightly increases with the rise in the D_r .

Figure 3.24 displays the influence of GF on the dilatancy rate of representative GTCM specimens with $(D_{50,R}/D_{50,G})=1.2$. Dilatancy of GTCM decreases with decreasing GF in the mixture. The stress ratio at peak (η_{peak}) is plotted against minimum results of the dilatancy function ($\dot{D}_{min}$) (which occurs concurrently with peak strength) in Figure 3.25. A plausible trend line to fit η_{peak} and $\dot{D}_{min}$ based on following formula is drawn for the GTCM specimens with different gravel fraction (GF).

$$\eta_{peak} = \eta_0 - (1 - N) \dot{D}_{min} \quad (3.16)$$

Where N is dimensionless and density-independent material property. η_0 is the stress ratio at $\dot{D}_{min}=0$ and determined as the intercept of fitting line and the vertical axis. As can be seen from Figure 3.25 (a), η_0 and N decreases with decreasing GF. Furthermore, GTCM specimens with mean particle size ratio of $(D_{50,R}/D_{50,G})=3.5$ and $(D_{50,R}/D_{50,G})=0.35$ exhibit higher dilation in comparison to that of $(D_{50,R}/D_{50,G})=1$.

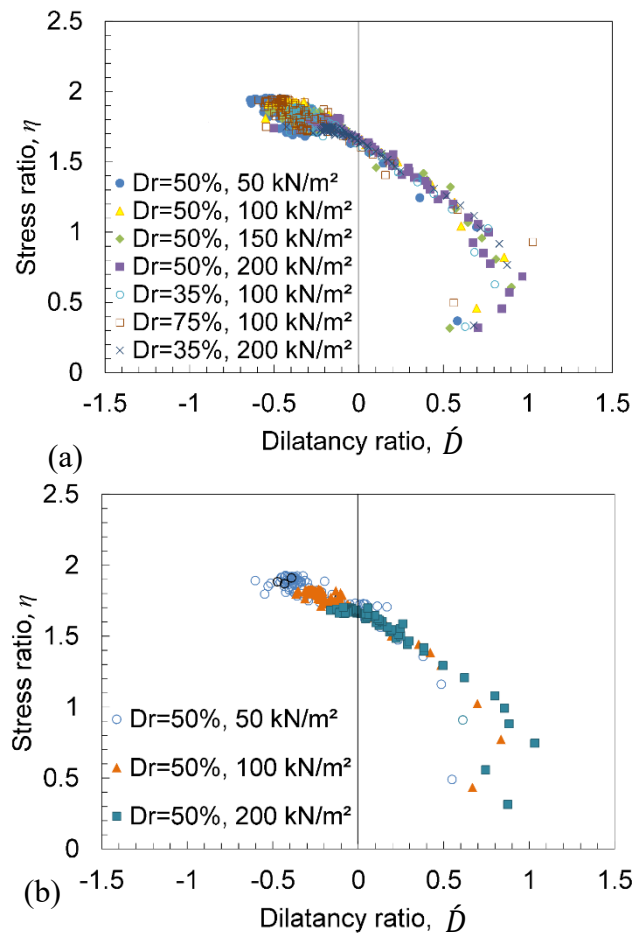


Figure 3.23 Stress-Dilatancy of the gravel at different relative density and confining pressure: (a) G1 (b) G2

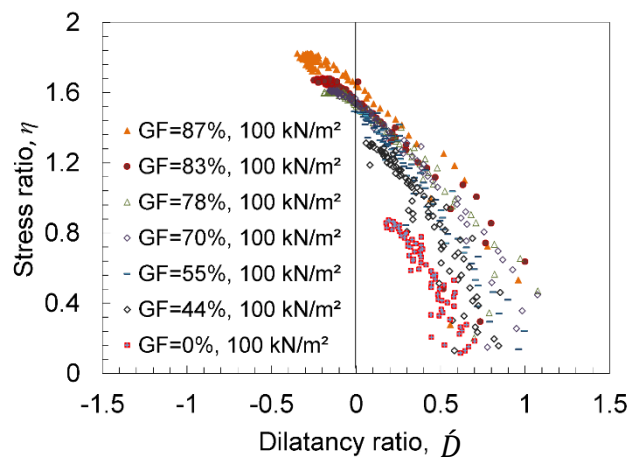


Figure 3.24 Stress-Dilatancy of the G1TCH1 mixture with different GF at $D_r = 50\%$ and $\sigma_3 = 100 \text{ kN/m}^2$

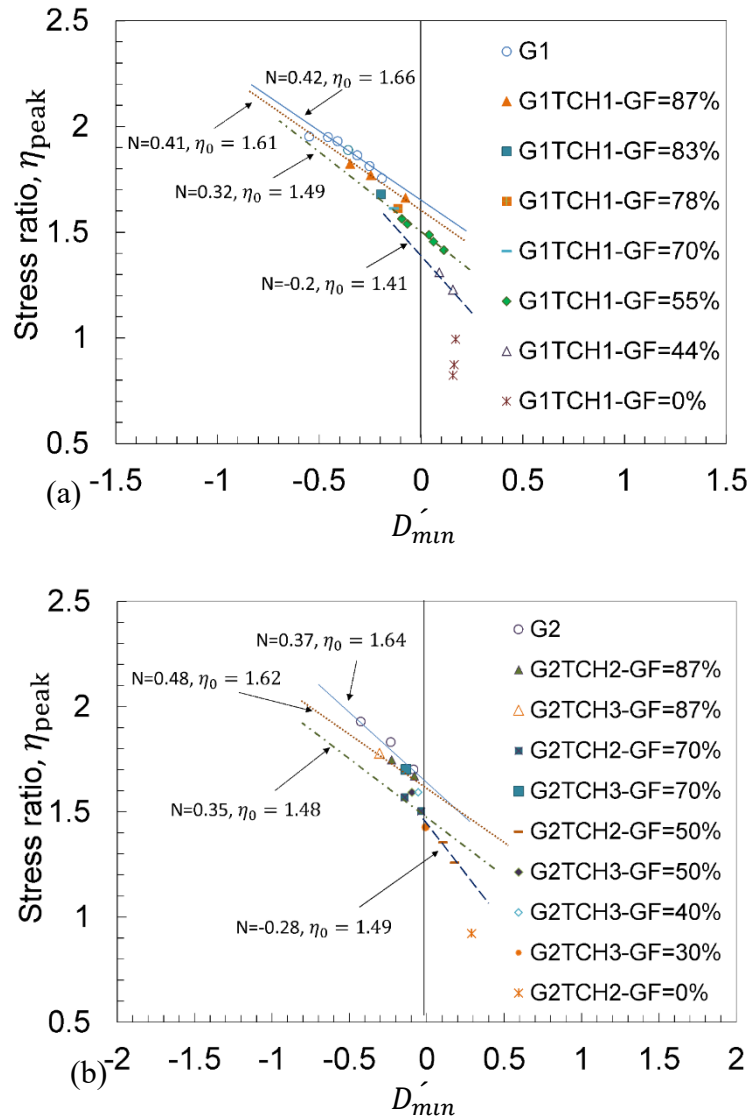


Figure 3.25 The relationship between the stress ratio and minimum dilatancy:

(a) G1TCH1 (b) G2TCH2 and G2TCH3

3.4 CONCLUSION AND SUMMARY

In this chapter the method used for setting up, saturation, and consolidation of specimens was presented for tests conducted on the triaxial apparatus. In this study, the triaxial compression tests were performed on consolidated drained and undrained specimens of GTCM at strain rate of 0.1%/min. The mathematical and theoretical

expressions used for analyzing the mechanical behavior of GTCM were also presented.

Mechanical properties of gravel and gravel-tire chips mixture was thoroughly investigated in this experimental study in order to examine its feasibility as an alternative geo-material for a wide range of geotechnical applications.

Two different type of gravel and three different type of tire chips with varying particle size and characteristics were tested. The effects of particle characteristics, degree of compaction, and gravel fraction in gravel-tire chips mixture (GTCM), effective confining pressure, drainage boundary condition on shear stress-strain response and other mechanical characteristics of GTCM were examined.

Results of present study can offer insight into major factors affecting physical and mechanical behavior of reinforced soil and should be taken into account in the construction field. The principle conclusions of this study are presented below:

- The soil particle characteristic, particularly whether the base soil is an inherently crushable or not, has an influence on the stress-strain, volumetric strain behavior and Young's modulus of gravel and GTCM. The aforementioned effect was found to be more determinative at higher effective confining pressures where soil would exhibit noticeable particle breakages. On the other hand, tire chips size was found to have almost negligible effect on shear strength of GTCM with GF=0%. However it might have minor influence on specimen's volume changes during shearing.
- Stress-strain and dilatancy behaviour of GTCM specimens are remarkably influenced by gravel fraction. Three distinguishable behavioral zones: gravel like behavior, gravel-tire chips like behavior and tire chips like behavior, have

been confirmed. The gravel like behavior zone can be described as a zone where GTCM displays well defined peak shear strength followed by a residual strength at higher axial strains due to domination of gravel particles in mixture. In the gravel-tire chips like zone, neither gravel or tire chips is dominant in mixture. GTCM exhibits gravel-tire chips like behavior with almost indistinct peak shear strength and a reduction in dilatancy was observed. In the tire chips like zone, tire chips particles form GTCM matrix and as a result, considerable reduction in shear strength associated with highly contractive behavior was observed. The boundaries where behavioral zones are separated could be controlled by several factors such as particle characteristics, size ratio ($D_{50,R}/D_{50,G}$) and confining pressure.

- The effect of relative density on improving the shear strength and increasing the dilation behavior of GTCM reduces with decreasing gravel fraction in mixture. Relative density almost has no influence on stress strain and dilatancy of GTCM with GF=0%.
- GTCM specimens with larger tire chips-gravel particle size ratio ($D_{50,R}/D_{50,G}$) yield a larger shear strength at given relative density and confining pressure. The lower the particle size ratio ($D_{50,R}/D_{50,G}$) the greater specific surface area of tire chips grains, which means more tire chips to tire chips particle contacts. This can be attributed to relatively low shear strength of GTCM with lower particle size ratio.
- The rise in the confining pressure enhances peak shear strength and initial tangent modulus of GTCM and such a tendency is prominent at a higher gravel

fractions. Peak friction angle decreases with a decreasing gravel fraction in GTCM. However, apparent cohesion decreases when gravel fraction is between 0 and 50%.

REFERENCES

- Agustian, Y. & Goto, S. (2008). Strength and deformation characteristics of scoria in triaxial compression at low confining stress. *Soils and Foundations*, 48(1): 27-39.
- Benda, C. C. (1995). *Engineering Properties of Scrap Tires Used in Geotechnical Applications: Report 95-1, February 1995*. Vermont Agency of transportation.
- Bishop, A. W. & Blight, G. E. (1963). Some Aspects of Effective Stress in Saturated and Partly Saturated Soils. *Géotechnique*, 13(3): 177-197.
- Changho, L., Hosung, S. & Jong - Sub, L. (2014). Behavior of sand–rubber particle mixtures: experimental observations and numerical simulations. *International Journal for Numerical and Analytical Methods in Geomechanics*, 38(16): 1651-1663.
- Evans, T. M. & Valdes, J. R. (2011). The microstructure of particulate mixtures in one-dimensional compression: numerical studies. *Granular Matter*, 13(5): 657-669.
- Foose, G. J., Benson, C. H. & Bosscher, P. J. (1996). Sand Reinforced with Shredded Waste Tires. *Journal of Geotechnical Engineering*, 122(9): 760-767.
- Gotteland, P., Lambert, S. & Balachowski, L. (2005). Strength characteristics of tyre chips-sand mixtures. *Studia geotechnica et mechanica*, 27(1-2): 55-66.
- Hardin, B. O. (1985). Crushing of Soil Particles. *Journal of Geotechnical Engineering*, 111(10): 1177-1192.
- Hazarika, H. & Abdullah, A. (2016). Improvement effects of two and three dimensional geosynthetics used in liquefaction countermeasures. *Japanese Geotechnical Society Special Publication*, 2(68): 2336-2341.
- Janbu, N. (1963). Soil compressibility as determined by odometer and triaxial tests. *Proc. European Conf. Soil Mech. Found Eng., Wiesbaden*, 119-25.
- Kaushik, M. K., Kumar, A. & Bansal, A. (2015). Performance Assessment of Gravel–Tire Chips Mixes as Drainage Layer Materials Using Real Active MSW Landfill Leachate. *Geotechnical and Geological Engineering*, 33(4): 1081-1098.

- Ladd, R. (1978). Preparing Test Specimens Using Undercompaction. *Geotechnical Testing Journal*, 1(1): 16-23.
- Lade, P. V. (2016). *Triaxial testing of soils*. John Wiley & Sons, Ltd, United Kingdom.
- Lade, P. V., Yamamuro, J. A. & Bopp, P. A. (1996). Significance of Particle Crushing in Granular Materials. *Journal of Geotechnical Engineering*, 122(4): 309-316.
- Liu, J., Zou, D., Kong, X. & Liu, H. (2016). Stress-dilatancy of Zipingpu gravel in triaxial compression tests. *Science China Technological Sciences*, 59(2): 214-224.
- Lopera Perez, J. C., Kwok, C. Y. & Senetakis, K. (2017b). Micromechanical analyses of the effect of rubber size and content on sand-rubber mixtures at the critical state. *Geotextiles and Geomembranes*, 45(2): 81-97.
- Mashiri, M. S., Vinod, J. S., Sheikh, M. N. & Tsang, H. H. (2015). Shear strength and dilatancy behaviour of sand-tyre chip mixtures. *Soils and Foundations*, 55(3): 517-528.
- Noorzad, R. & Raveshi, M. (2017). Mechanical Behavior of Waste Tire Crumbs–Sand Mixtures Determined by Triaxial Tests. *Geotechnical and Geological Engineering*, 35(4): 1793-1802.
- Perez, J. C. L., Kwok, C. Y. & Senetakis, K. (2017a). Investigation of the micro-mechanics of sand–rubber mixtures at very small strains. *Geosynthetics International*, 24(1): 30-44.
- Shahnazari, H. & Rezvani, R. (2013). Effective parameters for the particle breakage of calcareous sands: An experimental study. *Engineering Geology*, 159 (Supplement C): 98-105.
- Sheikh, M. N., Mashiri, M. S., Vinod, J. S. & Tsang, H.-H. (2013). Shear and Compressibility Behavior of Sand & Tire Crumb Mixtures. *Journal of Materials in Civil Engineering*, 25(10): 1366-1374.
- Yang, S., Lohnes, R. & Kjartanson, B. (2002). Mechanical Properties of Shredded Tires. *Geotechnical Testing Journal*, 25(1): 44-52.
- Zornberg, J. G., Cabral, A. R. & Viratjandr, C. (2004). Behaviour of tire shred – sand mixtures. *Canadian Geotechnical Journal*, 41(2): 227-241.

CHAPTER 4

DYNAMIC CHARACTERISTICS AND LIQUEFACTION RESISTANCE OF GRAVEL TIRE CHIPS MIXTURE

4.1 INTRODUCTION

There are few natural hazard that can have catastrophic consequences and be unpredictable as earthquake, yet evidence exists for repeating disasters in the same location. Many countries around the world have suffered from earthquake in the history. Historical records of destruction caused by earthquakes in Japan can be dated back to 1,300 years ago. In the japan there is an average of 2 earthquake with magnitude of $M=1.5$ per day.

However, unlike unpreventable nature of earthquakes, their impact on life, property and economy could be managed. In recent years, disaster mitigation efforts are concentrated on improving design methods, building codes, gaining knowledge of structure's behaviour under extreme load of earthquake and developing novel technical means to mitigate the risk to the buildings, property and environment from the earthquake ground motion. However, the key issue in most of developing and developed countries is to find a balance between the economic costs of seismic mitigation measures, reliability and environmental impacts (Hazarika et al. 2018).

About 1 billion waste tires are generated and discarded in all over the world

annually. Considerable amount of those waste tires are used for energy production purposes. However this can increase emission of hazardous gases such as CO, CO₂ and SO₂ to the atmosphere. Reusing waste tire materials as Scrap Tire Derived Materials (STDMS) can reduce CO₂ release and help preserving our ecosystem. Nowadays, STDMS are being adopted in several civil engineering applications as alternative non-dilative geomaterials with growing advance (Lee et al. 1999; Hazarika et al. 2010; Kaushik et al. 2015).

Previous studies on the use of STDMS in civil and geotechnical applications have shown that sand-STDMS can be considered as a promising ground improvement method for preventing seismic and liquefaction induced structural damage during earthquake (Hazarika et al. 2006; Hazarika et al. 2008; Tsang 2008; Hazarika and Abdullah 2016; Otsubo et al. 2016).

Low hydraulic conductivity of sand and sand-STDMS mixtures, high liquefaction susceptibility of sand, high particles segregation potential of sand and STDMS in binary mixture, low bearing capacity of sand-STDMS mixture are some of the key issues associated with utilization of sand-STDMS mixture in geo-structures (Mashiri et al. 2015; Anvari and Shooshpasha 2016).

Gravel-Tire Chips Mixture (GTCM) is introduced by (Hazarika and Abdullah 2016) with the goal of providing solution for drawbacks of existing methods. Previous studies have already shown that gravelly soil possess higher permeability in comparison to that of sandy soil (e.g. Sherard et al. 1984). In addition, footings constructed on gravelly soil yields higher bearing in comparison to that of sand (Bowles 1988).

Design, construction and maintenance of structures constructed on the GTCM needs an understanding of dynamic behaviour of these materials. However, there is a lack of study on the dynamic properties of GTCM at the range of medium to large shear strains. ($\gamma > 0.05\%$).

Therefore, the liquefaction resistance and dynamic characteristics such as shear modulus and damping ratio of the GTCM were roughly investigated at range of medium to large shear strains.

4.2 APPARATUS, EQUIPMENT AND LAYOUT OF EXPERIMENTS FOR CYCLIC TRIAXIAL TESTING

In this section, the most influential parameters on dynamic behaviour of GTCM are defined and then layout of conducted cyclic triaxial tests are presented in detail. In addition, the specimen preparation and testing methodology for cyclic triaxial tests such as specimen setup, saturation, and consolidation and shearing under cyclic loading are also thoroughly explained.

4.2.1 SELECTION OF PARAMETERS AND LAYOUT OF EXPERIMENTAL TESTS

List of determinative parameters on the mechanical behaviour of GTCM is already given in Table 4.1. As is shown in chapter4, gravel fraction ($GF = V_{Gravel}/V_T$) and degree of compaction (D_r) were found to have the most and the least influence on monotonic behaviour of GTCM. Therefore this study aims to investigate the effects of gravel fraction ($GF = V_{Gravel}/V_T$) in gravel-tire chips mixture (GTCM) and

effective confining pressure (σ'_{3c}) on dynamic characteristics and liquefaction resistance of gravel and GTCM. Table 4.1 lists the parameters and testing conditions on the gravel tire chips mixture.

Table 4.1 GTCM specimens testing conditions and list of parameters

List of parameter/ Testing condition	Range of variation
Gravel fraction ($GF = V_{Gravel}/V_T$), %	$30 \leq G_F \leq 100$
Tire chips–gravel particle size ratio ($D_{50,R}/D_{50,G}$)	1.2
Degree of compaction (D_r), %	50%
Effective confining pressure (σ'_{3c}), kN/m ²	50, 100, 200
Stress ratio ($CSR = \sigma_d/2\sigma_3$)	$0.1 \leq CSR \leq 0.45$
Drainage boundary condition	Undrained

4.2.2 CYCLIC TRIAXIAL TESTING APPARATUS

The cyclic triaxial tests were conducted in large diameter cyclic triaxial testing system by Marutani Testing Machine Company. The machined equipped with hydraulic servo actuator that can apply uniform cyclic loading with the maximum loading capacity of 1 kN and the frequency in the range of 0.001 to 5Hz.

The machine also utilized displacement transducer with resolution of 0.1 microns, and volume change measuring transducer with capacity of 50 cm³. The cyclic triaxial system is facilitated by a 6-channel data logger with 16 bit data acquisition.

A code written in Visual basic environment was used for data acquisition and

controlling servo-hydraulic loading system. The schematic view of triaxial apparatus and equipment is shown in Fig. 4.1. The triaxial apparatus could conduct test on specimens of 38 to 100 mm in diameters.

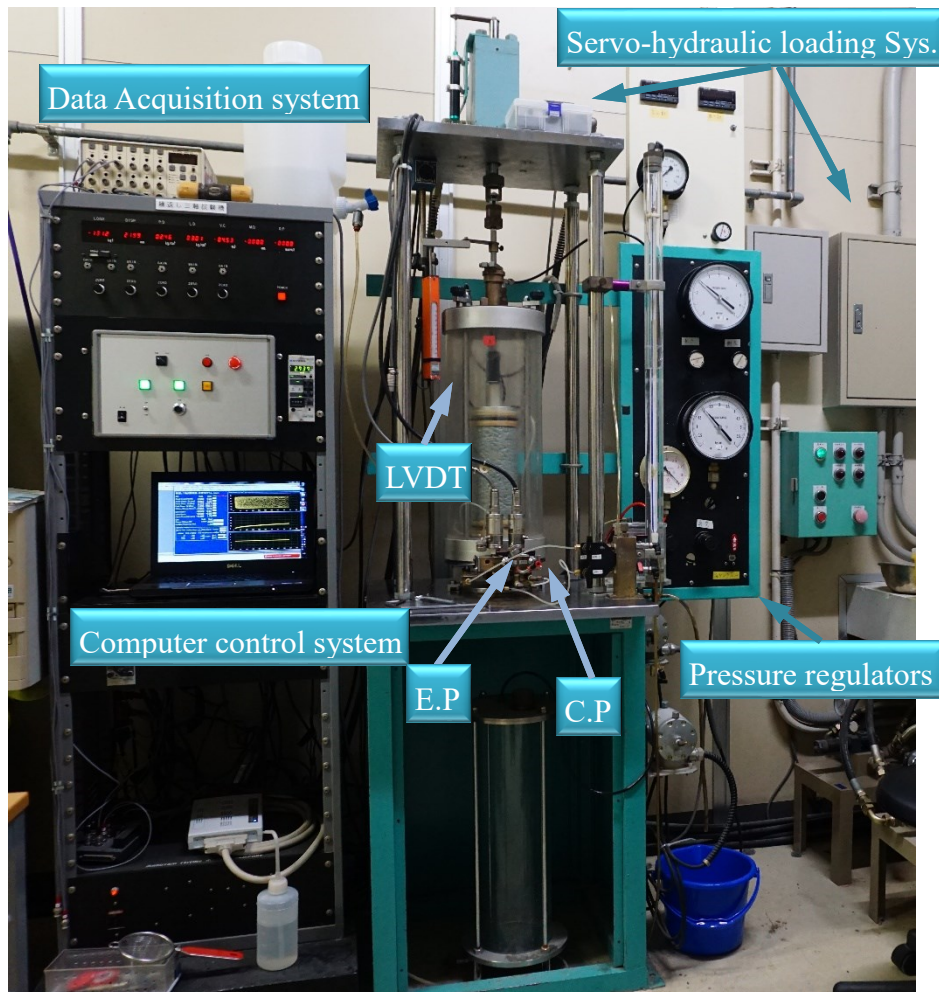


Figure 4.1 Schematic view of triaxial apparatus

4.2.3 SPECIMEN PREPARATION

The cyclic triaxial tests were carried out on the gravel and GTCM specimens prepared in a split mold with an inner diameter of 100.6 mm and height of 200 mm.

In First step, a non-porous latex rubber membrane (with the thickness of 0.3mm) was attached to the pedestal of cyclic triaxial apparatus and secured in place by rubber O-rings. Split mold was placed around the membrane and secured in place with a pair of fasteners. A small vacuum was applied to the mold. This vacuum seals the membrane to the mold's wall and decreases friction between the soil and membrane. A filter paper was placed on top of pedestal's porous stone.

The GTCM specimens were prepared using the under-compaction method (Ladd 1978). Mixtures of desired relative densities were obtained by measuring weights of gravel and tire chips, then they were mixed carefully by hand, placed into the mold and compacted into 10 layers. Another filter paper was placed on the top of sample and top cap was fixed in place by screws.

At the next step, membrane fold over around the top cap and sealed in place with rubber bands and O-rings. A small vacuum is applied to the drainage lines to create an effective confining pressure on the specimen before removing the forming mold. It should be noted that removing the mold vacuum and applying a vacuum to the sample was done simultaneously.

Next step, the height and diameter of specimen was carefully measured using a Vernier caliper with resolution of 0.1 mm. Before starting the saturation process, CO₂ was allowed to flow through with a slow rate from bottom of specimen and flush out air trapped in specimen. Samples were saturated by allowing de-aired water to flow

through from bottom of the sample. The back pressure technique was adopted to enhance the degree of saturation of samples.

The cell pressure and back pressure were simultaneously increased by an increment of 5 kPa per minute to maintain the effective confining pressure constant. A 200 kPa backpressure was found to be sufficient to dissolve any small amount of air in the pore water.

In this study, the degree of saturation was measured by closing the back pressure inlet and increasing the cell pressure gradually by 50 kPa in very small steps (1 kPa). Then Skempton's B value is calculated from Eq. 4.1. Full saturation was assumed to be achieved when Skempton's B parameter ($\Delta u / \Delta \sigma_3$) was greater than 0.95.

An isotropic consolidation pressure was applied to samples, while maintaining constant initial backpressure (200 kN/m²). During consolidation, an axial load was applied to specimen to counter-balance uplift due to increasing the cell pressure. It should be noted that the consolidation pressure was applied incrementally in very small steps to provide sufficient time to adjust the counterbalanced load. The specimen was allowed to drain from the backpressure inlet till measured changes in height and volume of specimen volume were less than 0.01 mm and 0.1 ml respectively.

Stress controlled cyclic triaxial tests were carried out by exerting extension and compression loads using a hydraulic piston. After the consolidation and before applying the cyclic load, drainage valves to the specimen were closed and axial displacement were set to zero. Specimen was cyclically loaded using a 0.1 Hz sinusoidal load form where the stresses varies between peak compression and extension values.

The cyclic load was applied to specimen until either cyclic double amplitude strain exceeds 20% or the number of load cycles exceeds 1000. Following the cyclic testing, specimen was carefully removed from triaxial setup, then dried for determining the mass for dry unit weight calculations.

4.2.4 MATHEMATIC FORMULAE FOR THE ANALYSIS OF UNDRAINED CYCLIC TRIAXIAL TESTS

Following mathematical formulas were used for the analysis of the cyclic triaxial test results:

$$\varepsilon_1(\%) = \frac{\Delta L_1}{L_1}, \varepsilon_3(\%) = \frac{\Delta L_3}{L_3}, \varepsilon_v(\%) = \frac{\Delta V}{V_0} \quad (4.1)$$

$$\varepsilon_v(\%) = \varepsilon_1 + 2\varepsilon_3 = 0 \quad (4.2)$$

$$\varepsilon_3 = -\frac{1}{2}(\varepsilon_1) \quad (4.3)$$

Where ε_1 , ε_3 and ε_v are axial strain, radial strain and volumetric strain respectively.

$$\sigma'_3 = \sigma_3 - \Delta u \quad (4.4)$$

$$q = \sigma_1 - \sigma'_3 \quad (4.5)$$

$$\varepsilon_q = \frac{2}{3}(\varepsilon_1 - \varepsilon_3) = \varepsilon_1 \quad (4.6)$$

$$\gamma = \frac{3}{2}\varepsilon_q \quad (4.7)$$

$$\tau_{max} = \frac{q}{2} \quad (4.8)$$

Where σ_3 (kN/m²), σ'_3 (kN/m²) and Δu (kN/m²) are confining pressure, effective confining pressure and excess pore water pressure respectively. q (kN/m²) and ε_q (%) are deviatoric stress and strain respectively. p' (kN/m²) and τ_{max} are effective mean stress and maximum shear strength respectively.

4.3 RESULTS AND DISCUSSION

4.3.1 STRESS PATHS

4.3.1.1 Effect of gravel fraction

Fig. 4.2. and Fig 4.3. , present typical results of cyclic triaxial tests carried out on GTCM specimens with initial relative density of 50% at an effective confining pressure of 100 kPa.

As it is evident, the effective mean stress (p') decreases with cyclic deviator stress (q), however none of the GTCM samples did reach the state of zero mean effective stress at the conclusion of cyclic loading . Therefore, it can be concluded that initial liquefaction of GTCM samples were not achieved. The decrease in the effective mean stress (p') occurs due to the rapid generation of excess pore water pressure during stress controlled cyclic loading.

For GTCM specimens with GF=100% and GF=87%, strain softening occurrence starts from very first cycle of loading. The subsequent unloading from the peak point of deviatoric stress leads to extensive increase in pore water pressure moving the GTCM towards to state of zero mean effective confining pressure. Reloading in the

extension region of the stress cycle causes the GTCM to undergo further deformation and its mean effective stress moves along failure envelope. Repetition of loading and unloading cycles causes a progressive increases in cyclic deformation following rapid loss of shear strength due to the accumulation of excess pore water pressure. This mechanism of the failure is similar to that of flow failure.

In the case of GTCM specimens with $GF=44\%$ and $GF=30\%$, the cyclic deformation increases progressively due to the gradual increase in pore water pressure without strain softening. It should be noted that the magnitude of permanent deformations depends on the duration of loading and for the samples subjected to the cyclic loadings of long duration, cyclic mobility can generate damaging levels of soil deformations (Kramer 1996). The medium dense and dense sandy and gravely soils show similar liquefaction behavior under cyclic loading. This mechanism of the failure is similar to that of cyclic mobility failure which is associated with medium dense to dense soil, where, in contrast to previous one, the stability of granular mixture is noticeably maintained.

4.3.1.2 Effect of confining pressure

The effect of confining pressure on the stress paths of GTCM with $GF=100\%$ and $GF=30\%$ at relative density of 50% is shown in Fig. 4.4 and Fig. 4.5 respectively. As can be seen from the Fig. 4.4, for a given cyclic stress ratio ($CSR=0.35$), the reduction in the effective confining pressure greatly enhances shear resistance of gravel. In other words, gravel exhibits dilative tendency during undrained cyclic shearing when it is subjected to low effective confining pressure. This mechanism is similar to that of

gravel or sand with a higher relative density conducted under relatively higher confining pressure (Verdugo and Ishihara 1996).

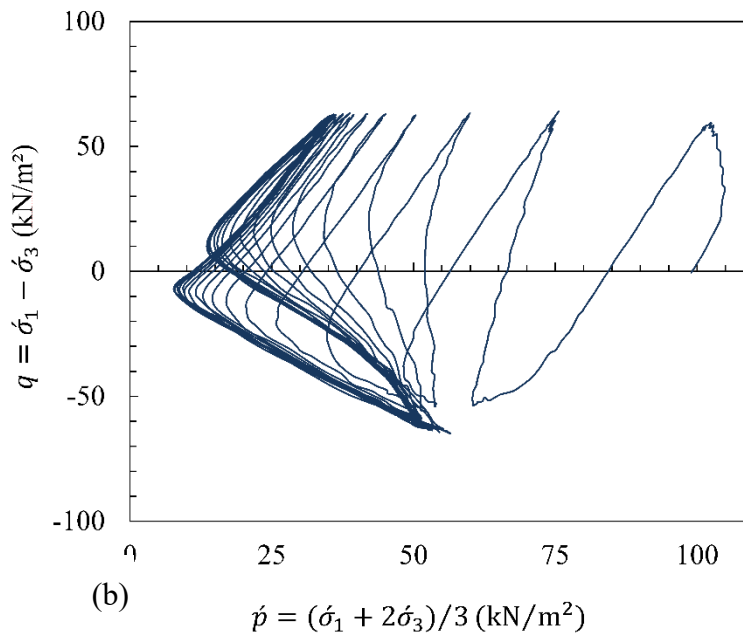
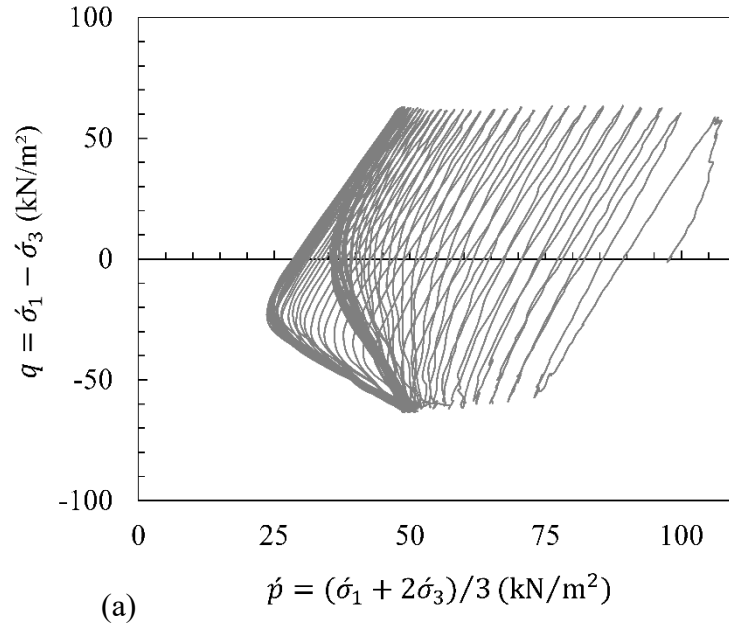


Figure 4.2 Cyclic stress paths of GTCM at **CSR = 0.3** and Dr=50% and $\sigma'_3 = 100 \text{ kN/m}^2$: (a) GF=100%; (b) GF=87%.

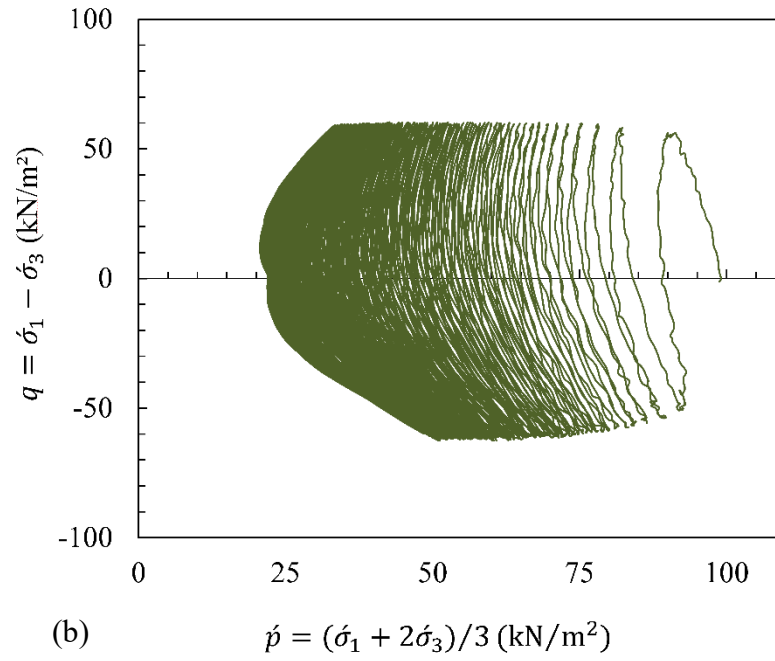
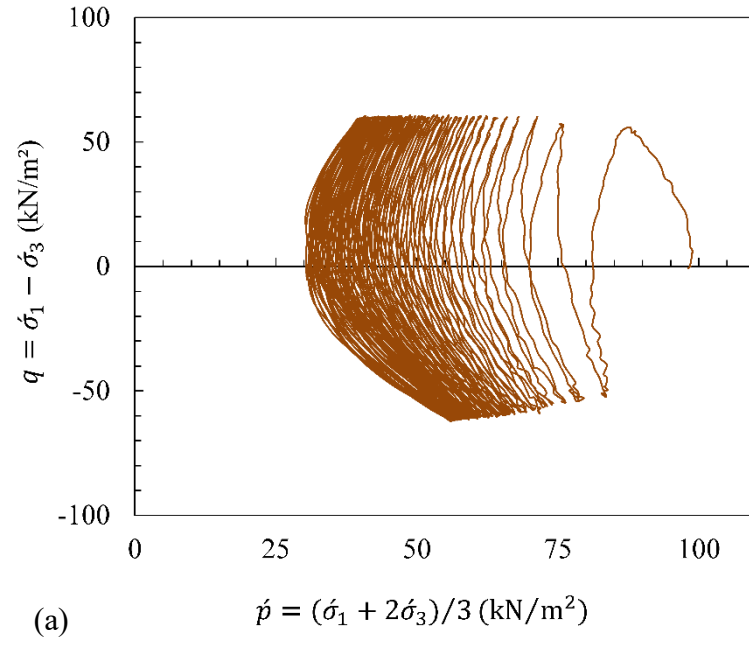


Figure 4.3 Cyclic stress paths of GTCM at **$CSR = 0.3$** and $Dr=50\%$ and $\sigma_3 = 100 \text{ kN/m}^2$: (a) $GF=44\%$; (b) $GF=33\%$.

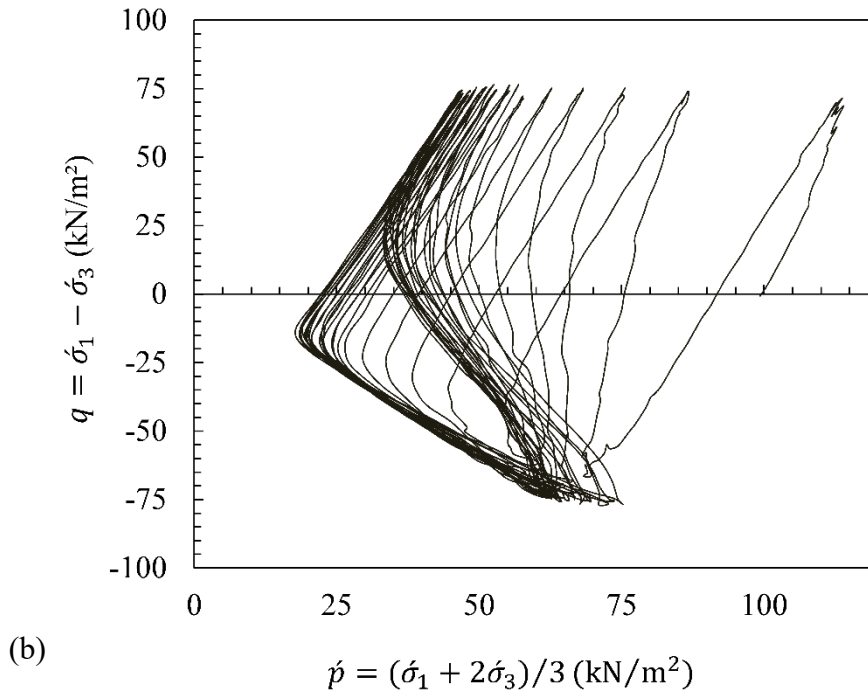
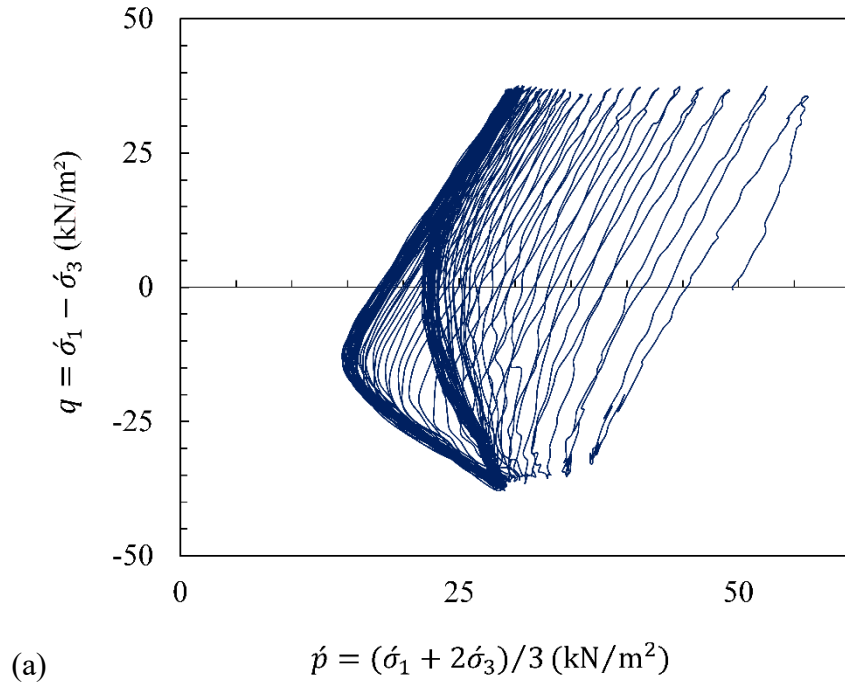


Figure 4.4 Cyclic stress paths of GTCM with GF=100% at Dr=50% and **CSR =**

0.35: (a) $\sigma_3 = 50 \text{ kN/m}^2$; (b) $\sigma_3 = 100 \text{ kN/m}^2$.

As can be seen from Fig. 4.5, GTCM with GF=30%, shows higher liquefaction resistance at the lower effective confining pressure.

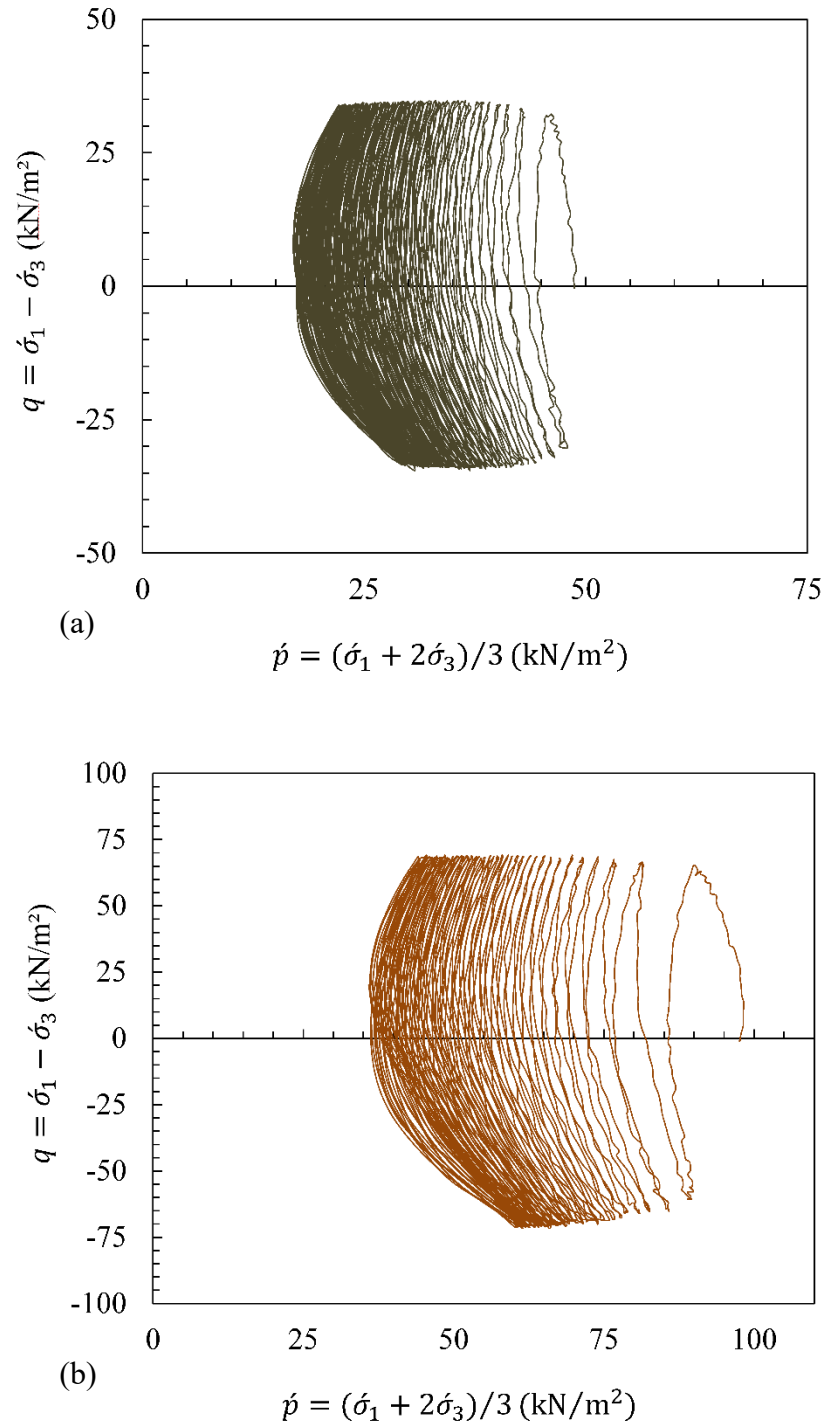


Figure 4.5 Cyclic stress paths of GTCM with GF=100% at Dr=50% and **CSR = 0.35**: (a) $\sigma_3 = 50$ kN/m²; (b) $\sigma_3 = 100$ kN/m².

4.3.2 LIQUEFACTION RESISTANCE OF GTCM

4.3.2.1 Effect of gravel fraction

Figure 4.6 shows the effect of gravel fraction on the evolution of excess pore water pressure of GTCM specimens at $\dot{\sigma}_3 = 50 \text{ kN/m}^2$, $D_r=50\%$ and $\text{CSR}=0.3$. The results indicated that, for GTCM specimens with $\text{GF}<87\%$, the liquefaction resistance increased as the gravel fraction decreased. In addition, to better understand the liquefaction susceptibility of GTCM, the number of the cycles required to cause $R_u=0.8$ versus cyclic stress ratio ($\text{CSR}=\dot{\sigma}_d/2\dot{\sigma}_3$) is plotted in Figure 4.7.

As is mentioned in previous section, the onset of liquefaction was not occurred for none of GTCM specimens. It has been reported that gravelly soils especially poorly graded are less susceptible to liquefaction than fine sandy and silty sand soils with uniform grain size distribution (Towhata 2008; Kokusho 2017). The other reason is the high permeability of the gravel which would accelerate dissipation of induced excess pore water pressure during the dynamic loading.

When small amount of tire chips is added to the mixture (5% by weight or 13% by volume), some of the solid gravel particles are being replaced by tire chips soft particles with relatively low stiffness. However, the GTCM skeleton is still formed by gravel particles, therefore considering tire chips soft inclusions as voids in the mixture, GTCM specimen exhibits gravel like behavior in relatively loose state. For GTCM specimens with $\text{GF}<87\%$, the liquefaction resistance increases with decreasing gravel fraction in mixture.

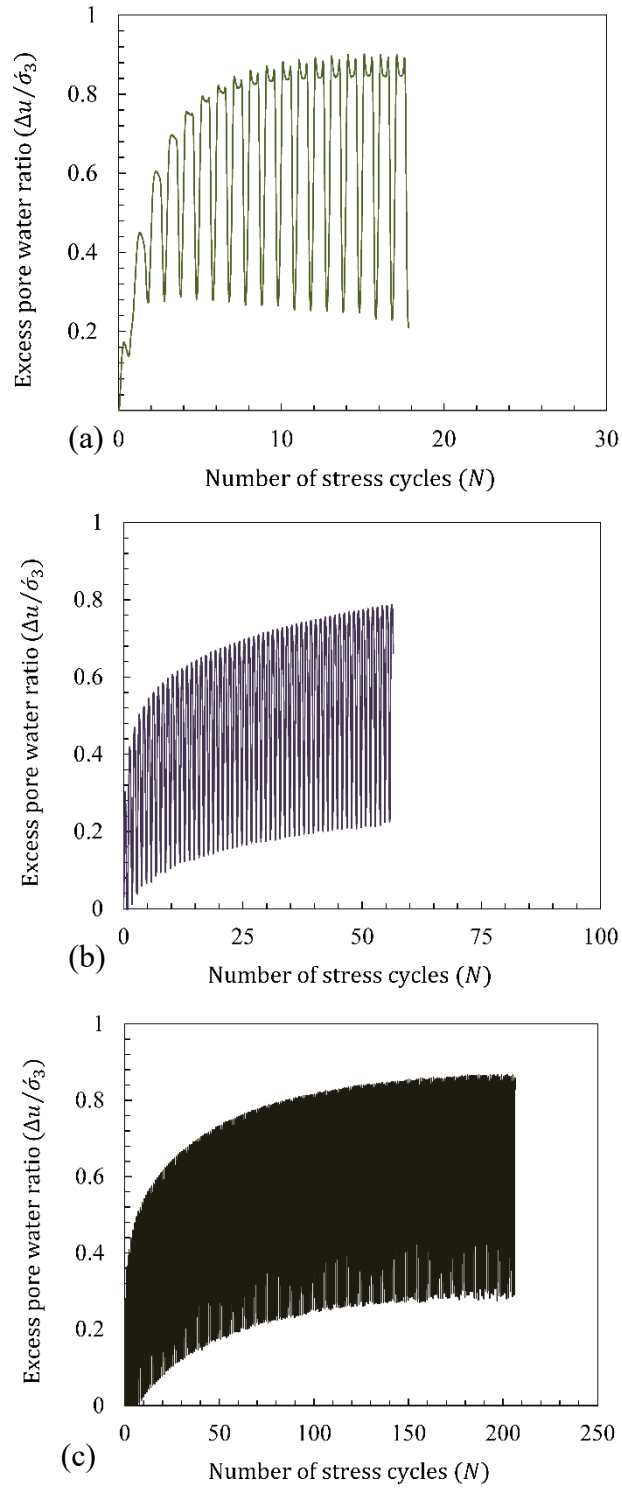


Figure 4.6 The effect of gravel fraction on the evolution of excess pore water ratio of GTCM with different GF at $Dr=50\%$, $CSR=0.3$, $\sigma_3 = 100 \text{ kN/m}^2$: (a) GF=87%; (b) GF=44% (c) GF=30%.

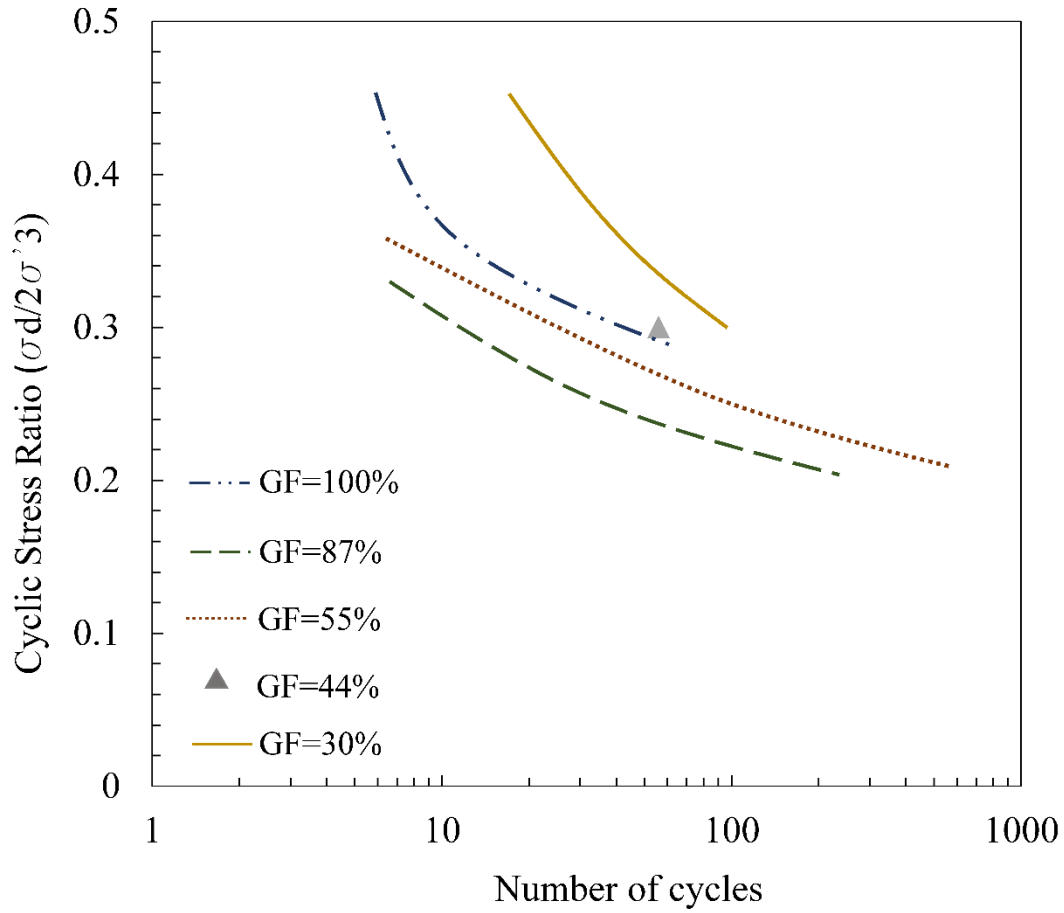


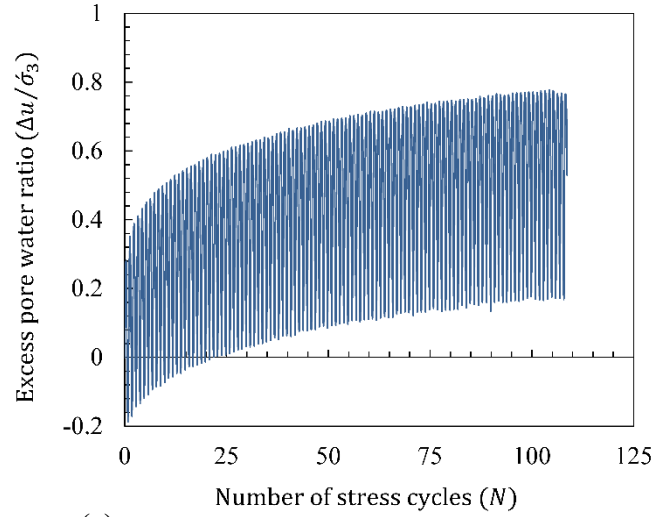
Figure 4.7 Number of cycles to liquefaction versus the CSR at various GF(%).

4.3.2.2 Effect of the confining pressure (σ_3)

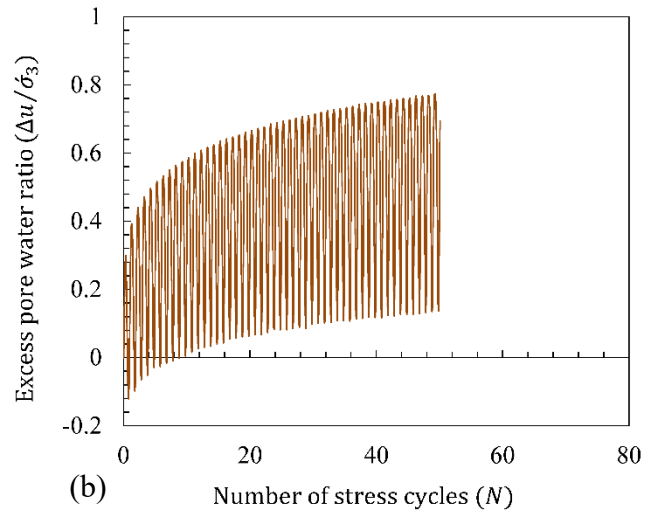
As can be seen from Fig. 4.8, the rise in effective confining pressure remarkably suppressed dilative behavior and reduced liquefaction resistance of representative GTCM specimen. Similar finding was reported later by (Vaid et al. 1985) on the liquefaction resistance of sandy soil. However, aging effect due to slow deposition of granular soils was not considered in this study.

Previous experimental studies on permeability of sand and sand-tire chips revealed the reduction in the hydraulic conductivity of mixture with the effective

confining pressure (e.g. (Edil and Bosscher 1994)). Therefore, higher permeability might be one of the reasons for the higher liquefaction resistance of GTCM at lower effective confining pressure.



(a)



(b)

Figure 4.8 The effect of effective confining pressure on the evolution of excess pore water ratio of GTCM versus number of cycles at GF=30%, Dr=50% and

$$\sigma_d / 2\sigma_{3c} = 0.35: \quad (a) \quad \sigma_3 = 50 \text{ kN/m}^2; \quad (b) \quad \sigma_3 = 100 \text{ kN/m}^2$$

Moreover, the influence of effective confining pressure on the liquefaction potential of GTCM was assessed for the representative specimens with GF=100% and GF=30%. The number of the cycles required to cause $R_u=0.8$ versus cyclic stress ratio ($CSR=\sigma_d/2\sigma'_3$) is plotted in Figure. 4.9.

The results indicate that, the liquefaction resistance of GTCM increases with the decrease in the effective confining pressure levels. Furthermore, the GTCM with GF=100% appears to be more sensitive to variation in the effective confining pressure than GF=30%. Similar mechanical behaviour was reported in section 4.3.2.1 for GTCM specimens with $GF \leq 50\%$ under monotonic loading.

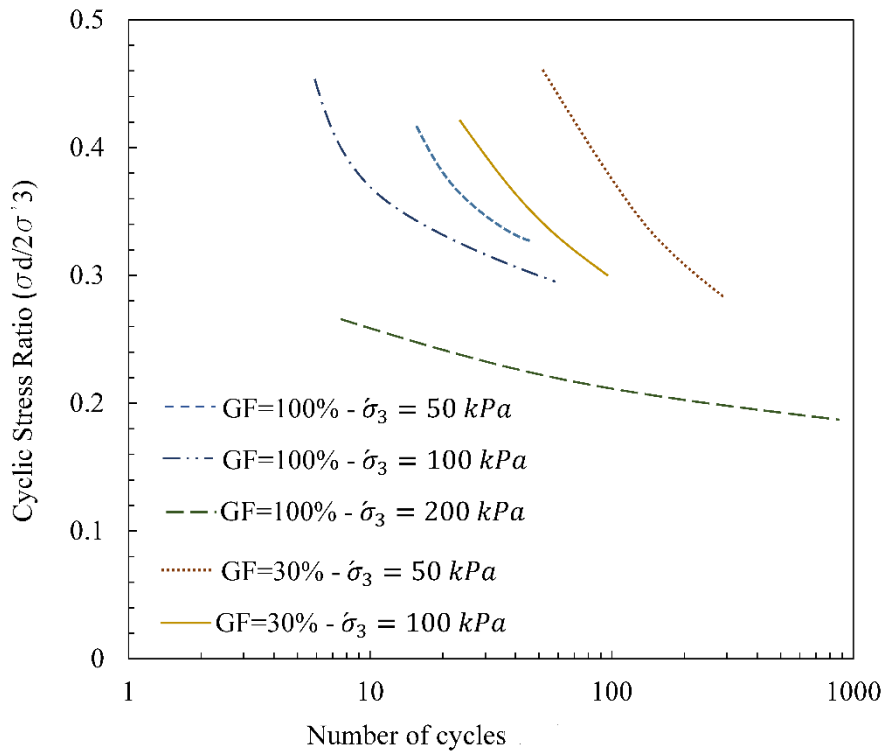


Figure 4.9 Number of cycles to liquefaction versus the CSR at various effective confining pressures (σ'_3)

4.3.3 SHEAR MODULUS AND DAMPING RATIO OF GTCM

In order to obtain hysteresis loops of GTCM samples, the sampling frequency of the data logger was set at 100 data points per cycle of loading.

Evaluation of shear modulus (G) and damping ratio (D) can be calculated from following expressions:

$$G = \frac{\tau_{max} - \tau_{min}}{\gamma_{max} - \gamma_{min}} \frac{1}{3} \times \frac{(q_{max} - q_{min})}{\varepsilon_{q,max} - \varepsilon_{q,min}} \quad (4.9)$$

$$D = \frac{1}{4\pi} \frac{\Delta W}{W} = \frac{1}{4\pi} \frac{\oint \tau d\gamma}{(0.125 \times \Delta\tau \times \Delta\gamma)} \quad (4.10)$$

Where q_{max} and q_{min} are maximum and minimum deviatoric stresses respectively. $\varepsilon_{q,max}$ and $\varepsilon_{q,min}$ are maximum and minimum deviatoric strains, respectively. τ_{max} and τ_{min} are the maximum and minimum shear stresses corresponding to the maximum (γ_{max}) and minimum shear strains (γ_{min}), respectively.

Furthermore, $\Delta\tau$ and $\Delta\gamma$ are the difference between maximum and minimum shear stresses and shear strains, respectively. ΔW is the area of the hysteresis loop and W is the area of right triangle shown in Fig. 4.10. A MATLAB code was written to accelerate the calculation process.

4.3.3.1 Effect of gravel fraction

Fig. 4.11 displays the evolution of shear modulus (G) versus the number of cycles for different fraction of gravel in mixture at cyclic stress ratio of CSR=0.3.

For the GTCM specimens with GF=100% and GF=87%, shear modulus

decreased drastically with the number of loading cycle within the few cycles of loading. The build-up of excess pore water pressure, in fact, causes reduction in gravel inter-particles contact which leads to the loss of GTCM stiffness.

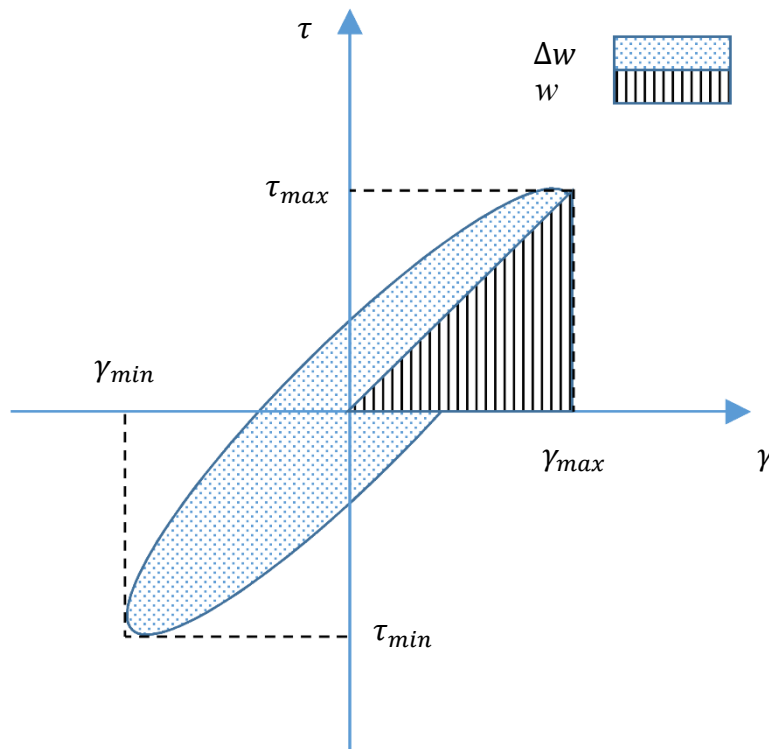
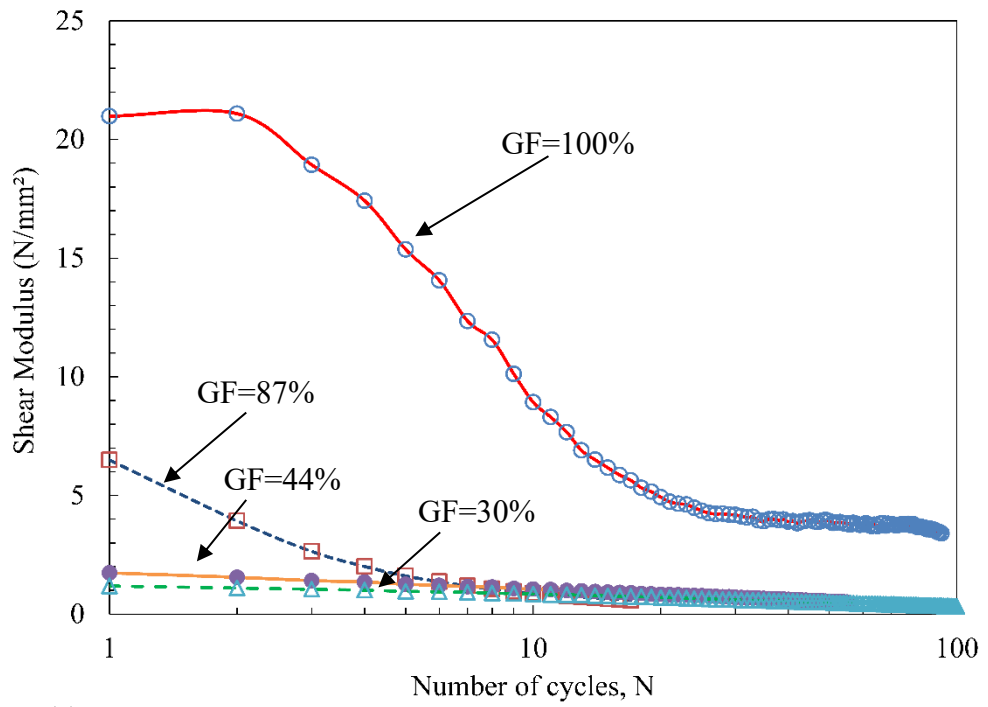
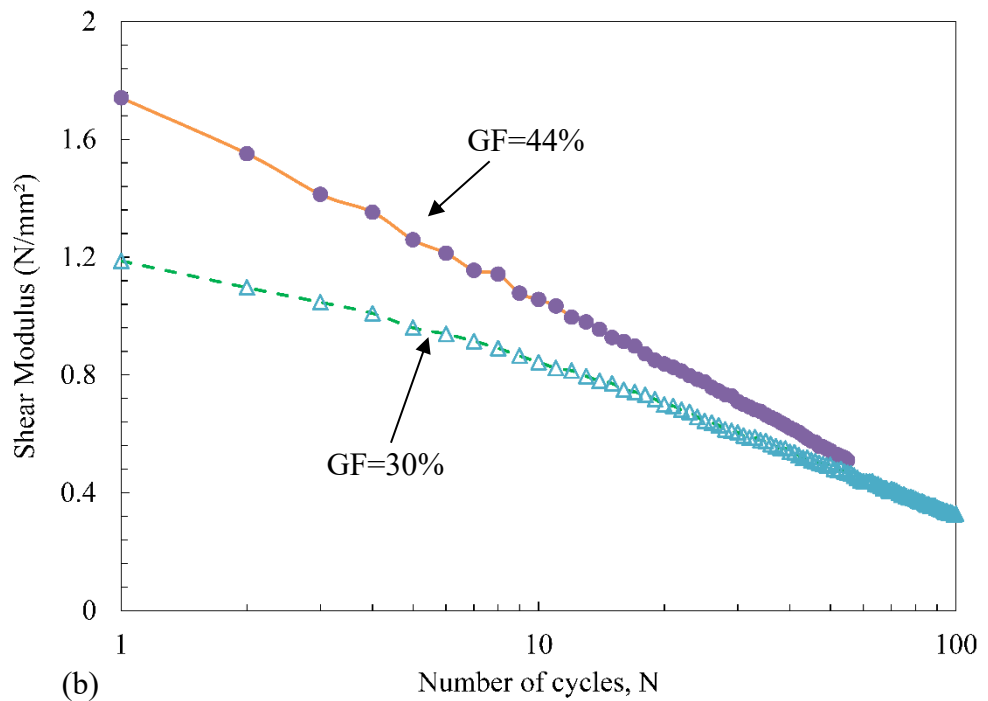


Figure 4.10 Definition of cyclic shear modulus and damping ratio

Variation of damping ratio of GTCM mixtures with gravel fraction and shear strain is shown in Fig 4.12. Damping ratio slightly increases with decreasing gravel fraction from 100% to 44%. The reduction in damping ratio value may occur due to rapid increase in the pore water pressure during cyclic loadings. High pore water pressure decreases inter-particle contacts resulting in significant reduction in frictional energy loss in soil skeleton with the number of cycles and axial strain (Brennan et al. 2005; Mashiri et al. 2016).



(a)



(b)

Figure 4.11 The evolution of shear modulus versus number of cycles for GTCM at different gravel fractions (GF) : (a) $30\% \leq GF \leq 100\%$ (b) $30\% \leq GF \leq 44\%$.

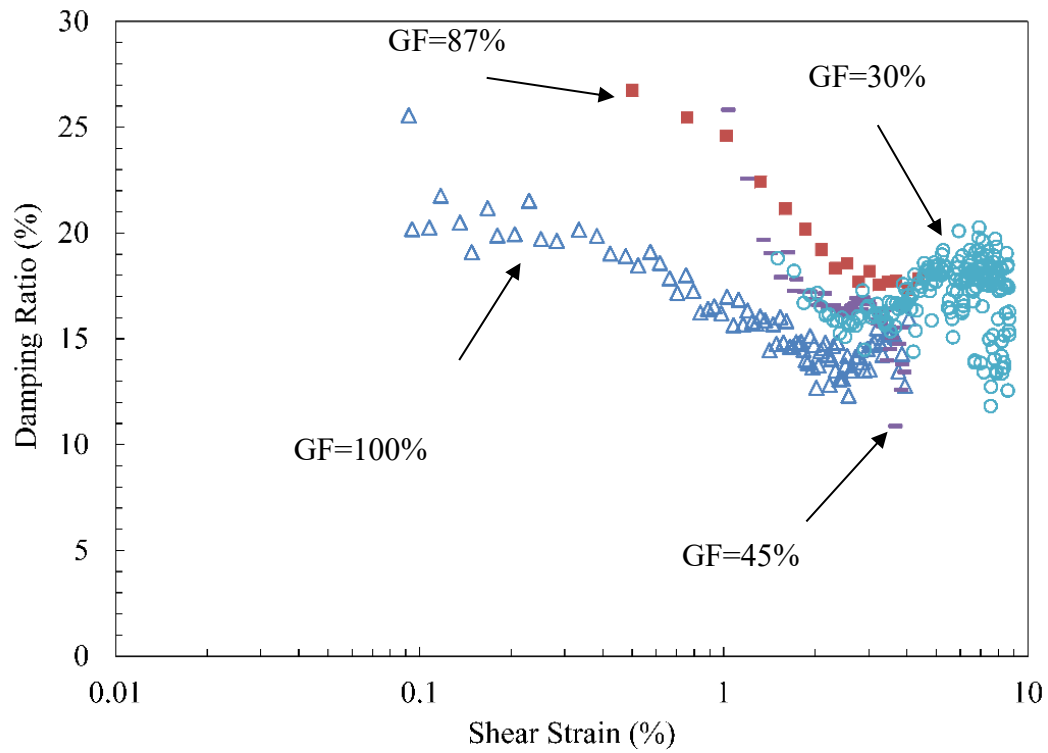


Figure 4.12 Effect of gravel fraction on damping ratio of GTCM

4.3.3.2 Effect of the confining pressure

The effect of confining pressure on the shear modulus of GTCM at the CSR=0.4 and GF=100% and 30% is shown in Fig. 4.13. Shear modulus increases with an increase in the effective confining pressure. The rise in the effective confining pressure, increases gravel-tire chips inter particles friction resulting in a significant increase in shear stiffness of GTCM.

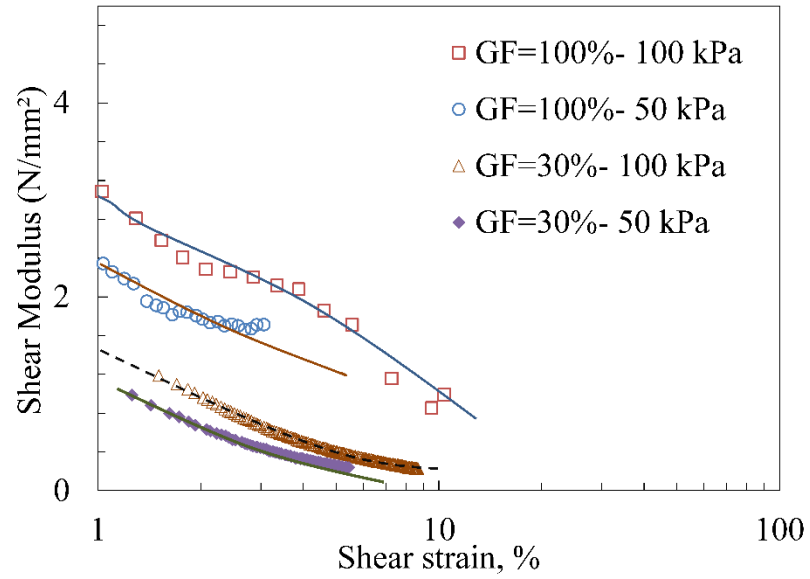


Figure 4.13 the effect of confining pressure on shear modulus of GTCM with GF=100% and GF=30% at CSR=0.4.

4.4 SUMMARY AND CONCLUSION

The liquefaction resistance and dynamic characteristics of GTCM were thoroughly examined by undrained cyclic triaxial tests at the range of medium to large shear strains ($\gamma > 0.05\%$). The effect of gravel fraction (GF), confining pressure (σ'_3) and shear stress ratio (CSR) on dynamic behaviour of GTCM were also investigated. Shear modulus and damping ratio curves of GTCM were established for the range of medium to large shear strains ($\gamma > 0.05\%$). The following conclusion can be drawn:

- For a given relative density and confining pressure, shear modulus and damping ratio of GTCM were highly influenced by gravel fraction from 100% to 44%. For gravel fraction $GF < 44\%$, addition of tire chips inclusion to the mixture does not seem to considerably affect the shear modulus of GTCM.

- For a constant relative density and gravel fraction in mixture, shear modulus of increased with an increase in the effective confining pressure level.
- Two GTCM behavioral zone: gravel like and gravel-tire chips like behavior can be used to explain liquefaction potential as well as dynamic behavior of GTCM specimens.
- Liquefaction resistance of GTCM specimens are remarkably influenced by gravel fraction in mixture. For higher gravel fractions ($GF > 87\%$), soil matrix are mainly formed by gravel and thus adding small amount of tire chips decreases liquefaction resistance due to reduction in gravel inter-particle contacts during loading. However, for $GF < 87\%$, liquefaction resistance increases with a decrease in gravel fraction in mixture. Because mixture tends to exhibits gravel-tire chips like behavior or tire chips like behavior (non-liquefiable materials).
- The level of effective confining pressure make a remarkable contribution to the liquefaction resistance of GTCM. Liquefaction resistance was found to increase with decreasing the effective confining pressure.

REFERENCES

- Anvari, S. M. & Shooshpasha, I. (2016). Influence of size of granulated rubber on bearing capacity of fine-grained sand. *Arabian Journal of Geosciences*, 9(18): 707.
- Bowles, J. E. (1988). *Foundation analysis and design*. McGraw-Hill, New York.
- Brennan, A. J., Thusyanthan, N. I. & Madabhushi, S. P. (2005). Evaluation of Shear Modulus and Damping in Dynamic Centrifuge Tests. *Journal of Geotechnical and Geoenvironmental Engineering*, 131(12): 1488-1497.
- Edil, T. & Bosscher, P. (1994). Engineering Properties of Tire Chips and Soil Mixtures.

- Geotechnical Testing Journal*, 17(4): 453-464.
- Hazarika, H. & Abdullah, A. (2016). Improvement effects of two and three dimensional geosynthetics used in liquefaction countermeasures. *Japanese Geotechnical Society Special Publication*, 2(68): 2336-2341.
- Hazarika, H., Kohama, E. & Sugano, T. (2008). Underwater Shake Table Tests on Waterfront Structures Protected with Tire Chips Cushion. *Journal of Geotechnical and Geoenvironmental Engineering*, 134(12): 1706-1719.
- Hazarika, H., Sugano, T., Kikuchi, Y., Yasuhara, K., Murakami, S., Takeichi, H., Karmokar, A. K., Kishida, T. & Mitarai, Y. (2006). Flexibility and stability enhancement of structures during earthquakes using a novel geosynthetic material. *Geosynthetics Engineering Journal*, 21125-130.
- Hazarika, H., Yasuhara, K., Kikuchi, Y., Karmokar, A. K. & Mitarai, Y. (2010). Multifaceted potentials of tire-derived three dimensional geosynthetics in geotechnical applications and their evaluation. *Geotextiles and Geomembranes*, 28(3): 303-315.
- Hazarika, H., Yokota, H., Endo, S. & Kinoshita, T. 2018. Cascaded Recycle of Waste Tires—Some Novel Approaches Toward Sustainable Geo-Construction and Climate Change Adaptation. In: Krishna, A. M., Dey, A. & Sreedeeep, S. (eds.) *Geotechnics for Natural and Engineered Sustainable Technologies: GeoNEst*. Singapore: Springer Singapore.
- Kaushik, M. K., Kumar, A. & Bansal, A. (2015). Performance Assessment of Gravel–Tire Chips Mixes as Drainage Layer Materials Using Real Active MSW Landfill Leachate. *Geotechnical and Geological Engineering*, 33(4): 1081-1098.
- Kokusho, T. (2017). *Innovative Earthquake Soil Dynamics*. CRC Press.
- Kramer, S. L. (1996). *Geotechnical Earthquake Engineering*. Prentice Hall, Inc., Upper Saddle River, New Jersey.
- Ladd, R. (1978). Preparing Test Specimens Using Undercompaction. *Geotechnical Testing Journal*, 1(1): 16-23.
- Lee, J., Salgado, R., Bernal, A. & Lovell, C. (1999). Shredded tires and rubber-sand as lightweight backfill. *Journal of geotechnical and geoenvironmental engineering*, 125(2): 132-141.
- Mashiri, M., Vinod, J. & Sheikh, M. (2016). Liquefaction Potential and Dynamic Properties of Sand-Tyre Chip (STCh) Mixtures. *Geotechnical Testing Journal*, 3969-79.
- Mashiri, M. S., Vinod, J. S., Sheikh, M. N. & Tsang, H. H. (2015). Shear strength and

- dilatancy behaviour of sand-tyre chip mixtures. *Soils and Foundations*, 55(3): 517-528.
- Otsubo, M., Towhata, I., Hayashida, T., Liu, B. & Goto, S. (2016). Shaking table tests on liquefaction mitigation of embedded lifelines by backfilling with recycled materials. *Soils and Foundations*, 56(3): 365-378.
- Sherard, J. L., Dunnigan, L. P. & Talbot, J. R. (1984). Basic properties of sand and gravel filters. *Journal of Geotechnical Engineering*, 110(6): 684-700.
- Towhata, I. (2008). *Geotechnical Earthquake Engineering*. Springer-Verlag Berlin Heidelberg.
- Tsang, H. H. (2008). Seismic isolation by rubber–soil mixtures for developing countries. *Earthquake Engineering & Structural Dynamics*, 37(2): 283-303.
- Vaid, Y. P., Chern, J. C. & Tumi, H. (1985). Confining Pressure, Grain Angularity, and Liquefaction. *Journal of Geotechnical Engineering*, 111(10): 1229-1235.
- Verdugo, R. & Ishihara, K. (1996). The steady state of sandy soils. *Journal of the Japanese Geotechnical Society : soils and foundation*, 36(2): 81-91.

CHAPTER 5

MODELLING PACKING DENSITY OF GRANULAR MIXTURES: AN ARTIFICIAL INTELLIGENCE APPROACH

5.1 INTRODUCTION

Maximum and minimum void ratios are key characteristics which affect volume change tendency, the hydraulic conductivity and mechanical behavior of the geomaterials . Due to unique physical and mechanical properties of Scrap Tire Derived Materials (STDM) like low unit weight, low bulk density, high hydraulic conductivity, and high elastic deformability, they are being adopted in civil engineering applications with an advance growing interest each year (Hazarika et al. 2008).

Recently, Gravel tire chips mixtures (GTCM) have been introduced to solve drawbacks of using sand-tire chips mixture in geotechnical applications such as low hydraulic conductivity and low bearing capacity of that geomaterials reinforced with STDM (Hazarika et al.2017; Pasha et al. 2017).

Research on mechanical behavior of soils, over last few decades, has revealed that physical properties and stress-strain behavior are in correlation with nature of the soil (such as the mineralogy and shape grain particles and fine content) as well as physical state of soil (which can be described by relative density, fabric and stress state of the soil) (Cubrinovski and Ishihara 2002; Hsiao et al. 2015) . Humphres (1957) who

was the first to propose a method for estimating maximum packing density of soil with different sizes.

An empirical method was introduced by Lade et al. (1998) to predict the minimum void ratio of binary mixture of spheres with different size of particles based on results of a series of minimum void ratio tests on sand-silt mixture; However, it has been shown that this method is only valid for the higher small to large mean particle size ratios ($D_{50,Large} \gg D_{50,Small}$) (Vallejo 2001; Chang et al. 2015).

Although extensive experimental (Hsiao et al. 2015) and numerical studies (Ng et al. 2017) on packing density of granular mixtures with different size and shape particles were presented so far, But applicability of existing mathematical methods for predicting void ratios and examining physical characteristics of soil-tire chips mixtures were not yet examined. Furthermore, existing models were proposed to predict packing density of binary mixtures with rigid particles. However, the tire chips particles might deform under compression and fill the porous space of soil-tire chips the system.

Some studies have adopted Equivalent void ratio by assuming the volume of tire solids as part of the total volume of voids due to low stiffness of tire chips (Feng and Sutter 2000; Anastasiadis et al. 2011). However, applicability of the proposed correlations has not yet been examined and it is believed to be valid for small amount of tire chips inclusion in soil-tire chips solid matrix.

To the best of author's knowledge, there is no study on the modelling void ratio characteristics of reinforced soil with tire chips taking into account the important features of mixture such as mean particle size ratio ($D_{50,R}/D_{50,G}$) and tire chips

inclusion in the mixture.

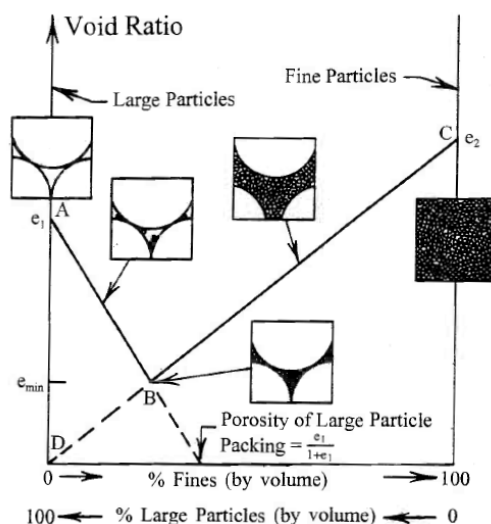
Therefore, this study aims to introduce new model using Artificial Intelligence (AI) technique. Artificial Neural Network (ANN) is employed to simulate complex void ratio characteristics of binary mixture taking into account important features of granular materials mixed with tire chips. The result of study helps to assess the void ratio characteristics of GTCM. Particularly, the study highlights the effect of gravel fraction, mean particle size ratio of tire chips to gravel ($D_{50,R}/D_{50,G}$) on maximum and minimum void ratio of GTCM. The results of experimental tests on the maximum and minimum void ratio of GTCM from section 3.5 were used to construct AI models.

5.2 MATERIAL PROPERTIES AND TESTING PROGRAMS

Two sets of gravel (G1 and G2) were examined in this study. Both sets of gravel were carefully selected to have relatively close mean grain size ($D_{50,G1} \approx D_{50,G2} = 4.3$ mm) and coefficient of uniformity $U_c \approx 2.17$. Both G1 and G2 gravels are classified as poorly graded (GP) according to JGS-0051. In order to investigate the influence of particle size ratio ($D_{50,R}/D_{50,G}$), in addition to the impact of relative content ratio of tire chips on void ratio characteristics of GTCM, 3 sets of tire chips (TCH1, TCH2 and TCH3) were used in this study. TCH1 has uniformity coefficient of $U_c \approx 2.2$ and particle size ratio of ($D_{50,R}/D_{50,G}$) ≈ 1.2 . The materials TCH2 and TCH3 have a similar uniformity coefficient of $U_c \approx 1.4$ but different particle size ratios of ($D_{50,R}/D_{50,G}$) = 0.35 and ($D_{50,R}/D_{50,G}$) = 3.35 respectively. Particle size distributions of gravel and tire chips is already provided in Fig. 3.2 in chapter 3. In order to investigate the effect of particle size ratio of tire chips to gravel ($D_{50,R}/D_{50,G}$) and

gravel fraction ($GF=V_G/V_T$) on Void ratio Characteristics of GTCM, A series of vibratory test were conducted on Gravel and GTCM mixtures according to JGS-0161 standard. Particle size ratio of tire chips to gravel ($D_{50,R}/D_{50,G}$) varied between 0.35 and 3.35, gravel fraction varied between 0 to 100 percent. Details on the testing apparatus and methodology were provided in section 3.5 in chapter 3.

Results of experiments on maximum and minimum void ratios of GTCM with different particle size ratio ($D_{50,R}/D_{50,G}$) and gravel fraction (GF) is already provided in Fig. 3.5 in chapter 3. Theoretical value of the minimum void ratio ($e_{\min,T}$) for binary mixture with two different particle size can be calculated from the void ratio of large particles (e_1) and fine particles (e_2) in as is shown in Fig. 5.1 (Lade et al. 1998).



Comparison between the theoretical value of minimum void ratio of GTCM with $(D_{50,R}/D_{50,G})=0.35$ and experimental results is shown in Fig. 5.2. For $(D_{50,R}/D_{50,G})=0.35$, the minimum value of minimum void ratio is achieved when $Gf \cong 80\%$. This finding is also in agreement with the values reported by (Li et al. 2016) on sand-rubber with particle size ratio of $(D_{50,R}/D_{50,S})=0.25$.

Although the optimum gravel fraction value where the minimum void ratio is achieved is in good agreement with that of obtained from experimental result, but the theoretical minimum value of void ratio is lower than that of experimental value. Because theoretically, the particles were assumed to be sphere with large to small particle size ratio $D_{50,L}/D_{50,S} \gg 7$. Furthermore the deformation of particles within the binary mixture was disregarded in calculation of theoretical value of minimum void ratio.

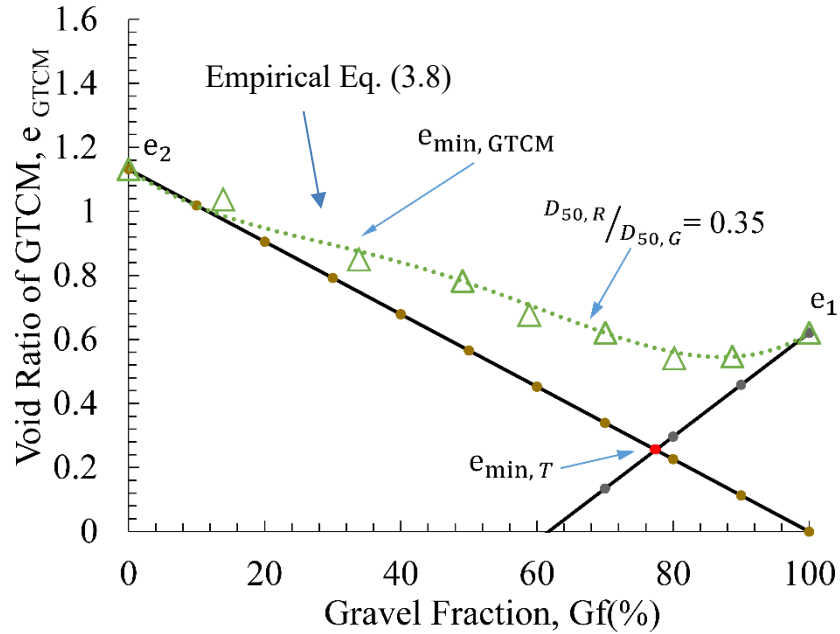


Figure 5.2 Minimum void ratio of GTCM with $D_{50,R}/D_{50,G}=0.35$

5.4 ARTIFICIAL INTELLIGENCE

Artificial intelligence is an area of computer science that deals with the design of intelligent machine that attempts to mimic human cognition ability. The essence of AI techniques in solving any real problems are: (a) there should be enough data available for the problem we are going to solve; (b) a pattern should exist between inputs and outputs of the system; (c) it should be very difficult or sophisticated to pin down it mathematically. Therefore, AI models are information or data based models that rely on the information alone to determine the framework and parameters that govern the system and do not need any assumptions about the behaviour of the system.

Assume a system comprises of inputs (x) and outputs (y), and there is a pattern between them. The goal in the AI learning is to find a function like $y = f(x)$ that minimizes the error between actual values and outputs predicted by the AI model. In the real world, it is most likely to encounter a very complex and non-linear systems, and in such a situation conventional regression models are incapable of capturing relationship between input and outputs without having prior knowledge on the nature of the system. On the other hand, AI technique can be applied to solve such a problem, without having prior knowledge of the nature of existing non-linearity. Common AI techniques are artificial neural network (ANN), genetic programming (GP), support vector machines (SVM) and evolutionary polynomial regression (EPR).

Geotechnical engineering is about understanding how the infrastructure interacts with the ground and deals with materials such as soil, rock that, by their nature shows uncertainty in behavior due to the imprecise physical characteristics originated from physical and chemical process associated with formation of these materials. Therefore,

modeling the physical and mechanical characteristics of these materials are complex and beyond the capability of most of traditional physical and mathematical methods used in engineering. Recently, AI has gained attention among researchers, particularly those who work on the modeling the sophisticated behavior of geotechnical materials. Because this technique exhibits excellent predictive ability in comparison to the other common methods.

The AI technique has been implemented in several fields of geotechnical engineering. For instance, ANN technique has been implemented to estimate the soil characteristics such as soil compressibility (Kurnaz et al. 2016), soil permeability (Park 2011) and shear strength parameters as well as (Besalatpour et al. 2012) predict the behavior of foundations (Lee and Lee 1996; Ahmad et al. 2007; Shahin 2014; Pooya Nejad and Jaksa 2017; Park et al. 2018). GP has been implanted to predict shear strength of soil (Johari et al. 2011), optimization of design parameters of reinforced earth wall (Manahiloh et al. 2015) and assessing of liquefaction potential of soil (Bagheripour et al. 2012). EPR technique was used for prediction of saturated water content (Khoshkroudi et al. 2014) and settlement prediction of shallow foundations (Shahnazari et al. 2014).

As mentioned earlier in previous section, no study was conducted on void ratio characteristics of granular mixture with STD. Therefore, in the following section we have introduced a new model based on ANN technique to predict void ratio characteristics of gravel-tire chips mixture.

5.5 ARTIFICIAL NEURAL NETWORK MODEL

5.5.1 OUTLINE OF ARTIFICIAL NEURAL NETWORK (ANN)

Human brain is the central organ of the human nervous system which consists of a very large number of cells, called neurons. These neurons are connected to each other within the nervous system. It is estimated that there are 10^{11} neurons in a human brain, and they are connected to the other ones with 10^4 connections (Demuth et al. 2014). A simple neuron is formed by the cell body, the dendrites which transmit the electrical signals into the cell body, and the axon which transmits the electrical signals from the cell body out to the other neurons (see Fig. 5.3). The contact between the axon of one neuron and a dendrite of another one is called a synapse. The strength of these synapses determines how the signal is transported from one neuron to other one and it is given by complex biochemical processes. Transportation of signals between neurons is done by complex biochemical process that directly depends on the synapses.

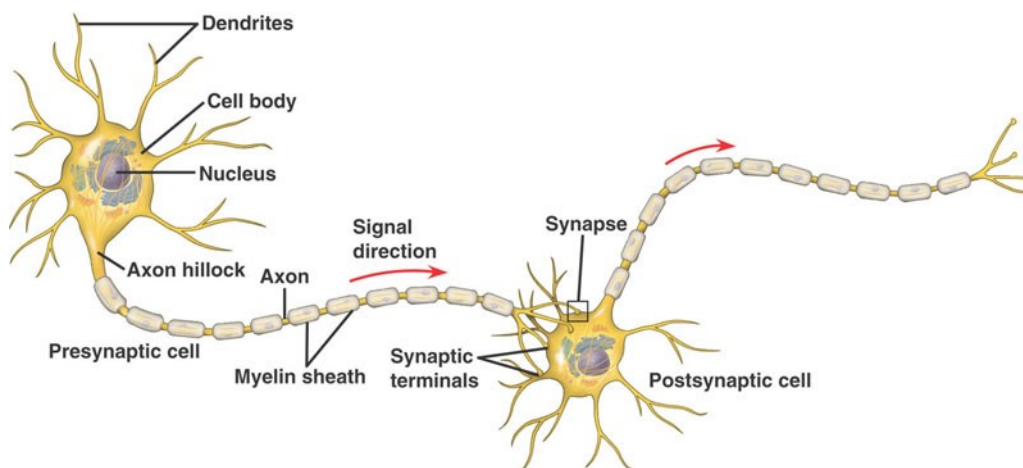


Figure 5.3 Neuron in human nervous system and its connection (wikispace.com)

The first mathematical model of a neuron which is capable of logical operation, was proposed by McCulloch and Pitts (McCulloch and Pitts 1943). As it can be seen from Fig 5.4, the single neuron in this model, receives inputs $x_1, x_2, \dots, x_N$ and generates one output, y . The inputs are processed in linear combination as follows:

$$u = b + \sum_{i=1}^n w_i x_i \quad (5.2)$$

Where $w_1, w_2, \dots, w_N$, are the strength of the synapses and b is the bias, which contributes to the output of neuron. For convenience the threshold, b , is considered as another weight, w_0 , transport an input $x_0 = 1$ into the neuron. Therefore Eq. 5.2, can be rewritten as :

$$u = \sum_{i=0}^n w_i x_i \quad (5.3)$$

In the next step, an activation function is employed to compute the output from combined inputs:

$$y = f(u) \quad (5.4)$$

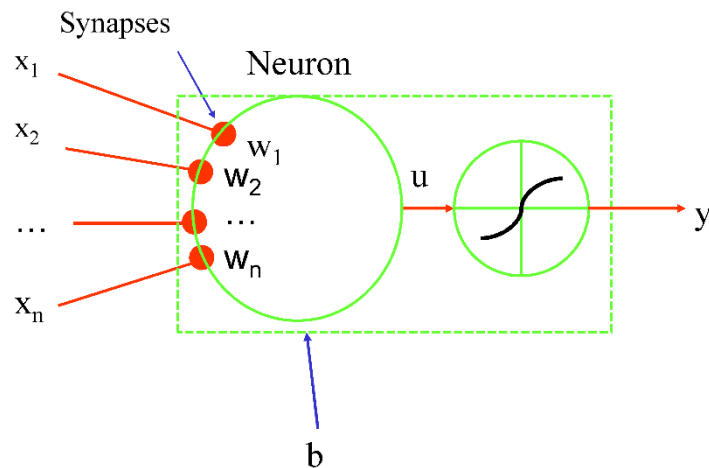


Figure 5.4 McCulloch and Pitts' ANN model

Several activation functions have been introduced for different types of neural networks. These activation functions are shown in Fig. 5.5. Derivatives of Sigmoid and hyperbolic functions can be computed by taking the values of functions directly (Quiza et al. 2012). Arctangent has the similar functionality as the hyperbolic tangent but yields a slower increment. Step activation function is suitable for classification tasks rather than approximation ones. Gaussian function is widely used in radial basis function networks.

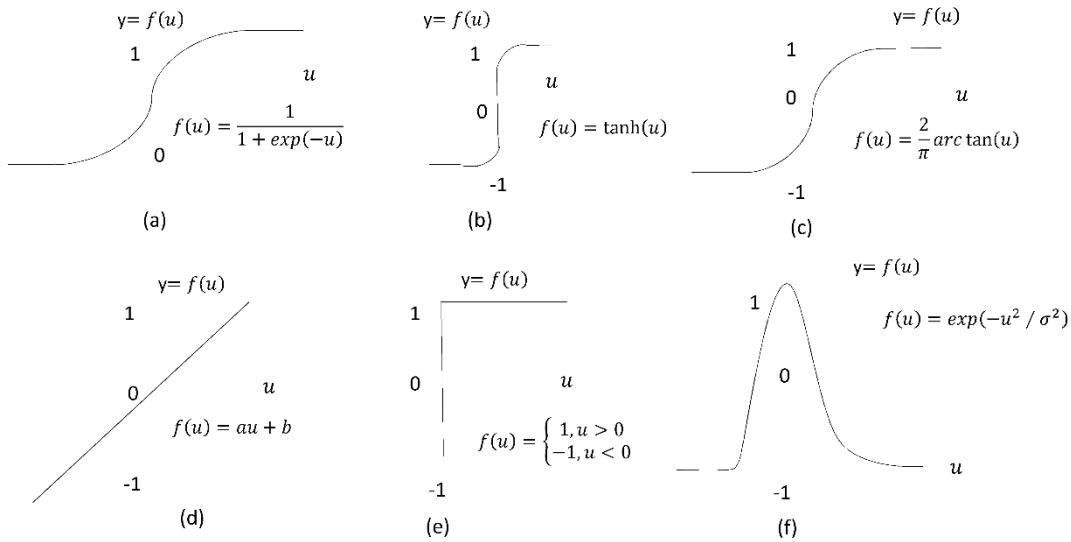


Figure 5.5 Activation functions: (a) sigmoid (b) hyperbolic tangent (c) arctangent (d) linear function (e) step function (f) Gaussian radial function

5.5.1.1 Artificial neural network topology

Neurons within the neural network are connected to each other in a certain topology. Neurons in ANN are represented by nodes and arcs as synapse. Let's assume that neurons are arranged in $N + 1$ layers, each of them contains $M^0, M^1, \dots, M^N$. First layer contains inputs of ANN. No mathematical computations are performed in this layer. Inputs in this network is represented as $[X_0, X_2, \dots, X_{M(0)}]^T$. The output layer

give the M^N outcomes, $[Y_0, Y_2, \dots, Y_{M(N)}]^T$. Input and output of layers 1 to N-1 cannot be represented explicitly because of nature of hidden layers (see Fig. 5.6).

In Feedforward Neural Network, there is no connection between output of a neuron to the input of another neuron in pervious layer. In other word there is no close loop in the topology of network. Therefore, the information passes only from the input layer directly through any hidden layers to the output layer. Radial Basis Function Neural Networks (RBFN), self-organizing maps (SOM) and Multi-Layer Perceptron (MLP) are examples of feed forward neural networks.

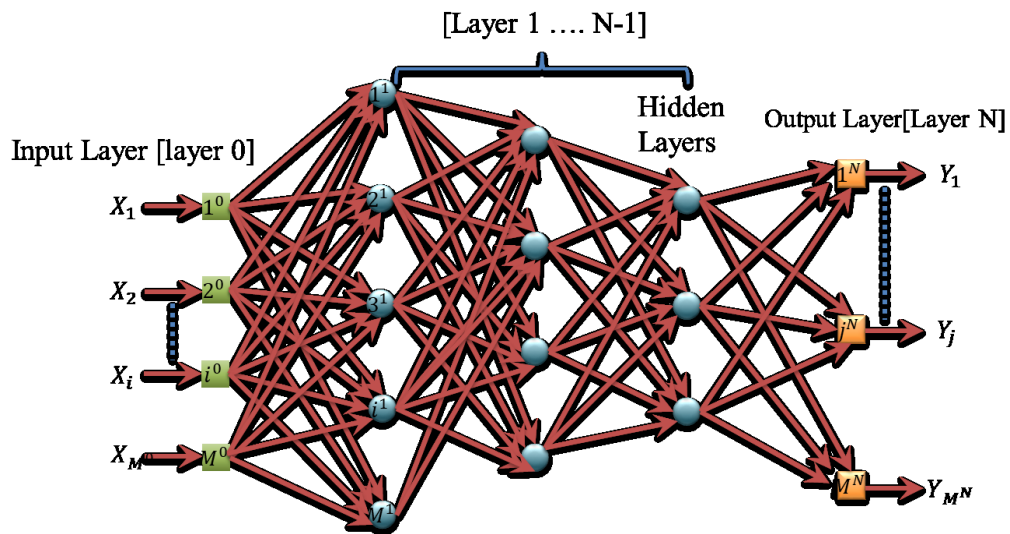


Figure 5.6 Architecture of a neural network

In recurrent neural networks, the output of a neuron may be connected to input of another neuron in pervious layers. In other words there is a closed loop in topography of neural network. Elman network and Hopfield network are examples of recurrent neural networks.

5.5.1.2 Types of learning

Learning or training is a method that employs mathematical rules to improve artificial networks performance by adjusting weights and bias levels of a network when a network is simulated over a specific data sets. There are three types of learning or training:

- Supervised learning: where inputs and outputs of training data sets are known before starting training procedure.
- Reinforcement learning: which no correct values of outputs are provided. This learning method allows neural network to automatically determine the desired behavior within a specific context (reward signals), in order to maximize its performance.
- Unsupervised learning: outputs are not available, therefore the weights and biases are adjusted in response to the inputs only.

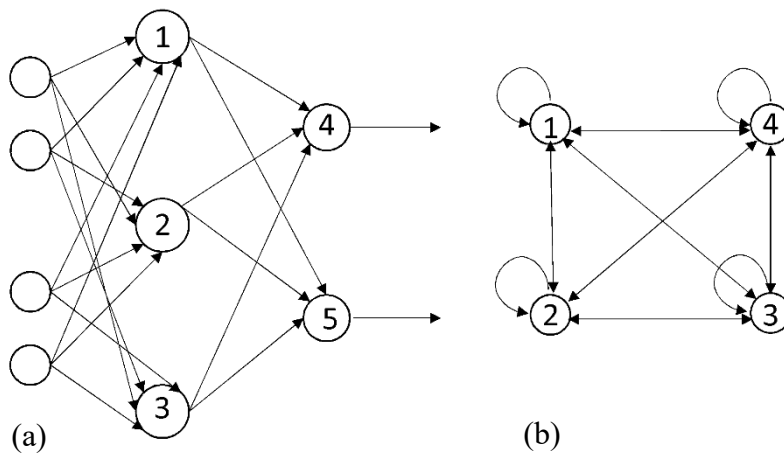


Figure 5.7 Topology of neural networks: (a) Feedforward (b) Recurrent

5.5.1.3 Feedforward Neural Network with back propagation algorithm

The backpropagation neural network is a multilayer feedforward neural network that employed generalized delta rule for learning. Figure 5.8 shows the architecture of a back propagation ANN. In this type of neural network, processing units in each layer would send their output to the processing units in upper layers.

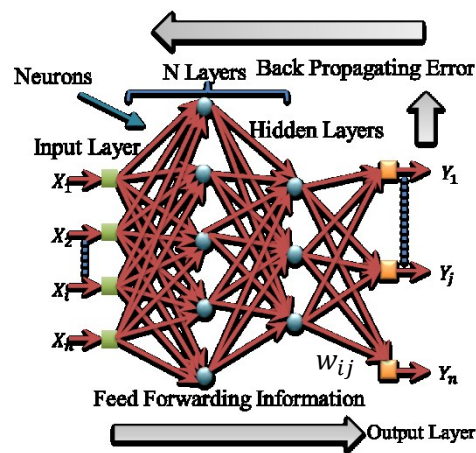


Figure 5.8 backpropagation neural network

Let's assume the weight of the connection between units i and j , w_{ij} . At the beginning of a neural network train process, connection weights are assigned random values. The connection weights are adjusted during the training of the neural network in an iterative process. At the end of successful training process, when the iterative process has converged, the connection weights of whole neural network has captured and stored. Such a trained neural network is ready to be used. The computational procedure of a backpropagation can be summarized as: the feedforward computation of information and back propagation of errors by comparing target and neural network outputs. The computational process in each units of each layer are performed as following:

1) The input u_j is computed as follows

$$u_j = \sum_{k=1}^M w_{jk} o_k \quad (5.5)$$

Where o_k = output from units affecting unit j , and M = number of units affecting unit j .

2) An activation function is employed to compute the output:

$$a_j = f_j(u_j), \quad (5.6)$$

Let's assume activation function F_j is a sigmoid function. Then for the values taken in the range of $(-1.0, 1.0)$.

$$f(u) = (1 / (1 + e^{-u-\theta})) \quad (5.7)$$

Where θ is the bias value.

3) Output is computed from activation values.

$$o_j = a_j \quad (5.8)$$

4) The computed output values are sent off to other processing units.

Several algorithm have been introduced to do the learning process automatically. But for the simplicity, generalized delta rule which is one of supervised learning algorithm is employed in this example (Rumelhart 1986) . The adjustment of the weights of the connections can be accomplished through applying the gradient descent on the total error in a given training data set.

$$\Delta w_{ij} = \phi \nabla E(w_{ij}) = \phi \delta_j o_j \quad (5.9)$$

Where $\varphi = a$ is the constant learning rate, $\nabla E(w_{ij})$ = gradient of the total error with respect to the weight between units i and j , and δ_j = gradient of the total error with respect to the combined input at unit j . δ_j is computed from the comparison between the expected activations t_j and the computed activation a_j :

$$\delta_j = (t_j - a_j) f'(u_j) \quad (5.10)$$

Where f' is the derivative of the activation function.

At the hidden units the expected activations are not known a priori. The following equation calculates δ_j for the hidden units:

$$\delta_j = (\sum_{k=1}^M \delta_k w_{jk}) f'(u_j). \quad (5.11)$$

In this equation, the error obtained in a hidden unit depends on the error of the others affecting that unit.

5.5.2 ARTIFICIAL NEURAL NETWORK MODEL FOR PACKING DENSITY OF GRANULAR MIXTURE WITH TIRE CHIPS

In this study, the feed-forward ANN in which information moves forward from the input layer directly towards output layer through any hidden layers was selected. Back propagation learning algorithm (BPP) which uses the gradient decent laws and is suitable for prediction problems, is also implemented. A total number of 72 minimum and maximum void ratio tests are used as the database for building ANN model. The goal of the model is to predict maximum and minimum void ratio of

GTCM binary mixture for the given gravel fraction and particle size ratio of tire chips to gravel ($D_{50,R}/D_{50,G}$). The architecture of the network is determined as follows and is illustrated in Fig. 5.9.

Where $e_{\max,G}$ and $e_{\max,R}$ are maximum void ratio of gravel and tire chips, $e_{\min,G}$ and $e_{\min,R}$ are minimum void ratio of gravel and tire chips respectively. A MATLAB code is written to determine neurons (nodes) in the hidden layer by a trial and error method. In this method, training of networks starts with minimum number of nodes in the first hidden layer and mean squared error is calculated and compared with the allowable threshold error. If the error exceeds the threshold value, next neuron is added to the hidden layer. The above iterative process is repeated until the desired stopping criterion is met. In order to reduce time consumed during training process of ANN model, maximum number of neuron in each hidden layer is limited to 8.

$$\text{Input vector} = [e_{\max,G}, e_{\max,R}, e_{\min,G}, e_{\min,R}, \text{GF} (\%), (D_{50,R}/D_{50,G})]$$

$$\text{Output} = [e_{\max,\text{GTCM}}, e_{\min,\text{GTCM}}]$$

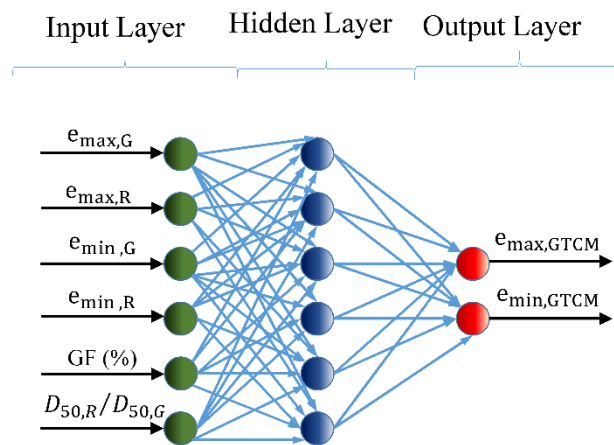


Figure 5.9 Architecture of proposed ANN model

In order to have efficient model with high performance and reduce the noise, size of input space and have a smother relationship, the input data are preprocessed using Min-Max normalization method before training process starts. Eight training algorithms have been assessed for this study. The Levenberg-Marquardt algorithm which has been shown to have better performance for training moderate size of a Multilayer Perceptron (MLP) was selected for training the ANN. Furthermore, “*transigmoid*” and “*pureline*” transfer functions are chosen for each neuron in hidden and output layers of ANN.

Previous studies have shown that there is no correlation between the performance of model and proportion of training, testing and validation data sets (Shahin et al. 2004). In this study, the data is randomly divided into three subsets: training (60%), validation (20%), testing (20%). During the learning or training process, training data sets are used to obtain ANN parameters in each layer (Weights and biases) by minimizing the error function. In order to avoid overfitting the network, the error on the validation data set is monitored during training process. The training will stop when the error on the validation data set begins to rise.

Further training of network will over fits data and prevent generalization. At the next stage, the testing data set is introduced to the ANN and its performance is evaluated. In this study, the proposed neural network model has 6 nodes in the input layer, 6 nodes in the single hidden layer and 2 nodes in the output layer (Fig. 5.9).

Once the ANN performance is evaluated, ANN is utilized to conduct a parametric study. As is mentioned at the beginning of this section, the optimum number of hidden layers and neurons in each hidden layers are obtained based on criterion defined to terminate the training process.

Mean squared error between the target and predicted values of all outputs over all possible configurations was monitored constantly. In order to assess the performance of ANN model, the measured error during the training process is plotted with that of error measured during testing process, training will stop where the testing errors starts to rise while the training errors constantly decreasing. Training must stop to avoid overtraining and final performance of ANN is measured at this point.

5.5.3 ASSESSING PERFORMANCE OF MODEL OVER TRAINING, VALIDATION AND TESTING DATA SETS

A comparison of artificial neural network simulations with laboratory results over training data sets are shown in Fig. 5.10. . As can be seen from the plot, predicted and the measured values of void ratios on different percentage of gravel fraction are in good agreement. The performance of the optimum ANN model over training,

validation and testing data sets are depicted in Fig. 5.11. It should be noted that for the brevity, only simulations on maximum void ratio of GTCM with different particle size ratio and gravel fraction is shown in the figure.

Fig. 5.12 shows the comparison between the predicted values of maximum void ratio $e_{\max, \text{GTCM}}$ and minimum void ratio $e_{\min, \text{GTCM}}$ of GTCM with $D_{50,R}/D_{50,G}=3.35$ by ANN model simulation and laboratory results. As can be seen from the plot, predicted and the measured values of void ratios on different percentage of gravel fraction are in good agreement. However significant differences between estimated values of void ratios given by equation proposed by Anastasiadis et al. (2011) and experimental values can be observed.

$$e_{eq} = ((V_{voids} + V_{Tire})/V_{soil}) \quad (5.12)$$

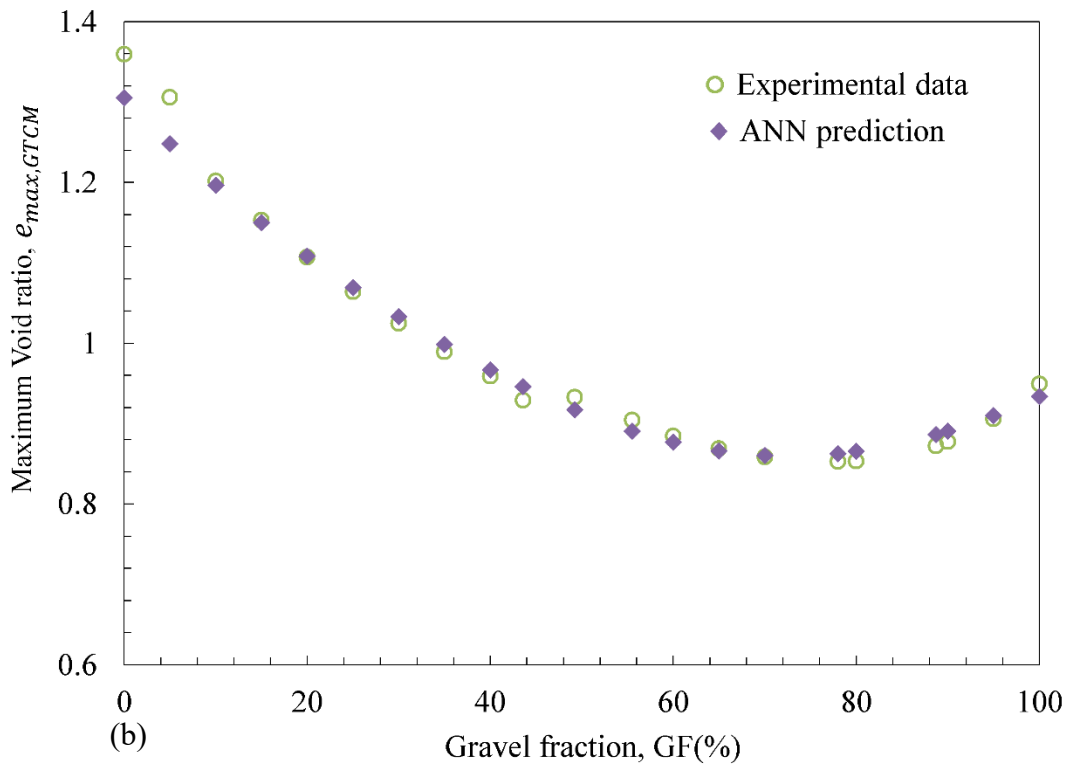
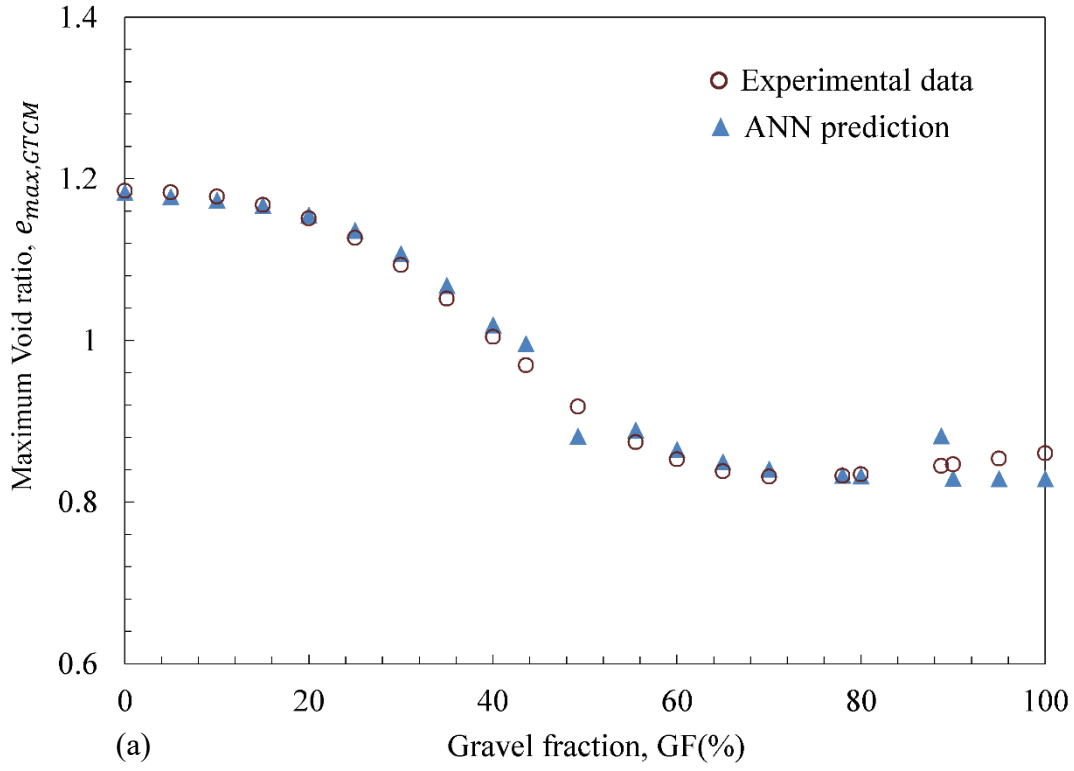


Figure 5.10 Comparison of ANN simulation with experimental data: (a)

$D_{50,R}/D_{50,G} = 1.2$; (b) $D_{50,R}/D_{50,G} = 0.35$

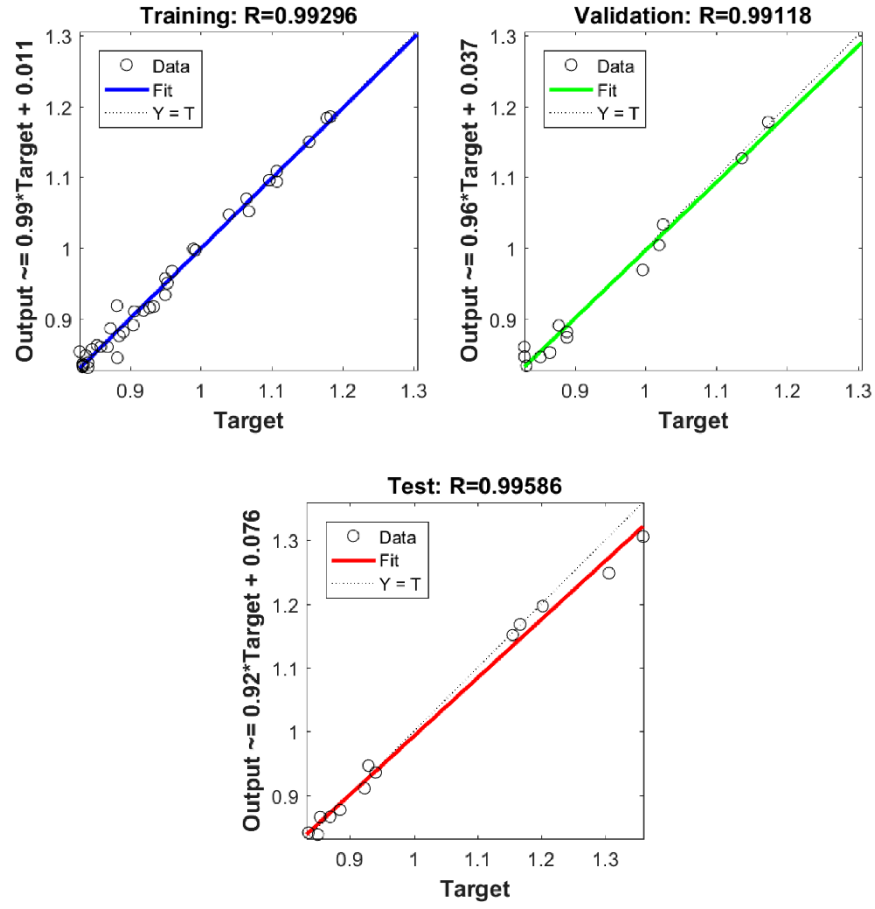


Figure 5.11 Performance of the ANN Model over: (a) Training; (b) Validation
(c) Testing datasets

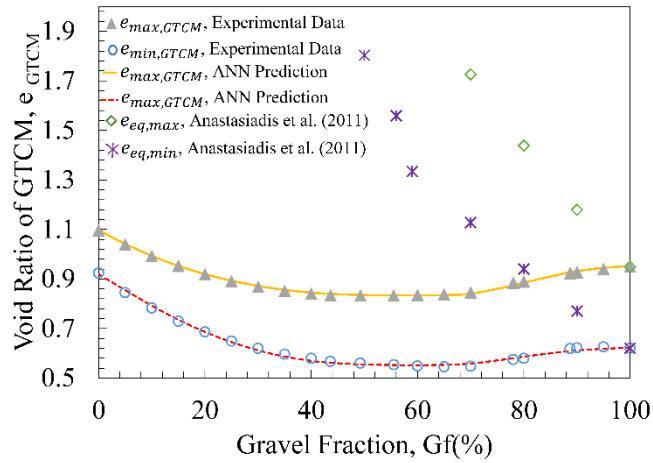


Figure 5.12 Comparison of ANN simulation with experimental data for GTCM

$$\text{with } D_{50,R}/D_{50,G} = 3.35$$

It seems that Eq. 5.12, overestimates values of void ratio, mainly due to considering tire chips in mixture as voids. This shows that the effect of tire chips on void ratio characteristics of GTCM mixture cannot be disregarded.

5.6 SUMMARY AND CONCLUSION

Void ratio characteristics of geomaterials such as gravel-tire chips mixture are key parameters that affect volume tendency, hydraulic conductivity and shear strength behavior of these materials. Most of empirical and theoretical models proposed for estimating void ratio characteristics of binary mixtures of spheres or non-spheres with different particles size ratio, dismiss the deformation of particles within the mixture. Therefore, these models are not suitable for the predicting packing density of gravel-tire chips where two materials with different level of stiffness exist in mixture.

In this study, a new model using Artificial Neural Network (ANN) is developed to estimate maximum and minimum void ratio of GTCM. The effect of gravel fraction (GF) and particle size ratio of tire chips to gravel ($D_{50,R}/D_{50,G}$) on void ratio characteristics of GTCM is also examined. Based on the results of this study, following conclusions can be drawn:

- Theoretical model proposed by Lade et al. (1998) for prediction of void ratio of binary mixtures of sphere particles with different particle size, could estimate the optimum gravel fraction where the minimum value of void ratio is observed for GTCM. However, this model was not successful in prediction of minimum void ratio of GTCM. This was mainly because of dismissing the

deformation of particles in binary mixtures.

- A feed-forward artificial neural network model using MLPs with back-propagation training algorithm can be employed to model very sophisticated void ratio characteristics of gravel tire chips mixture with relatively high resolution.
- The final ANN model was used to predict the maximum and minimum void ratio of additional testing data set. The obtained values were compared with observed values from experiments on GTCM. The results showed that ANNs model were capable of accurately simulating and generalization of the complex void ratio characteristics of granular mixture with tire chips. Furthermore, comparison between estimated values by ANN and those obtained from equivalent void ratio equation indicated that equivalent void ratio expression overestimates the value of maximum and minimum void ratio and has significant degree of tolerance.

REFERENCES

- Ahmad, I., Hesham El Naggar, M. & Khan, A. N. (2007). Artificial neural network application to estimate kinematic soil pile interaction response parameters. *Soil Dynamics and Earthquake Engineering*, 27(9): 892-905.
- Anastasiadis, A., Senetakis, K., Pitilakis, K., Gargala, C. & Karakasi, I. (2011). Dynamic Behavior of Sand/Rubber Mixtures. Part I: Effect of Rubber Content and Duration of Confinement on Small-Strain Shear Modulus and Damping Ratio. *Journal of ASTM International*, 9(2): 1-19.
- Bagheripour, M. H., Shooshpasha, I. & Afzalirad, M. (2012). A genetic algorithm approach for assessing soil liquefaction potential based on reliability method. *Journal of Earth System Science*, 121(1): 45-62.

- Besalatpour, A., Hajabbasi, M. A., Ayoubi, S., Afyuni, M., Jalalian, A. & Schulin, R. (2012). Soil shear strength prediction using intelligent systems: artificial neural networks and an adaptive neuro-fuzzy inference system. *Soil Science and Plant Nutrition*, 58(2): 149-160.
- Chang, C. S., Wang, J.-Y. & Ge, L. (2015). Modeling of minimum void ratio for sand–silt mixtures. *Engineering Geology*, 196: 293-304.
- Cubrinovski, M. & Ishihara, K. (2002). Maximum and minimum void ratio characteristics of sands. *Soils and Foundations*, 42(6): 65-78.
- Demuth, H. B., Beale, M. H., Jess, O. D. & Hagan, M. T. (2014). *Neural Network Design*. Stillwater, OK, USA, Martin Hagan Publisher.
- Feng, Z.-Y. & Sutter, K. G. (2000). Dynamic properties of granulated rubber-sand mixtures. *Geotechnical Testing Journal*, 23(3): 338-344.
- Hazarika, H., Kohama, E. & Sugano, T. (2008). Underwater Shake Table Tests on Waterfront Structures Protected with Tire Chips Cushion. *Journal of Geotechnical and Geoenvironmental Engineering*, 134(12): 1706-1719.
- Hsiao, D.-H., Phan, V. T.-A., Hsieh, Y.-T. & Kuo, H.-Y. (2015). Engineering behavior and correlated parameters from obtained results of sand–silt mixtures. *Soil Dynamics and Earthquake Engineering*, 77: 137-151.
- Humphres, H. W. (1957). A method for controlling compaction of granular materials. *Highw. Res. Board Bull.*, 159: 41-57.
- Johari, A., Javadi, A. A. & Habibagahi, G. (2011). Modelling the mechanical behaviour of unsaturated soils using a genetic algorithm-based neural network. *Computers and Geotechnics*, 38(1): 2-13.
- Khoshkroudi, S. S., Sefidkouhi, M. A. G., Ahmadi, M. Z. & Ramezani, M. (2014). Prediction of soil saturated water content using evolutionary polynomial regression (EPR). *Archives of Agronomy and Soil Science*, 60(8): 1155-1172.
- Kurnaz, T. F., Dagdeviren, U., Yildiz, M. & Ozkan, O. (2016). Prediction of compressibility parameters of the soils using artificial neural network. *SpringerPlus*, 5(1): 1801.
- Lade, P. V., Liggio Jr, C. D. & Yamamuro, J. A. (1998). Effects of Non-Plastic Fines on Minimum and Maximum Void Ratios of Sand. *Geotechnical Testing Journal*, 21(4): 336-347.
- Lee, I.-M. & Lee, J.-H. (1996). Prediction of pile bearing capacity using artificial neural networks. *Computers and Geotechnics*, 18(3): 189-200.
- Li, B., Huang, M. & Zeng, X. (2016). Dynamic Behavior and Liquefaction Analysis

- of Recycled-Rubber Sand Mixtures. *Journal of Materials in Civil Engineering*, 28(11): 04016122.
- Manahiloh, K. N., Nejad, M. M. & Momeni, M. S. (2015). Optimization of Design Parameters and Cost of Geosynthetic-Reinforced Earth Walls Using Harmony Search Algorithm. *International Journal of Geosynthetics and Ground Engineering*, 1(2): 15.
- McCulloch, W. S. & Pitts, W. (1943). A logical calculus of the ideas immanent in nervous activity. *The bulletin of mathematical biophysics*, 5(4): 115-133.
- Ng, T.-T., Zhou, W. & Chang, X.-L. (2017). Effect of Particle Shape and Fine Content on the Behavior of Binary Mixture. *Journal of Engineering Mechanics*, 143(1): C4016008.
- Park, H. I. (2011). Development of Neural Network Model to Estimate the Permeability Coefficient of Soils. *Marine Georesources & Geotechnology*, 29(4): 267-278.
- Park, J. K., Cho, D. H., Hossain, S. & Oh, J. (2018). Assessment of Settlement Profile Caused by Underground Box Structure Installation with an Artificial Neural Network Model. *Transportation Research Record*, 0361198118756901.
- Pooya Nejad, F. & Jaksa, M. B. (2017). Load-settlement behavior modeling of single piles using artificial neural networks and CPT data. *Computers and Geotechnics*, 899-21.
- Quiza, R., López-Armas, O., & Davim, J. P. (2012). Hybrid modeling and optimization of manufacturing: Combining artificial intelligence and finite element method. Springer-Verlag Berlin Heidelberg.
- Rumelhart, D. E. (1986). Learning internal representations by error propagation. *Parallel distributed processing*, 1(8).
- Shahin, M. A. (2014). Load–settlement modeling of axially loaded steel driven piles using CPT-based recurrent neural networks. *Soils and Foundations*, 54(3): 515-522.
- Shahin, M. A., Maier, H. R. & Jaksa, M. B. (2004). Data Division for Developing Neural Networks Applied to Geotechnical Engineering. *Journal of Computing in Civil Engineering*, 18(2): 105-114.
- Shahnazari, H., Shahin, M. A. & Tutunchian, M. A. (2014). Evolutionary-based approaches for settlement prediction of shallow foundations on cohesionless soils. *International Journal of Civil Engineering*, 12(1): 55-64.
- Vallejo, L. E. (2001). Interpretation of the limits in shear strength in binary granular mixtures. *Canadian Geotechnical Journal*, 38(5): 1097-1104.

CHAPTER 6

ESTIMATING DYNAMIC PROPERTIES OF GRANULAR MIXTURES WITH TIRE CHIPS USING ARTIFICIAL INTELLIGENCE

6.1 INTRODUCTION

In the majority of soil dynamic problems such as ground response analysis, an accurate estimation of dynamic properties such as shear modulus and damping ratio as function of shear strain amplitude is an important factor in specifying resistance and dynamic response of soil and structures constructed above or below the ground.

Reinforcing granular materials such as sand with tire chips is a new soil improvement technique that has recently been introduced to protect civil and geotechnical structures such as retaining walls, residential houses and embankments against earthquake and liquefaction induced damage (Hazarika et al. 2006; Hazarika et al. 2008a; Hazarika et al. 2010; Hazarika and Abdullah 2016; Hazarika et al. 2018).

Sand tire chips mixture is a conventional granular mixture that has been thoroughly investigated in literature. Dynamic studies on sand tire chips as attenuation vibration mixture yield promising results in mitigating the earthquake induced loads on geotechnical structures (Hazarika et al. 2008b; Tsang 2008). A series of cyclic direct shear tests and resonant column was carried out on sand-rubber mixtures by several researchers to investigate the effect of waste rubber materials on small strain dynamic

properties of granular mixtures. (e.g. Foose et al. 1996; Feng and Sutter 2000; Edinçliler et al. 2004) . A study on the Ottawa sand rubber mixture showed that a narrow scattered band of normalized shear modulus can be defined using a reference strain in a hyperbolic model (Feng and Sutter 2000).

A series of torsional resonant column tests were carried out by (Anastasiadis et al. 2011; Senetakis et al. 2012) on the sand-rubber and gravely sand- rubber mixture to investigate small strain dynamic properties in a range of shearing strain amplitudes from 10^{-4} % to 10^{-3} %. In their study rubber content varied between 0% to 35% and effective confining pressure in the range of 25-400 kPa. They reported that rubber content has significant effect on the shear modulus and damping ratio of granular mixture with rubber. They found out that small strain shear modulus (G_0) significantly decreases with rubber content in mixture. Mean effective confining pressure was found to increase shear modulus of reinforced soil at low rubber content in mixture. They introduced a modified hyperbolic model using equivalent void ratio ($e_{eq} = ((V_{voids} + V_{Tire})/V_{soil})$) taking into account important features of granular mixture such as rubber content ratio, effective confining pressure and particle size ratio. Their model has limitations such as large number of parameters that needs to be calibrated against the experimental data and is only valid for small range of shear strains.

Nakhaei et al. (2012) conducted a series of large-scale consolidated undrained cyclic triaxial tests to obtain shear modulus and damping ratio of gravely sand mixed with different percentage (0, 8, 10 and 14% by weight) of granulated rubber at different effective confining pressures. Outcome showed that regardless of level of the

confining pressure, shear modulus steadily decreases as rubber content increases in mixture. They concluded that damping ratio decreases with an increases in rubber inclusion in the mixture for the confining pressures of 50 and 100 kN/m². However, this trend was reversed for the confining pressures of 200 and 300 kN/m².

They proposed a modified version of (Hardin and Drnevich 1972) Hyperbolic model to represent shear modulus reduction curves of reinforced soil. This model has introduced 5 new parameters that need to be calibrated against the experimental data. However, proposed model overestimates the values of shear modulus ratio ($G/G_{\max}$) at very low confining pressures and underestimates it at high confining pressure, especially when higher percentage of rubber is used in mixture.

As explained in preceding chapters, gravel-tire chips mixture has recently been introduced to overcome the limitation of sand-tire chips mixture such as low permeability and low liquefaction resistance (Hazarika et al. 2010; Hazarika and Abdullah 2016). However, to the best of authors knowledge, there is no study can be found in literature to model dynamic properties of gravel-tire chips mixture.

Furthermore, Majority of previous empirical models proposed for estimating dynamic characteristics of reinforced granular soils with tire chips are actually modified version of Hardin hyperbolic model (Hardin 1978). Implementation of such complex empirical expressions may require definition of a large number of parameters that needs to be calibrated against large number of experimental data which might be expensive and time consuming.

Main objective of this chapter is to introduce new model using two different Artificial Intelligence (AI) techniques, Artificial Neural Network (ANN) and Support

Vector Machine (SVM) approaches that can simulate complex dynamic characteristics of GTCM mixtures taking into account important features of granular materials. It is worthwhile to mention that dynamic properties from chapter 5, were used to construct AI models.

6.2 ARTIFICIAL INTELLIGENCE MODEL

6.2.1 SUPPORT VECTOR MACHINES

Support vector machines (SVMs) are one of the learning systems that employs leaning techniques in the framework of structural risk minimization and theory of Vapnik-Chervonenkis (VC) bonds. This method utilizes a theorem space of linear equations in n-dimensional feature space, trained with learning algorithm according to optimization hypothesis that implements learning bias attains from statistical learning postulate. This method have been introduced by (Vapnik 1964) for the first time. Despite being appealing in theory, it couldn't receive the attention which it deserved till 1992, because it was believed to be not suitable for practical application. However SVMs were taken seriously after reporting excellent performance on practical learning application such as computer vision, digit recognition and text categorization. Since then a lot of research papers have published comparing results of SVMs models with that of Artificial Neural Networks and other statistical models on the benchmark problems (Feng and Lipo 2003; Meyer et al. 2003; Cherkassky and Mulier 2007).

6.2.1.1 Application of SVMs in civil and geotechnical engineering

Pal (2006) investigated the viability of support vector machines (SVM) based classification method in assessing liquefaction potential of soil using actual data sets obtained from standard penetration test (SPT) and cone penetration test. They found out that SVMs based models produced satisfactory accuracy (over 96%) over trained data sets. Goh and Goh (2007) have applied SVM technique to assess soil liquefaction potential using in situ measurements based on the CPT tests. They claimed that the results of study showed a 98% success rate for the data sets used for training and testing their model. Maalouf et al. (2008) has conducted a study on the use of SVM in predicting the resilient modulus (M_R) of Hot Mix Asphalt (HMA) specimens for given temperature and material properties. They found out that Support Vector Regression (SVR) model was superior to the least squares (LS) in terms of performance. (Das et al. 2011) employed two Artificial Intelligence (AI) Techniques (SVMs and ANN) for prediction of maximum dry density (MDD) and unconfined compressive strength (UCS) of cement stabilized soil. They found out that A SVMs based model with radial basis kernel function can predict MDD and UCS of wide range of soils for given input parameters liquid limit (LL), plasticity index (PI), clay fraction (CF)%, sand (S)%, gravel Gr(%), moisture content (MC) and cement content (%) (Ce) with high resolution. Mozumder et al. (2013) used Support Vector Regression (SVR) and ANN models for predicting the uniaxial compressive strength of Fiber Reinforced Polymer (FPR) confined concrete. They found out that SVMs based model exhibited better performance over ANN and existing strength predictive models in terms of correlation coefficient (R), Root Mean Squared Error (RMSE) values (Mozumder et al. 2017).

Moduli et al. (2013) used four different artificial intelligence approaches, artificial neural network (ANN), genetic programming (GP), support vector machine (SVM), and relevance vector machine (RVM) to estimate the uplift capacity of suction caisson in clay based on data sets collected from the literature. The GP model was found to exhibit slightly better performance based on statistical criteria's in comparison to other models.

Kohestani and Hassanlourad (2016) used two AI models (ANN and SVR) for prediction of mechanical behavior of different carbonate soils using a series of data sets obtained from CD Triaxial tests on different carbonated sandy soils. They found out that a Multi-Layer Perceptron ANN yields better performance in prediction of stress-strain behavior of Carbonate soils for given input variables of axial strain (ϵ_1), relative density (D_r), confining pressure (σ_3), maximum void ratio (e_{max}), minimum void ratio (e_{min}), and carbonate calcium content.

Debnath and Dey (2018) proposed a SVR based model for prediction of the bearing capacity (q_{rs}) of unreinforced sand bed and geogrid-reinforced sand bed resting over a group of stone columns floating in soft clay. They used 219 experimental data sets to develop SVR model. The SVR model was trained by considering following parameters as input parameters: bearing capacity of unreinforced soft clay (q_u), settlement to diameter of the footing ratio (s/D), thickness of the unreinforced sand bed (USB) and the geogrid-reinforced sand bed (GRSB) to diameter of the footing ratio (t/D), diameter of the geogrid-reinforced layer to diameter of the footing ratio (d/D), and length to diameter of the stone column ratio (L/d_{sc}) as input parameters, and the bearing capacity of geogrid-reinforced stone column composite foundation (q_{rs}) as

the single output parameter. They concluded that the SVR model with the ERBF kernel function exhibits the better generalization ability of the training with lowest statistical error.

6.2.1.2 Basics of Statistical Learning Theory

This section reviews some of the concepts of theory of statistical learning which SVMs are based on and developed by Vapnik (1999) .

6.2.1.2.1 Classification Problem

Suppose we are given two class pattern recognition, Given data set M of N samples: $(\mathbf{x}_1, y_1), (\mathbf{x}_2, y_2), \dots, (\mathbf{x}_N, y_N)$ each sample consists of $\mathbf{x}_i$ of l length, $\mathbf{x}_i = (x_1, x_2, \dots, x_l)$ and $y_i \in \{-1, 1\}$.

What is required is now to find a classifier with decision function, $f(\mathbf{x})$, such as:

$$f(\mathbf{x}_i) = y_i, \quad \forall (\mathbf{x}_i, y_i) \in M. \quad (6.1)$$

The performance of such a classifier can be calculated in terms of loss or error function defined as follows:

$$L(f(\mathbf{x}), y) = \begin{cases} 1 & \text{if } y \neq f(\mathbf{x}) \\ 0 & \text{if } y = f(\mathbf{x}) \end{cases} \quad (6.2)$$

6.2.1.2.2 Empirical risk minimization:

If we are given the binary classification task as above, considering a learning with a set of adjustable α . The machine is required to find α in which learns the mapping $\mathbf{x} \rightarrow y$. This will result in mapping of $\mathbf{x} \rightarrow f(\mathbf{x}, \alpha)$.

The accuracy of defined machine can be obtained by the Empirical risk function as below:

$$R_{emp}(\alpha) = \frac{1}{N} \sum_{i=1}^N L(f(x_i, \alpha), y_i) \quad (6.3)$$

Where the N is the size of data set used for training. Majority of machine learning methods such as Neural Networks (NN), SVMs (Support Vector Machines) and classical methods such as least square or maximum likelihood utilized this risk minimization principle which is called Empirical Risk Minimization (EMP). However, there is a tendency to overfitting the data if the complexity of machine is high. Furthermore, a smaller error on the training data sets doesn't suggest a better generalization ability.

6.2.1.2.3 *Structural Risk Minimization*

A novel statistical technique called Structural Risk Minimization (SRM) was proposed to take into account the complexity of learning machine when it looks up for α to learn the map $x \rightarrow y$. Expected risk associated with hypothesis $f(x_i, \alpha)$ can be defined as follows:

$$R_{exp}(\alpha) = \int L(f(x_i, \alpha), y_i) dP(x, y) \quad (6.4)$$

Where $P(x, y)$ is the prior probability distribution. However the problem is that Expected risk cannot be obtained explicitly, since $P(x, y)$ is unknown in most classification tasks. The theory of uniform convergence of probability was developed in the 70's and 80's, includes a description of necessary and sufficient conditions as well as bounds on the derivation of the risk by calculating the upper bond as defined bellow (Vapnik, 1952). For a $\alpha \in \Lambda$ and $N > h$, a typical uniform VC bound, which

holds with probability $1-h$, can be obtained from following equation:

$$R_{exp}(\alpha) \leq R_{emp}(\alpha) + VC(h)$$

$$VC(h) = \sqrt{\frac{h(\log \frac{2N}{h} + 1) - \log(\frac{\eta}{4})}{l}} \quad (6.5)$$

Where $VC(h)$ is Vapnik and Chervonenkis dimension (Vapnik 2013).

6.2.1.2.4 VC dimension

VC dimension is the largest set of points of X that can be shattered by the learning machine and is measure of its capacity. Let's assume the training data sets of points X . if machine can correctly assign all labels to the instances in X by mapping $x \rightarrow f(x, \alpha)$, then we can say X is shattered by learning machine.

The complexity and capacity of a VC dimension is proportional to the number of free parameters in the classifier. The larger the number of free parameters the larger the VC dimension and lower the empirical risk. Because they are capable of modeling complex decision surfaces. However referring to Eq. 6.5, we can expect a decrease in the confidence of empirical risk with increasing the complexity of learning machine (See Fig. 6.1). SVM tries to keep balance between the quality of data approximation (minimizing training errors) and the complexity of function (Vapnik 2013).

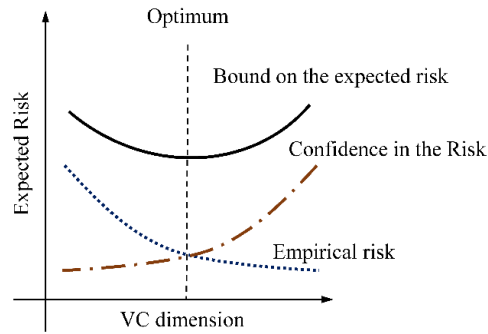


Figure 6.1 Correlation between empirical risk, expected risk, VC dimension

(Ech-Cherif et al. 2002).

6.2.1.2.5 Linear Classification

Consider the binary classification problem with training input data points as x_i ($x_1, x_2, \dots, x_m$) are assigned to two classes target $y_i=+1$ or $y_i=-1$ as negative example. Considering the data patterns are linearly separable, the input space can be split into two parts by the hyperplane defined as follows:

$$f(x) = \{(w^T x + b)\} = 0 \quad (6.6)$$

$(w^T x)$ indicates inner products of w^T and x . The vector w indicates the weight of separating hyperplane and the scalar b indicates the offset of hyperplane from the origin. Eq. 6.6 could also be expressed in the following way:

$$\{(w^T x + b)\} \geq 0 \quad \text{for} \quad y_i = +1 \quad (6.7)$$

$$\{(w^T x + b)\} < 0 \quad \text{for} \quad y_i = -1 \quad (6.8)$$

As illustrated in Fig 6.2, there are infinite possible planes that can correctly separate two classes +1 (red circles) and -1 (white circles).

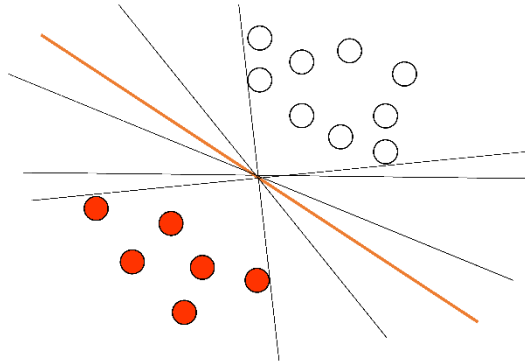


Figure 6.2 Example of binary classification

6.2.1.2.6 Maximizing Margin between the classes

Let's assume the margin between positive and negative classes is φ . The SVM objective is to find a Hyperplane M that maximizes the margin φ between two set of classes. As is shown in Fig. 6.3, the supporting planes M_+ and M_- determines boundaries for the margin. The data points that lies on these planes and acts as support to the classification hyperplanes are called support vectors. For any point situated on the plan M_+ we have $\{(w^T x + b)\} = +1$. And similarly for any point situated on the plan M_- we have $\{(w^T x + b)\} = -1$. The margin between two hyperplanes M_+ and M_- can be calculated as:

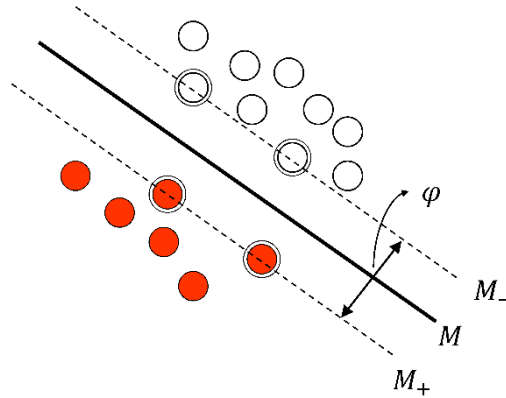


Figure 6.3 Optimal plane that maximizes the margin φ

$$M_+ - M_- = \frac{|(w^T x_+ + b)|}{\|w\|} + \frac{|(w^T x_- + b)|}{\|w\|} = \frac{2}{\|w\|} \quad (6.9)$$

So the hyperplane that optimally discriminate the data is the one that minimizes:

$$\psi(w) = \frac{\|w\|}{2} = 0.5w^T w \quad (6.10)$$

Subject to the following constraints:

$$y_i \{(w^T x + b)\} \geq +1 \quad (6.11)$$

Note that this solution is independent of the bias b . Varying b will move the optimal hyperplane in the direction of w and the maximum margin will remain the same.

6.2.1.2.7 *Lagrangian formulation*

The objective is to solve a minimization problem of $0.5w^T w$ with a set of inequality constraints from Eq. 6.11. The theory of Lagrangian multipliers is used to solve this problem (Burges 1998). The Lagrangian formulation of the problem is:

$$L(w, b, \alpha) = 0.5w^T w - \sum_{i=1}^m \alpha_i \{y_i(w^T x_i + b) - 1\} \quad (6.12)$$

Where α_i is the Lagrange multipliers. The above expression is also called the primal formulation. That could be considered as a convex quadratic programming problem because the objective function $L(w, b, \alpha)$ itself is convex. If we differentiate $L(w, b, \alpha)$ with respect to w and b and setting the results equal to zero, we have:

$$w = \sum_{i=1}^m \alpha_i y_i x_i \quad (6.13)$$

$$\sum_{i=1}^m \alpha_i y_i = 0 \quad (6.14)$$

If we expand the Eq. 6.8 term by term, we can obtain dual problem as follows:

$$L(w, b, \alpha) = 0.5w^T w - \sum_{i=1}^m \alpha_i y_i w^T x_i - b \sum_{i=1}^m \alpha_i y_i + \sum_{i=1}^m \alpha_i \quad (6.15)$$

By comparing Eq. 6.15 with Eq. 6.14, we conclude that the third term on the right side of Eq. 6.15 equals zero. Eq. 6.16 can be obtained by multiplying Eq. 6.13 by

w^T and then expanding it:

$$w^T w = \sum_{i=1}^m \alpha_i y_i w^T x_i = \sum_{i=1}^m \sum_{j=1}^m \alpha_i \alpha_j y_i y_j x_i^T x_j \quad (6.16)$$

We can now rewrite the Eq. 6.15 as follows:

$$L(w, b, \alpha) = \sum_{i=1}^m \alpha_i - 0.5 \sum_{i=1}^m \sum_{j=1}^m \alpha_i \alpha_j y_i y_j x_i^T x_j \quad (6.17)$$

Considering constraints in Eq. 6.14, the SVM training will look up for the optimum

Lagrange multipliers that maximize $L(w, b, \alpha)$ in Eq. 6.17 and subject to $\alpha_i \geq 0$. Note that only some of the data points have non-zero α_i which are called support vectors.

6.2.1.3 Nonlinear classification

When data sets are nonlinearly separable. A vector $z = \varphi(x)$ is used to map the each vector x into a higher dimensional space. So the Lagrangian function can be modified for the high-dimensional space as follows:

$$L(\alpha) = \sum_{i=1}^m \alpha_i - 0.5 \sum_{i=1}^m \sum_{j=1}^m \alpha_i \alpha_j y_i y_j \varphi^T(x_i) \varphi(x_j) \quad (6.18)$$

Where $\varphi^T(x_i) \varphi(x_j)$ is the inner product of two vectors induced in higher space. This can be replaced by a kernel function $K(x, x_i)$. Polynomial kernel function $(x^T x_i + 1)^d$ and radial basis kernel function $\exp [\|x - x_i\|^2 / 2\sigma^2]$ are two commonly used kernel functions. Where d and σ are kernel parameters that needs to be determined in advance. Selection of a suitable function assists SVM in separating non-separable data in the original space to separable data in higher dimensional feature space (Fig. 6.4).

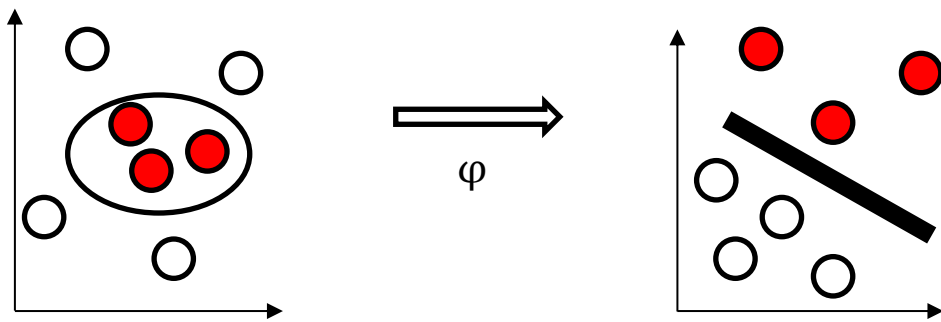


Figure 6.4 Nonlinear mapping of linearly inseparable data into higher dimensional space to make them linearly separable

6.2.2 SUPPORT VECTOR REGRESSION (SVR)

If the target variables involve categorical data, a SVM model need to be used, however when the target variables are continues data Support Vector Regression (SVR) model should be employed.

If a set of observation data are given as $\{(x_1, y_1), (x_2, y_2), \dots, (x_k, y_k)\}$, where $x_i \in \mathbb{R}^n$ input values and $y \in \mathbb{R}^n$. The ε -insensitive loss which is the magnitude of the difference between the predicted value and the radius ε of the tube function can be expressed as follows:

$$L_{\varepsilon}(y) = \begin{cases} 0 & \text{if } |y - f(x)| \leq \varepsilon \\ |y - f(x)| - \varepsilon & \text{otherwise} \end{cases} \quad (6.20)$$

The non-linear regression function can be presented as below:

$$f(x) = \{(\mathbf{w}^T \mathbf{x} + b)\} = 0 \quad (6.21)$$

Where b = bias and w = weight vector. The main objective in SVR is to find a function, $f(x)$ that almost has a ε deviation from the actual output (y_i). So this goal can be achieved by minimizing the following expression:

$$\psi(\mathbf{w}) = \frac{\|\mathbf{w}\|^2}{2} = 0.5\mathbf{w}^T \mathbf{w} \quad (6.22)$$

Subject to the following constraints:

$$+y_i - \{(\mathbf{w}^T \mathbf{x} + b)\} \leq +\varepsilon \quad (6.23)$$

$$-y_i + \{(\mathbf{w}^T \mathbf{x} + b)\} \leq +\varepsilon \quad (6.24)$$

By introducing slack variables ξ_i, ξ_i^* ($i = 1 \dots n$), optimization function now can be expressed (Fig. 6.5) :

$$\psi(\mathbf{w}, b, \alpha) = 0.5\mathbf{w}^T \mathbf{w} + C \sum_{i=1}^m (\xi_i + \xi_i^*) \quad (6.25)$$

Subject to the following constraints:

$$y_i - \{(w^T x + b)\} \leq \varepsilon + \xi_i \quad (6.26)$$

$$-y_i + \{(w^T x + b)\} \leq \varepsilon + \xi_i^* \quad (6.27)$$

Where C = constant known as the regularization or penalty parameter. The function in Eq. 6.25 can be transformed in the form of a Lagrange function as follows:

Therefore, the goal would be maximizing the following expression:

$$W(\alpha, \alpha^*) = -\frac{1}{2} \sum_{i,j=1}^n (\alpha_i + \alpha_i^*) (\alpha_i^* - \alpha_i) K(x_i, x_j) + \sum_{i=1}^n y_i (\alpha_i^* - \alpha_i) - \varepsilon \sum_{i=1}^n (\alpha_i + \alpha_i^*) \quad (6.29)$$

Where K is the kernel function and defined as follows:

$$K(x_i, x_j) = \phi(x_i) \phi(x_j) \quad (6.30)$$

α, α^* and b are calculated by solving the above expressions considering following condition:

$$\sum_{i=1}^n (\alpha_i - \alpha_i^*) = 0, \quad 0 \leq \alpha_i, \alpha_i^* \leq C, \quad i = 1, 2, 3, \dots, n. \quad (6.31)$$

The regression function can be rewritten as:

$$f(x) = \sum_{i=1}^n (\alpha_i - \alpha_i^*) K(x, x_i) + b \quad (6.32)$$

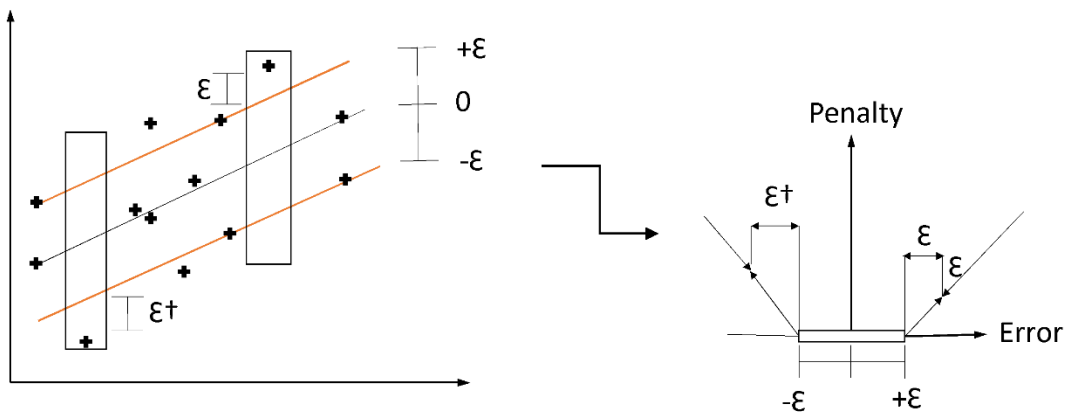


Figure 6.5 Linear SVM regression

6.2.2.1 SVR model development and database preparation

In order to obtain accurate prediction of dynamic properties of GTCM such as shear modulus and damping ratio, the important factors affecting shear modulus and damping ratio need to be determined and taken into account in developing of an efficient model. The results from a series of cyclic triaxial tests on GTCM with particle size ratio of $D_{50,R}/D_{50,G}=1$, are utilized in this section. Material properties, testing condition and layout of experiments are already presented in section 5.2 of chapter 5.

In this study, the SVR model has a gravel fraction (GF), effective confining pressure (σ_3), cyclic stress ratio ($CSR=\sigma_d/2\sigma_3$), shear strain amplitude (γ) as input parameters and, shear modulus (G) and damping ratio (D) as output. A data sets consisting of 3006 shear modulus and damping ratio measurements of GTCM was employed in our analysis. 2900 data sets out of 3006 were randomly chosen for training and validation of proposed model whereas the remaining 106 data sets were excluded from training data sets and used to test the constructed model.

Before the training of SVM model data sets were randomly shuffled, in order to make sure that the model is not learning a specific order and faster convergence is observed. The algorithm utilized for data shuffling was simply relied on selecting two data rows (consisting of the input and outputs) randomly and swapping them together. In this study radial basis function was selected as optimal kernel function.

Support vector regression based model for predicting shear modulus and damping ratio of GTCM can be expressed as follows:

$$G = \text{SVR} (GF, \sigma_3, \sigma_d/2\sigma_3, \gamma) \quad (6.33)$$

$$D = \text{SVR} (GF, \sigma_3, \sigma_d/2\sigma_3, \gamma) \quad (6.34)$$

Optimal values of C , ε and kernel parameter σ are obtained on a trial and error basis and performance of model is assessed using two statistical indices, namely coefficient of determination (R^2) and root mean squared error (RMSE).

$$R^2 = 1 - \frac{\sum_{i=1}^n (y_i - Y_i)^2}{\sum_{i=1}^n (y_i - \bar{y})^2} \quad (6.35)$$

$$RMSE = \sqrt{\frac{\sum_{i=1}^n (y_i - Y_i)^2}{n}} \quad (6.36)$$

Where y_i = observed value; Y_i = predicted value; n = number of data points; $\bar{y}$ = mean of the observed value.

6.2.2.2 Results of SVR model and discussion

Optimal values of penalty parameter (C), loss Function (ε) and kernel parameter (σ) for both shear modulus and damping ratio SVR models are given in Table 6.1. Table 6.2, summarizes the best performance of the model on training data set corresponds to optimal values of kernel and loss function parameter.

Table 6.1 Optimal Values of Penalty Parameter, Loss Function, and
Kernel Parameter for SVR Model Development

Radial basis kernel, RBF	Shear Modulus (G)	Damping Ratio (D)
C	2.16	5.8
ε	0.02	0.05
σ	1	1

Table 6.2 Statistical performance of all models over the training data sets

Statistical parameter	Shear Modulus (G)	Damping Ratio (D)
R²	0.95	0.78
RMSE	1.19	3.11
Max	24.36	38.81
Min	0.22	0.1
Standard deviation	5.39	5.71

Comparison between observed values of shear modulus and predicted values by SVR model for GTCM with different gravel fraction at effective confining pressure of 100 kN/m² is presented in Fig 6.6. A SVR model with values of penalty parameter, loss function, and kernel parameter given in Table 6.1, provided R² and RMSE values of 0.95 and 1.19 for training data set. This means, as is shown in Fig. 6.6, observed values of shear modulus of GTCM are in good agreement with the predicted ones. Furthermore, RBF based SVR model of damping ratio showed lower performance over training data sets in comparison to that of shear modulus. This might happened due to the high dispersion of damping ratio data which made it difficult to fit to the any pattern.

However, In order to assess the ability of proposed SVR model to generalize to new data, further analysis was performed on the independent testing data set which was excluded from main data set used for training the model. Table 6.3, summarizes the performance of the proposed model on independent testing set.

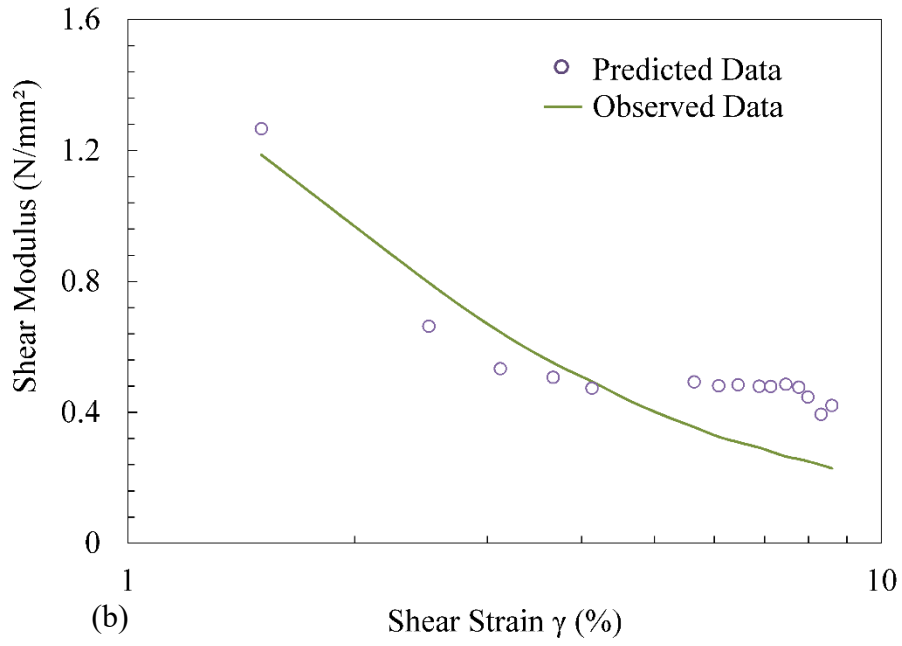
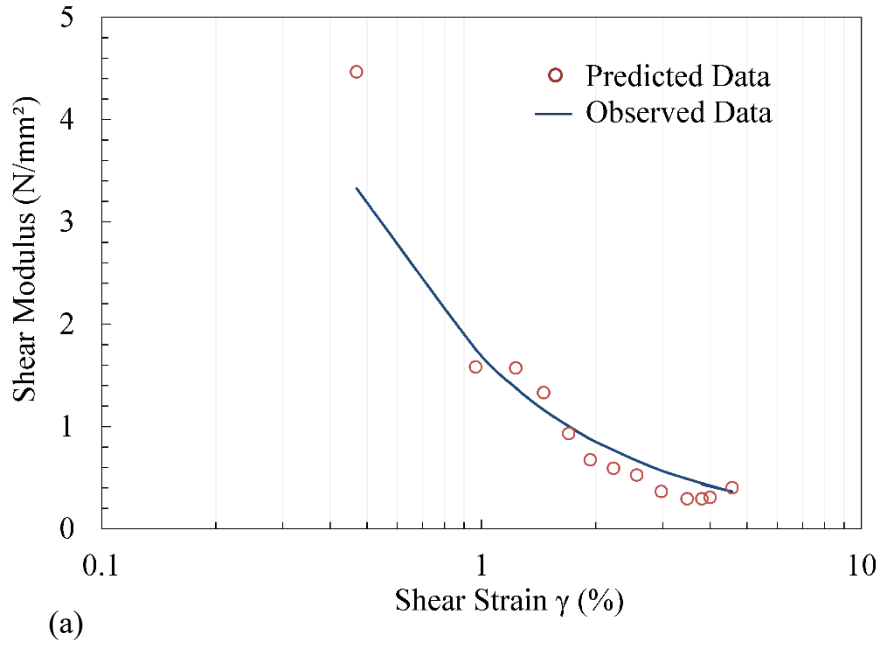


Figure 6.6 Comparison between observed and predicted values of shear modulus for training data sets using SVR: (a) GF=55%, $(\sigma_d/2\sigma_3)=0.25$; (b) GF=44%, $(\sigma_d/2\sigma_3)=0.3$

A comparison between predicted and observed values of shear modulus and damping ratio of GTCM with GF=87% at CSR=0.25 is displayed in Figure 6.7.

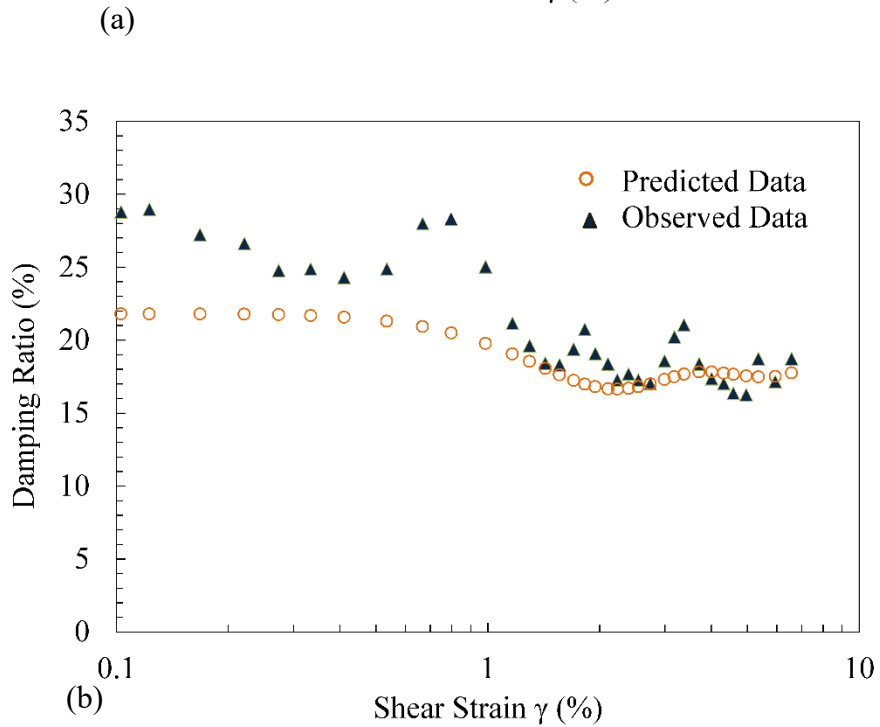
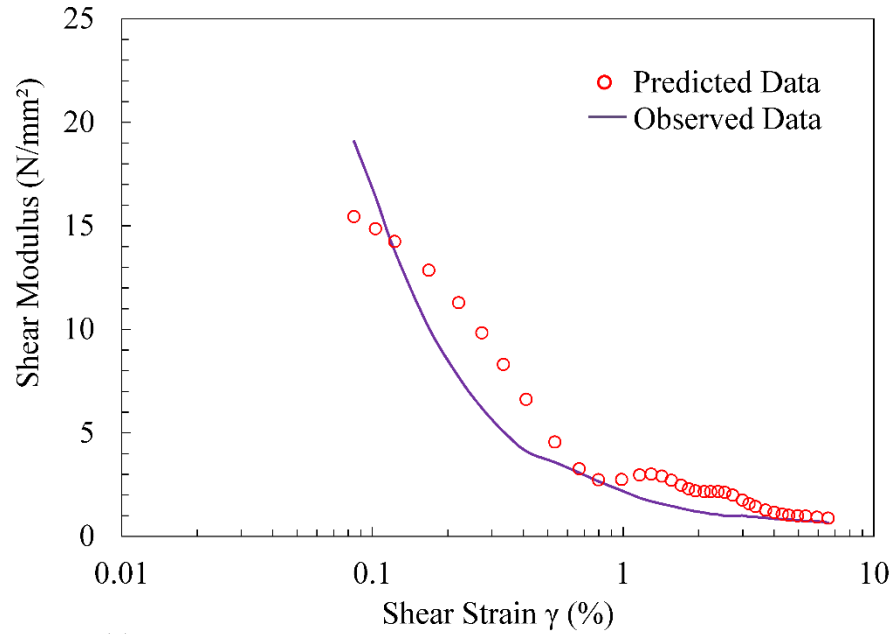


Figure 6.7 Comparison between observed and predicted values for new testing data sets using SVM at GF=87%, $(\sigma_d/2\sigma_3)=0.25$: (a) Shear modulus (b) Damping ratio.

Table 6.3 Statistical performance of all models over the independent testing data sets

Statistical parameter	Shear Modulus (G)	Damping Ratio (D)
R²	0.92	0.71
RMSE	1.55	3.90
Standard deviation	4.61	4.85

As is given in Table 6.3 and shown in Fig. 6.7, the proposed model yielded a reasonably good but slightly lower performance over the independent testing data set in comparison to that of training data set. Although SVM based model shows a satisfactory generalization performance and could predict shear modulus of granular materials with relatively high resolution, but yielded slightly lower performance in generalization and estimation of damping ratios of GTCM.

6.2.3 ARTIFICIAL NEURAL NETWORK MODEL

The application of ANN in civil engineering is introduced in the early 1990s by (Goh 1994) which involved the feasibility of ANNs to predict the liquefaction potential of soil. Recently, artificial neural networks (ANNs) have been successfully adopted to many applications in geotechnical engineering such as estimating capacity of driven pile in cohesionless soil (Kurup and Griffin 2006), soil stratification (Hegazy and Mayne 2002) and slope stability analysis (Ferentinou and Sakellariou 2007). However very limited studies can be found in literature to investigate applicability of this

method for modeling dynamic properties of soil. (Ghodrati and Araei 2017) introduced an artificial neural network based model for predicting shear modulus and damping ratio of gravelly materials. They used a database comprised of a series of cyclic triaxial tests on 12 different gravelly materials. The confining pressures and loading frequencies and shear strain were considered as inputs and shear modulus and damping ratio as outputs of multilayer perceptrons (MLPs) for predicting behavior of gravelly materials. They found that ANN is a reliable tool to capture the dynamic behavior of gravelly materials.

6.2.3.1 ANN model development and database preparation

Selection of appropriate ANNs architecture is one of the most essential and complicated tasks of building a model. In this study, the feed-forward MLPs in which information moves forward from the input layer directly towards output layer through any hidden layers was selected. Back propagation learning algorithm (BPP) which uses the gradient decent laws and is suitable for prediction problems, is implemented. The detail on the structure of feedforward ANN and how it operates is already provided in section 6.4 of chapter 6.

A total number of 3006 shear modulus and damping ratio values of GTCM are used as the database for building ANN model. 106 out of 3006 data sets were excluded from main training database for verification purpose. The goal of the model is to predict shear modulus and damping ratio of gravel and GTCM for a given gravel fraction (GTCM) and mean effective confining pressure. The architecture of the network is determined as follows and is illustrated in Fig. 6.8.

Input vector $\{X\} = \{\sigma_d/2\dot{\sigma}_3, \gamma, \dot{\sigma}_3, GF (\%)\}$

Output $\{Y\} = \{G\}$

Output $\{Y\} = \{D\}$

A MATLAB code is written to determine neurons (nodes) in the hidden layer by a trial and error method. In this method, training of networks starts with minimum number of nodes in the first hidden layer and sum squared error is calculated and compared with the allowable threshold error. If the error exceeds the threshold value, next neuron is added to the hidden layer. The above iterative process is repeated until the desired stopping criterion is met.

The Levenberg-Marquardt algorithm which has been shown to have better performance for training moderate size of a Multilayer Perceptron (MLP) was selected for training the ANN (Levenberg 1944; Marquardt 1963).

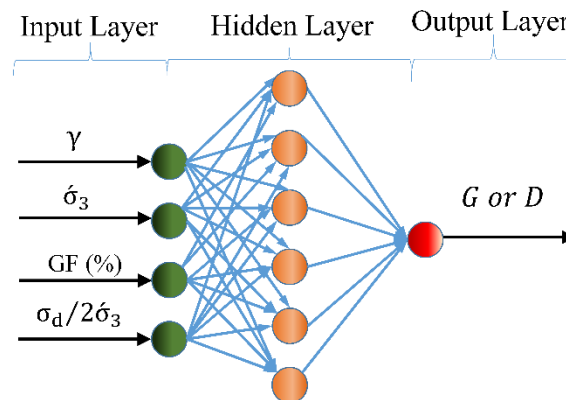


Figure 6.8 Architecture of ANN model

The data is randomly divided into three subsets: training (60%), validation (20%), testing (20%). During the learning or training process, training data sets are used to obtain ANN parameters in each layer (Weights and biases) by minimizing the error function. In order to avoid overfitting the network, the error on the validation data set is monitored during training process. The training will stop when the error on the validation data set begins to rise. Further training of network will over fits data and prevent generalization. At the next stage, the training data set is introduced to the ANN and its performance is evaluated.

In this study, the proposed neural network model has 4 nodes in the input layer, 6 nodes in the hidden layer, and 1 nodes in the output layer (Fig. 6.8). Once the ANN performance is evaluated, ANN is utilized to conduct a parametric study. As is mentioned at the beginning of this section, the optimum number of hidden layers and neurons in each hidden layers are obtained based on criterion defined to terminate the training process.

Mean squared error between the target and predicted values of all outputs over all possible configurations was monitored constantly. In order to assess the performance of ANN model, the measured error during the training process is plotted with that of error measured during testing process, training will stop where the testing errors starts to rise while the training errors constantly decreasing. Training must stop to avoid overtraining and final performance of ANN is measured at this point.

The performance of proposed model on predicting shear modulus of GTCM was assessed by comparing predicted values by model for training, validation and testing data sets are plotted against the target values. As can be seen from Fig. 6.9, the

coefficient of correlation (R) is used for performance assessment of the model over three datasets.

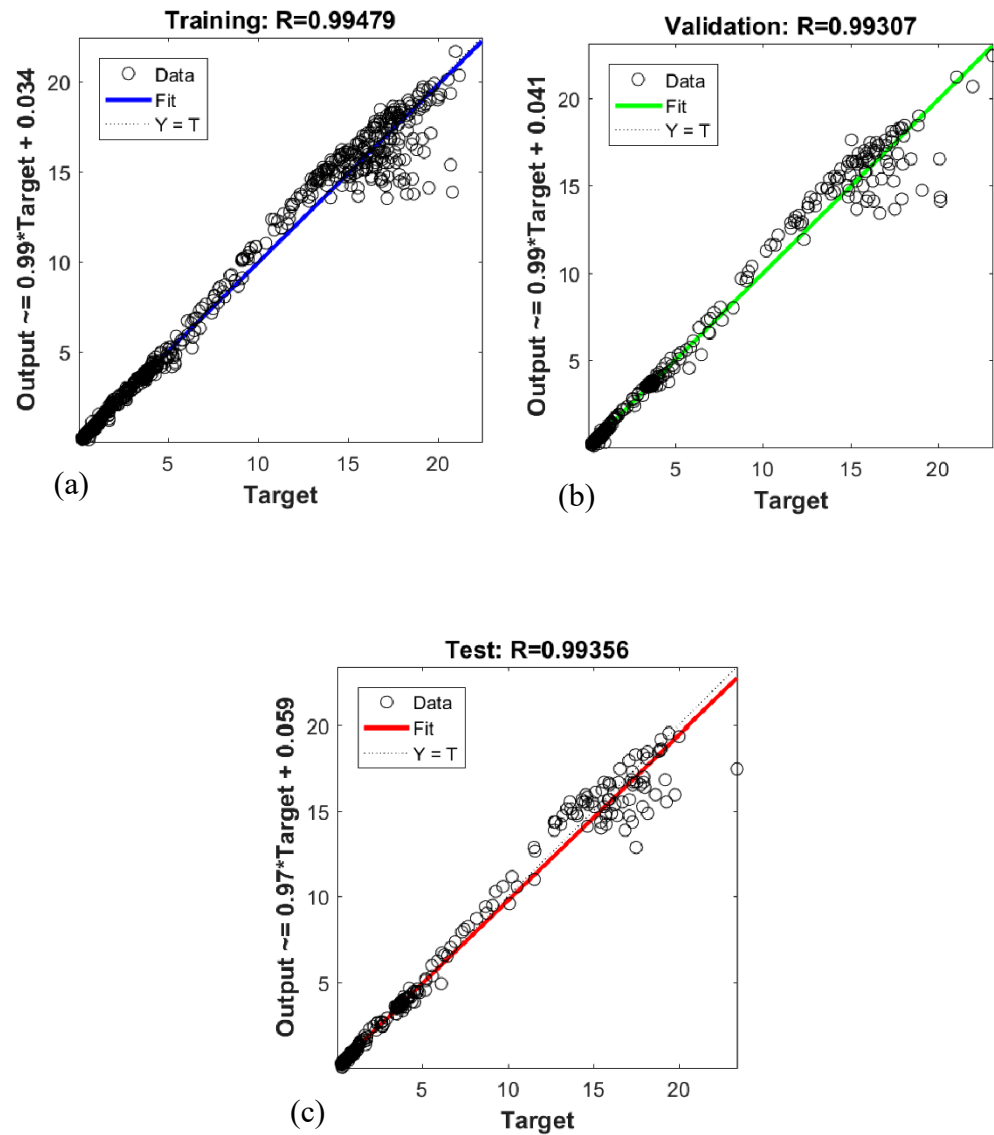


Figure 6.9 Performance of the ANN Model over: (a) Training; (b) Validation (c)

Test datasets

As can be seen from Fig. 6.9, there is such a strong correlation between estimated and target values of shear modulus for all three datasets. Fig. 6.10a shows the comparison between the predicted values of shear modulus by ANN model simulation and laboratory results for GTCM with GF=87% at the effective confining pressure of $\sigma_3=100$ kPa and stress ratio of $(\sigma_d/2\sigma_3)=0.25$. It should be noted that independent testing data set was not utilized for training of ANN model.

As can be seen from the plot, predicted and the measured values of shear modulus are in very good agreement. Performance of ANN model is assessed by performing a linear regression between the network outputs and the corresponding targets. A very high coefficient of correlation ($R>99\%$) is obtained for the tested data set. (See Fig. 6.10b)

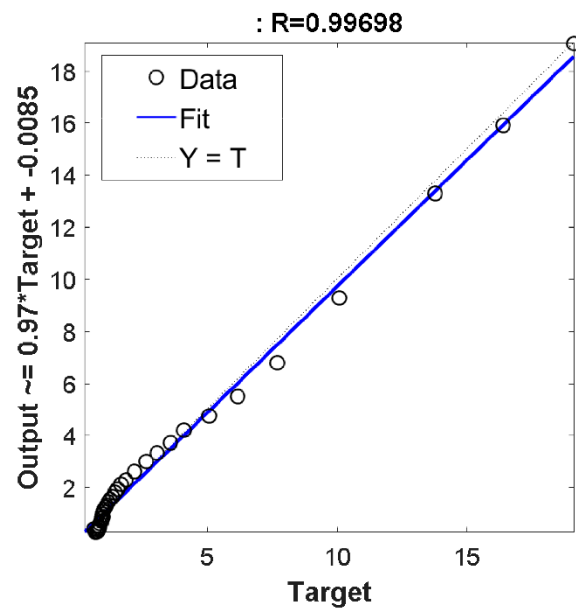
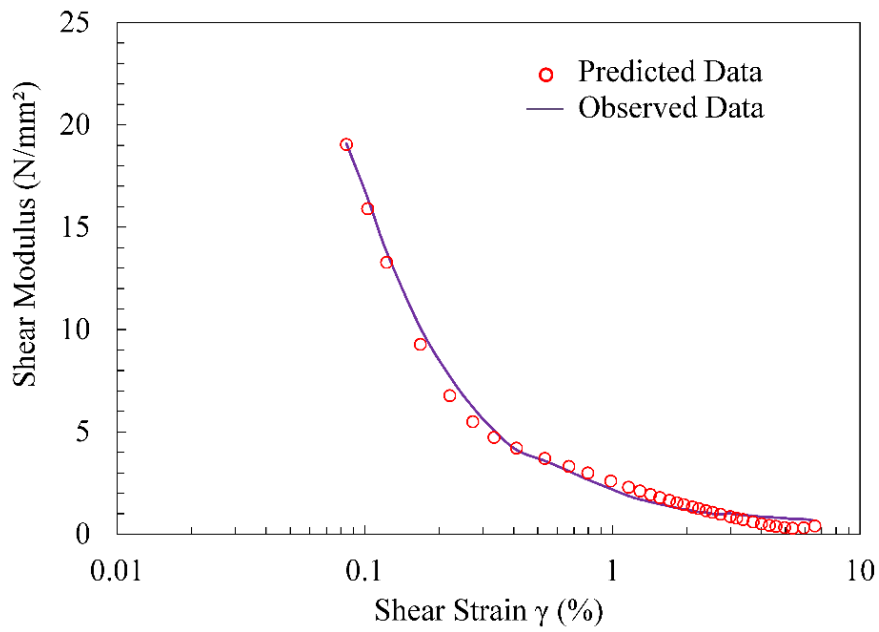


Figure 6.10 Comparison between observed and predicted values of the shear modulus for independent testing dataset using ANN at GF=87%, $(\sigma_d/2\sigma_3)=0.25$

(b) Performance of the ANN Model over independent testing dataset

6.3 SUMMARY AND CONCLUSION

Previous studies on granular mixture with Scrap Tire Derived Materials (STDM) has shown effectiveness of these materials in mitigation liquefaction susceptibility and earthquake induced loads on geotechnical structures. Therefore, estimating the dynamic behavior of granular mixtures with STDM such as tire chips has been a topic of increasing interest in recent years. Complex relationship between different factors affecting the dynamic properties of these materials together with dispersed behavior of some of dynamic characteristics of these materials such as damping ratio opened new research area in geotechnical engineering.

In this chapter, two different AI techniques, ANN and SVM were used to model the dynamic characteristics of GTCM. Four input parameters, confining pressure, gravel fraction, cyclic stress ratio and shear strain; also shear modulus and damping ratio was considered as outputs. The results from the cyclic triaxial tests on the specimens of GTCM was used to develop the models. Based on the findings of this study following conclusion are drawn:

- Based on the findings of this study, a feed-forward artificial neural network model with back-propagation training algorithm can be employed to model sophisticated dynamic characteristics of granular mixtures with relatively high resolution.
- Outcome of this study show that the Support Vector Machine with the RBF kernel function shows satisfactory performance on generalization and prediction of dynamic properties of GTCM yields relatively low statistical error.

- Although result of ANN and SVR model showed that both the models are suitable tools for estimation dynamic characteristics of granular mixture in terms of performance parameters i.e. R-value, RMSE, but ANN based model yields better performance on generalization of training data sets in comparison to that of SVM.

It should be noted that ANN and SVM models, like all other machine learning methods, perform best in interpolation rather than extrapolation. Consequently, the developed ANN and SVM models performs best when it is used for the ranges of input variables.

References

- Anastasiadis, A., Senetakis, K., Pitilakis, K., Gargala, C. & Karakasi, I. (2011). Dynamic Behavior of Sand/Rubber Mixtures. Part I: Effect of Rubber Content and Duration of Confinement on Small-Strain Shear Modulus and Damping Ratio. *Journal of ASTM International*, 9(2): 1-19.
- Burges, C. J. C. (1998). A Tutorial on Support Vector Machines for Pattern Recognition. *Data Mining and Knowledge Discovery*, 2(2): 121-167.
- Cherkassky, V. & Mulier, F. M. (2007). *Learning from data: concepts, theory, and methods*. John Wiley & Sons.
- Das, S. K., Samui, P. & Sabat, A. K. (2011). Application of Artificial Intelligence to Maximum Dry Density and Unconfined Compressive Strength of Cement Stabilized Soil. *Geotechnical and Geological Engineering*, 29(3): 329-342.
- Debnath, P. & Dey, A. K. (2018). Prediction of Bearing Capacity of Geogrid-Reinforced Stone Columns Using Support Vector Regression. *International Journal of Geomechanics*, 18(2): 04017147.
- Ech-Cherif, A., Kohili, M., Benyettou, A. & Benyettou, M. (2002). Lagrangian support vector machines for phoneme classification. *Proceedings of the 9th International Conference on Neural Information Processing*, 2002. ICONIP '02., Singapore, 5: 2507-2511.

- Edinçliler, A., Baykal, G. & Dengili, K. (2004). Determination of static and dynamic behavior of recycled materials for highways. *Resources, conservation and Recycling*, 42(3): 223-237.
- Feng, C. & Lipo, W. (2003). Gene expression data analysis using support vector machines. *Proceedings of the International Joint Conference on Neural Networks*, 3: 2268-2271.
- Feng, Z. & Sutter, K. (2000). Dynamic Properties of Granulated Rubber/Sand Mixtures. *Geotechnical Testing Journal*, 23(3): 338-344.
- Ferentinou, M. D. & Sakellariou, M. G. (2007). Computational intelligence tools for the prediction of slope performance. *Computers and Geotechnics*, 34(5): 362-384.
- Foose, G. J., Benson, C. H. & Bosscher, P. J. (1996). Sand Reinforced with Shredded Waste Tires. *Journal of Geotechnical Engineering*, 122(9): 760-767.
- Ghodrati, A. & Araei, A. A. (2017). Artificial Neural Networks for Modeling Shear Modulus and Damping Behavior of Gravelly Materials. *International Journal of Geomechanics*, 17(2): 04016060.
- Goh, A. T. C. (1994). Seismic Liquefaction Potential Assessed by Neural Networks. *Journal of Geotechnical Engineering*, 120(9): 1467-1480.
- Goh, A. T. C. & Goh, S. H. (2007). Support vector machines: Their use in geotechnical engineering as illustrated using seismic liquefaction data. *Computers and Geotechnics*, 34(5): 410-421.
- Hardin, B. O. (1978). The nature of stress-strain behavior for soils. *Proceedings of the ASCE geotechnical, Vol. 1. Engineering Division Specialty Conference on Earthquake Engineering and Soil Dynamics*, Pasadena, California. June 19–21, pp. 3-90.
- Hardin, B. O. & Drnevich, V. P. (1972). Shear Modulus and Damping in Soils. *Journal of the Soil Mechanics and Foundations Division*, 98(7): 667-692.
- Hazarika, H. & Abdullah, A. (2016). Improvement effects of two and three dimensional geosynthetics used in liquefaction countermeasures. *Japanese Geotechnical Society Special Publication*, 2(68): 2336-2341.
- Hazarika, H., Kohama, E. & Sugano, T. (2008a). Underwater Shake Table Tests on Waterfront Structures Protected with Tire Chips Cushion. *Journal of Geotechnical and Geoenvironmental Engineering*, 134(12): 1706-1719.
- Hazarika, H., Sugano, T., Kikuchi, Y., Yasuhara, K., Murakami, S., Takeichi, H., Karmokar, A. K., Kishida, T. & Mitarai, Y. (2006). Flexibility and stability enhancement of structures during earthquakes using a novel geosynthetic material.

Geosynthetics Engineering Journal, 21:125-130.

- Hazarika, H., Yasuhara, K., Karmokar, A. K. & Mitarai, Y. (2008b). Shaking table test on liquefaction prevention using tire chips and sand mixture. *Proceedings of the International Workshop on Scrap Tire Derived Geomaterials - Opportunities and Challenges*, 215-222.
- Hazarika, H., Yasuhara, K., Kikuchi, Y., Karmokar, A. K. & Mitarai, Y. (2010). Multifaceted potentials of tire-derived three dimensional geosynthetics in geotechnical applications and their evaluation. *Geotextiles and Geomembranes*, 28(3): 303-315.
- Hazarika, H., Yokota, H., Endo, S. & Kinoshita, T. 2018. Cascaded Recycle of Waste Tires—Some Novel Approaches Toward Sustainable Geo-Construction and Climate Change Adaptation. *In: Krishna, A. M., Dey, A. & Sreedeeep, S. (eds.) Geotechnics for Natural and Engineered Sustainable Technologies: GeoNEst*. Singapore: Springer Singapore.
- Hegazy, Y. A. & Mayne, P. W. (2002). Objective Site Characterization Using Clustering of Piezocone Data. *Journal of Geotechnical and Geoenvironmental Engineering*, 128(12): 986-996.
- Kohestani, V. R. & Hassanlourad, M. (2016). Modeling the Mechanical Behavior of Carbonate Sands Using Artificial Neural Networks and Support Vector Machines. *International Journal of Geomechanics*, 16(1): 04015038.
- Kurup, P. U. & Griffin, E. P. (2006). Prediction of Soil Composition from CPT Data Using General Regression Neural Network. *Journal of Computing in Civil Engineering*, 20(4): 281-289.
- Levenberg, K. (1944). A Method For The Solution of Certain Non-Linear Problems In Least Squares. *Quarterly of Applied Mathematics*, 2(2): 164-168.
- Maalouf, M., Khoury, N. & Trafalis, T. B. (2008). Support vector regression to predict asphalt mix performance. *International Journal for Numerical and Analytical Methods in Geomechanics*, 32(16): 1989-1996.
- Marquardt, D. W. (1963). An Algorithm for Least-Squares Estimation of Nonlinear Parameters. *Journal of the Society for Industrial and Applied Mathematics*, 11(2): 431-441.
- Meyer, D., Leisch, F. & Hornik, K. (2003). The support vector machine under test. *Neurocomputing*, 55(1): 169-186.
- Mozumder, R. A., Roy, B. & Laskar, A. I. (2017). Support Vector Regression Approach to Predict the Strength of FRP Confined Concrete. *Arabian Journal for*

- Science and Engineering*, 42(3): 1129-1146.
- Nakhaei, A., Marandi, S. M., Sani Kermani, S. & Bagheripour, M. H. (2012). Dynamic properties of granular soils mixed with granulated rubber. *Soil Dynamics and Earthquake Engineering*, 43:124-132.
- Pal, M. (2006). Support vector machines - based modelling of seismic liquefaction potential. *International Journal for Numerical and Analytical Methods in Geomechanics*, 30(10): 983-996.
- Senetakis, K., Anastasiadis, A. & Pitilakis, K. (2012). Dynamic properties of dry sand/rubber (SRM) and gravel/rubber (GRM) mixtures in a wide range of shearing strain amplitudes. *Soil Dynamics and Earthquake Engineering*, 33(1): 38-53.
- Tsang, H. H. (2008). Seismic isolation by rubber-soil mixtures for developing countries. *Earthquake Engineering & Structural Dynamics*, 37(2): 283-303.
- Vapnik, V. (1964). A note one class of perceptrons. *Automation and remote control*.
- Vapnik, V. (2013). *The nature of statistical learning theory*. Springer science & business media.
- Vapnik, V. N. (1999). An overview of statistical learning theory. *IEEE Transactions on Neural Networks*, 10(5): 988-999.

CHAPTER 7

MODELLING STRESS-STRAIN BEHAVIOUR OF GRANULAR MIXTURE WITH STDMS

7.1 INTRODUCTION

Safe recycling of scrap tires has become a major concern in most of developing countries such as Japan. Thermal recycling of scrap tires has been a common practice for past few decades in Japan. However, this may increase the CO₂ emission to the atmosphere as well as the risk of global warming and climate change induced geo-disasters. On the other hand, recycling of scrap tires as Scrap Tire Derived Materials (STDM) is considered as an alternative approach to reduce the potential environmental risk associated with burning scrap tires.

The use of STDMS as geomaterials in civil engineering applications has gained significant research attention in recent times. Granular materials such as sand are mixed with STDMS and utilized in civil engineering projects due to their unique engineering properties such as low unit weight, high vibration absorption capacity and high hydraulic conductivity (Humphrey and Manion 1992; Ahmed 1993; Hazarika et al. 2018). The mechanical behaviour of granular soils mixed with STDM has been the topic of several studies over the last few decades. Among the important contributions to the knowledge includes the works on the effect of the addition of STDM, primarily very large size tire shreds, chips and strips to the sand (e.g.(Edil and Bosscher 1994;

Foose et al. 1996; Zornberg et al. 2004; Gotteland et al. 2005; Kaushik et al. 2015; Mashiri et al. 2015; Kaushik et al. 2017), and addition of tire crumbs or chips with relatively small particles to the sand on mechanical behaviour of granular materials (e.g.(Ahmed 1993; Masad et al. 1996; Youwai and Bergado 2003; Kawata et al. 2007; Lee et al. 2007; Sheikh et al. 2013; Ehsani et al. 2017)). Gravel-Tire Chips Mixture (GTCM) was found to exhibit high permeability, high bearing capacity and low differential settlements when they are used in geotechnical projects. Therefore, they can be considered as an excellent alternative for the sand-tire chips mixture (Niiya et al. 2012; Chu et al. 2016; Hazarika and Abdullah 2016). However, there is no unique way to predict and describe the mechanical behaviour of these materials, mainly because of vast diversity in materials, apparatus and conducting methods employed by each of those studies.

Modelling soil behaviour plays a key role in successful predicting of the behaviour of geotechnical structures. Advanced material models which address complex behaviours such as yielding, softening, hardening and dilatancy, aim to build mathematical models to define the relationship between stress-strains. Many researches have been devoted to develop mathematical soil models based on various assumption and frameworks (Duncan and Chang 1970; Dafalias and Manzari 2004). However, in spite of a lot of research on the mechanical behaviour of granular mixtures with STD, very few material models have been introduced to predict the behaviour of granular soil mixed with STD. A simple nonlinear model has been developed by (Lee et al. 1999) using basic hyperbolic model which was introduced by (Duncan and Chang 1970) for the first time. The model could simulate stress-strain behaviour of

sand-tire chips mixture up to peak state. However, it was not successful in capturing post peak behaviour, dilation and plastic strains of reinforced soil. A hypo-plasticity model was introduced by (Youwai and Bergado 2003) to capture the stress-strain behaviour of sand-tire shreds mixture using critical state framework. Although the model could reasonably capture the stress-strain and deformation behaviour of reinforced soil, especially at higher fraction of sand in mixture. But for most of their specimens the critical state of sand-tire shreds was not attained due to the tendency of dilation of reinforced soil even at axial strains as high as 25%. Therefore, they assumed that the critical state was achieved at the axial strain of 25%.

As mentioned earlier, the difficulties in developing an appropriate material model for reinforced soil with STD, originate from the difficulties in the modelling mechanical behaviour of these materials. These materials exhibit very complex behaviour which cannot be observed in conventional soils. In order to meet the requirement for predicting the behaviour of these materials with high accuracy, the material model needs to be more sophisticated. This need for high accuracy always causes increased complexity in material parameter determination and computations. However, the more the material parameters the higher computation process expenses. Furthermore, complexity of material models makes them difficult to use. Therefore, the aim of this chapter was to develop an artificial intelligence based material model for GTM that is capable of capturing complex stress-strain behaviour of reinforced soil. The model then is verified through modelling stress-strain behaviour of reinforced soil in different initial state.

7.2 ARTIFICIAL INTELLIGENCE BASED MATERIAL MODELLING

In the recent years, some researchers have devoted their efforts to develop nonlinear material models based on artificial intelligence techniques. Among the different techniques, ANN was the most widely used pattern recognition technique to model material behaviour. First constitutive model is proposed by (Ghaboussi et al. 1991). Later on ANN technique was implemented to model behaviour of rocks in rock mechanics (Millar and Clarici 1994). A constitutive model was developed by (Logar and Turk 1997) for predicting soft soil behaviour using a neural network. The results from oedometer loading tests on a silty soil were used to train a feed forward neural network. The trained neural network was used to determine the tangential oedometer modulus. A recurrent neural network (RNN) model was proposed by (Jian - Hua et al. 1998) for simulating and predicting shear behaviour of two different soils. Laboratory based experimental data were used for modelling including a set of strain controlled undrained tests and a set of stress controlled drained tests performed on a residual Hawaiian volcanic soil. Axial strain, pore water pressure, void ratio were selected as input in their model and deviatoric stress and pore water pressure in next step were obtained as output of network. (Javadi et al. 2012) used Evolutionary Polynomial Regression (EPR) technique to model the behaviour of unsaturated soils. The parameters used for modelling of the behaviour of unsaturated soils during shearing were initial water content, initial dry density, mean net stress, axial strain, suction, volumetric strain, and deviator stress. They should that this technique is capable of capturing complex behaviour of the saturated soils.

7.3 DEVELOPING ANN BASED MATERIAL MODEL FOR GRANULAR MATERIAL MIXED WITH STDM

7.3.1 DATABASE FOR DEVELOPING ANN MODEL

The granular mixture with STDM is very heterogeneous. Because the mixture comprises of two different materials with different particle density and stiffness. Therefore the shearing behaviour of such material is much more complex than that of many common soils. Results of experimental research in chapter 3, has revealed that the important parameters that govern the behaviour of GTCM as a granular mixture are its gravel fraction, particle size ratio of tire chips to gravel, relative density, and effective confining pressure level. Therefore, 42 triaxial test results on GTCM reported in chapter 3 were used to develop the necessary database. The summary of the experimental tests is presented in Table 7.1. The relatively large size of the database is well suited for evaluating the potential of developing comprehensive neural network based reinforced soil models. 40 tests out of 42 tests were used for training the model. And 2 tests were excluded from the database and used for validating the final model independently.

7.3.2 ANN MODELLING PROCEDURE

The objective of study was to develop a neural network model for representing the deviator stress-axial strain, and volumetric strain axial strain relationship of GTCM with varying gravel fraction, particle size ratio of tire chips to gravel, relative density,

and effective confining pressure level.

Table 7.1 Summary of triaxial tests used for training the ANN model

Mixture Group	$D_{50,R}/D_{50,G}$	GF (%)	D_r (%)	σ_{3c} (kN/m ²)	ANN Status
G1TCH1	1.2	0	50	50, 100, 200	Training
			75	100	Training
		44	50	100,200	Training
		55	35	100	Training
			50	50, 200	Training
			50	100	Testing
			75	100, 200	Training
		70	50	100	Training
		78	50	100	Training
		83	50	100	Training
		87	50	50, 100, 200	Training
		100	35	100, 200	Training
			50	50, 100, 150, 200	Training
			75	100	Training
G2TCH2	0.35	0	50	100	Training
		50	50	100, 200	Training
		70	50	100, 200	Training
		87	50	100, 200	Training
		100	50	50, 100, 200	Training
G2TCH3	3.35	0	50	100	Training
		30	50	100	Training
		40	50	100	Testing
		50	50	100	Training
		70	50	100	Training
		87	50	100	Training

In general, representation of an appropriate ANN model depends on the selection of the type of neural networks, data acquisition, processing, and design of representation layout for inputs and outputs of system. This might depend on the nature of the problem, but also by the way the model is going to be employed. In this study multilayer feedforward backpropagation ANN which uses the gradient decent laws is used to model soil behaviour. The detail on how this type of neural networks operate is provided in section 5. Two ANN models were developed to capture stress- axial strain (ANN-q) and axial strain volumetric strain of GTCM (ANN- ε_v). In this study, Particle size ratio $R_s=(D_{50,R}/D_{50,G})$, gravel fraction (GF), effective confining pressure (σ_{3c}), relative density (D_r), current axial strain $\varepsilon_{1(n)}$ were considered as input, and current state of deviatoric stress q_n and volumetric strain $\varepsilon_{v(n)}$ as output of networks.

ANN-q:

Input = $[(D_{50,R}/D_{50,G}), GF, \sigma_{3c}, D_r, \varepsilon_{1(n)}]$

Output = $[q_n]$

ANN- ε_v :

Input = $[(D_{50,R}/D_{50,G}), GF, \sigma_{3c}, D_r, \varepsilon_{1(n)}]$

Output = $[\varepsilon_{v(n)}]$

A 5728 out of 6000 data points was used for training the network. In this study, the cross-validation method in which data is randomly divided into three subsets: training (70%), validation (15%), testing (15%) was employed. Architecture of ANN

is determined by selecting the number of hidden layers and neurons (nodes) in each layer as well as interconnection scheme. Other feature of training and testing datasets are presented in Table 7.2. The number of hidden layers and the number of neurons in each hidden layer are influenced by the complexity of the problem, characteristics of training data, and learning algorithm. However, previous studies have shown that a three-layer feedforward ANN with sufficient number of neurons in hidden layer can approximate any nonlinear relationship (Hornik et al. 1989). A code is written in the MATLAB R2017 environment to develop an ANN model and used for training and testing of it.

In order to have efficient model with high performance and reduce the noise, size of input space and have a smother relationship, the input data are preprocessed using Min-Max normalization method before training process starts. Furthermore, before the training of ANN models data sets were randomly shuffled, in order to make sure that the model is not learning a specific order and faster convergence is observed. The algorithm utilized for data shuffling was simply relied on selecting two data rows (consisting of the input and outputs) randomly and swapping them together. The Levenberg-Marquardt algorithm which has been shown to have better performance for training moderate size of a Multilayer Perceptron (MLP) was selected for training the ANN.

Furthermore, “*transigmoid*” and “*pureline*” transfer functions are chosen for each neuron in hidden and output layers of ANN. The number of hidden layers and nodes are determined using a trial and error method. In this method, training of networks starts with minimum number of nodes in the first hidden layer and mean squared error

is calculated for testing data set and compared with the allowable threshold error. If the error exceeds the threshold value, next neuron is added to the hidden layer. Maximum number of the nodes in each hidden layer was limited to 10. The above iterative process is repeated until the desired stopping criterion is met.

Table 7.2 Feature of training database for ANN model

	R_s	D_r (%)	GF (%)	σ_{3c} (kN/m ²)	ε_1 (%)	q_n (kN/m ²)	$\varepsilon_{v(n)}$ (%)
Min	0.35	20	0	50	0	0	-9.27
Max	3.35	75	100	200	20	916.6	8.04
Mean	1.40	55.58	68.06	120.8	9.95	313.12	1.844
variance	0.98	95	1130.05	2812.25	33.3	48884	10.47

During the learning or training process, training data sets are used to obtain ANN parameters in each layer (Weights and biases) by minimizing the error function. In order to avoid overfitting the network, the error on the validation data set is monitored during training process. The training will stop when the error on the validation data set begins to rise. Further training of network will over fits data and prevent generalization. At the next stage, the testing data set is introduced to the ANN and its performance is evaluated.

In this study, the final ANN-q model has 5 nodes in the input layer, 6 nodes in the first hidden layer, 6 nodes in the second hidden layer and 1 nodes in the output layer. Furthermore, the final ANN- ε_v has 5 nodes in the input layer, 6 nodes in the first

hidden layer, 6 nodes in the second hidden layer and 1 nodes in the output layer (Fig 7.1).

As is mentioned earlier in this section, the optimum number of hidden layers and neurons in each hidden layers are obtained based on criterion defined to terminate the training process. Mean squared error between the target and predicted values of all outputs over all possible configurations was monitored constantly. In order to assess the performance of ANN model, the measured error during the training process is plotted against error measured during testing process, training will stop where the testing errors starts to rise while the training errors constantly decreasing. Otherwise, ANN will learn the noises in the training dataset. Therefore, training must stop to avoid overtraining and final performance of ANN is measured at this point. It should be noted that the maximum of epochs were limited to 1000.

7.3.3 PERFORMANCE OF NEURAL NETWORK

Figure 7.2 shows the variation of error measure during training of the ANN models. Besides, performance of the network during training was also evaluated using the validation and testing patterns as shown in Fig. 7.2. The performance of the optimum ANN-q and ANN- ϵ_v models over training, validation and testing data sets are depicted in Fig. 7.3 and Fig. 7.4 respectively.

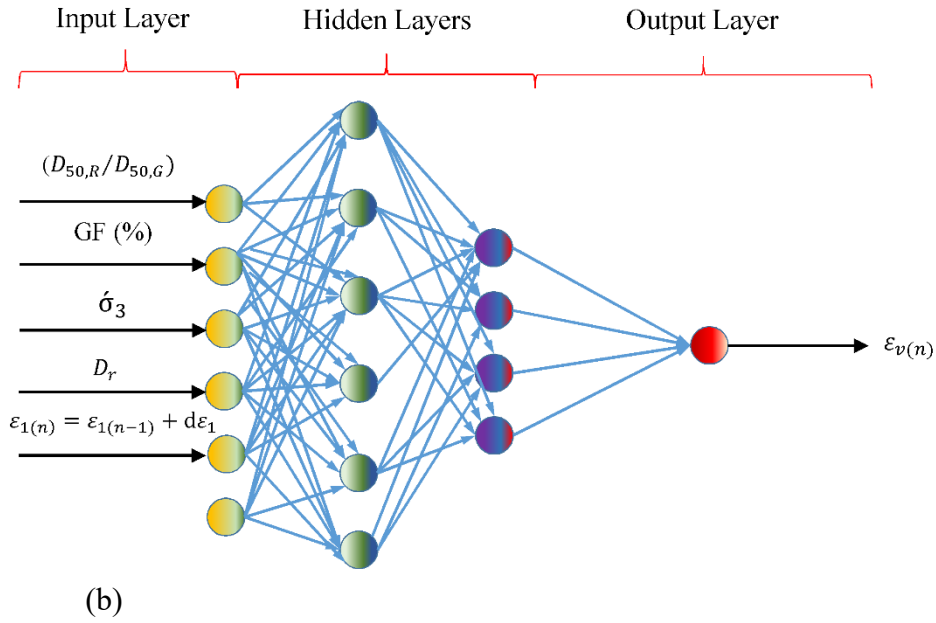
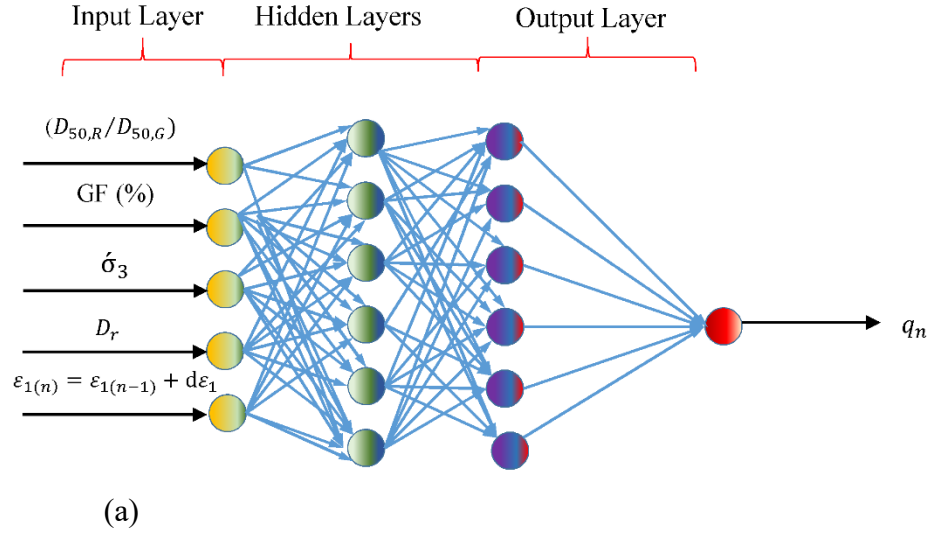
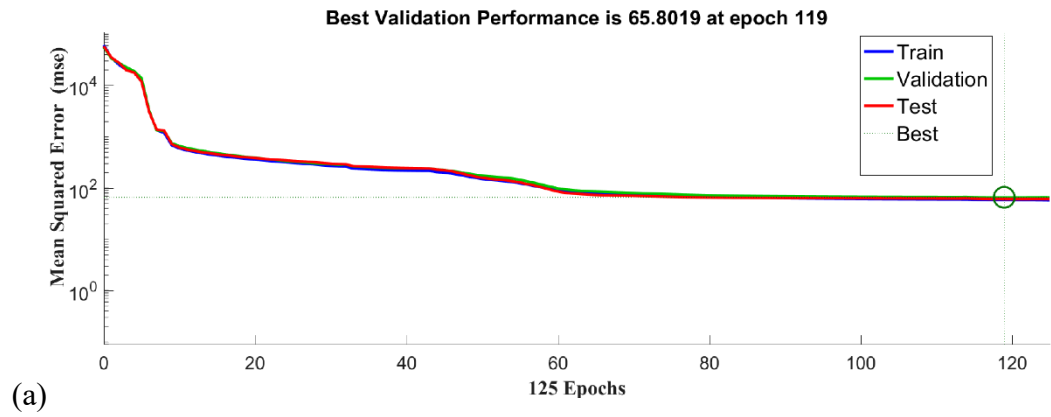


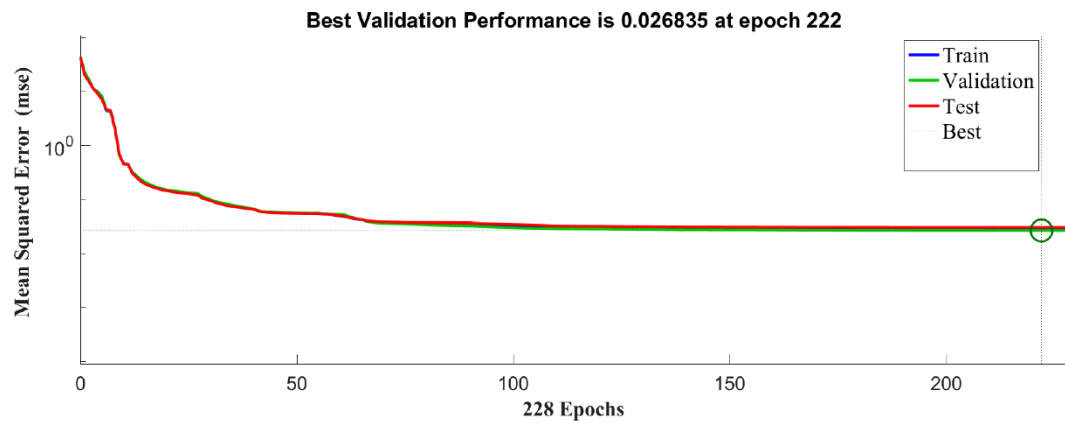
Figure 7.1 Architecture of neural network models (a) ANN-q (b) ANN- ε_v

For ANN-q, training stopped in 119 epochs where measured error on testing dataset starts to increase (Early stopping). However, for ANN- ε_v the training stopped at the end of 228 epochs which was less than maximum of epochs 1000. In other words,

Overtraining did not happen during the training process, and therefore the early stopping method was not used.



(a)



(b)

Figure 7.2 Performance of the proposed ANN models during training (a) ANN-q (b)

ANN- ϵ_v

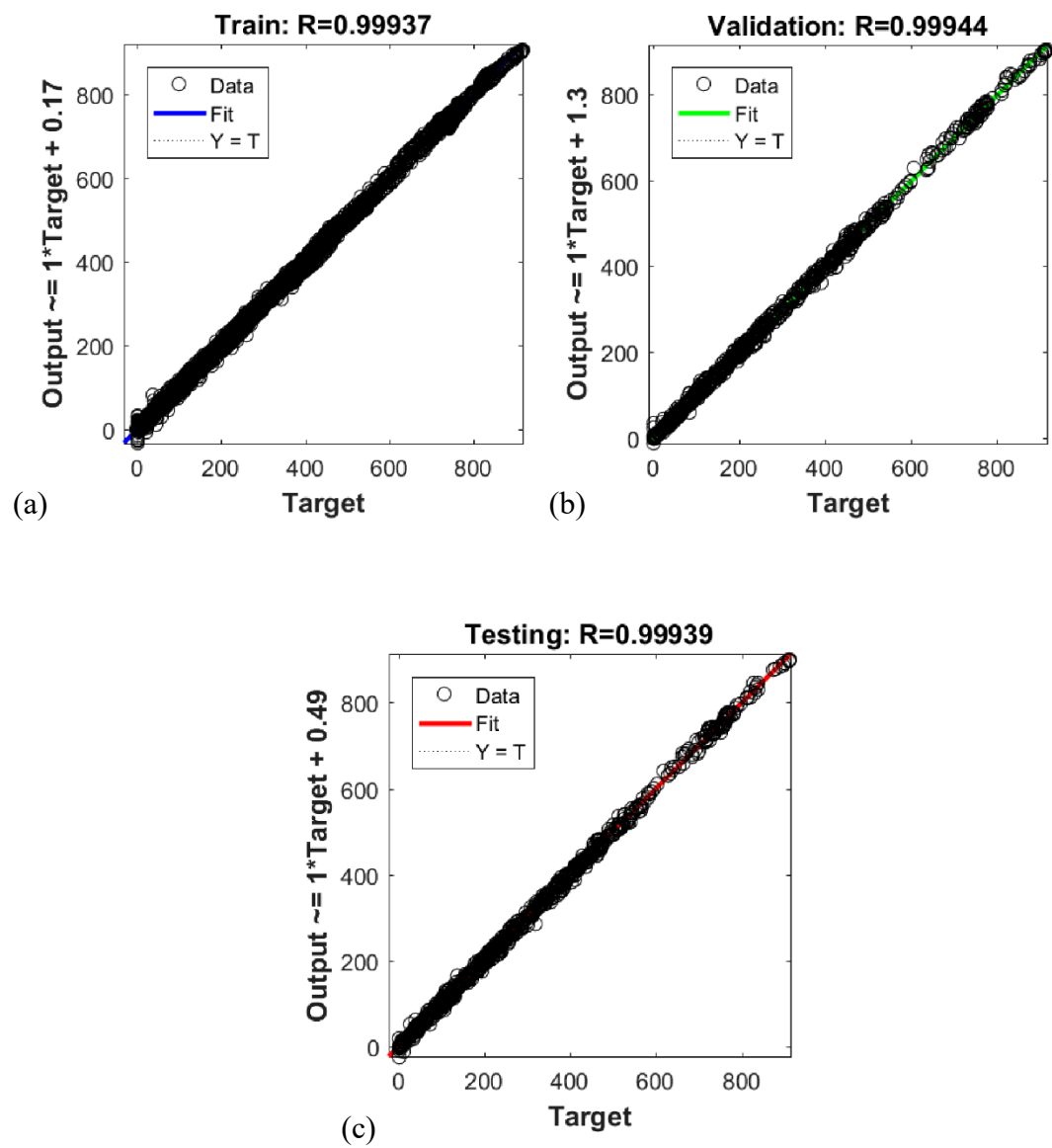


Figure 7.3 Performance of the ANN-q Model over: (a) Training; (b) Validation
 (c) Testing datasets

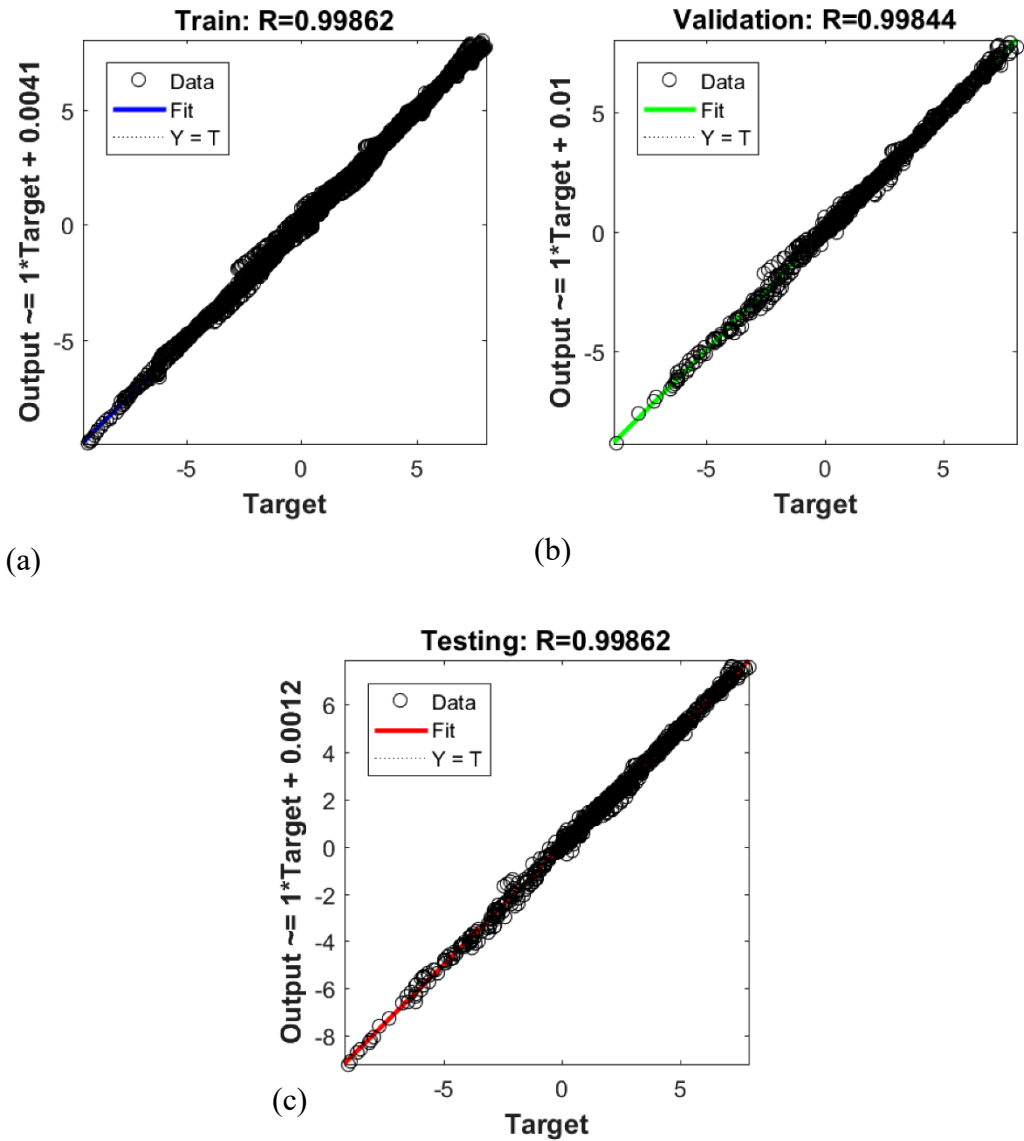


Figure 7.4 Performance of the ANN- ϵ_v Model over: (a) Training; (b) Validation (c) Testing datasets

7.3.4 ANN MODELS SIMULATIONS AND PREDICTIONS

After training of ANN models is over, the networks were utilized to simulate the stress-strain and volumetric strain GTCM specimens during triaxial compression tests.

In the first step, the ANN- q and ANN- ε_v were used to simulate stress-strain and volumetric strain behaviour all of the specimens used in the training of networks.

Fig. 7.5, shows the stress–strain as well volume change behaviour simulated for the triaxial test specimens of G2TCH3 with particle size ratio of 3.35 at $D_r=50\%$ and $\sigma_{3c}=100 \text{ kN/m}^2$ used for the training phase. As seen from figure the ANN models are capable of simulating the training results with high accuracy.

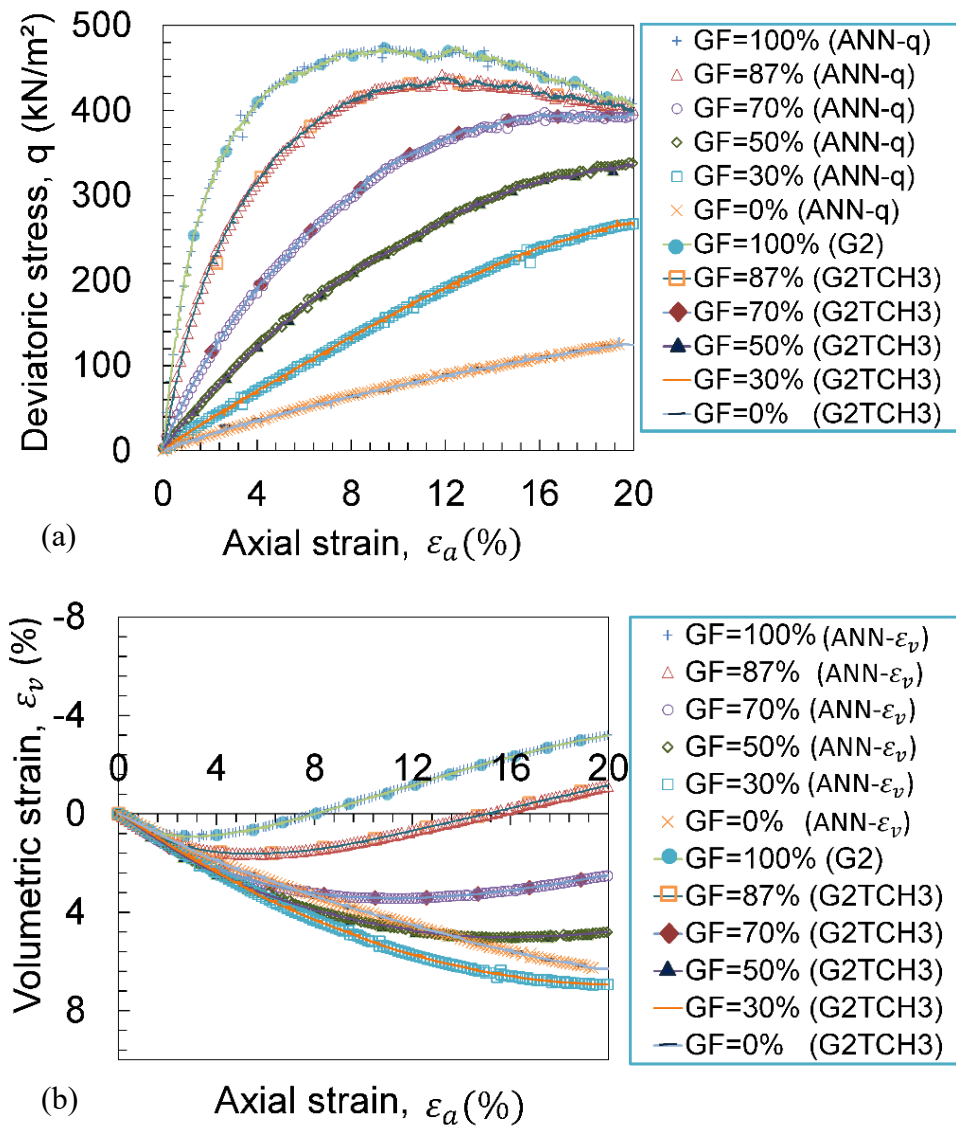


Figure 7.5 Comparison between experimental data and simulation of the (a) ANN- q and (b) ANN- ε_v for G2TCH3 specimens at $D_r=50\%$ and $\sigma_{3c}=100 \text{ kN/m}^2$

In order to evaluate the ability of ANN models to generalize the behaviour of reinforced soil, the ANN models were tested on different testing condition that was not experienced during the training phase. The results were validated against the independent testing datasets that were not used for training the networks. Furthermore, predicted values by ANN models were compared with those simulated by the Hardening Soil (HS) model. The isotropic HS model is an advanced soil model that is widely has been used in numerical simulation of different geotechnical applications (Schanz 1999). In this model, the relationship between the vertical strain ε_1 and deviatoric stress q in primary triaxial test is hyperbolic. For the drained triaxial test this relationship can be approximated as follows:

$$\varepsilon_1 = \frac{q_a}{2E_{50}} [(\sigma_1 - \sigma_3)/q_a - (\sigma_1 - \sigma_3)] \quad \text{for } q < q_f \quad (7.1)$$

Where q_f is the ultimate deviatoric stress and the quantity is q_a are defined as:

$$q_f = \frac{6 \sin \varphi_p}{3 - \sin \varphi_p} (p + c \cot \varphi_p) , \quad q_a = q_f / R_f \quad (7.2)$$

Where the q_f is derived from the Mohr-Coulomb failure criterion in which c and φ_p are the strength parameters at failure (Fig 7.6). R_f is the failure ratio which needs to be less than 1. The soil stiffness is represented by E_{ref}^{50} , E_{ref}^{oed} , E_{ref}^{ur} that, respectively, state the secant stiffness for primary triaxial loading, the tangent stiffness for primary oedometric loading, elastic stiffness for unloading and reloading at a reference pressure (100 kN/m²). ν_{ur} is the elastic Poisson's ratio for unloading/reloading. In addition, the parameter m defines the hyperbolic stress dependency of the stiffness with respect to the reference stiffness. ψ is the dilatation angle. In this study, the HS constitutive parameters are calibrated against the

experimental data for specimens G1TCH1 with GF=55% and G2TCH3 with GF=44% at relative density of 50% and confining pressure of 100 kN/m² (Table 7.3).

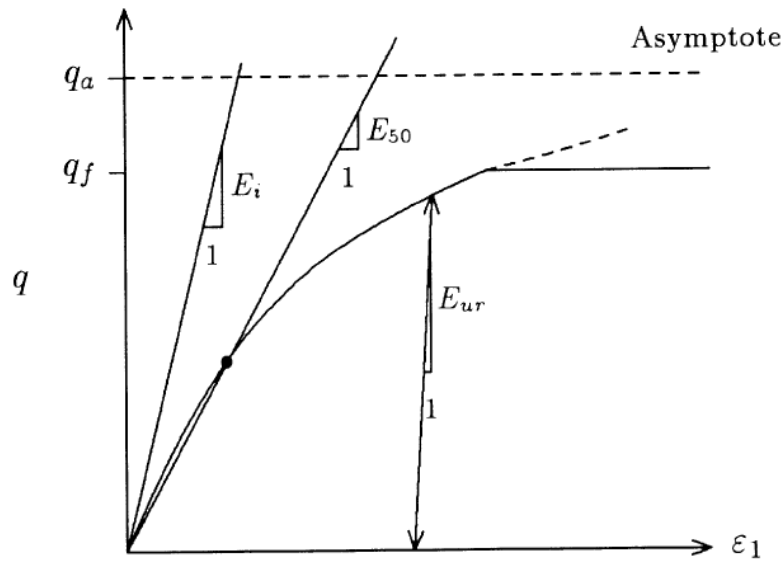


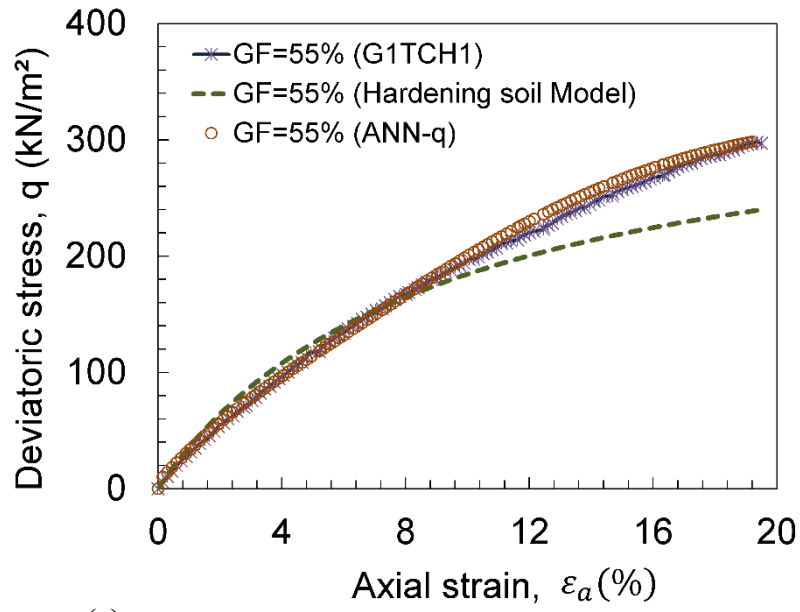
Figure 7.6 Hyperbolic stress-strain relationship for standard drained triaxial test
(Schanz 1999)

Table 7.3 Hardening soil model parameters for GTCM specimens

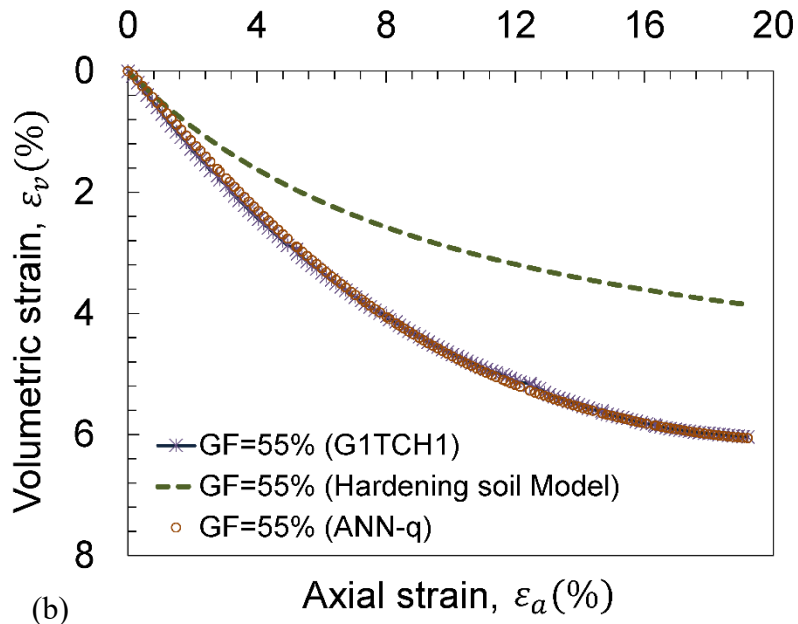
sample	φ_p (Deg)	c (kN/m ²)	ψ (Deg)	E_{ref}^{50} (kN/m ²)	E_{ref}^{oed} (kN/m ²)	E_{ref}^{ur} (kN/m ²)	ν_{ur}	γ_{sat} (kN/m ³)	m	R_f
G1TCH1- GF=55%	33	19	0	2000	2000	6000	0.25	15.71	0.5	0.9
G2TCH2- GF=40%	34	18	0	2500	2500	7500	0.22	14.29	0.5	0.9

To see if the ANN models are capable of simulating new testing condition, two “artificial” tests were conducted using the trained ANN models. In these simulations, two samples G1TCH1 with GF=55% and G2TCH3 with GF=40% were loaded following a conventional triaxial path at confining pressure of 100 kN/m². It should be noted that the ANN models were not experienced these new testing condition during the training of networks. Furthermore, HS model was used to simulate the same artificial tests and its performance was compared with that of ANN models (Fig. 7.7 and Fig. 7.8).

The results indicates that ANN models are capable of predicting stress-strain and volumetric strain behaviour of GTCM specimens with a reasonable accuracy (Fig. 7.9 and Fig 7.10). On the other hand, the HS model showed relatively poor performance in predicting both stress strain and volumetric strain behaviour of GTCM. The final ANN models showed that they are able to generalize the behaviour of GTCM specimens under different testing condition and ready to be used for parametric study.



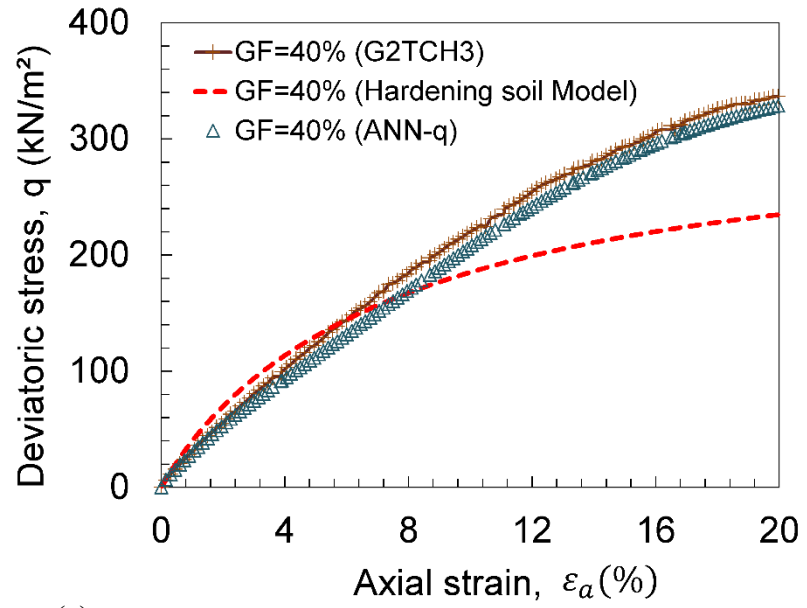
(a)



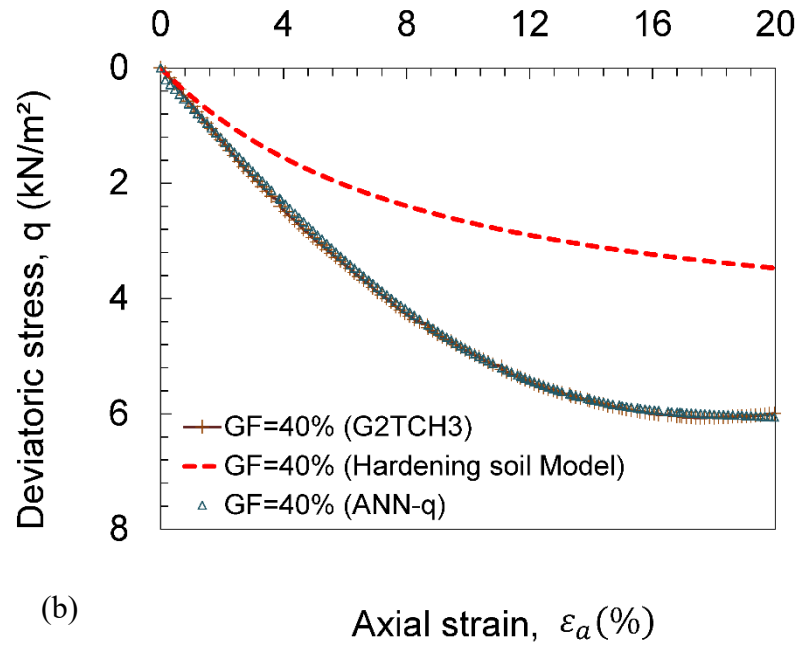
(b)

Figure 7.7 The ANN and HS models results for simulation of (a) deviatoric stress-axial strain (b) volumetric strain-axial strain behavior of G1TCH1 with GF=55% at

$D_r=50\%$ and $\dot{\sigma}_{3c}=100 \text{ kN/m}^2$.



(a)



(b)

Figure 7.8 The ANN and HS models results for simulation of (a) deviatoric stress-axial strain (b) volumetric strain-axial strain behavior of G2TCH3 with GF=40% at $D_r=50\%$ and $\sigma_{3c}=100$ kN/m².

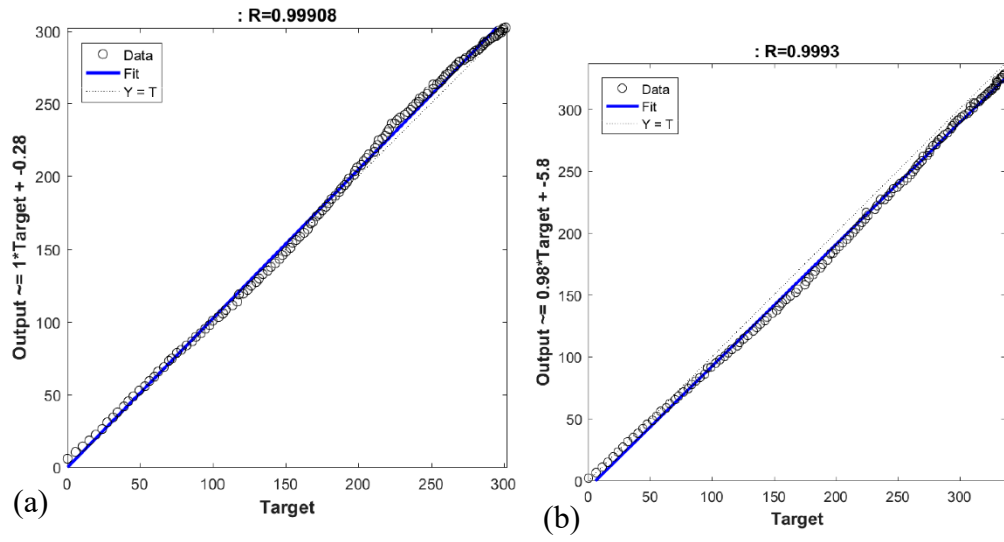


Figure 7.9 performance of ANN-q over training dataset (a) GF=55% (b) GF=40%

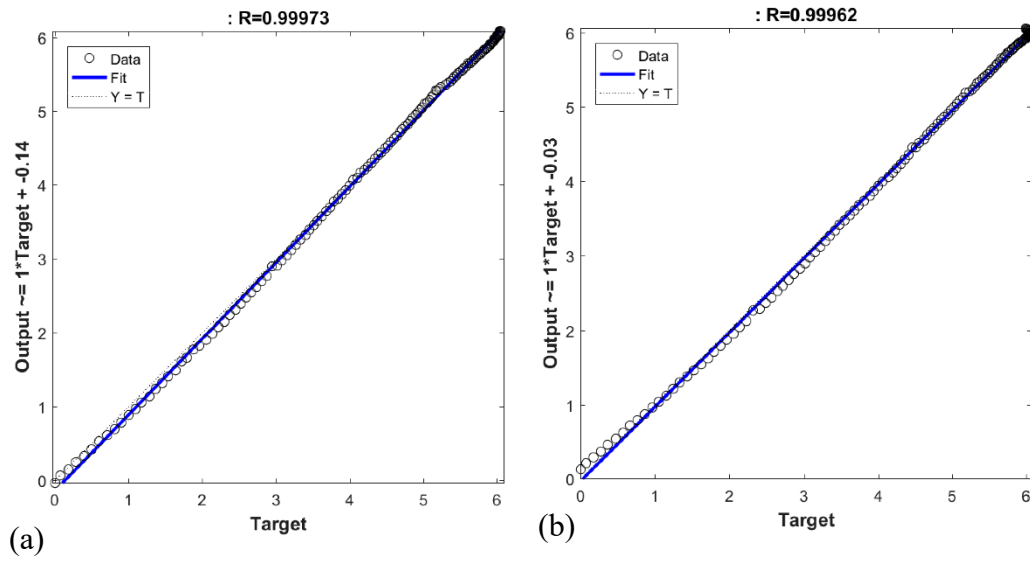


Figure 7.10 performance of ANN- ϵ_v over training dataset (a) GF=55% (b) GF=40%

7.4 PARAMETRIC ANALYSIS

After assessing the performance of proposed ANN models by applying those to untrained testing datasets. Trained material models can be used to conduct the parameter analysis. For instance, ANN-q model and ANN- ε_v were used to investigate the effect of GF in mixture on the deviatoric stress and volumetric strain-axial strain behaviour of the G1TCH1 mixture group. The result of parametric analysis is plotted in Fig. 7.11(a).

The outcome of analysis revealed that ANN-q model was capable of generalizing and predicting complex stress-strain behaviour of GTCM. The ANN model could successfully simulate some important features of the GTCM such as non-linear behaviour and distinct peak shear strength at failure for specimens in gravel-like behavioural zone. As well as linear behaviour of these materials at lower GF in the mixture. Similarly, ANN- ε_v was able to successfully simulate the complex volumetric behaviour of G1TCH1 specimens with different GF fraction. As seen from Fig 7.11 (b) a smooth transition from gravel like behaviour at higher GF (where mixture exhibited marginal contractive behaviour followed by a dilative behaviour) to tire chips like behaviour (where mixture exhibited complete linear and contractive behaviour) can be observed.

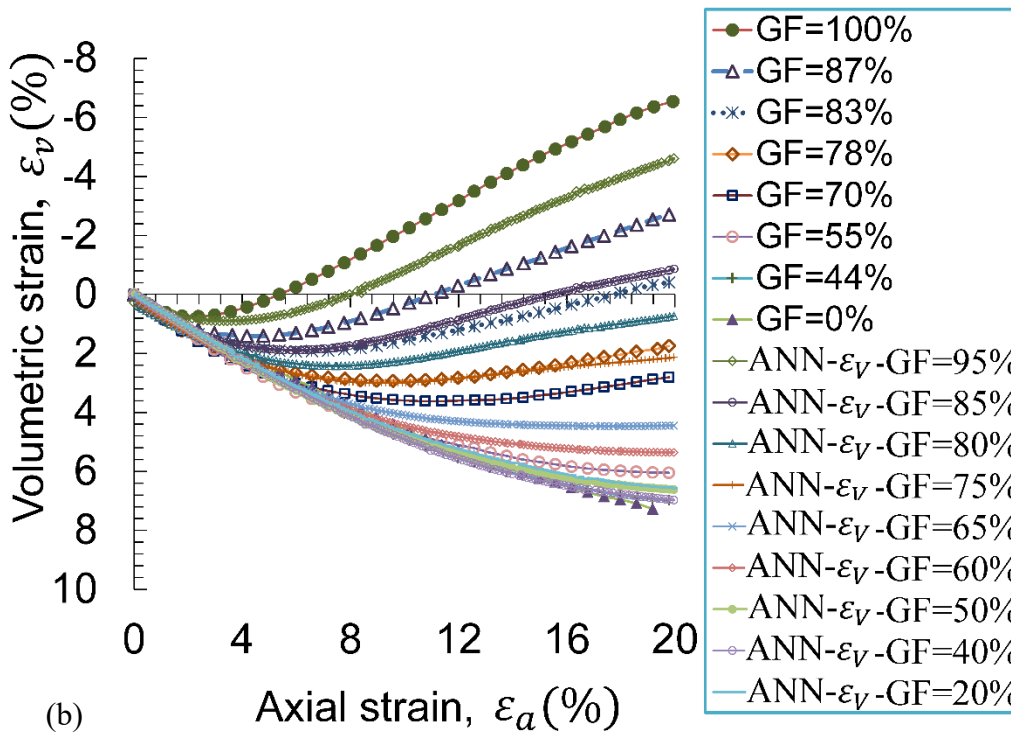
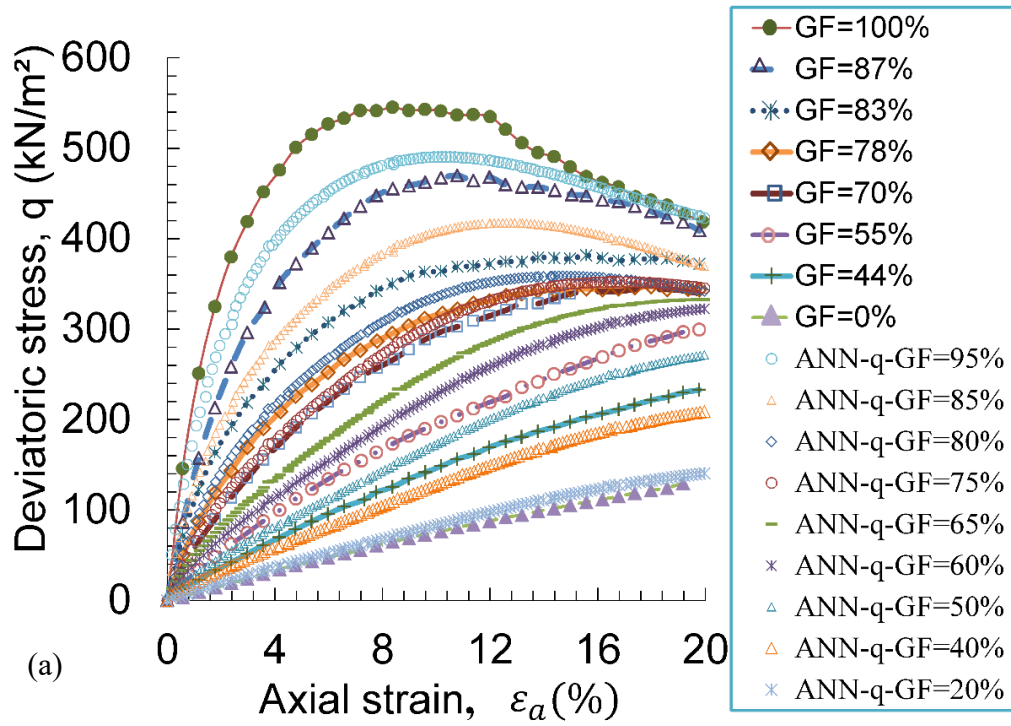


Figure 7.11 The effect of GF in G1TCH1 using (a) ANN-q and (b) ANN- ε_v

7.5 RELATIVE IMPORTANCE OF THE INPUT PARAMETERS

Sensitivity analysis was performed to determine the relative importance and contribution of each input parameter on the output of ANN-q model. The results of sensitivity analysis can reduce cost and time consumed to optimize steps in design process. Several methods have been proposed to quantify the importance of independent variables in predicting output of ANN models. Connection weight algorithm which uses final weights of connections of neurons in hidden layer to output layer (Olden and Jackson 2002). However, this method is applicable for ANN with single hidden layer. Similar method to connection weight method was proposed by Garson (1991) considering absolute values of final connections. The drawback of this method is that no information is provided for the direction of relationship between the input and output values. Partial derivatives (PD) of the ANN with respect to the input variables were implemented by Dimopoulos et al. (1999) to compute the relative importance of ANN parameters.

In the present study the input variables were eliminated one at time to calculate the relative importance of that input on the output of ANN. In this method, each input variable is replaced by its mean value and the ANN starts retraining while maintaining the initial structure intact. Mean squared error (MSE) was used to simply rank the input variables from maximum to minimum value of MSE. As can be seen from the table gravel fraction followed by confining pressure are most important parameters affecting deviatoric stress value of GTCM. However, relative density was found to have less impact on the output of model.

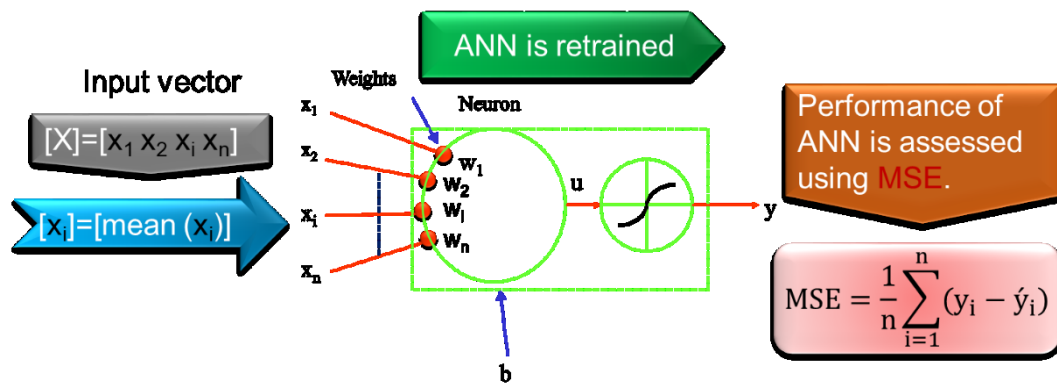


Figure 7.12 Procedure for identifying relative importance of input variables

Table 7.4 Relative importance of input variables on the output of (ANN-q)

Input Variables	MSE (ANN-q)	Rank
Gravel fraction (GF)	24850.6	1
Confining pressure (σ'_{3c})	16151.3	2
Particle size ratio ($D_{50,R}/D_{50,G}$)	544.93	3
Relative density (D_r)	139.55	4

7.6 SUMMARY AND CONCLUSION

Modelling soil behaviour plays a key role in successful predicting of the behaviour of geotechnical structures. Although, a lot of researches have been conducted on the mechanical behaviour of granular mixture with STD, very few material models were introduced for simulating stress-strain behaviour of these materials. On the other hand the neural network-based approach to material modelling,

provides an alternative way to model the complex behaviour of materials having prior knowledge or assumption about mechanical behaviour of those materials.

In this study, the feasibility of this approach was studied through constitutive modelling of the behaviour of gravel-tire chips mixture subjected to monotonic loading condition. Based on the analysis and discussion on the performance of the ANN based material models of granular mixture with STDM under various testing and loading conditions, it can be concluded that the use of artificial intelligence in modelling stress-strain and volumetric strain behaviour of these materials is reliable and promising.

- 1- A feedforward ANN model, using the backpropagation training algorithm can be used to simulate the mechanical behaviour of granular materials with relatively reasonable accuracy.
- 2- The prediction of the stress-strain behaviour by ANN based material models of granular mixture with tire chips match very closely with the experimental data. The models also can generalize well on the untrained stress-strain with different testing condition by yielding a reasonable predictions.
- 3- Comparison between results of simulations of ANN models applied to the new untrained data sets and those obtained from plasticity hyperbolic model revealed that ANN exhibits better performance in predicting stress-strain behaviour of granular material without any prior knowledge on new testing condition.

Finally, the generalization ability of these models can be improved by including new data sets with new testing conditions. It should be noted that ANN models, like all other machine learning methods, perform best in interpolation rather than

extrapolation. Consequently, the developed ANN material models performs best when it is used for the ranges of input variables.

References

- Ahmed, I. 1993. Laboratory Study on Properties of Rubber-Soils, *Joint Highway Research Project*. Indiana Department of Transportation and Purdue University, West Lafayette, Indiana.
- Chu, C., Hazarika, H. & Ishibashi, I. (2016) Experimental evaluation of the tire chips and gravel mixed reinforced layer on preventing liquefaction under residential building. 7th Japan-Taiwan Workshop on Geotechnical Hazards from Large Earthquakes and Heavy Rainfall, Pingtung, Taiwan. 100-102.
- Dafalias, Y. F. & Manzari, M. T. (2004). Simple Plasticity Sand Model Accounting for Fabric Change Effects. *Journal of Engineering Mechanics*, 130(6): 622-634.
- Duncan, J. M. & Chang, C. Y. (1970). Nonlinear Analysis of Stress and Strain in Soils. *Journal of the Soil Mechanics and Foundations Division*, 96(No.5): pp. 1629-1653.
- Dimopoulos, I., Chronopoulos, J., Chronopoulou-Sereli, A. & Lek, S. (1999). Neural network models to study relationships between lead concentration in grasses and permanent urban descriptors in Athens city (Greece). *Ecological Modelling*, 120(2): 157-165.
- Edil, T. & Bosscher, P. (1994). Engineering Properties of Tire Chips and Soil Mixtures. *Geotechnical Testing Journal*, 17(4): 453-464.
- Ehsani, M., Shariatmadaria, N. & Mirhosseini, S. (2017). Experimental study on behavior of soil-waste tire mixtures. *Scientia Iranica. Transaction A, Civil Engineering*, 24(1): 65.
- Foose, G. J., Benson, C. H. & Bosscher, P. J. (1996). Sand Reinforced with Shredded Waste Tires. *Journal of Geotechnical Engineering*, 122(9): 760-767.
- Garson, G. D. (1991). Interpreting neural-network connection weights. *AI expert*, 6(4): 46-51.
- Ghaboussi, J., Garrett, J. H. & Wu, X. (1991). Knowledge Based Modeling of Material Behavior with Neural Networks. *Journal of Engineering Mechanics*, 117(1): 132-153.
- Gotteland, P., Lambert, S. & Balachowski, L. (2005). Strength characteristics of tyre chips-sand mixtures. *Studia geotechnica et mechanica*, 27(1-2): 55-66.

- Hazarika, H. & Abdullah, A. (2016). Improvement effects of two and three dimensional geosynthetics used in liquefaction countermeasures. *Japanese Geotechnical Society Special Publication*, 2(68): 2336-2341.
- Hazarika, H., Yokota, H., Endo, S. & Kinoshita, T. 2018. Cascaded Recycle of Waste Tires—Some Novel Approaches Toward Sustainable Geo-Construction and Climate Change Adaptation. In: Krishna, A. M., Dey, A. & Sreedeeep, S. (eds.) *Geotechnics for Natural and Engineered Sustainable Technologies: GeoNEst*. Singapore: Springer Singapore.
- Hornik, K., Stinchcombe, M. & White, H. (1989). Multilayer feedforward networks are universal approximators. *Neural Networks*, 2(5): 359-366.
- Humphrey, D. N. & Manion, W. P. Properties of tire chips for lightweight fill. Grouting, soil improvement and geosynthetics. ASCE, 1992, pp. 1344-1355.
- Javadi, A. A., Ahangar-Asr, A., Johari, A., Faramarzi, A. & Toll, D. (2012). Modelling stress–strain and volume change behaviour of unsaturated soils using an evolutionary based data mining technique, an incremental approach. *Engineering Applications of Artificial Intelligence*, 25(5): 926-933.
- Jian - Hua, Z., M., Z. M. & A., A. S. (1998). Modelling of shearing behaviour of a residual soil with Recurrent Neural Network. *International Journal for Numerical and Analytical Methods in Geomechanics*, 22(8): 671-687.
- Kaushik, M. K., Kumar, A. & Bansal, A. (2015). Performance Assessment of Gravel–Tire Chips Mixes as Drainage Layer Materials Using Real Active MSW Landfill Leachate. *Geotechnical and Geological Engineering*, 33(4): 1081-1098.
- Kaushik, M. K., Kumar, A. & Bansal, A. (2017). Performance of tire chips–gravel combinations with nonwoven geotextile and encapsulated tire chips layers used as filter/separator under incremental stress levels. *European Journal of Environmental and Civil Engineering*, 1-34.
- Kawata, S., Hyodo, M., Orense, P., Yamada, S. & Hazarika, H. Undrained and drained shear behavior of sand and tire chips composite material. Proceedings of the international workshop on scrap tire derived geomaterials—opportunities and challenges, Yokosuka, Japan. 2007, pp. 277-283.
- Lee, J.-S., Dodds, J. & Santamarina, J. C. (2007). Behavior of Rigid-Soft Particle Mixtures. *Journal of Materials in Civil Engineering*, 19(2): 179-184.
- Lee, J. H., Salgado, R., Bernal, A. & Lovell, C. W. (1999). Shredded Tires and Rubber-Sand as Lightweight Backfill. *Journal of Geotechnical and Geoenvironmental Engineering*, 125(2): 132-141.

- Logar, J. & Turk, G. (1997). Neural network as a constitutive model of soil. *Zeitschrift Fur Angewandte Mathematik Und Mechanik*, 77S195-S196.
- Masad, E., Taha, R., Ho, C. & Papagiannakis, T. (1996). Engineering Properties of Tire/Soil Mixtures as a Lightweight Fill Material.
- Mashiri, M. S., Vinod, J. S., Sheikh, M. N. & Tsang, H. H. (2015). Shear strength and dilatancy behaviour of sand-tyre chip mixtures. *Soils and Foundations*, 55(3): 517-528.
- Millar, D. & Clarici, E. Investigation of back-propagation artificial neural networks in modelling the stress-strain behaviour of sandstone rock. *Neural Networks*, 1994. IEEE World Congress on Computational Intelligence., 1994 IEEE International Conference on. 27 Jun-2 Jul 1994 1994, pp. 3326-3331 vol.5.
- Niiya, F., Hazarika, H., Yasufuku, N. & Ishikura, R. Cyclic frictional behavior of two and three dimensional geosynthetics used in liquefaction countermeasure. the 5th Taiwan-Japan Joint Workshop on Large Earthquakes and Heavy Rainfall, Tainan, Taiwan:CD-ROM., 2012, pp.
- Olden, J. D. & Jackson, D. A. (2002). Illuminating the “black box”: a randomization approach for understanding variable contributions in artificial neural networks. *Ecological Modelling*, 154(1): 135-150.
- Schanz, T. (1999). Formulation and verification of the Hardening-Soil Model. *RBJ Brinkgreve, Beyond 2000 in Computational Geotechnics*, 281-290.
- Sheikh, M. N., Mashiri, M. S., Vinod, J. S. & Tsang, H.-H. (2013). Shear and Compressibility Behavior of Sand&Tire Crumb Mixtures. *Journal of Materials in Civil Engineering*, 25(10): 1366-1374.
- Youwai, S. & Bergado, D. T. (2003). Strength and deformation characteristics of shredded rubber tire – sand mixtures. *Canadian Geotechnical Journal*, 40(2): 254-264.
- Zornberg, J. G., Cabral, A. R. & Viratjandr, C. (2004). Behaviour of tire shred – sand mixtures. *Canadian Geotechnical Journal*, 41(2): 227-241.

CHAPTER 8

CONCLUSIONS AND FUTURE WORK

8.1 CONCLUSIONS

Scrap Tire Derived Materials (STDM) are adopted in the field of geotechnical engineering with special emphasis on geo-disaster mitigation and, the objective of promoting recycling of hazardous industrial by-products. Previous studies on the use of gravel tire-chips mixture (GTCM) as a novel geomaterial in the field of geotechnical engineering have shown that these materials can be a promising replacement for sand-STDM mixtures with objective of compensating the limitation of preceding method such as low permeability and low bearing capacity when they are used in geotechnical projects. Prior to apply these materials in civil engineering projects, the mechanical behaviour of GTCM should be thoroughly investigated. Until now, the physical and mechanical and dynamic properties of GTCM are largely unknown.

The goal of this study is to determine the important factors affecting physical, mechanical and dynamic behaviour of gravel as granular material mixed with STDMs. Another goal of this study is to introduce a novel artificial intelligence (AI) based model as an alternative to conventional mathematical models to capture physical and mechanical behaviour of these materials. For this purpose, a series of maximum and minimum void ratio tests were conducted to investigate the effect of different parameters on packing density of GTCM. The results were used to develop an ANN

based model for packing density of granular mixture with STDm. Furthermore, a series of CD and CU triaxial tests were conducted on GTCM specimens in order to evaluate the effect of different parameters such gravel fraction (GF) in mixture, particle size ratio of tire chips to gravel, relative density, effective confining pressure and drainage condition on stress-strain and dilatancy behaviour of the mixture. A new model is proposed to predict tangent modulus and stress-dilatancy of GTCM. In addition, a series of CU cyclic triaxial tests were performed to investigate the effect of gravel fraction and effective confining pressure on the dynamic properties and liquefaction resistance of GTCM. ANN and SVM based models were developed using experimental data set to predict shear modulus and damping ratio of GTCM. The accuracy of the models has been verified by applying the models to the new testing data sets. The performance of the models were assessed in terms of the Mean Square Error (MSE) and coefficient of correlation (R). A feedforward neural network was used to develop models for simulating stress-strain and volumetric strain behaviour of GTCM subjected to the subjected to the conventional triaxial stress paths. The performance of proposed material models were assessed by applying the models to untrained independent testing data sets and the results were compared to those simulated by a mathematical plasticity soil model. Based on the conducted experimental and numerical analyses, the following conclusions could be drawn:

- (1) Packing density of binary mixture of soft and rigid particles with two different sizes was found to be highly influenced by the proportion of large size and small size particles in the total volume of solids as well as relative size of the large and small particles. For the mixtures with non-mono sized particles, an

optimum value of GF exists in which the binary mixture is in its densest state.

- (2) Three distinguishable behavioral zones: gravel like behavior, gravel-tire chips like behavior and tire chips like behavior, were observed for GTCM specimens. The gravel like behavior zone can be described as a zone where GTCM displays well defined peak shear strength followed by a residual strength at higher axial strains. In the gravel-tire chips like zone, neither gravel or tire chips is dominant in mixture. GTCM exhibits gravel-tire chips like behavior with almost indistinct peak shear strength and a reduction in dilatancy was observed. In the tire chips like zone, tire chips particles form GTCM matrix and as a result, considerable reduction in shear strength associated with highly contractive behavior was observed.
- (3) The boundaries where GTCM behavioral zones are separated could be influenced by several factors such as particle characteristics, size ratio ($D_{50,R}/D_{50,G}$) and confining pressure.
- (4) The rise in the relative density of GTCM, enhances the shear strength at failure. However, the influence of relative density on shear strength of GTCM decreases with decreasing GF in mixture.
- (5) For a given GF in mixture, GTCM specimens with $D_{50,R}/D_{50,G} = 3.35$ and $D_{50,R}/D_{50,G} = 0.35$ exhibits higher shear strength than that of $D_{50,R}/D_{50,G} = 1.2$.
- (6) Stress-dilatancy relationship of GTCM was found to be influenced by gravel fraction in mixture. Dilatancy at peak shear strength (D_{min}) was found to decrease with decreasing gravel fraction in mixture. Furthermore, the effect

of effective confining pressure and relative density on minimum dilatancy of GTCM specimen decreases with decreasing gravel fraction in mixture.

- (7) The shear modulus of GTCM specimens decreases with decreasing GF in mixture. However, maximum shear modulus was found to be less influenced by GF at GTCM like and tire chips like behavioural zones.
- (8) Liquefaction resistance of GTCM specimens was found to increase with increasing tire chips inclusion in the mixture at GTCM and tire chips like behavioural zones. The rise in the confining pressure, decreases permeability of GTCM specimens which leads to a decrease in liquefaction resistance of mixture.
- (9) ANN was found to be an efficient technique to model complex void ratio characteristics of granular mixture with a reasonable accuracy. Furthermore, ANN based model has shown better performance in predicting packing density of granular mixture with STDm in comparison to the conventional mathematical model which disregarded shape and deformation of tire chips particles .
- (10)Based on the finding of this study, ANN and SVR techniques were found to be suitable tools for estimation dynamic characteristics of granular mixture with reasonable currency, however ANN based model yielded better performance on generalization and prediction of dynamic behavior of mixture in comparison to that of SVM.

ANN based material model with feedforward backpropagation algorithm was capable of capturing complex stress-strain and volumetric strain behaviour of

GTCM with excellent accuracy. The model could simulate stress-strain and volumetric strain behaviour of new untrained testing data sets with high accuracy. Furthermore, ANN based model showed better performance in predicting mechanical behaviour of GTCM in comparison to that of mathematical plasticity model.

8.2 FUTURE WORK

In this dissertation, physical, mechanical and dynamic behaviour of GTCM has been thoroughly studied. Most important factors affecting stress-strain as well as dynamic properties and liquefaction potential of GTCM were determined. An attempt was made to assess viability of AI techniques in material modelling of granular mixture with STDm. However, there are still some areas left to explore and answers unanswered. The following suggestions are therefore made for future research on the topic:

- (1) Although, the effect of important factors on monotonic and dynamic behaviour of GTCM have been investigated in this study. However, the behaviour of these mixtures was found to be mostly influenced by three parameters, gravel fraction, particle size ratio of tire chips to gravel and effective confining pressure. In this study, the value of confining pressures was limited to the range of 50-200 kN/m². Therefore, further experimental work is necessary to understand the behaviour of GTCM under very high and low level of the confining pressures.
- (2) The effects of loading frequency and initial shear stress on the dynamic

behaviour of GTCM were not considered in this study. Therefore, further experimental work is required to understand the influence of those parameters on liquefaction resistance and dynamic properties of mixture.

- (3) In this study, an artificial intelligence based model was introduced to simulate packing density of granular mixtures with STD. However, the effects of soil and STD type were disregarded in this study. Generalization ability of model can be improved by retraining the network with larger collection of data sets comprises of different types of granular mixture with STD such as sand or gravel-tire shreds mixture.
- (4) The performance of proposed material model for granular mixture could be improved by training model on the stress-strain data with reloading and unloading inside the failure envelope.
- (5) The developed material model in this study can be extended to model the stress-strain behaviour of granular mixture with STD in general stress-state as long as sufficient experimental results is provided.