MACHINE LEARNING SHEAR WAVE VELOCITY PREDICTION BASED ON MULTI-CHANNEL ANALYSIS OF SURFACE WAVE

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DEDICATION

This thesis is dedicated to my family, friends and supervisors, who has supported and instilled confidence in me throughout the completion of this thesis. Each and everyone of you played a constant role in guiding me through the constant challenges and self-doubt, inspiring me in completing the thesis.

ABSTRACT

Shear Wave Velocity (V_s) profile plays a crucial part in determining seismic site classification. However, field measurement incurs extra cost and time. Economic factors urge the need for a cheaper and faster alternative. Previous studies proposed the use of empirical equations, however there are growing evidence that Machine Learning (*ML*) methods may produce better results. Thus, this study was designed to develop a feasible method of predicting V_s value using *ML* Models. Due to the impact of weathering profile on seismic site classification, the results of this study are limited to sites with similar geological formation of the study area, which is composed of granitic rocks. The study utilized four types of *ML* algorithms to develop the predictive model. The *ML* algorithms used were Multi Linear Regression (*MLR*), Random Forest (*RFR*), Artificial Neural Network (*ANN*) and Support Vector Machine (*SVR*). The independent variables are Standard Penetration Resistance (N_{spt}) and depth of soil (D_s), while the dependent variable is V_s. Consequently, this study conducted a Multichannel Analysis of Surface Wave (*MASW*) survey to get the required dataset. Furthermore, this study verified the V_s profiles using N_{spt} data. In addition, the hyperparameters for the *ML* models were determined using Random Search and *k*-fold Cross Validation. On top of that, this study also used Coefficient of Determination (R^2), Mean Absolute Error (*MAE*) and Root Mean Squared Error (*RMSE*) as the performance metrics for model selection. The best *ML* model was determined to be *RFR* based on the performance metrics (R^2 = 0.9, *MAE* = 16.93 and *RMSE* = 19.79). It was then determined that the average percentage difference between the actual and predicted V_{s30} was 10.7%. This study also presents the development of a software, *pyMASW*, for the processing of the raw seismic data. In conclusion, the *RFR* model can predict V_{s30} values for seismic site classification with an accuracy of 89.3%.

ABSTRAK

Profil Halaju Gelombang Ricih (V_s) memainkan peranan penting dalam menentukan klasifikasi kawasan seismik. Walau bagaimanapun, pengukuran lapangan memerlukan kos dan masa tambahan. Faktor ekonomi mendorong perlunya alternatif yang lebih murah dan cepat. Kajian sebelumnya mencadangkan penggunaan persamaan empirikal, namun terdapat bukti yang semakin meningkat bahawa kaedah Pembelajaran Mesin (*ML*) dapat memberi hasil yang lebih tepat. Oleh itu, tujuan kajian ini adalah untuk mengkaji kaedah yang mampu meramalkan nilai V_s menggunakan Model *ML*. Oleh kerana kesan daripada profil luluhawa kepada klasifikasi kawasan seismik, hasil kajian ini terbatas kepada lokasi dengan formasi geologi kawasan kajian yang serupa, iaitu batuan granit. Kajian ini menggunakan empat jenis algoritma *ML* sebagai model ramalan. Algoritma *ML* yang digunakan adalah Regresi Linear Berganda (*MLR*), Hutan Rawak (*RFR*), Jaringan Saraf Tiruan (*ANN*) dan Mesin Vektor Sokongan (*SVR*). Pemboleh ubah bebas adalah nilai ketukan *N* daripada Ujian Penusukan Piawai (N_{spt}) dan kedalaman tanah (D_s), sementara pemboleh ubah bersandar adalah V_s. Seterusnya, kajian ini melakukan tinjauan Analisis Gelombang Permukaan Berbilang Saluran (*MASW*) untuk mendapatkan set data yang diperlukan. Selanjutnya, kajian ini mengesahkan profil V_s menggunakan data N_{spt}. Di samping itu, kajian ini menentukan hiperparameter untuk model *ML* menggunakan kaedah Pencarian Rawak dan Pengesahan Silang Lipat-k. Di samping itu, kajian ini juga menggunakan Pekali Penentuan (R^2), Ralat Mutlak (*MAE*) dan Ralat Punca Kuasa Dua Min (*RMSE*) sebagai metrik pemilihan model. Model *ML* terbaik dalam kajian ini adalah *RFR* berdasarkan metrik prestasi ($R^2 = 0.9$, $MAE = 16.93$ dan $RMSE = 19.79$). Kajian ini juga mendapati bahawa perbezaan peratusan purata antara V_{s30} yang sebenarnya dan yang diramalkan adalah 10.7%. Selain itu, kajian ini turut menghasilkan sebuah perisian, *pyMASW*, yang digunakan untuk memproses data seismik. Kesimpulannya, model *RFR* dapat meramalkan nilai V_{s30} untuk klasifikasi kawasan seismik dengan ketepatan 89.3%.

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LIST OF ABBREVIATIONS

ANN	-	Artificial neural network
CPT	-	Cone penetration test
FFT	-	Fast Fourier transform
GUI	-	Graphical user interface
MAE	-	Mean absolute error
MASW	-	Multichannel analysis of surface waves
ML	-	Machine Learning
MLR	-	Multi-linear regression
NEHRP	-	National Earthquake Hazards Reductions Program
RFR	-	Random forest
RMSE	-	Root mean squared error
RL	-	Reduced Level
SASW	-	Spectral analysis of surface waves
SPT	-	Standard penetration test
SVR	-	Support vector machine

LIST OF SYMBOLS

24-ch	-	24-channel survey layout
48-ch	-	48-channel survey layout
a	-	Amplitude
$A_s(\omega, c_{test})$	-	Summed amplitude for a given set of ω and c_{test}
C	-	Calm (field condition)
c_{test}	-	Testing Rayleigh wave phase velocity
$c_{test,max}$	-	Maximum testing Rayleigh wave phase velocity
$c_{test,min}$	-	Minimum testing Rayleigh wave phase velocity
$c_{e,q}$	-	Rayleigh wave phase velocity of q-th layer in experimental dispersion curve
$(c_{e,q}, \lambda_{e,q})$	-	Experimental dispersion curve
$c_{t,q}$	-	Rayleigh wave phase velocity of q-th layer in theoretical dispersion curve
$(c_{t,q}, \lambda_{t,q})$	-	Theoretical dispersion curve
D	-	Length of receiver spread
D_s	-	Depth of soil
dt	-	Sampling interval
dx	-	Spacing between receiver
f	-	Frequency
h	-	Layer thickness vector
h_i	-	Thickness of the i-th layer
h_{init}	-	Initial estimate of layer thickness vector
k	-	Wave number
L	-	Length of line spread
$\mathbf{K}$	-	System stiffness matrix
$\mathbf{K}_{e,i}$	-	Element stiffness matrix of the i-th layer
$k_{t,q}$	-	Wave number of the q-th point in a given theoretical dispersion curve
N	-	Noisy (field Condition)
N_{spt}	-	Standard penetration resistance
$P_j(\omega)$	-	Phase spectrum of Fourier transformed seismic wave trace recorded by the j-th geophone
Q	-	Number of points in a given dispersion curve
R	-	Frequency of receiver (geophone)

R^2	- Coefficient of determination
S	- Weight of source (hammer)
T	- Total recording time
$u_j(t)$	- Seismic wave trace recorded by the j-th geophone
$\tilde{u}_j(\omega)$	- Fourier transformed seismic wave trace recorded by the j-th geophone
$\tilde{u}_{j,norm}(\omega)$	- Fourier transformed seismic wave trace recorded by the j-th geophone normalized in the displacement and angular frequency dimensions
v	- Velocity
VN	- Very noisy (field condition)
V_s	- Shear wave velocity
V_{s30}	- Average shear wave velocity up to depth of 30 m
X_1	- Distance from between source and first receiver
x-t	- Displacement-time domain
x- ω	- Displacement-angular frequency domain
x_j	- Distance from source to j-th geophone
Z_{max}	- Maximum depth achievable
α	- Compressional wave velocity vector
α_i	- Compressional wave velocity of i-th layer
β	- Shear wave velocity vector
β_i	- Shear wave velocity of i-th layer
β_{init}	- Initial estimate of shear wave velocity vector
ϵ_i	- Error for iteration i in inversion analysis
$\Delta\epsilon_i$	- Amount of improvement at iteration i compared to iteration i-1
λ	- Wavelength
$\lambda_{e,q}$	- Wavelength of the q-th point in a given experimental dispersion curve
$\lambda_{t,q}$	- Wavelength of the q-th point in a given theoretical dispersion curve
ρ	- Mass density vector
ρ_i	- Mass density of i-th layer
$\varphi_{test}x_j$	- Phase shifts for a given set of ω and c_{test}.
v	- Poisson's ratio vector
v_i	- Poisson's ratio of i-th layer
ω	- Angular frequency
ξ	- Minimum improvement of error

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CHAPTER 1

INTRODUCTION

1.1 Background of Research

A structure's seismic site can be categorized into six categories: class A, B, C, D, E and F (Building Seismic Safety Council, 2015). In order to obtain the most accurate site classification, the average shear wave velocity up to the depth of 30 m (V_{s30}) needs to be acquired. This classification is a crucial part in designing an earthquake resistant structure. Generally, slower average Shear Wave Velocity (V_s) value would imply greater soil amplification (Building Seismic Safety Council, 2015). Furthermore, V_s is considered a key component in predicting soil response to seismic loading (Tan et al., 2013). V_s is defined as the velocity of a shear wave, also known as S-wave or secondary waves. A particular wave may be classified as a shear wave based on the particle motion in the medium through which the wave passes through. The resultant particle motion of a shear wave would move in perpendicular to the direction of the wave's propagation. Obtaining the V_{s30} profile of a site is an important part of determining the characteristics of earthquake motion at the site. It is an integral step for structural engineers in determining the seismic site classification and seismic design forces. However, field measurement of V_s would incur additional cost and time son top of the geotechnical investigations while requiring specialized personnel to conduct the test. Therefore, a cheaper and faster alternative is needed for when field measurement is not economically feasible.

Furthermore, through common geotechnical investigation such as bore logging, information about type of soils and penetration resistance (N_{spt}) can be easily obtained. N_{spt} is a soil property derived from an in-situ dynamic penetration test through the Standard Penetration Resistance (*SPT*) Test. N_{spt} is defined as the number of blows required to drive the sampler through 300 mm of soil. This value can be then used for geotechnical design purposes. The ability to use this simple and inexpensive geotechnical test of the sites to obtain V_s profile would be a favorable alternative to conducting costly in-situ V_s measurement. Indeed, there are many studies conducted in the past which presents empirical correlation between V_s and N_{spt} (Kirar, Maheshwari, & Muley, 2016). However, through the bore log alone, a lot more information such as type of soil can be obtained which can help in the prediction of V_s in addition to N_{spt}.

There are several in-situ tests which can be used to measure V_s. These include cross-hole test, suspension logging, downhole test, seismic reflection, seismic refraction and surface wave test (Tan et al., 2013). Surface wave test, such as Spectral Analysis of Surface Wave (*SASW*) and Multichannel Analysis of Surface Waves (*MASW*), are considered the simplest and most efficient technique of measuring shear wave velocity. The difference between the two technique is that *SASW* is typically deployed in a dual-station setup while MASW is deployed in a multi-station setup. An advantage of *MASW* over *SASW* is that a multi-station setup allows a wider and deeper range as well higher level of redundancy (Tan et al., 2012).

Efforts has been made by researchers to establish empirical correlations between V_s and standard penetration resistance (N_{spt}). These relations are mostly described in the form of Equation (1.1).

$$V_s = xN_{spt}^{\ y} \tag{1.1}$$

where x and y are constant coefficients which are determined through regression analysis. Equation (1.1) is a power equation model. Thus, x is a parameter which affects the amplitude while y affects the curvature of the relationship (Gautam, 2016). In addition, most of the correlations are region specific. Thus, it may not be applicable to different regions around the worlds.

This thesis presents the implementation of Machine Learning (*ML*) algorithm to develop a predictive model for V_s. In order to develop the predictive model which will be used to predict N_{spt}, four *ML* algorithms will be considered. The *ML* algorithms used are Multi Linear Regression (*MLR*), Random Forest (*RFR*), Artificial Neural Network (*ANN*) and Support Vector Machine (*SVR*).

1.2 Problem Statement

Obtaining the Shear Wave Velocity (V_s) profile of a site is an important part of determining the characteristics of earthquake motion at the site. However, field measurement of V_s using the *MASW* method would incur additional cost and time while requiring specialized personnel to conduct the test. When using the *MASW* method to obtain V_{s30} profile, results may also vary due to a need for the process of manually picking the dispersion curve. This is highly dependent on the experience and expertise of the person conducting the analyses. Differences in the dispersion curve that were manually picked would result in inconsistent results in terms of the final profile. Therefore, a cheaper and faster alternative is needed for cases where field measurement is not economically feasible while also capable of producing consistent results.

Previously, various empirical correlation between V_s and N_{spt} has been proposed by researchers for the purpose of V_s prediction. Regardless, most of these correlations are specific to a region and not applicable to all region (Kirar et al., 2016). Furthermore, most of the existing V_s empirical model proposed are based on conventional statistical regression method. However, conventional statistical regression method shouldn't be the only method considered for a prediction model, considering recent advances in *ML* algorithms. For the purpose of industrial applications, *ML* algorithms should be considered alongside conventional statistical regression method in order to optimize the accuracy of parameter prediction. Thus, this study proposes the use of four *ML* models to predict V_s value using N_{spt} value as the input.

1.3 Objectives of Research

The aim of this research is to develop a feasible method of predicting shear wave velocity value for seismic site classification. In order to achieve that aim, the following objectives were set:

i. To develop a tool for processing raw for processing raw Multichannel Analysis of Surface Wave (MASW) data in order to obtain Shear Wave Velocity (V_s) profile.
ii. To develop predictive models using Machine Learning (*ML*) with Shear Wave Velocity (V_s) as the dependent variable.
iii. To verify the performance of the Machine Learning (*ML*) prediction models using observed data collected through *MASW* method.

1.4 Scope of Research

This study will focus on seismic site classification using shear wave velocity as detailed in MS EN 1998-1:2015 (2017). Meanwhile, soil parameters which are going to be used as inputs for the *ML* models are N_{spt} and *RL*s. In addition, the V_s data will be collected using the multichannel analysis of surface waves (*MASW*) technique. Particularly, shear wave velocity up to 30 m depth will be the focus of this research.

1.5 Significance of Research

A structure's seismic site classification is important in order to assess how vulnerable the structure's site is to ground movement. Through the development of the V_s prediction model, engineering projects would be able to benefit in three different aspects: efficiency, convenience and cost saving.

1.6 Limitations of Research

An important factor of a seismic site classification is the weathering profile of a particular site's geological formation. More specifically, it is of particular importance because the rate of weathering is highly dependent on the type of rock formation. The site that is used for the data collection phase of this research is situated above a granite bedrock formation. This factor will directly influence the results of the study, therefore the results and implications of this study should only be applied to sites that has a similar geological profile.

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