MODELLING SOIL PORE WATER PRESSURE USING SIGMOID KERNEL FUNCTION

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CIVIL AND ENVIRONMENTAL ENGINEERING

UNIVERSITI TEKNOLOGI PETRONAS

SEPTEMBER 2016

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Dissertation submitted in partial fulfilment of
the requirements for the
Bachelor of Engineering (Hons)
(Civil and Environmental Engineering)

SEPTEMBER 2016

Universiti Teknologi PETRONAS,

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CERTIFICATION OF APPROVAL

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A project dissertation submitted to the
Civil and Environmental Engineering Programme
Universiti Teknologi PETRONAS
in partial fulfilment of the requirement for the
BACHELOR OF ENGINEERING (Hons)
(CIVIL AND ENVIRONMENTAL ENGINEERING)

Approved by,

____

(Dr Muhammad Raza Ul Mustafa)

UNIVERSITI TEKNOLOGI PETRONAS
BANDAR SERI ISKANDAR, PERAK
September 2016

CERTIFICATION OF ORIGINALITY

This is to certify that I am responsible for the work submitted in this project, that the original work is my own except as specified in the references and acknowledgements, and that the original work contained herein have not been undertaken or done by unspecified sources or persons.

NURUL SYAHIRAH BINTI KAMARUL BAHRIN

ABSTRACT

Pore-Water Pressure (PWP) is an influential parameter for monitoring slope stability responses to rainfall especially in the area that prone to experience slope failure. Monitoring PWP that is in the form of nonlinear complex data however is expensive and require quite tedious task through traditional approach for evaluation purposes. In respond to that, recently, PWP able to be modelled by soft computing techniques - Support Vector Machine (SVM). SVM will determine the optimal linear separating plane in high dimension feature space of nonlinear complex data by its numerous kernel function technique. The data on rainfall is collected at slope site of Universiti Teknologi PETRONAS, Perak. The study is merely to predict PWP fluctuations occur based on the rainfall event at instrumented slope by developing two SVM model using Sigmoid Kernel Function technique. The model is then evaluated by coefficient of determination (R^2) and mean square error (MSE) to obtain optimum meta-parameters. Model 1 shows a better result in term R^2 and MSE compared to Model 2 by 20.3%. The study successfully demonstrated Sigmoid Kernel Function model is effective to predict accurate PWP and can be applied in any slope management studies.

ACKNOWLEDGEMENTS

I would like to express the deepest appreciation to my supervisor, Dr Muhammad Raza Ul Mustafa, who continually and convincingly conveyed a spirit of adventure in regard to research and an excitement in regard to teaching. In addition, a thank you to Mr Nuraddeen Muhammad Babangida who introduced me to soft computing technique, Support Vector Machine (SVM). Without his guidance and persistent help, this dissertation would not have been possible.

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CHAPTER 1

INTRODUCTION

1.1 Project Background

Pore Water Pressure (PWP) as in general, is the indicator of the existence of water filled the voids that exert external forces within the soil. This is influenced by either the physical location of the soil or other natural factor like rainfall that results in fluctuation of PWP reading. The presence of the water resulting the soil to become more saturated that relates to the pressure difference within the soil. This can be illustrated by the parameter of pressure readings, buoyancy effect and shear strength of the soil. Zero reading of PWP indicates the soil voids are filled with air, negative reading of PWP indicates the soil voids are partly filled with the water while positive reading of PWP is when the soil voids are fully filled with the water. Varies in reading of PWP affects in the shear strength of the soil. The saturated state of the soil has achieved buoyancy effect and thus, reflects to the reducing shear strength in the soil. In fact, shear resistance is proportionally depending on the shear strength of the soil. Therefore, the reduction in shear resisting capacity of the soil due to the increase of PWP and decrease of the shear strength is unfavourable. This is because the reduction of shear resisting capacity of the soil will cause slope failure and leads to landslides. Hence, in hydrological perspectives, knowledge on PWP is vital in order to study seepage analyses, forecast possible failures on the slope, design slope and evaluates the slope responses to rainfall.

Previous studies had been conducted to model and predict PWP by using data-driven models on artificial intelligence. Most past studies showed artificial neural network (ANN) had successful demonstrate PWP modelling. Nonetheless, recently, support vector machines (SVM) had been noticed to perform as well as ANN. This study is going to prove on how Sigmoid kernel function (one of SVM's techniques) can be used to predict and model PWP.

1.2 Problem Statement

Rainfall often notably as one of the factors that weakens the earth slope. It can be found by number of ways and the way it increases saturation's degree of soil thus loosen the bonds of the surface tension between the particles of the soil (Borja & White, 2010). Borja and White (2010) also stated that if the volume of water infiltrates is large enough, the degree of saturation of the soil increases and thus able to produce downhill frictional drag on the slope. The increase degree of saturation in the soil affect the excess volume of water that can no longer infiltrate into the slope and then discharged as surface runoff that caused the slope erodibility.

The implications of slope instability can be widely seen through landslides tragedy all over the world. Landslides that occurred from the past decades back in 1982 until recently 2006 had documented numbers of fatalities and severe destruction. Massive rainfall and the preparedness to it diagnosed as the primary factor of the landslides event. Due to that, studies related to seepage analyses, slope stability analyses, engineered slope design and evaluating slope responses to rainfall is needed. PWP is the element that contribute to the studies as it can demonstrate both predicting and modelling of rainfall.

Past studies had successful practiced neural networks as a tool to predict PWP responses to rainfall. However, recently, support vector machine (SVM) has the same ability as neural networks to be used for similar purposes. Sigmoid kernel function is one of the techniques falls under SVM and is going to be introduced in this research to prove on how effective it is to predict and model variation responses of rainfall.

1.3 Objectives

The objectives of this research that is prediction of pore water pressure responses to rainfall are as follows;

- To predict pore water pressure responses to rainfall using Sigmoid Kernel function.
- To evaluate the model performance by using statistical measures.

1.4 Scope of study

The scope of this research will focus on;

- The application of Sigmoid kernel function for modelling pore water pressure responses to rainfall using Matlab software.
- The performance of the model using coefficient of determination (R^2) and mean square error (MSE).

CHAPTER 2

LITERATURE REVIEW

Numerous past studies had come out with the same idea of pore water pressure has significant impact on the slope stability through the evaluation effect of the increase in pore water pressure on the stability of the slope (Yoshinaka et al., 1997; Furuya et al., 2006; Matsuura et al., 2008; Huang et al., 2012). Mustafa et al. (2012) has stated that the increase in pore water pressure contribute to the reducing shear strength of soil and thus caused slope failures. Further studies then conducted to prove the statement by various type of approaches and techniques.

The data to be used in the study however consist of complex relationships. Data-model driven on artificial intelligence able to demonstrate the complex relationship in model manner. Artificial Neural Networks (ANNs) is one of the approaches falls under artificial intelligence that works just as human nervous systems that consists of neurons (illustrated as below).

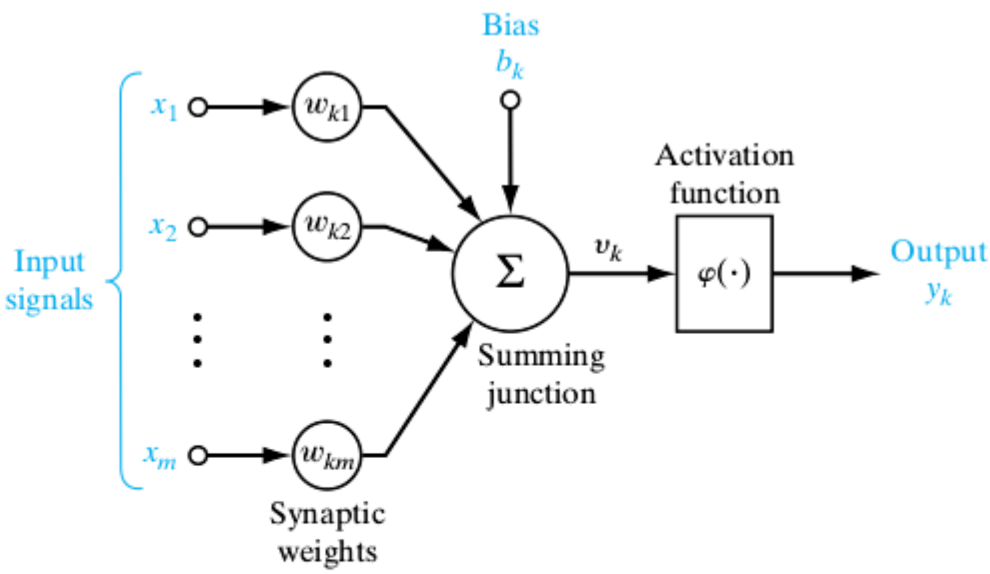

Figure 1: Simple block diagram of neuron

ANN had been successful widely used in various field of engineering including geotechnical (Mustafa et al., 2012). Goh (1995) had a research in providing the estimation of maximum wall deflection for braced excavations by developing a neural network model (Tarawneh, 2016). Kahraman (2005) introduced multi-layered perception (MLP) approach in ANN to determine the prediction of carbonate rocks saw ability through shear strength parameters. Kaunda (2014) demonstrated on how different rock types examined through ANN simulations and the responses to principal stress effects. Momeni et al. (2015) presented the utilization of particle swarm optimization in order to predict unconfined compressive strength of the rocks by modelling ANN. In hydrology aspect, there are several studies that had successful use the application of ANN in predicting quality of water (May and Sivakumar 2009) and forecast of river flow (Dibike and Solomatine 2001).

There are researches done (Mustafa et al. 2010, 2012, 2013) to predict pore water pressure using the same application of ANN. In the research, the prediction using ANN is being tested by different techniques of scaled conjugate gradient (SCG) learning algorithm, radial basis function neural network (RBFNN) and multilayer perceptron. The outcome of the research by SCG learning algorithm is applicable to be used to predict non-linear behaviour as variation of pore water pressure during rainfall event. While RBFNN modelling has slight lacking of the ability to explain functional relationships between variables, it does have the advantage of using limited number of parameters. Whereas multilayer perception technique indicated the during both training and testing with gradient descent (GD), gradient descent with momentum (GDM), SCG and Levenberg-Marquardt (LM) algorithm, LM is identified as the ultimate training algorithm as least time and minimum error obtained for soil pore water pressure.

Recently, support vector machine (SVM) that is another artificial intelligence component, had gained vast attention from researchers for its ability to utilize linear function in a high dimensional feature space. Various researches that used SVM approach which introduced by Vapnik and others in early of 1990s, have achieved a successful outcome especially in hydrological field of study for example study carried out by Lin et al. (2013) using SVM approach to forecast typhoon flood. In the study, a two-stage SVM-based model is developed to yield 1-to 6-h lead time runoff forecasts. The model developed is undergone pre-process the information of typhoon and then forecasting the rainfall. The rainfall data is set as an input data to predict the flood module. Tehrany et al. (2014) also use SVM approach to map flood susceptibility in GIS. The data validated by SVM parameter indicate the proposed method improved flood modelling by 29%. Shrestha and Shukla (2015) has study on the evapotranspiration using hydro-climatic variables with SVM approach. They discovered SVM model is performing better and more accurate compared ANN and Relevance Vector Machine. Research done by Kundu et al. (2016) using Least Square (LS) technique of SVM model to study the future changes in rainfall, temperature and reference evapotranspiration in the central India. The model is evaluated based on its efficiency by different statistical method.

Other than research stated, SVM has contributed in many more as in following figure;

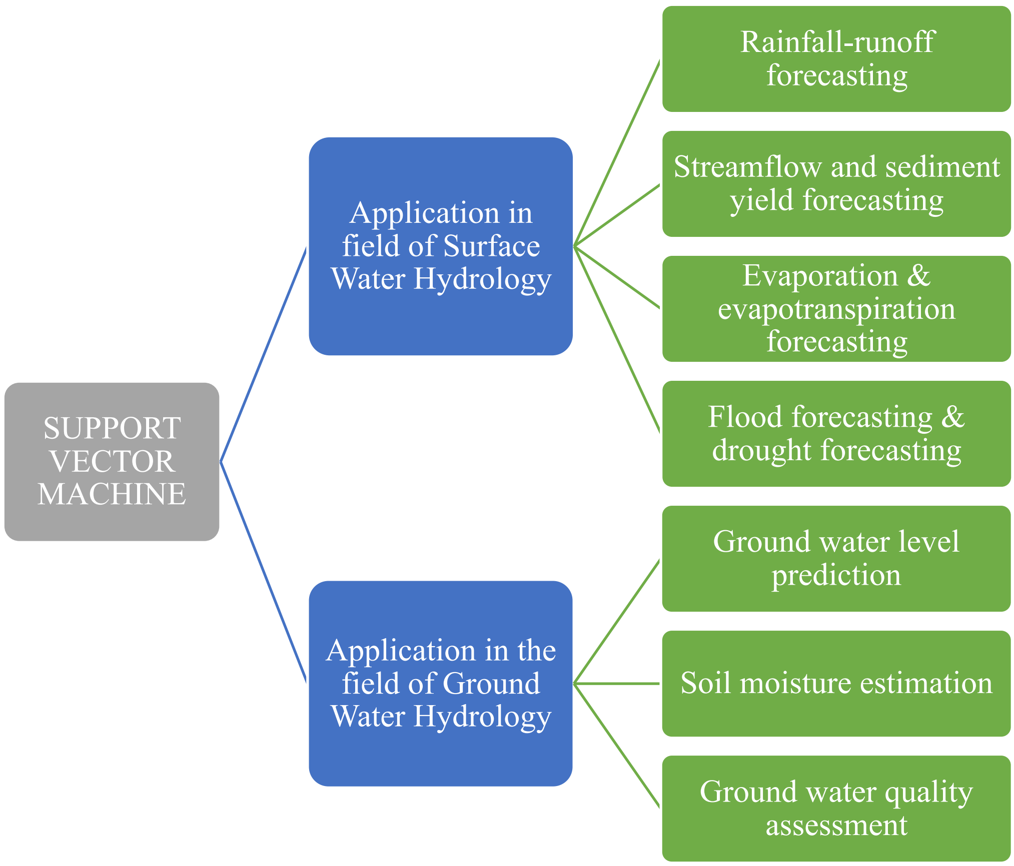

Figure 2: Applications of Support Vector Machine

N and Deka (2013) stated the contribution of SVM in hydrology aspects has been in significant number due to its promising and reliable analysis through series of development. SVM has given insight to be successful in classification problems, regression and forecasting through its machine learning techniques. Due to that, Babangida et. al (2016) has come out with the idea of using SVM approach to predict pore water pressure response to rainfall. Support vector regression technique is being used for modelling the data responses to rainfall and has proven show good results compared to their previous study using ANN. Based on its performance, the same SVM approach but with different technique of Sigmoid kernel function is going to be used in this study to evaluate on the performance of the pore water pressure prediction since there is no study focusing on it being done yet.

CHAPTER 3

METHODOLOGY/PROJECT WORK

This chapter illustrate methodology of the project that covers for study area, instruments used, data source and modelling process.

3.1 Study area

Study area for this project is located on the selected slope within the grounds of Universiti Teknologi PETRONAS that close to Block 5. The selected soil slope is about 11 m high. Following figures show location of this project.

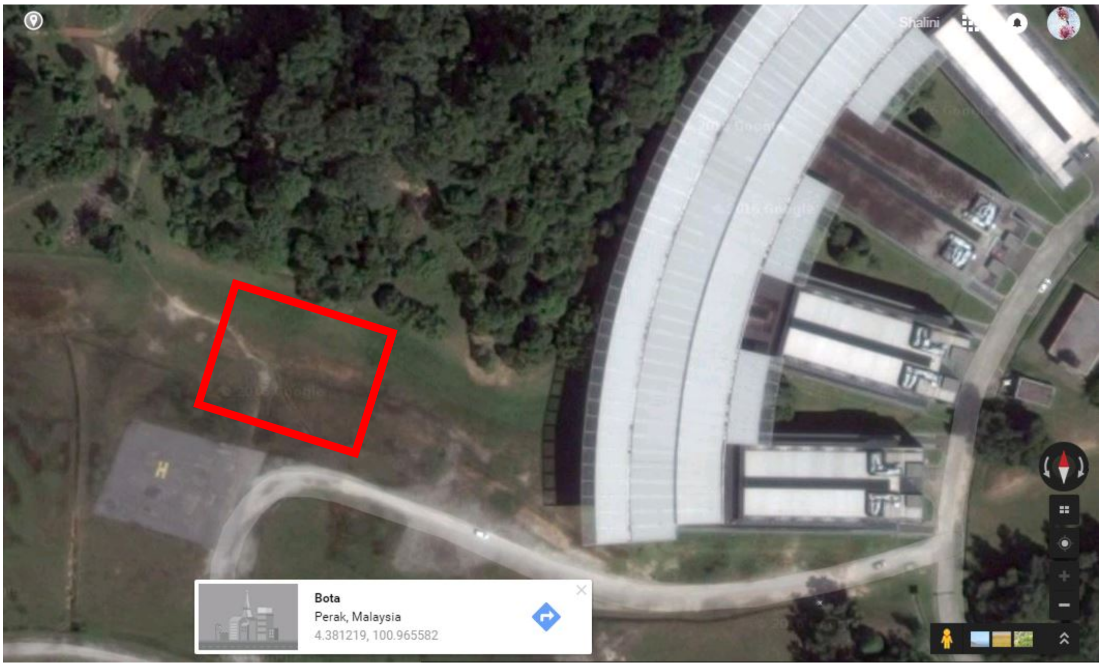

Figure 3: Location of the study area

Figure 4: Location of tensiometers and tipping bucket rain gauge at study area

Slope variables are vital to be used in this project. Following are the parameters for site detail and soil properties of the slope;

1. Slope properties
    - Area
    - Slope angle
    - Slope height
    - Topography

2. Soil engineering properties
    - Water content
    - Liquid limit
    - Plastic limit
    - Effective cohesion
    - Soil type
    - Angle of friction

3.2 Instrument and Data Source

3.2.1 Tensiometers

Figure 5: Tensiometers

Measuring devices to be used in this project are tensiometers. The primary function of tensiometers are to obtain soil water contain from the rainfall. The tensiometers is installed in the depth of 0.6 m.

3.2.2 Tipping Bucket Rain Gauge

Figure 6: Tipping bucket rain gauge

Figure 7: Tipping bucket rain gauge information

Tipping Bucket Rain Gauge is primarily functioning to evaluate the rainfall. It comprises of a funnel that collects the rainfall then channelled it to the metallic tipping bucket measuring system. Then reed switch will detect when the bucket has tipped and produces a momentary contact closure signal. The cycle keeps continue as long as the rainfall continues to fall. The rainfall gauge then will connect to a data logger as it detected and recorded the data through a counter channel. The time interval set is 30 minutes.

3.3 Support Vector Machines

As stated by Babangida et. al. (2016), Support Vector Machines (SVM) is being discovered as a reliable soft computing method that promotes method of learning classification, interpolation, functional estimation and etc. (Kecman, 2001).

SVM govern discriminative classifier that defined by separating hyperplane. The operation in SVM algorithm enable to find the largest minimum distance of hyperplane so that the hyperplane will not cause noise in the data and thus affect the generalization of data. The equation of hyperplane is as following;

$$f(x) = x'\beta + b = 0 \qquad (1)$$

where $\beta \in R^d$ and b is a real number.

By introducing this SVM approach, it is enables the use of linear classifiers as solutions for nonlinear problems for example pore water pressure data prediction. Nonlinear transformation also can be illustrated by various techniques of Kernels such as polynomials, radial basis function, multilayer perception (neural network), Sigmoid kernel function and etc. In order to supervised learning model, SVM need to undergone process of training, classifying and tuning. SVM approach will use Support Vector Regression as the model implementation and Sigmoid kernel function as the technique to implement and thus evaluate the model.

3.4 Sigmoid Kernel Function

Sigmoid kernel function or also known as Hyperbolic Tangent Kernel has been chosen to model pore water pressure. The kernel training vectors involved in this study derived from SVM training vector which is as follows;

$$K(x_i, x_j) \equiv \phi(x_i)^T \phi(x_j) \quad (2)$$

While for Sigmoid kernel function vector is as follows;

$$k\ (x, y) = tanh\ (\gamma x^T y + r) \quad (3)$$

Based on the training vector, SVM model using sigmoid kernel function is equivalent to a two-layer, perceptron neural network. Therefore, the result originated from Sigmoid kernel function will then compared to predicted values in identifying the performance of the model and the factor contributes to the variance of the result.

3.5 Support Vector Regression Model

Support Vector Regression (SVR) is used as evaluator in the process of developing the model. Mean Square Error (MSE) being used to measure model accuracy. This can be shown by following formula;

$$MSE = \frac{1}{n}\sum_{n=1}^{n}\left(\hat{Y} - Y\right)^2 \qquad (4)$$

Low values of MSE are desirable as indicator to get how close the model predictions with observed values. Coefficient of determination (R^2) with the high value is desirable in demonstrating the unity value that shows the strength relationship between model predictions and observed values. This can be shown as in following formula;

$$R^2 = \frac{\sum(u-\bar{u})^2 - \sum(\hat{u}-u)^2}{\sum(u-\bar{u})^2} \qquad (5)$$

The kernel function selected, as for this case, Sigmoid kernel function, then will be used in model implementation along with other parameters of regularization parameter, C and width of corridor minimized by SVM, ε. This is done by trial and error method in order to determine most reliable values for respective parameters.

3.6 Development of Sigmoid Kernel Function Model

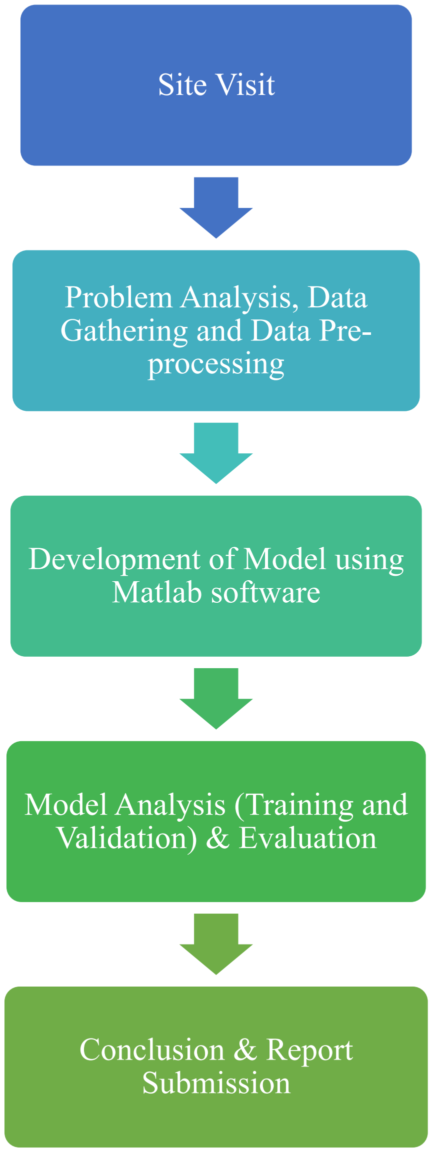

Figure 8: Sigmoid Kernel Function Model development

3.7 Gantt chart

A total of 14 weeks are given to complete this project. Gantt charts for Final Year Project 1 & 2 are stated below;

Table 1: FYP1 Gantt Chart

Week / Details	1	2	3	4	5	6	7	8	9	10	11	12	13	14
Selection of Project Title	■	■												
Preliminary Research Work		■	■	■	■									
Submission of Extended Proposal						●								
Proposal Defence								■	■					
Project work continues										■	■	■		
Submission of Interim Draft Report													●	
Submission of Final Interim Report														●

● Deadline

Table 2: FYP2 Gantt Chart

Details \ Week	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15
Project Work Continues															
Submission of Progress Report							●								
Project Work Continues															
Pre-SEDEX										●					
Submission of Draft Final Report											●				
Submission of Dissertation (soft bound)												●			
Submission of Technical Paper												●			
Viva													●		
Submission of Project Dissertation (Hard Bound)															●

● Deadline

3.8 Key Milestone

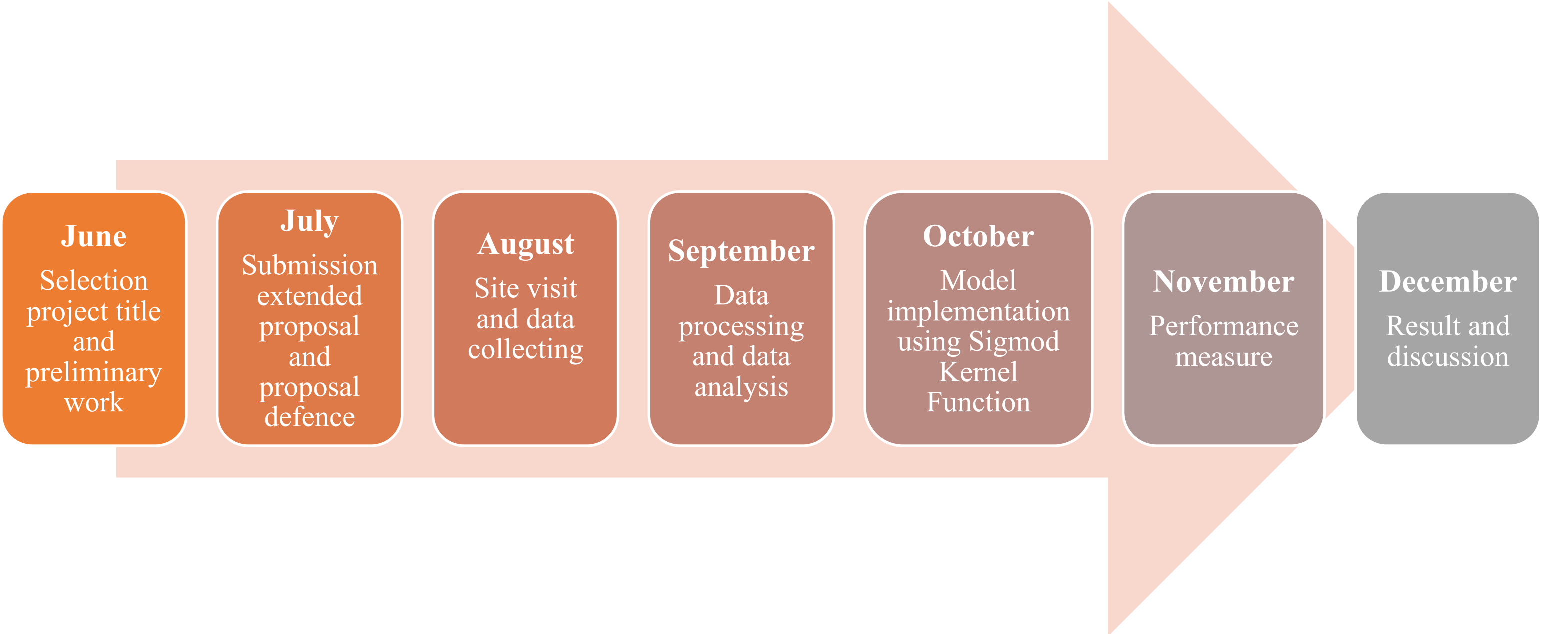

Figure 9: Key Milestone

CHAPTER 4

RESULT AND DISCUSSION

This chapter illustrated model development of support vector machine. Model development of support vector machine need particular consideration in determining its input combination and right meta-parameters. This is including the analysis of data.

4.1 Data Analysis

An entirely month of data in November 2014 is selected in this study. A total of 1440 of data points for pore water pressure (PWP) and rainfall respectively used in this study. All data points need to be divided into training and testing datasets in order to model the prediction of PWP with a better accuracy. The selection of both training and testing datasets are according to the data analysis with the breakdown of 70% for training and 30% for testing that has been successfully practiced through past studies by Mustafa et al. (2012), Rahardjo et. al. (2008) and Babangida et. al. (2016). Following is the preliminary data analysis;

Table 3: Data Analysis

Data statistics	PWP	Rainfall
Number (N)	1440	1440
Mean	-8.787	0.171
Standard Deviation	1.174	1.424
Min	-11.5	0
Max	-4.9	30.5
Skewness	0.376	13.909

The maximum, minimum and mean of PWP data points show negative value which means the slope is not experiencing low slope stability. Same goes to rainfall data points, with its minimum value of zero and maximum value of 30.5, the mean of data points is 0.171 which means the frequency of the slope experiencing and receiving rain events are not continuously same throughout the entire month. Same goes to the skewness of the data points, PWP experiencing positive skewness and rainfall experiencing negative skewness respectively.

The graph of both PWP and rainfall are illustrated as following;

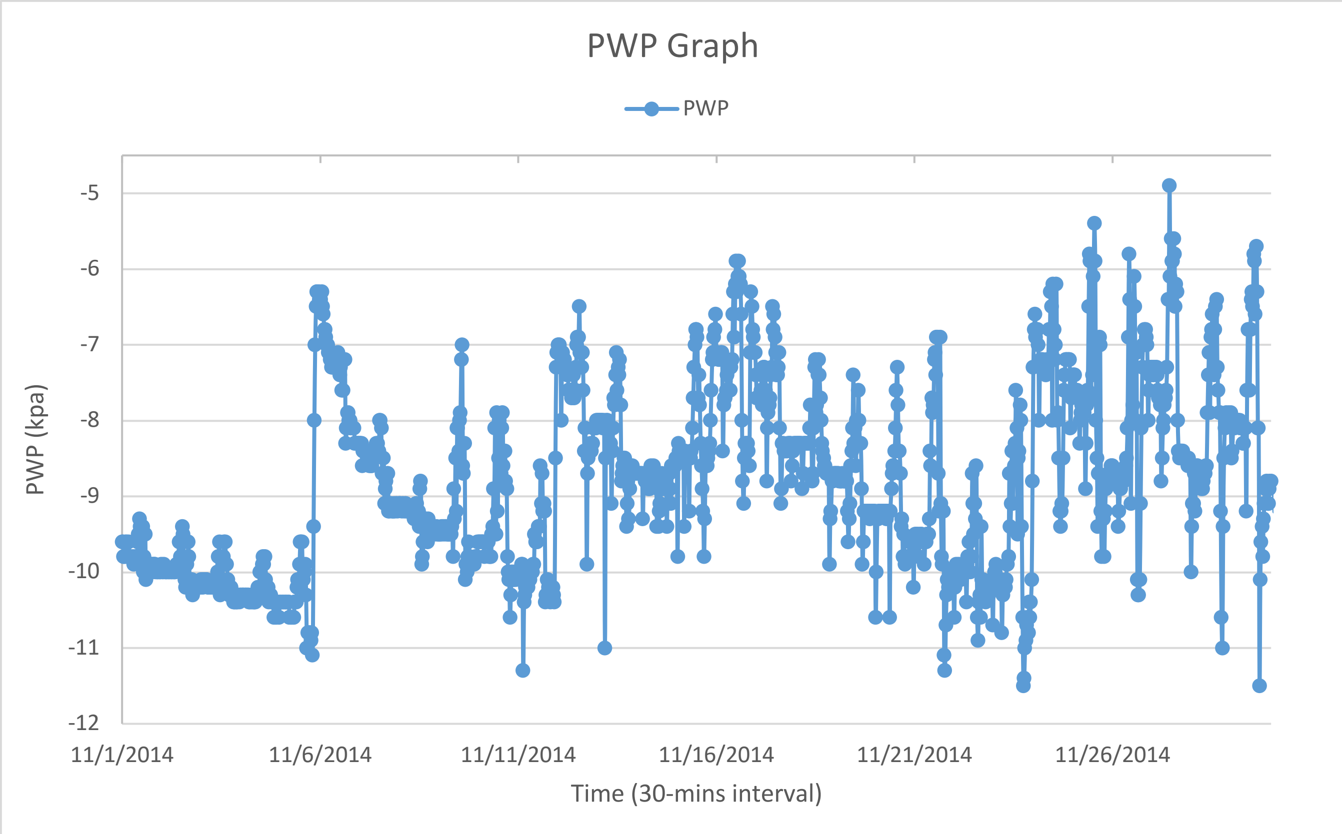

Figure 10: PWP Graph

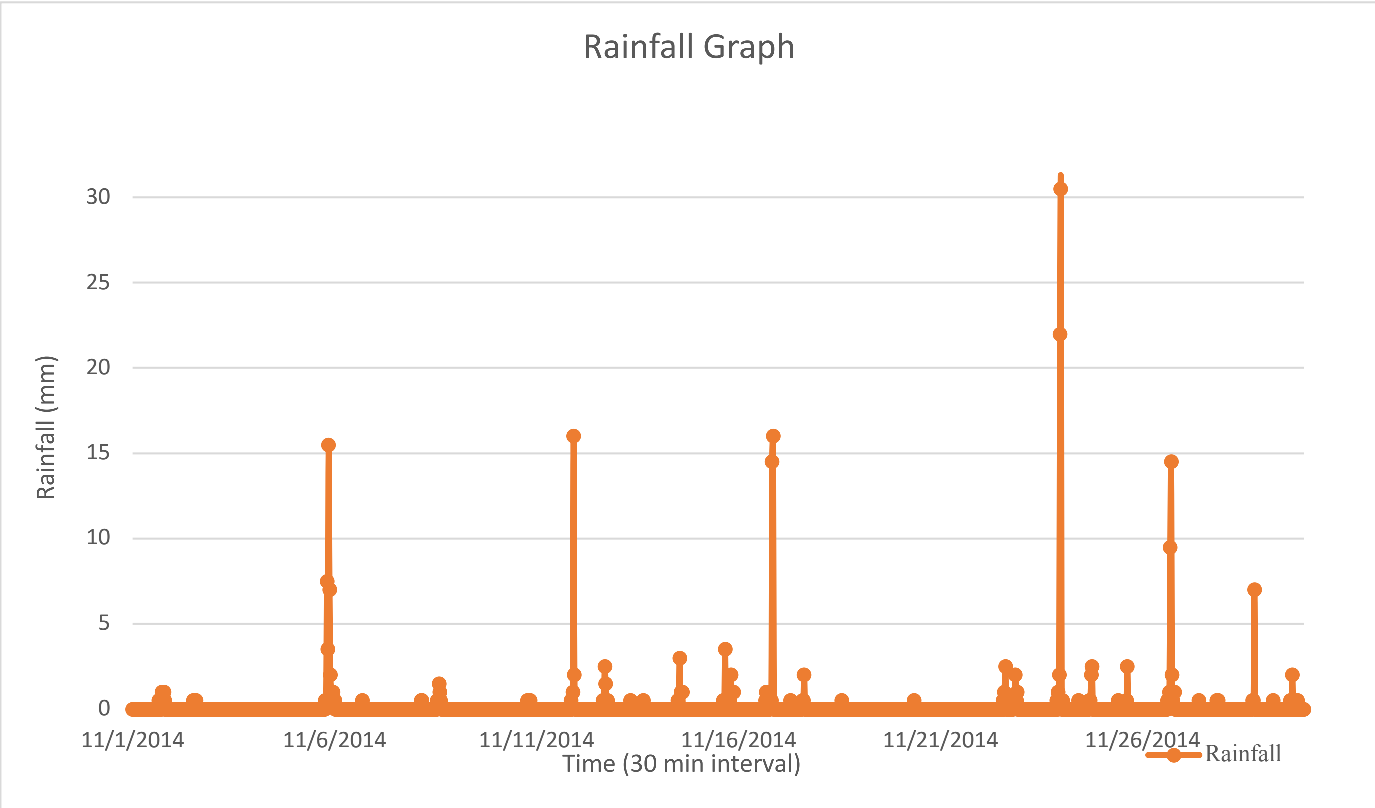

Figure 11: Rainfall Graph

Based on the graphs above, it shows that most and maximum data points for both PWP and rainfall falls towards the end of month. Hence, it is preferable to select the training datasets starting from 10th November till 30th November 2014 in order to train the datasets with the worst case of data points and ease the testing process to take place. Whilst testing datasets are selected starting from 1st November till 9th November 2014.

However, to validate the effectiveness and accuracy of aiming selected datasets, it will be compared with the different selection of training and testing datasets. The training datasets are selected from the beginning of November to 22nd November of 2014 whereas testing datasets are selected from 22 November to the end of November 2014.

The model is labelled as Model 1 and Model 2 to represent two different selection of datasets respectively. Model 1 is representing training datasets from 10th

November till 30th November 2014 while Model 2 is represent training datasets from beginning of November till 22nd November 2014.

Table 4: Number of data points for training and testing

	Model 1		Model 2	
	Training	Testing	Training	Testing
Date of data points	10th November – 30th November 2014	1st November – 10th November 2014	1st November – 22nd November 2014	22nd November – 30th November 2014
Number of data points	1008	432	1008	432

4.2 Normalization of data

However, the datasets are consisting of large variance from one points to another. This can be illustrated by the standard deviation in data analysis. Both maximum and minimum value for PWP and rainfall are having larger value from its standard deviation which tells us some of data points are experiencing both extra small and extra large value.

Thus, to close the large gap between the data points, it is better to normalize the data points into a smaller range of value. In this study, the range of -1 to 1 is selected according to following equation;

$$v_{p}= 2 \text{ x } \frac{(x_p - x_{min})}{(x_{max} - x_{min})} - 1 \qquad (6)$$

Where;

v_p = normalized or transformed dataset

x_p = original dataset such that $1 \leq p \leq P$ and P = number of data

x_{min}, x_{max} = minimum and the maximum value of the original dataset respectively

According to Rojas (1996), data normalized helps in speed up the data processing during training and lower the possibility of prediction error. In addition, it prevents the data points with large variance overshadow lower variance data points beside ensures the prediction efficiency and save computational time by down scaling the input features (Babangida et al., 2016).

4.3 Model Input Structure

According to Babangida et al. (2016), it is important to focus in model input structure as varies in selected inputs data will result significant rise to different model and affect the model accuracy. This has been proved through the studies done by Mustafa et al. (2012) and Rahardjo et al. (2008) that adopted different numbers of present and antecedent for both rainfall and PWP. The adoption of antecedent rainfall events will result sharp rise in PWP due to its enough total rainfall. However, antecedent rainfall itself is not enough to provide a good prediction. Hence, antecedent PWP also needed to enhance a good prediction of PWP (Babangida et al., 2016).

The input features as stated by Babangida et al. (2016) are established by using detailed cross correlation analysis between PWP and rainfall as well as auto correlation analysis of PWP. Following is the input patterns used by Mustafa et al. (2012) in equation 6 and Rahardjo et al. (2008) in equation 7.

$$U_t = f_{\mathrm{SVR}}\left(U_{(t-1,\ \ldots.,\ t-5)}, r_{(t,\ t-1,\ t-2)}\right) \qquad (7)$$

$$U_t = f_{\mathrm{SVR}}\left(U_{(t-1,\ t-2)}, r_{(t,\ t-1,\ \ldots.,\ t-5)}\right) \qquad (8)$$

Where

t = time index of the order of 30 min

U_{t-n} = PWP at any time $t-n$

r_{t-n} = rainfall at any time $t-n$

f_{SVR} = model type

The latest study by Babangida et al. (2016) found that, the limitation used of input features for both antecedent rainfall and PWP record gives better result.

Due to that, the study has come out with the following optimum input patterns that give increase in accuracy;

$$U_t = f_{\mathrm{SVR}}\ (U_{(t\text{-}1,\ t\text{-}2,\ t\text{-}3)},\ r_{(t,\ t\text{-}1,\ t\text{-}2)}) \tag{9}$$

Therefore, above input pattern is adopted in this study accordingly.

4.4 Implementation of SVR

For SVR implementation, sigmoid kernel function is selected based on the following formula;

$$k\ (x, y) = \tanh\ (\gamma x^T y + r) \qquad (3)$$

According to Kisi and Cimen (2011) and Lin and Lin (2005), the parameters selected in the model implementation: cost (C), gamma (γ), epsilon (ε) and coef0 (r). C parameter is a positive constant capacity control parameter, γ is constant that reduces model space and controls the solution's complexity, while ε is loss function that describes regression vector without all data input whereas r is a shifting parameter that controls the threshold of mapping. The other input value is t which represent sigmoid kernel function value.

As stated by Babangida et. al. (2016), all kernel parameters stated above have to be calibrated according to its default value as following;

Table 5: Input Paramaters

Parameters	Value
svm_type (-s) *constant for all training and testing datasets	Default: 3
kernel_type (-t) *constant for all training and testing datasets	Default: 3
cost (-c)	Default: 1
gamma (γ/-g)	Default: 1
epsilon (ε/-p)	Default: 0.1
coef0 (-r)	Default: 0

The value of -c, -g, -p and -r are adjusted by trial and error method in MATLAB software with LIBSVM (a library for support vector machines) to obtain best accurate result based on performance measure as stated below.

4.5 Performance Measure

The performance measure selected for this study to obtain best accuracy of prediction are coefficient of determination (R^2) that shows the model fits the data (1 indicates perfect fit while 0 indicates poor fit) and mean square error (MSE) where smaller value approaching to 0 is desirable.

4.6 Results and Discussion

The result of trial and error method for each parameter in the MATLAB software is as following. There are 20 sets of trial and error method altogether that has the input values of;

i. 5 sets of constant value of all parameters except gamma, γ
ii. 5 sets of constant value of all parameters except cost constant, c
iii. 5 sets of constant value of all parameters except epsilon, ε
iv. 5 sets of constant value of all parameters except coefθ, r

with the best previous value used for the constant value for each 5 sets respectively.

Table 6: Model 1 trial and error input for parameters value

SET	Parameters value						Performance Result		
	Type of SVM (epsilon-SVR), s	Type of kernel function (Sigmoid), t	Cost constant, c	Gamma, γ	Epsilon, ε	Coefθ, r	R^2 (Good = 1)	MSE (Good = 0)	Number of support vector, nSV
1	3	3	1	0.01	0.001	-1	0.92894	0.008552	998
2	3	3	1	1	0.001	-1	0.0900857	206.067	1008
3	3	3	1	2	0.001	-1	0.04055	159.257	1008
4	3	3	1	0.001	0.001	-1	0.916125	0.08964	1002
5	3	3	1	0.1	0.001	-1	0.949332	0.005034	990
6	3	3	0.1	0.1	0.001	-1	0.936045	0.00694	986
7	3	3	0.01	0.1	0.001	-1	0.922561	0.065383	1006
8	3	3	0.001	0.1	0.001	-1	0.92089	0.145665	996
9	3	3	2	0.1	0.001	-1	0.949235	0.004973	980
10	3	3	3	0.1	0.001	-1	0.949026	0.004994	963
11	3	3	3	0.1	0.01	-1	0.948979	0.005087	842
12	3	3	3	0.1	0.1	-1	0.950101	0.006006	294
13	3	3	3	0.1	1	-1	-1.#IND	0.232013	0
14	3	3	3	0.1	0.0001	-1	0.949026	0.004998	1004
15	3	3	3	0.1	0.02	-1	0.948647	0.005289	670
16	3	3	3	0.1	0.01	-2	0.948474	0.005208	845
17	3	3	3	0.1	0.01	-0.1	0.592007	0.659466	993
18	3	3	3	0.1	0.01	-3	0.935515	0.007291	883
19	3	3	3	0.1	0.01	-0.03	0.536383	1.13164	997
20	3	3	3	0.1	0.01	-1.5	0.949127	0.005113	847

Table 7: Model 2 trial and error input for parameters value

SET	Parameters value						Performance Result		
	Type of SVM (epsilon-SVR), s	Type of kernel function (Sigmoid), t	Cost constant, c	Gamma, γ	Epsilon, ε	Coefθ, r	R^2 (Good = 1)	MSE (Good = 0)	Number of support vector, nSV
1	3	3	1	0.1	0.001	-1	0.786142	0.032367	943
2	3	3	1	1	0.001	-1	0.105182	340.557	1006
3	3	3	1	2	0.001	-1	0.000727	516.759	1008
4	3	3	1	0.001	0.001	-1	0.689069	0.111573	1008
5	3	3	1	0.01	0.001	-1	0.716055	0.042707	1001
6	3	3	0.1	0.1	0.001	-1	0.731194	0.040295	986
7	3	3	0.01	0.1	0.001	-1	0.698654	0.085452	1006
8	3	3	0.001	0.1	0.001	-1	0.696611	0.175099	1002
9	3	3	2	0.1	0.001	-1	0.788679	0.032358	882
10	3	3	3	0.1	0.001	-1	0.788794	0.032442	880
11	3	3	3	0.1	0.01	-1	0.789002	0.031952	685
12	3	3	3	0.1	0.1	-1	0.781272	0.032642	197
13	3	3	3	0.1	1	-1	5.72E-17	0.151547	0
14	3	3	3	0.1	0.0001	-1	0.788881	0.032561	986
15	3	3	3	0.1	0.02	-1	0.787915	0.032047	551
16	3	3	3	0.1	0.01	-2	0.780316	0.032927	703
17	3	3	3	0.1	0.01	-0.1	0.001726	0.740202	989
18	3	3	3	0.1	0.01	-3	0.728064	0.040657	791
19	3	3	3	0.1	0.01	-0.03	0.032184	1.29113	993
20	3	3	3	0.1	0.01	-1.5	0.786132	0.032243	689

Based on overall results, set number 5 for Model 1 and set number 11 for Model 2 show the most optimum result according to its performance result of R^2 and MSE that most approaching to 1 and 0 respectively.

Model 1 resulted 0.949332 and 0.005034 for R^2 and MSE respectively. While Model 2 resulted 0.789002 and 0.031952 for R^2 and MSE respectively. This can be concluded that Model 1 is having the most optimum result compared to Model 2 due to the variance of the rainfall and PWP data used for both training and testing. The variance and standard deviation of rainfall and PWP data in Model 2 used for training are less than for its testing that indicates higher variability of rainfall and PWP data used and it is expected Model 2 will experience greater loss of accuracy compared to Model 1. Hence, this is proving the expected result of selection datasets earlier with Model 1 is having better accuracy by 20.3% rather than Model 2.

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4.6.1 Model 1 Result Analysis and Discussion

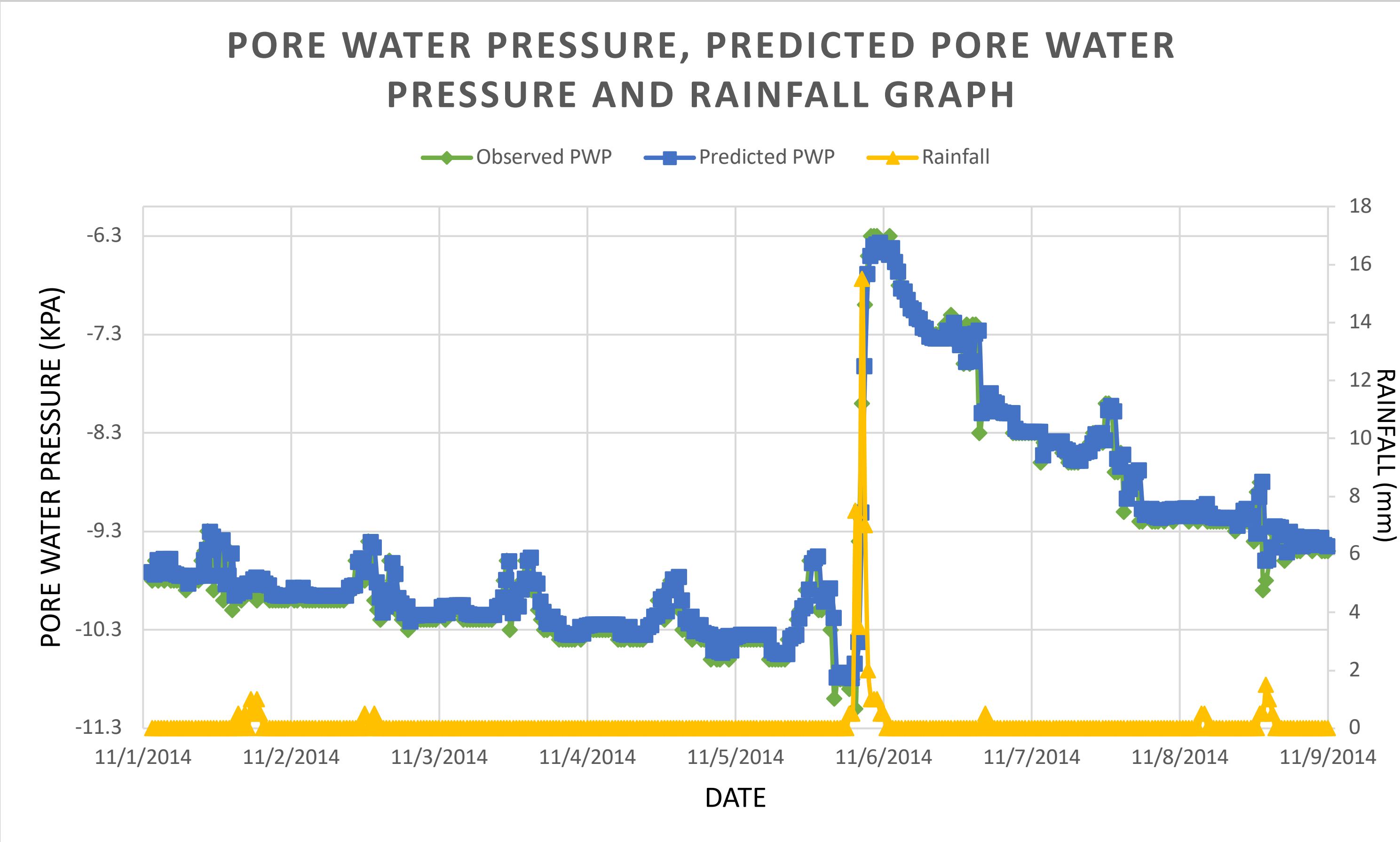

Figure 12: Pore Water Pressure, Predicted Pore Water Pressure and Rainfall Graph

Results from Model 1 is discussed here as it shows better result of R^2 and MSE. Based on PWP, Predicted PWP and Rainfall graph, the model able to show good prediction as it predicts with small difference to observed values. This can relate to the used of number of antecedent PWP and rainfall condition. According to Babangida et al. (2016), the increase input features for rainfall antecedent demonstrate better result up only to two antecedent records (ideal model features) as it yielded a small MSE with considering computational ease and time factor. Beyond two antecedent records, howbeit show only slight improvement compared to two antecedent records. Nonetheless, addition of rainfall features solely does not significantly improve the result. Number of PWP used improve the result as well with the limitation up to three antecedent records. This is because, beyond three antecedent records will yield loss of accuracy in predictions. Thus, features from one to three lag records able to provide better modelling results as it decreases model complexity and computational burden that enhance improvement in accuracy. Therefore, Model 1 is having the most optimum input patterns that promotes best accuracy.

The selection values of 1, 0.1, 0.001 and -1 for cost constant, gamma, epsilon and Coefθ respectively give a good model combinations prediction as the values are much closer to their respective default value. According to Raghavendra and Deka (2014), smaller value of cost constant will cause the learning machine experiencing poor approximation due to under fitting of training data whereas larger value of cost constant will cause the training data overfits and making way for more complex learning. For epsilon, its smaller value will yield complex learning machine while its larger value will yield more flat estimated of the regression function. Hence, less complex model is built with none of input features dominated one another.

However, number of Support Vector (nSV) in this study is showing more than 50% of the training set which tells over-fitting problem has occurred. This is reflected what has been stated by Mattera and Haykin (1999) that nSV should be around half the number of the training data points to avoid over-fitting problem. The higher value of nSV will result a good accuracy during training but there was loss of accuracy during testing. However, this is does not mean there is no good model with high number of SVs, in fact number of SVs may largely depend on how well the data set is structured (Babangida et al., 2016). Due to that, as for this study, the large number of SVs might be happened due to a poorly structured and noisy data set used in the process (Mattera and Haykin, 1999).

In addition, instead facing over-fitting problem and the model also showed the difficulties to predict on extreme points as we can be seen on 5th November 2014 and 6th November 2014 in PWP, Predicted PWP and Rainfall graph. This can also be clearly illustrated as in following graph of extent of agreement between observed and predicted PWP records;

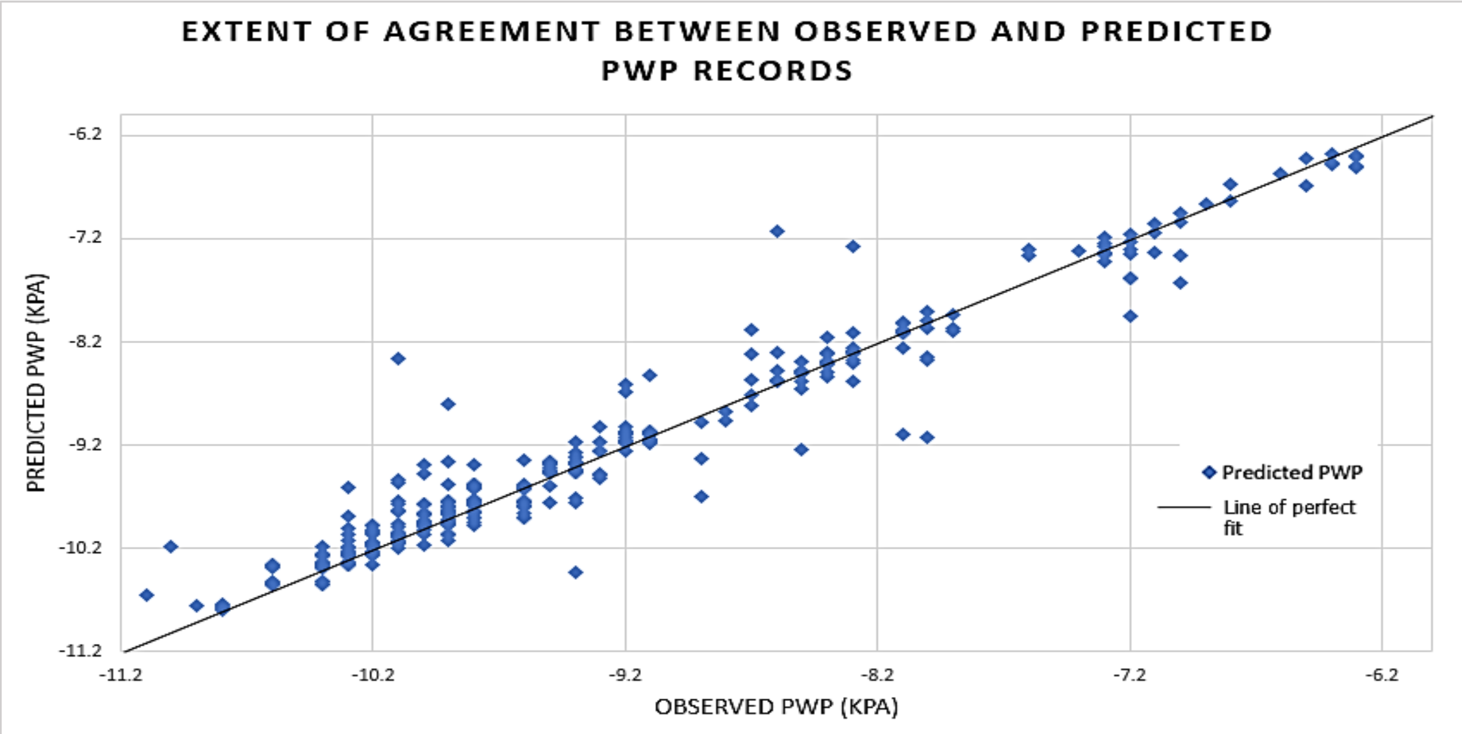

Figure 13: Extent of agreement between observed and predicted PWP records

PWP points on both 5th November 2014 and 6th November 2014 in the above graph shows furthest from line of perfect fit. According Babangida et. al. (2016), despite of rainfall, this extreme points are influenced by large temperature that exert by movement of water vapor from high temperature region to low temperature region. Hence it is quite difficult to predict extreme points accurately without the input of temperature. Since fluctuation of PWP with temperature is not covered in this study, nevertheless, the developed model able to show great promise in the prediction of PWP by only using rainfall data. It can be readily used to overcome PWP fluctuation is short period of time and thus, can be applied to slope management studies.

CONCLUSION AND RECOMMENDATION

Pore Water Pressure (PWP) as in general, is the indicator of the existence of water filled the voids that exert external forces within the soil. By predicting the soil PWP, one can know the possible condition of soil with particular external factors. The model is successfully predicting PWP for 1 month of data with the usage of antecedent PWP and antecedent rainfall alone without other influencing factor for example evaporation, temperature and deep percolation. Despite of the difficulties to predict extreme points accurately, the model shows a great promised in predict PWP. The difficulties in predict extreme points are also influenced by other factor such as temperature which is not significantly covered in this study. Hence, the technique used in this study is able to solve PWP problems especially in the short period of time.

Model 1 yielded a better result compared to Model 2 with the statistical measure of R-squared and MSE. Albeit the number of Support Vectors are more than 50% of total data points which tell loss of accuracy has occurred, it is most likely caused by other influencing factors such as evaporation and deep percolation. Due to that, the depth used in the instrumented slope might be too shallow for the failure plane to exist. Thus, it is suggested to have a deeper regions prediction to be compared with as in this study for future recommendation. Furthermore, instead of using only rainfall data, prediction of PWP response towards climatic data such as evaporation also would be interesting to be discovered.

Nevertheless, this study of demonstrating the capability of Sigmoid Kernel Function to be used as tool to model PWP predictions is a successful and can be applied for necessary safety measures to be taken towards slope failure and slope management studies.

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APPENDICES

Following is the used in the MATLAB software for both training and testing data purposes. The codes originated same as in the study carried out by Babangida (2016).

```
Command Window
>> load('matlab.mat')
>> load('matlab.mat')
>> model=svmtrain1(TrainingTarget,TrainingFeatures,'-s 3 -t 3 -c 1 -g 0.1 -p 0.001 -r -1');
*
optimization finished, #iter = 741
nu = 0.976190
obj = -96.083657, rho = -0.248815
nSV = 990, nBSV = 980
>> [predicted_label,accuracy,prob_estimates]=svmpredict (TestingTarget,TestingFeatures,model);
Mean squared error = 0.00503418 (regression)
Squared correlation coefficient = 0.949332 (regression)
>>
```

Figure 14: Codes used in MATLAB software