PREDICTION OF SOIL PORE WATER PRESSURE RESPONSES TO RAINFALL USING RADIAL BASIS KERNEL FUNCTION

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UNIVERSITI TEKNOLOGI PETRONAS

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by

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17121

Dissertation submitted in partial fulfillment of
the requirements for the
Bachelor of Engineering (Hons)
Civil Engineering

SEPTEMBER 2016

Universiti Teknologi PETRONAS
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CERTIFICATION OF APPROVAL

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Approved by,

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(Dr Muhammad Raza Ul Mustafa)

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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.

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(NURULAIN HUSNA BINTI MOHD ANUAR)

ABSTRACT

Pore Water Pressure (PWP) prediction is important in analyzing the strength and effective stress of the soil. Increase of PWP will cause slope failure in areas susceptible to landslide. Stability is determined by the equalization of shear strength and shear stress analyses. Knowledge in pore water pressure is important in hydrological analysis, such as seepage slope strength analyses, engineered slope design and assessing slope reactions to rainfall. The main aim of this work is to forecast pore water pressure variations in response to rainfall utilizing Radial Basis Kernel Function and to evaluate model performance using statistical measures. Support Vector Machine (SVM) is an algorithm which is based on kernel function, and this makes the selection of kernel an important one when implementing the SVM. This selection is dependent on the issue we want to model. The kernel function that is frequently used in previous studies is Radial Basis Function (RBF). It is also necessary to make decision on the measurement of precision that will be used for the performance of the model. Small values of Root Mean Square Error (MSE) are desirable. On the contrary, the Coefficient of Determinant, R^2, is expected to have a high value, near to unity. Radial Basis Kernel Function is the most suitable technique to model the pore water pressure. This is because the modelling result from the software predicts the value of the PWP well enough and gave a good performance. Some of the points are not predicted well in the model, which might be because of other criteria such as temperature.

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CHAPTER 1

INTRODUCTION

1.1 Background of Study

Pore-water pressure (PWP) can be generally defined as the pressure applied inside the soil by water held in void in a rock or soil. The pressure is said to be positive when the soil is completely saturated, and is measured corresponding to the height of the water in a piezometer above the purpose of intrigue. The pressure is zero when the soil pores are filled with air. The pressure is negative when the voids are partly filled with water (in which case surface-tension forces operate to achieve a suction effect and the shear strength of the soil is increased) (Schnellmann, Busslinger, Schneider, & Rahardjo, 2010) PWP is imperative in dissecting the strength and viable stress of the soil. Increase of PWP will bring about slope failure in locations vulnerable to landslide. Stability is dictated by the equalization of shear strength and shear stress. An initially stable slope may be at first affected by preliminary factors, causing the slope to be conditionally unstable. Triggering factors of a failure of slope can be climatic occasions which a slope is actively unstable, prompting to mass movements. Increment in shear stress can cause mass movements, for instance loading, lateral pressure and transient forces. On the contrary, shear strength may drop caused by weathering, fluctuations in pore water pressure and organic material. Knowledge in pore water pressure is significant in analyzing hydrology, for example analyses of drainage and slope stability, design of engineered slope and assessing slope reactions to rainfall.

Landslides are one of the intermittent natural hazard issues all through most of Malaysia. As indicated in local daily paper reports, overwhelming rainfalls triggered various landslides and mud flows along numerous parts in Peninsular

Malaysia. These landslides cost a fortune of property loss and some even cause fatal incidents. The landslides that happened along the New Klang Valley Express (NKVE) area in the year 2003 have alarmed the authorities and a few governmental associations towards the solemnness of the administrative and avoidance of landslides. These incidents that occur in the country are mostly triggered by tropical rainfalls leading to failure of the surface of the rock along the fracture, joint and cleavage planes. The lithological units of Malaysia are quite stable yet nonstop of uncontrolled urbanization causes deforestation and disintegration of the layers of the covering soil, thus leading to serious danger to the slopes.

Previous studies done by (Imrie, Durucan, & Korre, 2000; Karunanithi, Grenney, Whitley, & Boove, 2991) have used Artificial Neural Network (ANN) to predict streamflow. The study concluded that this method is superior when compared to the conventional models. Modelling of rainfall-runoff process using ANN has started with a study done by (Halff, Halff & Azmoodeh, 1993) who utilized ANN with three layers of feedforward architecture to predict hydrographs. From that point forward, many studies in the context of modelling rainfall-runoff utilizing ANN were done. Furthermore, another algorithm was proposed in (K.-I. Hsu, Gupta, & Sorooshian, 1995), called the linear least squares simplex (LLSSIM), for ANN training. It uses a mix of optimization technique; linear least squares and multi-start simplex methods. The algorithm was observed to be more effective and proficient than the backpropagation technique, which is ordinarily used by most researchers. In (Smith & Eli, 1995), the backpropagation method in ANN was used to forecast peak discharge and time to peak by leveraging simulated data from a synthetic catchment.

Support Vector Machine (SVM) is a new universal learning recommended by (V.Vapnik, 1995) which applies to both regression and recognition of patterns. SVM is a linear machine (or network) with a few exceptionally pleasant properties. It can provide a decent generalization of performance on the problem of pattern classification, in spite of the fact that it does not incorporate the knowledge of problem-domain.

1.2 Problem Statement

Pore Water Pressure is widely used in slope studies since the measurement and monitoring of the PWP levels is troublesome. It is important to understand the knowledge of PWP, particularly its variances during and after rainfall occurrences, because these are the time when the levels of PWP could worsen so badly or even reach undesirable threshold beyond which failure could actually happen. PWP is commonly measured and monitored through an instrumentation program of slope that is set up particularly for that reason. However, this technique is tedious, expensive and inconvenient. One approach to circumvent the program is to attempt in predicting the PWP with software tools..

1.3 Objective of Study

The primary objective of this work is to predict pore water pressure responses to rainfall with the following specific objectives:

1) To predict the variations of pore water pressure in response to rainfall by using Radial Basis Kernel function.
2) To evaluate the model performance using statistical measures.

1.4 Scope of Study

The scope of study is limited to the followings:

1) The application of Radial Basis Kernel function for modelling pore water pressure responses to rainfall using MATLAB
2) Evaluate the result of pore water pressure prediction model using Mean Square Error (MSE), Squared Coefficient of Determination (R^2) and No of Support Vector (nSV)

CHAPTER 2

LITERATURE REVIEW

2.1 Hydrological Modelling

Hydrological models give us an extensive range of important applications in the planning and administrative activities of the multi-disciplinary water resources. They can be formulated with deterministic, probabilistic and stochastic methods for the surface and ground water systems characterization together with the modelling of coupled systems like hydro-ecology, hydro-geology and weather. However, because of the resource constraint sand the confined extent of available measurement approaches, there are impediments to the availability of spatial-temporal data (Pechlivandis, Mcintyre, & Wheather, 2011). Therefore, there comes a need to generalize the data obtained from the existing measurements using special methods like the support vector machine and the hybrid models of it. The applications of the hydrological model have an extent variety of objectives, depending on the issues that need to be studied (Pechlivandis et al, 2011).

Statistically, the analysis of hydrologic data requires the user to understand the essential definitions and knows the reason and constraints of SVM. An application of SVM for hydrological analyses needs the physical phenomena measurement. The person who models the network needs to assess the precision of the collected data and must have a basic knowledge on the way the data are accumulated and processes prior to modelling activities. The most common used data in hydrological studies incorporates rainfall, snowmelt, stage, streamflow, and evaporation and watershed characteristics.

2.2 Malaysia Landslide Problem

Landslides are major natural geological disasters which each year contributes to the huge amount of property damage including both direct and indirect expenses. Malaysia encounters frequent landslides each year, with the latest incidents happened in 2000, 2001, 2004, 2007, 2008 and 2009. Referring to the local newspaper, heavy rainfalls have activated landslides and mud flows along the highways of east coast in the Peninsular Malaysia, Sabah and the Penang Island (Pradhan and Lee, 2009). The regions that were hit the worst are along the Penang Island and Cameron Highlands, which are the mountainous areas of the peninsular. This natural disaster caused loss of million dollars of property and even lives. The degree of the damages could be reduced if a life-long early alarm system anticipating the mass movements in the landslide inclined areas would have been in place. The landslides that happened along the New Klang Valley Express Highway (NKVE) area in the year 2003, which was triggered by heavy rainfalls, have given hints to the administrations and other governmental associations on the significance of landslide management and prevention. Figure 2.1 and Figure 2.2 are a few cases of landslide that happened in the country.

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Figure 2.1: Karak Highway Landslide on Nov 11, 2015 (source: google image)

Figure 2.2: Bukit Lanjan Landslide (source: google image)

2.3 Support Vector Machine

Support vector machines are developed based on statistical learning theory and are acquired from the auxiliary hazard minimization hypothesis to minimize the empirical risk and the confidence interval of the learning network in request to obtain good generalization ability. It has been proved that SVM algorithm turns out to be exquisitely robust and efficient for classification (V.Vapnik, 1995) and regression (Vapnik, Golowich, & Smola, 1997). The present basic SVM algorithm was proposed by (Cortes & Vaonik, 1995). The excellence of this method is twofold; it is brief enough that scholars with adequate knowledge can promptly understand, yet it is powerful that the precision of the method's prediction overpowers numerous other approaches. The essential thought behind SVM is to outline the original sets of data from the input space to a high dimensional space so that the problem of classification becomes less complex in the feature space. SVMs have the possibility to procreate the obscure relationship that exists between a set of input parameters and the output of the system.

The preparatory target of SVM classification is to build up decision boundaries in the feature space which differentiate data points towards distinguished classes. SVM contrasts from other classification strategies outstandingly. It tends to create an ideal separating hyperplane between two classes to minimize the generalization error and thus maximizing the margin. On the off chance that any two classes are distinguishable from among the infinite number of linear classifiers, SVM verifies that hyperplane has minimize the generalization error (i.e. error for the unseen test patterns) and on the contrary if the two classes are non-divisible, SVM tries to look that hyperplane which maximizes the margin and in the meantime, minimizes an amount relative to the amount of errors of misclassification. Therefore, the chosen hyperplane will have the greatest margin between the two classes, where the margin can be defined as the sum of the displacement between the separating hyperplane and the closest points on either side of the two classes (Vapnik, 1997)

The classification of SVM and thus its ability of prediction can be seen by dealing with four basic concepts:

1) The Separation Hyperplane
2) The Hard-Margin SVM
3) The Soft-Margin SVM, and
4) Kernel Function

Originally, SVM models were developed for the classification of linearly separable classes of objects, as illustrated in Figure 2.3. Consider a two-dimensional plane comprising linearly separable objects of two distinguished classes {class (+) and class (*)}. The objective is to search a classifier which isolates them perfectly. There can be various approaches to classify/separate those objects yet SVM tries to find a unique hyperplane which results in a maximum margin (i.e. SVM augments the separation between the hyperplane and the closest data point of each class). The objects of class (+) are framed behind hyperplane H1, whereas class (*) objects are framed by hyperplane H2. The objects of each class which precisely fall over the hyperplane H1 and H2 are called as support vectors. Most “important” training points are support vectors as they define the hyperplane and have coordinate bearing on the ideal area of the decision surface. The obtained maximum margin is indicated as i. When only support vectors are utilized to denote the separating hyperplane, sparseness of solution develops when dealing with extensive data sets.

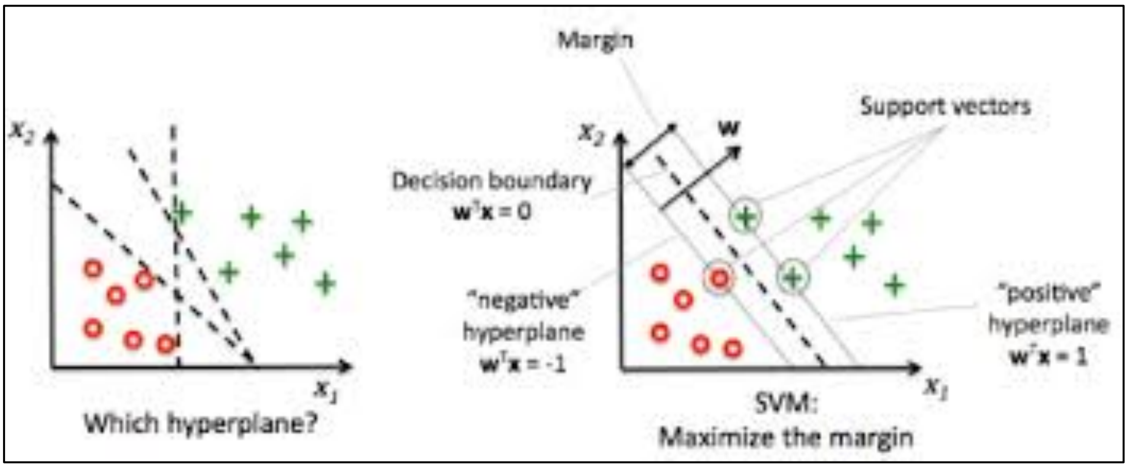

Figure 2.3: Maximum separation hyperplane

In real time issues, it is impractical to decide a correct separating hyperplane isolating the data inside the space and we might also get a bended decision boundary in a few cases. Hence, SVM can likewise be utilized as a classifier for non-separable classes (Figure 2.4). In such cases, the initial input space can always be outlined to some higher-dimensional feature space, called Hilbert space, using nonlinear functions, also denoted as feature functions (as illustrated in Figure 2.4 and Figure 2.5). Indeed in spite of the fact that feature space is high dimensional, it could not be practically feasible to utilize directly the feature functions for hyperplane classifications. Hence in such cases, nonlinear mapping instigated by the feature functions is used for computation using special nonlinear functions named as kernels.

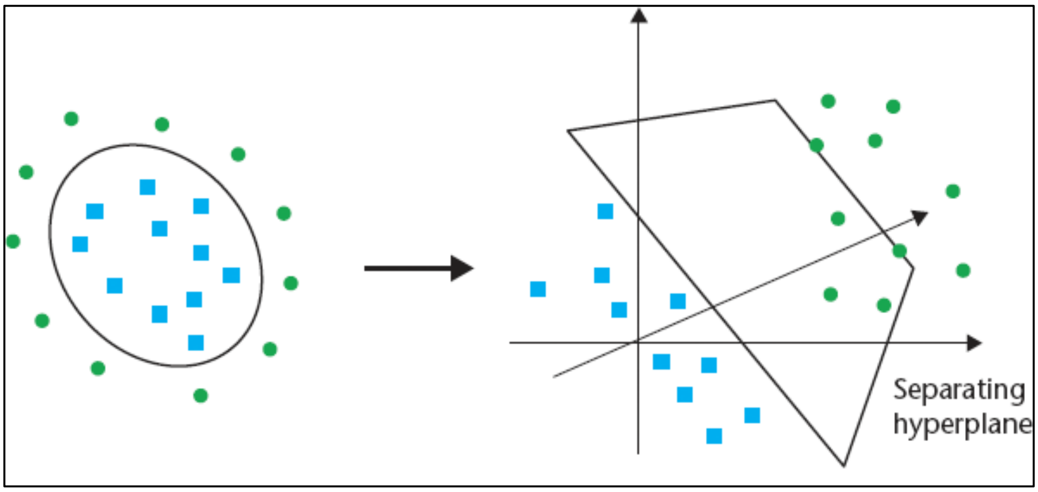

Figure2.4: Linear separation in feature space

In the mapping to higher dimensions, SVM utilizes a few kernel functions, which give a simple avenue that leads from non-linearity to linearity for algorithms, through simple expressions of the dot product of the input. Examples of basic kernels include linear kernel, polynomial kernel, sigmoid kernel and the one that will be discussed in this work is radial basis function kernel (RBF). These kernels are respectively expressed in Equations 1-4.

$$\mathrm{k(x,y)} = x^t\mathrm{y} + \mathrm{c} \dots\dots\dots \quad (1)$$

$$\mathrm{k(x,y)} = (-\gamma x^t\mathrm{y} + \mathrm{r})^d \dots\dots\dots \quad (2)$$

$$\mathrm{k(x,y)} = \exp(-\gamma\ \|x - y\|^2) \dots\dots\dots \quad (3)$$

$$\mathrm{k(x,y)} = \tanh\ (\gamma\ x^t\mathrm{y} + \mathrm{c}) \dots\dots\dots \quad (4)$$

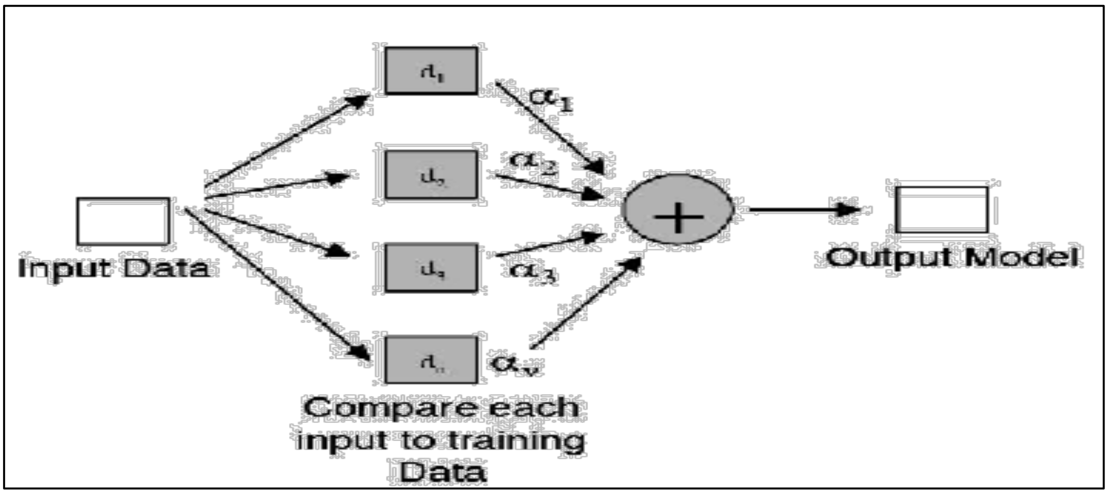

Figure 2.5: SVM map the input space into a high-dimensional feature space

SVM emphasizes on the choice of kernel function one needs to make while executing the SVM. The choice relies on the type of problem that wants to be modelled. The most broadly used kernel function is Radial Basis Function (RBF). In several applications, RBF Kernel is considered as the default kernel, and is used accordingly.

Sound choice of kernels provides the magnificent generalization performance. The relationship or likeness between two different classes of data points is delineated using kernel functions. Kernels have the upper hand of operating in the input space, which the classification problem result is a weighted total of kernel functions assessed at support vectors. The Kernel trick permits SVMs to shape nonlinear boundaries by using the different types of kernel as mentioned previously. The nonlinear kernels act in providing the SVM with the capability to model complex separating hyperplanes.

The unique qualities of SVM classification and kernel techniques are:

1) Their execution is ensured as they are purely based on theoretical samples of statistical learning;
2) Search space has a one of a kind minimal;
3) Training is profoundly robust and effective;
4) The ability of generalization empowers trade-off.

Some of such studies incorporated of (P Samui & Sitharam, 2011) where SVM is used to predict liquefaction susceptibility of soils. The work of (Lamorski, Parchepsky, Slawinski, & Walczak, 2008) and (Twaravaki, Simunek, & Schaap, 2009) in which an SVM model of pedotransfer function was built up to estimate soil moisture retention curve utilizing the properties of soil hydraulic. (Zhao, 2008) and (Pijush Samui & Karthikevan, 2013) have used SVM to foresee slope dependability index from factor of safety (FS), using data that included soil shear strength variables. Despite the success recorded in these models, using RBF just because it is the most typical kernel that was used is not sufficient enough for justification. Hence, this study will assess and do comparison in the performance metrics of a few basic kernels in modelling the nonlinear complicated responses of pore-water pressure to rainfall. This is with a view to choosing the best kernel for such system modelling.

The greatest advantage of SVM is the kernel trick is used to establish expert information about a problem so that both the complexity of the model and error prediction is minimized in a simultaneous manner.

The following three principles of mathematics are involved in the SVM algorithms:

- Principle of Fermat (1638)
- Principle of Lagrange (1788)
- Principle of Kuhn–Tucker (1951)

Support Vector Machines have their advantages. SVMs are capable of producing accurate and robust classification results, notwithstanding when inputs are non-monotone and are not separable linearly. So they can assist to assess more applicable information advantageously (Cristianini & Shawe-Taylor, 2000). The structural risk minimization principle provides SVM the desirable property to maximize the margin and thereby the generalization ability does not deteriorate and is able to predict the unseen data instances (Saunders, Gammerman & Vovk, 1998; Smola, Scholkopf, & Muller, 1998). By properly setting the value of C – regularization parameter one can easily suppress the outliers and thus SVMs are robust to noise (V.Vapnik, 1995). A key feature of SVM is that it automatically identifies and incorporates support vectors during the training process and prevents the influence of the non-support vectors over the model. This causes the model to cope well with noisy conditions (Han, Chan, & Zhu, 2007). With some key actual training vectors embedded in the models as support vectors, the SVM has the potential to trace back historical events so that future predictions can be improved with the lessons learnt from the past (Han et al., 2007). Input vectors of SVM are quite flexible; hence various other influential factors (such as temperature, relative humidity, and wind speed) can be easily incorporated into the model (Jamalizadeh et al., 2008).

SVMs have recently presented generally new statistical learning method. Because of its strong hypothetical statistical frame-work, SVM has turned out to be considerably much more robust in numerous areas, particularly on noised mixed data, than the local model which only uses classical chaotic approaches (Yu, Liong, & Babovic, 2004).

The SVM has delivered substantial expectations in recent couple of years as they have been effective when applied in problems of classification, regression and predicting; as they incorporate aspects and strategies from machine learning, statistics, analyses of mathematics and convex optimization. Aside from having a solid flexibility, global, optimization and a decent performance generalization, they also suit the classification of small specimens of data. Internationally, the application of these approaches in the area of hydrology has considerably progressing since the first articles began to show up in conferences in the early 2000s (Sivapragasm, Liong, & Pasha, 2001). This study aims at reviewing the essential theory behind SVM and the available SVM models, discussing the recent developments in research, and exhibiting the challenges and constraints for future work of the hydrological impacts of climate change.

Advancement and use of simulation models for rainfall-runoff has been a design as a research subject in hydrology. Rainfall-runoff (R-R) relation in a watershed simulation has two main approaches that have been developed; knowledge-based and data-driven. A lot of researches have been done depending on the approach of knowledge-based method like the approach of physical and conceptual. Generally, these approaches impersonate complexity of real world runoff behavior and conceptualize runoff forms and catchment properties (Hoesseine & Mahjouri, 2016). In their studies, SVR-GANN (Support Vector Regression combined with geomorphic-based ANN model) is being utilized to simulate the day by day runoff in a watershed to lessen the pitfalls while keeping up the advantages of ANN. The execution of this model is contrasted with ANN-based Back Propagation Algorithm (ANN-BP), Traditional SVR, ANN-based Genetic Algorithm (ANN-GA), Adaptive Neuro-Fuzzy Inference System (ANFIS) and GANN. In conclusion from the studies, SVR-GANN model is good and reliable to be utilized as a method to model rainfall-runoff. However, it was encouraged to explore more research to study this model's efficiency in terms of simulation of event-based rainfall runoff.

A study was conducted to estimate the variation of pore-water pressure (PWP) in response to rainfall with the use of Radial Basis Function Neural Network (RBFNN) (Mustafa, Rezaur, Rhardjo, & Isa, 2012). The network was used to replace the common Multilayer Perceptron (MLP) architecture to solve the problems of complex modeling (Luo & Unbehaun, 1998). As conclusion, 8-10-1 structure at a spread of 3.0 was recognized as the best configuration network to outline the non-linear pattern of PWP at soil depth of 0.5 meters. However, the work stated that RBFNN lacks the capacity to clarify the underlying functional relationships between the parameters required for PWP changes unlike a mathematical model, which is physically based, yet has the upper hand of utilizing predetermined number of variables.

The transformation process of rainfall into runoff over a catchment is so complicated, not linear, and displays the variability of both temporal and spatial. Artificial Neural Network (ANN) approach was adopted for the modelling of rainfall-runoff. This has added a new dimension to the framework theoretic modelling technique and it has been used in recent years to deal with numerous problems related with hydrology and water resources engineering (Rajurkar, Kothyari, & Chaube, 2002). An ANN can be treated mathematically as a global estimate having the capacity to learn from samples, not needing the explicit physics (Rajurkar et al., 2002).

2.4 Clustering using SVM

Clustering is often formulated as a discrete optimization problem. The main objective of cluster analysis is to segregate objects into groups, such that the objects are more “alike” to each other than the objects of other groups. Clustering is categorized under unsupervised learning of an underlying data concept. Clustering applications frequently deal with vast datasets and data with complex behaviors. Improving the training process of SVM using clustering methods has been analyzed with many varieties. Cluster-SVM quickens the training process by the distributional personalities of the training dataset. Firstly, the algorithm segregates the data into various pairwise of separate clusters and after that the representatives of the clusters are used to train an initial SVM, depending on which the support vectors and non-support vectors are distinguished roughly (refer to Figure 2.6). The clusters consisting of only non-support vectors are supplanted with their representatives to diminish the quantity of training data essentially and in this manner the speed of the training process is improved.

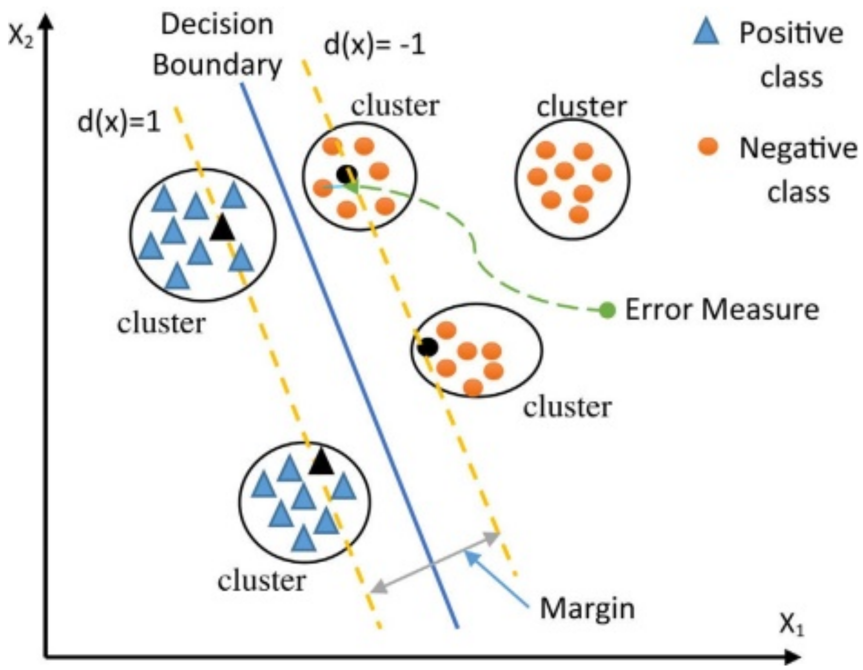

Figure 2.6: SVM Clustering

2.5 Support Vector Regression

Considering a straightforward linear regression problem on a training data set = { u_i, v_i; I = 1, . . ., n} with vector inputs u_l and linked targets v_i. A function g(u) must be defined approximately in order to connect the inherited relations between the data sets and thus it can be utilized in the later part to induce the output v for a new input data u.

Standard SVM regression utilized a loss function L_ε (v, g(u)) which depicts the deviation of the approximated function from the original one. A few sorts of loss functions can be mined in the literature e.g. linear, quadratic, exponential, Huber's loss function, and so forth. In the present setting the standard Vapnik's – ε insensitive loss function is utilized which is expressed as

$$L\varepsilon\left(v, g(u)\right) = \begin{cases} 0 & for|v - g(u)| \leq \varepsilon \\ |v - g(u)| - \varepsilon & otherwise \end{cases} \quad \dots\dots\dots\dots\dots\dots\dots (5)$$

Using the function, one can discover g(u) that can better estimate the real output vector v and has at most tolerance error ε from the real incurred targets v_i for all training dataset, and simultaneously as flat as would be prudent. Consider the regression function expressed by

$$g(u) = w \cdot u + b \dots\dots\dots\dots\dots\dots\dots\dots\dots\dots\dots\dots\dots\dots\dots\dots\dots\dots\dots\dots\dots\dots\dots\dots\dots. (6)$$

Which w ∈ $.\chi$ is the space input; b ∈ R is the biases and (w·u) is the dot product of w and u vectors. Flatness in Equation (6) alludes to a smaller value of variable vector w. By reducing the standard ||w|| can be determined alongside model complexity. Hence regression problem can be expressed as the following problem of convex optimization.

$$\min_{w,b,\xi,\xi^\circ} \frac{1}{2}\left||\mathrm{w}|\right|^2 + C\sum_{i=1}^{n}(\xi_i, \xi^\circ{}_i)$$

$$v_i - (w \cdot u_i + b) \leq \varepsilon + \xi^\circ{}_i \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots \text{(7)}$$

$$(w \cdot u_i + b) - v_i \leq \varepsilon + \xi^\circ{}_i$$

$$\xi_i, \xi^\circ{}_i \geq 0, \quad i = 1,2, \ldots \ldots, n$$

Where ξi $and\xi^\circ$ represents the slack variables introduced to assess the training samples deviation outside the ε-insensitive area. The trade-off between the flatness of g and the amount up to which deviation larger than ε are endured is portrayed by C > 0. C is a positive constant affecting the level of penalizing loss when training error happens. Underfitting and overfitting of the training dataset are kept away by minimization of the regularization term w^2 /2 with the error term $C\sum_{i=1}^{n}(\xi_i, \xi^o{}_i)$ in Equation 7, which represents the primal objective function.

Now, the issue is managed by developing a Lagrange function from the primal objective function by presenting a dual set of parameters, α_i and $\bar{\alpha}_i$ for the relating constraints. The conditions of optimality are exploited at the corresponding saddle points of a Lagrange function which leads to the formulation of the dual optimization problem.

$$\max_{\alpha_i, \bar{\alpha}_i} \quad -\frac{1}{2}\sum_{i,j=1}^{n} \alpha_i - \bar{\alpha}_i(\alpha_j - \bar{\alpha}_j)(u_i - \mathrm{u}_j) - \varepsilon\sum_{i=1}^{n}(\alpha_i + \bar{\alpha}_i) + \sum_{i=1}^{n} v_i(\alpha_i - \bar{\alpha}_i)$$

$$\textstyle\sum_{i=1}^{n}(\alpha_i - \bar{\alpha}_i) \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots \text{(8)}$$

$$\textit{subject to} \quad 0 \leq \alpha_i \leq C, \quad i = 1,2, \ldots \ldots, n$$

$$0 \leq \bar{\alpha}_i \leq C, \quad i = 1,2, \ldots \ldots, n$$

After indicating the Lagrange multipliers, α_i and $\bar{\alpha}_i$, w and b which are the parameter vectors can be assessed under Karush-Kuhn-Tucker (KKT) complementarity conditions, which are not explained herein. Hence, the estimation is a linear regression function can be defined as

$$g(u) = \sum_{i=1}^{n} \alpha_i - \bar{\alpha}_i \,(u_i - u) + b \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots (9)$$

Therefore, the regression expansion of SVM is developed; where it is determined as a linear combination of the training patterns v_i and b can be discovered by utilizing the primary constraints. For $|g(u)| \leq \varepsilon$ Lagrange multipliers might be non-zero for every examples inside the ε-tube and these remaining coefficients are called support vectors.

CHAPTER 3

METHODOLOGY

3.1 Study Area

The area of study is situated in Perak, which is located on the west coast of the Peninsular of Malaysia. The state has an estimated region of 21,000 km^2 with 187 km of coastline. The weather in the area is warm and sunny during the day, while it is cool at night for the entire year, with infrequent rain usually in the evenings. The surrounding temperature is genuinely steady, from 23 ^oC to 33 ^oC, and moistness frequently more than 82.3%. Rainfall per annum is measured at 3,218 mm. The chosen site is a slope within the ground of Universiti Teknologi PETRONAS (UTP) near the Block 5 area. The chosen area is selected due to its strategic location which is easily reachable and open to rainfall. Figure 3.1 shows the location of the site in the Perak Map. The red circle indicates the site location.

Figure 3.1: Location of the site in the Perak Map

The chosen slope has a height of about 11 meters and is 20 meters long, with an angle of 33^{o} to the horizontal. The surface of the surrounding of the instrument is turfed, and free from inception and interruption. Figure 3.2 shows an image from Google Earth where it demonstrates the location of the instrument installed. Undisturbed soil sample was gathered to a 2-metres depth from the surface of the slope and the fundamental properties of the soil were ascertained. Based on United States Department of Agriculture (USDA) soil classification system, general behaviors of the soils, from three distinctive boreholes, demonstrates the content of top 1 meter of the soil is sandy clay, and clay from that point onwards. The permeability of the soil at main 1 meter is 2.78 x 10^{-5} cm/s.

Figure 3.2: Location of Study Area and Instrument Installed

3.2 Instrumentation

Transducers were fitted in the tensiometers to empower automated logging and installed at the location. The tensiometers were installed at the crest at 0.6 meters depth (Crest A) and at a depth of 1.5 meters (Crest B), and another set at a mid-slope of 0.6 meters and 1.5 meters for Toe A and Toe B respectively. At the same place, the tensiometers were spaced 0.5 meters apart. Then, to measure rainfall events, it is necessary to set up a tipping bucket rain gauge at the toe. All instruments are then attached with data loggers. At a resolution of 1-hour intervals, pore-water pressure (PWP) and rainfall data were gathered. Though redundant information may be gathered amid relatively long periods drought; nevertheless, this high resolution is expected to viably estimate the PWP behavior during and instantly after rainfall occasions. The reason is because these are the times when PWP might hit the levels than can bring about problems in a slope. Figure 3.3 illustrates the installed instrument at the site.

Figure 3.3: The instrument on the site

3.3 Model Development

Advancement of the SVR model needs some basic thought with respect to the selection of input combination and the privilege optimal meta-parameters. The same data and input features will be utilized for the comparison of the SVR model's development.

3.3.1 Data Collection

Rainfall and PWP data were collected for 1 hour-interval for a period of 1 month. The data is specifically from 1st March 2015, at 0000 hours until 31st March 2015 at 2359 hours. They are collected from the data logger at the site. The data for March 2015 is chosen because the instruments at that period were still in good condition. All the errors are to be avoided because it will somehow affect the performance of the model in predicting the correct value of PWP. Toe A data is chosen because the objective is to model the response of PWP and this can be simulated in a better way with a set of data that contains as much fluctuation of PWP as possible, and these fluctuations are much called at shallow depth.

3.3.2 Data Reprocessing

From the data that have been collected from the site, all 744 data have been firstly processed to get the statistics of the data. The statistics that will be used in developing the model are:

1) N – Number of data points
2) Min – Minimum value of the data
3) Max – Maximum value of the data
4) SM – Sample Mean
5) SD – Sample Standard Deviation
6) SK – Skewness
7) VAR – Variance

The statistical value is important in order to see the behavior of the data, which is significant in determining the division of the data for training and testing data set. All the critical points such as minimum and maximum data need to be categorized in training data set in order to train the model at critical part. Furthermore, more data is also needed in the training data set. Based on the reprocessing data, 70% will be chosen as Training Data set and 30% will be chosen as Testing Data set. Then, these data sets are initially normalized between 0 and 1, which is a process called data scaling. It is a standard technique utilized in data mining and modeling to avoid points with huge variances that dominate the results to the detriment of other points with moderately much smaller variance; this guarantee maintenance of input data sparsity. Moreover, down scaling the features will save computational time since SVM kernel includes inner products of the features.

3.3.3 Model Input Structure

One of the very important stages in model development is model input selection. Diverse choice of inputs will give distinctive output and precision of the model. From Mustafa et al. (2002) The Radial Basis Function (RBF) ANN model of PWP for modelling responses to rainfall was produced as a function present -day and two antecedent conditions of rainfall (r_t, r_{t-1}, r_{t-2}) and three antecedent conditions of PWP (U_{t-1}, U_{t-2}, U_{t-3}). These input components were developed using detailed cross connection analysis between PWP and rainfall, and auto correlation analysis of PWP. In this review, the same input features will be exploited in one of the models. These features are more disposed to PWP and area some of the time portrayed herein as the 'PWP-inclined model'. The input model is expressed as in Equation (10).

$$U_t = f_{SVR}\ (U_{(t-1,t-2,t-3)}\ )\ ,(r_{(t,t-a,t-2)}\ )\ldots\ldots\ldots\ldots\ldots..(10)$$

Referring to (Babangida et al. 2016), for rainfall antecedent records, expanding input elements to higher antecedent record resulted a small mean square error (MSE). Two antecedent records show a slight positive change with addition of input elements from higher antecedent records. Addition of excessively numerous rainfall features will not give any significant affect to the result, the best model features are the present time and until two antecedent records of rainfall. Moreover, addition of antecedent records will add to the complexity of the model and computational weight with evidently no huge positive change in the precision, features from one to three lag records could provide better outcomes.

3.3.4 IMPLEMENTATION OF SVR

SVR implementation for cases of nonlinear, the most vital step is the choice of appropriate kernel function. For time arrangement, the radial basis function (RBF) kernel has been the best. The basis kernels' comparison was done by CRONE (Crone, Lessman, & Pietsch, 2006) in what they called "Exhausted Empirical Comparison". They came to a conclusion that RBF is the selected approach on most time series. Among the basic kernels, RBF ends up giving better outcomes in time series modeling of rainfall and resulting runoff (Dibike, Velickov, Solomatine, & Abbott, 2001). (C.-W.Hsu, Chang, & Lin, 2003) in their manual, regarding the use of SVM, encouraged the utilization of RBF, thus in this work of time series of PWP and rainfall, RBF will be used.

Optimization of one parameter of RBF Kernels needs to be done alongside the parameters of SVR, which sums up to a total of three parameters which are

1. Kernel Parameters (γ)
2. Cost Parameters (C)
3. Radius of the error insensitive tube (ε)

These parameters are optimized to have a model with the best performance. They are mutually dependent and therefore are optimized simultaneously. The selection of cost parameters (C) and the radius of the error insensitive tube (ε) will be hugely dependent on the behaviors of the dataset, for instance, a noisy data suits better with a greater value of ε. Several techniques exist to optimize these parameters, some of which are largely related not only on the optimization of the parameters but the minimization in the computational time as well. However, try and error method search is utilized in this project in finding the optimal parameters

3.3.5 PERFORMANCE MEASURES

Two measures will be considered to develop model in this study;

a) The coefficient of determinant (R^2) – which will show how good the model fits the data (Indicate 1 as perfect fit and 0 indicate poor fit)
b) Mean Square Error (MSE) – which smaller values are desired
c) No of Support Vector – which lower value than training data set are desired.

3.4 PROJECT MILESTONE AND GANTT CHART

Table 3.1: Project Milestone

Activity	Dateline	Actual Submission	Percentage
Topic Selection	26th May 2016	26th May 2016	**-**
Extended Proposal	23th June 2016	23th June 2016	**10%**
Proposal Defenses	14th July 2016	14th July 2016	**20%**
Interim Draft Report	11th Aug2016	11th Aug 2016	**40%**
Interim Report	18th Aug 2016	18th Aug 2016	**50%**
Progress Report	25th Oct 2016	25th Oct 2016	**60%**
Pre-SEDEX	16th Nov 2016	16th Nov 2016	**70%**
Final Report	30th Nov 2016	30th Nov 2016	**80%**
Technical Report	07th Dec 2016	07th Dec 2016	**85%**
Final Viva	13st Dec 2016	13st Dec 2016	**90%**
Hardbound Thesis	09th Jan 2017	09th Jan 2017	**100%**

Table 3.2: Gantt chart for FYP1 and FYP2

Week / Details	FYP1														FYP2													
	1	2	3	4	5	6	7	8	9	10	11	12	13	14	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																												
Submission of Interim Report																												
Project Work																												
Submission of Progress Report																												
Pre-SEDEX																												
SEDEX																												
Submission of Final Report																												
Submission of Technical Paper																												
Final Viva																												
Submission of Project Disertation																												

CHAPTER 4

RESULT AND DISCUSSION

4.1 DATA STATISTICAL

A month of 1-hour interval data from 1st March 2015 until 31st March 2015 was collected and analyzed to see the behavior of the data. Total number of data is 744, and the analysis of the data is shown in **Table 4.1** below;

Table 4.1: Descriptive Statistics of PWP and Rainfall

Data Statistics	Pore Water Pressure (kPa)	Rainfall (mm)
N	744	744
Min	-18.60	0.00
Max	-4.10	26.50
SM	-9.93	0.10
SD	2.27	1.32
SK	0.08	14.50
VAR	5.16	1.74

N- No of Data, Min-Minimum, Max-Maximum, SM-Sample Mean, SD- Sample Standard Deviation, SK-Skewness, VAR-Variance

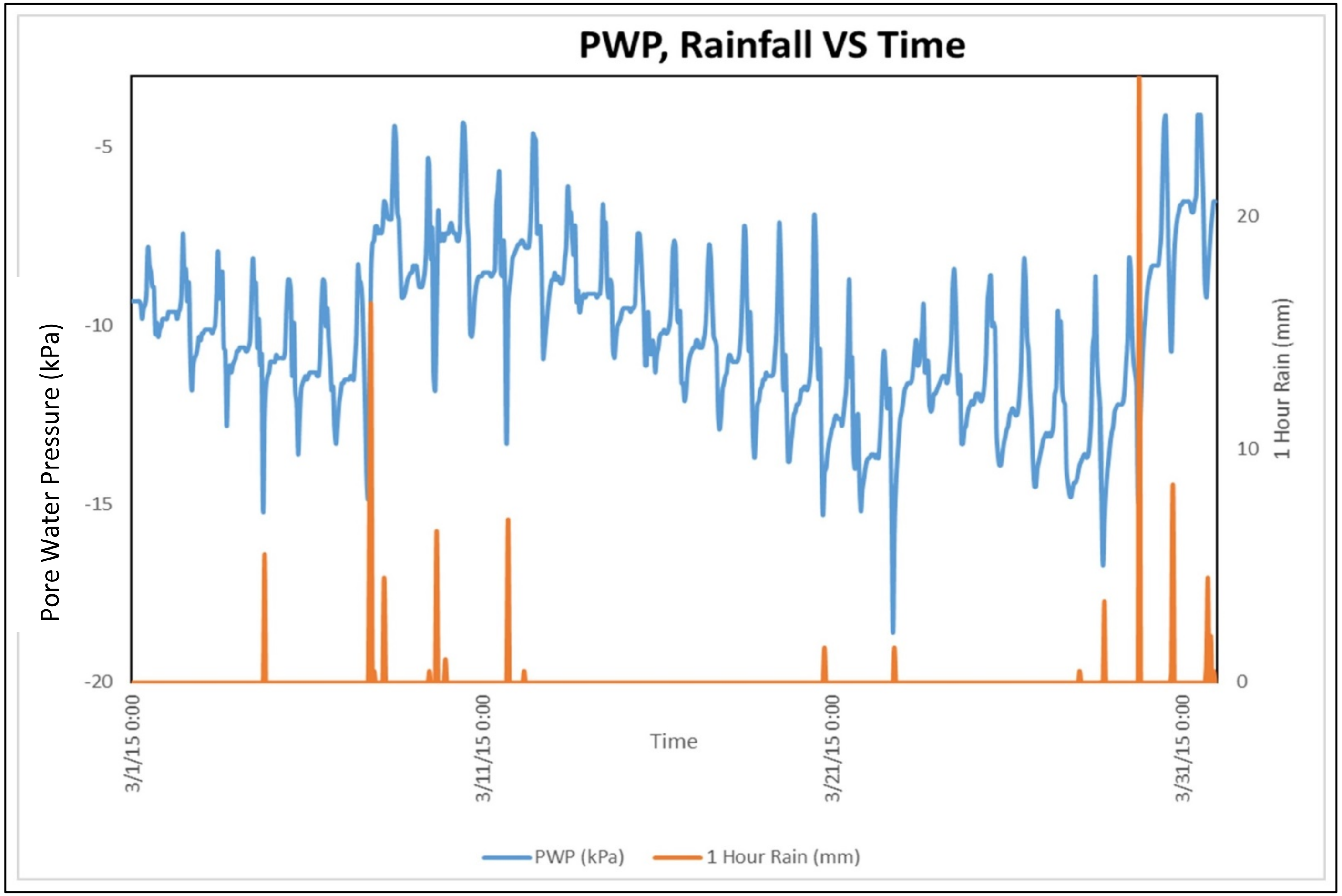

Figure 4.1: Graph of PWP, Rainfall VS Time

Based on the statistical data conducted, it is shown that PWP and rainfall has quite a huge range of the minimum and maximum value. Hence, this clearly proves that normalization of data is necessary in order to scale down the range and assist the software to process them in the model.

The variance, σ^2, is a measure of how far each value of the data set is from the mean. The statistical data obtained above demonstrates that the data set does not have a high value of variance, which shows that it is good enough to be used for modelling purpose. The variance values for rainfall and pore-water pressure of the data set are 5.16 kPa and 1.74 mm respectively, while the Sample Mean values are -9.93 kPa for PWP and 0.10 mm for rainfall.

Based on Figure 4.1, we can see that the data critical point for both rainfall and PWP are towards the end part of the time. This is significant to understand for the selection of training and testing data set. The data will be partitioned into the two aforementioned sets with a 70:30 ratio. It is determined that the training data set will be covered from the top of the data, and the rest will be the testing data set. The reason is because these data covered by the training data set are the ones that have high value, which is a good characteristic to be used for training and ultimately expected to produce a good model performance. Therefore, from 744 data, training data set will contain the first 521 data while training data set will have the other 223 data.

Generally, it is known that groundwater is not static, as it is a piece of a dynamic stream framework. It moves into and through aquifers from regions of high elevation of water-level to areas that have low elevation of the water-level. The fluctuation of the groundwater level is because of the changes of aquifer storage include either the addition or extraction of water from the aquifer, both through means of nature and involvement of human. Naturally, the groundwater recharge happens where the earth materials are adequately permeable to permit water to move in a descending manner through them. It happens most effortlessly in unconfined aquifers where water given by precipitation moves downward from land surface until the water comes to the water table.

The water table is the limit between the unsaturated areas below it where basically all of the interconnected pore spaces are loaded with water. When recharge happens in an unconfined aquifer, the water table ascents to a higher elevation, much like water level in bucket that rise when there is addition of water to it. One inch of precipitation moving underground to the water table will bring about a significantly more than an inch rise to the groundwater level. This happens due to the volume of aquifer occupied mostly by rock, sand or other solid geologic material, while water can only fill in the void or pore spaces between them. The most critical changes of water level that happen during the springtime of the year is because of the occurrence of recharge, which is when precipitation is at its highest and the rates of evaporation and plant usage are low. This fluctuation, thus, will be good for the model to make predictions

4.2 NORMALIZATION OF RAW DATA

One of the fundamental steps to the development of the model is to scale the data into an appropriate range, in order to maintain a strategic distance from huge values ruling over the smaller ones. The data will be scaled in a range of -1 and 1. It is also required to decide on the accuracy measurement to be used in determining the performance of the model. The normalization process of the data is expressed as in Equation (11)

$$v_p = 2\ X\ \frac{\left(x_p - x_{min}\right)}{\left(x_{max} - x_{min}\right)} - 1 \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots (11)$$

Where

vp = normalized or transformed data set

xp = original data set such that 1 ≤p≤P

P = number of data

$x$min = minimum value of original data sets

$x$max = maximum value of original data sets

Table 4.2: Descriptive Statistics of Normalized PWP and Rainfall in Training and Testing Sets

Data Statistics	Testing Sets (70%)		Training Sets (30%)	
	Rainfall (mm)	Pore Water Pressure (kPa)	Rainfall (mm)	Pore Water Pressure (kPa)
N	521	521	220	220
Min	0.00	0.00	0.02	0.40
Max	1.00	1.00	.0.77	1.00
SM	1.00	0.44	0.39	0.99
SD	0.05	0.17	0.12	0.05
SK	-17.63	-0.20	-0.14	-8.70
VAR	0.00	0.03	0.02	0.00

N-No of Data, Min-Minimum, Max-Maximum, SM-Sample Mean, SD- Sample Standard Deviation, SK-Skewness, VAR-Variance

4.3 MODELLING AND PERFORMANCE MEASURES

Modelling in MATLAB software requires optimization of three parameters so as to achieve the best performance of the model. The parameters are the Kernel Parameter (γ), Cost Parameter (C) and the Radius of the Error Intensive Tube (ε). The parameters are dependent to each other, thus making it necessary for them to be optimized simultaneously. In this study, the parameters are optimized with the trial-and-error approach, keeping in mind that the selection of C and ε values will be largely dependent on the behaviors of the data set (Babangida, 2016).

The parameter C checks the smoothness or flatness of the approximation function. A smaller value of C yields a learning machine with poor approximation due to under fitting of training data, whereas a greater C-value will over fit the training data and sets its objective to minimize only the empirical risk, making way for more complex learning. The parameter ε is related to the smoothening process of the complexity of the estimation function and monitors the width of the ε-insensitive region used for fitting the training dataset. It affects the amount of support vectors, and both the approximation function's complexity and ability of generalizing. Besides that, ε also monitors the accuracy of the approximation function, as smaller values will cause more quantity of support vectors.

Low values of Mean Square Error (MSE) as shown in Equation 12 are necessary, as they demonstrate the closeness of the model estimations to the observed values. On the contrary, a high value near to unity is required when coefficient of determinant, R2, is used as expressed in Equation 13. Both of these values illustrate the relationship strength between the predicted and observed values.

$$MSE = \frac{1}{n}\sum_{i}^{n}(\tilde{u}_i - u_i)^2 \quad \ldots\ldots\ldots\ldots\ldots\ldots \quad (12)$$

$$R^2 = \frac{\sum(u_i - \bar{u}_i)^2 - \sum(\tilde{u}_i - u_i)^2}{\sum(u_i - \bar{u}_i)^2} \quad \ldots\ldots\ldots\ldots\ldots\ldots \quad (13)$$

Where

ũ and u = values of observed and predicted PWP respectively

ū = mean of the observation values

n = number of observations

k = number of model parameters

A few tests have been done in the software. Table 4.3 shows some of the trial-and-error process that has been conducted. The table indicates that the most optimum value for the parameters is 2, 3 and 0.009 for C, γ and ε respectively. The Mean Squared Error (MSE) obtained for the data is 0.0035, which is a great result as it is approaching to 0. Furthermore, the Coefficient of Determinant, R^2, obtained is 0.8975, which is close and approaching to 1. The outcomes of the model show that the model is great enough to be used for the prediction of PWP and rainfall.

Another measurement made in the model performance is the number of Support Vector (nSV). This measurement is dependent on the amount of slack variables that are permitted and also depends on the data distribution. Large number of slack will make large amount of support vectors, and vice versa. Some data are not possible to have a high level of accuracy, thus a search for the best fit has to be done. The result of the model is 329 nSV from 521 data in the training data set is produced, which is approximately 63% of the data set.

Table 4.3: List of some try and error that have been done

Cost Parameter (C)	Kernel Parameter (γ)	Radius of the Error Intensive Tube (ε)	Mean Squared Error (MSE)	Squared Correlation Coefficient (R2)	No of Support Vector (nSV)
0	3	0.009	ERROR	ERROR	ERROR
1	3	0.009	0.0037	0.8929	327
2	3	0.009	0.0035	0.8975	329
3	3	0.009	0.0036	0.8952	330
4	3	0.009	0.0037	0.8925	331
2	0	0.009	0.0039	0.8844	331
2	1	0.009	0.0040	0.8823	323
2	2	0.009	0.0037	0.8931	322
2	3	0.009	0.0035	0.8976	329
2	4	0.009	0.0037	0.8925	329
2	3	1.000	0.0408	$-8.6e^{-16}$	0
2	3	0.900	0.0408	$-8.6e^{-16}$	0
2	3	0.090	0.0038	0.8906	70
2	3	0.0009	0.0037	0.8930	498

Figure 4.2 shows the extent of argument between observed and predicted data. The line of the graph shows the best fit line. Most of the data falls in the best fit area, which indicates that the data are predicted well in the model.

Figure 4.3 illustrates the estimated PWP using SVR model and the corresponding observed data recorded of PWP. It demonstrates that the predicted PWP has the same trend with the observed PWP, which means that Radial Basis Kernel Function based model is excellent for the prediction of PWP. However, there are a few extreme points that are difficult to be predicted accurately by the model due to influences from rainfall and might also be because of temperature effect as well.

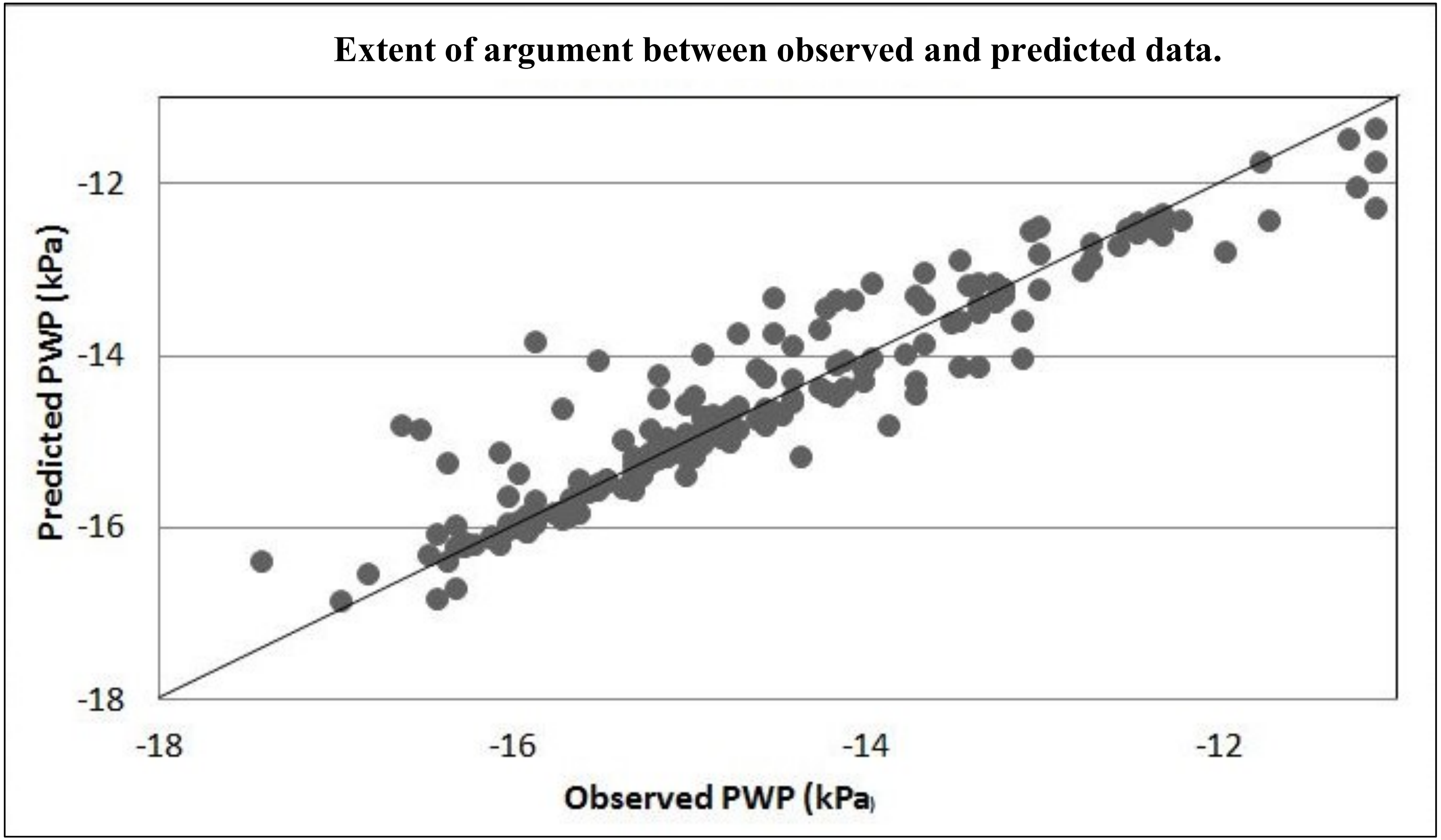

Figure 4.2: Extent of argument between observed and predicted data.

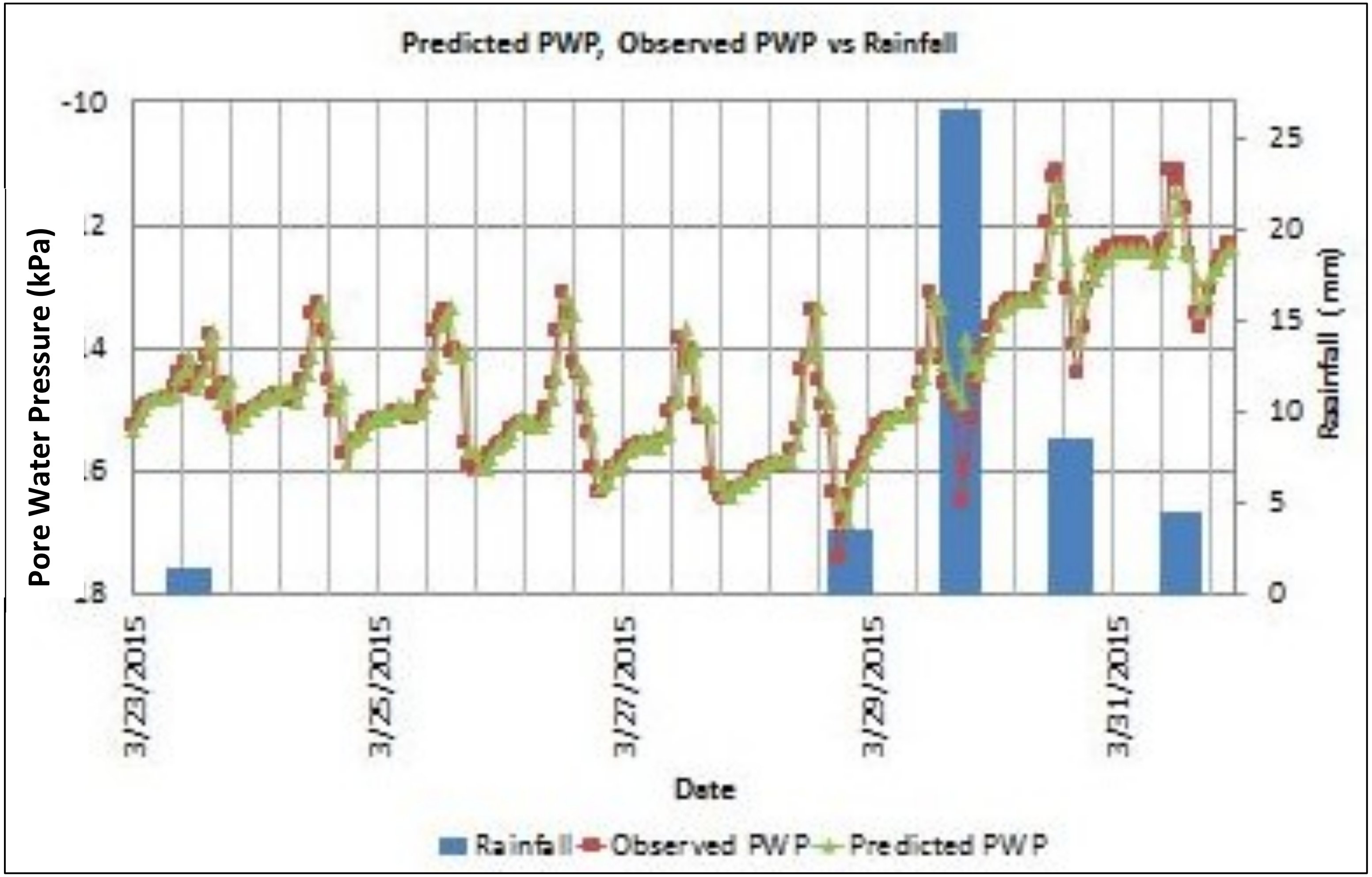

Figure 4.3: Predicted PWP using SVR model and corresponding observed recorded of PWP:

CHAPTER 5

CONCLUSION AND RECOMMANDATION

Pore-water pressure (PWP) is the pressure applied on its surrounding by water held in voids in rock or soil. It is necessary to understand the pore-water pressure responses to rainfall for the analysis of hydrology. Previously, field instrument is used to get the information on pore-water pressure. This method, however, is tedious. Hence, this study will be a more appropriate and convenient approach to predict pore-water pressure.

Predicting PWP with Radial Basis Kernel Function of Support Vector Machine (SVM) is a good technique to be used. The outcome of the model from MATLAB software proves that the model can predict the pore-water pressure well enough by giving a good performance. However, some points are not predicted well in the model, due to other uncontrolled factors like surrounding temperature. On the bright side, most of the data has been predicted excellently in the model, which dominates the overall result and can be concluded that the objectives are achieved.

As recommendation for future work, it is encouraged to use more data for the modelling process. The meaning of this is to collect the data of 30-minutes interval, instead of 1-hour interval, for a period of 3 months, rather than only 1 month. The reason behind this is so that the model will have more data to be processed in order to obtain a better prediction result. Other than that, other criteria need to be considered as well, such as the surrounding temperature, as the pore-water pressure is not only affected by rainfall but these other factors as well.

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APPENDICES

APPENDIX A: MATLAB CODING

```
>> model=svmtrain1(TrainingTarget1,TrainingData1,'-s 3 -t 2 -c 2 -g 3 -p 0.009')
*.
WARNING: using -h 0 may be faster
*
optimization finished, #iter = 1145
nu = 0.595511
obj = -26.273644, rho = -0.435655
nSV = 329, nBSV = 296

model =

    Parameters: [5x1 double]
      nr_class: 2
       totalSV: 329
           rho: -0.4357
         Label: []
    sv_indices: [329x1 double]
         ProbA: []
         ProbB: []
           nSV: []
       sv_coef: [329x1 double]
           SVs: [329x6 double]

>> [predicted_label,accuracy,prob_estimates]=svmpredict
(TestingTarget1,TestingData1,model);
Mean squared error = 0.00353684 (regression)
Squared correlation coefficient = 0.897592 (regression)
```