SPATIAL INTERPOLATION OF SOIL ENGINEERING PROPERTIES BY MODIFIED INVERSE DISTANCE WEIGHTING METHOD

BY

MR. THONGCHAI PHOTHONG

A DISSERTATION SUBMITTED IN PARTIAL FULFILLMENT
OF THE REQUIREMENTS FOR THE DEGREE OF DOCTOR
OF PHILOSOPHY IN ENGINEERING
FACULTY OF ENGINEERING
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ABSTRACT

The basic of the inverses distance weight method has been improved by many researches. Not only power parameter but also sensitivity, anisotropy ratio, anisotropy angle and searching radius are incorporated to the model. In addition the cross validation processes is introduced to filter the best parameters for the observed data. However, the method can further be developed. This study proposes a simple technique and a small modification of the IDW function but more ability to improve the estimation results. Firstly the random technique, it can be added in parameters searching step to receive the parameters that more represents the natural phenomena of the interesting area. Secondly a coefficient of anisotropy angle parameter will be modified to respond the anisotropy effect.

This study uses 164 bore holes with 23 layers data with in the Bangkok province to test the model. The 4 models, IDW. Tomczak IDW (Tomczak, 1998), MIDW (modified IDW) and Cubic Spline are evaluated. With the random technique the observed data patterns that are feed to the searching parameters step reveal the best parameters to imitate the natural phenomena of the area. The root means square errors of the study case decreases numerously from the worst random to best random case 11 %. The coefficient, called geographic modification, is introduced into the MIDW, to reflect the anisotropy angle parameter and to decrease the RMSE of the model.

Keywords: Bangkok Clay, Spatial Interpolation, Inverse Distance Weight, Random Technique, Anisotropy Angle

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LIST OF ABBREVIATIONS

Symbols\Abbeviations	Terms
S_u	The Undrained Shear Strength
λ	The Weighting Distance
β	The Power Parameter
δ	The Smoothing Parameter
μ	The Mean of Variable
ρ	The Anisotropy Ratio Parameter
RMSE	The Root Mean Square Error
OIDW	The Ordinary Inverse Distance Weight
TIDW	The Tomczak Inverse Distance Weight
MIDW	The Modified Inverse Distance Weight

CHAPTER 1
INTRODUCTION

This chapter is divided into five sections. Section 1.1 shows why this research is interesting and motivates the use of spatial analysis to study soil engineering properties of soft bangkok clay. Section 1.2 introduces the interpolation methods that is used in this dissertation. The problems statement and contributions will be described in Section 1.3 and 1.4.

1.1 Motivation

In land management projects such as town planning, agricultural, engineering, and environmental projects, it is important to know soil properties of that developed area as part of the project feasibility evaluation. The soil fertile will be analyzed for agricultural, town planing and environmental projects that relate to top soil. In addition the soil properties at lower elevations will be used in engineering project. Therefore, soil properties can be categorized to agricultural and engineering properties. Both have a lot of difficulties to estimate because of variations in spatial patterns of soil properties.

Soil engineering properties are required for one of the most important steps of building foundation design as for soil bearing capacity estimation. From building type, site shape and location, number of soil boring and depth will be specified by engineers. Soil samples are collected and some testing might be carried out in-situ such as the standard penetration, vane shear test, etc. The collected samples are sent to a laboratory for other necessary testings such as sieve analysis, atterberg's limits testing, unit weight, undrained shear strength test, etc. Test result summary is used by the engineer to calculate, among others, soil bearing capacity. Getting the summary of testing result is costly and time consuming. Therefore in one site location only one or two soil borings will be assigned and used to represent soil properties of the whole area.

For a particular case, soil strata at some locations are quite change rapidly. Mere two soil borings may not be able to represent soil engineering properties, as these properties will be vastly deviated from actual properties. With wrong understanding of soil properties, engineer can do wrong in foundation design. This in turn may impose great risk to the entire project.

For a case of preliminary and feasibility study stage, if possible, it is necessary to have a good confident of engineering soil properties with only small spending.

For soil boring characteristics aspect, the distance between boring of the same project very short about 10-500 meters but in the other hand the distance of boring of the different project start from 0.9 km. to 60 km. As shows in Figure 1.1.

In addition, the preliminary soil profile of undrained shear strength shows complexity of lines, Figure 1.2. Figure 1.2 represents center line of the profile. It passes through study area from bottom left to upper right of the map. The center line also passes the bore holes in the same project and different project. The turn points of center line are illustrated as triangles on profile chart.
The profile lines of each depth from 1.50 m. to 18.25 m. are drawn in Figure 1.3.

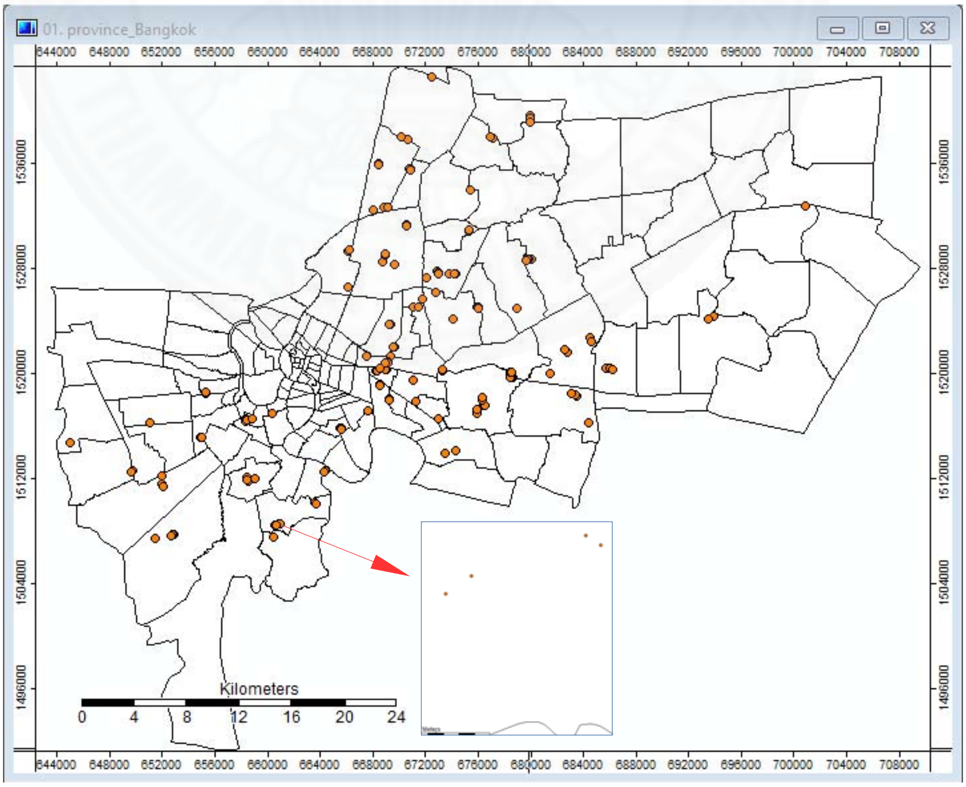


Figure 1.1 Location of soil boring.

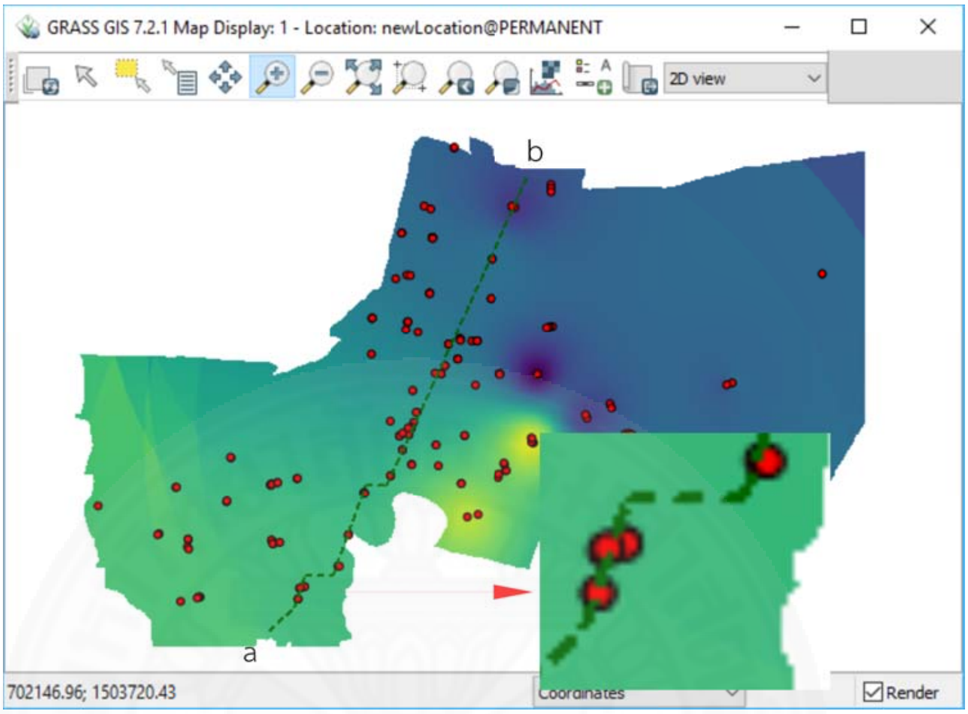


Figure 1.2 The center line of the undrained shear strength profile.

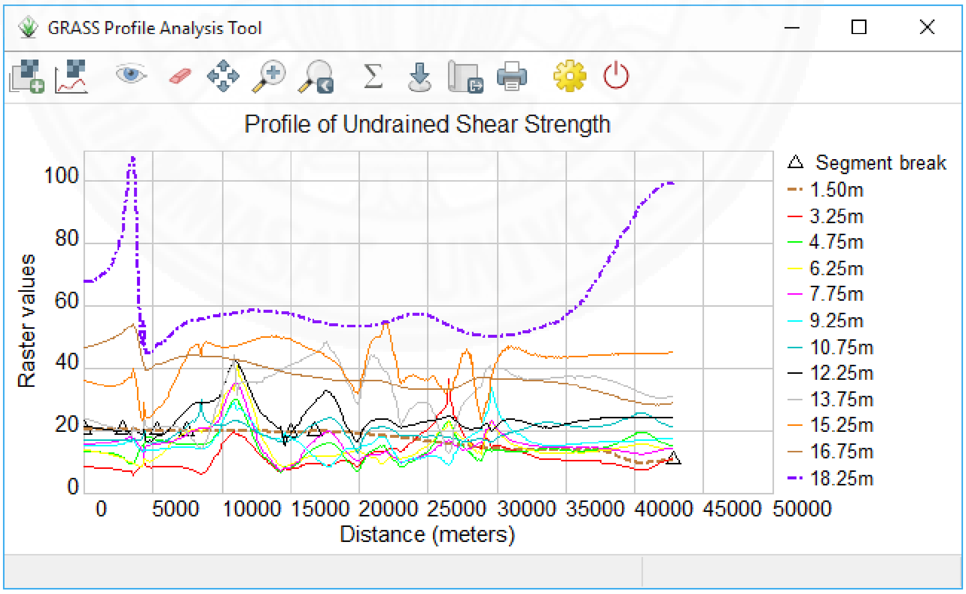


Figure 1.3 The undrained shear strength profile.

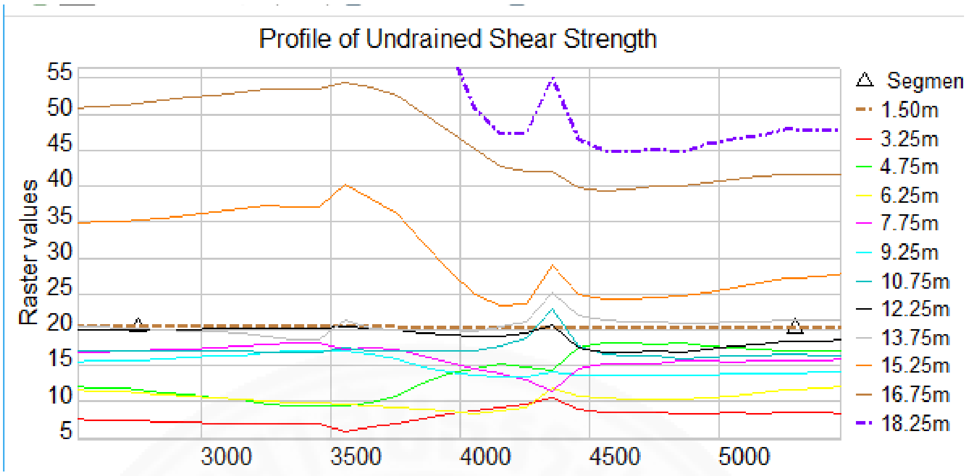


Figure 1.4 Profiles of undrained shear strength at 1000 – 6000 m.

The pattern of lines are very complex. An example is the line that shows the values of undrained shear strength of depth 1.50 m. (magenta dash line). The value is about 20 kN/m^2 from 1000 – 6000 m but the line cross other lines that should have the higher values, as Figure 1.4.

All of these cases have inspired to this research work in applying spatial analysis to gain knowledge of soil engineering properties through spatial interpolation, by using sampling data in the area.

1.2 Spatial Interpolation Methods

The spatial interpolation method can be divided into non-geostatistics, geostatistics and intelligent method. This section gives short explanation of the selected model will be used in this dissertation.

1.2.1 Inverse Distance Weight Method

To understand the natural phenomena of soil engineering properties many mathematics modeling for estimating unsampled data are studied. The inverses distance weight (IDW) method is one of the most frequency used in spatial interpolation. It is a deterministic or non-geostatistic modeling. The concept of the

IDW is the value of unsampled points are more similar to sampled points that have closer distance than further away sampled points. The distance effect is represented by weights as:ghg

$$\lambda_{ij}=\frac{1/d_{ij}^{\beta}}{\sum_{i=1}^{n_j} 1/d_{ij}^{\beta}} \tag{1.1}$$

Where d_{ij} is the simple Euclidean distance between unsampled location j to sampled location i . n_j is number of sampled points that use to estimate value of location j . As shows in Figure 1.5. Then the value of location j can be expressed as:

$$P_j=\sum_{i=1}^{n_j} \lambda_{ij} P_{ij} \tag{1.2}$$

Where P_{ij} is interesting value of sampled point i refer to point j . β is weighting power. The weighting power will effect the influence of sampled points as shows in Figure 1.7. Low weighting power, dashed line, makes more average and less localized. In contrast with high weighting power, full line, makes less average and high localized. The results create from IDW will not exceed the maximum and minimum of sampled values.

Tomczak [1998] introduced extension of the IDW mathematic model that incorporated anisotropy and smoothing parameter as:

$$\lambda_{ij}=\frac{1/(d'_{ij}+\delta)^p}{\sum_{i=1}^{n_j} 1/(d'_{ij}+\delta)^p} \tag{1.3}$$

Where d'_{ij} is the effective distance which is formulated by:

$$d'_{ij}=\sqrt{A_{xx}\Delta x^2+A_{xy}\Delta x\Delta y+A_{yy}\Delta y^2} \tag{1.4}$$

where

$$A_{xx}=[\frac{\cos(\theta)}{\rho}]^2+[-\sin(\theta)]^2 \tag{1.5}$$

$$A_{xy}=2[\frac{\cos(\theta)}{\rho}\frac{\sin(\theta)}{\rho}+-\sin(\theta)\cos(\theta)] \tag{1.6}$$

$$A_{yy}=[\cos(\theta)]^2+[\sin\frac{(\theta)}{\rho}]^2 \tag{1.7}$$

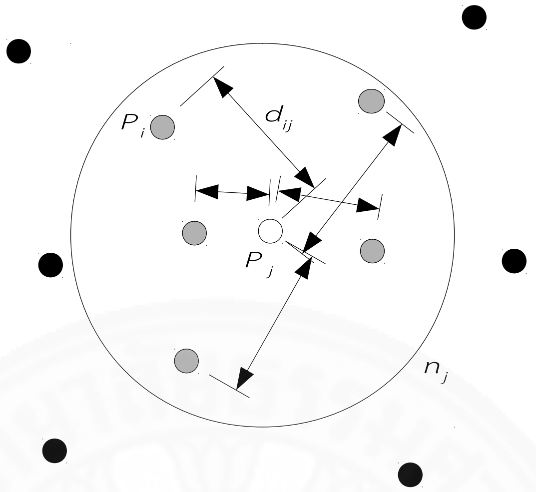


Figure 1.5 Unsampled point j within sampled points i that have n_j number.

Δx and Δy are distance in x and y directions from unknown to known locations. Figure 1.6 illustrates concept of equation 1.3. ρ is anisotropy ratio equals a/b. In isotropic case ρ equals 1. θ is the anisotropy angle measured from x axis.

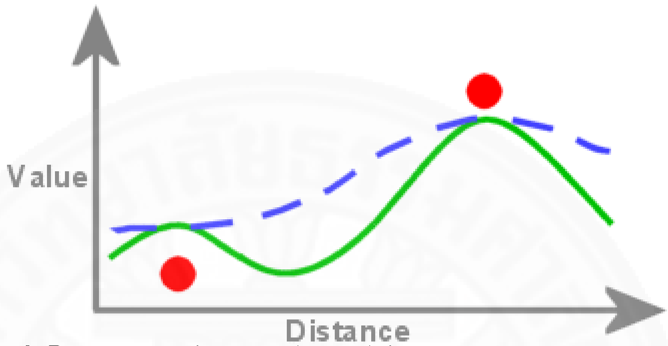
1.2.2 Cubic Spline Interpolation

Cubic Spline is a piecewise polynomial degree 3 that used to interpolate unknown value by known values, as shows in Figure 1.8. $S(x)$ is a piecewise cubic spline function as:

$$S(x)=\begin{cases} a_0x^3+b_0x^2+c_0x+d_{0,}\, t_0\le x\le t_1 \\ a_1x^3+b_1x^2+c_1x+d_{1,}\, t_1\le x\le t_2 \\ \ldots \\ a_{n-1}x^3+b_{n-1}x^2+c_{n-1}x+d_{n-1},t_{n-1}\le x\le t_n \end{cases} \tag{1.8}$$

Where {(t_0 , $f(t_0)$), (t_1 , $f(t_1)$),…,(t_n , $f(t_n)$),} is points and known data. The 4 coefficients a, b, c, d have to be specified with the cubic spline properties:

Figure 1.6 The concept of effective distance and anisotropy.



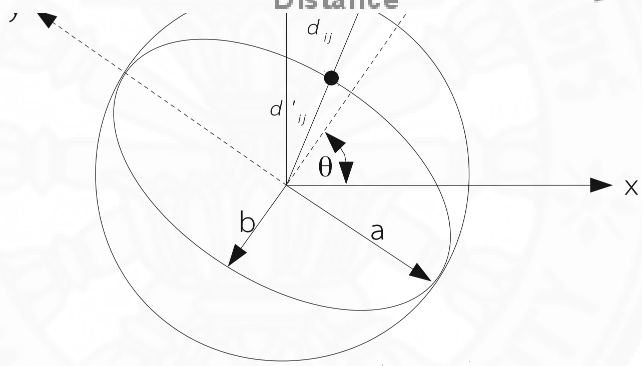


Figure 1.7 The respond of weighting power in IDW (SIG, 2017).

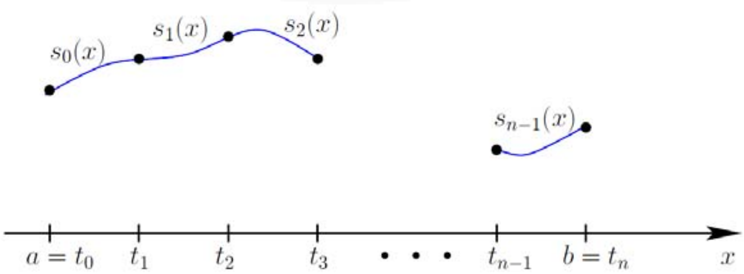


Figure 1.8 Piecewise polynomial (Karving , 2008).

$$S(x_j)=f(x_j),\ j=0,1,\ldots n$$
$$S_j(x_{j+1})=S_{j+1}(x_{j+1}),\ j=0,1,\ldots n-2$$
$$S'_j(x_{j+1})=S'_{j+1}(x_{j+1}),\ j=0,1,\ldots n-2$$
$$S''_j(x_{j+1})=S''_{j+1}(x_{j+1}),\ j=0,1,\ldots n-2$$

1.2.3 Geostatistics Interpolation

This method will consider interesting properties of each locations as random variables. It means a value of interesting property on a point can be many values not just one value base on statistical theory. Many points combined together calls regionalized variable. The possible value will have its mean and variance. Figure 1.9 shows concept of random variables. To analyze function of random variables, the similarity of point to another point will be formalized same as the IDW concept. In addition, three more definitions relate to random variables have to be addressed are stationarity, variogram and kriging. The stationarity is an assumption that the random variable of the interesting region have the same degree of variation. As:

$$Z(x)=\mu+\varepsilon(x) \tag{1.9}$$

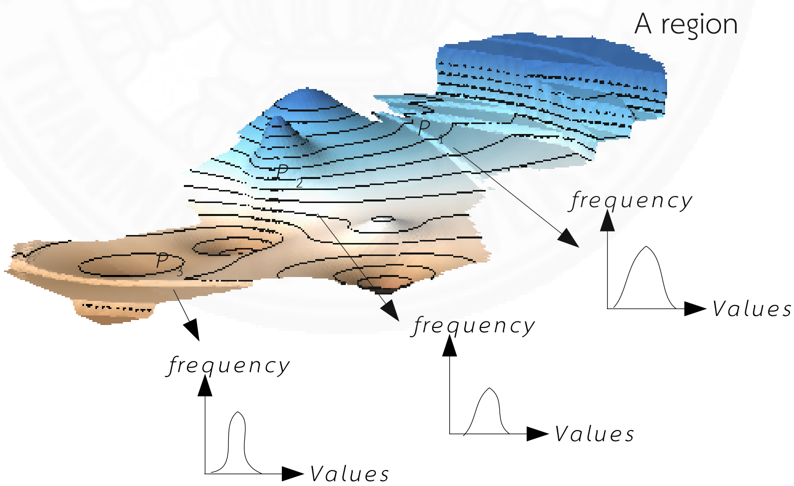


Figure 1.9 Every points in the region have it own distribution, mean and variance.

Where Z is the value of the variable at location x. μ is the mean of the variable and $\varepsilon(x)$ is a random part. The covariance of two random variables can be formed by the separation h as:

$$C(h)=E[\varepsilon(x)\varepsilon(x+h)] \quad (1.10)$$

Replace $\varepsilon(x)$ in equation 1.10 with 1.9

$$C(h)=E[\{Z(x)\}\{Z(x+h)\}-\mu^2] \quad (1.11)$$

If equation 1.11 is an intrinsic stationarity, the expected different should be zero.

$$E[Z(x)-Z(x+h)]=0 \quad (1.12)$$

Where E is an expectation. With spatial relation the covariance can be replaced the variance.

$$Var[Z(x)-Z(x+h)]=E[\{Z(x)-Z(x+h)\}^2]=2\gamma(h) \quad (1.13)$$

Where $\gamma(h)$ is the variogram. It is a function of h and $x+h$. To understand the characteristics of the random variables or properties the experimental variogram have to examine. This step is calculating the variogram from sampled data with varieties of h as

$$\gamma(h)=\frac{1}{2m(h)}\sum_{i=1}^{m(h)}\{z(x_i)-Z(x_i+h)\}^2 \quad (1.13)$$

Where $z(x_i)$ and $z(x_i+h)$ are sampled values of z at locations x_i and x_i+h. The $m(h)$ is number of paired that produces the same lag, h. With different h can draw a graph of semivariances that constitute the experimental or sample variogram. For one dimension variogram with different h can draw a graph on Figure 1.10. After the variogram plot has produced the next step is create variogram model that fit the graph as in Figure 1.11. The power function is fit on the graph. It can be spherical and exponential function.Then the kriging will be used to predict value of unsampled points by using data from the variogram function. It has many types of kriging such as simple kriging, ordinary kriging and kriging with trend and also the anisotropy can be considered in geostatistic (Oliver and Webster, 2015).

1.2.4 Intelligent System

The intelligent system will be addressed is artificial neural networks. The artificial neural networks (ANN) is computer programming model that mimics the human brain cell. The typical model is in Figure 1.12.

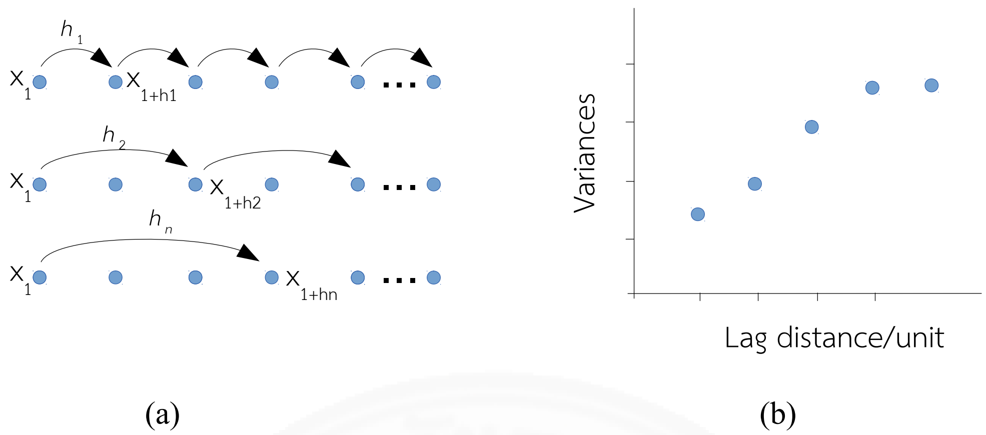


Figure 1.10 The one dimension variogram (a) calculate data of $\gamma(h)$ with lag h_1 to h_n (b) the semivariances plot

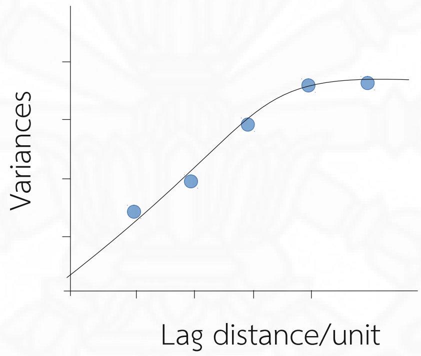


Figure 1.11 A function of power function

The model has three layers as input, hidden and output layer. The sampled variables are put into the model in the input layer node. The estimation function will be calculated in the hidden layer and the results will show on the output layer. The number of layers and nodes in input and hidden layer use trial and error method to find the best amount. The efficiency of the model will checked for stop the training by the root mean squared error (RMSE).

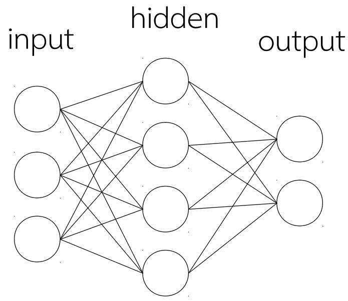


Figure 1.12 The mimic of the artificial neural networks.

The ANN model is not deterministic or geostatistics model. It uses simple weight sum calculation in the model. This model was used to learn and simulate patterns of obtained data moreover it shown the good results.

1.3 Problem Statement

The previous summary depicts the potential of the spatial interpolation models that can interpolate unsampled data and interpret pattern of soil engineering property. Therefore the problem statement of this research is observing a technique and modification of the inverses distance weight method to interpolate the undrained shear strength at unsampled points.

1.4 Dissertation Contributions

The core contribution is a methodology to enhance a selected model in the spatial interpolation of undrained shear strength. The proposed method will selected the best sampled pattern to represent the undrained shear strength of the region.

The second contribution is modification of the selected model to decrease the root mean square errors of the interpolation.

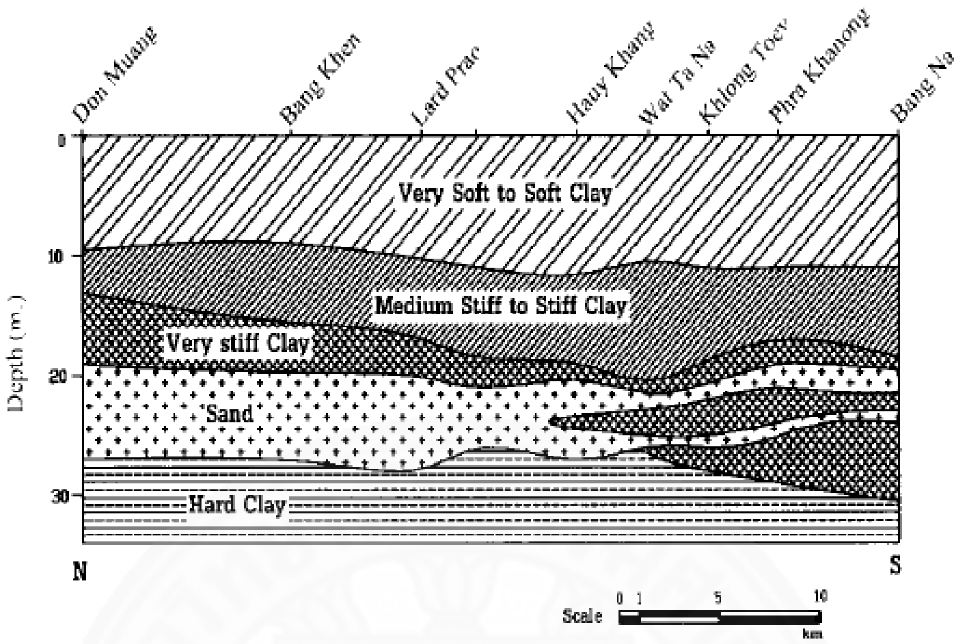
CHAPTER 2
REVIEW OF LITERATURE

The previous research will be reviewed in this chapter to compile research methodologies and techniques that can be used and developed in this research. The first section 2.1 reviews the relate topic of soil engineering properties and the Bangkok's soil properties. The section 2.2 to 2.4 will concern about spatial interpolation of non-geostatistics, geostatistics, artificial neural networks and hybrid system.

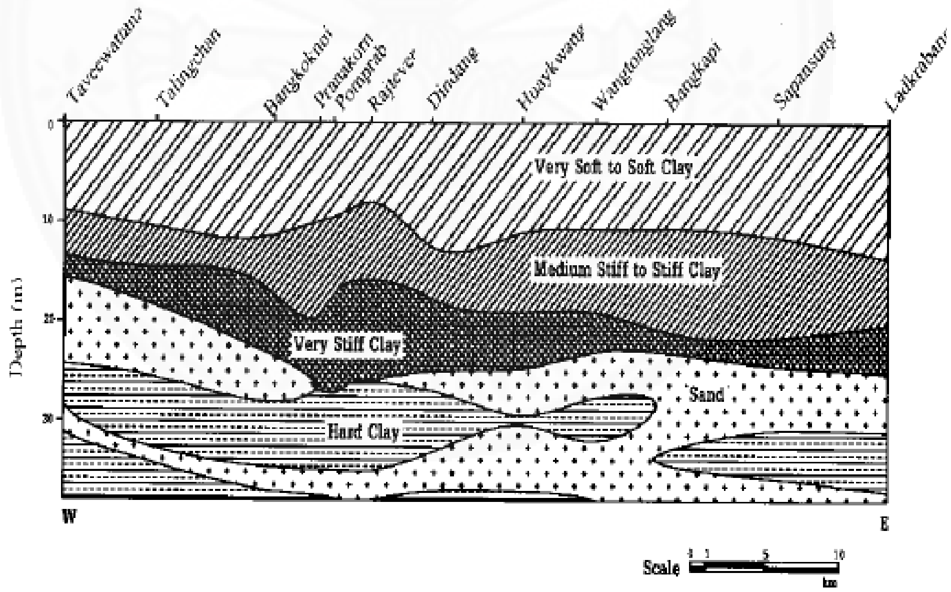
2.1 Soil Engineering Properties

Soil engineering properties are very importance information for planning, designing, monitoring and management of engineering projects such as analysis soft strata zone that effect to road embankment to prevent settlement, analysis earthquake zone effect and the effect of using ground water in Thailand. Especially Bangkok clay, it is problematic soil in engineering discipline ([Soralump,Mairaing,KUNSUWAN & Surinkum 2010]). Soralump *et al.* (2010) also addressed in their research not intent to estimate values of unobserved locations because of engineering safety.

The Bangkok clay exposed by the sedimentation process from Quaternary deposits until now. The weathering and deposition process are made stress on subsoil consistently it causes soil engineering properties remodel and soil physical creep. The soil engineering properties of Bangkok clay were observed and studied by many researcher including Horpibulsuk *et al.* (2004; 2007). Th*ey studied the* engineering properties of Bangkok clay by considering the effect of microstructure. The soil profile of Bangkok had been depicted from Don-muang (north) to Bangna (south) and from Taveewattna (west) to Ladkabang (east) as in Figure 2.1 and engineering properties of average soil depth are in Table 2.1. The soil profile are well draw. The layer of different soil type separate clearly by range of soil engineering properties along the distance about 60 km. From Table 2.1 the undrained shear strength resembles the best to do the task because no overlay in the values.



(a)



(b)

Figure 2.1 Bangkok's soil profile (a) north to south (b) west to east (Horpibulsuk *et al.* , 2004).

Table 2.1 Soil engineering properties (Horpibulsuk *et al.* , 2004).

Soil type	Thick-ness (m)	w_n (%)	LL (%)	PL (%)	S_u (kPa)
Soft clay	12 - 18	43 - 98	39 - 97	21 - 37	13 – 25
Med. to Stiff clay	3 – 10	26 - 66	29 - 71	13 - 31	44 – 100
Very stiff clay	2 – 6	17 – 45	20 – 58	11 – 24	111 – 180
1^{st} sand	2 – 6	18 - 22	-	-	-
Hard clay	15 - 20	15 - 27	22 - 54	10 - 25	202 - 577

This is a good contribution to this research to use the undrained shear strength to be considered. In addition Horpibulsuk *et al.* (2004; 2007). no mentioned of spatial relation of undrained shear strength. Only illustrated relationship of the field yield stress and the undrained shear strength as

$$\sigma'_{yf} = 3.78 S_u + 7 \tag{2.1}$$

Where σ'_{yf} is the field yield stress in kPa unit.

Familiar as the *general B*angkok's soil layers was described by Muktabhant et. al. (1967) (cited in [Suwanwiwattana,Chantawarangul,Mairaing & Apaphant 2001]) the first layer, 1-2 meters, is top soil or weathered clay with high shear strength and low water content property. The second layer, 2-12 meters, is soft clay composed of soft dark gray and medium gray clay with low shear strength and high compressibility. The third layer, 12-20 meters, is stiff clay. The last layer, 20-25 meters, is sand and gravel layer (Figure 2.2).

Suwanwiwattana *et al.* (2001) presented the development of geotechnical database of Bangkok subsoil using GRASS-GIS. The research used non-geostatistic spline in GRASS to interpolate spatial relation of results of standard penetration test (SPT) to classify strata of soil types. The result was satisfactory when was compared to the original three soil profiles that manually draw. Remarkable, the distance of testings sample sites was only 100x100 square meter. It is alike this research mention that short distance the undrained shear strength profile not complicate compares to longer distance.

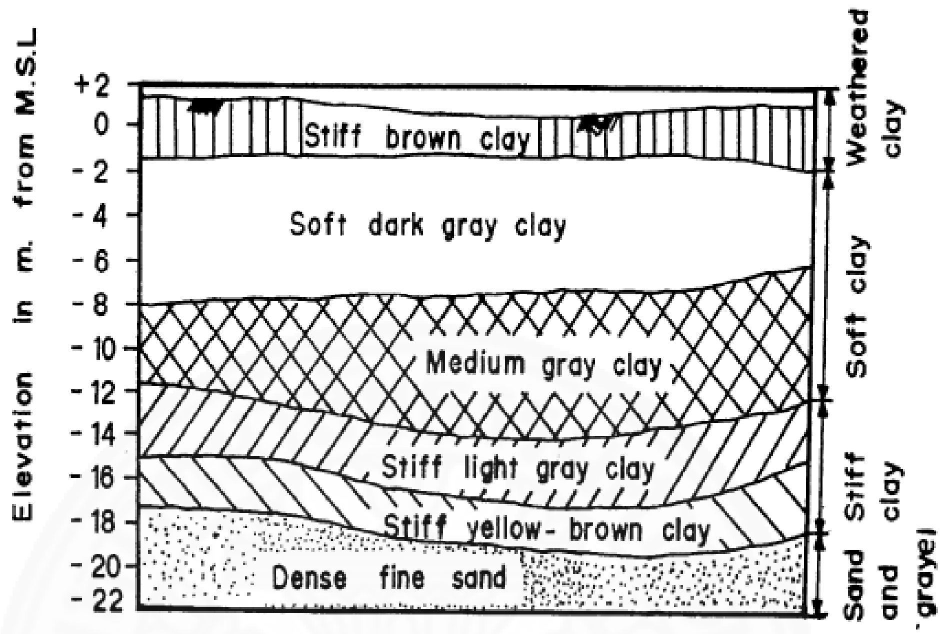


Figure 2.2 Typical Bangkok's soil profile ([Muktabhant 1967])

2.2 Non-Geostatistic Methods

In spatial interpolation it has a method call non-geostatistic or deterministic model that is a mathematics model without consider random variable.

Li and Heap (*2008) re*viewed 42 spatial interpolation methods in three non-geostatistical interpolators, geostatistical interpolators and combined methods. The models name show in Table 2.2. Many types of non-geostatistic method but only two, the inverses distance weight method and cubic spline, are investigated. In two dimension space, the inverses distance weight method has been developed and improved continuously since 1968 by Shepard (1968). Tomczak (1998) introduced the IDW automation system with anisotropy examined. The parameters of the IDW

Table 2.2 The spatial interpolation methods (Li and Heap, 2008).

Non-geostatistical	Geostatistical		Combined method
	Univariate	Multivariate	
Nearest neighbours	Simple kriging	Universal kriging	Classification combined other interpolation methods
Triangular irregular network related interpolations	Ordinary kriging	SK with varying local means	Trend surface analysis combined with kriging
Natural neighbours	Block kriging	Kriging with an external drift	Lapse rate combined with kriging
Inverse distance weighting	Factorial kriging	Simple cokriging	Linear mixed model
Regression models	Dual kriging	Ordinary cokriging	Regression trees combined with kriging
Trend surface analysis	Indicator kriging	Standardised OCK	Residual maximum likelihood-empirical best linear unbiased predictor
Splines and local trend surfaces	Disjunctive kriging	Principal component kriging	Regression kriging
Thin plate splines	Model-based kriging	Colocated cokriging	Gradient plus inverse distance squared
Classification	Simulation	Kriging within strata	
Regression tree		Multivariate factorial kriging	
Fourier series		Indicator kriging	
Lapse rate		Indicator cokriging	
		Probability kriging	
		Simulation	

will be calculated by cross-validation and also the value of variable by jackknife approach. With the jackknife approach, the confidence on the estimated value can be created. De Mesnard (2013) was commented on the zero distance effect. If the estimating points are closed to some sampled points, the remotely sampled points not affect to the estimate value.

The IDW method is one among the spatial interpolation methods that frequently used to study and apply in soil agriculture properties estimation. Dumitru *et al. (*2013) *addres*sed in their study the IDW method is not suitable for the area that have high different of elevation. Robinson and Metternicht (2006) and Göl *et al.* (2*017) ev*aluated the spatial interpolation techniques, geostatistics and non-geostatistic included the IDW, to estimate soil property, pH and soil organic carbon respectively. They found not only one method outperform for all aspect of test both number and type of variable.

The cubic spline is selected to be another one method that will be used in this research. This method outperforms among the other in Phothong and Witchayangkoon (2015) studied. The study investigated non-geostatistics and the ANN method to calculate the undrained shear strength of Bangkok clay. North and Livingstone (2013) compared linear and cubic spline methods to create water profiles. The conclusion was same as Metternicht (2006) and Göl *et al.* (2017) no one the best for all aspect. The linear spline as good to control the minimum and maximum of the estimated values aspect but the estimated values trend to bias because the values will higher than minimum and lower than maximum. The cubic spline better in the bias situation but the calculated value trend to over estimate. This situation always happen when the observed distance close to each other meanwhile observed values differ in magnitude.

The research's comments will be analysis, compile and use in this research targets.

2.3 Geostatistics Metod

The soil science discipline have been applied the geostatistics method to assess, describe and predict soil properties since late 1980s. Goovaerts (1999)

encouraged researcher to use the geostatistics method to model spatial patterns of interesting variables. The reliable semivariogram calculation demanded at least 150 sampled data and more for anisotropic soil properties. The soil sampling location and magnitude also effect to spatial interpretation of attribute values. Furthermore he informed three types of kriging, simple kriging, orinary kriging and kriging with trend and compared results of different types of kriging, as shown in Figure2.3.
Figure 2.3 shows one dimension sampled data in upper picture. The middle picture shows means are used in all kriging types and the last picture shows results of each kriging types.

Mazzella and Mazzella (2013) also encouraged to apply the geostatistics in data analysis, interpolation and evaluation like as Goovaerts (1999). The types of variogram model are depicted in Figure 2.4. The sampled data locations somehow effect the patterns of variogram plot. The sampled locations shows on Figure 2.5 have 3 patterns, type I, II and III. The yellow circle shows range of sampling points. If the pair of data that represents the variables is unsampling, type I, and only sampled, type II, its affects the nugget effect value and sill value. The type III observed locations are in the range of sampling grid will reflect the trend of variogram shape as increase lag distance will invrease trend, value of short lag distance will affect contentiously of attribute variable and the maximum lag distance will represent the highest value of variogram value. Whereupon the krige diagram should be plotted to evaluate the kriging model. The calculated values will plot versus the measured values and the good of estimation will show 45^{o} line as Figure 2.6.

Some applications on the geostatistic, the universal kriging was the most accurate for estimate soil properties compared to ordinary kriging, inverse distance weighting and spiles addressed by Omran (2012). 146 samples of topsoil were used in his study.

2.4 Artificial Neural Networks and Hybrid System

Soil properties are modeled by many researcher with targets of accuracy and reliability. Gangopadhyay *et al.* (1999) illu*strated* a powerful performance of a combination tool of ANN and GIS. The ANN used to classify subsurface aquifer characteristics and GIS received that data to estimate depth-averaged aquifer parameters such as transmissivity, leakage factor and storage coefficient. The multilayer perceptron with the back-propagation algorithm was used. The input for

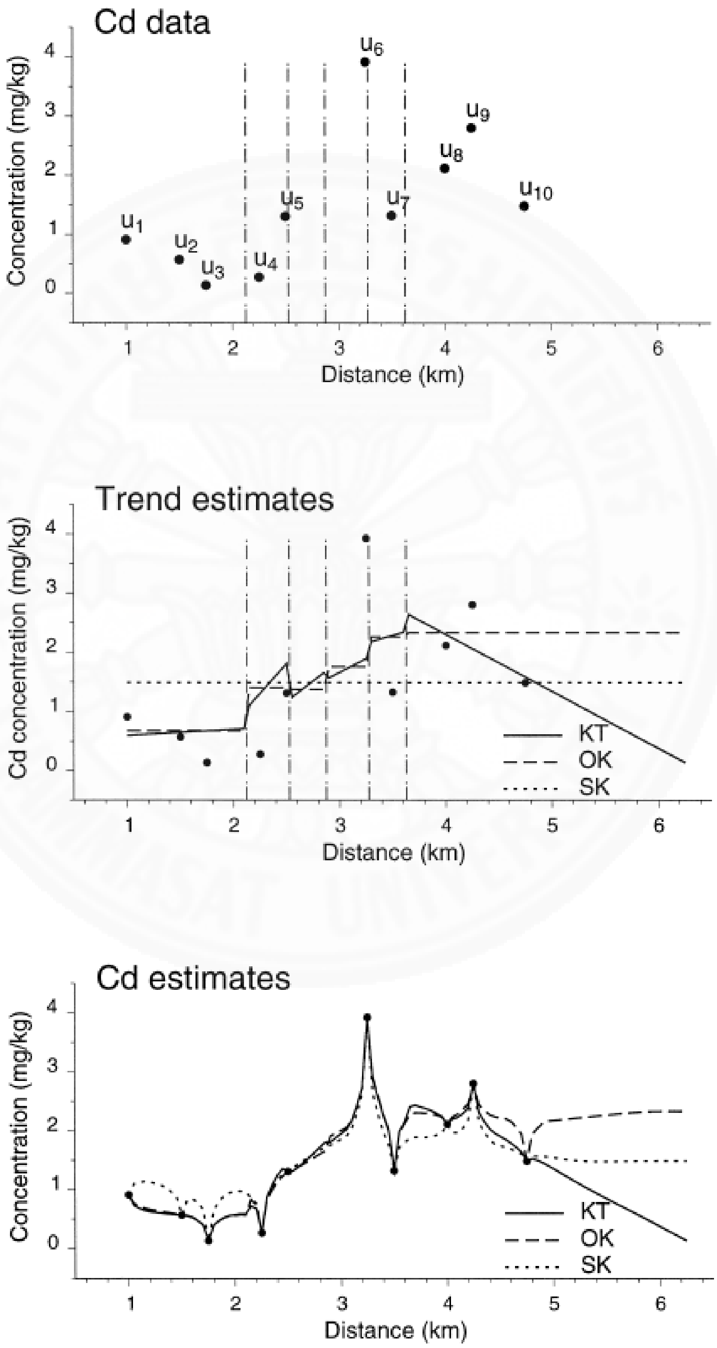


Figure 2.3 Three types of kriging, simple kriging (SK), orinary kriging (OK) and kriging with trend (KT) results.

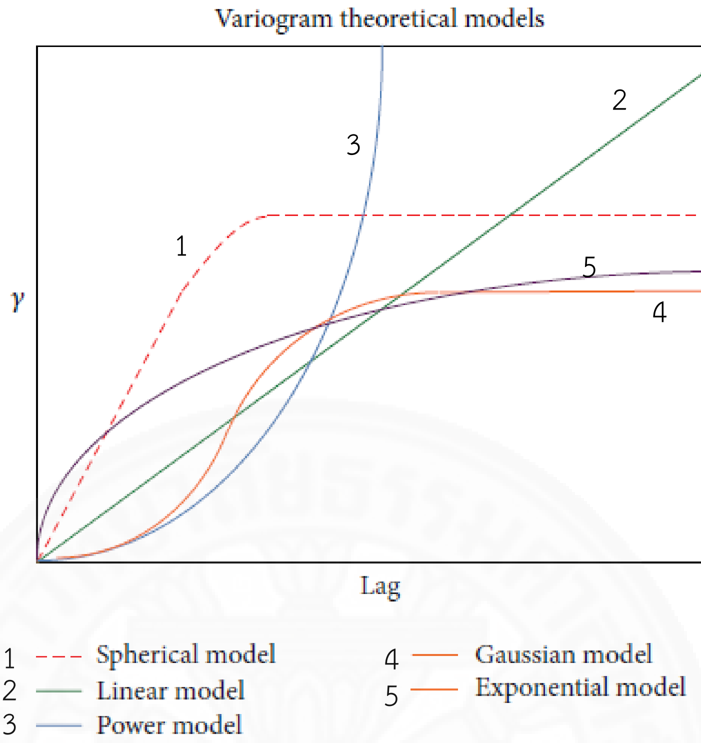


Figure 2.4 Five types of the variogram model (Mazzella and Mazzella, 2013; Trangmar *et al.*, 1986).

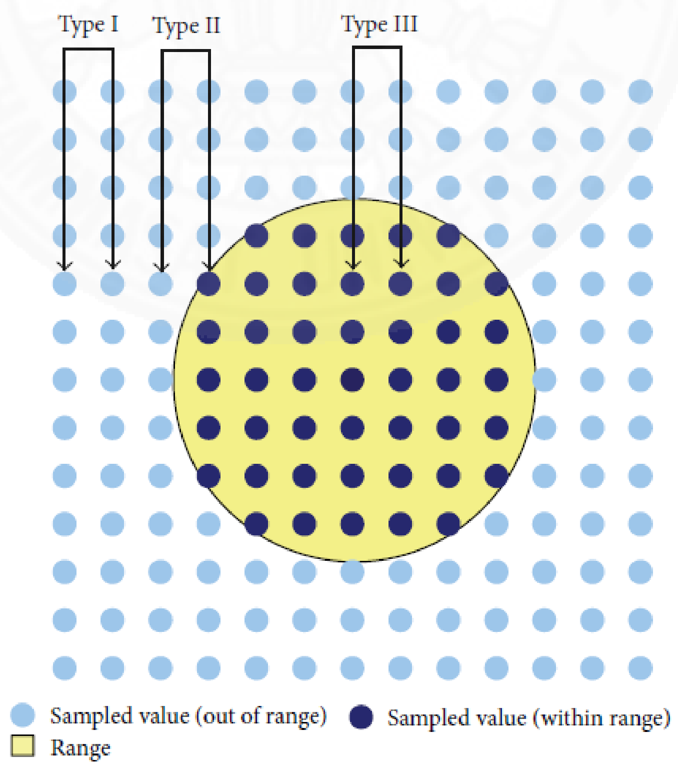


Figure 2.5 Example of regular grid sampling pattern (Mazzella and Mazzella, 2013).

ANN were location (x, y), depth, z, and extend of particular type material type, z-from and z-to. The output information was the aquifer material present for the input depth zone. It was very large number of iterations when the ANN model used the whole depth, 200 meters, of the monitoring well. The samples were divided to four

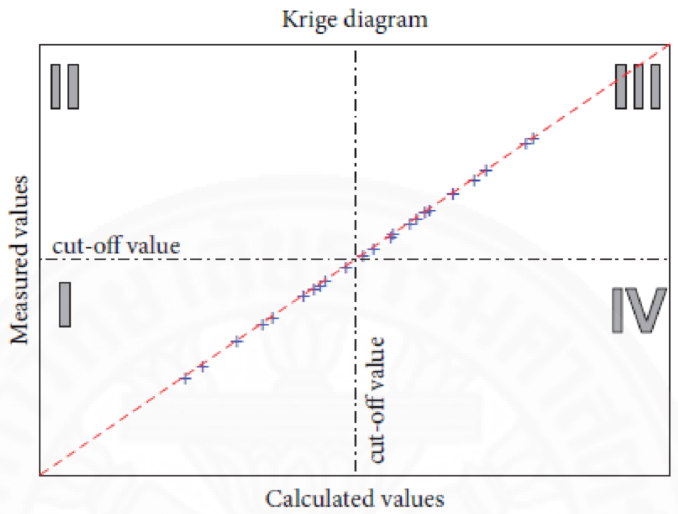


Figure 2.6 The 45° line of the krige diagram (Mazzella and Mazzella, 2013).

strata by the variation of sand frequency, each strata was 50 meters. Therefore, the normalization factor used for 50 depth. The normalization also applied to coordinates, x and y. In addition, the depth extend between two aquifer material types was divided into 10 levels because changing of material types between that two layers.

With a few of samples, 41 sites for Xhantic Ferralsols soil type and 92 sites for Rhodic Ferralsols soil type, Utset *et al.* (2000) *remar*ked the combined kriging and soil map gets the best bias estimations of soil bulk density and field capacity of both soil types. But only Rhodic Ferralsols soil type, the kringing predictions showed more accurate results because of samples size were enough available.

Zhao *et al.* (2009) *use*d the ANN to predict high resolution of soil texture map because though field survey is time consuming and expensive. The input of the ANN were coarse resolution and DEM data. The coarse composes of clay map, sand map. The DEM data is soil terrain factor map, soil drainage map, soil deliver ratio map and vertical position map. The relative overall accuracy was 88% for clay content and 81% for sand content.

A new modified hybrid model (MANNG) of Artificial Neural Networks (ANN) and Kriging have been used by Nourani (2012) to estimate groundwater level at the Shabestar plain. The first stage is calibration of ANN. Data from 11 piezometers were used. The inputs are present month rainfall (Rt-1), lake water surface level (LELt-1) at the present month, ground water levels in present from first to twelfth previous months (ELt-1,ELt-2,...,ELt-12). The output of the ANN model is the preceding month of ground water level (Elt,ELt,...,ELt). Hidden layers number of the model were defined by trial and error procedure begin from two up to fifty and finally got 3 hidden layers used in the model. The Root Mean Squared Error (RMSE) and coefficient of effectiveness (CE) were used to evaluate and find the best model. The second stage is spatial estimation. The groundwater level and salinity of following month at interesting point (ELSt) was estimated by the Cokriging approach. The Variogram map was plotted to illustrate an influence over distance. The Spherical, Gaussian and Spherical model were used to fit the Variogram map. Finally a cross-validation process were performed to evaluate the results. The results of the MANNG were better than old model 3% and more efficient.

Prasomphan and Mase (2013) illustrated an adaptive artificial neural network model to predict unobserved data. The model used only the interested data and different of observed and nearest surrounding points in x and y directions to train the model. The results were compared to kriging algorithms were most accurate in most cases. The research suggested too much number of neighbors might be caused bias in the training process and time consuming and missing data should places in edge of the region to get rid of the edge effect.

Ma and Fu (2003) succeeded to use self-organizing mapping (SOM) networks to classify 21 soil types. Ma and Fu (2003) remarked the self organizing mapping (SOM) artificial neural networks can be used to classify 9 indexes soil physical properties with a good results.

An unsupervised neural network, self-organizing map (SOM), is apart of a novel hybrid modeling of spatial continuity illustrated by Friedel and Iwashita (2013). This model proposed to estimate spatial relations and uncertainty of unobserved field variables with measured data.

Some main ideas from Jain *et al.* (19*96), th*e ANN applications can apply to pattern classification, clustering/categorization, function approximation, prediction/forecasting, optimization, content-addressable memory and control. For non linear prediction problems, the notable solving networks is feed forward network with two hidden layers combines to supervised learning paradigm and back propagation learning algorithm.

Heaton (2008) represented three rules of thumb in his book to number of neurons in hidden layers. The first is the number of hidden neurons should have between the size of input and output layer. The second is the number of hidden neurons should have 2/3 the size of input neurons plus the size of output neurons. The last is the number of hidden neurons should not more than twice of input neurons.

Previous researches show afford to understanding environmental characteristics but still have a new frontier to study both a new technique and a new parameter to be simulated.

CHAPTER 3
RESEARCH METHODOLOGY

This chapter will provide detail of research methodologies. The first section 3.1 , the IDW and cubic spline concept and workflow will be used in this study are presented. Then section 3.2 shows the proposes method in this study. Finally section 3.3 study area and sampling data will be illustrated. The combination step of this research is depicted in Figure 3.1.

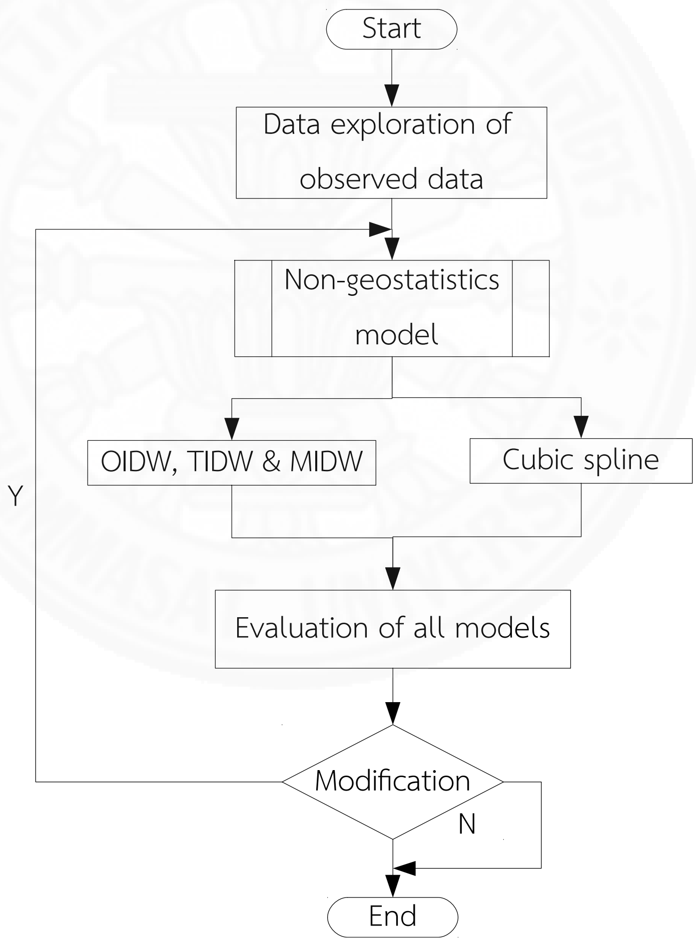


Figure 3.1 The framework overview.

3.1 The Inverse Distance Weighting (IDW)

The IDW in this research have three types Ordinary IDW (OIDW), Tomczak IDW (TIDW) and Modified IDW (MIDW). The OIDW is shown in equation 1.1 and 1.2. Only one parameter is considered. The TIDW is the spatial interpolation processes of the IDW base on Tomczak (1998) that is reviewed and the propose technique, MIDW, will be addressed.

The technique has been proposed by Tomczak (1998) can be divided to two sections, cross-validation and jackknife. The target of cross-validation section is to seek for the best parameters for the model with trial and error concept. An example is for all observed data such as 5 in Figure 3.2. Step 1, all parameter will be set to basic state, power equals 0, anisotropy ratio equals 1, anisotropy angle 0, smoothing parameter equals 0, search radius will be set to 0.5 km. then the estimate value of location 1 will be calculated by the left 2-5 points. Therefore the residual error at location 1 can be calculated by $Z_1 - Z_1^o$, Z_1 is estimated value at location 1, Z_1^o is observed data at point 1 that be removed for estimation. With the same parameters the calculation will carry from point 1 to 5. The RMSE of the calculation can be found and the best RMSE will the data to choose the best parameters for the IDW modelling. After all parameters be found the next section, jackknife, will be run to calculate attribute value and confidence level of unsampled locations. The first step in the jackknife section is calculate pseudo value at point i , Z_i^* as:

$$Z_i^* = n\, Z_{all} - (n-1) Z_{-1}, i = 1,2,\ldots n \tag{3.1}$$

Where Z_{all} is estimated value of point j by using all observed points. Z_{-1} is estimated value of point j by using n-1 observed points and the removed data point is point i . An example at Figure 3.2, if five data points are observed and the estimating location is triangle point.

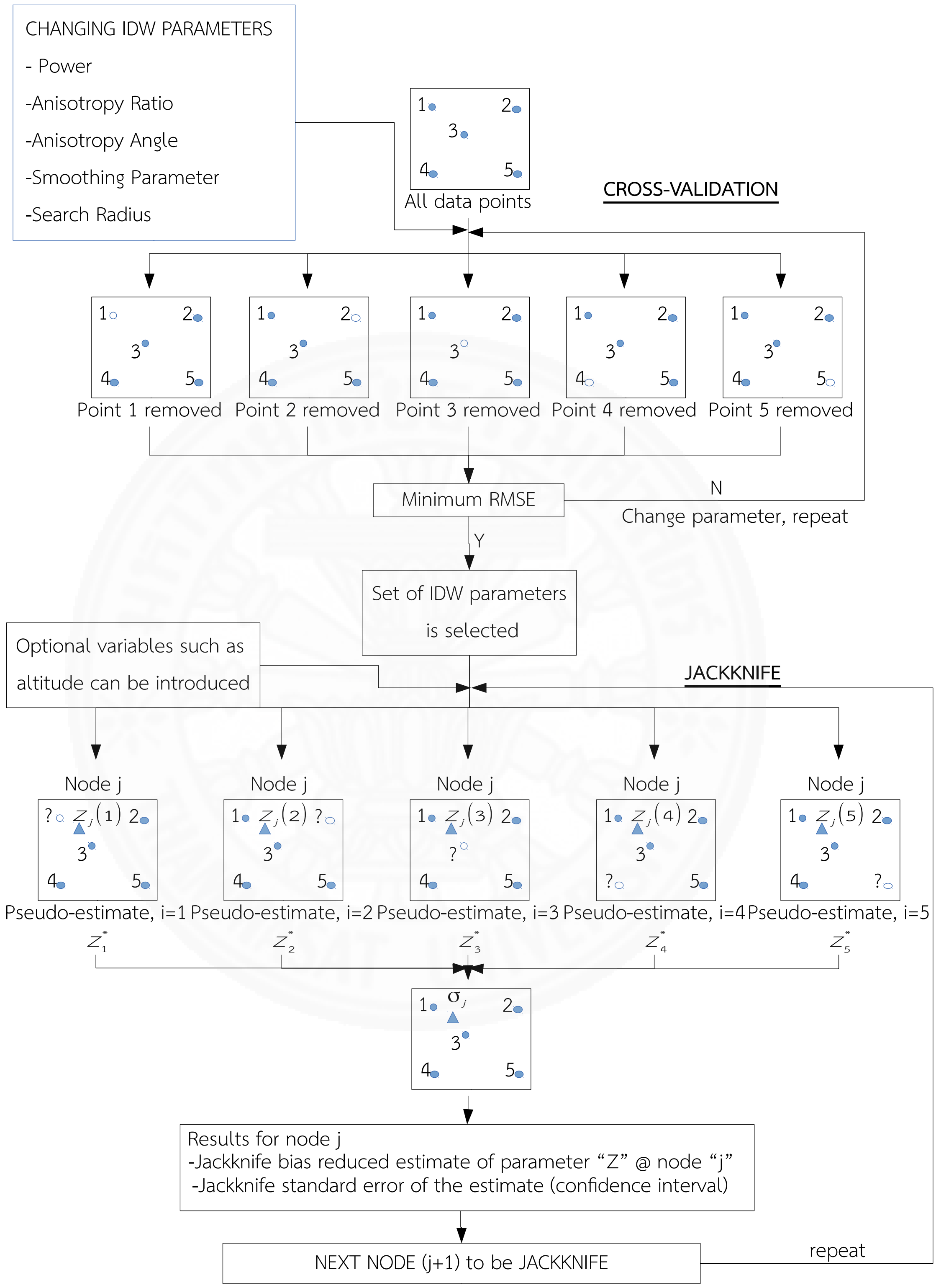


Figure 3.2 The schematic flow diagram of cross-validation and jackknife

$$Z_1^* = 5 * Z_{all} - 4 * Z_{-1},\ i = 1 \tag{3.2}$$

$$Z_2^* = 5 * Z_{all} - 4 * Z_{-1}, i = 2$$

$$Z_3^* = 5 * Z_{all} - 4 * Z_{-1}, i = 3$$

$$Z_4^* = 5 * Z_{all} - 4 * Z_{-1}, i = 4$$

$$Z_5^* = 5 * Z_{all} - 4 * Z_{-1}, i = 5$$

where Z_{-1} of i equls 1 is estimated value at point j without observed value at point i . Z_{-1} of i equls 2 is estimated value at point j without observed value at point 2 etc. Therefore the jackknife spatial interpolation of point j is

$$Z_j = \frac{\sum_{i=1}^{n} Z_i^*}{n} \tag{3.3}$$

Then the value of σ_j will calculate by

$$\sigma_j = \sqrt{\frac{1}{n(n-1)} \sum_{i=1}^{n} (Z_i^* - Z_j)^2} = \sqrt{\frac{n-1}{n} [\sum_{i=1}^{n} (Z_i^*)^2 - \frac{1}{n} \sum_{i=1}^{n} (Z_i^*)^2]} \tag{3.4}$$

The proposes model has two parts, can be depicted on Figure 3.3. The first part is the random technique, the same set of data will be random at ten times then each times will be divided to training data set, 75% and testing data set, 25%. The training data set use in parameters searching step. The testing data set uses to test the selected parameters. The second part is modification of TIDW. The anisotropy calculation will be modified by geometry parameter. The geometry parameter is illustrated in Figure 3.4 and .

$$\eta = |(dN/dN')| \tag{3.4}$$

Where η is the geometry parameter of point 1. dN is distance from x or E axis and dN' is distance of point 1 from rotated axis x' or E'. The geometry parameter will apply at distance calculation as shows below.

The transform coordinate equation 1.4 be rewrite here

$$d'_{ij} = \sqrt{A_{xx} * \Delta x^2 + A_{xy} * \Delta x * \Delta y + A_{yy} * \Delta y^2} \tag{3.5}$$

With matrix form

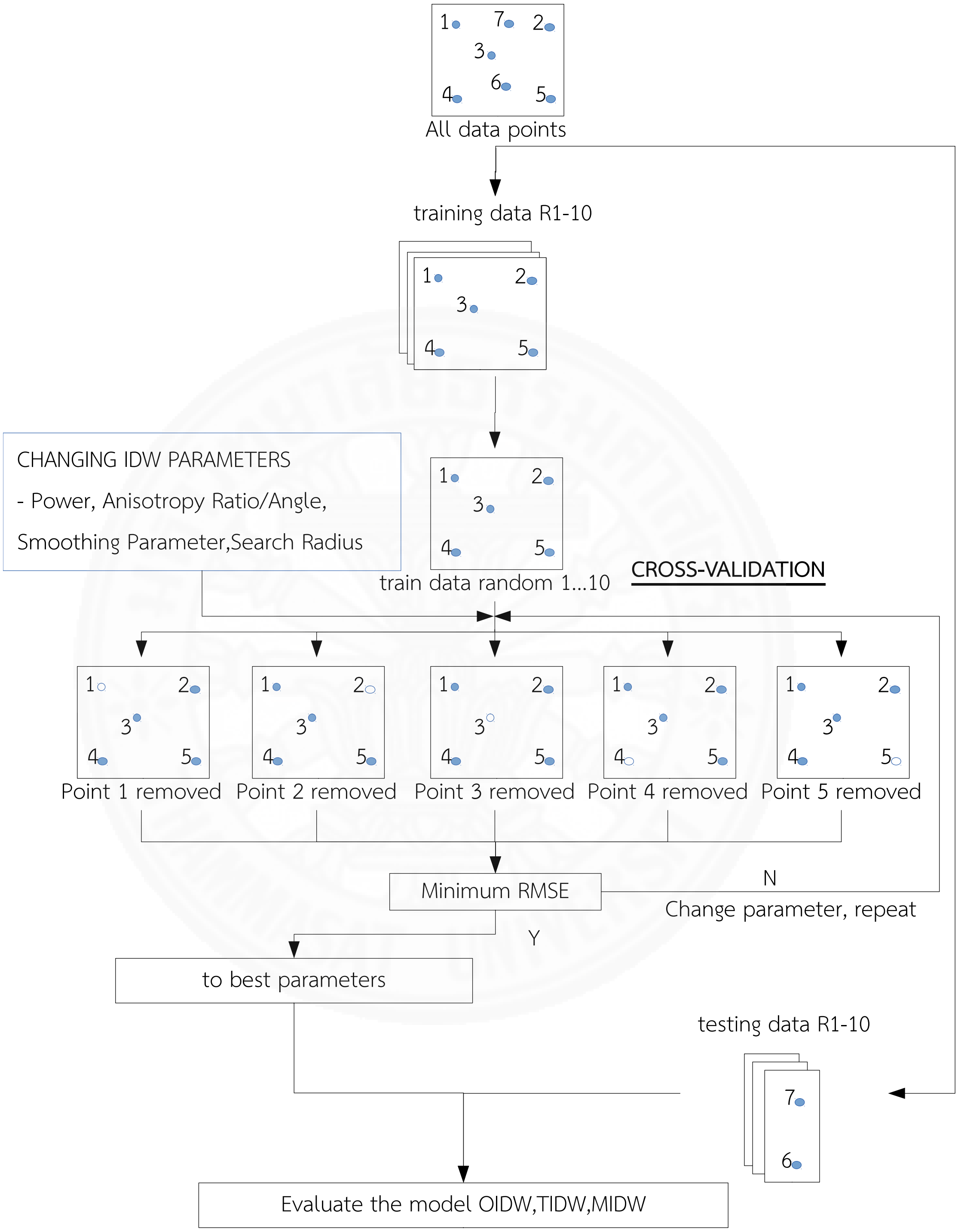


Figure 3.3 The random technique.

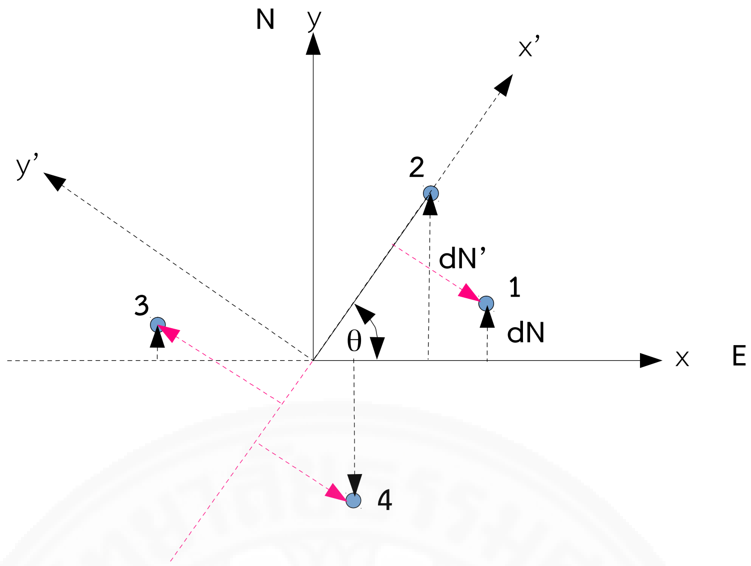


Figure 3.4 The random technique.

$$d'_{ij} = \sqrt{\left(\frac{-\sin(\theta)\Delta E}{\rho} + \cos(\theta)\Delta N\right)^2 + \left(\frac{\cos(\theta)\Delta E}{\rho} + \sin(\theta)\Delta N\right)^2} \quad (3.6)$$

With the geometry parameter

$$d'_{ij} = \sqrt{\left(\frac{\left[\frac{-\sin(\theta)\Delta E}{\rho} + \cos(\theta)\Delta N\right]}{\eta}\right)^2 + \left(\frac{\cos(\theta)\Delta E}{\rho} + \sin(\theta)\Delta N\right)^2} \quad (3.7)$$

The MIDW model will use distance equation 3.7 and the cubic spline to simulate undrained shear strength.

CHAPTER 4
RESULTS AND DISCUSSION

This chapter will show results by step of methodology from data exploration to spatial interpolation.

4.1 Data Exploration

The study area of this research is the Bangkok province, Thailand. It has 1,568.737 square kilometers covering by coordinates (1491347, 643245) and (1543301, 709475)(N, E) with about 6 million people (Strategy and Evaluation Department Bangkok Metropolitan Administration, 2012). The general Bangkok's soil layers by was described by Muktabhant et. al. (1967) (cited in Suwanwiwattana et. al., 2001) the first layer, 1-2 meters, is top soil or weathered clay with high shear strength and low water content property. The second layer, 2-12 meters, is soft clay composed of soft dark gray and medium gray clay with low shear strength and high compressibility. The third layer, 12-20 meters, is stiff clay. The last layer, 20-25 meters, is sand and gravel layer (Figure 2.1).

This research used boring data from 74 sites that have 164 soil bore holes around Bangkok. The 3911 soil sampling were tested. Figure 1.1 shows the location of 164 boring data on the Bangkok base map.

The coordinate of each boring is found by Google Earth then CSV format of the coordinates are imported to GRASS. The soil bore holes scatter around the region as in Figure 4.1. The depths of the soil bore holes are vary from 21 to 79.775 meters.

The distance between bore holes of the same site very closely compares from site to site. Figure 4.2 shows a frequency plot of distance of bore holes to bore holes. Table 4.1 displays a relevant information to Figure 4.2 with some statistic data below the table. The frequency plot in Figure 4.2 has 35 classes with 1 km range. The shape is not normal distribution with 0.653 skewness. The median of data is 14,941 meters.

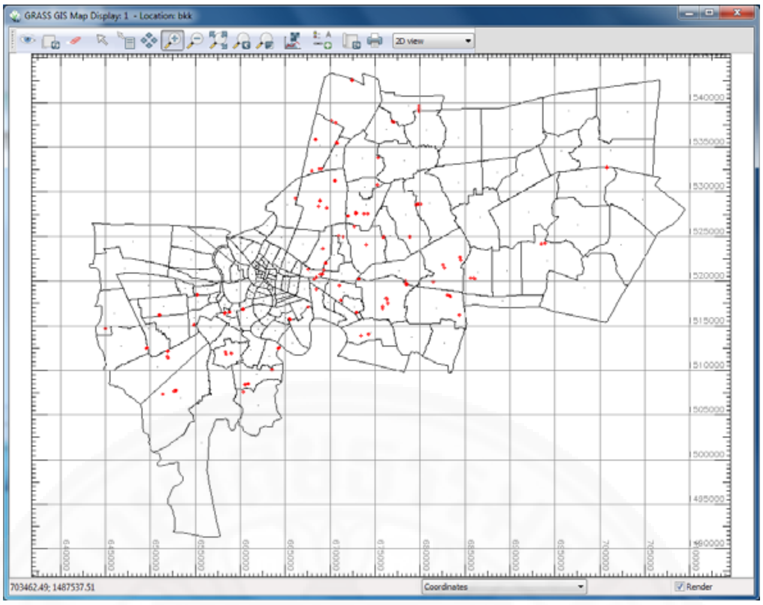


Figure 4.1 The 164 soil bore holes location in the Bangkok map

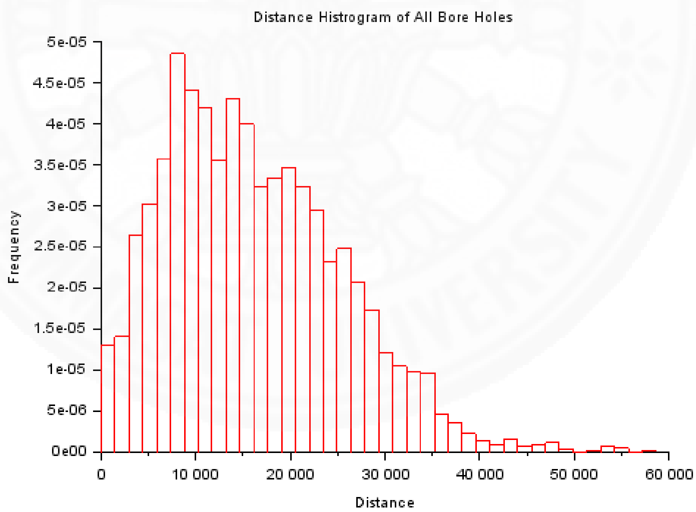


Figure 4.2 Frequency plot of distance of a selected sample bore hole to other bore holes

The standard penetration test (N) and undrained shear strength (S_u) are plotted in Figure 4.3. The most of S_u are in the range 2-19 meters depth and the most of N starts from depth 19 meters until end of boring. The values 120 of N are the replacement to the filed data reported by numbers per inch.

Table 4.1 Tabular information of the frequency plot in Figure 4.2

class	LowBound	UppBound	Class Mark	Freq.	RelFreq.	CumFreq.	RelCumFreq.
1	0	1500	750	230	0.0192743	230	0.0192743
2	1500	3000	2250	258	0.0216207	488	0.040895
3	3000	4500	3750	482	0.0403922	970	0.0812872
4	4500	6000	5250	551	0.0461745	1521	0.127462
5	6000	7500	6750	685	0.0574038	2206	0.184865
6	7500	9000	8250	859	0.0719853	3065	0.256851
7	9000	10500	9750	772	0.0646945	3837	0.321545
8	10500	12000	11250	756	0.0633537	4593	0.384899
9	12000	13500	12750	637	0.0533814	5230	0.43828
10	13500	15000	14250	771	0.0646107	6001	0.502891
11	15000	16500	15750	651	0.0545546	6652	0.557446
12	16500	18000	17250	590	0.0494427	7242	0.606888
13	18000	19500	18750	608	0.0509511	7850	0.65784
14	19500	21000	20250	560	0.0469287	8410	0.704768
15	21000	22500	21750	608	0.0509511	9018	0.755719
16	22500	24000	23250	478	0.040057	9496	0.795776
17	24000	25500	24750	445	0.0372915	9941	0.833068
18	25500	27000	26250	402	0.0336881	10343	0.866756
19	27000	28500	27750	362	0.030336	10705	0.897092
20	28500	30000	29250	278	0.0232967	10983	0.920389
21	30000	31500	30750	169	0.0141624	11152	0.934551
22	31500	33000	32250	209	0.0175145	11361	0.952066
23	33000	34500	33750	161	0.013492	11522	0.965558
24	34500	36000	35250	123	0.0103076	11645	0.975865
25	36000	37500	36750	91	0.00762591	11736	0.983491
26	37500	39000	38250	27	0.00226263	11763	0.985754
27	39000	40500	39750	42	0.00351965	11805	0.989273
28	40500	42000	41250	19	0.00159222	11824	0.990866
29	42000	43500	42750	15	0.00125702	11839	0.992123
30	43500	45000	44250	18	0.00150842	11857	0.993631
31	45000	46500	45750	18	0.00150842	11875	0.99514
32	46500	48000	47250	26	0.00217883	11901	0.997318
33	48000	49500	48750	5	0.000419006	11906	0.997737
34	49500	51000	50250	1	8.38012e-05	11907	0.997821
35	51000	52500	51750	2	0.000167602	11909	0.997989
36	52500	54000	53250	10	0.000838012	11919	0.998827
37	54000	55500	54750	10	0.000838012	11929	0.999665
38	55500	57000	56250	2	0.000167602	11931	0.999832
39	57000	58500	57750	0	0	11931	0.999832
40	58500	60000	59250	2	0.000167602	11933	1

mediam = 14941 :quart=8.87e+03 :inter quatile= 1.35e+04 :variance= 8.6e+07: skewness= 0.653

This research will consider only S_u within the depth 30 meters because number of sample data beyond 30 meters have not many and the selected depth is enough for small construction. In addition at the depth 18.25 meters is enough to cover the transition layer from clay to sand. Figure 4.4 shows S_u within 18.25 meters depth.

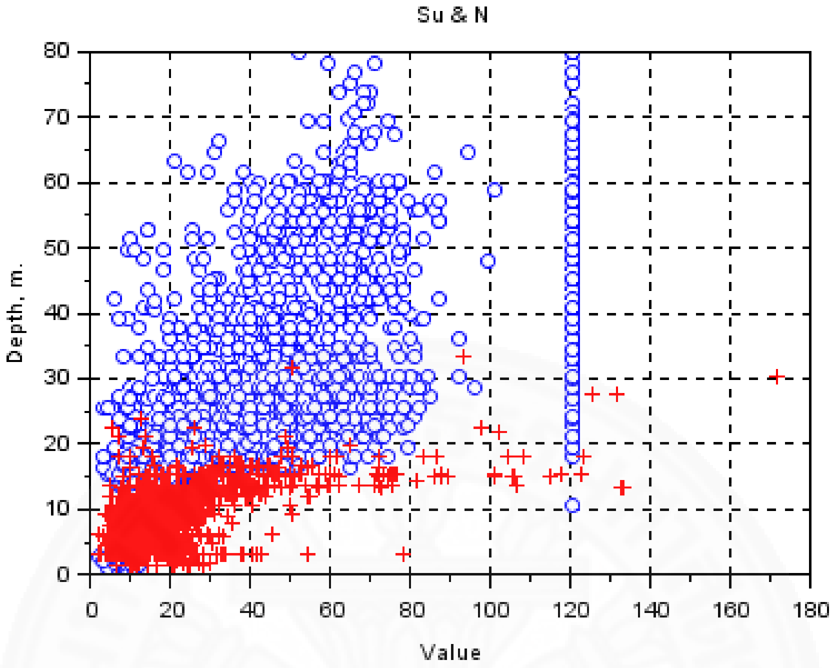


Figure 4.3 The standard penetration number (N) and undrained shear strength (S_u) with depth

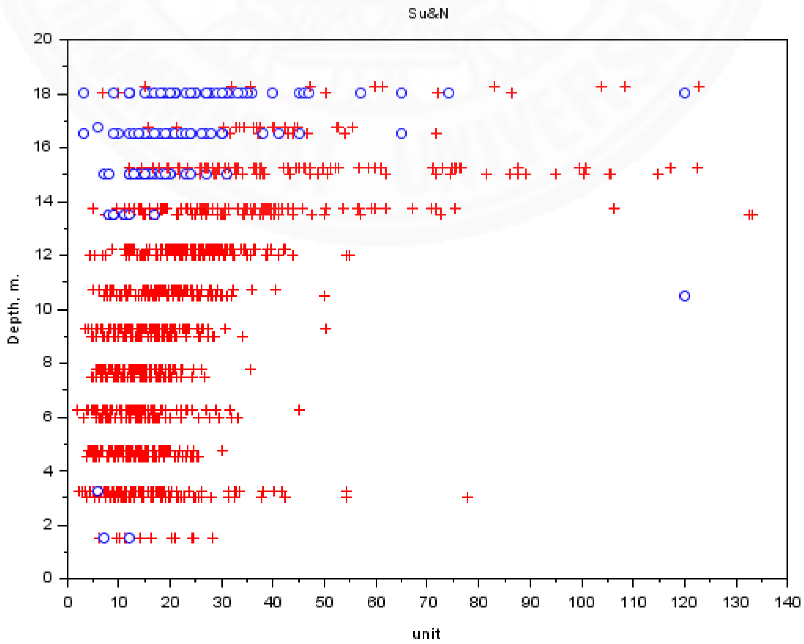


Figure 4.4 S_u and N with 18.25 meters depth

The S_u values surrounded by N values might show a bulb of different soil type. Figure 4.5 shows an example of soil profile that drew by a civil engineer. The soil strength of each layers is separated by S_u and N. Soil types are assigned by soil classification method. A bulb of different soil type can occur such as BH-2 at 8-9 meters depth. The undrained shear strength plots of each layer are shown in Figure 4.6-4.8.

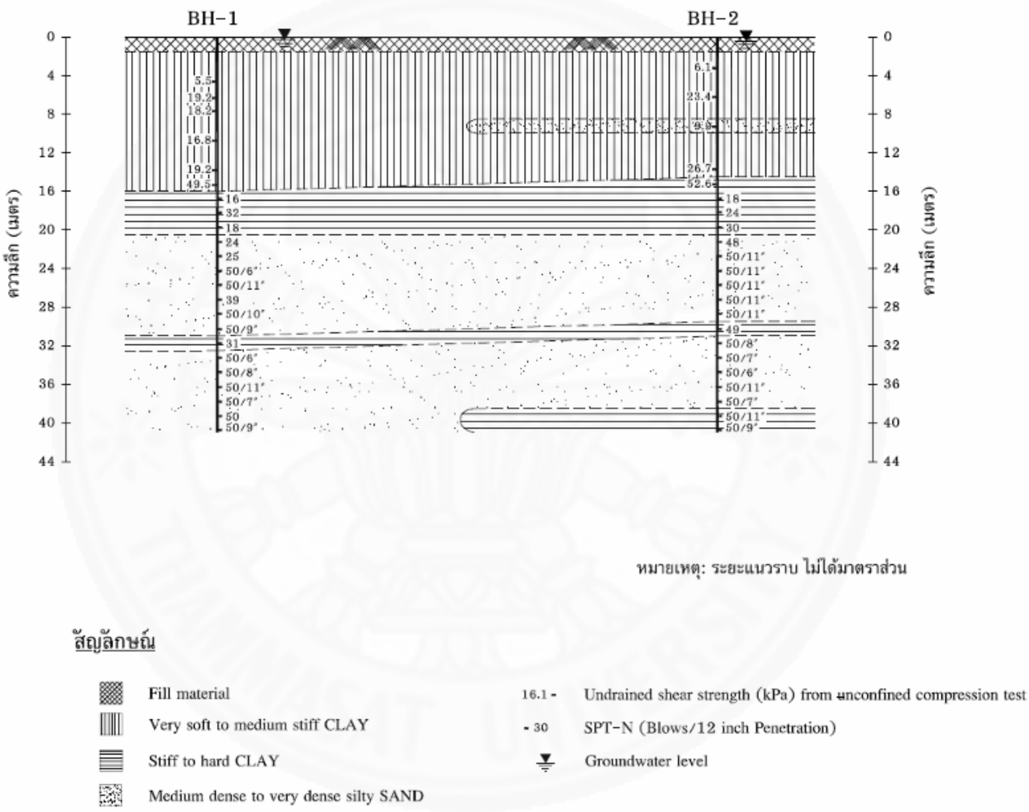


Figure 4.5 An example of soil profile

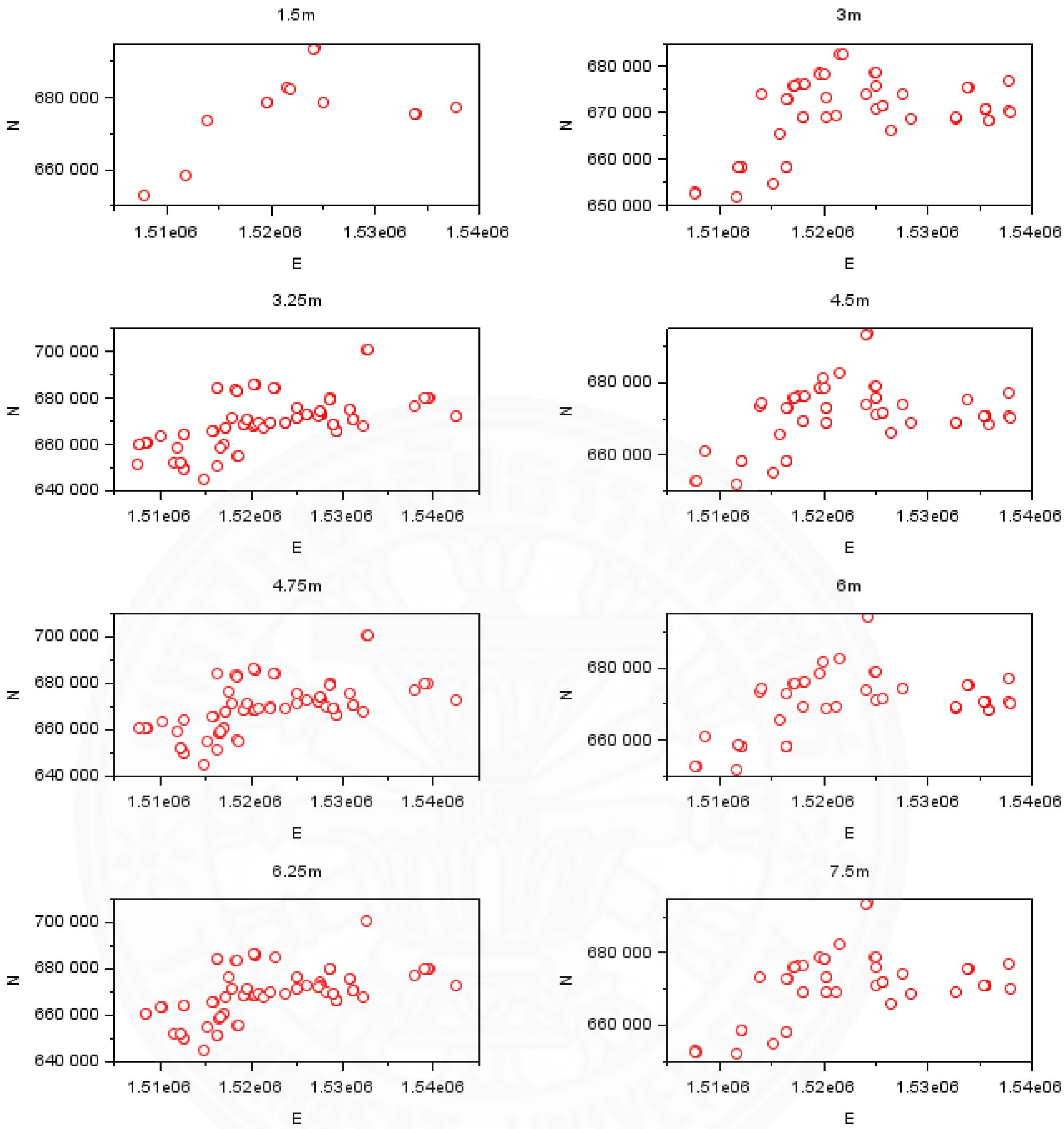


Figure 4.6 The undrained shear strength plots 1.5-7.5 m. depth

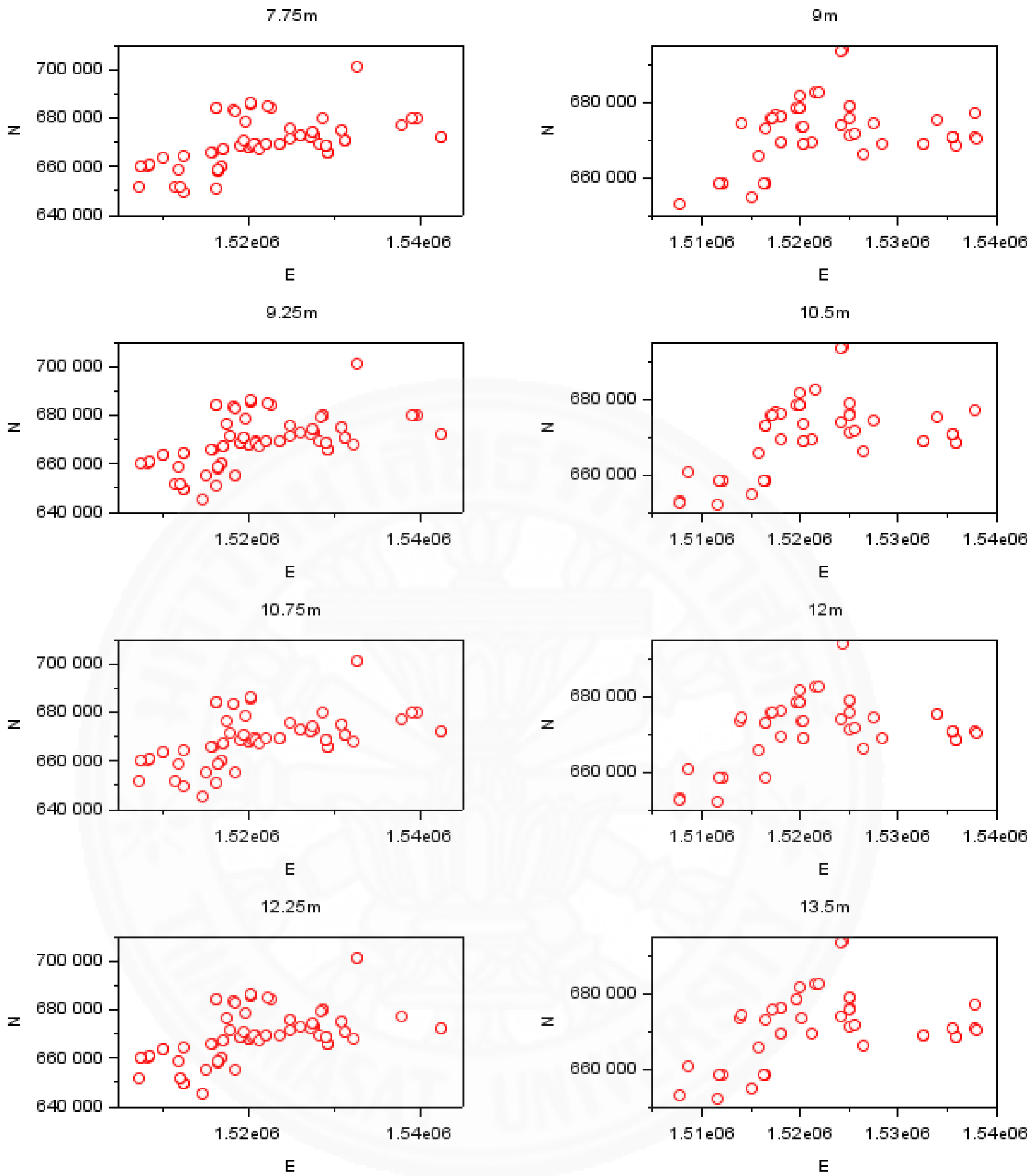


Figure 4.7 The undrained shear strength plots 7.75-13.5 m. depth

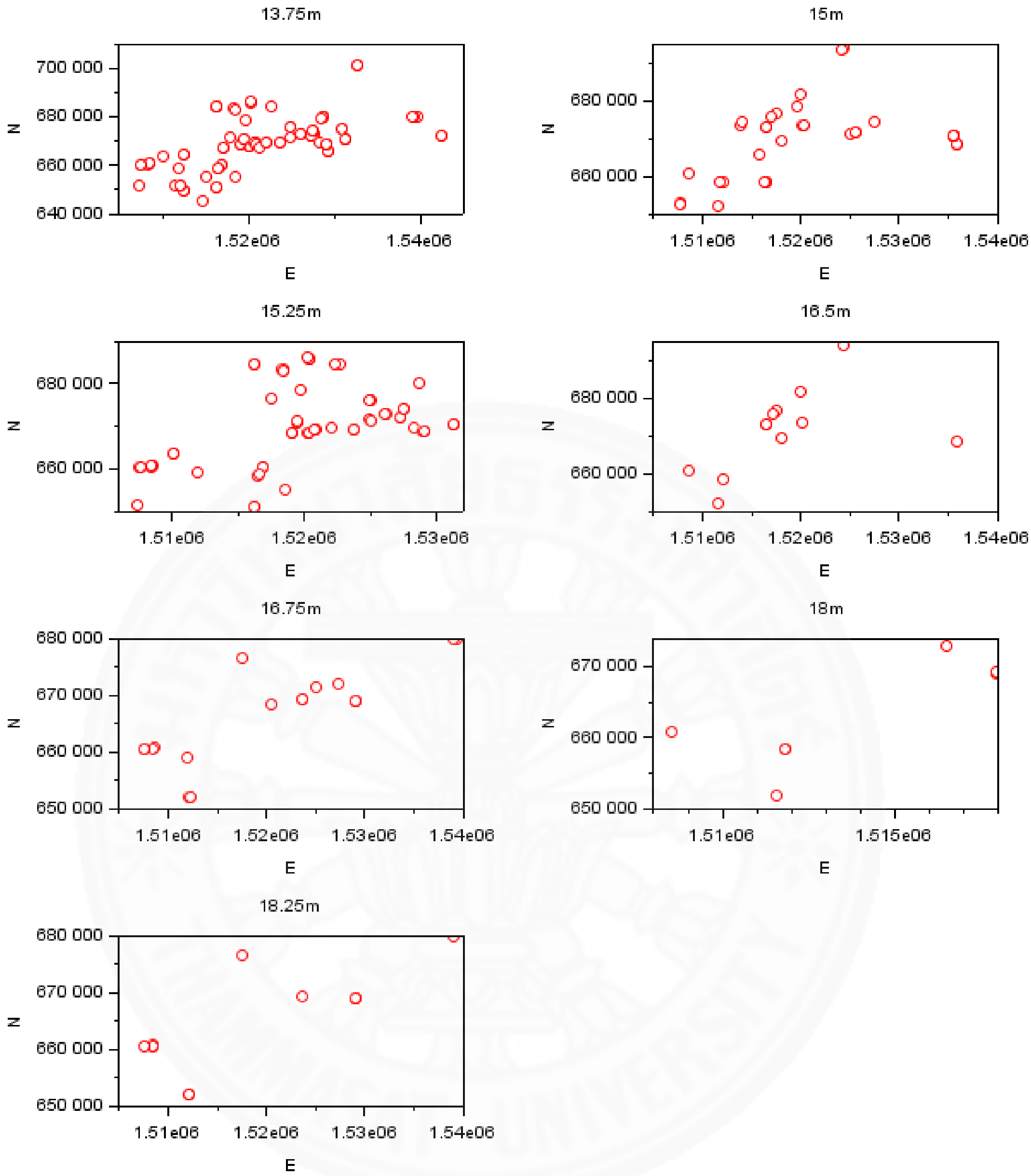


Figure 4.8 The undrained shear strength plots 13.75-18.25 m. depth

Table 4.2 Number of undrained shear strength per depth

Number	Depth, m.	Su, kPa
1	1.5	13
2	3	52
3	3.25	86
4	4.5	56
5	4.75	78
6	6	45
7	6.25	79
8	7.5	47
9	7.75	74
10	9	54
11	9.25	87
12	10.5	49
13	10.75	77
14	12	49
15	12.25	84
16	13.5	43
17	13.75	85
18	15	34
19	15.25	57
20	16.5	12
21	16.75	18
22	18	7
23	18.25	12

4.2 The Inverse Distance Weight

4.2.1 Cross Validation Step

The OIDW is original IDW that has only power parameter incorporated in the mathematic model. The power parameter will be tried by user to find the best fit to the model. The evaluation process uses the lowest RMSE to decide the best parameters. In this research the searching parameter step or cross validation step of Tomczak (1998) will be applied to find power parameter of the OIDW. The cross validation step will be run with the 1st random data of 23 layers. The RMSE plot versus power are plot in Figure 4.9–4.12. Figure 4.9 is plot of layer 1-6 with depth 1 -6 meters. Figure 4.10 is plot of layer 7-12 with depth 6.25-10.5 meters. Figure 4.11 is plotted of layer 13-18 with depth 10.75 -15 meters. Figure 4.12 is plotted of layer 19-23 with depth 15-25-18.25 meters and plotted all together. The selected parameters at minimum RMSE are shown in Table 4.3. Most of the power parameter is 1 because the RMSE increases when power increase as layer 2, 3 meters depth. Only some of the power parameter more than 1 such as layer 1, 10, 16 and 19. The selected power parameter are used to calculate the anisotropy ratio. The RMSE changes when the anisotropy ratio change. The plotted results are illustrated in Figures 4.13-4.16 and the selected anisotropy ratio of each depth shown in Table 4.3.

For the anisotropy angle, Tomczak (1998) mathematic model has not affect to this parameter when the angle change. Therefore the line of graph shows parallel line of all layer as shows in Figure 4.17.

With the MIDW the anisotropy angle takes effect to the model. Figure 18-21 shows the anisotropy angle cross-validation plotted of each layer.

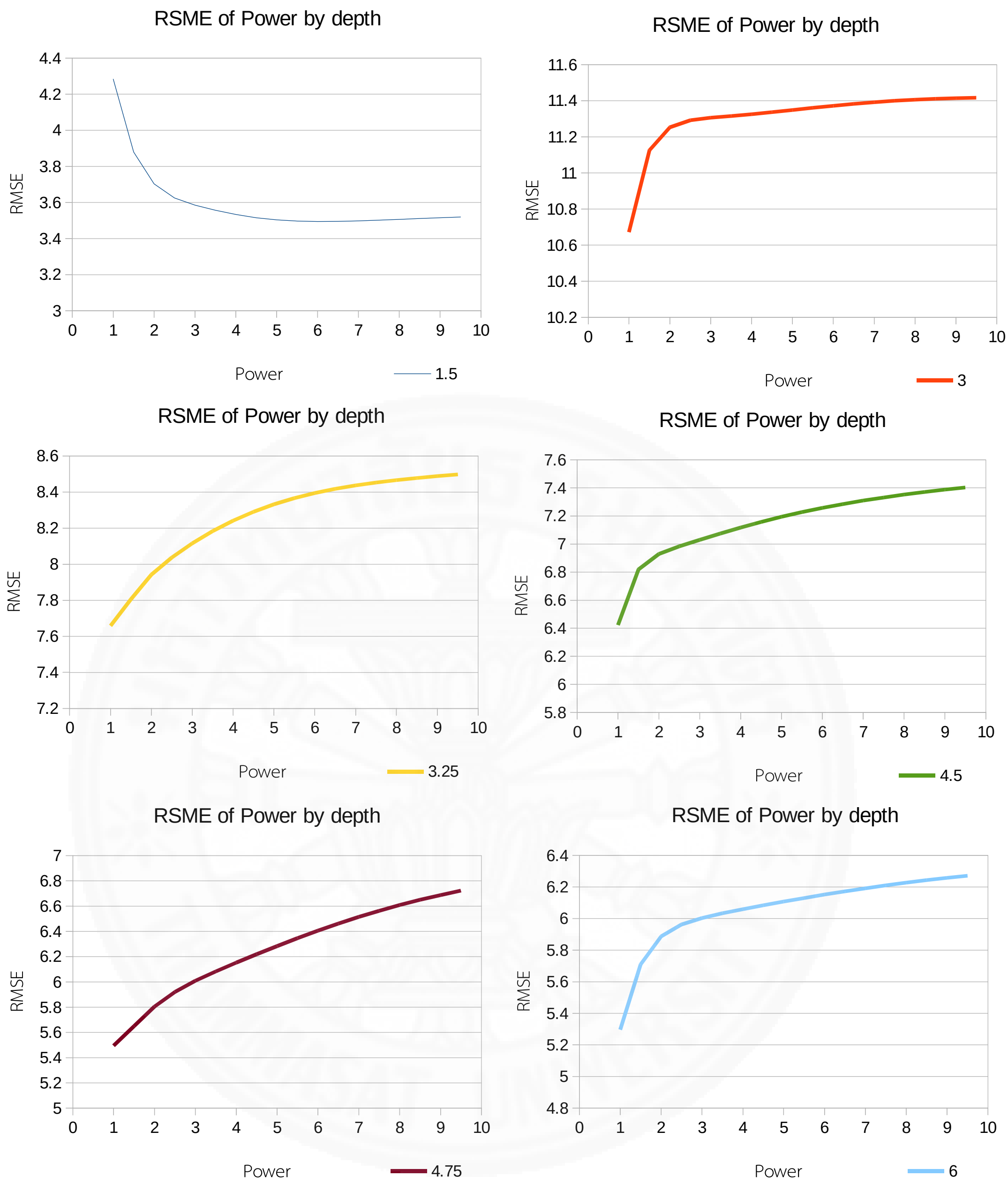


Figure 4.9 The power cross validation results of 1st random data at 1.5-6 m depth.

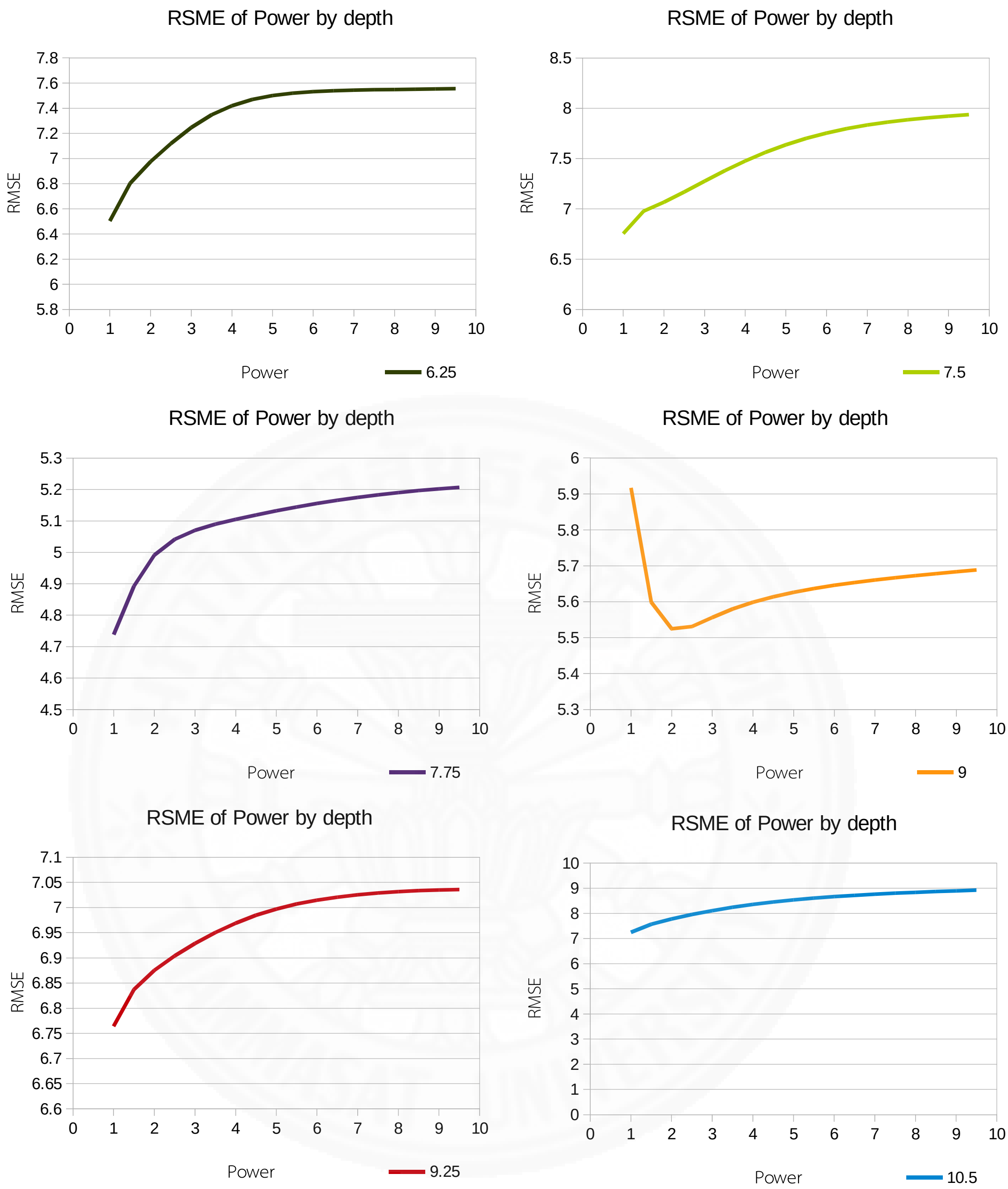


Figure 4.10 The power cross validation results of 1st random data at 6.25-10.5 m depth.

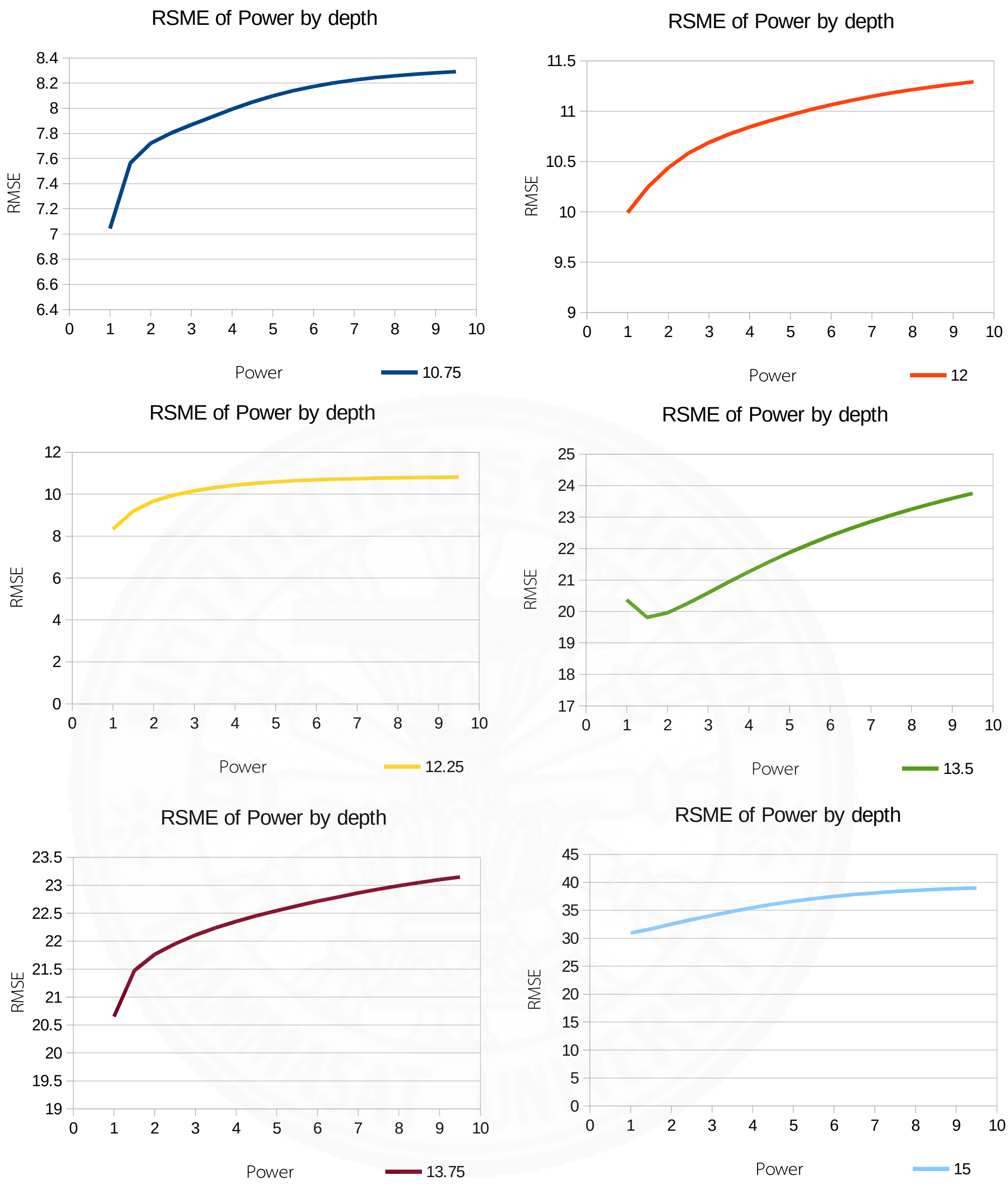


Figure 4.11 The power cross validation results of 1st random data at 6.25-10.5 m depth.

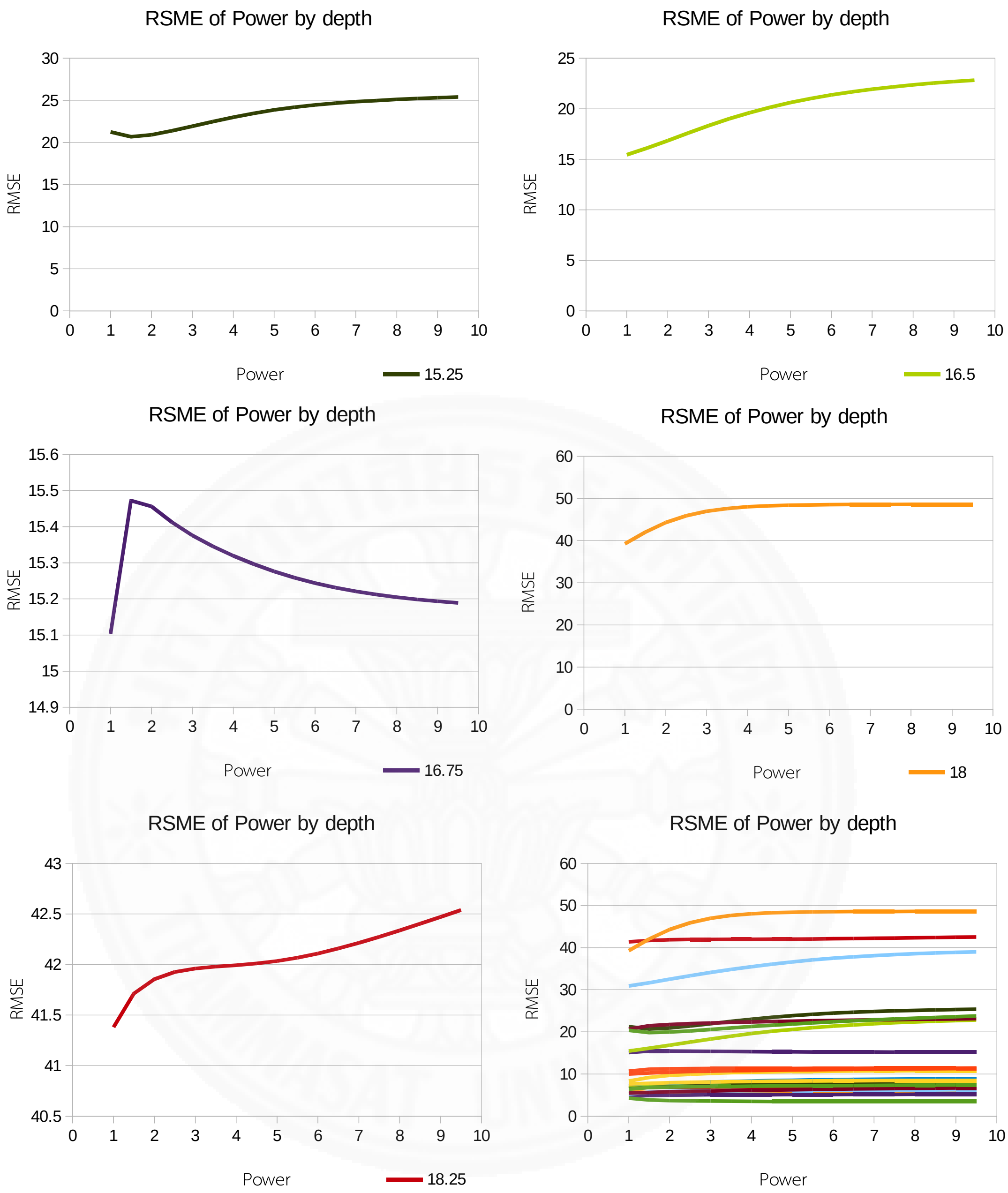


Figure 4.12 The power cross validation results of 1^{st} random data at 1525-18.25 m depth.

Table 4.3 The selected parameters at minimum RMSE of 1st random.

Layers	Depth, m.	Parameters at 1st random			
		Power	AR	AA	AA
		O&T-IDW	TIDW	TIDW	MIDW
1	1.5	6	1.5	0	140
2	3	1	2	0	10
3	3.25	1	1	0	90
4	4.5	1	10	0	0
5	4.75	1	1	0	40
6	6	1	1	0	50
7	6.25	1	1	0	90
8	7.5	1	1	0	60
9	7.75	1	1	0	70
10	9	2	1	0	90
11	9.25	1	10	0	10
12	10.5	1	1	0	60
13	10.75	1	1	0	110
14	12	1	1	0	60
15	12.25	1	10	0	0
16	13.5	1.5	1	0	110
17	13.75	1	10	0	0
18	15	1	2.5	0	170
19	15.25	1.5	3.5	0	170
20	16.5	1	1	0	80
21	16.75	1	10	0	0
22	18	1	1	0	60
23	18.25	1	1.5	0	60

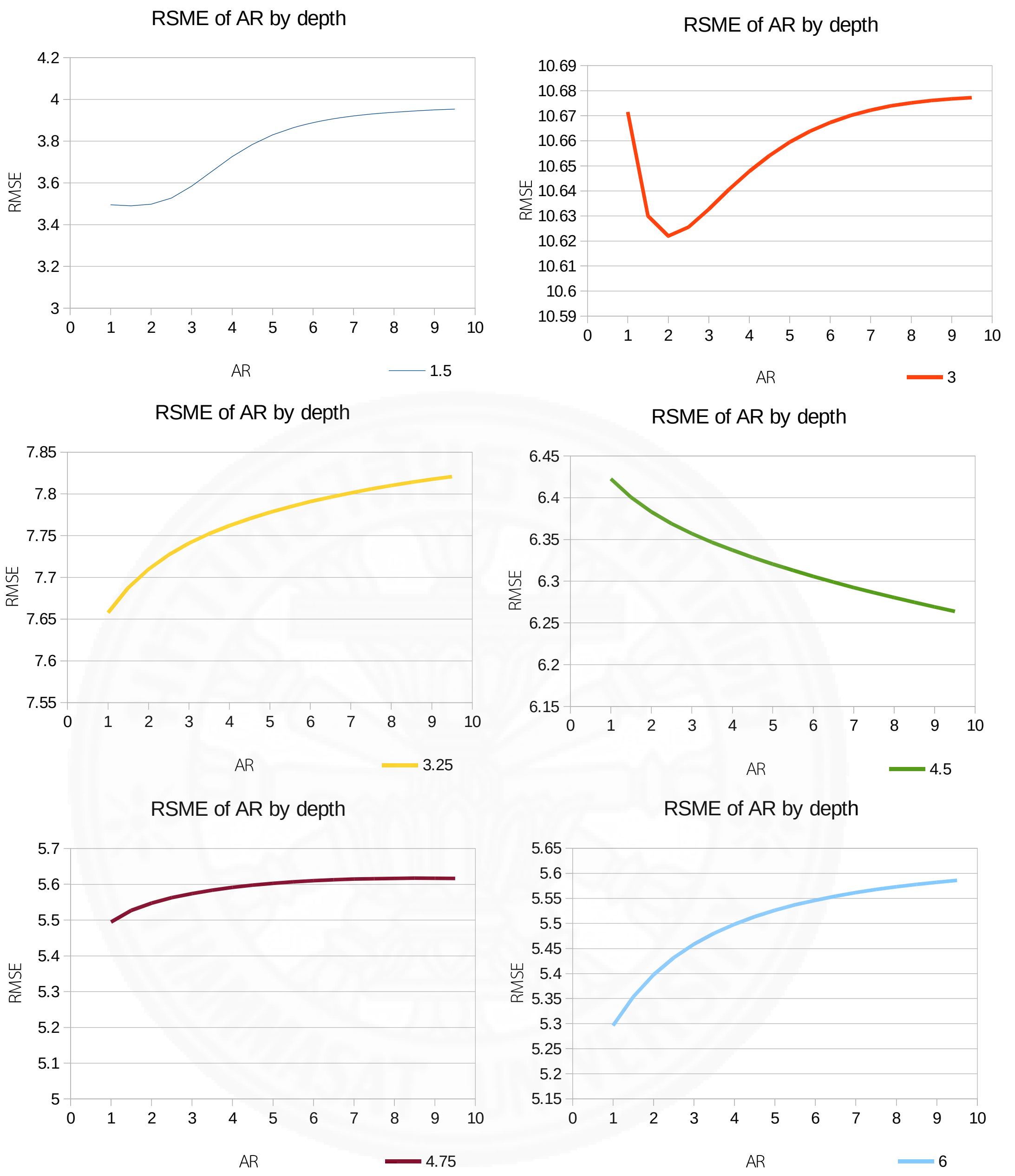


Figure 4.13 The anisotropy ratio cross validation results of 1st random data at 1.5-6 m depth.

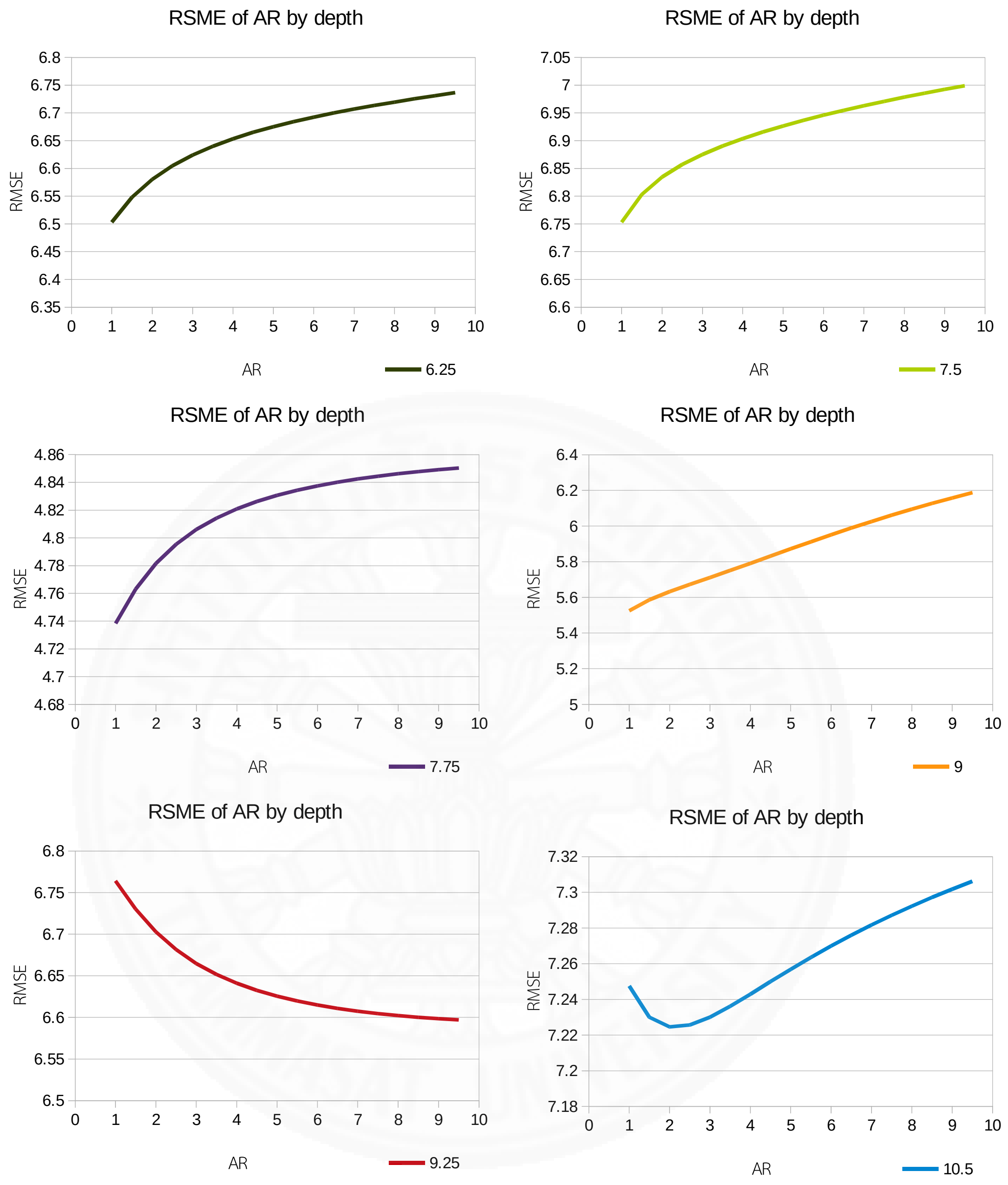


Figure 4.14 The anisotropy ratio cross validation results of 1st random data at 6.25-10.5 m depth.

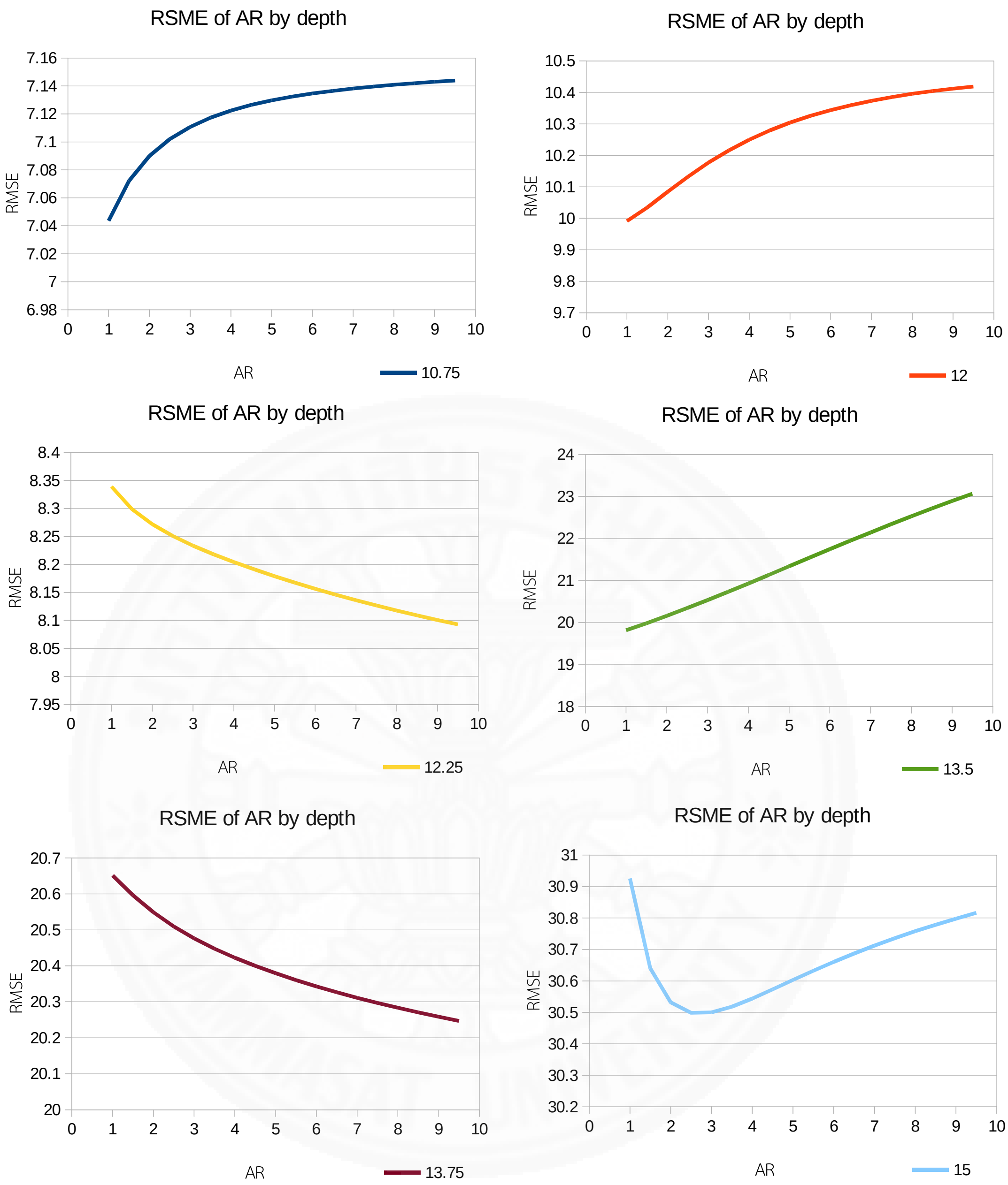


Figure 4.15 The anisotropy ratio cross validation results of 1st random data at 10.75-15 m depth.

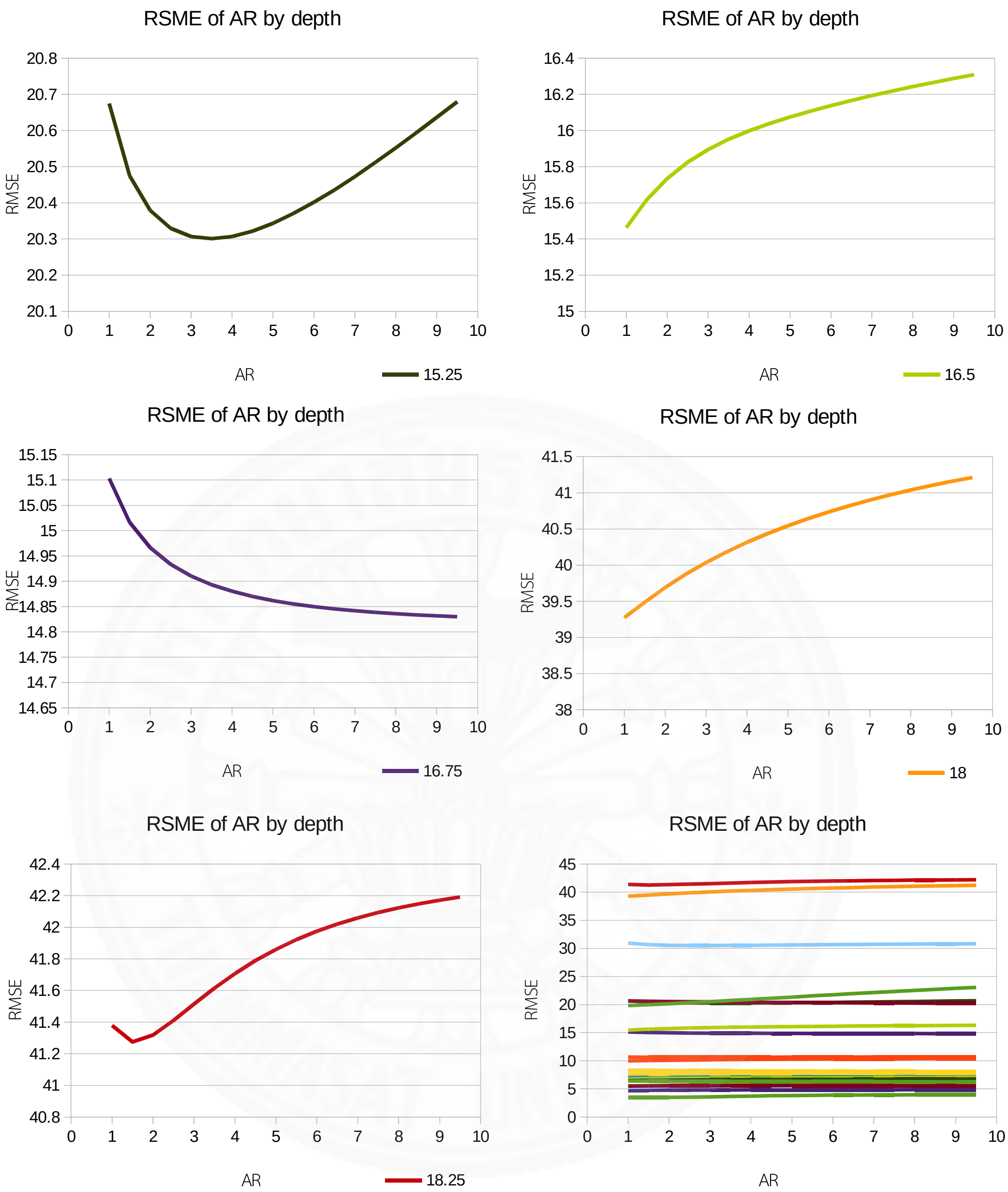


Figure 4.16 The anisotropy ratio cross validation results of 1st random data at 15.25-18.5 m depth.

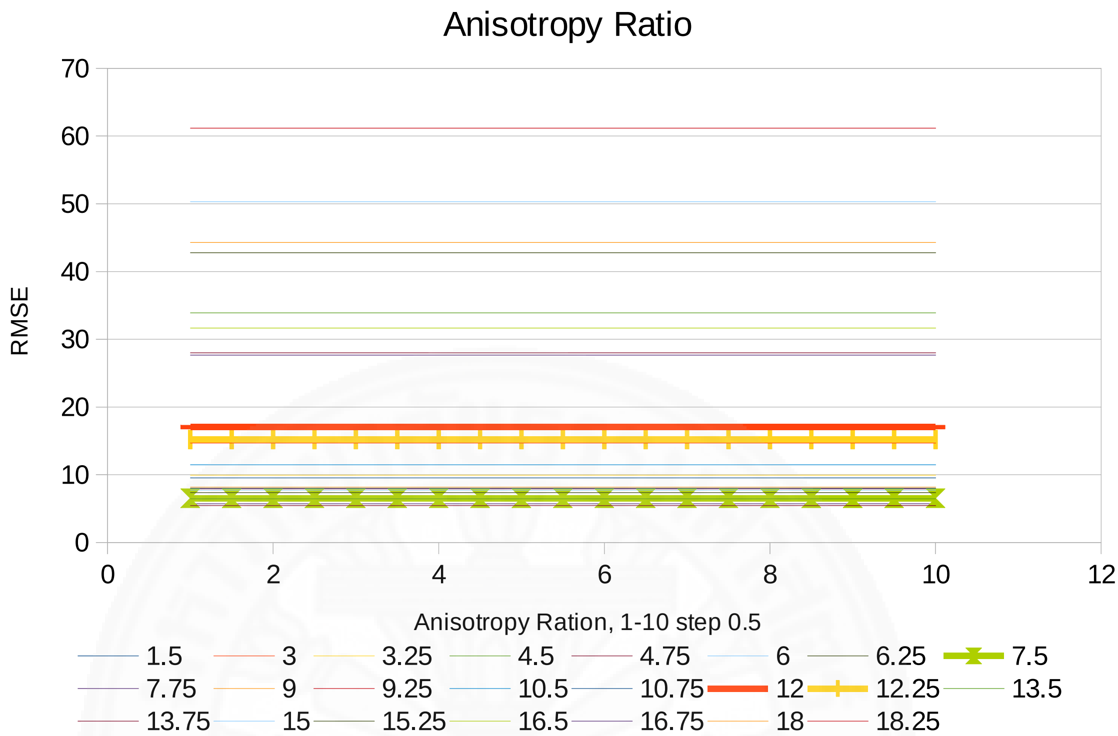


Figure 4.17 the anisotropy angle of cross-validation plot for each depth.

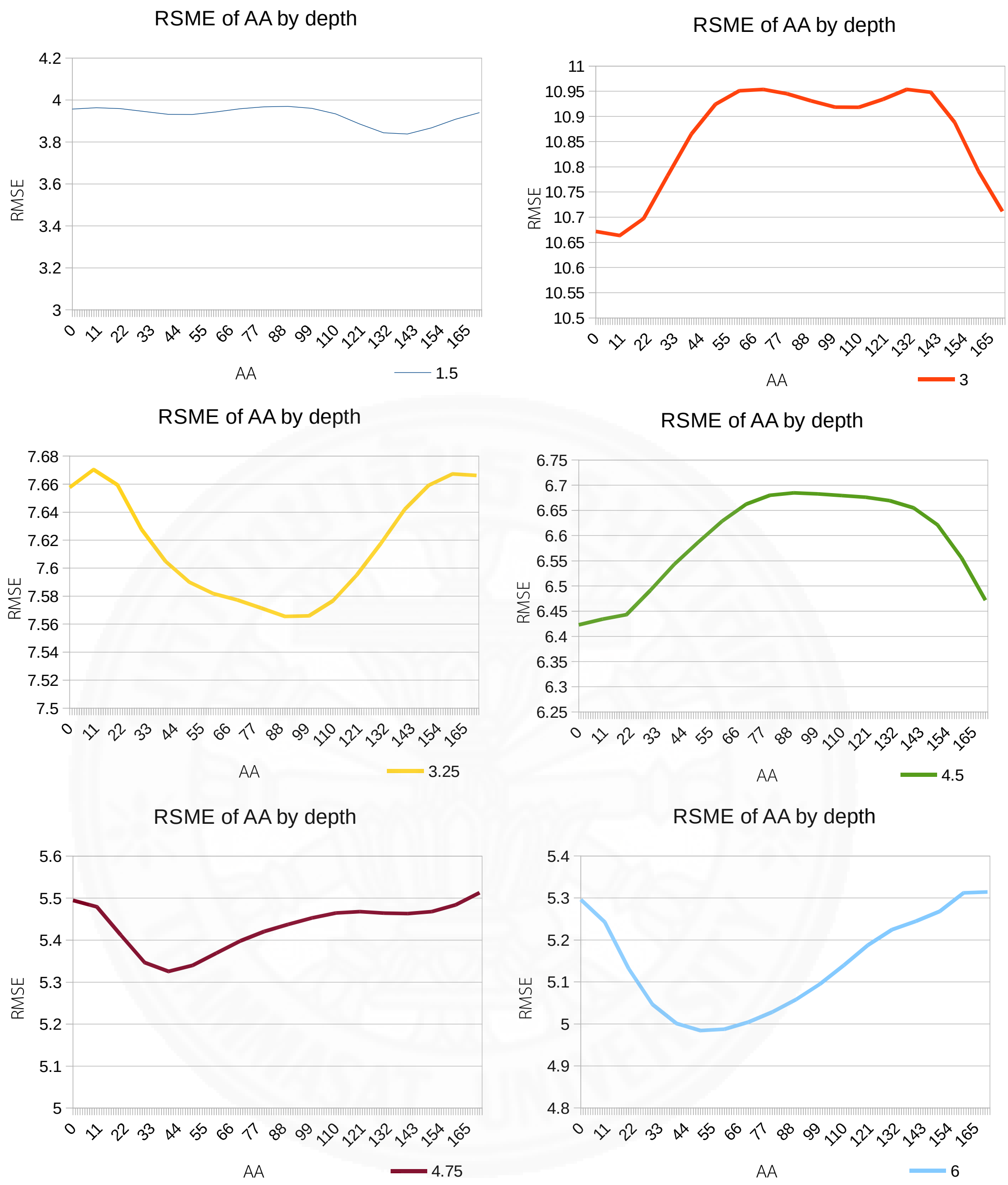


Figure 4.18 The anisotropy angle cross validation results of 1st random data at 1.5-6 m depth.

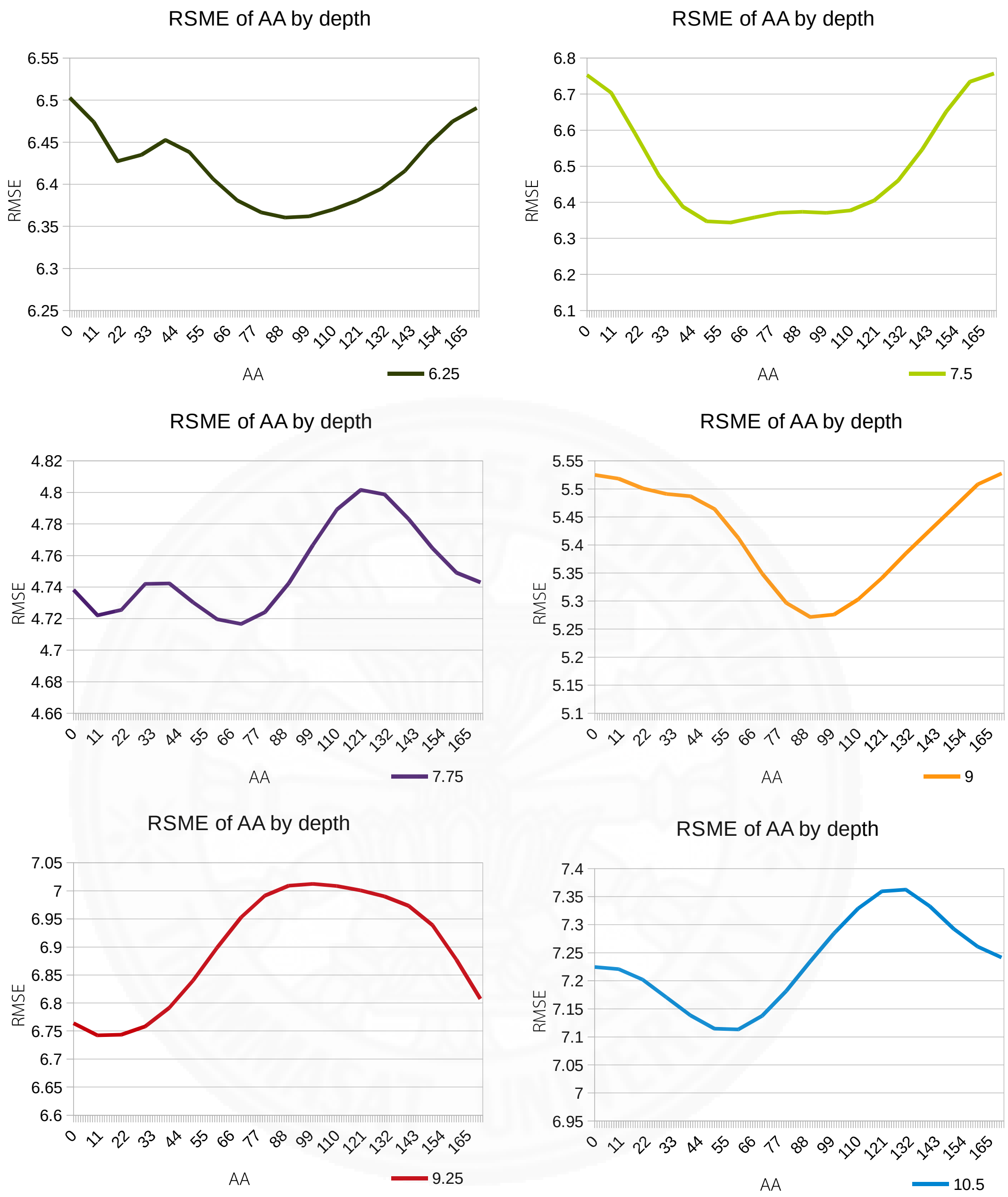


Figure 4.19 The anisotropy angle cross validation results of 1st random data at 6.25-10.5 m depth.

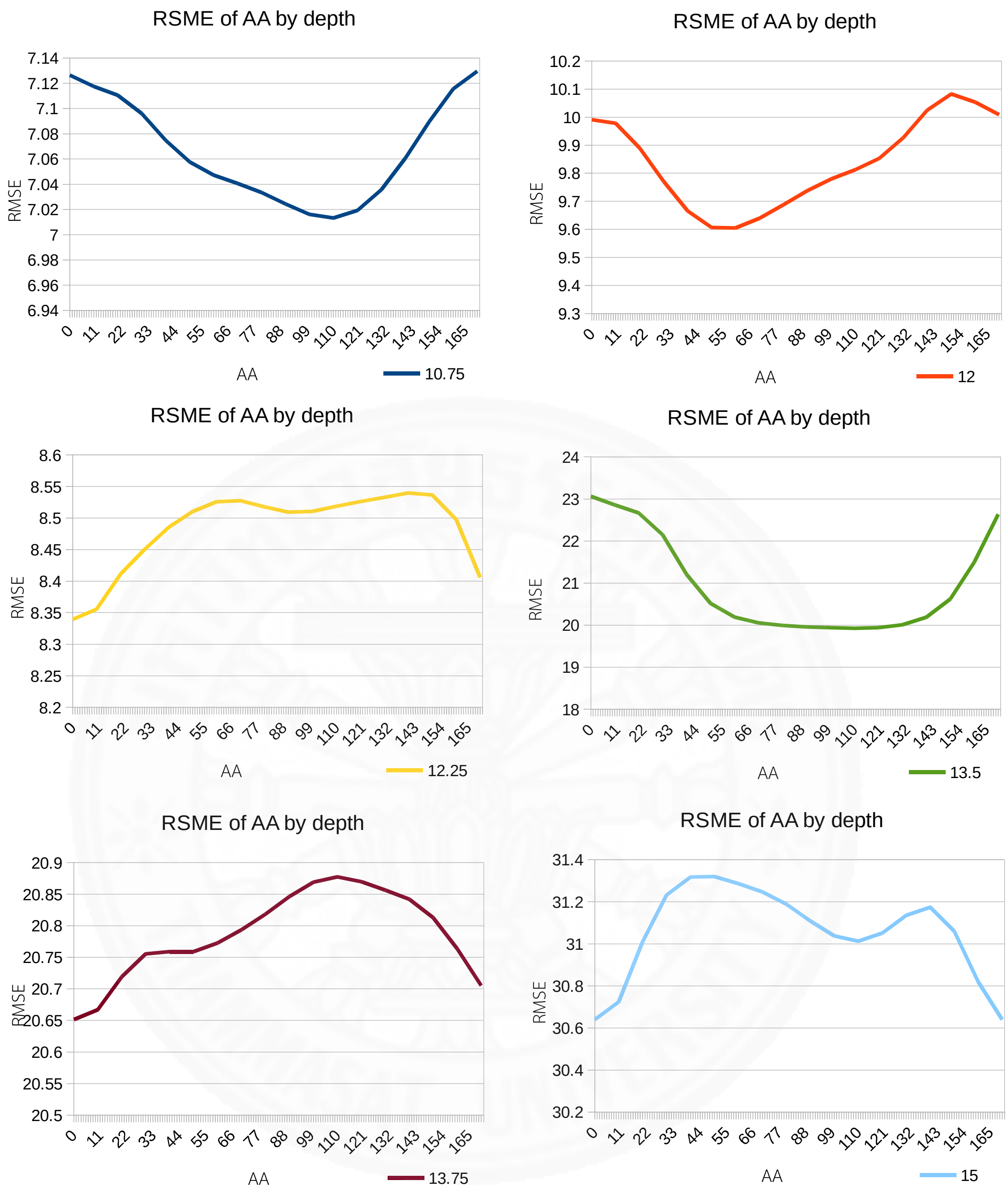


Figure 4.20 The anisotropy angle cross validation results of 1st random data at 10.75-15 m depth.

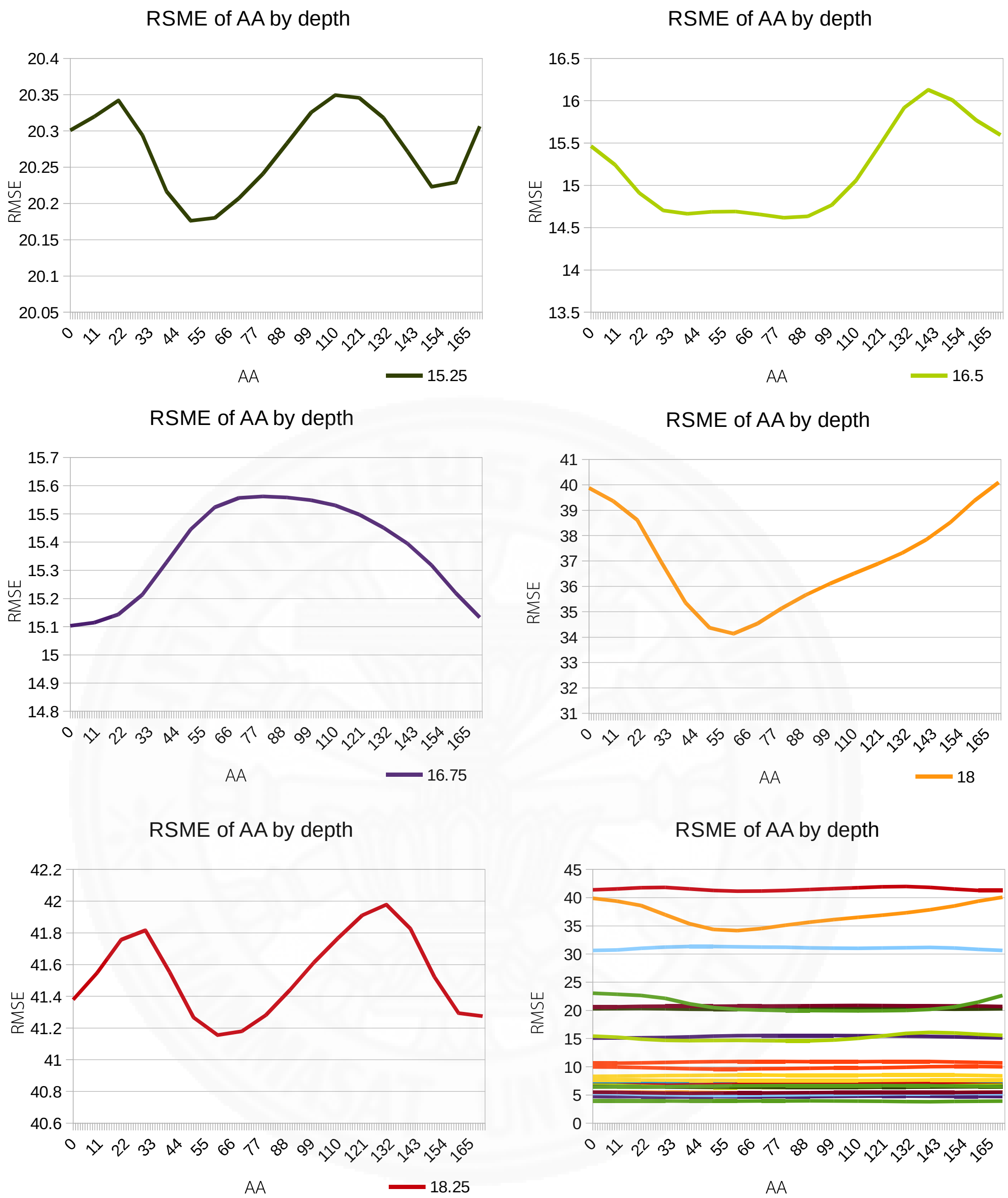


Figure 4.21 The anisotropy angle cross validation results of 1st random data at 15.25-18.25 m depth.

4.2.2 The Estimation Step

This step will use trining data set to be known points of the estimation unknown points. For model evaluation the testing data set will use to calculate the RMSE. For the OIDW, the power equal 1.5 at layer19 or 15.25 meters depth is selected because the pattern of observed data scatter around the Bangkok area then the other. The anisotropy ratio and angle is not affect the model therefore 1 and 0 will be use respectively.

For the TIDW, the anisotropy ratio will be set to 3.5 but the anisotropy angle is 170. The RMSE of 1st random of all model are on Table 4.4. The last column is result estimation of the cubic spline. The cubic spline is run from SAGA GIS software (Conrad et al., 2015).

Table 4.4 The RMSE of each model by using the parameters from the 1st random data.

Layer 19, 1st Random								
Number	N	E	Depth	Su	OIDW	TIDW	MIDW	CSPLINE
1	1527533	674208	15.25	99.5	46.443093	46.368559	46.368738	56.52935
2	1507554	660360	15.25	32.6	44.234356	44.246782	44.246177	26.36278
3	1527267.1	671969.07	15.25	17.8	48.282706	48.852508	48.890603	33.411835
4	1520337	685636	15.25	75.7	55.033261	56.328767	56.148871	63.227268
5	1510107	663475	15.25	41.9	55.994246	56.320272	56.345146	22.913048
6	1516205	650970	15.25	49.5	52.620001	52.667682	52.668256	47.134003
7	1527273.82	671991.2	15.25	16.5	48.379444	48.815873	48.850826	33.411835
8	1529027	668833	15.25	19.8	26.03412	25.945848	25.951248	13.911095
9	1528987	668831	15.25	21.7	26.262952	26.470962	26.494569	13.911095
10	1518479	655225	15.25	19.7	61.853788	58.671512	59.513632	46.842564
11	1531221	670509	15.25	27.3	30.176933	29.646483	29.618862	28.583748
12	1508379	660478	15.25	12.1	32.95253	32.01035	32.069092	26.873676
13	1526105	672699	15.25	61	70.462945	70.400366	70.446245	34.316494
14	1518438	683012	15.25	32.9	32.881271	33.072547	32.985765	48.043964
				RMSE	23.755696	23.345283	23.470414	18.7656872

4.2.3 The Random Technique

The random technique can investigate the best parameters that be represent the interested variable. The best parameters of all layer and the random number by the random technique are shown in Table 4.5.

Table 4.5 The best parameters from the 1st – 10nd random data.

Layers	Depth, m.	Parameters			
		Power	AR	AA	Random
		O-T-M IDW		MIDW	
1	1.5	3	1	170	9
2	3	1	6.5	100	5
3	3.25	1	10	80	10
4	4.5	1	10	10	4
5	4.75	1	1	10	10
6	6	1	1	50	1
7	6.25	1	1	120	6
8	7.5	1	1	110	6
9	7.75	1	1	20	2
10	9	2	1	80	1
11	9.25	5	2	160	5
12	10.5	1	2	30	1
13	10.75	1	1	120	3
14	12	1.5	1	50	10
15	12.25	1	10	10	2
16	13.5	2.5	10	170	5
17	13.75	1	1	20	4
18	15	1.5	2	10	7
19	15.25	1.5	2	20	3
20	16.5	1	1	120	8
21	16.75	1	10	30	8
22	18	2	4	120	7
23	18.25	1	10	40	4

At layer 19 the parameters are used to calculate the RMSE of each model, the results are shown in Table 4.6.

Table 4.6 The RMSE of each model at layer 19 by using the parameters from the 1st-10nd random data.

OIDW	TIDW	MIDW	CSPLINE
20.94097	21.00099	20.826826	27.2312666

The MIDW gets the lowest RMSE. Then the layer 11 is selected to test the model and Table 4.7 shows all RMSE.

Table 4.7 The RMSE of each model at layer 11 by using the parameters from the 1st-10nd random data.

Power	AR	AA	SAGA
5	2	160	
OIDW	TIDW	MIDW	CSPLINE
8.0733261	8.2501984	8.0177276	9.11346778

From Table 4.4, the lowest RMSE is produced from the cubic spline and the RMSE quite differ from other model. That means the cubic spline and the 1st random data are suitable to represent the undrained shear strength of layer 19 than other models. For the three model of IDW, the lowest is TIDW and the maximum RMSE is OIDW. The RMSE different of OIDW and TIDW comes from the anisotropy ratio.

The RMSE different of OIDW and TIDW comes from the anisotropy angle and in this step it increases the RMSE. If the calculation of layer 19 uses parameters from the random technique as in Table 4.5, the MIDW produces the lowest RMSE even though the TIDW is higher than the OIDW.

CHAPTER 5
CONCLUSIONS AND RECOMMENDATIONS

5.1 Conclusions

The random technique and modified inverses distance weighting model are the propose method that improves Tomczak (1998) model. One of the most concern for spatial interpolation is number and location of samples. With the random technique, the samples will be randoms and divided to training and testing data set. The training data set is used to calculate parameters that represent the variable of the area. The testing data uses to calculate the RMSE of the model. In addition the modification of anisotropy section of the TIDW can fine tune the estimated results. The combination of both propose method can increase accuracy of the estimation. It can produce the good results over the other model. This study found the power parameter takes a great effect to the model, followed by the anisotropy ratio. The anisotropy angle only fine tune the results.

5.2 Recommendations

In the future this proposed model can be developed to 3D and incorporated with random variable.

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APPENDICES

APPENDIX-A
PAPER

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Spatial Interpolation of Unconfined Compressive Strength for Soft Bangkok Clay Via Random Technique and Modified Inverse Distance Weight Method

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ABSTRACT

The basic of the inverses distance weight method has been improved by many researches. Not only power parameter but also sensitivity, anisotropy ratio, anisotropy angle and searching radius are incorporated to the model. In addition the cross validation processes is introduced to filter the best parameters for the observed data. To further develop, this study proposes a simple technique and a small modification of the IDW (modified IDW (mIDW)) function but increase ability to improve the estimation results. First, the random technique can be added in cross validation searching step to receive the possibly best parameters to better represent the natural phenomena of the interested areas. Second, with mIDW a coefficient of anisotropy angle parameter is modified to respond the anisotropy effect. The modified IDW is added a coefficient call geographic modification, to reflect the anisotropy angle parameter.

This study uses 164 bore holes with 23 layers data for Bangkok to test the model. This study evaluates four models: IDW, Tomczak IDW (Tomczak, 1998), mIDW, and Cubic Spline. With the random technique the observed data patterns that are feed to the searching parameters step reveal the best parameters to imitate the natural phenomena of the area. This study finds mIDW model is better than IDW, Tomczak IDW, and Cubic Spline. The root means square errors of the study case decreases numerously from the worst random to best random case by 11 %.

1. Introduction

Soil engineering properties are required for many kinds of civil engineering works such as

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road, building and dam design. Soil samples are collected and some testing might be carried out in-situ such as the standard penetration, vane shear test, etc. The collected samples are sent to a laboratory for other necessary testing such as sieve analysis, Atterberg's limits testing, unit weight, unconfined compression test, etc. Getting the summary of testing result is costly and time consuming. Also for one site location, only one or two soil borings will be assigned and used to represent soil properties of the whole area. For a particular case, soil strata at some locations are quite rapidly changed. Therefore, only two soil borings may not be able to represent soil engineering properties of the area, as these properties will be vastly deviated from actual properties. With misapprehension of soil properties/strata-profile, engineers can do wrong in foundation design. This in turn may impose great risk to the entire project. In a case of preliminary and feasibility study stage, if possible, it is necessary to have a good confident of engineering soil properties with only small spending.

All of these cases have inspired to this study in applying spatial analysis to gain and affirm knowledge of soil engineering properties through spatial interpolation, by using sampling data in the areas.

2. Literature Review

To understand the natural phenomena of soil engineering properties many mathematics modeling for estimating unsampled data are studied and classified to non-geostatistic, geostatistics and hybrid system (Li and Heap , 2008, Horpibulsuk et al., 2004: 2007). The inverses distance weight method is one of non-geostatistic models that has been used and commented such as Dumitru et al. (2013) addressed in their study the IDW method is not suitable for the area that have high different of elevation. Robinson and Metternicht (2006) and Göl et al. (2017) evaluated the spatial interpolation techniques, geostatistics and non-geostatistic included the IDW, to estimate soil property, pH and soil organic carbon respectively. They found not only one method outperform for all aspect of test both number and type of variable. De Mesnard (2013) was commented on the zero distance effect. If the estimating points are closed to some sampled points, the remotely sampled points not effect to the estimate value. In addition, in development aspect the IDW was developed and improved continuously since 1968 by Shepard (1968). Tomczak (1998) introduced the IDW automation system with anisotropy examined. The parameters of the IDW will be calculated by cross-validation and also the confidence on the estimated value be calculated by jackknife approach. The anisotropy parameter is enhanced with the flow direction of the river (Merwade et al., 2006). The distance in the IDW model is switched with an elliptical distance.

The sampling location and number also affect the estimation values (Webster and Oliver, 2007; Kanevski, 2013). Unfortunately soil boring locations and number can be assigned only in a project no relationship between projects to another project. The locations of a construction project will be located by investors, associated with their economic growth.

This study proposes a simple technique with a small modification of the IDW model but more ability to improve the estimation results. Firstly the random technique, it can be added in parameters searching step to receive the parameters that more represents the natural phenomena of the interesting area. Secondly a coefficient of anisotropy angle parameter will be modified to respond the anisotropy effect.

3. Procedure

3.1 Methodology

The foundation mathematical model for IDW is given as

$$P_j = \sum_{i=1}^{n_j} \lambda_{ij} P_{ij} \quad (1),$$

where P_{ij} is interesting value of sampled point i refer unsampled point j as Figure 1. The λ_{ij} is weighting distance as proposed by Tomczak (1998) as Equation (2).

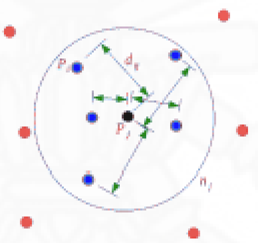

Figure 1: Unsampled point j within sampled points i that have n_j number.

From Tomczak (1998) the effective distance is

$$\lambda_{ij} = \frac{1/(d'_{ij}+\delta)^p}{\sum_{i=1}^{n_j} 1/(d'_{ij}+\delta)^p} \quad (2),$$

where d'_{ij} is the effective distance which is formulated by:

$$d'_{ij} = \sqrt{A_{xx} * \Delta x^2 + A_{xy} * \Delta x * \Delta y + A_{yy} * \Delta y^2} \quad (3)$$

with

$$A_{xx} = \left[\frac{cos(\theta)}{\rho}\right]^2 + [-sin(\theta)]^2 \quad (4)$$

$$A_{xy} = 2 * \left[\frac{cos(\theta)}{\rho} * \frac{sin(\theta)}{\rho} + (-sin(\theta) * cos(\theta))\right] \quad (5)$$

$$A_{yy} = [cos(\theta)]^2 + \left[sin\frac{(\theta)}{\rho}\right]^2 \quad (6).$$

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Figure 2 illustrates concept of equation 2-5 where ρ is anisotropy ratio (a/b). In isotropic case ρ equals 1. Anisotropy angle θ is measured from x axis, as in Figure 2.

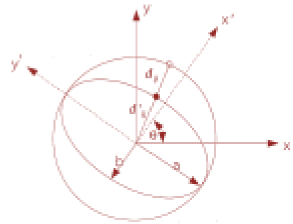

Figure 2: The concept of effective distance and anisotropy.

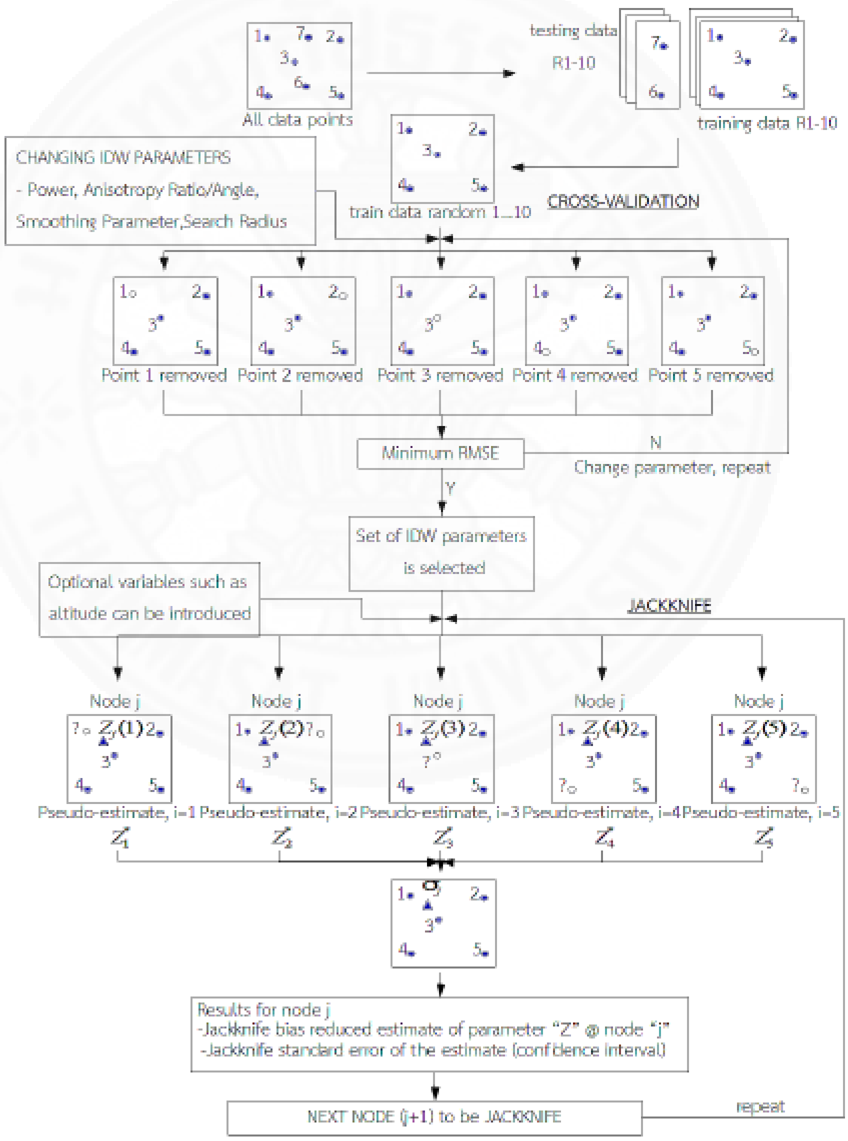

Figure 3: The cross-validation and jackknife procedure of Tomczak (1998) with random technique.

The random technique takes observed data at random ten times. Each time, random data is divided to training and testing group with 75% and 25%. The training group is used to train the model or searching for parameters in Tomczak (1998) procedures. The testing group is used to calculate root means square errors of the selected parameters (Figure 3).

Another form of equation 2 is coordinate transform with coefficient ρ can be given as

$$N' = \frac{-sin(\theta)E}{\rho} + cos(\theta)N$$
$$E' = \frac{cos(\theta)E}{\rho} + sin(\theta)N \quad (7).$$

Then,

$$d_{ij} = \sqrt{N'^2 + E^2} \quad (8)$$

with the proposed modification

$$N' = \frac{\frac{-sin(\theta)E}{\rho} + cos(\theta)}{\eta} \quad (9)$$

where η is the geometry modifier as shown in Figure 4.

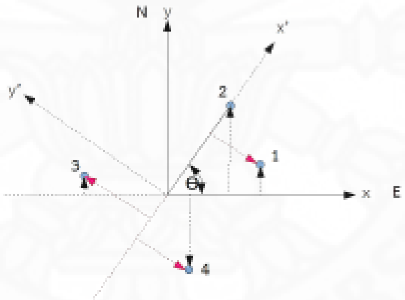

Figure 4: The black arrows are distance from E to points orΔN.
The red arrows are distance from E after transformation.

If the distance from E of any points is shorter after the axis is rotated, it cause that points are more effect to the estimate value in that direction conversely the distance longer, causes less effect. The value of η is given as

$$\eta = \Delta N / \Delta N' \quad (10)$$

Also the results will be compared with the cubic spline model that recommend in Phothong and Witchayangkoon (2015).

Ref. code: 25595410300130ZFN

3.2 Data Sampling

The soil engineering property in this case study is unconfined compressive strength (Su). This data obtains from 164 soil boring logs within the Bangkok province as Figure 5, with sampled size 1198 numbers. The sampled data scatter in 23 soil layers from 1.5 to 18.25 meters in depth.

Figure 5: The 164 soil bore holes location in Bangkok

The sampled data will be feed to cross-validation processes to search for parameters . If the process is searching for the power parameter, the anisotropy ratio will set to 1 and the anisotropy angle set to 0. The smoothing parameter (set to 0) and searching radius (use all data) are not considered in this study. After the power is chosen the anisotropy ratio is run with range 1 to 10 step 0.5. The anisotropy angle is run in the last step, with range 0 to 170 degrees with 10 degrees step. All searching processes are run by both IDW by Tomczak (1998) and mIDW models.

3.3 Results & Discussion

The results of cross-validation process of the first random are shown in Table 1. The parameter at layer 19 will be selected to test the model by related testing data. The training data are known data in the IDW equation. The estimating locations are the testing data locations. The rmse of testing data will be calculated to compare the respondent of each model. The results are shown in Table 2.

If the random technique has been applied to layer 19, the different power searching results will illustrate on Figure 6. With the same random technique the anisotropy ratio and angle are shown in Figures 7 -8.

In Table 1 shows the results from cross-validation processes. The most frequent seen values of the power and anisotropy column are 1 that are selected from criteria the minimum rmse. The one value of the power parameter and the anisotropy ratio mean the results are only average by distance or ordinary the IDW and all direction have same properties respectively. On the other hand the layer 19 shows obvious results of all parameters. This indicates the collected data have a pattern that can be the best represented. However the random technique can reveal the best pattern of sampled data with lowest rmse. An example is the power parameter as in Figure 6 using data at random ten times yielding the same graph shape, each with a minimum value. The third random produces the lowest the rmse as shown in Table 3. In addition, with the all parameters the modified IDW shows the best rmse in Table 5, same as Layer 11 on Table 6.

Table 1: cross-validation of data in each layers with the first random

Number	Depth, m.	Power	Anisotropy Ratio	Anisotropy Angle
		TIDW/mIDW	TIDW/mIDW	mIDW
1	1.5	1	1	150
2	3	1	1	30
3	3.25	1	1	10
4	4.5	1	1	0
5	4.75	1	1	40
6	6	1	1	70
7	6.25	1	1	90
8	7.5	1	1	40
9	7.75	2	1	50
10	9	1	1	100
11	9.25	1	1	30
12	10.5	1	2	50
13	10.75	1	4.5	70
14	12	1	1	50
15	12.25	1	1	0
16	13.5	1.5	1	150
17	13.75	1	1	10
18	15	1	2.5	0
19	15.25	1.5	3.5	170
20	16.5	1	1	50
21	16.75	1	1	170
22	18	1	1	0
23	18.25	1	1	80

Table 2: cross-validation of data in each layers with the first random

Layer 19, Testing

Number	N	E	Depth	Su	IDW	TIDW	GIDW	CSPLINE
1	1527533	674208	15.25	99.5	46.443093	46.368559	46.368738	56.52935
2	1507554	660360	15.25	32.6	44.234356	44.246782	44.246177	26.36278
3	1527267.1	671969.07	15.25	17.8	48.282706	48.852508	48.890603	33.411835
4	1520337	685636	15.25	75.7	55.033261	56.328767	56.148871	63.227268
5	1510107	663475	15.25	41.9	55.994246	56.320272	56.345146	22.913048
6	1516205	650970	15.25	49.5	52.620001	52.667682	52.668256	47.134003
7	1527273.82	671991.2	15.25	16.5	48.379444	48.815873	48.850826	33.411835
8	1529027	668833	15.25	19.8	26.03412	25.945848	25.951248	13.911095
9	1528987	668831	15.25	21.7	26.262952	26.470962	26.494569	13.911095
10	1518479	655225	15.25	19.7	61.853788	58.671512	59.513632	46.842564
11	1531221	670509	15.25	27.3	30.176933	29.646483	29.618862	28.583748
12	1508379	660478	15.25	12.1	32.95253	32.01035	32.069092	26.873676
13	1526105	672699	15.25	61	70.462945	70.400366	70.446245	34.316494
14	1518438	683012	15.25	32.9	32.881271	33.072547	32.985765	48.043964
				RMSE	23.755696	23.345283	23.470414	18.7656872

With the criteria minimum rmse the interesting parameters can be read from the graph and shown in Table 3. The random number 3 produces the best rmse.

Table 3: The parameters searching from layers 19 with the third random.

Layer	Depth, m.	Power	Anisotropy Ratio	Anisotropy Angle
		TIDW/mIDW	TIDW/mIDW	mIDW
19	15.25	1.5	2	20

Figure 6: The power searching of layer 19, using data at random ten times in succession.

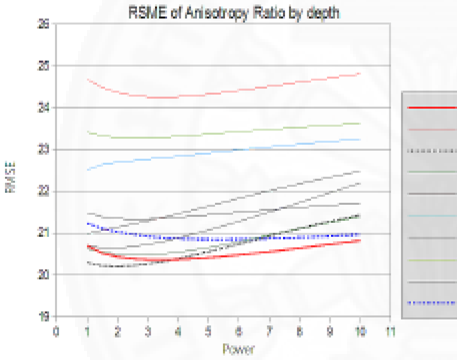

Figure 7: The anisotropy ratio searching of layer 19, using data at random ten times in succession.

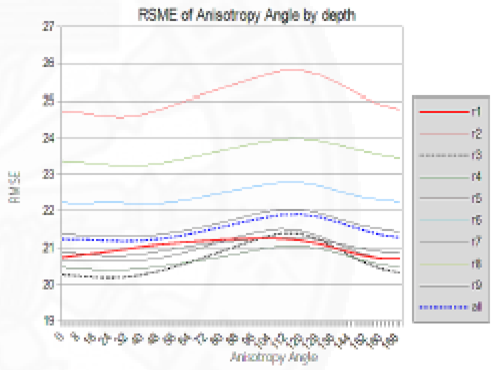

Figure 8: The anisotropy angle searching of layer 19, using data at random ten times in succession.

The parameters from Table 4 are put into any the IDW equation, the results shown in Table 5.

Table 5: The results using parameters from Table 4.
Training and testing data from the third random.

Layer 19 random 3, Testing

IDW	TIDW	GIDW	CSPLINE
20.94097	21.00099	20.826826	27.2312666

With the same procedure, the layer number 11 at depth 9.25 meters can produce the parameters and results at Table 6.

Table 6: The parameters and results for layer 11.

Layer 11	Random5	Testing		
Power	AR	AA		
5	2	160		
IDW	TIDW	GIDW	GIDW2	CSPLINE
8.0733261	8.2501984	8.0878867	8.0177276	9.11346778

The inverses distance weighting method, frequency used by many researchers, is easy to use and understand as well as it can be modified to fit the interested phenomena. One of the most concerns for spatial interpolation is number and location of samples. With the random technique, the samples are randomly sampled and divided to training and testing data set. The training data set is used to calculate parameters that represent the variable of the area. The testing data uses to calculate the rmse of the model. In addition the modification of an anisotropy section of the IDW can fine tune the estimated results. The combination of both purposes method can increase accuracy of the estimation. It can produce the good results over the other model. From this study found the power parameter takes a great effect to the model, follow by the anisotropy ratio. The anisotropy angle does only fine tune the results.

4. Conclusion

The random technique and modified IDW can produce the good results over the other model. The random technique also can be used to find good patterns of sampling data to represent the area. The power parameter takes a great effect to the model, follow by the anisotropy ratio. The anisotropy angle is only fine tuning the results. In the future this proposed model can be developed to 3D and incorporated with random variable.

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