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FRAMEWORK FOR RELIABILITY BASED DESIGN OF GEOTECHNICAL STRUCTURE: RANDOM FIELDS APPROACH

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Framework for Reliability Based Design of Geotechnical Structure: Random Fields Approach

by

Aduot Madit Anhiem

Dissertation submitted in partial fulfillment of
the requirements for the
Bachelor of Engineering (Hons)
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Universiti Teknologi PETRONAS

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CERTIFICATION OF APPROVAL

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ADUOT MADIT ANHIEM

A project dissertation submitted to the
Civil Engineering Programme
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in partial fulfillment of the requirements for the
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CIVIL ENGINEERING

Approved by,

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AP Dr Indra Sati Hamonangan Harahap

UNIVERSITI TEKNOLOGI PETRONAS

TRONOH, PERAK DARUL RIDZUAN
September 2012

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CERTIFICATION OF ORIGINALITY

I certify that this dissertation reports original work by me during the university project except as specified in the references and acknowledgments, and that the original work contained herein has not been undertaken or done by unspecified sources or persons.

ADUOT MADIT ANHIEM

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ABSTRACT

In recent years, there has been a significant trend for adoption of the reliability based design in the geotechnical engineering field due to uncertainties and risks which are central features of geotechnical engineering. The current practices in reliability based design have been based on factors of safety using Load and Resistance Factor Design (LRFD), and a probabilistic framework which is deterministic technique in analyzing linear failures using form. The objective of this study is the integration and implementation of Reliability Based Design (RBD) using random field approach in geotechnical engineering; aims in provision of a harmonized framework of geotechnical structures design in mitigating the risk and incorporating the uncertainties in the design. The study was made through a reinforced slope with soil nails, and two slope analyses were carried out. The methodology is based on form with set varied soil parameters, and integrated approach of Monte carlo simulation and Adaptive Radial based Importance Sampling on random fields of two soil spatial variables. The analysis of a slope results are presented as factors of safety, probability of failures, reliability index and with a realized slope failure. The results of this approach have verified the actual performance of the geotechnical structure with better quantified measures of slope stability using random fields which are dynamic due to the environmental influences as compared to form with set varied soil parameters where daily influences on soil are not taken into account. The approach provides critical mode of failures due to the variation of the soil parameters and reliability, based design to ensure structural safety, with an economic value.

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TABLE OF CONTENTS

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LIST OF FIGURES

`

IST OF TABLES

`

CHAPTER 1

INTRODUCTION

1.1 BACKGROUND OF STUDY

Recently in design of the geotechnical structures, there has been a potential development in reliability based design (RBD). This development involves risk mitigation, and to curb the risks, geotechnical engineers furthered different methods to optimize the failures of the structures designed and constructed from the initial stages of design and construction. Reliability Based design provides consistent means of managing uncertainties to the associated environmental impendence, such as earthquake, mudslide and other risks such as structural failures triggered by geotechnical uncertainties.

1.1.1 Design Optimization

The exponential increase in design computation has led to number of large scale simulation tools like codes, finite element methods for the analysis of complexities in engineering framework. The availability of complex simulation models has provided and presented a better actual systems engineers needed to improve designs. This improve designs are classified as design optimization. Optimization is translated to optimal designs characterized by minimal cost with a satisfying performance of the system. The most important part in design optimization is getting design variables that optimizes an objective function and satisfies the performance constraints.

Engineers, most of the times asssumes the design variables in a complexity, as determinstic and parametric, and it is known that a deterministic design optimization does not account for uncertainties that exist in modeling and simulation, therefore a variety of different uncertainties types are present, and need to be taken into consideration in the design optimization.

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1.1.2 Reliability Based Design Optimization Approaches

Reliable designs; are designs at which chances of failures of the sytem are minimal. In reliability based design there are are two forms of uncertainties, which include; variations in certain parameters, which are either controllable or uncontrolable and this is attributed to the dimensions of the structure, and the materail properties of the structure. Second is model uncertainties and errors associated with simulation tools used for simulation based design.

Uncertainties in simulation based design are inherently present and need to be accounted for in the design process, they can lead to large variations in the performance characteristics of the system and high chances of failure. Therefore any design which does not consider uncertainties are unrelaible and are prone to catastrophic failures.

Reliability based design optimization (RBDO) approaches deal with obtaining optimal designs characterized by a low probability of failure and they should not be mistaken as probabilistic approaches. In RBDO approaches, the main aim is to achieve a higher reliability within a lower cost, by characterizing the important uncertain vairables and the failure modes of the structure. So it is important that the design addressses critical failure modes and the overal system failure. The approaches has relaibility index, or the probability of failure corresponding to either mode or the system, and they are usually computed and performed using a probabilistic reliability analysis. The approaches are; layman approach where there is too reliant to Load and Resistance Factor Design (LRFD), here the effects of various combinations of loads are evaluated, and there is an assumption that; distribution of loads and resistance are known, and probabilistic distributions and values controling the parameters such as means and standard deviations are known, then summarized by knowing the failure criterion.

The second approach is, First Order Reliability Method (FORM), (Ang & Tang, 1984) which is the main stream method for reliability analysis. This method transforms a reliability analysis problem into an approximate optimization problem so that the required computation is minimized. Nonetheless, such transformation comes with some premises and tradeoffs: (a) to make the optimization problem tractable, the number of random variables of the target problem cannot be too many;

(b) the problem at hand is better to be lightly nonlinear to avoid large bias in the estimated reliability; and (c) the engineers must have basic skills for solving nonlinear optimization problems.

The third approach is Monte Carlo Simulation (MCS). MCS is general for the number of random variables and the problem complexity; hence the limitation of FORM can be easily overcome. Moreover, the basic idea of MCS is very simple and intuitive. Finally, geotechnical models can be treated as black boxes when implementing MCS. All these features make MCS attractive for practicality. The only criticism for MCS is that it is inefficient for problems with very small failure probabilities (or with very high reliabilities). However, this limitation has been gradually removed by the recent advancements in the Monte Carlo based reliability methods, all these techniques are elaborated (Enevoldsen and Sorensen 1994).

The approach used here for soil nailing in consideration of reliability based design is MSC- Random Field Approach, together with Adaptive Radial Based Importance Sampling (ARBIS) which are more reliable in computation of small failures (linear or non-linear) as for the generated parameters to be used in design. Soil nailing is an in situ reinforcement technique used to stabilise slopes and retain excavations. The principal reinforcing materials are nails, which are inserted into the earth as passive inclusions providing reinforcement to the earth that help the earth structure to gain its overall strength. A factor, which makes soil nailing technique more desirable than other earth reinforcing methods when performed on cuttings or excavations, is its easy and flexible top-down construction (Taib 2010). The analysis and behavior of the retaining walls will be elaborated and discused in depth.

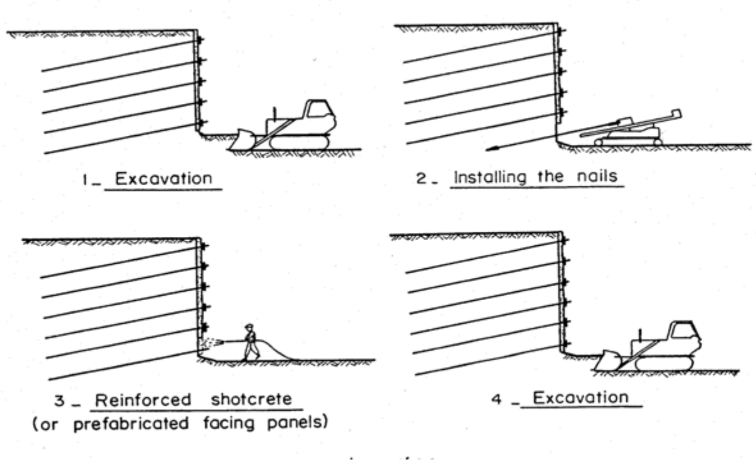

Figure 3.1: Soil Nailing Process

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1.2 Problem Statement

Safety and reliability has been of a concern in geotechnical engineering. The analysis and quantification of uncertainties, has been only through probabilities and reliabilities using various approaches which are not robust, though they serve the purpose of risk and uncertainties quantification. The practical and theoretical applications of probability and reliability based design are continuous efforts made in areas of geotechnical engineering, and they have not been influenced by any deterministic and perceptible degree, and it has been a routine that most of the engineers are skeptical of reliability theories as applied in geotechnical engineering problems.

The slope failures especially for retaining walls are not described and identified, as the structure is subjected to different loadings which have visible and invisible structural failures.

When coming to the application of probabilistic methods in reliability based design there is oversimplification of the problems, to suits the specific target of the project but the realities reflected are neglected by the approaches devised earlier such as non linear failures of the structures.

Looking to probabilistic methods which are used as the determining factors of reliability, not all engineers are well versed with a comprehensible probability and when it comes to the analysis of the simulated or the modeled, condition to the parameters or the variability; engineers are reluctant to make use of what they perceive but rely on engineering judgment which is cost related and insufficient in terms of structure performance relative to cost incurred and to be incurred.

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1.3 Objectives

The purpose of this study is to improve ways of handling the reliability based design using random fields approach on soil nailing practices since it the engineers are reliant to it and are developing and establishing indices and codes to consider any soil variability.

The objectives of this project are as follows:

1. To develop frameworks for reliability based design by incorporating all the variables in design phase by using FORM, MCS and ARBIS
2. To evaluate the influences of variations in critical parametric frameworks.
3. To present a unified framework for different uncertainties associated with the design of geotechnical structure.
4. To improve and integrate the approaches used in determining and mitigating the associated risks in geotechnical structures.

1.4 Scopes of the Project

The studies will be based only on Slope Soil Nailing of the retaining walls, and the only approaches used are; FORM and random fields, based on simulation with MCS and ARBIS.

- To understand the failure mechanism of the slope by incorporating the uncertainties affecting design and reliability of the structure.
- To use reliability analysis to obtain the factor of safety using Monte Carlo Simulation and Adaptive Radial Based Importance Sampling.
- Improvement of Reliability Based Design and simulating all the soil variables in random fields to achieve the framework of Reliability Based Design.

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1.5 Significance and Relevancy of the Project

The framework for reliability based design is of importance in civil engineering and geotechnical engineering for the analysis of uncertainties which are categorized into natural variability (information insensitive, aleatory), and modeling (information sensitive, epistemic). Though different design patterns and formats were used to explicitly address the uncertainties, still there are observe failures which studies have shown; the observed failures are dominated by human factors in design, therefore it can be deduced that the formats such as factor of safety, limit state design factors have contributed less in addressing the challenges posed by uncertainties in geotechnical structures. Also there has been overdesign of the structures, which is costly, because the factor of safety used is dependent and relative to the individual judgment. The approach of framework for reliability based design applied here will help in mitigation of structural associated failures, due to uncertainties, and an optimized design will be achieved in geotechnical structures design which is cost effective.

1.6 Feasibility of the Project within the scope and Time Frame

The project is feasible in consideration to the completion of the project. This project is divided into two phases where each phase is 14 weeks. The feasibility details relative to the time are as follow:

- Time allocated for the two phases is sufficient for data collection and data analysis as well compiling the results.
- Computer lab/Softwares: MATLAB used to run FORM, Monte Carlo simulation and Adaptive Radial Based Sampling on stochastic data.
- Sufficient Research papers and journals on ASCE and Geotechnical Engineering and Environmental Engineering
- Reference text books and codes availability in Universiti Teknologi PETRONAS Information Resource Center.

Hence the tools, equipments and information required to work on the project are available, therefore the project will be completed and delivered within the time frame.

CHAPTER 2
LITERATURE REVIEW

2.0 Introduction

Geotechnical engineering has been challenged by the risks encountered due to uncertainties, and this has put forth the need to review, revised and improve the design factors and methods; therefore there are demands placed to the expertise and geotechnical engineers; to focus on how to prevent and handle uncertainties at structural capacity, and what reliability do the structure has, for futuristic performance and hazards, though the design factors used to mitigate the risk associated to structural failures. The public and the engineers have much concern on safety of the structures and they are aware of what safety is, and the recent studies have gone further to incorporate the reliability based design of structures such that the probabilities of failures are resolved.

Cornell (1969) Reliability based design is a simple concept, but mathematically the calculations required to develop a consistent method of maintaining an acceptably low probability of failure is quite complex. All the complexities related to design are resolved by development of the reliability index to simplify probabilistic design by Kulhawy and Phoon (2002). The analytic definition of reliability index β by Rosenblueth and Esteva (1972) is defined as:

$$\beta = \frac{\mathrm{Log}_e M_{FS}}{\sqrt{COV_F^{\,2} + COV_Q^{\,2}}}$$

Where β is the reliability index

$COV_Q = S_Q/M_Q$= coefficient of variation of capacity resistance

$COV_F = S_F/M_F$= coefficient of variation of load

S_Q and S_F = standard deviation of capacity and load respectively

M_{FS} = Mean factor of safety

M_Q = Mean of capacity Q

M_F = Mean of Load F

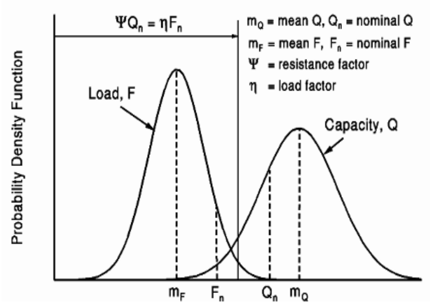

Figure 4.1: Simplified Reliability Based Design

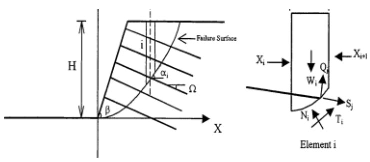

Figure 4.2: Soil Nail Reinforcement Analysis

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2.1 Random Field

Random fields are used to describe spatial variability as applied by Vanmarcke (1983) and Baecher & Christian (2003). Baecher & Christian (2003) application of random fields to geotechnical issues is based on the assumption that spatially variable of concern is the realization of a random field, which is defined as a joint probability distribution.

Random field theory and practice is a powerful framework for the assessment of spatial variability because it provides statistical results useful for planning and other strategies in sampling, generating interferences and inclusion of spatial variation reliability by Baecher and Christian (2003).

The spatial dependency of a random field is expressed through an autocorrelation function $\rho(\tau)$ where τ is the lag between points; more so spatial averaging has been shown to be an effective simplification of the real random field. According to Baecher and Christian a random field is considered stationary if it satisfies two conditions:

1. The mean and the variances of a given soil at a given depth W(Z) are the same regardless of the absolute location of Z, and
2. The correlation coefficient between $W(Z_1)$ and $W(Z_2)$ is the same regardless of the absolute locations of Z1 and Z2;

Rather it depends only on the distance between Z1 and Z2 where data scatter becomes an issue.

To consider spatial averaging in a reliability analysis, variance, Vanmarcke (1983) of soil parameters are reduced by multiplying a factor that depends on the scale of fluctuation. This factor is the value of the variance function that can be obtained by integration of an autocorrelation function.

$$I^2 = f(L, \theta) = 0.5\,(\theta/L)^2\,[2L/\theta - 1 + \exp(-2L/\theta)] \qquad (2.1)$$

L is the characteristic length to a potential failure surface.

`

2.1.1 Random field model

2.1.1.1. The spatial variability of soil

One of the main sources of heterogeneity is inherent spatial soil variability, i.e. the variation of soil properties from one point to another in space due to different depositional conditions and different loading histories by Elkateb, Chalaturnyk and Robertson (2002). Spatial variation is not a random process; rather it is controlled by location in space. Statistical parameters such as the mean and variance are one-point statistical parameters and cannot capture the features of the spatial structure of the soil by El-Ramly, Morgenster and Cruden (2002). Spatial variations of soil properties can be effectively described by their correlation structure (i.e. autocorrelation function) within the framework of random fields as detailed by Vanmarcke (1983)

A Gaussian random field is completely defined by its mean, variance, and autocorrelation function. Autocorrelation functions commonly used in geotechnical engineering have been presented by Li and Lumb (1987) and Rackwitz (2000). In this study, an exponential autocorrelation function is used and different autocorrelation distances in the vertical and horizontal directions are used as follows: are autocorrelation distances in the horizontal and vertical directions, respectively.

2.1.1.2. Random fields Discretization

The spatial fluctuations of a parameter cannot be accounted for if the parameter is modelled by only a single random variable. Therefore, it is reasonable to use random fields for a more accurate representation of the variations when spatial uncertainty effects are directly included in the analysis. Because of the discrete nature of numerical methods; such as finite element or finite difference formulation, a continuous-parameter random field must also be discretized into random variables.

This process is commonly known as discretization of a random field. Several methods have been developed to carry out this task, such as the spatial average method, the midpoint method, and the shape function method. These early methods are relatively inefficient, in the sense that a large

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number of random variables are required to achieve a good approximation of the field. More efficient approaches for discretization of random fields using series expansion methods such as, the orthogonal series expansion, and the expansion optimal linear estimation method have been introduced by Sudret and Der Kiureghian.

A comprehensive review and comparison of these discretization methods have been presented by *Sudret et al.* (2002) and Matthies *et al. (2002)*.

All series expansion methods result in a Gaussian field, which is exactly represented as a series involving random variables and deterministic spatial functions depending on the correlation structure of the field. The approximation is then obtained as a truncation of the series. The accuracy of the representation depends on the number of terms used in the series expansion and the particular expansion method used.

In this study, the correlated Gaussian random generation is adopted to discretize anisotropic random fields of soil properties in the dimensional space, since the method generates a spatially correlated Gaussian distributed random field defined by the available quantitative descriptors of variability Ehlschlaeger and Goodchild (1994).

2.2 Serviceability Failure in Random Fields

Serviceability failure is said to occur when the excavation induced wall or ground movement exceeds specified limiting values

It is essential to have the ability to accurately "predict" the maximum wall deflection and ground settlement during the design of excavated soil and structural geometry.

Effect of inherent spatial variation of soil properties has been demonstrated in many geotechnical problems, and modeling of this variation with random field theory has already been reported, a rigorous simulation of the random, Griffiths and Fenton (2009) field within the Finite Element Modeling (FEM) based solution frame demands a large amount of computation time which is not practical for analyzing complicated problems such as wall and ground responses in a braced excavation, Schweiger and Peschl (2005).

To approximate the effect of a random field appears to be a feasible alternative for analysis for the probability of serviceability failure.

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2.3 Random Variables

In reliability analysis there are two types of variables deterministic and random variables by U. S Army Corps of Engineers (2006). Deterministic variables are represented by a single value because of the value that variable is known exactly. A deterministic variable are represented by a probability density function, which defines the relative likelihood that the random variables assumes various ranges of values.

According to U. S Army Corps of Engineers (1995) the fundamental building blocks of reliability analysis are random variables. In Mathematical terms a random variable is a function defined on a sample space that assigns a probability or likelihood to each possible event within the sample space. In practical terms a random variable for which the precise value is uncertain, but some probability can be assigned, assuming any specific value or range of values (discrete or continuous random variables).

2.4 Spatial Variability

In geotechnical analysis, the uncertainties crops up from the mechanical properties of the soil materials. The uncertain material properties tend to vary in space as well within homogenous soil strata. Studies have shown that spatial variability of the soil has important influence on computed reliability by Rackwitz, Papaioannour, and Griffins.

According to Honjo (2011) spatial variability of geological identical geotechnical parameters are conveniently modeled by the random field (RF) theory in geotechnical RBD, therefore the geotechnical parameters are determined by themselves and already exist at every point, thus our ignorance (Epistemic uncertainty (Baecher and Christian, 2003)), we model them using RF for our convenience for simplification of the idealized problem.

Accurate representation of the spatial variability of the uncertain soil material requires random field modeling. If the stochastic discretion of the random filed is used as part of a finite element reliability analysis procedure, a large number of random variables is required. An efficient method for dealing with such higher dimensional problems is the simulation relative to frameworks for reliability based design.

`

2.5 Spatial Variability Evaluation

In the application of probabilistic models for reliability analysis there is need of characterizing soil in a probabilistic way. Phoon and Kulhawy evaluated geotechnical properties; on an exhaustive data provided. The emphasis was on describing a coefficient of variation. The coefficient of variation describes the relationship between standard variation and mean of property.

More so there has been a concept of spatial averaging which was described by Vanmarcke as follows; the variability of the average soil properties over large domain is less than that over a small domain. The reduced variability of soil properties over a large domain can be characterized by the variance function, which is related to the autocorrelation function. The exponential model which is widely used is:

$$\rho(\Delta z) = \exp(-2\,[\Delta z]/\theta) \qquad (2.2)$$

Where $[\Delta z]$ is the distance between any two points in the field; θ is the scale of fluctuation that is used to normalize $[\Delta z]$.

Recent years have shown a trend to place the treatment of uncertainty on a more formal basis, in particular by applying Reliability Theory in Geotechnical engineering.

At the outset that reliability approaches do not remove uncertainty and do not alleviate the need for judgment in dealing with world geotechnical problems but provide a way of quantifying the uncertainties and handling them in a consistent manner.

According to Baecher and Christian, experienced engineers recognize that the world is imperfectly knowable, and rest of the process is to discover how to deal with the imperfection.

`

2.6 Uncertainties and Reliability Analysis

According to Mohsen, Kourosh, Mostafa, Sharifzadeh (2011); geotechnical engineering analysis and design, various sources of uncertainties are encountered and recognized. Several features usually contribute to such uncertainties, like:

1. Those associated with inherent randomness of natural; processes
2. Model uncertainty reflecting the inability of the simulation model, design technique or empirical formula to represent the system's true physical behavior, such as calculating the safety factor using a limiting equilibrium of slices
3. Data uncertainties, which is inclusive of measurement errors, data inconsistency and non-homogeneity and data handling.

In reliability analysis; Phoon (2008) points that reliability analysis focused on the probability of failure and it allows the engineer to carry out a broader range of parametric studies without actually performing thousands of design checks with different inputs one at a time. According to US Army Corps of Engineer, engineering reliability analysis can be used in the estimation of the probability of a system surviving for a given failure; therefore this reliability analysis requires variables parameters as inputs. Other than that, Li (1995) proved that reliability analysis for deteriorating reinforced concrete structures where the resistance deterioration is caused by the corrosion of the reinforcing steel in industrial can be analyzed.

Geotechnical engineers almost always have to deal with uncertainty, Juang (1996, 2003), whether it is formally acknowledged or not. Uncertainty in soil parameters is dealt with by using an appropriate factor of safety.

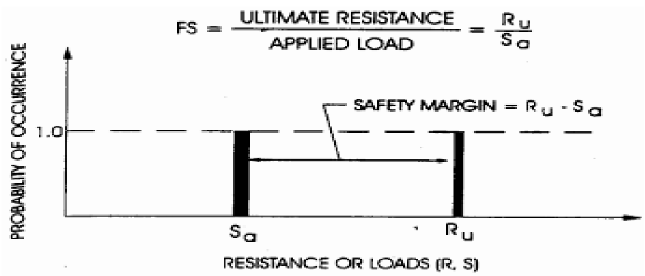


Figure 2.2 Factor of Safety Analysis

Duncan (2000) proposed the concept of the highest conceivable value and lowest conceivable value as a way to estimate the uncertainty of a soil parameter. He suggested that the standard deviation (σ) of a soil parameter may be estimated by taking the difference between the highest conceivable value and the lowest conceivable value and dividing it by 6.

An important design consideration is to ensure the probability of exceeding the maximum wall deflection is less than the threshold value.

In a deterministic analysis, the factor of safety is defined as the ratio of resisting to driving forces on a potential sliding surface. The safety of the structure is put in consideration, if the calculated safety of factor exceeds unity. Probability theory and reliability analyses provided a rational framework for dealing with uncertainties and decision making under uncertainty. Depending on the level of sophistication, the analyses provide one or more of the following outputs.

- Probability of failure and Reliability Index
- The most probable combination of parameters leading to failure
- Sensitivity of result to any change in parameters

In Duncan (2000) review on slope stability assessment methods, he pointed out that *"Through regulation or tradition, the same value of safety factor is often applied to conditions that involve widely varying degrees of uncertainty. This is not logical."*

Whereas, in a probabilistic framework; the factor of safety is expressed in terms of its mean value as well as its variance in geotechnical analysis. Reliability analysis is therefore used to assess uncertainties in engineering variables such as factor of safety in stability based structures. The reliability index β, is often used to express the degree of uncertainty in the calculated factor of safety.

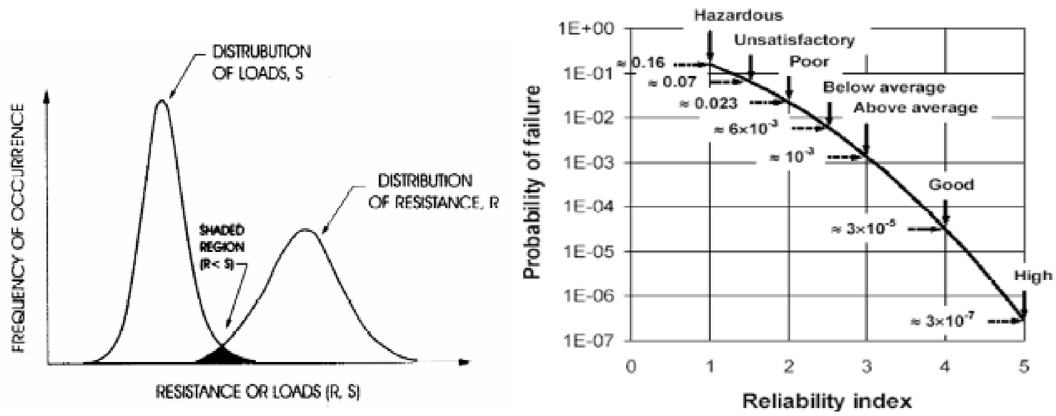


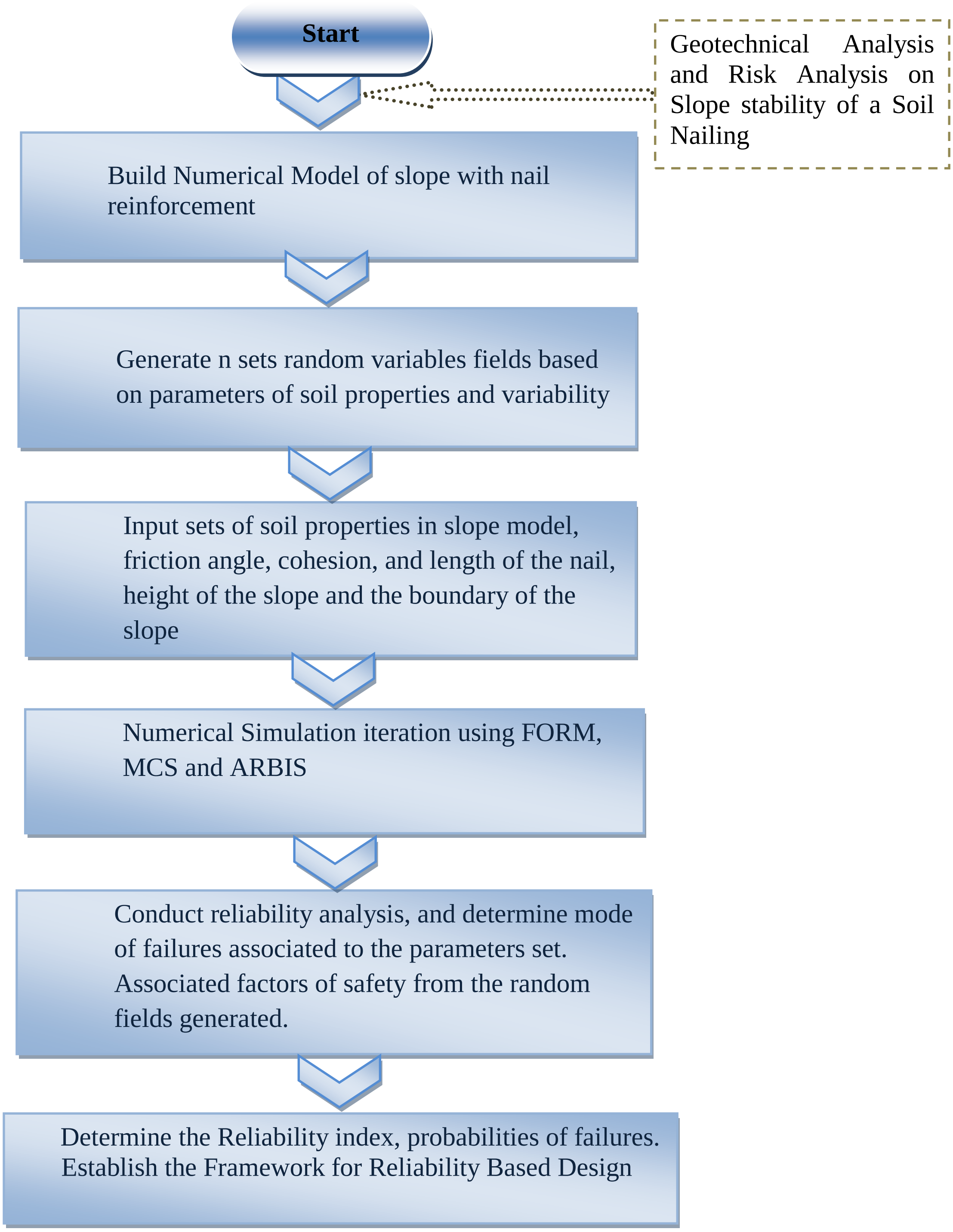
Figure 2.3 Normal Distribution and reliability index

CHAPTER 3

METHODOLOGY

3.1 RESEARCH METHODOLOGY

3.1.1 Project Methodology



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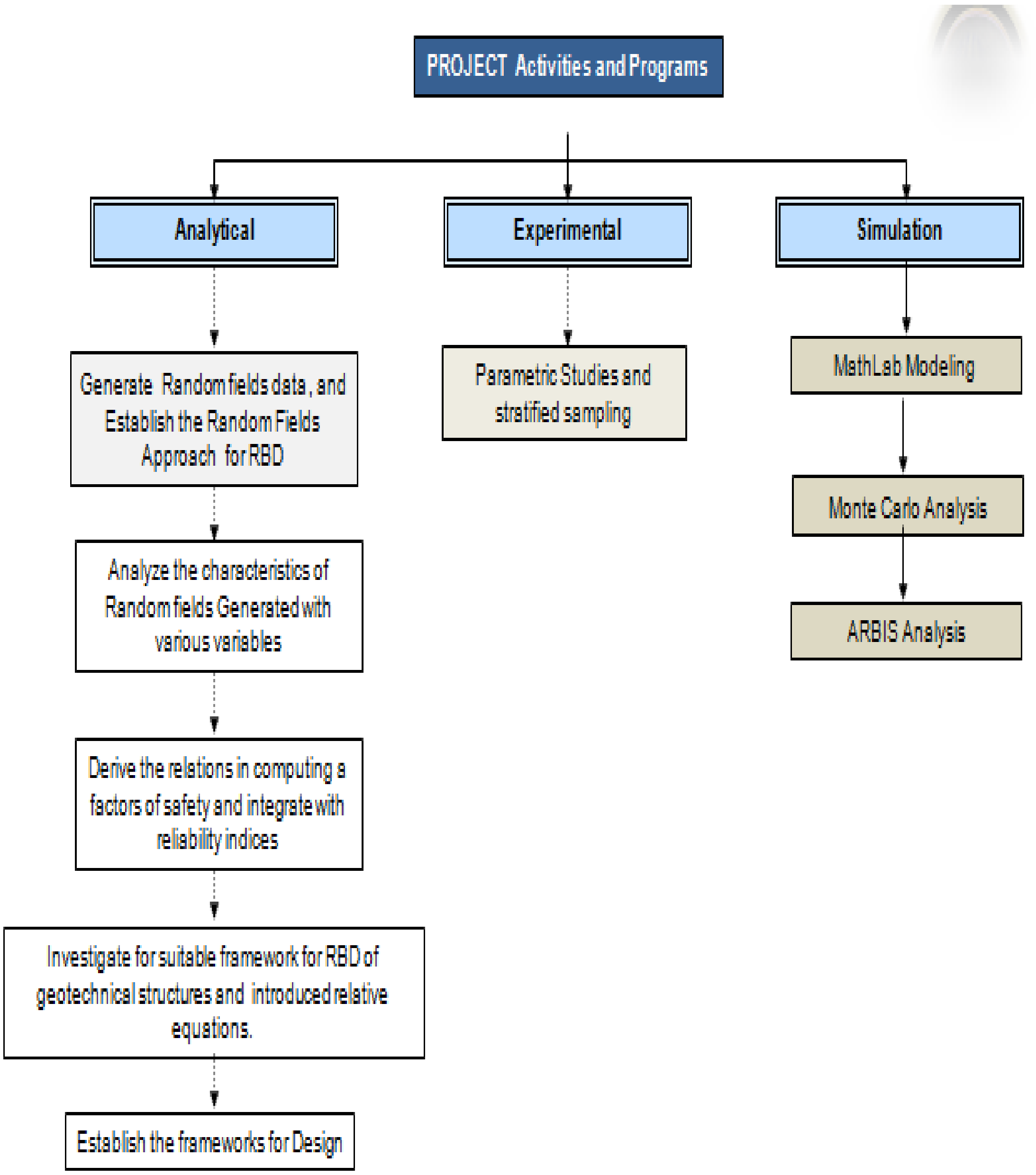
3.1.2 Project Activities and Programs, and Work flow



3.2 Project Progress

FINAL YEAR PROJECT 1 TIME LINE

Gantt Chart time line is detailed below:

Title of Activity/Task	**Timeline** Undergraduate (University Semester target time)													
	1	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**9**	**10**	**11**	**12**	**13**	**14**
1. Topic selection														
2. Preliminary Research														
3. Develop Project Proposal														
4. Literature review														
5. Software and data collection														
6. Softwares learning														
7. Software Applications and Practice														
8. Data Analysis & Simulation Techniques														
9. Proposal defence														
10. Final Report FYP1														
	15	**16**	**17**	**18**	**19**	**20**	**21**	**22**	**23**	**24**	**25**	**26**	**27**	**28**
11. Literature Review														
12. Data Generation														
13. Modelling of the Slope														
14. Progress Report and Pre-EDEX														
15. Monte Carlo Simulation (MCS) application														
16. Adaptive Radial Based Importance Sampling (ARBIS) Review														
17. Comparison and Analysis of the data														
18. Final Report FYPII														
19. VIVA														

Figure 3.1: Preliminary Gantt chart

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3.3 Project activities and tools required

1) Computer Workstation Lab Equipment
    - Computer
    - Reliability Based design Tools (Monte Carlo Simulation Software -Risk Analysis software)
    - MathLab
    - Workstation
    - Geotechnical Design Tools

Monte Carlo Simulation is define as a problem solving technique used to approximate the probability of certain outcomes by running multiple trail runs, called simulations, using random variables.

Simulation is done to understand and control complex stochastic systems, and since they systems are too complex to be understood and control, we use analytic and numerical methods.

- Analytical Methods examine many decision points at once but is only limited to simple models.
- Numerical Methods handle more complex models but still limited but it has to have repeated computations for each decision point.
- Simulation handles very complex and realistic systems and needs repetition for each decision point.

2) Modeling the system

Before simulating we need to have a good model which should facilitate understanding of the system, and capture the salient details of the system, omitting factors that are not relevant.

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3.4 Random Field Generation

Geometrical and material imperfections are put in consideration in a deterministic design; the imperfections are random fields (stochastic processes) and are modelled. The reliability based designed is sensitive to imperfections that are the geometry and the boundary conditions. For a reliable design the boundary, the geometry and the parameters are incorporated in optimizing design in the stochastic analysis.

The generation of correlated random fields is by application of Karhunen _ Loève expansion random fields, with a value decomposition of a matrix. The decomposition of matrix decomposes a symmetric, non negative definite matrix into a triangular matrix.

The Karhunen –Loève (K-L) Expansion

The K_L expansion is seen as a special case of the orthogonal series expansion where the orthogonal functions are chosen as the eigenfunctions of a Fredholm integral of the second kind with the auto covariance function as kernel (covariance decomposition).

Karhunen_Loève expansion theorem;

Given a second order Random Fields (RF), $a = a(x, \omega)$ with continuous covariance function $c(x, y) = Cov_a(x, y)$, denote by $\{(\lambda_m, a_m(x))\}$ the eigenpairs of the (compact) integral operator

$$C: L^2(D) \rightarrow L^2(D), \quad (3.1)$$

There exists a sequence $\{\xi_m\}m\in N$ of random variables with

$$<\xi_m> = 0\ \forall_m,\ <\xi_m\xi_n> = d_{m,n}\ \forall_{m,n} \quad (3.2)$$

Such that the Karhunen _ Loève (KL) expansion is

$$a(x, w) = \acute{a}(x) + \sum_{m=1}^{\infty} \sqrt{\lambda_m\, a_m\ (x)\xi_m\xi_m\ (w)} \quad (3.3)$$

This converges uniformly on D and in $L^2_{p.}$

`

The covariance functions c(x, y) are continuous on D xD as well as symmetric and of positive type. The covariance operators C are compact hence spectra consist of countable many eigenvalues accumulating at most at zero. Covariance operators are selfadjoint and positive semi definite.

The analogy of singular value expansion of integral operator is;

$$A: L^2(D) \to L^2(D), \qquad f(x) \to A_f(w) := \int_D^0 f(x)a(x,w)dx, \tag{3.4}$$

$$A *: L^2{}_p \to L^2(D), \qquad \xi(w) \to (A * \ \xi)(x) := \int_D^0 \xi(w)a(x,w)dP(w) \tag{3.5}$$

$$C = A * A \tag{3.6}$$

Variance

For normalized eigenfunctions $a_m(x)$

$$Var_a(x) = c\ (x,x) = \sum_{m=1}^{\infty} \lambda_m\, a_m(x)^2 \tag{3.7}$$

$$\int_D^0 Var_a(x)\ dx = \sum_{m=1}^{\infty} \lambda_m\, (a_m, a_m)D = trace\ C \tag{3.8}$$

For constant variance which is stationary random fields, this defines the variance.

$$Var_a\ \sigma^2 > 0, \qquad \sum_{m=1}^{\infty} \lambda_m = |D|\sigma^2 \tag{3.9}$$

Truncated KL Expansions

For computational purposes, KL expansion is truncated after M terms:

$$a^M(x,w) = \acute{a}(x) + \sum_{m=1}^{M} \sqrt{\lambda_m\, a_m\ (x)\xi_m \xi_m\ (w)} \tag{3.10}$$

Truncation error

$$< \|a - a^M\|^2 D >= \sum_{m=M+1}^{\infty} \lambda_m \tag{3.11}$$

M is chosen such that sufficient amount of total variance of Random field is retained.

`

CHAPTER 4
RESULTS AND DISCUSSIONS

4.1 Slope Reliability Analysis

The reliability analysis of slopes has been a challenging task for engineers because the soil constitutes discontinuities due to spatial variability in various forms, resulting in different modes and types of slope failures. The slope failures are at times functional failures or a complete collapse due to self weight and premature deterioration of the slope due to environmental factors. To avoid any type of failure at design phase, uncertain design parameters require a higher factor of safety than when the design parameters are known. The approaches used compare how uncertain and certain parameters can be handled effectively and with satisfactorily performance, since the approaches consider functional failures and degree of uncertainties, and analytical approach; where reliability index, probability of failures and factors of safety are determined.

4.1.1 Soil Nailing in Random Field Model in Slope Reliability Analysis

The random field modelling of the slope is realized, and elements of slope parameters are constant and for investigation the influences of spatial variability on probability of failures, factor of safety and reliability index, mechanical properties are kept constant except for the cohesion and frictional angle which are random fields generated. Soil Nailing is an insitu soil reinforcement which enhances the stability of slopes, retaining walls and excavations. A soil nailed system is enhanced by transfer of loads from the free surfaces in between the soil nail heads to the soil nails and redistribution of forces between soil nails. The failure mode of a soil nailed system is ductile therefore, slope failure is gradual.

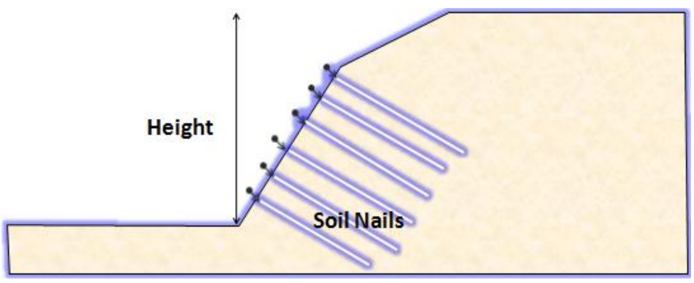


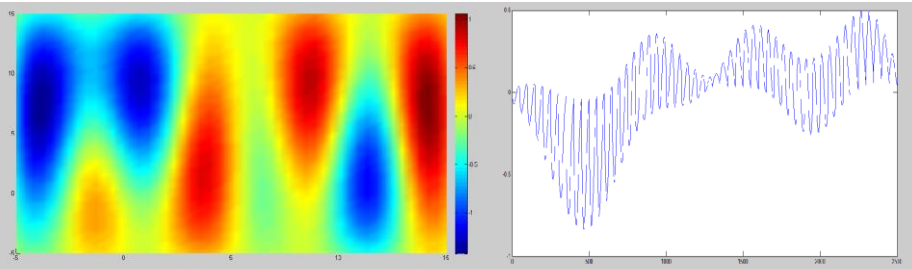
Figure 4.1 Slope_Soil Nail Model

4.1.2 Application of Random Field Model in Slope Reliability Analysis

MATLAB is used to generate random fields, and analysis of the slope reliability was carried out, since the random fields are generated in the normal space. The random fields are initially generated and properties are assigned to affecting parameters. The analysis take into account the failure mode, factors of safety, probabilities of failures, and reliability index by employing First Order Reliability Method (FORM) on non-random field slope, and using Monte Carlo Simulation (MCS) and Adaptive Radial Based Importance Sampling (ARBIS) on random fields realizations.

Generated Random Fields

Mode 1: 50x50 Random Fields (Friction Angle)   Plot of random fields



Mode 2: 150x150 Random Fields (cohesion)   Plot of Random fields

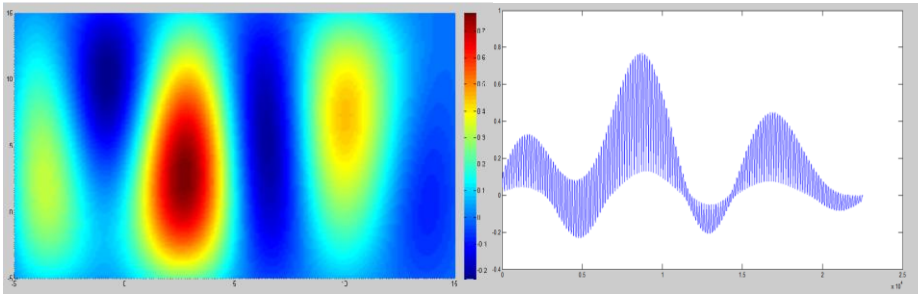


Figure 4.2 Random Fields generated

The random fields generated and plotted gets distinctive and finer as the size of realization increases. The random fields define spatial variability of the soil and defined parameters are cohesion and frictional angle.

`

4.1.3 Slope Modes of failures, factor of safety, probability of failure and reliability index

In analysing and determining failures with a consideration on factor of safety, probability of failures and probability, there are two cases used to compare the results, which are non-random fields' application and random fields' application. For non-random fields, the affecting parameters are set and varied with chosen values, while random fields generated are used for analysis, though both are incapable of detailed characterization of the spatial variations of a soil deposit, because sufficient observations are difficult to realize.

Case 1. Effects of Cohesion and Friction angle: non Random Field Model

Most of the time, for the influences of earth stress and self weight, the properties varies with depth. In this case, the frictional angle and cohesion of the soil are assumed and varied to see the desired effect. This method uses FORM for the analysis of factor of safety, probability of failures and reliability index are determined.

For FORM analysis, the mean values, variances and correlation of each variable are determined using;

Mean Value, $\mu_g = g(\mu_{x_1,}\mu_{x_2,}\mu_{x_3,}, \dots \dots \dots \mu_{x_n,})$

Variance, ${\delta_g}^2$

$$
{\delta_g}^2 = \sum_{i=1}^{n} ((\frac{\partial g}{\partial x_i})^2)\, \partial x_i
$$

The probability of failure is determined using reliability index which is;

$$
\beta = min_f \sqrt{(\frac{x_i - E_i}{\delta_i})^T (R)^{-1} (\frac{x_i - E_i}{\delta_i})}
$$

Where xi = set of random variables

Ei =vector of mean value

R= the correlation

δ= Standard deviation

f = failure domain.

The results of failures and factor of safety, probability of failure and reliability index of the figures below are tabulated as shown, when the slope is anchored or not.

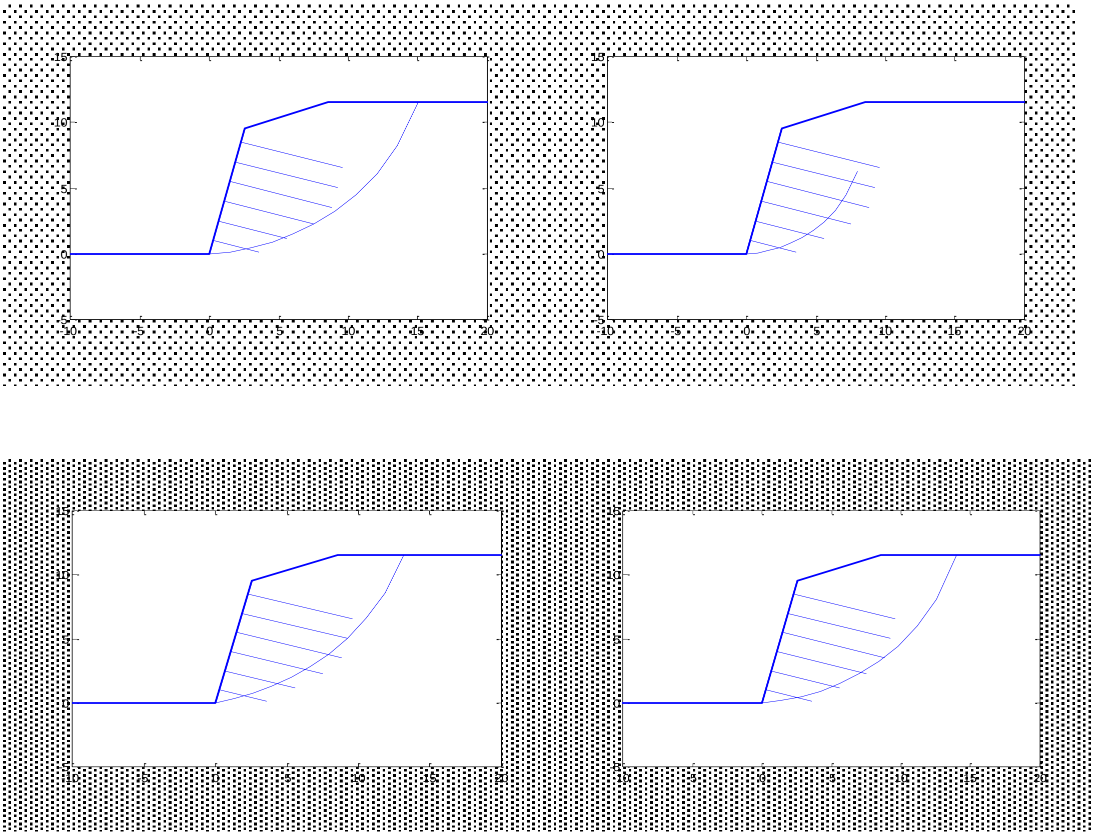


Figure 4.3: Modes of Failures for non random fields: Various modes of slope failures due to non random field fields but varied parameters (cohesion and friction angle). The trial slip surfaces are modeled with the Entry Exit slip surface. The surfaces exit at the toe of the slope. The soil is assumed to be homogenous and all analysis done with fixed geometry and variable material or soil properties.

`

Table 4.1 Effects of Cohesion with constant Friction Angle

	1	2	3	4	5
C' cohesion	5.0	10.0	15.0	20.0	25
Θ' friction angle	35^0	35^0	35^0	35^0	35^0
FOS	1.3330	1.4571	1.5751	1.6930	1.8110
FOS1	1.0534	1.1918	1.3301	1.4672	1.6007
β	3.5342	5.5615	6.4594	7.5165	8.6944
P_f	2.0448e-4	1.3372e-8	5.2566e-11	2.8134e-14	1.7428e-18
FOS min non anchored	1.0534	1.53832	1.3301	1.4672	1.6007
FOS min anchored	1.3526	1.9531	1.5899	1.7085	1.8271

Table 4.1 shows the effect of the cohesion, with constant friction angle of soil to the slope. Cohesion influences the soil strength, as well the friction angle. The two parameters results show an increase in cohesion increases the strength of the soil hence an increase in factor of safety, reliability index and lesser probability of failures. The factor of safety of non anchored slope is less than the factor of safety of anchored slope.

Table 4.2 Effects of friction angle with constant Cohesion

	1	2	3	4	5
C' cohesion	5.0	5.0	5.0	5.0	5.0
Θ' friction angle	10^0	15^0	20^0	25^0	30^0
FOS	0.4446	0.6128	0.7785	0.9536	1.1340
FOS1	0.3685	0.4887	0.6142	0.77480	0.8929
β	5.7908	4.3322	2.5208	0.25208	1.4685
P_f	3.5016 e-9	7.380e-6	0. 0059	0.3002	0.0710
FOS min non anchored	0.3685	0.4887	0.6142	0.7480	0.8929
FOS min anchored	0.4617	0.6171	0.7802	0.9542	1.1433

Table 4.2 shows the effect of the friction angle with constant cohesion of slope soil. Both parameters have influence on soil strength and as there is increase in friction angle the factor of safety increases, which are observed when the slope soil is anchored and non-anchored. The reliability index decreases as the frictional angle increases, as well as for probability of failure increases to up to 25^0 and gets lesser as the frictional angle reaches 35^0 due to soil particles orientation and interlocking.

`

Case 2. Random Field Model

For this case, the cohesion of soil *c*, the friction angle Ѳ', are statistically characterized as random fields. The factor of safety of the slope is greater than 1.0 and the edge of failure is easily noted. The simulations of the results for the slope are presented below, and critical failure zones are automatically found and the shapes of failure are linear, circular or non-linear. The simulation was carried out using Monte Carlo Simulation (MCS) and Adaptive Radial Based Importance Sampling (ARBIS).

The inputs of random fields distribute the cohesion and friction angle with a relative spatial variability, and the distributions come from the same normal distribution. The generations of two random variables cohesion and friction angle are scattered within the slope, and they are finer and dispersive when the number of slices are increased. After the random field of cohesion, friction angle is built, the probabilistic analysis based on MCS and ARBIS are performed. For any input cohesion and friction angle parameters (mean and standard deviation), the slope analysis is repeated number of times until various output are of interest. During each simulation of the Monte Carlo Simulation, each element of the soil is random.

In the simulation, the soil properties are determined, and the associated probabilities of failures P_f are calculated and their reliability index is computed as detailed in the table (2).

`

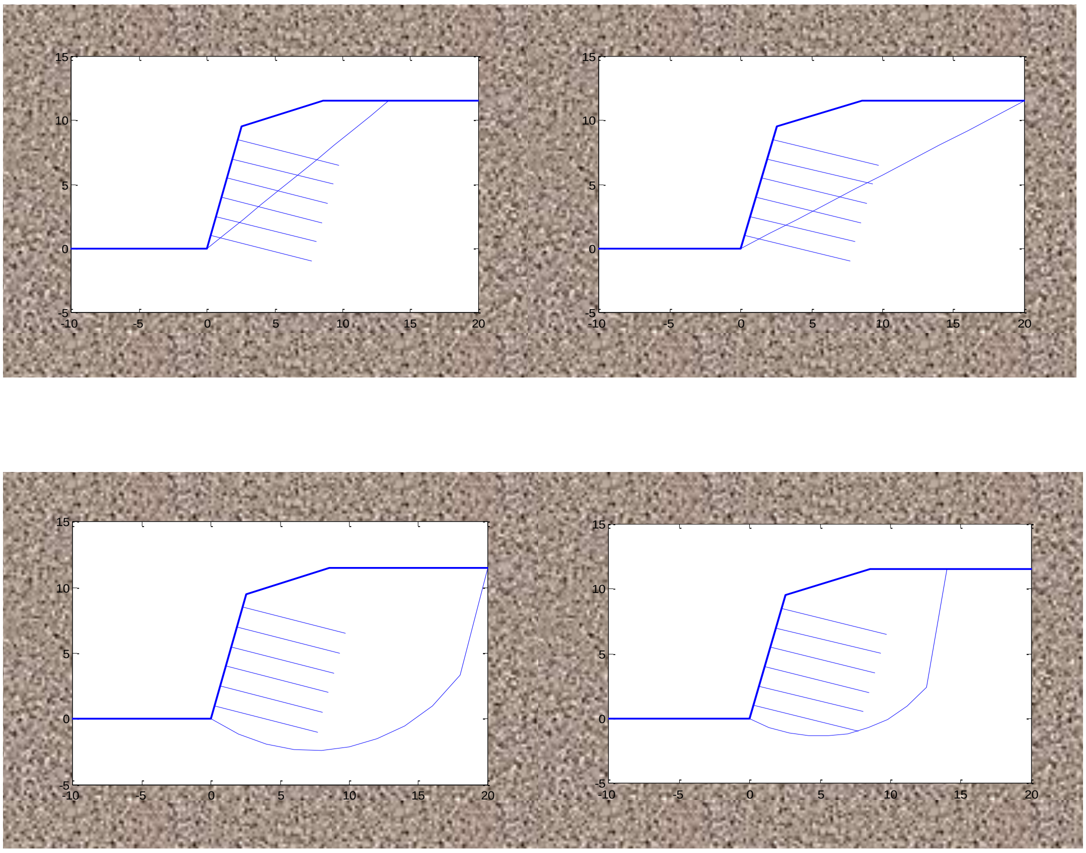


Figure 4.4: Modes of Failures for Random fields: Various modes of slope failures due to random field fields with random parameters (cohesion and friction angle). The trial slip surfaces are modeled with the Entry Exit slip surface. The surfaces exit at the toe of the slope. The soil characteristics are considered random for the analysis and the slope geometry are fixed. Four modes of failures are as shown above where the failure is linear and non linear.

`

Table 4.3 Effect of Random fields of Cohesion and Friction Angle

	1	2	3	4	5
C’ cohesion Ө’ friction angle	**Corr. Sigma= 0.5, Mean= 5, phi = pi*35/180**				
FOS	1.8933	4.6945	2.6795	3.8984	1.4726
FOS1	1.0974	0.9377	0.8598	0.7716	0.5621
β	0.115	0.6293	1.4221	1.4714	1.3205
P_f	0.4556	0.2646	0.0775	0.0706	0.0933
FOS min non anchored	0.9698	0.7693	0.6494	0.6865	0.8314
FOS min anchored	1.2656	1.1825	0.8684	1.1454	1.0111

Table 4.3 shows the Effect of Random fields of Cohesion and Friction Angle of soil to the slope. Cohesion influences the soil strength, as well the friction angle. The two parameters are random and they are automatically correspondingly to each other at random points, and it is observed that the factor of safety is greater than 1, and the probabilities of failures ranges from 0.0706 to 0. 4556. The reliability indices realized are from 0.115 to 1.4714. When the soil in anchored the factor of safety is greater than the one not anchored.

`

CHAPTER 5
CONCLUSION AND RECOMMENDATIONS

5.1 Conclusion

In conclusion, the probabilistic slope stability analysis was investigated through First Order Reliability Method (FORM) based on a numerical simulation that considers set varied soil properties, and through Monte Carlo Simulation and Adaptive Radial Based Importance sampling, based on numerical simulation that considers the spatial variability of random field soil properties.

The soil properties, cohesion and friction angle are discretized and both are studied under random fields and non random soil properties. The failure probability was obtained based on Monte Carlo Simulation performed with the soil properties cohesion and friction angle.

All the processes including random field modelling, slope analysis, probabilities analysis, reliability indices, are performed with a build in program. The results obtained shows that random field approach is more reliable, since it shows the physical variability of the soil with time, and better factor of safety are obtained than only using non random fields.

The framework for RBD will have an economical impact whereby safety is maximized with a reasonable cost, since the contributing elements to uncertainties, spatial variables, and parameters of the slopes are incorporated in the approach devised. The approach used will mitigate the slope failures.

5.2 Recommendations

The recommendations on the approach is too be more inclusive on the associated factors of failures of the slope such as water ground level, the seepage and the human activity on the slope. Also there should be studies to be done on effects to the size of the nail, which might have some influences on the stability of the slope.

`

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`

APPENDICES

Appendix A1: Input Data using FORM

```
function [allData]=inputData(dummy)
%function
[Entr,N,FS,probData,geomData,soilData,ancData,R,allData]=inputData(d
ummy)
clear
%
% SOIL DATA
%
%
%
%  ©  Indra S.H. Harahap
%

GamaSoil=18;
Phi=10;
Phi=Phi*pi/180;
Coh=5.0;
%
% GEOMETRY DATA
H=[9.5 2];
W=[2.546 6.0];
Cover=[  -25.0        0;
           0         0;
         W(1)      H(1);
       W(1)+W(2)  H(1)+H(2);
          100     H(1)+H(2)];
%
LRod=[3.4 5.1 6.7 7.6 7.6 7.6]; % Length of Rod
Th=[1.0 2.5 4.0 5.5 7.0 8.5];   % Location of Rod
Eta=15;                         % Nail inclination for horizontal
Eta=Eta*pi/180;
%
%
% SLIDING DATA
%
Tx=W(1)+W(2);                  % Trial Xout   %
%R=50;                         % Radius
Rguess=4.7452;
%
% stableMin is a function to obtain radius R for a given factor of
safety
% FS. Original R is initial guess.
%
Xout=W(1)+Tx; Yout=H(1)+H(2);
%
Xin=0; Yin=0;
Entr.Xin=Xin;
Entr.Yin=Yin;
Entr.Xout=Xout;
Entr.Yout=Yout;
%
D=sqrt((Xout-Xin)^2+(Yout-Yin)^2);
%
% set default value for geometric data
allData.Geom.W=W;
```

`

```
allData.Geom.H=H;
allData.Geom.Cover=Cover;
%
% Set default soil data
allData.Soil.Gama=GamaSoil;
allData.Soil.Phi=Phi;
allData.Soil.Coh=Coh;
%
% set default values for anchor data
allData.Anc.Eta=Eta;
allData.Anc.Th=Th;
allData.Anc.LRod=LRod;
%
% Set default values for problem data
N=10;                          % Number of slices
FS=0;                          % factor of safety
R=0;                           % radius of circle
Fmin=9999;                     % minimum factor of safety
allData.Prob.Entr=Entr;
allData.Prob.N=N;
allData.Prob.FS=FS;
allData.Prob.R=R;
allData.Prob.D=D;
allData.Prob.OPT=[];
allData.Prob.Fmin=Fmin;
%

%
```

Appendix A2: Input Data (RANDOM FIELDS) using MCS and ARBIS

```
function [allData]=inputData(dummy)
%function
[Entr,N,FS,probData,geomData,soilData,ancData,R,allData]=inputData(d
ummy)
clear
% Variables:
%       XX(i,1): mean
%       XX(i,2): standars deviation
%       XX(i,3): 1 normal distribution
%                2 lognormal distribution
%       XX(:,4): covariance

%
DIM=2;     % Number of probabilistic design variables
%
% (1) Soil data
%     The next four variables must be provided
nLayer=1; allData.Layer=1;
%
% Iteration Parameters consult MATLAB manual for further explanation
allData.Algol.TolFun=0.001;            % Tollerance for function
evaluation
allData.Algol.MaxIter=500;             % Maximum number of iteration
allData.Algol.MaxFunEval=20000;        % Maximum function evaluation
allData.Algol.TolX=0.001;              % Tollerance
allData.Algol.Algorithm='active-set'; % Algorithm
```

`

```
%
%    Statistical data of problem parameters
%    Note that standard deviation will be calculated later
%    mean      std-dev  dist  cov         Note
Unit
XX=[  5.0        999     1    0.1;      % cohesion
(kPa,   ton/m3)
    34*pi/180   999     1    0.1;      % friction angle
(rad)
      18        999     1    0.05;     % gamma unit weight soil
(kN/m3, ton/m3)
   0.025        999     1    0.05;     % diameter of nail         (m)
  412000        999     1    0.05;     % yield strength of nail
(kPa,   x1000ton/m3)
   0.100        999     1    0.20];    % drill hole diameter      (m)

mu=XX(:,1); cov=XX(:,4); sigma=mu.*cov; XX(:,2)=sigma;
%
% Store data into structure
K=3;
%allData.Prob.lb=mu-K*sigma;  % lower limit of DV's
%allData.Prob.ub=mu+K*sigma;  % upper limit of DV's;
%
Coh=XX(1,1);
Phi=XX(2,1);
GamaSoil=XX(3,1);
Diam=XX(4,1);
Fy=XX(5,1);
Hole=XX(6,1);

%
allData.XX=XX;
allData.DIM=DIM;
allData.Soil.XX=XX;
%
%
% (2) Geometry data
%     The next three variables must be provided
H=[9.5 2];
W=[2.546 6.0];
Cover=[  -25.0        0;
           0         0;
         W(1)      H(1);
       W(1)+W(2)  H(1)+H(2);
           100    H(1)+H(2)];
%
% (3) Nail/rod data
%     The next three variables must be provided
LRod=[7.7 7.7 7.7 7.7 7.7 7.7]; % Length of Rod
%LRod=[10.0 10.0 10.0 15.0 15.0 15.0]; % Length of Rod
%LRod=[7.7 7.7 7.7 15.0 15.0 15.0];    % Length of Rod
%LRod=[7.7 7.7 7.7 10.0 10.0 10.0];    % Length of Rod

Th=  [1.0 2.5 4.0 5.5 7.0 8.5]; % Location of nail rod from the
bottom
Eta=15; Eta=Eta*pi/180;         % Nail inclination from horizontal
(+ve clockwise)
%
SV=1.5;    % vertical distance of nail   (m)
SH=1.1;    % horizontal distance of nail (m)
Tmax=25.0; % maximum value of grout soil shear strength (kPa)
```

`

```
TF=10.;     % maximu value normal force of concrete facing can resist
(MN)
%
% SLIDING DATA
%
% CALCULATE bottom (Xin,Yin) and top (Xout,Yout) entrance poinst
% Bottom entrance point is at (0,0)
Tx=W(1)+W(2);                       % Trial Xout
Xin=0; Yin=0; Xout=W(1)+Tx; Yout=H(1)+H(2);
%
Entr.Xin=Xin;
Entr.Yin=Yin;
Entr.Xout=Xout;
Entr.Yout=Yout;
%
D=sqrt((Xout-Xin)^2+(Yout-Yin)^2); % R must be >=D
%
% set default value for geometric data
allData.Geom.W=W;
allData.Geom.H=H;
allData.Geom.Cover=Cover;
%
% Set default soil data
allData.Soil.Gama=GamaSoil;
allData.Soil.Phi=Phi;
allData.Soil.Coh=Coh;
%
% set default values for anchor data
allData.Anc.Eta=Eta;
allData.Anc.Th=Th;
allData.Anc.LRod=LRod;
allData.Anc.Diam=Diam;
allData.Anc.Fy=Fy;
allData.Anc.Hole=Hole;
allData.Anc.SV=SV;
allData.Anc.SH=SH;
allData.Anc.Tmax=Tmax;
allData.Anc.TF=TF;

% Set default values for problem data
N=10;                         % Number of slices
FS=0;                         % factor of safety
R=99999;                      % radius of circle
Fmin=9999;                    % minimum factor of safety
%
allData.Prob.Entr=Entr;
allData.Prob.N=N;
allData.Prob.FS=FS;
allData.Prob.R=R;
allData.Prob.D=D;
allData.Prob.OPT=[];
allData.Prob.Fmin=Fmin;
%
%  - END - of data
```

`

Appendix B: Soil Calculations

```
function [QQ,LL,ExFlag]=soilCalc(R,allData)
%
%    ExFlag: exit flag
%       0 = OK
%       1 + error in R < D
% called from:  (1) stableMin

display (' Inside soilCalc')
%geomData.W;
%R;
ExFlag=0;
QQ=0; LL=0;

Arc=[];
Alpa=[];
Weight=[];
N=allData.Prob.N;
for i=1:N
    Ybot(i)=0;
    Ytop(i)=0;
end
Entr=allData.Prob.Entr;
Xin=Entr.Xin;
Yin=Entr.Yin;
Xout=Entr.Xout;
Yout=Entr.Yout;

W=allData.Geom.W;
H=allData.Geom.H;
Cover=allData.Geom.Cover;
[NCover,m]=size(Cover);

GamaSoil=allData.Soil.Gama;
Phi=allData.Soil.Phi;
Coh=allData.Soil.Coh;

D=sqrt((Xout-Xin)^2+(Yout-Yin)^2);
if(R<=D/2)
    ExFlag=1;
    return
end

Delta=asin(D/2/R);
Alpha=atan((Yout-Yin)/(Xout-Xin));
Beta=Delta-Alpha;
sin(Beta);
cos(Beta);

X0=R*sin(Beta);    % X0 and Y0 are center of circle
Y0=R*cos(Beta);    %
X0^2+Y0^2-R^2;
%
Del=2*Delta/N;
DX=(Xout-Xin)/N;
%
Xbot=[]; Ybot=[]; Xbot(1)=Xin; Ybot(1)=Yin;
```

`

```
for i=1:N
    Xbot(i+1)=Xbot(1)+i*DX;
    A=1;
    B=-2*Y0;
    C=(X0-Xbot(i+1))^2+Y0^2-R^2;
    D=sqrt(B^2-4*A*C);
    Y1=(-B+D)/(2*A);
    Y2=(-B-D)/(2*A);

    Ybot(i+1)=Y0-sqrt(R^2-(Xbot(i+1)-X0)^2);
    Ybot(i+1)=Y1;

    for j=2:(NCover)
        if Xbot(i)>Cover(j,1)
        elseif Xbot(i)>+Cover(j-1,1)
            DXX=Cover(j,1)-Cover(j-1,1);
            DYY=Cover(j,2)-Cover(j-1,2);
            Yt=Cover(j-1,2)+(Xbot(i)-Cover(j-1,1))*DYY/DXX;
         end
    end

    if abs(Yt-Y1)<0.001
        Yb=Y1;
        Ybot(i+1)=Y1;
    else
        Yb=Y2;
        Ybot(i+1)=Y2;
    end
end
%
for i=1:N
    Alpa(i)=atan((Ybot(i+1)-Ybot(i))/(Xbot(i+1)-Xbot(i)));
    Arc(i)=sqrt((Ybot(i+1)-Ybot(i))^2+(Xbot(i+1)-Xbot(i))^2);
    Arc(i)=DX/cos(Alpa(i));
    Arm(i)=(Xbot(i+1)+Xbot(i))/2-X0;
end
%Arc=Arc
Xtop=[]; Ytop=[]; Xtop(1)=Xbot(1); Ytop(1)=Ybot(1);
[NCover,m]=size(Cover);
for i=1:N+1
    Xtop(i)=Xbot(i);
    for j=2:(NCover)
        if Xbot(i)>Cover(j,1) %&& Xbot(i)>=Cover(j-1,1)
        elseif Xbot(i)>=Cover(j-1,1)
            DXX=Cover(j,1)-Cover(j-1,1);
            DYY=Cover(j,2)-Cover(j-1,2);
            Ytop(i)=Cover(j-1,2)+(Xbot(i)-Cover(j-1,1))*DYY/DXX;
         end
    end
end
% Calculate AREA
    Yb=Ybot;
    Yt=Ytop;
for i=2:(N+1)
    Area(i-1)=0.5*((Ytop(i)-Ybot(i))+(Ytop(i-1)-Ybot(i-1)))*DX;
end
%Area=Area
Weight=GamaSoil*Area;
%
  corr.name = 'exp';
  corr.c0 = [1 1]; % anisotropic correlation
```

`

```
  mesh = [Xbot(:) Ybot(:)]; % 2-D mesh
   mesh
%
%    % set a spatially varying variance (must be positive!)
  corr.sigma=0.5; mean=5;
  [Coh,KL] = randomfield(corr,mesh, 'mean',mean, ...
                'trunc', 10);
%
   mean = (pi*35/180);corr.sigma= 0.1*mean;
   [Phi,KL] = randomfield(corr,mesh, 'mean',mean, ...
                'trunc', 10);
%
for i=1:N
   % QQ=QQ+(Coh*Arc(i))+Weight(i)*cos(Alpa(i))*tan(Phi);
    QQ=QQ+(Coh(i)*Arc(i))+Weight(i)*cos(Alpa(i))*tan(Phi(i));
    LL=LL+Weight(i)*sin(Alpa(i));
end
%These are valid for plotting graph
allData.Geom.Xtop=Xtop;
allData.Geom.Ytop=Ytop;
allData.Geom.Xbot=Xbot;
allData.Geom.Ybot=Ybot;
allData.Geom.Alp=Alpa;
```

Appendix C: Random Fields Generation

```
% Random fields generation (2-D):
%    % build the correlation struct
   corr.name = 'exp';
   corr.c0 = [0.2 1]; % anisotropic correlation

   x = linspace(-5,15,50);
   [X,Y] = meshgrid(x,x); mesh = [X(:) Y(:)]; % 2-D mesh

%    % set a spatially varying variance (must be positive!)
   corr.sigma = cos(pi*mesh(:,1)).*sin(2*pi*mesh(:,2))+1.5;

   [F,KL] = randomfield(corr,mesh, ...
            'Lowmem',1, 'trunc', 10);

   % plot the realization
   DDDD=reshape(F,50,50);
   surf(X,Y,DDDD); view(2); colorbar;
```

Appendix D: Slope Analysis

Appendix D1: Slope Analysis

```
[allData]=inputData(0);
%z=allData.Prob.N;
%
%
% STATISTICAL DATA OF SOIL PARAMETERS
%
mu=[allData.Soil.Gama allData.Soil.Coh allData.Soil.Phi];
```

`

```
sigma=[2 2 2*pi/180];
cov=[ 0.05 0.1 0.1];

mu=mu';
sigma=sigma';
cov=cov';
lb=mu-sigma; % the bounds are restricted to one standard deviation
ub=mu+sigma;
%
XX(:,1)=mu;
XX(:,2)=sigma;
XX(:,3)=1;
allData.Prob.XX=XX;
allData.Prob.lb=lb;
allData.Prob.ub=ub;
tt=XX;
%
Bound(1)=8;
Bound(2)=20;
%
%
% TESTING SUBROUTINE
X=0;
X=15; % X absis of is exit point, the ordinate will be manually
calculated
allData.Prob.OPT=0;
[FOS1]=fun1(X,allData)
% Find minimum FOS for unnailed slope
allData.Prob.OPT=0;
[Rmin1,Fmin1]=minFOS(X,allData);
%
% Find minimum FOS for nailed slope
X=15;
allData.Prob.OPT=1;
[Rmin2,Fmin2]=minFOS(X,allData);
```

Appendix D2: Slope Analysis

```
%Fglobal probData
%
%  GET PROBLEM DATA
[allData]=inputData(0);
%
%
% STATISTICAL DATA OF SOIL PARAMETERS
%
mu=[allData.Soil.Gama allData.Soil.Coh allData.Soil.Phi];
sigma=[2 2 2*pi/180];
cov=[ 0.05 0.1 0.1];

mu=mu';
sigma=sigma';
cov=cov';
lb=mu-sigma;
ub=mu+sigma;
%
XX(:,1)=mu;
XX(:,2)=sigma;
XX(:,3)=1;
```

`

```
allData.Prob.XX=XX;
allData.Prob.lb=lb;
allData.Prob.ub=ub;
tt=XX;
%
Bound(1)=8;    % exit poimt bound
Bound(2)=20;
%
%
% No anchor at all
%
A=4; B=2; CC=0;
%
LL=allData.Anc.LRod;
[m,n]=size(LL');
%
% No anchor failure
  CASE= 'NO ANCHOR FAILURE'
%
  allData.Prob.OPT=1;
  allData.Anc.LRod=LL;
%
% Find Entrance points that produre min FOS
  [XEntr,Fmin]=entrCalc(Bound,allData);
 %
  W=allData.Geom.W;
  H=allData.Geom.H;

  Xout=W(1)+XEntr; Yout=H(1)+H(2);
%
  Xin=0; Yin=0;
  Entr.Xin=Xin;
  Entr.Yin=Yin;
  Entr.Xout=Xout;
  Entr.Yout=Yout;
%
  CASE='Find R for FOS=1 (soil+anchor)';

  Xin=0; Yin=0;
  Entr.Xin=Xin;
  Entr.Yin=Yin;

  H=allData.Geom.H;
  Xout=XEntr; Yout=H(1)+H(2);
  Entr.Xout=Xout;
  Entr.Yout=Yout;
  D=sqrt((Xout-Xin)^2+(Yout-Yin)^2);
  Rguess=1.1*D/2;
%
  allData.Prob.Fmin=Fmin;   %
  allData.Prob.Entr=Entr;   %
  allData.Prob.FS=Fmin;     %
  allData.Prob.OPT=1;       %
%
  options=optimset('LargeScale','off','Display','off',
'Algorithm','active-set');

[R,Fmin,exitflag]=fmincon(@fosCalc,Rguess,[],[],[],[],0,[],[],option
s,allData)
%
  allData.Prob.FS=0;
```

`

```
  [FOS]=fosCalc(R,allData);
%
CC=CC+1;
%plotNail(allData,A,B,CC)
%
```

Appendix D3: Slope Analysis

```
%  GET PROBLEM DATA
[allData]=inputData(0);
%
% STATISTICAL DATA OF SOIL PARAMETERS
soilData=allData.Soil;
ancData=allData.Anc;
geomData=allData.Geom;
probData=allData.Prob;

mu=[soilData.Gama soilData.Coh soilData.Phi];
sigma=[2 2 2*pi/180];
cov=[ 0.05 0.1 0.1];

mu=mu';
K=3;
sigma=sigma';
cov=cov';
lb=mu-K*sigma;  % lower and upper limit of DV's
ub=mu+K*sigma;  %
%
XX(:,1)=mu;
XX(:,2)=sigma;
XX(:,3)=1;
probData.XX=XX;
probData.lb=lb;
probData.ub=ub;
%
allData.Geom=geomData;
allData.Anc=ancData;
allData.Soil=soilData;
allData.Prob=probData;
%
% No anchor failure
  CASE= 'NO ANCHOR FAILURE'
  allData.Prob.OPT=1;         % soil nail problem
%
  Bound(1)=8;
  Bound(2)=20;
%
  [x,beta,allData]=slopeBeta(mu,Bound,allData);
    x
    beta=abs(beta)
    Pf=normcdf(-beta)
%
A=1; B=1; CC=1;
%
plotNail(allData,A,B,CC)
```