THE EFFECT OF LIMITED SITE INVESTIGATIONS ON THE DESIGN AND PERFORMANCE OF PILE FOUNDATIONS

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To my wife Dian Andini, my sons Alif Ardian Arsyad and Muhammad Terzaghi Ramadhan,
and my parents Muhammad Arsyad Kadiro and Yusniar Yusuf

Preface

The work described in this thesis was undertaken over the period of 2 years, between July 2006 and July 2008, within School of Civil, Environmental, and Mining Engineering at the University of Adelaide. Throughout the thesis, all materials, techniques, concepts and conclusions obtained from other sources have been acknowledged in the text.

Abstract

The research presented in this thesis focuses on the quantification of the effect of limited site investigations on the design and performance of pile foundations. Limited site investigation is one of the main causes of structural foundation failures. Over the last 30 years, most site investigations conducted for infrastructure projects have been dictated by minimum cost and time of completion, rather than meeting the need to appropriately characterise soil properties (Institution of Civil Engineers 1991; Jaksa et al. 2003). As a result, limited site investigations remain common, resulting in a higher risk of structural foundation failure, unforeseen additional construction, and/or repair costs. Also, limited site investigations can result in over-designing foundations, leading to increased and unnecessary cost (ASFE 1996).

Based on the reliability examination method for site investigations introduced by Jaksa et al. (2003) and performed by Goldsworthy (2006), this research investigated the effect of limited site investigations on the design of pile foundations. This was achieved by generating three-dimensional random fields to obtain a virtual site consisting of soil properties at certain levels of variability, and by simulating various numbers of cone penetration tests (CPTs) and pile foundations on the generated site. Once the site and the CPTs were simulated, the cone tip resistance (q_c) was profiled along the vertical and horizontal axes.

The simulated q_c profiles yielded by the CPTs were then used to compute axial pile load capacity termed the pile foundation design based on site investigations (SI). In parallel, the axial pile load capacity of the simulated pile foundation utilising the "true" cone tip resistance along the simulated pile was also determined. This is termed "the true" design, or the benchmark pile foundation design, and referred to as pile foundation design based on complete knowledge (CK). At the end of this process, the research compared the pile foundation designs based on SI and those based on CK. The reliability of the foundation design based on SI was analysed with a probabilistic approach, using the Monte Carlo technique.

The results indicated that limited site investigations have a significant impact on the design of pile foundations. The results showed that minimum sampling efforts result in a high risk of over- or under-designing piles. More intensive sampling efforts, in contrast, led to a low risk of under- or over-design. The results also indicated that the levels of spatial variability of the soil are notable factors that affect the effectiveness of site investigations. These results will assist geotechnical engineers in planning a site investigation in a more rational manner with knowledge of the associated risks.

Statement of Originality

This thesis contains no material which has been accepted for the award of any other degree or diploma in any university or other tertiary institution and, to the best of my knowledge and belief, contains no material previously published or written by another person, except where due reference has been made in the text.

I give consent to this copy of my thesis, when deposited in the University Library, being made available for loan and photocopying.

Signed : .... Date:………………………..

Acknowledgments

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have made for me throughout my life. Finally, I am indebted to Allah Subhanahu Wata’ala for the strength, nourishment and opportunities which I have been blessed with during this period of study.

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Notation

A_n	Net sectional area of pile toe
A_b	Cross-sectional area of pile base
APS	Australian Partnership Scholarship
A_{si}	Surface area of the pile shaft in contact with the soil
A_s	Gross surface area of the pile shaft
ASTM	American Standard of Testing Materials
CK	Complete Knowledge
CLPD	Centre of Learning and Professional Development
COV	Coefficients of variation
CPT	Cone Penetration Test
D	Diameter or width of the pile
DFT	Discrete Fourier transform
DMT	Dilatometer test
E	Young Modulus
FFT	Fast Fourier transform
f_i	Average unit skin friction of the soil layer i
FOSM	First order second moment
f_s	Sleeve friction of the CPT
f_{su}	Ultimate friction value along the pile shaft
GA	Geometric average
GIS	Geographic information system
GLS	Generalised least-squares
i	Soil layer

HA	Harmonic average
i^{+h}	Distance between the two points, X^i *and* X^{i+h}
KBS	Knowledge Base System
k_c	Penetrometer load capacity factor
LAS	Local average subdivision
LCPC	Laboratoire Central des Ponts et Chausseés, France
LFRD	Load and resistance factor design
MA	Moving average
m_ψ	Sample mean
n	Number of soil layers along the pile shaft
N	SPT number
N_b	Standard penetration number, N, at pile base
n_t	total population size
OLS	Ordinary least-squares
P	Probability of over-design or under-design
PDA	Pile driving analyser
Q_{all}	Allowable load capacity of a single pile
Q_b	Ultimate load at the pile base
Q_{CK}	Pile load capacity based on the complete soil properties
q_b	Unit load at the pile base
q_c	Cone tip resistance
q_{eq}	Equivalent cone resistance at the level of the pile tip
Qs	Ultimate load along the pile shaft
Q_{SI}	Pile load capacity based on site investigations
q_u	unit load of the pile
Q_{ult}	Ultimate load of the soil at the pile base
q_s	Limit unit skin friction at the level of the layer i, and l_i

R_d	Radial distance between a borehole and a pile
SA	Standard arithmetic average
SAPAC	South Australian Partnership for Advanced Computing
SF	Safety factor
SI	Site investigation
SOF	Scale of fluctuation
SPT	Standard penetration test
TBM	Turning bands method
TT	Triaxial test
$Var(\mu)$	Variance of the sample mean
W	Weight of pile
$X(x + \tau)$	Sample at a distance τ from position x
$X(x)$	Sample at position x
X_i	Value of property X at location i
X_{i+h}	Value of property X at location
X_{ln}	Log normal variable
μ	Mean
$\|\tau_j\|$	Separation distance
$\xi(z)$	Soil property
σ^2	Sample standard deviation
σ_e^2	Variance of equipment errors
δ_I	Estimated displacement
ρ_{ij}	Correlation coefficient between the i^{th} and j^{th} sample
σ_m^2	Total variance of measurement
σ_p^2	Variance of procedural errors
σ_r^2	Variance of random errors
σ_{sv}^2	Variance of soil variability

θ	Scale of fluctuation
Ψ	Sample data
μ_{lnx}	Mean of log normal variable
σ_{lnx}	Standard deviation of log normal variable

Chapter One

Introduction

1.1 THE CONTEXT OF THE STUDY

Site investigations are conducted in civil engineering and building projects to obtain geotechnical and geological data about a site. These data enable engineers or other geotechnical experts to model soil parameters and to develop geotechnical or structural engineering designs (Baecher and Christian 2003; Clayton et al. 1995). In the case of designing foundations in particular, the geotechnical and geological data derived from site investigations are preliminary information for the process of determining the type, allowable bearing capacities and settlements of the foundations and locating the groundwater table around them (Bowles 1996).

1.2 THE NATURE OF THE PROBLEM

Over the last 30 years, the scope of site investigations undertaken in most construction projects declined to the point of being inadequate (Institution of Civil Engineers 1991). The scope of site investigations is often minimised in order to reduce the initial cost of construction, and is rarely related to the need to appropriately characterise ground conditions. These inadequate site investigations remain one of the main factors in the failure of structural foundations, leading to unforeseen additional construction or repair costs. At the other extreme, inadequate site investigations can result in over-design of the foundation, increasing the cost unnecessarily (ASFE 1996).

A number of researchers have developed methods to seek the appropriate scope of site investigations. Toll (1998) reviewed artificial intelligence methods known as knowledge based systems (KBSs), used in planning the scope of site investigations. The earliest KBS method, developed by Wharry and Ashley (1986) and Siller (1987), was SOILCON. Following this, a simple prototype KBS for soil investigation was introduced by Alim and Munro (1987) and further developed by Halim et al. (1991) in order to incorporate probabilistic analysis for planning site investigation programs. However, Toll (1998) suggests that these KBS methods are unable to deal with substantial problems such as geometric and quantitative problems of site investigations.

More recently, Parsons and Frost (2002) introduced a method incorporating the geographic information system (GIS) and geostatistics in order to quantitatively assess the scope of site investigations. The GIS is used to optimise multiple sampling locations of investigations within a site, while geostatistics, involving ordinary and indicator kriging, is employed to generate probabilistic values of those sampling locations. Parsons and Frost (2002) concluded that the GIS-geostatistics based method is able to evaluate and compare various site investigation strategies. Moreover, the GIS-geostatistics based method is effective in evaluating the sensitivity of site investigations to additional samplings as well as in determining the optimum quantities, appropriate types and effective locations of the site investigations.

Goldsworthy et al. (2004) and Jaksa et al. (2005) performed a combination of random field simulations and finite element analyses to investigate the appropriate scope of site investigations for designing shallow foundations. Their research aimed to quantify the appropriate number of site investigation boreholes, including the geometrical patterns and the type of soil tests, specified statistically within certain levels of variability. By simulating various numbers of boreholes, the reliability of pad foundation design was quantified using a Monte Carlo approach.

The use of probabilistic analysis for examining the adequacy of site investigations is one of the current methods developed to achieve a better approach in planning site investigation programs (Baecher and Christian 2003). As Jaksa et al. (2003) and Goldsworthy (2006) have recommended, the use of probabilistic analysis for reliability assessment of site investigations in relation to foundation design should be explored further to a number of different site investigation techniques and other types of foundation. This current research sought to add to the existing body of knowledge by examining the reliability of site investigations in relation to the design of pile foundations.

1.3 STATEMENT OF THE RESEARCH PROBLEM

The research described in this thesis examined the reliability of site investigations in the design of pile foundations. The research aimed to:

- quantify the reliability of site investigations with respect to the design of pile foundations;
- quantify the effect of limited site investigations on the design of pile foundations and to what extent it results in over- or under-design; and
- develop an alternative approach to determining the appropriate scope of site investigations in the design of pile foundations which is based on the level of variability of the soil.

1.4 METHODOLOGY

The study employed a method incorporating the generation of three-dimensional random fields as models of a site using the local average subdivision (LAS) technique developed by Fenton and Vanmarcke (1990), and the computation of axial pile load capacity using the Laboratoire Central des Ponts et Chausseés method developed by Bustamante and Gianaselli (1982). The research simulated a number of site investigation scenarios on the models, and quantified their reliability in the design of pile foundations within the Monte Carlo framework, as proposed by Jaksa et al. (2003).

1.5 ORGANISATION OF THE THESIS

The thesis details the research undertaken to quantify the reliability of site investigations on the design of pile foundations. In Chapter 2, the existing literature is reviewed regarding the development of site investigation strategies and techniques and a number of methods for estimating the axial load capacity of piles. This includes the development of statistical methods to deal with uncertainty in geotechnical engineering. The development of probabilistic methods for pile foundation designs is also presented.

Chapter 3 provides an overview of the methodology used in the research, including the model of three-dimensional random fields as a virtual soil model using the LAS method, the simulation of site investigation schemes, the computation of axial pile load capacity using the LCPC method, and the implementation of Monte Carlo simulations as a reliability framework. Chapter 3 also provides the verifications of the methodology are presented. These include a number of analytic and numerical simulations undertaken to verify that the research generated reliable simulations conforming to random field theory, the LAS, the LCPC method and the Monte Carlo simulations.

Chapter 4 presents results obtained from these simulations as well as analysis of these results. The effect of limited site investigations on the design of pile foundations is described, including the influence of the radial distance of a cone penetration test (CPT) from the simulated pile foundation and, in Chapter 5, the effect of several site investigation schemes incorporating various numbers of CPTs. The results obtained from the simulation are generated with various levels of variability specified by the coefficients of variation (COVs) and scale of fluctuation (SOF) values. The level of influence of the length of the simulated pile and of anisotropic soil properties on the reliability of site investigations is also examined.

Finally, a summary and conclusion of the research, as well as areas for future research, are presented in Chapter 6.

Chapter Two

Literature Review

2.1 INTRODUCTION

This chapter provides a context for later chapters of the thesis, and reviews various site investigation techniques, available methods of designing pile foundations, and methods of dealing with uncertainties in geotechnical engineering. At the conclusion of the chapter, stochastic methods incorporating geotechnical uncertainty applied to designing pile foundation design are presented.

2.2 CHARACTERISATION OF GROUND CONDITIONS

The characterisation of ground conditions might be defined as a process of obtaining geotechnical and geological information in order to determine soil parameters and to model geotechnical or structural engineering design. Baecher and Christian (2003) divided the characterisation of ground conditions into two phases. First is a preliminary investigation or desk study, which involves collecting information about the regional geology and geological history. The second phase is a site investigation designed to obtain data based on detailed measurements of soil properties.

The geological information obtained from the preliminary investigation are data consisting of the stratigraphy of the ground including the thickness and types of each soil or rock layer (Baecher and Christian 2003). This information is used to identify the process of the geological formation of the ground. Baecher and Christian (2003) classify geological information as qualitative. The other, geotechnical information, may be viewed as data sets incorporating the physical and engineering properties of the soil revealed from in situ and/or laboratory tests. This information expresses the mechanical behaviour of the soil and is used to predict its response to the proposed loads. Bowles (1996) noted that the information can be used in foundation system design, including determining the type of foundation and estimating its load capacity and settlement.

A number of papers illustrate the scope of the characterisation of ground conditions. Tomlinson (1969) suggests that the scope correlates to the importance of the structure for which the soil is being characterised, the complexity of the ground, the design of the foundation layout, and the availability of data on existing foundations on similar ground. Furthermore, Rowe (1972) classifies the level of importance of projects into three categories. The first category (Group A) is defined as those projects that are considered both important and risky. Their complexity requires extensive site investigation, as well as sophisticated design necessitating a great deal of subsurface information. These kinds of projects include dams, large underground openings, and major and sensitive projects. The second category (Group B) contains more modest projects that are considered less important or risky than those in Group A. Rowe (1972) has suggested that Group B projects suffer from the difficulty of determining how large the site investigation should be. The third category (Group C) represents the most routine and lowest risk projects. Such projects require minimal site investigation.

Bowles (1996) noted that generally the characterisation of ground conditions might be achieved by several simple activities, such as borehole drilling into the ground, collecting samples for visual inspections and laboratory testing. Clayton et al. (1995) added these to preliminary desk studies and air photograph interpretations. In addition, Jaksa et al. (2003) indicate that appropriate characterisation of ground conditions involves a plan of borehole drilling, material sampling, and laboratory and/or in situ testing. The number, depth and locations of these boreholes, samples, and tests are defined by the geometry of the structure, the loads imposed by the structure and the anticipated subsurface profile.

Baecher and Christian (2003) explain further about the scope of the characterisation of ground conditions. They point out that the characterisation of ground conditions should be carried out in three steps, as shown in Figure 2-1. First is reconnaissance that collates a general review of the local and regional geology. The reconnaissance is performed with geological and surveying equipment, air photos, and records of nearby existing construction. Second is a preliminary investigation which confirms the qualitative hypothesis taken from the reconnaissance and establishes a quantitative hypothesis. In this phase, the preliminary investigation is conducted through a limited number of boreholes, field mapping, and geological surveys. Third is a detailed investigation which confirms the quantitative hypothesis. This phase consists of a comprehensive boring program, accurate geometrical information, detailed mapping, and additional geophysical surveys, if necessary.

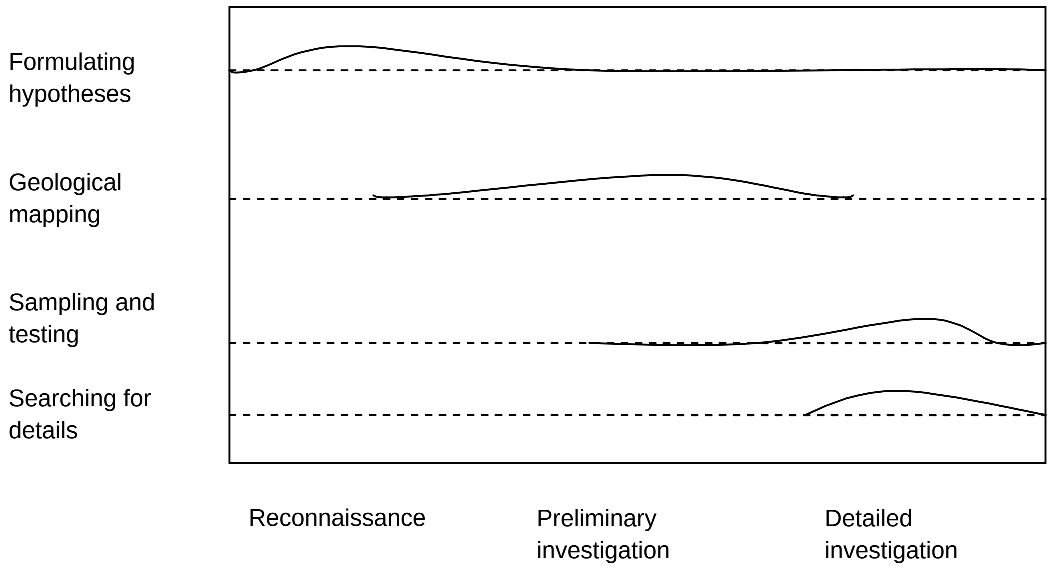

Figure 2-1 Traditional phases of characterisation of ground conditions (after Baecher and Christian, 2003)

Currently, the scope of the characterisation of ground conditions is often determined by the budget and timeline for construction projects (Jaksa et al. 2003). These factors have been considered important when deciding the amount and the type of site investigations. As explained by the Institution of Civil Engineers (1991), over the last 30 years the scope of site investigations has often been governed by a desire to achieve minimum cost and against a background of time constraints. Clients or designers prefer to allocate a limited amount of their budgets to site investigation, then design the foundations conservatively to overcome inadequate data from limited investigations (Bowles 1996). Moreover, generally, geotechnical engineers use more intuitive methods of engineering judgement based on extensive experience with site conditions rather than analysis based on strategy and inference (Baecher and Christian 2003).

As a result, the geotechnical data obtained from limited characterisation of ground conditions can be both inadequate and or inappropriate. This situation can lead to foundation failure and a high level of financial and technical risk (Institution of Civil Engineers 1991; Littlejohn et al. 1994; National Research Council 1984; Temple and Stukhart 1987). Inadequate site investigation is one of main reasons for construction cost overruns and constructions delays, as well as potential injury to the structure's occupants (Institution of Civil Engineers 1991; National Research Council 1984; Temple and Stukhart 1987).

2.2.1 The Cone Penetration Test (CPT)

As explained previously, the scope of the site investigation can be divided into field investigation consisting of drilling and in situ testing and laboratory testing. In the next two sections, two in situ tests will be examined: the cone penetration test (CPT) and the standard penetration test (SPT), which are the most commonly used tests employed to characterise the ground for infrastructure projects (Bowles 1996).

The CPT is standardised in ISSMFE (1989) and D3441-75T (ASTM 1987). The test consists of pushing a cone of standard dimensions into the ground at a rate of 10 to 20 mm/s and recording its resistance (Bowles 1996). As shown in Figure 2-2, the cone penetrometer consists of a 60^o cone tip with of 10-15 cm^2 of cross sectional area, and a friction sleeve with a surface area of 150-184 cm^2 with a length of 13.3 cm (Olsen and Farr 1986). The data recorded by the standard CPT are the cone tip resistance, q_c, sleeve friction, f_s and depth (Bowles 1996).

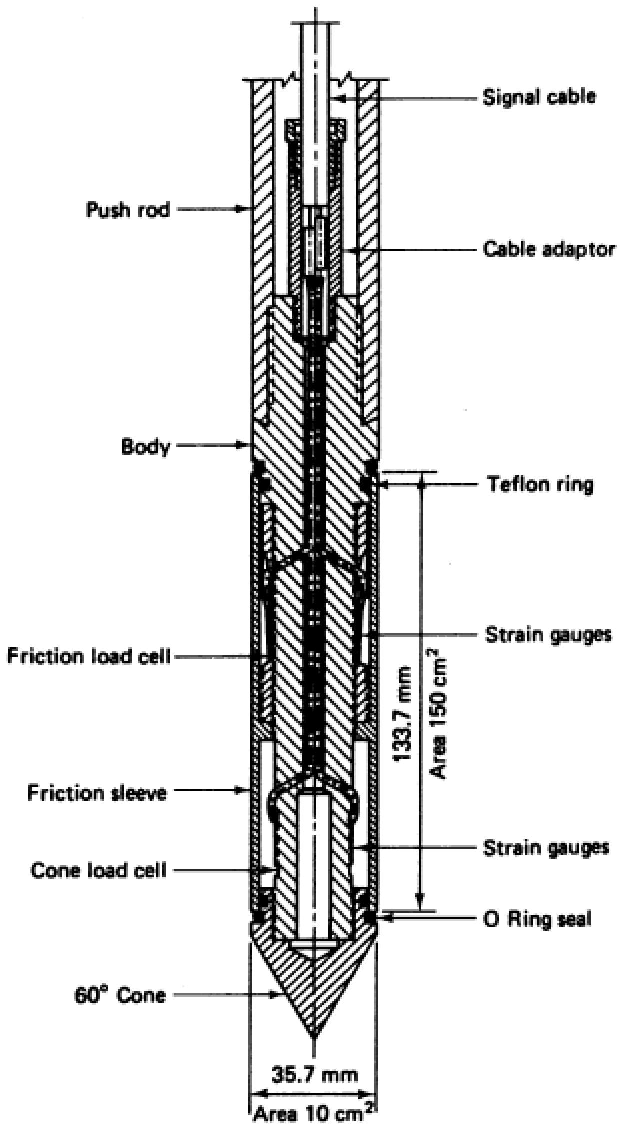

Figure 2-2 Schematic of cone penetration test (after Holtz and Kovacs, 1981)

There are four types of CPT: mechanical, electrical, piezocone electric friction, and seismic cone (Bowles 1996; ISSMFE 1989). These may incorporate additional sensors to measure such factors as lateral stress, cone pressure, seismic response, electrical resistivity, heat flow, radioisotope presence and acoustic noise, in order to enhance interpretation (Lunne et al. 1997).

In terms of accuracy, like all tests, the CPT has measurement errors due to the influence of factors such as pore water pressure around the cone, filter location, temperature change, inclination, axial loading of the cone, calibration errors, and the effect of wear (Lunne at al. 1997). Therefore, the CPT must be regularly calibrated and normalized with respect to the measured soil parameter (Olsen and Farr 1986). To obtain reliable data, the CPT should be complemented with other site investigation tools including boreholes, sampling, and laboratory testing (Lunne et al. 1997).

However, it is suggested that the CPT method is more reliable than other in situ tests for the following reasons:

- The CPT is a robust, simple, fast, reliable and economical test providing continuous sounding of subsurface soil (Abu-Farsakh and Titi 2004; Lunne et al. 1997);
- There is a similarity of form between the cone penetrometer and a pile (Abu-Farsakh and Titi 2004);
- The CPT measurement error is the lowest of any other in situ device at about 7% to 12% (Orchant et al. 1988), compared with the SPT which is about 27% to 85% (Lee et al. 1983); and
- In environmental applications, the CPT prevents direct human contact with potentially contaminated material (Lunne et al. 1997).

2.2.2 Standard Penetration Test (SPT)

The standard penetration test (SPT) is currently the most popular and economical method of obtaining ground conditions (Bowles 1996). As shown in Figure 2-3, the SPT consists of the following (ASTM 1992):

- driving the standard split-barrel sampler a distance of 460 mm into the soil at the base of the boring at the desired test depth;
- using a 63.5 kg driving mass (or hammer) falling free from a height of 760 mm; and
- counting the number of blows to drive the sampler the last two 150 mm increments (total = 300 mm) to obtain the SPT *N* number.

As mentioned, the process of determining *N* values by using the SPT involves summing the blow counts for the last two 150 mm increments (ASTM 1992). The test is halted if the following conditions occur:

- 50 blows are required for any 150 mm increment;
- 100 blows are obtained to drive 300 mm; and
- 10 successive blows produce no advance.

NOTE:
This figure is included on page 11 of the print copy of the thesis held in the University of Adelaide Library.

Figure 2-3 Schematic of standard penetration test (SPT) (after Bowles, 1996)

Despite the SPT being widely used, a major shortcoming is that it is not reproducible (Bowles 1996). Research focussing on SPT equipment and its effects, conducted by Gibbs and Holtz (1957), found that overburden pressure and the length of the drill rod are significant factors affecting the SPT N-value. Other factors such as the use of a worn driving shoe, and pushing a rock also might influence the accuracy of the SPT (Bowles 1996).

In terms of the effect of driving energy, Kovacs and Salomone (1982) point out that the driving energy influences the N-value by about 30% – 80% of the SPT result. This means that the SPT results might vary depending on the type of equipment, drive hammer configuration, and the release mechanism used (Bowles 1996).

2.2.3 Mappings and Samplings

The most basic tasks in the characterisation of ground conditions are mapping local and regional geological formations, creating vertical profiles and inferring the continuity and homogeneity of important deposits (Baecher and Christian 2003).

In geotechnical engineering, there is limited information on sampling strategies in site investigations. One paper by Ferguson (1992) investigates a range of sampling patterns that is capable of detecting contaminated land. These sampling patterns include random, regular grid, stratified random, and stratified systematic unaligned, as shown in Figure 2-4. Among these patterns, a regular grid pattern was regarded as the best pattern (Bell et al. 1983; Bridges 1987; Department of Environment 1988; Lord 1987; ICRCL 1987; Smith and Ellis 1986) because it is widely known and used, and more systematic than others (Baecher and Christian 2003). However, Ferguson (1992) suggests that another pattern, namely herringbone, as shown in Figure 2-5, produces better results.

NOTE:
This figure is included on page 12 of the print copy of the thesis held in the University of Adelaide Library.

Figure 2-4 Four different sampling patterns: (a) regular (square); (b) stratified random; (c) simple random and (d) stratified systematic unaligned (after Ferguson, 1992)

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This figure is included on page 13 of the print copy of the thesis held in the University of Adelaide Library.

Figure 2-5 Herringbone sampling patterns (after Ferguson, 1992)

There are no obvious guidelines for determining the number and depth of sampling activities to be carried out during subsurface exploration of a project (Bowles 1996). The following samples show the variety of guidelines available for sampling using boreholes:

- In the context of investigations for road pavements, the boreholes or test pits should be located every 30 metres. (AUSTROADS 1992);
- With regards to buildings, the Taiwan Building Code specifies that one borehole should be drilled every 600 m^2 of site area or 300 m^2 of building area, with a minimum of 2 boreholes being drilled (Moh 2004);
- Again, in relation to buildings, Bowles (1996) recommended that at least three borings should be drilled for level ground and five are preferable if the site is not level; and
- The position and maximum depth of boreholes should be decided based upon general site geology, field investigation costs, and the nature of the project (Olsen and Farr 1986). It is suggested, for example, that the CPT be located at the corner of the building, a heavy load point, or a potential soft zone, and performed in the configuration of two dimensional cross section which has various patterns, such as triangular, tic-tac, and cross. The depth of the CPT depends on the structure of the load.

2.3 PILE FOUNDATION DESIGN

A pile foundation is a type of substructure which is relatively long and slim and which transmits load through the soil strata of low bearing capacity to deeper soil or rock strata having a higher bearing capacity (Tomlinson 1969). Whilst the design of pile foundations involves the assessment of both the pile foundation's load carrying capacity and settlement, the work undertaken in this research was confined to examining pile foundation carrying capacity. Examination of pile settlement is beyond the scope of this study.

2.3.1 Pile Load Capacity

The maximum allowable load that can be safely supported by a pile can be calculated by dividing the ultimate load capacity, Q_{ult}, by a safety factor, SF (Bowles 1996).

$$Q_{all} = \frac{Q_{ult}}{SF} \qquad \textbf{2-1}$$

The ultimate load capacity of a single pile is calculated by summing the ultimate shaft resistance and base resistance, then subtracting the weight of the pile (Poulos and Davis 1990):

$$Q_{ult} = Q_{su} + Q_{bu} - W \qquad \textbf{2-2}$$

where: Q_{su} is the ultimate shaft resistance;

Q_{bu} is the ultimate base resistance; and

W is the weight of the pile.

The method for estimating the ultimate pile load capacity can be approached by using a method based on soil mechanics (static approach), or using pile driving data (dynamic approach) (Poulos and Davis 1990).

Static methods. The basic formula of the static method proposed by Chellis (1961) is:

$$Q_{ult} = A_s f_{su} + A_b P_{bu} \qquad \textbf{2-3}$$

where: A_s is the surface area of the pile in contact with the soil;

f_{su} is the ultimate friction value along the pile shaft;

A_b is the area of the pile base; and

P_{bu} is the ultimate load of the soil at the pile base.

Dynamic methods. Dynamic methods are based on vertical movement and blows from a driving hammer. These methods assume that the vertical energy generated by the blow of a driving hammer can be measured to provide data that indicate the load capacity of the pile (Poulos and Davis 1990). The dynamic method has been expressed using various formulae, as shown in Table 2-1.

Table 2-1 Dynamic methods (after Bowles, 1996)

However, Bowles (1996) points out that dynamic methods can be unreliable over various ranges of pile capacity. Therefore, he has suggested improving dynamic methods by combining them with a record of the pile driving history, and performing a static load test on the pile.

One type of dynamic method is that of the stress wave equation. This method estimates pile load capacity based on an analysis of hammer impacts (Rausche 2004). The stress wave equation method has become widely used as part of the popular pile driving analyser (PDA) (Likins et al. 2000) which can be applied to verify the pile load capacity of bored and driven piles (Bowles 1996).

Bowles (1996) points out that the stress wave equation might be applied to estimating pile-driving stresses, yet the equation is rarely used to predict pile load capacity. Poulos and Davis (1990) suggest that the stress wave equation method can produce inaccurate predictions of pile load capacity because of the 'set up' in soft-clay soils which can significantly affect the pile load capacity.

Full scale loading test. The alternative method of predicting pile load capacity is full scale pile load tests (Tomlinson 1969). Pile load tests are more accurate because they are able to include the effect of soil variability and the effect of construction method (Bowles 1996). Moreover, this test is more reliable because of its ability to obtain axial load capacity directly (Tomlinson 1969). However, both Tomlinson (1969) and Bowles (1996) note that the pile load test is often not undertaken because this method requires significant loads, and may be inefficient for work in the field.

Standard penetration test (SPT) based methods. In situ tests, such as the standard penetration test (SPT) and the cone penetration test (CPT), can be applied to estimate pile load capacity (Poulos and Davis 1990). Meyerhof (1956, 1976) proposes an empirical equation (Eq 2-4) which is based on SPTs, in US tons, for displacement piles in saturated sand, whereas Eq. 2-5 is for small displacement piles such as steel H-piles.

$$Q_{ult} = 4N_b A_b + \frac{N_s A_s}{50} \qquad \textbf{2-4}$$

$$Q_{ult} = 4N_b A_n + \frac{N_s A_s}{100} \qquad \textbf{2-5}$$

where N_b is the standard penetration number, N, at pile base;

A_b is the sectional area of pile base;

N_s is the average value of N along pile shaft;

A_n is the net sectional area of pile toe; and

A_s is the gross surface area of shaft.

Shioi and Fukui (1982) introduced another formula:

$$Q_{ult} = q_u A_p \qquad \textbf{2-6}$$

where A_p is the cross sectional area of the pile

q_u is defined in Table 2-2

Table 2-2 Shio and Fukui Method (1982) (after Bowles, 1996)

NOTE:
This table is included on page 17 of the print copy of the thesis held in the University of Adelaide Library.

Other methods that use the SPT are Hansen (1970), Janbu (1976), and Vesić (1975). Bowles (1996) compares the available methods in order to find the best. He argues that the Meyerhof formula is too optimistic, whereas the Vesić formula is too conservative. He concludes that the Janbu formula might be a the preferred method.

Cone penetration test (CPT) based methods. Abu-Farsakh and Titi (2004) state that CPT-based pile load capacity formulae are generally written in the following form:

$$Q_{ult} = q_b A_b + \sum_{i=1}^{n} f_{si} A_{si} \qquad \textbf{2-7}$$

where q_b is the unit load capacity at the pile base;

A_b is the cross-sectional area of the pile base;

f_i is the surface area of the pile shaft in contact with layer i ;

A_{si} is the pile shaft are interfacing with layer i; and

n is the number of soil layers along the pile shaft.

Various modifications have been applied to Equation 2-7 using empirical factors (see Table. 2-3).

Table 2-3 Summary of CPT-based methods (after Abu-Farsakh and Titi, 2004)

NOTE:
This table is included on page 18 of the print copy of the thesis held in the University of Adelaide Library.

2.3.2 LCPC Method

Bustamante and Gianaselli (1982) have confirmed that pile load capacity can be estimated using the CPT. Having determined the pile load capacity using LCPC, they compared the results to the those obtained from full scale load tests. The verification tests were undertaken on 96 deep foundations of various types, diameters and lengths. The full scale load tests were carried out on 197 piles, 172 of which were tested in the laboratory.

The LCPC method proposed by Bustamante and Gianaselli (1982) incorporates a pile load equation developed by modifying the Begemann (1963) and Van Der Ween (1957) formulae for calculating tip resistance, and modifying the Dinesh Mohan (1963) formula for calculating skin friction.

The LCPC method (Bustamante and Gianaselli 1982) is summarised as:

$$Q_{ult} = Q_b + Q_s$$

$$Q_b = q_{eq} k_c A_b$$

$$Q_s = \sum_{i=1}^{L} q_s C_p l_i \tag{2-8}$$

$$q_s = \frac{q_c}{\alpha}$$

where Q_b is the load capacity at the pile base;

Q_s is the load capacity along the entire length of the pile shaft;

q_{eq} is the equivalent cone resistance at the level of the pile tip;

k_c is the penetrometer load capacity factor;

α is a constant depending on the nature of the soil and the construction method of the pile;

L is the embedded length of the pile;

a is the clipping distance at the pile base;

C_p is the circumference of the pile shaft;

A_b is the area of the base of the pile; and

q_s is the limit unit skin friction at the level of the layer i, and the length of the layer l_i.

The parameter q_{eq} is calculated by averaging q_c over a distance a (=1.5 x D) above and below the pile tip, as shown in Figure 2-6, then eliminating the values q_c higher than $1.3q'_c$ and lower than $0.7\, q'_c$.

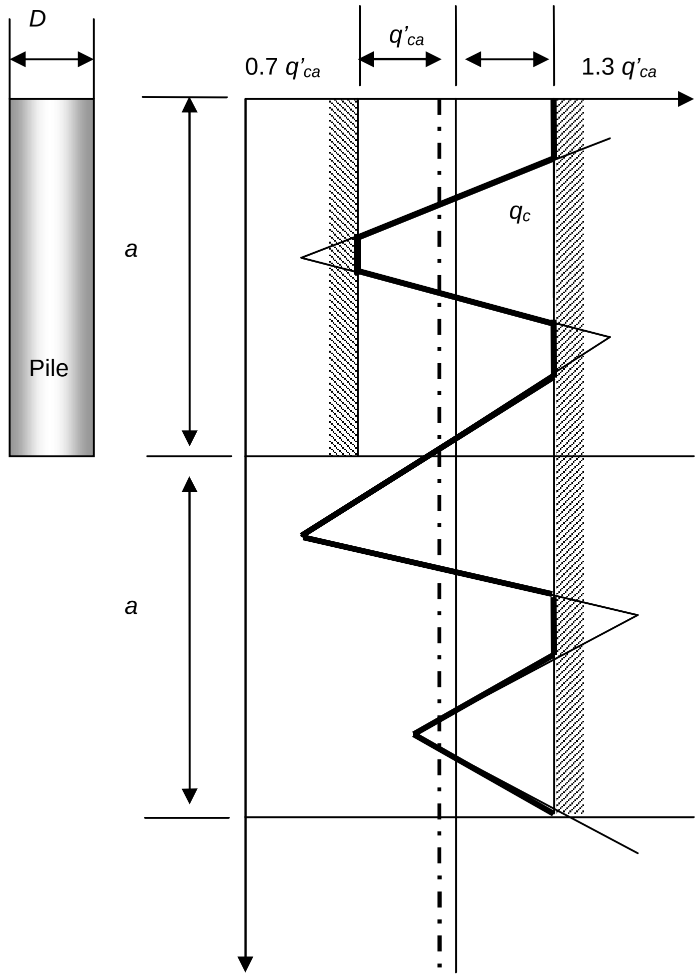

Figure 2-6 Diagram of method used to determine q'_{ca} (after Bustamante and Gianaselli, 1982)

Tables 2-4 and 2-5 show the values of k_c and the coefficient of α in relation to the nature of soil and pile type.

Table 2-4 Determination of factor k_c based on pile type and nature of the soil (after Bustamante and Gianaselli, 1982)

Nature of soil	q_c (10^5 Pa)	Factors k_c	
		Group I	Group II
Soft clay and mud	< 10	0.4	0.5
Moderately compact clay	10 to 50	0.35	0.45
Silt and loose sand	≤ 50	0.4	0.5
Compact to stiff clay and compact silt	> 50	0.45	0.55
Soft chalk	≤ 50	0.2	0.3
Moderately compact sand and gravel	50 to 120	0.4	0.5
Weathered to fragmented chalk	> 50	0.2	0.4
Compact to very compact sand and gravel	> 120	0.3	0.4

Table 2-5 Determination of coefficient α and maximum soil skin resistance based on pile types and the nature of soil (after Bustamante and Gianaselli, 1982)

Nature of soil	q_c (10^5 Pa)	Coefficient α				Maximum value of q_s (10^5 Pa)					
		Category									
		I		II		I		II		III	
		IA	I B	IIA	IIB	I A	I B	IIA	IIB	IIIA	IIIB
Soft clay and mud	< 10	30	30	30	30	0.15	0.15	0.15	0.15	0.35	
Moderately compact clay	10 to 50	40	80	40	80	0.35	0.35	0.35	0.35	0.8	≥ 1.2
Soil and loose sand	≤ 50	60	150	60	120	0.35	0.35	0.35	0.35	0.8	
Compact to stiff clay and compact silt	> 50	60	120	60	120	0.35	0.35	0.35	0.35	0.8	≥ 2.0
Soft chalk	≤ 50	100	120	100	120	0.35	0.35	0.35	0.35	0.8	
Moderately compact sand and gravel	50 to 120	100	200	100	200	0.8	0.35	0.8	0.8	1.2	≥ 2.0
Weathered to fragmented chalk	> 50	60	80	60	80	1.2	0.8	1.2	1.2	1.5	≥ 2.0
Compact to very compact sand and gravel	> 120	150	300	150	200	1.2	0.8	1.2	1.2	1.5	≥ 2.0

2.4 UNCERTAINTY IN GEOTECHNICAL ENGINEERING

2.4.1 Soil Variability

Inherent soil variability is one of the main sources of uncertainty in geotechnical engineering. Uzielli et al. (2007) define soil variability as the variation of properties from one spatial location. Besides inherent soil variability, Phoon and Kulhawy (1999a) suggest that measurement error, statistical estimation error, and transformation error are also primary sources of uncertainty. Such uncertainty is termed epistemic (Lacasse and Nadim 1996). Orchant et al. (1988) argue that measurement errors occur because of inaccuracies in measurement devices, the limitations of the test standard in terms of procedural errors, and scatter of test results that are not based on inherent soil variability but are rather random testing effects.

Phoon et al. (1995) summarised the variability of soil properties in statistical terms, as shown in Table 2-6. It should also be noted that this variability is influenced by uncertainties due to measurement error (Goldsworthy 2006) which is treated below.

Table 2-6 Variability of soil properties (after Phoon et al, 1995)

NOTE:
This table is included on page 22 of the print copy of the thesis held in the University of Adelaide Library.

Soils are naturally variable due to their processes of formation and continuous environmental alteration (Uzielli et al. 2007). Uzielli et al. (2007) explain that the sorts of external forces that may influence the variability levels of soil include external stress, weather, chemical reaction, new substances, and human intervention such as soil improvement, excavation, and filling. They suggest, however, that soil variability is influenced by more formation processes rather than weathering processes. Similarly, formation processes are the main factor in determining the complexity and variety of physical soil properties (Jaksa 1995). Fenton (1999) suggests that these features of soil variability occur in both natural and man-made soils.

2.4.2 Statistical Uncertainty

Statistical uncertainty results from limited sampling which provides inaccurate information of ground conditions (Goldsworthy 2006). Statistical uncertainty is described as the variance in the estimate means (Filippas et al. 1988), as explained by de Groot (1986) in the following equation:

$$Var(\mu) = \frac{\sigma^2}{n} \qquad \textbf{2-9}$$

where $Var(\mu)$ is the variance of the sample mean;

σ^2 is the sample standard deviation; and

n is the number of samples.

In terms of correlated samples, Filippas et al. (1988) introduced the relationship as shown in Equation 2-10.

$$Var(\mu) = \frac{\sigma^2}{n} + 2\frac{\sigma^2}{n^2}\sum_{i=1}^{n}\sum_{j=i+1}^{n}\rho_{ij} \qquad \textbf{2-10}$$

where ρ_{ij} is the correlation coefficient between the i^{th} and j^{th} sample

Baecher and Christian (2003) suggest that the variance of the sample mean should consider the location of the sampling. Therefore they propose that the variance of the sample mean be correlated to spatial sampling as shown in Equation 2-11.

$$Var(\mu) = \frac{\sigma^2}{n}\frac{n_t - n}{n_t} \qquad \textbf{2-11}$$

where n_t is the total population size

Jaksa (1995) has also investigated the variability of soil properties using over 200 CPT data. The result showed that the COV of q_c is about 60%. The results of other similar investigations that have been conducted by several researchers are shown in Table 2-7.

Table 2-7 Statistical uncertainties of various sites (after Goldsworthy, 2006)

NOTE:
This table is included on page 24 of the print copy of the thesis held in the University of Adelaide Library.

2.4.3 Measurement Uncertainty

Measurement uncertainty arises from inaccurate measurement of soil properties. This uncertainty is incorporated in the characterisation of the ground and in parameters and models (Baecher and Christian 2003). Errors of measurement produce data scatter with bias and statistical uncertainty leading to systematic errors (Whitman 2000).

Measurement uncertainty can be divided into two categories: systematic and random errors (Lee et al. 1983; Orchant et al. 1988). Systematic errors are the consistent underestimation or overestimation of soil properties (Jaksa 1995). Systematic errors are caused by equipment and procedural errors occurring during the measurement of soil properties (Orchant et al. 1988). These errors can be considered as a bias (Lumb 1974).

Random errors, on the other hand, are the variation of test results which is not directly related to soil variability, equipment and procedural errors (Jaksa 1995). These errors generally have zero mean, influencing the test results of soil properties equally, both above and below the mean (Baecher 1979; Snedecor and Cochran 1980).

Orchant et al. (1988) introduced the following relationship to quantify measurement errors.

$$\sigma_m{}^2 = \sigma_e{}^2 + \sigma_p{}^2 + \sigma_r{}^2 \qquad \textbf{2-12}$$

where $\sigma_m{}^2$ is total variance of measurement;

$\sigma_e{}^2$ is the variance of equipment errors;

$\sigma_p{}^2$ is the variance of procedural errors; and

$\sigma_r{}^2$ is the variance of random errors.

The equation above does not, however, deal with soil variability. Therefore, Jaksa (1995) suggests that the formula of quantification of measurement errors could be improved by using the variance of soil variability $\sigma_{sv}{}^2$ as described by Equation 2-13:

$$\sigma_m{}^2 = \sigma_e{}^2 + \sigma_p{}^2 + \sigma_r{}^2 + \sigma_{sv}{}^2 \qquad \textbf{2-13}$$

Many researchers have investigated measurement errors of in situ tests used in characterizing the ground conditions. The results of these measurement errors have been summarised by Phoon and Kulhawy (1999c) as shown in Table 2-8.

Table 2-8 Measurement error of geotechnical tests (adapted from Phoon and Kulhawy, 1999c and Goldsworthy, 2006)

Test type	Measurement errors (in coefficient of variation, %)					
	Equipment	Procedure	Random	Total	Range	Researchers
Cone penetration test (CPT)	3	5	5 – 10	7 – 10	5 – 15	Orchant et al. 1988
Standard penetration test (SPT)	3 – 75	5 – 75	12 – 15	14 - 100	15 – 45	Lee et al. 1983
					27 – 85	Orchant et al. 1988
Dilatometer test (DMT)	5	5	8		11	Orchant et al. 1988

2.5 QUANTIFYING GEOTECHNICAL UNCERTAINTY

Uncertainty in geotechnical engineering can be accommodated by using stochastic and statistical methods. Some of these methods are treated briefly in the following sections.

2.5.1 Classical Descriptive and Inferential Statistical Analysis

It is widely accepted that the quantification of the variability of soil properties requires classical descriptive statistical analysis. The purpose of classical statistical analysis is to describe the variability of sample data and to fit the sample data with probability distribution functions (Uzielli et al. 2007). This form of analysis involves calculating sample moments, visual inspection of scatter and drawing a histogram. The commonly adopted sample moments are the mean, variance, skewness, and kurtosis.

The mathematical equations for these moments respectively are described by the following equations.

Sample mean:

$$\mu_{\psi} = \frac{1}{n}\sum_{i=1}^{n}\psi i \qquad \textbf{2-14}$$

Sample variance:

$$\sigma_{\psi} = \sqrt{\frac{1}{n-1}\sum_{i=1}^{n}(\psi_i - \mu_{\psi})^2} \qquad \textbf{2-15}$$

where n is the number of sample

ψ is sample data

Uzielli et al. (2007) suggest that there are no amount of data that can represent populations perfectly. The reason is that the amount of data is always limited in practice, and the sample statistics cannot describe the statistic of the population due to its bias and some degree of uncertainty.

After analysing sample data using descriptive statistics, the quantification of soil variability also requires inferential statistical analysis. This analysis can model the sample patterns associated with randomness and uncertainty in order to draw general inferences about the variable parameter or process. Uzielli et al. (2007) explain that the form of inferential statistical analysis depends on the selection of distribution type, estimation of distribution parameters, and goodness-of-fit testing of the resulting distribution. The process incorporating both descriptive and inferential statistical analysis is described in Figure 2-7.

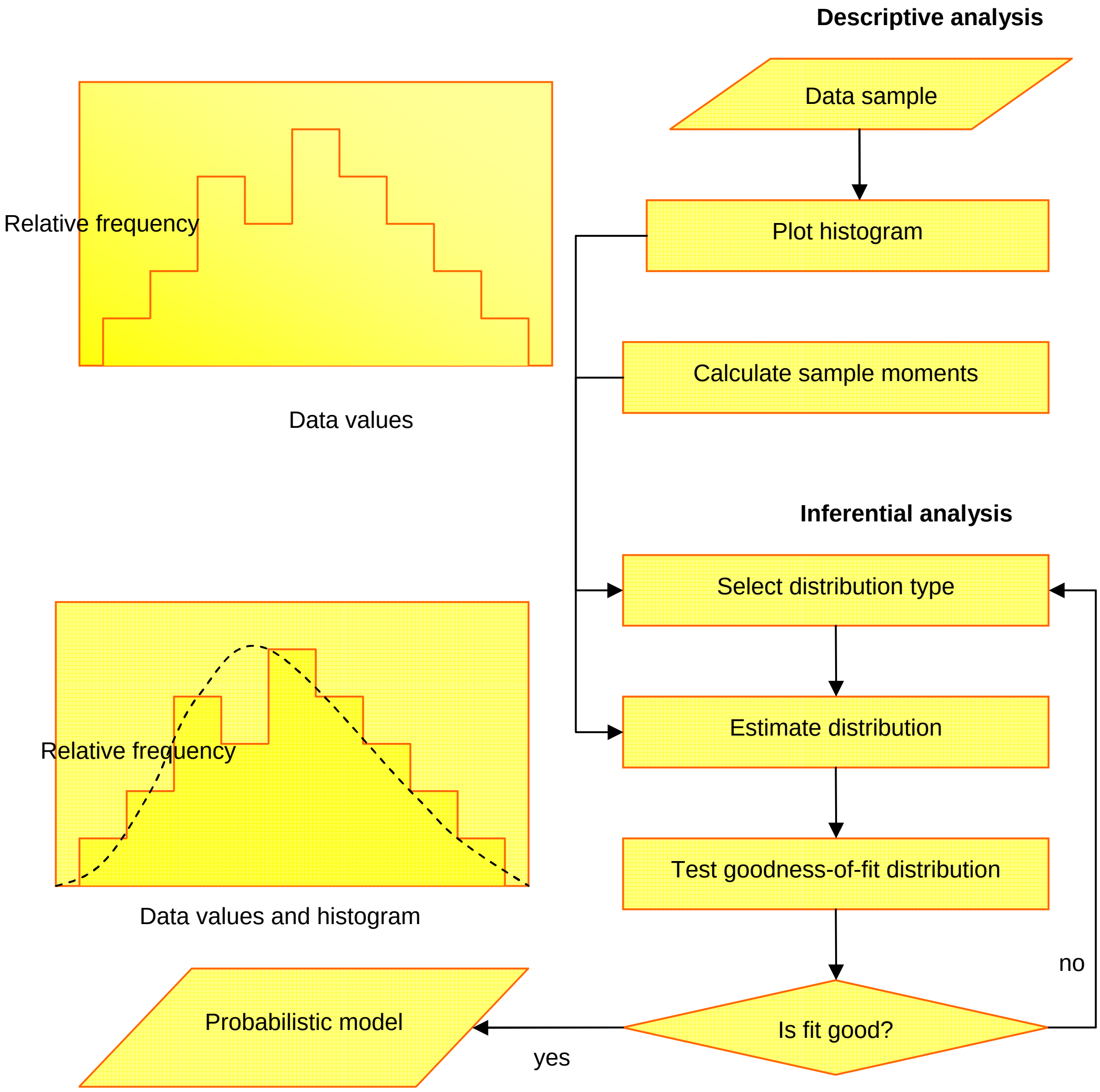

Figure 2-7 Integrated descriptive and inferential analysis for probabilistic modelling of a random variable (after Baecher and Christian, 2003)

There are several probability density functions that are usually used in geotechnical engineering. These include the uniform, triangular, normal, log-normal, and type –I Pearson beta distributions. To select which is the appropriate distribution, Uzielli et al. (2007) suggest using the principle of maximum entropy (Jaynes 1978) and the Pearson based system (Rethati 1988). The appropriate distribution of a data set can also be determined by conducting distribution fitting or maximum likelihood analysis (Ang and Tang 1975; Baecher and Christian 2003), and testing their goodness-of-fit using the Shapiro test (Shapiro and Wilk 1965) or Kolmogorov-Smirnov tests.

However, there are a number of factors to take into consideration when using probability density functions for modelling soil data patterns. Baecher and Christian (2003) point out that the use of probability density functions is appropriate for practical purposes as long as the application is for well known soil properties. Baecher and Christian (2003) argue that there is only a limited set of probability density functions that can satisfactorily fit a wide range of observed soil properties distribution.

Probability density functions have been applied in geotechnical engineering by some researchers. For example, Corotis et al. (1975) examined a number of soils and described them using the normal and log-normal distributions. The goodness-of-fit test of the Kolmogorov-Smirnov was applied to data sets from three soil types. The results showed that most of the measured soil properties fitted within the normal distribution rather than the log-normal distribution. Lacasse and Nadim (1996) reviewed probability density functions for a number of soil properties. It was found that the best-fit distribution may depend on soil type. However, several researchers e.g. Bredja (2000), Fenton (1999), Lumb (1966), Hoeksema and Kitanidis (1985), Sudicky (1986) agree that the majority of soil properties are appropriately modelled using a log-normal distribution.

2.5.2 Second Moment Statistics

Geotechnical uncertainty is best quantified by means of the second moment statistic, such as the variance, standard deviation or the coefficient of variation (COV). The COV is expressed as:

$$COV_{\psi} = \frac{\sigma_{\psi}}{\mu_{\psi}} \qquad \textbf{2-16}$$

Uzielli et al. (2007) note that the coefficient of variation (COV) is widely used in geotechnical variability analysis because it is dimensionless and it clearly and simply express the dispersion about the mean. Furthermore, Phoon and Kulhawy (1999b) also consider the COV to be a useful measurement in analysing soil variability. This COV enables one to use data from other sources if there are no data available from the field.

Despite the application of second moment statistics to enable the quantification of the uncertainty of soil variability due to its simplicity and lack of dimension, the accuracy of this technique requires the modelling of uncertainty in the data input (Uzielli et al. 2007). This means that second moment statistics is inadequate in terms of achieving some degree of confidence because the technique is not compatible with uncertainty propagation techniques. Uzielli et al. (2007), therefore, suggest that uncertainty propagation techniques should be used, and should be compatible with random variable methods, for instance, the Monte Carlo technique.

2.5.3 First Order Second Moment (FOSM) Method

The first order second moment (FOSM) method is used to investigate the propagation of second moment uncertainty (Uzielli et al. 2007). The FOSM method uses a modified Taylor series within the first two moments of a random variable. The FOSM method approximates the central tendency parameter (mean) and dispersion parameter (standard deviation) of a random variable.

Ang and Tang (1975) indicated that the FOSM method is an effective means of investigating the propagation of second moment uncertainty. Besides that, Uzielli et al. (2007) suggest that the FOSM method can describe the formulation of total uncertainty models.

However, Uzielli et al. (2007) note that the FOSM method cannot avoid errors because the FOSM method ignores the higher order Taylor series. In addition, as Griffiths et al. (2002) point out, the FOSM method describes the random variables using only their mean and standard deviation, without taking account of the form of the probability density function.

2.6 SPATIAL CORRELATION ANALYSIS

Both second moment statistics and the FOSM method do not take into account spatial variation. However, Uzielli et al. (2007) argue that involving spatial variation in describing soil variability is very important, particularly for geotechnical engineering, because:

- The site characterisation of compositional and mechanical parameters of soil conducted in geotechnical engineering is measured and described with spatial variation;
- In-situ tests that measure parameter values of soil are usually related to spatial location; and
- Large scale projects, such as dams and roads, must take account of spatial variation.

To perform spatial correlation analysis, it is essential to understand stationarity. Spatial correlation analysis can be in error if stationarity of data is not carried out first (Uzielli et al. 2007). A data set is said to be stationary if (Brockwell and Davis 1987):

- the mean, μ, is constant with distance; that is, no trend or drift exists in the data;
- the variance, σ^2, is constant with distance (homoscedastic);
- the are no seasonal variations; and
- there are no irregular fluctuations.

Several researchers make different comments about stationarity. Vanmarcke (1983) and Baecher & Christian (2003) state that stationarity is similar to statistical homogeneity. However, Baecher & Christian (2003) suggest that this stationarity is just an assumption that may not be true in the real world. Furthermore, Fenton (1996) and Baecher & Christian (2003) explain that stationarity usually depends on scale.

Within the domain of a site, the data may appear stationary, but over a larger region, the data may not be stationary. Therefore, Phoon et al. (2003) has introduced a formal hypothesis test for rejecting the null hypothesis of stationarity.

Jaksa (2007) states that stationarity is performed in both random field theory and geostatistics as a common method of analysing soil variability. If data appear to be a non stationary, the data can satisfy stationarity using data transformation. There are two common types of data transformations: decomposition and differencing. Another type that could be used is variance transformation.

Bowemann and O'Connell (1979) have defined the autocorrelation function as measuring the correlation between two random field observations separated by a lag. Autocorrelation functions are modelled as a finite-scale stochastic process.

The autocorrelation function of a stochastic process describes the variation of strength of the spatial correlation as a function of the spatial separation distance between two spatial locations at which data are available (Uzielli et al. 2007). In the discrete case, the sample autocorrelation of a set of data is given by:

$$\hat{R}\left(\tau_j\right) = \frac{\sum_{i=1}^{n-|j|}\left(\psi_i - \mu_\psi\right)\left(\psi_{i+|j|} - \mu_\psi\right)}{\sum_{i=1}^{n}\left(\psi_i - \mu_\psi\right)^2} \qquad \textbf{2-17}$$

where μ_ψ is the mean of the data set;

n is the number of data points;

τ_j is the separation distance

J is 1, 2,…, K

K is n/4, as suggested by Box and Jenkins (1970)

Uzielli et al. (2007) note that the autocorrelation function has been widely used for investigating spatial variability in geotechnical engineering. A number of researchers have used this function such as Akkaya & Vanmarcke (2003), Baecher & Christian

(2003), Cafaro and Cherubini (2002), Fenton & Vanmarcke (2003), Jaksa et al. (1997), and Phoon and Kulhawy (1996).

To identify spatial correlation structure in a data set of soil, several theoretical autocorrelation models can be used to provide a function of separation distance τ. To calculate the SOF, these autocorrelation models are often fitted to the sample autocorrelation function of the data set. Jaksa (1995) and Uzielli et al. (2007) present those autocorrelation models introduced by Vanmarcke (1977, 1983) as shown in Table 2-9.

Table 2-9 Theoretical autocorrelation functions used to determine the scale of fluctuation (after Vanmarcke, 1977, 1983)

Autocorrelation function	Formula	Scale of fluctuation
Simple exponential	$R(\tau)=e^{-\lvert\tau\rvert/b}$	2b
Cosine exponential	$R(\tau)=e^{-\lvert\tau\rvert/\alpha}\cos(\tau/\alpha)$	α
Second order Markov	$R(\tau)=e^{-\lvert\tau\rvert/d}\left(1+\frac{\lvert\tau\rvert}{d}\right)$	4d
Squared exponential	$R(\tau)=e^{-(\lvert\tau\rvert/c)^2}$	$\sqrt{\pi}c$
Triangular	$R(\tau)=1-\frac{\lvert\tau\rvert}{\alpha}$ for $\lvert\tau\rvert \le a$ $R(\tau)=0$ for $\lvert\tau\rvert \ge a$	α

Uzielli et al. (2007) suggest that the choice of a suitable correlation structure for the data set is determined by comparing the goodness-of-fit of the autocorrelation function of the data set to one or more autocorrelation models. The autocorrelation model that yields the maximum determination coefficient would be selected as the best-fit model.

2.7 RANDOM FIELD MODELLING OF SOIL VARIABILITY

In order to simulate soil profiles that exhibit the same spatial variation as real soils, two techniques are often used: random field theory and geostatistics. They are very similar in nature and, as random field theory is incorporated in this study, essentially because the simulation tools are readily available and appropriate to this work, geostatistics will not be treated here.

Random field theory is a method developed from the field of economics and the concept of Brownian motion in the early 1900s and formulated as an n-dimensional extension of classical time series analysis (Vanmarcke 1983). Jaksa (1995) and Lunne et al. (1997) have given an example of the application of random field theory in geotechnology by measuring the cone tip resistance of the CPT, q_c, with depth. Jaksa (2007) argues that random field theory is able to incorporate spatial variability of soils since this theory assumes the values at adjacent distances are more related, that is autocorrelated, than those at large distances.

Vanmarcke (1977, 1983) introduced the formula of a random field as shown in Equation 2-18.

$$\beta(x, x+\tau) \equiv \beta_\tau = COV\left[X(x), X(x+\tau)\right] = \mathrm{E}\left[X(x)X(x+\tau)\right] \qquad \textbf{2-18}$$

where X(x) is a sample at position x

$X(x + \tau)$ is a sample at a distance τ from position x

The covariance is expressed as correlation, given by Equation 2-19.

$$\rho(x, x+\tau) \equiv \rho_\tau = \frac{Cov\left[X(x)X(x+\tau)\right]}{\sigma_X^{\;2}} = \frac{\beta(x, x+\tau)}{\sigma^2{}_X} \qquad \textbf{2-19}$$

As an additional measure, Vanmarcke (1977, 1983) introduced the scale of fluctuation to describe the correlation structure of the soil. The scale of fluctuation (SOF) is defined as the distance within which two samples in the field are considered reasonably correlated.

The analysis of correlation structure in random field theory is described similarly in the spatial correlation analysis that has been explained in some previous sections.

Vanmarcke (1977) notes that random field theory can model the spatial variability of geotechnical materials. There are minimally three parameters needed: (1) the mean, μ; (2) a measure of the variance, σ^2 (standard deviation or coefficient of variations), and (3) the scale of fluctuation, θ, which express the correlation of properties with distance. The scale of fluctuation can be quantified by fitting an autocorrelation functions sample to the autocorrelation model. Basically, Vanmarcke (1983) has proposed a variance function method and a mean crossing approximation besides an autocorrelation function. However, most practitioners prefer the autocorrelation functions which fit with autocorrelation models using ordinary least-squares regression (Jaksa 2007).

The application of random field theory to soil variability has been conducted by a number of researchers by simulating soil variabilities, a practice which has become possible since computers have improved in processing speed and graphic capabilities (Fenton and Vanmarcke 1990). Based on random field theory, researchers are able to model and to simulate the spatial variability of soil, and to quantify the reliability of geotechnical designs (Fenton and Vanmarcke 2003; Griffiths et al. 2002). Furthermore, the simulations can also describe and analyse the variability of soil properties in various sites (Akkaya and Vanmarcke 2003; Jaksa 1995; Kulatilake and Um 2003; O'Neill and Yoon 2003). The method of simulating soil variability is explained in detail in Section 2.8.

2.8 QUANTIFICATION OF THE RELIABILITY OF SITE INVESTIGATIONS IN RELATION TO THE DESIGN OF FOUNDATION

The approach adopted in this research is based on a framework developed by Jaksa et al. (2003) which focussed on quantifying the reliability of site investigations in relation to foundation design. The same framework has also been employed by Goldsworthy (2006). As shown in Figure 2-8, the framework is initiated by generating a 3-dimensional random field as a model of a 3-dimensional soil profile with a certain level of variability. The random field models statistically described the soil profiles using three parameters: mean (μ), coefficient of variation (COV), and scale of fluctuation (SOF), as discussed earlier.

NOTE:
This figure is included on page 35 of the print copy of the thesis held in the University of Adelaide Library.

Figure 2-8 Flowchart of simulations (after Goldsworthy, 2006)

The main component of the framework was the simulation of 3-dimensional soil profiles for obtaining a virtual model of the real soil. It is generally understood that obtaining all soil properties in a site is impossible. The reason is that the effort of conducting tests at every point and at every depth beneath the soil is neither feasible nor practical (Clayton 1995). Therefore, the simulation of a 3-dimensional soil profile is needed (Jaksa and Fenton 2002).

2.8.1 Simulation of 3-Dimensional Random Field

As explained previously, in order to model the spatial variability of soil within a site, Goldsworthy (2006) performed random field modelling. The model required three parameters: mean, coefficient of variation (COV), and scale of fluctuation (SOF), for modelling the spatial variability of the soil properties. The parameters describe the target distributions and correlations of the structure of the soil properties in the model. In the next section, those parameters are explained.

2.8.2 Target Distribution and Correlation of Simulated Soil

The target distribution of the simulated soil profiles was described as the coefficient of variation (COV), and their correlation structures were described as the scale of fluctuation (SOF). Both parameters represented the level of variability of the simulated soil profiles. The COV was defined as the ratio of standard deviation to the mean (local value of trend line), and the scale of fluctuation as a parameter representing the (vertical or horizontal) distance in which the soil properties had strong correlations (Akkaya and Vanmarcke 2003).

To understand the correlation of the SOF to the variability performances of soil profiles, Goldsworthy (2006) illustrated 4 soil profiles with different scales of fluctuation. As shown in Figure 2-9, there was a SOF of 1 meter (a), a SOF of 2 metres (b), a SOF of 4 metres (c), a SOF of 8 metres (d), a SOF of 16 metres (e), and a SOF of 32 metres (f). The SOF was uniform in three directions of the 3D soil profile, a condition termed as anisotropy. It can be seen in Figure 2-9, the SOF has a significant impact on the level of variability of the simulated soil. A low value SOF shows highly random spatial correlations, whereas the high SOF exhibits strong correlations.

NOTE:
This figure is included on page 37 of the print copy of the thesis held in the University of Adelaide Library.

Figure 2-9 Elastic Modulus Values for a Soil COV of 50% and SOF of (a) 1 m, (b) 2 m, (c) 4 m, (d) 8 m, (e) 16 m, and (f) 32 m (after Goldsworthy, 2006).

In order to indicate the various levels of variability in the soil, Goldsworthy (2006) specified a range of COV and SOF values generated. These ranges are for the mean (μ), coefficient of variation (COV), and scale of fluctuations (SOF) in both the horizontal, θ_h, and vertical directions, θ_v. A low COV represents a more uniform soil, while a high COV refers to heterogeneous soil.

Conforming to random field theory, the statistical distribution of soil properties in a log normal was conducted. Lumb (1966), Hoeksema and Kitanidis (1985) and Sudicky (1986) state that most soil properties can be represented by the log normal distribution. This is because the soil properties, as well as soil resistance (q_c) are strictly non-negative (Fenton and Vanmarcke 1990).

In terms of correlation structure, Goldsworthy (2006) employed the Markov model as a finite scale model, as shown in Equations 2-20 and 2-21. Fenton (1996) observes that the Markov model is commonly used for modelling soil properties. The Markov model generates an exponentially decaying correlation. Fenton (1996) suggests that this model does not simulate the large number of correlations that has been shown in some soil deposits. The large scale of the correlations is more related to the phenomenon of fractals. However, Jaksa and Fenton (2002) argue that soils, in fact, do not reveal fractal behaviour. Thus, the use of finite scale models was considered suitable for this research.

$$\rho(\tau) = \sigma^2 \exp\left[-\sqrt{\left(\frac{2\tau}{\theta}\right)^2}\right] \tag{2-20}$$

$$\rho(\tau_1, \tau_2, \tau_3) = \sigma^2 \exp\left\{-\sqrt{\left(\frac{2\tau_1}{\theta_1}\right)^2 + \left(\frac{2\tau_2}{\theta_2}\right)^2 + \left(\frac{2\tau_3}{\theta_3}\right)^2}\right\} \tag{2-21}$$

2.8.3 Local Average Subdivision (LAS) Method

Random field theory has become a common method for modelling the spatial variability of soil, which is the main geotechnical uncertainty. Through the measurement of the autocovariance and autocorrelation functions, random field theory is able to describe correlations between properties at different distances. The variability of the correlation distance of soil properties within a site is well known as the correlation structure. The local average subdivision (LAS) method introduced by Fenton and Vanmarcke (1990) can be used to generate a model of a 3D geotechnical profile which has a certain level of variability and reveals a correlation structure. The principle process of the LAS is shown in Figure 2-10.

Basically, six random field generators are available to generate the model: moving average (MA) methods, discrete Fourier transform (DFT) method, covariance matrix decomposition, fast Fourier transform (FFT) method, turning bands method (TBM), and local average subdivision (LAS) method. Fenton (2002) has suggested that three of them, the moving average (MA), discrete Fourier transformation (DFT) and the covariance matrix decomposition method, can generate random fields that conform to the target distribution and correlation structure with a high degree of accuracy. However, they require complex calculations and are exhaustively time consuming. In contrast, the fast Fourier transformation (FFT), turning bands method, and local average subdivision (LAS) are very efficient, even though they are less accurate than the MA, the DFT and CMD. Fenton (2002) adds that the LAS is the fastest of the approximate methods. In one experiment for simulating a two-dimensional random field (128 x 128 elements), the LAS is 45% faster than the FFT and 370% faster than the TBM using 64 lines.

NOTE:
This figure is included on page 39 of the print copy of the thesis held in the University of Adelaide Library.

Figure 2-10 Matrix of LAS (after Fenton and Vanmarcke, 1990)

2.8.4 Transformation of Generated Soils

The local average subdivision (LAS) generates a 3D random field and distributes its soil properties in a normal distribution. However, it must be noted that soil properties are strictly non-negative values, and consequently perform log normal behaviour. For this reason, Goldsworthy (2006) has conducted the transformation of the random field simulated by LAS from a normal into the required log normal distribution by using Equations 2-22, 2-23 and 2-24.

$$X_{\ln} = \exp(\mu_{\ln x} + \sigma_{\ln x} X) \tag{2-22}$$

$$\mu_{\ln x} = \ln(\mu_x) - \tfrac{1}{2}\sigma_{\ln x}^2 \tag{2-23}$$

$$\sigma_{\ln x} = \sqrt{\ln\left(1 + \frac{\mu_x^2}{\sigma_x^2}\right)} \tag{2-24}$$

where X_{ln} is the log normal variable;

X is the normal variable from the generated random field;

μ_{lnx} is the mean of log normal variable;

σ_{lnx} is the standard deviation of log normal variable;

μ_x is the mean of normal variable; and

σ_x is the standard deviation of normal variable.

NOTE:
This figure is included on page 40 of the print copy of the thesis held in the University of Adelaide Library.

Figure 2-11 Sample (a) mean and (b) standard deviation of elastic modulus values at the surface (z=1) from a simulated soil with a COV of 50% and a SOF of (i) 1 m, (ii) 4 m and (iii) 16 m (after Goldsworthy, 2006)

Goldsworthy (2006) also investigated the effects associated with the transformation. Therefore, he plotted a certain sample mean and standard deviations of the simulated soil profiles averaged over 1000 realisations, as shown in Figure 2-11.

NOTE:
This figure is included on page 41 of the print copy of the thesis held in the University of Adelaide Library.

Figure 2-12 Sample (a) mean and (b) standard deviation of elastic modulus values using field translation and a soil with a COV of 50% and a SOF of (i) 1 m, (ii) 4 m and (iii) 16 m (after Goldsworthy, 2006)

Goldsworthy (2006) found the presence of gridding or aliasing in the sample mean and standard deviation for all soil investigated. This is because of cross-cell covariance in the LAS (Fenton 1994). To overcome this effect in the sample mean, Goldsworthy (2006) conducted a field translation. This involves generating a field that is significantly larger than the required field. The desired field is then sub-sampled from within the larger field with an origin (x =0, y = 0, z = 0). The location of each sub-sample changes for each subsequent Monte Carlo realisation. The locations of the origin are controlled along a diagonal to ensure a uniform selection of origin locations. As a result, the use of the field translation process has reduced the effect of gridding significantly as shown in Figure 2-12.

2.8.5 Soil Parameter and Reduction Techniques

The various boreholes tested during the simulation produced a number of simulated soil profiles that needed to be transformed into a single simulated soil profile. Consequently, several averaging techniques were adopted, such as Goldsworthy (2006) has performed. The reduction techniques were:

- the standard arithmetic average, SA

$$SA = \frac{1}{n}\sum_{i=1}^{n} x_i \qquad \textbf{2-25}$$

- the geometric average, GA

$$GA = \left(\prod_{i=1}^{n} x_i\right) \qquad \textbf{2-26}$$

- the harmonic average, HA

$$\frac{1}{HA} = \frac{1}{n}\sum_{i=1}^{n}\frac{1}{x_i} \qquad \textbf{2-27}$$

where n is the number of samples;

x_i is the value of simulated soil profiles obtained from the simulated boreholes;

s_i is the distance between the j_{th} sample location and the pile foundation; and

s_{tot} is the total distance between all sample locations and the pile foundation.

2.8.6 Effect of Site Investigations on the Design of Pad Foundations

Goldsworthy (2006) conducted studies on the impact of limited site investigations in relation to the probability of under- and over-design of pad foundations. He employed the LAS to generate 3-dimensional soil modulus, and simulated site investigation plans. To analyse foundation designs which based on settlement approach, he utilised finite element method as a benchmark design or the design based on complete knowledge (CK), and various available settlement formulae as foundation design based on the data obtained from the simulated site investigation (SI). The comparisons between the CK design and the SI design drew a number of conclusions as the following:

- A highly variable soil yields a site investigation with a higher probability of under-design;
- Increased site investigation plan has a greater impact on the probability of over-design;
- The SA reduction technique yields the highest probability of under-design and the lowest probability of over-design;
- The effect of increased site investigation plan is the greatest when using the SA; and
- Differences between the types of soil tests are exaggerated for the probability of over-design.

2.9 SUMMARY

Existing available literature indicates that the effect of limited site investigation on the performance and design of pile foundations can be quantified using the LAS method, which is based on random field theory, and the LCPC method. Random field theory has commonly been performed to analyse and to model soil variability, which is the main problem in geotechnical engineering; while the LCPC has been widely regarded as the most accurate method for computing pile load capacity. Furthermore, it has been demonstrated that the quantification of the effect of limited site investigation on shallow foundations is an example of the beneficial application of stochastic theory in the geotechnical engineering. This framework of the quantification has been well developed and is applicable. Chapter 3 details the generation of 3-dimensional soil profiles and Monte Carlo simulations used in this research.

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Chapter Three
Description of Research Method

3.1 INTRODUCTION

This chapter discusses the method used to examine the effect of limited site investigations on the design of pile foundations. An overview of the method is explained in detail, including the critical aspects and any assumptions or simplifications that were considered necessary.

3.2 SOIL PROFILE SIMULATIONS

As explained in Chapter 2, the research was conducted by utilising the reliability framework which has been developed by Jaksa et al. (2003), and performed by Goldsworthy (2006). The framework was initiated by generating a 3-dimensional random field as a model of a 3-dimensional soil profile with a certain level of variability, as shown in Figure 3-1.

Once the soil profiles were generated, a number of soil resistance, q_c, profiles along vertical and horizontal directions were obtained. After that, a number of cone penetration test (CPT) soundings were simulated to represent various schemes, with a number of pile foundations. The simulated CPTs yielded soil resistance profiles which were employed to estimate axial pile load capacities. This was regarded as the pile foundation design based on site investigations (SI). In parallel, the axial pile load capacity of the simulated the pile foundation used ‘the true’ soil resistance values along the pile. In addition, the axial pile load capacities of the simulated piles were also determined. This was termed 'the truth' design or benchmark pile foundation design, and was regarded as the pile foundation design based on complete knowledge (CK).

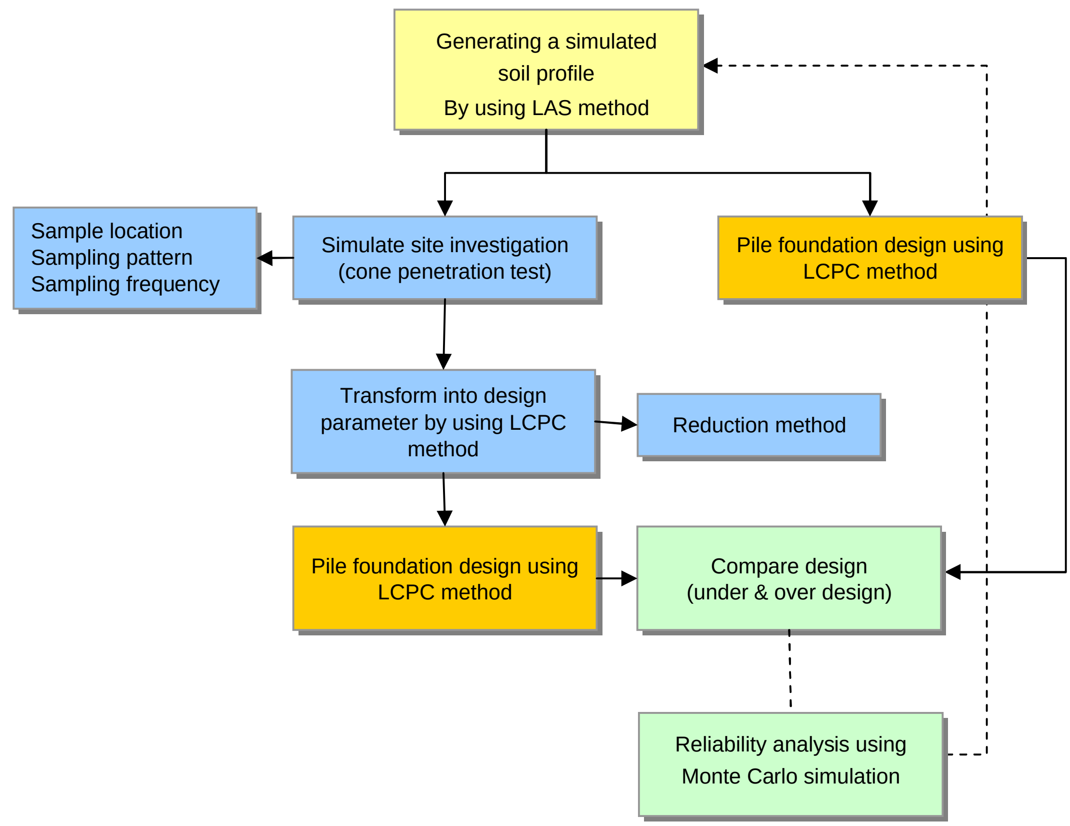


Figure 3-1 Flowchart of simulations (adapted from Jaksa et al., 2005 and Goldsworthy, 2006)

At the end of the process, a comparison between the pile foundation designs based on SI and those based on CK was conducted. The reliability of the foundation design based on SI was analysed using a stochastic approach involving the Monte Carlo technique (Rubinstein 1981).

In order to represent the various levels of soil variability, a range of COV and SOF values was specified. These ranges are shown in Table 3-1 for the mean (μ), coefficient of variation (COV), and scale of fluctuations (SOF) in both the horizontal θ_h, and vertical directions θ_v. A low COV soil whose properties vary rapidly over short distances, whereas a high COV refers to soils whose properties vary more slowly over short distances.

Table 3-1 Matrix of simulations

Soil resistance, q_c	
Mean (μ)	5000 kPa
Coefficient of variation, COV (σ/μ)	20%, 50%, 100%, 200%
Scale of fluctuation (SOF)	
Horizontal (θ_h)	1, 10, 20, 100 m
Vertical (θ_v)	1, 10, 20, 100 m
Anisotropy (θ_h: θ_v)	1:1, 2:1

A number of computer codes compiled in FORTRAN 77 language were used to simulate the 3D soil profiles. The codes were developed by Fenton (1990). Besides generating 3D soil profiles, the computer codes for conducting simulated site investigation schemes were also modified. The codes were developed by Goldsworthy (2006). The computer codes performed a range of site investigations involving different numbers and patterns of boreholes. For simulating a pile foundation and computing axial pile load capacities, computer codes based on the LCPC method were developed.

All computer codes were executed in UNIX and performed by the supercomputer server *Hydra* of SAPAC, and the Terzaghi and the Vanmarcke dual-processor PC-server at the School of Civil and Environmetal Engineering the University of Adelaide.

3.2.1 Size of Simulated Sites

Three-dimensional soil profiles were simulated by creating a virtual model of a site 64 m × 64 m in plan and 32 m in depth. The size was considered to be representative of typical building construction sites, while the depth was sufficient for simulating realistic pile foundations. Extension of the size beyond that proposed was not feasible due to the excessive computational time required when conducting calculations.

The simulated site was divided into a finite number of elements. The total number of elements is governed by the LAS method which imposes that is be a multiple of 2^n

(Fenton and Vanmarcke 1990). That is, the total number of elements in each direction must be either 2^1, 2^2, 2^3, …, 2^n. As a consequence, the simulated site had a field size of 256 × 256 × 128 or a total of 8,388,608 elements.

The research was therefore performed on a simulated site of 256 x 256 x 128 elements, with an element size being 0.25 m × 0.25 m × 0.25 m in size. The number of elements in the vertical and horizontal directions was varied in order to ensure that the simulation could be efficiently processed; and vertical direction was assigned to simulate a pile length of 30 metres. A single realisation of the simulation was undertaken consisting of preliminaries, the generation of a random field, the design using complete knowledge (CK) data, the design using site investigations (SI) data and post-processing results. As shown in Table 3-2, a single simulation of soil resistance (q_c) profiles, as is explained in the next section, took 21.3 seconds. This means that, for 1,000 realisations, the simulation was run for 21,308 seconds, or almost 6 hours.

Table 3-2 Time-run for 1 realisation of the simulation

Task	Time(secs)	% of Time
Program preliminaries	0.0002	0.001
Random field generation	9.3	43.7
Design using CK data	0.002	0.01
Design using SI data	11.9	55.8
Post-processing results	0.11	0.54
Entire program	21.3	100

3.2.2 Site Investigations

As discussed in Chapter 2, a site investigation is designed to characterise the ground at a number of specific locations. The number of locations and the amount of samples taken or in situ test performed dictate the adequacy of the site investigation. For the purposes of the current research, several strategies were used for the investigations and included varying sampling locations and the number of samples taken.

Sampling strategies adopted for this research were typical of those conducted for conventional building construction projects. Currently, it is widely accepted that a minimum sampling regime should include sampling the soil at the centre and/or the corners of a site. This is generally considered an effective and efficient degree of sampling, providing enough information is obtained to minimise the possibility of design failure. The current research investigated the quantity of sampling (boreholes) that could be considered as the optimal number of samplings, including their placement on a site.

As shown in Figure 3-2, the site investigation size for the simulation was based on a single pile foundation placed at the centre of a field with x and y coordinate x and y of 25 and 25 m, respectively. The assumes a site of 50 m × 50 m, where $L_x = L_y = 50$ m. For the first investigation, different locations of a CPT were simulated. The locations of the simulated CPTs were selected by systematically translating the position of the simulated site. The CPT locations finally ended at the farthest distance from the pile at coordinate x_i and y_i. Due to the element size of 0.25 m × 0.25 m in the plan, the number of CPT locations was 200 elements in the x-direction and 200 elements in the y-direction. As a result, the total number of CPT locations was 40,000.

The second investigation examined the influence of the numbers of CPT soundings were simulated within the plan area, and a number of pile foundations was also simulated. As shown in Figures 3-3 and 3-4, a plan with 9 pile foundations was simulated in an area, and 12 different sampling strategies were examined, specified by different numbers of CPT soundings. These sampling strategies were the same as those performed by Goldsworthy (2006) in examining their effects on the design of pad foundations.

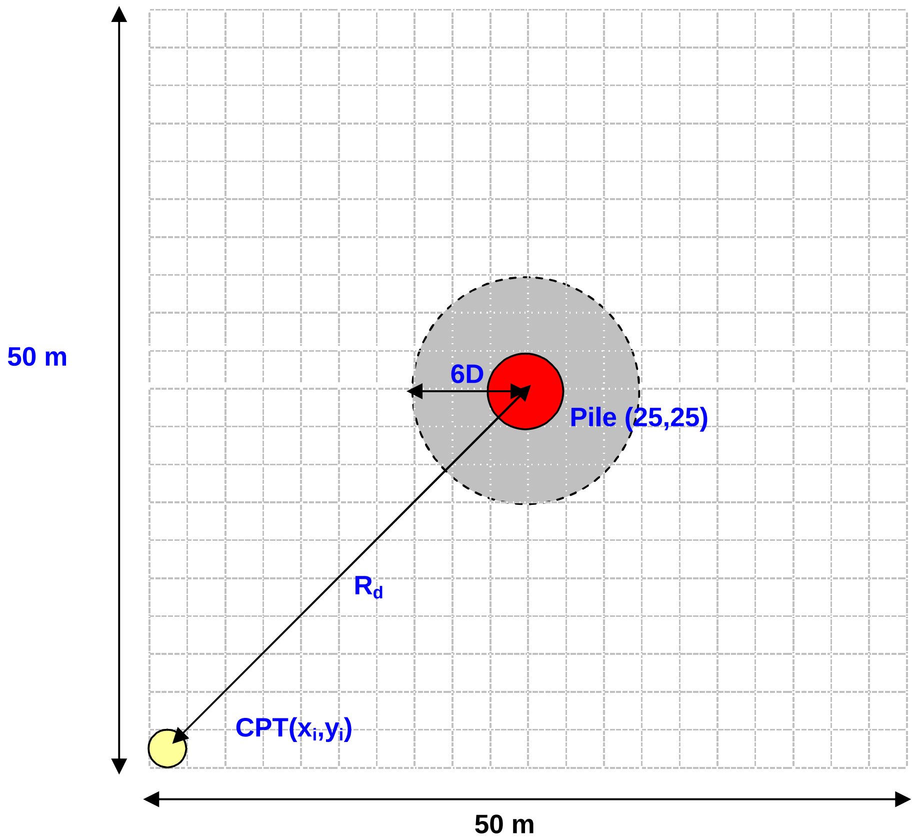


Figure 3-2 Simulation of various radial distances of a CPT

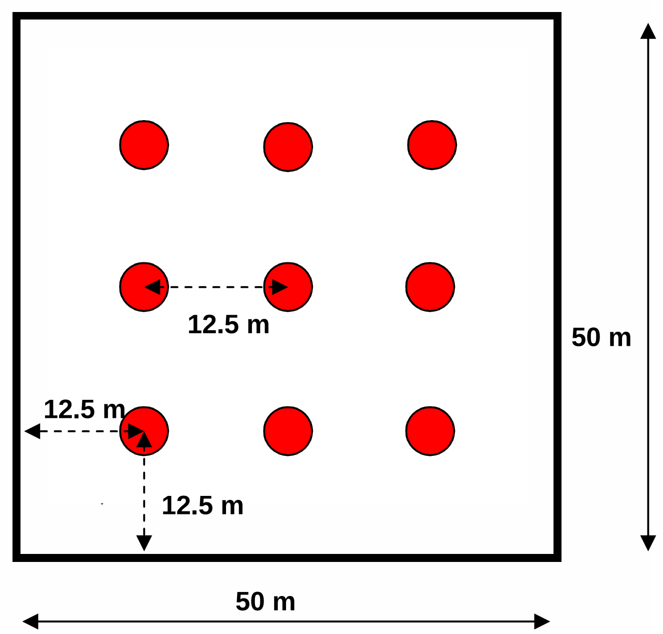


Figure 3-3 Plan of simulated pile foundations

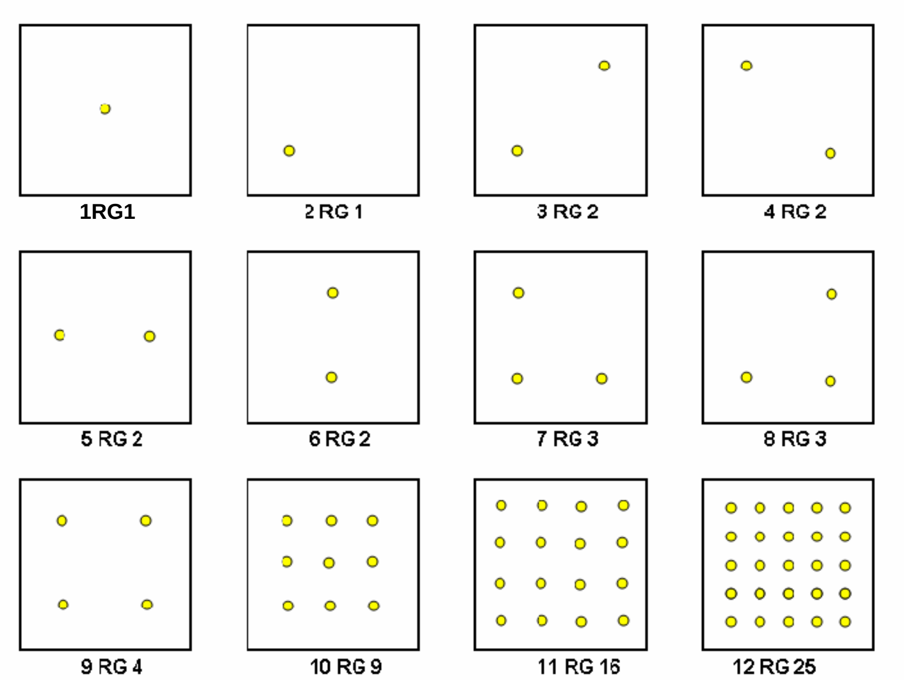


Figure 3-4 Site Investigation schemes

3.2.3 Type of Soil Test

As discussed in Chapter 2, there are a number of soil tests commonly incorporated into site investigations. The results of the tests can then be used to make decisions about pile designs. The current research, however, examined only one of these soil tests, namely the cone penetration test (CPT), due to its robustness and the high degree of reliability when compared to other in situ tests. Another reason for only considering the CPT is that the scope of the current research obviated against multiple soil tests due to the length of time it would take to conduct numerical simulations. As is explained in Chapter 5, multiple soil tests is an opportunity for future research.

The interval of a simulated CPT in the vertical direction was set at 0.25 m. It should be noted that this interval is larger than that normally performed in the field (0.01 m). This was a result of the restrictions imposed on the element size due to computational time. As will be discussed in the next section, however, the interval of the CPT was considered to be appropriate and reasonable for estimating pile designs and quantifying the reliability of site investigations.

It is also important to note that the CPT produces errors in its measurement and transformation, as discussed in Chapter 2, leading to uncertainties, but the errors are much smaller than for other soil tests. However, this research assumed that there was no error for the simulated CPTs. Future research when comparing different test method, would need to incorporate these errors CPT.

3.3 PILE FOUNDATION DESIGN METHODOLOGY

The design of a pile foundation is limited to the axial load carrying capacity of a single pile, and it should be noted that other factors, such as settlement and the pile load capacity of pile groups, were not taken into account, although this may investigated in future research.

As mentioned in Chapter 2, the axial pile capacity was examined using the LCPC method of Bustamante and Gianaselli (1982), which is a CPT-based technique.

Based on q_c values for the classification of soil, the research specified three different the mean of q_c values for the simulations of 3D soil profiles. As shown in Table 3-3, the mean of q_c represent the type of simulated soil. In relation to construction method of piles, the research determined pile load capacity for bored as Group I and II, and driven piles as Group II and III. In the LCPC method, the type of pile influences the way in which the factor of k_c is assigned for the calculation of pile tip resistance, and coefficient (α) and maximum values of q_s for the calculation of pile skin resistance.

Table 3-3 mean of q_c values of the simulations

Mean of q_c values (kPa)	Type of soil
1,000	Soft Clay and mud
5,000	Moderately stiff clay or compact silt
10,000	Moderately compact sand and gravel

As mention previously, soil elements 0.25 × 0.25 × 0.25 m in size were simulated. Therefore, a single pile with a 0.5 metres diameter needed to be assessed by averaging soil properties over four horizontal elements when computing the pile load capacity. However, the influence that lateral distance of soil properties contributes to axial pile load capacity needs to be included. Teh and Houlsby (1991) estimated the influence zone for a cone penetrometer as it penetrates the ground. They found that for a cone 0.15 metres in diameter, the influence radius is 1 metre from the centre of the cone. Similarly, Jaksa (1996) pointed out that for a pile diameter of 0.3 metres, the influence radius is 2 metres. Therefore, the current research assumed that the influence radius for a pile with a diameter of 0.5 metres was 3 metres from the centre of the pile, or 6 times the diameter, as shown in Figure 3-2. Consequently, a pile foundation needs to average the soil properties over 576 elements in the plan dimension.

3.4 MONTE CARLO SIMULATIONS

As mentioned previously, this research utilised a framework based on Monte Carlo analysis to generate simulated soil profiles randomly while conforming to the same statistical characteristics represented by the original mean, COV and SOF. The simulated soil profile was used to analyse pile load capacity as an aspect of foundation design based on site investigation data and complete knowledge of the soil. The following section explains the definition of the design of pile foundation using a Monte Carlo simulation, as well as the number of realisations that was required to achieve reliable results.

3.4.1 Metrics

The output of the simulation in this research consisted of pile load capacities, determined on the basis of either the results of a site investigation or complete knowledge of a simulated pile foundation. These pile load capacities were calculated in each realisation of the Monte Carlo analysis. Furthermore, the capacities were compared in order to determine whether the pile was under- or over-designed.

A pile load capacity calculated using data from a simulated site investigation would be considered under-designed when the calculations yield a larger load capacity than that based on complete knowledge of the simulated pile foundation, and over-designed when the site investigation yields a smaller load capacity than that required based on complete knowledge.

The reliability of site investigations in n realisations is calculated in Equation 3-1 as follows:

$$P = \frac{Q_{SI} - Q_{CK}}{Q_{CK}} \times 100\% \tag{3-1}$$

where P is the probability of over-design or under-design

Q_{SI} is the pile load capacity based on site investigations

Q_{CK} is the pile load capacity based on the complete knowledge of the soil properties

3.4.2 Number of Realisations

Monte Carlo analysis performs a number of realisations to simulate random distributions of soil properties. Despite the fact that the distribution of soil properties will vary in each realisation, the mean variance and the correlation structure remains essentially the same. However, an insufficient number of realisations would have resulted in an inaccurate estimation being developed in the current research. Therefore, the various results of different numbers of realisations were examined to ensure that the quantity of realisations was sufficient that a high degree of confidence could be place on the results. The examining the number of realisations is given in the Section 3.5.3.

3.5 VERIFICATION OF THE METHOD

The accuracy of the results derived from the research depends on the simulations of the soil profiles that are required to satisfy local average subdivision (LAS) as the method of modelling the 3D random fields. Consequently, it was necessary to perform a number of verifications in order to ensure that the modeling and simulations conducted during the research were reliable. This section presents the verification of the modelling of the 3-dimensional soil profiles, including the verification of the LCPC method to ensure that this technique was accurately implemented when estimating axial pile load capacities; and the verification of the Monte Carlo simulation to ensure accurate results associated with computing probabilistically the impact of limited site investigations on pile foundation design.

3.5.1 Verifying the Model of the 3D Random Field

As discussed previously, this research used local average subdivision (LAS) to generate 3-dimensional random fields that could conform to the target normal distribution defined by the mean and variance, and the correlation structure defined by the scale of fluctuation (SOF). Similar verification of the LAS has also been performed by Goldsworthy (2006). The following section presents a number of verifications of simulated soil profiles including the verifications of the simulated mean, variance and simulated correlation structure.

Mean and standard deviation. Vanmarcke (1983) suggests that the target mean and variance of a 3D random field is not exactly the same as the sample mean and sample variance simulated within the model. This is because element sizes and the scale of fluctuation have a significant influence on the simulation result. Therefore, comparison was conducted between the target mean and variance, and the sample mean and variance from the simulation. The comparison was performed over 20 soil types specified with different levels of variability described by the COV and SOF, as shown in Table 3-4.

It should be noted that the sample mean was computed by averaging the mean of the soil resistance values (q_c) simulated for each element within a 3-dimensional random field over 1,000 Monte Carlo realisations. Similarly, the standard deviation was computed by averaging the standard deviation over 1,000 Monte Carlo realisations.

Table 3-4 Comparison between target and sample mean and standard deviation of simulated soils

Soil		Mean (kPa)		Error (%)	Standard Deviation (kPa)		Error (%)
COV (%)	SOF (m)	Target	Sample		Target	Sample	
5	1	5000	4998.4	0.032	250	215.6	13.760
5	10	5000	5000.7	0.014	250	247.8	0.880
5	20	5000	4998.0	0.040	250	239.2	4.320
5	100	5000	5015.4	0.308	250	180.7	27.720
20	1	5000	4975.1	0.498	1000	856.8	14.320
20	10	5000	5002.0	0.040	1000	991.9	0.810
20	20	5000	4997.0	0.060	1000	952.9	4.710
20	100	5000	5059.6	1.192	1000	725.3	27.470
50	1	5000	4859.5	2.810	2500	2072.3	17.110
50	10	5000	5001.9	0.040	2500	2482.4	0.700
50	20	5000	5030.3	0.610	2500	2384.4	4.620
50	100	5000	5136.4	2.730	2500	1796.5	28.140
100	1	5000	4579.5	8.410	5000	3641	27.180
100	10	5000	5009.3	0.190	5000	4989.9	0.200
100	20	5000	4947.3	1.050	5000	4596.4	8.070
100	100	5000	5252.6	5.050	5000	3409.3	31.810

In order to provide a clear illustration of the results shown in Table 3-4, the effect of increasing the COV on the sample mean and the target mean is shown in Figure 3-5 (a) and (b). It was found that as the COV increases, the sample mean diverges from the target mean. The significant impact of increasing the COV on the difference between the sample mean and the target mean occur at a small values of SOF, such as a 1 metre. Yet, for a SOF of 10 metres, the increasing COV had almost no influence on the difference. Figure 3-5 (b) demonstrates that the standard deviation of the sample diverges from the target standard deviation as the COV rises. The SOF of 1 and 100 metres seems to yield the greatest diversion of standard deviation between the target and the sample.

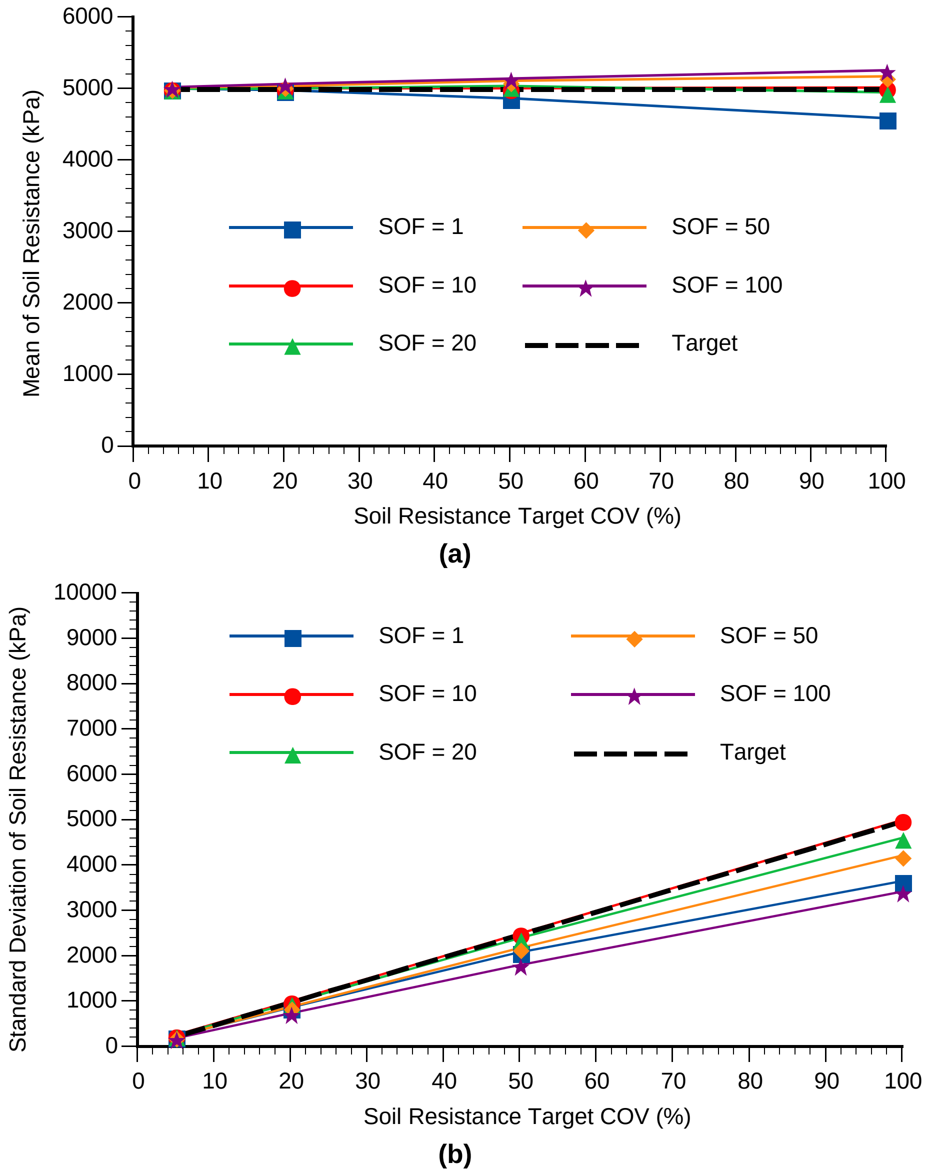


Figure 3-5 Effect of target soil COV on the sample (a) mean and (b) standard deviation

It can be seen from Table 3-4 that as COV increase, the differences between the target means and the sample means rise. Similarly, the differences between the target standard deviation and the sample standard deviation rise when the COVs increase. In addition, Table 3-4 reveals that the SOF influences the difference between the targets and the samples. As the SOF rises, the differences of mean and standard deviation between the targets and the samples increases, with the exception of scales of fluctuation of 1 metre. This is due to the effect of local averaging. Furthermore, it was observed that a SOF of 10 metres yields the lowest disparities of mean and standard deviation between the targets and the samples compared to other scales of fluctuation.

The effect of increasing the SOF on the mean and standard deviation of the samples and the targets is shown in Figure 3-6 (a) and (b) respectively. It is shown in Figure 3-6 (a) that the sample means approach the target mean as the SOF increases. Yet, the sample mean exceeds the target mean when the SOF increases from a SOF of 50 up to 100 metres. In contrast, Figure 3-6 (b) demonstrates that the standard deviation of the sample does not surpass the target standard deviation, even though the SOF increases.

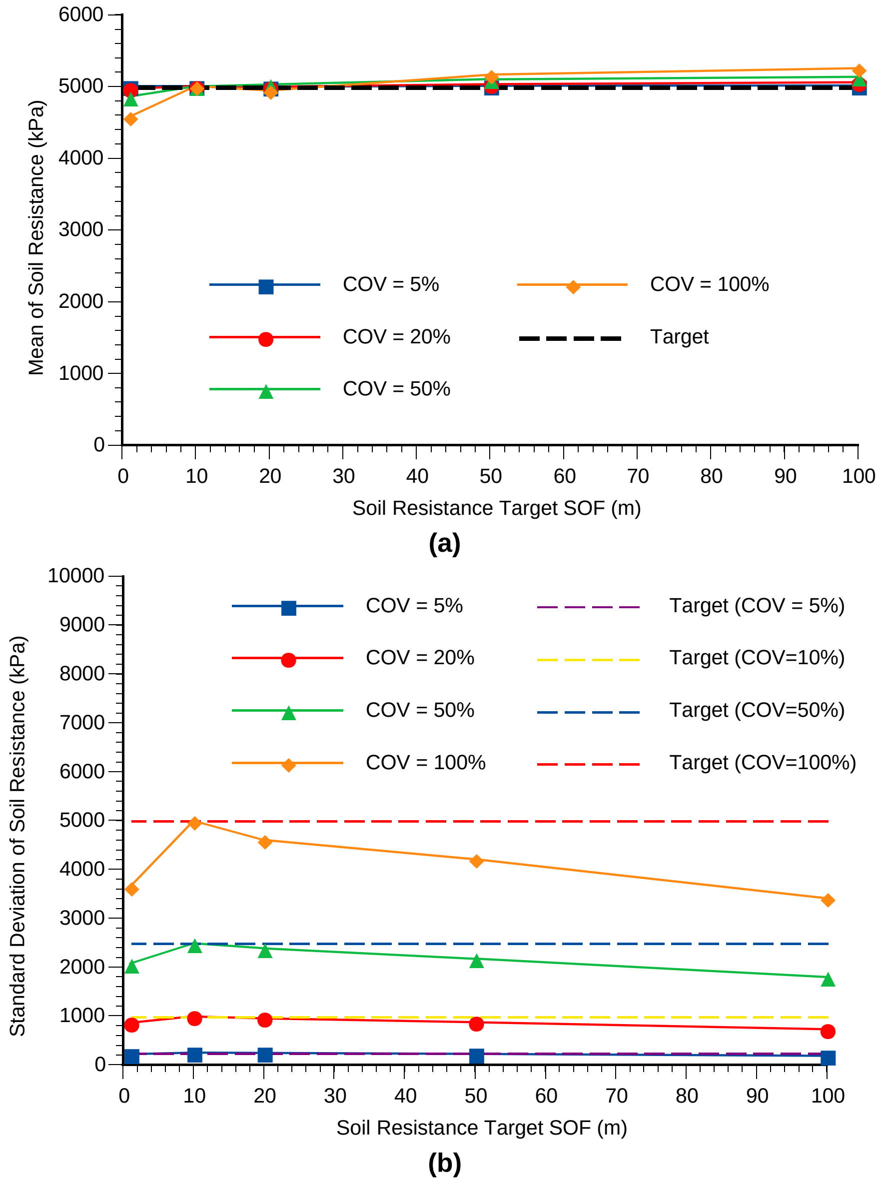


Figure 3-6 Effect of target soil SOF on the sample (a) mean and (b) standard deviation

It can be seen from Figure 3-7 that the standard deviation of the sample approaches the target standard deviation while the SOF increases from 8 to 10 metres. Similarly, Goldsworthy (2006) also found that a SOF of 8 to 16 metres affects the maximum sample standard deviation. Therefore, it might be considered that the SOF of 10 metres is the worst case SOF representing the highest variability in the simulated soil, and as consequence would produce conservative results (Goldsworthy 2006; Griffiths et al. 2002).

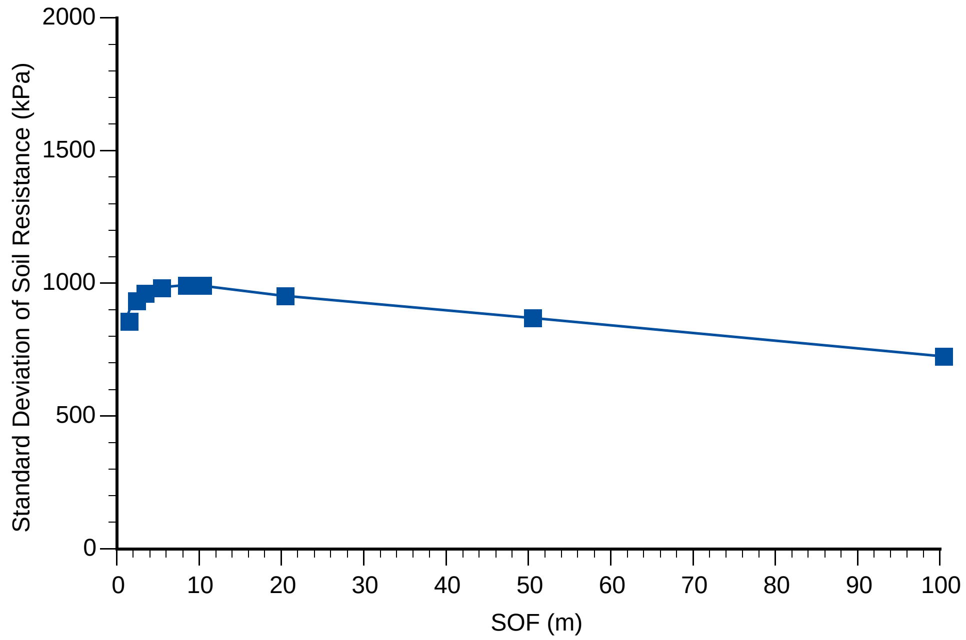


Figure 3-7 Sample standard deviation of soil resistance for different SOFs

The reason why a certain SOF yields the highest standard deviation is that the small SOF means the soil properties are varying rapidly and would average out over a typical domain size (Goldsworthy 2006). The small SOF, the SOF of 1 metre, leads to a small standard deviation. On the other hand, for high SOF, in this case referring to the SOF of 100 metres, the soil is highly correlated, indicating that the standard deviation is also small. However, when the SOF lies between small to high which is between 10 and 20 metres, for instance, the standard deviation is high.

Correlation structure. The simulated soil profiles were generated with the LAS method where its correlation structure could be identified with a number of theoretical autocorrelation models. This meant that the correlation structure of the simulated soil profiles fitted the autocorrelation models.

The results shown in Figures 3-8 and 3-9 suggest that ACF simulated soil profiles well fit to the theoretical ACF. The goodness of fit ACF simulated soil profiles to the theoretical ACF only occur on the SOF of 1 and 10 metres. Yet, for the high SOF such as 20 and 100 metres, the ACF of simulated soil profiles is affected. As shown in Figure 3-9 (a), the increase of SOF has impact on the fitness of the ACFs, whereas the COV does not influence the ACF, shown in Figure 3-9(b).

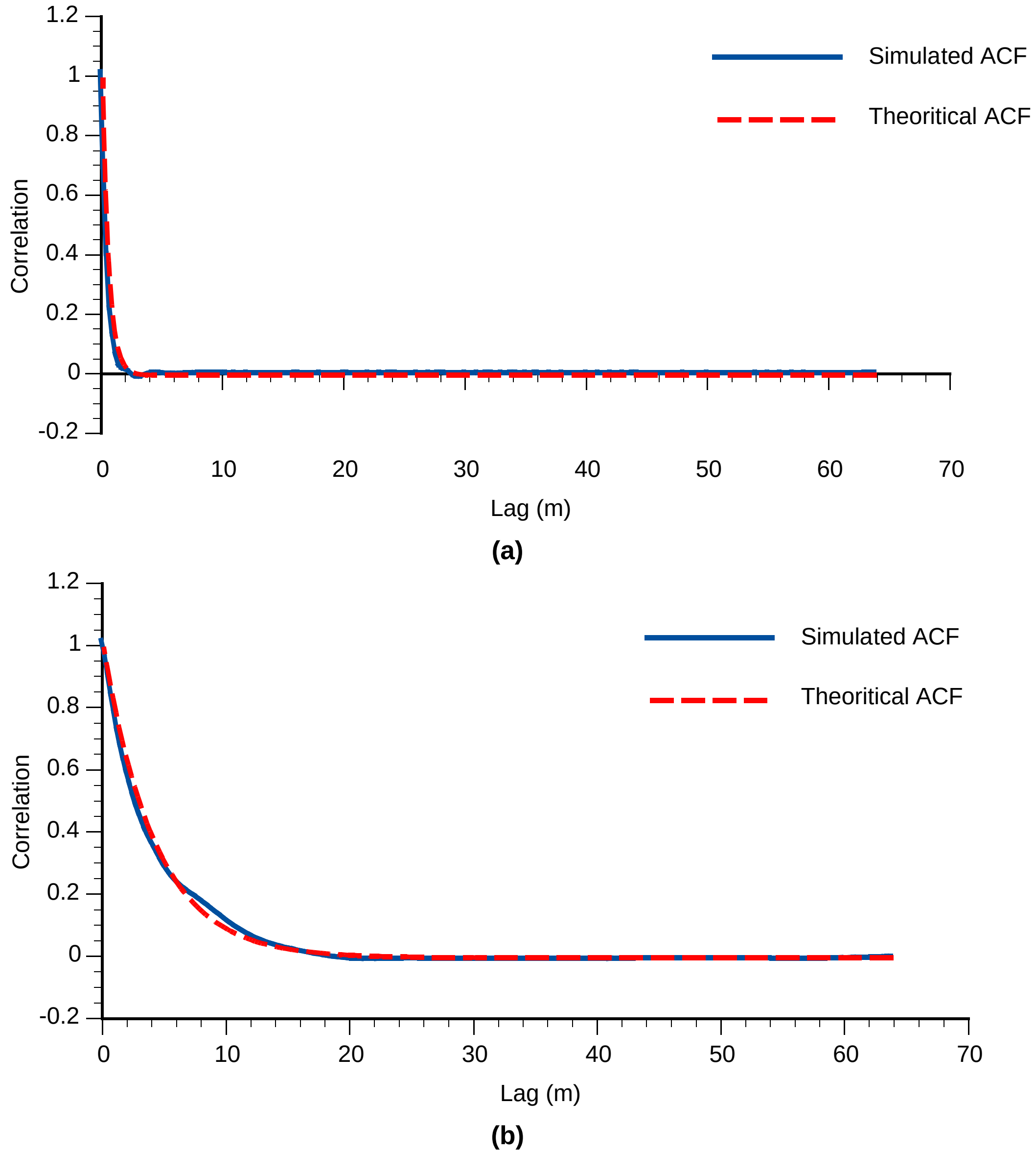


Figure 3-8 Correlation structure of simulated field for the soil with COV of 50% and (a) SOF of 1 m and SOF of 10 m

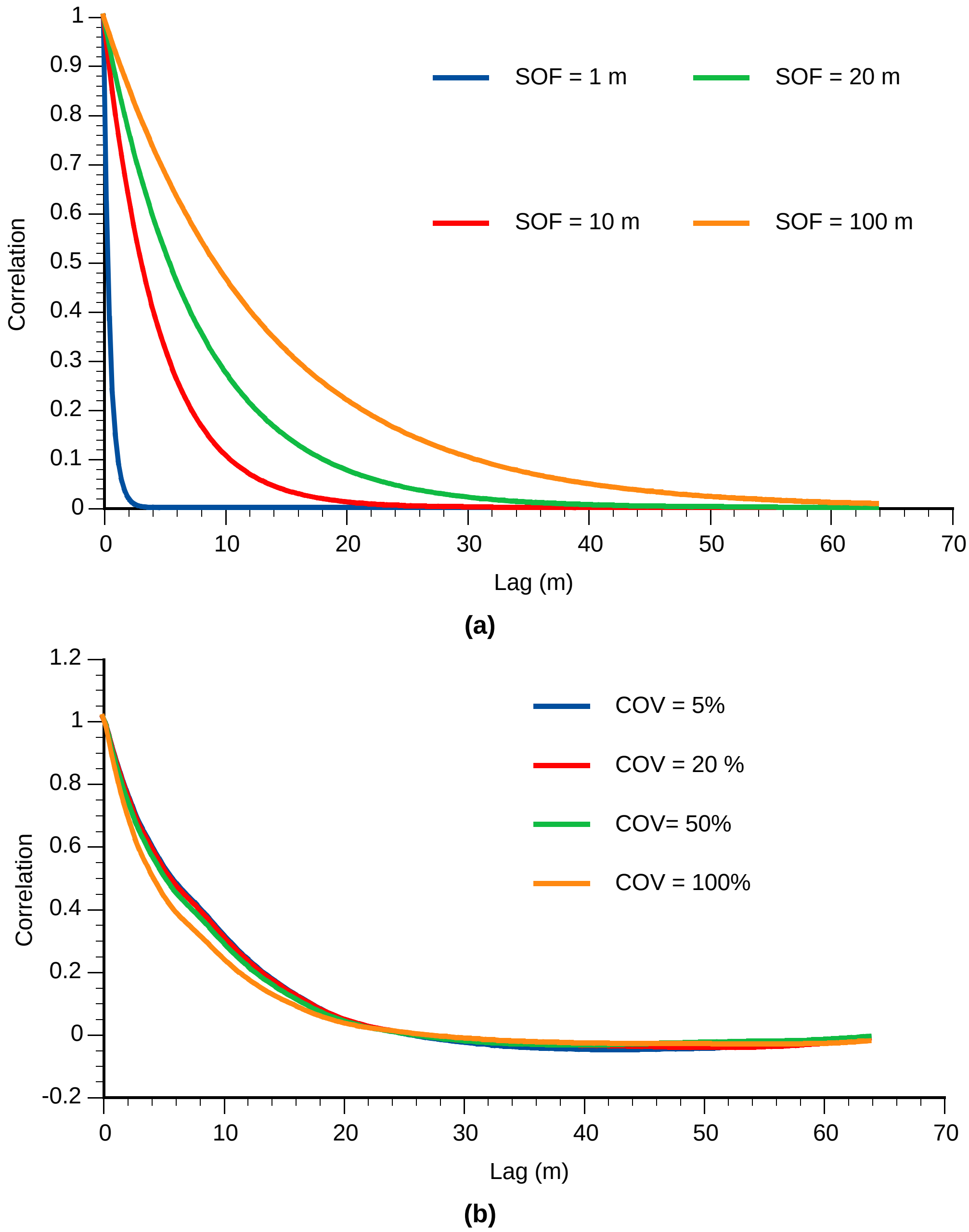


Figure 3-9 Correlation structures of simulated soil for (a) increasing target SOF and (b) increasing target COV

3.5.2 Verifying the Implementation of the LCPC Method

As described in Chapter 2, the research reported in this thesis utilised the LCPC to estimate axial pile load capacity. To ensure that the LCPC method was implemented appropriately, comparisons were conducted between the pile load capacities calculated using computer simulation and those calculated using a spreadsheet in Microsoft *Excel*.

A pile foundation was positioned in the centre of a site, 50 × 50 m area and a depth of 32 m. The size of the pile was 30 m long and 0.5 m in diameter. Two types (driven pre-cast pile and plain bored pile) were simulated. The simulation was generated for 8 levels of soil variability. An Excel spreadsheet for computing pile load capacity was also developed.

The examples of the simulations and of the spreadsheet calculations are shown in Table 3-5. The process of computing pile load capacities in detail are given in Appendix A. It can be seen that the difference between results is negligible.

Table 3-5 Comparison between pile load capacity using simulation program and the spreadsheet Microsoft *Excel*

Type of pile	COV	SOF			Pile axial load capacity (kN)		Error (%)
					simulated	manual calculation	
Driven precast pile	20%	1	1	1	1190.6	1190.59	0.001
		10	10	10	1190.4	1190.39	0.000
	50%	1	1	1	1057.8	1057.85	-0.005
		10	10	10	1509.8	1509.82	-0.001
Plain bored pile	20%	1	1	1	1082.3	1082.00	0.028
		10	10	10	1155.9	1155.85	0.004
	50%	1	1	1	1108.7	1108.65	0.005
		10	10	10	1322.7	1322.70	0.000

3.5.3 Verifying the Implementation of Monte Carlo Simulations

The use of Monte Carlo simulation in quantifying the reliability of site investigation strategies is influenced by the adequacy of its realisations. Sufficient realisations will guarantee the accuracy of the simulation. In order to examine this, number of realisations was established for a driven pile foundation, a single CPT sounding of site investigation, and COV soil of 30%, SOF of 1 metre. As shown in Figure 3-10, the probability of over-design of a pile foundation is inconsistent while conducting 50 to 700 realisations of a Monte Carlo simulation. After 900 realisations, the result is relatively stable.

For a soil COV of 5%, Figure 3-10 shows that the probability of over-design of the pile foundation is fluctuated. However, after 1,000 realisations, the result plateaud. It can be concluded, therefore, that the sufficient number of realisations of Monte Carlo simulations is 1,000 at a minimum.

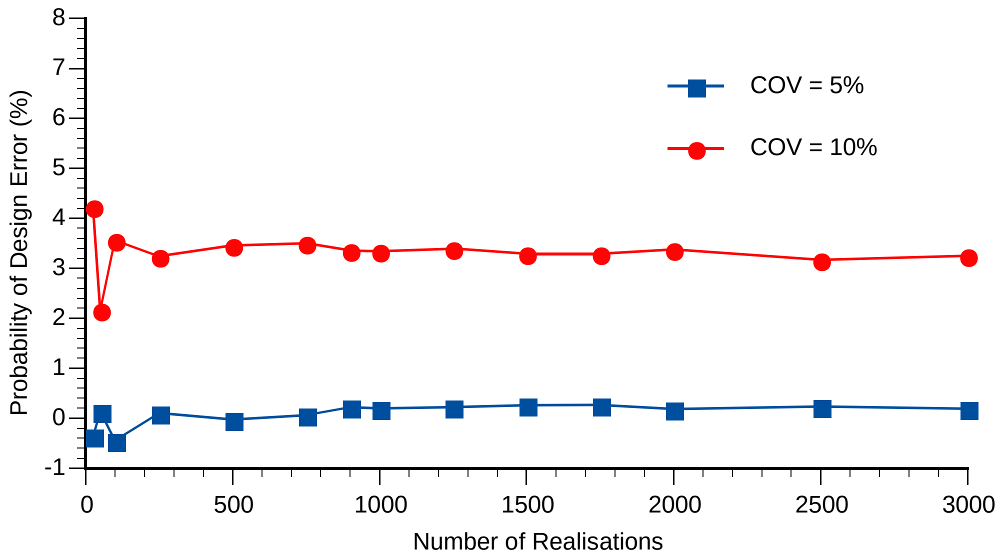


Figure 3-10 Probability of design error using Monte Carlo simulation

3.6 SUMMARY

This chapter has described the method employed to investigate the effect of limited site investigations on the design and performance of pile foundations. A variety of methods were used to deal with soil variability, including the estimation method of pile foundation design, sampling methods associated with site investigation strategy, and Monte Carlo simulation for quantifying probabilistically the impact of limited site investigations on the pile foundation design.

Verification analyses indicated that the methods used in the research accurately simulate 3-dimensional soil profiles exhibiting variability, compute the pile load capacities in accordance with the pile foundation designs, and support the use of Monte Carlo simulations in order to determine the influence of limited boreholes during site investigation on the design of pile foundations.

The verification results indicate that sample statistics of the simulated soil profiles agree well with the target statistics adopted to generate the field. Therefore, it can be verified that the method used was suitable to simulate the variability of soil properties. Furthermore, the comparison between computing pile load capacity using computer codes, and computations using a Microsoft *Excel* spreadsheet conducted in the verification analyses demonstrated that the adopted method accurately reflected the implementation of the LCPC method. Finally, investigations regarding the sufficient number of realisations provided in the Monte Carlo simulation verified that 1000 realisations yield stable and accurate predictions of the probability of design error as an impact of limited site investigations.

Chapter Four
Effect of Radial Distance of a Single CPT Sounding on the Probability of Under- and Over-Design of a Pile Foundation

4.1 INTRODUCTION

As was established in Chapter 2, the reliability of site investigations is unknown since construction projects generally prefer to minimise their scopes, and consequently prepare conservative foundation designs. This chapter investigates the optimum scope of site investigations when designing a pile foundation, which consists of four sections. The first section deals with the effect of a CPT on the design of pile foundations, including the effect of radial distance, that is, the distance between the CPT and the pile. The second section considers the influence of the type and size of the pile on the quantification of the effect of the CPT investigations on the pile design. The third section examines the influence of mean soil resistance values (q_c) when quantifying the effect of a CPT on the pile design. The last section discusses the quantification of the effect of the CPT on the pile design for anisotropic soil.

It was expected that the distance between a CPT sounding and a pile foundation would have a significant impact on its design. It is commonly believed that the closer a CPT sounding is to the location of the pile foundation, the more reliable the data for designing the pile. The current research was looking to establish the maximum distance between the CPT sounding beyond which the pile design is effectively unreliable. This distance will be termed the 'critical distance'.

The research also sought to determine whether reliable designs are affected by the type and size of the pile, and the mean of the soil resistance values in relation to the simulations. The influence of anisotropic soil is also examined because the correlation structure of soil is often anisotropic with the horizontal SOF being lower than the vertical SOF (Jaksa et al. 2005).

4.2 SOIL VARIABILITY

The variability of soil properties was expected to be a factor in quantifying the effects of site investigations on pile design. Therefore, the simulation of a cone penetration test (CPT) sounding and a single pile foundation was conducted using 3-dimensional soil profiles. The 3D soil profiles were generated statistically within a certain variability specified using the coefficient of variability (COV) and the scale of fluctuation (SOF). The simulated soil was, in the first instance, isotropic, meaning that the SOF values for vertical and horizontal directions were the same. As shown in Figure 4-1, the simulated CPT was located at a position from which the various radial distances from the CPT to the pile foundation were measured. There were 40,000 locations of the CPT generated over the simulated soil, with the longest R_d being 34.50 metres, and the shortest R_d at 0.25 metres. The distance between two closed locations of the CPT was 0.25 metres in horizontal direction, as well as 0.25 metres in vertical direction.

The process of simulation was initiated by generating 3D random fields consisting of soil resistance values. This created a virtual model of a site. Once the 3D fields were generated, a CPT was simulated in a position at the corner of the site, and a single pile foundation was created at the centre. The design of a pile was computed using the soil resistance values located over the pile area within 6 × pile diameter, a design based on complete knowledge (CK). The design of a pile using soil resistance values obtained from the CPT was also prepared, a design based, therefore, on site investigation (SI). In the final process, a comparison between the design based on CK and the design based on SI was conducted to quantify the impact of the CPT on pile design, and whether the design was over- or under- specified. This process was performed for a single realisation. For the next realisation, the framework of the process remained the same, with the location of the CPT moving to the next element within the site.

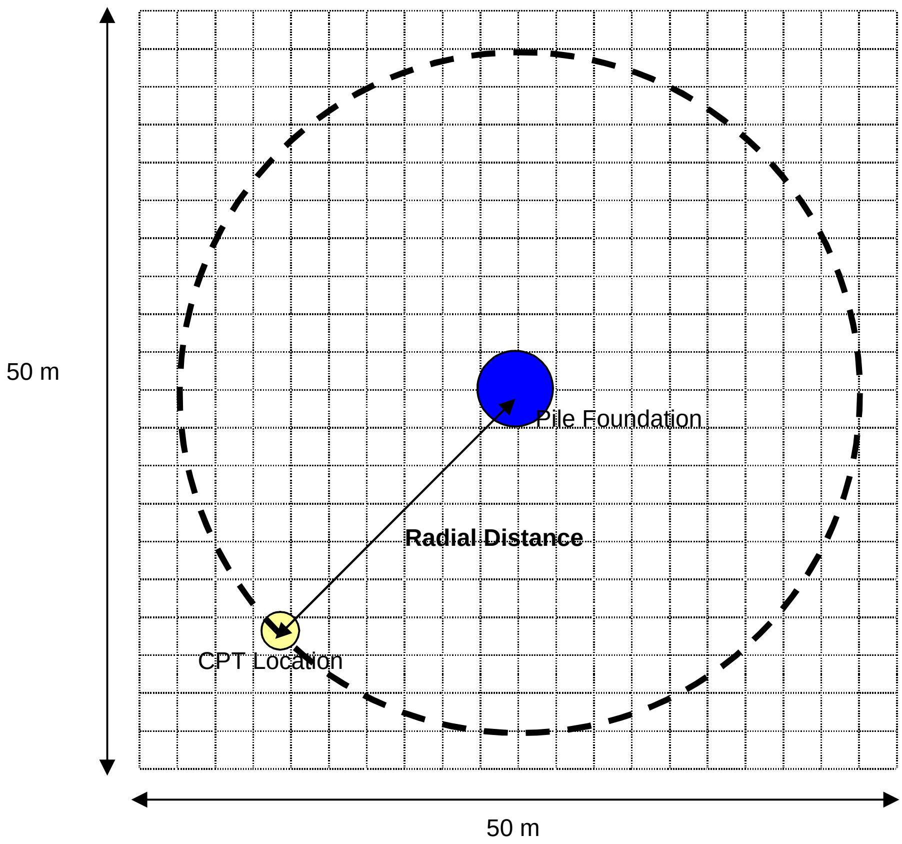
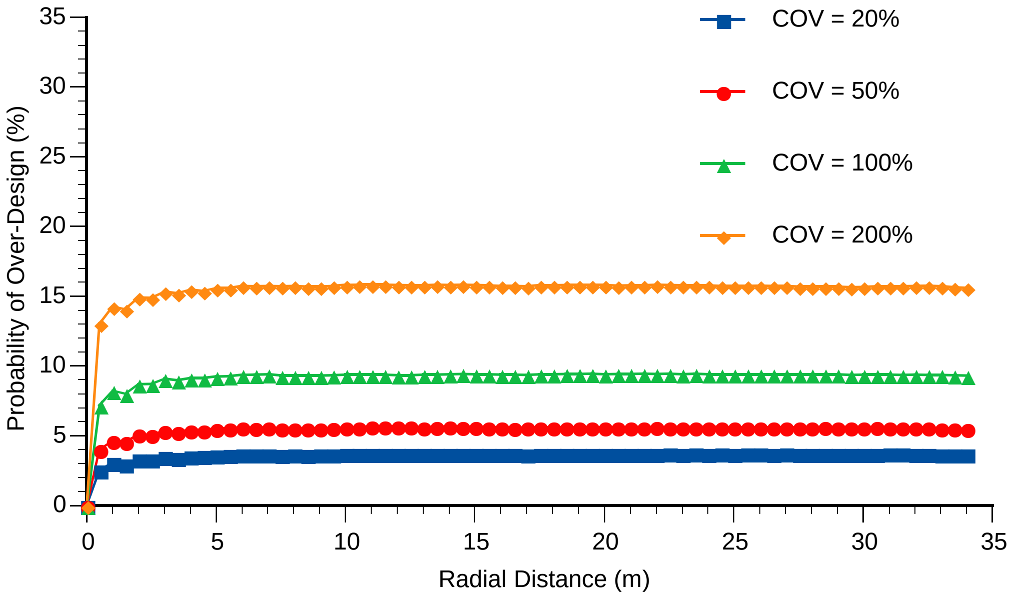


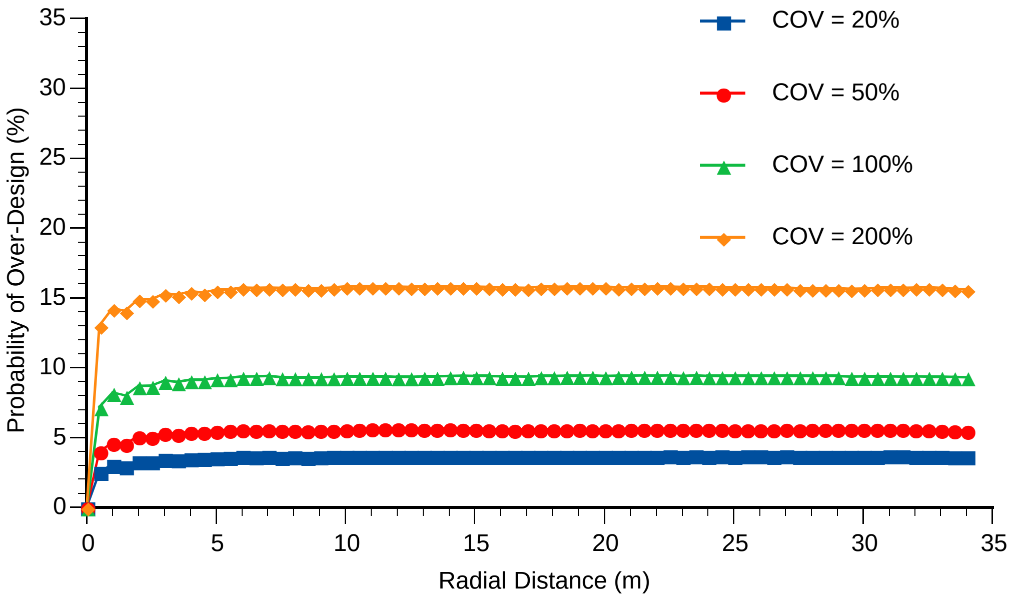
Figure 4-1 Plan view of the grid layout used for the simulated 3D data

The simulation assumed that the mean soil resistance value (q_c) of the simulated soil profiles was 5,000 kPa, and the length and diameter of the pile was 30.0 metres and 0.5 metres, respectively. The mean soil resistance profile was set at 5,000 kPa as this value is the median of soil resistance data for computing pile load capacities based on the LCPC method. In terms of the size of the pile, the length was set at 30 metres as this represents a relatively deep pile. However, the influence of pile length and diameter is examined in Section 4.3.

Results are presented in Figure 4-2 for the soil with a small SOF (1 metre) and Figure 4-3 for the soil with a large SOF (10 metres). The results also show the influence of increased COV. The figures are separated into two parts. Figures 4-2(a) and 4-3(a) show the probability of under-design of the simulated pile, whereas Figures 4-2(b) and 4-3(b) illustrate the probability of over-design of the simulated pile.



(a)



(b)

Figure 4-2 Effect of radial distances on the probability of (a) under- and (b) over-design, for an increasing soil COV and a SOF of 1 metre

From the results shown in Figures 4-2(a), and (b), the following trends can be observed:

- As the radial distance between the CPT and the pile increases, both the probability of under-design and over-design of the pile foundation increase;

- At certain distances, the probability of under- and over-design level off. This occurs when the CPT is located at around 3 to 4 metres from the pile; and
- The probability of under- and over-design for a soil with a high COV is higher than it is for a soil with a low COV, as one would expect.

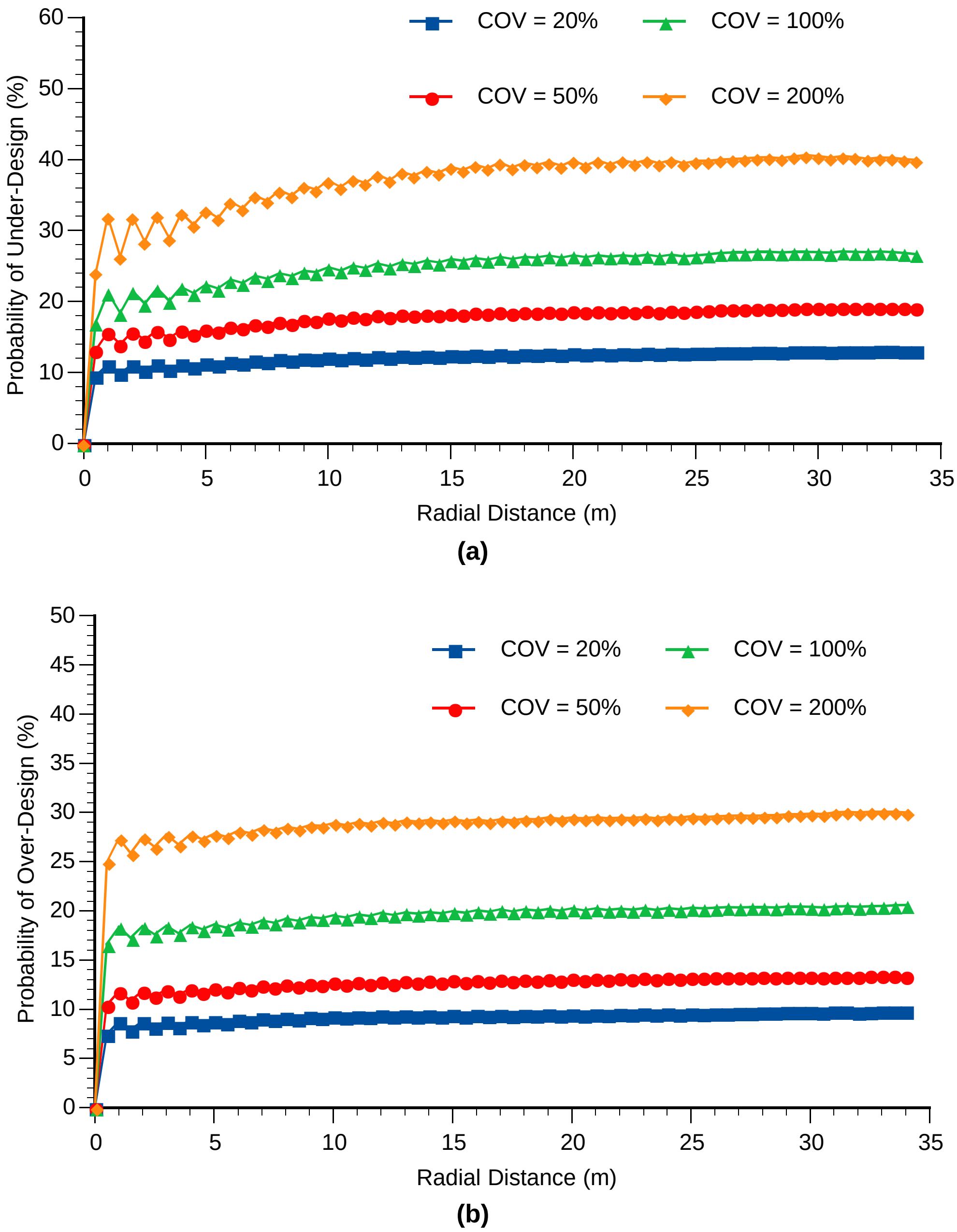


Figure 4-3 Effect of radial distances on the probability of (a) under- and (b) over-design, for an increasing soil COV and a SOF of 10 metres

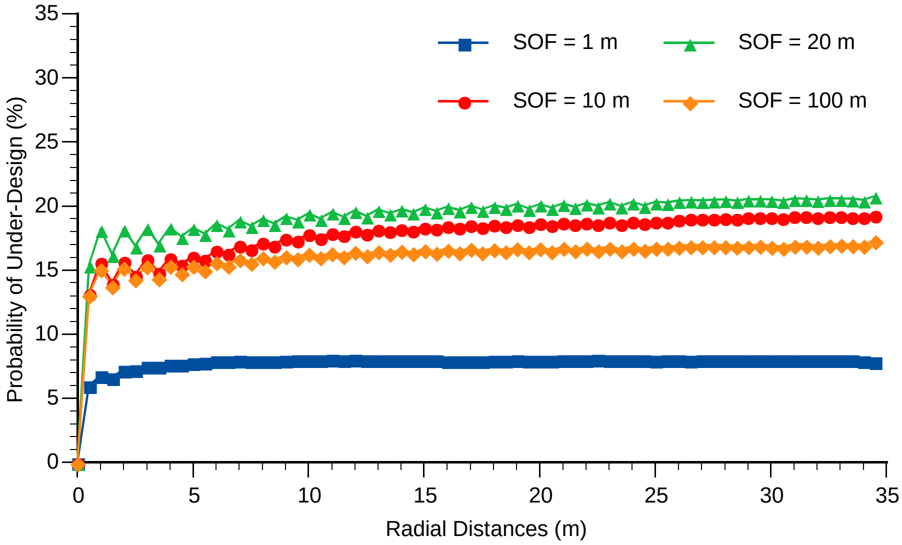
From the results shown in Figures 4-3(a) and (b), the following trends can be observed:

- Similar to the results of the soil with an SOF of 1 metre, as the radial distance between the CPT and the pile increases, the probability of either under-design or over-design of the pile foundation also increases;
- For certain distances, the probability of under- and over-design achieves a consistent a plateau. These were encountered at around 25 metres from the pile. In comparison, the distances are longer than that of the SOF of 1 metre; and
- Again, the probability of under- and over-design for a soil with a high COV is higher than that for a soil with a low COV.

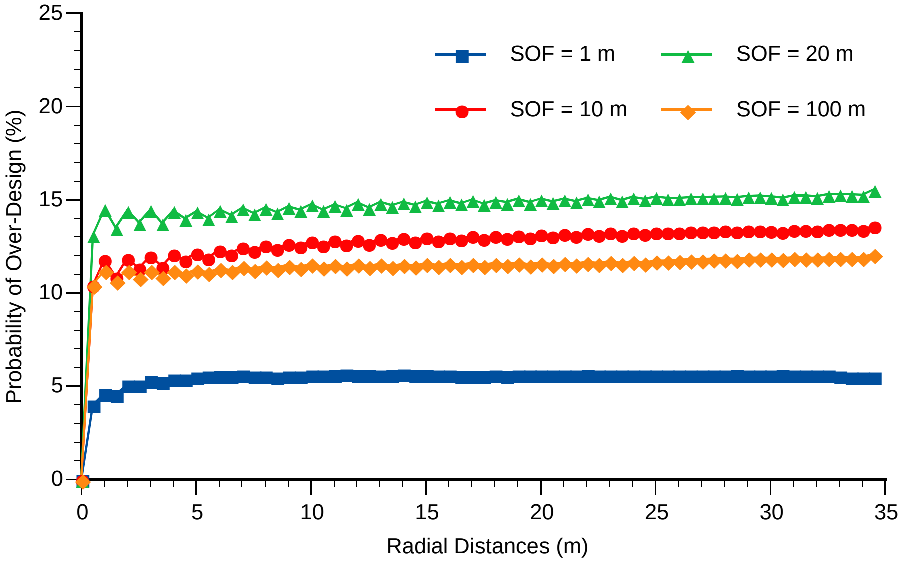
The increase in probability of under- and over-design as the radial distance between the CPT and the pile foundation increases is in agreement with the expectation that the radial distance of CPTs from the pile foundation has a significant impact on its design. These results were observed for soil with both low and high scales of fluctuation. In addition, the level of variability of the soil, as established by the COV, appeared also to have a marked influence on the design. At the same radial distance, a CPT simulated in soil with a high COV would yield a higher probability of under- or over-design than was the case for soil with a low COV. Intuitively, the closer the CPT is to the pile, the lower the probability of the design being over- or under- specified would be.

The results also revealed certain radial distances where the probability of the under- and over-design of the pile levelled off. These were considered the critical distances. For instance, for the soil with a SOF of 1 metre, the critical distances were more than 5 metres from the pile; whereas the critical distances for soil with a SOF of 10 metres were more than 22 metres from the pile. These results are due to the fact that, as the SOF increases, there are ‘pockets’ of soil that contain soil whose properties are closer in value. Hence, for a SOF of 10 m, there exists pockets of harder, as well as, pockets of weaker, soil. If the CPT encounters one or other of these pockets, the design will vary more significantly than for soils with lower SOFs where such pockets do not exist.

The probability of under- and over-design for an increasing SOF was investigated. Simulations were conducted on the soils with similar levels of COV and an increasing SOF. The soil SOF was set to equal 1, 10, 20, and 100 metres. The COVs of the soil were set to 50%. It was assumed that the pile was bored with a length of 30 metres, and the diameter of 0.5 metres. The CPT conducted in isotropic soil, i.e. $\theta_h = \theta_v$.



(a)



(b)

Figure 4-4 Effect of radial distances on the probability of (a) under- and (b) over-design, for an increasing soil SOF and a COV of 50%

From the results shown in Figures 4-4(a) and (b), 4-5, and other figures as shown in Appendix B, the following trends were observed:

- The probabilities of under- and over-design for a soil with a high SOF are greater than those for a soil with a low SOF. However, in the case of soil with a SOF of 100 metres, the probabilities of under- and over-design are lower than those with SOF of 10 and 20 metres;
- There are certain critical distances beyond which the probabilities of under and over-design become stable; and
- The critical distance increases as the SOF of the soil increases. The longest critical distance accounted for was for a soil SOF of 20 metres; this might be regarded as the worst case of SOF.

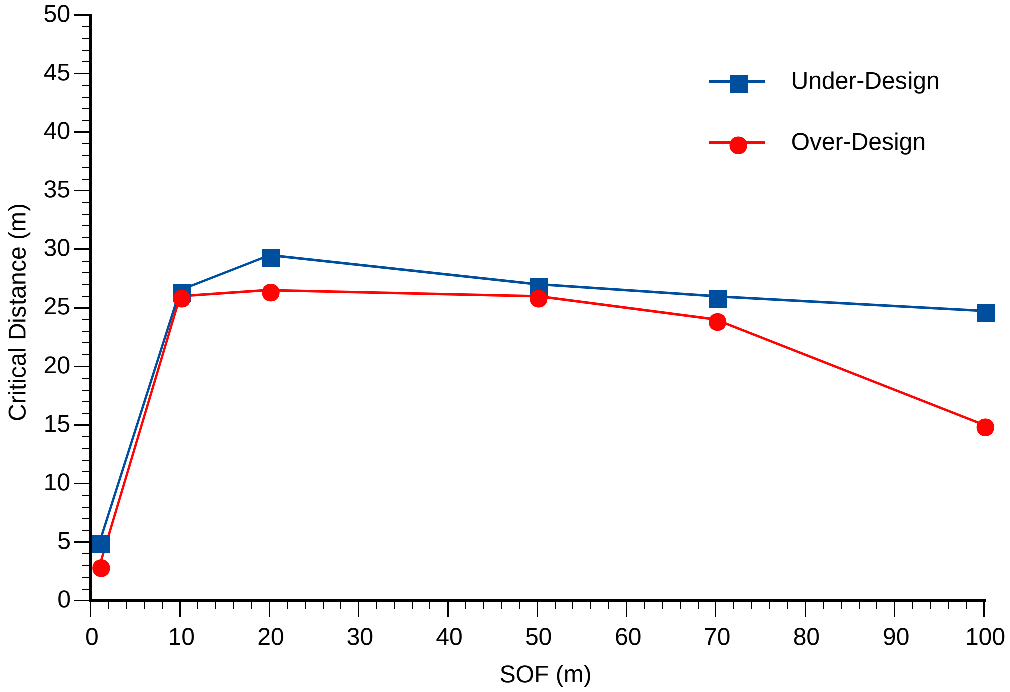


Figure 4-5 Critical distances for an increasing SOF, COV is set to 50%

The worst case SOF of 20 metres for the pile foundation is different from that found by Goldsworthy (2006) which was 8 metres for shallow foundations. This might be caused by the difference in the test methods used. The current research utilised pile load capacity as the method for designing foundations, whereas Goldsworthy (2006) used serviceability (foundation settlement) criteria. It should be noted that the concept of critical distance as examined here, is based on an assessment of the statistical properties and is expected to different to that which would be obtained if an examination of soil mechanics was carried out.

4.3 TYPE AND SIZE OF PILE FOUNDATIONS

The effect of the size and the type of the foundation on the probability of over- or under-design was also investigated as part of the research. It was expected that the size and type of the pile would have a marked influence on the ability to quantify the reliability of site investigations of pile designs. The simulation included 4 different lengths (5, 10, 20 and 30 metres), 3 different diameters (0.5, 0.7, and 1.2 metres), and 3 types (driven precast pile, plain bored pile, cast screw piles) of pile foundation.

The process of simulation was similar to the previous simulations: a single pile foundation was located at the centre of the simulated soil, and a CPT was located within a certain radial distance from the pile. The diameter of the pile was 0.5 metres; the simulated soil was isotropic with a SOF of 10 metres and a COV of 50%, and a mean of soil resistance values of 5,000 kPa.

From the results shown in Figures 4-6(a) and (b), the following trends were observed:

- As the radial distance between the CPT and the pile increases, the probability of under- and over-design also increases; and
- The probability of under- and over-design of the shorter piles appeared higher than the probability of under- and over-design of longer piles.

Figure 4-6 shows that the length of the pile is notable factors in quantifying the probability of under- and over-design of the pile. For shorter pile foundations, the CPT position yields higher probabilities when compared longer piles. This is because, shorter piles, the soil properties are averaged over a shorter length and, hence variations over this distance are more significant.

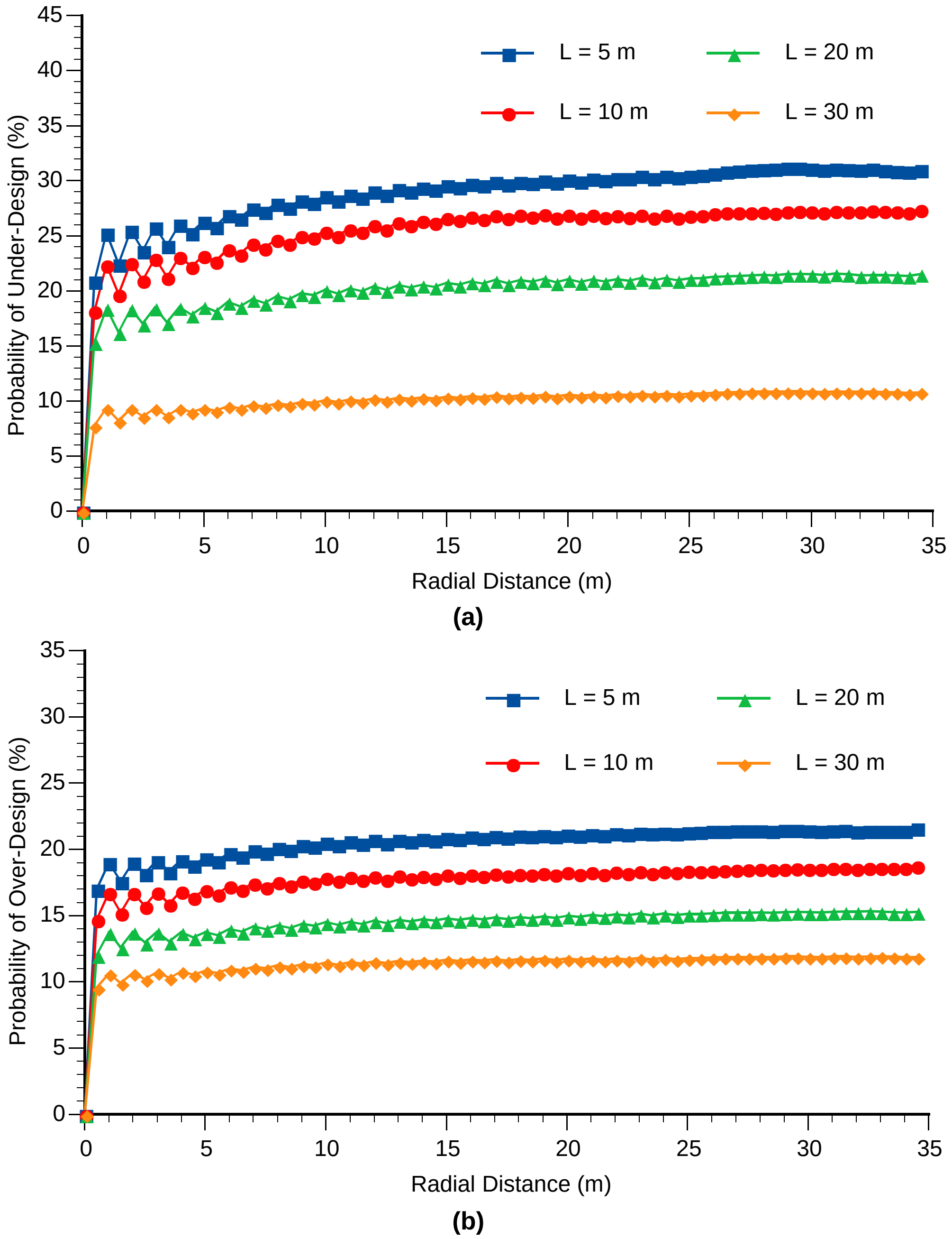
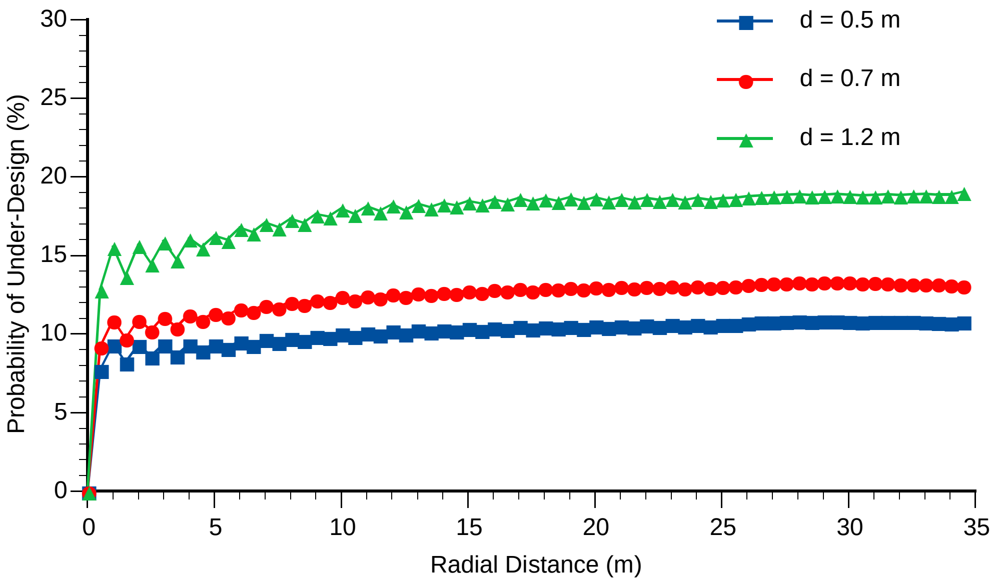


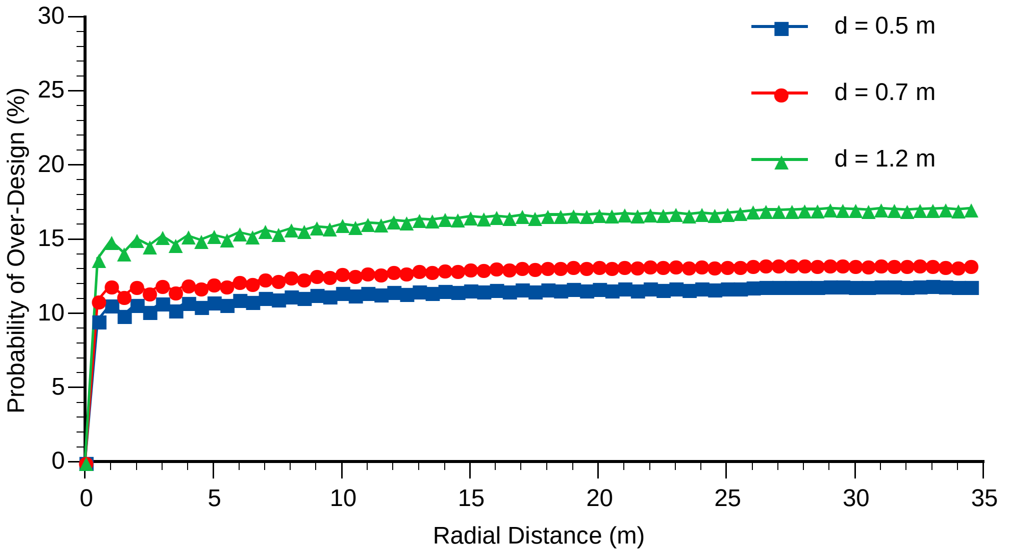
Figure 4-6 Influence factor of the length of pile foundation on (a) the probability of under- and (b) over-design for the soil with SOF of 10 metres and a COV of 50%

From the results shown in Figures 4-7, the following trends were observed:

- The diameter of the pile foundation has a significant impact on the probability of under- and over-design. It can be seen that, for the same length, thicker piles yield a higher probability of under- and over design than the thinner piles.



(a)



(b)

Figure 4-7 Influence factor of the diameter of pile foundation on (a) the probability of under- and (b) over-design for the soil with SOF of 10 metres and a COV of 50%

Furthermore, Figure 4-7 indicates that for pile foundations with larger diameters, the CPT position yields higher probabilities than it does for piles with smaller diameters. It is suggested that the number of soil resistance elements over the area of the pile which contains variability affect the probability of under- and over-design. The more elements over the area of the pile, the more possible that under- and over-design will occur.

From the results shown in Figures 4-8(a) and (b), the following trends can be observed:

- The effect of the CPT position in terms of the probability of under- and over-design is similar for driven, bored and cast screw piles.

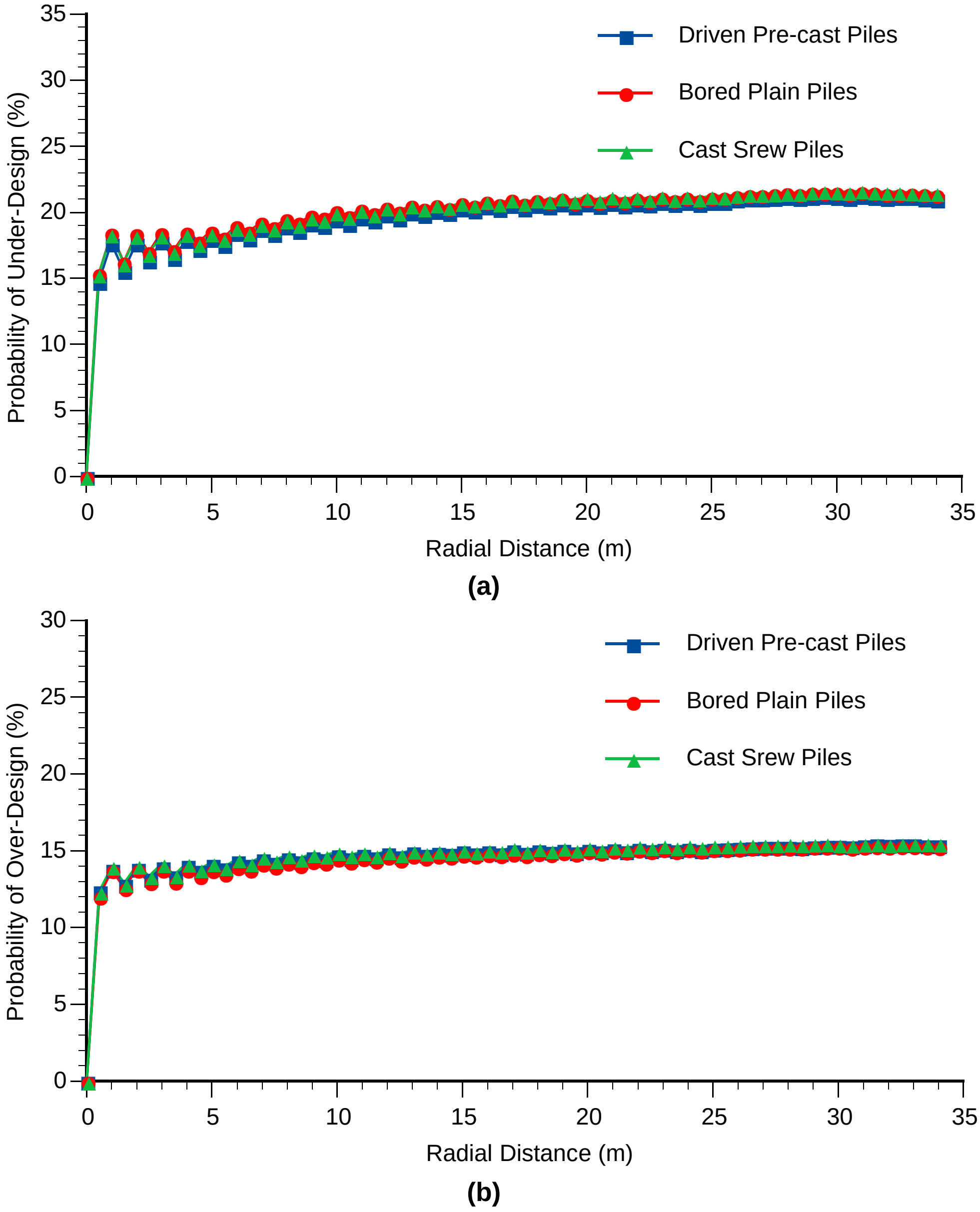


Figure 4-8 Influence of the type of pile foundation on (a) the probability of under- and (b) over-design for soil with a SOF of 10 metres and COV of 50%

In the case of different construction methods, Figure 4-8 shows that the type of foundation does not influence the probability of under- and over-design. This is due to the fact that, the method employed in this research, that is the LCPC method, performs consistently for each construction method, estimating pile load capacity for a simulated pile foundation and for a simulated site investigation. Once those capacities are compared, the results will be similar for all types of foundation.

4.4 MEAN OF SOIL RESISTANCE VALUES

It was noted previously that the simulations generated 3D soil profiles with a mean soil resistance (q_c) of 5,000 kPa. However, results of the simulated investigations might differ if the mean values are higher or lower than 5,000 kPa. Therefore, several 3D soil profiles were generated in separate simulations with different mean values of soil resistance. The first simulations generated soil with a mean value of 1,000 kPa representing a soft clay or loose sand. The second simulation had a mean value of 10,000 kPa, representing a hard clay or dense sand.

Again, the simulations consisted of a single pile foundation located at the centre of the site. CPTs were located at certain radial distances from the pile. The diameter of the pile was again 0.5 metres, and the length of the pile was 30 metres. The simulated soil was isotropic with a SOF of 10 metres and a COV of 50%.

The results in Figure 4-9, show that the simulations of 3D soil profiles with different mean values of soil resistance yield different probabilities of under- and over-design. For instance, 1,000 kPa of mean soil resistance yields a lower probability than soil means of 5,000 and 10,000 kPa.

These results are in contrast with those obtained by Goldsworthy (2006), who found that the mean value of the Young's modulus - the central parameter that he simulated - had no influence on the reliability of the design of a pad footing system based on a certain level of investigation. However, his work involved adjusting the sizes of the footings to meet some prescribed settlement criteria. In contrast, the work in the present study has involved determining the allowable design capacities of a pile foundation whose dimensions are fixed, which is somewhat different to the process adopted by Goldsworthy (2006).

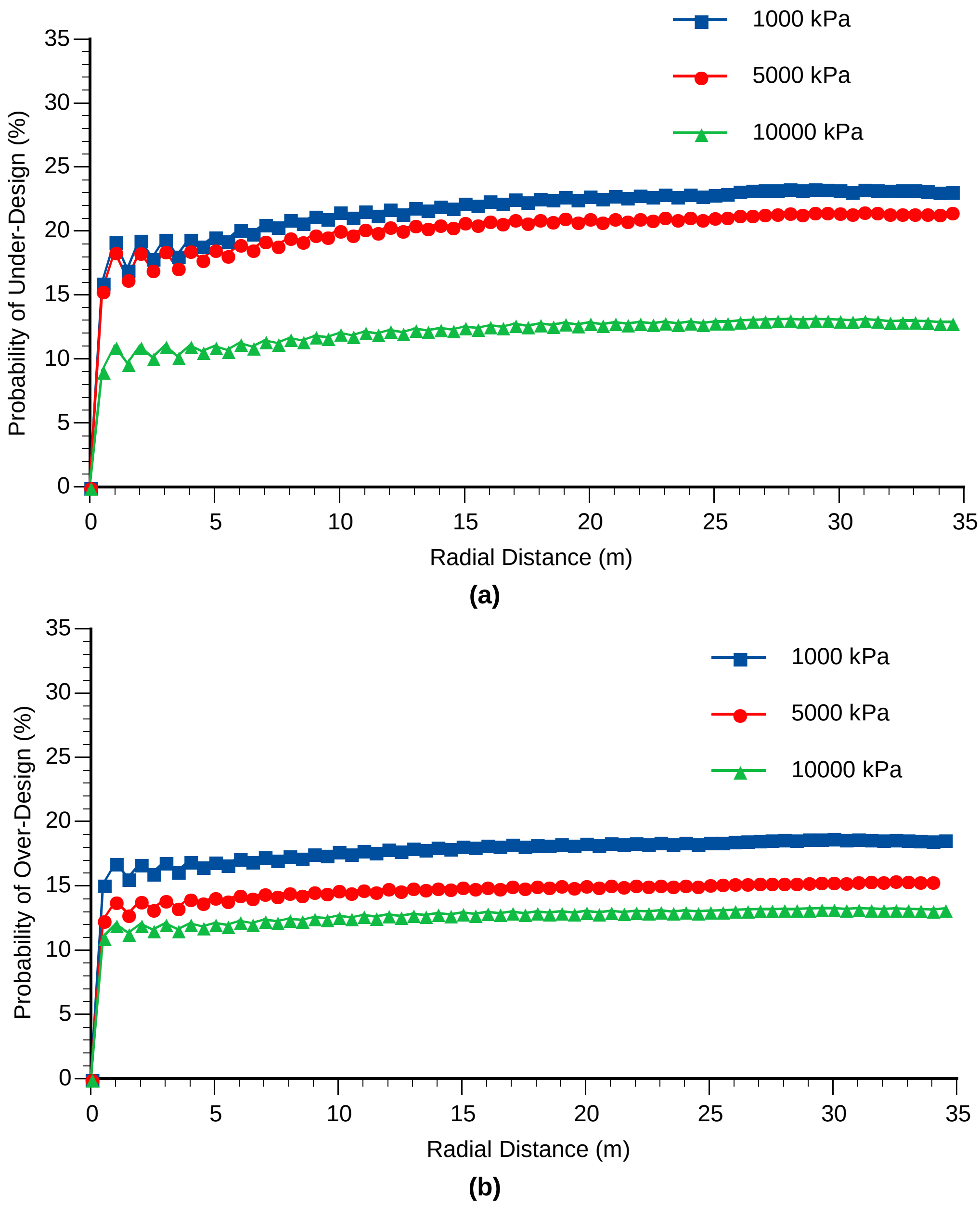


Figure 4-9 Influence factor of the mean of soil resistance values on (a) the probability of under- and (b) over-design for the soil with SOF of 10 metres and COV of 50%

The results given in Figures 4-9, demonstrate that the mean value of the soil resistance influences the probabilities of under- and over-design of the pile. This behaviour is due to the fact that a log-normal distribution is used to simulate the soil resistance values. At low values of the mean of the soil resistance, such as q_c = 1,000 kPa, lower values of qc are encountered more often than would be the case for higher q_c values, which will reduce the allowable axial capacity and increase the probabilities of under- and over-design of the pile.

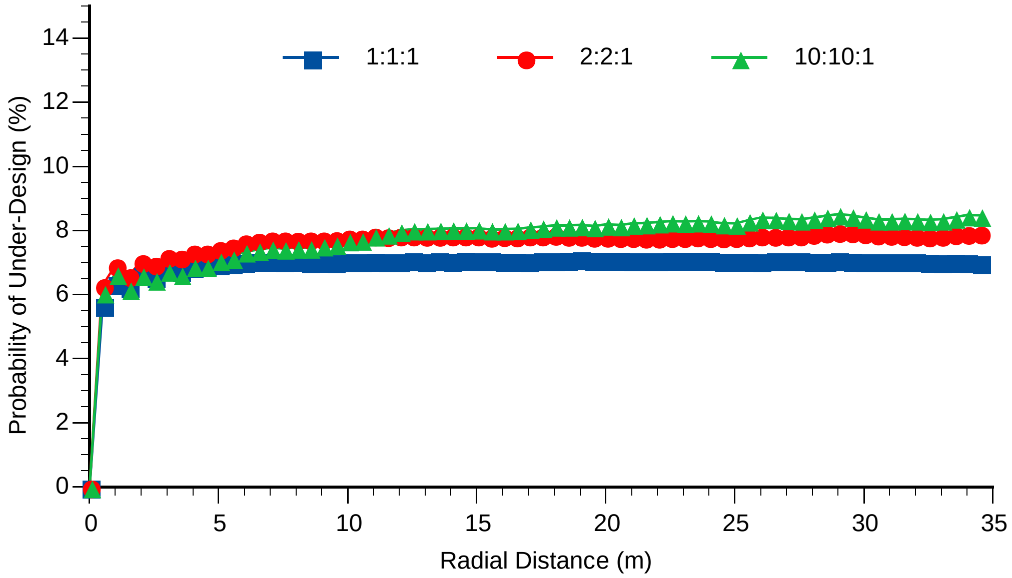
4.5 ANISOTROPIC SOILS

As described in Chapter 2, most soils in reality are anisotropic. Jaksa et al. (2005) have suggested that the process of forming soil occurs mainly in the horizontal plane and the SOF in the horizontal direction is usually greater than the SOF in the vertical direction. Here, the effect of soil anisotropy on pile design is investigated. To do this, soil with differing SOFs was simulated. These soils included isotropic soil with the same SOF in both the vertical and horizontal directions; anisotropic soil with twice the SOF in the horizontal than in vertical direction; and anisotropic soil with ten times the SOF horizontally to that vertically. The soil variability was set to a COV of 50% and the pile size was assumed to be 20 metres in length and 1.0 metre in diameter.

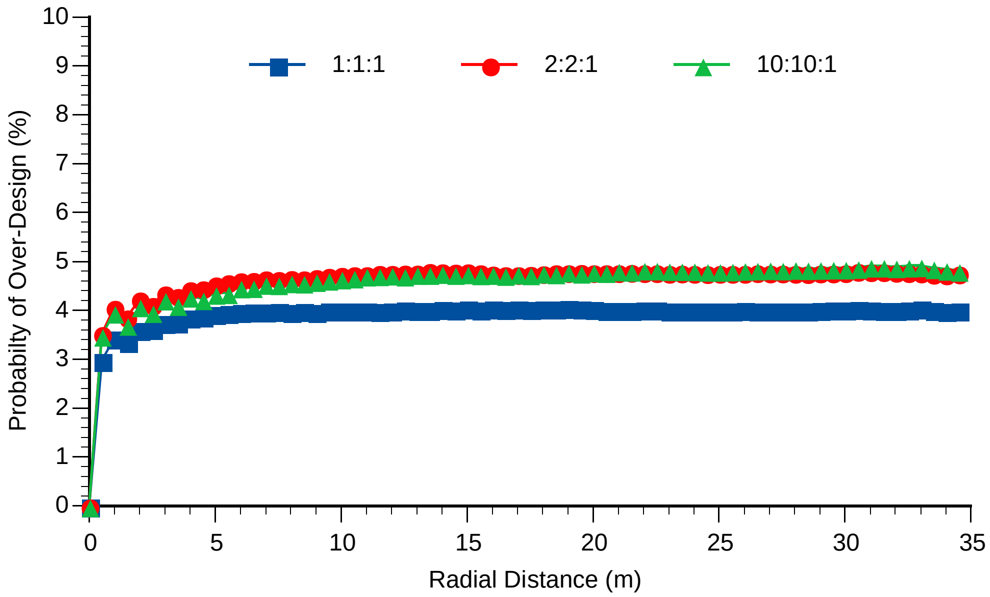
From the results shown in Figures 4-10, the following trends can be observed:

- As radial distances increase, the probability of under- and over-design increases; and
- The probability of under- and over-design on anisotropic soil is marginally higher than the probability for isotropic soil.

Basically, there is no significant difference between isotropic and anisotropic soils in terms of the probabilities of under- and over-design. Figure 4-10 reveals that anisotropic soils yield slightly higher probabilities than isotropic soils. The isotropic soil specified a uniform SOF in both the horizontal and vertical direction. This result correlates with the analysis in Section 4.2 that indicates that soil with higher SOF yields higher probabilities of under- and over-design. That is why the probabilities for the soil SOF of 10:10:1 are higher than those of soil a SOF of 2:2:1 and 10:10:1. Furthermore, the SOF in the horizontal direction has little effect on the probabilities. Due to the computation of pile load capacities, which is effectively more of a vertically computation than a horizontal one, spatial variabilities in the vertical directions have a more significant effect than variabilities in the horizontal direction.



(a)



(b)

Figure 4-10 Effect of the anisotropic soil on (a) the probability of under- and (b) over-design for soil with a COV of 50%

4.6 SUMMARY

The results in this chapter have shown that radial distances between CPTs used in a site investigation for a pile foundation have a significant impact on the pile foundation design. The results indicated that the closer the CPT is located to the proposed pile, the lower the probability of under- and over-design being obtained. In contrast, locating the CPT further from the pile results in a higher probability of error in the resulting pile design. However, at certain distances, it was found that the probabilities of under- and over-design become relatively stable. Considered as critical distances, these are influenced by the magnitude of the soil SOF. The results indicated that the type of pile has no impact on quantifying the effect of the radial distance of the CPT due to the consistency of the LCPC method applied. Yet, the size of the pile, i.e. length and diameter and the mean soil resistance values, influence the probabilities. Finally, it was found that the anisotropic soil slightly affects the probabilities of under- and over-design.

Chapter Five
Effect of the Number of CPT Soundings Used in Site Investigations on the Probability of Under- and Over-Design of Pile Foundations

5.1 INTRODUCTION

As explained in Chapters 1 and 2, one of the main problems associated with structural foundation failures is inadequate site investigations. This chapter investigates the effect of such inadequate site investigations for the design of pile foundations. As explained in Chapter 3, the investigations were conducted by generating a 3-dimensional virtual soil site. To investigate the site, 9 pile foundations and 12 site investigation plans were generated, each plan consisting of a certain number of CPT locations for the site investigation.

5.2 SOIL VARIABILITY

Investigations of the reliability of site investigations within various levels of soil variability, expressed by the coefficient of variation (COV) and the scale of fluctuation (SOF) were conducted. As shown in Figure 5-1, 9 piles were simulated, configured in 3 rows and 3 columns and separated 12.5 metres from each other. The coordinates of the piles are given in Table 5-1. The piles were assumed to be bored piles with a diameter of 0.5 metres, and a length of 20 metres. The simulated soil was isotropic with a mean soil resistance (q_c) of 5,000 kPa.

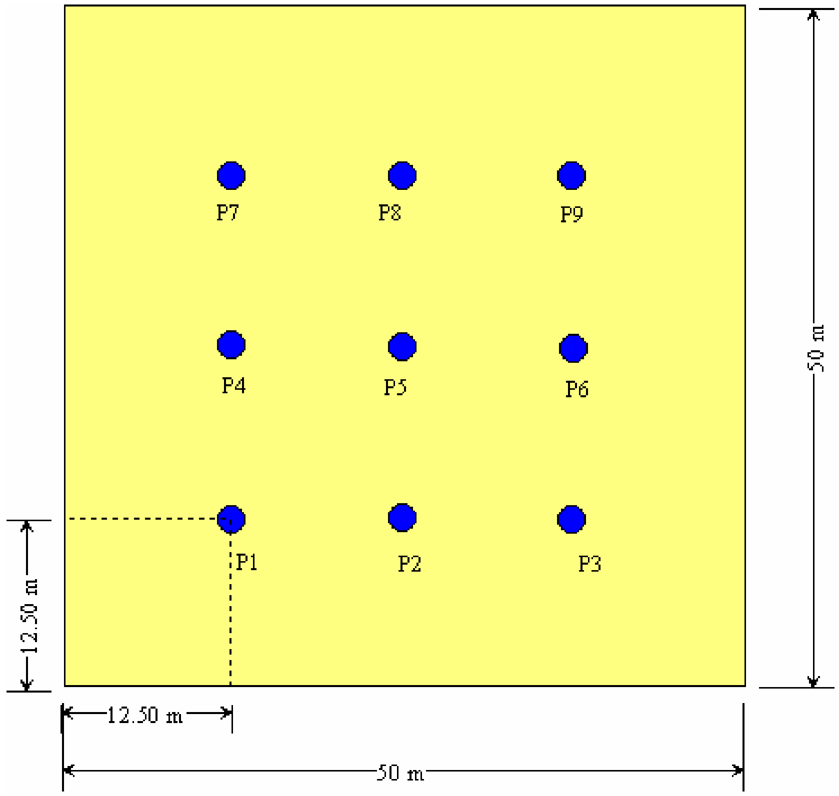


Figure 5-1 Plan view of site with 9 piles

Table 5-1 Coordinates of piles

No. Pile	Location	
	X	Y
P1	12.50	12.50
P2	25.00	12.50
P3	37.50	12.50
P4	12.50	25.00
P5	25.00	25.00
P6	37.50	25.00
P7	12.50	37.50
P8	25.00	37.50
P9	37.50	37.50

Twelve site investigation plans containing a range of number of CPTs and locations were established ranging from 1 to 16 CPTs, as shown in Figure 5-2. The position of the CPTs was determined by those normally adopted in typical site investigations.

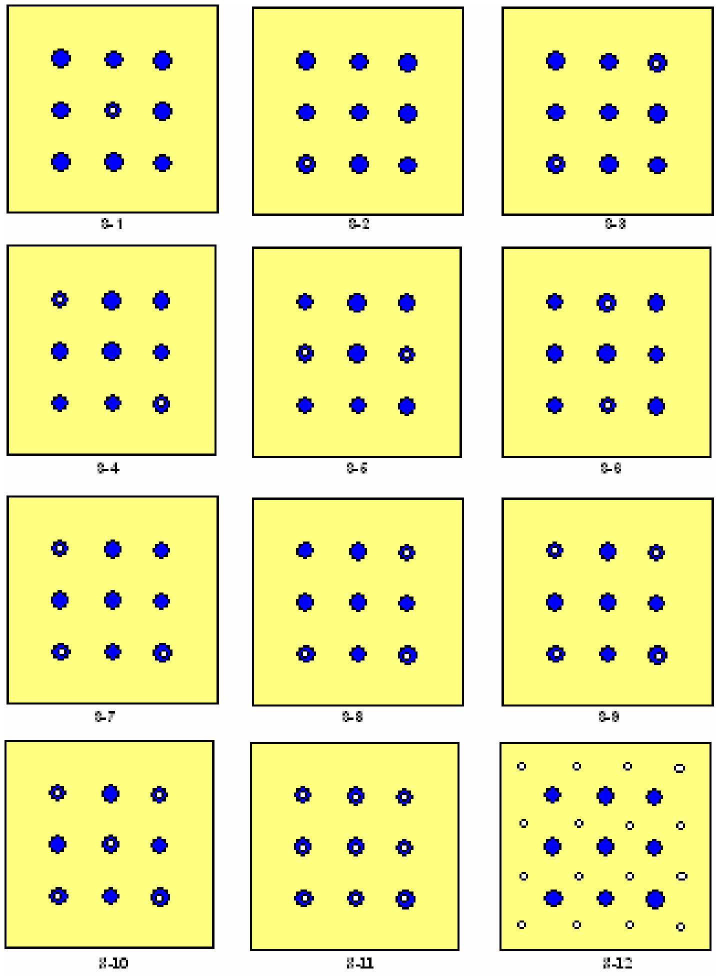


Figure 5-2 Site Investigation plans examined

The results of the simulations are presented in Figure 5-3 for soil with a low SOF (1 metre) and Figure 5-4 for soil with a high SOF (10 metres).

From the results shown in Figures 5-3(a) and (b), the following trends were observed:

- The increase in sampling effort diminishes the probability of under-and over-design of the piles. For instance, with a soil COV of 200%, the minimum sampling (one CPT) yields a probability of 11.50% of under-design, whereas the maximum sampling (16 CPTs) results in only a 3% probability of under-design;

- For a SOF of 1 m, sampling efforts greater than 5 CPTs have little impact on the probability of under- and over-design. Therefore, it is suggested that a sampling effort of 5 CPTs is the optimum for achieving the lowest probability of under- and over-design; and

- Sampling efforts conducted on soil with a high COV yield higher probabilities than those conducted on soil with a low COV. This is because the soil with a high COV is more heterogeneous and erratic than that with a low COV. Therefore, minimum sampling efforts produce higher risks of failure and over-design compared to more intensive samplings.

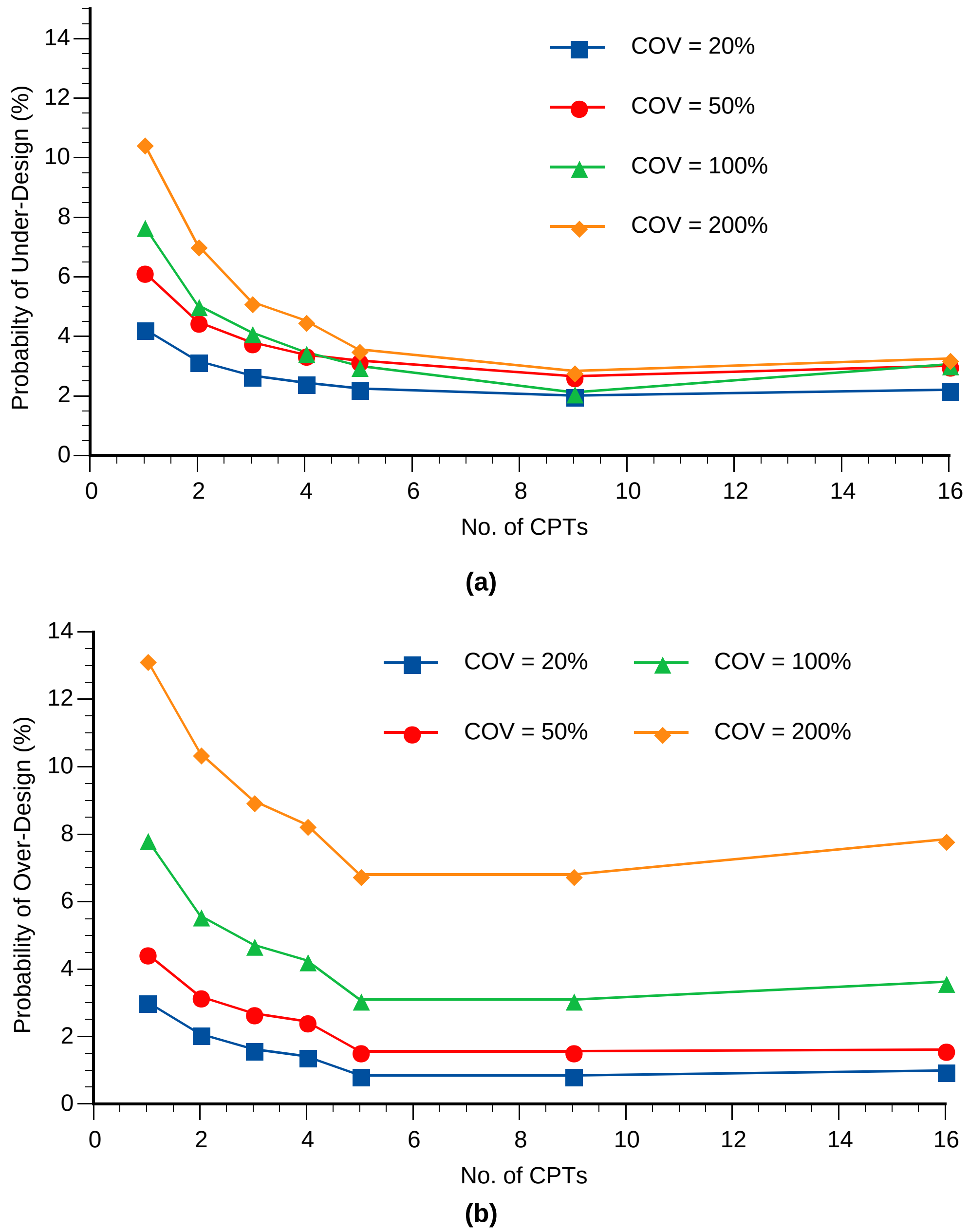


Figure 5-3 Effect of samplings efforts on the probability of (a) under- and (b) over-design, for an increasing soil COV and a SOF of 1 metre

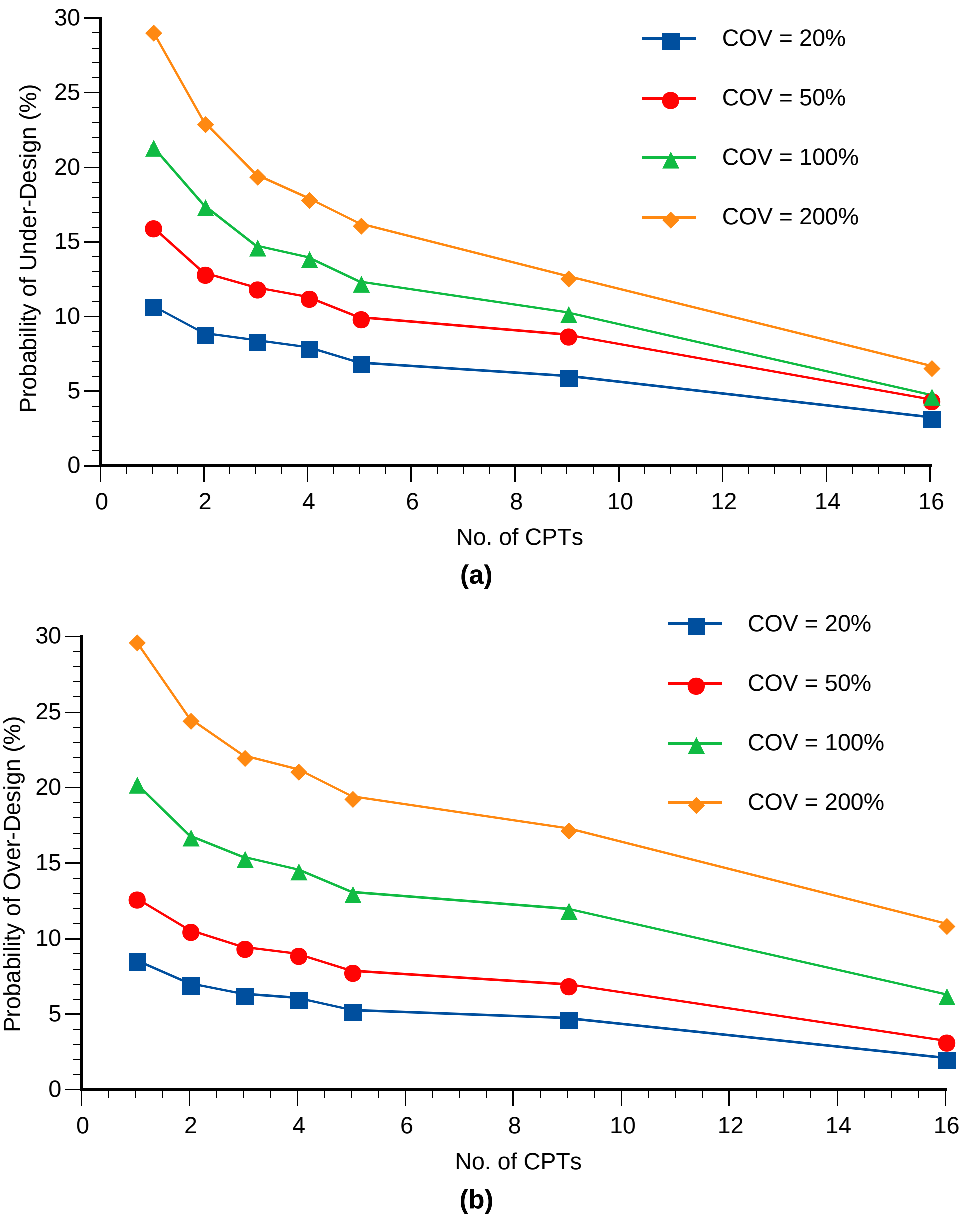


Figure 5-4 Effect of sampling efforts on the probability of (a) under- and (b) over-design, for an increasing soil COV and a SOF of 10 metres

From the results shown in Figures 5-4 (a) and (b), the following trends were observed:

- The increase of sampling efforts reduces the probability of under- and over-design of the piles. For instance, for the soil with a COV of 100%, the sampling effort of one CPT yields a risk of being 21% under-designed and 20% over-designed, whereas sampling with 16 CPTs yields a 5% and 7% risk, respectively;

- The lowest probabilities can be achieved using of 16 CPTs. This indicates that undertaking 16 CPTs is the optimum sampling effort, particularly for the soil with SOF of 10 metres, noting that 16 CPTs was the maximum sixe of investigation examined; and
- The soil with a high COV yields a higher probability of under- and over-design than a soil with a low COV.

It was found that there is benefit from increasing sampling effort for either the soil with low or the soil with high spatial variability (SOF). This is because increasing the number of CPTs significantly diminished the possibility of the under- or over-design of pile foundations. It was indicated that for soil with a high level of variability (COV), more CPTs are needed in order to obtain the optimum design of the pile foundation. This is opposite to what is needed for soil with a low level of variability. Soil with high variability is erratic in terms of the soil characteristics over a large area and should be investigated with more intensive site investigations than those for soil with a low level of variability.

Figures 5-5 (a) and (b) present the results of simulations conducted for soil with COV of 50% and various SOFs ranging from 1 metre to 100 metres. From the results shown in Figures 5-5 (a) and (b), and other figures as shown in Appendix C, the following trends can be observed:

- For all values of SOF, an increased number of CPTs decreases the probability of the under- or over-design of the piles. For example, in terms of soil with a SOF of 100 metres, a site investigation consisting of one CPT produces a risk of 18% under-design and 14% over-design of the piles. In contrast, 16 CPTs results in a risk of over- or under-specification of 5% and 4%, respectively.

The soil with a high SOF yielded higher probabilities than those for the soil with a low SOF, with the exception of the SOF of 100 metres. It can be seen that the risk given by the investigations for the soil with a SOF of 100 metres is lower than that for the soil with SOFs of 10 and 20 metres. The soil SOF of 20 metres yielded the highest probabilities compared to the other soil SOFs.

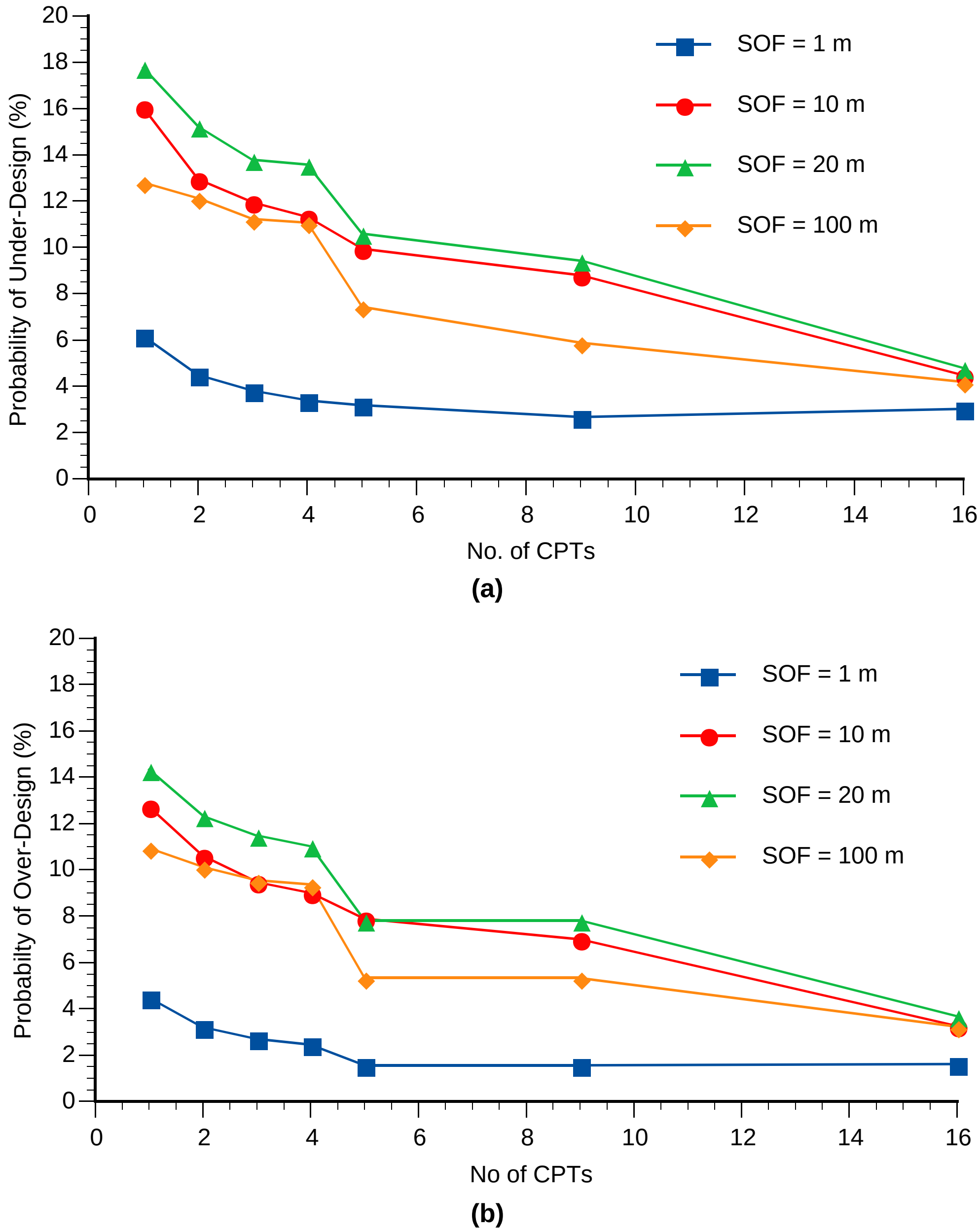


Figure 5-5 Effect of sampling on the probability of (a) under- and (b) over-design, for an increasing soil SOF and a COV of 50%

In the case of investigating the optimum number of CPTs for obtaining an appropriate pile design, in relation to SOF and COV, Figures 5-6 (a) and (b) present the results of simulations conducted for soil with various SOFs ranging from 1 metre to 100 metres with increasing COV.

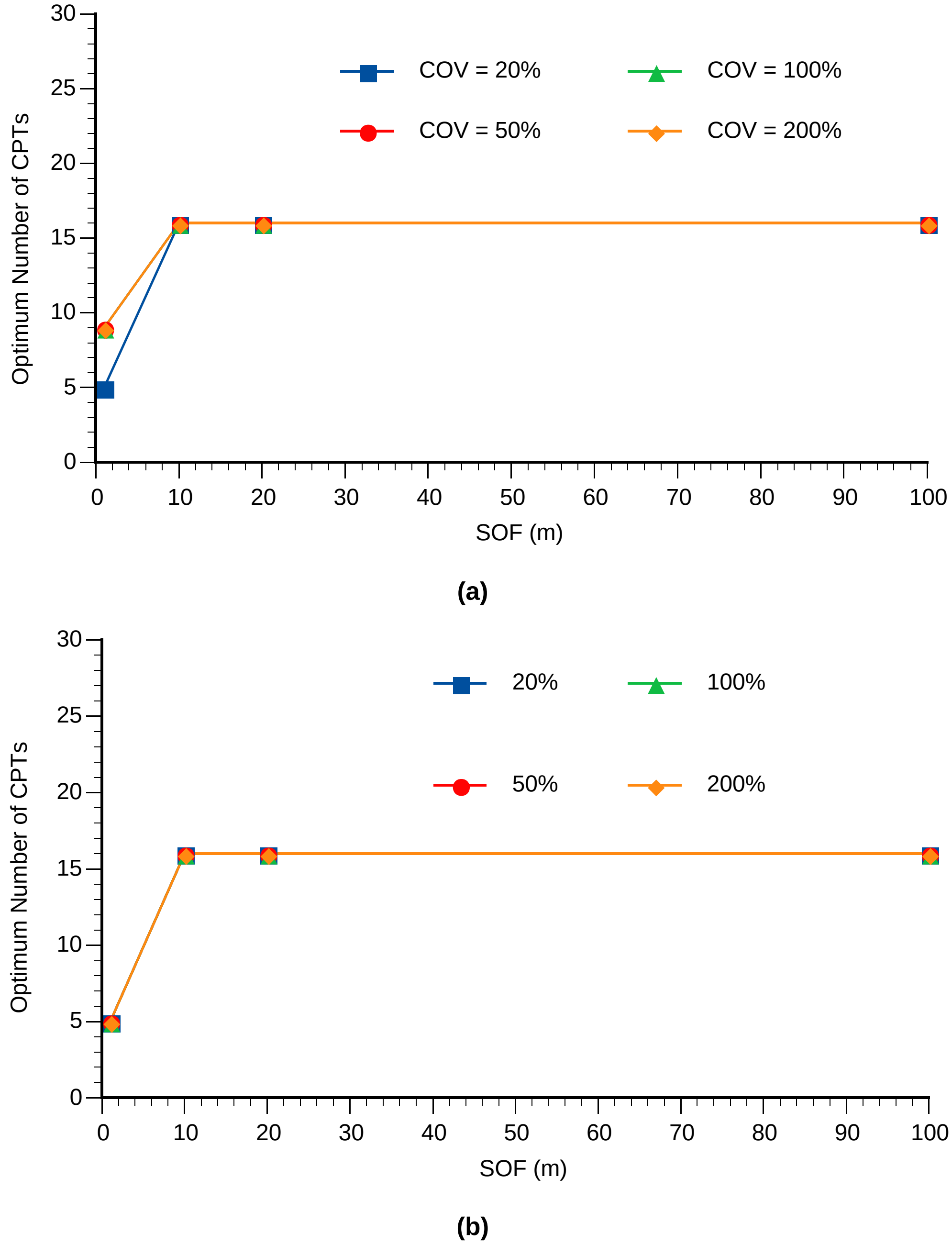


Figure 5-6 Effect of SOF on the optimum number of boreholes of (a) under- and (b) over-design, for an increasing soil COV

From the results shown in Figure 5-6, the following trends can be observed:

- For all soil values of COV examined, increasing SOF increases the optimum number of CPTs needed to achieve an appropriate pile design. For example, in terms of the soil with a SOF of 1 metre, the optimum number of CPTs is 5, whereas those with a SOF of 10 and 20 metres this increased to be 16 CPTs;

- The optimum number of CPTs conducted for the soil with a high COV is higher than those for the soil with a low COV, particularly for soil with SOFs of 1 and 100 metres. It can be seen that the optimum number of CPTs for the soil with a COV of 100% is higher than that for the soil with a COV of 20% and 50%; and

- The values of SOF of 10 and 20 metres yield the highest optimum number of CPTs compared to other values of SOF. Therefore, it can be suggested that the worst case of SOF is between 10 and 20 metres for the pile configuration investigated.

Based on those results, the soil SOFs have a significant impact on the probability of the under- or over-design of a pile foundation. Site investigations conducted on a site with a small scale SOF resulted in a lower probability than those conducted on the area with a large scale SOF.

As shown in Figure 5-7, the soil with small SOF contains small pockets with the same colours, whereas the soil with a large SOF shows several big pockets. As mentioned previously in Chapter 4, for a large SOF, there are pockets of harder, as well as, pockets of weaker. If the CPTs encounters one or other of these pockets, the design will vary more significantly than for soils with lower SOFs where such pockets do not exist.

Figure 5-7 3D soil profiles: (a) small SOF (random soil profiles), (b) large SOF (continuous soil profiles) (after Jaksa et al., 2005)

5.3 NUMBER OF PILES

The previous simulations were developed based on the assumption that 9 piles were located on the site. This might be unrealistic when compared with common construction projects. Further simulations were hence carried out involving various numbers of piles in order to investigate the effect of the number of piles on the probability of under- or over-design.

As shown in Table 5-2, simulations were conducted for a variety of quantities of piles, such as 25, 49, 64, and 100. The configurations of the piles were in regular grids with the same number of row and columns. For instance, the 100 piles were located in 10 rows and 10 columns. The length and diameter of the piles were 20 metres and 1 metre, respectively. The soil COV and SOF was set to 50%, and 10 metres, respectively, and the mean of the soil resistance values was 5,000 kPa.

Table 5-2 Number of piles for the simulations

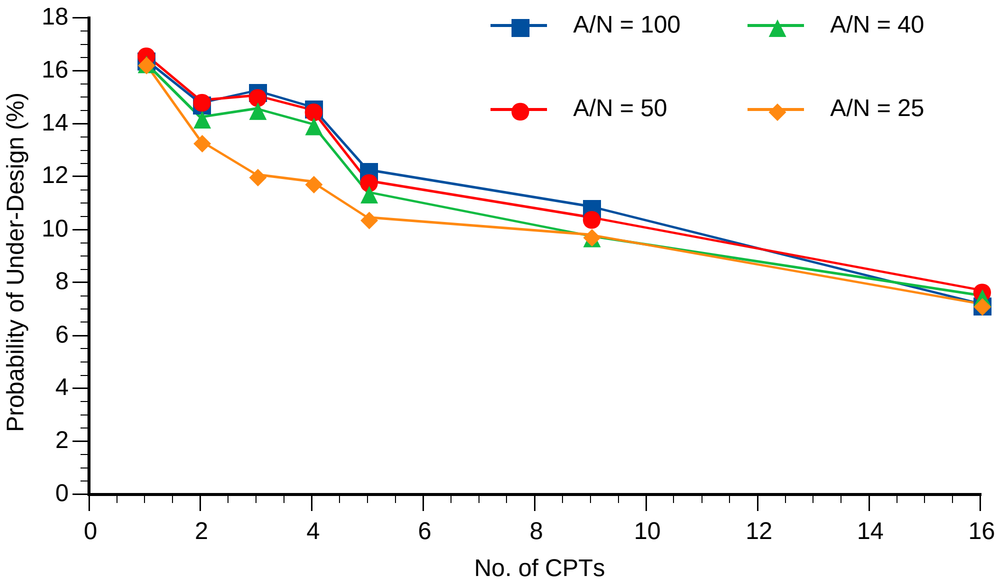
No. of Piles (N)	25	49	64	100
Configurations	5 x 5	7 x 7	8 x 8	10 x 10
Distances between each pile (d), m	10	8	7	5
A/ N (m2/pile)	100	50	40	25

A comparison between the ratio of the area and the number of piles (*A/N*) was conducted. A small ratio represents a large number of piles, whereas a large ratio represents a small number of piles on the site.

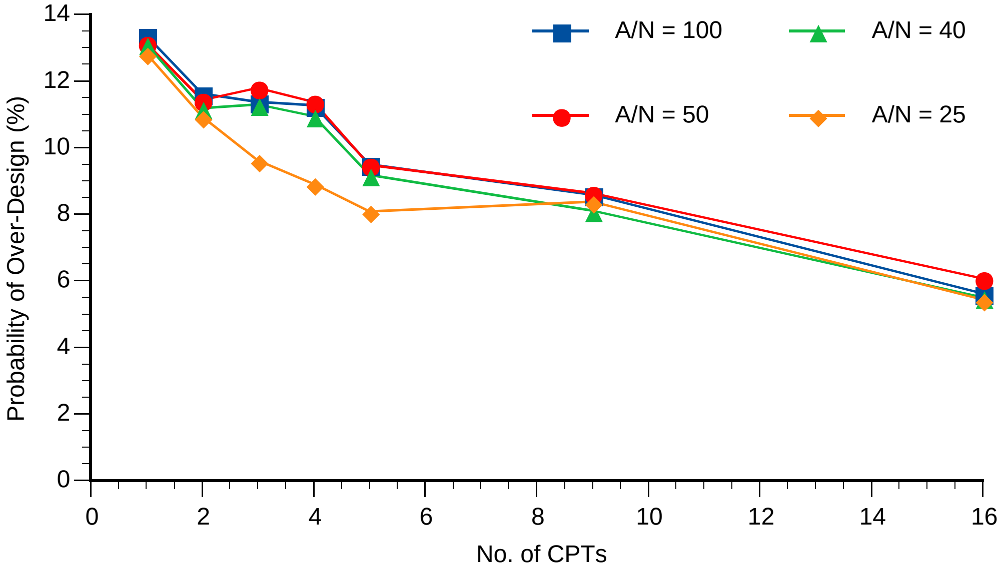
From the results shown in Figure 5-8(a) and (b), the following trend can be observed:

- For all numbers of piles, the increase of the sampling effort decreased the probability of under- or over-design. The number of piles appeared to have minimal impact on the probability.

Yet, 100 piles yielded lower probabilities than other numbers of piles. This is because a sampling effort conducted on a site with a few piles (less than 100 piles) yields higher risk rather than those sites with a lot of piles (64 to 100 piles). The more piles designed over a site, the lower the probability of under- and over- design would be. Another reason is that the averaging of pile load capacities over the area with a lot of piles decreases the probability of under- and over-design.



(a)



(b)

Figure 5-8 Effect of the number of piles on the probability of (a) under- and (b) over-design, for different averaging methods on the soil with a COV of 50% and a SOF of 10 m

This agrees well with what was expected in that the number of piles within the area had an impact on the probability of under- and over-design. The results show that the probabilities over different numbers of piles, in particular for the 100 piles are significantly affected. This might be caused by the fact that averaging of the pile load capacities over the area reduces the probabilities. The more pile load capacities averaged over an area, the lower the probability of under- and over-design would be.

5.4 REDUCTION TECHNIQUES

Simulations were also conducted to examine a number of reduction methods including standard arithmetic (SA), geometric average (GA) and harmonic average (HA). As explained in Chapter 3, these reduction techniques, proposed by Goldsworthy (2006), can be used as alternatives to average pile load capacities obtained from site investigation plans. The soil variability was set at COV = 50% and SOF = 10 metres. Furthermore, the pile size was assumed to be 20 metres in length and 1.0 metre in diameter.

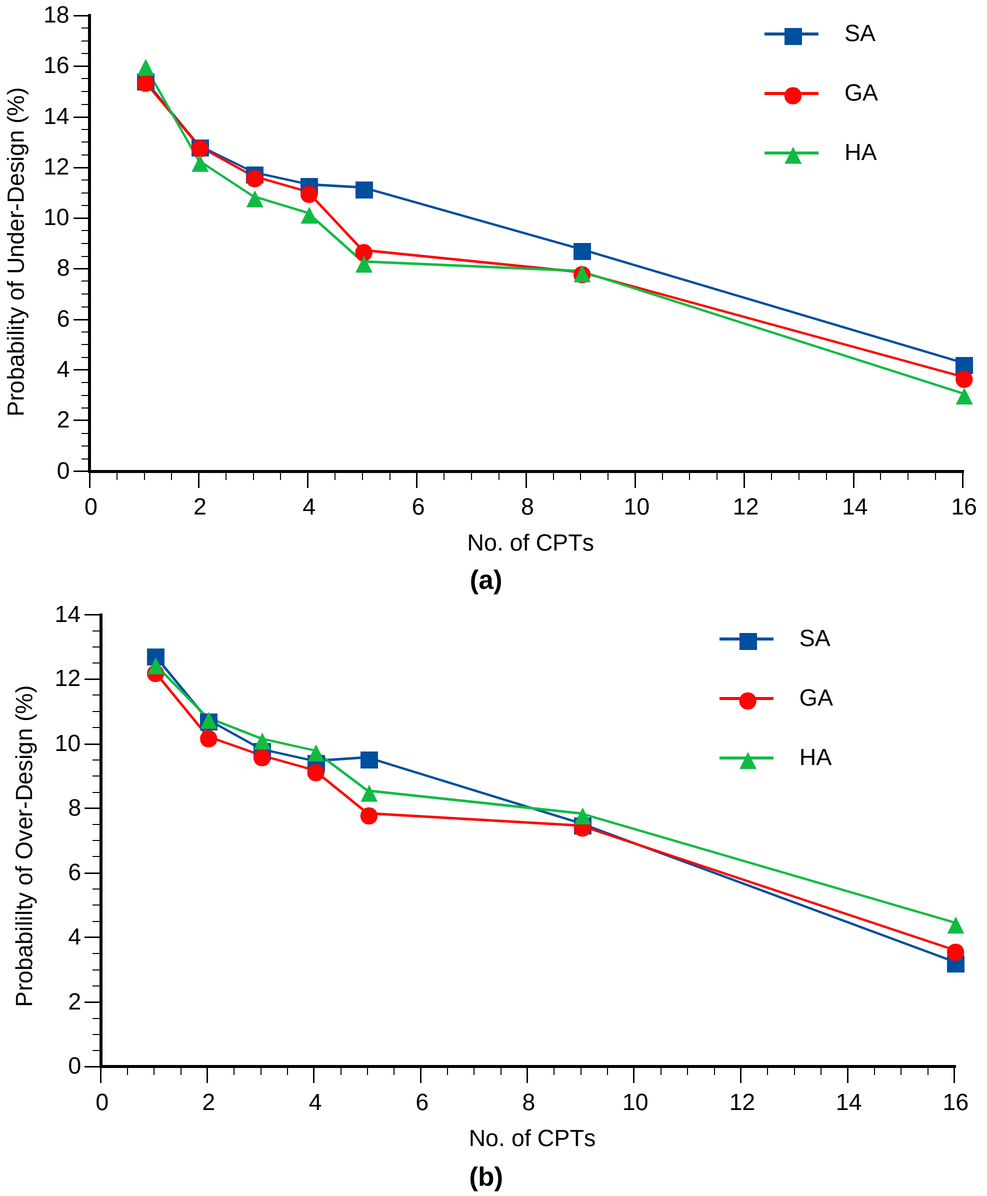


Figure 5-9 Effect of sampling effort on the probability of (a) under- and (b) over-design, for different averaging methods on the site with a COV of 50% and a SOF of 10 m

From the results shown in Figure 5-9 (a) and (b), the following trends can be observed:

- The HA technique yields a slightly lower probability of under-design than the GA and SA techniques. On the other hand, the GA technique yields a lower probability of over-design than the SA and HA.
- In general, the reduction method has little impact on the probabilities, and the GA and HA techniques appear to provide little additional benefit over the commonly adopted SA technique.

The results reveal that the HA and GA yield the lowest probability. For 16 CPTs, SA also yields the lowest probability of over-design, similar to that for the GA. It can therefore be concluded that applying the GA technique might yield the lowest estimated probability. These results agree well with the conclusion of Fenton and Griffiths (2002) that, in spatially random soil, the GA method performs better than the other techniques. However, the results of the present study indicate there is little difference between the three approaches. Hence, given that the SA method is the most common and well-understood of the three, it is recommended that SA be adopted.

5.5 ANISOTROPIC SOIL

As described in Chapter 2, most soil is anisotropic soil which means that the SOF of the soil is different in the horizontal and vertical directions. It has been explained previously that the spatial correlation of soil (SOF) in the horizontal direction is generally higher than that in the vertical direction (Jaksa et al., 2005). Three types of soil with different SOF levels were, therefore, simulated for this study as shown in Table 5-3 and consistent with the results presented in the previous chapter. Soil variability was set at COV = 50% and the pile dimensions were assumed to be 20 metres in length and 1.0 metre in diameter.

From the results shown in Figures 5-10 (a) and (b), the following can be observed:

- For the soil with a SOF ratio in the horizontal (θ_H) and vertical (θ_V) directions of 1:1:1 and 2:2:1, the probability of under- or over-design of the piles is likely to be similar. The probability of over- or under-design for the soil with a SOF of 10:10:1 is higher than that for the soil SOF of 1:1:1 and 2:2:1.

Table 5-3 Isotropic and anisotropic soil

No. of Type	SOF (m)		
	X	Y	Z
1	1	1	1
2	2	2	1
3	10	10	1

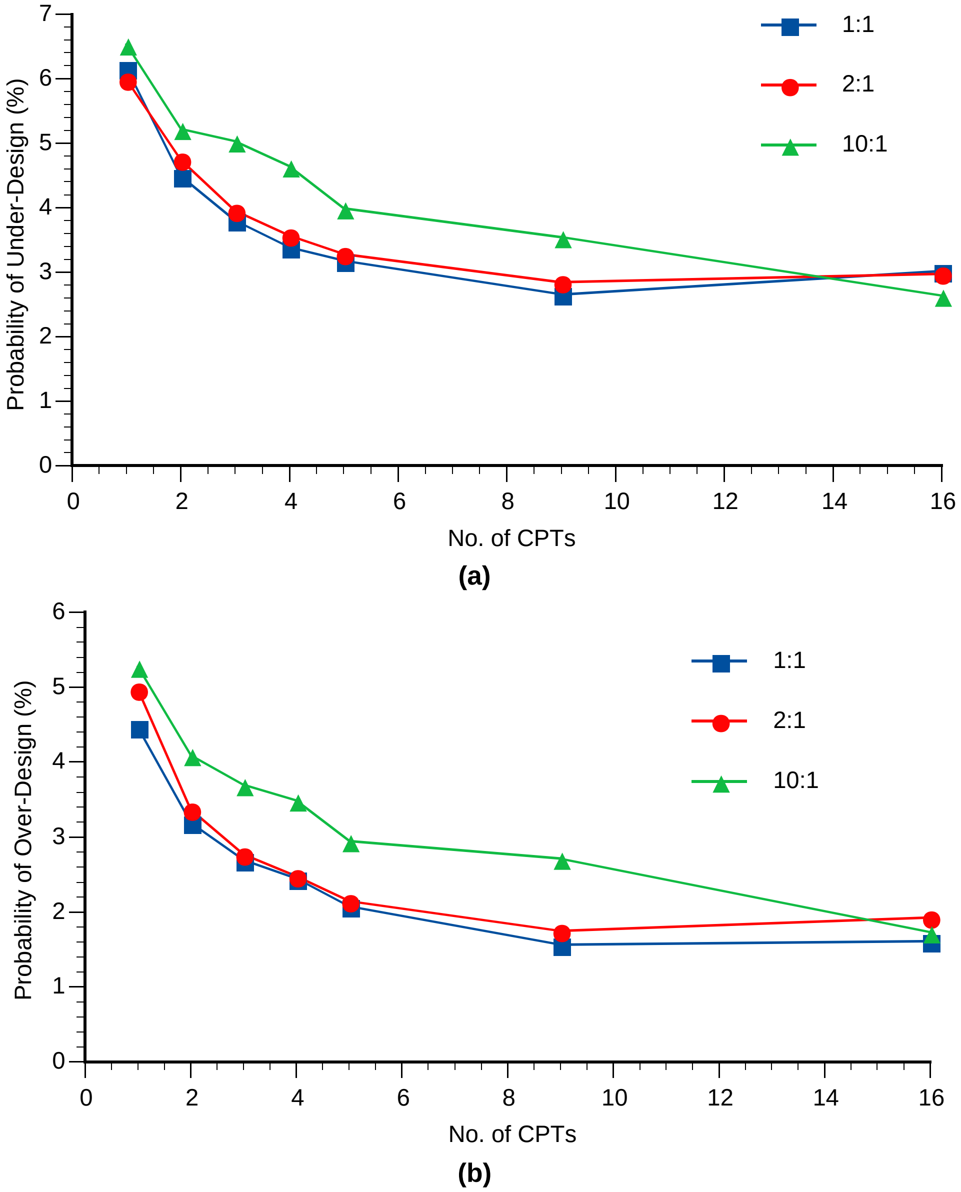


Figure 5-10 Effect of sampling efforts on the probability of (a) under- and (b) over-design, for isotropic and anisotropic soils

The influence of anisotropy on the reliability of site investigations was significant, which is in contrast with the results presented in Chapter 4. The anisotropic soil, as shown in Figure 5-10 as the soil SOF of 10:10:1, provided a greater risk of both under- or over-design than the isotropic soil. However, this result differed from the soil SOF of 2:2:1, which showed that the probability was likely to be similar to the soil SOF of 1:1:1 (isotropic). Therefore, in this context, SOFs of 1 m and 2 m are relatively small.

In contrast, the soil SOF of 10:10:1 metres produced considerably different results. Furthermore, the large SOF, such as the SOF of 10 metres, as demonstrated by Figure 5-5, increased the possibility of under- or over-design when compared to the small SOF. The reason for this was explained previously in Section 5.2.

5.6 SUMMARY

The results in this chapter have shown that an increased number of CPTs in site investigations have a significant impact on the reliability of the design of pile foundations. The results indicate that a more intensive sampling effort results in a lower probability of under- and over-design. The number of piles in the simulation has significant impact on the probability of under- or over-design, as well as the averaging methods. However, for the reasons described above, anisotropic soil had be a significant influence on the reliability of site investigations with respect to pile foundations. This is in contrast to what Goldsworthy (2006) found in relation to shallow foundations. As shown in Figure 5-7, that is, as θ_H increases relative to θ_V larger zone of material with more similar soil properties become apparent implying that the site investigation is more likely to under- and over-estimate the pile capacity. This effect is exacerbated when a greater number of piles are present on the site.

Chapter Six
Summary and Conclusions

6.1 SUMMARY

The study has quantified the risk of site investigations with respect to a pile foundation design. The risks were examined by incorporating soil variability and by varying the scope of the site investigations conducted. This study focused on site investigations consisting of cone penetration tests (CPTs) and on axial load capacities of a single pile. Random field theory, in particular, the local average subdivision (LAS) method was used to generate 3D soil profiles and the LCPC method of Bustamante and Gianaselli (1982) was used to convert the simulated cone tip resistance (q_c) values into axial pile load capacities.

Chapter 3 described the methodology implemented to investigate the risks and reliability of site investigations. Verifications of the methodology were performed to evaluate the accuracy and reliability of the simulations. The results indicated that the methodology was accurately implemented when simulating 3D soil profiles, computing pile load capacities and performing Monte Carlo simulations. The results also verified that the methodology adopted was reliable in predicting probabilities of pile foundation design error as a function of the scope of site investigations.

Chapter 4 described the simulation of a single CPT and a pile foundation within a site. The CPT was located at a various positions on the site, whereas the pile was located at the centre. Using Monte Carlo analysis, the reliability of using the CPT-based data in relation to the design of the pile was quantified including the probabilities of under- and over-design. A number of findings were obtained:

- The closer the CPT is located to the pile, the lower the probabilities of under- and over-designed;

- There is a critical distance found where the probabilities of under- and over-design do not vary with increasing distances, and this critical distance depends on the scale of fluctuation;
- The probabilities of under- and over-design of the pile is not influenced by the method of pile construction because the LCPC method directly account for the method of installation; and
- The size of the pile, the mean value of penetration resistance, and soil anisotropy were also found to be significant.

In Chapter 5, dealing with the effects of a number of CPTs and pile foundations within a site, it was found that:

- Increasing the number of CPTs decreased the probability of under- and over-design of piles;
- For soils with high variability, additional CPTs are needed in order to obtain the optimum pile design;
- For soils characterised by a low SOF, 5 CPTs were found to be adequate to achieve an optimum pile design, whereas for soils with a large SOF, up to 16 CPTs were required;
- A SOF of 20 metres was found to give the severe results;
- The total number of piles involved in the design had a significant effect on overall probability of under- and over-design; and
- A higher degree of anisotropy of the scale of fluctuation resulted in higher probabilities if under- and over-design.

6.2 RECOMMENDATIONS FOR FUTURE RESEARCH

The quantification of the risk and reliability of limited site investigations in relation to pile foundation design presented in this thesis focused on pile load capacity. While the results of this study were encouraging, they are only applicable to axial pile load capacity. One would anticipate that somewhat more beneficial results would be obtained by incorporating other pile design criteria such as the pile settlement (serviceability). As a result, the simulation would be able to quantify the financial risk associated with potential excessive settlement of pile design in relation to the scope of site investigations, as was carried out by Goldsworthy (2006).

In the present research, only the capacity of a single pile has been considered. However, it is more common that piles are designed to act in a group. The load capacity of pile groups requires further research, followed by settlement of the groups.

The investigation of the risk and reliability of limited site investigations presented in this thesis are based on the simulation of three-dimensional soil profiles based solely on cone tip resistance values, q_c. Soil shear strength parameters such as c and ϕ, combined with other pile capacity design theories require investigation.

This work, too, has examined 3D soil profiles consisting of only a single layer. In reality, soil profiles are extremely complex consisting often of multiple layers with non-horizontal and non-planar boundaries. In order to obtain more realistic probabilities of over- and under-design, future work will need to consider more complex geological horizons.

The type of site investigations presented in this thesis was based solely on the CPT. This is because the CPT is regarded as the most robust, economic and reliable in-situ test. However, other types of site investigation, including the standard penetration test (SPT), the dilatometer test (DMT), and the triaxial test need to be explored in future research in order to obtain a comprehensive understanding of the different tests, combination of different tests, and their impacts on combining soil on pile foundation design.

6.3 CONCLUSIONS

Based on the research undertaking using LCPC method for pile design, it can be concluded that when performing a single CPT close to the location of the pile reduces the risk of under- and over-design of the pile. This is particularly true for soils of high variability. Where several CPTs are conducted, there is an optimum number of tests, which depend on the variability of the soil and scale of fluctuation.

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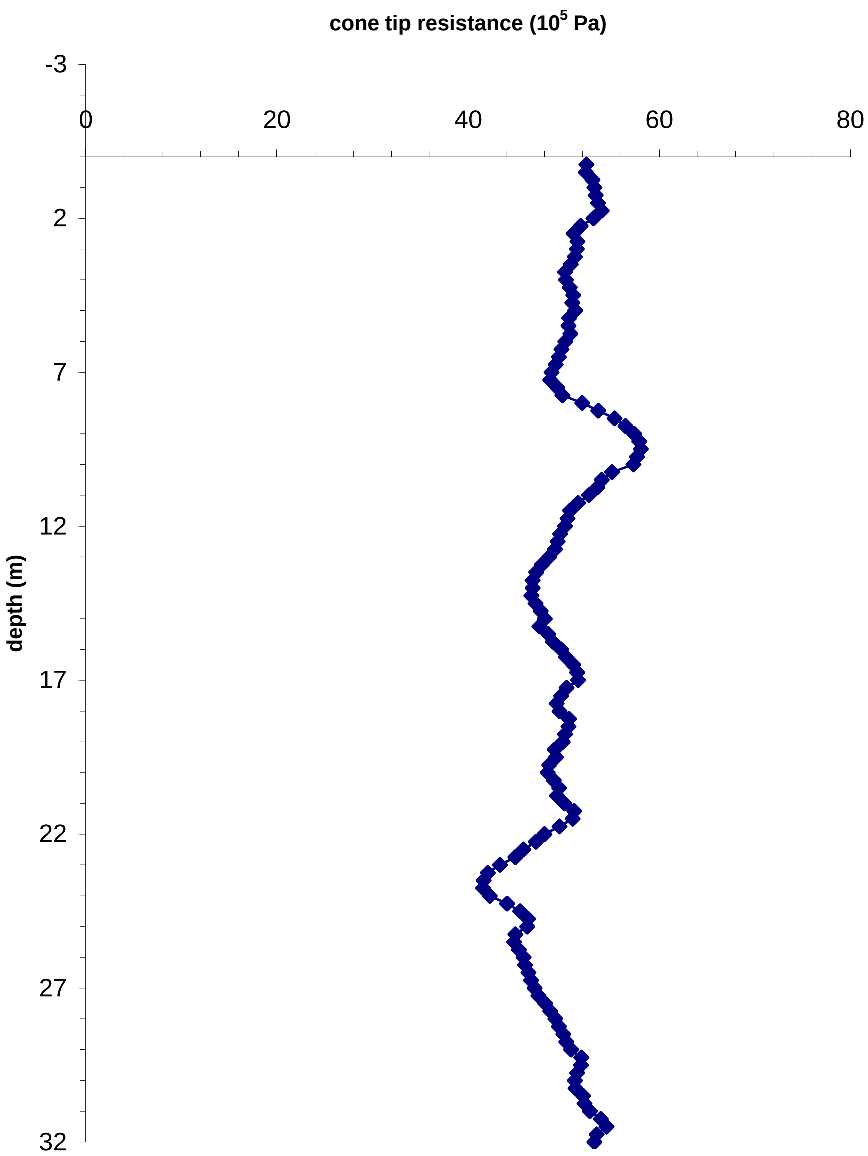
APPENDIX A

The Computation of Pile Load Capacity Based on the LCPC Method Using the Spreadsheet *Microsoft Excel*

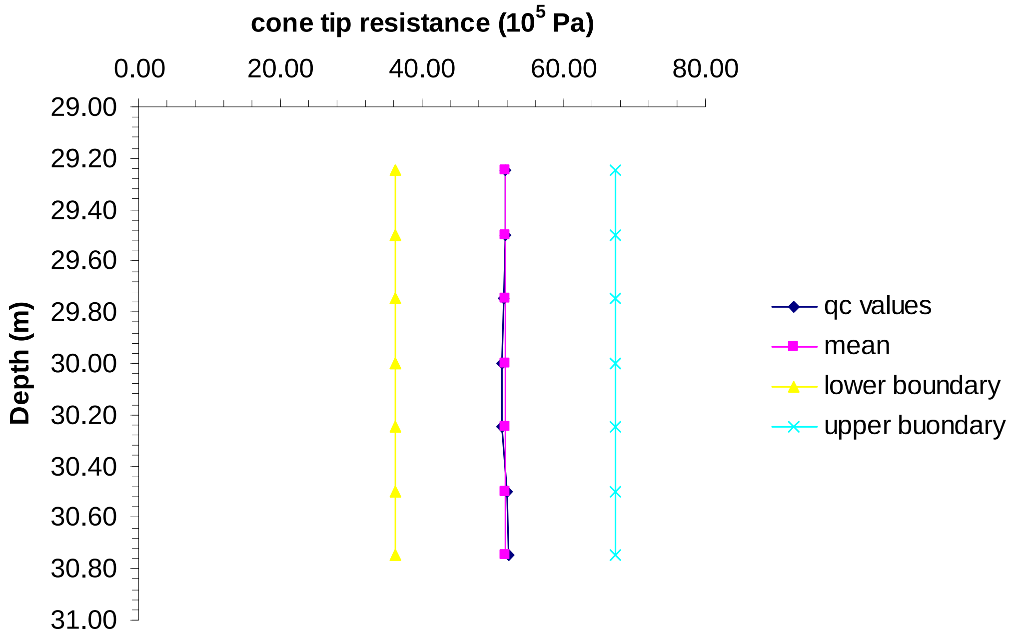
Pile Data			
Length	=	30	m
Diameter	=	0.5	m
a	=	0.75	m
L_1	=	29.25	m
L_2	=	30.75	m

The simulated soil profiles with a COV soil of 50%, and a SOF soil of 10 metres.



Clipping Method

Depth	q_c	average	Lower	upper	q_c'
29.25	51.86	51.68	36.176	67.184	51.86
29.50	51.82	51.68	36.176	67.184	51.82
29.75	51.42	51.68	36.176	67.184	51.42
30.00	51.18	51.68	36.176	67.184	51.18
30.25	51.25	51.68	36.176	67.184	51.25
30.50	52.06	51.68	36.176	67.184	52.06
30.75	52.17	51.68	36.176	67.184	52.17
			total Average		51.68



Depth (m)	q_c (10^5 Pa)	k_c	α	q_s (10^5 Pa)	max q_s (10^5 Pa)
0.25	52.37	0.4	100	0.52	0.52
0.50	52.31	0.4	100	0.52	0.52
0.75	53.02	0.4	100	0.53	0.53
1.00	53.22	0.4	100	0.53	0.53
1.25	53.36	0.4	100	0.53	0.53
1.50	53.6	0.4	100	0.54	0.54
1.75	53.98	0.4	100	0.54	0.54
2.00	53.12	0.4	100	0.53	0.53
2.25	51.78	0.4	100	0.52	0.52
2.50	51.04	0.4	100	0.51	0.51
2.75	51.44	0.4	100	0.51	0.51
3.00	51.38	0.4	100	0.51	0.51
3.25	51.17	0.4	100	0.51	0.51
3.50	50.74	0.4	100	0.51	0.51
3.75	50.16	0.4	100	0.50	0.50
4.00	50.26	0.4	100	0.50	0.50
4.25	50.66	0.4	100	0.51	0.51
4.50	51.02	0.4	100	0.51	0.51
4.75	50.93	0.4	100	0.51	0.51
5.00	51.23	0.4	100	0.51	0.51
5.25	50.58	0.4	100	0.51	0.51
5.50	50.53	0.4	100	0.51	0.51
5.75	50.7	0.4	100	0.51	0.51
6.00	50.19	0.4	100	0.50	0.50
6.25	49.78	0.4	60	0.83	0.35
6.50	49.5	0.4	60	0.83	0.35
6.75	49.18	0.4	60	0.82	0.35
7.00	48.74	0.4	60	0.81	0.35
7.25	48.61	0.4	60	0.81	0.35
7.50	49.34	0.4	60	0.82	0.35
7.75	49.88	0.4	60	0.83	0.35
8.00	51.96	0.4	100	0.52	0.52
8.25	53.63	0.4	100	0.54	0.54
8.50	55.34	0.4	100	0.55	0.55
8.75	56.45	0.4	100	0.56	0.56
9.00	57.36	0.4	100	0.57	0.57
9.25	57.9	0.4	100	0.58	0.58
9.50	58.07	0.4	100	0.58	0.58
9.75	57.67	0.4	100	0.58	0.58
10.00	57.29	0.4	100	0.57	0.57
10.25	55.07	0.4	100	0.55	0.55
10.50	53.99	0.4	100	0.54	0.54
10.75	53.51	0.4	100	0.54	0.54
11.00	52.64	0.4	100	0.53	0.53
11.25	51.53	0.4	100	0.52	0.52
11.50	50.69	0.4	100	0.51	0.51
11.75	50.42	0.4	100	0.50	0.50
12.00	50.14	0.4	100	0.50	0.50
12.25	49.64	0.4	60	0.83	0.35
12.50	49.37	0.4	60	0.82	0.35

Depth (m)	q_c (10^5 Pa)	k_c	α	q_s (10^5 Pa)	max q_s (10^5 Pa)
12.75	49.1	0.4	60	0.82	0.35
13.00	48.51	0.4	60	0.81	0.35
13.25	47.75	0.4	60	0.80	0.35
13.50	47.15	0.4	60	0.79	0.35
13.75	46.78	0.4	60	0.78	0.35
14.00	46.77	0.4	60	0.78	0.35
14.25	46.64	0.4	60	0.78	0.35
14.50	47.06	0.4	60	0.78	0.35
14.75	47.62	0.4	60	0.79	0.35
15.00	48.05	0.4	60	0.80	0.35
15.25	47.46	0.4	60	0.79	0.35
15.50	48.41	0.4	60	0.81	0.35
15.75	48.87	0.4	60	0.81	0.35
16.00	49.74	0.4	60	0.83	0.35
16.25	50.26	0.4	100	0.50	0.50
16.50	51.01	0.4	100	0.51	0.51
16.75	51.4	0.4	100	0.51	0.51
17.00	51.51	0.4	100	0.52	0.52
17.25	50.31	0.4	100	0.50	0.50
17.50	49.76	0.4	60	0.83	0.35
17.75	49.29	0.4	60	0.82	0.35
18.00	49.58	0.4	60	0.83	0.35
18.25	50.57	0.4	100	0.51	0.51
18.50	50.5	0.4	100	0.51	0.51
18.75	50.13	0.4	100	0.50	0.50
19.00	49.9	0.4	60	0.83	0.35
19.25	49.09	0.4	60	0.82	0.35
19.50	49.21	0.4	60	0.82	0.35
19.75	48.52	0.4	60	0.81	0.35
20.00	48.34	0.4	60	0.81	0.35
20.25	48.98	0.4	60	0.82	0.35
20.50	49.53	0.4	60	0.83	0.35
20.75	49.32	0.4	60	0.82	0.35
21.00	50.09	0.4	100	0.50	0.50
21.25	51.12	0.4	100	0.51	0.51
21.50	50.95	0.4	100	0.51	0.51
21.75	49.58	0.4	60	0.83	0.35
22.00	48.02	0.4	60	0.80	0.35
22.25	47.09	0.4	60	0.78	0.35
22.50	45.79	0.4	60	0.76	0.35
22.75	44.98	0.4	60	0.75	0.35
23.00	43.36	0.4	60	0.72	0.35
23.25	42.09	0.4	60	0.70	0.35
23.50	41.64	0.4	60	0.69	0.35
23.75	41.58	0.4	60	0.69	0.35
24.00	42.28	0.4	60	0.70	0.35
24.25	44.1	0.4	60	0.74	0.35
24.50	45.48	0.4	60	0.76	0.35
24.75	46.29	0.4	60	0.77	0.35
25.00	46.21	0.4	60	0.77	0.35

Depth (m)	**q_c (10^5 Pa)**	**k_c**	**α**	**q_s (10^5 Pa)**	**max q_s (10^5 Pa)**
25.25	44.98	0.4	60	0.75	0.35
25.50	44.83	0.4	60	0.75	0.35
25.75	45.33	0.4	60	0.76	0.35
26.00	45.83	0.4	60	0.76	0.35
26.25	45.96	0.4	60	0.77	0.35
26.50	46.34	0.4	60	0.77	0.35
26.75	46.59	0.4	60	0.78	0.35
27.00	46.98	0.4	60	0.78	0.35
27.25	47.38	0.4	60	0.79	0.35
27.50	48.08	0.4	60	0.80	0.35
27.75	48.62	0.4	60	0.81	0.35
28.00	49.14	0.4	60	0.82	0.35
28.25	49.52	0.4	60	0.83	0.35
28.50	49.98	0.4	60	0.83	0.35
28.75	50.27	0.4	100	0.50	0.50
29.00	50.77	0.4	100	0.51	0.51
29.25	51.86	0.4	100	0.52	0.52
29.50	51.82	0.4	100	0.52	0.52
29.75	51.42	0.4	100	0.51	0.51
30.00	51.18	0.4	100	0.51	0.51
30.25	51.25	0.4	100	0.51	0.51
30.50	52.06	0.4	100	0.52	0.52
30.75	52.17	0.4	100	0.52	0.52
31.00	52.76	0.4	100	0.53	0.53
31.25	53.89	0.4	100	0.54	0.54
31.50	54.49	0.4	100	0.54	0.54
31.75	53.47	0.4	100	0.53	0.53
32.00	53.21	0.4	100	0.53	0.53

q_{ca} = 51.68 $\times 10^5$ Pa

k_c = 0.4

q_{si} = 51.98 $\times 10^5$ Pa

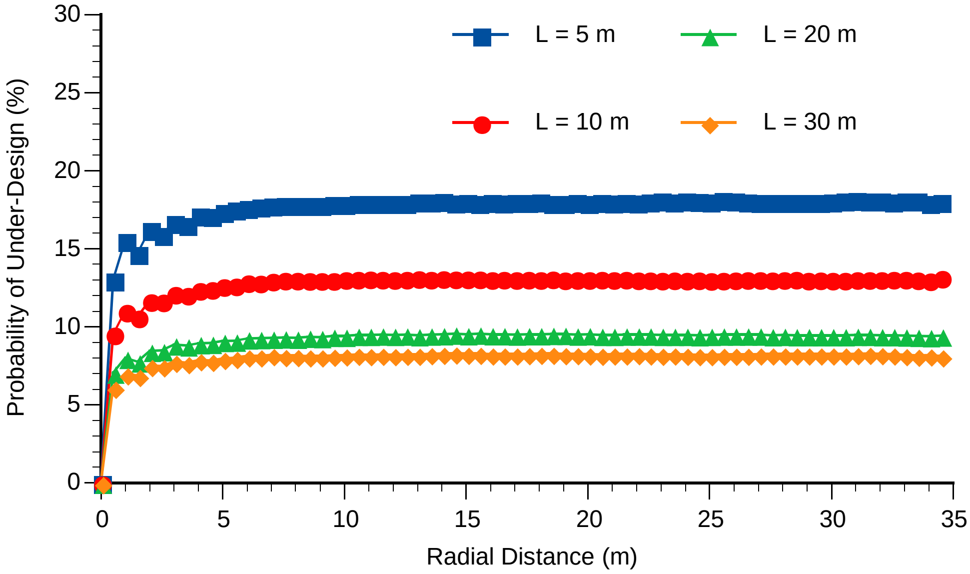
Q^P = qca x kc x 3.14 x D^2 x 0.25 = 405.893771 kN

Q^F = qsi x 3.14 x D x L = 2041.1006 kN

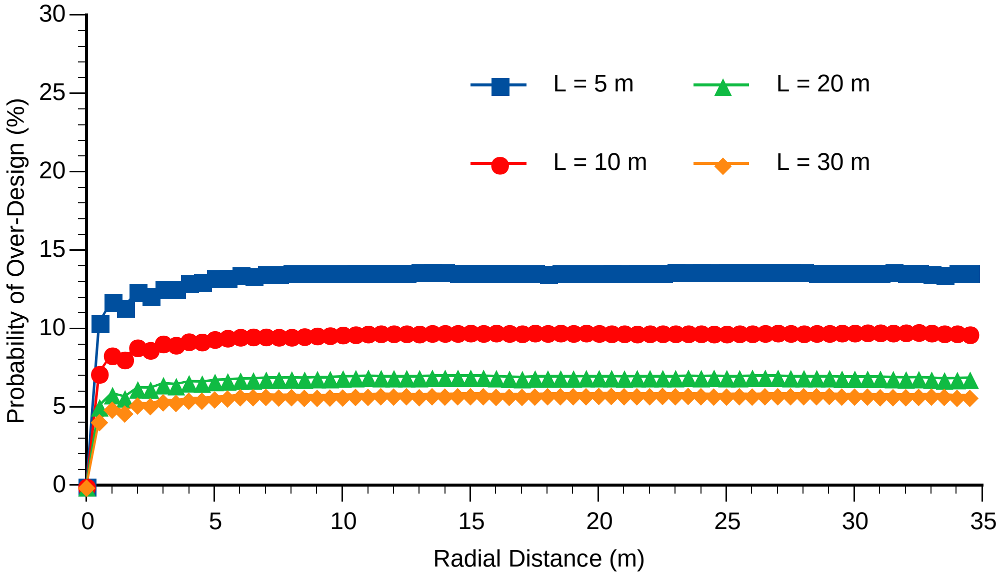
Q^N = QL / 3 + QL / 2 = 1155.85 kN

APPENDIX B

Effect of Radial Distance of a Single CPT Sounding on the Probability of Under- and Over-Design

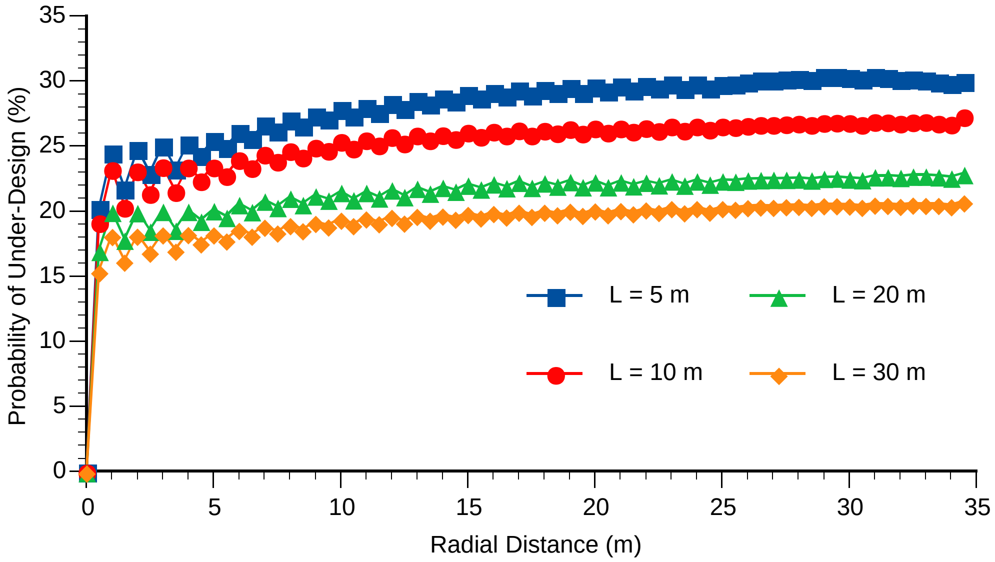


(a)

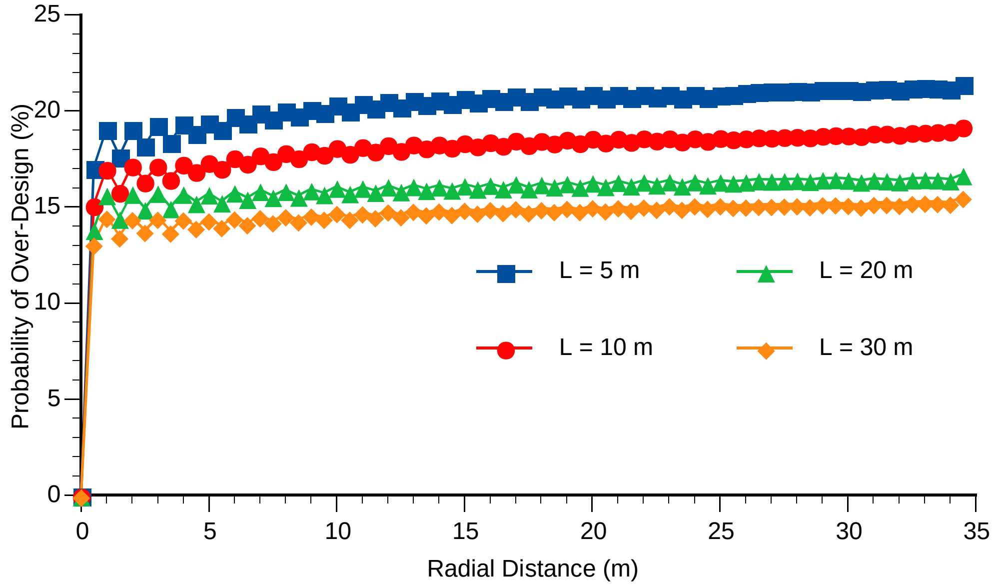


(b)

Figure B-1 Effect of radial distances on the probability of (a) under- and (b) over-design, for an different length of piles (COV of 50%, and SOF of 1 metre)

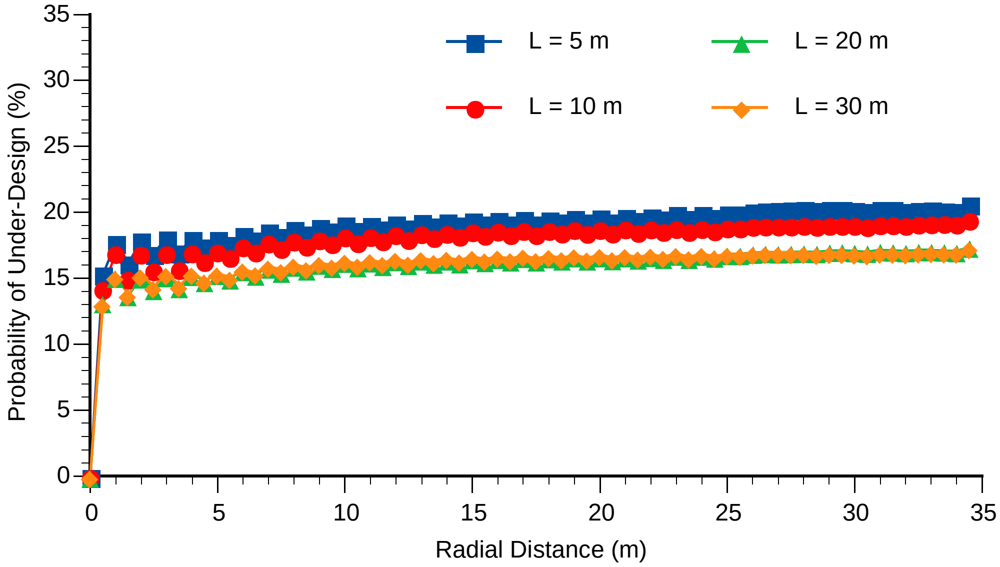


(a)

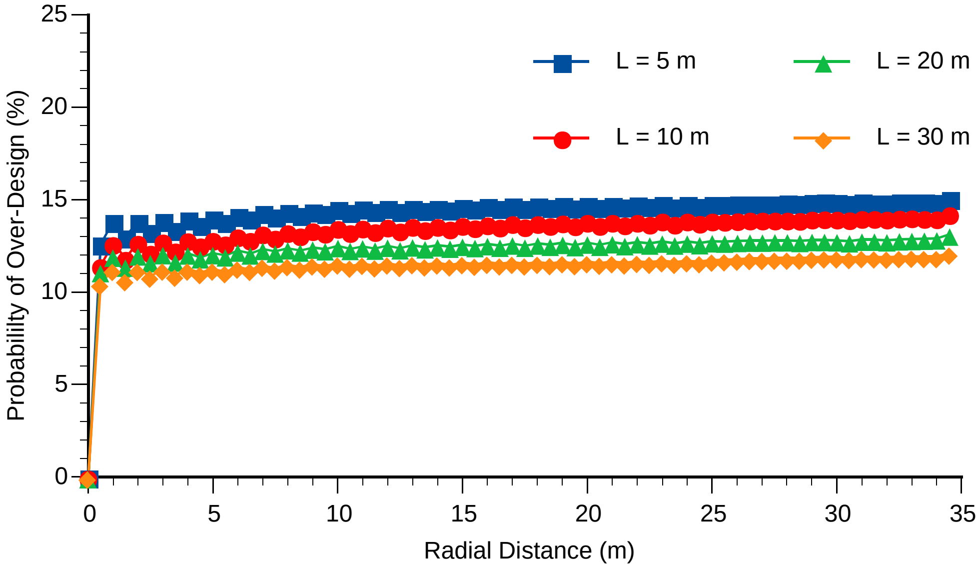


(b)

Figure B-2 Effect of radial distances on the probability of (a) under- and (b) over-design, for an different length of piles (COV of 50%, and SOF of 20 metres)



(a)

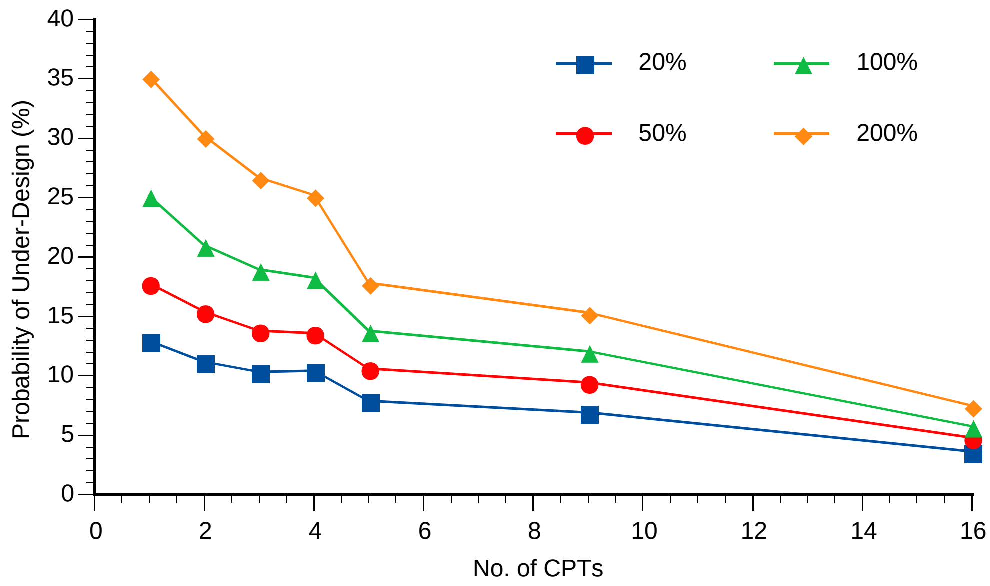


(b)

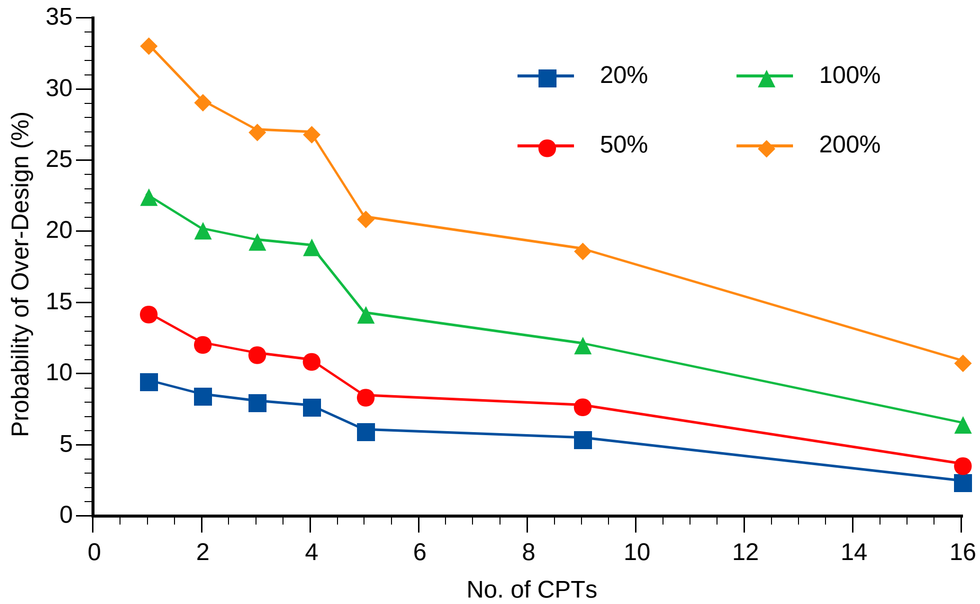
Figure B-3 Effect of radial distances on the probability of (a) under- and (b) over-design, for an different length of piles (COV of 50%, and SOF of 100 metres)

APPENDIX C

Effect of Number of CPT Sounding Used in Site Investigations on the Probability of Under- and Over-Design

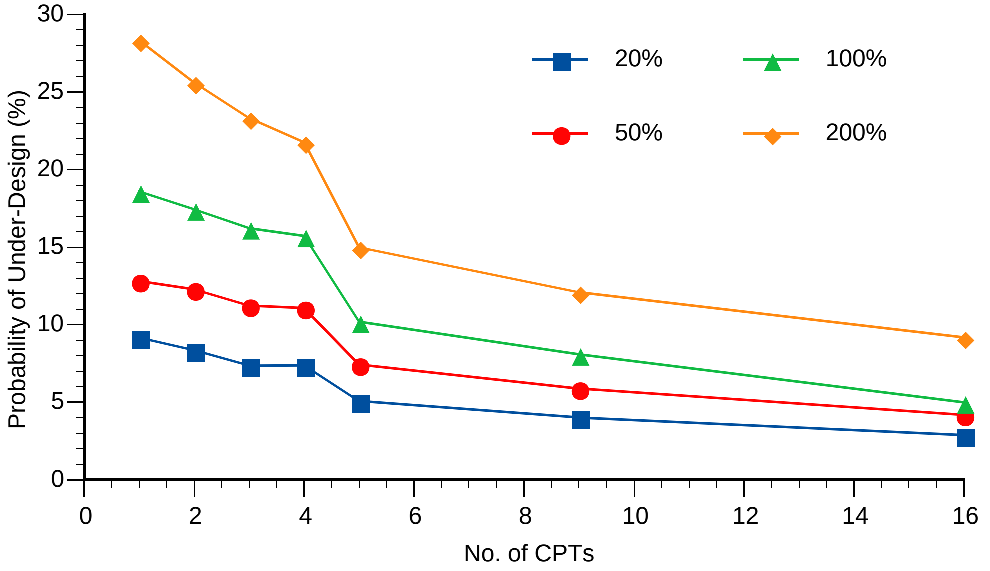


(a)

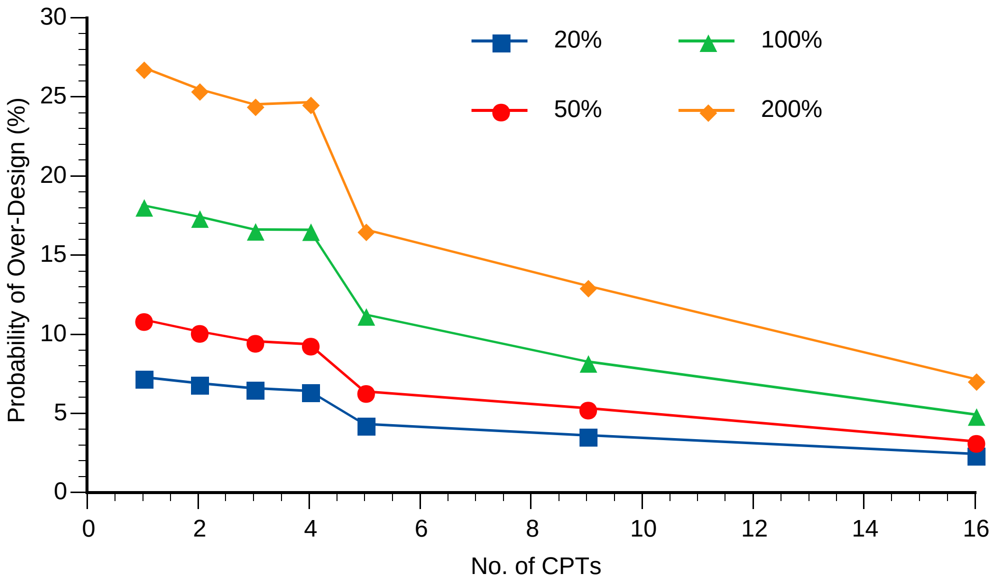


(b)

Figure C-1 Effect of sampling efforts on the probability of (a) under- and (b) over-design, for an increasing COV (SOF of 20 metres)



(a)



(b)

Figure C-2 Effect of sampling efforts on the probability of (a) under- and (b) over-design, for an increasing COV (SOF of 100 metres)

ADDENDUM

ABSTRACT

Page iii, paragraph 1 replace with:

The results showed that minimum sampling efforts result in a high probability of over- or under designing piles. More intensive sampling efforts, in contrast, led to a low probability of under- or over-design.

CHAPTER 1 - INTRODUCTION

Page 2 paragraph 1 add:

At the other extreme, inadequate site investigations can result in foundation over-design, increasing the overall cost of construction due to the use of conservative design (ASFE 1996).

Page 2 Paragraph 4 change to:

Goldsworthy et al. (2004) and Jaksa et al. (2005) performed a combination of random field simulations and finite element analyses to investigate the appropriate scope of site investigations for designing shallow foundations. Their results were the quantification of the appropriate number of site investigation boreholes, including the geometrical patterns and the type of soil tests, specified statistically within certain levels of variability.

Page 3, Paragraph 1 add:

As Jaksa et al. (2003) and Goldsworthy (2006) have recommended, the use of probabilistic analysis for reliability assessment of site investigations in relation to foundation design should be explored further to examine a number of different site investigation techniques and other types of foundation. Jaksa et al. (2003) developed a framework to quantify the reliability of site investigation, and Goldsworthy (2006) focused on quantifying the reliability of site investigations, such as the cone penetration test (CPT), the standard penetration test (SPT), the dilatometer (DMT) and the triaxial test (TT), on the design of shallow foundations, such as pad foundations. Therefore, this current research seeks to add to the existing body of knowledge by examining the reliability of site investigations in relation to the design of pile foundations.

Page 3, Section 1.4 change to:

The study employs a method of (i) simulating 3-D random field to simulate the variability of soil properties found within a soil deposit so that properties at all locations are known; (ii) simulating a site investigation by sampling discrete properties as would be undertaken in the field; (iii) using both complete knowledge of the site and the results of the Laboratoire Central des Pontes et Chaussees method; (iv) comparing the designs based on complete knowledge of the site and those obtained from sampling to measure the appropriateness of the site investigation.

Page 4, Paragraph 2 change to:

Chapter 3 provides an overview of the methodology used in the research, including generating three-dimensional random fields as a virtual soil model, simulating site investigation strategies, and the comparison between pile load capacities based on site investigation and those based on complete knowledge, and implementing Monte Carlo simulations as a reliability framework. Chapter 3 also provides the verification of the methodology. This includes a number of analytic and numerical simulations undertaken to verify the methods utilized in the research.

Page 4 Paragraph 3, second sentence add:

The effect of limited site investigations on the design of pile foundations is described, including the influence of the radial distance, that is, the distance measured radially from a cone penetration test (CPT) to the simulated pile foundation and…

Page 4 Paragraph 3, sentence 3, add:

The results obtained from the simulation are generated with various levels of variability of the cone resistance values of the soil, specified by the coefficients of variation (COVs) and scale of fluctuation (SOF).

CHAPTER 2 – LITERATURE REVIEW

Page 5 Paragraph 1 change to:

This chapter provides a background for Chapter 3 (methodology) of the thesis. This chapter reviews the relevant literature relating to various site investigation techniques, available methods of designing pile foundations, and methods of dealing with uncertainties in geotechnical engineering.

Page 5, Paragraph 3, Sentence 3, add:

Baecher and Christian (2003) classify geological information as qualitative information used in preliminary investigation.

Page 5 Paragraph 3 sentence 4, change to:

Geotechnical information may be viewed as data sets incorporating the physical and engineering properties of the soil revealed from in situ and/or laboratory tests.

Page 6 Paragraph 2 sentence 1 change to:

The scope of the characterisation of ground conditions has been examined by a number of researchers.

Page 10, paragraph 2, point 2, delete:

There is a similarity of form between the cone penetrometer and a pile (Abu-Farsakh and Titi 2004).

Page 10, paragraph 3, point 3, replace with:

The CPT is a reliable and accurate test procedure with the lowest coefficient of variation of any in situ test method in current use (Lee et al. 1983; Orchant et al. 1988; Jaksa 1995).

Page 12, Paragraph 3, first sentence replace with:

Currently, guidance is very limited for planning sampling strategies used in geotechnical site investigation.

Page 14, Paragraph 2, Sentence 1, add:

The maximum allowable load (Q_{all}) that can be safely supported by a pile can be calculated by dividing the ultimate load capacity, Q_{ult}, by a safety factor, SF (Bowles 1996).

Page 15, replace Table 2-1 with:

NOTE:
This table is included on page Addendum-5
of the print copy of the thesis held in the
University of Adelaide Library.

For a double acting steam hammer,

A_r is the ram cross-sectional area;

p is the steam or air pressure;

For a single-acting and gravity hammer ($A_r p = 0$)

s is the penetration of last 10 to 20 blows for steam hammers;

h is the height of the ram;

e_h is the hammer efficiency;

E_h is manufacturer's hammer-energy rating;

W_p is weight of the pile including the weight of the pile cap, all of the soil 'plug', driving shoe, and capblock (also includes anvil for double –acting steam hammers); and

W_r is the weight of ram (for double-acting hammers include weight of casing.

Page 16, paragraph 4, sentence 3: Replace "the SPT" with "the SPT results".
Meyerhof (1956, 1976) proposes an empirical equation (Eq 2-4) which is based on the SPT results in US tons, for displacement piles in saturated sand, whereas Eq. 2-5 is for small displacement piles such as steel H-piles.

Page 17, add Table 2-2:

NOTE:
This table is included on page Addendum-6 of the print copy of the thesis held in the University of Adelaide Library.

L_b is the pile penetration depth into point-bearing stratum;

N is the statistical average of the SPT N_{55} numbers in a zone about 8B above to 3B below the pile point; and

D is the diameter of the pile.

Page 17, Paragraph 2, sentence 1, rephrase to:
Other methods that use the results of the SPT are Hansen (1970), Janbu (1976), and Vesić (1975).

Eq 2 -7 : replace with:

$$Q_{ult} = q_b A_b + \sum_{i=1}^{n} f_i A_{si}$$

Table 2-3 add:

q_c is the cone resistance of the results of the CPT;

q_s is the skin friction unit of the results of the CPT; and

A_{si} is the pile shaft are interfacing with layer i.

Paragraph 1, sentence 2 change to:

The LCPC Method is a technique used to estimate pile load capacities based on CPT results, developed in 1982 by Bustamante and Gianalaselli from the Laboratoire Central des Ponts et Chausseés, France.

Page 19, Eq. 2-8 add:

Q_{ult} is the ultimate load capacity of the pile;

l_i is the thickness of the layer i;

q_c is the cone resistance of the soil.

Parameter a has been defined previously on Page 20.

Page 20 paragraph 1, replace with:

The parameter q_{eq} is calculated by averaging q_c over a distance a (=1.5 x D) above and below the pile tip, as shown in Figure 2-6, then eliminating the values q_c higher than 1.3q'_{ca} and lower than 0.7 q'_{ca}.

Page 20, Paragraph 2 add:

Tables 2-4 and 2-5 show the values of k_c and the coefficient of α in relation to the nature of soil and pile type. The groups I and II in the Table 2-4 and Table 2-5 represent the installation type of pile foundations.

Page 22, Paragraph 1, sentence 2: change to:

Uzielli et al. (2007) define soil variability as the variation of soil properties from one spatial location to another.

Page 24, Paragraph 1, the Table 2-7 change to:

"statistical uncertainty" is changed to "soil variability".

Table 2-7 soil variability of various sites (after Goldsworthy, 2006)

NOTE:
This table is included on page Addendum-8 of the print copy of the thesis held in the University of Adelaide Library.

Page 25, Paragraph 3, change to:

The equation above does not, however, deal with soil variability. Therefore, Jaksa (1995) suggests that the formula for quantification of measurement errors may be influenced by soil variability, σ_{sv}^2 as described by Equation 2-13:

Page 28, Paragraph 3, last sentence, add:

Similarly, Fenton (1999) suggested that most soil properties are strictly non-negative, which is a condition appropriately approximated by a lognormal distribution.

Page 29, Paragraph 2, sentence 1 change to:

Second moment statistics are able to quantify the uncertainty of soil variability due to their simplicity and lack of dimension, in the case of coefficient of variation. However, this technique requires the modelling of uncertainty in the input data in order to be more accurate (Uzielli et al. 2007).

Page 29, Paragraph 2, the last sentence change to:

This means that second moment statistics are inadequate in terms of achieving some degree of confidence because the technique is not compatible with other statistical techniques.

Page 30, Paragraph 1, sentence 1 replace with:

…using only their mean and standard deviation, without taking into account the form of the probability density function.

Page 30, paragraph 2, sentence 2 replace with:

Spatial correlation analysis can be in error if stationarity of data are not carried out first (Uzielli et al. 2007).

Page 30 Paragraph 3, Sentence 2, add:

To perform spatial correlation analysis, it is essential to understand stationarity. In most geotechnical engineering scenarios, insufficient data has become a real problem (Spry et al. 1988). Therefore, a mathematically tractable function is commonly fitted to the in situ soil property data to best represent the trend. This process is termed detrending, and is necessary for a successful and meaningful statistical analysis. Once the data are detrended, the remaining residuals are modelled as a *stationary* process or field (Jaksa 1995, Goldsworthy 2006).

Page 31, Paragraph 2, Sentence 1, replace with:
Jaksa (1995) suggest that the application of both random field theory and geostatistics are facilitated by stationary data, therefore non-stationary data must be transformed to stationary data.

Page 31, paragraph 2, sentence 2: change to:
If data appear to be a non stationary, the data can be detrended and modelled as stationary data using data transformation.

Page 31, paragraph 2, sentence 2 replace with:

If data appear to be non-stationary, the data can satisfy stationarity using data transformation.

Page 31, between paragraph 2 and 3 change to:
There are two common types of data transformations: decomposition and differencing. Another type that could be used is variance transformation. Regarding variance transformation, a number of techniques are available to ensure whether the data are stationary, and then to enable the data to be modeled. One of the techniques is the *autocorrelation function* (Jaksa, 1995).

Page 31, eq 2-17, add with:

ψ is a population, $\psi_1, \psi_2, \ldots \psi_n$;

j is the lag; and

K is the maximum number of lags

Page 32, Table 2-9 add:

To identify spatial correlation structure, δ, in a data set of soil, which essentially measures the distance over which properties exhibit strong correlation (the correlation distance), several theoretical autocorrelation models can be used to provide a function of separation distance, τ. To calculate the SOF, these autocorrelation models are often fitted to the sample autocorrelation function of the data set. Jaksa (1995) and Uzielli et al. (2007) present those autocorrelation models introduced by Vanmarcke (1977, 1983) as shown in Table 2-9.

Table 2-9 Theoretical autocorrelation functions used to determine the scale of fluctuation(δ) (after Vanmarcke, 1977, 1983)

Autocorrelation function	**Formula**	**Scale of fluctuation, δ**
Simple exponential	$R(\tau) = e^{-\lvert\tau\rvert / b}$	2b
Cosine exponential	$R(\tau) = e^{-\lvert\tau\rvert / \alpha} \cos(\tau / \alpha)$	α
Second order Markov	$R(\tau) = e^{-\lvert\tau\rvert / d}\left(1 + \frac{\lvert\tau\rvert}{d}\right)$	4d
Squared exponential	$R(\tau) = e^{-(\lvert\tau\rvert / c)^2}$	$\sqrt{\pi c}$
Triangular	$R(\tau) = 1 - \frac{\lvert\tau\rvert}{\alpha}$ for $\lvert\tau\rvert \le a$ $R(\tau) = 0$ for $\lvert\tau\rvert \ge a$	α

b, α, d , c are the range of distance.

Page 33, Paragraph 1, sentence 2: replace with:

Random field theory is incorporated in this study as the simulation tools are readily available and appropriate to this work. As a result, geostatistics is not used in the present study.

Page 33, Eqs. 2-18 and 2-19, change to:

Vanmarcke (1977, 1983) introduced the formula of a random field which utilize covariance between properties $\beta(x, x+\tau)$ separated by a lag or distance $(x, x+\tau)$ as shown in Equation 2-18.

$$\beta(x, x+\tau) \equiv \beta_\tau = COV\left[X(x), X(x+\tau)\right] = \mathrm{E}\left[X(x)X(x+\tau)\right] \qquad \text{2-18}$$

Where $X(x)$ is a sample at position x

$X(x+\tau)$ is a sample at a lag τ from position x.

E[.] is expectation of the operator.

The covariance $\rho(x,x+\tau)$ is expressed as correlation between two properties separated by a lag or distance, $(x,x+\tau)$, which ranges between 0 and ± 1, given by the equation 2-19.

$$\rho(x, x+\tau) \equiv \rho_\tau = \frac{Cov\left[X(x)X(x+\tau)\right]}{\sigma_X{}^2} = \frac{\beta(x, x+\tau)}{\sigma^2{}_X} \qquad \text{2-19}$$

Where $X(x)$ is a sample at position x

$X(x+\tau)$ is a sample at a lag τ from position x.

σ_X is standard deviation

Page 33, Paragraph 5 change to:

As an additional measure, Vanmarcke (1977, 1983) introduced the scale of fluctuation to describe the correlation structure of the soil. The scale of fluctuation (SOF) is defined as the distance within which two samples in the field are considered reasonably correlated. To calculate the SOF, the autocorrelation models, as shown in Table 2-9, are fitted to the sample autocorrelation function of the data set by comparing the goodness-of-fit of the autocorrelation function of the data set to one or more autocorrelation models. This enables the same SOF fit to two or more correlation structures.

Page 34, Paragraph 2, sentence 2 replace with:

Generally only three parameters are needed: (1) the mean, μ; (2) a measure of the variance, σ_2 (standard deviation or coefficient of variations), and (3) the scale of fluctuation, θ, which express the correlation of properties with distance.

Page 34, Paragraph 2 change to:

The SOF can be quantified by fitting a sample autocorrelation function to the theoretical autocorrelation model, shown in Table 2-9. The autocorrelation is a measure of the correlation between data from the same sample set. By comparing the goodness-of-fit of the autocorrelation function of the sample to the autocorrelation model, a suitable correlation structure can be determined. Therefore, the SOF expresses the correlation structure of the data.

Page 35, Paragraph 1 change to:

The soil profiles were modelled as a 3-dimensional random field utilizing three statistical parameters: mean (μ), coefficient of variation (COV), and scale of fluctuation (SOF).

Page 36, Sections 2.8.1 and 2.8.2 add:

2.8.1 Simulation of 3-Dimensional Random Field

As explained previously, in order to model the spatial variability of soil within a site, Goldsworthy (2006) performed random field modelling. The model required three parameters: mean, coefficient of variation (COV), and scale of fluctuation (SOF), for modelling the spatial variability of the soil properties. The COV was defined as the ratio of standard deviation to the mean (local value of trend line), and the SOF as a parameter representing the (vertical or horizontal) distance in which the soil properties had strong correlations (Akkaya and Vanmarcke 2003).

2.8.2 Target Distribution and Correlation of Simulated Soil

The target distribution of the simulated soil profiles was set to a lognormal distribution, and their correlation structures employed a Markov model. Both parameters represented the level of variability of the simulated soil profiles. The COV was defined as a normalized measured of variance, and the formulation for the COV is the standard deviation of the sample divided (or normalized) by the mean. The scale of fluctuation is defined as a parameter representing the (vertical or horizontal) distance in which the soil properties had strong correlations (Akkaya and Vanmarcke 2003).

Page 36, Paragraph 3 change to:

The COV was defined as a normalized measured of variance, and the formulation for the COV is the standard deviation of the sample divided (or normalized) by the mean. The scale of fluctuation is defined as a parameter representing the (vertical or horizontal) distance in which the soil properties had strong correlations (Akkaya and Vanmarcke 2003).

Page 36, Paragraph 4 change to:

To understand the correlation of the SOF to the variability performances of soil profiles, Goldsworthy (2006) illustrated 4 soil profiles with different scales of fluctuation. As shown in Figure 2-9(a) to (f), SOFs of 1, 2, 4, 8, 16 and 32 metres were respectively examined. The SOF was uniform in three directions of the 3D soil profile, a condition termed as isotropic. It can be seen in Figure 2-9, the SOF has a significant impact on the level of variability of the simulated soil. This is also influenced by the sampling interval of 0.5 m and domain size of 60 points (30 m). Figure 2-9(a) shows an example when the scale of fluctuation (SOF) is close to the sampling interval and much smaller than the domain size. Figure 2-9(f) illustrates an example when the SOF is much larger than the sampling size and greater than the domain size.

Page 37, Paragraph 1, change to:

A low COV represents a more uniform soil, while a high COV refers to more variable soil.

Page 37, Paragraph 2 change to:

Goldsworthy (2006) verified that the statistical distributions of the sample soil data were lognormal. It is noted that most soil properties can be represented by the log normal distribution due to the soil properties are strictly non-negative ((Lumb 1966; Hoeksema and Kitanidis 1985; and Sudicky 1986, Fenton and Vanmarcke 1990). Therefore Goldsworthy (2006) suggested that a lognormal distribution have an impact in quantifying the reliability of site investigation on shallow foundations.

Page 38, Eqs. 2-20 and 2-21 add:

Thus, the use of finite scale models was considered suitable for this research. The 1-D exponentially decaying correlation structure is given by:

$$\rho(\tau) = \sigma^2 \exp\left[-\sqrt{\left(\frac{2\tau}{\theta}\right)^2}\right] \qquad \textbf{2-20}$$

where	$\rho(\tau)$	is the correlation at lag distance τ ;
	σ_2	is the variance; and
	θ	is the scale of fluctuation.

The 1-D correlation structure shown in Equation (2-20) becomes the 3-D exponentially decaying correlation structure given by:

$$\rho(\tau_1, \tau_2, \tau_3) = \sigma^2 \exp\left\{-\sqrt{\left(\frac{2\tau_1}{\theta_1}\right)^2 + \left(\frac{2\tau_2}{\theta_2}\right)^2 + \left(\frac{2\tau_3}{\theta_3}\right)^2}\right\} \qquad \textbf{2-21}$$

where	$\rho(\tau_1, \tau_2, \tau_3)$	is the correlation due to lag distances, τ_1, τ_2 and τ_3;
	σ_2	is the variance; and
	θ_1, θ_2 and θ_3	are the scales of fluctuation in the same direction as the corresponding lag distances.

Page 38, Paragraph 2, sentence 1 add:

Random field theory has become a common method for modelling the spatial variability of soil, which is one of the main geotechnical uncertainties besides measurement error and transformation model uncertainty (Filippas et al. 1988).

Page 38, paragraph 2 change to:

The local average subdivision (LAS) method introduced by Fenton and Vanmarcke (1990) can be used to generate a model of a 3D random field conforming to a normal distribution and target correlation structure. In the previous discussion, the soil properties typically reveal lognormal distributions due to the properties are strictly non-negative. Therefore Goldsworthy (2006) transform the random field simulated by LAS from a normal into lognormal distribution. The principle process of the LAS is shown in Figure 2-10.

Page 39, Paragraph 2 change to:

Due to the LAS generates 3D random field conforming a normal distribution, the transformation the random field simulated from a normal to lognormal distribution is needed. This is explained in detail in Section. 2.8.4.

Page 39, Paragraph 2, sentence 2 change to:

However, it must be noted that soil properties are strictly non-negative values, and consequently demonstrate log normal behaviour.

Page 39, section 2.8.4, sentence 2, replace with:

Soil properties are strictly non-negative values, and consequently can exhibit a log normal distribution.

Page 40: Paragraph 1 moved to Page 40 before Figure 2-11.

Page 41, Paragraph 1 add:

Figure 2-11 shows what Goldsworthy (2006) stated as the presence of *gridding* when the sample element mean and standard deviation for soils are investigated. It is demonstrated that, when the SOF increases, the size of the gridding appears to increase, as shown in Figure 2-11(iii).

Page 42: Paragraph 1 moved to before Figure 2-12.

Page 42, Paragraph 1, sentence 4, add:

The location of each sub-sample is changed for each subsequent Monte Carlo realisation. The Monte Carlo (Rubinstein 1981) simulation is a one which involves generating simulated soil properties based on a random selection, while still conforming to the same spatial statistics (mean, COV and SOF).

Page 42, Section 2.8.5: change to:

There are a number of the CPTs simulated in the generated 3D random fields. The pile load capacities obtained from the simulated CPTs vary across the site. Therefore, they need to be transformed into a single pile load capacity using what Goldsworthy (2006) suggested as the "reduction technique". A number of reduction techniques are treated in this section.

Page 43, Section 2.8.6., add:

To analyse shallow foundation designs which were based on a settlement approach, Goldsworthy (2006) utilized the finite element method as a benchmark design or the design based on complete knowledge (CK), and various available settlement formulae as the foundation design based on the data obtained from the simulated site investigation (SI). The foundation design is regarded as under-designed when the design based on CK is larger than that based on SI. On the other hand, the foundation design is regarded as over-designed when the design based on CK is smaller than that based on SI.

CHAPTER 3 – DESCRIPTION OF RESEARCH METHOD

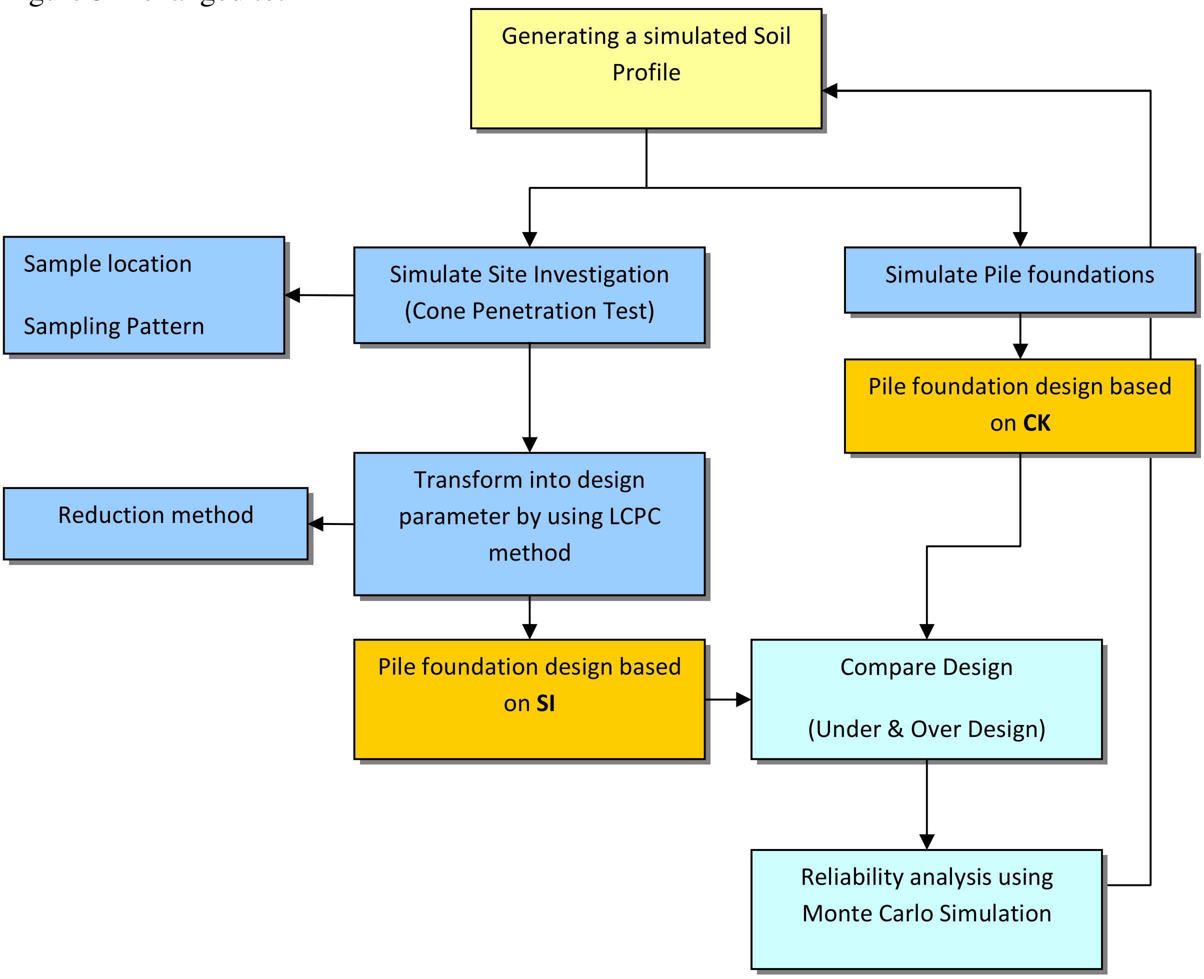
Page 45, Paragraph 3 Sentence 1 replace with:
Once a 3-dimensional random field was generated, a number of soil resistance, q_c, profiles along the vertical and horizontal directions were obtained.

Page 45, Paragraph 3 change to:
As explained in Section 3.2 and 6.2, random field generate cone resistance values, q_c, which is set up from the input of mean of q_c, COV and SOF in the simulation. The simulation of three-dimensional soil profiles is based solely on generating the cone tip resistance values, q_c. In the future, soil shear strength parameters such as c and ϕ can be generated, combined with other pile capacity design theories.

Page 45, Paragraph 3 replace with:
Once a 3-dimensional random field was generated, a number of soil resistance, q_c, profiles along vertical and horizontal directions was obtained. After that, a number of cone penetration test (CPT) soundings were simulated to represent various schemes, with a number of pile foundations. The simulated CPTs yielded the soil resistance profiles which were employed to estimate axial pile load capacities. This was regarded as the pile foundation design based on site investigations (SI). In parallel, the simulated piles yielded the soil resistance located along the simulated piles. The soil resistances were used to determine the "true" axial pile load capacities

of the piles. This was termed 'the truth' design or benchmark pile foundation design, and was regarded as the pile foundation design based on complete knowledge (CK).

Figure 3-1 changed to:



Page 46, Paragraph 3, sentence 3 replace with:

A low COV soil is a soil whose properties are relatively consistent, whereas a high COV soil refers to soils whose properties have greater variability.

Page 48, Paragraph 2 change to:

The research was therefore performed on a simulated site of 256 × 256 ×128 elements, with each element being 0.25 m × 0.25 m × 0.25 m in size. This number and size of elements was deemed appropriate when considering both numerical accuracy and efficient computational processing. While it would have been desirable to include a greater number of elements, and hence reduce their equivalent size, this would have yielded dramatically increased computational effort. The number of vertical elements was set to 128 in order to simulate a pile 30 metres in length.

Page 48, Paragraph 2, sentence 3 change to:

A single realisation to simulate 3-dimensional random field was undertaken consisting of preliminaries, the generation of cone resistance profiles, the simulation of the CPTs and pile foundations, the design using complete knowledge (CK) data, the design using site investigation (SI) data and post-processing of the results.

Page 49, Paragraph 1, sentence 2 and 3 change to:

The locations of sampling at a site, and the number of samples taken dictate the adequacy of the site investigation. For the purposes of the current research, several sampling strategies were used for the investigations including varying locations and the numbers of samples taken.

Page 49, Paragraph 3, sentence 1 change to:

As shown in Figure 3-2, a single pile foundation was simulated at the centre of the site, with its x and y coordinate being (25, 25).

Page 49, Paragraph 3, sentence 2 change to:

The 3D simulated site had plan dimensions of 50 m × 50 m, where $L_x = L_y = 50$ m, and a depth of 50 m.

Page 49, Paragraph 3 change to:

For the first investigation, different locations of a single CPT were simulated. The locations of the simulated CPTs were selected by systematically moving the position around the site. As shown in Figure 3-2, the first location of the CPT was simulated at the edge of the site with the position of (X_1,Y_1) for the first realization in the simulation. Next, in the second realisation, the location moved horizontally the next position of (X_2,Y_1). In the same manner, for the 200th realization, the position of the CPT was at (X_{200},Y_1). The position of the CPT then moved vertically, with respect to Figure 3-2 to (X_2,Y_1). The process continues in a similar fashion until he simulated CPT moves to the final position of (X_{200},Y_{200}). Each position of the simulated CPT yielded a cone resistance profile which was used to estimate pile load capacity for the pile design based on SI. At the same time, the simulated pile located at the centre also yielded cone resistance profiles. The region of the pile that yielded the cone resistance profiles is the grey area around the pile, as shown in Figure 3-2, with a radius of 6 pile diameters (6*D*). The design of the pile which employed these central cone resistance profiles was regarded as the true design, based on CK.

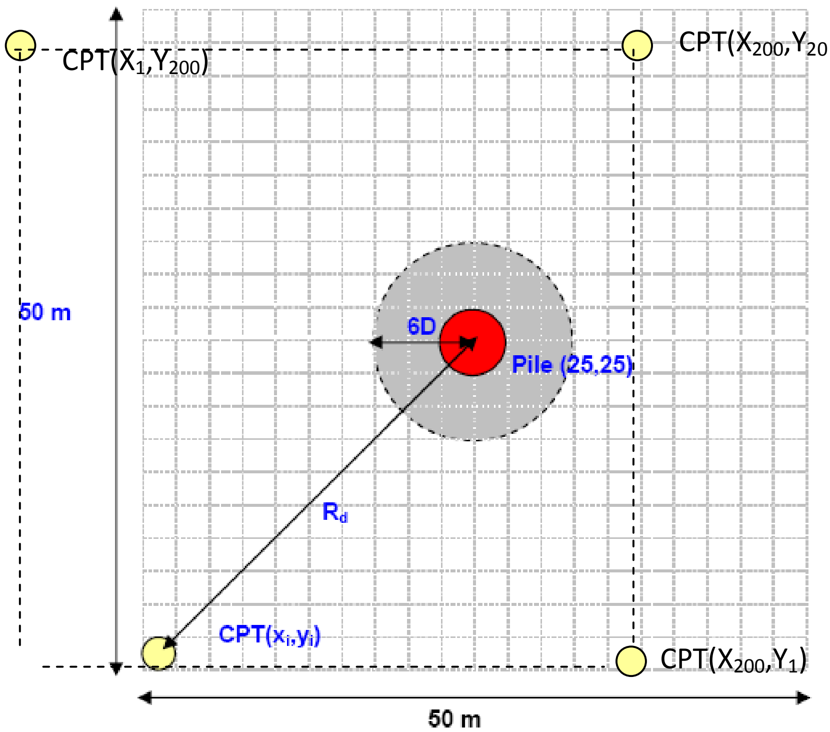


Figure 3-2 Simulation of various radial distances of a CPT

Page 49, Paragraph 4 change to:

In the second investigation, the influence of a number of CPTs on the design of pile foundations was examined. Therefore, 12 sampling strategies were simulated on a site with 9 simulated piles. As shown in Figure 3-3, the red circles are the pile locations. The vertical and horizontal spacings of the piles was set to 12.5 m. It is assumed that the horizontal and vertical spacings are the same for the pile group. The sampling strategies consist of different numbers of CPTs and positions, as shown in Figure 3-4. These sampling strategies were the same as those conducted by Goldsworthy (2006) when he examined their effects on the design of pad foundations.

Page 51, Paragraph 2, sentence 1 change to:

The interval of the simulated cone resistance values in the vertical direction was set at 0.25 m. It should be noted that this interval is larger than that normally performed in the field (0.01 m). This was a result of the restrictions imposed on the element size due to computational time, as discussed previously.

Page 52, Paragraph 1, sentence 3 change to:

Future research would incorporate measurement and transformation errors of in situ testing when quantifying the influence of site investigations on the design of pile foundations.

Page 52, Paragraph 2, Sentence 4 change to:

The design of a pile foundation is limited to the axial load carrying capacity of a single pile, and it should be noted that other factors, such as settlement and the pile load capacity of pile groups, were not taken into account, although this may be investigated in future research.

Page 52, Paragraph 4, sentence 1 change to:

The research specified three different mean q_c values for the simulations of 3D soil profiles. Different mean q_c values represents different types of simulated soil in order to examine their influence on the efficacy of site investigations with respect to pile foundation design.

Page 53, Paragraph 1, Sentence 2 change to:

Therefore, a single pile with a 0.5 metre diameter needed to be assessed by averaging soil properties over four horizontal elements when computing the pile load capacity.

Page 53, Paragraph 1, sentence 3 change to:

However, Jaksa (1995) suggested that the lateral extent of soil properties influences axial pile load capacity. Therefore, in this case, the lateral distance of soil properties around the pile needs to be included.

Page 53, Paragraph 2, sentence 2 change to:

The simulated CPTs yielded the soil profiles which can be used to estimate pile load capacity. This is regarded as the pile design based on site investigation (SI). In parallel, the simulated CPTs yielded the profiles that can be used as the 'true' design of the piles, or based on complete knowledge (CK).

Page 54, Paragraph 1, sentence 1 change to:

A pile load capacity calculated using data from a simulated site investigation would be considered under-designed when the calculations yield a larger load capacity than that based on complete knowledge of the simulated pile foundation, and be over-designed when the pile load capacity based on the simulated site investigation yields a smaller load capacity than that based on complete knowledge. It is noted that the comparison between pile design based on SI and CK is conducted for the same diameter, length and type of pile.

Page 54, Paragraph 3, sentence 1 change to:

The accuracy of the results derived from the research depends on the simulations of the soil profiles that utilise local average subdivision (LAS) to satisfy the target distribution (lognormal), statistics (mean and COV) and correlation structure (SOF).

Page 55, Paragraph 2 add:

As discussed previously, this research used local average subdivision (LAS) to generate 3-dimensional random fields that conform to the target a lognormal distribution defined by the mean and variance, and the correlation structure defined by the scale of fluctuation (SOF). It is noted that, as explain in Section 2.8.4, the distribution of soil profiles is lognormal as soil properties are strictly non-negative.

Page 57, Paragraph 1, sentence 5 add:

This is due to the effect of local averaging where soil properties generated by LAS are average values of surrounding elements. Vanmarcke (1983) concluded that the averaged values are influenced by correlation distance or SOF. He determined that the variability of the averaged values decreased as the SOF became smaller.

Page 58, Paragraph 1, sentence 2 add:

It is shown in Figure 3-6(a) that the sample means approach the target mean as the SOF increases. Yet, the sample mean exceeds the target mean when the SOF increases from a SOF of 50 up to 100 metres. A higher SOF means soil properties in a field correlated. Goldsworthy (2006) also obtained similar results, and concluded this is also affected by a lognormal distribution of the soil properties.

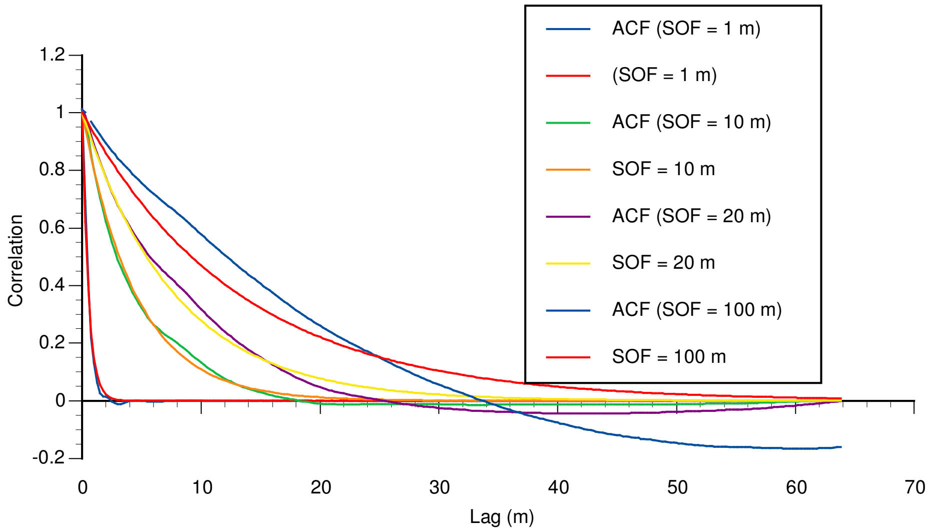
Page 59, Paragraph 2 add:

The reason why a certain SOF yields the highest standard deviation is that small SOFs implies the soil properties vary rapidly over short distances and would average out over a typical domain size (Goldsworthy 2006). The small SOF, i.e. 1 metre, leads to a small standard deviation. On the other hand, for high SOFs, in this case the SOF of 100 metres, the soil is highly correlated, indicating that the standard deviation is also small. However, when the SOF lies between small to high which is between 10 and 20 metres, for instance, the standard deviation is high. The SOF between 10 and 20 metres is regarded as the worst case SOF. These SOFs represent the maximum sample standard deviation. It is noted the element size is 0.25 m. The ratio of SOF to element width is 40.

Page 60, Paragraph 1 add:

The results shown in Figures 3-8 and 3-9 suggest that the simulated soil profiles fit well to the theoretical ACF. The goodness of fit of the simulated soil profiles to the theoretical ACF only occur at SOFs of 1 and 10 metres. Yet, for high SOFs, such as 20 and 100 metres, the ACF of the simulated soil profiles is affected. This is because the soil with higher SOFs is highly correlated. Their correlation structures represent small standard deviations. Therefore, the ACF of higher SOFs shows a deviation from the target ACF. As shown in Figure 3-9 (a), increasing SOF influences the fitness of the ACFs, whereas the COV does not, as shown in Figure 3-9(b).

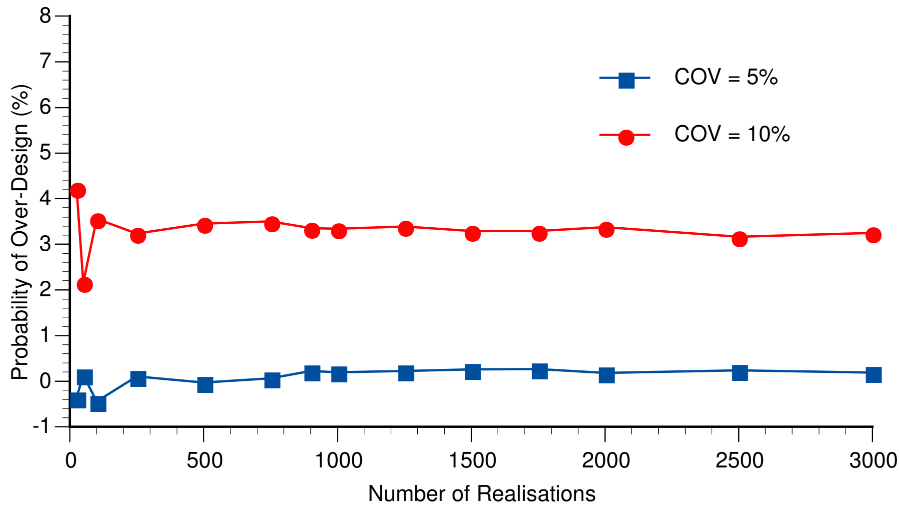
Replace Figure 3-9 with:



Page 62, Paragraph 3 change to:

In order to examine this, a number of realisations was established for a driven pile foundation, a single CPT sounding, and soil COV of 10% and SOF of 1 metre.

Replace Figure 3-10 with:



Page 63, Paragraph 2, sentence 2 change to:
A number of methods were explained in this chapter including the method of generating 3-dimensional random fields; the method of estimating pile load capacity based on CPT results, site investigation sampling strategies, and Monte Carlo simulation for quantifying probabilistically the impact of limited site investigations on the pile foundation design.

Page 63, Paragraph 3 change to:
Verification analyses indicated that the methods used in the research accurately simulate 3-dimensional soil profiles exhibiting variability, compute the pile load capacities in accordance with the pile foundation designs, and support the use of Monte Carlo simulations in order to determine the effect of limited CPT soundings during site investigation on the design of pile foundations.

Page 63, second sentence change to:
However, after 1,000 realisations, the result was constant.

CHAPTER 4 – EFFECT OF RADIAL DISTANCE OF A SINGLE CPT SOUNDING ON THE PROBABILITY OF UNDER- AND OVER-DESIGN OF PILE FOUNDATIONS

Page 65, Paragraph 1, sentence 3 change to:
The first section deals with the effect of a CPT sounding on the design of pile foundations, especially the impact of radial distance, that is, the distance between a CPT sounding and the pile, on the probability of under- and over-design of pile foundations.

Page 66, Paragraph 1, sentence 1 change to:

The influence of anisotropic soil is also examined because the correlation structure of soil is often anisotropic with the horizontal SOF being higher than the vertical SOF (Jaksa et al. 2005).

Page 66, Paragraph 2, the last sentence change to:

The distances between the simulated CPT soundings were 0.25 metres vertically and horizontally in plan view.

Page 66, Paragraph 3, the last sentence change to:

This process was performed for a single realisation. For the next realisation, the process remained the same, with the location of the CPT moving to the next element within the site. Overall, 40,000 pile designs based on SI for each Monte Carlo realization were completed to target convergence for each pile design based on SI.

Page 70, Paragraph 3 replace with:

The process of determining a critical distance is:

- averaging the probability of under-design or over-design for the same radial distance between the simulated CPT and the simulated pile,
- plotting the graph,
- for a certain distance, the probability of under- or over-design is evaluated by the distance corresponding to the probabilty stabilising. Thjs distance is a critical distance, i.e. the maximum distance where the CPT sounding still influences the design. Beyond this distance, the CPT has little or no effect.

Page 72, Paragraph 1 add:

It is possible that this observed behaviour is influenced by the numerical simulation process. This warrants further investigation, which is recommended for future work.

Page 72, Paragraph 2 change to:

Element size used by Goldsworthy was 0.5 m. This research used 0.25 m. It is different. The impact is the different of worst case. The worst case here is 10 m. The domain/field size is 40 m, compared to what Goldsworthy (2006) conducted is 16 m.

Page 73, Paragraph 1 add:

The worst case SOF is the SOF where yielded the highest variable property of soil in a site. The worst case SOF is not a physical property, but based on an assessment of statistical properties.

Page 73, Paragraph 2, Sentence 2 change to:

It was expected that the size and type of pile may influence the reliability of site investigations for the design of pile foundations.

Page 73, Paragraph 5 add:

This is because, for shorter piles, the soil properties are averaged over a shorter length and, hence variations over this distance are more significant. In addition, this phenomenon can be explained by the effect of local averaging. In a random field, the averaged value is dependent on the averaging domain. If the averaging domain, in this case is for a shorter pile, is small, the apparent variability increases (Vanmarcke, 1983). This is why the probability of under- and over-design for the shorter pile is higher than that for longer piles.

Page 78, Paragraph 1 add:

The results given in Figures 4-9, demonstrate that the mean value of the soil resistance influences the probabilities of under- and over-design of the pile. This behaviour is affected by the fact that a log-normal distribution is used to simulate the soil resistance values. At low values of the mean of the soil resistance, such as q_c = 1,000 kPa, lower values of q_c are encountered more often than would be the case for higher q_c values, which will reduce the allowable axial capacity and increase the probabilities of under- and over-design of the pile.

Page 79, Paragraph 4 add:
Due to the computation of pile load capacities, which is effectively more of a vertical computation than a horizontal one, spatial variability in the vertical direction has a more significant effect than variability in the horizontal direction. In future research, soil with a larger SOF in the vertical direction should be investigated.

CHAPTER 5 – EFFECT OF THE NUMBER OF CPTs USED IN SITE INVESTIGATIONS ON THE PROBABILITY OF UNDER- AND OVER-DESIGN OF PILE FOUNDATIONS

Page 86, Paragraph 1, sentence 2 change to:
This is because soil with a high COV is more heterogeneous and variable than that with a low COV.

Page 86, Paragraph 1, sentence 3 change to:
Therefore, minimum sampling efforts yielded higher probabilities of under- and over-design compared to more intensive sampling.

Page 87, Paragraph 1, sentence 2 change to:

For instance, for the soil with a COV of 100%, the sampling effort of one CPT yields a probability of being 21% under-designed and 20% over-designed, whereas sampling with 16 CPTs yields 5% and 7% probabilities, respectively;

Page 88, Paragraph 2, sentence 1 change to:

It was found that there is benefit from increasing sampling effort for either the soil with low or high SOF.

Page 88, Paragraph 2 change to:

It was indicated that for soil with a high COV, more CPTs are needed to obtain a lower probability of under- and over-design. This is opposite to what is needed for soil with a low COV. Soil with a high COV is highly variable and should be investigated with more intensive site investigations than those for soil with a low level of variability.

Page 88, Paragraph 4 change to:

For example, in terms of soil with a SOF of 100 metres, a site investigation consisting of one CPT yielded a probability of 18% under-design and 14% over-design. In contrast, 16 CPTs results in probabilities of over- or under-design of 5% and 4%, respectively.

Page 88, Paragraph 5 change to:

It can be seen that the probability of under- and over-design given by the investigations for the soil with a SOF of 100 metres is lower than that for the soil with SOFs of 10 and 20 metres.

Page 91, Paragraph 1 (Point 1) change to:

- The optimum number of CPTs conducted for the soil with a high COV is similar to those for the soil with a low COV. Yet, for the soil COV of 20%, the optimum number of CPTs is less than soil with a high COV, in case of the probability of under-design.

Page 91, Paragraph 1 (Point 2): change to:

- The values of SOF of 10, 20, and 100 metres yield the highest optimum number of CPTs compared to other values of SOF.

Page 91, Paragraph 2 change to:

The worst case of SOF is the SOF which yielded the highest variable soil property, compared to other SOFs. The worst case of SOF has a statistical meaning; therefore the worst case of SOF can be employed in the probability and statistical framework.

Page 92, Paragraph 1 add:

From the results shown in Figure 5-8(a) and (b), the following trend can be observed:

- For all numbers of piles, the increase of the sampling effort decreased the probability of under- or over-designs. The number of piles appeared to have minimal impact on the probability. However, 100 piles yielded lower probabilities than other numbers of piles. This is likely due to the fact that more piles coincided with the locations of the CPT soundings.

Page 93, Paragraph 1 add:

This is likely to be caused by local averaging, as discussed previously. In this case, a number of pile load capacities for a large number of piles are averaged over the area.

Page 94, Paragraph 1 add:

Simulations were also conducted to examine a number of reduction methods including standard arithmetic (SA), geometric average (GA) and harmonic average (HA). The reduction methods are used to average pile load capacities based on data from the simulated CPT soundings. This is regarded as the pile load capacity based on SI information which is then compared to the capacities based on CK information.

Page 95, Paragraph 2 add:

- the reduction method of SA appears to yield more conservative result,s compared to the GA and HA techniques.

Page 97, Paragraph 1, sentence 2 change to:

The anisotropic soil, as shown in Figure 5-10 as the soil SOF of 10:10:1, provided a greater probability of both under- and over-design than the isotropic soil.

CHAPTER 6 – SUMMARY AND CONCLUSION

Page 99, Paragraph 1, sentence 1 change to:

The study has quantified the effect of limited site investigations with respect to a pile foundation design.

Page 99, Paragraph 2, sentence 1 change to:

Chapter 3 described the methodology implemented to investigate the reliability of site investigations.

Page 100, Paragraph 3, sentence 1 change to:
The quantification of the effect of limited site investigations in relation to pile foundation design presented in this thesis focused on pile load capacity.

Page 101, Paragraph 3, sentence 1 change to:
The investigation of the effect of limited site investigations presented in this thesis is based on the simulation of three-dimensional soil profiles based solely on cone tip resistance values, q_c.

Page 106, Paragraph 3, sentence 1 change to:
Based on the research undertaken using the LCPC method for pile design, it can be concluded that when performing a single CPT close to the location of the pile reduces the probability of under- and over-design of the pile.