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Data gathering, interpretation, reliability and geotechnical models

J.R.L. Read *CSIRO Earth Science and Resource Engineering, Australia*

Abstract

The geotechnical model is the cornerstone of open pit design (Read and Stacey, 2009). It must be in place before the steps of setting up the geotechnical domains, allocating the design sectors and preparing the slope design can commence. The processes that must be followed to construct the model are outlined in this paper. They include recent advances in assessing parameter and model uncertainty, in particular, a modified Bayesian approach that has been developed to estimate the expected value of the measure of reliability. Overall, they form part of a system of reporting confidence in the geotechnical model and matching target levels of geotechnical effort with target levels of confidence in the data at each stage of project development.

1 Introduction

Gathering geotechnical data for an open pit slope design requires keen observation and attention to detail, a clear understanding of why the data is being gathered, what it is to be used for, and the impact it will have on the reliability of the final design.

Historically there has been a tendency towards the belief that, 'the more information that is available, the better'. This is often not the case. The objective should be to gather only pertinent data and build a geotechnical model that provides the slope design engineer with the information needed to correctly assess the inherently variable properties and characteristics of the natural materials being dealt with. This objective raises the need for the slope design engineer to understand the causes of any uncertainties in the geotechnical model and how they may affect the reliability of the developed slopes. Read and Stacey (2009) proposed guidelines for a system of reporting the confidence in the geotechnical information used in slope design, matching target levels of geotechnical effort with target levels of confidence in the data at each stage of project development. The system has gained widespread acceptance across the industry, but it remains subjective. For the future, there is a need to develop objective measures of uncertainty that can be confidently used by the stakeholders, particularly the design engineer, the owner, and the investor, to help them assess the geotechnical viability of the slope designs adopted for the project.

2 Slope design process

The slope design process has been described in depth by Read and Stacey (2009) and is summarised in Figure 1. The objective is to optimise the configuration of the open pit in the context of safety, ore recovery and financial return, recognising that the operators and investors expect that walls of the open pit will be stable for the life of the pit. If any instabilities occur, at the very least they must be manageable.

Essential steps in the process include:

- Formulating a geotechnical model for the pit area, the model being comprised of four components; the geological, structural, rock mass and hydrogeological models.
- Populating the geotechnical model with relevant data.
- Dividing the model into geotechnical domains.
- Subdividing the domains into design sectors.

- Designing the slope elements in the respective sectors of the domains.
- Assessing the stability of the resulting slopes in terms of the project acceptance criteria.
- Defining the implementation and monitoring requirements for the designs.

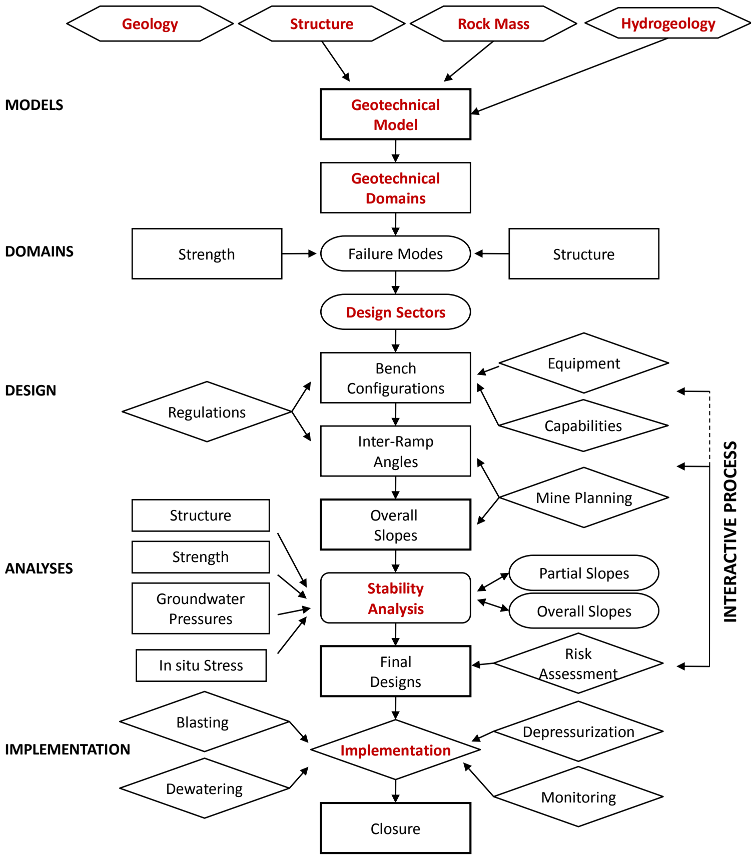

Figure 1 The slope design process

As noted by Read and Stacey (2009), at the end of the process the resulting slope design must be technically sound, taking into account safety, the equipment available to implement the designs, mining rates, and the acceptable risk levels.

3 Data gathering

Suggested levels of effort required to collect and populate each component of the geotechnical model with the data required to establish a slope design are given in Read and Stacey (2009) and are summarised in Table 1.

It is important to understand that the mining company developing the project is accountable for defining the level of work required at each project stage, including the level of detail and the level of confidence required of the data, no matter whether it is performed in-house or by consultants. In all cases, the objectives of the process are to: i) identify opportunities, ii) reduce uncertainty and improve confidence, iii) reduce risk, and iv) identify the preferred development option (Beale and Read, 2013). The weight given to these objectives may vary between companies and/or mine sites, with the actual level of effort depending on factors such as the site conditions encountered and the applicable regulatory controls.

Table 1 Suggested levels of geotechnical effort by project stage

	Project Stage				
Project Level Status	**Conceptual**	**Pre-feasibility**	**Feasibility**	**Design and Construction**	**Operations**
Geotechnical Level Status	**Level 1**	**Level 2**	**Level 3**	**Level 4**	**Level 5**
Geotechnical characterisation and design status	Pertinent regional information; geotechnical assessment of advanced exploration data; 'order of magnitude' cost estimates and slope designs	Assessment and compilation of initial mine scale geotechnical data; preparation of initial geotechnical database and 3D model; preliminary slope designs to assess if mining is technically and economically viable	Ongoing assessment and compilation of all new mine scale geotechnical data; enhancement of geotechnical database and 3D model slope designs in the order of ± 5°	Refinement of geotechnical database and 3D model; mining believed to be potentially economic and production finance secured	Ongoing maintenance of geotechnical database and 3D model; pit slope optimisation based on additional data available, slope performance and operating experience

An account of the wide range of methods and technologies available for gathering the data required for the geotechnical model across the various stages of project development is beyond the scope of this paper. In brief, for the geological and structural models, they range from direct or digital mapping and sampling of surface outcrops, trenches and adits, to direct and indirect geophysical surveys, rotary augering and core drilling. For the rock mass model they include laboratory intact rock strength index and mechanical property tests, field and laboratory tests to determine the strength of structural defects, and rock mass classification systems to estimate the rock mass strength. For the hydrogeological model they include everything from the collection of historical regional hydrogeological data, to the collection of hydrogeological data 'piggy-backed' on mineral exploration and resources drilling programmes, and routine water level monitoring programmes, in specifically installed groundwater observation wells and/or piezometers.

For detailed accounts of the commonly used methods and technologies the reader is referred to Read and Stacey (2009).

4 Data reliability

4.1 Background

The need for slope design engineers, along with mine operators, corporate management and the investment community, to recognise and report the reliability of the geotechnical data used in open pit slope designs was identified and addressed by the project sponsors at an early stage of the CSIRO large open pit research project (the LOP project). A sponsor sub-committee was formed which recommended that, to provide guidelines for the level of certainty required at each stage of project development, the target levels of effort summarised in Table 1 should be matched with suggested target levels of confidence in the data. These target levels are outlined in Table 2 and are set out in detail in Read and Stacey (2009).

Table 2 Suggested levels of geotechnical effort and target levels of data confidence by project stage

	Project Stage				
Project Level Status	**Conceptual**	**Pre-feasibility**	**Feasibility**	**Design and Construction**	**Operations**
Geotechnical Level Status	**Level 1**	**Level 2**	**Level 3**	**Level 4**	**Level 5**
Geotechnical characterisation	Pertinent regional information	Assessment and compilation of initial mine scale geotechnical data	Ongoing assessment and compilation of all new mine scale geotechnical data	Refinement of geotechnical database and 3D model	Ongoing maintenance of geotechnical database and 3D model
Target Levels of Data Confidence in Each Model					
Geology	>50%	50–70%	65–85%	80–90%	>90%
Structural	>20%	40–50%	45–70%	60–75%	>75%
Hydrogeological	>20%	30–50%	40–65%	60–75%	>75%
Rock Mass	>30%	40–65%	60–75%	70–80%	>80%
Geotechnical	>30%	40–60%	50–75%	65–85%	>80%

In Read and Stacey (2009), Table 8.1 is followed by descriptive guidelines for estimating the level of confidence in the data at each level of development (pp. 218–219). For consistency with the reporting of exploration results, mineral resources and reserves, the guidelines were purposely matched with the descriptive framework used by the 2004 Australian JORC code (JORC, 2004).

As noted in the introduction, although the system outlined by Read and Stacey has gained widespread acceptance across the industry, it remains subjective. The need is to develop objective measures of uncertainty that can be confidently used by the slope design engineer, the owner, and the investor to help them assess the reliability of the slope design.

4.2 Parameter uncertainty

A number of statistical and probabilistic methods available in the public domain can be used to: a) organise geotechnical parameters in a structured manner, and b) distinguish between populations within or across different geotechnical domains. However, once organised, the end question always remains – how reliable are the parameters?

At the feasibility stage of project development**,** the expected value, standard deviation and coefficient of variation for the range of values in the data set being examined are most commonly used to assess the inherent uncertainty of the data set. Guided by the measure of the coefficient of variation, where values of less than 10 per cent are considered to be low and values greater than 30 per cent are high, it is customary to accept the expected (average) value as the measure to be used in the design that will be adopted for mining (Read, 1994; Read and Stacey, 2009).

Although the coefficient of variation provides a useful, subjective estimate of performance (backed by assessments of items such as the integrity of the database and the field sampling and laboratory testing methods used to gather the data), it falls short of furnishing a numerical measure of the reliability of the data.

To overcome this difficulty, a modified Bayesian approach has been developed from 'Reliability-based Design in Civil Engineering' (Harr, 1996) that estimates the expected value of the reliability of the data in a framework of success and failure.

It is shown by Harr (1996) that the Bayesian approach asserts that the expected value of reliability, E[R] is given as:

$$E[R] = (S + 1)/(S + F + 2) \tag{1}$$

Where:

S = the number of successes and F is the number of failures in N trials. The classic example is, before the single toss of a fair coin, where S = F = 0, the expected value of the reliability of either face showing is 50%.

Using a spreadsheet, Equation 1 provides a straightforward and quick means of estimating the reliability of the elements of a set of data. This is demonstrated in Table 3, wherein the estimated reliabilities of 24 (N = 24) laboratory derived unconfined compression strength (UCS) values measured in MPa, are obtained for a rock type AA. The average value of the 24 UCS tests is 94 MPa, the standard deviation is 65 MPa, and the coefficient of variation is 69%. The dataset is real and the designers selected 94 MPa as the feasibility level design UCS value.

In Table 3, the 24 observed UCS values are shown 'sorted' and their occurrences are as noted. The success and failure of say the value '37' is obtained as follows:

If 37 is chosen as the design value, there would be two lesser possible values (17 and 23) and the selection of 37 would produce F = 2, S = 24–2 = 22, and the expected value of the reliability of 37, from Equation 3.9.5a, is 0.88 (percent). In this context, there would be an 88 percent probability that the actual UCS values is greater than or equal to 37 MPa.

The results listed in Table 3 provide valuable information about the reliability (or unreliability) of the data and, in particular, of the selected design UCS value of 94 MPa.

With this in mind, two steps can be used to assess the reliability of the selected design UCS value.

1. Examine the standard deviation and the coefficient of variation of the selected design value. In the above example, both are high (standard deviation = 65 MPa, coefficient of variation = 69%), which immediately suggests that 94 MPa is not an appropriate value for a feasibility level design.
2. Check the expected value of reliability for the value of 94 MPa in Table 3. The value is approximately 38%, which is well outside the range of 60 to 75% for feasibility level studies and just outside the suggested range of 40 to 65% for pre-feasibility level studies as suggested for the rock mass model in Table 2.

Steps 1 and 2 clearly indicate that a) the selection of 94 MPa as the feasibility level design UCS value was a poor decision, and that b) the dataset (N = 24) is too small. From the wide range of test values it is likely that it includes a significant number of low values that represent breakage across defects within the samples rather than through the intact rock.

To further illustrate the decision making process, Table 4 shows the results of laboratory UCS tests for Rock Type AA together with those for Rock Types BB, CC and DD from the same site. As for Rock Type AA, the average UCS values reported for Rock Types BB, CC and DD were selected as the feasibility level design values for those rock types.

Table 3 Spreadsheet to estimate the reliability of rock type AA laboratory UCS values

N = 24	Sorted Values	Occurrence	Cumulative Failures	Successes 'S'	S+1	S+F+2	
		0					E[R]
	17	1	0	24	25	26	0.96
	23	1	1	23	24	26	0.92
	37	1	2	22	23	26	0.88
	43	1	3	21	22	26	0.85
	46	1	4	20	21	26	0.81
	46	1	5	19	20	26	0.77
	48	1	6	18	19	26	0.73
	51	1	7	17	18	26	0.69
	52	1	8	16	17	26	0.65
	56	1	9	15	16	26	0.62
	56	1	10	14	15	26	0.58
	59	1	11	13	14	26	0.54
	59	1	12	12	13	26	0.50
	67	1	13	11	12	26	0.46
	86	1	14	10	11	26	0.42
	98	1	15	9	10	26	0.38
	111	1	16	8	9	26	0.35
	148	1	17	7	8	26	0.31
	169	1	18	6	7	26	0.27
	172	1	19	5	6	26	0.23
	178	1	20	4	5	26	0.19
	182	1	21	3	4	26	0.15
	216	1	22	2	3	26	0.12
	230	1	23	1	2	26	0.08

Table 4 Reliability of laboratory derived UCS values for rock types AA, BB, CC and DD

Analysis Results	AA (N = 24)	BB (N = 33)	CC (N = 41)	DD (N = 19)
Lab UCS: average value, MPa	94	51	60	84
Lab UCS: standard deviation	65	36	37	52
Lab UCS: coefficient of variation, %	69	71	61	61
Reliability, % of average laboratory UCS value	38	42	44	38

The results for Rock Types BB, CC and DD are similar to the outcomes obtained for Rock Type AA. From the coefficients of variation, Step 1 shows that selecting 51, 60 and 84 as the design UCS values for rock types BB, CC and DD was a poor decision. Step 2 shows that reliabilities of the selected values do not meet the requirements for a feasibility level study and are only marginal for a pre-feasibility level study.

Poor datasets from a real mine site were deliberately chosen to demonstrate the process of establishing the level of confidence in the design parameter, for two reasons.

1. To illustrate the value of using the coefficient of variation as a screening mechanism when making decisions about the level of confidence in the selected design parameter. In the UCS analyses illustrated, no attention was given to anything but the average UCS value. The potential consequences of the unreliably high values selected leave little to the imagination.
2. To illustrate that there is a statistical mechanism available which provides a straightforward and quick means of estimating the expected value of parameter reliability.

4.3 Model uncertainty

Through-going fault traces and the boundaries between lithologies and alteration units within geotechnical domains and design sectors are positional, as are the boundaries of the domains and design sectors themselves. Consequently, it is difficult if not impracticable to derive probability distributions from measured values that reflect their locations (Read and Stacey, 2009).

Two solutions offer themselves.

1. To use subjective assessments prepared by competent geologists, engineering geologists and geotechnical engineers, acting individually or as members of a review panel, as a means of quantifying the uncertainty associated with model geometries and boundaries.
2. To use generalised plurigaussian simulation to simulate lithologies and structures as a means of quantify the uncertainty associated with model geometries and boundaries.

Subjective assessments prepared either by an individual ‘competent person’, or a group of ‘competent persons’ acting together in a review panel, have become a standard operating procedure in open pit mining. It has been noted (Read and Stacey, 2009) that many aspects of the process by which individuals making a subjective judgement accept responsibility for their judgements raise questions of credibility and defensibility. For example, an overbearing panel member can disrupt the process of reaching consensus. However, experience over the last 10 to 15 years has shown that a well chosen review panel can work together to produce an effective and balanced opinion of the geotechnical issues under review. The process also recognises that the judgement and opinion of experienced practitioners are important and of value.

The use of generalised plurigaussian simulations to help quantify the uncertainty associated with model geometries and boundaries requires an understanding of variograms and kriging, as applied in geostatistics, and with simulating Gaussian or normally distributed random functions.

By and large, geotechnical engineers are familiar with normally distributed random functions but are less familiar with variograms and kriging. Variograms define the variance of the difference between field values at two locations (x and y) across realizations of the field (Cressie, 1993). Kriging is a form of regression analysis which estimates that the value at an unknown point should be the average of the known values at its neighbors, weighted by the neighbors' distance to the unknown point (Matheron, 1963). Figure 2 examples a one-dimensional data interpolation by kriging.

Plurigaussian simulation extends the sampling statistics of variograms and kriging to simulating facies and lithotypes (Armstrong et al., 2011). As outlined in Armstrong et al., truncated gaussian simulations were developed for simulating lithotypes found in oil reservoirs where the lithotypes occur in sequential order, for example, sandstone overlain by shaly sandstone and then shale (Matheron et al., 1987, Dowd et al., 2003). The development followed the logic that it was more sensible to simulate the architecture of the reservoir first and then to generate suitable values of porosity and permeability once the lithotype was known. Subsequently, plurigaussian simulations were designed to produce a much wider range of patterns than could be modelled by truncated gaussian simulations and to allow for more complicated types of contacts between facies (Galli et al., 1994; Dowd et al., 2006).

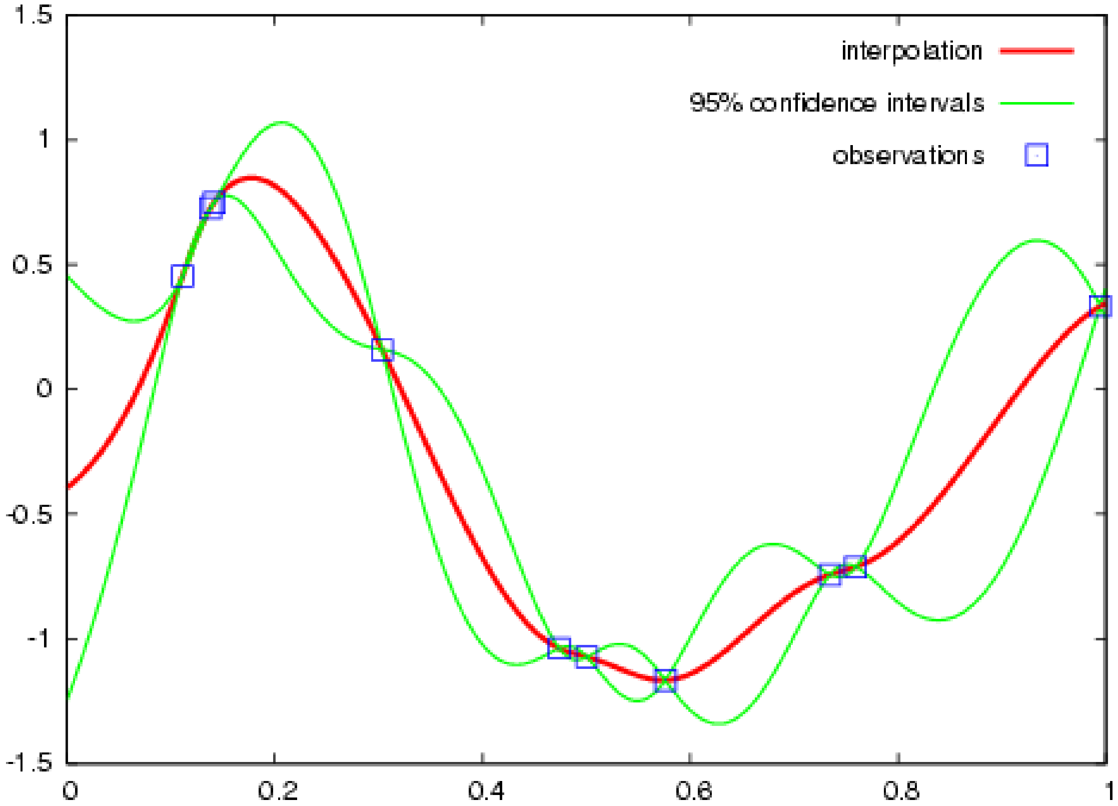

Figure 2 Example of one-dimensional data interpolation by kriging, with confidence intervals. Squares indicate the location of the data. The kriging interpolation is in red. The confidence intervals are in green (source: Wikipedia; example.krig.png)

Truncated and plurigaussian simulations as developed by the petroleum industry have been taken up by the mining industry to simulate mineral deposits, for example, quartz vein controlled gold mineralisation where there are two variables, the quartz vein and the gold grade (Dowd, 2012), and for simulating rock fractures (Dowd et al., 2007). After considering the information presented by Dowd (2012), the LOP Sponsors concluded however that, although the method appears applicable to single lithologies and structures or single sets of lithologies and structures, at least for now it is too complex a process to apply to a complete model.

5 Conclusions

The coefficient of variation is a valuable screening mechanism when making decisions about the level of confidence in a selected design parameter. However, it is subjective and falls short of furnishing a numerical measure of the reliability of the data. To overcome this difficulty, a modified Bayesian approach has been developed to estimate the expected value of the reliability of a dataset. The method uses a simple spreadsheet format and can be applied to any set of geotechnical data such as rock mass and hydrogeological parameters, UCS and *K*.

It is difficult if not impracticable to derive probability distributions from measured values that reflect the locations of through-going fault traces and the boundaries between lithologies and alteration units within geotechnical domains. It is possible that generalised plurigaussian simulations can be used to quantify the uncertainty associated with single structures or single sets of structures within a model, but for now it is thought that it is too complex a process to apply to a complete model. Thus, the use of subjective assessments using the judgement and opinion of experienced practitioners as a means of quantifying the uncertainty associated with model geometries and boundaries is likely to remain as the standard operating procedure in open pit mining for the foreseeable future.

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