Robustness in geotechnical design

Report of ISSMGE TC205/TC304 Working Group

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1 Introduction

The purpose of the Working Group was to examine how sufficient robustness can be ensured in geotechnical designs, using reliability analysis or other safety formats. The members of the group first set out to define the term "robustness" in a relevant way and then exchanged emails and papers to develop an understanding of how it can be provided in geotechnical design and codes of practice.

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2 Definitions

2.1 Introduction

The term "robustness" can take several different meanings. The issue of concern to designers and to codes of practice is the robustness of a civil engineering construction, usually in its final form but also during the process of construction. This is therefore the subject of this report.

Two principal types of robustness have been identified by the group:

a) The ability of the final design to accommodate events and actions that were not foreseen or consciously included in design.
b) The sensitivity of the final design to variations of the known parameters within their anticipated range of uncertainty.

The body of this report is concerned with the first of these types of robustness. A paper concerned with the second type of robustness is presented in the Appendix.

2.2 Accommodating what is unforeseen

This definition of robustness relates, in particular, to the ability of the construction to withstand without failure events and actions that were not foreseen or consciously included in design. Although the precise nature of such actions may be unknown to the designer, their magnitude can be considered: society expects that a construction will be able to withstand moderate unforeseen events and actions, but probably not extremely severe ones. A design that produces such a construction can be termed a "robust design".

A concise definition is given by ISO 2394, which equates robustness to "damage insensitivity". This will be taken to be the basic definition used in this report.

> Ability of a structure to withstand adverse and unforeseen events (like fire, explosion, impact) or consequences of human errors without being damaged to an extent disproportionate to the original cause (ISO 2394:2014, 2.1.46).

An alternative definition, with the same basic meaning, could help designers to understand the degree of robustness required:

> Ability of a structure to withstand adverse events that are unforeseen but of a magnitude such that society will expect that our designs can accommodate them, having tolerance against mistakes within the design process and during construction.

2.3 Local damage and progressive failure

The term robustness is often applied to a complete structure rather than to an individual element of it. For example, CEN (2016) *Practical definition of structural robustness vDraft*, gives a definition of structural robustness:

> Structural robustness is an attribute of a structural concept, which characterizes its ability to limit the follow-up indirect consequences caused by the direct damages (component damages and failures) associated with identifiable or unspecified hazard events (which include deviations from original design assumptions and human errors), to a level that is not disproportionate when compared to the direct consequences these events cause in isolation.

Robustness is often linked to the ability to prevent progressive failure, which could lead to damage disproportionate to cause (eg COST (2011) *Structural robustness design for practising engineers*). This is probably consistent with strict limit state definitions in which ultimate limit state (ULS) is a state of danger, but as a practical design expedient ULS is often considered as only localised failure, not necessarily dangerous in itself. EN 1990 3.3(3) is relevant to this: "States prior to structural collapse, which, for simplicity, are considered in place of the collapse itself, may be treated as ultimate limit states."

Val (2006), discussing robustness of framed structures, provides a definition similar to that of ISO 2394, and then offers as an alternative:

> The robustness of a structure can be defined as ability of the structure to withstand local damage without disproportionate collapse, with an appropriate level of reliability.

2.4 Resilience

Robustness can be distinguished from "resilience", which refers to the ability of a structure to be recovered after it has failed. On the other hand, a complete structure, or a system such as a metro system, might be considered robust if its members are all resilient, so that local failures can be repaired without failing the complete system (Huang et al 2016, GR6595).

3 Events and actions relevant to robust design

In most design processes, "lead variables" are identified and the possibility that they might adopt extreme values, or occur in adverse combinations, is considered in some way. Lead variables are usually actions (loads), material strengths and component resistances. However, most designs are also affected by a large number of "secondary variables", which the design is expected to accommodate.

Robustness relates to the ability of a construction to withstand events and actions that were not foreseen or consciously included in design, in effect because they were considered "secondary". These have to be judged in their context. For example, in a building structure if a heating engineer puts a 150mm hole through a wall, it would be unacceptable for the wall to fail; however, if the same hole were put through a 250mm column the heating engineer, not the column designer, could be liable for the failure that ensued.

The definition of robustness given in ISO2394, in common with EN1990, mentions as examples fire, explosion, impact and human errors. Human errors occur both in design and construction, the latter often resulting in geometric inaccuracies in the construction. In a geotechnical context, other secondary variables could include sedimentation or erosion around a structure in water, excavation of small trenches etc, or of the ground above a structure relying on the weight of ground, disturbance caused by burrowing animals, unidentified loading above retaining walls, and vandalism of various kinds.

If these events are very large, it might be judged that the designer should have allowed for them, or they might lead to successful insurance claims or prosecution of the perpetrators. However, where they are only moderate in magnitude, clients and society reasonably expect that they will not cause significant problems to constructions. In this respect, although the events themselves are unforeseen at the time of design, the magnitude that a design must able to accommodate is understood, at least roughly. For example, whilst all structures may be expected to have reasonable robustness against vandalism, ability to resist more severe acts of terrorism is only required in the specifications of more exceptional structures.

In reliability work, the term “black swan” is used to describe something that was unforeseeable and that has an extreme impact - https://en.wikipedia.org/wiki/Black_swan_theory . The implication is that nobody could have prepared for the disaster that was caused, and society would accept that no designer could be blamed. Robustness relates to events that are also unforeseen but are of smaller magnitude, such that society will expect that robust designs can accommodate them. It might be helpful to think of these as grey swans – signets – they are neither black nor white and somewhat smaller.

4 Ensuring robustness in various design formats

4.1 Prescriptive measures relevant to robustness

Studies of robustness in structural design highlight two important prescriptive measures: provision of redundancy or “alternative paths”, and “tying the structure together”. In the “alternative path” method individual members are removed in the analysis to prove robustness of the structure. Val (2006) notes:

> It is stressed that the removal of a single vertical load bearing element "is not intended to reproduce or replicate any specific abnormal load or assault on the structure". Rather, member removal is simply used as a "load initiator" and serves as means to introduce redundancy and resiliency into the structure.

As a geotechnical example of this, Simpson et al (2008) argued that the Nicoll Highway collapse in Singapore probably would not have occurred, despite human errors, if the design had included a check for loss of a single strut in the excavation; this was a requirement in the Singapore code at the time of design.

As with other issues related to safe design, checking, review and supervision of design and construction are extremely valuable. In some cases, these processes may suggest that some “unforeseen” events and actions should be classified as “foreseeable” and consciously included in the design process.

4.2 Use of partial factor methods

In this report, the term "partial factor methods" will be taken to include all safety formats in which factors of safety are spread among several variables. The variables include actions (loads), effects of actions such as internal forces derived in calculations, material strengths, and resistances of structural components (such as bending capacity) or of bodies of ground (such as bearing resistance). Thus all the "Design Approaches" of Eurocode 7 and all LRFD formats are included as "partial factor methods". Some of the partial factors may be "model factors".

Many studies have been carried out to derive values for partial factors using reliability analysis (eg Schweckendiek et al 2012 – OTHER REFS NEEDED). However, in practice, almost all values used in modern codes of practice have been derived by calibration against previous experience of successful design. Sometimes, further reliability studies have been used to provide additional justification. *(Do we know of any examples in which partial factors have been chosen or modified as a result of reliability studies?)* The disadvantage of calibration processes is that the "successful" designs demonstrated adequate success in terms of both ultimate and serviceability limit states and also with regard to robustness. So it is difficult, if not impossible, to determine which of these criteria actually required the factors used. However, calibration against existing experience shows that the factors adopted have provided, at least, a level of robustness that has been found to be adequate.

EC7 notes one particular aspect of robustness, without using that word: the accommodation of small geometric variations. For these it says:

> The partial action and material factors (γ_F and γ_M) include an allowance for minor variations in geometrical data and, in such cases, no further safety margin on the geometrical data should be required. (EC7, 2.4.6.3(1))

CEN (2014) *Robustness in Eurocodes* notes that: "The national partial safety factors are also expected to cover a (part of)" the effects of errors in design and execution. (Section 2, page 4).

It may be concluded, therefore, that the use of partial factor methods with values derived by calibration against existing successful experience, is a valid approach to provision of adequate robustness. Their values are roughly aligned with typical coefficients of variation of the lead parameters, which, as will be noted below, is probably an optimal strategy.

4.3 Direct use of reliability methods

The potential benefit of reliability methods over partial factor methods is that they can take account directly of the real uncertainty of the lead variables, for which data may be available. This would allow the safety of designs to be gauged by a reliability index, β, which, in principle, is related to the probability of failure, intended to be very low. Reliability methods are generally more complicated to implement than partial factor methods, so designers and codes of practice are only likely to adopt them if they are shown to have clear advantages.

The Working Group has not been able to suggest practicable methods of accommodating robustness (type (a) in 2.1, as discussed in 2.2) in reliability based design. It is possible that a major study of civil engineering failures, of large and small magnitude, might provide a database that could be used as an input to reliability studies. This would give, for example, objective data on the occurrence and significance of humans errors in design. However, an immediate problem arises that in many cases the detailed analysis of failures is confidential to legal proceedings, so accumulation of reliable data would be very difficult.

It might be possible to calibrate reliability methods against past experience in the same way that partial factor methods have been calibrated. (*EXAMPLES of this being done?*) This could mean that values of the reliability index β, which relates to the probability of the lead variables dominating the design, could be chosen so as to reproduce previous successful designs, which are considered to have sufficient robustness. Unfortunately, this would lose the logical connection between reliability index, probability of failure and the actual uncertainty of the lead variables.

It was noted above that while actions and events for which robustness is needed are not identified at the time of design, their magnitude is roughly determined by what is acceptable to society. Because they are independent of the lead variables, they are also independent of the range of uncertainty of those variables. This means that the magnitudes of unforeseen actions and events, for which robustness is required, cannot be measured on the same scale as the uncertainties of the lead variables. Hence, simply designing for larger β might not achieve what is required.

Consider, for example, a situation in which the coefficients of variation of the lead variables are considered to be very small. In that case, a large value for β could be achieved with little change to the design, and no significant robustness to meet unforeseen actions and events. In this respect, the use of partial factors with values roughly aligned to typical coefficients of variation of the lead variables, but not tuned specifically for individual designs, appears to be advantageous.

4.4 Use of reliability methods to determine partial factors for inclusion in standards

Reliability methods can be used as a means of fixing suitable values for partial safety factors in standards. This avoids the need for skill in reliability theory on the part of designers. An example related to partial factors used in the design of flood defences in the Netherlands is discussed by Schweckendiek et al (2012).

The process of a rigorous reliability exercise as part of the design development of such major structures, requiring careful discussion among experts of several disciplines, is considered to have benefits in raising issues that might normally be overlooked and encouraging proper investigation of the parameters controlling the design. It could be that this process will, in itself, improve robustness against "unforeseen" events and actions by forcing more of them to be explicitly foreseen and accommodated in the design. This is usually to be expected when designs are critically reviewed by a multi-disciplinary team with a high level of expertise. One possible danger that must be avoided is that the process becomes so dominated by probability expertise that clear thinking about the physical processes involved gets crowded out.

It seems likely that studies of this type will provide valuable insights to the process of setting values for partial factors. In relation to robustness, a key issue is to ensure that the eventual designs are able to accommodate, to a reasonable extent, events and actions beyond those normally included in conventional designs.

4.5 Direct assessment of design values

If design values are assessed directly, such as by using "worst credible values", attention could be concentrated entirely on the lead variables, as tends to happen in reliability analyses, making no provision for robustness. Alternatively, directly assessed design values could be consciously chosen so as to make an allowance for robustness. Such an approach would have no calibration to past successful design, and it would be very difficult to standardise.

5 Concluding remarks

This report has concentrated on "type (a)" robustness identified in 2.1: the ability of the final design to accommodate events and actions that were not foreseen or consciously included in design. In the Appendix to this report, an alternative form of robustness is discussed (type(b)): the sensitivity of the final design to variations of the known parameters within their anticipated range of uncertainty.

For type (a) robustness it is noted that the margins of safety required may relate more to the magnitudes of the lead variables, which govern the overall geometry and strength of the structure, than to their uncertainties. In this case, simply reducing the target probability of failure or increasing the reliability index β calculated for the lead variables may not provide the robustness required. A partial factor approach may more readily accommodate this requirement. Similarly, carrying out design for the "worst credible" values of the lead variables may not provide the required robustness.

For large projects, processes that involve critical reviews of designs or proposed design standards by multi-disciplinary teams of experts are likely to identify a larger range of situations and variables for which the designs should be checked. They will therefore increase robustness by transferring some events and actions from the category of "unforeseen" (and therefore not explicitly designed for) to "foreseen". Rigorous study using reliability schemes and processes will probably be helpful in this respect, provided the concentration on reliability expertise is not allowed to eclipse the other skills needed in the critical review.

References

(Note: GR numbers given below for references relate to documents in the working group's Sharefile.)

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APPENDIX

The following paper is concerned with the second type of Robustness described in 2.1 of the report above: the sensitivity of the final design to variations of the known parameters within their anticipated range of uncertainty.

Report on Robust Geotechnical Design
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Report on Robust Geotechnical Design

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1. Introduction

This report represents a short review on the robust geotechnical design (RGD) proposed by Dr. Juang and his colleagues. In the context RGD, an optimal design is seeked with respect to design robustness and cost efficiency, while satisfying the safety requirements; and thus, RGD is generally implemented as multi-objective optimization problem. The safety requirements, in RGD, may be evaluated with either deterministic (i.e., factor of safety-based) or probabilistic (i.e., reliability-based) approach based on the characterization of the uncertain input parameters, this is consistent with the traditional geotechnical design approaches. A design, in RGD, is considered robust (i.e., having high degree of design robustness) if the system response of concern is insensitive to, or robust against, the variation in the uncertain input parameters. And, the optimal design, in RGD, is seeked through carefully adjusting the "design parameters" (i.e., parameters that can be easily controlled by the engineer, such as the geometry) without reducing the uncertainty in the "noise factors" (i.e., uncertain input parameters that could not be characterized accurately). In this report, two main elements in RGD, namely, robustness measure and multi-objective optimization, are discussed. Next, the procedures for implementing the RGD is outlined. Finally, the RGD is illustrated with cases study, including braced excavation, shield tunnel, and retaining wall; the results of which demonstrate the versatility and effectiveness of the RGD.

2. Elements in Robust Geotechnical Design

Two fundamental elements in RGD, in terms of the robustness measure and the multi-objective optimization, are detailed in this section.

2.1 Robustness measure

According to the level of characterization of the uncertain input parameters (or noise factors), three levels of robustness measure could be employed in RGD: (1) site-specific data is quite limited and only the nominal values of the noise factors could be approximately estimated, the gradient-based sensitivity index (SI) (Gong et al. 2016b) could be employed; (2) site-specific data is limited and the upper bounds and lower bounds of the noise factors could be characterized, the fuzzy set-based signal-to-noise ratio (SNR) (Gong et al. 2014a&2015) could be employed; and (3) more site-specific data availability is achieved and the probability distributions of the noise factors could be characterized, however, the statistical information of the distributions (e.g., coefficient of variation) cannot be calibrated accurately, the reliability-based feasibility index (β_β) (Juang et al. 2012&2013; Juang and Wang 2013; Khoshnevisan et al. 2014; Huang et al. 2014a) could be adopted.

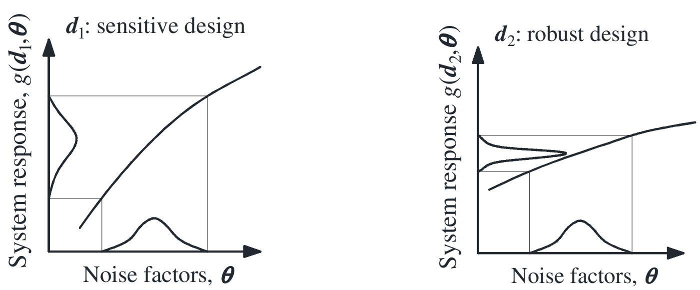
2.1.1 Gradient-based sensitivity index

In reference to Figure 1, two different designs (referred to herein as $\boldsymbol{d}_1$ and $\boldsymbol{d}_2$) are compared. Here, $\boldsymbol{d}_2$ is seen more robust than $\boldsymbol{d}_1$ against the variation of noise factors $\boldsymbol{\theta}$, as the gradient of the system response to the noise factors is lower in the case of $\boldsymbol{d}_2$ than in $\boldsymbol{d}_1$. As such, the design robustness can be effectively evaluated using the gradient of the system response to the noise factors (Gong et al. 2014b). Here, the gradient of the system response to the noise factors, ∇g, at a check point of noise factors, $\boldsymbol{\theta}'$, can be expressed as follows.

$$\nabla g\big|_{\boldsymbol{\theta}=\boldsymbol{\theta}'} = \left\{ \left.\frac{\partial g(\boldsymbol{d},\boldsymbol{\theta})}{\partial \theta_1}\right|_{\boldsymbol{\theta}=\boldsymbol{\theta}'}, \left.\frac{\partial g(\boldsymbol{d},\boldsymbol{\theta})}{\partial \theta_2}\right|_{\boldsymbol{\theta}=\boldsymbol{\theta}'}, \mathrm{L}, \left.\frac{\partial g(\boldsymbol{d},\boldsymbol{\theta})}{\partial \theta_n}\right|_{\boldsymbol{\theta}=\boldsymbol{\theta}'} \right\} \tag{1}$$

Commented [BS1]: What is L?

where $g(\boldsymbol{d}, \boldsymbol{\theta})$ represents the system performance of concern, which is a function of the design parameters ($\boldsymbol{d}$) and noise factors ($\boldsymbol{\theta}$); and, n represents the number of noise factors. In situations where only the nominal values of the noise factors, denoted as $\boldsymbol{\theta}_n$, could be characterized and available to the engineer, the nominal values of noise factors can be reasonably assigned as the checkpoint in Eq. (1): $\boldsymbol{\theta}' = \boldsymbol{\theta}_n$.



(a) Sensitive design (b) Robust design

Figure 1. Illustration of the sensitivity of the system response to noise factors (Gong et al. 2014b)

While the gradient ∇g, defined in Eq. (1), is shown as an effective indicator of the design robustness, two problems need to be resolved before the robust design optimization could be implemented. First, the gradient is an n-dimensional vector; as the units of noise factors are different, the mathematical operation of this vector could be a problem. Second, the gradient is a vector rather than a scalar; it is not as convenient and effective as a scalar to use for screening candidate designs in the design pool.

To solve the first problem, each partial derivative in the gradient vector, $\left.\frac{\partial g(\boldsymbol{d},\boldsymbol{\theta})}{\partial \theta_i}\right|_{\boldsymbol{\theta}=\boldsymbol{\theta}'}$, is multiplied by a scaling factor of θ_i' so that the effect of the units of noise factors on the design robustness can be eliminated. Then, the gradient vector shown in Eq. (1) is re-written as follows, which is defined herein as the normalized gradient vector (**J**):

$$\mathbf{J} = \left\{ \left.\frac{\theta_1'\partial g(\boldsymbol{d},\boldsymbol{\theta})}{\partial \theta_1}\right|_{\boldsymbol{\theta}=\boldsymbol{\theta}'}, \left.\frac{\theta_2'\partial g(\boldsymbol{d},\boldsymbol{\theta})}{\partial \theta_2}\right|_{\boldsymbol{\theta}=\boldsymbol{\theta}'}, \mathrm{L}, \left.\frac{\theta_n'\partial g(\boldsymbol{d},\boldsymbol{\theta})}{\partial \theta_n}\right|_{\boldsymbol{\theta}=\boldsymbol{\theta}'} \right\} \tag{2}$$

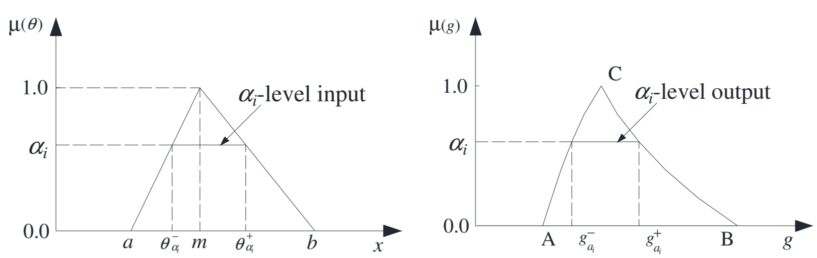
Note that a noise factor that exhibits higher variability could contribute more to the design robustness. Thus, a weighting factor, which indicates the contribution of the noise factor to the robustness, might be adopted in formulation of the normalized gradient vector (**J**), which is detailed in Gong et al. (2016a). To solve the second problem, the Euclidean norm of the normalized gradient vector, which signals the length of the normalized gradient vector (**J**), is adopted and defined herein as the sensitivity index (SI).

$$\mathrm{SI} = \sqrt{\mathbf{J}\mathbf{J}^{\mathrm{T}}} \tag{3}$$

The sensitivity index (SI) shown in Eq. (3) yields a single value representation of the normalized gradient vector. As can be seen, a higher SI value signals lower design robustness, as it indicates a greater variation of the system response in the face of the uncertainty in the noise factors.

2.1.2 Fuzzy set-based signal-to-noise ratio

A fuzzy set is a set of ordered pairs, [θ, $\mu(\theta)$], where a member θ belongs to the set with a certain confidence, called membership grade, $\mu(\theta)$. These ordered pairs collectively define a membership function that specifies a membership grade for each member. Note that although the membership function is not a probability density function (PDF), a membership grade does give a degree of confidence that a member θ belongs to this set. If the highest membership grade in a fuzzy set is normalized to 1 and the shape of the membership function is unimodal, this fuzzy set becomes a fuzzy number. For a geotechnical parameter with known upper bound and lower bound, the membership function could be conveniently constructed by setting the membership grade at θ = upper bound or upper bound to 0, while the membership grade at θ = the average of the upper bound and the upper bound to 1, as shown in Fig. 2(a). As such, the uncertain input parameters are modeled with triangular fuzzy numbers (i.e., the fuzzy numbers with a triangular shape membership function). Of course, other membership function, such as trapezoidal shape, may be used.



(a) α-cut interval of a fuzzy input number (b) Fuzzy output from vertex method

Figure 2. Geotechnical analysis with fuzzy input data

For a geotechnical system with fuzzy input data, the uncertainty propagation may be studied with vertex method (Dong and Wong 1987). In the context of vertex method, the corresponding interval of output, in terms of $g_{a_i}^{-}$ and $g_{a_i}^{+}$, for the α_i-cut level of input fuzzy data (see Figure 2b) is able to be obtained through 2^n deterministic analysis, where n represents the number of fuzzy input data. After finishing the analysis of all α-cut levels, the final fuzzy output could be easily constructed, which represents the final outcomes of the uncertainty propagation through the solution model. Detailed information of the system performance could be provided from which. For example, the mean and standard deviation of the system performance $g(\boldsymbol{d}, \boldsymbol{\theta})$, denoted as $E[g]$ and $\sigma[g]$, respectively, can readily be derived from the fuzzy out shown in Figure 2(b), using the formulation in Gong et al. (2014a&2015). Then, the signal-to-noise ratio (SNR), defined below, is constructed to measure the design robustness (Phadke 1989).

$$\mathrm{SNR} = 10\log_{10}\left(\frac{E^2\left[g(\boldsymbol{d},\boldsymbol{\theta})\right]}{\sigma^2\left[g(\boldsymbol{d},\boldsymbol{\theta})\right]}\right) \tag{4}$$

Here, a higher SNR signals lower variability of the system response, and thus higher design robustness.

2.1.3 Reliability-based feasibility index

Note that although the probabilistic distributions of the noise factors could be determined, the statistical (e.g., coefficient of variation) of the noise factors could not be characterized with certainty because of the limited availability of site-specific data. However, the failure probability estimate obtained from the probabilistic approach is often greatly dependent upon the adopted statistical information of the uncertain input parameters. In consideration of the uncertainty in the statistical characterization of the noise factors, the failure probability of a geotechnical system may not be able to be accurately derived and which will be uncertain. In such a circumstance, the variation of the failure probability, which could arise from the uncertainty in the statistical characterization of the noise factors, needs to be estimated and minimized in the context of RGD. That is to say, the variation of the failure probability may be adopted as the robustness measure (Juang et al. 2012&2013). A smaller variation of the failure probability signals lower variability of the system response (i.e., failure probability in the context of the probabilistic approach), and thus higher design robustness. It is noted that the target failure probability might be different for different geotechnical system and the magnitude of the variation of the failure probability could vary in a significant range. Thus, the reliability-based feasibility index (β_β), defined below, could be employed (Juang et al. 2012&2013; Huang et al. 2014a).

$$\beta_\beta = \frac{\ln\left[\dfrac{\mathrm{P}_{f\mathrm{T}}}{\mathrm{P}_{f\mathrm{mean}}}\sqrt{1+(\mathrm{P}_{f\mathrm{std}}/\mathrm{P}_{f\mathrm{mean}})^2}\right]}{\sqrt{\ln\left[1+(\mathrm{P}_{f\mathrm{std}}/\mathrm{P}_{f\mathrm{mean}})^2\right]}} \tag{5}$$

where $P_{f\mathrm{T}}$ represents the target failure probability; and, $P_{f\mathrm{mean}}$ and $P_{f\mathrm{std}}$ represent the mean and standard deviation of the failure probability. As can be seen in Eq. (5), the failure probability is assumed to be lognormally distributed; here, the feasibility index (β_β) can be interpreted as the feasibility probability of the geotechnical system that the target failure probability is stratified:

$$\Phi\left(\beta_\beta\right) = \Pr[\mathrm{P}_f < \mathrm{P}_{f\mathrm{T}}] \tag{6}$$

where $\Phi(\cdot)$ represents the cumulative distribution of the standard normal variable, and $\Pr[P_f < P_{f\mathrm{T}}]$ represents that the target failure probability of this geotechnical system could be stratified in the face of the uncertainty in the statistical characterization of the uncertain input parameters.

For a given set of statistics of the uncertain input parameters, the failure probability (P_f) of the geotechnical system can readily be estimated with the probabilistic methods such as first order reliability method (FORM) (Low and Tang 2007), Monte Carlo simulation (MCS), and point estimate method (PEM) (Zhao and Ono 2000). In consideration of the uncertainty in the statistical characterization of the noise factors, the two-loop probabilistic analysis should be conducted. The inner loop is employed to estimate the failure probability for a given set of statistics of the noise factors, this is similar to the existing probabilistic analysis. The second loop is employed to derive the mean and standard deviation of the failure probability that arise from the uncertainty in the statistics of the noise factors. To this end, the PEM-FORM (Juang et al. 2013), PEM-MCS, and weighted MCS (Peng et al. 2016) may be employed.

2.2 Multi-objective optimization

The essence of RGD is to seek an optimal design with respect to design robustness and cost, while satisfying the safety requirements. Once the system response of concern is chosen, and the design robustness, cost, and safety are evaluated, the optimal design could be obtained through a multi-objective optimization formulated as follows.

$$\begin{array}{ll} \text{Find:} & \text{design parameters } \boldsymbol{d} \\ \text{Subject to:} & \boldsymbol{d} \in \text{design space } \boldsymbol{DS} \\ & \text{satisfying safety requirements} \\ \text{Objectives:} & \text{maximizing design robustness} \\ & \text{minimizing cost} \end{array} \tag{7}$$

Based on the level of characterization of the uncertain input parameters, the safety requirements may be evaluated using either the deterministic (i.e., factor of safety-based) or probabilistic (i.e., reliability-based) approach; similarly, the design robustness can be evaluated using the either the gradient-based sensitivity index (SI), fuzzy set-based signal-to-noise ratio (SNR), or reliability-based feasibility index (β_β).

In reference to the optimization setting shown in Eq. (7), a single best optimal design is generally unattainable since these two objectives, robustness and cost, are conflicting. The multi-objective optimization in this scenario yields a set of "non-dominated" designs, the collection of all these non-dominated designs is known as Pareto front (Deb et al. 2002). Among all the designs on the Pareto front, none is superior or inferior to others on the Pareto front with respect to both objectives, but they are all superior to the designs in the feasible domain. Figure 3 shows a conceptual sketch of Pareto front in a bi-objective optimization problem. Note that the utopia point, shown in Figure 3, is an unattainable design, the concept of which is discussed later.

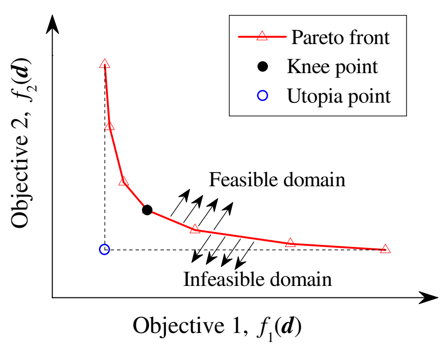


Figure 3. Conceptual sketch of Pareto front and knee point in a bi-objective optimization

The Pareto front in Figure 3 could be easily obtained with the multi-objective optimization algorithms such as "Non-dominated Sorting Genetic Algorithm" version II (NSGA-II) developed by Deb et al. (2002). The derived Pareto front is problem-specific, which could be employed as a design aid to assist in making an informed design decision. For example, at a preferred (pre-specified) cost level, the design with the highest robustness among all points on the Pareto front can be taken as the final design. On the other hand, at a pre-specified robustness level, the design with the least cost among all points on the Pareto front can be taken as the final design. The choice of an appropriate level of cost or robustness, however, is problem-specific. When no such a design preference is specified, the knee point on the Pareto Front, which yields the best compromise between robustness and cost efficiency, may be taken as the most preferred design in the design space. Interested readers are referred to Branke et al. (2004) and Deb and Gupta (2011) for detailed procedures for identifying the knee point on the Pareto Front.

Instead of the genetic algorithms such as NSGA-II, the Pareto front shown in Figure 3 could also be identified with the simplified procedure detailed in Khoshnevisan (2015), in which the bi-objective optimization is transformed into a series of single-objective optimizations. Further, the owner or client may be only interested in the most preferred design in the design space (i.e., the knee point on the Pareto front), and not the Pareto front per se. Thus, a simplified procedure is further developed in Gong et al. (2016b), in which the multi-objective optimization is solved through a series of single-objective optimizations and the knee point on the Pareto front could be identified directly (Khoshnevisan et al. 2014; Gong et al. 2016b).

3. Procedures for Implementing Robust Geotechnical Design

The procedures for implementing the proposed RGD could be summarized in the following main steps:

Step 1: Describe the geotechnical problem of concern with mathematical models. Here, the system response of concern, noise factors, and design parameters are identified; meanwhile, the design (safety) requirements, design robustness, cost, and design space are formulated.

Step 2: Carry out the robust design optimization considering design robustness, cost efficiency, and safety requirements using the optimization setting shown in Eq. (7), where the design robustness and safety requirements for each candidate design could be analyzed based on the level of characterization of the uncertain input parameters (or noise factors). The results of the optimization culminate in a Pareto front showing a tradeoff between design robustness and cost efficiency for all the non-dominated designs that satisfy the safety requirements. Here, the Pareto front can be identified using either the genetic algorithms such as NSGA-II (Deb et al. 2002) or simplified procedure in Khoshnevisan (2015).

Step 3: Select the most preferred design on the derived Pareto front. In principle, either the least cost design that is above a pre-specified level of design robustness or the most robust design that falls within a pre-specified cost level may be selected as the most preferred design in the design space. Alternatively, the knee point, which represents the best compromise solution in the design space, may be identified (Branke et al. 2004; Deb and Gupta 2011). It is worth noting that the most preferred design in the design space could also be identified directly with the simplified procedure in Gong et al. (2016b).

4. Cases Study

To demonstrate the versatility and effectiveness of the RGD, three cases, including braced excavation, shield tunnel, and retaining wall, are studied in this section.

4.1 Case 1: Robust design of braced excavation

The first case concerns the robust design of a shoring system, which consists of soldier piles (i.e., reinforced concrete piles) with timber laggings and tieback anchors, for an excavation in a sandy soil deposit, as shown in Figure 4. The robust design of this case is detailed in Gong et al.

(2016b). In this case, the diameter of the concrete soldier pile (D), length of the concrete soldier pile (L), interval of concrete soldier piles (I), vertical spacing of tieback anchors (V), horizontal spacing of tieback anchors (H), and the angle of tieback anchors with respect to the horizontal direction (α) are taken as the design parameters. Whereas, the preload of tieback anchors is chosen at 20 ton per tieback, and the length of tieback anchors is set at 8.0 m based on local practice. For illustration purpose, a discrete design space is considered, which specifies the possible selections of the design parameters, as listed in Table 1, and 38,500 candidate designs are considered.

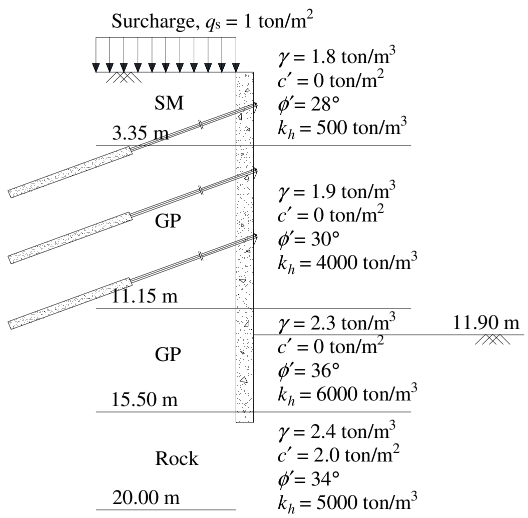


Figure 4. Excavation with a shoring system of soldier piles and anchor tiebacks

Table 1. Design space of the design parameters for Case 1

Design parameter	Design space
Diameter of the solider pile, D (m)	{0.3 m, 0.4m, 0.5m, 0.6 m, 0.7 m}
Length of the solider pile, L (m)	{14 m, 15 m, 16 m, 17 m, 18 m, 19 m, 20 m}
Horizontal interval of the solider pile, I (m)	{D, D + 0.1 m, D + 0.2 m, …, D + 1.0 m}
Vertical spacing of tieback anchors, V (m)	{2.0 m, 2.5 m, 3.0 m, 3.5 m}
Horizontal spacing of tieback anchors, H (m)	{1.5 m, 2.0 m, 2.5 m, 3.0 m, 3.5 m}
Installed angle of the tieback anchor, α (°)	{10°, 15°, 20°, 25°, 30°}

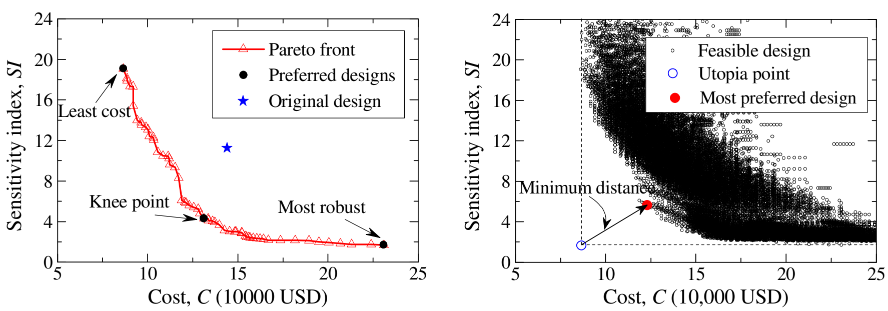
The drained cohesion (c'), drained friction angle (ϕ') and modulus of horizontal subgrade reaction (k_h), along with the surcharge behind the wall (q_s), are considered the noise factors (i.e., uncertain input parameters). Due to the limited availability of site specific-data, only the nominal values of the noise factors could be estimated; as such, the design robustness is measured herein by the gradient-based sensitivity index (SI). Through which, the variations in the noise factors are recognized but there is no need to perform a detailed statistical characterization of the noise factors, as the system response (i.e., stability and deformation) and its sensitivity with respect to the noise factors could be approximately evaluated with the nominal values of the noise factors.

In general, the safety requirement of a braced excavation is evaluated through the limiting factors of safety and limiting maximum wall and/or ground deformation (JSA 1988; TGS 2001; PSCG 2000). Here, TORSA, a commercially available FEM code based on the beam-on-elastic-foundation theory (Sino-Geotechnics 2010), is used to compute the system responses, including the factor of safety again push-in failure (F_{S1}), factor of safety against basal heave failure (F_{S2}), and the maximum wall deflection (y). In RGD, the maximum wall deflection is chosen as the system response of concern for the purpose of defining the design robustness; whereas, the safety requirement is evaluated with the computed factors of safety and wall deformation.

For a shoring system project, the cost (C) should be the sum of the cost on excavation, cost on soldier pile wall and cost on tieback anchors. Because the site dimensions and excavation depth, in the specified project, are predefined based on the project's requirements, the cost on excavation will not affect the optimization results, and only the cost on the shoring system is considered in the robust design optimization. The detailed formulation of the cost (C) could be found in Gong et al. (2016b). The robust design optimization setting of this case is depicted in Figure 5.

Find: $\boldsymbol{d}$ (design parameters)
Subject to: $\boldsymbol{d} \in \boldsymbol{S}$ (design space)
$Fs_1 > 1.5$ (factor of safety against push-in failure)
$Fs_2 > 1.5$ (factor of safety against basal heave failure)
$y < 0.7\% H_f$ (maximum wall deflection requirement)
Objectives: min SI (sensitivity of maixmum wall deflection to noise factors)
min C (cost)

Figure 5. Robust optimization setting for Case 1 (where H_f is the final excavation depth)



(a) Genetic algorithm NSGA-II (b) Simplified procedure

Figure 6. Results of the robust design for Case 1

Applying the genetic algorithm NSGA-II (Deb et al. 2002), the robust design optimization shown in Figure 5 yields a Pareto front, as plotted in Figure 6(a); then, the knee point is located, which is also plotted in Figure 6(a). Meanwhile, the robust design is carried out using the simplified procedure in Gong et al. (2016b); with which, the knee point is identified directly without constructing the Pareto front and the results are plotted in Figure 6(b). Note that the difference between the knee point obtained by the simplified procedure and that obtained by the multi-objective optimization algorithm NSGA-II is quite negligible. Next, a comparison with the original design that was selected by the engineering firm is made. The original design is the one designed by an experienced engineering firm (Hsii-Sheng Hsieh, personal communication 2013) without the knowledge of RGD. While the original design appears to be a sound engineering practice, offering a compromise between the least cost design and the most robust design, it is inferior to the knee point on the Pareto front, as the latter is more robust and cost less. Through this real-world application, the advantages of RGD are demonstrated.

The design parameters of these designs are tabulated in Table 2. Here, the knee point on the resulting Pareto front is obtained by the normal boundary intersection approach (Deb and Gupta 2011) and marginal utility function approach (Branke et al. 2004). These two approaches yield the same design, denoted as $\boldsymbol{d}_{2\text{-}1}$. The difference between the design parameters of the most preferred design obtained by the simplified procedure, denoted as $\boldsymbol{d}_{2\text{-}2}$, and those of $\boldsymbol{d}_{2\text{-}1}$ is relatively small and could be ignored. The results show that the most preferred design obtained by the simplified procedure is practically the same as the knee point on the Pareto front obtained by the multi-objective optimization method, which requires a two-step solution (developing a Pareto front by the multi-objective optimization using genetic algorithms such as NSGA-II, and then searching for knee point on the Pareto front). From there, the effectiveness of the simplified procedure is demonstrated.

Table 2. Most preferred design obtained with different approaches for Case 1

Adopted approach	Design parameters						Design performances			Cost, C (10,000 USD)	Sensitivity index, SI
	D (m)	L (m)	I (m)	V (m)	H (m)	α (°)	Fs_1	Fs_2	y (cm)		
NSGA-II and normal boundary intersection approach, $\boldsymbol{d}_{2\text{-}1}$	0.6	18	1.6	3.0	2.0	10	5.67	2.96	3.48	13.12	4.28
NSGA-II and marginal utility function approach, $\boldsymbol{d}_{2\text{-}1}$	0.6	18	1.6	3.0	2.0	10	5.67	2.96	3.48	13.12	4.28
Simplified procedure, $\boldsymbol{d}_{2\text{-}2}$	0.5	18	1.4	3.0	2.0	10	5.67	2.96	4.94	12.31	5.58
Original design, $\boldsymbol{d}_0$	0.5	17	0.6	3.0	2.5	20	4.46	2.75	4.13	14.42	11.22

4.2 Case 2: Robust design of shield tunnel

The second case considers the robust design of the cross section of a shield tunnel in Shanghai, as shown in Figure 7. The robust design of this case is detailed in Huang et al. (2014b). In this case, the segment thickness (t), steel reinforcement ratio (ρ), and diameter of joint bolt (D_j) are dealt as the design parameters and which are to be optimized in a pre-assigned design space. The soil resistance coefficient (Ks), soil cohesion strength (c), soil friction angle (φ), ground water table (H_{GWT}), and surcharge (q_0) are considered as the noise factors. Here, only the upper and lower bounds of the noise factors can be estimated and which are tabulated in Table 3. The other deterministic parameters to assess the tunnel performance, in terms of the structure safety (i.e., ULS performance) and serviceability (i.e., SLS performance), are tabulated in Table 4.

The design robustness, in this case, is evaluated using the fuzzy set-based signal-to-noise (SNR), the cost (C) is represented by the material cost of one tunnel ring that consists of segment concrete cost, steel reinforcement cost and joint bolts cost, and the safety requirements (i.e., ULS and SLS behavior) are evaluated using the reliability indexes that are derived from the fuzzy outputs. The formulations of the design robustness, cost, and safety requirements are detailed in Gong et al. (2014a).

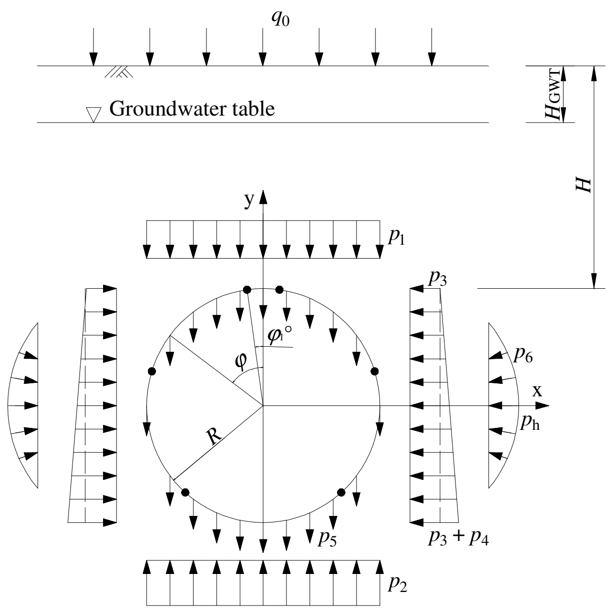


Figure 7. Analysis model of shield tunnels (Huang et al. 2014b)

In this case, the design parameters (t, ρ, D_j) are to be optimized in the contiguous design space of [0.2 m, 0.5 m], [0.5%, 4.0%] and [10.0 mm, 50.0 mm] such that the design robustness and cost efficiency are maximized simultaneously. The robust design optimization setting of this case is set up as follows.

$$\begin{aligned}
&\text{Find:} && (t, \rho, D_j) \\
&\text{Subjected to:} && 0.2\text{m} \le t \le 0.5\text{m}; 0.5\% \le \rho \le 4.0\%; 10\text{mm} \le D_j \le 50\text{mm} \\
& && |\beta_1 - 4.2| \le 0.1\%; |\beta_2 - 2.7| \le 0.1\% \\
&\text{Objectives:} && \text{Maximizing the robustness index of ULS, SNR}_1 \\
& && \text{Maximizing the robustness index of SLS, SNR}_2 \\
& && \text{Minimizing the cost, } C(t, \rho, D_j)
\end{aligned} \tag{8}$$

where $\beta_{\beta 1}$ and $\beta_{\beta 2}$ represent the reliability index of this shield tunnel with respect to the ULS and SLS behavior, respectively; and, SNR_1 and SNR_2 represent the design robustness of this shield tunnel with respect to the ULS and SLS performance, respectively.

Table 3. Parameters characterizing membership functions of noise factors

Noise factors	Lower	Mode,	Upper

	bound, a	$m = (a + b)/2$	bound, b
Soil resistance coefficient, Ks (kN/m^3)	3500	9250	15000
Soil cohesion strength, c (kN/m^2)	0	7.5	15
Soil friction angle, ϕ (°)	30	32.65	35.3
Ground water table, H_{GWT} (m)	0.5	1.25	2
Ground surcharge, q_0 (kN/m^2)	0	10	20

Table 4. Constant parameters involved in the tunnel design

Category	Parameter	Value
Tunnel geometry parameters	Embedded depth, H (m)	15.0
	Tunnel inner radius, R_{in} (m)	2.75
	With of tunnel ring, b (m)	1.0
	Joint position of half structure, φ_i (°)	8, 73, 138
Tunnel segment	Unit weight of concrete, γ_c (kN/m^3)	25.0
	Elastic modulus of concrete, E_c (kN/m^2)	35×10^6
	Compression strength of concrete, f_c (kN/m^2)	39×10^3
	Ultimate plastic strain of concrete, ε_p	0.0033
Reinforcement steel	Elastic modulus of steel, E_s (kN/m^2)	210×10^6
	Yielding strength of steel bar, f_y (kN/m^2)	345×10^3
	Thickness of protective cover, a (m)	0.05
Joint bolts	Bolt length, l_b (m)	0.4
	Number of bolts at each joint	2
	Distance from joint bolts to tunnel inside surface, h	t/3

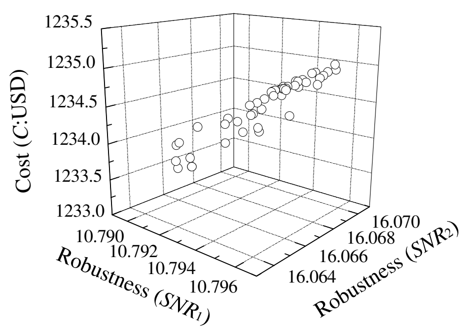


Figure 8. Resulting non-dominated optimal designs for Case 2

With the robust design optimization setting shown in Eq. (8), the RGD of this shield tunnel is readily conducted with NSGA-II (Deb et al. 2002). In this non-dominated optimization using NSGA-II, the population size is assigned as 50 while the generation number is set as 100. The resulting non-dominated optimal designs are depicted in Figure 8, the tradeoff relationship between the robustness (i.e., SNR_1 and SNR_2) and cost is clearly illustrated: design robustness tends to increase with the cost. Thus, the desire to maximize the design robustness and the desire to minimize the cost are two conflicting objectives.

Note that while the obtained non-dominated optimal designs shown in Figure 8 concentrate in a relative narrow range due to the safety requirements adopted, no single best design could be screened out. In order to further ease the decision making in the RGD of shield-driven tunnels, the knee point on the Pareto front is identified. The resulting knee point is employed as the most preferred design and the best compromise among the conflicting design objectives. The design parameters of the identified knee point are: t = 288.1 mm, ρ = 1.16 %, D_j = 49.2 mm, and corresponding 3-D coordinate in Figure 8 is: SNR_1 = 10.793, SNR_2 = 16.070, C = 1234.2 USD.

To demonstrate the significance of the RGD of shield tunnels, a comparison among the robust design, probabilistic design and current practice (i.e., design adopted in Shanghai) is conducted, and the results are listed in Table 5. Comparing with probabilistic design and current practice, the design parameters of robust design are notably adjusted: the segment thickness is decreased while the steel reinforcement ratio and joint bolts diameters are increased; that is to say, the joint stiffness is increased while the stiffness of segment is decreased. This adjustment of the design parameters of the shield tunnel is quite reasonable. Though the resulting robustness indexes (SNR_1 and SNR_2) do not change much, the variation (i.e., COV) of tunnel performances do decrease significantly. For example, the variation of the system performance of the robust design is significantly reduced (as large as 30% for ULS) whereas the cost is only increased by 25%. Thus, the significance of the RGD is illustrated.

Table 5. Comparison among three design designs for Case 2

Category	Parameter	Robust design	Probabilistic design	Current practice
Design parameters	t (mm)	288.1	343.5	350.0
	ρ (%)	1.16	0.83	0.50
	D_j (mm)	49.2	28.5	30.0
Safety	β_1 of ULS	4.20	4.20	2.51
	β_2 of SLS	2.70	2.70	3.08
Robustness	SNR_1 of ULS	10.793	10.160	8.533
	SNR_2 of SLS	16.070	16.210	16.424
Cost	C (USD)	1234.2	1175.5	988.9
Coefficient of variation (COV)	Fs_1 of ULS	0.289	0.310	0.374
	Fs_2 of SLS	0.157	0.155	0.151

4.3 Case 3: Robust design of retaining wall

The third case considers the robust design of a retaining wall, as shown in Figure 9. The robust design of this case is detailed in Huang et al. (2014a). In this case, the base width (a) and top width (b) of the retaining wall are treated as the design parameters, and which are to be optimized in the discrete design space of $\{(a, b)|\ a$ = 0.2 m, 0.4 m, 0.6 m and b = 0.6 m, 0.7 m, 0.8 m, …, 3.0 m$\}$. The unit weight of the backfill soil (γ), soil friction angle (φ), friction angle between the backfill and retaining wall (δ), and the adhesion (c_a) are considered as the noise factors. Here, the noise factors are characterized as uncertain variables, however, the statistics of which could not be estimated with certainty. The statistical information of the noise factors are tabulated in Table 6; note that the COVs of the noise factors are assumed to be lognormally distributed. Here, the performances regarding the overturning and sliding failure are studied.

The safety requirements are evaluated using the mean of the failure probabilities (i.e., P_{f1} and P_{f2} for the overturning and sliding failure, respectively), the design robustness is evaluated using the reliability-based feasibility index (i.e., $\beta_{\beta 1}$ and $\beta_{\beta 2}$ for the overturning and sliding failure, respectively), and the cost (C) is evaluated using the volume of the retaining wall. Detailed formulations of these factors could be found in Huang et al. (2014a).

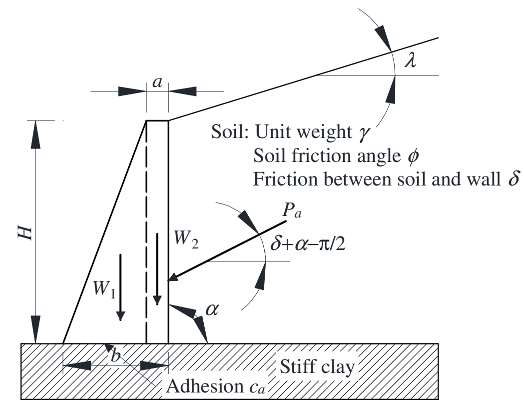


Figure 9. Schematic diagram of the retaining wall design for Case 3

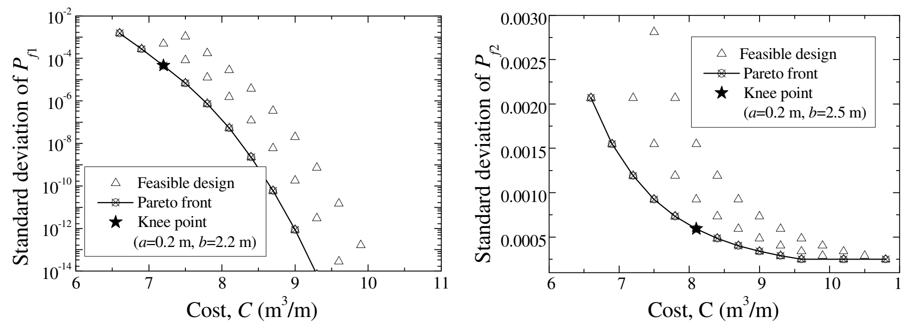
Table 6. Statistical information of the noise factors for Case 3

Noise factors	Distribution type	Mean, μ	Coefficient of variation, COV	Mean of COV, μ_cov	Standard deviation of COV, σ_cov
Unit weight, γ_s	Normal	18kN/m^3	2~10%	6.5%	1.17%
Friction angle, ϕ	Normal	35°	5~20%	10%	2.50%
Friction between soil and retaining wall, δ	Normal	20°	5~20%	10%	2.50%
Adhesion between wall base and clay, c_a	Normal	100kPa	10~30%	15%	3.33%

Table 7. Identified final designs for Case 3

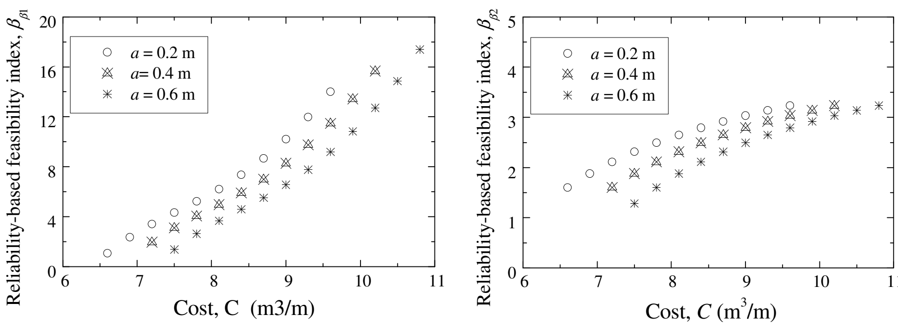
Target reliability-based feasibility index, $\beta_{\beta T}$	Confidence level, Pr[$P_f < P_{fT}$]	Identified final design	Reliability-based feasibility index, β_β	Cost, C
$\beta_{\beta T}$ =1.5	93.32%	a = 0.2 m b = 2.1 m	$\beta_{\beta 1}$ = 2.36 $\beta_{\beta 2}$ = 1.88	6.9m^3/m
$\beta_{\beta T}$ =2.0	97.72%	a = 0.2 m b = 2.2 m	$\beta_{\beta 1}$ = 3.41 $\beta_{\beta 2}$ = 2.11	7.2 m^3/m
$\beta_{\beta T}$ =2.5	99.38%	a = 0.2 m b = 2.5 m	$\beta_{\beta 1}$ = 6.21 $\beta_{\beta 2}$ = 2.65	8.1 m^3/m
$\beta_{\beta T}$ =3.0	99.87%	a = 0.2 m b = 2.8 m	$\beta_{\beta 1}$ = 10.21 $\beta_{\beta 2}$ = 3.03	9.0 m^3/m

Figure 10 shows the tradeoff relationship between the variation of the failure probability and the cost, the variation of the failure probability generally decreases with the increase of the cost. Next, the reliability-based feasibility indexes of these discrete candidate designs are studied and the results are plotted in Figure 11; as expected, the reliability-based feasibility index often increases with the cost. With the aid of Figure 11, the final design could be readily identified. For example, Table 7 illustrates the resulting robust designs that are identified for a series of target reliability-based feasibility indexes.



(a) Overturning failure mode (b) Sliding failure mode

Figure 10. Tradeoff between the variation of the failure probability and the cost (Case 3)



(a) Overturning failure mode (b) Sliding failure mode

Figure 11. Relationship between the reliability-based feasibility index and the cost (Case 3)

Discussion and Conclusion

The uncertainties in soil parameters, solution model, applied loads, and those caused by the construction, often make it difficult to ascertain the performance of a geotechnical design. In traditional deterministic approaches, these uncertainties could not be explicitly characterized and included in the design analysis; rather, a conservative factor of safety (FS) is adopted based on the concept of "calculated risk". This FS-based design approach often leads to an inefficient over-design with an unknown and/or inconsistent safety level, although under-design is also a possibility. To achieve a more rational and consistent assessment of the safety, the reliability-based design (RBD) approach has long been suggested as an alternative. The RBD approach for the design of a geotechnical structure is often implemented with a target reliability index, which is derived from a cost-benefit analysis that balances investment and risk considering the failure probability and consequence.

In the context of RBD approach, the performance of a geotechnical structure is analyzed using probabilistic methods that consider explicitly uncertainties in input parameters and/or solution models. It is noted that although various methods have been investigated to estimate the statistics of soil parameters and model errors, the statistics of soil parameters and those of model errors could not be characterized with certainty due to limited availability of site-specific data. Because of the difficulty in obtaining the accurate statistical characterization of soil parameters and model errors in practice, the RBD approach is not widely applied in geotechnical practice; rather, the load and resistance factor design (LRFD) approach, which is a simpler variant of the RBD approach by design, is more commonly used. The LRFD code employs partial factors (e.g., resistance factors and load factors), which have been calibrated to achieve a target reliability index approximately over a range of design scenarios covered by the code. The resulting design is a function of the specified partial factors and selected nominal values, with due consideration of cost. As is well recognized, LRFD is meant to be a simpler variant of the more demanding RBD; the ideal outcome is that the design obtained by LRFD could achieve the same target reliability index as that obtained by RBD. However, the standard LRFD approach that involves fixed partial factors cannot cover all design scenarios involving different levels of variation of soil parameters and model errors. For a given design scenario, the use of the standard LRFD code may lead to a design that deviates from the target reliability index by an unknown amount, more likely on the conservative side but under-design is also a possibility..

In such circumstances, the robust geotechnical design (RGD) philosophy was advanced. With which, the uncertainty in the predicted performance of a given geotechnical design could be effectively reduced in the face of recognized but unquantified uncertainties (i.e., the uncertainties in soil parameters, solution model, applied loads, and those caused by construction). The purpose of robust design is to derive a design that effectively accounts for the effect of the variation in “noise factors” while simultaneously considers the safety and cost efficiency. In this report, the RGD, along with the fundamental issues of how the design robustness is measured, how the robust design optimization is conducted, and how the most preferred design in the designs space is selected, is presented and illustrated with cases studies. Based upon the results outlined in this report, the versatility and significance of the RGD are demonstrated.

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