Structural Safety 33 (2011) 64–73

Contents lists available at ScienceDirect

Structural Safety

journal homepage: www.elsevier.com/locate/strusafe

Computational intelligence methods for the efficient reliability analysis of complex flood defence structures

Greer B. Kingston [a], Mohammadreza Rajabalinejad [b], Ben P. Gouldby [a,*], Pieter H.A.J.M. Van Gelder [b]

[a] HR Wallingford Ltd., Howbery Park, Wallingford, Oxfordshire OX10 8BA, United Kingdom
[b] Faculty of Civil Engineering and Geosciences, Delft University of Technology, 2600 GA Delft, The Netherlands

ARTICLE INFO

Article history:
Received 24 November 2008
Received in revised form 12 August 2010
Accepted 19 August 2010
Available online 27 September 2010

Keywords:
Flood defence
Structural reliability
Artificial neural networks
Genetic algorithms
Adaptive sampling
Response surface function

ABSTRACT

With the continual rise of sea levels and deterioration of flood defence structures over time, it is no longer appropriate to define a design level of flood protection, but rather, it is necessary to estimate the reliability of flood defences under varying and uncertain conditions. For complex geotechnical failure mechanisms, it is often necessary to employ computationally expensive finite element methods to analyse defence and soil behaviours; however, methods available for structural reliability analysis are generally not suitable for direct application to such models where the limit state function is only defined implicitly. In this study, an artificial neural network is used as a response surface function to efficiently emulate the complex finite element model within a Monte Carlo simulation. To ensure the successful and robust implementation of this approach, a genetic algorithm adaptive sampling method is designed and applied to focus sampling of the implicit limit state function towards the limit state region in which the accuracy of the estimated response is of the greatest importance to the estimated structural reliability. The accuracy and gains in computational efficiency obtainable using the proposed method are demonstrated when applied to the 17th Street Canal flood wall which catastrophically failed when Hurricane Katrina hit New Orleans in 2005.

1. Introduction

Floods are a widespread and potentially devastating natural hazard. Recent serious flood events throughout the world, such as the 2002 and 2005 European floods, the New Orleans event in 2005 [1,2] and the 2007 UK summer floods [3], have prompted a shift away from flood protection policies that consider a 'standard of protection' towards risk-based flood assessment methods, which take into account the probability of flooding and the related consequences. In much of the developed world, the probability of flooding has been modified by the construction of flood defences (e.g. dikes, flood gates), which form an important part of a broader approach to integrated flood risk management. Thus, to support credible estimates of the probability of flood inundation, the structural reliability of flood defences, given uncertain strength and loading conditions, must be taken into account.

In traditional structural reliability analysis, failure of a structure arises when the loads acting upon the structure, S, exceed its bearing capacity, or resistance, R. Here, R and S are functions of the basic random variables $\mathbf{X} = \{X_i,\ i = 1,\ldots,K\}$, which describe the material properties of, and the external loads applied to, the structure. The problem is then typically presented in the following generalised form [4]:

$$P_f = P[g(R,S) \leqslant 0] = \int_{g(R,S)\leqslant 0} f_{\mathbf{X}}(\mathbf{x})d\mathbf{x} \tag{1}$$

where P_f gives the probability of failure; $f_{\mathbf{X}}(\mathbf{x})$ is the multivariate probability density function of $\mathbf{X}$; and $g(R,S)$ is the well known limit state function (LSF), which is often defined as $g(\mathbf{X}) = R - S$. In system based flood risk analysis models, where series of flood defences protect urban areas and there is a requirement to model the consequences of failure in terms of damage to infrastructure through inundation, it can be convenient to consider the *fragility* of individual flood defence cross-sections (e.g. see [5]), which is the probability of failure conditional on loading, defined by:

$$P_f = P[g(\mathbf{X}) \leqslant 0 | S = s] \tag{2}$$

In some cases, the relationships between R and S are known explicitly and $g(\mathbf{X})$ can be expressed in closed form (or the problem can be suitably simplified such that this is the case). However, in other more complex cases, such as those involving geotechnical instabilities, the LSF can only be evaluated implicitly through a more complex numerical model, such as a finite element (FE) model. For the majority of flood defences, a simplified numerical method (e.g.

* Corresponding author.
E-mail addresses: g.kingston@hrwallingford.co.uk (G.B. Kingston), b.gouldby@hrwallingford.co.uk (B.P. Gouldby).

0167-4730/$ - see front matter © 2010 Elsevier Ltd. All rights reserved.
doi:10.1016/j.strusafe.2010.08.002

Bishop's simplified method) may suffice and, in many cases, will be all that the limited available geotechnical data lends itself to. However, for more critical defences whose failure would result in catastrophic flooding (e.g. storm surge barriers; defences that protect areas lying below sea level in the Netherlands and New Orleans), a full finite element (FE) analysis may be warranted. In these cases, evaluating the probability of failure of the flood defence can be problematic for reasons discussed as follows.

For all but the simplest cases, the integral in (1) is analytically intractable and some method is required to estimate *Pf*. Methods available for this include gradient-based methods (the so-called FORM and SORM approaches) and simulation-based methods (e.g. Monte Carlo methods, Riemann integration) [4]. However, neither of these approaches is directly suitable for estimating the probability of complex flood defence failures where evaluation of the LSF is implicit. The former methods require explicit knowledge of the LSF, as it is necessary to estimate the gradient of the LSF with respect to the basic variables, whilst the latter, simulation-based approaches can be computationally prohibitive, since, for each realisation of the basic random variables, a complete FE analysis is required, which itself requires considerable computational effort.

To overcome the difficulties associated with complex reliability analyses, a number of authors have proposed the use of the Response Surface Method (RSM) [6–9], whereby a so-called response surface function (RSF), which is a more computationally efficient and explicit mapping of the response surface, is used as a *surrogate* or *emulator* of the actual response surface. In the original RSM, RSFs commonly take the form of low order polynomials (usually quadratic). However, the accuracy of such functions in approximating the shape of the actual LSF is limited due to the rigid and non-adaptive structure assumed [10]. This, in turn, limits the accuracy of the estimated P_f. More recently, artificial neural networks (ANNs) have been proposed as alternative RSFs to those employed using the RSM [10–17]. These models have been shown to outperform the traditional RSM due to their superior mapping capabilities and flexible functional form [10]. ANNs also have the advantage of being applicable to higher dimensional problems than the traditional RSM [18].

Despite these advantages, ANNs have not been widely used in reliability analyses of complex systems due to the large number of implicit LSF evaluations that are still required for fitting the ANN model. In most applications of ANN-based RSFs, samples have been generated by standard Monte Carlo simulation (MCS), which may lead to an insufficient covering of the mapping domain, particularly for problems with low failure probability. This is illustrated in Fig. 1, which shows that, using standard MCS, the most probable sampling domain results in limited samples about the limit state $g(\mathbf{X}) = 0$, even if the number of samples is large. This would then lead to an inadequate description of the limit state, which is the region of the actual response surface that must be represented most accurately for the successful application of RSFs in reliability analyses. However, attempts to reduce any inaccuracies in the limit state description by generating a larger set of samples for fitting the ANN then leads to a required effort comparable to direct MCS with the complex FE model.

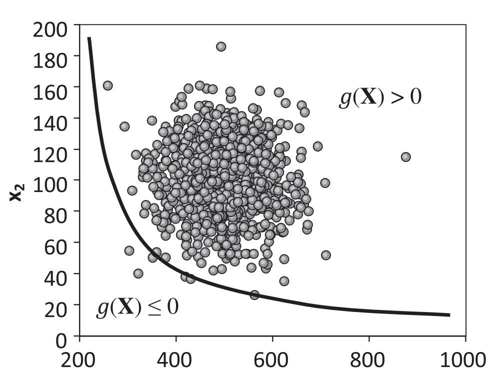

Fig. 1. Inadequate coverage of the mapping domain obtained with standard MCS.

Whilst a variety of importance sampling strategies have been proposed, these are not without their limitations [4]. In this paper, a new adaptive sampling technique based on a genetic algorithm (GA) is presented for focusing the sampling of the actual LSF towards the limit state. This method exploits the population-based search and exploration capabilities of GAs to provide efficient coverage of the entire parameter space with the most densely sampled area being that around the limit state $g(\mathbf{X}) = 0$. This enables the most accurate mapping of the ANN-based RSF in the most important region.

The remainder of this paper is structured as follows: in Section 2, the development of an ANN-based RSF for flood defence reliability analysis is described, whilst in Section 3, the new GA adaptive sampling method used to help train the ANN is presented, together with its advantages over conventional sampling regimes. In Section 4, application of the ANN together with the GA adaptive sampling approach is demonstrated in a case study involving the reliability analysis of the 17th Street flood wall, which catastrophically failed when Hurricane Katrina hit New Orleans. The use of the ANN-based RSF in a Monte Carlo based reliability analysis is compared to direct MCS of the actual implicit LSF in order to assess the accuracy and efficiency of the proposed method and the results are discussed in relation to their implications for flood risk modelling and management. Finally, in Section 5, the conclusions of the paper are drawn.

2. ANN-based RSF

Whilst the LSF describing a complex failure mechanism may not be known explicitly, for *N* limited discrete samples of $\mathbf{X} = \mathbf{x}_n$, where $n = 1,\ldots,N$, the implicit LSF $g(\mathbf{x}_n)$ can be evaluated. The aim in developing a RSF is to find the explicit function $\bar{g}(\mathbf{X})$ that provides the best fit to the set of discrete samples $\{g(\mathbf{x}_n), n = 1,\ldots,N\}$. It is then assumed that if the approximating function $\bar{g}(\mathbf{X})$ fits the discrete samples sufficiently well, particularly in the region around the actual limit state $g(\mathbf{X}) = 0$, a reliable estimate of the probability of failure can be obtained. However, one of the difficulties associated with this approach lies in the fact that the limit state in most realistic structural problems has a highly nonlinear, yet unknown, functional form [9] and that this function is difficult to approximate to a sufficient degree of accuracy given only limited discrete samples of $\mathbf{X}$.

ANNs are especially suited for use as RSFs, as they are able to extract a complex, nonlinear input–output mapping from synthetic data samples without in-depth knowledge of the underlying implicit LSF. Furthermore, once developed, ANNs are relatively quick to run; the necessary characteristic that makes RSFs valuable in situations where quick estimation is required (e.g. in MCS where repeated evaluations of the LSF are performed). A significant advantage of the ANN modelling approach over the more traditional polynomial RSFs is that, being data-driven and model-free, ANNs do not require any restrictive assumptions about the functional form of the LSF, as the latter methods do. In fact, their flexible functional form makes it possible for ANNs to model any continuous function to an arbitrary degree of accuracy and, as such, they are often considered to be 'universal function approximators' [19,20].

Originally designed to mimic the functioning of the brain [21], ANNs are composed of a number of highly interconnected processing units called nodes or *neurons*. Individually, these nodes only