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Slope reliability analysis using surrogate models via new support vector machines with swarm intelligence

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ABSTRACT

Surrogate model methods are attractive ways to improve the efficiency of Monte Carlo simulation (MCS) for structural reliability analysis. An intelligent surrogate model based method for slope system reliability analysis is presented in this study. The novel machine learning technique ν-support vector machine (ν-SVM) is adopted to establish the surrogate model to predict the factor of safety via the samples generated by Latin hypercube sampling. Global optimization algorithms particle swarm optimization and artificial bee colony algorithm are adopted to select the hyper-parameters of ν-SVM model. The applicability of the ν-SVM based surrogate model for slope system reliability analysis is tested on four examples with obvious system effects. It is found that the proposed surrogate model combined with MCS can achieve accurate system failure probability evaluation using fewer deterministic slope stability analyzes than other approaches.

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1. Introduction

Slope stability evaluation is a classical geotechnical engineering problem that is highly amenable to probabilistic treatment. There are several categories of uncertainties encountered in predictions of slope stability, such as material properties, analytical methods, and boundary conditions. In this study, the uncertainty of material properties to probability of failure is discussed. To take uncertainties into account, probabilistic methods are needed in slope stability analysis [1]. In the literature, many reliability analysis methods are developed to estimate the probability of failure of the critical slip surface. However, there may exist many different potential failure modes or slip surfaces in a slope. The failure probability of a certain slip surface will be smaller than that of the whole slope system [2]. Therefore, reliability analysis method considering system effects is required to evaluate the system failure probability more accurately [3].

System reliability of soil slopes has received considerable attention in recent years. Oka and Wu [2], Chowdhury and Xu [4], Low et al. [5] adopted reliability-bounds theories to predict the upper and lower bound values of the system failure probability. Griffiths et al. [6] investigate the failure probability of slopes using the finite-element model combined with the Monte Carlo framework. Chinget al. [7] proposed an approach based on importance sampling for estimating slope system reliability. Wang et al. [8] developed a subset simulation based approach for improving efficiency and resolution of Monte Carlo simulation (MCS) at relatively small probability levels. Some studies [9-12] also present system reliability analysis methods via the identification of representative failure modes or slip surfaces.

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MCS is a straightforward approach to evaluate the system reliability [13]. The disadvantage of MCS is that the computational effort could be extremely intensive. Response surface methods (RSM) or surrogate model methods [14-16] are effective ways to improve the performance of MCS. However, there still has no consensus on how to choose the modeling method for establishing the surrogate model and how to generate the calibration samples, because of the complexity of system reliability analysis problems. A traditional polynomial RSM has been verified unable to approximate the limit states accurately in probabilistic slope stability evaluation [3]. Therefore, Ji and Low [17] proposed stratified RSM to approximate the limit state function. Few works [3,18,19] have verified the effectiveness of MCS directly combined with surrogate models on system slope reliability analysis. Zhang et al. [3] proposed a Kriging-based response surface method, and found that the proposed RSM combined with MCS can accurately estimate the system failure probability. Kang et al. [18] proposed an efficient surrogate model using Gaussian processes assisted by computer experiments to generate calibration samples. They found only 10*D* to 15*D* (*D* is the number of uncertain variables) samples are needed to establish an accurate Gaussian processes surrogate model for predicting factor of safety. For a slope with four uncertain parameters, only 60 calibration samples are needed, which is much less than the samples needed in other works. In our previous study [19], we found support vector regression with ε-tube is a promising tool to build the surrogate model. In some examples, the SVR surrogate model performs well than the Gaussian processes model. Effects of sample number and ranges for generating samples are also studied. However, it is not easy to set a suitable ε range for optimization.

The ν-support vector machines (ν-SVM) are introduced by Schölkopf et al. [20] as a variation of the conventional support vector machines (SVM) [21]. The ν-SVM not only has the same advantages of SVM, such as retaining the principle of SVM and having good generalization capability, but also has additional advantages over SVM. The parameter ν has intuitionistic mean and can directly provide information on the number of support vectors used in regression. In ν-SVM, by introducing the parameter $\nu \in (0, 1]$in the primal problem, the size of ε is calculated by the algorithm automatically. Setting the range for ν is more convenient than setting a suitable range for ε. The ν-SVM model exhibits excellent performance in many engineering problems, such as determination of soluble solids content [22], sensor error modeling [23], inverse analysis of slopes [24].

In this study, ν-SVM is adopted to establish the surrogate model for predicting factor of safety in slope reliability analysis. Meanwhile, there is no general guideline on how to set the hyper-parameters of ν-SVM. Swarm intelligence optimization algorithms, such as particle swarm optimization (PSO) [25] and artificial bee colony algorithm (ABC) [26-29] provide effective approaches for selecting the model parameters. PSO and ABC are both innovative population-based global optimization techniques developed recently, and they are adopted to optimize the surrogate models.

2. System probabilistic stability analysis of slopes

2.1. Probability of failure and reliability index

As with all slopes, the safety evaluation is based on inputs, primarily loads and site characteristics. Since the soil properties are estimated from incomplete data and cannot be determined precisely, an uncertainty is associated with them [30]. According to experience, a safety factor can be applied to account for this. But difficulty is encountered for this approach where experience is inadequate or nonexistent. Then reliability analysis provides an effective way to take the uncertainties into account and estimating their effects on safety.

Reliability is commonly expressed as a probability of failure or a reliability index. The former can be presented as

$$P_f = P\{g(\boldsymbol{x}) \le 0\} = \int_{g(\boldsymbol{x})\le 0} f_{\boldsymbol{x}}(\boldsymbol{x}) d\boldsymbol{x}, \tag{1}$$

where $f_x(\boldsymbol{x})$ is the joint probability density function, $\boldsymbol{x} = [x_1, x_2, \ldots, x_D]$ is the uncertain variables, $g(\boldsymbol{x})$ is the limit state function and $g(\boldsymbol{x}) = 0$ is the boundary between stable and unstable status of the slope.

The limit state function for slope reliability analysis is usually defined as

$$Z = g(\boldsymbol{x}) = F_s(\boldsymbol{x}) - 1.0, \tag{2}$$

where F_s is the factor of safety predicted by a deterministic slope stability analysis method. Although many different methods can be applied to slope stability analysis, but limit equilibrium methods are stillthe most commonly adopted. When limit equilibrium method is adopted, the problem is statically indeterminate, and some simplifying assumptions are necessary in order to solve the problem. Several methods were proposedbased on different assumptions, such as simplified Bishop's method [31], Spencer's method [32] etc.

It is difficult to directly calculate the *D*-fold integral value in Eq. (1) [15]. Therefore, MCS and reliability index based methods were developed to solve this problem. The reliability index β is defined as $\beta = \mu_Z/\sigma_Z$. When the performance function *Z* is normally distributed and linear, and the random variables x_i are statistically independent. The failure probability can be calculated as $P_f = \Phi(-\beta)$, where Φ is the standard normal cumulative distribution function.

First-order reliability methods (FORM) and second-order reliability methods (SORM) are developed to evaluate the reliability index value. Originally, the FORM is developed based on a first-order Taylor series expansion. However, the reliability index is strongly dependson the mathematical expansion of limit state function. Hasofer and Lind [33] proposed an invariant approach to calculate β. The Hasofer–Lind reliability index is defined as the minimum distance from the origin to the most

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