

Chapter 7

Reliability Analysis of Slope Using MPMR, GRNN and GPR

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ABSTRACT

First Order Second Moment Method (FOSM) is generally for determination of reliability of slope. This article adopts Minimax Probability Machine Regression (MPMR), Generalized Regression Neural Network (GRNN) and Gaussian Process Regression (GPR) for reliability analysis of slope by using FOSM. In this study, an example of soil slope is given regarding how the proposed GPR-based FOSM, MPMR-based FOSM and GRNN-based FOSM analysis can be carried out. GPR, GRNN and MPMR have been used as regression techniques. A comparative study has been carried out between the developed GPR, MPMR and GRNN models. The results show that MPMR gives better performance than the other models.

INTRODUCTION

The determination of reliability of slope is a challenging task in civil engineering. Researchers use First Order Second Moment Method (FOSM) has been used for reliability analysis of slope by many researchers (Wu and Kraft, 1970; Cornell, 1971; Alonso, 1976; Tang et al., 1976; Vanmarcke, 1977; Husein et al., 2000). However, FOSM is a time consuming method for implicit performance function. Implicit performance function is common for Bishop (1955) method of slope stability analysis. Bishop (1955) used the method of slices in obtaining stability of slopes. In order to solve the problem, Bishop assumed that the resultant of interslice forces acts in the horizontal direction. This method is being used very widely in the literature. The results obtained from this method compares very closely with the more rigorous approaches like the finite element method. Researchers try to overcome this problem by using different approaches such as Response Surface Method (Wong, 1985; Faravelli, 1989; Bucher and Bourgund, 1990; Rajashekhar and Ellingwood, 1993; Kim and Na, 1997; Guan and Melchers, 2001; Kaymaz and McMahon, 2004; Nguyen et al., 2009; Roussouly et al., 2013; Jiang et al., 2014b), multi-plane sur-

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faces method, and multi-tangent-plane surface (Guan and Melchers, 1997). But, these approaches are only appropriate for nonlinear concave or convex limit state surface. Researchers use Artificial Neural Networks (ANNs) to solve the problem of implicit performance (Hurtado and Alvarez, 2001; Gomes and Awruch, 2004; Deng Jian et al., 2005; Deng Jian, 2006; Elhewy et al., 2006; Cardoso et al., 2008). However, ANN suffers from the different limitations such as black box approach, low generalization capability, overtraining problem, arriving at local minima, etc (Park and Rilett, 1999; Kecman, 2001).

This chapter examines the potential of Minimax Probability Machine Regression (MPMR), Generalized Regression Neural Network (GRNN) and Gaussian Process Regression (GPR) for reliability analysis of slope by using FOSM. The FOSM demands the values and partial derivatives of the performance function with respect to the design random variables (Halder and Mahadevan, 2000). Such calculations could be time-consuming or cumbersome when the performance functions are implicit (Baecher and Christian, 2003). The analysis of slope by Bishop (1955) method gives implicit performance functions. Here, MPMR, GRNN and GPR have been used to predict implicit performance functions. GPR is a probabilistic, non-parametric model. In GPR, different kinds of prior knowledge can be applied. It has been successfully applied for solving different problems (Xu et al., 2011; Ruiz and Binefa, 2012; Kemmler et al., 2013; Holman et al., 2014). Xu et al.(2011) successfully adopted GPR for prediction of spatiotemporal physical phenomena. Ruiz and Binefa(2012) used GPR for modelling facial expressions dynamics. GPR was used by Kemmler et al.(2013) for detecting instances of unknown categories. Holman et al.(2014) successfully applied GPR for estimation of daily crop evapotranspiration. MPMR is developed based on Minimax Probability Machine Classification and it does not assume any data distribution (Lanckriet et al., 2002a). There are lots of application of MPMR in the literatures (Liu, 2005; Liu et al., 2006; Cheng and Liu, 2006; Sun et al., 2009). Liu(2005) showed that the developed MPMR gave excellent performance for prediction of chaotic load time series. GRNN is often used for function approximation. It has been shown that, given a sufficient number of neurons, GRNN can approximate a continuous function to an arbitrary accuracy. GRNN is comprised of three layers of artificial neurons. Many applications of GRNN are available in the literatures (Heddami et al., 2011; Kaveh et al., 2012; Singh and Murthy, 2013; Plawiak, 2014). Heddami et al.(2011) successfully applied GRNN for prediction of coagulant dosage rates in water-treatment plants in Algeria. Kaveh et al.(2012) successfully adopted GRNN to solve the size optimization problem of steel truss structures subjected to ground motions. Singh and Murthy(2013) used GRNN for detection sensor faults in longitudinal dynamics of an F8 aircraft model. GRNN has been used by Plawiak(2014) to estimate the state of consumption of a pump based on dynamic pressure or vibrations. GRNN, MPMR and GPR have been used as regression techniques. In this paper, an example is given regarding how the proposed GPR-based FOSM, MPMR-based FOSM and GRNN-based FOSM analysis can be carried out. A comparative study has been carried out between the developed GPR, MPMR and GRNN models.

DETAILS OF FOSM

The behaviour of slope is described by the following performance function(Z).

$$Z = g\left(x_1, x_2, x_3, \dots, x_n\right) = F\left(x_1, x_2, x_3, \dots, x_n\right) - 1 \quad (1)$$

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