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# Probabilistic back analysis based on Bayesian and multi-output support vector machine for a high cut rock slope

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## ABSTRACT

Uncertainty of geomechanical parameters is an important consideration for rock engineering and has a very important influence on safety evaluation, design, and construction. Back analysis is a common method of determining geomechanical parameters but traditional deterministic back analysis cannot allow for consideration of this uncertainty. In this study, a new probabilistic back analysis method is proposed that integrates Bayesian methods and a multi-output support vector machine (B-MSVM). In this B-MSVM back analysis method, Bayesian was used to deal with the uncertainty of geomechanical parameters and a multi-output support vector machine (MSVM) was adopted to build the relationships between displacements and those parameters. The proposed method was applied to a high abutment rock slope at the Longtan hydropower station, China. At Longtan, the uncertainty of the two types of geomechanical parameters, Young's modulus and lateral pressure coefficients of in situ stress, were modeled as random variables. Based on the parameters identified by probabilistic back analysis, the computed displacements agreed closely with the measured displacement data monitored in the field. The result showed that B-MSVM presented the uncertainty of the geomechanical parameters reasonably. Further study indicated that the performance of B-MSVM could be improved greatly by updating field monitoring information regularly. The proposed method provides a significant new approach for probabilistic back analysis and contributes to the determination of realistic geomechanical parameters.

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## 1. Introduction

Rock materials are inherently anisotropic, inhomogeneous, and have discontinuities, and these variations in characteristics inevitably lead to uncertainty in practical engineering. Therefore, it is essential to take into account the uncertainty in determining geomechanical parameters because these uncertainties have a great influence on project design, stability analysis, and construction (Li et al., 2014; Wu, 2015). Evaluating this uncertainty remains one of the most challenging tasks of rock engineering. To obtain reasonable parameters for geomaterials, back analysis based on field measurements has been used for over 30 years (Deng and Lee, 2001; Feng et al., 2004; Feng and Lewis, 1987; Gioda and Jurina, 1981; Oreste, 2005; Pichler et al., 2003; Sakurai, 1987; Sakurai et al., 1986; Sakurai and Takeuchi, 1983; Vardakos et al., 2012; Yu et al., 2007; Zhao and Yin, 2009). In traditional back analysis, the geomechanical parameters obtained are deterministic values but this traditional approach has one major drawback. The deterministic approach cannot account for the geomechanical parameter uncertainties.

To take the uncertainty into account, many engineers have adopted probabilistic back analysis (Chowdhury et al., 2004; Gilbert et al., 1998; Li et al., 2013; Luckman et al., 1987; Park et al., 2005; Wang et al., 2013; Zhang et al., 2010, 2013). Probabilistic back analysis provides a logical way to incorporate information from other sources into the analysis. It does, however, require knowledge of complex statistical techniques and is difficult to conduct compared with traditional back analysis methods (Zhang and Li, 2010). If either deterministic or probabilistic back analysis is employed, the statistical calculations are very complex and can require significant computer resources, especially for large-scale problems. To improve the efficiency of back analysis, machine learning (or predictive analysis) methods such as artificial neural networks (ANNs) and support vector machines (SVMs) have been successfully used to present the complex relationships between geomechanical parameters and displacement (Zhao and Yin, 2009; Feng et al., 2004). However, both ANNs and SVMs still have some limitations (Zhao et al., 2012). The standard formulation of an SVM can only deal with single output problems and is not suitable for problems in geotechnical engineering that deal with multiple outputs. This limitation not only increases the computation time required but also introduces errors because the correlation between different outputs is not taken into account (Tuia et al., 2011).

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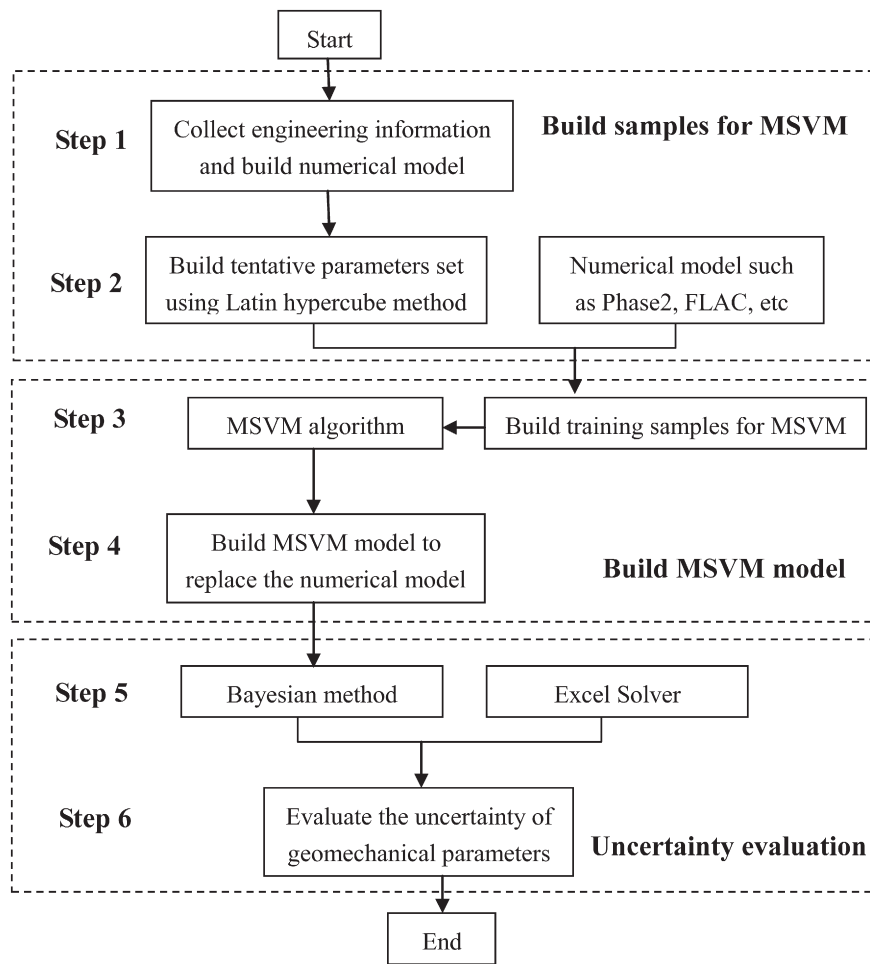


Fig. 1. Flowchart of B-MSVM probabilistic back analysis.

Fortunately, the algorithm of a multi-output support vector machine (MSVM) can overcome this limitation.

Bayesian approaches have been introduced to solve systems of equations involving uncertainty and have been applied to a number of geotechnical engineering problems (Bayraktarli et al., 2011; Cheung and Tang, 2005; Hu et al., 2015; Gilbert and Tang, 1995; Juang et al., 1999; Miranda et al., 2009; Najjar and Gilbert, 2009; Wang et al., 2014; Zhang and Li, 2010). Dilip and Babu (2013) combined reliability analysis and back analysis to identify design parameters of pavements. However, in rock engineering, displacement is a reliable information and can be easily obtained. Thus back analysis method based on displacement has been widely adopted. According to the investigation of previous references, research on Bayesian theory applied to displacement back analysis is still scarce. This paper proposes a new approach to probabilistic back analysis to estimate the uncertainty of geomechanical parameters. This approach integrates MSVM, Bayesian methods, and displacement back analysis. The method proposed here was verified by applying it to a high abutment slope at the Longtan hydropower station in Tian'e County, China.

In this paper, Section 2 describes the MSVM algorithm in detail. Section 3 presents the main ideas and procedures for a probabilistic back analysis based on Bayesian methods. A case study used to verify the proposed method is given in Section 4 and conclusions are in Section 5.

## 2. Multi-output support vector machine (MSVM)

MSVM was proposed based on single output support vector machines developed by previous workers (Suykens and Vandewalle,

1999; Wu, 2015). Suppose there are  $N$  observable data sets. If the observable output is a vector with  $Q$  variables to be predicted, i.e.,  $y \in R^Q$ , we need to solve a multidimensional regression estimation problem in which we must find weight vectors  $W^j$  and  $b^j$  ( $j = 1, 2, \dots, Q$ ) for every output. Tuia et al. (2011) have investigated a multi-output support vector machine. We can directly generalize the single support vector machine to solve the multidimensional case, leading to the minimization as.

$$L_p(W, b) = \frac{1}{2} \sum_{j=1}^Q \|W^j\|^2 + C \sum_{i=1}^N L(u_i), \quad (1)$$

where

$$\begin{aligned} u_i &= \|e_i\| = \sqrt{(e_i^T e_i)}, \\ e_i^T &= y_i^T - \varphi(x_i)W - b^T, \\ W &= [W^1, W^2, \dots, W^Q], \text{ and} \\ b &= [b^1, b^2, \dots, b^Q]. \end{aligned}$$

$L_p(W, b)$  is a function with respect to  $W$  and  $b$ ,  $y_i$  is the  $i^{\text{th}}$  observable output,  $N$  is the number of observable data set,  $\varphi(\cdot)$  is a nonlinear transformation to the feature space, which is usually a higher dimension space, and the constant  $C$  is a hyper parameter which determines the trade-off between the regularization and the error reduction term.  $L(u)$  is a quadratic epsilon-insensitive cost function defined by the following equation, which is a differentiable form of the Vapnik insensitive loss function  $\varepsilon$ .

$$L(u) \begin{cases} 0 & u < \varepsilon \\ u^2 - 2u\varepsilon + \varepsilon^2 & u \geq \varepsilon \end{cases} \quad (2)$$

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