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Research paper

New design equations for estimation of ultimate bearing capacity of shallow foundations resting on rock masses

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ABSTRACT

Rock masses are commonly used as the underlying layer of important structures such as bridges, dams and transportation constructions. The success of a foundation design for such structures mainly depends on the accuracy of estimating the bearing capacity of rock beneath them. Several traditional numerical approaches are proposed for the estimation of the bearing capacity of foundations resting on rock masses to avoid performing elaborate and expensive experimental studies. Despite this fact, there still exists a serious need to develop more robust predictive models. This paper proposes new nonlinear prediction models for the ultimate bearing capacity of shallow foundations resting on non-fractured rock masses using a novel evolutionary computational approach, called linear genetic programming. A comprehensive set of rock socket, centrifuge rock socket, plate load and large-scaled footing load test results is used to develop the models. In order to verify the validity of the models, the sensitivity analysis is conducted and discussed. The results indicate that the proposed models accurately characterize the bearing capacity of shallow foundations. The correlation coefficients between the experimental and predicted bearing capacity values are equal to 0.95 and 0.96 for the best LGP models. Moreover, the derived models reach a notably better prediction performance than the traditional equations.

1. Introduction

Foundations are commonly used as the lowest parts of the civil engineering structures to transmit the applied loads to the underlying soil or rock. According to the properties of the rock mass and its beneath layer, the failure of rocks under applied loads may occur through several mechanisms (Sowers, 1979). Comprehensive descriptions about these failure mechanisms are provided in Canadian Foundation Engineering Manual and the National Cooperative Highway Research Program (NCHRP) reports (Becker, 1996; Paikowsky et al., 2004, 2010; Canadian Geotechnical Society, 2006). It is well-known that the bearing capacity failure of shallow foundations on jointed rock masses depends on the ratio of space between joints (S) to foundation width (B), joint condition, rock type, and the condition of the underlying layer of rock mass (Bishoni, 1968; Sowers, 1979). The most widely used approaches to determine the bearing capacity of foundations on rocks can be classified into three groups: (1) analytical methods, (2) semi-empirical methods, and (3) in-situ and full-scaled testing methods. The analytical and semi-empirical methods are widely used for the bearing capacity prediction, particularly in the pre-design phases. The analytical methods such as finite element and limit equilibrium methods relate the bearing capacity to the footing geometry and rock properties (Terzaghi, 1946; Bishoni, 1968; Sowers, 1979; Goodman, 1989). The general forms of the analytical models are given in Table 1. The semi-empirical methods often propose a correlation between the bearing capacity and rock mass properties based on the empirical observations and experimental test results (Carter and Kulhawy, 1988; Bowles, 1996; Hoek and Brown, 1997, 1988). Some of the main equations obtained by the empirical approaches are summarized in Table 2.

Generally, the models obtained by the analytical, finite element and empirical approaches have both advantages and disadvantages

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Table 1
General forms of equations made by the analytical methods.

Reference	Equation (analytical method)		Factor
Terzaghi (1946)	$q_{ult} = cN_c + 0.5\gamma BN_\gamma + \gamma DN_q$	$N_c = 2N_\phi^{0.5}(N_\phi + 1)$ $N_\gamma = N_\phi^{0.5}(N_\phi - 1)$ $N_q = N_\phi^2$	$N_\phi = \tan^2\left(45 + \frac{\phi}{2}\right)$
Bishoni (1968)	$q_{ult} = \alpha JcN_{cr}$	For circular footings: $\alpha = 1$ For square footings: $\alpha = 0.85$	$N_{cr} = \frac{2N_\phi}{N_\phi+1}(\cot\phi)\left(\frac{S}{B}\right)\left(1 - \frac{1}{N_\phi}\right) - N_\phi(\cot\phi) + 2N_\phi$
Sowers (1979)	$q_{ult} = 2c\tan\left(45 + \frac{\phi}{2}\right)$	–	–
Goodman (1989)	For fractured rocks: $q_{ult} = q_u(N_\phi + 1)$ For non-fractured rocks: $q_{ult} = q_u\left(\frac{1}{N_\phi - 1}\left(N_\phi\left(\frac{S}{B}\right)^{(N_\phi-1)/N_\phi} - 1\right)\right)$		$N_\phi = \tan^2\left(45 + \frac{\phi}{2}\right)$

q_{ult}: bearing capacity of shallow foundation on rock; D: depth of foundation below ground surface; c: the cohesion intercepts for the rock mass; ϕ: angle of internal friction for the rock mass; γ: effective unit weight of the rock mass; B: breadth or width of foundation; $N_Ø$, N_c, N_q and N_γ: non-dimensional bearing capacity factors as exponential functions of ϕ; N_c: bearing capacity factor; S: discontinuity spacing; S/B: ratio of joint spacing to foundation width; q_u: unconfined compressive strength of rock.

(Jiao et al., 2012; Chen et al., 2013). For the case of bearing capacity of a shallow foundation on a jointed rock mass, parameters such as the ratio of joint spacing to foundation breadth or loading width, as well as rock mass qualities such as joint conditions (open or closed), rock type and rock mass strength are influencing (Sowers, 1979; Paikowsky et al., 2010). As represented in Table 1, the analytical methods only include the physical and mechanical properties of rock mass and geometry of foundation. Thus, they do not take into account the important role of the rock type and its qualitative mass parameters such as rock quality designation (RQD), rock mass rating (RMR), and geological strength index (GSI). On the other hand, the empirical methods often relate the bearing capacity to qualitative and rock mass classification parameters and do not account for the geometry of the foundations or space between joints (Table 2). The drawbacks of the existing analytical and empirical methods imply the necessity of developing new models correlating the bearing capacity factor to both quantitative and qualitative parameters.

Computational intelligence (CI) techniques are considered as alternatives to traditional methods for tackling real world problems. They automatically learn from data to determine the structure of a prediction model. Artificial neural network (ANN), fuzzy inference system (FIS), adaptive neuro-fuzzy system (ANFIS), and support vector machines (SVM) are well-known branches of CI. These techniques have been successfully employed to solve problems in engineering field (e.g., Das and Basudhar, 2006; Gullu and Ercelebi, 2007; Das and Basudhar, 2008; Gullu and Ercelebi, 2008; Zorlu et al., 2008; Cabalar and Cevik, 2009a,b; Sivapullaiah et al., 2009; Yaghouby et al., 2009; Al-Anazi and Gates, 2010; Kulatilake et al., 2010; Yaghouby et al., 2010a,b, 2012; Gullu, 2012, 2013). Besides, these techniques have been used to predict the bearing capacity of shallow foundations resting on soil layers (Soleimanbeigi and Hataf, 2005; Padmini et al., 2008; Kuo et al., 2009; Kalinli et al., 2011). Despite the good performance of ANNs, FIS, ANFIS, SVM and many of the other CI methods, they are considered black-box models. That is, they are not capable of generating practical prediction equations. In order to cope with the limitations of the existing methods, a robust CI approach, namely genetic programming (GP) has been introduced (Koza, 1992). GP is an evolutionary computational approach. It uses the principle of Darwinian natural selection to generate computer programs for solving a problem. GP has several advantages over the conventional and other similar techniques. A notable feature of GP and its variants is that they can produce prediction equations without a need to pre-define the form of the existing relationship (Çanakcı et al., 2009; Guven et al., 2009; Gandomi et al., 2010; Alavi et al., 2011; Alavi and Gandomi, 2011; Gandomi et al., 2011a; Azamathulla and Zahiri, 2012). This technique has been shown to be a powerful tool for the prediction of the bearing capacity of shallow foundations on soils (Adarsh et al., 2012; Shahnazari and Tutunchian, 2012; Tsai et al., 2012; Pan and Tsai, 2013).

However, application of GP and other CI techniques to the modeling of the bearing capacity of shallow foundations resting on rock masses is conspicuous by its absence. This paper proposes a novel subset of GP, namely linear genetic programming (LGP) to derive precise predictive equations for the ultimate bearing capacity of shallow foundation resting in/on jointed (non-fractured) rock. A comprehensive and reliable set of data including 102 previously published rock socket, centrifuge rock socket, plate load and large-scaled footing load test results is collected to develop the models. The robustness of the proposed models is verified through different validation phases.

2. Evolutionary computation

Evolutionary computation (EC) is a subdivision of CI inspired by the natural evolution. Some of the subsets of EC are evolutionary strategies (ES) and evolutionary programming (EP). These techniques are collectively known as evolutionary algorithms (EAs).

Table 2
General forms of equations made by the empirical methods.

Reference	Equation (empirical method)	Factor
Bowles (1996)	$q_{ult} = q_r \times (\mathrm{ROD})^2$	$m = m_i\exp\left(\frac{\mathrm{GSI}-100}{28}\right)$ $s = \exp\left(\frac{\mathrm{GSI}-100}{9}\right)$
Hoek and Brown (1997, 1988)	$\sigma_1 = \sigma_3 + (mq_c\sigma_3 + sq_c^2)^{0.5}$	
Carter and Kulhawy (1988)	$q_{ult} = q_u(m + \sqrt{s})$	

RQD: rock quality designation (rock mass classification); q_r: ultimate strength of rock determined by uniaxial compression test; $ó_1$: major principal stress (compressive stresses are taken as positive); $ó_3$: minor principal stress; GSI: geological strength index (rock mass classification); m and s: material constants in the Hoek and Brown failure criterion; q_c: uniaxial compression strength of intact rock.