



Maximum surface settlement based classification of shallow tunnels in soft ground



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ABSTRACT

Prediction of the maximum surface settlement due to shallow tunnelling in soft grounds is a valuable metrics in ensuring safe operations, particularly in urban areas. Although numerous researches have been devoted to this issue, due to the complexity and a large number of the effective parameters, no comprehensive solution to the problem is available. In this study, a shallow tunnel classification system (STCS), based on maximum settlement, is proposed. The STCS holds on the results of several tunnelling projects around the world. The classifier categorises a tunnel based on geometry, ground, and performance characteristics. A decision tree classification method, after training with 20 cases, was successful to predict the maximum settlement for 14 tunnelling projects. The maximum surface settlement predictions were in the form of assigning a class label to each tunnel. Four tunnel classes were defined as follow: (i) class A (maximum settlement < 9.9 mm), (ii) class "B" ($10 \leq$ maximum settlement < 19.9 mm), (iii) class "C" ($20 \leq$ maximum settlement < 29.9 mm), and (iv) class "D" (maximum settlement $\geq$ 30 mm). The most explanatory independent variables were selected, by the STCS, as follow: tunnel depth, diameter, volume loss, and normalised volume loss. The proposed classification scheme can be employed as a decision making aid in settlement prediction/prevention in shallow tunnelling in soft grounds. The STCS is proposed as a supplemental tool to the observational methods, and it is not expected to be a stand-alone measure for settlement.

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1. Introduction

Shallow tunnelling in soft grounds induces both lateral and vertical surface movements (Boscardin and Cording, 1989). Ground settlement (surface vertical movement) is a critical threat to both the surface (Papastamos et al., in press; Melis et al., 2002) and sub-surface facilities (Vorster et al., 2005), particularly in urban areas (Liao et al., 2009). As a result of the rapid growth in infrastructure developments, many subway/metro tunnels are under construction around the world. Lower depth and soft ground are the two major characteristics of these underground spaces which occasionally result in considerable surface settlements. Thus, settlement control is a critical phase of every shallow underground construction activity to ensure both the surface and underground safety. A primary essential information for settlement control is an estimate/prediction of the magnitude of surface movements before tunnelling. To address this important issue, several researchers

have attempted to predict (maximum) surface settlement induced by shallow tunnelling. Because of the complexity and unknown relationships and interactions between the many effective parameters on surface settlement, deriving a closed form mathematical solution is very difficult (Peck, 1969; Rowe, 1983; Verruijt and Booker, 1996). Hence, many researchers tried to employ other approaches, including empirical (Hsieh and Ou, 1998; Lee et al., 1999; Zhang et al., 2009; Chen et al., 2011), numerical (Melis et al., 2002; Sun and Liu, 2002; Kasper and Meschke, 2004; Ding et al., 2004), and artificial intelligence methods (Kim et al., 2002; Suwansawat and Einstein, 2006; Neaupane and Adhikari, 2006). Although the analytical, empirical, numerical, and artificial intelligence methods have several advantages in addressing the issue; there are major constraints in application. For instance, in analytical methods there are many simplifications such as a plain strain assumption (Chou and Bobet, 2002), elastic behaviour (Park, 2004), and/or soil isotropy (Franzius et al., 2005).

In empirical methods such as (González and Sagaseta, 2001), the interpretations will be applicable only in the same conditions (Ou et al., 1993) and, hence, there will be a lack of model generalisation (Bobet, 2001).

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In the numerical methods, model building should be very sophisticated by incorporation of many details (Addenbrooke et al., 1997; Lee and Ng, 2005). This leads to very time consuming model building and running. In artificial intelligence methods (e.g., artificial neural networks), the outputs are in the form of a black box solution (Huang, 2009), hence, no functional relationship will be rendered (Lim et al., 2000). Consequently, no comprehensive solution to the problem of settlement modelling and prediction is available. Perhaps the most widely used techniques in surface settlement prediction are observational methods (Terzaghi and Peck, 1948, 1967; Meyerhof, 1956, 1965; DeBeer and Martens, 1957; Hough, 1969; Peck and Bazaraa, 1969; Burland and Burbidge, 1985; Affipour et al., 2011; Ghorbani et al., 2012). These methods are based on direct observation of settlement in actual shallow tunnels or prototypes. The direct observations have been correlated with in situ test results such as standard/cone penetration tests.

In this study, a shallow tunnel classification system (STCS), based on maximum settlement, is proposed. The STCS holds on the results of several tunnelling projects around the world. The classifier categorises a tunnel based on geometry, ground, and tunnelling performance parameters. A tunnel will be classified into one of the four classes A–D for very limited to very large settlements, respectively. The classification will be used in the assessment of the buildings and adjacent structure protection. Several tunnelling projects considered a total settlement of less than 1 cm (class A, see Table 1) to be insignificant to damage surface facilities. The Redline and MGLLE Los Angeles metro, West Side CSO Tunnel, Portland, Oregon; East Side CSO Tunnel, Portland, Oregon; ECIS, Los Angeles, California are some examples of the successful urban shallow tunnelling projects that adopted a 1 cm critical settlement policy (Parsons Brinckerhoff Co., 2012).

Classification and regression trees are machine-learning methods for constructing prediction models from data. Olden et al. (2008) mentioned the advantages of the decision trees as follow: (1) inherently nonparametric and, therefore, not affected by heteroscedasticity that affects parametric procedures; (2) invariant to monotonic transformations of the data, thus eliminating the need for data transformations; (3) able to handle mixed numerical data, including categorical, interval, and continuous variables; (4) able to deal with missing variables; (5) not affected by outliers (the outliers are isolated into a node, and have only a minimal effect on splitting); (6) able to detect and reveal interactions in the data set; (7) able to effectively deal with higher dimensionality (i.e., it can identify a reduced set of important variables from a large number of submitted variables); (8) relatively simple to interpret graphically.

Although decision trees have been successfully employed in solving a wide range of geotechnical, geological, and environmental problems (Glastonbury and Fell, 2008; Saito et al., 2009; Häring et al., 2012; Emmer and Vilímek, 2014), this is the first application of the method in tunnel classification based on settlement. Decision tree classification was opted in this study due to the above-mentioned advantages, as well as its successful application in a wide range of geotechnical/geological engineering disciplines. Thus, the novelty of the work is in the application of the decision

trees for a better understanding/forecasting of ground settlement induced by shallow tunnels in soft grounds. The contribution of this study is in proposing a tunnel classification system (STCS) based on the amount of maximum settlement. Applicability of STCS will be in the estimation of settlement before starting the tunnelling project by assigning a class label to the tunnel. However, the proposed classifier is limited to the case of shallow tunnelling in soft grounds and is able to predict only the maximum vertical settlement.

2. Case studies

2.1. Database

Parameters of several case studies around the world (UK, USA, Canada, Thailand, Brazil, and Germany) were obtained from (Neaupane and Adhikari, 2006). The tunnels were constructed for metro or sewer applications. There were 34 cases with 7 variables, including: tunnel depth (D), diameter (Z), volume loss (V_s), normalised volume loss (V_s/V_t), soil strength (C_u), ground water level (GW), and construction method (CM) (see Table 2). V_s/V_t is the ratio of the volume of the settlement through per unit length of the tunnel (V_s) to the ground loss during excavation (V_t). It is an important variable in calculating the ground loss (Atkinson and Potts, 1979). The variables D , Z , V_s , and V_s/V_t are geometric parameters. The C_u and GW are ground parameters. The CM is a tunnelling performance parameter. Descriptive statistics of the measured maximum settlements are graphically shown in Fig. 1. The mean and standard deviation of the observations are 18.4 mm and 13.1 mm, respectively. Application of the Anderson–Darling normality test (Anderson and Darling, 1952), at 5% significance level, resulted in a P -value of less than 0.005, which demonstrated the non-normality of the observations. The strike marks in Fig. 1 shows existence of several outliers in the settlement data. Non-normality and outliers are problematic issues for several traditional statistical methods that can be dealt with effectively by decision trees (Olden et al., 2008). The statistics of other parameters are presented in Table 3. The Application of the Grubbs' test for outliers (Grubbs, 1950), at 5% significance level, revealed existence of several outliers in the variables depth, diameter, Vol. loss, V_s/V_t , and C_u . In many statistical methods (such as multiple regressions) these outliers should be either removed or transformed to meet the assumptions of the methods. However, in decision trees the outliers can be handled effectively. Hence, they were not altered in this study. All variables, except for GW and CM, are numerical. The two linguistic variables, GW and CM, were converted to numerical ones by assigning integers. The GW was classified into two categories; the water level above the tunnel crest was taken as 1, and below the tunnel was taken as 2. In 31 cases (90%), the underground water level was below the tunnel's crest. The CM was classified as 1 and 2 for hand-mined shield and mechanical shields, respectively. Twenty one cases were hand-mined and the remaining were mechanically shielded tunnels.

2.2. Parameter selection

Although there are many effective variables on shallow tunnelling-induced settlement, the three major influential categories include: tunnel geometry, ground conditions, and tunnelling performance (e.g., tunnelling rate). Tunnel depth and diameter (Loganathan and Poulos, 1998) are the two important variables that are related to the geometry. Mechanical properties of the ground (soil), cohesion and friction angle, (Bernat and Cambou, 1998), and the underground water level (Wongsaroj et al., 2007) are the two major variables in the category of ground conditions.

Table 1
Tunnels classes.

Maximum settlement (mm)	Class
0–9.9	A
10–19.9	B
20–20.9	C
>30	D

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