Application of a Generalised MPK Model with Data Fusion Approaches for Landslide Risk Assessment

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Abstract. The constitutive modelling of unsaturated soil behaviour within the MPK framework using data fusion approaches are discussed to envisage a practical approach for the evaluation and monitoring of landslide-prone areas. The present study focuses on improvements in subsurface suction distribution estimations via electrical resistivity tomography (ERT), which can be used to generate quasi-continuous suction profiles (QCSP) for numerical modelling. An explicit petro geophysical transfer function between suction and resistivity is presented herein, which was derived from the Waxman-Smits electrical resistivity model and the Van Genuchten equation for soil water retention curves. For efficient numerical modelling, a selective correction approach (SCA) is presented for petro geophysical transfer function updating procedure. The data acquisition and analysis architecture are envisaged within a data cloud platform, which is highly attractive within the context of internet-of-things (IoT). Although the focus of this work is on suction estimations, a similar approach can be used for estimation of other constitutive variables required within the MPK framework.

Keywords: Data fusion · Suction · MPK framework

1 Introduction

Kodikara [1] proposed a framework called MPK (Monash – Peradeniya – Kodikara), whereby the suction is treated as a dependent variable in the context of the volumetric behaviour of compacted soils as illustrated in Fig. 1. The framework is based on the traditional compaction curves for the first time in constitutive soil modelling, which is developed by considering the volumetric behaviour of soils. The primary constitutive variables of this framework are the void ratio (e), moisture ratio (e_w) and net stress (p), and has been validated experimentally in various studies [2–7]. The loading wetting state boundary surface (LWSBS) consists of various static compaction curves for different loading, and it is envisaged as the loosest state of the compacted soil. This surface is regarded as an upper boundary (loosest state of soil) for the volumetric behaviour of the compacted soils and can be found through simple water content

testing. In addition, the MPK framework is encapsulated the following properties: (a) smooth transition from unsaturated to saturated soil behaviour; (b) the constitutive model parameters can be easily obtainable; (c) it can capture most phenomenological observations of both saturated and unsaturated soils.
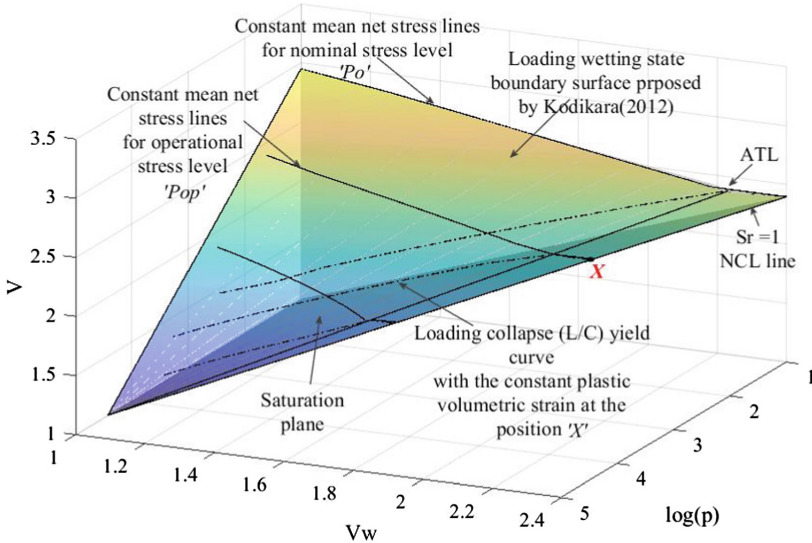

Fig. 1. The MPK framework proposed by Kodikara [1].

The deformation stress state slope stability generally requires the initial stress state parameters along with the constitutive model. The accuracy of the prediction of the field conditions depends on the measurements of the in-situ deformation stress state parameters and the ability of the constitutive model to predict the actual real soil behaviour [8–12]. The measurements of the initial in-situ parameters (moisture content, suction and void ratio) are strenuous by discrete measures such as boreholes and laboratory testing. In the case of suction, discrete point measurements are generally acquired, and the interpolation of these measurements for estimating quasi-continuous suction profile (QCSP) is difficult. For applications in deformation stress state landslide failure analysis, the lack of high-density spatial data is a major limitation.

In this paper, the use of data fusion techniques from electrical resistivity tomography (ERT) and discrete suction measurements are discussed in order to generate quasi-continuous suction fields, which can serve as inputs to the MPK framework. Rather than a simple assemblage of data from the ERT and suction measurements, a discussion is made on how these streams of data can be used strategically in deformation stress state analysis.

2   Data Fusion Approach

Data fusion is termed as an improved version of raw data obtained through sensors with the help of other sources of information. Data fusion classifications are based on the relations between data sources, input/output data types and their nature, the abstraction levels, and type of architecture. In this paper, one of the categories of Dasarathy's classification (data in-feature out (DAI-FEO)) is utilized [13]. This approach is predicting environmental features from raw data. In this paper, the raw data is from the ERT measurements, which are transformed through various processing stages in order to retrieve the QCSP at the site of interest. The overall measurement and processing architecture of the proposed concept is shown in Fig. 2. There are 3 important phases involved in acquiring the computed suction field as shown in Fig. 2. Phase A consists of laboratory measurements in order to develop an initial petro geophysical transfer function for retrieving suction from soil resistivity. Phase B involves field measurement, whereby the subsurface apparent resistivity profiles are acquired from ERT and inverted to provide the true subsurface resistivity variations, and the point scale suction measurements are acquired using discrete sensors. Phase C stage involves the major processing stage, whereby the true resistivity variations are transformed to the QCSP using the initial mode, which is subsequently updated based on the level of error and within a selective correction approach (SCA) framework. The individual phases are explained in detail as follows.

2.1   Phase A: Laboratory Testing and the Formulation of the Initial Petro Geophysical Transfer Function

The Waxman-Smits (WS) model [14] defines the relationship between soil resistivity (reciprocal of conductivity), porosity, and volumetric water content as given in Eq. 1.

$$\frac{1}{\rho} = \sigma = \frac{1}{\phi^{-\mathbf{m}}}\left[\sigma_{\mathrm{w}}\left(\frac{\theta}{\phi}\right)^{\mathbf{n}} + (1 - \phi^{-\mathbf{m}})\sigma_{s}\right] \tag{1}$$

where, σ is the soil conductivity (S m^{-1}), ϕ is the porosity (dimensionless), σ_w is the conductivity of the pore fluid (S m^{-1}), θ is the volumetric water content (dimensionless), σ_s is the surface conductivity (S m^{-1}) and can be reasonably assumed for predominant clay types at a given field site, and m and n are the cementation factor and Archie's exponent respectively. On the other hand, the Van Genuchten [15] equation, which describes the soil water retention curves (SWRC), can be written in terms of the volumetric water content for a range of suction values (s) as shown in Eq. 2.

$$\theta = \frac{1}{\left(1 + \left(\frac{s}{a}\right)^{\mathbf{n}^*}\right)^{\mathbf{m}^*}} \tag{2}$$

where, a (kPa), m^* (dimensionless), and n^* (dimensionless), are the parameters related to air entry value, asymmetric shape of the curve and the rate of change of the slope of the curve respectively. The parameter a does not define any specific point in the SWRC. Therefore, to incorporate the inflection point properties, Eq. 2 needs to be

modified. In other words, the point with maximum slope, which plays a critical role where air phase and water phase becomes discontinuous and continuous, can be incorporated in constitutive modelling of unsaturated soils as it lies on the Line of optimum (LOO) of the compaction curve. Hence, the point of inflection can be obtained by as per Eq. 3.

$$\frac{d^2\theta}{d(\ln s)^2} = \frac{-m^* n^* s^{n^*-1}}{a^{n^*}} \left(1 + \left(\frac{s}{a}\right)^{n^*}\right)^{-m^*-2} \left\{ n^* \left(1 + \left(\frac{s}{a}\right)^{n^*}\right) - \frac{(m^*+1)n^* s^{n^*}}{a^{n^*}} \right\} \quad (3)$$

Consequently, at the inflection point, the volumetric water content and suction are $\theta^L = \left(\frac{m}{1+m}\right)^m$ and $a_w = am^{-1/n}$ respectively. Following these arguments, Eq. 2 can be rewritten as:

$$\theta = \frac{1}{\left(1 + \frac{1}{m^*}\left(\frac{s}{a_w}\right)^{n^*}\right)^{m^*}} \quad (4)$$

Following Eqs. 1 and 4, the relationship between suction and electrical resistivity can be explicitly stated as per Eq. 5. The petro geophysical transfer function given by Eq. 5 can be used to determine the suction from ERT measurements, provided the other parameters are known.

$$\frac{1}{\rho} = \sigma = \frac{1}{\phi^{-m}} \left[\sigma_w \left(\frac{\left(1 + \frac{1}{m^*}\left(\frac{s}{a_w}\right)^{n^*}\right)^{-m^*}}{\phi} \right)^n + (1 - \phi^{-m})\sigma_s \right] \quad (5)$$

It is noted that there are 7 material parameters (m, m^*, n, n^*, a_w, σ_s and σ_w) in Eq. 5 along with the porosity parameter. A pre-assessment of porosity is needed before the petro geophysical transfer function in Eq. 5 can be calibrated for the material parameters. A similar petro geophysical transfer function was obtained by Piegari and Di Maio [16] for predicting the suction distribution at field-scale through ERT measurements.

The initial laboratory testing involves suction and electrical resistivity measurements on a suite of soil samples acquired from the field of interest. The laboratory suction measurements can be conducted using the HYPROP test equipment and WP4C dewpoint potentiometer for low (up to 150 kPa) and high suction (>150 kPa) ranges respectively to obtain the SWRC. The electrical resistivity measurements can be conducted at different soil moisture contents using the Wenner 4-point method. The suite of suction and electrical resistivity measurements at different moisture contents can then be used to ascertain the feasibility of Eq. 5 and simultaneously provide initial estimates of the 7 material parameters. As mentioned previously, a porosity value will need to be ascertained, which is representative of the soil samples and is also applicable generally to the field. The generalisation of a single porosity estimation at field level may not be highly accurate and can be refined. However, it is not the intent of this work to provide the manner in which porosity estimation refinements can be conducted. Rather, the aim of this paper is to provide an indication of how suction profiles can be generated using ERT.

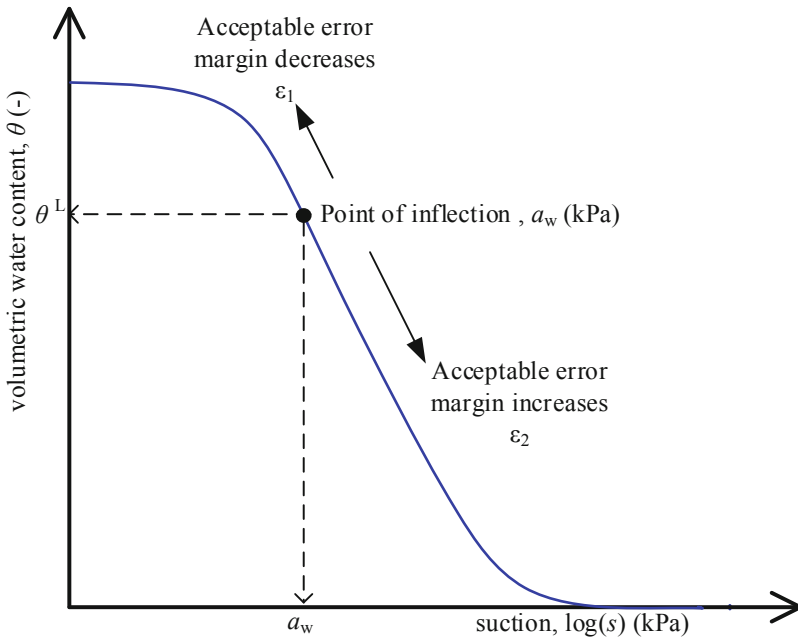## 2.2 Phase B: ERT and Suction Measurements and Processing

Electrical resistivity tomography is an advanced geophysical technique, which is used to characterize the subsurface material characteristics remotely from the ground surface. A complete description of the ERT method is not required here and can be found in [17]. However, it is noted that there are two ways ERT measurements can be acquired for the purpose of work discussed in this paper. Permanently installed electrodes can be placed strategically within the field of interest, and the measurements can be transmitted wirelessly to a data cloud. Alternatively, the measurements can be acquired using an autonomous vehicle retrofitted with drag-along electrodes, that can acquire ERT measurements and also transmit the data stream to a cloud network. Either approach is suitable and can be decided based on the frequency of measurements required, measurement refinement needs, consequence of failure, and economical feasibility. Data from the ERT measurements can be retrieved from the cloud and processed to obtain apparent resistivity distributions in the subsurface. The apparent resistivity distributions will need to be transformed into true resistivity distributions through inversion processes [18]. Integrating knowledge on known local geological conditions to improve the inversion process can also be seen as an added layer of data fusion problem. The ERT can be used to acquire either 2D or true 3D resistivity distributions and for the purpose of estimating suction profiles, the latter is preferred.

Field suction distributions can be measured directly using tensiometers with a maximum measuring capacity of 100 kPa [19] or up to 200 kPa [20, 21]. Since in the field suction can be > 200 kPa, the ultra-high capacity tensiometer with a maximum capacity of 7 MPa developed by Mendes, Gallipoli [22] can also be utilised. The finite point-scale measurements of suction can be conducted using a suite and a mixture of the various tensiometers mentioned. Here again, measurements from the tensiometers can be configured to be transmitted wirelessly to the data cloud. In this manner both the ERT and suction data streams can be accessed via data cloud for processing, avoiding the need for manual site visitations for data collection.

2.3 Phase C: Suction Profiles from ERT and Selective Correction Approach

In the first execution of the model predictions, the QCSP is obtained with the initial petro geophysical transfer function from Phase A. A comparison of the QCSP at selected locations with the actual suction measurements from the tensiometers will indicate the level of error in the estimated QCSP. Note, the selected locations refer to the locations where the tensiometers are located. Since the QCSP at field scale can be a computationally demanding feature to improve in every execution step, alternate correction approaches need to be considered. These alternative approaches should weigh the benefit of improvising the complete QCSP against the improvements in deformation stress state modelling using the MPK framework. In this paper, we suggest the selective correction approach (SCA), which can be seen as an optimised model updating procedure based on the errors involved in the computed and measured suction values as follows.

Fig. 2. Estimation of the quasi-continuous suction profile via electrical resistivity tomography involving the selective correction approach for petro geophysical transfer function updating.

Fig. 3. A typical soil water retention curve showing the point of inflection. Relatively high accuracies in suction values are needed for $S_F < a_w$ to ensure accurate constitutive unsaturated soil modelling. The acceptable error margins in suction generally increases beyond a_w. This basis forms the concept of selective correction approach.

The hydraulic behaviour of unsaturated soils is well captured by the SWRC, where the change in the volumetric water content follows a 'S' shaped pattern with the log-scaled suction as shown in Fig. 3. As the initial suction variation is low up to the air transition, high accuracy (error margin, ε_1 of 0.05) is needed for efficient modelling using the MPK framework. Furthermore, hence the Bishop's effective stress is applicable in this region, the need of accuracy of suction is further emphasised. However, the same error margin is not necessarily needed at relatively higher suction values, *i.e.*, a relatively larger ε_2 can suffice at higher suction, and hence lower volumetric water content, values. The SCA will be a programmed software routine within the data analysis, which will investigate the relative deviations between the suction values from direct measurements and the estimations within the QCSP derived using the petro geophysical transfer function. If for a given low suction range the difference is higher than 0.05, the petro geophysical transfer function will be updated accordingly by varying the material parameters to minimise the error. Similarly, different error margins can be associated with different suction ranges and the relative differences between estimated and measured suction determined during each execution in order to decide if the petro geophysical transfer function needs to be updated. Apart from saving computational time, the SCA approach will ensure that resources are more focussed in improving the estimations that will directly improve the deformation stress state

modelling with the MPK framework. Furthermore, this approach will minimise unnecessary petro geophysical transfer function updates for the complete suction range in every model iteration, which itself can exist as a difficult optimisation problem.

3   Conclusions and Future Implementations

Accurate constitutive modelling of unsaturated soil behaviour within the MPK framework relies on accurate input of relevant constitutive variables. In regards to suction, the expensive tensiometers and point-scale nature of measurements necessitate the use of alternative techniques that can assist in high-density estimations of sub-surface suction profiles. In this work we presented a methodology that can be utilised for efficient monitoring of subsurface quasi-continuous suction profiles via electrical resistivity tomography and data fusion approaches, for validation and calibration, that can be implemented within a data cloud architecture.

Retrieval of suction from soil electrical resistivity was based on a petro geophysical transfer function, which needs to be initially developed with laboratory soil samples. Updates and recalibration of the petro geophysical transfer function using field measurements can then be conducted using a selective correction approach, which is based on the error margins acceptable within the MPK framework. Developments in the refinement of the selective correction approach discussed in the paper will be highly beneficial to achieving this aim. Moreover, the methodology discussed can be extended to the estimation of the other constitutive variables necessary in the MPK framework, thereby enabling the constitutive modelling of unsaturated soil to be implementable within the context of IOT. This should be pursued further.

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