Construction and Building Materials 138 (2017) 214–221

Contents lists available at ScienceDirect

Construction and Building Materials

journal homepage: www.elsevier.com/locate/conbuildmat

Rapid soil classification using artificial neural networks for use in constructing compressed earth blocks

Jase D. Sitton, Yasha Zeinali, Brett A. Story *

Southern Methodist University, Lyle School of Engineering, Department of Civil and Environmental Engineering, Dallas, TX, United States

HIGHLIGHTS

- A framework is presented for rapid soil classification for CEB using artificial neural networks.
- The system uses both quantitative and qualitative field data streams to assign a classification.
- Both the quantitative and qualitative filed data streams are critical for accurate classification.

ARTICLE INFO

Article history:
Received 27 October 2016
Received in revised form 30 January 2017
Accepted 2 February 2017

Keywords:
Compressed earth block
Artificial neural networks
Soil analysis

ABSTRACT

Compressed earth blocks (CEBs) represent a cost-effective, sustainable, and environmentally-friendly building alternative to traditional masonry elements. Block performance depends heavily on the qualities of the soil used and it is important to be able to identify a soil's qualities rapidly in the field. Soil classification systems such as the Unified Soil Classification System (USCS) provide standardized methodologies with which to evaluate the qualities of a soil, however these methods require laboratory space and specialized equipment which are often unavailable in field conditions. This paper presents an artificial neural network framework that processes qualitative and quantitative field test data in lieu of ASTM laboratory test results. This neural network approach rapidly and accurately assigns USCS classifications to various soils based solely on qualitative and quantitative field soil analysis.

1. Introduction

1.1. Compressed earth blocks

Compressed earth blocks (CEBs) represent a cost-effective, sustainable, and environmentally-friendly building alternative to traditional masonry elements. CEB construction comprises low-cement, compressed local soil brick units that are rapidly and efficiently manufactured on site. CEB construction uses local soil as the primary component, which provides advantages over traditional masonry elements including lower cost, increased energy efficiency, and lower environmental impact [1–13].

One significant challenge with prolific CEB construction is the lack of standardization in the United States and internationally [2,6,8,12]. The United States, France, New Zealand, and different parts of Africa have standards that address soil selection and CEB construction, however they vary widely in their recommendations. Some of these standards address the qualities of the soil found through laboratory or field soil analysis, while others rely on the strength of the cured block to determine suitability for construction. Jiménez Delgado and Guerrero [7] provide an excellent review of international standards, normative documents, and technical documents that address CEB construction.

The ultimate behavior (e.g. structural resistance, energy efficiency, constructability) of a CEB structure is dependent on properties of the character of soil, which vary based on location [1,2,4–8,10–12,14,15]. Soil classification standards such as the Unified Soil Classification System (USCS) and the American Association of State Highway and Transportation Officials (AASHTO) require laboratory testing; therefore, standardized assessment of soil characteristics in the field may be difficult. Typically, field tests provide primarily qualitative data collected by builders of varying experience; some quantitative data can also be collected [8,10].

Soil properties of interest in CEB construction are particle distribution, clay content, and plasticity. Particle distribution and clay

Abbreviations: CEB, compressed earth block; ANN, artificial neural network; USCS, Unified Soil Classification System; ASTM, American Society of Testing and Materials; AASHTO, Association of State Highway and Transportation Officials.

* Corresponding author.
E-mail address: bstory@lyle.smu.edu (B.A. Story).

http://dx.doi.org/10.1016/j.conbuildmat.2017.02.006
0950-0618/

content establish the makeup of a soil, but is also important to understand how a soil behaves; the plasticity of a soil establishes the behavior when water is introduced. These properties affect mix acceptability and govern the ability of the soil to form a solid brick. Laboratory procedures to characterize these soil properties are detailed in ASTM D422 and ASTM D4318 [16,17]. The Unified Soil Classification System (USCS) is a widely-used soil classification system that uses the aforementioned soil properties to assign a soil a classification. The USCS can be found in ASTM D2487 [18].

1.2. Rapid soil classification

The need for rapid soil classification is not limited to CEB construction. Regardless of the type of earthen construction selected (e.g. extruded bricks, adobe, rammed earth, and wattle and daub), it is apparent that understanding the quality of soil at a site is crucial to successful earthen construction [7,8,15]. For this paper and specifically CEB construction, the USCS classification system is used.

Obtaining a soil's classification through USCS requires specialized equipment and laboratory space, which are rarely available in remote locations or developing areas. Current efforts in rapid soil classification focus on the use of spectroscopy or spectrometry; these methods require specialized equipment and intensive analysis [19].

An alternative to more expensive and specialized analysis methods is manual field soil analysis, which includes quick tests performed with simple tools on site [8,10]. These tests are designed so that builders can quickly estimate soil properties to determine soil acceptability for CEB unit construction; these data have not been used to obtain rigorous, ASTM quality scientific measurements as tests yield qualitative and quantitative data that maybe subjective or imprecise. The primary challenge in rapid soil classification in field conditions is the collection and analysis of data that can accurately and efficiently determine critical soil parameters and, subsequently, a classification [19].

This paper presents an artificial neural network framework that relates the results of qualitative and quantitative field soil analyses to standardized laboratory soil analyses and, ultimately, USCS classification. Neural networks are an appropriate alternative to deterministic methods when the input-output relationship is intractable or difficult to implement [20–22]. Neural networks can also be trained to be fault-tolerant, robust classifiers that are capable of utilizing all data, quantitative and qualitative, to make an assessment. In this paper, neural networks fuse qualitative and quantitative field assessment data and establish the relationship between field data and USCS soil classifications, which has the advantage of the speed of field soil analysis while still providing useful information about the soil.

2. Material and methods

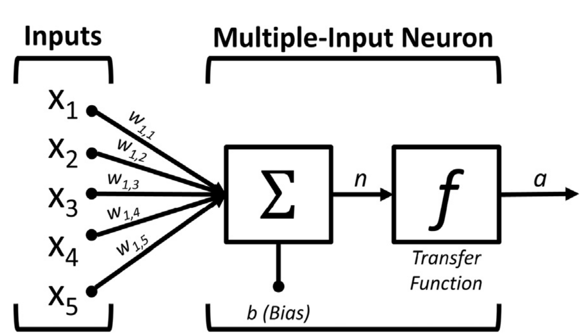
2.1. Neural networks

Artificial neural networks are analytical models designed to mimic the input/output associations of the human neural structure. They are powerful pattern recognizers and classifiers and are particularly suitable for problems that are too complex to be modeled and solved by classical mathematics and traditional procedures [23–26]. Neural networks are capable of modeling input-output functional relations even when mathematically explicit formulas are unavailable; this is achieved by training the networks (e.g. weight adjustment, statistical optimization) on known input/output data until the network can appropriately represent the input/output space [22–24,26]. Bhargavi and Jyothi [27,28] have applied Naïve Bayes data mining techniques and genetic algorithms to rapidly classify soils based on field data. In this work, the machine learning techniques operate on a dataset of quantitative standardized field data obtained from direct tests using specialized equipment.

The complex, nonlinear relationship between USCS classification, Y, and diagnostic field test data streams, X, is difficult to ascertain deterministically, and neural networks are an appropriate technique for establishing this relationship. Material properties, data collection techniques, and other uncertainties contribute to difficulties in developing the relationship. One common and effective type of neural network used in engineering applications is the feed-forward backpropagation neural network. These neural networks are made up of multiple-input neurons that are theorized to mimic the function of neurons in the brain. Neurons receive an input vector and produce an output. In feed-forward neural networks, each input in the input vector is multiplied by a unique, initially random, numerical weight. These weighted inputs are then summed and a constant bias is added to shift the output of the neuron so that constant portions of linear relationships may be captured. This value is then passed through a transfer function, which is essentially a normalization function and can take many different forms (e.g. a threshold function, piecewise-linear function, or sigmoid function) to obtain the output of the neuron [23,24]. Fig. 1 shows a diagram of a multiple-input neuron, where $x_{1\ldots R}$ are the network inputs in the input vector, $w_{i,1\ldots R}$ are the unique weights applied to each input, b is the constant bias added to the summation of the weighted inputs, n is the output of the neuron that is fed into the transfer function f, and a is the final output of the neuron.

Neural networks are organized into layers. The input layer and output layer contain the input data and the resulting output data. Hidden layers between the input and output layers contain the neurons and are connected by the weights; there may be any number of hidden layers, and it has been shown, theoretically, that a two-layer network may map any non-linear relationship [29]. Each layer is a vector containing any number R of neurons, and the output of that layer is a vector of length R containing the output from each neuron in that layer. This output vector is then passed as the input vector for the next hidden layer; the process repeats through all hidden layers until the final output of the network is reached.

The neural networks utilized in this paper are feed-forward backpropagation neural networks. In the case of feed-forward backpropagation, the training occurs by the adjustment of the synaptic weights. The weights are initialized as random numbers. The first pass of the training dataset are input into the network and an output is generated. If this output does not match the target



$$a = f\left(\sum_{j=1}^{5} w_{i,j} x_j + b\right)$$

Fig. 1. Multiple-input neuron diagram.