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Research paper

Multivariate adaptive regression splines and neural network models for prediction of pile drivability

Wengang Zhang, Anthony T.C. Goh*

School of Civil and Environmental Engineering, Nanyang Technological University, Singapore 639798, Singapore

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ABSTRACT

Piles are long, slender structural elements used to transfer the loads from the superstructure through weak strata onto stiffer soils or rocks. For driven piles, the impact of the piling hammer induces compression and tension stresses in the piles. Hence, an important design consideration is to check that the strength of the pile is sufficient to resist the stresses caused by the impact of the pile hammer. Due to its complexity, pile drivability lacks a precise analytical solution with regard to the phenomena involved. In situations where measured data or numerical hypothetical results are available, neural networks stand out in mapping the nonlinear interactions and relationships between the system's predictors and dependent responses. In addition, unlike most computational tools, no mathematical relationship assumption between the dependent and independent variables has to be made. Nevertheless, neural networks have been criticized for their long trial-and-error training process since the optimal configuration is not known a priori. This paper investigates the use of a fairly simple nonparametric regression algorithm known as multivariate adaptive regression splines (MARS), as an alternative to neural networks, to approximate the relationship between the inputs and dependent response, and to mathematically interpret the relationship between the various parameters. In this paper, the Back propagation neural network (BPNN) and MARS models are developed for assessing pile drivability in relation to the prediction of the Maximum compressive stresses (MCS), Maximum tensile stresses (MTS), and Blow per foot (BPF). A database of more than four thousand piles is utilized for model development and comparative performance between BPNN and MARS predictions.

1. Introduction

Piles are long, slender structural elements used to transfer the loads from the superstructure through weak strata onto stiffer soils or rocks. The selection of the type of pile depends on the type of structure, the ground conditions, the durability (e.g., to corrosion) and the installation costs. For driven piles, the impact of the piling hammer induces compression and tension stresses in the piles. Hence, an important design consideration is to check that the strength of the pile is sufficient to resist the stresses caused by the impact of the pile hammer. One common method of calculating driving stresses is based on the stress-wave theory (Smith, 1960) which involves the discrete idealization of the hammer-pile-soil system. As the conditions at each site is different, generally a wave equation based computer program is required to generate the pile driving criteria for each individual project. The pile driving criteria include: (i) hammer stroke vs. blow per foot (BPF) (1/set) for required bearing capacity; (ii) maximum compressive stresses vs. BPF; (iii) maximum tension stress vs. BPF. However, this process can be rather time consuming and requires very specialized knowledge of the wave equation program.

The essence of modeling/numerical mapping is prediction, which is obtained by relating a set of variables in input space to a set of response variables in output space through a model. The analysis of pile drivability involves a large number of design variables and nonlinear responses, particularly with statistically dependent inputs. Thus, the commonly used regression models become computationally impractical. Another limitation is the strong model assumptions made by these regression methods.

* Corresponding author. Tel.: +65 6790 5271; fax: +65 6792 0676.
E-mail address: ctcgoh@ntu.edu.sg (A.T.C. Goh).
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An alternative soft computing technique is the artificial neural network (ANN). The ANN structure consists of one or more layers of interconnected neurons or nodes. Each link connecting each neuron has an associated weight. The "learning" paradigm in the commonly used Back-propagation (BP) algorithm (Rumelhart et al., 1986) involves presenting examples of input and output patterns and subsequently adjusting the connecting weights so as to reduce the errors between the actual and the target output values. The iterative modification of the weights is carried out using the gradient descent approach and training is stopped once the errors have been reduced to some acceptable level. The ability of the trained ANN model to generalize the correct input–output response is performed in the testing phase and involves presenting the trained neural network with a separate set of data that has never been used during the training process.

This paper explores the use of multivariate adaptive regression splines (MARS) (Friedman, 1991) to capture the intrinsic nonlinear and multidimensional relationship associated with pile drivability. Similar with neural networks, no prior information on the form of the numerical function is required for MARS. The main advantages of MARS lie in its capacity to capture the intrinsic complicated data mapping in high-dimensional data patterns and produce simpler, easier-to-interpret models, and its ability to perform analysis on parameter relative importance. Previous applications of the MARS algorithm in civil engineering include predicting the doweled pavement performance, estimating shaft resistance of piles in sand and deformation of asphalt mixtures, analyzing shaking table tests of reinforced soil wall, determining the undrained shear strength of clay, predicting liquefaction-induced lateral spread, and assessing the ultimate and serviceability performances of underground caverns (Attoh-Okine et al., 2009; Mirzahosseini et al., 2011; Samui, 2011; Samui and Karup, 2011; Samui et al., 2011; Zarnani et al., 2011; Lashkari, 2012; Zhang and Goh, 2013, 2014a, b; Goh and Zhang, 2014). In this paper, the back propagation neural network (BPNN) and MARS models are developed for pile drivability predictions in relation to the maximum compressive stresses (MCS), maximum tensile stresses (MTS), and blow per foot (BPF). A database of more than four thousand piles is utilized for model development and comparative performance between BPNN and MARS predictions.

2. Neural network algorithm

A three-layer, feed-forward neural network topology shown in Fig. 1 is adopted in this study. As shown in Fig. 1, the back-propagation algorithm involves two phases of data flow. In the first phase, the input data are presented forward from the input to output layer and produce an actual output. In the second phase, the errors between the target values and actual values are propagated backwards from the output layer to the previous layers and the connection weights are updated to reduce the errors between the actual output values and the target output values. No effort is made to keep track of the characteristics of the input and output variables. The network is first trained using the training data set. The objective of the network training is to map the inputs to the output by determining the optimal connection weights and biases through the back-propagation procedure. The number of hidden neurons is typically determined through a trial-and-error process; normally the smallest number of neurons that yields satisfactory results (judged by the network performance in terms of the coefficient of determination R^2 of the testing data set) is selected. In the present study, a Matlab-based back-propagation algorithm BPNN with the Levenberg–Marquardt (LM) algorithm (Demuth and Beale, 2003) was adopted for neural network modeling.

3. MARS algorithm

MARS was first proposed by Friedman (1991) as a flexible procedure to organize relationships between a set of input variables and the target dependent that are nearly additive or involve interactions with fewer variables. It is a nonparametric statistical method based on a divide and conquer strategy in which the training data sets are partitioned into separate piecewise linear segments (splines) of differing gradients (slope). MARS makes no assumptions about the underlying functional relationships between dependent and independent variables. In general, the splines are connected smoothly together, and these piecewise curves (polynomials), also known as basis functions (BFs), result in a flexible model that can handle both linear and nonlinear behavior. The connection/interface points between the pieces are called knots. Marking the end of one region of data and the beginning of

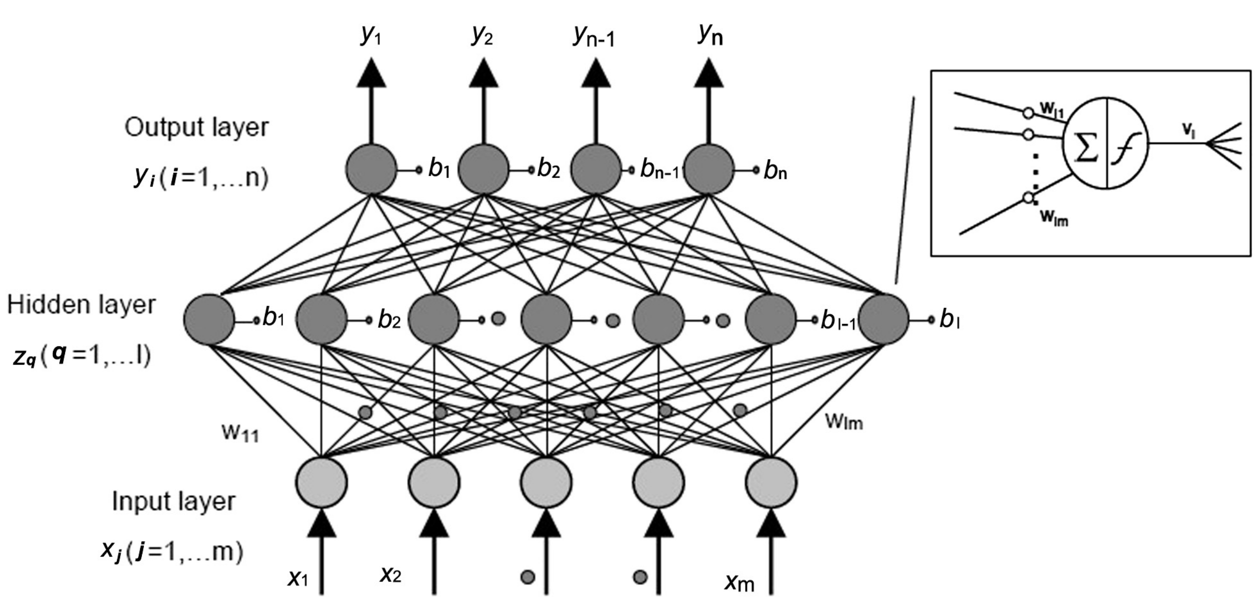

Figure 1. Back-propagation neural network architecture used in this study.