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Stability assessment of homogeneous slopes loaded with mobile tracked cranes—An artificial neural network approach

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Abstract: Construction projects often involve the use of mobile crawler cranes to excavate, backfill, dredge or move material and equipment on or near slopes. Crane manufacturers often only provide guidelines for the safe operation of cranes with respect to over tipping. However, the complex interaction of many variables such as the crane, its load, the slope geometry and its geotechnical properties can create slope instability. In this study, an artificial neural network was developed to predict the stability of these slopes loaded by mobile cranes. The neural network was built and trained using a set of slope stability models that were constructed using the above parameters via Monte Carlo sampling. The trained network was capable of predicting the factor of safety of a loaded slope and the location of the critical failure surface with relatively low error. In addition, the quality of the network's output was investigated using multiple metrics, such as the correlation ratio or the mean squared error and quite high correlation was achieved. Thus, the predicting capabilities of the network can be used with confidence to aid the positioning of mobile cranes on slopes without a need to perform slope stability analysis for each scenario.

Subjects: Sustainable Mining; Rock Mechanics; Soil Mechanics; Georisk & Hazards; Hydraulic Engineering

Keywords: slope stability; crawler crane; artificial neural network

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PUBLIC INTEREST STATEMENT

Construction projects involve mobile cranes to excavate or move material and equipment on or near slopes. Crane manufacturers often only provide guidelines for the safe operation of cranes with respect to over tipping. Complex interaction of many variables such as the crane, its load, the slope geometry and its material properties can create slope instability. In this study, an artificial neural network was developed to predict the stability of slopes loaded by mobile cranes. The neural network was built and trained using a set of slope stability models. The network was capable of predicting the factor of safety of a loaded slope and the location of the critical failure surface with relatively low error. The quality of the network's output was investigated using multiple metrics and high correlation was achieved. The predicting capabilities of the network can be used with confidence to aid the positioning of mobile cranes on slopes.

1. Introduction

Quite a few civil engineering construction projects can encounter a slope stability issue at some point during the course of a project. Often the slope instability occurs as a result of a construction activity itself; such as during foundation excavation or backfilling, dredging operations on levees, or by imposing an excess surcharge on a slope. To dredge, excavate or move construction materials or equipment, a mobile tracked crane (also called crawler crane) is frequently operated on the top slope surface. Therefore, the assessment of the slope's stability has to consider a moving surcharge (the crawler crane and its load) in addition to the *in situ* soil conditions and slope geometry. The crawler crane itself can travel along and perpendicular to the slope, thus shifting the load created by it. However, most often the critical combination of the soil conditions in conjunction with the crane and its transported load that precipitates slope instability. The load carried by a crane is transferred as both a vertical force and a moment to its tracks, depending on the boom length and its inclination. Although there are guidelines for crane operation prescribing the envelope of safe boom length and angles (Hitachi Sumitomo Heavy Industries, n.d.), these were developed to ensure the safety of a crane against over tipping. There exist only basic guidelines regarding the safe distance of a crane to a slope, such as the equivalent of a distance of one excavation depth for hard soils and twice the excavation depth for soft soils (Zoomlion Heavy Industry Science and Technology Inc., n.d.). To evaluate the stability of a slope loaded with crawler cranes, one has to take into account soil properties, slope geometry and the location and load carried by a crawler crane. There are virtually infinite combinations of these key factors that need to be considered to thoroughly assess the safety of a slope. It is not enough to consider the extreme cases only, such as the crane being closest to the slope edge, because there can be other combinations of loads and crane locations and orientations that can lead to slope failure. Motivated by the complex interaction of these parameters, the study summarized in this paper developed an artificial neural network (ANN) to predict the factor of safety (FS) of a slope loaded with a crawler crane. To our knowledge, an ANN for assessing slope stability due to mobile cranes has not been done before. Thus, what is novel about the proposed approach is that it can simultaneously consider the load and location of the crane along with the slope and its properties; it has the ability to predict the factor of safety using the ANN without the need to create and analyse a slope stability problem for every possibility and combination of parameters. Also, what is innovative in the presented use of the ANN is that it can be applied to rapidly explore what-if scenarios to position the crane and plan its route without compromising the stability of a slope. The ANN was built, trained and validated using a data-set of parameters describing the slope and loading, sampled from a representative distribution for each parameter using a Monte Carlo technique. Artificial neural networks have been in use in many areas of engineering (Figueiredo, Park, Farrar, Worden, & Figueiras, 2010; Salehi, Burgueño, Das, Biswas, & Chakrabarty, 2016; Salehi, Das, Chakrabarty, Biswas, & Burgueño, 2015; Silva et al., 2016) for example. Specifically, the use of ANNs in geotechnical engineering is not entirely uncommon; they have been applied to estimate deformation of diaphragm walls in clays (Kung, Hsiao, Schuster, & Juang, 2007), to assess shallow landslide potential (Caniani, Pascale, Sdao, & Sole, 2007; Gomez & Kavzoglu, 2004), estimate lateral movement of braced excavations (Goh & Kulhawy, 2004; Goh, Wong, & Broms, 1995), estimate rock modulus (Sonmez, Gokceoglu, Nefeslioglu, & Kayabasi, 2006), and ANNs were used for debris flow prediction (Chang & Chao, 2006) as well. More specifically, ANNs were used to predict the stability of slopes validated by back analysis (Choobbasti, Farrokhzad, & Barari, 2009), highway slopes subjected to earthquake loading (Lin, Chang, Wu, & Juang, 2009), and slopes comprised of clayey soils (Abdalla, Attom, & Hawileh, 2012). Thus, ANNs represent a quite useful approach in dealing with complex, multi-variable problems. Although natural slopes can be inherently heterogeneous, comprised of multiple layers of different materials, quite a few constructed slopes are made of a single material. Thus, our study was confined to homogeneous slopes only. Nevertheless, the proposed approach can be applied to heterogeneous slopes as well, if the soil layers and their properties are known. The paper begins by reviewing the stability of homogeneous slopes, the pressure distribution due to crawler cranes and the theory behind neural networks. Sampling of key model parameters, creation of slope stability models, development and training of the ANN and its validation concludes the paper.

2. Background

In order to develop a predictive ANN model, background information is presented first for the stability analysis of homogeneous slopes, the pressure on a slope resulting from crawler cranes and their loads and a brief description of the salient features of ANNs.

2.1. Slope stability of homogeneous slopes

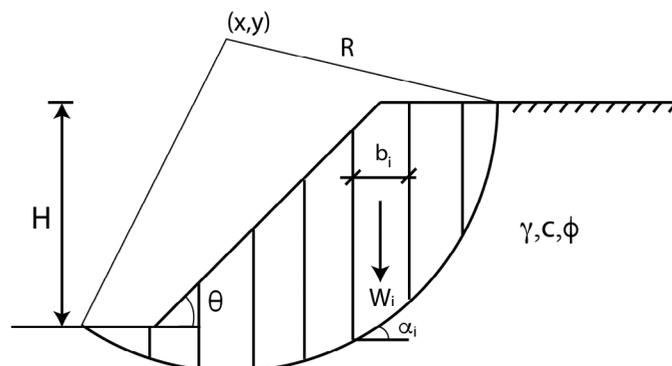
The most prevalent type of instability of constructed or natural homogeneous slopes can be characterized by a circular failure surface (Nash, 1987; Siddappa & Shanthakumar, 2014; Xiao, Li, Ding, & Liu, 2015). There are many slope stability analysis methods suitable to capture this type of failure; the traditional ones are based on limit equilibrium (Nash, 1987), and more recently, finite element-based methods using the principle of Shear Strength Reduction (Hammah, Curran, Yacoub & Corkum, 2004). Since it is not clear how to easily describe the failure surface obtained by the finite element method by a center of the failure circle and its radius, our approach was to use a traditional limit equilibrium method; Bishop's Simplified Method (Nash, 1987). Bishop's Simplified Method is proven to predict the factor of safety for homogeneous slopes with high accuracy (Das, 2007; Zsaki, 1999), and it is routinely used by practicing engineers as a standard method of slope stability assessment. Bishop's Simplified Method is capable of capturing a circular failure surface and it only requires three parameters to uniquely identify it, which are the x and y coordinates of the center of a failure circle and its radius. Figure 1 illustrates the general setup of a model used by Bishop's Simplified Method, while the factor of safety equation for this method is shown in Equations (1) and (2) (Nash, 1987).

$$F_s = \frac{\sum \frac{1}{m_i} [c' b_i + (W_i - u_i b_i) \tan \phi']}{\sum W_i \sin \alpha_i} \quad (1)$$

$$m_i = \frac{\tan \phi'}{F_s} \sin \alpha_i + \cos \alpha_i \quad (2)$$

where F_s is the factor of safety, c' and ϕ' are the soil's cohesion and friction angle. With respect to the i -th slice; b_i is the width of a slice, W_i is the weight of a slice, u_i is the pore water pressure acting on a slice, and α_i is the angle of inclination of the base of the i -th slice. For a detailed derivation of the factor of safety equation, the reader is referred to Nash (1987). For Bishop's Simplified Method, any additional load or surcharge applied on the surface of the slope can be easily incorporated into the factor of safety equation. The distributed surcharge pressures are converted into per-slice forces and added to the weight of the affected slice. Equations (1) and (2) calculate the solution only for a specified circular failure surface located at coordinates (x, y) with a radius of R . Within a slope, a search is required to locate the critical failure surface with the lowest factor of safety among the infinite number of possible ones. There are many methods available for this, such as a brute-force grid search (Slide User's Manual, 2015) or optimization schemes like the Simplex method, Rosenbrock's method or similar (Zsaki, 1999). The research presented in this paper used the grid-search method,

Figure 1. Setup of slope and slices for Bishop's Simplified Method.



as implemented in Rocscience’s Slide slope stability analysis software (Slide User’s Manual, 2015). It is a relatively efficient and comprehensive technique to search for the location and radius of the critical failure surface for a given model by computing the factor of safety of failure circles located at grid points and varying the radii of a circle. For each grid point, only the circle radius with the smallest factor of safety is retained, which can be plotted as a contour map, as illustrated in Section 4.

2.2. Loads imposed on slopes due to crawler cranes

A mobile or crawler crane and its load exerts a pressure on the crest of a slope. The pressure distribution depends not only on the combined weights of crane and load, but on the eccentricity due to the location of the load being lifted, which in turn depends on the boom length and angle. Common practice is to lay a timber mat under a crawler crane to aid the distribution of load (Liu, Chan, & Gerbrandt, 2008). With low values of eccentricity, a trapezoidal pressure distribution is generated, however, if the eccentricity is high, there is a risk of the crane’s rear portion lifting up and losing contact with the ground resulting in a triangular pressure distribution (Liu et al., 2008). Generally, this results in unsafe crane operation. There have been studies to assess the bearing capacity of soils loaded with crawler cranes (Liu et al., 2008), and it was found that the non-uniform load due to the crane could be represented with an equivalent pressure distribution. In this study, the crane load representation, as shown in Figure 2, can be characterized by a minimum (q_{min}) and maximum (q_{max}) pressure, which can be computed using Equations (3) through (8) (Liu et al., 2008).

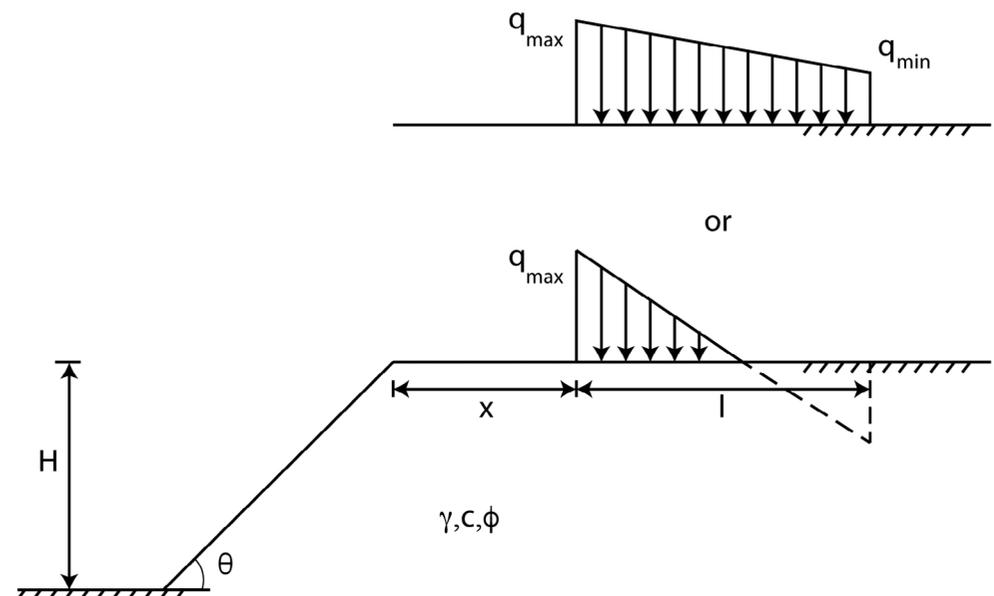
$$q_{min}^{max} = \frac{W + G}{lb} \pm \frac{M_1 + M_2}{S} \tag{3}$$

where W is the load being lifted by a crane, G is the self-weight of a crane, l is the contact length of crane tracks and soil, b is the out-of-plane width of the timber mats. Moments M_1 and M_2 are due to the eccentricity of the load, first transferred to the pivot point of the boom (M_1) and then to the center of gravity of the crane (M_2). S is the section modulus for a rectangular contact area of the timber mat and soil. Thus in Equation (4) the pivot point (M_1) can be computed.

$$M_1 = WL_{boom} \cos \beta \tag{4}$$

where L_{boom} is the boom length and β is the inclination of the boom with respect to the horizontal. While, the center of gravity of the crane (M_2) can be calculated from Equation (5) as

Figure 2. Equivalent pressure distribution due to crawler crane and its load.



$$M_2 = We \tag{5}$$

In Equation (5), e is the distance between the pivot point of the boom and the center of gravity of the crane. The section modulus for a rectangular area is given by Equation (6) as

$$S = \frac{bl^2}{6} \tag{6}$$

Thus, substituting Equations (4) through (6) into Equation (3) yields (Liu et al., 2008).

$$q_{min}^{max} = \frac{W + G}{lb} \pm \frac{WL_{boom} \cos \beta + We}{\frac{bl^2}{6}} \tag{7}$$

which can be further simplified to

$$q_{min}^{max} = \frac{1}{lb} \left[(W + G) \pm 6W \left(\frac{L_{boom} \cos \beta + e}{l} \right) \right] \tag{8}$$

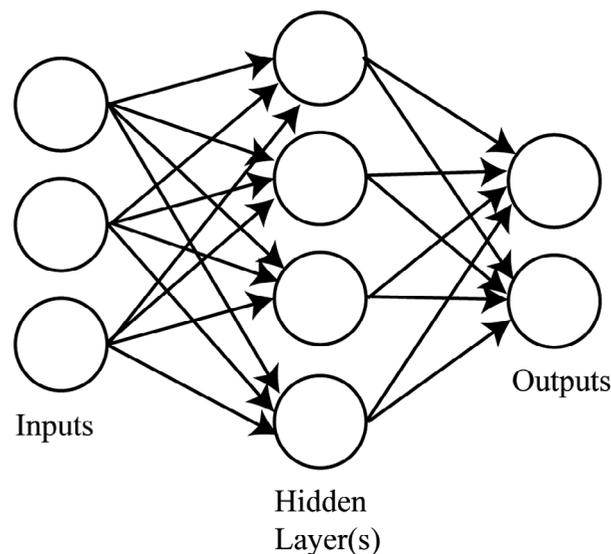
to give the maximum and minimum ground pressures (Equations (7) and (8)) due to the crawler crane and its load, which will be used in the subsequent sections.

2.3. Artificial neural networks

Artificial Neural Networks, or ANNs are a class of models analogical to the central nervous system in a biological system (Gurney, 1997). An ANN uses a large amount of input data to approximate functions, and its internal structure is comprised of interconnected nodes, like the neurons in a brain, where they can transmit information and communicate interactively (Gurney, 1997). Figure 3 illustrates the structure of an ANN schematically.

The ANN is driven by input data or stimuli, which in turn are processed by the internal or hidden layers of neurons and an output is generated as a result. The mathematical representation of an ANN can be thought of as inputs, multiplied by their respective weights that contribute to an activation function, which generates an output. The key is to somehow adjust the weights, in what it is often called the training or learning phase, to enable the function describing a system to generate the desired output. Since there can be hundreds or thousands of weights to adjust to find the

Figure 3. Conceptual representation of an ANN.



optimal set, there has to be an algorithmic approach to achieve this. Thus, there have been a number of algorithms developed for a systematic adjustment of weights, e.g. training of the ANN. Most notable of which are the Backpropagation algorithm (Rumelhart & McClelland, 1986), Simulated Annealing (Cheng, 2007), and Particle Swarm Optimization (Xiao et al., 2015). Judging from the published literature in the geotechnical field (Chang & Chao, 2006; Choobbasti et al., 2009; Goh et al., 1995; Lin et al., 2009), the Backpropagation algorithm seems to be the most prevalent. It is relatively easy to implement and appears to be robust enough. Thus, this method was adopted in our research to train the ANN. The transfer function used in our ANN was of sigmoid-type, which other researchers have used in the past with success (Lin et al., 2009).

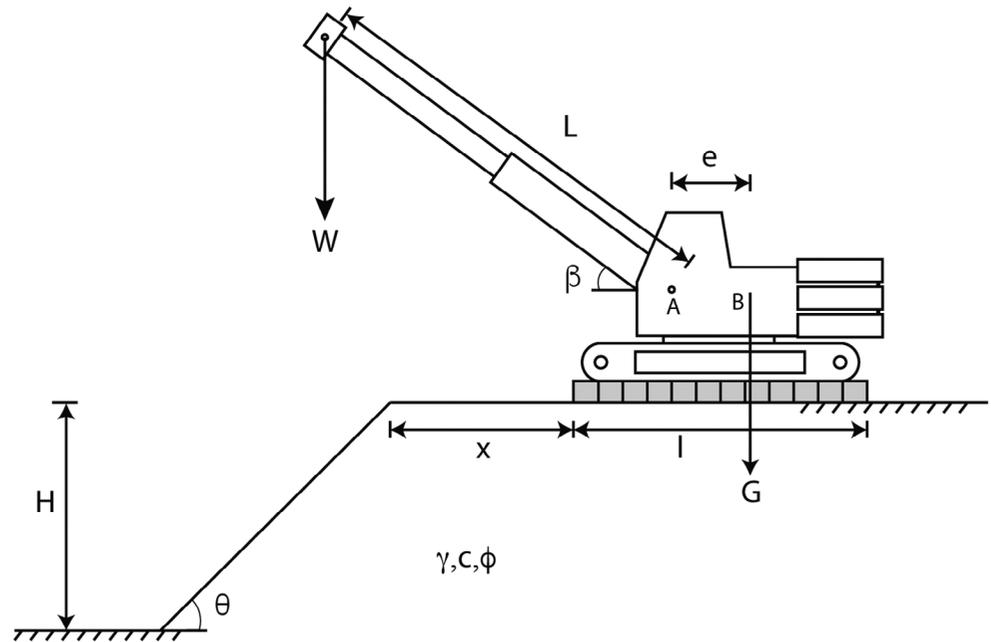
The Backpropagation training algorithm is a multi-layered, feed-forward type algorithm. In the algorithm, the artificial neurons are arranged in different layers and send signals forward, towards the output. Once an output is computed, the “errors” (differences between actual results and expected outputs) are propagated backwards to adjust the weights. Similar to other methods, the ANN in this case was divided into three main parts; the input layer, output layer and one or more intermediate hidden layers between the input and output layers. The process of the Backpropagation algorithm is called supervised learning (Mehryar, Afshin, & Ameet, 2012). The algorithm proceeds in an iterative manner to adjust the weights such that the error becomes zero, or suitably small, and the final outputs are in accordance with the expected outputs. When the error achieves this minimal value, it is said that the ANN has learned the training data. For the model in our case, subsequent sections on ANN will develop the training and validation sets and specify the criteria for acceptable performance of our ANN.

3. Slope stability model and identification and sampling of model parameters

The crawler crane operating on the top of a slope along with the geometric and geotechnical properties of a slope presents a system with quite a few potential variables. The previous section discussed the representation of a crane and its load as an equivalent ground pressure, as a function of the load lifted (W), the length of a boom (L_{boom}) and its inclination (β), the eccentricity (e), which is the distance between the center of gravity of the crane body (at B) and the pivot point of the boom (A). The crane’s self-weight, applied at (B) can be represented by a downward force (G), as defined on Figure 4. The timber mat, on which the crane is positioned, can be characterized by its distance from the crest of a slope (x) and its length (l). Thus, using Equation (8), the maximum ground pressure and its distribution can be calculated. The geometry of the slope was defined by its height (H) and slope inclination angle (θ). The homogenous slope’s geotechnical properties were represented by the soil’s unit weight (γ), cohesion (c) and angle of friction (ϕ). Some of the parameters are constant for a given crane; eccentricity (e), the self-weight of a crane (G), and the length of a timber mat (l). These values can be found in a documentation supplied by the crane manufacturer (Hitachi Sumitomo Heavy Industries, n.d.; Zoomlion Heavy Industry Science and Technology Inc., n.d.). The nine remaining parameters were treated as true variables in our analyses.

In order to describe these parameters, it was required to establish their credible range to be used for the slope stability models. The maximum load carrying capacity of a crane, the length and inclination of its boom can be determined from literature, such as (Hitachi Sumitomo Heavy Industries, n.d.; Zoomlion Heavy Industry Science and Technology Inc., n.d.). However, care must be taken to select a combination of W , L and β such that the stability of the crane is not jeopardized. The working ranges and crane rating charts supplied with a crane (Hitachi Sumitomo Heavy Industries, n.d.; Zoomlion Heavy Industry Science and Technology Inc., n.d.) were used to set up a simple rule-based spreadsheet to check for the validity of a randomly sampled set of the three parameters. The range for the distance of a crane from the crest of a slope (x) was selected such that a crane is located within three slope heights from the crest. A simple numerical experiment confirmed that a crane carrying a maximum load located beyond this distance did not change the factor of safety of a slope by more than two percent, as compared to the same unloaded slope. The parameters of slope geometry (H , θ) were selected such that to represent common slopes found in civil and mining engineering projects, drawn from literature (Ai, 2016). Similarly, the range of soil properties (γ , c , ϕ) for

Figure 4. Parameters in the slope stability model for a slope loaded with a crawler crane.



the homogeneous slope was selected based on a literature survey drawn from more than a dozen sources (Ai, 2016).

Table 1 summarizes the range of parameters used in this study along with the fixed parameters (that are a characteristics of a particular crane). The parameters established in Table 1 were sampled using a Monte Carlo sampling procedure to create a set of values from which a model can be built. Thus, for each parameter, assuming they were uniformly distributed, a value can be chosen using an independent random number using Equation (9) as

$$x_i = x_{min} + (x_{max} - x_{min})y_{rnd}$$

where x_i is a parameter (from Table 1) sampled for use in the i -th model. The values of x_{min} and x_{max} are the lower and upper limits of the parameter's established range and y_{rnd} is a random number between 0 and 1, inclusive.

Table 1. Model parameters

Parameter	Range
Load lifted (W), (kN)	0–490
Length of a boom (L_{boom}), (m)	6–12
Boom inclination (β), (degrees)	30–80
Crane's distance from the crest of a slope (x), (m)	0–3H
Slope height (H), (m)	3–30
Slope inclination angle (θ), (m)	10–70
Soil's unit weight (γ), (kN/m ³)	11.53–24.72
Soil's cohesion (c), (kPa)	0–60
Soil's angle of friction (ϕ), (degrees)	17–41
Eccentricity (e), (m)	1*
Crane's self-weight (G), (kN)	482*
Length of timber mat (l), (m)	4.71*

*Hitachi sumitomo heavy industries.

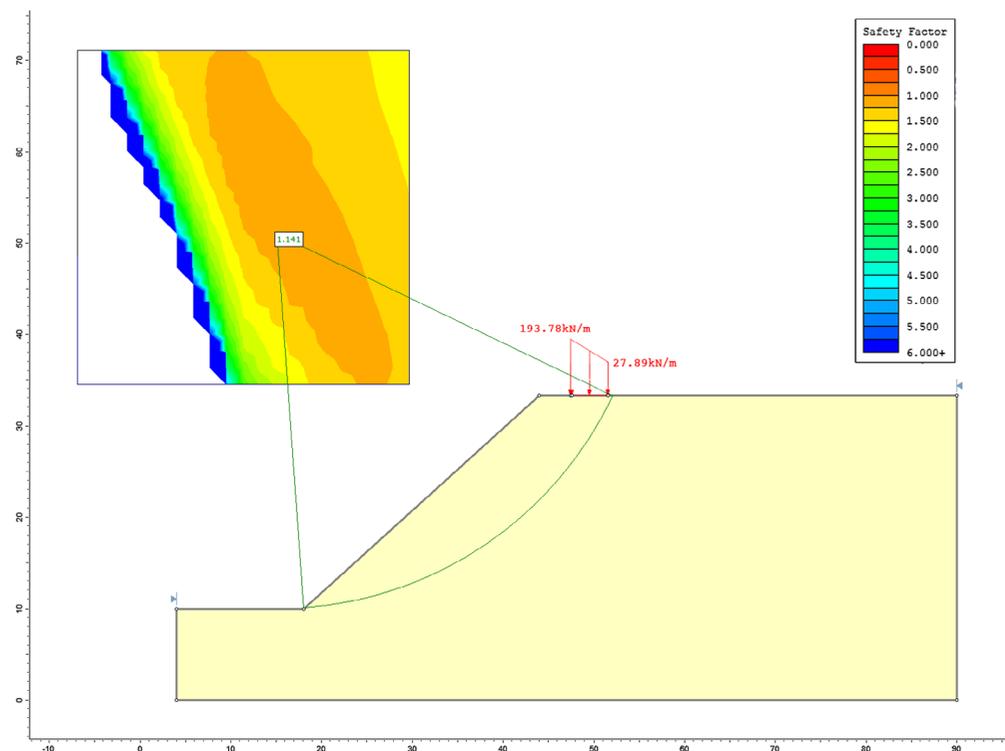
By independently sampling each parameter, a definition of a complete slope stability model can be established. Note, the pressure distribution caused by the crane and its load can be computed using Equation (8).

4. Generation and analysis of slope stability models

Sampled parameters from Table 1 were used to generate slope stability models incorporating the crane and its load positioned on the crest of a slope. Slide from Rocscience Inc. (Slide User's Manual, 2015) was used to create the models and carry out slope stability analysis. In the software, default values were accepted for Bishop's Simplified Method; the failure surface was subdivided into 25 slices and the number of iterations for factor of safety convergence was limited to 50 (Slide User's Manual, 2015). Grid search was employed to find the global minimum factor of safety. The grid was comprised of 21 by 21 search points automatically located by Slide and 100 trial radii were used at each search point. As an outcome of the stability analysis, the minimum factor of safety, along with the location (x, y, R) of the critical circular failure surface were recorded. These four values will be the requested output from the ANN as well. Figure 5 shows a typical slope loaded with a pressure distribution from a crane. Note that Slide allows only uniform and triangular loads to be applied, so in general, a trapezoidal pressure distribution (cf. Figure 2) was composed of a uniform one and a triangular one. Figure 5 also shows a critical failure surface for this model along with the contours of factor of safety.

General statistics of the analyzed slope stability models can shed some light on the overall behavior of homogeneous slopes loaded with crawler cranes. Out of the 150 models analyzed, where the number 150 will be justified in the next section, 35 percent had a factor of safety below unity, signifying slope instability. The lowest factor of safety was 0.54, while the highest was 3.18. On average, the factor of safety was found to be 1.44. In order to assess the effect of having a load on the crest of a slope due to a crawler crane, the same models were analyzed without a load. For these models, the percent of failing slopes has dropped to 14, while the average factor of safety has increased to 1.74 (an almost 21 percent increase). The lowest factor of safety for the unloaded slopes was 0.75,

Figure 5. A typical slope stability model as analyzed by Slide (Rocscience Inc.), showing the critical failure surface and the contours of factor of safety.



while the highest was 4.91. Thus, the loads imposed by crawler cranes can affect the stability of slopes as compared to the unloaded slopes by as much as 20%.

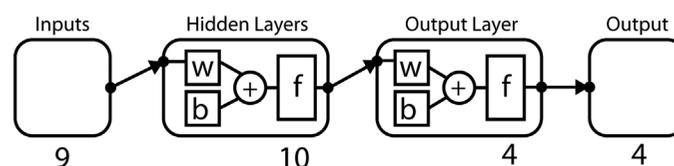
The slopes generated from the input parameters sampled and the resulting factor of safety and location of the critical failure surface comprise the input and desired outputs of the ANN, which will be established in the next section.

5. Development, testing and validation of the Artificial Neural Network

Perhaps the most important question in creating an ANN is that what accuracy is expected from it. The predicting capabilities of an ANN, and therefore its accuracy, are a function of the size and quality of a data-set that was used in creating and training it. There seems to be no clear consensus in the literature as to what constitutes a good data-set size. In particular, literature in which an ANN was used to assess the stability of a slope, reports data-set sizes of as high as three thousand (Kung et al., 2007), others report a size of about a thousand (Lin et al., 2009), down to a few hundred (Abdalla et al., 2012; Sonmez et al., 2006), further down to over a hundred (Chang & Chao, 2006; Goh et al., 1995). Thus, it can be concluded that there can be a great variation in the data-set size used in developing a successful ANN. Ultimately, the predicting power of an ANN needs to be measured against the validation data-set, in our case created from the Monte Carlo sampling of the input parameters. One has to appreciate that results obtained from any computation in the field of geotechnical engineering are as good as the quality of the input parameters. Soil and rock properties are seldom known better than to be within 10–20 percent of their true value, as influenced by sampling techniques, access to site, etc. Therefore, the predicting capabilities of an ANN need to be assessed keeping this data-limited nature of geotechnical engineering in mind. Our approach was to incrementally increase the data-set size used for ANN development until a satisfactory (in the context of above facts) predicting power was achieved as measured by the correlation coefficient, which will be discussed further on. For a data-set of 150 models, the error in ANN's prediction became relatively small with a good correlation between input and output. Thus, we concluded that such data-set size would provide adequate accuracy, as it will be discussed in the next section.

The ANN was developed using MATLAB's Neural Network Toolbox (2012). The structure of the ANN, as shown in Figure 6, was comprised of nine inputs (cf. Table 1's first nine parameters), a hidden layer with ten neurons, and an output layer generating four outputs, which are the prediction of the location of the failure surface's x and y coordinates, its radius and the resulting factor of safety. The number of neurons in the hidden layer was arrived at by finding the maximum correlation coefficient possible by trial and error, which was achieved with ten neurons in the hidden layer. The final value of correlation coefficient will be discussed later. MATLAB had provided users with three training algorithms; Levenberg-Marquardt, Bayesian Regularization, and the Scaled Conjugate Gradient algorithm. The Levenberg-Marquardt algorithm was recommended for problems in geotechnical engineering (Kung et al., 2007) due to its highest processing speed and efficiency even though it requires more memory than the other two functions (MATLAB Neural Network Toolbox, 2012), thus we have adopted it for our ANN. The subdivision of the data-set into training, validation and testing groups was achieved by trying literature-reported ratios of 50:50(25:25) (Gomez & Kavzoglu, 2004), 60:20:20, 70:20:10, 80:20 (Chang & Chao, 2006), and 70:15:15. Most researchers only split their data-set into training and validation (Chang & Chao, 2006; Gomez & Kavzoglu, 2004; Kung et al., 2007). The performance of the ANN was measured using the correlation coefficient, and in our case, the highest value was achieved for the 70:15:15 split. Thus, all the input data samples were randomly divided into 70% for training, 15% for validation, and 15% for testing.

Figure 6. Structure of the ANN, as developed in MATLAB's Neural Network Toolbox.



A measure of success for the various phases of ANN development (training, testing and validation) can be assessed by finding the correlation between the inputs and the output generated by an ANN. Figure 7 gives an overview of the ANN's behavior, based on our input data-set. The training phase achieved a correlation (as measured by the r -value) of about 0.979, which is considered quite good. While both the validation and testing phases attained somewhat less, at 0.922 and 0.908, respectively. Overall, the ANN scored an r -value of 0.964. The plots for individual phases are shown in Figure 7.

Similarly, the error histogram (Figure 8) shows the distribution of errors (differences between the input factor of safety and the output one from the ANN) for all data samples. The overall tendency of the results converged toward the Zero Error line, and it demonstrated that the output of the ANN results approximates well the target data.

To further assess the predicting accuracy of our ANN, an independent data-set, not part of the previous 150 samples, was used. Twenty models generated from Monte Carlo sampling from the data ranges in Table 1 were analyzed in Slide and the resulting factors of safety and the location of the critical failure surface (x, y, R) were recorded. For the same input data-set, the ANN was used to predict the same four quantities for each model. In addition to metrics such as an error histogram or a correlation coefficient (r) between the input and output, literature reports various other metrics

Figure 7. Performance of the ANN through various phases of development and testing as reported by MATLAB (The MathWorks Inc., 2012).

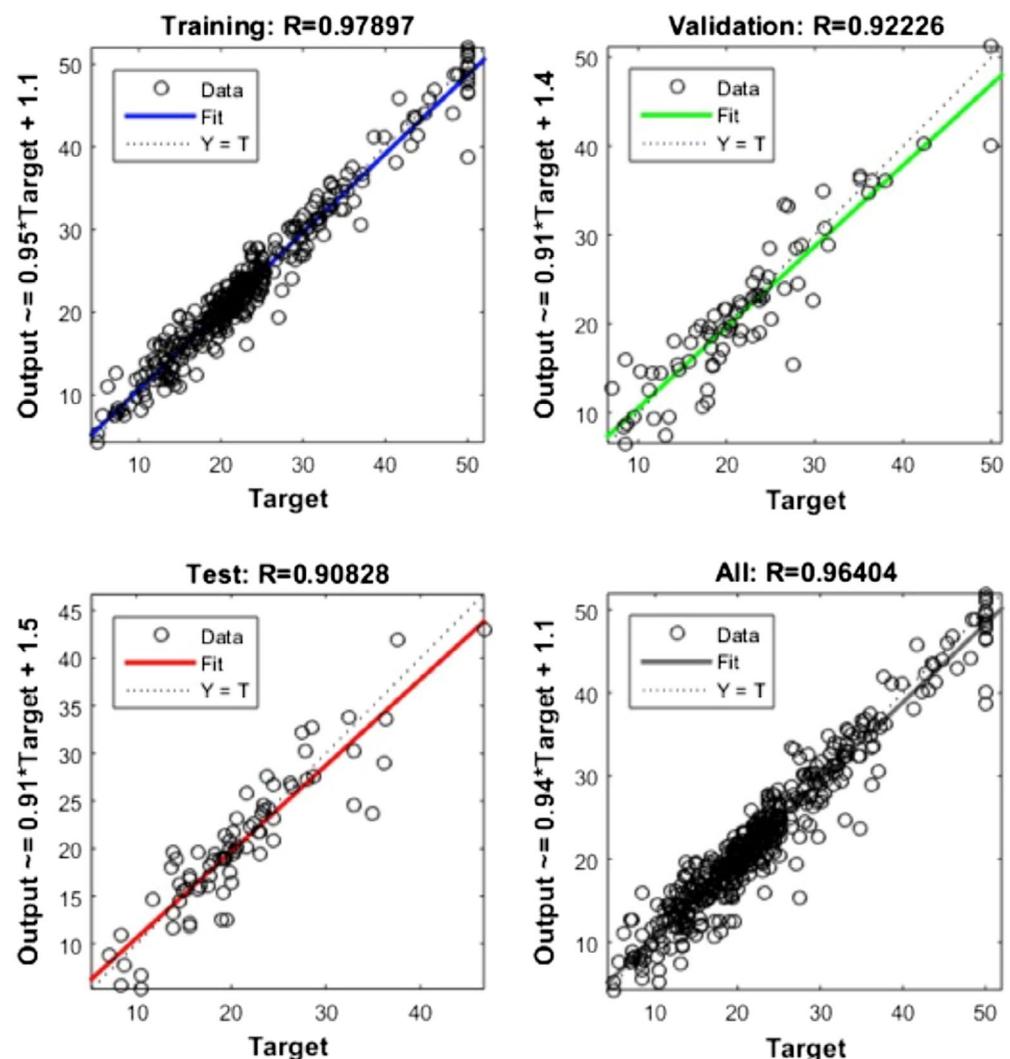
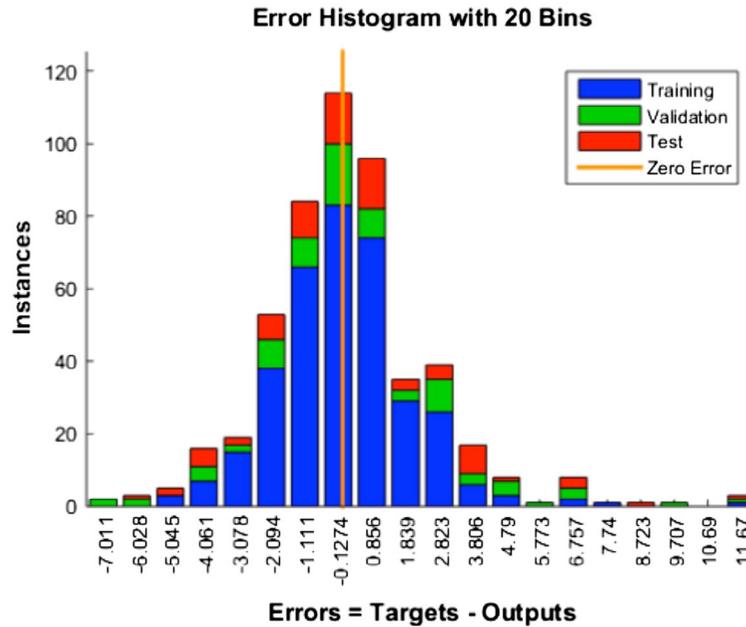


Figure 8. Error histogram for the results of ANN in comparison with the input data-set as reported by MATLAB (The MathWorks Inc., 2012).



that can be used to assess the ANN’s predictive capabilities. Quantities such as Mean Squared Error (MSE), Normalized Mean Squared Error (NMSE), Mean Absolute Error (MAE), Mean Absolute Percent Error (MAPE), and the Maximum and Minimum Absolute Error can be used (Abdalla et al., 2012). For the definition of these quantities, the reader is referred to a book on statistics, such as DeGroot (1989).

Based on the metrics in Table 2, the ANN’s predicting capabilities were quite satisfactory. The correlation coefficient for all the four output parameters was above 0.99 signifying a very good correlation between the Slide slope stability analysis results and the ANN’s prediction. The maximum absolute error (Max. AE) was a little over 1.5 (in meters) for two output quantities (the x and y coordinates of the critical failure surface) while for the factor of safety, the Max. AE was 0.036 (note that the range of FS was 0.54 to 3.18 in the data-set). The highest Mean Squared Error was for the y location of the center of critical circular failure surface and the same parameter was found to be to have the highest Mean Absolute Error. Our coefficient of correlation of 0.99, in comparison with what others have reported; 0.98 (Goh et al., 1995), 0.82 (Sonmez et al., 2006), 0.93 (Chang & Chao, 2006), was found to be very high. This gives confidence in our ANN and its predicting capabilities, particularly if evaluated in the context of uncertainty in estimating soil properties for geotechnical design.

Table 2. Measures of error between the ANN prediction and actual slope stability analysis

Metric	Output-FS	Output-x	Output-y	Output-R
MSE	0.000253	0.098492	0.546522	0.399033
NMSE	0.000180	0.000153	0.000193	0.000210
MAE	0.011365	0.236110	0.514020	0.426775
MAPE	0.934677	0.999598	0.980999	0.996075
Min. AE	0.000205	0.003573	0.006125	0.004984
Max. AE	0.036699	1.564954	1.565929	0.745145
r	0.999031	0.998542	0.998905	0.999504

6. Conclusion

The operation of a mobile or crawler crane atop a slope is part of many construction processes, from excavations, dredging to moving construction material or equipment. The rudimentary guidelines supplied by crane manufacturers often address only the stability of the crane itself not considering its effect on its operating environment. The only recommendations regarding the position of a crane with respect to a slope appear to be empirically based. The research presented in this paper considers the system of a loaded crane, a slope with its geometry and the soil properties. Homogeneous slopes, be natural or constructed, tend to fail along a circular failure surface, which was adopted in this paper's slope stability model. After identifying key parameters comprising the system, a representative range was established for each parameter derived from a literature search. via the process of random sampling, a set of slope stability models were created and analyzed to find the location and factor of safety for each critical failure surface. These model parameters served as an input to an artificial neural network, which was built and trained to generate the same output as the slope stability analysis software. The performance of the neural network proved to be quite satisfactory in predicting the factor of safety of a set of independent models. The accuracy of the artificial neural network was measured by a set of metrics such a correlation between the input and output, the mean squared error and maximum absolute error. It was found that the network was capable of maintaining high accuracy in predicting the location of the critical failure surface and the associated factor of safety. Thus, with an artificial neural network, it is possible to accurately assess the effect of positioning a mobile crane on a construction site without the need to build a slope stability model for every case. The tool presented in this paper has the ability to be useful for practicing engineers and it is considerably more versatile than the empirically based recommendations given in crane manuals.

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