ISSN: 0128-7680
Pertanika J. Sci. & Technol. Supplement 9(1):73 - 79 (2001)

The Determination of Pile Capacity Using Artificial Neural-net: An Optimization Approach

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ABSTRACT

From standard static formula for bearing capacity of a single pile foundation, an algorithm using a reliability approach for the determination of service load was developed. Using the developed algorithm, the safety measures involved are such as reliability index and the probability of failure; instead of only factor of safety if conventional deterministic approach is used. In this study, the developed algorithm is further expanded to include computation of the weight-matrix of a sequential associative feedback-type neural net model for the determination of service load of a single pile is introduced. The proposed technique concludes improved efficiency over the conventional method of commissioning the functional formula of the weights by exploiting the structural properties of the matrices appeared in the codification of the service load to a single pile problem as a quadratic zero-one optimization program. Those structural attributes are distinguished and described in terms of template-matrix contributions of the constraint functions of the quadratic optimization, to the weight-matrix asynchronous auto-associative neural net. It is stated by using those templates, the weight matrix can be taken in intuitively. Performance results of this research study reveal that neural net deterministic approach could be a better choice for implementation in identifying the required weight-matrix.

Keywords: Design chart, reliability design approach, auto-associative feedback neural-net, pile foundation, static formula, learning, potential function, fuzzy-information processing

INTRODUCTION

We can consider that neural net is a mathematical modeling of information process. It provides a method of representation of relationship, which is quite dissimilar from the sequential, conventional logic based digital computer. It represents a quantum range of artificial neural processing model. These are relatively simple mathematical constructs that are often thought to loosely model biological metaphor systems. It's representation involves densely inter-linked networks. The inherent computational speed and parallelism of neural net is the basic characteristics. Researchers approach neural nets from divergent perspectives. Summarizing all the approach is a fairly complex task, since neural net is rapidly changing. However, from architectural viewpoint, current neural net theory has three main branches: perceptron, associative memory, and biological models. These are suggestive labels, not a classic terminology, which shows the branches and researchers associated with each branch. The perceptron branch associated with Rosenblat in the 1950s is a good example. Currently, most neural nets are perceptron of one form or another. The associative memory branch is the source of current research to which Hopfield in 1982 published an influential paper which gave attention to the associative properties of a class of neural nets. Neural nets model are being accepted in the civil engineering problems (Goh 1995). Neural net can address the tasks of interpretation, classification, prediction, estimation and optimization. In civil engineering problem, most of the neural net applications have focused in feed-forward neural nets, while a few significant work has contributed in using recurrent feedback type neural net. Usually, the feed-forward neural net is more applicable in civil engineering application as compared to other class of problems to which the purpose-state is priorly known to a given initial state (such as a sequence of n × 1 input column load vectors). On the other hand, recurrent feedback neural net (auto-associative neural net) is used where the conclusion is not known in advance. The determination of service load of a single pile by reliability approach can be an optimization problem. Among feedback neural nets, the associative neural net indicates a better fit to solving a combinatorial optimization issue. An auto-associative neural net is a single layer feedback neural net in a dynamic system, evolving in time, in either a sequential discrete or continuous output space. The transition in neural net towards an asymptotically stable solution (i.e., a minimum, local or global), is a dissipated potential function, E. A combinatorial optimization problem can be mapped on to an auto-associative feedback configuration of neural net by building pertinent potential function to which the global minimum is a solution of the optimization process. One of the difficult tasks facing designers is the translation of optimization problem into the minimization of this function. Moreover, the derivation of the weight matrix, associated with this function of the associative feedback neural net, involves complex symbolic computations. The purpose of this paper is to present a simplistic way to derive the weight-matrix of a neural net for the determination of the service loading (capacity divided by the assumed factor of safety) of a single pile foundation. The service load of a single pile have been developed earlier (Ab. Malik 1996); this study is to develop a neural net model for it. The implementation of neural net is described after a brief introduction of neural net.

NEURAL-NET

From an application perspective, one can explore neural net suits in nonlinear, parallel processing and adaptive. The term neural net is defined by a combined adaptive network and parallel processing technology. So, it requires a coherent study including application need, neural net model, and parallel processing. A neural net is an abstract sophisticated information process simulation system imitates the biological nature that pertains to the class of machine learning. It is a process of acquiring and retrieving knowledge. Neural net is characterized not only by its architecture but also by the type of neurons used by the learning procedure and by the principle of operation. It processes as deterministic or stochastic systems. In deterministic neural nets, all parameters and signals are deterministic nature. In stochastic neural nets, signals and parameters (linked-weights) are changed randomly (some probability) by some random amount.

Our sequel in-search and analysis will aim to address the following questions during the undertake of this development and research project:

1. How does the auto-associative feedback memory-based neural net algorithm behave with a current prototype Single pile loading test system?
2. Given a fixed set of training data set pattern, is it better to adjust the linear weight-matrix after each pattern or (In which case the method becomes a version of neural net for linear or quadratic programming) all the patterns?
3. How far do the answer of the first two questions apply to the related method such as mapping on recurrent neural net multi-layer perceptron (MLP) based architecture?

OPTIMIZATION PROCEDURE FOR DETERMINATION OF CAPACITY: DETERMINISTIC VS. RELIABILITY APPROACHES

The determination of predicted capacity, Q_p (and consequently the allowable capacity, Q_a) can be computed by a depth integration process preferably set up on a spreadsheet for calculations for every foot of the embedded length of pile. The recommended procedures can summarized as:

Select the recommended factor of safety, SF, or reliability index, β, to the respective method of determination. Determine the perimeter surface area of pile shaft, A_s and the toe bearing area, A_t. The reliable method to determine the pile capacity is to perform a loading test. The pile could be loaded by using a hydraulic jack and jacking against reaction piles, or a weighted platform. Piles are often tested after driving when load test equipment has been made. A detailed comparison of the various methods or testing systems is beyond the scope of this paper. The density function ¶(q) can be determined from the previously developed algorithm (Ab.Malik 1996) :

$$f(q) = Q_p = \left(\sum_{i=1}^{n} \left[(p'_{ov} K_s \tan\delta)_i \right] (A_s)_i + (p'_t N^*_q A_t) \right)$$

$$= \sqrt{\left(\sum_{i=1}^{n} [Q_s] + Q_t \right)^2} \tag{1}$$

Where, Q_p, Q_s, Q_t are the predicted capacity, shaft capacity, and toe capacity respectively from the recommended equations. Also, note that this density function is selected to be quadratic for mathematical reasons only because and the total predicted capacity from the algorithm may be found from the different criteria. The variability of the predicted capacity of a particular site, s.

QUADRATIC ZERO-ONE PROGRAMMING TO SOLVING PILE CAPACITY

It was originally developed for the equality constrained optimization problem, which we repeat here for convenience. Minimize

$$f(x) = c^T x + \tfrac{1}{2} x^T Q x, \ldots \tag{2}$$

$x \in \{0, 1\}^n$, where $c \in \Re^n$, $Q \in \Re^{n\times n}$ is a symmetric n×n matrix. The components of the design vector x can take only discrete (binary) values 0 or 1. In other words, the design vector x is represented by an n-dimensional cube called a unit hypercube with vertices at the points $x = [x_1, x_2, \ldots, x_n]^T$, $x_i \in \{0, 1\}$ $(i = 1, 2, \ldots, n)$. In ordinary, such a unit hypercube has 2^n distinct vertices which corresponds to 2^n possible states of the neural net employed to solve the problem. The problem is written equivalently as min

$$f(x) = x^T Q^* x, \; x \in \{0, 1\}^n$$

where,
$q'_{ii} = c_j + q_{ij}/2$
subject to $h_i(q) = 0$ $(i=1,2, \ldots, n)$, $q \in \Omega \subset \Re^n$.

For this , we will put the construct of the Lagrange function below as

$$L(Q,\lambda) = f(Q) + \sum_{i=1}^{n} \lambda_i h_i(q), \tag{3}$$

where the components of the vector $\lambda = [\lambda_1, \lambda_2, \ldots, \lambda_n]^T$ are the Lagrange multiplier.

1[st] type of constraint of the pile loading optimization refers to the Pile settlement movement s_i of each activity si and this could be expressed as

$$h_i^{(1)}(Q) = \sum_{k_1(i)}^{K_2} q_i^{(k)} - s_i \tag{4}$$

I = 1,2,& , I with I denoting the total number of noncritical tests, while $k_1(i)$ and $k_2(i)$ are expressed as

$$k_1(i) \cong EST_i + 1 \tag{5}$$
$$k_2(i) \cong EST_i + s_i + TF_i \tag{6}$$

in eqns. (5) and (6), ESTi and TFi denote, the earliest start time and the total float of activity i.

Having a defined constrains associated with the single Pile loading test patterns and a procedure of augmented Lagrangian multiplier optimization, the equality- constrained quadratic optimization has been replaced by the unconstrained minimization of the augmented Lagrangian

$$L(Q) = f(Q) + \sum_{i=1}^{I} \lambda_i h_i^{(1)}(Q) + \frac{1}{2}\sum_{i=1}^{I} \beta_i\left[h_i(Q)\right]^2 + \tag{7}$$

Where λ_i, β_i denote the Lagrange multiplier and associated penalty parameters. The augmented Lagrangian has been interpreted as the signal Potential function of an auto-associative feedback (Hopfield) neural net. Consequently, a solution to the single pile loading problem can be obtained by minimizing the augmented Lagrangian function,

$$E = L + \text{factors of safety functions.} \tag{8}$$

The augmented optimization of this phase onto the proposed neural net architecture, is frame-work modelled to next section.

MAPPING MULTIPLIER OPTIMIZATION ONTO THE FEEDBACK ASSOCIATIVE NEURAL NET

In order to design neural net for a specified optimization problem, we attempt to construct a suitable computational function whose minimization leads to a system of differential equations. There are a number of approaches in the use neural net to optimization problem; such as follows:

i) Searching type neural net (Parallel Feedback associative - memory or BAM neural net)
ii) Self- organization map (SOM)
iii) MLP recurrent neural net
iv) Hybrid method combining the above approaches.

In a search type neural net, the neural net is set up in such a way that the dynamic of the network is constrained toward a local minimum which represent a possible solution.

$$\frac{du_m}{dt} = \frac{1}{c}\left(\sum_{n=1}^{N} T_{mm} V_n - \frac{u_m}{s_m} + x_m\right) \tag{9}$$

$$v_m = g_m(u_m) = \frac{1}{2}\left(1 + \tanh \lambda_{u_m}\right) \tag{10}$$

The output of each neuron (PN) is represented by v_m, which is related to u_m called the net input, by the output function, g_m. λ_{u_m} scale constant which control the speed of the convergence of neural net. The augmented Lagrangian E of Eqn. (3) can be written in a matrix form as

$$f(x) = E(Q) := c^T x + \tfrac{1}{2} x^T Q x + \vartheta \tag{11}$$

where, ϑ is a constant, and the unconstrained optimization problem that consists of minimizing the augmented Lagrangian E of Eqn. (11) can be solved on line by employing the neural network architecture proposed by Savin *et al.* The basic building block of this architecture is a feedback associative neural net, whose dynamics result in minimizing an potential function $E_H(v)$, which in a quadratic form of the output vector x i.e.

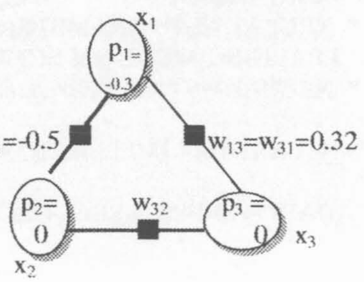
$$E_H(v) = -t^T v - \tfrac{1}{2} v^T W v \tag{12}$$

In Eqn. (12), t is a column vector denoting the threshold inputs to the neurons, and W is symmetric matrix whose entries are given by the weights of the neural net. To consider of Feedback associative neural net to minimize the Lagrangian E of Eqn. (11), the output v of a feedback associative net (Hopfield) is interpreted as the design vector x associated with a given project, and the weight matrices of the neural net are replaced as

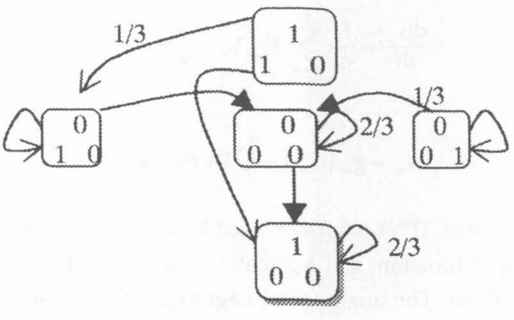
$$t = -c \text{ and } -Q = W \tag{13}$$

The key problem facing the mapping of the Pile loading issue on to a Hofield neural net is auto-associated with deriving an efficient technique for determining the matrices Q and c of Eqn. (11). Potential function,

$$E = -\frac{1}{2}\sum_{m=1}^{M}\sum_{n=1}^{N} T_{mn} u_m V_n + \frac{1}{\lambda}\sum_{m=1}^{M}\frac{1}{s_m}\int_0^{v_m} g_m^{-1}(v)\,dv - \sum_{m=1}^{M} x_m v_m \tag{14}$$



(a)



(b)

Fig. 1. A simplified auto-associative feedback neural net and its partial-state transitions

DEVELOPING NEURAL-NET: CAPACITY OF SINGLE PILE

Developing on neural net prototype is depicted by the requisite phase-cycle of a Neural net. Prototype from the conceptual to implementation steps. The phase cycle of developing an neural net prototype as described in appendix Fig. 2 and Fig. 3 includes the following issues (Al-Sugair 1997): Neural net feasibility-study, Initialization and Algorithm analysis, data-set preparation for train/or learning, neural-net architecture selection, net test and reliability factors, net-training, neural-net self-organization & adaptation and Implementation.

CONCLUSIONS

These findings are feasible and theoretically feasible, given the relatively small sample of a single pile calculation and suggest the possibility of developing a model method to

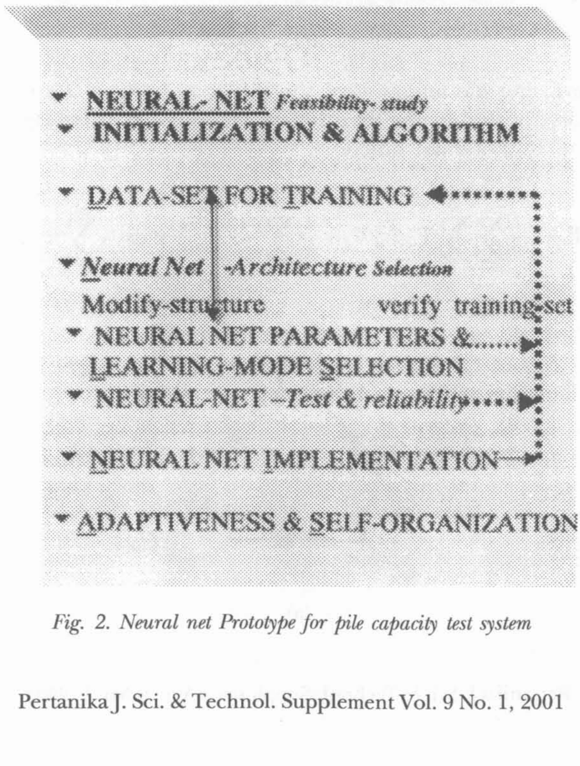


Fig. 2. Neural net Prototype for pile capacity test system

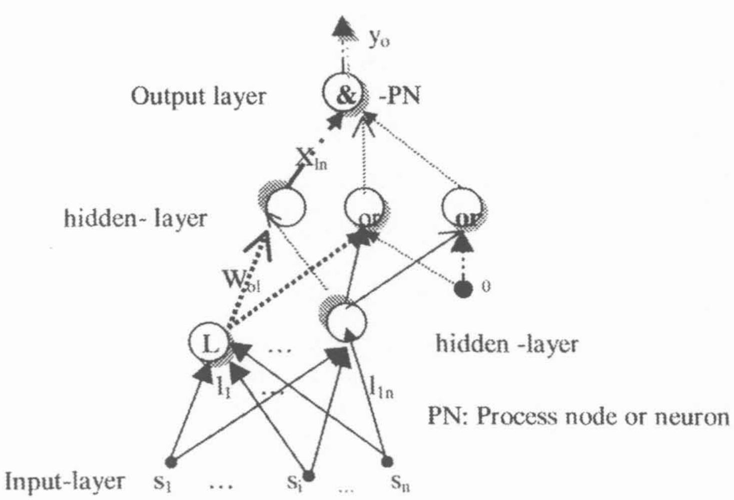


Fig. 3. A fuzzy neural-net model

allow optimization of resulting nonlinear weight-matrix concentrations on the basis of the configuration of the neural net. If these results are reproduced in large-scale research studies, that could provide a cheap and effective model method to asses different single pile loading spreadsheet design test plans.

We believe these are two important factors coming from the present research. Apart from that, this paper will also provide some attention to some aspect of program development. We hope that these results may provide the necessary impetus to applying feedback neural net (reduce-flaws) to non-linear and adaptive system identification.

ACKNOWLEDGEMENT

This research wouldn't have been such a success without the support and comfort, as well as assistance from the Ministry of Science, Technology and Environment, Universiti Putra Malaysia and GeoEnTech Sdn. Bhd. We wish to express sincere thanks to those for a number of superb discussion of the neural-net.

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