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The Development of a Predictive Damage Condition Model of Light Structures on Expansive Soils using Hybrid Artificial Intelligence Techniques.

Norhaslinda Yasmin Osman

Dissertation

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For my father, Osman Marzuki, with Love,

(28th August 1944 – 23rd August 2006)

If Only I knew... I would change my actions If Only I knew... *I* would finish on time If Only I knew... I would work extra hard If Only I knew... I would free my time If Only I knew... I would listen more If Only I knew... I would make you more proud of me If Only I knew... I would express how I feel If Only I knew... I would take care of you If Only I knew... I would hug you tighter If Only I knew... I would tell you to forgive me If Only I knew... I would remind you how much I Love you If Only I knew... I would Thank You from the bottom of my heart Now I know... I will miss you immensely

By: Linda Osman

I Love You Papa & Thank You Greatly

ABSTRACT

Expansive soils have damage light structures due to movement of soil which was a common problem all around the world. Soils exhibiting expansive properties were common throughout Australia. The damage to light structures founded on expansive soils in Victoria occurred mainly in properties built on quaternary basaltic clays and Tertiary to Ordovician clays. A review of existing literature in the area of expansive soils showed a lack of a thorough scientific diagnostic of the damage to light structures founded on expansive soils. Very few studies had been performed on damage to light structures on expansive soils in Victoria.

There were no models so far to predict damage condition to light structures. More over, most of the reports on damage to light structures on expansive soils in Victoria were poorly documented. The aim of this research project was to develop a model to predict the damage condition of light structure on expansive soils in Victoria.

A hybrid Neural Network trained with Genetic Algorithm was adopted for the development of the Predictive Damage Condition model. The Neural Network and Genetic Algorithm toolboxes from MATLAB[®] version 7.1 were used. The development of a Predictive Damage Condition model was driven by the shortage of defined quantitative studies and methods of selecting the factors that influenced the damage to light structure on expansive soils.

The data used was based on information extracted from the Building Housing Commission which was recorded by different engineering companies based only on the tenants complain and site investigation of the properties. A series of factors that were believed to be dominant in influencing damage to light structures were chosen including: structural type, foundation, the presence of vegetation, soil type, age, and climate change.

The model showed that it was able to resolve the problems facing light structures on expansive soils. First and foremost, the Predictive Damage Condition model was able to predict the damage condition or damage class using different combinations of factors. It was also possible to identify the factors contributing to the damage of the structure and to assess their relative importance in causing damage to light structures on expansive soil. It was found that the *construction footing* and *vegetation* were the most important among all the other input parameters. *Change in Thornthwaite Moisture Index* or climate was ranked second. *Construction wall* and *age*, were ranked third and fourth respectively while both *region* and *geology* were ranked fifth. In addition, *Change in Thornthwaite Moisture Index* was noted to have the strongest correlation with other input parameters.

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First and foremost, I would like to dedicate this thesis to my father, *Osman Marzuki*, who did not have the chance to see its completion. Papa, without you none of this would happen. I wish you could see this. Your everlasting love, encouragement and support have motivated me to pursue this path. Thank you so much for everything that you have given me all my life. I miss you tremendously and I hope I have made you proud. I love you Papa.

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DECLARATION

I hereby declare that the thesis entitled "The Development of a Predictive Damage Condition Model of Light Structures on Expansive Soils Using Hybrid Artificial Intelligence Techniques" submitted in fulfilment of the requirements for the Degree of Doctor of Philosophy in the Faculty of Engineering and Industrial Sciences of Swinburne University of Technology, is my own work and that it contains no material which has been accepted for the award to the candidate of any other degree or diploma, except where due reference is made in the text of the thesis. To the best of my knowledge and belief, it contains no material previously published or written by another person except where due reference is made in the text of the thesis.

Norhaslinda Yasmin Osman

July 2007

PUBLICATIONS

The following publications have been based on part of this work:

Refereed Conferences:

- McManus, K J, Lopes, D & Osman, N Y 2003, 'The Influence Of Drought Cycles On The Thornthwaite Moisture Index Contours in Victoria Australia' an International Conference on Problematic Soils, Nottingham, United Kingdom, 28 – 30 July 2003, CI-Premier, Singapore pgs 357.
- McManus, K J, Lopes, D & Osman, N Y 2004, 'The Effect oThornthwaite Moisture Index Changes in Ground Movement Predictions in Australian Soils', Proceedings of the 9th Australian New Zealand Conference on Geomechanics, Auckland, New Zealand, 2004, pgs 555-561.
- **3. Osman, N Y**, McManus, K M, Tran, H D & Krezel, Z A 2005, 'The Prediction of Damage Condition in Regards to Damage Factor Influence of Light Structures on Expansive Soils in Victoria, Australia' International Symposium on Neural Networks And Soft Computing in Structural Engineering, Waszczyszyn, Z, Cracow, Poland, 2005, Eccomas C7.
- 4. Osman, N Y & McManus, K J 2005, 'The Ranking of Factors Influencing the Behaviour of Light Structures on Expansive Soils in Victoria, Australia' Proceedings of the Eighth International Conference on the Application of Artificial Intelligence to Civil, Structural and Environmental Engineering., Topping, B H V, Rome, Italy, 2005, Civil-Comp Press, Paper 56.
- Osman, N Y, McManus, K & Ng, A W M 2005, 'Management and Analysis of Data for Damage of Light Structures on Expansive Soils in Victoria, Australia' Proceedings of the 1st International Conference on Structural Condition Assessment, Monitoring and Improvement, Perth, Australia, 12-14th December, 2005, CI-Premier, Singapore 283-290.
- 6. Osman, N Y, Ng, A W M & McManus, K J 2006, 'Selection of Important Input Parameters Using Neural Network Trained With Genetic Algorithm for Damage to Light Structures' Proceedings of The Fifth International Confer-

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- Osman, N Y, Lopes, D & McManus, K J 2006, 'An Artificial Intelligence Examination of the Influence of Geological Conditions and Changes in Climate on Damage to Light Structures in Victoria' Proceedings of the 7th Young Geotechnical Professionals Conference, Adelaide, 18-21 October 2006.
- 8. Osman, N Y, & McManus, K J 2007, 'Analysis of a Model of Damage Condition to Light Structures Using Clamping and Pruning Techniques' Proceedings of the Ninth International Conference on the Application of Artificial Intelligence to Civil, Structural And Environmental Engineering, Topping, B H V, Civil-Comp Press, Stirlingshire, Scotland.

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- 10. Osman, N Y, and McManus, K J, Predicting the Damage Classifications for Light Structures on Expansive Soils in Victoria, Australia, Using a Neural Network Approach. Advances in Engineering Software, Elsevier. (Submitted 2006 and Under Review)
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- 14. Osman, N Y, McManus, K J, House Distressed Research Findings, Foundation and Footings Society – ACSEV Joint Workshop "Raising The Standard", 11th October, 2005, Box Hill Institute, Foundation and Footings Society, 2005.
- 15. Osman, N Y, McManus, K J, 'The Prediction of Damage Condition of Light Structures on Expansive Soil in Victoria, Australia Using an Artificial Intelligent Approach', ONE Day Workshop - Neural Networks for Civil Engineering Applications, 9th November 2005, University Putra Malaysia, Malaysia, 2005.

Monographs:

16. McManus, K. J, Lopes, D, and Osman, N Y, Thornthwaite Moisture Index As a Guide to the Effects of Soil Changes in Victoria. R.M.I.T. Climate Change Project - Section 2, RMIT, <u>In Process</u>.

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NOTATION AND SYMBOLS

Abbreviation

A	Age
BHC	Building Housing Commission
ChgTMI	Change in Thornthwaite Moisture Index
CF	Construction Footing
CW	Construction Wall
df	degree of freedom
Ep	Evapotranspiration
G	Geology
IM	Inner Melbourne
mse	mean squared error
msereg	mean squared error with regularisation
msw	mean squared network weights and biases
R	Region
RS	Raft Slab

SF	Strip Footing
TMI	Thornthwaite moisture index
TMIN	Thornthwaite moisture index (1960-1990)
TMIO	Thornthwaite moisture index (1940-1960)
V	Vegetation
WM	West Melbourne

Roman Letters

D	deficit
d	surplus
do_k^p	network output value for pattern
dx_i^p	input value for pattern
$gp(x _{xi=\overline{x}i})$	generalisation performance of network
H_s	design suction change
h	maximum number of hidden neurons
<i>h</i> _i	hidden layer input
i	number of neurons in the input layers

I _n	number of indicator
I _{max}	maximum value of numeric indicator
I_s	shrink-swell index
т	number of fitted coefficients
n	number of data point
0	number of neurons in the output layers
S_i	sensitivity of input
p	pattern
pF	soil suction
PN	total number of data pattern
W _{ji}	input weights
W _{jo}	output weights
\overline{x}_i	mean value
У	response value
ŷ	predicted response value
y s	surface movement

Greek letters

γ	regularisation parameter
$\xi(x_i)$	impact ratio