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Predicting House Damage Class Using Artificial Intelligence Method

N.Y. Osman-Schlegel

School of Architecture and Built Environment, Deakin University, Geelong Waterfront Campus,
Victoria, Australia
linda.osman@deakin.edu.au

Abstract

The unsatisfactory performance of light structures founded on expansive soils subject to seasonal movements is frequently reported since the early 1950's in Australia. Excessive movements have caused damage to numerous structures that have not been adequately designed to accommodate soil volume changes. However, the sole presence of expansive soil is not necessarily the main cause of damage. Other factors such as vegetation, climate factors, types of construction materials and geology type may also contribute. This paper presents a model which predicts the damage class by analyzing combinations of the contributing factors using artificial intelligence methods. This model can help to identify if any serious and urgent repairs are necessary and immediate actions could be initiated without delay.

Keyword: house damage, artificial intelligence, light structures, damage class, structural movements

1. Introduction

The structural system for a light structure must be capable of transmitting both vertical and lateral loads. For all loading conditions it is important for the structural system of the house to be continuous from the roof through to the foundations with clearly defined load paths [1].

Lightly loaded buildings such as houses are especially vulnerable to damage because these structures are often less able to suppress the differential heave of the swelling foundation soil [2]. Researchers have been trying to predict structural movements on expansive soil for years [3]. However, it is not easy as there are many factors that need to be considered such as the type and behavior of expansive soils, type of footings, climates and the presence or removal of vegetations and other buildings

In Melbourne, Australia, the analysis of damage to public housing stock in the western suburbs of Melbourne showed increased damage in the last decade with increasing complaints of damage in recent times have been reported to building practitioners [4]. The danger zones for footing failures in Victoria according to Archicentre Ltd. [5] are concentrated in the western and north western suburbs with approximately 50% of the houses affected by foundation movement.

The worldwide interest in research on expansive soils in the last four decades resulted in numerous methods being proposed for the prediction of soil movement [6]. The Housing Industry Association has estimated that more than 1000 houses could be damaged due to a problem called slab heave which is an upward movement in the concrete slab foundation that creates unsightly cracks in the plaster of a house's internal walls [7]. Although an analytical tool for the prediction of movement is extremely important, there has been a slow advancement in the development of such a tool for solving practical engineering problems.

It is known that the sole presence of expansive soil is not necessarily the main cause of damage to structures. Other factors such as vegetation, climate factors, types of construction materials and

geology type may also contribute to damage. This paper presents a model which predicts the damage class by analyzing combinations of factors using artificial intelligence methods.

2. Database

The data is extracted from reports obtained from the Building Housing Commission, Victoria which owns and manages over 73,000 properties across Victoria. The reports are recorded by different engineering companies based only on the tenants complain and site investigation of the properties. 600 housing damage reports are extracted for the purpose of this project. A series of factors that are known to be dominant in causing damage to light structures are chosen including: structural type, footing type, the presence of vegetation, soil type, age, and climate change [3]. However, not all the information needed is available in the Building Housing Commission reports. Therefore, important information such as climate, geology and vegetation had to be extracted from relevant maps.

The change in climate, presence of vegetation, and the structural characteristic are the factors that have the most influence on the movement of light structures. Changes in climate influence the seasonal and long term effect of the volume change of the soil thus leading to ground movement. In addition, vegetation causes movements of buildings of up to 150mm settlement and 100mm heave [8]. Another important factor that influences the movement of structure is its structural characteristic. These factors depend on the ability of the structure to absorb movement. For example, raft footings have the advantage of reducing differential settlements and they are the most suitable footing type in expansive soils. As for the wall type, brick veneer is less prone to damage due to its capability of absorbing flooring movements.

Most of the information in the reports is text form. In order to use this information for analysis purposes it is transformed into numeric form. The information is uniformly mapped into the $\{0, 1\}$ interval. This is to ensure uniformity across the values in all categories. Since all values are between 0 and 1, there will not be any bias towards larger or smaller values.

This is important to avoid any learning bias.

3. Artificial Intelligence method

A Neural Network is a computing paradigm inspired by the human brain which consists of an interconnected group of simple processing elements, called neurons that are working together to generate an output function. As in nature, the Artificial Neural Network changes its connection structure based on information that flows through the network. The output function is largely determined by the connections between the processing elements. The goal of the network is to learn or to discover some association between the input and output patterns, or to analyze, or to find the structure of the input patterns [9].

Genetic Algorithms are a class of search algorithms modeled on the process of natural evolution and have been shown in practice to be very effective at function optimization, efficiently searching large and complex (multimodal, discontinuous, etc.) spaces to find nearly global optima [10]. Genetic Algorithm generally improve the current best candidate monotonically by keeping the current best individual as part of its population while it searches for better candidates [11].

A hybrid Neural Network trained with Genetic Algorithm is adopted for the development of a model for the prediction of the damage class based on the chosen input parameters. The model is based on the selected options and variables from the hybrid Artificial Intelligence technique as shown in Figure . The benefit of a hybrid Artificial Intelligence model lays in the fact that it can be used to derive an unknown functional relationship between the input parameters and the output

purely based on observations. This is particularly useful in the application of Building Housing Commission data because the complexity of the data makes the design of such a function by hand impractical.

The model is derived under the assumption that there is a functional relationship between the input parameters M and the damage class (DC) as shown in equation (1).

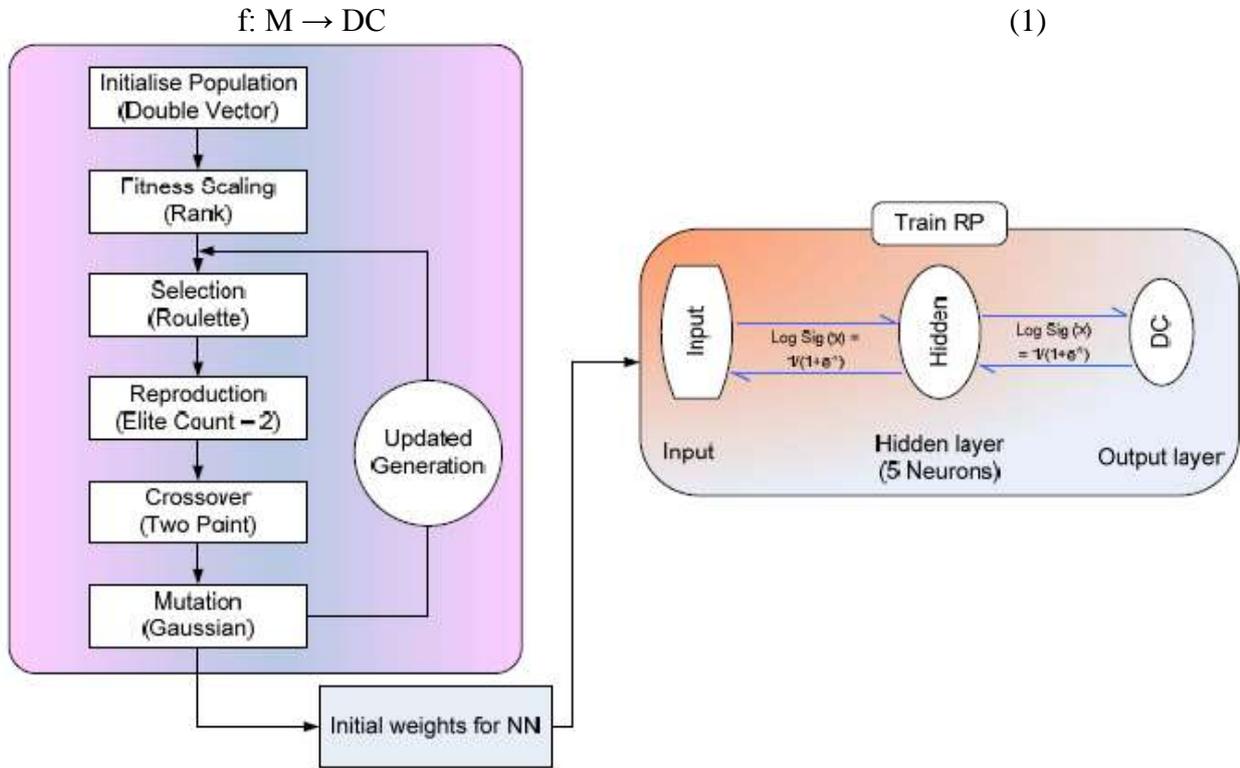


Figure 1

4. Prediction of damage class

Damages in light structures vary from slight to moderate or severe damage. Categorization of visible damages in structures is critical for assessing the potential effect of expansive soils. The slight, moderate, and severe categories are in most cases based on crack size and pattern. Table refers to the 5 damage classes that are the possible output of the model. The classification of damage and descriptions are adopted from the Australian Standard 2870 [12].

A simulation function is used to predict the damage class. A simulation function simulates the input (the scenario) and the network (the model), and returned an output (damage class). Since the output values would give a mean value, a scaled output value for each damage class is developed as shown in Table 1. For example, a property would have damage class 0 when the output value of the simulation function is between 0 and 0.125.

Table 1

<i>Damage Class</i>	<i>Scale</i>	<i>Description</i>
0	$0 < DC \leq 0.125$	Hairline cracks, insignificant movement of slab from level
1	$0.125 < DC \leq 0.375$	Fine cracks (do not repair). Slab reasonably level

2	0.375<DC≤0.625	Distinct crack. Change in level
3	0.625<DC≤0.875	Wide crack. Change in level
4	0.875<DC≤1.000	Extensive repair work. Gaps in slab. Change in level

Scenarios with typical combinations of parameters in real life as shown in

Table 2 are used for prediction. However, due to the possibility of various different scenarios, only eight scenarios are predicted. The first scenario (Scenario 1) acts as “guidance” when the variables for each input parameters are changed (Scenarios 2 to 8). Scenarios 2 to 8 were used to compare other variables with scenario 1 which is considered to have “extreme” variables except geology. The variables for the parameters used in scenario 1 have been shown to influence damage to light structures. For example, West Melbourne showed the most reported damage. On top of that, it is assumed that old buildings are more prone to damage.

Table 2

<i>Scenario</i>	<i>Region</i>	<i>Footing</i>	<i>Wall</i>	<i>Geology</i>	<i>Age</i>	<i>Vegetation</i>	<i>Climate</i>
1	WM	RS	BV	Tertiary	41-50	Presence	Dry
2	IM	RS	BV	Tertiary	41-50	Presence	Dry
3	WM	SF	BV	Tertiary	41-50	Presence	Dry
4	WM	RS	DB	Tertiary	41-50	Presence	Dry
5	WM	RS	BV	Quaternary	41-50	Presence	Dry
6	WM	RS	BV	Tertiary	1-10	Presence	Dry
7	WM	RS	BV	Tertiary	41-50	Adjacent	Dry
8	WM	RS	BV	Tertiary	41-50	Presence	Wet

WM-West Melbourne, IM-Inner Melbourne, RS-Raft Slab, SF-Strip Footing, BV-Brick Veneer, DB-Double Brick

The output values for the damage class for scenarios 1 to 8 after simulation are shown in Table . Most of the scenarios with the exception of scenario 8 gave damage class 2. Scenario 8 with different climate condition gives the highest output value of 0.746 which falls in damage class 3. This indicates that wet climate conditions cause more significant damage.

In Table , when double brick is used in the scenario, the output value is higher compared to brick veneer. This is somehow not surprising as houses constructed with brick veneer are not as prone to cracking as solid brick (double brick) houses in reactive soil areas. Due to its brittleness, double brick houses are prone to cracking even when the walls have undergone only small distortion.

There is an increase in the output values, when different variables are used for different parameters. This shows that all these parameters are significant in predicting damage class.

The presence of vegetation for example has an influence in the damage class. The output value for scenario 6 which uses a “younger” (1 to 10 years old) house is higher than scenario 1 with older (41-50 years old) house. This indicates that old houses are not necessarily being prone to damage. “Younger” houses are as prone to damage as older houses due to factors such as climate, type of wall etc.

Table 3

<i>Scenario</i>	<i>Output Value</i>	<i>Damage Class</i>
1 (Guidance)	0.470	2
2 (Different region)	0.512	2
3 (Different footing)	0.481	2
4 (Different wall)	0.506	2
5 (Different geology)	0.524	2
6 (Different age)	0.507	2
7 (Different vegetation)	0.580	2
8 (Different climate)	0.746	3

5. Conclusion

Numerous light structures founded on expansive soils in Victoria, Australia suffer from ground movement due to edge heave or under floor drying settlement in the clay beneath them. This movement is caused by swelling and shrinkage of the expansive soils underlying the property. The sole presence of expansive soil is not necessarily the main cause. Other factors such as vegetation, climate factors, types of construction materials and geology type may also contribute to damage. The only solution for other factors that cause damage is to inspect the damage and to make a judgement of the problems since there is no models so far as to predict damage class to light structures. The only available method for the classification of the damage is that in the Australian Standards 2870. However, this method can only be used when damage has already occurred. The model on the other hand, could predict damage before the damage occurred provided that all the parameters needed to use the model are at hand.

The development of this model which predicts damage class of houses is helpful to analyze the long term behavior of light structures on expansive soils in order to enable the government to better maintain social housing building stocks. It is expected that the model could also assist building practitioners and home owners in predicting the damage class of any type of light structures. This will help to identify if any serious and urgent repairs are necessary where immediate actions could be initiated without delay. On top of the actual damage class prediction, the model serve as an essential tool for a better understanding of the parameters that influenced the damage to light structure founded on expansive soils and a practical way of dealing with the problem

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