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Application of Fuzzy Set Theory to Evaluate the Stability of Slopes

Tarig Mohamed[1, a] and Anuar Kasa[2, b]

[1]Department of Civil & Structural Engineering, UKM, Malaysia

[2]Department of Civil & Structural Engineering, UKM, Malaysia

[a]tarigmohalam@gmail.com, [b]anuar@eng.ukm.my

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Abstract. An artificial intelligence tools, Adaptive Neuro Fuzzy Inference System (ANFIS), was used in this study to predict the stability of slopes. Data used in this study were 300 various designs of slope. Those designs were created by using Slope/W which calculated factors of safety using various limit equilibrium methods (LEM) such as Bishop, Spencer and Morgenstern-Price. The input parameters consisted of height of slope, H (1–10 m), unit weight of slope material, γ (15-22 kN/m^3), angle of slope, θ (11.31°-78.69°), coefficient of cohesion, c (0-50 kN/m^2) and internal angle of friction, ϕ (20°- 40°) and the output parameter is the factor of safety. To build the fuzzy inference system, 243 rules were used at 60 epochs. The number of membership function for the any input was three and the type of membership function for output was linear. ANFIS obtained regression square (R^2) of one for Bishop, one for Janbu, one for Morgenstern-Price and one for Ordinary. The result proved that ANFIS may possibly predict the safety factor with good precision and nearly to the target data.

Introduction

An exposed ground surface that stands at an angle with the horizontal is called slope. Slope stability problem has been an important issue in geotechnical engineering. Slope failure is a common natural disaster which takes place around the world. The evolution of slope stability analyses in geotechnical engineering has followed closely the developments in soil. Geotechnical engineers have to pay particular attention to geology, ground water and shear strength of soils in assessing slope stability. Therefore, slope investigation and classification are important for the community [1,2,3,4,5].

Geotechnical engineers frequently use limit equilibrium methods (LEM) of analysis when studying slope stability problems. The methods of slices have become the most common methods due to their ability to accommodate complex geometrics and variable soil and water pressure conditions. During the past three decades approximately one dozen methods of slices have been developed. They differ in (i) the statics employed in deriving the factor of safety equation and (ii) the assumption used to render the problem determinate [6,7,8,9].

System modeling based on conventional mathematical tool is not well suited for dealing with ill-defined and uncertain systems. By contrast, a fuzzy inference system (FIS) employing fuzzy if-then rules can model the qualitative aspects of human knowledge and reasoning processes without employing precise quantitative analyses. This fuzzy modeling or fuzzy identification, first explored systematically by Takagi and Sugeno, has found numerous practical applications in control, prediction and inference. However, there are some basic aspects of this approach which are need of better understanding. More specifically (i) no standard methods exist for transforming human knowledge or experience into the rule base and database of a fuzzy inference system, (ii) there is a need for effective methods for tuning the membership functions (MFs) so as to minimize the output error measure or maximize performance index [10,11,12,13,14].

Fuzzy if-then rules or fuzzy conditional statements are expressions of the form *IF A then B*, where *A* and *B* are labels of fuzzy sets characterized by appropriate MFs. Due to their concise form, fuzzy if-then rules are often employed to capture the imprecise modes of reasoning that play an essential role in the human ability to make decisions in an environment of uncertainty and imprecision. Another form of fuzzy if-then rules, proposed by Takagi and Sugeno, has fuzzy sets involved only in the premise part. Both types of fuzzy if-then rules have been used extensively in both modelling and control. Through the use of linguistic labels and MF, a fuzzy if-then rule can easily capture the spirit of "rule of thumb" used by humans. From another angle, due to the qualifiers on the premise parts, each fuzzy if-then rule can be viewed as local description of the system under consideration [10,15,16,17].

Fuzzy inference systems (FIS) are also known as fuzzy-rule-based systems, fuzzy models, fuzzy associative memories (FAM), or fuzzy controllers when used as controllers. Basically a fuzzy inference system is composed of five functional blocks: (1) a rule base containing a number of fuzzy if-then rules, (2) a database which defies the membership function of the fuzzy sets used in the fuzzy rules, (3) a decision-making unit which performs the inference operations on the rules, (4) a fuzzification interface which transforms the crisp inputs into degrees of match with linguistic value, (5) a defuzzification interface which transform the fuzzy results of the inference into crisp output. Usually, the rule base and the database are jointly referred to as the knowledge base [10].

Depending on the types of fuzzy reasoning and fuzzy if-then rules employed, most fuzzy inference systems can be classified into three types: (1) the overall output is the weighted average of each rule's crisp output induced by the rule's firing strength and output MF, (2) the overall fuzzy output is derived by applying "max" operation to the qualified fuzzy outputs, (3) Takagi and Sugeno's fuzzy if-then rules [10,15,18,19,20].

The power of Artificial Intelligent (AI) becomes more authoritative when the system is programmed to cater the need of complex applications. Adaptive Neuro-fuzzy Inference System (ANFIS) Model using neuro adaptive learning techniques which are similar to those of neural networks was originally presented by Jang. Given an input/output data sets, ANFIS constructs FIS whose MF parameters are adjusted using back propagation algorithm or other similar optimization techniques. Hence, the advantages of a fuzzy system can be combined with a learning algorithm [21,22,23,24].

Methodology

The methodology for this study could be divided into three steps; (i) Designing slopes. Height of slope (H), unit weight of soil (γ), angle of slope (θ), coefficient of cohesion (c) and internal angle of friction (ϕ) were used as input parameters. To design the slopes, many possibilities were considered for the input parameters by fixing some of them and changing the others. The angles of slope were calculated by considering horizontal and vertical length of the slope, (ii) Calculation of safety factors. Slope/W which applied limit equilibrium methods i.e. Bishop, Janbu, Morgenstern-Price and Ordinary, was used to compute factors of safety for 300 different designs. The comprehensive formulation of the software made it possible to easily analyze both simple and complex slope stability problems using a variety of methods, (iii) Adaptive Neuro-Fuzzy Inference Systems (ANFIS) prediction. After carrying out the stability analyses, ANFIS was used to formulate the mapping from a given input to an output. For this research, linear output and 243 rules were used for generating fuzzy inference system (FIS). For training the FIS, 60 epochs, hybrid method and zero errors tolerance were used. The mapping then provided a basis from which decisions could be made.

Results and Discussion

The result of this research can be divided into three parts; (i) Designed slopes. In this research, 300 different designs of slopes were established. Different variables including height of slope (H), unit weight of soil (γ), angle of slope (θ), coefficient of cohesion (c), and internal angle of friction (ϕ) were used as the input parameters for designing, (ii) Factors of safety. The results of the calculated safety factors can be classified as (1) less than one, (2) greater than one, and (3) greater than 1.5, (iii) Prediction by Adaptive Neuro Fuzzy Inference Systems (ANFIS). By using 300 training data, ANFIS model was used as a function of different parameters. Prediction using ANFIS produced average percentage error of 0.0915 for Bishop, 0.0928 for Janbu, 0.0917 for Morgenstern-Price and 0.0935 for Ordinary. Figure 1 until 4 show the comparison of calculated factors of safety using LEM and predicted factors of safety using ANFIS. In addition, ANFIS obtained regression square (R^2) of one for Bishop, one for Janbu, one for Morgenstern-Price and one for Ordinary.

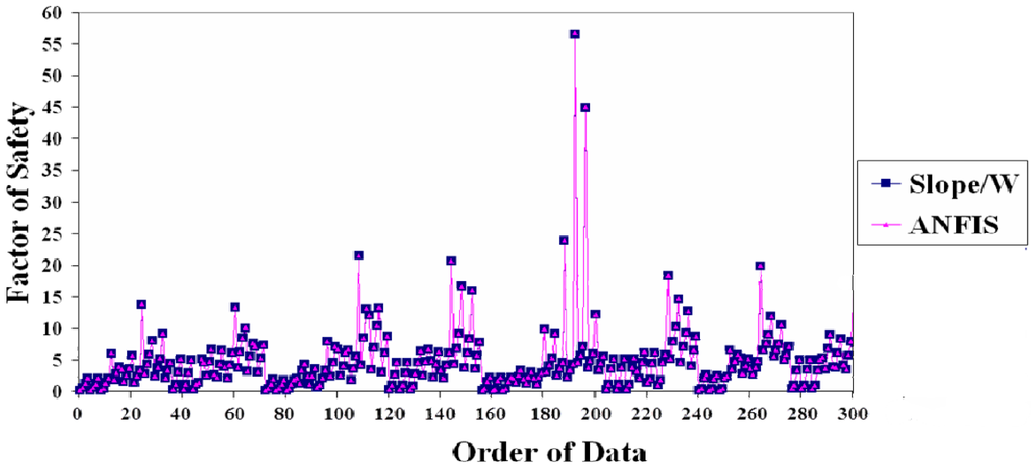

Fig.1 Comparison of calculated factor of safety using Bishop and predicted using ANFIS

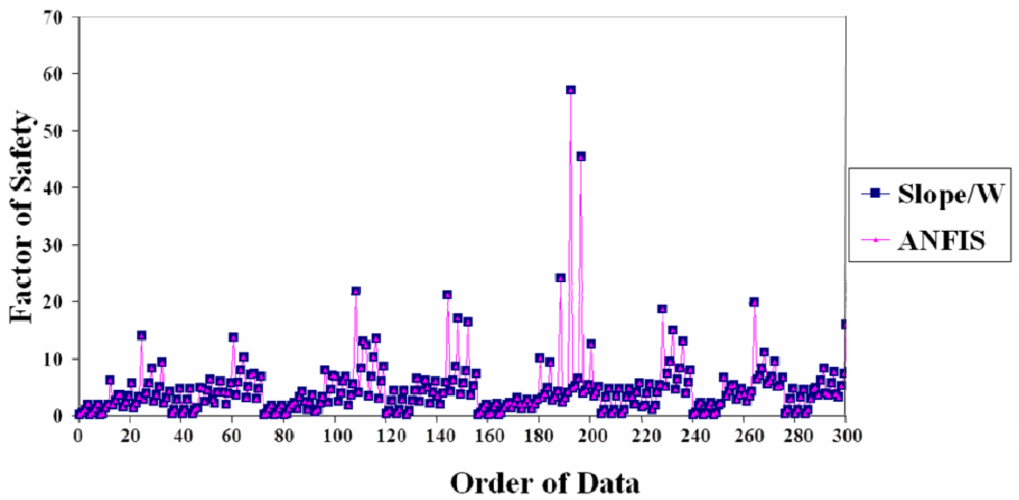

Fig.2 Comparison of calculated factor of safety using Janbu and predicted using ANFIS

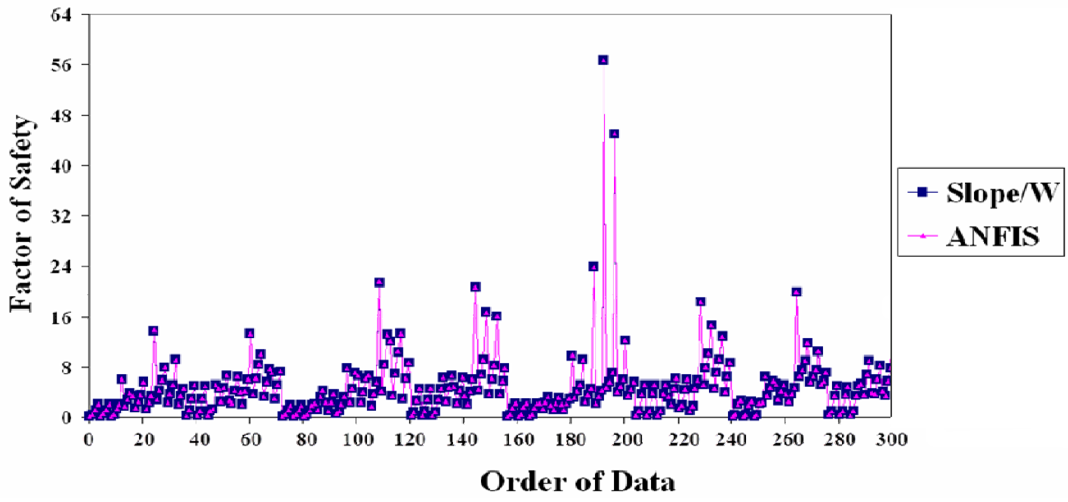

Fig.3 Comparison of calculated factor of safety using Morgenstern-Price and predicted using ANFIS

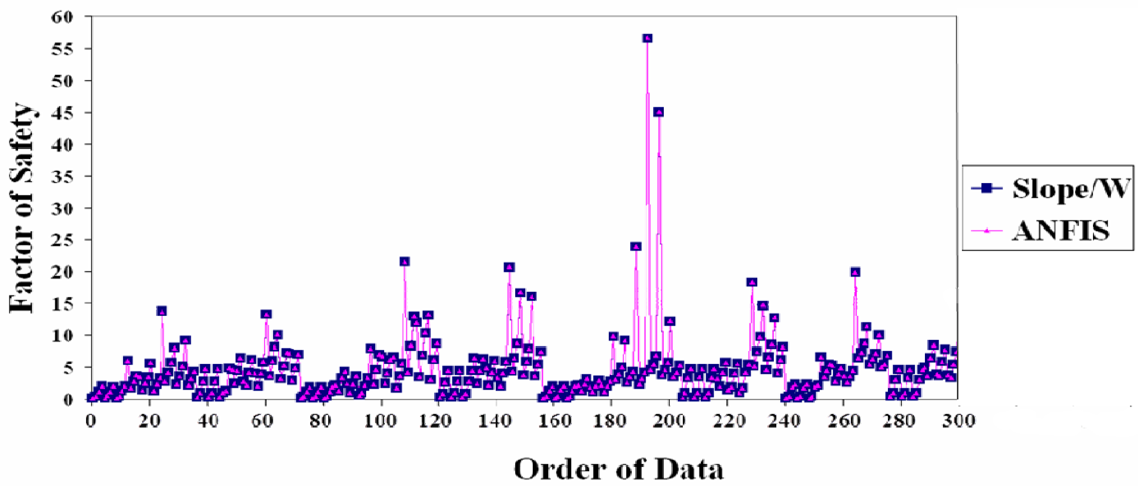

Fig.4 Comparison of calculated factor of safety using Ordinary and predicted using ANFIS

Conclusion

As a conclusion, this research has achieved all the desired objectives. The results of this study can be considered as a major contribution to the field of knowledge since the use of Adaptive Neuro Fuzzy Inference Systems (ANFIS) for prediction of slope stability as carried out in this research has not been conducted before. The results show that ANFIS could really predict the factor of safety very well since the values of R^2 for all cases are very close to one and could predict the safety factors with high accuracy compared with other methods. Thus, ANFIS could be a suitable tool for predicting the stability of slope in future research.

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