APPLICATION OF NEURAL NETWORKS IN SEISMIC SOIL SLOPE STABILITY ANALYSIS

A DISSERTATION

submitted in partial fulfilment of the requirements for the award of the degree

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in

EARTHQUAKE ENGINEERING

(With Specialization in Soil Dynamics)

By

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CANDIDATE'S DECLARATION

I hereby declare that the work presented in this dissertation entitled **"Application of Neural Networks in Seismic Soil Slope Stability Analysis"**, in partial fulfilment of the requirements for the award of the degree of **Master of Engineering** in **Earthquake Engineering** with specialization in **Soil Dynamics**, submitted to the **Department of Earthquake Engineering**, University of Roorkee, Roorkee, India, is an authentic record of my own work carried out for the period from August, 1998 to March, 1999 under the supervision of **Mr. A.D. Pandey**, Reader and **Mr. S. Mukerjee**, Reader, Department of Earthquake Engineering, University of Roorkee, Roorkee, India.

The matter embodied in this dissertation has not been submitted for the award of any other degree or diploma.

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ABSTRACT

The advent of digital computers has seen the emergence of analytical tools in analysis and design of Civil Engineering systems, which earlier seemed too complex or rigorous. At this stage Artificial Intelligence techniques - especially Artificial Neural Nets, or Neural Nets, are beginning to dominate most of the analytical and design aspects. The basic advantage in the use of Neural Nets being the capability of handling imprecise, imperfect and incomplete data while yet producing acceptable solutions.

In the present study the application of Neural Nets has been examined with specific reference to the analysis of slope of a typical Earth Dam for the following cases:

1. Determination of minimum factor of safety when conventional inputs are provided for a specific problem.
2. The inverse problem of determination of the critical failure surface when the minimum factor of safety and conventional parameters are provided as inputs.
3. Determination of minimum factor of safety and critical failure surface when conventional parameters are provided as inputs.

The Neural Nets were formed to perform satisfactorily and a subsequent parametric study with regard to

a. Relation between horizontal seismic coefficient and minimum factor of safety.

b. Relation between pore water pressure and minimum factor of safety.

c. Relation between angle of internal friction of the soil in shell portion of earth dam section and minimum factor of safety.

d. Relation between angle of internal friction of the soil in core portion of earth dam section and minimum factor of safety.

indicates that the results are consistent with the underlying Physics of the problem.

The potential of application of Neural Nets to augment/replace analytical procedures is amply demonstrated and scope for further studies has been indicated.

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CHAPTER 1

INTRODUCTION

1.1 GENERAL

The stability analysis of slopes plays an important role in Civil Engineering. Stability analysis is used in the construction of highways, railroads, runways, canals and development of natural resources such as earthdams as well as many other human activities involving building construction and excavations. The cost of earthwork would be minimum if the slopes are made steepest. However, very steep slopes may not be stable. A compromise has to be made between economy and safety and the slopes provided are neither too steep nor too flat. In other words, the steepest slopes which are stable and safe should be provided. The failure of a slope may lead to considerable loss of life and property. It is, therefore, essential to check the stability of proposed slopes, in any construction environment. With the development of modern methods of testing of soils and stability analysis, a safe and economical design of a slope is possible.

Often, though the slope is stable in static condition it may fail due to the sudden occurrence of vibrations caused by an earthquake. Failure results from increased stresses within a soil mass, or loss of strength during dynamic loading conditions imposed by an earthquake. If the existing soil beneath the slope is loose saturated fine sands and non plastic silty sands liquefaction of soil may occur due to earthquake loads this also leads to major failures of slopes. Many land slides triggered by earthquakes have resulted in major disasters. Hence there is a need to analyse the slope by considering seismic loads if the slope of the earthwork is located in seismically active zone. Hence, in any case the stability analysis of slopes is very much necessary to ensure safety.

1.2 OBJECTIVE OF THE PRESENT STUDY

Different methods of slope stability analysis based on different approaches are available each of which involve different simplifying assumptions yet leading to complex calculation and are time consuming. These methods requires complete inputs with regard to geometry of the slope and strength properties of the soil, and environmental features such as moisture content, pore water pressure, seismicity etc.

In this present study an attempt has been made to develop Neural Network models based on a typical configuration of an earth dam [11] as shown in Fig. 3.2, for

1) Determination of minimum factor of safety based on the following inputs:
    a) Soil properties,
    b) Pore water pressure,
    c) Seismic coefficients and
    d) Critical failure surface.
2) Determination of critical failure surface based on the following inputs:
    a) Soil properties,
    b) Pore water pressure,
    c) Seismic coefficients and
    d) Minimum factor of safety.
3) Determination of minimum factor of safety and critical failure surface based on the following inputs:
    a) Soil properties,
    b) Pore water pressure and
    c) Seismic coefficients.

The Neural-Networks have been developed and tested using the data obtained from a computer program for pseudostatic analysis using method of slices [4].

CHAPTER 2

REVIEW OF LITERATURE

2.1 GENERAL

The failure of a mass of soil located beneath a slope is called a slide. It involves a downward and outward movement of the entire mass of soil that participates in the failure. Usually, slides are due to excavation or undercutting the foot of an existing slope. However, in some instances, they are caused by a gradual disintegration of the structure of the soil, starting at hair cracks which subdivide the soil into angular fragments. In others, they are caused by an increase of the pore water pressure in a few exceptionally permeable layers, or by a shock that liquefies the soil beneath the slope.

2.2 TYPES OF SLOPE FAILURES

A slope may have any one of the following type of failures.

2.2.1 Rotational Failure

This type of failure occurs in finite slopes by rotation along a slip surface by downward and outward movement of the soil mass as shown in Fig. 2.1. Rotational slips are further divided into three types.

(a) Slope failure or face failure :

This failure occurs along a surface that intersects the slope above the toe. This can occur when the slope angle α is very high and the soil in the upper part of the slope is relatively weak as shown in Fig. 2.1a.

(b) Toe failure :

The failure occurs along the surface that passes through the toe. Toe failure occurs in steep slopes when the soil mass above the base and below the base is homogeneous. This is the most common mode of failure as shown in Fig. 2.1b.

(c) Base failure :

If the failure surface passes below the toe then toe then it is called base failure. This can occur when the soil below the toe is relatively weak and soft and the slope is flat as shown in Fig. 2.1c.

2.2.2 Translation Failure

This type of failure occurs in an infinite slope along a long failure surface parallel to the slope as shown in Fig. 2.2. The shape of the failure surface is influenced by the presence of any hard stratum at a shallow depth below the slope surface. Translational failures may also occur along slopes of layered materials.

2.2.3 Wedge Failure

A failure along an inclined plane is known as plane failure or block failure as shown in Fig. 2.3. It occurs when distinct blocks and wedges of the soil mass become separated. A plane failure is similar to translational failure in many respects. However, unlike translational failure which occurs in an infinite slope, a plane failure may occur even in a finite slope, consisting of two different materials or in a homogeneous slope having cracks, fissures, joints or any other specific plane of weakness.

2.3 MECHANISM OF SLOPE FAILURE

Rupture surface or failure plane is the line joining points of weakness. Here points of weakness mean the points at which the shear strength of the soil is less than the forces causing sliding. After rupture, the overlying mass of soil can move by gravity; until rupture occurs motion is opposed by the shear resistance of the soil. When this is overcome, resistance is diminished and the soil mass slides down. The stability of any slope depends upon the shear strength of the soil. Shear strength depends upon the cohesion, angle of internal friction of the soil and the effective normal stress on the rupture surface at the instant of failure. Shear stresses (forces causing sliding) are developed due to the gravity forces, seepage forces and earthquake forces.

2.4 FORCES CAUSING SLIDING

The most important forces which cause instability are the force of gravity and the force of seepage. In areas of seismic activity, earthquake forces may also be an important factor causing instability. In earlier days, earth dams were not designed to withstand earthquake forces. It was thought that earth dams had an inherent ability to withstand the effect of earthquakes, a reasoning based on the observation that very few earth dams, designed rationally, suffered any damage during earthquakes. However, it is now well understood that ignoring seismic forces is to invite disaster.

Cyclic loads induced by earthquakes decrease the stability of a slope by inducing shear stresses, increasing pore pressures and decreasing the soil strength. Indeed, liquefaction is an external manifestation of the decrease in shear strength. Cohesionless soil deposits of clean fine sands and non-plastic silty sands containing less than 5% fines passing the No. 200 sieve and the permeability in the range of 10^{-5} to 10^{-3} m/sec. are most susceptible to liquefaction.

2.5 FACTORS CONTRIBUTING TO SLOPE FAILURE

(a) The type of soil of which or in which the slope is made;

(b) The geometry of the cross section of the slope;

(c) Weight and loads, and weight and load distribution (gravity is one of the principal causes of all slides);

(d) Increase in moisture content of the soil material, water is the principal factor in promoting slides because it adds wight to the unit weight of soil; water decreases the magnitude of cohesion in soil, thus decreasing its shear strength. Water from atmospheric precipitation and the melt-waters of snow, upon entering into the soil, decrease the factor of safety, of the slopes in question. Water is the most aggressive factor contributing to many slides, particularly in unconsolidated soils;

(e) Vibrations and Earthquakes.

2.6 C-ϕ Analysis-Method of Slices (Swedish Circle Method)

This method was first introduced by Fellenius (1926) and is also known as the Swedish circle method. Fig. 2.4 shows the section of a slope with AB as the trial slip surface. For a soil having C-ϕ strength parameters, the shear strength at different points on the slip surface varies according to the value of effective normal stress at those points. In this method, the soil mass above the assumed slip circle is divided into a number of vertical slices of equal width, as shown in Fig. 2.4. The number of slices may vary from 6 to 12, when hand computations are to be used.

In the conventional method, the forces between the slices are neglected and each slice is considered to be an independent column of soil of unit thickness. If slice no. 5 is taken as a typical slice, the weight of the slice W is calculated from.

$$W = \gamma\ hb$$

Where γ is the bulk unit weight of the soil, h is the average height of the slice and b its width. The line of action which can be taken to pass through the mid-width point of the slice, meets the base of the slice of length 1 at A'. The weight W is plotted as a vector $A'B'$ and then resolved into its normal and tangential components N and T respectively at A'. Since the normal component N passes through A' and the centre of rotation O, it does not have a driving moment, but mobilises frictional resistance along the slip surface. The tangential component, T, causes the rotating moment. In the end slice such as lice no. 1 in Fig.2.4, the tangential component may act in an opposite direction, causing a restoring moment. T is taken as positive when causing a driving moment and negative when causing a resisting moment. The algebraic sum of T will always be positive and contribute to the driving moment.

Considering the whole slip surface AB of length L, the total driving and resisting forces are:

Driving forces $= \Sigma T$

Resiting force $= \Sigma c'l + \Sigma N \tan\phi' = c'L + \Sigma N \tan\phi'$

Driving moment $= R\,\Sigma T$

Resisting moment $= R\,c'L + R\,\Sigma N \tan\phi'$

The factor of safety against sliding, F is written as:

$$F = \frac{cL + \Sigma N \tan\phi}{\Sigma T} \qquad (2.1)$$

Since N = W cos α and T = W sin α , Eq. 2.1 can also be written in the form

$$F = \frac{cL + \Sigma W \cos\alpha \tan\phi}{\Sigma W \sin\alpha} \qquad (2.2)$$

The method of slices can be used for homogeneous or stratified soils and can also be used where seepage is taking place and pore pressures are present in the soil. Inter-slice forces are ignored in this method. This method underestimates factor of safety hence this method is conservative. Strictly, only applicable to circular failure surfaces.

2.7 PSEUDO-STATIC ANALYSIS

A pseudostatic analysis is one in which the dynamic effect of the earthquake is replaced by a static force. If the maximum acceleration due to an earthquake is known, the inertial force on an element of soil is obtained by multiplying the mass of the element with the acceleration. In considering the equilibrium of the sliding mass, this force is included and a factor of safety of more than one is allowed, thus ensuring that no movement of the sliding mass occurs. The inertial force acts only for a brief period in a cycle and lasts for only a few cycles. But the pseudo static analysis makes no distinction between this transient inertial force and other static forces acting for a much longer duration.

If (αg) is the earthquake acceleration and W is the weight of the slice, the inertial force on it is taken as αW. The inertial force should be taken at the centroid of the slice, but to simplify the calculations, it is moved down to the base of the slice like the other forces acting on the slice. Fig. 2.5 shows the forces acting on a typical slice. It can be seen that the effect of the inertial force is to add the force ($\alpha W \cos\theta$) or (αN) in the tangential direction, while a force ($\alpha W \sin\theta$) or (αT) is decreased from the normal direction. Thus the expression for the factor safety now changes to

$$F=\frac{cL+\Sigma(N-U-\alpha T)\tan\phi}{\Sigma(T+\alpha N)} \tag{2.3}$$

A minimum factor of safety of just over one is considered acceptable when considering the effect of earthquake forces. The seismic coefficients commonly used in Japan range from 0.12 to 0.25, depending on the location of the dam, type of foundation and the failure potential downstream of the dam.

2.8 INDIAN STANDARD CODE OF PRACTICE IS: 1893 - 1984

As per the Indian Standard Code IS: 1893 - 1984 the procedure for finding out the seismic coefficient, which depends upon the height of the dam and the lowest point of the rupture surface, shall be as follows:

(a) The fundamental period of the structure can be determined from

$$T=2.9H_t\sqrt{\rho/G} \tag{2.4}$$

where,

T = fundamental period of the earth dam in sec,

H_t = height of the dam above toe of the slope,

ρ = mass density of the shell material, and

G = modulus of rigidity of the shell material

(b) Using the computed value of T and 10% damping, S_a/g can be determined from average acceleration spectrum curves as shown in Fig. 2.6.

(c) The design seismic coefficient α_h can be determined from the Response Spectrum Method using the expression

$$\alpha_h=\beta I F_o \frac{S_a}{g} \tag{2.5}$$

where,

β = a coefficient depending upon the soil-foundation system as shown in Table 2.1

I = a factor dependant upon the importance of the structure as shown in Table 2.2

F_o = seismic zone factor for average acceleration spectra as shown in Table 2.3

S_a/g = average acceleration coefficient as read from Fig. 2.6 for appropriate natural period and damping of the structure.

For checking slope failure with the lowest point of the rupture surface at any depth y below top of dam, the value of equivalent uniform seismic coefficient shall be taken as:

$$\alpha_y=\left(2.5-1.5\frac{y}{H}\right)\alpha_h \tag{2.6}$$

where,

H = total height of the dam

The stability of the upstream slope of an earth or rockfall dam shall be tested with full reservoir level, with horizontal forces due to earthquake acting in upstream direction and vertical forces due to earthquake (taken as one half of horizontal) acting upwards.

For preliminary design, a factor of safety of unity shall be accepted as being adequate for ensuring stability of upstream slope. The factor of safety need be tested only for failure surface which passes through the lower half of the dam.

The stability of the downstream slope shall also be tested as in the upstream slope case except that the horizontal force due to earthquake should be considered acting in the downstream direction.

2.9 SELECTION OF SEISMIC COEFFICIENT

A major difficulty in the pseudo-static approach arises from the fact that there is no simple method for determining an appropriate value for the seismic co-efficient α . In the past empirical values based on judgement and experience have been used, $\alpha = 0.1$ to 0.15 as typical US practice, $\alpha = 0.15$ to 0.25 as typical Japanese practice; higher values have been used in exceptional cases. Empirical values may lead to safe designs, in many cases but it is necessary to develop a logical approach for assessing their validity and selection, an arbitrary value for α is no longer considered adequate.

The adoption of static inertia force equal to the maximum acceleration during an earthquake (rigid-body response) has been suggested as an alternative to the use of empirical values. However, this procedure is likely to be very conservative for two reasons:

1 Only low stiff embankments or embankments in narrow canyons may respond essentially as rigid structures. There is ample field evidence to prove that most earth dams do not behave as rigid structures and that each has its own individual response different from that of others.

2. An earthquake inertia force is applied only for a very short period. Replacing a transient force of such short duration by a pseudo-static force representing the maximum acceleration is unrealistic. Therefore, a value of a equal to the maximum ground acceleration is likely to be overconservative even for a rigid embankment.

In this present study the horizontal seismic coefficients are considered based on seismic coefficient method as per IS: 1893-1984 using the relation

$$\alpha_h = \beta I \alpha_o \qquad (2.7)$$

where,

α_o = Basic horizontal seismic coefficient as shown in Table 2.3.

The vertical seismic coefficients are considered as half of the horizontal seismic coefficients.

2.10 PORE WATER PRESSURE

For purposes of design it is convenient to distinguish three critical stages of pore pressure development in an earth dam.

2.10.1 Pore Pressure During Construction

When an earth dam is built of soil of low permeability, excess pore pressures develop in the air and water voids due to compaction carried out during construction or due to its own weight. The pore pressures developed depend upon the placement water content, method of compaction, weight of the overlying layers and the rate of dissipation of pore pressure during construction.

2.10.2 Pore Pressure Under Steady Seepage Condition

When the reservoir on the upstream of the dam is filled, water starts seeping through the dam. After sometime, the steady seepage condition is established and a well-defined phreatic line is formed. The soil below the phreatic line is saturated and subjected to pore water pressure. On the upstream slope, the seepage forces are directed inwards and hence tend to increase the stability. However, on the downstream slope, the direction of the seepage forces is such that they decrease the stability. The steady seepage condition is, therefore, critical for the downstream slope of an earth dam.

2.10.3 Pore Pressure Under Sudden Drawdown Condition

The critical condition for the stability of the upstream slope of an earth dam is when there is a sudden drawdown in the reservoir upstream. If the soil is of low permeability, no appreciable change in the water level inside the slope takes place when the reservoir level goes down. The weight of water which is still present in the soil tends to cause sliding of the wedge, as the water pressure which was acting on the upstream slope to balance this weight has been suddenly removed.

CHAPTER 3

NEURAL NETWORK APPROACH

3.1 INTRODUCTION TO NEURAL NETWORKS

Neural networks provide a unique computing architecture whose potential has only begun to be tapped. Used to address problems that are intractable or cumbersome with traditional methods, these new computing architectures inspired by the structure of the brain are radically different from the computers that are widely used today. Neural networks are massively parallel systems that rely on dense arrangements of interconnections and surprisingly simple processors.

Artificial neural networks take their name from the networks of nerve cells in the brain. Although a great deal of biological detail is eliminated in these computing models, the artificial neural networks retain enough of the structure observed in the brain to provide insight into how biological neural processing may work. Thus these models contribute to a paramount scientific challenge the brain understanding itself.

3.2 ARTIFICIAL NEURAL NETWORKS THE BASIC STRUCTURE

Neural networks are responsible for making significant advances in the traditional AI fields of speech and visual recognition. Investment managers are creating investment models to better manage money and improve profits. Marketing professionals are employing neural networks to accurately target products to potential customers. Geologists can increase their probability of finding oil. Lenders use neural networks to determine the credit risk of loan applicants. Scientists and engineers use them to model and predict complex phenomena, such as prediction of critical slip surface and minimum factor of safety of a complex slope at a site. The variety of problems that can be solved effectively by neural networks is virtually endless.

A human brain continually receives input signals from many sources and processes them to create the appropriate output response. Our brains have billions of neurons that interconnect to create elaborate neural networks. These networks execute the millions of necessary functions needed to sustain normal life. For some years now, researchers have been developing models, both in hardware and software, that mimic a brain's cerebral activity in an effort to produce an ultimate form of artificial intelligence.

The back propagation model, however, is largely responsible for changing this trend. It is an extremely effective learning tool that can be applied to a wide variety of problems. Back propagation related models require supervised training. This means they must be trained using a set of training data where known solutions are supplied.

Therefore, training of the neural network is essentially carried out through the presentation of a series of example patterns of associated input and output values. The most commonly used learning system, and the one adopted in this present study, is the back propagation model.

Back propagation type neural networks process information in interconnecting processing elements, known as neurons or neurodes or nodes. These nodes are organized into groups, known as layers. There are three distinct types of layers in a back propagation neural network:

i. The input layer,

ii. The hidden layer or layers, and

iii. The output layer.

A network consists of one input layer, one or more hidden layers and one output layer. Connections exist between the nodes of adjacent layers to relay the output signals from one layer to the next. Fully connected networks occur when all nodes in each layer receive connections from all nodes in each preceding layer. Information enters a network through the nodes of the input layer. The input layer nodes are unique in that their sole purpose is to distribute the input information to the next processing layer, i.e. the first hidden layer. The hidden and output layer nodes process all incoming signals by applying factors to them, known as weights. Fig. 3.1 shows the architecture of a typical neural network consisting of three layers of interconnected neurodes. All inputs to a node are weighted, combined and then processed through a transfer function that controls the strength of the signal relayed through the node's output connections. The transfer function serves to normalize a node's output signal strength between 0 and 1. There are generally two types of transfer functions, the sigmoid function and the Gaussian function. Network processing continues through each node and layer until the network's response is obtained at the output layer.

When a network is used in the interrogating mode, processing ends at the output layer. During training, the network's response at the output layer is compared to a supplied set of known answers, known as training targets. The errors are determined and back propagated through the network in an attempt to improve the network's response. The nodal weight factors are adjusted by amounts determined by the training algorithm. The iterative procedure of processing inputs through the network, determining the errors and back propagating the errors through the network to adjust the weights constitutes the learning process. One training iteration is complete when all supplied training cases have been processed through the network. The training algorithms adjust the weights in an attempt to drive the network's response error to a minimum.

Two factors are used to control the training algorithm's adjustment of the weights.

They are the learning rate coefficient η , and the momentum factor α . The learning rate determines the amount that each weight will change during each learning cycle, and the momentum factor determines the amount that each weight will change relative to the change in the previous learning cycle. If the learning rate is too fast, i.e. η is too large, network training can become unstable. If η is too small, the network will learn at a very slow pace. The momentum factor α . has a smaller influence on learning speeds, but it can influence training stability and promote faster learning for most networks. In this present study the learning rate is considered as 0.5 and the momentum factor is considered as 0.8 for all the networks.

On the satisfactory completion of the training phase, verification of the performance of the neural network is then carried out using patterns that were not included in the training set. This determines the quality of the predictions in comparison to the desired outputs. This is often called as testing phase. No additional learning occurs during this phase.

3.3 SOIL SLOPE DATA FOR NEURAL NETWORK MODELLING

Statistical methods are commonly used to model complex relationships involving a number of variables. This is often complex and cumbersome, also to formulate the statistical model, the important parameters must be known. By comparison, the modelling process in neural networks in more direct, as there is no necessity to specify a mathematical relationship between the input and output variables. The neural network is capable of capturing complex nonlinear interactions between input and output variables in a system. In addition, it can generalize correct responses that only broadly resemble the data in the training set. In this present study the data for training, testing and interrogating the neural networks are generated using a computer program for pseudostatic analysis using method of slices [4], using the program one can get critical slip surface corresponding to minimum factor of safety for a given soil slope. The input parameters used to generate data are as shown in Table 3.1. Using this data 120 different combinations of problems were generated. The geometry of the slope is constant for all the 120 problems. The geometry of the slope used in this study is as shown in Fig. 3.2.

3.4 FORMULATION, TRAINING AND TESTING OF THE NEURAL NETWORKS FOR SLOPE STABILITY ANALYSIS

For this study of slope stability analysis for a typical earth dam as shown in Fig. 3.2, three different models containing different number of input variables and different number of output variables were investigated. The input variables and output variables used in three different models are as follows ;

i. Total number of input variables used in this model are 15.

$\alpha_h, \alpha_v, WP, \gamma_1, \phi_1, C_1, \gamma_2, \phi_2, C_2, \gamma_3, \phi_3, C_3,$ XC, YC and R. Output from this model is FOS as shown in Fig. 3.3.

ii. Total number of input variables used in this model are 13.

$\alpha_h, \alpha_v, WP, \gamma_1, \phi_1, C_1, \gamma_2, \phi_2, C_2, \gamma_3, \phi_3, C_3$ and FOS. Outputs from this model are XC, YC and R as shown in Fig. 3.4.

iii. Total number of input variables used in this model are 12.

$\alpha_h, \alpha_v, WP, \gamma_1, \phi_1, C_1, \gamma_2, \phi_2, C_2, \gamma_3, \phi_3$ and C_3. Outputs from this model are XC, YC, R and FOS as shown in Fig. 3.5.

Where

α_h = Horizontal seismic coefficient

α_v = Vertical seismic coefficient

WP = Pore water pressure parameter

γ = Dry density of the soil

ϕ = Angle of internal friction of the soil

C = Cohesion

XC = Horizontal coordinate of centre of the critical slip circle

YC = Vertical coordinate of centre of the critical slip circle

R = Radius of critical slip circle and

FOS = Minimum factor of safety

The following information is required when designing a network:

i. The number of input node,

ii. The number of hidden layers,

iii. The number of nodes in each of the hidden layers, and

iv. The number of output nodes.

3.4.1 The Input Layer

The input layer of a neural network has the sole purpose of distributing input data values to the first hidden layer. The number of nodes in the input layer will be equal to the number of input data values in the model. The total number of input neurons considered for training, testing and interrogating the neural network model 1 are 15, the total number of input neurons considered for training, testing and interrogating the neural network model 2 are 13 and the total number of input neurons considered for training, testing and interrogating the neural network model 3 are 12. The soil properties such as γ, ϕ, C are considered as γ_1, ϕ_1, C_1 for shell portion of a typical earth dam section, γ_2, ϕ_2, C_2 for core portion of a typical earth dam section and γ_3, ϕ_3, C_3 for foundation soil as shown in Fig. 3.6, in the input layer for training, testing and interrogation of all the three models. The geometry of the slope is not considered as input for training, testing and interrogation of the three models, because the geometry is constant for all the 120 problems. The input data used for training, testing and interrogating the neural network are shown in Table 3.2,

Table 3.3 and Table 3.4 respectively.

3.4.2 The Hidden Processing Structure

Choosing the number of hidden layers and the number of hidden nodes in each layer is not an easy task. Currently there is no thumb rule for determining the optimal number of neurodes in the hidden layer or the number of hidden layers, except through experimentation. Many factors play a part in determining what the optimal configuration should be. These factors include the quantity of training patterns, the number of input and output nodes and the relationships between the input and output data. When a network's hidden processing structure is too large and complex for the model being developed, the network may tend to memorize input and output sets rather than learn relationships between them. Such a network may train well but test poorly when presented with inputs outside the training set. Also, network training time will significantly increase when a network is unnecessarily large and complex. In this present study single hidden layer is considered for each model the number of hidden neurons in model 1 are 15, in model 2 are 13 and in model 3 are 12.

3.4.3 The Output Layer

In this present study three models with different set of outputs were considered. In the first model the output layer consisted of only one neurode, representing the minimum factor of safety of the slope. In the second model the output layer consisted of three neurodes, representing the centre (XC, YC) and radius (R) of a critical slip surface. In the third model the output layer consisted of four neurodes, representing the minimum factor of safety (FOS), centre (XC, YC) and radius (R) of slip surface. The output data used for training and testing of the neural networks are shown in Table 3.5 and Table 3.6

3.4.4 The Transfer Function

A node's transfer functions serves the purpose of controlling the output signal strength for the node, except for the input layer which uses the inputs themselves. These functions set the output signal strength between 0 and 1. The input to the transfer function is the dot product of all the node's input signals and the node's weight vector. The sigmoid transfer function is the most widely used function for back propagation neural networks, which is also used in this study. The sigmoid function acts like an output gate that can be opened (1) or closed (0). Since the function is continuous, it is also possible for the gate to be partially opened, i.e. somewhere between 0 and 1. Models incorporating sigmoid transfer functions usually exhibit better generalization in the learning process and often yield more accurate models, but may also require longer training times.

3.4.5 Training of the Neural Network

All the neural network analysis for the stability analysis were carried out by using the Neural Planner program. Neural Planner is a neural network system for Micro-soft Windows. It allows to produce multilayered neural networks using a simple graphical editor or create standard three layer networks from training files. There are also facilities for producing training, testing and interrogating files in the Neural Planner. The Neural Planner can learn from training files, self test using testing fields and be interrogated by interrogating files.

3.4.6 The Training Data

A total of 120 cases of data with different seismic coefficients, Pore water pressures and soil parameters were generated using a computer program for pseudostatic analysis using method of slices [4]. Among the 120 cases of data 72 cases of data were used for training, 24 cases for testing and 24 cases for interrogation.

Some preprocessing of the data are usually required before presenting the input patterns to the neural network. This usually involves scaling or normalization of the input patterns to values in the range 0-1. This is necessary because the sigmoid transfer function modulates the output to values between 0 and 1. Normalization of the data can be as simple as either dividing the values by the maximum value or by subtracting the minimum value and then dividing the values by the range, which is the maximum value minus the minimum value. The input patterns for both the training and testing phase were prepared, and the normalization was done automatically by the neural network program.

All the neural network analyses, for this study, were carried out with the learning rate $\eta=0.5$, and the momentum factor $\alpha=0.8$. These optimal values of learning rate and momentum factor were determined through trail and error. Training of the neural network was carried out until the average sum squared errors over all the training patterns were minimized.

Once the neural network has been trained, the seismic stability analysis of any slope can be easily obtained by putting the required input data of that slope in the interrogating file section, and interrogating the trained neural network for that data.

CHAPTER 4

NUMERICAL STUDIES

4.1 COMPARISON OF THE RESULTS

After training and testing of the Neural Networks, model 1, model 2 and model 3. The networks has been interrogated for about 24 sets of input data and the results obtained from all the three Networks are compared with the results obtained from conventional method and the results are shown in Table 4.1, 4.2 and 4.3 respectively.

4.2 PARAMETRIC STUDY

The results used in this parametric study to plot graphs are shown in Table 4.4. In this present study the analysis is carried out for different horizontal seismic coefficients based on seismic zoning factors as per IS: 1893-1984. A graph is plotted between the minimum factors of safety obtained from neural network and different horizontal seismic coefficients, keeping all the remaining parameters constant as shown in Fig. 4.1. It is observed from the graph that as the horizontal seismic coefficient increases the factor of safety decreases which is consistent with both theory and practice.

A graph is plotted between the minimum factors of safety obtained from neural network and different pore water pressure parameters, keeping all the remaining parameters constant as shown in Fig. 4.2. It is observed from the graph that as the pore water pressure increases the factor of safety decreases which is consistent with both theory and practice.

A graph is plotted between the minimum factors of safety obtained from neural network and different ϕ values keeping all the remaining parameters constant as shown in Fig. 4.3 and Fig. 4.4. It is observed from the graph that as the ϕ value increases the factor of safety also increases, which is also consistent because the major strength of the soil depends on angle of internal friction, therefore, strength of the soil is more if ϕ value is more and hence factor of safety increases.

4.3 OBSERVATIONS

In this present study the problem is analysed for a particular slope i.e. the geometry of the slope is same for all sets of problems as shown in Fig. 3.2 [11], with different horizontal seismic coefficients, different pore water pressure parameters and for different sets of soil parameters such as γ, ϕ, C as shown in Table 3.1. It is observed that the neural networks performed successfully. All the three models were interrogated for no testing (0 cycles per test), 100 cycles per test, 200 cycles per test and 300 cycles per test. It is observed that the model at 200 cycles per test was performed well and it is also observed that the neural network of model1 performed successfully, therefore, it clearly implies that more the number of input data greater the accuracy of the results.

4.4 DISCUSSIONS

In the present study the analysis is conducted for a particular slope, even though the geometry of the slope is not considered as input for training, testing and interrogating the neural network, the results obtained are very good so that the neural network does not require the complete data to analyse the problem. The performance of a neural network depends on how a network has been trained, i.e. the number of inputs and combination of inputs. The present study for the performance of neural networks in stability analysis of slopes, leads to the observation that neural networks perform successfully.

CHAPTER 5

CONCLUSIONS

On the basis of numerical studies conducted and results obtained from Neural Networks, as discussed in the foregoing chapters, it can be concluded as follows :

1. The results obtained from all the three Neural Networks are very much in agreement with the results as obtained from conventional method of analysis, hence it can be concluded as Artificial Neural Networks can augment/replace conventional method of analysis.
2. Using Neural Networks, which give the failure surface as output when the factor of safety is considered as input, indicates that there is a possibility of solving inverse problems using Neural Nets.
3. All the three Neural Network models are trained without using the geometry of the slope as input even though, the results obtained from all the three Neural Network models are very much close to the results obtained from conventional method of analysis, hence it can be concluded that there is a possibility of solving problems with incomplete data using Neural Nets.
4. The parametric study results obtained from Neural Networks are in keeping with the Physics of the problem, hence it can be concluded that the solutions follow trends consistent with theory/practice.
5. On the basis of the performance of Neural Networks in seismic soil slope stability analysis finally it can be concluded as the Neural Networks offer immense possibilities in future.

CHAPTER 6

SCOPE FOR FURTHER STUDIES

In this present study all analysis is carried out for a typical earth dam with constant geometry and limited sets of combinations of soil parameters. Once the Neural Network is trained considering differing geometry of the slope, Soil parameters, pore water pressure and seismic coefficients, one can develop a generalised Neural Network model, which can be used to analyse any type of slope in any condition.

Since the Neural Nets are capable of solving inverse problem, Neural Nets can be used to get optimal slopes and failure surfaces for given factor of safety and other conditions.

In this study theoretically generated data is used for the analysis, but it is suggested that laboratory/field data for training the Neural Network should be used to provide more realistic training patterns and hence more realistic solutions.

REFERENCES

1.. Arora, K.R., *"Soil Mechanics"*, Standard Publishers Distributors, New Delhi, Third Edition, 1992.

2. Bromhead, E.N., *"The Stability of Slopes"*, Blackie Academic and professional, 2nd Edition.

3. Bharat Singh and Sharma, H.D., *"Earth and Rockfill Dams"*, Sarita Prakashan, Meerut, First Edition, June 1976.

4. Chaturvedi, M.C. and Lavania, B.V.K., *"Computer Analysis of Slope Stability"*, Journal of Institute of Engineers, Nov. 1970.

5. Chowdhury, R.N., *"Slope Analysis"*, Developments in Geotechnical Engineering, Vol. 22, Elsevier Scientific Publishing Company, Amsterdam, Oxford, New York, 1978.

6. Dayhoff, J.E., *"Neural Network Architectures an Introduction"*.

7. Durgesh Kumar Gupta, *"Neural-Nets for Evaluation of Liquefaction Potential"*, M.E. Dissertation, Deptt. of Earthquake Engineering, University of Roorkee, Roorkee, March, 1998.

8. Gopal Ranjan and Rao, A.S.R., *"Basic and Applied Soil Mechanics"*.

9. IS: 1893-1984, *"Indian Standard Criteria for Earthquake Resistant Design of Structures"*, Fourth Revision.

10. Jumikis, A.R., *"Soil Mechanics"*, Affiliated East-West Press Pvt. Ltd., New Delhi, 1962.

TABLE 2.3 Values of Basic Seismic Coefficients and Seismic Zone Factors in different Zones (IS: 1893-1884, Clauses 3.4.2.1, 3.4.2.3 and 3.4.5)

Sl. No.	Zone No.	Method	
		Seismic Coefficient Method	Response Spectrum Method
		Basic horizontal seismic coefficient, α_o	Seismic zone factor for average acceleration spectra, F_o
1.	V	0.08	0.40
2.	IV	0.05	0.25
3.	III	0.04	0.20
4.	II	0.02	0.10
5.	I	0.01	0.05

TABLE 3.1 Input Parametres Used in this Study

Horizontal Seismic Coefficient α_h	Vertical Seismic Coefficient α_v	Pore Water Pressure Parameter WP	Dry Unit Weight γ, Angle of Internal Fliction ϕ and Cohesion C of Soil								
			For shell Portion			For Core Portion			For Foundation Soil		
			γ_1 t/m³	ϕ_1^o	C_1 t/m²	γ_2 t/m³	ϕ_2^o	C_2 t/m²	γ_3 t/m³	ϕ_3^o	C_3 t/m²
0	0	0	1.7	20	0	1.5	10	2	1.8	25	5
0.03	0.015	0.25	1.8	25	0	1.6	15	1.5	1.9	30	4
0.06	0.03	0.5	1.9	30	0	1.7	20	1.0	2.0	35	3
0.12	0.06	1	2.0	35	0	1.8	25	0.5	2.1	40	2
0.15	0.075		2.1	40	0	1.9	30	0.1	2.2	45	1
0.24	0.12										

TABLE 3.2 Input Parametrès Used for Training the Neural Networks

Sl. No.	α_h	α_v	WP	γ_1 t/m^3	ϕ_1^o	C_1 t/m^2	γ_2 t/m^3	ϕ_2^o	C_2 t/m^2	γ_3 t/m^3	ϕ_3^o	C_3 t/m^2
1.	0	0	0	2.1	40	0	1.9	30	.1	2.2	45	1
2.	0	0	0	1.9	30	0	1.7	20	1	2	35	3
3.	0	0	0	1.7	20	0	1.5	10	2	1.8	25	5
4.	0	0	.25	2.1	40	0	1.9	30	.1	2.2	45	1
5.	0	0	.25	1.9	30	0	1.7	20	1	2	35	3
6.	0	0	.25	1.7	20	0	1.5	10	2	1.8	25	5
7.	0	0	.5	2.1	40	0	1.9	30	.1	2.2	45	1
8.	0	0	.5	1.8	25	0	1.6	15	1.5	1.9	30	4
9.	0	0	.5	1.7	20	0	1.5	10	2	1.8	25	5
10.	0	0	1	2.1	40	0	1.9	30	.1	2.2	45	1
11.	0	0	1	1.9	30	0	1.7	20	1	2	35	3
12.	0	0	1	1.7	20	0	1.5	10	2	1.8	25	5
13.	.03	.015	0	2.1	40	0	1.9	30	.1	2.2	45	1
14.	.03	.015	0	1.9	30	0	1.7	20	1	2	35	3
15.	.03	.015	0	1.7	20	0	1.5	10	2	1.8	25	5
16.	.03	.015	.25	2.1	40	0	1.9	30	.1	2.2	45	1
17.	.03	.015	.25	2	35	0	1.8	25	.5	2.1	40	2
18.	.03	.015	.25	1.7	20	0	1.5	10	2	1.8	25	5
19.	.03	.015	.5	2.1	40	0	1.9	30	.1	2.2	45	1
20.	.03	.015	.5	1.8	25	0	1.6	15	1.5	1.9	30	4

11. Khaudem Ibopishak Singh, *"Exslope-An Expert System for Slope Stability"*, M.E Dissertation, Deptt. of Earthquake Engineering, University of Roorkee, Roorkee, Feb. 1996.

12. Terzaghi, K., Peck, R.B. and Mesric, Gholamreza, *"Soil Mechanics in Engineering Practice"*, John Wiley & Sons, Third Edition.

TABLE 2.1 Values of β for different Soil-Foundation Systems (IS: 1893-1884, Clause 3.4.3)

Sl. No.	Type of Soil Mainly Constituting the Foundation	Values of β for					
		Piles Passing through any Soil, but Resting on Soil Type I	Piles not covered under Col 3	Raft Foundations	Combined Isolated RCC Footings with Tie Beams	Isolated RCC Footings without Tie Beams or Unreinforced Strip Foundations	Well Foundations
1.	Type I Rock or hard Soils	1.0	-	1.0	1.0	1.0	1.0
2.	Type II Medium Soils	1.0	1.0	1.0	1.0	1.2	1.2
3.	Type III Soft Soils	1.0	1.2	1.0	1.2	1.5	1.5

Note : The value of β for dams shall be taken as 1.0

TABLE 2.2 Values of Importance Factor, I (IS: 1893-1984, Clauses 3.4.2.3 and 3.4.4)

Sl.No.	Structure	Value of Importance Factor, I
1.	Dams (all types)	3.0
2.	containers of inflammable or poisonous gases of liquids	2.0
3.	Important service and community structures, such as hospitals; water towers and tanks; schools;important bridges; important power houses; monumental structures; emergency buildings like telephone exchange and fire bridge; large assembly structures like cinemas, assembly halls and subway stations.	1.5
4.	All others	1.0

TABLE 2.3 Values of Basic Seismic Coefficients and Seismic Zone Factors in different Zones (IS: 1893-1884, Clauses 3.4.2.1, 3.4.2.3 and 3.4.5)

Sl. No.	Zone No.	Method	
		Seismic Coefficient Method	Response Spectrum Method
		Basic horizontal seismic coefficient, α_o	Seismic zone factor for average acceleration spectra, F_o
1.	V	0.08	0.40
2.	IV	0.05	0.25
3.	III	0.04	0.20
4.	II	0.02	0.10
5.	I	0.01	0.05

TABLE 3.1 Input Parametres Used in this Study

Horizontal Seismic Coefficient α_h	Vertical Seismic Coefficient α_v	Pore Water Pressure Parameter WP	Dry Unit Weight γ, Angle of Internal Fliction ϕ and Cohesion C of Soil								
			For shell Portion			For Core Portion			For Foundation Soil		
			γ_1 t/m³	ϕ_1^o	C_1 t/m²	γ_2 t/m³	ϕ_2^o	C_2 t/m²	γ_3 t/m³	ϕ_3^o	C_3 t/m²
0	0	0	1.7	20	0	1.5	10	2	1.8	25	5
0.03	0.015	0.25	1.8	25	0	1.6	15	1.5	1.9	30	4
0.06	0.03	0.5	1.9	30	0	1.7	20	1.0	2.0	35	3
0.12	0.06	1	2.0	35	0	1.8	25	0.5	2.1	40	2
0.15	0.075		2.1	40	0	1.9	30	0.1	2.2	45	1
0.24	0.12										

TABLE 3.2 Input Parametres Used for Training the Neural Networks

Sl. No.	α_h	α_v	WP	γ_1 t/m³	ϕ_1^o	C_1 t/m²	γ_2 t/m³	ϕ_2^o	C_2 t/m²	γ_3 t/m³	ϕ_3^o	C_3 t/m²
1.	0	0	0	2.1	40	0	1.9	30	.1	2.2	45	1
2.	0	0	0	1.9	30	0	1.7	20	1	2	35	3
3.	0	0	0	1.7	20	0	1.5	10	2	1.8	25	5
4.	0	0	.25	2.1	40	0	1.9	30	.1	2.2	45	1
5.	0	0	.25	1.9	30	0	1.7	20	1	2	35	3
6.	0	0	.25	1.7	20	0	1.5	10	2	1.8	25	5
7.	0	0	.5	2.1	40	0	1.9	30	.1	2.2	45	1
8.	0	0	.5	1.8	25	0	1.6	15	1.5	1.9	30	4
9.	0	0	.5	1.7	20	0	1.5	10	2	1.8	25	5
10.	0	0	1	2.1	40	0	1.9	30	.1	2.2	45	1
11.	0	0	1	1.9	30	0	1.7	20	1	2	35	3
12.	0	0	1	1.7	20	0	1.5	10	2	1.8	25	5
13.	.03	.015	0	2.1	40	0	1.9	30	.1	2.2	45	1
14.	.03	.015	0	1.9	30	0	1.7	20	1	2	35	3
15.	.03	.015	0	1.7	20	0	1.5	10	2	1.8	25	5
16.	.03	.015	.25	2.1	40	0	1.9	30	.1	2.2	45	1
17.	.03	.015	.25	2	35	0	1.8	25	.5	2.1	40	2
18.	.03	.015	.25	1.7	20	0	1.5	10	2	1.8	25	5
19.	.03	.015	.5	2.1	40	0	1.9	30	.1	2.2	45	1
20.	.03	.015	.5	1.8	25	0	1.6	15	1.5	1.9	30	4

(Continued)

Sl. No.	α_h	α_v	WP	γ_1 t/m³	ϕ_1^o	C_1 t/m²	γ_2 t/m³	ϕ_2^o	C_2 t/m²	γ_3 t/m³	ϕ_3^o	C_3 t/m²
21.	.03	.015	.5	1.7	20	0	1.5	10	2	1.8	25	5
22.	.03	.015	1	2.1	40	0	1.9	30	.1	2.2	45	1
23.	.03	.015	1	2	35	0	1.8	25	.5	2.1	40	2
24.	.03	.015	1	1.7	20	0	1.5	10	2	1.8	25	5
25.	.06	.03	0	2.1	40	0	1.9	30	.1	2.2	45	1
26.	.06	.03	0	2	35	0	1.8	25	.5	2.1	40	2
27.	.06	.03	0	1.7	20	0	1.5	10	2	1.8	25	5
28.	.06	.03	.25	2.1	40	0	1.9	30	.1	2.2	45	1
29.	.06	.03	.25	1.8	25	0	1.6	15	1.5	1.9	30	4
30.	.06	.03	.25	1.7	20	0	1.5	10	2	1.8	25	5
31.	.06	.03	.5	2.1	40	0	1.9	30	.1	2.2	45	1
32.	.06	.03	.5	1.8	25	0	1.6	15	1.5	1.9	30	4
33.	.06	.03	.5	1.7	20	0	1.5	10	2	1.8	25	5
34.	.06	.03	1	2.1	40	0	1.9	30	.1	2.2	45	1
35.	.06	.03	1	2	35	0	1.8	25	.5	2.1	40	2
36.	.06	.03	1	1.7	20	0	1.5	10	2	1.8	25	5
37.	.12	.06	0	2.1	40	0	1.9	30	.1	2.2	45	1
38.	.12	.06	0	1.9	30	0	1.7	20	1	2	35	3
39.	.12	.06	0	1.7	20	0	1.5	10	2	1.8	25	5
40.	.12	.06	.25	2.1	40	0	1.9	30	.1	2.2	45	1
41.	.12	.06	.25	1.8	25	0	1.6	15	1.5	1.9	30	4
42.	.12	.06	.25	1.7	20	0	1.5	10	2	1.8	25	5

(Continued)

Sl. No.	α_h	α_v	WP	γ_1 t/m³	ϕ_1^o	C_1 t/m²	γ_2 t/m³	ϕ_2^o	C_2 t/m²	γ_3 t/m³	ϕ_3^o	C_3 t/m²
43.	.12	.06	.5	2.1	40	0	1.9	30	.1	2.2	45	1
44.	.12	.06	.5	2	35	0	1.8	25	.5	2.1	40	2
45.	.12	.06	.5	1.7	20	0	1.5	10	2	1.8	25	5
46.	.12	.06	1	2.1	40	0	1.9	30	.1	2.2	45	1
47.	.12	.06	1	1.8	25	0	1.6	15	1.5	1.9	30	4
48.	.12	.06	1	1.7	20	0	1.5	10	2	1.8	25	5
49.	.15	.075	0	2.1	40	0	1.9	30	.1	2.2	45	1
50.	.15	.075	0	2	35	0	1.8	25	.5	2.1	30	2
51.	.15	.075	0	1.7	20	0	1.5	10	2	1.8	25	5
52.	.15	.075	.25	2.1	40	0	1.9	30	.1	2.2	45	1
53.	.15	.075	.25	1.9	30	0	1.7	20	1	2	35	3
54.	.15	.075	.25	1.7	20	0	1.5	10	2	1.8	25	5
55.	.15	.075	.5	2.1	40	0	1.9	30	.1	2.2	45	1
56.	.15	.075	.5	1.8	25	0	1.6	15	1.5	1.9	30	4
57.	.15	.075	.5	1.7	20	0	1.5	10	2	1.8	25	5
58.	.15	.075	1	2.1	40	0	1.9	30	.1	2.2	45	1
59.	.15	.075	1	2	35	0	1.8	25	.5	2.1	40	2
60.	.15	.075	1	1.7	20	0	1.5	10	2	1.8	25	5
61.	.24	.12	0	2.1	40	0	1.9	30	.1	2.2	45	1
62.	.24	.12	0	2	35	0	1.8	25	.5	2.1	40	2
63.	.24	.12	0	1.7	20	0	1.5	10	2	1.8	25	5
64.	.24	.12	.25	2.1	40	0	1.9	30	.1	2.2	45	1

(Continued)

Sl. No.	α_h	α_v	WP	γ_1 t/m³	ϕ_1^o	C_1 t/m²	γ_2 t/m³	ϕ_2^o	C_2 t/m²	γ_3 t/m³	ϕ_3^o	C_3 t/m²
65.	.24	.12	.25	1.8	25	0	1.6	15	1.5	1.9	30	4
66.	.24	.12	.25	1.7	20	0	1.5	10	2	1.8	25	5
67.	.24	.12	.5	2.1	40	0	1.9	30	.1	2.2	45	1
68.	.24	.12	.5	2	35	0	1.8	25	.5	2.1	40	2
69.	.24	.12	.5	1.7	20	0	1.5	10	2	1.8	25	5
70.	.24	.12	1	2.1	40	0	1.9	30	.1	2.2	45	1
71.	.24	.12	1	1.8	25	0	1.6	15	1.5	1.9	30	4
72.	.24	.12	1	1.7	20	0	1.5	10	2	1.8	25	5

TABLE 3.3 Input Parameters Used for Testing the Neural Networks

Sl. No.	α_h	α_v	WP	γ_1 t/m³	ϕ_1^o	C_1 t/m²	γ_2 t/m³	ϕ_2^o	C_2 t/m²	γ_3 t/m³	ϕ_3^o	C_3 t/m²
1.	0	0	0	1.8	25	0	1.6	15	1.5	1.9	30	4
2.	0	0	.25	2	35	0	1.8	25	.5	2.1	40	2
3.	0	0	.5	2	35	0	1.8	25	.5	2.1	40	2
4.	0	0	1	1.8	25	0	1.6	15	1.5	1.9	30	4
5.	.03	.015	0	2	35	0	1.8	25	.5	2.1	40	2
6.	.03	.015	.25	1.8	25	0	1.6	15	1.5	1.9	30	4
7.	.03	.015	.5	1.9	30	0	1.7	20	1	2	35	3
8.	.03	.015	1	1.8	25	0	1.6	15	1.5	1.9	30	4
9.	.06	.03	0	1.8	25	0	1.6	15	1.5	1.9	30	4
10.	.06	.03	.25	2	35	0	1.8	25	.5	2.1	40	2
11.	.06	.03	.5	1.9	30	0	1.7	20	1	2	35	3
12.	.06	.03	1	1.8	25	0	1.6	15	1.5	1.9	30	4
13.	.12	.06	0	2	35	0	1.8	25	.5	2.1	40	2
14.	.12	.06	.25	2	35	0	1.8	25	.5	2.1	40	2
15.	.12	.06	.5	1.9	30	0	1.7	20	1	2	35	3
16.	.12	.06	1	2	35	0	1.8	25	.5	2.1	40	2
17.	.15	.075	0	1.9	30	0	1.7	20	1	2	35	3
18.	.15	.075	.25	1.8	25	0	1.6	15	1.5	1.9	30	4

(Continued)

Sl. No.	α_h	α_v	WP	γ_1 t/m³	ϕ_1^o	C_1 t/m²	γ_2 t/m³	ϕ_2^o	C_2 t/m²	γ_3 t/m³	ϕ_3^o	C_3 t/m²
19.	.15	.075	.5	2	35	0	1.8	25	.5	2.1	40	2
20.	.15	.075	1	1.9	30	0	1.7	20	1	2	35	3
21.	.24	.012	0	1.8	25	0	1.6	15	1.5	1.9	30	4
22.	.24	.012	.25	1.9	30	0	1.7	20	1	2	35	3
23.	.24	.012	.5	1.8	25	0	1.6	15	1.5	1.9	30	4
24.	.24	.012	1	1.9	30	0	1.7	20	1	2	35	3

TABLE 3.4 Input Parameters Used for Interrogating the Neural Networks

Sl. No.	α_h	α_v	WP	γ_1 t/m^3	ϕ_1^o	C_1 t/m^2	γ_2 t/m^3	ϕ_2^o	C_2 t/m^2	γ_3 t/m^3	ϕ_3^o	C_3 t/m^2
1.	0	0	0	2	35	0	1.8	25	.5	2.1	40	2
2.	0	0	.25	1.8	25	0	1.6	15	1.5	1.9	30	4
3.	0	0	.5	1.9	30	0	1.7	20	1	2	35	3
4.	0	0	1	2	35	0	1.8	25	.5	2.1	40	2
5.	.03	.015	0	1.8	25	0	1.6	15	1.5	1.9	30	4
6.	.03	.015	.25	1.9	30	0	1.7	20	1	2	35	3
7.	.03	.015	.5	2	35	0	1.8	25	.5	2.1	40	2
8.	.03	.015	1	1.9	30	0	1.7	20	1	2	35	3
9.	.06	.03	0	1.9	30	0	1.7	20	1	2	35	3
10.	.06	.03	.25	1.9	30	0	1.7	20	1	2	35	3
11.	.06	.03	.5	2	35	0	1.8	25	.5	2.1	40	2
12.	.06	.03	1	1.9	30	0	1.7	20	1	2	35	3
13.	.12	.06	0	1.8	25	0	1.6	15	1.5	1.9	30	4
14.	.12	.06	.25	1.9	30	0	1.7	20	1	2	35	3
15.	.12	.06	.5	1.8	25	0	1.6	15	1.5	1.9	30	4
16.	.12	.06	1	1.9	30	0	1.7	20	1	2	35	3
17.	.15	.075	0	1.8	25	0	1.6	15	1.5	1.9	30	4
18.	.15	.075	.25	2	35	0	1.8	25	.5	2.1	40	2

(Continued)

Sl. No.	α_h	α_v	WP	γ_1 t/m³	ϕ_1^o	C_1 t/m²	γ_2 t/m³	ϕ_2^o	C_2 t/m²	γ_3 t/m³	ϕ_3^o	C_3 t/m²
19.	.15	.075	.5	1.9	30	0	1.7	20	1	2	35	3
20.	.15	.075	1	1.8	25	0	1.6	15	1.5	1.9	30	4
21.	.24	.12	0	1.9	30	0	1.7	20	1	2	35	3
22.	.24	.12	.25	2	35	0	1.8	25	.5	2.1	40	2
23.	.24	.12	.5	1.9	30	0	1.7	20	1	2	35	3
24.	.24	.12	1	2	35	0	1.8	25	.5	2.1	40	2

TABLE 3.5 Output Parameters Used for Training the Neural Networks

Sl. No.	Centre of Slip Circle		Radius of Slip Circle	FOS
	XC (m)	YC (m)	R (m)	
1.	80	0	100	1.81
2.	80	0	100	1.25
3.	80	0	100	.74
4.	80	0	100	1.64
5.	80	0	100	1.12
6.	80	0	100	.66
7.	80	0	100	1.47
8.	80	0	100	.79
9.	80	0	100	.59
10.	80	0	100	1.13
11.	80	0	100	.76
12.	80	0	100	.45
13.	80	0	100	1.68
14.	80	0	100	1.16
15.	60	0	100	.68
16.	80	0	100	1.52
17.	80	0	100	1.27
18.	60	0	100	.61
19.	80	0	100	1.36
20.	80	0	100	.74
21.	60	0	100	.54
22.	80	0	100	1.04
23.	80	0	100	.86
24.	60	0	100	.41
25.	80	0	100	1.57
26.	80	0	100	1.31
27.	60	0	100	.63
28.	80	0	100	1.42
29.	80	0	100	.77
30.	60	0	100	.56
31.	80	0	100	1.27

Sl. No.	Centre of Slip Circle		Radius of Slip Circle	FOS
	XC (m)	YC (m)	R (m)	
32.	80	0	100	.68
33.	60	0	100	.5
34.	80	0	100	.97
35.	80	0	100	.79
36.	60	0	100	.37
37.	80	0	100	1.38
38.	80	0	100	.95
39.	60	0	100	.54
40.	80	0	100	1.24
41.	60	0	100	.66
42.	60	0	100	.48
43.	80	0	100	1.11
44.	80	0	100	.92
45.	60	0	100	.43
46.	80	0	100	.83
47.	60	0	100	.43
48.	60	0	100	.32
49.	80	0	100	1.29
50.	80	0	100	1.08
51.	60	0	100	.5
52.	80	0	100	1.16
53.	60	0	100	.79
54.	60	0	100	.45
55.	80	0	100	1.04
56.	60	0	100	.55
57.	60	0	100	.4
58.	80	0	100	.78
59.	80	0	100	.64
60.	60	0	100	.29
61.	60	0	100	1.08
62.	60	0	100	.89
63.	60	0	100	.41

(Continued)

Sl. No.	Centre of Slip Circle		Radius of Slip Circle	FOS
	XC (m)	YC (m)	R (m)	
64.	60	0	100	.97
65.	60	0	100	.51
66.	60	0	100	.37
67.	60	0	100	.85
68.	60	0	100	.7
69.	60	0	100	.33
70.	60	0	100	.63
71.	60	0	100	.32
72.	60	0	100	.24

TABLE 3.6 Output Parameters Used for Testing the Neural Networks

Sl. No.	Centre of Slip Circle		Radius of Slip Circle	FOS
	XC (m)	YC (m)	R (m)	
1.	80	0	100	.99
2.	80	0	100	1.31
3.	80	0	100	1.22
4.	80	0	100	.6
5.	80	0	100	1.4
6.	80	0	100	.83
7.	80	0	100	.93
8.	80	0	100	.55
9.	80	0	100	.86
10.	80	0	100	1.18
11.	80	0	100	.86
12.	80	0	100	.51
13.	80	0	100	1.15
14.	80	0	100	1.03
15.	80	0	100	.75
16.	80	0	100	.69
17.	60	0	100	.88
18.	60	0	100	.62
19.	80	0	100	.86
20.	60	0	100	.52
21.	60	0	100	.57
22.	60	0	100	.65
23.	60	0	100	.44
24.	60	0	100	.41

TABLE 4.1 Comparison of Results obtained from conventional method and Results obtained from Neural Network Model 1

Sl. No.	Results from conventional method	Results from Neural Network Model 1			
		0 Cycles/test	100 Cycles/test	200 Cycles/test	300 Cycles/test
	FOS	FOS	FOS	FOS	FOS
1.	1.51	1.55	1.56	1.57	1.57
2.	.89	.9	.87	.89	.87
3.	1	1.01	.99	1.01	.99
4.	.93	.93	.92	.94	.93
5.	.92	.93	.91	.93	.91
6.	1.04	1.04	1.05	1.05	1.03
7.	1.13	1.13	1.15	1.14	1.13
8.	.7	.7	.71	.71	.7
9.	1.08	1.08	1.09	1.08	1.07
10.	.97	.97	.99	.98	.97
11.	1.05	1.06	1.09	1.06	1.05
12.	.65	.65	.66	.66	.65
13.	.74	.75	.75	.74	.74
14.	.85	.85	.88	.86	.86
15.	.59	.59	.61	.59	.59
16.	.56	.57	.57	.56	.57
17.	.69	.7	.7	.7	.69
18.	.97	.98	1.01	.97	.97
19.	.7	.7	.72	.71	.71
20.	.4	.4	.41	.39	.39
21.	.73	.72	.74	.72	.72
22.	.8	.79	.8	.78	.79
23.	.57	.57	.57	.57	.57
24.	.51	.52	.51	.51	.52

TABLE 4.2 Comparison of Results obtained from conventional method and Results obtained from Neural Network Model 2

Sl. No.	Results from conventional method			Results from Neural Network Model 2											
				0 cycles/test			100 cycles/test			200 cycles/test			300 cycles/test		
	Centre of Slip Circle		Radius of Slip Circle	Centre of Slip Circle		Radius of Slip Circle	Centre of Slip Circle		Radius of Slip Circle	Centre of Slip Circle		Radius of Slip Circle	Centre of Slip Circle		Radius of Slip Circle
	XC (m)	YC (m)	R (m)	XC (m)	YC (m)	R (m)	XC (m)	YC (m)	R (m)	XC (m)	YC (m)	R (m)	XC (m)	YC (m)	R (m)
1.	80	0	100	79.99	0	100	79.99	0	100	79.99	0	100	79.99	0	100
2.	80	0	100	79.99	0	100	79.99	0	100	79.99	0	100	79.99	0	100
3.	80	0	100	79.99	0	100	79.99	0	100	79.99	0	100	79.99	0	100
4.	80	0	100	79.99	0	100	79.99	0	100	79.99	0	100	79.99	0	100
5.	80	0	100	79.99	0	100	79.89	0	100	79.99	0	100	79.99	0	100
6.	80	0	100	79.99	0	100	79.99	0	100	79.99	0	100	79.99	0	100
7.	80	0	100	79.99	0	100	79.99	0	100	79.99	0	100	79.99	0	100
8.	80	0	100	79.99	0	100	79.99	0	100	79.99	0	100	79.99	0	100
9.	80	0	100	79.99	0	100	79.99	0	100	79.99	0	100	79.99	0	100
10.	80	0	100	79.99	0	100	79.99	0	100	79.99	0	100	79.99	0	100
11.	80	0	100	79.99	0	100	79.99	0	100	79.99	0	100	79.99	0	100
12.	80	0	100	79.99	0	100	79.99	0	100	79.99	0	100	79.99	0	100
13.	60	0	100	60	0	100	60	0	100	60	0	100	60	0	100
14.	80	0	100	79.63	0	100	78.47	0	100	79.99	0	100	79.66	0	100
15.	60	0	100	60	0	100	60	0	100	60	0	100	60	0	100
16.	80	0	100	66.02	0	100	62.78	0	100	79.99	0	100	64.08	0	100

(Continued)

Sl. No.	Results from conventional method			Results from Neural Network Model 2											
				0 cycles/test			100 cycles/test			200 cycles/test			300 cycles/test		
	Centre of Slip Circle		Radius of Slip Circle	Centre of Slip Circle		Radius of Slip Circle	Centre of Slip Circle		Radius of Slip Circle	Centre of Slip Circle		Radius of Slip Circle	Centre of Slip Circle		Radius of Slip Circle
	XC (m)	YC (m)	R (m)	XC (m)	YC (m)	R (m)	XC (m)	YC (m)	R (m)	XC (m)	YC (m)	R (m)	XC (m)	YC (m)	R (m)
17.	60	0	100	60	0	100	60	0	100	60	0	100	60	0	100
18.	80	0	100	79.99	0	100	79.98	0	100	79.99	0	100	79.99	0	100
19.	60	0	100	60	0	100	60.01	0	100	60.03	0	100	60	0	100
20.	60	0	100	60	0	100	60	0	100	60	0	100	60	0	100
21.	60	0	100	60	0	100	60	0	100	60.05	0	100	60	0	100
22.	60	0	100	60	0	100	60	0	100	60.05	0	100	60	0	100
23.	60	0	100	60	0	100	60	0	100	60.05	0	100	60	0	100
24.	60	0	100	60	0	100	60	0	100	60.04	0	100	60	0	100

TABLE 4.3 Comparison of Results obtained from conventional method and Results obtained from Neural Network Model 3

Sl. No.	Results from conventional method				Results from Neural Network Model 3															
					0 cycles/test				100 cycles/test				200 cycles/test				300 cycles/test			
	Centre of Slip Circle		Radius of Slip Circle	FOS	Centre of Slip Circle		Radius of Slip Circle	FOS	Centre of Slip Circle		Radius of Slip Circle	FOS	Centre of Slip Circle		Radius of Slip Circle	FOS	Centre of Slip Circle		Radius of Slip Circle	FOS
	XC (m)	YC (m)	R (m)		XC (m)	YC (m)	R (m)		XC (m)	YC (m)	R (m)		XC (m)	YC (m)	R (m)		XC (m)	YC (m)	R (m)	
1.	80	0	100	1.51	79.99	0	100	1.56	79.99	0	100	1.56	79.99	0	100	1.52	79.99	0	100	1.52
2.	80	0	100	.89	79.99	0	100	.85	79.99	0	100	.92	79.99	0	100	.82	79.99	0	100	.82
3.	80	0	100	1	79.99	0	100	.93	79.99	0	100	1	79.99	0	100	.89	79.99	0	100	.89
4.	80	0	100	.93	79.99	0	100	.85	79.99	0	100	.92	79.99	0	100	.83	79.99	0	100	.83
5.	80	0	100	.92	79.99	0	100	.89	79.99	0	100	.9	79.99	0	100	.91	79.99	0	100	.9
6.	80	0	100	1.04	79.99	0	100	.98	79.99	0	100	1	79.99	0	100	.97	79.99	0	100	.97
7.	80	0	100	1.13	79.99	0	100	1.05	79.99	0	100	1.09	79.99	0	100	1.06	79.99	0	100	1.06
8.	80	0	100	.7	79.99	0	100	.65	79.99	0	100	.68	79.99	0	100	.68	79.99	0	100	.68
9.	80	0	100	1.08	79.99	0	100	1.03	79.99	0	100	1.04	79.99	0	100	1.08	79.99	0	100	1.07
10.	80	0	100	.97	79.99	0	100	.93	79.99	0	100	.92	79.99	0	100	.93	79.99	0	100	.93
11.	80	0	100	1.05	79.99	0	100	.99	79.99	0	100	.99	79.99	0	100	1	79.99	0	100	1
12.	80	0	100	.65	79.99	0	100	.6	79.99	0	100	.64	79.99	0	100	.64	79.99	0	100	.64
13.	60	0	100	.74	60	0	100	.72	60	0	100	.75	60.01	0	100	.74	60.01	0	100	.74
14.	80	0	100	.85	79.77	0	100	.85	79.69	0	100	.84	79.74	0	100	.83	79.75	0	100	.83
15.	60	0	100	.59	60	0	100	.58	60	0	100	.59	60	0	100	.6	60	0	100	.6
16.	80	0	100	.56	78.8	0	100	.54	78.81	0	100	.55	79.83	0	100	.58	79.82	0	100	.58

(Continued)

Sl. No.	Results from conventional method				Results from Neural Network Model 3															
					0 cycles/test				100 cycles/test				200 cycles/test				300 cycles/test			
	Centre of Slip Circle		Radius of Slip Circle		Centre of Slip Circle		Radius of Slip Circle		Centre of Slip Circle		Radius of Slip Circle		Centre of Slip Circle		Radius of Slip Circle		Centre of Slip Circle		Radius of Slip Circle	
	XC (m)	YC (m)	R (m)	FOS	XC (m)	YC (m)	R (m)	FOS	XC (m)	YC (m)	R (m)	FOS	XC (m)	YC (m)	R (m)	FOS	XC (m)	YC (m)	R (m)	FOS
17.	60	0	100	.69	60	0	100	.69	60	0	100	.73	60	0	100	.7	60	0	100	.7
18.	80	0	100	.97	79.99	0	100	.97	79.99	0	100	1.01	79.99	0	100	.97	79.99	0	100	.97
19.	60	0	100	.7	60.01	0	100	.7	60.09	0	100	.7	60.21	0	100	.7	60.2	0	100	.7
20.	60	0	100	.4	60	0	100	.39	60	0	100	.4	60	0	100	.39	60	0	100	.39
21.	60	0	100	.73	60	0	100	.71	60	0	100	.76	60	0	100	.74	60	0	100	.75
22.	60	0	100	.8	60	0	100	.78	60	0	100	.81	60	0	100	.8	60	0	100	.8
23.	60	0	100	.57	60	0	100	.53	60	0	100	.56	60	0	100	.56	60	0	100	.57
24.	60	0	100	.51	60	0	100	.47	60	0	100	.5	60	0	100	.48	60	0	100	.49

TABLE 4.4 Results obtained from Neural Network Model 1 used in Parametric Study

Sl. No.	α_h	α_v	WP	γ_1 t/m^3	ϕ_1^o	C_1 t/m^2	γ_2 t/m^3	ϕ_2^o	C_2 t/m^2	γ_3 t/m^3	ϕ_3^o	C_3 t/m^2	Results from conventional method FOS	Results from Neural Network Model 1 FOS
1.	.04	.02	.4	1.85	32	0	1.75	18	1.25	2	38	3.5	.89	.91
2.	.08	.04	.4	1.85	32	0	1.75	18	1.25	2	38	3.5	.81	.85
3.	.1	.05	.4	1.85	32	0	1.75	18	1.25	2	38	3.5	.77	.81
4.	.18	.09	.4	1.85	32	0	1.75	18	1.25	2	38	3.5	.64	.68
5.	.2	.1	.4	1.85	32	0	1.75	18	1.25	2	38	3.5	.61	.64
6.	.16	.08	.2	1.95	33	0	1.8	27	1.2	1.95	36	2.8	1.01	.94
7.	.16	.08	.3	1.95	33	0	1.8	27	1.2	1.95	36	2.8	.97	.91
8.	.16	.08	.6	1.95	33	0	1.8	27	1.2	1.95	36	2.8	.83	.80
9.	.16	.08	.7	1.95	33	0	1.8	27	1.2	1.95	36	2.8	.79	.71
10.	.16	.08	.9	1.95	33	0	1.8	27	1.2	1.95	36	2.8	.7	.63
11.	.14	.07	.75	1.87	26	0	1.85	22	1.4	2.1	37	4.2	.61	.62
12.	.14	.07	.75	1.87	27	0	1.85	22	1.4	2.1	37	4.2	.62	.63
13.	.14	.07	.75	1.87	28	0	1.85	22	1.4	2.1	37	4.2	.63	.64
14.	.14	.07	.75	1.87	29	0	1.85	22	1.4	2.1	37	4.2	.64	.66
15.	.14	.07	.75	1.87	32	0	1.85	22	1.4	2.1	37	4.2	.66	.69
16.	.18	.09	.8	1.92	31	0	1.82	12	1.3	1.92	42	3.3	.38	.4
17.	.18	.09	.8	1.92	31	0	1.82	14	1.3	1.92	42	3.3	.42	.44
18.	.18	.09	.8	1.92	31	0	1.82	16	1.3	1.92	42	3.3	.46	.48
19.	.18	.09	.8	1.92	31	0	1.82	18	1.3	1.92	42	3.3	.5	.54
20.	.18	.09	.8	1.92	31	0	1.82	24	1.3	1.92	42	3.3	.63	.62

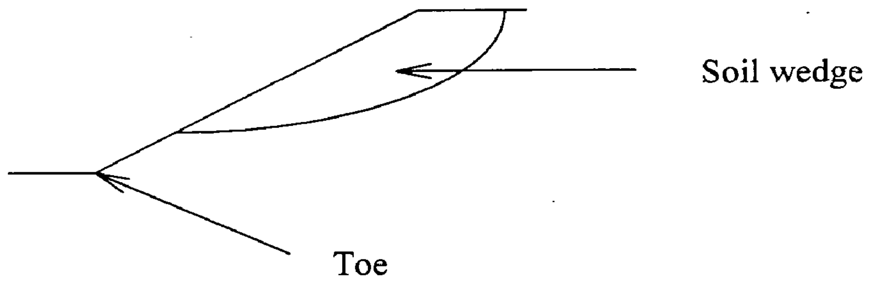

Fig.2.1(a) Slope failure above toe

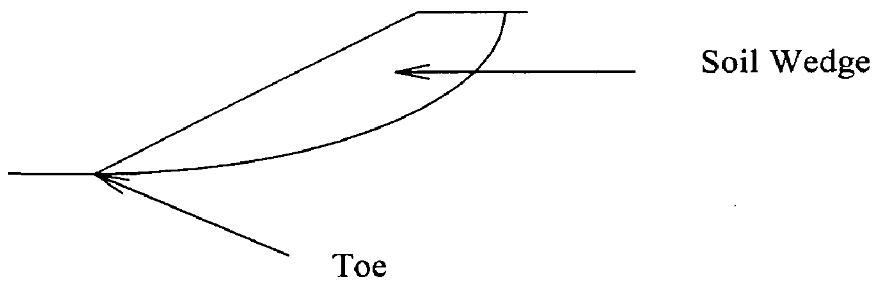

Fig.2.1(b) Slope failure through toe

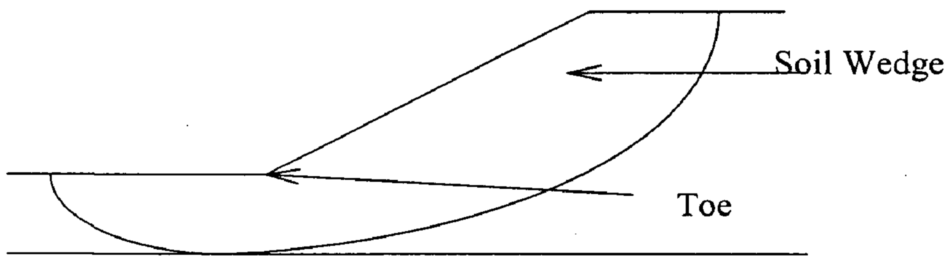

Fig.2.1(c) Base failure

Fig 2.1 Rotational failure

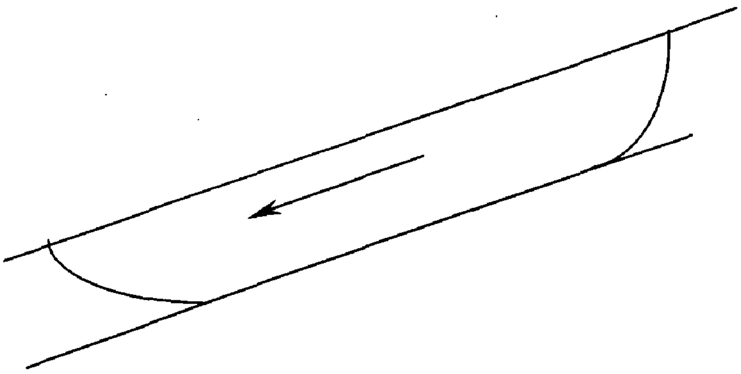

Fig.2.2 Translational failure

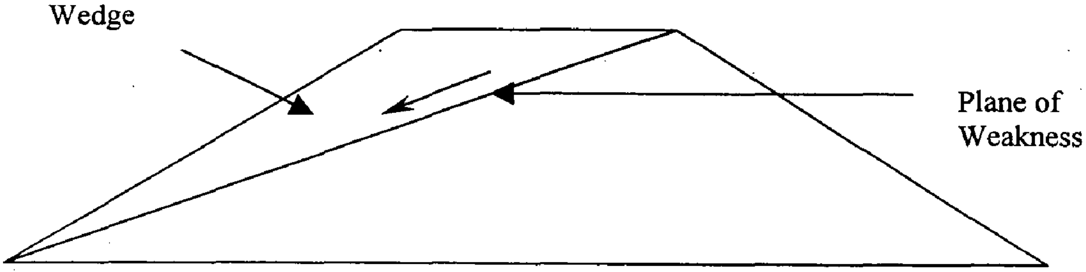

Fig.2.3 Wedge failure

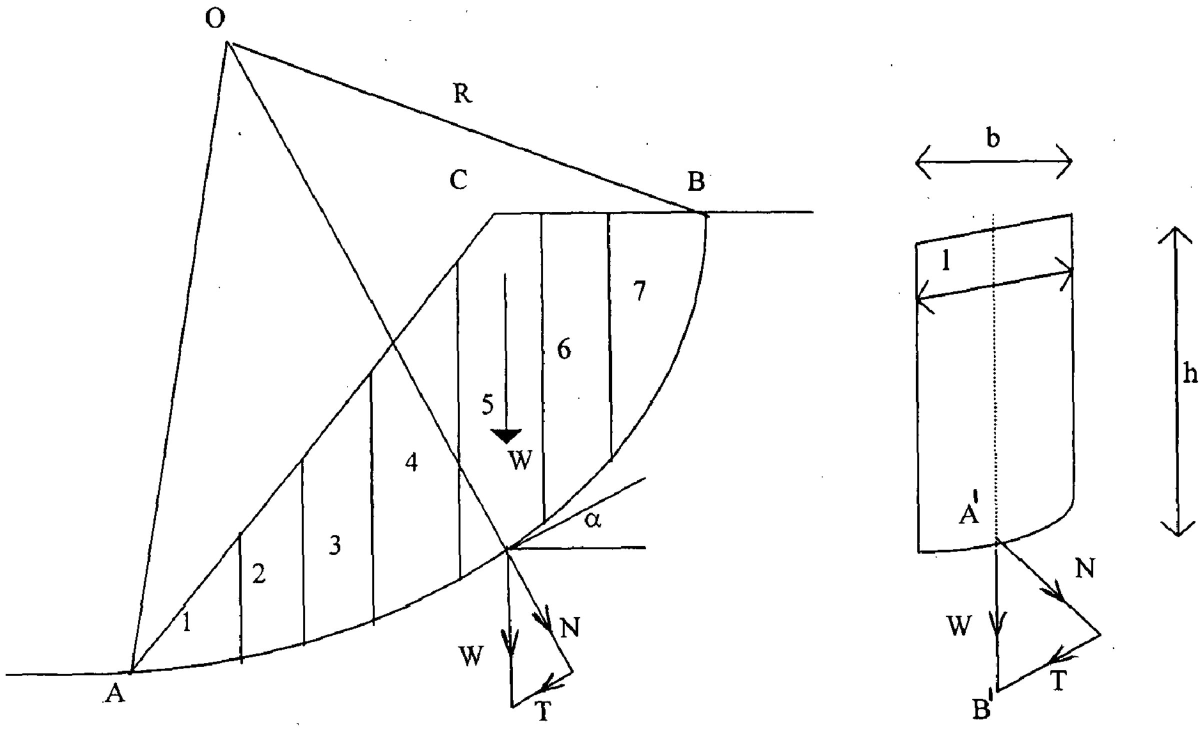

Fig. 2.4. C - ϕ analysis- method of slices

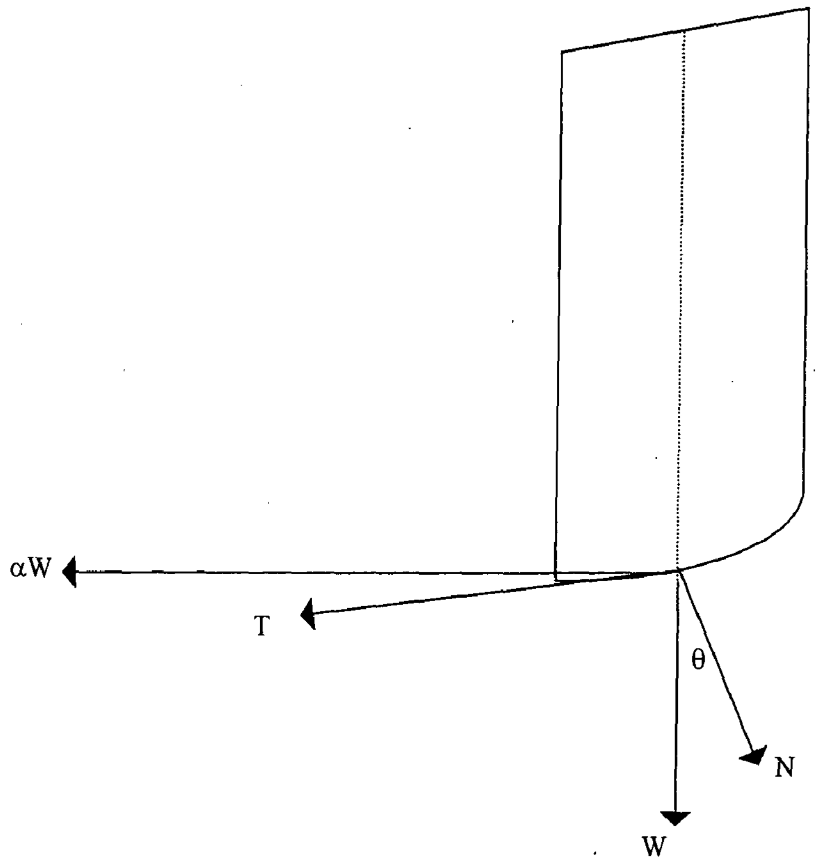

Fig.2.5 Inertial forces due to earthquake

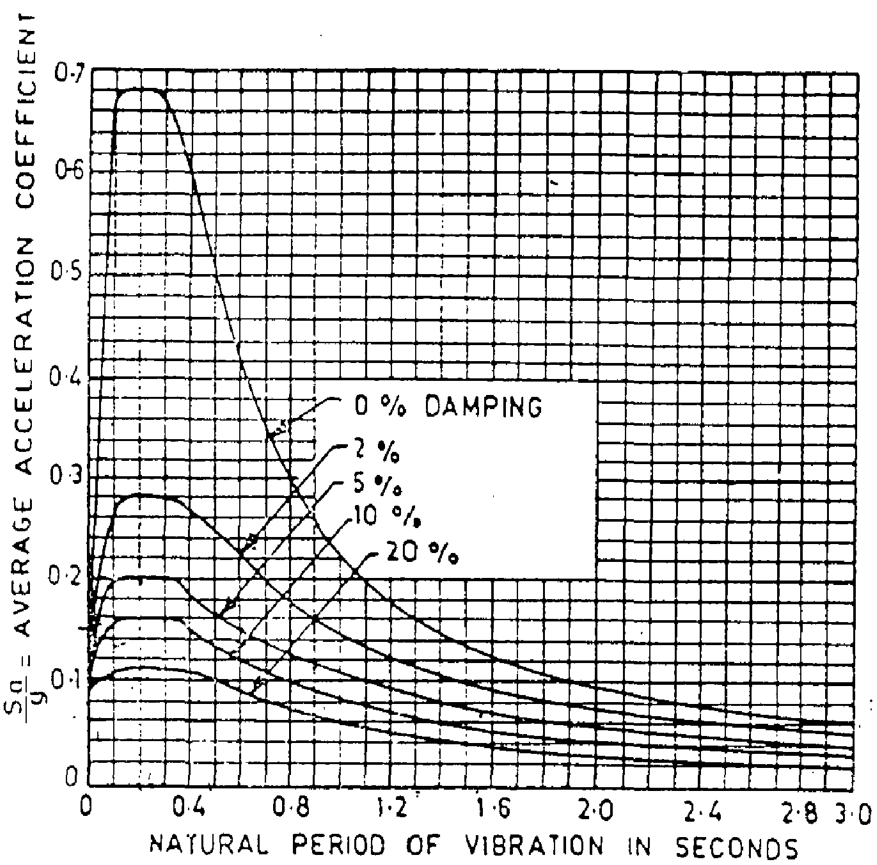

Fig. 2.6 Average acceleration spectra

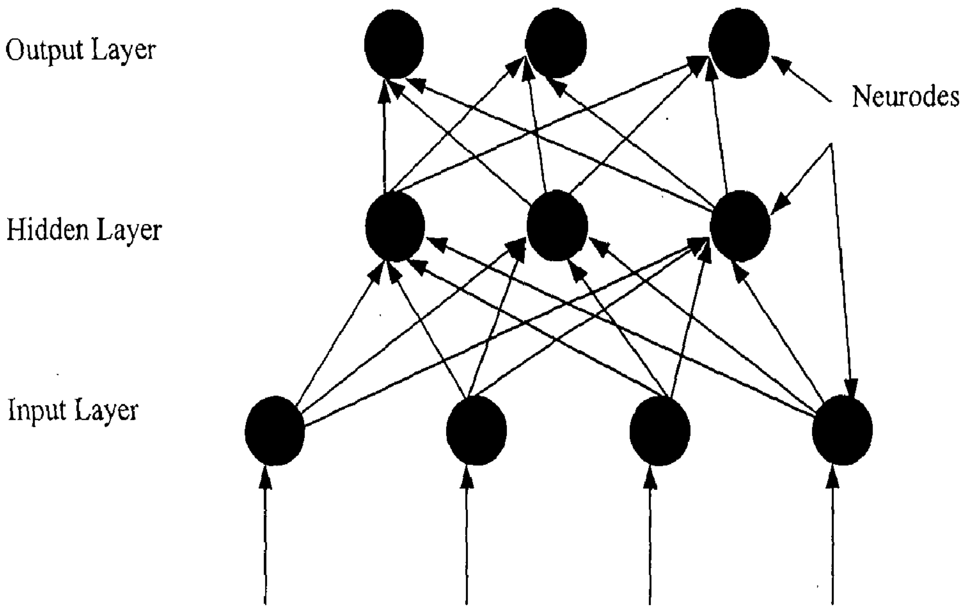

Fig. 3.1 Typical Neural-Network Architecture

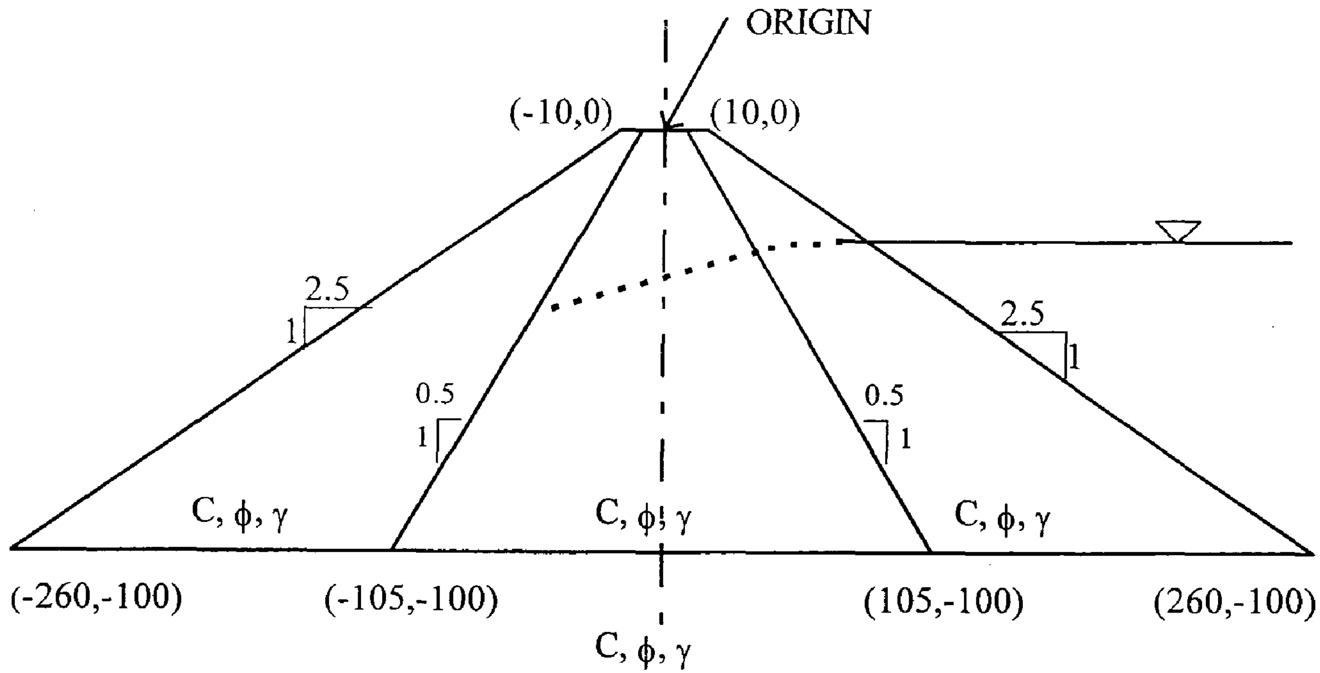

Fig. **3.2** Details of soil slope stability example used in the program

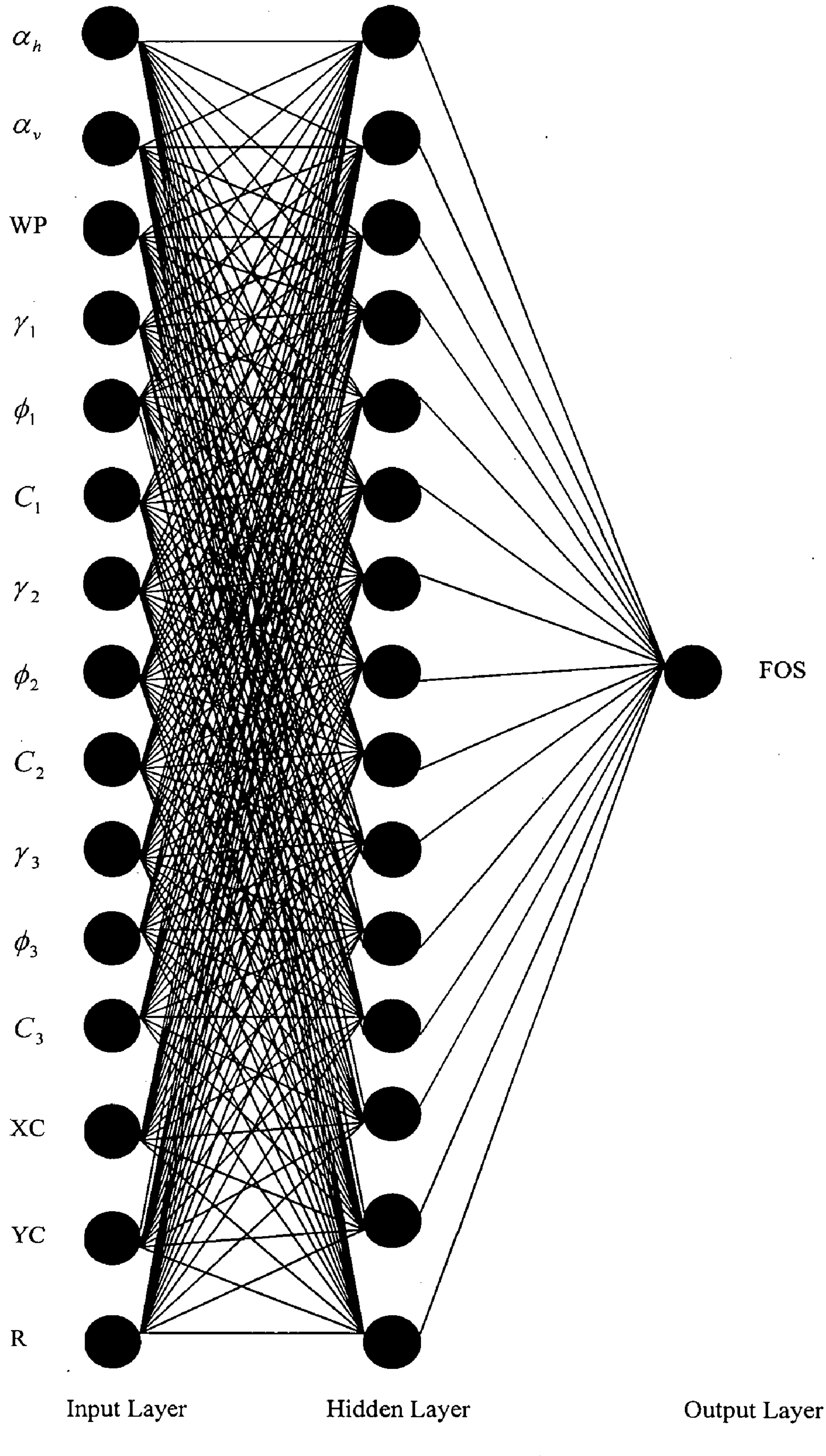

Fig. 3.3Neural Network model 1

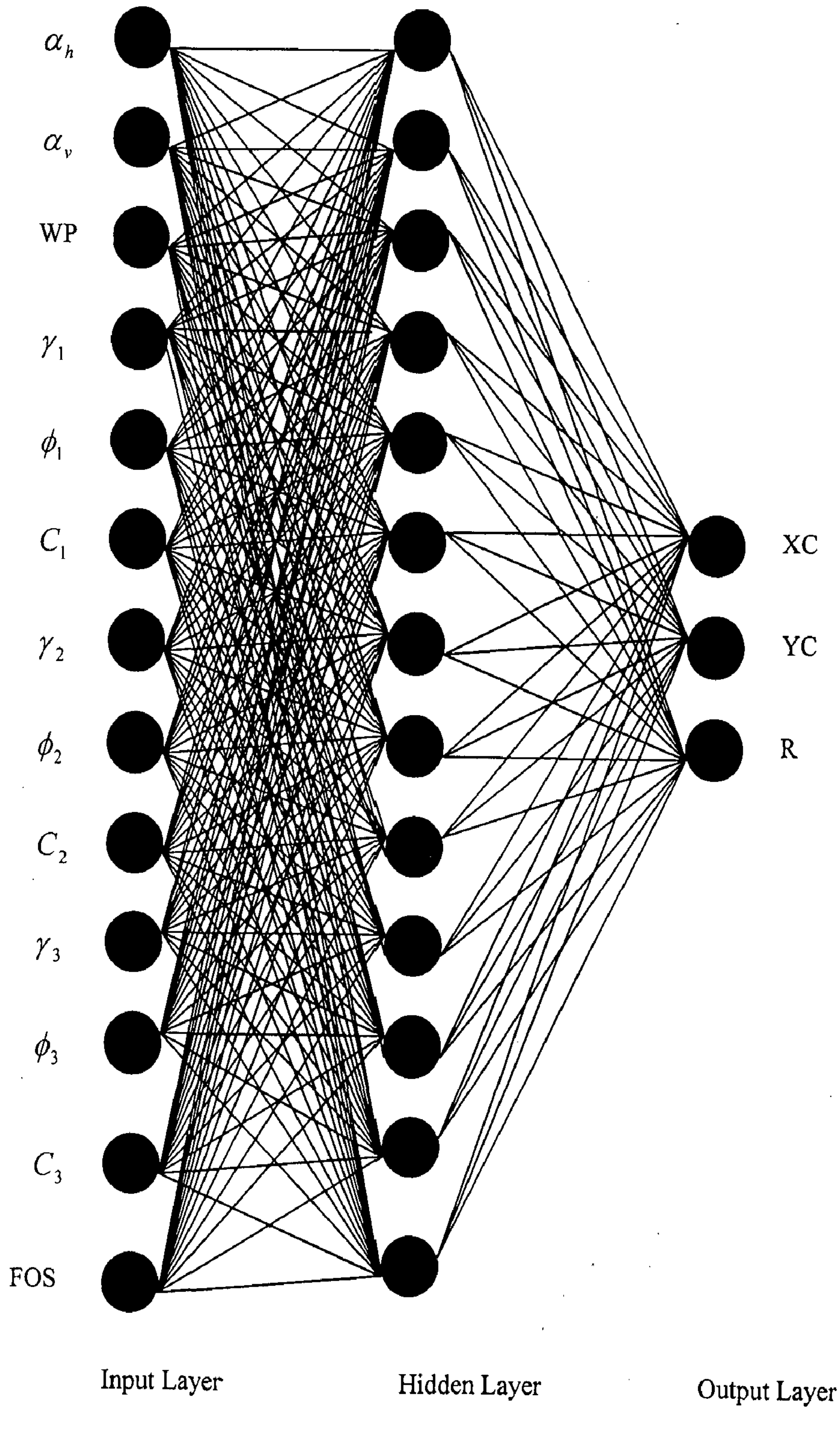

Fig.3.4 Neural Network model 2

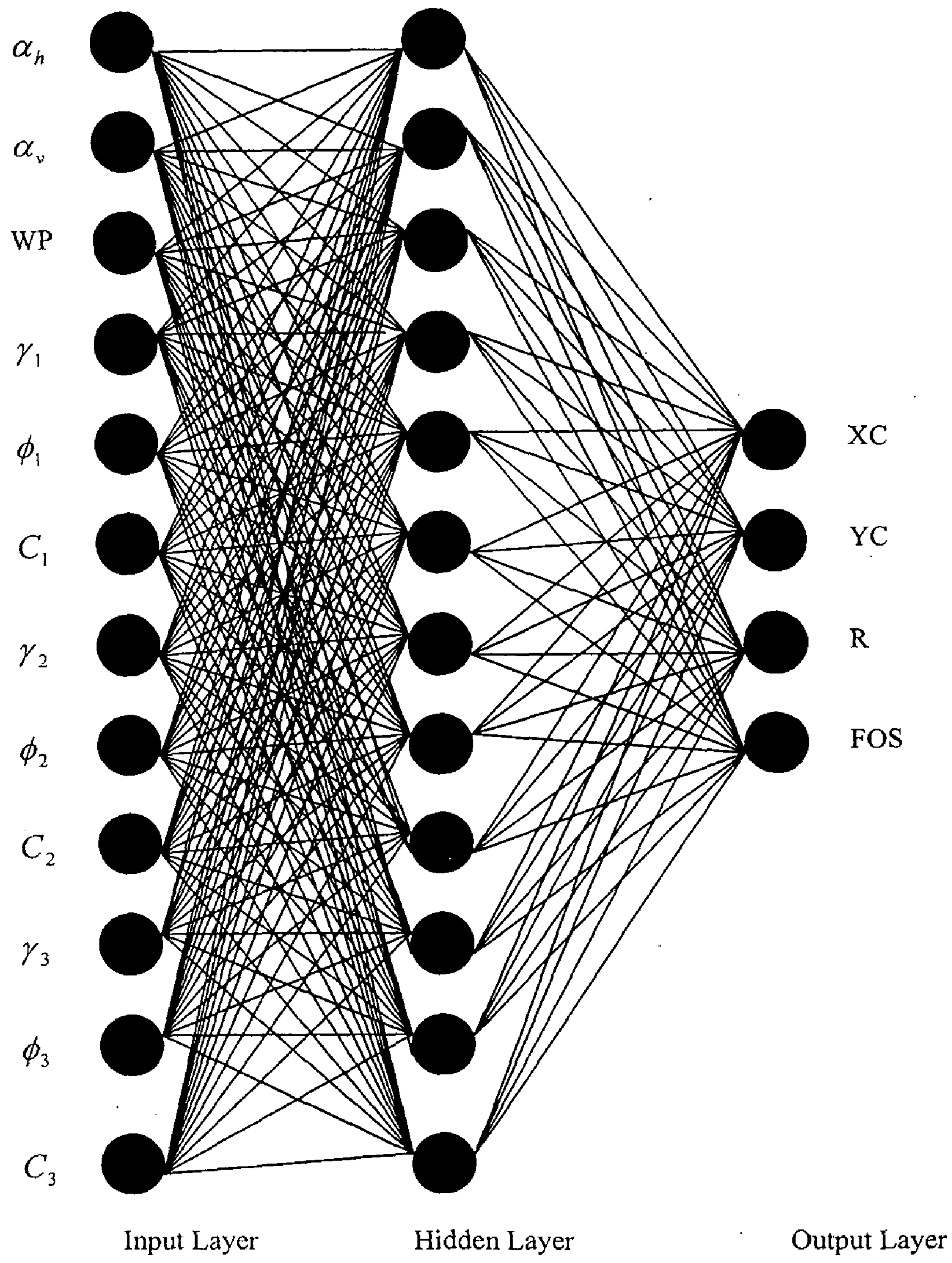

Fig.3.5 Neural Network model 3

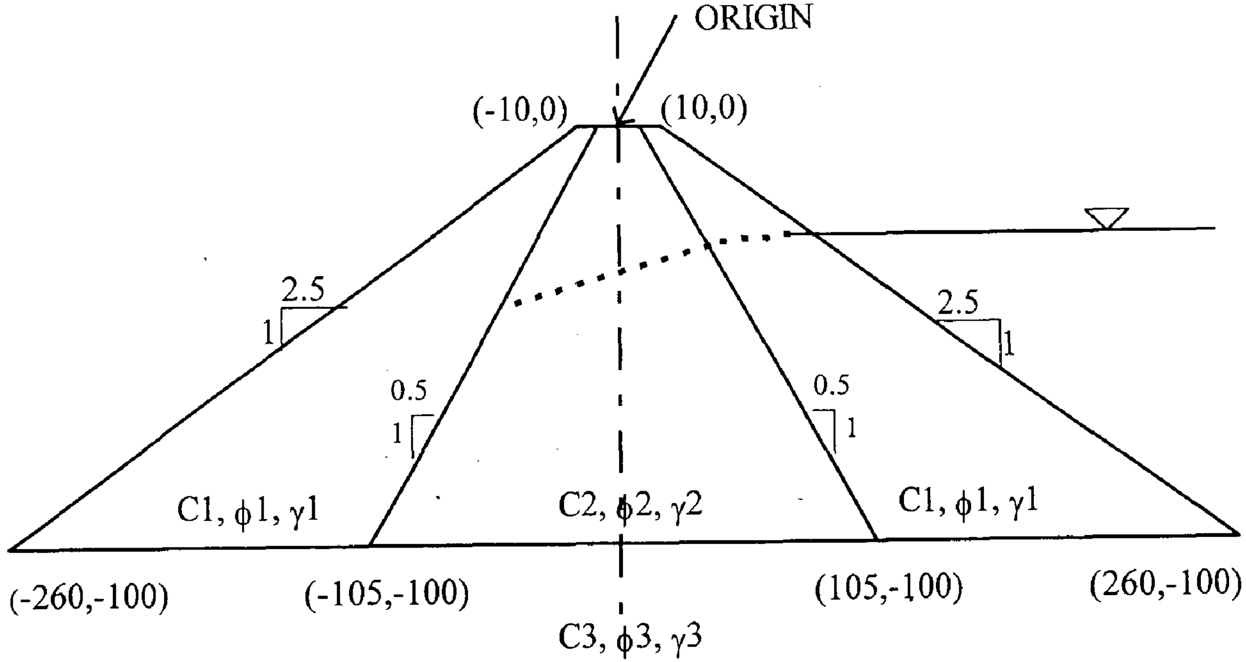

Fig **3.6** Details of soil slope stability example used in Nueral Network.

Fig.4.1 Relation between α_h and FOS

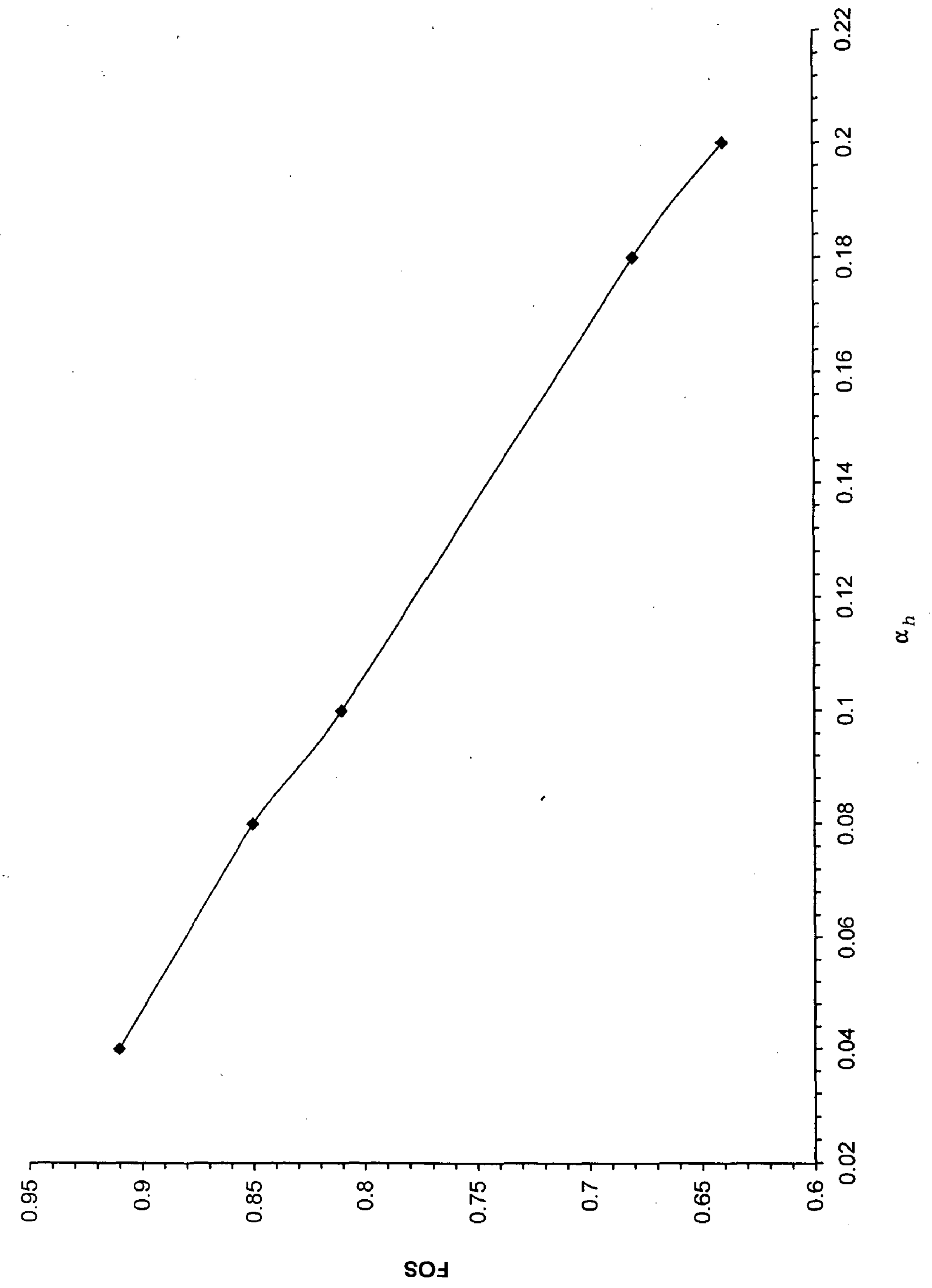

Fig.4.2 Relation between WP and FOS

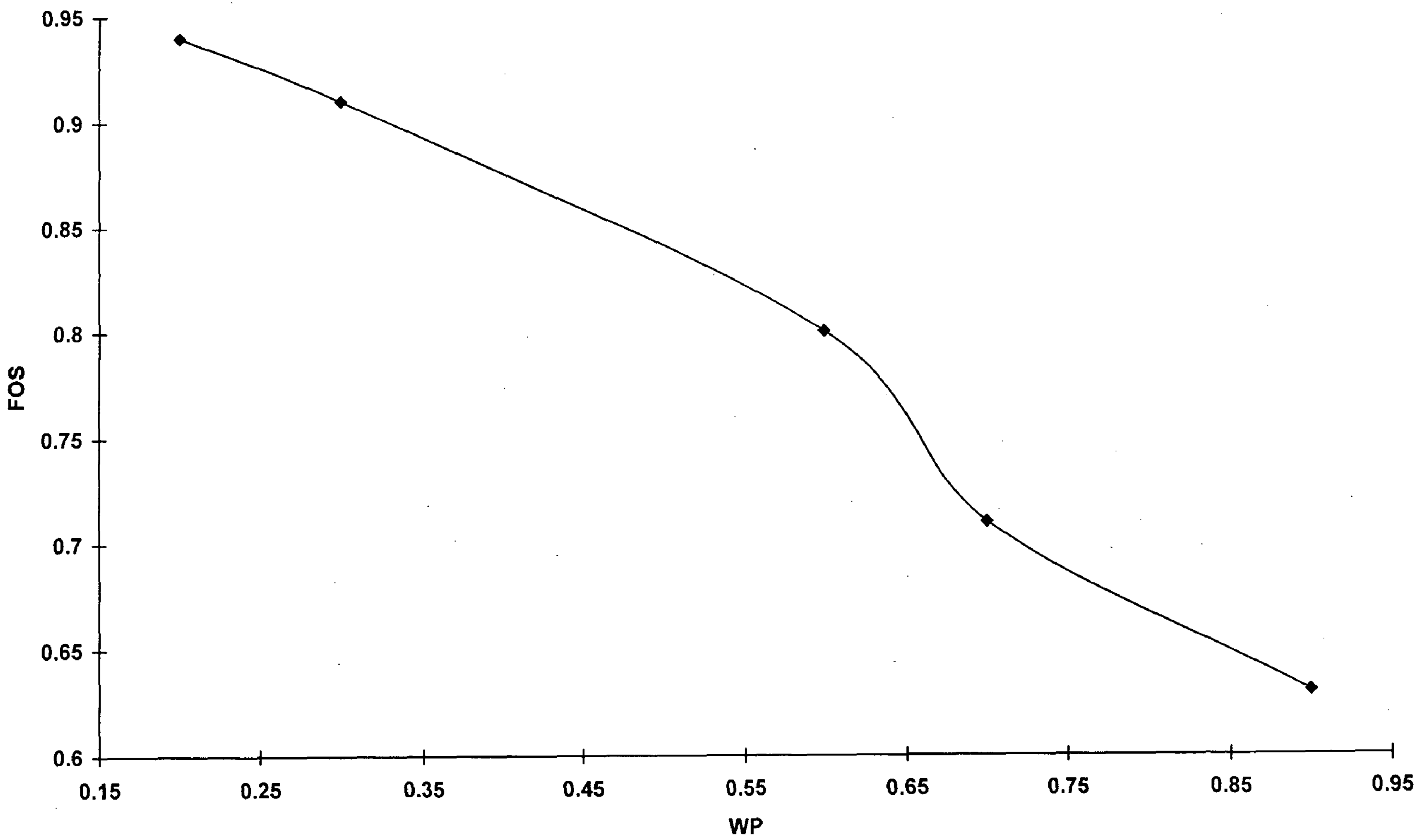

Fig.4.3 Relation between ϕ_1 AND FOS

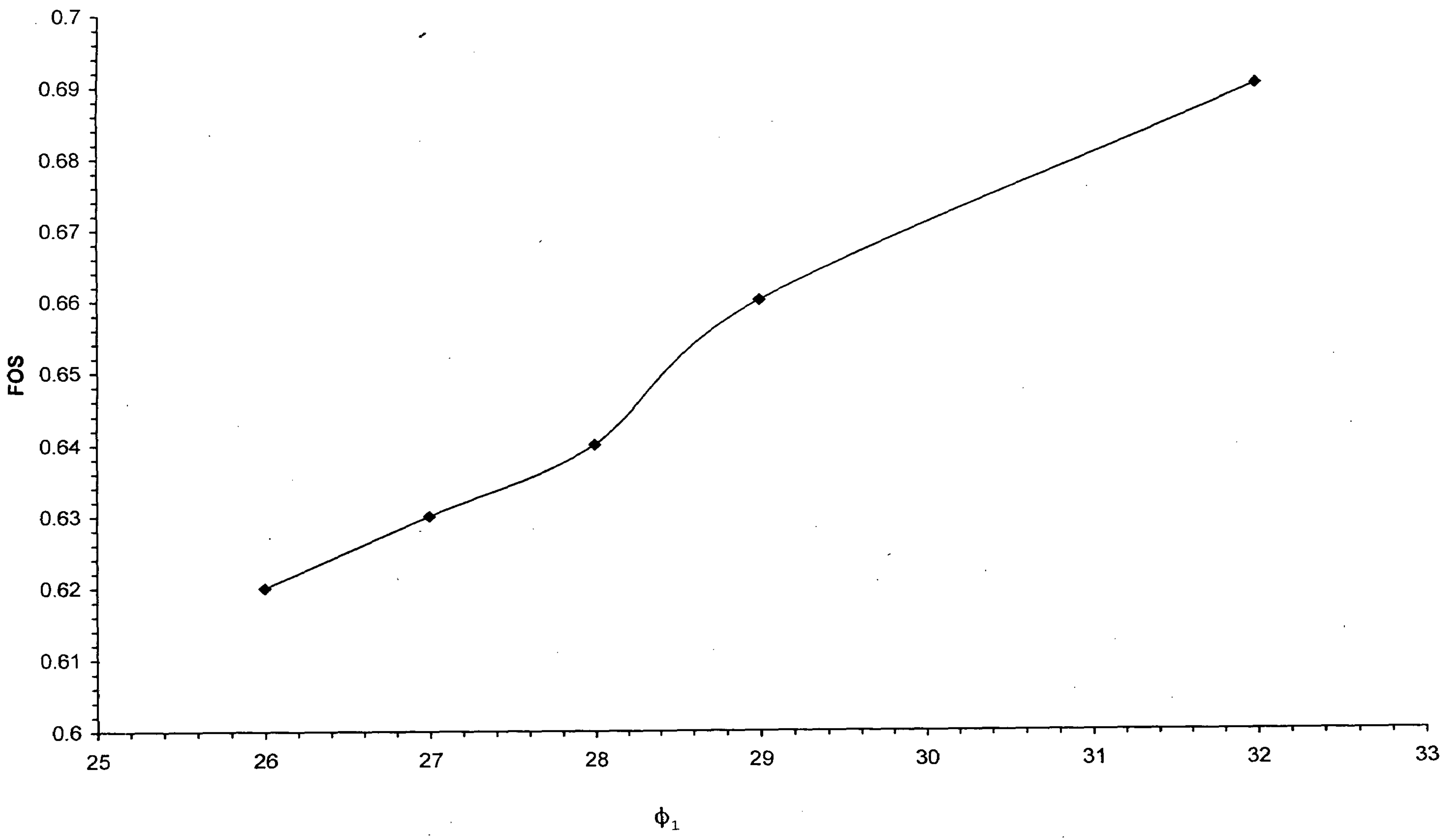

Fig.4.4 Relation between ϕ_2 and FOS