Application of Soft Computing Techniques for Prediction of Slope Failure in Opencast Mines

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by

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based on research carried out

under the supervision of

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Supervisors' Certificate

This is to certify that the work presented in the dissertation entitled *Application of Soft Computing Techniques for Prediction of Slope Failure in Opencast Mines* submitted by *Abhijeet Dutta*, Roll Number 711MN1172, is a record of original research carried out by him under my supervision and guidance in partial fulfillment of the requirements of the degree of B. Tech & M. Tech Dual Degree in *Mining Engineering*.

Neither this dissertation nor any part of it has been submitted earlier for any degree or diploma to any institute or university in India or abroad.

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Declaration of Originality

I, *Abhijeet Dutta*, Roll Number *711MN1172* hereby declare that this dissertation entitled *Application of Soft Computing Techniques for Prediction of Slope Failure in Opencast Mines* presents my original work carried out as a B.Tech and M. Tech Dual Degree student of NIT Rourkela and, to the best of my knowledge, contains no such material previously been published or been written by another person, nor any material has been presented by me for the award of any degree of NIT Rourkela or any other institute. Any such contribution made to this research by others, with whom I shall have worked at NIT Rourkela or elsewhere, is explicitly acknowledged in the dissertation. Works of other authors cited in this dissertation have been duly acknowledged under the sections "Reference" or "Bibliography".

I have also submitted my original research works to the scrutiny committee for the evaluation of my thesis.

I am thus fully aware that in case of any non-compliance detected in the future, the Senate of NIT Rourkela may withdraw the degree awarded to me on the basis of the present thesis.

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Abstract

One of the most arduous jobs in the industry is mining which involves risk at each working stage. Stability is the main focus and of utmost importance. For avoiding a slope from being failed, working is to be carried out according to the guidelines and safety standards. The FOS (Factor of Safety) of the slope being currently worked on has to be calculated and monitored frequently so that the working conditions are absolutely safe. FOS when calculated by traditional deterministic approach cannot represent the exact state at which the slope exists, though it gives a rough idea of the conditions and overall safety factor. Various approaches like numerical modelling, soft computing techniques allow us with the ease to find out the stability conditions of an unstable slope and the probability of its failure in near-by time. In this project, the stability conditions of some of the benches of ***Bhubaneswari Opencast Project***, located in Talcher, have been evaluated using the soft-computing techniques like ***Artificial Neural Network*** implemented using ***MATLAB*** and then the results are being compared with the ***Numerical Model*** results from the software ***FLAC*** which deploys Finite Difference Method. A particular slope (CMTL-179, Seam-3) has been studied and the respective factor of safety for each slope has been predicted using both the Artificial Neural Network and FLAC. Initially the data related to bench height, slope angle, lithology, cohesion, internal angle of friction, etc. are determined for the respective rock of the slope of which the FOS is to be calculated. For calculation of cohesion and internal angle of friction, ***Triaxial Testing*** has been done. Then these data are imported into an artificially trained network using various training functions. The data sets used for training the network are collected from various references that rely on the classical method of computing factor of safety using the cohesion, bench geometry and internal angle of friction of a single rock type. Then a compilation of all such case studies has been done for training the neural network using the software, MATLAB. A total of 14 training functions were used to train the model. The best training was found in ***Scaled Conjugate Gradient Backpropagation*** which corresponds to a regression coefficient of 91.36% during training and 88.24% overall. The best ***Validation Performance*** was also found at 60 epochs with Mean Squared Error of 0.069776. According to the trained neural network, it was found that the slope was 44.5% stable with a FOS 1.0226. Using the software FLAC, it was found that the slope was stable with FOS=1.17. The Neural Network Tool is used

for training the data set in which a set of data is channelized for being trained and the training functions are changed to evaluate the best and worst cases possible while designing the slope or the conditions in the already developed slope. The aim is to improve precision and reduce uncertainty for achieving robustness and low solution cost and for developing a generic model which can be used to predict the slope stability by implementing an experience-based model. It is very difficult to predict if a slope shall be 100% susceptible to fail or 0% susceptibility for failure. The generic model will thus allow us to get a range of probability for the slope to fail so that necessary arrangements can be made to prevent the slope failure.

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CHAPTER-1

INTRODUCTION

1 Introduction

1.1 Background of the Problem:

Slope of the mines and quarries, which are more than 100 metres deep, are regarded as "geotechnical structures" (Fleurisson, 2012). The designs and implementation of the slopes must be conducted according to the rules and standards laid down by the governing or monitoring bodies. The principles and design conditions must be discussed in details to analyze the current and future outcomes.

Slope Stability Problems are always a part of concern in opencast method of mining especially with pit slopes. With varying geo-mining conditions, the designs have to be reviews frequently. Slope failures are often caused by improper designs of slopes and sometimes by wrong assessment of the slope designs. Several factors are responsible for slope failure like geological structures, water pressure, overall slope angle, external weight like overburden on slope, tension cracks, joints, etc. Slope stability analysis of open cast mine is a routine event and required for operating safely. Monitoring slope stability enables warning against any type of failure before it actually happens and that could provide sufficient time to evacuate the area. Assessment of the stability of slopes in open pit mines at different stages of mining is important for the safe and economic mining operations. Slopes are generally designed based on the geotechnical data and physico-mechanical properties of rock/soil. From geotechnical data, the rock mass quality is assessed, and from this, the rock mass properties are estimated. Using the rock mass properties stability of the slopes is evaluated from empirical, analytical and numerical techniques.

In homogenous, isotropic ground conditions, the factor of safety can be determined for predefined failure modes using limit equilibrium method (Hoek. and Bray, 1981; Hoek, 1986; Piteau & Martin, 1981; Zanbak, 1983). Similarly, using analytical solution given by Xiao Yuan & Wang Sijing (1990), flexural breaking of rock mass can be determined. Design charts can be developed using limit equilibrium method. Some design charts are available for plane, wedge, circular modes of failure (Hoek & Bray, 1981), and for toppling failure (Choquet &Tanon, 1985; Zanbak, 1983). The field engineer can use them if the basic geotechnical properties are known. These charts are useful to analyze only simple types of predetermined failures, but not for determining the slope angle which depends on the rock mass stability.

Slope of mines and quarries, which are more than 100 metres deep, are regarded as “geotechnical structures” (Fleurisson, 2012). The designs and implementation of the slopes must be conducted according to the rules and standards laid down by the governing or monitoring bodies. The principles and design conditions must be discussed in details to analyse the current and future outcomes. The slopes in Bhubaneswari Opencast are being designed for extension upto 240 metres depth, while the current working is now at 150 metres depth.

For analyzing slope stability problems, conventional slope analysis methods such as limit equilibrium method and finite difference methods are used which are also called deterministic methods. The cohesion and internal angle of friction are important factors determining the stability of a slope in an opencast mine. Numerical modeling softwares such as FLAC/Slope, OASYS and RockSlope are also used to assess the stability problems. To know the exact slope failure behaviors, probabilistic methods (Stankovic,2013) should be used apart from deterministic methods to calculate the reliability of the slope.

The factor of safety (FoS) in deterministic analysis is defined as the ratio of forces resisting the sliding to the forces driving the surface of the potential sliding surface. The slope of the sliding surface is considered to be safe if and only if the factor of safety value clearly exceeds unity.

1.2 Objectives of the Project:

- To determine the geotechnical parameters namely cohesion, internal angle of friction of the Shale and Coal in Bhubaneswari OCP, Talcher.
- To collect data from various research papers relating to factor of safety and probability of failure of slope.
- To train the data collected from various resources in the Artificial Neural network with varying training functions and observing the best and worst case of prediction from various training functions.
- Modelling the slope of the opencast mine from which samples are collected in FLAC/Slope for numerical modelling.
- Comparison of the results from FLAC model with that of the predicted values of factor of safety in the Artificial Neural network.

CHAPTER-2

LITERATURE REVIEW

2 Literature Review

Slope Stability analysis is conducted for measuring the most feasible, safe and economic designs of the slope and the corresponding balancing equations. Slope stability is generally defined as the ratio of the resistive forces acting against the driving force on the inclined surface to failure by collapsing or sliding (McCarthy, 2007). The major concerns of stability analysis of slopes is to observe and review failure mechanisms, locating critically danger slopes and finding out the slope susceptibility.

For determining the stability of a slope, along with the engineering principles, deterministic and probabilistic approaches are also used for calculating the factor of safety of a slope. At any point when the aggregate sliding mass is thought to have form a cylindrical shape, a unit width adjacent to the substance of the incline is usually taken for analysis, and the slip surface of the slope's cross sectional area is the segment of the circle. The forces acting on the assumed failure mass are determined which affects the equilibrium and the rotational moments of these forces are computed with respect to the point representing the circular arc's centre. In this methodology, the weight of the material in sliding mass is considered as the external load on the face and the slope's top contribute to moments which cause movement. The shear strength of the soil provides resistance to the sliding on the assumed failure surface.

To show if failure occurs, a computational method is used to equate moments that will resist movement to the forces that causes movement. To calculate the resisting moment, the maximum shear strength owned by the soil is used. The factor of safety against sliding or movement is expressed as:

$$\text{FOS}= \frac{\text{Moments Resisting the Sliding (resisting force)}}{\text{Moments Causing the Sliding (driving force)}}$$

Due to the fact that we are dealing with the natural raw data, untamed by the mankind, geotechnical engineering has become more and more complex area of engineering. Due to this reason that this area of engineering is concerned with concepts, judgement, perception of experience that cannot be represented strictly numerically. Often empirical relationships are employed for estimation of factor of safety, which cannot be purely relied upon because the models do not take into account the effect of moisture. Also the time taken for calculation is too long and the models are just empirical. They cannot determine the probability of failure. But in soft computing techniques, all these loopholes can be plugged in. Soft computing techniques like artificial neural networks rely upon the previous experience of the input data and corresponding output data. Any ambiguity in data set can be tolerated in soft-computed methodologies.

Soft computing resembles the process of human brain. It does not rely upon the crisp values and binary numbers. It uses soft values and fuzzy sets. Soft computing techniques are capable of addressing imprecision and uncertainty. The application of soft computing techniques in the mining industry is fairly extensive and covers a considerable number of applications. The main difficulties in decision making process in mining industry can be as follows:

- Uncertainties in commodity markets.
- Geological and Geotechnical uncertainties of rock mass.
- Lack of clarity of qualitative mining activities.
- Subjectivity of individual decision makers.
- Uncertain effect of weights of single, multiple and mutual relationships.
- Possibility of undefined mechanisms of rock mass behaviors.

Artificial neural networks are systems that have been inspired by biological nervous systems. There are many types of neural networks which serve a variety of purposes and applications including pattern recognition, identification, classification, speech, vision, and control systems. The common characteristic of all neural networks is that they are trained to perform a specific function. All that is needed is a training set for the network to learn how to perform its function. Once the network is trained, inputs are presented to the network and a set of outputs is produced. No physical understanding of the relationships between the inputs and the outputs is needed (Mehrotra et al, 2000). This can be useful for complex systems such as drilling, where it is difficult to consider all of the interactions at once. Neural networks are often classified by their training processes. There are two main types: supervised learning and unsupervised learning. The main difference between the two is the composition of the training set. Supervised networks require both a training input set and a corresponding set of target outputs to which it can compare its performance. Unsupervised networks only require a set of training inputs (Mehrotra et al, 2000).

Soft computing techniques help to overcome such difficulties in mining related subjects. The definition of soft computing is a collection of methodologies that aim to exploit tolerance for imprecision and uncertainty to achieve tractability, robustness and low solution cost.

The principal soft computing techniques can be classified as fuzzy algorithms, neural networks, supporting vector algorithms, evolutionary communication, machine learning and probabilistic reasoning. The initial model of artificial neural network (ANN) was first designed by Mc Culloh and Pitts and this was considered as the first study of artificial intelligence. A neural network has to be configured such that the application of a set of inputs produces the desired set of outputs. Various methods to set the strengths of the connections exist. One way is to set the weights explicitly, using a priori knowledge. Another way is to train the neural network by feeding it teaching patterns and letting it change its weights according to some learning rule (Abraham, 2004).

2.1 Factors on which stability of slope depends:

1. Geometry of the Slope
2. Gravitational Force
3. Geological Structures
4. Groundwater
5. Time
6. Angle of Internal Friction
7. Dynamic Forces
8. Cohesion
9. Lithology
10. Method of Mining

The above factors are the results of all the movements is caused by the soil in which it moves from high points to low points. The gravitational force component is considered to be very important that acts in the direction of the probable failure motion (Das, 2008).

2.1.1 Major Failure Modes:

2.1.1.1 Circular Failure:

In rotational slips the shape of the failure surface in section may be a circular arc or a non-circular curve.

In general, circular slips are associated with homogeneous soil conditions and non-circular slips with non-homogeneous conditions. Translational and compound slips occur where the form of the failure surface is influenced by the presence of an adjacent stratum of significantly different strength. Translational slips tend to occur where the adjacent stratum is at a relatively shallow depth below the surface of the slope: the failure surface tends to be plane and roughly parallel to the slope. Compound slips usually occurs where the adjacent stratum is at greater depth, the failure surface consisting of curved and plane sections.

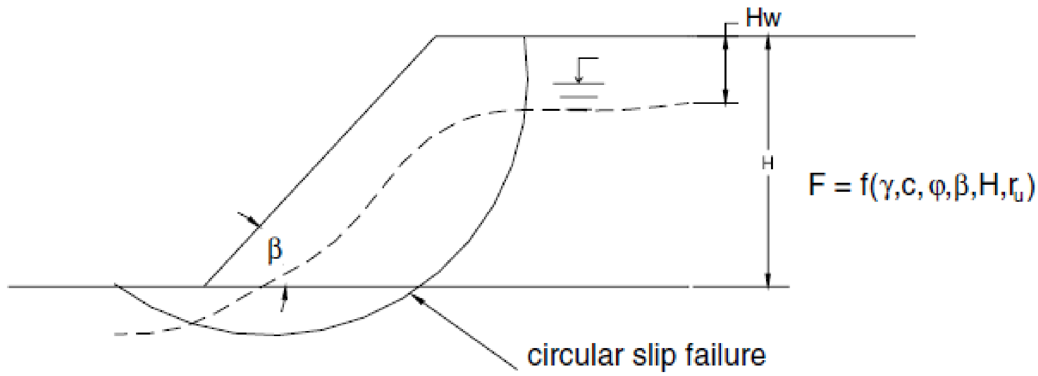


Figure 2-1: Circular Failure

2.1.1.2 Planar Failure:

A rock slope undergoes this mode of failure when combinations of discontinuities in the rock mass form blocks or wedges within the rock which are free to move. The pattern of the discontinuities may be comprised of a single discontinuity or a pair of discontinuities that intersect each other, or a combination of multiple discontinuities that are linked together to form a failure mode.

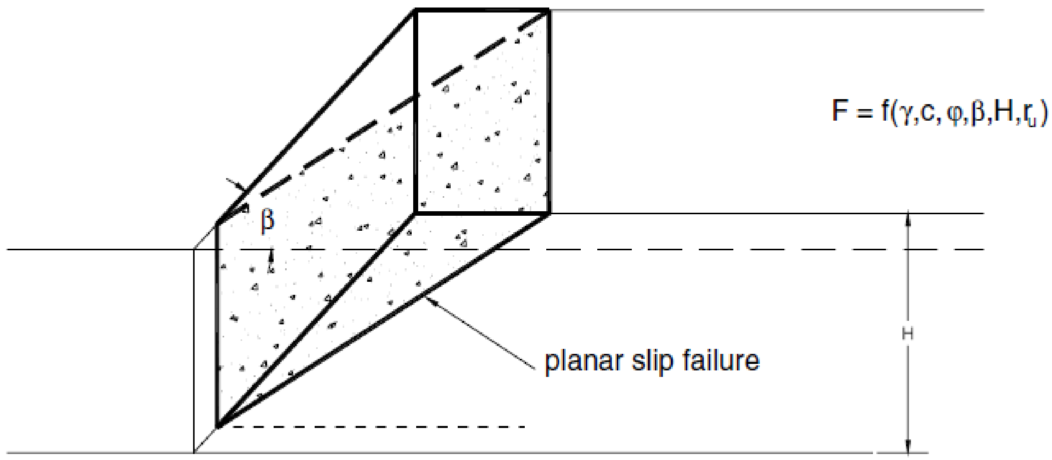


Figure 2-2: Planar Failure

2.1.1.3 Wedge Failure:

Wedge failure of rock slope results when rock mass slides along two intersecting discontinuities, both of which dip out of the cut slope at an oblique angle to the cut face, thus forming a wedge-shaped block Wedge failure can occur in rock mass with two or more sets of discontinuities whose lines of intersection are approximately perpendicular to the strike of the slope and dip towards the plane of the slope. This mode of failure requires that the dip angle of at least one joint intersect is greater than the friction angle of the joint surfaces and that the line of joint intersection intersects the plane of the slope.

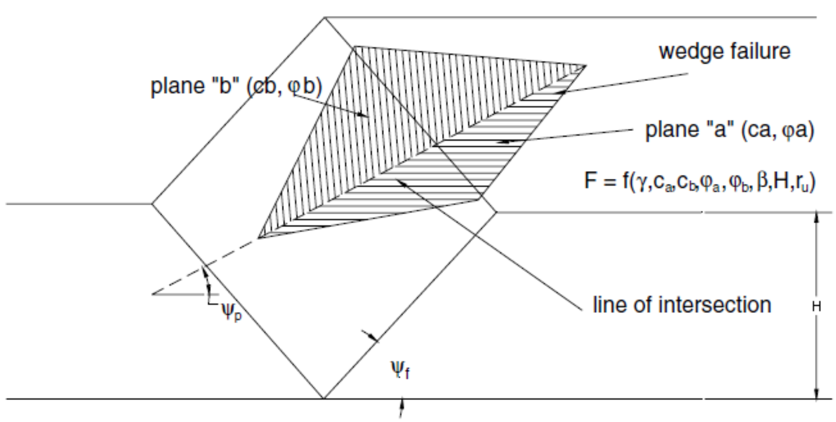


Figure 2-3: Wedge Failure

2.1.1.4 Toppling Failure

Toppling failures occur when columns of rock, formed by steeply dipping discontinuities in the rock rotates about a fixed point or near the base of the slope, followed by slippage between the layers. The COG of the column or the slab must fall outside the dimension of its base in toppling failure.

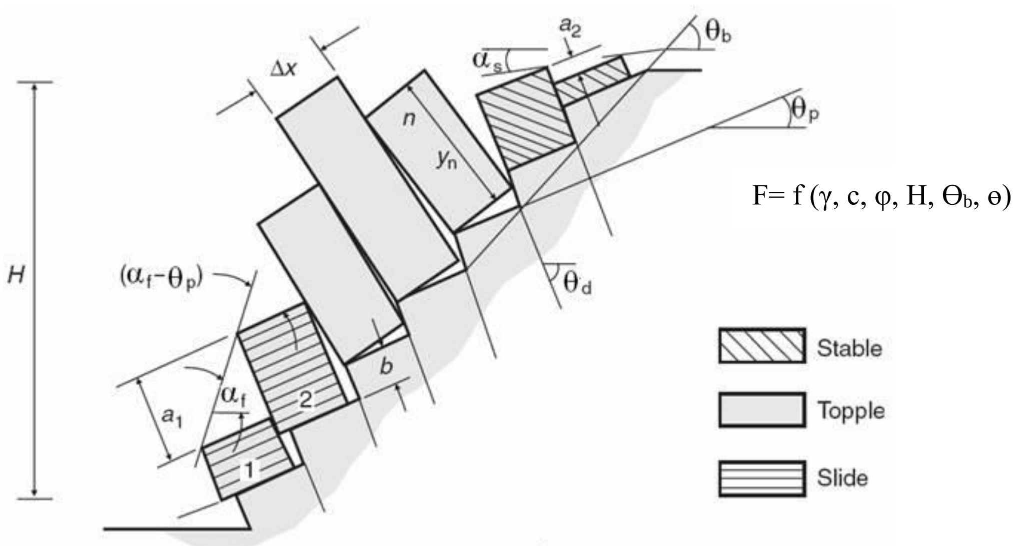


Figure 2-4: Toppling Failure

2.2 Triaxial Testing

A triaxial shear test is a common method to measure the mechanical properties of many deformable solids, especially soil (e.g., sand, clay) and rock, and other granular materials or powders. There are several variations on the test.

In a triaxial shear test, stress is applied to a sample of the material being tested in a way which results in stresses along one axis being different from the stresses in perpendicular directions. This is typically achieved by placing the sample between two parallel platens which apply stress in one (usually vertical) direction, and applying fluid pressure to the specimen to apply stress in the perpendicular directions. (Testing apparatus which allows application of different levels of stress in each of three orthogonal directions are discussed below, under "True Triaxial test".)

The application of different compressive stresses in the test apparatus causes shear stress to develop in the sample; the loads can be increased and deflections monitored until failure of the sample. During the test, the surrounding fluid is pressurized, and the stress on the platens is increased until the material in the cylinder fails and forms sliding regions within itself, known as shear bands. The geometry of the shearing in a triaxial test typically causes the sample to become shorter while bulging out along the sides. The stress on the platen is then reduced and the water pressure pushes the sides back in, causing the sample to grow taller again. This cycle is usually repeated several times while collecting stress and strain data about the sample. During the test the pore pressures of fluids (e.g., water, oil) or gasses in the sample may be measured using Bishop's pore pressure apparatus.

From the triaxial test data, it is possible to extract fundamental material parameters about the sample, including its angle of shearing resistance, apparent cohesion, and dilatancy angle. These parameters are then used in computer models to predict how the material will behave in a larger-scale engineering application. An example would be to predict the stability of the soil on a slope, whether the slope will collapse or whether the soil will support the shear stresses of the slope and remain in place. Triaxial tests are used along with other tests to make such engineering predictions.

2.3 The Economic Impacts associated with an Unstable Slope:

1. Loss of production.
2. Extra stripping cost for recovering and handling of failed material.
3. Extra and unnecessary cost of cleaning of the area.

4. Unnecessary cost associated with the rerouting the haul roads.
5. Production delays.
6. Risk of production delays.

The stability of slopes is basically judged by the factor of safety. Factor of safety is defined as the ratio of the resisting forces to the distributing forces. Resisting forces depends on cohesion and angle of friction, while the disturbing force is related to gravity and ground water condition. If the factor of safety is greater than unity, then the slope is stable but if it drops below unity the slope becomes unstable.

2.4 Neural Networks:

Backpropagation, an abbreviation for backward propagation of errors is a common method of training artificial neural networks used in conjunction with an optimization method such as gradient descent. The method calculates the gradient of a loss function with respect to all the weight in the network. The gradient is fed to the optimization method which in turn uses it to update the weights, in an attempt to minimize the loss function.

Backpropagation requires a desired output for each input value in order to calculate the loss gradient function. It is therefore considered to be supervised learning method, although it is also used in some unsupervised networks. It is generalization of the delta rule to multilayered feed-forward networks, made possibly by using the chain rule to iteratively compute gradients for each layer. The various studies conducted relating to slope stability with soft-computing and other techniques are in the table as follows:

Table 2-1: Summary of representative studies predicting rock mass performance

Author	Object	Soft Computing Technologies						Auxiliary Methods	
Yang and Zhang	ES	EXS	FUA	ANN	NEF	GA	GEP	RSE	
Deng and Lee	DG			✓				FEM	
Kim et. al.	DG			✓		✓		RSE	SA
Li et. al.	DG		✓	✓					
Li et. al.	DG		✓	✓		✓	✓		
Alimoradi et. al.	RMR			✓				TSP230	
Darabi et. al.	TC, SS			✓				FDM	RA
Rafiai and Moosavi	TC			✓				FDM	DOE
Mahdevari and Toravi	TC			✓				SA	RA
Li et. al.	DG		✓					MWC	RAC
Yurdakul et. al.	SE_{CUT}				✓			ANFIS	DENFIS
Ghasemi et. al.	Pillar Sizing		✓						
Choobbasti et. al.	DG			✓				PSE	
Guo et. al.	DG			✓				WIPS	

EXS, expert system; FUA, fuzzy algorithm; ANN, artificial neural network; NEF, neuro fuzzy system; GA, genetic algorithm; GEP, genetic programming; ES, engineering state (either stable or unstable); DG, displacements and/or ground settlement; SECUT, specific cutting energy; RMR, rock mass rating; TC, tunnel convergence; SS, subsidence; RSE, relative strength of effects; FEM, finite element method (numerical analysis); TSP230, tunnel seismic prediction; FDM, finite difference method; SA, sensitivity analysis; MWC, modified Wiebols–Cook criterion; RA, simple and/or multiple regression analysis; DOE, design of experiments technique; RAC, Rafiai criterion; ANFIS, adoptive network based fuzzy inference system; DENFIS, dynamic evolving neuro-fuzzy inference system; PSO, particle swarm optimisation; WIPS, wavelet intelligence prediction system.

2.4.1 Components of the Neural Network

2.4.1.1 The Neuron

The sigmoid equation is what typically used as a transfer function between neurons. It is similar to the step function but it is continuous and differentiable.

$$\sigma(x) = \frac{1}{1+e^{-x}}$$

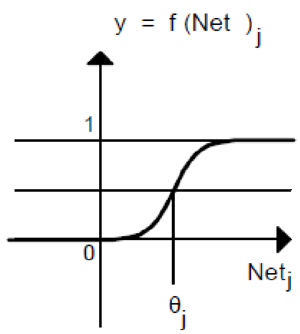


Figure 2-5: The Sigmoid Function

2.4.1.2 Single Input Neuron

The single input neuron is depicted as follows:

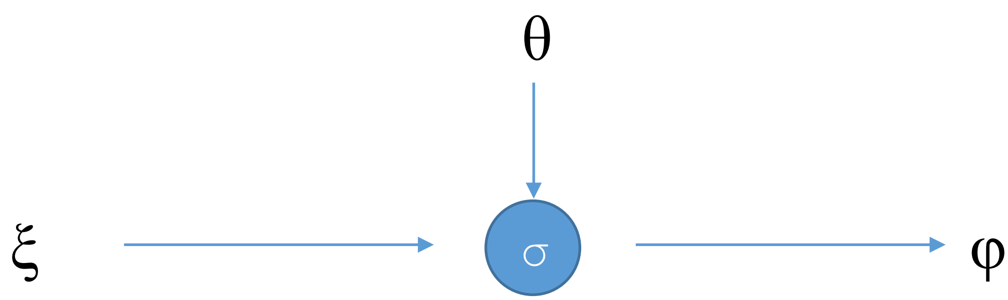


Figure 2-6: A single input neuron

$\varphi = \sigma(\xi w + \theta)$

Here,

φ= output value

ξ= input value

w= weight

θ= bias value

2.4.1.3 Multiple Input Neuron

The multiple input neuron is depicted as follows:

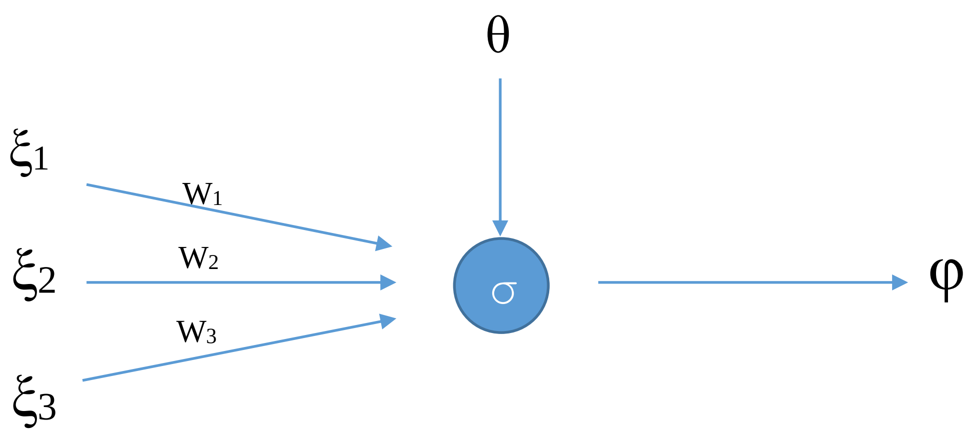


Figure 2-7: A multiple input neuron

$$\Phi = \sigma \,(\, w_1\,\xi_1 + w_2\,\xi_2 + w_3\,\xi_3\,)$$

Here,

φ= output value

ξ= input value

w= weight

θ= bias value

2.4.1.4 A Neural Network

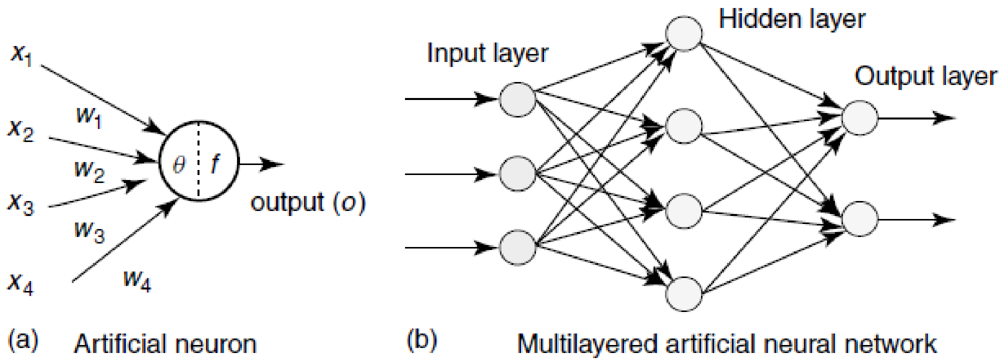


Figure 2-8: A Neural Network with Multiple Hidden Layers

2.4.2 Supervised Neural Networks Structure: Feedforward Networks

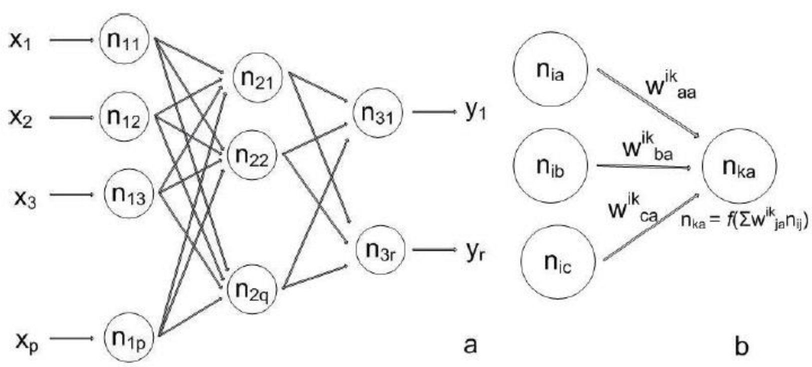


Figure 2-9: Supervised Learning (a -> b)

The number of nodes in the input layer is equal to the length of the input vector. The next layer is the hidden layer. The number of hidden layers can vary; some networks do not have a hidden layer while others have multiple hidden layers. For simplicity this example has only one hidden layer. The number of hidden layers and the number of nodes in the hidden layer(s) depend on the complexity of the network function. The final layer is the output layer and it computes the final outputs. The number of nodes in the final layer is equal to the desired length of the output vector. The information introduced to the network is always moving forward from the first layer to the final layer, hence the name feedforward neural network (Mehrotra et al, 2000). The role of f is to determine which pieces of information are fed forward in the network (Mehrotra et al, 2000). Ideally the transfer function is differentiable and saturating for training purposes. (Hornik, 1990).

To summarize, the feedforward neural network process is as follows:

1. An input is introduced to the input layer.

2. The input layer passes its weighted inputs to the first hidden layer.

3. The hidden layer sums its weighted inputs, passes the sum through its transfer function, and presents its outputs to the next layer. This is repeated for each of the hidden layers.

4. Once the output layer has been reached, it calculates the sum of its weighted inputs and passes the sum through its transfer function to produce the final output.

2.4.3 Supervised Neural Networks Training: Backpropagation

Before the feedforward process can be implemented, the network must be trained to determine the optimal weights. The weights are extremely important in determining the network function. Initially, weights are randomly assigned. During the training process, the network learns which weights work best for its purpose and adjusts them accordingly (Mehrotra et al, 2000).

As mentioned above, supervised neural networks require a set of target outputs in their training sets. The learning process involves presenting the training inputs to the network, calculating outputs with the current weights, comparing the network output to the desired outputs, then changing the weights accordingly. The learning algorithm must determine which weights to change and what the change in weight should be. The most common type of supervised learning algorithm for feedforward networks is backpropagation (Carpenter, 1989).

The goal of backpropagation is to minimize the error function between the calculated output and the desired output. Usually the error function is mean squared error (mse), although other options such as mean absolute error can also be used. The error function is minimized with the gradient descent rule, which states that the weight change should be in the direction of the negative gradient of error with respect to weight dE/dw. The algorithm evaluates this gradient for each weight in the network. Essentially, backpropagation algorithms search for the global minimum in the error function by adjusting weights (Mehrotra et al, 2000). There are many backpropagation training algorithms and they all rely on the basic backpropagation equation for a specific weight change shown in the equation below:

$$\Delta w_{jl}^{ik} = -\alpha \frac{\partial E}{\partial w_{ij}}$$

Where w_{jl}^{ik} is the weight connecting the node j in layer i to node l in layer k, α is the learning rate, and E is the error function.

While the gradient determines the direction of the weight change, the learning rate determines the magnitude of the weight change. A large value of α allows for quick learning but may cause the weights to oscillate and not converge. A small value of α causes slow learning (Mehrotra et al, 2000). Backpropagation has some limitations. The most significant are over fitting and local minima. Over fitting occurs when the network cannot generalize, or perform well on all ranges of inputs, not just on those used in the training set. The goal of backpropagation is to find the global minimum of the error function, yet there is always the danger of getting trapped in a local minimum. Excessive training can cause the network to memorize the training set and reduce its ability to adapt to new inputs. Over fitting can be avoided by selecting the appropriate size of network and evaluating the network performance while training the network. Limiting the number of nodes in the hidden layers will not allow the network enough resources to memorize the data. Nonetheless, selecting the number of nodes must be done with care as too few will not allow the network enough power to perform its designated task. The performance of the network can be evaluated during the training process by dividing the training set into a training set and a testing set. The normal training algorithm is implemented with only the training set. After each weight update, the algorithm calculates the error with respect to the testing set. Once the testing set error becomes significantly worse than the training set error, the training algorithm terminates (Sietsma and Dow, 1991).

A local minimum could be substantially different from the global minimum. One well known solution for dealing with local minima is momentum. It takes into consideration the previous few weight changes, allowing it to respond to recent changes in the error function as well. This causes the algorithm to ignore small changes in the error surface and avoid small local minima (Mehrotra et al, 2000).

Simple competitive learning is performed with a two-layer network. The input layer is connected directly to the output layer with weights. The nodes in the output layer are also interconnected with weights. The number of input nodes is equal to the length of the input vector. The number of output nodes depends on the desired number of classes or clusters (Kohonen, 1982).

2.5 Solving Slope Stability Problems with Neural Network:

The particular engineering problem of slope stability performance assessment involves several parameters. The impact of these parameters on stability of slopes was investigated through the use of threshold logic units with adjustable weights. The input data for slope stability estimation consist of values of the following input parameters: the unit weight γ, the cohesion c, the angle of internal friction φ, the slope angle β, the height H, and the pore water pressure ratio r_u according to water table height H_w, for soil or highly fractured rock slopes. As an output, the networks estimate the factor of safety F and the stability S. The former can be modeled as a function approximation problem while the latter can be modeled both as a function approximation problem and a classification model, assuming a circular mode of failure. Training took place for the specific range of values that cover the training data sets. The performance of the networks was measured through the error function and the results were compared to standard analytical methods and regression techniques. Furthermore, the relative importance of the parameters was studied using the method of partitioning of weights and compared to the results using the information theory approach. This methodology was initially used by, where the simple ANNs that were applied (one output layer) proved to converge in the case of the particular engineering problem. For this reason, a computer program was written in FORTRAN. Batch training took place, and the results were realistic compared to the safety factor values that resulted from nomograms. This work initially formulated an ANN to predict the status of stability which is not accomplished through standard engineering techniques. A probabilistic approach was implemented following the rule; when S tends to 1 the slope is more probable to remain stable, whereas when S tends to 0 the slope is more probable to fail. The ANN that was developed was able to give an initial notion on the variation among the contribution of the weights to the estimation of safety factor, giving information on both their positive and negative contribution. In a one hidden layer network what determines the value of the output is the absolute magnitude of the partial sum of the positive products. A program was written in MATLAB computing environment in order to conduct computer simulations and a two hidden-layered ANN was developed.

2.6 Solving Slope Stability Problems using FLAC

FLAC stands for Fast Lagrangian Analysis of Continuum. This software takes input as the slope geometry, the rock types and the corresponding strength properties like cohesion, internal angle of friction, tension, dilation angle etc. This software also takes into account, the water table. The software finally calculates the factor of safety and shows the maximum zone of shear. It also shows the contours of shear strain. The steps involved for rapid model development are:

1. Creating the slope Geometry.
2. Addition of rock layers.
3. Specification of material either manually or from a database.
4. Positioning a planar or a non-planar material/interface.
5. Location of the water table (if present).
6. Application of any loading surface.
7. Installing structural support (if any).
8. Meshing.
9. Calculating FOS.
10. Printing the plot as generated.

2.6.1 Analysis Procedure:

2.6.1.1 Build Stage

For specific model, the slope conditions are defined in the build stage as follows:

- Changes to the slope geometry,
- Addition of layers
- Specification of materials and weak plane
- Application of surface loading
- Position of water table
- Installation of reinforcement

Some spatial regions can also be excluded from the FOS calculation.

2.6.1.2 Solve Stage

In this stage, FOS is calculated. The resolution of numerical mesh is selected and FOS is then calculated. The different parameters can be selected for for inclusion in the strength reduction approach to calculate FOS.

2.6.1.3 Plot Stage

After the solution is complete, several output selections are available in this plot stage for displaying the failure surface and recording the results. Model results are available for subsequent access and comparison to other models in the project. All models created within a project along with their solutions can be saved in different format, the project files can be easily restored and results viewed at alter time.

CHAPTER-3

DESCRIPTION OF THE MINE

3 Description of the Mine

Talcher coalfield, located in Brahmani valley to the north of Mahanadi river, constitutes the south eastern member of the lower Gondwana basin within Mahanadi valley group of coalfields.

The coalfield spreads over 80Km on the strike (east-west) and 26Km on dip rise (north-south) covering an area of about 1860 sq. Km. (coal bearing) of which about 201 sq. Km has been explored in detail in the southern part of the coalfield. In the northern part, an area of about 53 sq. Km. also has been explored in detail. Major portion of coalfield is situated in the district of Angul, Odisha, whereas part areas of the coalfield spread over to Dhenkanal, Deogarh and Sambalpur districts.

The reserves ooff Talcher coalfield as per GSI as on 1.4.2014 are given below:

Table 3-1: Coal Reserves in Talcher Coalfield

Depth Range (m)	Reserves (in Mt)			
	Proved	Indicated	Inferred	Total
0-300	12311.10	13304.77	4746.6	30362.47
300-600	0.00	7131.67	1917.40	9049.07
600-1200	0.00	991.60	466.33	1457.93
Total:	12311.10	21428.04	7130.33	40869.47

3.1 Location & Communication

Bhubaneswari mining block comprising of an area of 5.8 s. km. is surrounded by NH 23 and Sakhigopal block in the east, Lingaraj project in the South, Ananta expansion project in the west & Arkhapal block in the north. The area is connected by all weather metalled road to Bhubaneswar which is at a distance of about 170Km. The limiting geographical coordinates of the block are as follows:

Latitudes: $20^0$57’59” – $20^0$58’43” (North)

Longitudes: $85^0$09’10” – $85^0$11’37” (East)

The proposed block is well connected by road and rail. The nearest railhead is Talcher on Bhubaneswar-Talcher-Sambalpur line of East Coast railway and is located at a distance of 6Km. NH-23 connecting Angul and Rourkela passes adoining the Kaniha STPS of NTPC.

3.2 Topography & Drainage

The area of the block is characterized by both level as well as undulating topography. Elevations of the area vary between 85 to 210m above MSL. The main drainage is controlled by the southerly flowing Brahmani river situated at the eastern extremity of the coalfield and east of Talcher town. The eastern boundary of the block is about 4Km west from this river. A small seasonal nallah is flowing along the northern periphery of the project.

3.3 Dip and Strike

The strike generally trends WNW-ESE to E-W. Dip varies from 2^0 to 7^0 towards north. The general dip is around 5^0. Within the mining block the strike varies from WNW-ESE to NE-SW with 2.5^0 to 7^0 dip due ENE to NW.

3.4 Geology

The block has an area of 5.8 sq. Km. A total of 18,635 is drilled out boreholes, giving a borehole density of 19 boreholes/sq.Km. The mine block also consists of 5.8 sq.Km, wherein a total of 14655.45m is drilled involving 99 boreholes. In the mining block, 12 coal seams and two local seams occur in the Barakar formation and one seam (in five splits) occurs in Karharbari formation. In the Bhubaneswari Coal Block, 13 coal seams and 3 local seams occur. The geological sequence proceeds as Coal-Sandy Shale-Sandstone.

3.5 Coal Quality

- Type of coal : Bituminous , non-coking
- Ash content : 22.9 – 48.2%
- Inherent Moisture : upto 8%
- Abrasivity : Slightly abrasive
- Maximum lump size : (-) 100mm
- Surface moisture : Varies with season
- Specific gravity : 1.45 (F-Grade)
- Bulk density : 0.8 t/m3 for volumetric & 1.2 t /m3 for weight consideration
- Quality of coal : Av. Grade “F”

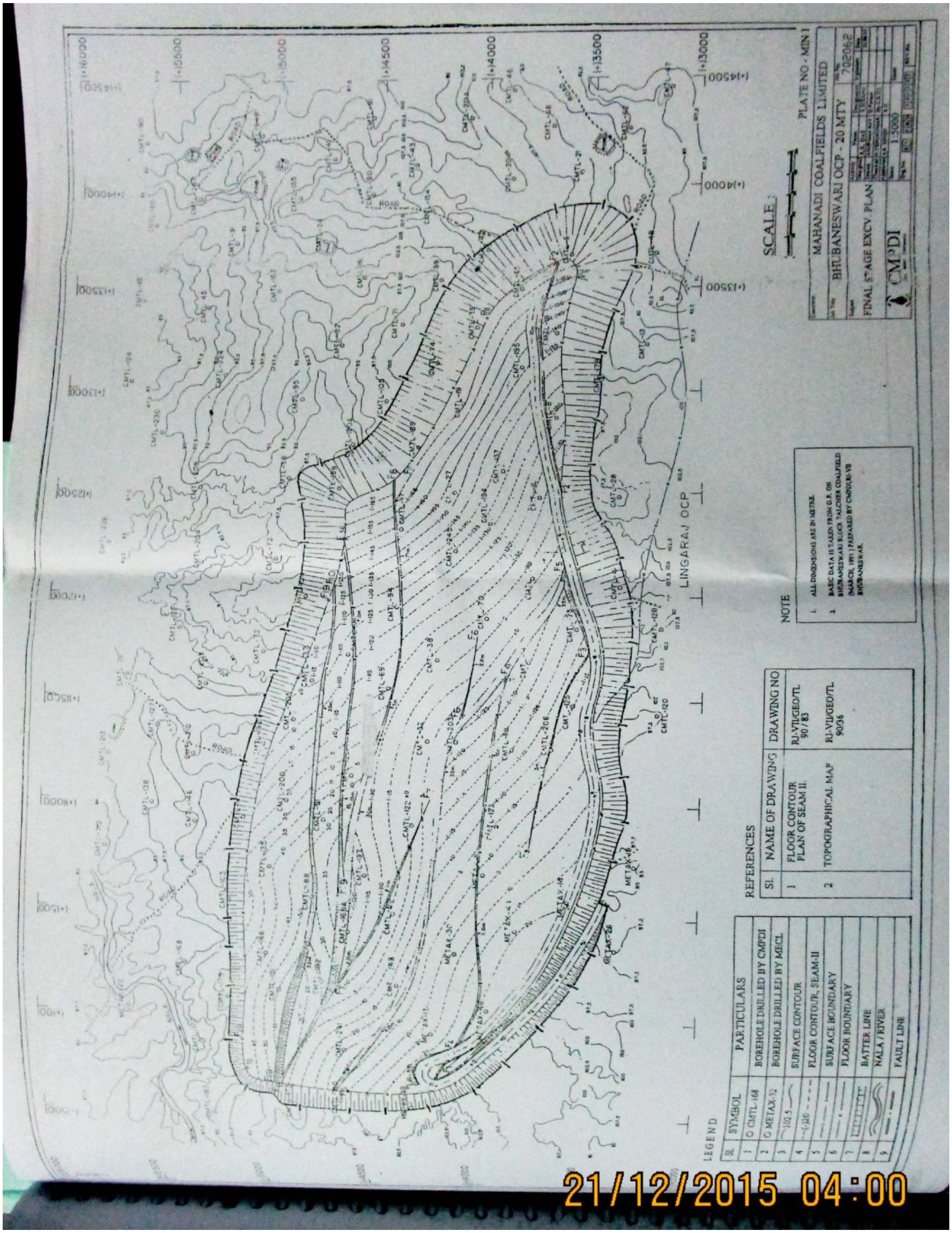


Figure 3-1: Final Stage Excavation Mine Plan

CHAPTER-4

PROJECT METHODOLOGY

4 Project Methodology

The project work procedure flow-chart for this project has been shown in the flow sheet below:

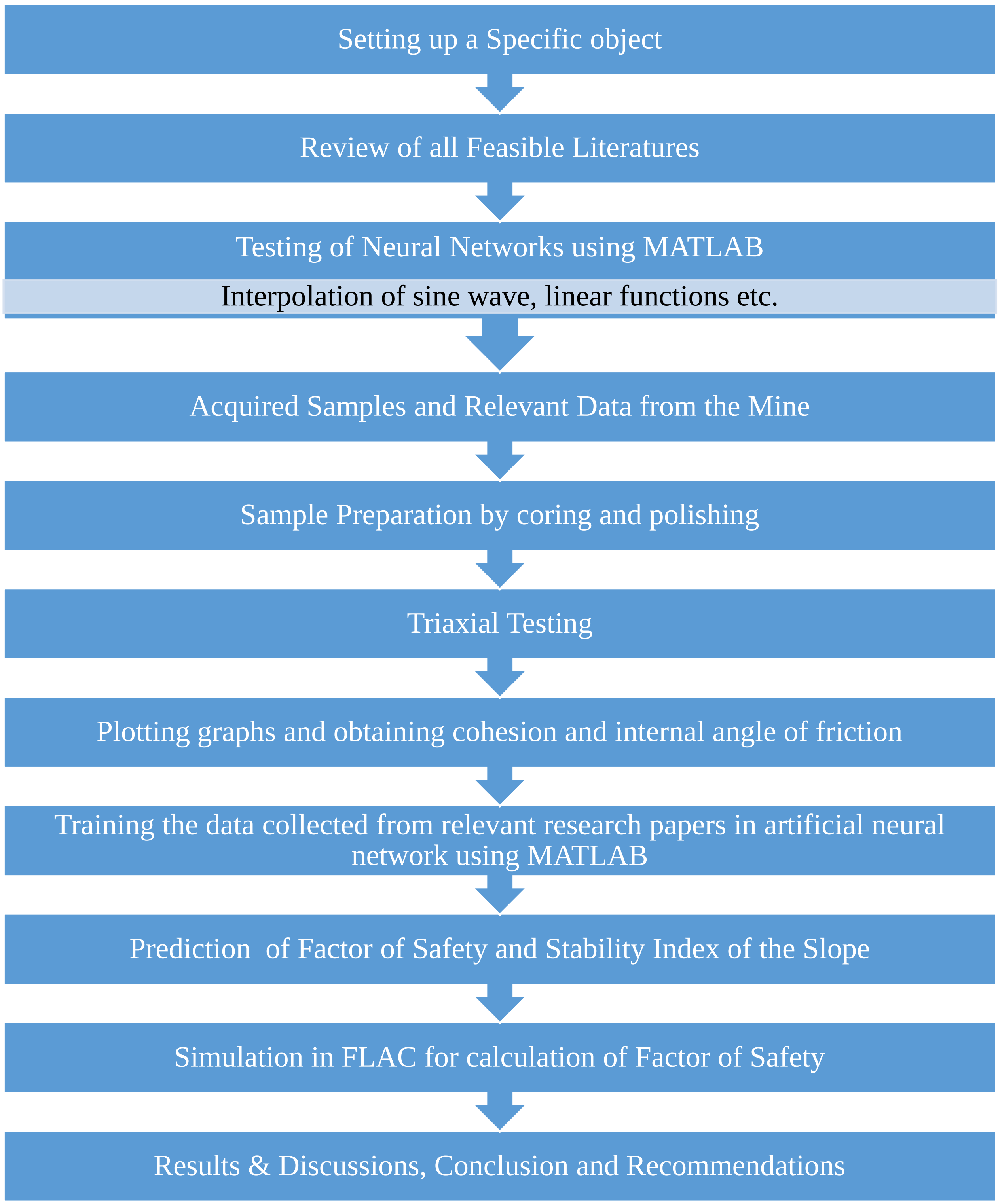


Figure 4-1: Flowchart of Methodology adopted.

4.1 Research Strategies

- Various Literatures were referred to learn about the types of slope failure and the factors that affect the stability of slopes.
- Since the slope stability problems occur more at greater depths and the current working in Bhubaneswari Opencast mines was at 150m depth, so the samples and relevant data were collected for evaluation of slope stability of that part of the mine.
- Triaxial testing was carried out for the evaluation of cohesion and internal angle of friction.
- Various research papers were referred for collection of data to be trained in the Artificial Neural Network.
- 14 Artificial Neural Networks were created with 14 different training functions for evaluation of performance of each and every training function. Finally, one training function was chosen for prediction of FOS and Stability Index.
- FLAC model was created with 3 benches immediate to the bench which showed a bit of ground stability issues like gross stability problems and local stability problems.

4.2 Field Visit and Collection of Samples

The samples to be studied were collected from Bhubaneswari Mines, Talcher (MCL, Coal India). The individual benches in the slope were varying from 60 degrees to 70 degrees. The overall slope angle was found to be 26 degrees. The maximum and minimum depth was 187.5 metres and 35.0 metres during the time of sample collection as on date 20 December,2015. The average gradient of the haul roads were 4.5 degrees, which varied from 4 degrees from 15 degrees. The bench height specifications are as follows:

Table 4-1: Max. and Min. Bench heights

For Coal Seams	14 Cu. M. EHS Backhoe	9-10 Cu. M. EHS Backhoe
Maximum Bench Height	10m	10m
Working Bench Height	34m	32m
Bench Slope	70 degrees	70 degrees

For Overburden	14 Cu. M. EHS Backhoe	9-10 Cu. M. EHS Backhoe
Maximum Bench Height	15-20m	10m
Working Bench Height	44m	32m
Bench Slope	70 degrees	70 degrees

Figure 4-2: Shale Sample Collected from Bhubaneswari Mines, Talcher

Ground water table was found to be 3-5 metres below the ground level. Hence no adverse impact was observed pver time as reported by the authorities. Also, the moisture content was found to be 3.81 % to 8.0 %.

Angle of repose of the overburden benches in Bhubaneswari Opencast Project was 37 degrees and for coal, it was 45 degrees.

Other physical properties are as follows:

Table 4-2: Physical Properties of Coal

Compressive Strength	132.506 Kg/cm^2
Tensile Strength	15.47 Kg/cm^2 – 38.04 Kg/cm^2
Shear Strength	3.842 Kg/cm^2 – 39.12 Kg/cm^2

The slope geometry was as follows:

Table 4-3: Slope Geometry

Bench Height-Coal	10m
Bench Height-Overburden	10m
Bench Width	32m
Bench Slope Angle	70 degrees
Overall Slope Angle	26 degrees

Figure 4-3: Coal Sample Collected from Bhubaneswari Mines, Talcher

4.3 Triaxial Testing

Triaxial testing is done after preparation of rock sample by coring and polishing. The following apparatus was used for the testing as shown in figure.

Initially, the coring process was done followed by polishing. The machines set-ups used for the coring and polishing process are as shown in figure.

Figure 4-4: Coring machine

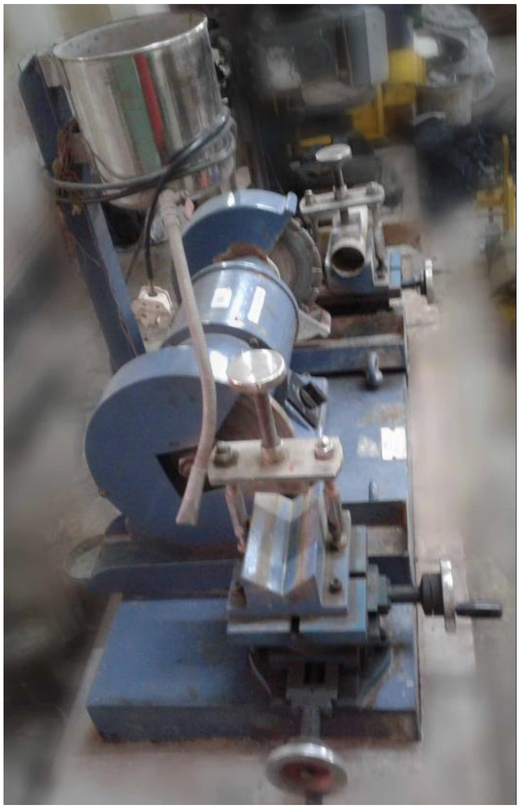


Figure 4-5: Polishing Machine

Figure 4-6: Triaxial Apparatus

Figure 4-7: Constant Load Machine

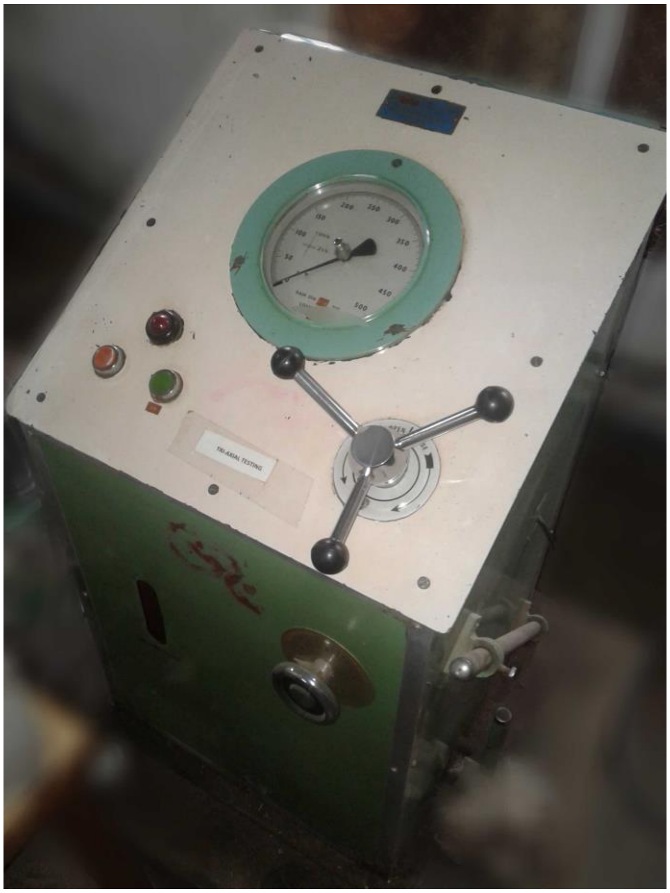


Figure 4-8: Major Stress Break-up Apparatus

The test was carried out for determination of the cohesion and internal angle of friction values. Stress was applied to the sample of coal and shale in a way which results in stresses along one axis being different from the stresses in perpendicular directions. This is typically achieved by placement of the sample between two parallel platens which can apply stress in one direction while applying fluid pressure to the specimen to apply stress in the perpendicular directions. Then the neural network was created in MATLAB for evaluation of the performance of the network.

The ANN is initially to be tested to review its performance before actual import of the data. So, a dry run of the network was carried out with first a linear function and then a sinosuidal wave as shown in figure:

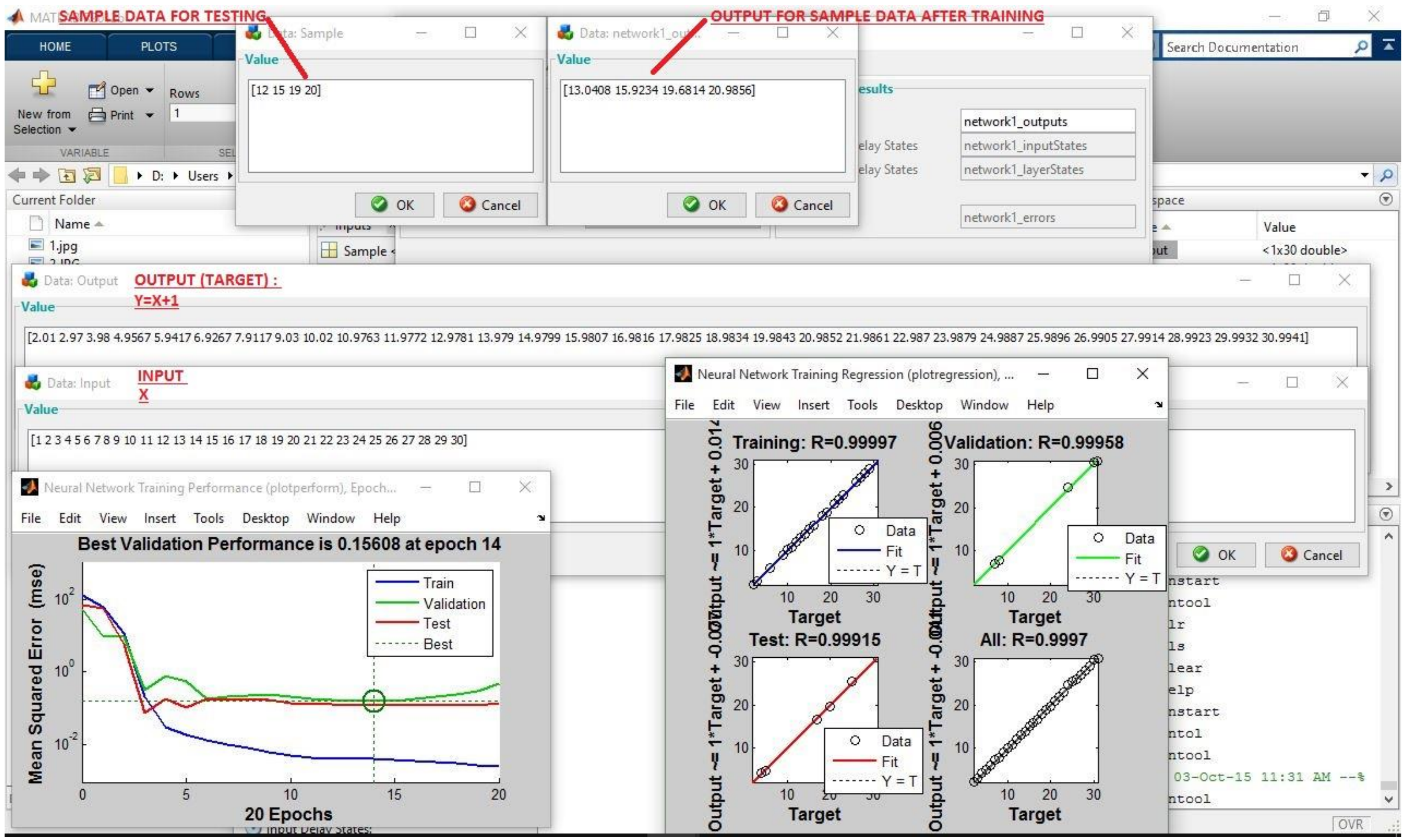


Figure 4-9: Checking network performance

- LINEAR FUNCTION: y=x+1+e
  - Error e : [0,0.05]
  - Overall R = 99.97%

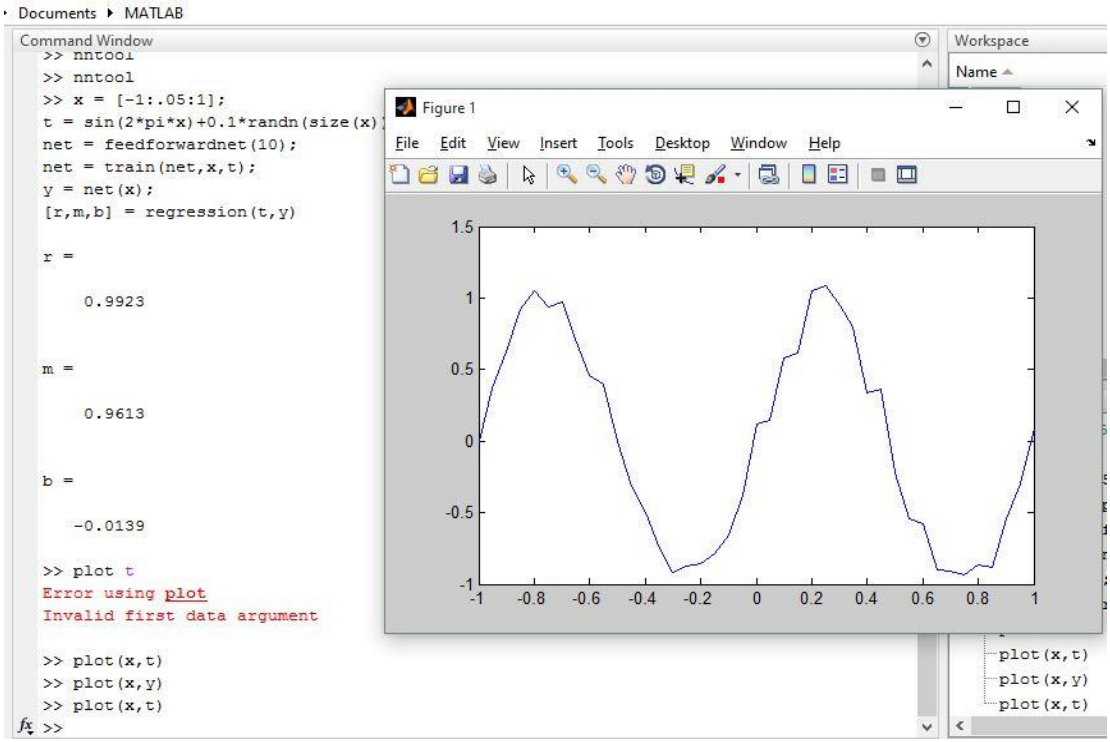


Figure 4-10: Checking Network Performance

SINUSOIDAL FUNCTION: t=sin(2*pi*x)+0.1*randn(size(x))

- Network: Feedforward Network with Backpropagation
- Results: Overall R=99.23%

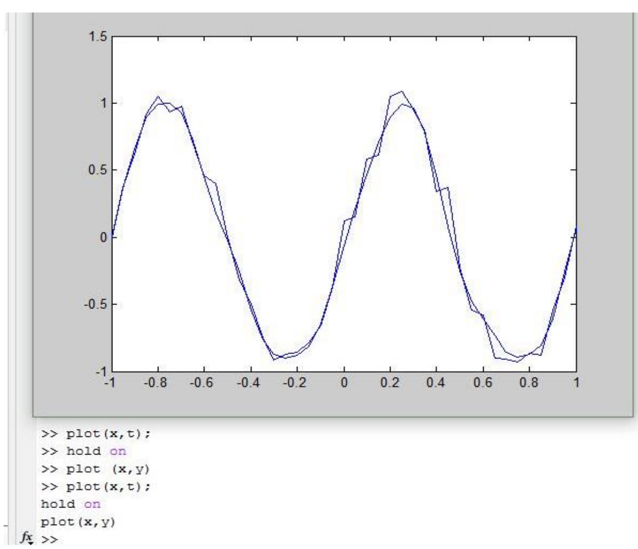


Figure 4-11: Superimposition of the perfect sinewave and the plot with random error

4.4 Data Collected for Training in Artificial Neural Networks

The following data were collected from various reference for training in the Artificial Neural Network which were used for prediction of factor of safety and Stability index.

Table 4-4: Data for Training

Density (kN/m3)	Cohesion (kPa)	Friction Angle (degrees)	Slope angle (degrees)	Mining Depth (m)	Factor Of Safety	Stability Index
18.68	26.34	15	35	8.23	1.11	0
16.5	11.49	0	30	3.66	1	0
18.84	14.36	25	20	30.5	1.875	1
18.84	57.46	20	20	30.5	2.046	1
28.44	29.42	35	35	100	1.78	1
28.44	39.23	38	35	100	1.99	1
20.6	16.28	26.5	30	40	1.25	0
14.8	0	17	20	50	1.13	0
14	11.97	26	30	88	1.02	0
25	120	45	53	120	1.3	1
26	150.05	45	50	200	1.2	1
18.5	25	0	30	6	1.09	0
18.5	12	0	30	6	0.78	0
22.4	10	35	30	10	2	1
21.4	10	30.4	30	20	1.7	1
22	20	36	45	50	1.02	0
22	0	36	45	50	0.89	0
12	0	30	35	4	1.46	1
12	0	30	45	8	0.8	0
12	0	30	35	4	1.44	1
12	0	30	45	8	0.86	0
23.47	0	32	37	214	1.08	0
16	70	20	40	115	1.11	0
20.41	34.9	13	22	10.67	1.4	1
19.63	11.97	20	22	12.19	1.35	0
21.82	8.62	32	28	12.8	1.03	0
20.41	33.52	11	16	45.72	1.28	0
18.84	15.32	30	25	10.67	1.63	1
18.84	0	20	20	7.62	1.05	0
21.43	0	20	20	61	1.03	0
19.06	11.71	28	35	21	1.09	0
18.84	14.36	25	20	30.5	1.11	0

21.51	6.94	30	31	76.81	1.01	0
14	11.97	26	30	88	0.625	0
18	23	30.15	45	20	1.12	0
23	0	20	20	100	1.2	1
22.4	100	45	45	14	1.8	0
22.4	10	35	45	10	0.9	0
20	20	36	45	50	0.96	0
20	20	36	45	50	0.83	0
20	0	36	45	50	0.79	0
20	0	36	45	50	0.67	0
22	0	40	33	8	1.45	1
24	0	40	33	8	1.58	1
20	0	24.5	20	8	1.37	1
18	5	30	20	8	2.05	1

4.5 FLAC Simulation

FLAC/Slope was used for calculation of FOS of Bhubaneswari OCP, Talcher, which was used to compare the results found from that of the ANN.

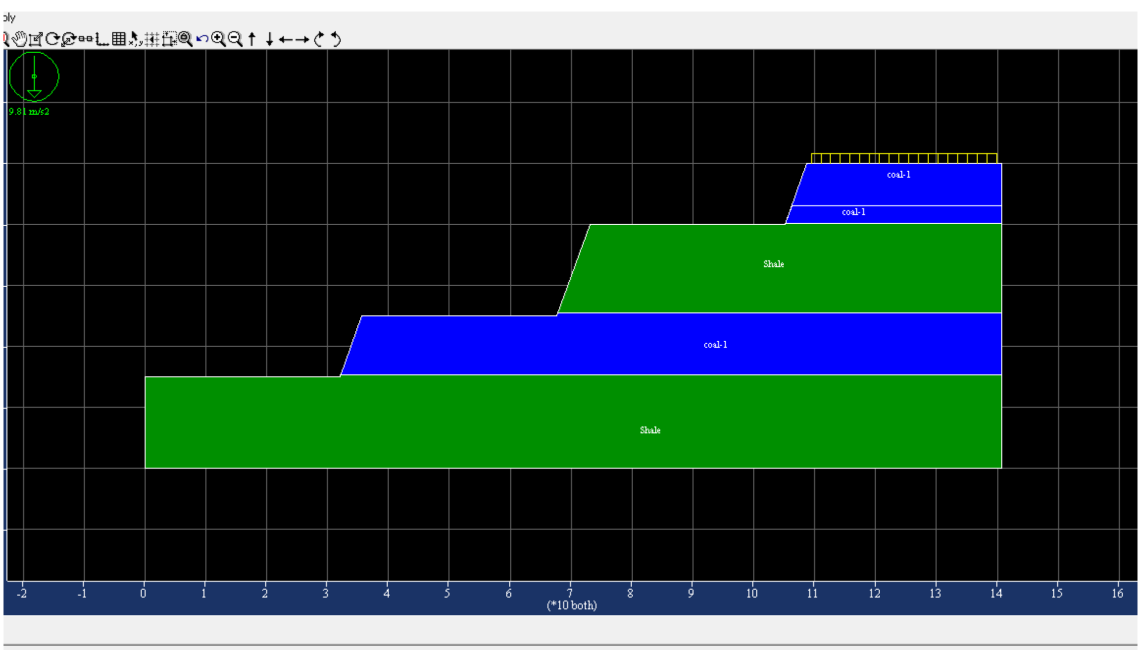


Figure 4-12: Importing the rock types for simulation of FOS

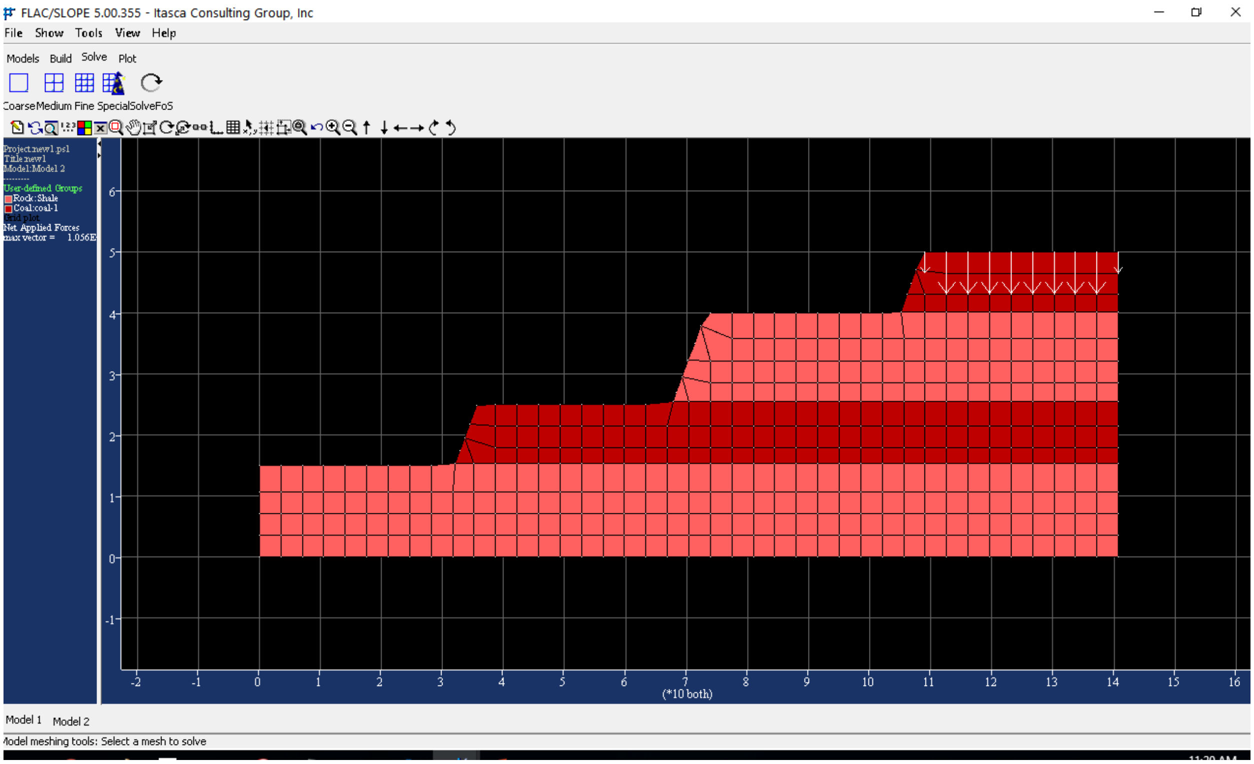


Figure 4-13: Meshing for analysis and results

The meshing is done for the analysis of the FOS of the slope. During the process of meshing, the whole geometry is created into various zones and each zone is solved along with neighboring zones, thus creating a matrix of results converging into one result. The Fast Lagrangian Analysis is done and the results are obtained after bracketing. Sometimes, if the slope is very stable, then the FOS is over 64 and the FOS calculation is suspended prematurely.

CHAPTER-5

RESULTS

5 Results

Various training functions were tested to determine which training function to be used for training the available data. The following were the results of performance and validation.

5.1 ANN Training for determination of best fit training function

5.1.1 TRAINBFG: BFGS quasi-Newton backpropagation

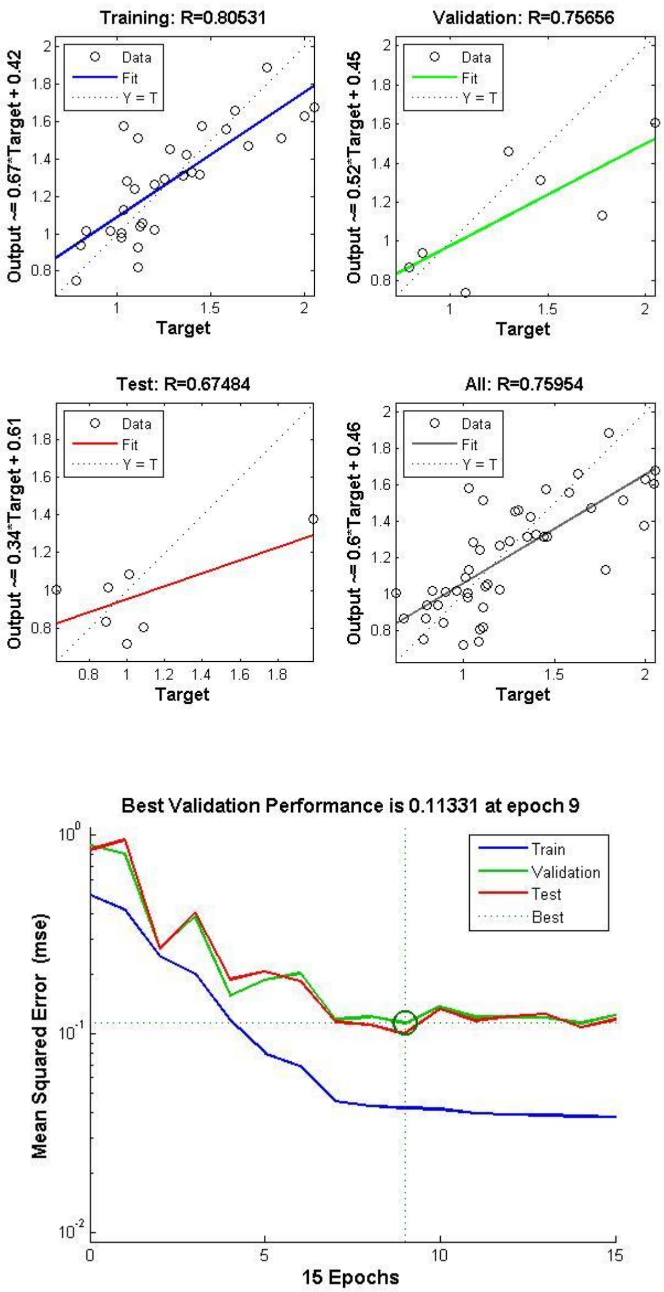
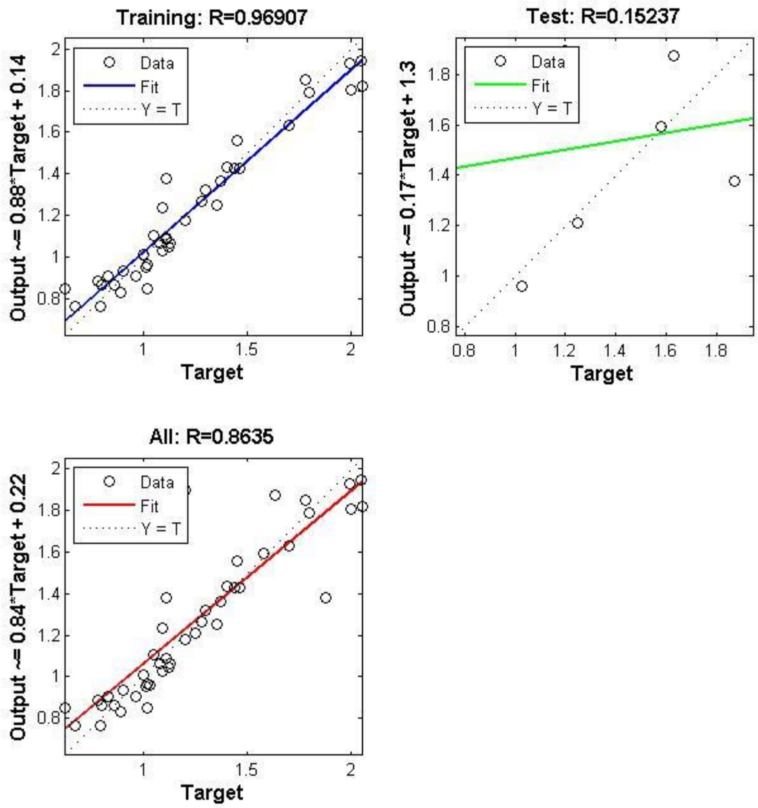


Figure 5-1: Training with TRAINBFG: BFGS quasi-Newton backpropagation

5.1.2 TRAINBR: Bayesian regularization backpropagation



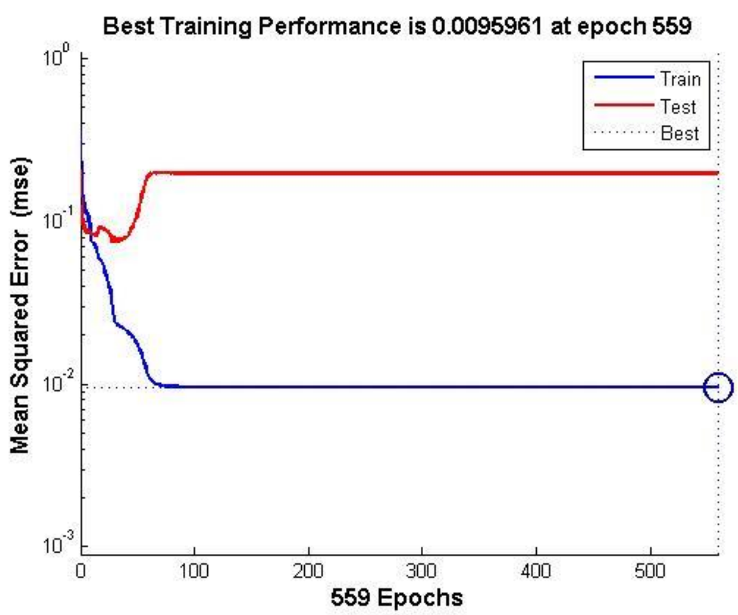


Figure 5-2: Training with TRAINBR: Bayesian regularization backpropagation

5.1.3 TRAINCGB: Conjugate gradient backpropagation with Powell-Beale restarts

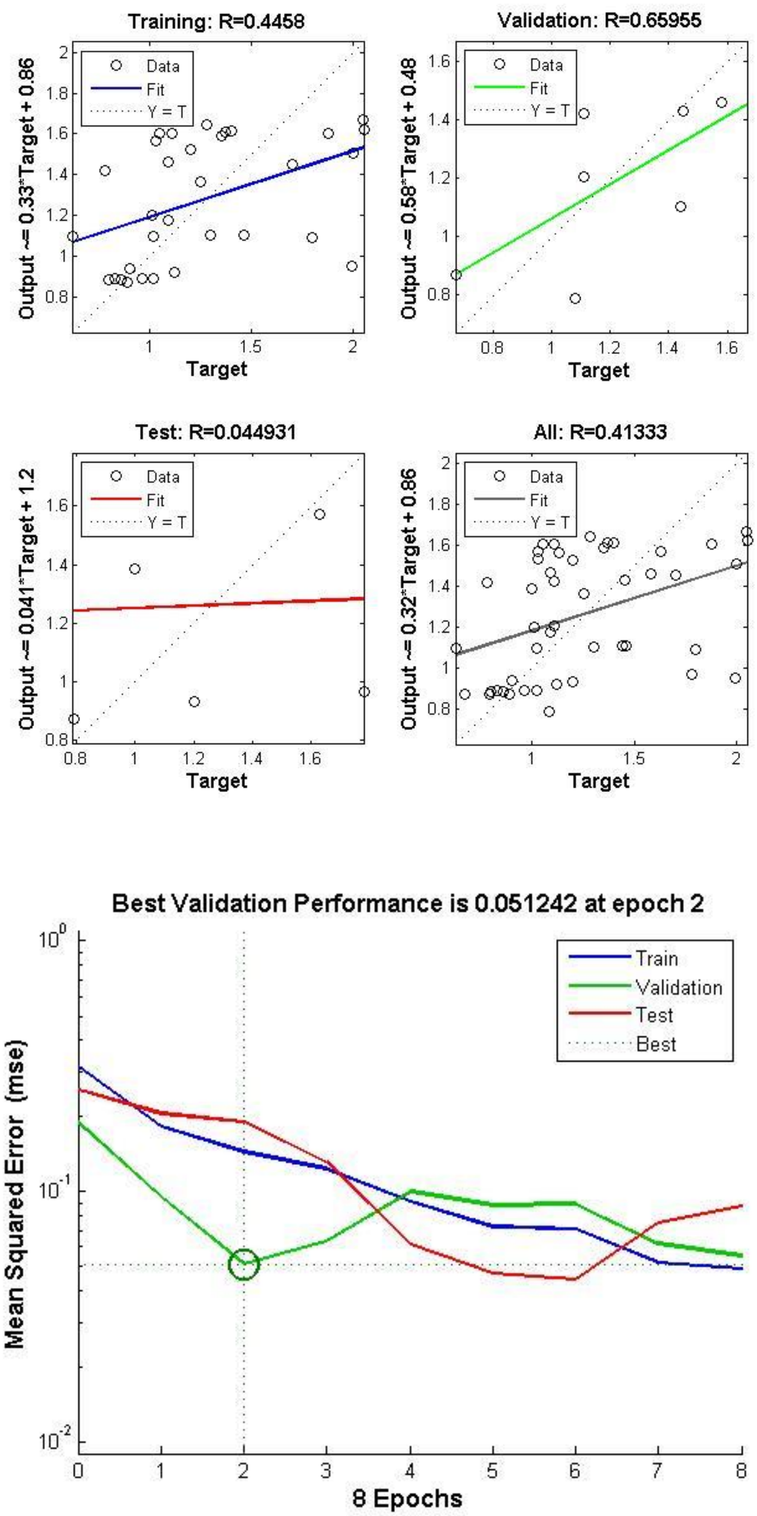


Figure 5-3: Training with TRAINCGB: Conjugate gradient backpropagation with Powell-Beale restarts

5.1.4 TRAINCGF: Conjugate gradient backpropagation with Fletcher-Reeves updates

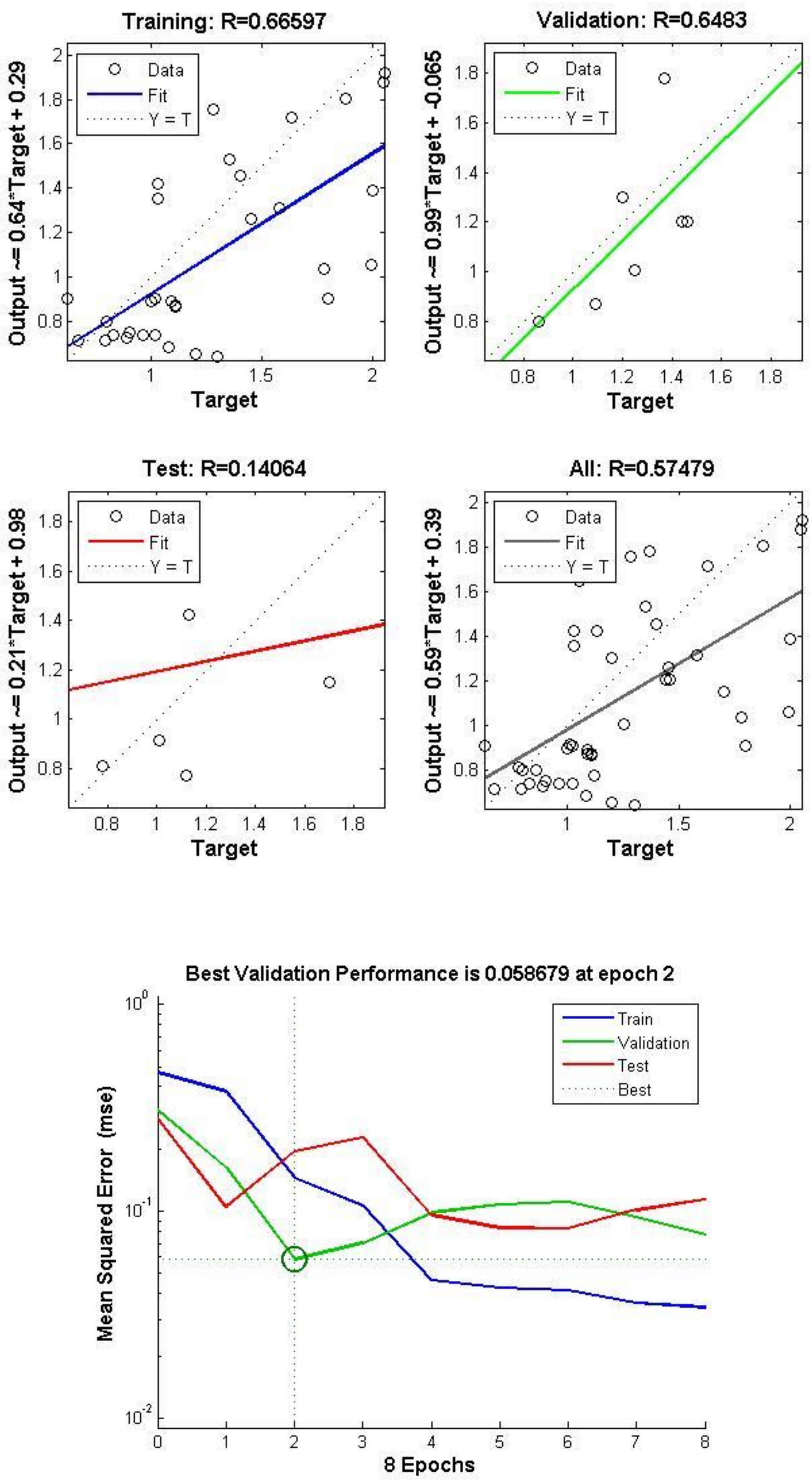


Figure 5-4: Training with TRAINCGF: Conjugate gradient backpropagation with Fletcher-Reeves updates

5.1.5 TRAINCGP: Conjugate gradient backpropagation with Polak-Ribiére updates

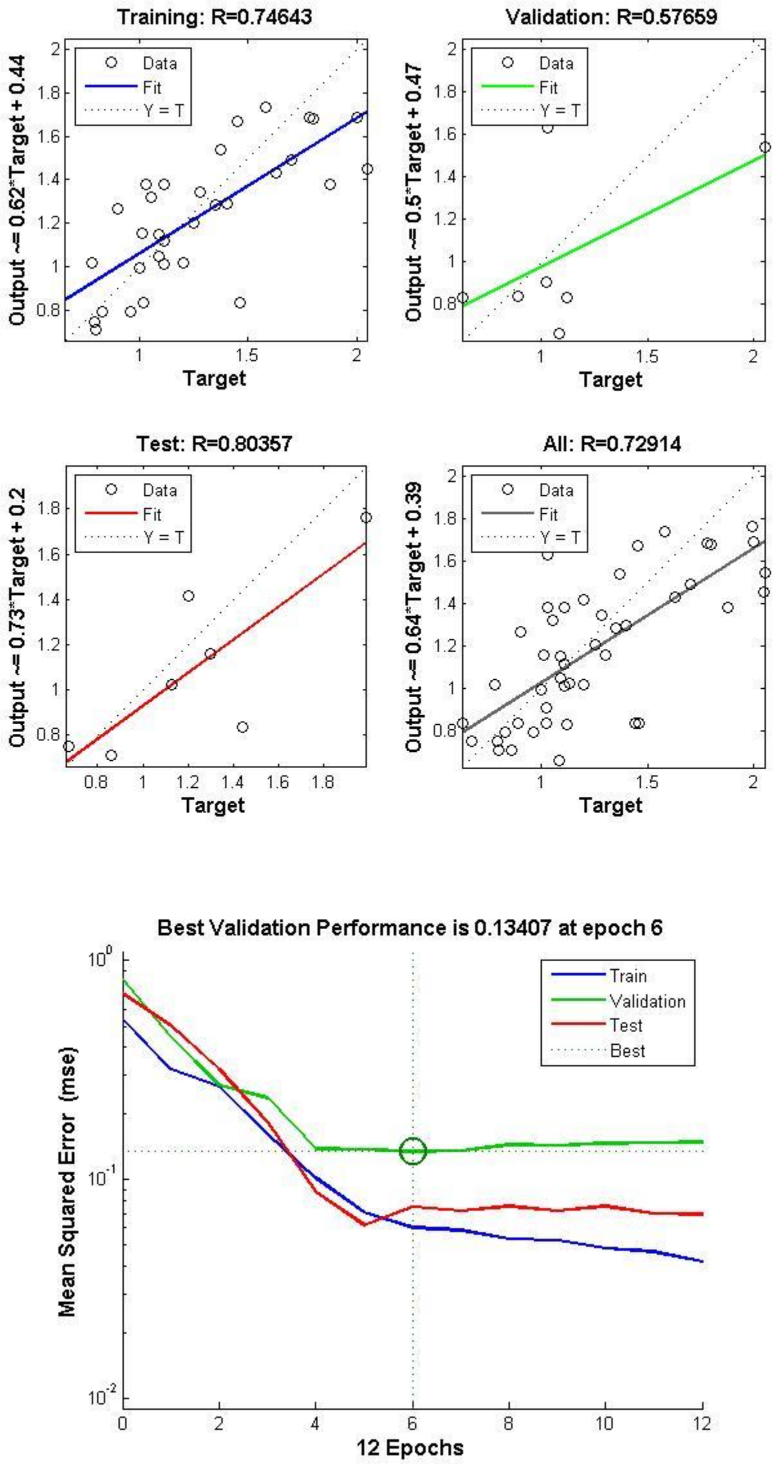


Figure 5-5: Training with TRAINCGP: Conjugate gradient backpropagation with Polak-Ribiére updates

5.1.6 TRAINGD: Gradient descent backpropagation

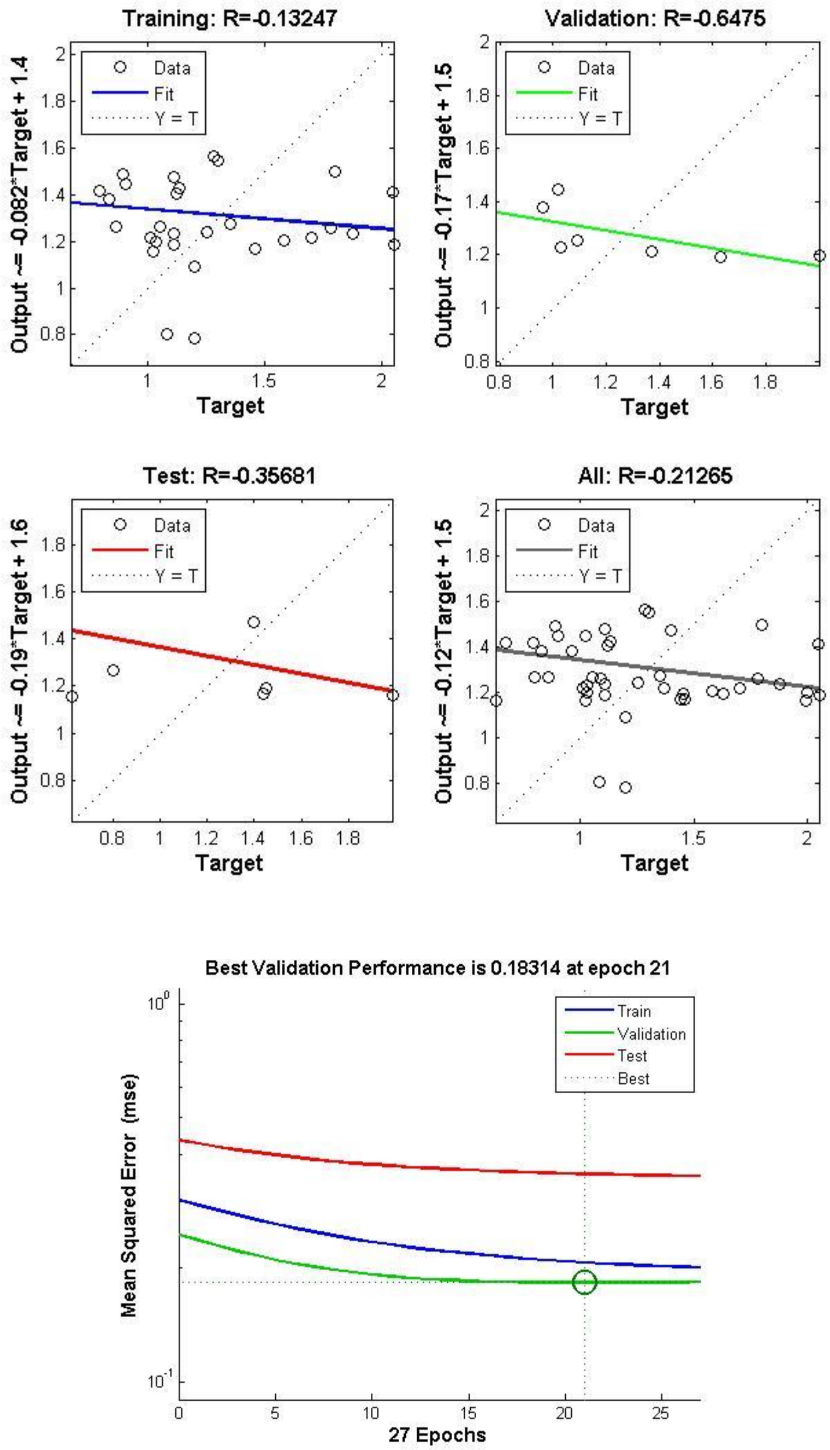


Figure 5-6: Training with TRAINGD: Gradient descent backpropagation

5.1.7 TRAINGDM: Gradient descent with momentum backpropagation

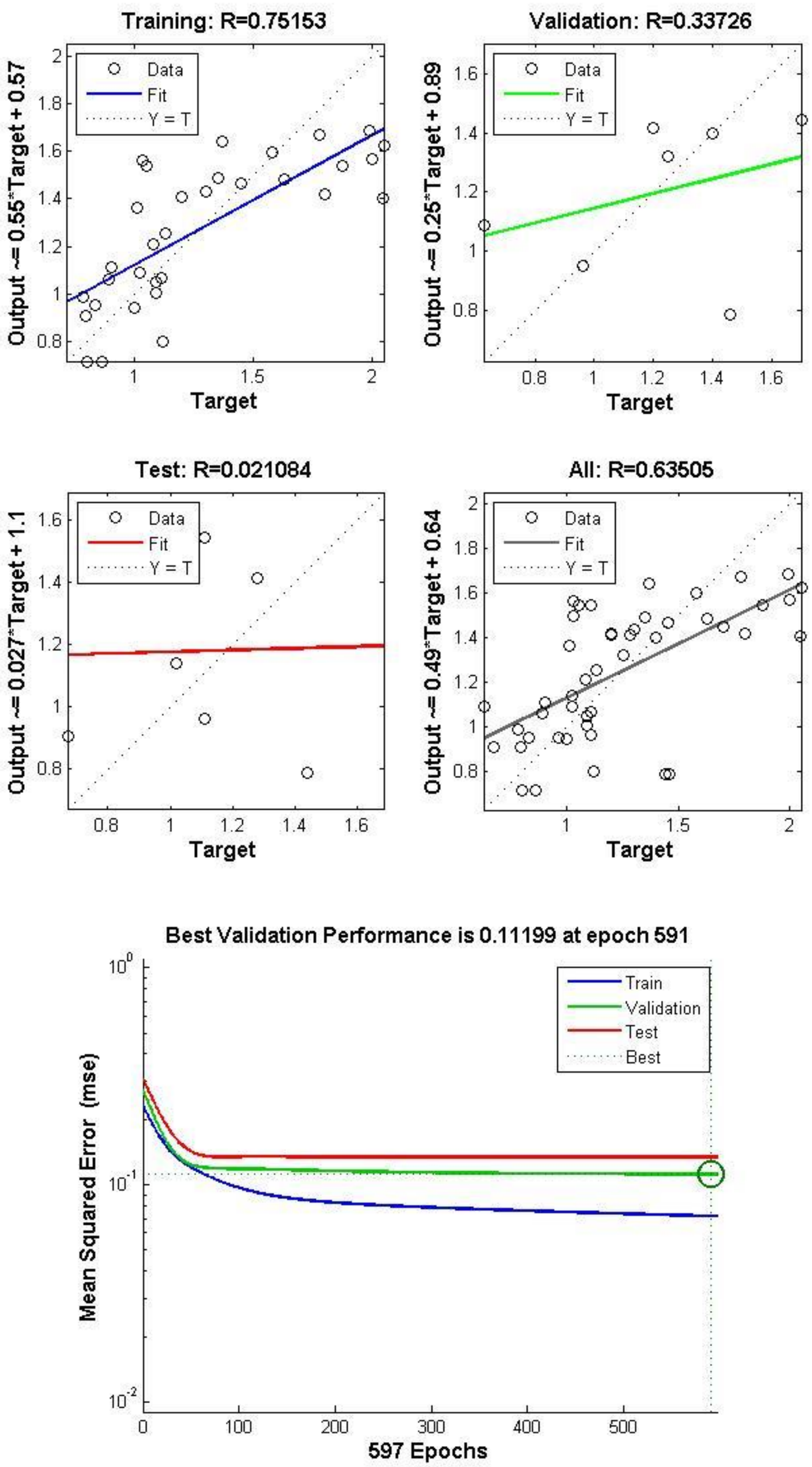


Figure 5-7L Training with TRAINGDM: Gradient descent with momentum backpropagation

5.1.8 TRAINGDA: Gradient descent with adaptive learning rate backpropagation

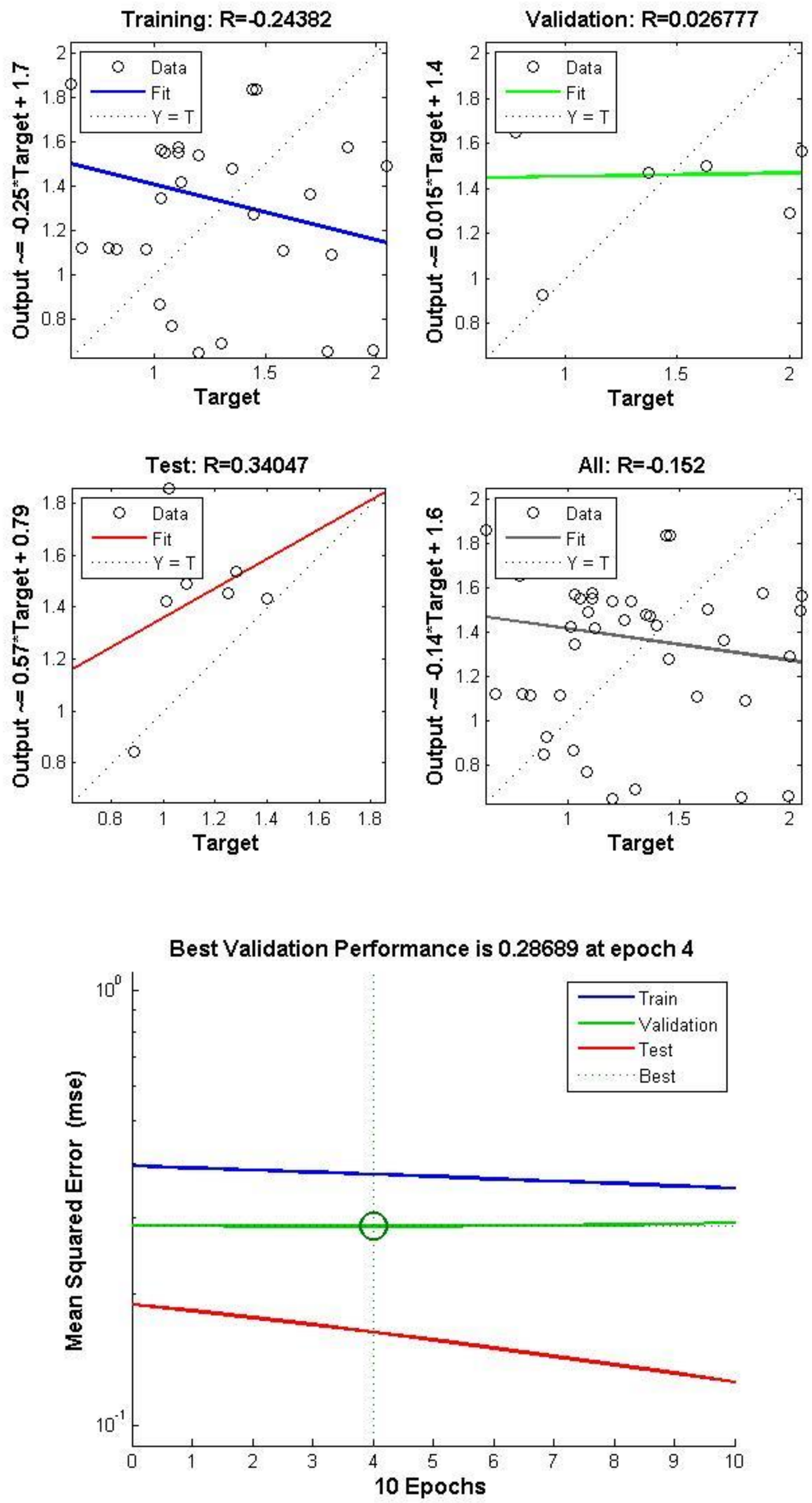


Figure 5-8: Training with TRAINGDA: Gradient descent with adaptive learning rate backpropagation

5.1.9 TRAINGDX: Gradient descent with momentum and adaptive learning rate backpropagation

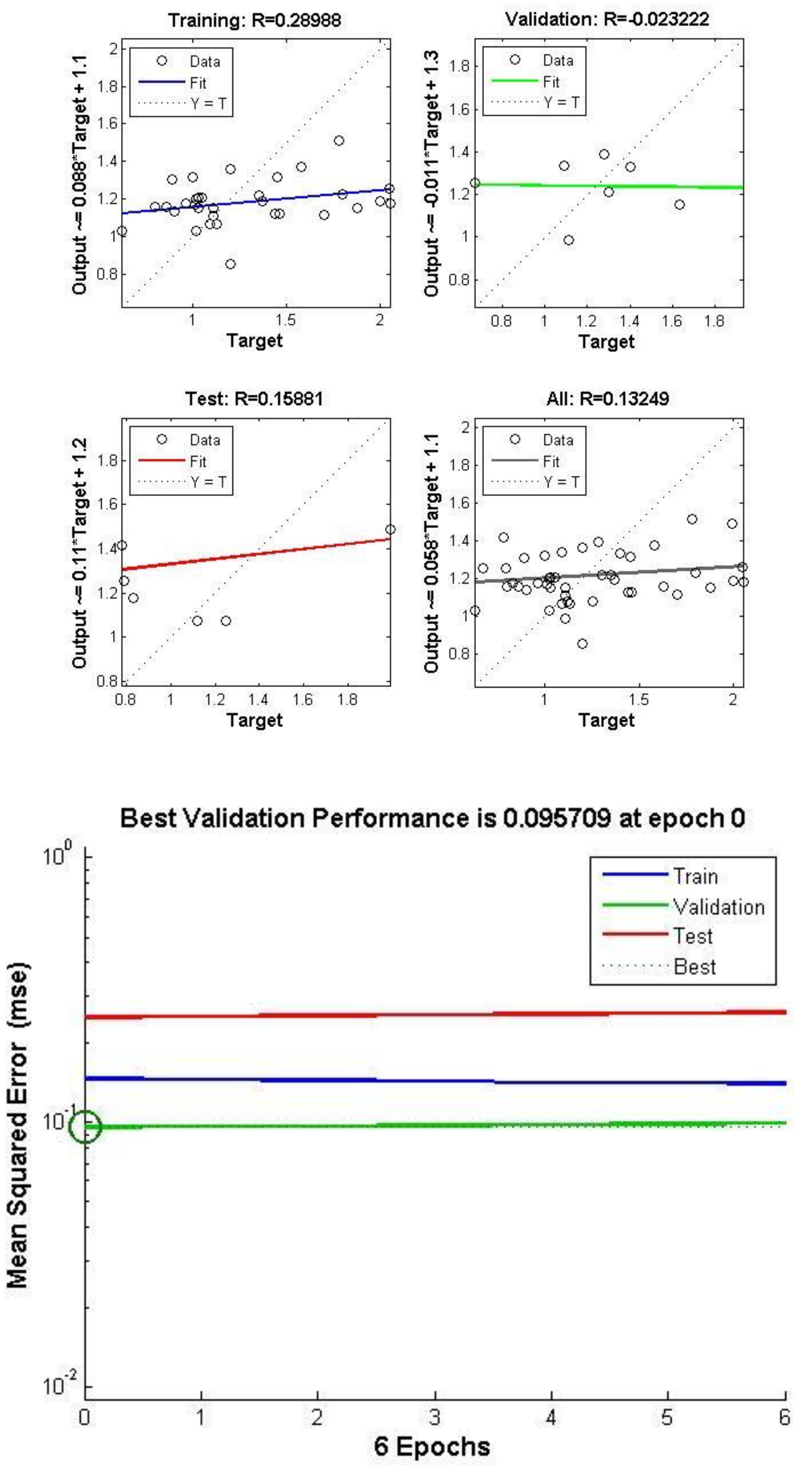


Figure 5-9: Training with TRAINGDX: Gradient descent with momentum and adaptive learning rate backpropagation

5.1.10 TRAINLM: Levenberg-Marquardt backpropagation

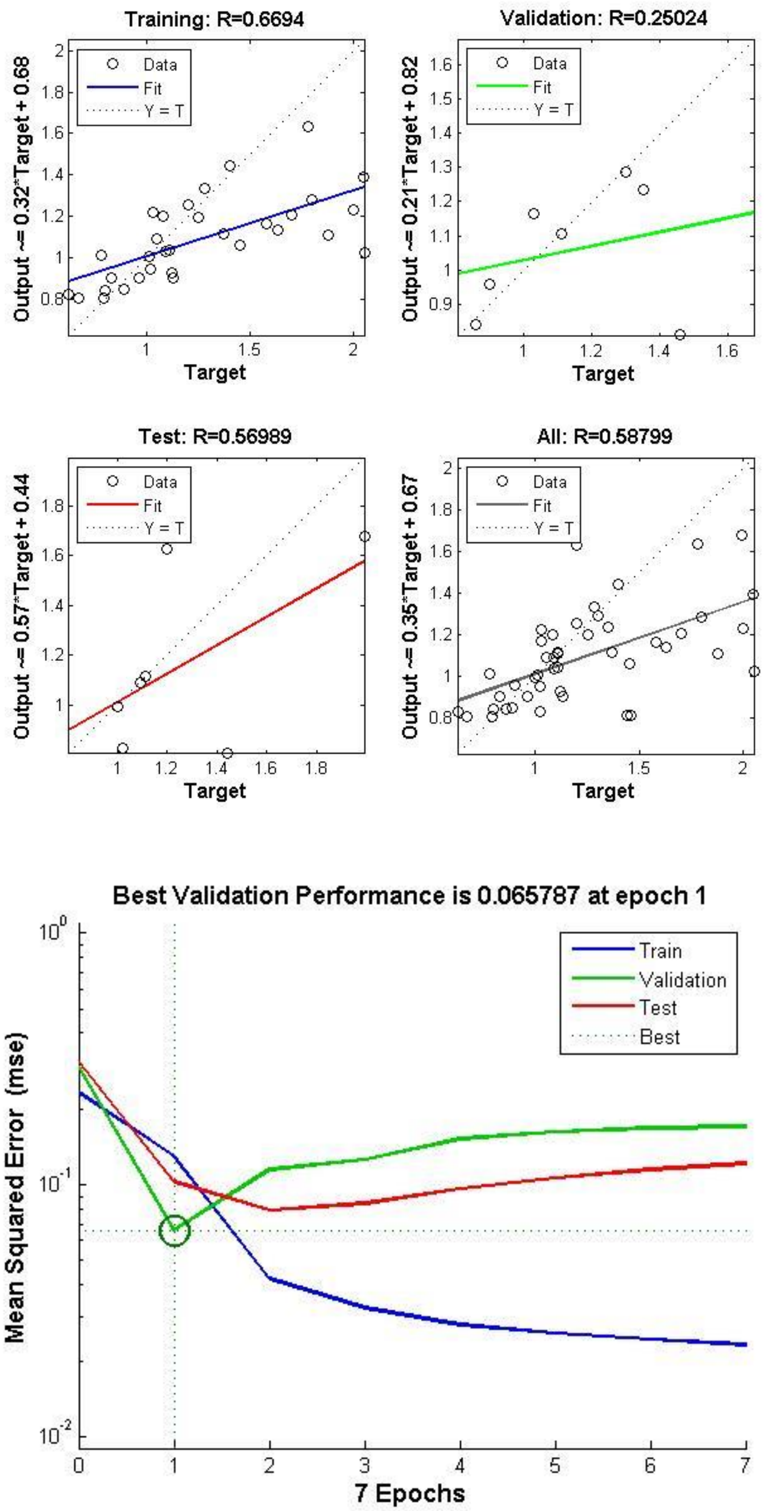


Figure 5-10: Training with TRAINLM: Levenberg-Marquardt backpropagation

5.1.11 TRAINOSS: One-step secant backpropagation

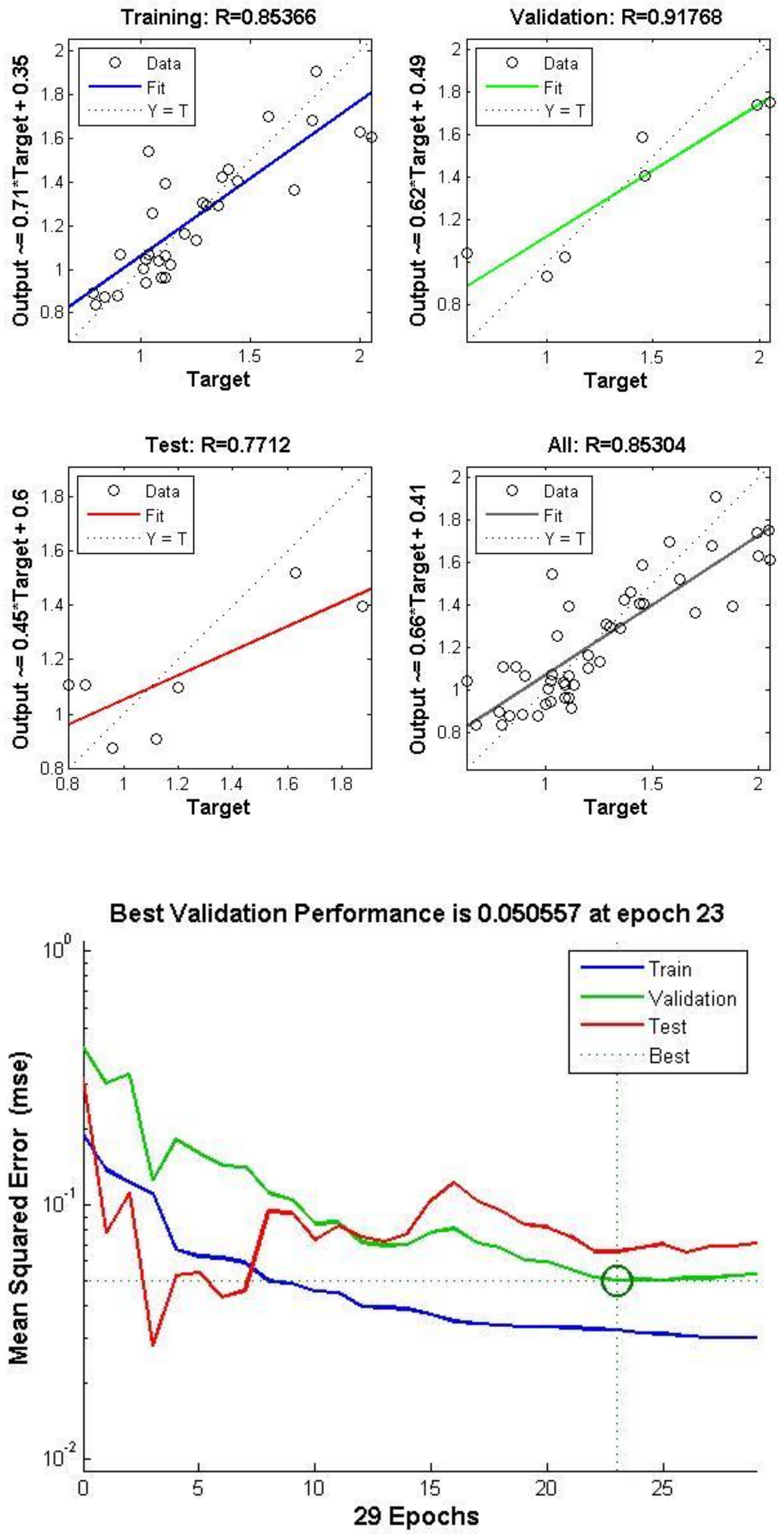


Figure 5-11: Training with TRAINOSS: One-step secant backpropagation

5.1.12 TRAINR: Random order incremental training with learning functions- Random weight bias rule

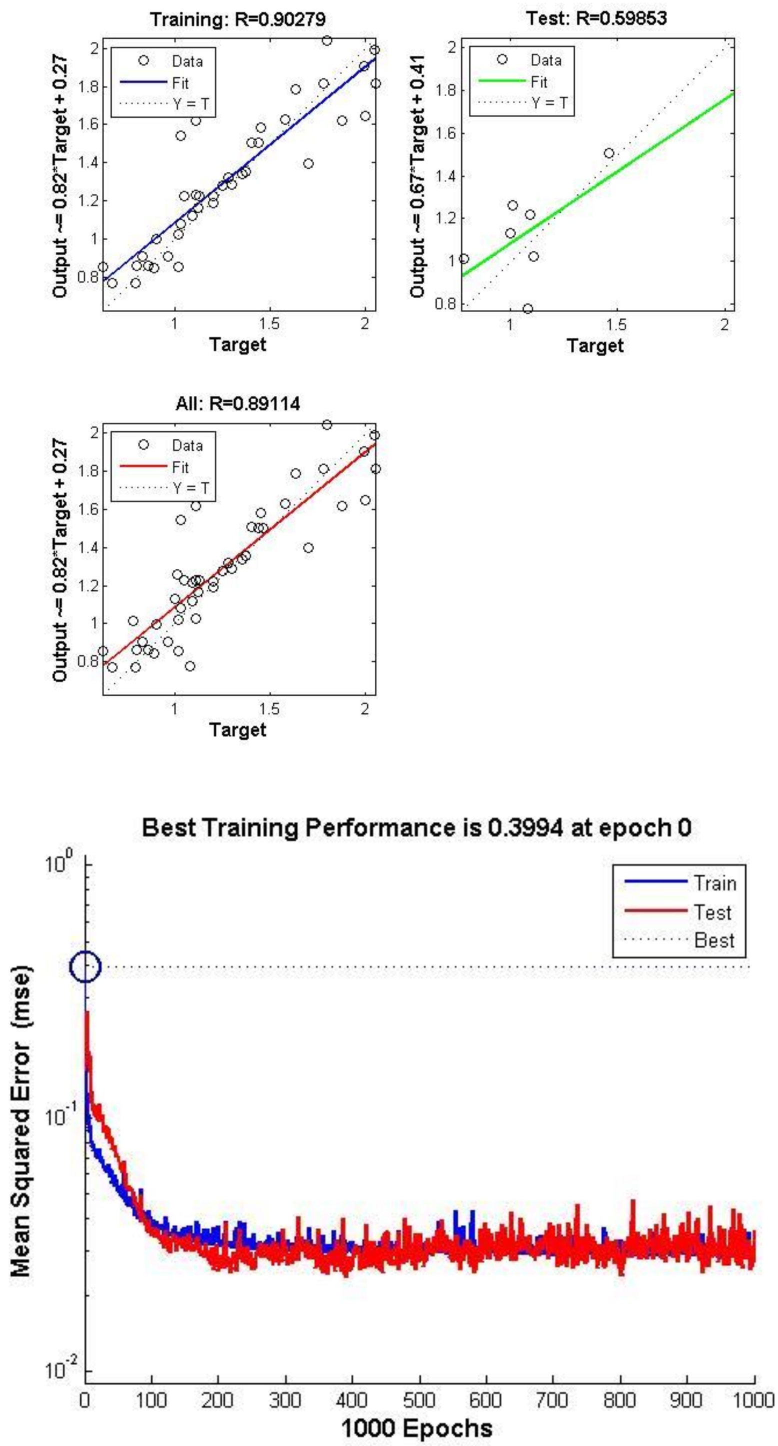


Figure 5-12: Training with TRAINR: Random order incremental training with learning functions- Random weight bias rule

5.1.13 TRAINRP: Resilient backpropagation

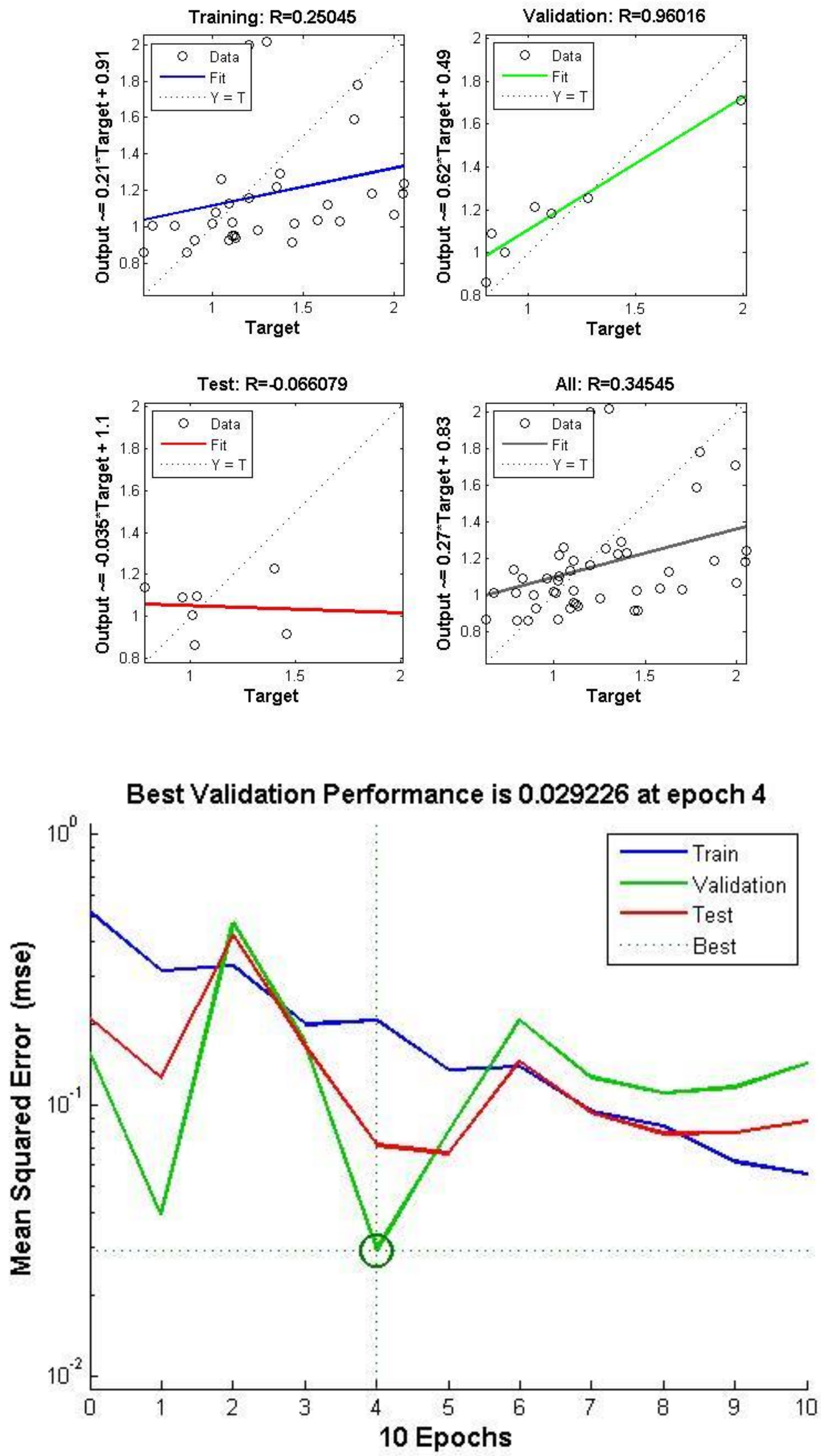


Figure 5-13: Training with TRAINRP: Resilient backpropagation

5.1.14 TRAINSCG: Scaled conjugate gradient backpropagation

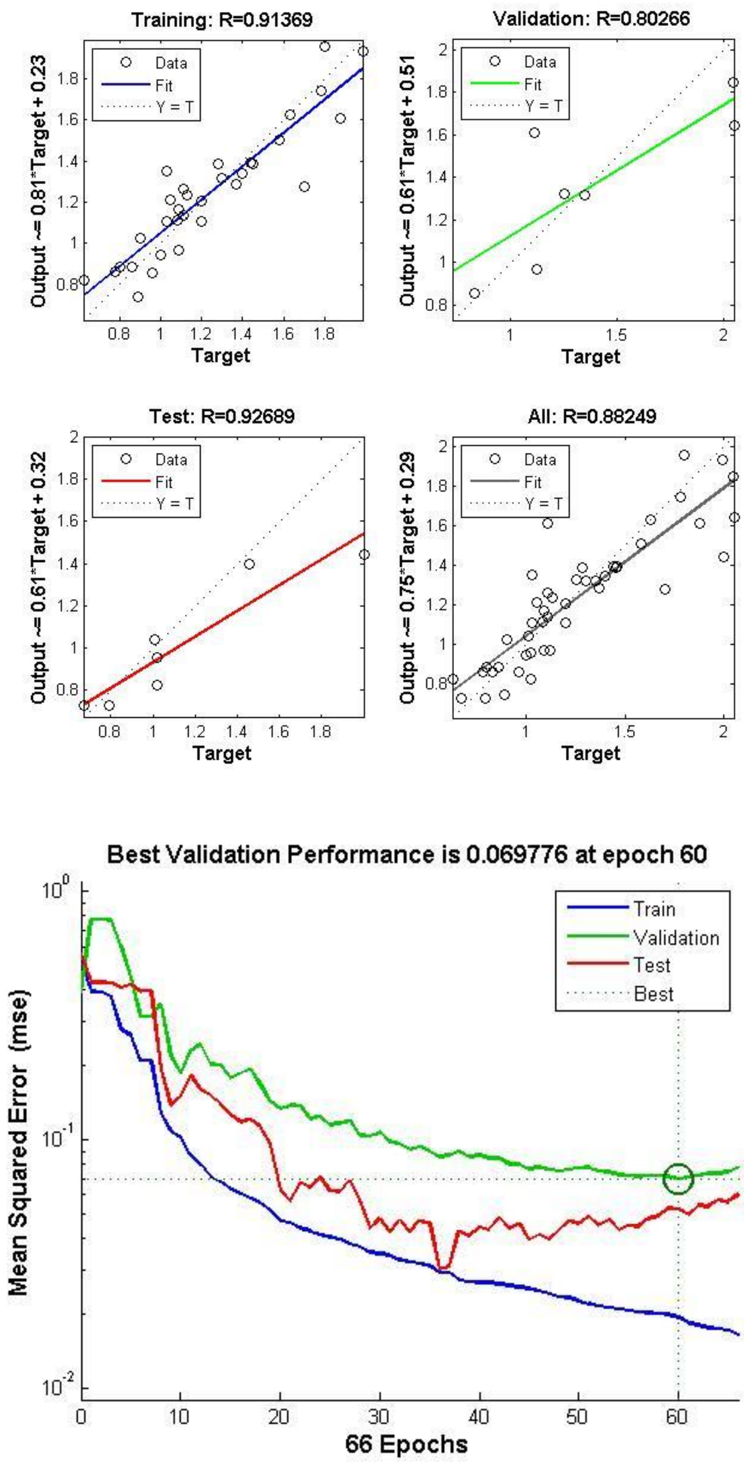


Figure 5-14: Training with TRAINSCG: Scaled conjugate gradient backpropagation

Table 5-1: Performances of the Training Functions: Summary

Sl. No.	Training Functions	Regresssion9				Validation Performance	
		Training	**Validation**	**Testing**	**All**	**MSE**	**Epochs**
1	TRAINBFG: BFGS quasi-Newton backpropagation	80.53	75.65	67.48	75.94	0.11	9/15
2	TRAINBR: Bayesian regularization backpropagation	96.9	15.23	-	86.35	0.009	559/559
3	TRAINCGB: Conjugate gradient backpropagation with Powell-Beale restarts	44.58	65.95	4.49	41.33	0.051	2/8
4	TRAINCGF: Conjugate gradient backpropagation with Fletcher-Reeves updates	66.59	64.83	14.06	57.47	0.058	2/8
5	TRAINCGP: Conjugate gradient backpropagation with Polak-Ribiére updates	74.63	57.65	80.35	72.91	0.134	6/12
6	TRAINGD: Gradient descent backpropagation	-0.1324	-0.6475	-0.3568	-0.21265	0.183	21/27
7	TRAINGDM: Gradient descent with momentum backpropagation	75.15	33.72	2.108	63.505	0.1119	591/597
8	TRAINGDA: Gradient descent with adaptive learning rate backpropagation	-0.24	0.026	0.34	-0.152	0.28689	4/10
9	TRAINGDX: Gradient descent with momentum and adaptive learning rate backpropagation	0.28988	-0.02322	0.15881	0.13249	0.095709	0/6
10	TRAINLM: Levenberg-Marquardt backpropagation	66.94	25.024	56.989	58.799	0.0657	1/7
11	TRAINOSS: One-step secant backpropagation	85.366	91.768	77.12	85.304	0.05055	23/29
12	TRAINR: Random order incremental training with learning functions-Random weight bias rule	90.27	59.85		89.11	0.3994	0
13	TRAINRP: Resilient backpropagation	25.045	96.016	-0.06608	34.4545	0.029226	4/10
14	TRAINSCG: Scaled conjugate gradient backpropagation	91.369	80.266	92.689	88.249	0.069776	60/66

5.2 Prediction of FOS and Stability Index of Slope- Bhubaneswari OCP using ANN

5.2.1 FOS Prediction

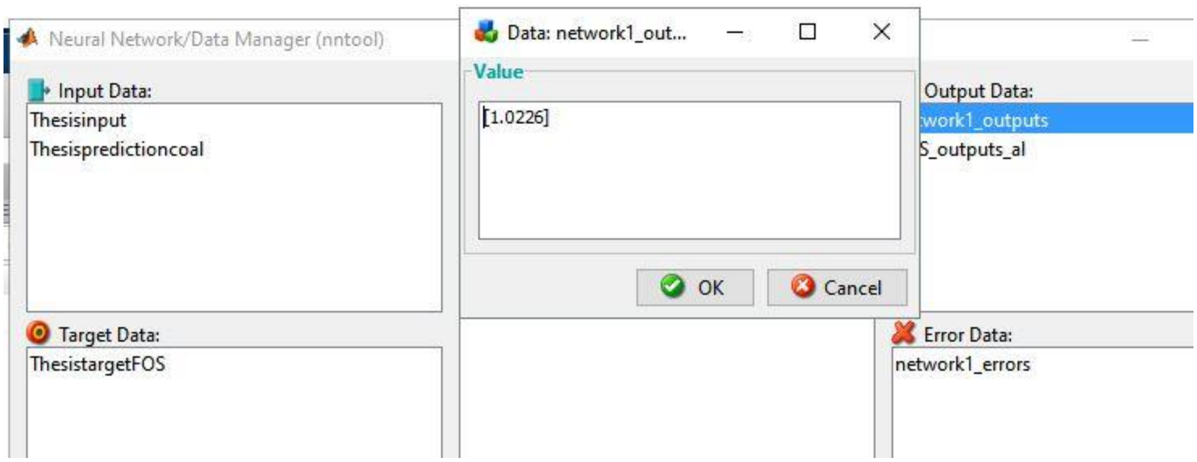


Figure 5-15: FOS (Coal Properties imported) Predicted

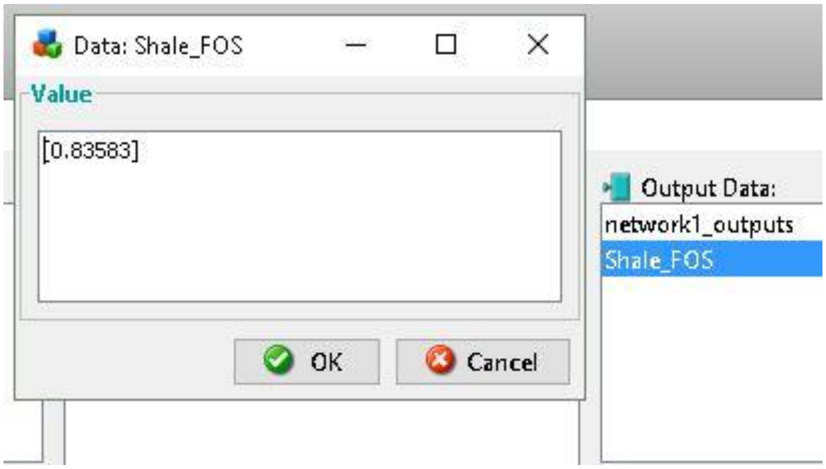


Figure 5-16: FOS (Shale/Sandy Shale Properties imported) Predicted

5.2.2 Stability Index Prediction:

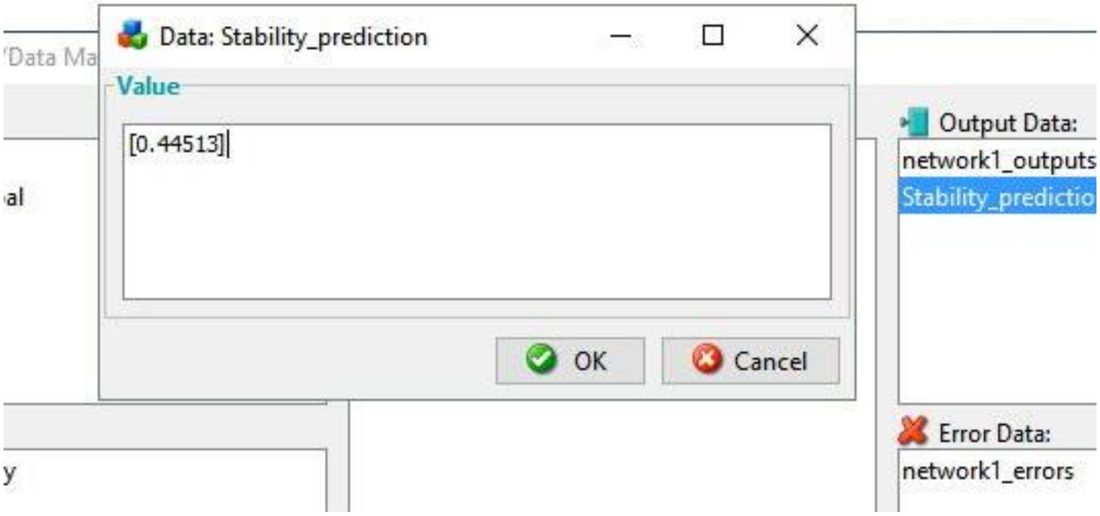


Figure 5-17: Stability Index of Bench with Coal Predicted

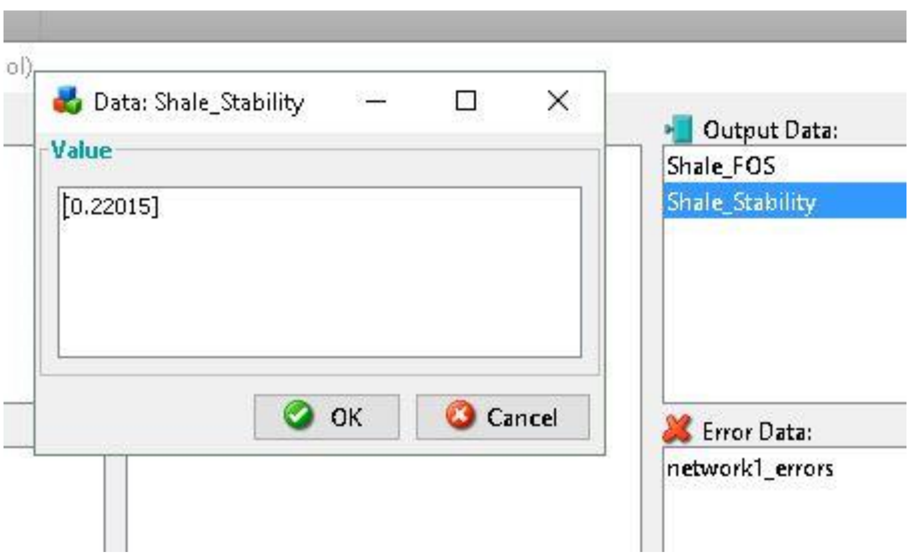


Figure 5-18: Stability Index of Bench with Shale/Sandy Shale Predicted

5.3 Results from FLAC

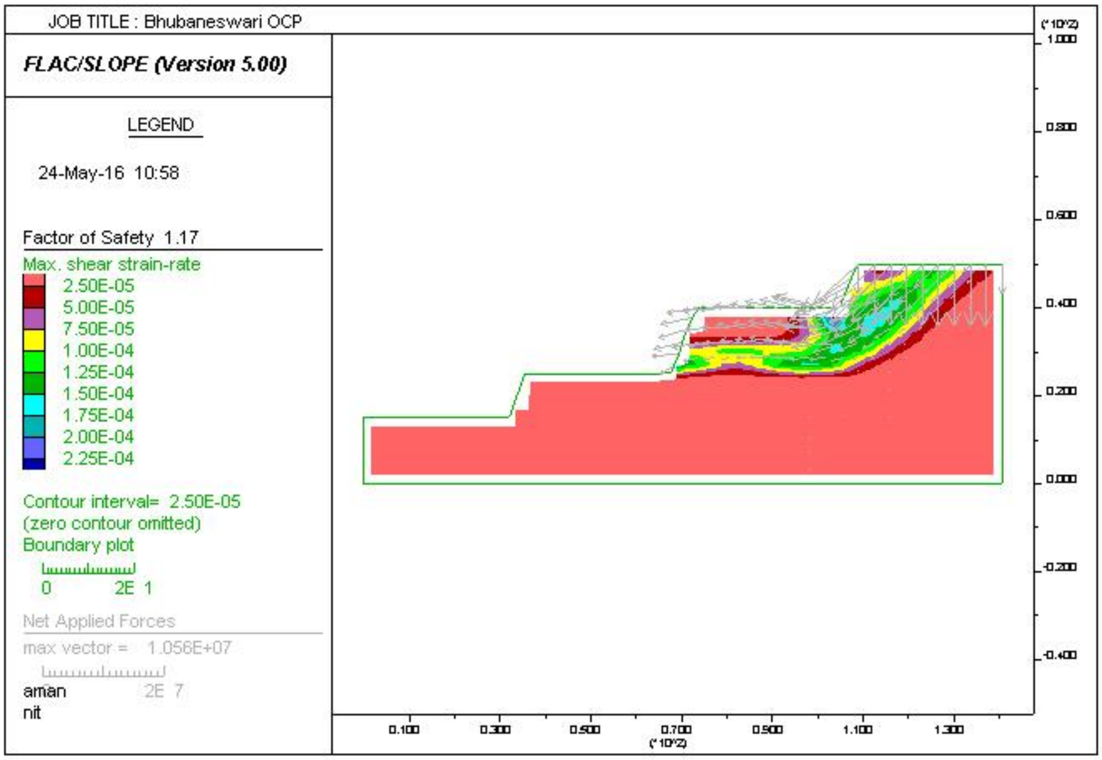


Figure 5-19: FOS Calculation and Shear Strain Diagram

After acquiring the results, the following table concludes and validates the results acquired from Artificial Neural Network with FLAC.

Table 5-2: Comparision of results from FLAC and ANN

Methodology	Factor of Safety	Stability Index
FLAC	1.17	-
ANN	1.022	44.51%

CHAPTER-6

CONCLUSION

6 Conclusion

The following were inferred from the project work done using ANN and FLAC for prediction of the slope stability of a particular slope in Bhubaneswari Opencast Mines, Talcher.

- While training the data sets, it was found that the training function-TRAINSCG: Scaled conjugate gradient backpropagation trained the data set much better. It is because of the algorithm of the training function that allowed the training function and the bias to fit much better with each other and produce good results.
- It was found that the slope had a safety factor close to 1 (1.0226) and a stability index of 44.51%. This means that there might be chances of failure (55.49%) and thus necessary precautionary measures should be taken to avoid any such mis-happenings.
- From the FLAC simulation, results were quite evident that the slope was quite stable except some disturbances on the upper bench of the strata, whose geology was composed of shale and sandy shale. It was also reported by the authorities of the Opencast Project that some ground control problems were related to the benches with mostly sandy shale and shale.
- The difference in the results of ANN and FLAC is quite evident from the fact that some data points were considered as 0 if the data was not available, because the neural network always needs some input in the form of a number. If the data points could have been found, then the results might have been more accurate.
- The stability index shows that the slope is almost 55% prone to failure. This can be inferred from the fact that various agents and factors are responsible for the stability of slope and if any of the factors go wrong, then that might have a huge impact on the stability of the slopes. It is also obvious from the stability index results of ANN that the bench with shale rock geology predominantly had lower stability index than the bench with predominantly coal geology.

CHAPTER-7

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