Predictions of Shear Displacement in Fully Grouted Rock Bolt

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ABSTRACT

An effective strata control is one of the most important components for the safe design of an underground mine workings. In underground mining operations, approximately 50 percent of the accidents occur due to the fall of roof or side walls. It is essential that a safe and efficient support system will ensure moral confidence to the miner, thereby improving safety and productivity. Bolting is one of the methods to strengthen roofs and provide a good support to weak rock mass.

There are some known methods to determine the shear displacement under in-situ as well as in the laboratory. These methods are tedious and time consuming. In the present investigation, Jordan-Elman network backed Genetic algorithm technique is used for the prediction of shear displacement, taking into account hole diameter and bolt dimensions, forces and normal displacement as input parameters. The method of genetic algorithms is a search technique based on the mechanics of natural selection and natural genetics implemented by coding each state of a particular optimization problem as a string of binary digits. In Jordan-Elman network context units have been used which provides the network with the ability to extract temporal information from the data set.

Network with five input processing elements, two hidden layer, each having 4 processing elements and context unit time of 0.8, and one output neurons is designed. Tanhaxon transfer function has been used for each of the two hidden layer. The coefficients of correlation among the predicted and observed values are high, encouraging and the percentage error obtained is also very low.

Keywords: Rock bolt; Grouting; Jordan-Elman network; Strength of rock

1. INTRODUCTION

Rock bolt plays an important role as one of the most widely used strengthening systems for underground excavation as well as for rock slope also. Some method has been proposed to estimate the reinforcing effect, but the mechanism and bolt effect in jointed rock mass is not clearly discussed (Freeman,1987; Bjornfot and Stephanson,1984a). So, a series of laboratory shear tests were performed to explain the support mechanism of rock bolt in jointed rock mass subject to shear deformation.

Numerous researchers have carried out field monitoring on rock bolts (Freeman,1987; Sun, 1984; Bjornfot and Stephanson,1984b). Freeman (1987) performed pioneering work in studying the performance of fully grouted rock bolts in the Kielder experimental tunnel. He monitored the loading process of the bolts and the distribution of stresses along the bolt .On the basis of his monitoring data, he proposed the concepts of 'neutral point', 'pick up length' and 'anchor length'. At the neutral point, the shear stress at the interface between the bolt and the grout medium is zero, while the tensile axial load of the bolt has a peak value. The pick up length refers to the section of the bolt from the near end of the bolt (on the tunnel wall) to the neutral point. The shear stresses on this section of the bolt pick up the load from the rock and drag the bolt towards the tunnel. The anchor length refers to the section of the bolt from the neutral point to the far end of the bolt (its seating deep in rock).The shear stress in these sections of the bolt anchor the bolt to the rock mass. These concepts clearly outline the behavior of fully grouted rock bolts in a deformed rock formation (Stillborg,1999).

The use of rock bolts has increased dramatically since 1950's and the type of bolts mainly used were mechanical expansion shell bolts (Bjornfot and Stephanson,1984a; Barton and Choubey, 1977). Determination of shear displacement during bolting is an important task and at the same time difficult to precisely determine in the laboratory. Hence, an attempt has been made to study the shear displacement from various simple parameters which influence the grouting (Barton and Bakthar, 1983).

Some researchers used application of soft computing tool for prediction of physico-mechanical properties of rock mass (Singh et al., 2001; Singh et al., 2005, Singh et al., 2007). This paper presents an alternative modeling approach for the prediction of shear displacement during grouting. The principle constituent of the modeling approach is Jordan-Elman network. The model has been designed with 1 input processing elements (PEs), 2 hidden PEs and 1 output PEs. The focus here is not only on how to construct the model but, also on how to use this modeling framework to interpret the results and asses the reliability of the model.

2. JORDAN-ELMAN NETWORK

Jordan and Elman networks extend the multilayer perceptron with context units, which are processing elements (PEs) that remember past activity (Elman, 1990; Jordan,1986). Context units provide the network with the ability to extract temporal information from the data set. In the Elman network, the activities of the first hidden PEs are copied to the context units, while the Jordan network copies the output of the network. Networks which feed the input and the last hidden layer to the context units have been used as shown in Fig. 1 (Jordan, 1986).

The context unit remembers the past of its inputs using what has been called a recency gradient, i.e., the unit forgets the past with an exponential decay. This means that events that just happened are stronger than the ones that have occurred further in the past. The context unit controls the forgetting factor through the time constant and the useful values are between 0 and 1. A value of 1 is useless in the sense that all of the past is factored in. On the other extreme, a value of zero means that only the present time is factored in (i.e., there is no self-recurrent connection). The closer the value is to 1, the longer the memory depth and the slower the forgetting factor (Hertz et al., 1991).

The theory of neural networks with context units can be analyzed mathematically only for the case of linear PEs. In this case the context unit is nothing but a very simple lowpass filter. A lowpass filter creates an output that is a weighted (average) value of some of its more recent past inputs. In the case of the Jordan context unit, the output is obtained by summing the past values multiplied by the scalar Γ^n as shown in the Fig. 2.

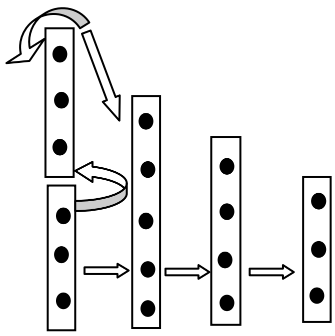

Fig. 1 - Network structure

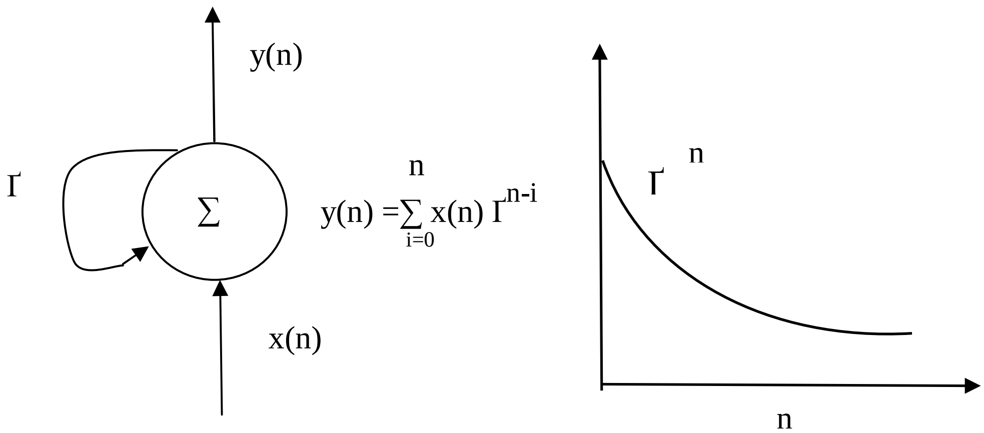

Fig. 2 - Context unit response

Notice that an impulse event x(n) (i.e. x(0)=1, x(n)=0 for n>0) that appears at time n=0, will disappear at n=1. However, the output of the context unit is t^1 at n=1, t^2 at n=2, etc. This is because these context units are called memory units, because they "remember" past events. it should be less than 1, otherwise the context unit response gets progressively larger (unstable) (Freeman and Sakura,1991).

The Jordan network and the Elman network combine past values of the context units with the present inputs to obtain the present net output. The input to the context unit is copied from the network layer, but the outputs of the context unit are incorporated in the net through adaptive weights. This network uses straight backpropagation to adapt all the network weights. The context unit time constant is pre-selected .One issue in these nets is that the weighting over time is inflexible since we can only control the time constant (i.e. the exponential decay). Moreover, a small change in t is reflected in a large change in the weighting .It is due to the exponential relationship exist between the time constant and the amplitude. In general, we do not know how large the memory depth should be, so this makes the choice of t problematic, without a mechanism to adapt it.

3. SHEAR LINE DISTRIBUTION AROUND A BOLT

Rock bolts are installed with an initial setting load of about 500 to 1000 kg acting upwards direction in the usual case. Efforts are being made to determine the total effect of this upward thrust. This upward thrust combined with gravity load, can lead to the development localized shear stress that tend to extend upward and away from the bolt head at an angle. This angle is observed to be 35° for most of the rock types (Bjustrom, 1974; Aastrup and Sallstrum, 1961).

Obvert and Duvall (1967) observed that shear failure will occur when the maximum shear stress reaches a value greater than rock strength. This mechanism should be slightly modified if these shear lines pass through planes of weakness (ASCE, 1974). As the rock fails, adjacent bolts will have to resist lateral movement along the shear plane and load will be transferred to the bolt which will be caused due to shear failure. As shear slip occurs, irregularities will cause the opposing faces to separate and the resistance of this vertical separation will develop the tension strain. Tension at one point in center will cause compression above and below, as the bolt resists movement in a vertical direction (ASTM, 1978; Bussey,1961).

The stresses in different section of the bolt can be now described in detail as given in Fig. 3.

(i) On the section $0<=x<x_o$ zero shear stress and a constant axial stress in the bolt i.e.

$$\Gamma_b (x) = 0 \tag{1}$$

$$\sigma_b (x) = \sigma_{bo} \tag{2}$$

(ii) On the section $x_o <= x < x_1$, the interface is partially decoupled

$$\Gamma_b (x) = s_t \quad (3)$$
$$\sigma_b (x) = \sigma_{bo} - 4s_t/d_b(x-x_o) \quad (4)$$

(iii) On the section $x1 <= x < x_2$, the interface is partially decoupled with the residual shear strength linearly increasing to the peak value.

$$\Gamma_b (x) = \omega s_p + (x-x1)\Delta(1-\omega)sp \quad (5)$$

$$\sigma_b (x) = \sigma_{bo} -2s_p /d_b[2\omega(x-x_0)+(1-\omega)/ \Delta(x-x_1)^2] \quad (6)$$

where, $\Delta = x_2-x_1$, and $\omega = s_r/s_p$, the ratio of residual shear strength to the peak shear strength.

(iv) On the section $x > x_2$, the deformation is compatible across the interface and no decoupling occurs.

$$\Gamma_b (x) = s_p e^{-2\alpha(x-x_2/d_b)} \quad (7)$$

$$\sigma_b (x)=2s_p e^{-2\alpha(x-x_2/d_b)} \quad (8)$$

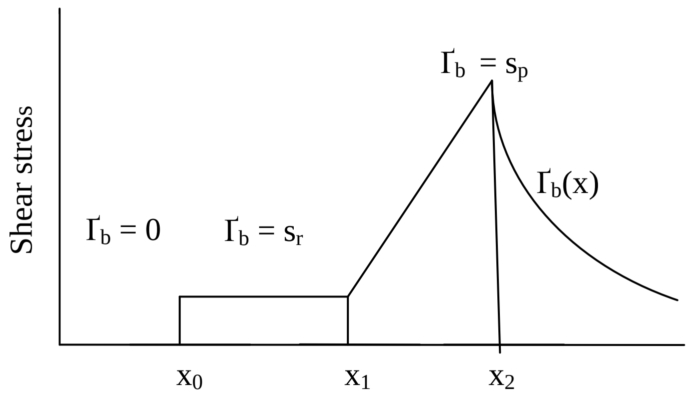

Fig. 3 - Shear stress on fully grouted bolt

4. EXPERIMENTAL TECHNIQUES

Several different rock bolting systems commonly used in mines exist which were tested under shear conditions (Cambefort, 1977). The rock models were designed in such a way that when they will be loaded under compression (under a servo controlled MTS stiff Testing Machine) a shear force component will act on the bolt. This arrangement will be necessary for each type of grouting material.

5. BOLTING AND GROUTING MATERIALS

The bolts employed in these tests were of three types:

(i) 16 mm diameter smooth steel bolts in 24 diameter hole,
(ii) 16 mm diameter corrugated steel bolts in 24 mm diameter holes and
(iii) 12mm diameter smooth steel bolt in 20 mm diameter holes.

The three different grouting materials used in the present study were;

(i) Resin,
(ii) Inorganic cement and
(iii) Portland cement.

Fine grained, equiangular, isotropic sandstone was used for the shear block test as described in detail by Srinivas et al. (1997). Strength properties of Chunar sandstone is shown in Table1.

Table 1 - Physico-mechanical properties of Chunar sandstone

Property	Average Value
Uniaxial compressive Strength	92.1 MPa
Tensile Strength	6.58 MPa
Shear Strength	14.5 MPa
Point Load Strength Index	4.35 MPa
Longitudinal Wave velocity	3.451 km/sec

The preparation of rock models primarily involves cutting the large blocks into cubical shapes, drilling holes and making smooth shear surfaces. Large pieces of rock blocks obtained from the field are cut into perfect cubes of 15 cm size using a stone cutting diamond saw machine. A vertical hole of required diameter was drilled at the centre of one of the faces of the cube with the help of a diamond coring bit (Singh,1976) and a diagonal cut is given by the stone saw through one of the adjacent faces of the cube, in which the hole was made. This gives a smooth shear surface which cuts the hole axis at an angle of 45°. Two types of hole diameters were used; 20 and 24 mm, which were drilled by a diamond core drill.

6. NETWORK ARCHITECTURE FOR JORDAN-ELMAN MODEL

In this network, two hidden layers have been used. The step size, momentum rate etc. have been optimized using genetic algorithm. Total of 233 data sets have been taken for network. For Jordan-Elman model 213 data sets were used for the network training and 20 data sets for testing and validation. Each of the two hidden layer has 4 processing elements (PEs). Tanhaxon transfer function has been used for each of the two hidden layer. Context time has been taken to be 0.8 because a value of 1 is useless in the sense that all of the past is factored in. On the other extreme, a value of zero means that only the present time is factored in (i.e., there is no self-recurrent connection). The closer the value is to 1, the longer the memory depth and the slower the forgetting factor.Integrator Axon has been chosen to be transfer function of context unit.

7. RESULTS AND DISCUSSIONS

The results are presented in this section to demonstrate the performance and applicability of the network. Unlike a linear system, a neural network is not guaranteed to find the global minimum. A neural network can actually arrive at different solutions for the same data, given different values of the initial network weights. The initial network weights define the starting point on the error surface. As the network transverses, the error surface in the direction of the minimum error, it sometimes gets caught in a local minimum. Thus, in order to develop a statistically sound neural network model, the network must be trained multiple times. Thus, network was trained with 10 runs each with 100 training epochs. The correlation coefficient between predicted and observed values is 0.975 (Fig. 6). Mean absolute percentage error (MSE) and normalized absolute percentage errors (NMSE) for the variables are 3.744 and 0.0777 respectively as shown in Table 2. Figure 7 exhibits the graph which gives the average of the multiple training runs along with the standard deviation boundaries. Wide spread in the standard deviation shows that each run can take a significantly different path to the solution. The goal is to try and find a neural network model for which multiple trainings approach the same final MSE. This can be seen by noting that the standard deviation decreases as the final epoch is approached. Figure 8 shows variation of MSE for all the 10 runs each with 100 epochs. Sensitivity analysis of each input has been done and shown in Table 3. This shows that network is equivalent to three input i.e. hole diameter (m), bolt diameter (m), and normal displacement (D_N) as rather than the five input parameters. Figure 4 shows the performance of the network output.

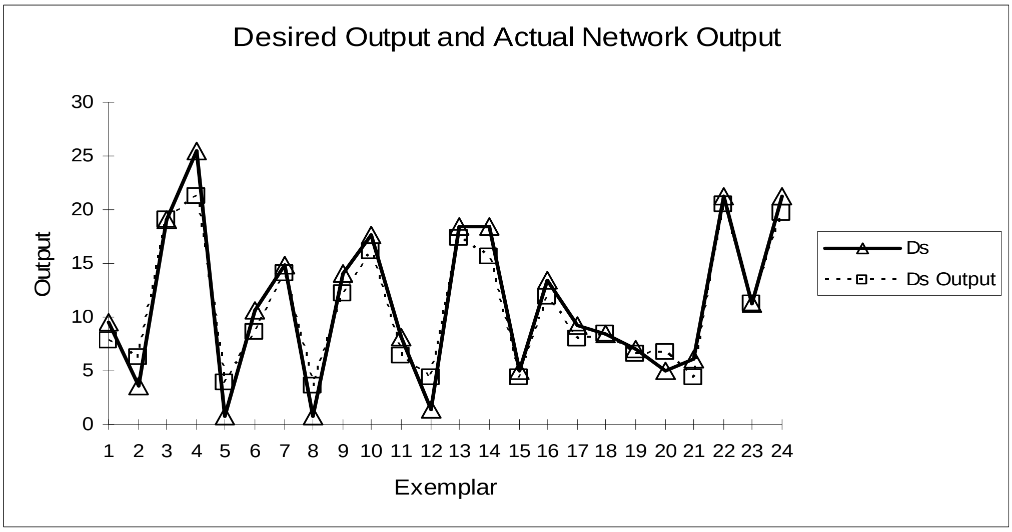

Fig.4 - Graph between observed and predicted values for Ds

Table 2 - Output parameters for network

Performance	Ds
MSE	3.744243466
NMSE	0.07765033
MAE	1.619724049
Min Abs Error	0.010315475
Max Abs Error	4.194972229
R	0.9499

Table 3 - Output parameters for network and their relative importance

Sensitivity	Ds
Hole Dia (mm)	0.766413093
Bolt Dia (mm)	0.991334498
Dn	0.538634539
Fn	0.013803082
Fs	0.013768551

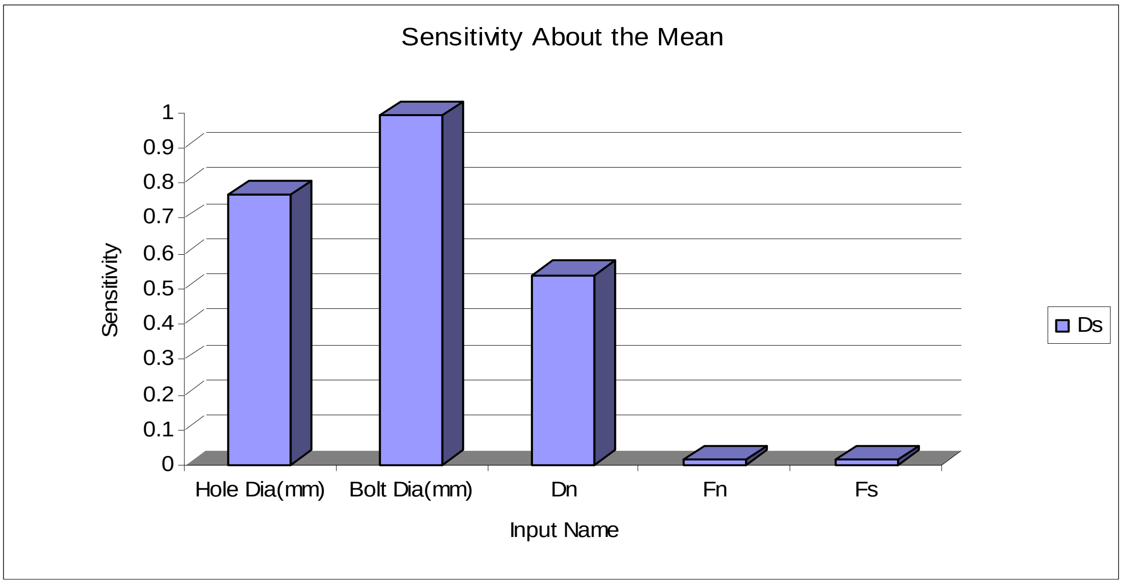

Fig. 5 - Measure of the relative importance among the inputs of the Jordan-Elaman Network for hole diameter

MSE is minimum at the run number 1 and epoch number 48 having a value of 0.008 as shown in Tables 4a and 4b. Sensitivity analysis indicate trend of the increment of shear displacement (Ds) with the variation of each input. After doing sensitivity analysis in order to grasp a degree of effects of input parameters used in this network on the output shear displacement (Ds), it is found that bolt diameter have great influence on it while shear force has the least influence (Fig. 5 and Table 3). Observed and predicted values of shear displacement (D_S) along with the percentage errors are given in Table 5.

Sensitivity analysis measures the effect of small changes in the input channels on the output, and is computed over the whole training set. It can be used to identify superfluous input channels. One can prune the input space by removing the insignificant channels. This will reduce the size of the network, which in turn reduces the complexity and the training times. The basic idea is that the inputs to the network are shifted slightly and the corresponding change in the output is reported either as a percentage or a raw difference.

By performing sensitivity analysis on a trained network irrelevant inputs have been found and eliminated. The elimination of irrelevant inputs reduces data collection cost and can improve network's performance. Furthermore, sensitivity analysis can give insights into the underlying relationships between the inputs and outputs. The network learning has been disabled during this operation such that the network weights are not affected.

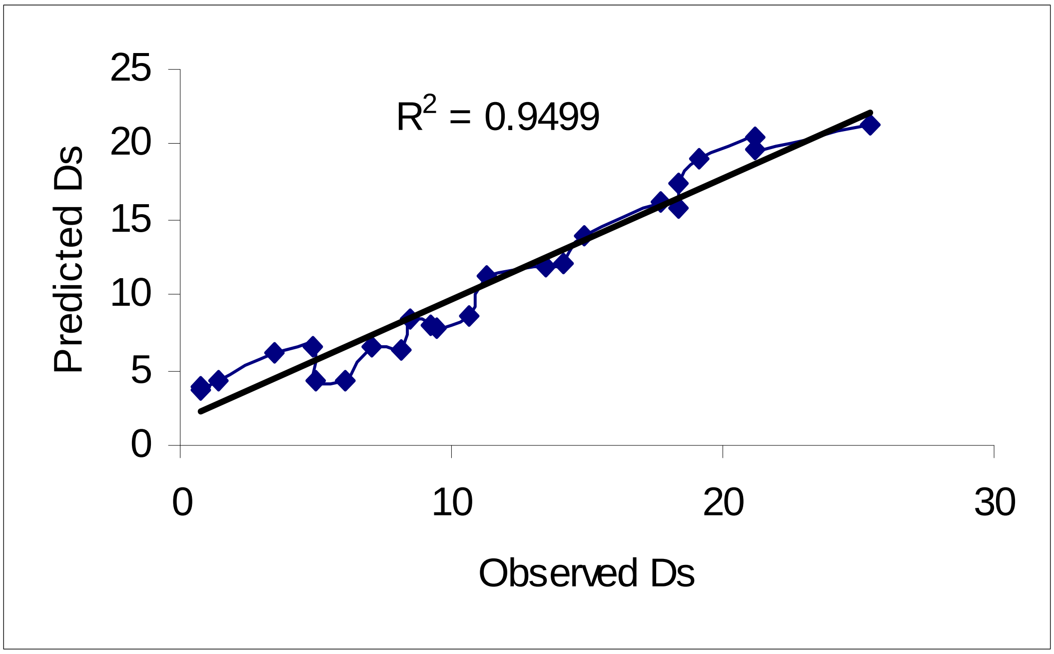

Fig.6 - Correlation between observed and predicted values of Ds by Jordan-Elman network

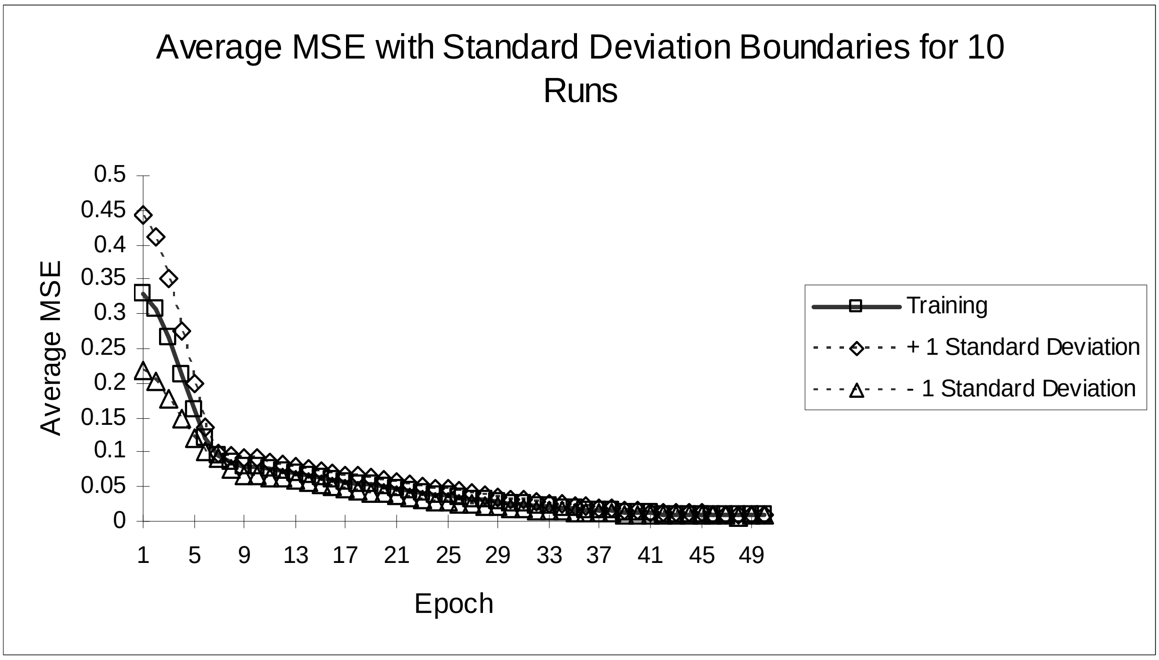

Fig.7 - Performance graph of the average mean square error (MSE) vs number of epochs for 10 Runs for Ds predicted by Jordan-Elaman Network

Table 4(a) - Output parameters for network

All Runs	Training Minimum	Training Standard Deviation
Average of Minimum MSEs	0.008391098	0.000255172
Average of Final MSEs	0.008391098	0.000255172

Table 4(b) - Output parameters for best network

Best Network	Training
Run #	1
Epoch #	48
Minimum MSE	0.007972477
Final MSE	0.007972477

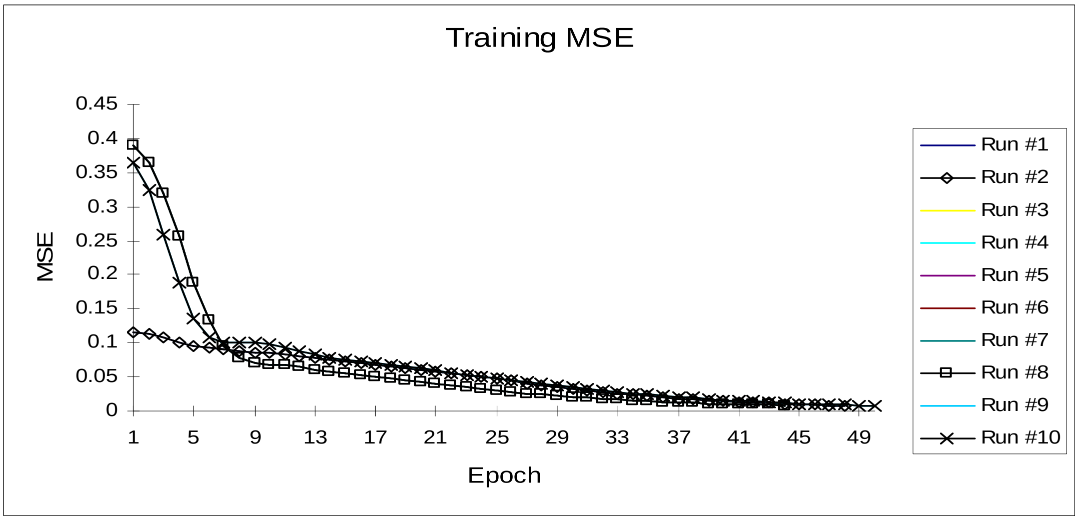

Fig.8 - Performance graph of the mean square error Vs number of epochs for 10 Runs for Ds predicted by Jordan Elaman network

The MSE is the average of the squares of the difference between each output PE and the true sleep stage (desired output). In Table 2, the MSE of Ds is 3.47442. The size of the mean square error (MSE) can be used to determine how well the network output fits the desired output, but it does not necessarily reflect whether the two sets of data move in the same direction.

Hence prediction of shear displacement in this paper is important in half-anchored rock bolting. This study can be used to easily predict the stability of mine structure during bolting and also the effect of bolt diameter and hole diameter on these rocks especially in case of coal mines, where weak shale or coarse grained sandstone (or mudstone) roofs are present which are very common in Indian coal mines.

Table 5 - Observed and predicted values of Shear displacement from Jordan-Elman model along with the percentage error

Sl. No.	Hole Dia(mm)	Bolt Dia(mm)	Dn	Fn	Fs	Ds	Ds Output	%error
1	24	16	6.5	72	101.82	9.48	7.799093	17.73108
2	20	12	2.5	5	7.07	3.53	6.217529	-76.134
3	24	16	13.5	23.5	33.23	19.09	19.0726	0.09116
4	20	12	18	25	35.36	25.45	21.25503	16.48319
5	20	12	7.5	32	45.25	10.6	8.570607	19.14522
6	24	16	10.5	17.5	24.75	14.85	13.99607	5.750339
7	20	12	10	25	35.36	14.14	12.17107	13.92455
8	24	16	12.5	36.5	51.61	17.67	16.12713	8.731598
9	20	12	6	51	72.12	8.2	6.45029	21.33793
10	24	16	13	25	35.36	18.38	17.42174	5.213604
11	24	16	13	62.5	88.39	18.36	15.68299	14.58068
12	24	16	3.5	63	89.1	4.95	4.354674	12.02678
13	20	12	9.5	41	57.98	13.43	11.89931	11.39756
14	24	16	6.5	50	70.72	9.19	8.02297	12.69891
15	24	16	6	36	50.91	8.48	8.443133	0.434748
16	24	16	5	62	87.68	7.07	6.532864	7.597396
17	24	16	4.3	136.5	193.04	6.08	4.345314	28.53103
18	24	16	15	39.5	55.86	21.21	20.50679	3.315464
19	20	12	8	48.5	68.58	11.31	11.29968	0.091207
20	20	12	15	25.5	36.06	21.21	19.70509	7.095305

Hole Dia = Hole diameter; Bolt Dia = Bolt diameter; Dn = Normal displacement; Fn = Normal force; Fs = Shear force; Ds = Shear Displacement

$$MSE = \frac{\sum_{j=0}^{P} \sum_{i=0}^{N} (d_{ij} - y_{ij})^2}{N\ P} \qquad (1)$$

where

P = number of output processing elements,

N = numbers of exemplars in a data set,

y_{ij} = network output for exemplar i for processing element j, and

d_{ij} = desired output for exemplar i for processing element j.

The normalized mean squared error (NMSE) is defined by the following formula:

$$NMSE = \frac{P\ N\ MSE}{\sum_{j=0}^{P} \frac{N \sum_{i=0}^{N} d_{ij}^{2} - \left(\sum_{i=0}^{N} d_{ij} \right)^{2}}{N}} \tag{2}$$

where
P = number of output processing elements,
N = numbers of exemplars in a data set,
MSE = mean square error, and
d_{ij} = desired output for exemplar i for processing element j.

8. CONCLUSIONS

Jordan-Elman method presented in this paper shows a good potential to model complex, and multivariate problems. Considering the complexity of the relationship among the input and the output, results obtained are very close and inspiring. This modeling is an emerging computational network which feed the input and the last hidden layer to the context. Perhaps the most interesting feature of this approach is that we can cope scientifically with subjectivity and uncertainty in the engineering process, rather than blindly avoiding them. Grout mixtures, pressures, pumping rates, depth of grout holes, and drilling and grouting sequence of the holes are determined in the field. In flowing water conditions the use of quick-setting grouts incorporating accelerators with the possible addition of fillers, completely sealed or reduced the flow to acceptable levels. So grouting prediction is useful to check water infiltration in underground mine and tunnels.

Experimentally it has been found that resin grouted bolts have achieved maximum shear resistance with small shear displacement compared to other types. This type of grouting is well suited for rock reinforcement, particularly in fractured and jointed rock, where shear movements usually dominate. This study can be used to easily predict the shear displacement in fully grouted rock bolts especially in case of coal mines.

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