Analysing Structural Failure Of Bridgesemploying Bridge Parameters And Stochastic Modelling

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Abstract- *Structural failure in pertaining to bridges is extremely challenging to assess.. Stochastic and statistical computing is being explored to derive conclusive decisions where human intervention is difficult in time and resource constrained situations. One such situation is bridge failures in cases of seismic impacts. In case of earthquakes, it is necessary to immediately evaluate the possibility of damage to bridges as they are critically important to carry out relief operations while carrying population and essential goods. However, human inspection in earthquake stricken areas may take a lot of time increasing the risk of using bridges which are severely damaged thereby risking human life. Hence, quick automated tools are required which can predict bridge damages quickly and based on less number of parameters with relatively high accuracy. This work presents a back propagation based neural network architecture for bridge failure prediction. The data set used is the Stanford Earthquake Dataset (STEAD). It has been shown that the proposed work attains high classification accuracy and low computation complexity making the model effective for quick evaluation of bridges from seismic impacts.*

Keywords: Structural Failure,Stanford Earthquake Dataset (STEAD),Bridge damage estimation,), Classification Accuracy.

I. INTRODUCTION

The damage state of a bridge has significant implications on the post-earthquake emergency traffic and recovery operations and is critical to identify the post-earthquake damage states without much delay. Currently, the damage states are identified either based on visual inspection or pre-determined fragility curves. Although these methodologies can provide useful information, the timely application of these methodologies for large scale regional damage assessments is often limited due to the manual or computational efforts [1]. Earthquakes have a cascading detrimental effect on bridge structures that are the critical links in transportation networks [2]. The damage state evaluation of the bridges is critical for assessing the rapid recovery of transportation networks. The damage state of the bridges has been conventionally evaluated by visual inspection; a team of trained engineers visually inspects the bridge and identifies whether the bridge can be safely re-opened to public according to some specific guidelines. The visual inspection methodology is often time-consuming and may take several weeks to several months or longer to finish the inspection procedure, depending on the extent of damage and the availability of qualified inspectors [3].

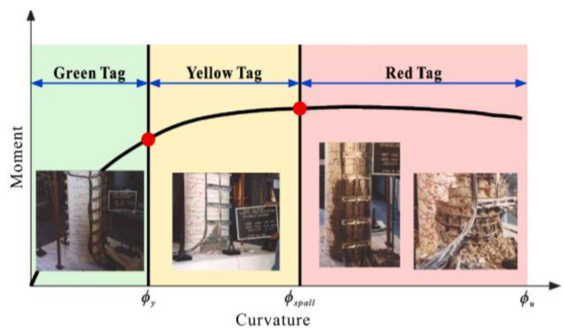

Fig. 1 Bridge column capacity and corresponding tags

The challenges in the pandemic stricken scenario worldwide needed to reanalyse the pharmaceutical supply chain and its relatable issues.

1.2 Challenges in bridge damage detection.

To take an informed decision for the recovery process, it is critical to identify the damage state of a bridge in the aftermath of an earthquake [3]. The simple and widely strategy adopted for the rapid damage assessment of the bridge is the implementation of fragility curves in earthquake alerting systems [4]. Various researchers have generated fragility curves for infrastructure portfolios. However, the variation in the geometric, structural, and material properties across the bridges in a region necessitates the grouping of bridge classes for the generation of fragility curves. Such a grouping often leads to the fragility curves of bridge classes rather than bridge-specific fragility curves, i.e., it merely accounts for important attributes of a specific bridge's structural design.Due to the need of large data sets pertaining to bridge failure analysis needs to be analysed [4], it is necessary to use computational tools which are fast, accurate and can handle copious amounts of data [5].

II. STATISTICAL MODELS

Evolutionary statistical algorithms are a set of such algorithms which show the aforesaid characteristics [6].

Evolutionary Statistical algorithms try to mimic the human attributes of thinking which are [7]:

1) Parallel data processing
2) Self-Organization
3) Learning from experiences

Some of the commonly used techniques are discussed below:

1)Statistical Regression: These techniques are based on the time series approach based on the fitting problem that accurately fits the data set at hand. The approach generally uses the auto-regressive models and means statistical measures. They can be further classified as[8]:

a) Linear
b) Non-Linear

Mathematically:

Let the time series data set be expressed as [9]:

$$Y = \{Y1, Y2 \ldots \ldots \ldots \ldots \ldots \ldots . . Yt) \quad \textbf{(1)}$$

Here,

Y represents the data set

t represents the number of samples

Let the lags in the data be expressed as the consecutive differences.

The first lag is given by:

$$\Delta Y_1 = Y_{t-1} \quad \textbf{(2)}$$

Similarly, the j^{th} lag is given by:

$$\Delta Y_j = Y_{t-j} \quad \textbf{(3)}$$

2) Correlation based fitting of time series data: The correlation based approaches try to fit the data based on the correlation among the individual lags. Mathematically it can be given by [10]:

$$A_t = corr(Y_t, Y_{t-1}) \quad \textbf{(4)}$$

Here,

Corr represents the auto-correlation (which is also called the serial correlation)

Y_t is the t^{th} lagged value

Y_{t-1} is the $(t-1)^{st}$ lagged value

The mathematical expression for the correlation is given by

$$corr(Y_t, Y_{t-1}) = \frac{conv(Y_t, Y_{t-1})}{\sqrt{varY_t, varY_{t-1}}} \quad \textbf{(5)}$$

Here,

Conv represents convolution given by [11]:

$$conv\{x(t), h(t)\} = \int_{t=1}^{\infty} x(\vartheta)h(t-\vartheta)d\vartheta \quad \textbf{(6)}$$

Here,

ϑ is a dummy shifting variable for the entire span of the time series data

t represents time

Y_t is the t^{th} lagged value

Y_{t-1} is the $(t-1)^{st}$ lagged value

X is function 1

H is function 2

Var represents the variance given by [12]:

$$var(X) = X_i - E(X) \quad \textbf{(7)}$$

Here,

Xi is the random variable sample

E represents the expectation or mean of the random variable X

3) Finite Distribution Lag Model (FDL): This model tries to design a finite distribution model comprising of lags fitted to some distribution such as the normal or lognormal distributions. Mathematically [13]:

$$Y_t = \alpha_t + \delta_1 z_1 + \cdots \ldots \ldots \ldots \ldots . \delta_t z_t + \mu_t \quad \textbf{(8)}$$

Here,

Y_t is the time series data set

α_t is a time dependent variable

δ_1 is a time-varying co-efficient

z is the variable (time variable)

t is the time index

μ_t is the time dependent combination-coefficient

4) Artificial Neural Networks (ANN): In this approach, the time series data is fed to a neural network resembling the working of the human based brain architecture with a self-organizing memory technique [14].

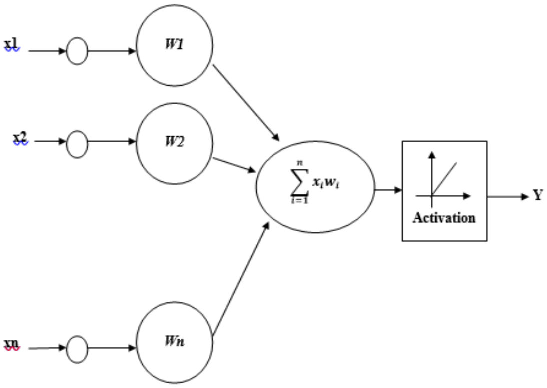

Fig.2 Mathematical Model of Neural Network

The approach uses the ANN and works by training and testing the datasets required for the same. The general rule of the thumb is that 70% of the data is used for training and 30% is used for testing. The neural network can work on the fundamental properties or attributes of the human brain i.e. parallel structure and adaptive self-organizing learning ability. Mathematically, the neural network is governed by the following expression:

$$Y = f\left(\sum_{i=1}^{n} X_i \, . \, W_i + \theta_i\right) \qquad \textbf{(9)}$$

Here,

X_i represents the parallel data streams

W_i represents the weights

θ represents the bias

f represents the activation function

The second point is critically important owing to the fact that the data in time series problems such as sales forecasting may follow a highly non-correlative pattern and pattern recognition in such a data set can be difficult. Mathematically:

$$x = f(t) \qquad \textbf{(10)}$$

Here,

x is the function

t is the time variable.

The relation f is often difficult to find being highly random in nature.

The neural network tries to find the relation f given the data set (D) for a functional dependence of x(t).

The data is fed to the neural network as training data and then the neural network is tested on the grounds of future data prediction. The actual outputs (targets) are then compared with the predicted data (output) to find the errors in prediction. Such a training-testing rule is associated for neural network. The conceptual mathematical architecture for neural networks is shown in the figure below where the input data is x and fed to the neural network [15].

4) Fuzzy Logic

Another tool that proves to be effective in several prediction problems is fuzzy logic. It is often termed as expert view systems. It is useful for systems where there is no clear boundary among multiple variable groups. The relationship among the inputs and outputs are often expressed as membership functions expressed as[16]:

A membership function for a fuzzy set A on the universe of discourse (Input) X is defined as:

$$\mu A : X \rightarrow [0, 1] \qquad \textbf{(11)}$$

Here,

each element of X is mapped to a value between 0 and 1. It quantifies the degree of membership of the element in X to the fuzzy set A.

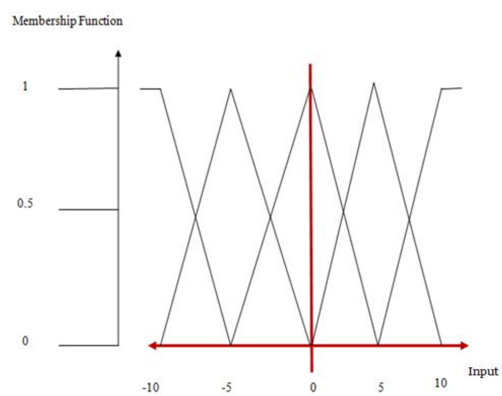

Fig.3 Graphical Representation of Membership Functions

Here,

x axis represents the universe of discourse (Input).

y axis represents the degrees of membership in the [0, 1] interval.

The final category is neuro fuzzy expert systems which governs the defining range of the membership functions.

III. PREVIOUS WORK

This section presents a brief summary of the salient points in the proposed work.

Mangalathu, et al. in [1] proposed that the damage state of a bridge has significant implications on the post-earthquake emergency traffic and recovery operations and is critical to identify the post-earthquake damage states without much delay. Currently, the damage states are identified either based on visual inspection or pre-determined fragility curves. Although these methodologies can provide useful information, the timely application of these methodologies for large scale regional damage assessments is often limited due to the manual or computational efforts. This paper proposes a methodology for the rapid damage state assessment (green, yellow, or red) of bridges utilizing the capabilities of machine learning techniques. Contrary to the existing methods, the proposed methodology accounts for bridge-specific attributes in the damage state assessment. The proposed methodology is demonstrated using two-span box-girder bridges in California. The prediction model is established using the training set, and the performance of the model is evaluated using the test set. It is noted that the machine learning algorithm called Random Forest provides better performance for the selected bridges, and its tagging accuracy ranges from 73% to 82% depending on the bridge configuration under consideration. The proposed methodology revealed that input parameters such as span length and reinforcement ratio in addition to the ground motion intensity parameter have a significant influence on the expected damage state.

Malekjafarian et al. in [2] proposed that a machine learning algorithm for bridge damage detection using the responses measured on a passing vehicle. A finite element (FE) model of vehicle bridge interaction (VBI) is employed for simulating the vehicle responses. Several vehicle passes are simulated over a healthy bridge using random vehicle speeds. An artificial neural network (ANN) is trained using the frequency spectrum of the responses measured on multiple vehicle passes over a healthy bridge where the vehicle speed is available. The ANN can predict the frequency spectrum of any passes using the vehicle speed. The prediction error is then calculated using the differences between the predicated and measured spectrums for each passage. Finally, a damage indicator is defined using the changes in the distribution of the prediction errors versus vehicle speeds. It is shown that the distribution of the prediction errors is low when the bridge condition is healthy. However, in presence of a damage on the bridge, a recognisable change in the distribution will be observed. Several data sets are generated using the healthy and damaged bridges to evaluate the performance of the algorithm in presence of road roughness profile and measurement noise. In addition, the impacts of the training set size and frequency range to the performance of the algorithm are investigated.

Guo et al. in [3] proposed that bridge health monitoring system has been widely used to deal with massive data produced with the continuous growth of monitoring time. However, how to effectively use these data to comprehensively analyze the state of a bridge and provide early warning of bridge structure changes is an important topic in bridge engineering research. This paper utilizes two algorithms to deal with the massive data, namely Kohonen neural network and long short-term memory (LSTM) neural network. The main contribution of this study is using the two algorithms for health state evaluation of bridges. The Kohonen clustering method is shown to be effective for getting classification pattern in normal operating condition and is straightforward for outliers detection. In addition, the LSTM prediction method has an excellent prediction capability which can be used to predict the future deflection values with good accuracy and mean square error. The predicted deflections agree with the true deflections, which indicate that the LSTM method can be utilized to obtain the deflection value of structure. What’s more, we can observe the changing trend of bridge structure by comparing the predicted value with its limit value under normal operation.

Bao et al. in [4] proposed that Structural health monitoring (SHM) is a multi-discipline field that involves the automatic sensing of structural loads and response by means of a large number of sensors and instruments, followed by a diagnosis of the structural health based on the collected data. Because an SHM system implemented into a structure automatically senses, evaluates, and warns about structural conditions in real time, massive data are a significant feature of SHM. The techniques related to massive data are referred to as data science and engineering, and include acquisition techniques, transition techniques, management techniques, and processing and mining algorithms for massive data. This paper provides a brief review of the state of the art of data science and engineering in SHM as investigated by these authors, and covers the compressive sampling-based data-acquisition algorithm, the anomaly data diagnosis approach using a deep learning algorithm, crack identification approaches using computer vision techniques, and condition assessment approaches for bridges using machine learning algorithms. Future trends are discussed in the conclusion.

Silva et al. in [5] showed that The structural health monitoring (SHM) field is concerned with the increasing demand for improved and more continuous condition assessment of engineering infrastructures to better face the challenges presented by modern societies. Thus, the applicability of computer science techniques for SHM applications has attracted the attention of researchers and practitioners in the last few years, especially to detect damage in structures under operational and environmental conditions. In the SHM for bridges, the damage detection can be seen as the end of a process to extract knowledge regarding the structural state condition from vibration response measurements. In that sense, the damage detection has some similarities with the Knowledge Discovery in Databases (KDD) process. Therefore, this chapter intends to pose damage detection in bridges in the context of the KDD process, where data transformation and data mining play major roles. The applicability of the KDD for damage detection is evaluated on the well-known monitoring data sets from the Z-24 Bridge, where several damage scenarios were carried out under severe operational and environmental effects.

Mei et al. in [6] proposed that Bridge health monitoring is a very important part for infrastructure maintenance. Traditional bridge health monitoring techniques require sensors to be installed on bridges, which is costly and time consuming. In order to resolve this issue, new damage detection techniques by installing sensors on passing-by vehicles on bridges and considering vehicle bridge interaction (VBI) have gained much attention from researchers in last decade. In this paper, a novel damage detection technique utilizing data collected from sensors mounted on a large number of passing-by vehicles is developed. First, an approach based on Mel-frequency cepstral coefficients (MFCCs) is introduced. Then, an improved version based on MFCCs and principal component analysis (PCA) taking advantage of mobile sensor network is proposed to overcome the deficiencies in the approaches that utilize single measurement. In the improved approach, the acceleration data is first collected from all the vehicles within a certain period. Then, the transformed features that are related to bridge damage are extracted from MFCCs and PCA. The damage can be identified by comparing the distributions of these transformed features. The results from the numerical analysis and lab experiments show that the approach not only identifies the existence of the damage, but also provides useful information about severity.

IV. PROPOSED SYSTEM MODEL

The proposed system model employs the scaled conjugate gradient (SCG) based approach for the classification problem. The reason for choosing the SGC algorithm lies in the relatively low computational and time complexity of the algorithm which allows to be used feasibly for real time data applications. The SGC approach uses the concept of steepest descent in regression learning which is explained subsequently [17].

Fundamentally, the learning capability of the SCG algorithm is based on the temporal learning capability governed by relation [18]:

$$\boldsymbol{w(i) = f(i,e)} \qquad \textbf{(12)}$$

Here,

w (i) represents the instantaneous weights

i is the iteration

e is the prediction error

The weight changes dynamically and is given by:

$$\boldsymbol{W_k \xrightarrow{e,i} W_{k+1}} \qquad \textbf{(13)}$$

Here,

W_k is the weight of the current iteration.

W_{k+1} is the weight of the subsequent iteration.

(i) Regression Learning Model

Regression learning has found several applications in supervized learning algorithms where the regression analysis among dependednt and independent variables is needed. Different regression models differ based on the the kind of relationship between dependent and independent variables, they are considering and the number of independent variables being used. Regression performs the task to predict a dependent variable value (y) based on a given independent variable (x). So, this regression technique finds out a relationship between x (input) and y(output). Mathematically [19],

$$\boldsymbol{y = \theta_1 + \theta_2 x} \qquad \textbf{(14)}$$

Here,

x represenst the state vector of inut variables

y rperesenst the state vector of output variable or variables.

Ɵ1 and Ɵ2 are the co-efficents which try to fit the regression learning models output vector to the input vector.

By achieving the best-fit regression line, the model aims to predict y value such that the error difference between predicted value and true value is minimum. So, it is very important to update the θ1 and θ2 values, to reach the best value that minimize the error between predicted y value (pred) and true y value (y). The cost function J is mathematically defined as:

$$\boldsymbol{J = \frac{1}{n}\sum_{i=1}^{n}(pred_1 - y_i)^2} \qquad \textbf{(15)}$$

Here,

n is the number of samples

y is the target

pred is the actual output.

(ii) Gradient Descent in Regression Learning

To update θ1 and θ2 values in order to reduce Cost function (minimizing MSE value) and achieving the best fit line the model uses Gradient Descent. The idea is to start with random θ1 and θ2 values and then iteratively updating the values, reaching minimum cost. The main aim is to minimize the cost function J. The critical aspect about steepest descent is the fact that it repeatedly feeds the errors in every iteration to the network till the errors become constant or the maximum number of allowable iterations are over. The technique to achieve faster convergence is the back propagation method which is essentially feeding back the errors of each iteration to from the output towards the input till convergence.

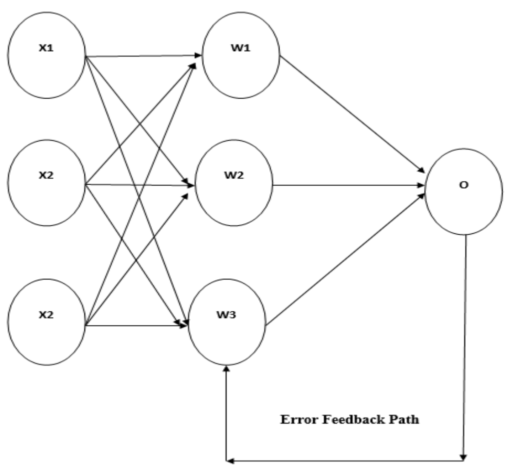

Fig.4Architecture ofBack Propagation

This can be mathematically given by:

$if\ PF \neq constant$
$for\ (k = 1, k \leq k_{max} = constant, k = k + 1)$
{
$W_{k+1} = f(X_k, W_k, e_k)$
}
else
{
$W_{k+1} = W_k\ \&\&\ training\ stops$
}

Here,
X_k is the input to the kth iteration
W_k is the weight to the kth iteration
W_{k+1} is the weight to the (k+1)st iteration
e_k is the error to the kth iteration
k is the iteration number
PF is the performance function deciding the end of training
k_{max} is the maximum number of iterations

Thus if the error is within tolerance, which is generally not feasible to find beforehand in time series data, the training is stopped if the performance function (which can be the training error) becomes constant for multiple iterations or the maximum number of iterations are over. Now there are various ways in which the error can be minimized. However, the steepest fall of the error with respect to weights is envisaged. It is depicted in the figure below:It can be seen from figure 1 that although the error in training keeps plummeting in all the three cases of gradient descent, the gradient 3 or g3 attains the maximum negative descent resulting in the quickest training among all the approaches and hence the least time complexity. This would be inferred from the number of iterations which are required to stop training. Thus the number of iterations would be a function of the gradient with which the error falls.

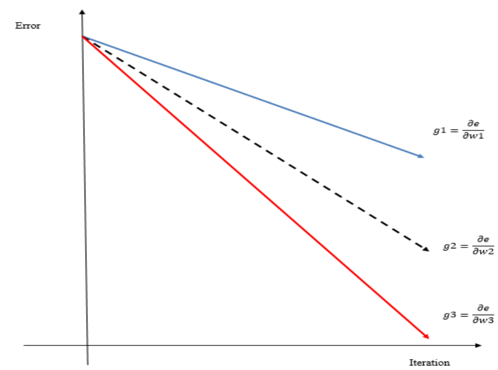

Fig.5 The concept of Steepest Descent

This is mathematically given by:

$$\boldsymbol{k_n = f(g = \frac{\partial e}{\partial w})} \quad \textbf{(16)}$$

Here,
k_n is the number of iterations to stop training.
g is the gradient
w is the weight
e is the error
f stands for a function of

The proposed methodology uses two key components one of which is the training algorithm and the other is the training optimization algorithm. Both are explained in this section

(iii) The Scaled Conjugate Gradient (SCG) Algorithm

There are several ways to implement the back propagation technique in the neural networks. One consideration however always remains that of the least time and space complexity so as to reduce the amount of computational cost that is associated with the training algorithm. The essence of the scaled conjugate gradient algorithm is the fact that it has very low space and time complexity making it ideally suited to large data sets to be analyzed in real time applications where the time is a constraint. The training rule for the algorithm is given by:

$$A_0 = -g_0 \qquad \textbf{(17)}$$

A is the initial search vector for steepest gradient search

g is the actual gradient

$$w_{k+1} = w_k + \mu_k g_k \qquad \textbf{(18)}$$

Here,

w_{k+1} is the weight of the next iteration

w_k is the weight of the present iteration

μ_k is the combination co-efficient

The final accuracy is computed as [20]:

$$Ac = \frac{TP+TN}{TP+TN+FP+FN} \qquad \textbf{(19)}$$

Here,

TP represents true positive

TN represents true negative

FP represents false positive

FN represents false negative

V. EXPERIMENTAL RESULTS

The experimental results obtained in the study are presented in this section. The system has been designed on Matlab. The STEAD dataset has been used for system modelling. The parameters considered are:

1) Age
2) Earthquake Magnitude
3) Distance from Epicenter
4) Damaged or not.

The data set parameters are depicted in figure 6.

1	Age (year)	Earthquake Magnitude	Distance to epicenter (miles)	Damaged or not?
2	53	6.9	59.9	1
3	57	4.7	50.0	0
4	67	4.0	6.9	0
5	79	4.0	6.3	0
6	82	4.4	5.4	0
7	80	3.5	8.1	0
8	75	3.6	5.7	0
9	75	3.8	5.6	0
10	71	4.2	13.8	0
11	50	4.1	8.8	0
12	48	4.3	13.3	0
13	44	5.8	29.0	0
14	21	5.7	32.0	0
15	15	6.7	11.1	1
16	60	4.7	5.8	0
17	54	4.3	10.4	0
18	50	4.9	3.2	0
19	50	5.1	20.2	0
20	48	5.0	5.5	0
21	47	5.1	5.4	0
22	47	5.1	3.7	0
23	24	4.2	6.1	0

Fig.6Used Data Set Parameters

1	x2 = Age (yr)	x4 = Earthq...	x5 = Distan...	y1 = Dama...
2	53	6.9000	59.9000	1
3	57	4.7000	50	0
4	67	4	6.8900	0
5	79	4	6.3000	0
6	82	4.4000	5.4000	0
7	80	3.5000	8.1000	0
8	75	3.6000	5.7000	0
9	75	3.8000	5.6000	0
10	71	4.2000	13.8000	0
11	50	4.1000	8.8000	0
12	48	4.3000	13.3000	0
13	44	5.8000	29	0
14	21	5.7000	32	0
15	15	6.7000	11.1000	1
16	60	4.7000	5.8000	0
17	54	4.3000	10.4000	0
18	50	4.9000	3.2000	0
19	50	5.1000	20.2000	0 Conv
20	48	5	5.5000	0
21	47	5.1000	5.4000	0
22	47	5.1000	3.7000	0
23	24	4.2000	6.1000	0

Fig.7Importing data to Matlab workspace

The next step becomes importing the data to the MATLAB workspace so that the training and target data can be split. The split ratio used in this work has bene chosen as 70:30 as a standard thumb rule.

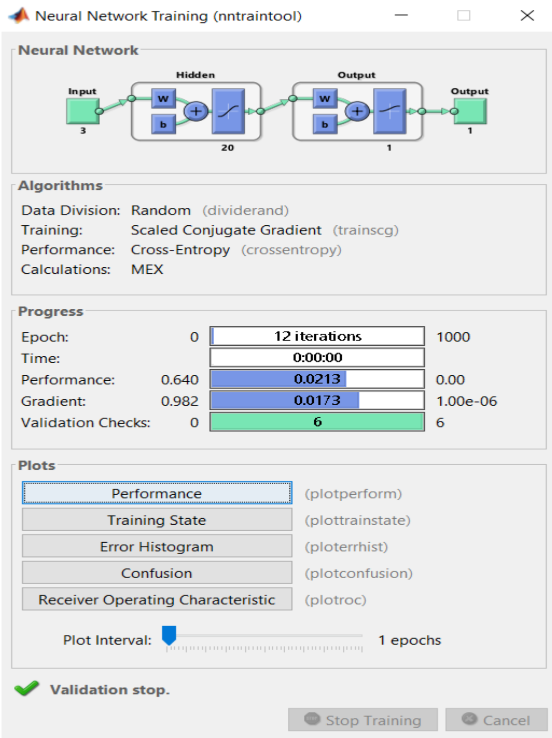

Fig.8Designed Neural Network

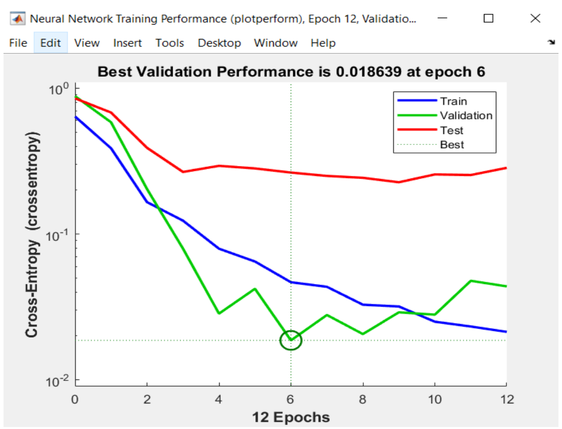

Fig.9Variation of MSE w.r.t. iterations

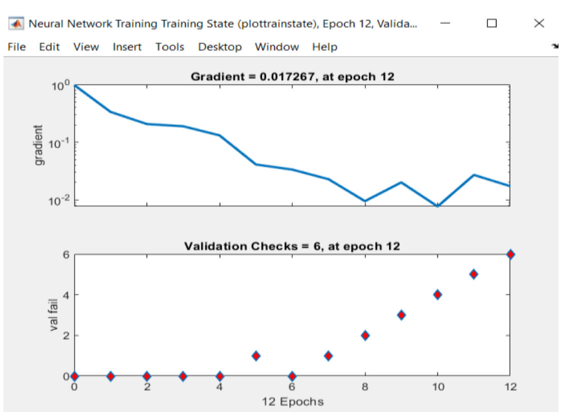

Fig.10Variation of gradient and μ w.r.t. iterations

Fig.11 Confusion Matrix

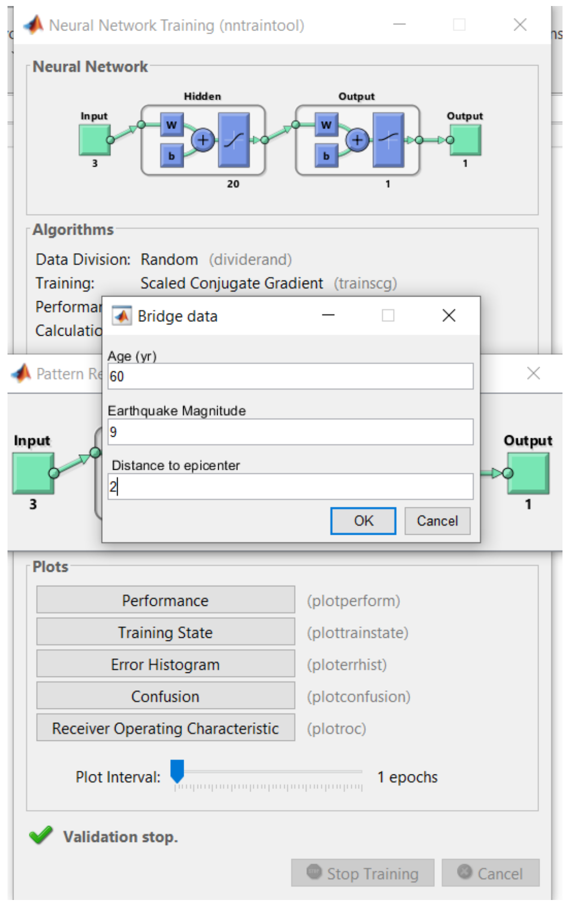

Fig.12 Prototype Testing

To test on an actual prototype of bridges, a case study of India has been chosen, in which an earthquake measuring 6.9 on the Richter scale has been considered with the epicentre located 22.72 N, 88.06 E near the Nepal-Sikkim border, about 68km NW of Gangtok with a focal length of 19.7km, as reported by the United States Geological Survey (USGS, www.usgs.gov).

The Indian Metrological Department (IMD) reported the epicentre 27.7N, 88.2E. with a focal length of 10km in Sikkim.

Table 1. Simulation under Indian Conditions in Case Study

S.No.	Magnitude.	Distance	Age	Result
1	6.9	2km	5	D
2	6.9	5km	10	D
3	6.9	10km	15	D
4	6.9	500km	20	ND
5	6.9	1000km	25	ND

The simulation for the proposed system has been made for bridges with ages ranging between 5years and 25 years.

The distance simulated is very near (2km to 10km) and far off (500km and 10000km).

The model accurately predicts the case of the bridge as damaged (D) and not damaged (ND).

The model can be further refined and fine tuned to specific geographical locations and conditions with more exhaustive statistical datasets fed to the model. The proposed model also outperforms the existing baseline technique with cited in [20] (Ac=91.16%) in terms of classification accuracy, which can be attributed to the steepest descent based back propagation algorithm of the approach.

VI. CONCLUSION

From the previous discussions, it can be concluded that it is mandatory to rapidly assess the damage to bridges in case of a recent earthquake as bridges are crucial for carrying out relief operation and transporting essentials. However, waiting for human inspection of all bridges in an earthquake hit zone can be extremely time consuming. Hence, an automated trained statistical model is extremely useful to assess the damage rapidly.

This work presents a back propagation based neural network model which is capable of predicting potential damages with very less number of parameters thereby ruling out human intervention. The model is trained using the back propagation based neural network and attains a high accuracy of around 98% with relatively low number of iterations. Thus it can be concluded the proposed model is effective in quick and accurate seismic bridge damage prediction.

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