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An Estimation Method of Geo-environmental Risk Index Based on Feed Forward Neural Network for Surveilling Underground Facilities

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Abstract

In this paper, we present the estimation method for using a feed forward neural network for surveilling underground facilities. Firstly, we propose the estimation model for calculating Geo-environmental risk index. This proposed model is consisted of three layers, namely data acquisition layer, Geo-environmental risk index estimation layer, and performance evaluation layer. In data acquisition layer, we have used three parameters as inputs that are compaction, granularity, and ground water level in underground facilities. In estimation the machine learning algorithm feed forward neural network (FFNN has been used for Geo-environmental risk index estimation. In performance evaluation layer the root mean square error (RMSE), mean absolute percentage error (MAPE), and mean absolute error (MAE) have been used to measure the estimated Geo-environmental risk index of FFNN. It is depicted from the results that the FFNN performs better and this system would help the caretaker to take measure before the happening of any accident due to underground facilities.

Keywords: *Geo-environmental, Risk Index), Feed Forward Neural Network(FFNN) Performance Evaluation. Root Mean Square Error (RMSE)*

1. Introduction

The basic problems identified by geo-environmental engineers to prevent different areas of the surface and also to clean up different areas of surface. The geo-environmental risk is also contributed to the underground risk; therefore, it is very necessary to escape from such as risk. Machine learning approaches for estimation and prediction have been used extensity in many areas.

Neural networks are very extensively used in many areas for prediction. It is very useful while solving the non-linear problem and very efficient method for solving complex applications. In the last two decades the ANNs have been used extensively used in order to analyze prediction problems in different situations. There ANNs is a learning approach having different types namely Self-Organization Map (SOM), feed forward neural network (FFNN), and recurrent neural network *etc*. In the proposed work we have used the feed forward neural network (FFNN) which has been proved a best for prediction. In the FFNN the connection between nodes does contain cycle. In the FFNN the information flows in one direction. No assumptions are made for the relationship between inputs and outputs [1, 2, 3]. Nowadays the researchers are taking interest in the use of CART analysis. It is like a tree-building method differs from conventional analysis techniques for data. The CART method is quit useful while creating decision rules and its performance is far better than other conventional methods. The CART has the ability to

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reveal the complicated interactions between predictors which may be not possible for conventional multivariate methods [4, 5]. The deep extreme learning machine has been proposed which is the combination of deep learning and extreme learning machine (ELM) and its basic purpose was to take benefit from both of them. The ELM was proposed by Huang *et al.*, [6] is a simple algorithm which is consisted of input layer, one hidden layer and one output layer. In the proposed work we have used the deep extreme learning machine in which we have used three hidden layers.

A lot of research has been carried for risk assessment in different areas. Many and different type of methods are proposed for underground risk index calculation by different authors. Kim *et al.*, in [7], provide a method for Incheon International Airport, the basic purpose of the proposed was to work on tunneling digging as well to continue the operations of the Airport. This approach was an efficient approach and without stopping the operations of the Airport they were working on tunneling. Sturk *et al.*, in [8], suggested another method in order to carry out the risk analysis and to assess risk. This project was for rail in Thailand. Image processing also play a key role in underground risk analysis and to assess risk. Alam *et al.*, in [9] applied the image processing technique in underground facilities in order to monitor these facilities, such as to detect crack, to monitor progress of work, etc. Many other methods have also been suggested for risk index estimation and prediction. Fayaz *et al.*, in [10] suggested an approach name integrated hierarchical fuzzy model in order to assess the risk of underground structure. Like image processing the fuzzy logic is also play a key role in risk assessment and analysis and the fuzzy logic has been deployed in numerous fields. The key objective of this work is to estimate the geo-environmental risk.

The objective of this is to find the estimated risk index for Geo-environmental risk index. The traditional way to estimate the risk index by experts is very costly and time consuming. Some other machines such as fuzzy logic are also very popular risk index estimation methods, but the fuzzy logic also requires experts to design rules. Therefore, in the proposed approach we have used machine learning algorithm to find the estimated Geo-environmental risk index in order to assist the caretaker to take measure before happening of any accident.

The structure of the papers is organized as below, the related work is explained in detail in Section 2. The proposed estimation methodology is explained in detail, and the material and estimation methods are deeply explained in Section 3. The experimental results and the performance evaluation are described in Section 4. In Section 5 the paper is concluded.

2. Related Work

Many researches have been done to calculate risk index in various areas using different approaches. In this section different methods used in different areas for risk index assessment have been discussed in detail.

A methodology based on Quantity Risk Assessment (QRA) has been proposed in order to assess risk for urban areas road tunnels. As there are immense traffic on road tunnels of urban area and it is very difficult to evaluate the operation of road tunnels in urban areas. Different types of events have been used in QRA model in order to assess risk road tunnels in urban areas [11, 12]. A new QRA model was developed by Meng *et al.*, [19], for evaluation of risk of non-homogenous urban road tunnels because the existing QRA contains several drawbacks. In this method the division of urban area in parts is carried out. A risk rank value is assigned to each part of the road tunnel.

Another method that is used extensively in many areas for risk calculation is fuzzy logic. Many researchers have used the fuzzy logic in different areas for different purposes in various fields. Blockely *et al.*, in [13] suggested the idea of fuzzy logic, such as fuzzification, membership functions, union, implication, aggregation, defuzzificatin, *etc*.

The idea of fuzzy fuzzy event tree analysis (FETA) in order to identify events was given by Cho *et al.*, [14]. Another method proposed by Wang *et al.*, in [15] in order to analyze bridge risk assessment. They introduced the concept of adaptive fuzzy inference system (ANFIS) for bridge risk assessment. Their proposed method can help the high way agencies to monitor the risks regularly. The proposed method is very useful and economical to assess bridge risk assessment. The proposed method also outperforms other counterparts' algorithms, such as multiple regression analysis (MRA).

Besides these algorithms many image processing techniques are also used by researchers to monitor underground structure. Image processing techniques have extensively have been used in order to monitor structure health [16,17], health monitoring and crack monitoring [18,19]. Dark line has been used in order to identify crack monitoring.

3. Proposed Methodology of Geo-environmental Risk Index Estimation

In the proposed Geo-environmental risk index estimation model, the feed forward neural network (FFNN) algorithm has been used for Geo-environmental risk index estimation. There are three parameters that have been taken into account for Geo-environmental risk index estimation namely compaction, granularity, and ground water level. These parameters are feed to FFNN for Geo-environmental risk index estimation. In the performance evaluation layer of the proposed model root mean square error (RMSE), mean absolute error (MAE) and mean absolute percentage error (MAPE) have been used to measure the performance of estimated layer results. The structure diagram for geo-environmental risk index is shown in Figure 1.

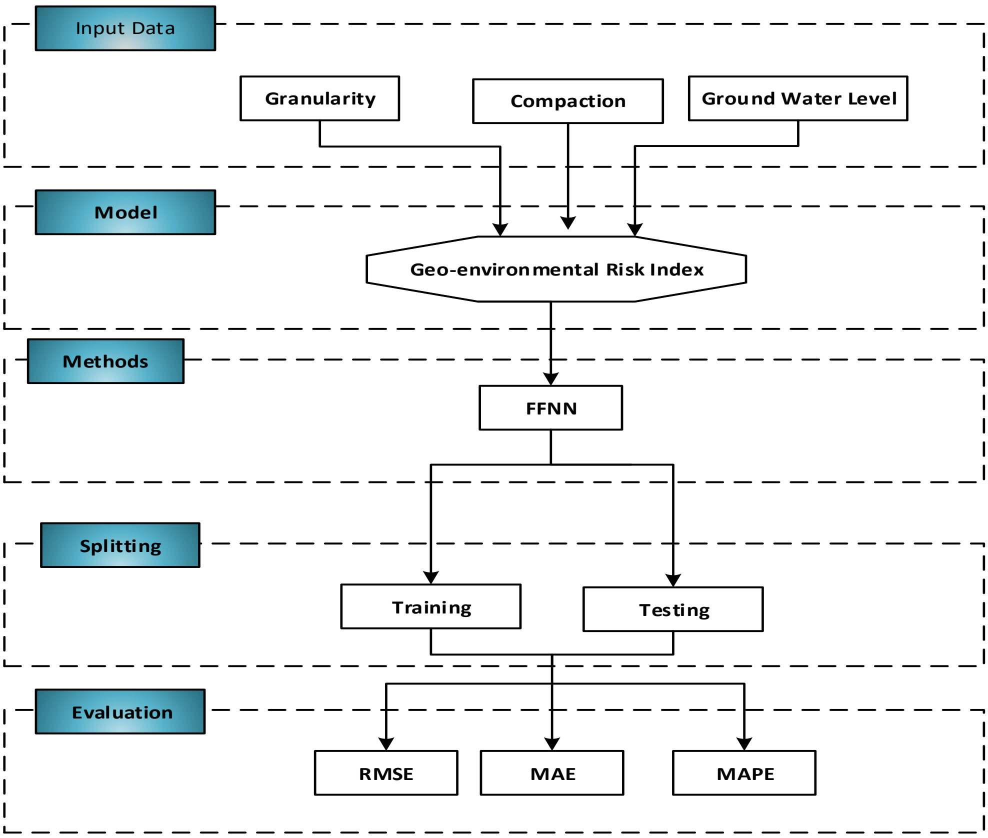
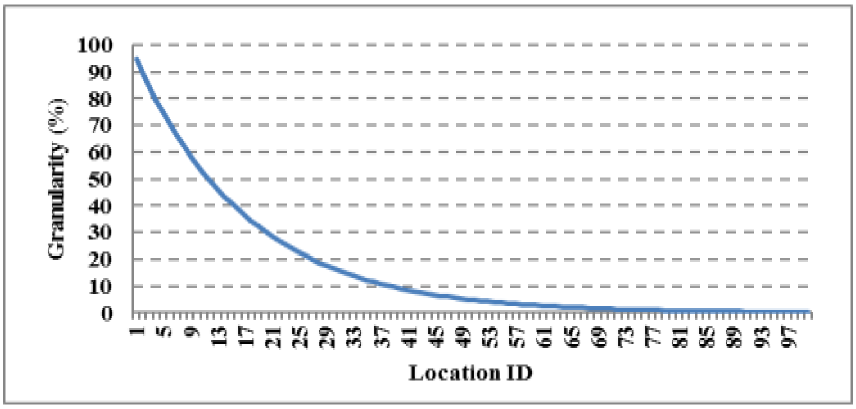
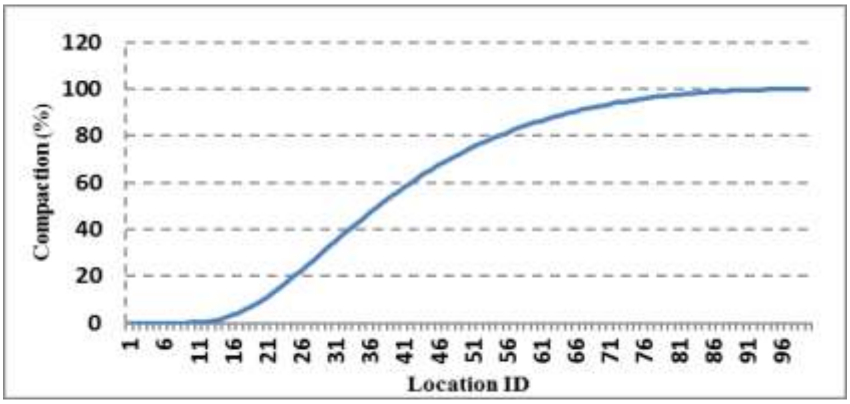


Figure 1. Proposed Model for Geo-Environmental Risk Index Estimation

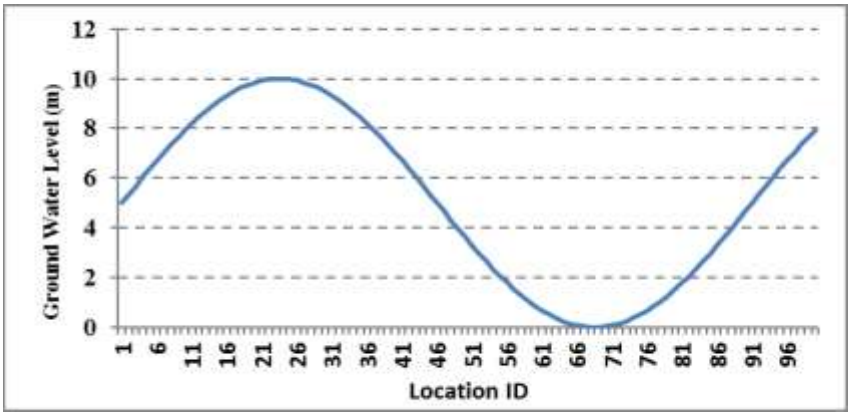
There are five layers in this structure diagram, first is the input data layer in which the input data are given, such as granularity, compaction, and ground water level. The second layer is the model layer in which the model is given, in this work the model is geo-environmental. The third layer is the method layer, in the method layer the feed forward neural network has been used. The fourth layer is the splitting layer and in splitting layer the percentage split method has been used in which the data is divided into a particular ration into training and testing. Here in the proposed work the 70% data is given to training and 30% to testing. In order to measure the performance of the proposed model we have used root mean square error (MSE), mean absolute percentage error (MAPE), and mean absolute error (MAE).



(a) Graularity



(b) Compaction



(c) Ground Water Level

Figure 2. Input Data Graphical Representation for Geo-Environmental Risk Index Estimation

3.1. Input Data

The following exponential functions are used to generate some input data for Geo-environmental risk index for compaction, granularity and ground water level parameters using different functions. Ground water is the water present beneath Earth's surface in soil pore spaces and in the fractures of rock formations. In geotechnical engineering, ground compaction is the process in which a stress applied to a soil. The following mathematical formulas are used for generating input data.

$$f_1 = 95 - \frac{e^{0.0092x}}{100} \tag{1}$$

$$f_2 = \frac{1}{\mu} e^{\frac{-x}{\mu}} \tag{2}$$

$$f_3 = \mathrm{Sin}(x) \tag{3}$$

Figure 2 shows input data graphical representation for geo-environmental risk index estimation. The input data consisted of three different parameters namely granularity, compaction and ground water level. The x-axis represents the location id and y-axis represents granularity, compaction and ground water level.

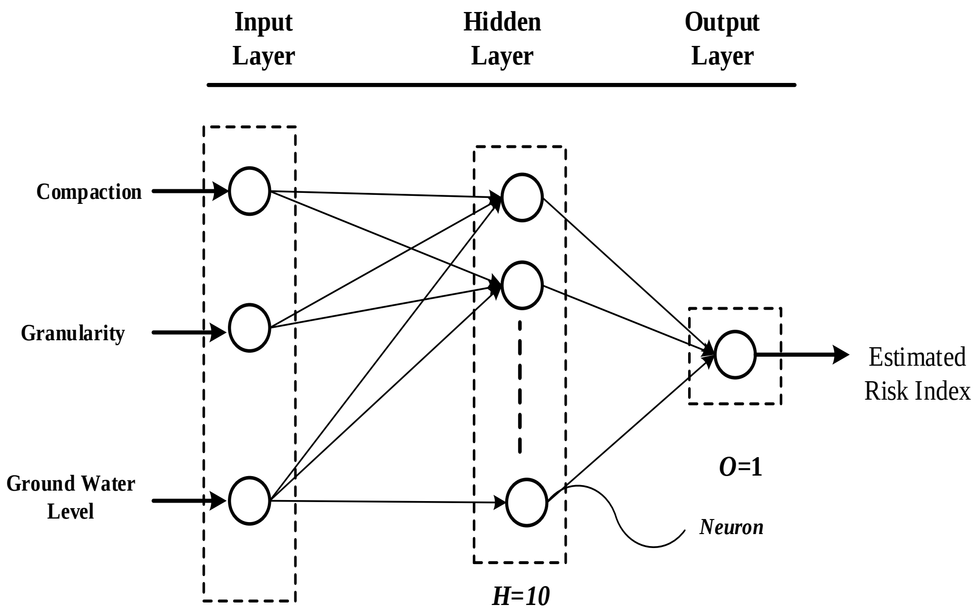


Figure 3. Structure Diagram of Feed Forward Neural Network for Geo-Environmental Risk Index Estimation

3.2. Estimation Method

In the proposed approach we have used different machine learning algorithms for Geo-environmental risk index estimation. The discussion of the used machine learning algorithm is given in detail below.

In the proposed method we have used the feed forward neural network (FFNN) for Geo-environmental risk index estimation. In the FFNN we have specified three neurons in the input layer, ten neurons in hidden layer, and one neuron in output layer. FFNN having single hidden layer uses the below mathematical formulation for function approximation.

$$f(x) = \sum_{j=1}^{N} w_j \psi_j \left[\sum_{i=1}^{M} w_{ij} x_i + w_{io} \right] + w_{jo} \tag{4}$$

Where N signifies the total number of hidden units, M signifies the total number of inputs, and Ψ signifies the activation function for each hidden unit. The structure diagram for the proposed feed forward network is given below.

Figure 3 shows the structure diagram of feed forward neural network for geo-environmental risk index estimation. There are three inputs to the feed forward neural network namely compaction, granularity, and ground water level. For each input a neuron is defined in the input layer, hence in the input layer three neurons are defined. We have tried different number of neurons in the hidden layer in combination with input layer neurons and output layer neuron. We defined 10 neurons in the hidden layer because it is more suitable combination with input and output layer neurons.

3.3. Performance Evaluation

The performance of the machine learning algorithms have been measured using root mean square error (RMSE), mean absolute error (MAE), and mean absolute percentage error (MAPE). The mathematical representation of RMSE, MAE and MAPE are represented in equation 5, 6, and 7.

$$\text{RMSE} = \sqrt{\frac{1}{N} \sum_{k=0}^{n} (A - E)^2} \tag{5}$$

$$\text{MAE} = \frac{1}{N} \sum_{i=1}^{n} |A_i - E_i| \tag{6}$$

$$\text{MAPE} = \frac{1}{N} \sum_{i=1}^{n} \frac{|A_i - E_i|}{A_I} \times 100 \tag{7}$$

Where n is the total number of observations, A is the actual value and E is the estimated value.

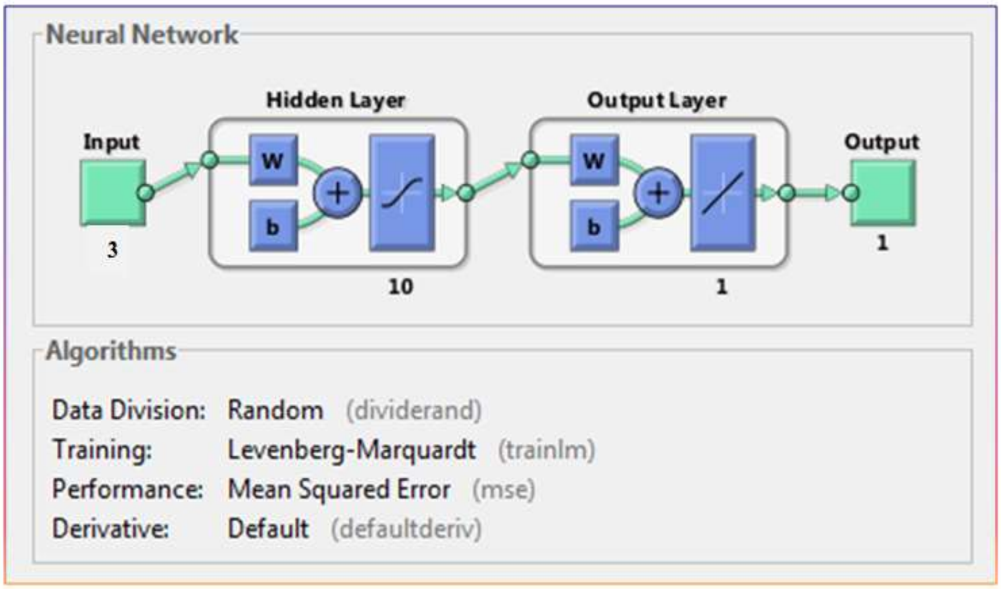


Figure 4. Feed Forward Neural Network Structure for Geo-Environmental Risk Index

4. Experimental Results and Discussion

All implementations of the proposed approach have been carried out using MATLAB R2010a version 7.10.0.499 with an Intel core i5 system having windows 7 operating system. Following are some experimental results different machine learning algorithms.

Figure 4 shows the implemented structure of feed forward neural network in which we have used the Levengerg-Marqurdt method for training. There are there three neurons in the input layer, 10 neurons in the hidden layer and one neuron in the output layer. We tried different combination of hidden layer neurons with input and output layer neuron, but this combination is the best suited combination and the feed forward neural network perform better on these input parameters with this combination.

Figure 5 illustrates the actual risk index values and the estimated risk index values using feed forward neural network for Geo-environmental. The actual risk index values for Geo-environmental risk index is represented by blue line and the estimated risk index values are represented by green line. Here we have used different machine learning algorithms in order to find best estimated Geo-environmental risk index.

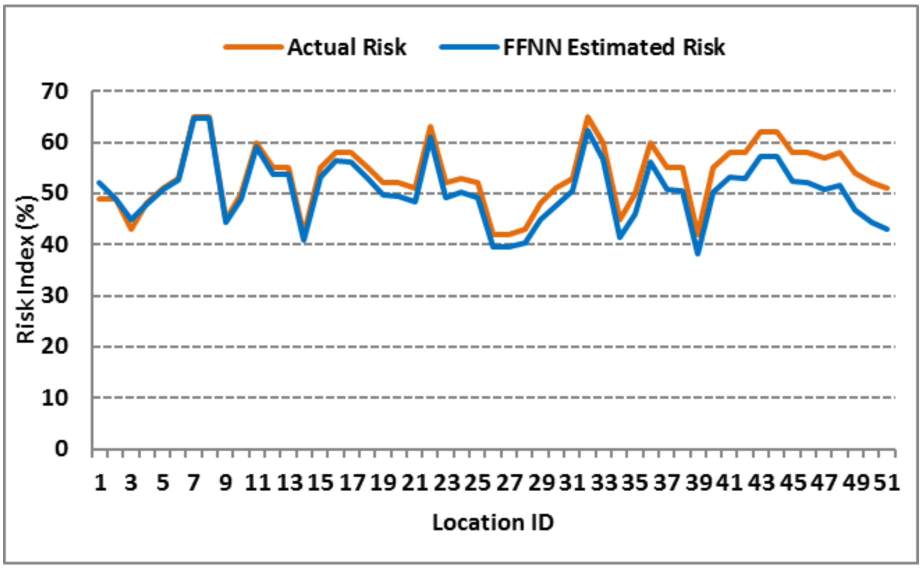


Figure 5. The Actual and Estimated Risk Index Values for Geo-Environmental Risk Index using Feed Forward Neural Network

The performance of the estimated risk index for Geo-environmental risk index is evaluated using the root mean square error, mean absolute error, and mean absolute percentage error. These measurement metrics have been used to measure the performance of feed forward neural network for Geo-environmental risk index. In Table 1 the MAE, RMSE and MAPE values for FFNN are given.

Table 1. Performance FFNN for Geo-environmental Risk Index Estimation

	Feed Forward Neural Network
MAE	2.9591
RMSE	3.5174
MAPE	5.9782

The results given in table 1 are further represented graphically in Figure 6. The purpose of graphical presentation is to better elaborate the results. We have used three different performance evaluators in order to measure the results of the feed forward neural network from every aspect. The results indicates that the feed forward neural network perform better on these three input parameters and the combination of hidden layer neurons with input layer neurons and output layer neuron.

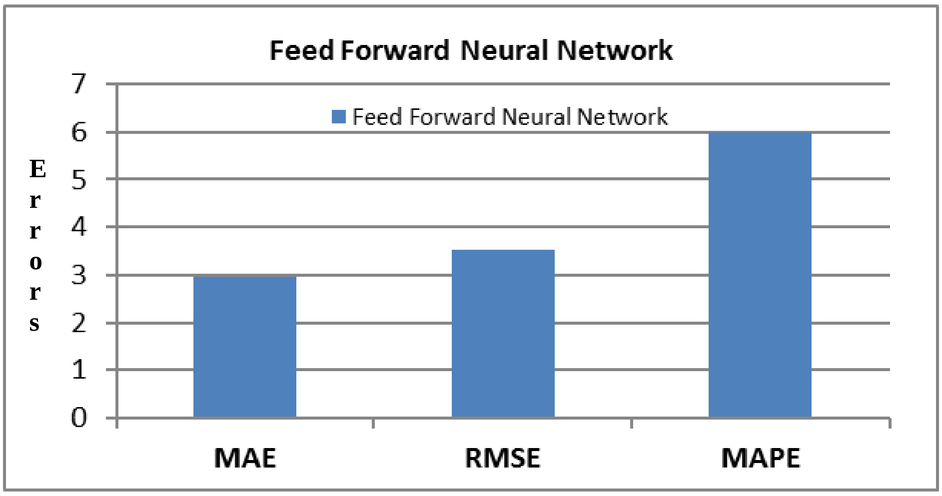


Figure 6. Geo-environmental Risk Index Estimation Performance Measurement

6. Conclusion

In this paper, we have designed a novel methodology for Geo-environmental risk index estimation for surveilling underground facilities. In the proposed work, we have used the machine learning techniques to estimate the risk index for Geo-environmental. Three parameters namely granularity, compaction and ground water level of underground facilities have been used as inputs to feed forward neural network for Geo-environmental risk index estimation. The percentage split has been used in which we have divided the data into training and testing ratios. The outputs results of these machine learning algorithms are then evaluated using root mean square error (RMSE), mean absolute error (MAE), and mean absolute percentage error (MAPE). The values of these metrics indicate that the FFNN performs well and this method can help the manager to take measure before any hazards.

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