International Journal of Engineering & Technology, 7 (4.39) (2018) 545-549

International Journal of Engineering & Technology

Website: www.sciencepubco.com/index.php/IJET

Research paper

A Risk Estimation Methodology Based on Machine Learning Algorithms in Underground Metro Structures

Muhammad Fayaz[1]andDo-Hyeun Kim*[2]

Department of Computer Engineering, Jeju National University, Jeju, 63243, Republic of Korea
**Corresponding author E-mail: kimdh@jejunu.ac.kr*

Abstract

Background/Objectives: Underground risk index assessment is a very challenging task due to the unavailability of underground features information. A lot of factors normally contribute in underground failures. Underground failures occur in a random manner, but a proficient underground risk assessment method can avoid underground failures. Metro risk is a serious threat to underground structures.
Methods/Statistical analysis: In this paper, we have proposed a risk index assessment methodology for underground metro structure. The proposed methodology consisted of three stages, namely the data layer, the risk index estimation layer, and performance evaluation layer. Two parameters, namely year of burial, and degree of depression have been used in the proposed work. These parameters are then further used as inputs to risk index estimation layer. The feed-forward neural network (FFNN) and classification and regression tree (CART) have been used in the risk index estimation layer for metro structure risk index estimation. The output of the neural network is further evaluated in performance evaluation layer, where root means square error (RMSE), mean absoluter error (MAE) and mean absolute percentage error (MAPE) have been used.
Findings: It is very difficult to develop a methodology to asses underground risk index taken into all parameters. Underground risk index analysis is very complicated due to its complex nature. The only one way is to assess one by one. The proposed method estimates the risk index of metro structure risk index. The proposed method can be efficiently used to estimate risk index of underground structure.
Improvements/Applications: We have used machine learning algorithms such as FFNN and CART for metro structure risk index estimation which is a novel idea. The results indicate that the performance of CART is better as compared to FFNN.

Keywords: *Neural Network, Metro Structure, Risk Assessment, Underground Risk, Metro Structure*

1. Introduction

The monitoring of underground facilities is a very tedious job. Underground facilities are linked with several problems, i.e., leakage, liquefaction, earthquake, land sliding, etc. In order to ensure the safety of the people, it is very obligatory to timely evaluate the underground risks. Underground risk can be assessed by using different techniques, such as sustainability, through experts, and through risk rating [1]. Normally different risk factors are integrated in order to obtain a final risk underground risk index. Usually, in order to assess the underground risk a lot of subjective judgments are required from good experts. But it is extremely difficult to find experts with high potential knowledge; this method is also very expensive and time-consuming [2,3].
A lot of underground failures are occurring due to ineffective underground methods, many authors tried to develop an effective underground risk index method. Many factors are involved in underground failures, so it is necessary to have an effective method for each factor. Fayaz et al. [4] proposed a method for geo-environmental risk index estimation. The factors they have considered for geo-environmental risk index are granularity, compaction, andground-water level. The feed-forward neural network has been used for geo-environmental risk index estimation. Different performance evaluation metrics have been used to measure the performance of the proposed method. Similarly, they proposed another method for underground risk index based on hierarchical fuzzy logic [2]. In this method different factors, such as water supply risk index probability, water supply pipeline risk index severity, sewerage supply pipeline risk index probability, sewerage supply pipeline risk index severity, metro structure risk index probability, metro structure risk index probability, metro structure risk index severity, geo-environmental risk index probability and geo-environmental risk index severity. In the proposed method the hierarchical fuzzy inference has been used to optimize rules in the rule base. A special configuration model has been used named integrated model. This hierarchical method significantly shrinks the number of rules. Similarly, Fayaz et al, [5] proposed another method to analyze and visualize water supply risk index. They have taken into different factors, such as leakage, age, depth and length in to analyze the risk of water supply pipelines. In the proposed method they used the hierarchical fuzzy logic and geographical information system to assess risk and visualize risk. Wang et al in [6] proposed a method for bridge risk index assessment in their proposed method they used the adaptive neuro-fuzzy inference system for bridge risk assessment. They considered four factors to assess bridge risk in Britain. The proposed method is an effective method for bridge risk assessment. Fayaz et al. [7], proposed a method to analyze and predict underground risk index. Their proposed method can be categorized into two main parts namely analysis and prediction. For analysis they have used the risk index hierarchical fuzzy logic model and for prediction the Kalman filter has been used.
In this paper, we have proposed a risk index estimation

Copyright © 2018 Authors. This is an open access article distributed under the Creative Commons Attribution License, which permits unrestricted use, distribution, and reproduction in any medium, provided the original work is properly cited.

methodology for underground metro structure. The objective of this paper is to design an effective methodology for metro structure risk index estimation to avoid failures timely. The metro structure risk index also contributes to underground failures; hence an efficient method can avoid underground failures. Different factors have been considered in order to accurately metro structure risk index. In the recent decades, researchers have tried to proposed effective risk assessment and estimation in many areas. The risk assessment methods are necessary to measure to avoid accidental loss.

The organization of the structure of the paper is carried as: Section 2 explains the proposed work, results and discussion detail are given in Section 3 and the paper is concluded in Section 4.

2. Proposed Metro Structure Risk Estimation Methodology

The suggested methodology is illustrated in figure 1 comprises a differentlayer, namely the data layer, the risk index estimation layer, and performance evaluation layer. In the data layer different relevant parameters are used to make a dataset. In risk index estimation feed forward neural network and classification and regression tree has been usedto estimate risk for metro structure risk index. The output of the neural network is further evaluated in performance evaluation layer where RMSE, MAE and MAPE have been used.

2.1. Data Layer

In the proposed methodology, we have used three parameters, namely compaction, granularity, and ground-water level.

2.2. Feed Forward Neural Network

Neural networks are the most common and most effective AI models in order to predict risk index. Neural networks are well in order to solve non-linear problems. The ANNs are capable to resolve complicated glitches. The applications of neural networks have been carried out in many areas for risk index estimation and prediction. There are many types of neural networks, such as feed-forward neural network, back propagation neural network and recurrent neural network. In the proposed work, we have FFNN, it is a simple neural network and information always moves in one direction; it never goes backward. FFNN have the capability of a function f approximation that relates $R_m \rightarrow R$ deprived of building norms about the relationship between the input and outputs. The FFNN requires the user to describe the structural configuration by considering the hidden layers and hidden neurons [8,10]. FFNN with a hidden layer for function estimation has the below mathematical depiction:

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

Where N signifies the entire number of hidden elements, M signifies the entire number of inputs, and Ψ signifies the activation function for each hidden unit. The configuration diagram of the planned feedforward network is specified in Figure 2.

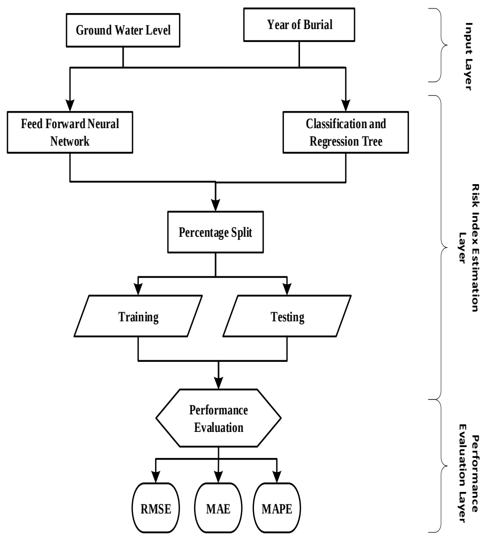


Figure.1: Proposed Risk Index Estimation Methodology in Underground Metro Structure

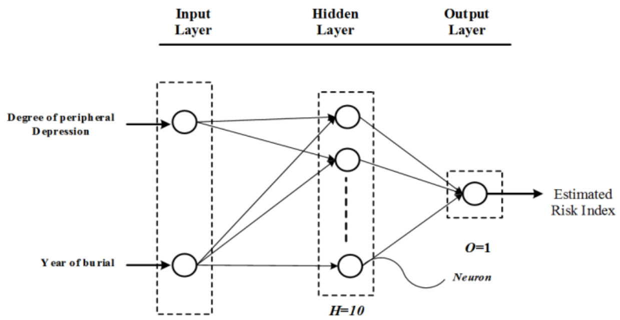


Figure 2: Structure Diagram of the proposedfeed-forward neural network for Geo-environmental risk index estimation

In this work, the following network structure is used:single hidden layer (with varying number of neurons), tangent sigmoid function denoted by ϕ(x) at the hidden layer,linear function denoted by χ(x).

$$\phi(x) = \frac{2}{1+e^{-2x}} \tag{2}$$

$$\chi(x) = \text{linear}(x) \tag{3}$$

In order to validate the mode, we have used the percentage split method in which the data is divided into some specific ratio for training and testing. In this study, we have used a different splitting ratio in order to find the best fit method. Levenberg–Marquardt algorithm is used for training, which is one of the most popular training algorithms for FFNNs with gradient descent based method.

2.3. Classification and Regression Tree (CART)

Now-a-days, the CART has been used extensively for estimation and prediction purposes in different areas. CART is an altered method for traditional data analysis techniques. In different areas CART has been found a very efficient to create decision rules which do good as compared to other rules used in conventional techniques. The CART has the ability to solve the complicated interactions between predictions which are very difficult for other conventional techniques to solve. The methodology of CART used in this work is outlined here. The enhanced recursive partitioning algorithm is utilized for the CART. This enhanced recursive partitioning improves the performance of the CART and also improves the convergence time. The algorithm works in stepsprocess by which a decision tree is built by either splitting or not splitting each node on the tree into two child nodes [9]. The structure model for the CART in our proposed model is depicted in figure 3.

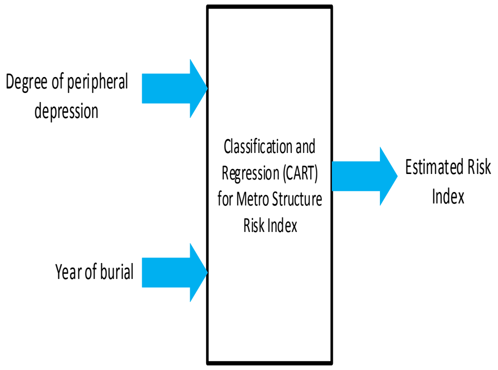


Figure 3: Proposed structure model of classification and regression tree for metro structure risk index estimation

The model inputs are defined as:

$$X(t)=[y(t-30;....;y(t-1);h;d;A;L;T(t)] \tag{4}$$

where y(t -n);...; y(t - 1) is risk values for metro structure from different locations, h is set of heights, d is the set of depth, A is the set of age and L is the set leakage values. The percentage split method has been applied in which the 70% data is used for training and 30% for testing.

2.4. Performance Evaluation

In the performance evaluation layer different metrics, such as root mean square error (RMSE), mean absolute error (MAE) and mean absolute percentage error (MAPE) [9] have been used to measure the performance of estimated results. These metrics can be represented mathematically as below.

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

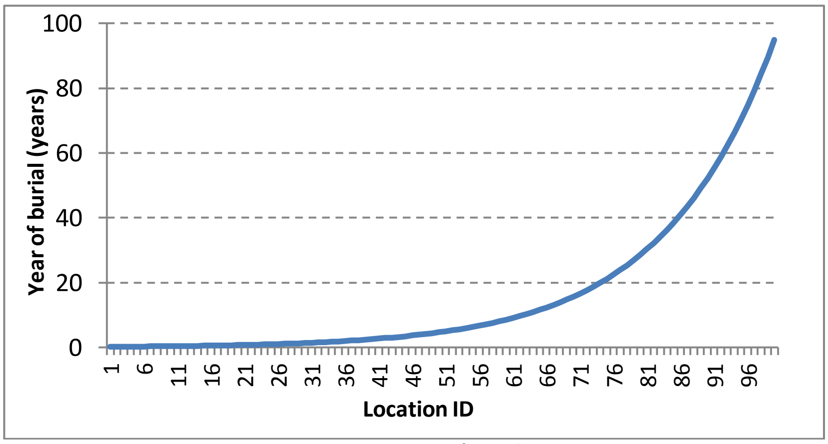
$$\text{MAE} = \frac{1}{N}\sum_{i=1}^{n}|A_i - E_i| \tag{6}$$

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

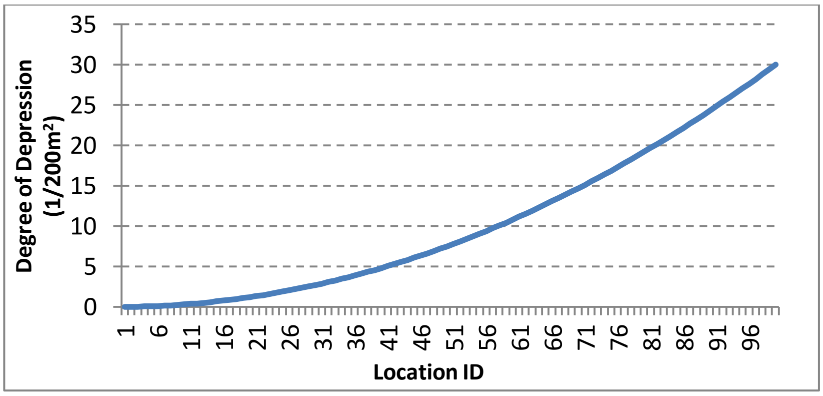
Where n number of observations, A is the targeted value and E is the projected value.

3. 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 functions are used to generate some exponential input data for metro structure risk index for the year of burial and ground-water level parameters. Groundwater is the water present beneath Earth's surface in soil pore spaces and in the fractures of rock formations.



a. Year of Burial



(b) The degree of Peripheral Depression

Figure 4: Input data graphical representation for metro structure risk index estimation

In geotechnical engineering, a depression in geology is a landform sunken or depressed below the surrounding area. Year of burial means when the pipes are buried the older the pipes the greater of the probability of leakage. Equation 8 and Equation 9 have been used to generate data for year of burial and probability leakage parameters respectively.

$$f_2 = \frac{e^{0.0092x}}{100} \quad (8)$$

$$f_3 = \frac{x^2}{3.2} \quad (9)$$

Figure 4 show the graphical representation of the above equation generated values.

The following figures illustrate the targeted risk index values and the estimated risk index values using feedforward neural network for metro structure risk index. The actual risk index values for metro structure risk index is represented by a blue line and the estimated risk index values are represented by a green line. Here we have used different machine learning algorithms in order to find the estimated metro structure risk index.

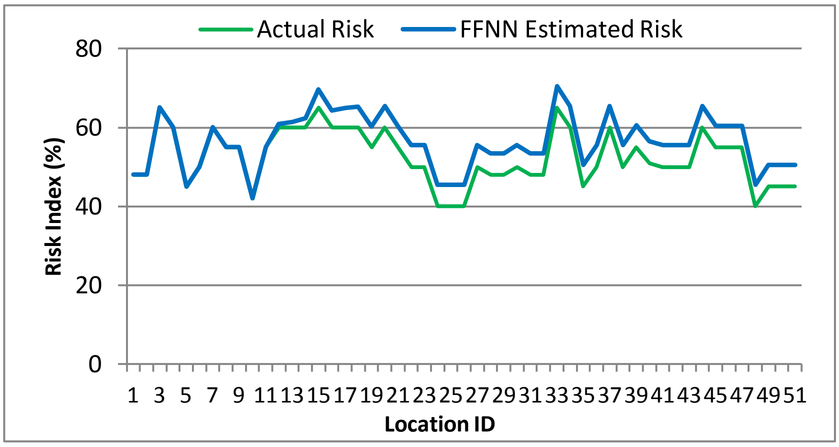


Figure 5: Actual and estimated risk index values for metro structure risk index using feed-forward neural network

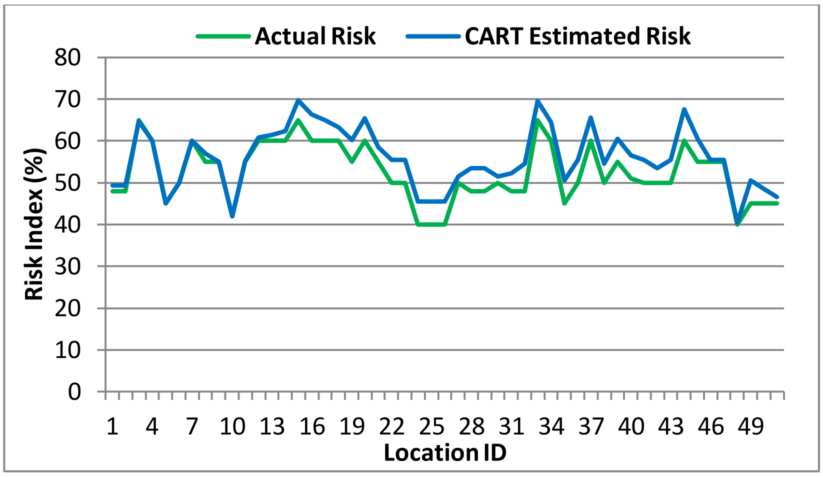


Figure 6: The actual and estimated risk values risk index for a metro structure using classification and regression tree

The performance of the estimated risk index for metro structure risk index is evaluated using the RMSE, MAEand MAPE. These metrics have been used to measure the performance of feed-forward neural network and classification and regression tree.

Table 1: Performance FFNN, and CART for metro structure risk index estimation

Statistical Measure	Feed Forward Neural Network(FFNN)	Classification and Regression Tree(CART)
MAE	3.9958	3.4913
RMSE	4.6148	4.1777
MAPE	7.0722	6.189

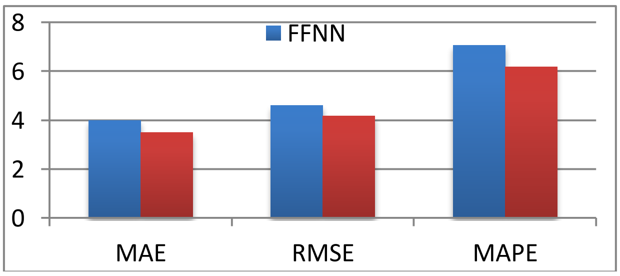


Figure 7: Metro structure risk index estimation performance measurement

The values of the root mean square error, mean absolute error, and mean absolute percentage error indicate the performance of CART is better as compared to FFNN[10].

4. Conclusion and Future Work

In the proposed method, we have proposed a methodology for metro structure risk index estimation. The proposed methodology consisted of three-layer, namely the input layer, the risk index estimation layer and performance evaluation layer. The input layer has data related information, the risk index estimation layer consists of feed-forward neural network and classification and regression tree. In order to evaluate the performance of estimation results of FFNN and CART, three well-known performance evaluators have been used. The results indicate that the performance of CART is better as compared to the neural network. In future, we would take into account more parameters for metro structure risk index and more AI methods for metro structure risk index estimation.

Acknowledgments

This research was supported by the MSIT (Ministry of Science and ICT), Korea, under the ITRC(Information Technology Research Center) support program(IITP-2017-2016-0-00313) supervised by the IITP(Institute for Information & communications Technology Promotion), and this paper was performed for the Development of Radar Payload Technologies for Compact Satellite in Korea Aerospace Research Institute, funded by the Ministry of Science and ICT. Any correspondence related to this paper should be addressed to DoHyeun Kim; kimdh@jejunu.ac.kr.

References

[1] Sturk R, Olsson L, Johansson J. Risk and decision analysis for large underground projects, as applied to the Stockholm ring road tunnels. Tunnelling and Underground Space Technology. 1996 Apr 1;11(2):157-64.

[2] Fayaz M, Ullah I, Park DH, Kim K, Kim D. An integrated risk index model based on hierarchical fuzzy logic for underground risk assessment. Applied Sciences. 2017 Oct 11;7(10):1037.

[3] Paolucci R, Pitilakis K. Seismic risk assessment of underground structures under transient ground deformations. InEarthquake Geotechnical Engineering 2007 (pp. 433-459). Springer, Dordrecht.

[4] Fayaz M, DH, Kim D. An Estimation Method of Geo-environmental Risk Index Based on Feed Forward Neural Network for Surveilling Underground Facilities. International Journal of Advanced Science and Technology, 113,11-20,2018

[5] Fayaz M, Ahmad S, Ullah I, Kim D. A Blended Risk Index Modeling and Visualization Based on Hierarchical Fuzzy Logic for Water Supply Pipelines Assessment and Management. Processes. 2018 May 22;6(5):61.

[6] Wang YM, Elhag TM. An adaptive neuro-fuzzy inference system for bridge risk assessment. Expert Systems with Applications. 2008 May 1;34(4):3099-106.

[7] Fayaz M, Ullah I, Kim DH. Underground Risk Index Assessment and Prediction Using a Simplified Hierarchical Fuzzy Logic Model and Kalman Filter. Processes. 2018 Jul 29;6(8):103.

[8] Wahid F, Ghazali R, Fayaz M, Shah AS. Statistical features based approach (SFBA) for hourly energy consumption prediction using neural network. Networks. 2017;8:9.

[9] Ullah I, Ahmad R, Kim D. A Prediction Mechanism of Energy Consumption in Residential Buildings Using Hidden Markov Model. Energies. 2018 Feb 3;11(2):358.

[10] Abhaya Kumar Samal, Pradeep Kumar Mallick, Jitendra Pramanik and Subhendu Kumar Pani, "Functional Link Artificial Neural Network (FLANN) based Design of a Conditional Branch Predictor", Cognitive Informatics and Soft Computing, (Part of AISC Springer), Vol: 768, ISBN: 978-981-13-0617-4, pp 131-152, 2018. (https://link.springer.com/chapter/10.1007/978-981-13-0617-4_14).