Journal of Science and Technology in Civil Engineering NUCE 2018. 12 (5): 51–62

A RISK ASSESSMENT FRAMEWORK FOR CONSTRUCTION PROJECT USING ARTIFICIAL NEURAL NETWORK

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Article history:
Received 20 June 2018, Revised 13 July 2018, Accepted 20 August 2018

Abstract

The current trend of increasing construction project size and complexity results in higher level of project risk. As a result, risk management is a crucial determinant of the success of a project. It seems necessary for construction companies to integrate a risk management system into their organizational structure. The main aim of this paper is to propose a risk assessment framework using Artificial Neural Network (ANN) technique. Three main phases of the proposed framework are risk management phase, ANN training phase and framework application phase. Thereby, Risk Factors are identified and analysed using Failure Mode and Effect Analysis (FMEA) technique. ANN model is created and trained to evaluate the impact of Risk Factors on Project Risk which is represented through the ratio of contractor's profit to project costs. As a result, the framework with successful model is used as a tool to support the construction company in assessing risk and evaluate their impact on the project's profit for new projects.

Keywords: risk management; risk assessment; Artificial Neural Network (ANN); Failure Mode and Effect Analysis (FMEA); construction project.

https://doi.org/10.31814/stce.nuce2018-12(5)-06

1. Introduction

Construction industry is characterized by high level of risks and uncertainties. In reality, many construction projects experience large variations in cost and time because risk events happen during project life cycle. Project Management Institute (PMI) defined risk as an uncertain event or condition that, if it occurs, has a positive or negative effect on one or more project objectives [1]. The current trend of construction industry is the increase of project size and complexity, which results in higher level of project risk. Thompson and Perry attributed the failure of projects to the lack of effective risk management, which often leads to failure of milestones and objectives [2]. Therefore, risk management is a crucial determinant of the success of a project. The risk management process generally includes the process of risk identification, risk analysis and risk responses. Nowadays, it becomes necessary for construction companies to integrate a risk management system into their organizational structure [3].

Many researchers have studied on risk assessment systems which mainly focus on identifying risk factors, analyzing their probability and impact in order to minimize the impact of risks on project objectives [4–6]. For doing risk analysis, many techniques such as Monte Carlo Simulation [5], Fuzzy logic [4, 5, 7], Hierarchical Analytical Analysis (AHP) [4], Failure Mode and Effect Analysis (FMEA) [4] have been utilized to analyze the behavior of risks.

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Artificial Neural Network (ANN) is an Artificial Intelligence technique which is believed to have broad applications in risk management [8]. McKim used the neural network for identifying risks [9]. Wenxi used back-propagation neural network for assessing risks in highway projects in China [10]. In 2009, Wenxi and Danyang developed an approach that used combination of fuzzy logic and neural network to evaluate risk of highway projects [11]. Elhag and Wang used ANN to model bridge risk score and risk categories [12]. Pedro used ANN to assess project risk through the prediction of the contractor's profit considering risk factors [3]. However this research did not state clearly the values of risk factors and the method to achieve them.

The main aim of this paper is to propose a framework that assesses project risks using ANN technique. Three main phases of the proposed framework are risk management phase, ANN training phase and framework application phase. A list of Risk Factors is created and analyzed to determine risk values using FMEA method. The input data for the ANN model are Risk Factors and the output data is the Project Risk which is represented through the ratio of contractor's profit to the project costs. Risks' values and Project Risk of a set of finished projects are fed into ANN model in order to train and test the model. As a result, the satisfied ANN model can be used as a tool which supports a construction company to assess risk and to evaluate their impacts to the project's profit for new projects. The following sections will explain the research approach in detail.

2. Artificial Neural Network

Artificial Neural Network (ANN) is an information processing technology that simulates the human brain and the nervous system. ANN was first introduced in 1943 by [13]. Like the human brain, neural networks can learn from experience, generalize from previous data to new ones and abstract essential information from input data. The main components of ANN are nodes (also referred to as neurons) and synaptic transmissions with weight factors. A node in ANN represents main characteristics of a biological neuron. In neural networks, nodes are arranged in layers and each node in one layer is linked to nodes of the next layer. A neural network may consist of two or more layers which are named as input, output and hidden layers. That means that a neural network may or may not have hidden layers. In neural network, nodes receive and analyse signals to produce output signals which become input ones for the nodes in next layer. The function of a node is illustrated in Fig. 1. Whereby, the node receives n inputs $X_1, X_2, \ldots, X_n$. Then, it calculates the sum, $u = X_1W_1 + X_2W_2 + \ldots + X_nW_n$, and receives the output y which is obtained from further modifying the sum u by an activation function $f(u)$. Hence, the output y can be expressed as $y = f\left(\sum X_iW_i\right)$. The output is delivered to nodes in the next layer, where a computation similar to the one described above takes place. When the node is in the output layer, values obtained are results of the neural network.

ANN has many advantages over conventional methods. Traditional regression models require explicit representation of the relationship in statistical models [14]. Furthermore, those models cannot learn by themselves and cannot respond adequately to considerably incomplete or unknown data. Conversely, ANN is a self-adaptive method, which can learn from the set of data through adjusting the values of weights W to optimize its behaviour during training. The adjustment of weights is performed by applying learning algorithms, which cause the network to learn the solution to solve problem. The neural network can be trained

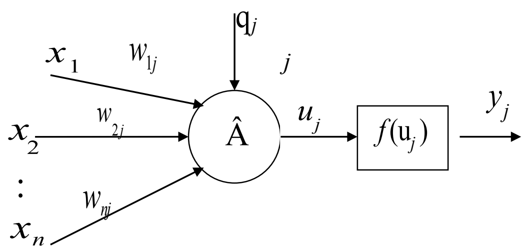

Figure 1. Function of a node in neural network

until the difference between the network output values and the desired values, referred to as output error, meets requirement. Besides, ANN can determine complicated relationships in a set of data. Hence, ANN can solve complex nonlinear problems with a greater degree of accuracy [15].

Neural network has been successfully utilized for solving various problems in science and engineering [16]. In construction project management, ANN can be used to provide assistance to contractors in predicting and managing project cash flow and cost [17]; assist with decision making in financial investments, allocation of risk [18, 19], assess design constructability [16], safety management [20] . . . With its many advantages, ANN is suitable to be used in this study to assess construction project risks.

3. Proposed framework to assess project risk using ANN technique

This study proposes a framework to assess project risk which is represented through the ratio of contractor's profit to project cost. This framework can be used as a tool to assist contractors in forecasting project profit when considering risk factors. The proposed framework structure is represented in Fig. 2, which consists of three main phases carried out in a construction company. The first phase is risk management, the second one is the training and testing of ANN model, and the third one is the application of the model to new projects. At the risk management phase, the identification and analysis of Risk Factors are performed. At the phase of ANN training, the model is created, trained and tested with the input and output data which are the values of Risk Factors and the ratio of the contractor's profit to project cost, respectively. The main idea is that through the data of a set of finished

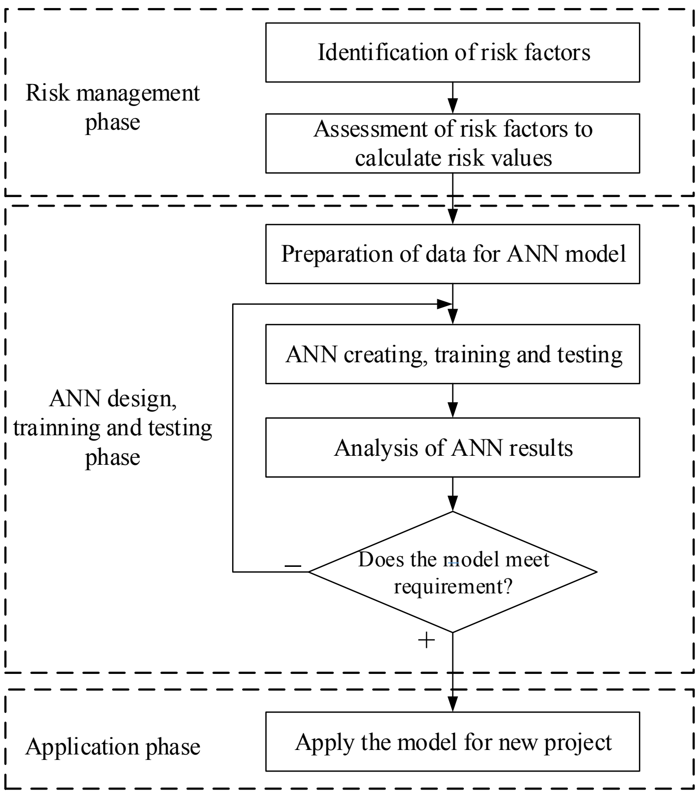

Figure 2. Proposed framework to assess project risk

projects, the model will be created, trained and tested in order to produce as accurate as possible the ratio of contractor's profit to project cost. When the output error meets requirement, the successful model can be used to analyse and evaluate the impact of Risk Factors on the contractor's profit in new projects.

The following sections will explain each task of the framework in detail. In this paper, a set of hypothetical data is used to illustrate the results of the model. Case study with empirical data will be collected in further research.

3.1. Identification of Risk Factors

There are many types of risks that can occur during the project life cycle. In general, it is difficult to create a general guideline of Risk Factors in all construction projects [3]. For different projects and contractors, the number of Risk Factors and their types may be different. However, for a specific contractor, they normally carry out similar types of projects and therefore have similar types of Risk Factors. In order to use the proposed framework to assess project risk, the contractor needs to figure out Risk Factors that it has normally encountered when performing projects. In this paper, Risk Factors are identified through a comprehensive literature review [3, 6, 21–23]. Thereby, 6 groups of Risk Factors along with 17 potential factors that are considered typical in every construction project are proposed as shown in Fig. 3. This classification can be used as a guide to identify the potential risks in a project.

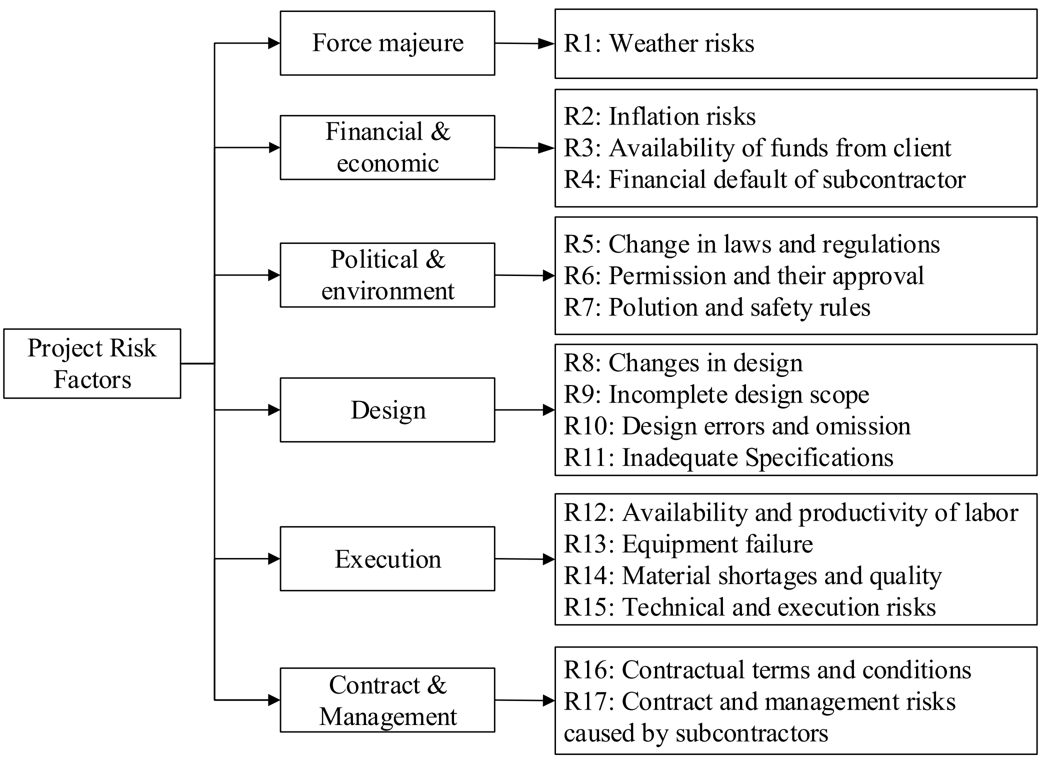

Figure 3. Proposed classification of Risk Factors

3.2. Assessment of Risk Factors

This section discusses the assessment of Risk Factors in order to identify their values (RV) which are used as input data for the ANN model. The assessment of Risk Factors needs to be performed for each project in the set of considered projects.

In this study, FMEA is used to assess and calculate the risk values (RV). FMEA is recognized as one of the most beneficial techniques in reliability programs, which is suggested to be used in the context of risk management [4]. FMEA is about failure modes and their effects, hence it is necessary to define the term “failure mode”. “Failure mode” can be defined as the inability of a design, a process weakness and production errors [18]. At the risk management context, “failure mode” can be defined as “risk” [1, 4]. Following the traditional FMEA method, a failure mode is defined through assessing its occurrence (O), severity (S), and detection (D). For the purpose of this research, the following terminologies are used:

- Occurrence (O) is referred to as probability of occurrence (P) and is defined over the range of 1 to 5. The probability of occurrence of a risk demonstrates the chance that risk may occur. For example, weather risk such as raining has high chance of occurrence at rainy season.

- Severity (S) is referred to as the level of risk impact (I) on project schedule and project scope and is defined over the range of 1 to 5.

- Detection difficulty (D) is referred to as the level of detection/control difficulty (D) and is defined over the range of 1 to 5. The variable D shows the ability of the project team to detect risk event, control risk causes and control the consequence of the risk event. Assessment of this variable needs to consider the ability of the construction company. For example, the project team has high difficulty in detecting and controlling the inflation risks.

- RV is the value of Risk Factors, which can be calculated using Eq. (1), and is defined over the range of 1 to 125.

$$RV = P \times I \times D \tag{1}$$

where the definitions of the assessment range for each variable P, I, D are proposed as shown in Table 1. This proposed assessment range can be used as a guide for the contractor. However, it can be calibrated to suit for different construction companies and project context.

3.3. Input and output data for ANN model

The data for ANN model includes the value of Risk Factors (RV) and the value of Project Risk (PR). As discussed above, RV is identified by using the FMEA method, while Project Risk is defined by Eq. (2). For each finished project, the information of contractor’s profit and the total cost it paid for project construction are collected.

$$PR = \frac{\text{Contractor's profit}}{\text{Project cost}} \cdot 100\% \tag{2}$$

In order to clarify the relationship between input and output data used in the ANN model, Fig. 4 describes how the data is organized in order to feed the ANN model. Where RV is the input vector, where i represents the Risk Factor number, j represents the project number, RV is the value of Risk Factors. PR is the output vector, where j represents the project number, PR represents the value of Project Risk. m, n is the number of Risk Factors and projects, respectively.

In order to illustrate the description of the proposed framework and its results, hypothetical data of 15 finished projects along with 17 Risk Factors is used as shown in Table 2. The list of Risk Factors

Table 1. Proposed definition of assessment range for FMEA variables

Variable value	Explanation of assessment range		
	Probability of occurrence (P)	Impact (I)	Detection/Control (D)
1 (Very low)	< 1% chance: Event is highly unlikely to occur.	Insignificant duration change, less than 1% of project duration. Scope change or quality degradation is not noticeable.	The project team has no difficulty in detecting risk event, controlling the risk causes and controlling the consequence of the risk event.
2 (Low)	From 1% to 15%: Event is unlikely to occur.	The time extension is from 1% to 3% of project duration. Fewer areas of scope or quality are affected.	It is low difficult for project team to detect the risk event, control the risk causes and control the consequence of the risk event.
3 (Medium)	From 15% to 40% chance: Event may occur.	The time extension is from 3% to 7% of project duration. Major areas of scope or quality are affected.	It is medium difficult for project team to detect the risk event, control the risk causes and control the consequence of the risk event.
4 (High)	From 40% to 70% chance: Event is expected to occur.	The time extension is from 7% to 10% of project duration. Scope changes or quality are not acceptable to the client.	It is highly difficult for project team to detect the risk event, control the risk causes and control the consequence of the risk event.
5 (Very high)	> 70% chance: Event will certainly occur.	The time extension is larger than 10% of project duration. Project scope or quality does not meet expectations.	The project team cannot detect risk event, control the risk causes and control the consequence of the risk event.

is represented in Fig. 3. The value of Risk Factors is identified using Eq. (1). The output values in Table 2 are calculated using Eq. (2). Although this data is hypothetical, the value of every Risk Factor is reasonably assessed based on its nature and experience on risk management of the authors.

3.4. Creating, training and testing ANN model

As soon as the data for the model is ready, the next step is to create, train and test ANN model in order to produce desired results. Over time, many types of neural network with different structures and information processing capabilities have been developed [24]. Multilayer Perceptron (MLP) neural technique, a Feed-forward network, with the use of software SPSS Inc, is chosen for this study. MLP is a common neural network type, which is easy to understand and has been used in many research fields

$$\begin{bmatrix} RV_{11} & RV_{12} & \cdots & RV_{1j} & \cdots & RV_{1n} \\ RV_{21} & RV_{22} & \cdots & RV_{2j} & \cdots & RV_{2n} \\ \vdots & \vdots & & \vdots & & \vdots \\ RV_{i1} & RV_{i2} & \cdots & RV_{ij} & \cdots & RV_{in} \\ \vdots & \vdots & & \vdots & & \vdots \\ RV_{m1} & RV_{m2} & \cdots & RV_{m3} & \cdots & RV_{mn} \end{bmatrix} \qquad \begin{bmatrix} PR_1 & PR_2 & \cdots & PR_j & \cdots & PR_n \end{bmatrix}$$

Input vector — Output vector

Figure 4. Organization of input and output data for ANN model

Table 2. Data for ANN model

Project	Input																	Output
	R1	R2	R3	R4	R5	R6	R7	R8	R9	R10	R11	R12	R13	R14	R15	R16	R17	PR
P1	45	20	16	75	30	24	9	24	18	80	24	18	24	24	16	20	12	4.15%
P2	75	40	60	32	30	50	12	24	12	16	24	16	8	32	12	48	40	2.79%
P3	100	45	75	50	60	40	16	36	80	30	16	8	12	24	45	40	12	−0.51%
P4	80	30	100	40	20	24	48	30	16	16	12	36	32	30	16	16	60	1.95%
P5	75	30	75	48	20	50	18	48	18	18	24	60	36	18	32	18	75	0.38%
P6	100	60	32	45	20	40	12	30	36	40	24	8	18	20	20	45	20	1.48%
P7	60	20	48	48	60	60	24	60	24	32	32	24	24	40	30	24	32	1.01%
P8	75	30	40	36	30	60	24	75	20	75	12	16	24	18	20	24	30	1.48%
P9	60	30	40	32	15	60	12	48	30	16	36	20	18	16	30	30	24	3.08%
P10	75	15	32	32	30	32	12	24	16	18	24	40	8	10	32	24	30	4.53%
P11	75	30	50	40	20	20	24	36	32	16	36	24	24	32	32	24	48	1.88%
P12	80	40	16	60	30	36	64	60	30	30	24	24	16	36	12	16	32	1.23%
P13	45	40	20	80	30	24	18	80	24	18	16	18	12	18	45	30	40	1.99%
P14	75	30	60	45	15	40	16	36	32	40	18	8	12	8	20	50	30	−0.66%
P15	75	15	64	48	40	20	18	75	12	40	12	60	9	60	36	60	12	0.88%

[16, 24]. The main steps of designing an ANN model are (1) determination of model architecture and (2) determination of training process, which will be discussed in the following sections.

a. The network architecture

The proposed MLP network includes an input layer which has 17 nodes representing 17 Risk Factors, hidden layers and an output layer with 1 node representing the PR. In theory, a neural model can have many hidden layers. However, many researches have proved that a maximum of 2 hidden layers are enough for a MLP network to solve nonlinear problems with desired accuracy [25]. Fig. 5 shows the architecture of the risk-assessment MLP model with 1 hidden layer. Hidden nodes have functions of receiving signals from input nodes, calculating and delivering output results to the output layer. W is a weight matrix that links nodes in the input layer to nodes in the hidden layer, while V is the weight matrix that links hidden nodes to output nodes. In order to calculate output for each node, it is required to choose activation functions for hidden and output layers. The available activation functions are Sigmoid, Hyberbolic Tangent, Identity and Softmax. The principle of calculating output for nodes is already explained in section 2.

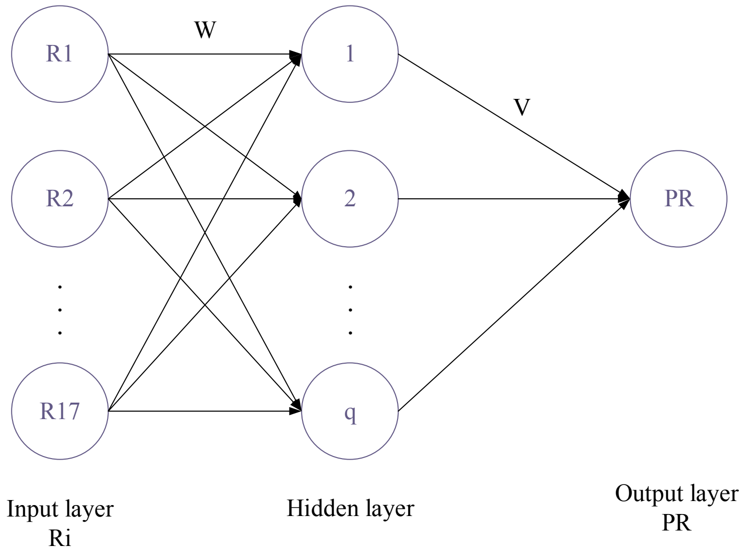

Figure 5. Risk assessment model with 1 hidden layer

b. Training and testing the model

There is no formal method to derive a network configuration for a specific problem [26]. Findings of a sensible good set of parameters including the number of hidden nodes, hidden layers and initial weights are normally based on trial and error. The process of trial and error is called the training process. For training and testing purpose, 15 projects used in this study are divided into 2 sets of data, one set includes 11 projects used for training and the rest is used for testing. Tested data was not used as part of training procedures. Tested data was selected randomly from the raw data set.

Basically, the training process starts with the setting of weights and biases in the network to small random values. Output of each node in the input layers is calculated first, then they are fed into the following layer and the calculation takes place again. This process is repeated until the output in the output layer is obtained. More detail of the calculation method can be referred to section 2. The output error of a model is measured by using error functions. This study observes an error function namely Sum of Squares which is represented by Eq. (3)

$$SSE = \frac{1}{2}\sum_{i=1}^{p}(y_i - d_i)^2 \tag{3}$$

where y_i is the predicted output produced by the network; d_i is the desired output; p is the total number of cases.

The goal of training process is to minimize this error function. To do so, through the back-propagation process, the numerical values of weights are adjusted by applying a learning algorithm, such as Gradient Descent or Scaled Conjugate Gradient algorithm, so that the network output value becomes closer to the desired output. If the predicted output value is larger than the desired value, the values of weights are decreased. Conversely, if the predicted output is lower than the desired one, the values of weights are increased. Training stops when either of the two criteria is met: (1) the minimum relative change in training error ratio is less than 0.001, or (2) the number of epochs, which is the number of updates, reaches 10000.

3.5. Results and discussion

Tables 3 and 4 show the *SSE* of MLP models resulting from training and testing processes corresponding to different experiment scenarios. The learning algorithm used for those experiments is Scaled Conjugate Gradient and the activation functions for hidden layer and output layer are Hyberbolic Tangent and Identity respectively. The selection of the best model is based on the error generated by each model. That is to say, the model with lowest SSE is considered the best assessment model.

The training process is performed for 11 projects, while the testing process is done with the rest four projects. After experimentation with various topologies, it is found that MLP models with two hidden layers do not produce better results than ones with one hidden layer, see Table 3. This is consistent with other studies [16, 27, 28], which demonstrates that no improvement could be achieved with more than one hidden layer. Furthermore, the model with two hidden layers is much more complicated than the one with one hidden layer [24]. Therefore, using MLP model with one hidden layer is reasonable for this research. Experiments to determine the number of hidden nodes are also important. Table 4 shows the *SSE* of one-hidden-layer MLP models with different number of hidden nodes. The best performance is achieved by the model MLP5 with 7 hidden nodes. Increasing the number of hidden nodes beyond this value range produces no better results. The reason is that too many hidden nodes result in too many connections, thus producing a network that memorises the input data and lacks the ability to generalize good output value [16].

Table 3. ANN model's results based on number of hidden layers

Model	Hidden layer	Training	Testing
		SSE	*SSE*
MLP1	1	0.004	0.335
MLP2	2	0.109	0.225

Table 4. ANN model's results based on number of hidden nodes

Model	Hidden nodes	Training	Testing
		SSE	*SSE*
MLP3	3	0.114	0.775
MLP4	5	0.006	1.012
MLP5	7	0.003	0.191
MLP6	9	0.072	0.926
MLP7	11	0.014	0.761

The results of the experiment reveal that the best network is the model MLP5 which includes 17 input nodes, 7 hidden nodes and 1 output node. This model has the minimum *SSE* which is 0.003 on the training samples and 0.191 on testing samples. Fig. 6 shows the comparison between the desired value and predicted values produced by model MLP5. The predicted outputs can be divided into two groups. Eight projects have the predicted outputs which are above the desired outputs while the rest seven projects have the predicted values which are below the desired ones. The range of overestimating varies from 0.01% to 0.93% with an average of 0.155%. The range of underestimating varies from 0.01% to 0.31% with an average of 0.068%. It can be seen in Fig. 6 that the model is able to imitate very well the Project Risk in projects 1, 6, 12 and 14, where the differences between desired and predicted output are 0.01% and 0.02%. The model can follow closely in project 2, 13 and very closely in the rest projects except for project 5. The predicted value in project 5 is considerably greater than the desired value with the difference is 0.93%. However, the overall results show that the model MLP5 can be used to assess project risk and can be applied for new projects. Based on the predicted Project Risk which is represented through the ratio of the profit to project cost, the constructor can forecast profit they may earn when perform construction that experiences risk.

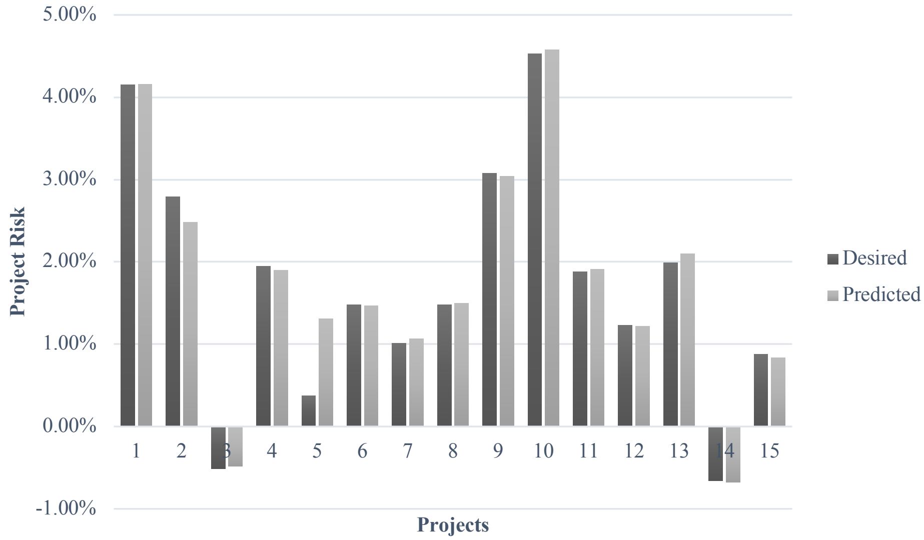

Figure 6. Desired output vs. predicted output produced by MLP5 model

4. Conclusion

Risk management contributes to the success of construction projects. This paper proposed a risk assessment framework with three main phases including risk management phase, ANN model creating and training phase and framework application phase. The framework provides an approach to assess Risk Factors using the FMEA method and to evaluate the impact of risk on contractor's profit using ANN technique. As a result of a comprehensive literature review, six groups along with 17 common Risk Factors were identified in this study. In order to assess the Risk Factors using FMEA method, this paper proposed an assessment range for Probability (P), Impact (I) and level of Detection (D). The list of Risk Factors and the assessment range can be used as a guideline for contractors to identify and assess Risk Factors. However, they can be calibrated to be suitable for a specific contractor and project context. The illustration of the proposed framework and its results were done by using a set of hypothetical data. A number of scenarios were trained and tested in order to figure out the best ANN model, which can produce results with as small Sum of Square error as possible. As a result of the experiment, the best model was the MLP5 with a 17-node input layer, a 7-node hidden layer and a 1-node output layer. Through the example, it can be concluded that this research approach is an adaptable approach that offers a different way of assessing risks, for the contractor benefits.

The proposed framework is suitable for using by contractors who perform projects which experience a generic list of Risk Factors. The main constraint in using the framework is one related to the data for training and testing the ANN model. Having a small set of data may lead to less accurate results. The reason is that ANN models need to learn from set of past projects which should be big enough for the model to produce accurate results for new projects.

The framework can be used as a tool which supports contractors in assessing project risks and evaluate their impact on construction profit. The framework should be used at the initiation stage of construction phase. Consequently, the contractor can perform suitable response actions to avoid or reduce risks. In further research, the framework will be validated with empirical data. Furthermore, additional research can focus on the use of combination of FMEA, ANN and Fuzzy logic in the framework to assess project risk.

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