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RISK ASSESSMENT AND MANAGEMENT OF SUSTAINABLE CONSTRUCTION PROJECTS USING ARTIFICIAL NEURAL NETWORKS

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Abstract

In recent years, significant attention has been paid to the use of Artificial Neural Network (ANN) techniques in the construction sector due to their ability to handle big data, predict risks, results accuracy, make reliable assessments, and solve complex nonlinear problems. This paper introduces a comprehensive sustainable methodology for risk assessment that is supported by artificial intelligence (AI). The methodology consists of four phases; phases one and two determine the risk factors impacting sustainable construction (SC) by collecting data from projects in Iraq (phase one) and conducting semi-structured interviews (phase two). Phase three applies a Failure Mode and Effect Analysis method to identify the risk factor values and apply an ANN model. Phase 4 uses the Absolute Percentage Deviation method to verify the proposed model. The study findings indicate that the ANN-based model provides more accurate and reliable risk assessments for SC projects than traditional methods. The model effectively integrates and analyses multiple variables and factors across the project life cycle, providing a comprehensive and dynamic view of risks and their potential impact.

Keywords: ANN, Artificial intelligence, FMEA, Risk assessment, Sustainable construction, Traditional and advanced risk assessment.

1. Introduction

Due to climate change and environmental pollution, there is an increasing demand among many sectors to address sustainable development (SD), especially following the emergence of the COVID-19 epidemic and war in Ukraine. The Europe's Sustainable Development Report [1] identified 17 sustainable development goals (SDGs) for all sectors. In 2015, the United Nations (UN) agreed that all members should be committed to implementing the 17 SDGs before 2030 [2]. They also stated that the primary purpose is to promote sustainability across all fields for both developed and developing countries, meet the current and future needs of stakeholders, contribute significantly to developing SD for society, and address challenges and priorities in the process of adopting and localising the SDGs.

According to Qazi et al. [3], the SDG index measures each country's overall fulfilment of the 17 SDG goals by considering the three dimensions of sustainability (economic, social, and environmental). Further, an average SDG score between 0-100 has been identified, whereby 0 indicates the lowest performance while 100 indicates the highest. For instance, Iraq scored 62.3 and ranked 115 in its progress toward achieving the 17 SDGs [4]. Governments must take the necessary steps to develop and implement SD policies and regulations and support the achievement of the 17 SDGs. In addition, they can establish a clear vision that incorporates sustainability in all sectors and adopts the latest technology to implement sustainable construction efficiently.

Sustainable construction (SC) projects can be classified as a subset of SD. They can be defined as "the creation and reliable management of a healthy built environment based on resource-efficient and ecological principles" [5]. According to the USA Environmental Protection Agency [6], sustainable construction refers to the economic, social, and environmental pillars of construction projects. SC means placement and construction design efficiency, the minimising of energy consumption, water efficiency, the use of eco-friendly materials, a focus on internal operations and maintenance, environmental quality improvements, and reductions to waste and toxic materials.

However, SC faces many challenges that delay its implementation. For example COVID-19 was considered one of the most critical challenges to impact SD. It caused one of the most considerable economic downturns since World War II and adversely affected SD dimensions (including SC) due to the lockdown policies, trade-offs, workforce shortages and management deficiencies [7].

Several studies have shown that the implementation of SC involves various risks that affect its use. For instance, Nguyen and Macchion [8] listed the main risks affecting the implementation of sustainable buildings and created a risk assessment model for SD projects. A study by Okoye et al. [9] found that SC projects encounter various sustainability risks, which have different levels of impact on projects and varying likelihoods of occurrence. Qazi et al. [10] discussed sustainable construction projects and their classification of risk. At the same time, El-Sayegh et al. [11] determined the risks significantly impacting the United Arab Emirates (UAE) SC projects.

Artificial Neural Network (ANN) are artificial intelligence (AI) techniques that are widely used to assess risk in several sectors, including construction. ANN is a robust computational tool that captures and describes complex relationships between inputs and outputs [12]. It can be a valuable tool in risk assessment due to its ability to analyse large amounts of data, identify potential risks, allow businesses to make more informed decisions, automate information, assist and monitor ongoing risks and implement mitigation strategies which can help businesses operate more efficiently and effectively and reduce their overall risk exposure.

Despite the features of AI, it is crucial to understand that it is not a replacement for human judgement and expertise and should be used as a supplement to traditional risk assessment methods. However, this paper proposes a comprehensive sustainable methodology for risk assessment and management support. The objectives of this research are:

OB1: To determine key factors that influence sustainable risk assessment and management processes in construction projects, with a focus on sustainability.

OB2: To investigate the potential and develop an ANNs-based risk assessment and management model for sustainable construction projects in developing countries.

2. Background on Sustainable Construction

2.1. Risks and sustainable construction (SC)

In recent years, SC projects have become one of the solutions to reduce air pollution and mitigate climate change, as the traditional construction industry is considered the most significant contributor to CO_2 emissions. The Implementation of SC is subject to many risks [13]. According to Okoye et al. [9], the key risks that substantially affect the success of SC projects in Nigeria are knowledge and awareness of technology, cost, regularity frameworks, material availability, and socioeconomic issues.

However, this study focuses only on social and economic risks; the study does not consider other important risk factors associated with SC, such as contractual issues, skills shortages, and the lack of construction contractors. El-Sayegh et al. [11] ranked according to the importance of the risk factors. They said that the significant risk factor is the need for greater awareness, followed by funding shortages, constant design changes, design deficiencies, and the limited time to implement sustainable construction. One major drawback of this study was that innovative approaches were not used to determine and evaluate the risk factors.

Ismael and Hussain [14] studied and explained the current state of SC projects. The challenges and risks facing the implementation of SC in Iraq include the identification of critical risk factors, low public awareness, the absence of regulations and legislation, poor leadership, management, financial and design constraints, and technical and social issues.

However, other important risk factors should be noted, such as the lack of standards to implement SC, political instability, the slow adoption of advanced technology, and the limited number of contractors and professionals working in this field. Hwang et al. [15] listed the various risks associated with Singapore's residential SC. These include the complexity of procedures to obtain approvals, unforeseen site conditions, high initial costs, the shortage of sustainable materials and equipment, a lack of awareness, and employment constraints. However, the paper fails to suggest solutions or develop a risk assessment model for use by Singapore's sustainable construction companies.

2.2. Risk assessment tools used in SC

Several tools can be used to identify, assess, and prioritise risks associated with SC. Table 1 shows the existing tools in widespread use.

Table 1. SC methods used in previous studies.

Application	Year	Methods Used	References
Risk assessment	2023	Bayesian Belief Network	[3]
Risk assessment	2023	Deep Multilayer Perception Neural Network (MLP-NN)	[16]
Risk assessment	2023	• Fuzzy Set Theory • Analytical Hierarchy Process	[8]
Risk assessment	2022	• AHP • BBN	[17]
Risk assessment	2022	• Analytical Network Process • Probabilistic Neural Networks	[18]
Risk assessment	2022	• Monte Carlo-DEMATEL. • Fuzzy Parsimonious Analytic Network Process ANP.	[19]
Risk assessment	2021	Probability and Impact & Monte Carlo and Risk matrix.	[10]
Risk assessment	2018	Artificial Neural Network	[20]
Risk assessment	2023	Deep Neural Network.	[21]

Based on the above information, most studies have considered traditional risk assessment tools and identified risk factors of construction projects. Only a few studies highlighted the assessment of risks that affect SC projects. In this paper, an Artificial Neural Network (ANN) multilayer perception (ANN-MLP) model is developed to assess risk factors that impact SC projects in developing countries.

The main advantages of using the ANN method are: 1) the ability to learn from previous projects, 2) the ability to solve complex nonlinear problems and identify complex links in a data set, 3) deal with a large amount of input data, 4) generates quick predictions after training which are incredibly accurate and 5) obtain precise findings despite small amounts of input data.

2.3. Sustainable construction in Iraq

SC is recently considered a successful driver in accomplishing the UNSDGs. It integrates environmental impact, energy efficiency, resource efficiency, indoor environmental quality, economic benefits, sustainable waste management, climate change mitigation and social responsibility. Therefore, the construction sector can contribute significantly to developing the future of sustainable development. Iraq is highly active in construction development due to its economic power, the production of crude oil, and the natural resources it possesses.

However, there is a need to reconstruct the country, including its infrastructure, hospitals, roads and bridges, and residential and commercial buildings, after destruction between 2003 and 2014. In addition, there has been a sizeable growth in its population. In 2022, Iraq's population was estimated at 45.52 million [22], highlighting the need for a sustainable construction industry. Iraq's construction sector is an essential driver for economic growth and infrastructure development. It plays a pivotal role in providing work opportunities for many people, as it employed 16.3% of the Iraqi workforce in 2021 [23].

Moreover, in the past few years, there has been increasing demand for sustainable construction (SC) in Iraq due to the government strongly supports the development of SC cities. It has started to allocate a considerable budget to embrace SC to 1) reduce environmental pollution and global warming emissions., in which Iraq was ranked 167 amongst the most polluted countries [24], and 2) provide a construction that ensures thermal insulation construction against the extreme summer heat and reduces the consumption of electrical energy consumption [25].

Therefore, Iraq's government identified several opportunities to invest in sustainable construction, such as Aljawahari Sustainable City. The city is located to the west of Baghdad and consists of 29,000 houses with service projects and infrastructure [26]. However, the implementation of SC in Iraq faces several challenges and risks that substantially affect its adoption. Ismael and Hussain [14] pointed out that the most critical risk factors that impact SC projects in Iraq include a lack of awareness, low professional skills, political instability, the slow adoption of modern technology, poor management, the lack of standards for implementation, and contractual issues.

3. Artificial Implementation Methods and Results

To meet the research objectives, a mixed qualitative and quantitative method is used, with a special reference to Iraq. Figure 1 depicts the research methodology used.

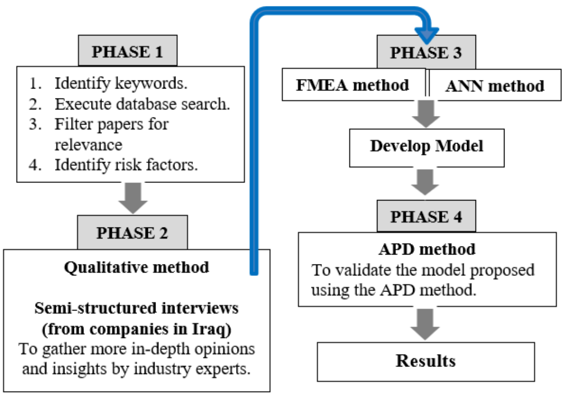

Fig. 1. Research methods.

3.1. Phase 1: Identifying the main risk factors

In this phase, an extensive literature review was conducted to understand SC's current status and identify the main risk factors that impact SC projects in developing countries, with a special focus on SC projects in Iraq.

3.2. Phase 2: Semi-structured interviews

A semi-structured interview was carried out to develop profound insight into the risk factors affecting Iraq's sustainable construction projects. According to Galletta

[27], semi-structured interviews aim to effectively investigate complicated phenomena or situations. Al-Saffar et al. [28] indicated that semi-structured interviews were employed in several studies to determine managerial factors and practices associated with construction and engineering management.

Moreover, they help researchers to understand professionals' and experts' viewpoints in the field of SC. As such, the authors selected semi-structured interviews (using open-ended questions) to assess the risk factors affecting SC projects in Iraq. A total of 30 senior managers, professionals and academics participated in either face-to-face or online interviews. The participants worked at the Iraqi Ministry of Construction and Housing, in private construction companies and consultant engineering offices in public universities.

The sample selection criteria were as follows: 1) the participant works in SC with a minimum of 15 years' experience; 2) the participant is officially registered with the Iraqi Engineers Union; 3) The company is officially registered with the Registrar of Companies at the Iraqi Ministry of Trade; and 4) the company has undertaken at least four SC projects in Iraq. Further, the profiles of the interviewees are illustrated in Table 2.

Table 2. Profile of interviewees.

No. of Interviews	Construction Role	Years of experience	Education level		
			BSc.	MSc.	PhD.
9	Senior manager	15-23	5	1	3
14	Professionals	16-25	11	3	0
7	Academic	18-27	0	3	4

Upon completing the semi-structured interviews, the authors applied content analysis to determine the most significant risk factors. Collis and Hussey [29] define content analysis as a research analysis tool that analyses the text of data to obtain a deep understanding or interpretation.

Moreover, A study by Krippendorff [30] demonstrated that content analysis is a powerful tool for analysing qualitative and quantitative data where invaluable information can be obtained from verbal, written, or video files. Following the content analysis, 23 major risk factors were reported in the literature and confirmed by the Iraqi interviewees, as depicted in Table 3. However, Table 4 shows a list of Iraqi projects and companies involved with SC that have been considered in the current analysis. The study adopted fourteen sustainable construction projects in Iraq, including the type of project, sustainable construction features, and the sources of information.

Table 3. The main risk and sub-risk factors of SC.

Main Factors	Sub-Risk Factors	References
Management	RF1: Limited time for the implementation of sustainable construction projects.	[10, 11]
	RF2: Lack of specialists and professionals in sustainable construction management.	[9, 11] & Interviews.
	RF3: Improper sustainable project feasibility and planning.	[9, 31]
	RF4: Unclear contract conditions for dispute resolutions.	[32]
	RF5: Poor communication among project stakeholders.	[9]

Financial	RF6: Inflation.	[10, 15].
	RF7: Currency exchange rate.	[9, 15]
	RF8: High initial sustainable construction cost.	[31]
	RF9: Payback period (lifecycle cost).	[33] & interviews
	RF10: Poor estimation of sustainable construction.	[9, 15]
Technical	RF11: Inaccurate sustainable design information	[11, 34]
	RF12: Continuous change in design during construction.	[11]
	RF13: Experience with new technology.	[9, 31] & Interviews
	RF14: Complicated construction techniques and difficult processes	[8, 10]
Material	RF15: Unavailability of sustainable materials	[8, 11]
	RF16: Sustainable and efficient materials	[9]
	RF17: The cost of sustainable materials is high.	[15] & Interviews
Legal	RF18: Delays to government approvals for sustainable construction	[11] & interviews
	RF19: Changes in sustainable codes and regulations.	[10, 11]
	RF20: The need for a corresponding sustainable construction contract.	[15]
Social	RF21: Lack of awareness and knowledge.	[8]
	RF22: Construction safety while working on sustainable features.	[31]
	RF23: Damage from misuse	[15, 31]

Table 4. A list of 14 Iraqi SC projects.

Project	Project Type	Sustainable Features	Reference
A	SC College	-Energy and water efficiency (E1). -Waste management (WM1).	Interviews
B	Houses	E1 & WM1.	Interviews
C	Houses	E1 & WM1, Indoor air quality (IAQ), and Sustainable construction materials (SCM)	Interviews
D	Houses	Sustainable architectural design (passive cooling and heating technique) (SAD), E1, (IAQ), SCM and RCC	[35] & Interviews
E	Schools	SAD, E1, IAQ, SCM and RCC.	[35] & Interviews
F	SC hospital	Sustainable design (SD1), E1, IAQ, SCM, Re-use recycling (RR1) and RCC	[35] & Interviews
G	SCB	SD1, E1, IAQ, SCM, RR1 and Renewable energy (RE1)	[36] & Interviews
H	SB	E1	Interviews
I	SCB	E1, SD and WM1	[25] & Interviews
J	SCB	E1, SD and WM1	Interviews
K	SC schools	E1	[37] & Interviews
L	SCB	E1 and RCC	[37] & Interviews
M	SCB	SD, E1, IAQ, SCM, RR1 and RE1	[38] & Interviews
N	SCB	E1 and RCC	Interviews

**SCB: Sustainable Construction Building*.

3.3. Phase 3: Quantitative methods

3.3.1. Failure mode effect analysis

The FMEA method suggested by Valis and Koucky [39], is used in the current study. FMEA is a method used to analyse the potential failure modes of the different parts of a system and assess the impact of these failures. "Failure Mode" refers to process weaknesses, faults, or problems in the sequence of the processes, production errors and design inability, which may directly impact clients. The FMEA method was described to assess the risk occurrence, severity, and detection of the risk. Table 5 shows the definition of the three variables definition and their range. The risk Priority Number (RPN) could be calculated using Eq. (1) within 1 to 5 range.

$$RPN = O \times S \times D \quad (1)$$

Table 5. Definition of the three variables and their range.

Variable	Definition	Range
Occurrence (O)	Probability of risk occurrence	1-5
Severity (S)	Degree of risk effect on a project timetable	1-5
Detection (D)	Level of risk detection by a project team	1-5

3.3.2. Artificial neural network

ANN is a model for processing information composed of interconnected artificial neurons that address poorly defined problems and predict or approximate unknown functions [40]. An ANN is a valuable method used for resolving complex qualitative or quantitative problems where the relationship between the mathematical and statistical techniques of parameters are highly interconnected, and the data are ambiguous, noisy or tend to include errors [41].

3.3.3. ANN architecture design

The nodes in ANN are referred to as neurons. Every neuron can generate an output based on the signal. The neurons are organised into layers, and there is also a link between every neuron in each layer with the neuron in the following layer. The function used in the ANNs method is illustrated in Fig. 2.

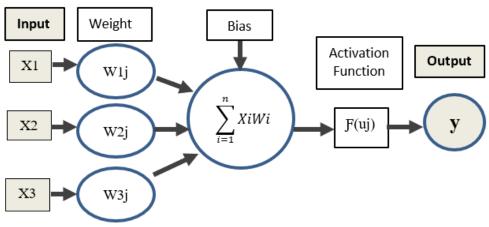

Fig. 2. The function of ANN.

where, X = Input value, W = Neuron weight, J = Project number, Y = Output value. Each input (X1, X2, …, Xn) is multiplied by the weight (Wij). The product and bias are added to calculate the sum (∑) that is enacted using an activation function F(uj) to generate an output, which can be calculated using Eq. (2).

$$y = f(\sum XiWi) \quad (2)$$

Each neuron in a neural network has its own bias. Offsetting the result through bias is necessary to handle the non-zero inputs, model complex decision boundaries, break symmetry, and handle imbalanced data. In this way, a network can adapt to various patterns and data distributions, ultimately improving its performance and generalisation abilities. In neural networks, errors can occur due to bias, variance, data quality/quantity, feature representation, model architecture/hyper-parameters, and conceptual/formulation issues. The bias error occurs when a model consistently deviates from the actual values.

As a result, it is necessary to improve the data quality to select informative features, optimise the model architecture, and fine-tune the hyper-parameters to achieve better predictions. The activation function uses mathematical operations to determine the significance of the neuron's input to the network. It also plays a crucial role in the efficient realisation of ANN due to its ability to perform the large number of calculations needed by modern applications, such as natural language processing, classification of risk, and anomaly detection in data [42]. The ANN consists of three layers as follows:

Input Layer: This layer gathers information and data from related sources and transforms them into a network of signals consistent with the problem's nature and characteristics. Also, the exact number of neurons equals the number of input variables. Eventually, the outputs of this layer are considered as input for the following layer (i.e. hidden layer).

Hidden Layer: This layer is located between the input and output layers. All computation for addressing nonlinear problems occurs in this layer. The hidden layer's neurons adopt inputs which are the outputs of the input layer. The number of layers and neurons in the hidden layer can change depending on the complexity of the data.

Output Layer: The data is processed in this layer, and the nature and characteristics of the problem will determine the number of outputs. Also, all output neurons in this layer will be linked to the neurons in the hidden layer. The weighted outputs, determined by the hidden layer, represent the inputs for the output layer.

Table 6 shows the definition and assessment range of the three FMEA variables.

Table 6. The assessment range of three FMEA's variables.

Variables	(O)	(S)	(D)
1 Very Low	The likelihood of the event is extremely low and could statistically be less than 1%	There is a minor change in the project's time, quality, and cost. Statistically, the percentage could be less than 1% and not be noticed.	The project team can easily detect the risk factors that occurred.
2 Low	The likelihood of the event is low and statistically could be from 1% to 20%	The time extension or cost overrun ranges from 1% to 4%. Project quality could also be affected by the same percentage.	The project team has low difficulty in detecting risk factors that occur.
3 Medium	The likelihood of the event is extremely low and could statistically be from 21% to 50%	The time extension or cost overrun ranges from 4% to 7%. Project quality could also be affected by the same percentage.	The project team has medium difficulty in detecting risk factors.
4 High	The likelihood of the event is extremely low and could statistically be from 51% to 75%	The cost overrun ranges from 3% to 7% to 10%. Project quality could also be affected by the same percentage.	It is challenging to detect the risk that occurred.
5 Very High	Likelihood of the event is extremely low and could statistically be 76% to 100%	The time extension or cost overrun is more than 10%. Project quality could also be affected by the same percentage.	The project team are unable to detect the risk factors that occurred.

For this research, an ANN technique was applied using SPSS software to evaluate the 23 risks associated with 14 SC projects in Iraq. ANN inputs are identified using the FMEA method. Table 7 shows the ANN input data with the 23 risk factors (RF1 to RF23) and 14 SC projects (P1 to P14).

Table 7. Input data (in percentages) with 23 risk factors and 14 projects for the ANN model.

RF \ P	1	2	3	4	5	6	7	8	9	10	11	12	13	14
RF1	60	30	60	75	80	48	32	27	80	25	32	80	64	64
RF2	75	75	20	18	75	27	100	20	18	50	48	36	45	15
RF3	48	80	36	32	64	24	27	16	27	40	40	27	60	45
RF4	32	27	45	18	32	80	80	32	36	48	45	45	15	64
RF5	60	10	50	60	32	30	80	30	30	32	27	20	30	27
RF6	25	25	36	36	16	40	32	32	50	50	32	80	40	24
RF7	25	100	25	18	75	60	20	32	25	25	27	80	32	20
RF8	25	20	24	24	40	32	80	27	12	32	48	27	16	75
RF9	30	20	16	48	100	16	125	18	12	60	45	18	40	40
RF10	25	25	27	18	48	80	64	27	25	32	32	30	8	12
RF11	60	75	30	20	100	48	80	45	20	50	24	48	8	64
RF12	48	50	16	18	64	20	32	18	16	20	36	20	36	8
RF13	32	30	24	50	36	40	100	27	60	80	45	45	12	36
RF14	20	75	24	30	24	80	60	24	12	80	64	80	18	75
RF15	25	80	75	75	80	50	80	80	80	100	18	32	27	45
RF16	27	27	20	48	64	48	45	32	16	16	16	20	45	18
RF17	50	75	16	75	100	32	32	16	27	25	27	16	27	16
RF18	32	18	100	18	45	100	48	25	16	64	45	80	80	40
RF19	45	27	12	36	36	27	20	18	8	36	36	24	16	12
RF20	36	40	27	24	45	27	24	27	27	80	64	27	100	20
RF21	30	80	20	75	16	25	80	80	125	75	32	100	80	24
RF22	40	100	20	40	20	25	16	9	30	16	36	18	12	32
RF23	18	18	32	45	27	15	9	20	20	48	27	27	20	64
RF23	20	20	48	27	27	20	64							

The example in Table 8 shows how the RPN value of 60 was calculated for project 1 (P1) and risk factor 1 (RF1) using the O, S and D values.

Table 8. How the RPN value of 60 was calculated for P1 and RF1.

Project	Project 1			
	O	**S**	**D**	**RPN**
RF1	5	4	3	60

Using Eq. (1), getting: RPN = O × S × D = 5 × 4 × 3 = 60 (i.e. 60%).

Additionally, the ANN output value can be calculated using Eq. (3) below:

$$\text{Project Risk (PR)} = (\text{Project profit} / \text{Project cost}) \times 100\% \tag{3}$$

Table 9 shows the PR of 14 projects as the output of the ANN model.

Table 9. Output data for ANN model.

Project	PR	Project	PR
P1	3.25%	**P8**	4.15%
P2	0.40%	**P9**	1.01%
P3	1.25%	**P10**	0.55%
P4	1.88%	**P11**	1.42%
P5	1.95%	**P12**	2.35%
P6	0.53%	**P13**	0.75%
P7	1.33%	**P14**	5.00%

For example, the PR for Project P1 is calculated using Eq. (3), as follows:

PR for P1 = (Project profit / Project cost) × 100%,

= (3,250/100,000) × 100% = 3.25%.

3.3.4. ANN-Based multilayer perception model

The neural network MLP technique is used in this paper. MLP is a feed-forward neural network which can produce an output from input data [20]. MLP uses back-propagation as a supervised learning technique due to the presence of multiple layers of neurons. The MLP network in this research includes the following:

- The input layer contains 23 RF neurons representing the risks of 14 SC projects.
- The hidden layer.
- The output layer includes one neuron representing project risk (PR).

The Hyperbolic Tangent method was chosen as the activation function for the hidden layer as it is widely used due to its benefits, such as inclusiveness and high accuracy. It also allows for data centring and simplifies learning for the next layer. Additionally, it covers the full range of inputs from -1 to 1 to produce an output [42]. The activation function "Identify" was used for the output layer.

In MLP, the input neurons send signals to the hidden neurons, and then hidden neurons compute and deliver output results to the output layer. For the ANN training and testing in this study, 14 projects were utilised and divided into two sets. The first set consisted of 11 projects (about 78.5% of the sample), which were used for training, and the second set consisted of 3 projects (around 21.5% of the sample) which were used for testing. To identify the output error in the model, the sum of squares (SSE) was calculated using Eq. (4).

$$SSE = \frac{1}{2}\sum_{i=1}^{p}(y_i - d_i)^2 \quad (4)$$

where, p = The total number of projects selected, y_i= The predicted output, and di = The actual output.

The SSE value, calculated automatically by the ANN system, serves as a metric to assess the model, and the most suitable model is identified as the one with the lowest SSE value for both training and testing samples. In the range of SSE values considered, which spans from 0.01 to 0.31, the selected ANN model exhibited an SSE value of 0.02 in the training sample. This value is close to the lowest possible value of 0.01. After several training and testing experiments, the best model was produced.

Figure 3 shows the best model produced by the ANN, which consisted of the 23 risk factors among the SC projects in Iraq. These formed the inputs and one output (project risk), with one hidden layer and four hidden nodes. The hidden layers H (1:1) to H (1:4) represent intermediate layers within the neural network architecture. The numbers inside the parentheses (1:1) to (1:4) indicate a specific relationship or ratio between two elements represented by H. Detailed analysis of the ANN and hybrid ANN-GA artificial structures have been reported by Ismail et al. [43], and Alnaimi and Al-Kayiem [44] using various activation functions and many hidden layers. Their hybrid technique could be adopted and compare the results with the current ANN model.

Figure 4 compares the actual and predicted values created by the ANNs model. It shows that the model can predict project risk (PR) values with a high degree of accuracy in projects 3, 4, 5, 7, 8, 10, 11, 12, and 14. In contrast, the actual PR value of Project 1 is higher than the predicted value by 1.54%. At the same time, the actual PR value is less than the predicted value for Projects 2 (by 0.91%) and 6 (by 0.73%).

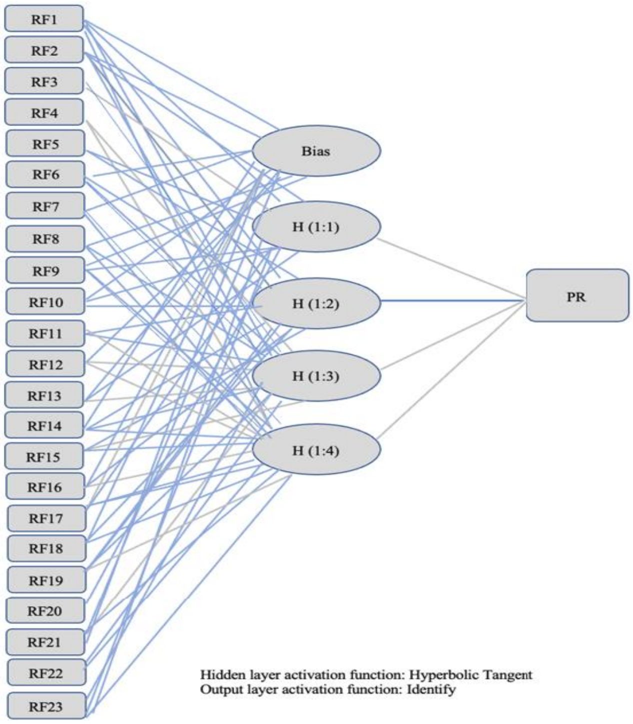

Fig. 3. The proposed ANNs model.

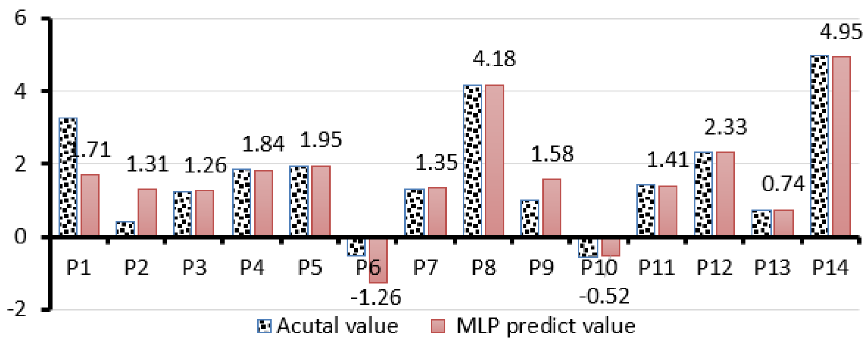

Fig. 4. ANN actual values versus the MLP predicted value.

Figure 5 shows that RF2 occupied the top rank among the other risk factors in terms of impact, followed by RF11 and RF20. On the other hand, RF6 has the lowest impact.

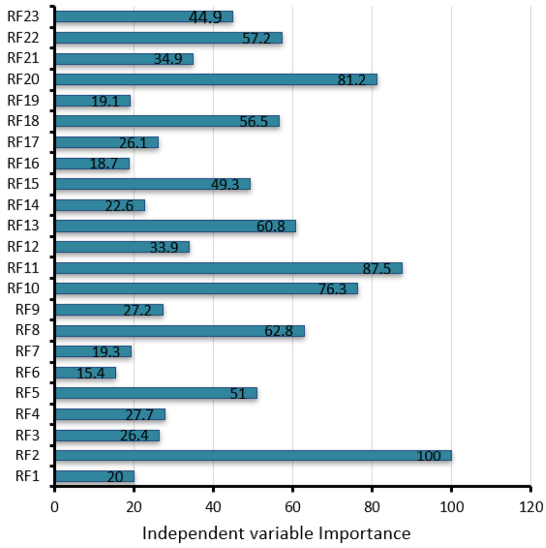

Fig. 5. Importance of the predicated factors.

3.4. Phase 4: Validation of the ANN model using the absolute percentage deviation

To validate the model, the authors used the APD indicator, which is a measure of the prediction accuracy of a model to compare actual value with predicted value. Table 10 shows the results of the APD. According to Patel and Jha [45], a model is considered reasonable if the APD assessment results are less than 10%. Therefore, the ADP results shown in Table 10 are acceptable and reliable, i.e., the model's performance is high.

Table 10. APD results in percentages.

Project	PR Actual Value	MLP Predicted Value	APD
1	3.25	1.71	1.54
2	0.40	1.31	0.91
3	1.25	1.26	0.01
4	1.88	1.84	0.04
5	1.95	1.95	0
6	-0.53	-1.26	-0.76
7	1.33	1.35	0.02
8	4.15	4.18	0.03
9	1.01	1.58	0.57
10	-0.55	-0.52	-0.02
11	1.42	1.41	0.01
12	2.35	2.33	0.02
13	0.75	0.74	0.01
14	5.00	4.95	0.05

4. Conclusions and Limitations

This paper has reviewed the risk factors that impact SC projects. Data were obtained from SC projects in developing countries, specifically from selected projects in Iraq. A literature review and the analysis of semi-structured interviews identified six main factors and 23 sub-factors that impact SC projects. Furthermore, the FMEA method was used to identify the weight of the factors by calculating the probabilities of risk occurrence (O), risk severity (S) and risk detection level by the project team (D). The ANN method was implemented to develop a model that assesses the risk impacts of SC projects.

In addition, several scenarios were trained and tested to select the most suitable ANN model. The results showed that the most appropriate model with a small SSE error consisted of 23 input layers, one hidden layer, a four-node hidden layer, and one node output layer. Furthermore, APD was applied to validate the proposed model. The results showed that the actual values of project risk (PR) value were reasonable and acceptable when compared with the values predicted by the ANN model. This paper has contributed to the knowledge by providing SC companies with a model that can be used for the assessment of risk factors using a method (ANN) that can be used to solve complex problems. However, to ensure the effectiveness of neural network models, cultural and contextual factors specific to Iraq, such as local regulations and socioeconomic conditions, may need to be appropriately incorporated into the model.

In future studies, the hybrid ANN method, Bayesian belief networks, and genetic algorithms to assess risk factors and cost estimations are recommended. Another research possibility is to develop an Artificial Intelligence (AI) model that automatically identifies the risk factors of SC projects and modifies the weights and biases of these factors to enable more accurate predictions and results.

Nomenclatures

d_i	The actual output
f(uj)	Activation Function
y_i	The predicted output

Abbreviations

ANN	Artificial Neural Network
APD	Absolute Percentage Deviation
FMEA	Failure Mode Effect Analysis
MLP	Multilayer Perception
RPN	Risk Priority Number
SC	Sustainable Construction
SD	Sustainable Development
SSE	Sum of Square

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