

MSCA based Deep Recurrent Neural Network for Statistics Risk Management in Construction Projects

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Abstract

Risk management plays a vital role in various construction activities to maximise construction profitability and reduce the loss of construction projects. Managing risk in construction projects is considered the most significant process in achieving the objectives in terms of quality, cost and time. Also, it is necessary to prioritise and identify the most probable risk that occurs during construction projects. Due to the unanticipated risk, around 40% of construction projects are dropdown in developing countries. This paper aims to develop and identify the project delay risk at a minimum duration of time and cost. Our paper comprises of five major phases: Identification of risk source and its factors, Systemization and Pre-processing of the dataset, Analysis of dataset constraints, Sensitivity data computation, and Tool selection using DRNN-MSCA to determine the risk, thereby establishing an effective and accurate prediction analysis. Here, the machine learning algorithm, namely the Deep Recurrent Neural Network (DRNN) and the Modified Sine Cosine Optimization Algorithm (MSCA), is integrated to minimise the inter-dependence and the complexity of the construction delay. The 5-point Likert scale computes the probability and the variables impact by the measures from very low to a very high level. Finally, the performance of the proposed approach is calculated and compared with a few other existing approaches such as ANN (Artificial Neural Network), RF-GA (Random forest and Genetic algorithm) and ML (Machine learning). The results reveal that the proposed approach provides a superior accuracy performance is 81.65%, with less cost and time delay.

Keywords

Construction project, risk management, DRNN, MSCA, prediction analysis, time, cost



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Introduction

The construction projects comprise various grouping endeavours associated with engineering-based construction works of diverse classes or categorisations. It also involves both a dynamic and complex atmosphere that measures the impact of the most probable instances of risk and uncertainty (Srinivasan & Rangaraj, 2020). At the present time, project management has been utilised extensively across numerous industrial sectors. In the context of defining project management, "A project is considered as a transient or short term attempt that consists of a distinctive point of departure and a terminal or destination point that results in remarkable product or service". There are a few limitations that demonstrate the project management, which includes time, scope, quality, cost, risk and resources (Leslie Appiah, 2020; Al-Subaie et al., 2021). Due to certain limitations, the organisation fails to perform their project within the framework and to overcome such shortcomings, the organisation must spot out the risk of the project, which includes quality, scope, time, cost etc. that creates a momentous impact during selecting a contractor and the assigning of the project to the contractor (Fakhratov et al., 2020). The process involved in project management comprises of a distinct procedure set that includes quantitative and qualitative risk performances, controlling the risk factor, identification of potential risk as well as the preparation of risk plan responses (Nawaz et al., 2019; Vaníčková & Szczepańska-Woszczyzna, 2020).

Risk management plays a vital role in various construction activities to maximise construction profitability and to reduce the loss of construction projects. On the other hand, the construction risk influences the quality, cost and time duration of the project. Therefore, it is necessary to prioritise and identify the most probable risk occurring during the construction projects (Ortiz, Pellicer & Molenaar, 2019; Velumani, Nampootheri & Mariusz, 2021). Numerous surveys demonstrated by various research scholars were conducted between the managerial personnel, engineers and contractors to analyse the risk while constructing projects. Risk management in terms of construction projects identifies the major factors that potentially influence the performances that result in probable losses, namely the scheduling, workmanship and quality (Adeleke et al., 2019). The organisation's main intention is to identify the risk and implement various corrective measures to mitigate various potential impacts associated with them (Rahman & Adnan, 2020). Risk can be reduced or even eliminated in companies by adhering to the principles of sustainable business development (Kasych and Vochozka, 2018). According to Kliestik et al. (2020), earning management is responsible for maximising short-term and long-term profit. Earning management must cooperate with risk management to achieve their aims (Bacik et al., 2019; Dvorsky et al., 2021).

In addition to this, the technique that estimates and identifies the risk based on personal and property is referred to as the risk assignment. Although the construction project comprises of numerous variables, therefore, the correlations, dependency, and causality seem difficult to determine (Yazdani et al., 2019). Because of diverse activities, construction projects have become more risky and complex between various companies worldwide. On the other hand, the construction projects undergo numerous risk factors during working conditions, construction practices, political conditions among host and home countries, as well as mixed cultures. Thus, risk management plays a vital role in decision making progression during the construction of the project (Abazid & Harb, 2018; Uğural, Giritli & Urbański, 2020). The construction sector also comprises of various stack holders that create a very big challenge in the industry. The project failure during the construction requires huge time and cost, and it must be assessed and evaluated with respect to various scenarios (Lam & Siwingwa, 2017).

This paper proposes five major phases: Identification of risk factors and its source that comprises of Proprietor, Resource Person, Construction Contractor, Layout model, Labour, Stocks and Resources, Apparatus, Time Delay and Cost, Climate as well as External Risk, Systemization and Pre-processing of the dataset, Analysis of dataset constraints, Sensitivity data computation, and Tool selection using DRNN-MSCA to determine the risk thereby establishing an effective and accurate prediction analysis at minimum time and cost. The contribution and organisation of the paper are obtained in the following section.

- Developing five various phases to determine the risk and to minimise the inter-dependence and the complexity of the construction delay.
- Integrating DRNN-MSCA to establish an effective and accurate prediction analysis at minimum time and cost.
- Comparing our proposed approach with other existing approaches to evaluate the effectiveness of the system.

The following section provides the organisation of our work. Section 2 depicts the summary of various literature works regarding risk management on construction projects. Section 3 describes the proposed methodology using five different phases. Also, the DRNN-MSCA algorithm is integrated for the effective prediction of risk. In section 4, the results of the proposed approach and the comparative analysis of other existing approaches are presented. Finally, section 5 concludes the article.

Literature Review

Several research scholars conducted a number of researches and experiments regarding risk management on construction projects. In order to gain a better understanding, the summary of a few existing research works are delineated in the following section.

The study by Burduk et al. (2021) demonstrated in the Failure Mode and Effect Analysis (FMEA) to determine the causes and effects of failures and determine the corrective actions. This approach has given an idea for Deep Recurrent Neural Network (Burduk et al., 2021).

The research conducted by Siwiec and Pacana (2021), Vaněk et al. (2020) and Wolniak (2019) demonstrated in the Failure Mode and Effects Analysis (FMEA). The analysis implies that discontinuous technology involves more risks than continuous conveyance. This finding is also the answer to the research question asked by the authors in the Introduction. However, the higher degree of risk in discontinuous technology does not necessarily mean that it cannot be used when deciding on overburdened transport technology (Vaněk et al., 2020).

The study by Mustafa et al. (2020) demonstrated the integration of a three-dimensional building information model (3D-BIM) to identify risk management in the construction sectors. The evaluation metrics obtained in this approach was rank, mean and RII weightage score that evaluates the risk in terms of quality, time and cost. The experimental analysis was conducted with respect to the above three parameters, and the results revealed that the 3D-BIM approach identifies the risk at the early period with enhanced coordination. But this approach failed to identify a large percentage of risk using 3D-BIM analysis (Mustafa et al., 2020). Vrbka, Šuleř and Horák (2019) analysed the construction sector in the Czech Republic by using ANN to identify the leaders in this industry.

A novel approach for risk management was developed by Mahmoudi et al. (2020), and it revealed the utilisation of three different approaches, namely the Best Worst (BW) approach, Grey Relation (GR) analysis and Analytic Hierarchy (AH) process for risk minimisation. Score, rank, distinguishing coefficient, grey relation grade were the performance measures employed in this approach. This approach failed to define significant factors involved in the identification of risk for construction projects (Mahmoudi et al., 2020).

Zhang and Mohandes (2020) research demonstrated Occupational Health and Safety in green building construction projects using a Holistic Z-numbers-based Risk Management (HZRMS) approach. The performance metrics employed in this approach are Magnitude, risk weight, safety risk, rank, frequency. This approach is involved in identifying the critical safety risk during the construction of projects, but the implementation is complex (Zhang & Mohandes, 2020). According to Krulický and Horák (2019), buildings can be considered good investment assets, so risk management in construction projects is also very important for real estate investors.

A critical success factor (CSF) framework for effective implementation of risk management was proposed by Bu Qammaz and AlMaian (2020). Rank, cluster, time were the evaluation measures employed in this approach. This approach provides minimum risk in the construction phase but is less effective (Bu Qammaz & AlMaian, 2020).

Integrated risk management framework for tolerance-based mitigation strategy decision that supports modular construction projects. Coefficient value, risk impact, input percentile were the performances that are evaluated in this approach. The experimental results were conducted, and the analysis revealed that this approach was provided with enhanced modularisation performances with a low rate of accuracy (Enshassi et al., 2019).

Innovations are the driving force of economic life in countries (Gavurova et al., 2021a; Gavurova et al. 2021b). According to Jiříček and Dostálová (2018), research and innovation in the business sector require EU investment to support the competitiveness of small and medium-sized enterprises. The development of supply chain risk management approaches for construction projects was proposed by the researchers (Shojaei & Haeri, 2019). They developed a ground theory framework to enhance the performances and to identify the risk mitigation scenario. The evaluation metrics employed in this approach was weight, rank, supply chain risk. In addition, this approach failed to address managerial issues. According to Rowland and Šuleř (2019), the level of risk can be regulated using sub-system management of organisational culture. The diversification of specific tasks and the associated diversification of responsibilities for their fulfilment ultimately have a positive effect on reducing the risks associated with a particular project.

Chatterjee et al. (2018) proposed a hybrid MCDM technique for risk management in construction projects. There are three different types of risk employed in this approach, namely the external risk, internal risk and project risk. The experimental analysis was conducted, and the analysis reveals that this approach consists of high sensitivity and reliability values and failed to determine the hidden risk (Chatterjee et al., 2018).

Mhetre et al. (2016) utilised a work breakdown structure (WBS), and risk breakdown structure (RBS) to establish an effective risk management system. The performance measures employed in this approach are rank, and weightage score. This approach was provided with a minimum value of risk, but the implementation seems complex in this approach (Mhetre et al., 2016).

Hamzaoui et al. (2019) developed an organised method of risk analysis that employed two different approaches, namely MADS and MOSAR approach. Cost, time, the quality percentage was the metrics employed

in this approach. In addition to this, organised approaches are employed in the easy identification of risk. But this approach failed to consider the safety barrier during the risk management process (Hamzaoui et al., 2019).

Wang et al. (2018) developed a meta-network-based risk evaluation and control method for industrialised construction projects. Risk factors, cost, time, rate of probability were the performance measures employed in this approach. The analysis revealed that this approach was provided with a high rate of feasibility. But the effectiveness of the system is very low, which is the major drawback of this approach. The summary of the existing literature works is discussed in Table 1.

Table 1: Summary of existing related works

References	Techniques/ Approaches	Evaluation Metrics	Merits	De-Merits
(Burduk et al., 2021)	Failure Mode and Effect Analysis (FMEA)	Risk assessment for the loading and haulage processes with the use of ANN	Grouped causes of the problem	Limited to liner model project.
(Mustaffa et al., 2020)	3D-BIM Model	Identification of early risk and enhanced coordination	Rank, mean, RII weightage score	An only small percentage of risk is identified
(Mahmoudi et al., 2020)	BWM, GRA, AHP	Minimum potential risk	Score, rank, distinguishing coefficient, grey relation grade	Failed to define significant factors
(Zhang & Mohandes, 2020)	HZRMS approach	Critical safety risk identification	Magnitude, risk weight, safety risk, rank, frequency	Complex during implantation
(Bu Qammaz & AlMaian, 2020)	CSF framework	Minimum risk in the construction phase.	Rank, cluster, time	Ineffective risk management
(Enshassi et al., 2019)	Symmetric risk management framework	Enhanced modularisation performances	Coefficient value, risk impact, input percentile	Low accuracy
(Shojaei & Haeri, 2019)	Ground theory approach	Enhanced performance in identifying the risk mitigation scenario	Weight, rank, supply chain risk	Failed to address managerial issues
(Chatterjee et al., 2018)	Multi-criteria decision-making process	High sensitivity and reliability	Internal, external and project risk	Hidden risks are undetermined
(Mhetre et al., 2016)	WBS, RBS	Minimum risk failure	Rank, weightage score	Difficult to implement and high time consumption
(Hamzaoui et al., 2019)	MADS, MOSAR	Easy identification of risk failures	Cost, time, quality percentage	Failed to consider safety barrier
(Wang et al., 2018)	Meta network analysis	High rate of feasibility	Risk factor, cost, time, rate of probability	ineffective

Proposed Methodology

This section comprises of five major phases: Identification of risk source and its factors, Systemization and Pre-processing of the dataset, Analysis of dataset constraints, Sensitivity data computation, and Tool selection using DRNN-MSCA to determine the risk, thereby establishing an effective and accurate prediction analysis. In addition to this, the machine learning algorithm, namely the Deep Recurrent Neural Network (DRNN) and the Modified Sine Cosine optimisation Algorithm (MSCA), is integrated to minimise the inter-dependence and the complexity of the construction delay. The overall architectural diagram for the DRNN-MSCA based prediction of risk delay in the construction project is represented in Fig. 1.

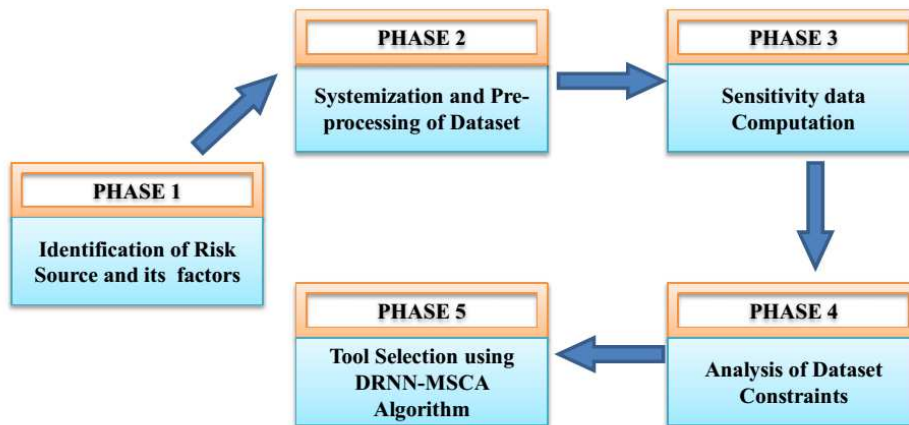


Fig.1. DRNN-MSCA based prediction of risk delay in construction project

Phase 1: Identification of risk source and its factors

The initial phase involves the determination of appropriate risk sources and their factors. Here the risk factors are obtained from diverse surveys and are adopted subsequently in our present research. Here, the risk factors employed in this paper relate to Proprietor, Resource Person, Construction Contractor, Layout model, Labour, Stocks and Resources, Apparatus, Time Delay and Cost, Climate, and External Risk. Eventually, the lists of each individual risk factor are determined from various risk source categorisations. In addition to this, such types of risks are recognised from various research articles regarding construction methodologies, engagement of the stakeholder, geographical conditions, availability of resources, political situations etc. The following section elaborates on the types of risk and their identified risk factors.

Proprietor: The risk factors, namely lack in the planning of the project, progress delay, poor coordination among the resource person and the proprietor, progress delay, conflict among joint ownership, changing of orders, work suspension.

Resource Person: Postponement during reviewing, inspecting, approving significant variations, an argument among design engineer and consultant, lack of experience by the consultant, communication lacking among the resource person and the proprietor.

Construction Contractor: Poor site supervision and management, repeated changing of contractors, very slow mobilisation of site, rework because of construction errors, lack while investigating sites, ineffective planning of the project, argument among Construction contractor and proprietor or resource person.

Layout model: Lacking team experiences while designing, delay in designing of construction based documents, incomplete drawings, disagreement with the owner.

Labour: Inadequate labour, inexperienced labour, labour shortage, the argument between the labours, unqualified labour.

Stocks and Resources: Damage of sorted resources, construction material shortage, lack of resources, change in specification during construction, variation in the type of materials.

Apparatus: Equipment shortage, Low equipment efficiency, lacking high technological equipment, repeated breakdown of equipment, Low productivity equipment, Improper functioning of the equipment.

Time Delay and Cost: Permission delay from the municipality, delay in getting approval from government sectors, delay in obtaining services from various resources such as electricity, telephone and water, price fluctuations, too short of original contract duration.

Climate: Risk occurs due to unexpected sub-surface and surface conditions, adverse weather conditions like storm, heavy rain and wind etc.

External: Accident occurrences during the construction of sites, a dispute among neighbours, mistakes in contract documents, inefficient penalty delay, communication lack among projects.

Phase 2: Systemization and Pre-processing of the dataset

The data employed in developing the predictive tool analysis comprises of 100 construction projects from 48 firms that experienced diverse degrees of time delay. The specific project linked with various data variables is represented by the data record in the specified dataset. In order to evaluate the illustrated dataset, the initial meeting and the project type is sorted. In accordance with the records of risk sources and factors, the index scales are categorised into two categories that are mentioned in Tables 2 and 3. The initial scale narrates the consequences of the severity towards affecting the objective of the project time. Secondly, the recurrence frequency is related to the entire project. Then the whole risk is computed by multiplying the time overrun (TO) of the corresponding two score values (Xia et al., 2017).

Tab. 2. Index scale for Consequence severity

Consequence Severity	
Index range	Statement
0.05	Negligible TO
0.25	<10% TO
0.45	10-20%TO
0.65	20-30%TO
0.85	>30%TO

Tab. 3. Index scale for recurrence frequency

Recurrence Frequency	
Index range	Statement
0.15	Exceptional
0.35	unusual
0.55	Lessen
0.75	regular
0.95	Widely prevalent

Phase 3: Analysis of dataset constraints

During the gathering of data, it is necessary to consider numerous limitations and constraints. Initially, the data gathered should relate to the construction, design, operation and finance based entities. Secondly, the data gathered should consider only the data regarding the Construction project and not the categorisation of the construction projects. Thirdly, the size of the project is considered in which the data assembles the duration of the contract for approximately two to three years. Finally, the data is gathered only from the project Construction in which the time overrun is assumed to be greater than zero. In addition to this, the quality and integrity of the data are ensured by adopting numerous contemplated considerations. It is also necessary to consider the project containing adequate evidence and records with reliable data.

Phase 4: Sensitivity data computation

In order to gain a better understanding, it is necessary to evaluate the exploratory data analysis from the gathered data records. For facilitating the performances, the exploratory data analysis is intended to provide the three most significant insights, namely smoothed frequency curves and variable frequency counts, the sensitivity analysis exploring the dependencies of time overrun in accordance with various risk sources as well as the sensitivity analysis exploring the dependencies of time overrun in accordance with various risk sources among themselves.

Phase 5: Tool selection using DRNN-MSCA

In predictive data analysis, machine learning is considered as one of the most promising tools that integrate the complex datasets from various sectors, namely data mining, artificial intelligence, analysis of the database, patterns of interest, statistics, pattern recognition etc. (Tixier et al., 2017; Bhatt et al., 2021). Machine learning and its prediction ability were used in various research. Krulický, Kalinová a Kučera (2020) use machine learning for prediction USA export to the People's Republic of China. Also, Vrbka et al. (2020) use machine learning of ANN to estimate the development of the trade balance between the USA and the People's Republic of China. Here, in this paper, the DRNN along with MSCA is employed in predicting the risk that is explained in the following section.

Deep Recurrent Neural Network (DRNN)

Fig.2 represents the structural diagram of DRNN. In general, the DRNN comprises of three various layers, namely the input layer, output layer and a set of hidden layers. The recurrent connection or a recurrent link is found in between the hidden layers. The output of the previous step is provided as the input of the subsequent step, and the iteration process is continued with respect to the information obtained from the hidden state. The major merit of employing the DRNN classifier is that the DRNN operates more effectively under the input length of various features (Pune Borhade & Nagmode, 2020). The mathematical formulations involved in DRNN are expressed in the following section.

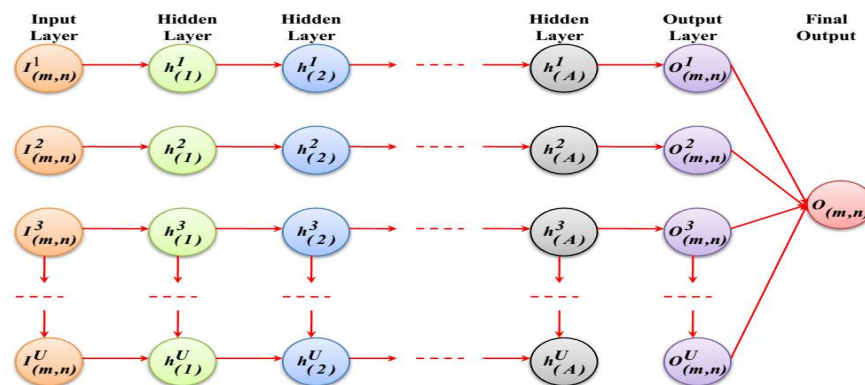


Fig.2. Architecture of DRNN

The DRNN that defines the input and the output vector with respect to the m^{th} layer at the n^{th} time is represented in the following section.

$$\text{Input vector} : I_{(m,n)} = \{I^1_{(m,n)}, I^2_{(m,n)}, \dots, I^A_{(m,n)}, \dots, I^U_{(m,n)}\} \quad (1)$$

$$\text{Output vector} : O_{(m,n)} = \{O^1_{(m,n)}, O^2_{(m,n)}, \dots, O^A_{(m,n)}, \dots, O^U_{(m,n)}\} \quad (2)$$

From equations (1) and (2), the arbitrary number and the total number of units of the m^{th} layer are represented by A and U , respectively. Then the input propagation weight and the recurrent weight with respect to the m^{th} layer are derived in the following section.

$$\text{Input propagation weight: } I_{(m)}^W \in X^{U \times \alpha} \quad (3)$$

$$\text{Recurrent weight: } R_{(m)}^W \in X^{U \times \beta} \quad (4)$$

From Equations (3) and (4), α and β signify the total number of units and the arbitrary unit number of the $(m - 1)^{\text{th}}$ layer, respectively. Then the set of weights is represented as X . Therefore, the input and the output vector component with respect to the arbitrary layer are represented as follows.

$$I_{(m,n)}^A = \sum_{H=1}^{\alpha} L_m^{AH} O_{(m-1),L}^H + \sum_{H=1}^{\alpha} \varphi_m^{AJ} O_{(L-1),m}^J \quad (5)$$

From equation (5), the elements of $I_{(m)}^W$ and $R_{(m)}^W$ are represented as L_m^{AH} and φ_m^{AJ} respectively. Then the element based on the output vector with respect to the arbitrary function is represented as,

$$O_{(m,n)}^A = \sigma_m [I_{(m,n)}^A] \quad (6)$$

From equation (6), the activation function is represented as σ_m . In general, there are different types of activation function, namely the sigmoid function, rectified linear unit function as well as logistic sigmoid function. The mathematical expressions for each respective function are mentioned as follows.

$$\begin{aligned} \text{Sigmoid: } \sigma_m &= \text{TanH}(I) \\ \text{ReLU: } \sigma_m &= \text{Max}(I, H) \\ \text{Logistic Sigmoid: } \sigma_m &= \frac{1}{[1+e^{-I}]} \end{aligned} \quad (7)$$

Then the expression for the bias with respect to the output layer is determined as follows.

$$O_{(m,n)} = \sigma_m [I_{(m)}^W O_{(m-1),L} + R_{(m)}^W O_{(L-1),m}] \quad (8)$$

From equation (8), the output of the classifier is represented as $O_{(m,n)}$.

Modified Sine Cosine Algorithm (MSCA)

Sine Cosine Algorithm (SCA)

Mirjalili (2016) developed a novel Meta-heuristic algorithm named sine cosine algorithm that replicates the characteristics and behaviour of sine, cosine trigonometric functions. Followed by the random generation of position, the solutions are updated dynamically based on the command of a known global optimal solution. Then the evolutionary process of SCA and the updated equation in terms of both exploration and exploitation phase is represented in the following section.

$$A_X^{T+1} = \begin{cases} A_X^T + R_1 \sin(R_2) |R_3 Z_X^T - A_X^T|; & \text{If } R_4 < 0.5 \\ A_X^T + R_1 \cos(R_2) |R_3 Z_X^T - A_X^T|; & \text{If } R_4 \geq 0.5 \end{cases} \quad (9)$$

From equation (9):

$$\begin{aligned} Z_X^T &= \text{ArgMin}\{F(Z_X^{T-1}), F(A_X^T), \dots, F(A_L^T)\}; T \in [1, T] \\ R_1 &= A - T \frac{A}{t} \end{aligned} \quad (10)$$

From equation (9), the random number is denoted by R_4 and the random values may range from $[0, 1]$. Then the region of the next position that is present in between the destination and the solution is denoted by R_1 ; the movement outwards the destination is represented by R_2 . The maximum iteration number and the current iterations are represented by t and T respectively and the constant term is denoted as A .

Modified Sine Cosine Algorithm (MSCA)

Like various other evolutionary approaches, the sine cosine algorithm undergoes the defect of pre-mature convergence with complex and tricky optimisation issues. Therefore to overcome such shortcomings, the performances of the SCA are modified and enhanced by employing three various strategies: Quasi Opposition

Learning, Elite-Guide progression, Adaptive Mutation. The mathematical formulation of each respective strategy is obtained in the following section.

➤ Strategy 1: Quasi Opposition Learning

The quasi opposition based learning strategy is employed and acts as an effective tool to conquer the loss of population diversity due to the gathering of swarms. In addition, this strategy is also employed in enhancing the performance of the agent and in swarm diversification (Kumar Roy et al., 2013). Therefore, the swarm's global exploitation capability, which is to be enhanced, is formulated by:

$$B_{X,Y}^T = \begin{cases} C_Y + R_5(C_Y - A_{X,Y}^T); & \text{If } A_{X,Y}^T < C_Y \\ C_Y - R_5(A_{X,Y}^T - C_Y); & \text{If } A_{X,Y}^T \geq C_Y \end{cases}; \text{Where } X \in [1, x], Y \in [1, y]$$

$$C_Y = \frac{1}{2}[A_Y^{MAX} - A_Y^{MIN}] \quad (11)$$

From equation (11), the Y^{th} value of X^{th} quasi opposition solutions at T^{th} number of iteration is denoted as $B_{X,Y}^T$. Then the maximum and the minimum value of the Y^{th} value is represented as A_Y^{MAX} and A_Y^{MIN} respectively. Y and R_5 signifies the total number of variables, and the random values range from $[0, 1]$.

➤ Strategy 2: Elite-Guide progression

In SCA, the evolutionary model utilises only the global optimal solution, whereas the elite agents are not taken into consideration which results in the convergence of local minimum value with very high probability. Therefore, in order to conquer such issues, the evolutionary mode in terms of the random weighting process is employed (Issa et al., 2018). The following mathematical equation provides a valuable solution that enhances the rate of convergence and search space, respectively. Thus,

$$A_X^{T+1} = \begin{cases} A_X^T + R_1 \sin(R_2)|R_3 Z_X^T - A_X^T|; & \text{If } R_4 < 0.5 \\ A_X^T + R_1 \cos(R_2)|R_3 Z_X^T - A_X^T|; & \text{If } R_4 \geq 0.5 \end{cases} \text{Where } X \in [1, x], T \in [1, t] \quad (12)$$

$$Z_X^T = R_6 Z_X^T + R_7 W_X^T + R_8 M_X^T; \text{Where } X \in [1, x], T \in [1, t] \quad (13)$$

$$W_X^T = \text{Arg } \underset{W_X^T \neq Z_X^T}{\text{MIN}} \{F(Z_X^{T-1}), F(A_X^T), \dots F(A_L^T)\}; T \in [1, T] \quad (14)$$

$$M_X^T = \text{Arg } \underset{W_X^T \neq Z_X^T, W_X^T \neq M_X^T}{\text{MIN}} \{F(Z_X^{T-1}), F(A_X^T), \dots F(A_L^T)\}; T \in [1, T] \quad (15)$$

From the above equation, the second and third best optimal solution is represented by W_X^T and M_X^T , respectively. R_6, R_7, R_8 Signifies the total number of variables and the random values ranges from $[0, 1]$. Thus,

$$R_6 + R_7 + R_8 = 1 \quad (16)$$

➤ Strategy 3: Adaptive Mutation

In SCA, the current swarm fails to store the best optimal solution that further minimises the useful hidden information, and such issues can be conquered by employing an adaptive mutation strategy. In addition to this, a temporary swarm is developed by combining the modified evolution approach and quasi opposition learning approach. Therefore the updated equation by employing the adaptive mutation strategy is obtained as follows.

$$Q_X^T = \begin{cases} N_{INDEX}^T + a_c [Z_X^T - W_X^T] \text{If } (S_X \geq \gamma) \\ G_X^T \text{If } (S_X < \gamma) \end{cases}$$

$$\text{Where } Z_X^T = \text{ArgMin}\{F(Z_X^{T-1}), F(A_X^T), \dots F(A_L^T)\}, X \in [1, x],$$

$$T \in [1, t], a_c = R_9 + R_{10} * \frac{T}{T} \text{ and } S_X = \frac{|F(Z_X^T)|}{\sum_{X=1}^X |F(Z_X^T)|} \quad (17)$$

From the above equation, the mutation solution with respect to the T^{th} number of iteration is denoted as Q_X^T . a_c and S_X signifies the adaptive coefficient and the coefficient in determining the activation of the mutation operator. R_9, R_{10} signifies the total number of variables, and the random values range from $[0, 1]$ and $[-0.9, 0.1]$ respectively.

Formation of DRNN-MSCA algorithm

In this section, the DRNN, one of the machine learning approaches integrated with the modified sine cosine algorithm containing various three strategies, are developed to effectively predict risk with minimum time delay and cost. The execution procedure involved in forming the DRNN-MSCA is illustrated in the following section.

Step 1: The output obtained from the DRNN is provided as an input to the modified sine cosine algorithm. Here initially, the sizes of the swarm, maximum iteration numbers are defined, followed by the initialisation of the random population.

Step 2: Determine the objective function for the entire solution with respect to the problem that takes place during the position updated and during the evaluation of the optimal global solution.

Step 3: Followed by obtaining a global solution, the intermediate swarm is obtained by employing the quasi opposition learning strategy as mentioned in equation (11).

Step 4: Then, the off-spring swarm is determined by using Elite-Guide progression of equation (12) to (16).

Step 5: Setting a temporary swarm organised in an ascending order to obtain the best optimal solution. Then the adaptive mutation updated strategy is then employed based on equation (17) to generate the subsequent solutions for the next process.

Step 6: The iteration is stopped if the maximum iteration is met by achieving the optimal global solution. Else, return to step 2. Therefore the flow diagram for the formation of the DRNN-MSCA algorithm is represented in Fig. 3.

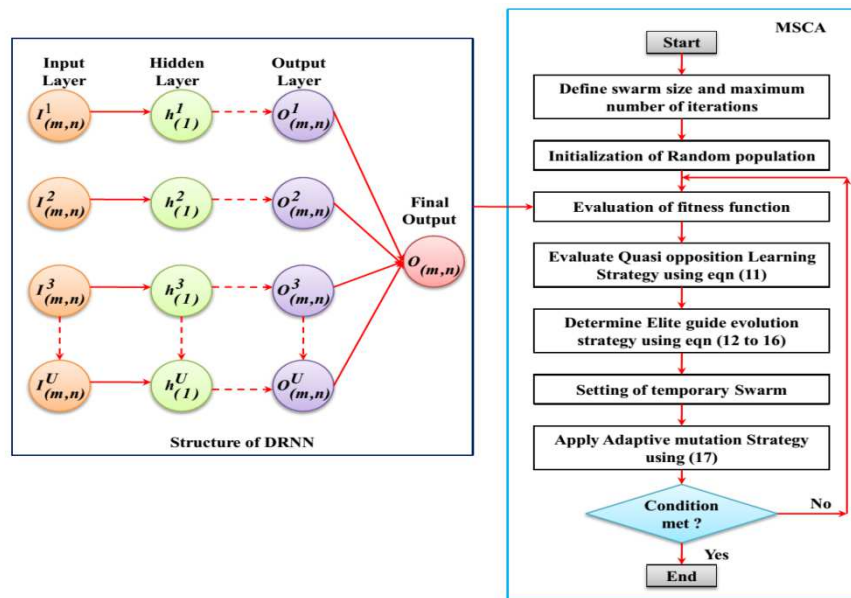


Fig.3. Formation of DRNN-MSCA algorithm

Results and Discussion

The questionnaires were distributed to resource person, proprietor and Construction contractor's responses from several organisation levels. The respondents who participated in the survey had many years of experience in treating several projects types. The respondent's characteristics that participated in the survey are reviewed in Table 4. Table 4 demonstrates that a maximum of the respondents (54%) are working with the resource person organisation, about 35% of the respondents from the owner and 11% of the respondents from the Construction contractor. All the respondents had experience managing large projects, with 65% of respondents executed in Construction projects. The important number of respondents, i.e. 24% of the respondents, has executed more than 100 projects. In accordance with the response, 88% is achieved in dealing the Construction projects from various organisations.

Tab. 4. Respondents statistics

Parameter	Frequency	Percentage %
<i>Organisation type</i>		
Proprietor	23	30
Resource person	26	37
Construction Contractor	24	34
<i>Project type</i>		
Building	52	65
Infra-Roads and Bridges	6	7
Industrial Projects	14	18
Other	11	14
<i>Number of executed projects</i>		
< 50	23	32
50 – 100	17	24
> 100	17	24

Data collection

The assembled data contained 100 completed projects with various degrees of time overrun. The gathered data consists of historical documents of earlier projects which were examined to separate the risk delay measurement in the construction projects. These documents consist of specifications, schedule baselines, contract documents and change order records. The data collection is completed by the arrangement and construction of the questionnaire survey. The respondent's characteristics that participated in the survey are reviewed in Table 5.

Every questionnaire form consists of a construction project and an additional ten variables. The first variable indicates the delay level, and the other nine variables refer to the risk delay sources in the construction project. Every risk source provided with scores depends on two scales. The first scale was the risk probability of occurring in the construction project. The second scale was the impact of the sources on the construction project. The second was linked to the sources on the construction project delay, as depicted in Table 5.

The entire risk impact was computed by multiplying the two scales. The Cronbach coefficient is utilised to calculate the inner consistency, and the value ranges from 0 to 1. If the value of the coefficient is less than 0.3 so it cannot be accepted. Then the value of the reliability is low level. If the coefficient value is greater than 0.7, it represents the consistency at a high level for the index table and can be highly accepted. For this analysis, the Cronbach is found to be 0.951 (Shanmugapriya & Subramanian, 2013; Cindrela Devi & Ananthanarayanan, 2017).

Tab. 5. Probability scales and risk delay impact in the construction projects

Scale	Probability	Impact
Very low	0.1	0.04
Low	0.25	0.15
Medium	0.55	0.25
High	0.75	0.45
Very high	0.95	0.85

The probability and the variables impact were computed by the 5-point Likert scale by the measures from very low to a very high level. The input variables were categorised as very low, low, medium, high and very high. The output variables were classified into three classes. This method resulted in three kinds of delay levels which decreased the bias throughout the artificial intelligence execution model. Delay level was classified as: < 50 % delay, 50 - 100 % delay, and > 100% delay. The questionnaire was assigned to calculate the reliability of the questionnaire and to inspect the issues, and establish the items which are more confusing than the others. The result of Cronbach's alpha validates questionnaire reliability. The identified sources of risk are proprietor, resource person, Construction contractor, layout model, labour, stocks & resources, apparatus, time & delay, climate and external. The reliability test for the time and cost overruns is tabulated in Table 6.

Tab. 6. Reliability test for time and cost overruns

Factors	Cronbach alpha
Project-related	0.718
Responsibility of the contractor	0.761
Responsibility of the subcontractor	0.701
Responsibility of the consultant	0.791
Responsibility of the owner	0.707
Management condition	0.856
Design and Documentation	0.789
Economic circumstances	0.304
Materials	0.832
Environmental circumstances	0.698
Labour and equipment	0.771
Government relations	0.887
Financial groups	0.725
Construction parties	0.826

Political groups	0.738
Constructional items	0.736
Overall Cronbach alpha value	0.951

The most important factor that causes the construction cost overrun is based on the project life cycle and categorised as internal and external issues as depicted in Table 7. It is concluded that the important degree of agreement between the respondents for the cost overrun occurrence in the non-infrastructure Indian construction projects.

Tab. 7. The important factor for the causes of cost overrun

Stage of the project	Internal issues	External issues
Pre-planning stage	Financial issues	Regularity approval delays
Planning & layout model stage	Scope creep	Alterations in-laws and dictatorial structure
	Layout model/ alterations in the specification	Political difficulties
	A deprived assortment of resource person	Unexpected site situations
Execution and supervising	Unsuccessful acquisition planning	
	Rework	
	Inefficient planning & supervising	Inflation/ price fluctuations
	Construction delays	
	Delay in opinion-making	
	Contractual arguments	

Performance evaluation

The performance evaluation of the predicted method was computed by the class performance and the entire performance measures. The performance is evaluated for three different metrics, namely precision, sensitivity and specificity. The entire performance of the predicted model is computed by using accuracy and classification error. Confusion matrices are the particular table that is capable of depicting the classification model performance. The confusion matrixes for the proposed DRNN-MSCA approach are shown in Table 8, in which the classifiers are primarily organised to train the whole dataset. The confusion matrix consists of an integer that reflects the counts of assured classifications.

Tab. 8. Confusion matrix for DRNN-MSCA classifications

Actual class	Predicted Class			Totals
	< 50% Delay	50 – 100% Delay	> 100 % Delay	
< 50% Delay	18	5	2	25
50 – 100% Delay	0	15	1	16
> 100 % Delay	2	2	9	13
Totals	20	22	12	-

The entire accurate predictions are situated in the diagonal of the table, and this assists the visual inspection of the error matrix, that is, any nonzero values outside the diagonal. Some key terms for the classifier need to be clarified first before computing the model performances from the matrices.

True positives (Tp): Prediction numbers that are precisely assigned to the class (i.e., matrix diagonal value for the respective class).

False positives (Fp): Prediction numbers that are mistakenly assigned to the class (i.e., the sum of values in the respective class column apart from the Tp).

False negatives (Fn): Prediction numbers that was mistakenly unidentified as the class assignments (i.e., the sum of values in the respective class row apart from the Tp).

True negatives (Tn): prediction numbers that were precisely identified as not intimacy to the class (i.e., the sum of values of the entire rows and columns excluding the row and column of that particular class).

The two model entire performance indices utilised in this research are accuracy and misclassification error. Accuracy is the percentage of the total number of accurate classifications to the total number of predicted classifications by the model, and likewise, the misclassification error is the percentage of the straight misclassifications. The entire accuracy is recognised as the ratio among the sum of diagonal values and the sum of the table. Hence, the confusion matrix of the model has high numbers in the diagonal values and small numbers other than the diagonal values. The performance evaluation consists of a precision, specificity, sensitivity, false-positive rate and false-negative rate are computed from the confusion matrices as shown in the below equations correspondingly.

$$Precision = \frac{T_p}{T_p + F_p} \quad (18)$$

$$Specificity = \frac{T_n}{T_n + F_p} \quad (19)$$

$$Sensitivity = \frac{T_p}{T_p + F_n} \quad (20)$$

$$F_{pr} = \frac{F_p}{F_p + T_n} \quad (21)$$

$$F_{nr} = \frac{F_n}{T_p + F_n} \quad (22)$$

$$Accuracy = \frac{T_p + T_n}{T_p + F_p + T_n + F_n} \quad (23)$$

$$Classification\ error = 1 - accuracy \quad (24)$$

The examination of the gathered data based on 100 projects was conducted to predict the sources of delay issues efficiently. The properties of the data compiled and delay sources distributions among the construction projects are demonstrated in Fig 4.

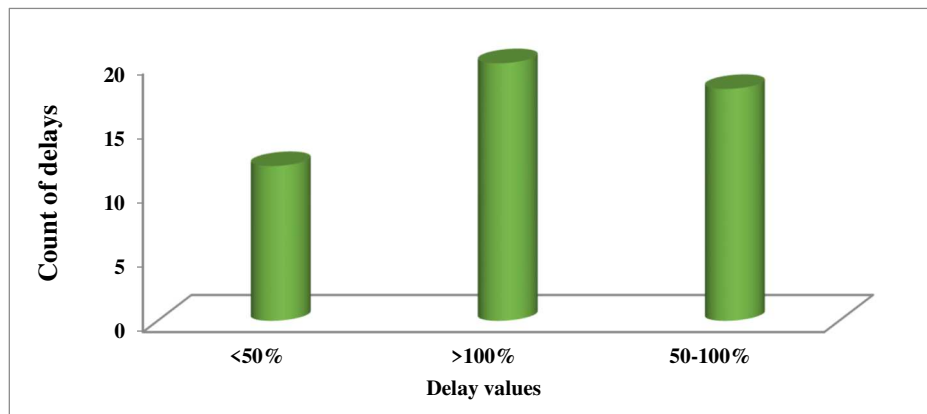


Fig.4. Frequency delay counts in the construction project

Depending upon the reported results, Fig 5 shows the project counts by <50% delay, 50 – 100 % delay and > 100% delay were 12 (30%), 18 (40%) and 20 (50%) correspondingly. From this, it can be observed that a high percentage of the projects associates with > 100% delay class. Fig 5 illustrates the delay source distribution between every delay class problem that was achieved from the past records, pilot study and distributed questionnaire. These results exposed the delay sources values of the Construction contractor, proprietor, resource person, time and external factors have more impact than the other sources of delay. Proprietor, resource person, Construction contractor, and project are indicated as the internal risk sources that impact the project delay. External factors are discussed by the particular conditions which are experienced in the study area in a way that strictly affects the construction industry. These circumstances have a massive impact on project stockholders and project performance. Contrastingly, the application of the robust predictive method can donate to estimate an exact duration in the construction projects and examine delay risk sources that arise from the dynamic and complex nature of the construction region.

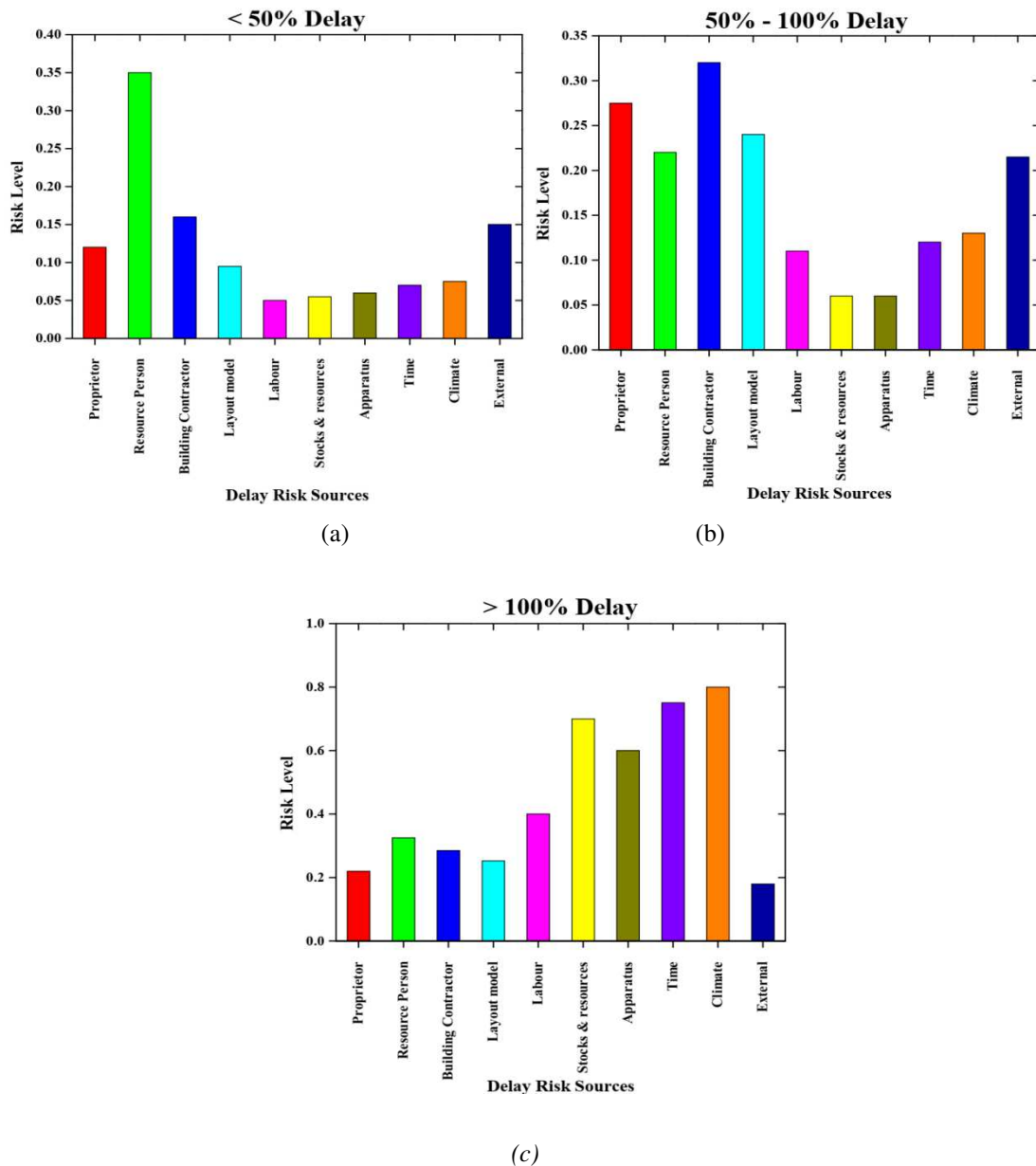


Fig. 5. (a) Delay sources distribution for the projects with class < 50% (b) Delay sources distribution for the projects with class 50 - 100% (c) Delay sources distribution for the projects with class > 100%

Table 9 shows the comparison of accuracy and misclassification error between the various classifiers such as ANN, RF-GA and ML with the proposed approach DRNN-MSCA. The performance measures are computed for both the training as well as the testing. It can be concluded that the proposed approach performs well in both the training as well as the testing process.

Tab. 9. Comparison of various classifiers for accuracy and misclassification error

Performance metrics	ANN	RF-GA	ML	DRNN-MSCA
Accuracy	73.58% (43.5%)	75.84% (45.8%)	76.45% (48.5%)	81.65% (52.9%)
Misclassification error	28.61% (54.9%)	25.42% (52.4%)	23.54% (50.5%)	21.54% (45.2%)

The visual interpretations of the model performance by the classifiers are plotted in Fig 6. The performance of the various classifiers such as ANN (Alias et al., 2015), RF-GA (Yaseen et al., 2020; Gondia et al., 2020) is compared with the proposed DRNN-MSCA approach is shown in Fig 6. The overall prediction performance of the proposed approach is high. The value of the metrics such as precision, sensitivity, specificity, false-positive rate and false-negative rate for the proposed classifier is high when compared with other classifiers.

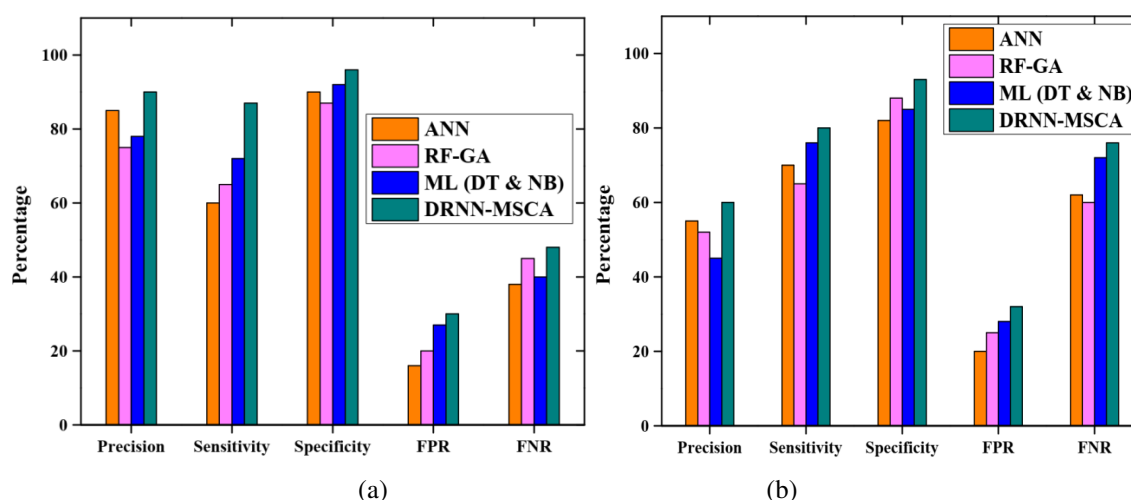


Fig.6. Comparison of classifiers for (a) training and (b) testing performances

Conclusion and Future Scope

At the present time, project management has been utilised extensively across numerous industrial sectors. Numerous surveys demonstrated by various research scholars were conducted between the managerial personnel, engineers and contractors to analyse the risk while constructing projects. The organisation's main intention is to identify the risk and implement various corrective measures to mitigate various potential impacts associated with them. This paper proposed five major phases, namely the Identification of risk source and its factors, Systemization and Pre-processing of the dataset, Analysis of dataset constraints, Sensitivity data computation, and Tool selection using DRNN-MSCA. The initial phase involves the determination of appropriate risk factors and their sources, namely Proprietor, Resource Person, Construction Contractor, Layout model, Labour, Stocks and Resources, Apparatus, Time Delay and Cost, Climate as well as External Risk. The second phase predicts developing the predictive tool analysis comprises 100 construction projects from 48 firms that experience diverse degrees of time delay. The dataset analysis and sensitivity data are computed in the third and fourth phases. The fifth phase comprises of Tool selection using DRNN-MSCA to determine the risk, thereby establishing an effective and accurate prediction analysis. Finally, the performance of the proposed approach is calculated and compared with a few other existing approaches such as ANN, RF-GA, and ML. The experimental analyses are conducted, and the results reveal that the proposed approach provides superior performance with less cost and time delay. The limitation of this work is that 100 construction projects have been identified carefully and evaluated risk, and these 100 construction projects are highly correlated with the time and money. However, the accuracy and error will be changed based on the selection of projects and numbers. The existing approaches were analysed with our proposed techniques. It was achieved around 81.65%. In future, non-correlative construction projects could be identified and evaluated. This suggestion work is to be compared with other traditional approaches and modern approaches.

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