Pakistan Journal of Life and Social Sciences

www.pjlss.edu.pk

https://doi.org/10.57239/PJLSS-2024-22.2.001499

RESEARCH ARTICLE

Research on Dynamic Monitoring and Analysis Methods of Construction Project Performance Based on Digital Twin

Yuejun Liu[1*], Faizatul Akmar Abdul Nifa[2], Lim Kong Teong[3]

[1,2,3] School of Technology Management & Logistics, UUM College of Business, Universiti Utara Malaysia, Kedah Darul Aman, 06010, Malaysia

[1] Hebei University of Architecture, Zhangjiakou, 075000, China

[2] Disaster Management Institute, Universiti Utara Malaysia, Kedah Darul Aman, 06010, Malaysia

ARTICLE INFO

Received: Oct 12, 2024

Accepted: Dec 23, 2024

Keywords

Construction Project Performance

Dynamic Monitoring

Digital Twin (DT)

Intelligent Social Spider mutated Flexible Long Short Term Memory (ISS-FLSTM)

***Corresponding Author:**

beijingwojia2008@163.com

ABSTRACT

The construction sector has seen an outstanding transition in recent years, owing to advances in digital technology. One such innovation that has received a lot of attention is the idea of the digital twin (DT), which is a virtual component of a physical asset or process that is constantly updated with real-time data. DT technology allows construction professionals to monitor, simulate, and optimize project performance, cost, time, and quality using data from sensors, Building Information Modeling (BIM), and IoT devices. The purpose of the research is to develop dynamic monitoring and analysis methods for construction project performance that have highlighted the potential of integrating DT technology. This research proposes a deep learning algorithm, Intelligent Social Spider mutated Flexible Long Short Term Memory (ISS-FLSTM), to predict the construction performance. Varieties of sensors are placed across construction sites to record crucial performance data in real-time. The raw data gathered from sensors is preprocessed, including normalization, addressing missing data, and noise filtering. The system uses insights to predict risks, optimize resource allocation, and support informed decision-making, using DEM to validate the DT's high-accuracy simulation of real-world conditions. The findings show the proposed method significantly improves the system's capability to predict the construction performance compared to traditional approaches, which is evaluated in terms of recall (97.3%), precision (96.2%), accuracy (95.4%), RMSE (50.416), R^2 (0.995), and MAE (39.231). This research demonstrates that deep learning and DTs can be employed to provide a reliable and data-driven approach to improving the effectiveness, sustainability, and performance of building projects.

INTRODUCTION

Construction activities are diverse and complex tasks composed of various tasks, which require organizing and planning of activities in order to accomplish specific objectives like time, cost, quality etc. Performance monitoring is the assessment of a given number of factors, which affects the progress of the project in particular area, like time, resource, cost, etc. [1]. Performance monitoring significantly improves results and reduces threats since construction projects often encounter difficulties such as delays, cost increases, and safety concerns [2].

DT is one of such recent popular concepts that has received a lot of attention in recent time [3]. DT technology, initially utilized in manufacturing and aerospace industries, is implemented here in construction to model a system or physical property for its entire life cycle. This forms the DT that enables the emulation and thus the monitoring and optimization of several processes in real-time for performance improvement, decision-making and predictive analytics [4].

A DT is therefore a dynamic representation of a construction project in as much as the design and materials, operations and surrounding environment may be concerned. DT can offer timely and accurate information on the performance of construction project and potential threats that may emerge by taking data from sensors, BIM, GIS, and IoT gadgets [5].

DT systems significantly improve construction project supervision, management, and performance by tracking and forecasting real-time data. They provide information on project progression, resource consumption, cost management, and can model scenarios for unexpected delays. This helps project managers select effective plans and detect potential risks on construction sites [6].

DT systems may also enhance resource management by offering data about employees, supplies and material. Such a level of comprehension assists in preventing wastage whilst ensuring that available resources are used well to save costs and meet project schedules [7]. DT contributes to integrated decision-making across the construction project life cycle and gives an understanding of project development from preconstruction through construction and post construction [8].

Another advantage includes the ability of the DT technology to support cooperation. A DT is a very dynamic data-driven system for sharing information between engineers, contractors, architects, project managers, and other stakeholders. This also decreases the chances of misunderstandings and mistakes since everyone works towards the same objectives [9]. Additionally, by employing DT technology in construction projects, a better sustainable approach is enhanced. Construction projects may reduce their environmental effects through the application of DTs to improve material consumption, waste management, and energy usage [10].

An innovative DL approach called ISS-FLSTM was suggested to forecast building performance using the DT technology.

Contributions

- The building performance data was gathered from the Kaggle source.
- The data is pre-processed using Z-score normalization and Kalman filtering techniques.
- The features are extracted from the data using the Independent Component Analysis (ICA) approach.
- A novel DL-based strategy known as ISS-FLSTM was introduced with the integration of DT technology to predict building performance.

The remaining sections are organized as follows: Section 2 - Related Works, Section 3 - Methodology, Section 4 - Results and Discussion, and Section 5 - Conclusion.

RELATED WORKS

By providing insight into how a DT system interacts with BIM from a construction-related management perspective, research [11] intended to address the research gap in DT systems and a wide range of applications during construction. It demonstrated the entire potential of DTs during the project lifecycle's construction stage. The research offered several benefits of the DT for construction project administration, along with verified operations. It suggested that construction firms employ the 10 DT services that have been established to solve the low productivity and effectiveness that the sector continues to experience.

Using a more effective Mask R-CNN model with a deployment method on the Streamlit network for indoor construction advancement tracking, research [12] used DL and computer vision for automatic visual recognition and work-in-progress computation of as-built building parts. The digitalization of construction project administration was greatly advanced by their research, which developed a model specifically designed for automatically evaluating ongoing projects of interior building parts and described how to implement the system on a cloud-based platform.

A novel methodological structure for the 3D reconstruction of DDT designs at building sites was presented in research [13], which makes it possible to monitor the construction area from every possible perspective inside a 3D model environment. Their approach demonstrated an outstanding 95% reconstruction accuracy, highlighting its substantial potential to improve the effectiveness of building a DDT structure.

An innovative vision-based structure for storm preparedness on construction sites was suggested in research [14]. The suggested methodologies were predicted to assist practitioners in swiftly recognizing, localizing, and assessing possible wind-borne derbies in construction areas, allowing for the efficient and timely implementation of storm preparedness strategies.

Using an exploratory approach, research [15] investigated the possible combination of DL-integrated DT to promote Construction 4.0. The results demonstrated that the DL-integrated DT framework could enable Construction 4.0 by integrating cognitive skills to identify intricate and unexpected behaviors and reasoning on constantly changing optimization techniques to assist in making choices.

Through examining real-time innovative construction and carbon emissions tracking, research [16] offered a comprehensive perspective on DT uses in the PSC. The results of the scientometric examination indicated research on fields including energy and emissions control, AI-powered choice-making, and integrating blockchain with DT for prefabrication had great demand.

The possible incorporation of DT systems throughout several construction phases, from basic design to project delivery, was evaluated in research [17]. Results showed that DT could function as the basis of a data-driven lifecycle that obtained ever more data and knowledge and eventually enabled well-informed decision-making.

A powerful and innovative instrument for tracking the development of a building project was presented by research [18]. It was built on the idea of a DT and used an Unreal Engine-created video game-like application. The outcome was an interactive application that resembled a video game and comprised a timeline tool that enabled users to travel through the construction phases captured in the as-built designs and contrast them with the as-designed models.

A comprehensive analysis of the research on the key elements in charge of creating DT technological uses in the construction sector was provided in the research [19]. Their research demonstrated the increasing importance of DTs in construction and established the foundation for future developments in the area to fully realize its potential for changing built environment procedures.

To identify lessons acquired from the use of DTs in construction and manufacturing, research [20] examined both of the areas. The results showed that, while the use of DTs in manufacturing was superior to construction, it has yet to achieve its full potential.

A comprehensive process structure for CV-CPM was developed by repeatedly classifying the many concepts, devices, technologies, and strategies, as presented by the research [21]. The framework's four stages were identified and shown to have a significant impact on each other.

An innovative 2D building construction performance tracking system for PPVC known as WAVBCPM was presented in research [22]. The outcomes indicated that WAVBCPM successfully tackled practical issues.

A multi-tasking computer vision technique for improved construction safety tracking was presented in research [23]. The findings showed that the combined dataset could be used in real construction areas more successfully.

A technique for automatic progress tracking and reporting in construction tasks was presented in research [24] that combined data from a DL model with the UWB network. The results demonstrated the need for more research on enhancing integrated approaches for effective progress monitoring.

A sophisticated technique for identifying construction activities was provided in research [25] utilizing the newly developed semi-supervised Ladder network and CNN. The findings showed that a Ladder-CNN trained with 10% labeled data could produce greater accuracy compared to a supervised CNN.

Building Information Modelling (BIM), and artificial intelligence, were unique approaches that were used in the research [26] to create a model that employed neural networks to detect damage in bridge architecture. The outcomes demonstrated the increased precision attained when using the enhanced neural network technique to identify damage in bridge structures.

METHODOLOGY

The building performance data was collected from the Kaggle source. The data is then pre-processed using the Kalman filter and Z-score normalization. ICA was employed for extracting the features of the data. An innovative ISS-FLSTM approach was introduced for predicting the performance of the construction project based on the DT technology displayed in Figure 1.

Figure 1: Overall flow of ISS-FLSTM

Data collection

The building performance data was gathered from the Kaggle source Building Performance Dataset. It resembles several elements of construction project tracking over time and is designed for time series analysis and optimization research. It contains 50,000 records that reflect data acquired within one-minute intervals. The data set includes various factors relating to managing projects, climate conditions, resource utilization, safety, and performance indicators.

Data preprocessing by using Z-score normalization

Z-score normalization is the most widely used for the prediction of building performance, which transforms all input values into a single measure with a SD of one and an average of zero. For each variable, the SD and mean are determined. The calculated SD and mean are used for normalizing each value of a variable W. The calculation for modification is provided in Equation (1).

$$z = \frac{\left(w - mean\ (W)\right)}{std}(W) \tag{1}$$

Where $mean\ (W)$ represents the attribute's mean and $std\ (W)$ represents its SD.

Kalman filtering

The Kalman filter method is a popular optimization data processing process employed in several approaches. By creating a mathematical framework to determine the current moment's state update values, the Kalman filter method integrates the data from the present moment with the state update values from the prior moment.

The system's transformed equation of state is provided in Equation (2).

$$W_{l+1} = \Phi_{\frac{l+1}{l}} W_l + X_l \tag{2}$$

Where the system noise at moment l is represented byX_l, the state transfer matrix is represented by$\Phi_{(l+1)/l}$, and the state vectors at moment $l\ and\ l+1$ are represented by$W_l\ and\ W_{l+1}$.

The system's observational calculation is shown in Equation (3).

$$Y_{l+1} = G_{l+1} W_{l+1} + U_{l+1} \tag{3}$$

Where, U_{l+1} - System's measurement noise at that moment $l+1$;Y_{l+1} – System's measurements at moment $l+1$, and G_{l+1} - System's observation matrix at that moment $l+1$.

At l moments W_l, the ideal estimate is indicated by $\widehat{W}_l$. The ideal anticipated value at l moments W_{l+1} is shown by $\widehat{W}_{(l+1)/l}$. The recursive procedure for the Kalman filter appears as follows,

State forecast calculation,

$$\widehat{W}_{(l+1)} = \Phi_{\frac{l+1}{l}} \widehat{W}_l \tag{4}$$

Covariance forecast calculation,

$$O_{l+1} = \Phi_{\frac{l+1}{l}} O_l \Phi^S_{\frac{l+1}{l}} + R_l \tag{5}$$

Filter gain calculation,

$$L_{l+1} = O_{\frac{l+1}{l}} G^S_{l+1} \left(G_{l+1} O_{\frac{l+1}{l}} G^S_{l+1} + Q_{l+1} \right)^{-1} \tag{6}$$

State assessing calculation,

$$\widehat{W}_{(l+1)} = \widehat{W}_{\frac{l+1}{l}} + L_{l+1} \left(Y_{l+1} - G_{l+1} \widehat{W}_{\frac{l+1}{l}} \right) \tag{7}$$

Filtered covariance update calculation,

$$O_{l+1} = (J - L_{l+1} G_{l+1}) O_{\frac{l+1}{l}} \tag{8}$$

The covariance matrix of the prediction error estimates at moment l for moment $l+1$ is represented by the formula $O_{(l+1)/l}$.

To estimate the system's total state information, a Kalman model is constructed and the system is iterated using the building performance.

Feature extraction by using ICA

To identify hidden components from a set of observations or observable data, ICA is a relatively recent statistical and computational approach that ensures the sources are as independent as possible.

The initial and individually independent source $t(s) = t_1(s), t_2(s), \dots, t_m(s)$ at time point s is linearly combined with the observed variables $w(s) = w_1(s), w_2(s), \dots, w_m(s)$ on the computational level such that it may be stated as:

$$w(s) = Bt(s) \tag{9}$$

Where B represents a full-rank mixing matrix. Equation (9) is frequently expressed as follows in ICA standards:

$$z = Xw \tag{10}$$

Where the IC is indicated by$z = z_1, z_2, \dots, z_m$, and the demixing matrix is$X = B^{-1}$. Several ICA techniques could be employed to calculate the ICs and demixing matrix simply from the mixed observations.

The retrieved components are independent and non-gaussian according to the ICA assessment standards. Non-gaussian may be measured using kurtosis (β_1). Kurtosis values for the Gaussian ICs are equal to 0, sub-Gaussian $\beta_1 \leq 0$, and super-Gaussian $\beta_1 \geq 0$. Kurtosis's standard measure is described in Equation (11).

$$\beta_1 = \frac{E(w-\mu)^4}{(E(w-\mu)^2)^2} - 3 = \frac{\mu_4}{\sigma_4} - 3 \tag{11}$$

The standard kurtosis methods are also susceptible to outliers because they are mostly dependent on sample averages. Furthermore, the fact that outliers are increased to the third and fourth powers in the traditional metrics of kurtosis significantly increases their influence. By using an accurate measure of kurtosis in ICA, it intends to solve the presented issue. Moors suggested a quantile kurtosis substitute for β_1. The degree of moors kurtosis is shown in Equation (12).

$$Kurtosis = \frac{(F_7 - F_5) + (F_3 - F_1)}{(F_6 - F_2)} \tag{12}$$

F_j is the j^{th} octile, therefore $F_j = E^{-1}\left(\frac{j}{8}\right)$. The value of Moor's quantile kurtosis for Gaussian ICs is equal to 1.23.

ISS-FLSTM

The use of an innovative ISS-FLSTM approach enhances the possibility of tracking the performance of construction projects related to DT technologies. This model integrates the intelligent behavior and flexibility of improved social spider (ISS) optimization and the FLSTM network, which is a DL architecture known for its temporal pattern learning ability.

In construction project management, performance data is often complex and dynamic, requiring proper forecasting and identifying anomaly detection methodologies. Using the evolution technique suggested by social spider networks, the ISS-FLSTM performs exceptionally well, enabling the model to adapt to changing conditions in a project and make accurate predictions on performance indicators such as cost overruns, schedule delay, and resource allocation issues.

Continuous project performance monitoring is further enabled by ISS-FLSTM, which incorporates DT technology, creating a real-time DT of physical assets and processes. The integration enhances decision-making by enabling the project managers to simulate the various scenarios, optimize resources, and eliminate risks efficiently. This ensures that the model is capable of responding to several diverse data, which is highly significant given the unpredictability of many construction projects. Algorithm 1 shows the pseudocode for ISS-FLSTM.

Algorithm 1: ISS-FLSTM

```
import numpy as np
import tensorflow as tf
from tensorflow.keras.models import Sequential
from tensorflow.keras.layers import LSTM, Dense
from spider_optimization import SocialSpiderOptimizer
def load_and_preprocess_data():
  data = load_project_data()
  data_normalized = normalize_data(data)
  return data_normalized
def build_flexible_lstm_model(input_shape):
  model = Sequential()
  model.add(LSTM(64, input_shape = input_shape, return_sequences = True))
  model.add(LSTM(64))
  model.add(Dense(1, activation = 'linear'))
  model.compile(optimizer = 'adam', loss = 'mean_squared_error')
  return model
def optimize_lstm_with_spider(model, data):
  optimizer = SocialSpiderOptimizer()
  mutated_model_params = optimizer.optimize(model, data)
  return mutated_model_params
def train_model(model, data):
    X_train, y_train = prepare_training_data(data)
  model.fit(X_train, y_train, epochs = 50, batch_size = 32)
def evaluate_model(model, data):
  X_test, y_test = prepare_testing_data(data)
  predictions = model.predict(X_test)
  performance_metrics = evaluate_predictions(predictions, y_test)
  return performance_metrics
def main():
  data = load_and_preprocess_data()
  input_shape = (data.shape[1], 1)
```

$lstm\_model\ =\ build\_flexible\_lstm\_model(input\_shape)$

$mutated\_params\ =\ optimize\_lstm\_with\_spider(lstm\_model, data)$

$lstm\_model.set\_weights(mutated\_params)$

$train\_model(lstm\_model, data)$

$performance\ =\ evaluate\_model(lstm\_model, data)$

$print("Performance\ Metrics: ", performance)$

$if\ \_\_name\_\_\ ==\ "\_\_main\_\_":$

$main()$

Flexible LSTM

An FLSTM model leverages the DT design to predict construction performance based on data analysis, pattern identification, and forecasting outcomes. It helps provide an effective approach to management in building tasks, enhances effectiveness, and improves decision-making.

LSTM

RNN has an issue with learning information over a long period with a diminishing gradient, which means that previous learning outcomes disappear if the time gap is extended. To address these issues, LSTM is suggested. LSTM cell states are calculated as follows in Equations (13- 18):

$$j_s = \sigma\left(X_j \times [g_{s-1}, W_s] + a_j\right) \tag{13}$$

$$e_s = \sigma(X_e \times [g_{s-1}, W_e] + a_e) \tag{14}$$

$$P_s = \sigma\left(X_p \times [g_{s-1}, W_s] + a_p\right) \tag{15}$$

$$\widetilde{D}_s = tanh(X_d \times [g_{s-1}, W_s] + a_d) \tag{16}$$

$$D_s = e_s \times D_{s-1} + j_s \times \widetilde{D}_s \tag{17}$$

$$g_s = P_s \times \tanh(D_s) \tag{18}$$

The IG, FG, and OG are denoted by $j_s, e_s, and\ P_s$ in Equations (13 - 15). Equation (16) shows that $\widetilde{D}_s$ is a novel cell state candidate value. The previous cell state D_{s-1} is updated into the new cell state D_s employing Equation (17), and the LSTM cell serves as a state data accumulator.

Where, a_d - Bias of CCS; a_j - Bias of IG; a_p - Bias of OG; a_e - Bias of FG; X_p - Weights of the OG; X_j - Weights of the IG, X_d - Weights of the CCS, and X_e - Weights of the FG.

FLSTM

The FLSTM used D_{s-1} for the IG, FG, and OG. D_{s-1} influences the IG, FG, and OG of the LSTM.

The IG layer gets data from both the preceding CI and the HL. The data is then calculated to provide the following output as shown in Equation (19):

$$\begin{cases} j_s = \sigma\left(X_j \times [D_{s-1}, g_{s-1}, W_s] + a_j\right) \\ \widetilde{D}_s = tanh(X_d \times [D_{s-1}, g_{s-1}, W_s] + a_d) \end{cases} \tag{19}$$

Equation (19) shows that j_s is the IG's output, whereas $W_s\ and\ g_{s-1}$ represent the output and input of the preceding HL. The bias of the IG and $\widetilde{D}_s$ is represented by $a_j\ and\ the\ a_d$. The activation function is denoted by σ, and the subsequent soft function is utilized.

$$\sigma_{softsign}(w) = \frac{w}{1+|w|} \tag{20}$$

The FG's output follows the same calculation algorithm as the IG, but with distinct weights X_e and bias a_e, as indicated in Equation (21).

$$e_s = \sigma(X_e \times [D_{s-1}, g_{s-1}, X_e] + a_e) \tag{21}$$

The process of updating from the prior cell state D_{s-1} to the CCS D_s is indicated by Equation (22).

$$D_s = e_s \times D_{s-1} + j_s \times \widetilde{D}_s \tag{22}$$

The CI, memory, and output of the preceding HL determine the outcomes, as displayed in Equation (23).

$$\begin{cases} P_s = \sigma\left(X_p \times [D_s, g_{s-1}, W_s] + a_p\right) \\ \qquad g_s = P_s \times \tanh(D_s) \end{cases} \tag{23}$$

In Equation (23), $P_s, g_s \; and \; a_p$ represent the gate's outputs, the current HL, and the bias for P_s.

ISS optimization

The ISS algorithm integrates DT technology to enhance the forecasting of building performance. The ISS mimics the actions of social spiders to fine-tune parameters and make accurate predictions of the results of a construction project. When combined with data in real-time from DT, it improves the decision-making process, resource distribution, and project management in complex construction conditions. A novel swarm method called SSO performs optimization by simulating the actions of social spiders. Numerous applications employ SSO, in which the location of spiders through the spider web, which is the process of converting information between spiders, is the solution to the optimization issue. The spiders use vibrations that are sent as they travel to a new location to communicate with one another. Spider j and spider i vibrate because of spider$i$'s weight and location.

$$Vib_{ji} = x_i f^{-c_{ji}^2}, c_{ji} = \left\|w_j - w_i\right\| \tag{24}$$

Where the weight spider i, denoted by x_i, is described in Equations (25 & 26).

$$x_i = \frac{E(x_i) - worst_w}{best_w - worst_w} \tag{25}$$

$$best_w = \max_{l=1,\dots,M} E(w_l), worst_w = \min_{l=1,\dots,M} E(w_l) \tag{26}$$

Where, $E(w_i)$ - Value of the FF derived from the evaluation of w_i.

Spiders may be classified into two genders, males and females, and their positions can be updated using the two methods. The female spider uses the following method to modify its location.

$$w_{E_j}^{l+1} = \begin{cases} w_{E_j}^l + \alpha \times Vibd_j \times \left(w_d - w_{E_j}^l\right) + \beta \times Viba_j \times \left(w_a - w_{E_j}^l\right) + \delta \times (\xi - .5), & rand \geq on \\ w_{E_j}^l - \alpha \times Vibd_j \times \left(w_d - w_{E_j}^l\right) - \beta \times Viba_j \times \left(w_a - w_{E_j}^l\right) + \delta \times (\xi - .5), & otherwise \end{cases} \tag{27}$$

Where, l - Number of iterations; on - Threshold that moves the spider in or out of the vibration source; and $\alpha, \beta, \delta, rand \; and \; \xi$ - Random values that range between 0 and 1.

The spider with the highest weight that is closest to the position is represented by the individual w_d, and the ideal individual is w_a. The vibration that the ideal spiders transmit is denoted as $Viba_j$; $x_a = max_{l=1,\dots,M} x_l \; and \; Viba_j = x_a f^{-c_{ja}^2}$. Additionally, the vibration delivered by the closest spider with the highest weight is known as the $Vibd_j$; $Vibd_j = x_d f^{-c_{jd}^2}$ and $x_d > x_j$. Equation (27) employs the first calculation if the female focuses on moving in the direction of the vibration source. If they choose to travel away from the source, the subsequent calculation is employed.

In contrast to the female approach, the males adjust their location according to whether they are dominated or not. Non-dominated spiders attract females by attempting to migrate into the center of male spiders to transform into strong males. The male modify their locations as follows in Equation (28):

$$w_{n_j}^{l+1} = \begin{cases} w_{n_j}^l + \alpha \times Vibe_j \times \left(w_e - w_{n_j}^l\right) + \delta \times (\xi - .5), & x_{n_j} \geq ind_{med} \\ w_{n_j}^l + \alpha\left(\eta - w_{n_j}^l\right), & otherwise \end{cases} \tag{28}$$

Where, $\eta = \sum_{i=1}^{Mn} w_{n_j}^{l+1} . x_{Me+i} / \sum_{i=1}^{Mn} x_{Me+i}$; ind_{med} - Average weight of all male spiders, and Mn - Number of male spiders.

Males who weigh more than the average are considered as dominating; otherwise, they are regarded as non-dominant. $Vibe_j$ is the vibrations sent by the closest female, and it is described as follows: $Vibe_j = x_e f^{-c_{je}^2}$. w_e is the nearest female to j^{th} male.

The last stage is mating, in which the dominant male and female lay on their neighbor with a pairing radius determined as follows in Equation (29):

$$q = \frac{\sum_{i=1}^{m}\left(w_i^{high} - w_i^{low}\right)}{2m} \tag{29}$$

The parents are chosen using a roulette wheel method because this neighbor may have a single female and more than one male. Following the generation of the offspring, the FF for each is calculated and compared to the worst parents.

To discover the best subset of attributes without affecting the classifier's effectiveness, an enhanced version of the SSO method known as ISS was introduced. It is based on the concepts of rough sets.

The ISSO algorithm begins by randomly allocating each spider's location, from which the spider population is created. Subsequently, it uses Equations (30 & 31) to transform each spider's location into a BV of length M, which is the entire amount of attributes.

$$EO\left(w_j^i(s)\right) = \frac{1}{1 + f^{-w_j^i(s)}} \tag{30}$$

$$w_j^i(s+1) = \begin{cases} 1 & if\ EO\left(w_j^i(s)\right) > \epsilon \\ 0 & otherwise \end{cases} \tag{31}$$

Where the value of the spider at iteration s is $\epsilon \in [0,1]$ and $w_i(s)$. The chosen attributes for every spider w_j are the ones that match 1s, whereas the unselected features match 0 s.

The efficiency of solutions in the suggested approach is assessed using the dependence degree $\gamma_Q(C)$. However, the quantity of chosen attributes is not taken into account. As a result, it employed the identical FF that specified in Equation (32).

$$E(Q) = \rho\gamma_Q(C) + (1-\rho)\left(1 - \frac{|Q|}{|D|}\right) \tag{32}$$

Where $|\cdot|$ is the feature set's length. The parameter ρ balances the number of chosen attributes and the quality of categorization ($\rho \in [0,1]$). The FF for every spider is calculated and contrasted with the global fitnessE_{best}. E_j is utilized in place of E_{best}, and its location w_j becomes the reduct set Q, if the FF's present value is higher. Following that, each spider's location is modified based on its type. This procedure is carried out repeatedly until the stopping criterion is reached.

RESULT

The ISS-FLSTM method was used in Python 3.10 to perform the necessary operations on a Windows 11 laptop equipped with an Intel i5 9th Gen and 16 GB of RAM. The ISS-FLSTM approach is evaluated with traditional approaches such as Multi-view convolutional neural network (MVCNN) [27], particle swarm optimized artificial neural network (PSO-ANN) [28], and Artificial neural network (ANN) [29].

DT is a digital representation of a building or other infrastructures constructed to predict its behavior. Real-time data from sensors and models enables construction process monitoring, modeling and optimization of the construction process. This improves decisions and productivity where it helps to forecast such as cost, schedule, and quality. Figure 2 displays the construction project prediction based on DT.

Figure 2: Construction project prediction based on DT

Construction project performance

The task is being completed about the plan and it has a 72% progress rate for the set tasks. It indicates the fact with nearly an absolute humidity of 93.8% and therefore can have an impact on the conditions of the location. The resources were used efficiently with a high utilization rate of 92.1%. The risk of the project can be estimated to be moderate because the risk rate was 61.8%. A safer environment has to be provided at the workplace and this has been indicated by the safety incident rate of 26.2%. The metrics of construction project performance are displayed in Figure 3.

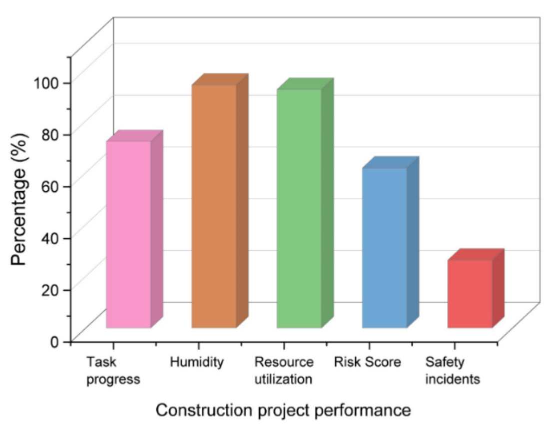

Figure 3: Output of construction project performance

Confusion matrix

A confusion matrix provides a measure of the accuracy of the classification of a given model with the help of actual and expected values, which depict true positive, false positive, true negative, and false negative. The matrix is divided into four subcategories, which include underperforming, satisfactory, proficient, and exceptional. It shows in each column the construction project's proportion of actual states predicted for each category. For example, 40.4% of actual underperforming instances were overestimated to be satisfactory, but 32.2% of actual underperforming cases were correctly classified as underperforming. Figure 4 displays the output of the confusion matrix.

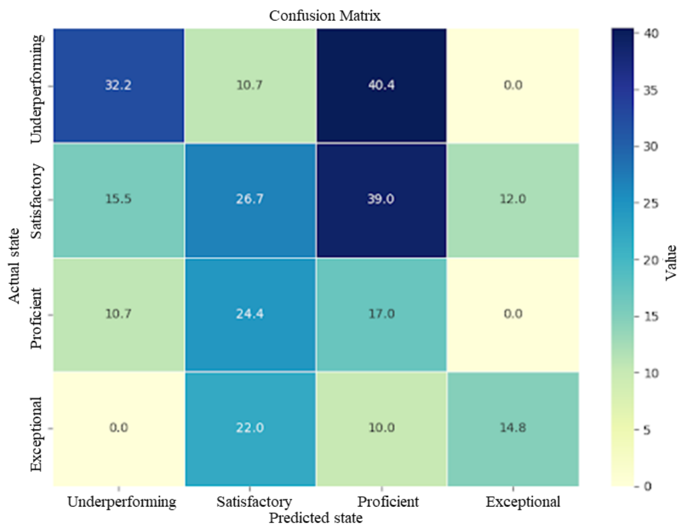

Figure 4: Output of confusion matrix

Precision

Precision is defined as the comparison of predictions of a model with the actual performance when using DT technology to estimate construction performance. It determines the proportion of the accurately forecasted results out of all the successful forecasts. The proposed ISS-FLSTM strategy has a precision value of 96.2%, while the conventional PSO-ANN and MVCNN approaches have precision values of 90.2% and 89.2%, as displayed in Figure 5.

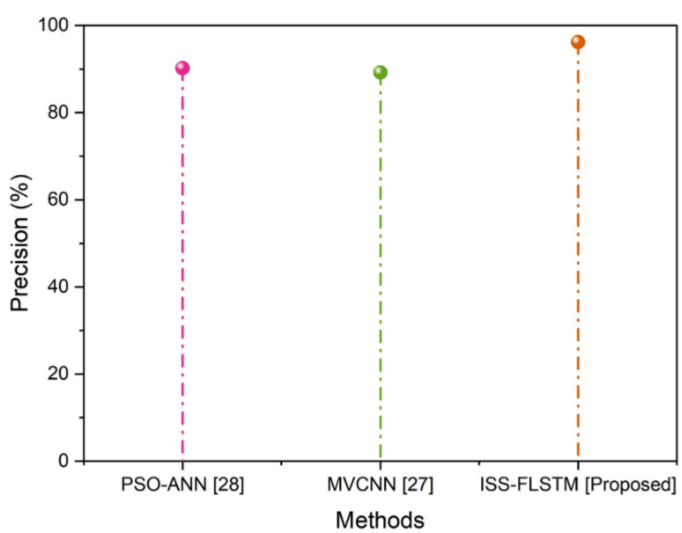

Figure 5: Result of precision

Accuracy

The accuracy for DT-based construction performance prediction considers the correspondence of model predictions to actual construction data, considering cost, time, quality, and resource consumption. Compared to the traditional techniques, the proposed ISS-FLSTM strategy has an accuracy value of 95.4%; however, the traditional PSO-ANN and MVCNN approaches have low accuracy values of 90.9% and 88.9%, as shown in Figure 6.

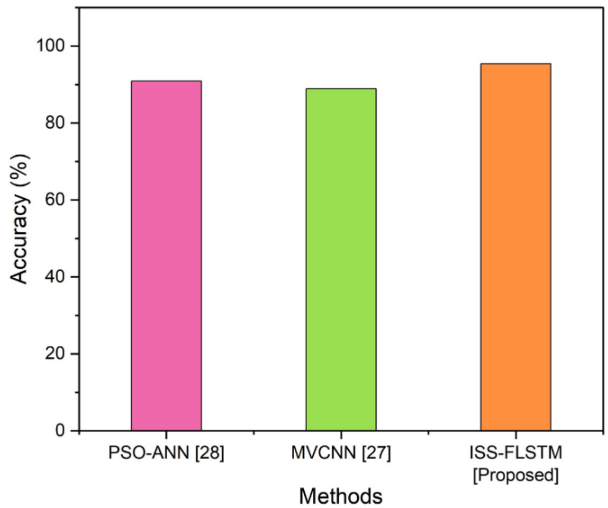

Figure 6: Outcome of accuracy

Recall

The recall measures the capability of a model together with the DT technology to predict the results for construction by correctly identifying positive instances. It evaluated the proportion of true positive instances that were classified to ensure the model minimizes false negatives, which are important in precise construction performance and decision-making. The recommended ISS-FLSTM strategy has a recall value of 97.3% when compared to the conventional PSO-ANN and MVCNN approaches, which have low recall values of 91.2% and 85.2%, as shown in Figure 7. Table 1 displays the result of precision, accuracy, and recall.

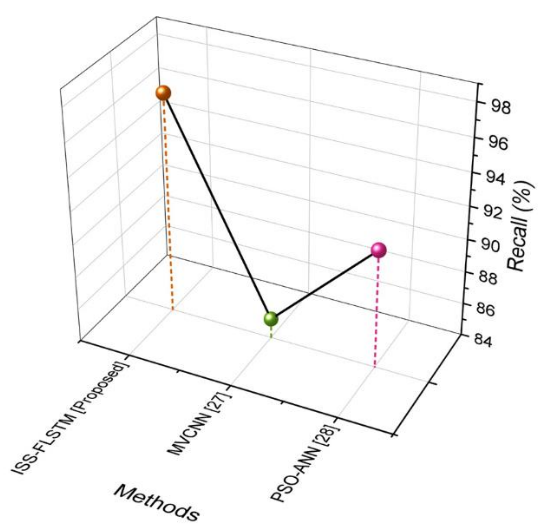

Figure 7: Outcome of recall

Table 1: Result of precision, accuracy, and recall

Methods	Precision (%)	Accuracy (%)	Recall (%)
MVCNN [27]	89.2%	88.9%	85.2%
PSO-ANN [28]	90.2%	90.9%	91.2%
ISS-FLSTM [Proposed]	96.2%	95.4%	97.3%

MAE

The MAE evaluates the average absolute deviation of projected values of construction performance from the actual values to determine how accurate the DT technology is at forecasting. It presents a simple error metric; better prediction performance implies lower MAE, which enhances the flow of decisions in optimization and construction management processes. In comparison, the suggested ISS-FLSTM strategy has an MAE value of 39.231, whereas the traditional PSO-ANN and ANN approaches have high MAE values of 41.120 and 48.347, respectively, as displayed in Figure 8.

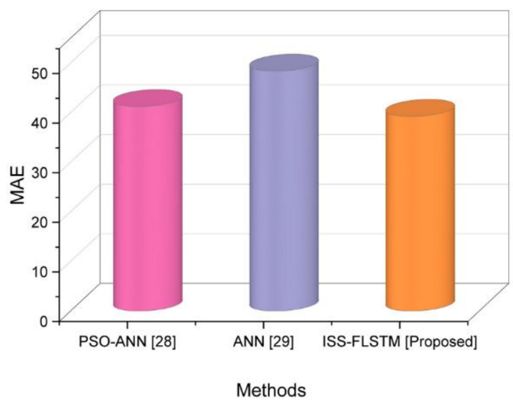

Figure 8: Result of MAE

R-squared (R^2)

R^2 is used to evaluate the quality of fit in predictive models, including the construction performance forecast applying DT technology. R^2, which indicates a higher value means that the DT model enhances the decision-making process in construction, and provides an understanding of the various factors that affect the results. In comparison, the suggested ISS-FLSTM technique has an R^2 value of 0.995, while the conventional PSO-ANN and ANN approaches have low R^2 values of 0.966 and 0.988, as displayed in Figure 9.

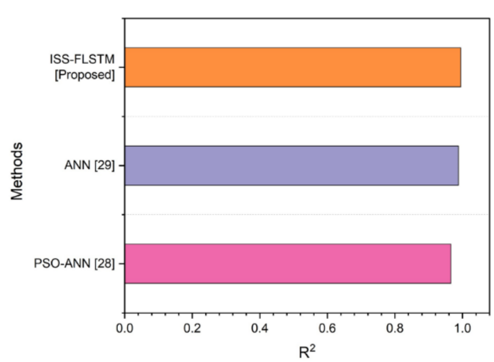

Figure 9: Outcome of R^2

RMSE

The RMSE evaluates the DT technology's prediction models of construction performance. It gives details of the model performance through the calculation of the square root of the average square differences between ideal and actual values, indicating the magnitude of the prediction errors. When compared to the traditional methods, the suggested ISS-FLSTM approach has a low RMSE value of 50.416, whereas the conventional PSO-ANN and ANN strategies have RMSE values of 64.16 and 72.527, respectively, as shown in Figure 10. Table 2 displays the results of MAE, R^2, and RMSE.

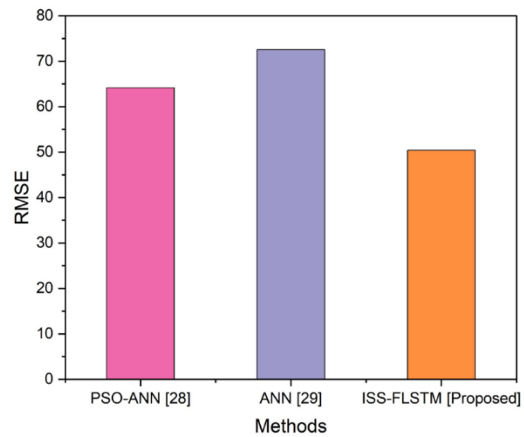

Figure 10: Outcome of RMSE

Table 2: Result of MAE, R^2, and RMSE

Methods	MAE	R^2	RMSE
PSO-ANN [28]	41.120	0.966	64.16
ANN [29]	48.347	0.988	72.527
ISS-FLSTM [Proposed]	39.231	0.995	50.416

Discussion

The construction project is in a transitional phase due to DT technology, it offers a significant instrument to predict and improve the efficiency in various phases of the projects. MVCNN [27] has limitations when used in predicting building performance using DT. MVCNN has multi-view configurations, and this causes the design to be less suitable for real-time performance prediction due to the high processing power required. It has problems in identifying sequential or temporal data, which is crucial in construction processes. However, the scalability and flexibility of MVCNN are constrained because it often requires large labeled datasets with high efficiency for training, and obtaining such data in the construction industry may be expensive or time-consuming.

The PSO-ANN [28] would have less robust performance for noisy or missing data, which are often encountered in real-world DT applications. Even though PSO enhances ANN by finding correct weights, it could face issues with early convergence to a solution of low quality, if applied to high dimensional, complicated problems like predicting building performance. Other limitations include the dependency on hyperparameters adjustment and the problem of overfitting to small datasets.

ANNs [29] have a major drawback of overfitting, especially while using DT technology for building performance prediction where data could be sparse or unbalanced. The limitation is that it is often challenging to understand how forecasts are made, which can be critical for the decisions made in the construction of buildings. Additionally, ANNs are incapable of maintaining temporal or geographical relations, which are the main characteristics of DT data. They are less useful in practical real-time applications because of the substantial concentration on feature engineering, which prolongs the development process and makes it more complicated. To overcome these challenges, a novel ISS-FLSTM was introduced to forecast the performance of the construction based on the DT technology.

CONCLUSION

The use of DT technology has caused a major transformation in the construction industry in recent years. The building performance data was obtained from the Kaggle source. To predict building performance, a novel DL approach called ISS-FLSTM was introduced based on DT technology. The suggested method is evaluated in terms of recall (97.3%), precision (96.2%), accuracy (95.4%), RMSE (50.416), R^2 (0.995), and MAE (39.231). Several challenges are associated with using DT technology to forecast construction performance, including data accuracy issues, high costs, integration issues, and real-time issues dependent on reliable sensor networks. Future enhancements include reduced costs, real-time analytics, and further incorporation of AI, integration with IoT, and complex predictive maintenance to enhance the efficiency of construction activities.

DECLARATION OF COMPETING INTEREST

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

DATA AVAILABILITY

Data will be made available on request.

FUNDING

This research received no external funding.

REFERENCE

1. Pal A, Lin JJ, Hsieh SH, Golparvar-Fard M. Automated vision-based construction progress monitoring in built environment through digital twin. Developments in the Built Environment. 2023 Oct 11:100247.
2. Jiang Y, Su S, Zhao S, Zhong RY, Qiu W, Skibniewski MJ, Brilakis I, Huang GQ. Digital twin-enabled synchronized construction management: a roadmap from construction 4.0 towards future prospect. Developments in the Built Environment. 2024 Jul 26:100512.
3. Li T, Li X, Rui Y, Ling J, Zhao S, Zhu H. Digital twin for intelligent tunnel construction. Automation in Construction. 2024 Feb 1;158:105210.
4. Mahmoodian M, Shahrivar F, Setunge S, Mazaheri S. Development of digital twin for intelligent maintenance of civil infrastructure. Sustainability. 2022 Jul 15;14(14):8664.
5. Torres J, San-Mateos R, Lasarte N, Mediavilla A, Sagarna M, León I. Building Digital Twins to Overcome Digitalization Barriers for Automating Construction Site Management. Buildings. 2024 Jul 20;14(7):2238.
6. Ye Z, Ye Y, Zhang C, Zhang Z, Li W, Wang X, Wang L, Wang L. A digital twin approach for tunnel construction safety early warning and management. Computers in Industry. 2023 Jan 1;144:103783.

7. Piras G, Muzi F, Tiburcio VA. Digital management methodology for building production optimization through digital twin and artificial intelligence integration. Buildings. 2024 Jul 10;14(7):2110.

8. Adu-Amankwa NA, Rahimian FP, Dawood N, Park C. Digital Twins and Blockchain technologies for building lifecycle management. Automation in Construction. 2023 Nov 1;155:105064.

9. Alnaser AA, Hassan Ali A, Elmousalami HH, Elyamany A, Gouda Mohamed A. Assessment framework for BIM-digital twin readiness in the construction industry. Buildings. 2024 Jan 18;14(1):268.

10. Li X, Luo J, Li Y, Wang W, Hong W, Liu M, Li X, Lv Z. Application of effective water-energy management based on digital twins technology in sustainable cities construction. Sustainable Cities and Society. 2022 Dec 1;87:104241.

11. Aktürk B, Irlayıcı Çakmak P. Digital twins for enhanced construction project management. Smart and Sustainable Built Environment. 2024 Sep 30.

12. Ekanayake B, Wong JK, Fini AA, Smith P, Thengane V. Deep learning-based computer vision in project management: Automating indoor construction progress monitoring. Project Leadership and Society. 2024 Dec 1;5:100149.

13. He J, Li P, An X, Wang C. A Reconstruction Methodology of Dynamic Construction Site Activities in 3D Digital Twin Models Based on Camera Information. Buildings. 2024 Jul 10;14(7):2113.

14. Kamari M, Ham Y. AI-based risk assessment for construction site disaster preparedness through deep learning-based digital twinning. Automation in Construction. 2022 Feb 1;134:104091.

15. Kor M, Yitmen I, Alizadehsalehi S. An investigation for integration of deep learning and digital twins towards Construction 4.0. Smart and Sustainable Built Environment. 2023 Apr 10;12(3):461-87.

16. Yevu SK, Owusu EK, Chan AP, Sepasgozar SM, Kamat VR. Digital twin-enabled prefabrication supply chain for smart construction and carbon emissions evaluation in building projects. Journal of Building Engineering. 2023 Aug 23:107598.

17. Moshood TD, Rotimi JO, Shahzad W, Bamgbade JA. Infrastructure digital twin technology: A new paradigm for future construction industry. Technology in Society. 2024 Jun 1;77:102519.

18. Ospina-Bohórquez A, López-Rebollo J, Muñoz-Sánchez P, González-Aguilera D. A digital twin for monitoring the construction of a wind farm. Infrastructures. 2023 Jan 6;8(1):10.

19. Afzal M, Li RY, Shoaib M, Ayyub MF, Tagliabue LC, Bilal M, Ghafoor H, Manta O. Delving into the Digital Twin Developments and Applications in the Construction Industry: A PRISMA Approach. Sustainability. 2023 Nov 30;15(23):16436.

20. Abanda FH, Jian N, Adukpo S, Tuhaise VV, Manjia MB. Digital twin for product versus project lifecycles' development in manufacturing and construction industries. Journal of Intelligent Manufacturing. 2024 Jan 31:1-31.

21. Reja VK, Varghese K, Ha QP. Computer vision-based construction progress monitoring. Automation in Construction. 2022 Jun 1;138:104245.

22. Chua WP, Cheah CC. Deep-Learning-Based Automated Building Construction Progress Monitoring for Prefabricated Prefinished Volumetric Construction. Sensors. 2024 Nov 2;24(21):7074.

23. Liu L, Guo Z, Liu Z, Zhang Y, Cai R, Hu X, Yang R, Wang G. Multi-Task Intelligent Monitoring of Construction Safety Based on Computer Vision. Buildings. 2024 Aug 6;14(8):2429.

24. Shamsollahi D, Moselhi O, Khorasani K. Data integration using deep learning and real-time locating system (RTLS) for automated construction progress monitoring and reporting. Automation in Construction. 2024 Dec 1;168:105778.

25. Meng Q, Wang S, Zhu S. Semi-supervised deep learning for recognizing construction activity types from vibration monitoring data. Automation in Construction. 2023 Aug 1;152:104910.

26. Yang H, Xia M. Advancing bridge construction monitoring: AI-based building information modeling for intelligent structural damage recognition. Applied Artificial Intelligence. 2023 Dec 31;37(1):2224995.

27. Utkucu D, Ying H, Wang Z, Sacks R. Classification of architectural and MEP BIM objects for building performance evaluation. Advanced Engineering Informatics. 2024 Aug 1;61:102503.

28. Santarsiero G, Mishra M, Singh MK, Masi A. Structural health monitoring of exterior beam–column subassemblies through detailed numerical modelling and using various machine learning techniques. Machine Learning with Applications. 2021 Dec 15;6:100190.

29. Sharma S, Arora HC, Kumar A, Kontoni DP, Kapoor NR, Kumar K, Singh A. Computational Intelligence-Based Structural Health Monitoring of Corroded and Eccentrically Loaded Reinforced Concrete Columns. Shock and Vibration. 2023;2023(1):9715120.

APPENDIX

Mask R-CNN	Mask Recurrent Convolutional Neural Network	CV-CPM	Computer-Vision-Based Construction Progress Monitoring
IG	Input gate	SSO	Social spider optimization
2D	Two-dimensional	IC	Independent component
HL	Hidden layer	OG	Output gate
DDT	Dynamic digital twin	BV	Binary vector
		UWB	Ultra-wideband
PPVC	Prefabricated prefinished volumetric construction		
SD	Standard deviation	CI	Current input
FG	Forget gate	3D	Three-dimensional
PSC	Prefabrication supply chain	WAVBCPM	Window-based automated visual building construction progress monitoring
FF	Fitness function	CCS	Current cell state