Dynamic Monitoring and Analysing Method of Construction Project Performance Based on Digital Twin

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Abstract
Higher-level management and monitoring systems must be developed to maintain increasing global civil infrastructure projects. One such innovation in the construction industry is the Digital Twin (DT), which helps businesses address the evolving needs for smart city development and infrastructure growth through enhanced project management and execution. In this paper, we introduce a DT framework that will digitally describe construction areas in real-time through the use of Internet of Things (IoT) sensors, Building Information Modelling (BIM), and machine learning (ML). The computer program periodically collects and analyses data using sensors associated with the environment along with 3D imaging sensors (LiDAR, photogrammetric cameras). More effective project management and monitoring are the result of linking this data with BIM systems, allowing for reports on the construction development. In order to promote proactive management, this system uses ML algorithms to analyze patterns and predict future risks. For superior prediction and decision-making by the DT, this system's dual-input layout processes both spatial and temporal data. The framework enables a method to collect data in real-time and use them to achieve early detection of issues, improved resource management, and enhanced project outcomes.

Keywords: Smart City Development, Resource Management, Digital Twins, Building Information Modeling, Machine Learning, Decision-Making

INTRODUCTION
The growth of urbanization boosts the economy, and the requirement for improvement in old infrastructure has contributed to a significant rise in the frequency of civil infrastructure development worldwide in the last few decades. Projections show that the surge will continue due to the factors that increase with transportation, utilities, and building investments. This expansion demands efficient management and monitoring tools for handling complex construction projects. Effective project management will contribute to completing infrastructure projects by ensuring they meet the expected standards, timelines, and budgets. As the projects continue to grow in scale and complexity, the demand for advanced management techniques also increases. Creating efficient construction project management requires systematic planning, resource allocation, and task coordination.

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A Digital Twin (DT) is a virtual model that mirrors an actual physical object or a system. The DTs are powered by sensor data input, and they simulate real-world conditions and can predict outcomes and plan actions. They are used in various sectors for optimization, maintenance prediction, and planning. The DT is applied in construction to provide and render significant transformative potential. They create a detailed digital copy of the construction site by integrating real-time field data with advanced simulation methods. This allows for constant, up-to-date monitoring and testing of different scenarios to make informed decision-making and better manage risk. The potential and the ability of DT in terms of real-time monitoring and analysis are essential in large-scale construction environments that are prone to rapid changes and have minimal error tolerance levels. In this approach, the DT presents construction-related customers with an adaptable and dynamic platform for real-time insight into the construction process, enabling individuals to promptly identify challenges and make rapid changes that improve goals and legal compliance, contributing to superior project management and execution.

For the goal of maintaining building initiatives, this investigation suggests a DT design that makes use of IoT sensors, BIM, and ML to develop a digital model of the construction location in real time. Climate and 3D camera sensors like LiDAR and photogrammetric cameras collaborate regularly to collect and analyze data in this network. A centralized approach that combines with BIM ensures continuous tracking and review of the building process by communicating the collected data. Proactive project management is provided with feasibility through ML algorithms to analyze the collected data for deviations and make reliable forecasts about possible future issues. To aid decision-making, the design makes a great deal of a dual-input system that examines spatial and temporal data to enhance the model's predictive capabilities. According to some standards, the tests demonstrate which the design works as envisaged.

LITERATURE REVIEW

Researchers [1-2] presented new DT platforms for building-level dynamic management of the construction technique. They built a design that combines data from multiple sources, such as BIM and real-time data from Internet of Things (IoT) sensors, to help improve decision-making. By using augmented reality and other novel applications, the developers have the potential to predict device failures. [3-4] suggested a combined DT model to handle the manufacturing procedure of floating wind turbines (FWTs), a form of renewable energy construction. By manipulating and manipulating sensor data using a digital 3D model, the model enables it feasible to analyze the global state of the turbines in real-time. A case report on a twin-barge float-over project showed proof of their DT's value for recognizing graphical building plans, generating early monitoring, and reporting building variances.

To predict, visualize, and analyze the development of the tunnel's construction, [6-8] made a DT-driven system that uses ML. They attempted to construct their model by combining ML models with data collected from real-
time building techniques. The findings indicate that the ML-integrated DT model accurately predicted tunnel construction performance and eliminated timing and cost problems from tunneling works.

A Shape-Performance Integrated Digital Twin (SPI-DT) paradigm was developed by [9] for application in construction research, particularly for significant machinery segments such as boom cranes. Employing data from many data sources, such as sensors located throughout the machinery, the DT model builders incorporated mathematical, logical, and artificial intelligence (AI) features. Both the computational speed and the safety assessments of building site tools have been demonstrated to be significantly improved by the SPI-DT.

[10] aimed to provide an alternative strategy to resource assessment by using the DT method in the context of the ever-changing machining process and the inherent uncertainty of production items. Digital Twin-based Machining Process Evaluation (DT-MPE) system, real-time mapping between CNC data and design process data, and methodology analysis based on DT data were the primary tools they used to construct their framework. They employed the components of an underwater diesel engine to illustrate how DT's approach could improve intelligent decision-making for challenging products.

[11] presented a system-oriented DT paradigm that may be utilized to detect dynamic features related to the machining processes. Their approach utilizes the Frequency Response Function (FRF) and structural dynamics theory to assess the process's real-time efficiency. Optimizing and eliminating variables, evaluating dynamic-correlated factors, and measuring manufacturing safety were all shown by the accurate dynamic process simulation results.

In their research, [12] probed into the challenges linked to building information modeling (BIM), cyber-physical systems (CPS), and data-driven design. Their examination of 468 publications helped them to present a precise overview of DT and to outline its elements within the field of building. By clarifying the core distinctions between DT and other similar approaches, the research provided here provides a basis for future developments in the field of research.

[13] introduced a DT-based decision-analysis paradigm for tunnel O&M. Study of the tunnel life cycle during its application. With semantic web technology and a rule-based reasoning engine, spatial-temporal data has been analyzed. They set their model to use in the Wenyi Road Tunnel in Hangzhou, China, and showed how efficiently it supported maintenance and operation decisions, especially when detecting the source of problems and creating more efficient approaches.

**METHODOLOGY**

**Proposed Digital Twin Architecture**

The DT architecture proposed in this work combines IoT sensors, BIM, and ML to create a dynamic and interactive construction management system [14-15]. The model facilitates real-time monitoring and management of construction projects to help stakeholders make informed decisions swiftly and effectively. The architecture of the system (Fig. 2) is explained below:

**i) Input Layer**

The data source for the model is provided by the physical layer that incorporates a network of 3D imaging sensors, including LiDAR, photogrammetric cameras, thermal cameras, and wireless environmental sensors, which are distributed throughout the construction site. The data from the sensors are then transmitted in real-time to a centralized processing system in various file formats, including 3D point clouds (.ply and .Las), high-resolution images (.jpeg, .png), thermal data (.tiff), and environmental data logs (.csv, .txt). The real-time data from the physical layer is dynamically integrated with digital models within the BIM system. Machine Learning algorithms are then employed to process and analyze the incoming data. The processed data is then utilized to create detailed simulations and visualizations of the construction process that provide the stakeholders with a clear and comprehensive view of the construction project's current and projected future states. Feedback from
the ML analysis and the outputs from simulations are continuously fed back into the system to influence the digital and physical layers, enabling real-time adjustments in construction scheduling and resource allocation.

Figure 2: Proposed Learning Model

The ML model in this framework, as shown in Fig. 2, is initiated with a dual input layer that processes two distinct data types. Convolutional Neural Network (CNN) layers extract spatial features referring to the physical layout and location changes from high-resolution images and 3D scans collected by LiDAR and photogrammetric sensors. Internet of Things (IoT) sensors continuously input the LSTM layers' sequential data on motion, heat, and tension parameters. In order to gain an improved comprehension of the changing nature and progression of the building process, these different stages examine their connections and patterns that develop over time. The dual input layer executes several kinds of preliminary tasks on both data types to make sure they are suitable for the neural network layouts of the two types of networks:

**Resizing Images**: Leveraging OpenCV, spatial data, particularly radiographs, and high-resolution images, are reduced to an identical size.

**Normalizing Sensor Outputs**: Temporal data from IoT sensors is normalized using a Min-Max scaling technique, which adjusts the data to a standard scale without distorting differences in the ranges of values.

**Converting 3D Scans**: LiDAR-generated 3D scans are converted into a standardized format, typically a .ply/.obj file compatible with CNN.

ii) CNN Pipeline

In the convolutional layer, the input spatial data undergoes an initial transformation. This begins with the computation of matrix $A$ as a linear transformation of input matrix $G$, incorporating the weight matrix $\omega_1$ and bias $\beta_1$. Simultaneously, matrix $B$ is derived from $G$ through a different linear transformation using weights $\omega_2$ and bias $\beta_2$, and is then activated using the ReLU function to introduce non-linear characteristics:

\[
A = G \times \omega_1 + \beta_1 \\
B = G \times \omega_2 + \beta_2 \\
f(G) = A \circ \text{ReLU}(B)
\]
In these EQU (1) and EQU (3), $\omega_1$ and $\omega_2$ represent the transformation weight matrices, while $\beta_1$ and $\beta_2$ are the biases. The ReLU activation function adds non-linearity and $\circ$ signifies the element-wise multiplication between matrices. To prevent the model from overfitting and to ensure it generalizes well across diverse datasets, we incorporate a Dropout layer. This layer randomly nullifies the outputs of a fraction of neurons during each iteration of the training process. If a neuron is deactivated, its output becomes zero, and if it remains active, its output is scaled by a factor dependent on the deactivation probability, EQU (4).

$$y'_i = \begin{cases} 
0 & \text{with probability } q \\
\frac{y_i}{1-q} & \text{with probability } (1-q) 
\end{cases}$$

(4)

Here, $q$ is the dropout probability, indicating the likelihood of a neuron's output being reset during training. The Max-Pooling Layer reduces the spatial dimensions of the input feature matrix, which decreases the computational load and also enhances the model's ability to detect dominant features. Using a pooling stride of 2, this layer evaluates the maximum values within specified pooling areas of the input matrix $P$, defined by the filter size $T$, to produce a reduced output matrix $Q$, EQU (5).

$$Q(i,j) = \max_{m,n \in [1,T]} P_{2i+m,2j+n}$$

(5)

### iii) LSTM Pipeline

The LSTM (Long Short-Term Memory) pipeline analyzes sequential temporal data collected from IoT sensors. The LSTM processes the input data as described below:

**Input Gate:** This gate controls the extent to which a new data element $S_t$, derived from the input $X_t$, should be allowed to enter the cell state. The input gate involves the following transformations: EQU (6) and EQU (7).

$$I_t = \sigma(W_i \cdot [H_{t-1}, X_t] + b_i)$$

(6)

$$C_\tilde{t} = \tanh(W_c \cdot [H_{t-1}, X_t] + b_c)$$

(7)

Here, $W_i$ and $W_c$ are the weight matrices for the input gate and cell candidate, respectively, $b_i$ and $b_c$ are bias terms, and $\sigma$ denotes the sigmoid activation function, which ensures that the input values are between 0 and 1. $C_\tilde{t}$ represents the candidate values for the updates to the cell state.

**Forget Gate:** This gate decides the information that should be discarded from the cell state, facilitating the model's ability to forget the non-essential information, EQU (8).

$$F_t = \sigma(W_f \cdot [H_{t-1}, X_t] + b_f)$$

(8)

Where $W_f$ represents the weight matrix for the forget gate and $b_f$ is the bias. The sigmoid function $\sigma$ again modulates the outputs.

**Cell State Update:** This crucial step combines the outputs of the input and forget gates to update the cell state $C_t$, effectively allowing the network to retain important long-term information while discarding the irrelevant EQU (9).

$$C_t = F_t \circ C_{t-1} + I_t \circ C_\tilde{t}$$

(9)

The cell state from the previous timestep $C_{t-1}$ is modulated by the forget gate output $F_t$, and the input gate's output $I_t$ scales the candidate's values.

**Output Gate:** This gate controls the output of the LSTM unit, which is based on the cell state but filtered through the gate, EQU (10) and EQU (11).

$$O_t = \sigma(W_o \cdot [H_{t-1}, X_t] + b_o)$$

(10)

$$H_t = O_t \circ \tanh(C_t)$$

(11)
where \( W_o \) and \( b_o \) are the weight matrix and bias for the output gate, respectively. The final output \( H_t \) of the LSTM unit at time \( t \) is then computed, which will be used by subsequent layers or as a final output for prediction.

**iv) Feature Concatenation:** The outputs of the CNN and LSTM pipelines, \( h(F) \) from the CNN and \( H_t \) from the LSTM are concatenated along their feature dimensions, EQU (12),

\[
Z_t = \text{concat}(h(F), H_t)
\]  

(12)

This concatenated vector \( Z_t \) contains comprehensive feature sets encompassing spatial details from the site and temporal dynamics of the construction process.

**v) Transformation Layer:** A dense layer follows the concatenation to transform the combined features into a format suitable for prediction tasks. This involves a transformation using a weight matrix \( W_z \) and a bias \( b_z \), EQU (13).

\[
Y_t = \text{ReLU}(W_z \cdot Z_t + b_z)
\]  

(13)

Here, the ReLU activation function adds non-linearity, enhancing the model's ability to learn complex patterns from the combined features.

**vi) Prediction Layer:** This layer actively predicts potential project delays, resource allocation requirements, and imminent critical events. It executes a linear transformation on the fused features to generate prediction outputs, EQU (14).

\[
P_t = W_p \cdot Y_t + b_p
\]  

(14)

Here, \( W_p \) is the weight matrix, and \( b_p \) the bias for this specific layer. The output \( P_t \) provides detailed forecasts tailored to critical management needs, including scheduling adjustments, cost management, and safety monitoring.

**Experimental Setup**

The current case study analyzes the Apartment Complex Construction (ACC) project in Singapore using the lens of the recommended DT model, focusing on its practical testing. The plan is to construct a 15-story business complex on 4.2 acres. In order to execute the DT model experiment, the hardware setup requires an Intel Xeon Gold 6230 CPU and 256 GB of DDR4 memory. In addition to climate sensors (such as pressure and temperature monitors), the sensor system comprised photogrammetric cameras (for landscape views) and light detecting and ranging (LiDAR) sensors (for 3D modeling). The network system featured both private Wi-Fi and Ethernet connections. In order to manage the DT's simulations and 3D models, the software setup comprised building information modeling (BIM) tools such as Autodesk Revit and Navisworks. For monitoring the processing of data, applications developed in languages such as R and Python were used. Data analysis libraries used included NumPy and Pandas. Researchers developed and tested ML models that could predict problems with TensorFlow and PyTorch.

**Analysis**

**i) Delay Prediction Accuracy**
Fig. 3 demonstrates how the recommended DT model improves the state-of-the-art regarding delay prediction, achieving an accuracy rate of 92% and an overall performance level of 100%. Due to its real-time data analytics and ML features, the proposed algorithm can adapt to active project updates and perform complex data analyses. The Advanced Predictive Model, meanwhile, demonstrates its value by attaining a relative performance of 97% and an accuracy of 89%. It utilizes predictive analytics to forecast project outcomes but does not fully integrate real-time data. On the other hand, the Traditional Project Management Tool (TPMT) achieves 85% accuracy and a relative performance of 92%. This model relies on historical data rather than real-time inputs, which constrains its ability to anticipate and mitigate delays promptly. Finally, the Baseline Historical Model shows an accuracy of 80% and a relative performance of 87; it depends only on historical data without the support of advanced analytics and so the lowest performance.

Fig. 4: Resource Utilization accuracy and its relative performance
ii) Resource Utilization Accuracy Comparison

As shown in Fig. 4, the Proposed DT achieves a resource utilization accuracy of 88% and a relative performance of 100%. The proposed model effectively predicts and manages resource allocation for cost savings and operational efficiencies. The Advanced Resource Management Tool achieves 84% accuracy and a 95% relative performance compared to the proposed DT. The Traditional Resource Planning Tool and the Baseline Static Model show lower accuracies of 80% and 75%, respectively, demonstrating less effectiveness in optimizing resource usage with relative performances of 91% and 85%.

![Risk Identification Accuracy Comparison by Different Management Models](image)

**Figure 5**: Risk Identification accuracy and its relative performance

iii) Risk Identification Accuracy Comparison

For the Risk Identification analysis depicted in Fig. 5, the Proposed DT outperforms other models with an accuracy of 95% and a relative performance of 100%. The Advanced Safety Monitoring System, with a 90% accuracy and 95% relative performance, performs slightly less than the DT. The Conventional Risk Assessment Tool and the Baseline Risk Model show lower accuracies of 85% and 78%, respectively, showing decreasing effectiveness in foreseeing and managing risks, which is reflected by relative performances of 89% and 82%.
iv) System Responsiveness Comparison

Regarding System Responsiveness projected in Fig. 6, the Proposed DT model achieves the fastest responsiveness at 5 seconds, with a relative performance of 100%. The Integrated Project Management System has a responsiveness time of 10 seconds, halving the relative performance to 50%. TPMT and the Baseline Manual System are significantly slower, with responsiveness times of 30 seconds and 60 seconds and even lower relative performances of 17% and 8%, respectively.

Figure 6: System Responsiveness Analysis

Figure 7: Cost Efficiency Analysis
v) Cost Efficiency Comparison
As shown in Fig. 7, the Proposed DT model achieves the highest cost efficiency with a 30% cost reduction and a relative performance score of 100%. The Integrated Project Management System also shows commendable cost savings at 20%, which is a 67% relative performance compared to the DT. TPMT provides modest savings at 10%, showing a significant drop in efficiency with a relative performance of 33%. The Baseline Manual System, which relies on traditional methods, provides minimal cost savings at 5%, demonstrating a relative performance of just 17%.

![Impact on Project Schedule by Different Management Models](image)

**Figure 8: Project Schedule Analysis**

vi) Impact on Project Schedule Comparison
Regarding schedule management, as shown in Fig. 8, the Proposed DT model leads with a 15% reduction in the project timeline and a perfect relative performance score of 100%. The Advanced Project Management Tool provides a lesser schedule reduction of 10%, equivalent to a 67% relative performance against the DT. The TPMT provides a 5% reduction corresponding to a 33% relative performance. The Baseline Manual Planning method achieves a minimal 2% reduction in schedule time and a relative performance of only 13%.

CONCLUSION AND FUTURE WORK
Integrating Digital Twin (DT) technology in construction project management has significantly contributed to addressing the complexities of infrastructure development. This work proposed DT architecture for construction project management that uses technologies such as Internet of Things (IoT) sensors, Building Information Modeling (BIM), and Machine Learning (ML) to create a virtual representation of construction sites. The system employs 3D imaging and environmental sensors to monitor and collect the data corresponding to construction aspects. The model uses an ML algorithm to improve construction progress prediction and incorporates BIM data from an example project in Singapore. Consequently, performance improves, problems are reduced, and resources are more effectively deployed. Compared with different models, this one performed superior in predicting delays, using resources successfully to detect risks, being more sensitive to system input, reducing financial resources, and maintaining projects on schedule. In every metric, the model is superior to the other models in accuracy.
REFERENCES


