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Digital Twin Technology-driven Dynamic Monitoring and Early Warning System for Construction Progress

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Abstract

Construction schedule delay problems are one of the most serious issues affecting the construction industry. Conventional construction schedule monitoring methods are limited by low data collection rates, multi-source information, and delayed response to schedule problems. Real-time deviation identification and early warning are difficult. This paper presents a digital twin-based technology for dynamic construction schedule monitoring and early warning. The system uses a four-layer structure to integrate BIM, IoT, and schedule management data to support sub-hourly continuous updates to the virtual construction site. At the deviation identification layer, a weighted composite deviation index method is developed by combining geometric construction ratio, resource consumption ratio, and time-based schedule performance index. The method uses trend extrapolation to create a dual-path deviation identification system. At the early warning layer, a three-level early warning protocol system (Blue, Orange, Red) with clear escalation paths and feedback mechanisms is developed. The system was applied to an eight-month period during the structural frame construction phase of a 28-story residential building project in eastern China. The results show that the system achieves a detection accuracy of 91.9%, an average detection time that is 87% less than the traditional 4D BIM method, and a cumulative schedule slippage that is 52% less. This study proves the feasibility of digital twin-based real-time construction schedule management. The study provides a reference for the application of digital twin-based intelligent schedule management technology in the construction industry.

Keywords

Digital Twin; Construction Progress Monitoring; Early Warning System; Building Information Modeling; Internet of Things; Composite Deviation Index.

1. Introduction

Delays in the project schedule have been a problem in the global building industry. Empirical research has shown that a large proportion of large-scale building projects have been facing problems related to delay, which has led to cost overruns, disputes, and a lot of waste in resources [1]. The traditional management mechanism for project progress is mainly based on the principles of Gantt chart comparison, earned value analysis, and manual site inspection, which is primarily based on discrete and low-frequency modes of data collection. The disadvantage in this mechanism is that the delay in updating the information and collecting multi-source data is likely to result in managerial decisions being made after the problem has already been visible, with little room for risk avoidance [2].

Digital twin (DT) technology has been rapidly advancing in recent years, which has provided an opportunity to overcome the problems in the traditional project progress management mechanism. The basic principle behind the digital twin is to establish a mapping relationship between a real entity and its virtual image, which would enable continuous synchronization

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between the physical building site and the virtual image by utilizing multi-source data, including building information modeling (BIM), IoT, and unmanned aerial vehicles (UAV) [3]. Unlike the traditional mechanism, which is mainly based on single-source data, the DT mechanism is able to integrate geometric information, resource consumption, and environmental factors into a single model, which would enable continuous situational awareness on the building site.

Nevertheless, the existing research trend in this direction indicates certain research gaps. The application of digital twins during the construction phase has been focused primarily on geometric modeling and space visualization, with limited research emphasis on schedule-level analysis [4]. Although construction progress monitoring has experienced various generations of technological evolution from manual documentation to the integration of 4D BIM, the lack of continuous bidirectional data exchange has limited the timely detection of construction deviation. The research trend related to construction early warning has focused primarily on developing analytical tools as standalone components without continuous integration with updated scene data. The research trend related to the integration of digital twins, construction progress monitoring, and early warning systems as a whole system with validation through actual construction projects remains limited.

To fulfill the research gaps identified above, this study aims to achieve three research objectives. The first research objective of this study is to propose a multi-layer digital twin system that combines data from BIM, IoT, and schedule management into a continuously updated construction progress representation model. The second research objective of this study is to propose a weighted composite construction deviation detection algorithm with a tiered system of early warning, which translates quantified schedule deviation into actionable levels of early warning. The third research objective of this study is to propose a validation of the proposed system through a real-world building construction project with its improvement over conventional systems.

2. Literature Review

2.1. Digital Twin Technology in Construction

The term digital twin was first used in the context of aerospace product lifecycle management, with a focus on simulation, prediction, and optimization of a physical asset through a virtual replica of the same [5]. This has now evolved into a five-dimensional theoretical framework, including the physical entity, the virtual model, data, services, and the interface between the physical and virtual spaces.

In the AEC industry, initial digital twin research has focused primarily on the operation of physical facilities, including aspects of facility maintenance, health monitoring, and energy performance simulation [6]. More recent research has attempted to extend the digital twin paradigm into the active construction phase, with a focus on real-time sensor network integration with laser scanning technology and BIM for synchronization of the physical space with its digital replica. However, schedule-level analysis has not been well explored.

2.2. Construction Progress Monitoring Methods

Construction progress monitoring has developed through three generations. The first generation includes manual and document-based techniques such as Gantt charts, S-curves, and earned value management. This generation is limited in terms of update rate and spatial resolution. The second generation introduced sensor-assisted techniques such as GPS tracking, RFID-based material tracking, and UAV-based photogrammetry with image recognition. This allows for quantification of construction progress in a semi-automated way [7]. The third generation includes BIM-based techniques such as 4D simulation and automatic comparison between as-built and as-planned models. However, one limitation that all these techniques share is the lack of real-time two-way data flow with a dynamic site model. Additionally, the capability to raise alarms is not integrated into the process. Table 1 presents a summary of the characteristics and limitations of these techniques in comparison with the proposed DT-based system.

Table 1. Comparison of progress monitoring approaches

Criterion	Gen I (Manual)	Gen II (Sensor)	Gen III (4D BIM)	Proposed DT System
Update Frequency	Weekly–biweekly	Daily–sub-daily	Daily (batch)	Sub-hourly (continuous)
Spatial Resolution	Activity-level	Equipment/material	Element-level	Element + real-time attributes
Detection Latency	7–14 days	3–7 days	2–5 days	< 1 day
Predictive Capability	None	Limited	Moderate	Multi-source trend projection
Data Integration	Single source	Multiple but siloed	Unified BIM	Fused spatiotemporal twin
Early Warning	None	None	Manual rule-based	Automated tiered + closed-loop

2.3. Early Warning Mechanisms in Project Management

The research in construction early warning systems can be classified into three categories. Threshold rule engines provide ease of use but require parameters that are difficult to generalize. Statistical process control is objective in nature but is limited to the stationarity of the process, which is usually violated in construction environments. Machine learning classifiers have gained popularity in recent times, with research using ensemble methods and neural networks for predicting schedule delay under data-rich environments [9], as well as agent-based simulation for incorporating stakeholder interactions in delay prediction [10]. However, their practical application is limited due to the scarcity of training data. All three categories of research face the common problem of being isolated modules that do not interact with a dynamically updated site model; they receive intermittent and potentially outdated information.

2.4. Research Gap

The field of digital twin studies has not fully utilized schedule-level monitoring. The monitoring of progress does not take advantage of the synchronization provided by a digital twin. Early warning does not take advantage of a model backbone in real-time. The intersection of these three gaps, which is an integrated system with deviation detection and early warning in a construction phase digital twin with field validation, is where the gap lies and is what this study aims to contribute to.

3. System Architecture and Algorithm Design

3.1. Design Requirements

For a digital twin-based construction progress management system to be considered effective, three design requirements must be met. The first of these is model persistence (R1), where the virtual copy of the construction site is to be updated at sub-hourly intervals. This is to ensure that the virtual replica of the construction site is always up to date rather than being processed at periodic intervals. The second is multi-source data fusion (R2), where heterogeneous data streams including geometric information, resource information, and environmental information are to be ingested, cleansed, and fused at near real-time intervals to eliminate the problem of data silos that is common in conventional construction progress management. The third is structured alerting (R3), where a tiered alerting system is to be provided to enable the completion of the cycle of monitoring, alerting, correcting, and updating.

3.2. Four-Layer Architecture

The suggested system will be composed of four layers, each of which will be associated with one or more of the design requirements. The Physical Perception Layer, which will support R2, will be responsible for acquiring raw data from the construction site via IoT sensor networks, UAV photogrammetry, and check-in interface methods. The Data Integration Layer, which will support R2, will be responsible for receiving heterogeneous data, performing data cleansing, timestamp mapping, semantic mapping of BIM element IDs to sensor channels, and solving coordinate system transformation to generate a unified spatiotemporal database. The Digital Twin Modeling Layer, which will support R1, will be responsible for associating the IFC-based BIM with real-time status attributes such as geometric completion percentage, resource consumption, and environmental status. This layer will maintain a dynamically updated 3D/4D construction model at sub-hourly intervals. The Application Service Layer, which will support R3, will be responsible for delivering the progress monitoring dashboard, deviation detection engine, and early warning module to stakeholders via web and mobile channels. Figure 1 below shows the four-layer architecture of the suggested system.

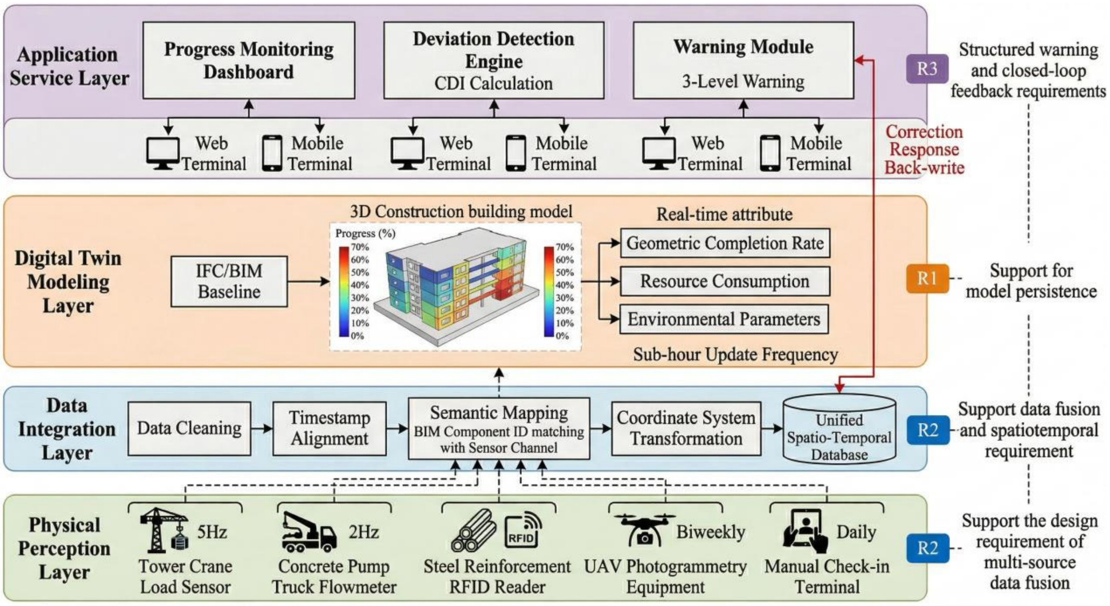


Figure 1. Four-layer digital twin system architecture with design requirement annotations

3.3. Multi-Source Weighted Deviation Detection Algorithm

Traditionally, deviation detection usually employs a Schedule Performance Index (SPI) to measure the time variance between planned and actual progress [11]. The proposed algorithm utilizes the availability of multiple data sources, which is a unique feature of a digital twin environment, by computing three independent indicators of progress at each cycle of the monitoring process. The geometric completion ratio can be calculated through point cloud difference or image recognition with respect to the BIM model. The ratio of resource consumption can be calculated by comparing the cumulative consumption of materials delivered and labor attendance with respect to the allocated amount. The time-based SPI value can be calculated through traditional earned value calculation. The three values are aggregated into a Composite Deviation Index (CDI) through a weighted aggregation method. The weight of each value is preset through a stage-data source mapping table, with higher weightage given to geometric sensing during the structural frame phase, when visual recognition of progress is possible, and higher weightage given to resource consumption during the finishing phase, when visual recognition of completion is limited.

The CDI is continuously monitored within a window of the most recent cycles; a persistent value below the threshold will activate a deviation indicator. Meanwhile, the system will also analyze the cumulative progress curve using a piecewise linear trend model to project the estimated date of completion through weighted regression of the most recent cycles of monitoring. The severity of deviation is also determined as the difference in days between the projected date of completion and the contract deadline. This dual-method detection system provides the benefits of timeliness from instantaneous CDI calculation and foresight from trend projection. Figure 2 depicts the complete process from data ingestion to CDI calculation to tiered decision.

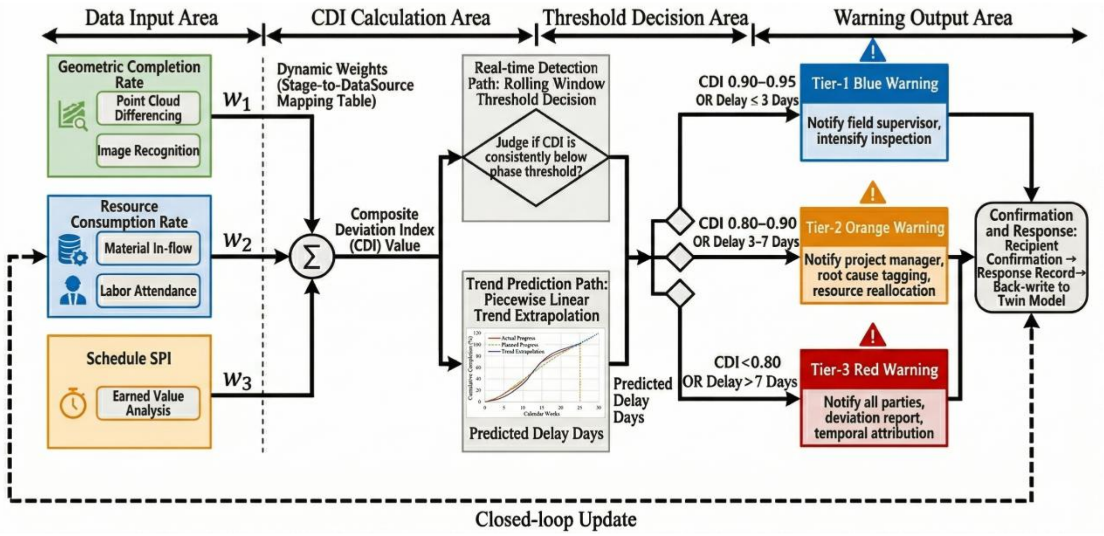


Figure 2. Multi-source weighted deviation detection and tiered early warning workflow

3.4. Tiered Early Warning Mechanism

The early warning module has been designed to interpret the deviation metrics in a three-tier alert system, which is based on industry standard thresholds, adaptable per project [12]. Tier-1 (Blue — Caution): The module sends a warning message to the site supervisor when the CDI falls between 0.90 and 0.95 or when the projected delay is within 3 calendar days. The response action is to increase the rate of on-site inspections for the specific activity. Tier-2 (Orange — Warning): The module sends a warning message to the project manager when the CDI falls between 0.80 and 0.90 or when the projected delay is between 3 and 7 days. The response action involves a preliminary root cause tag being generated by correlating the deviation signal with concurrent environmental or resource anomalies in the twin. Tier-3 (Red — Critical): The module sends a critical message to the owner, contractor, and supervision engineer when the CDI falls below 0.80 or when the projected delay exceeds 7 days. The response action involves a deviation report being generated, which includes a time series attribution analysis. Each response action in the three-tier system involves an acknowledgment-and-response action from the intended party, which is recorded and feeds back into the twin model, thus forming a complete cycle. The threshold criteria, intended party, and response protocol in the three-tier system are summarized in Table 2.

Table 2. Early warning threshold classification and response protocol

Alert Tier	Color Code	CDI Range	Projected Delay	Notification Target	Recommended Action	Feedback Requirement
Tier-1	Blue (Caution)	0.90–0.95	≤ 3 days	Site supervisor	Increase on-site inspection frequency	Dashboard acknowledgment
Tier-2	Orange (Warning)	0.80–0.90	3–7 days	Project manager	Resource reallocation, overtime scheduling	Written response with action plan
Tier-3	Red (Critical)	< 0.80	> 7 days	Owner, contractor, supervision engineer	Emergency meeting, schedule re-baselining	Multi-party signed deviation report

4. System Implementation

4.1. Technology Stack

The system's backend is built using the Python Flask framework for RESTful API services, with PostgreSQL extended with TimescaleDB for efficient storage of time series sensor data. For parsing the BIM model, the system uses the IfcOpenShell library for interpreting IFC files and extracting attribute information from elements. The frontend is built using the Vue.js framework for a single-page application, with Cesium.js for 3D visualization of geospatial information and ECharts for dynamic schedule analytics charts. For real-time data communication, the system uses the MQTT protocol for IoT sensor data ingestion, Apache Kafka for event-driven processing using a message queue, and WebSocket push for notification to the frontend clients and SMS gateway for notification to mobile terminals.

4.2. Module Deployment

The system consists of five modules, each of which plays an important role. These modules are controlled by a role-based access control layer. The Data Acquisition Module handles sensor registration, data validation, and device heartbeat status. The Twin Synchronization Module handles the geometric and semantic synchronization of the BIM model with the real-world environment at a default interval of 45 minutes by using IFC element matching and point cloud registration. The Progress Analytics Module calculates the three values of project progress, CDI fusion, and trend projection. The Early Warning Module carries out the tiered logic, response action recording, and feedback entry recording into the twin model. The Visualization Module renders the digital twin scene with the 3D BIM model superimposed by the project progress indicators. Table 3 shows the data source type, acquisition device, and update frequency.

Table 3. Data sources, acquisition devices, and update frequencies

Data Category	Device	Frequency	Resolution
Structural load	Tower crane load cell	Real-time (seconds)	Per device
Concrete volume	Pump flow meter	Real-time (seconds)	Per device
Rebar delivery	RFID reader	Per batch	Element-level
Site geometry	UAV photogrammetry	Biweekly	cm-level point cloud
Labor attendance	Facial recognition terminal	Daily	Individual
Weather conditions	Third-party weather API	Hourly	Station-level
BIM baseline (static input)	IFC file import	Per version release	Element-level

4.3. Key Implementation Challenges

Three non-trivial engineering challenges were faced. The first challenge was in BIM-IoT semantic alignment. Since sensor identifiers do not inherently relate to IFC model elements' GUIDs, a semi-automatic mapping tool was created to propose such pairings based on spatial relationships and element types. This reduced manual mapping effort by 60%. The second challenge was browser-based 3D rendering performance. Due to the size of the full tower BIM model, significant frame rate degradation was noticed. LOD reduction and progressive mesh loading techniques were employed to ensure that the frame rate was consistently above 24 FPS. Peak data throughput resilience was also a challenge faced. During the concrete pouring phase, data generation rates increased significantly. Kafka consumer group auto-scaling was achieved by implementing container orchestration rules. Additionally, a dead-letter queue was created to ensure that messages that were missed by the system were processed again. This minimized data loss to less than 0.3% of total data. Figure 3 shows the module deployment structure and communication protocols on the left panel. The 3D dashboard interface prototype showing a progress-coded digital twin model with an active Tier-2 alert badge is shown on the right panel.

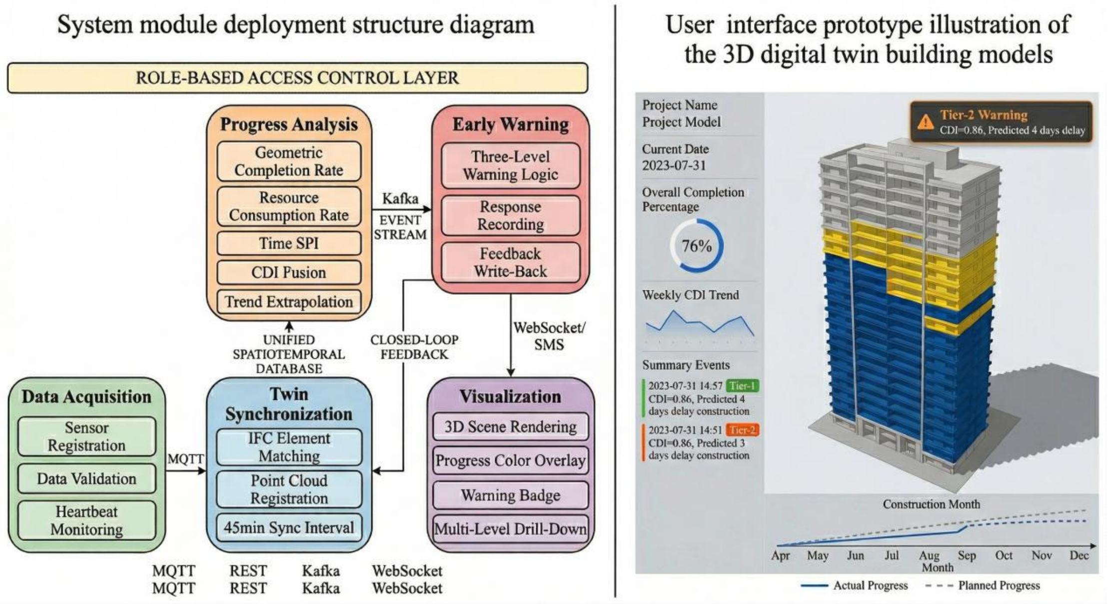


Figure 3. System deployment diagram and user-interface prototype

5. Case Study and Validation

5.1. Project Description

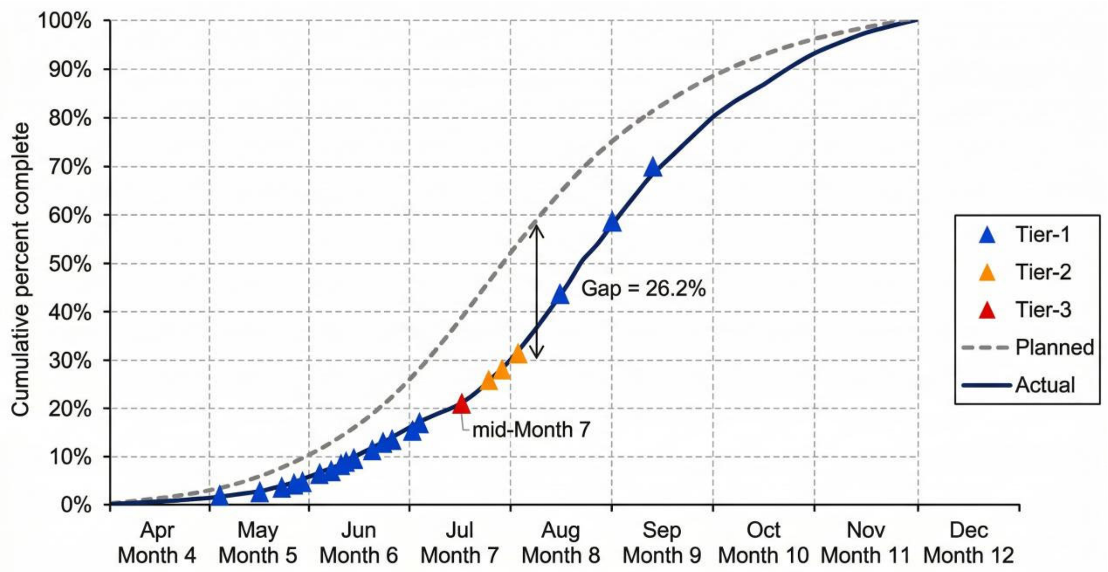
The validation case is a 28-story reinforced concrete residential building under construction in eastern China, with a total floor area of 32 000 m^2. The building has a contractual construction period of 18 months, with a conventional construction sequence consisting of foundation, structure, secondary structure, and finishing work. The digital twin system was implemented during the structure frame work package, which corresponds to months 4 to 12. A total of 156 Work Breakdown Structure (WBS) activities are included. Twenty-two IoT sensors are installed on site, consisting of tower crane load cells, concrete pump flow meters, rebar RFID readers, as well as bi-weekly UAV photogrammetric surveys. The conventional 4D BIM management tool that has been in use on this site was taken as the baseline.

5.2. Results and Early Warning Performance

During the deployment period of eight months, the system accumulated a total of 1.2 million data records, with the digital twin model being updated at a mean interval of 45 minutes. There were 37 deviation events detected during this period, of which 34 were confirmed to be actual events using manual verification. This corresponds to a detection accuracy of 91.9%. Out of the 34 actual events detected, 29 were Tier-1 (Blue), 4 were Tier-2 (Orange), and 1 was a Tier-3 (Red) event. The three false positives were related to concrete-pouring phases of the project. They were caused by transient sensor drift due to vibration from the concrete-pouring process. However, after the installation of the adaptive noise rejection filter at the mid-point of the project, there were no false positives of this type reported.

5.3. Comparative Analysis

In comparison with the conventional 4D BIM monitoring baseline, it can be seen that the digital twin system showed a remarkable performance in three performance metrics. The average detection latency decreased from 6.2 days to 0.8 days, which means a remarkable 87% improvement. The average response-to-correction cycle also showed a 67% improvement, from 9.5 days to 3.1 days. The total schedule slippage at the end of the monitored period was 11 calendar days, which is a 52% reduction compared with the conventional system's estimation of 23 days. Figure 4 shows the planned and actual cumulative progress S-curves, in which alert events are marked at their respective temporal positions and colored according to their respective tier. Table 4 provides a summary of the performance metrics.



Data calculated based on cumulative weighted completion rates of 156 WBS activities

Figure 4. Planned versus actual cumulative progress S-curves with alert markers

Table 4. Validation results

Performance Metric	Conventional 4D BIM Baseline	Proposed DT System	Absolute Improvement	Relative Improvement
Detection Accuracy	—	91.9%	—	—
Mean Detection Latency (days)	6.2	0.8	5.4	87%
Mean Response Cycle (days)	9.5	3.1	6.4	67%
Cumulative Schedule Slippage (days)	23	11	12	52%

5.4. Discussion

The outcome of the validation exercise affirms the effectiveness of embedding the deviation detection in a live-updated digital twin in reducing the time gap between the occurrence and response to deviations. The tiered mechanism has shown effectiveness in the allocation of managerial attention, with 85% of deviations being addressed at the Tier-1 level, indicating that basic early alerts are sufficient to prompt timely responses to most deviations. The single Tier-3 case resulted from an unexpected ingress of groundwater, which simultaneously affected the waterproofing of the foundation and the installation of the reinforcement, indicating a multi-factorial delay. In a typical monitoring scenario, where the cause is environmental rather than operational, this would have been detected much later.

The deployment also demonstrated the operational limits of the system. The geometric sensing accuracy under heavy rain and fog was not as good as expected, which affected the registration quality of point clouds. Moreover, finishing work such as plastering and painting still heavily relies on manual check-in inputs because the recognition capability for this work has not yet been mature. These limitations specify the circumstances under which this system could work well and pinpoint possible improvement directions.

6. Conclusion

The research has introduced a digital twin-based dynamic monitoring and early warning system for construction progress management. The contributions are aligned with the three objectives. At the architectural level, a four-layer digital twin structure that incorporates BIM, IoT, and schedule management information was developed to support the continuous updating of the virtual site at a subhourly frequency. At the algorithmic level, a weighted Composite Deviation Index that integrates geometric completion ratio, resource consumption ratio, and time-based SPI was proposed, along with a dual-path detection approach. This has improved the timeliness and dimensionality of deviation identification. At the validation level, an eight-month field test on a 28-story residential building demonstrated a 91.9% detection accuracy, 87% reduction in mean detection latency over the traditional 4D BIM approach, and 52% reduction in cumulative schedule slippage.

Some limitations are recognized. The validation was done in one project with a focus on only the structural frame stage. The validation results' generalization needs further investigation. The progress capture in the finishing stage was still heavily dependent on human input due to insufficient levels of automation. The accuracy of geometric sensing was impacted by unfavorable weather conditions to an extent that impacted the ability to perform all-weather continuous monitoring.

The future research will focus on four different avenues. The first avenue is to expand system deployment to different project types to investigate its generalization ability. The second avenue is to integrate computer vision technology to recognize construction activities to reduce dependence on human check-ins. The third avenue is to substitute the existing piecewise linear trend prediction with deep learning technology to perform multi-factor delay prediction with LSTM/Transformer architecture. The fourth avenue is to investigate digital twin technology to enable progress awareness and management for multiple projects running concurrently.

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