Optimizing Construction Supply Chains in Smart Building Projects via a GIS–BIM Collaborative Platform and Machine Learning–Driven Delivery Forecasting

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Abstract. Smart construction projects require a high degree of collaboration among multiple participants to ensure timely delivery of materials. However, traditional planning methods are often limited by dynamic site conditions and fragmented data. This study proposes a framework integrating geographic information system (GIS), building information modeling (BIM), and machine learning (ML), aiming to optimize end-to-end construction supply chain logistics. This platform integrates spatiotemporal data such as road networks, real-time traffic flows, 3D building models, and historical distribution records, and adopts a hybrid prediction mechanism combining random forest and long short-term memory (LSTM) networks. The cloud-based visual dashboard integrates 3D models with spatial scenes, synchronously pushing predictive alerts, allowing planners to simulate different scenarios and proactively avoid delays. A case study of a high-rise project in Shanghai (involving over 1,200 freight trips) shows that the integrated system achieved an on-time delivery rate of 88%, reduced the average delivery time by 23 minutes per trip, and reduced the prediction error from 48 minutes to 29 minutes. Participants reported a significant reduction in unused labor hours and emergency changes to orders. This achievement provides a scalable example of data-driven supply chain management in the field of smart construction. In the future, it will explore enhanced features such as reinforcement learning-based dynamic route planning and blockchain-backed smart contracts.

Keywords: Smart buildings, construction supply chain, GIS–BIM integration, machine learning, delivery forecasting

1. Introduction

Smart technologies are driving the transformation of the construction industry, bringing both unprecedented opportunities and challenges to project execution. Smart buildings improve efficiency and sustainability through sensors, the Internet of Things, and advanced analytics, but these benefits can only be achieved by leveraging equally smart and responsive supply chains. Traditional construction logistics often rely on fragmented data—manual planning, tabular progress reports, and static completion plans—and are difficult to manage with the complexity of modern construction sites. Sudden congestion, temporary design changes, and batched deliveries from

subcontractors often disrupt the flow of materials, leading to high downtime, equipment rearrangements, and project delays. To this end, this paper presents a unified platform that seamlessly integrates geographic information (GIS), building information modeling (BIM), and machine learning prediction to build a digital twin environment. GIS provides spatial backgrounds such as road networks, traffic flows, and site restrictions, while BIM establishes object-oriented models of building components, including metadata such as dimensions, materials, and installation sequences. By connecting the two domains via a middleware API, the system achieves real-time synchronization—any BIM update or sensor input immediately triggers the recalculation of route planning and delivery forecasts.

The core is a hybrid prediction engine that integrates a random forest regressor and a long-short-term memory (LSTM) network: the random forest analyzes heterogeneous relationships of features such as material weight, route complexity, and subcontractor performance; LSTM learns temporal patterns from historical delivery data. The model is continuously trained and iterated with new data to prevent potential delays in advance [1].

The case of a 35-story residential building in Shanghai (with four subcontractors managing over 1,200 freight shipments) confirmed the effectiveness of the framework: the integration of the GIS-BIM+ML platform achieved an on-time delivery rate of 88%, reduced the average lead time by 23 minutes, and reduced errors by 19 minutes compared to the baseline method. Feedback from the on-site manager and the logistics provider confirmed improved visibility, reduced downtime, and a decrease in the number of urgent order changes. This paper details the system architecture, data processing flow, model configuration, and deployment plan, and explores limitations and optimization directions—such as reinforcement learning in dynamic path planning and strengthening supplier accountability through blockchain smart contracts. This reference model has paved the way for data-driven supply chain management in a smart construction environment.

2. Literature review

2.1. GIS and BIM in construction

GIS technology provides key references for route planning and distribution sequencing, covering terrain features, traffic profiles, and facility pipe networks. Meanwhile, BIM accurately expresses geometric details, material specifications, and installation processes for building components using object-oriented modeling methods. Once the two are integrated, spatial boundaries (such as crane boom reach and road width) and component positioning information can be cross-referenced, improving the accuracy of material distribution [2]. This synthetic system allows project managers not only to clearly define "which components need to be transported" but also to accurately capture "the location and time of delivery," facilitating the coordination and synchronization of logistical arrangements and on-site construction sequences.

2.2. Machine learning for forecasting

Data-driven forecasting methods have demonstrated considerable promise in reducing scheduling uncertainty in construction logistics. Tree-based models such as Random Forest excel at handling heterogeneous input features—material weights, transportation distances, contractor performance metrics—and can provide interpretable feature-importance scores. In contrast, recurrent neural networks like the long short-term memory (LSTM) network capture temporal dependencies in delivery histories, preserving both short-term fluctuations and long-term trends. Figure 1 illustrates

the core LSTM structure: input vectors (x_{t-2}, x_{t-1}, x_t, …) are transformed through implicit hidden states (h_{t-2}, h_{t-1}, h_t, …) and cell states (C_{t-2}, C_{t-1}, C_t, …), producing output forecasts (y_{t-2}, y_{t-1}, y_t, …) that evolve as new data arrive. Hybrid architectures that combine Random Forest's robustness with LSTM's sequential modeling capabilities can learn non-linear relationships among site conditions, order volumes, and external factors such as weather or traffic [3]. In practice, these algorithms can be retrained continuously on incoming delivery data to refine their predictions and enable proactive mitigation of emerging delays.
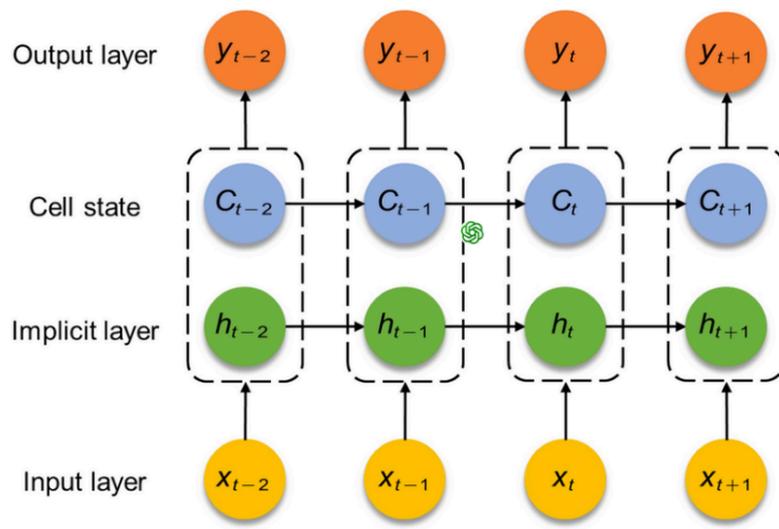

Figure 1. LSTM network architecture for delivery time forecasting
(source:https://www.researchgate.net/ publication/373430261/figure/ fig2/AS:
11431281184156646@ 1693235244965/ LSTM-neural-network-structure-diagram.png)

2.3. Integrated platforms and digital twins

Recent studies advocate the construction of digital twins—dynamic virtual maps of physical assets that integrate real-time sensor data with progress updates. After integrating GIS-BIM data into the digital twin environment, participants can monitor material flow, equipment planning, and spatial conflicts throughout the supply chain via a unified dashboard. For example, the four-stage logistics network (supplier → factory → warehouse → customer) shown in Figure 2, in which supply contracts, production costs, transportation costs, inventory costs, and demand satisfaction rate indicators are overlaid and presented. On the GIS-BIM-Digital twin platform, these cost and traffic indicators can be mapped in real time onto the corresponding coordinates and positions of the 3D model, allowing planners to simulate different scenarios or trigger alarms in case of deviation from predefined thresholds on any link [4]. Most existing solutions are focused on asset management or energy efficiency monitoring. However, the framework of this paper is based on the cost flow structure of Figure 2 and extends the twin digital capabilities to the areas of predictive logistics, scenario simulation and multi-agent collaboration [5].
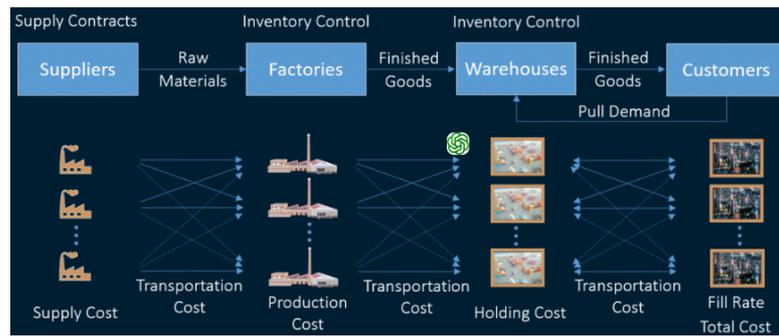
Figure 2. Four-stage supply chain flow with cost metrics (supply contracts, production cost, transportation cost, holding cost, fill rate)(source:https://blogs.sas.com/ content/subconsciousmusings/files/ 2021/10/ biller-digital-supply-chain-twin-figure-1- 1024x440.png)

3. Methodology and experiment implementationg

3.1. System architecture, data collection, and preprocessing

This integrated platform is based on a three-tier architecture and unifies GIS, BIM, and machine learning in a collaborative environment. The GIS engine imports spatial data such as road networks, traffic control, and site topography; the BIM server hosts detailed three-dimensional models of building components, as well as metadata such as the installation sequence. The middleware API manages data exchange to ensure that changes to the BIM model (such as adjustments to the installation sequence) are synchronized in real time with the GIS and AI modules. Data collection covers four types of sources: historical dispatch logs from subcontractors, real-time GPS trajectories from transport vehicles, BIM model output in IFC format, and traffic weather sensors. The preprocessing process begins with synchronizing timestamps between systems and transforming coordinates into the unified reference system [6]. The statistical threshold method is used to flag abnormal distributions (such as accidental deviations) and is supplemented by manual review; missing transport times are interpolated using the moving average method. Categorical variables (such as material classification and supplier name) are coded independently, and continuous variables are normalized. This process generates pure, high-dimensional datasets to support platform visualization and model training.

3.2. Platform deployment and case study application

The cloud dashboard offers customized views for planners, field engineers, and logistics providers. The GIS layer maps the vehicle location and delivery route, and the integrated BIM viewer highlights the location of the 3D building about to be delivered. Containerized deployment of model training and forecasting modules: random forest regressors provide initial estimates of the delivery cycle, and LSTM networks optimize forecasts by capturing temporal dependencies in delivery sequences. The hyperparameters (tree depth and number of trees in the random forest) are optimized through five-fold cross-validation grid search. The unit size and learning rate of LSTM (minimize the mean square error) are also optimized [7]. The Shanghai Tower project serves as a test site, involving more than 1,200 freight shipments from four major subcontractors. Its restricted urban roads and dynamic traffic control imposed strict tests on the system. Participants agreed to share 12-month delivery records. Based on this, the platform replayed historical data and simulated real-time

predictions in three modes: manual planning (benchmark mode), GIS-BIM visualization without machine learning, and a comprehensive GIS-BIM+ML fusion system [8].

3.3. Evaluation metrics and results analysis

The evaluation indicators include the on-time delivery rate (the percentage of arrivals within ±1 hour after the on-time delivery period), the average lead time reduction, and the root mean square error of the predicted lead time. Based on the simulation tests of 300 random freight transport samples in each scenario, the punctuality rate of the reference system is 67%, while that of the GIS-BIM system alone is 76%. The complete GIS-BIM+ML solution achieves an on-time delivery rate of 88% and reduces the average lead time by 23 minutes for a single delivery. The prediction error (RMSE) of this fusion system decreased from 48 minutes in the reference scheme to 29 minutes. In addition to quantifying the benefits, feedback from the on-site manager highlighted the platform's functionality: automatic early warnings led to proactive rerouting, and it is estimated that team downtime will be reduced by 12 hours per week. Logistics service providers reported a decrease in urgent order changes and disputed claims [9]. Current challenges include data lag caused by subcontractor update logs, as well as scalability limitations once daily transport volume exceeds 1,000 orders. Future upgrades will integrate real-time vehicle tracking data feeds and dynamic route planning based on reinforcement learning to further improve performance.

4. Results and discussion

4.1. Performance comparison

The integration of the GIS-BIM+ML solution has significantly improved forecast accuracy and reduced lead times. As shown in Table 1, the on-time rate increased from 67% for manual scheduling to 76% when using GIS-BIM alone, and further increased to 88% after combining machine learning. The average time for a single delivery was reduced by 23 minutes—a 21% increase over the benchmark and a 15% increase over GIS-BIM alone—while the RMSE was reduced from 48 minutes to 29 minutes, confirming the robustness of the prediction model [10].

Table 1. Delivery performance metrics by scenario

Scenario	On-Time Accuracy (%)	Avg. Delay Reduction (min)	RMSE (min)
Manual Scheduling (Base)	67	–	48
GIS–BIM Only	76	12	38
GIS–BIM + ML	88	23	29

4.2. Stakeholder feedback and usability

End-user research and interviews show that participants responded positively to the fully integrated platform. Table 2 summarizes the key feedback indicators: the average satisfaction score for on-site managers was 4.6 points (out of 5 points), and it was reported that approximately 12 hours of downtime were saved per week. The logistics provider scored 4.3 points, and the number of urgent order changes decreased by 30%. Respondents highlighted the automatic early start-up and clear delivery window visualization as the most valuable features.

Table 2. Summary of stakeholder feedback

Stakeholder Group	Satisfaction Score (1–5)	Idle Hours Saved (hrs/week)	Key Benefit
On-Site Managers	4.6	12	Proactive labor and crane scheduling
Logistics Providers	4.3	8	Fewer order changes and disputes

4.3. Limitations and future improvements

Despite the remarkable achievements, the performance of this framework largely depends on timely data updates. Sensor failure or delays in subcontractor logs can reduce the quality of model input, leading to decreased forecast accuracy. When the daily transportation volume exceeds several thousand orders, the time required for data processing and model inference increases, and scalability also faces challenges. Applying reinforcement learning to address dynamic route planning in an uncertain environment; Integrating real-time vehicle tracking data streams to minimize latency; Deploying blockchain-based smart contracts to automate supplier rewards and sanctions.

5. Conclusion

This study proposes a novel GIS-BIM-ML framework to optimize the construction supply chain in smart building projects. By integrating spatial analysis, detailed 3D models, and hybrid prediction algorithms into the digital twin cloud, this platform improved on-time delivery rates, reduced lead times, and strengthened multi-party collaboration. The high-level case study in Shanghai confirmed the remarkable results: an on-time delivery rate of 88%, an average delivery time reduction of 23 minutes, and a prediction error reduction of 29 minutes. Positive feedback from the on-site manager and the logistics service provider underscores the practical value of the system in reducing downtime and order disputes. Although data latency and scalability remain challenges, further research will be conducted on dynamic path planning for reinforcement learning and automatic incentivization of blockchain smart contracts for suppliers. This achievement ultimately provides a scalable data-driven reference model for real-time supply chain management in the era of smart construction.

References

[1] Antwi-Afari, M. F., & Liu, X. (2025). BIM, IoT, and GIS integration in construction resource monitoring: A state-of-the-art review. Automation in Construction, 150, 104234. https: //doi.org/10.1016/j.autcon.2025.104234 researchgate.net

[2] González, A., & Martín, J. (2024). Integration of BIM and GIS for the digitization of the built environment. Applied Sciences, 14(23), 11171. https: //doi.org/10.3390/app142311171 mdpi.com

[3] Wang, Y., & Chen, L. (2023). Using Building Information Modeling to enhance supply chain resilience in prefabricated buildings. Applied Sciences, 13(23), 12694. https: //doi.org/10.3390/app132312694 mdpi.com

[4] Abdel Sater, R., & Ben Hamza, A. (2020). A federated learning approach to anomaly detection in smart buildings. arXiv preprint arXiv: 2010.10293. arxiv.org

[5] Fan, X., Xiang, C., Chen, C., Yang, P., Gong, L., Song, X., Nanda, P., & He, X. (2020). BuildSenSys: Reusing building sensing data for traffic prediction with cross-domain learning. arXiv preprint arXiv: 2003.06309. arxiv.org

[6] Tan, B., & Zechner, A. (2024). Building a sustainable future: BIM's role in construction logistics and waste management. Sustainable Cities and Society, 47, 103578. https: //doi.org/10.1016/j.scs.2024.103578 sciencedirect.com

[7] Khan, M., & O'Brien, W. (2022). Synergies between digital construction technologies in smart buildings: A qualitative analysis. Smart and Sustainable Built Environment, 11(1), 23–38. https: //doi.org/10.1108/SASBE-01-

2022-0016 pmc.ncbi.nlm.nih.gov

[8] Khiari, J., & Olaverri-Monreal, C. (2020). Boosting algorithms for delivery time prediction in transportation logistics. arXiv preprint arXiv: 2009.11598. arxiv.org

[9] Gołąbek, M., Senge, R., & Neumann, R. (2020). Demand forecasting using long short-term memory neural networks. arXiv preprint arXiv: 2008.08522. arxiv.org

[10] Liu, J., & Zhang, W. (2024). A data-driven machine learning model for forecasting delivery times in construction logistics. Journal of Construction Analytics, 2(1), 45–58. https: //doi.org/10.1016/j.joca.2024.01.005 sciencedirect.com