Intelligent Construction Schedule Dynamic Prediction System with Multimodal Data Fusion

Peihua Long

Department of Civil and Transportation Engineering, Guangdong University of Technology, Guangdong, China

longpeihua000@gmail.com

Abstract. The construction industry faces persistent challenges in dynamic schedule management due to heterogeneous data, environmental uncertainty, and reliance on static methods, resulting in inefficiencies and schedule delays. This study addresses these gaps and proposes a multimodal data fusion (MDF)-driven framework to enhance real-time schedule prediction and decision-making. The methodology includes collecting data through APIs, IoT sensors, BIM, and RFID; pre-processing for cleansing, normalization, and integration; and training Random Forest Models to capture non-linear relationships and feature interactions to construct spatio-temporally consistent datasets. The results show that weather extremes (e.g., prolonged rainfall) have a significant impact on the foundation phase, while labor shortages and RFI upgrades are strongly associated with delays in the structural phase. A prototype system integrating BIM and real-time data visualization demonstrated its practical efficacy by providing coded progress alerts for dynamic resource optimization. This research emphasizes the transformative potential of MDF to reduce construction risk and advance intelligent schedule management. Future work should incorporate advanced AI techniques and empirical data to further improve forecasting accuracy and facilitate the development of resilient and adaptive project management systems.

Keywords: Multimodal Data Fusion (MDF), Dynamic Schedule Management, Construction Delay Prediction.

1. Introduction

With the rapid development of the construction industry, real-time monitoring of construction progress for dynamic management is critical to project success. However, the construction industry has long faced significant challenges in project schedule forecasting and dynamic management due to complex construction site conditions, heterogeneous data sources, and lack of real-time decision support systems [1]. These challenges frequently end up in resource allocation inefficiencies, cost hikes, and schedule overruns. Traditional construction schedule management methods typically rely on critical path analysis with Gantt charts, often relying on static data inputs that are difficult to adapt to dynamic environmental changes such as weather disruptions, resource shortages, or equipment failures and infrastructure aging. However, these methods struggle to adapt to dynamic environmental changes, such as weather disruptions, resource shortages, equipment failures, and aging infrastructure. Moreover, manual schedule adjustments are time-consuming and prone to errors, further limiting their effectiveness in large-scale and high-complexity projects. With the advancement of Industry 4.0 technologies, emerging technologies such as Internet of Things (IoT), BIM, computer vision, and Artificial Intelligence (AI) [3] have been able to capture multimodal data (e.g., sensor measurements, image/video streams, LIDAR scans, and textual logs) from the construction site, significantly enhancing in improving the prediction accuracy [2].

Multimodal Data Fusion (MDF) enables systematic identification of key causal factors and early detection of dynamic risks by integrating heterogeneous data streams (e.g., weather data, RFI quantities, change orders, resource allocation records, and progress logs, and other multidimensional information). It has become a core method for intelligent construction management.

The convergence of building information modeling (BIM) and the Internet of Things (IoT) in recent years has driven the digital transformation of construction schedule management [4]. Research has shifted from early unimodal data analysis to cross-modal correlation analysis. Despite the progress that has been made, existing approaches still face challenges, such as 1. Data heterogeneity hinders integration: text-based variable-following orders and structured resource records are difficult to characterize in a unified way. 2. Insufficient real-time performance: Most models rely on historical data for training and are unable to dynamically respond to unforeseen events (e.g., labor shortages due to epidemics). This study aims to explore which factors have the greatest impact on construction schedule delays under the combined effect of multimodal data and to provide theoretical support and practical guidance for intelligent construction schedule management systems.

2. Research methodology

2.1. Data collection

2.1.1 Weather Data

Collect historical weather data during construction, including temperature, precipitation, wind speed, humidity, and other indicators. Extreme weather events can cause delays, increase safety risks, and impact resource availability. Collection method: 1. Real-time retrieval of historical and forecast weather data of the construction area in real time by accessing the API of China Meteorological Administration (CMA) or the third-party meteorological data platform (e.g. openweathermap). 2. Through the IoT sensors at the construction site: deploy multimodal sensors such as temperature and humidity sensors (DHT22) and anemometers. Collect data in real time and communicate via WiFi network [5]. Satellite and remote sensing data: Integration of satellite-based weather monitoring systems to provide additional insights into climate patterns and severe weather warnings.

2.1.2 Number of RFI's

To obtain the number and detailed information of RFIs (Requests for Information) stored in archives or project management systems, two primary data collection methods can be employed. First, digital project management platforms (e.g., Procore, Oracle Primavera) can be used to export RFI records for a specified time period (e.g., May 2024 to April 2025). Using the system's built-in reporting features, extract data fields such as: RFI number (e.g., RFI-2024-005), submission date, response date, processing time (in days), submitting party (e.g., contractor or superintendent), associated construction activity (e.g., earthwork, structural pouring), issue type (e.g., design conflict, material defect, construction error), status (e.g., pending, resolved, disputed), and estimated impact (e.g., delay in days, cost change). Additionally, automated data capture via system APIs (e.g., Procore REST API) enables seamless integration with external analysis tools such as Python Pandas. Second, for RFIs stored in paper or non-structured digitl formats, OCR technology (e.g., Tesseract engine) can be applied to scanned PDFs or Word documents to extract textual data, which can then be processed using regular expressions (Regex) to identify and structure key information fields.

2.1.3 Progress Record

Record the actual construction progress against the project plan to identify delay points. Collection method:

1) Highly detailed as-built data is obtained from the construction site in a reasonable amount of time and then embedded into a BIM (Building Information Modeling) based construction schedule (e.g., Gantt Chart) to form a 4D model (3D geometry + timeline) that contains the structural units and resource requirements that are scheduled to be completed in each phase. Finally, the point cloud data obtained from the mobile LiDAR technology and the 4D design model is exploited to determine the Percentage of Completion (POC) of the accomplished construction schedule and compare it to the planned POC. The specific process is illustrated in Figure 2. [6]

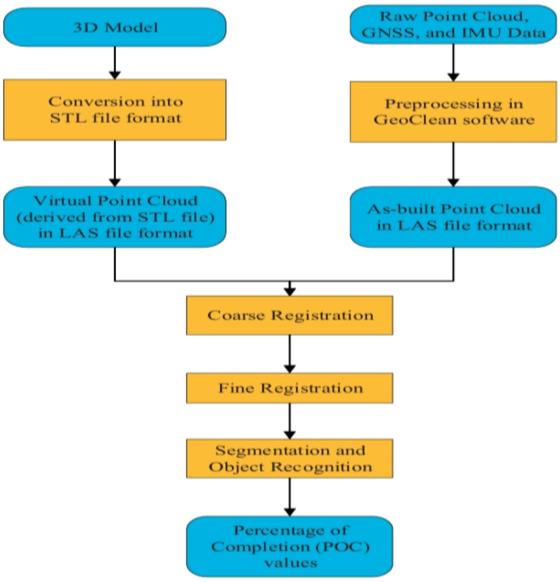

Figure 1. Proposed framework for project progress tracking [6]

Exploit the Digital Construction Monitoring (DCM) prototype system that combines CAD drawings, digital images, and planned construction schedules to automatically calculate project schedule percentages and display them in Microsoft Project. The proposed DCM prototype system is organized into four phases: inputting information, processing information, displaying results, and taking action. The system exploits Visual Basic and Microsoft Access for data integration and computation, integrates AutoCAD drawings, digital images, and progress schedules, and finally generates Gantt charts in Microsoft Project. The specific flowchart is shown in Figure 2 [7].

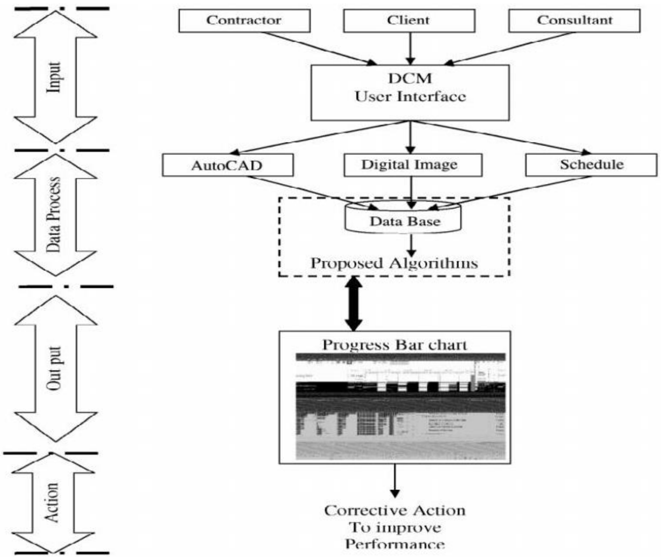

Figure 2. Developed framework of digital construction monitoring [7]

2.1.4 Resource Allocation Records

Capture the allocation of labor, equipment, and materials during construction and then record it through project management software or a resource scheduling system. Collection method:

1) Labor Force Allocation Records: RFID-tagged smart helmets: Employees wear helmets with built-in RFID chips that use regional positioning base stations (like UWB) or the construction site access control system to automatically record the time of entry and exit as well as the work area.

2) Records of equipment usage: Use of IoT sensors: To track the operational status (working hours, idling rate) in real time, GPS and vibration sensors are fitted in cranes, mixers, and other machinery.

2.2. Data preprocessing

2.2.1 Data cleansing

Missing value processing:

Time series data (weather data):

Short-time missing (e.g., single-hourly temperature data missing): A linear interpolation method is used to calculate missing values based on the values at adjacent points in time before and after. For example, if the temperature at 10:00 a.m. is missing, the average of the temperatures at 9:00 a.m. and 11:00 a.m. will be taken to fill in.

Long-term missing (e.g., missing precipitation data for multiple consecutive days): Using historical mean values for the same period to replace, such as the average precipitation for the same date and area over the past 3 years, or extrapolated from similar weather patterns by K-Nearest Neighbor Interpolation (KNN).

Number of RFIs (Request for Information tickets):

If RFI records are missing on a particular day, they need to be manually verified and completed in conjunction with the project management log or the supervision daily report. If it is not possible to complete the record, it will be marked as "Not Recorded" to avoid misinterpretation by the model.

Resource allocation records:

Missing labor hours or material usage will be filled in based on historical averages for similar tasks. For example, if the average daily labor hours for a particular type of concrete placement task is 7 hours, this value will be applied to fill in the missing value.

Duplicate data processing:

Detecting time series data: check for duplicate records under the same timestamp (e.g., two temperature values occurring on a particular day).

Resource allocation records: Compare the exact duplicate entries in the fields of task ID, date, resource type, etc., by hash function. The first record is then retained, and subsequent duplicate entries are deleted. If there are minor differences in the duplicates (e.g., fluctuating temperature values, minor differences in final concrete setting time), the mean or the plural is taken and merged.

Error data processing:

Z-score method: Calculate standard deviation multiples of data points from the mean, excluding extreme values with absolute values exceeding 3 (e.g., 400 mm of precipitation in a single day).

Specific method of calculating Z-score:

Determine if the data fit into a Z-score (normal distribution).

Calculate the mean and standard deviation.

Apply the Z-score formula.

Deal with special cases (e.g., skewed distributions).

Take the example of calculating Z-score values for weather data:

Z(temperature) = (27.5 - 20) / 2.5 = 3 (The temperature on a particular day is 27.5°C);

Z(precipitation) = (18 - 13) / 3.7 = 1.35 (Precipitation of 18 mm on a particular day).

(Temperature: A 30-day average daily temperature of 20°C with a standard deviation of 2.5°C is assumed. Precipitation: The daily average precipitation is assumed to be 13mm with a standard deviation of 3.7mm.)

CONCLUSION: Temperature is 3 standard deviations above average, and precipitation is 1.35 standard deviations above average.

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2.2.2 Data standardization and normalization

By standardizing the data, firstly, the interoperability of the data can be improved: the use of standard classification systems and data structures facilitates comparisons and analyses with other databases and studies. Secondly, it enhances data traceability: Uncertainty scores and weighted uncertainty scores make it possible to understand the origin and reliability of the data, and to assess the impact of the data on the results of the study. Thirdly, it facilitates data sharing and collaboration: standardized data structures and methods make it easy for users to contribute data and conduct further analysis [8].

2.2.3 Data Integration

Aligning multi-modal data collected from different sources to the same time-frame or project task.

1) Time-frame alignment:

Time windows are divided by construction phase (e.g., foundation work, main structure), and weather, RFIs, and resource data are tied to the progress of each phase.

2) Space and task ID alignment:

The correlation of data, such as weather, to the coordinates of BIM components within the construction area can be considered analogous to the mapping of the BIM model. And unique WBS codes are assigned to each task and unique WBS codes are assigned to each task [9].

2.3. Model Selection and Training

2.3.1 Select the appropriate model

First, to initially identify the correlation of the factors, the Pearson correlation coefficient can be used to calculate the linear correlation between the numerical variables. For example, weather data (e.g., temperature, rainfall) may be negatively correlated with construction progress, and resource allocation (e.g., amount of labor) may be positively correlated. Scatterplots are then plotted with visualization tools to observe distribution patterns between pairs of variables and identify potential nonlinear relationships or outliers. Second, due to the complexity of the multimodal data (weather, RFI, resource allocation, and construction schedule), models that capture nonlinear relationships and feature interactions need to be selected. In this paper, Random Forest (RF) is chosen because it is suitable for processing numerical and categorical data, can automatically capture the nonlinear relationships and interactions between features, has no need for feature processing of the obtained point cloud data, and is suitable for multimodal structured data fusion scenarios [10].

3. Results

In this study, by constructing an intelligent construction progress management analysis framework with Multimodal Data Fusion (MDF) as the core, the key influencing factors of construction progress delays are mined by utilizing heterogeneous data sources, such as measured weather data, number of RFI work orders, construction progress records, and resource allocation records. The main findings are as follows: There are significant differences in the degree of influence of different modal data on construction progress

The joint analysis of Pearson's correlation coefficient and Random Forest Model reveals that extreme weather events (e.g., continuous rainfall, strong winds) are highly negatively correlated with construction delays, which are more obvious especially in the foundation construction and outdoor work stages; while insufficient labor and equipment inputs are the main endogenous causes of delays in the structural construction stage. The lack of labor and equipment input is the main internal cause of delays in the structural construction phase. In addition, an increase in the number of RFIs usually indicates a large number of technical or coordination problems on the construction site, which also shows a significant positive correlation with schedule delays.

System integration and visualization application show initial results

The preliminary prototype system can realize real-time display and deviation warning of construction progress by integrating multimodal data with BIM model. In the test project, the system automatically updates the results of progress deviation analysis on a daily basis and displays them in the form of color coding in the 3D model interface, which facilitates the project manager to intuitively grasp the implementation status of key nodes and the optimization proposal of resource distribution.

4. Conclusion

This study adopts a multimodal data fusion approach to systematically integrate heterogeneous data sources—including weather conditions, RFI volumes, resource allocation records, and construction progress—to develop an intelligent construction schedule prediction model. Leveraging IoT sensors, BIM modeling, and standardized processes for automated data acquisition and cleaning, the framework ensures high-quality, spatio-temporally aligned datasets. By applying a random forest model to identify key factors contributing to schedule delays, the study aims to enhance project dynamic management efficiency, mitigate construction risks, and provide both theoretical and practical support for intelligent construction schedule management systems. The principal contribution of this paper is to systematically illustrate how the multimodal data collected during the construction process can be used and combined with various techniques and mathematical models currently available to achieve the effect of dynamic prediction of construction progress. This study lacks empirical data and has yet to incorporate more sophisticated techniques and methodologies, such as artificial intelligence. With the advent of the AI era, research endeavors should establish more profound links with AI to enhance the efficiency and precision of the prediction system.

References

[1] Liu Guangkui. Analysis of risk prevention methods for combined construction progress of highway engineering projects [J]. Urban Construction Theory Research (Electronic Edition), 2023, (19): 117-119. DOI: 10.19569/j.cnki.cn119313/tu.202319039.

[2] Zhao, F., Zhang, C., & Geng, B. (2024). Deep multimodal data fusion. ACM Computing Surveys, 56 (9), 1–36. https://doi.org/10.1145/3649447.

[3] Ensafi, M., Alimoradi, S., Gao, X., & Thabet, W. (2022). Machine Learning and Artificial intelligence Applications in building Construction: Present status and Future Trends. Construction Research Congress 2022, 116–124. https://doi.org/10.1061/9780784483961.013.

[4] Xu, Star. (2019). Research on Construction Progress Management of Municipal Engineering Based on BIM. Construction Technology Research. 2. 10.32629/btr.v2i1.1746.

[5] Rani, S. S., Janet, J., Ramya, K., & Gomathy, V. (2020). IoT based climate prediction using ANN for green networking. IOP Conference Series Materials Science and Engineering, 993 (1), 012090. https://doi.org/10.1088/1757-899x/993/1/012090.

[6] Nisha, P., & Yelda, T. (2020) Bridge Construction Progress Monitoring Using Lidar and 4D Design Models, Automation in Construction, 109: 102961.

[7] Memon, Z. A., & Mustaffar, M. (2006). A systematic approach for monitoring and evaluating the construction project progress. The Institution of Engineers, Malaysia (Vol. 67, No. 3, September 2006). http://dspace.unimap.edu.my:80/xmlui/handle/123456789/13560.

[8] Gursans, G., Aldrick, A., Allison, B., Melanie, T., Bolaji, O., Molly, M., Kaan, I., Alexander W., O., & Shoshanna, S. (2022) A Construction Classification System Database for Understanding Resource Use in Building Construction., Scientific data, 9.1.

[9] ZHANG Fei-Fei, WANG Xi, WANG Xue-Ying, et al. Multi-source and multi-modal data fusion technology and prospect in oil and gas well engineering [J]. Natural Gas Industry, 2024, 44 (09): 152-166.

[10] GAO Wang, LIU Yuzhan, GUO Yajuan, et al. Random forest-based GNSS observation roughness fitting calibration method [J]. Journal of Instrumentation, 2025, 46 (01): 42-53. DOI: 10.19650/j.cnki.cjsi.J2413355.