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# Dynamic Cost Control of Construction Engineering Projects Using Multi-Source Data Fusion

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**Abstract:** The cost of large and complex construction projects is highly dynamic during the construction process due to design changes, material price fluctuations, on-site visas, and other factors. Traditional methods are difficult to capture the true cost status promptly, which can easily lead to the delayed discovery of deviations and missed control windows. In response to this pain point, this study proposes a dynamic cost control framework that combines digital twins and multi-source data fusion and takes a general building complex project as an example to conduct experimental verification. The results show that the actual cumulative cost of the project is 19.8287 million yuan, and the relative prediction error of the proposed method is 0.08%. The proposed method can effectively improve the cost prediction accuracy during the entire project cycle, and the relative error of the cumulative cost prediction in the later stages of the project is controlled within 1%. The number of over-limit incidents in each construction stage is significantly reduced. The number of over-limit incidents in the main structure stage is reduced from 4 to 1, a decrease of 75.00%. Research shows that the dynamic cost control method that combines digital twins and multi-source data fusion can realize the transformation of project cost from post-event control to process control. This study provides a feasible technical path and decision-making support method for the whole-process cost management of complex construction projects.

**Keywords:** Dynamic control of project cost, state vector, feedback adjustment, cost management.


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## 1. Introduction

During the implementation of large-scale and complex construction projects, project costs usually show highly dynamic changes and are affected by multiple factors, including design adjustments, construction schedule deviations, material price fluctuations, and on-site visa changes (Liu and Luo, 2025). Target cost management and dynamic cost tracking mechanisms have been widely used in current project management practice. However, in practical applications, cost control remains based on post-event statistics and periodic summaries, which makes it difficult to reflect the actual cost status during project implementation in a timely manner (Nwadigo et al., 2022; Rehman, 2025). This results in delayed discovery of cost deviations and slow response to control measures, ultimately increasing the risk of out-of-control project costs. As the scale of construction projects expands and the implementation process becomes more complex, engineering projects will continue to generate large amounts of heterogeneous data during the design, construction, and procurement phases. However, these data are stored in a dispersed, separate manner in the existing cost management system. They serve single functions, such as measurement, settlement, or statistical analysis, and have not yet established a unified cost status expression and a dynamic decision-support mechanism for the entire project process (Tagliaro et al., 2025). The failure to effectively integrate multi-source data directly limits the accuracy of cost prediction and the real-time nature of control decisions. In recent years, Digital Twin (DT) technology has achieved real-time perception and evolution prediction of engineering status by constructing a dynamic mapping model of physical engineering entities in digital space. This provides a new technical path for the transformation of engineering management models (Fang et al., 2022; Zhang et al., 2022). However, existing research mostly focuses on progress management, construction simulation, and operation and maintenance monitoring. In project cost control, the application of DT remains at the level of visual display or static cost mapping. A closed-loop prediction and control mechanism with cost status as the core has not yet been formed, making it difficult to support the dynamic cost control needs during project implementation. Against this background, this study takes construction engineering projects as the research object, combines DT technology and multi-source data fusion methods, and proposes a dynamic cost control method oriented to the project implementation process, to achieve early identification and dynamic control of cost deviations.

The innovation of this study lies in the construction of a unified cost state representation model. Compared with traditional dynamic cost control methods and system dynamics frameworks, the unified cost state vector achieves structural enhancements in the representation of project costs. Conventional methods are generally based on stage-based statistical indicators or cumulative data analysis, making it difficult to establish a continuously updatable state representation. Although system dynamics emphasizes causal feedback mechanisms, it typically relies on macro-level aggregated variables and lacks fine-grained alignment with actual engineering data. By constructing a time-indexed cost state vector that integrates cumulative cost, consumption rate, and adjustment factors into a unified framework, this study enables continuous updating of cost status and closed-loop regulation within a DT environment, thereby transforming cost management from post-event analysis to process-oriented control.

## 2. Literature Review

Focusing on the issue of cost management and control of construction engineering projects, many scholars have carried out a large amount of research work from different technical paths and management perspectives. Tang (2024) proposed the whole-process dynamic cost management in view of the problem that construction project investment is easy to get out of control. It used information and refined methods to calculate, analyze, and control costs in real time at each stage of decision-making, design, and construction, thereby maximizing investment benefits. Shafiei et al. (2023) proposed dynamic modeling and policy optimization of quality costs based on system dynamics to address the imbalance problem between project quality and cost. It analyzed the interaction between prevention and failure costs through causal loop diagrams and simulations, thereby achieving the greatest reduction in total quality costs. Li et al. (2025) proposed a cross-domain spatiotemporal data fusion framework to address scattered and difficult sharing of multi-sector data in DT cities. This framework unified address mapping and entity encapsulation through Bert+PtrNet+ESIM, and connected heterogeneous information to the geographical base, thereby improving urban governance efficiency and service capabilities. Jayamaha et al. (2024) proposed an Enterprise Resource Planning (EPR) adaptation framework with 14 functions × 16 stages of mapping to address the lack of collaboration in cost management of housing construction projects in Sri Lanka and the lack of scenarios for EPR application. Through two rounds of Delphi interviews and content analysis, it identified 18 types of pain points and matched system modules, thereby achieving simultaneous improvements in cost management efficiency and corporate competitive advantages.

Rafsanjani and Nabizadeh (2023) proposed a real-time interconnection reference model that integrates virtual design and construction, DT, artificial intelligence, and virtual reality to address high costs caused by insufficient real-time monitoring and optimization in the architecture, engineering, and construction industry. This model has been verified by global application forecasts and US$3.5 billion in cost savings, thereby achieving cost optimization and efficiency improvement in the entire design-construction-operation and maintenance process. Mohandes et al. (2025) developed a system for obstacle identification to address hindered promotion of DT, limited operational and maintenance performance, and sustainable improvement in Hong Kong housing construction projects. This framework identified five major bottlenecks: lack of tools, poor real-time communication, difficulty in data measurement and multi-agent sharing, and uncertain quality, and quantified their differences. It achieved precise optimization of DT implementation paths and simultaneous improvement of project cost-environmental protection dual benefits. Building Information Modeling (BIM) in the construction stage has problems with low efficiency and a lack of DT applications. Aktürk and Irlayıcı Çakmak (2025) combined literature synthesis and questionnaire quantification to couple DT and BIM from the perspective of construction management for the first time, thus achieving significant improvements in on-site productivity and project management efficiency.

To sum up, existing research has made useful explorations into construction project cost management issues from different perspectives, such as full-process dynamic cost management, system dynamics modeling, information system integration, and DT and multi-source data fusion. However, current research still has the following shortcomings: First, most cost management methods are still based on staged analysis or post-event evaluation, which is difficult to describe the continuous evolution characteristics of the cost status during the project implementation process, and there is a lack of close connection between cost prediction and control; Second, relevant research is mostly focused on the progress, quality, or operation and maintenance level, and in cost control scenarios, it is still based on visual display or static mapping, and a dynamic prediction and control closed loop with cost status as the core has not yet been formed; Third, in the existing research on digital or information-based cost management, the linkage mechanism between engineering data, market data, and management decision-making is still imperfect. Given the above research gaps, this study takes construction engineering projects as the research object, introduces DT technology and a multi-source engineering data fusion method, and aims to provide an implementable dynamic cost control technology path for complex construction engineering projects. The innovation is reflected in the systematic integration of multi-source cost data fusion, DT modeling, and cost control mechanisms, thereby realizing a full-process management model of project cost.

## 3. Research Methodology

### 3.1. Multi-Source Project Cost Data Fusion and Unified Cost Status Modeling

During the implementation of construction projects, the formation and evolution of project costs are not determined by a single source of information but are the result of the continuous coupling of multiple types of data, such as design information, construction progress, contract pricing, and material market prices in the time dimension (Raj, 2025). Therefore, to achieve effective integration of multi-source engineering cost data within a unified framework, this study first establishes a 3D mapping relationship among components, processes, and time, and unifies data from different sources into specific engineering units and their corresponding construction stages (Victar and Waidyasekara, 2025). The project cost status is defined as the comprehensive cost representation of the project under the joint action of the current implementation conditions and the external market environment at a given time node, as shown in Eq. (1).

$$\mathbf{C}(t)=\left[C_{\text{acc}}(t),C_{\text{rate}}(t),C_{\text{adj}}(t)\right] \tag{1}$$

In Eq. (1), $\mathbf{C}(t)$ is the unified cost state vector of the project at time $t$. $C_{\text{acc}}(t)$ is the cumulative project cost as of time $t$, which is used to describe the scale of costs incurred. $C_{\text{rate}}(t)$ is the cost consumption rate per unit time, reflecting the dynamic characteristics of cost growth during project implementation. $C_{\text{adj}}(t)$ is a cost adjustment item introduced by factors such as material price fluctuations, design changes, and on-site visas. It is used to describe the impact of external uncertain factors on the project cost. The cumulative cost $C_{\text{acc}}(t)$ is obtained by adding up the cost contributions of each engineering unit at different construction stages, as shown in Eq. (2).

$$C_{\text{acc}}(t)=\sum_{i=1}^{N}Q_i(t)\cdot P_i(t) \tag{2}$$

In Eq. (2), $Q_i(t)$ is the amount of work completed by the $i$-th engineering unit before time $t$. $P_i(t)$ is the comprehensive unit price of the corresponding engineering unit. $N$ is the total number of engineering units. The expression of the cost consumption rate $C_{\text{rate}}(t)$ is shown in Eq. (3).

$$C_{\text{rate}}(t)=\frac{C_{\text{acc}}(t)-C_{\text{acc}}(t-\Delta t)}{C_{\text{acc}}(t)} \tag{3}$$

In Eq. (3), $\Delta t$ is the time interval between adjacent time nodes. Cost adjustment item $C_{\text{adj}}(t)$ is used to describe the impact of material price fluctuations and engineering changes on the project cost, as shown in Eq. (4).

$$C_{\text{adj}}(t)=\sum_{j=1}^{M}\Delta P_j(t)\cdot Q_j(t) \tag{4}$$

In Eq. (4), $\Delta P_j(t)$ is the change of type $j$ key material at the time $t$ relative to the benchmark price. $Q_j(t)$ is the consumption of the corresponding material. $M$ is the number of material types included in the analysis. Due to the long-term scattered storage and independent use of engineering cost data, it is difficult for existing cost management methods to form an overall depiction of the engineering cost evolution process (Chen et al., 2022). Therefore, this study integrates multi-source data and unifies the cost status modeling process, transforming project cost from its original scattered, discrete records into a continuous, updatable status vector. The process of multi-source cost data fusion logic and unified cost status modeling is shown in Fig. 1.

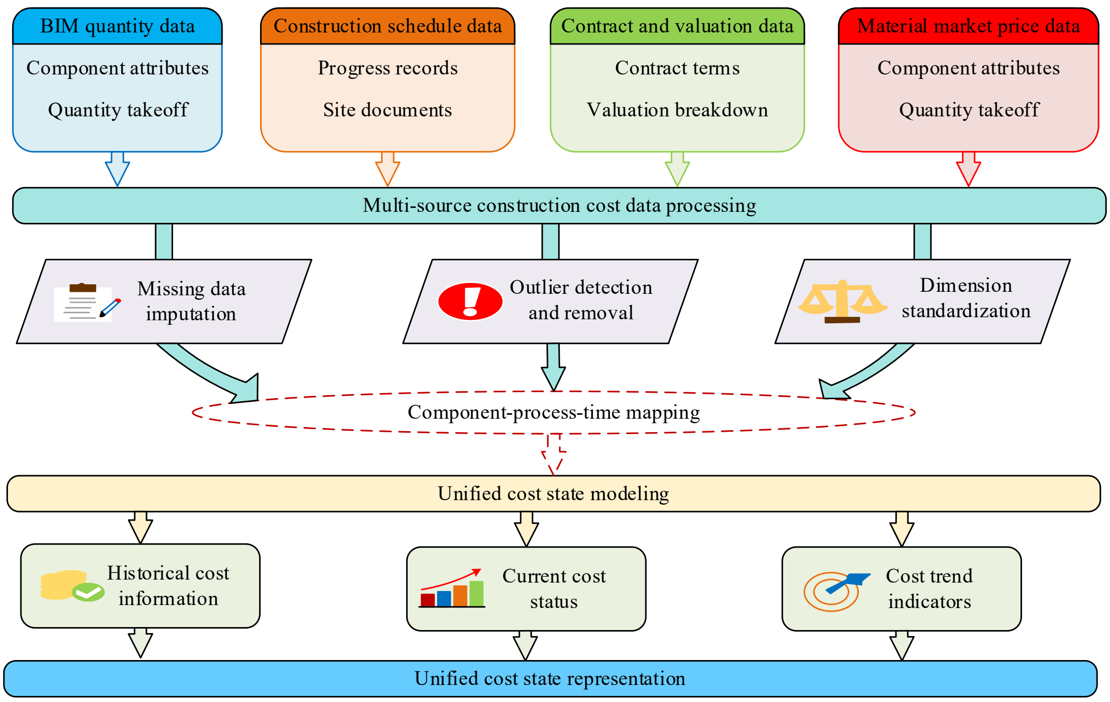



**Fig. 1.** Flowchart of multi-source engineering cost data fusion and unified cost status modeling

In Fig. 1, this study takes the construction cost formation mechanism as the main line and uses multi-source heterogeneous data, such as BIM, construction progress, contract pricing, and material market prices as input. It achieves unified alignment of different data sources in time and space dimensions through the mapping relationship between components, processes, and time. In the data preprocessing stage, the original data are corrected for missing values, outliers are removed, and the data are unified in dimensions. Secondly, the fused cost-related data are mapped to a unified cost state space to form a cost state vector including cumulative cost, cost consumption rate, and cost adjustment items, to achieve a comprehensive representation of the dynamic evolution characteristics of project cost.

### 3.2. DT Model Construction and Dynamic Mapping of Construction Project Cost

Based on completing the fusion of multi-source project cost data and unified cost status modeling, to achieve real-time perception and evolution prediction of project cost during the implementation process, this study further constructs a construction project cost DT model. The unified cost state vector is used as the input of the DT model, and the engineering cost changes in the physical space are mapped to the digital space (He et al., 2024). In the DT environment, the twin state of project cost in digital space can be expressed as Eq. (5).

$$\mathbf{C}^{\mathrm{DT}}(t) = f(\mathbf{C}(t), \Theta) \tag{5}$$

In Eq. (5), $\mathbf{C}^{\mathrm{DT}}(t)$ is the DT state of project cost at time $t$. $f(\cdot)$ is the cost status mapping function. $\Theta$ is the parameter set of the DT model, which describes the cost evolution rules and engineering constraints. To enable dynamic updates to the DT cost model, this study adopts a time-series-based status update mechanism to continuously correct the DT cost status. The update process is shown in Eq. (6).

$$\hat{\mathbf{C}}^{\mathrm{DT}}(t+k) = g(\mathbf{C}^{\mathrm{DT}}(t), k) \tag{6}$$

In Eq. (6), $\hat{\mathbf{C}}^{\mathrm{DT}}(t+k)$ is the prediction result of the project cost status after $k$ time steps in the future. $g(\cdot)$ is the cost prediction function used to describe the trend in cost evolution with construction progress. Through the above modeling process, the construction project cost DT model can enable dynamic mapping and real-time updates between the physical project cost status and the digital cost model, so that the project cost can exhibit a perceptible, predictable evolution in the digital space. The DT model construction logic machine and its dynamic mapping relationship are shown in Fig. 2.

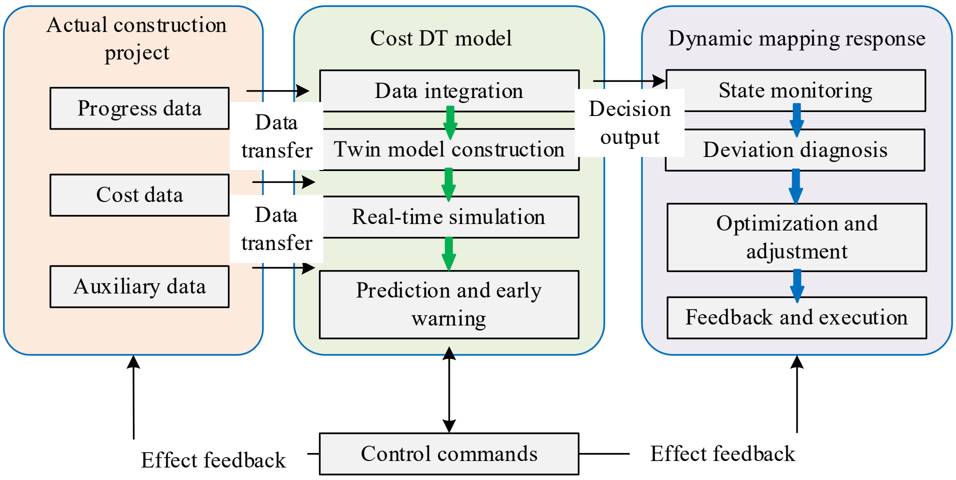



**Fig. 2.** DT model construction and dynamic mapping for building construction co

In Fig. 2, this study takes the unified cost state vector as input and synchronizes the cost information collected in real-time in the physical project to the digital space through the state mapping mechanism to form the DT state of the project cost. During the project implementation process, as the construction progress advances, material prices fluctuate, and change events occur, the physical cost status is continuously updated, and the dynamic evolution of the DT model is driven through the mapping and update mechanism. Based on the current DT cost status, the model further predicts future cost change trends across the project's stages, providing a real-time, updatable basis for identifying cost deviations and enabling dynamic control.

### 3.3. Dynamic Control and Feedback Mechanism of Project Cost based on DT

On the basis of unified cost status modeling and the construction of the project cost DT model, project cost management has further shifted from status perception and evolution prediction to dynamic regulation. This study builds a dynamic control and feedback mechanism for project cost in a DT environment to perform real-time identification, control triggering, and effect feedback on cost deviations. To quantify the degree to which the project cost deviates from the target state, the project cost deviation is defined as Eq. (7) (Riduwan et al., 2023).

$$D(t) = \hat{C}_{\text{acc}}^{\text{DT}}(t) - C_{\text{tar}}(t) \tag{7}$$

In Eq. (7), $D(t)$ is the project cost deviation at time $t$. $\hat{C}_{\text{acc}}^{\text{DT}}(t)$ is the cumulative cost predicted by the DT model. $C_{\text{tar}}(t)$ is the target cost or planned cost of the corresponding stage. Considering that deviation at a single moment is difficult to reflect the evolutionary trend of cost risk, the cost deviation change rate index is introduced, as shown in Eq. (8).

$$R(t) = \frac{D(t) - D(t - \Delta t)}{\Delta t} \tag{8}$$

In Eq. (8), $R(t)$ is the rate of change of cost deviation with time. When $R(t)$ continues to be positive and the value increases, it indicates that the project cost has a tendency to further deviate from the target and requires early intervention and control. Based on the cost deviation amplitude and changing trend, the dynamic cost control triggering discriminant function is constructed as shown in Eq. (9).

$$U(t) = \begin{cases} 1, & |D(t)| > \delta_1, |R(t)| > \delta_2 \\ 0, & \text{otherwise} \end{cases} \tag{9}$$

In Eq. (9), $U(t)$ is the cost control trigger flag. $\delta_1$ is the cost deviation threshold. $\delta_2$ is the cost deviation change rate threshold. When the control triggering conditions are met, the project cost dynamic mechanism will start. After that, control is triggered, and corresponding cost-control measures are implemented to target key cost sources during project implementation. The control strategy focuses on optimizing construction organization, adjusting resource allocation, and revising material procurement strategies (John, 2023; Zhou et al., 2022). When the DT model predicts that the cost will continue to deviate from the target in the future stage, feedforward control of the project cost is carried out by adjusting the construction rhythm, optimizing process connections, and revising the procurement plan. When obvious cost deviations occur, feedback corrections will be made to address them by strengthening cost constraints, compressing non-critical expenditures, or adjusting local plans (Mojumder et al., 2022). The overall operating logic of the DT-based engineering cost dynamic control and feedback mechanism is shown in Fig. 3.

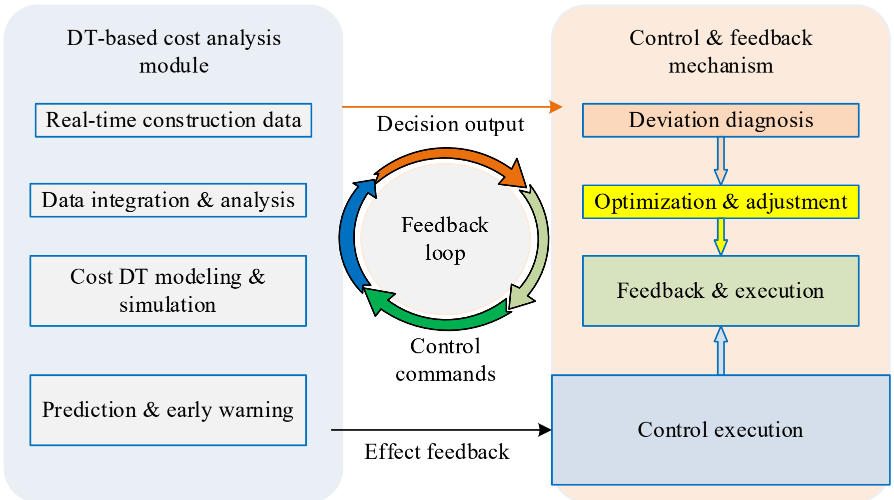



**Fig. 3.** Dynamic control and feedback mechanism for engineering costs based on DT

In Fig. 3, this study uses the project cost DT model as the core to achieve real-time identification and dynamic control of cost deviations by continuously obtaining the current project cost status and its predicted values. When the cost deviation exceeds the preset threshold and shows an expansion trend, the dynamic control mechanism is triggered to generate corresponding control measures for key cost sources during project implementation. After the control measures are implemented at the project site, their actual effects are fed back to the unified cost status model through multi-source engineering data and drive the synchronous update of DT cost status.

## 4. Empirical Research and Result Analysis

### 4.1. Project Cases and Data Sources

To verify the engineering applicability and practical effectiveness of the dynamic cost control method for construction projects based on the fusion of DT and multi-source data, a large construction project is selected as the object of empirical research to carry out case analysis. The research object is a comprehensive construction project. The project content covers multiple sub-projects such as main structure construction, mechanical and electrical installation, and decoration engineering, and the construction period spans a long period. During the project implementation process, BIM is used simultaneously for project quantity management, and the entire process of construction progress, contract pricing, and on-site visa information is recorded through the project management system. In terms of data sources, the project cost-related data used mainly includes four categories: project quantity and component attribute data extracted based on BIM, construction progress and site management data, contract and list pricing data, and material market price data. The basic information and data scale of the project cases are summarized in Table 1.

**Table 1.** Basic information and data scale of the engineering case

| Item | Description |
|---|---|
| Project type | Large-scale building construction project |
| Construction period | Multiple-stage construction over a long duration |
| Major work sections | Structural works, MEP installation, finishing works |
| BIM model content | Building components and quantity information |
| Progress data | Work package progress and site records |
| Cost data | Contract valuation and cost breakdown |
| Price data | Key material market prices |
| Data update frequency | Weekly/event-driven updates |

In terms of data processing, to ensure the reliability and repeatability of the empirical analysis results, this study performs preprocessing on the original data, including timestamp alignment, missing data correction, outlier screening, and dimension unification across different data sources. The processed multi-source data are input into the unified cost status model and the project cost DT model. In addition, the experimental configuration: the hardware platform uses a high-performance workstation with multi-core processors and sufficient memory resources. The software environment includes BIM processing software, engineering project management systems, and data analysis and visualization tools. The operating system is a mainstream 64-bit environment.

### 4.2. Dynamic Prediction of Project Cost and Verification of Status Consistency

To objectively evaluate the effectiveness of the proposed engineering cost DT model in dynamic prediction and state mapping, this study compares two methods: Plan-Based Dynamic Cost Tracking (PB-DCT) and System Dynamics-based Cost Prediction Model (SD-CPM). The dynamic prediction comparison of different cost prediction methods during the project implementation is shown in Fig. 4.

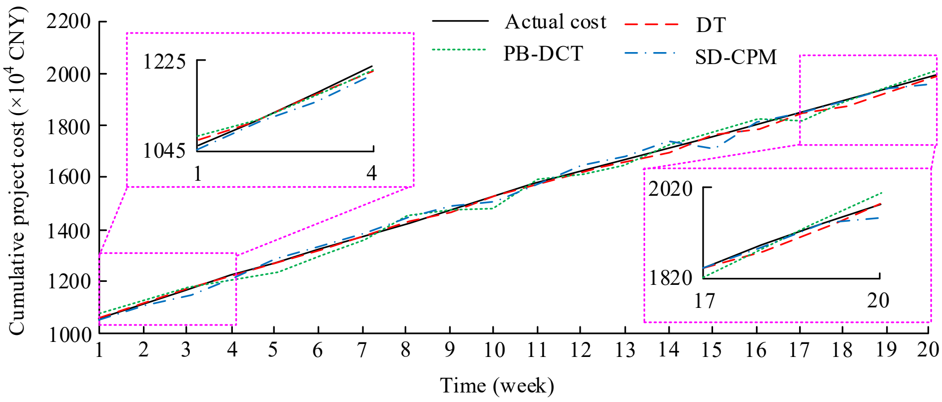
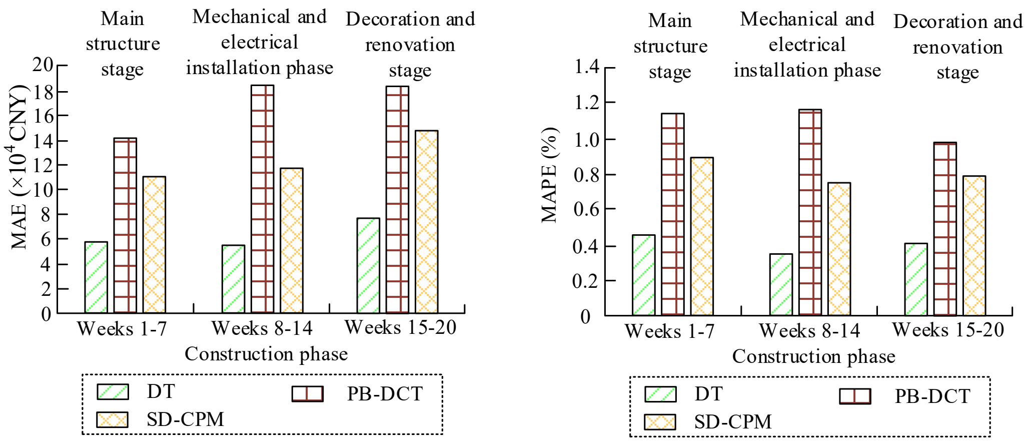



**Fig. 4.** Comparison of dynamic prediction results for project cost

In Fig. 4, by the 20th week, the actual cumulative cost of the project is 19.8287 million yuan, and the relative error of DT prediction is 0.08%, while the relative prediction errors of PB-DCT and SD-CPM are 1.23% and 1.50%. This shows that the DT method can still maintain high prediction accuracy when the cost scale is large in the later stages of the project. Judging from the partial magnification results of the initial stage of the project (weeks 1-4), the actual cumulative cost of the project increases from 10.5248 million yuan to 12.1265 million yuan. The forecast value of DT in the fourth week is 12.0125 million yuan, which is 0.94% less than the actual cost, while the forecast value of SD-CPM is 11.947 million yuan, which is 1.48% less than the actual cost. Although each method has a certain degree of underestimation in the early stages of the project, the overall error level of the DT method is controlled within 1%, showing enhanced adaptability. Combining the prediction results from the mid-term project stage (weeks 5-14) and the late project stage (weeks 17-20), the DT-based dynamic prediction method for project cost maintains high prediction accuracy throughout the entire project cycle. The overall relative error is controlled within 1%, and the error fluctuation range is significantly smaller than that of PB-DCT and SD-CPM. The prediction stability and error distribution characteristics of different methods under different construction stages are shown in Fig. 5.

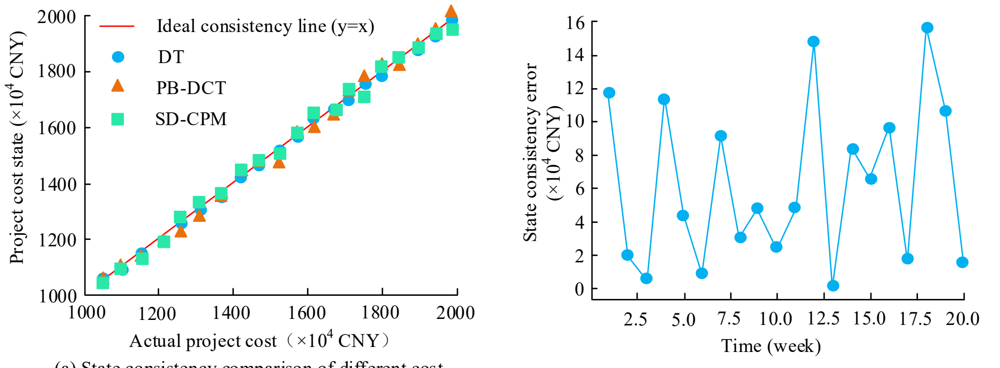
In Fig. 5(a), in the main structure stage (weeks 1-7), the Mean Absolute Error (MAE) of DT is 57,000 yuan, which is 59.97% and 48.93% lower than PB-DCT and SD-CPM. In the electromechanical installation stage (weeks 8-14), the MAE of DT is further reduced to 70.26% and 53.60% lower than those of the two methods. In the decoration and decoration stage (weeks 15-20), DT's MAE is 76,500 yuan, which is still significantly smaller than PB-DCT and SD-CPM. This shows that this research method effectively reduces the MAE of project costs across different construction stages and demonstrates greater stability in stages with complex construction content and diverse cost components. Fig. 5(b) is the Mean Absolute Percentage Error (MAPE) result. The dynamic prediction method of project cost based on DT maintains a low and stable relative error level in each construction stage. On this basis, this study compares the DT cost status with the actual project cost status, as shown in Fig. 6.




(a) Comparison of prediction errors at different construction stages

(b) Trends in prediction errors at different construction stages

**Fig. 5.** Comparison of prediction results of different methods




(a) State consistency comparison of different cost methods

(b) Temporal variation of cost state consistency error

**Fig. 6.** Validation results of digital twin cost state consistency

In Fig. 6(a), the cost status scatter points corresponding to DT are closely distributed near the ideal consistency reference line y=x, and there is no obvious systematic shift, indicating that the DT cost status can more accurately map the physical engineering cost status. Fig. 6(b) analyzes the consistency error between the DT cost status and the actual project cost status from the time dimension. The DT model can continuously track the dynamic changes in the physical engineering cost status. Finally, this study analyzes the evolution characteristics of project cost deviations under two scenarios with/without the introduction of the DT dynamic control mechanism, as shown in Fig. 7.

In Fig. 7(a), without the DT control mechanism, the project cost deviation exhibits large fluctuations during construction. The maximum positive deviation reaches 440,700 yuan (week 10), and the minimum negative deviation reaches -264,300 yuan (week 8). The span of the deviation interval is large, and the positive and negative deviations alternate frequently, indicating that the cost deviation lacks an effective suppression mechanism. After introducing the DT dynamic control mechanism, the overall amplitude of the cost deviation has significantly converged, and the extreme value range of the deviation has been reduced. In Fig. 7(b), the DT dynamic control mechanism can not only reduce the absolute amplitude of the cost deviation but also effectively improve the time stability of the deviation.

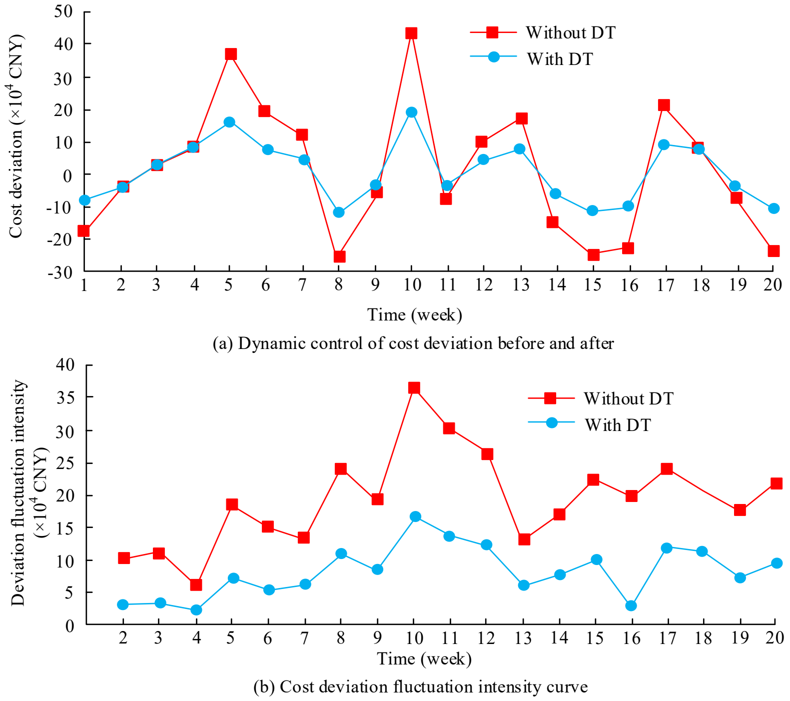



**Fig. 7.** Validation results of dynamic cost control based on DT

### 4.3. Verification of the Dynamic Control Effect of Project Cost based on DT

This study further verifies the effectiveness of the DT dynamic control mechanism from the perspective of risk events, such as the frequency of cost deviation over-limit behavior and its time evolution characteristics. In the two cases of introducing/not introducing the DT dynamic control mechanism, the phased distribution characteristics of project cost overrun behavior and its accumulation process over time are shown in Fig. 8.

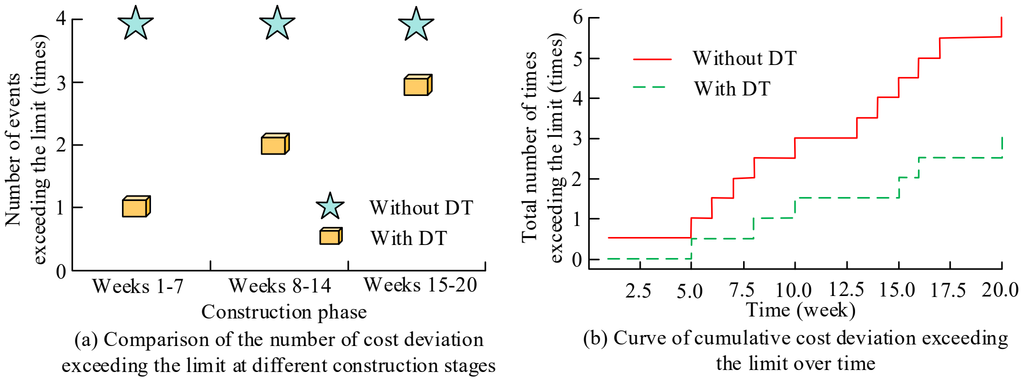
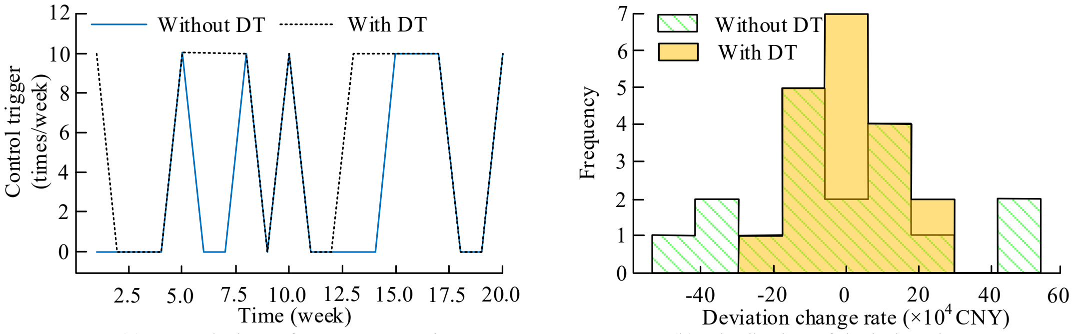



**Fig. 8.** Validation of cost deviation exceedance suppression based on DT

Fig. 8 shows that the dynamic control mechanism of project cost based on DT can not only reduce the number of cost overrun events in a single construction stage, but also effectively inhibit the continuous accumulation of cost deviation risks throughout the entire construction cycle. After introducing the DT dynamic control mechanism, the number of over-limit events in each construction stage is significantly reduced. The number of over-limit events in the main structure stage is reduced from 4 to 1, a decrease of 75.00%. Without the introduction of a DT control mechanism, over-limit events continue to accumulate as construction progresses, and by the end of the construction, the cumulative number of over-limit events reaches 12 times. In contrast, after the introduction of the DT dynamic control mechanism, the cumulative number of overruns is reduced by 50.00%. Therefore, this study further analyzes the performance of the DT-based engineering cost dynamic control mechanism in terms of the smoothness of adjustment and rationality of intervention, as shown in Fig. 9.

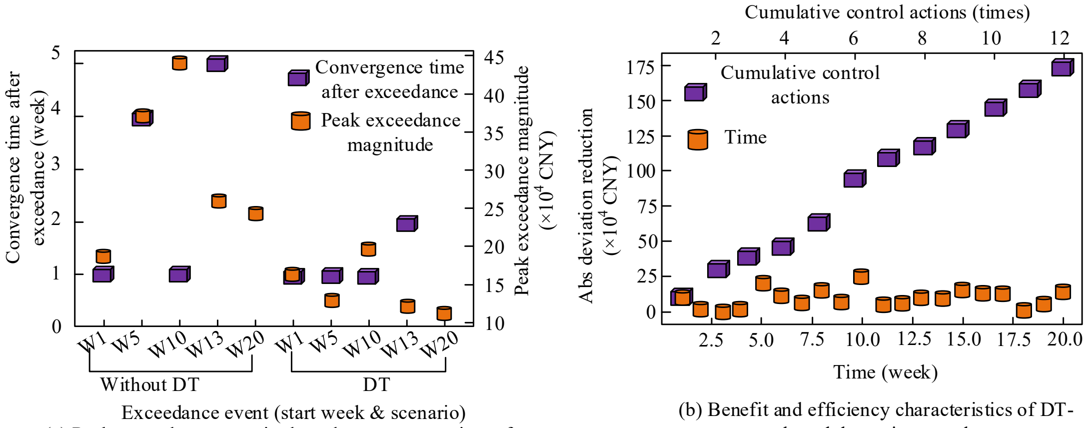



(a) Control trigger frequency over time

(b) Distribution of deviation change rate

**Fig. 9.** Validation of stability and smoothness of DT based dynamic cost control

In Fig. 9(a), when DT is not introduced, the control trigger shows obvious intermittent and sudden characteristics. In some construction cycles, the number of triggers is relatively high, while in adjacent cycles, there are no triggers for a long time, and the overall trigger distribution is uneven. After the introduction of DT, control triggers are distributed more continuously and orderly during the construction cycle, and control actions can be intervened in time when the deviation is still within the controllable range. In Fig. 9(b), the DT-based engineering cost dynamic control mechanism is not only more reasonable in triggering timing but also shows better smoothness and stability during the adjustment process. The performance of DT dynamic control in terms of response efficiency and control gain is shown in Fig. 10.




(a) Peak exceedance magnitude and convergence time of exceedance events

(b) Benefit and efficiency characteristics of DT-based dynamic control

**Fig. 10.** Validation of efficiency and response characteristics of DT based dynamic cost control

In Fig. 10(a), without the introduction of DT, the peak amplitude of project cost overrun events is mainly distributed in the range of 184,700-440,700 yuan, and the corresponding convergence time is generally long, up to 5 weeks. This shows that the recovery process of cost deviation after exceeding the limit is slow, and the adjustment lags behind. The peak amplitude of over-limit events based on the DT control method is significantly reduced, and the overall concentration is between 109,800 and 198,300 yuan. In Fig. 10(b), DT dynamic control can effectively transform control investment into continuous cost improvement. This shows that the dynamic control mechanism of engineering cost based on DT has advantages in reducing the severity of overruns, shortening the deviation recovery period, and improving control revenue efficiency. Finally, this study quantitatively evaluates the proposed method from the full cycle and comprehensive performance levels, as shown in Table 2.

**Table 2.** Comparison of comprehensive performance indicators for dynamic cost control

| Indicator | Without DT | With DT |
|---|---|---|
| MAE (×104 CNY) | 18.92 | 8.73 |
| RMSD (×104 CNY) | 22.61 | 10.84 |
| IAE (×104 CNY·week) | 378.43 | 174.26 |
| Coefficient of variation | 0.61 | 0.42 |
| Comprehensive efficiency index | 0.53 | 1 |

In Table 2, after the introduction of DT dynamic control, the project cost MAE is reduced by 53.85%, and the Root Mean Square Deviation (RMSD) is reduced by 52.07% compared with that without the introduction. This shows that the overall fluctuation in cost control accuracy and deviation has been reduced. The Integral of Absolute Error (IAE) of the proposed method is reduced by 53.96% compared with the method without DT. The proposed method reduces the IAE by 31.15% and increases the comprehensive control efficiency index by 88.68%. These results indicate that the cost deviation evolution process of this research method is more stable, the degree of discreteness is reduced, it performs better in overall control efficiency and resource utilization efficiency, and it has strong engineering application feasibility and promotion value.

## 5. Conclusion

To address the difficulties in continuously perceiving cost status and the lag in deviation response during construction, this study proposes a dynamic cost control method for construction projects integrating DT technology and multi-source data fusion. By establishing a unified cost state vector model, multi-source cost data are consistently represented across temporal and spatial dimensions, and a dynamic mapping and prediction mechanism is constructed within the DT environment. Empirical results demonstrate that the proposed method maintains high prediction stability and deviation control capability across different construction stages, effectively suppressing the fluctuation amplitude and recovery duration of cost deviations. The findings verify the internal consistency between unified state modeling and the DT-based dynamic mapping mechanism, indicating that the improvement in cost control performance stems not only from error optimization but also from a structural transformation from discrete statistical management to continuous process-oriented regulation.

Theoretically, the unified cost state representation and dynamic closed-loop control model proposed in this study extend the application boundary of DT technology in construction cost management, shifting its role from visualization-oriented support to dynamic regulatory control. From a managerial perspective, the study facilitates changes in decision-making processes. Managers can shift from regular post-event accounting to continuous monitoring based on unified cost status, and from experience-based corrective measures to feed-forward intervention based on DT forecasts. Managers can use quantified deviation thresholds and trend indicators to make control decisions more objectively and in a timelier manner, thereby enhancing the initiative and responsiveness of the entire process cost governance.

Although the research method has shown good applicability and control effect in engineering demonstrations, it still has certain limitations. The case analysis is mainly based on a single large-scale construction project and has not yet covered different types of projects or extreme material price fluctuation conditions. In addition, current cost control strategies rely on rules and threshold settings, and adaptive or intelligent optimization mechanisms have not yet been fully introduced. Future work will further verify the universality of the method in multi-project types and multi-region projects and combine machine learning or reinforcement learning methods to conduct self-learning and dynamic optimization of the cost control strategy. The purpose is to further enhance the intelligence level of project cost management and the value of project promotion. The proposed method is constructed based on multi-source data alignment and time-indexed modeling, and its structure does not depend on a specific project type. By adjusting the definitions of engineering units and cost parameters, it can be adapted to different project categories and scales. For example, large-scale projects with abundant data resources are more conducive to fully leveraging the advantages, while small and medium-sized projects can implement the approach by simplifying the state dimensions. However, the method relies to some extent on the level of project digitalization and data completeness. In projects with limited information infrastructure or smaller scale, the balance between implementation cost and expected benefits needs to be carefully evaluated.

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## Institutional Review Board Statement

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## Declaration of Artificial Intelligence (AI) Tools

The author confirms that no AI tools were used in the preparation of this manuscript.

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