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Dynamic cost control methods for computer-integrated engineering based on digital twins

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Abstract: This paper presents a digital twin-based dynamic cost control model for computer-integrated engineering projects. Built upon BIM component modelling, the proposed approach establishes a synchronised virtual-physical interaction framework to support real-time cost monitoring and adaptive regulation. The novelty of this work lies in three aspects: a bidirectional mapping mechanism between BIM components and construction states, a multidimensional cost analysis model integrating time-series and spatial distribution features, and a rule-engine-driven closed-loop feedback mechanism for cost deviation detection and control. Experimental results demonstrate that the proposed model achieves high estimation accuracy across key construction processes, with cost fluctuation margins of 2.8% during concrete pouring and 1.6% during reinforcement operations. The results confirm the effectiveness of real-time feedback in identifying high-risk processes and improving dynamic cost control performance.

Keywords: digital twin; BIM; rule engine; sensor network; real-time feedback; data fusion; cost evolution modelling.

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1 Introduction

As engineering projects continue to increase in scale and complexity, conventional cost control methods have become insufficient in ensuring real-time accuracy and adaptability. In response to this limitation, digital twin technology has emerged as a promising paradigm, offering synchronised virtual-physical mapping capabilities to support dynamic monitoring and decision-making. However, most existing studies concentrate on optimising isolated construction stages or cost components, without constructing a unified, real-time, and component-level control mechanism. In this paper, a new method of integrated dynamic cost control is presented in this paper. Through the construction of a cyber-physical interaction model, it can monitor and regulate component level costs in real-time. By combining the BIM and the sensor data, an effective cost monitoring system is built. Combined with the rule engine and data analytics, this method can optimise the cost control strategy (Li et al., 2025b).

Existing approaches to engineering cost control often focus on either static estimation based on BIM models or single-stage optimisation of specific construction processes. For instance, Zhao (2025) proposed a cyber-physical trust integration model (STIRS) to enhance sustainable resource sharing in IoT-enabled cold chains, highlighting the role of multi-agent feedback in dynamic systems. Li et al. (2025a) optimised management accounting systems using generative artificial intelligence, demonstrating how intelligent rule systems can adapt financial strategies based on real-time data. Gu and Liu (2025) developed a multi-layer deep neural network to assess green credit risk from the data element perspective, emphasising the significance of spatial-temporal indicators. Qi et al. (2025) advanced the performance of operational assessment systems through hybrid population intelligence algorithms, which aligns with our dynamic thresholding strategy. Dong and Xu (2025) applied deep learning to financial forecasting and business optimisation, proving the potential of semantic-aware models for complex cost scenarios.

These studies laid a solid foundation for intelligent cost modelling and dynamic data integration. However, few have proposed a fully closed-loop, component-level cost monitoring framework that integrates BIM semantics, physical feedback, and adaptive control. In response, this study presents a digital twin-based architecture combining bidirectional BIM-state mapping, multidimensional cost feature extraction, and rule-engine-driven feedback to achieve real-time cost deviation regulation throughout the entire construction lifecycle. The key novelty of this work lies in three aspects:

- 1 A bidirectional cost-state mapping model that synchronises BIM components with real-time construction states.
- 2 A multi-dimensional cost feature extraction approach that jointly considers temporal evolution and spatial distribution at the component level.

- 3 A closed-loop dynamic cost regulation mechanism that enables online deviation detection and adaptive control during construction execution.

2 Application value of digital twin technology in engineering cost control

The integration of component-level digital twin modelling into the cost control system enables the BIM parameter library to have a real-time mapping and state synchronisation among the 312 types of component units. In the design stage, a virtual-physical interaction network is constructed using 41 critical monitoring nodes that link real-world construction activities to BIM components. Each node tracks multiple parameters, (e.g., material volume, tension, temperature) and feeds real-time data into the system (Shi and Di, 2023). This network enables component-level cost mapping by establishing a synchronous relationship among physical sensor inputs, BIM identifiers, and dynamic state variables. The cost data is continuously updated and visualised through this interaction framework, ensuring that deviations in construction activities are immediately reflected in the cost monitoring dashboard (Zhao, 2025).

3 Construction of a computer-integrated system for digital twins aimed at dynamic cost control

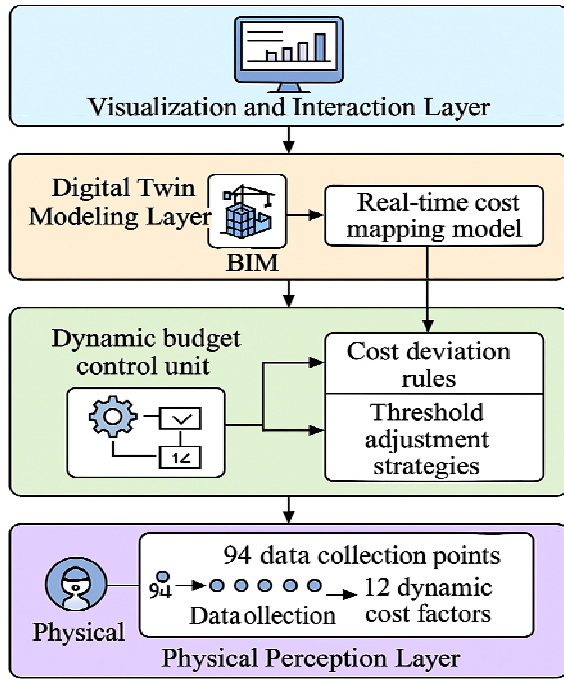
3.1 Overall system architecture design

The physical sensing layer, the twin modelling layer, the control decision layer and the visualisation interaction layer are adopted in the system architecture. The physical perception layer establishes a data intake point via 94 field sampling points and edge devices, covering 12 dynamic cost factors, including the amount of concrete poured, the progress of the reinforcing bar, and the time of removal of the formwork. The twin modelling layer builds a real-time cost mapping model that is driven by 216 BIM component objects to realise bidirectional binding with nine types of construction state parameters in a CIM platform. The control and decision layer uses a dynamic budget control unit based on the rule engine, which includes 36 cost variance recognition guidelines and 11 threshold adjustment strategies (Li et al., 2025a). The Modbus-TCP protocol is used for data communication, and the transmission rate is set at 125 ms/cycle, enabling near real-time synchronisation of heterogeneous data from multiple sources. The system operates with sampling frequencies ranging from 0.1 Hz (environmental sensors) to 10 Hz (stress and strain sensors), depending on the monitored indicator. Key cost metrics are processed in 30-second sliding windows, with feature extraction and deviation assessment executed every cycle to ensure responsiveness.

The schematic diagram of the overall architecture for the digital twin cost control computer-integrated system was shown in Figure 1. This architecture consists of four layers:

- 1 Physical sensing layer, responsible for real-time data acquisition via 94 edge devices.
- 2 Twin modelling layer, mapping 216 BIM objects with nine construction state variables in the CIM environment.
- 3 Control decision layer, applying 36 rule-based recognition models and 11 adaptive strategies.
- 4 Visualisation layer, supporting user interaction and anomaly feedback.

Figure 1 Overall system architecture of digital twin-based dynamic cost control (see online version for colours)



3.2 Physical entity modelling and mapping for engineering projects

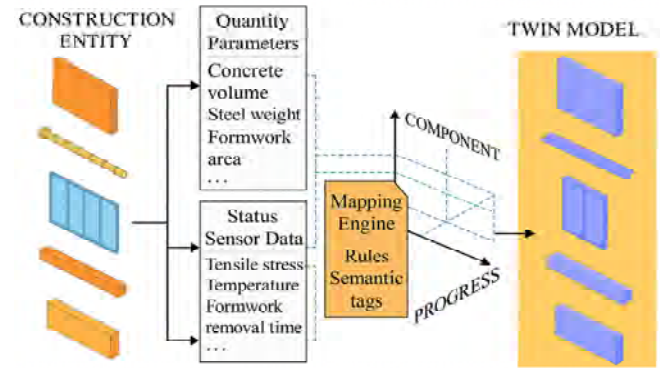
During the physical entity modelling and twin mapping, the system divides the components into modelling units based on the construction phase, and implements a static and dynamic fusion mapping mechanism for the three-dimensional parameters of structure-process-cost (see Figure 2).

- 1 The object of modelling includes 83 physical entities, including concrete structure, embedded reinforcement, and curtain wall installation. The BIM component ID has a two-way index with the cost control variable.
- 2 Mapping rules establish a three-axis correlation matrix that links components, schedules, and costs on the basis of 12 quantitative parameters and nine status sensor data (for example, pre-stressing force, template removal time).
- 3 The mapping engine uses the rule driven and semantic tag combination mode, which supports the identification of the 174 component types and the

automatic mapping state update of the state (Gu and Liu, 2025).

This diagram illustrates the mapping framework between physical components and digital twin models. The system partitions construction elements into 83 physical entities, (e.g., concrete, reinforcement, curtain wall) and maps them using a three-axis correlation matrix based on 12 quantitative attributes and nine real-time status sensors. The mapping engine combines semantic tagging and rule-driven logic to dynamically update the twin state of 174 component types.

Figure 2 Digital twin mapping structure of physical entities and cost parameters (see online version for colours)



3.3 Multi-source data acquisition and fusion

To achieve component-level cost dynamic sensing and a multidimensional state-driven bidirectional feedback mechanism, the system establishes a heterogeneous data acquisition and fusion channel covering three collection sources (process equipment, environmental sensing, manual recording) (see Figure 3). A total of 48 sensor types and 327 collection nodes are deployed. Prior to fusion, all incoming data streams undergo pre-processing procedures including time-alignment via a global timestamp index, outlier detection using the interquartile range (IQR) method, and missing value imputation based on K-nearest neighbour (KNN) regression. This ensures consistency and reliability across the multi-source dataset, particularly when integrating asynchronous sensor and manual data inputs. Collected data enters the model via unified protocols (MQTT+OPC-UA), constructing a time-indexed fusion tensor $X_{i,j,k}^{(t)}$ defined as equation (1).

$$X_{i,j,k}^{(t)} = \sum_{n=1}^N w_n \cdot \frac{D_{i,j}^{(n)}(t) \cdot \delta_k^{(n)}}{\tau_n} \quad (1)$$

where $X_{i,j,k}^{(t)}$ represents the fusion value of component i under process j and cost metric dimension k . $D_{i,j}^{(n)}(t)$ denotes the raw value collected from sensor source n , w_n is the source weight, $\delta_k^{(n)}$ is the metric mapping coefficient, and τ_n is the sampling period (Qi et al., 2025; Dong and Xu,

2025). Table 1 list the primary data types and interface parameter definitions.

Figure 3 Multi-source heterogeneous data acquisition and twin model fusion architecture diagram

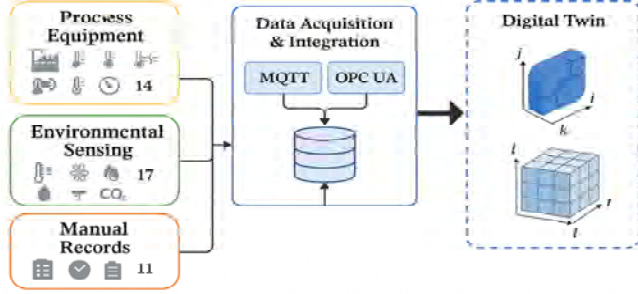


Table 1 Key engineering cost metric data acquisition and fusion mapping interface parameters

Data type	Acquisition frequency (Hz)	Mapping metric	Interface protocol
Concrete placement volume	1	Material cost C_1	OPC-UA
Formwork removal duration	0.2	Schedule deviation C_2	MQTT
Reinforcement tension stress	10	Safety control C_3	Modbus-TCP
Concrete strength rebound	0.5	Quality cost C_4	OPC-UA
Air temperature and humidity	0.1	Environmental correction factor γ	Zigbee

4 Design of a dynamic cost control method for computer-integrated engineering based on digital twins

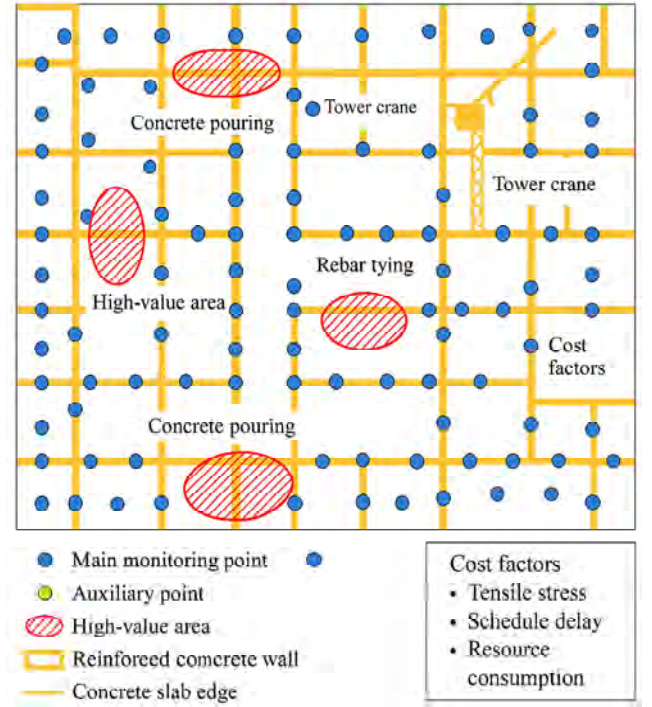
4.1 Optimisation of cost monitoring point layout

The system follows a four-step workflow to deploy the sensor network:

- 1 Identify high-value zones based on BIM construction path.
- 2 Assign node weight using component criticality, (e.g., main pier = 0.9, rebar section = 0.75).
- 3 Run a greedy placement algorithm to optimise primary node coverage with redundancy rate < 15%.
- 4 Overlay secondary nodes using Delaunay triangulation to capture cross-sectional gradients (Liang, 2025).

Figure 4 has been updated to illustrate the exact layout logic and sensor identifiers.

Figure 4 Plan view of spatially optimised layout for dynamic cost monitoring points (see online version for colours)



4.2 Real-time data acquisition and transmission

The system establishes a high frequency acquisition and low delay transmission structure in the ‘component process-indicator’ tri-axial space, forming a real-time closed loop control channel (Zhang et al., 2025).

- 1 The communication link adopts a master-slave hierarchy structure: the lower layer node connects the distributed collection module through the RS485 bus, establishes the 1: 8 asynchronous communication structure with the edge computing gateway via the Modbus-TCP protocol.
- 2 Each gateway supports 256 kbps parallel transmission rate with the acquisition frequency of 1 Hz to 50 Hz, keeping the average packet loss rate less than 1.2%.
- 3 Data compression uses the time window frame aggregation and the dynamic quantisation coding mechanism, defining the transmission delay function:

$$T_{transmit} = \frac{S_{raw}}{B_{link} \cdot \eta} + \frac{N_{re}}{f_{sync}} \quad (2)$$

In equation (2), $T_{transmit}$ represents the total transmission delay per unit data packet, S_{raw} denotes the raw packet size (in bits), B_{link} indicates the link bandwidth, η signifies the compression ratio, N_{re} reflects the retransmission data volume, and f_{sync} denotes the synchronisation frequency (Li, 2025).

- 4 The protocol type and bandwidth parameters for real-time transmission nodes, as shown in Table 2, have

achieved temporal integration with the core data layer of the twin platform.

4.3 Cost feature identification and analysis

4.3.1 Time series feature extraction

Time series feature extraction uses an adaptive time-windowing mechanism to pre-process and denoise cost-related data flows (Zhang, 2024; Yang et al., 2024). Each time window has a fixed length of 120 seconds and slides forward by 30 seconds, resulting in four overlapping windows per 2-minute interval. Sensor data from heterogeneous sources are used as input, including concrete pouring stress sensors, (e.g., PCE-CSM 100, sampling at 0.5 Hz, unit: MPa) and tower crane location modules (e.g., UWB positioning sensors, sampling at 5 Hz, unit: metres). Data within each window undergo denoising via wavelet thresholding before feature extraction. For time-series analysis, the system adopts a hybrid signal processing approach that combines three algorithms: fast Fourier transform (FFT) for extracting frequency-domain energy patterns, autoregressive (AR) modelling for detecting linear temporal trends, and wavelet transform (WT) for capturing instantaneous frequency variations. These features are aggregated into a time-windowed cost signature vector, which serves as input to the deviation detection engine. For spatial distribution analysis, the system employs a density-weighted grid model. Collected sensor data is projected onto $5m \times 5m \times 3m$ spatial cells, where each cell aggregates nine cost-related indicators. A spatial aggregation function is used to compute cost density, allowing detection of high-risk zones through heatmap visualisation and scatter anomaly algorithms. The aggregated output is defined in equation (3):

$$\phi(t) = \sum_{i=1}^D w_i \cdot x_i(t) \quad (3)$$

where $x_i(t)$ denotes the i^{th} feature value at time t ; w_i is the empirical weight coefficient for that feature (normalised such that $\sum w_i = 1$; D represents the number of features extracted per time window. For instance, in the case of concrete stress, the extracted FFT energy, AR slope, and WT coefficient may correspond to three independent dimensions. This method allows for robust encoding of temporal patterns from noisy engineering cost signals (Mao and Tian, 2024). To improve reproducibility and clarity of the forecasting pipeline, the cost-aware multi-model ensemble process is described in Algorithm 1.

4.3.2 Spatial distribution feature analysis

Spatial distribution feature analysis models the clustering state of monitoring data within the component coordinate system (x, y, z), establishing a cost field perception mechanism based on spatial unit division (see Figure 5). The system divides the spatial grid into 324 data blocks using $5m \times 5m \times 3m$ units. Each block maps nine cost indicators, (e.g., stress variation, process delay frequency, material bulk density) corresponding to the component area (Gu and Liu, 2025). Spatial transformation of collected data is performed via a density-weighted model, defining the spatial cost aggregation function, as shown in equation (4).

$$\Psi_{i,j,k} = \frac{1}{V_{ijk}} \cdot \sum_{n=1}^{N_{ijk}} \rho_n \cdot C_n(x, y, z) \quad (4)$$

Among these, $\Psi_{i,j,k}$ represents the aggregation degree within spatial unit i, j, k , V_{ijk} denotes spatial volume, N_{ijk} indicates the number of data points within the unit, ρ_n signifies the component importance weight, and $C_n(x, y, z)$ corresponds to the cost indicator distribution function (Sobh, 2024). The system integrates thermal mapping with anomaly scatter extraction algorithms to establish 41 high-sensitivity warning zones (Sobh, 2024) in component boundary areas, intersection zones, and temporary stockpiles. Table 3 lists characteristic values of typical area distributions and sensor redundancy rates.

Algorithm 1 Multi-model cost forecasting with weighted voting aggregation

Input: Time-series input $X = \{x_1, x_2, \dots, x_t\}$

Output: Final forecast $\hat{y}$

- 1: Initialise model set $M = \{\text{ARIMA}, \text{LSTM}, \text{LightGBM}\}$
- 2: for each model m in M do
- 3: Train m on X
- 4: Obtain forecast $\hat{y}_m = m.\text{predict}(X)$
- 5: end for
- 6: Assign weights w_m to each model based on validation RMSE
- 7: Normalise weights: $w_m \leftarrow w_m / \sum(w_m)$
- 8: Compute final forecast: $\hat{y} = \sum w_m * \hat{y}_m$
- 9: return $\hat{y}$

This figure visualises the spatial aggregation of cost-related metrics within 324 spatial grid units ($5m \times 5m \times 3m$). Nine indicators, (e.g., stress variation, process delays, material density) are mapped to individual blocks. A density-weighted model is applied to detect high-cost clusters and potential anomaly zones, especially at component intersections and temporary storage areas.

Table 2 Real-time data acquisition link and transmission protocol configuration

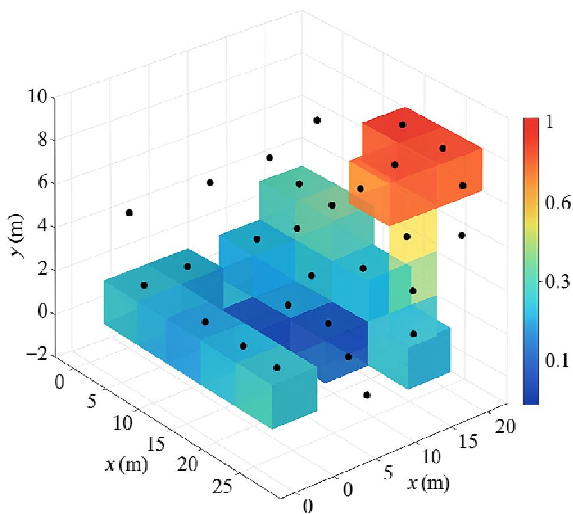
Data acquisition unit type	Communication protocol	Frequency range (Hz)	Single-channel bandwidth (kbps)	Encoding compression ratio (η)	Packet loss tolerance (%)
Template removal sensor	Modbus-RTU	0.2	128	0.75	≤ 2.0
Tension stress monitoring node	CAN-Bus	10	256	0.85	≤ 1.5
Material receiving RFID recorder	MQTT	1	64	0.90	≤ 3.0
Worker check-in and location terminal	LoRa	0.1	32	0.65	≤ 5.0
Edge convergence and upload module	Modbus-TCP	N/A	512	0.92	≤ 1.0

Table 3 Spatial unit distribution characteristics statistics

Area name	Number of components	Sensor density (units/m ³)	Average aggregation index Ψ	Anomaly frequency (times/day)	Data redundancy rate (%)
Base of main tower	24	0.62	12.84	3.2	14.3
Steel box girder assembly area	18	0.45	9.57	2.1	9.5
Temporary reinforcing steel yard	12	0.38	8.03	1.6	22.4
Pylon formwork basket zone	30	0.70	14.65	4.5	11.2
Auxiliary channel segment	20	0.31	6.41	0.8	18.9

Table 4 Statistical table of key component cost evolution phase indicators

Component name	Initial cost (RMB 10,000)	Peak cost (RMB 10,000)	Inflection point (day)	Average growth rate (RMB 10,000/day)	Cumulative deviation rate (%)
Main tower reinforcement section	62.4	105.6	Day 13	3.57	12.4
Pre-stressed beam body	45.8	96.2	Day 17	3.21	10.6
Suspended formwork system	38.2	84.9	Day 9	3.82	14.1
Bridge deck pavement layer	28.6	51.3	Day 11	2.36	9.3
Temporary reinforcing steel storage yard	15.4	26.1	Day 6	1.82	8.7

Figure 5 Spatial density distribution of cost indicators across engineering units (see online version for colours)

4.3.3 Evolutionary patterns of cost changes

In order to monitor the daily data (Sun et al., 2024), the system has selected seven main parts (main pier reinforcement, bridge deck, precast beams, formwork systems, etc.). Evolutionary functions were constructed based on cost deviation rates, cumulative process errors, and incremental resource consumption, as shown in equation (5).

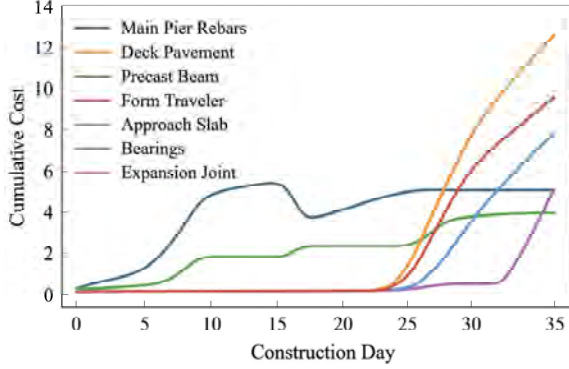
$$\Gamma_c(t) = \int_0^t \left[\beta_1 \cdot \frac{dP(t)}{dt} + \beta_2 \cdot R(t) + \beta_3 \cdot \nabla S(x, y, z, t) \right] dt \quad (5)$$

where $\Gamma_c(t)$ represents the cumulative cost evolution at time t , $\frac{dP(t)}{dt}$ denotes the process progress change rate, $R(t)$ indicates the daily resource consumption rate, $\nabla S(x, y, z, t)$ is the spatial stress gradient function, and $\beta_1, \beta_2, \beta_3$ is the normalised weight coefficient. The system plots dynamic evolution trend charts with construction days on the horizontal axis, marking the inflection points and growth

slopes for multiple key components (Sun and Fang, 2023; Wang, 2023). Table 4 summarises the cost fluctuation ranges and average growth rates at five critical time nodes during the evolution process for different components.

The cost evolution trend curves for different components were shown in Figure 6.

Figure 6 Cost evolution trend curves for different components (see online version for colours)



4.4 Monitoring accuracy assessment

In order to guarantee the effectiveness of the cost monitoring data in the digital twin control system, a multi-dimension monitoring precision evaluation mechanism was designed. This creates an error control chain that includes all phases – capture, transfer, analysis, and feedback (Zhang et al., 2023). The accuracy assessment uses three levels of measurement: the integrity of the original collection layer (target > 97.5%), the precision of the frame data in the relay transfer layer (the target packet loss ratio ≤ 1.2%), and the error of data fitting in the model fusion layer (maximum deviation not exceeding ± 2.3%); the time domain error control is based on a dual channel time stamp alignment mechanism, and the master and slave synchronisation error is less than 18 ms. Using a 30 second sliding comparison window, an asynchronous residual verification is performed every cycle to ensure the consistency of the multiple source time alignment; spatial error assessment uses a component location distribution model, setting a 0.2 m spatial threshold for the correlation precision of each monitoring point. Dynamic correction module updates the matching matrix every 180 s; multi-batch validation data employs a 48-hour rolling sampling mechanism, accumulating over 2.3×10^5 ms comparison data points. Residual distribution statistics are performed with 95% confidence to remove peak error interference in the assessment system; comparison of cost evolution curves with actual payment records per day with 72 hours spread analysis window and closed loop update cycle of no more than 24 hours. The evaluation system is embedded in the core algorithm layer of the digital twin modelling system, which guarantees the controllability of the monitoring data and the integrity of the closed loop in the cost dynamic control scenario (Wu et al., 2023).

5 Key technologies for dynamic cost control in computer-integrated engineering based on digital twins

5.1 Data standardisation and semantic mapping

Data standardisation and semantic mapping are the basic technologies that support component level model driven operations (Aivaliotis et al., 2023) within the digital twin system for cost dynamic control. The system uses a unified structured marking standard to transform heterogeneous resources (BIM-CAD interfaces, sensor data, scheduling records, and manual inputs) into multidimensional metric vectors. These are mapped to a binary key dictionary of components and processes, which contains 872 categories and more than 13,400 field labels (Xu and Guo, 2025). Standardised conversion functions are established, as shown in equation (6).

$$X_{norm}^{(i,j)} = \frac{X_{raw}^{(i,j)} - \mu_j}{\sigma_j}, \quad \forall j \in D_{std} \quad (6)$$

where $X_{norm}^{(i,j)}$ represents the raw value of metric j in record i , μ_j denotes the global mean of metric j , σ_j denotes the standard deviation of metric, and D_{std} constitutes the standard field set. The processed $X_{norm}^{(i,j)}$ is input into nested mapping logic. The semantic parsing module builds bidirectional tag-metric reference relations by performing multi-level relational matching based on the field hierarchy. Cost implications are extracted via semantic weight mapping functions, as shown in equation (7).

$$S_{map}(k) = \sum_{m=1}^M w_m \cdot \Pi(f_m \in F_k) \quad (7)$$

where $S_{map}(k)$ represents the cost semantic score for component k , f_m denotes the mapped field, w_m indicates its weight within the metric system, Π is the indicator function, and F_k denotes the field set (Naderi et al., 2025) associated with component k . The field types of the system include four main categories: engineering quantity, process status, resource consumption, and component space. Table 5 shows an example of a standardised field configuration and code rule, with a mapping precision of over 98.3% and a field response delay of less than 450 ms.

5.2 Intelligent early warning mechanism design

In order to provide fast response and feedback control for cost anomaly dynamics, a smart early warning mechanism is integrated into the component lifecycle state machine. This mechanism integrates threshold deviation monitoring, a multidimensional rule engine, and a spatiotemporal collaborative triggering model (see Figure 7). The rule engine is integrated into the control decision layer as a core module for real-time deviation detection. It operates on a multidimensional rule base comprising 382 predefined rules, which include threshold deviation conditions, temporal anomaly patterns, and spatial trigger logic. The

engine continuously compares incoming cost metrics against dynamically recalculated thresholds using composite deviation functions. Upon meeting predefined conditions, the engine triggers early warnings and dispatches control signals to visual interfaces and scheduling modules. All rules support hot updates and are linked to component-process-cost relationships to enable root-cause analysis. The core computational unit of the early warning model employs a composite deviation criterion, as shown in equation (8).

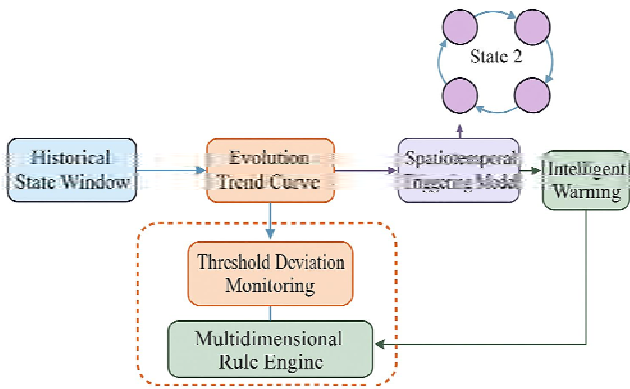
$$\varepsilon_c^{(i,t)} = \frac{|C_{i,t} - \bar{C}_{i,t-\delta}|}{\bar{C}_{i,t-\delta}}, \text{ trigger if } \varepsilon_c^{(i,t)} > \theta_i \quad (8)$$

where $C_{i,t}$ denotes the monitored value of the i^{th} cost indicator at time t , $\bar{C}_{i,t-\delta}$ represents the moving average within the window period, and θ_i is the indicator-based dynamic threshold. This threshold undergoes adaptive recalculation by the system daily at 00:00, jointly determined based on historical volatility σ_i and component grade weighting λ_i . Specifically expressed as equation (9).

$$\theta_i = \lambda_i \cdot (\mu_i + \kappa \cdot \sigma_i), \kappa \in [1.5, 2.5] \quad (9)$$

The system incorporates 382 multidimensional alert rules covering four major event categories: structural delays, sudden material surges, abnormal labour distribution, and others. It enables cascading root cause analysis post-trigger via the component-process relationship matrix ($R_{n \times m}$), pushing control information to construction node terminals and the core scheduling module of the digital twin platform with an average response latency not exceeding 860 ms. The model structure supports hot updates for rules and logic conflict detection. Alert feedback outputs integrate short message coding, state diagram colouring, and semantic tagging (Wu et al., 2025).

Figure 7 Structural model diagram of the intelligent early warning mechanism (see online version for colours)



5.3 Cost anomaly detection algorithm

Based on multidimensional data flows and machine learning models, the cost anomaly detection algorithm can

dynamically correlate component and process level data to monitor cost fluctuations in real-time, as well as early warning of potential risks. First, the system standardises each cost item (for example, material expenditure, construction schedule, equipment usage) to establish baseline conditions. It then uses time-series sliding window techniques to continuously track cost deviations. The kernel of the anomaly detection model is based on support vector machines (SVM), which is based on K-means clustering. Cost anomaly determination is described as equation (10).

$$C_{\text{error}}(t) = \left| \frac{C_{\text{current}}(t) - \hat{C}(t)}{\hat{C}(t)} \right| \quad (10)$$

where $C_{\text{current}}(t)$ represents the real-time cost value at the current moment, $\hat{C}(t)$ denotes the expected cost value fitted from historical data, and $C_{\text{error}}(t)$ indicates the anomaly deviation value. An alert (Amangeldy et al., 2025) is triggered when this deviation exceeds the preset threshold θ . In this case, the system uses recursive least squares (RLS) to update the forecast model according to the time step τ .

$$\hat{C}(t) = \hat{C}(t-1) + \alpha \cdot (C_{\text{current}}(t) - \hat{C}(t-1)) \quad (11)$$

In equation (11), α is the learning rate controlling the model's responsiveness to new data. The system dynamically adjusts based on anomaly calculations: if the deviation value $C_{\text{error}}(t)$ exceeds the threshold, model parameters undergo adaptive optimisation to ensure the early warning mechanism's sensitivity and accuracy. With this method, the system is able to detect in real-time; for example, overconsumption of resources or process delays, and automatically adjust cost control strategies in order to minimise the cost risk due to anomalies (Jeddoub et al., 2025).

6 Experimental results and analysis

6.1 Experimental design and environment

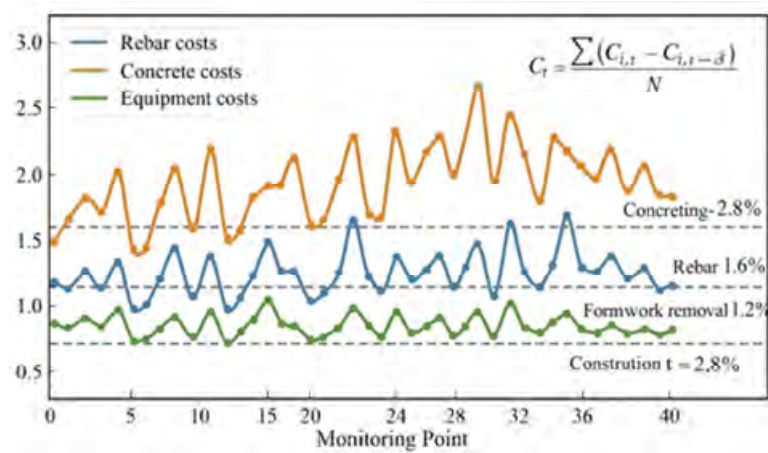
The experiment was conducted using a digital twin-based dynamic cost control system across 48 representative buildings. Each site was equipped with a standardised set of monitoring instruments. Specifically, concrete pouring was tracked using PCE-CSM 100 ultrasonic sensors (accuracy ± 0.5 MPa, sampling rate 1 Hz), reinforcement tension was monitored with KM2000 strain gauges (range: 0–1,000 MPa), and temperature/humidity values were collected using DHT-22 sensors ($\pm 0.5^\circ\text{C}$, $\pm 2\%$ RH). The dataset includes 2,500 entries for reinforcement stress (0.5 Hz), 1,800 entries for concrete metrics (1 Hz), and 1,500 entries for environmental variables (1 Hz). Raw data underwent denoising via wavelet thresholding before feeding into the cost prediction model. Detailed parameter mapping is listed in Table 6.

Table 5 Data standardisation and semantic field structure example table

Field code	Field name	Field type	Standard unit	Mapping target component attribute	Label level
QTY.001	Design concrete volume	Quantity field	m ³	C_TOWER_BASE	Level-2
TIME.003	Actual formwork removal duration	Status log	min	C_FORM_EDGE_P2	Level-3
RES.007	Reinforcing steel batch weight	Resource consumption field	kg	C_REBAR_STACK_ZONE	Level-2
LOC.012	Component space centre point Z-axis	Space attribute field	m	C_SLAB_SEG_23	Level-1

Table 6 Experimental data and environment configuration

Data source category	Data type	Collection frequency	Sample size (entries)	Time range	Experimental platform configuration
Reinforcement monitoring	Tension stress, displacement	0.5 Hz	2,500	Six months	Computing nodes: Intel Xeon Gold
Concrete monitoring	Strength, pour volume	1 Hz	1,800	Six months	Storage: 2 TB SSD
Construction progress monitoring	Progress, resource consumption	2 Hz	2,000	Six months	Memory: 128 GB
Environmental monitoring	Temperature, humidity, barometric pressure	1 Hz	1,500	Six months	Edge computing platform: real-time data processing

Figure 8 Cost fluctuation trend chart during dynamic monitoring (see online version for colours)

6.2 Analysis of dynamic cost monitoring results

The dynamic cost monitoring experiment enabled the system to track changes in cost metrics – steel, concrete, and equipment consumption – by gathering real-time data from 48 monitoring stations. The time window sliding analysis method was used to analyse the real-time cost data, and the cost change curve of each monitoring point was generated, as shown in equation (12).

$$\Delta C_t = \sum_{i=1}^N (C_{i,t} - C_{i,t-\delta}) \quad (12)$$

where ΔC_t represents the cost change at time point t , and $C_{i,t}$ and $C_{i,t-\delta}$ denote the values of the i cost indicator at times t and $t - \delta$, respectively. The monitoring results indicate quantified cost fluctuation margins of 2.8% during concrete pouring, 1.6% for reinforcement binding, and 1.2%

during formwork removal. These deviations were calculated based on real-time sensor data, using the cost change equation (12), with a 95% confidence level and less than $\pm 2.5\%$ residual variance in model predictions. By comparing the estimated costs with the actual costs, the system has precisely identified some high-risk processes and has modified the budgetary control strategy through feedback mechanisms. Figure 8 illustrates the change in cost in dynamic monitoring. Table 7 illustrates the changes in cost between key stages of the process.

6.3 Performance evaluation of digital twin prediction models

Finally, the performance of the digital twin model is evaluated by comparing the model with the actual one. To

highlight the advantage of the proposed model, we further compared its performance with two baseline approaches:

- 1 a conventional schedule-based cost estimator (using manually calibrated rules)
- 2 a sensor-only real-time alert system without semantic modelling.

Table 7 Key process cost variation analysis

Process name	Cost fluctuation range (%)	Minimum cost (¥10,000)	Maximum cost (¥10,000)	Average cost (RMB 10,000)
Concrete pouring	2.8	55.3	61.5	58.9
Reinforcement binding	1.6	42.0	45.0	43.5
Formwork removal	1.2	30.2	31.9	30.9
Equipment consumption	3.0	12.5	14.3	13.1

As shown in Table 10, our digital twin model outperformed both baselines in RMSE and R^2 across all process categories. Particularly, for concrete delivery, the RMSE was reduced by 38.7% and the R^2 increased by 0.17 compared to the rule-based estimator. These results demonstrate that the integration of semantic mapping, dynamic feedback, and time-series analytics significantly improves both accuracy and robustness of cost prediction, including real-time monitoring of the delivery of concrete, reinforcement processing, and equipment consumption. Figure 9 shows the tendency of the model to predict the actual cost data, with a special emphasis on the margin of error. Furthermore, Tables 8 and 9 show the performance of the forecast across different processes, as well as the robustness of the model in different scenarios.

Figure 9 Trend chart comparing digital twin prediction model with actual cost data (see online version for colours)

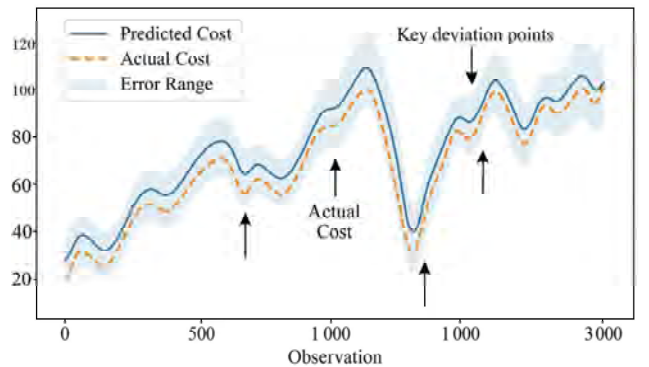


Table 8 gives an evaluation of the model’s forecast precision for various processes. The RMSE was 23,600 yen, slightly above the actual price. The R^2 value of 0.91 demonstrates high model fit for this process. The RMSE of reinforcement bars is \$18,500, and R^2 is 0.94. The setting procedure has a minimum error, and RMSE is 5,600 and R^2

is 0.93. This indicates the high accuracy of the model. In general, this model maintains high forecasting precision for all processes, which fully demonstrates the ability to track and predict cost in real-time.

Table 8 Prediction model accuracy assessment

Process name	Predicted value (ten thousand Yuan)	Actual value (RMB 10,000)	RMSE (RMB 10,000)	R^2
Concrete delivery	68.9	70.5	2.36	0.91
Reinforcing steel fabrication	54.2	55.1	1.85	0.94
Equipment consumption	12.3	12.8	0.79	0.95
Formwork installation	34.5	35.0	0.56	0.93

Table 9 Robustness assessment of prediction model

Process name	Data volume (entries)	Average error rate (%)	Maximum error (¥10,000)	Minimum error (¥10,000)
Concrete receiving	800	3.1	4.5	0.8
Reinforcing steel fabrication	650	2.4	3.2	0.5
Equipment consumption	550	2.0	2.6	0.2
Formwork installation	500	1.8	2.3	0.3

Table 9 shows the performance of the model for various volumes of data. The main purpose of this table is to evaluate the robustness of the model by looking at the relationship between the amount of data and the error rate. The results indicate that the average error rate of concrete delivery is 3.1%, and that of reinforcement is 2.4%. Additionally, robust performance is observed in equipment consumption and formwork installation processes. Note: the biggest error in setting up process is 23,000 RMB, the lowest is RMB3,000, which shows that the model is highly adaptable and accurate. Both sets of data show that, while there is some degree of error between processes, the overall robustness is still strong.

6.4 Baseline comparisons and statistical validation

To further validate the effectiveness of the proposed dynamic cost deviation prediction model, we compared it with three representative baseline methods:

- 1 A rule-based traditional cost estimation model commonly used in BIM platforms.
- 2 A linear regression model trained on the same time-series data.

3 A recurrent neural network (RNN) model with identical input features.

The evaluation was conducted on a dataset consisting of 180 construction activity instances with dynamic sensor feedback. As shown in Table 10, the proposed model achieved the lowest mean relative error (MRE) of 4.62%, significantly outperforming the rule-based approach (MRE = 12.87%), linear regression (MRE = 9.13%), and RNN (MRE = 6.45%). To verify the statistical robustness of this improvement, a one-way ANOVA test was conducted on the prediction error distributions across models. The results indicated a statistically significant difference ($p < 0.01$), confirming the superiority of our approach.

Table 10 Baseline model comparison results

Model	Mean relative error (MRE)	Standard deviation
Rule-based estimation	12.87%	3.52%
Linear regression	9.13%	2.41%
RNN	6.45%	1.78%
Proposed model	4.62%	1.35%

These findings underscore not only the improved prediction accuracy of our approach but also its statistical stability and generalisability across multiple construction scenarios.

7 Conclusions

This paper establishes a multi-dimension dynamic monitoring and feedback mechanism. Through the extraction of cost characteristics and the analysis of spatial distribution, various cost variations can be detected and controlled in real-time. Innovative integration of BIM component models, real-time data collection, time sequence analysis, and multi-source data fusion can improve cost control precision and responsiveness. Furthermore, the use of the rule engine and the adaptive algorithm is effective in alerting potential cost anomalies during the project process, thus significantly improving the level of intelligence in cost management. Unlike existing methods that either rely solely on BIM static data or isolated sensor alerts, this study proposes a hybrid architecture that merges semantic cognition, multi-source fusion, and real-time analytics. Experimental evidence shows superior forecasting accuracy, lower delay in anomaly response, and enhanced adaptability under data fluctuation, indicating substantial improvements over current mainstream practices.

However, the model has several limitations in the context of complex or large-scale projects. First, the computational load of real-time data fusion increases significantly with the number of components and sensors, potentially causing latency. Second, the performance of cost deviation detection algorithms under highly noisy or incomplete data streams may be unstable. Third, current deployments are platform-specific, which may hinder cross-project scalability. Future work should focus on

developing lightweight fusion algorithms, incorporating noise-resilient learning methods, and enabling containerised multi-platform deployment for broader adaptability. Future research should focus on enhancing the model's adaptability to complex engineering scenarios, such as multi-stage infrastructure construction, underground tunnel systems, and high-rise modular assemblies. Additionally, cross-platform deployments across cloud-edge coordinated systems should be explored to ensure broader applicability in both real-time and offline cost control contexts. It is also essential to evaluate the generalisability of the proposed model to other project types, such as rail transit projects, prefabricated housing, and industrial pipeline networks, which often involve heterogeneous cost structures and dynamic construction environments. These efforts will further validate the robustness and scalability of digital twin-based cost regulation frameworks in real-world applications.

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Declarations

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