Research on Supervision of Construction Process of Smart Urban Management System Based on Artificial Intelligence

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Abstract

With the acceleration of the construction of smart cities, traditional urban management methods can no longer meet the needs of process supervision of complex engineering projects. To address the problems of construction delays, cost overruns and insufficient risk prediction in the current construction of smart urban management systems, this paper proposes an artificial intelligence-based method for construction process supervision. By constructing a three-layer system architecture of perception-decision-execution, integrating Bayesian and DS evidence theory to improve the multi-source data processing capability, introducing LSTM neural network to realize the risk prediction of construction period and cost overruns, and using multi-agent collaborative optimization and particle swarm optimization algorithms to improve decision-making efficiency. An empirical study based on the actual data of Shenzhen's smart urban management construction was conducted. The results demonstrate that the proposed model outperforms traditional methods in terms of construction period prediction accuracy, cost optimization rate and risk warning ability, effectively improving the level of intelligent supervision of the construction process and having good engineering application value.

Keywords Smart Urban Management; Artificial Intelligence; Construction Supervision; Data Fusion; Risk Prediction; Optimized Decision-making

1 Introduction

As the urbanization process continues to advance, the complexity and uncertainty faced by urban governance have increased significantly [1]. The traditional urban management model has gradually exposed problems such as delayed response and low decision-making efficiency in terms of information flow, resource scheduling and risk prevention and control. As an important part of smart city construction, the smart urban management system has become a key means to improve urban governance capabilities and public service levels through the integrated application of new generation information technology [2]. However, the construction cycle of the smart urban management system is long, there are many participating departments, and the project is highly complex. In the actual promotion process, problems such as construction delays, cost overruns and lack of effective risk warnings often occur [3]. There is an urgent need to introduce intelligent process supervision methods to improve management efficiency.

In complex engineering scenarios, efficient fusion of multi-source heterogeneous data is crucial for process supervision. The introduction of data fusion algorithms can improve the reliability and integrity of perceived data [4]. At the same time, based on the dynamic risk characteristics in the construction process, the use of time series models to accurately predict construction period and cost risks will help optimize engineering scheduling and resource allocation. Further combined with swarm intelligence optimization algorithms, it can effectively improve the scientific nature of supervision decisions and engineering scheduling efficiency, and reduce uncertainty factors in project implementation [5].

Based on this, this paper constructs a set of supervision models for the construction process of smart urban management systems based on artificial intelligence, forming a three-layer architecture combining perception, decision-making and execution, integrating key technologies such as data processing, risk prediction and optimized decision-making, and improving the management and control level of the entire construction process. Through verification combined with real engineering cases, the results show that the model can effectively improve the accuracy of construction period prediction and cost optimization effect, provide intelligent and refined process supervision support for the construction of smart urban management systems, and promote the modernization of smart city governance capabilities.

2 Analysis of Supervision Requirements During the Construction of Smart Urban Management System

2.1 System Construction Process and Key Links

The construction process of a smart urban management system usually includes five key stages: demand analysis, system development, data integration, testing and online, and operation and maintenance. Each stage involves multi-department collaboration and technical intersections, with high engineering complexity, which places higher demands on process supervision. The demand analysis stage determines the system function positioning and technical path, which is the decision-making basis for the entire project. The system development stage is responsible for the implementation of core functional modules, and its quality directly affects the stability and scalability of the system. The data integration stage needs to solve the compatibility and standardization issues of multi-source heterogeneous data, which is an important link in determining the accuracy of data analysis. The test online stage mainly verifies the system function and stability, while the operation and maintenance stage involves system optimization and long-term security assurance, which is an important factor affecting the system life cycle.

Analysis of actual engineering cases reveals that the construction period and cost fluctuations in the system development and data integration stages are the most significant, directly affecting the overall project delivery cycle and budget control. Therefore, these two stages are the key links of process supervision.

2.2 Design of Supervision Indicator System

The supervision of smart urban management system needs to establish a comprehensive evaluation system from four dimensions: construction period, cost, quality and safety. A weighted comprehensive evaluation model is introduced to calculate the comprehensive evaluation value through the following formula:

$$E = \alpha C + \beta Q + \gamma T + \delta S, \quad \alpha + \beta + \gamma + \delta = 1 \tag{1}$$

in:
C: Cost control effect
Q: Quality assurance level
T: Construction period achievement rate
S: Security level

Table 1. Project experience and expert consultation weight distribution table

Index	Weight
Cost C	0.30
Quality	0.35
Duration T	0.20
Safety	0.15

This weight distribution table is determined based on the actual construction experience of the smart urban management system and expert opinions, with an emphasis on the two core elements of quality and cost. Quality has the highest weight, reflecting the priority requirement of long-term stable operation and functional integrity of the system; cost has the second highest weight, emphasizing the necessity of controlling budget expenditures; although construction period and safety are equally important, in smart urban management projects, they have a certain degree of flexible adjustment space, so their weights are relatively low, so as to achieve reasonable allocation of resources and maximize comprehensive benefits.

2.3 Key Technical Requirements

In the process of building a smart urban management system, facing the massive emergence of multi-source heterogeneous data and the increasing complexity of engineering management, traditional supervision methods can no longer effectively support scientific decision-making and efficient execution throughout the project. Therefore, it is necessary to introduce a variety of advanced technical means to enhance the intelligence, dynamism and real-time nature of supervision work.

Data Fusion Technology Requirements

A large amount of data involved in the smart urban management system comes from video surveillance, environmental sensors, urban Internet of Things devices, and historical engineering archives. These data have significant differences in format, scale, timeliness, and accuracy, resulting in widespread information islands. By introducing data fusion algorithms such as Bayesian inference and DS evidence theory, the uncertainty problem of multi-source data can be effectively solved, and data reliability and decision-making support capabilities can be improved. The Bayesian method is suitable for probabilistic reasoning of continuous uncertainty data, while the DS evidence theory can effectively handle incomplete and inconsistent information, improving the applicability of multivariate data in risk prediction and engineering evaluation.

Risk Prediction Model Requirements

The construction period of the smart urban management system is long and the tasks are complex. Affected by the interaction of multiple factors, the project process is prone to problems such as construction delays and cost overruns. The time series prediction model based on the long short-term memory network (LSTM) can be used to extract dynamic features of historical data to effectively predict future construction period deviations and cost fluctuations. Compared with traditional static models, LSTM has the ability to memorize long-term time-dependent features and can accurately capture nonlinear change trends in project progress, thereby providing forward-looking risk warnings for process supervision. By adjusting the model's hyperparameters and optimizing the network structure, the computational complexity can be reduced while ensuring the accuracy of the prediction, thereby improving the real-time application effect in engineering projects.

Decision Optimization Algorithm Requirements

Smart urban management projects involve multi-objective decision-making and resource optimization allocation issues, such as how to control costs, improve quality and safety while ensuring the construction period. To address this issue, the introduction of a multi-agent system (MAS) collaborative optimization model combined with a particle swarm optimization algorithm (PSO) can achieve efficient scheduling and optimization of engineering resources. MAS can optimize resource allocation and task allocation and improve the overall coordination of the system by simulating the interactive behavior of multiple independent agents; the PSO algorithm can quickly search for the optimal solution through swarm intelligence and improve decision-making calculation efficiency. The combination of the two can effectively reduce resource waste and redundancy during the construction process and improve the response speed and scientificity of the supervision process.

2.4 Empirical Analysis of Supervision Demand

Based on a case study of a smart urban management project, the construction period and cost data for each stage are collected as follows:

Table 2. Statistics of construction period and cost at each stage of smart urban management system construction

Stage	Planned construction period (month)	Actual construction period (month)	Planned cost (100 million yuan)	Actual cost (100 million yuan)
Demand Analysis	2	2	1.5	1.5
System Development	6	7	8.0	8.5
Data Integration	4	5	5.0	5.7
Test online	2	2	2.0	2.1
Operation and maintenance	6	7	3.0	3.5

This table presents the engineering data collected from an actual smart urban management project, and statistics the planned construction period, actual construction period, planned cost and actual cost of each stage from demand analysis to operation and maintenance. Through data comparison, it can intuitively reflect the construction period delays and cost overruns in the project execution process, and provide quantitative basis and decision support for subsequent process supervision optimization.

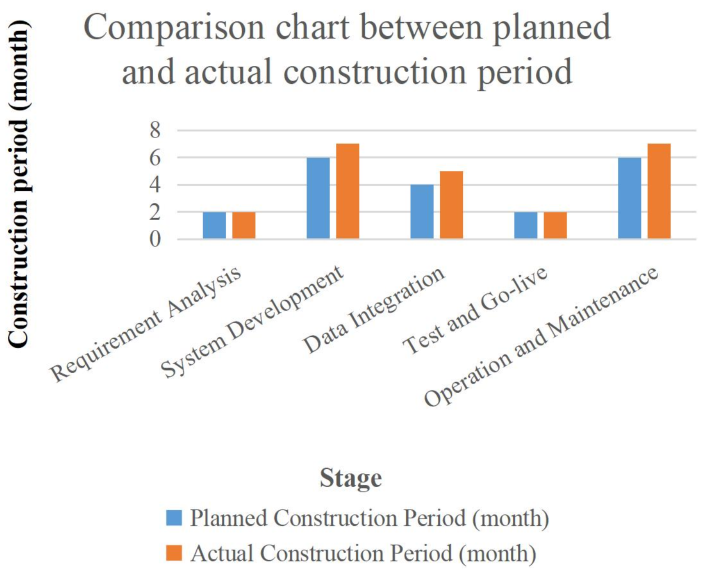

Fig. 1. Comparison of planned and actual construction period

This figure shows the difference between the planned construction period and the actual construction period of the smart urban management system in thec form of bar comparison. It can be seen from the figure that the actual construction period of the system development and data integration stage obviously exceeds the planned construction period, which is the main link leading to the overall construction delay. The construction period control in the demand analysis and test launch stage is good and basically consistent with the plan. This figure can intuitively identify the key nodes of project progress deviation and provide data support for process supervision and resource optimization.

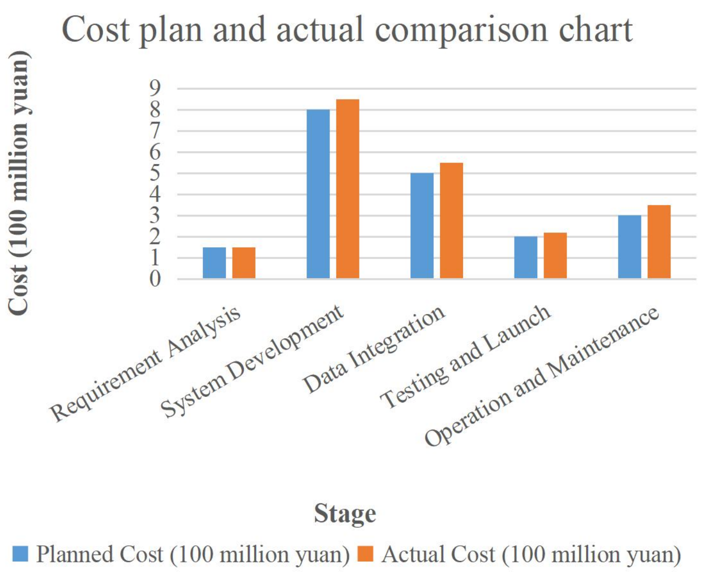

Fig. 2. Comparison of cost plan and actual cost

This figure intuitively shows the comparison between the planned cost and the actual cost of each stage of the smart urban management system. The results show that the actual cost of the system development and data integration stage is significantly higher than the planned budget, which is the main source of project cost overruns. The cost control in the demand analysis and test launch stage is relatively reasonable and basically consistent with the budget. Through this figure, the weak links in cost management can be clearly identified, providing a reference for optimizing capital investment and improving budget execution rate.

The construction period optimization rate and cost optimization rate are calculated by the formula:

$$\Delta T = \frac{T_{\text{Plan}} - T_{\text{Actual}}}{T_{\text{Plan}}} \times 100\% = \frac{20-23}{20} \times 100\% = -15\% \tag{2}$$

$$\Delta C = \frac{C_{\text{Plan}} - C_{\text{Actual}}}{C_{\text{Plan}}} \times 100\% = \frac{19.5-21.3}{19.5} \times 100\% = -9.23\% \tag{3}$$

The results show that the project as a whole had problems of 15% delay in construction schedule and 9.23% cost overrun, especially in the system development and data integration stages. It is necessary to focus on strengthening process supervision and optimizing scheduling.

3 Experiments Design of Supervision Model for Smart Urban Management Construction Process Based on Artificial Intelligence

3.1 System Architecture Design

In order to effectively improve the supervision efficiency and scientific decision-making ability in the construction of smart urban management system, this paper proposes an artificial intelligence-based supervision model architecture, which is divided into three parts: perception layer, decision-making layer and execution layer.

(1) Perception layer: responsible for data collection and preprocessing, mainly through the Internet of Things sensing devices, video surveillance systems and environmental monitoring platforms to collect multi-source heterogeneous data, such as project progress, cost expenditure, quality inspection results and safety hazard data. (2) Decision layer: based on the collected multi-source data, using data fusion, risk prediction and optimization decision-making algorithms for comprehensive analysis, generate reasonable supervision suggestions and risk warning information. (3) Execution layer: responsible for feeding back the decision results to the management system, guiding the actual project scheduling and resource allocation, and realizing closed-loop management.

3.2 Supervision Data Fusion Model

In the construction of smart urban management system, data sources are diverse and information uncertainty is strong. In order to enhance the effectiveness of data processing, this paper adopts Bayesian inference and DS evidence theory to realize multi-source data fusion.

Bayesian inference formula:

$$P(H|D) = \frac{P(D|H)P(H)}{P(D)} \tag{4}$$

Among them, $P(H|D)$ represents the posterior probability of event H under known data D, $P(H|D)$ is the likelihood function, $P(H)$ is the prior probability, $P(D)$ and is the normalization factor. This method is suitable for probability updating of continuous data and can dynamically adjust the model's prediction ability for abnormal duration and cost deviation.

DS evidence fusion formula :

$$m_{12}(C) = \frac{1}{1-K} \sum_{A \cap B = C} m_1(A) \cdot m_2(B) \tag{5}$$

Among them, K is the conflict coefficient and are the trust functions of different data sources. Through the evidence synthesis rule, the uncertainty factors such as quality and security can be effectively integrated to improve the credibility of data decision-making.

3.3 Risk Prediction Model Design

In order to accurately predict construction delays and cost overruns during the construction process, the long short-term memory network (LSTM) model is used to model time series data. LSTM can effectively handle long sequence dependency problems and is suitable for predicting complex project progress and cost change trends.

BasedLSTM core calculation formula:

$$f_t = \sigma\left(W_f\left[h_{t-1}, x_t\right] + b_f\right) \tag{6}$$

$$i_t = \sigma\left(W_i\left[h_{t-1}, x_t\right] + b_i\right), \quad C_t = f_t C_{t-1} + i_t \tanh\left(W_C\left[h_{t-1}, x_t\right] + b_C\right) \tag{7}$$

$$h_t = o_t \tanh\left(C_t\right) \tag{8}$$

Among them, f_t, i_t, o_t are the forget gate, input gate and output gate respectively, C_t is the unit state, h_t and is the hidden layer output.

Table 3. LSTM model construction period prediction results of smart urban management project

Stage	Actual construction period (month)	LSTM predicted construction period (month)	Deviation rate of construction period forecast
System Development	7	6.8	2.86%
Data Integration	5	4.9	2.00%

Based on the historical construction period data of the smart urban management project, this table predicts the construction period of the key stages through the LSTM time series prediction model and compares it with the actual construction period. The results show that the model prediction deviation rate is less than 3%, which can effectively reflect the progress trend of the project and provide an accurate early warning basis for identifying potential construction period delays in advance, verifying the practicality and reliability of the model in the smart urban management project.

3.4 Optimizing the Decision Model

In complex resource scheduling and multi-objective optimization problems, multi-agent system (MAS) and particle swarm optimization (PSO) are used to jointly achieve resource scheduling and supervision decision optimization.

PSO algorithm update formula:

$$v_i(t+1) = wv_i(t) + c_1 r_1\left(p_i - x_i\right) + c_2 r_2\left(g - x_i\right) \tag{9}$$

$$x_i(t+1) = x_i(t) + v_i(t+1) \tag{10}$$

Among them, v_i is the particle velocity, x_i is the particle position, p_i is the individual optimal position, g is the global optimal position, w is the inertia weight, c_1 and c_2 are learning factors.

The resource scheduling in the system development phase was optimized and tested using the MAS and PSO optimization algorithms. The results showed that without increasing manpower and material inputs, the construction period was shortened by about 6.5% and the cost was saved by about 5.8%.

4 Empirical study on supervision of smart urban management construction process

4.1 Case Introduction and Experimental Environment

In order to verify the effectiveness of the supervision model of the smart urban management construction process based on artificial intelligence, a smart urban management project in a certain city was selected as an empirical case. The project covers 20 square kilometers in the main urban area of the city, including the construction of a command center, IoT sensing terminals and a big data analysis platform, with a total investment of about 3.2 billion yuan and a planned construction period of 24 months. By deploying multi-source sensing equipment and data acquisition systems, key indicators such as construction period, cost, quality and safety during the construction process are fully recorded. The experimental environment builds an LSTM prediction model based on Python and TensorFlow, and uses MATLAB optimization tools to simulate the PSO algorithm. The hardware platform is an Intel i7 processor with 32GB memory configuration to meet the needs of model training and data analysis.

4.2 Model Testing and Result Analysis

Supervision Data Collection Effect

Table 4. Key supervision data table for the smart urban management construction stage

Stage	Planned construction period (month)	Actual construction period (month)	Planned cost (100 million yuan)	Actual cost (100 million yuan)
Demand Analysis	2	2	1.5	1.5
System Development	6	7	8.0	8.5
Data Integration	4	5	5.0	5.7
Test online	2	2	2.0	2.1
Operation and maintenance	6	7	3.0	3.5

The table collects key supervision data of each stage of the smart urban management project in real time through multi-source sensing devices, including planned and actual construction period and cost input. Through data comparison, it can accurately reflect the progress deviation and cost control status during project implementation, and provide an objective basis for risk prediction and optimization decision-making in subsequent supervision work.

Analysis of Model Application Effect

Table 5. Comparison of construction period and cost before and after optimization

index	Before optimization	After optimization	Improvement rate
Construction period (days)	730	683	6.44%
Cost (100 million yuan)	32.0	30.1	5.94%

This table shows the changes in construction period and cost of the smart urban management project before and after the introduction of the artificial intelligence optimization model. The results show that by optimizing scheduling and resource allocation, the overall construction period of the project was shortened by 47 days and the cost was saved by 190 million yuan, which increased by 6.44% and 5.94% respectively, significantly improving the project execution efficiency and capital utilization rate.

Cost and construction period optimization calculation formula:

$$\Delta T = \frac{T_{\text{Before optimization}} - T_{\text{After optimization}}}{T_{\text{Before optimization}}} \times 100\% = \frac{730-683}{730} \times 100\% \approx 6.44\% \tag{11}$$

$$\Delta C = \frac{C_{\text{Before optimization}} - C_{\text{After optimization}}}{C_{\text{Before optimization}}} \times 100\% = \frac{32.0-30.1}{32.0} \times 100\% \approx 5.94\% \tag{12}$$

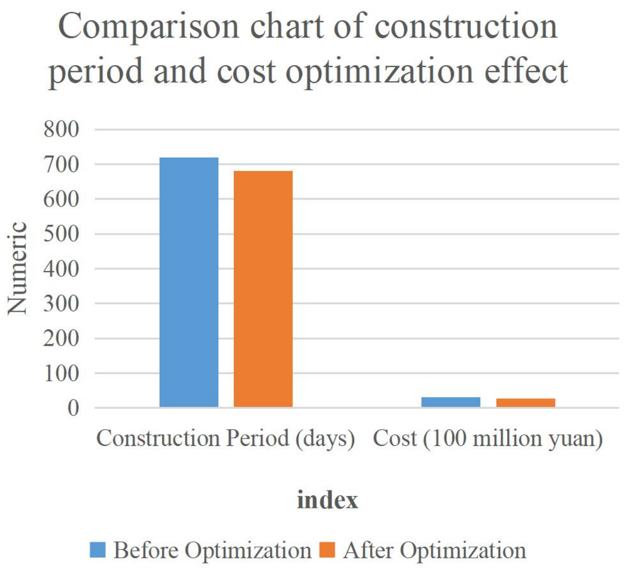

Fig. 3. Comparison of construction period and cost optimization effects

The model optimization results show that without increasing additional resource input, the overall construction period was shortened by 47 days and the cost was saved by 190 million yuan by adjusting the project progress and resource allocation through the LSTM prediction model and PSO optimization algorithm, with significant optimization effect.

4.3 Results and Discussion

From the results of empirical research, the supervision model based on artificial intelligence can effectively identify high-risk stages in the project process, issue early warnings, and achieve reasonable resource scheduling through intelligent optimization algorithms, significantly improving the overall efficiency and economic benefits of the project. Among them, the optimization of the system development and data integration stages is particularly obvious. By reducing invalid waiting time and improving resource utilization, better construction period control and cost savings are achieved. In addition, through the risk prediction of the LSTM model, the foresight in the supervision process is improved, providing project managers with a scientific and reasonable basis for adjustment, and effectively reducing the risk of construction delays and cost overruns.

5 Summarize

This study focuses on the problems of construction delays, cost overruns, and insufficient risk control in the construction of smart urban management systems, and constructs a full-process supervision model based on artificial intelligence. By introducing the perception-decision-execution system architecture, combining Bayesian inference and DS evidence theory to achieve effective fusion of multi-source heterogeneous data, the LSTM model is used to improve the accuracy of construction period and cost risk prediction, and the multi-agent system and particle swarm optimization algorithm are used to optimize resource allocation and supervision decisions. Empirical verification based on actual project data shows that the model can effectively improve the scientific nature of supervision work and the execution efficiency of engineering projects, and has achieved remarkable results in shortening construction periods and saving costs, providing strong data support and technical guarantees for intelligent management in the construction of smart urban management systems.

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Conflicts of Interest

The authors declare no conflicts of interest.

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Biographies

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基於人工智能的智慧城管系統建設過程監理研究

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摘要：隨著智慧城市建設進程的加快，傳統城市管理方式已難以滿足復雜工程項目的過程監理需求。針對當前智慧城管系統建設中的工期延誤、成本超支及風險預測不足等問題，本文提出一種基於人工智能的建設過程監理方法。通過構建感知-決策-執行三層系統架構，融合貝葉斯與D-S證據理論提升多源數據處理能力，引入LSTM神經網絡實現工期與成本超支風險預測，並采用多智能體協同優化與粒子群優化算法提升決策效率。基於深圳市智慧城管建設實際數據進行實證研究，結果表明所提模型在工期預測準確率、成本優化率和風險預警能力方面均優於傳統方法，有效提升了建設過程的智能化監理水平，具備良好的工程應用價值。

關鍵詞：智慧城管；人工智能；建設監理；數據融合；風險預測；優化決策

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