Design and Implementation of Construction Project Cost Decision Support System Driven by Artificial Intelligence

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Abstract: The traditional decision-making method of construction project cost depends on manual experience and static data model, which has some problems such as inefficient data utilization, lagging dynamic response and weak risk prediction. This study constructs a dynamic cost decision support system (DSS) based on artificial intelligence, aiming at solving the above problems and promoting the digital transformation of the construction industry to data-driven and intelligent decision-making. The system adopts hierarchical architecture, including data layer, algorithm layer, application layer and interaction layer, and realizes the whole process from multi-source data perception to intelligent decision-making suggestion. The data layer is responsible for the collection, fusion and governance of multimodal data, and is deeply integrated with BIM model. The algorithm layer includes dynamic cost prediction, risk identification and early warning, multi-objective optimization decision-making and other modules, and uses deep learning, transfer learning, reinforcement learning and other technologies to model and optimize. The application layer provides real-time cost kanban, risk early warning center, intelligent scheme optimizer and other functional modules to provide decision support for different users. The interactive layer presents the system results with a visual and interactive interface to ensure the effective transmission of decision suggestions. The case verification shows that the system can significantly improve the accuracy of cost prediction, realize early detection and early warning of risks, generate quantitative and feasible optimization schemes, and effectively assist managers to make scientific decisions. This study provides a new theoretical framework and practical tools for the intersection of AI and engineering management, and has broad application prospects.

1. Introduction

As a key part of project management, construction project cost decision-making affects project investment benefit and resource utilization efficiency [1]. Traditional cost decision-making relies on manual experience and static data model, which has the problems of inefficient data utilization, lagging dynamic response and weak risk prediction. In recent years, the development of artificial intelligence (AI) technology has provided new solutions to these problems. Nevertheless, the current research mostly focuses on the application of single technology, lacking the systematic integration of the whole chain of "data-model-decision" and not fully considering the complex constraints in construction engineering [2-3]. In this study, an AI-driven dynamic cost decision support system (DSS) is constructed, and the transformation from "passive estimation" to "active optimization" is realized by integrating multi-modal data and intelligent algorithms. On the theoretical level, break through the traditional static assumption and establish a dynamic model of cost-risk-resource coupling to fill the theoretical gap in the overlapping field of AI and project management; On the practical level, it provides real-time cost monitoring and risk early warning for the owners, helps the builders to optimize resource allocation, reduce waste, and promotes the digital transformation of the construction industry to data-driven and intelligent decision-making.

2. System design framework

The AI-driven construction project cost DSS adopts a hierarchical structure of "data-driven, model-empowered and decision-oriented", which opens up the whole process from multi-source

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data perception to intelligent decision-making suggestions [4-5]. The overall design framework of the system is divided into four core layers: data layer, algorithm layer, application layer and interaction layer (Figure 1).

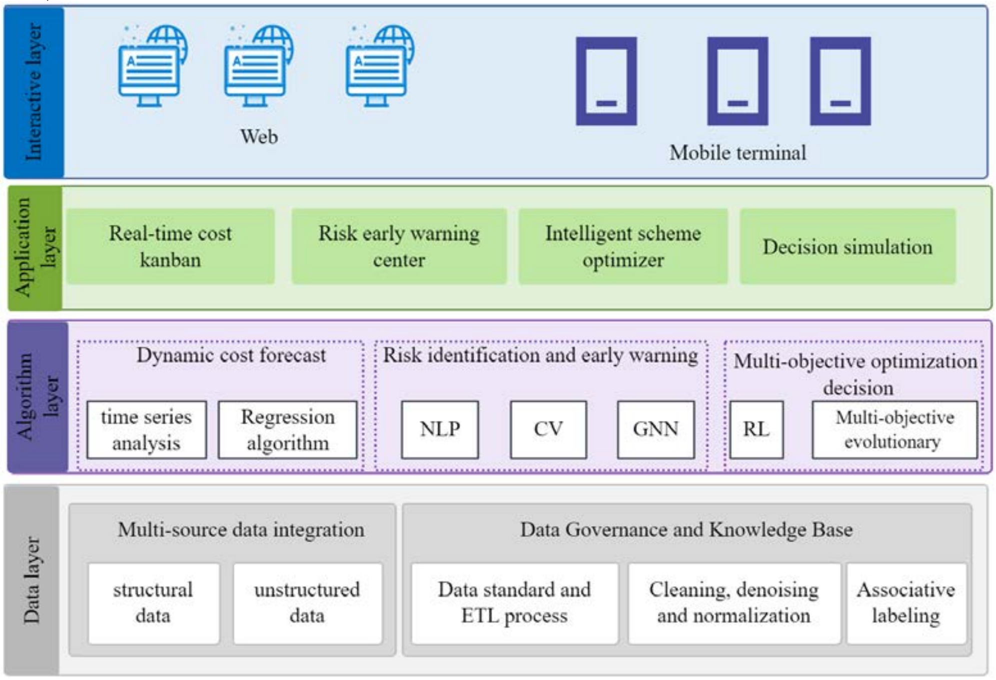

Figure 1 Overall framework of AI-driven construction project cost DSS

2.1 Data layer

The data layer is the cornerstone of the whole system, which is responsible for the collection, fusion and management of multi-modal and full-cycle data. The system accesses and integrates structured data and unstructured data [6]. Special attention is paid to the deep integration with BIM model, and the geometric information and attribute information of components are automatically extracted, which provides a high-precision basis for cost calculation. Establish a unified data standard and ETL (extraction, transformation and loading) process, and clean, denoise, normalize and correlate the original data to form a high-quality training data set. Finally, a continuously updated "historical project cost knowledge base" is constructed as a benchmark for model training and comparative analysis.

2.2 Algorithm layer

The algorithm layer is the intelligent engine of the system, which encapsulates the core AI model and decision algorithm, and is responsible for mining rules from data, forecasting and optimizing. Among them, the dynamic cost prediction module is based on time series analysis and regression algorithm, and integrates real-time dynamic data such as material price, labor rate and construction schedule to realize rolling prediction and correction of cost and overcome the lag of traditional static estimation. The risk identification and early warning module uses natural language processing (NLP) technology to analyze engineering texts and identify risk descriptions. Computer vision (CV) technology is used to analyze the site images and automatically identify potential risk points such as construction deviation and potential safety hazards [7-8]. The graph neural network (GNN) is used to evaluate the risk probability and its potential impact on the cost. The multi-objective optimization decision-making module establishes a multi-objective coupling optimization model of cost-time limit-resources-quality-risk. Using reinforcement learning, multi-objective evolutionary algorithm, etc., under the premise of satisfying various complex engineering constraints, Pareto optimal solution set is automatically generated, which provides decision makers with a variety of feasible combinations of resource allocation and construction schemes [9].

2.3 Application layer

The application layer transforms the intelligent output of the algorithm layer into specific functional modules for different user roles. Real-time cost kanban provides owners and project managers with dynamic dashboards of total project cost and partial project cost, and visually displays budget implementation, deviation warning and future trend prediction. The risk early warning center displays all kinds of risk events identified by the system, including risk type, location, level, possible cost overrun and suggested countermeasures, so as to realize active intervention. The intelligent scheme optimizer provides an interactive interface for users. Users can input specific constraints, the system calls the optimization module for calculation, and visually outputs the recommended scheme and its detailed cost-benefit evaluation report. Decision simulation allows users to make a "What-If" simulation deduction of the recommended scheme, evaluate the impact of different external changes on the final cost of the project, and improve the robustness of decision-making.

2.4 Interactive layer

As the portal of the system, the interactive layer provides users with a visual and interactive operation interface in the form of Web or mobile applications. Through charts, three-dimensional BIM model linkage and early warning push, the complex analysis results are presented to users in an intuitive and easy-to-understand form to ensure the effective transmission and adoption of decision-making suggestions.

All levels of the system call data and instructions through the standardized API interface, forming a closed-loop decision support ecology: the application layer receives the user's needs and triggers the algorithm layer to calculate, and the algorithm layer calls the high-quality data of the data layer, and finally returns the intelligent decision support results to the application layer and the interaction layer to present to the users.

3. Key technology realization

3.1Multimodal data fusion and BIM integration technology

Develop a special BIM data parser (based on IFC standard) to automatically extract information such as the number and type of components, and map them with the items in the cost list. Using OCR and NLP technology to extract key information from scanned documents and texts. Construct a unified "project data map" to associate entities, attributes and relationships, and provide rich semantic information for subsequent analysis.

3.2 Dynamic cost forecasting model based on deep learning

Space-time GNN (STGNN) with attention mechanism. Each cost impact factor is regarded as a time series node, and the correlation diagram between nodes is constructed (based on engineering logic). The model can capture the dynamic change of time dimension and the spatial dependence between factors at the same time, thus achieving more accurate cost prediction than traditional ARIMA and single LSTM [10].

3.3 Risk identification based on transfer learning and small sample learning

Aiming at the problems of few risk samples and difficult labeling in construction projects, the transfer learning strategy is adopted. Pre-training CV model in a large general image data set, and then fine-tuning it with a relatively small number of marked engineering site images, so that it can quickly adapt to specific tasks such as crack detection and personnel wear identification. Similarly, NLP models such as BERT, which are pre-trained on large corpora, are used to understand the risk semantics in engineering texts, and high-accuracy text risk classification and extraction are realized.

3.4 Multi-objective optimization algorithm considering complex constraints

An improved multi-objective reinforcement learning (MORL) algorithm is adopted. The engineering project is modeled as a sequential decision-making process. The actions of agents are to allocate resources and adjust working procedures, and the reward function integrates multiple objectives such as cost, time limit, quality and safety. Through algorithm search, a set of non-dominant solutions, that is, a series of "optimal" trade-off schemes, are output. The key breakthrough lies in embedding complex engineering constraints into the algorithm in the form of hard constraints or penalty functions to ensure the feasibility of the generated scheme.

3.5 System development and engineering landing

Micro-service architecture is adopted to develop the system, and each core function module is deployed independently, and communication is carried out through RESTful API to ensure the scalability and maintainability of the system. The back-end is developed in languages such as Python (Pytorch/Tensor Flow, SciKit-Learn) and Java/Scala(Apache Spark for Big Data Processing). The front end uses the framework of React/Vue to build a visual interface. The database adopts the mixed storage mode of relational database and time series database to process structured data and time series data efficiently. Finally, Docker containerized deployment ensures the stable operation of the system in different environments.

4. Case verification and effect analysis

A super-high-rise residential building project in a city (with a total construction area of 150,000 ㎡) was selected as a pilot project for landing application for six months. The project is connected to this system in the main structure construction stage. The system accesses the BIM model of the project, historical procurement data, real-time material price API, weekly progress report and on-site security monitoring video stream. The system automatically fuses the latest data on a weekly basis to forecast the total project cost. The risk early warning system analyzes the engineering logs and site images in real time, and identifies two main risks: "the construction progress of the core tube is lagging behind" and "the price of steel bars continues to rise in the near future". In view of the risk of "schedule lag", the project management entered the constraint condition of "shortening the construction period by 15 days, but controlling the upper limit of cost overrun within 2%". The system calls the multi-objective optimization module to generate three sets of alternative schemes.

Comparing the system output results with the traditional methods, the key results are as follows: Table 1. The error rate between the final cost of system dynamic prediction and the actual settlement cost is significantly lower than that of traditional static estimation.

Table 1 Comparison of cost forecasting errors

Cost forecasting method	Forecast final cost (ten thousand yuan)	Actual settlement cost (ten thousand yuan)	Absolute error rate
Traditional static estimation	125,500	127,800	1.80%
System dynamic prediction in this paper	127,200	127,800	0.47%

The system issued an early warning at the initial stage of steel bar price fluctuation, and accurately predicted its potential impact on the total cost (about 1.5% overrun), which enabled the purchasing department to purchase orders in advance and successfully avoided the cost overrun of 1.05 million yuan caused by price increase. At the same time, through the automatic analysis of on-site images, the system found the abnormal displacement of formwork support in a certain working face 7 days earlier than manual inspection, successfully warned a potential safety and quality accident and avoided rework losses. The management finally adopted the scheme B recommended by the system. Through fine resource reallocation (allocating workers on non-critical paths to core tube construction), the project shortens the construction period by 12 days (reaching 80% of the original target), while only increasing the cost by 0.8%, far below the upper bound of 2%, thus achieving a good balance between cost and construction period. Figure 2 shows the balance relationship of the three schemes in cost, construction period, resource intensity and quality and safety risks, and scheme B is in the most balanced position.

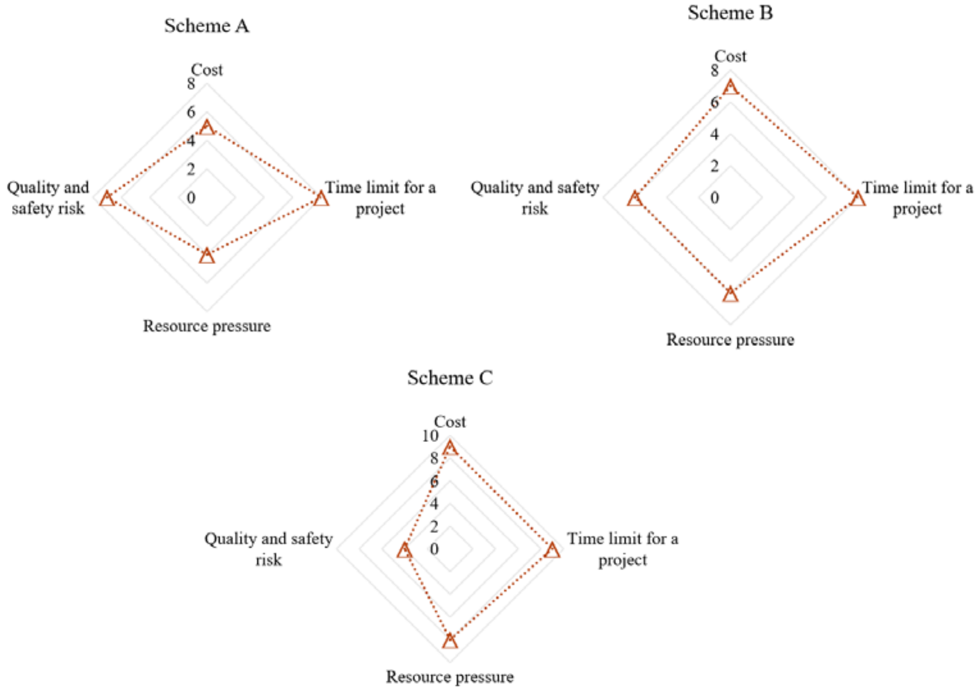

Figure 2 Comparison of radar images of the effects of various optimization schemes

Case verification shows that this system has successfully changed the cost management from "passive and static" to "active and dynamic". It not only significantly improves the accuracy of cost forecasting, realizes early detection and early warning of risks, but also generates quantitative and feasible optimization schemes based on complex constraints, effectively assisting managers to make scientific decisions, which proves its theoretical value and great practical application potential.

5. Conclusion

In this study, a construction project cost DSS based on AI is successfully constructed, and the transformation from "passive estimation" to "active optimization" is realized by integrating multi-modal data and intelligent algorithms. On the theoretical level, the system broke through the traditional static assumption and established a dynamic model of cost-risk-resource coupling, which filled the theoretical gap in the cross field of AI and project management. In practice, the system provides real-time cost monitoring and risk early warning for the owners, helps the builders to optimize resource allocation and reduce waste, and promotes the digital transformation of the construction industry to data-driven and intelligent decision-making. This study not only made an important breakthrough in theory, but also showed great potential in practical application. The system provides strong support for the decision-making of construction project cost, helps to improve the efficiency and effect of project management, and promotes the intelligent development of construction industry.

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