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Research on Intelligent Cost Estimation of Engineering Foundation Projects Based on CSIs Theory

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Abstract: Against the backdrop of rapid development in China's construction and infrastructure sectors, discrepancies between project budgets and actual costs have become pronounced, manifesting in project overruns and suspensions, posing significant challenges. To address inaccuracies in investment targets and operational complexities, this study focuses on a beam-bridge construction project in a district of Shijiazhuang city as a case study. Drawing upon historical analogs, the project employs a Work Breakdown Structure (WBS) to decompose the engineering works. Building on theories of Cost Significant (CS) and Whole Life Costing (WLC), the study constructs Cost Significant Items (CSIs) and develops a CNN-BiLSTM-Attention neural network for nonlinear prediction. By identifying significant cost drivers in engineering projects, this paper presents a streamlined cost estimation method that significantly reduces computational burdens, simplifies data collection processes, and optimizes data analysis and forecasting, thereby enhancing prediction accuracy. Finally, validation with real-world cost fluctuation data demonstrates minor errors, meeting predictive requirements across project execution phases.

Keywords: Project management; Cost Significant Items (CSIs); Engineering costing; Intelligent estimation

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1. Research background

The entire lifecycle of engineering projects typically includes conceptual (preparation), development (construction), maintenance (updates), and termination (dismantling) phases. During this period, the Net Present Value (NPV) method aptly captures the cost scenarios across these phases, facilitating the derivation of sub-project life costs and Cost Significant Items (CSIs). CSIs, derived from the "80-20 rule," extract projects that constitute the top 20% of unit costs and contribute to 80% of the total cost, thereby reducing computational complexity and eliminating irrelevant factors. Subsequently, using a specific project cycle as an example, project components are extracted for cost analysis, focusing on core research elements and employing neural networks for cost prediction, which is crucial for analyzing the overall lifecycle costs of projects.

In related research, Duan *et al.* explored a comprehensive cost prediction method integrating CSIs, Fuzzy Inference System (FIS), and WLC, providing a model that combines multiple cost factors for forecasting [1]. Liu *et al.* studied environmental cost estimation methods for green high-speed rail construction, enhancing cost prediction accuracy through CS and Backpropagation Neural Network (BPNN) methods [2]. Duan and Xu further investigated a road engineering valuation model based on Self Organizing Map-Radial Basis Function (SOM-RBF) neural networks, demonstrating the advantages of neural networks in handling nonlinear cost data [3]. Wang *et al.* focused on a dynamic optimization control system for highway construction progress, proposing an integrated approach to project management and cost control [4]. Zhou *et al.* showcased the application of the Complete Ensemble Empirical Mode Decomposition with Adaptive Noise-Squeeze-and-Excitation-Convolutional Neural Network-Bidirectional Long Short-Term Memory (CEEMDAN-SE-CNN-BiLSTM) model in soybean futures price forecasting, offering insights into forecasting complex datasets, albeit with limited direct relevance to construction projects [5]. Zhou validated the effectiveness of quantum bee colony algorithms in Building Information Modeling (BIM) cost management [6]. Liu and Huang and Peng *et al.* demonstrated the benefits of hybrid predictive models, such as Particle Swarm Optimization-Backpropagation Neural Network (PSO-BP) and Salp Swarm Algorithm-Least Squares Support Vector Machine (SSA-LSSVM), which excel in handling complex datasets and improving prediction accuracy [7,8]. Similarly, Li and Ma successfully merged AutoRegressive Integrated Moving Average (ARIMA) with exponential smoothing techniques to speed up and refine cost prediction in construction projects [9]. Yong *et al.* explored the synergy of biogeography-based optimization with backpropagation neural networks, optimizing investment estimation for university construction projects [10]. Fan *et al.* and Liu *et al.* further pushed the boundaries by employing ensemble models that combine various algorithms, significantly improving the predictive performance in non-linear cost data scenarios [11,12]. Lastly, earlier works by Chen *et al.* and Zhang leveraged machine learning and genetic algorithms respectively, to enhance the precision and applicability of cost prediction models across different engineering projects [13, 14]. Guo *et al.* investigated the impact of foundational material projects in construction engineering on the overall project cost through urban renewal big data platforms [15].

2. Model building

2.1. Case study: extraction of CSIs

This case study focuses on the construction of a city viaduct (beam-bridge) on the northern Second Ring Road of Shijiazhuang. The total investment of this project is 264.1 million yuan, with a span of 229.7 m and 8 lanes in both directions. It includes 17 sets of bridge piers (abutments) and is a typical prestressed concrete-supported box girder structure. Based on the list of major engineering material requirements throughout its lifecycle (see **Table 2.1**) and the distribution of engineering cost CSIs (see Table **2.2**), this study extracts prefabricated component reinforcement bars as the research subject, specifically Φ25HRB400 grade steel (formerly known as grade III screw steel).

Table 2.1. List of main engineering material requirements for the whole life cycle of a bridge

ID	Lifecycle stage	Primary material(s)	Secondary material(s)	Additional equipment/tools	Remarks
I1	Design stage	Prestressed concrete beams	Test blocks, reinforcement	Model test materials	
I2	Construction stage (base, pier, superstructure)	Concrete, gravel, sand	Reinforcement, anticorrosive coating	Pile foundation machinery, molds	Waterproofing in base materials
I3	Construction stage (road surface, safety facilities)	Asphalt, safety barriers	Gravel, traffic signs	Roller, installation tools	Line marking for road surface
I4	Maintenance stage (routine and major repairs)	Inspection equipment, replacement parts	Concrete patches, bearings	Repair materials, joints	Includes anticorrosive coating
I5	Demolition/remodeling stage	Demolition machinery	Concrete, reinforcement	Cutting, recycling processing equipment	

Table 2.2. Total cost and distribution of CSIs for the beam-bridge project

Method	Total sub-projects	CSIs content	CSIs cost percentage (%)	CSIs project percentage (%)	Total cost (billion RMB/KM)
Initial cost sub-projects	13	(1) Bridge Pier Foundation Construction (2) Bridge Abutment Construction (3) Production and Installation of Prestressed Concrete Beams	82.38	19.85	1.16
WLC sub-projects	19	(1) Bridge Pier Foundation Construction (2) Bridge Abutment Construction (3) Production and Installation of Prestressed Concrete Beams (4) Reinforced Concrete Bridge Deck Construction (5) Bridge Routine Maintenance and Upkeep	86.31	17.92	1.28
Sub-Projects' WLC	26	(1) Bridge Pier Foundation Construction (2) Bridge Abutment Construction (3) Production and Installation of Prestressed Concrete Beams (4) Bridge Routine Maintenance and Upkeep	84.57	18.64	1.28

2.2. Constructing a WLCS-based database

(1) Determining discount rate: This study focuses on the quantity lists of completed highway construction projects and maintenance costs during operational phases as its research objects. Parameters necessary for cost calculation, such as discount rates, were sourced from industry websites like China Highway Network and Road Construction Cost Network. The method for determining discount rates varies widely. This study adopts a widely accepted academic approach, combining a risk-free rate of return and risk premium. The risk-free rate of return excludes risk factors from capital costs. The selection of the risk-free rate can refer to information on fixed-rate national bond yields published by "China Bond Information Network." Based on the collected research project periods, an average national bond rate of 2.47% over the entire period is selected as the risk-free rate. The risk premium is estimated using the Capital Asset Pricing Model, based on selected publicly listed highway companies in China and Hong Kong, resulting in a rate of 3.67%. The discount rate is thus the sum of these two values, 6.96%, which for convenience can be approximated as 7% for calculations.

(2) Sample selection: The urban highway viaducts primarily include foundations, piers, concrete beams,

and other components. Following international and domestic case studies, this research selects 17 similar projects to build a database, using four newly completed projects as validation samples to assess model prediction accuracy.

(3) Determining CSIs: For the sample projects, Cost Significant Items (CSIs) are calculated to determine the average per kilometer unit cost for each segment of the viaduct. Subsequently, the WLCS unit prices for each segment of the highway are compiled and compared against the average unit cost of 69 for segmental items. Segments with costs exceeding the average are identified as significant projects.

2.3. CNN-BiLSTM-Attention neural network

In handling time-series data, Convolutional Neural Networks (CNNs) demonstrate significant capabilities in feature extraction. However, CNNs have limitations in capturing long-term dependencies within time-series data. In contrast, Bidirectional Long Short-Term Memory networks (BiLSTMs) effectively address the issue of long-term dependency in time-series data. By employing forward and backward memory units, BiLSTMs capture dynamic dependencies of past and future information. By combining these networks, the CNN-BiLSTM model integrates CNN's advantages in spatial feature extraction with BiLSTM's strengths in time-series prediction, thereby significantly enhancing prediction accuracy.

However, when facing scenarios with numerous features and large datasets, the CNN-BiLSTM model may overlook critical feature information at certain key moments, thereby affecting overall learning and prediction capabilities. Introducing an Attention mechanism significantly improves upon this limitation. By assigning different weights to data from various time points, the Attention layer highlights features in the time-series that have the most significant impact on prediction results, further optimizing the model's performance and prediction accuracy. The structure of the CNN-BiLSTM-Attention neural network model is illustrated in **Figure 2.1**.

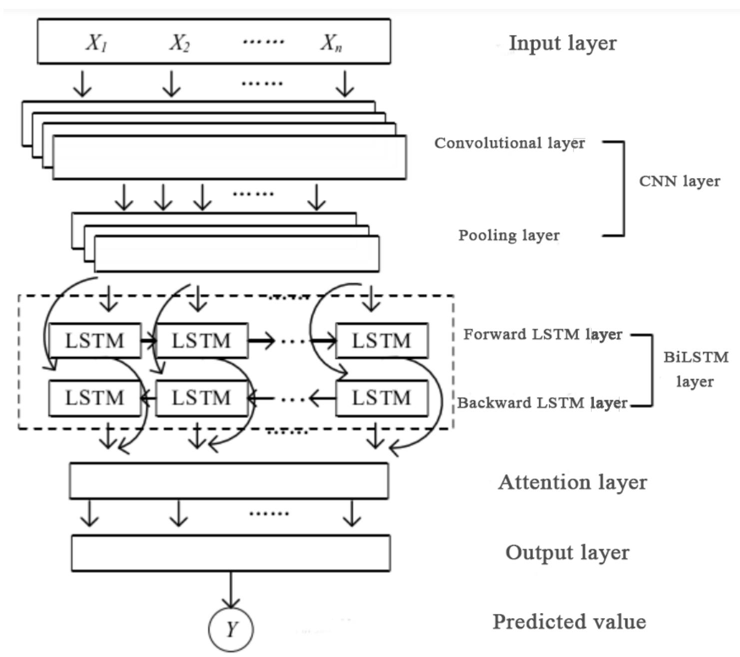


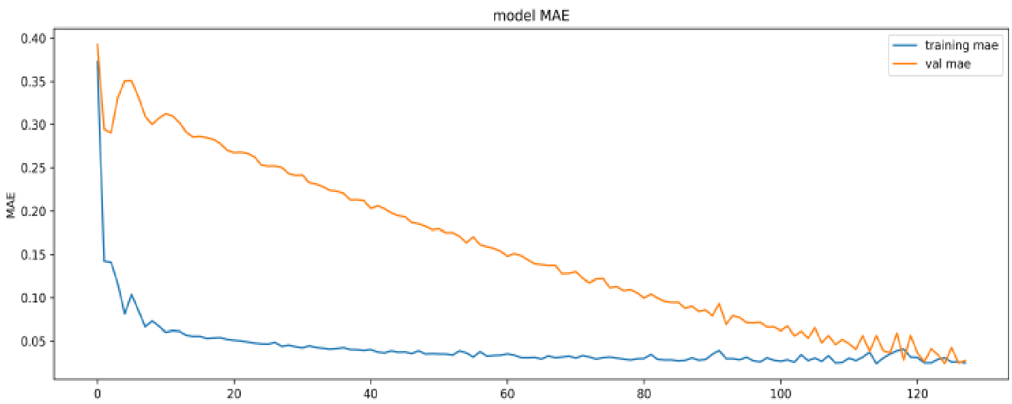
Figure 2.1. Structure of the CNN-BiLSTM-Attention neural network model

3. Model application

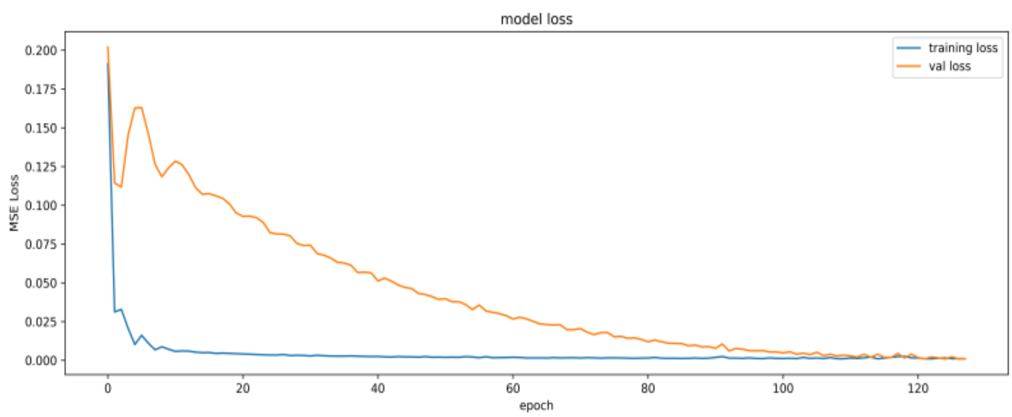
3.1. Unit price forecast

Following the extraction of prefabricated component reinforcement bar data, this study expanded its predictions by incorporating historical market prices, exchange rates, international iron prices, domestic oil and coal prices, regional GDP, and fixed investment in transportation. Daily data from 2012 to 2023 was utilized, with the model undergoing 150 iterations. The training and validation data were split in an 8:2 ratio. The training process, loss function, and prediction outcomes are depicted in **Figure 3.1**. Similarly, this approach was applied to estimate the costs of other foundational projects within the construction, enabling the derivation of stage-specific costs and overall lifecycle costs based on the CSIs principle, thereby achieving intelligent estimation.

(a) Neural network training process



(b) Model loss function



(c) Comparison of predicted and actual values

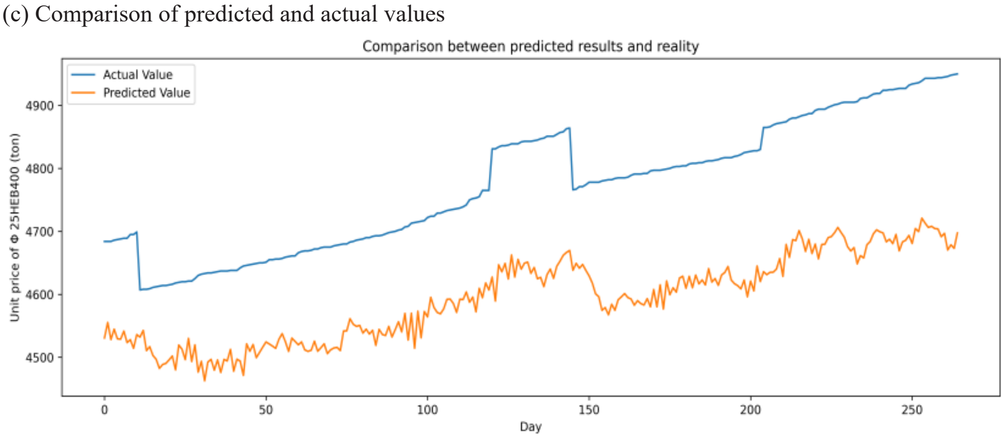


Figure 3.1. Effectiveness of Φ25HRB400 unit price prediction model

According to the unit price prediction results of Φ25HRB400, the average price error is 50 yuan (RMB), with a maximum error of 78 yuan and a minimum error of 20 yuan. The error rate is 1.1%, which meets the requirements of high-precision measurement of engineering cost in the new era and can be applied in practical engineering.

3.2. Engineering cost estimation

In the study, by referring to historical similar engineering cases and the actual design and construction of this project, the WBS-WLC-CSIs method was used to extract significant projects (including bridge pier foundation construction, bridge pier construction, production and installation of prestressed concrete beams, bridge deck laying, etc.) and conduct key material cost and demand analysis. Furthermore, based on the cost prediction of key materials (such as predicting the unit price of Φ25HRB400 and calculating demand), the proportion of significant costs, and the proportion of cost in different stages of the entire life cycle of the project, accurate and intelligent prediction of the entire life cycle cost of the project can be achieved.

In practical applications, taking the # 15, # 16, and # 17 pier (abutment) sections as an example: the span of this area is 30.5 m, and the predicted cost of each pier (including pile foundation, support system, etc.) is 3.2913 million yuan, 3.4928 million yuan, and 3.3135 million yuan, respectively. The actual cost is 3.3298 million yuan, 3.5027 million yuan, and 3.3469 million yuan, with an average prediction error of 0.77%. Within this range, the predicted cost per square meter of the bridge deck is 38,200 yuan (including prestressed box girders, bridge deck paving, drainage and waterproofing, expansion joints, asphalt, and railings, etc.). The actual cost per square meter is 38,900 yuan, with a prediction error of 0.18%. The total cost within this range is predicted to be 3.485 billion yuan, with an actual total cost of 3.497 billion yuan and a prediction error of 1.12%. The predicted total life cycle cost is 3.602 billion yuan, and the prediction error of the executed part is 1.96%.

In summary, by calculating the total cost of each sub-project (unit price multiplied by demand), and then adding up the costs of all sub-projects, the significant project cost is obtained, and the estimated total cost of the entire project is obtained. These predicted results are very close to the actual costs, with an error that meets the high-precision cost estimation requirements of engineering (< 3%), which can help project managers more effectively control costs and budget execution, and improve project management efficiency and engineering cost accuracy.

4. Conclusion

This study successfully achieved intelligent estimation of project foundational costs by integrating CSI theory with advanced neural network technology. Focused on a viaduct construction example in a specific area of Shijiazhuang, the integration of historical data and relevant economic indicators proved beneficial for accurately predicting project costs. This validation underscores the practical application value of intelligent estimation methods in construction projects. With ongoing technological advancements and richer data resources, intelligent estimation methods based on the CSIs theory hold promise for broader application, revolutionizing engineering project management by enhancing cost accuracy and efficiency. This advancement is poised to significantly propel sustainable development and innovation within the construction and infrastructure sectors.

Disclosure statement

The authors declare no conflict of interest.

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