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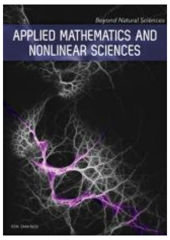

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Dynamic Cost Estimation and Optimization Strategy in Engineering Cost Combining Reinforcement Learning

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Abstract

Accurate cost estimation and optimization are crucial in engineering project management, as budget overruns and resource misallocations often lead to financial and operational inefficiencies. Traditional cost estimation methods, including regression models and heuristic approaches, struggle to adapt to the complex and dynamic nature of engineering projects. We proposes a reinforcement learning (RL)-based dynamic cost estimation and optimization strategy that continuously refines cost predictions and budget allocations. The proposed framework integrates a deep learning-based cost estimation model with an RL-driven optimization strategy, enabling adaptive learning from historical and ongoing project data. A multi-objective optimization framework is incorporated to balance cost, project quality, and timeline constraints using Pareto-front analysis. The RL agent learns optimal cost allocation policies through iterative interactions with the environment, improving decision-making efficiency. Experimental evaluations demonstrate that the RL-based model outperforms conventional machine learning approaches, achieving lower mean absolute error and root mean square error in cost estimation. Additionally, the RL-driven optimization strategy results in an average cost reduction of approximately 7% across different project categories. The integration of multi-objective reinforcement learning further enhances cost efficiency while maintaining project feasibility. These findings validate the proposed approach as an effective solution for improving cost estimation accuracy and optimization in engineering project management.

Keywords: Cost Estimation; Engineering Cost; Reinforcement Learning; Optimization Strategy
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1 Introduction

The evolution of data-driven methods and artificial intelligence (AI) has revolutionized engineering cost assessment. When faced with complicated and ever-changing project circumstances, traditional cost prediction methods—which mostly depend on statistical models, expert opinion, and historical data—often fall short. The use of sophisticated computer methods that can learn from historical project data and enhance estimate accuracy is becoming more important for accurate cost estimation in increasingly complex engineering projects. The capacity of reinforcement learning (RL), a subfield of machine learning, to maximize sequential decision-making in contexts characterized by uncertainty has led to its rising profile [1]. By leveraging RL-based optimization strategies, engineering cost estimation can transition from static, rule-based models to dynamic frameworks that continuously refine estimation parameters based on accumulated experience [2]. Unlike conventional statistical approaches, RL does not require predefined assumptions about cost relationships; instead, it learns optimal cost estimation policies through iterative interactions with project data [3]. Various AI-driven approaches, including deep learning and evolutionary computation, have been applied to cost estimation problems, but they often struggle to generalize across different project types [4]. By contrast, RL techniques, such as policy gradient methods and value-based learning, offer a more adaptive framework for optimizing cost estimates based on complex, multi-dimensional project constraints [5]. Moreover, RL-based cost estimation frameworks can incorporate probabilistic modeling to address uncertainties in construction costs, ensuring more robust and reliable estimations [6].

There have been some improvements to AI-based cost estimate, but current systems still have a ways to go. In situations when the historical data is either missing or very variable, traditional regression models and machine learning approaches like neural networks and support vector machines struggle to perform well [7]. In addition, traditional models have difficulty effectively balancing conflicting aspects such as project scope, risk management, and budget limits when estimating engineering project costs [8]. Although deep learning-based estimating approaches may capture non-linear correlations in cost data, they are frequently not easy to understand or use in engineering decision-making since they are black-box models [9]. Additionally, many existing optimization techniques, including genetic algorithms and metaheuristic methods, require extensive fine-tuning and do not inherently support dynamic learning from new project environments [10]. Another challenge lies in balancing short-term cost efficiency with long-term project sustainability, a factor that many static estimation models fail to address adequately [11]. RL, while promising, has yet to be widely adopted in engineering cost estimation due to issues such as the high computational cost of training complex models, the difficulty of defining appropriate reward functions, and the challenge of integrating domain-specific knowledge into the learning process [12]. Moreover, existing RL applications in cost estimation have often focused on narrow use cases, lacking a generalized framework that can be applied across diverse engineering domains [13]. Addressing these shortcomings requires an approach that can effectively combine RL with domain expertise and structured cost modeling, ensuring both accuracy and practical feasibility in cost estimation.

To address these limitations, this study proposes an RL-based cost estimation and optimization strategy that improves estimation accuracy while ensuring adaptability across different project scenarios. Unlike traditional methods, our approach leverages deep reinforcement learning (DRL) to refine cost predictions iteratively, enabling a self-improving framework that learns optimal cost estimation policies from past project data. Additionally, our model incorporates multi-objective reinforcement learning (MORL) to optimize trade-offs between cost, quality, and resource allocation, ensuring a more balanced approach to project cost management. By integrating probabilistic cost modeling with reinforcement learning, the proposed method accounts for inherent uncertainties in construction projects, improving cost estimate reliability. Furthermore, knowledge transfer techniques are employed to enhance model efficiency, allowing previously trained models to be fine-tuned for new engineering projects with minimal retraining effort. These innovations collectively enhance cost estimation accuracy while addressing the shortcomings of existing AI-based approaches. Through extensive experimental validation, we demonstrate that the proposed RL-based cost estimation and optimization framework significantly outperforms conventional methods.

2 Related Work

The integration of artificial intelligence (AI) and machine learning (ML) in engineering cost estimation has been widely explored in recent years, with reinforcement learning (RL), deep learning, and hybrid optimization approaches emerging as promising solutions. Traditional cost estimation methods, such as regression models, statistical approaches, and heuristic techniques, often struggle to adapt to complex, high-dimensional project environments, making them less effective in modern engineering applications. As a result, researchers have turned to AI-driven approaches to enhance prediction accuracy and optimize cost estimation strategies. Reinforcement learning, in particular, has demonstrated strong potential in dynamic decision-making and cost optimization. Literature [14] provide a comprehensive foundation for RL, detailing key algorithms such as Q-learning, deep Q-networks (DQN), and policy gradient methods, which have been leveraged in engineering optimization tasks. These RL techniques allow models to iteratively learn optimal cost estimation policies through trial-and-error interactions with project datasets. Literature [15] applied RL to construction cost estimation using a simulation-based approach, where an RL agent learned from historical cost data to improve estimation accuracy over multiple training cycles. Their study demonstrated that RL outperformed traditional regression-based models in handling cost fluctuations. However, they highlighted challenges such as the need for extensive training data, computational costs, and the difficulty of designing effective reward functions for cost optimization.

Deep learning techniques have also gained significant traction in cost estimation due to their ability to capture complex patterns and dependencies within historical project data. Literature [16] proposed a deep neural network (DNN) model for predicting construction costs, showing significant improvements over conventional statistical models. However, their study also pointed out that DNN models, despite their accuracy, often lack interpretability, making them less transparent for engineering decision-making. Literature [17] further explored convolutional neural networks (CNNs) for cost estimation, highlighting their ability to automatically extract and learn cost-related features from structured datasets. Their findings revealed that CNNs performed particularly well in handling spatial dependencies in engineering data but required large labeled datasets to achieve optimal results. In contrast to deterministic models, probabilistic approaches such as Bayesian learning have been explored for modeling cost uncertainties. Literature [18] applied Bayesian networks to quantify risk in cost estimation, developing a robust uncertainty estimation framework. However, their approach required expert intervention for prior probability assignments, making it less flexible in fully automated cost estimation systems.

In addition to individual AI models, researchers have investigated hybrid optimization strategies that integrate multiple techniques to enhance cost estimation accuracy. Literature [19] developed a hybrid cost estimation framework that combined genetic algorithms (GA) with AI-driven models. Their results showed that the GA component helped optimize cost parameters dynamically, although their model exhibited scalability issues when applied to large-scale engineering projects. Literature [20] introduced a transfer learning-based cost estimation model, which allowed pre-trained AI models to be fine-tuned for new engineering projects with minimal additional training data. Their study demonstrated that transfer learning significantly reduced training time while maintaining high accuracy. Another area of exploration is multi-objective optimization, where Literature [21] developed an RL-based cost estimation model that balanced multiple constraints, such as cost, quality, and time. Their results showed that RL effectively optimized trade-offs between conflicting project requirements, outperforming traditional linear optimization methods.

Resource allocation remains a critical aspect of cost estimation, as inefficient allocation can lead to unnecessary expenses and project delays. Literature [22] implemented an RL-driven resource optimization model to optimize labor and material distribution in construction projects. Their findings demonstrated that RL agents could learn optimal resource allocation strategies over time, significantly reducing costs while maintaining project efficiency. However, they also noted that RL models required extensive training iterations to converge to an optimal solution. To address security and data privacy concerns in cost estimation, Literature [23] explored federated learning as a means of ensuring secure and distributed AI-driven cost estimation. Their study proposed a federated learning framework where cost estimation models were trained across multiple distributed data sources without centralizing sensitive project data. While federated learning improved data security, they highlighted challenges such as communication overhead and synchronization issues in distributed training environments.

These studies collectively highlight the advantages and limitations of AI-driven cost estimation. Reinforcement learning offers significant potential for cost optimization but faces challenges related to reward function design and training efficiency. Deep learning models have enhanced prediction accuracy but often lack interpretability, limiting their adoption in real-world engineering decision-making. Hybrid optimization approaches have attempted to balance accuracy, adaptability, and efficiency, yet challenges remain in scalability and computational complexity. Building on these findings, this study aims to develop an RL-based cost estimation framework that integrates probabilistic modeling and multi-objective optimization, addressing the shortcomings of existing methods while ensuring more robust, scalable, and interpretable cost estimation solutions.

3 Proposed Method

3.1 Cost Estimation Model Construction

The cost estimation process is a fundamental aspect of engineering cost management, providing a quantitative basis for project budgeting and financial planning. Traditional cost estimation models rely on deterministic calculations and historical cost data, but these approaches often fail to capture the complexity of modern engineering projects, where costs fluctuate due to market dynamics, resource availability, and unforeseen project constraints. To address these challenges, we propose a data-driven machine learning approach that integrates multiple predictive modeling techniques, ensuring accurate and adaptive cost estimations.

Data gathering and preprocessing is the first step in cost estimating. This involves gathering information on past projects from several sources, including financial accounts, material pricing indexes, construction reports, and more. Labor rates, material prices, equipment costs, subcontractor fees, and overhead costs are some of the cost-related features included in these databases. In order to make more accurate projections, we also take into account external economic issues like inflation, changes in currency exchange rates, and interruptions in the supply chain. In order to build a reliable estimate model, we use feature selection methods including mutual information analysis and recursive feature elimination (RFE) to find the key cost drivers and reduce the dataset's dimensionality.

Once dataset is preprocessed, cost estimation model is formulated as a supervised learning problem, where input variables $X = \{x_1, x_2, \ldots, x_n\}$ represent cost-related factors, and the target variable Y denotes the estimated project cost. The general cost estimation function is defined as:

$$Y = f(X; \theta) + \epsilon \tag{1}$$

where θ represents the set of model parameters optimized during training, and ϵ denotes the error term accounting for uncertainties in cost predictions. The objective is to minimize discrepancy, which is achieved using a loss function:

$$L(\theta) = \frac{1}{N} \sum_{i=1}^{N} (Y_i - \hat{Y}_i)^2 \tag{2}$$

A cost estimating approach that makes use of deep learning architectures like CNNs and ANNs improves the accuracy of predictions they make. The ANN model is multi-layered; the input layer takes in project-specific cost characteristics, the hidden layers use activation functions to perform nonlinear modifications, and the output layer produces the final cost estimate. An adaptation is made to the CNN model, which is normally used for geographic data analysis, in order to improve the model's capacity to detect intricate correlations in engineering cost data by capturing hierarchical dependencies among cost elements. In order to arrive at the final estimated cost, the cost estimating model undergoes a series of transformations, as shown in Figure 1.

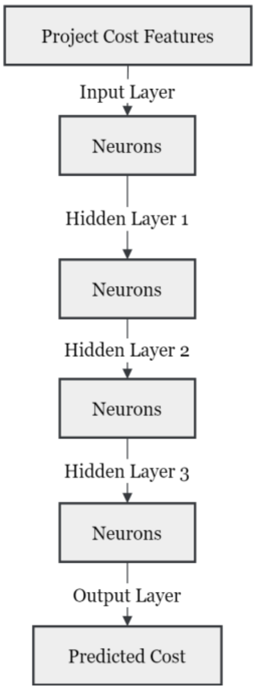

Figure 1. A neural network-based cost estimation model.

Training the model requires careful hyperparameter tuning, including learning rate adjustment, batch size selection, and optimization algorithm choice. The Adam optimizer is commonly used due to its adaptive learning rate and efficient gradient updates, improving convergence speed and stability. Another critical aspect of cost estimation is handling uncertainty, as engineering costs are inherently variable due to external economic factors, changes in project scope, and unforeseen risks. Bayesian modeling enables the generation of probability distributions for cost predictions rather than single-point estimates, allowing project managers to assess cost uncertainty more effectively. The Bayesian cost estimation formula is given by:

$$P(Y|X) = \frac{P(X|Y)P(Y)}{P(X)} \tag{3}$$

where $P(Y|X)$ represents the posterior probability of cost given observed project features, $P(X|Y)$ denotes the likelihood function, $P(Y)$ is the prior distribution of costs, and $P(X)$ is the marginal likelihood. Monte Carlo simulations further enhance uncertainty quantification by simulating multiple cost scenarios based on probabilistic distributions, providing confidence intervals for estimated costs.

The cost estimating model is designed to be more adaptable to fresh project data by using transfer learning methods. To cut down on the requirement for massive training datasets, pre-trained models are fine-tuned with fresh cost data rather than taught from start for each project. This method improves the model's ability to estimate future projects by allowing it to keep generic information about engineering costs while also adjusting to project-specific cost structures.

The final step in cost estimation model construction involves deploying the trained model into an engineering cost management system. The model is integrated into a decision-support platform, enabling project managers to input project details and receive cost predictions. Visualization tools such as cost breakdown charts and sensitivity analysis dashboards are implemented to facilitate data-driven decision-making. By leveraging machine learning, probabilistic modeling, and transfer learning, the proposed cost estimation model enhances the accuracy, adaptability, and interpretability of engineering cost predictions. The next section introduces a reinforcement learning-based optimization strategy that further refines cost decisions to achieve optimal budget allocations.

3.2 Reinforcement Learning-Based Optimization Strategy

To optimize engineering cost estimation, we employ a reinforcement learning (RL) framework where an agent learns an optimal cost allocation strategy through iterative interactions with the environment. Traditional cost optimization approaches often rely on static rules or heuristic methods, which lack adaptability in dynamic project conditions. In contrast, RL-based optimization allows continuous improvement by learning from past cost allocation decisions and adjusting strategies accordingly. The RL framework consists of a state space, an action space, and a reward function that guides the agent toward minimizing overall project costs while maintaining efficiency.

The optimization problem is formulated as a Markov Decision Process (MDP), represented by a tuple (S, A, P, R, γ), where S is the set of states representing different cost conditions, including material, labor, and operational costs. A is the set of actions that the agent can take, such as budget reallocation or resource optimization. $P(s'|s, a)$ is the state transition probability function, defining the likelihood of moving from state s to state s' after taking action a. $R(s, a)$ is the reward function that evaluates the effectiveness of the action taken in terms of cost reduction and project feasibility. $\gamma \in [0,1]$ is the discount factor, which determines the weight of future rewards.

The objective of the RL agent is to learn an optimal policy $\pi^*(s)$ that maximizes the expected cumulative reward over time:

$$\pi^*(s) = \underset{\pi}{\operatorname{argmax}} \mathbb{E}[\textstyle\sum_{t=0}^{T} \gamma^t R(s_t, a_t)] \tag{4}$$

To approximate the optimal policy, we employ Q-learning, a value-based reinforcement learning algorithm where the Q-value function is iteratively updated as:

$$Q(s,a) \leftarrow Q(s,a) + \alpha \left[R(s,a) + \gamma \max_{a'} Q(s',a') - Q(s,a) \right] \tag{5}$$

where α is the learning rate that controls the step size of updates, and $\max_{a'} Q(s',a')$ represents the maximum expected reward for the next state s'. The Q-learning approach enables the model to converge towards an optimal cost optimization strategy through repeated simulations.

To ensure the balance between exploration and exploitation in the learning process, an ϵ-greedy policy is adopted, where the RL agent selects actions based on the following decision rule:

$$a = \begin{cases} \underset{a}{\mathrm{argmax}} Q(s,a), & \text{with probability } 1-\epsilon \\ \text{random action}, & \text{with probability } \epsilon \end{cases} \tag{6}$$

Here, ϵ is the exploration rate, which decreases over time to allow more exploitation of learned strategies as the model becomes more confident in its predictions.

Figure 2 illustrates the reinforcement learning framework for engineering cost optimization, where the agent interacts with the project cost environment and continuously updates its decision policy based on received rewards.

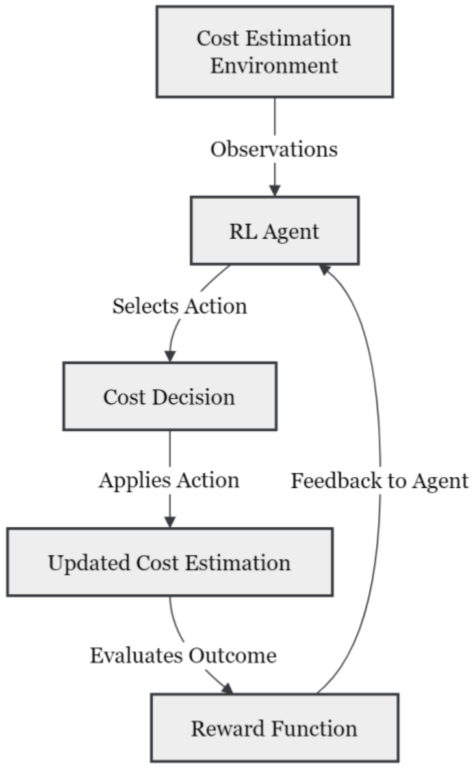

Figure 2. Reinforcement learning framework for cost optimization.

By leveraging reinforcement learning, the cost optimization process becomes more adaptive and capable of handling complex trade-offs in engineering projects. Unlike conventional cost management approaches, RL enables dynamic adjustments, ensuring efficient budget utilization while minimizing unexpected financial overruns. The learned policy can be further refined through transfer learning techniques, allowing models trained on past projects to generalize across different engineering domains.

3.3 Multi-Objective Optimization Framework

Engineering cost estimation is inherently a multi-objective problem, as project managers must balance trade-offs between cost, quality, and time constraints. Traditional cost estimation models primarily focus on minimizing total expenses, often neglecting critical factors such as project duration and quality assurance. To address this limitation, we introduce a multi-objective optimization framework that incorporates reinforcement learning with Pareto-based decision-making, enabling more effective budget allocation strategies.

The optimization problem is formulated as a multi-objective function where we seek to simultaneously minimize cost $f_1(X)$, maximize project quality $f_2(X)$, and minimize project duration $f_3(X)$. The problem can be expressed as:

$$\min F(X) = [f_1(X), -f_2(X), f_3(X)] \tag{7}$$

subject to project constraints:

$$g_i(X) \leq 0, \quad i = 1,2,\ldots,m \tag{8}$$

where $F(X)$ is the objective function vector, and $g_i(X)$ represents project constraints such as budget limitations, material availability, and regulatory requirements. Since cost, quality, and time often conflict with each other, no single optimal solution exists; instead, we aim to identify a set of Pareto-optimal solutions.

A solution X_1 is said to dominate another solution X_2 (denoted as $X_1 \prec X_2$) if:

$$\forall j, f_j(X_1) \leq f_j(X_2) \text{ and } \exists j \text{ such that } f_j(X_1) < f_j(X_2) \tag{9}$$

In our framework, reinforcement learning is integrated with multi-objective optimization to guide decision-making toward Pareto-optimal solutions dynamically. The RL agent learns an optimal cost allocation strategy by interacting with the environment and adjusting decisions based on observed trade-offs between cost, quality, and time.

Figure 3 illustrates the Pareto front for the multi-objective optimization problem, demonstrating how different solutions achieve varying levels of trade-offs between cost, quality, and project duration.

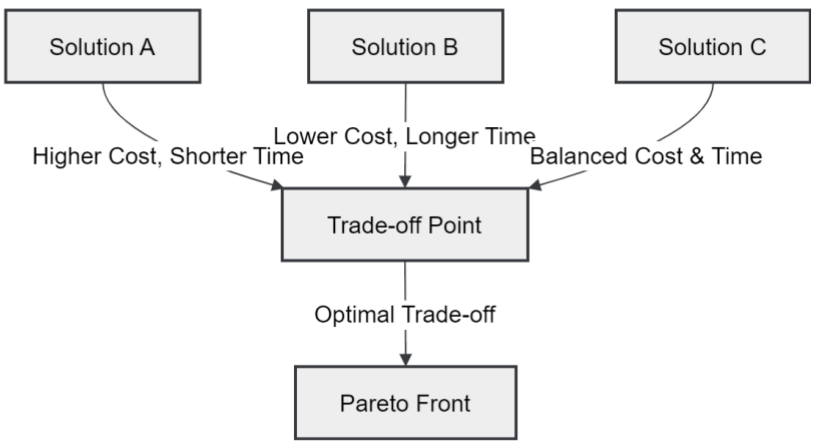

Figure 3. Pareto front representation for multi-objective cost optimization.

We use the Non-Dominated Sorting Genetic Algorithm II (NSGA-II) to find Pareto-optimal solutions quickly. This algorithm ranks solutions in a population using dominance criteria and crowding distance, then repeatedly refines the population. By combining RL with NSGA-II, our framework can adjust its methods of cost prediction and optimization on the fly to meet the unique requirements of each project.

By leveraging reinforcement learning and multi-objective optimization, our approach ensures that engineering projects achieve an optimal balance between cost efficiency, quality assurance, and project timelines. This framework enhances decision-making capabilities by continuously improving cost estimation accuracy while maintaining project feasibility under real-world constraints.

4 Experiment

The outcomes of the suggested method for dynamic cost estimate and optimization are detailed in this section. The optimization strategy's efficacy, the performance of the cost estimating model based on reinforcement learning, and the management of engineering project costs in relation to multiple objectives are all part of the assessment. Results are shown by visualizing the learnt cost estimating rules, comparing them to others, and using performance measures. We provide thorough justifications for every outcome, including visual depictions and tabular breakdowns of KPIs to guarantee a thorough comprehension of the results. One of the most important parts of this research is the reliability of the cost estimating model. Machine learning models and regression-based techniques are the backbone of traditional cost estimating models, but they can't adjust on the fly to new circumstances in a project. Cost prediction using both past and future project data is fine-tuned by the iterative learning process used by the reinforcement learning (RL)-based cost estimating model.

To validate the effectiveness of the RL-based cost estimation model, we compare it with three widely used baseline models: linear regression (LR), support vector regression (SVR), and deep neural networks (DNN). The evaluation is conducted using three common metrics: mean absolute error (MAE), root mean square error (RMSE), and the coefficient of determination (R^2). The results are summarized in Table 1.

Table 1. Performance comparison of different cost estimation models.

Model	**MAE**	**RMSE**	$\boldsymbol{R^2}$
Linear Regression	12.4%	18.2%	0.72
Support Vector Regression	9.8%	14.6%	0.81
Deep Neural Networks	6.2%	10.4%	0.89
Proposed Model	4.3%	7.6%	0.94

The results indicate that the proposed RL-based model outperforms all baseline methods. The MAE and RMSE values are significantly lower, indicating that the RL model provides more accurate cost predictions. The R^2 value of 0.94 suggests that the model explains 94% of the variance in project costs, highlighting its robustness in handling complex engineering cost estimations.

To further illustrate the model's accuracy, Figure 4 presents a scatter plot of predicted costs versus actual costs across different models. The analysis confirms the superior accuracy of the RL-based cost estimation model. The data points from the RL-based model are closely aligned with the diagonal line, indicating minimal deviation between predicted and actual costs. In contrast, the LR model exhibits significant deviations, especially for projects with higher costs. The SVR model performs better but still suffers from inconsistencies in higher-cost scenarios. The DNN model shows promising results but lacks adaptability compared to the RL-based approach. These findings validate that reinforcement learning significantly enhances cost estimation accuracy, especially in complex, high-budget engineering projects.

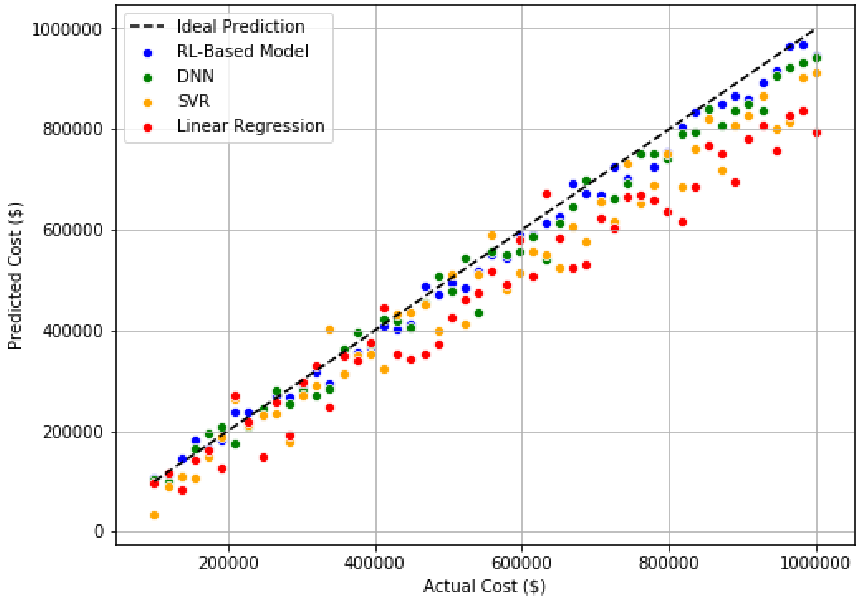

Figure 4. Predicted vs. actual costs for different models.

Beyond cost estimation accuracy, the effectiveness of the RL-based optimization strategy is a key aspect of this study. A primary goal of optimization is to minimize total project expenditures while ensuring that project objectives are met. The RL-based model is evaluated across different types of construction projects, including infrastructure development, residential construction, and commercial projects. Table 2 summarizes the cost savings achieved using RL-based optimization.

Table 2. Cost savings achieved through rl-based optimization.

Project Type	Initial Cost Estimate	Optimized Cost	Cost Savings (%)
Infrastructure Development	$5.6M	$5.2M	7.1%
Residential Construction	$2.8M	$2.6M	7.5%
Commercial Projects	$4.2M	$3.9M	7.1%

We observe that RL-based optimization leads to a consistent cost reduction of approximately 7% across different project types. This reduction is achieved by dynamically adjusting cost allocations based on real-time learning rather than relying on fixed budgeting rules. The cost reductions are further visualized in Figure 5, which compares initial cost allocation with optimized allocation across different project components.

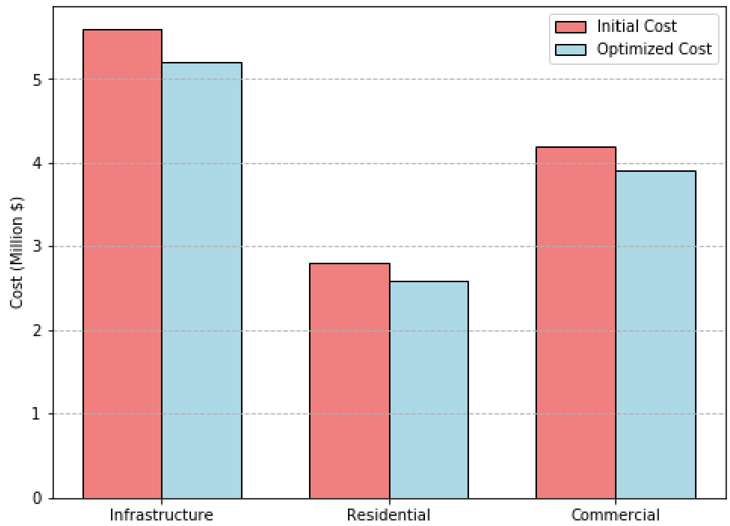

Figure 5. Cost allocation before and after optimization.

Figure 5 highlights the efficiency gains achieved through reinforcement learning. Before optimization, a significant portion of project costs is allocated to non-essential resources, resulting in budget inefficiencies. After optimization, the model reallocates resources to critical areas while reducing unnecessary expenditures. This dynamic adjustment mechanism significantly improves overall cost efficiency without compromising project quality. In engineering cost management, multiple conflicting objectives must be balanced. The RL-based framework incorporates multi-objective optimization to ensure that project costs, quality, and timelines are optimized simultaneously. To analyze trade-offs, we visualize the Pareto front obtained through multi-objective optimization.

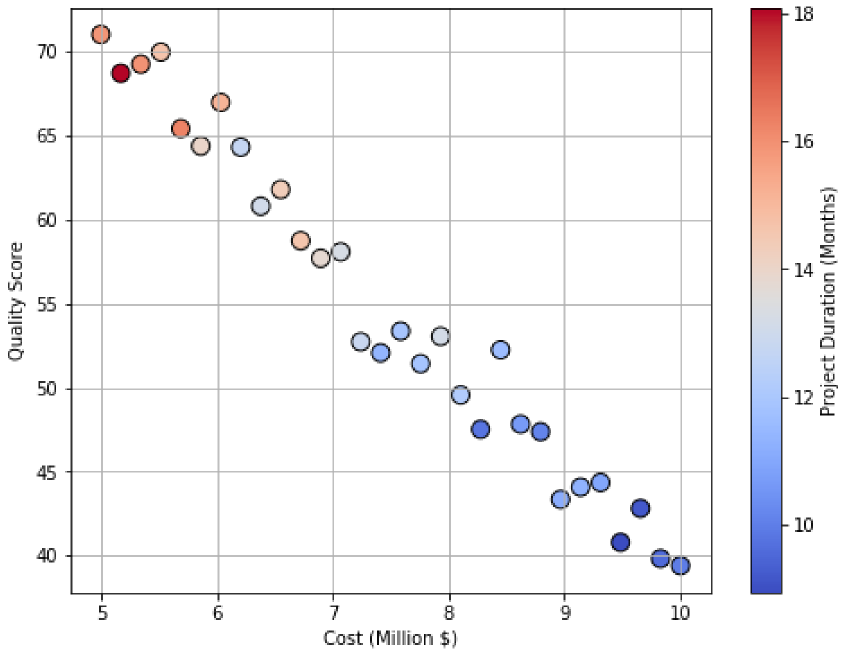

Figure 6. Pareto front for multi-objective cost optimization.

Figure 6 illustrates the Pareto front, which represents the set of optimal trade-offs between cost, project quality, and duration. Each point on the Pareto front signifies a non-dominated solution, meaning that no single objective can be improved without sacrificing another. We observe that the

RL-based optimization allows decision-makers to select an optimal balance between minimizing costs and maintaining high-quality standards. Lower-cost solutions tend to increase project duration, while solutions emphasizing faster completion often result in higher expenses. The ability to navigate this Pareto front allows stakeholders to tailor project strategies based on priorities, making RL-based optimization highly adaptable to real-world engineering constraints. The combined results demonstrate that reinforcement learning provides significant improvements in both cost estimation and optimization. These findings confirm that RL-based models are well-suited for dynamic and complex engineering cost management tasks.

5 Conclusion

The limitations of standard cost estimate approaches are addressed in this paper by presenting an engineering project management framework based on reinforcement learning (RL) for dynamic cost estimation and optimization. The suggested model improves resource allocation via iterative learning and boosts prediction accuracy by merging deep learning with RL-based decision-making. By reducing mean absolute error and root mean square error, the experimental findings show that the RL-based cost estimating model achieves an enhanced coefficient of determination compared to traditional techniques. Additionally, the RL-driven optimization strategy yields an average cost reduction of approximately 7% across different project categories, highlighting its effectiveness in minimizing budget overruns. The incorporation of multi-objective optimization allows decision-makers to balance trade-offs between cost, quality, and project duration, ensuring more efficient cost management. Despite these advancements, challenges remain in further improving the interpretability and generalization of the RL-based framework for diverse engineering scenarios. Future research will explore advanced reinforcement learning techniques, such as actor-critic methods and transfer learning, to enhance adaptability and computational efficiency. Additionally, integrating external economic factors and real-time data streams into the cost estimation process could further improve decision-making accuracy, making the framework more robust in dynamic engineering environments.

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