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DATABASE DEVELOPMENT AND REPAIR COST PREDICTION BASED ON INFRASTRUCTURE MAINTENANCE RECORDS

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Abstract

As infrastructure ages, accurately predicting maintenance costs and efficiently allocating limited budgets have become increasingly critical. Existing studies have primarily focused on estimating costs at the overall facility level. However, precise models that incorporate element level data can account for specific repair methods and their prices. This study first established a systematic facility breakdown structure in element levels based on infrastructure maintenance regulations in Korea and developed a cost database by collecting data from maintenance records according to the determined structure. The unit cost prediction models by different repair methods at element levels like decks, piers, and drainages were eventually developed using the Extreme Gradient Boosting (XGBoost) algorithm. The results showed that the study generated 30 prediction models for bridges with an average accuracy of 87.2% and 12 models for tunnels with an average accuracy of 85.5%. This study provides maintenance managers and policymakers with quantifiable cost information to enhance the accuracy and efficiency of maintenance planning and supports the development of maintenance strategies.

Introduction

Bridges, tunnels, and water supply systems, collectively referred to as social infrastructure, play a vital role in enabling daily life and supporting national economic activity. However, as the service life of these facilities continues to increase, the aging of infrastructure has emerged as a critical issue in terms of public safety and maintenance management. In response, the South Korean government enacted the Special Act on the Safety and Maintenance of Facilities, establishing a legal framework for the systematic inspection and management of aging infrastructure. According to this Act, facilities that have been in service for over 30 years are classified as aging infrastructure (Ministry of Land, Infrastructure, and Transport, 2024). Notably, the proportion of facilities exceeding 30 years of service is rapidly increasing, and within the next decade, aging facilities are expected to account for approximately 25% of all infrastructure, totaling around 120,000 facilities. This raises significant concerns about the increased likelihood of accidents, such as collapses, due to structural deterioration. For instance, the collapse of the Dorim pedestrian bridge in South Korea in January 2023 was attributed to construction defects and inadequate repair and maintenance practices. This case highlights the urgent need for establishing an effective and systematic maintenance plan to ensure safety and extend the lifespan of infrastructure facilities.

Among various maintenance strategies, the development of repair cost planning is particularly crucial. Maintenance costs directly influence budget allocation, resource optimization, and the long-term sustainability of infrastructure management. However, current information systems used for infrastructure maintenance face significant challenges in managing repair cost data comprehensively due to unstructured data formats and disparate information. For instance, the Facility Management System (FMS), operated by the Korea Infrastructure Safety and Technology Corporation, manages facility registration information, inspection and diagnostic reports, and design documents. However, as maintenance reports are stored in unstructured formats such as PDFs or TIFs, it is challenging to systematically organize or integrate the data. In the maintenance reports, repair costs are divided based on the damage types of individual elements and the applied repair methods, with the total cost calculated as their sum. The current FMS system, however, records repair costs only as aggregate totals without distinguishing costs for individual elements. This data structure makes it difficult to accurately assess costs for individual elements and creates challenges in optimizing budgets and prioritizing maintenance strategies (Ministry of Land, Infrastructure, and Transport, 2024).

To address these challenges, this study first aims to establish a standardized facility breakdown structure to systematically collect and manage facility data. Based on this structure, inspection and diagnosis data is organized into a database (DB), which is then utilized to develop a maintenance cost prediction model. The developed model is expected to effectively support decision-making processes such as maintenance planning and budget optimization. By doing so, the study seeks to enhance the accuracy and efficiency of maintenance operations.

Literature Review

Maintenance Cost Prediction Based on Statistical Analysis

Li et al. (2012) utilized historical maintenance data to predict maintenance costs for educational buildings in Taiwan by applying three linear regression methods. Hasan et al. (2018) investigated road maintenance projects in the United States, using statistical models to estimate project costs. Their study defined parameters such as project size, location, and environmental factors, and developed cost estimation formulas through regression analysis. Similarly, Smith et al. (2020) developed a cost prediction model for bridge maintenance projects across Europe, incorporating variables like bridge size, years in use, and average daily traffic to derive a predictive formula. While statistical analysis provides a simple and efficient approach for early-stage maintenance cost predictions, it has notable limitations. These methods often fail to capture complex interactions and nonlinear relationships among variables. They primarily rely on the assumption of a linear relationship between independent and dependent variables, which limits their ability to reflect real-world cost complexities. Additionally, the quality of predictions heavily depends on the quality of the input data. Issues such as missing or inaccurate data undermined the reliability of the model and the prediction results were thus not suitable for practical use.

As a result, while statistical methods are suitable for basic and early-stage network-level predictions, they require complementary approaches to address their limitations. Techniques such as machine learning with more trustable data, which can model nonlinear relationships and account for complex interactions, offer promising alternatives to enhance prediction accuracy and reliability.

Maintenance Cost Prediction Using Machine Learning Models

Wang et al. (2022) utilized data from 268 real-world bridges to build a maintenance cost sample DB and develop cost prediction models. Their study identified eight key factors affecting maintenance costs using the Random Forest algorithm. They applied Artificial Neural Networks (ANN) and Convolutional Neural Networks (CNN) to compare the performance of these prediction models. Similarly, Cabrera and Silva (2023) analyzed maintenance budget allocation in DPWH Region XII (Philippines) between 2019 and 2022. Using data from eight district engineering offices, they developed an ANN-based model to predict final budget allocations based on input variables such as road length, equivalent maintenance kilometers, bridge length, and road conditions. Cheng et al. (2009) introduced a hybrid model combining ANN and Fuzzy Logic, offering an innovative approach to effectively handle uncertainty and nonlinearity in maintenance cost predictions.

Existing machine learning-based prediction models primarily focus on estimating costs at the overall facility level, often neglecting detailed cost variations at the element level. Repair costs, however, vary significantly depending on the type of damage and the repair methods applied to individual elements. For instance, cracks in a bridge deck require surface repair, whereas corrosion demands sectional repair, resulting in markedly different costs.

To address these limitations, this study developed a cost prediction model at the element level. This model quantifies the damage types and repair methods for each element, enabling more precise unit cost calculations. Consequently, it enhances the accuracy of budget allocation and improves the reliability of cost predictions.

Research Methodology

This study presents a systematic approach to developing predictive models for repair and reinforcement costs and establishing an integrated DB for infrastructure maintenance. As shown in <Figure 1>, the research proceeds as follows: (1) Establishment of a facility breakdown structure, (2) Database development, and (3) Development of repair and reinforcement unit cost estimation models.

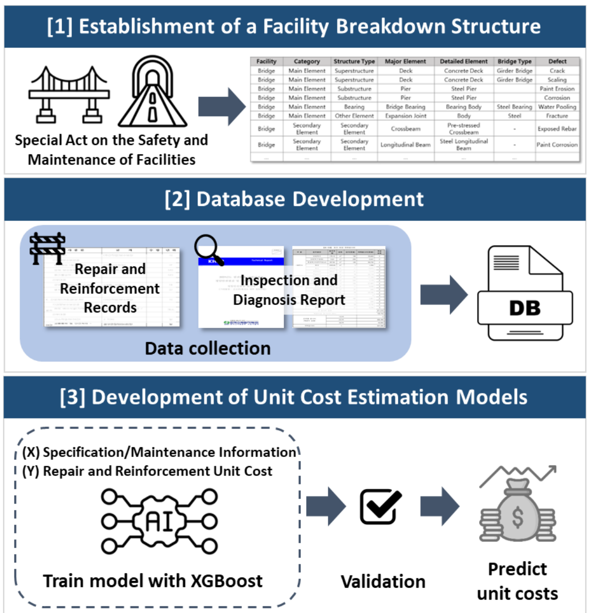

Figure 1: Research Process

Establishment of a Facility Breakdown Structure Establishing clear data collection standards is essential for constructing a DB of repair and reinforcement costs for infrastructure. This study designs a facility breakdown structure based on damage units to ensure consistency in data collection and to develop a reliable cost prediction model. The framework enables systematic collection and efficient management of damage type data for infrastructure and its elements.

Following the detailed guidelines for infrastructure safety and maintenance, this study refines the breakdown structure by categorizing major structural elements and damage types. This approach allows for a detailed analysis of damage locations and specific structural components for each type of infrastructure.

According to the Special Act on the Safety and Maintenance of Facilities in South Korea, infrastructure is classified into 15 types, including bridges, tunnels, ports, port counter facilities, dams, estuary banks, sluice gates, embankments, drainage pump stations, water supply systems, wastewater treatment plants, retaining walls, cut slopes, utility tunnels, and buildings. Among these 15 types, this study focuses only on bridges and tunnels for feasibility purposes. Therefore, the breakdown structure is applied to bridges and tunnels, serving as the foundation for developing predictive models.

Database Development

Data collection

The content here explains the process of extracting essential information from inspection and diagnosis reports and repair and reinforcement records to construct a comprehensive DB. From the inspection and diagnosis reports, general project information and element-level data are extracted and structured into the DB. Key details such as facility ID, facility name, inspection year, primary damage types, evaluation grades, condition assessment indices, and stability assessment coefficients are included. This data serves as a critical foundation for facility maintenance planning. Similarly, the repair and reinforcement records focus on general construction details and element-level repair data, including information such as repair costs, repair methods, repair quantities, and pre- and post-repair conditions. These records are organized to improve the transparency and reliability of maintenance operations. Data such as project timelines, total costs, and detailed repair quantities are integrated into the DB to optimize maintenance budget allocation.

By consolidating and structuring data from these sources, the DB becomes robust for monitoring facility conditions, prioritizing repair needs, and enhancing the precision of maintenance cost estimations.

Data preprocessing

The bridge repair and reinforcement dataset comprises 94,491 records collected from 2013 to 2023. Each record includes detailed information for individual elements, such as repair method name, method code, repair quantity, unit, repair cost, repair date, and type of repair or reinforcement. Next, the tunnel repair and reinforcement dataset consist of 19,178 records collected from 2021 to 2023, containing data such as repair method name, repair quantity, unit, repair cost, and repair date.

To enhance data reliability, preprocessing steps were implemented. Missing values, such as “NaN” or “0,” and errors, such as incorrect method codes assigned to unrelated elements, were removed. Repair types with significant cost deviations, including seismic reinforcement and reconstruction, were excluded to avoid introducing noise into the predictive model. Data with inconsistent units were standardized to representative units. For example, in the case of injection methods applied to deck slabs, only data with "m" and "m^2" units were retained, while other units were discarded.

To improve usability, repair and reinforcement records were merged with structural specification data. For bridges, the repair records were linked to bridge and element specifications using a bridge identification number. A new variable, "service days," was introduced to calculate the service life by measuring the days between the completion date and the repair date. Additionally, a new variable, "repair unit cost," was created by dividing the repair cost by the repair quantity. For tunnels, repair and reinforcement records were merged with tunnel specification data using the FMS management number. A "service days" variable was also calculated to represent the service life at the repair date. However, due to the lack of detailed element specifications (e.g., width, height, shape), some variables were excluded from the analysis; available variables such as completion year, tunnel type, length, and number of lanes were utilized for model development.

Since historical repair costs and current costs differ in value despite being nominally identical, temporal adjustments were necessary. According to the Construction Cost Index (CCI) published monthly by the Korea Institute of Civil Engineering and Building Technology (KICT, 2023), the average annual growth rate of the construction cost index since 2010 has been approximately 4.2%, with some years exceeding a 10% increase. Consequently, all data were adjusted to reflect values as of January 2024. Historical unit costs were converted to present values using the following equation (Eq. 1), where RC_{past} represents the historical unit cost of the repair method, and RC_{recent} explains the adjusted unit cost:

$$RC_{recent} = RC_{past} \div \left(\frac{CCI_{past}}{CCI_{recent}}\right) \qquad (1)$$

Development of Repair and Reinforcement Unit Cost Estimation Models

To improve the accuracy of unit cost predictions, this study first removes outliers using the Interquartile Range (IQR) method. The IQR is defined as the range between the first quartile (25%) and the third quartile (75%). Data points exceeding 1.5 times this range are identified as outliers and eliminated. Even after removing the outliers, the cost values still cover a wide range, limiting the precision of predictions. To address this problem, the process converts unit costs into intervals by transforming them into categorical variables, enabling interval prediction. Two methods handle the interval creation: quantile-based binning, which generates intervals of equal size based on quantiles, and equal-range binning, which divides the data into intervals of equal range.

The comparison between models, using surface repair method data for deck elements, revealed that equal-range binning performs better than quantile-based binning in both interval validation accuracy and mean error. As shown in <Table 1>, quantile-based binning tended to create excessively wide intervals because of extreme values. Wider intervals increase the discrepancy between values within the interval and their representative value, leading to lower prediction accuracy and greater errors.

Table 1: Validation Results for Training Models by Binning Methods

Equal-range binning		Quantile-based binning	
Average Binning Validation Accuracy	Average MAE	Average Binning Validation Accuracy	Average MAE
87.2%	53,068(KRW)	81.9%	60,190(KRW)

Based on these results, equal-range binning was identified as the optimal approach for the model. Rather than predicting costs directly, the approach provides representative values for each interval. The comparison included models with interval counts of 3, 5, and 7. Performance evaluation relied on interval validation accuracy and Mean Absolute Error (MAE), as summarized in <Table 2>.

Table 2: Interval Binning Performance Evaluation

Repair Method	Surface Repair (Deck)			Asphalt Overlay (Pavement)		
Number of bins	3	5	7	3	5	7
Interval Validation Accuracy (%)	80.97	70.51	66.91	90.19	89.96	82.54
MAE (KRW)	82,933	77,634	79,476	11,398	9,182	9,866

The results showed that increasing the number of intervals leads to more misclassified predictions, which increases the error due to the use of representative values. Conversely, fewer intervals create excessively wide ranges, preventing detailed predictions. The analysis identified five intervals as the optimal choice. This configuration balances interval validation accuracy and MAE, ultimately improving both the reliability and precision of the model. To evaluate the performance of cost prediction models, the analysis compared five classification models using surface repair data for deck elements, as shown in <Table 3>.

Table 3: Classification Model Comparison

Classification Algorithm	Accuracy	Precision	Recall	F1-score
K-Nearest Neighbor	0.70	0.60	0.47	0.53
Support Vector Machine	0.76	1.00	0.56	0.72
Random Forest	0.85	1.00	0.72	0.84
AdaBoost	0.43	0.42	0.53	0.47
XGBoost	0.91	1.00	0.92	0.89

The evaluation used accuracy, precision, recall, and F1-score as metrics. Among the models, XGBoost demonstrated the best performance, achieving an accuracy of 0.91, precision of 1.00, recall of 0.92, and an F1-score of 0.89. These results confirmed XGBoost's superior reliability and precision for cost predictions.

The Random Forest classifier achieved balanced performance with an accuracy of 0.85 but fell short of XGBoost. In contrast, SVC and KNN classifiers showed high precision but relatively low recall, which limits their ability to identify all positive cases. Adaboost performed the worst, with low accuracy and F1-score, making it unsuitable for cost prediction tasks.

In conclusion, the performance comparison demonstrates that XGBoost achieved the highest accuracy and recall, establishing it as the optimal algorithm for cost prediction.

Results and Discussion

Results of Facility Breakdown Structure

The facility breakdown structure was developed based on the detailed guidelines for infrastructure safety and maintenance. <Table 4> presents an example of the breakdown structure for bridges. A structured input system was designed to systematically record key components and damage information for each facility type. For bridges, structural types were categorized into superstructures and substructures. The superstructure was further divided into deck slabs and piers, with deck slabs defined as specific components that included damage types such as cracking, spalling, and coating damage.

Table 4: Facility Breakdown structure Example

Facility	Category	Structure Type	Major Element	Detailed Element	Element Type	Defect
Bridge	Main Element	Super-structure	Deck	Concrete Deck	Girder Bridge	Crack
Bridge	Main Element	Super-structure	Deck	Concrete Deck	Girder Bridge	Scaling
Bridge	Main Element	Sub-structure	Pier	Steel Pier		Paint Erosion
Bridge	Main Element	Sub-structure	Pier	Steel Pier		Corrosion
Bridge	Main Element	Bearing	Bridge Bearing	Bearing Body	Steel Bearing	Water Pooling
Bridge	Secondary Element	Secondary Element	Crossbeam	Pre-stressed Crossbeam		Exposed Rebar

Results of Data Construction

Using the developed facility breakdown structure, a DB was constructed by extracting general construction information and element-level data from inspection and diagnosis reports as well as repair and reinforcement records. <Table 5> presents the results of extracting bridge and tunnel data from these sources for DB development. For instance, in the case of bridges, a total of 33,394 data rows were generated from 498 element-level inspection and diagnosis reports, and 53,958 data rows were produced from 583 repair and reinforcement records. Based on the extracted data, predictive models were developed, focusing on bridges and tunnels.

Table 6: Variables for Estimating Repair and Reinforcement Unit Costs by Method

Facility Level Variables	Repairment Variables	Element	Element Level Variables	Number of Variables
Completion date Facility type Road lane Total length Total width Total height Design live load Average daily traffic Average daily truck traffic Seismic design application Competent authority Management agency (region) Management agency (subregion)	Quantity of the repairment Completion date of repairment Bridge age	Deck	Detail element type, Main superstructure, Span length, Deck material, Deck thickness, Deck strength, Pavement type, Pavement thickness	24
		Girder	Detail element type, Main superstructure, Span length, Girder structure type, Girder strength, Number of girders, Girder spacing	23
		Crossbeam	Detail element type, Main superstructure, Span length, Crossbeam spacing, Number of crossbeams	21
		Pier/Abutment	Detail element type, Main substructure, Water depth, Support type	20
		Bearing	Detail element type, Main substructure, Bearing type, Bearing capacity, number of bearings	21
		Expansion joint	Detail element type, Main superstructure, Expansion joint type, Expansion joint gap	20
		Pavement	Detail element type, Main superstructure, Pavement type, Pavement thickness	20
		Drainage	Detail element type, Main superstructure, Span length	19
		Railing/curb	Detail element type, Main superstructure, Span length, Railing type	20

Table 5: Data Aggregation Table for Database Integration

Facility	Inspection Report	Rows of Inspection DB	Repair Report	Rows of Repair DB
Bridge	498	33,394	583	53,958
Tunnel	103	3,075	178	19,170

Model Performance Results

Bridge Model Results and Discussion

The bridge dataset was refined by removing unnecessary variables and adding relevant ones, resulting in a total of 16 variables. As shown in <Table 6>, independent training datasets were created for each bridge element. Since the detailed variable configuration differed for each element, independent training data were prepared to suit each specific element. As a result of the analysis, 30 repair methods were identified as suitable for bridge model development.

When training the bridge model using the XGBoost algorithm, key hyperparameters such as 'learning_rate,' 'n_estimator,' and 'col_sample' were adjusted to analyze performance variations. Eighty percent of the dataset was allocated for training, while the remaining 20% was reserved for validation. The training results are presented in <Table 7>, indicating that the representative unit cost estimation model for bridge repair methods achieved an average interval validation accuracy of 87.2%.

To complement the evaluation of model accuracy, the Mean Absolute Error (MAE) and the Mean Absolute Percentage Error (MAPE) were additionally calculated. MAPE provides a normalized measure of prediction error relative to actual costs, allowing for intuitive interpretation in percentage terms. As shown in <Table 7>, the MAPE values for the bridge repair methods ranged from 10.9% to 26.4%, depending on the specific repair methods. While some repair methods showed relatively high percentage errors, this can be attributed to large cost variations between repair types or small sample sizes in certain categories. Considering these contextual factors, the model is deemed to have an acceptable level of predictive performance for early-stage budget estimation. Several repair methods with MAPE values below 15% exhibited relatively stable predictive behavior, suggesting the model's practical applicability to real-world cost estimation tasks.

Table 7: Summary of Unit Cost Estimation Model Results by Bridge Repair and Reinforcement Method

Element	Repair Method	Data Count	Interval Validation Accuracy (%)	MAE (KRW)	MAPE (%)
Deck	Grouting	1,010	87.13	6,557	14.7
	Surface repair	5,737	92.51	6,830	10.8
	Section repair	3,728	70.51	77,634	26.7
Girder	Surface repair	911	91.30	10,798	12.1
	Filling & Grouting	235	87.50	7,130	12.6
	Section repair	1,146	66.96	76,471	20.3
	Coating	2,070	85.51	14,779	22.5
Crossbeam	Surface repair	225	95.65	4,888	17
	Section repair	443	80.00	70,511	22.5
	Coating	285	89.66	13,607	10.9
Pier/ Abutment	Filling & Grouting	2,459	86.18	8,583	17
	Section repair	4,577	72.71	69,575	26.4
	Surface repair	6,640	89.16	7,304	10.9

Tunnel Model Results and Discussion

For tunnels, a total of seven variables were selected, including four specification variables (completion year, tunnel type, length, and number of lanes) and three repair and reinforcement record variables (repair quantity, repair date, and adjusted cost). The analysis identified 12 repair methods as suitable for tunnel model development.

The XGBoost algorithm was applied to train the tunnel model, following the same approach as the bridge model, with key hyperparameters adjusted. 80% of the dataset was used for training, and 20% was used for validation. The training results are presented in <Table 8>, and the unit cost estimation model for tunnel repair methods showed an average interval validation accuracy of 85.5%. Predictive accuracy was primarily evaluated using MAE, and MAPE was additionally calculated to assess the model's relative error in comparison to actual costs. The analysis revealed that MAPE values ranged from 12.6% to 26.3%, depending on the repair type, with several repair methods recording error rates below 15%. Given that tunnel repairs often involve significant cost variability due to differences in structural types and construction methods—and that some repair types had limited data, this level of predictive performance is considered sufficiently practical for use in early-stage budget planning.

Table 8: Summary of Unit Cost Estimation Model Results by Tunnel Repair and Reinforcement Method

Element	Repair Method	Data Count	Interval Validation Accuracy (%)	MAE (KRW)	MAPE (%)
Pavement of bridge	Grating Replacement	112	8.70	16,093	26.3
	Surface Repair	53	100.00	1,887	14.6
Drainage	Drainage Repair	106	54.55	34,657	23.4
	Drainage Replacement	90	100.00	11,767	15.3
Pavement of decked structure	Surface Repair	160	100.00	984	15.2
	Surface Treatment	96	100.00	1,076	16
Pavement of asphalt	Surface Repair	78	100.00	105,519	21.9
	Surface Treatment	104	38.10	2,344	25.5
Retaining wall	Replacement	58	100.00	19,875	16.9
Pedestrian walkway railing	Replacement and Repair	128	100.00	2,362	14.3
Pavement of underpass	Surface Repair	112	100.00	1,488	12.6
Hume tube of underpass	Replacement and Repair	84	100.00	10,364	20.5

Conclusion

This study established a facility breakdown structure tailored to individual components, systematically collected and organized maintenance cost data, and proposed a unit cost estimation model for repair methods to enhance the accuracy of infrastructure maintenance cost predictions. By applying the XGBoost algorithm to analyze bridge and tunnel data, interval-based unit costs were predicted, and the model's performance was evaluated. The results showed an average prediction accuracy of 87.2% for bridges and 85.5% for tunnels, indicating the potential to contribute to infrastructure maintenance budge estimation.

The key contributions of this study are as follows: first, inspection and diagnosis reports, along with repair and reinforcement records, were collected and organized into a comprehensive DB. This DB facilitates the structured management of facility conditions and maintenance histories, providing a robust foundation for data-driven decision-making in maintenance planning. By standardizing inspection and repair histories, the model enhances the reliability and practicality of cost prediction. Second, an XGBoost-based unit cost estimation model was developed using inspection and diagnosis data. This model improves the reliability of repair cost predictions and provides a quantitative foundation for cost adjustments and maintenance planning. Additionally, by reflecting the conditions of infrastructure facilities, the model enables more accurate cost estimations and contributes to improved overall maintenance efficiency. Nevertheless, this study highlights several limitations. The DB does not sufficiently account for external factors such as regional labor costs and material price fluctuations, which may impact the accuracy of repair cost estimation. Employing a single XGBoost model for all elements also fails to consider the unique characteristics and data distributions of individual elements, thereby limiting the model's ability to achieve optimal accuracy for specific repair methods.

To address these limitations, future research should focus on collecting more extensive datasets across a wider range of infrastructure types and incorporating external factors such as regional labor costs, material prices, and environmental conditions into the data to enhance both the practical applicability and predictive performance of the model. In addition, various algorithms such as Random Forest, Artificial Neural Networks (ANN), and other potential machine learning algorithms can be applied and compared to identify the most suitable model for each component or type of repair. These efforts will contribute to the development of more precise and adaptive cost estimation models for infrastructure maintenance.

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References

Abdallah, M. (2024) Maintenance Optimization System to Maximize Performance of Bridges within Available Budget. Center for Transformative Infrastructure Preservation and Sustainability (CTIPS), University of Colorado Denver. Approved August 17, 2024.

Almeida, J.O., Delgado, R.M., & Teixeira, P.F. (2016) A bridge life-cycle cost optimization methodology. In: Life-Cycle of Engineering Systems: Emphasis on Sustainable Civil Infrastructure. CRC Press, pp.8.

Bayraktar, M.E., & Hastak, M. (2009) Bayesian Belief Network Model for Decision Making in Highway Maintenance: Case Studies. Journal of Construction Engineering and Management, 135(12), pp.1357–1369.

Bouabaz, M., & Hamami, M. (2008) A Cost Estimation Model for Repair Bridges Based on Artificial Neural Network. American Journal of Applied Sciences, 5(4), pp.334–339.

Cabrera, M.S., & Silva, D.L. (2023) Neural Network-Based Prediction of the Performance Budget for Road Defects and Highway Maintenance. 2023 3rd IEEE International Conference on Software Engineering and Artificial Intelligence (SEAI), 1–7.

Cheng M-Y., Tsai H-C., & Hsieh W-S. (2009) Web-based conceptual cost estimates for construction projects using Evolutionary Fuzzy Neural Inference Model. Autom Constr 18(2):164–172.

Frangopol, D.M., Enright, M.P., & Estes, A.C. (1999) Integration of maintenance, repair, and replacement decisions in bridge management based on reliability, optimization, and life-cycle cost. TRB Transportation Research Circular, 498, pp.G-1/1–G-1/12.

Hasan, M., & Rashid, T. (2018) Statistical cost estimation models for road maintenance projects in the United States. Journal of Infrastructure Systems, 24(2), 04018007.

Karaaslan, E., Bagci, U., & Catbas, N. (2021) A Novel Decision Support System for Long-Term Management of Bridge Networks. Applied Sciences, 11(11), pp.5928.

Kim, J. (2003) Long-Life Repair Design and Construction Case of I-710 Highway in the U.S. Road, 5(3), pp.3–54.

Korea Economic Daily. (2023) Aging Infrastructure Over 30 Years Old Expected to Account for 45% of Total Infrastructure in 10 Years.

Korea Institute of Civil Engineering and Building Technology. (2023) Guidelines for Safety and Maintenance of Facilities (Safety Inspection and Diagnosis Section).

Korea Institute of Civil Engineering and Building Technology. (2024) 2023 National Safety Statistics Yearbook.

Lee, G., Chang, T., & Chi, S. (2023) Data-Driven Bridge Maintenance Cost Estimation Framework for Annual Expenditure Planning. Journal of Management in Engineering, 39(2), pp.04023028.

Lee, Y. (2015) Aging Infrastructure Facilities: Urgent Need for Performance Improvement Measures – Focusing on Cases and Policy Implications from the U.S. and Japan. CERIK Journal, 2015(6), pp.10–11.

Li, Y., & Guo, Z. (2012) Development of a cost predicting model for maintenance of university buildings using regression analysis. Journal of Construction Engineering and Management, 138(3), 345–353.

Ministry of Land, Infrastructure and Transport. (2024) Facility Integrated Information Management System FMS Website. Available at: www.fms.or.kr.

Ministry of Land, Infrastructure and Transport. (2024) Integrated Bridge and Tunnel Management System. Available at: https://nbms.kict.re.kr/.

Seo, J., & Oh, J. (2021) Current Status of Safety and Maintenance Information Systems for Facilities. Journal of the Korean Society of Space Structures, 21(3), pp.4–8.

Smith, J., & Williams, K. (2020) Predicting maintenance costs for bridge rehabilitation projects using regression analysis. European Journal of Civil Engineering, 28(4), 529–543.

Wang, C., Yao, C., Zhao, S., Zhao, S., & Li, Y. (2022) A Comparative Study of a Fully-Connected Artificial Neural Network and a Convolutional Neural Network in Predicting Bridge Maintenance Costs. Applied Sciences, 12(7), pp.3595.

Yoon, K. (2000) Restoration Case of Kobe Route No. 3 of Hanshin Expressway in Japan. Journal of Korean Society of Steel Construction, 12(3), pp.24–29