Automated Decision-Making Tool for Optimal Long-Term Scheduling of MRR Strategies: A Case Study on Bridges

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Abstract – Maintenance, repair, and replacement (MRR) strategies for bridges are critical requirements for infrastructure management, demanding effective decision-making to balance cost and performance objectives. This research presents an automated decision-making tool designed to optimize long-term scheduling of MRR strategies, addressing the complexities of multi-objective problems in bridge management. The tool integrates performance modeling with a modified genetic algorithm to generate optimal MRR plans, ensuring efficient resource allocation while maintaining structural integrity. A case study demonstrates the tool's application, predicting bridge deterioration and proposing cost-effective MRR actions under performance-based contracting frameworks. Results highlight significant cost savings and enhanced bridge serviceability through timely interventions. While the tool currently focuses on bridge decks, it establishes a foundation for future enhancements to include additional bridge components and broader infrastructure networks. This study advances automated MRR scheduling by offering a robust solution for sustainable bridge management.

Keywords – Automation; Decision-Making; Maintenance, Repair, and Replacement (MRR); Optimal MRR Strategies; Long-Term Scheduling; Modified Genetic Algorithm (GA); Sustainable Bridge Asset Management; Infrastructure Management

1 Introduction

The optimization of bridge maintenance, repair, and replacement (MRR) strategies has gained substantial attention in infrastructure management, especially with the introduction of automated decision-making tools that enhance scheduling efficiency. These approaches utilize various mathematical models, algorithms, and data-driven techniques to assess the optimal timing and scope of MRR interventions for bridges. Predictive algorithms further enhance decision-making by identifying optimal MRR strategies based on projected deterioration. The study by Bolukbasi et al. [1] presents an optimization model that employs deterioration curves to forecast the degradation of bridge components, allowing for more timely and effective scheduling of rehabilitation activities. In a similar vein, Alsharqawi et al. [2] introduced an integrated condition rating and forecasting methodology to provide accurate condition assessments for bridge decks. This dual-method approach allows for a refined understanding of bridge deck health, contributing to effective long-term scheduling and resource allocation for MRR strategies. Furthermore, Neves et al. [3] proposed a probabilistic optimization model that combines preventive and essential maintenance actions, underscoring the value of a hybrid approach in optimizing bridge maintenance costs while maintaining safety standards.

Implementing performance-based contracting (PBC) has emerged as a valuable approach to bridge maintenance, focusing on setting specific performance metrics and outcomes rather than prescribing maintenance actions. This approach incentivizes contractors to meet defined service levels, often resulting in more efficient use of resources and improved bridge performance over time. Alsharqawi et al. [4] highlight the advantages of PBC in maintaining transportation assets, particularly bridges, by setting outcome-focused targets that contractors must meet to fulfill their obligations. Similarly, performance-based approaches in bridge maintenance have been shown to support innovative solutions, including the use of advanced materials and real-time monitoring systems, which help contractors maintain the infrastructure within specified parameters [5]. The use of PBC aligns with the goals of long-term scheduling in bridge maintenance as it provides structured, measurable goals that guide the maintenance schedule, allowing for optimized resource allocation and enhanced reliability of bridge infrastructure over its lifecycle [6].

2 Literature Review

Automated decision-making tools and frameworks play a crucial role in optimizing the long-term scheduling of MRR for infrastructure, especially for bridge networks. These tools address complex, multi-objective problems involving cost, reliability, traffic flow disruption, and network performance, among others. Multi-objective models in bridge maintenance scheduling often aim to minimize both maintenance costs and traffic delays. For instance, Mao et al. proposed a bi-level programming model that minimizes traffic delays while maximizing the number of bridges maintained within budget constraints. By using a simulated annealing algorithm, the model has shown effectiveness in reducing maintenance costs and traffic disruptions [7]. Another approach, developed by Bocchini and Frangopol, introduces a probabilistic framework utilizing multi-objective genetic algorithms for preventive maintenance scheduling across a highway bridge network. Their model optimizes between cost and network performance, offering bridge managers a Pareto front of solutions to balance engineering and economic considerations [8]. Montazeri and Touran propose a reliability-based decision-making framework, emphasizing the importance of life-cycle performance and maintenance costs. Their model aids bridge managers in evaluating the best repair and replacement strategies across a bridge's lifespan, considering structural specifications and budget limitations [9]. Computational models help optimize bridge maintenance schedules under uncertainty. Liu and Frangopol developed a probabilistic maintenance planning model using Monte Carlo simulations to address uncertainties in bridge deterioration, which improves prediction accuracy and provides confidence-based maintenance solutions [10]. For network-level optimization, Orcesi and Cremona introduced a genetic algorithm-based model that considers the bridge's position within a transportation network, which ensures optimal resource distribution and maintains the level of service across the network [11].

An important aspect of automated MRR tools involves balancing cost and reliability. Frangopol et al. demonstrated how integrating reliability-oriented models with cost analysis could enhance bridge maintenance planning by identifying economically viable MRR schedules that ensure safety over the structure's lifetime [12]. This approach aligns with the work of Liang et al., who developed decision criteria based on cost-benefit theory to maintain bridge deck pavement, underscoring the importance of a balanced approach in prioritizing both safety and budget considerations [13]. Lee et al. developed a preference-based maintenance scheduling method tailored for bridges in Korea, balancing life-cycle costs with bridge performance. Their multi-objective optimization model allows for stakeholder preferences, helping decision-makers choose cost-effective maintenance strategies [14]. The integration of innovative decision support model under performance-based contract settings has advanced MRR scheduling significantly. Alsharqawi et al. developed a model capable for budget optimizing of MRR decisions under PBC settings. Implementing the model enables contractors to execute various MRR plans under different budget and performance requirements, where each resulting plan is optimal along the contract period [15], [16].

In recent years, the complexity of bridge MRR scheduling has underscored the need for advanced automated tools that leverage algorithmic optimization to streamline decision-making. Traditional approaches to MRR scheduling are often constrained by manual assessments and simplistic cost-benefit analyses, which may fall short in capturing the dynamic and multi-faceted nature of bridge deterioration and maintenance requirements. An automated, algorithm-based tool can enhance this process by rapidly processing large datasets, predicting deterioration with high accuracy, and generating optimized schedules that minimize maintenance costs while maximizing bridge reliability and performance. This data-driven approach to MRR scheduling is essential for infrastructure managers seeking to allocate resources effectively, reduce traffic disruptions, and ensure the long-term safety and functionality of bridge networks.

3 Development of Automated Tool

The automated decision-making support tool inputs, tools, techniques, and outputs are illustrated in Figure 1 and discussed in the following sections. The proposed tool in this paper considers bridge deck in particular because it deteriorates faster than other components due to its direct exposure to traffic in addition to the external environmental factors (e.g., freeze-thaw cycling) [17], [18].

The development of the automated tool involves two key components: first, modeling the performance of the bridge deck, and second, optimizing the selection of MRR strategies.

3.1 Performance Modeling

3.1.1 Performance Evaluation

To evaluate current performance, assessing the condition of the bridge deck is essential. This assessment provides insights into the physical state of the infrastructure and an estimate of its remaining useful life or maximum lifespan. Regular detailed inspections are conducted to identify significant defects and evaluate the extent of bridge deterioration. In North America, visual inspection and close observation of bridge elements are commonly used due to their low cost and minimal expertise requirements. If severe damage is identified during visual inspection, a more comprehensive condition survey is conducted using both destructive and non-destructive testing methods [2].

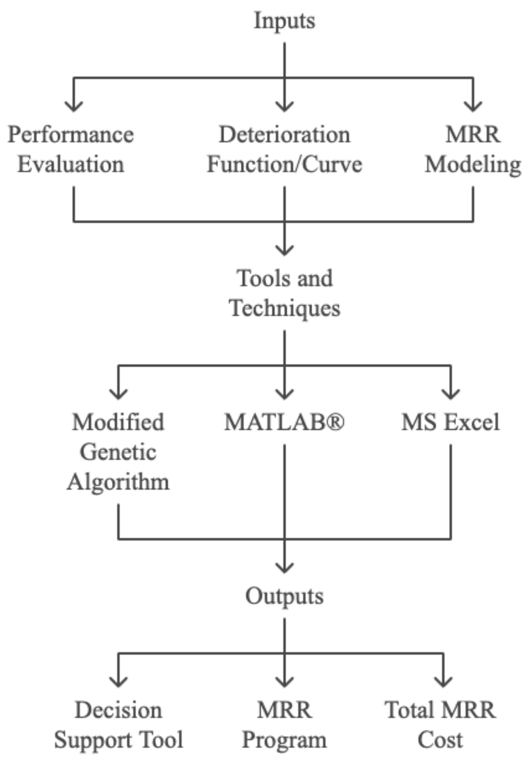

Figure 1. Development of the decision-making support tool inputs, tools, techniques, and outputs

3.1.2 Deterioration Function

To estimate element degradation over time, probabilistic or stochastic models are used, given that bridge deterioration follows a stochastic, rather than deterministic, process. Among these models, the Weibull distribution function (WDF) is frequently employed due to its advantages including: (i) it has been proven its effectiveness in representing concrete deterioration, and (ii) its parameters are straightforward to calculate [2]. Future performance rates are predicted based on the most recent inspection or condition assessment, providing a realistic representation of deterioration over time using Equation 1:

$$P(t) = 1 \times e^{ln(P_i)(t/t_i)^3} \quad (1)$$

where: P = component performance at time t; P_i = performance at time t_i ; and t_i = inspection time.

3.1.3 MRR Modeling

MRR modeling involves identifying appropriate MRR strategies, estimating the resulting performance improvements, and calculating the associated costs. These MRR strategies are categorized into three types based on the bridge deck's performance (Table 1). For bridge decks in good condition, routine maintenance can be performed. Bridge decks with poor performance may require repair actions, such as increasing deck thickness through localized concrete repairs. For decks with critical performance levels, full deck replacement is recommended.

Modeling performance improvement and predicting the deterioration behavior of an asset after a MRR action is essential. The improvement values associated with each type of MRR relied on a study that was performed by Seo [19], as shown in Table 1. According to the literature review, performance is estimated to improve by 20% when repair actions are implemented to the bridge deck. In the case of bridge deck replacement, performance increases to approximately 90%. For maintenance actions, no performance improvement occurs, but this action slows the deterioration rate of the bridge deck, resulting in a gradual decline over time.

Calculating MRR costs is typically performed either as a fixed percentage of the initial construction or replacement cost, or as a unit cost. For instance, Seo [19] proposed predefined percentage-based estimates for different types of MRR, while Abu Dabous and Alkass [20] developed unit cost models for each MRR type. Each MRR action's unit cost includes direct costs, indirect costs, and a markup to cover contractor profit and contingency. Table 1 summarizes MRR action costs as a percentage of initial construction costs [19] and as fixed unit costs [20] , with unit costs adjusted to 2024 Canadian dollars for inflation.

Table 1. MRR strategies, improvements, and costs per strategy

MRR Strategy	**Improvement**	**MRR Cost**	
		% of initial construction	**unit cost ($/m^2)**
Maintenance	0%	28.5%	$58.39
Repair	20%	65.0%	$1,098.89
Replacement	90%	100.0%	$1,438.72

3.2 Optimizing MRR Strategies

3.2.1 Long-Term Scheduling

As discussed earlier, integrating innovative PBC frameworks within a decision-making support methodology has significantly advanced MRR scheduling. There is a strong shift towards PBCs over traditional contracts for infrastructure management, including bridges, primarily due to cost savings. Additional advantages noted in the literature [21] include but not limited to more integrated services, improved asset management, and economies of scale. This approach incentivizes contractors to achieve specified service levels, often leading to more efficient resource use and enhanced bridge performance over time. Furthermore, the use of PBCs aligns with long-term bridge maintenance goals by providing structured, measurable objectives that guide the maintenance schedule, optimize resource allocation, and improve bridge reliability over its lifecycle [6]. Consequently, the proposed automated tool incorporates PBC settings.

3.2.2 Modified Genetic Algorithm

Since genetic algorithms (GAs) can provide a comparable level of accuracy in the area of global optimization while being more time efficient than conventional optimization techniques [22], they have been extensively used by many researchers in maintenance optimization problems for bridge management. Recently, Ghodoosi et al. [23], Xie et al. [24], Allah Bukhsh et al. [25], and Alsharqawi et al. [15] proposed models to find optimal maintenance and rehabilitation strategies using genetic algorithms. As a modification to the well-known GAs, several works started to design customized variants of the GA. These customized variants use multiple chromosomes with real numbers that represent the different parts of the solution for each individual rather than one chromosome. In addition, the GA operators are specially designed to fit the problem context. The modified GA starts with feasible individuals satisfying all constraints, which makes it easier to search for the optimal solution compared to the case of the original GA, where the feasibility of individuals might not be satisfied. It is worth noting that in this type of modified GA, a certain number of operators is defined and applied in all iterations; thus, the probabilistic nature of changing the individuals is removed, which reduces the number of parameters needed to be tuned. In this research, a modified GA is used due to its quick convergence and excellent performance, as in this modified GA, for each individual, a chromosome defines the potential MRR actions over the planning years. The chromosomes are generated in a way to satisfy the predefined performance thresholds. The population is replaced with a new random one in case of no improvement over several generations. The modified GA code is developed using MATLAB® software language and optimization toolbox.

In order to solve the MRR optimization problem, this algorithm starts by generating V individuals, each individual ($v \in V$) contains a random MRR strategy for each n year ($n \in N$). It sets the global total MRR cost to $+\infty$ and the global average performance to $-\infty$. In each iteration δ ($\delta \in \varphi$), the algorithm performs the following steps:

1. It calculates the yearly performance for each individual (p_v^n).
2. Then, it checks in each year if the yearly performance is within the limits and modifies the selected MRR strategy randomly as an attempt to fix any performance violation.
3. It calculates the average performance for each individual (P_v).
4. It calculates for each individual v the total MRR cost.
5. It identifies the local minimum total MRR cost and the local maximum average performance and uses them to update the global total MRR cost to $+\infty$ and the global average performance.

It is worth noting that the modified GA differs than the original GA in the following aspects: i) the generated population is feasible prior applying any operator; ii) the entire population is discarded if the optimal solution did not improve for iteration and a new population is generated randomly to allow for more diversity in the searching domain; and iii) the probability of crossover and mutation are eliminated. Crossover and mutation operators are applied in a different manner. In each iteration, the population is divided into subsets. Each subset has five individuals. The five individuals in the subset are ranked based on their fitness value. The best individual in the subset is selected and the five operators are applied on it. It should be noted that the first operator is do nothing which keeps the individual unchanged. Therefore, each subset of five individuals is replaced with a new subset containing the best individual in the subset and four new individuals.

3.2.3 Optimized MRR Program

As previously mentioned, bridge MRR actions are typically categorized into maintenance {2}, repair {3}, replacement {4} and no action {1} which is a do-nothing strategy. Specific MRR actions can be found under each category. With these four major categories, several combinations of actions can be generated over the analysis period producing large number of strategies or possible solutions. The longer the analysis period, the larger the search space is because the number of possible solutions equals to the number of MRR actions raised to the power of number of years (i.e., analysis or contract period). For example, if the analysis period is ten years and there are four different MRR actions, the search space will be 1,048,576 (4^{10}). Accordingly, the modified GA-based optimization technique, as a non-linear mathematical modeling, is used to obtain an optimal or near-optimal solution from this large list of solution while meeting the needs and constraints related to the PBC settings. This approach can consider all possibilities and produce enhanced and robust solutions compared to the existing tools and simplified matrices typically used in practice.

The output from the automated tool is an optimized MRR program in which the MRR actions should be executed are determined, the performance prediction in each year is forecasted, and the calculations of the net present value (NPV) during the specified years of MRR plan is estimated. Furthermore, the deterioration curve forecasts the performance for the same duration. The performance of the bridge deck before and after MRR is computed, and performance values are determined based on the Weibull distribution function discussed earlier. The performance improvement is defined based on the type of the applied MRR action.

4 Application of the Tool

4.1.1 Description and Assumptions

A case study is discussed here as a proof of concept and illustration of the presented decision-making support model. The model is applied to a bridge located in Québec, Canada. Names and exact locations of the bridge are not given for confidentiality purposes as per agreements with data providers. An optimization scenario was carried out over the initial remaining life-cycle time of the bridge (till year 2040). The implementation of PBCs over periods of 10 years or more has proven to be an effective strategy for the sustained preservation of transportation networks. Additionally, the Australian experience with the 10-year contract in New South Wales (NSW) demonstrates that realistic PBC criteria and targets are both achievable and effective on a network-wide scale. For the MRR plan, a budget equals to \$225,000 is set allowing for a possibility to cover the cost of replacing the bridge deck.

To run the tool, users must input the condition rating, construction year, year of the last inspection from the latest inspection report, and current year. The tool automatically calculates the current performance, utilizing its embedded deterioration function. Additional input variables are required to execute the decision-making optimization process. These variables include the duration of the MRR plan, budget constraints, interest rate (i=4% is used in this study), and performance thresholds. Moreover, MRR costs are incorporated based on the MRR modeling formulation, as showed in Table 1. Table 2 summarizes the case study data attributes. The subsequent section will present a set of trade-off list detailing MRR actions applied.

Table 2. Case study data attributes

Bridge Attribute	Input
Construction Year	1965
Age	58
Construction Cost	N/A
Area (square meter)	152
Inspection Year	2021
Performance at Inspection Year	63.99%

4.1.2 Results and Discussion

The 2021 inspection assessed the bridge deck's physical condition at 63.99%, indicating poor performance during that year. Using performance modeling, deterioration curves were mapped, starting with the ideal deterioration curve (representing ideal performance), knowing that the bridge was constructed back in 1965. To create the deterioration curve (performance without intervention), data from the 2021 inspection survey was used, and the curve was plotted using Eq. 1, with t_i corresponding to 2021. Implementing the automated tool on the case study allowed for the reconstruction of the updated deterioration curve (performance with MRR intervention).

The implementation of the modified GA-based optimization technique presented earlier provides a variation of MRR strategies applied at various years throughout the time horizon of the described scenario. Figure 2 shows the bridge deck performance without and with MRR interventions after applying the developed tool. The present worth of the optimized scenario for the case study is also calculated. The total MRR actions costs equal to \$1,686,557.11. Table 3 presents the optimal MRR program developed from applying this tool where the MRR action and its corresponding cost are shown. In this case, it is suggested that the contracting agency tendering the contract can allocate a budget of no more than the total MRR actions costs. The budget assignment is based on the developed decision-making support tool which minimizing the total cost while maximizing the performance.

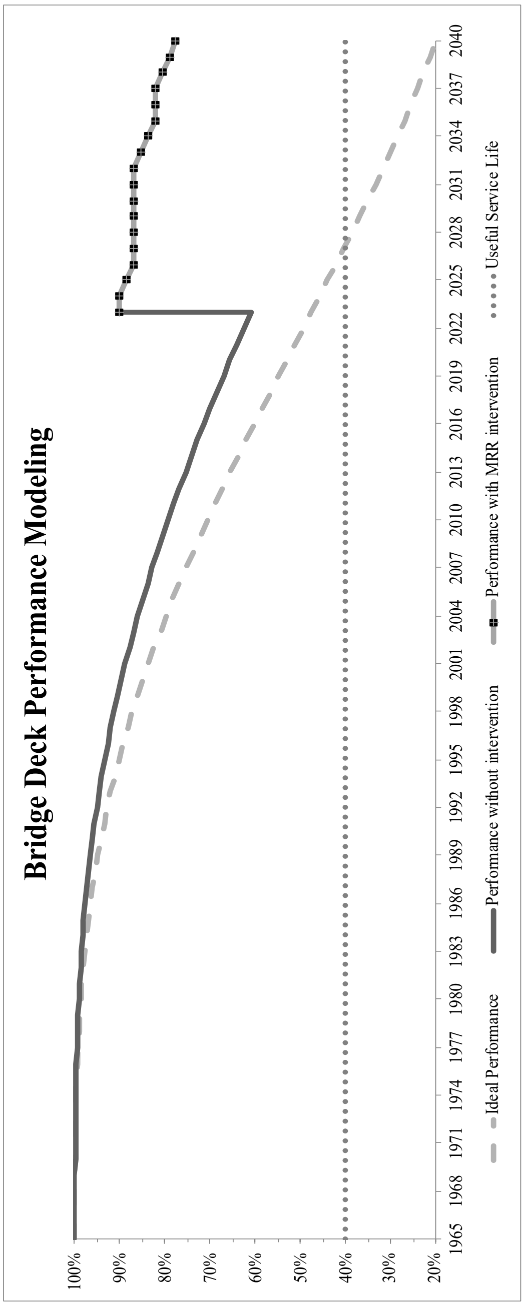

Figure 2. Case study performance modeling, including curves without and with MRR interventions

Based on the performance monitoring data, actual performance may vary compared to the predicted from the deterioration curve. Using real time data after performing inspections, the MRR program may be updated by running the tool again. The significance of this is that re-optimization of the MRR program using real time data and continuous validation of deterioration curve may result in cost saving and higher profit to the contractor in case of overestimating the deterioration rate and consequently scheduling the MRR action earlier than needed.

Table 3. Case study optimal MRR program

Year	MRR Action	MRR Cost	Total MRR Cost
0			$ 1,686,557.11
1	{4}	$ 210,274.46	
2	{2}	$ 4,591.20	
3	{3}	$ 148,490.20	
4	{3}	$ 142,779.04	
5	{4}	$ 179,743.49	
6	{3}	$ 132,007.25	
7	{3}	$ 126,930.05	
8	{3}	$ 122,048.12	
9	{3}	$ 117,353.96	
10	{3}	$ 112,840.35	
11	{1}	$ -	
12	{3}	$ 104,327.24	
13	{3}	$ 100,314.66	
14	{3}	$ 96,456.40	
15	{1}	$ -	
16	{2}	$ 2,651.30	
17	{3}	$ 85,749.39	
18	{1}	$ -	

5 Conclusion

The majority of existing decision-making methodologies for bridge management aim to balance the dual objectives of maintaining or extending bridge serviceability while minimizing total costs. These inherently conflicting goals significantly complicate the decision-making process. To address this bi-objective optimization challenge, this research has developed an automated decision-making tool for the long-term scheduling of MRR strategies. The convergence of probabilistic models and multi-objective optimization approaches in this study underscores the advancements in MRR planning, enhancing both efficiency and effectiveness. Further, research findings concluded that integrating the PBC approach into the MRR decision-making process offers better results in long-term plans. The developed tool not only achieves substantial cost savings but also prolongs the functional lifespan of bridges through timely and strategic maintenance interventions. By enabling bridge managers to tailor MRR strategies to various conditions and constraints, this tool promotes sustainable and efficient resource utilization while ensuring the serviceability and structural integrity of bridge infrastructure over time.

However, the research does have certain limitations: (1) the study primarily focused on bridge decks, without extending the tool's application to other bridge components or related assets; (2) the effects of MRR actions on bridge performance were restricted to maintenance, repair, and replacement strategies; (3) user and external costs (e.g., user delays) associated with MRR actions were excluded from the calculation of MRR unit costs, though these costs could be incorporated in future studies; and (4) the 10-year planning horizon was chosen to align with common performance-based contracting practices, yet it limits the direct comparison of predicted MRR plans against the actual long-term degradation of bridge decks.

To address uncertainties inherent in long-term forecasts, the tool supports periodic re-optimization with updated inspection data, and future work will incorporate extended monitoring and sensitivity analyses to further validate model predictions. Moreover, future research could expand the scope of the tool to encompass additional bridge elements and broader infrastructure networks, further enhancing its applicability and impact. Additionally, future work could integrate real-time sensor data from structural health monitoring systems to dynamically update the predefined deterioration models.

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