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A Simheuristic Approach to Scheduling Sustainable and Reliable Maintenance for Bridge Infrastructure

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Abstract: Designing maintenance strategies for a vast portfolio of aging infrastructures requires decision-makers to ensure adequate safety levels while addressing the requirements on service interruptions, costs, and workforce availability. This study addresses the problem of scheduling maintenance interventions for a portfolio of bridges, aiming to minimize CO_2 emissions while meeting minimum reliability requirements and adhering to workforce and budget constraints. To achieve this, we present a Simheuristic algorithm that combines a metaheuristic core based on the Adaptive Large Neighborhood Search metaheuristic with a Monte Carlo simulation module. This integration allows for the evaluation of optimized scheduling solutions, accounting for the inherent randomness in the structural deterioration process. The proposed approach is tested in a comparative analysis against traditional time-based and condition-based scheduling methods. Results from diverse bridge portfolios demonstrate that the proposed algorithm offers improved performance in terms of both total costs and CO_2 emissions.

Keywords: scheduling optimization; bridge maintenance; sustainability

MSC: 90B36; 90B25; 90C27

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1. Introduction

Infrastructure Asset Management (IAM) aims to ensure structural safety and reliability through a comprehensive strategy that includes inspections, continuous monitoring, and maintenance activities. The scheduling of these activities focuses on improving and maintaining structural safety at minimal costs while addressing limited resources and regulatory requirements and leveraging the expertise of asset managers. Consequently, the optimized planning of activities such as inspections, monitoring, and maintenance plays a crucial role in enhancing various aspects of IAM. Inspection strategies are partly dictated by regulatory standards, which are the rules and guidelines set by governing bodies. For instance, in Italy, the guidelines for managing and monitoring bridges and viaducts establish inspection methods and the prioritization of interventions [1].

In contrast, the current regulatory codes lack specifications on planning maintenance activities, which, in addition to ensuring minimum safety requirements, can be optimized for different objectives.

In this context, each infrastructure owner can decide to ensure structural safety by optimizing the maintenance schedule according to specific goals. The complexities of this task have led to different contributions in the scientific literature, each proposing distinctive approaches to tackle these challenges. Most approaches propose methods to optimize maintenance planning, ensuring cost-effectiveness while maintaining the reliability of structures. Kong and Frangopol [2], Saydam and Frangopol [3] have focused on reducing the infrastructure life-cycle costs while maintaining a specified reliability index. Various planning strategies have been explored, including the work by Ghodoosi et al. [4], who developed an optimization framework incorporating financial models and genetic algorithms to assess life-cycle costs precisely. Their approach was tested on a supported bridge deck, obtaining substantial cost reductions. For large portfolios of bridges, Morcous and Lounis [5] proposed a similar optimization method and combined it with Markov chain models to manage the complexity of the problem by grouping homogeneous facilities. Aiming to optimize maintenance scheduling with limited resources, Nili et al. [6] introduced a simulation-based Bridge Maintenance Optimization framework that integrates genetic algorithms and discrete event simulation to optimize bridge maintenance schedules, considering constraints like workspace and crew limitations. Within the same spirit, in their work Allah Bukhsh et al. [7] proposed a solution approach that optimizes multi-year maintenance plans for bridges using heuristic rules, Markov chains, and genetic algorithms to maximize performance within budget constraints.

Another aspect to point out is the unpredictability of infrastructure degradation, which needs to be modeled in optimization problems as a stochastic variable. For instance, Ghafoori et al. [8] developed machine learning models using the US National Bridge Inventory data to forecast the deterioration rate of bridges and improve intervention strategies within a dependable scenario. While these approaches have made significant contributions to the field, more emphasis should be placed on reducing the environmental impact of maintenance operations. The infrastructure sector plays a crucial role in carbon emissions through the construction of new roads and railways and the upkeep of existing facilities [9]. To effectively address climate change, there is an urgent need to optimize resource use and cut emissions [10]. In this direction, Peng et al. [11] introduced optimization methodologies that consider sustainability criteria. In their multi-objective formulation, they incorporated factors like failure probability, life-cycle costs, and the environmental impact of maintenance activities during the bridge service life. Sustainability aspects are also addressed in the works of Sun et al. [12], Gokasar et al. [13], Lei et al. [14]. Gokasar et al. [13] designed a tool for prioritizing bridge maintenance, which includes emissions caused by detours in its calculations. Nevertheless, their tool prioritizes bridges needing maintenance rather than providing a detailed schedule. The predominant focus in the existing scientific literature tends to revolve around minimizing costs when scheduling maintenance operations. When sustainability criteria are taken into account, the impact of traffic detours is often overlooked or oversimplified. This can lead to a limited understanding of emissions and the effects of interventions that significantly affect traffic flow. According to Xu and Guo [15], in reinforced concrete bridges, the emissions from detours can exceed the direct emissions from the intervention. Furthermore, many studies are limited to individual bridges rather than addressing the broader context of structural portfolios.

The present work aims to fill this gap by introducing an algorithmic framework that minimizes the carbon footprint of maintenance operations for a portfolio of aging bridges. This framework ensures safety levels and takes into account economic and workforce resources. In our approach, CO_2 emissions are calculated as a combination of emissions from maintenance interventions and pollution resulting from detours. The core of our methodology is an optimization process based on the Adaptive Large Neighborhood Search algorithm (ALNS) [16–18], which thoroughly explores the solution space and interfaces with a Monte Carlo simulation module. This stochastic simulation module accounts for the uncertainties inherent in the structural deterioration process, allowing for a more robust evaluation of the analyzed solutions' reliability. The resulting methodology is referred to as Sim-ALNS.

This work aims to significantly impact real-world infrastructure management, offering a practical and comprehensive approach to bridge maintenance that considers safety, sustainability, and resource constraints. With the aim of validating the proposed approach for a diverse range of bridge infrastructures, this work compares the maintenance solutions of Sim-ALNS against conventional maintenance paradigms. The results assess the proposed approach's competitivity compared to other traditional scheduling strategies. The paper is structured as follows. Section 2 offers a brief description of the problem and the optimization algorithm is reported, while the details of the Sim-ALNS solution strategy are discussed in Section 3. The computational experiments that assess the performance of the proposed approach are described in Section 4, while Section 5 reports the corresponding results. Lastly, Section 6 provides the concluding remarks.

2. Mathematical Formulation

As stated in the introductory section, successful infrastructure management requires ensuring high levels of safety for users and limited service interruptions. All this must be managed economically and in the workforce with low resources. To this end, it is possible to formalize the problem as follows.

Let $B = \{b_1, b_2, \ldots, b_n\}$ be a portfolio of bridges to be maintained, and let T be a time horizon within which the service needs to be guaranteed. The set of possible maintenance interventions $I = \{i_1, i_2, \ldots, i_m\}$ is such that each $i \in I$ is associated with a cost C_i, a workforce demand W_i, an average improvement in reliability R_i, and a level of traffic interruption L_i. The aim of the problem studied in the present work is to schedule a set of maintenance interventions on the bridges of B such that the total CO_2 emission E over T is minimized, while ensuring an adequate level of safety for the users of the bridges, within the resource availability of the infrastructure's owner.

In this context, the emission related to an intervention i on bridge b_j is computed as the sum of two distinct terms, E_{dir} and E_{det}. The first term, E_{dir}, represents the emission directly implied by the intervention's activities and energy consumption, while the second term, E_{det}, measures the emissions that would result from the detour caused by the bridge's closure or a traffic limitation.

Therefore, E_{det} is computed as:

$$E_{\text{det}} = T_i \cdot D \cdot (V \cdot P_{\text{car}} \cdot e_{\text{car}} + V \cdot P_{\text{truck}} \cdot e_{\text{truck}}) \tag{1}$$

where T_i is the duration of intervention i (in days), D is the detour distance (in km), V is the average daily traffic on the bridge, P_{car} and P_{truck} are, respectively, the percentages of traffic represented by cars and trucks, and e_{car} and e_{truck} are the average emissions per km for cars and trucks, respectively.

Moreover, let x be an optimized schedule; then, the operations in x shall be planned so that three distinct constraints are required:

- R1 At any time $t \in [0, T]$, the reliability index of each bridge $b_i \in B$ should be always larger than a user-defined threshold;
- R2 The total costs of the interventions planned on B within the time horizon should not exceed a maximum budget, B_{max};
- R3 At any time $t \in [0, T]$, the workforce usage implied by the interventions planned in x should not exceed the maximum workforce availability, WF_{max}.

To model the natural aging process of a bridge, the decrease in reliability can be modeled as proposed by Frangopol et al. [19] (Figure 1). For each bridge, the reliability index can be specified as a combination of two parameters, an initial reliability β_0 and a decaying rate α. At any time, an intervention improves the reliability of a certain amount γ and, for a limited time interval, yields an improved decaying factor α'.

Figure 1 provides a clear representation of a modeling strategy for the aging phenomenon of a structure in general. However, in many application scenarios, the nature of the variables involved is stochastic rather than deterministic. This means that at any point in time t, the actual value of reliability can be seen as a random variable, the distribution and mean value of which can be estimated through experience and empirical data. Therefore, the deterioration pattern of a bridge is more accurately represented by Figure 2. As detailed in Section 3.2, the proposed solution framework includes Monte Carlo sampling to accurately evaluate the reliability of the maintenance schedule planned by the optimization algorithm.

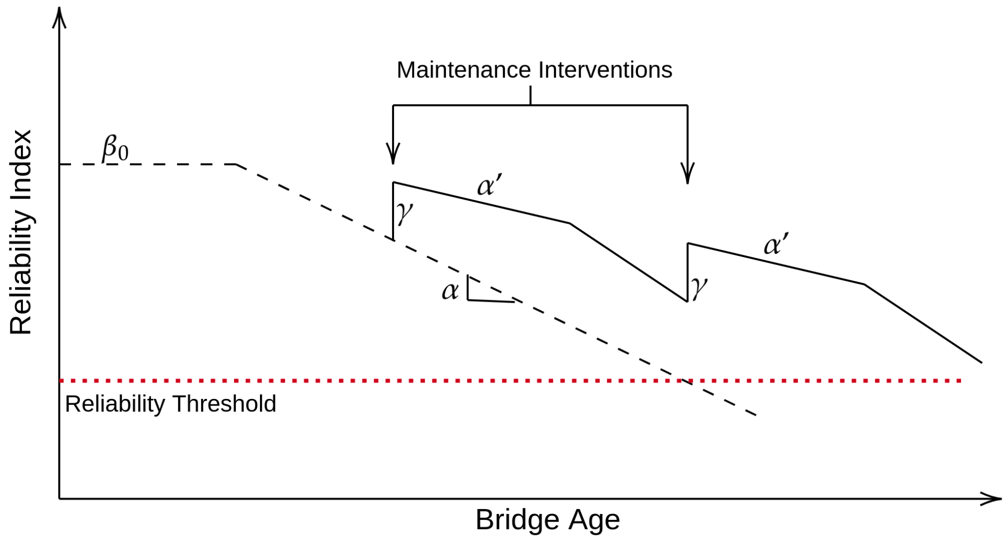

Figure 1. Evolution of the reliability index of a bridge.

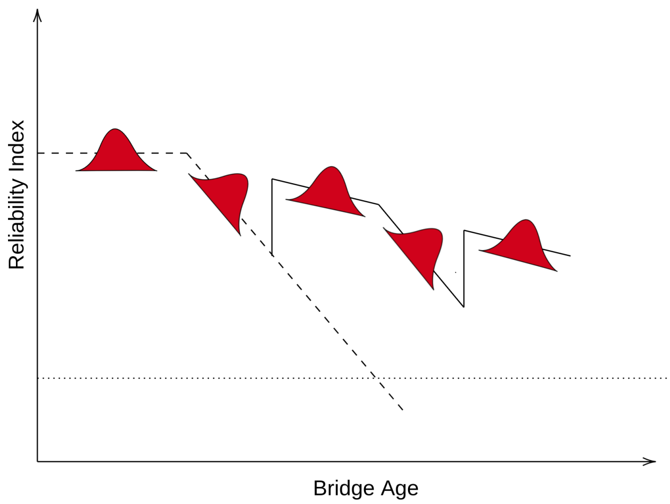

Figure 2. Representation of the impact of uncertainty on the health state of a bridge.

3. Proposed Solution Methodology

The approach described in the present work relies on two interacting modules: an optimization core to achieve the best possible maintenance schedule and a Monte Carlo simulation algorithm to accurately evaluate the reliability indices of the bridges to be maintained. Both components are detailed in the following sections.

3.1. Adaptive Large Neighborhood Search

Adaptive Large Neighborhood Search (ALNS) is a metaheuristic algorithm proposed for solving complex optimization problems. Introduced by Ropke and Pisinger [16], ALNS generalizes Large Neighborhood Search (LNS). LNS is a heuristic algorithm that iteratively modifies an initial solution x with two distinct procedures, one that introduces random perturbations to x, named destroy operator, and a repair operator whose purpose is to optimize the perturbed solution to yield improved performances. Unlike LNS, ALNS implements several destroy and repair operators, respectively collected in sets D and R, to explore the solution space more broadly. According to its optimization strategy, ALNS randomly selects two operators from D and R to modify the current solution x at each iteration. Throughout the process, the randomized choice of the heuristics uses selection probabilities related to the past success of each operator.

The flowchart of Figure 3 shows the general structure of ALNS. The first operations of the algorithm initialize the current solution x, the best solution x_{best}, and the set of probabilities p used in the random selection process. The main loop explores the solution space and iterates until it verifies the stopping rule. At each iteration, ALNS selects a destruction and a repair heuristic from the relative sets and modifies x. As a result of these operations, a new solution, $\bar{x}$, is obtained.

ALNS accepts $\bar{x}$ as the current solution according to an acceptance rule. In accepting a new current solution, ALNS balances the drive to improve the objective function with a diversification approach that avoids stagnating in locally optimal solutions early in the search process. Moreover, if $\bar{x}$ improves the current best objective function, the best solution found is updated. At the end of each iteration, ALNS updates the selection probabilities of the destruction and repair heuristics. The final output of the algorithm is the best solution found in the search process.

In particular, the updating procedure for selection probabilities is performed according to the following rule. Let $h \in R \cup D$ be a given destroy or repair operator used in the last iteration, and let $\bar{x}$ be the solution achieved at the end of such iteration; then, the selection probability p_h of h is updated as:

$$p_h = p_h \cdot \mu + \sigma \cdot (1 - \mu), \tag{2}$$

where μ is a decay factor, and σ is a scalar reward such that:

$$\sigma = \begin{cases} \sigma_1, & \text{if } \bar{x} \text{ has been accepted;} \\ \sigma_2, & \text{if } \bar{x} \text{ has improved the current solution;} \\ \sigma_3, & \text{if } \bar{x} \text{ has improved the best solution,} \\ \sigma_4, & \text{Otherwise.} \end{cases}$$

The present work uses a Simulated Annealing (SA) strategy as an acceptance criterion. SA is a well-known paradigm in the landscape of optimization, as it allows the implementation of a diversification element in the search process by possibly accepting worsening solutions during the exploration of the solution space. Using a characteristic parameter τ, SA computes the difference ΔE between the objective function value of the new solution $\bar{x}$ and the current solution x. Then, the probability of accepting $\bar{x}$ as the new current solution, $P(\Delta E)$, is:

$$P(\Delta E) = \begin{cases} 1, & \text{if } \Delta E < 0; \\ e^{-\Delta E/\tau}, & \text{otherwise.} \end{cases} \tag{3}$$

During the iterations of ALNS, τ decreases, so the probability of accepting worsening solutions is reduced as the search process progresses.

Pools D and R of destructive and repair heuristics implemented to optimize the carbon footprint of maintenance operations are as follows.

Operating on a current maintenance schedule x for the n bridges of B, D comprises three distinct operators, all of which use an input percentage parameter ρ that regulates the disruption's intensity:

1. Random activity removal (RAR): a random ρ of the maintenance activities scheduled in x are removed from the solution.
2. Random bridge schedule removal (RBR): a random ρ of the bridges is selected. RBR removes all the maintenance activities scheduled on such bridges.
3. Random activity type removal (RTR): a random ρ of the activity types is selected. RTR removes from x all maintenance interventions of such types.

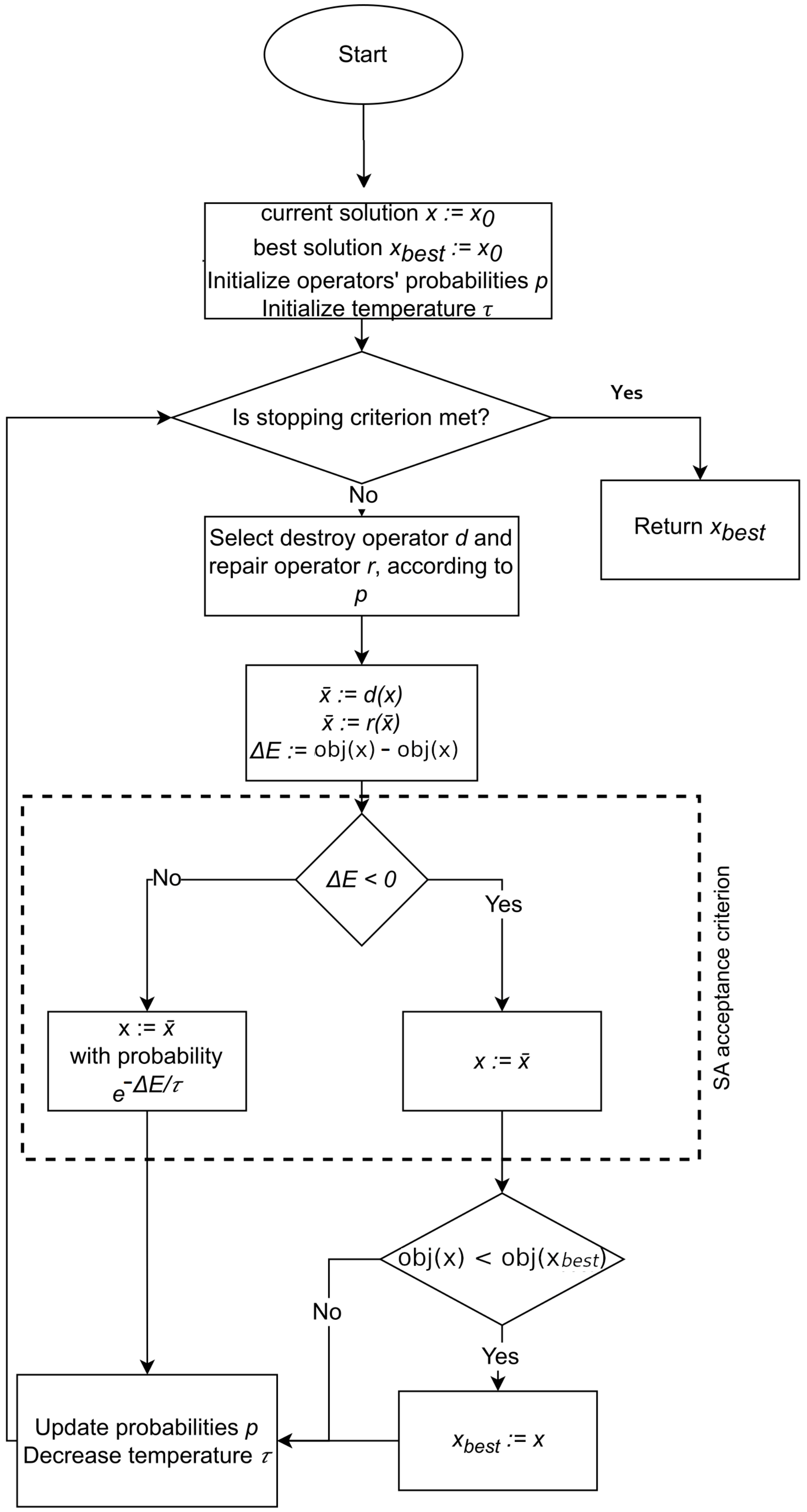

Figure 3. Flowchart of the ALNS framework.

Figure 4 presents a graphical representation of the destroy operators considered in ALNS. The example shows the following:

- The RAR that randomly selects for deletion the intervention of type i_1 for bridge b_2 in quarter 5, intervention i_2 in quarter 4 of b_5, and intervention of type i_1 scheduled for b_6;
- The RBR that shows the deletion of all interventions addressing bridges b_2 and b_3;
- The RTR operator that deletes all interventions of types i_1 and i_3 from the schedule.

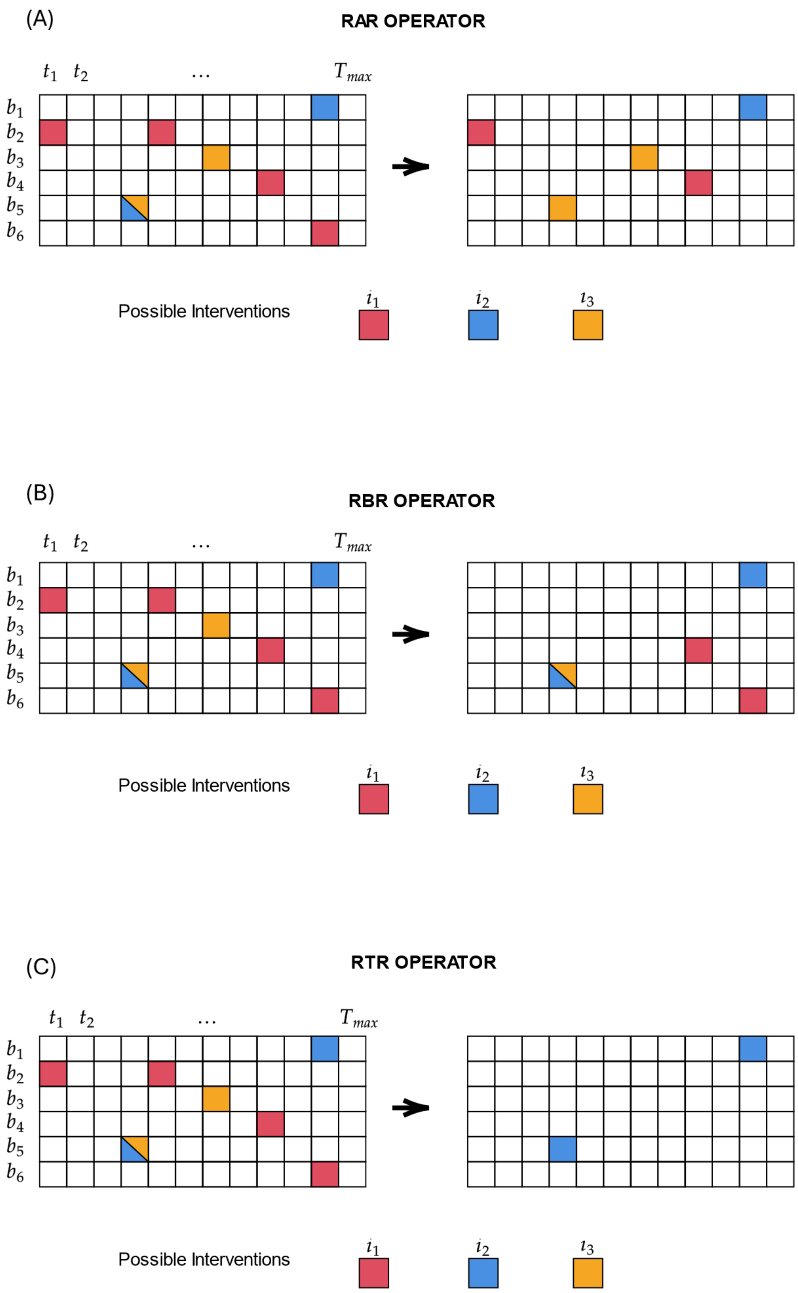

Figure 4. (**A**) Graphical representation of the destroy RAR operator. (**B**) Graphical representation of the destroy RBR operator. (**C**) Graphical representation of the destroy RTR operator.

Respectively, the operators implemented in set R are as follows:

1. First Possible Improvement (FPI): The set B of bridges is iterated sequentially. FPI schedules the first intervention on each bridge to improve the objective function value until all bridges exceed the reliability threshold throughout the time horizon.
2. Best Intervention in Bridge Sequence (BBS): The set B of bridges is iterated sequentially. On each bridge, BBS schedules the best intervention for the lowest possible emissions until all the bridges exceed the reliability threshold throughout the time horizon.
3. Greedy Cost Repair (GCR): This operator prioritizes scheduling interventions based on their cost, starting with the least expensive. It attempts to maximize the number of interventions within the available budget, ensuring that budget constraints are respected.
4. Reliability Boost (RB): The operator focuses on maximizing the improvement in bridge reliability by scheduling interventions that offer the highest reliability increase. It prioritizes interventions that address the most critical reliability issues first, aiming to rapidly improve the overall health of the bridge network.

3.2. Monte Carlo Simulations

Classically, problems of the optimization literature were described using deterministic formulations, yet their applications to real-world scenarios constantly faced the challenges implied by uncertainty. Accordingly, when the optimization algorithms do not account for stochasticity, the solutions achieved may be unstable or not feasible in practical applications [20]. Therefore, a growing stream of research combined the power of metaheuristic algorithms with the assessment provided by Monte Carlo simulations [21]. These hybrid simulation–optimization approaches allow for the correct assessment of promising solutions by evaluating the uncertainties that characterize the problem of interest.

As Section 2 discussed, in the context of bridge maintenance planning, the reliability index of each structure is related to uncertain information. Indeed, for the epistemic uncertainties of the model assumptions or the noise and incompleteness in data, at each stage of the time horizon, the decaying factor α of the reliability index can be seen as a random variable.

To this end, at each time stage t within the time horizon, the reliability index can be obtained as the reliability value corresponding to the previous time instant, $t-1$, diminished according to a stochastic α factor. In our framework, this stochasticity is modeled as a Weibull random variable, with shape and scale, respectively, equal to 0.05 and 2, therefore giving:

$$\beta(t) = \beta(t-1) - \Delta T \cdot (\alpha - wblrnd(0.05, 2)) \tag{4}$$

In summary, the proposed approach uses Monte Carlo simulations to accurately assess the feasibility of each maintenance schedule under various conditions. In this approach, each evaluation of a new solution x involves a user-defined number of Monte Carlo samplings of the stochastic variables throughout the time horizon $[0, T]$, ensuring that the planned maintenance operations in x satisfy the requirement R1 of Section 2 for each simulated scenario.

To balance the reliability of structural assessments with computational performance, the Monte Carlo simulation module follows a two-stage process. In fact, during the execution of ALNS, the solutions are evaluated using a lower number of simulations, n_{sim}. On the contrary, at the end of the optimization process, the best solution found is assessed with a higher number of simulations, $N_{sim} > n_{sim}$, to appraise the feasibility with higher accuracy. In the numerical experiments, n_{sim} and N_{sim} are, respectively, equal to 25 and 100 repetitions. The value of N_{sim} was set to 100 as preliminary tests with a larger number of runs did not exhibit no significant differences in the final distribution of reliability.

4. Computational Analysis

The numerical experiments that assess the performance of the proposed metaheuristic approach rely on the comparison of the solutions achieved by ALNS with solutions obtained using the time-based and condition-based maintenance strategies. The analyses use a benchmark containing geographical and logistic information available for existing bridges and consider three different scenarios arranged in decreasing order of mean reliability index. The benchmark set featured in the numerical analyses is thoroughly described in Section 4.1, while the computational results are presented in Section 5. Our proposal was implemented in Matlab 2022, and the experiments were run on a 3.50 GHz Intel Core I9 processor with 64 GB of RAM. The characteristic parameters of the ALNS algorithms, as defined in Section 3.1, are reported in Table 1, that also reports their best configuration, as found in a preliminary set of experiments. Among those, it is noted that while μ and σ_i were set to fixed values, ρ was selected uniformly at random in the interval $(0, 1)$ at each call of a destroy operator.

Table 1. Parameters of the ALNS algorithm.

Parameter	Meaning	Setup
μ	Decay factor	0.9
σ_1	Reward for acceptance	2
σ_2	Reward for improvement	4
σ_3	Reward for best solution	10
σ_4	Default reward	1
ρ	Intensity of perturbation	$U(0, 1)$
$N_s im$	Number of post-optimization simulations	100

4.1. Benchmark Dataset

The dataset used in the numerical experiments is extracted from the bridge data provided by the Federal Highway Administration (FHWA) of the U.S. Department of Transportation. The full dataset, retrievable online [22], comprises over 600 thousand structures, with the aim of precisely inventorying the bridges of the US. Each bridge is cataloged using a wide range of information, collected in a maximum of 117 items, including structural and historical data, ownership, geographical location, and so on. The bridges used in the computational experiments of the present section are 15 PSC highway bridges of the District of Columbia. The structures were built between 1942 and 2012 and present span lengths ranging from 13.7 m to 23.2 m. For each bridge, Table 2 reports the main geometric characteristic and a summary of the daily traffic record.

Table 2. Summary of the bridges considered in the numerical experiments.

ID	Year Built	L	W	Detour	Avg Daily Traffic	Avg Daily Truck Traffic
#	[y]	[m]	[m]	[Km]	#	%
1	1942	13.7	26.5	0	55,700	4
2	1942	17.1	26.5	0	55,700	4
3	1942	14.3	26.5	0	55,700	4
4	1959	21.9	47.3	2	153,700	5
5	1959	12.5	28.0	3	153,700	5
6	1963	21.3	8.4	2	12,500	5
7	1959	14.9	24.4	2	150,600	4
8	1964	17.4	11.9	2	19,700	1
9	1964	15.9	14.6	2	24,500	1
10	1964	18.6	13.7	2	15,800	1
11	1964	22.6	11.4	3	10,400	1
12	1962	21.3	41.5	3	10,700	1
13	1972	21.6	41.5	2	58,000	5
14	2012	23.2	20.1	0	86,500	4
15	2012	22.9	18.0	3	86,500	4

Subsequently, starting from the bridges summarized in Table 2, this work considers three scenarios, arranged in decreasing order of mean reliability index at $t = 0$. These scenarios are denoted as "Moderate", "Low", and "Critical", and are characterized by initial mean β values of $3.25, 3.5$, and 4.2. Lastly, the maintenance interventions considered in the algorithm are summarized in Table 3.

In the analyses, the minimum reliability considered for the structures is 2.5, the time horizon considered is 20 years, while the total available budget is 10 million euros to be spent on the whole portfolio.

Table 3. Summary of the possible maintenance operations considered in the analyses.

Name	**Traffic**	**Average Cost**	**Average Reliability Improvement**	**Work Force**
-	**-**	**[Euro/m^2]**	**[-]**	**[Units/m^2]**
Surface Repair	Normal	469.00	0.375	0.016
Crack injection	Limited	588.00	0.250	0.020
FRP jacketing	Limited	1254.40	0.975	0.022
Component replacement	Closure	2667.00	1.605	0.093

4.2. Comparative Analysis Setup

The performance of the scheduling suggested by ALNS, in terms of both costs and emissions, compared to traditional maintenance strategies such as periodic and reactive maintenance. This comparison aims to underscore ALNS's adaptability to various structural conditions and test its capabilities in providing reliable schedules for structural maintenance.

Periodic maintenance policies typically schedule interventions based solely on the time since the last intervention. An intervention time (T_d) is set, and minor maintenance is performed whenever T_d elapses from the previous intervention. In contrast, reactive maintenance focuses on the actual condition of the structure. Interventions are only scheduled if a bridge approaches structural failure following an inspection or assessment. In this case, a confidence index (F_c) sets an intervention threshold that closely aligns with the safety limit.

In this study, both strategies serve as benchmarks to assess the feasibility of ALNS in real-world scenarios. For periodic maintenance, a T_d of 15 years is set for low-impact interventions, while a high-impact intervention is initially planned to address pre-existing critical conditions. A failure confidence index of 5% is set for the reactive maintenance strategy, with a high-impact intervention scheduled if the reliability index is projected below 1.05 times the safety threshold index.

5. Numerical Results

Table 4 reports the computational results achieved in the numerical experiments. For each scenario and each maintenance strategy, the solution performance is compared regarding emissions and costs.

Analyzing the results, the first behavior that can be pointed out is that periodic maintenance is the strategy characterized by the least competitive performance. This is widely expected, as also pointed out in the scientific literature, since the fixed-time schedule of periodic maintenance often results in frequent and unnecessary maintenance operations. Therefore, this property is reflected in both the economic cost and the emissions related to this approach, which are significantly larger than those achieved by both Sim-ALNS and the reactive strategy in all scenarios.

On the contrary, the maintenance schedule achieved by a reactive approach is more competitive in terms of costs and emissions, as its operations are strictly related to the reliability indexes of the structures of interest. This is especially true in the *moderate* scenario, where the initial state of the portfolio is good enough to require only a limited number of interventions over the time horizon. Nevertheless, the performance achieved by Sim-ALNS is comparable in the moderate scenario and significantly better in the *low* and *critical* cases.

Table 4. Comparison of the optimized solution (ALNS) with the maintenance schedule of the reactive maintenance and periodic maintenance approaches.

Moderate Maintenance Strategy	**Sim ALNS**	**Reactive**	**Periodic**
Cost [EUR]	2.18×10^6	2.75×10^6	5.05×10^6
Emission [CO_2 ton]	1.04×10^4	1.05×10^4	5.40×10^5
Low Maintenance Strategy	**Sim ALNS**	**Reactive**	**Periodic**
Cost [EUR]	4.48×10^6	7.08×10^6	1.19×10^7
Emission [CO_2 ton]	2.46×10^4	2.85×10^4	1.52×10^5
Critical Maintenance Strategy	**Sim ALNS**	**Reactive**	**Periodic**
Cost [EUR]	5.68×10^6	1.05×10^7	1.19×10^7
Emission [CO_2 ton]	3.38×10^4	4.08×10^4	1.52×10^5

Indeed, as the portfolio's global reliability worsens, i.e., for the low and critical scenarios, the advantages of using the proposed approach are notably increased, as both the costs and the emission values are markedly reduced with respect to the competing approaches. These results evidence how an optimization approach is a valuable resource whenever the average number of interventions to be planned within the time horizon is high.

The impact of the three initial reliability levels on the performance of SimALNS is illustrated in Figures 5 and 6. These two graphs show the total cost incurred and emissions produced over time. A lower distribution of reliabilities across the portfolio is expected to lead to interventions that are (i) generally more expensive and (ii) required earlier as time passes. This trend is evident in all pairwise comparisons between two consecutive levels of initial reliability.

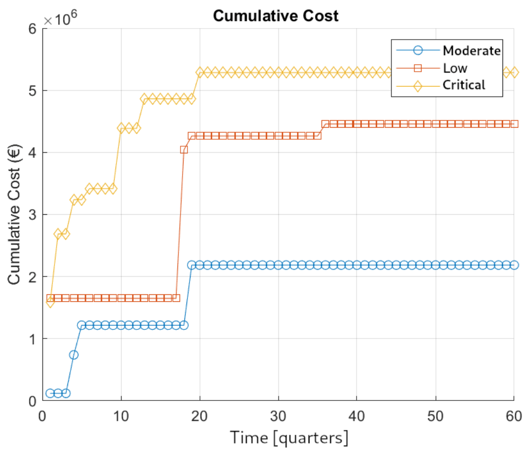

Figure 5. Evolution of the costs implied by the interventions over the time horizon for the three scenarios.

Additionally, the three maintenance strategies can be compared using the *low* scenario as the reference point (*low* is selected as the reference since it represents the intermediate level of average reliability used in the experiments). Figures 7 and 8 illustrate the evolution of costs and emissions for each maintenance approach. When examining cumulative costs over time, it is evident that the periodic approach leads to recurring, significant spikes in expenditure due to its fixed intervention schedule. In contrast, the reactive strategy and SimALNS, which are informed by the structural health of the bridges, achieve similar safety levels with fewer interventions. However, SimALNS adopts a more proactive stance than the reactive approach, scheduling maintenance earlier and focusing on smaller, less disruptive interventions. This reduces both overall costs and emissions.

As shown in Figure 7, the time-based strategy results in more frequent, unnecessary traffic disruptions, while the reactive strategy, which triggers interventions only when reliability nears the safety threshold, leads to larger, more resource-intensive repairs.

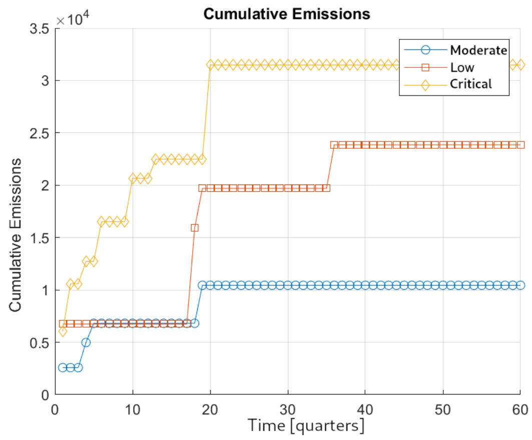

Figure 6. Evolution of the cumulative emissions over the time horizon for the three scenarios.

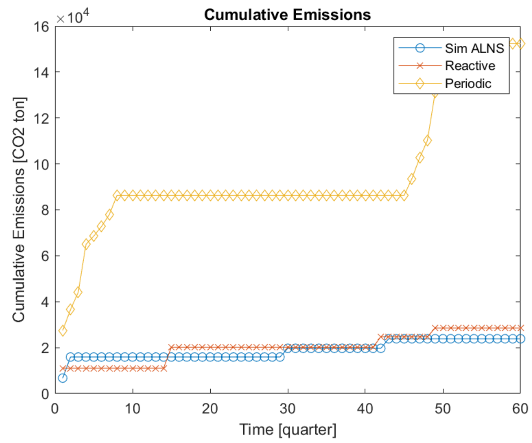

Figure 7. Evolution of emissions for each maintenance approach (*low* case).

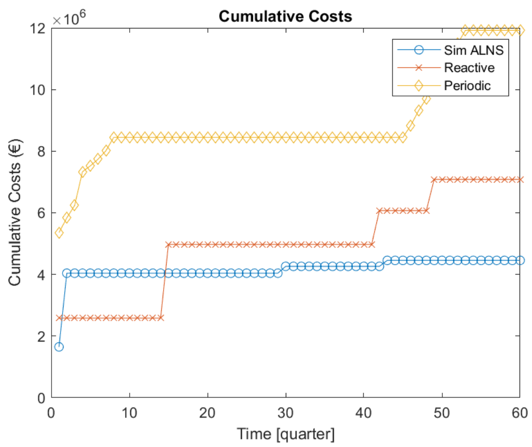

Figure 8. Evolution of expenditures for each maintenance approach (*low* case).

6. Conclusions

This paper deals with optimizing the carbon footprint of maintenance operations on a set of aging bridges. To this end, the problem was formally described as an objective function that considers the pollution caused by the detours implied by traffic interruptions. The maintenance schedule pursued in this work is subject to three different constraints, requiring that, at any time within the time horizon, the reliability indices of the structures need to be above a certain threshold and that the total costs and periodic workforce implied by the operations need to be below the maximum values allowed. To solve this problem, this paper presents a hybrid optimization–simulation algorithm that combines the intensification ability of an ALNS metaheuristic with the stochastic simulation of the Monte Carlo approach. Accordingly, the proposed approach can broadly explore the solution space in the pursuit of optimized solutions while correctly accounting for the uncertainty that characterizes the optimization scenario.

In the numerical experiments, the proposed approach was compared with two well-established maintenance strategies: periodic and reactive maintenance approaches. The computational results evidence that the SimALNS algorithm can achieve improved solutions in terms of emissions and costs compared to its two competitors. In future research, this approach will be combined within a specific structural health monitoring framework for PSC bridges [23] so that, at any time, the reliability indices can be estimated with higher accuracies and formulate a feedback framework that automatically plans CO_2-efficient maintenance interventions as soon as the monitoring process detects structural criticalities.

Ultimately, the approach discussed in this paper aims to bridge the gap between classical cost–reliability optimization and the sustainability-oriented management of infrastructure portfolios, by properly accounting for the stochasticity of the degradation phenomenon. Accordingly, future academic contributions can extend this work by exploring the integration of additional stochastic environmental and social impact metrics into the optimization framework.

Moreover, future lines of research could build upon this research by investigating dynamic scheduling methods able to adjust maintenance operations in real time, on the basis of data collected by structural health monitoring systems. Such advancements could further improve the adaptability and efficiency of sustainable maintenance scheduling.

Lastly, the methodology's optimization core will be extended so that bridge portfolios of larger sizes can be managed in short computational times.

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References

1. Ministero delle Infrastrutture e dei Trasporti. Linee Guida per la Classificazione e Gestione del Rischio, la Valutazione della Sicurezza ed il Monitoraggio dei Ponti Esistenti. Decreto del Ministero delle Infrastrutture e dei Trasporti. 2020. Available online: https://cslp.mit.gov.it/circolari-e-linee-guida/linee-guida-la-classificazione-e-gestione-del-rischio-la-valutazione-della (accessed on 19 September 2024).
2. Kong, J.S.; Frangopol, D.M. Life-cycle reliability-based maintenance cost optimization of deteriorating structures with emphasis on bridges. *J. Struct. Eng.* **2003**, *129*, 818–828. [CrossRef]
3. Saydam, D.; Frangopol, D.M. Risk-based maintenance optimization of deteriorating bridges. *J. Struct. Eng.* **2015**, *141*, 04014120. [CrossRef]

4. Ghodoosi, F.; Abu-Samra, S.; Zeynalian, M.; Zayed, T. Maintenance cost optimization for bridge structures using system reliability analysis and genetic algorithms. *J. Constr. Eng. Manag.* **2018**, *144*, 04017116. [CrossRef]
5. Morcous, G.; Lounis, Z. Maintenance optimization of infrastructure networks using genetic algorithms. *Autom. Constr.* **2005**, *14*, 129–142. [CrossRef]
6. Nili, M.H.; Taghaddos, H.; Zahraie, B. Integrating discrete event simulation and genetic algorithm optimization for bridge maintenance planning. *Autom. Constr.* **2021**, *122*, 103513. [CrossRef]
7. Allah Bukhsh, Z.; Stipanovic, I.; Doree, A.G. Multi-year maintenance planning framework using multi-attribute utility theory and genetic algorithms. *Eur. Transp. Res. Rev.* **2020**, *12*, 3. [CrossRef]
8. Ghafoori, M.; Abdallah, M.; Ozbek, M.E. Machine Learning–Based Bridge Maintenance Optimization Model for Maximizing Performance within Available Annual Budgets. *J. Bridge Eng.* **2024**, *29*, 04024011. [CrossRef]
9. Creutzig, F.; Agoston, P.; Minx, J.C.; Canadell, J.G.; Andrew, R.M.; Quéré, C.L.; Peters, G.P.; Sharifi, A.; Yamagata, Y.; Dhakal, S. Urban infrastructure choices structure climate solutions. *Nat. Clim. Chang.* **2016**, *6*, 1054–1056. [CrossRef]
10. Atwoli, L.; Erhabor, G.E.; Gbakima, A.A.; Haileamlak, A.; Ntumba, J.M.K.; Kigera, J.; Laybourn-Langton, L.; Mash, R.; Muhia, J.; Mulaudzi, F.M.; et al. COP27 Climate Change Conference: Urgent action needed for Africa and the world. *Lancet Oncol.* **2022**, *23*, 1486–1488. [CrossRef] [PubMed]
11. Peng, J.; Yang, Y.; Bian, H.; Zhang, J.; Wang, L. Optimisation of maintenance strategy of deteriorating bridges considering sustainability criteria. *Struct. Infrastruct. Eng.* **2022**, *18*, 395–411. [CrossRef]
12. Sun, X.Y.; Dai, J.G.; Wang, H.L.; Dong, W.W.; Wang, J. Decision support system for optimizing the maintenance of RC girder bridge superstructures in consideration of the carbon footprint. *J. Bridge Eng.* **2015**, *20*, 04015022. [CrossRef]
13. Gokasar, I.; Deveci, M.; Kalan, O. CO2 Emission based prioritization of bridge maintenance projects using neutrosophic fuzzy sets based decision making approach. *Res. Transp. Econ.* **2022**, *91*, 101029. [CrossRef]
14. Lei, X.; Dong, Y.; Frangopol, D.M. Sustainable Life-Cycle Maintenance Policymaking for Network-Level Deteriorating Bridges with a Convolutional Autoencoder–Structured Reinforcement Learning Agent. *J. Bridge Eng.* **2023**, *28*, 04023063. [CrossRef]
15. Xu, G.; Guo, F. Sustainability-oriented maintenance management of highway bridge networks based on Q-learning. *Sustain. Cities Soc.* **2022**, *81*, 103855. [CrossRef]
16. Ropke, S.; Pisinger, D. An adaptive large neighborhood search heuristic for the pickup and delivery problem with time windows. *Transp. Sci.* **2006**, *40*, 455–472. [CrossRef]
17. Ferone, D.; Festa, P.; Fugaro, S.; Pastore, T. Hybridizing a matheuristic with ALNS for the optimal collection and delivery of medical specimens. *Int. Trans. Oper. Res.* **2023**, *32*, 90–116. [CrossRef]
18. Windras Mara, S.T.; Norcahyo, R.; Jodiawan, P.; Lusiantoro, L.; Rifai, A.P. A survey of adaptive large neighborhood search algorithms and applications. *Comput. Oper. Res.* **2022**, *146*, 105903. [CrossRef]
19. Frangopol, D.M.; Kong, J.S.; Gharaibeh, E.S. Reliability-based life-cycle management of highway bridges. *J. Comput. Civ. Eng.* **2001**, *15*, 27–34. [CrossRef]
20. Chica, M.; Juan Pérez, A.A.; Cordon, O.; Kelton, D. Why simheuristics? Benefits, limitations, and best practices when combining metaheuristics with simulation. *SORT Stat. Oper. Res. Trans.* **2020**, *44*, 311–334. [CrossRef]
21. Festa, P.; Pastore, T.; Ferone, D.; Juan, A.A.; Bayliss, C. Integrating biased-randomized GRASP with Monte Carlo simulation for solving the vehicle routing problem with stochastic demands. In Proceedings of the 2018 Winter Simulation Conference (WSC), Gothenburg, Sweden, 9–12 December 2018; pp. 2989–3000.
22. National Bridge Inventory (NBI) of the U.S. Department of Transportation. 2021. Available online: https://www.fhwa.dot.gov/bridge/nbi.cfm (accessed on 25 October 2024).
23. Mariniello, G.; Pastore, T.; Asprone, D.; Cosenza, E. Layout-aware Extreme Learning Machine to Detect Tendon Malfunctions in Prestressed Concrete Bridges using Stress Data. *Autom. Constr.* **2021**, *132*, 103976. [CrossRef]