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Integrating Inspection and Monitoring Data for RL-Enhanced Sustainable Life-cycle Management of Infrastructure Networks

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Abstract: Existing civil infrastructure may face challenges from deterioration and harsh environmental conditions, necessitating effective management strategies to ensure resilience and sustainability. The abundance of inspection and structural health monitoring (SHM) data provides a valuable opportunity for assessment and management using reinforcement learning (RL). This study presents a sustainable management framework for infrastructure network incorporating inspection and SHM data, aiming to establish more efficient life-cycle maintenance policies that prioritize safety and sustainability. Initial probabilistic deterioration models for grouped infrastructure are developed with Markov models, with subsequent Bayesian updating based on real-time SHM data. The sustainability assessment is conducted, incorporating safety, economic viability, and low-carbon factors, with the results transformed into a utility model to inform optimization rewards. The final sustainable management planning is achieved with RL techniques. Key findings highlight the framework's ability to integrate various data sources, enabling accurate predictions of structural performance and sustainable maintenance needs. The optimal management policy derived from RL ensures good sustainable performance while balancing regional budgetary constraints. Validation on a transportation infrastructure network demonstrates practical utility, with efficient maintenance practices leading to improvements in both efficiency and sustainability compared to traditional methods. Overall, this framework offers a promising approach to sustainable infrastructure management.

Keywords: sustainable life-cycle management; infrastructure network; smart structure; reinforcement learning; carbon footprint; structural health monitoring

1. Introduction

In the rapidly evolving landscape of infrastructure management, the concept of sustainability has become increasingly vital (Bocchini et al., 2014; Ellingwood & Lee, 2016; Kim & Frangopol, 2020). Civil infrastructure, subjected to various environmental, loadings, and aging factors, require effective management strategies to ensure service performance (Bocchini & Frangopol, 2011; Saidi et al., 2018). The breakdown and deterioration of infrastructure systems, along with their regular maintenance, entail significant material usage (Martins et al., 2024; Neves & Frangopol, 2005). This consumption of materials, in turn, results in substantial energy expenditure, financial losses, and carbon emissions. Sustainable life-cycle management for smart infrastructure offer a holistic approach to enhancing the resilience, efficiency, and longevity of civil assets while minimizing environmental impact and maximizing socio-economic benefits.

Measured data is essential for civil infrastructure management, encompassing structural health, performance, and environmental impact. This data is typically gathered through regular inspections, monitoring systems, and other measurement techniques. Regular inspections often rely on visual inspections for detecting defects like cracks and corrosion by inspectors or robots (Charron et al., 2019; Perry et al., 2020). The wealth of information provides insights into structural states based on assessment standards, laying the groundwork for accurate and reliable deterioration models (Feng et al., 2023; Frangopol & Bocchini, 2012). This rapid and low-cost method fits to the distinct features and needs of the grouped civil infrastructure, facilitating periodic data acquisition (Lei et al., 2022).

In addition to regular inspections, structural health monitoring (SHM) systems are widely deployed on civil infrastructure systems to timely monitor their responses and performance (Lei, Siringoringo, et al., 2023; Lei et al., 2021; Okasha & Frangopol, 2012). These systems contain a variety of sensors, including those measuring strain, vibration, temperature, and more, to continuously collect data on the structural behavior and environmental conditions. By analyzing this real-time data, performance indicators are derived to assess the performance and health of infrastructure (Ni & Xia, 2016). Performance assessment results obtained from SHM data provide valuable information for updating of deterioration model of grouped civil infrastructure.

Structural deterioration models aim to extract intricate patterns in historical data to anticipate potential scenarios. By integrating advanced analytical techniques such as correlation analysis and machine learning, previous studies have established several deterioration models with different types to reflect instinct deterioration features (Lei et al., 2024). Miao et al. (Miao et al., 2023) developed a Long Short-Term Memory (LSTM) model to discern the relationships between structural states and deterioration factors, achieving an accuracy exceeding 80%. Liu et al. (Liu et al., 2021) employed a Convolutional Neural Network (CNN) model to forecast the structural states of bridge components, demonstrating robustness with a maximum mean-squared-error near 0.5 over a 26-year forecast period. In a comparative study, Miao and Yokota (Miao & Yokota, 2024) evaluated the predictive capabilities of Markov chain (MC) and Recurrent Neural Network (RNN) models for structural state prediction. Their findings indicated that RNN-predicted deterioration to a worse state occurs in less time than MC-predicted deterioration, with a difference of less than 5 years. Additionally, Moscoso et al. (Moscoso et al., 2024) introduced a two-step cluster analysis approach to model deteriorations, yielding results comparable to those of MC deterioration models. These models incorporate variations in environmental conditions, material properties, and other influential factors that affect the degradation of infrastructure assets over time. Probabilistic models, in particular, are valuable for evaluating the risk of infrastructure failure under diverse scenarios.

Civil infrastructure continually deteriorates due to environmental factors and daily usage. To ensure the prediction accuracy of deterioration models, it is necessary to update them with new information. Ghodoosi et al. (Ghodoosi et al., 2018) utilized ground penetrating radar (GPR) to create localized defect maps for updating deterioration models of concrete bridge decks. Tran et al. (Tran et al., 2020) explored the use of dynamic Bayesian networks to update deterioration models using spatially distributed inspection data. Li and Jia (Li & Jia, 2020) introduced modifications to the likelihood function to incorporate both complete and incomplete inspection data in a Bayesian framework for model updating. Gu and Li (Gu & Li, 2022) applied the Bayesian updating theorem to update deterioration models using available in-situ data and investigated the influence of prior distribution and inspection data volume on the updating process. Jiang et al. (Jiang et al., 2023) developed a digital twin framework for life-cycle management of steel bridges, incorporating Bayesian inference for updating deterioration models with real-time data. Liljefors and Kohler (Liljefors & Köhler, 2023) employed Bayesian networks to update corrosion-induced deterioration models with measured data, providing valuable insights into infrastructure state for informed decision-making on maintenance and rehabilitation strategies. These studies demonstrate the importance of continuous model updating to ensure the effectiveness of infrastructure management practices.

Besides evaluating structural longevity and resilience, sustainable assessments of infrastructure network are vital, which encompassing various factors such as safety considerations, environmental impact, economic viability, and societal implications (Sabatino et al., 2016). Previous research for sustainable assessments of infrastructure network under service loads or multi-hazard scenarios were completed empirically, qualitatively, and quantitatively (Dong & Frangopol, 2017; Dong et al., 2013; Kim et al., 2020; Yang & Frangopol, 2020). Shen et al. (Shen et al., 2011) introduced key indicators for assessing the sustainability performance of infrastructure projects, derived from input from stakeholders, experts, and industry clients using fuzzy theory. Dong et al. (Dong et al., 2014) computed sustainable metrics for a transportation network in the USA under seismic scenarios. Abdelkader et al. Papajohn et al. (Papajohn et al., 2017) devised the MARS (Metaframework for Assessing Ratings of Sustainability) system, consisting of several key rules, which could serve as a base for creating new rules. Shahtaheri et al. (Shahtaheri et al., 2018) formulated a multi-criteria sustainable assessment for infrastructure during early design phases, considering initial costs, structural damage, casualty costs, and CO_2 emissions. (Abdelkader et al., 2022) developed a multi-stage policy-making approach integrating a neural network model and an optimization model to predict sustainable resource allocation. Sharma et al. (Sharma et al., 2023) proposed a social, ecological, and economic resilience assessment for urban water network to promote sustainable usage. Pan et al. (Pan et al., 2023) designed a multi-level framework for the sustainability assessment of infrastructure network, encompassing contexts, methods, measures, and results, while considering synergies between system components.

Traditional approaches to sustainable management planning often rely on predetermined schedules or reactive strategies (Zhou et al., 2022). Heuristic algorithms are frequently employed to generate effective policies for optimizing infrastructure network management. Hadjidemetriou et al. (Hadjidemetriou et al., 2022) considered the state and importance of individuals within the system when scheduling the application of preventative maintenance. Santos et al. (Santos et al., 2018) developed a multi-objective genetic algorithm (GA) for sustainable road pavement management taking into account agency costs, user costs and CO_2 emissions. Zhang et al. (Zhang et al., 2023) utilized GA and particle swarm optimization (PSO) to address multi-objective optimization issues in sustainable planning. Omidian and Khaji (Omidian & Khaji, 2023) presented a systematic methodology for policy-makers to opt optimal retrofit planning that balance life-cycle costs and structural performance. Asif et al. (Asif et al., 2023) explored sustainable water management planning under climate change scenarios in North America. Effective sustainable assessment methods provide insights into the overall impact and performance of interventions, contributing to the development and implementation of management policy.

Reinforcement learning (RL) has emerged as a powerful tool in optimizing management of complex civil infrastructure systems (Cheng & Frangopol, 2022; Lei & Dong, 2022). Cheng and Frangopol (Cheng & Frangopol, 2021) introduced a RL-based approach for load rating projects of grouped bridges. Andriotis and Papakonstantinou (Andriotis & Papakonstantinou, 2021) presented a management optimization method with a decentralized multi-agent RL model, considering the life-cycle risks and budget constraints. Lei et al. (Lei, Dong, et al., 2023) proposed an RL life-cycle management framework with convolutional autoencoder agent for network-level bridges, improving regional safety and reducing management cost simultaneously. Additionally, Lai et al. (Lai et al., 2024) design a synergetic-informed RL agent for precisely optimize the life-cycle maintenances with large discrete action spaces. However, given the dynamic nature of structural health and evolving environments, there is a need for more adaptive approaches. Few studies have explored RL methods for optimizing life-cycle sustainable management of aging civil infrastructure network, particularly incorporating real-time data updating.

This study develops a sustainable management framework for smart infrastructure network integrating inspection and SHM data, which features several key contributions. Firstly, the framework effectively integrates multi-source measured data to establish and update deterioration models, quantify sustainable measures, and optimize life-cycle management intelligently. Secondly, it enables updating of probabilistic deterioration models using SHM data, ensuring accuracy and responsiveness to changing states. Finally, the established framework utilizes RL agents to optimize life-cycle maintenance policies while considering real-time monitoring data and sustainable measures. In addition to the introduction, this study consists of six sections. Section 2 introduces the overall sustainable management framework for smart infrastructure network. Section 3 details the establishment and updating of probabilistic deterioration models with the assistance of inspection and SHM data. Section 4 presents utility-based sustainable assessment methods incorporating safety, economy, and low-carbon considerations. Section 5 focuses on life-cycle maintenance policy optimization based on RL. Section 6 validates the proposed framework, with emphasis on bridge networks. Finally, Section 7 provides concluding remarks.

2. Sustainable management framework for infrastructure networks

In the era of smart infrastructure, where advancements in technology and data analytics are transforming the way managing civil infrastructure assets, the integration of sustainable practices has become paramount. The sustainable management framework for smart infrastructure should offer a structured approach to optimize the performance, resilience, and longevity of infrastructure assets while minimizing environmental impact and maximizing socio-economic benefits.

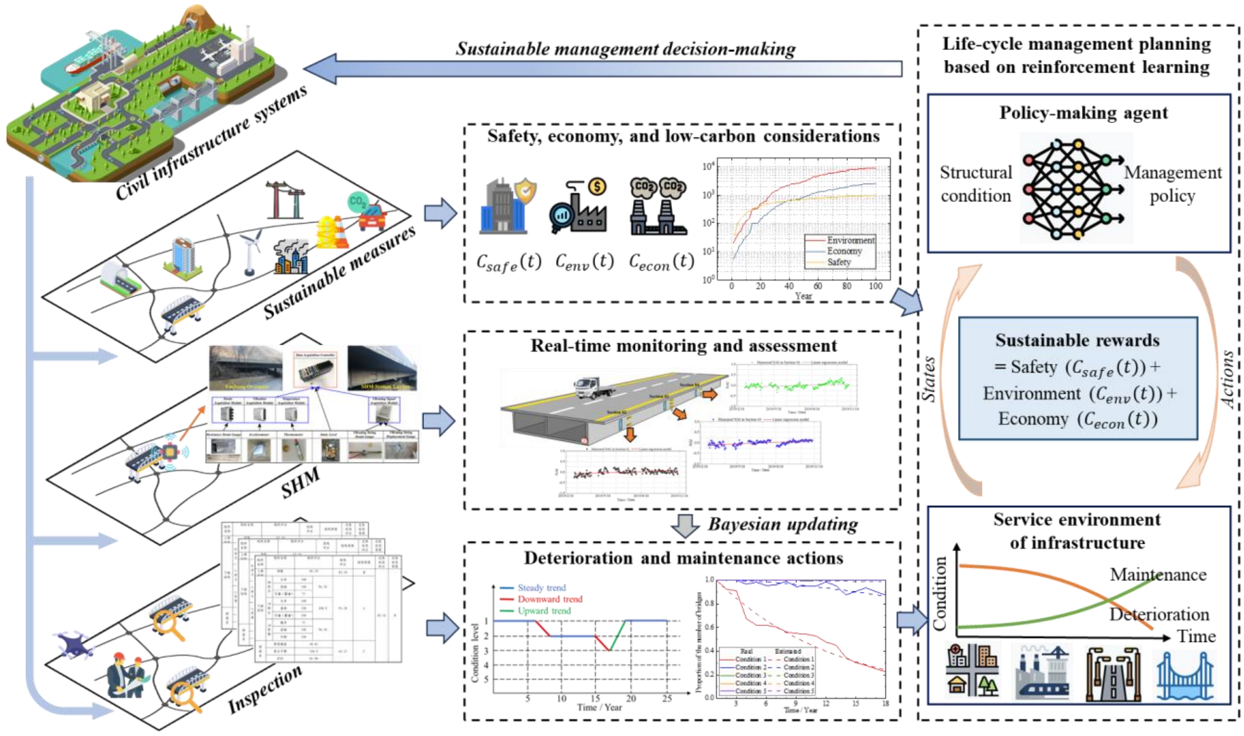


Figure 1 Sustainable life-cycle management framework for infrastructure network

The proposed entire sustainable life-cycle management framework for smart infrastructure network, illustrated in Figure 1, encompasses a holistic approach that considers various facets of sustainability, including safety, economic viability, and low-carbon considerations. It leverages cutting-edge technologies such as SHM, data analytics, and reinforcement learning to establish predictive models, assess asset health, and optimize maintenance strategies.

Deterioration models play a pivotal role in the effective management of civil infrastructure, serving as indispensable tools for assessing and predicting structural performance. One of the primary sources of data used in developing deterioration models is multi-year inspection reports. Automated inspection systems utilizing drones and robots further enhance data collection efficiency. By systematically analyzing these reports, engineers and asset managers can identify patterns of deterioration, assess the rate of deterioration, and anticipate future maintenance needs. By employing statistical techniques and machine learning algorithms, predictive models can be established to quantitatively track the progression of deterioration over time.

Continuously updating deterioration models with real-time data from SHM systems is essential to ensure the accuracy and reliability of these models. By integrating SHM data into the modeling process, engineers can capture the dynamic behavior of infrastructure assets and account for changes in structural states over time. One effective approach to updating deterioration models is through Bayesian updating. As new SHM data becomes available, the model is updated using Bayes' theorem, which quantifies how the likelihood of model parameters changes. This iterative process allows the model to evolve and become more accurate over time, as it incorporates additional information and learns from past observations.

Comprehensive sustainability assessments should consider structural safety, economic budget, environmental impact, etc. Structural safety is a foundational aspect of sustainability assessments, ensuring the infrastructure systems are maintained to withstand all demands of their intended states. Economic budget is another critical consideration, as infrastructure assets should be financially sustainable over their lifecycle. Environmental impact assessment evaluates factors like greenhouse gas emissions and energy consumption. By considering a wide array of factors, sustainability assessments can help strike a balance in infrastructure management, ensuring both long-term viability and resilience.

RL algorithms offer a powerful approach for optimizing life-cycle maintenance planning in civil infrastructure management. Established deterioration models using historical inspection, maintenance, and SHM data are integrated into the RL environment to simulate stochastic performance variation over time. Rewards are defined based on sustainable measures and formulated using the utility model. The neural network (NN)-based RL agent learns from interactions within the established environment through repeated trials. By continuously adjusting its actions based on received rewards and learned experiences, the RL agent could output optimized maintenance planning strategies that maximize sustainable effectiveness.

This sustainable management framework continually adapts to changing states and climate change impacts by updating deterioration models, assessment methodologies, and maintenance strategies based on evolving data, technology advancements, and past experiences. It enables proactive addressing of maintenance needs, efficient resource allocation, and enhancement of overall sustainability and resilience of civil infrastructure networks.

3. Structural deterioration of infrastructure network

3.1 Inspection and monitoring data from infrastructure network

Inspection and monitoring data assess structural condition through distinct approaches, offering a diverse range of information. These data sources offer a comprehensive perspective for condition assessment and management of infrastructure networks, complementing each other to improve safety and reliability. SHM data can increase the accuracy of inspections, while continuous data collection enables the development of effective management strategies (Frangopol & Kim, 2022). The unique features of inspection and monitoring data are explained below and illustrated in Figure 2.

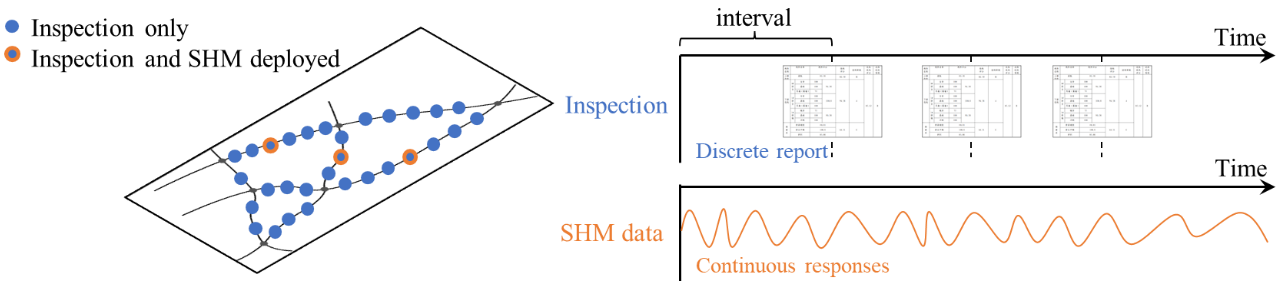


Figure 2 Inspection and SHM data of infrastructure network

Inspection data typically involve human observation, which can include visual checks, manual measurements, and photographic evidence. These assessments often focus on identifying visible signs of structural defects. This type of data is usually documented in reports, often follow standardized formats to ensure consistency and reliability. Inspections are typically conducted at regular intervals, providing a periodic snapshot of the infrastructure's condition. The frequency of inspections depends on factors like infrastructure type, age, and usage. Inspections yield qualitative observations and quantitative measurements, guided by official standards to ensure accurate assessment.

SHM data are generated continuously through sensors and automated systems, allowing for real-time tracking of structural conditions and environmental changes. Monitoring involves various sensor types, including strain gauges, accelerometers, temperature sensors, and displacement sensors, providing a comprehensive view of infrastructure behavior. Since monitoring is continuous, it generates large volumes of data over time, enabling trend analysis and predictive modeling. Compared with inspection data, SHM data provide more precise and quantitative measurements of infrastructure performance.

The combination of inspection and monitoring data provides a comprehensive view of the infrastructure's condition, enabling more efficient data-driven decision-making for its management (Kim et al., 2013). However, due to financial constraints, the widespread implementation of SHM systems in infrastructure networks may not be feasible. In such cases, regularly and widely conducted inspections serve as a fundamental basis for infrastructure management, while strategically placed SHM systems provide crucial real-time supplementary information. Both types of data contribute to assessing safety risks and identifying critical maintenance needs, reducing the likelihood of catastrophic failures. Inspection and monitoring data help optimize maintenance schedules and budgets, ensuring that resources are allocated efficiently and effectively.

3.2 Deterioration model establishment from inspection data

Multi-year inspection reports, with their comprehensive documentation of structural states, material assessments, and maintenance activities, serve as a rich source of historical data. The establishment of deterioration models from multi-year inspection reports plays a pivotal role in proactive infrastructure management, providing insights into the long-term health and performance of civil structures. Leveraging the wealth of inspection data allows for the development of robust deterioration models that aid in predicting future deterioration, implementing targeted maintenance strategies, and optimizing resource allocation.

Establishment of deterioration models involves a multi-step approach, encompassing data compilation, temporal analysis, feature extraction, and model development. Probabilistic deterioration models recognize the inherent uncertainties in deterioration processes and address these uncertainties by integrating stochastic elements. Among these probabilistic approaches, MC models emerge as a widely utilized framework, which represent deterioration as a sequence of states and transitions, capturing the dynamic nature of deterioration progression. Each state in the MC model represents a particular structural state, while transitions between states depict the probabilistic evolution of the structural state over time.

MC simulation is a crucial component of RL-based management systems, particularly in the context of Markov Decision Processes (MDPs), where MC models are employed to represent structural deteriorations and maintenance effects under uncertainty through discrete state sequences. MDPs utilize MCs along with associated rewards to guide decision-making processes. This approach enables the simulation of structural deterioration processes and the assessment of maintenance actions' impact on structural states over time.

Based on multi-year inspection reports of civil infrastructure, the deterioration with Markov model could be determined with the statistics of state transmissions and the least squares method. The predictive capability of the established deterioration models enables infrastructure stakeholders to foresee potential risks, prioritize maintenance efforts, and optimize the utilization of resources over the lifecycle of the infrastructure.

3.3 Deterioration model updating from structural health monitoring

In the realm of civil infrastructure management, the integration of SHM data into deterioration models marks a significant leap towards real-time decision-making and proactive maintenance strategies. SHM systems provide continuous and precise data on the state of infrastructure, offering a dynamic and evolving perspective on structural integrity. This wealth of real-time information enables the development of deterioration models that can be updated and refined, ensuring their relevance in the face of changing states and unforeseen challenges.

Traditionally, deterioration models have relied on historical data and periodic inspections, presenting limitations in adaptability to current structural states. The advent of SHM technologies has transformed this landscape by offering a continuous stream of data, capturing subtle changes that might go unnoticed during sporadic inspections. This constant monitoring facilitates the establishment of models that not only predict deterioration trends but also dynamically adapt to the real-time health status of the structure.

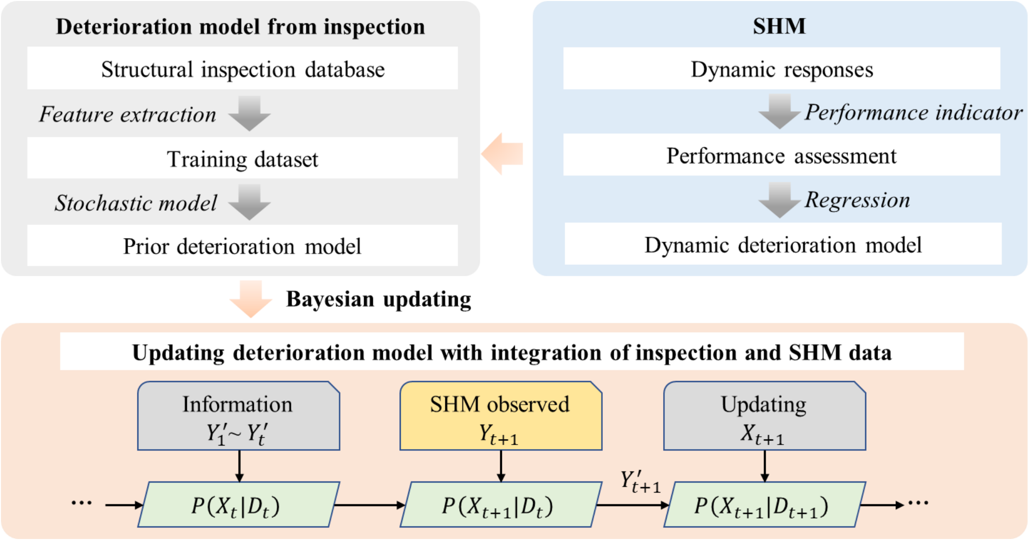


Figure 3 Structural deterioration models update from SHM

Bayesian updating allows for the seamless integration of new observations, enhancing the accuracy of predictions and the robustness of the model. Figure 3 provides a statistical framework to adjust model parameters, accommodating both the prior knowledge encoded in the model and the real-time information provided by SHM. The dynamic and adaptive nature of Bayesian updating ensures that the deterioration models remain relevant and effective, even as structures undergo changes over time. The core of Bayesian updating involves updating the structural state model using Bayes' theorem. In the context of integrating SHM and inspection data, the updating equation can be expressed as:

$$P(\theta_{deterioration}|D_{SHM}) = \frac{P(D_{SHM}|\theta_{deterioration}) \cdot P(\theta_{deterioration})}{P(D_{SHM})} \tag{1}$$

where, $P(\theta_{deterioration}|D_{SHM})$ denotes the posterior distribution of structural deterioration parameters given SHM data; $P(D_{SHM}|\theta_{deterioration})$ denotes the likelihood of the SHM data given the structural deterioration parameters; $P(\theta_{deterioration})$ denotes the prior distribution representing prior knowledge about the structural deterioration parameters; $P(D_{SHM})$ denotes the marginal likelihood or evidence. This term represents the overall probability of observing the SHM data, considering all possible states of deterioration. It's a normalization factor ensuring that the posterior probabilities sum to 1. It can be calculated by summing over all possible states of deterioration and their associated likelihoods and priors: $P(D_{SHM}) = \sum_{\theta} P(D_{SHM}|\theta)\, P(\theta)$.

The process begins with a prior probability distribution, representing the initial beliefs about the deteriorations before observing new data. This prior knowledge is typically based on historical multi-year inspection reports. The likelihood function quantifies the probability of observing the given SHM data, given the current deterioration model. It establishes the connection between the model's predictions and the actual observed structural health information. Bayesian updating calculates how well the model aligns with the newly acquired data. Through Bayes' theorem, the prior knowledge is combined with the likelihood function to compute the posterior distribution. This distribution represents the updated probability of deterioration parameters given both the prior knowledge and the observed SHM data.

Bayesian methods can inherently adapt to new information. With SHM consistently supplying data, deterioration models undergo evolution, resulting in a more precise depiction of the current structural state. These methods excel in handling uncertainty, particularly crucial in civil infrastructure where variables are dynamic and uncertainties are prevalent. The iterative process of Bayesian updating fosters continuous learning, enhancing comprehension of structural behavior and enabling more informed and precise predictions of future deterioration with each update.

4. Sustainability assessment with safety, economy, and low-carbon considerations

4.1 Sustainable measures quantification

Sustainable measures encompass integrated considerations of safety, economy, and environmental impact. Safety measures involve ensuring the structural integrity and resilience of infrastructure assets. Economic considerations focus on balancing budgets in maintenance with long-term financial sustainability. Environmental considerations encompass reducing carbon emissions, minimizing energy consumption, and mitigating ecological impacts. Effective sustainable measures quantification aims to improve structural performance while minimizing negative impacts on society and the environment.

Safety measures for civil infrastructure network can be determined by integrating the outcomes of visual inspections with the assessed state levels. These state levels of each individual structure within the network in year t act as indicators of the operational state of the infrastructure. These enable the prediction of future structural states using methodologies like MDPs. As a result, safety measures are calculated based on the cumulative structural state levels across all components of the infrastructure network.

Economic measures are assessed in monetary terms, comprising both direct economic loss and indirect economic cost. Direct economic loss encompasses expenses related to maintenance labor, materials, machinery, among others. It is typically linearly proportional to the structure width and length of structure. The monetary loss due to repair actions of structure is weighted with the coefficients for no action, repair action, and replacement action of 0, 0.2, and 1.0, respectively. Indirect economic loss refers to the potential failure risks of each structure i contributing to reconstruction costs in year t. Additionally, constant discount rate is employed in the life-cycle economic cost assessment to consider the temporal effect of costs (Dong et al., 2013; Dong et al., 2014).

Environmental measures primarily focus on the carbon footprint with CO_2 emissions resulting from traffic detours and maintenance actions. The CO_2 emissions due to traffic detour on the infrastructure network are estimated based on detour length, considering the relationship between the original length and corresponding detoured length, as well as detour duration. CO_2 emissions per kilometer are determined by factors such as fuel consumption and energy carbon production (Xu & Guo, 2022; Zhao et al., 2019). CO_2 resulting from maintenance actions is due to direct emissions from the implemented maintenance actions, which depend on the material and geometry of the structure, and indirect emissions from damaged bridges due to potential failure risks.

4.2 Multi-attribute utility model establishment

The utility model serves to quantify the desirability of different outcomes, assigning numerical values based on perceived benefits or drawbacks. It's also adaptable to account for the risk attitude of decision-makers. In sustainable management, this model evaluates and compares strategies based on their impact on sustainability goals. To accommodate varying value ranges of different consequences, utility models normalize each consequence within the range of 0 to 1 based on the maximum value of each consequence. The single-attribute utility model could consider the risk attitude of the policy maker.

As shown in Figure 4, by translating sustainability metrics, such as environmental impact, economic cost, and safety, into utility scores, decision-makers can assess the overall desirability of different management options. It allows for a systematic and quantitative evaluation of trade-offs between competing objectives and helps identify strategies that maximize overall utility or satisfaction.

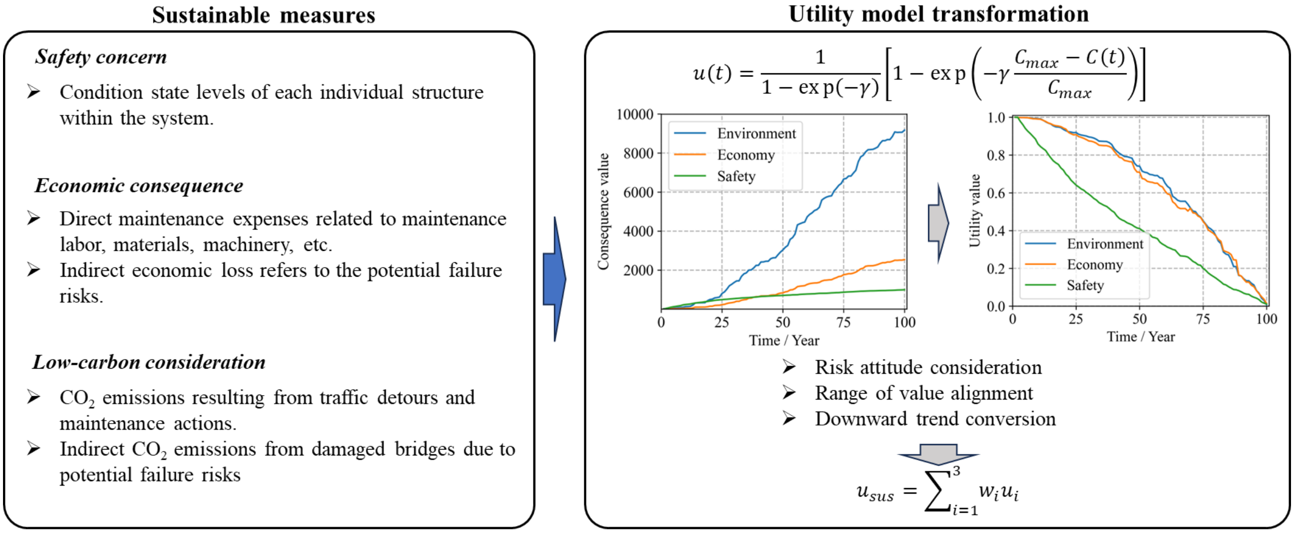


Figure 4 Establishment of multi-attribute utility model considering sustainability

In the sustainable multi-attribute utility model, environmental, economic, and safety consequences are assembled using weighting factors derived from each single-attribute utility model. These weighting factors reflect the preferences of policy makers' attitudes. Importantly, the sum of all weighting factors should equal 1.

5. Life-cycle maintenance planning based on RL

In the landscape of infrastructure management, the integration of cutting-edge technologies is revolutionizing the way we approach the life-cycle maintenance of civil infrastructures. RL, a branch of machine learning, has emerged as a powerful paradigm for optimizing decision-making processes in dynamic and complex environments. In the context of life-cycle maintenance planning, RL provides a framework where the decision-making agents learn experiences and adapt maintenance strategies based on interactions with its environment, making decisions that maximize long-term performance and sustainability while considering uncertainties and changing states, as shown in Figure 5.

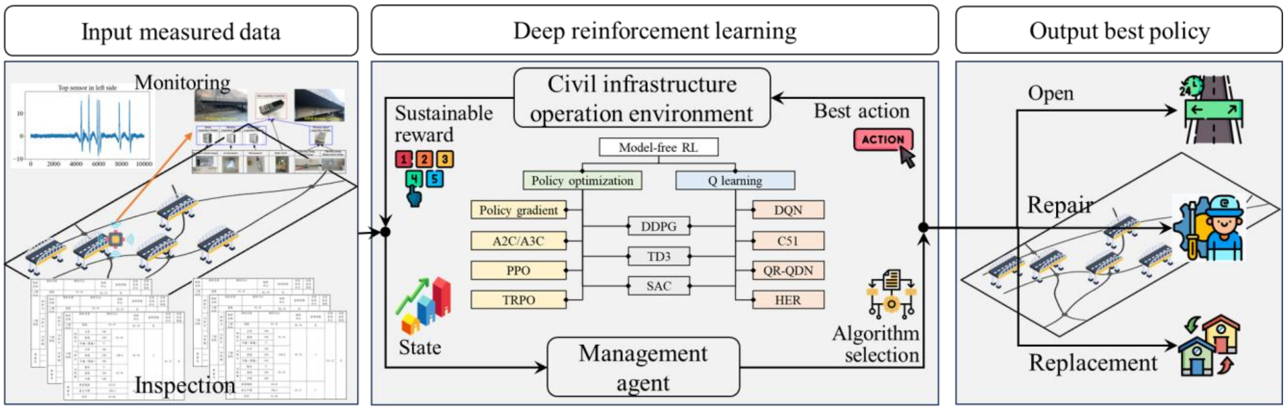


Figure 5 RL framework for sustainable management of civil infrastructure network

RL begins by defining a comprehensive state representation that encapsulates the current state, historical data, and relevant environmental factors affecting the infrastructure. Agents in RL take actions from a set of available options, such as performing maintenance or replacing members. The model learns to select actions that optimize the long-term health and sustainable performance of the structure. A crucial aspect of RL is the establishment of a reward system, providing feedback on the consequences of actions. The agents receive positive rewards for decisions that enhance its health and negative rewards for those leading to deterioration. Over time, the agents learn to maximize cumulative rewards.

Q-Learning is often used to train agents to make optimal decisions in an environment. It falls under the broader category of model-free RL, meaning that it does not require a model of the environment and learns solely from interacting with it. The primary goal of Q-Learning is to find an optimal policy for an agent to take actions in various states of an environment, maximizing the cumulative reward over time. The Q-values are updated iteratively based on the agent's experiences, allowing it to learn the best actions to take in different situations. The Q-value update equation is central to Q-Learning and is used to update the Q-values for a given state-action pair. The update of Q-values is as follows:

$$Q(s,a) \leftarrow Q(s,a) + \alpha \cdot [R(s,a) + \gamma \cdot max_{a'} Q(s',a') - Q(s,a)] \tag{2}$$

where, $Q(s,a)$ denotes the Q-value for state s and action a; α denotes the learning rate, controlling the impact of new information on the Q-values; $R(s,a)$ denotes the immediate reward for state s and taking action a; γ denotes the discount factor, representing the agent's preference for immediate rewards over future rewards; $Q(s',a')$ denotes the Q-value for the next state s' and all possible actions a'.

The agent's policy, determining the action to take in a given state, is often based on a greedy strategy:

$$a^* = \text{arg}max_a Q(s,a) \tag{3}$$

where, a^* denotes the action that maximizes the Q-value for the current state s; The agent exploits its current knowledge to make decisions.

In reinforcement learning, agents often use experience replay, where past experiences are stored in memory and randomly sampled during training. Memory capacity refers to the maximum number of experiences stored in memory. Experience replay can help stabilize training and improve sample efficiency. RL allows decision-making agents to adapt its maintenance plans in real-time, considering changing environmental state and evolving structural health data. By learning from historical experiences, it optimizes resource allocation, directing maintenance efforts to where they are most essential, thus enhancing efficiency. The iterative learning process inherent in RL ensures that the maintenance planning strategies continually improve over the life-cycle of the infrastructure. This adaptability enhances long-term resilience and sustainability.

6. Case study for management of bridge network

6.1 Introduction to the bridge network

The sustainable management for smart infrastructure network proposed in this study is applied to a simplified bridge network to optimize life-cycle maintenance policies. This bridge network consists of 6 nodes and 8 links, as illustrated in Figure 6, depicting the distribution of small- and middle-span concrete beam bridges across various roads and their respective lengths. The detour distances for roads numbered 1 through 11, in the event of bridge failures, are as follows: 10.1 km, 8.3 km, 14.7 km, 5.7 km, 7.6 km, 10.0 km, 8.1 km, 8.5 km, 7.5 km, 6.4 km, and 12.7 km. This transportation network is running with several typical types of cars, buses, and trucks.

Inspection data for these bridges is collected to establish the initial structural deterioration model. Additionally, one of the bridges is equipped with SHM systems to collect real-time data for model updating purposes. The primary objective of this study is to optimize the 100-year life-cycle maintenance policy for the bridges within the network.

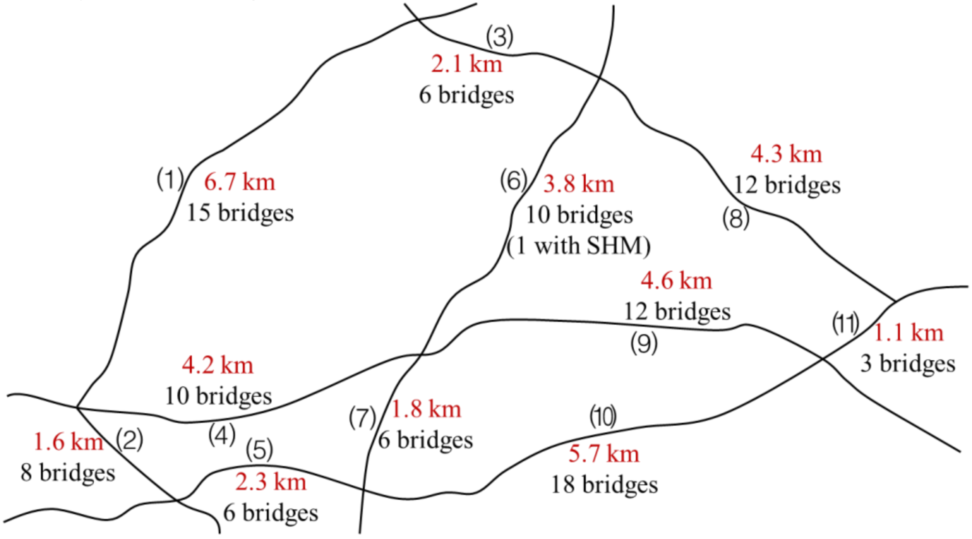


Figure 6 Transportation network layout

6.2 Deterioration of grouped bridges from inspection

The years of accumulated inspection data serve as a reliable foundation for evaluating and forecasting the state of regional bridges. This data includes essential structural information and records of structural states, forming a comprehensive database. Within this database, three distinct state trends are identified by comparing data from consecutive years: steady, downward, and upward trends. It is assumed in this study that steady and downward trends indicate deterioration of the bridge structure, while upward trends signify the effectiveness of maintenance efforts. The deterioration model is formulated within the Markov chain to capture the uncertainties associated with deterioration and align with subsequent RL optimization processes.

The structural state levels, ranging from 1 to 5, provide a quantitative description of the overall structural state of the bridge. Level 1 represents the best structural state, whereas Level 5 indicates the worst. In the absence of maintenance, considering uncertainties related to materials and loads, the time-variant probability distribution of structural failure for this bridge network is depicted in Figure 7. This distribution highlights a significant probability of failure in later phases of operation, underscoring the urgent need for optimal management strategies to enhance structural performance.

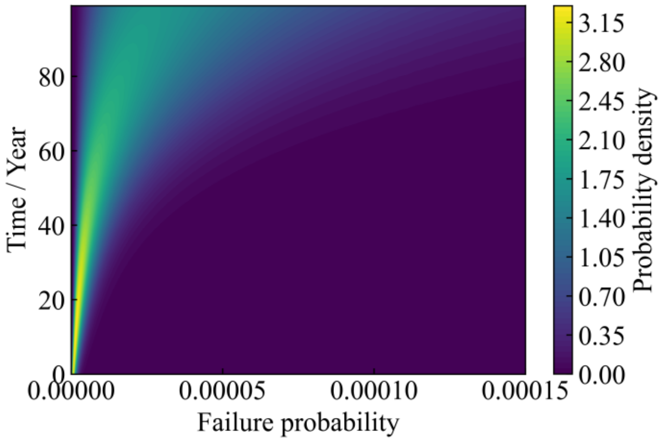


Figure 7 Probability distributions of failure without maintenance

6.3 Updated deterioration model based on SHM data

The structural deterioration model mentioned above is constructed using historical inspection data. With the deployment of a SHM system on one of the bridges within the network, additional information representing current structural states can be gathered from real-time monitoring data. Specifically, the monitored bridge is a small- to middle-span concrete beam bridge with an integrated box-shaped structure. Strain gauges installed on the middle of the main span of the girder are utilized to calculate and represent the states of the measured bridge and update the deterioration model, as shown in Figure 8.

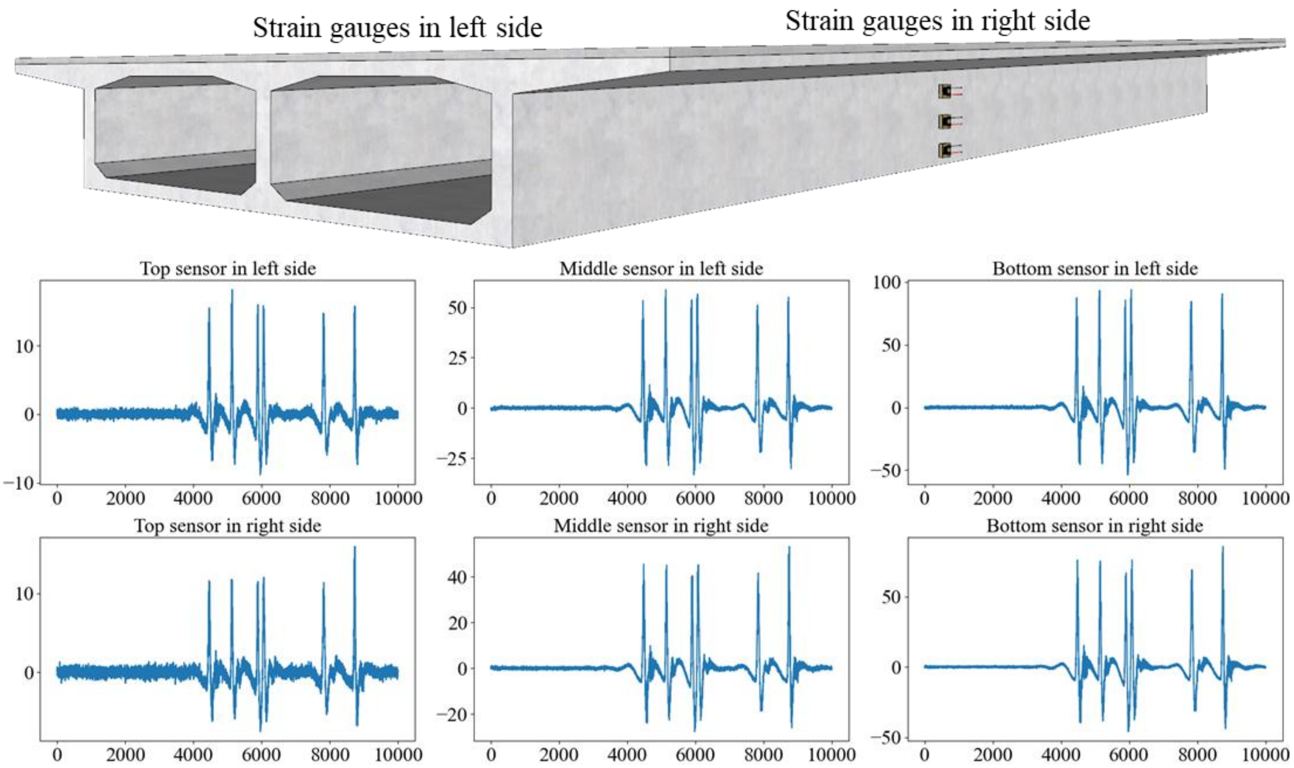


Figure 8 Part of measured strains at the middle of span

The location of the neural axis serves as an intrinsic feature of the structure, as it is solely influenced by the sectional profiles and material characteristics. To quantify this feature, a neutral axis indicator is established using a control chart, which transforms the location of the neural axis into a range between -1 and 1. The effectiveness of this performance indicator has been validated in the previous study (Xia et al., 2020). To align with the structural state classification of inspection data, the neural axis indicator is evenly distributed into five state levels, each with an interval of 0.2. In Figure 9, the measured performance indicator and associated thresholds for each structural state are shown. It is evident that the majority of the data falls within Level 1, with some transitioning to Level 2. This distribution of data serves as a robust foundation for updating the original deterioration model.

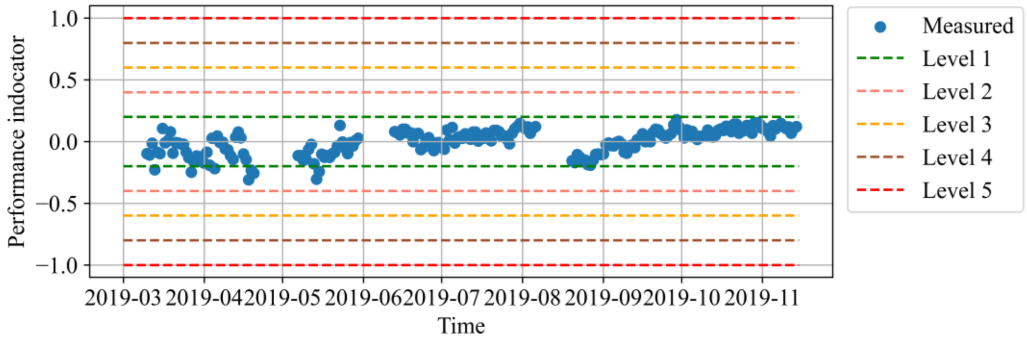


Figure 9 Performance indicator of the measured bridge over approximately one year

With Bayesian updating, the deterioration model can be refined using insights derived from monitoring data. Figure 10 illustrates the distribution of structural states with both the original and updated deterioration models over the life cycle. Since the measured data only contains the structure stays in Level 1 and Level 2 data, the Markov chain for deterioration model only focuses on updating the probabilities of structures remaining in Level 1 and transitioning from Level 1 to Level 2. Following the update, it becomes evident that the probability of structures remaining in Level 1 decreases, while the probability of transition from Level 1 to Level 2 increases. Further refinement and precision in updating the deterioration model can be achieved by installing SHM systems on additional bridges and extending the duration of monitoring over longer periods.

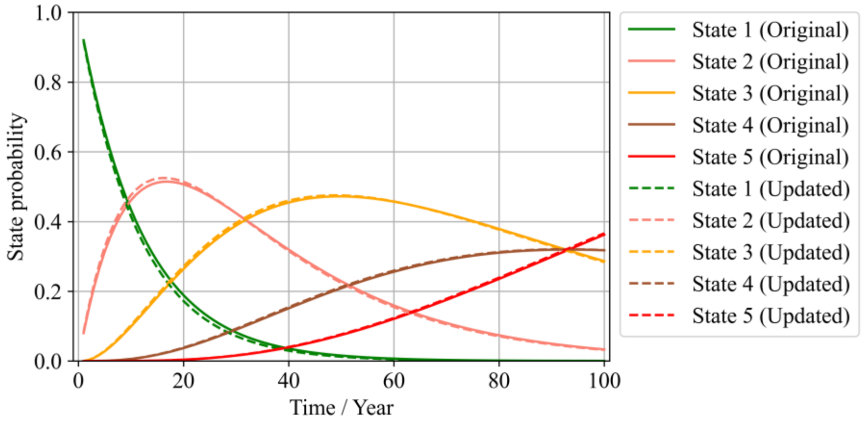
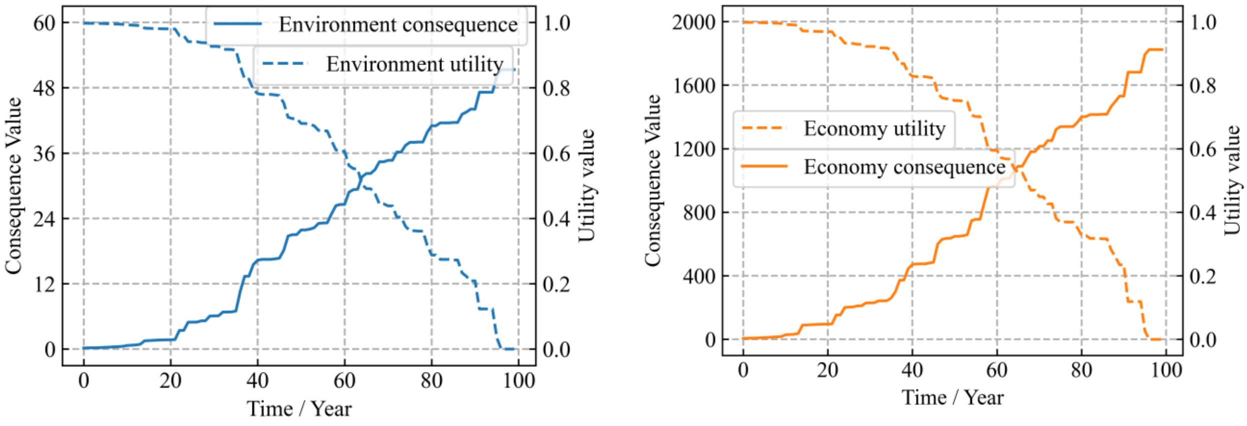


Figure 10 Proportion of structural states with both the original and updated deterioration models throughout the life cycle

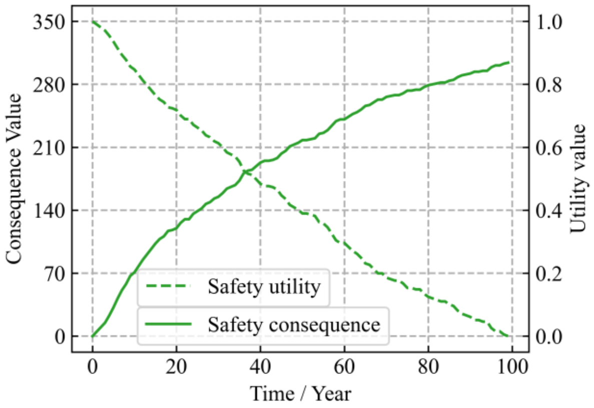
6.4 Sustainability assessment

Sustainable assessment encompasses environmental, economy, and safety assessments. Environmental assessment focuses on CO_2 emission. Traffic volumes play a significant role in influencing CO_2 emissions from traffic detours under sustainable maintenance policies. The traffic volume data is obtained from traffic survey stations, revealing that trucks constitute approximately 22.58% of the total traffic, buses account for 38.91%, and small vehicles represent 21.12%. CO_2 emissions per kilometer for common vehicles are determined based on a combination of fuel consumption and energy carbon production. Regarding CO_2 emissions resulting from material consumption during maintenance activities, the average unit carbon emission is $k_{env}^{rec} = 33600\ g/m^2$, as reported by (Xu & Guo, 2022). In assessing economic loss, the average unit monetary loss attributed to reconstructions is $k_{econ}^{rec} = \$1294/m^2$, as reported by (Dong et al., 2014; Sabatino et al., 2015). An inflation rate of 0.02 is considered in this study.

With the Bayesian updated deterioration model, the annual CO_2 emission, monetary loss, and safety of grouped bridges under no maintenance are computed. In Figure 11, it can be observed that during the initial 20 years of operation, the annual environmental, economic, and safety metrics experience a sharp increase each year, followed by a gradual decrease in the rate of escalation. Due to the absence of maintenance actions, the economic consequences remain relatively low, while the regional safety is notably compromised. Figure 11 also depicts the annual economic, social, and environmental utility values under no maintenance and risk-acceptance attitudes. These utility values decrease from 1 to 0 over the lifetime of the bridge.



(a) Environmental (b) Economy



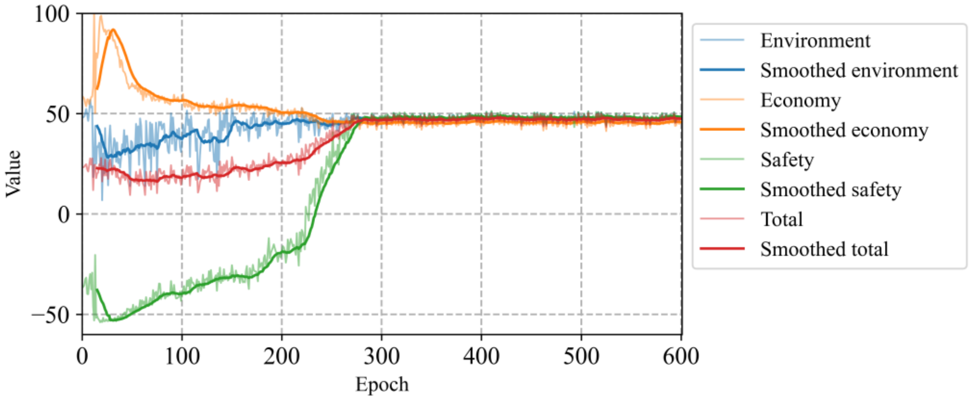
(c) Safety

Figure 11 Sustainability attributes throughout the life-cycle without maintenance

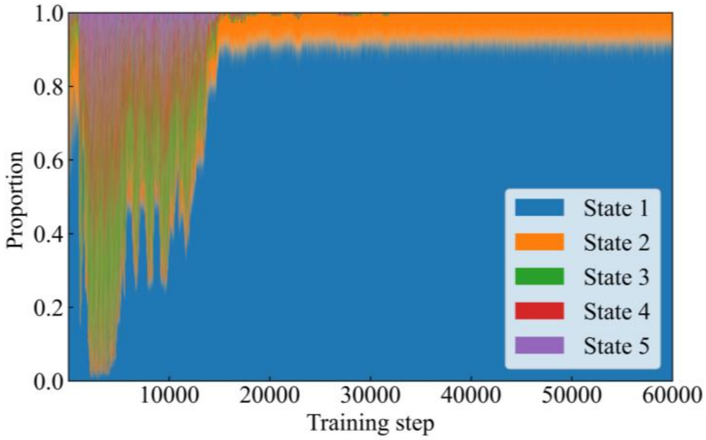
6.5 Life-cycle maintenance optimization

In the RL-based training for optimizing life-cycle maintenance of grouped bridges, several key parameters should be defined. The training epoch refers to the number of iterations the entire dataset undergoes during model training and is set to 1000. Memory capacity is set to 50. Mini-batch training involves dividing the dataset into smaller subsets, with a size set to 400. The learning rate controls the step size of parameter updates during training, is set to 0.001. The discount factor, determining the importance of future rewards in the agent's decision-making process, set to 0.95. It scales down future rewards to account for the uncertainty of future actions. A discount factor closer to 1 gives more weight to future rewards, while a discount factor closer to 0 prioritizes immediate rewards. The ε-greedy algorithm, a common exploration-exploitation strategy in RL, balances between exploring unknown actions and exploiting known actions with high expected rewards. ε represents the probability of choosing a random action instead of the action with the highest expected reward, set to 0.1. A higher ε value encourages more exploration, while a lower ε value prioritizes exploitation. The maximum values for environmental, economic, and safety consequences in the utility model is set as 30, 150000, and 20, respectively.

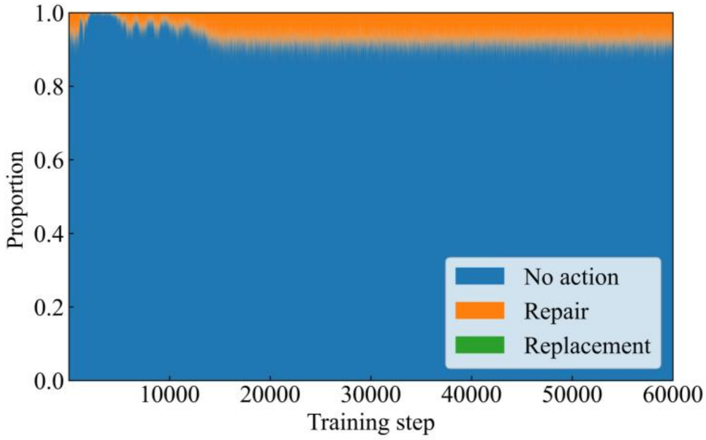
Figure 12 (a) shows the accumulated life-cycle utility of economic, environmental, safety, and total metrics for grouped bridges at the end of each epoch during the training stage. Before the 280th epoch, each curve exhibits significant fluctuations. Through trial and error, the model consistently adapts and refines its understanding of the features, ultimately converging towards near-global optimal planning solutions within the established interactive environment. This enables the model to develop a balanced strategy aimed at maximizing sustainable metrics for the infrastructure network. Given that this training consists of 600 epochs aimed at optimizing a 100-year life-cycle management strategy, Figure 12 (b) and (c) illustrate the variations in state proportions and maintenance action proportions at each step of the training process. Corresponding to the fluctuations in training rewards, the structural state is generally in poor condition when fewer maintenance actions are chosen. However, during the stable training phase, maintenance actions are properly implemented, ensuring the structural state remains in good condition.



(a) Sustainable rewards vairations in each epoch



(b) Structural state proportion variations in each step



(c) Maintenance action proportion variations in each step

Figure 12 Model performance in the training

Figure 13 shows the optimized policy at the end of each training epoch, with the coordinate value of each point reflects the life-cycle cumulative values of grouped bridges for each sustainable metric. The projection grey points on the axial surface depict the trends of each attribute variation during training. The red point, along with the dashed projection lines, represents the optimal maintenance policies in terms of environmental, economic, and safety metrics, which are 1110, 5880000, and 746, respectively. Compared to the most effective traditional maintenance policy, the trained optimal policy improves nearly 10% in each sustainable metric.

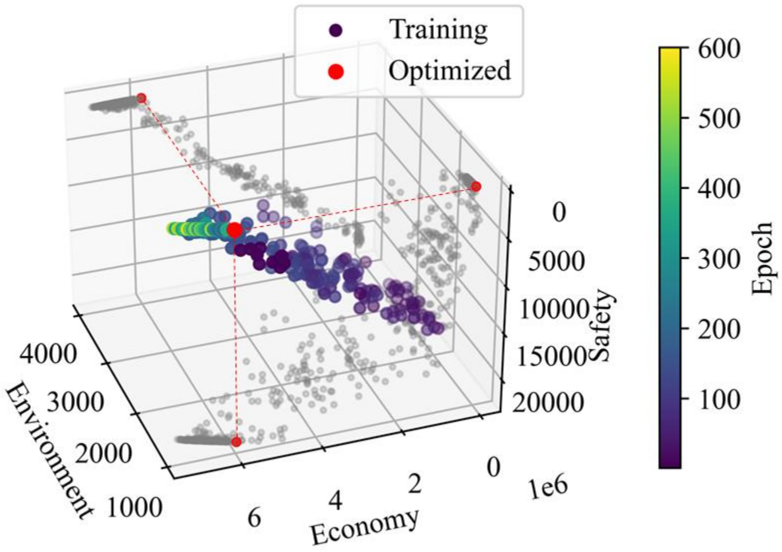
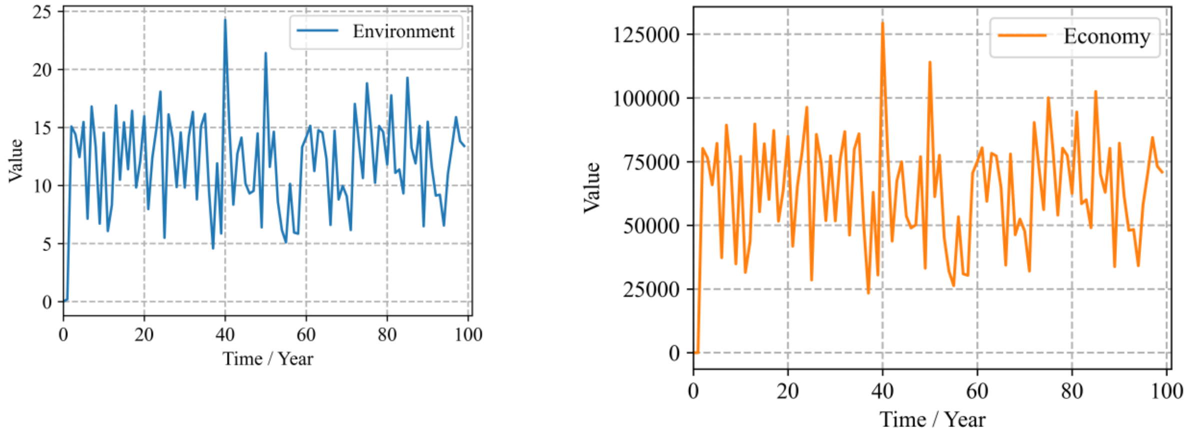
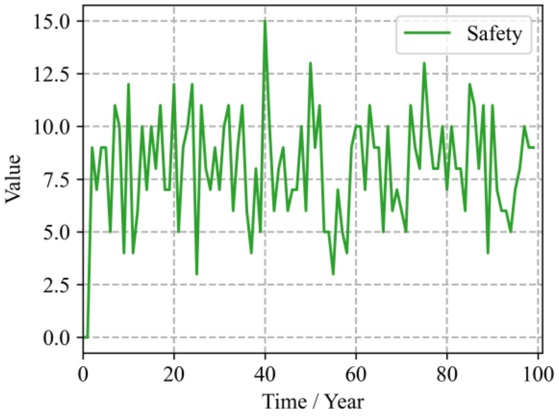


Figure 13 Optimized management policies from each training epoch

The subsequent part describes the life-cycle maintenance planning under the final optimized policy. Figure 14 shows the annual consequences of environmental, economic, and safety attributes from a grouped perspective. The minor fluctuations observed in individual attributes throughout the entire life-cycle underscore the relative stability of the optimal maintenance policy. Such stability may enhance the policy implementation.



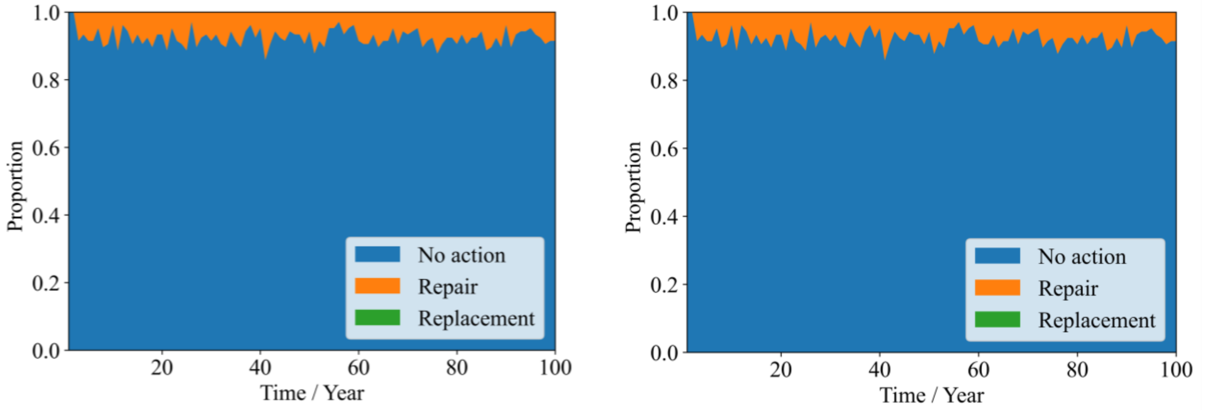
(a) Environmental (b) Economy



(c) Safety

Figure 14 Annual changes in sustainability consequences of the optimal policy

Figure 15 provides insight into the annual changes in grouped bridge states and management actions. In Figure 15 (a), it's evident that the majority of bridges maintain state Level 1 throughout their life-cycle. On average, 7.64% of bridges are in State Level 2, with a maximum proportion of 14.15% of bridges reaching State Level 2. No bridges are observed at State Level 3. This underscores the effectiveness of the optimal management policy in maintaining superior service performance for the grouped bridges. In Figure 15 (b), it can be observed that the optimal management policy employs a select number of efficient management actions to ensure the good state of grouped bridges. Of these actions, repair is primarily selected as a preventative measure, with an average proportion of 7.53%.



(a) Proportion of the state level (b) Proportion of the maintenance action

Figure 15 Annual changes in structural states and maintenance actions under the optimal policy

Figure 16 presents the state-level variations for each bridge over its life-cycle, as represented by each road, providing an individualized perspective. This visualization illustrates how each bridge exhibits distinct structural state variations depending on the applied maintenance strategy. Consistent with Figure 15 (a), each bridge remains within either Level 1 or Level 2, indicating a moderate state of wear and tear. The varying patterns in Figure 15 highlight the impact of different maintenance approaches on the structural state of bridges over time. By ensuring that bridges maintain a state Level 1 or 2, the applied maintenance strategies help to optimize the balance between structural safety and environmental impact, within the constraints of available budgetary resources. This approach contributes to a sustainable infrastructure management strategy while minimizing long-term risks and maintaining public safety.

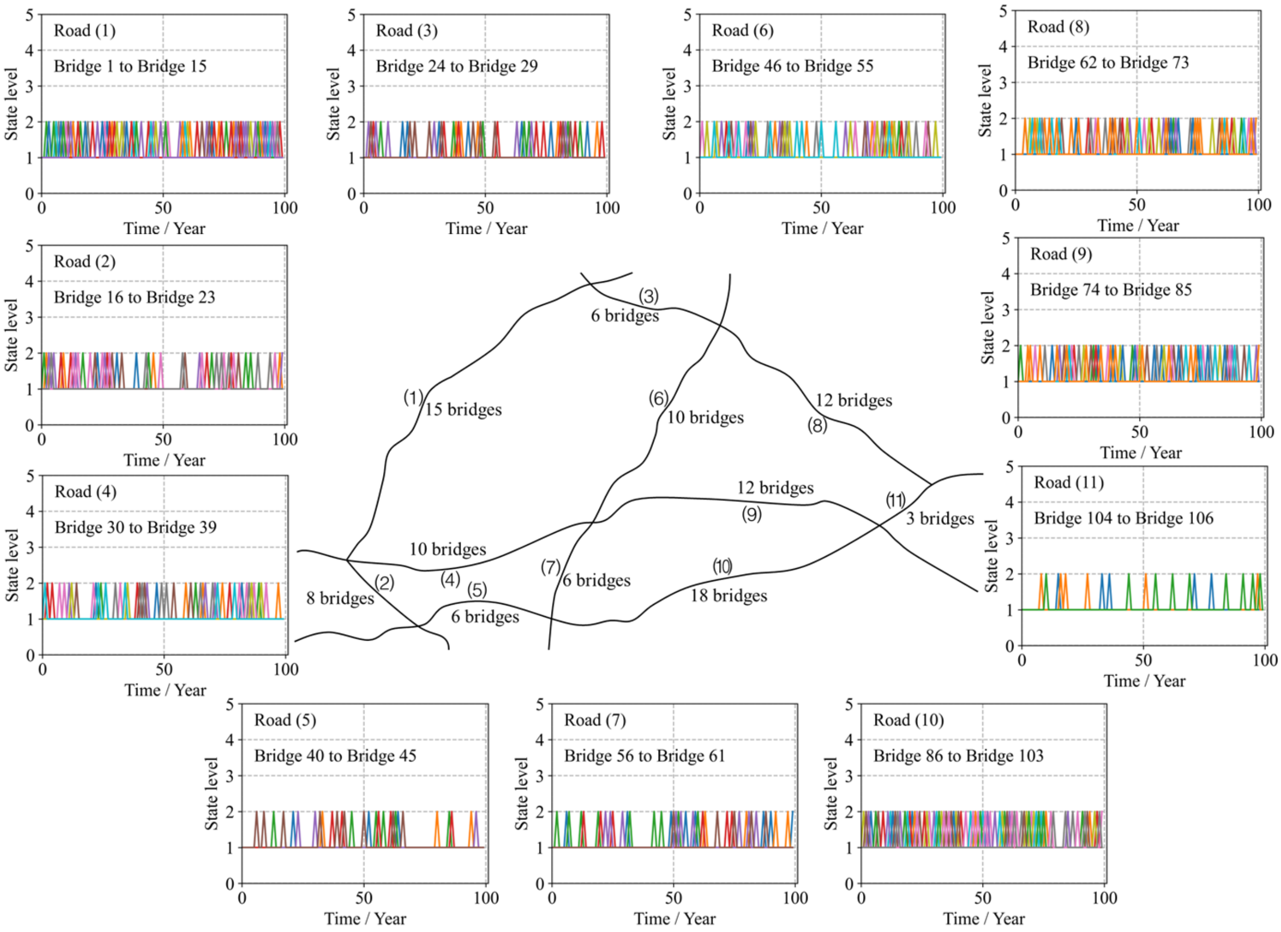


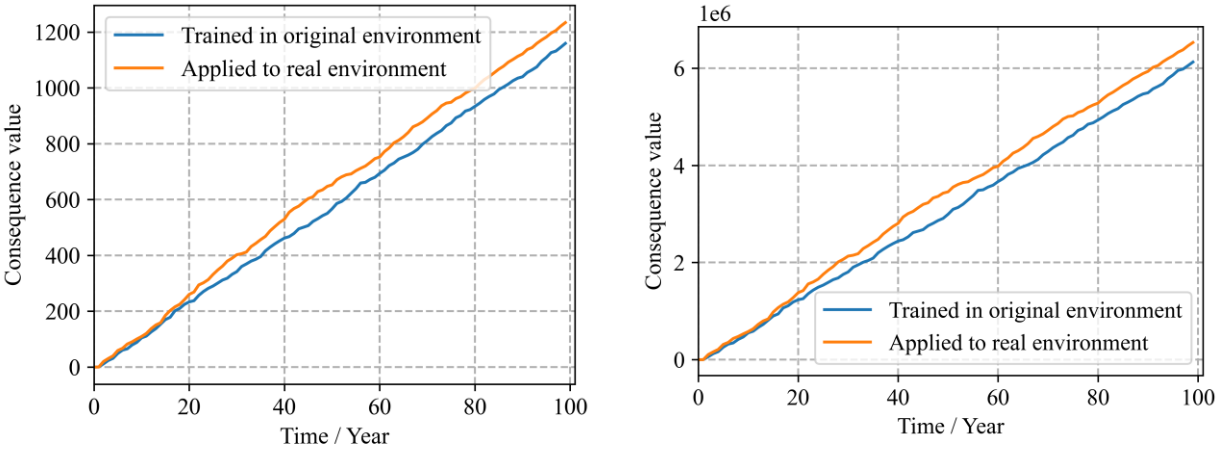
Figure 16 Annual variations in individual structural states

6.6 Impact of SHM data

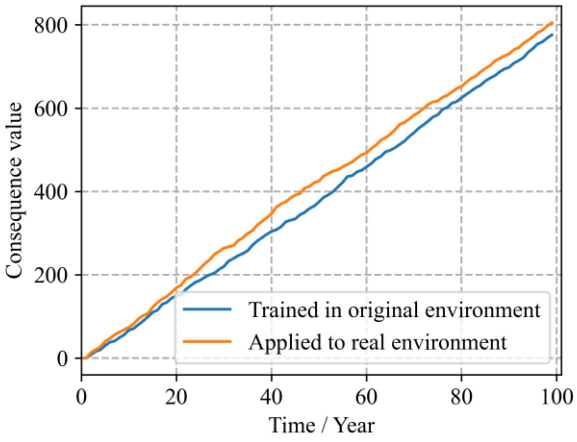
This section is designed to investigate how the sustainability of infrastructure networks is influenced by incorporating SHM. This system relies on an agent trained within a given baseline environment, as represented by the solid line in Figure 10. The life-cycle performance of this agent is then compared to that in an updated environment that incorporates SHM data, represented by the dashed line in the same figure.

Figure 17 presents the results of the cumulative performance of the infrastructure network, examining environmental impact, economic efficiency, and safety over time. The data underscores a growing divergence between the original environment and the updated environment, suggesting that without SHM data to refine the model, the predictions and resulting decisions can lead to less optimal outcomes. The initial gap between the models is relatively small. However, as time progresses, the absence of SHM-driven updates causes the gap to widen. By the end of the life-cycle, the discrepancies between the baseline and updated models are significant, with environmental impact differing by 6.44%, economic efficiency by 6.56%, and safety by 3.74%.

These results suggest that incorporating SHM data into life-cycle management not only improves the accuracy of predictive models but also has tangible benefits for the sustainability of infrastructure networks. The use of SHM data allows for more informed decision-making, reducing environmental impacts, improving economic efficiency, and enhancing safety.



(a) Environmental (b) Economy



(c) Safety

Figure 17 Sustainability attributes throughout the life-cycle without maintenance

7. Conclusions

This study introduces a sustainable management framework for infrastructure network incorporating inspection and SHM data, aimed at determining optimal life-cycle maintenance policies to ensure safety and sustainability. It employs advanced technologies such as machine learning, Bayesian updating, and reinforcement learning to develop predictive models, assess asset health, and optimize maintenance strategies. Inspection data is utilized to create the initial deterioration model using Markov chain methodology, accounting for uncertainties. Subsequently, real-time data from SHM systems is incorporated to update the model based on measured performance indicators. Before maintenance optimization, a sustainability assessment of the infrastructure network is conducted with safety, economic viability, and low-carbon considerations. The final near-global optimal management planning is accomplished with the aid of reinforcement learning techniques. To validate the proposed framework, it is applied to a transportation infrastructure network comprising a large quantity of bridges. Conclusions drawn from this study are as follows:

1) One key aspect of the framework is its ability to integrate various data sources, including periodic inspection data and real-time data from SHM systems. By utilizing these data, the framework gains access to a rich repository of information about the state and behavior of the structures. This updating dataset facilitates the establishment and continuous updating of

deterioration models, enabling more accurate predictions of structural performance and maintenance needs.

2) The optimal management policy derived from RL agent ensures good service and sustainable performance of the infrastructure network. By transforming sustainability metrics into utility models to construct the reward function for RL, the framework selects actions that promote long-term sustainability. Moreover, it ensures that available budgetary resources maintain a balance between sustainable regional impact, achieving a better trade-off among the three main objectives of the infrastructure network.
3) The validation of the framework on a transportation network containing a large quantity of bridges demonstrates its practical utility and effectiveness in real-world scenarios. The optimized policy utilizes a limited number of actions to maintain the overall health of the grouped structures. No bridge deteriorates to state Level 3. Compared to traditional state-based methods, it holds nearly 10% increase in efficiency and sustainability.
4) Incorporating SHM data into life-cycle management is crucial for accurate modeling and achieving sustainable infrastructure networks. The integration of SHM data leads to better-informed decisions that contribute to reduced environmental impacts, enhanced economic efficiency, and improved safety over time. By the end of the life-cycle, these sustainability metrics experience improvements ranging from 3% to 7%.

Declarations

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