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Deep reinforcement learning for optimal life-cycle management of deteriorating regional bridges using double-deep Q-networks

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Abstract. Optimal life-cycle management is a challenging issue for deteriorating regional bridges. Due to the complexity of regional bridge structural conditions and a large number of inspection and maintenance actions, decision-makers generally choose traditional passive management strategies. They are less efficiency and cost-effectiveness. This paper suggests a deep reinforcement learning framework employing double-deep Q-networks (DDQNs) to improve the life-cycle management of deteriorating regional bridges to tackle these problems. It could produce optimal maintenance plans considering restrictions to maximize maintenance cost-effectiveness to the greatest extent possible. DDQNs method could handle the problem of the overestimation of Q-values in the Nature DQNs. This study also identifies regional bridge deterioration characteristics and the consequence of scheduled maintenance from years of inspection data. To validate the proposed method, a case study containing hundreds of bridges is used to develop optimal life-cycle management strategies. The optimization solutions recommend fewer replacement actions and prefer preventative repair actions when bridges are damaged or are expected to be damaged. By employing the optimal life-cycle regional maintenance strategies, the conditions of bridges can be controlled to a good level. Compared to the nature DQNs, DDQNs offer an optimized scheme containing fewer low-condition bridges and a more cost-effective life-cycle management plan.

Keywords: condition assessment; deteriorating structures; life-cycle management; regional bridges; reinforcement learning

1. Introduction

In recent decades, the massive construction of civil infrastructure has supported economic development and social progress (Dong *et al.* 2014, Zhang *et al.* 2021, Zheng *et al.* 2021). According to a survey report provided by China's Ministry of Transport in 2020, the country has 912,800 bridges totaling 66,285,534 meters (Xia *et al.* 2022). Quite a few bridges are classified as having minor damage or worse, which become potential safety risks to the serviceability of transportation networks (Yang *et al.* 2020). Similar situations have also been reported in other nations (Chen *et al.* 2007, Zhang *et al.* 2020). Bridge maintenance plans employ cost-effective approaches to extend the life of bridges while decreasing the life-cycle cost. Highway administrations constantly struggle with a lack of funding, thus it's critical to cost-effectively optimize the life-cycle management plan for regional bridges.

The typical passive management strategy usually performs measurement when significant deterioration is observed. In recent years, active management strategies based on historical data have grown popular (Liu *et al.* 2021). Chalabi and Lorenc (2013) focused on the preventive maintenance of series systems, minimizing the cost, and maximizing the system availability. Hadjidemetriou *et al.* (2022) proposed a bridge management optimization method for bridge networks to allocate predictive maintenance. Deterioration models for individual structures take into account uncertainties. It also grouped maintenance of structures to reduce traffic disruption and setup costs. The maintenance actions improve the structural conditions but will bring certain costs. Preventive maintenance is generally recognized as a cost-effective way to reduce failures and keep production systems in excellent working order. Modeling the deteriorations of structures and optimizing their management are two essential parts.

Existing bridges undoubtedly suffer cracks, fractures, and erosions due to loads, structural defects, material quality, environmental conditions, and other factors (Jung *et al.* 2019, Lei *et al.* 2022a, b). Regular bridge inspection is an effective method to keep track of the structural status of regional bridges (Li *et al.* 2019, Lee *et al.* 2021). It follows a standardized visual inspection procedure to evaluate the structural conditions each year. Several governments and regions throughout the world have created their own bridge datasets to hold structural inspection data (Fan *et al.* 2021). The National Bridge Inventory (NBI) consists of statistical data collected by the Federal Highway Administration from state departments of transportation to assess the condition level of bridges in the United States. Chinese bridge inspection data is recorded at the local bridge administration. Many years of regional inspection data

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imply the deterioration characteristics and effect of maintenance actions and their interrelationship.

Probabilistic approaches could include unobserved factors, measurable mistakes, and intrinsic uncertainties that might exist in the deterioration or maintenance process (Bocchini and Frangopol 2011, Ge and Kim 2021a). They introduce the stochastic process to mimic structural deteriorations (Law and Li 2010, Frangopol and Bocchini 2012, Ge and Kim 2021b). The Markov decision process (MDP) is a discrete-time stochastic process commonly used to model structural deteriorations (Xia *et al.* 2012). The distinctive feature of a Markov chain is that the potential future states are fixed, regardless of how the process got to its current state. It might not be a reasonable assumption when assessing the structural condition. Cheng and Frangopol (2021) proposed a method based on MDP to compare the life-cycle cost of four load rating-based policies. The MDP model creates load rating-based inspection planning, and dynamic programming is used to find the optimal plans. Bocchini *et al.* (2013) proposed an efficient, accurate, and simple MDP model for the life-cycle analysis of bridge groups. It improved the computing efficiency and simplified implementations compared to a comprehensive probabilistic life-cycle technique.

Deep learning algorithms can mine vast amounts of data for intrinsic relevance and inherent characteristics (Lydon *et al.* 2019, Ye *et al.* 2019, Lei *et al.* 2021a). Ti *et al.* (Ti *et al.* 2020, 2021, Yang *et al.* 2022) designed a neural network-based framework for wind turbine response modeling. The results of the surrogate model show good agreement with the numerical simulations and measurement data. Convolutional neural networks (CNNs) are a sort of model that can rapidly and efficiently extract multi-level features from many inputs (Mondal and Jahanshahi 2020, Oh *et al.* 2021). CNNs have been widely employed in various fields of data-driven and image-related civil engineering, including image classification, object identification, semantic segmentation, and instance segmentation (Lee and Koh 2021, Huynh *et al.* 2021). For structural assessment, Liu and Zhang (2020) employed the NBI database to select over twenty features and train CNNs for three primary bridge parts: superstructure, substructure, and deck in structural evaluation. Fiorillo and Nassif (2020) applied CNNs to discover correlations between structural elements and NBI ratings, after which they predicted future element degradation trends. Using historical bridge data from the previous three decades in Texas, Zhu and Wang (2021) coupled CNNs and recurrent neural networks (RNNs) to forecast the future condition levels of bridges in the next three to four years. These promising findings indicate that convolutional mathematical models can be used to extract hidden characteristics from high-dimensional inspection data. Deep learning models may also examine the connection between the bridge conditions and management decisions.

Reinforcement learning is an unsupervised optimization technique that may produce actions, future states, and rewards based on the training environment (Mnih *et al.* 2015). Memarzadeh and Pozzi (2019) proposed a model-free deep reinforcement learning method with safe exploration to optimize the recovery process of infrastructure systems. Wei *et al.* (2020) used reinforcement learning to tackle maintenance optimization problems for cable-stayed and beam bridges. Yang (2022) employed reinforcement learning and surrogate modeling for the adaptive risk-based life-cycle management of large-scale structures. It also considers the effects of the spatial granularity of inspection and maintenance actions on the resultant life-cycle cost. Zhang and Si (2020) improved the condition-fixed maintenance strategies for multi-component systems based on reinforcement learning. Multiple components with stochastic and economic dependencies are handled. The inspection and maintenance planning were created by Andriotis and Papakonstantinou (2021) using a multi-agent RL model. It does well formulate the plans, focusing on life-cycle risk-based limits and financial constraints. Guan *et al.* (2022) developed a high precision dominant failure modes determination approach based on deep reinforcement learning. Cheng and Frangopol (2021b) utilized deep reinforcement learning to efficiently solve the MDP for a bridge system with a large state space. They obtained cost-efficient load rating schemes suited to the preferences of decision-makers. The maintenance actions improve the structural conditions but will bring certain costs (Xia *et al.* 2021). The optimal maintenance strategy balances the improved condition and the total cost. It should match the reasonable and affordable maintenance actions from a life-cycle perspective (Kabir *et al.* 2014, Cheng *et al.* 2019). The following are some of the benefits of reinforcement learning for bridge management: 1) Reinforcement learning is a decision-maker that can use new knowledge from the environment to take the maximum suited decisions. 2) It may gradually increase output accuracy and output the most important regional management actions. 3) It allows to development optimal maintenance plans to fit various restrictions. 4) Its computing ability is efficient, allowing it to make real-time decisions in the face of uncertainty.

This study develops a deep reinforcement learning framework using the double-deep Q-networks (DDQNs) to optimize the life-cycle management of deteriorating regional bridges. DDQNs method could handle the problem of the overestimation of Q-values in the Nature DQNs. The assumption behind the idea of Nature DQNs is that the best action has the maximum estimated Q-value, whereas the best action often has smaller Q-values than the non-optimal one in most cases. Such Q-values have lots of noise, and it is hard to determine whether the action with the maximum estimated Q-value is the best. DDQNs reduce overestimation by decomposing the max operation in the target into action selection and action evaluation. In addition, this study also reveals the regional bridge deterioration features and the effect of maintenance actions extracted from years of inspection reports and optimizing the life-cycle management strategies for regional highway bridges with the proposed method. By employing the trained life-cycle regional maintenance strategies, the conditions of bridges can be controlled to a good level.

The remainder of this study is organized as follows: Section 2 introduces the overall life-cycle management framework and the DDQNs techniques. The safety and economic indicators contained in the reward functions are also depicted. Section 3 illustrates measured data of regional bridges from inspection reports, and the extracted probability transfer matrices of deterioration and maintenance actions are also represented. The proposed method is validated by developing life-cycle management strategies for regional highway bridges within Section 4. Some conclusions and limitations of this study are illustrated in Section 5.

2. Life-cycle management optimization with DDQNs

2.1 Overall framework

The reinforcement learning methodology includes a maintenance agent and a task environment that should be constantly updated. They interact in a specific sequence in order to maximize the total benefits. The reinforcement learning agent generates maintenance rules and actions, while the task environment rewards the agent for acting. The agent could receive observations about this action and new state information from the training environment, output actions, and related rewards to inform the agent of how good or bad the action was. Furthermore, the developed reinforcement learning system can generate potential management strategies for various restrictions. The stakeholders' perspectives might define the effective management strategy. The life-cycle management optimization framework with DDQNs used in this study is shown in Fig. 1.

The efficiency of the maintenance approach is determined with the actual structural condition and deterioration information. The measured data comprises a variety of condition-related information. The effects of maintenance actions on regional deterioration can be inferred from multi-year regional measurement data. Reinforcement learning may be used to discover the optimal plans for regional bridges. The following is a list of procedures in the proposed framework:

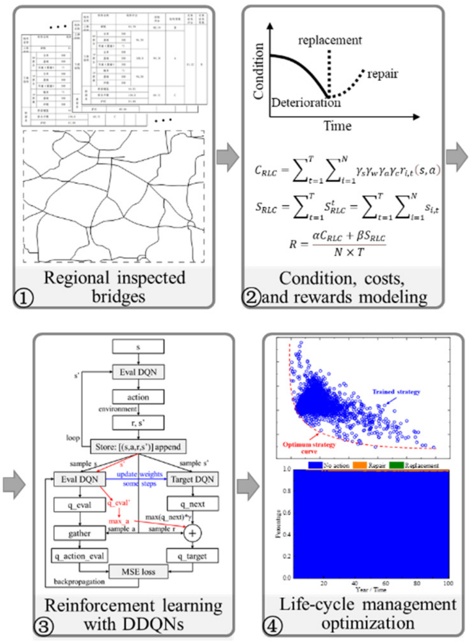


Fig. 1 Life-cycle management optimization framework with DDQNs

1) Inspection reports collection: The inspection report of each bridge in the area are archived in the management department. Regular inspection reports the structural conditions, damage, and maintenance actions. The data in the inspection report is transformed into a machine-readable format for training the reinforcement learning model.
2) Condition, costs, and rewards modelling: For life-cycle optimization, the regional deterioration, maintenance, and cost functions are critical. The multi-year regional measured data contains the regional deterioration features and the influence of maintenance measures. The stochastic influence of intrinsic uncertainties in the life-cycle degradation process is simulated using probabilistic models.
3) Reinforcement learning with DQNNs: The reinforcement learning method determines the finest maintenance approach for regional bridges with constraints. By engaging with the maintenance surroundings, reinforcement learning could learn to perform optimum actions. The agent's maintenance operations, responses to current conditions, and rewards are all part of these interactions.
4) Life-cycle management Optimization: The reinforced learning models might provide many optimal life-cycle maintenance options to fit various constraints. Each regional bridge's annual maintenance actions and structural condition levels can be forecasted in each optimized life-cycle plan. The stakeholders' preferences can help in choosing an effective management strategy.

2.2 Reinforcement learning with DDQNs

DDQNs are derivatives of DQNs in improving the model optimization performance by modifying the calculation of rewards of actions (Van Hasselt *et al.* 2016). The algorithm theories for DQNs and DDQNs are almost the same, as illustrated in Figs. 2-3. Light grey blocks are the main components of these two algorithms. The hollow blocks are the outputs of estimated states, actions, and rewards. Some main operations are illustrated beside the arrow lines, and the blue arrows represent the development of the model parameters from the evaluated network to the target networks. The most important differences between the two algorithms for calculating the next Q values in the target network are highlighted in red.

The agent in the Nature DQNs monitors the structural condition s_t, chooses a maintenance action a_t, and accepts a reward r_t at each step. The output maintenance policy $\pi(a|s)$ links structural states with maintenance procedures. The agent receives feedback on how excellent or awful the activity was. The purpose of the RL agent is to maximize its predicted total reward, which is calculated by discounting

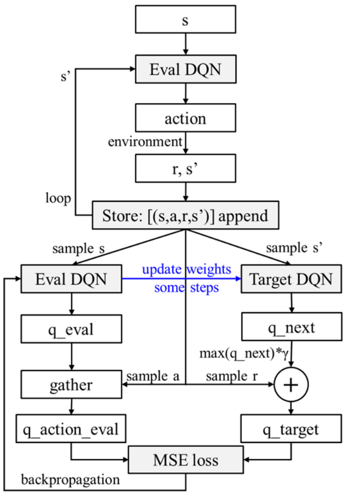


Fig. 2 Nature DQNs algorithm

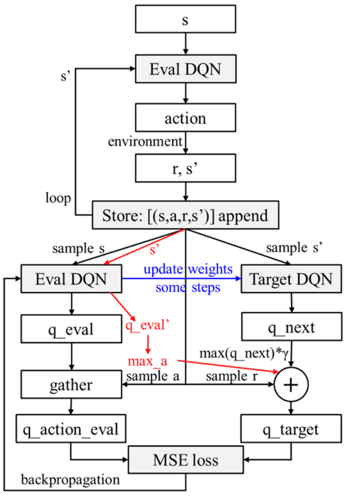


Fig. 3 Double DQNs algorithm

the benefits by a factor $\gamma \in [0,1]$ at each step to represent their value to the current state. At the same time, the return is $R_t = \sum_{t'=t}^{T} \gamma^{t'-t} r_{t'}$ where T is the step taken after the episode ends. The predicted return after monitoring the structural condition and conducting a maintenance action under a maintenance policy is the action-value function $Q^{\pi}(s,a) = \mathrm{E}[R_t | s_t = s, a_t = a, \pi]$, and the optimal action-value function is the highest potential value that any maintenance policy can accomplish, $Q^{*}(s,a) = argmax\, Q^{\pi}(s,a)$. A deep neural network $Q(s;a) = Q(s;a;\theta)$ is the most frequent way to express the action-value function in RL. DQN might be created using the Q-learning algorithm to update the parameters in the action-value function iteratively $Q(s;a;\theta)$ towards the end target. For each update i, the current parameters θ are updated by the stochastic gradient descent algorithm in the direction of the loss. Subsequently, maintenance actions are selected at each time step t through the greedy algorithm relative to the current Q-network (Arulkumaran *et al.* 2017). Therefore, in the Nature DQNs, the estimation of the Q value is as follows

$$Y_t^{DQN} = R_{t+1} + \gamma \max_{a} Q(S_{t+1}, a; \boldsymbol{\theta}_t^-) \tag{1}$$

The agent's optimum policy in Nature DQNs is always to pick the best action in every given condition. However, since the agent has no prior knowledge of the environment, it must first estimate Q values and then update them at each iteration. The ideal policy in DQNs states that the agent will take the non-optimal action in any given state when it has the highest Q-value. Such a problem is called the overestimation of action value (Q-value). DDQNs reduce overestimation by decomposing the max operation in the target into action selection and action evaluation. Therefore, the following is the revised estimation of Q value in DDQNs using the target network

$$Y_t^{DDQN} = R_{t+1} + \gamma Q\left(S_{t+1}, \operatorname*{argmax}_{a} Q(S_t, a; \boldsymbol{\theta}_t); \boldsymbol{\theta}_t^-\right) \tag{2}$$

The autoencoder-structured model detects the relationship between condition levels and maintenance actions. The encoder receives the condition data with the management year of regional bridges and extracts hidden features of these bridges. The convolutional filter plays an important role in deeply extracting the features. Data used in this study is extracted from years of inspection reports which contain lots of condition-related information about the measuring bridge. The decoder generates the maintenance actions of regional bridges using the encoder's compressed features. The transposed convolutions layers are used for upsampling and decompressing the extracted high-level abstracts into useful information. It comprises a nonlinear weighted upsampling of the feature extracted by the encoder until the target maintenance actions are reached. The correlation among bridge performances could be identified with the autoencoder model.

The input vector element contains the condition levels of each bridge and the management year. The last two digits represent the management year (100-year life-span using 00~99), while the front elements represent the structural condition level of each bridge (0~4, 0 stands for the intact condition, while four stands for the most severe damage condition). It has a size of N to represent the conditions of each bridge. The output vector of the neural network is the recommended maintenance action of regional bridges with a length of N, and each bridge holds one recommended action. The activation functions are used to determine the output of neural networks. Due to the gradient vanishing effect, the hyperbolic tangent function is more suitable than the rectified linear unit function in very deep neural networks. The activation functions are sigmoid and argmax functions to output the most appropriate action for each bridge. To improve the training efficiency, the proposed architecture is trained by mini-batch (Lei, Sun *et al.* 2020).

2.3 Indicators and rewards

The reinforcement learning model receives feedback on the actions' effectiveness through rewards. The cumulative benefits can illustrate the long-term cost-effectiveness of the proposed actions. The reward function in this study is based on regional structural safety and maintenance costs. The safety indicator might be calculated based on the current or expected condition levels. Labor expenses, material costs, equipment costs, and so on should all be included in the cost indication (Wang *et al.* 2021). Cost-effectiveness in maximizing structural safety while lowering life-cycle expenses should be the most appropriate management technique (Frangopol *et al.* 2017).

Since it is challenging to calculate the precise total maintenance costs for each bridge, this study applies a streamlined function to establish the life-cycle cost indicator C_{RLC}. As illustrated in (3), for each bridge, the size, maintenance needs, and present condition of the bridge are taken into account. The expenses are totaled up to get the entire regional cost, and the yearly cost is added to get the total life-cycle maintenance cost. According to the cost function, the cost of maintenance for a particular operation is related to the sizes, types, and levels of bridges. Surveys, codes, or the bridge expert's specifications can be used to derive the reference cost figures and coefficients. The authors of this study specifically state the expenses since the study does not place much importance on the precise amount. The life-cycle safety indicator S_{RLC} is calculated with the sum of the condition levels of each bridge in the region for the life-cycle, as shown in Eq. (4).

$$C_{RLC} = \sum_{t=1}^{T} C_{RLC}^{t} = \sum_{t=1}^{T} \sum_{i=1}^{N} \gamma_s \gamma_w \gamma_a \gamma_c r_{i,t}(s,a) \tag{3}$$

$$S_{RLC} = \sum_{t=1}^{T} S_{RLC}^{t} = \sum_{t=1}^{T} \sum_{i=1}^{N} s_{i,t} \tag{4}$$

where, C_{RLC} denotes the regional life-cycle bridge maintenance cost; T denotes the life span; N denotes the total number of the bridge; γ_s and γ_w denote the structure size factor, and they denote the structure length and width, respectively; γ_a denotes the maintenance action factor, and the coefficient of no action and repair action are 0 and 0.2, respectively; γ_c denotes the condition factor, and the coefficient of condition level 1 to 5 are set as 0.4, 0.5, 0.6, 0.8, and, 1.0, respectively. If the replacement is chosen as the maintenance action, the γ_a and γ_c are determined with 1.0, since the replacement of the structural member is irrelevant to the condition of the current structural state.

Eq. (5) illustrates how the reward relates to the regional cost indicator and safety indicator. The factors α and β are intended to strike a balance between the management strategy's priorities for safety and economy. ${}^{\alpha}\!/_{\beta} > 1$, ${}^{\alpha}\!/_{\beta} = 1$, and ${}^{\alpha}\!/_{\beta} < 1$ would result in the regional life-cycle management plan that the economy, balance, and safety favor. The total number of bridges and life span are used to standardize the final reward.

$$R = \frac{\alpha C_{RLC} + \beta S_{RLC}}{N \times T} \tag{5}$$

where, S_{RLC} denotes the regional life-cycle bridge safety indicator; $s_{i,t}$ denotes the structural condition level of the ith bridge in the year of t.

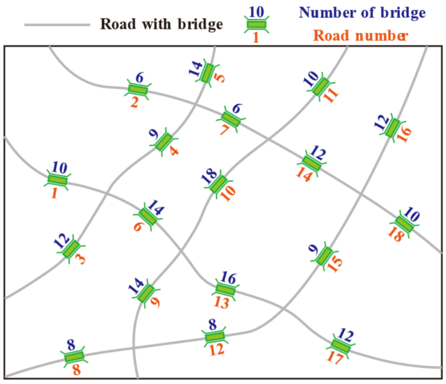


Fig.4 Regional bridges in a local transportation network

3. Regional bridges and condition modelling

3.1 Regional bridges with regular inspections

The proposed DDQNs-based framework for life-cycle management scheme optimization of regional bridges is illustrated using highway bridges that are extracted from a local transportation network in China. This study designed a local transportation network containing 200 bridges based on a real highway transportation network profile in China. The designed virtual bridge network consisting of 18 roads is shown in Fig. 4. Most are middle- and small-span concrete beam bridges. The stakeholders gather the structural condition levels yearly through regular visual inspection to master their service performance.

In China, the regular visual inspection is also referred to as the technical condition assessment. It mainly includes assessing the condition levels of bridge components and whole structures. The "Standards suggest the hierarchical analysis method for Technical Condition Evaluation of Highway Bridges" (JTG/T H21-2011) to comprehensively evaluate the structural condition of highway bridges. In the hierarchical analysis flowchart, the bridge components' condition levels are first evaluated based on the suggested key performance indicators and their control limits. Then, the condition levels of the bridge superstructure units, bridge substructure units, and bridge deck units are calculated with the condition levels of the bridge superstructure components, bridge substructure components, and bridge deck components. Finally, the overall technical condition of the bridge system is evaluated with the full consideration of each bridge unit.

Two assessment indicators are used in the JTG/T H21-2011: structural ratings and condition levels. The structural rating is a 100-point scale indicator, and the condition level contains five levels. They map with each other. When the bridge inspector inspects the bridge, all components in the bridge structure will be inspected and scored with the structural rating. Each component type is deducted from the full score of 100 points for varying degrees of structural damage and the corresponding deduction values. The structural condition levels are determined from Level 1 to Level 5 based on the relationship between structural ratings and condition levels, which is listed in Table 1. The condition level is one digit that describes the general

Table 1 The relationship between structural ratings and condition levels

Condition levels	Structural ratings
Level 1	[95, 100)
Level 2	[80, 95)
Level 3	[60, 80)
Level 4	[40, 60)
Level 5	[0, 40)

structural condition of the bridge unit and system being rated from 1 to 5. Level 1 represents that the bridge has no damage and stays in the best structural conditions. Level 5 represents the bridge with the worst structural conditions and is unsuitable for service.

This study uses the whole bridge structure's condition levels for condition modelling. Although three main structural parts are also essential in all regional small-and medium-span bridges, the smaller categories may lead to data error problems because some components are not common. Furthermore, the computational expense of deep reinforcement learning will surge significantly since lots of detailed safety and economic indicators appear in consideration of smaller categories of bridges.

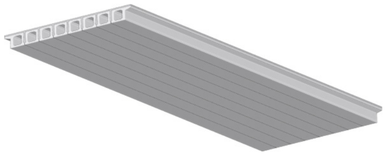
3.2 Regional bridges with regular inspections

Bridge condition data of parts of highway bridges in China is extracted from years of inspection reports to be used in this study to establish the deterioration models and manage their condition levels from a life-cycle perspective. The superstructure of middle- and small-span concrete beam bridges in this region mainly belong to three types: hollow slab beam, T-shaped beam, and box-shaped beam (Xia *et al*. 2020, Lei *et al*. 2021b). Each superstructure type of middle- and small-span bridge in the local transportation network is shown in Fig. 5.

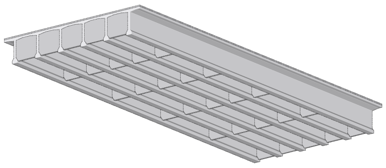
In this region, bridge condition categories of Level 1 and Level 2 account for over 80% of all bridges, indicating that the majority of these bridges are in good condition, despite the potential consequences of continued regular maintenance. It also reveals the effect of maintenance actions from a large amount of data. Several bridges remain in poor condition, and the potential for safety concerns may influence their capacity to provide service in the transportation network.

3.3 Condition transfer modelling

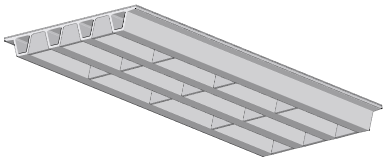
In the reinforcement learning environment of life-cycle management, the state functions play important roles in reflecting the impact of deterioration and maintenance actions on structural conditions. This study employs the MDP to simulate the structural deterioration and effects of maintenance actions. It provides a mathematical framework for modelling decision-making in environments where outcomes are partially random and partly controlled by a decision-maker. The process is in some state at each step, and the decision-maker can take any action available in that state. In the next time step, the process responds by moving into a new state at random and rewarding the decision-maker accordingly.



(a) Hollow slab beam



(b) T-shaped beam



(c) T-shaped beam

Fig. 5 Main superstructure types of middle- and small-span bridge

Table 2 State transition probability matrix (***P***)

Next year \ Current year	Level 1	Level 2	Level 3	Level 4	Level 5
Level 1	$p_{1,1}$	$p_{1,2}$	…	$p_{1,j}$	…
Level 2	$p_{2,1}$	$p_{1,1}$	…	$p_{2,j}$	…
Level 3	…	…	…	…	…
Level 4	$p_{i,1}$	$p_{i,2}$	…	$p_{i,j}$	…
Level 5	…	…	…	…	…

The transition matrix (shown in Table 2) is essential for the MDP. Given the current states and management actions, the state transition probability matrix determines the future states. The $p_{i,j}$ denotes the probability of transition from current condition Level i to next Level j.

The condition data estimate the condition transfer modeling of structural deterioration. The changes in condition levels could reflect the actual deterioration of the structure. It represents the current environment of the deterioration task and tells the agent what situation it is in currently. As shown in Table 3, the diagonal elements are the largest values in their rows and columns. It represents those structures have the ability to withstand external loads and erosion while remaining in their existing state. If the bridge condition is Level 1 this year, the elements in the first row show that it has a probability of 0.92 of remaining in Level 1 next year, with a risk of 0.08 of dropping to Level 2. It is unlikely that it will deteriorate to a lower condition level, as normal deteriorations cannot result in a sudden reduction in condition levels.

Fig. 7 depicts the application of a degradation model to

Table 3 State transition probability matrix of structural deterioration

Current year Next year	Level 1	Level 2	Level 3	Level 4	Level 5
Level 1	0.92	0.00	0.00	0.00	0.00
Level 2	0.08	0.98	0.00	0.00	0.00
Level 3	0.00	0.02	0.98	0.00	0.00
Level 4	0.00	0.00	0.02	0.99	0.00
Level 5	0.00	0.00	0.00	0.01	1.00

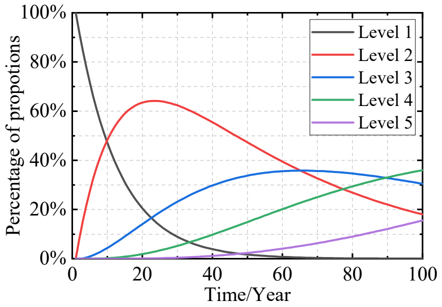


Fig. 6 Condition level distributions with univariate analysis of bridge age

Table 4 State transition probability matrix of replacement actions

Current year Next year	Level 1	Level 2	Level 3	Level 4	Level 5
Level 1	1.00	1.00	1.00	1.00	1.00
Level 2	0.00	0.00	0.00	0.00	0.00
Level 3	0.00	0.00	0.00	0.00	0.00
Level 4	0.00	0.00	0.00	0.00	0.00
Level 5	0.00	0.00	0.00	0.00	0.00

Table 5 State transition probability matrix of repair actions

Current year Next year	Level 1	Level 2	Level 3	Level 4	Level 5
Level 1	1.00	1.00	0.20	0.10	0.05
Level 2	0.00	0.00	0.80	0.25	0.15
Level 3	0.00	0.00	0.00	0.65	0.30
Level 4	0.00	0.00	0.00	0.00	0.50
Level 5	0.00	0.00	0.00	0.00	0.00

simulate the life-cycle deterioration of regional bridges. The degradation result is an average of a 1000-time deterioration simulation using the established MDP model, since the state transition probability matrix comprises the likelihood that the structural condition would worsen from the present level to each of the other worse levels. Almost all bridges deteriorate to Condition 2 or lower by the time they reach their 60th year. The fraction of bridges with inadequate structural ratings have risen over time. There are no bridges with Condition 1 in the 100th year. However, there are 18% with Condition 2, 30% with Condition 3, 36% with Condition 4, and 16% with Condition 5. As a result, it is critical to developing regional bridge maintenance policies to better ensure the overall condition of the regional transport system and assure its long-term serviceability.

The purpose of maintenance actions is to cause the reinforcement learning agent to modify its state. The model includes three sorts of maintenance actions: no action, repair, and replacement. Replacement activities and repair actions are two types of maintenance actions. Their impact on improving structural conditions varies, and the state transition probability matrix could also be used to simulate their impacts. The condition levels of damaged structures will be upgraded to Level 1 after the replacement activities are completed, regardless of their previous state. As a result, Table 4 depicts the state transition probability matrix of replacement activities.

Table 5 depicts the state transition probability matrix of repair actions. The likelihood that the repair action will raise the damaged structure by one condition level is the largest. The repair action with the lowest likelihood is the one that restores the structural condition to its optimal state. It can be seen that the effect of repair measures on the improvement of structural condition levels is different every time. The repair operation may occasionally improve the damaged structure's condition by one level; other times, it may improve the structure's condition to the highest level.

4. Life-cycle management optimization

In this study, 200 bridges were randomly selected from the bridges of the road network in Fig. 4 to form a life-cycle regional bridge management and maintenance optimization case study, and the proposed DDQNs framework was used to perform this optimization. The whole life span of the bridges was designed to be 100 years. The statistical distribution of the lengths and widths of the 200 bridges is depicted in Figs. 8 and 9, respectively. This is because the maintenance cost of the bridges used in this study is directly related to their overall length and width. Fig. 8 shows that the total lengths of the bridges are under 100 m, and the maximum span of each bridge is 20 m, which are middle- and small-span bridges. The width statistics in Fig. 9 are based on the number of lanes. In the Chinese code, 7.0 m to 10.5 m is two lanes, 10.5 m to 14.0 m is three lanes, and 14.0 m to 17.5 m is four lanes. The vast majority of bridges are designed for two or three lanes. Furthermore, the case studies only investigated the impacts of regular degradation on structural condition levels, not the consequences of extreme hazards.

Since the bridges in the case study are extracted from the above transportation network, their deterioration trends and maintenance behavior effects should also obey the condition transfer models extracted in Section 3.3. An accurate regional function is required for a successful maintenance strategy. As a result, state transition matrices in Tables 2 to 4 depict their deterioration, replacement actions,

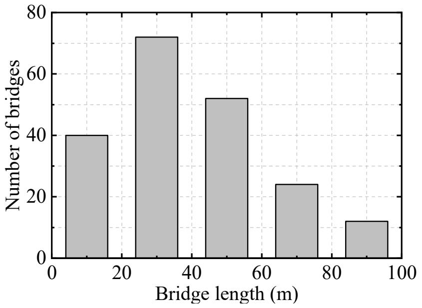


Fig. 7 Span distribution of regional bridges

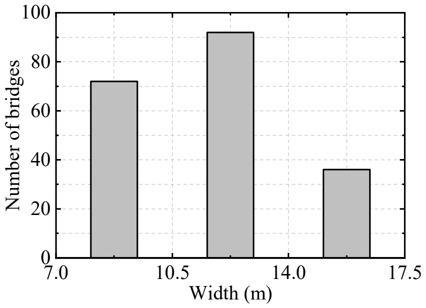


Fig. 8 Width distribution of regional bridges

and maintenance activities behaviors, respectively, in the DDQNs-based life-cycle management optimization model. They fully imply the deterioration performance as well as the maintenance effects of the bridges. The reward function in Eq. (5), which incorporates regional structural safety and total whole-life cost in the assessment indicators, is used to consider the cost of inspection, repair, replacement activities, and structural safety.

4.1 Reinforcement learning model training

Before utilizing the autoencoder to output maintenance actions, the bridge condition data should be structured in a machine-understandable manner. The output dataset discretizes maintenance operations into binary coding while the input dataset discretizes structural condition levels 1 through 5 into 0 to 4. To represent the condition level of each bridge, the input data is a one-dimensional vector with 200 elements. The recommended maintenance actions are represented as a one-dimensional vector with 200 entries. The DDQNs are used to create the best life-cycle maintenance strategies for regional bridges in order to keep them in good working order while maximizing cumulative benefits and lowering costs.

The training epoch is set as 2000 to fully extract the high-dimensional features and produce optimal strategies in practice. Some important values of parameters in the DDQNs model are listed in Table 6. The suggested DDQNs models were tested on a PC with an Intel i7-8700K processor, NVIDIA GTX 1080 graphics card, and 32GB of RAM running the Windows operating system. Python 3.7 and associated libraries (Sklearn, Pytorch) were chosen to create and train DL models. The proposed model was trained on an NVIDIA 1080 (2560 CUDA cores and 8GB GDDR5X RAM) utilizing CUDA and cuDNN for performance optimization.

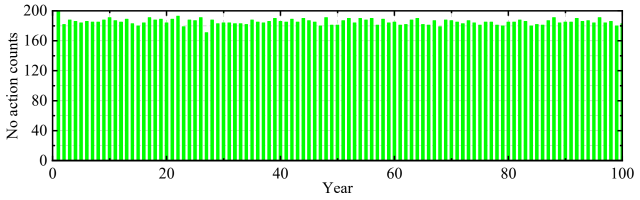
Table 6 Performance comparison between DQNs-based and DDQNs-based methods

Parameters	Values
Memory capacity	2000
Batch size	200
Learning rate	0.001
Discount factor	0.95
The ε in ε-greedy algorithm	0.1
Steps to start learning	2000
Intervals to learn	20
Intervals to update target Q-network	200

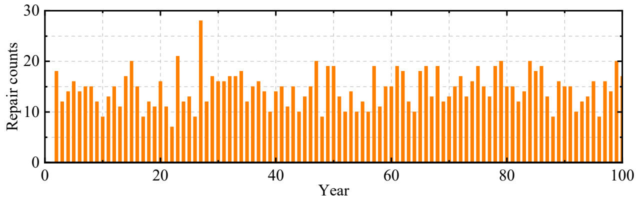
4.2 Management performance

The average regional structural conditions of the optimal strategies continue to improve as the number of training epochs grows. Continuous learning improves life-cycle cost-effectiveness significantly. The number of different maintenance actions, structural conditions of regional bridges, and the overall cost of associated maintenance plans each year, are presented from a regional perspective during their entire life cycle.

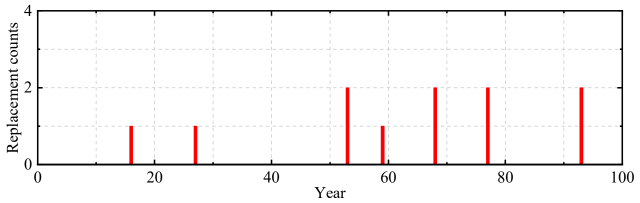
Fig. 10 indicates the number of different maintenance actions in regional bridges over the life cycle in the trained optimum management plan. The majority of bridges do not require maintenance or replacement due to the steady rate



(a) no maintenance action

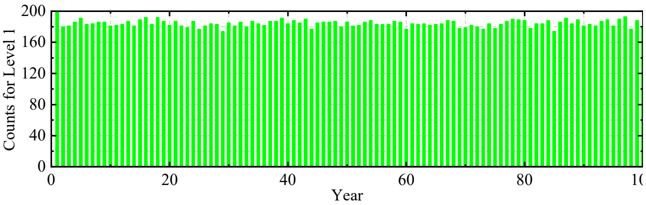


(b) repair maintenance actions

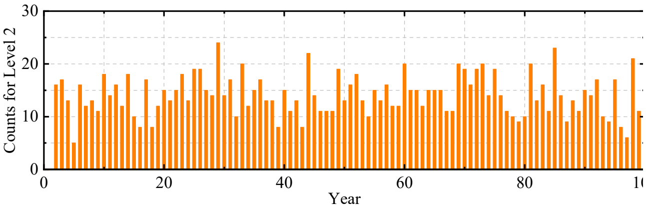


(c) replacement maintenance actions

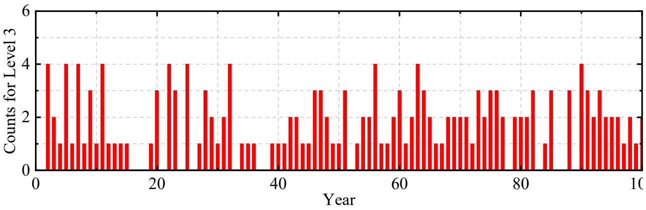
Fig. 9 Number of actions in regional bridges during the life cycle



(a) Level 1



(b) Level 2



(c) Level 3

Fig. 10 Number of regional bridges during the life cycle

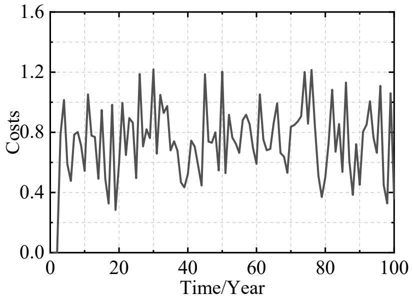


Fig. 11 Annual costs in the optimal management scheme

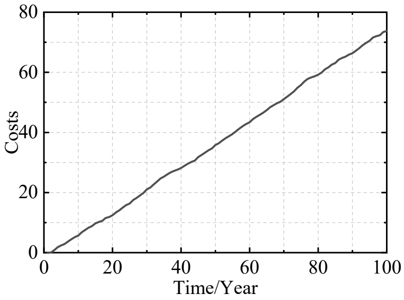


Fig. 12 Cumulative costs in the optimal management scheme

of structural deterioration. When bridges are damaged or are expected to be damaged, the available budgetary resources are primarily used to repair them. In the regional life-cycle, only 11 times of replacement actions are carried out, as shown in Fig. 10(c). In order to preserve resources, the agent chose to replace them less often.

Table 7 Setting of some important parameter values in DDQNs model

Algorithms	DQNs	DDQNs
Total bridges in Level 2	1368	1400
Total bridges in Level 3	201	174
Total costs	75.27	73.78

Fig. 11 depicts the number of regional bridges with Level 1 to Level 3 during the life cycle. Under the optimal management plan, there are no bridges at Level 4 or Level 5. Regional bridges are in great condition when optimal practices are implemented throughout their life cycle. The majority of them are in Levels 1 and 2, with some Level 3 bridges thrown in for good measure. In Fig. 11(c), with up to 4 bridges at Level 3 in 10 years and only 2% of the entire 200 bridges at Level 3 and below, this is a much more desirable strategy.

From an economic point of view, Fig. 12 depicts the annual costs in the optimal management scheme. The annual maintenance cost fluctuates between 0.4 to 1.2. In year 75, the maximum cost for one year is 1.203, and there are other six years with similar costs. Fig. 13 depicts the cumulative costs in the optimal management scheme. It shows a steady upward trend. The final total cost reaches 73.78. It indicates that the proposed strategy is effective in picking the optimal policy. The trained optimal maintenance techniques are well-suited to constraints and maximize the life-cycle cost-effectiveness of maintenance actions.

4.3 Comparison with the nature DQNs

DDQNs are designed to have a more accurate estimation of the actions in the interactive environment. Compared to the nature DQNs, DDQNs handle the problem of the overestimation of Q-values. This section intends to compare the optimal management schemes produced by these two methods, and Table 7 lists their performance. From the safety perspective, Total bridges in Level 2 and total bridges in Level 3 in the whole life span of regional bridges are chosen to represent the safety performance. The total costs in the whole life span of regional bridges are chosen to represent the economic performance.

Compared to the DDQNs-based strategy, the optimum management scheme developed by DQNs has more bridges for level 3 states and fewer bridges for level 2 states, as shown in Table 7. DDQNs may provide a scheme to guarantee that infrastructure is more secure throughout its life-span. Furthermore, the DDQNs-based solution generates the optimum management scheme at a reduced total cost. It may be inferred that the DDQNs-based method can more cost-effectively optimize the life-cycle management scheme of regional bridges.

5. Conclusions

This study offers a deep reinforcement learning framework using DDQNs to optimize the life-cycle management of deteriorating regional bridges. The framework contains the entire optimization procedure from inspection reports collection to condition, costs, reward modeling, and life-cycle management optimization. Detailed descriptions of the reinforcement learning architecture and models are given. The proposed method could produce optimal maintenance plans based on restrictions to maximize maintenance cost-effectiveness to the greatest extent possible. A case study containing hundreds of highway bridges provides decades of inspection data to identify regional functions and help agents better understand the regional life-cycle management task. The case study validates the effectiveness and efficiency of the proposed method. Several conclusions regarding the developed DDQNs-based method can be drawn:

1) Reinforcement learning allows the agent to learn better maintenance behaviors in an interactive environment. Its regional structural deterioration features and the effect of maintenance actions are determined by years of regional inspection reports. The designed autoencoder-structured DDQNs model efficiently learns features from real historical data and produces more precise target management actions.
2) The developed method is capable of producing optimal maintenance plans with the consideration of the overall safety and life-cycle costs of regional bridges. The optimization results contain fewer replacement actions and prefer the repair actions when bridges are damaged or are expected to be damaged. By employing the trained life-cycle regional maintenance strategies, the conditions of bridges can be controlled to a good level.
3) DDQNs provide an optimized scheme with fewer low-condition bridges and lower overall costs when compared to nature DQNs. The problem of overestimation of Q-values in the Nature DQNs is mitigated by the DDQNs method. The ideal maintenance plan achieves a better balance between the overall cost and the improved condition. The agents have the budgetary capacity to afford expenditures for keeping better condition.

This study mainly focuses on the regional life-cycle bridge maintenance planning from an economic and safety perspective. It employs the reinforcement learning technique in the field of life-cycle management tasks of regional bridges. Future studies will use the reinforcement learning technique to find cost-optimized and environmentally friendly life-cycle solutions that consider social and environmental factors for regional bridges.

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