Interactive reinforcement learning innovation to reduce carbon emissions in railway infrastructure maintenance

Sresakoolchai, Jessada; Kaewunruen, Sakdirat

DOI:
10.1016/j.dibe.2023.100193

Document Version
Peer reviewed version

Citation for published version (Harvard):
Sresakoolchai, J & Kaewunruen, S 2023, 'Interactive reinforcement learning innovation to reduce carbon emissions in railway infrastructure maintenance', *Developments in the Built Environment*, vol. 15, 100193. https://doi.org/10.1016/j.dibe.2023.100193

Journal Pre-proof

Interactive reinforcement learning application to reduce carbon emissions in railway infrastructure maintenance

Jessada Sresakoolchai, Sakdirat Kaewunruen

PII: S2666-1659(23)00075-3

DOI: https://doi.org/10.1016/j.dibe.2023.100193

Reference: DIBE 100193

To appear in: *Developments in the Built Environment*

Received Date: 15 May 2023

Revised Date: 30 June 2023

Accepted Date: 1 July 2023

Please cite this article as: Sresakoolchai, J., Kaewunruen, S., Interactive reinforcement learning application to reduce carbon emissions in railway infrastructure maintenance, *Developments in the Built Environment* (2023), doi: https://doi.org/10.1016/j.dibe.2023.100193.

Interactive reinforcement learning application to reduce carbon emissions in railway infrastructure maintenance

Jessada Sresakoolchai and Sakdirat Kaewunruen*

School of Civil Engineering, University of Birmingham, B15 2TT, Birmingham, United Kingdom

*Email: s.kaewunruen@bham.ac.uk

*Tel.: +44 (0) 121 414 2670

HIGHLIGHTS

- The first reinforcement learning model for railway carbon emissions reduction
- Field data robustly enables the creation of customized environments for the model
- Environment's states are obtained from defective track geometry and track component
- A complex combination of maintenance activities is adopted as an action space
- Reduce the defect and carbon emissions using an interactive and dynamic approach

ABSTRACT: Carbon emission is one of the primary contributors to global warming. The global community is paying great attention to this negative impact. The goal of this study is to reduce the negative impact of railway maintenance by applying reinforcement learning (RL) by optimizing maintenance activities. Railway maintenance is a complex process that may not be efficient in terms of environmental aspect. This study aims to use the potential of RL to reduce carbon emission from railway maintenance. The data used to create the RL model are gathered from the field data between 2016-019. The study section is 30 kilometers long. Proximal Policy Optimization (PPO) is applied in the study to develop the RL model. The results demonstrate that using RL reduces carbon emission from railway maintenance by 48%, which generates a considerable amount of carbon emission reduction and reduces railway defects by 68%, which also improves maintenance efficiency significantly.

Keywords: reinforcement learning, carbon emission, railway system, maintenance, railway defects, environmental impact

1 INTRODUCTION

Carbon emission is currently one of the major drivers of catastrophic global warming and climate change. Climate change is caused by the accumulation of greenhouse gases such as carbon dioxide in the atmosphere [1]. These gases trap heat from the sun and cause the Earth's surface temperature to rise. This leads to a range of negative impacts such as more frequent and severe events [2, 3]. As a result, carbon emission is garnering increased attention. Worldwide communities then attempt to diminish it in order to minimize environmental impacts. Rail transportation is one of the most environmentally friendly ways of transportation [4]. However, activities in the railway system contribute to carbon emission. Because railway projects have a long service life, the operating and maintenance phases also contribute to carbon emissions about 6% [5] of the total carbon emission. As a result, reducing carbon emissions in railway activities will have a substantial impact on the environment.

Railway maintenance may be done in several methods, including corrective maintenance, preventive maintenance, and predictive maintenance (condition-based maintenance) [6]. In brief, corrective maintenance is performed when something fails. Preventive maintenance tends to be routine maintenance when the maintenance is performed although there is nothing fails. Predictive maintenance is an approach for planning maintenance based on the current condition of components. Predictive maintenance appears to be the most reasonable alternative for doing maintenance operations nowadays since it performs just what is required to preserve railway infrastructure in acceptable conditions. Maintenance is

scheduled according to the existing state of each railway component and section. Maintenance will be undertaken only if there is a risk of failure or some values reach thresholds. However, the main challenge of applying predictive maintenance is it needs a reliable tool for predicting and planning. It can be seen that optimal decision-making will result in minimum defect and cost [7]. Fortunately, there are many machine learning techniques that are being developed and computational power become more powerful compared to the past decade, the application of predictive maintenance becomes increasingly feasible.

Nowadays, deep reinforcement learning (RL) is employed to tackle a wide range of problems. However, its use in railway maintenance is currently restricted. Through model training, an agent in the RL model which is used as a representative will learn to maximize rewards or limit penalties. In this study, carbon dioxide (CO2) is selected as a representative of greenhouse gas because CO2 is the most abundant greenhouse gas (65%) used to determine rewards for the RL agent along with defects. During the training process, maintenance activities will be performed by the agent to minimize the defect occurrence. However, maintenance activities also create CO2 which is calculated based on the energy and material used for each maintenance activity. Therefore, the agent has to perform maintenance activities to minimize occurring defects while the agent has to limit the number of maintenance activities as necessary to limit the amount of CO2 as well. The amount of carbon emission is used as a reward.

The aim of this study is to use RL to minimize carbon emission from railway maintenance activities. The scope of this study will be limited to railway maintenance activities. This study

will apply PPO to create a deep RL model because it produces many superior outcomes while it is more stable. PPO requires the least amount of time for training [8]. Field data are applied to create the RL model using Monte Carlo simulation and further analysis. The customized environment of the reinforcement learning model is created based on the real characteristic of the railway system. Normal distribution and Monte Carlo simulation are used to code the environment to generate the following step when the agent takes action. Track geometry parameters and component defect probabilities will be improved or deteriorated based on the actions the agent takes. For example, when the agent chooses to perform tamping, some parameters will be improved. This information is based on the field data. However, it is worth noting that there are multiple options for the agent to take action because there are seven maintenance activities that the agent can take and each maintenance activity is independent. A further description is presented in 3.2. The customized environment of RL is created to meet the challenges of this study. The study's contributions include that the created RL model can be employed by railway operators to more efficiently schedule railway maintenance operations when carbon emission from maintenance activities is decreased, as is the number of railway defects. As a result of fewer defects in railway networks, it will result in a more environmentally friendly railway system, and improved serviceability, trustworthiness, and safety [9, 10]. Furthermore, railway operators can apply the created RL model to support decision-making for railway maintenance. This conforms to the challenge statement of Network Rail [10] which aims to improve the technical strategy in different aspects such as asset management, social and environmental, maintenance, operation, and cost management. For asset management, important aspects are Reliability, Availability, Maintainability, Safety (RAMS). RAMS is an important tool to improve the availability of the

system. RAMS has to be applied from the beginning of the project. At the same time, it should be updated along the project to ensure good asset management. This study also aims to improve RAMS in the railway system by developing the RL model to improve the reliability of the system by decreasing defects, availability by keeping tracks free from defects, maintainability by decreasing the severity of defects, and safety will be a result of the good quality track. It can be seen that the RL model that will be developed in this study will have benefits for asset management not limited to the environmental aspect only. This study's novelty is it is the first paper using RL to reduce carbon emission in railway maintenance, which has never been done before. Furthermore, the proposed RL approach is unique since it is based on a customized environment that is tailored to the problem.

2 LITERATURE REVIEW

RL was initially presented in the early 1980s. It was created to address issues such as how to respond or what to do in certain scenarios [11]. The goals of varied responses are to maximize rewards or consequences from actions. An agent is utilized and trained as a representative to know how to respond to various scenarios. The agent is not instructed what to do, rather it must discover for itself how to maximize rewards at the final stage. A problem is that each action influences not just the immediate rewards but also what happens following the timestep (stage) and the total rewards at the final stage. All of these are crucial features of RL that other types of machine learning approaches lack and cannot address. For more detail, RL can be used to solve problems continuously and it uses information from previous stages to take actions from the following stages. Other categories of machine learning do not have this capability because they perform prediction only one time in an epoch. For example, supervised learning will receive a set of features and predict labels. Unsupervised learning will

discover the insights from the data without labeling the dataset. However, RL receives a set of features or states and the agent will take action based on the states. The environment of the RL model will also generate a new stage based on the action and these processes will repeat until the end of the training. An example of RL application in the railway industry is train rescheduling to minimize delay by regulating the movements of rolling stock in real-time and continuously [12].

Chess and other game players, industrial robots, and pilot assistance in passenger automobiles are all examples of prominent RL applications [11]. To tackle RL difficulties, a variety of strategies are employed. The simplest of the initial approaches is the Tabular Solution Method. The idea for this approach came from the trial-and-error process. Every feasible stage from various actions is represented in tabular form. When all possibilities are provided, the RL agent will know what the optimum action is when dealing with different stages. However, it can be observed that the crucial drawback is that this approach can only be used when the options of stages and actions are restricted. In other words, the number of stages and actions are clear and known such as Tic-Tac-Toe where every possible stage is known. However, this approach is not suitable for the problem in this study because the railway system is complicated and the possibility of states is unlimited. Otherwise, it would be impossible to describe all feasible stages and appropriate actions. Other approaches, such as Markov Decision Processes, Dynamic Programming, or Monte Carlo Methods, were created to be utilized with RL to solve this constraint and have the potential to solve problems with unlimited possibilities such as chess or other games. Many strategies have been created over the last decade to extend the potential of RL, and other current RL models have been established and demonstrated to be more effective.

The first terminology to be noted is a stage. Stages are various environmental conditions at different timesteps. In each stage, two components, the agent and the environment, constantly interact. The environment will provide information to the agent via stages and rewards. The agent will then respond by taking action against the environment. Following that, the environment will give the agent new stages and rewards. The available actions are categorized into action spaces. This procedure will be repeated till the training is completed. Figure 1 depicts a flowchart of this procedure. A reward is given to the agent at each stage based on how successfully the agent reacts to the environment. At the end of the training, rewards such as win-loss results may be awarded. This might vary based on the problem being attempted to tackle. This information will be used to choose the optimal policy for the agent. It is worth noting that the policy in this study refers to a strategy that an agent uses to take action in the environment. It defines how the agent selects actions based on the states of the environment. A policy can be different depending on the RL algorithms and problems. The goal of RL is to find an optimal policy that maximizes the rewards or long-term performance in the environment.

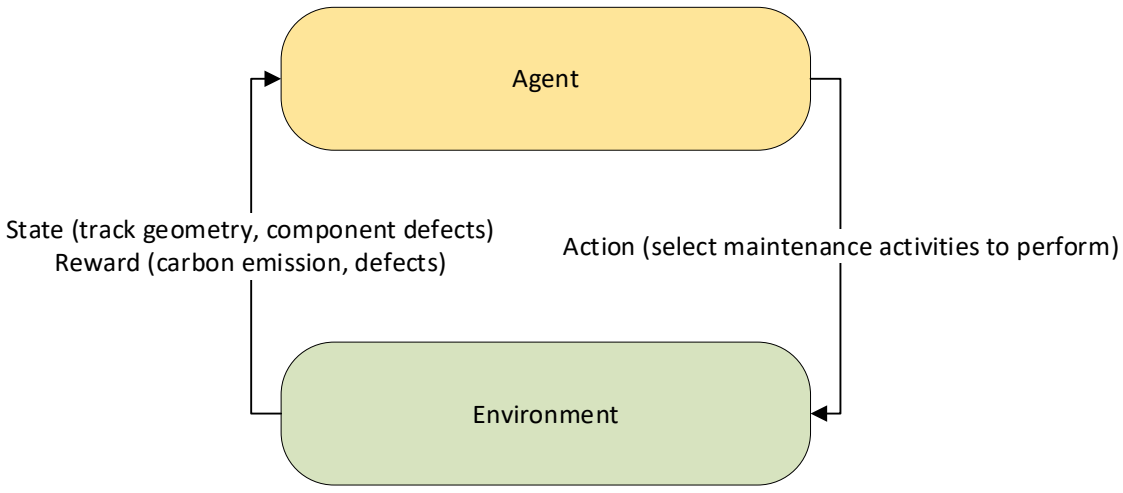


Figure 1 Flowchart of the RL model

RL has become more prominent in recent years. It has been used in a variety of domains [13], including communication and networking [14], biology [15], electrical systems [16], robotics [17], transportation [18], medical [19], finance [20], or engineering [21]. Following are some instances of RL applications.

In the railway industry, RL has been used in a variety of ways. Sedghi et al. [22] conducted a literature review on this subject. The majority of the techniques in their assessment were based on mathematics or probabilistic approaches such as stochastic modal, mixed integer programming, simulation, Markovian model, and machine learning, which are popular today and deliver satisfactory performance. The stochastic modal considers the uncertainty of the environment. Instead of selecting a single deterministic action for each state, a stochastic policy assigns a probability distribution over the available actions based on the states. Mixed integer programming is a mathematical optimization technique that is used to optimize the policies of agents. The Markovian model is a fundamental mathematical framework used in RL to model and solve sequential decision-making problems. It captures the future state and reward depending on the current state and action based on the past stages. Machine learning is the most advanced approach because agents are trained multiple times which allows agents to learn from the environment to have abilities to choose the best action under certain situations.

Šemrov et al. [23] used Q-Learning to reschedule single-track trains. The agent's action spaces were comprised of two actions: stop and go. The delay was used to compute rewards. The model was tested with a three-station scenario. It was discovered that utilizing RL might help to lessen railway delays. Cui et al. [24], Khadilkar [25], and Zhu et al. [12] also corroborated

this observation. Other railway sector uses of RL include control [26], power management [27-29], inspection [30], and alignment optimization [31].

RL has not been widely used in railway maintenance. Only one research has been conducted by Mohammadi and He [32]. Deep Q-learning (DQN) was used to create a decision-making tool for railway maintenance. This method used the track quality index (TQI) and the hazard index as inputs. These two indications were obtained using RL. These two were then utilized to train the RL model. Their action spaces included five activities: preventative tamping, preventive grinding, condition-based tamping, condition-based grinding, and renewal. When compared to the baseline, they discovered that using the suggested technique might minimize the TQI and hazard index. However, the study's research gap is that they employed summary indices such as TQI and hazard indexes instead of precise track geometry parameters. Previous years' maintenance tasks were not included, and the action spaces might be expanded for greater comprehensiveness. Furthermore, new sophisticated or cutting-edge strategies should be tested in order to increase the overall effectiveness of the RL model.

According to the literature review, the use of RL for railway infrastructure maintenance and carbon emission reduction is still in its early stages, with relatively little research available. There are gaps in research in this area that can be filled. For example, each track geometry parameter may be taken into account for more practical, comprehensive maintenance operations that can be incorporated into the RL model, or field data can be linked with the RL model. As a result, the goal of this study is to address as many of these gaps as possible by creating a method for using RL to reduce carbon emission from railway infrastructure

maintenance based on each track geometry parameter and individual track component defect. To guarantee that the produced model mimics the real-world condition as closely as possible, detailed maintenance operations and filed data are part of the RL model development.

3 METHODOLOGY

3.1 *RL model and Proximal Policy Optimization (PPO)*

RL is one of the three major types of machine learning besides supervised and unsupervised learning. RL is gaining popularity at the moment. Agents in RL models are trained and learn from their environment [33]. Environments feature rules that agents must comply with, such as limitations and available actions. Agents will interact with their environments based on their states ($s_t \in S$ where S is possible states), which can be a discrete timestep ($t = 1, 2, 3, \dots, n$), by completing actions ($a_t \in a(s_t)$) in states (s_t) where $a(s_t)$ feasible action exists. Following that, agents will be rewarded (or penalized R_t) for their actions [32]. The states will then transition to the next state, and the agents will conduct their acts once more. This method will be repeated until the training or environment states are completed. The goal of agent training is to increase rewards or decrease penalties.

PPO will be used in this study to create the RL model for a variety of reasons. PPO is by far the most highly sophisticated and best algorithm. It is designed to be more stable than other policy gradient methods, making it easier to train agents in complex environments. It achieves the greatest reward in the shortest number of steps and with the least instability. It can learn effectively with fewer samples and less fine-tuning than other policy gradient methods. In terms of flexibility, PPO can be applied to a wide range of tasks and environments, including

223 those with continuous or high-dimensional action spaces. Furthermore, in comparison to
224 other RL methods, the training period is quite short [8, 34]. PPO is designed to find an optimal
225 policy by updating the policy using data collected from interactions with an environment. In
226 the beginning, PPO will collect data by executing the current policy in the environment. The
227 information that is collected in this step is states, actions, rewards, and other relevant
228 information. Then, it will compute how much better or worse an action is compared to the
229 average action at a particular state. This is used to update policies. Then, PPO will update the
230 policy by performing multiple epochs of policy updates using the collected data. In each step,
231 the policy is updated to maximize the objective function. These processes are repeated again
232 and again until the convergence is achieved. As a result of its performance, advancement, and
233 novelty, PPO has been deemed the best methodology in this study.

234 3.2 *Data Characteristics and Preparation*

235 MRS Logística S.A. has provided field data for a 30-km railway section from 2016 to 2019. The
236 data comes from a variety of sources, including track geometry measurements, rail
237 component defect inspection reports, and actual maintenance records for the heavy haul rail
238 networks.

239 Track geometry cars gather foot-by-foot track geometry parameters to obtain track geometry
240 parameters or the sampling rate is 100 Hz. Superelevation, longitudinal level (10m chord),
241 longitudinal level (20m chord), alignment (10m chord), alignment (20m chord), gauge, and
242 twist (20m chord) are all included in the data sets. Seven track geometry parameters will be
243 employed as inputs to the RL model. In other words, they will be utilized in the states specified
244 by the agent to determine the following actions. The reason for using the track geometry

parameter is this is the fundamental information that every railway operator has. Moreover, this information directly represents the quality of the track. Thresholds are established by the company as four priorities. Priority 1 indicates that the track geometry parameters are extremely poor and that track sections should be maintained as soon as possible, whilst priority 4 indicates that track sections should be included in the normal maintenance schedule. In this scenario, priority 4, the least worried trigger level, will be selected as the threshold for the RL model to consider rewards and penalties since the goal of this study is to execute a predictive maintenance approach that keeps the track free of defects or limit them to a minimum. Figure 2 depicts the threshold for each track geometry parameter which is the base operating conditions (BOCs) according to MRS Logística S.A. Track sections with track geometry parameters that surpass the threshold are regarded as defective, and the number of defects is determined by the number of exceeding track geometry values.

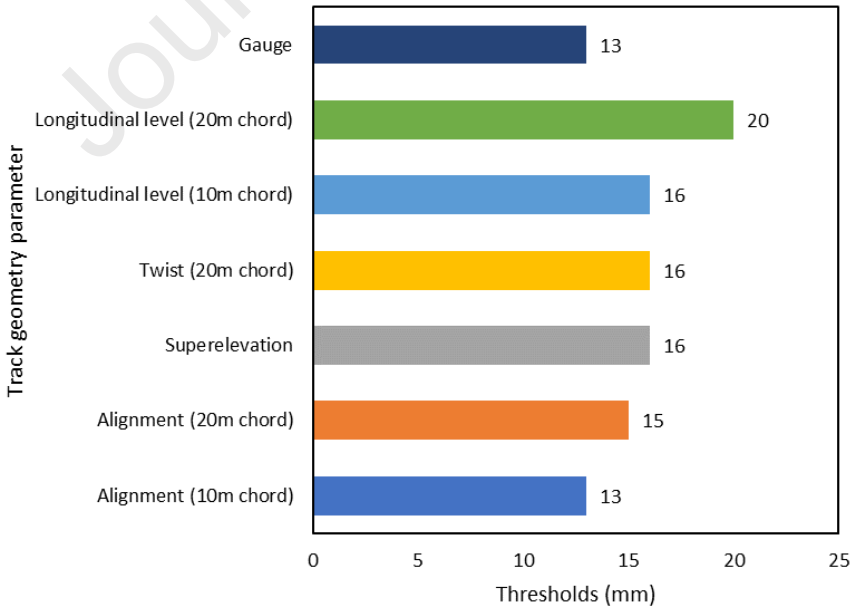


Figure 2 Track geometry parameter thresholds [35]

The following data source is defect inspection reports, which gather various track component defects. There are 71 various forms of track component defects, which vary according to the track component. There are different types of component defects such as broken rails, broken frogs, or missing sleepers. To simplify the analysis, they are divided into five groups depending on track components: ballast, fastener, rail, sleeper, and switch and crossing. If defects are discovered, certain track sections are deemed defective, and the total number of defects is determined by the number of track component defects. When track geometry and component defects are combined, there are a total of 12 defect categories: seven for track geometry defects and five for track component defects.

The final information source is maintenance records. Tamping, rail grinding, ballast cleaning, sleeper replacement, rail replacement, fastening component replacement, and ballast unloading are the seven maintenance activities listed. The RL model's action space will be these seven maintenance activities. In this scenario, the action space may be thought of as seven binary spaces in which each maintenance activity can be performed or not performed. It is worth emphasizing that, in practice, maintenance activities are more sophisticated because they may be performed individually. They can be mixed in any number from 0 to 7. As a result, the probability combination principle is used to consider the alternative actions in each state of the RL model. Equation 1 is used to determine the total combination with repetition, where n is the number of alternatives and r is the size of the combination. n equals seven in the equation, and r can be modified from zero to seven. The total number of possible actions or combinations is 128. There are almost one million sets of data from maintenance records that could be regarded as thorough enough to analyze maintenance activities,

281 changes in track geometry parameters, and the incidence of track component defects in
282 normal distribution patterns.

$$Total\ combinations = \frac{n!}{(n-r)!\,r!} \qquad \text{Equation 1}$$

283 Every data source is integrated to combine and process to be prepared as the preliminary
284 input of the RL model. These data will be utilized to create a customized RL environment.
285 Different maintenance activities can be integrated with each stage, resulting in a high degree
286 of variation in maintenance activities undertaken. Nevertheless, the datasets are abundant
287 enough to enable this heterogeneous action space through numerical processing. In other
288 words, the data is large enough to predict how much track geometry properties would
289 improve or degrade when maintenance activities are carried out. In this case, the lower
290 number is preferable. The size of the degradation and improvement are considered based on
291 the field data. The relationships between the change in degradation and improvement are
292 based on the maintenance activities performed. For example, when tamping is performed,
293 the track geometry parameters will improve and the size of improvement is based on the field
294 data from track geometry measurement and maintenance report. Simultaneously, how much
295 the possibility of each track component defect will rise or diminish when alternative
296 maintenance actions based on the same principle are done. Some examples for
297 demonstrating a clearer view are given following.

298 As mentioned, seven maintenance activities. These activities have been collected from the
299 maintenance report which covers the maintenance of the track structure. Figure 3 and Figure
300 4 demonstrate examples of improvements and degradation in track geometry parameters

when tamping is performed or is not performed in the context of a normal distribution. It should be noted that the positive numbers represent the deterioration while the negative numbers represent the improvement because the low-track geometry parameters are desirable. As representations, the mean and standard deviation (SD) are utilized. The figures show only two simple examples that are being analyzed. There are additionally 127 more instances based on potential actions that will be utilized to create the relationships between actions and states in the RL model. Figure 5 also illustrates track component defects as an example of the likelihood's change when component defects are not identified and identified when rail grinding is conducted and not conducted respectively. From the figure, the chance of defects to occur tends to decrease when the maintenance is performed and increase when the maintenance is not performed. However, these numbers of probability are mathematically limited to be in the range of zero to one. This is also included in the code to create the customized environment for the RL model which will be described in the following section. The figure only represents a simple scenario of the track component defects. In reality, there are more intricate combinations of maintenance activities that impact the track component defect incidence that is analyzed and used as inputs in the RL model in forms of the association between actions and states. The most complicated issue is determining how to update the states when the agent conducts actions. In this scenario, the states are divided into twelve sub-states that represent track geometry parameters and track component defect occurrences. States are real numbers that indicate the extent of abnormalities in track geometry parameters while they are binary integers that indicate whether or not a track component defect exists. Changes in each state are evaluated while updating the states of the RL model utilizing field data including track geometry measurements, defect inspection

reports, and maintenance records as mentioned previously. Changes in states are based on this data using a normal distribution associated with the aforementioned specified maintenance actions. Now that all of the necessary data has been processed. The environment for the RL model can be created. The reason for using normal distribution without considering time-series data of the change in track geometry parameter is because the data are not continuous and they depend on different performed maintenance activities. Therefore, the transition model has a limitation to be applied with the reinforcement learning model in this study.

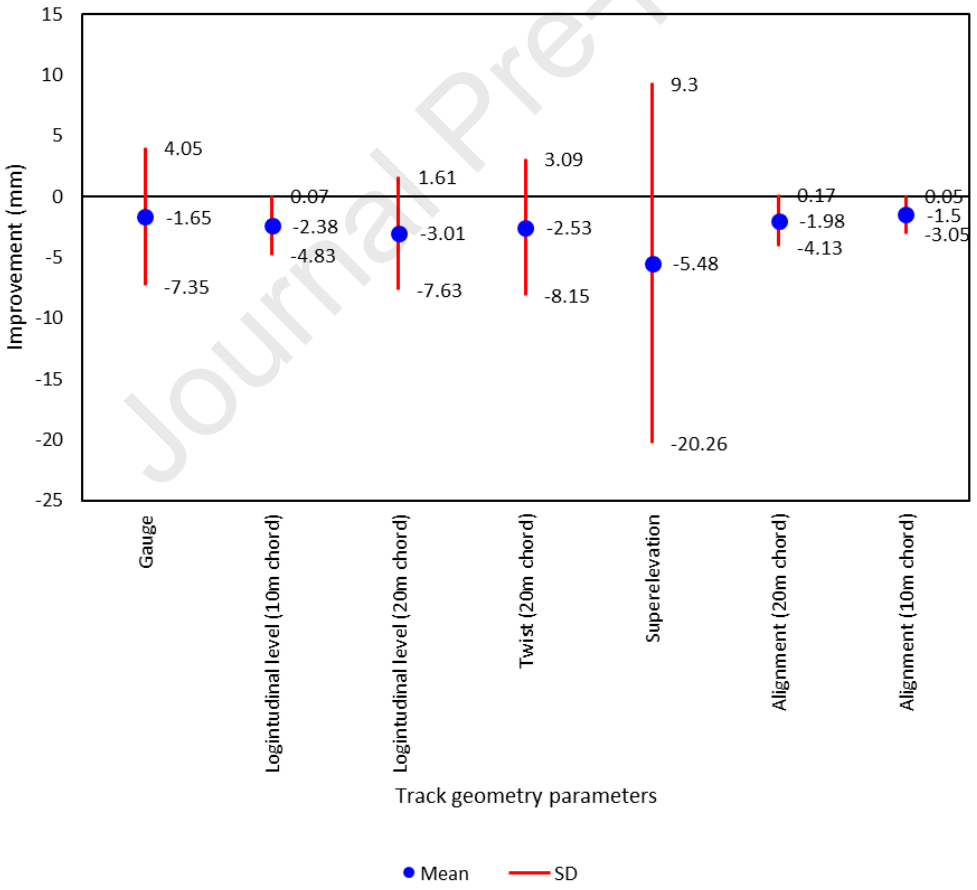
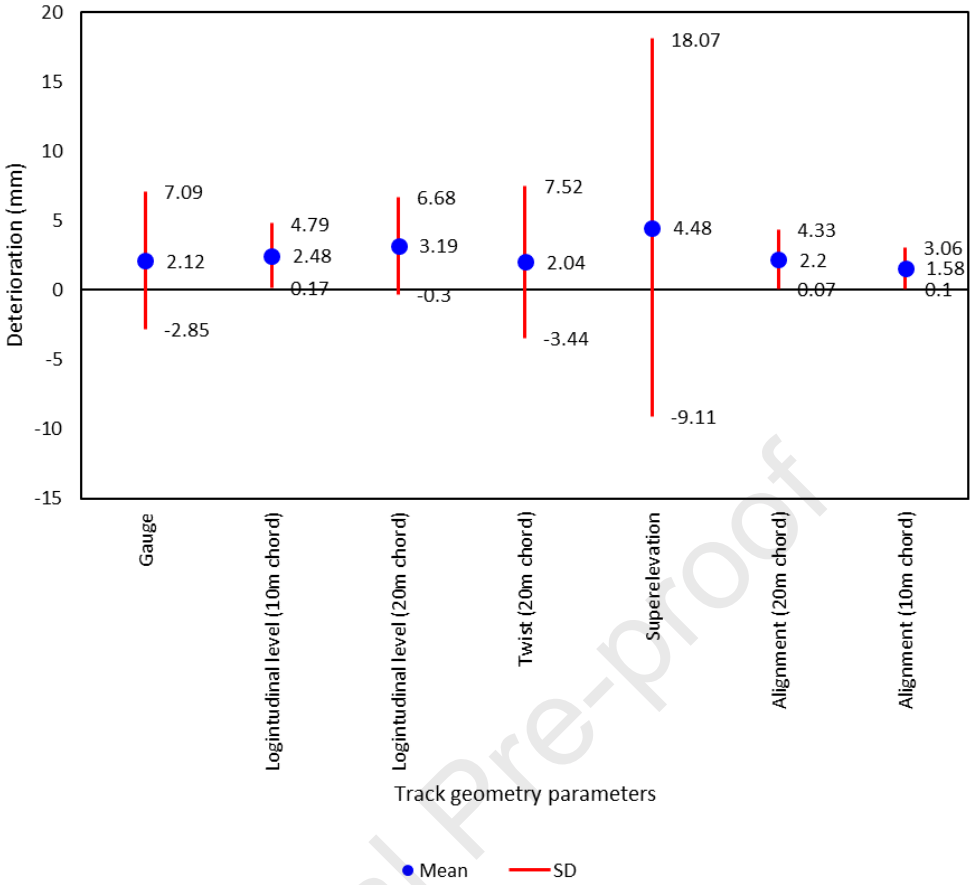


Figure 3 Track geometry parameters' improvement when tamping is performed



335

336 Figure 4 Track geometry parameters' deterioration when tamping is not performed

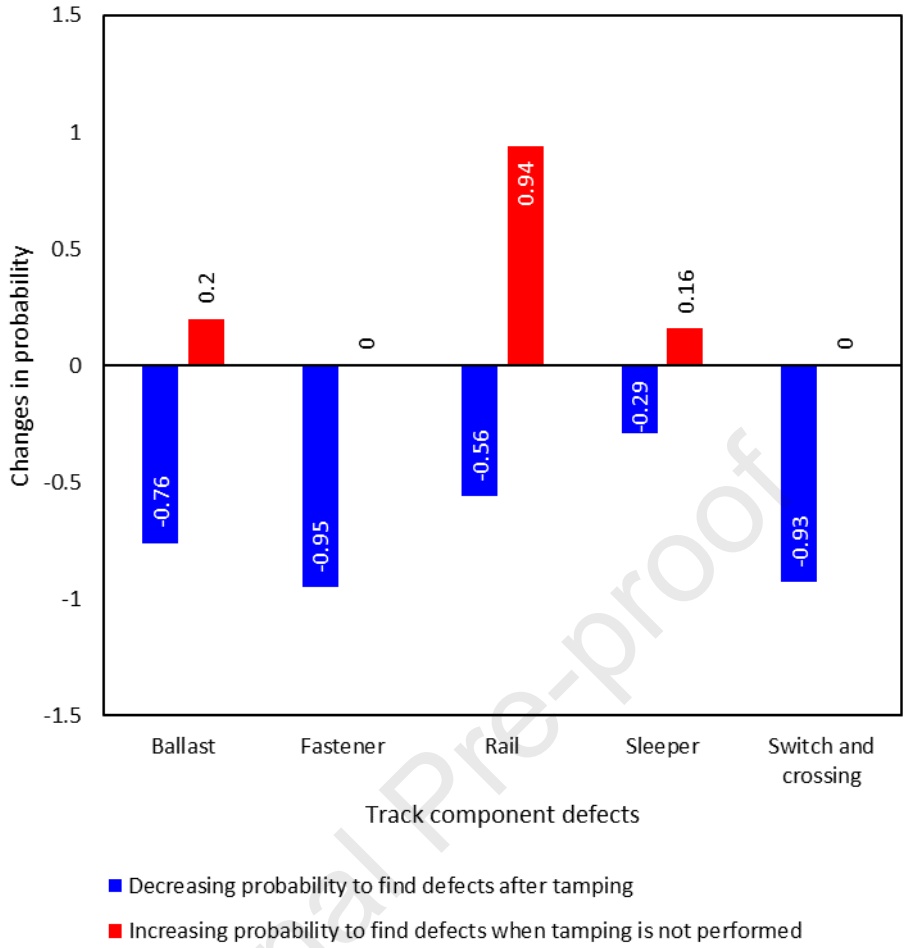


Figure 5 Relationship between defect occurrence and rail grinding

3.3 *Problem description and customized environment*

To achieve the purpose to train the RL agent, the problem in this study is unique. Therefore, a customized environment has to be created to match the problem in this study. To create the customized environment, OpenAI Gym is the employed platform. In addition, Stable Baselines are used to develop the RL agent. The first step of the customized environment creation is to define the action space and observation space. The dimension of the action space and observation space have to correspond to the number of available actions and states. In this case, the dimension of the action space will be seven (types of maintenance activities) and the dimension of the observation space will be 12 (values to consider defects). In the study, the action space is discrete when it is in the form of multi-binary (do or not do)

while the observation space is continuous or the box (real number representing track geometry parameters and probability of component defect occurrence). The step is used to represent each stage or timestep in the environment. The reset function is used to reset the environment to the initial step and retrain the RL agent because the agent will be trained multiple times. states are variables that are collected in the observation space which the agent uses as information to choose the next action. Rewards can be defined in each step or at the final step of the training. Rewards can be defined based on states. The done function is used to tell the agent that it reaches the final step of the training and the environment has to be reset to train the agent again.

The agent will learn how to perform maintenance activities based on 12 states which include seven track geometry parameters and five track component defects. There are five maintenance activities as available combined actions so 128 different maintenance actions are feasible. Varied combinations of maintenance actions result in different improved and degraded track geometry characteristics, as well as the chance of track component defect incidence, as determined by field data analysis. The RL agent tries to decrease the carbon emission generated from maintenance activities while maintaining tracks free from defects. A non-defective track means that the track section has no track component defects and no track geometry parameters that exceed established criteria. Because this study has not included the maintenance cost in the training process of the agent, the agent selects the maintenance activities to perform based on the carbon emissions and the current status of defects. To avoid the bias of the agent to select only maintenance activities that cause small carbon emissions, the rewards (penalties) based on defects are set to have high values to

ensure that the agent will try to prevent the occurring defects instead of minimizing carbon emissions.

Figure 6 demonstrates the complete process of the RL model. Every parameter in the first state is defined based on the field data. The agent must next take action by deciding which maintenance tasks are required to be performed. Following the action, the environment will respond by producing a set of new states that take into account the right values of each state depending on the previously given field data to ensure that it is adequate for real-world applications. This method will be repeated till the training is completed. Penalties from two categories are used to determine rewards: carbon emission and defect incidences. Track geometry defects are determined through Figure 2, whereas track component defects are determined by occurrence. Because agent training strives to limit carbon emission while maintaining the track defect-free, the penalties for defect incidence in this study are particularly substantial compared to the penalties based on carbon emission. Loss and policy entropy are utilized to demonstrate the performance of the RL model. The loss indicates the model's deviation from expectation, while the policy entropy shows how successfully the agent responds to challenges. The desired values for these two parameters are both 0. During the training process, the timestep is set to be 100 years as the service life of the project which should be comprehensive in many cases of railway projects that the service life can be ranged from 50 to 70 years. In addition, because the maintenance plan is prepared on an annual basis, therefore, one step of the RL model represents one year of the operation and maintenance stage of the railway project.

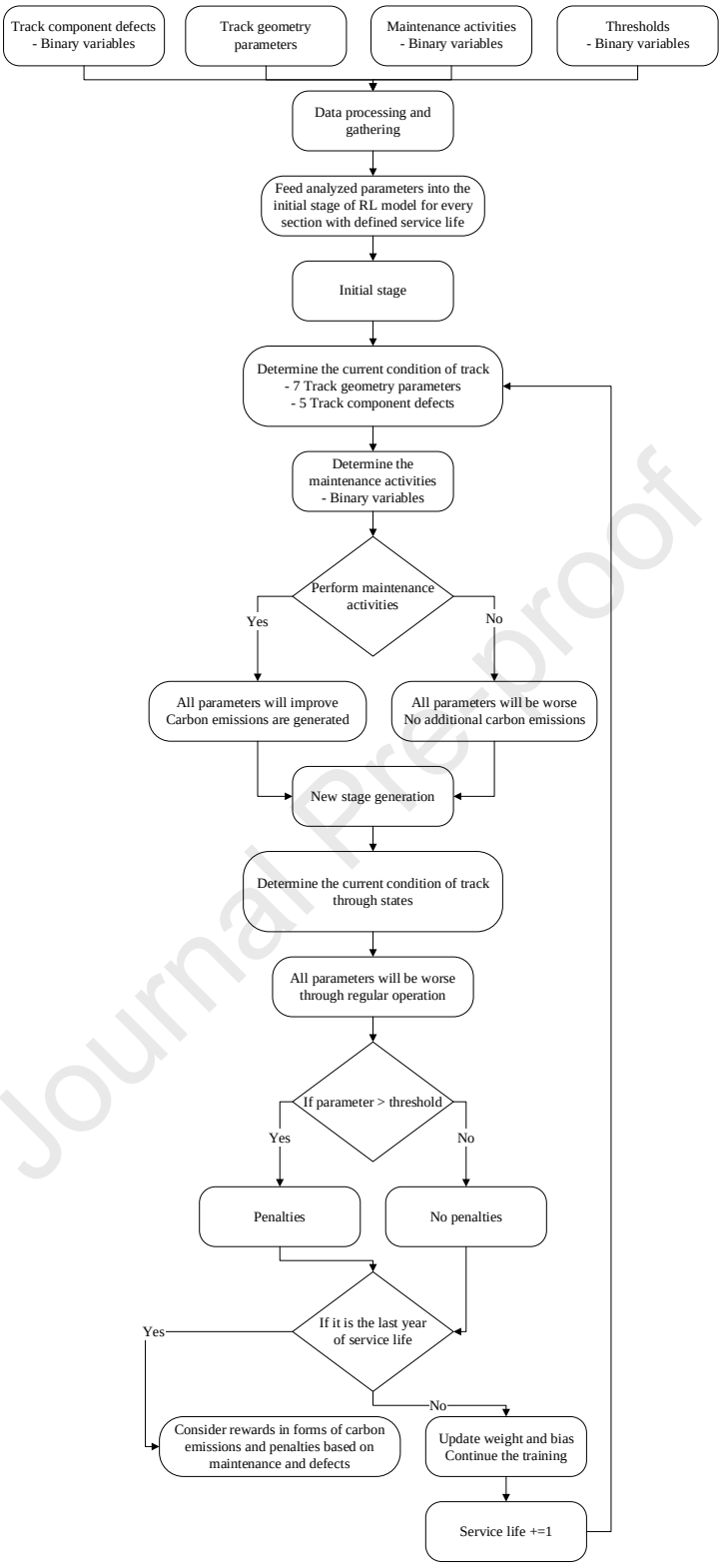


Figure 6 The RL model's workflow

For the determination of carbon emission, the study will limit carbon emission to maintenance activities and employed materials solely. For the carbon emission created by

maintenance operations, two sources of carbon emission are considered: material consumption and electricity utilized to operate the equipment or machine. Some procedures may solely involve materials since a machine is not necessary. At the same time, some maintenance procedures may not necessitate the use of materials, resulting in carbon emission based only on the energy used to operate the machine. Table 1 shows the calculation in further detail. As previously stated, the total carbon emission of various maintenance activities will be supplied to the RL to train the agent. From the table, the speed and power information are gathered from different sources such as specifications or catalogs. Then, the energy consumption is calculated based on the speed and power of the machine and the length of the track section. In this case, the length of a track section is one foot where the carbon emission from electricity generation is 0.509 (kg CO2e) [36, 37]. Then, the carbon emission based on the material is calculated. For ballast, the carbon emission from the production is 3.4 kg CO2e/ton [38]. The sleeper production generates a carbon emission of 0.124 kg CO2e/kg [39] and assumes that the sleeper weight is 70 kg. Last, the carbon emission from steel production is 1.85 kg CO2e/kg [40].

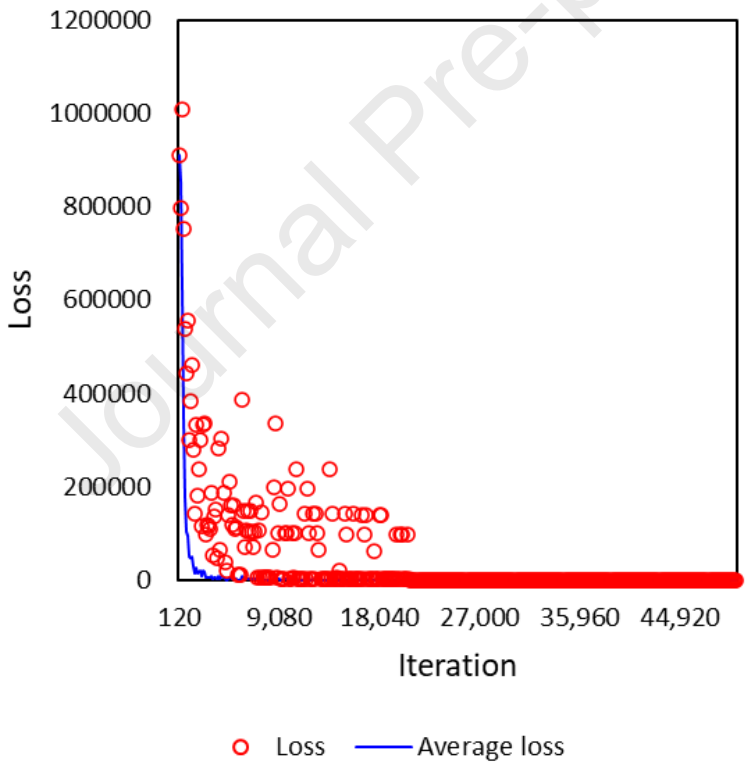
Table 1 Carbon emission from maintenance activities

Maintenance activities	Speed (km/h)	Duration for a section (h)	Power (kW)	Energy consumption (kWh)	CO2e from Electricity (kg CO2e)	Type of material	Material use	CO2e from material (kg CO2e)	Total CO2e (kg CO2e)
Tamping	56 [41]	5.36E-06	130.5 [41]	6.99E-04	3.56E-04	-	-	-	3.56E-04
Rail grinding	8 [42]	3.75E-05	120.0 [42]	4.50E-03	2.29E-03	-	-	-	2.29E-03
Ballast cleaning	48 [43]	6.25E-06	838.9 [43]	5.24E-03	2.67E-03	Stone	2,900 kg [43]	6.16E-06	2.67E-03
Sleeper replacement	48 [44]	6.25E-06	36.0 [44]	2.25E-04	1.15E-04	Concrete	1 set	8.68	8.68E+00
Rail replacement	160 [45]	1.88E-06	20.0 [45]	3.75E-05	1.91E-05	Steel	0.6 m	66.6	6.66E+01
Fastening components replacement	-	-	-	-	-	Steel	2 sets (19.48 kg) [46]	36.04	3.60E+01
Ballast unloading	5 [47]	6.00E-05	1491.4 [47]	8.95E-02	4.55E-02	-	-	-	4.55E-02

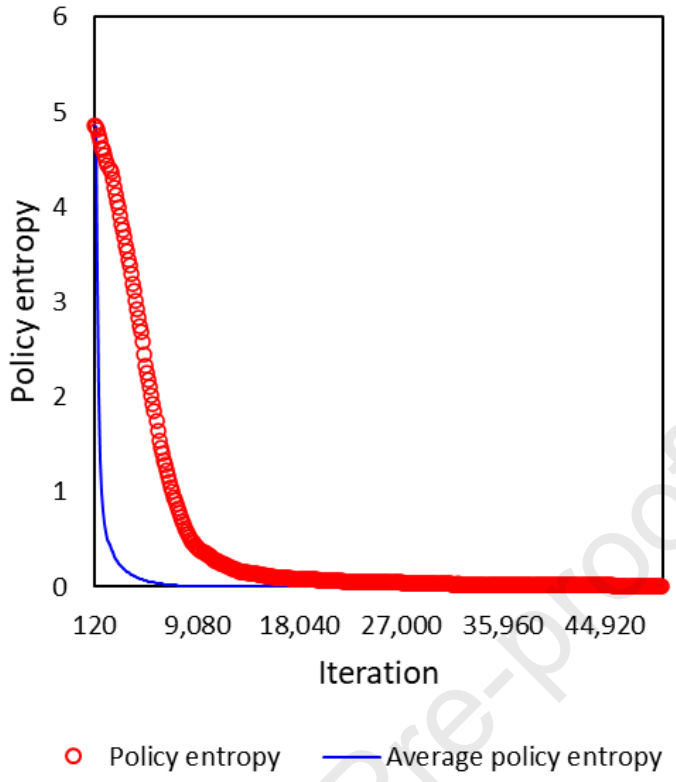
4 RESULTS AND DISCUSSION

4.1 *RL model training*

The RL model has been coded to train for 100,000 iterations or training cycles. Python is used to create the RL model. PPO was utilized to develop the RL model. Figure 7 presents the training's loss and policy entropy. When the training is completed, the expected loss and policy entropy should be close to 0. It can be observed that after 20,000 epochs of training, the loss is near 0, indicating that the RL model has been optimized and the training is complete. The iteration is shown in the figure through 40,000 to provide a clear view.



(a)



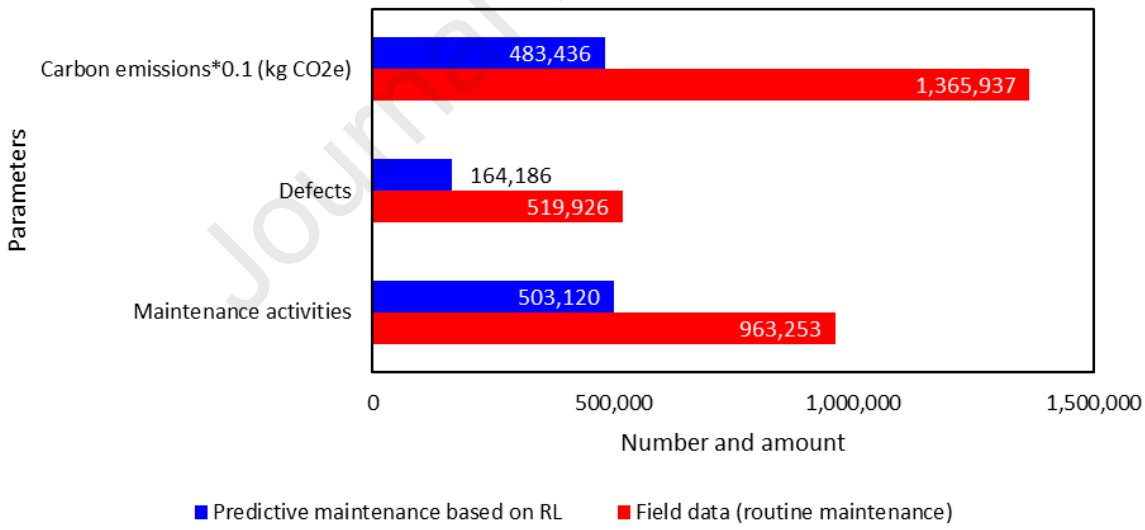
(b)

Figure 7 RL model training progress (a) loss and (b) policy entropy

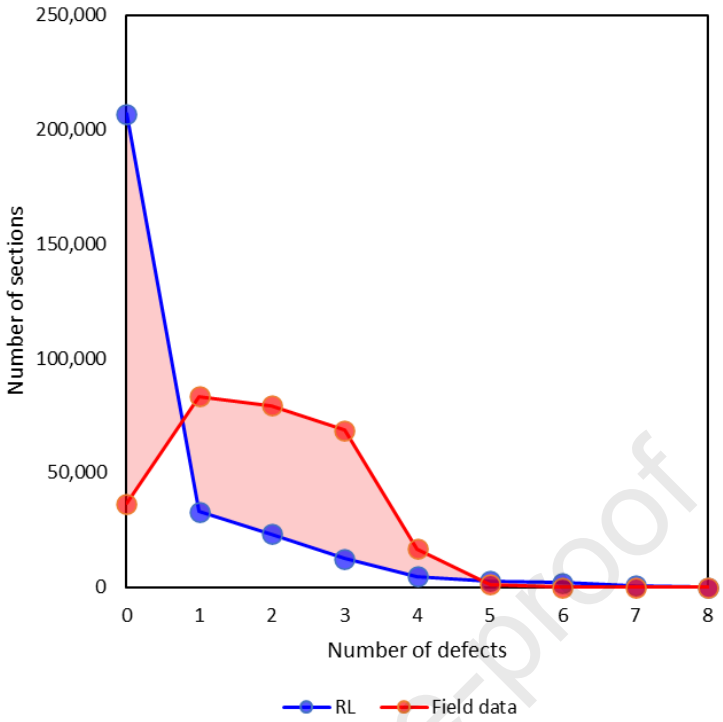
4.2 *RL model performance*

Figure 8 (a) illustrates the variations in the number of maintenance activities conducted, defects that occurred, and carbon emission using field data or routine maintenance and the RL model that can be called predictive maintenance. Figure 8 (b)-(d) demonstrates the distribution of the number of defects, maintenance activities, and cumulative carbon emissions along track sections respectively. The number of maintenance activities performed from the field data is 963k, whereas the number of maintenance activities performed through RL is 503k. In that instance, using the RL model to make a maintenance decision can reduce the number of maintenance tasks by 48%. The number of occurring defects from the field data is roughly 520k, whereas the amount from the RL model is decreased to 164k. The calculation shows that it reduces the number of defects by 68%. In terms of carbon emission,

performed maintenance activities based on filed data emit 13.7k tons CO2e, whereas performed maintenance activities based on RL emit just 4.83k tons CO2e. This suggests that the new technique can decrease carbon emission from railway maintenance by up to 65%. According to the findings, the created RL model significantly enhances overall maintenance efficiency in terms of operation and environment. This is consistent with the preliminary analysis's finding that maintenance was not carried out efficiently. Some track sections necessitate more attention while others require less. When maintenance is performed properly, efficiency may be greatly increased. It can be inferred that the proposed RL model may greatly reduce carbon emission from railway maintenance operations, which is consistent with the study's goal.

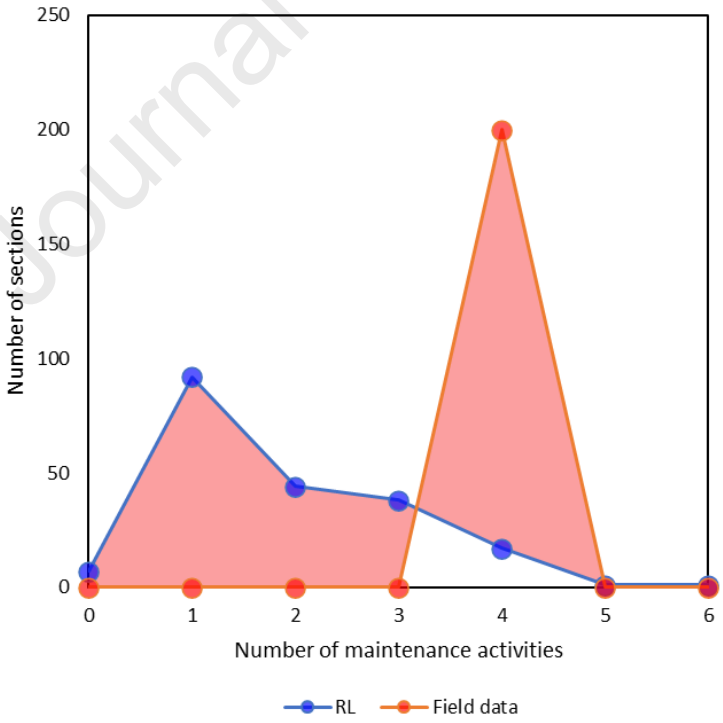


(a)



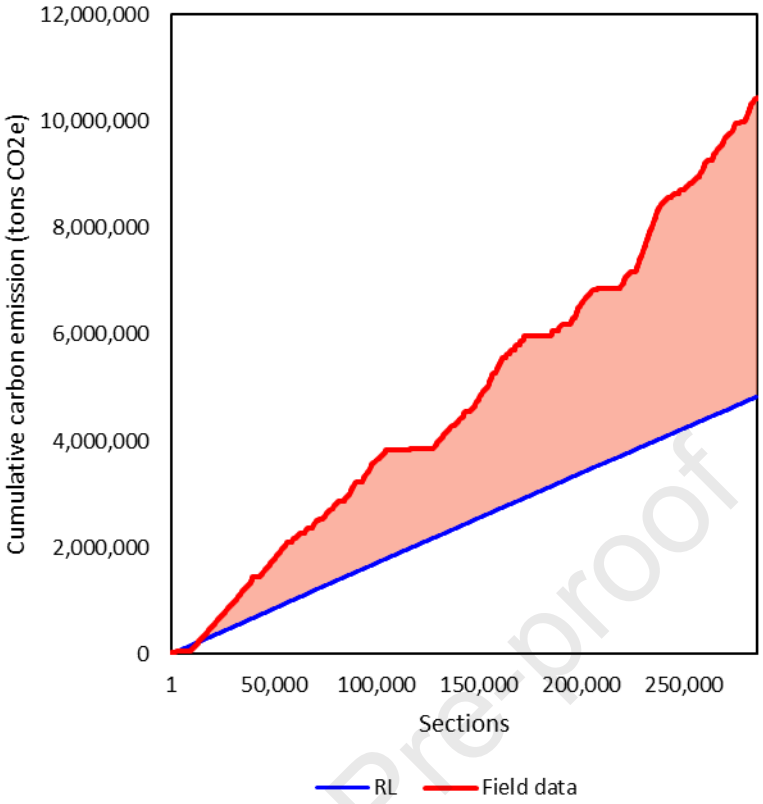
444

445 (b)



446

447 (c)



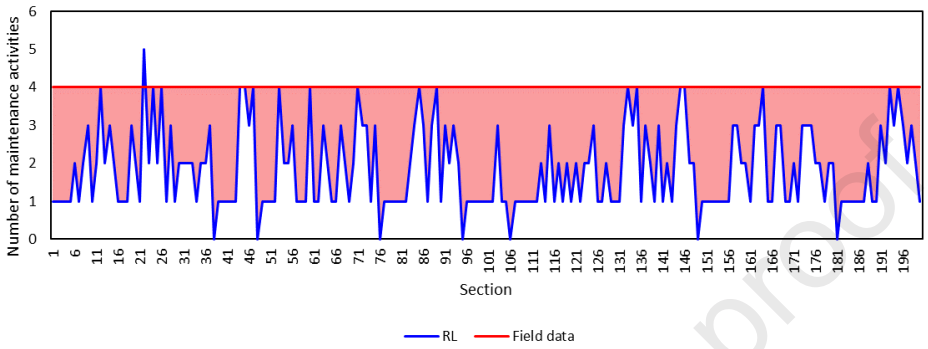
448

449 (d)

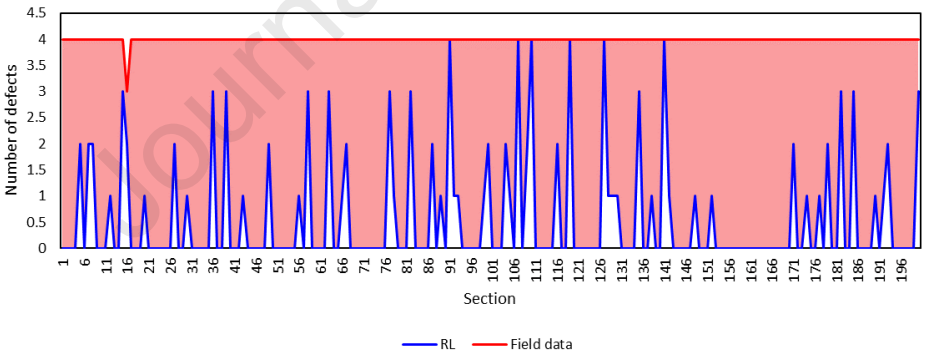
450 Figure 8 Comparison of overall results between field data and RL model (a) overall result, (b)
451 number of defects distribution, (c) number of maintenance activities distribution, and (d)
452 cumulative carbon emission along sections

453

454 4.3 *Examples of RL model application*

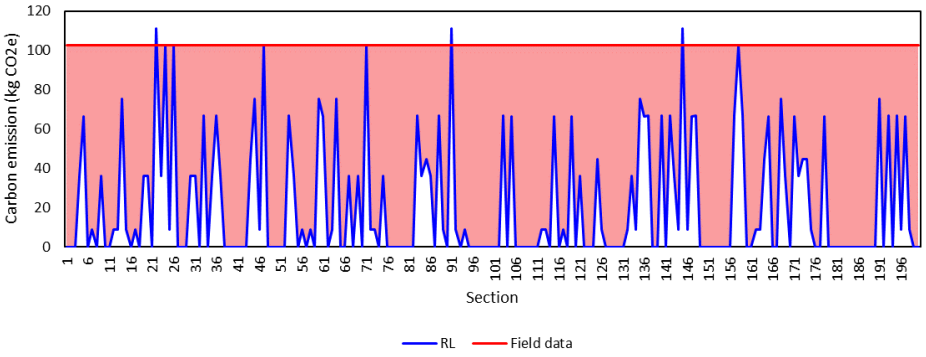


(a)



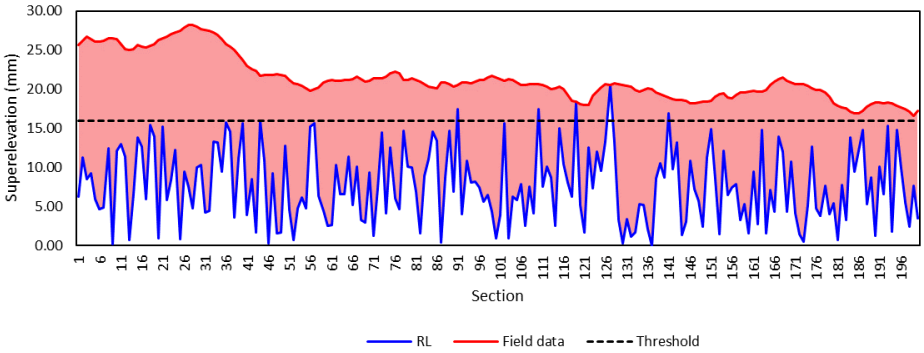
455

456 (b)



457

458 (c)

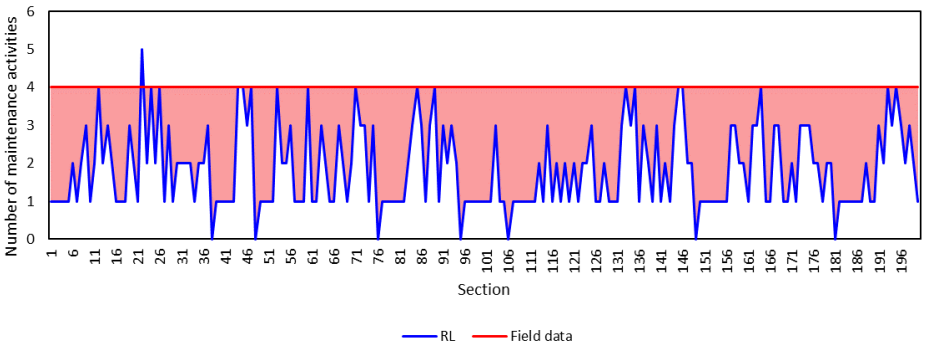


459

460 (d)

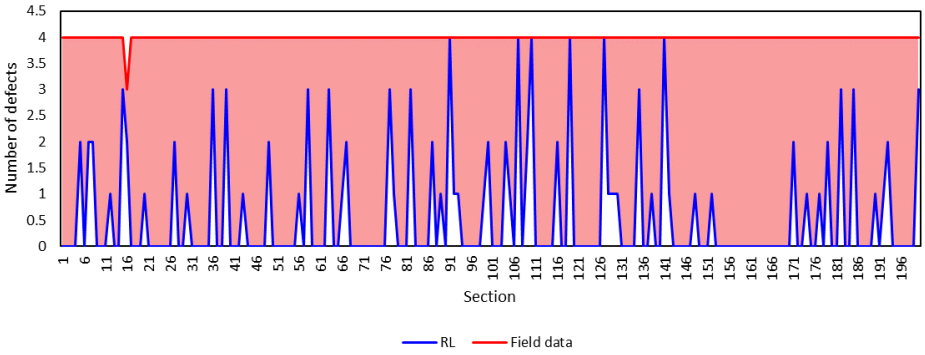
461 Figure 9 shows samples of the first 200 track sections. It is clear that the RL model reduces
462 the overall amount of maintenance activities, defects, and carbon emission. However, due to
463 the stochastic nature of the railway system, the number from the RL model is occasionally
464 larger than the field data. Although certain track sections are maintained, defects do develop,
465 which poses a challenge in the railway industry. Some part of track geometry parameters is
466 demonstrated using superelevation as an example. According to the maintenance guide, the
467 superelevation threshold is 16 mm. All values from the first 200 sections of the field data
468 surpass the threshold, which is unsatisfactory. However, the results of the RL model
469 demonstrate that the majority of the superelevation is within an acceptable range, while
470 there are a few sections where the values surpass the threshold, which can occur.

471

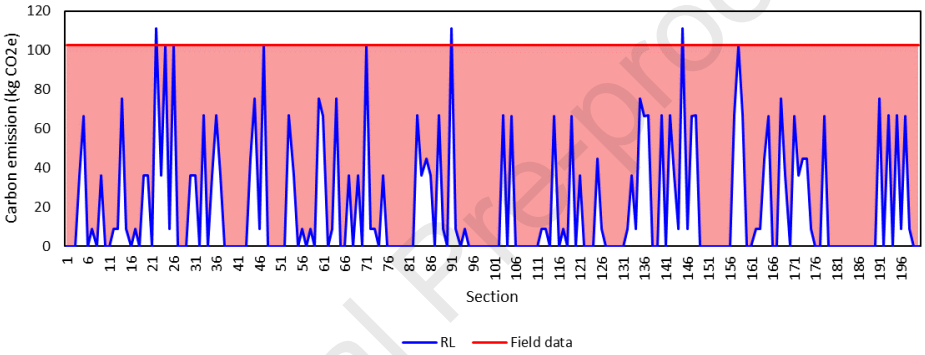


472

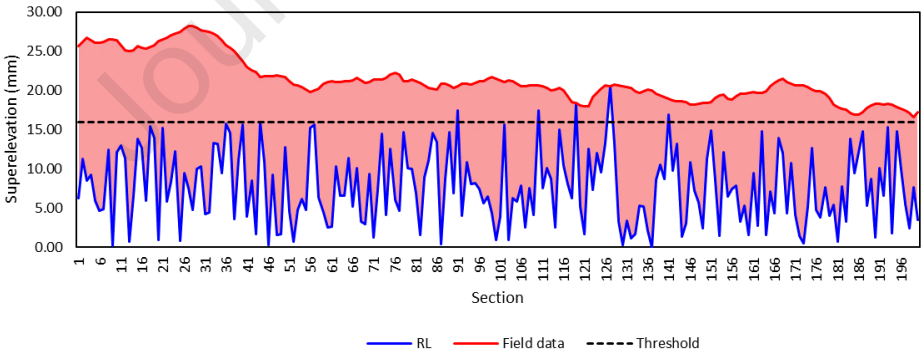
(a)



(b)



(c)



(d)

Figure 9 Examples of differences between field data and RL model (a) maintenance activities, (b) defects, (c) carbon emissions, and (d) superelevation

From Table 1, rail and fastening component replacements generate the highest carbon emission. The use of RL can reduce the number of these two activities by 17% and 72% respectively. For more detail, rail replacement is planned to perform while rail grinding can

also be performed to improve track quality and causes less carbon emission. At the same time, fastening component replacement might not be performed efficiently because they are not defective. These are examples of how RL can improve maintenance efficiency and reduce carbon emissions based on what RL learns from data. Railway operators can apply the approach proposed in this study with their data to improve maintenance efficiency by inputting the current status or parameters of the railway infrastructure and using the developed RL model to prepare maintenance plans. From the results, the RL model can reduce carbon emissions, the number of defects, and maintenance costs. It is believed that they will be able to reduce defects, maintenance costs, and carbon emissions because RL learns from data and is not biased.

5 CONCLUSION

The objective of this study is to use the RL model to minimize carbon emission from railway maintenance. The PPO approach was utilized to create the RL model. The states utilized to train the agent are made up of 12 parameters extracted from track geometry parameters to track component defects. The action spaces for the RL agent are created by combining seven maintenance activities. Rewards are dependent on the carbon emission from maintenance activities undertaken and defects discovered in track sections. These characteristics make the model developed in this study novel and unique. As a result, the RL agent is trained to minimize carbon emission while maintaining defect-free railway tracks. Field data obtained from the 30km track between 2016 and 2019 was utilized to create the RL model.

The proposed RL model can achieve the study's goal. It highlights the possibility of lowering carbon emission from railway maintenance by decreasing maintenance efforts while limiting

defects that develop. The findings of the RL model demonstrate that it may cut maintenance activities by 48%, defects by 68%, and carbon emission by 65% when compared to field data which is a significant improvement that has never been achieved by using other techniques. Moreover, contributions of the developed RL model besides the carbon emission and defect reduction are it can improve the reliability and serviceability of train services because it reduces the probability of system failure, enhance maintenance and asset management, reduce environmental impacts, improve resource allocations, improves the safety of passengers and railway staff, or integrate new technology and support the autonomous system. In conclusion, the developed RL model can resolve the pain points of railway maintenance. Railway maintenance can be complex and complicated. Corrective maintenance is not efficient because the system has to fail first before being fixed. Preventive maintenance is sometimes too much in terms of maintenance. The developed model can make predictive maintenance feasible and efficient. Maintenance can be done based on data not feeling or experience which can be biased. Therefore, it can be tracked and improved over time. It is worth noting that the maintenance cost has not been considered in this study due to the confidentiality issue. However, including this part of the data can absolutely improve the realism of the study.

This study will assist railway decision-making groups in better track inspection and maintenance schedules. Using the methodology provided by this study, they may use their database data to train the RL model. The produced model may then be used to assist or even drive selections, which is the ultimate objective of the data-driven concept. Some restrictions, such as cost, machine, or human resource limitations, can be added or adjusted in the environment to satisfy their circumstances. Railway operators can apply the developed RL

models by inputting the geometry data, maintenance records, and defect inspection. Then, the models are used to identify maintenance activities that should be performed to maintain tracks in good condition with the lowest carbon emission. Then, the models will update themselves and be ready to receive new data from the following years or stages before identifying the next proper actions continuously. The degree and priority of maintenance can also be put in action spaces to provide various states that will be interesting for the next stage of the investigation. Furthermore, the following inspection and measurement plan might be determined by the current track conditions and maintenance activities. This will undoubtedly represent real-world applicability, but it will also complicate the study. It is, nonetheless, intriguing and has the potential to enhance reinforcement learning to mimic real-world events as closely as feasible.

6 AUTHOR CONTRIBUTIONS

Sakdirat Kaewunruen: Conceptualization, Methodology, Validation, Resources, Data Curation, Supervision, Funding Acquisition. **Jessada Sresakoolchai**: Conceptualization, Methodology, Software, Validation, Formal analysis, Investigation, Writing - Original Draft, Writing - Review & Editing, Visualization.

7 DECLARATION OF INTERESTS

The authors declare no competing interests.

8 ACKNOWLEDGMENT

The authors also wish to thank the European Commission for the financial sponsorship of the H2020-RISE Project no. 691135 “RISEN: Rail Infrastructure Systems Engineering Network”,

which enables a global research network that addresses the grand challenge of railway infrastructure resilience and advanced sensing in extreme environments (www.risen2rail.eu).

9 REFERENCES

1. Swe, T.M., P. Jongvivatsakul, and W. Pansuk, *Properties of pervious concrete aiming for LEED green building rating system credits.* Eng. J., 2016. **20**(2): p. 61-72.
2. Frelich, L.E. and P.B. Reich, *Will environmental changes reinforce the impact of global warming on the prairie–forest border of central North America?* Front. Ecol. Environ., 2010. **8**(7): p. 371-378.
3. Houghton, J., *Global warming.* Rep. Prog. Phys., 2005. **68**(6): p. 1343.
4. Andersson, E., O. Fröidh, S. Stichel, T. Bustad, and H. Tengstrand, *Green Train: concept and technology overview.* Int. J. Rail Transp., 2014. **2**(1): p. 2-16.
5. Rungskunroch, P., Z.-J. Shen, and S. Kaewunruen, *Getting it right on the policy prioritization for rail decarbonization: Evidence from whole-life CO2e emissions of railway systems.* Frontiers in Built Environment, 2021: p. 60.
6. Szwedo, J.D. *Preventive, predictive and corrective maintenance*.
7. Mohammadi, R. and Q. He, *A deep reinforcement learning approach for rail renewal and maintenance planning*, in *Reliability Engineering & System Safety*. 2022, Elsevier. p. 108615.
8. Yarram, S. and V.V. Krishna *COMPARISON OF REINFORCEMENT LEARNING ALGORITHMS*. 2022.
9. Network Rail, *Reliable and resilient track geometry*. 2022.
10. Network Rail. *Challenge statements*. 2022; Available from: https://www.networkrail.co.uk/industry-and-commercial/research-development-and-technology/research-and-development-programme/challenge-statements/.
11. Sutton, R.S. and A.G. Barto, *Reinforcement learning: An introduction*. 2018: MIT press.
12. Zhu, Y., H. Wang, and R.M.P. Goverde. *Reinforcement learning in railway timetable rescheduling*. 2020. IEEE.
13. Li, Y., *Reinforcement learning applications.* arXiv preprint arXiv:1908.06973, 2019.
14. Luong, N.C., D.T. Hoang, S. Gong, D. Niyato, P. Wang, Y.-C. Liang, and D.I. Kim, *Applications of deep reinforcement learning in communications and networking: A survey.* IEEE Commun. Surv. Tutor., 2019. **21**(4): p. 3133-3174.
15. Mahmud, M., M.S. Kaiser, A. Hussain, and S. Vassanelli, *Applications of deep learning and reinforcement learning to biological data.* IEEE Trans. Neural Netw. Learn. Syst., 2018. **29**(6): p. 2063-2079.
16. Zhang, Z., D. Zhang, and R.C. Qiu, *Deep reinforcement learning for power system applications: An overview.* CSEE J. Power Energy Syst., 2019. **6**(1): p. 213-225.
17. Kormushev, P., S. Calinon, and D.G. Caldwell, *Reinforcement learning in robotics: Applications and real-world challenges.* Robotics, 2013. **2**(3): p. 122-148.
18. Abdulhai, B. and L. Kattan, *Reinforcement learning: Introduction to theory and potential for transport applications.* Can. J. Civ. Eng., 2003. **30**(6): p. 981-991.
19. Zhou, S.K., H.N. Le, K. Luu, H.V. Nguyen, and N. Ayache, *Deep reinforcement learning in medical imaging: A literature review.* Med Image Anal, 2021. **73**: p. 102193.
20. Kolm, P.N. and G. Ritter, *Modern perspectives on reinforcement learning in finance.* Modern Perspectives on Reinforcement Learning in Finance (September 6, 2019). The Journal of Machine Learning in Finance, 2020. **1**(1).
21. Andriotis, C.P. and K.G. Papakonstantinou, *Managing engineering systems with large state and action spaces through deep reinforcement learning.* Reliab. Eng. Syst. Saf., 2019. **191**: p. 106483.
22. Sedghi, M., O. Kauppila, B. Bergquist, E. Vanhatalo, and M. Kulahci, *A taxonomy of railway track maintenance planning and scheduling: A review and research trends.* Reliability Engineering & System Safety, 2021. **215**: p. 107827.

23. Šemrov, D., R. Marsetič, M. Žura, L. Todorovski, and A. Srdic, *Reinforcement learning approach for train rescheduling on a single-track railway.* Transp. Res. B: Methodol., 2016. **86**: p. 250-267.
24. Cui, Y., U. Martin, and W. Zhao, *Calibration of disturbance parameters in railway operational simulation based on reinforcement learning.* J. Rail Transp. Plan. Manag., 2016. **6**(1): p. 1-12.
25. Khadilkar, H., *A scalable reinforcement learning algorithm for scheduling railway lines.* IEEE trans Intell Transp Syst, 2018. **20**(2): p. 727-736.
26. Wang, H., Z. Han, Z. Liu, and Y. Wu, *Deep Reinforcement Learning Based Active Pantograph Control Strategy in High-Speed Railway.* IEEE Trans. Veh. Technol., 2022.
27. Xu, J. and B. Ai, *Experience-driven power allocation using multi-agent deep reinforcement learning for millimeter-wave high-speed railway systems.* IEEE trans Intell Transp Syst, 2021.
28. Zhu, F., Z. Yang, F. Lin, and Y. Xin, *Decentralized cooperative control of multiple energy storage systems in urban railway based on multiagent deep reinforcement learning.* IEEE Trans. Power Electron., 2020. **35**(9): p. 9368-9379.
29. Deng, K., Y. Liu, D. Hai, H. Peng, L. Löwenstein, S. Pischinger, and K. Hameyer, *Deep reinforcement learning based energy management strategy of fuel cell hybrid railway vehicles considering fuel cell aging.* Energy Convers. Manag., 2022. **251**: p. 115030.
30. Zhong, J., Z. Liu, H. Wang, W. Liu, C. Yang, Z. Han, and A. Núñez, *A looseness detection method for railway catenary fasteners based on reinforcement learning refined localization.* IEEE Trans. Instrum. Meas., 2021. **70**: p. 1-13.
31. Gao, T., Z. Li, Y. Gao, P. Schonfeld, X. Feng, Q. Wang, and Q. He, *A deep reinforcement learning approach to mountain railway alignment optimization.* Comput.-Aided Civ. Infrastruct. Eng., 2022. **37**(1): p. 73-92.
32. Mohammadi, R. and Q. He, *A deep reinforcement learning approach for rail renewal and maintenance planning.* Reliability Engineering & System Safety, 2022. **225**: p. 108615.
33. Kaelbling, L.P., M.L. Littman, and A.W. Moore, *Reinforcement learning: A survey.* J Artif Intell Res, 1996. **4**: p. 237-285.
34. Alibabaei, K., P.D. Gaspar, E. Assunção, S. Alirezazadeh, T.M. Lima, V.N.G.J. Soares, and J.M.L.P. Caldeira, *Comparison of on-policy deep reinforcement learning A2C with off-policy DQN in irrigation optimization: A case study at a site in Portugal.* Computers, 2022. **11**(7): p. 104.
35. MRS Logística S.A., *Track geometry thresholds*. 2019.
36. Kaewunruen, S., J. Sresakoolchai, and Y.-h. Lin, *Digital twins for managing railway maintenance and resilience.* ERJ Open Res., 2021. **1**(91): p. 91.
37. Kaewunruen, S., M. AbdelHadi, M. Kongpuang, W. Pansuk, and A.M. Remennikov, *Digital Twins for Managing Railway Bridge Maintenance, Resilience, and Climate Change Adaptation.* Sensors, 2022. **23**(1): p. 252.
38. Meddah, M.S. *Recycled aggregates in concrete production: engineering properties and environmental impact*. 2017. EDP Sciences.
39. Rempelos, G., J. Preston, and S. Blainey, *A carbon footprint analysis of railway sleepers in the United Kingdom.* Transp Res D Transp Environ, 2020. **81**: p. 102285.
40. Hall, J., *Cleaning Up The Steel Industry: Reducing CO2 Emissions with CCUS.* 2021.
41. Networkrail, *Track treatment fleet*. 2022.
42. Pouget, *MACHINES FOR TRACK WORK.* 2022.
43. Progressrail, *KERSHAW® KSC2000 SHOULDER CLEANER.* 2022.
44. Geismar, *SLEEPER CHANGING MACHINE.* 2022.
45. Vossloh, *Rail Replacement Wagon SWW.* 2022.
46. Anyang General International Co., L., *Rail Fastening System.* 2022.
47. European Patent Office, *Wagon for unloading ballast on a railway.* 2007.

Interactive reinforcement learning innovation to reduce carbon emissions in railway infrastructure maintenance

Jessada Sresakoolchai

School of Civil Engineering, University of Birmingham, B15 2TT, Birmingham, United Kingdom

Sakdirat Kaewunruen*

School of Civil Engineering, University of Birmingham, B15 2TT, Birmingham, United Kingdom

*Email: s.kaewunruen@bham.ac.uk

*Tel.: +44 (0) 121 414 2670

HIGHLIGHTS

- The first reinforcement learning model for railway carbon emissions reduction
- Field data robustly enables the creation of customized environments for the model
- Environment's states are obtained from defective track geometry and track component
- A complex combination of maintenance activities is adopted as an action space
- Reduce the defect and carbon emissions using an interactive and dynamic approach

Key novelties:

This is an original paper, which has neither previously nor simultaneously in whole or in part been submitted anywhere else. The paper presents a world-first novel AI-based decision making tool to help reduce carbon emission in railway maintenance, which is one of the primary contributors to global warming throughout the whole lifecycle of the critical asset and infrastructures. The new data-driven method capable of co-simulations with other GUI frameworks using real-world datasets is highly innovative, and novel and we have obtained the field data from joint research collaboration with rail industry globally. Not only can this method deal with rail geometry, but it can also effectively manage complex infrastructure component replacement and repairs, driven by sustainability goals. This can be successful with the computer-aided innovation that enables co-simulation. This outcome will lead to the better understanding and implementation of novel data-driven decision making framework for environmental-friendly maintenance of infrastructures, which are very critical to sustainable development worldwide.

Declaration of interests

☒ The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

☐The authors declare the following financial interests/personal relationships which may be considered as potential competing interests: