

# Risk and Resilience of Railway Infrastructure: An Assessment on Uncertainties of Rail Accidents to Improve Risk and Resilience Through Long-Term Data Analysis



Panrawee Rungskunroch, Anson Jack, and Sakdirat Kaewunruen

## 1 Introduction

Recently, the reduction of railway accident has become a critical development for railway authorities. It leads to provide sustainability development on the rail network. Based on the UIC's report, the railway accident has been slightly decreased due to high technologies applied to the system [1]. However, an attempt to make zero accident is a challenge to rail authorities.

The railway infrastructure failures have shown an increasing trend to a railway accident based on the collected long-term accident data set. The fraction of infrastructure failures is changed from 4.19% to 5.14% during 2000–2019; moreover, the severity level of an accident by infrastructure failures have illustrated at a high level. Also, more than 70% of all accident shows as a train derailment.

The research has created two novelty models through the Python programming language. Firstly, the main problem is that railway risk and resilience contain various uncertainties; therefore, the Bayesian method is taken to understand the uncertainties of railway accident and predict probabilities on each type of accident in the future. Then, the risk-based DT model has been provided to evaluate the risk level. This model offers precisely the risk level based on fatalities and injuries rates. This is a direct benefit for railway authorities to provide an effective plan to combat avoidable accidents.

---

P. Rungskunroch (✉) · A. Jack · S. Kaewunruen  
School of Engineering, University of Birmingham, Birmingham B15 2TT, UK  
e-mail: [pxr615@student.bham.ac.uk](mailto:pxr615@student.bham.ac.uk)

## 2 Literature Reviews

An attempt to reduce railway accidents has occurred across the railway operators and other related sectors. High technologies and new policies have been applied to the railway operation to eliminate all network risks. As a result, the number of railway accident illustrated slightly decreased in some areas. The European Union agency for railways (ERA) reveals an overall number of Europe's railway accidents that it has been reduced by almost one-third within five years [2]. The evidence can imply that the safety level on the rail network has been successfully improvement. The research deeply studies the causes of railway accidents. We classified them into seven groups including driver's error, signalmen's error, infrastructure failures, improper maintenance, human's error, natural causes, and contributing factors. Nevertheless, the cause of infrastructure failures has slightly increased. It has changed from 4.19% between 2000 and 2010 to 5.14% during 2011–2019.

Regarding the railway accident from infrastructure failures, using high technologies and other monitoring techniques can prevent railway accidents [3, 4]. Previous studies state that installing technologies can increase safety infrastructure, such as using sensors on the rail network to prevent hazardous events [5–7]. Also, some studies suggest providing effective maintenance to the network [8, 9]. However, the failure in railway infrastructure has occurred from climate change. And, it may lead to an unexpected railway accident. Some scholars study on the cold weather impacts on the railway infrastructure in Sweden [10]. The research aims to provide high quality and secure service for winter climate. As a result, the study finds that the weather condition impacts the safety level and suggests improving maintenance condition. Another research also provides a solution to reduce the accident from infrastructure failures. The study stated that installing a thermoelectric heater to heat rail pads is purposed to maintain railway infrastructure's condition [11].

With the aims at evaluating risk among railway network, various methods have been taken to develop risk models. Several studies focus on increasing railway performance by using decision tree (DT) methods [12]. Also, the fuzzy logic and Bayes methods are taken to improve the reliability across the railway industry [13, 14]. On the other hand, some authors plan to avoid railway accident by providing safety policies [15]. Similarity, other research applies the analytical hierarchy process (AHP), maximum absolute weighted residual (MAWR), maximum entropy method (MEM), fault tree analytic (FTA) and Petri-net (PT) methods [16–19]. Several studies also focus on accident analysis to predict the accident rate from long-term accident data. Researchers provide methods to reduce the accident rate on a freight train for dangerous products [18, 20].

These are rarely analysed in the literature about the different damage size on each accident. Also, only a few studies intend with a number of fatalities and injuries passenger. To fill those research gaps, this study examines two novelty models including;

1. The prediction model based on Bayesian theorem to understanding uncertainty and forecasting future accident.

**Table 1** The summary of the infrastructure failures' sub-cause of railway accident

Cause of accident	Sub-cause of accident
Infrastructure failures	Track geometry
	Frogs, switches and track appliances
	Other ways and structure (bridge/design construction)
	Rail joint bar
	Roadbed

2. The risk-based DT model to evaluate the risk level from the long-term railway accident data sets.

By analysing through both novelty models, the study's outcomes show a high accuracy risk score; moreover, the research's prediction model can update real-time information of railway accidents. Those advantages lead to a high-level evaluation of the risk and resilience of the railway infrastructure.

### 3 Methodology

#### 3.1 Data Availability

This study collected railway accidents from official companies, government, and rail authorisations' reports worldwide. Also, the research focuses on passenger train accidents that occurred during 2011–2019 [2, 21, 22]. The 1005 appropriately data sets of infrastructure failures, including injuries and fatalities, are provided in this study.

There are five main sub-causes of infrastructure failures that are frequently investigated after an accident, as shown in Table 1. The research also classified an effect with train after an accident into three groups including collision, derailment, and other effects (such as fire, bomb, and vandalism).

#### 3.2 An Application on the Bayesian Network

The Bayesian statistic is a frequently used analytic tool explaining the probability of two events, which relates to prior knowledge. The Bayesian outcome shows a term of conditional probability. It also can be converted to the likelihood of a single event, as illustrated in Eqs. 1 and 2.

$$P(A|B) = \frac{P(B|A) * P(A)}{P(B)} \tag{1}$$

$$P(B) = \frac{P(B|A) * P(A)}{P(A|B)} \quad (2)$$

Given 'A' is an effect with train after an accident consists of A1 (collision), A2 (derailment), and A3 (other causes). Given 'B' is an infrastructure failure that is one of the causes of a railway accident. Therefore, the posterior probability of train derailment (TD) from railway infrastructure failure (IF) is shown in Eq. 3, and the probability of infrastructure failure is shown in 4 as follows;

$$P(TD|IF) = \frac{P(IF|TD) \times P(TD)}{P(IF)} \quad (3)$$

$$P(IF) = \frac{P(IF|TD) \times P(TD)}{P(TD|IF)} \quad (4)$$

The prediction model has created based on the Bayesian concept through the Python programming language. The causes and effects with a train after an accident are predicted based on the conditional probability through prediction model. The result leads to estimate damage's size of railway accident by infrastructure failures.

### 3.3 Research Framework

Figure 1 shows a whole research framework. The research collected long-term secondary accident data sets from railway companies, authorities, and official report. All the recorded data sets are cleaned and verified. Only the accident data set that occurs from infrastructure failures accidents is taken in the pre-processing stage. Then, the development of the prediction model is provided. In this part, there are two involved with data sets, including the prior belief and likelihood. At the end of this section, the prediction model at 95% efficiency level has been created.

Next, the prediction model has taken to estimate railway accident rate that happens from infrastructure failures. After that, the novelty risk-based decision tree model has been provided to evaluate the risk level. The model involves injuries and fatalities numbers, and the outcome shows in the range 1–32 that score 1–8 means low risk, score 9–16 means moderate risk, 17–24 means high risk, and 25–32 means too high risk.

### 3.4 Risk Prediction Model

The risk and resilience of train accident are hard to predict because it relates to many external factors and contains with uncertainties. This study characterise different aspects of a train after accident into three groups including collision, derailment,

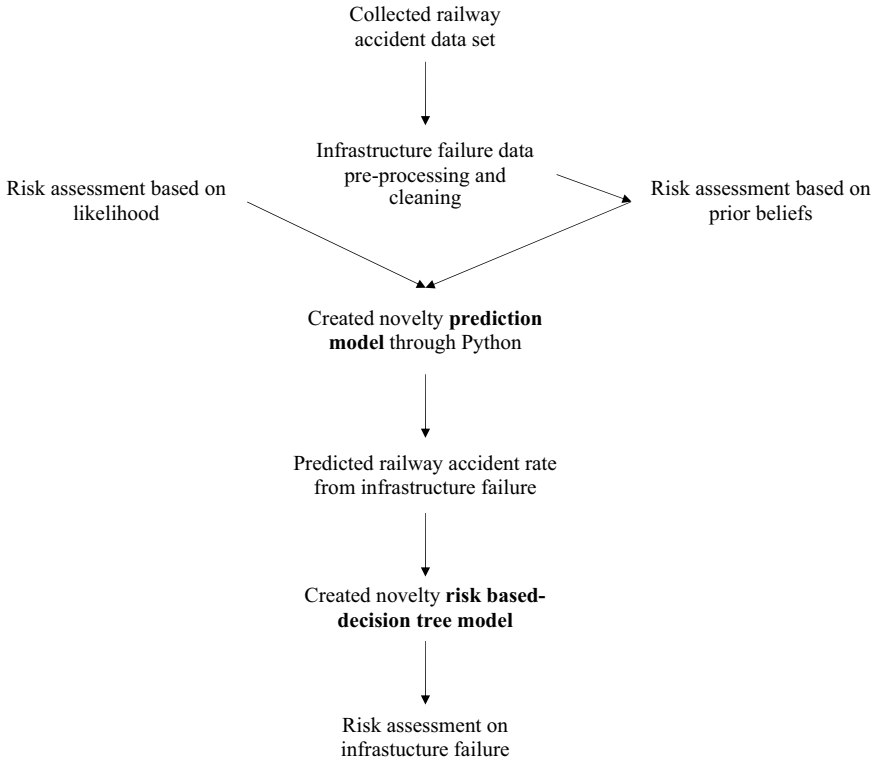


Fig. 1 A whole research framework

and other effects. And, each effect with train after an accident causes difference in damage's size.

Therefore, the risk prediction model has been created to evaluate the future's railway accident risks. The outcome leads to precisely prevent accidents. Within this case, the prediction model adopts the Bayes' theory by using two data sets, including prior knowledge and collected data. The novelty prediction model has been developed through Python. This study found that using posterior distribution at 4:4:1 has provided the highest efficiency prediction result. Also, it has been qualified with FRA's data set at 95% effective level to verify this model's effect.

Figure 2 shows the comparison on the posterior distribution among train collision, derailment, and other effects with train, and the outcome shows probability at 0.279, 0.651, and 0.070, respectively. The result can interpret that the rail's infrastructure failures have a high effect on train derailment.

	mean	sd	hpd_2.5%	hpd_97.5%	mcse_mean	mcse_sd	ess_mean	ess_sd	ess_bulk	ess_tail	r_hat
Collision	0.279	0.074	0.142	0.423	0.002	0.002	1301.0	1179.0	1331.0	1161.0	1.0
Derailment	0.651	0.076	0.508	0.795	0.002	0.001	1302.0	1302.0	1321.0	1133.0	1.0
Other	0.070	0.039	0.010	0.145	0.001	0.001	1938.0	1898.0	1819.0	1225.0	1.0

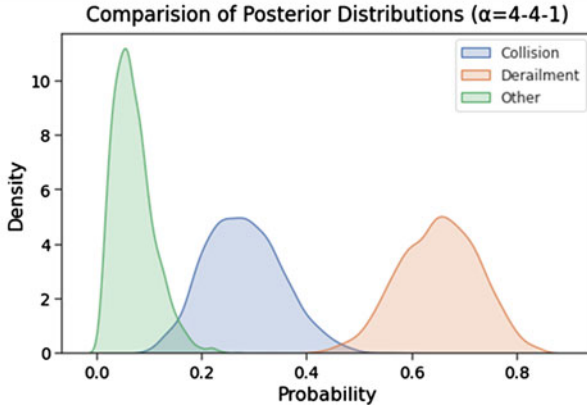


Fig. 2 An analysis of railway risk from infrastructure failures

### 4 Evaluating Risk Level Through DT Models

The DT, which is a non-supervised tool, is widely applied to classify complex decision rules [23]. Within this study, the risk-based DT model is provided to evaluate the risk level. Five essential factors of this research consist of fatalities and injuries rate, probabilities of collision (A1), derailment (A2), and other causes (A3). All factors have been placed as a decision node to design a useful decision tree into the complex decision rules.

Regarding the decision nodes, the research places fatalities rate at 12 people per accident, and injuries rate at 66 people per accident as the main decision nodes. With that, threshold number has been provided by the average number of global railway accident between 2000 and 2019. Next, A1, A2, and A3’s probabilities are placed as a threshold by comparing with the global average A1, A2, and A3 values. As shown in Fig. 3, the outcomes are classified at DT’s leaves into 32 scales of risk levels, which the small number means low risk and large number means high risk.

### 5 Result and Discussions

The analysis result through the DT model shows that the severity level of infrastructure failures equal to 18, which is at a high-risk level, as shown in Fig. 4. Based on the collected data, the accident by infrastructure failures bring an average number of fatalities and injuries at 12 and 66 people per accident. The severity of an accident

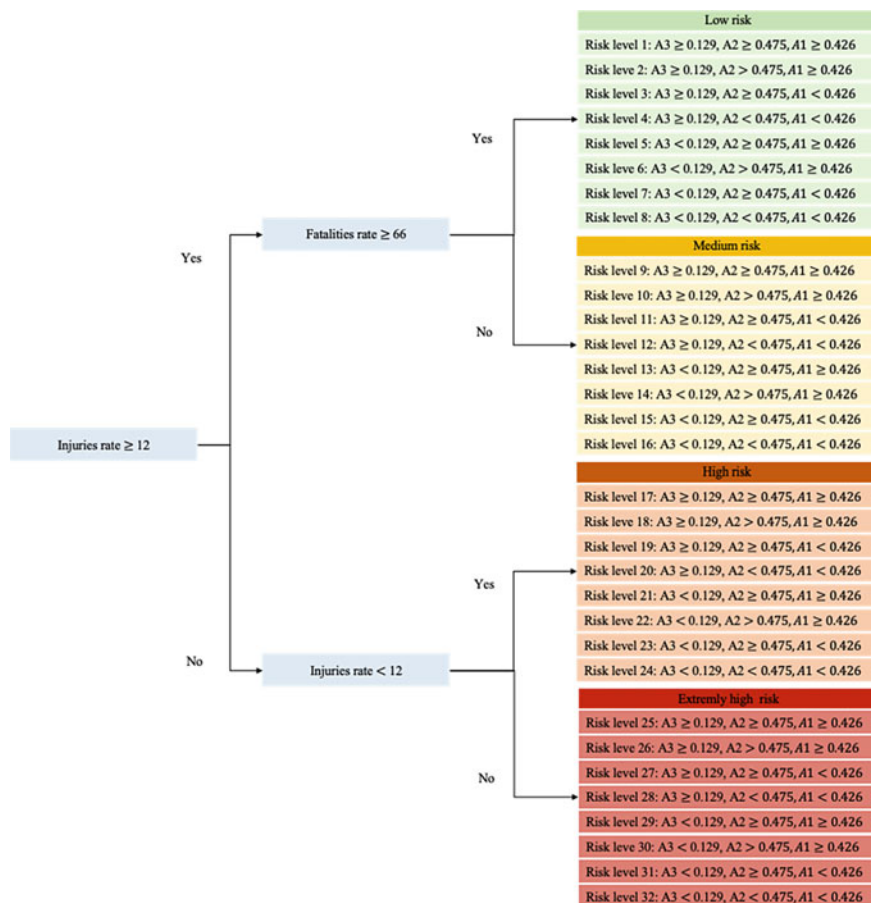
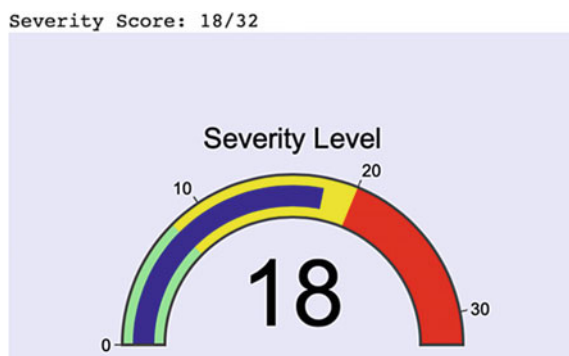


Fig. 3 The created risk-based decision tree framework

Fig. 4 Risk interface's result analysis through the risk-based DT model



compared with other causes of the accident is high. Moreover, the posterior probability of other effects is above the global rate. Therefore, all factors turn the risk level of infrastructure failures into ‘high risk’ level.

Our finding on the risk-based DT states that the railway accident by infrastructure failures should not be neglected. Infrastructure is the most important part of the rail network. The infrastructure failures have occurred from many reasons such as poor design, lack of maintenance, global warming, natural disaster, etc. Hence, its defect is possible to show in ‘high risk’ level. This study provides practical recommendations to avoid future railway accidents as follows;

– *Providing an effective maintenance plan:*

Most of the railway accidents by infrastructure failures have occurred from lack of maintenance. As mentioned, attempting to repair outdated infrastructure is a challenge for a civil engineer [24–26]. It is because some of the railway infrastructures have been built since 1800s such as London underground. Moreover, this study finds that an adequate proper maintenance plan is needed to prevent unexpected railway accident.

– *Increase the safety level on the rail track:*

Due to uncertainty events that can occur during the operation, such as natural disaster, the rail track’s increasing safety level is needed as a critical operation plan. Some issues should be deeply concerned about, such as landslide, drainage flow. Adequate safety and earthwork plans can lead to preventing long-term railway accident.

– *Maintain operational performance:*

As mentioned, the railway accident contains uncertainties, which can be occurred by external factors such as a natural disaster [27, 28]. Therefore, the fundamental improvement is to maintain operational performance into normal conditions. In some cases, installing new equipment on rail’s infrastructure is required to re-operate the system. The research recommends the rail authorities to combines high-technologies with an effective schedule maintenance plan. By following these solutions, they should decrease the accident by infrastructure failures.

## 6 Conclusion and Future Work

With the dramatic growth of railway infrastructure, the evaluation of the railway’s risk and resilience has played an essential role in maintaining the safety level. Rail authorities have provided various policies to reduce the number of railway accidents. Also, the new technologies, equipment, and strategies have been addressed along with the network. However, railway accident contains uncertainties, especially from external factors. Hence, this research generates two new novelty models including (i) the prediction model that uses for estimating future accident. The model adopted



long-term accident data sets and combined with Bayes' theorem. The prediction rate is more than 95%. It becomes a direct benefit to rail authorities to precisely prevent an accident. (ii) The risk-based DT model to evaluate risk level that shows severity level of accident. The model uses long-term data to measure the severity level of an accident by infrastructure failures. The result shows the severity level is scored at 18 of 32, which can be interpreted at 'high risk'. The main conclusion that can be drawn is that the rail accident by infrastructure failures are harmful to a passenger, and it should be eliminated to make the network reach safety level. This study's prediction model illustrates high accuracy outcomes. The model can also be up-to-date, based on real-time railway accidents. Future research should consider the effect of railway accident on infrastructure more carefully by maintaining all equipment in normal conditions. Also, the research relates to high-technologies with rail's infrastructure to prevent severe natural disasters. These can lead to sustainable development on a rail network.

**Acknowledgements** The first author gratefully acknowledges the Royal Thai Government for the Ph.D. scholarship at the University Of Birmingham, United Kingdom and the RISEN funding for one year at University of California, Berkeley. The first author also thanks to the second and third authors for giving recommendation during studying Ph.D. at UOB. The third author acknowledges the Australian Academy of Science (AAS) and the Japan Society for the Promotion of Sciences (JSPS), for the JSPS Invitation Fellowship for Research (Long-term), Grant No. JSPS-L15701, at the Railway Technical Research Institute (RTRI) and the University of Tokyo, Japan. The authors are sincerely grateful to the European Commission for the financial sponsorship of the H2020-RISEN Project No. 691135 "RISEN: Rail Infrastructure Systems Engineering Network", which enables a global research network that tackles the grand challenge of railway infrastructure resilience and advanced sensing in extreme environments ([www.risen2rail.eu](http://www.risen2rail.eu)).

## References

1. UIC: UIC Safety report 2019—Significant Accident Public report (2019). ISBN 978-2-7461-2863-7
2. ERA (European union agency for railway): ERAIL database (2018). Available at: [https://www.era.europa.eu/activities/rail-accident-investigation\\_en](https://www.era.europa.eu/activities/rail-accident-investigation_en). Accessed on 20 Dec 2020
3. Ngamkhanong, C., Kaewunruen, S., Costa, B.J.A.: State-of-the-Art review of railway track resilience monitoring. *Infrastructures* **3**, 3 (2018)
4. Kaewunruen, S., Wu, L., Goto, K., Najih, Y.M.: Vulnerability of structural concrete to extreme climate variances. *Climate* **6**, 40 (2018)
5. El Miloudi, El Koursi, Bruyelle, J.L: Railway accident prevention and infrastructure protection. *J. Civil Eng. Architecture*, David Publishing Company, pp. 96–107 (2016). <https://doi.org/10.17265/1934-7359/2016.01.010>
6. Krezo, S., et al.: Field investigation and parametric study of greenhouse gas emissions from railway plain-line renewals. *Transp. Res. Part D: Transp. Environ.* (2016). <https://doi.org/10.1016/j.trd.2015.10.021>
7. Kaewunruen, S., Sussman, J.M., Matsumoto, A.: Grand challenges in transportation and transit systems. *Front. Built Environ.* (2016). <https://doi.org/10.3389/fbuil.2016.00004>
8. Al-Douri, Y.K., Tretten, P., Karim, R.: Improvement of railway performance: a study of Swedish railway infrastructure. *J. Mod. Transport.* **24**, 22–37 (2016). <https://doi.org/10.1007/s40534-015-0092-0>

9. Lu, C., Cai, C.: Overview on safety management and maintenance of high-speed railway in China. *J. Transp. Geotechnics* **25** (2020). <https://doi.org/10.1016/j.trgeo.2020.100397>
10. Stenström, C., Famurewa, S.M., Parida, A., Galar, D.: Impact of cold climate on failures in railway infrastructure. In: *The Second International Congress on Maintenance Performance Measurement & Management Conference*, University of Sunderland, Sunderland, UK, pp. 1–9, 12–13 September 2012
11. Yang, F., Gao, M., Cong, J., Wang, P.: System dynamics modelling and experimental study of railway track with thermoelectric heater/generator in extreme weather conditions. *J. Cleaner Prod.* **249**,(2020). <https://doi.org/10.1016/j.jclepro.2019.119367>
12. Zhou, J.L., Lei, Y.: A slim integrated with empirical study and network analysis for human error assessment in the railway driving process. *Reliab. Eng. Syst. Saf.* (2020). <https://doi.org/10.1016/j.res.2020.107148>
13. Dindar, S., et al.: Bayesian Network-based probability analysis of train derailments caused by various extreme weather patterns on railway turnouts. *Saf. Sci.* (2018). <https://doi.org/10.1016/j.ssci.2017.12.028>
14. Jia, C., Xu, W., Wang, H.: Study of management information system of railway permanent way safety risks and comprehensive evaluation. In: *Procedia Engineering* (2011). <https://doi.org/10.1016/j.proeng.2011.08.239>
15. Dindar, S., Kaewunruen, S., An, M.: Bayesian network-based human error reliability assessment of derailments. *Reliab. Eng. Syst. Saf.* (2020). <https://doi.org/10.1016/j.res.2020.106825>
16. Song, H., Schnieder, E.: Evaluating fault tree by means of colored petri nets to analyse the railway system dependability. *Saf. Sci.* (2018). <https://doi.org/10.1016/j.ssci.2018.08.017>
17. Liu, C., et al.: An improved risk assessment method based on a comprehensive weighting algorithm in railway signaling safety analysis. *Saf. Sci.* (2020). <https://doi.org/10.1016/j.ssci.2020.104768>
18. Huang, W., Liu, Y., et al.: Fault tree and fuzzy D-S evidential reasoning combined approach: an application in railway dangerous goods transportation system accident analysis. *Inf. Sci.* (2020). <https://doi.org/10.1016/j.ins.2019.12.089>
19. Vileiniskis, M., Remenyte-Prescott, R.: Quantitative risk prognostics framework based on Petri Net and Bow-Tie models. *Reliab. Eng. Syst. Saf.* (2017). <https://doi.org/10.1016/j.res.2017.03.026>
20. Harris, N., Ramsey, J.: Assessing the effects of railway infrastructure failure. *J. Oper. Res. Soc.* **45**, 635–640 (1994). <https://doi.org/10.1057/jors.1994.101>
21. ETSC (European Transport Safety Council): *Transport Safety Performance in the EU a Statistical Overview* (2003). Available at: [https://etcs.eu/wp-content/uploads/2003\\_transport\\_safety\\_stats\\_eu\\_overview.pdf](https://etcs.eu/wp-content/uploads/2003_transport_safety_stats_eu_overview.pdf). Accessed on: 28 Feb 2021
22. Eurostat (EC): *Rail accident fatalities in the EU* (2020). Available at: [https://ec.europa.eu/eurostat/statistics-explained/index.php/Rail\\_accident\\_fatalities\\_in\\_the\\_EU](https://ec.europa.eu/eurostat/statistics-explained/index.php/Rail_accident_fatalities_in_the_EU). Accessed on: 28 Feb 2021
23. Zheng, Z., Lu, P., Tolliver, D.: Decision tree approach to accident prediction for highway-rail grade crossings: empirical analysis. *Transp. Res. Rec.* (2016). <https://doi.org/10.3141/2545-12>
24. Kaewunruen, S., Sussman, J.M., Einstein, H.H.: Strategic framework to achieve carbon-efficient construction and maintenance of railway infrastructure systems. *Front. Environ. Sci.* (2015). <https://doi.org/10.3389/fenvs.2015.00006>
25. Rungskunroch, P., Kaewunruen, S., Shen, Z.-J.: An improvement on the end-of-life of high-speed rail rolling stocks considering cfrp composite material replacement. *Front. Built Environ.* **5**,(2019). <https://doi.org/10.3389/fbuil.2019.00089>
26. Binti Sa'adin, S.L., Kaewunruen, S., Jaroszweski, D.: Heavy rainfall and flood vulnerability of Singapore-Malaysia high speed rail system. *Austr. J. Civil Eng.* (2016). <https://doi.org/10.1080/14488353.2017.1336895>

27. Sáadin, S.L.B., Kaewunruen, S., Jaroszweski, D.: Operational readiness for climate change of Malaysia high-speed rail. In: Proceedings of the Institution of Civil Engineers: Transport (2016). <https://doi.org/10.1680/jtran.16.00031>
28. Binti Sa'adin, S.L., Kaewunruen, S., Jaroszweski, D.: Risks of climate change with respect to the Singapore-Malaysia high speed rail system. *Climate* **4**, 65 (2016)