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Implications of Climate Change in Life Cycle Cost Analysis of Railway Infrastructure

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Abstract:
Extreme weather conditions from climate change, including high or low temperatures, snow and ice, flooding, storms, sea level rise, low visibility, etc., can damage railway infrastructure. These incidents severely affect the reliability of the railway infrastructure and the acceptable service level. Due to the inherent complexity of the railway system, quantifying the impacts of climate change on railway infrastructure and associated expenses has been challenging. To address these challenges, railway infrastructure managers must adopt a climate-resilient approach that considers all cost components related to the life cycle of railway assets. This approach involves implementing climate adaptation measures to reduce the life cycle costs (LCC) of railway infrastructure while maintaining the reliability and safety of the network. Therefore, it is critical for infrastructure managers to predict "How will maintenance cost be affected due to climate change on different RCP's scenarios?"

The proposed model integrates operation and maintenance costs with reliability and availability parameters such as mean time to failure (MTTF) and mean time to repair (MTTR). The proportional hazard model (PHM) is used to reflect the dynamic effect of climate change by capturing the trend variation in MTTF and MTTR. A use case from a railway in North Sweden is studied and analyzed to validate the process. Data collected over a 20-year period is analyzed for the chosen use case. As a main result, this study has revealed that climate change may significantly influence the LCC of switch and crossing (S&C) and can help managers to predict the required budget.

Keywords: life cycle cost (LCC) analysis, switch and crossing(S&C), railway infrastructure, climate adaptation

1. Introduction

Switches and crossings (S&Cs) are mechanical devices used in railway systems to direct trains from one track to another. They are especially critical in complex railway networks. Despite many efforts to improve design and reliability, S&Cs are more complicated in design, construction, and application, so they are exposed to more stress than simple lines, leading to more damage. According to the International Union of Railways report, S&Cs are a significant cost driver, accounting for about 25% to 30% of the total maintenance and renewal annual budget. The complexity and high susceptibility to damage of S&Cs make their maintenance a vital component of ensuring the safety and reliability of railway systems. Life cycle cost (LCC) analysis is a powerful tool for managers to evaluate the actual costs of assets to plan budgets.

Zoeteman (2001) proposed a life cycle cost approach to facilitate design and maintenance decision-making, even without advanced maintenance planning tools, employing expert judgment alongside empirical data. Nissen (2009) investigated the LCC values of S&Cs in the Swedish rail network to understand design and maintenance strategy improvements that can be planned to reduce the life cycle cost by displaying quantitative values. Reddy et al. (2007) presented the development of models on the maintenance cost of rail tracks according to rolling contact fatigue (RCF), traffic wear, and lubrication. By comparing industry reports and previous research assessments, Tavares and Kaewunruen presented the LCC approach and conducted a cross-cutting economic analysis of the implementation, operation, and maintenance strategies Tavares de Freitas and Kaewunruen (2016)(Tavares de Freitas and Kaewunruen (2016). A stochastic LCC model for the rail of the railway track that incorporates poor inspections was developed. In order to enable quantification of the related uncertainty within the estimated LCC using the Monte Carlo simulation, a new model was designed (Vandoorne and Gräbe 2018). LAPASOV et al. (2019) analyzed the S&C's life cycle and divided it into subsystems to determine critical components and their need for maintenance. They gave an example of how to choose the most appropriate S&C using system breakdown and cost identification. Cahyo et al. (2021) developed a cost-effective strategy to assist companies in purchasing and managing the inventory of critical engine parts. They showed that using LCC calculation with Monte Carlo simulation can aid decision-makers in identifying the most cost-effective approach over the long term.

For railway S&Cs, LCC includes purchase price, maintenance and repair expenses, and replacement costs. LCC analysis can help organizations make informed decisions and optimize investments. Determining LCC for railway infrastructure is complex due to uncertainties such as traffic density, axle loads, and speed. The LCC formula includes design, installation, maintenance, and replacement costs. The total cost of ownership can be estimated by adding these costs. O&M costs are an important factor to consider when evaluating the LCC of an S&C. Factors such as design life, materials used, environmental conditions (e.g., high precipitation or extreme temperature), and traffic volume impact maintenance activities.

Climate change and its associated impacts, e.g., extreme weather severity and frequency, have a detrimental effect on the efficiency of rail operations and associated expenses. Extreme weather phenomena, including heavy rain, snowfall, freezing temperatures, and strong winds, have the potential to cause disruptions and malfunctions in the railway infrastructure of northern Europe. According to research, adverse climatic conditions are responsible for 5 to 10% of overall system failures and 60% of delays in this railway network region (Garmabaki et al. 2021). Swarna et al. (2022) evaluated the Global Warming Potential (GWP) of life cycle assessment (LCA) and LCCA for climate change adaptation options in diverse Canadian locales. In another research, the impacts of climate change on the operation of the US rail network were investigated by Cahyo et al. (2021). The potential sensitivity of the US rail system to projected temperature rises from climate change is highlighted in their study. Garmabaki et al. (2022) presented recommendations for achieving climate resilience in transportation networks by examining the effects of climate change on railway infrastructure.

The impact of climate change on maintenance can affect the cost of repairing actions as a secondary effect. Extreme weather conditions are causing various failures, and infrastructure management must plan for repairs, which can be costly. In this research, the impact of climate change on the repair cost of S&C is investigated for the north of Sweden, utilizing Cox PH model. Furthermore, assessing climate impact on railway assets requires fusing various sparse databases, including maintenance database asset registry, weather station data, and expert knowledge information. The rest of the paper is as follows; data collection is explained in Section 2. Cost analysis is discussed in Section 3. The methodology and case study are discussed in Section 4. Finally, in Section 5, the results of this study are provided.

2. Data collection and data analysis

The data has been collected from various sources, including the Ofelia (from Trafikverkets failure system) database, which contains information on all failures reported to the train control center, and the BIS database (Asset Information System), which provides information on the assets involved in the reported failures. Combining these two databases provided the essential dataset for the analysis process. The Climate ID was extracted from Ofelia database for each individual failure. Climate ID is an ID developed within the CliMaint project to extract the failures associated with the cause code for each weather parameter. Climate ID is helpful in identifying and investigating climate-related failures and describes how it impacts railway operations.

Figure 1 illustrates the percentage of failures in various regions in Sweden. Figure 2 and Figure 3 illustrate the non-climate and climate failures in different Sweden zones, respectively. The number of assets that existed in each district is shown in Figure 4. In the current research, the Nord area has been selected as a case study. Asset in Nord area of Sweden includes 11.0 percent of the total assets, which contribute to 25 percent of climatic failure. The Nord region data was extracted from the original database in the first step. After analyzing the failure dates, we calculated the repair time and selected data with a repair time of less than 480 minutes, as the experts recommended. Because at some railway stations, maintenance for S&Cs may not be prioritized, especially if there are multiple S&Cs that fail and remain unused for long periods. Also, climatic failures do not need a long time of reparation.

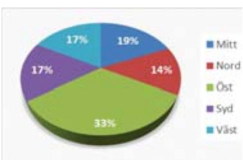

Figure 1 Distribution of failures in different regions

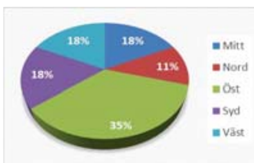

Figure 2 Distribution of NonClimatic failures in different zones

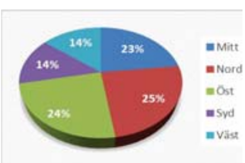

Figure 3 Distribution of climatic failures in different regions

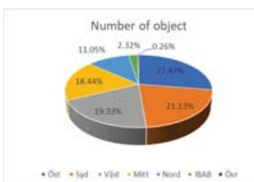

Figure 4 Distribution of assets in different regions

3. Cost Analysis

The cost of developing S&Cs includes expenses related to acquisition and installation, which are generally constant. In this study, we are focusing on operational costs associated with repair and maintenance actions. Thus, some maintenance actions, including snow cleaning (Snöröjning), Cleaning (Rensning), Repair (Reparation), Washing (Rengöring), Lubrication (Smörjning), Control (Kontroll), Adjustment (Justering), and Recovery (Återställning) are considered. The percentage of these actions can be seen in Table 1. By analyzing this data, we can better understand the specific actions that are most frequently performed and identify potential areas for improvement in terms of reducing operational costs and improving overall performance. According to available data, snow cleaning has the highest cost of about 35% (Figure 5),

Table 1 Maintenace actions for climatic failure in Sweden

Actions	Percentage
Snow cleaning	41.88%
Cleaning	26.20%
Adjustment	9.60%
Washing	9.47%
Lubrication	4.12%
Control	1.84%
Reparation	1.33%
Recovery	1.05%
Other	4.06%

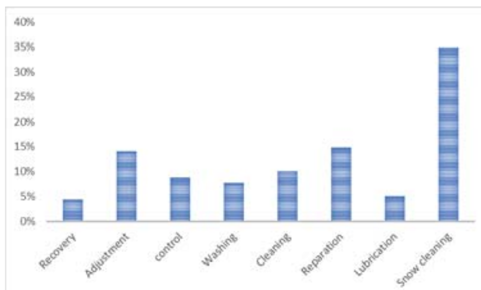

Figure 5 Distribution of actions cost in Nord zone.

The analysis of extreme weather conditions revealed six categories: Abnormal temperature, Flood, Fire, Snow and Ice, Strom/snowstorm, and thunderstorm. Among these categories, the frequency of Fire, Flood, and Thunderstorms is relatively low compared to the other categories for S&C assets. The main climatic reasons for failures in the Nord region are Snow and Ice, Abnormal temperature, and Strom/Snowstorms. According to analysis in this region, climatic failures account for 52% of all failures, while non-climatic failures account for 48%. Table 2 shows the cost of climatic failures in the Nord region. As can be seen, 83.3% of the climatic failure costs are related to Snow and Ice, indicating that actions to mitigate the impact of this weather condition are essential for the region.

Table 2 Cost according to Climate ID for Nord region

Climate ID	Percentage of cost repair
Abnormal temperature	6.68%
Fire	0.01%
Flood	0.02%
Snow and ice	83.28%
Storm / Snowstorm	9.94%
Thunderstorm	0.07%

Figure 6 illustrates the cost percentage for each maintenance action across all parts of the S&C system. This analysis provides a comprehensive view of the cost distribution across different maintenance actions and can help prioritize actions that are more expensive and potentially have a greater impact on system reliability.

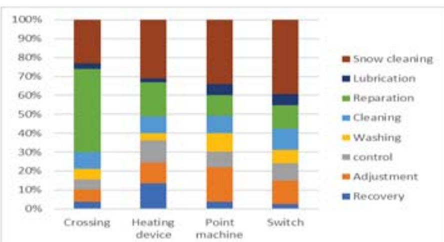

Figure 6: The cost of actions according to each part of S&C

Figure 7 shows the cost percentage of each action for a specific asset (asset ID 2960022). The cost breakdown for each asset can vary depending on its location, usage, and other factors, and identifying these differences can help optimize maintenance plans for each asset individually.

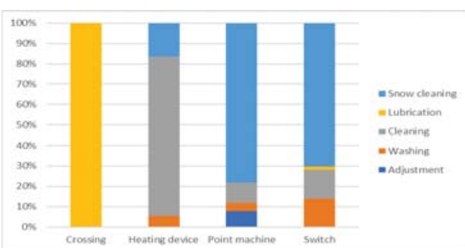

Figure 7 The cost of actions for S&C #2960022

The maintenance and repair costs play the main role in LCC analysis. The present value of all costs over the expected service life of the S&C is obtained using an appropriate discount rate to account for the time value of money. The various actions taken to treat component failures should be reflected in the LCC model for S&C maintenance. Due to their criticality and failure rate, we are just focusing on the switch, point machine, crossing, and heating system. The cost per action is one of the most challenging pieces of information to obtain when developing the LCC model. Depending on the information available, the model will be more precise in determining costs. In this study, the cost is modeled using the following equation Calle-Cordón et al. (2018):

$$LCC = n_s \sum_k \sum_i \sum_j \frac{1}{(1+r)^k} \frac{M}{MTBF_{ij}} \{C_{P_j} + MTTR_{ij}(n_{L_i} C_L + C_{E_i})\} \quad (1)$$

Where, n_s is the number of S&C; the sums run over the type of action, type of component, and number of periods (in years); MTBFij is the Mean-Time-Between-Failure of component j and a failure mode associated to action i; M is the mean-time to do one action; CP is the cost of the component (in monetary units); MTTRij is the Mean-Time-To-Repair of component j (in minute unit) and a failure mode associated to action i; n_L is the number of workers needed for a given action; C_L is labor cost (in monetary units/hour); and C_E is the equipment cost needed to carry out the intervention.

4. Framework

Figure 8 depicts the framework of the analysis process, including three main steps:

- data collection and data preprocessing,
- identify the model for LCC and RAMS,
- impact of climate change on LCC.

4.1 Data collection and data preprocessing

As described in Section 2, the initial dataset was constructed from two databases, and then for this dataset, preprocessing was done to ensure its quality. Preprocessing involved cleaning the data to remove invalid or incorrect values and eliminating outliers that could affect the analysis results.

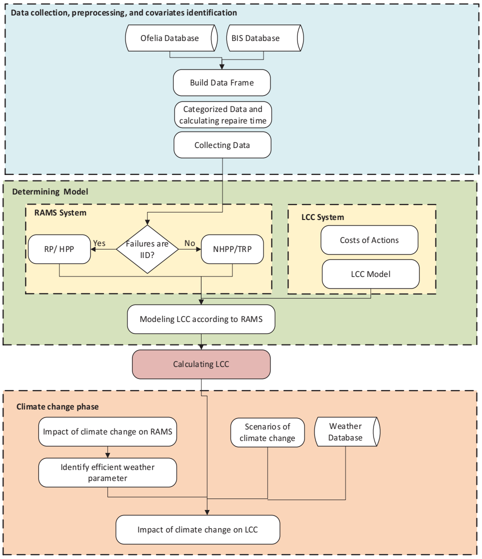

Figure 8 Framework of workflow

4.2 LCC model parameters according to RAMS analysis

In this section, the model presented in Equation 1 is utilized for LCC analysis. MTBF and MTTR for action ith and component jth must be estimated. MTTRs are calculated on the duration of 2001-2018; results are shown in Table 33. The trend test is implemented at the first step for estimation of MTBF to determine whether the failure data follow homogeneous behavior. This test is carried out to see if the cumulative failure time significantly increases or decreases, which can provide important details about the system or component's reliability.

Table 3 Mean time to repair

Actions	Switch	Crossing	Point Machin	Heating Device
Snow cleaning	71.108	87.305	66.05	71.262
Adjusment	65.828	126.72	68.783	76.645
Control	52.483	48.729	50.397	57.859
Reparation	110.821	184.306	115.629	102.375
Recovery	65.348	121.758	84.623	65.471
Cleaning	56.633	57.945	56.823	57.121
Washing	64.331	57.624	63.877	66.707
Lubrication	52.341	42.06	55.261	48.225

The statistical analysis results indicate that the null hypothesis was rejected for Snow cleaning, Adjusment, Recovery, and Cleaning actions per component in all statistical tests, and the cumulative failure time shows the trend. On the other hand, for some actions including Control, Repairation, Washing, and Lubrication , there were not enough evidence to reject null hypothesis. The switch part's results are presented in Table 4.

Table 4 Trend test for all actions of Switch part

	Actions	beta	theta	t0	Distribution
Switch	Snow cleaning	1.276	563.62		NHPP
	Adjustment	0.758	18.73		NHPP
	Control	0.8423	167.66		Weibull 2P
	Reparation	0.8831	238.31	0.51656	Weibull 3P
	Recovery	1.441	3935.7		NHPP
	Cleaning	1.8	3384.4		NHPP
	Washing	0.5528	166.47	0.0165	Weibull 3P
	Lubrication	0.6899	222.19	0.01656	Weibull 3P

4.3 Calculating LCC

Equation 1 is utilized to determine the LCC over a span of 26 years. Figure 9 shows the evolution of the cost of maintenance in this period. As can be seen, the 'Snöröjning' (Snow Cleaning) shows the highest portion of the total cost over the mentioned period, and the 'Reparation' has the next rank.

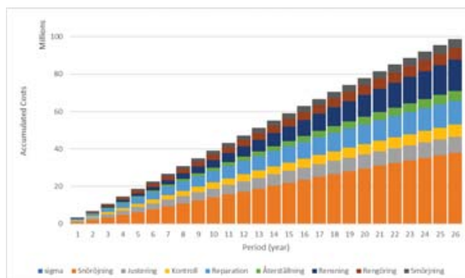

Figure 9 Maintenance costs in a 26-year period

4.4 Impact of climate change on LCC

There are several scenarios of the climate change approach. The 2013-2014 assessment report AR5 of the UN Climate Panel (IPCC) employs four scenarios known as RCPs or "Representative Concentration Pathways" to predict future climate changes SMHI (2023). Four RCP scenarios, RCP2.6, RCP4.5, RCP6, and RCP8.5, differ in their assumptions about future climate scenarios. Also, the SSP Scenario, or Shared Socioeconomic Pathways Scenario, describes different socioeconomic developments. The five SSP scenarios are SSP1 (Sustainability), SSP2 (Middle of the Road), SSP3 (Regional Rivalry), SSP4 (Inequality), SSP5 (Fossil-Fueled Development) Masson-Delmotte et al. (2021). In these scenarios, the focus is primarily on long-term trends in global climate and greenhouse gas emissions. However, the effects of climate change can be seen in changes to local weather patterns and extreme weather events, such as heatwaves, droughts, floods, and storms. Figure 10 illustrates the precipitation of these scenarios for Norrbotten in Sweden.

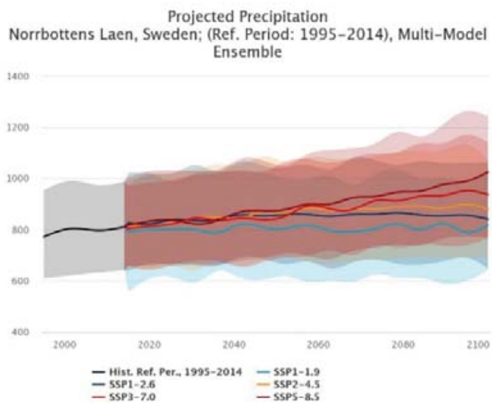

Figure 10 Precipitation Scenario World Bank Group (2021)

This study uses the proportional hazards model to identify climate parameters' impact on the hazard rate. We consider two approaches to using climate change scenarios: the first approach is investigating the impact of the precipitation as a climate change parameter in reliability variables (time between failure) for Nord area. The second approach is the research on the impact of weather parameters as climate change parameters on reliability parameters for a specific asset (Asset ID 2960022).

4.4.1 Impact of climate change on reliability parameters

Cox proportional hazards model (Cox 1972) was used to identify the main climate parameters that impact the railway asset. The model assumes that the hazard function can be decomposed into the multiplication of a baseline and exponential functions linked to the effects of the explanatory variables, also known as covariates (Bendell, Wightman, and Walker 1991). The hazard model formula for the Cox PH model, is shown in Equation 2:

$$h(t, \boldsymbol{X}) = h_0(t) e^{\sum_{i=1}^{p} \beta_i X_i} \quad (2),$$

where X is the predictor vector variable. A hazard ratio (HR) represents the hazard for one individual divided by the hazard for another individual, where the individuals being compared differ in their predictor values, denoted by X's.

$$HR = \frac{h(t, \boldsymbol{X_2})}{h(t, \boldsymbol{X_1})} = \frac{h_0(t) e^{\sum_{i=1}^{p} \beta_i X_{2i}}}{h_0(t) e^{\sum_{i=1}^{p} \beta_i X_{1i}}} = e^{\sum_{i=1}^{p} \beta_i (X_{2i} - X_{1i})} \; (3)$$

The prepared dataset for Cox PH analysis, including temperature, humidity, precipitation, and wind speed, were chosen from the data available on the SMHI website. It is important to note that the effects of the selected covariates are not immediate but gradual. Therefore, the average hourly value of covariates during the 24 hours preceding the failures is calculated and used as input in the Cox PH model to account for the meteorological effects.

4.4.2 Use-case 1:Nord area

In this section, we used five S&Cs as a sample for conducting Cox PH analysis. The covariate values and time between failures were used to set up the Andersen-Gill model using STATA 15 software. The model reveals that humidity and Wind speed are ineffective; therefore, Temperature and Precipitation are selected for the analyses. Table 5 shows the results of the Cox PH model after dropping the Humidity and Wind speed parameters.

Table 5 Results after dropping humidity and wind speed parameters

Covariate	Coef. β_i	HR	P-value
Temperature (T)	-0.05	0.95	0.00
Precipitation (P)	1.94	6.96	0.00

Based on the data provided, the average precipitation in Sweden during the reference period 1971-2000 was 58 mm/month. The RCP4.5 scenario predicts that the average precipitation during the period 2011-2040 will be 63 mm/month, indicating an increase of about 8%. Additionally, the average temperature is expected to increase from 2.3 Celsius to 3.9 Celsius, representing a temperature rise of about 41% SMHI (2023). When these variations are incorporated into Equation 3, it can be estimated that the hazard rate will increase by approximately 14%. By applying this parameter in LCC model, the amount of LCC can rise to 14% value after year 18th. Figure 11 shows the variation of LCC over 26 years. The blue bars indicate the cost without considering the climate change scenario, and the red one considers the precipitation due to SSP2 4.5 scenario. It can be found that the effect of climate change in this scenario is associated with a significant influence on LCC.

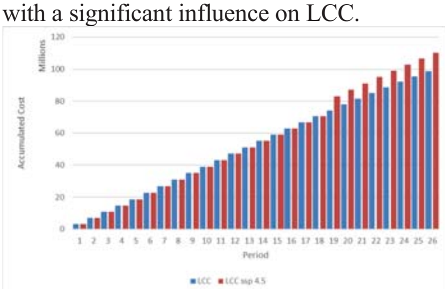

Figure 11 Impact of Precipitation on Cost Maintenance according to Scenario RCP 4.5 or SPP2

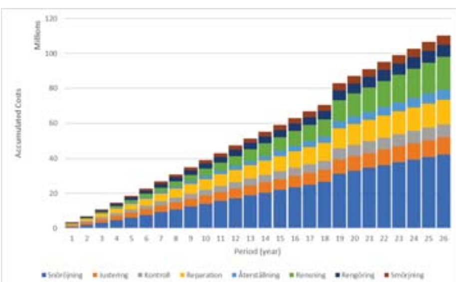

Figure 12 Impact of Precipitation on Cost Maintenance according to Scenario RCP 4.5 for each action

Figure 12 presents the cost of the different actions; it shows that snow cleaning cost includes 25 to 38 percent of the total cost over the 26 years, and reparation actions cost differs between 13 to 15 percent. Moreover, the summation of these costs is more than 51 percent of LCC over the 26 years. In addition, the Lubrication (Smörjning) action cost includes 5 percent of the total cost over the same period.

4.4.3 Use-case 2: A specific asset

This use-case describes a particular asset (#2960022)which is located in the northern region, which experiences high precipitation levels. The model reveals that humidity and Wind speed are ineffective; therefore, Temperature and Precipitation are selected for the analyses.

Table 6 shows the results of the Cox PH model after dropping the Humidity and Wind speed parameters.

Table 6 Results after dropping humidity and wind speed parameters

Covariate	Coef. β_i	HR	P-value
Temperature (T)	-0.05	0.95	0.00
Precipitation (P)	4.52	92	0.00

Similar to Use-case 1, according to RCP4.5 scenario and using Equation 3, it can be estimated that the hazard rate will increase by about 40% for this asset. The variation of this increment in LCC is shown in Figure 13. Based on the information presented in Figure 13, if the increment of precipitation and temperature according to RCP4.5 will occur, then it is evident that the annual cost significantly increases after the 18th year. An 8% increase in precipitation could substantially impact this asset's Hazard rate and LCC.

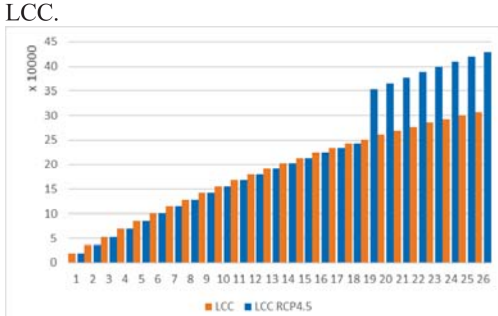

Figure 13 Impact of Precipitation on Cost Maintenance according to Scenario RCP 4.5 for asset #2690022

5. Conclusion

The LCC is a useful tool for infrastructure managers to compare different alternatives based on their total life cycle costs and provide them with a significant indicator to consider their plans in the long term.

On the other side, the effect of climate change on transport infrastructures' operation is noticeable.

Therefore, decision-makers need to consider climate change consequences in their decision-making process. In this paper, after constructing and integrating several databases, the LCC model has been developed. Two use-cases have been considered to assess the impact of climate change on LCC, and the result is compared. The results have shown that the change in precipitation pattern according to RCP 4.5 scenario will lead to a 14 percent increase in total cost for the Nord area and a 40 increase in total cost for a specific asset. In the future, we are working on utilizing machine learning to extract different patterns of impacts on LCC.

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Bibliography

Cahyo, Winda Nur, Riza SI Raben, Haryo Prawahandaru, Bayu A. Swasono, Riyan Tri Sutartono, and Taufiq Immawan. 2021. "Policy Analysis on Spare Part Inventory of Critical Asset with Life Cycle Cost Approach."IOP Publishing, .

Calle-Cordón, A., Noemi Jiménez-Redondo, J. Morales-Gámiz, F. García-Villena, J. Peralta-Escalante, Amir Garmabaki, Stephen Mayowa Famurewa, Emanuel Duarte, and João Morgado. 2018. "Combined RAMS and LCC Analysis in Railway and Road Transport Infrastructures." Proceedings of the 7th Transport Research Arena TRA.

Garmabaki, A. H. S., Johan Odelius, Adithya Thaduri, Stephen Mayowa Famurewa, Uday Kumar, Gustav Strandberg, and Javad Barabady. 2022. "Climate Change Impact Assessment on Railway Maintenance."Research Publishing, .

Garmabaki, AHS, Adithya Thaduri, Stephen Famurewa, and Uday Kumar. 2021. "Adapting Railway Maintenance to Climate Change." Sustainability 13 (24): 13856.

LAPASOV, Furkat, Kyuhyoung Choi, and LEE Jongwoo. 2019. "A Study on Life Cycle Cost on Railway Switches and Crossings."IEEE, .

Masson-Delmotte, Valérie, Panmao Zhai, Anna Pirani, Sarah L. Connors, Clotilde Péan, Sophie Berger, Nada Caud, Y. Chen, L. Goldfarb, and M. I. Gomis. 2021. "Climate Change 2021: The Physical Science Basis." Contribution of Working Group I to the Sixth Assessment Report of the Intergovernmental Panel on Climate Change 2.

Nissen, Arne. 2009. "Development of Life Cycle Cost Model and Analyses for Railway Switches and Crossings." International Journal of COMADEM 12 (2): 10-19.

Reddy, Venkatarami, Gopinath Chattopadhyay, Per-Olof Larsson-Kråik, and Doug J. Hargreaves. 2007. "Modelling and Analysis of Rail Maintenance Cost." International Journal of Production Economics 105 (2): 475-482.

SMHI. "Advanced Climate Change Scenario Service." SMHI., https://www.smhi.se/en/

Swarna, Surya Teja, Kamal Hossain, and Alyssa Bernier. 2022. "Climate Change Adaptation Strategies for Canadian Asphalt Pavements; Part 2: Life Cycle Assessment and Life Cycle Cost Analysis." Journal of Cleaner Production 370: 133355. doi:10.1016/j.jclepro.2022.133355.

Tavares de Freitas, Rodrigo and Sakdirat Kaewunruen. 2016. "Life Cycle Cost Evaluation of Noise and Vibration Control Methods at Urban Railway Turnouts." Environments 3 (4): 34.

Vandoorne, Rick and Petrus J. Gräbe. 2018. "Stochastic Rail Life Cycle Cost Maintenance Modelling using Monte Carlo Simulation." Proceedings of the Institution of Mechanical Engineers, Part F: Journal of Rail and Rapid Transit 232 (4): 1240-1251.

World Bank Group. "Climate Change Knowledge Portal.", https://climateknowledgeportal.worldbank.org/.

Zoeteman, Arjen. 2001. "Life Cycle Cost Analysis for Managing Rail Infrastructure: Concept of a Decision Support System for Railway Design and Maintenance." European Journal of Transport and Infrastructure Research 1 (4).

[a] www.ltu.se/adapturbanrail

[b] www.ltu.se/CliMaint